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Impact of COVID-19 on monthly water consumption on a tropical tourism island: case study of Phuket (Thailand)

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ABSTRACT

Phuket is a tropical island in Thailand that is famous for tourism. The COVID-19 pandemic resulted in the number of tourists reducing to almost zero. Since tourism contributes around one-half of the gross provincial product of Phuket, the impact was so severe that even the numbers of people employed and registered as locals decreased. Analysing the data from January 2015 to March 2021, we found that the total, residential and non-residential monthly consumptions dropped significantly after Thailand's State of Emergency was declared in March 2020. Unlike other studies that reported residential consumption increasing when people were required to stay home for a prolonged period, Phuket's residential consumption decreased by more than 10% from the pre-COVID-19 level, possibly due to the drop in peer-to-peer accommodation bookings. To study the impact on consumption in detail, we modelled using cascade regression analysis by dividing the predictors into three groups, namely socioeconomics, weather and calendar period. The results showed that the number of guest arrivals was the most statistically significant in all types of consumption and should be used as a predictor for water demand forecasting models in tourism areas.

Key words: climate, COVID-19, Thailand, tourism, tropical island, water consumption

HIGHLIGHTS

- The first study on the impact of COVID-19 on water consumption on a tropical island.
- The reduction of tourists impacted residential and non-residential consumptions.
- Residential consumption decreased during the outbreak, opposite to other reports.
- The study used the recent data, and the models can estimate consumptions during the outbreak.
- The weather and calendar impacts were also included in the models.

INTRODUCTION

On January 17, 2020, Thailand reported the first COVID-19 patient outside China. During the first wave of the pandemic, a maximum daily peak of 188 new COVID-19 cases associated with a boxing stadium and drinking venue was confirmed on March 22, 2020. Consequently, a nationwide curfew was enforced on April 3, 2020 (Dechsupa *et al.* 2020). Abiad *et al.* (2020a) evaluated the effects of the outbreak on developing Asian economies by comparing the COVID-19 outbreak with the economic impact of the severe acute respiratory syndrome (SARS) outbreak in 2003. The impacts included lower tourism numbers and business activity, as tourist arrivals from China contributed approximately 28% to total arrivals to Thailand in 2018. Tourism provides the main income for Thai residents, where the total and international tourism receipts were around 18% and 13.5% of the gross domestic product in 2017. Later, Abiad *et al.* (2020b) updated the impact of the COVID-19 pandemic as it extended into 2021. Revised tourism losses reflect extended travel restrictions and the latest passenger survey results. The protracted halt in global tourism, coupled with increased travel aversion, implied substantial tourism losses into 2021 and bode ill for many tourism-dependent economies in developing Asia.

Bhowmick *et al.* (2020) presented a COVID-19 contamination scenario in the urban and rural water cycle with potential human exposure. They suggested that contaminated raw water and leaky water distribution networks can lead to COVID-19 transmission. The World Health Organization (WHO 2020) published a guideline to provide safe water, sanitation and waste management and hygienic conditions essential for preventing illness and protecting human health during the COVID-19 outbreak. WHO recommended that the residual concentration of free chlorine should be $\geq$0.5 mg/l after at least 30 min of contact time at pH $<$ 8.0 for effective centralized disinfection. García-Ávila *et al.* (2021) developed a drinking water distribution network model for a part of Azogues City, Ecuador, using EPANET software (Rossman 2000) and found that about 45% of the model nodes did not comply with the WHO recommendation. Thus, it is important to assess and optimize the quantity of chlorine in water distribution networks, e.g., Javadinejad *et al.* (2019), Lipiwattanakarn *et al.* (2021).

Recent studies showed the impact of the COVID-19 pandemic on potable water demand. For example, Bich-Ngoc & Teller (2020) investigated the changes in outbound tourism on daily water demand in Liège, Belgium. The water demand was mainly from residential use (more than 80%). Instead of a regular multiple linear regression, they used a cascade model by dividing predictors into four groups, namely trend, holiday, weather and calendar. Although their available outbound tourism data were limited to December 2018 before the outbreak, they concluded that the threat due to dry and hot weather on increased water demand was higher than the threat from fewer outbound tourists. Balacco *et al.* (2020) studied the effect of restriction measures due to the COVID-19 spread on water demand in Ruglia, Italy. Using the instantaneous flow data of water consumption from January 1 to April 30 for 2019 and 2020, they highlighted the influence of the change in lifestyle on the daily water demand pattern, such as the shift in the morning peak by a delayed wake up by about two hours and the absence of a classic water peak demand during lunchtime. Kalbusch *et al.* (2020) used water consumption data collected using telemetry representing 17% of the total consumption from February 21 to April 12, 2020, in Joinville, Southern Brazil. They found that the restrictive actions caused a decrease in water consumption in the non-residential category, but an increase in the residential category. Dzimińska *et al.* (2021) used a cluster analysis to study the change in hourly water consumption in three apartment buildings in Bydgoszcz, Poland, between May 16, 2019, and October 6, 2020. They found increasing water consumption during the day and night, between 2:00 and 4:00 during the pandemic. Lüdtke *et al.* (2021) analysed hourly and daily water consumption in Wasserbeschaffungsverband WBV Harburg, northern Germany, from January 1, 2006, until June 28, 2020, using linear mixed models. They found 14.3% higher residential water consumption per day with higher morning and evening demand peaks. Shrestha *et al.* (2021) reported an increase in residential water consumption and a decrease in commercial consumption during the nationwide lockdown in Nepal during March–April 2020. Abu-Bakar *et al.* (2021) analysed data from 11,528 households over 20 weeks from January 2020 in the southern and eastern regions of England and found that the average household consumption was 284 litres per household per day (l/h/d) before the COVID-19 lockdown and increased to 411 l/h/d in week four in May (46% above pre-lockdown average). Rizvi *et al.* (2021) analysed a domestic consumption profile for selected customer meters up to June 2020 and found a 30% increase in consumption during the month of Ramadan and the COVID-19 crisis.

