Estimating outdoor water use allowing for the possible impacts of climate change

by

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Abstract

Climate change may stress water supply systems due to both diminishing water resources and rising climate driven water use. Reducing the sensitivity of residential outdoor water use to climatic factors is desirable for climate change adaptation. Outdoor water use is also attractive for achieving water savings, because outdoor use is more elastic than indoor use. This study was aimed at estimating residential outdoor water use for the purpose of estimating how it would be impacted by climate change.

A conceptual model was formulated to derive irrigation water use for vegetated areas around the home from climate variables. The model was based on the modification and adaptation of an existing residential end-use model for outdoor water demand to include climate change parameters. The resulting irrigation water end-use model is suitable for assessing water use for specific vegetation types maintained around the home. Application of the model to the case of leafy vegetables grown in the backyard garden was demonstrated in this study. The growth of vegetables in backyard gardens is often linked to nutritional food security in developing countries, stressing the importance of research to better understand the impacts of climate change on water use for garden irrigation.

In this research study, outdoor water use events were studied using sound recorded at outdoor taps. The automatic detection algorithm applied to the recorded sound signals performed reasonably well with precision and recall rates of at least 80%. Diurnal water use patterns derived at the outdoor tap revealed time periods of peak water use.

An exploratory analysis of water billing records for the city of Lilongwe showed that water use increased with plot size, similar to previously reported research in southern Africa. Summer peaking factors also increased with plot size. In a follow-up study, panel linear regression analysis was used to create an empirical relationship between household water use and the independent variables: plot size and theoretical irrigation requirements. Predictions for ensemble averages of temperature and rainfall projections for 2050 showed an increase of 1.5% in annual water use under the low emissions scenario and 2.3% under the high emissions scenario.

Finally, the performance of temperature and rainfall as independent variables in water use regression models was compared to the use of theoretical irrigation requirements. Empirical analysis of a residential water use dataset for 12 North American cities showed that the transformation of temperature and rainfall to irrigation requirements, using a suitable set of parameter values, improved the performance of the water use regression models.

The results of this study show that garden irrigation will increase due to climate change, but the increase is relatively small compared to the expected population growth and urbanisation in many parts of Africa. The impact of climate on expected water use was examined using simple and effective techniques that were employed at relatively low cost. Water utilities and planners could employ the methods and tools reported on here to better plan for the additional expected increase in outdoor water use resulting from climate change.

Opsomming

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d	number of days in a given month
d_m	number of days in the month
D_r	root zone depletion
D_{r1}	root zone depletion just before water application
D_{r2}	root zone depletion just after water application
$DeltaT_m$	temperature anomaly for month m
e_s	saturation vapour pressure
e_a	actual vapour pressure
ET_o	Reference crop evapotranspiration
ET_c	crop evapotranspiration
f	over-irrigation and under-irrigation factor
G	soil heat flux density
H_0	null hypothesis
H_1	alternative hypothesis
IR	net irrigation requirement
$IReq$	monthly averaged daily theoretical irrigation requirement
k	window number
K_c	crop coefficient
$K_{c\ i}$	crop coefficient on day $_i$
K_s	reduction factor dependent on available soil water
L_{stage}	length of crop growth stage

MIR	estimated monthly outdoor irrigation water use
n	sample number
p	allowable moisture depletion
$P_{future,d-m}$	projected rainfall for day *d* and month m,
$P_{observed,d-m}$	observed rainfall for day *d* and month m under the reference period
$PSize$	plot size
r_j	effective rainfall on day $_j$
R_n	net radiation at the crop surface
$RatioP_m$	rainfall ratio for month m
s	surface area of the vegetation type
T	mean daily air temperature at 2 m height
T_{min}	minimum daily air temperature
T_{max}	maximum daily air temperature
TAW	total available soil moisture in the root zone
$T_{future,d-m}$	future temperature for day d and month m
$T_{observed,d-m}$	observed temperature for day *d* and month m under the reference period
u_2	wind speed at 2 m height
u_i	Any factor specific to subject i or time period i not included in a fixed effect or random effects model
v_{it}	independently and identically distributed error term
w_j	soil moisture depletion in the soil on day $_j$
W_L	window length
$x_k(n)$	audio sample at the kth position in window n.

X_{it}	vector of independent variables
Y_{it}	dependent variable
Z_r	Root zone depth
α	regression model intercept
β	regression coefficient
Δ	slope of the saturation vapour pressure curve at temperature T
ε	efficiency of the irrigation system
ε_{it}	error term
γ	psychrometric constant
μ	mean of Gaussian probability distribution
θ_{FC}	moisture content at field capacity
θ_{PWP}	moisture content at permanent wilting point
σ	standard deviation of Gaussian probability distribution

Abbreviations and acronyms

A2	Storyline from the Special Report on Emissions Scenarios
AADD	Average annual daily demand
AMDD	Average monthly daily demand
AWC	Available water capacity
B1	Storyline family from the Special Report on Emissions Scenarios
CIP	Climate Information Platform
CIWU	Climate Impact Water Use
CSAG	Climate Systems Analysis Group
DFID	Department or International Development
FAO	Food and Agricultural Organisation of the United Nations
FEM	Fixed effects model
GCM	Global Circulation Model
GHG	Greenhouse gas
GIS	Geographical information system
IPCC	Intergovernmental Panel on Climate Change
LUANAR	Lilongwe University of Agriculture and Natural Resources
kL	kilolitres
Kpbs	kilobytes per second
MP3	MPEG layer 3
PVC	Polyvinyl chloride
OLS	Ordinary least squares

RCM	Regional Climate Model
RCP	Representative concentration pathway
RCP4.5	Stabilisation without overshoot pathway to4.5 W/m2 at stabilisation after 2100
RCP8.5	Rising radiative forcing pathway leading to 8.5 W/m2 in 2100
REM	Random effects model
REUM	Residential end-use model
REUS	Residential end-uses of water study
SH	Study home
SIC	Schwarz Information Criterion
SIMDEUM	Simulation of water demand, and end-use model
TAW	Total available water
WSUD	Water sensitive urban design

Chapter 1. Introduction

1.1 Background and motivation

Worldwide, utilities are faced with challenges to meet rising water demands due to population growth and urbanisation (Danilenko *et al*., 2010). Many cities need new and diversified water sources. New water sources are, however limited, often harder and expensive to develop. Apart from the development of new sources of water, effective water demand management at the household level can potentially play an important role in curbing present use and reducing the impact of future water shortages (Breyer *et al.* 2012).

Additionally, climate change is a prominent threat that is likely to alter the dynamics of water supply systems in the future. The sub-Saharan region is expected to get hotter and drier over the coming decades. Temperatures could rise by about 3°C by the end of the century (Kusangaya *et al*. 2014). 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). Many cities already experience water shortages during hot dry summer periods. Climate change may further strain water supply by increasing climate related residential water use such as garden irrigation.

Periods of acute water supply shortages have traditionally been managed by introducing water use restrictions, primarily targeting outdoor water use (Atwood *et al*., 2007; Jacobs *et al*., 2007; Survis and Root, 2012). In the long term, water demand management measures need to reduce the responsiveness of residential water use to variations in climatic factors (Breyer and Chang, 2014). Unlike indoor water use, which remains relatively constant throughout the year, outdoor water use is highly variable even among customers within the same location. This high elasticity of outdoor water use (Mansur & Olmstead, 2012) makes it an attractive option for achieving water savings at the household level. The water savings potential could be significant, depending on the nature of outdoor water end uses.

Knowing the amount of water used outdoors and understanding the nature of the outdoor water end uses are prerequisites for effective planning and implementation of the related conservation strategies. Models are useful for predicting water use and for estimating the effects of related factors on water usage. Models that relate water use to the underlying drivers are an effective decision support tool for planning and management of urban water supplies.

End-use modelling is a more recent and effective approach to relate water use to factors at the household level (Jacobs and Haarrhoff, 2004; Blokker *et al*. 2009). The verification of end-use models requires collection of water usage data at the fixture level. The high temporal and spatial resolution of end-use data provide greater detail about water use at the home than aggregated water use records. End-use modelling can therefore allow greater flexibility in the representation of water use processes.

Regression models are among the most popular for empirical analysis of water use in literature since they permit development of statistical relationships between water use and other factors available to the modeller. Cross-sectional analyses are usually performed on water use data that contains information about various factors of interest measured on the water users. Time series analysis are also commonly used when the water use dataset spans a sufficiently long period of time. Panel data regression techniques are more recent with a capability for analysis of data collected on multiple units and over multiple time periods. There are a few reported water use studies that show the suitability of panel data analysis on water consumption records.

1.2 Problem statement

Outdoor water end use modelling has generally received less attention compared to indoor water end-use modelling. One challenge in outdoor water end use modelling is the greater influence of the consumer behaviour of the water users which contrasts with the greater dependence of indoor usage on plumbing fixture type (White *et al*., 2004). The close association between outdoor water use with climatic factors entails the need for a substantially long outdoor water end use dataset that allows a study of water use variation during different seasons of the year.

Generally high resolution smart water meters are used for collection of end-use data at household level and the extraction of water end-use events requires specialised software. The cost of equipment necessary for collecting residential end-use data is prohibitively high, often making application impractical in developing countries. Furthermore, available end-use datasets are mostly too short for comprehensive climate related modelling.

The alternative application of regression analysis can easily allow the inclusion of climatic factors in various flexible ways. Many utilities have water use databases which span only a few years but comprise numerous customer accounts. Detailed customer related information, however, is not always available to the water managers of researchers. The choice of the statistical analysis technique for examining the impacts of climatic factors needs to consider these data related limitations.

1.3 Research aim and objectives

The aim of the study was to develop tools for estimating outdoor water use in order to assess the impacts of climate change. The specific objectives of the research project were as follows:

1. To conduct a review of key concepts related to the prediction of future climate
2. To modify and adapt the outdoor demand component of the existing Residential End Use Model for the assessment of climate change impacts
3. To assess the suitability of sound recording for the study of water use at outdoor fixtures (To undertake a field study of water use at outdoor fixtures by using sound recording and its suitability for application in end-use modelling)
4. To carry out a study of the monthly variation of water use and its relationship to climatic factors in the study area
5. To develop empirical relationships between water use and climatic factors and examine potential impacts of projected future climate change on water use.

1.4 Research significance

The outdoor water end-use model presented in this study has potential to improve representation of outdoor irrigation water use. A calibration method is demonstrated which may improve outdoor water end use modelling through the determination of suitable values for parameters that are normally difficult to measure in a practical manner at household level. Calibration is also necessary for tuning parameter values obtained from literature to describe characteristics of outdoor water using features but where the field conditions differ from the standard conditions.

The application of sound recording at the outdoor tap considered in this research is a low-cost alternative technique that has potential to improve knowledge and understanding of the nature of outdoor water use especially in low-income regions. Although this research does not consider the estimation of flow rate from the recorded signals, there is potential to apply this technique with other approaches such as contingency valuation techniques to obtain data that is suitable for outdoor water end use modelling.

The empirical analysis of customer monthly water use records presented in this research utilises data that is often routinely collected by public institution in most cities to examine the influence of climate related factors on residential water use. Most empirical studies reported in literature require additional information to be collected from customers depending on the statistical analysis techniques chosen and the factors under consideration. The goal in this research was to apply a methodology that can effectively be applied for climate change impact assessments on water use in southern African cities with minimal additional financial requirements. If the underlying assumptions are satisfied, regression models can provide vital insights into water use from limited and readily accessible information.

1.5 Delineations and limitations

The models applied in this research focus on garden irrigation only. Swimming pools are known to significantly impact residential water use in other cities, Cape Town for example. Swimming pools were, however, not addressed in this work because they were not common in the study area. Outdoor water use includes other components besides garden irrigation such as car washing and cleaning of hard surfaces. These uses are less closely associated with climatic factors and are not considered in this study.

Water end-use study are concerned with the determination of the intensity, duration, and time of occurrence of water use events in order to characterise the water use profile of plumbing fixtures. The analysis of sound signals recorded at the outdoor tap in this study focused only on the duration and time of occurrence of water use events at the outdoor tap. The determination of flow rate from the sound signals was beyond the scope of this study.

Sound from pipe flow is dependent on the properties on the pipes and the plumbing configuration. None of these factors were explicitly addressed in the field study conducted to characterise outdoor tap water use events. Water pressure also impacts the intensity of flow sound. This research, however, did not consider the effects of pressure on the recorded sound signals.

The outdoor water end-use model proposed in this research, referred to as the CIWU model, was not fully applied due to lack of a comprehensive water end-use dataset. The determination of outdoor water use profiles targeted only 10 homes due to resource constraints. As already stated above, the event data collected lacked flow rate measurements. Instead the concepts in the CIWU model were successfully demonstrated on a single home where a suitable dataset was available.

1.6 Main Assumptions

Outdoor water use was assumed to be predominantly driven by garden irrigation. This assumption is considered reasonable in the study area because other known major outdoor water end uses such as swimming pools were relatively uncommon.

There are also outdoor water uses which do not directly result from evapotranspiration losses such as car washing and cleaning of hard surfaces. These water end uses were assumed to be affected marginally by climatic factors and were not considered in all the analyses presented.

It was assumed in this study that climatic factors mainly influence outdoor irrigation water use. Indoor water use was assumed to remain constant throughout the year irrespective of climatic factors.

The empirical study of water use records employed panel data analyses. The application of panel data analysis to estimate the regression models presented were considered to have effectively accounted for potential bias due to omission of time-invariant factors among the customers. There was, however, potential bias due to factors that vary over the year, but these are assumed to have had minor effects on the results.

1.7 Chapter overview

This dissertation comprises 9 chapters. Chapter 1 provides a brief introduction highlighting issues related to residential outdoor water use. Chapters 2, 3, 5 and 6 are published papers and are formatted according to the requirements of the journals in which they were published whereas Chapters 7 is an unpublished paper which was formatted according to the journal to which it was being submitted at the time of compiling this manuscript.

Chapter 2 presents a brief review of water end-use modelling, and a review of global climate modelling including the prediction and downscaling of predicted climate to local scale. A theoretical framework for estimating residential irrigation water use is presented allowing for the assessment of the impacts of changes in climatic factors. Chapter 2 also presents a theoretical framework for estimation of domestic irrigation water use and the application of predicted future climate condition to assess the impacts of climate change.

Chapter 3 presents a study of water use at the outdoor tap using sound recording. The suitability of sound recording for collecting outdoor water end-use data was examined by applying both manual and automated event extraction techniques.

Chapter 4 describes the application of the irrigation water end use model presented in Chapter 2 to a dataset collected for leafy vegetables. The dataset used was collected as part of the field work reported in the study in Chapter 3. An exhaustive search applied to identify parameters of best fit was described.

Chapter 5 presents research into the monthly variation in residential water use for the city of Lilongwe in relation to plot size. The average annual daily demand was compared to findings from similar studies in southern Africa. In Chapter 6 plot size and theoretical irrigation requirements, computed from weather data, were used to estimate a panel linear regression model for predicting monthly water use. The procedure for the computation of irrigation requirements was adopted from the outdoor water end-use model presented in Chapter 2. The fitted model was used to assess the impact of predicted future climate on water use for the city of Lilongwe.

In Chapter 7, the performance of water use models regressed on the derived variable theoretical irrigation requirements was further examined for a range of climatic environments. The outcomes were compared to the alternative use of the variables temperature and rainfall.

Chapter 8 links the findings of the independent papers in a general discussion and addresses limitations of the research. Chapter 9 presents the conclusions based on the research findings, summarises contributions and makes recommendations for future research.

Chapter 2.

A conceptual theoretical framework to integrally assess the possible impacts of climate change on domestic irrigation water use

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ABSTRACT

Southern Africa is likely to experience higher evapotranspiration and altered rainfall characteristics due to global warming and climate change. Climate-driven water use may potentially stress water supply facilities due to increased demand and reduced surface water yield. This paper presents a conceptual theoretical framework for assessing impacts of climate change on domestic irrigation water use. The prediction of climatic conditions that may potentially influence future water use is reviewed together with regional capacity for downscaling global climate projections. The impact assessment of water use is based on the modification and adaptation of an existing end-use model for water demand to include parameters for climate change. The Penman-Monteith equation and the soil water balance equation are incorporated for the estimation of daily water needs of vegetated areas in residential properties. The paper also discusses data requirements and a calibration procedure to improve model fit to the observed domestic irrigation water use. The proposed approach could form a basis for constructing a detailed model for planning various adaption measures relating to climate-driven domestic irrigation water use.

Keywords: climate change, outdoor water use, end-use model, irrigation water use

INTRODUCTION

Research context

Domestic water use comprises indoor and outdoor components. Water is needed outdoors mainly for garden irrigation – to water vegetation such as lawns, flowerbeds and trees. Other outdoor water uses include pool top-ups, washing of cars, washing of hard surfaces, etc.. Water may also be used for small-scale urban agriculture – to grow edible plants like herbs, fruit and vegetables. Various climatic parameters impact outdoor water use, including, for example, rainfall, evapotranspiration and ambient temperature (Balling *et al*., 2008; Praskievicz and Chang, 2009; Breyer and Chang, 2014). This climatically-driven water use profile is particularly true for edible plants with seasonal growth.

Climate change has been reported to affect parameters requisite for estimating irrigation requirements (Gutzler and Nims, 2005; Balling and Cubaque, 2009), and may thus have important implications for modelling residential outdoor water use. To study the impacts of climate change on residential outdoor water use, it is vital to incorporate biophysical inter-relationships pertinent to outdoor water using features. In this regard, water end-use models are more likely to produce better results compared to models that are built on aggregated water use measurements (Bennett *et al*., 2013). Research is still needed to estimate the impact of climate change on water use at the end-use level, thereby augmenting other existing broad-scale efforts aimed at assessing the current and future capacity of water resources to meet domestic, agricultural and environmental water requirements.

Objectives

The main objective of this paper is to present a conceptual theoretical framework for a Climate Impact Water Use (CIWU) model that would integrate climate change impacts into a residential end-use model for estimating domestic irrigation water use. The goal is to present a framework or tool that could ultimately feed into a more complex model in future to predict long-term impacts of climate change on outdoor water use. In this paper, the focus is on lawn and garden irrigation which, when present on a residential property, contributes significantly to water use (Jacobs *et al*., 2007).

Pricing, technological change and other socio-economic factors have also been reported to influence water use (Howe and Lineweaver, 1967; Butler and Memon, 2006). While such factors may change over time and thereby impact domestic irrigation water use, they have been disregarded in the modelling framework presented. Instead, the proposed end-use model allows for the analysis of the impact of predicted changes in climatic parameters on domestic irrigation water use of a specific residential property in a 'static environment' wherein non-climatic parameters remain constant.

Motivation

On a global scale, impacts of climate change on the water cycle are mainly manifested in the increased intensity and frequency of extreme events (Rana *et al*., 2014; Niang *et al*., 2014). The Mediterranean and southern Africa regions are generally expected to experience a significant decline in water resources due to global warming (IPCC, 2007; Niang *et al*., 2014). Thus, sustainable management of water resources and implementation of action plans to deal with possible water shortages require a good understanding of water end-uses and their response to climate change.

Water supply utilities are already facing pressure to maintain supply in the face of increasing water use and uncertain supply (Danilenko *et al*., 2010). Outdoor water use restrictions have already been applied extensively in many cities to manage water supply shocks (Atwood *et al*., 2007; Jacobs *et al*., 2007; Survis and Root, 2012). Any future increase in domestic irrigation water requirements that may be brought about by climate change could potentially further stress water resources due to increased water use, possibly combined with reduced surface water yield (Kusangaya *et al*., 2014). Accurate modelling of water use in the context of climate change is essential to effectively plan and implement future water management strategies.

STATE-OF-THE-ART CONCEPTS IN CLIMATE CHANGE AND WATER END-USE MODELLING

Climate change

Global warming due to increasing concentrations of greenhouse gases (GHG) in the atmosphere is expected to cause significant changes in future climate. According to the IPCC (2013), global temperatures will continue to rise given the present levels of anthropogenic GHG emissions. The direct effect of higher temperatures is increased atmospheric water demand and the intensification of the hydrological cycle. The intensification of extreme events is expected even in areas that are bound to experience decreased rainfall due to global warming, such as the Mediterranean Basin and some parts of southern Africa (Niang *et al*., 2014).

Global circulation models (GCMs) are widely used to generate forecasts of future climate (Dufresne, 2006; Rana, 2014; Servat, 2014; André, 2014). Prediction of future climate is a complex undertaking involving many physical, chemical and biological processes. Confidence in the application of GCMs has been growing with improved computing capabilities that have made it possible to perform numerically-intensive simulations within reasonable lengths of time. There are now a large number of GCMs available from different institutions around the world. The results of the IPCC fifth assessment, made public for potential use by the scientific research community, are based on the analysis of 27 GCMs (IPCC, 2007; IPCC, 2013). It has now become the norm to assess future climate conditions from an ensemble of GCMs in order to reduce regional and seasonal bias exhibited by individual models (Graham *et al*., 2011; Faramarzi *et al*., 2013). Table 2.1 provides an inventory of 16 of the most sophisticated GCMs amongst the 27 GCMs used by IPCC.

