Research Paper

Classifying household water use into indoor and outdoor use from a rudimentary data set: a case study in Johannesburg, South Africa

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ABSTRACT

Distinguishing between indoor use and outdoor use is becoming increasingly important, especially in water-scarce regions, since outdoor use is typically targeted during water restrictions. Household water use is typically measured at a single water meter, and the resolution of the metered data is typically too coarse to employ on commercially available disaggregation software, such as flow trace analysis. This study is the first to classify end-use events from a rudimentary data set, into indoor use or outdoor use. This case study was conducted in Johannesburg, South Africa, and quantified the volume of water used indoors and outdoors at 63 residential properties over 217 days. A recently developed model for classifying water use events as either indoor or outdoor, based on rudimentary water meter data, was employed in this study. A total of 212,060 single end-use events were classified as being either indoor or outdoor. The indoor and outdoor consumptions were compared with survey results. It was found that 30% of all events were outdoor, based on the total volume.

Key words | end-use events, low resolution data, residential water demand, water classification models

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HIGHLIGHTS

- This case study was successful in classifying water use into indoor and outdoor water use events from coarse end-use data.
- An average of 30% of the total water demand was classified as being outdoor use.
- Classification tools implemented in this case study (PEET and WEAM) could be useful to monitor whether homes adhere to water restrictions, especially if outdoor use is limited or prohibited.

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INTRODUCTION

Household water consumption

The demand for water continues to increase due to rapid rates of population growth (Vörosmarty *et al.* 2005). Water utilities require detailed and accurate information regarding residential water consumption when developing water demand management (WDM) strategies. The effectiveness of applying WDM strategies is reduced because of the limited understanding of residential consumption (Sahin *et al.* 2016). Better knowledge and understanding of how and where households consume water allow for targeted and effective WDM strategies as well as economic incentives (Nguyen *et al.* 2013).

Household end-uses include the shower, washing machine, toilet, dishwasher, taps and garden irrigation (Nguyen *et al.* 2013). Residential water consumption could fundamentally be classified as either indoor use or outdoor use. Table 1 summarises a range of water end-use studies reporting on indoor and outdoor water use as distinct components of total household water consumption. Studies conducted during periods with water restrictions enforced are not included in Table 1. The end-use studies presented in Table 1 were based on high-resolution data (0.014–0.1 L/pulse meter readings taken every 1–10 s) and employed flow trace analysis software for end-use classification. Metered data recorded at such high frequencies are considered 'high-resolution' data.

Conventional and smart water meters

Smart meters record water consumption information and communicate this information on a real-time basis (Cole & Stewart 2013). Smart meters are regarded as water meters linked to loggers that record at high-resolution frequencies, allowing for automated data measurement readings and real-time monitoring (Giurco *et al.* 2008). The value derived from smart meter data is dependent on the meter resolution and the logging frequency. Smart meters are able to record high-resolution data at volumetric measurements of 0.014 L/pulse (compared with the 0.5 or 1.0 L/pulse measured by conventional mechanic meters), and at logging

Table 1 | Residential indoor and outdoor water consumption

		Percentage of total water demand			
End-use study	**Location**	**Indoor (%)**	**Outdoor (%)**	**Leaks (%)**	**Comment**
Mayer & DeOreo (1999)	USA	35.8	58.7	5.5	
Loh & Coghlan (2003)	Perth, Australia	45.0	54.0	1.0	
Roberts (2005)	Yarra Valley, Australia	68.9	25.4	5.7	Average annual contributions
Heinrich (2007)	Auckland, New Zeeland	88.0	8.0	4.0	
Beal *et al.* (2011)	Brisbane, Australia	79.5	7.2	13.3	Leaks, dishwasher, irrigation and bath water use were reported in some, but not all, of the homes. In homes where outdoor use was reported, outdoor use was reported to be 20.6% of the total consumption.
	Gold Coast, Australia	86.3	9.4	4.3	
	Sunshine Coast, Australia	79.1	6.8	14.1	
	Ipswich, Australia	95.4	1.7	2.9	
Willis *et al.* (2009)	Gold Coast, Australia	91.0	8.0	1.0	Sample group reported a high level of concern for water conservation.
		85.0	14.0	1.0	Sample group reported a medium level of concern for water conservation.
Hussien *et al.* (2016)	Duhok city, Iraqi Kurdistan	96.0	4.0	0.0	Medium- to high-income households. Study was conducted over winter months. Hussien *et al.* (2016) suggests outdoor consumption to be much higher over the summer period.
		92.4	7.6	0.0	
		91.8	8.2	0.0	

