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Regional-scale variability of cold water temperature: Implications for household water-related energy demand

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A B S T R A C T

Residential water use accounts for at least 80% of water-related energy (WRE) demand (primarily through water heating) in the residential urban water system. Cold water temperature (CWT) is a key determinant in predicting residential WRE but variation of CWT within water networks has not been quantified and is not accounted for in water heating energy consumption guidelines. Here, we analysed the spatiotemporal variability in CWT over the course of a year (2013) using 5760 measurements from 1255 urban water system sampling locations across the Yarra Valley Water region in Melbourne, Australia. CWT varied across the study site from 12–28 °C during summer and 9–15 °C during winter. Spatial clusters of higher CWT regions (hot spots) and lower CWT regions (cold spots) were also observed. The CWT variability impact on annual household WRE demand was estimated to be between −17 to +19% (−640 to +680 kWh/hh.yr) change in water heating for sample households, which is dependent on the geographical location of the household within the study site. However, households located in cold spot regions will have almost twice the amount of WRE demand than average, conversely, WRE demand will be lower than average in hot spot regions.

Monthly mean CWTs diverged from the Australian Standards for hot water system energy consumption guidelines value by −21 to +47%. The magnitude of CWT variability and associated energy required for water heating are comparable with the total energy used by water utilities to deliver water supply and sewage disposal services. Variation in water heating could be as large as −4.6 kWh/hh.d (hot spot in March) and 3.6 kWh/hh.d (cold spot in July), more than three times the total energy used to deliver water supply and sewage disposal services for this region. Accounting for CWT variability could increase accuracy of regional-scale WRE demand and hot water system performance.

1. Introduction

Water end use processes have significantly higher energy intensity than the energy required for water supply and sewage disposal services (Kenway, S. J. et al., 2011; Lee and Tansel, 2012; Olsson, 2015; Rothausen and Conway, 2011). At least 80% of water-related energy (WRE) demand in the residential urban water supply system is caused by household water use (Elías-Maxil et al., 2014; Kenway et al., 2008). However, residential WRE is often not considered by utilities and end users. This may be because water utilities have little direct control over WRE in households. Widening the water utilities perspective on energy use to include residential WRE demand presents opportunities to attain whole-of-system reduction in WRE demand of urban water systems (IWA, 2014). For example, solar hot water systems (SHWSs) can reduce WRE by 50–85% for an average household (Sanders and Webber, 2015), thereby significantly reducing related GHG emissions. Minimising residential WRE demand is therefore important in ensuring long-term sustainability of urban water systems.

The indirect implications of water management on WRE have not been greatly considered (Siddiqi and de Weck, 2013), in particular, the impact of cold water temperature (CWT) on residential WRE demand through water heating energy consumption (Kenway, S. J. et al., 2011; Kenway et al., 2013). For example, Kenway et al. (2014) observed that a 2 °C reduction in CWT could increase household WRE demand by 6%. Correspondingly, Kaufmann et al. (2013) estimated a 1 °C rise in CWT could reduce state-wide annual residential natural gas consumption by 5.6%. Water utility management of CWT in the distribution network has potentially, a substantial influence on household WRE demand.

There is significant evidence that CWT is not a constant value in water distribution networks but varies spatially and temporally (Abrams and Shedd, 1996; Bors et al., 2014; Burch and Christensen, 2007; Lee, 1987). Thus, quantifying the spatiotemporal variability of CWT is important for estimating household WRE demand. For instance, a constant CWT of 15 °C is often assumed in calculations for the daily

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energy consumption of electric hot water systems (EHWSs) (Standards Australia, 1997) and the minimum energy performance of gas hot water systems (GHWSs) (Standards Australia, 2010) whilst SHWS performance is assessed using average monthly CWT values derived by dividing Australia into four climate zones (Standards Australia, 2008). However, the assumption of constant CWT values within each climate zone can introduce errors in predicting energy changes in large-scale adoption of SHWSs (Mills, 2004). The spatiotemporal variability of CWT may therefore be important to regional-scale predictions of WRE demand. Moreover, more accurate CWT values could enable more accurate predictions of changes in household WRE demand in response to policy, infrastructure and market changes (e.g. increased use of SHWSs through state government rebate schemes to achieve state government renewable energy targets).

Many different factors could be contributing to the observed spatial and temporal variability of CWT in water distribution networks. For instance, ambient air temperature affects CWT at the source (e.g. reservoir water temperature) (Mo et al., 2016) and through the distribution network (e.g. ground temperature) (Burch and Christensen, 2007). Studies also reveal a rise in regional urban subsurface temperatures (Benz et al., 2016; Menberg et al., 2013; Zhu et al., 2015) which could contribute to higher CWTs. CWT also interacts with the built environment. For example, position of water pipes relative to other infrastructure and landscape features (e.g. roads, groundwater, and forested areas). Additionally, in many urban water systems, water is stored temporarily in above-ground metal tanks which could affect local CWT. The temperature of the source water may vary substantially (e.g. desalination, recycled water, reservoirs at different altitudes and depths) and thus also has the potential to affect CWT in the distribution network. In practice, the observed variability in CWT is likely to be caused by a combination of factors, which probably vary across the water distribution network and over time. Investigation of these factors is not possible. In this paper however, our work opens the possibility and need to understand them in future.

