UHERO
THE ECONOMIC RESEARCH ORGANIZATION
AT THE UNIVERSITY OF HAWAIʻI

# Tourism Water Use During the COVID-19 Shutdown
# A natural experiment in Hawaiʻi

by

Nathan DeMaagd, Peter Fuleky, Kimberly Burnett, and Christopher Wada

Working Paper No. 2021-8

November 1, 2021

UNIVERSITY OF HAWAIʻI AT MANOA
2424 MAILE WAY, ROOM 540 • HONOLULU, HAWAIʻI 96822
WWW.UHERO.HAWAII.EDU

# TOURISM WATER USE DURING THE COVID-19 SHUTDOWN

## A natural experiment in Hawai‘i

Nathan DeMaagd*[1], Peter Fuleky[1,2], Kimberly Burnett[1], and Christopher Wada[1]

[1]University of Hawai‘i Economic Research Organization, 2424 Maile Way, Saunders Hall 540, Honolulu, HI, 96822

[2]University of Hawai‘i at Mānoa Department of Economics, 2424 Maile Way, Saunders Hall 542, Honolulu, HI, 96822

**Abstract.** Many of the most popular tourist destinations are on small islands whose resources are in limited supply, and the effects of climate change and increasing tourism tend to worsen the outlook. In this study, we identify the relationship between tourism and water use on the Hawaiian island of O‘ahu. Hawai‘i closed almost entirely to tourism during the COVID-19 pandemic, which provides a unique natural experiment to study the relationship between tourism and water use. Empirically, we estimate that a 1% decline in the number of tourists was associated with a 0.4% to 0.65% lower water use in the hotel sector. However, decreased water use from a drop in Airbnb reservations was offset by an increase in work-from-home arrangements for residents.

Keywords: Tourism, water demand, COVID-19

*Corresponding author: demaagdn@hawaii.edu, 1-808-956-2325. Research interests: empirical microeconomics, natural resource management, climate change.

## Highlights

- The shutdown of tourism on O‘ahu during COVID-19 provided a unique natural experiment.
- A variety of data sources and methods were used to study the effect on water use.
- Water consumption in hotels dropped significantly, as expected.
- A decline in Airbnb water use was offset by work-at-home accommodations for residents.

# Author contributions

- Nathan DeMaagd – Conceptualization, methodology, software, formal analysis, data curation, writing - original draft, visualization
- Peter Fuleky – Conceptualization, methodology, formal analysis, supervision, funding acquisition, project administration, writing - review and editing
- Kimberly Burnett – Conceptualization, resources, writing - original draft, writing - review and editing
- Christopher Wada – Conceptualization, writing - original draft, writing - review and editing

# 1 Introduction

Water security is often understood as the capacity of a population to safeguard access to water resources in sufficient quantity and quality to sustain livelihoods and socio-economic development (UNESCO 2012). Globally, more than 600 million people do not have access to clean drinking water and a staggering 2.4 billion lack adequate sanitation (EIU 2017). Maintaining adequate freshwater supplies in Pacific islands is of particular concern as sea-level rise, changing temperature, and shifting rainfall patterns stress fragile water resources (Mcleod et al. 2019; Izuka and Keener 2013). As acknowledged at the 2021 United Nations Climate Change Conference, water is the primary medium through which humanity will feel the effects of climate change (COP26 2021). The importance of water management is accentuated when there is near complete reliance on groundwater as in Hawai‘i, where 99% of drinking and half of all water use is sourced from aquifers (Izuka, Engott, et al. 2018; Holding et al. 2016; Tribble 2008). While the situation has not yet escalated to a dire stage on the island of O‘ahu, which accommodates Honolulu, the capital of and largest city in Hawai‘i, there is growing evidence that available freshwater resources on the island have been diminishing over time (Bassiouni and Oki 2013).

In most countries, the tourism sector comprises less than 5% of total domestic water use (Gössling 2015), but hotels and resorts tend to be intensive water users (EPA 2012). In 2019, the number of tourists was about 17% and 12% of the resident population in the state of Hawai'i and the island of O'ahu, respectively, so it is important to understand the impact of the tourism industry on the precariously-balanced water supply. This is especially true given the potential climate change effects on water availability and further expansion of the tourism industry. Although tourism only increases global water consumption by less than 1% and this is not forecasted to increase significantly in the future, an increase in tourism may strain water resources in regions of the world where tourism is highly concentrated (Gössling et al. 2012). Several islands like Nicaragua (LaVanchy 2017), Bali (Cole 2012; Sudiajeng et al. 2017) and Zanzibar (Gössling 2001) whose economies rely heavily on tourism already show evidence of unsustainable groundwater use. In the case of Bali, research into the relationship between tourism and water use has been instrumental in raising awareness and shaping public policy (Cole, Wardana, and Dharmiasih 2021).

This concentration of tourism and the effects it may have on water resources is emerging as a concern in Hawai‘i, and on O‘ahu in particular, where the number of tourists visiting the state/island grew by 50% between 2009 and 2019. However, unlike the developing economies of the aforementioned locations, O‘ahu is a tourist destination with a highly-developed economy where the strain on water resources is a concern even without consideration of tourism-specific use. Residential water consumption on the island accounts for about 55% while hotels and resorts account for about 5% of total municipal water use but, in per-capita terms, tourists use approximately the same amount of water as residents. Thus, our study serves to be one of the first to examine tourism and water use on a dense, urban island.

The majority of previous literature on the topic of tourism and water use has largely focused on direct water use by tourist infrastructure such as hotels, swimming pools, spas, golf courses and water parks (Charara et al. 2011; Gössling 2001; Hof and Schmitt 2011; Rico-Amoros, Olcina-Cantos, and Saurí 2009; Tortella and Tirado 2011), and we also start with a direct approach. We first analyze the relationship between tourism levels and the associated changes in hotel water consumption, while controlling for other variables like temperature and rainfall that are expected to affect water use decisions. Since transient vacation rentals such as Airbnbs have an important role in tourist accommodation, we also analyze water use in residential neighborhoods as a function of Airbnb reservations. Lastly, we use granular SafeGraph data representing daily visits to restaurants and other so-called "points of interest" in high traffic tourist areas to examine indirect water use outside of hotels and accommodation, a component of tourism-related water consumption that has received considerably less attention in previous literature. We hope these results may be used in other studies that examine future trends and tourism projections to understand how these changes may affect future water use.