frequencies of 1, 5 or 10 (Kowalski & Marshallsay 2005; Roberts 2005; Mead & Aravinthan 2009; Willis *et al.* 2011; Beal & Stewart 2013; Nguyen *et al.* 2013). The high-resolution time series data may be paired with advanced flow trace analysis software to disaggregate end-use events. Smart meters, however, are not common. The costs of smart water meters are relatively higher than regular water meters. Additionally, more data are required to be communicated, stored and processed, which requires additional infrastructure and technical staff with the relevant expertise.

Water utilities often collect water use data manually on a monthly, quarterly, or biannual basis (Nguyen *et al.* 2013). Current water metering systems predominantly rely on mechanical water meters, which generate a pulse after a specified volume has passed through the water meter, say every 0.5, 1.0 or 5.5 L (Roberts 2005; Cole & Stewart 2013), without being able to record the time of any particular event smaller than the meter pulse volume (Nguyen *et al.* 2013). Data recorded at these resolutions are too coarse for commercially available end-use disaggregation software (Meyer *et al.* 2020). Subsequently, investigations into household end-use consumption have never been conducted despite some studies reporting on more regular recording frequencies of 15 min (Pretorius *et al.* 2019), or 1 h (Cardell-Oliver *et al.* 2016).

CONTEXT

Numerous former end-use studies have contributed significantly to understanding household water demand at end-use level. Extracting and identifying end-uses from high-resolution water meter data at entry to the property (e.g. measured at the consumer meter) were pioneered by De Oreo *et al.* (1996) and Mayer *et al.* (1999). End-use models and flow sensing approaches were developed in parallel. These end-use studies employed high-resolution smart meters, which are not commonly available, especially not in developing countries such as South Africa.

The volumetric resolution of the high-resolution end-use studies, which were successful in disaggregating end-uses, ranged from 0.014 L/pulse (Beal & Stewart 2011) to 0.1 L/pulse (Pastor-Jaboloyes *et al.* 2018). Typical residential water meters used in South Africa were found to have a volumetric resolution of 1.0 L/pulse – the same resolution applied to this study. Cominola *et al.* (2018) found that sub-minute metering resolutions are needed for end-use studies. Data measured at a volumetric volume of larger than 0.1 L, with sub-minute recording frequencies, were termed as rudimentary data in this paper. This research focussed on extracting knowledge from rudimentary end-use data.

OBJECTIVES

Specific objectives of the case study were to:

- determine outdoor and indoor water use expressed as a percentage of the total household water demand and
- better understand household water consumption within the case study site.

APPROACH

In order to classify water use events into indoor use and outdoor use, individual events first had to be extracted from the measured data. Meyer *et al.* (2020) developed a Python End-use Extraction Tool (PEET), which was employed on the data set to extract event characteristics, namely duration (D), volume (V) and flow intensity (I), of individual end-uses from a time series. The Water End-use Apportionment Model (WEAM) was utilised to categorise the extracted end-use events as being indoor or outdoor, based on the three event characteristics (i.e. D, V, I). WEAM, developed by Meyer *et al.* (submitted), was selected as the classification model for this case study, due to its applicability on rudimentary data sets.