Most of the previous studies were in Europe and limited to 2020. There has been no study in detail of a tourism island in tropical Asia. Thus, this study aimed to fill a research gap by investigating the impact of the COVID-19 pandemic on water consumption in Phuket, southern Thailand. Phuket is one of the most famous tourism islands in Asia, with on average approximately one million guest arrivals at accommodation establishments per month and the resultant tourism activity earning over THB 450 billion in 2019 (48.13% of gross provincial product). In 2020, the average number of guest arrivals reduced to about 300,000 people per month, and tourism earnings fell to THB 100 billion (Ministry of Tourism & Sports 2021). Phuket was one of the first provinces that confirmed COVID-19 patients in Thailand (Department of Disease Control 2021), and its water demand was greatly impacted by the tourism loss due to the outbreak. Tantrakarnapa *et al.* (2020) found that the number of infected cases was significantly associated with the number of tourists and their activities in Thailand. Bakker & Twining-Ward (2018) studied the emergence of peer-to-peer (P2P) accommodation in the tourism industry, driven by technology such as Airbnb. P2P accommodation gives new opportunities for ordinary residents to offer rooms or entire homes to a global marketplace of consumers (Priporas *et al.* 2017). It is broadly known today as the sharing economy, and its growth is accelerating at a faster rate in emerging markets. This may result in water consumption in some registered residential properties being used by tourists instead of the real residents. Thus, in this study, we investigate the COVID-19 impact on total, residential and non-residential monthly water consumptions in Phuket, Thailand, up to March 2021.

MATERIALS AND METHODS

Data

Phuket is a province in the southern part of Thailand. It consists of the island of Phuket, the largest island in Thailand, and 32 other small islands surrounded by the Andaman Sea. Phuket Island has an area of 543 km^2 with a registered population of approximately 400,000 people. There are two weather stations on the Island, as shown in Figure 1. The Provincial Waterworks Authority (PWA), Phuket Branch, delivers a potable water supply to customers on the Island with a service area of 398 km^2. The consumption volume and the production capacity are around 2,000,000 and 3,000,000 m^3/month, respectively. In March 2021, the number of customers was 65,123 consisting of 52,235 residential meters and 12,888 non-residential meters.

Table 1 shows a list of the data from this study. The data were divided into three categories: water consumption, socioeconomics and weather. The water consumption data were from the PWA on a monthly basis, consisting of total water consumption (D_T), residential water consumption (D_R) and non-residential water consumption (D_N). The socioeconomic data consisted of the number of guest arrivals at accommodation establishments (N_G), the number of people employed (N_E) and the number of people in the registered population (N_P) from two sources, the Ministry of Tourism and Sports (MTS) and the National Statistical Office (NSO). Since the data from MTS and NSO were collected at different time scales, we interpolated the N_E and N_P data to a monthly time scale. However, N_P was extrapolated for three months during January–March 2021. The weather data on a monthly basis consisted of mean temperature (T), rainfall (R), mean wind speed (W) and mean humidity (H) from the two weather stations of the Thai Meteorological Department (TMD). The data were used to investigate the total, residential and non-residential water consumption patterns on a monthly time scale in the period January 2015–March 2021, covering the period before and after the Thailand's State of Emergency due to the COVID-19 pandemic.

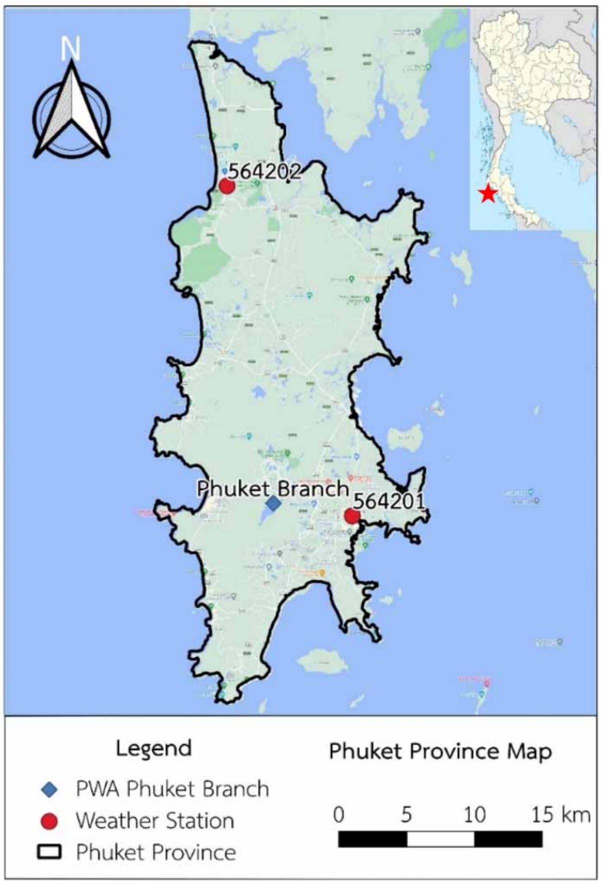

Figure 1 | Map of Phuket with locations of Provincial Waterworks Authority (PWA), Phuket branch, and weather stations. The small insert shows a map of Thailand, with Phuket located in the south (red star). The background map is taken from Google Street Map.

