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SMART METERING AND SOCIO-ECONOMIC APPROACHES FOR URBAN WATER SUSTAINABILITY DURING DROUGHT IN CAPE TOWN, SOUTH AFRICA

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Background: Urban water systems face increasing pressure from climate-driven droughts, population growth, and infrastructural limitations. In Cape Town, prolonged droughts have highlighted inequalities in household water access and consumption patterns. Understanding how socio-economic disparities and behavioural responses interact with municipal water management is essential to inform equitable, efficient, and sustainable water governance. **Objectives:** This study investigates how household socio-economic status, local infrastructure, and smart water metering influence water consumption patterns, identifies unaccounted-for water, and assesses strategies to improve demand-side management during droughts in rapidly urbanising cities. **Methods:** A multi-component, spatially grounded methodology was applied across six Cape Town suburbs representing three income tiers. Secondary data, including monthly billing records, water meter readings, and socio-economic indicators, were analysed using descriptive statistics, trend analyses, and unaccounted-for water assessment. Stratified random sampling ensured proportional representation of households across income categories. Geographic Information Systems (GIS) were used to map consumption patterns and detect spatial disparities. Comparative analyses quantified variations in water demand, billing anomalies, and behavioural responses, while scenario-based evaluation examined the effectiveness of smart metering and demand-side interventions under differing drought conditions. **Results:** Findings reveal substantial heterogeneity in water consumption and billing across income tiers, with high variability driven by socio-economic disparities, household size, and settlement patterns. Negative consumption and unaccounted-for water indicate operational inefficiencies and potential socio-economic stress. Smart metering enabled improved detection of leaks and anomalous usage, but its effectiveness was moderated by affordability and compliance. Demand-side interventions, including tiered tariffs, volumetric restrictions, and public awareness campaigns, demonstrated potential to reduce consumption, particularly in higher-income households. Proactive and reactive strategies combined improved resilience and demonstrated the importance of equity-centred governance. Results showed that technical solutions alone are insufficient without concurrent socio-economic and behavioural considerations. **Conclusion:** Urban water resilience under drought requires integrated, equity-focused strategies combining technical, economic, and behavioural interventions. Smart metering and demand management are most effective when measures are taken to reduce socio-economic inequalities. The study' s novelty lies in combining municipal water billing records, socio-economic classifications, and GIS-based demographic mapping to examine disparities in urban water allocation and unaccounted-for water during drought conditions. This work advances knowledge by demonstrating how GIS-supported demographic analysis can contextualize patterns of water allocation, billing irregularities, and unaccounted-for water across socio-economic areas.

Keywords: urban water management; climate change adaptation; sustainable; smart water metering; water scarcity; drought resilience; spatial analysis (GIS); water consumption behaviour; unaccounted-for water (UFW); socio-economic assessment.

INTRODUCTION

The consequences of drought are particularly severe in underdeveloped and developing countries, where constrained economic resources and weak institutional capacity limit effective responses within urban water systems. Poor economic governance in the water sector often exacerbates existing inequalities in water demand, availability, and affordability, intensifying the socio-economic impacts of prolonged drought (Parker et al., 2022; Babuna et al., 2023; Ortuzar et al., 2025). In this context, demand-side management has emerged as a critical strategy for mitigating drought impacts without incurring substantial capital expenditure, particularly in rapidly urbanising regions exposed to climate-driven hydrological variability (Aboelnga et al., 2019; Dilling et al., 2019).

Cape Town's recent drought provides a well-documented example of systemic stress within an urban environmental water system. Since 2015, the Western Cape region experienced one of the most severe droughts of the 20th and early 21st centuries, affecting approximately 3.7 million residents (Sousa et al., 2018). By late 2017, critically low dam levels led to warnings that municipal water supply systems could be shut down. This event is widely known as "Day Zero". The drought was primarily driven by an unprecedented three-year rainfall deficit (Burls et al., 2019), with projections indicating similar risks for other municipalities (Pascale et al., 2020; IPCC, 2022).

In response, the City of Cape Town implemented progressively stringent demand management interventions, including water restrictions, tariff restructuring, and the deployment of advanced monitoring technologies such as smart water meters (Ziervogel, 2019). These measures were effective in reducing aggregate demand; however, they also revealed critical vulnerabilities in system performance, including uneven consumption patterns, infrastructure constraints, and affordability-related disconnections (Brühl & Visser, 2021; Cook et al., 2021; Faragher & Carden, 2023). These dynamics highlight the need to understand how technological monitoring systems interact with socio-economic conditions to influence the stability, efficiency, and environmental safety of urban water supply systems.

Water is a complex environmental resource that functions simultaneously as an economic good and a critical component of urban infrastructure systems. Its spatial variability, essential nature, and limited substitutability make its management inherently challenging. While economic instruments such as pricing, subsidies, and demand management are widely used to regulate consumption, their effectiveness depends on how well they are integrated with the physical and operational characteristics of water supply systems (Wutich, 2025; Grafton et al., 2020; Bruno & Jessoe, 2021).

In practice, increasing demand, ageing infrastructure, and environmental change undermine both the efficiency and equity of water distribution. A key challenge in urban systems is the

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high proportion of non-revenue water, resulting from leakage, metering inaccuracies, billing inefficiencies, and non-payment (Farley & Trow, 2021). These losses not only reduce system efficiency but also distort economic signals intended to regulate demand, thereby weakening the effectiveness of pricing-based interventions (Maziotis et al., 2023).

At the same time, conventional economic analyses of water systems rarely integrate real-time monitoring technologies, such as smart metering, with spatially explicit system data. This disconnect limits the ability to evaluate system performance, detect anomalies in water distribution, and link consumption behaviour with infrastructure conditions in a dynamic and spatially resolved manner.

Historically, water management strategies focused on supply augmentation through large-scale infrastructure. However, there has been a shift towards demand-side and data-driven approaches, including the use of digital monitoring technologies and spatial analytics to improve system efficiency and resilience (Palermo et al., 2022; Rousso et al., 2024).

Nevertheless, the combined application of GIS-based spatial analytics and smart water metering for the evaluation of urban water system performance remains underdeveloped. This gap constrains the ability to conduct integrated assessments that link spatial consumption patterns with real-time monitoring data, thereby limiting insights into system efficiency, resilience, and environmental risk. Urban water supply systems operate as complex engineered networks consisting of source abstraction, treatment, transmission, distribution, and end-use consumption components. System performance is typically evaluated in terms of efficiency, reliability, and loss minimisation. Under drought conditions, these systems experience increased hydraulic and operational stress, necessitating enhanced monitoring, control, and demand-side optimisation.

