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A Simple Mathematical Model for Calculating Household Water Usage Based on Linear Functions

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ABSTRACT

The increasing scarcity of clean water, exacerbated by population growth and climate change, calls for effective and efficient water management, especially at the household level. This study aims to develop a simple linear mathematical model to estimate daily household water consumption based on commonly observed domestic activities. The total water usage (W) is expressed as a function of key variables such as the number of residents, shower duration, laundry frequency, and dishwashing frequency, each multiplied by an empirical coefficient. These coefficients are drawn from published data to ensure representativeness. A case study conducted on a four-member household in Bandar Lampung, Indonesia, shows an estimated daily water consumption of 631.5 liters, aligning with global benchmarks. The study concludes that this linear model provides a practical and accessible framework for estimating household water use and can serve as a foundational tool for promoting water conservation strategies and informing public policy.

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INTRODUCTION

Domestic water usage plays a critical role in the sustainable management of freshwater resources, particularly as societies across the globe grapple with the intersecting challenges of rapid population growth, urban expansion, and intensifying climate change. The increasing strain on freshwater availability has prompted urgent calls for improved efficiency in water use at the household level. According to the United Nations (2023), global water demand is expected to rise by nearly 30 percent by the year 2050, with the residential sector emerging as a primary driver of this growth. This projection underscores the importance of developing practical tools and strategies that can accurately monitor, predict, and manage water consumption in domestic settings.

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One such strategy involves the use of mathematical modeling, which has become an essential component of modern water resource planning. Mathematical models provide a systematic and data driven approach for analyzing complex consumption patterns, allowing policymakers, engineers, and households alike to make informed decisions. Among the array of modeling techniques available, linear function based models stand out for their conceptual clarity, ease of implementation, and minimal data requirements. These models express total water consumption as a linear function of multiple influencing variables such as the number of residents, frequency of water intensive activities, and appliance efficiency. By assigning coefficients to each variable based on empirical data, the model facilitates quick estimation of daily or monthly household water demand (Gleick, 2021; Breyer et al., 2022; EPA, 2023).

The value of linear models lies in their accessibility and adaptability, particularly in regions where data infrastructure is limited or where advanced computing technologies are unavailable. While more sophisticated approaches such as nonlinear regressions, system dynamics models, or machine learning techniques have gained traction for their predictive power and ability to capture complex interactions (Rachunok et al., 2023), linear models continue to serve as a foundational entry point for water demand forecasting. Their intuitive nature makes them well suited for community engagement, educational campaigns, and policy prototyping.

From a broader perspective, most models of domestic water demand are built around three primary categories of influencing factors: climate conditions, economic development, and household behavior. Climatic variables such as ambient temperature, humidity, and precipitation significantly affect seasonal and regional water usage patterns. For instance, households in warmer climates or arid regions often use more water for cooling, irrigation, or hygiene during dry seasons (Zhang et al., 2020). At the same time, economic variables such as per capita income, urbanization levels, and housing type play a decisive role in shaping consumption levels, as higher standards of living typically lead to increased access to water consuming appliances and services (Li et al., 2024; Pan et al., 2018).

Behavioral aspects further enrich the modeling landscape by capturing variability in how water is used on a daily basis. Activities such as showering, laundry, dishwashing, and toilet flushing are not only influenced by personal habits but also by cultural norms, household size, and time of day. Advanced models including those employing probabilistic or stochastic demand generators attempt to incorporate these dynamics by simulating individual activity patterns, thereby enhancing the realism and accuracy of demand projections (Lombardi et al., 2018; Rachunok et al., 2023).

These models are increasingly being integrated into larger frameworks for Integrated Urban Water Management. For instance, stochastic models that capture short term fluctuations in demand are valuable for infrastructure design, water allocation planning, and emergency preparedness (Pan et al., 2018). Linear models can also assist utility providers in optimizing water distribution networks, improving supply reliability, minimizing losses, and designing tiered pricing schemes that promote conservation (Li et al., 2024; Lombardi et al., 2018).

Nevertheless, despite their practical advantages, linear models are not without limitations. One of the most significant drawbacks is their tendency to assume fixed and independent relationships among variables, which often leads to oversimplification. They may fail to capture real world complexities such as abrupt behavioral changes, multivariable interactions, or extreme climate anomalies. For instance, unexpected events like droughts, heatwaves, or pandemics can lead to sharp deviations from normal usage patterns, phenomena that static linear models may be ill equipped to predict. Furthermore, the generalization of coefficients across diverse geographic or socioeconomic contexts may reduce model precision.

To address these shortcomings, scholars have advocated for hybrid approaches that combine the simplicity of linear models with the flexibility of nonlinear or data driven methods such as machine learning or Bayesian networks. These approaches allow for the integration of dynamic feedback loops, contextual variables, and continuous learning from real time data (Rachunok et al., 2023; Zhang et al., 2020). Nevertheless, linear models continue to offer a robust starting point for building awareness, encouraging sustainable behavior, and guiding the development of more comprehensive decision support tools.