Table 1 | Overview of available data in categories

Data	Time scale	Period	Source
Water consumption			
Total water consumption (D_T)	Monthly	2015/01–2021/03	PWA
Residential water consumption (D_R)	Monthly	2015/01–2021/03	PWA
Non-residential water consumption (D_N)	Monthly	2015/01–2021/03	PWA
Socioeconomics			
Guest arrivals (N_G)	Monthly	2015/01–2021/03	MTS
People employed (N_E)	Quarterly	2014/Q4–2021/Q1	NSO
Registered population (N_P)	Yearly	2014–2020	NSO
Weather			
Mean temperature (T)	Monthly	2015/01–2021/03	TMD
Rainfall (R)	Monthly	2015/01–2021/03	TMD
Mean wind speed (W)	Monthly	2015/01–2021/03	TMD
Mean humidity (H)	Monthly	2015/01–2021/03	TMD

The impact of the COVID-19 pandemic appeared to be clear after January 2020 with steep drops in D_T and D_N, as shown in Figure 2(a). In January 2020, D_T and D_N were 2,102,518 m^3/month and 1,170,338 m^3/month, respectively, but in May 2020, they reduced to 1,331,493 m^3/month (−36.7%) and 522,727 m^3/month (−55.3%), respectively. For D_R, many studies reported that residential consumption increased due to a work-from-home policy during the COVID-19 outbreak. However, D_R in this study surprisingly decreased along with D_T and D_N but at a milder rate. D_R in January 2020 was 932,180 m^3/month and dropped to 808,766 m^3/month (−13.2%) in May 2020. Phuket's main industries are tourism and hospitality. Wannasuth & Wichasin (2021) indicated that before the pandemic, the sharing economy (P2P accommodation) had grown rapidly so that even foreigners came to conduct this business in Thailand. Boros *et al.* (2020) studied the effects of COVID-19 on Airbnb in 15 cities around the world and found that Airbnb had experienced a rapid drop in bookings. Thus, we hypothesize that a decrease in booking P2P accommodation affected the drop in D_R during the COVID-19 outbreak. After May 2020, the values of D_T, D_R and D_N did not change much. Comparing Figure 2(a) and 2(b), the monthly pattern of N_G was similar to those for D_T, and D_N. The maximum N_G value of 1,524,977 arrivals in January 2020 dropped to the minimum N_G value of 3,621 arrivals (−99.8%) in May 2020. The impact can be seen in N_E and N_P as well, where the general trends of N_E and N_P were increasing before the pandemic. N_E reduced from 322,774 people in Q4 2019 to 296,070 (−8.27%) in Q4 2020, and N_P also reduced from 416,582 people in 2019 to 414,471 (−0.51%) in 2020.

Phuket has a tropical monsoonal climate. The southwestern monsoon from the Indian Ocean during May–October brings a stream of warm moist air towards Phuket and causes heavy rain (rainy season). The northeastern monsoon draws cold air from the South China Sea during November–April (dry season), which is thus the best time for tourists to visit Phuket due to cool breezes and blue skies. Figure 3 shows the variation of monthly meteorological data from January 2015 to December 2020. Phuket is warm year-round with monthly mean temperature in the range 27–31 °C (Figure 3(a)). Its location avoids most typhoons and tropical storms. The monthly rainfall is in the range 0–600 mm/month (Figure 3(b)). The monthly mean wind speed is quite steady (1–4 knots), with August having the strongest winds (Figure 3(c)). Figure 3(d) shows the yearly pattern of monthly mean humidity with little variation, similar to the rainfall pattern.

METHODS

Bich-Ngoc & Teller (2020) applied a cascade model of regression analysis to investigate the daily water demand in Liège, Belgium, because of the high multicollinearity among the predictors. Their statistical model was adapted from Wong *et al.* (2010) and Maidment & Parzen (1984). In the current study, we followed the cascade model concept used by Bich-Ngoc & Teller (2020). However, our predictors were divided into three groups, namely socioeconomics, weather and calendar period, and we predicted three types of consumption: total, residential and non-residential.