A potentially effective approach to the identified problem is the integration of municipal billing records, demographic GIS layers, and water allocation datasets to identify spatial disparities and administrative inefficiencies associated with urban water distribution. In contrast to traditional approaches, which treat economic and technical analyses separately, this proposed approach is expected to combine real-time consumption monitoring with socio-economic indicators to identify system inefficiencies and spatially explicit vulnerabilities.

Understanding the flow of water from source to end user is fundamental to evaluating the performance and integrity of urban water supply systems. Standardised water balance frameworks, such as those proposed by the International Water Association (IWA), decompose total system input into authorised consumption, real losses, and apparent losses (Iwanek, 2018). These frameworks provide a basis for identifying inefficiencies within different components of the distribution network, including transmission systems, distribution pipelines, and household connections.

Accurate quantification of these components relies on the integration of multiple data sources, including production records, billing data, and flow measurements from district metered areas (Alegre et al., 2016; Ong et al., 2023). Recent advances in smart metering technologies enable more granular, real-time monitoring of consumption patterns and system anomalies, offering new opportunities to improve leak detection, demand management, and infrastructure performance (Soares Ascenção et al., 2023; Taloma et al., 2025).

However, the integration of these heterogeneous datasets within spatially explicit analytical frameworks remains limited. In many cases, production data, billing records, and metering information are analysed independently, constraining the ability to develop a coherent system-level understanding of water distribution dynamics. This fragmentation restricts the identification of spatial inefficiencies, limits the detection of infrastructure-related anomalies, and reduces the effectiveness of data-driven approaches for monitoring and optimising urban water system performance.

Together, these developments highlight the importance of data-driven approaches for improving system monitoring, asset management, and long-term urban water planning (Hangan et al., 2022).

The socio-economic and environmental context of the Western Cape plays a critical role in shaping water demand, access, and system vulnerability. Historically, water availability has influenced settlement patterns and resource use in the region (Enqvist & Ziervogel, 2019). Today, the region exhibits significant spatial variability in climate and rainfall, driven by complex topography and Mediterranean climatic conditions (Engelbrecht & Monteiro, 2021; Conradie et al., 2022).

This variability contributes to uneven water availability across the region, which, when combined with socio-economic disparities, results in differentiated exposure to water scarcity and affordability constraints.

Despite extensive research on urban water demand, pricing, and conservation strategies, few studies have systematically integrated smart water metering with GIS-based spatial analysis to evaluate urban water system performance under drought conditions. This gap limits our understanding of how socio-economic disparities, infrastructure constraints, and temporal consumption patterns interact to influence both system efficiency and equitable access. Thus, there is a growing need for a conceptual shift from viewing unaccounted-for water solely as a technical infrastructure problem toward interpreting it as a combined socio-technical and allocation-related phenomenon.

In particular, limited attention has been given to how administrative billing anomalies and unaccounted-for water can be interpreted within a socio-economic and spatial allocation framework during drought conditions. Existing studies predominantly treat such anomalies as technical errors rather than as indicators of structural inequalities and institutional inefficiencies within urban water systems.

The aim of this study is to develop a techno-economic assessment framework that combines municipal billing records, socio-economic indicators, and GIS-based demographic mapping to identify disparities in water allocation, billing anomalies, and unaccounted-for water across urban areas. By applying this integrated approach in Cape Town, the study seeks to uncover previously unquantified patterns of water scarcity, consumption behaviour, and tariff-related constraints.

It is hypothesised that integrating spatial demographic analysis with municipal billing and water allocation records will reveal distinct zones of vulnerability where socio-economic disparities, administrative inefficiencies, and water allocation irregularities converge, thereby supporting the development of more equitable and resilient urban water management strategies.

MATERIALS AND METHODS

Study area

Cape Town has been widely recognised as a critical case study of urban water system vulnerability under extreme drought conditions. During the 2015–2019 drought, the city faced the prospect of "Day Zero", when municipal water supplies were projected to be completely depleted within a relatively short period of time. In response, the municipality implemented progressively stricter water restrictions (Levels 3–6B, according to the city's official drought management framework) aimed at reducing consumption and maintaining overall system functionality and operational stability.

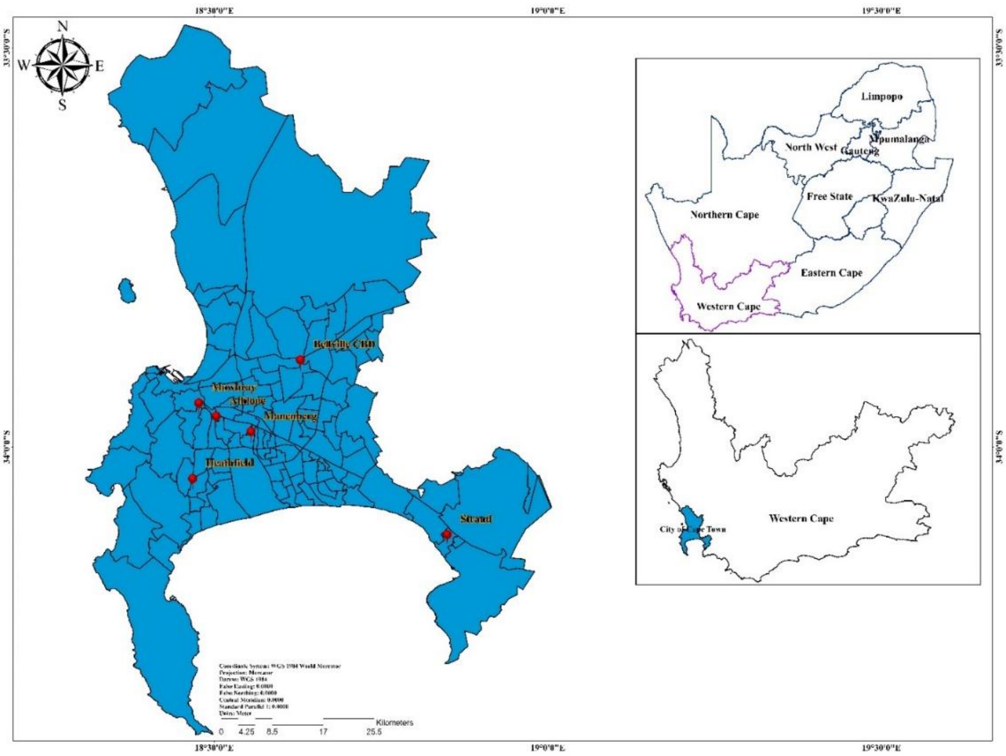

Figure 1. Study area of the 6 focus areas (the authors' own development)

The Western Cape, the fourth largest of South Africa's nine provinces and the country's southernmost point, is shown in Figure 1. Along with the Atlantic and Indian seas in the west and south, the province also has shared borders with the provinces of the Northern Cape and Eastern Cape in the north and east, respectively. It is important to consider historical events as well as local elements that have influenced the current water situation in Cape Town (Kaziboni, 2024).

