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DOI: https://doi.org/10.64388/IREV9I8-1714016

Water Supply in Ibadan North Local Government

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Abstract- Access to reliable water supply remains a major challenge in rapidly urbanizing cities of developing countries. This project was undertaken to examine the water supply situation in Ibadan North Local Government Area, with the aim of understanding the sources of water available to residents, the level of adequacy and reliability of supply, and the challenges faced in meeting daily water needs. The choice of the study area was informed by its high population density and its importance as a residential and commercial hub within Ibadan metropolis. Structured questionnaire were administered to residents to assess the water supply, determine the water consumption of the study area. The result of the questionnaire were analyzed using Microsoft Excel. A well yield test was carried out to know how much water flows into the well from surrounding rock or soil ion a given time, the water supply for the area was designed. For the prediction of household water demand, Machine learning algorithms which includes linear regression, SVR, Neural Network, random forest regression models were developed and evaluated using metrics like MAE, RMSE, MAPE and R2 The study combines field data, observations, and analytical methods to provide a realistic picture of water supply conditions in the area. Emphasis was placed on presenting findings in a clear and practical manner so that the outcomes of the study can be useful not only for academic purposes but also for policy makers, water supply agencies, and other stakeholders involved in urban water management. The random forest model outperformed the linear model, achieving an R2 of 0.99 It is hoped that the findings and recommendations presented in this project will contribute, in a modest way, to ongoing efforts aimed at improving water supply planning and management in Ibadan North Local Government Area and similar urban settings.

Keywords: Evaluation, Household Characteristics, Ibadan North, Machine Learning, Water Supply

I. INTRODUCTION

Water supply is essential for public health, economic development, and environmental sustainability. However, many urban centers in sub-Saharan Africa continue to experience water shortages due to rapid population growth, aging infrastructure, climate variability, and poor planning. In Nigeria, less than half of urban residents have reliable access to piped water, forcing many households to depend on wells, boreholes, and water vendors.

Access to clean and sufficient water is one of the most fundamental needs of any urban population. Yet, across many cities in sub-Saharan Africa, including Nigeria, this basic necessity is increasingly under threat. The high rate of urbanization, population increase, shifting rates of consumption and variability in climatic conditions have been pooled together to exert colossal pressure on the existing water supply infrastructure. Specifically, this challenge is pronounced in such urban centres in Nigeria such as Ibadan which is one of the largest and densely populated cities. The demand of water in the city is ever-increasing, whereas the supply systems cannot meet the demand because of the old-fashioned infrastructure, lump-sum funding, and insufficiently grounded planning.

Water supply is the provision of water by public utilities commercial organizations, community endeavors or by individuals, usually through a system of pumps and pipes. The supply of fresh water in Nigeria for domestic and drinking purposes are from three sources which include surface water (river, stream, pond, lakes,etc), groundwater or sub-surface water (hand dug well, borehole) and rainwater. In Nigeria, groundwater is a major source of water used for domestic purposes, while surface water is prone to pollution rainfall is the purest of natural water.

Despite the presence of surface and groundwater resources, the existing water supply infrastructure is unable to meet growing demand, particularly in densely populated areas such as Ibadan North LGA. Conventional demand estimation methods, based largely on per capita assumptions and trend extrapolation, have proven inadequate in capturing the complex drivers of urban water consumption.

Recent advances in machine learning provide opportunities for improved water demand forecasting by integrating demographic, climatic, and socio-economic variables. This study therefore assessed the water supply situation in Ibadan North LGA and explored the application of data-driven models to support sustainable urban water management.

II. MATERIALS AND METHOD

Study Area
Ibadan North LGA is located at the core of Ibadan metropolis, Oyo State, Nigeria. The area is characterized by high population density, mixed land use, and intense residential and commercial activities. It experiences a tropical climate with distinct wet and dry seasons, annual rainfall of about 1,200–1,500 mm, and average temperatures ranging from 25–30°C

Data collection
The methods of data collection adopted for this project included

- Structured questionnaires administered to households to assess water sources, daily consumption, and supply reliability.
- Field hydrogeological investigations including a well-yield test.
- Population data and climatic records

Tools and software used
The tools and software used in this research are Microsoft excel, Google map and python

Data analysis
Questionnaire responses were analyzed using descriptive statistics. Water consumption patterns were related to household size, income, and seasonal variations. For demand forecasting, selected machine learning models (including regression and tree-based algorithms) were evaluated using historical consumption and explanatory variables such as temperature, rainfall, and population.

