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Household water demand estimation and its implications for water accessibility: a case study

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Abstract

The accessibility to water, particularly for household purposes, is crucial for maintaining a healthy lifestyle. This study aimed to develop predictive models using multiple regression analysis to forecast household water usage and to assess the importance of water demand forecasting in improving water use efficiency and accessibility within households. Data for this research were collected through questionnaires and analyzed using both descriptive and inferential statistics. Household water usage was categorized into ten distinct components, including drinking, cooking, bathing, washing, cleaning, car washing, lawn watering, cooling, incidental use, and livestock-related use. These components were distributed proportionally with in the cooling and washing regimes, ranging from 0.12% to 38.53% of the total water usage, respectively. The results of the regression analyses indicated that two components of home water usage, specifically washing and car washing, could predict overall household water use with a confidence level of 95%. The coefficient of determination (R^2) was found to be 0.872, with a standard error of 28.91. Conversely, the incidental use component did not exhibit statistical significance and could be disregarded in further calculations. Therefore, it is essential to consider the predictive components, washing and car washing, as they significantly contribute to excessive water consumption within households. Addressing these components can enhance the efficient utilization and unrestricted accessibility of this vital resource.

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Introduction

Unrestricted access to potable water is a prerequisite to healthy living. The need for water in the contemporary times transcends beyond the conventional uses such as drinking, cloth washing, car washing, cooking, bathing. Water is required for various purposes in homes and the pace is on the rise in view of the increase in population, advancement in technology, expansion in the economy at various levels, the prevalence of COVID-19 disease, to mention only a few. Most of the cure or preventive measures of various diseases and sicknesses have been found to be greatly water-associated. Considering the numerous water needs and the finite nature of water resources, as indicated by Nauges and Whittington (2010), it is essential to emphasize the importance of accurate domestic water forecasting. This is crucial for ensuring consistent access to water supply both in terms of location and time. Furthermore, the global impact of climate change has intensified the demand for uninterrupted water supply, leading to concerns expressed by Fontanazza et al. (2014). They lamented that domestic water supply is often irregular, characterized by unexpected and fluctuating demand patterns.

It is well-established that the supply of fresh water resources is limited. Therefore, effective management is imperative to achieve sustainable distribution and efficient utilization, as highlighted by Glecick et al. (2011). Water use efficiency (WUE), defined as the ratio of actual water consumption to the minimum required for a specific purpose, plays a critical role in ensuring uninterrupted water availability within households and merits greater emphasis and encouragement, as noted by Crouch et al. (2021). By focusing on WUE, water wastage can be minimized, and the available potable water can be efficiently managed to sustain human livelihood (Rahim et al., 2019).

In today's world, some regions face water scarcity while others have sufficient water resources. For those areas where equilibrium remains elusive, accurate projections of domestic water use can significantly enhance efficient utilization and accessibility, as suggested by Gustavo et al. (2009). However, as observed by Lee and Derrible (2020), this exercise is beset with various challenges. These challenges include a lack of reliable data, deficient water-related policies (especially in developing countries), the public perception of water as a common good, unpredictable weather conditions, inadequate resource management (covering allocation, facility maintenance, seasonal rainfall events, competitive uses of water, susceptibility of water sources to various contaminations, among others) (Fan et al., 2013).

To compound these challenges, Munbi et al., 2002; Karamouz et al., 2011; Babić et al., 2014 added that climate change scenarios, population growth, land-use changes, globalization, economic development, technological innovations, and the extent of international cooperation further complicate water use forecasting, particularly in transboundary water resource management scenarios.

Developing predictive models for forecasting domestic water demand necessitates the consideration of various factors that interact to determine household water usage. Such factors encompass population size and density, climatic variables like rainfall, temperature, and evaporation rates, available infrastructure in the study area, income levels, education levels, proximity to water sources, among others (Ogunbode et al., 2014; Reynaud, 2015; Pena-Guzman et al., 2016). Consequently, various models are available in the literature, each tailored to its specific context based on these different determinants.