This case highlights broader challenges faced by rapidly urbanising regions in southern Africa, where climate variability and population growth place increasing pressure on water resources (Kusangaya et al., 2014; Bhaga et al., 2020; Nkhata, 2022). The Cape Town case is particularly suitable for a combined techno-economic and spatial analysis because it exhibits pronounced variability in water consumption across socio-economic groups and spatially heterogeneous infrastructure performance. The availability of detailed municipal billing records and geospatial datasets enables linking spatial and temporal consumption patterns with household-level socio-economic and geographic characteristics, allowing for an integrated assessment of system efficiency, equity, and resilience.

Methodology

The research methodology employed a multi-component approach to data collection in order to address the study's objectives comprehensively. The primary analytical technique consisted of a trend analysis of household water consumption across six selected suburbs within Cape Town (Figure 2). This approach relied exclusively on secondary data sources, encompassing both quantitative records, such as monthly billing and meter readings, and qualitative contextual information relating to socio-economic conditions and municipal water management practices. The data covered the period from 2019–2021 and were obtained in formats including CSV for billing data and shapefiles for GIS layers, sourced from the City of Cape Town open data portal (https://www.capetown.gov.za/Family%20and%20home/residential-utility-services). The use of secondary data facilitated the identification of temporal patterns in water use as well as insights into consumer behaviour and attitudes toward water demand management.

Figure 2 illustrates the population density and income classifications of the six study areas: Bellville CBD, Mowbray, Athlone, Manenberg, and Heathfield. These data were obtained from the City of Cape Town's publicly accessible administrative datasets, which provide neighborhood-level demographics, socio-economic, and infrastructural indicators widely used in spatial assessments of urban services (City of Cape Town, 2021). To enhance analytical precision, data categories were systematically developed to organize and interpret information associated with the targeted population in a manner consistent with established approaches in socio-spatial water research (Simpson et al., 2019). The selected suburbs represent three distinct income tiers within the metropolitan region, capturing variations in household water use across income categories while accounting for environmental factors such as microclimates, population density, and settlement forms (Pasquini & Cowling, 2015; Wolski et al., 2018). The spatial configuration, density gradients, and proximity to differing rainfall zones further support the assessment of socioeconomic and geographic interactions in shaping water demand (Enqvist & Ziervogel, 2019).

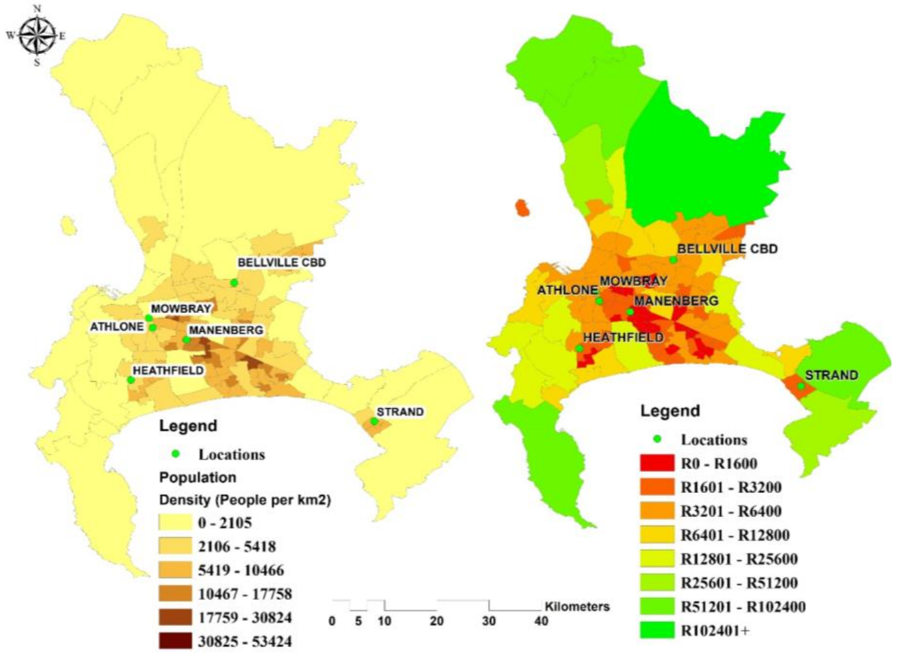

Figure 2. Depicts the population density and economic income bracket for Bellville CBD, Mowbray, Athlone, Manenberg, and Heathfield, Cape Town, Western Cape region

The GIS data were standardized using ArcGIS Pro (version 3.2, ESRI), and shapefiles were projected to WGS 84 / UTM zone 34S. In this study, GIS analysis was primarily used to spatially classify study areas according to population density, income grouping, and settlement characteristics, and to compare these demographic zones with patterns observed in municipal water allocation and billing datasets. GIS outputs were therefore used as contextual analytical layers rather than as a real-time hydraulic monitoring system. Population and income data were linked to billing records using both census data and geocoded household coordinates provided through the open-access data portal of the controlling water authority. All datasets were anonymized to protect individual households, and sample datasets are provided in the Supplementary Material to ensure reproducibility.

Sample survey methodology

A stratified random sampling approach was employed to select residential suburbs representing different income categories within the Cape Town metropolitan area. Stratification allowed the study population to be divided into mutually exclusive, non-overlapping income-based strata, from which simple random samples were independently drawn. The strata were defined using household income percentiles and census data for 2019–2021 ensuring proportional representation of each socio-economic group (Etikan & Bala, 2017).

The sample size was calculated using the finite population correction formula:

$$N_s = \frac{N \times Z^2 \times P(1-P)}{(N-1)\times e^2 + Z^2 \times P(1-P)}, \quad (1)$$

where N_s represents the sample size, N is the population size, Z is the Z-score corresponding to the selected confidence level (1.96 for 95% confidence), P is the estimated response proportion (0.8), and e is the margin of error (±0.10).

For large population sizes, the formula was simplified to:

$$N_s = \frac{Z^2 \times P(1-P)}{e^2}, \quad (2)$$

Substituting the study parameters yielded:

$$N_s = \frac{1.96^2 \times 0.8(1-0.8)}{0.1^2} = 61.47.$$

Based on this calculation, a minimum of 61 households per suburb was sampled to achieve a 95% confidence level, assuming an expected response proportion of 80% and a precision of ±10%. The random selection process was conducted using Python version 3.11, Pandas version 3.0, and NumPy version 2.0, and anonymized sample IDs are included in the Supplementary Material. Stratification ensured the inclusion of all income tiers, minimized sampling error, and enabled targeted comparisons among socio-economic and spatial subgroups (Etikan & Bala, 2017).