III. RESULTS AND DISCUSSION

Population study
The population estimation is a very important part of the water demand analysis since the population size is directly proportional to the current and prospective water needs. Using exponential growth method. The exponential growth model is expressed as:

$$P_n = P_o e^{rt}$$

where: r=annual population growth rate t = time interval in years =2026- 2006= 20years Pn=projected population at present year (2026) P_0= population sample (from 2026 census) e= base of natural logarithms

For this study, a moderate urban growth rate of 2.5% per annum was assumed, which is consistent with values commonly applied in Nigerian urban population studies. The projection period considered spans 20 years, from 2006 to 2026.

Substituting into the equation:

$$P_{2026} = 308{,}119 \times e^{0.025\times 20}$$

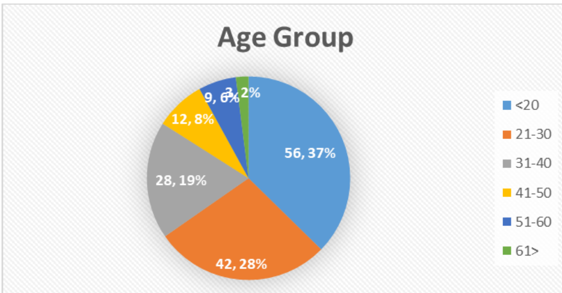
$$P_{2026} \approx 508{,}000$$

Therefore, the estimated population of Ibadan North Local Government Area in 2026 is approximately 508,000 people. This projected population forms the basis for subsequent water demand forecasting and scenario analysis in this study. The present population at 2026 is 508,000 to be projected to 2046. $P_{2026} = 837{,}550$

Sources and Adequacy of Water Supply
Results show that the majority of households rely on groundwater sources, particularly hand-dug wells and boreholes. Public piped water supply was found to be irregular and unreliable, serving less than one-third of the population. During dry seasons, households experienced acute shortages and increased dependence on private vendors.

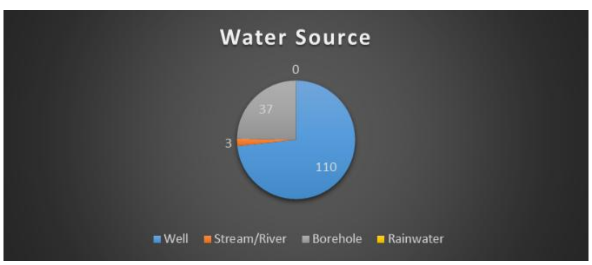
Age Group	Frequency	Percentage
<20	56	37.33333333
21-30	42	2
31-40	28	18.66666667

41-50	12	8
51-60	9	6
61>	3	2
	150	100



Water sources available

Water Source	Frequency	Percentage
Well	110	73.33333333
Stream/River	3	2
Borehole	37	24.66666667
Rainwater	0	0
Total	150	100

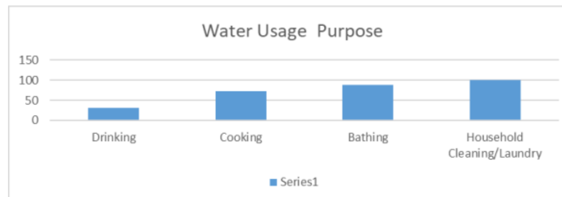


Water Consumption Patterns

Average daily household water consumption varied significantly with household size and income level. Higher-income households consumed more water due to the use of water-intensive appliances, while lower-income households relied on rationing and alternative sources. Seasonal variations were evident, with higher consumption during the dry season

