Estimating Scenarios for Domestic Water Demand under Drought Conditions in England and Wales

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Abstract

This paper presents preliminary results from the development of IMPETUS model, a domestic water demand microsimulation model which was developed to estimate the results of a range of scenarios of domestic demand under drought conditions. The model is intended to enable water resource management practitioners to assess the likely impact of potential interventions in particular catchment areas. It has been designed to be driven by seasonal catchment level forecasts of potential hydrological droughts based on innovative climate and groundwater models. The current version of the model is driven by reconstructed historical drought data for the Colne catchment in the East of England from 1995 to 2014. This provides a framework of five drought phases (Normal, Developing, Drought, Severe and Recovering) which are mapped to policy driven interventions such as increased provision of water efficiency technologies and temporary water-use bans. The model uses UK Census 2011 data to develop a synthetic household population that matches the socio-demographics of the catchment and it microsimulates (at the household level) the consequences of water efficiency interventions retrospectively (1995-2014). Demand estimates for reconstructed drought histories demonstrate that the model is able to adequately estimate end-use water consumption. Also, the potential value of the model in supporting cost-benefit analysis of specific interventions is illustrated. We conclude by discussing future directions for the work.

Keywords Climate change-Domestic water demand-Drought-End uses-Microsimulation

Acknowledgements This work was supported by the UK Natural Environment Research Council funded "IMPETUS: Improving Predictions of Drought for User Decision-Making" project under the RCUK Drought Programme via grant NE/L010216/1.

An earlier version of this paper was presented at the International Water Association (IWA) Efficient Conference 2017, Bath, UK 18-20 July.

INTRODUCTION

The Department for Environment, Food and Rural Affairs (DEFRA 2008) states that as a result of growing population, and changes in the way people use water in the UK, more than half of the current public water supply is for residential use. As a result, controlling domestic water demand is a priority in the UK. Whilst work on improved 'water supply' side forecasting is well established, limited attempts to effectively address uncertainties related to climate change and water demand management measures in demand forecasting models for longer term resource planning purposes have been reported. In the UK, the total range of forecasts found in Water Resource Management Plans of UK water providers is almost 50%, demonstrating the uncertainty and the high geographic variance of water demand (Atkins 2015). As a result there are few tools that can enable stakeholders to assess the likely costs and benefits of particular conservation and/or intervention measures (Parker and Wilby 2013).

There is a general consensus that the UK will probably experience warmer conditions and lower summer rainfall (Jenkins et al. 2010; Parker 2014; Water UK 2016) Repeated occurrences of dry winters, prolonged lack of rainfall and lack of ground water recharge due to urban flooding, can lead to drought conditions which in turn increase the risk of water resources not meeting quality standards (Met Office 2014, Environment Agency UK 2017). In South East England, a region already suffering water stress, summer precipitation is projected to decrease by 9% by the 2080s (Jenkins et al. 2010). Droughts have severe impacts on societies, economies, and agriculture and forward planning is critical for managing the potential impacts of drought. Early warning of impending drought conditions making use of improved meteorological, hydrological and also demand forecasts would enable stakeholders to take appropriate demand mitigation actions and to effectively manage diminishing water resources to minimize adverse impacts. Continued lack of rainfall can lead to temporary water restrictions imposed by water providers on non-essential uses such as garden watering and car washing. A few studies show that temporary use bans (TUBs) can decrease consumption by over 30%, especially for high water users (Polebitski and Palmer 2010). In parallel, UK water providers have been launching domestic water efficiency initiatives over the past ten years and recent research has shown that there is scope for substantial per capita water savings especially if the programs are focused on certain groups such as smaller and financially stretched households (Manouseli et al. 2017).

However, little is still known about householders' response to drought or water efficiency measures in the UK and there are few if any studies which incorporate this evidence into models of demand forecasting in support of operational decisions about the most likely cost-effective drought management measures. In addition, accurate long term forecasting is restricted by the difficulties in gathering all the necessary data, as it is usually hard and costly to collect (Memon and Butler 2006; Atkins 2015). Further, Census data are commonly published as separate aggregated tables rather than microdata resulting in information loss (Clarke et al. 1997) and forcing area level 'average' projections. To address these limitations, and following a substantial evidence and methods review (Manouseli, Anderson, and Nagarajan 2017), we have implemented a microsimulation model of domestic end-use water demand.