Data integration and pre-processing

Billing records, GIS shapefiles, and demographic datasets were integrated using ArcGIS Pro (version 3.2, ESRI) and Python (version 3.11), with Pandas, GeoPandas, and NumPy libraries. Monthly water consumption data were aggregated into annual averages for each household to account for seasonal variation and inconsistencies in meter-reading intervals. Outliers, missing values, and duplicate entries were systematically identified and corrected following standardized data-cleaning protocols (Wang et al., 2024; Berlotti et al., 2025).

Spatial linkage was performed using geocoded meter locations and census block IDs to align consumption data with population density and income information. All pre-processing scripts and GIS workflows are included in the Supplementary Material to ensure full reproducibility.

Required datasets

The following datasets were used:
– municipal billing records (2019–2021): volumes of water consumed per household per billing period, customer type, and spatial identifiers;
– GIS shapefiles (2019–2021): boundaries of suburbs, census blocks, and distribution zones;
– demographic and socio-economic data (2019–2021): income, household size, population density, and settlement type.

These datasets enabled the analysis of consumption patterns across income groups and geographic zones, as well as the estimation of economic impacts related to water demand management (Alegre et al., 2016). All datasets were anonymized and linked using standardized IDs, and example datasets are provided in the Supplementary Material for verification.

RESULTS

Spatial demographic classification derived from GIS mapping was used to compare socio-economic areas with municipal water allocation records and patterns of unaccounted-for water (UFW). This comparison revealed that billing anomalies and unexplained water deficits were not uniformly distributed across study areas, suggesting potential links between socio-economic structure, administrative inefficiencies, and water allocation disparities.

Beyond conventional consumption analysis, the results indicate that recurring billing anomalies and negative allocation values may contain diagnostically relevant information regarding administrative inefficiencies, unequal allocation structures, and potential forms of water vulnerability across socio-economic areas.

Tables 1–6 present descriptive statistics for the six study areas, namely Athlone, Bellville, Heathfield, Manenberg, Mowbray, and Strand, using two principal variables: billed amounts (ZAR) and water consumption (kL). The datasets cover the 2019–2021 period and include commercial, internal, domestic, industrial, other, and unassigned customer categories.

Table 1. Billed amounts (ZAR) by customer category and suburb, 2019

Location	Stats	Commercial	Internal	Domestic	Industrial	Other	Not assigned
Athlone	Min	–203	2370	441378	400	52243	1751
	Max	153851	5167	817645	1001	108195	4809
	Median	126320	3184	635731	400	86035	3675
	SD	42986	687	107990	175	15592	796
Bellville	Min	345333	–264311	875	0	–72279	13080
	Max	1250327	120215	38850	0	178024	19317
	Median	593892	49030	26291	0	34910	16176
	SD	210592	95877	10170	0	54648	1931
Heathfield	Min	11118	–49299	239913	0	–170112	2691
	Max	18201	1212	381914	0	47169	6275
	Median	14244	754	328129	0	29777	3087
	SD	2102	13847	38114	0	56221	1219
Manenberg	Min	–25360	435179	–4202654	–2228	93193	1097
	Max	27962	650548	1161275	3282	247707	40100
	Median	11244	566306	785131	895	160160	20374
	SD	12254	64686	1449612	1222	37274	9200
Mowbray	Min	–826856	3568	395947	0	123066	1071
	Max	1236818	7473	715496	0	319160	2288
	Median	225355	4633	512755	0	196933	1651
	SD	424003	1027	94859	0	51406	283
Strand	Min	186043	99166	1257122	21405	157654	23728
	Max	308345	180728	2413774	39496	538007	48753
	Median	254820	118592	2045366	30578	327170	42681
	SD	35039	23549	301931	5037	85340	6391

Across all study areas, commercial consumers exhibited the greatest variability in both billing amounts and water consumption, reflecting heterogeneous operational demand, tariff exposure, and differing scales of economic activity. Domestic consumption patterns were comparatively more stable but displayed clear socio-economic differentiation among suburbs. High standard deviations, extreme maximum values, and recurrent negative records collectively suggest that municipal water datasets contain both technical and administrative irregularities that may influence the interpretation of urban water demand and unaccounted-for water.

Negative billing and consumption values occurred across multiple customer categories and study areas. These records most likely reflect billing adjustments, meter rollover events, interdepartmental reconciliations, retrospective corrections, or credit balances applied to accounts rather than physically negative water use (Santos, 2024). Rather than excluding these values, they were retained within the descriptive dataset because they provide analytically relevant information regarding administrative inconsistencies, billing adjustments, and apparent losses within the broader municipal water distribution system.

Comparison across suburbs demonstrates pronounced disparities in both maximum charges and consumption volumes. Commercial billing values ranged from ZAR 153,851 in Athlone to ZAR 1,250,327 in Bellville during the 2019 assessment period, while maximum commercial water consumption varied from 4,449 kL in Athlone to 20,019 kL in Bellville. Similarly, substantial variation was observed among domestic consumers, particularly in Manenberg and Strand, where exceptionally high standard deviations indicate highly uneven consumption and billing distributions.

The descriptive statistics further suggest that water allocation and financial exposure are strongly differentiated across socio-economic areas within the municipal service network. Bellville and Mowbray generally exhibited higher commercial billing values, consistent with greater concentrations of business activity and commercial water demand, whereas Manenberg displayed substantial variability in domestic records, including large negative values, potentially indicating recurrent billing adjustments, reporting irregularities, or allocation inconsistencies over time. Such patterns highlight the importance of contextual socio-economic interpretation when evaluating urban water datasets (Arbués et al., 2003; Barberán et al., 2022).