Water uses

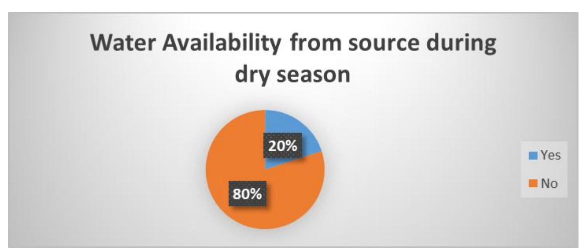
Water Usage	Frequency	Percentage (Based on Data Set = 150 people)
Drinking	47	31.33333333
Cooking	110	73.33333333
Bathing	132	88
Household Cleaning/Laundry	150	100



The average daily water consumption by the residents in the area from the questionnaire analysis is 40litres

Water availability from source during dry season

Water Availability from source during dry season	Frequency	Percentage
Yes	30	20
No	120	80
	150	100



Demand forecasting

Well Yield

Diameter of well= 40cm

At 6pm,water level was at a depth of 38cm

Volume of water $=\pi \times r^2 \times h$

$= 3.142 \times 40^2 \times 38$

$=191{,}034cm^3$

=191litres

At 6am, water level in the well was at a depth of 160cm,

Volume of water $=\pi \times r^2 \times h$

$= 3.142 \times 40^2 \times 160$

$=804{,}352\text{cm}^3$

$=805$litres

At 6pm,water level in the well was at a depth of 44cm

Volume of water $=\pi \times r^2 \times h$

$= 3.142 \times 40^2 \times 44$

$= 244$litres

Well recharge rate $= \frac{\text{yield}}{\text{time}} = \frac{(805-244)\text{litres}}{12}$

$= \frac{561}{12} = 46.75$

$= 47$L/hr

4.5 Design of Water Supply

1. Design period: 20 years (From 2026 – 2046)
2. Population growth rate: 2.5% per annum
3. Per capita water demand: 135 L/capita/day
4. Allowance for commercial, institutional & public use: 15%
5. Allowance for system losses (NRW): 25%
6. Supply system type: Hybrid surface + groundwater
7. Storage provision: 35% of average daily demand
8. Minimum supply hours target: 24 hours

POPULATION PROJECTION

Base Population

Population Growth Formula

Exponential growth method: $P_n = P_o e^{rt}$

$P_{20}=508{,}000e^{(0.025*20)}$

$P_{20}\approx 837{,}550$ persons

AVERAGE DAILY WATER DEMAND

Domestic Demand

$Q_d=P_{20}\times q$

Q_d =837,550 persons ×135 L/capita/Day

Q_d = 113,069,250 L/day= 113.1 ML/D

ALLOWANCE FOR COMMERCIAL & INSTITUTIONAL USE

$Q_{ci}=0.15\times 113.1$

$Q_{ci}=16.97$ ML/D

Total Demand Before Losses

$Q_{total}=113.1+16.97$

$Q_{total}=130.07$ ML/D

ALLOWANCE FOR SYSTEM LOSSES (NRW)

Assume 25% losses:

$Q_{design}=Q_{total} \times (1+0.25)$

$Q_{design}=130.07\times 1.25= 162.59$ ML/D

SOURCE ALLOCATION DESIGN

Surface Water Contribution (60%)

$Q_{surface}=0.60\times 162.59$

$Q_{surface}=97.56$ ML/D

Groundwater Contribution (40%)

$Q_{ground} =0.40\times 162.59$

$Q_{ground} = 65.04$ ML/D

MAXIMUM DAY AND PEAK HOUR DEMAND

Maximum Day Demand (MDD)

Maximum Day Factor = 1.2

MDD = $1.2\times Q_{design}$

MDD=1.2×162.59 = 195.108 ML/D

Peak Hour Demand (PHD)

Peak Hour Factor = 1.8

PHD=$(1.8\times Q_{design})/24$

PHD=(1.8×162.59)/24= 12.2 ML/hr

STORAGE RESERVOIR DESIGN

Storage Requirement

Provide 35% of average daily demand:

V=0.35×162.59

V=56.91 ML

DISTRIBUTION PIPE DESIGN

Design Flow Rate

Q=162.59/(24×3600)

Q=1.88 m^3/s

Pipe Diameter (Using Velocity Criterion)

