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# A hybrid model of machine learning for classifying household water-consumption behaviors

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ABSTRACT

Classifying household water-consumption behaviors is crucial for providing targeted suggestions for water-saving behaviors and enabling effective resource management and conservation. Although it is common knowledge that energy consumption is closely coupled with household water consumption, the effectiveness of energy consumption information in classifying household water-consumption behaviors remains unexplored. This study proposes a hybrid model of long short-term memory (LSTM) and random forest (RF) using water and electricity consumption as inputs to classify household water-consumption behaviors. Data from three households in Beijing collected from January to March 2020 were used for the case studies. The hybrid model achieved a macro F1 score of 0.89 at a 5-min resolution, outperforming the standalone LSTM and RF models. Additionally, the inclusivity of time-series electricity consumption improves the accuracy (F1 scores) of classifying bathing and laundry behaviors by 0.12 and 0.20, respectively. These findings underscore the scientific value of integrating electricity consumption as a proxy variable in water-consumption behavior classification models, demonstrating its potential to enhance accuracy while simplifying data acquisition processes. This study establishes a framework for demand-side water management aimed at empowering residents to understand their own water-energy consumption behavior patterns and engage in personalized water conservation efforts.

## 1. Introduction

With economic development and urbanization, urban water consumption, particularly household water consumption, has increased rapidly (Dolan et al., 2021). According to WRI's Aqueduct, global household water demand increased by 600% between 1960 and 2014 (Flörke et al., 2013). The volume of household water consumption in China surged from 6.8 billion $m^3$ in 1980 to 77 billion $m^3$ in 2010, a more than tenfold increase (Wang et al., 2018). There were projections indicating that by 2050, global household water consumption could increase by 50%–250% compared with that in 2010 (Wada et al., 2016). This escalation has led to water scarcity, which is a significant factor restricting sustainable development and underscores the urgent need for water conservation strategies.

Classifying household water-consumption behaviors is vital for unlocking potential water-saving measures (Cominola et al., 2023; Russell and Fielding, 2010), such as providing personalized water-saving suggestions, positively facilitating water conservation endeavors (Liu et al., 2016), and enabling managers to scrutinize and refine their incentive measures based on detailed information about water end uses (Gleick et al., 2003). Based on the water-consumption behavior classification, households could adjust their high water-consumption behavior, which could lead to significant water savings of up to 28% (Kneebone, 2018). However, despite its importance, there remain critical gaps in the methods and frameworks used for classifying water-consumption behaviors.

Existing research on household water-consumption behavior classification has primarily relied on high-resolution data collected at sub-minute intervals (i.e., data collection intervals of <1 min) (Cominola et al., 2019; Heydari et al., 2022). While these approaches achieve high accuracy, they are resource-intensive, costly, and often require invasive monitoring systems that raise privacy concerns. This limits their scalability and practical application. Recent advancements suggest that coarser temporal resolutions—such as minute-level data—can provide comparable classification accuracy while reducing costs and avoiding intrusive monitoring (Britton et al., 2013). However, the effectiveness of minute-level resolution data for behavior classification remains theoretical. Furthermore, although machine learning techniques have been

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widely applied in this domain, new algorithmic approaches (e.g., hybrid machine learning methods) are still needed to enhance classification modeling accuracy (Huang et al., 2022; Manandhar et al., 2023; Nguyen et al., 2015).

Another critical gap lies in the limited integration of the water-energy nexus into existing classification models. Water-related activities such as laundry and bathing are closely linked to electricity consumption, yet most studies fail to incorporate this interdependence (Fidar et al., 2010; Plappally, 2012; Wang et al., 2022). Recent evidence suggests that integrating electricity consumption data as a proxy for water-consumption behaviors can significantly improve classification accuracy (Li et al., 2024). However, challenges such as the need to align electricity and water consumption data, or the requirement for specialized monitoring systems that involve installing numerous sensors in households, have hindered widespread adoption.

Research on classifying household water-consumption behaviors has identified gaps in the inclusion of the water-energy nexus, underexplored utilization of hybrid machine learning methods, and limited temporal resolution for data acquisition. To fill these research gaps, this study makes the following contributions: (1) develop a neural-network-based hybrid machine learning model, leveraging non-invasive devices to classify household water-consumption behaviors using both water and electricity consumption data; (2) demonstrate the effectiveness of incorporating electricity consumption as a proxy variable by capturing interdependencies between water and electricity consumption; (3) identify an optimal temporal resolution for data collection, showing that minute-level resolutions can achieve high performance while reducing costs and avoiding intrusive monitoring; and (4) validate the proposed method through a case study, providing empirical evidence for their effectiveness in practical applications. Therefore, this study proposes a method for household water-consumption behavior classification that offers greater practical applicability.

The remainder of this paper is organized as follows. The Literature review section identifies main research gaps on household water-consumption behaviors. The Data and method section provides the research framework, describes the feature variables, introduces the Long Short-Term Memory (LSTM) and Random Forests (RF) hybrid model. The Results section shows a descriptive statistical analysis of the characteristics of household water and electricity consumption and compares the performance of the hybrid model with that of the LSTM and RF models. The impact of different temporal resolutions and electricity proxies on water-consumption behavior classification is also analyzed. The Discussion section compares the results of this study with those of other studies and explores the insights for water management and household water conservation. The Conclusion summarizes the key findings and limitations of this study.

## 2. Literature review

Critical research gaps on household water-consumption behavior classification persist in three key dimensions: the limited application of hybrid machine learning methods, the challenges associated with high-resolution data collection, and the effectiveness of integrating the electricity consumption data as a proxy into classification models.

### *2.1. Methods for classifying household water-consumption behaviors*

Household water-consumption behavior classification has evolved through various methods, each with distinct advantages and limitations. Early studies relied on **tree-based algorithms**, such as Trace Wizard (DeOreo et al., 1996) and Identiflow (Kowalski and Marshallsay, 2003), which classify water consumption based on physical characteristics like volume, duration, and flow rate. Another approach involves **Bayesian-based methods** (such as HydroSense (Froehlich et al., 2011)) that integrate data from multiple pressure sensors across household appliances. These methods leverage probabilistic models to achieve moderate or even quite high accuracy (e.g., 70% (Nguyen et al., 2013) and 90% (Froehlich et al., 2011)). However, the high cost of installing numerous pressure sensors and the associated privacy concerns make them impractical for large-scale applications.

To address these challenges, **machine learning methods** have been increasingly adopted in recent years. Long Short-Term Memory (LSTM) networks are particularly advantageous for capturing complex temporal dependencies inherent in time series data related to water consumption (Bennett et al., 2013; Cascone et al., 2023; Ismail Fawaz et al., 2019). For instance, an LSTM model applied to data from 83 households achieved an average root mean square error (RMSE) of 0.40, demonstrating its strong predictive capabilities for various water-consumption behaviors (Rahim et al., 2019). As for classification, Random Forest (RF) classifiers have been utilized for household water-consumption behavior classification based on high-resolution data obtained from smart water meters. These models have consistently shown high performance, achieving weighted F1-scores above 0.85 when trained on datasets aggregated at different temporal resolutions (Heydari et al., 2022). Comparative studies indicate that RF outperforms other traditional algorithms like Support Vector Machines (SVM) and Logistic Regression (Log-reg), establishing itself as a preferred method in this domain (Heydari and Stillwell, 2024). In addition, hybrid machine learning models that combine multiple algorithms have shown great promise by leveraging the strengths of different algorithms (Huang et al., 2022; Manandhar et al., 2023; Nguyen et al., 2015). For instance, Autoflow and EU2016 utilize hidden Markov models (HMM), artificial neural networks (ANN), and dynamic time warping (DTW) to decompose total water consumption into specific behaviors, achieving accuracies between 85% and 90% (Beal et al., 2011; Bennett et al., 2013; Nguyen et al., 2014). Despite their effectiveness, these methods typically require high-resolution data collected at subminute intervals, which increases costs.