Microsimulation is an established methodology in urban and regional modelling. It has been used since 1957 (Orcutt 1957) mainly to examine the effect of policies before they are implemented (Birkin et al. 1996; Tanton et al. 2009; Anderson 2012) as well as for tax and benefit modelling (Harding et al. 2009). Microsimulation has also been proved to be extremely useful in generating small area estimates using survey data and a large volume of research has been undertaken in this direction in Britain and Australia. The main benefit of such models is that they allow a survey designed for generating large area estimates to be used to produce reliable estimates on the micro-level (households or individuals) as well, avoiding the need to increase the sample size (Tanton, Williamson, and Harding 2014).

Recently published research shows that there is scope of using the technique in the area of resource demand for the residential sector. (Zuo, Birkin, and Malleson 2014) used the technique to investigate variations in energy demand within and between household groups, taking climate change and behavioural changes into account. A detailed survey by the UK Department of Energy and Climate Change was used in this study. (Chingcuanco and Miller 2012) used household energy microdata in Toronto, putting forward a model of residential space heating demand-a first step towards a comprehensive urban energy demand model.

However, microsimulation has not been as widely used in the field of urban water demand forecasting (Clarke et al. 1997; Mitchell 1999; Williamson et al. 2002). Williamson et al. (2002) used a ‘static microsimulation’ method in their study. A 30% increase in household water consumption was predicted for the Yorkshire Water region from 1991 to 2025 and the most probable cause of this increase was consumer behaviour change. They compared these results with those resulted from (Herrington 1996) who used a micro-components based model, stressing that the demographic part of his model was driven only by changes in average household size. However, they acknowledge that their model has limited application to small areas. Advocates of ‘static microsimulation’ claim that this technique addresses the limitations that micro-component studies have, such as the lack of spatially relevant information on trends, by incorporating enhanced spatial resolution and a stronger approach to dealing with household consumption monitor data that usually suffer from bias. Instead of classifying households into a limited number of groups (e.g. household size, Acorn class), each household is represented by a list of potentially unique attributes relating to water-consuming behaviour (Williamson et al. 2002).

The process described in the present work comprises the first stage of modelling. Our second stage will be using household responses to a water-using practices survey and will infer monthly consumption out of the reported practices for a sample of 1800 households. The IMPETUS practices-based model will explore whether the introduction of practices in a microsimulation model improves our understanding of how water is used in the household and how drought management measures implemented during relevant drought phases affected domestic water demand.

METHODS

The model reported here uses a synthetic sample of 1800 households, which was created to match the distribution of household sizes reported by the UK Census 2011 for the Colne catchment in the East of England. The end uses (micro-components) that are incorporated in the model are: Basin, Bath, Dishwasher, External, Kitchen Sink, Shower, WC and Washing Machine (see Figure 1).

We started by setting each component to the relevant median litres per day as reported in Table 1 (Parker 2014) and applied occupancy based adjustments using coefficients from (Parker 2014) (regression coefficients for 2, 3, 4 and 5 occupants-Table A.3 & Table A.4). To introduce random variation into the micro-components’ distributions we then applied a skewed normal distribution to each household micro-component using the original occupancy-based median as the distribution mean. Unfortunately, we had no information on the correct standard deviation (s.d) nor skewness but through experimentation we have identified a range of s.d values and xi (skewness) parameters that, when used with the R function rsnorm for the simulation of a stationary Gaussian time series (Wuertz et al. 2016), produce results that are similar to Parker's (2014) per capita/day distributions.

Table 1 Descriptive statistics of the daily microcomponent values. Source: Parker (2014)

	Metered				Unmetered			
	Mean % of daily total l/H	Mean/ Median (l/H)	Standard Error (l/H)	Sample Size	Mean % of daily total l/H	Mean/ Median (l/H)	Standard Error (l/H)	Sample Size
Basin	11	24/17	0.09	81976	10	34/27	0.07	166298
Bath	10	62/55	0.19	29419	15	89/83	0.14	95589
Dishwasher	4	26/23	0.09	17205	2	27/25	0.05	23684
Kitchen sink	17	38/32	0.1	85114	16	53/46	0.09	173665
Shower	7	46/31	0.16	22750	7	51/40	0.12	66496
WC	36	84/78	0.17	80323	34	116/113	0.14	167485
Washing machine	15	85/78	0.17	33266	16	101/88	0.13	89555

Monthly values for mean temperature, overall rainfall and total sunshine hours for the East of England, which includes the Colne catchment area, were extracted from the UK Met Office website. Although these are available from 1910 onwards, we extracted values between 1995 and 2012 to match the CEH reconstructed historical drought series (see below) and applied the monthly and climate related regression coefficients reported in (Parker 2014) to the micro-component values for each household to produce estimated baseline consumption (litres/day) for each household for each month during the period 1995-2014. Specifically, the coefficients were used to implement monthly adjustments for mean daily temperature, sunshine and rainfall, as well a year on year increase/reduction in demand for both metered and unmetered households. This produced an overall dataset of 1800 households for each of the 120 months.