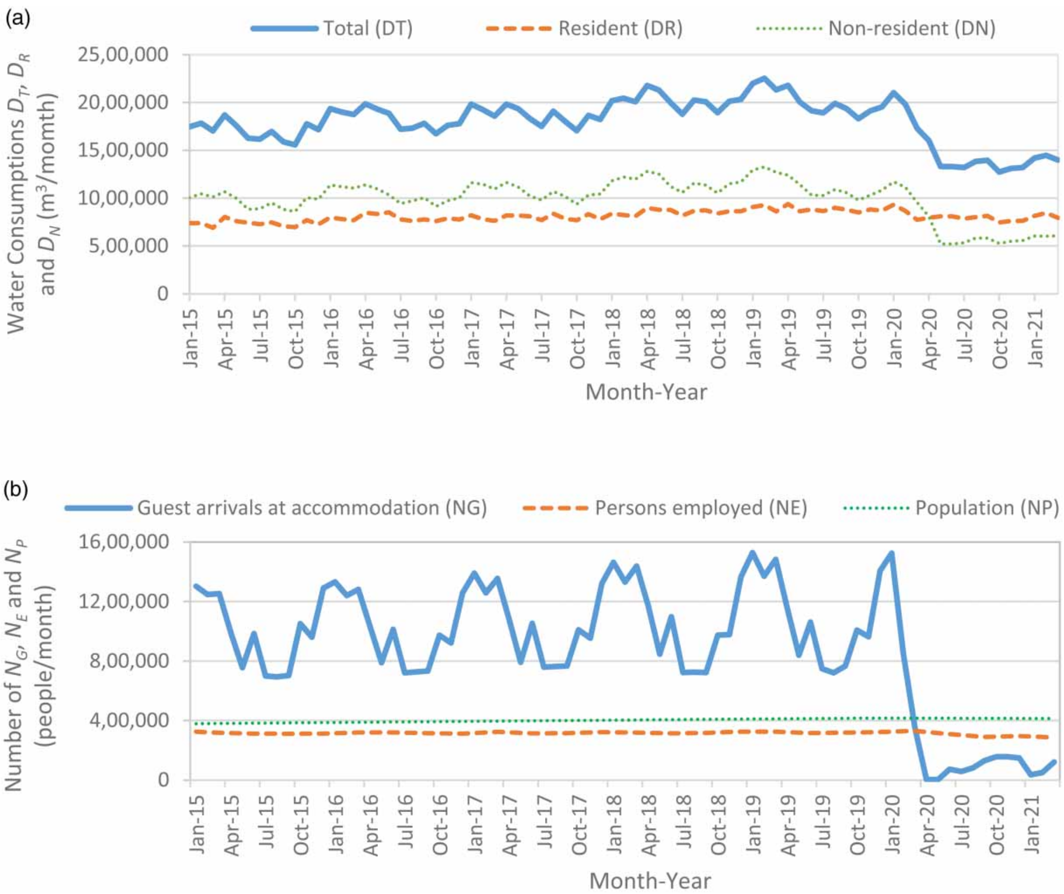

Figure 2 | Time series of (a) water consumption data and (b) socioeconomic data.

The cascade method for total, residential and non-residential monthly water consumptions (D_T, D_R, D_N) used in this analysis (Figure 4) consists of three transformations. A first transformation is applied in the linear regression analysis using the socioeconomic data ($Y_{T,1}$, $Y_{R,1}$, $Y_{N,1}$), considered as base water use components. Then the residuals from the first transformation ($e_{T,1}$, $e_{R,1}$, $e_{N,1}$) are passed to the second linear regression analysis using the weather data ($Y_{T,2}$, $Y_{R,2}$, $Y_{N,2}$) as seasonal water use components. Finally, the residuals from the second transformation ($e_{T,2}$, $e_{R,2}$, $e_{N,2}$) are used for the third linear regression analysis based on the calendar data ($Y_{T,3}$, $Y_{R,3}$, $Y_{N,3}$) as calendrical water use components. The residuals from the third transformation ($e_{T,3}$, $e_{R,3}$, $e_{N,3}$) are considered as random error series ($N(0, \sigma)$). Thus, the cascade method can be expressed as:

$$(D_T, D_R, D_N) = (Y_{T,1}, Y_{R,1}, Y_{N,1}) + (e_{T,1}, e_{R,1}, e_{N,1}) \tag{1}$$

$$(e_{T,1}, e_{R,1}, e_{N,1}) = (Y_{T,2}, Y_{R,2}, Y_{N,2}) + (e_{T,2}, e_{R,2}, e_{N,2}) \tag{2}$$

$$(e_{T,2}, e_{R,2}, e_{N,2}) = (Y_{T,3}, Y_{R,3}, Y_{N,3}) + (e_{T,3}, e_{R,3}, e_{N,3}) \tag{3}$$

$$(e_{T,3}, e_{R,3}, e_{N,3}) \sim N(0, \sigma) \tag{4}$$

where the subscripts T, R and N denote total, residential and non-residential consumptions, respectively, and the subscripts 1, 2 and 3 denote the first, second and third transformations, respectively. The base water use components ($Y_{T,1}$, $Y_{R,1}$, $Y_{N,1}$), the

