Research Paper

Estimating the impact of climate change on residential water use using panel data analysis: a case study of Lilongwe, Malawi

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ABSTRACT

In this study, panel linear models were used to develop an empirical relationship between metered household water use and the independent variables plot size and theoretical irrigation requirement. The estimated statistical model provides a means of estimating the climate-sensitive component of residential water use. Ensemble averages of temperature and rainfall projections were used to quantify potential changes in water use due to climate change by 2050. Annual water use per household was estimated to increase by approximately 1.5% under the low emissions scenario or 2.3% under the high emissions scenario. The model results provide information that can enhance water conservation initiatives relating particularly to outdoor water use. The model approach presented utilizes data that are readily available to water supply utilities and can therefore be easily replicated elsewhere.

Key words | climate change, panel linear models, residential water use

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INTRODUCTION

Climate change is likely to alter the dynamics of water supply systems. Water supply utilities face challenges to maintain adequate supply to growing urban populations and climate change is likely to exacerbate the situation. In the sub-Saharan region, there is a general risk of reduced flows from existing surface water sources as rising temperature and changing rainfall patterns alter catchment yield (Kusangaya et al. 2014). A study to examine hydrological impacts of climate change in Malawi by Adhikari & Nejad-hashemi (2016) has found a high likelihood of increased surface yield in the northern parts, whereas the southern parts are prone to droughts. McSweeney et al. (2014) have instead predicted a decrease in summer rainfall and a rise in wet season rainfall but no significant changes in annual rainfall. There is a consensus, however, that temperature and evapotranspiration will increase with climate change

in the southern Africa region (Kusangaya et al. 2014). Temperature rise is expected to be higher in the dry season (Faramarzi et al. 2013). Historic records from Malawi show that temperature has already risen by 0.9 °C between 1960 and 2006 (McSweeney et al. 2014). Climate change may therefore further strain water supply systems by increasing climate-related water use. The significance of the impacts of climate on urban water use is reflected in the growing body of research on the subject. Water demand management, especially in relation to climate-driven residential water use, will potentially play an important role in abating future urban water supply shortages (Breyer et al. 2012). Knowledge of the relationships between climatic conditions and water use is necessary for effective planning and management of future water use. At present, reduced water use could also curb operating costs and help

postpone expensive infrastructure projects to develop untapped water sources.

A recent study of residential water use at selected neighborhoods in the city of Lilongwe revealed considerable seasonal variation of water use (Makwiza & Jacobs 2016). The study focused on formal residential settlements with private connections, although a large proportion of residents in the city still live in informal settlements served by communal water points and an estimated 25% still lack access to piped water (UN-HABITAT 2011). Most of the residential customers included in the study lived in single family semi-detached homes built on relatively large plots. All the homes included were metered separately and billed on a monthly basis. Water use was found to be closely related to residential plot sizes. Similar positive relationships between plot size and water use have been reported in South Africa and Namibia based on empirical analyses (Jacobs *et al.* 2004) and based on end-use modeling (Jacobs & Haarhoff 2004). The climate sensitive component of residential water use in Malawi was reported to be 24% of the annual residential usage. These observations indicated considerable outdoor water use and raised questions about potential impacts climate-induced changes might have on residential water use in the city of Lilongwe.

