Journal of Water Resources Planning and Management

Projections of Domestic Water Demand over the Long-Term: A Case Study of London and the Thames Valley

Rizwan Nawaz[1], Philip Rees[2], Stephen Clark[3], Gordon Mitchell[4], Adrian McDonald[5], Michelle Kalamandeen[6], Chris Lambert[7] and Ross Henderson[8]

Abstract

This case study implements long-term projections of domestic water demand for a UK water company, Thames Water. Projections of per household consumption (PHC) and households were combined to yield future demand. Regression models predicted PHC using the determinants of occupancy, property type, ethnicity and rateable value, drawing on 2006-2015 domestic water use data as a baseline. A model was developed for diffusing savings in per capita consumption (PCC), drawn from published studies of interventions. PCC declines were converted to PHC reductions using

[1] Rizwan Nawaz
Research Associate in Water Futures, The University of Sheffield, Department of Civil & Structural Engineering, The University of Sheffield, Mappin Street, Sheffield, S1 3JD, UK, n.r.nawaz@sheffield.ac.uk ORCID 0000-0001-5601-2164.

[2] Philip Rees
Professor Emeritus, University of Leeds, School of Geography, University of Leeds, Leeds LS2 9JT, UK, p.h.rees@leeds.ac.uk ORCID 0000-0002-4276-9091

[3] Stephen Clark
Post-Doctoral Research Fellow, University of Leeds, Leeds Institute for Data Analytics, University of Leeds, LS2 9JT, UK, s.d.clark@leeds.ac.uk ORCID 0000-0003-4090-6002.

[4] Gordon Mitchell
University of Leeds, Associate Professor, School of Geography, University of Leeds, Leeds LS2 9JT, UK, g.mitchell@leeds.ac.uk ORCID 0000-0003-0093-4519.

[5] Adrian McDonald
Professor Emeritus, University of Leeds, School of Geography, University of Leeds, Leeds LS2 9JT, UK, a.t.mcdonald@leeds.ac.uk.

[6] Michelle Kalamandeen
PhD Student, University of Leeds, School of Geography, University of Leeds, Leeds LS2 9JT, UK, mikaguyana@gmail.com. ORCID 0000-0001-5385-7444.

[7] Christopher Lambert
Supply Demand Senior Technical Adviser, Strategy, Planning and Assurance, Wholesale Water Thames Water Utilities Ltd, Clearwater Court, Vastern Road, Reading RG1 8DB, UK
chris.x.lambert@thameswater.co.uk

[8] Ross Henderson
Water Resources Planning Specialist, Thames Water Utilities Ltd, Clearwater Court, Vastern Road, Reading RG1 8DB, UK, ross.henderson@thameswater.co.uk.

baseline ratios. Interventions were grouped into Business as Usual, Light Green (limited intervention) and Dark Green (extreme intervention) scenarios. Projected households were generated by property type, occupancy and ethnicity for Thames Water's resource zones for 2011 to 2101 and multiplied by projected PHCs to yield water demand projections. By 2101, the 2011 water demand of 1,225 million litres a day grew 90% under Business as Usual, 69% under Light Green and 46% under Dark Green.

Introduction

Context

London and the Thames Valley is situated in a 'seriously water stressed' UK region (EA, 2013) (Fig. 1). Annual rainfall is low; per capita water supply is lower than in many hotter and drier Mediterranean and African countries (GLA 2011). Thames Water Utilities Limited (hereafter Thames Water), the UK's largest water provider, supplies almost 10 million customers (Thames Water 2017). Thames Water's needs include projections of domestic water demand to 2100 for its strategic plans. To achieve this goal, the population, households, per household consumption (PHC) and per capita consumption (PCC) need to be projected. To do this, the authors model and predict baseline PHC by households classified by property type, occupants and ethnicity, which are key drivers of water consumption. Scenarios of household water saving measures and projections of future PHCs are then developed. Multiplication of scenario PHCs by projected households produces alternative projections of domestic water demand.

In England and Wales water utilities are privately owned but required, under a set of national and European regulations, to produce detailed plans for future domestic water supply. The current minimum planning horizon for a statutory Water Resources Management Plan (WRMP) in England and Wales is 25 years, although Baker et al. (2016) argue that domestic water demand should be projected to 2100. It can take a quarter of a century to plan and build a large water supply facility, which should be viable for use, given maintenance, for as long as possible. This reduces the cost of paying back loans.

Since households account for about half of the water consumed in London and the Thames Valley, it is important to understand how household change will affect water demand. The UK, Australia, and the USA adopt a range of forecasting approaches (Rinaudo 2015), although Parker and Wilby (2013) claim "there is surprisingly little literature on UK household water demand estimation and forecasting under a changing climate". Selection of a forecasting approach is dependent on the regulatory context, geographical scale, available data and technical capacity. Water utilities also need to assess uncertainty in future water demand projections (House-Peters and Chang 2011), so that new supply infrastructure can be developed if growth in demand is faster than forecast or plans postponed if growth is lower than forecast.

Research Questions and Overall Aim

The questions this paper seeks to answer are as follows. How can household water consumption in the Thames Water region be best estimated? What drives water consumption in the region? What is the best model for projecting domestic water consumption using the drivers? How will domestic water demand change in the future? The aim of this paper is to understand, under a set of demographic and water consumption scenarios, how water demand in London and the Thames Valley will change between 2011 and 2101.

Overview of the Analysis System

To achieve the aim, the authors built a system for projecting domestic water demand (Fig. S2). The system implements four analyses which are connected. The first analysis projects the populations of local authorities covering the Thames Water supply region by ethnicity (Rees et al. 2016, Wohland 2017) and converts the results to water resource zones. The second analysis uses the projected populations and information from official forecasts and the 2011 Census to produce household projections (Rees and Clark 2018). The third analysis predicts recent PHCs based on key determinants, including household size, property type and ethnicity of the head. The fourth analysis project PHCs under three scenarios which reflect increasing water saving efforts by the utility and consumers. This paper focuses on the third and fourth analyses and brings together their results to project domestic water demand from 2011 to 2101.

Outline of the Paper

The next section reviews methods for analysing household water demand. The third section describes the Thames Water study area and the Domestic Water User Survey (DWUS). The fourth section describes the regression method used to predict PHCs and the intervention and diffusion model for projecting PHCs. The fifth section discusses the performance of 13 alternative models of domestic water demand and selects preferred models. The sixth section projects PHCs under alternative water saving scenarios and multiplies them by the projected households to yield domestic water demand. Finally, findings are summarised and a discussion is provided on possible improvements.

Review

Despite issues with data quality and multiplicity of drivers (Haque et al. 2017), water demand forecasting studies are numerous and varied ranging from analysis by Whitford (1972), Gato et al. (2007) and Polebitski et al. (2011) to more recent work by Hussein et al. (2016), Haque et al. (2017)). All household water demand forecasts require an understanding of the determinants. In our study, we make a distinction between determinants under the control of water utilities and those that are not (Gegax et al. 1998).

Determinants under Utility Control

Charging for water by volume consumed is a policy lever that utilities use to regulate household water consumption (Grafton et al. 2011). In the UK, metered customers (paying by volume) use less water than unmetered customers (paying a fixed-rate), but the scale and longevity of water savings are uncertain (Staddon 2010). To understand the impact on water consumption of customers moving from a fixed-rate to a volumetric-rate, metering trials have been undertaken in the UK since 1989. The first trials involved 53,000households in the Isle of Wight and reported 10% savings (Gadbury and Hall 1989). The National Water Metering Trials, covering 12 areas across the UK, ran from 1989 to 1993 and found 11% water savings from metering (Smith and Rogers 1990). A large-scale metering trial conducted by Southern Water reported larger savings of 16.5% (Ornaghi and Tonin 2015). About half of households in the UK are now metered, but because meter installation has been largely voluntary, uptake has been higher among low water users, which may exaggerate the water savings. The difficulty of attributing water consumption reductions to charging for use is also complicated by the Hawthorne effect. This identifies that the behaviour of householders changes, if they are aware their water use is monitored (Wickstrom and Bendix 2000). Despite these concerns the effect of metering on consumption is introduced into the forecasting model, using the Southern Water reduction finding, which is based on a Universal Metering Programme reaching 500,000 households by 2015.

Studies report that raising prices reduces consumption, but only moderately (Espey et al. 1997, Brookshire et al. 2002, Dalhuisen et al. 2003, Kenney et al. 2008 & 2012, Arbues et al. 2013). Mitchell and McDonald (2015) argue that numerous water conservation measures are insufficient without a pricing incentive and propose a “Cap and Trade” (C&T) approach, in which water resource abstractions are limited to long-term, sustainable supply, with abstractions allocated via tradeable electronic permits. Although pricing-based interventions generally tend to disadvantage low income households, this is avoided in the C&T approach since every user (household, firm) gets an allowance. If they use more than their allowance they have to purchase more in an open market of ‘allowance’ certificates. If they are thrifty with water, and use less, they can sell their surplus allowance into that open market, and benefit financially from being water wise. The scheme is therefore more favourable to low income households than straight price rises, assuming transaction costs are controlled. Although Cap and Trade is operational in many domains, particularly for atmospheric emissions, its use for managing water resources remains exploratory.

Non-price determinants under utility control include funding the installation of water-efficient fixtures and raising awareness of the need for water saving. The effects on consumption of installing water efficient fixtures have been investigated with mixed results. A review of studies from Australia, the UK and USA concluded that water reductions of between 9% and 12% were possible through installation of devices such as tap aerators (Fielding et al. 2012). More comprehensive programmes aimed at replacing existing water intensive appliances with highly efficient ones may lead to reductions of between 35% and 50% (Inman and Jeffrey 2006). Waterwise (2011, 2012) reviewed eight UK water company projects together with the Save Water Swindon trial findings (Table 1). The findings indicate a range of uptake rates (6 to 60%) as well as expected reductions in consumption (1.2% to 14.9%) with an average saving of 9.4%.

Despite the water savings reported, uncertainty persists due to the 'rebound' effect. This occurs when technical progress improves the efficiency of resource use but the consumption rate increases because the perceived cost has dropped (Memon and Butler 2006). For example, if householders install a water efficient showerhead, they may take longer showers. Fielding et al. (2012) ascribe some findings on water use in a sample of Australian households to the rebound effect. Based on water use data and surveys collected from 1,008 households, the effect of water efficient technology was found to be mixed: some water efficient appliances were associated with lower water use, while others were associated with more water use. Water demand management studies need to consider both technology and householder behaviour.

Another strategy will be to educate households about water saving through home visits, letters, telephone conversations, web portals and in-home displays (IHDs). Portals and IHDs provide real-time information to the householder on consumption through a 'smart' meter. Information on real-time and average usage at the individual household and neighbourhood levels can be derived. In a review of 21 studies exploring the effect of smart water meters on domestic water consumption, Sønderlund et al. (2016) reported savings ranging from 2.5% to 28.6%, with an average of 12.5%. Frederiks et al. (2016) conclude that savings are generally to be expected at the lower end, based on evidence from higher quality trials.

Determinants not under Utility Control

Research shows clear relationships between demographic, socio-economic and property variables on the one hand and household water consumption on the other. Unsurprisingly, households with more occupants use more water (Jeffrey and Gearey 2006, Fielding et al. 2013). Household size also directly influences water consumption per person (PCC), with larger households having smaller PCCs due to scale economies (Memon and Butler 2006). Other demographic determinants include income and household water saving preferences (Renwick and Green 2000, Cavanagh et al. 2002, Memon and Butler 2006). The influence of age on domestic water consumption is uncertain. Gregory and Leo (2003) report higher use amongst older people as they spend more time at home and use more water in gardening. Additionally, Makki et al. (2013) report that teenagers use more water, as a greater self-awareness promotes increased cleanliness and more frequent showering.

Smith and Ali (2006) argue that ethnicity must be considered when modelling domestic water demand in areas with diverse populations. Consumption varies by ethnic group, due to differences in water use for religious/spiritual cleansing (Wa'el et al. 2016, Nawaz et al. 2014). As noted by Medd et al. (2007) and Elizondo and Lofthouse (2010), this determinant remains under-researched. However, Thames Water (2015a) provides useful insights into water use practices by faith (Christian, Hindu, Jewish, Muslim and Sikh). Potential water savings were identified in the kitchen for some groups (Hindu, Muslim, Pentecostal Christian and Sikh) and in the garden for others (Anglican Christian, Jewish). Traditional practices (of cooking and garden watering) may need to change to reduce water consumption in the home. Housing attribute determinants include house type, house age, size of house/garden and water-use technologies installed (Renwick and Green 2000, Cavanagh et al. 2002). Kenney et al. (2008) conclude that employing these features in models of demand needs care as dwelling attributes (e.g. property type) are correlated with household characteristics (e.g. income). Weather can impact seasonal water consumption, most notably in households with outdoor water use, particularly garden watering and some studies have investigated the impacts of climate change on domestic water consumption in England (e.g. Downing et al. 2003; HR Wallingford, 2012).