Household water demand forecasting represents a vibrant field within water resources management and hydrology, with numerous models having been developed, tested, and applied (Ogunbode and Ifabiyi, 2017, Qiao et al., 2022, Adamowski and Karapataki, 2010). Despite the challenges associated with forecasting domestic water demand, this exercise remains crucial at local, regional, and international levels. Accurate prediction, based on sufficient and reliable data, can promote efficient resource utilization and help reduce unnecessary wastage. Additionally, water use forecasting can facilitate equitable resource allocation among various sectors and users, ultimately promoting prudent resource management (Wafula and Ngigi, 2015; Liu and Xue, 2017; Munbi et al., 2002). Recognizing the significance of water demand forecasting, it can contribute to effective future planning and resource management. It also aids governing bodies and relevant agencies in formulating timely strategies to alleviate water scarcity and address issues related to water resource management.

Several models have been developed to forecast water demand, including Regression analysis (Ogunbode, 2015). In this study, the author created forecast models for each Local Government Area (LGA) in Oyo State, Nigeria, as well as for the entire state. The differences in the models for each LGA were attributed to variations in the prominent variables that serve as determinants of water demand. Similarly, Haque et al. (2021) employed a combined statistical approach of Principal Component Analysis (PCA) and Regression Analysis (RA) to generate predictive models for water demand forecasting in Australia. This combination was used to eliminate potential issues of multicollinearity among the variables.

Approaches to deriving water demand prediction models, such as regression analysis, time series analysis, computational/intelligence methods, and stochastic models, were outlined by Fontanazza et al. (2014). Additionally, Lee and Derrible (2020) assessed 12 predictive statistical techniques and found that machine learning algorithms outperformed regression methods. However, it was established that combining these predictive models enhances their overall performance (Jumin et al., 2020; Lee and Derrible, 2020).

One of the fundamental necessities required for optimal academic performance is access to clean and safe drinking water. As Nnametu et al. (2015) pointed out, academics serve as the cornerstone for imparting quality knowledge in any economy striving for growth. Both Olawunni et al. (2012) and Nnametu et al. (2015) emphasized that academics bear substantial responsibilities, including teaching, research, and the dissemination of knowledge to address human challenges and foster development. These activities extend beyond the conventional 7 days a week or 24 hours a day. Hence, to ensure optimal performance, unrestricted access to basic amenities like potable water is essential.

Considering this, effective long-term prediction of water usage is expected to lead to unhindered access to this resource, ultimately enhancing the focus and performance of academics in their primary roles.

This study employed multiple regression analysis to create a predictive model for forecasting domestic water demand among households within the Bowen University community. This choice was made for several reasons: it offers simplicity and ease of determination, it can be adapted for both short- and long-term timeframes (Fontanazza et al., 2014), it identifies independent variables that influence the dependent variable in a simplified manner, and it elucidates the relationship between independent and dependent variables (Jeon, 2015; Mudashiru, 2021). The aim of this study was to generate predictive models for forecasting household water use in the study area. The objectives were (i) identification of the main areas of home water use in the study area; (ii) quantification of various components of domestic water use; (iii) development of predictive model based on the components of home water use discovered; and (iv) expression of the relationships between water use efficiency and water accessibility and the implication for the model.

Method of study

Study Area

The study was carried out inside Bowen University, Iwo, Nigeria. The University is located in Iwo Local Government Area (LGA) of Osun State, which shares boundaries with Oluponna and Ile-Ogbo, both in the Ayedire LGA of Osun State. The University covers an area of 933.34ha and has an estimated population of 6000. Records from the Works and Maintenance Unit of the University puts an average consumption of water per day as 700,000 litres from groundwater outlets, mainly boreholes. The study deliberately selected University senior staff category in view of their perceived desire for their readiness to ensure adequate comfort in term of availability of basic amenities in their respective residences, including potable water. This study is expected to form the basis for water use projection among people of similar features. The Bowen University community has about 6,500 people including students, academic and non-academic staff and services providers. Bowen University is served with both pipe-borne and ground water as the major source of water for household uses and for other uses within academic areas such as cleaning, sanitation, input in laboratory and any other aspect of teaching and learning.