This paper presents a further analysis of the consumption data used by Makwiza & Jacobs (2016) with the aim of estimating potential changes in water use that may result from the occurrence of specific predicted climate change scenarios. Panel data analysis techniques were used to fit a regression model of the monthly billed consumption at each property in relation to the plot size and the theoretical irrigation requirement. Different types of methods are available in literature for forecasting residential water use. Regression analysis is among the commonly used statistical methods to model water use. Most authors employ cross-sectional regression to relate water use recorded at a given point in time to a set of independent variables. Other authors utilize time series analysis to model trends and seasonality in water use datasets that extend over multiple monthly or annual time periods. When cross-sectional and time series observations are combined in a single panel linear regression model, there is reduced bias from unobserved individual effects resulting in improved parameter estimates (Wooldridge 2015). Panel linear regression techniques are not yet very popular in water use modelling but their use is likely to increase with better management of customer records in electronic databases. With panel data analysis, it was possible to estimate regression coefficients taking into account the variation of water use both among customers and over time. Martínez-Espiñeira (2002), Worthington *et al.* (2009) and Polebitski & Palmer (2009) have effectively applied panel data analysis techniques to residential water use. The panel linear analysis was used to find the average change in water use at a property that would result from climate change due to predicted future temperature and rainfall conditions. Unlike traditional regression or time series analysis, panel linear models reduce bias in model estimates by controlling for unobserved heterogeneity in the subjects. The fitted model was used to estimate water use for the year 2050 from 10 Global Climate Model (GCM) projections for the city of Lilongwe.

METHODOLOGY

Datasets and data preprocessing

Water use data originally provided by the Lilongwe Water Board for the years 2009–2014 contained monthly records for 11,378 customers. The water use data had been previously screened to remove customers with missing plot size information and to remove irrelevant and irregular monthly consumption records. A detailed description of the steps followed is given in Makwiza & Jacobs (2016). In the present study, the entire record set for 2012 was discarded because of a significant reduction in water use that occurred in that year due to maintenance works at the Lilongwe Water Board. An additional filter was also applied to the dataset in the present study to remove customers with more than three missing monthly water use records per year in order to create a more balanced panel dataset. This further step improved the performance of the panel linear models used in the subsequent analyses. In addition, each customer account had to have records in all the years spanning the data. The final water use dataset contained 2,146 customers and a total of 115,497 monthly records.

Daily weather data observed at Chitedze Research Station from 2009 to 2014 were applied in the computation of climatic variables. Climate change projections for Chitedze Research Station were obtained from the Climate Information Platform hosted by the University of Cape Town (Climate System Analysis Group n.d.). Ten GCM outputs were available at 50 km grid resolution for two greenhouse gas emission scenarios, namely RCP4.5 and RCP8.5 (also referred to as B1 and A2, respectively). The RCP4.5 scenario assumes low emissions of greenhouse gases while RCP8.5 assumes high emissions of greenhouse gases. The list of GCMs included on the Climate Information Platform is given in Table 1. The climate projections downloaded for Chitedze Research Station comprised monthly minimum temperatures, monthly maximum temperatures and monthly total rainfall spanning the years 1960–2100. Only the periods between 2009 and 2014 and between 2045 and 2065 were used in this study.

Future daily climate projections

Projections for a 21-year-long period centered on the year 1950 were extracted from the downloaded climate change data. The mean values of the monthly minimum and maximum temperature and the monthly rainfall were

calculated for the 21-year period. Corresponding mean values were calculated for GCM projections for the period 2009–2014 to form a baseline for determining the expected departures in temperature and rainfall due to future climate change. The 2009–2014 reference period was chosen to match the length of the available customer water use dataset. In addition, consistent daily weather observations were available for the same period. Temperature anomalies and rainfall ratios for 2045–2065 were calculated relative to the mean values for the 2009–2014 period. The delta change technique (Hay *et al.* 2000) was used to create sequences of future daily temperature and rainfall by applying monthly temperature deltas and precipitation ratios to the corresponding actual daily weather observations for the baseline period. According to Poulin *et al.* (2011), the computation of the future daily temperature and rainfall can be represented by the following equations:

$$T_{future,d-m} = T_{observed,d-m} + DeltaT_m \qquad (1)$$

$$P_{future,d-m} = P_{observed,d-m} \times RatioP_m \qquad (2)$$

where $T_{future,d-m}$ is the future temperature for day d and month m, $T_{observed,d-m}$ is the observed temperature for day d and month m under the reference period and $DeltaT_m$ is

