Domestic water consumption determinants in urban neighborhoods: A case study of Vijayawada, India

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Abstract. Domestic water consumption accounts for a large share of urban water demand. The present study discusses a study on domestic water consumption in ten different neighborhoods in Vijayawada, India. The study examines the relationship between per capita water consumption and various socio-economic, physical, and supply-related variables. The study conducted a primary survey of 117 households to collect data on water consumption and related factors. Multiple regression analysis was used to identify the significant determinants of per capita water consumption. The study found that supply continuity, household size, household income, building height, building age, and annual water charges significantly affect per capita water consumption in the studied neighborhoods. The study also found that different types of neighborhoods have different per capita water consumption levels and determinants. The study results assist urban planners and local bodies in systematically managing water demands through spatial and policy solutions. The study identifies that urban planners and local bodies can manage water demands through effective spatial and policy solutions.

Keywords: Domestic water consumption, determinants, neighborhood, per capita water consumption, consumption pattern

1 Introduction

The urban population growth in India has led to increased residential water demands and water scarcity, affecting almost half of the urban population. Water scarcity is estimated to affect around 222 million (46.06%) of India's urban population (He et al., 2021). To manage water supply, local governments need to evaluate domestic water demand. Existing literature has identified various factors affecting household water usage in urban areas. The Ministry of Urban Development has developed performance indicators for the Urban Local Bodies in India, including the per capita water supply, which has a Service Level Benchmark (SLB) of 135 liters per capita per day (lpcd) (MOUD, 2009). However, the average domestic water supply in Indian ULBs is only 69.25 lpcd (Ali & Dkhar, 2018). The present study examines the impact of socio-economic, physical, and supply-related variables on water consumption in ten neighborhoods of the Indian metropolis of Vijayawada.

2 Study Area

Vijayawada is the second largest city in Andhra Pradesh state, India, with a projected population of 1.14 million by 2021 (Census of India, 2011). Vijayawada Municipal Corporation (VMC) is the local administrative body that provides basic amenities such as water supply and sanitation in the city. While meeting the SLB for the per capita water supply of 135 lpcd, the city depends heavily on alternative sources. Therefore, the present study investigates the water consumption behavior in ten neighborhoods in the city with varying socio-economic, physical, and supply-related features. Multiple linear regression is used in this study to determine the crucial drivers of water usage in different neighborhood types and the density of the dwelling units (DU), a unit of accommodation in a building, or a portion. The current study used a primary survey to obtain water use data and socio-economic, physical, and water supply situations from 117 households. The impact of different socio-economic and supply-related variables is evaluated in ten neighborhoods with varying spatial characteristics (plans and DU densities).

3 Background

According to the existing literature, per capita and household level water consumption have multiple determinants associated with socio-economic, physical, and water supply characteristics. Several studies have examined the impact of household size (number of people living in a household) on water consumption (Ghavidelfar et al., 2018; Kumar et al., 2021; Mostafavi et al., 2018), with findings indicating that larger households tend to use more water but have lower per capita consumption due to economies of scale. Water supply continuity (average supply hours per day) also plays a role in household water consumption, with intermittent supply systems leading to increased usage (Bandari & Sadhukhan, 2021). Household income (Hussien et al., 2016) and water charges (Ghavidelfar et al., 2017) are significant water consumption determinants. Building age and height have also been linked to increased water consumption (Dias et al., 2018; Silva et al., 2021). Previous studies on water consumption in Indian cities have found that average built-up area, income, recreational area, education, household location, non-revenue water, and supply continuity are significant determinants of water consumption (Anil Kumar & Ramachandran, 2019; Kumar et al., 2021). The present study focuses on six determinants of water consumption which include *household size* (HHS), *household average monthly income in rupees* (INCM), *building age* (BAGE), *building height in meters* (BHGT), *hours of water supply per day* (CNTY), and *annual water charges in rupees* (BILL). Urban planning strategies and neighborhood characteristics can also impact water consumption, such as the density of dwelling units (DU) and buildings. The present study surveyed households in three different classifications of dwelling densities and neighborhood types: organic, planned, and slums.