DESCRIPTION OF STUDY SITE

Johannesburg, located in South Africa, is serviced by Johannesburg Water (JW). Residential water use in Johannesburg is normally measured and billed monthly. JW commissioned this case study and set out to determine to what extent measured rudimentary data can be used to obtain water end-use information at a household level. The study site comprised 63 homes in the Lonehill suburb, Johannesburg, and was conducted from September 2016 to January 2018. The study sample was divided into 54 residential semi-detached town houses in a security complex and 9 stand-alone residential properties. The plot sizes range from approximately 150 to 250 m^2 within the security complex and from approximately 1,000 to 1,500 m^2 for the stand-alone properties. The people per household (PPH) ranged from 1 person to 4 people. Lonehill is a middle- to high-income suburb. The suburb has a literacy rate of more than 92%, covers a land area of about 5 km^2, and has an average household income more than double that of South Africa and Gauteng Province. Johannesburg's rainfall is concentrated in the warm summer period. During winter, Johannesburg experiences dry seasons. The month with the lowest number of average rain days (2 days) is June (winter), and the highest number of average rain days (15 days) is January (summer).

DATA COLLECTION

Metered data

Sensus iPerl water meters were installed at the 63 properties and recorded water flow measurements at a resolution of 1 L/pulse (in line with common utility meter resolutions). The meters were combined with data loggers (recording at 15 s intervals), in order to investigate what level of household water consumption information can be obtained from a rudimentary data set. The meters were paired with loggers to allow for sub-minute recordings, which is required for end-use extraction. The study period (September 2016 to January 2018) was selected because of the availability of resources (e.g. students and research funds) and physical access to the meters within the security complex. The data measured by the water meter were transmitted and stored on an FTP server, 30 km from the study site. Smart meter data were missing during some days (or prolonged periods). While some vacancy of property is normal, other challenges regarding the infrastructure and software contributed to the zero consumption days. Ilemobade *et al.* (2018) discussed the factors that contributed to and exacerbated the anomalies in the data set and also presented the process of cleaning the raw data set. The total number of days with recorded consumption was 217 days. Data from the JW billing system were also collected for the period June 2016 to May 2017.

Questionnaires

Detailed information on the properties and their residents were gathered using questionnaires (surveys). The questionnaires were developed and administered to willing household respondents in 2017. Prior to administration, ethics clearance was applied for and obtained from the University of the Witwatersrand, Johannesburg. Roughly half of the study sample completed the surveys (32 out of the 63), of which 24 (68%) opted to remain anonymous. Of the 32 survey responses received, only 11 respondents indicated their physical address. Only 11 of the homes could thus be linked to corresponding water meter data. In addition to the surveys, meter verification exercises were conducted at six properties. The meter verification involved simultaneously taking smart meter and consumer meter readings at specific end-uses (i.e. toilet, bath, shower and basin). This exercise, while simple, provided valuable additional information about the validity of the smart meter and consumer meter readings. The meter verification exercises also allowed for on-site leak inspections, and no real leaks were reported.

DATA PROCESSING

Prior to data analysis, 9 homes were removed from the study sample due to poor data quality. Thus, 54 homes remained in the study sample. Because of the rudimentary nature of the data (limited to 1 L/pulse), Meyer *et al.* (2020) could not distinguish between actual low flow events and leaks (intensities <0.067 L/s) and categorised these events as minor events. All other extracted events were ascribed as major events. In order to classify end-use events, all minor events were removed from the data set and were labelled as unknown events. The final data set thus only consisted of major events. Major events comprised 75.8% of all event consumption in the extracted data set, meaning 24.2% of the initial data set was filtered out and labelled as unknown events. The final data set presented by Meyer *et al.* (2020) consisted of 212,060 major end-use events.