Table 2.1 Characteristics of 16 GCMs

GCM name	Institution	Country of origin	ID according to CMIP3
BCC_BCM2.0	Bjerkness Centre for Climate Research	Norway	BCM2.0
CCCMA_CGCM3.1	Canadian Center for Climate Modelling and Analysis	Canada	CGCM3.1(T47)2
CNRM_CM3	Météo-France / Centre National de Recherches Météorologiques	France	CNRM-CM3
CSIRO_MK3.5	Australia's Commonwealth Scientific and Industrial Research Organisation	Australia	CSIRO_MK3.5
GFDL_CMD2.0	US Dept. of Commerce/NOAA/Geophysical Fluid Dynamics Laboratory	USA	GFDLCM2.04
GFDL_CMD2.1	US Dept. of Commerce/NOAA/Geophysical Fluid Dynamics Laboratory	USA	GISS-ER6
GISS_MODE_E_R	NASA/Goddard Institute for Space Studies	USA	e for Spa
INGV_ECHAM4	INGV, National Institute of Geophysics and Volcanology	Italia	ECHAM4.6
INMCM3.0	Institute for Numerical Mathematics	Russia	INMCM3.0
IPSL_CMD4	Institut Pierre Simon Laplace	France	IPSLCM4
MIROC3.2_MEDRES	CCSR/National Institute for Environmental Studies/FRCGC	Japan	MIROC3.2
MIUB_ECHO_G	Meteorological Institute of the University of Bonn, Meteorological Research Institute of KMA, Model and Data group at MPI-M	Germany/ Korea	ECHO-G1
MPI_ECHAM5	Max Planck Institute for Meteorology	Germany	ECHAM5/MPI-OM
MRI_CGCM2.3.2a	Meteorological Research Institute	Japan	MRICGCM2.3.2
UKMO_HadCM3	Hadley Centre for Climate Prediction, Met Office	UK	UKMOHadCM3
UKMO_HadGEM1	Hadley Centre for Climate Prediction, Met Office	UK	UKMOHadGEM1

Versatile as they are, GCMs can only give valid outputs at grid scales that are essentially too coarse for most impact studies, particularly when the focus is on water use of relatively small residential neighbourhoods. Working at grid sizes larger than around 350 km^2 to 450 km^2, GCMs fail to capture the spatial and temporal patterns of second-order processes, for example, rainfall, with the same level of consistency as first-order atmospheric processes (Hardy, 2003). Regional downscaling is required to bring the GCM outputs to grid scales of about 10 km^2 to 50 km^2. Two basic approaches are available for downscaling. The first approach, known as dynamical downscaling, links a regional climate model (RCM) of smaller grid size to the relevant GCM. RCMs are based on similar theoretical foundations to those used in GCMs and offer results with finer spatial resolution (Rana *et al*., 2014). However, the scope of RCMs is limited to their regions of validity. Alternatively, statistical downscaling can be used to transfer GCM projections to the area of interest by coupling the regional and local climate through available observations. Statistical downscaling has much fewer computational requirements than dynamical downscaling but the final results will inherit any anomalies in the available data (Graham *et al*., 2011). According to Maraun *et al*. (2010), consensus between results from dynamical downscaling and statistical downscaling is a better indicator of validity of the results.

A key issue when using future climate projections is quantifying the uncertainty inherent in the successive stages of modelling. Some climate processes are not yet well understood in terms of climate modelling. Thus, errors can be introduced into the results leading to an over- or underestimation of future climate (Schulze, 2011). The anthropogenic GHG emission scenarios used in GCMs are based on assumptions of highly unpredictable socio-economic and technological statuses of the future. The GCMs themselves comprise parameterisations that oversimplify processes of many local climate phenomena they represent. Hence it is desirable to introduce as little additional uncertainty as possible in the downscaling or sequent modelling stages.

In the African context, climate change simulations are usually carried out by using GCMs suggested by the IPCC. The severe lack of observed climate data and credible studies conducted on spatial and temporal variation of climate across Africa preclude an accurate assessment of future regional climate scenarios of most African regions (Gbesso *et al*., 2014; Kling *et al*., 2014; Rana *et al*., 2014). Projections of extreme weather conditions, as of the IPCC report published in 2001, were not available for wide portions of Africa due to inadequacy of data (DFID, 2004). The case in South Africa, however, seems to be different from the rest of the continent. South Africa seems to have more active participation in global climate change programmes and a wealthier literature resource of work on climate change than the rest of the continent (Ziervogel *et al*., 2014). International efforts are underway to develop regional climate models, especially for the southern African part. The UK Department for International Development (DFID) had supported the development of a regional climate model called ACCURATE from the Hadley Centre (DFID, 2004). CORDEX-Africa is yet another joint programme meant to increase the availability and quality of downscaled climate projections for Africa. In addition, South Africa has implemented strategic actions to better understand the implications of climate change at national level. The Climate Systems Analysis Group (CSAG) affiliated to the University of Cape Town has generated future climate scenarios on a daily scale for national and local application using five GMCs, namely, CGCM3.1, CNRM-CM3, ECHAM5/MPI-OM, GISS-ER and IPSL-CM4 (Schultze, 2011).

Residential water end-use modelling methods

Reliable water use estimates are the basis for most decisions water utilities and practitioners have to make concerning the design, operation and management of water distribution systems (Donkor *et al*., 2012). If water use estimates are obtained precisely at the spatial scale of individual residential properties, a marked improvement is evident in the performance of various aspects of the corresponding water supply network models (Xu and Goulter, 1998; Alvisi *et al*., 2014). End-use modelling has been recognised to be the key to enhancing the spatial and temporal resolution of water use estimates entered as inputs at demand nodes in water supply network models. Flow rates and pressure variation in the distribution system can then be determined more precisely leading to better design of hydraulic components (Garcia *et al*., 2004). In addition, contaminant and disinfectant travel times can be determined more accurately in network water quality models (Blokker *et al.*, 2008). Water conservation studies have also demonstrated the potential of end-use models to achieve future water savings through effective implementation of bottom-up water demand management measures as a supplement to the usual top-down approaches (Macy, 1999; Mayer *et al*., 2003; Willis *et al*., 2009).

Several residential water end-use models have been proposed (Buchberger and Wu, 1995; Alvisi *et al*., 2003; Jacobs and Haarhoff, 2004; Garcia *et al*., 2004; Blokker *et al*., 2009; Bennett *et al*., 2013) since the development of technologies for effectively disaggregating metered consumption into water end uses at individual plumbing fixtures. Buchberger and Wells (1996) first showed that water use events at a residential stand can be represented by rectangular pulses characterised by their intensity, duration and frequency. Subsequently, models for simulating residential water use estimates were based on regenerating the patterns of occurrence of the pulses observed at the residential stand connection in probabilistic functions

(Buchberger and Wu, 1995; Alvisi *et al*., 2003; Garcia *et al*., 2004; Blokker *et al*., 2009; Alvisi *et al*., 2014). Although the earlier stochastic end-use models, once calibrated, reproduce the water use events reasonably well, they do not hypothetically relate the simulated water usage to the inherent characteristics of the residential stand concerned. Consequently, extrapolating the simulation models in time or transferring the models to other locations demands recalibration of the model parameters using a new set of end-use data.

The residential end-use model (REUM), however, was developed to estimate water use from parameters that define characteristics of the respective water-using fixtures (Jacobs and Haarrhoff, 2004). Multiple facets of residential water use were addressed in REUM, namely, indoor water use, outdoor water use, hot water use and wastewater flow. REUM was formulated to produce monthly averaged outputs from inputs of typical parameter values. Scheepers and Jacobs (2014) later increased the indoor model complexity by describing all indoor parameters stochastically and modifying this model component to output hourly water-use estimates.

The cost associated with collecting and processing end-use data is perhaps the major challenge to the application of stochastic water end-use models. Blokker *et al*. (2009) demonstrated in the Simulation of Demand and End-Use Model (SIMDEUM) that water use events can alternatively be generated from parameters derived from household characteristics of the residential stands. The advantage of SIMDEUM is that it avoids expensive data-logging exercises by utilizing household characteristics as model inputs derived primarily from household survey data. SIMDEUM, however, does not consider parameters for outdoor water use and may therefore not perform equally well where outdoor water use features are dominant. Generally, the more versatile residential water end-use models remain confined to indoor water end uses.

The outdoor water use model proposed by Jacobs and Haarhoff (2004) estimated outdoor water consumption from pan evaporation and rainfall. A similar formulation was adopted by DeOreo *et al*. (2011) for estimating outdoor water use in an end-use study in California. Later work by Du Plessis and Jacobs (2014) applied the outdoor demand component of REUM to residential estates in South Africa. Unlike the original model, Du Plessis and Jacobs (2014) used separate parameters to model evapotranspiration from plant surfaces and evaporation from open water surfaces. In each case, outdoor water use was assumed to essentially result from replenishing of water lost from evaporating surfaces. Outdoor consumption was deduced from monthly averaged pan evaporation and effective rainfall data but temperature, which is an important component in climate projections, was not included. Pan evaporation is also known to be sensitive to local conditions and requires application of carefully chosen pan coefficients (Sumner and Jacobs, 2005).

The estimation of outdoor water use is a fundamental issue in modelling residential water demand in southern Africa. One factor that makes outdoor water demand modelling problematic is the large variation observed between seasons and geographical locations. Correlating water use estimates and measured consumption is further complicated by uncertain behavioural responses of consumers to landscape water needs (Du Plessis and Jacobs, 2014). Considerable variability in outdoor consumption often occurs amongst residential stands of similar characteristics (Jacobs and Fair, 2012). Nevertheless, there is a close association between residential water use and stand area (Jacobs *et al*., 2004; Van Zyl *et al*., 2008; Griffioen and Van Zyl, 2014).

ADAPTED DOMESTIC IRRIGATION WATER END-USE MODEL

Model development

The concept of the proposed CIWU model builds on the REUM outdoor demand model (Jacobs and Haarhoff, 2004) and extends the underlying concepts to include basic weather variables for the study of the impact of climate change on domestic irrigation water use. A set of equations for evapotranspiration and soil water balance were built into CIWU and used to model domestic irrigation water requirements on a daily time-step, in a similar manner to crop water use modelling in case studies by Kuo and Liu (2003) and Smith *et al*. (2012). A calibration scheme using end-use data is suggested for adjusting model parameters to attain best fit to the observed water use while fine-tuning the model to show good agreement with the incidence of irrigation water use events. Notable climate-driven outdoor water uses are pool filling, lawn irrigation and garden irrigation. Other residential water uses located outdoors may also be indirectly influenced by climatic factors and therefore portray seasonal patterns, for example, pool top-ups, car washing etc. The focus in the CIWU model, however, is on domestic irrigation water use. Therefore, the other outdoor water end uses have not been included in the conceptual model presented. The resulting calibrated model is expected to give satisfactory outdoor water use estimates in areas where lawn and garden irrigation are predominant.

Estimation of daily domestic irrigation water needs

Modelling of domestic irrigation water use relies on conceptualizing atmospheric water demand and soil-plant-water interrelationships. Water applied to the landscape is normally lost into the atmosphere through evapotranspiration from the soil and plant surfaces.

Atmospheric water demand is defined as water loss from a hypothetical crop growing in non-limiting conditions, conventionally referred to as reference crop evapotranspiration (Allen *et al*., 1998). Several methods exist for estimating reference crop evapotranspiration, each with unique advantages. The Hargreaves method, for example, models reference crop evapotranspiration accurately enough in certain regions from temperature data alone (Jensen *et al*., 1997). The Penman-Monteith method is chosen here because it has been shown to perform more consistently in different geographical regions than other methods (Sumner and Jacobs, 2005; Benli *et al*., 2010). According to Allen *et al*. (1998), reference crop evapotranspiration is given by:

$$ET_o = \frac{0.408\Delta(R_n - G) + \gamma\frac{900}{T+273}u_2(e_s - e_a)}{\Delta + \gamma(1 + 0.34\ _2)} \qquad (1)$$

where:

ET_o is the reference evapotranspiration (mm/d)

R_n is the net radiation at the crop surface (MJ/m^2·d)

G is the soil heat flux density (MJ/m^2·d)

T is the mean daily air temperature at 2 m height (°C)

u_2 is the wind speed at 2 m height (m/s)

e_s is the saturation vapour pressure (kPa)

e_a is the actual vapour pressure (kPa)

Δ is the slope of the saturation vapour pressure curve at temperature T (kPa/°C)

γ is the psychrometric constant (kPa/°C)

Crop evapotranspiration, ET_c, is related to daily reference crop evapotranspiration by

$$ET_c = K_c \times K_s \times ET_o \qquad (2)$$

where:

K_c is a crop coefficient

K_s is a reduction factor dependent on amount of water left in the soil

Some garden plants are seasonal and their crop coefficients vary within the year. The crop coefficient at each growth stage can be expressed as follows (Allen *et al*., 1998):

$$K_{c\,i} = K_{c\,prev} + \left[\frac{i - \sum L_{prev}}{L_{stage}}\right]\left(K_{c\,next} - K_{c\,prev}\right) \tag{3}$$

where:

i is the day number within the growing season

$K_{c\,i}$ is the crop coefficient on day i

L_{stage} is the length of the stage under consideration

$\sum(L_{stage})$ is the sum of the lengths of all previous stages

The reduction factor, K_s, is given by:

$$K_s = \begin{cases} 1 & , \quad (TAW - D_r) \geq (1-p) \cdot TAW \\ \frac{TAW - D_r}{(1-p) \cdot TAW} & , \quad otherwise \end{cases} \tag{4}$$

where:

K_s is the reduction factor dependent on available soil water

D_r is the root zone depletion in mm

TAW is the total available soil moisture in the root zone in mm

p is the fraction of TAW that a crop can extract from the root zone without suffering water stress.

Incorporating the soil water balance equation

Hypothetically, irrigation takes place to refill the root zone when a given fraction of the available water, p, has been depleted. The amount of water applied at a given event is assumed to be equal to the depth necessary to bring the soil moisture to field capacity. For a plant with an effective root zone, Z_r (measured in mm), the total available water (TAW) at field capacity is:

$$TAW = 1000(\theta_{FC} - \theta_{PWP})Z_r \tag{5}$$

where:

θ_{FC} is the moisture content at field capacity

θ_{PWP} is the moisture content at permanent wilting point

The water stored in the soil at any time is tracked by maintaining a soil-water balance at a daily time-step (Kuo and Liu, 2003; Davis and Dukes, 2010) instead of monthly averages used in REUM. Groundwater contribution and effective rainfall are the two inputs of the water balance equation that are particularly difficult to measure or estimate. Since the water table is usually below 1 m in residential neighbourhoods, its effect on the root zone will be negligible. At a daily time-step, it is reasonable to assume that effective rainfall is limited to the amount that fills up the root zone (Davis and Dukes, 2010). Any rainfall in excess of this amount is assumed to be lost as runoff or deep percolation. The irrigation water use is given by the following simplified form of the soil-water balance equation:

$$IR_{e,j} = w_{e,j-1} - w_{e,j} + ET_{c\ e,j} - r_j \tag{6}$$

where:

IR is the net irrigation requirement

ET_c is the crop evapotranspiration

r is effective rainfall

w is soil moisture depletion in the soil at a given time

subscripts e and j denote end use and day of the year, respectively

The landscape is assumed to be divided into areas comprising plants of similar water use characteristics. Once suitable parameter values have been estimated for each type of feature, the landscape water use can be computed from the daily water requirement of each peculiar plant area. For any given period, n, the outdoor water use, is calculated from the summation of values of the irrigation requirement, IR, obtained at each time-step. Unlike monthly averaged water use estimates in REUM (Jacobs and Haarhoff, 2004), the monthly domestic irrigation usage is derived from the summation of the daily irrigation requirements as:

$$MIR_m = \sum_{e=1}^{n} \left((f_e \times \varepsilon_e \times s_e) \sum_{i=d}^{d+d_{month}} IR_{e,i} \right) \tag{7}$$

where:

MIR is the estimated monthly outdoor water use

ε represents the efficiency of the irrigation system

f relates to over-irrigation and under-irrigation

s is the surface area of the vegetation type

IR is the irrigation requirement

d is the number of days in the month

n is the number of types of vegetated surfaces

subscripts m and e denotes month and outdoor end use respectively.

Data requirements

As outdoor water use is estimated from outdoor water-using features, the presence and characteristics of the various features need to be determined as accurately as possible for the location of interest. End-use models typically have huge data requirements at their development stages. Populating parameters for each determinant of the domestic irrigation water use model requires, at minimum, data that describes the weather, the characteristics of landscape features and calendars of seasonal garden activities.

Weather data plays a central role in simulating atmospheric water demand. In some regions, acquiring weather data may not be a straightforward task. The model may not be effectively applied in regions where weather data of satisfactory quality is not available. The common issues are sparse networks of weather stations, or stations reporting only a subset of the desired weather variables or in some cases extended periods of missing values. The increased availability of automated weather stations, most of which are capable of continuous and remote data acquisition, is expected to help overcome these challenges.

Data required to populate parameters that characterise vegetated surfaces, including the cropping patterns of seasonal plants, can be sourced through household surveys, fixture audits and the use of geographical information systems (GIS). A number of case studies have demonstrated that landscape features can be demarcated, characterised and measured using aerial photographs or high-resolution satellite images (Mayer *et al*., 1999; Du Plessis and Jacobs, 2014; Hof and Wolf, 2014). DeOreo *et al*. (2011) have shown that the latter approach yields better results than measurements provided by survey respondents. For effective model calibration, a corresponding data set of actual irrigation water use is necessary.

Model calibration

Calibration is necessary to ensure that the irrigation water use model reproduces observed values reasonably well under the given climatic conditions. Some of the model biophysical parameters cannot be determined directly without elaborate laboratory analyses or experimentation. Soil properties in particular can be expensive and time consuming to measure. Even if the measurements were carried out, it is unlikely that the scale would be representative of the heterogeneity of the landscapes in all the neighbourhoods concerned (Wagener and Wheater, 2006). In addition, suitable over- and under-irrigation factors need to be identified considering the end users would not apply the exact amounts of water required by the plants. Reliable over-irrigation or under-irrigation factors are particularly challenging to determine because of uncertainty in human behaviour. The root zone depletion levels also need to correspond with the end-user water application intervals. Similar challenges in parameter estimation are addressed through calibration in other water-related applications. Numerous case studies that utilise parametric calibration have been published in water distribution network modelling (Madsen, 2000; Van Vuuren, 2002; Van Dijk *et al*., 2008), rainfall-runoff modelling (Ndiritu and Daniell, 1999) of watersheds, etc. The calibration process involves the systematic adjustment of parameter values to achieve good agreement between model outputs and the observed values. The parameter values have to be maintained within their acceptable ranges, based on physical and mathematical constraints, while the model performance is evaluated by an objective function until an optimum is reached. A common optimisation scheme is to minimise the sum of squares of deviations between simulated water use and observed consumption.

If end-use data is available, optimisation can focus on multiple facets of the observed outdoor water end uses. One such strategy would be to minimise the sums of squares of the total volumetric water use as well as the observed frequencies of water application events. The benefit realised from using the second objective function is that the final model will generate water application events that reflect the frequency of water application of the consumers. The use of multiple objectives on the other hand leads to computational complexity. The solution may not be a straightforward set of parameters but pareto-optimal solutions encapsulating the entire range of the feasible parameter values (Madsen, 2000). Solving the optimisation problem requires choice of an appropriate algorithm. The two broad classes are local and global optimisation algorithms (Duan *et al*., 1992). Global optimisation algorithms have the advantage of avoiding local minima by examining the entire search space to arrive at a global minima or maxima. Genetic algorithms are quite popular for solving global optimisation problems because of their simplicity, which nonetheless comes at the expense of processing time and computing resources (Koppel and Vassiljev, 2009).

INTEGRATING CLIMATE CHANGE IMPACTS INTO THE DOMESTIC IRRIGATION WATER-USE MODEL

The irrigation water end-use model, once properly calibrated to suit a given location, provides the means to assess potential impacts of future climatic conditions on irrigation water use in that location. Figure 2.1 shows a schematic of the CIWU modelling framework. Potential future water use is evaluated by inputting weather data sets generated from projections of climate models for a selected climate change scenario. It is then possible to make comparisons of the prevalent water use with the projected usage for selected future climate scenarios. The sensitivity of irrigation water use to geographical characteristics implies downscaling to smaller spatial scales applicable to cities.

The proposed CIWU model is a potential tool for planning of various adaptation measures under climate change relating to domestic irrigation water use. Several options for managing domestic irrigation water use are viable. The choice of the actual measures to implement would consider the savings attained by checking water use estimates predicted by the model as an appropriate variable is adjusted over its feasible range. For example, xeriscaping can be reflected in the model by reducing the size of irrigated areas in the model. Introduction of irrigation equipment that reduces water losses means a higher value of irrigation efficiency becomes applicable in the model. A smaller crop coefficient would be used to represent a change to drought-tolerant landscaping plants.

CONCLUSIONS

This paper has discussed an integrated modelling approach for assessing impacts of climate change on domestic irrigation water use. Modifications to REUM outdoor water demand model associated with climatic parameters have been presented. The Penman-Monteith equation has been introduced into REUM for calculating potential evapotranspiration in the place of pan evaporation. The modified model is formulated to simulate water use at daily time-steps by maintaining a soil-moisture balance of the root zone. Weather data and information on landscape characteristics are the required inputs, whereas measured irrigation water use data is necessary for calibration. Calibration is required to select optimal values of some biophysical parameters which cannot be measured directly in a practical manner. Coupled with future climate projections from GCMs and relevant GHG emission scenarios, the proposed CIWU model can allow the quantification of uncertainty in the simulation of future domestic irrigation water use. The theoretical framework presented provides a potential tool for planning of various adaptation measures relating to climate-driven domestic irrigation water use.