Our main source of identification of the tourism/water consumption relationship is the large-scale statewide shutdown of tourism due to the COVID-19 pandemic. This event provides a unique natural experiment to study the relationship between tourism and water use on O'ahu, and adds to the growing body of research investigating the effects of COVID-19 on tourism (Yang, Zhang, and Rickly 2021) and literature using experiments in hospitality and tourism (Viglia and Dolnicar 2020). Recreational travel was put on hold due to this exogenous shock, with hotel and resort occupancy dropping to essentially zero for about six months. As seen in Figure 1, the large and sudden change in the number of tourists on the island coincides with a similarly significant change in the consumption of water in these locations. We also examine how the pandemic affected water consumption within and between other locations, such as restaurants and residences. These results are in part also influenced by the prevalence of transient vacation rentals like Airbnb in residential locations, as well as a significant shift to work-from-home arrangements in many sectors. Using parcel-level water consumption data at the monthly frequency, we aim to quantify the pattern of water consumption across these various sectors on O'ahu.

The remainder of the article is organized as follows: Section 2 describes our data. Section 3 outlines three different empirical models used in our analysis. Section 4 provides the results of these analyses. The discussion in Section 5 summarizes and compares our models, and explores the implications of our results.

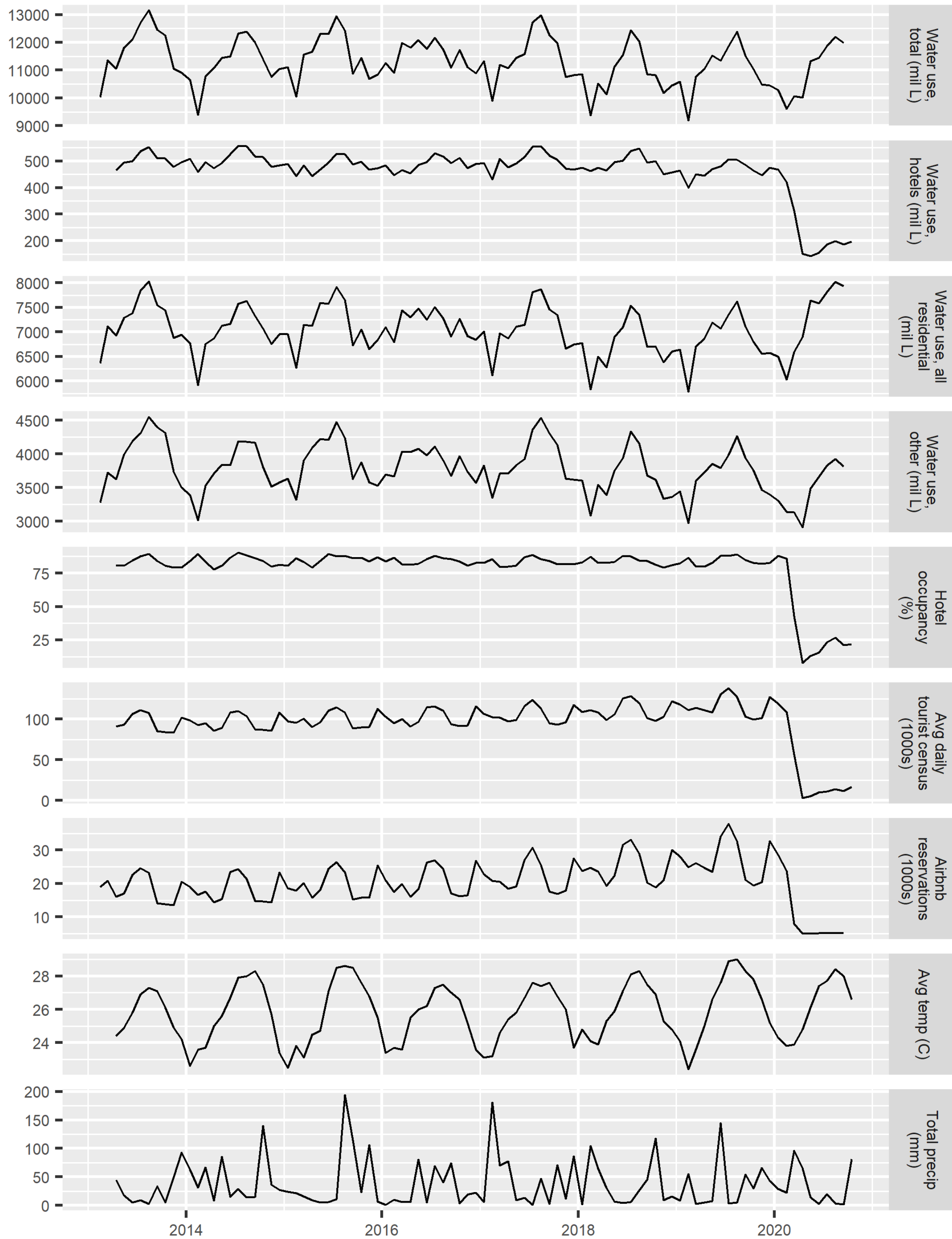


Figure 1: Aggregate (island-wide) monthly time series spanning the February 2013 to October 2020 period. Airbnb occupancy is assumed to be zero beginning April 2020. Aggregate monthly water use for all other types of parcels in the fourth subplot includes offices, commercial and industrial consumers.

## 2 Data

Our analysis relied on several data sets with different spatial granularity and temporal aggregation. Monthly water use data were obtained from the Honolulu Board of Water Supply for all properties on O'ahu for the period from January 2013 to October 2020. These data include information about billing start and end dates, and the quantity of water consumed by the property. It also provides the classification of the properties, such as commercial, hotel, single family home, high-density residential, industrial, or government. Individual properties in the data are identified by their tax map key. These tax map keys are used for identification of individual properties for all tax and other local government matters, and are used here for data matching purposes. For consistency, we refer henceforth to tax map keys and individual properties as parcels.

Monthly aggregate hotel occupancy and tourist census data for the sample period from February 2013 to October 2020 were obtained from the University of Hawai'i Economic Research Organization (UHERO 2021). Hotel occupancy is the percent of available rooms occupied, while tourist census is the number of tourists present on O'ahu on an average day within a month. Because seasonal weather patterns are correlated with both water use and tourist counts (see, for example, Ouyang et al., 2014 and Ghimire et al., 2016), it is important to control for weather in our models. Average monthly temperature and monthly rainfall were obtained from the NOAA database for the Honolulu International Airport (NOAA 2021).