Downing et al. (2003) determined percentage increase in domestic water demand based on four climate change scenarios and concluded that increases of 1.6% to 3.3% were likely by the 2050s for the single Water Resource Zone considered in the Thames Water region (Swindon/Oxfordshire). The more recent investigation, by HR Wallingford adopted the UKCP09 (Murphy et al., 2009) climate change projections to determine the impact on domestic water consumption. The full ensemble of 10,000 UKCP09 climate projections were used to develop 10,000 potential future Per Capita Consumption (PCC) factors for the Thames Valley by the 2030s. Three future changes (from base year of 2011) in annual average PCC were then reported on the basis of the 90^{th}, 50^{th} and 10^{th} percentile values (0.90%, 0.53% and 0.17%). Expected changes in PCC as a result of climate change were derived for different property types with the largest increase for detached households and no change for flats. A direct comparison with the work of Downing et al. (2003) is not possible but it is clear that smaller increases are expected according to the HR Wallingford investigation.

During prolonged dry spells utilities may implement drought orders to restrict some water use activities, such as garden watering (e.g. Thames Water 2015b). Such measures are driven by both anticipated lower supply and increased demand when water becomes scarcer as temperatures rise and rainfall decreases under climate change. However, their use implies a loss of customer service which water utilities seek to avoid through long range planning and operational management. In this paper, the effects of climate change on domestic water demand are considered by using climate change factors from the HR Wallingford (2012) study and applying to the overall demand forecasts.

Overall, demand-side management controls appear limited in effect. For example, Inman and Jeffrey (2006) concluded that demand management initiatives could lead to reductions of 10% to 20% over a 10 to 20-year period. Syme et al. (2000) argued that information campaigns to promote voluntary domestic water conservation could reduce water use 10% to 25%, although, during droughts, higher reductions were achieved. These studies indicate that whilst moderate reductions could be achieved through voluntary demand management efforts and a small price increase, greater reductions would require stringent mandatory policies and larger price rises. Thus, our ability to influence the trajectories of people's water use and to offer associated scenarios appears limited (Anderson and Stoneman 2009).

Scenario Building

Scenarios are views of the world in narrative form, providing a context for managerial decisions (Raven and Elahi 2015). Scenarios are useful when the future is uncertain and can help identify strategies for responding to different possible futures (Ramirez and Van der Heijden 2007). Lindgren and Bandhold (2009) note that scenarios are useful because they display divergent thinking, reduce complexity and are easy to communicate. There are few other credible alternatives for long-term planners. Hunt et al. (2012) identified 450 scenarios for future water demand published between 1997 and 2011. They concluded that the most relevant for UK-based research were the Policy Reform, Market Forces, Fortress World and New Sustainability Paradigm scenarios, characterized by internally consistent narratives that provide an understanding of Social, Technological, Economic, Environmental and Political forces. These scenarios were considered distinct enough to facilitate stakeholder thinking about alternative futures.

Changes to current PCC under future scenarios need to be determined for long-term demand forecasting. Drawing on findings in previous research, we use three scenarios of future water consumption: Business as Usual, Light Green and Dark Green. In the Business as Usual scenario, only two changes are assumed: (1) the small decline rate in water consumption observed in the years 2006-2015 in Thames Water's DWUS (see 3.2 below) data continues, and (2) the compulsory metering of households, in progress, rolls forward to completion by 2030. In the Light Green scenario, in addition to Business as Usual reductions, further interventions by the water utility (e.g. a further cycle of home visits and improved information to households via smart meters) will persuade households to make further savings in their water consumption. These interventions have been trialled by many water companies and have been found effective. In the Dark Green scenario, more extreme interventions, such as stronger building controls, better appliance availability, mandatory retrofitting and strong fiscal controls, are assumed to produce further reduction in household water use. Climate change is accounted for by adopting the PCC changes reported by HR Wallingford (2012) for the London and Thames Valley region (see section 2.2). The 90th, 50th and 10th percentile PCC change (%) values are assumed to be representative of the Business as Usual, Light Green and Dark Green scenarios, respectively.

Each scenario is combined with a demographic scenario which projects WRZ ethnic populations using a sub-national cohort-component model for LADs (Rees et al. 2016). The fertility, mortality and international migration assumptions are aligned to those used by the Office for National Statistics (ONS) in its 2014 national population projections. New estimates of internal migration rates by ethnicity are developed for a 5-year period and assumed constant in future. Projected populations are converted into projected households (Rees and Clark 2018).

Study Area and Data

Study Area

The Thames Water supply area (Fig. 1) covers about 8,000 km^2 across 60 Local Authority Districts (LADs) in SE England and is divided into six Water Resource Zones (WRZs) – Guildford, Henley, Kennet Valley, London, Slough-Wycombe-Aylesbury (SWA) and Swindon & Oxfordshire (SWOX) (Thames Water 2015b) (see Fig. S1). Each day, around 2,600 million litres of water are supplied to the 9.9 million customers across London and the Thames Valley (Thames Water 2017).

The Thames Water Domestic Water User Survey (DWUS): Sample Representativeness

Householders in England and Wales are charged a fixed tariff (when unmetered) or by water volume (when metered). The fixed tariff is based on the rateable value (RV) of the home, which is determined by the UK Valuation Office. For domestic customers with a meter, charges include a fee dependent upon volume used. In the past, most customers paid a fixed (unmetered) charge, but this is changing as utilities install water meters to persuade households to reduce consumption. In London, the percentage of properties metered in 2011 was 23% and in the WRZs outside London the percentage of properties metered ranged from 39% in Slough-Wycombe-Aylesbury WRZ to 53% in Henley WRZ. In London, the targets for compulsory metering in 2030 are 65% for flats and 67% for other properties. In WRZs outside London the targets were 65% for flats, and between 79% (Guildford) and 87% (Kennet Valley) for other properties (Thames Water 2014).

To estimate consumption for unmetered households, Thames Water organises a DWUS, a sample of households whose consumption is monitored via a meter, but who pay on a fixed charge basis. Householders are asked to volunteer but offered a small financial incentive. The DWUS contains records of consumption linked to data on household structure and water using devices. Householders are asked to complete a DWUS survey sent each October. The Thames DWUS records household structure (adults, children, occupancy, and ethnicity), water appliance ownership, property type, car ownership and income band. This information, combined with rateable value, provides a range of attributes associated with water consumption.

From detailed daily records, annual average consumption in litres per person per day was computed. Ten years (2006 – 2015) of consumption and DWUS data for sample households in London and the Thames Valley were available. Demand forecasts with an annual time step are an input to the wider water resource management planning process, in which further risk based planning estimates are made by water companies. Techniques sufficient to meet the statutory requirements are explained in detailed industry guidance (e.g. UKWIR 2016a, 2016b). For example, Monte Carlo methods applied in conjunction with historical observations of within year demand and deployable output are applied to determine probability density function of supply-demand balance representing annual average dry years and more extreme cases. Additional methods are used to address the impacts of climate change in water resource planning (UKWIR 2013, UKWIR 2018). This risk based planning downscales aggregate forecasts to produce supply/demand estimates at finer spatial and temporal scales, which in turn inform asset and network operations management.

At least 1000 properties were included each year in the DWUS with annual variability as households were recruited or lost because of in- and out-moves or through opting for payment on a metered tariff. Records constitute household-property spells and exceed the number of properties logged because of turnover. In 2006, 1846 properties were logged; the number rose to 2,296 in 2008 and then declined to 1,471 in 2015. After removing faulty records (~27%), the number of valid household-property spell records in the DWUS was 19,238 over the 2006-2015 period.

Inaccuracies in the DWUS exist due to biases. The scheme is voluntary and a (small) financial incentive to join the survey may introduce an income bias. Householder awareness of monitoring can alter behaviour (Wickstrom and Bendix 2000), whilst bias can also be introduced through (usually smaller) households switching to paying on a metered basis, aiming to lower charges. Switching rates have been much higher in the DWUS than in the rest of the customer base. The remaining households in the DWUS have a higher average water use, but newly recruited unmetered households will rebalance the DWUS. However, biases are assumed to be small, partly as meters are external and not readily visible. McDonald (2002) estimated these biases to collectively under-represent total demand by 1-2%, and it is likely that this is reducing as compulsory metering is rolled out.

Sample representativeness in relation to demographic and household attributes was tested by comparing percentages of households in ethnicity-occupancy combinations in the 2006-2015 DWUS with those in the mid-way 2011 Census. Table 2 shows that differences between the Census and DWUS percentage distributions are present though not large. The index of dissimilarity between the two percentage distributions is 9.9, at the lower end of a possible 0 (wholly similar) to 100 (wholly dissimilar) range. The distributions of households across each housing type in the DWUS and the Census (not shown here), were similar, although some differences were observed for Henley, the WRZ with the smallest number of households in the DWUS sample.

Household Consumption Based on the DWUS

Table S1 shows observed PHC across the DWUS sample households by ethnicity, property type, and occupancy for each of the 6 WRZs. Other Ethnic Households comprise 93% of all records in London and the Thames Valley while South Asian households make up 7%. For all property types and Other Ethnic households, consumption increases steadily as occupancy increases. This is also true for South Asian households except in the 5 and 6+ occupant categories, where the sample is very small or nil. South Asian households consume more water than Other Ethnic households of the same size or property type. Table 3 summarizes PHCs for the two ethnicities for all WRZs and shows variation in consumption by property type, controlling for occupancy. Highest PHC is reported for detached dwellings and lowest PHC for flats. PHCs for semi-detached and terraced dwellings are similar and their rank depends on household ethnicity. For Other Ethnic households, higher PHC is reported for semi-detached dwellings than terraced in 4 out of 6 occupancies. For South Asian households higher PHC is reported for terraced dwellings than semi-detached in 4 out of 6 occupancies.

Rateable Value Imputation

A supplementary method is used to handle the large number of missing values for rateable value. Of a total of 19,238 records, 9,022 records were missing rateable value (47%). If cases with missing values are systematically different from cases without, the results can be misleading. There is no simple rule for deciding whether to leave data as they are, to drop cases with missing values or to impute missing values (Garson 2015). Bagheri et al. (2014) recommend that imputation should not be used if over 50% of data are missing, though some authors use lower cut-offs. On this basis it was decided to impute the missing values. Rateable value data was infilled using the 'Missing Value Analysis' (MVA) feature in SPSS. The MVA performed three primary functions: (1) description of the pattern of missing data, for example, where the missing values are located, the extent of missing data and whether values are missing at random; (2) estimation of the means, standard deviations, co-variances, and correlations based on both the Expectation-Maximisation (EM) algorithm (Dempster et al. (1977)) and the Multiple Imputation (MI) estimation method (Rubin 1976); (3) substitution (imputation) of missing values with estimated values.

In the next section, the categorical regression method and the MVA imputation method are used to model the Thames Water DWUS household-spell records to provide both coefficients measuring the strength of each predictor variables and better baseline estimates for forecasting.

Methods for Predicting and Forecasting PHCs

A range of regression methods are used for modelling domestic water demand. Independent Component Regression (ICR) is employed by Haque et al. (2017) and Evolutionary Polynomial Regression (EPR) by Hussien et al. (2016). However, Hussien et al. (2016) found both a Multiple Linear Regression (STEPWISE) approach and EPR offered similarly good predictions of domestic consumption. We therefore use the standard regression method.

Regression Models of PHC

Our general model design is as follows. The continuous dependent variable was PHC classified by a set of independent, categorical, variables. The model type used was an Ordinary Least Squares (OLS) regression with categorical independent variables for 4 Property Types, 6 Occupant Numbers, 2 Ethnic groups and 6 WRZs and continuous variables, the rateable value and a time trend. Property type and ethnicity interactions were included. We also tested a model with only two WRZ groupings (London and Not London) and substituted Adult and Child Numbers for Occupant Numbers.

The categorical regression model (Long 1997) assigns coefficients to dummy variables. For a cell table, only one of the variables categories is set to 1; the other categories will be 0. The PHC for household h of occupant number i, property type j, ethnicity k and Water Resource Zone l is predicted by:

$$PHC^h_{i,j,k,l} = b^0 + \sum_i b^{(1)}_i O^h_i + \sum_j b^{(2)}_j T^h_j + \sum_k b^{(3)}_k E^h_k + \sum_l b^{(4)}_l Z^h_l + \sum_{j,k} b^{(5)}_{j,k} (T^h_j \times E^h_k) + b^{(6)} R^h + b^{(7)} (ln(Y - 2005)) \quad (1)$$

The categorical independent variables are: O, Occupancy, T, Property Type, E, Ethnicity and Z, Water Resource Zone. The continuous independent variables are: R for Rateable Value and ln(Y), which is the natural logarithm of years since the start of the DWUS records. Each category is represented by a dummy variable except for rateable value and time. Coefficient $b^{(0)}$ indicates the constant value of PHC for the reference category and coefficients $b_i^{(1)}$ to $b_{j,k}^{(5)}$ indicate the influence of predictor categories on PHCs, while $b^{(6)}$ measures the impact of rateable value specific to a household and $b^{(7)}$ measures influence of the time trend applied to all households.

A Model for the Diffusion of Water Saving Interventions

When interventions aimed at altering water use behaviour are implemented, uptake is not immediate. A model tracking the diffusion of innovations (Rogers 1976) is used to represent the time path of take up. Use of such a model helps in understanding the rate at which ideas and technologies are likely to spread. A linear function was adopted for diffusion, where the links of behaviours to parameters are fully transparent. The linear functions are applied to interventions with fixed durations planned by water companies. Interventions are not persisted with when all households who can reasonably be expected to adopt the innovation have done so. For example, some households may be too poor to afford the expense of retrofitting the intervention into an existing property, so that the intervention does not reach them. It was assumed that interventions occur over short periods of 5 to 15 years. Once the end year is reached the adoption level is held at the limit value.