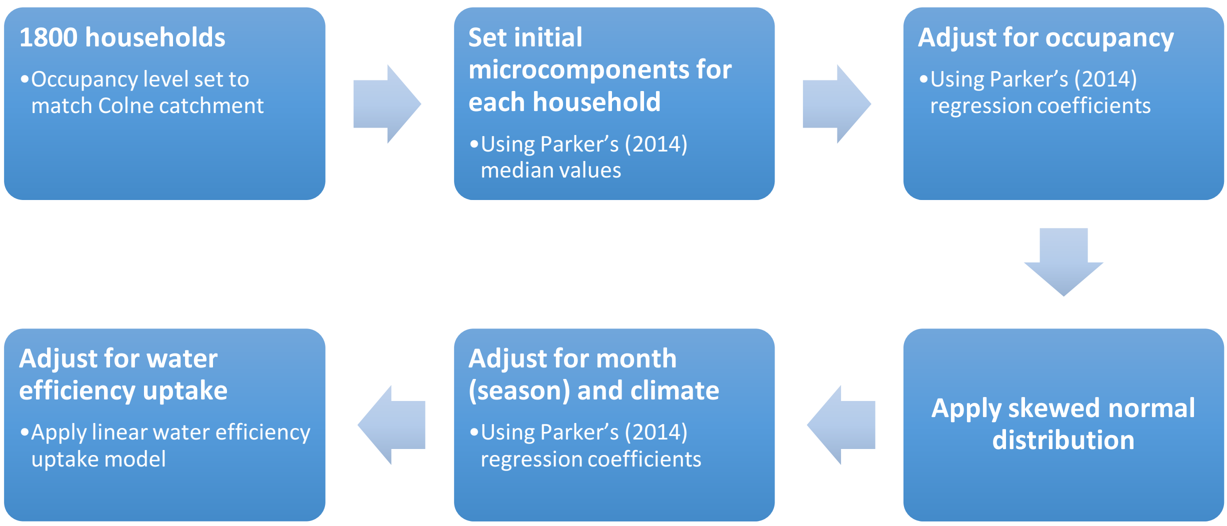

Figure 1: Structure and procedural flow of IMPETUS baseline model

Finally, we used a simple linear uptake model to estimate the uptake of dual flush WCs and low flow shower heads over this period. EST data suggested that by 2011, 41% of households had a dual flush WC and 25% had a low flow shower head (Energy Saving Trust 2013). Further it was estimated that 2% of households per year switch from single to dual flush WCs and 1% switch from a normal to a low flow shower head. The simple uptake model we have implemented assumes that all appliances are switched at the same time and that uptake is randomly distributed. Further, once a switch has occurred, the EST report suggests that dual flush WCs lead to a 47% reduction in WC water use whilst the value for low flow shower heads is 61%. The final output of the baseline model was therefore estimated litres per day for each of the listed micro-components for each month of the period 1995-2014 for a sample of 1800 households.

The final stage of the model's formation was the introduction of reconstructed historical seasonal drought series for 1995-2014 provided by the Centre for Hydrology (CEH, (Parry et al. 2016)) which indicates 'drought phase' in each month. The drought histories were used to apply additional efficiency interventions in the five relevant drought phases (Normal, Developing, Drought, Severe Drought and Recovering. Drought histories were provided by the CEH, from 1994 until 2012. For the Normal phase, no additional efficiency measures were introduced in the model. For the Developing phase, double the rate of baseline water efficiency uptake was introduced. Accordingly, this was tripled and quadrupled for the Drought and Severe Drought phases respectively. Additionally, for the Drought and Severe Drought phases, a temporary use ban was introduced, affecting the highest 14% and 28% of consumers respectively. Based on discussions with industry stakeholders and recent research (UKWIR 2013), we hypothesized that only 44% of them would comply with the restrictions and would in turn reduce their consumption by 18%. As before, the output of this model was also estimated litres per day for each of the listed micro-components for each month of the period 1995-2014 for a sample of 1800 households but adjusted to model the potential consequences of the above drought response scenarios.