### *2.2. Data acquisition and temporal resolution*

The optimal balance between the temporal resolution of water consumption data in terms of model accuracy remains uncertain (Hall et al., 2025). In existing studies, the intervals for collecting water consumption data ranged from a few seconds to a few hours. Subminute resolution data are widely adopted for the classification of water consumption (Mazzoni et al., 2023). Collection at this resolution typically requires invasive equipment (Bastidas Pacheco et al., 2022) as it requires the addition of sensors or custom hardware and software to meters (Stewart et al., 2018). High-resolution data collection often incurs greater costs, such as the need for more precise equipment and the difficulty in recruiting participants. However, coarser temporal resolutions, although more cost effective, may compromise the effectiveness of the models. For instance, resolutions coarser than an hour are considered relatively crude for classifying water-consumption behaviors (Britton et al., 2013). The trade-off between classification accuracy and cost highlights the significance of investigating the effectiveness of water-consumption behavior classification across different minute-level resolutions.

The challenge of data acquisition could be partially addressed by the advent of technologies such as smart water meters and flow sensors (Darby, 2010; Gurung et al., 2015; Stewart et al., 2018). Measurement methods are primarily divided into invasive and non-invasive types (Cominola et al., 2018). Invasive measurement involves installing sensors on individual water-consuming devices, such as washing machines and showerheads, and is commonly used for water-consumption behavior classification. For instance, one study installed 92 flow sensors in a household to record second-by-second readings of the sensors (i.e., the temporal resolution is 1 s) (Kropp et al., 2022). Yet, invasive measurement has high costs and privacy concern (Attallah et al., 2021; Heydari et al., 2022; Kropp et al., 2022; Mazzoni et al., 2023; Meyer et al., 2021; Nguyen et al., 2015). In contrast, non-invasive measurement recording the total household water consumption at only a single monitoring point in each household is installed by water utility company, making it more suitable for large-scale use (Ellert et al., 2015; Vitter and Webber, 2018a).

### 2.3. Proxy of electricity in household water-consumption behaviors classification

Existing approaches reaching the high classification accuracy (exceeding 81% (Attallah et al., 2021; Kropp et al., 2022; Mazzoni et al., 2021; Meyer et al., 2021; Nguyen et al., 2015; Rahim et al., 2021)) often rely on multidimensional water-related metrics, such as start and end times of water-consumption behaviors (Mazzoni et al., 2021; Rahim et al., 2021), duration (Kropp et al., 2022; Mazzoni et al., 2021; Meyer et al., 2021; Nguyen et al., 2015; Rahim et al., 2021), total water consumption (Mazzoni et al., 2021; Nguyen et al., 2015), water flow rate (Attallah et al., 2021; Mazzoni et al., 2021; Meyer et al., 2021), and maximum flow rate (Kropp et al., 2022; Nguyen et al., 2015; Rahim et al., 2021), which require high-resolution data and invasive measurements. These approaches are effective at the cost of being resource-intensive. By contrast, electricity consumption data, which can be easily obtained from household smart meters without additional monitoring devices, offers a scalable and non-invasive alternative.

The theoretical foundation for incorporating electricity consumption lies in the water-energy nexus, which highlights the interdependence between water and energy use in households (Vitter and Webber, 2018a, 2018b). Major water-consumption behaviors, such as laundry, dishwashing, and bathing, are inherently energy-intensive due to their reliance on appliances like washing machines and water heaters (Fidar et al., 2010; Plappally, 2012; Wang et al., 2022). Studies have demonstrated that leveraging electricity consumption data can significantly enhance classification accuracy (Ellert et al., 2015, Nguyen et al., 2017; Vitter and Webber, 2018a, 2018b). For instance, using a binary variable (0/1) to indicate the operational status of key appliances, such as washing machines and dishwashers, improved the accuracy of laundry and dishwashing classifications from 71% to 87% (Vitter and Webber, 2018a). Furthermore, incorporating detailed electricity consumption data through circuit-level monitoring further increased overall classification accuracy from 90.4% to 93.1% (Nguyen et al., 2017). These findings underscore the potential of electricity data as a "proxy" for water-consumption behaviors, capturing patterns that are otherwise difficult to discern using water-related metrics alone (Bongungu et al., 2022; Li et al., 2024; Wang et al., 2023).

## 3. Data and method

### 3.1. Research framework

The research design encompassed three components (Fig. 1). First, historical time series data on water and electricity consumption were collected from three households in Beijing. Second, a hybrid model combining the LSTM and RF models was developed to classify the three water-consumption behaviors considered in this study: bathing, cooking, and laundry. Finally, a comprehensive evaluation was conducted to assess the performance of the proposed model, including the models' overall performance (i.e., macro F1 score) and individual behavioral performance (i.e., F1 score). The influence of different temporal resolutions and electricity proxies on the classification of water-consumption behavior was examined.

### 3.2. Input features and output labels

Three types of input features are used in this study: water consumption, electricity consumption, and time. Water consumption is a direct indicator of household water-consumption behaviors. To effectively capture time-related patterns, this study used sine and cosine transformations for the time variable, considering the temporal sequence within a day and the cyclic nature of daily patterns (Mahajan et al., 2021). Employing this commonly used method for encoding cyclical data, the time variable was transformed into two dimensions, $T_{sin}$ and $T_{cos}$, as shown in formulas (1) and (2).

$$T_{isin} = \sin\left(\frac{2\pi \bullet i}{\max(i)}\right) \quad (1)$$

$$T_{icos} = \cos\left(\frac{2\pi \bullet i}{\max(i)}\right) \quad (2)$$

where.

$T_{isin}$ represents the sine transformation of the time variable $i$;

$T_{icos}$ represents the cosine transformation of the time variable $i$;

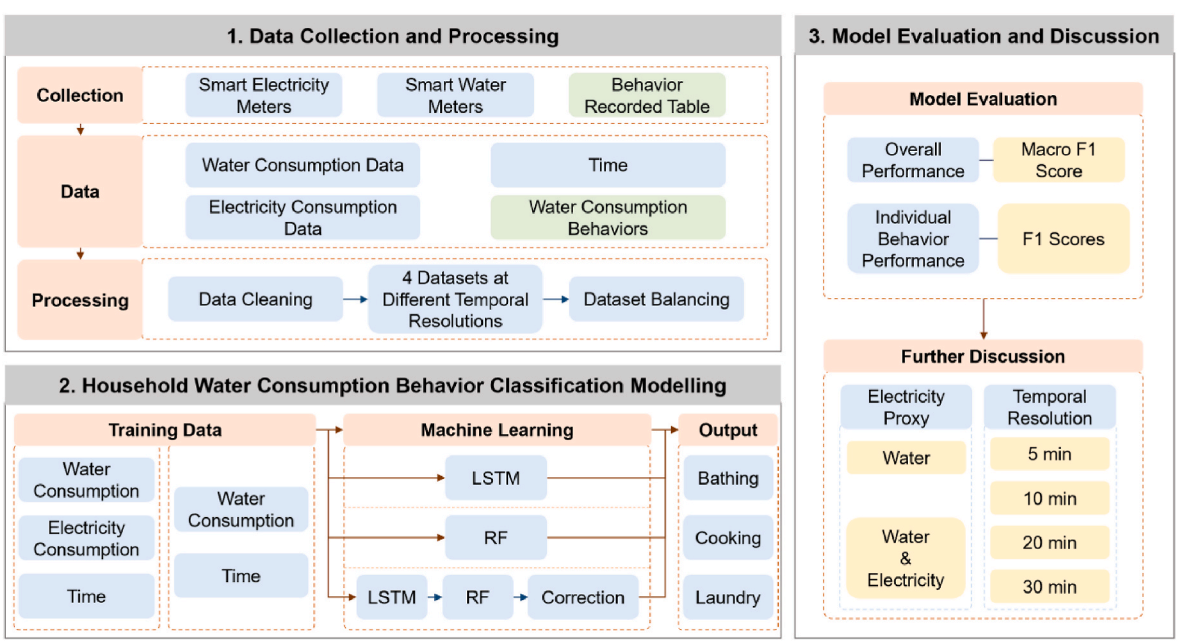


**Fig. 1.** Research design.

$i$ represents the time variable, indicating a specific time point within the day (e.g., if the temporal resolution is 5 min, $i = 1$ represents the time interval from 00:00–00:05, and max($i$) is 288).