4 Research design

The present study has selected ten different neighborhoods of Vijayawada based on neighborhood type and dwelling unit densities. Further, based on the limited time and financial resources, 117 households were surveyed to procure the water consumption data and the performance of the households for the studied consumption determinants. However, a minimum of 30 households have been surveyed for each neighborhood type to ensure the effectiveness of the parametric analyses used in this study (Chang et al., 2006).

The studied neighborhoods fall into three types: organic, planned, and notified slums. Organic neighborhoods result from uncontrolled expansion based on resident preferences, while planned neighborhoods follow default space order principles (Novitasari et al., 2021). Notified slums are specific neighborhoods identified by urban local bodies, with 111 such slums in Vijayawada (Lakshmi & Ramamurthy, 2019). For the present study, each neighborhood type is classified based on DU density: low density (<60 DUs per Ha), medium density (60-75 DUs per Ha), and high density (>75 DUs per Ha). Ten neighborhoods have been selected for the study after integrating neighborhood type with the DU densities (refer to Figure 1 and Table 1).

Table 1. Studied neighborhoods, neighborhood type, and DU density

Neighborhood	Type	DUs	Area (Ha)	DUs per Ha
1. APHB HIG Colony	Planned	81	3.68	22.00[(a)]
2. Bhavanipuram	Organic	269	5.07	53.05[(a)]
3. Devi Nagar	Slum	742	7.10	104.49[(c)]
4. KL Rao Nagar	Slum	512	8.54	59.98[(a)]
5. Krishna Lanka	Organic	392	6.27	62.50[(b)]
6. Lurdhu Nagar	Slum	512	8.50	60.23[(b)]
7. RTC Colony	Planned	598	8.35	71.63[(b)]
8. VAMBAY Colony	Planned	1144	7.88	145.26[(c)]
9. Vinchipet	Organic	865	7.36	117.57[(c)]
10. Yanamalakuduru	Organic	254	4.09	62.18[(b)]

DU: Dwelling Unit | (a) Low DU density | (b) Medium DU density | (c) High DU density

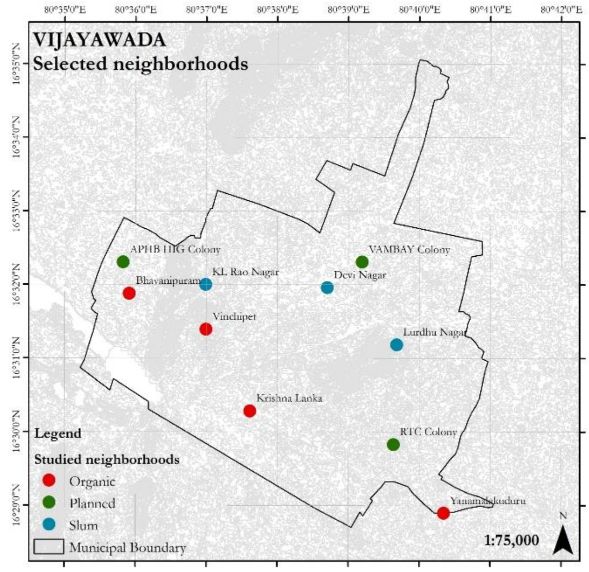

Figure 1. Studied neighborhoods

Per capita daily water consumption (PCC) was calculated by dividing household consumption by household size. Data was also collected on six variables, including household size (HHS), average monthly income (INCM), building age (BAGE), building height (BHGT), supply continuity (CNTY), and annual water charges (BILL). Descriptive statistics for each neighborhood type and overall are presented in Table 2.