The parameters that control the rollout of interventions are: first, the reduction in daily litres of water that could be achieved by the intervention; second, the limit as a proportion of the reduction applied to all households; third, the start and end years of the intervention; fourth, the assumption that there is no reduction before the start of the intervention; and fifth, the assumption that after the end of the intervention, the reduction in PCC continues at the limit set. PCC reductions are converted into PHC reductions for household types, using ratios of PHC to PCC established in the baseline PHC estimates.

Assuming continuation of the PCC reduction after initial diffusion is a weak assumption. There is some UK evidence to suggest that water savings are not sustained over time (Fielding et al. 2013; Sønderlund et al. 2016). The Waterwise (2011) report based on four domestic trials estimates that the half-life of an intervention (i.e. time by which water savings decay by a half) is 8.4 years. Savings do cumulate over time, but only because a conservation effort is made each year to reach a new set of households. However, a reversion function was not implemented in our projections, because there is uncertainty about which interventions experience reversion. So, our projections of water demand reduction reported should be regarded as optimistic.

The following equations are used to implement the diffusion of interventions. Let R_k^* be the full water reduction achievable from an intervention and let R_k^y represent reduction in PCC for intervention k in year y. Let sy_k be the start year for intervention k, ey_k be the end year for intervention k and r_k^L be the limit to the reduction for intervention k, expressed as a proportion.

If year y < start year sy, then set

$$R_k^y = 0 \quad (2).$$

If year y >= start year sy and <= end year ey, then set

$$R_k^y = (\text{y} - sy_k + 1) \times (r_k^L/(ey_k - sy_y + 1)) \times R_k^* \quad (3).$$

If year y > end year ey, then set

$$R_k^y = r_k^L \times R_k^* \quad (4).$$

Table 4 shows the water demand interventions grouped by Business as Usual, Light Green and Dark Green scenarios. The table reports the PCC reduction expected from the intervention in percentage terms (as in the literature) and in absolute terms (used in the diffusion model). The diffusion limits are chosen as 50% in the Light Green interventions and 60 to 75% in the Dark Green interventions. It is rare for water saving interventions to be adopted by all households. A 15-year interval is assumed between start and end year for each intervention. Light Green interventions start in the first four decades of the projection; Dark Green interventions are assumed to start in the fifth to seventh decades. For the last two decades of the projection horizon no new interventions are assumed.

The next step is to convert the projected PCCs after the intervention reductions have been applied into future PHCs under each scenario. The projected PCCs for all households are converted into PHCs for the different household types using PHC-PCC ratios based on the baseline modelled PHC values.

Water Saving Interventions under a Business as Usual (BaU) Scenario

In the 2006-2015 period, there was a slow reduction in water consumption. A logarithmic trend was fitted to DWUS household records and assumed to apply in the Business as Usual scenario throughout the projection period. Note that reductions diminish over time. Over the 90-year period the trend reduces PCC by only 7.1 litres per day.

The Business as Usual scenario includes the roll out of Thames Water's metering programme. As many households as possible are to be compulsorily switched to metering over the 2011 to 2030 period. After 2030 the percentage of metered households is assumed to remain constant to 2101. The percentage converted to meters reaches an upper limit of 78% to 88% for WRZs outside London for all house types except flats. For flats an upper limit of 65% is assumed because it is difficult to retrofit meters in older flatted properties. In London, metering reaches 69% for all property types except flats where a 65% upper limit is assumed. Variable tariffs are not assumed because, although households save money by reducing consumption when supplies are restricted due to droughts, evidence from a Colorado study (Kenney et al. 2008) found no long-term water savings.

Water Saving Interventions under a Light Green (LG) Scenario

In this scenario, the public have a stronger sense of their responsibilities in relation to the environment and recognise the need for action to adapt to climate change. Governments have responded to these concerns. Over coming decades, we assume public awareness will increase. Sustainability receives increasing attention within school curricula leading to a growing generation of environmentally aware householders. To achieve sustainability prices are increased. The public are willing to try out innovative water saving technologies such as nearly waterless toilets, in-house water treatment and smart-meters. The water sector invests in intense engagement with water consumers leading to substantial cuts in wastage. Tailored interventions by Thames Water working in collaboration with environmental organisations result in improved efficiencies, especially amongst communities of Indian, Pakistani and Bangladeshi (South Asian) heritage. The ambition is to lower PCC by 20%. Water savings are to be achieved primarily through encouraging voluntary installation of water efficient fixtures and raising awareness through smart metering. This is a scenario based on voluntary interventions, but the pricing effect of metering in the Business as Usual scenario is included in the Light Green scenario. Of the total 20% reduction in consumption, voluntary installation of water efficient fixtures is expected to contribute to half of this (with a ~50% uptake) and the remaining half is expected to arise from better customer awareness of water use (through in-home displays) and identification of customer-side leaks (through smart meters).

Water Saving Interventions under a Dark Green (DG) Scenario

The general ambition under the Dark Green scenario is to lower PCC by a further 35%. A future under the Dark Green scenario is based on the effect of regulatory levers, aiming for a sustainable future. Water regulation changes require long-term thinking beyond short-term Asset Management Planning cycles, technical developments and changes in public perceptions, so that waste is minimised. There is greater collaboration amongst the water and energy regulators enabling real-time usage information being shared with customers leading to improved efficiencies. Water inefficient devices are gradually phased out and appliances are now given a water efficiency rating as well as an energy efficiency rating. Government incentivises the environmental technologies industry to increase uptake. The combined effect of installation of water efficient fixtures and behaviour change leads to 30% water savings. A mandatory Cap and Trade scheme for all households is introduced and is assumed to lead to a further 5% reduction with 60% of households actively participating in the scheme(see Table 4).

Water Saving Interventions: A Summary

The average PCC water saving information is summarised in Table 4. The average PCC savings in the 90-year projection under the Light Green scenario and the Dark Green scenario are 29.8 and 52.0 litres per capita per day respectively. The Table 4 values look precise because this is what the source literature or the calculations deliver. However, they are all uncertain, particularly those in the Dark Green scenario. The Dark Green scenario is based on substantial changes in public and political support for water saving. The scenario represents circumstances at the outer edge of the envelope of possible water futures. However, it is still important to understand the potential for these measures to affect growth in overall demand.

Predictions of PHC

Using the methods explained in Section 4, a systematic sequence of models for predicting PHC was calibrated. Table 5 assembles results from the models 1 to 9 which use the occupancy variable while Table 6 reports on models 10 to 13 using adult and child numbers. Model 1 only uses occupancy and has a goodness of fit of 32.3% (R^2) between predicted and observed PHCs. Model 12 has the highest R^2 of 44.7%. The coefficients of the categorical determinants indicate how many litres of water per day less or more a household in a given category consumes than households in the reference category. The trend coefficient indicates the reduction in consumption per year during the DWUS observation period, 2006-2015, reflecting growing awareness by water consumers of the need to conserve water and adoption of some water saving devices, e.g. eco-washing machines and dual flush toilets. The regression coefficient for rateable value indicates the change in consumption per £GBP of rateable value. Tables 5 and 6 also report the number of households in the dataset used in each model: 19,238 households make up the full set of household-water consuming spells after cleaning; 10,308 is the reduced set after removal of records without rateable values. Significant coefficients are identified at the 1% and 5% levels using a bold and underline function respectively.

Models using Occupancy

Models 1 to 9 show a consistent gradient of rising PHC from lowest to highest occupancy with returns to scale, as PCC declines with increasing occupancy. Models 2 to 7 add property type to occupancy. Models 4 and 5 introduce dummy variables for each WRZ, while models 6 to 9 reduce the WRZ classification to the London WRZ (LON, the reference category) and WRZs outside the London WRZ (Not LON). Models 3 to 7 add ethnicity (reference category South Asian households) to the predictors. In models 8 and 9, ethnicity is combined with property type to investigate whether combinations have higher or lower PHCs, controlling for the influence of the other predictors.

Model 1 uses occupancy alone to predict PHC. The coefficients for all categories are significant and behave as expected: the smaller the household, the lower the predicted consumption. Model 1 accounts for 32.3% of the variance in observed PHC. Model 2 uses occupancy and property type. The R^2 only increases to 33.0% but retaining property type is vital as many water saving options adopted when projecting PHC are specific to property type. The property coefficients are smaller than those for occupancy: households in detached properties use most water compared to households in flats; households in terraced properties use less water than detached, except in Model 7. The PHCs of semi-detached households are close to those terraced properties, but lower in most models. Model 3 adds ethnicity to occupancy and property type. The R^2 rises to 36.8%. Ethnicity is retained in subsequent models. Other Ethnic households consume 180 litres per day less than South Asian headed households in this model.

The difference between these ethnic groupings is associated with religious observance (Thames Water 2015a). Most Pakistani and Bangladeshi household members are practising Muslims, whose faith requires washing before daily prayers. The Hindu and Sikh faiths also emphasize the importance of bathing and cleansing. The difference may also be due to factors other than religious observance. These include the cooking practices amongst South Asian households requiring more water for dish-washing (Thames Water 2015a). Other Ethnic households may have shifted water consumption outside the home by eating out (Warde and Martens 2000).

Model 4 adds dummies for the six WRZs to the Model 3 predictors. The improvement in R^2 over Model 3 is slight, to 37.0%. No WRZ coefficients are significant, indicating there are no WRZ effects not already accounted for by the variation in household types across WRZs. Model 5 adds rateable value to the Model 4 predictors, resulting in an increase in R^2 to 41.5%. A higher rateable value signals a larger housing unit, which may have an additional bathroom and a larger garden requiring watering. The variable captures heterogeneity in water use within property types.

Model 6 uses dummy variables for the London WRZ and a Not-London WRZ groupings. The R^2 is 36.9%. This was only a tiny improvement over Model 2, but the two areas were retained for the forecasting model at the request of Thames Water. Model 7 adds rateable value to the Model 6 predictors, together with a time trend and rateable value, resulting an increase in R^2 to 41.6%. However, when rateable value is added, 47% of household-spell cases drop out because records with rateable value missing are omitted. There is a price to pay: predictions of PHC values in many household categories used in the forecasting model are unreliable because of smaller sample sizes.

Model 8 includes occupancy, property type, ethnicity, two WRZ groupings and interactions between property type and ethnicity, seeking to identify combinations that give rise to significantly higher or lower PHC. The R^2 reaches 37.9%, suggesting little is added to predictions by including these interactions. Model 9 adds a time trend to the Model 8 predictors to capture reductions in PHC because of changing water consumption behaviour. Log time in years was used to taper initial savings over the latter part of the projection period. As in Model 8, R^2 is 37.9%.

Models Using Adult and Child Numbers

In Models 10 to 13, adult and child number variables are substituted for occupancy categories. This produces a small improvement in goodness of fit when equivalent models are compared. Model 10 accounts for 33.6% of the observed variance in PHC, a small improvement over the 32.3% of Model 1. Model 11 predicts PHC adding property type as a determinant with rateable value but no imputation of missing values. The R^2 is 42.4%. Model 12 predicts PHC with adult/child numbers, rateable value (with no imputation of missing values), and interactions (dropping cases where rateable value is missing). The R^2 is 44.7%. This provides the highest R^2 but at the cost of reduction in sample size. This results in no PHC values being generated for many South Asian household combinations. To provide PHC values for these combinations, Model 13 (R^2 of 40.7%) was developed with missing rateable values imputed. The final adopted predictions therefore combine outputs from Model 12 (to provide PHC estimates of various household input combinations) with outputs from Model 13 (to provide PHC estimates of household characteristic combinations particularly for South Asians where model 12 could not provide the output data). The R^2 for this synthesized result is 43.3%. This combination is employed for final predicted PHCs for use as 2011 baseline values in forecasting.

Validation of the Chosen Models

These R^2 levels compare favourably with equivalent models of individual behaviour in social science research. For example, studies in Finney and Catney (2012) report Pseudo R^2 of between 10 and 50% for regression models predicting migration using individual survey data. In another study, Williamson et al. (2002) included several predictors of domestic water consumption at the micro-component scale including the number of residents, number of bedrooms, washing machine and dishwasher ownership as well as property type and tenure. Their model was able to explain 44% of the observed variance. The remainder was attributed to water use behaviour. Wa'el et al. (2016) carried out an analysis of household PCC in the city of Dudok (Iraqi Kurdistan), achieving R^2 values of 63% to 92% for all households. The authors administered a face-to-face household survey which included more determinant variables than were available to us and which avoided missing variable problems.

A comparison of our average observed PHC values for 288 household types (6 WRZs × 2 ethnicities × 4 property types × 6 occupancies) with average modelled PHCs yields an R^2 correlation of 63%. Table 7 compares modelled PHC values with measured values by ethnicity and housing type for both within and outside London. Comparisons are generally good except for modelled PHC of South Asians living outside London in flats, owing to a small sample size. We consider the goodness of fit achieved in our analysis to be good.