Table 2. Water consumption (kL) by customer category and suburb, 2019

Location	Stats	Commercial	Internal	Domestic	Industrial	Other	Not assigned
Athlone	Min	–961	24	20188	0	–88	58
	Max	4449	74	29015	112	143	173
	Median	79	43	24980	0	18	141
	SD	1267	12	2343	31	59	30
Bellville	Min	44	–59965	123	0	–1360	801
	Max	2019	17349	1795	0	4964	1083
	Median	1062	1113	1226	0	1189	915
	SD	484	18163	418	0	1509	96
Heathfield	Min	110	–1109	10127	0	6	–518
	Max	489	13	13729	0	101	182
	Median	443	10	12131	0	13	112
	SD	148	309	942	0	25	178
Manenberg	Min	–1082	8340	–318813	–106	10	–176
	Max	1047	12819	536547	115	9307	1377
	Median	348	10730	61379	17	15	630
	SD	492	1424	233210	49	2568	330
Mowbray	Min	–28462	93	16014	0	–1510	35
	Max	27855	249	32269	0	94	65
	Median	6773	126	19224	0	41	51
	SD	11925	41	4150	0	432	8
Strand	Min	367	112	79958	582	–144	1319
	Max	1564	750	98180	1306	6655	1833
	Median	537	690	89913	838	3500	1585
	SD	354	234	5327	184	1622	152

Table 3. Billed amounts (ZAR) by customer category and suburb, 2020

Location	Stats	Commercial	Internal	Domestic	Industrial	Other	Not assigned
Athlone	Min	–203	0	18515	0	3834	0
	Max	153851	5167	817645	1001	108195	4809
	Median	126320	3175	621006	400	86035	3675
	SD	52002	1168	206488	220	26314	1298
Bellville	Min	22777	–25441	0	0	245	0
	Max	60161	24951	0	0	257	0
	Median	47683	21600	0	0	251	0
	SD	10061	13538	0	0	6	0
Heathfield	Min	0	100	6584	0	544	1887
	Max	0	133	26876	0	9366	2026
	Median	0	102	13536	0	597	1949
	SD	0	9	4557	0	2419	43
Manenberg	Min	0	14645	14379	0	0	0
	Max	0	194192	22470	0	86	0
	Median	0	160755	19370	0	84	0
	SD	0	43912	2010	0	37	0
Mowbray	Min	35408	0	6294	0	–75110	178
	Max	51676	0	17641	0	166874	270
	Median	42708	0	8664	0	55109	241
	SD	4907	0	2789	0	54176	22
Strand	Min	–410	0	31828	1775	–8423	–291
	Max	25470	620	48224	3437	24816	2268
	Median	16993	182	38691	1910	18403	1857
	SD	6464	154	4313	479	8863	644

Descriptive statistical analysis remains an important component of urban water demand research because it enables the identification of anomalies, outliers, irregular consumption behaviour, and tariff-related variability that may influence subsequent modelling and policy development (Olmstead, 2007; Dias & Ghisi, 2024). In the present study, these descriptive patterns also provide insight into possible administrative and allocation-related inefficiencies associated with UFW.

Components of unaccounted-for water (UFW)

Figure 3 illustrates the principal components of unaccounted-for water, defined as the difference between total supplied water and total measured or billed consumption within the municipal distribution network. These discrepancies may arise from a range of interconnected factors, including physical losses, metering inaccuracies, billing anomalies, unauthorized consumption, or broader administrative inconsistencies within the municipal water management system (Santos, 2024).

Table 4. Water consumption (kL) by customer category and suburb, 2020

Location	Stats	Commercial	Internal	Domestic	Industrial	Other	Not assigned
Athlone	Min	–961	0	622	0	–88	0
	Max	4449	74	29015	112	143	173
	Median	70	42	24980	0	18	141
	SD	1267	17	7092	31	59	49
Bellville	Min	342	–1271	0	0	0	0
	Max	1622	540	0	0	0	0
	Median	1346	420	0	0	0	0
	SD	368	487	0	0	0	0
Heathfield	Min	0	0	252	0	10	9
	Max	0	1	566	0	169	13
	Median	0	0	387	0	14	11
	SD	0	0	72	0	43	1
Manenberg	Min	0	280	743	0	0	0
	Max	0	1699125	1181	0	0	0
	Median	0	2410	980	0	0	0
	SD	0	469004	111	0	0	0
Mowbray	Min	768	0	165	0	–22	1
	Max	1306	0	515	0	104	7
	Median	1008	0	254	0	44	5
	SD	164	0	82	0	29	2
Strand	Min	–234	0	1229	4	73	–26
	Max	661	19	2031	39	430	73
	Median	388	3	1496	9	275	55
	SD	222	5	206	10	111	24

Table 5. Billed amounts (ZAR) by customer category and suburb, 2021

Location	Stats	Commercial	Internal	Domestic	Industrial	Other	Not assigned
Athlone	Min	0	0	18515	0	759	0
	Max	3257	0	817645	0	4774	0
	Median	2025	0	621006	0	2303	0
	SD	706	0	206488	0	1249	0
Bellville	Min	25438	6293	0	0	–59262	0
	Max	63993	56558	0	0	3008	0
	Median	40506	18196	0	0	257	0
	SD	10208	11878	0	0	16625	0
Heathfield	Min	0	100	6584	0	302	–291
	Max	0	110	26876	0	634	25440
	Median	0	107	13536	0	445	1956
	SD	0	3	4557	0	120	6744
Manenberg	Min	0	0	14379	0	0	0
	Max	0	154473	22470	0	88	0
	Median	0	129598	19370	0	87	0
	SD	0	38846	2010	0	24	0
Mowbray	Min	32498	0	6294	0	–103259	216
	Max	58384	0	17641	0	65703	275
	Median	44939	0	8664	0	20253	229
	SD	6623	0	2789	0	42135	19
Strand	Min	8210	0	31828	–1113	13471	848
	Max	19500	0	48224	5106	28293	2161
	Median	16364	0	38691	1883	18597	1153
	SD	2833	0	4313	1400	4031	460

Water demand is categorized into residential, commercial, industrial, business, and institutional sectors to support more accurate forecasting, allocation, and long-term infrastructure planning processes (Alegre et al., 2016; Fang et al., 2024). These classifications enable a more detailed assessment of sector-specific consumption patterns and variations in overall water demand across the municipal system. Measurements are obtained upstream of the distribution network, thereby enabling clearer differentiation between supply-side operational processes and downstream distribution losses occurring within the network infrastructure (Estrada et al., 2025).

Water billing for selected sites for 2019

Prior to analysis, all billing and consumption records were subjected to a structured validation protocol to identify anomalous values and potential inconsistencies within the municipal database. Negative water consumption values, which are physically implausible, were identified across multiple suburbs and customer categories. These records most likely resulted from meter rollover events, post-billing credit adjustments, interdepartmental reconciliations, retrospective invoice corrections, or other administrative adjustments within the municipal accounting system (Santos, 2024).