Table 2. Mean values of the dependent and independent variables

Neighborhood type	ORG	PLN	SLM	OVRL
PCC	136.46	150.14	102.25	127.63
CNTY	5.38	18.94	3	8.21
HHS	5.64	4.66	4.98	5.13
INCM	22523.81	27843.75	13348.84	20606.84
BAGE	21.83	17.41	23.02	21.06
BHGT	5.43	4.13	3.63	4.41
BILL	1752.86	2053.12	774.42	1475.38

ORG: Organic | **PLN**: Planned | **SLM**: Notified Slum | **OVRL**: Overall

5 Results and Discussion

Multiple linear regression was performed on household data using PCC as the dependent variable. In this analysis, the households were divided into two datasets. The training dataset consists of 80% of the households (N=93). The remaining 20% of the households (N=24) were considered in the testing dataset. The results and the observations of the multiple linear regression are discussed in detail in this section. The regression model had an R-squared value of 0.752 and an adjusted R-squared value of 0.735, indicating a 73.5% precision in predicting the dependent variable. The model had high goodness of fit and was significant at a 1% significance level with a p-value of 2.2^{e-16}. The study found that household size, building age, and building height had negative coefficients, while average household monthly income and annual water charges had positive regression coefficients. Previous studies have shown that household income is a significant determinant of water consumption, and water prices can reduce water consumption. The study also found that the relationship between building age and water consumption was converse in the studied neighborhoods due to the minimal attention given to water-efficient appliances and installations.

The Variance Inflation Factor (VIF) values for CNTY (2.816), INCM (3.452), HHS (1.206), BAGE (1.101), BHGT (2.138), and BILL (3.269) are less than 5, indicating low multicollinearity. The Durbin-Watson test shows minimal autocorrelation of 2.028, and the Breusch-Pagan test indicates homoscedasticity (p-value = 0.240). Residuals are normally distributed based on the Shapiro-Wilk test (p=0.153). The model has adequate predictability based on the Root Mean Square Error (RMSE) of 20.69 lpcd per household.

The study found that household size has a positive coefficient while the number of hours of the water supply has a negative coefficient. Household income and annual water charges have positive coefficients, and building age and height have negative coefficients. These results are contrary to previous studies, which indicate that household size increases water consumption but decreases per capita consumption, and building age and height increase water consumption (Vallès-Casas et al., 2017). However, the study is specific to Indian urban areas and suggests that older buildings may have less efficient water installations, leading to higher per capita water consumption. These findings can be helpful for water managers and urban planners to address challenges associated with domestic water consumption.

Similarly, multiple linear regression has been performed for the surveyed households of the different neighborhood types considered in this study. The goodness of fit for the regression models of all the neighborhood types is summarized in Table 3. All the models have been significant at the 1% significance level. Organic neighborhoods had the highest coefficient of determination ($R^2_{adjusted}$) of 0.774, followed by notified slums (0.600) and planned neighborhoods (0.550). The $R^2_{adjusted}$ of all the 117 households together was 0.730.

Table 3. Summary of the regression models and significance levels for each neighborhood type

Neighborhood type	ORG	PLN	SLM	OVRL
N	42	32	43	117
R	0.89	0.75	0.80	0.75
R^2	0.79	0.56	0.64	0.74
$R^2_{adjusted}$	0.77	0.55	0.60	0.73
F value	47.76	38.95	1.60	53.33
d_f	41	31	42	116
p-value*	$5.75e^{-13}$	$7.12e^{-7}$	$5.3e^{-8}$	$2.44e^{-30}$

*The p-values in the bold indicate that the constant (intercept)/variable is significant at the 1% significance level
ORG: Organic | **PLN**: Planned | **SLM**: Notified Slum | **OVRL**: Overall

The statistically significant variables for each neighborhood type are different, as summarized in Table 4. All the models have fulfilled the assumptions of multiple linear regression. These assumptions include the absence of multicollinearity, autocorrelation, and heteroscedasticity. The residuals have been distributed normally, and the sum of residuals is equal to zero.