RESULTS AND DISCUSSION

Results validation for IMPETUS baseline model. The "At Home with Water" report by (Energy Saving Trust 2013) analyzes water use in British households, using datasets of self-reported water demand information of more than 86,000 households, recorded through the Water Energy Calculator, an online self-completion tool. The tool also enables consumption disaggregation into micro-components. Micro-component litres/household/day reported by EST were compared to the results derived from our baseline model (Figure 2) for validation purposes. Comparing these values with the IMPETUS model is not straightforward as not all of the usages match to the micro-components modelled. However, the chart attempts to show all values on the same graphs as far as possible. These charts suggest that compared to the EST (2013) estimates our model underestimates shower use and over-estimates bath use. However, given that the EST estimates used a self-selecting sample who may have been more likely to be 'careful' water users, this may be because respondents to the Water Energy Calculator were more likely to use showers than baths.

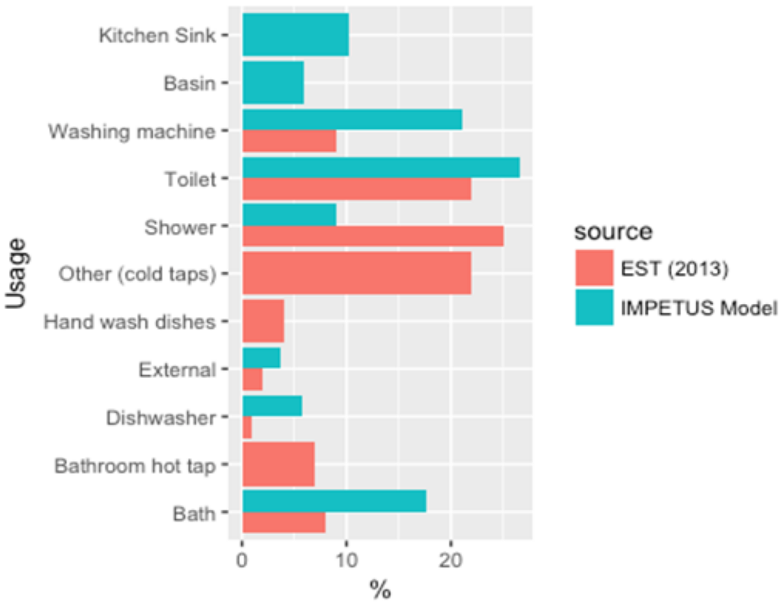

***Figure 2** Water consumption by use (% of total household use). Comparison of results from EST (2013) research and IMPETUS model. Wider bars indicate values which cannot be matched.*

Figure 3 presents the distribution of micro-components across all months for 2012 once all the adjustments described were implemented for the Seasonal consumption model (1995-2014). In general, metered households appear to consume less water than non-metered ones for all end uses whilst some signs of seasonality can be detected for the shower, external, bath and washing machine use.