Table 6. Water consumption (kL) by customer category and suburb, 2021

Location	Stats	Commercial	Internal	Domestic	Industrial	Other	Not assigned
Athlone	Min	0	0	–309	0	15	0
	Max	46	0	696	0	24	0
	Median	11	0	591	0	21	0
	SD	12	0	284	0	3	0
Bellville	Min	746	–172	0	0	–7	0
	Max	2027	1718	0	0	7	0
	Median	1257	283	0	0	0	0
	SD	330	441	0	0	3	0
Heathfield	Min	0	0	131	0	1	–3
	Max	0	0	1027	0	15	1005
	Median	0	0	437	0	9	13
	SD	0	0	225	0	5	279
Manenberg	Min	0	0	14	0	0	0
	Max	0	2441	1158	0	0	0
	Median	0	2080	1061	0	0	0
	SD	0	618	338	0	0	0
Mowbray	Min	782	0	233	0	–23	3
	Max	1603	0	436	0	104	7
	Median	1011	0	294	0	33	4
	SD	215	0	61	0	27	1
Strand	Min	123	0	1240	–103	1	24
	Max	441	0	1666	127	718	66
	Median	361	0	1471	9	302	33
	SD	80	0	131	47	177	15

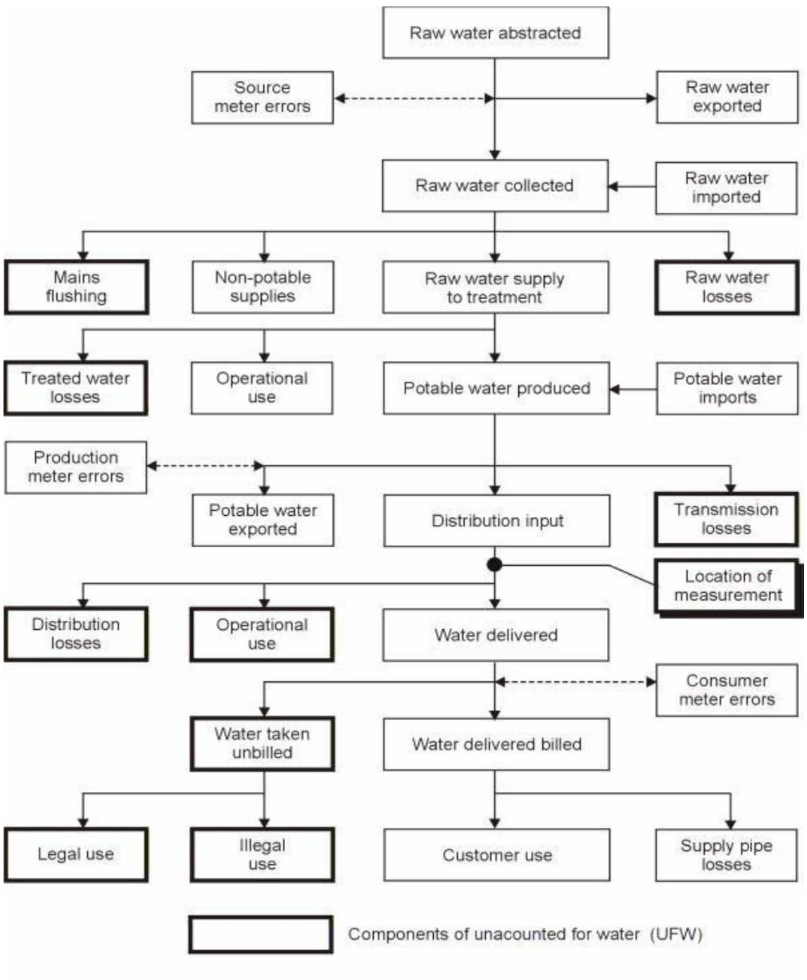

Figure 3. Unaccounted for water component

Rather than removing anomalous entries, flagged values were retained within the descriptive dataset to preserve the integrity of the municipal records and to document the extent of billing inconsistencies relevant to UFW assessment. For trend interpretation, negative values were treated as indicators of apparent losses or administrative adjustments rather than as physically measured consumption values. All flagged records are provided in the Supplementary Material to support independent verification and reproducibility.

Figure 4 presents representative monthly billing amounts and water consumption values for selected customer categories during 2019. Detailed monthly tariff and consumption plots for all study areas are provided in the Supplementary Material, while representative examples are presented here to highlight major temporal and socio-economic patterns.

Commercial consumers exhibited substantial variability in billing values throughout the year, reflecting fluctuating operational demand, tariff exposure, and seasonal economic activity, as well as broader shifts in business activity patterns. Domestic users consistently recorded the highest cumulative annual billing amounts and demonstrated clear seasonal consumption patterns, particularly during peak demand periods and periods of heightened household water use. By contrast, industrial consumption remained comparatively limited or absent within several study areas, suggesting either reduced industrial activity, structural differences in land use, or aggregation of such users under alternative customer classifications within the municipal billing system.

Water consumption trends broadly mirrored billing behaviour but were not always directly proportional due to tiered tariff structures, fixed service charges, periodic billing corrections, and various administrative adjustments within the municipal accounting system. Several customer categories exhibited negative consumption values, further reinforcing the importance of systematic data validation procedures and indicating the presence of apparent losses, metering inconsistencies, or retrospective account reconciliation and adjustment processes over time.

The observed variability across customer categories and suburban areas suggests that municipal billing datasets contain information extending beyond simple consumption reporting alone. In particular, recurring anomalies and irregular allocations may provide indirect indicators of administrative inefficiencies, unequal allocation practices, and localized forms of water vulnerability within the broader urban water distribution system.

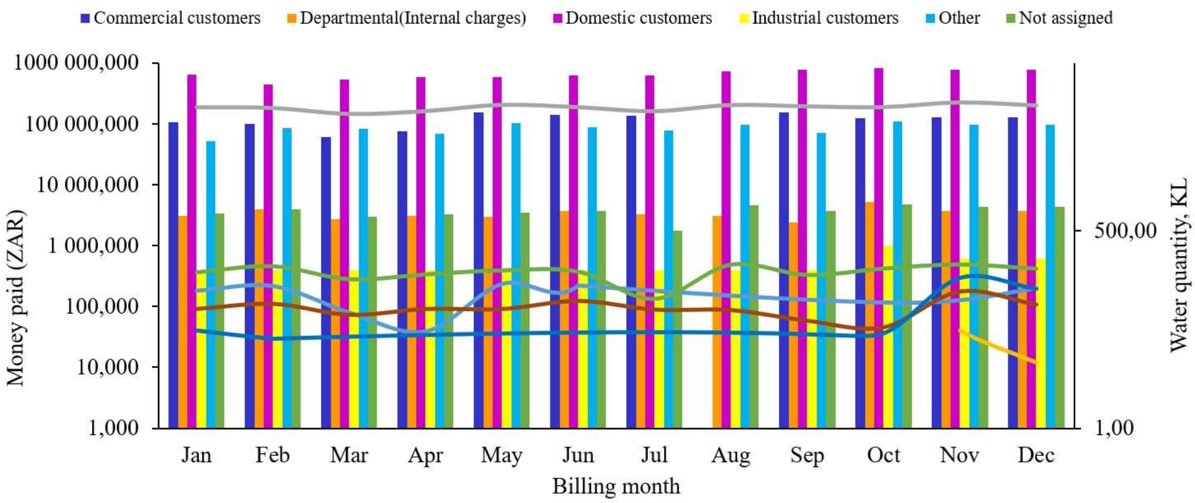

Figure 4. Monthly water billing amounts for selected customer categories across the designated study areas