The output labels represent household water-consumption behavior. In this study, bathing, cooking, and laundry were selected as the labeled behaviors. These three behaviors are the dominant household water-consumption behaviors, accounting for 43%–70% of total household water consumption (Zhang et al., 2021). Furthermore, the durations of these behaviors, in contrast to instantaneous actions, such as toilet flushing, are relatively extended, making them well suited for classification at minute-level temporal resolutions.

### 3.3. Water-consumption behavior classification modeling

This study proposes a hybrid model that combines LSTM and RF models to classify water-consumption behaviors occurring at a particular moment. RF is a traditional non-probabilistic classifier that can improve the classification performance and robustness through ensemble capabilities (Breiman, 2001). The LSTM is a classic neural network architecture specifically designed to handle long-term sequential data while retaining relevant information, making it suitable for capturing complex relationships within time-series data (Sagheer and Kotb, 2019). The model comprises four main parts.

a) Input Data: This part primarily includes the time information, water consumption data, and electricity consumption data (as a proxy) for the target and historical moments.
b) LSTM: The LSTM model is employed to extract features from historical time information and predict the probabilities of different water-consumption behaviors. The hyperparameters of the LSTM model used in this study are listed in Supplementary Material Table S1.
c) RF: The probabilities of each water-consumption behavior occurrence, along with the original input data consisting of time, water-consumption, and electricity consumption, are collectively input into the RF model to obtain the preliminary classification results of water-consumption behaviors. The hyperparameters of the RF model used in this study are listed in Supplementary Material Table S2.
d) Correction Module: Because the water-consumption behavior at each time step is independently classified, errors can occur when classifying specific time steps within long and complete water-consumption behaviors (details are provided in the Supplementary Material Fig. S1). The correction module is designed to overcome this limitation. It evaluates the consistency of the classification results for adjacent time steps and determines whether the same behavior occurs. Detailed rules and a flowchart of the correction module are shown in Supplementary Material Fig. S2.

### 3.4. Model performance evaluation

The household water-consumption behavior classification model can be considered a multi-classifier model. For individual behavior classification, four types of results may occur: true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN), as shown in Table 1. Metrics such as precision, recall, and F1 score are commonly used to evaluate classifier model performance (Grandini et al., 2020) and formulas (3)–(5). The precision represents the proportion of correctly classified occurrences among behaviors classified as a certain water-consumption behavior, whereas the recall represents the proportion of correctly classified occurrences among the actual occurrences of a certain water-consumption behavior (Goutte and Gaussier, 2005). In general, the precision and recall were negatively correlated. The F1 scores comprehensively assess the precision and recall of each classification.

**Table 1**
Confusion matrix.

| | | Modeling results | |
|---|---|---|---|
| | | 1 | 0 |
| Ground truth | 1 | TP | FN |
| | 0 | FP | TN |

*Notes:* "0" represents the absence of a specific behavior, whereas "1" represents the occurrence of that behavior.

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$Precision = \frac{TP}{TP + FP} \tag{4}$$

$$F1 = \frac{2 \bullet Precision \bullet Recall}{Precision + Recall} \tag{5}$$

A macro F1 score is used to measure the overall performance of the model. It addresses the potential biases caused by imbalanced samples and considers the contribution of each sample classification. The macro F1 score was calculated as the average of each individual behavioral F1 score calculated using formula (5), as shown in formula (6).

$$Macro\ F1 = \frac{1}{3}\left(F1_{Bathing} + F1_{Cooking} + F1_{Laundry}\right) \tag{6}$$

### 3.5. Model comparison

To assess the effectiveness of the developed hybrid model, a comparison was conducted between the performance of the hybrid model and those of the standalone LSTM and RF models. Additionally, the effectiveness of the models with different temporal resolutions (5, 10, 20, and 30 min) was evaluated to determine the appropriate temporal resolution for household water consumption management purposes.

Furthermore, the classification results were compared using only water and incorporating water and electricity proxies as inputs to the hybrid model. This comparison was accomplished by calculating the macro and individual behavioral F1 scores. The disparities observed in the performance between the water-only and water-electricity input models indicate the effectiveness of considering the water-energy nexus.

### 3.6. Data collection

#### 3.6.1. Case study

Data were collected from three volunteer households (HH1–HH3) in Beijing, China, from January to February 2020. The demographic characteristics of the three households are shown in Supplementary Material Table S3. Note that it was winter in Beijing, and the heating system used was municipal central heating rather than energy-intensive methods, such as heat pumps or air conditioners. Two categories of data were collected: smart-metered water/electricity consumption and behavioral record data. Smart water and electricity meters provided by Evavisdom were installed in the three households. These smart meters facilitated data collection through image reading or infrared transmission, allowing real-time data to be uploaded to the cloud platform (www.evavision.cn) using narrowband Internet of Things (NB-IoT) technology. Considering the smart meter battery capacity, NB-IoT signal strength, and transmission speed, the time interval of the smart metering was set to 5 min. The measurement units were 0.1 L for water consumption and 0.01 kW h for electricity consumption. Residents of the three households provided records of their water-consumption behaviors, as shown in Supplementary Material Table S4. These records included information on the specific types of water-consumption behaviors as well as the start and end times of each behavior.

#### 3.6.2. Data processing

The water/electricity consumption data were cleaned and missing values were filled by averaging the readings before and after the missing interval. Behavioral records and meter data were then matched based on time. This processing resulted in a dataset that contained household water-consumption behaviors, $T_{sin}$, $T_{cos}$, and water and electricity consumption at each time step at 5 min intervals. In total, 1923 records were included in the study, with bathing accounting for 10.7%, cooking for 64.8%, and laundry for 24.5%. In addition, the dataset was converted into three other versions at 10, 20, and 30-min intervals. The sample sizes at different temporal resolutions are listed in Table 2.

Datasets with different temporal resolutions were randomly split into training (70%) and testing (30%) sets. Notably, there was a significant discrepancy in sample sizes across behaviors, with cooking behavior having a substantially larger amount of data (ranging from 65% to 75%) than bathing and laundry behaviors. To address the potential bias towards the larger dataset and ensure balanced learning, the Synthetic Minority Over-sampling Technique (SMOTE) method was employed to oversample the bathing and laundry behaviors in the training set (Fernández et al., 2018). Detailed information is provided in Supplementary Material S1. This balancing procedure resulted in approximately equal sample sizes for the three behavioral classes in the training set.

## 4. Results

### 4.1. Descriptive analysis of household water-consumption behavior

#### 4.1.1. The correlation between household water and electricity consumption

As shown in Fig. 2, the peak and off-peak periods in water and electricity consumption generally align. For example, in the case of HH2, high electricity and water consumption peaks occurred at 10:00, 14:00–15:00, 17:00, and 20:00–21:00, whereas low electricity and water consumption valleys were observed at 16:00, 18:00–19:00, and 22:00–23:00. Statistically, there was a significant correlation between the average hourly water and electricity consumption throughout the day. The correlation coefficients for hourly water consumption and electricity consumption were 0.94, 0.85, and 0.63 for HH1, HH2, and HH3, respectively. This finding supports the feasibility of using electricity consumption as a proxy for water consumption in the following modeling.