Adopt: 1300 mm diameter ductile iron trunk main

PRESSURE REQUIREMENTS

Minimum pressure: 10–15 m

Maximum pressure: ≤60 m

Achieved through: Zonal reservoirs and Pressure reducing valves

PUMP CAPACITY (GROUNDWATER)

Assume:

- Borehole yield = 10 L/s

Number of boreholes required:

Q=65.04 ML/D

=752.8 L/s

N=752.8/10=75.28 boreholes

Provide:

- 85 boreholes (including standby)

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IV. SUMMARY OF DESIGN OUTPUTS

Component	Designed Value
Design population	0.84 million
Design demand	162.59 ML/D
Treatment capacity	97.56 ML/D surface + 65.04 ML/D groundwater
Storage volume	56.91 ML
Trunk main	1300 mm
Boreholes	~85

Distribution Network

The distribution network was modelled using WaterCAD.The distribution system is designed as a looped network (recommended for urban areas like Ibadan North) to ensure: Pressure stability, Reliability during pipe failure, Reduced head loss

System Components

Component	Description
Source	Borehole
Reservoir	Elevated service tank
Main pipes	Trunk & distribution mains
Nodes	Junctions at streets & zones
Valves	Isolation & control
Fire hydrants	At 150–200 m spacing

Parameter	Value
Elevation	235 m
Storage capacity	6,000 m³
Min level	2 m
Max level	6 m

Pipe Network Design

Pipe Material

- PVC / HDPE (recommended for Nigerian soil conditions)
- Hazen-Williams coefficient: C = 130

Pipe Sizing

Pipe ID	Length (m)	Diameter (mm)	Flow (L/s)
P1	300	300	80
P2	250	250	60
P3	180	200	45
P4	210	200	40
P5	150	160	30
P6	190	160	28
P7	140	110	18
P8	170	110	16
P9	200	90	12
P10	220	90	10

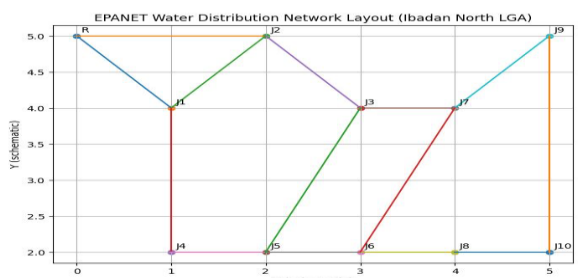
Head Loss Calculation

All pipes were sized to ensure:

- Head loss < 10 m/km
- Pressure at nodes ≥ 15 m (minimum WHO standard)
- Max pressure ≤ 60 m (to avoid pipe bursts)

Simulation Results (Expected Output)

Parameter	Result	Status
Min pressure	18 m	Acceptable
Max pressure	52 m	Safe
Max velocity	2.1 m/s	Acceptable
Headloss	< 8 m/km	Good
Supply coverage	100%	Satisfactory



Model results: what the numbers actually mean

Having trained and tuned a number of various algorithms, I can now have a good idea of their relative performance. The way they worked on the test set is as follows:

i. Linear Regression (The Baseline)

- Performance: MAE ~47.45L R^2 0.78.
- My Notes: This was an acceptable starting point, however, the R 2 of 0.78 is obviously below the target. It did not fare well at picking up on the non-

linear trends I observed during EDA and in particular when it was time to determine the effects of household size and income on demand.

ii. Random Forest (The most successful)

- Performance: MAE ~5.48L R^2 0.99.
- Best Params: 200 trees, Max Depth: 20.
- My Observation: This model is way to be the winner. It is a terrific R 2 of 0.99 and an average error (MAE) of only 5.5 Litres is truly exquisite when it comes to such survey data. It did an exquisite job of dynamic interplay between family size, type of building, and amount of water people are actually paying.

iii. Support Vector Regressor (SVR)

- Performance: MAE ~11.20L | R^2 0.96.
- My Observation: SVR performed quite well, but it was noticeably slower to tune and train than the other models. While a 0.96 R^2 is strong, it still couldn't quite catch up to the Random Forest's accuracy.