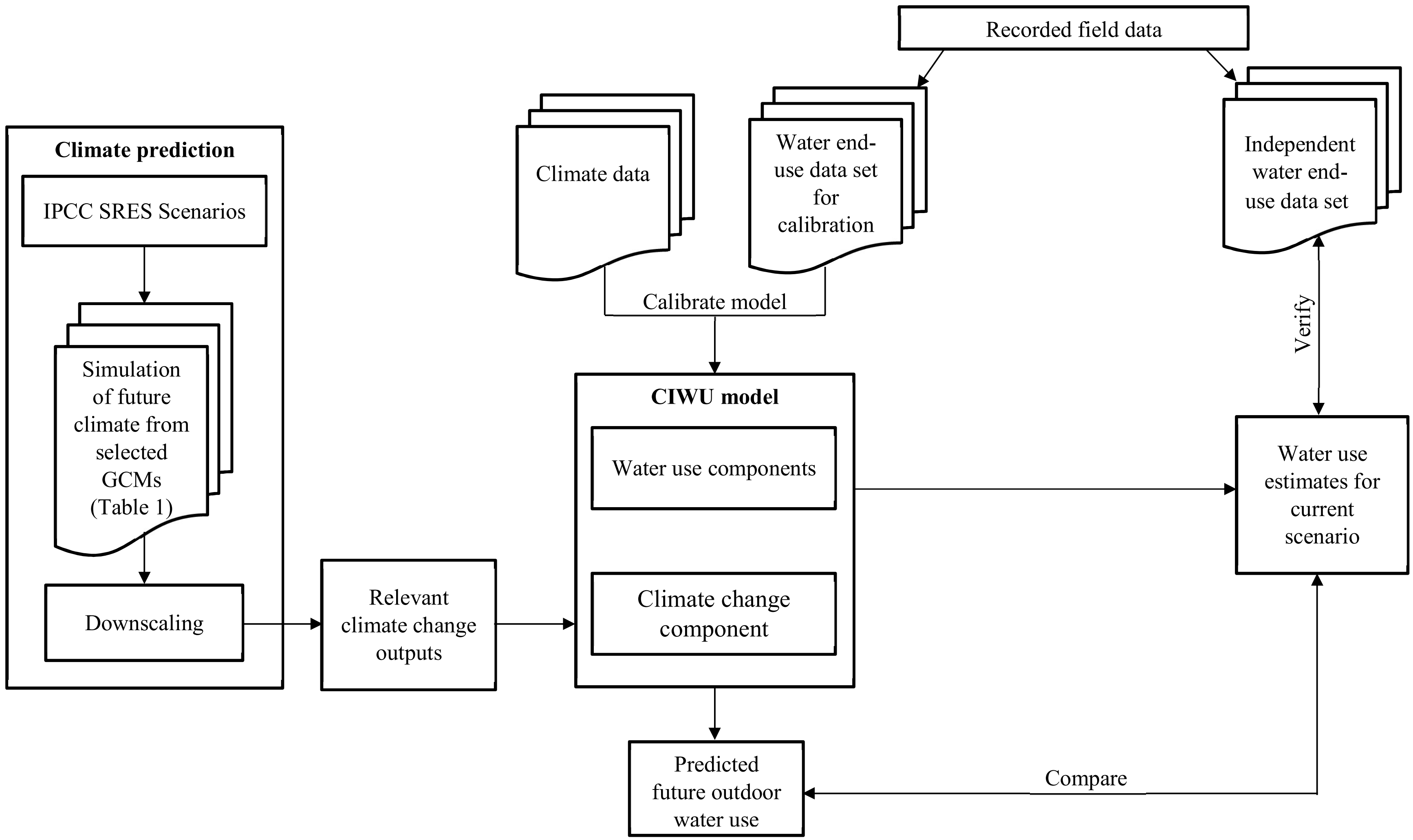

Figure 2.1 Schematic of CIWU modelling approach

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Chapter 3

Sound recording to characterize outdoor tap water use events

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ABSTRACT

Obtaining disaggregated water use at the home typically involves expensive smart metering. In this study, water use events at the outdoor tap were alternatively captured using recorded sound. Outdoor taps at 10 homes were fitted with small-sized microphones and digital sound recorders. Sound files recorded over a 1-month period were used in the analysis. In the preliminary analysis, a human operator browsed through the sound recordings, picking out tap use events based on visually recognizable waveform and spectrogram features, then audibly verifying each event identified before labeling. The performance of the corresponding automatic detection algorithm was reasonable, showing that water use events can be detected at precision and recall rates of at least 80% under suitable conditions. The results also showed that the technique is less suitable where the drop in pressure during peak demand periods results in significant reduction in the tap flowrate. Indirect flow sensing approaches are attractive for investigating water use event timing, because of the relatively lower cost when compared to conventional or smart water meters. Plumbing changes are not required as the recorder can be mounted on any exposed pipe section near the fixture of interest.

Key words | outdoor tap, sound, water use

INTRODUCTION

Assessing climate-related impacts on residential water use hinges to a large extent on the correct determination of outdoor water usage. Residential water end-use studies have further shown that disaggregated water use data unveils patterns of fixture usage that are hardly noticeable in aggregated water consumption records. Detailed knowledge of the usage of specific types of fixtures in the home improves the planning and evaluation of the relevant water conservation measures (DeOreo *et al.* 1996). A typical approach to obtain disaggregated water use data involves smart metering and flow trace analysis. The costs associated with smart metering are relatively high, so that the related studies have largely been confined to developed regions. Survey techniques such as questionnaires or diaries are cheaper but the accuracy of the results is often limited.

A number of studies have proposed indirect approaches for sensing water usage in the home at the fixture level. Human activity recognition, mediated by the home plumbing system, has been the main interest in most of the reported research. Chen *et al.* (2005), for example, examined the use of microphones to monitor the activities of patients in the bathroom. In similar work, Forgarty *et al.* (2006) mounted a microphone on the main supply pipe to sense flow every time water was used in the study home. The profile of fixture usage was then obtained by applying a pattern recognition computer algorithm. Other reported applications of microphone based flow sensing include oil and gas monitoring by Lapinski *et al.* (2007) and the monitoring of field sprayers by Zhang (2014). Froehlich *et al.* (2009) instead logged fixture use by a pressure sensor connected to the home plumbing system through any accessible valve. Kim *et al.* (2012) later tested the use of accelerometers, installed on pipework leading to water use fixtures in the home, to infer in real-time the fixture in use and estimate the flowrate from the measured pipe vibrations. Indirect flow sensing approaches are attractive because of the relatively lower total installation cost. Unlike inline mechanical flowmeters, accelerometers or microphone sensors do not require plumbing changes since they can be easily mounted on any exposed pipe section of the fixture of interest. Unfortunately, event volume cannot be reported as accurately as with smart metering technology.

The aim of the field study reported in this paper was to test the suitability of sound recording for capturing residential outdoor tap use events. The paper presents the microphone and sound recorder setup, the steps taken to abstract water use events from the sound recordings, and the results from the application of an automatic detection algorithm. The use of microphones was preferable to accelerometers because the recorded tap flow sound could be audibly verified during analysis. Precautions had to be taken, though, to avoid capturing sounds that would lead to privacy intrusion. The findings in this study demonstrate the potential for using recorded sound as a low-cost option for obtaining frequencies and durations of disaggregated water use events at the outdoor tap.

RESEARCH METHODOLOGY

Recorder choice and setup

Sound was captured at the outdoor tap using Sony ICD-PX333 recorders. The Sony ICD-PX333 model was chosen following a review of a number of digital sound recorders available at the time of the study. The selected sound recorder model had the capability to record continuously by automatically creating new files when the current recording reached the file size limit. The internal 4-gigabyte memory lasted approximately 6 weeks when recording at 8 kilobytes per second (kbps) in MPEG layer 3 (MP3) format. The 8 kbps recording setting was chosen because of the significant saving on computer storage space despite being the lowest recording quality for the ICD-PX333 model. The recorders were connected to an external pack of two D-type alkaline batteries instead of the usual AAA batteries in order to extend the battery life to match the total recording time of the ICD-PX333 recorder.

Study period and selection of study homes

The study was first conducted from December 2014 to January 2015 and later repeated from May 2015 to July 2015. The first study period captured the last few weeks of summer and extended into the rainy season while the second period fell in the cool dry season. Study homes were located in three neighborhoods in the City of Lilongwe, Malawi. In the first period of the study, 10 students from the Lilongwe University of Agriculture and Natural Resources (LUANAR) agreed to have the sound recorders installed at their homes. Most shortcomings in the recorder installation and setup procedure were discovered and addressed during the first study period.

Only three homes were carried over from the first to the second study period. The other seven homes were dropped either due to limited outdoor water use or not having replanted their backyard garden with new crops at the time the study was repeated. The seven homes were replaced by selecting additional homes from a larger sample of homes that had participated in an outdoor water use survey that was carried out at about the same time as the first study period. Discussions with a handful of homeowners from the survey participants led to the identification of those who had no objection to the continuous recording of sound at their outdoor tap. The final selection was based on the availability of a home garden that was irrigated exclusively from the outdoor tap. In addition, homes where the outdoor tap was located immediately next to the main house or another building were avoided to minimize interference of sound from other water use fixtures. Hosepipes were used for garden irrigation at seven of these homes while buckets were used at the other three. The analyses presented in this paper were, however, performed on 1-month long data from the second study period when there was more outdoor water use and the recordings were more consistent.

Installation of microphones and recorders

The outdoor taps were fitted with electret condenser microphones midway between the tap branch pipe. The microphones were covered by PVC rubber and firmly attached to the tap branch pipe using cable ties. The purpose of the rubber coverings was to protect the microphone from getting soaked with water and to block airborne sound that would complicate analysis. In order to block water vapor, the recorders were sealed in plastic pockets with tape. The sound recorders, including an external battery pack, were then covered inside tight-fitting plastic enclosures that were securely placed in a hole drilled next to the tap. Holes were made through one side of the enclosures to provide a passage for microphone wires and sealed in place with water-resistant adhesive. Gardena flow meters were screwed onto the taps to measure the total volume of water. The Gardena flowmeters stored the total volume of water used electronically and were read once every month. The volumetric flow measurements were, however, not used in the analyses because the flowmeters were tampered with at some of the homes. Figure 3.1 shows the complete microphone and recorder setup.

Figure 3.1 Complete setup of recorder (in PVC casing) and microphone (covered by a block of PVC rubber) at the outdoor tap.

Recordings for exploring the characteristics of sound from the taps

In order to get acquainted with characteristics of the flow induced sound, six water use events were recorded at each tap at the beginning of the study. First the tap was opened fully to reach the highest possible flowrate while filling a bucket of known volume. If a hosepipe was used for garden irrigation at the respective home it was connected to the tap, otherwise the water was run directly into a bucket. Secondly, the tap was opened just enough to reach steady flow and lastly the tap was run at an arbitrary intermediate flowrate. The procedure was repeated and the start and finish times of the events were noted. The first recordings provided insight into the expected properties of the subsequent audio signals.

Recording and preparation of recorded sound files for analysis

Files were transferred from the recorders to a computer once every month. The MP3 files were first split into 24-hour segments each of which had a size of 84 megabytes except the last file which was shorter. The 24-hour segment length was chosen because it simplified the matching of dates and their recordings while at the same time not being too large to load into computer memory for analysis. The audio files were uncompressed to WAVE format which can be read by most computer programs as ordinary binary files. The MP3 files were converted to 16-bit wave file at a sampling rate of 11,025 samples per second. The file conversion increased the file size to 1.86 gigabytes, approximately 22 times larger than the size of the original MP3 file.

Manual extraction of tap-use events

The 1-month long recordings from the second study period were manually analyzed by a human operator using Audacity software in order to abstract water use events. In order to visualize the sound properties at each point in time, duplicate audio tracks were added to a single timeline for each file being analyzed. The first track was displayed as a waveform, while the second track was changed to display as a spectrogram of 1,024 samples per window. An additional 'label' track was added to the timeline for marking and annotating water use events identified in the recording. Tap water use events were identified from changes in the amplitude of the waveform and visually distinguishable patterns in the spectrogram. For consistency, the audio tracks were scaled to fit a 2-minute long window in the available horizontal display area of the Audacity software user interface. The appropriate keys on the computer keyboard were pressed to scroll the tracks forward or backwards at 2-minute long intervals. Sounds lasting no more than 2 seconds were clearly recognizable. Any changes noted in the waveform or spectrogram were further examined by playing and listening to the respective segment. Sounds from other sources were separated from the typical hissing or splashing sound associated with a running tap. Only tap flow events lasting for at least 2 seconds were labelled. Once a file had been browsed through to the end, all labels created for each file were copied to an Excel workbook for further analysis. A single 24-hour file took about 15–30 minutes to analyze depending on the number of sound events present.

Audio features used for automatic change-point analysis

Manual abstraction of water use events from the sound files proved to be a laborious and time-consuming procedure. A more realistic approach is to use computational techniques to automate the detection of water use events from the sound files. An automatic algorithm was developed and applied in order to test the performance and suitability of the approach for detecting water use events from flow sound at the outdoor tap. The automated algorithm was implemented in Visual Basic for Applications but included a dynamic link library written in C++ for reading WAVE files.

Sound files typically contain huge amounts of data that take too long to process directly. The audio signals were reduced by computing the short-term energy of a moving window of length 2.5 milliseconds. The magnitude of the short-term energy generally increases when water is flowing in the pipe (Fogarty *et al.* 2006; Jacobs *et al.* 2015). Prior to the transformation of the signal by short-term energy, a Chebychev high-pass filter was applied to the recordings to attenuate frequencies below 700 Hz, which comprised most of the unwanted sounds. The normalized short-term energy, also referred to as the power of the signal, was computed by (Giannakopoulos & Pikrakis 2014):

$$E(k) = \frac{1}{W_L}\sum_{n=1}^{W_L}|x_k(n)|^2 \tag{1}$$

where k is the window number, n is the sample number, W_L is the window length and $x_k(n)$ is the audio sample at the kth position in window n.

Algorithm for change-point analysis

Change-point analysis was used to segment the signal. The goal of change-point analysis was to identify points in the signals where there were abrupt changes in the distribution of the short-term energy. Chen & Gupta (2011) have described a number of approaches that are commonly used for change-point analysis. In this study, the Schwarz Information Criterion (SIC) approach was adopted. The SIC method involves testing the null hypothesis that there is no change-point in a signal. The alternative hypothesis is that there is exactly one change-point in the signal.

Assuming a Gaussian distribution for the natural log transform of the short-term energy values with parameters (μ_1, σ_1), …, (μ_n, σ_n), the null hypothesis that was tested was:

$$H_0 : \mu_1 = \cdots = \mu_n = \mu \text{ and } {\sigma_1}^2 = \cdots = {\sigma_n}^2 = \sigma^2$$

against the alternative hypothesis:

$$H_1 : \mu_1 = \cdots = \mu_k \neq \mu_{k+1} = \cdots = \mu_n \text{ and } {\sigma_1}^2 = \cdots = {\sigma_k}^2 \neq {\sigma_{k+1}}^2 = \cdots = {\sigma_n}^2$$

where k is the location of the change point and n is the total number of samples. Chen & Gupta (2011) have presented a detailed derivation of the SIC approach based on the log likelihood functions under H_0 and H_1. The key formulae are given below. The SIC given no change point is calculated by:

$$SIC(n) = n\log 2\pi + n\log\hat{\sigma}^2 + n + n\log n \quad (2)$$

and the SIC assuming a change in mean and variance at any point k is calculated by:

$$SIC(k) = n\log 2\pi + k\log\hat{\sigma}_1^2 + (n-k)\log\hat{\sigma}_n^2 + n + 4\log n \quad (3)$$

where the variances σ^2, $\sigma_1{}^2$ and $\sigma_n{}^2$ are estimated from the signal. The minimum $SIC(k)$ is used to test the null hypothesis. A change point is considered to have occurred if:

$$SIC(n) > \min_{2\leq k\leq n-2}\{SIC(k)\} \quad (4)$$

The location of the change point corresponds to the value of k that minimizes $SIC(k)$. A binary segmentation algorithm as presented by Eckley *et al.* (2011) was then used to recursively apply the SIC change-point analysis procedure on the signal subsequences created at each step until no more change-points could be detected.

Automated detection of tap-use events

Segments in which flow was present were detected from the change point analysis results by applying a short-term energy threshold. Recordings from the first week of the study period were set aside as training samples for the determination of appropriate short-term energy thresholds tailored for the study home (SH) at hand. The performance of the automatic algorithm was assessed by comparing the detected tap flow event times to the manually abstracted flow event times. For each study home, precision was calculated as the percentage of the total detected time that coincided with the manually abstracted event times. Recall was obtained by expressing the coincident event time as a percentage of the total flow time obtained manually. The detection algorithm was applied at various systematically adjusted short-term energy threshold values. The suitability of each threshold value was evaluated by the F score, calculated according to Equation 5:

$$F\ score = (2 \cdot precision \cdot recall)/(precision + recall) \qquad (5)$$

The F score gives a harmonic mean between precision and recall commonly used to quantify the discrimination of classes by a classification algorithm (Polat & Güneş 2009). Higher values of the F score statistic are associated with better detector performance. The energy threshold value that gave the highest F score value was adopted and tested in the subsequent 3-week long sound recordings.

RESULTS

Waveform and spectrogram properties

In the absence of sound, the audio signal had a relatively low amplitude waveform. These sections were characterized by random noise normally referred to as "white noise". Ideal white noise is composed of all frequencies at generally equal levels. When played, these white noise segments had a clearly recognizable soft sound. The spectrograms for the silent segments of the signal were relatively sparse and uniform except for a slightly denser region in the low frequency band. Figure 3.2(a) shows a typical waveform and spectrogram for a white noise segment. The short-term energy signal was observed to follow a diurnal cycle with values that gradually increased during the day and dropped at night. The actual cause of the cyclic variation was not established but it is likely that the rise in noise level during the day and the increase in temperature of the tap branch pipe contributed to the observed variation. The magnitude of the diurnal change was, however, observed to be small in comparison to the changes caused by flow sound. The diurnal variation was therefore neglected.

Time periods when the tap was running were characterized by larger amplitudes in the signal waveform. Flow sound caused an increase in the color intensity of the spectrogram in the higher frequency bands. Unique horizontal bands could also be traced along the spectrogram which contrasted with other types of sounds in the signal. Figure 3.2(b) shows a waveform and spectrogram of flow sound for a tap with a hosepipe connected while Figure 3.2(c) shows the effect of running the water into a bucket. In many cases the onset of a tap use event showed a sudden and brief rise in the waveform amplitude, caused mainly by the rapid transition from low to high flow. The turning of the handle when opening or closing the tap also contributed to the louder sound observed at the start and end of most events, which was useful in cases where other sounds had to be screened out. As might be expected, the splashing of water running directly from the tap into a bucket was usually loud enough to mask the onset transient. Figure 3.2(d) represents an indoor water use event that was recognizable at the outdoor tap. It can be noted that the waveform amplitude was small for indoor events and that the spikes normally present at the start and end of tap use events were virtually absent.

Sound is conducted reasonably well through solids. As a result, sounds from objects hitting the tap or other objects nearby the tap were present in the recordings. In the majority of the cases, these sounds created easily noticeable irregularities in the signal waveform and spectrogram. An exception to this observation was the sound of objects being moved over surfaces nearby the tap, which had a similar spectrogram to that of flow sound. These noises, however, were not problematic because they were infrequent, only lasted for brief moments and were easy to distinguish audibly. Figures 3.2(e)–3.2(g) show the waveforms and spectrograms for the sound of an object hitting the tap, sound of hammering nearby the tap and an object being pushed over the ground near the tap respectively.

While there was not much indication of airborne sound in the recordings, the rubber microphone coverings did not seem effective at blocking loud and high pitched airborne sounds. Speech sound, for example, was rarely noted in the recordings while the sound of the barking of dogs, as shown in Figure 3.2(h), was found in most of the recordings. Occasionally, loose cable ties on the rubber coverings would open the microphone up to ambient noise but these cases were corrected soon after being discovered. Heavy vehicles passing by a nearby road generated intense but low frequency sound as shown in Figure 3.2(i). A mobile phone brought near the sound recorder could also cause interference in the audio signal as shown in Figure 3.2(j).