RESULTS AND DISCUSSION

Final data set

Only 11 of the 63 administered questionnaires provided useful information, which is why the focus of this study shifted to the 11 properties. The properties were renumbered accordingly, Home H01 through H11, in line with ethical requirements. Home H11 was the lone single, stand-alone residential property, and the other 10 homes were semi-detached town houses in a security complex. The number of people in each of the homes were determined from the questionnaire responses. There were several periods (months) over the study period with anomalies and measurement gaps. Potential reasons for these data gaps (i.e. infrastructure challenges) have been articulated earlier in earlier research (Ilemobade *et al.* 2018).

From May 2017 until September 2017, no meter data were recorded. Table 2 depicts the number of days in each month meter data were recorded. An assumption was made that days with measured data were an acceptable representation of the indoor and outdoor demand ratio for the particular month. In other words, even with data gaps, sufficient information was obtained from the recorded data to satisfactorily represent consumer behaviour in terms of outdoor use and indoor use. The only time this assumption was invalid was for April 2017, where 3 days of measured consumption was considered inadequate to represent the entire month's water use behaviour.

Classification results

PEET extracted end-use events and filtered out all minor events, which contributed to 24.2% of the total volume of the household demand. Subsequently, these minor events were categorised as 'unknown' consumption since it was unclear whether these minor events were indoor or outdoor low flow events or whether they were background leaks. The classification results obtained from employing WEAM on the data set are depicted in Table 3. Further investigation only focussed on the 11 homes chosen based on information obtained from survey responses. The proportion of indoor use and outdoor use as a percentage of the total consumption is also summarised in Table 3. Table 3 shows that the 11 homes selected was a good representation of the entire data set in terms of apportioned indoor use, outdoor

Table 2 | Dates with reported water use from meter measurements

Month	Sep 2016	Oct 2016	Nov 2016	Dec 2016	Jan 2017	Feb 2017	Mar 2017	Apr 2017	Oct 2017	Nov 2017	Dec 2017	Jan 2018
Number of recorded days	24	31	30	31	31	28	31	18	11	30	31	31
Home Code	Number of days with readings											
H01	15	22	24	4	10	12	21	4	0	0	0	0
H02	23	23	25	14	13	21	24	3	0	0	0	0
H03	23	22	29	14	12	21	24	3	11	13	19	16
H04	23	16	22	12	12	21	24	3	11	13	17	16
H05	23	19	23	10	12	20	24	2	11	13	16	14
H06	23	22	26	13	12	20	24	3	11	13	18	6
H07	23	21	28	10	12	17	24	3	11	13	13	17
H08	23	21	29	12	13	22	24	3	11	13	18	17
H09	20	17	23	11	11	19	23	3	11	12	18	17
H10	23	23	27	12	12	19	23	3	11	14	19	18
H11	23	23	29	13	12	22	24	3	11	13	20	17

Table 3 | Classification of end-use events

	Proportion of total demand (%)		
Data set	**Indoor use**	**Outdoor use**	**Unknown**
Entire data set	45.48	30.30	24.22
11 homes	46.98	30.43	22.59

use and unknown events as a percentage of the total demand.

Correlation between proportion of total water demand and factors influencing household water demand

The proportion of the total water demand classified as indoor and outdoor events, for each of the 11 homes over the total study period, is summarised in Table 4. The home-specific information, such as PPH and property size, are also included in Table 4.

Water restriction tariffs were introduced in September 2016, but since the water restrictions did not prohibit outdoor water use, the drought tariffs were assumed to have an insignificant impact on the outdoor use (Johannesburg Water 2016). Future research could be conducted to better understand the impact of social and environmental awareness, but these parameters were beyond the scope of this study. Home H09 showed inadequate results, with over 88% of the household water consumption categorised as unknown use, and was thus not further considered for analysis. Past studies showed a distinct correlation between PPH and the percentage of total demand attributed to indoor use (Jacobs *et al.* 2017). The indoor use proportion of total demand is higher for homes with higher occupants. This correlation is not so apparent in Table 4.