Table 4. Coefficients of variables and fitness of the regression models for each neighborhood type

Neighborhood type	Variable	Coefficient	Std. Error	t	p-value*	VIF	Durbin-Watson	Shapiro Wilk p-value	Breusch-Pagan p-value
Organic	constant	93.213	11.373	8.196	**0.000**	-	1.374[b]	0.591[c]	0.485[d]
	INCM	0.001	0.000	3.257	**0.002**	1.452[a]			
	HHS	-5.944	1.516	-3.922	**0.000**	1.005[a]			
	BILL	0.035	0.005	7.254	**0.000**	1.447[a]			
Planned	constant	168.137	18.408	9.134	**0.000**	-	1.226[b]	0.799[c]	0.809[d]
	HHS	-5.614	3.094	-1.815	0.077**	1.000[a]			
Notified slum	constant	116.525	18.489	6.303	**0.000**	-	2.412[b]	0.340[c]	0.284[d]
	HHS	-5.570	1.479	-3.766	**0.001**	1.080[a]			
	BAGE	-0.720	0.332	-2.17	**0.036**	1.291[a]			
	BHGT	-4.858	1.925	-2.524	**0.016**	1.111[a]			
	BILL	0.062	0.013	4.652	**0.000**	1.265[a]			
Overall	constant	131.456	9.131	14.396	**0.000**	-	1.827[b]	0.238[c]	0.124[d]
	CNTY	-1.274	0.404	-3.153	**0.002**	2.724[a]			
	HHS	-7.274	1.146	-6.345	**0.000**	1.089[a]			
	INCM	0.001	0.000	3.256	**0.002**	2.377[a]			
	BHGT	-3.026	1.160	-2.609	**0.010**	2.187[a]			
	BAGE	-0.819	0.270	-3.029	**0.003**	1.102[a]			
	BILL	0.040	0.004	9.252	**0.000**	3.367[a]			

*The p-values in the **bold** indicate that the constant (intercept)/variable is significant at the 5% significance level
**The variable (HHS) is significant at the10% significance level in planned neighborhoods
(a) The *Variance Inflation Factor* (VIF)< 5 denotes low multicollinearity among the variables in each model
(b) *Durbin-Watson test* values between 1.5 and 2.5 indicate negligible autocorrelation
(c) The *Shapiro Wilk test* p-value > 0.05 indicates the normal distribution of the residuals
(d) The *Breusch-Pagan test* p-value > 0.05 indicates the homoscedasticity of the variables

In organic neighborhoods, INCM, HHS, and BILL are significant at a 5% significance level. In planned neighborhoods, only HHS is significant at the 10% level. In notified slums, HHS, BAGE, BHGT, and BILL are significant at 5%. HHS is the only significant variable influencing consumption in all three neighborhoods.

Average household size negatively affects per capita water consumption at the 10% level. CNTY is a significant determinant in the overall model but not for any neighborhood type. INCM is significant in organic neighborhoods, while BILL significantly influences per capita water consumption in organic neighborhoods and notified slums. BHGT and BAGE are significant only in notified slums. Building characteristics affect water consumption more in notified slums than in non-slum neighborhoods.

6 Conclusion

In Vijayawada, the average water consumption is 150.14 lpcd in planned neighborhoods, 136.46 lpcd in organic neighborhoods, and 102.25 lpcd in notified slums. All regression models are significant at the 1% level, with different per capita water consumption determinants for each neighborhood type. The six independent variables are significant in all models, with their behavior strongly associated with neighborhood type. Supply continuity, household size, household income, building height, building age, and annual water charges are significant determinants of per capita water consumption overall. Household size is significant in all settlement types, while household income, size, and annual water charges are significant in organic neighborhoods. In planned neighborhoods, only household size is significant. In notified slums, household size, building height, age, and annual water charges are significant. These results can help water managers and urban planners address water consumption challenges.

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