To complete the validation, a comparison of total modelled water demand (Mld: million litres per day) for all WRZs averaged over each of five years (2011-2016) with observed data was made. Total 'modelled' water demand is a product of PHC values and projected household numbers. These water demand estimates are for occupied households to which it is necessary to added water demand due to hidden and transient populations, which include undocumented immigrants and second home populations. Finally, a small allowance of 10% of the average PCC value for a WRZ is made for water used in voids (empty properties), the number of which is assumed constant. Since the water demand model utilises population and household data from 2011 onwards, we compared our projected water demand with total Thames Water demand reported in the Ofwat Annual Returns from 2011-2015 (Fig. 3). There is a reasonably good fit between the two series. Although our projections under-estimate total domestic consumption, the important trend of an increasing consumption is maintained.

Final Modelled PHCs in the Thames Region

Fig. 3 presents the final values for modelled PHC for the London WRZ and Not London Zone by occupancy for eight property type-ethnicity combinations. In order of magnitude of effect, the charts show: first, that consumption increases from small to large households, second, that households with heads of South Asian ethnicity have higher consumption than equivalent households with Other Ethnic heads and third, that detached properties have the highest and flats the lowest consumptions, controlling for the other predictors. Also shown in the figure are error bars representing 95% confidence intervals. The size of each error bar provides an indication of sample size. The wider bars are generally observed for South Asian households. This is particularly the case for semi-detached properties and flats outside of London. Comparison with Table 3 shows that modelled values are in broad agreement with DWUS based estimates.

Projections of Water Demand

Computing the Water Demand Projections

Future water demand is computed as a product of projected household numbers (Rees and Clark 2018) and projected PHCs by scenario. The number of households is projected for 288 categories (6 WRZs × 2 ethnicities × 4 property types × 6 occupancies). Projected households are multiplied by corresponding projected PHCs to produce water demand projections. Added to these are the demand projections for hidden/transient populations and void properties.

Overview of Scenario Results

Fig. 4 presents the projected total water demand for the Thames Water region for the three scenarios. Demand under the Business as Usual scenario grows substantially to mid-century, driven by growth in households. The roll out of metering lowers the rate of growth a little to 2030 and the rate of growth picks up again thereafter, continuing to 2070. Population and household growth then slows down, until it reaches a plateau in the last decade of the century. The post 2070 slowdown in household growth is the result of natural decrease, the long-term result of assuming below replacement fertility and higher deaths due to waves of ageing baby boomers and immigrants. This natural decrease catches up with the assumed constant net addition to the population from international migration. The growth in population, particularly in London, is higher than in the country as a whole because of the high and growing share of the ethnic minority population, which becomes a majority population in most London Boroughs and many of the urban centres outside Greater London, such as Slough in the SWA WRZ.

Under the Business as Usual scenario water demand grows by 67% over the 50-year period 2011 to 2061 but only by 14% over the 40-year period between 2061 and 2101. The Light Green scenario promises a substantial reduction in the growth of water demand compared with the Business as Usual scenario. Growth between 2011 and 2061 is 49% but only 13% between 2061 and 2101. The Dark Green scenario pushes demand down further with growth of only 35% between 2011 and 2061, followed by only 8% between 2061 and 2101. The gaps between the Business as Usual and the two Green scenarios steadily widen to about 2085 but remain roughly constant thereafter. The intervention diffusions under the Green scenarios occur in the first part of the 90-year period.

Fig. 5 presents empirical prediction intervals (EPIs) for the three water consumption scenarios for five time periods (2021, 2041, 2061, 2081 and 2101) The EPIs were computed for the long-term population projection that underpins the growth in water consumption in the Thames region. There will be further uncertainty associated with the conversion of the population projections into households, in the forecasting of per capita and per household consumptions and in assumptions about water consumption in empty properties and by undocumented groups. The EPI computations use a set of historical errors for local authorities with small, medium and large populations reported in UKWIR (2015). The errors are derived by comparison of past sub-national projected populations for England with subsequent census-based population estimates. A piece wise linear function was employed to link EPIs to population size and a linear function used to relate projection error to length of the forecasting period (see Rees and Clark 2018). The 90% and 10% EPI limits produce an interval covering 80% of future outcomes, based on future population uncertainty. For the Business as Usual scenario, By 2101 the 90% value (2821 Ml/d) lies 21% higher than the water consumption forecast

(2332 Ml/day), while the 10% value (1842 Ml/day) is 21% lower (see Table S2). Taking the scenarios together as a set the 80% empirical prediction interval stretches in 2101 from a 10% value under the Dark Green scenario of 1414 Ml/day) , only 15% higher than the base line of 1225 Ml/day in 2011, to a 90% value under the Business as Usual scenario of 2821 Ml/day, which is 130% higher than 2011 consumption (see Table S2).

Sources of Change in Water Consumption

It is useful to understand the contributions of the different components to the growth of domestic water demand in the Thames Water region. Domestic water consumption increases because the population grows in all LADs and WRZs in the Thames Water region. The projections reported for the London and SWA WRZs are higher than alternative projections by the Greater London Authority and the Office for National Statistics (Rees et al. 2018). Our higher projections are a result of using LAD-ethnic group populations. Ethnic minority populations have a much younger age structure than the White British and Irish majority group. Several ethnic minority groups, including the South Asian groups, have fertility rates above the average. These two factors contribute to higher growth in South Asian and ethnic minority populations.

The projection of households in WRZs follow the growth in population but at a faster pace, because the 2014-based assumptions about household formation rates made by the Department of Communities and Local Government (DCLG) are used. These anticipate further falls in occupancy. There is a shift to smaller households because of ageing which is not cancelled out by rising numbers of young people staying longer in the parental home. Water demand is also higher because smaller households lack opportunities for scale efficiencies and so consume more water per capita. Households increase by 52% between 2011 and 2039 whereas population increases by 43%, for example. The DCLG projection of households assume that the decrease over recent decades in occupancy will persist in a modest fashion. So, average occupancy decreases to 2039. After then, this effect should not be as marked because household representative rates are held constant. These projected trends assume, optimistically, that sufficient new housing will be built to make such a decline in household size possible.

Water consumption does not grow as fast as either the population or households, reflecting the impact of metering and of the trend in consumer behaviour built into the Business as Usual scenario. Households grow by 52% between 2011 and 2039 period but water demand increases by only 36%. Changes in water saving behaviour under the Light Green and Dark Green scenarios claw back substantial parts of the Business as Usual increase in water demand as shown in Fig. 6.

Projected Water Demand under the Light Green Scenario

Fig. 6a decomposes total demand by property type for the Light Green scenario as an illustration of the detail of model outputs. The share of water demand from flats dominates throughout the period. However, demand from terraced properties increases slightly faster (79% growth, 2011 to 2101) compared with 66% for flats and 76% for semi-detached. Demand from detached property households grows by only 56%. These projections suggest that household densities are increasing. Is such an increase in density of population and households feasible? Between 2001 and 2008, new build density increased in London and the Wider South East region from 45 to 100 dwellings per hectare and this trend was incorporated in modelled housing growth to the 2030s by Mitchell et al. (2011).

Fig. 6b presents the decomposition of households by number of occupants. Water demand is projected to increase most for one-person households, by 116% by 2101. The increase in demand generally diminishes as occupant number increases with 80% growth for 2-person households, 46% for 3-person households and 37% for 4-person households. The increase for households with 5 and 6 or more occupants departs from this decreasing trend by occupant number with a 55% and a 99% increase, respectively.

Fig. 6c decomposes water demand by the two ethnic groupings. Total water demand increases by only 43% for the larger group (Other Ethnic), but by 274% for those in South Asian communities, reflecting their much higher demographic potential and continuing additions through immigration (Rees et al. 2016, 2017), coupled with the higher PCC and PHC consumptions of South Asian headed households.

Water Demand Projections for Water Resource Zones

The growth in water demand differs across the six WRZs (see Fig. S3). The greatest increase is in the London WRZ, powered by the highest population and household growth under the demographic scenario. London's growth in water demand levels off after the 2070s whereas growth in the WRZs outside London continues. This is a product of a rising internal out-migration from Greater London as constant rates are multiplied by a growing origin population, with the compensation from a positive balance from international migration remaining fixed. The Light Green and Dark Green scenarios have a relatively similar impact across WRZs because it is assumed there is no zonal variation in water saving behaviour beyond that built in to changes in household type mix and uptake of metering.

Discussion and Conclusions

This discussion compares the forecasts of water demand developed in this paper with the methods published in the literature covering six themes: scope (samples or populations), units (water using devices or individuals or households), coverage (sub-systems or whole systems), determinants (baseline analysis only or forecast), scenarios (with or without diffusion of interventions) and horizons (short-, medium- or long-term). We distinguish between academic studies and applied studies, the latter associated with an organization to which results must be delivered.

Most studies of the determinants of PCC or PHC use survey data. Surveys ask samples of households about their use of water using appliances and their characteristics. Academic studies (e.g Wa'el et al. 2016) gather primary data from a small sample of respondents. Our study uses secondary data for a large sample of responding households (DWUS) maintained by Thames Water. Such a survey is designed to enable estimates to be made for large customer supply areas (for example, the 6 WRZs). Most of these surveys are not carried out by professional social survey organizations (e.g. NatCen 2018, or Ipsos MORI 2018), so there is room for improvement in survey design and representativeness. We scaled up the results of our DWUS analysis by applying forecast weights for all customer households in the study region. Many academic studies end by saying that the research findings are applicable in water resource planning; our results were designed to be used in Thames Water's Water Resource Management Plan 2019 (Thames Water 2018).

Water demand studies use a variety of units when implementing the models of domestic demand (Parker and Wilby 2013). Many use the micro-components method of Ownership-Frequency-Volume applied to appliances in the household. Others focus on consumption by individuals (PCCs), convenient for combining with population projections. However, many studies adopt the household as the unit of observation for use in forecasting because of heterogeneity in households by structure and behaviour. This requires matching with projections of households, an approach we use in this case study. Note that domestic demand also includes consumption by people in communal establishments, in empty dwellings (estate agent and customer visits, leaks, squats), in second homes and by undocumented migrants. Thames Water projects these elements separately, some of these are included in our analysis (the ISS component in Figure 6).

Most academic studies focus on part of the domestic water demand system (Fig. 2), while we analyse all the necessary system modules. Water demand modelling studies stress inclusion of the widest range of potential explanatory variables but fail to develop a method for forecasting the significant determinants. Our approach was to focus on measuring the impact of the main drivers of water demand which we could forecast: occupancy, property type and ethnicity together with the addition of rateable value fixed at its baseline value. We also combined results from different regression models to overcome problems of small sample size in some of our 288 household types.

The main determinants in a baseline water demand model need to be forecast. We implemented demographic cohort-component methods for ethnic populations and projected households using headship rate methods, drawing on official practice. However, official household typologies were of little use in forecasting water demand, so we developed our own. Three scenarios for PCCs (Business as Usual, Light Green and Dark Green) were developed that envisaged a sequence of water saving interventions of increasing intensity rolling out over time. The diffusion was governed by a set of parameters based on literature of: the maximum PCC savings, the likely time for diffusion and the ceiling for adoption by households. Forecast households were multiplied by forecast PCCs converted into PHCs using baseline information from the Thames Water DWUS and the 2011 Population Census. We found only one other study using a similar method (Schultz et al. 2016).

Some attention is paid to the uncertainty in demographic and water demand forecasts but advice on using that knowledge is scarce. Wilson et al. (2018) provides guidance on applying prediction intervals to projections of local Australian populations and data trustworthiness. Historically, the concept of penalty functions in risk analysis was used as a tool for users projections (Keilman, 2008), though it was not applied to water demand forecasting. As such, further research is needed to test ideas about uncertainty and penalty functions in water resource planning. Currently, best practice is to refresh projections and the plans they inform at regular intervals.

The findings of the research were as follows: a considerable (e.g. 90% under Business as Usual) increase in water demand in the Thames Water region is projected, because population increases, driven by continuing immigration. We assume that the UK will still attract more immigrants than emigrants after it has left the European Union. This immigration will bring in diverse younger populations with a high potential to have children. Increasing ethnic diversity implies higher population growth. Because South Asian heritage households consume more water than average, there will be additional growth in water demand. Two scenarios were run that projected water saving by households which reduced growth moderately (the Light Green scenario) and considerably (the Dark Green scenario). How probable are these developments? At the time of writing, in 2018, the outcome of the Brexit negotiations between the UK Government and the European Union is unknown. In terms of water saving, we judge that the savings envisaged in the Light Green scenario are achievable. However, there will still be a very substantial growth in household demand. A large and rising gap between current water supply in the Thames Water region and future water demand indicates a need for further planned interventions, which should include reduction of leakage and more radical measures to drive down consumption, such as Cap and Trade. In conclusion, making long-term, strategic, water resources management plans for an economically important region under conditions of uncertain population and climate change is challenging. This paper offers one approach to furnishing an important input to this process.

Acknowledgements

The research reported in this paper was funded by Thames Water Utilities Limited though a Collaborative Research Agreement with the University of Leeds for the project Long-Term Population and Property Forecasts for Thames Water, 1 June 2016 to 30 September 2017. Thames Water provided confidential access to their Domestic Water User Survey anonymised dataset and gave valuable advice on the research at six meetings over the course of the project. Rizwan Nawaz received support from the Engineering and Physical Sciences Research Council under grant EP/I029346/1. The population projections were developed under Economic and Social Research Council grant ES/L013878/1 (NewETHPOP). The Principal Investigator was Philip Rees.