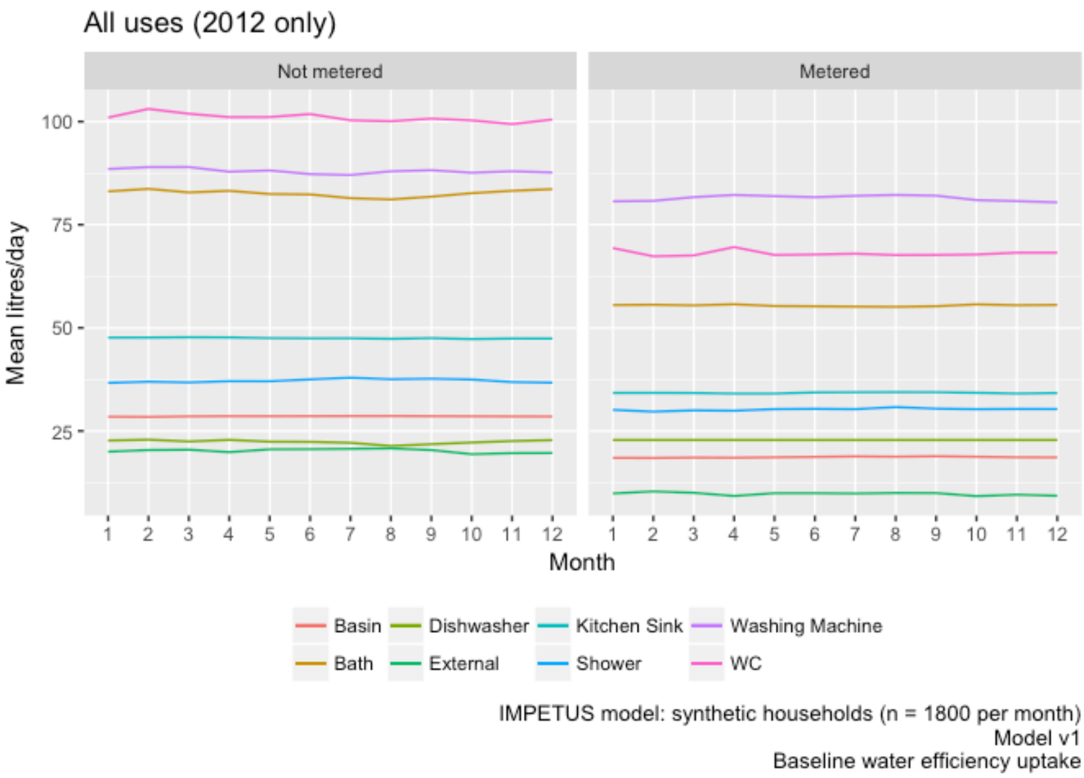

Figure 3 Output of the seasonal baseline model. Distribution of micro-components for 2012 for metered and unmetered households.

Figure 4 illustrates a comparison between the Baseline model and the Drought (final) model. It is evident that the additional water efficiency measures and the TUBs during specific drought phases have caused household consumption to decrease much quicker in the Drought model. The large impact of these measures during periods of Drought or Severe Drought is more prominent for the 1995-97 period, where consumption for the Drought model shows a very steep decline in line with the drought phases for this period (see Figure 5). This can be attributed to the Severe Drought that the Colne catchment was experiencing during that period. By the end of the period the baseline model showed a reduction of 6% whilst the drought model showed a reduction of 9.38% (Figure 4) whilst the maximum difference in consumption levels between the baseline and drought model was approximately 4.4% in May 2011, a period of drought in the Colne catchment (Figure 5).

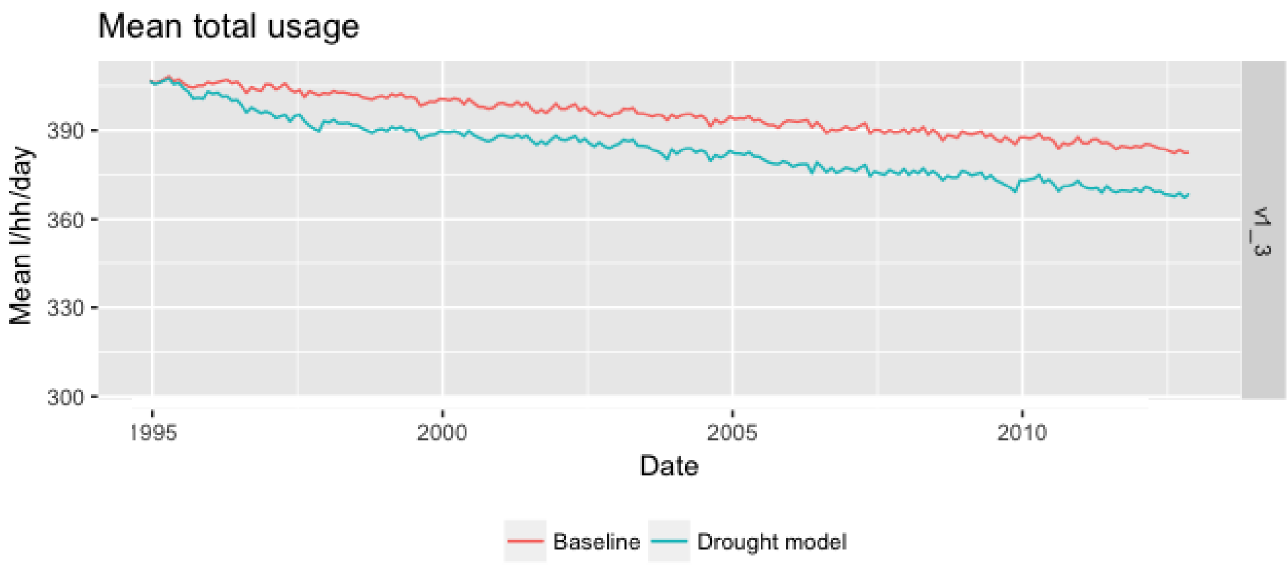

Figure 4 Comparison of IMPETUS Baseline and Drought models (Mean litres per household per day)