Data Collection

The questionnaire to be administered was considered technical and targeted towards senior staff of the University including academic and non-academic staff. For in-depth understanding of water use efficiency in homes, two hundred and twenty-seven (227) households among different categories of staff, including academics and non-academics, were interviewed. The bias for women was their traditional role in African homes. It is generally known that women are more burdened with water availability in homes for various purposes, so it is expected that water-related information are better sourced from women rather than men. Questionnaires were administered by visiting each respondent in their respective offices with enlightenment on how to complete the questionnaire. Each respondent was given about forty-eight to seventy-two hours to complete the questionnaire.

Structured questionnaire

The questionnaire comprised seventeen short, structured questions under two sections. Section A consisted of personal details of the respondents including name, level of education, income level, marital status, age, household size, religion and questions on attitudes towards repairing water related fixtures. Section B was a single table which used to generate data on various uses of water. This section had five major columns given different names for the purpose of this work. These were: (1) major water use component (also tagged Action, subcomponent (also tagged Specific Uses), action frequency per day/person *(f)* which specifies the number of times each subcomponent is carried out per day, water use estimate for each subcomponent in liters/day/person and finally, the sources of water used for each component which could be either hand-dug well (W) and borehole (B) – generally classified as groundwater; also pipe-borne water (P), rivers/streams (S) - typically called surface waters).

Data Analyses

Descriptive analysis was carried out using percentages in presenting home water use components while regression (R) analysis was used to generate predictive model to forecast household water uses (HWU) for the study area. Multiple regression analysis is known for its efficacy in deriving predictive models in water resources management and hydrology (Eslamian et al., 2016; Mudashiru, 2021). The Special Package for Social Scientists (SPSS version 16.0) was used for the test of collinearity and the development of the predictive model.

Domestic water use analysis

The result of the analysis of different areas of daily water use among the respondents was carried out and presented in Figure 1.

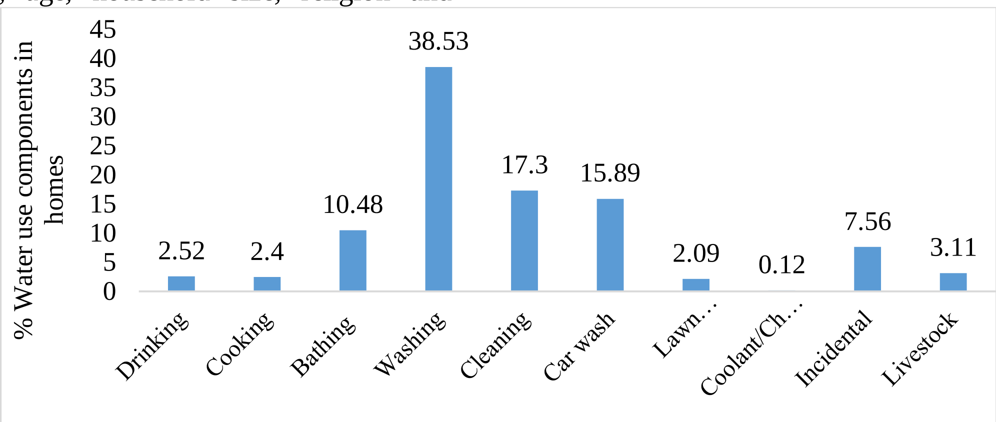

Figure 1. Household water use components in percentage

The breakdown reveals that water usage varies across different components, ranging from 0.12% for coolant/chiller to 38.53% for washing activities. Interestingly, the findings indicate that a smaller percentage (4.92%) of daily water usage is allocated to direct human consumption, including drinking (2.52%) and cooking (2.40%), compared to other purposes. This observation could potentially be attributed to the household sizes of the respondents.

Furthermore, the analysis indicates that water is predominantly used for cooling/chilling purposes, accounting for only 0.12% of daily usage. This suggests that such usage may be limited, possibly restricted to radiator cooling in respondents' vehicles, and the utilization of generators and similar equipment may not be encouraged due to the availability of infrastructure.

Moreover, the allocation of water for lawn watering (2.09%) and livestock (3.11%) implies limited availability of green spaces requiring irrigation and potentially discouragement of livestock keeping in the study area.