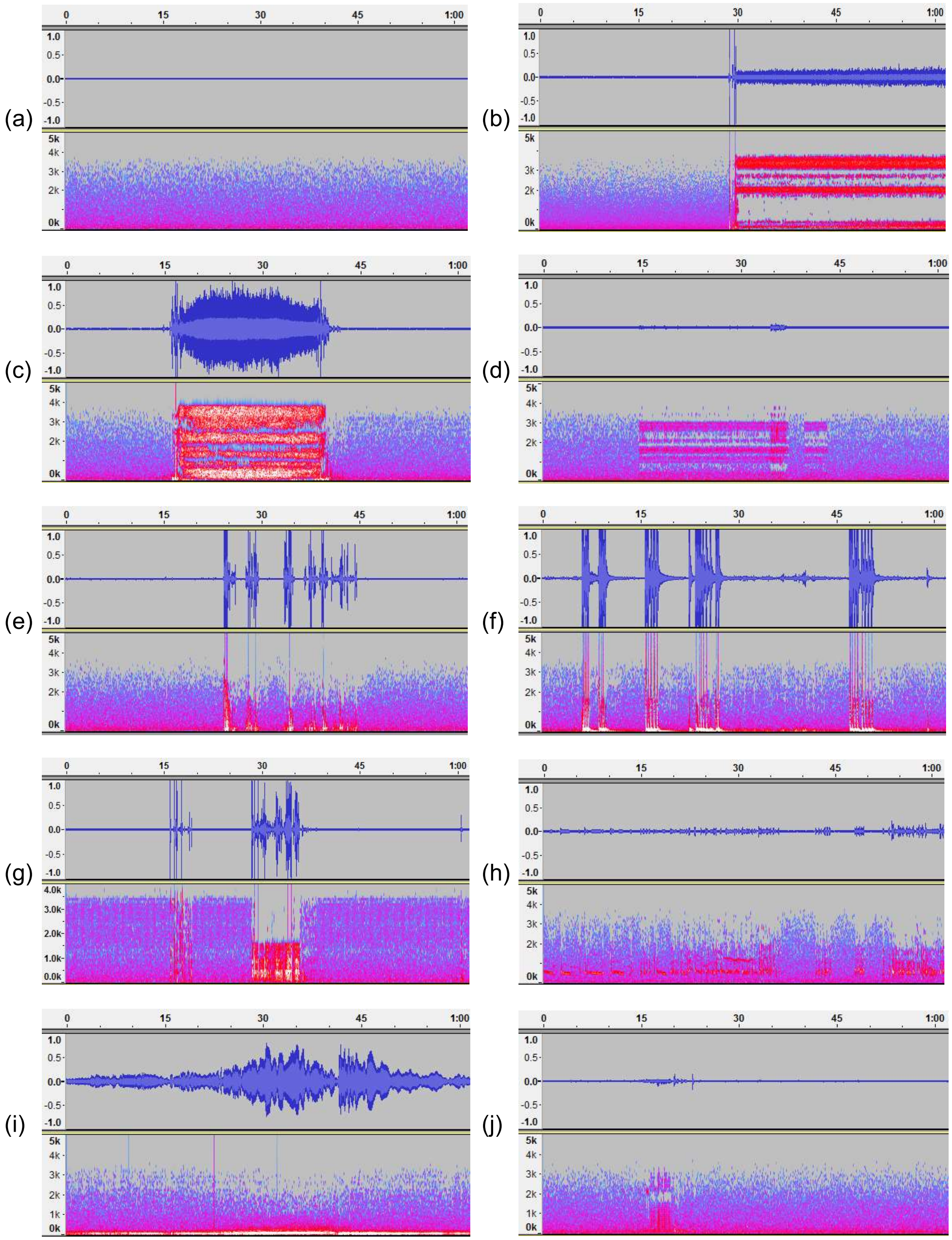

Figure 3.2 Waveforms and spectrograms of (a) white noise section with no sound recorded, (b) water running through a hosepipe, (c) water run into a bucket, (d) an indoor water use event, (e) object hitting tap and nearby objects, (f) hammering near the tap, (g) object sled over the ground near the tap, (h) dogs barking, (i) heavy vehicle passing through a nearby road and (j) mobile phone interference.

Comparison of manually extracted events and automatically detected events

The precision, recall and F score values obtained from the application of the automatic detection algorithm to the training and test data sets are given in Table 3.1. The detection algorithm performed well for SH1, SH2, SH3, SH4 SH5 and SH7. The high F score values for these homes were possible because the sound of flow in the recordings was generally louder, allowing higher energy detection threshold values to be used. Higher threshold values reduced false positives substantially, and contributed to overall good detection performance. On the contrary, the performance of the detection algorithm was poorer for homes that experienced low water pressure on a regular basis, typically during peak demand periods. According to the homeowners, SH8, SH9 and SH10 experienced significantly reduced water pressure during the morning. These three homes were located in the same neighbourhood near a stadium that was still under construction during the study period. It is likely that water pressure in the entire neighbourhood was affected by water use at the construction site. Lowering the threshold to detect the quieter flow sound in the recordings correspondingly increased false positives and reduced the precision.

Table 3.1 Performance of the detection algorithm

	Training dataset			**Test dataset**		
Study home	**Precision (%)**	**Recall (%)**	**F score**	**Precision (%)**	**Recall (%)**	**F score**
SH1	92.4	92.5	92.4	97.2	82.4	89.2
SH2	96.1	100.0	98.0	96.0	99.9	97.9
SH3	75.9	96.7	85.1	77.6	94.8	85.3
SH4	97.2	99.3	98.2	93.0	96.1	94.5
SH5	98.7	98.7	98.7	98.6	99.0	98.8
SH6	83.2	77.9	80.5	88.2	68.5	77.1
SH7	97.6	98.9	98.3	98.5	91.0	94.6
SH8	51.5	82.6	63.4	78.2	68.7	73.1
SH9	59.8	49.7	54.3	81.7	37.5	51.4
SH10	63.2	88.7	73.8	67.9	80.1	73.5

The quieter sound of flow related to reduced pressure also presented challenges for the human operator labelling water use events. In some cases, the sound of flow would gradually fade in the course of a long water use event until the waveform and spectrogram closely resembled non-flow sections. One could classify these sections as flow when in fact the tap temporarily stopped running, or on the contrary, there could merely have been a transition from loud and turbulent flow to quiet and smooth flow following a drop in flowrate. In the manual analysis, if the waveform, spectrogram or audible sound did not indicate flow, the corresponding segment was not labelled as flow even if it occurred between tap open and close events. Overall, the characterization of flow sound was less precise at low flowrates.

At SH6 and SH9, the outdoor tap was located between the water consumption meter and the house. Many events detected in the automatic algorithm lacked the noise of the tap open and close features shown in Figure 3.2(d), except that the amplitude of the waveform was larger. It was suspected that the outdoor tap standpipe branched off directly from the pipe running into the house so that the sounds of indoor water use events were just as loud in the recordings. The application of the simple energy threshold based technique alone did not effectively separate the sound of indoor water use events from the outdoor tap water use events, leading to reduced F scores at these two homes.

Outdoor water use characteristics

Figures 3.3 and 3.4 are presented to show the general pattern of water use at the outdoor taps of the study homes for the period analyzed. The summaries were limited to the study homes that had an F score of at least 85% in the test data detection results. SH6, SH8, SH9 and SH10 were therefore excluded in the results presented in Figures 3.3 and 3.4.

Although the study was targeted at water used for garden irrigation, most of the homeowners had indicated other uses of the outdoor tap that are ordinarily associated with indoor use, for example washing clothes or cleaning the house. Figure 3.3 presents the frequency distribution of the outdoor tap water use events according to duration, plotted on a logarithmic scale. At least 50% of all the water use events lasted 1 minute or less, indicating significant use of the outdoor tap for purposes other than irrigation at the homes where a hose pipe was used for irrigation.

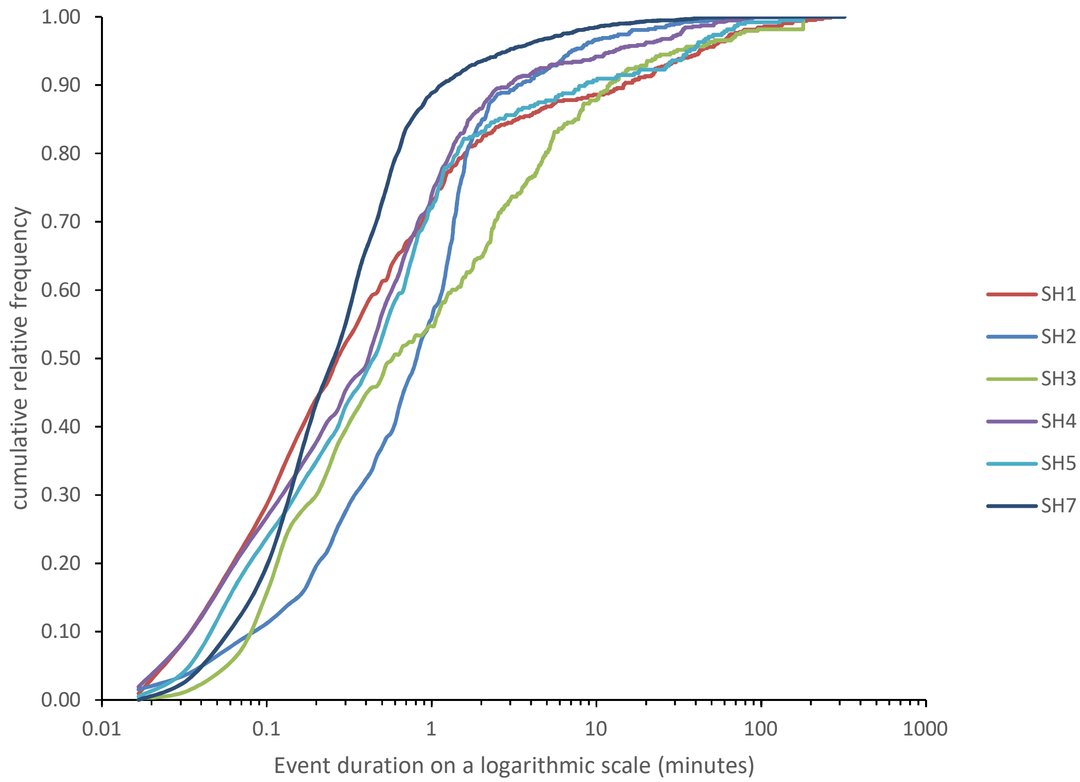

Figure 3.3 Frequency distribution of tap water use events by duration.

Figures 3.4 and 3.5 show the diurnal tap use pattern during weekdays and on weekends respectively. The horizontal axis represents the time of the day in hours while the vertical axis represents the total duration the tap was running during each respective hour averaged over the 1-month study period and the study homes. Generally, peak water use at the outdoor tap occurred between 8 and 11 am. Pressure at the outdoor tap is likely to vary with time throughout the day and from one household to another. As a result, the duration of tap use shown in Figures 3.4 and 3.5 does not exactly represent the intensity of water use. The two figures, however, portray periods during the day when most outdoor tap use activities occur.

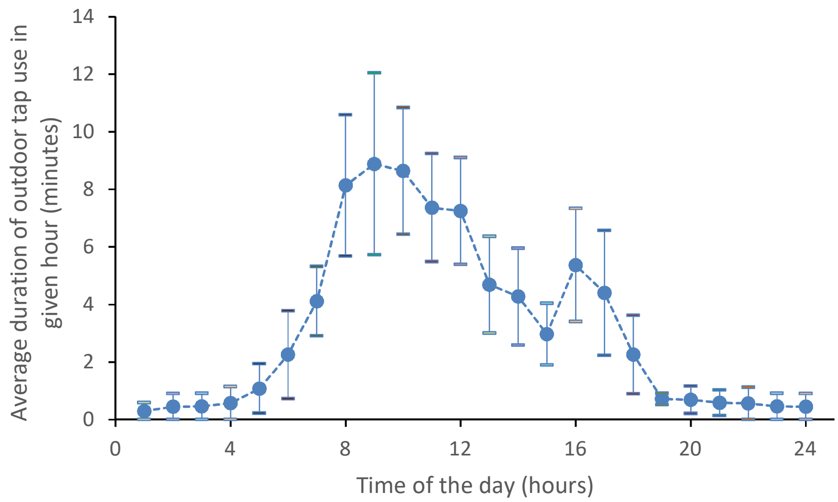

Figure 3.4 Diurnal water use pattern during weekdays.

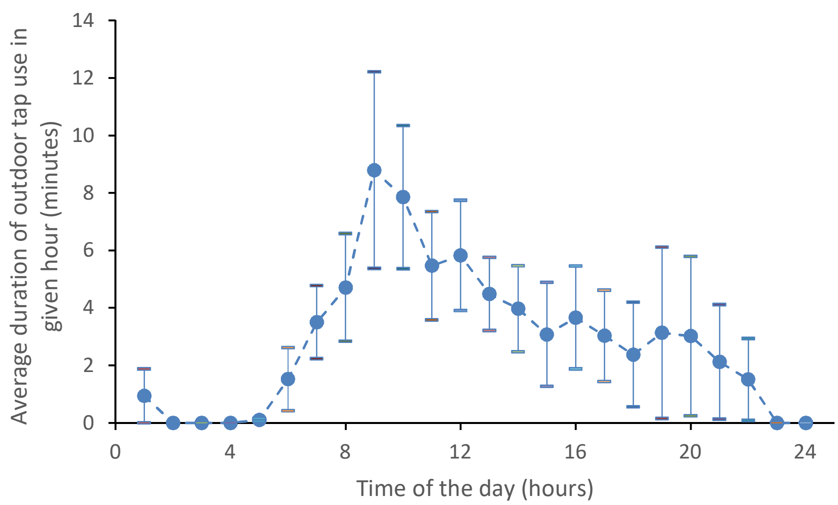

Figure 3.5 Diurnal water use pattern on weekends.

DISCUSSION

Privacy issues

It is likely that continuously recording sound, as was the case in this study, could potentially intrude into personal privacy of the homeowners. Presumably, recording speech sound would particularly raise concerns among many people. Besides privacy issues, continuous recording creates large files which dramatically increase storage requirements and computer processing time. The use of a barrier to block sounds, as in this study, may not sufficiently protect the homeowners' privacy. Another measure could be the use of custom designed modules that are configured to sample short durations of sound at intervals that render critical sounds, speech for instance, indecipherable. A similar configuration was used by Fogarty *et al.* (2006), though not for privacy reasons, with the benefit of low disk storage requirements. Alternatively, the signal could be preprocessed so that only the parameter values of interest are stored.

Further research

This study focused on detecting the start and finish times of the outdoor tap water use events. Some reported studies suggest the potential for estimating the flowrate from the flow induced sound or vibrations. Evans *et al.* (2004) have demonstrated that pipe flowrate is strongly correlated to the variance of the noise of audio signals from the pipe. Kakuta *et al.* (2012) developed a relationship between flowrate and the sound pressure level. Jacobs *et al.* (2015) have also shown correlation between flowrate and the amplitude of the peak modus frequency of the sound of a tap. However, these techniques are unlikely to achieve a similar performance for sound recorded at the outdoor tap because the flow induced sound usually mingles with other sounds, such as the running water striking the ground or splashing into a container. Additional challenges include the effect of pipe material, pipe size and age, as well as tap configuration. Further research is required to evaluate the accuracy of flowrate estimates that can be achieved for sound of flow at the outdoor tap. Apart from analytical methods used in the studies above, learned probabilistic models are a potential area that could be exploited to improve the performance of these techniques.

CONCLUSIONS

This paper presented findings from the use of sound to deduce the start and finish times of water use events at the outdoor tap. The analysis was performed on 1-month long sound recordings from the outdoor tap at 10 study homes. Flow sound was noted to have distinct spectral properties that were easily recognizable when the sound waveform was displayed as a spectrogram. The detection of water use events from the recordings was effectively automated by an SIC based segmentation algorithm and the application of a customised short-term energy detection threshold. The approach described is a low-cost alternative to smart metering that is especially suited to the study of outdoor water use.

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Chapter 4

Domestic irrigation water end-use modelling of leafy vegetables

INTRODUCTION

The CIWU model for estimating irrigation requirements for vegetated areas around the home was presented in Chapter 2. The characteristics of the irrigation water using features around the home must be known in order to make estimates using the CIWU model. Water use estimates may be made by applying typical soil and plant parameter values available in literature. The model calculates domestic irrigation water use by the application of mathematical formulae based on soil-plant-water interrelationships. The underlying equations are based on consumptive use from plants grown under standard conditions.

It is highly unlikely that the water users would water their gardens exactly according to the theoretical irrigation requirement. However, an increasing or decreasing plant water requirement would most likely be followed by an adjustment in the amount of water applied, especially if signs of water stress become apparent. Both over-irrigation and under-irrigation have been reported among residential water users in previous end-use studies (Mayer *et al*. 2011). In the CIWU model, plant water use can be represented in numerous flexible ways by choosing the appropriate parameter values. Calibration can therefore be applied to adapt the model parameters to the observed water use.

The purpose of this chapter was to fit the CIWU model to a dataset of actual observed residential irrigation water use for leafy vegetables. During the outdoor tap water use study reported in Chapter 3, a participant who watered his garden using a bucket agreed to maintain a daily record of the amount of water used at each irrigation event. A detailed two-month-long dataset was created indicating the number of buckets of water applied to the backyard garden and the time of each application. The dataset was used in this chapter to test and verify the performance of the CIWU model. The dataset was only sufficient to demonstrate the application of the CIWU model on a single end-use, namely irrigation of leafy vegetables.

METHODOLOGY

Fitting the CIWU model to measured water use involved choosing appropriate parameter values. Seven parameter values were identified from the irrigation water use model: the crop coefficient, K_c, the root zone depth, Z_r, the moisture content at field capacity, θ_{FC}, the moisture content at permanent wilting point, θ_{PWP}, the soil moisture depletion level just before water application, Dr_1, soil moisture depletion level after water application, Dr_2, and the irrigation factor, f_e. Crop factors for most plants are available in literature. For seasonal plants, separate K_c values are provided for the early, mid and late-season growth stages. To correctly apply these K_c values, the planting date must be known. Estimated values of θ_{FC} and θ_{PWP} are also available in literature for different types of soils. However, the determination of soil type requires special tests which were not carried out and which would be unnecessarily demanding considering the nature and aims of this research component. The values of Dr_1 and Dr_2 are dependent on soil moisture levels maintained by the water end user. To maintain unstressed plant growth, the values of Dr_1 and Dr_2 have to be kept close to 0, which is equivalent to the moisture content at field capacity. If the moisture depletion levels approach 1, the plant begins to suffer stress and uses less water. The irrigation factor includes the irrigation efficiency, which accounts for inevitable losses that occur during water application, and a factor representing the tendency for water users to over-irrigate or under-irrigate.

An exhaustive search was implemented to identify parameters of best fit. The search procedure required enumerating and testing all candidate solutions from which satisfactory results could be selected. For this analysis, the search involved testing the entire range of typical values for each parameter. The technique is computationally intensive and can easily become intractable. Two simplifications were made after scrutinizing the model structure in order to reduce the number of parameter combinations to be tested. The parameters root zone depth, Z_r, moisture content at field capacity, θ_{FC}, and the moisture content at permanent wilting point, θ_{PWP}, were first combined to find the total available water, TAW. The parameters Z_r, θ_{FC} and θ_{PWP} were therefore replaced by TAW in the exhaustive search. The upper and lower bound values of TAW were determined from the typical range of Z_r for leafy vegetables and the typical ranges of θ_{FC} and θ_{PWP}. Secondly, a suitable step value was chosen for each parameter to achieve reasonable precision while avoiding too many iterations. Further, a single K_c value was applied for the entire two-month period using the early, mid and late season K_c values to define the range of feasible values. Table 4.1 shows the feasible ranges and step values applied in the exhaustive search, which gave a total of 16,224 feasible parameter combinations. If the parameters were enumerated at half the step values given in Table 4.1, the number of cases to evaluate would have increased from 16,224 to 206,250.

Table 4.1 Ranges of parameters values and step values applied in the exhaustive search

Parameter	Feasible range (Allen *et al*. 1998)	Step value
K_c	0.70 – 1.05	0.05
Dr_1	0.0 – 0.6	0.05
Dr_2	0.0 – 0.6	0.05
Z_r	0.3 – 0.8 m	(lumped into TAW)
θ_{FC} - θ_{PWP}	50 – 200 mm/m	(lumped into TAW)
TAW	15 – 120 mm	10 mm

The penman monteith equation (described on page 14) was used to compute daily values of reference crop evapotranspiration. The weather data used in the calculations were obtained from Chitedze Research Station located about 20 km from the study home in Lilongwe, Malawi. Crop evapotranspiration was calculated using crop factors for leafy vegetables given by Allen *et al.* (1998). The daily crop evapotranspiration and the daily irrigation requirements were calculated using equations presented in Makwiza *et al.* (2015).

For each combination of parameter values, the simulated daily water use values were aggregated at weekly time steps, since water use tends to follow weekly cycles. The two-month water use dataset resulted in 8 weekly estimates of volumetric water use and a count of irrigation days. The total number of days when garden irrigation was observed was used as the first criteria for identifying potential parameter combinations. Only parameter combinations that produced the same number of irrigation events as in the dataset were examined further in the subsequent steps. To determine the goodness of fit, R^2 values were computed from the least squares fit between the simulated volumetric water use and the actual observed usage. The irrigation factor was estimated as the slope coefficient of the least squares fit. Parameter values that produced weekly volumetric use that closely resembled the actual observations were considered more suitable.

RESULTS

Table 4.2 shows the ranges of parameter values that were applied in the exhaustive search and the best-fit parameter values identified through the search procedure. Several other equally good solutions were obtained from the search results. The difference in the R^2 values between these alternative solutions were marginal so that the performance of any of the solutions in the model would be similar.

Figure 4.1 shows the correlation between measured irrigation water use and the crop evapotranspiration calculated from weather data. Figure 4.2 shows the correlation between the observed weekly water use and the theoretical irrigation requirement following selection of optimal parameters. The R^2 values show that there was better correlation between theoretical irrigation requirement and measured water use than there was between evapotranspiration and measured water use. There is however a danger that the model may fit the noise component on top of the underlying relationship considering that the dataset is relatively small. Under such circumstances, the estimated model would not fit a new dataset equally well.

Figure 4.3 presents the predicted irrigation water use and the measured water use ordered in time. The predicted irrigation water use presented incorporates the irrigation factor, estimated as the slope of the regression fit. The amount of water applied varied in response the water requirement, but the actual change was not always timely or proportional. The dataset is, however, too short to provide a clear picture.

Water was applied on 35 out of the 53 days of recorded water use. There was no indication of any pattern in the choice of irrigation days, but in many cases water was applied on several consecutive days.