Table 1 | List of GCMs extracted for use in this study

Climate model	Institution
MIROC-ESM	Météo-France/Centre National de Recherches Météorologiques, France
CNRM-CM5	Météo-France/Centre National de Recherches Météorologiques, France
CanESM2	Canadian Centre for Climate Modelling and Analysis, Canada
FGOALS-s2	National Key Laboratory of Numerical Modeling for Atmospheric Sciences and Geophysical Fluid Dynamics (LASG)/Institute of Atmospheric Physics, China
BNU-ESM	Beijing Normal University
MIROC5	Center for Climate System Research (University of Tokyo), National Institute for Environmental Studies, and Frontier Research Center for Global Change (JAMSTEC), Japan
GFDL-ESM2G	U.S. Department of Commerce/National Oceanic and Atmospheric Administration (NOAA)/Geophysical Fluid Dynamics Laboratory (GFDL), USA
MIROC-ESM-CHEM	Center for Climate System Research (University of Tokyo), National Institute for Environmental Studies, and Frontier Research Center for Global Change (JAMSTEC), Japan
GFDL-ESM2M	Geophysical Fluid Dynamics Laboratory (GFDL), USA
MRI-CGCM3	Meteorological Research Institute, Japan
Bcc-csm1-1	Beijing Climate Center (BCC), China Meteorological Administration (CMA)

the GCM temperature anomaly. Likewise, $P_{future,d-m}$ is the projected rainfall for day d and month m, $P_{observed,d-m}$ is the observed rainfall for day d and month m under the reference period and $RatioP_m$ is the GCM rainfall ratio.

Variables for statistical analysis

The dependent variable was the water use given by the average monthly daily demand (*AMDD*). *AMDD* was calculated by dividing each customers' monthly consumption by the respective number of days between meter readings. *AMDD* was measured in kilolitres per plot per day (kL/plot/day). It was important to convert monthly consumption to daily averages for the variates to be commensurable since monthly readings were often taken at irregular intervals.

Two independent variables and a product term between the two variables were considered in the analysis. The purpose of the product term was to introduce interaction effects between the main effects in the analysis. The first independent variable included in the analysis was the plot size (*PSize*), measured in m², for each customer in the water use dataset. Plot size is related to building size, the number of occupants, the number of water-using fixtures and the income levels. Plot size was therefore expected to explain much of the variation associated with indoor water use.

The second independent variable, daily irrigation requirement (*IReq*), and the product or interaction term (*PSize* IReq*) were considered to be most suitable to measure the effect of climatic variation on water use. Climatic factors essentially influence outdoor water use. It was assumed that water is applied outdoors primarily to replenish evapotranspiration losses from plant surfaces. Rainfall restores soil moisture losses and reduces the need to water the landscape. Temperature and rainfall time series were therefore transformed into theoretical irrigation requirements per unit area by first calculating the crop evapotranspiration and then applying the soil-water balance equation to incorporate effective rainfall. Irrigation water requirements were calculated based on indicative parameter values for turf grass. The estimated irrigation requirements were not expected to equate directly to the landscape irrigation but provided a means of isolating the weather-sensitive water use

component after scaling with an appropriate regression coefficient.

It was considered appropriate in this study to assume that garden irrigation was the main contributor to outdoor use. Research from various countries, including South Africa (Jacobs & Haarhoff 2007), USA (Mayer *et al.* 1999) and Australia (Beal & Stewart 2011) have noted that garden irrigation normally drives outdoor use. Garden irrigation may, however, not be representative of outdoor use under all conditions. For example, swimming pools have been found to contribute 37% (Siebrits 2012) and 7–8% (Fisher-Jeffes *et al.* 2015) to the total water use of residential properties in Cape Town. During water restrictions, outdoor irrigation may be banned, obviously invalidating the assumed relationship between weather and outdoor water use.