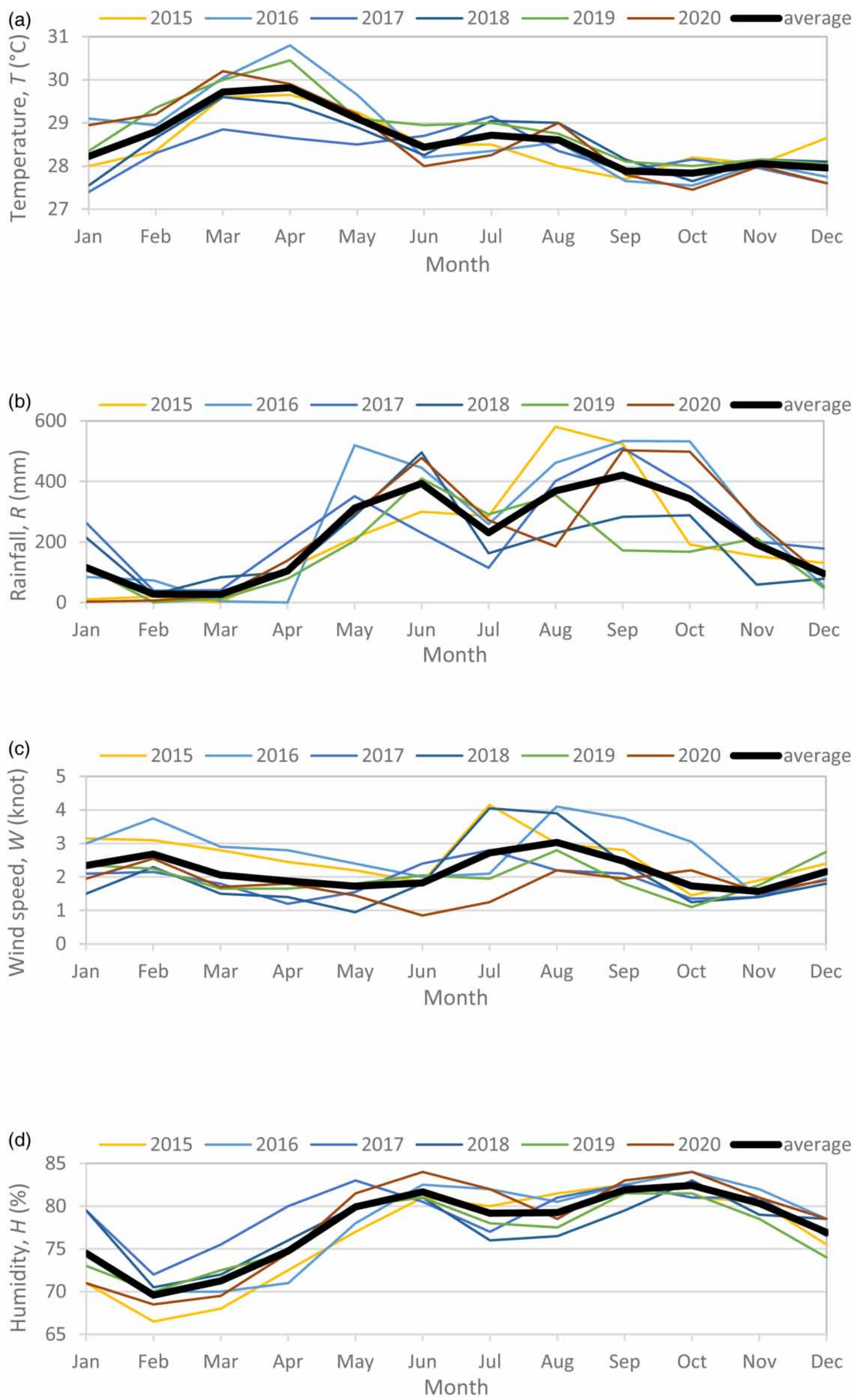

Figure 3 | Weather patterns of (a) mean temperature, (b) rainfall, (c) mean wind speed and (d) mean humidity.

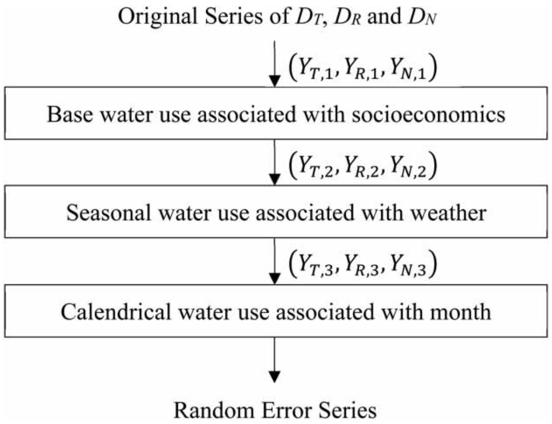

Figure 4 | Cascade of transformations of prediction models for total, residential and non-residential water consumptions (D_T, D_R and D_N).

seasonal water use components ($Y_{T,2}$, $Y_{R,2}$, $Y_{N,2}$) and the calendrical water use components ($Y_{T,3}$, $Y_{R,3}$, $Y_{N,3}$) are:

$$(Y_{T,1}, Y_{R,1}, Y_{N,1}) = (\alpha_{T,1}, \alpha_{R,1}, \alpha_{N,1}) + (\boldsymbol{\beta}_{T,\boldsymbol{p}1}, \boldsymbol{\beta}_{R,\boldsymbol{p}1}, \boldsymbol{\beta}_{N,\boldsymbol{p}1}) \times \boldsymbol{X}_{\mathbf{socio}} \tag{5}$$

$$(Y_{T,2}, Y_{R,2}, Y_{N,2}) = (\alpha_{T,2}, \alpha_{R,2}, \alpha_{N,2}) + (\boldsymbol{\beta}_{T,\boldsymbol{p}2}, \boldsymbol{\beta}_{R,\boldsymbol{p}2}, \boldsymbol{\beta}_{N,\boldsymbol{p}2}) \times \boldsymbol{X}_{\mathbf{weather}} \tag{6}$$