Table 4.2 Best-fit parameter values adopted identified from the exhaustive search

Parameter	Best-fit parameter values
K_c	1.00
Dr_1	0.5
Dr_2	0.4
TAW	45 mm

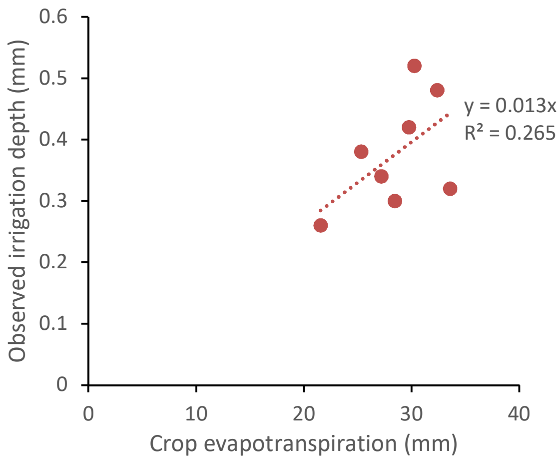

Figure 4.1 Correlation between observed irrigation and reference crop evapotranspiration

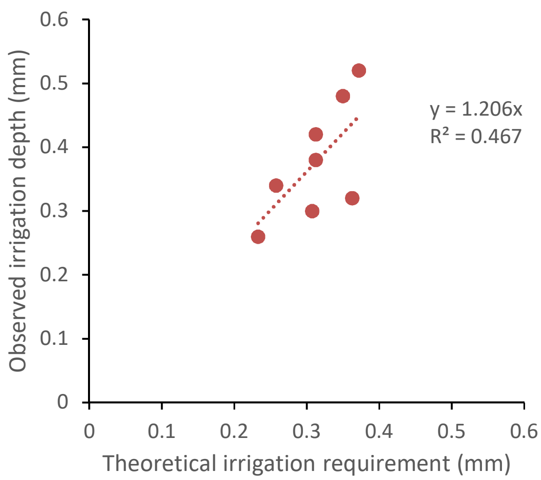

Figure 4.2 Correlation between observed and predicted irrigation water use

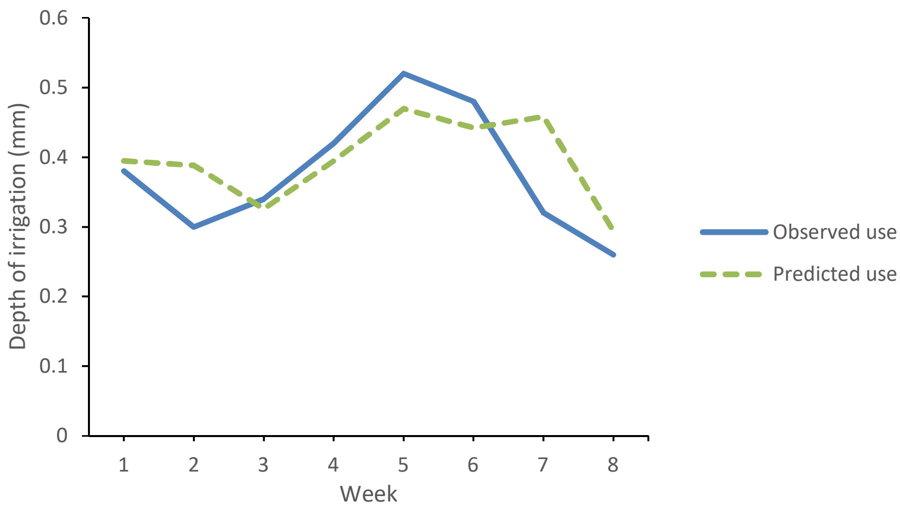

Figure 4.3 Actual and observed weekly water use

The main goal of formulating the irrigation water end-use model was to perform climate impact assessment. A comprehensive climate change analysis is beyond the scope of this chapter. Instead, the sensitivity of the fitted model to changes in temperature was assessed by increasing the input minimum and maximum daily temperature by 1°C, which resulted in only a 1% rise in the predicted irrigation water use.

DISCUSSION

The dataset used in the analysis included 8 data points after aggregating weekly water use. The limited 8-week period was not long enough to allow validation of the calibrated model. Essentially the data would have been split into two in order to use the first half for calibration and the other half for validation. Cross-validation is another approach that may be applied to prevent other pitfalls like overfitting given a dataset that is large enough. The dataset used in this study was, however, longer than most water end-use studies. The short duration of the majority of water end-use studies is a major limitation to the application of the CIWU model, especially in developing countries.

It was also not possible to test the performance of the model under rainfall conditions because the entire dataset was collected during the dry season. The inclusion of the water balance equation was meant to provide a fair estimate of effective rainfall. According to Brouwer (1986), the water balance approach is more reliable than most equations for estimating effective rainfall. Furthermore, the application of the water balance equation allows the simulation of water application frequencies on top of the water use estimates.

Once fitted, the model inputs can be varied to examine how the changes introduced affect the model outputs for the particular end-uses. Leafy vegetables considered in this study are one category of irrigation water end-uses at the home. The approach presented can be repeated for other types of garden plants in order to obtain representative parameter values.

CONCLUSION

In this chapter, the CIWU model was fitted to an actual observed water use dataset for leafy vegetables. The goal was to test the performance of the CIWU model following a choice of suitable parameter values. An exhaustive search procedure was used to test various combinations of feasible parameter values. The results showed that application of the CIWU using suitable parameter values improves the model fit but there is a need to test the model using a larger dataset that would allow validation or preferably cross validation. The analysis included only one irrigation water end use but the same procedure could be applied on other irrigation end-uses. Additionally the results can be extended to multiple households in a full-scale application of the CIWU model.

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Chapter 5.

Assessing the impact of property size on residential water use for selected neighbourhoods in Lilongwe, Malawi

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ABSTRACT

Malawi has one of the highest urbanisation rates in Africa, with an urban housing approach that favours large residential plot sizes. The impact of plot size on residential water use was evaluated by examining water use records, obtained for the period between January 2009 and December 2014, for formal residential properties in the City of Lilongwe. Water use increased with plot size in line with other reported research but the dataset contained a considerable proportion of large plots, which were also associated with higher residential water use than presented in similar studies. The findings of this study point to the need for collaboration between water managers and urban planners to promote increased access of urban water supplies by appropriately managing future residential plot sizes.

Keywords: residential plot size, urban water use, equitable water use

INTRODUCTION

Malawi is a relatively small landlocked country in southern Africa with an area of 118,484 km^2 and a subtropical climate. The population is estimated at 13 million and continues to grow at an estimated rate of 4.8% per annum (National Statistical Office 2008). A more recent and rather pressing situation with regard to urban water supply is the significant relocation from rural areas to urban centres. At an urban influx rate of 5.2% per annum, Malawi has one of the highest urbanisation rates in Africa (Government of Malawi 2013). Along with urban population growth has come an urgent need for new housing developments and the necessity to expand and upgrade infrastructure for effective service delivery (UN-HABITAT 2010). The population of Lilongwe, the capital and administrative city of Malawi, has more than doubled since 2000 (Brown 2011).

The Lilongwe Water Board is already under increasing pressure to raise its production to meet the progressively rising residential, commercial and industrial water demands. Currently, new residential water connections are considered the main factor driving up water use (Lilongwe Water Board 2012). Lilongwe Water Board (2015) estimated residential water use in Lilongwe at about 60% of the total supply in 2010 and projected disproportionately rising water use in the subsequent years where the residential sector becomes more dominant through population growth. In 2014, the Lilongwe Water Board reported a 5.6% deficit in water supply following which plans were made to expand one of its main reservoirs, Kamuzu Dam I, to achieve a daily yield increase of 28.9%. However, at the current trend of population growth in the City of Lilongwe, water demand will outstrip the newly proposed daily minimum reservoir yield by 2025 (Lilongwe Water Board 2015).

Strategies for managing residential water use at the household-level can therefore play an important role in curbing present demands and reducing the impact of future supply shortages. Residential water use results from indoor use, which comprises water used for food preparation and basic hygiene, and outdoor use, which comprises water used for gardening, car washing and the like. Indoor use remains fairly constant throughout the year whereas outdoor use is more responsive to changes in climatic factors. Access to sufficient quantities of water for indoor use is known to improve public health and hygiene, particularly where water connections are made to houses (Howard & Bartram 2003). Since outdoor water use is more elastic than indoor use, curtailment of this water use component is the primary way in which utilities manage short-term climate-related shortages (Jacobs *et al*. 2007). With regard to outdoor use, long-term conservation measures are aimed at reducing the responsiveness of water use to changes in climatic factors (Breyer & Chang 2014).

With improved management of customer water billing information at the Lilongwe Water Board and capabilities for retrieving datasets for substantially large numbers of customers spanning relatively long time periods, it is now possible to perform demand-side residential water use analyses for the City of Lilongwe. However, lack of readily available household-level socio-economic information precludes a detailed residential water use analysis. For single family houses, plot size has been reported to be the single most important factor affecting water use elsewhere (Jacobs *et al*. 2004; Van Zyl *et al*. 2008; Breyer & Chang 2014). Van Zyl *et al*. (2008) observed that plot size gave reliable water use estimates even when other significant determinants of water use were disregarded. Patterns of residential water use in relation to plot size can therefore provide useful insights into water use in the City of Lilongwe.

In this paper, patterns of water use for residential plots in selected neighbourhoods in the City of Lilongwe were examined using monthly customer billing records for the period 2009 to 2014. Annual averaged and monthly averaged daily water use were explored to derive patterns of water use in relation to residential plot size. In addition, the peak water use period and the minimum water use period were identified in order to examine the influence of seasonal factors on water use in distinct plot size categories. This analysis is of key interest, since residential plot sizes specified in the prevailing housing standards and guidelines (Government of Malawi 1987) are generally quite large, and considered unsustainable in meeting future housing demands (Brown 2011). The results are an important input for consideration in framing policy and strategies for both urban land use planning and water supply management.

METHODS

Datasets

Household-level water billing records for the period between January 2009 and December 2014 were obtained from the Lilongwe Water Board in February 2015. A query was run to extract billing records from the customer database for six neighbourhoods identified as predominantly residential out of the 58 neighbourhoods in the city of Lilongwe. Neighbourhoods closest to the city centre were selected, because these were known to be least affected by pressure drops during peak demand periods and experienced the fewest water supply outages. These neighbourhoods also happen to be amongst the oldest formal residential developments in the city of Lilongwe. Most of the plots in the six selected neighbourhoods were developed from the 1970s and can therefore be assumed to have minimal use of piped water for construction purposes, with few vacant plots.

The original dataset contained a total of 681,797 meter readings for 11,378 customers. Aggregating repeated readings taken at meter replacements resulted in 666,476 unique monthly records. The dataset was retrieved by customer water account numbers to protect customer personal information. The attributes included were meter reading, meter read date, plot number, neighbourhood code, tariff code and actual billed monthly consumption.

The Lilongwe Water Board provides a single metered connection per residential plot. Semi-detached houses are normally built on adjacent plots that have separate lease agreements and are also furnished with separate water meter connections. Larger sized plots have a single water meter, although it is common to have a second smaller dwelling unit meant to be a guest wing or a servants' quarters. Plots that have swimming pools are provided with an additional water meter that is charged at a commercial tariff.

Residential plot layout maps on hard copies and a few in GIS format were obtained from the Lilongwe City Assembly, the Malawi Housing Cooperation and the Lands and Surveys Department. The Lilongwe City Assembly is a local government authority that undertakes town planning, including allocation of serviced plots for private housing development. The Malawi Housing Corporation is a parastatal responsible for the development and provision of housing in urban areas. The Malawi Housing Corporation has become a major housing provider in cities since its establishment in 1964. The Lands and Surveys Department coordinates all land survey tasks and is the custodian of nationwide mapping information from various land use sectors.

Weather data for the City of Lilongwe was obtained from Chitedze Research Station. The City of Lilongwe lacks a broad network of weather stations (Department of Climate Change and Meteorological Services n.d.). Although the selected weather station lies about 20 to 30 km away from the study sites, it was the preferred station because it has the most complete and consistent record of historic weather in Lilongwe. Daily weather records were aggregated at monthly intervals to correspond with water meter read intervals in the water use data. These weather data were used to determine average monthly temperature and rainfall for the six-year study period.

Water use data processing and screening

The plot layouts acquired were used to obtain plot sizes and to identify single family detached or semi-detached residential plots. At various points during analysis, the plot layouts were checked against high resolution aerial photographs available at the Lands and Surveys Department to verify whether the originally-planned plot layout matched the existing site plot layout. The hard copy layout maps were scanned, imported into Quantum GIS software, geo-referenced and digitised. The digitised file was combined with the available GIS-based residential plot layouts to form a single shape file. Plot sizes were extracted by plot number from the attributes of the combined GIS file. The table of plot sizes created was joined to the customer water use table using the plot numbers field available in both data tables. Not all customer water accounts could be matched to corresponding plot size information because some customer records did not have plot numbers. Likewise, plot numbers were missing for some plots in the layout maps. The plot sizes were used to group all customers into plot sizes categories at 500 m^2 class intervals ranging from 0-500 m^2 to 7,000-7,500 m^2.

A series of filter criteria were applied to remove customer records that were not relevant to the study and records that contained irregularities. Table 5.1 shows the number of customers and monthly records retained at each processing stage. Non-residential customers were removed using an appropriate tariff code provided in the data. All customers whose plot sizes could not be found were removed. Customers with plot sizes exceeding 8,000 m^2 were also removed from the data. Wherever more than five monthly records were missing for a customer in a particular year, the entire yearly record of that customer was discarded. It was observed that long meter read intervals usually gave water use readings that were not consistent with the rest of the customers' water use records, mostly being too low for the given period. A plausible reason could be readings taken after a period of vacancy of dwelling units. There were also a few extraordinarily large records taken over very short periods. It was decided to discard all records with meter read intervals shorter than 20 days or longer than 40 days. Monthly records exceeding 600 kilolitres (kL) were considered too high for residential connections and these were excluded from the analysis. A few records were noted to have meter read dates that fell outside the data extraction period. Any records with such erroneous entries were removed from the dataset.

Table 5.1 Number of customers and monthly records retained at each processing stage

Step	Description	Number of customers remaining	Number of monthly records remaining
1	Total number of records extracted	11,328	681,797
2	Aggregate duplicate monthly meter readings	11,328	666,476
3	Remove non-residential connections	10,725	638,275
4	Remove customers whose plot sizes were not available	4,074	281,550
5	Remove customers with plots larger than 8,000 m^2	4,066	280,995
6	Remove yearly customer records with more than five gaps or zeros	4,005	274,067
7	Remove meter readings less than 20 days and greater than 40 days	4,005	245,743
8	Remove monthly consumption readings greater than 600 kL	4,004	245,418
9	Remove records with meter read dates falling outside study period	4,004	245,411

Computation of key variables

The average annual daily demand (AADD) and average monthly daily demand (AMDD) were calculated for each customer for each year. The AADD for each customer was obtained by dividing the total annual consumption by the number of days in that year. The AMDD was calculated by dividing the monthly consumption by the number of days between consecutive meter readings. Monthly consumption records typically span across consecutive months. The AMDD obtained from a given billed consumption was assigned to the month when the latter meter reading was taken.

In order to compare the interactive effect of seasonal weather changes and plot size on water use, monthly peak factors were calculated for each plot size category. Monthly peak factors were calculated by dividing the highest AMDD by the AADD for the whole six-year period. Peak factors are conventionally used to calculate peak flow requirements for the design of water supply systems, and therefore provide a sound basis for comparison of summer peak water use with other studies.

RESULTS AND DISCUSSION

Plot size distribution

Table 5.2 gives the distribution by plot size category of the 4,004 customers that met the filter criteria presented in the previous section. The table also shows the spread of the customers in each of the six selected neighbourhoods. In all subsequent analyses, customers falling in each plot size category are lumped together irrespective of neighbourhood.

Table 5.2 Plot size distribution

Plot size category (m^2)	Neighbourhood						Total number of customers	Percentage of the sample (%)
	A	B	C	D	E	F		
0 – 500	638	504					1,142	28.5
500 – 1,000	396	251		192			839	21.0
1,000 – 1,500	13	18	7	212		10	260	6.5
1,500 – 2,000	5		130	302		16	453	11.3
2,000 – 2,500			66	324		55	445	11.1
2,500 – 3,000			14	65	1	44	124	3.1
3,000 – 3,500				20	11	55	86	2.1
3,500 – 4,000				8	18	162	188	4.7
4,000 – 4,500				1	88	38	127	3.2
4,500 – 5,000					138	47	185	4.6
5,000 – 5,500				2	30	13	45	1.1
5,500 – 6,000					37	7	44	1.1
6,000 – 6,500				1	20	5	26	0.6
6,500 – 7,000	1			1	15	1	18	0.5
7,000 – 7,500					22		22	0.6

Water use patterns across customers

The AADD of all customers calculated for the period between 2009 and 2014 ranged from 1.2 to 1.5 kL/plot/day. Figure 5.1 shows the frequency distribution and the cumulative frequency distribution of AADD for the year 2014. The household-level AADD had a positive skew that resembled the frequency distribution of plot sizes in the study sample. About 90% of the customers had AADD values below 2.5 kL/plot/day. The other 10% customers accounted for at least 25% of the total consumption in the study sample. The highest water users were found among the top 2% of the customers, with AADD ranging from 5 to 10 kL/plot/day.

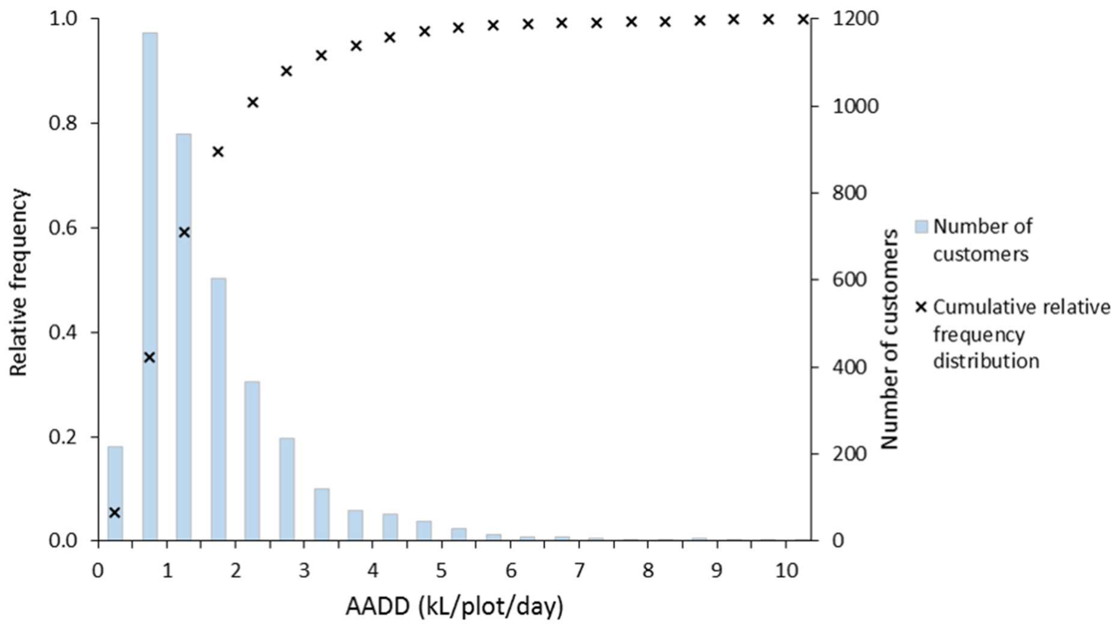

Figure 5.1 Frequency distribution of AADD

Water use by plot size category

The mean AADD values for the distinct plot size categories are plotted in Figure 5.2. Water use clearly increases with plot size up to about 5,000 m^2. The relationship between AADD and plot size is less clear for the larger plot size categories. The variance increases for the larger plots sizes, leading to larger standard errors, meaning that the mean water use estimates become less precise than in the smaller plot size categories as shown in Table 5.3. The exact cause of the large variation could not be established from the available data. Obviously the relatively smaller number of properties larger than 5000 m^2 made the differences in water use to stand out. Furthermore, one of the neighbouhoods where some of the largest properties were located had a stream running through it. It is likely that some of the households in this neighbourhood used the stream or shallow wells to complement their outdoor water needs, leading to lower billed water consumption relative to plot size.