Calculation of irrigation requirements (*IReq*)

A method for estimating irrigation requirements was described in Makwiza *et al.* (2015) and was applied here with some modifications. The reference crop evapotranspiration was calculated using the Hargreaves equation (Hargreaves & Allen 2003):

$$ET_o = 0.0023 R_a (T + 17.8) \sqrt{T_{max} - T_{min}} \qquad (3)$$

where ET_o is the reference evapotranspiration (mm/day), R_n is the extraterrestrial radiation (mm/day), T is the mean daily air temperature (°C), T_{min} is the minimum daily air temperature (°C) and T_{max} is the maximum daily air temperature (°C). Crop evapotranspiration, ET_c, was calculated from the reference crop evapotranspiration by the following equation (Allen *et al.* 1998):

$$ET_c = K_c \cdot ET_o \qquad (4)$$

where K_c is a crop coefficient.

A daily soil-water balance was used to restrict effective rainfall to the amount necessary to fill the root zone depth at any time step. The daily theoretical irrigation requirements were estimated by evaluating the following equation

recursively (Makwiza et al. 2015):

$$IR_j = w_{j-1} - w_j + ET_{cj} - r_j \qquad (5)$$

where IR is the net irrigation requirement (mm), ET_c is the crop evapotranspiration (mm), r is the effective rainfall (mm), w is the soil moisture depletion (mm) in the root zone and subscript j denotes day of the year. The total available water was calculated from the following equation:

$$TAW = 1000 \cdot (\theta_F - \theta_{PWP}) \cdot Z_r \qquad (6)$$

where TAW is the total available water (mm), θ_F is the moisture content at field capacity (mm/m), θ_{PWP} is the moisture content at permanent wilting point (mm/m) and Z_r is the root zone depth (m).

Effective rainfall at each iteration was calculated as the amount required to fill the root zone depth. Irrigation was assumed to take place when moisture depletion in the root zone depth reached 40% of the total available water at field capacity. The theoretical irrigation requirement in a day was calculated as the depth required to refill the root zone depth. The water balance calculations were performed assuming typical soil and plant parameters of turf growing on a sandy loam soil. The soil and plant parameter values used in the calculations were adopted from Allen et al. (1998) and are given in Table 2.

The monthly averaged daily irrigation requirement (mm), $IReq$, was calculated by the following equation:

$$IReq = \frac{1}{d_m} \cdot \sum_{j=d_m}^{j=1} IR_j \qquad (7)$$

where d_m is the number of days in the month, IR is the theoretical irrigation requirement (mm) and j denotes the day of the month.

Table 2 | Soil and plant parameters used for estimating irrigation requirements

Parameter	Value
Allowable moisture depletion, p	40%
Crop coefficient, K_c	0.85
Moisture content at field capacity, θ_F	270 mm/m
Moisture content at permanent wilting point, θ_{PWP}	150 mm/m
Root zone depth, Z_r	0.50 m

Statistical model for predicting water use

A statistical model of residential water use was fitted using panel data analysis techniques. The choice of the appropriate panel linear model was based on a comparison of the performance of the pooled ordinary least squares (OLS) specification, the fixed effects model (FEM) specification and the random effects model (REM) specification. A detailed description of these three panel data models is given by Wooldridge (2015).

The pooled OLS model is efficient in the absence of subject or time-specific effects. However, pooled OLS model estimates are prone to bias where important variables have been omitted. The pooled OLS model was expressed as:

$$AMDD_{it} = \alpha + \beta_1 PSize_{it} + \beta_2 IReq_{it} + \beta_3 (PSize*IReq)_{it} + \varepsilon_{it} \qquad (8)$$

where α, β_1, β_2 and β_3 are coefficients, ε is the error term and i and t are indices for customers and monthly time periods respectively.

The FEM controls unobserved heterogeneity between the subjects, customers in this case, by introducing a unique intercept for each subject. The coefficient estimates are, therefore, consistent and unbiased. The FEM estimator, however, drops all time-invariant variables. For this reason, the FEM could not include plot size as an independent variable. The FEM was expressed as:

$$AMDD_{it} = (\alpha + u_i) + \beta_1 IReq_{it} + \beta_2 (PSize * IReq)_{it} + v_{it} \qquad (9)$$

where u_i is the fixed effect specific to customer i that was not included in the model, v_{it} is an independently and identically distributed error term and the other terms are as previously defined.