Nightly Airbnb reservation status for all units on O'ahu from October 2018 to October 2020 is provided by Inside Airbnb (*Inside Airbnb* 2021). The monthly snapshots contain the reservation status for each night during the subsequent month. Since a reservation can be made or canceled between the time the data are scraped and the night of the reservation, the true occupancy status is not known with full certainty. This measurement error is assumed to be random prior to the COVID outbreak, with new reservations offsetting canceled ones, on average. In the wake of the COVID-19 outbreak in March 2020, however, the number of tourists to the state dwindled from about 30,000 per day to a few hundred. The hiatus in tourist arrivals was accompanied by mass-cancellations, and we assume Airbnbs had zero occupancy after April 2020 to help control for potential mis-identification of reservation status.

Because most Airbnb listings provide only an estimated location and not the exact location of the rental, data were aggregated to a grid as shown in Figure 2. Each grid cell measures one square kilometer, and we calculated each cell's aggregate monthly water use, expected Airbnb occupancy, number of residential units (with and without Airbnbs), and Airbnb density using the data above. These grid cells then become the observational units in one of the models discussed below. Figure 1 shows an aggregated time series for the data used in our hotel and Airbnb analyses. The significant drop in hotel water use in the first quarter of 2020 coincides with the decrease in tourism due to the COVID-19 pandemic but residential units see an overall increase in water

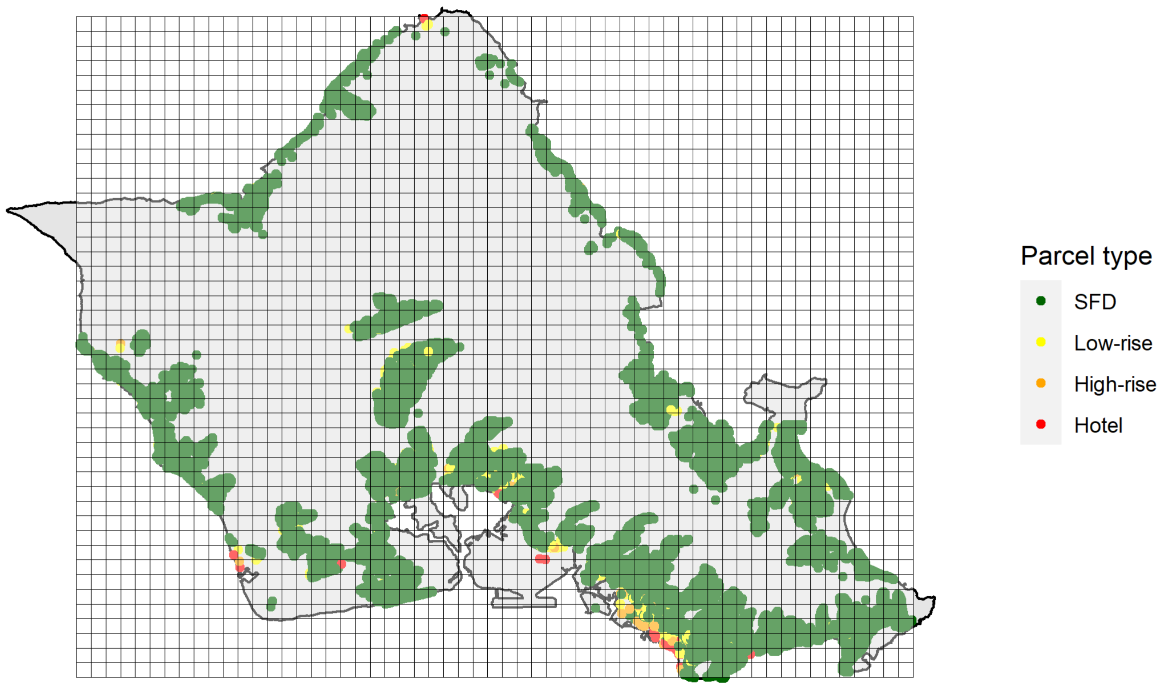


Figure 2: 1km×1km grid over all residential and hotel parcels on O'ahu. Because Airbnb locations are not exact, data were aggregated to a grid for analysis. SFDs are single family dwellings, and low- and high-rise are residential apartment and condominium units.

use, likely due to the significant increase in work-from-home arrangements for residents of the island.

Finally, we use data compiled by SafeGraph[1] to track foot traffic to various Points of Interest on O'ahu. These data rely on mobile phone GPS tracking to provide information on visited locations, dates of visits, and duration of stay. Points of Interest include hotels, but also other public spaces like parks, restaurants, and retail outlets. Because not all visitors may have mobile phones, or location tracking services may otherwise be unavailable, foot traffic information can only be used to estimate the *relative* levels of visitors at the island's Points of Interest. We assume that the fraction of visitors who have a tracked mobile phone stays relatively constant, so that a percent change in the number of tracked visits to a Point of Interest approximates the true percent change in the number of overall visits to the Point of Interest.

[1] `https://www.safegraph.com/`

# 3 Empirical strategy

Next we describe several modeling and estimation approaches, tailored to the data sets in our analysis. The models range from the aggregate to the fairly granular, depending on the spatial resolution of the particular variables used. The methods, in conjunction with the data, help us analyze water consumption from several perspectives.