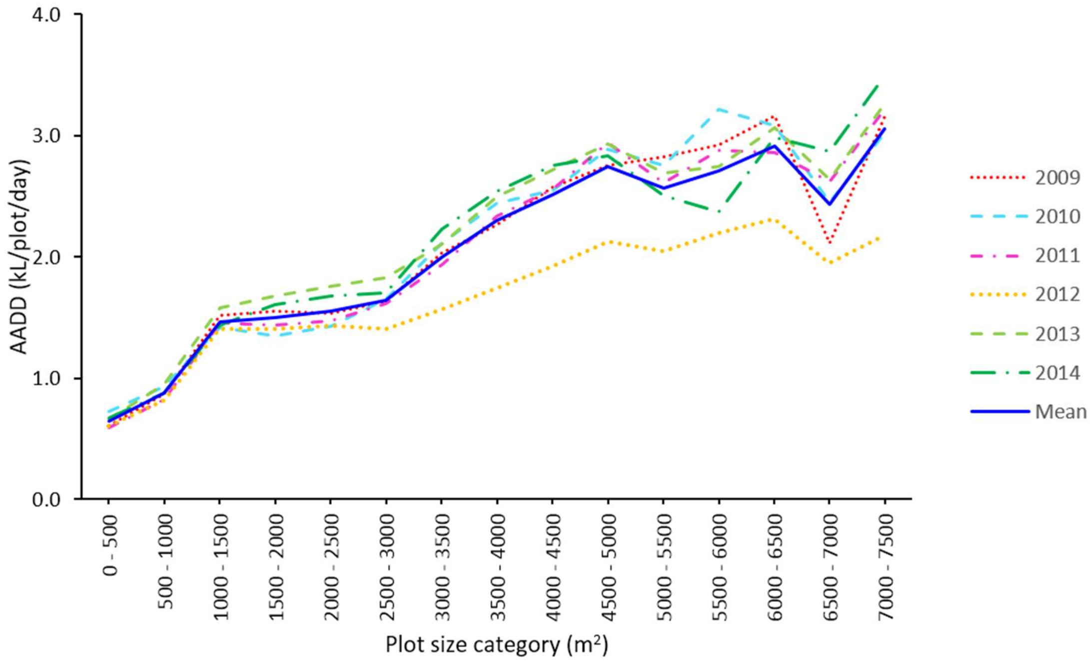

Figure 5.2 Water use variation with plot size

Table 5.3 Summary statistics for AADD by plot size category averaged over the period 2009 to 2014

Plot size category (m^2)	AADD (kL/plot/day)		
	Mean	Standard deviation	Standard error
0 – 500	0.648	0.367	0.004
500 – 1,000	0.878	0.655	0.009
1,000 – 1,500	1.470	0.820	0.022
1,500 – 2,000	1.506	0.886	0.017
2,000 – 2,500	1.554	0.972	0.019
2,500 – 3,000	1.642	1.025	0.038
3,000 – 3,500	2.000	1.299	0.058
3,500 – 4,000	2.306	1.640	0.049
4,000 – 4,500	2.513	1.846	0.068
4,500 – 5,000	2.748	1.837	0.056
5,000 – 5,500	2.570	1.758	0.109
5,500 – 6,000	2.713	2.116	0.133
6,000 – 6,500	2.915	2.398	0.198
6,500 – 7,000	2.435	1.949	0.189
7,000 – 7,500	3.055	1.961	0.171

Water use was notably lower in 2012 than for the other years. A follow-up with the Lilongwe Water Board revealed that major rehabilitation works were carried out at their water treatment facilities, including the replacement of intake pumps between March and December in that year (Lilongwe Water Board 2012). Delivery pressure was affected and water supply rationing was introduced. The Electricity Supply Commission of Malawi coincidentally happened to carry out maintenance works at their main power generation plant in the same period. Extensive load shedding was introduced which further disrupted pumping and water supply.

The mean AADD in 2012 was 12% lower than that calculated for the entire six-year study period. As would be expected, AADD dropped considerably in the larger plot size categories, while the smallest plot size categories barely showed any reduction in water use. Substantial water use reductions were observed in plot sizes larger than 2,500 m^2. The average daily use for the period 2009 to 2014 was used to calculate the percentage reduction in water use in each plot size category in 2012. The percentage water use reduction was 5.6% in the smallest plot size category (0 – 500 m^2), while at least 14.2% reduction occurred in the plot size categories larger than 2,500 m^2. The largest plot size category (7,000 – 7,500 m^2) had a water use reduction of 28.6%.

Monthly variation in water use

The monthly variation in water use is depicted by AMDD in Figure 5.3. The average monthly maximum temperature and average monthly rainfall for 2009 to 2014 are shown in Figure 5.4. Water use generally follows the seasonal trend of temperature and rainfall. Minimum water use was observed in March, one month after the period of highest rainfall in February.

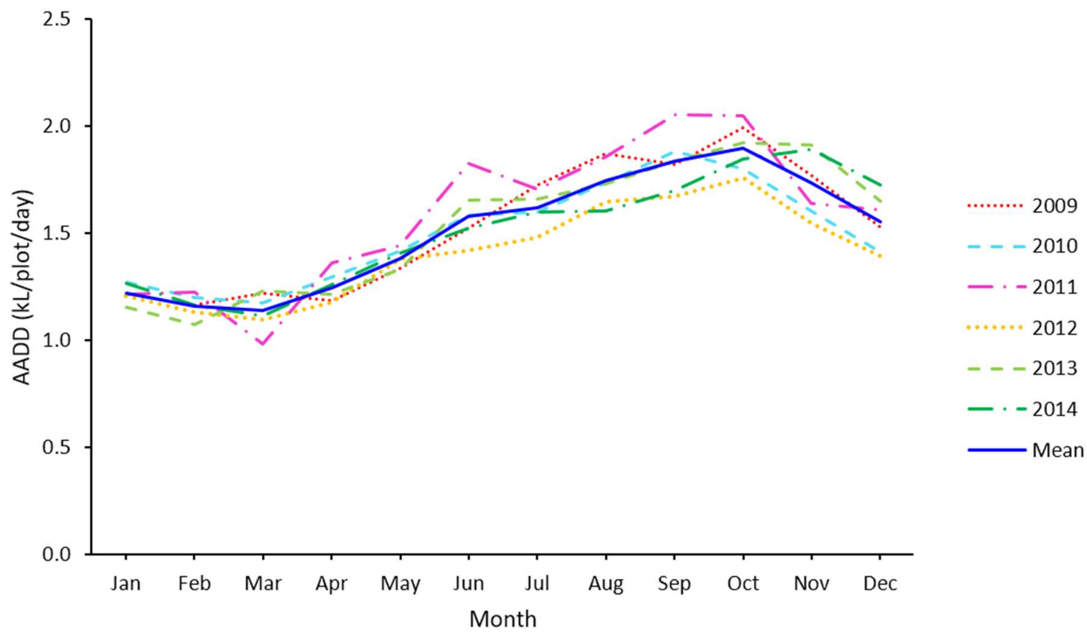

Figure 5.3 Overall annual variation in AMDD

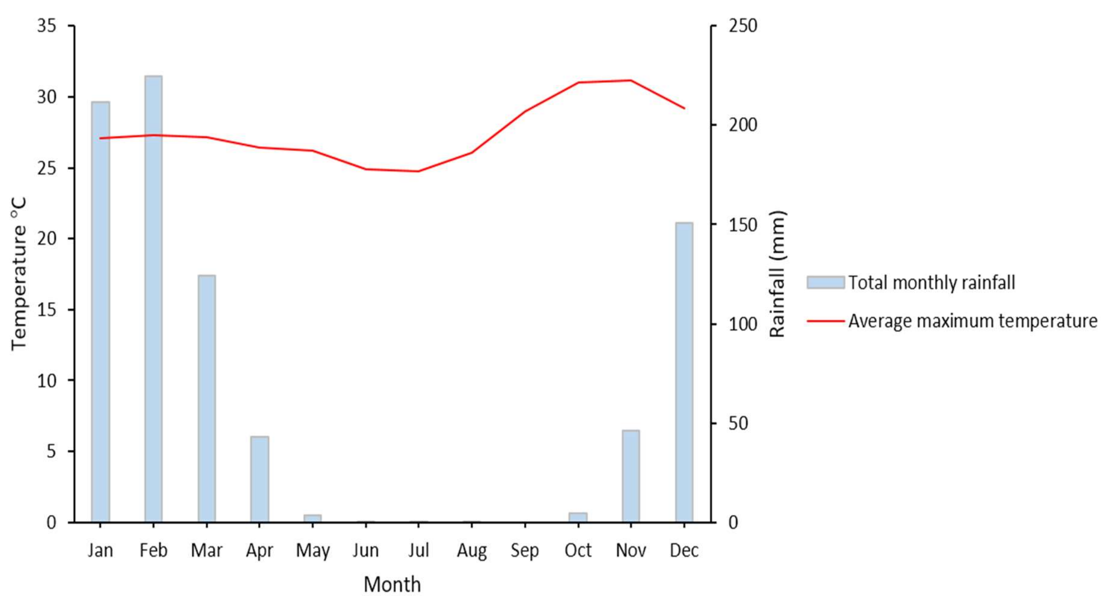

Figure 5.4 Seasonal variation in temperature and rainfall

Temperatures remain relatively moderate throughout the rainy season but reach the annual minimum later during the cool dry season between June and August. As expected, water use began to increase towards the end of the rainy season. It is likely that watering of landscapes is resumed around this time as evapotranspiration losses can no longer be replenished by rainfall. Water use, however, continued to increase as temperatures dropped from May throughout the cool dry season. Seasonal horticultural crops in backyard gardens, a common practice in Malawi, are planted during this time. The cool season is conducive to the establishment of certain leaf vegetables that are difficult to grow in hot weather.

Peak water use corresponded with maximum temperatures in October. Peak month water use in October was, on average, 70% higher than the minimum winter water use in March. Water use subsequently dropped at the start of the rainy season which was also accompanied by a decrease in temperatures.

Monthly patterns of water use in relation to plot size

Monthly variation in AMDD within each plot size category is given in Figure 5.5. The small plot size categories maintained nearly constant AMDD throughout the year, implying predominant indoor water use. This observation suggests that indoor water use responded negligibly to seasonal weather variations. There was a larger increase in summer water use for the larger plots than for smaller plots. Larger plots, generally have larger landscapes and a greater potential for outdoor water use than smaller plots.

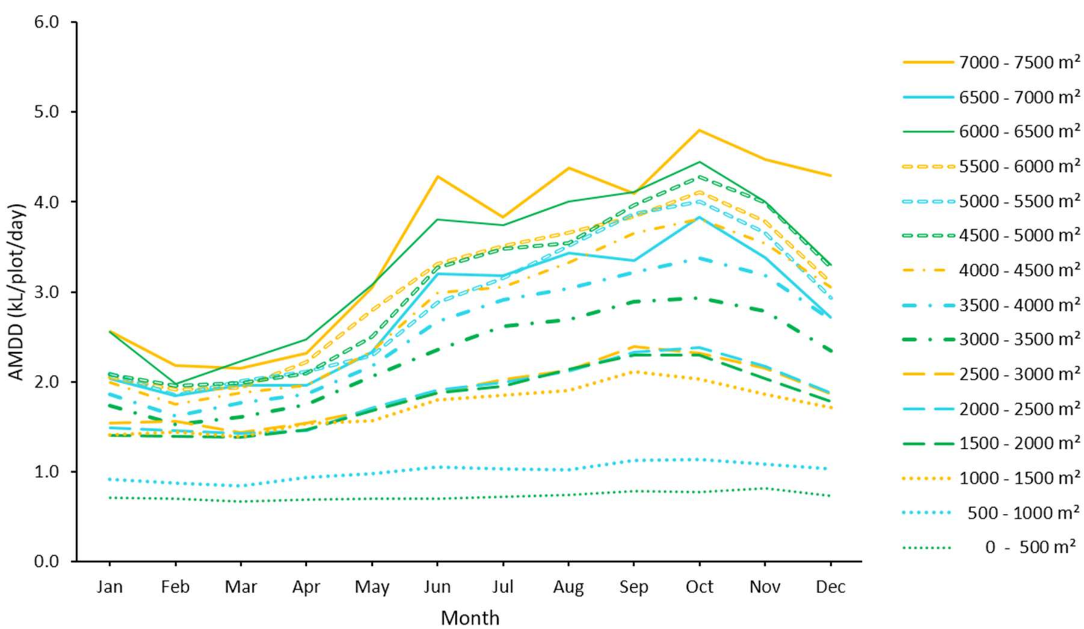

Figure 5.5 Variability of AMDD by plot size

Monthly peak factors for the highest usage month (October) were 1.2 and 1.5 respectively, for 0 – 500 m^2 and 1,500 – 2,000 m^2 plot size categories. Peak factors approached a maximum of 1.6 in the larger plot size categories. The seasonal water use component of the study sample was estimated at 24% by deducting the minimum winter water use recorded in March from water use in the rest of the months, and expressing the result as a fraction of total annual use.

Comparison of water use in this study with findings from similar studies

For the purpose of comparison with similar studies, AADD values obtained in this study for Lilongwe are presented in Figure 5.6 together with guideline curves for estimating AADD presented by Jacobs *et al*. (2004) and Van Zyl *et al*. (2008). The water use results show good agreement with the findings by Jacobs *et al*. (2004) for plot sizes between 0 and 2,050 m^2 reported for three different regions of South Africa and Windhoek in Namibia. Van Zyl *et al*. (2008) provided estimates of water use in South African towns and cities for up to 4,000 m^2 plots, although only 2.7% of the plots in their sample were classified in the range between 2,000 to 4,000 m^2. The AADD guideline curve recommended by Van Zyl *et al*. (2008), represented by the 50% confidence limit, overestimates water use of smaller plot sizes in Lilongwe but matches the results of this study for plots in the 3,500 to 4,000 m^2 category. For the purpose of comparison, per capita water use values for Lilongwe, some selected towns in Western Cape, South Africa and Windhoek in Namibia and are given in Table 5.4.

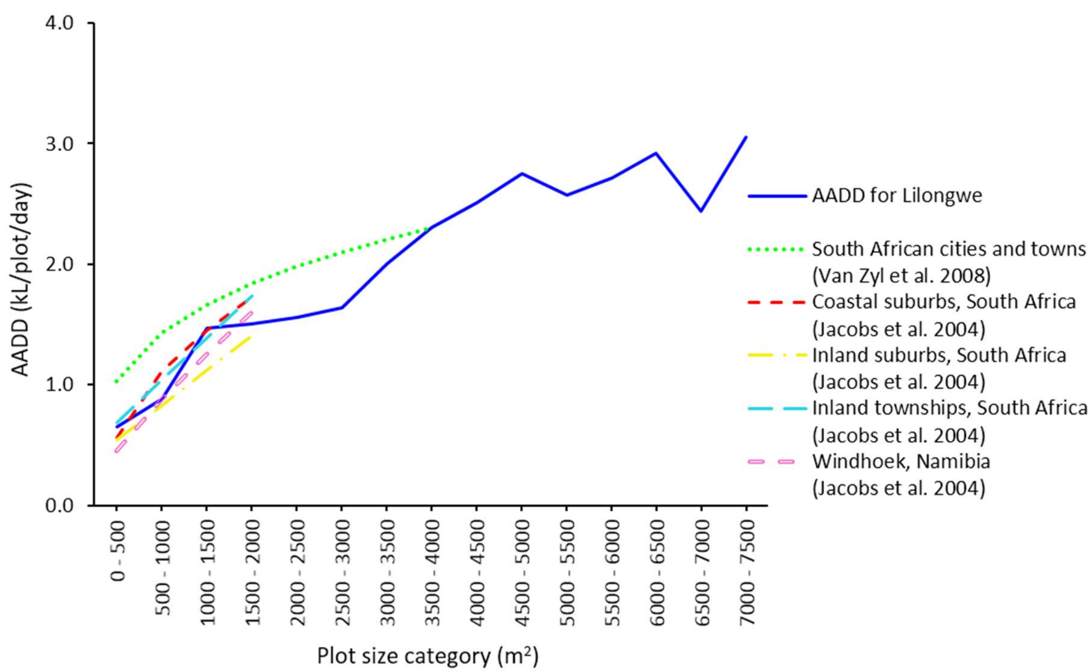

Figure 5.6 Comparison of AADD for Lilongwe to similar studies

Table 5.4 Per capita water use for selected towns

Town/City and country	Source	Per capita water use (litres/capita/day)
Lilongwe, Malawi	Lilongwe Water Board (2012)	64
Franschhoek, Western Cape, South Africa	Du Plessis (2007)	305
Paarl, Western Cape, South Africa	Du Plessis (2007)	325
Piketberg, Western Cape, South Africa	Du Plessis (2007)	180
Windhoek, Namibia	Uhlendahl *et al.* (2010)	200

Plot size and neighbourhood water use

The results presented in the preceding sections show that smaller plot sizes are related to low water use per household while at the same time being less sensitive to seasonal weather variation. Reducing plot sizes increases both housing density and the number of people in a neighbourhood. Jacobs *et al*. (2013) and Griffioen & Van Zyl (2014) reported relatively constant water use of about 10 kL/ha for residential neighbourhoods irrespective of the development density. Their findings suggest that plot density does not necessarily increase water use per unit area in a neighbourhood. However, the increase in the number of people causes a corresponding decrease in the water use per capita (Balling *et al.* 2008). Breyer & Chang (2014) have actually reported an overall reduced per capita water use attributed to increase in residential area density in Oregon. They argue that increased density of residential areas is a form of "retrofitting of the landscape" that reduces the potential for outdoor water use.

The need for collaboration in urban planning

The results of this study agree with other studies in the sense that water use increases with residential plot size. As temperatures increase in summer, water use increases more for larger plots, that is, summer peak factors are higher for large plot sizes than for smaller plot sizes. Formal residential plot sizes in Malawi have their origins in the early housing developments for government employees. The standard plot sizes were given in the planning standards and guidelines prepared then by the Ministry of Lands, Physical Planning and Surveys (Government of Malawi 1987). All plots were supposed to range from 300 m^2 to 4,000 m^2 depending on the designated density of the residential area, although these size limits appear to be occasionally ignored. These housing guidelines and standards favour the development of relatively large plot sizes that are inducing high seasonal peak factors and overall increase in water use at household level. The plot sizes in the standards have been criticised as taking too much urban space and being unsuitable for future climate-related challenges (UN-

HABITAT 2010; Brown 2011). The determination of plot sizes is, however, beyond the control of water supply managers. Thus collaboration is needed between the water supply sector, town planners and other stakeholders to achieve sustainable urban housing forms that take into account current and future water needs.

Study limitations

The total number of records used in the analyses was relatively smaller compared to similar studies conducted elsewhere in large metropolitan areas (Jacobs *et al*. 2004; Jacobs *et al*. 2007; Van Zyl *et al*. 2008). For this reason, the results were not separated by neighbourhood in all the analyses in spite of the distinct characteristic features of the selected six neighbourhoods. Non-homogeneous characteristics among the selected neighbourhoods that were not considered in the analyses, therefore, potentially introduced considerable variability in the results obtained from the combined dataset. Factors such as household size and socio-economic status are known to impact water use habits. Likewise, water pricing structure is a key factor influencing residential water use. Further research that incorporates detailed information on these factors would increase confidence in the observed results.

CONCLUSIONS

This study investigated the effects of plot size on water use of formal housing in the city of Lilongwe. Water billing records for 4,004 single-family customers, obtained through a series of screening criteria, were analyzed. The AADD, AMDD and summer peaking factors were examined with respect to plot sizes. The AADD increased with plot size category. The results showed a substantial proportion of large plots, which were also associated with higher water use than reported in similar studies elsewhere. Summer peaking factors were higher for larger plot size categories, suggesting substantial water usage for outdoor purposes. The results obtained provide a benchmark that water managers can use to estimate expected water use for new residential neighbourhoods. Water managers can, therefore, use the results to advocate urban residential forms that improve the level of access of households to adequate quantities of water from the available supplies in Malawi.

ACKNOWLEDGEMENTS

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Chapter 6.

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 is readily available to water supply utilities and can therefore be easily replicated elsewhere.

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

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 & Nejadhashemi (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 ºC 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 was 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 6.1. 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.

Table 6.1 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)

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:

$$T_{future,d-m} = T_{observed,d-m} + DeltaT_m \tag{1}$$

$$P_{future,d-m} = P_{observed,d-m} \times RatioP_m \tag{2}$$

where $T_{future,d\text{-}m}$ is the future temperature for day d and month m, $T_{observed,d\text{-}m}$ is the observed temperature for day d and month m under the reference period and $DeltaT_m$ is the GCM temperature anomaly. Likewise, $P_{future,d\text{-}m}$ is the projected rainfall for day d and month m, $P_{observed,d\text{-}m}$ 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 m^2, 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):

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

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

$$ET_c = K_c \cdot ET_o \tag{4}$$

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):

$$IR_j = w_{j-1} - w_j + ET_{c\,j} - r_j \tag{5}$$

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:

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

where TAW is the total available water (mm), θ_{FC} 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 6.2.

Table 6.2 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

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

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

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.

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:

$$AMDD_{it} = \alpha + \beta_1 PSize_{it} + \beta_2 IReq_{it} + \beta_3 (PSize * IReq)_{it} + (u_i + v_{it}) \quad (10)$$

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 6.1 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 ºC 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 ºC 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.

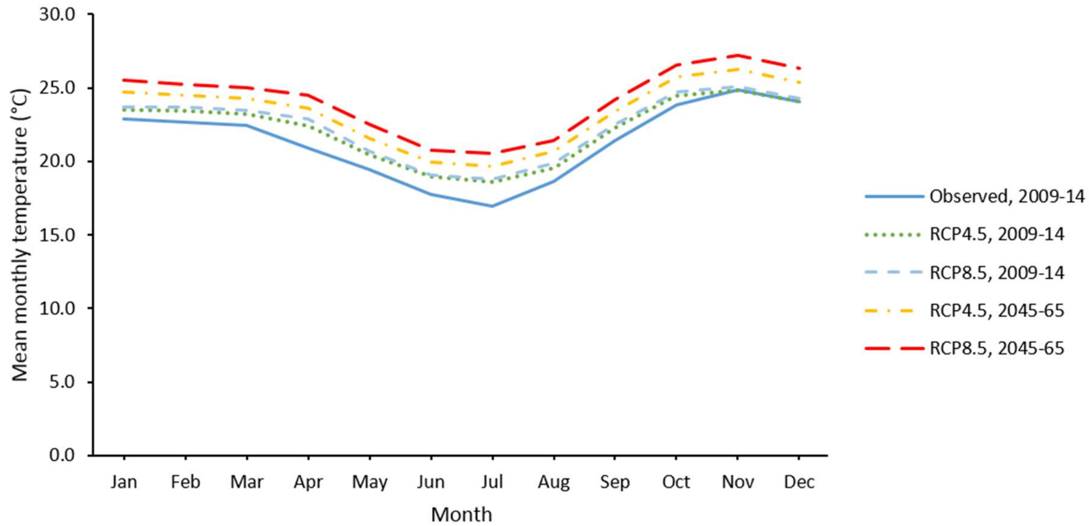

Figure 6.1 Mean monthly temperature for 2009–2014 and 2045–2065

The projected rainfall is shown in Figure 6.2. 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 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.