The REM treats unobserved effects as part of the random error component. The REM therefore does not perform well when prominent variables are missing from the model and may, unlike the FEM, give inconsistent coefficients. The REM was expressed as:

$$AMDD_{it} = \alpha + \beta_1 PSize_{it} + \beta_2 IReq_{it} + \beta_3 (PSize * IReq)_{it} + (u_i + v_{it}) \qquad (10)$$
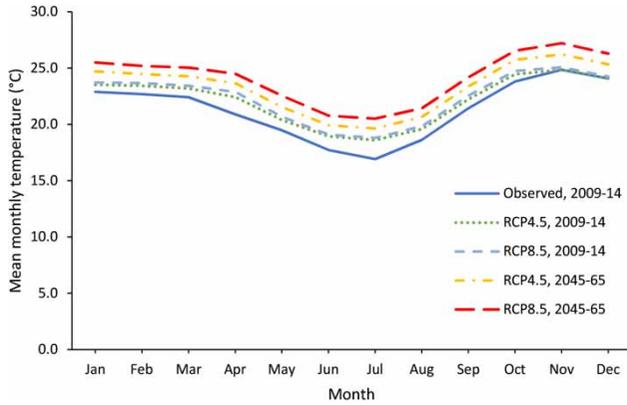
Figure 1 | Mean monthly temperature for 2009–2014 and 2045–2065.

where u_i is the random effect specific to customers or time periods not included in the model and all the other factors are as previously defined.

An F-test was conducted between the pooled OLS model and FEM estimates in order to ascertain the presence of fixed effects. Similarly, the pooled OLS model was compared to the REM using the Lagrange multiplier test to examine the presence of random effects. The final choice was between the FEM and the REM which was based on the Hausman test. The Hausman test checks if the coefficients of the REM are consistent with those obtained from the FEM. All the statistical analyses were carried out using the 'Linear Models for Panel Data' package (plm) in R statistical software (Version 3.3.1).
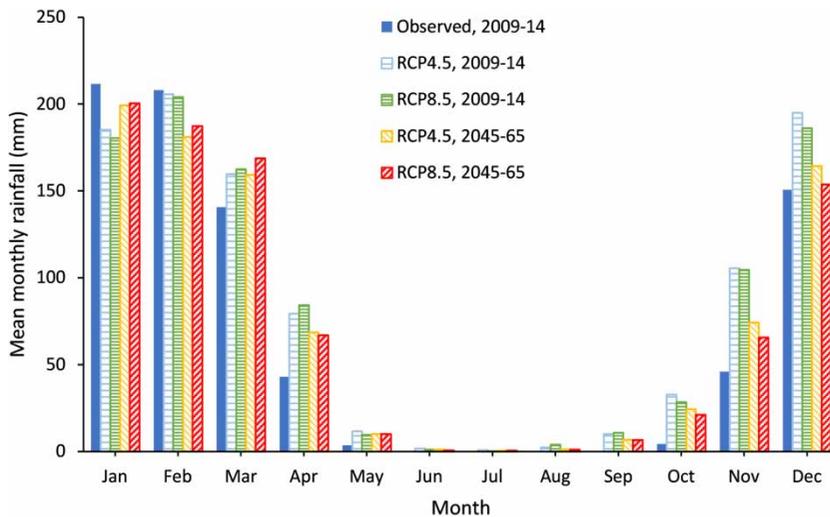
RESULTS AND DISCUSSION

Current and projected temperature and rainfall

Figure 1 shows monthly series of mean temperature observed for 2009–2014, and the mean GCM ensemble temperatures projected for 2009–2014 and 2045–2065. Both the recently observed temperatures and the projected temperatures showed a similar trend although the projected temperatures for 2009–2014 were about 1.0 °C higher than the actual observed temperatures. In comparison to the 2009–2014 GCM projections, the RCP4.5 and RCP8.5 temperature projections for 2045–2065 were 1.2 and 1.7 °C higher respectively. These differences indicate the predicted rise in temperature for 2045–2065. Another observation was that temperature projections for October, November and December were higher than the rest of the year. Interestingly, these are historically the hottest months during the year.