## 3.1 Hotel water use and aggregate tourism measures

Our first model is a time series regression of monthly hotel water use on monthly island-level predictors, estimated individually for each hotel. In other words, each hotel's water consumption is modeled as a hotel-specific fixed amount of water consumption, plus hotel specific sensitivity to island-wide seasonal and tourism components. The seasonal components include temperature and precipitation, and the tourism components include the number of tourists (Equation 1) and hotel occupancy (Equation 2) on Oʻahu. Specifically, our models are

$$\log(Water_{it}) = \alpha_{0i} + \alpha_{1i}\log(Tour_t) + \alpha_{2i}Temp_t + \alpha_{3i}\log(Rain_t) + u_{it}, \quad \text{for each hotel } i \tag{1}$$

$$\log(Water_{it}) = \alpha_{0i} + \alpha_{1i}\log(Occup_t) + \alpha_{2i}Temp_t + \alpha_{3i}\log(Rain_t) + u_{it}, \quad \text{for each hotel } i \tag{2}$$

where $\alpha_{0i}$ is a hotel-specific fixed amount of water consumption, $Water_{it}$ is the water use in hotel $i$ in month $t$, $Tour_t$ is the average daily number of tourists on Oʻahu in month $t$, $Occup_t$ is the aggregate occupancy rate of hotels on Oʻahu in month $t$, $Temp_t$ is the average temperature in degrees Celsius on Oʻahu in month $t$, $Rain_t$ is the aggregate monthly rainfall in millimeters on Oʻahu in month $t$, and $u_{it}$ is the error term. Note also that we use the notation $\log(\cdot)$ to denote the natural log, which allows us to interpret coefficient results approximately as percent changes. We maintain this notation throughout. Although the occupancy rate is recorded as a percentage, without the log-transformation of this variable the estimated $a_{1i}$ parameter in Equation (2) would not be comparable to other models. For example, when the occupancy rate is at 50%, a one *percentage point* increase or decrease in the original units to 51% or 49%, respectively, is actually a two *percent* change ($0.01/0.50 = 0.02$). The models in Equations (1) and (2) estimate the relationship between hotel water use and tourism activity, while controlling for weather. As in a random coefficient model (see Cohen et al., 2013), the aggregate effect across all hotels and the associated uncertainty can be obtained via the mean and variance of the individual coefficient estimates.

## 3.2 Point of interest water use and SafeGraph data

To exploit the full panel of water consumption that contains hotels but also includes other commercial locations like malls and restaurants, we use foot traffic data from SafeGraph. While water consumption is available at the parcel level, SafeGraph data can be even more granular when there are multiple individual Points of Interest within a parcel. For example a building may contain several restaurants, but we only have water billing data for the whole building. To maintain compatibility with water consumption, we use the number of visitors aggregated to the parcel level[2]. In our discussion of points of interest and foot traffic, we use the term "visitor" instead of "tourist" since we are dealing with visits to points of interest and we cannot differentiate between traffic by tourists and residents. We estimate the relationship between water consumption and total visitors at parcel $i$ in month $t$ using the time series regression

$$\log\left(Water_{it}\right) = \beta_{0i} + \beta_{1i}\log\left(Visitor_{it}\right) + \beta_{2i}Temp_t + \beta_{3i}\log(Rain_t) + u_{it}, \quad \text{for each parcel } i \tag{3}$$

where $\beta_{0i}$ is a parcel-specific fixed amount of water consumption, $Water_{it}$ is the water use for parcel $i$ in month $t$, $Visitor_{it}$ is the visitor count, and $u_{it}$ is the error term. We can then again obtain aggregate effects across all parcels by finding the mean and variance of the individual coefficient estimates.

For comparison with the random coefficient model, we run a simple model with the full panel data using the regression

$$\log(Water_{it}) = \beta_{0i} + \beta_1 \log(Visitor_{it}) + Month_t + u_{it}. \tag{4}$$

In this model, $\beta_{0i}$ is the parcel-specific fixed water consumption and $Visitor_{it}$ is the number of visitors to parcel $i$ in month $t$. The time series regression in Equation (3) allowed us to control for temperature and rainfall—which did not vary spatially in our data—via the location specific $\beta_{2i}$ and $\beta_{3i}$ coefficients. However, since we now want to use the full panel data, we replace the island-level temperature and rainfall controls with a month fixed effect, $Month_t$, to avoid collinearity.

A similar model can be used to study the relationship between water use and foot traffic by parcel type. For example, the impact of visitors on water use in hotels may differ from that in restaurants. The water use billing data designates the type of parcel, which we include in a two-

[2]Larger parcels may have more than one Point of Interest, with Points of Interest designated either "parent" or "child". The parent Point of Interest has the aggregate number of visitors at the location at large, so this metric is used in our analysis.

way fixed effects regression with type-specific visitor impacts

$$\log\left(Water_{it}\right) = \beta_{0i} + \sum_{j=1}^{J} \beta_j \log(Visitor_{it}) \times Type_j + Month_t + u_{it}. \tag{5}$$

Again, $\beta_{0i}$ is the parcel-specific fixed water consumption, $Visitor_{it}$ denotes the number of visitors to parcel $i$ in month $t$, $Type_{j=1\ldots J}$ are indicator variables assigning the parcel to one of $J$ type categories: city government, commercial, city park, hotel, mixed use, religion, and other miscellaneous types[3].

## 3.3 Airbnb occupancy empirical strategy

For the Airbnb analysis using our gridded data described above, we return to a random coefficient model. The empirical model estimating the relationship between residential water use and Airbnb reservations is thus,

$$\log\left(GridWater_{it}\right) = \gamma_{0i} + \gamma_{1i} \log\left(BnbRes_{it}\right) + \gamma_{2i} Temp_t + \gamma_{3i} \log(Rain_t) + u_{it}, \text{ for each grid cell } i, \tag{6}$$

where $GridWater_{it}$ is the quantity of water consumed by the residential units in grid-cell $i$ in month $t$, $BnbRes_{it}$ is the last known Airbnb reservation status in grid-cell $i$ in month $t$, $Temp_t$ and $Rain_t$ are monthly temperature and rainfall measures as in Equations (1) and (2), and $u_{it}$ is the error term. We do not have Airbnb occupancy data before October 2018, so we impute the missing data with predicted values from the model

$$BnbRes_{it} = \delta_{0i} + \delta_1 Tour_t + v_{it}, \text{ for each grid cell } i. \tag{7}$$

That is, using available data for the period from October 2018 to October 2020, we estimate a regression of monthly grid-level Airbnb reservations on aggregate monthly tourist counts, with grid cell fixed effects $\delta_{0i}$ and error term $v_{it}$. Using the estimated coefficients in Equation (7) and actual tourist numbers before October 2018, we impute grid-level Airbnb reservations before October 2018, which we denote $\widehat{BnbRes}_{it}$, and Equation (6) becomes

$$\log\left(GridWater_{it}\right) = \gamma_{0i} + \gamma_{1i} \log\left(\widehat{BnbRes}_{it}\right) + \gamma_{2i} Temp_t + \gamma_{3i} \log(Rain_t) + w_{it}, \text{ for each grid cell } i, \tag{8}$$

where $w_{it}$ is the new error term. Table 1 summarizes which datasets are used in which analyses.