#### 4.1.2. Average duration of different behaviors

Understanding the duration of water-consumption behaviors is crucial for accurate classification. The temporal resolution should be shorter than the behavior duration to capture multiple data points within a single event and reveal consumption trends. Moreover, variations in duration serve as a key temporal feature that enhances the model's ability to distinguish between different behaviors, thereby improving classification accuracy.

The average duration of household water-consumption behaviors in this study exceeded the temporal resolution of 5 min, as shown in Fig. 3. Among the three households, bathing, cooking, and laundry behaviors have average durations of 13.5 min, 18.5 min, and 41.4 min, respectively. These behaviors exhibited considerable variations in duration, with standard deviations of 7.1, 15.7, and 23.9. There were also differences in the behavior duration among the three households. The average bathing duration was similar across all three households. For cooking behavior, HH1 had the longest duration, averaging 26.9 min, followed by HH3, whereas HH2 had the shortest duration, averaging 13.5 min. For laundry behavior, HH1 and HH2 had similar durations, averaging 32.3 and 35.9 min respectively; however, HH3 had an average duration of 76.9 min, which may be attributed to the difference between an impeller (used in HH1 and HH2) and a drum washing machine (used in HH3).

**Table 2**
Sample sizes of water-consumption behaviors at different temporal resolutions.

| Water End-use Behavior | 5 min | 10 min | 20 min | 30 min |
|---|---|---|---|---|
| Bathing | 205 | 144 | 181 | 134 |
| Cooking | 1247 | 817 | 978 | 768 |
| Laundry | 471 | 259 | 182 | 125 |

#### 4.1.3. Time distribution of behaviors within a day

The time distributions of different water-consumption behaviors in the three households are summarized in Fig. 4. Overall, 54% of the bathing behaviors occurred during 20:00–24:00. Cooking behaviors were observed mainly during the period 8:00–20:00, indicating frequent occurrence during breakfast, lunch, and dinner. Laundry behaviors were more common in the morning, with 43% of laundry behaviors occurring within the temporal interval of 8:00–12:00.

### 4.2. Model performance comparison

#### 4.2.1. Overall performance

The macro F1 scores for the models at various temporal resolutions are shown in Fig. 5 (details are provided in Supplementary Material Table S5). Across different temporal resolutions, the average macro F1 score of the postcorrection hybrid model was 0.82. The hybrid model outperformed the sole models (i.e., RF and LSTM models) by 6.9%–13.4%, indicating the advantage of combining LSTM and RF for household water-consumption behavior classification. A comparison of the results of the hybrid model before and after the correction module revealed that the post-correction model exhibited an improvement from 3.9% to 7.8% in the macro F1 score.

Increasing the temporal resolution from 30 to 5 min led to substantial improvements in the macro F1 scores, reaching 14.1% from 0.78 to 0.89. Notably, the hybrid model achieved the highest performance at a 5-min resolution, with a macro F1 score of 0.89.

#### 4.2.2. Individual behavior performance

Among the three water-consumption behaviors, the post-correction hybrid model demonstrated the best performance in classifying cooking behavior (Fig. 6 and Supplementary Material Fig. S3), with an impressive F1 score of 0.94 at the 5- and 10-min temporal resolutions. For the other behaviors, the classification performance of bathing behavior outperformed that of laundry behavior by 0.03–0.14, except at a 30-min resolution. Notably, the classification performance of bathing and laundry behaviors is influenced by the temporal resolution. Increasing the resolution from 30 to 5 min resulted in a substantial improvement of 0.21 in the F1 score for bathing behavior and 0.10 for laundry behavior. However, the improvement for cooking behavior was relatively modest, with only a slight increase of 0.01 in the F1 score.

Furthermore, the post-correction model consistently outperformed the pre-correction model. The correction module enhanced the F1 score of bathing and laundry behaviors, with a maximum increase of 0.09 for bathing behavior and 0.08 for laundry behavior. Conversely, cooking behavior achieved a high F1 score >0.90, even before the application of the correction module, indicating a relatively smaller impact from the correction process.

### 4.3. The effectiveness of water-energy nexus on classifying water-consumption behaviors

The inclusion of the water-energy nexus has significantly enhanced the classification performance of the hybrid model. As depicted in Fig. 7, when the proxy of electricity was incorporated, the hybrid model achieved macro F1 scores ranging from 0.78 to 0.89. This represents a substantial increase of 0.04–0.08 compared to not considering the proxy of electricity. Moreover, the integration of electricity consumption consistently improved the classification performance for all three behaviors, with particularly notable enhancements observed in bathing (the highest, up to 0.14) and laundry behaviors. The F1 scores for

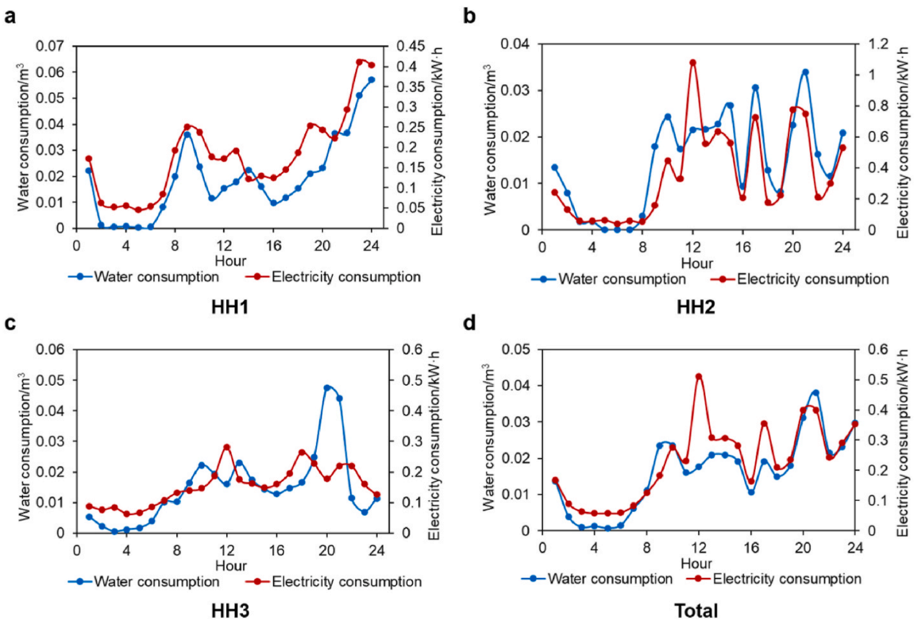


**Fig. 2.** Average hourly water and electricity consumption of HH1 (a), HH2 (b), HH3 (c) and three households in total (d) during the study periods.

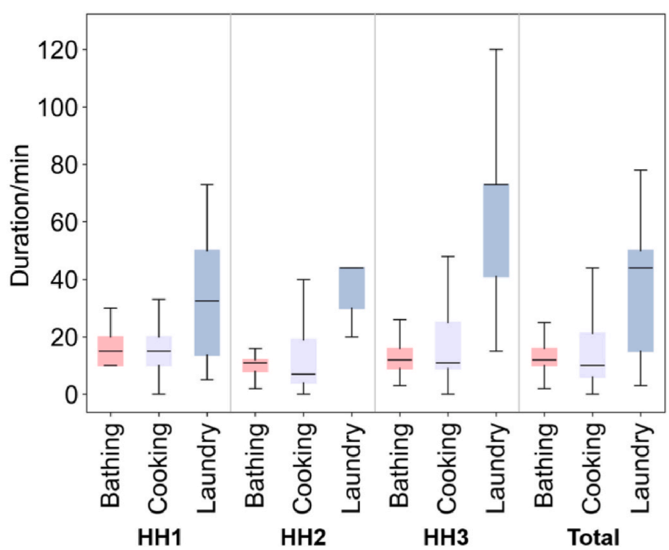


**Fig. 3.** Duration of the considered water-consumption behaviors of the three households.

cooking and laundry behaviors showed increases of 0.01–0.04 and 0.02–0.20, respectively.