The projected rainfall is shown in Figure 2. The change in rainfall is less obvious than that of temperature. A comparison of the projected rainfall and actual observed rainfall for the 2009–2014 period shows that the two rainfall series exhibit similar seasonal patterns but the projected rainfall substantially exceeds the observed rainfall at the beginning and towards the end of the rainy season (October, November and April). Relative to GCM projections for

Figure 2 | Mean monthly rainfall for 2009–2014 and 2045–2065.

2009–2014, projections for 2045–2065 showed a consistent decrease in rainfall from October to December. No consistent change was evident in the later months of the rainy season. Overall, there was a decrease of approximately 10% in projected annual rainfall for 2045–2065 under both RCP4.5 and RCP8.5 scenarios. It is generally acknowledged that future rainfall patterns are more difficult to predict. Vincent *et al.* (2014) have also argued that future rainfall patterns for Malawi are uncertain and could turn out wetter or drier than the prevailing rainy-season conditions.

Figure 3 shows the monthly mean evapotranspiration calculated by Hargreaves equation for 2009–2014 and 2045–2065. The difference in evapotranspiration between the two periods reflects the effect of temperature rise on plant water needs. The results suggest that plant water needs would increase throughout the year under the projected future temperatures. There was a more pronounced increase in evapotranspiration between October and December.

The theoretical irrigation requirements are shown in Figure 4. The predicted monthly irrigation requirements for 2045–2065 were generally higher throughout the year. Irrigation requirements were predicted to rise the highest between October and December due to both increased temperatures and reduced rainfall. The calculated annual rise in irrigation requirements was 5.8% under RCP4.5 and 8.8% under RCP8.5.

Regression analysis results

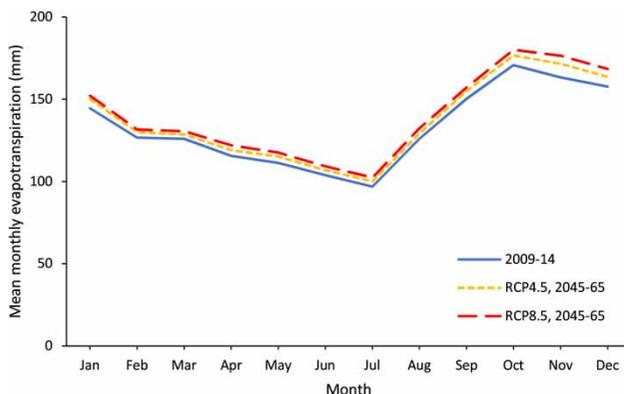The regression analysis results from the pooled OLS model, FEM and the REM are given in Table 3. The three model
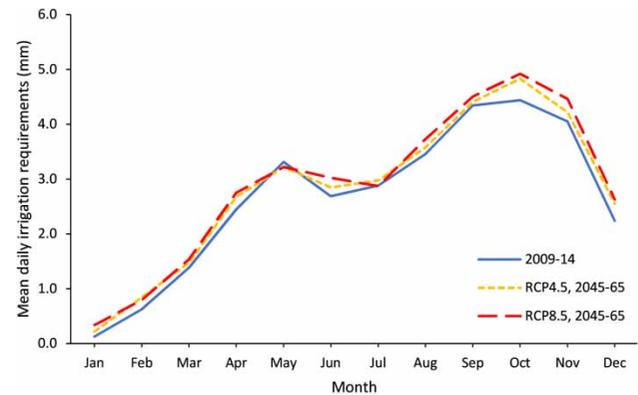
Figure 4 │ Calculated monthly irrigation requirements for 2009–2014 and 2045–2065.

specifications produced very similar coefficient estimates. All *p*-values were significant at alpha level of 0.001. The F-test between the pooled OLS model and the FEM was significant indicating the presence of unobserved individual specific effects, which in this case originated from time invariant customer effects. The FEM therefore produced better parameter estimates than the pooled OLS model. Likewise, the Langrange Multiplier test was significant showing that the REM gave better results than the pooled OLS model. The Hausman test was not significant indicating consistency in both the FEM and REM estimates. Hence all subsequent analyses were based on the REM since it is a more efficient specification than the FEM. The REM was also preferable to the FEM because its estimates included a coefficient estimate for *PSize*.