However, the results highlight that the majority of daily water consumption (72.46%) among the respondents is concentrated in activities such as bathing (10.48%), washing (38.53%), car washing (15.89%), and incidental uses (7.56%). These four categories of water usage are often associated with excessive or immeasurable utilization of the resource, particularly when accessibility is not a limiting factor and has minimal impact on the objects involved, whether human or otherwise. It is generally believed that the more water is used for these purposes, the greater the satisfaction derived. These findings align with the perspectives of Shaban and Sharma (2007); Ogunbode and Ifabiyi (2014); M'baya, 2008.

Application of Multiple Regression for Household Water Demand Forecasting

This method has been successfully applied in water use studies by several authors including Ayanshola et al. (2010) and Ifabiyi and Ahmed (2011). The method is an extension of simple linear regression in which more than one independent variable (X) is used to predict a single dependent variable Y. The predicted value is a linear transformation of the X variables such that the sum of squared deviation of the observed and predicted Y is a minimum.

Multiple regression function is given as:

$$\hat{Y} = \dot{\alpha} + ß_1 x_1 + ß_2 x_2 + \ldots\ldots ß_k x_k \quad (1)$$

Significance test of multiple regression statistic $\hat{Y}$ squared is given as

$$F = R^2_{Y\,1\ldots..J}/1\text{-}R^2_{Y\,1\ldots..J} * N - J - 1/J \quad (2)$$

where N is the number of predictors including the intercept, and J is the number of respondents.

Residual sum of squares also called Sum of Squared Errors (SSE) is given as:

$$SSE = \Sigma(y - \hat{y})^2 \quad (3)$$

Water use determinants in the study area were subjected to stepwise multiple regression analysis to determine the strength of each factor in predicting rural water use. The statistic was applied by Ifabiyi and Ahmed (2011) and Wang et al. (2021) to determine the factors that influence water demand in Ilorin, Nigeria.

The statistic employs one of several available statistical algorithms to order the entry (and/or deletion) of predictors from the model being constructed. It combines forward selection and backward elimination. At each step, the best remaining variable is added, provided it passes the significance at 5 percent criterion, then all variables currently in the regression are checked to see if any can be removed using the greater than 10 percent significance criterion. The process continues until no more variables are added or removed. Variables are checked at a time using the partial correlation as a measure of importance in predicting the dependent variable Y.

In order to be sure that no variance predictable from W enters the relationship between Y and X, the partial correlation computed from simple correlation is applied as given below:

$$r_{YX.W} = r_{XY} - r_{XW} r_{YW} / \sqrt{(1 - r^2_{XW})(1 - r^2_{YW})} \quad (4)$$

With Equation (1), one can calculate various first order partial correlations (controlling one variable). Also the second (or higher) order partial correlations is determined using basically the same formula as follows:

$$r_{YX.O} = r_{XY.O} - r_{XW.O}r_{YW.O}/\sqrt{(1 - r^2_{XW.O})(1 - r^2_{YW.O})} \quad (5)$$

where 'O' stands for other partial variables. The result of stepwise regression analysis is presented in Table 2, the summary of which is shown in Table 3. Three predictive models were generated to forecast TWU/Day among the respondents.

Table 2. Details of the predictive models generated by regression analysis

Model	Unstandardized Coefficients		Standardized Coefficients	T	Sig	Rem.
	β	S.E				
1. (Constant)	114.202	20.769		5.499	0.000	S
Washing	1.211	0.214	0.749	5.658	0.000	S
2 (Constant)	90.855	13.439		6.760	0.000	S
Washing	0.945	0.140	0.585	6.771	0.000	S
Car wash	1.308	0.205	0.550	6.365	0.000	S
3 (Constant)	78.416	13.123		5.976	0.000	S
Washing	0.799	0.139	0.494	5.746	0.000	S
Car wash	1.311	0.186	0.551	7.053	0.000	S
Incidental	1.483	0.589	0.208	2.517	0.019	NS

Table 3: Summary of the Model

Model	R Squared	Standard Error	Significance	Remarks
1.	0.561	51.34	0.000	S
.	0.877	31.96	0.000	S
3.	0.872	28.91	0.000	S