Supplemental Information

Supplemental tables (S1, S2) and figures (S1, S2, S3) can be accessed in the file Supplemental Information-R2.docx at http://archive.researchdata.leeds.ac.uk/466/

Data Availability

Data, models and code used in this study are available from third parties, the authors and online as described in the supplemental data file, Metadata-R2.docx which can be accessed along with files containing data and code at http://archive.researchdata.leeds.ac.uk/466/

References

Anderson, B. and Stoneman, P. (2009). Predicting the socio-technical future (and other myths). Chapter 2 in: Warren, P. and Brown, D. (ed.) ICT Futures: Trends in the Use of Information and Communication Technologies. Wiley, London.

Bagheri, N., McRae, I., Konings, P., Butler, D., Douglas, K., Del Fante, P. and Adams, R. (2014). "Undiagnosed diabetes from cross-sectional GP practice data: an approach to identify communities with high likelihood of undiagnosed diabetes." BMJ Open, 4, e005305. doi:10.1136/.

Baker, B., Grayburn, J. and Linares, A. (2016). How Should the Appropriate Horizon for Integrated Water Resource Planning be Ascertained? NERA Economic Consulting, London. (http://www.nera.com/content/dam/nera/publications/2016/NERA_TW_Horizon_Report.pdf) (April 8, 2018).

Brookshire, D., Burness, H., Chermak, J. and Krause, K. (2002). "Western urban water demand." Natural Resources Journal, 2(4), 873-898.

Cavanagh, S., Hanemann, W., Stavins, R. (2002). "Muffled price signals: household water demand under increasing-block prices." FEEM Working Paper No. 40.2002, Milan, Italy (https://gspp.berkeley.edu/assets/uploads/research/pdf/Cavanagh_Hanemann_Stavins_ASSA_Paper.pdf) (April 8, 2018).

Dalhuisen, J., Florax, R., de Groot, H. and Nijkamp, P. (2003). "Price and income elasticities of residential water demand: A meta-analysis." Land Economics, 79(2), 292–308.

Dempster A.P., Laird N.M. and Rubin D.B. (1977). "Maximum likelihood from incomplete data via the EM algorithm." Journal of the Royal Statistical Society, Series B, 39(1), 1–22.

Downing, T.E., Butterfield, R.E., Edmonds, B., Knox, J.W., Moss, S., Piper, B.S. and Weatherhead, E.K. (2003). "CCDeW: Climate Change and Demand for Water. Research Report." Stockholm Environment Institute Oxford Office, Oxford. (https://dspace.lib.cranfield.ac.uk/bitstream/handle/1826/3576/Climate_Change_and_Demand_for_Water-2003.pdf;sequence=1) (April 8, 2018).

Elizondo, G. and Lofthouse, V. (2010). "Towards a sustainable use of water at home: understanding how much, where and why?" Journal of Sustainable Development, 3(1), 3-10.

Espey, M., Espey, J. and Shaw, W. (1997). "Price elasticity of residential demand for water: A meta-analysis." Water Resources Research, 33(6), 1369-1374.

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

Fielding, K., Spinks, A., Russell, S., McCrea, S. and Gardner, J. (2013). "An experimental test of voluntary strategies to promote urban water demand management." Journal of Environmental Management, 114, 343-351.

Finney, N. and Catney, G. (ed.) (2012). Minority Internal Migration in Europe. Ashgate, Farnham.

Frederiks, E.R., Stenner, K., Hobman, E.V. and Fischle, M. (2016). "Evaluating energy behaviour change programs using randomised controlled trials: Best practice guidelines for policymakers." Energy Research & Social Science, 22, 147-164.

Gadbury, D. and Hall, M. (1989). "Metering trials for water supply." Journal of the Institution of Water & Environmental Management, 3(2), 182-187.

Garson, G. D. (2015). Missing Values Analysis and Data Imputation. Asheboro, NC: Statistical Associates Publishers.

Gato, S., Jayasuriya, N. and Roberts, P. (2007). "Forecasting residential water demand: case study." Journal of Water Resources Planning and Management 133(4), 309-319, doi.org/10.1061/(ASCE)0733-9496(2007)133:4(309)

Gegax, D., McGuckin, T. and Michelsen, A. (1998). "Effectiveness of conservation policies on New Mexico residential water demand." New Mexico Journal of Science 38, 104-126.

Grafton, R., Ward, M., To, H. and Kompas, T. (2011). "Determinants of residential water consumption: Evidence and analysis from a 10-country household survey." Water Resources Research, 47, W08537, doi:10.1029/2010WR009685.

Gregory, G. D. and Leo, M. D. (2003). "Repeated behaviour and environmental psychology: The role of personal involvement and habit formation in explaining water consumption". Journal of Applied Social Psychology, 33, 1261–1296.

Haque, M., de Souza, A. and Rahman, A. (2017). "Water demand modelling using independent component regression technique." Water Resources Management, 31, 299-312.

Herrington, P. (1996). Climate Change and the Demand for Water. HMSO, London.

House-Peters, L. and Chang, H. (2011). “Urban water demand modelling: Review of concepts, methods, and organizing principles.” Water Resources Research, 47(15), doi:10.1029/2010WR009624.
HR Wallingford. (2010). Analysis of the impacts of climate change: Impacts of climate change on the demand for water. Report reference EX6285.
HR Wallingford. (2012). Thames Water climate change impacts and water resource planning – climate change impacts on demand for the 2030s. Report reference EX6828, Release 1.0.
Hunt, D., Lombardi, D., Farmani, R., Jefferson, I., Memon, F., Butler, D. and Rogers, C. (2012). “Urban futures and the code for sustainable homes." Proceedings of the Institution of Civil Engineers, Engineering Sustainability, 165(ES1): 37-58.
Hussien, W.A., Memon, F.A. and Savic, D.A. (2016). “Assessing and modelling the influence of household characteristics on per capita water consumption.” Water Resources Management, 30, 2931-2955.
Inman, D. and Jeffrey, P. (2006). “A review of residential water conservation tool performance and influences on implementation effectiveness.” Urban Water Journal, 3(3), 127-143.
Ipsos MORI. (2018). About us. https://www.ipsos.com/ipsos-mori/en-uk/about-us. (December 3, 2018)
Jeffrey, P. andGearey, M. (2006), “Consumer reactions to water conservation policy instruments”. In Water Demand Management, (ed.) Butler, D. and Memon, F.A. pp. 303–329, IWA Publ., London.
Keilman, N. (2008). Using deterministic and probabilistic population forecasts. Chapter, pp.22-28 in Østreng, W. (ed.). Complexity: Interdisciplinary Communications 2006/2007. Centre for Advanced Study, Oslo. https://folk.uio.no/keilman/Complexity_Keilman.pdf (August 25, 2018).
Kenney, D., Goemans, C., Klein, R., Lowrey, J. and Reidy, K. (2008). “Residential water demand management: lessons from Aurora, Colorado 1.” Journal of the American Water Resources Association, 44, 192-207.
Lindgren, M. and Bandhold, H. (2009). Scenario Planning - Revised and Updated: The Link Between Future and Strategy. Second Edition. Palgrave Macmillan, Basingstoke.
Long, J. (1997). Regression Models for Categorical and Limited Dependent Variables. Sage Publications, Thousand Oaks CA.
Makki, A. A., Stewart, R. A., Panuwatwanich, K. and Beal, C. (2013). “Revealing the determinants of shower water end use consumption: enabling better targeted urban water conservation strategies.” Journal of Cleaner Production, 60, 129-146.
McDonald, A. (2002). “The Yorkshire Water Domestic Consumption Monitor, Assessment of Condition and Analysis of Demand in York.” Report, University of Leeds, Leeds.
Medd, W., Watson, M., Hopkins, P. and Olson, E. (2007). “Cultural diversity and sustainable water management in Greater London: the research agenda.” Report prepared for the Greater London Authority.” London.
Memon, F. and Butler, D. (2006). “Water consumption trends and techniques for demand forecasts.” Chapter 1, 1-26 in Butler, D. and Memon, F. (ed.) Water Demand Management. IWA Publishing, London.
Mitchell, G., Hargreaves, A., Namdeo, A. and Echenique, M. (2011). “Land use, transport, and carbon futures: the impact of spatial form strategies in three UK urban regions.” Environment and Planning A, 43(9), 2143-2163.
Mitchell, G. and McDonald, A. (2015). “Developing resilience to England's future droughts: Time for cap and trade?” Journal of Environmental Management, 149, 97-107.
Murphy, J.M., Sexton, D.M.H., Jenkins, G.J., Boorman, P.M., Booth, B.B.B., Brown, C.C., Clark, R.T., Collins, M., Harris, G.R., Kendon, E.J., Betts, R.A., Brown, S.J., Howard, T. P., Humphrey, K. A., McCarthy, M. P., McDonald, R. E., Stephens, A., Wallace, C., Warren, R., Wilby, R. and Wood, R. A. (2009). UK climate projections science report: climate change projections. Met Office Hadley Centre, Exeter. http://ukclimateprojections.metoffice.gov.uk/media.jsp?mediaid=87894&filetype=pdf. (August 25, 2018).
NatCen. (2018). NatCen: Social Research that works for society. http://natcen.ac.uk/ (August 25, 2018).
Nawaz, N., Lovett, J. and Tompkins, J. (2014). “Multi-faith and water efficiency communication–a methodological approach.” Policy Brief No. ULWW01, University of Leeds and Waterwise.
Ornaghi, C. and Tonin, M. (2015). “The effect of water metering on water consumption.” University of Southampton, Policy Note, ESRC grant No. ES/K01210X/1. http://www.oireachtas.ie/parliament/media/committees/futurefundingofdomesticwaterservices/metering/DE-0033a-Ornaghi--Tonin-paper-TheEffectofMeteringonWateeConservation.pdf (April 14, 2018).
Parker, J. and Wilby, R. (2013). “Quantifying household water demand: A review of theory and practice in the UK.” Water Resources Management, 27(4), 981-1011.
Polebitski, A.S., Palmer, R. and Waddell, P. (2011). “Evaluating water demands incorporating climate change and transitions in the urban environment.” Journal of Water Resources Planning and Management 137(3), 249-257.
Ramirez, R. and Van der Heijden, K. (2007). “Scenarios to develop strategic options: a new interactive role for scenarios in strategy. In Sharpe, B. and Van der Heijden, K. (ed.) Scenarios for Success: Turning Insights into Action. John Wiley, Hoboken NJ.

Raven, P.G. and Elahi, S. (2015). "The new narrative: Applying narratology to the shaping of futures outputs." Futures, 74: 49–61.
Rees, P. and Clark, S. (2018). "Household projections for long-term water demand forecasts: application to London and the Thames Valley." Population, Space and Place, submitted, in revision.
Rees, P., Clark, S., Wohland, P. and Kalamandeen, M. (2018). "Evaluation of sub-national population projections: A case study of the Thames Water region." Applied Spatial Analysis and Policy. https://doi.org/10.1007/S12061-018-9270-X.
Rees, P., Clark, S., Wohland, P., Lomax, N. and Norman, P. (2017). "Using the 2001 and 2011 Censuses to reconcile ethnic group estimates and components for the intervening decade for English local authority districts." Chapter 21, 277-293 in Stillwell, J. (ed.) The Routledge Handbook of Census Resources, Methods and Applications: Unlocking the UK 2011 Census. Routledge, Abingdon.
Rees, P., Wohland, P., Norman P., Lomax, N. and Clark, S. (2016). Population projections by ethnicity, challenges and solutions. Chapter 18, 383-408 in Swanson, D. (ed.) The Frontiers of Applied Demography. Springer, Switzerland.
Renwick, M. and Green, R. (2000). "Do residential water demand side management policies measure up? An analysis of eight California water agencies." Journal of Environmental Economics and Management, 40, 37-55.
Rinaudo, J-D. (2015). "Long-Term water demand forecasting." Chapter 11, 239-268 in Grafton, Q., Daniell, K., Nauges, C., Rinaudo, J-D. and Chan, N. (ed,) Understanding and Managing Urban Water in Transition. Springer, Dordrecht.
Rogers, E. (1976). "New product adoption and diffusion." Journal of Consumer Research, 2, 290-301.
Rubin, D.B. (1976). "Inference and missing data." Biometrika, 63, 581–590.
Schleich, J. and Hillenbrand, T. (2008). "Determinants of residential water demand in Germany." Ecological. Economics. 68(6), 1756–1769.
Slavíková, L., Malý, V., Rost, M., Petružela, L. and Vojáček, O. (2013). "Impacts of climate variables on residential water consumption in the Czech Republic." Water Resources Management, 27: 365-379.
Smith, A, and Ali, M. (2006). "Understanding the impact of cultural and religious water use." Water and Environment Journal, 20(4), 203–209.
Smith, A. and Rogers, D. (1990) "Isle of Wight water metering trial." Journal, Institution of Water & Environmental Management, 4(5), 403-409.
Sønderlund, A., Smith, J., Hutton, C., Kapelan, Z. and Savic, D. (2016). "Effectiveness of smart meter-based consumption feedback in curbing household water use: Knowns and unknowns" Journal of Water Resources Planning and Management, 142(12), doi: 10.1061/(ASCE)WR.1943-5452.0000703.
Staddon, C. (2010). "Do water meters reduce domestic consumption? A summary of available literature." Bristol: Department of Geography and Environmental Management, University of the West of England, Working paper. http://www.heednet.info/metering-defraHEEDnet.pdf (April 17, 2018).
Syme, G., Nancarrow, B. and Seligman, C. (2000) "The evaluation of information campaigns to promote voluntary household water conservation." Evaluation Review, 24(6), 539-578.
Thames Water (2014) Final Water Resources Management Plan 2015 – 2040. https://corporate.thameswater.co.uk/-/media/Site-Content/Thames-Water/Corporate/AboutUs/Our-strategies-and-plans/Water-resources/Our-current-plan-WRMP14/WRMP14_Section_0.pdf. (Accessed 17 April 2018).
Thames Water. (2015a). "Faith and Water Toolkit." Report by London Sustainability Exchange and University College London. https://issuu.com/londonsustainabilityexchange/docs/toolkit (April 17, 2018).
Thames Water. (2015b). "Final Water Resources Management Plan 2015-2040." Thames Water Utilities Limited, Reading. https://sustainability.thameswater.co.uk/-/media/site-content/corporate-responsibility/pdfs/wrmp14.pdf (April 17, 2018).
Thames Water. (2017). "Our supply area." Thames Water Utilities Limited, Reading. https://corporate.thameswater.co.uk/About-us/Our-business/Our-supply-area (April 17, 2018).
Thames Water. (2018). Our draft Water Resources Management Plan 2019. Appendix E. https://www.thameswater.co.uk/wrmp. (August 25, 2018).
Thames Water (2018) Shape Your Water Future. Draft Water Resources Management Plan 2019: Overview. https://corporate.thameswater.co.uk/-/media/Site-Content/Your-water-future-2018/WRMP-Glossy.pdf (December 7, 2018).
UKWIR (2013) Climate change and water demand - main report. UK Water Industry Research, https://www.ukwir.org/reports/13-CL-04-12/66621/Impact-of-Climate-Change-on-Water-Demand--Main-Report (December 7, 2018).
UKWIR. (2016a). WRMP19 Methods – Population, Household Property and Occupancy Forecasting: Guidance Manual. Report Ref. No, 15/WR/02/8. UK Water Industry Research: London. https://www.ukwir.org/eng/reports/15-WR-02-8/150150/WRMP19--Methods--PopulationHousehold-Property-and-Occupancy-Forecasting. (August 25, 2018).