[3] These include all types of residential parcels, industrial parcels, and other types we group together in the analysis that are less relevant when studying the effect of tourism on water use.

Table 1: Summary table describing which datasets are used in each analysis. For the models, “Hotel” refers to the monthly time series regressions using aggregate tourist measures, “POI” refers to the parcel-level analysis using the panel of billing data and SafeGraph Point of Interest foot traffic data, and “Airbnb” refers to the grid cell-level analysis of Airbnb reservations.

| Data | Model | | |
|---|---|---|---|
| | Hotel | POI | Airbnb |
| Water use | X | X | X |
| Aggregate tourism | X | | |
| SafeGraph foot traffic | | X | |
| Airbnb reservations | | | X |
| Temperature and rainfall | X | X | X |

# 4 Results

In the following subsections we discuss the results obtained in each of the models described above.

## 4.1 Hotel water use and aggregate tourism results

We first present the results of Equations (1) and (2), which are reported in Table 2. In the first model, we regress log mean aggregate hotel water use on log tourist count, with controls for monthly weather. Our coefficient estimate on tourist count is statistically significant and suggests that a 1% lower tourist count on the island is associated with about a 0.4% lower aggregate hotel water use, on average (since the main identification channel is the COVID-19-related shutdown, we interpret the coefficients with a weakening economic environment in mind). The second column is similar, except we regress water use on hotel occupancy with controls for weather. Here, a 1% lower hotel occupancy is associated with a 0.64% lower hotel water use, on average.

Note the discrepancy between the results of the two models: 1% lower aggregate tourist count yields about 0.4% lower aggregate hotel water use, but 1% lower hotel occupancy yields 0.64% lower hotel water use. The high prevalence of vacation rentals, like Airbnbs, across Hawai‘i may help to explain this discrepancy. When we use hotel occupancy rates to measure the level of hotel guests directly, the tighter relationship with hotel water use produces a larger coefficient estimate. However, a large number of tourists staying in vacation rentals will be counted in tourist counts, but will not contribute to hotel water use. Thus we would expect to see a lower coefficient on tourist counts, as observed here. We analyze the relationship between vacation rentals and water use in Section 4.3 below.

Table 2: Regression results corresponding to equations 1 and 2. A time series of aggregate monthly hotel water use is regressed onto time series of aggregate tourism measures, with controls for aggregate monthly weather.

| | *Dependent variable:* | |
|---|---|---|
| | Log mean aggregate water use (L/day) | |
| | (1) | (2) |
| Log tourist count (1000s) | 0.408*** | |
| | (0.013) | |
| Log hotel occupancy (%) | | 0.637*** |
| | | (0.018) |
| Avg. temp. (C) | 0.016*** | 0.012*** |
| | (0.005) | (0.004) |
| Log total precip (mm) | 0.008 | 0.004 |
| | (0.007) | (0.006) |
| Constant | 17.679*** | 16.845*** |
| | (0.147) | (0.143) |
| Observations | 94 | 94 |
| $R^2$ | 0.918 | 0.935 |
| Adjusted $R^2$ | 0.916 | 0.933 |
| Residual Std. Error (df = 90) | 0.083 | 0.074 |
| *Note:* | | *p<0.1; **p<0.05; ***p<0.01 |

Table 3: Random coefficient model results corresponding to equation 3. For each parcel, a time series of water use was regressed on the associated aggregate number of visitors at the parcel identified by SafeGraph. Time series of temperature and rainfall were included as controls. The table presents the aggregated results of the random coefficient model: the mean and standard error of the models' individual coefficients are reported.

| | Dependent variable: |
|---|---|
| | Log mean aggregate water use (L/day) |
| | (1) |
| Log tourist count | $0.16^{***}$ |
| | (0.013) |
| Avg. temp. (C) | $0.017^{***}$ |
| | (2.89e-3) |
| Log total precip. (mm) | $-0.016^{***}$ |
| | (1.49e-3) |
| Constant | $8.78^{***}$ |
| | (0.10) |
| Number of parcels | 5060 |
| Time series length (months) | 31 |
| *Note:* | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 |

## 4.2 Point of interest water use and SafeGraph results

Table 3 presents the results corresponding to Equation (3). As noted in Section 3, the results are the average estimates in a random coefficient model, where the monthly water use of each parcel was regressed onto the monthly visitor count at that parcel with controls for monthly weather. The average coefficient of 0.16 suggests that a 1% lower visitor count at a parcel is associated with an expected 0.16% lower water use at that parcel. The standard error of this mean coefficient is about 0.01.

With the random coefficient model, we obtained one regression result for each parcel, which allowed the coefficient of interest, log visitor count, to vary for each parcel. To check whether the aggregated mean of these coefficients presented in Table 3 is robust to the estimation method, we run a panel regression with the same data using Equation (4). Because temperature and rainfall vary only by time, not spatially, we can't use them in a standard panel regression, and we replaced them with month fixed effects. Unlike the random coefficient model where each parcel has its own coefficients, the panel model forces the coefficient to take the same value for all parcels.

Table 4: Regression of parcel water use onto SafeGraph foot traffic using the full panel data. In column 2, foot traffic is interacted with parcel type to compare the sensitivity of select location types to foot traffic. The 'Other' category includes state government, industrial, golf courses, all residential parcels, irrigation, agriculture, federal government, and fire hydrants. Parcel and month fixed effects are included. Errors are clustered by parcel and month.

| | *Dependent variable:* | |
|---|---|---|
| | Log mean aggregate water use (L/day) | |
| | (1) | (2) |
| Log visitor count | $0.191^{***}$ | |
| | (0.027) | |
| Log visitor count × City gov't | | $0.139^{**}$ |
| | | (0.053) |
| Log visitor count × Commercial | | $0.273^{***}$ |
| | | (0.036) |
| Log visitor count × City park | | $0.160^{**}$ |
| | | (0.065) |
| Log visitor count × Hotel | | $0.356^{***}$ |
| | | (0.035) |
| Log visitor count × Mixed use | | $0.133^{***}$ |
| | | (0.042) |
| Log visitor count × Religion | | $0.204^{***}$ |
| | | (0.055) |
| Log visitor count × Other | | $0.084^{***}$ |
| | | (0.019) |
| Month FE | **Y** | **Y** |
| Parcel FE | **Y** | **Y** |
| Observations | 145,182 | 145,182 |
| $R^2$ | 0.940 | 0.940 |
| Adjusted $R^2$ | 0.938 | 0.938 |
| Residual Std. Error | 0.564 (df = 140133) | 0.562 (df = 140127) |
| *Note:* | | $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$ |

The results of this robustness check are given in column 1 of Table 4. The coefficient on log visitor count, 0.191, is similar to the coefficient in Table 3, confirming there is little difference between aggregating coefficients from the random coefficient model and the single coefficient of the panel model.