The varying impacts of the water-energy nexus can be attributed to the inherent characteristics of each behavior. Bathing and laundry behaviors often involve the use of fixed appliances, such as water heaters and washing machines, which exhibit a consistent coupling relationship between water and electricity. Consequently, the water-energy nexus plays a more significant role in these behaviors, resulting in a relatively large improvement in their classification performance. Nevertheless, cooking behavior displays a diverse range of water and electricity consumption patterns owing to the various cooking techniques utilized. This diversity leads to a lack of a consistent correlation between water and electricity consumption, thereby diminishing the effectiveness of using the water-energy nexus.

## 5. Discussion

The proposed hybrid mode by integrating LSTM networks with RF for classifying household water-consumption behaviors improves the understanding of time-series patterns. This integration establishes a critical link between data resolution and classification accuracy, demonstrating that a temporal resolution of 5 min outperforms the subminute or hourly resolutions which are widely adopted in existing studies. Furthermore, the model provides a framework for analyzing the relationship between electricity consumption data and water-consumption behaviors, an area that has been underexplored in existing literature. This framework leverages data from smart water and electricity meters to enable accurate behavior classification without relying on high temporal resolution, thereby reducing the complexity and cost of data collection systems. This framework offers a practical foundation for homeowners to develop tailored water conservation strategies and supports scalable applications in diverse residential households.

### *5.1. Insights from comparative analysis*

The resolution of data collection strikes a balance between predictive capability and costs in academic research and practical management. Previous research on classifying household water-consumption behavior has predominantly focused on subminute temporal resolutions, such as 5 s (Mazzoni et al., 2023). This is accompanied by the high costs of intelligent metering devices, data storage, and computational resources (Cominola et al., 2018). Nevertheless, it has also been demonstrated that hourly data are too coarse to accurately classify household water-consumption behaviors (Britton et al., 2013). Therefore, in this study, the highest data resolution was set to 5 min, reducing the required temporal resolution compared with previous studies. Our results demonstrated that a 5-min resolution yields the best classification performance, with 5- and 10-min resolutions achieving a macro F1 score >0.80, significantly outperforming 20- and 30-min resolutions. This suggests that higher resolutions generally lead to better classification accuracy, with an optimal temporal resolution of 5 min. Moreover, to discern the impact of the input data size, this study also conducted an experiment in which the training sets of the 10-, 20-, and 30-min resolutions' datasets were oversampled to match the size of the 5-min resolution dataset. The results indicated that, similar to the classification

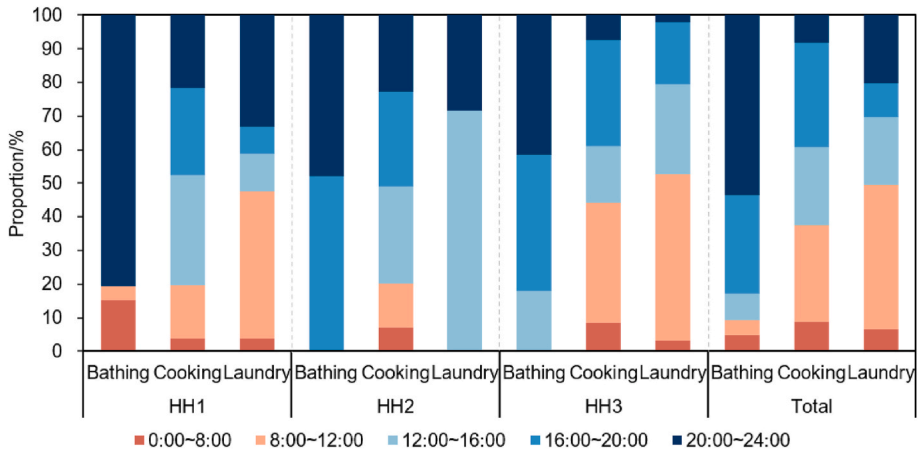


**Fig. 4.** Time distribution of the considered water-consumption behaviors of the three households.

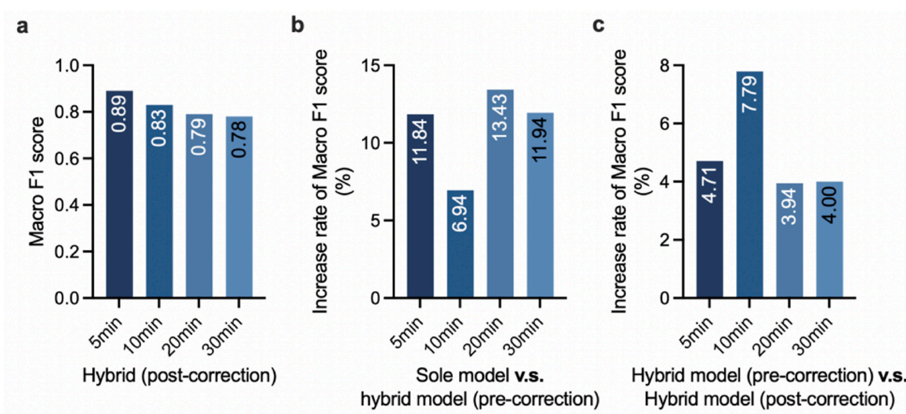


**Fig. 5.** Macro F1 scores of hybrid models at different time resolutions (a) and the improvements brought about by hybrid (b) and correction (c).

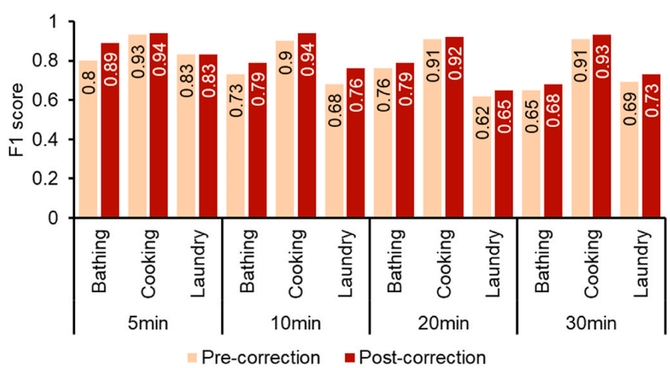


**Fig. 6.** Comparison of three behaviors' F1 scores before and after model correction.

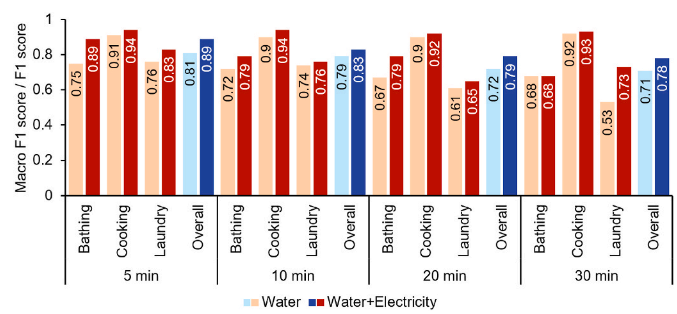


**Fig. 7.** The proxy of electricity on macro F1 score and three behaviors' F1 scores.

results before dataset augmentation, the 5-min resolution still exhibited the best performance (Supplementary Material Table S6).