UKWIR (2016b) WRMP 2019 Methods – Risk Based Planning. UK Water Industry Research, 243pp. https://www.ukwir.org/146387?object=151120

UKWIR (2018) Climate Change Modelling and the WRMP. UK Water Industry Research. https://www.ukwir.org/climate-change-modelling-and-the-wrmp-0

Wa'el, A., Memon, F. and Savic, D. (2016). “Assessing and modelling the influence of household characteristics on per capita water consumption.” Water Resources Management, 30(9), 2931-2955.

Warde, A. and Martens, L. (2000). Eating Out: Social Differentiation, Consumption and Pleasure. Cambridge University Press, Cambridge.

Waterwise (2011). “Evidence Base for Large-scale Water Efficiency, Phase II Final Report.” (http://www.waterwise.org.uk/resource/evidence-for-large-scale-water-efficiency-phase-ii-final-report-2011/) (April 17, 2018).

Waterwise (2012). Save Water Swindon, Phase 1 Evaluation Report. (http://www.waterwise.org.uk/wp-content/uploads/2018/02/Save-Water-Swindon-Baseline-Phase-1-Evaluation.pdf) (April 17, 2018).

Whitford, P. (1972). "Residential water demand forecasting." Water Resources Research, 8(4), 829-839,

Wickstrom, G. and Bendix, T. (2000). “The Hawthorne Effect: What did the original studies actually show?” Scandinavian Journal of Work, Environment and Health, 26(4), 363-367.

Williamson, P., Mitchell, G. and McDonald, A.T. (2002). “Domestic Water Demand Forecasting: A Static Microsimulation Approach”. Water and Environment Journal 168(4), 243–248.

Wilson, T., Brokensha, H., Rowe, F. and Simpson, L. (2018). “Insights from the evaluation of past local population forecasts.” Population Research and Policy Review, 37, 137-155. (https://doi.org/10.1007/s1113-017-9450-4).

Wohland, P., Rees, P., Clark, S., Lomax, N. and Norman, P. (2017). “ETHPOP website and database.” https://www.ethpop.org/ (April 17, 2018).

Table 1. Water savings reported in the Waterwise Evidence Base

Trial	Type of device installed[1]	Uptake rate (%)	No. properties included in trial	PCC reduction (%)
Preston Water Efficiency Initiative[2]	T, D	60	134	12.3
Wessex Water	D	45	103	6.6
United Utilities	D, C, S, R	9	208	9.2
Anglian Water Ipswich Area	D, C, S, R	10	552	14.2
Thames Water	D, C, S, R	9	727	7.9
Yorkshire Water	D, C, S, R	20	337	14.9
Severn Trent	D, C, S, R	9	680	8.2
Thames Water Self-Audit	C, S, R	6	525	1.2
Save Water Swindon[3]	C, S, R	46	900	9.9

Notes:

1. The types of device are as follows: D=Dual flush conversion device, C=cistern displacement device, S=showers, R=Tap inserts, regulators, restrictors and spray taps, L=repair of leaky taps.
2. Trial included repair of leaky taps.
3. Trial undertaken after the Waterwise Evidence Base completed.
4. The South West water trial that formed part of the Waterwise Evidence Base is excluded here since it was carried out during time of drought, which may have biased the results.

Source: Waterwise (2011, 2012)

Table 2. Percentage distribution of households by occupant number and ethnicity, 2011 Census and 2006-2015 DWUS, all Water Resource Zones, Thames Water.

Ethnicity/Occupancy	DWUS[1] 2006-2015	Census 2011
Other Ethnic[2]		
1 person	17.7	25.5
2 persons	35.5	27.2
3 persons	16.5	16.7
4 persons	15.4	15.1
5 persons	5.4	5.7
6+ persons	2.5	2.8
South Asian[3]		
1 person	0.8	1.0
2 persons	1.5	1.2
3 persons	1.5	1.3
4 persons	2.1	1.4
5 persons	0.7	1.0
6+ persons	0.4	1.2
Total	100.0	100.0
Index of Dissimilarity[4]	9.9	

Notes:

1. DWUS = Domestic Water User Survey
2. Other Ethnic = White British & Irish, White Other, Mixed, Chinese, Other Asian, Black African, Black Caribbean, Black Other, Other Ethnic.
3. South Asian = Indian, Pakistani & Bangladeshi
4. The Index of Dissimilarity is half of the sum of the absolute differences between percentages. The minimum index value is 0 and the maximum index value is 100.

Sources:

1. Census 2011 - household numbers computed by the authors from the ONS Census 2011 Individual Microdata and Local Authority Tables.
2. DWUS 2006-2015 - Computed by the authors from Thames Water's Domestic Water User Survey.

Table 3. PHC (litres per day) by ethnicity for property types and occupant number, all Thames Water Resource Zones, DWUS 2006-2015

Ethnicity	Occupants	Detached	Semi-detached	Terraced	Flat	Average PHC	Average PCC
Other Ethnic	1	192	203	192	180	189	189
	2	364	309	296	294	312	156
	3	449	397	415	364	407	136
	4	483	473	465	421	469	117
	5	609	591	540	473	568	114
	6+	707	626	811	486	710	101
South Asian	1	567	222	283	218	255	255
	2	451	365	491	317	419	210
	3	561	566	630	350	541	180
	4	618	698	797	472	721	180
	5	1208	968	911	185	939	188
	6+	na	869	861	663	861	123

Notes:
1. PCC = Per Capita Consumption, computed by dividing the PHC by the occupant number. An average of 7 persons is assumed in 6+ person households.
2. na = not available.

Source: Computed by the authors from Thames Water's Domestic Water User Survey (DWUS).

Table 4. Specific water demand interventions and their assumed parameters

Management options	Example interventions	PCC reduction (%)	PCC reduction (litres/day)	Peak diffusion (%)	Start Year	End Year
BUSINESS AS USUAL						
	Trend of behavioural change				2011	2101
	Metering	16.5		85%	2011	2018
BaU Total						
LIGHT GREEN						
Water Efficient Fixtures	Product replacement	10	14.9	50	2019	2034
Awareness raising	Smarter home visits Media campaigns School education Area-based promotional campaigns	10	14.9	50	2035	2049
LG Total		20	29.8			
DARK GREEN						
Water Efficient Fixtures	Product replacement	15	22.3	75	2019	2024
Awareness raising	Smarter home visits Media campaigns School education Area-based promotional campaigns	15	22.3	60	2035	2049
Pricing/ Incentives	Cap & Trade	5	7.4	60	2065	2079
Total		35	52.0			

Notes:
The reductions in PCC in the scenarios are applied cumulatively. So the Light Green scenario includes the Business as Usual (BaU) reductions, while the Dark Green (DG) scenario includes the Business as Usual and Light Green (LG) reductions.

Table 5. Regression model parameters for models of PHC using occupancy

Predictor	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**	**Model 9**
Adjusted R^2	**0.323**	**0.330**	**0.368**	**0.370**	**0.415**	**0.369**	**0.416**	**0.379**	**0.379**
Constant	**731**	**694**	**846**	**840**	**813**	**848**	**808**	**728**	**733**
Occupancy (Ref = Person 6+)									
Person 1	**-540**	**-523**	**-504**	**-504**	**-524**	**-503**	**-523**	**-498**	**-498**
Person 2	**-415**	**-411**	**-392**	**-392**	**-410**	**-391**	**-410**	**-387**	**-387**
Person 3	**-313**	**-309**	**-298**	**-297**	**-302**	**-296**	**-302**	**-291**	**-292**
Person 4	**-231**	**-231**	**-228**	**-227**	**-242**	**-227**	**-242**	**-225**	**-225**
Person 5	**-120**	**-118**	**-114**	**-115**	**-155**	**-114**	**-155**	**-113**	**-113**
Property Type (Ref = Flat)									
Detached		**63**	**70**	**77**	**48**	**76**	**61**		
Semi-detached		**27**	**33**	**38**	**22**	**37**	**35**		
Terraced		**39**	**38**	**39**	**46**	**39**	**61**		3
Ethnicity (Ref = South Asian)									
Other Ethnic			**-180**	**-178**	**-199**	**-179**	**-199**	-34	-33
WRZ (Ref = HEN)									
SWA				10	10				
LON				7	9				
KEN				-22	-14				
SWOX				-7	3				
GUI				-13	-8				
WRZ (Ref = LON)									
Not LON						**-15**	-10	**-15**	**-14**
Type-Ethnicity									
Detached-Other Ethnic								**48**	**48**
Detached-South Asian								**181**	**182**
Semi- Other Ethnic								8	8
Semi- South Asian								**160**	**161**
Terraced- Other Ethnic								3	
Terraced- South Asian								**218**	**216**
Flat- Other Ethnic								**-39**	**-39**
Flat- South Asian								**-72**	**-71**
Trend (Log Time)							-0.9		-4
Rateable Value					**0.3**		**0.3**		

Notes:
1. Dependent variable = PHC = Per Household Consumption in litres per day.
2. Cases = Household-Water Consumption Spells. For Models 1, 2, 3, 4, 6, 8, 9, the number of cases = 19,238. For Models 5 and 7 the number of cases = 10,308.
3. Significance: **bold** = significant at the 1% level, underline = significant at the 5% level.
4. SWA = Slough Wycombe & Aylesbury, LON = London, KEN = Kennet Valley, SWOX = Swindon & Oxfordshire, GUI = Guildford, HEN = Henley.
5. Other Ethnic & South Asian: for composition see Table 2.

Table 6. Regression model parameter estimates for PHC: models using adult and child numbers

Predictor	**Model 10**	**Model 11**	**Model 12**	**Model 13**
Adjusted R^2	**0.336**	**0.424**	**0.447**	**0.407**
Constant	**282**	**388**	**253**	**239**
Adult (Ref = Adult 1)				
Adult 2	**120**	**107**	**108**	**95**
Adult 3	**246**	**230**	**230**	**203**
Adult 4	**356**	**304**	**300**	**288**
Adult 5	**485**	**401**	**399**	**401**
Adult 6+	**605**	**617**	**620**	**534**
Child (Ref = Child 1)				
Child 0	**-87**	**-94**	**-97**	**-80**
Child 2	**70**	**62**	**56**	**56**
Child 3	**173**	**151**	**137**	**152**
Child 4	**191**	**164**	**164**	**164**
Child 5	88	27	21	95
Child 6+	**325**	196	187	**248**
Property Type (Ref = Flat)				
Detached		**58**		**54**
Semi-detached		**34**		**39**
Terraced		**57**		**58**
Basement Flat		**25**		**50**
Ethnicity (Ref = South Asian)				
Other Ethnic		**-197**	-22	**-162**
WRZ (Ref = LON)				
Not LON		-9	-9	-0.8
Type-Ethnicity				
Detached- Other Ethnic			20	
Detached-South Asian			**213**	
Semi-detached- Other Ethnic			2	
Semi-detached-South Asian			**86**	
Terraced- Other Ethnic			9	
Terraced-South Asian			**341**	
Flat- Other Ethnic			**-23**	
Flat-South Asian			-71	
Trend (Log Time)		-2	-3	-2
Rateable Value		**0.3**	**-0.3**	**0.7**

Notes:
1. Dependent variable = Per Household Consumption (PHC) in litres per day.
2. Cases = Household-Water Consumption Spells. For Models 10 and 13, the number of cases = 19,228. For Models 11 and 12 the number of cases = 10,308.
3. Significance: **bold** = significant at the 1% level, underline = significant at the 5% level.
4. SWA = Slough Wycombe & Aylesbury, LON = London, KEN = Kennet Valley, SWOX = Swindon & Oxfordshire, GUI = Guildford, HEN = Henley.
5. Models 12 and 13 are used in combination to provide baseline PHC values by occupancy number, property type and ethnicity by WRZs, for use in the forecasting model (see Fig.1).
6. Other Ethnic & South Asian: for composition see Table 2.