The panel regression also enables us to study the differences in the relationship between water use and visitor count across location types. In column 1 of Table 4, the coefficient 0.19 is much smaller than the coefficient estimates we found with our aggregate models for hotels in Section 4.1. One reason for this result is that the data used for the present model includes a wide variety of locations. In addition to hotels, it includes public parks and other government buildings, retailers, restaurants, etc. Reporting only a single coefficient for all location types may hide a wide range of coefficients whose magnitudes may depend on the type of locations the parcels represent. In column 2 of Table 4, we extend the panel model to include interactions with parcel type using Equation (5). Note that this model includes all parcel types but, for table size purposes, only select parcel types are reported. The 'Other' category includes those types that were not reported separately: state government, industrial, golf courses, all residential parcels, irrigation, agriculture, federal government, and fire hydrants.

The parcel type interactions reveal the variation in the coefficient we expect; specifically, for hotels, a 1% lower visitor count is associated with a 0.36% lower water use, which is a much larger difference than the 0.19% found when all location types were pooled. Note, however, that this coefficient is still smaller than the estimate we found in our regression using hotel occupancy (0.64%). One reason for this may be that some foot traffic in and around hotels may not be attributable to hotel guests and may not result in large amounts of water use. For example, many hotels on the beach may experience foot traffic that does not result in the use of hotel facilities. This would lead to a lower coefficient than we would expect to see if we measured only hotel guests. Commercial locations may have a significant coefficient because they may contain businesses whose water use is highly dependent on the number of visitors, like restaurants. The accuracy of estimation is better when there is clear separation of a parcel from its surroundings and from unrelated foot traffic, which is likely the case for religious institutions. In contrast, the foot traffic signal in city parks and at mixed use parcels is likely quite noisy. For parcels containing multiple Point of Interest locations like malls, we cannot further disaggregate the analysis since we only have water use at the parcel level rather than the Point of Interest level. However, even at this level of disaggregation, we still glean useful information about how water use at various types of businesses may be associated with the number of visitors they receive.

Table 5: Random coefficient model results corresponding to equation 8. For each grid cell, a time series of water use was regressed onto the associated aggregate number of Airbnb reservations. Time series of temperature and rainfall were included as controls. The table presents the aggregated results of the random coefficient model: the mean and standard error of the models' individual coefficients are reported.

| | Dependent variable: |
|---|---|
| | Log mean aggregate water use (L/day) |
| | (1) |
| Log Airbnb reservations | $-0.012$ |
| | (0.012) |
| Avg. temp. (C) | $0.025^{***}$ |
| | (0.0012) |
| Log total precip. (mm) | $-0.017^{***}$ |
| | (0.0013) |
| Constant | $11.78^{***}$ |
| | (0.109) |
| Number of grid cells | 438 |
| Time series length (months) | 24 |
| *Note:* | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 |

## 4.3 Airbnb occupancy results

The results of the Airbnb reservation model in Equation (8) are reported in Table 5. We see that the coefficient estimate on the variable of interest of interest (log-transformed Airbnb reservations) is neither statistically nor economically significant. This suggests that reservation status, and thus Airbnb occupancy, have no significant effect on water usage at an aggregate level in our data.

There are several potential reasons behind this result. First, due to uncertainty in exact Airbnb location, some error may have been introduced when sorting the Airbnb units into the 1 $km^2$ grid cells. Second, the proportion of homes leased out as vacation rentals tends to be low. Out of the approximately 245,000 residential units (including single family homes and individual apartment and condominium units) only about 16,000, or 6.5%, are listed as Airbnb rentals. Consequently, the effects of changes in vacation rental occupancy are likely overshadowed by random fluctuations in water use in most grid cells. Third, during the COVID-19 related shutdown of tourism there was an offsetting shift in residential behavior. A precipitous drop in tourism almost certainly led to a similarly sharp reduction in water use at Airbnb hosts. Unfortunately, the data does not allow us to isolate individual Airbnb locations from residential ones. Grid cells with high levels of Airbnb units typically also have high levels of residential units. During the shutdown, residents spent much more time at home due to loss of employment, work-from-home arrangements, and/or a lack of participation in activities that would have brought them out of their homes. In fact, SafeGraph data suggest that the fraction of island residents staying at home for the entire day doubled from about 20% prior to the pandemic to 42% in April of 2020 (Tyndall and Hu 2020). In short, any decrease in water use at Airbnbs during the shutdown may have been offset by residents consuming more water while staying at home.

We explore several modifications to this analysis. First, similarly to the regressions with Safegraph data in Section 4.2, we modify the Airbnb regression model from a random coefficient model to a panel regression model. This forces all grid cells in the data to have the same coefficient of interest. As with the former panel regression, we replace the weather controls with month fixed effects. The results of the panel regression using the gridded Airbnb data are in column 1 of Table 6. Again, we see that the coefficient estimate is statistically and economically insignificant. The potential reasons for this result, listed above, still apply.