Table 4 | End-use event classifications and household information

			Proportion of total demand (%)			
Home code	**PPH**	**Property size (m^2)**	**Indoor**	**Outdoor**	**Unknown**	**Total**
H01	4	201.9	65.3	30.0	4.7	100.0
H02	1	168.3	87.7	7.1	5.1	100.0
H03	4	207.5	59.0	18.8	22.2	100.0
H04	2	168.3	72.3	20.1	7.7	100.0
H05	3	237.9	40.6	40.1	19.3	100.0
H06	2	207.0	61.4	14.1	24.4	100.0
H07	2	167.5	60.1	10.3	29.6	100.0
H08	1	212.6	51.7	40.0	8.3	100.0
H09	1	167.9	6.7	4.3	88.9	100.0
H10	1	168.3	31.8	62.9	5.4	100.0
H11	3	1,141.8	39.3	46.8	13.9	100.0

The results depicted in Table 4 suggest no observed correlation exists between PPH and indoor use as a proportion of total household demand. This does not mean that indoor use does not increase with an increase in PPH since such a correlation has been reported on in numerous studies (Martinez-Espineira 2002; Liu *et al.* 2003; Bradley 2004; Mead & Aravinthan 2009; Blokker *et al.* 2010). It is impossible for both indoor use and outdoor use percentages to increase within a home since the total (100%) is fixed. Therefore, one reason the correlation between PPH and indoor use is possibly not shown in Table 4 is due to the smaller impact indoor events have on total demand. Indoor events typically have smaller volumes compared with outdoor event volumes.

The correlation between outdoor events and property size were also investigated. With the exception of House H10, an increase in property size results in a larger proportion of the total demand being attributed to outdoor use. Previous studies have reported on a direct relationship between outdoor water use and property size (Gato 2006; Jacobs & Haarhoff 2007; Fox *et al.* 2009). Due to outdoor use typically being larger volume events compared with indoor events, the increase in outdoor water demand has a more notable impact on the total demand.

Comparison between metered results, billing data and survey responses

The average daily household water use extracted from consumer meters (billing data) was compared with the derived average daily water use recorded by the smart meters. For the purpose of this comparison, the water use was evaluated over the total recording period for each device. In other words, zero consumption days were removed from the recording period, in order to restrict the impact of zero consumption on the average daily use. Table 5 provides a

Table 5 | Comparison between billing data and smart meter data

Home code		**H01**	**H02**	**H03**	**H04**	**H05**	**H06**	**H07**	**H08**	**H10**	**H11**
PPH		4	1	4	2	3	2	2	1	1	3
Municipal consumer meter (billing data)	Total water use over recording period (kL)	80	81	300	205	97.5	167	67	160	52	533
	Recording period (days)	329	294	329	329	329	329	329	298	329	329
	Water use per dwelling unit (L/du/day)	244	274	911	623	297	507	204	535	158	1,619
	Average per capita water use (L/c/d)	61	274	228	311	99	254	102	535	158	540
Smart meters	Total water use over recording period (kL)	28	35	157	66	26.3	80	51	157	92	240
	Recording period (days)	112	146	207	190	187	191	192	206	204	210
	Water use per dwelling unit (L/du/day)	247	241	760	348	141	418	268	761	452	1,144
	Average per capita water use (L/c/d)	62	241	190	174	47	209	134	761	452	38
Difference in average per capita water use (%)		1.0	12.1	16.6	44	52.6	17.5	31	42	187	29

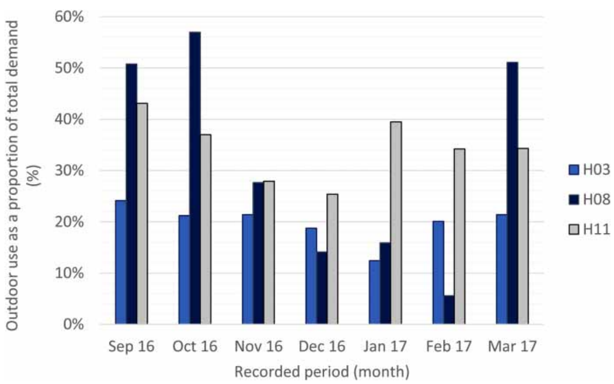

Figure 1 | Monthly outdoor consumption at Homes H03, H08 and H11.

summary of the results for the 10 homes with available consumer meter data linked to survey responses.