Table 7. Comparison of measured and modelled PHC

Property Type	Other Ethnicities		South Asian	
Measured/Modelled	**Outside London**	**London**	**Outside London**	**London**
Detached				
Measured	475	466	735	591
Modelled	474	467	636	667
Semi-detached				
Measured	461	407	589	671
Modelled	451	419	644	609
Terraced				
Measured	463	424	715	450
Modelled	463	455	649	621
Flats				
Measured	369	308	356	474
Modelled	426	368	622	512

Figure 1

Click here to access/download;Figure;Fig1-R2.tif

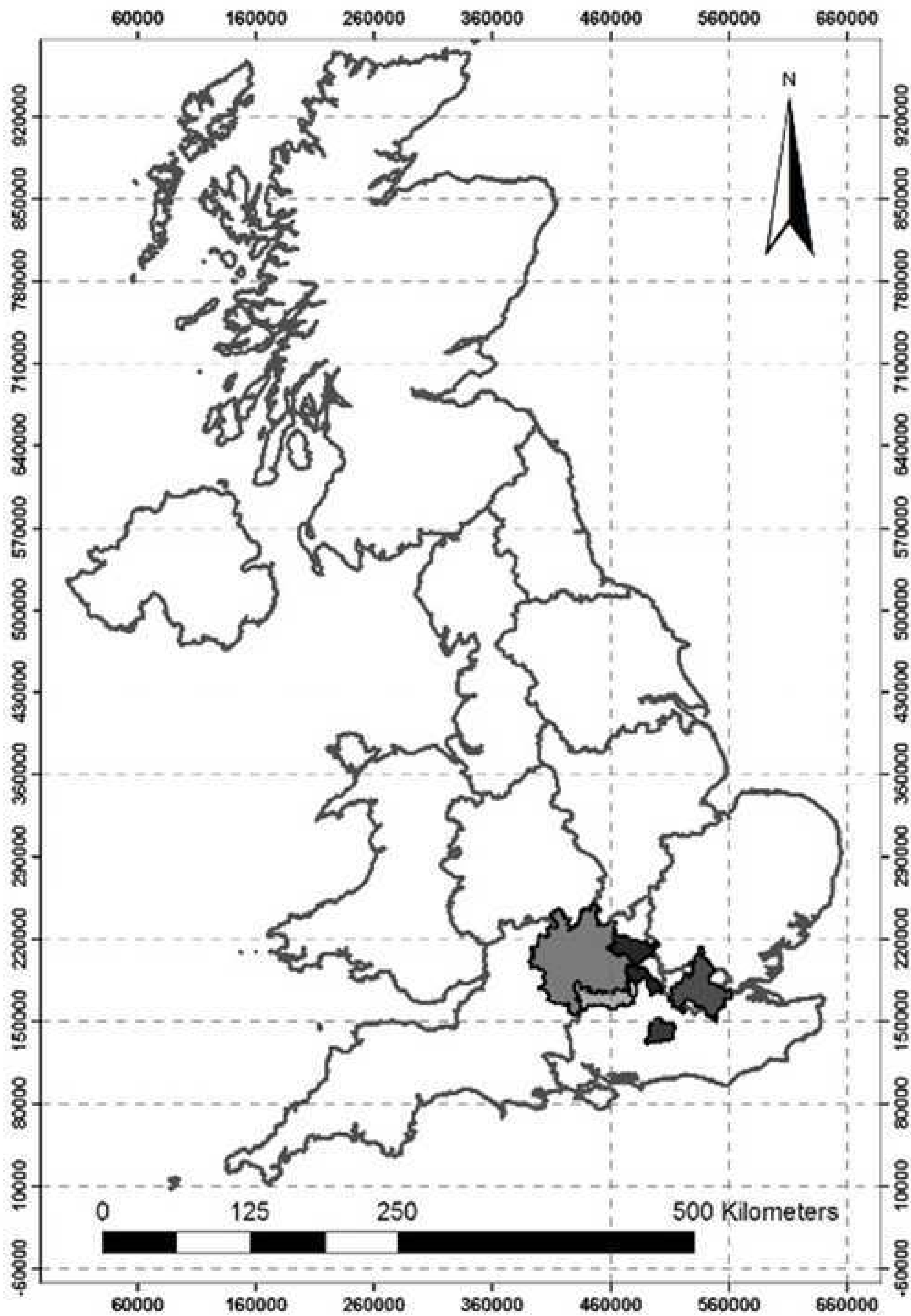


Figure 2

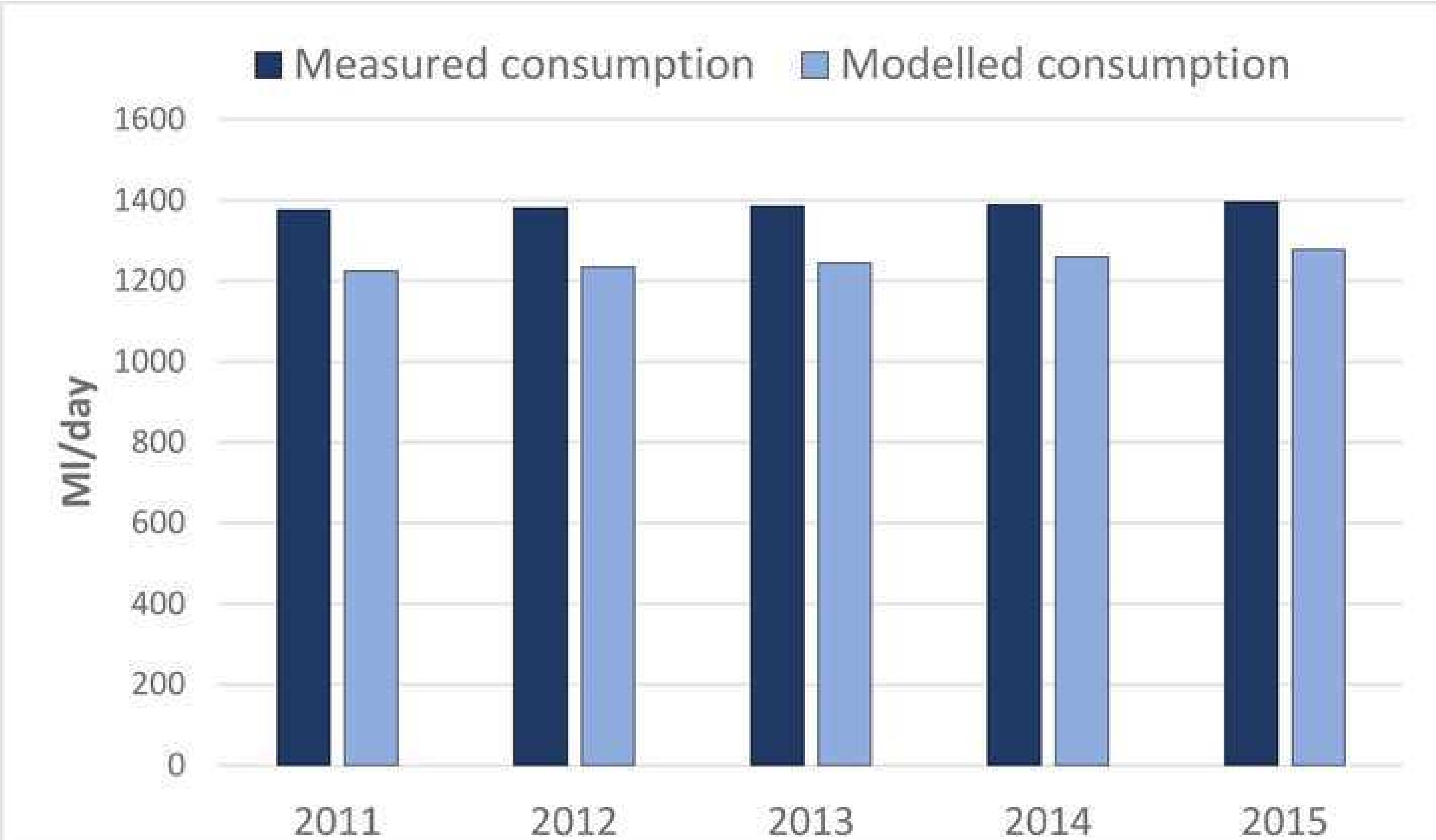

Measured consumption
Modelled consumption
1600
1400
1200
1000
800
600
400
200
0
Ml/day
2011
2012
2013
2014
2015

Figure 3

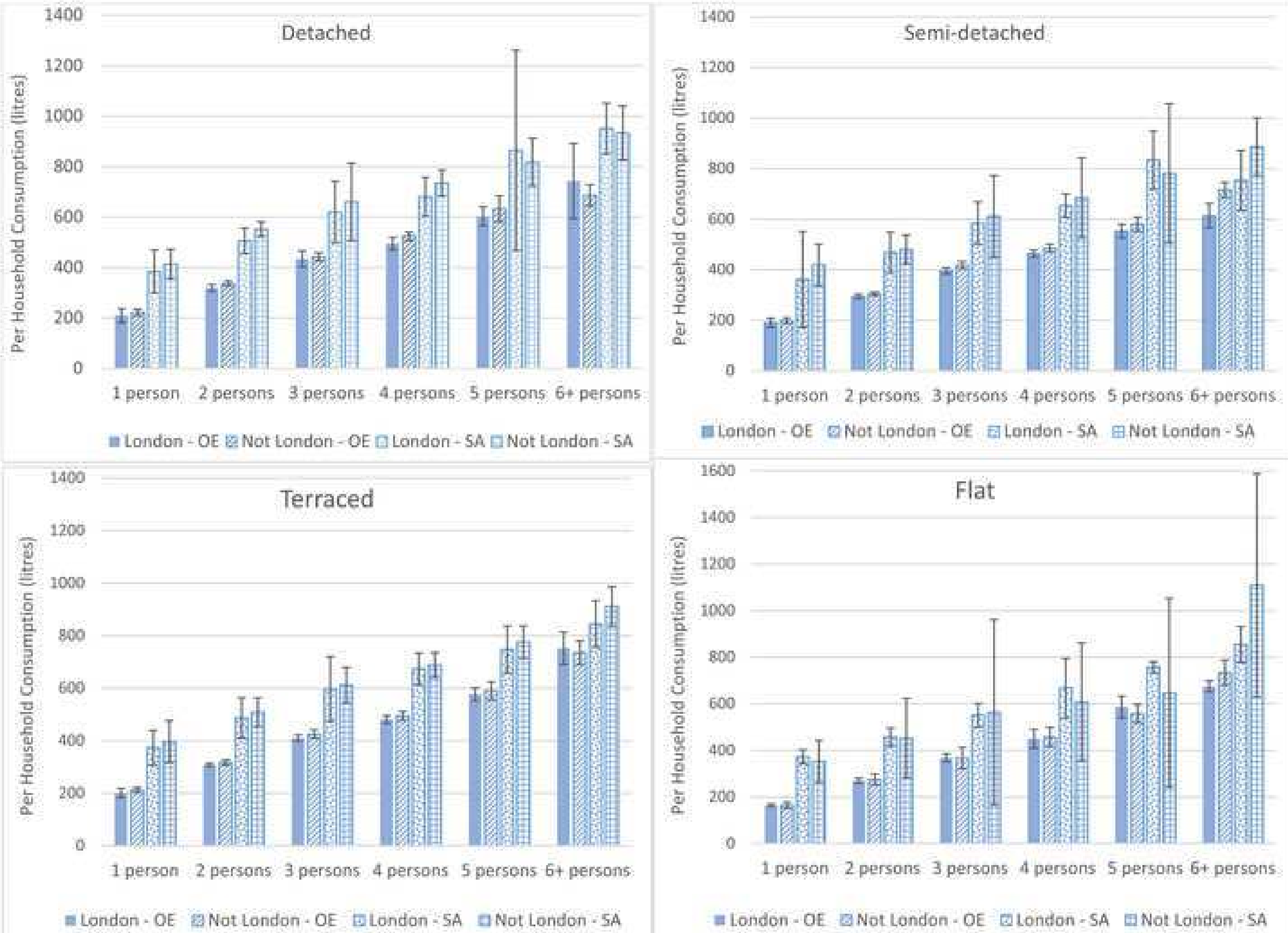

Detached
Per Household Consumption (litres)
1400
1200
1000
800
600
400
200
0
1 person
2 persons
3 persons
4 persons
5 persons
6+ persons
London - OE
Not London - OE
London - SA
Not London - SA
Semi-detached
Terraced
Flat
1600