Second, we modify the grid to reduce the impact of measurement error in Airbnb locations. Due to uncertainty in exact Airbnb location, some error may have been introduced when sorting the Airbnb units into the 1 $km^2$ grid cells. To check whether sorting Airbnb units into incorrect grid cells had a significant effect on the regression results, we increase the grid cell size to 2 $km^2$. This reduces sorting error, but also necessarily decreases the number of observations. We report the results in column 2 of Table 6. The estimated relationship between Airbnb reservations and

Table 6: Panel regression with fixed effects to compare with table 5. Instead of a random coefficient model with controls for weather, this model uses the full panel of grid data. Month fixed effects take the place of the controls for weather. Grid cell fixed effects are also included since all data are pooled. Errors are clustered by grid cell and month. Column 1 uses a 1 $km^2$ grid, and column 2 uses a 2 $km^2$ grid.

| | *Dependent variable:* | |
|---|---|---|
| | Log mean aggregate water use (L/day) | |
| | (1) | (2) |
| Log Airbnb reservations | 0.0002 | −0.011 |
| | (0.002) | (0.007) |
| Month FE | **Y** | **Y** |
| Grid cell FE | **Y** | **Y** |
| Observations | 33,368 | 15,431 |
| $R^2$ | 0.982 | 0.991 |
| Adjusted $R^2$ | 0.981 | 0.991 |
| Residual Std. Error | 0.212 (df = 32843) | 0.161 (df = 15158) |
| *Note:* | | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 |

Table 7: Panel regression as in table 6, except the data are limited to the indicated grid-level Airbnb density percentiles. Density is calculated as the number of Airbnb units relative to total residential units in the grid cell. Fixed effects for month and grid cell are included. Errors are clustered by grid cell and month.

| | *Dependent variable:* | | |
|---|---|---|---|
| | Log mean aggregate water use (L/day) | | |
| | (1) | (2) | (3) |
| Log Airbnb reservations | 0.005 | −0.002 | −0.011 |
| | (0.007) | (0.009) | (0.019) |
| Airbnb density percentile | 50th | 75th | 90th |
| Month FE | **Yes** | **Yes** | **Yes** |
| Grid FE | **Yes** | **Yes** | **Yes** |
| Observations | 16,367 | 8,187 | 3,364 |
| $R^2$ | 0.786 | 0.731 | 0.704 |
| Adjusted $R^2$ | 0.782 | 0.725 | 0.691 |
| Residual Std. Error | 0.245 (df = 16070) | 0.315 (df = 7995) | 0.451 (df = 3229) |
| *Note:* | | | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 |

water use remains statistically and economically insignificant.

Finally, we examine the impact of Airbnb density in grid cells on the results. Many grid cells have far more non-Airbnb residential units, potentially drowning out any signal from Airbnb units. To see if we can improve the signal-to-noise ratio, we perform the same panel regression as in Table 6, but limit the data to grid cells with high Airbnb densities. Airbnb density is calculated by dividing the number of Airbnb units in the grid cell by the total number of residential units (single family homes, along with individual apartment and condominium units). That is, for each grid cell $g$,

$$\text{Airbnb density}_g = \frac{\text{Total Airbnb units}_g}{\text{Total residential units}_g}.$$

We report the results in Table 7. The three columns show the results for grid cells above the 50th, 75th, and 90th percentile, respectively, in terms of Airbnb density. (For reference, Airbnb density is 3.6% in the median cell, 12.7% in the 75th percentile cell, and 46.2% in the 90th percentile cell.) Yet again, the coefficient estimates remain statistically or economically insignificant.

These robustness checks leave us with the conjecture that the insignificant results are likely driven by a change in resident behavior during the COVID-19 pandemic, rather than by data limitations. In Sections 4.1 and 4.2 where residents were not a confounding factor, the COVID-19 shock helped to identify the relationship between tourism and water consumption. Here the decline in water consumption due to the lack of tourists appears to be offset by an increase in water consumption due to residents staying at home. This conjecture is supported by the unusually high residential water use during the pandemic, also visible in Figure 1.

# 5 Discussion

In summary, this study aims to measure the relationship between tourism and water use on the island of O'ahu using several different strategies. First, we analyze aggregate tourist counts and their association with aggregate hotel water use. When tourism is measured by average daily tourist census on the island, we find that a 1% lower tourist census is associated with a 0.4% lower water use. However, when tourism is measured by hotel occupancy, a 1% lower occupancy is associated with a 0.64% lower water use. The reason for the difference in coefficient estimates may be that not all tourists counted in the census stay in hotels. Those who find accommodation in vacation rentals, like Airbnbs, do not use water in hotels. When we associate water use in hotels with hotel occupancy directly, we obtain a larger estimate.

We also aim to understand what the decline in mobility may reveal about patterns of water use at various points of interest in Hawai'i. When we measure tourism with foot traffic, our results suggest that a 1% lower foot traffic in hotels is associated with about a 0.36% lower water use in hotels. Here the low coefficient value may be due to the fact that not all foot traffic visiting the hotel comes from hotel guests. For example, many hotels have beaches and other attractions that may cause foot traffic to be on-location long enough to enter our data set, but ultimately use little to no water during their stay. We were also able to show that water consumption at various points of interest had different sensitivities to foot traffic depending on the location type.

Finally, considering our results and conclusions from the hotel water use above, we turned to Airbnb water use to see how much more water use could be explained by tourists who choose these accommodations. Regardless of our model, we were unable to estimate any relationship that was significantly different from zero, despite many tourists choosing to stay in these rentals and a clear decline in reservations during the pandemic. We think that the drop in Airbnb reservations during the COVID pandemic, which we hoped to use for identification, was offset by an increase in work-from-home arrangements for residents of the island. The decrease in water use from a lack of Airbnb reservations may then be offset by residents staying home and consuming more water there. Indeed, if we look again at Figure 1, we see that aggregate residential water use *increased* in 2020 compared to previous years. Limitations with the data that prevented us from accurately matching households and Airbnb units may have also been a contributing factor.

Looking ahead, the importance of understanding the relationship between water use and transient vacation rentals (TVR) relative to hotels and resorts will become less important on O‘ahu, as the number of TVRs has recently been significantly limited by local policymakers. However, this will not be the case in all locations across the country. A similar analysis may prove beneficial to understand this relationship in other tourist destinations that have a high number of TVRs, so long as it does not suffer from the same difficulties as our COVID-period study.

An additional point worth discussing is the analysis using foot traffic data and the makeup of tourists before, during, and after the COVID shutdowns. As mentioned in the data section above, foot traffic is measured only by tracked cell phones, where visited locations and duration of stay can be determined. We thus likely only have a small sample of the overall number of tourists to a location, which we assumed remained a constant fraction of total tourists over time. There is a possibility that this may not be the case, since during the shutdown the makeup of tourists (and even local families visiting various locations) may have changed to some degree.