The overall REM was significant (*p*-value <0.001) and all the model parameters were also significant (*p*-value <0.001). The R^2 values showed that the REM explained only 8.4% of the variation in the water use estimates. The R^2 value in the FEM model was also comparably low. This result was consistent with the large variability inherent in residential water use amongst customers. In similar studies, water use records are usually aggregated at block or city level, hence suppressing much of the variation with a subsequent improvement in the R^2 value (see Martínez-Espiñeira (2002) and Worthington *et al.* (2009)). Since the overall model was significant and all the parameters were significant, there is evidence to support the existence of a trend although the large variation reduces the precision of the model predictions. The standard error estimates of the REM were, however, reasonable because of the relatively

Figure 3 │ Calculated monthly evapotranspiration for 2009–2014 and 2045–2065.

Table 3 | Coefficient estimates and fit statistics for the pooled OLS model, FEM and REM

Parameter	Pooled OLS model		FEM		REM	
	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error
Constant	7.57×10^{-1}	1.07×10^{-2}			7.59×10^{-1}	2.47×10^{-2}
PSize	2.01×10^{-4}	4.96×10^{-6}			2.01×10^{-4}	1.13×10^{-5}
IReq	1.17×10^{-2}	3.54×10^{-3}	1.23×10^{-2}	2.80×10^{-3}	1.23×10^{-2}	2.80×10^{-3}
*PSize*IReq*	8.37×10^{-5}	1.64×10^{-6}	8.40×10^{-5}	1.29×10^{-6}	8.40×10^{-5}	1.29×10^{-6}
R^2	0.250		0.074		0.084	
p-value	0.000		0.000		0.000	
F-test for individual effects			<0.000			
Lagrange multiplier test					<0.000	
Hausman test					0.068	
Theta					0.829	

large number of customers in the sample (sample size of 2,149 homes as discussed earlier).

Change in water use with plot size

The sign of the *PSize* coefficient was positive, meaning that water use increased with plot size. Larger plots will usually contain larger dwelling units that are likely to have more occupants and more water using fixtures such as multiple bathrooms, toilets, washbasins and even higher plumbing and leakage losses. The estimated coefficient of 2.01×10^{-4} is the estimated effect of plot size on water use when the irrigation requirement is zero, which is nearly the case in winter. The results indicate that a 100 m² increase in building size results in an approximate increase of 0.020 kilolitres in indoor water use per household per day (kL/plot/day). This additional usage is on top of the average minimum use of 0.759 kL/plot/day given by the intercept term. The sum of the *constant* term and the *PSize* term therefore represent the climate insensitive component of water use in the model. Approximately 90% of the customers' plot size values were between 300 and 4,000 m². Based on the coefficient estimates, average indoor water use varied between 0.819 and 1.562 kL/plot/day. These results are similar to the average minimum winter use of 0.695 and 1.563 kL/plot/day determined in the previous study for plot sizes in the ranges of 0–500 and 3,500–4,000 m² respectively.

Change in water use with irrigation requirements

Effects of climate change can be assessed through *IReq* since changes in temperature or rainfall are reflected by changes in irrigation requirements. The coefficient estimates for *IReq* and the interaction term, *PSize*IReq*, exhibit the anticipated positive signs since an increase in irrigation requirements should result in higher water use. Substituting a typical small plot size and a typical large plot size into the fitted model provides a picture of the effect of changes in irrigation requirements on water use. Given a plot size of 300 m², a 1 mm rise in irrigation requirements is associated with a rise of 0.037 kL/day in water use. A corresponding calculation for a plot size of 4,000 m² gives a rise in water use of 0.348 kL/day. These results demonstrate that the relationship between water use and irrigation requirements is conditional on plot size. The effect of increased irrigation requirements on water use is greater for larger plot sizes.