Figure 5 presents contrasting billing and consumption patterns observed within the Strand study area during 2019. Commercial billing values remained consistently higher than those recorded for domestic consumers, reflecting differences in operational demand and tariff application. Internal departmental accounts and "Other" customer categories displayed considerable fluctuation, including occasional negative values associated with account reconciliation procedures and billing corrections.

Commercial water consumption similarly exhibited substantial monthly variation, while domestic consumption patterns remained comparatively stable throughout the year. Water use recorded under the "Not Assigned" category indicates that portions of municipal consumption could not be linked to clearly defined customer classifications, highlighting potential limitations in municipal data categorisation and account management procedures.

The persistence of negative billing and consumption values across multiple categories further supports the interpretation that portions of UFW may be associated not only with physical leakage but also with administrative inconsistencies, data-processing limitations, and allocation-related discrepancies within the municipal system.

Water billing for the selected sites for 2020

Patterns observed during 2020 remained broadly consistent with those identified for 2019, although several study areas exhibited reduced variability in domestic billing and consumption values. Commercial users continued to demonstrate the highest overall variability in both financial charges and recorded water use, while recurrent negative values persisted across selected customer categories. These patterns suggest that administrative adjustments and allocation inconsistencies remained present throughout the study period.

Water billing for the selected sites for 2021

The 2021 datasets similarly demonstrate continued heterogeneity across suburbs and customer categories. While several study areas exhibited more stable billing distributions relative to earlier years, substantial variability remained evident in both domestic and commercial records. Persistent anomalous entries and irregular allocation patterns reinforce the importance of robust municipal data validation procedures for improving the interpretation of UFW and urban water allocation dynamics.

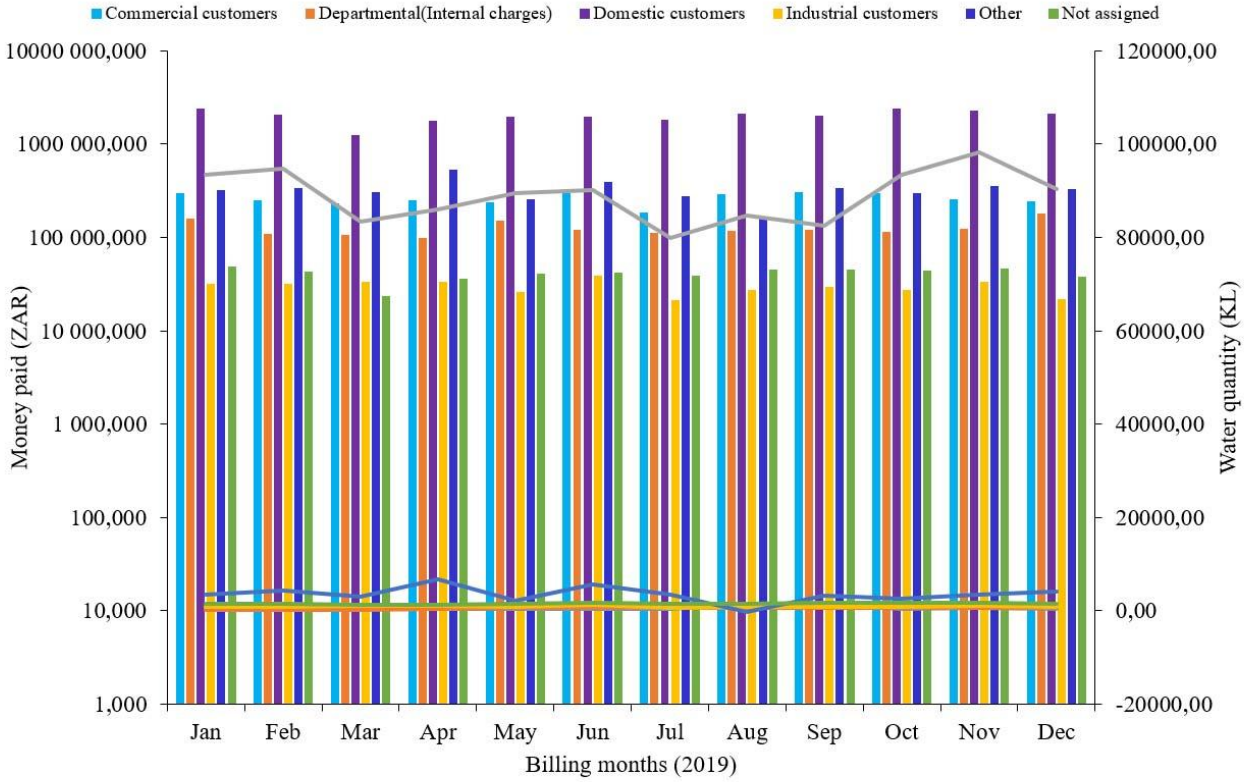

Figure 5. Water tariff structure in Strand for 2019

Negative values within the datasets represent discrepancies between allocated, billed, and recorded water volumes. Such discrepancies may arise from leakage within the distribution network, metering inaccuracies, unauthorized consumption, billing corrections, or retrospective reconciliation procedures. These findings highlight the importance of integrating technical monitoring with administrative oversight to improve urban water governance and reduce apparent losses within municipal water systems.

DISCUSSION

The results of this study demonstrate pronounced spatial and socio-economic heterogeneity in urban water consumption and billing outcomes across the selected Cape Town suburbs. The observed disparities in both monetary payments and water consumption reflect underlying differences in household composition, tariff structures, and patterns of water use, consistent with findings from recent urban water research.

The role of GIS in this study was not to perform advanced spatial modelling, but rather to provide demographic and socio-economic spatial context for interpreting municipal water allocation and billing records. Recent studies using high-resolution smart metering data have shown that consumption patterns are strongly associated with socio-economic characteristics such as income levels, household size, and user behaviour, highlighting the value of granular datasets in capturing demand heterogeneity and temporal variability (Wang et al., 2024).