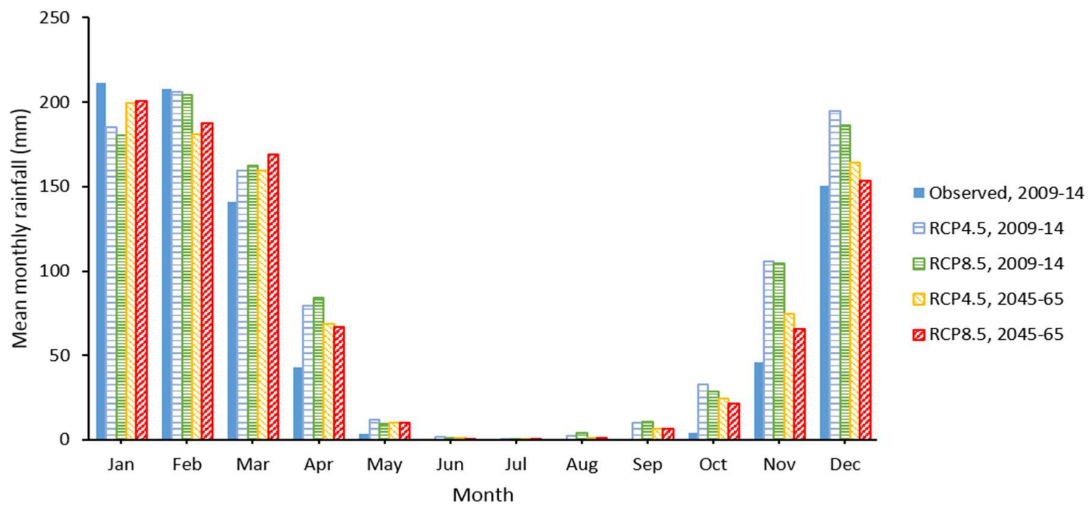

Figure 6.2 Mean monthly rainfall for 2009–2014 and 2045–2065.

Figure 6.3 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.

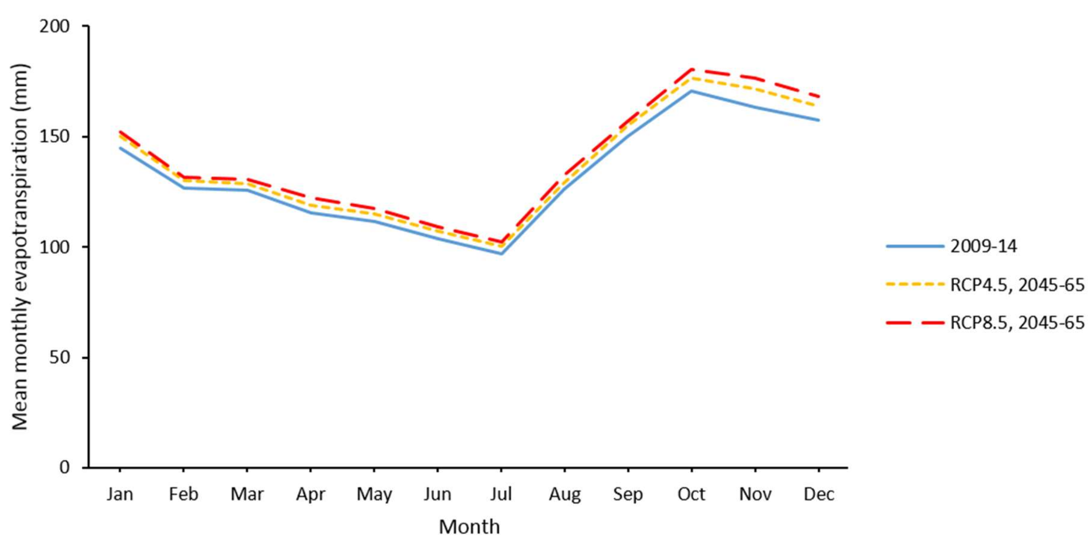

Figure 6.3 Calculated monthly evapotranspiration for 2009–2014 and 2045–2065.

The theoretical irrigation requirements are shown in Figure 6.4. 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.

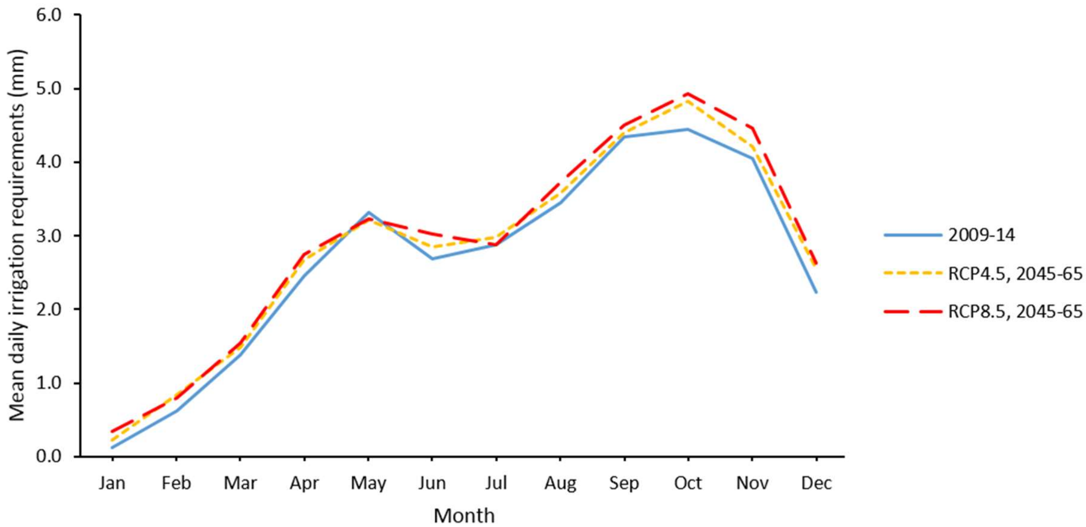

Figure 6.4 Calculated monthly irrigation requirements for 2009–2014 and 2045–2065.

Regression analysis results

The regression analysis results from the pooled OLS model, FEM and the REM are given in Table 6.3. The three model 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*.

Table 6.3 Coefficient estimates and fit statistics for the pooled OLS model, FEM and REM

	Pooled OLS model		FEM		REM	
Parameter	**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	

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 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 m^2 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 m^2. 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 m^2 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 m^2, 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 m^2 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 6.4 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 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).

Table 6.4 Predicted percentage change in monthly water use from 2009–2014 to the 2045–2065

	Absolute change (kL/plot/day)		Percent change (%)	
Month	**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

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 is 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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Chapter 7.

Improving performance of domestic water use regression models through the determination of optimal parameters for the transformation of weather inputs

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ABSTRACT

This study examined the performance of panel linear regression models fitted on garden irrigation requirements generated from temperature and rainfall time series using parameter values of best fit identified by an exhaustive search procedure. The goal was to examine if the transforming the weather data to irrigation requirements would improve the performance of the regression models in relation to garden water use. Data from the North American Residential End Uses of Water database (1999) were used in all the analysis. The R^2 values obtained were comparable to those from regression on temperature and rainfall but two advantages were noted with respect to regression on irrigation requirements. First the model intercept gave an estimate of indoor use which was, in the majority of the cases, more accurate than the estimate from minimum winter use. Secondly, the estimated coefficients were significant in all the cases. The regression on temperature and rainfall, however, produced nonsignificant coefficients for some locations.

Keywords: residential irrigation water use, parameters, climate variables

INTRODUCTION

Background

Residential water use displays a seasonal pattern, related to climatic factors. Seasonal variability is known to result primarily from outdoor water use. Typically, water use increases during hot summer months and decreases in winter. Establishing a relationship between water use and climatic factors is vital for planning conservation strategies connected to outdoor use and for the assessment of the impacts of climate change (Balling *et al.*, 2008). In water use regression models, the effects of climate are usually considered by introducing the variables temperature and precipitation (Taylor, 2012; Chang *et al.* 2014).

Makwiza *et al.* (2017) applied net irrigation requirements in a panel linear regression model in order to incorporate climatic factors in the analysis of residential water use, allowing for climate change. The net irrigation requirements were computed based on typical soil and plant parameters of lawn grass growing on a loamy soil. These parameters, however, could take different values depending on the assumed plant characteristics or soil properties. The selected combination of parameter values determines the estimates for evapotranspiration and effective rainfall with subsequent impact on the estimated net irrigation requirement.

Objective of this study

This study examined the goodness of fit of several regression models used for estimating garden irrigation. Panel linear regression analysis (Wooldridge, 2015; Worthington *et al.*, 2009) was applied to the average monthly daily demand ($AMDD$) as the dependent variable and the theoretical irrigation requirements, derived from observed weather data using optimal parameter values, as the independent variable. The models regressed on the irrigation requirements were compared to results of corresponding regression models on temperature and rainfall. The goal was to determine if the transformation of weather data to irrigation requirements, using suitable parameter values, would improve the explanatory power of weather inputs in the estimated regression model, and improve estimates of water use for garden irrigation. In order to keep the analysis and interpretation of the results simple, and considering that the analysis focused on garden irrigation, factors known to influence residential water use, for example income and property size, were neglected. The use of panel linear analysis was considered to address bias due to omission of variables that could be assumed constant over time such as property size.

METHODOLOGY

The data used in this study was obtained from the 1999 Residential End Uses of Water (REUS) database (Mayer *et al.*, 1999). The specific dataset was selected because it was purchased by the Stellenbosch University Water Research group (Civil Engineering) as part of an earlier project and all the required information for this study was contained in the dataset. An updated REUS database (version 2) was released by the Water Research Foundation in 2016 (DeOreo *et al.*, 2016) but this new version excludes customer billing records, hence the earlier 1999 REUS database was considered more appropriate for this study. The data were collected by Mayer *et al*. (1999) from study locations in 12 cities in North America. The water use records originated from a range of climatic conditions and were considered suitable for performance evaluation in this research study. The REUS database contained records for 1000 customers at each study location but more detailed information was provided by Mayer *et al*. (1999) for a subset of 100 customers from each location. The subsamples used in the analysis in this study were obtained from the groups of 100 customers with detailed information. Customers with swimming pools were however filtered out in the present study since the focus was on garden irrigation. Four datasets that were extracted from the database were

- Disaggregated water end-use data for two two-week long logging periods, one in summer and the other in winter
- Water use data from monthly or bi-monthly billing records for a one-year or two-year long period
- Responses to a questionnaire survey
- Weather data for the period of the study.

In the REUS database, the closest weather station to each customer was indicated by an identifier field (Mayer *et al*., 1999). The station identifier field was therefore used to link monthly water use records for each customer to the appropriate weather records, also included in the REUS database. Monthly net irrigation requirements were calculated for each customer according to the equations outlined in Makwiza *et al.* (2015, 2017). The main steps involved the calculation of potential evapotranspiration from weather data using the Hargreaves equation (Hargreaves and Allen, 2003) followed by the application of the water balance equation to estimate effective rainfall and daily net irrigation requirements.

Several parameters were described in the equations for computing irrigation requirements. The relevant parameters were the soil moisture content at field capacity (θ_{FC}), the soil moisture content at permanent wilting point (θ_{PWP}), the root zone depth (Z_r), the crop coefficient (K_c), the soil moisture depletion level before water application (Dr_1) and the soil moisture depletion level just after water application (Dr_2). Feasible ranges of these parameters were adopted from Allen *et al.* (1998). All analyses were carried out assuming uniform parameter values for all customers from the same location or city.

The parameters θ_{FC}, θ_{PWP} and Z_r are closely related. The difference between θ_{FC} and θ_{PWP} determines the available water capacity (AWC) of a given soil which typically varies between 50 and 200 mm/m, the lowest values representing sandy soils and the upper values in the range representing clayey soils. The parameter Z_r varies between 0.1 and 1.0 m for most shrubs, horticultural crops and lawn grass. The product of the root zone depth and the available water capacity gives the total available water, TAW, which is the maximum amount of water that can be stored in the soil for plant use. The various possible combinations of Z_r,

θ_{FC} and θ_{PWP} were therefore conveniently introduced using the single parameter, TAW. Given the feasible ranges of Z_r and AWC, the values of TAW were considered to range between 5 to 200 mm.

The crop coefficient determines the rate at which the water in the soil is lost through evapotranspiration. The crop coefficient was varied between 0.3 and 1.2 which covers the typical range for the majority of garden plants (Allen *et al.*, 1998). Water application was considered to occur when the soil moisture depletion level reached Dr_1. Water application was assumed to reduce the soil moisture depletion level to Dr_2. The parameters Dr_1 and Dr_2 took values between 0 and 1 corresponding to moisture content at field capacity and permanent wilting point respectively, and where Dr_2 was always less than Dr_1. If this moisture depletion level was below the allowable depletion level, typically 50%, then the plant suffered stress causing a reduction in consumptive use.

In order to identify suitable parameter values, different parameter combinations were enumerated with the aim of obtaining the best fitting regression model between water use and irrigation requirements. Suitable combinations of values for TAW, K_c, Dr_1 and Dr_2 were identified by carrying out an exhaustive search in which each parameter was varied sequentially at a chosen precision within its feasible range. The parameter TAW was enumerated in 10 mm increments. The parameter K_c was enumerated at 0.05 increments. Both Dr_1 and Dr_2 were enumerated at 0.05 increments. The calculation of monthly net irrigation requirements for each parameter combination also yielded the number of irrigation events per month. A filter was applied to remove all results where the calculated number of irrigation events for the peak summer month did not match the average number of events per month determined from the REUS questionnaire survey dataset collected by Mayer *et al.* (1999).

The generated irrigation requirements were combined with the monthly water use data to create a panel dataset. Panel linear regression analysis was then applied to determine the explanatory power of the net monthly irrigation requirements generated at each iteration. The set of parameter values that produced the highest R^2 values were adopted as the most appropriate for the location or city being analysed. The R^2 values from the regression analysis are a measure of the proportion of variation in the data that is explained by the model. The suitability of the regression model was further evaluated by the F-statistic for overall model significance and t-tests for significance of estimated coefficients.

Following the identification of suitable parameter values for estimating irrigation requirements, a comparison was made between the regression on net monthly irrigation requirements and regression on average monthly temperature and monthly rainfall. This comparison demonstrated whether the use of irrigation requirement improved the explanatory power of weather inputs in the regression model.

Panel linear regression requires the application of the most appropriate model specification between the pooled ordinary least squares (OLS) model, fixed effects model (FEM) and random effects model (REM). The selection criteria of the most appropriate among these three model specifications was summarised in Polebitski and Palmer (2009), Worthington *et al*. (2009) and Makwiza *et al*. (2017). The detailed description and derivation of each of the three model specifications are found in Woodridge (2015). The generic forms of the pooled, fixed effects and random effects are given by equation 1, 2 and 3 respectively.

$$Y_{it} = \alpha + \beta X_{it} + \varepsilon_{it} \tag{1}$$

$$Y_{it} = (\alpha + u_i) + \beta X_{it} + v_{it} \tag{2}$$

$$Y_{it} = \alpha + \beta X_{it} + (u_i + v_{it}) \tag{3}$$

where Y is the dependent variable,

X is a vector of independent variables,

α is an intercept,

β is a vector of variable coefficients,

ε is the error term,

i and t are indices for subjects and time periods respectively,

u_i includes any factor specific to subject i that was not included in the FEM or any factor specific to subjects or time periods not included in the REM,

v_{it} is an independently and identically distributed error term.

Based on the criteria described by Woodridge (2015), the F test was used to choose between the pooled OLS model and the FEM. The Langrange multiplier test was used to choose between pooled OLS model and the REM. Then the Hausman test was used to determine whether the REM outputs were as good as the outputs of the FEM. All the statistical analyses were carried out in R programming software using the 'Linear Models for Panel Data' package.

RESULTS AND DISCUSSION

The F test and the Lagrange multiplier tests indicated the existence of fixed effects and ruled out the utility of the pooled OLS model in all the cases. The Hausman test was not significant for all the regressions performed on irrigation requirements derived using the best-fit parameter values. Likewise, the Hausman test was not significant in all cases for the model regressed on temperature and rainfall, thus indicating that the coefficient estimates of the REM were as good as those of the FEM. All subsequent comparisons and discussion were therefore based on the outcomes of the REM.

For each study location, the exhaustive search produced several combinations of parameter values that gave similar R^2 values when the corresponding irrigation requirements were applied in the regression model. These sets of parameter values were considered equally good and any single combination could well be chosen for application. A further refinement could be possible if specific assumptions were made on the parameters. Table 7.1 presents one of the several realisations of the best fitting parameter values at each study location.

Table 7.1 Single instance of best fit combination of parameter values for each study location

Location	TAW (mm)	K_c	Dr_1	Dr_2
Boulder	150	0.60	0.20	0.15
Denver	20	0.65	0.90	0.80
Eugene	120	0.85	0.60	0.50
Las Virgenes	30	0.90	0.30	0.05
Lompoc	20	0.35	0.25	0.00
Phoenix	40	0.75	0.40	0.05
San Diego	70	1.05	0.20	0.05
Scottsdale	20	1.10	0.60	0.10
Seattle	120	1.00	0.70	0.65
Tampa	90	1.10	0.30	0.05
Walnut Valley	30	0.45	0.10	0.00
Waterloo	20	0.55	0.80	0.75

Table 7.2 gives a summary of the results from the panel linear regression analysis. The models performed better in some locations than others as discussed in more detail below. The R^2 values obtained from the regression on irrigation requirements were comparable to those from regression on temperature and rainfall. R^2 values were low for Tampa and Waterloo. The disaggregated end-use data provided in the REUS database (Mayer *et al.*, 1999) also indicated much lower irrigation water use for both Tampa and Waterloo compared to other locations. These locations received rainfall throughout the year which could have reduced the need for irrigation. Secondary historical weather data also shows that Waterloo has snow fall for close to 6 months in a year (Meteorological Service of Canada, n.d.) which would also limit irrigation water use.

The F-statistic was significant ($p<0.001$) in all the regression models presented and is not reported. The coefficient estimates for both the model intercept and the irrigation requirements term were significant ($p<0.001$) in all the cases. The coefficients for the regressions on temperature and rainfall were, however, not significant for some locations. In the case of Las Virgenes and Seattle, the rainfall coefficient was positive, which was contrary to the expected sign since an increase in rainfall should generally cause a reduction in garden water use.

An advantage of the model regressed on irrigation requirements is that the intercept has a clear and practical meaning. Setting the monthly irrigation requirement to zero leaves only the intercept in the model. The intercept can be interpreted as the weather insensitive water use which approximates indoor water use. In the model for temperature and rainfall, the intercept cannot be interpreted in the same manner, because the weather sensitive component of water use does not necessarily have to be zero when temperature and rainfall become zero. The minimum winter use needs to be estimated by substituting the correct temperature and rainfall values in the estimated regression equation.

Table 7.2 Panel linear regression results

Location/City	Sample size	Regression on irrigation requirements			Regression on temperature and rainfall			
		Intercept	Irrigation requirement coefficient	R^2	Intercept	Temperature coefficient	Rainfall coefficient	R^2
Boulder	99	0.713 ± 0.061***	0.597 ± 0.018***	0.472	0.679 ± 0.077***	0.083 ± 0.003***	-0.214 ± 0.031***	0.445
Denver	100	0.643 ± 0.110***	2.289 ± 0.112***	0.425	0.724 ± 0.165***	0.115 ± 0.006***	-0.266 ± 0.143***	0.386
Eugene	93	0.764 ± 0.060***	0.316 ± 0.013***	0.348	0.071 ± 0.109	0.090 ± 0.006***	0.003 ± 0.009	0.322
Las Virgenes	42	0.833 ± 0.205***	0.344 ± 0.025***	0.386	0.391 ± 0.402	0.110 ± 0.017***	0.257 ± 0.049***	0.394
Lompoc	100	0.821 ± 0.077***	0.585 ± 0.028***	0.263	-0.802 ± 0.209***	0.145 ± 0.012***	-0.023 ± 0.016	0.267
Phoenix	60	0.975 ± 0.147***	0.294 ± 0.021***	0.214	0.611 ± 0.164***	0.062 ± 0.004***	-0.202 ± 0.062**	0.219
San Diego	83	0.786 ± 0.117***	0.238 ± 0.016***	0.182	0.696 ± 0.172***	0.053 ± 0.007***	-0.142 ± 0.020***	0.193
Scottsdale	53	0.786 ± 0.107***	0.118 ± 0.009***	0.193	0.597 ± 0.117***	0.034 ± 0.003***	-0.192 ± 0.052***	0.183
Seattle	73	0.637 ± 0.039***	0.181 ± 0.133***	0.194	0.342 ± 0.098***	0.031 ± 0.005***	0.011 ± 0.123	0.148
Tampa	78	0.672 ± 0.075***	0.085 ± 0.016***	0.063	0.697 ± 0.109***	0.012 ± 0.005*	-0.025 ± 0.009**	0.029
Walnut Valley	74	0.556 ± 0.115***	0.812 ± 0.040***	0.452	-0.324 ± 0.286	0.127 ± 0.012***	-0.103 ± 0.028***	0.497
Waterloo	79	0.664 ± 0.037***	0.267 ± 0.052***	0.056	0.754 ± 0.051***	0.005 ± 0.001***	-0.030 ± 0.014*	0.040

Note: * t value significant at 0.05 level, ** t value significant at 0.01 level and *** t value significant at 0.001 level

The average indoor water use was also estimated by implementing two alternative methods. Previous research has shown that the recorded water consumption in the minimum winter month (MWC) could be used as an estimate of the indoor consumption (Gato *et al.*, 2007; Maidment *et al.*, 1985). End-use modelling could also be used to estimate indoor use as demonstrated by Mayer *et al.* (1999) and DeOreo *et al.* (2011). Indoor water consumption estimates based on the two approaches are presented in Table 7.3. The MWC estimates in Table 7.3 were calculated as the averages of the $AMDD$ for the customer sample at each location. The end-use estimates were calculated from disaggregated indoor water use for the winter and summer logging periods extracted from the REUS database. The values presented in Table 7.3 are the daily indoor water use averaged for each group of customers.