$$(Y_{T,3}, Y_{R,3}, Y_{N,3}) = (\alpha_{T,3}, \alpha_{R,3}, \alpha_{N,3}) + (\boldsymbol{\beta}_{T,\boldsymbol{p}3}, \boldsymbol{\beta}_{R,\boldsymbol{p}3}, \boldsymbol{\beta}_{N,\boldsymbol{p}3}) \times \boldsymbol{X}_{\mathbf{calendar}} \tag{7}$$

where α represents model intercepts, $\boldsymbol{\beta}$ represents vectors of model coefficients, $\boldsymbol{X}_{\mathbf{socio}}$ is the socioeconomic data having three predictors (N_G, N_E, N_P), $\boldsymbol{X}_{\mathbf{weather}}$ is the weather data having four predictors (T, R, W, H), and $\boldsymbol{X}_{\mathbf{calendar}}$ is the calendar data (months of the year).

To assess the efficiency of each transformation, each cascade model for each type of water consumption was divided into three sub-models as follows:

$$(D_{T,p1}, D_{R,p1}, D_{N,p1}) = (Y_{T,1}, Y_{R,1}, Y_{N,1}) \tag{8}$$

$$(D_{T,p2}, D_{R,p2}, D_{N,p2}) = (Y_{T,1}, Y_{R,1}, Y_{N,1}) + (Y_{T,2}, Y_{R,2}, Y_{N,2}) \tag{9}$$

$$(D_{T,p3}, D_{R,p3}, D_{N,p3}) = (Y_{T,1}, Y_{R,1}, Y_{N,1}) + (Y_{T,2}, Y_{R,2}, Y_{N,2}) + (Y_{T,3}, Y_{R,3}, Y_{N,3}) \tag{10}$$

There are options regarding selecting the predictors of the models. The model of Bich-Ngoc & Teller (2020) included every input piece of data as a predictor, regardless of whether or not its significance level of the p-value was below the threshold of 0.05. On the other hand, Wong *et al.* (2010) used trial-and-error analyses to examine the holiday effect on water consumption, divided the model into seven sub-models with all chosen predictors having p-values below 0.05 and then selected the most suitable sub-model. In the current study, we followed the approach of Wong *et al.* (2010) and applied trial-and-error analyses using the Statsmodels library in Python (Seabold & Perktold 2010). The criterion for choosing the suitable models was to have predictors with p-values below 0.05 as much as possible, because the efficiency should then be the highest and our models were monthly-based models with the possible maximum number of predictors being only 22. The data were divided into a training set from January 2015 to September 2020 (69 months) and a validation set from October 2020 to March 2021 (six months). We chose the data during the COVID-19 outbreak for the validation set to investigate the efficiency of our models in predicting consumptions during the pandemic.

RESULTS AND DISCUSSION

Model parameters

Table 2 shows the intercepts, coefficients and associated p-values of the cascaded regression analysis for the $D_{T,p}$, $D_{R,p}$ and $D_{N,p}$ models (8)–(10). Although the observed D_T value was always equal to D_R+D_N, the predicted $D_{T,p}$ was not necessarily equal to the predicted $D_{R,p}$+$D_{N,p}$. Thus, the value of each parameter in the $D_{T,p}$ model was not equal to the sum of the values

Table 2 | Parameters with *p*-values for total consumption ($D_{T,p}$), residential consumption ($D_{R,p}$) and non-residential consumption ($D_{N,p}$) models, where consumption unit is m^3/month

		$D_{T,p}$ model		$D_{R,p}$ model		$D_{N,p}$ model	
Parameter	**Unit**	**Coefficient**	***p*-Value**	**Coefficient**	***p*-Value**	**Coefficient**	***p*-Value**
First transformation based on socioeconomics							
Intercept 1	–	−3,384,014	0.0003	−797,787	<0.0001	−2,179,866	0.0018
N_G	person	0.34144	<0.0001	0.05562	<0.0001	0.27318	<0.0001
N_E	person	9.02590	0.0025			9.30365	0.0001
N_P	person	5.09675	0.0004	3.89252	<0.0001		
Second transformation based on weather							
Intercept 2	–	−1,945,197	0.0015	−522,670	0.0031	−1,392,504	0.0050
T	°C	66,093	0.0017	17,703	0.0035	47,458	0.0053
R	mm	243.078	0.0098	72.703	0.0079	154.869	0.0421
W	knot						
H	%						
Third transformation based on calendar period							
Intercept 3	–	−56,147	0.0018	−27,694	<0.0001		
Jan	–			48,912	0.0002		
Feb	–	100,400	0.0270	34,815	0.0056		
Mar	–						
Apr	–	120,176	0.0087	55,505	<0.0001		
May	–	101,765	0.0253	40,908	0.0013		
Jun	–			35,058	0.0053		
Jul	–						
Aug	–	115,700	0.0114	34,417	0.0062		
Sep	–	113,867	0.0127	26,743	0.0313		
Oct	–						
Nov	–	112,542	0.0223	50,553	0.0003		
Dec	–						

of each parameter in the $D_{R,p}$ and $D_{N,p}$ models. The first transformation based on socioeconomics showed that N_G was significant in every model with *p*-values less than 0.0001. As described earlier, the emergence of P2P accommodation in the tourism industry may result in residential water consumption being used by tourists instead of the real residents. Thus, guest arrivals influenced all types of water consumption in our Phuket case study. While N_E was significant in the $D_{T,p}$ and $D_{N,p}$ models, N_P was significant in the $D_{T,p}$ and $D_{R,p}$ models. These N_E and N_P results could be easily explained by the people being employed influencing non-residential water consumption while the registered population certainly consumed residential water.