iv. Artificial Neural Network (ANN)

- Performance: MAE ~12.95L | R^2 0.97.
- My Observation: I'm really happy with how the ANN turned out. Even though it's a bit of a "black box," the loss plot showed really quick convergence. Thanks to the dropout layers and early stopping I set up, I'm not seeing any signs of overfitting.

v. Voting Ensemble

- Performance: MAE ~19.00L | R^2 0.95.
- My Observation: I actually expected the ensemble to be my "ultimate" model by combining the strengths of RF, SVR, and LR, but it actually performed worse than the Random Forest on its own. It's balanced, but the weaker models (like Linear Regression) likely dragged down the high precision of the RF.

The Random Forest model is the clear winner for me. It offers the best mix of accuracy, processing speed, and interpretability. Because it handles this tabular survey data so effectively, this is the model I'm moving forward with for all my final forecasting and scenario analysis.

The performance comparison is summarized below:

Model	MAE (L)	RMSE (L)	R^2 Score	MAPE
Linear Regression	47.45	63.01	0.7799	117.8%
Random Forest (RF)	5.48	14.10	0.9890	5.99%
SVR	11.20	27.86	0.9570	17.9%
ANN (Neural Network)	12.95	22.93	0.9708	26.5%
Voting Ensemble	19.00	28.77	0.9541	42.1%

The Random Forest model emerged as the superior predictor for this tabular survey data. With an R^2 of 0.99, it effectively captured the complex, non-linear interactions that the Linear Regression baseline struggled to manage.

CONCLUSION

This\ study highlights the persistent challenges of urban water supply in Ibadan North LGA, where groundwater sources have become the primary means of meeting domestic demand due to unreliable public supply. Water consumption is strongly influenced by socio-economic and climatic factors, underscoring the need for improved forecasting tools.

The integration of machine learning-based demand forecasting offers a practical approach for enhancing water resource planning in Ibadan and other rapidly urbanizing cities. Adoption of such tools by water authorities could improve infrastructure investment decisions, reduce shortages, and support sustainable urban development. Water utilities should adopt data-driven demand forecasting tools to support planning and operations. Investment in upgrading and maintaining public water infrastructure is urgently needed. Groundwater abstraction should be regulated to prevent long-term depletion and quality deterioration. Household-level water conservation awareness programs should be promoted.

REFERENCES

[1] Adeleye, B. N., Osabuohien, E. S., & Bowale, E. I. K. (2019). Water infrastructure and sustainable development in Nigeria: The role of governance and institutions. Utilities Policy, 58, 1–10. https://doi.org/10.1016/j.jup.2019.03.004

[2] Agbede, O. A. (1991). Engineering geology of Nigeria. Rock View (Nig.) Ltd., Jos, Nigeria.

[3] Akintola, F. O. (1982). Hydrological atlas of Nigeria. University of Ibadan Press, Ibadan, Nigeria.

[4] Ayoade, J. O. (1988). Introduction to climatology for the tropics. Spectrum Books Ltd., Ibadan, Nigeria.

[5] Breiman, L. (2001). Random forests. Machine Learning, 45(1), 5–32. https://doi.org/10.1023/A:1010933404324

[6] Cortes, C., & Vapnik, V. (1995). Support-vector networks. Machine Learning, 20(3), 273–297. https://doi.org/10.1007/BF00994018

[7] Dalhuisen, J. M., Florax, R. J. G. M., de Groot, H. L. F., & Nijkamp, P. (2003). Price and income elasticities of residential water demand: A meta-analysis. Land Economics, 79(2), 292–308.

[8] Donkor, E. A., Mazzuchi, T. A., Soyer, R., & Roberson, J. A. (2014). Urban water demand forecasting: Review of methods and models. Journal of Water Resources Planning and Management, 140(2), 146–159.

[9] Fetter, C. W. (2001). Applied hydrogeology (4th ed.). Prentice Hall, Upper Saddle River, NJ, USA.

[10] Ghimire, S., & Barkdoll, B. D. (2020). Issues in municipal water demand forecasting and analysis. Journal of Water Supply: Research and Technology—AQUA, 69(2), 97–113.