The pandemic and its effects on the economy of O‘ahu allowed for an interesting study of the shifts in water consumption behavior before and during the large-scale shutdowns of tourism and other related commercial activities, along with the shift to work-from-home arrangements for many residents. However, care should be taken when interpreting the results beyond the scope of this analysis. The significant disruptions caused by the pandemic followed in the wake of extremely high capacity utilization in the tourism industry. The negative shock created (temporary) "slack" in the system, and we likely only observed a partial adjustment in water consumption. Since most hotels did not completely shut down, there remained a "fixed" amount of water consumption, for example for pools and other amenities. Consequently, we expected our coefficient estimates to be less than one, while a complete shutdown of hotel operations may have resulted in estimates closer to one. Further work will be required to determine whether our results carry over for more marginal changes, like a gradual change in tourism over time. Also, had the tourism industry experienced a positive shock, it would have been pushing against existing capacity constraints, a different situation from ours. Applying the relationships found here to an increase in tourism may not be appropriate since increases and decreases in tourism may affect water consumption asymmetrically.

Acknowledgement: This paper is funded in part by a grant/cooperative agreement from the National Oceanic and Atmospheric Administration, Project R/HE-32, which is sponsored by the University of Hawai‘i Sea Grant College Program, SOEST, under Institutional Grant No. NA18OAR4170076 from NOAA Office of Sea Grant, Department of Commerce. The views expressed herein are those of the author(s) and do not necessarily reflect the views of NOAA or any of its subagencies. UNIHI-SEAGRANT-JC-18-23.

## References


Bassiouni, Maoya and Delwyn S Oki (2013). "Trends and shifts in streamflow in Hawai 'i, 1913–2008". In: *Hydrological Processes* 27.10, pp. 1484–1500.

Charara, Nadim et al. (2011). "Water use efficiency in the hotel sector of Barbados". In: *Journal of Sustainable Tourism* 19.2, pp. 231–245.

Cohen, Jacob et al. (2013). *Applied multiple regression/correlation analysis for the behavioral sciences*. Routledge.

Cole, Stroma (2012). "A political ecology of water equity and tourism: A case study from Bali". In: *Annals of tourism Research* 39.2, pp. 1221–1241.

Cole, Stroma, Agung Wardana, and Wiwik Dharmiasih (2021). "Making an impact on Bali's water crisis: Research to mobilize NGOs, the tourism industry and policy makers". In: *Annals of Tourism Research* 87, p. 103119.

COP26 (2021). URL: `https://www.unwater.org/water-facts/climate-change/`.

EIU (2017). *Water security threats demand new collaborations: lessons from the Mekong River Delta*.

EPA (2012). *Energy Star Portfolio Manager DataTrends – Water Use Tracking*. [Online; accessed 2021-03-27]. URL: `https://www.energystar.gov/sites/default/files/buildings/tools/DataTrends_Water_20121002.pdf`.

Ghimire, Monika et al. (2016). "Estimation of residential water demand under uniform volumetric water pricing". In: *Journal of Water Resources Planning and Management* 142.2, p. 04015054.

Gössling, Stefan (2001). "The consequences of tourism for sustainable water use on a tropical island: Zanzibar, Tanzania". In: *Journal of environmental management* 61.2, pp. 179–191.

— (2015). "New performance indicators for water management in tourism". In: *Tourism Management* 46, pp. 233–244.

Gössling, Stefan et al. (2012). "Tourism and water use: Supply, demand, and security. An international review". In: *Tourism management* 33.1, pp. 1–15.

Hof, Angela and Thomas Schmitt (2011). "Urban and tourist land use patterns and water consumption: Evidence from Mallorca, Balearic Islands". In: *Land Use Policy* 28.4, pp. 792–804.

Holding, S et al. (2016). "Groundwater vulnerability on small islands". In: *Nature Climate Change* 6.12, pp. 1100–1103.

*Inside Airbnb* (2021). URL: `http://insideairbnb.com/`.

Izuka, Scot K, John A Engott, et al. (2018). *Volcanic aquifers of Hawai'i—Hydrogeology, water budgets, and conceptual models*. Tech. rep. US Geological Survey.

Izuka, Scot K and Victoria Keener (2013). "Freshwater and drought on Pacific Islands". In:

LaVanchy, G Thomas (2017). "When wells run dry: Water and tourism in Nicaragua". In: *Annals of Tourism Research* 64, pp. 37–50.

Mcleod, Elizabeth et al. (2019). "Lessons from the Pacific islands–adapting to climate change by supporting social and ecological resilience". In: *Frontiers in Marine Science* 6, p. 289.

NOAA (Apr. 2021). *National Weather Service Climate National Weather Service Climate National Weather Service Climate*. URL: `https://w2.weather.gov/climate/index.php?wfo=hnl`.

Ouyang, Yun et al. (2014). "A multi-scale analysis of single-family residential water use in the Phoenix metropolitan area". In: *JAWRA Journal of the American Water Resources Association* 50.2, pp. 448–467.

Rico-Amoros, Antonio Manuel, Jorge Olcina-Cantos, and David Saurí (2009). "Tourist land use patterns and water demand: Evidence from the Western Mediterranean". In: *Land Use Policy* 26.2, pp. 493–501.

Sudiajeng, Lilik et al. (2017). "Assessment and Evaluation on the Aquifer in Denpasar City". In: *Advanced Science Letters* 23.12, pp. 12161–12167.

Tortella, Bartolomé Deyà and Dolores Tirado (2011). "Hotel water consumption at a seasonal mass tourist destination. The case of the island of Mallorca". In: *Journal of environmental management* 92.10, pp. 2568–2579.

Tribble, Gordon W (2008). *Ground water on tropical Pacific islands: Understanding a vital resource*. US Department of the Interior, US Geological Survey.

Tyndall, Justin and Joshua Hu (2020). *Are Hawai'i Residents Staying Home?* URL: `https://uhero.hawaii.edu/are-hawaii-residents-staying-at-home/`.

UHERO (2021). URL: `https://data.uhero.hawaii.edu/#/`.

UNESCO (2012). *International Hydrological Programme, Strategic Plan of the Eighth Phase.*

Viglia, Giampaolo and Sara Dolnicar (2020). "A review of experiments in tourism and hospitality". In: *Annals of Tourism Research* 80, p. 102858.

Yang, Yang, Carol X Zhang, and Jillian M Rickly (2021). "A review of early COVID-19 research in tourism: Launching the Annals of Tourism Research's Curated Collection on coronavirus and tourism". In: *Annals of Tourism Research*, p. 103313.