Change in water use under future projected climate

Table 4 shows the predicted changes in monthly water use between 2009–2014 and 2045–2065 calculated using the fitted statistical model for RCP4.5 and RCP8.5 scenarios. The predicted rise in annual water use was 1.5% under RCP4.5 and 2.3% under RCP8.5. The highest predicted rise in water use was found in November and December. October is already a crucial month for water supply in Lilongwe

Table 4 | Predicted percentage change in monthly water use from 2009–2014 to the 2045–2065

Month	Absolute change (kL/plot/day)		Percent change (%)	
	RCP4.5	RCP8.5	RCP4.5	RCP8.5
Jan	−0.006	−0.001	−0.5	−0.1
Feb	0.023	0.034	2.0	2.9
Mar	0.017	0.016	1.4	1.4
Apr	0.011	0.020	0.8	1.5
May	0.019	0.032	1.3	2.2
Jun	0.008	0.019	0.5	1.2
Jul	0.016	0.025	1.1	1.7
Aug	0.016	0.023	1.1	1.5
Sep	0.020	0.033	1.2	2.0
Oct	0.020	0.033	1.2	2.0
Nov	0.036	0.057	2.1	3.3
Dec	0.073	0.103	4.9	7.0

because stream flows are lowest (Lilongwe Water Board 2015) while residential water use reaches its peak. Stream flows might remain low for a longer period than is the case under the current scenario considering that the early rains that occur in October and November are likely to decline according to the 2045–2065 projections. The rise in water use occurring together with reduced stream flows may potentially further strain water supply during this period. These predicted climate-related effects on water use are, however, small compared to other factors such as urban population growth, which is anticipated to affect water use to a greater extent (Lilongwe Water Board 2015).

Uncertainty and limitations of the climate projections

Like any other climate change study, the projected changes in water use are subject to uncertainty from several factors. There is uncertainty attached to the assumed emission scenarios that drive climate change, the inherent natural climatic variability, how well climate models represent global or regional climate dynamics and the effectiveness of the downscaling technique at recreating the local climatic conditions. In addition, the future values of the independent variables used as input in the statistical model in this study were derived from a relatively short period of daily weather records whereas long-term averages are typically used in climate change studies. These factors suggest that the actual changes in future water use due to climate change could differ from the predictions. The results however demonstrate that climatic changes could have adverse effects during some months even if the impact on the overall annual water use was small. The methodology presented could be used to reexamine the water use predictions in the near future using a longer time series as more data are accumulated in customer water use databases.

CONCLUSIONS

This research focused on modelling residential water use in Lilongwe, Malawi, under potential future climate change. A regression model was developed using monthly water use records for selected formal residential neighborhoods in the city of Lilongwe. Panel linear models were used to predict water use using plot size, the theoretical irrigation requirements and an interaction term between the two variables. Water use was found to increase with both plot size and irrigation requirements, but the effect of irrigation requirements on water use was greater for larger plot sizes. The estimated model was applied to downscaled future climate projections to examine potential impacts of climate change on residential water use. The expected increase in annual water use was found to be 1.5% under the RCP4.5 scenario and 2.3% under the RCP8.5 scenario. The results showed that water use may increase the most between November and December due to both reduced rainfall and increased irrigation water requirements. The estimated model gave an indication of the magnitude of the climate-sensitive component of residential water use in the city of Lilongwe while the predicted future water use provided insight to the impacts of climate change on water use. The results obtained are beneficial for planning present and future water conservation initiatives for the city of Lilongwe, especially regarding outdoor water use. The model was successfully developed and employed in an African city to predict future water use under two climate change scenarios and 10 GCM projections. The same approach would apply to any settlement for which downscaled climate projections and time series of monthly water use are available.

ACKNOWLEDGEMENTS

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