The large variations in billing and consumption observed among commercial and domestic users, together with instances of negative or zero values, underscore the complexity of real-world urban water systems. Although physically implausible, negative values in consumption and billing data frequently arise in empirical datasets due to meter rollover events, data entry errors, or post-billing adjustments, and must be carefully addressed through rigorous data cleaning and validation prior to analysis and interpretation.

These anomalies further emphasize the importance of robust quality assurance protocols in secondary data analysis, particularly when linking water consumption patterns to socio-economic indicators.

Spatial disparities in water use are further influenced by settlement form, infrastructure access, and demographic structure. Research has shown that urban morphology and socio-economic differentiation significantly affect water consumption behaviour, where densely populated or lower-income areas often exhibit different demand patterns compared to more affluent suburbs characterised by larger households and higher discretionary water use (e.g., irrigation and commercial activities) (Dias & Ghisi, 2024). In the context of Cape Town, this suggests that spatial variation in water demand is not merely a function of access or pricing, but also reflects long-standing structural factors shaping both household and commercial consumption.

The analysis of unaccounted-for water (UFW) further supports the notion that urban water systems exhibit inherent inefficiencies that vary across socio-economic and functional groups. UFW includes both physical losses (e.g., leakage) and apparent losses (e.g., metering or billing errors), which can distort the observed relationship between supplied and billed volumes. Understanding these components is essential for accurate water balance modelling and planning, as discrepancies between supply and consumption may obscure underlying system performance issues that affect both equity and operational reliability.

The pronounced seasonal and inter-annual variability observed in billing and consumption data aligns with broader evidence that urban water demand is sensitive to temporal drivers such as climate variability, temperature, and socio-economic conditions. Studies employing machine learning and time-series approaches have shown that meteorological variables, including humidity and atmospheric pressure, can significantly influence urban water usage patterns, reinforcing the multifactorial nature of demand dynamics beyond tariff structures alone (Zarrin et al., 2024).

From an economic and management perspective, the observed heterogeneity in consumption and billing outcomes suggests that a one-size-fits-all tariff or conservation policy is unlikely to achieve equitable or efficient outcomes. Instead, differentiated strategies that account for socio-economic conditions, spatial variation, and infrastructure capacity may be more effective. This aligns with calls in the literature for more nuanced governance frameworks that integrate spatial analytics, socio-economic profiling, and real-time monitoring to improve resource allocation and target conservation interventions.

The novelty of this study does not primarily lie in the application of advanced hydraulic modelling or smart-meter algorithms, but in reframing municipal billing anomalies and unaccounted-for water as analytically meaningful indicators within a socio-economic drought governance context. This perspective extends conventional urban water management approaches, which typically interpret such anomalies only as technical losses.

Moreover, the findings highlight the potential of smart metering technologies integrated with spatial datasets to generate actionable insights for municipal decision-making. Recent research on smart water systems has demonstrated that high-resolution consumption data can enhance leak detection, demand forecasting, and infrastructure optimisation, thereby supporting more adaptive and resilient water management practices (Licznar, 2023).

However, several limitations should be acknowledged. Secondary administrative datasets, while comprehensive in coverage, may contain inconsistencies or gaps that require careful pre-processing and validation, as evidenced by the presence of negative consumption values. Furthermore, socio-economic variables available at the neighbourhood level may not fully capture household-level behaviours or preferences. Future research would benefit from integrating primary survey data, higher-resolution smart meter datasets, and advanced modelling approaches (e.g., clustering and structural equation modelling) to further elucidate causal mechanisms linking socio-economic status, infrastructure access, and consumption behaviour.

Overall, this study contributes to the growing body of evidence that urban water demand is shaped by a complex interplay of socio-economic, spatial, and institutional factors. By leveraging integrated analytical frameworks combining economic, demographic, and spatial data, researchers and policymakers can better diagnose systemic inefficiencies, address inequities in access, and design targeted interventions that enhance sustainability and resilience in urban water systems.

CONCLUSION

The research objective was achieved, and the underlying hypotheses were partially supported. The results confirm the presence of substantial spatial and socio-economic heterogeneity in urban water consumption and billing behaviour across settlement types, while also demonstrating systematic inconsistencies in administrative water records.

The primary scientific contribution of this study lies in demonstrating that municipal billing irregularities and unaccounted-for water can provide insight into broader socio-economic and administrative patterns of urban water allocation during drought conditions. Rather than treating anomalous records solely as technical noise, the study shows their potential analytical value for identifying structural inefficiencies and spatial disparities in urban water governance.

Second, the analysis demonstrates that apparent anomalies in municipal datasets, particularly negative consumption values and recurrent billing adjustments, are not random artefacts but structurally informative signals reflecting the coexistence of physical system losses (e.g., leakage), operational inefficiencies, and administrative or socio-economic distortions in billing systems. These findings extend existing unaccounted-for water (UFW) frameworks by showing that such data anomalies can function as valuable diagnostic indicators of both infrastructural inefficiency and institutional constraint, rather than being treated solely as statistical noise or measurement error.

Third, the study contributes a context-specific evidence base from a highly unequal and rapidly urbanising metropolitan environment, where water demand is shaped by overlapping technical, behavioural, and socio-economic drivers. This extends the generalisability of smart metering-based water demand models beyond high-income or highly industrialised contexts, where most prior empirical evidence has been concentrated.

Overall, the findings confirm that urban water consumption cannot be adequately explained through isolated technical or economic variables. Instead, it emerges from an integrated system in which infrastructure performance, institutional data quality, and socio-economic heterogeneity jointly determine observed demand patterns. This result fills a critical empirical gap in spatially resolved urban water analytics and refines existing interpretations of water balance discrepancies in complex municipal systems.

The study therefore contributes a socio-technical interpretation framework for understanding water allocation disparities in drought-prone urban environments.

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Author's statements

Contributions

Conceptualization: N.D.-A., T.K.; Data curation: N.D.-A., A.X.; Formal analysis: N.D.-A., A.X.; Investigation: N.D.-A.; Methodology: all authors; Project administration: T.K.; Resources: N.D.-A.; Software: A.X.; Supervision: T.K.; Validation: N.D.-A., A.X.; Visualization: N.D.-A., A.X.; Writing – original draft: N.D.-A.; Writing – review & editing: all authors.

Declaration of conflicting interest

The authors declare no competing interests.

Financial interests

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Data availability statement

Data used for the study would be made available on request.

AI Disclosure

The authors declare that generative AI was not used to assist in writing this manuscript.

Ethical approval declarations

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Additional information

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