The meter verification exercise conducted as part of this study confirmed that the smart meters' errors are permissible. Thus, the high difference between the average per capita water use values for the mechanical meters (billing data) and the smart meters is most likely due to metering error of the mechanical meter. Past studies have reported meter errors as high as 53% due to meter aging (Mutikanga *et al.* 2011). Future research could possibly conduct field tests to evaluate the accuracy of the older mechanical meters, and determine whether newer meters should be installed. Accurate metering will result in accurate billing, which could potentially lead to an increased revenue for water service providers.

Survey responses from Home H08 and H11 indicated regular garden irrigation, which was also identified by the classification results. Figure 1 shows the high percentage of the total consumption classified as outdoor use for these two homes. The classification results also showed noticeable outdoor water consumption at Home H03; however, the survey results reported no garden irrigation at the property.

WEAM could thus be utilised to identify homes with garden irrigation events at properties who reportedly have no outdoor use. The application of WEAM could potentially prove very useful during times when water restrictions are in place, especially if outdoor use is not permitted.

The implementation of WEAM on rudimentary data, as presented in this study, suggests that end-use data recorded by typical utility meters (1 L/pulse) have more benefits than what is currently being explored. Although only major end-use events were analysed in this paper, the results presented provide valuable insight into the proportion of monthly water consumption used for indoor use and outdoor use at the study site. Based on the results obtained, and the robustness of PEET and WEAM to analyse rudimentary data sets, implementation of water demand measures can now be investigated in future research.

CONCLUSION

Understanding household water demand at the end-use level is important for effective WDM strategies. This paper presents a case study that was conducted in Johannesburg, South Africa. In the case study, household water demand was recorded with meter resolutions set to 1 L/pulse recorded at 15 s frequencies (rudimentary data). Specific objectives of this case study were to classify household water use events extracted from a rudimentary data set into indoor use and outdoor use and to better understand consumer consumption behaviour at the study site. This study, therefore, addressed the problem of classifying indoor and outdoor water use events with limited and rudimentary end-use data. PEET (Meyer *et al.* 2020) was used to extract end-use events from a rudimentary data set while WEAM (Meyer *et al.* submitted) was utilised to classify the extracted end-uses into indoor use or outdoor use. The results presented in this paper provide insight into the proportion of monthly water consumption used indoors and outdoors at the study site, expressed as a percentage of the total household water demand. Although PEET was successful in extracting end-use events from a rudimentary data set, a large portion of the total water demand (24.2%) was not classified.

Outdoor use was identified at all 11 homes, even though some residents did not report any garden irrigation. Classification tools implemented in this case study could thus be useful as an additional method to help monitor whether homes adhere to water restrictions, especially if outdoor use is limited or prohibited. An average of 30% of the total water demand was classified as being outdoor use (neglecting unclassified events) and was seasonally driven, with higher outdoor consumption occurring over the dry months.

Implementation of the proposed method requires a water utility to deploy a smart meter network with logging interval of 15 s or less and meter pulse volume of 1 L/pulse or less. Future research should investigate different meter resolutions (e.g. 0.5 L/pulse) to determine the optimal meter resolution to minimise the proportion of events classified as 'unknown'. Future research could also assess the impact of implemented WDM measures from rudimentary household water use data sets, considering the valuable insights obtained using PEET and WEAM.

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DATA AVAILABILITY STATEMENT

Data cannot be made publicly available; readers should contact the corresponding author for details.

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