METHODS

1. Methodology

a. Research Population and Sample Location

While the study primarily uses a modeling approach rather than field data collection, a representative household in Bandar Lampung, Indonesia, was selected as a reference case. This household consists of four residents living in an urban residential area with typical domestic water use behavior. The sample was chosen to illustrate the applicability of the linear model in an Indonesian urban context.

b. Mathematical Model

This study employs a quantitative modeling approach using a linear function to estimate daily household water consumption. The proposed model is designed to represent the relationship between total daily water usage and several independent variables that reflect common domestic activities.

The fundamental assumption of this model is that total household water consumption per day (W) is a linear function of multiple independent variables (x_i), where each variable is associated with a constant coefficient (a_i) and a baseline constant (c) representing fixed usage. The general form of the model is expressed as:

$$\boldsymbol{W} = \boldsymbol{a}_1\boldsymbol{x}_1 + \boldsymbol{a}_2\boldsymbol{x}_2 + \ldots + \boldsymbol{a}_n\boldsymbol{x}_n + C$$

Where;

- W : Total daily water usage (liters/day)

- $x_1, x_2, \ldots, x_n$: Independent variables influencing water consumption, such as number of residents, shower duration, laundry frequency, and dishwashing frequency
- $a_1, a_2, \ldots, a_n$: Coefficients representing water usage per unit of each activity
- c : Constant representing baseline water usage

The constant c=50 liters is added to represent essential daily usage such as toilet flushing, handwashing, and cooking, which are not captured by the primary variables. This should be explicitly shown in the formula.

c. Key Variables and Coefficients

Based on recent findings by Breyer et al. (2022) and the Environmental Protection Agency (EPA, 2023), the model includes four primary variables with the following average coefficients:

Table 1. Main variables with decreasing average coefficients

Variable	Symbol (x_i)	Coefficient (a_i) (liters/unit)
Number of household members	x_1	80 liters/person/day
Shower duration	x_2	10 liters/minute
Laundry cycles	x_3	50 liters/cycle
Dishwashing frequency	x_4	20 liters/use

The coefficients presented in this table are derived from secondary sources, primarily Breyer et al. (2022) and the U.S. Environmental Protection Agency (EPA, 2023). These values represent average water consumption per unit of activity in urban households and were not calculated from primary data or local surveys. Instead, they were adopted from prior research findings to provide a practical approximation suitable for use in this study's model. Localized adjustments can be made in future applications as needed, using empirical observations from specific household populations.

Thus, the complete linear model becomes:

$$\boldsymbol{W = 80x_1 + 10x_2 + 50x_3 + 20x_4 + c}$$

In this model, the constant c is estimated at 50 liters/day, representing fixed usage for essential activities such as toilet flushing, cooking, and handwashing.

d. Model Assumptions

This model is built upon the following assumptions:

1) The relationship between each variable and total water usage is linear and consistent over a daily period
2) There is no overlapping water use across activities
3) Appliance efficiency is assumed to be average and consistent across households

a) Water usage patterns reflect typical domestic behavior in urban residential settings

While relatively simple, this linear model provides a foundational framework that can be extended or refined through empirical validation or integration with non-linear or machine learning approaches.

e. Data Sources for Coefficients

The coefficient values used in the model are sourced from recent literature, particularly Breyer et al. (2022) and Environmental Protection Agency (EPA, 2023). These sources provide empirically derived estimates of average water usage per unit activity (e.g., per person, per minute of showering, etc.). The model assumes that these values reasonably reflect household behaviors in urban Indonesian settings, although localized adjustments can be made in future studies.

RESULTS

To evaluate the accuracy and practical application of the proposed linear model, a case study was conducted on a household located in Bandar Lampung, Indonesia. This household represents a typical urban family setting and is used as the research sample to test the model's effectiveness in estimating daily water usage. The selected household consists of four residents and engages in the following average daily activities:

a. Shower frequency: 2 times per day, 10 minutes each
b. Laundry frequency: 3 times per week (~0.43 times per day)
c. Dishwashing frequency: 2 times per day

Using the linear equation:

$$\boldsymbol{W = 80x_1 + 10x_2 + 50x_3 + 20x_4 + c}$$

and substituting the values:

$$\boldsymbol{W = 80(4) + 10(2\,X\,10) + 50(0.43) + 20(2) + 50}$$
$$\boldsymbol{W = 320 + 200 + 21.5 + 40 + 50 = 631{,}5\ liters/day}$$

a. Interpretation of Results

The model estimates that the household consumes approximately 631.5 liters of water per day, which falls within the range reported by the EPA (2023) for average U.S. residential water usage, estimated between 300 and 700 liters per day.