Using a hybrid model combining LSTM and RF, this study increased the accuracy of household water-consumption behaviors. The LSTM networks helped to better understand the time-series patterns of the input data and extract the behavioral possibilities hidden behind the consumption data, whereas the RF provided a more precise analysis of probabilistic tabular data (Grinsztajn et al., 2022). Combining their advantages can further enhance the accuracy. Compared to the sole model, the performance of the hybrid model (pre-correction) increased by 11.0% on average and by 13.4% at the maximum. We also compared our model with those used in previous studies (Table 3). Although the primary evaluation metric in this study was the macro F1 score, the results for other indicators are also provided (Supplementary Material Table S7). Previous models achieved weighted F1 scores ranging from 0.71 to 0.89, whereas the model proposed in this study achieved a weighted F1 score of 0.87–0.91. Similarly, previous studies reported accuracy ranging from 0.81 to 0.98, whereas the accuracy of the model proposed in this study ranged from 0.87 to 0.90. Regarding sensitivity, previous research has reported models with sensitivities >0.70, with some studies reaching 0.95. In this study, the sensitivity of the proposed model ranged from 0.75 to 0.89. Therefore, compared with existing research, this study achieved comparable performance in classifying water-consumption behavior using relatively low-temporal-resolution

**Table 3**
A comparison of existing household water-consumption behavior classification studies.

| Place Studied | Year Studied | Temporal Resolution | Methods | Electricity Proxy | Indicators | Performance | References |
|---|---|---|---|---|---|---|---|
| China | 2020 | 5 min, 10 min, 20 min, 30 min | LSTM + RF | ✓ | Macro F1 score<br>Weighted F1 score<br>Accuracy<br>Sensitivity | 0.78–0.89<br>0.87–0.91<br>0.87–0.90<br>0.75–0.89 | This study |
| Italy, Netherlands | 2018 for Italy, 2019–2020 for Netherlands | 1 min | Rules | × | Accuracy | 91% | Mazzoni et al. (2024) |
| USA | 2011 | 10 s | Model-based method (DTW); Learning-based method (SVM, RF, XGBoost, MLP) | × | Weighted F1 score | 0.71–0.72 | Pavlou et al. (2024) |
| USA | / | 4 s | DBSCAN + RF | × | Accuracy | 98% | Attallah et al. (2023) |
| Italy | 2018 | 1 min | Rules | × | Appliance contribution accuracy | 90.4%–97.5% | Mazzoni et al. (2021) |
| South Africa, Australia | 2016–2018 for South Africa, 2010–2012 for Australia | 5 s | SVM + RF + EDS | × | Accuracy | 81%–98% | Meyer et al. (2021) |
| Australia | 2010–2012 | 5 s | HMM + ANN | × | Accuracy | 85.9%–96.1% | Nguyen et al. (2015) |
| USA | 2021 | 5 s, 10 s, 30 s, 1 min | RF | × | Weighted F1 score | 0.73–0.89 | Heydari et al. (2022) |
| Australia | 2010–2013 | / | SOM + K-means + HMM + ANN | × | Accuracy | 86%–94.2% | Yang et al. (2018) |
| Spain | 2019–2020 | 5 s | Profile Recognition | × | Sensitivity | 70%–80% | Fontdecaba et al. (2013) |
| Australia | 2010–2013 | 10–120 s | SVM | ✓ | Sensitivity | 71%–87% | Vitter and Webber (2018a) |
| USA, Canada | 2016 | / | SVM | ✓ | Sensitivity | >87.1% | Vitter and Webber (2018b) |

*Notes*: The calculation of the indicators mentioned in this table is explained in detail in Supplementary Material S2.

data.

Understanding the impact of different temporal resolutions on the classification performance of a model is crucial for effective water utility management. Our study reveals that higher temporal resolutions generally lead to improved macro F1 scores, as evidenced by an increase of 14.1% (0.78–0.89) when transitioning from a 30-min temporal resolution to a 5-min temporal resolution. In addition, the sensitivity of specific behaviors to temporal resolution highlights the importance of selecting an appropriate resolution based on the behavior under investigation, considering the trade-off between model accuracy and cost. For instance, bathing and laundry exhibit increased classification performance at higher temporal resolutions owing to their longer durations and more regular water consumption patterns. By contrast, cooking behavior, which is characterized by shorter durations and diverse activities, is less sensitive to temporal resolution.

Moreover, the water-energy nexus, that is, the proxy for electricity, enables resource managers to estimate and understand the interplay between water and electricity consumption at the household level. Previous studies have largely overlooked the water-energy nexus, as shown in Table 3. The limited studies that have considered the water-energy nexus have only incorporated binary variables indicating the usage of washing machines or dishwashers (Vitter and Webber, 2018a, 2018b). This study highlights the importance of considering the water-energy nexus using electricity consumption as a proxy for water-consumption behavior classification. Our results demonstrate an effective enhancement of an average of 8.63% in the classification performance through the integration of the water-energy nexus. There is a close interconnection between water and electricity consumption within households, as the activities considered in this study (bathing, cooking, and laundry) involve water and electricity consumption. Similarly, in the classification of electricity-consumption behavior, a potential proxy for water consumption can also be considered. Policy-makers should incorporate a proxy mechanism for other resources such as energy when formulating policies related to household water consumption.

### 5.2. Practical implications

The hybrid model presented in this study highlights the value of mining water and energy consumption datasets, particularly in the context of the rapid adoption of smart water meters and smart home appliances. By leveraging water and electricity consumption data analytics, this model supports fine management strategies that can lead to more sustainable practices. The findings demonstrate that accurate classification of household water-consumption behaviors can be achieved without relying on high temporal resolution data, alleviating the burden associated with deploying complex and costly data collection systems. Furthermore, this hybrid model is not constrained by family-specific characteristics and can effectively explore behavioral patterns as long as sufficient data is available. Although the current implementation has been tested on only three households, its underlying framework shows strong potential for large-scale application across diverse households.

Accurately classifying household water consumption behaviors using the proposed model can provide valuable insights that enhance households' understanding and awareness of their water use, which is crucial for developing tailored water-saving recommendations. These insights can then be leveraged to promote more responsible consumption patterns and empower individuals to make informed decisions about their water usage. In contexts where marginal pricing of resources is not feasible, raising water conservation awareness and utilizing behavior-driven strategies for resource conservation become especially important (Olmstead and Stavins, 2009; Vivek et al., 2021).

### 5.3. Limitations

This study has several limitations that could be addressed in future research. Firstly, the model's testing on only three households limits the generalizability of the findings. Additionally, the methodological framework requires enhancement to increase adaptability to various data sources and to more effectively manage missing data or anomalies. Future studies should validate the model across a larger and more diverse households while optimizing its performance under different conditions to ensure its effectiveness in practical applications.

Secondly, while the integration of LSTM and RF effectively captures time-series patterns, it does not account for complex combined behaviors, such as simultaneous activities like bathing and laundry. Future research should explore advanced algorithms, e.g., waveform decomposition techniques, to accurately classify these combined behaviors and improve overall classification accuracy.

Lastly, although this study emphasizes the water-energy nexus, it lacks a comprehensive exploration of other influencing factors, such as demographic and economic characteristics, as well as other water-consumption behaviors (e.g., toilet flushing and faucet use). Incorporating these variables could provide a more nuanced understanding of household water-consumption patterns.

## 6. Conclusion

This study presents a novel framework for classifying household water-consumption behaviors through the integration of a hybrid model that combines LSTM and RF. By investigating the impact of electricity consumption as a proxy variable and comparing the classification performance under different temporal resolutions (i.e., 5 min, 10 min, 20 min, 30 min), this research proposes a practical approach that leverages the available water and energy consumption data from smart meters.