Previous studies have demonstrated the increasing importance of utilising spatiotemporal analysis techniques in determining: (i) urban water use for urban water management (Franczyk and Chang, 2009; Inamdar et al., 2013; Moore et al., 2015; Sohn, 2011), and (ii) residential water heating for urban energy management (Howard et al., 2012; Pereira et al., 2013; Taylor et al., 2014). In this study, spatial analysis of CWT data was used to identify statistically significant spatial variations of CWT across a subset of the Melbourne water distribution network. The associated CWT variability impact on residential WRE demand was evaluated using previously published results for CWT impact on household energy use presented in Kenway et al. (2014). The objective of the research was to: (i) use spatial statistical analysis to identify spatiotemporal variations in CWT, (ii) examine the relationship between CWT and the potential impact on household energy use, and (iii) examine the relationship between CWT and hot water system standards. This work was conducted as part of a wider project including collaboration across research, industry and government.

2. Method

2.1. Study area

The Yarra Valley Water (YVW) utility service area was selected for the main study site (Fig. 1(a–c), −37.97°S to −37.39°S, 144.80°E to 146.17°E). This area covers approximately 4000 square kilometres and includes 671,000 residential properties in Melbourne, Australia (YVW, 2013a). The region is classified as a temperate climate with no dry season, mild to warm summers, cold winters and a median annual rainfall over 800 mm (BOM, 2005).

2.2. Data and statistical analysis approach

YVW provided a dataset of 29,997 CWT measurements taken from 1496 sampling locations at frequency intervals of approximately four times per year over five consecutive years (2009–2013) covering the YVW water service area. GIS files of the water infrastructure layout and the YVW business boundary were also provided to assist with assessing the underlying patterns in the distribution of CWT effects on residential WRE demand. Georeferenced CWT sampling locations were converted to shapefiles using the software ArcGIS 10.3 (Esri, 2015).

There were three distinct stages of analysis in this study:

(i) *Characteristics of seasonal range of CWT across 5 years*. Characterised the seasonal range of CWT data from 2009 to 2013.
(ii) *Spatial analysis of CWT across YVW region for 12 months.* Assessed the spatial variability of CWT for each month of 2013 (January–December) using ArcGIS 10.3.
(iii) *Monthly CWT and WRE demand*. Characterised monthly CWT from stage 2 results, the associated impact on household WRE demand using CWT sensitivity results from Kenway et al. (2014) and the CWT deviation from hot water system energy consumption standards.

2.3. Characteristics of seasonal range of CWT across 5 years

Temporal variability of the CWT entering households situated within the geographical region serviced by YVW was characterised through box and whiskers plots of pooled CWT data for each month 2009–2013. The centre horizontal line of the box is the mean of the monthly subset of data, the top and bottom of the box are the 25th and 75th percentiles (quartiles) and the ends of the whiskers are the 5th and 95th percentiles. Previous investigations found that there may be a slight increase in inter-annual CWT in the study area over time, but that this increase was small compared to spatial and seasonal variability and could not be verified statistically due to changes in sampling methods (Grace et al., 2014). Thus, time-series analysis of inter-annual spatial variability in CWT is not included in this paper.

2.4. Spatial analysis of CWT across YVW region for 12 months

In the second stage of analysis, spatial variability in CWT data was quantified using the *Hot Spot Analysis* tool in ArcGIS 10.3, a spatial pattern analysis technique that can identify statistically significant spatial clusters of high values (hot spots) and low values (cold spots). The *Hot Spot Analysis* tool was applied to subsets of monthly data for 12 months of the most recently available complete year of CWT measurements (5760 measurements were taken between January–December 2013 from 1255 sampling locations). The null hypothesis for this type of spatial pattern analysis is 'Complete Spatial Randomness' (Fischer and Getis, 2010), i.e. the CWT values are randomly spread across the YVW service area. The null hypothesis can be rejected when there is a statistically significant spatial cluster of CWT measurements. Statistically significant spatial clusters signify that data values are not attributed to random chance and there is an underlying spatial process at work (Mitchell, 2005).

The spatial statistic technique behind the *Hot Spot Analysis* tool is the Getis-Ord $G_i^*(d)$ local statistic (Mitchell, 2005). The calculated $G_i^*(d)$ output of each CWT measurement is a z-score (measure of standard deviation) demonstrating the statistical significance of normally distributed CWT values and a corresponding p-value (probability) demonstrating the confidence level of the z-score. The statistic can separate clusters of high values from clusters of low values (Getis and Ord, 1992). A cluster of high CWT values (hot spot) was indicated by a statistically significant positive z-score whilst a cluster of low CWT values (cold spot) was indicated by a statistically significant negative z-score. Statistical significance was determined at the 90% ($p < 0.1$),