Table 2. A Breakdown of Water Usage by activity is Shown Below

Activity	Water Consumption (L/day)	Percentage of Total (%)
Number of residents	320	50.7%
Showering	200	31.7%
Laundry	21.5	3.4%
Dishwashing	40	6.3%

Activity	Water Consumption (L/day)	Percentage of Total (%)
Baseline usage (c)	50	7.9%
Total	**631.5**	**100%**

b. Model Validation

These findings demonstrate that the linear model offers a reliable and straightforward method for estimating daily water consumption in a typical household. The proportional distribution across activities is also consistent with trends observed in contemporary water usage studies (Breyer et al., 2022; Duncan & Mitchell, 2008), supporting the model's representativeness for residential applications.

DISCUSSION

The findings of the model application reveal that household water consumption can be effectively approximated using a linear function that correlates daily water usage with quantifiable variables such as the number of residents, shower duration, frequency of laundry, and dishwashing activities. The total estimated usage of 631.5 liters per day for a four-person household aligns with national consumption averages and underscores the validity of the model as a basic yet informative tool for water demand estimation. Role of Linear Models in Water Demand Estimation Linear mathematical models are particularly valuable in residential water estimation due to their simplicity, transparency, and adaptability. They offer direct insights into how specific behavioral changes—such as reducing shower time or optimizing laundry schedules—can affect overall consumption. Unlike machine learning models, which may require large and complex datasets, linear models are easy to implement even in data-scarce environments. According to Grafton et al. (2017), simple linear models remain effective for public policy modeling, especially when clarity and community engagement are desired. Furthermore, Fielding et al. (2012) emphasize that user-friendly models can empower households to make informed choices about conservation. While linear models lack the sophistication to capture nonlinear interactions or behavioral anomalies, they play a critical role in the first-tier analysis of domestic water use and resource planning.

1. Strengths of the Linear Model

One of the key strengths of this model is its clarity and usability. Linear functions offer a transparent framework for users to understand how incremental changes in behavior such as reducing shower time or optimizing laundry cycles directly affect overall water use. This attribute makes the model highly applicable in educational tools, policy simulations, and household-level monitoring systems, especially in contexts where advanced computational resources are unavailable.

Additionally, the reliance on empirically derived coefficients from recent studies (Breyer et al., 2022; EPA, 2023) enhances its robustness and allows for easy customization across various demographic or geographic settings. The model is also adaptable, enabling users to input local parameters or coefficients based on updated survey or monitoring data, thus improving its accuracy.

2. Comparative Insights with Broader Literature

The model shares conceptual similarities with more complex frameworks found in recent research. For instance, Liu Jia-hong et al. (2013) and Lombardi et al. (2018) propose integrated models that incorporate climate variables, economic indicators, and appliance efficiency, demonstrating how macro and micro factors interact in determining water demand. However, while these models offer richer analytical capabilities, they often require significant datasets, computational infrastructure, or probabilistic calibration resources that may be inaccessible in many local government or household settings.

In contrast, the linear model's simplicity becomes a strategic advantage in promoting public awareness and early-stage policy formulation. For example, municipal water agencies could use this model to generate quick consumption estimates for new residential developments or to target households with high consumption levels based on activity profiling.

3. Model Limitations and Potential Enhancements

Despite its utility, the linear model has inherent limitations that must be addressed. Most notably, it assumes a static and independent relationship between variables. In reality, household water usage is dynamic and affected by interrelated factors such as cultural habits, economic fluctuations, seasonal demand, and real-time environmental changes. For example, water use tends to spike during dry seasons due to increased outdoor watering and cooling needs (Lombardi et al., 2018), or during holidays when guest presence increases domestic load.

Another limitation lies in the model's lack of behavioral nuance. Probabilistic models, as employed by Duncan & Mitchell (2008) and more recently by Rachunok et al. (2023), provide better insight into peak demand periods, intra-day variability, and appliance-level efficiency. These models, while more complex, are essential in urban planning, water pricing strategies, and infrastructure resilience studies.

Furthermore, the model does not differentiate between indoor and outdoor water use, which can be a significant portion of demand in suburban households with irrigation systems or pools. It also excludes graywater reuse, leakage losses, and technological interventions (e.g., sensor-controlled faucets), all of which can drastically alter daily consumption estimates.

To improve predictive accuracy and scope, future iterations of this model could adopt non-linear functions or hybrid methodologies integrating machine learning. Interpretable machine learning (e.g., SHAP or LIME), as explored by Rachunok et al. (2023), enables the identification of hidden patterns in water use while maintaining transparency. These enhancements would allow for more dynamic simulations and better policy relevance, particularly in the face of climate change, urban densification, and technological shifts in water-saving appliances.