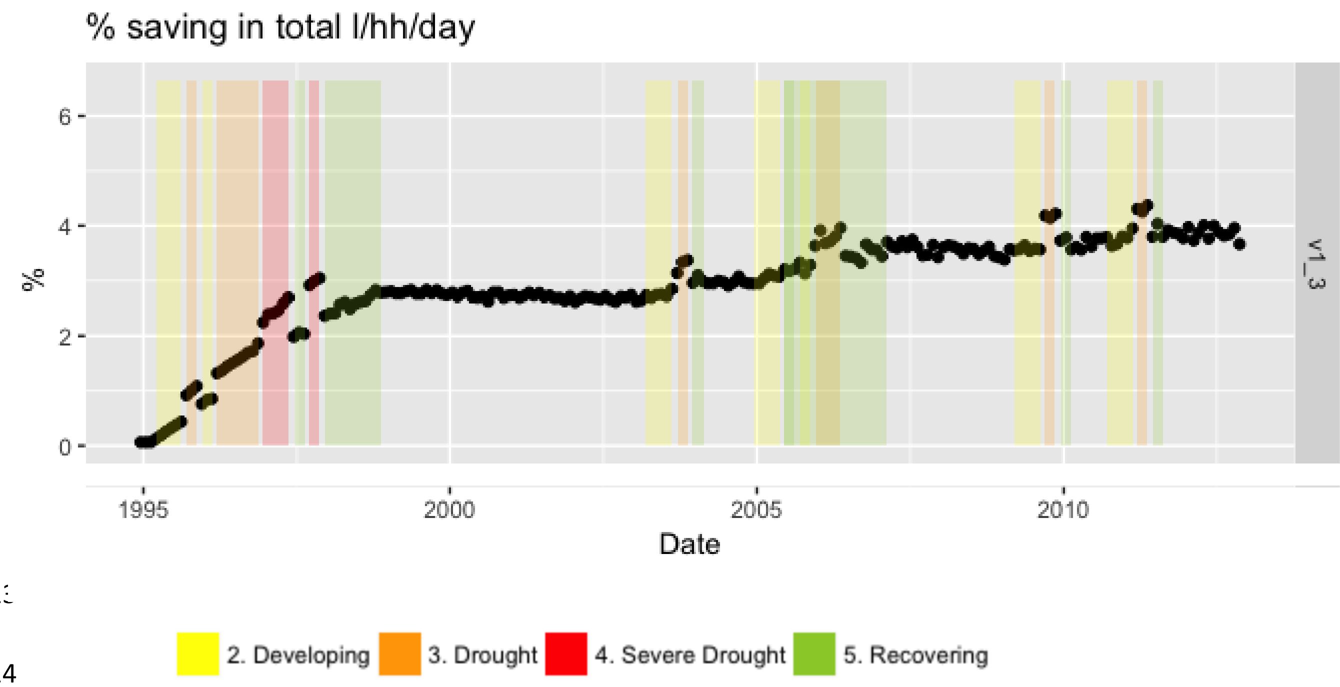

Figure 5 Comparison of IMPETUS Baseline and Drought models with drought phases overlay (% difference, Developing = "yellow", Drought = "orange", Severe Drought = "red", Recovering = “light green”)

Limitations

It should be noted that the regression coefficients used are part of an overall model of each micro-component's litres/day and includes a range of covariates that are not in our model such as day of the week, ACORN class, Temperature range, rainfall over previous seven days and an estimate of soil moisture deficit. This means that it may not be entirely appropriate to apply *just* the occupancy, climatic and monthly coefficients in the baseline estimation. However, without the ability to re-estimate the regression coefficients ((Parker 2014) with the reduced variable set, we have little choice.

CONCLUSIONS

Overall, the IMPETUS microsimulation model of micro-component consumption at the household level was able to adequately estimate end-use water consumption, subject to the limitations described above. Our model slightly overestimates some end uses as described earlier. Accounting for the usages that are not directly comparable (basin, taps, kitchen sink etc.) to results from a study conducted by EST (2013), the mean 'Total' usage figures were broadly comparable, showing that if more accurate and statistically significant adjustment coefficients are provided for occupancy and climate, the results would become much more robust. Our model in its final form, which takes drought histories into account as well as relevant water efficiency measures and TUBs, shows whether household consumption is affected by these interventions and how. This is a very important step towards integrated demand forecasting in times of drought, as the model can be modified to include future drought scenarios. The next step is the development of a second version of the model. The new version will use water consumption data derived from a detailed survey on water using practices at home, completed by 1800 households.

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