Figure 4

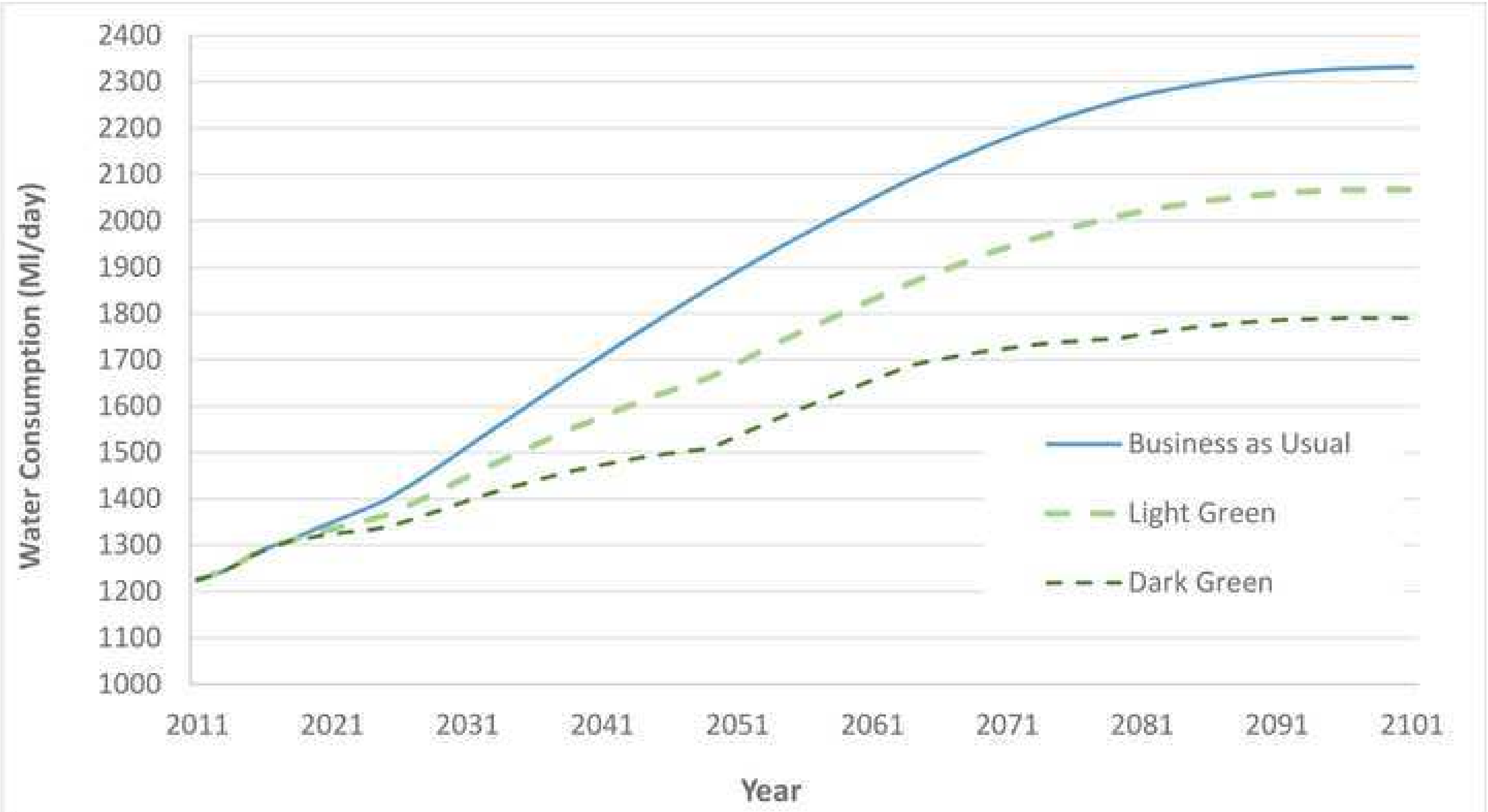
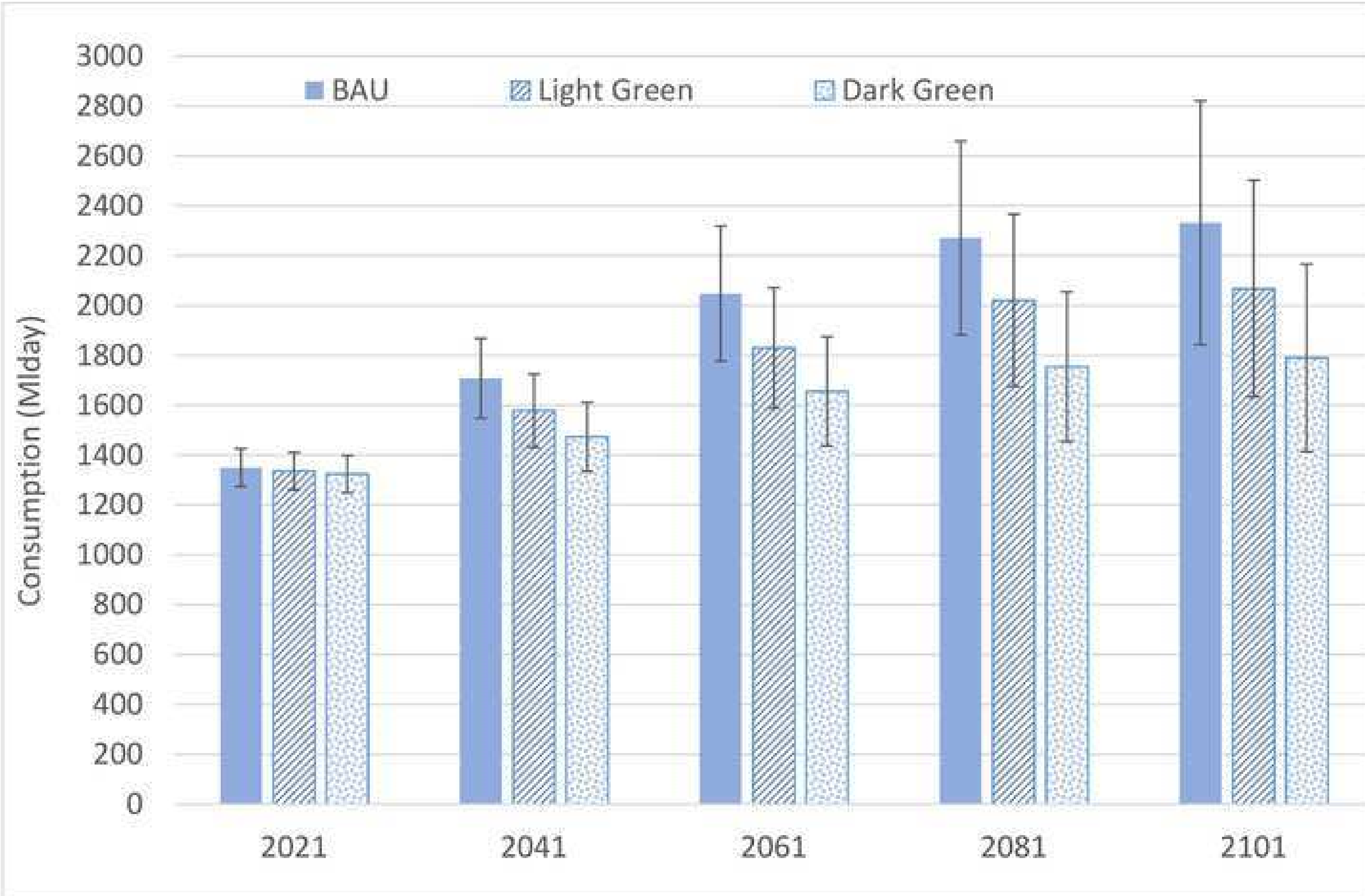

2400
2300
2200
2100
2000
1900
1800
1700
1600
1500
1400
1300
1200
1100
1000
Water Consumption (Ml/day)
2011
2021
2031
2041
2051
2061
2071
2081
2091
2101
Year
Business as Usual
Light Green
Dark Green

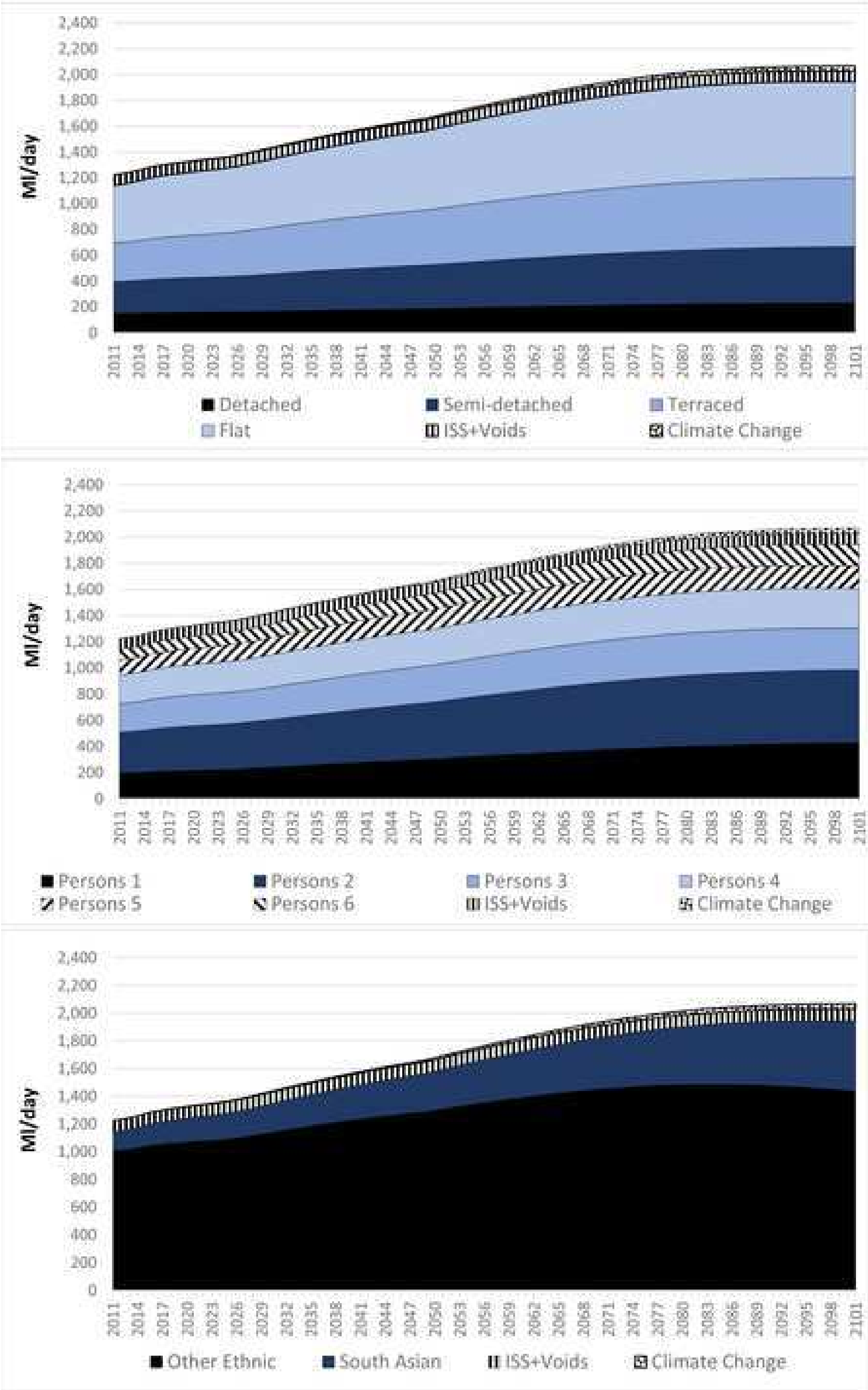
Figure 5



BAU
Light Green
Dark Green
Consumption (Ml/day)
3000
2800
2600
2400
2200
2000
1800
1600
1400
1200
1000
800
600
400
200
0
2021
2041
2061
2081
2101

Figure 6

Click here to access/download;Figure;Fig6-R2.tif



Paper WRENG-3754, Projections of Domestic Water Demand over the Long-Term: A Case Study of London and the Thames Valley

Figure Captions

===

Fig. 1 Map of the United Kingdom showing the territory supplied by Thames Water covering parts of London and the Thames Valley.

Fig. 2 Modelled annual consumption for all WRZs compared to values reported in Ofwat annual returns

Notes: Ofwat = Office of Water Regulation (for England and Wales)

Fig. 3 Modelled PHC (litres/household/day) by occupancy (1-6+), house type, ethnicity (OE – other ethnic; SA South Asian), for the London WRZ and Not London (5 WRZs outside London). The error bars represent 95% confidence intervals.

Fig. 4 Total domestic water consumption for all Water Resource Zones, by scenario

Fig. 5 Errors bars for all Water Resource Zones, in the Thames Water region, by scenario

Fig. 6 Total water demand classified by property type, occupancy and ethnicity, Thames Water region, Light Green scenario, 2011-2101. Notes: ISS = Irregular, Short-term Migrants and Second Addresses.
(6a) Total water demand by property type; (6b) Total water demand by occupant numbers
(6c) Total water demand by ethnicity