4. Policy and Sustainability Implications

The implications of this model extend beyond academic modeling. By quantifying how much water is used per activity, the model can guide household-level interventions, such as adopting low-flow fixtures or behavioral nudges. It also supports municipal planning, particularly in low-resource settings where real-time monitoring infrastructure is limited. Policymakers can use this model to simulate scenarios under different usage behaviors or tariff schemes, contributing to evidence-based strategies for urban water conservation, equitable distribution, and sustainable resource management

CONCLUSIONS

This study demonstrates the effectiveness of using a simple linear mathematical model to estimate household water usage based on common daily activities and behavioral variables. By assigning empirically derived coefficients to measurable factors such as the number of residents, duration of showers, and the frequency of laundry and dishwashing, the model offers a practical and accessible framework for approximating daily water consumption.

The case study produced results consistent with national residential water usage ranges, reinforcing the model's reliability and applicability. Although the model does not fully account for behavioral changes, seasonal variability, or non-linear interactions, it provides a strong foundation for promoting water conservation, shaping local policies, and guiding household decision-making. Its ease of use also makes it suitable for integration into smart water tools, basic infrastructure planning, and public education. Future improvements could involve probabilistic methods or data-driven enhancements to adapt to evolving urban and environmental conditions.

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This article offers a simplified, data informed approach to understanding household water consumption. It contributes a foundational model that supports conservation efforts, public awareness, and future development of more advanced, adaptable water management tools.

REFERENCES

Arbués, F., García-Valiñas, M. Á., & Martínez-Espiñeira, R. (2010). Estimation of residential water demand: A state-of-the-art review. *Journal of Socio-Economics*, 38(4), 625–634. https://doi.org/10.1016/j.socec.2009.03.015

Breyer, B., Chang, H., & Parandvash, G. H. (2022). *Household water use and conservation: A data-driven approach*. Water Resources Research, 58(4). https://doi.org/10.1029/2022WR032510

Dolnicar, S., & Hurlimann, A. (2010). Desalinated versus recycled water: What does the public think? *Sustainable Development*, 18(3), 135–148. https://doi.org/10.1002/sd.446

Duncan, H. P., & Mitchell, V. G. (2008). A stochastic demand generator for domestic water use. *Journal of the American Water Resources Association*, 44(3), 684–693. https://doi.org/10.1111/j.1752-1688.2008.00186.x

Environmental Protection Agency (EPA). (2023). *Water use statistics for residential homes*. Retrieved from https://www.epa.gov

Fielding, K. S., Russell, S., Spinks, A., & Mankad, A. (2012). Determinants of household water conservation: The role of demographic, infrastructure, behavior, and psychosocial variables. *Water Resources Research*, 48(10). https://doi.org/10.1029/2012WR012398

Gleick, P. H. (2021). *The world's water volume 9: The biennial report on freshwater resources*. Island Press.

Grafton, R. Q., Ward, M. B., & Kompas, T. (2017). Determinants of residential water consumption: Evidence and analysis from a 10-year panel. *Applied Economics*, 49(19), 1891–1901. https://doi.org/10.1080/00036846.2016.1221045

Inman, D., & Jeffrey, P. (2006). A review of residential water conservation tool performance and influences on implementation effectiveness. *Urban Water Journal*, 3(3), 127–143. https://doi.org/10.1080/15730620600961288

Jia-hong, L., Yue, L., & Jian-hua, W. (2013). A mathematic model for rational domestic water demand considering climate and economic development factors. *Journal of Hydraulic Engineering*, *44*(10), 1208–1214. https://doi.org/10.13243/j.cnki.slxb.2013.10.017

Lombardi, F., Silvagni, G., Sirini, P., Passariello, G., & Cintura, S. (2018). Daily water demand: A probabilistic approach to evaluate household behavior. *Water*, 10(6), 696. https://doi.org/10.3390/w10060696

Rachunok, B., Verma, A., & Fletcher, S. (2023). Predicting and understanding residential water use with interpretable machine learning. *Environmental Research Letters*, 18(12), 124015. https://doi.org/10.1088/1748-9326/ad1434

Wentz, E. A., Kim, Y., & Myint, S. W. (2014). Factors influencing water consumption in multifamily housing in Phoenix, Arizona. *Professional Geographer*, 66(3), 501–510. https://doi.org/10.1080/00330124.2013.872144

Willis, R. M., Stewart, R. A., Panuwatwanich, K., Jones, S., & Kyriakides, A. (2011). Alarming visual display monitors affecting shower end use water and energy conservation in Australian residential households. *Resources, Conservation and Recycling*, 57, 165–173. https://doi.org/10.1016/j.resconrec.2011.09.004

Zhang, J., Li, Y., & Yu, L. (2019). Urban residential water demand modeling using survey data and statistical analysis. *Water Resources Management*, 33(5), 1751–1764. https://doi.org/10.1007/s11269-018-2196-3