In the second transformation based on weather, four predictors were available, namely T, R, W and H. However, only T and R were significant in every model. In addition, the *p*-values of T were smaller than those of R. Makpiboon *et al.* (2020) studied the total water demand in three provinces (Bangkok, Nonthaburi and Samutprakarn) in Thailand using three different time scales (daily, monthly and seasonal) based on T and R. They found that both weather predictors were significant with the *p*-values of T smaller than those of R. Thus, our results agreed with their research results. Finally, 12 predictors (months of the year) were selected in the third transformation based on calendar period. For the $D_{T,p}$ and $D_{R,p}$ models, six months and eight months, respectively, were chosen. However, surprisingly, no month predictor was valid for the $D_{N,p}$ model due to the *p*-values being higher than the threshold value of 0.05. April had the highest coefficients with the lowest *p*-values in both the $D_{T,p}$ and $D_{R,p}$ models. This may have been due to the Thai New Year festival in the middle of April, when people in Thailand celebrate the holiday with traditional water ceremonies such as pouring water in ceremonies and in widespread public water splashing and more raucous events.

Predicted monthly water consumption

The comparisons between the observed water consumption and the final predicted values for the training and validation periods are shown in Figure 5. Figure 5(a) shows two types of D_T estimation, the final D_T model ($D_{T,p3}$) and the combination

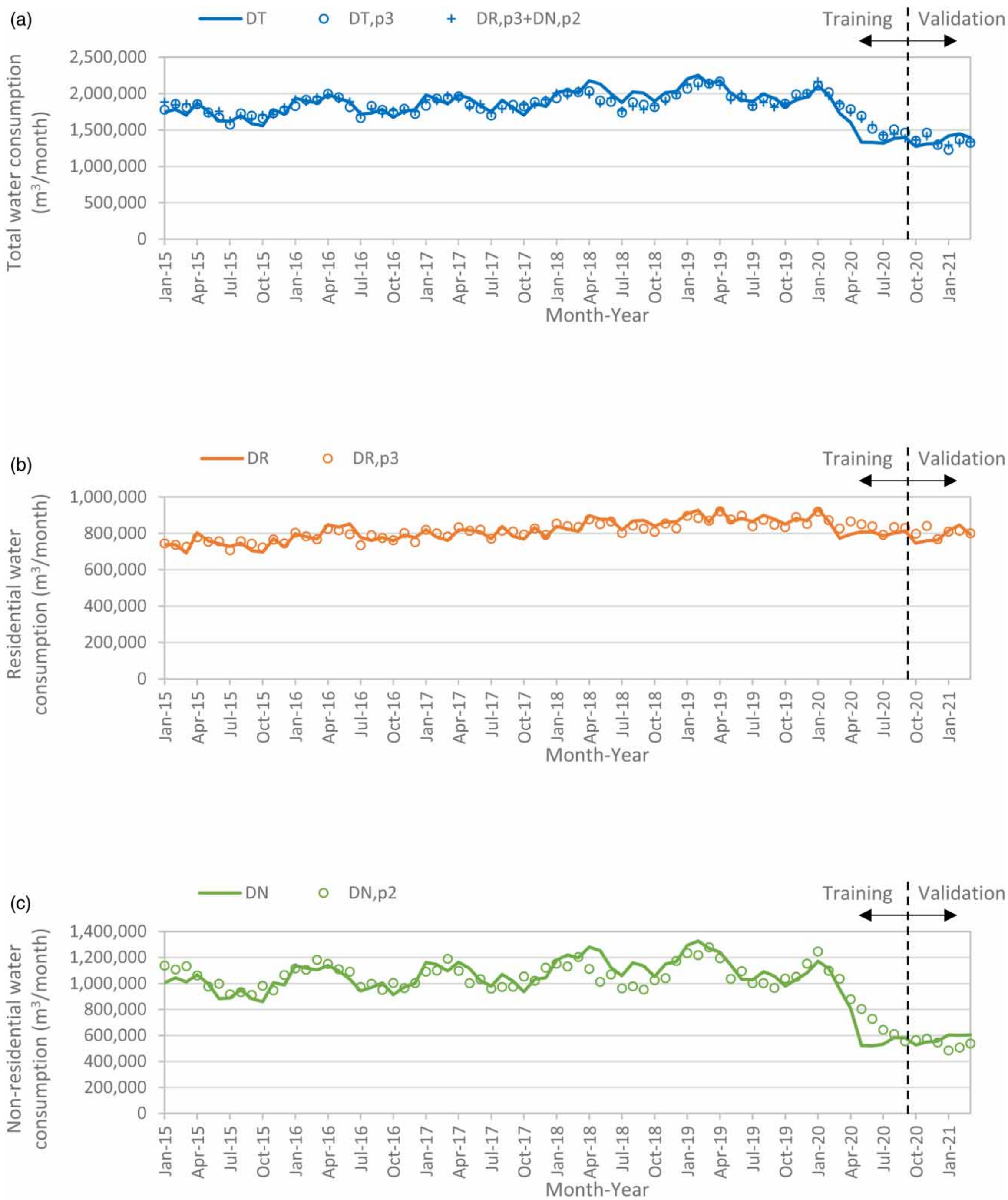

Figure 5 | Observed (line) and predicted (circle and plus markers) monthly consumption for (a) total consumption, (b) residential consumption and (c) non-residential consumption. The training and validation periods are before and after, respectively, the black vertical dashed line.