The results demonstrate that the hybrid model outperforms the standalone LSTM and RF models by 0.09–0.13. In addition, higher resolutions generally lead to better classification accuracy, as evidenced by the hybrid model's significantly higher macro F1 score of 0.11 at the 5-min resolution in comparison to that at the 30-min resolution.

Regarding specific behaviors, bathing and laundry behaviors demonstrated improved performance with higher resolutions, with optimal results observed at a 5-min resolution. The hybrid model exhibited less sensitivity to temporal resolution when classifying cooking behavior, consistently achieving an F1 score $>0.92$, demonstrating the model's robustness across different activities.

The inclusion of electricity consumption as a proxy variable proved beneficial, particularly for the classification of bathing and laundry behaviors. This consideration resulted in notable improvements in the F1 scores, with maximum increases of 0.12 and 0.20 for bathing and laundry behaviors, respectively. This integration underscores the importance of considering the water-energy nexus in future research, as it enhances understanding of household water-consumption patterns while simplifying data acquisition processes.

However, our study has some limitations. The study's data acquisition was not exhaustive, and complex combined behaviors may require advanced algorithms for accurate classification. Future research should expand the behaviors types analyzed and consider demographic factors to provide a more comprehensive understanding of household water-consumption patterns.

## CRediT authorship contribution statement

**Miao Wang:** Writing – review & editing, Writing – original draft, Methodology. **Zonghan Li:** Writing – review & editing, Data curation. **Yi Liu:** Writing – review & editing, Supervision. **Lu Lin:** Writing – review & editing, Funding acquisition. **Chunyan Wang:** Writing – review & editing, Supervision, Funding acquisition.

## Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Chunyan Wang reports financial support was provided by National Natural Science Foundation of China. Lu Lin reports financial support was provided by National Natural Science Foundation of China. Chunyan Wang reports financial support was provided by Young Elite Scientists Sponsorship Program by CAST. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.clrc.2025.100252.

## Data availability

Data will be made available on request.

## References

Attallah, N.A., Horsburgh, J.S., Bastidas Pacheco, C.J., 2023. An open-source, semisupervised water end-use disaggregation and classification tool. J. Water Resour. Plann. Manag. 149 (7), 04023024.
Attallah, N.A., Rosenberg, D.E., Horsburgh, J.S., 2021. Water end-use disaggregation for six nonresidential facilities in Logan, Utah. J. Water Resour. Plann. Manag. 147 (7), 05021006.
Bastidas Pacheco, C.J., Horsburgh, J.S., Beckwith, A.S., 2022. Impact of data temporal resolution on quantifying residential end uses of water. Water 14 (16), 2457.
Beal, C., Stewart, R., Huang, T., Rey, E., 2011. South East Queensland Residential End Use Study. Urban Water Security Research Alliance Brisbane, Australia.
Bennett, C., Stewart, R.A., Beal, C.D., 2013. ANN-based residential water end-use demand forecasting model. Expert Syst. Appl. 40 (4), 1014–1023.
Bongungu, J.L., Francisco, P.W., Gloss, S.L., Stillwell, A.S., 2022. Estimating residential hot water consumption from smart electricity meter data. Environ. Res.: Infrastructure and Sustainability 2 (4), 045003.
Breiman, L., 2001. Random forests. Mach. Learn. 45, 5–32.
Britton, T.C., Stewart, R.A., O'Halloran, K.R., 2013. Smart metering: enabler for rapid and effective post meter leakage identification and water loss management. J. Clean. Prod. 54, 166–176.
Cascone, L., Sadiq, S., Ullah, S., Mirjalili, S., Siddiqui, H.U.R., Umer, M., 2023. Predicting household electric power consumption using multi-step time series with convolutional LSTM. Big Data Research 31, 100360.
Cominola, A., Giuliani, M., Castelletti, A., Rosenberg, D.E., Abdallah, A.M., 2018. Implications of data sampling resolution on water use simulation, end-use disaggregation, and demand management. Environ. Model. Software 102, 199–212.
Cominola, A., Nguyen, K., Giuliani, M., Stewart, R.A., Maier, H.R., Castelletti, A., 2019. Data mining to uncover heterogeneous water use behaviors from smart meter data. Water Resour. Res. 55 (11), 9315–9333.
Cominola, A., Preiss, L., Thyer, M., Maier, H.R., Prevos, P., Stewart, R., Castelletti, A., 2023. The determinants of household water consumption: a review and assessment framework for research and practice. npj Clean Water 6 (1), 11.
Darby, S., 2010. Smart metering: what potential for householder engagement? Build. Res. Inf. 38 (5), 442–457.
DeOreo, W.B., Heaney, J.P., Mayer, P.W., 1996. Flow trace analysis to access water use. J. Am. Water Works Assoc. 88 (1), 79–90.
Dolan, F., Lamontagne, J., Link, R., Hejazi, M., Reed, P., Edmonds, J., 2021. Evaluating the economic impact of water scarcity in a changing world. Nat. Commun. 12 (1).
Ellert, B., Makonin, S., Popowich, F., 2015. International summit. Smart City 360°. Springer, pp. 455–467.
Fernández, A., Garcia, S., Herrera, F., Chawla, N.V., 2018. SMOTE for learning from imbalanced data: progress and challenges, marking the 15-year anniversary. J. Artif. Intell. Res. 61, 863–905.
Fidar, A., Memon, F., Butler, D., 2010. Environmental implications of water efficient microcomponents in residential buildings. Sci. Total Environ. 408 (23), 5828–5835.
Flörke, M., Kynast, E., Bärlund, I., Eisner, S., Wimmer, F., Alcamo, J., 2013. Domestic and industrial water uses of the past 60 years as a mirror of socio-economic development: a global simulation study. Global Environ. Change 23 (1), 144–156.
Fontdecaba, S., Sánchez-Espigares, J.A., Marco-Almagro, L., Tort-Martorell, X., Cabrespina, F., Zubelzu, J., 2013. An approach to disaggregating total household water consumption into major end-uses. Water Resour. Manag. 27, 2155–2177.