$p \leq 0.05$; Key-S- Significant; NS- Not Significant

Model 1: Apart from the constant value, Model 1 incorporates washing (W) component of HW demand as follows:

TWU=114.202 + 0.74W. (6)

(R^2=0.561; SE =51.34)

Model 2: The second model generated included washing (W) and car wash (A_W) components of HWU in the Model as follows:

TWU= 90.855 + 0.585W+0.550A_W. (7)

(R^2=0.877; SE =31.96)

Model 3: Three predictive factors were generated in this model as follows: (8)

TWU= 78.416+0.494W+0.551A_W + 0.208I, where I denote Incidental (R^2=0.872; SE =28.91).

All the predicting factors in the three models are significant at 95% level of confidence except the incidental component (P>0.05), the implications of which is that the factor may be disregarded in the computation of the final model as it is not significant in the prediction of the household water demand. However, the SE showed that Model 1 has the highest value in that order. The results of the analysis showed that the highest household water use component is domicile in the non-consumptive component which also included other uses than those derived in the analysis which could have possibly be the outliers causing high SE. It thus implied that the predictability of home water use based on any of the models should incorporate such components. Thus, the more inclusive of the non-consumptive water use components, the less is the SE incurred in predicting home water use. Consequently, the results here showed that Model 3 predicts HWU with greater accuracy than any of the other models generated.

Household Water Use Efficiency and Accessibility

The necessity for achieving and making sound forecast of HWU is premised on the efficient and guided uses of water in homes. For instance, it is already established that water use in homes is dependent on certain variables. It is expected that if water use in homes can be properly accounted for and the utilization of the resource is guided, water forecasting can be a worthwhile exercise. The following mathematical equations give pertinent information on Component Water Use and the relationship between water use efficiency and its accessibility:

$$X_i = \sum_{j=1}^{m_i} y_{ij}\,, \qquad i = 1,2,3,\dots,k, \qquad (9)$$

where

X_i denotes Component Water Use (cooking, bathing, washing and so on);

y_{ij} is the subcomponent water use (e.g washing plates, clothes, drainages etc. are sub components of washing); and

Σ denotes summation. Therefore,

$$\Delta X_{i_i} = X_i^{(r)} - X_i^{(r-1)} = \sum_{j=1}^{m_i}\left(y_{ij}^{(r)} - y_{ij}^{(r-1)}\right) \qquad (10)$$

where

ΔX_i is change in Component Water Use.

$X_i^{(r)}$ denotes Current Component Water Use.

$X_i^{(r-1)}$ denotes Previous Component Water Use.

Meanwhile, the sub component water use is dependent on water accessibility factors $(a_1, a_2, a_3, \dots\dots, a_q)$, such as income, water conservation facilities, government policies, etc. Thus,

$$y_{ij} = f_{ij}\left(a_1, a_2, a_3, \dots\dots, a_q\right). \qquad (11)$$

Water accessibility is also dependent on Water Use Efficiency Parameters $(e_1, e_2, e_3, \dots\dots e_{n.})$, for example irregular water flow, cost of water, change in season and so on. This can be expressed as follows:

$$a_s = g(e_1, e_2, e_3, \dots\dots, e_n), \; s = 1,2\dots, q. \qquad (12)$$

Conclusion and Recommendation

An investigation was conducted to forecast household domestic water demand using multiple regression with Bowen University senior staff as our case study. The analysis generated two components namely washing and car wash that significantly predict household water demand (*p*$\leq$*0.005)* with R^2 value of 0.872 and the standard error of 28.91. However, the incidental wash component which was included in Model 3 generated by the statistic was not significant, (p=0.019), thus, it could be excluded from the computation of the model. Compliance with the predictability of HWD using the regression model implies that household water use efficiency is optimally observed, especially, in such components which often give room for excessive use. Household water supply is sporadic and so susceptible to various factors that may exert influence on the efficacy of the predictive models generated. In view of this, sustainable accessibility to potable water for home use can be attained if the records of the predictive variables are optimally given utmost attention. It is, however recommended that further studies are conducted to validate and ensure the continuous applicability of model 3 which has the least standard error.

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