Mayer *et al*. (1999) consider the indoor water use estimates from end-use data to be more accurate than MWC estimates. As discussed earlier, the regression model intercepts also give an estimate of the indoor use. Overall, the MWC approach did not give superior indoor water use estimates than the regression model intercept. The indoor water use estimates from the regression model were generally reasonable with respect to the end-use estimates.

Table 7.3 Average indoor water use estimated from end-use data and from the minimum winter use approaches

Location	Sample size	End-use estimate (kL/day)	MWC estimate (kL/day)
Boulder	99	0.575 ± 0.029	0.523 ± 0.029
Denver	100	0.664 ± 0.043	0.806 ± 0.046
Eugene	93	0.675 ± 0.038	0.669 ± 0.032
Las Virgenes	42	0.700 ± 0.055	1.100 ± 0.134
Lompoc	100	0.664 ± 0.043	0.913 ± 0.062
Phoenix	60	0.764 ± 0.045	1.364 ± 0.099
San Diego	83	0.562 ± 0.030	0.978 ± 0.076
Scottsdale	53	0.588 ± 0.057	1.011 ± 0.079
Seattle	73	0.568 ± 0.035	0.650 ± 0.044
Tampa	78	0.609 ± 0.040	0.743 ± 0.056
Walnut Valley	74	0.798 ± 0.048	1.035 ± 0.059
Waterloo	79	0.759 ± 0.040	0.668 ± 0.048

CONCLUSION

This study has shown that temperature and rainfall can be converted to irrigation requirements by applying localised soil and plant parameter values. Two main criteria were used to select appropriate parameters values. First the number of irrigation events determined by water balance calculations for the peak summer month and the month of minimum winter use were matched with the average of the reported frequency of landscape irrigation. Secondly, parameter values were selected that generated net monthly irrigation requirements with the highest R^2 value in the water use regression model. Comparison with regression on temperature and rainfall showed that the transformation of the climate variables to irrigation requirements, using a suitable set of parameter values, improved the performance of the water use regression models. Regression modelling was applied in this study, but a similar search for best fitting parameters could be extended to a more dynamic water use model, which would allow the outdoor water use process to be represented with greater flexibility. A sufficiently long water use dataset (say 2 years) would be required at a high temporal resolution (say every second day), typical in residential water end-use datasets. The precision could also improve with sufficient information about landscape characteristics and usage.

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Chapter 8. General discussion

In this chapter, the findings of the individual papers presented in the previous chapters are discussed. The focus is on describing the overall significance of this research study and pointing out the main limitations to the research.

The work in the previous chapters present two main modelling techniques for estimating residential outdoor water use. The CIWU model described in Chapter 2 was based on end-use modelling while the panel linear regression analysis presented in Chapter 6 utilised water billing records. Both approaches were formulated on the principle that landscape irrigation is the major contributor to residential outdoor water use. This assumption was reasonable for the case study site (Lilongwe, Malawi) because other prominent outdoor water uses, like swimming pools, are relatively uncommon.

A straightforward approach to apply the CIWU model is to use typical parameter values available in literature for the vegetation types being considered. In work related to this research, Fuamba *et al*. (2016) implemented the CIWU model to leafy vegetables. Predicted changes for several future time horizons and greenhouse gas emission scenarios were reported. According to their analysis, temperature would rise by about 1°C by 2039 under RCP8.5 and induce a rise of 5% in water use for leafy vegetables in the Hermanus area in South Africa. It was possible to replicate this analysis for the case of Lilongwe (Malawi) by applying the climate change projections in Chapter 6 of this thesis. The ensemble climate projection for 2050 indicated a temperature rise of about 1.2°C that would cause a 3% increase in water use for leafy vegetables. Thus, the impact of warming on garden water use seems to depend on the regional climatic conditions. This approach assumes that the end-user waters the garden plants according to the theoretical irrigation requirement.

The analysis presented in Chapter 4 demonstrated a procedure that could be used to calibrate the CIWU model. The CIWU model was fitted to actual measured daily water use for leafy vegetables. The model parameter values were systematically adjusted and tested to identify a suitable combination that closely fitted the observed water use. This step can be used to determine realistic parameter values for each irrigation water end-use type in the study home or area that would be applicable in a broad scale implementation of the CIWU modelling approach.

The lack of a comprehensive end-use dataset prevented the full-scale implementation of the CIWU modelling approach as proposed in Chapter 2 to a case study site. The application of the model required information on vegetated areas maintained around the home, which could be derived easily from a survey conducted during the field data collection. It was also necessary to collect household level daily irrigation water use records over a sufficiently long period for calibration.

The application of sound recording did not fully resolve the need for a comprehensive water end-use dataset to apply in the proposed CIWU model. The detection of events at the outdoor tap was satisfactory in terms of event start time and duration. Earlier work examined the feasibility of predicting flow rate from the outdoor tap flow sound (Jacobs *et al*. 2015). The authors managed to correlate the sound signal and flowrate at the tap but the precision was too low for the technique to be adopted directly in this work to estimate flow rate and thus garden irrigation. As discussed in chapter 3, the recorded events also contained significant usage attributable to indoor activities but carried out at the outdoor tap (e.g., the washing of clothes in a basin at the outdoor tap). Despite these short-comings, the successful application of sound recording to detect outdoor tap use events was itself a notable achievement. Considering that developing countries are faced with limited data, extracting the start and end times of events allows for improved estimates of end-use volume to be made based on event volume, with flow rate assumed or measured. The result would notably improve the current state of affairs.

The case studies presented in Chapters 5 and 6 present estimates of outdoor water use from monthly water billing records. Water billing records usually comprise metered consumption per customer collected and archived by water utilities. Although there is only one water use measurement per household in a month or bi-monthly period, the available records normally extend over several seasons or years. This rich and readily available data would allow the application of the regression modelling approach described in Chapter 6 to other cities with monthly water use records.

The application of irrigation requirements in the water use regression model was unique to this research. The Lilongwe water use dataset provided little evidence of the advantage of using irrigation requirements in regression over the use of temperature and rainfall. There was a need to test the performance of this adapted approach under different weather conditions. Chapter 7 was added to address this shortcoming. The 12 study locations included in the 1999 REUS database provided the desired variety in weather and illustrated the application of the regression model to another region beyond Africa. The application of theoretical irrigation requirements makes the model easier to interpret because the observed household water use when irrigation requirement is equal to zero approximates to indoor use. The use of irrigation requirements therefore offers an advantage over regression on temperature and rainfall applied in similar studies. The disaggregated end-use data contained in the REUS database for each study location was vital for verifying the accuracy of the regression intercept as an estimate for indoor use.

The two approaches for modelling water use applied in this study are complementary. Regression modelling with climate inputs is appropriate for estimating weather driven water use of blocks of customers but lacks the necessary detail for pinpointing the exact contributors to the observed usage. The application of end-use modelling is more appropriate for application to specific target end-uses. Regression modelling can provide estimates of the potential savings at the beginning of an outdoor water conservation programme. The analysis of the contribution of specific outdoor water end-uses can be performed using the CIWU model. The CIWU model is helpful for planning the water conservation measures targeted at specific outdoor end uses. The end-use approach can also be used at planning phases when no measurements can be made. Either approach can be used for climate impact assessment as long as the baseline conditions are properly captured in the estimated model.

The models presented in this research have been formulated based on present water management practices. Residential irrigation water use habits could change significantly in the future due to factors such as technological, economic and social development. In view of potential future water supply challenges, urban planning and design is increasingly adopting water sensitive urban design (WSUD) concepts to maximise the beneficial effects of the hydrological cycle. Implementing WSUD involves the introduction of soil and water conservation practices such as rainwater harvesting tanks, rain gardens, water reuse and the like. The models presented in this research could, therefore, require modifications to suit future conditions. A detailed study of how residential irrigation water use would be affected by WSUD or other future developments was beyond the scope of this research.

Chapter 9. Conclusion

9.1 Summary of findings and conclusions

This study included a comprehensive review of outdoor water end-use modelling and key concepts relating to projection of future climate. End-use modelling is suitable for planning and implementing bottom-up water demand management measures as a supplement to the usual top-down approaches. There is a limited application of outdoor water end-use modelling compared to indoor water end-use modelling. One reason is that available residential water end-use datasets mostly cover periods that are too short for comprehensive outdoor water use modelling.

This study modified the existing REUM outdoor component to incorporate parameters for assessing impacts of climate change. The FAO Penman Monteith equation was incorporated for estimating evapotranspiration and the soil water balance equation for estimating effective rainfall. The resulting CIWU modelling approach allowed the direct input of temperature and rainfall records, which are the main outputs of global climate models.

The CIWU modelling approach was applied in related work to the case of leafy vegetables using a combination of typical parameter values. Leafy vegetables grown in backyard garden are a vital food supplement for many households in urban areas in Malawi. Since water users do not necessarily water their gardens according to the irrigation requirement under standard conditions, a separate analysis was performed to fit the predictions to observed water use through application of appropriate parameter values. An exhaustive search procedure was used to identify parameter values of best fit. The unique characteristic of the model was that the choice of suitable parameter values reproduced irrigation end-use events in terms of both the volume and frequency of water application. This later approach provides more realistic estimates from the CIWU model.

Outdoor water use was also investigated using sound recording at the outdoor tap at 10 study homes in Lilongwe. The use of sound recording provided a relatively cheaper technique for detecting outdoor water use events than other available technologies. The results showed that sound recording can be used to characterise water use events at the outdoor tap in terms of duration and time of occurrence. Application of an automatic algorithm showed that the tap use events could be detected at precision and recall rates of at least 80%. It was also observed that several activities normally carried out indoors were also performed at the outdoor taps, for example, washing of clothes.

A broad-scale study was also conducted to examine the influence of climatic factors on water use for selected neighbourhoods in the city of Lilongwe. The average monthly daily demand increased with plot size in line with similar research in southern Africa. Seasonal variation in water use accounted for about 24% of total annual water use. The maximum monthly water use in summer was 1.2 times higher than the annual average for the smallest plots size category of 0 - 500 m^2 and this factor increased to about 1.6 times the annual average for plots larger than 2,500 m^2. These relatively high seasonal peaks suggested considerable outdoor water use.

A panel linear regression model was fitted between water use and the independent variables plot size and the theoretical irrigation requirements derived for the period of study. In order to assess the impacts of climate change on water use, ensemble averages of projected baseline and future temperature and rainfall time series were transformed into theoretical irrigation requirements prior to input in the estimated regression model. The predicted changes in annual water use for the year 2050 were 1.5% and 2.3% under the low and high emissions scenarios respectively. The end of summer, which also marks the beginning of the rainy season, was noted to be the most critical period for water supply in the Southern African case study site (Lilongwe, Malawi). This period showed the highest rise in predicted water use due to both higher temperatures and reduced rainfall. This is also the period of the year when river flows are at a minimum.

The case study in Chapter 7 was conducted to compare the performance of temperature and rainfall as independent variables in water use regression models with the alternative use of theoretical irrigation requirements. The choice of the appropriate soil and plant parameter values for transforming temperature and rainfall to irrigation requirements were obtained through an exhaustive search. The results showed that the transformation of temperature and rainfall to irrigation requirements, using a suitable set of parameter values, improved the performance of the water use regression models.

9.2 Recommendations for further research

The application of sound recording has been limited to the detection of event duration and time of occurrence. The method is not yet fully developed to estimate the flow rate and thus the amount of water use on outdoor fixtures. Further research is needed on estimation of flow rate from the recorded sound signals. Other reported research reviewed in this study suggest different approaches for estimating flowrate from sound signals. Better results are likely to be achieved by using a combination of techniques that address the different flow conditions, for example combining vibration and/or sound and/or temperature sensing.

The CIWU modelling approach was not tested on a larger scale such a neighbourhood due to lack of a comprehensive outdoor water use dataset. As smart meters become commonplace, sufficient irrigation water use data may be become available for a thorough application of the CIWU model. Stochastic simulation modelling is another potential area for application of residential outdoor water end-use modelling. The inputs of the outdoor end-use model are not fixed but vary for different outdoor end-uses. Stochastic modelling may account for the degree of unpredictability in the outdoor water use estimates.

9.3 Summary of contributions

The model of outdoor irrigation water end use presented in this study provides a means of simulating both the irrigation water use for a fixture and the frequency of application. The application of conceptual models for estimating outdoor water use is not new, but the adaptations made to allow for climate change and the calibration approach presented increase the versatility of the model to represent domestic irrigation water use.

The combined application of panel linear analysis, plot size and weather data in a water use regression is unique to this research. This method worked reasonably well and represented customer water use reasonably well. Since the model uses data that is readily available to utilities, it is easy to replicate the methodology presented. In addition, the approach is suitable to developing countries with limited data when compared to comprehensive end-use studies abroad.

Several studies have explored the potential for using sound in fluid flow applications. However, the application of sound recording and automated event detection for characterising outdoor water use events has not been presented before. Although no accurate method has yet been developed to estimate flow rate from recorded sound, the technique presented in this study was useful for identifying end-use event start and end times (thus duration) and it is relatively inexpensive.

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Appendix A: Declarations of candidate and co-authors

Declaration by the candidate (Chapter 2)

The nature and scope of my contribution to Chapter 2 of this thesis, the published paper "A conceptual theoretical framework to integrally assess the possible impacts of climate change on domestic irrigation water use", were as follows:

Nature of contribution	Extent of contribution
- Conceptualised and wrote the paper - Review of literature	45%

The following co-authors contributed to Chapter 2 of this thesis, "A conceptual theoretical framework to integrally assess the possible impacts of climate change on domestic irrigation water use":

Name	e-mail address	Nature of contribution	Extent of contribution
M. Fuamba	musandji.fuamba@polymtl.ca	Assisted with editing and compilation of the paper	5%
F. Houssa	houssa.fadoua@gmail.com	Contributed to literature review and writing of the paper	45%
H. E. Jacobs	hejacobs@sun.ac.za	Assisted with editing and compilation of the paper	5%

Signature of candidate: ....
Date: ....12 OCTOBER, 2017......

Declaration by co-authors:

The undersigned hereby confirm that

1. The declaration above accurately reflects the nature and extent of the contribution of the candidate and the co-authors to Chapter 2 of this thesis "A conceptual theoretical framework to integrally assess the possible impacts of climate change on domestic irrigation water use",
2. No other author contributed to Chapter 2 of this thesis, "A conceptual theoretical framework to integrally assess the possible impacts of climate change on domestic irrigation water use" besides those specified above, and
3. Potential conflicts of interest have been revealed to all interested parties and that the necessary arrangements have been made to use the material in Chapter 2 of this thesis, "A conceptual theoretical framework to integrally assess the possible impacts of climate change on domestic irrigation water use".

Signature		Institutional affiliation	Date
F. Houssa	FH	Polytechnique Montréal	29-09-2017
M. Fuamba		Polytechnique Montréal	04th of october 2017
		Stellenbosch University	

Declaration by the candidate (Chapter 3)

The nature and scope of my contribution to Chapter 3 of this thesis, the published paper "Sound recording to characterize outdoor tap water use events", were as follows:

Nature of contribution	Extent of contribution
- Field data collection - Data analysis and writing of the paper	95%

The following co-authors contributed to Chapter 3 of this thesis, "Sound recording to characterize outdoor tap water use events":

Name	e-mail address	Nature of contribution	Extent of contribution
H. E. Jacobs	hejacobs@sun.ac.za	Contributed to writing of the paper	5%

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Declaration by co-authors:

The undersigned hereby confirm that

1. The declaration above accurately reflects the nature and extent of the contribution of the candidate and the co-authors to Chapter 3 of this thesis "Sound recording to characterize outdoor tap water use events",
2. No other author contributed to Chapter 3 of this thesis, "Sound recording to characterize outdoor tap water use events" besides those specified above, and
3. Potential conflicts of interest have been revealed to all interested parties and that the necessary arrangements have been made to use the material in Chapter 3 of this thesis, "Sound recording to characterize outdoor tap water use events".

Signature	Institutional affiliation	Date
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Declaration by the candidate (Chapter 5)

The nature and scope of my contribution to Chapter 5 of this thesis, the published paper "Assessing the impact of property size on residential water use for selected neighbourhoods in Lilongwe, Malawi", were as follows:

Nature of contribution	Extent of contribution
- Conceptualised and wrote the paper - Carried out data analysis	95%

The following co-authors contributed to Chapter 5 of this thesis, "Assessing the impact of property size on residential water use for selected neighbourhoods in Lilongwe, Malawi":

Name	e-mail address	Nature of contribution	Extent of contribution
H. E. Jacobs	hejacobs@sun.ac.za	Contributed to writing of the paper	5%

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Date: ....12 OCTOBER, 2017.......

Declaration by co-authors:

The undersigned hereby confirm that

1. The declaration above accurately reflects the nature and extent of the contribution of the candidate and the co-authors to Chapter 5 of this thesis "Assessing the impact of property size on residential water use for selected neighbourhoods in Lilongwe, Malawi",
2. No other author contributed to Chapter 5 of this thesis, "Assessing the impact of property size on residential water use for selected neighbourhoods in Lilongwe, Malawi " besides those specified above, and
3. Potential conflicts of interest have been revealed to all interested parties and that the necessary arrangements have been made to use the material in Chapter 5 of this thesis, "Assessing the impact of property size on residential water use for selected neighbourhoods in Lilongwe, Malawi".

Signature	Institutional affiliation	Date
	Stellenbosch University	

Declaration by the candidate (Chapter 6)

The nature and scope of my contribution to Chapter 6 of this thesis, the published paper "Estimating the impact of climate change on residential water use using panel data analysis: a case study of Lilongwe, Malawi", were as follows:

Nature of contribution	Extent of contribution
- Conceptualised and wrote the paper - Carried out statistical analysis	65%

The following co-authors contributed to Chapter 6 of this thesis, "Estimating the impact of climate change on residential water use using panel data analysis: a case study of Lilongwe, Malawi":

Name	e-mail address	Nature of contribution	Extent of contribution
M Fuamba	musandji.fuamba@polymtl.ca	Contributed to writing of the paper	5%
F Houssa	houssa.fadoua@gmail.com	Contributed to climate change modelling	25%
H. E. Jacobs	hejacobs@sun.ac.za	Contributed to writing of the paper	5%

Signature of candidate: ....

Date: ....21 OCTOBER, 2017.....

Declaration by co-authors:

The undersigned hereby confirm that

1. The declaration above accurately reflects the nature and extent of the contribution of the candidate and the co-authors to Chapter 6 of this thesis "Estimating the impact of climate change on residential water use using panel data analysis: a case study of Lilongwe, Malawi ",
2. No other author contributed to Chapter 6 of this thesis, "Estimating the impact of climate change on residential water use using panel data analysis: a case study of Lilongwe, Malawi " besides those specified above, and
3. Potential conflicts of interest have been revealed to all interested parties and that the necessary arrangements have been made to use the material in Chapter 6 of this thesis, "Estimating the impact of climate change on residential water use using panel data analysis: a case study of Lilongwe, Malawi".

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	Stellenbosch University	

Declaration by the candidate (Chapter 7)

The nature and scope of my contribution to Chapter 7 of this thesis, the unpublished paper "Improving performance of water use regression models through the determination of optimal parameters for the transformation of weather inputs", were as follows:

Nature of contribution	Extent of contribution
- Conceptualised the study and wrote paper - Carried out analysis	95%

The following co-authors contributed to Chapter 7 of this thesis, "Improving performance of water use regression models through the determination of optimal parameters for the transformation of weather inputs":

Name	e-mail address	Nature of contribution	Extent of contribution
H. E. Jacobs	hejacobs@sun.ac.za	Contributed to writing of the paper	5%

Signature of candidate: ....

Date: ....12 OCTOBER, 2017.........

Declaration by co-authors:

The undersigned hereby confirm that

1. The declaration above accurately reflects the nature and extent of the contribution of the candidate and the co-authors to Chapter 7 of this thesis "Improving performance of water use regression models through the determination of optimal parameters for the transformation of weather inputs",
2. No other author contributed to Chapter 7 of this thesis, "Improving performance of water use regression models through the determination of optimal parameters for the transformation of weather inputs" besides those specified above, and
3. Potential conflicts of interest have been revealed to all interested parties and that the necessary arrangements have been made to use the material in Chapter 7 of this thesis, "Improving performance of water use regression models through the determination of optimal parameters for the transformation of weather inputs".

Signature	Institutional affiliation	Date
	Stellenbosch University	