Froehlich, J., Larson, E., Saba, E., Campbell, T., Atlas, L., Fogarty, J., Patel, S., 2011. A Longitudinal Study of Pressure Sensing to Infer Real-World Water Usage Events in the Home. Springer, pp. 50–69.
Gleick, P., Wolff, G.H., Cushing, K.K., 2003. Waste Not, Want Not: the Potential for Urban Water Conservation in California. Pacific Institute for Studies in Development, Environment, Security.
Goutte, C., Gaussier, E., 2005. A Probabilistic Interpretation of Precision, Recall and F-Score, with Implication for Evaluation. Springer, pp. 345–359.
Grandini, M., Bagli, E., Visani, G., 2020. Metrics for multi-class classification: an overview. arXiv preprint. https://doi.org/10.48550/arXiv.2008.05756.
Grinsztajn, L., Oyallon, E., Varoquaux, G., 2022. Why do tree-based models still outperform deep learning on typical tabular data? Adv. Neural Inf. Process. Syst. 35, 507–520.
Gurung, T.R., Stewart, R.A., Beal, C.D., Sharma, A.K., 2015. Smart meter enabled water end-use demand data: platform for the enhanced infrastructure planning of contemporary urban water supply networks. J. Clean. Prod. 87, 642–654.
Hall, R., Kenway, S., O'Brien, K., Memon, F., 2025. Quantification of residential water-related energy needs cohesion, validation and global representation to unlock efficiency gains. Renew. Sustain. Energy Rev. 207, 114906.
Heydari, Z., Cominola, A., Stillwell, A.S., 2022. Is smart water meter temporal resolution a limiting factor to residential water end-use classification? A quantitative experimental analysis. Environ. Res.: Infrastructure and Sustainability 2 (4), 045004.
Heydari, Z., Stillwell, A.S., 2024. Comparative analysis of supervised classification algorithms for residential water end uses. Water Resour. Res. 60 (6), e2023WR036690.
Huang, J., Pang, C., Yang, W., Zeng, X., Zhang, J., Huang, C., 2022. A deep learning neural network for the residential energy consumption prediction. IEEJ Trans. Electr. Electron. Eng. 17 (4), 575–582.
Ismail Fawaz, H., Forestier, G., Weber, J., Idoumghar, L., Muller, P.-A., 2019. Deep learning for time series classification: a review. Data Min. Knowl. Discov. 33 (4), 917–963.
Kneebone, S.C., 2018. Catalysing Water Saving Behaviours in Australian Urban Households. Monash University.
Kowalski, M., Marshallsay, D., 2003. A System for Improved Assessment of Domestic Water Use Components.
Kropp, I., Pouyan Nejadhashemi, A., Julien, R., Mitchell, J., Whelton, A.J., 2022. A machine learning framework for predicting downstream water end-use events with upstream sensors. Water Supply 22 (7), 6427–6442.
Li, Z., Wang, C., Liu, Y., Wang, J., 2024. Enhancing the explanation of household water consumption through the water-energy nexus concept. npj Clean Water 7 (1), 8.
Liu, A., Giurco, D., Mukheibir, P., 2016. Urban water conservation through customised water and end-use information. J. Clean. Prod. 112, 3164–3175.
Mahajan, T., Singh, G., Bruns, G., Bruns, G., Mahajan, T., Singh, G., 2021. An Experimental Assessment of Treatments for Cyclical Data, p. 22.
Manandhar, P., Rafiq, H., Rodriguez-Ubinas, E., 2023. Current status, challenges, and prospects of data-driven urban energy modeling: a review of machine learning methods. Energy Rep. 9, 2757–2776.
Mazzoni, F., Alvisi, S., Blokker, M., Buchberger, S.G., Castelletti, A., Cominola, A., Gross, M.-P., Jacobs, H.E., Mayer, P., Steffelbauer, D.B., 2023. Investigating the characteristics of residential end uses of water: a worldwide review. Water Res. 230, 119500.
Mazzoni, F., Alvisi, S., Franchini, M., Ferraris, M., Kapelan, Z., 2021. Automated household water end-use disaggregation through rule-based methodology. J. Water Resour. Plann. Manag. 147 (6), 04021024.
Mazzoni, F., Blokker, M., Alvisi, S., Franchini, M., 2024. An enhanced method for automated end-use classification of household water data. J. Hydroinf. 26 (2), 408–423.
Meyer, B.E., Nguyen, K., Beal, C.D., Jacobs, H.E., Buchberger, S.G., 2021. Classifying household water use events into indoor and outdoor use: improving the benefits of basic smart meter data sets. J. Water Resour. Plann. Manag. 147 (12), 04021079.
Nguyen, K.A., Stewart, R.A., Zhang, H., 2014. An autonomous and intelligent expert system for residential water end-use classification. Expert Syst. Appl. 41 (2), 342–356.
Nguyen, K.A., Stewart, R.A., Zhang, H., 2017. Water end-use classification with contemporaneous water-energy data and deep learning network. In: World Academy of Science, Engineering and Technology, International Journal of Computer, vol. 12. Electrical, Automation, Control and Information Engineering, pp. 1–6, 1.
Nguyen, K.A., Stewart, R.A., Zhang, H., Jones, C., 2015. Intelligent autonomous system for residential water end use classification: Autoflow. Appl. Soft Comput. 31, 118–131.
Nguyen, K.A., Zhang, H., Stewart, R.A., 2013. Development of an intelligent model to categorise residential water end use events. J. hydro-environ. res. 7 (3), 182–201.
Olmstead, S.M., Stavins, R.N., 2009. Comparing price and nonprice approaches to urban water conservation. Water Resour. Res. 45 (4).
Pavlou, P.V., Filippou, S., Solonos, S., Vrachimis, S.G., Malialis, K., Eliades, D.G., Theocarides, T., Polycarpou, M.M., 2024. Monitoring domestic water consumption: a comparative study of model-based and data-driven end-use disaggregation methods. J. Hydroinf. 26 (4), 709–726.
Plappally, A., 2012. Energy requirements for water production, treatment, end use, reclamation, and disposal. Renew. Sustain. Energy Rev. 16 (7), 4818–4848.
Rahim, M.S., Nguyen, K.A., Stewart, R.A., Ahmed, T., Giurco, D., Blumenstein, M., 2021. A clustering solution for analyzing residential water consumption patterns. Knowl. Base Syst. 233, 107522.
Rahim, M.S., Nguyen, K.A., Stewart, R.A., Giurco, D., Blumenstein, M., 2019. Predicting Household Water Consumption Events: towards a Personalised Recommender System to Encourage Water-Conscious Behaviour. IEEE, pp. 1–8.
Russell, S., Fielding, K., 2010. Water demand management research: a psychological perspective. Water Resour. Res. 46 (5).
Sagheer, A., Kotb, M., 2019. Time series forecasting of petroleum production using deep LSTM recurrent networks. Neurocomputing 323, 203–213.
Stewart, R.A., Nguyen, K., Beal, C., Zhang, H., Sahin, O., Bertone, E., Vieira, A.S., Castelletti, A., Cominola, A., Giuliani, M., 2018. Integrated intelligent water-energy metering systems and informatics: visioning a digital multi-utility service provider. Environ. Model. Software 105, 94–117.
Vitter, J.S., Webber, M., 2018a. A non-intrusive approach for classifying residential water events using coincident electricity data. Environ. Model. Software 100, 302–313.
Vitter, J.S., Webber, M., 2018b. Water event categorization using sub-metered water and coincident electricity data. Water 10 (6), 714.
Vivek, V., Malghan, D., Mukherjee, K., 2021. Toward achieving persistent behavior change in household water conservation. Proc. Natl. Acad. Sci. USA 118 (24), e2023014118.
Wada, Y., Flörke, M., Hanasaki, N., Eisner, S., Fischer, G., Tramberend, S., Satoh, Y., Van Vliet, M., Yillia, P., Ringler, C., 2016. Modeling global water use for the 21st century: the Water Futures and Solutions (WFaS) initiative and its approaches. Geosci. Model Dev. (GMD) 9 (1), 175–222.
Wang, C., Li, Z., Ni, X., Shi, W., Zhang, J., Bian, J., Liu, Y., 2023. Residential water and energy consumption prediction at hourly resolution based on a hybrid machine learning approach. Water Res. 246, 120733.
Wang, C., Zhang, J., Long, J., Liu, Y., 2022. Panel data regression model for identifying the spatiotemporal characteristics and key factors influencing household water-energy consumption. J. Tsinghua Univ. (Sci. Technol.) 62 (3), 614–626.
Wang, X.-j., Zhang, J.-y., Gao, J., Shahid, S., Xia, X.-h., Geng, Z., Tang, L., 2018. The new concept of water resources management in China: ensuring water security in changing environment. Environ. Dev. Sustain. 20, 897–909.
Yang, A., Zhang, H., Stewart, R.A., Nguyen, K., 2018. Enhancing residential water end use pattern recognition accuracy using self-organizing maps and K-means clustering techniques: Autoflow v3. 1. Water 10 (9), 1221.
Zhang, L., Njepu, A., Xia, X., 2021. Minimum cost solution to residential energy-water nexus through rainwater harvesting and greywater recycling. J. Clean. Prod. 298, 126742.