of two final models of D_R and D_N ($D_{R,p3}$+$D_{N,p2}$). Both models do not give the same results because the values of the model parameters are slightly different, as shown in Table 2. The results for the $D_{R,p3}$ and $D_{N,p2}$ models compared with the observed values are shown in Figure 5(b) and 5(c), respectively. In the training period before the COVID-19 pandemic affected N_G, all model results matched reasonably well with the observations. However, during the early period of the pandemic when water demand plunged, our models overestimated consumption, especially between March and June 2020. There was a better fit to water demand in the validation period between October 2020 and March 2021.

Table 3 shows the detailed performance of the prediction models at each transformation, where R is the coefficient of correlation, RMSE is the root-mean-square error, and MAE and MAPE are the mean absolute error and mean absolute percentage error, respectively. Generally, an increase in transformations led to better efficiency of prediction in this study. In particular, the third transformation based on the calendar period increased the R values in both the training and validation periods. The D_R models had the best performance followed by the D_T and D_N models, respectively. Thus, the residential water demand was better estimated compared with the non-residential demand in this study. The $D_{T,p3}$ model and the $D_{R,p3}$+$D_{N,p2}$ model had similar performance levels. Although the performance based on the values for RMSE, MAE and MAPE was slightly lower in the validation period, the R values dropped substantially. This could be explained by the validation period we chose being during an abnormal situation (the COVID-19 outbreak). However, the RMSE, MAE and MAPE results indicated that our models could satisfactorily predict water demand during the outbreak. Recently, the Thai government has officially endorsed measures for Phuket to reopen for fully vaccinated international travellers without quarantine requirements from July 1, 2021, under the so-called 'Phuket sandbox' initiative. The Tourism Authority of Thailand (TAT) estimated that the sandbox would attract 100,000 international tourists in Q3 2021 (TAT 2021). Thus, our models could be helpful in estimating the increase in water demand after the reopening.

CONCLUSION

The total, residential and non-residential monthly water consumptions (D_T, D_R and D_N) on Phuket Island were investigated before and during the COVID-19 pandemic. After Thailand's State of Emergency was declared (in January and then extended in May 2020), the number of guest arrivals at accommodation establishments (N_G) plunged 99.8%, and D_T, D_R and D_N dropped 36.7%, 13.2% and 55.3%, respectively. While reductions in D_T and D_N are common as business slows down or stops, the reduction in D_R was surprisingly the opposite according to many reports. We hypothesize that the COVID-19 pandemic hit the tourism and hospitality industries hard, including the P2P accommodation service in Phuket. If many residential properties participated in that service, D_R would strongly depend on the tourism and hospitality industries. The COVID-19 impact can be seen in other socioeconomic parameters, namely the number of people employed (N_E) and the registered population number (N_P). The general trends in N_E and N_P were increasing before the pandemic. However, N_E reduced 8.27% between the fourth quarters of 2019 and 2020, and N_P decreased 0.51% from 2019 to 2020.

The cascade models of regression analysis for D_T, D_R and D_N were established using three predictor groups: socioeconomics, weather and calendar period. We trained our models using data from before and during the outbreak between

Table 3 | Performance of prediction models for each transformation

Indicator	$D_{T,p1}$	$D_{T,p2}$	$D_{T,p3}$	$D_{R,p1}$	$D_{R,p2}$	$D_{R,p3}$	$D_{N,p1}$	$D_{N,p2}$	$D_{R,p3}$+$D_{N,p2}$
Training period (2015/01–2020/09)									
R (–)	0.812	0.849	0.900	0.796	0.831	0.904	0.830	0.855	0.870
RMSE (m^3/month)	120,041	110,079	95,014	34,614	31,937	24,553	95,920	89,953	104,243
MAE (m^3/month)	95,652	86,787	73,558	27,610	26,278	19,884	75,065	69,245	79,093
MAPE (%)	5.29	4.85	4.18	3.40	3.25	2.45	7.84	7.38	4.44
Validation period (2020/10–2021/03)									
R (–)	−0.824	−0.759	−0.371	−0.959	−0.370	0.201	−0.772	−0.817	−0.603
RMSE (m^3/month)	104,967	102,245	115,197	51,067	47,945	40,862	64,288	70,458	94,887
MAE (m^3/month)	96,669	90,290	100,655	43,647	44,525	29,764	62,368	59,236	85,135
MAPE (%)	7.23	6.64	7.36	5.68	5.73	3.85	10.80	10.07	6.21

January 2015 and September 2020 and validated the models using data from October 2020 to March 2021. N_G was the most important predictor and should be used as a predictor for water demand forecasting models in tourism areas. Monthly mean temperature and rainfall were also significant in all models. In our case study, calendar predictors (months of the year) were not significant in the D_N model. Our final models provided satisfactory estimations for D_T, D_R and D_N during the abnormal COVID-19 situation.

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DATA AVAILABILITY STATEMENT

Data cannot be made publicly available; readers should contact the corresponding author for details.

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