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# Assessing the significance of tourism and climate on residential water demand: Panel-data analysis and non-linear modelling of monthly water consumptions

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A B S T R A C T

The concentration in time and space of tourists and of specific water-demanding touristic activities can add considerable pressure on available water supplies in coastal regions.

The impact of tourism has not been adequately addressed in the water demand literature, especially at sub-annual scale: the present study includes the role of tourism on the monthly water demand in a set of Mediterranean coastal municipalities in a panel data framework.

The influence of both climatic and touristic drivers on the water demand is investigated through a correlation analysis, thus deconstructing the seasonal variability of the consumption, and the development of both linear and non-linear models. The results demonstrate the improvement allowed by non-linear over linear modelling and the value of the information embedded in both climatic (in particular temperature daily maxima and minima and number of rainy days) and touristic determinants as drivers for the water demand at sub-annual scale.



## 1. Introduction

In Mediterranean regions, inherently affected by water scarcity conditions, the gap between water availability and demand is expected to further increase in the near future due to both climatic and anthropogenic drivers.

In particular, the high degree of urbanization and the concentration of population and activities in many coastal areas is often severely impacting the water availability also for the residential sector, especially in the dry summer season, when the demand is maximum and the water availability is minimum (EEA, 2010), confirming that socio-economic, in addition to climatic, changes will be the most important driver of shifts in future municipal water demand (Parkinson et al, 2016).

Water demand forecasting is the primary requirement for managing and planning of water supply systems. Short-term forecasting over the coming days, weeks or months, allows to optimise operational water management decisions (reservoir storages, emergency measures during water scarcity periods, etc.) and to help estimate revenues from water sales and short-term expenditures (i.e. energy pumping costs). Long-term forecasting allows instead to plan the investments on water supply and distribution systems, such as accessing new water sources, developing new treatment plans or enhancing the distribution networks.

Many water utilities still assume that the demand will evolve simply as a product of per-capita demand and a projection of population, whereas the predictive power of such methods is inadequate under changing conditions. It is therefore now acknowledged that in order to obtain reliable demand forecast, it is important evaluating, understanding, and modeling the factors that influence water use over both short-term and long-term intervals" (AWWA, 2013).

Urban water demand is guided by complex interactions between human and natural system variables at multiple spatial and temporal scales.

In the past, many studies have focused only on economic and other policy variables that can be decided by policy-makers and water utilities, so that their future evolution is known, but there is the need to keep into account also the factors that are not controlled by the water utilities and are characterized by an uncertain evolution.

Climate is certainly one of such factors: a large number of studies (see Section 2.1) have analysed the causal relationships

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between the demand and a number of different climatic variables and have developed urban demand models that include such drivers in the explanatory variables.

These models can successively be used by the water utilities to forecast the future water demand as a function of the predicted evolution of the meteorological variables, consisting in either long-term climate change scenarios or short-term seasonal forecasts.

As far as the impact of climate change and variability is concerned, understanding and modelling the influence of meteorological factors on urban demand is the first step for assessing the long-term pressure on the water supply system due to expected climatic scenarios. This approach is followed, for example, by Goodchild (2003); Babel et al., 2014; Haque et al., 2015b who first set up demand models driven by meteorological factors and then provide in input the same drivers obtained from climate change scenarios.

Analogously, for the purpose of operational management decisions, identifying the role of the whether variables in a monthly water demand model would immediately allow the inclusion of inputs deriving from weekly to seasonal meteorological forecasts (even if such numerical weather predictions are still affected by very large uncertainties over lead-times longer than a few days), thus resulting in improved short-term water demand forecasts: Tian et al. (2016) have recently proposed, for the first time, the use of weekly weather forecasts in input to a water demand model.

A full understanding of which variables are significant is a necessary prerequisite for improving the demand models. In coastal regions (but not only there), a very important factor in addition to climatic determinants is the influence of tourism on water use: such factor has not been adequately addressed in the literature so far and is generally neglected in water demand analyses.

Provided that an estimate on the expected touristic fluxes is available (for example through one of the many tourism demand forecasting models available for the tourism industry) also such variables might be directly used in input to the proposed model, to obtain a more accurate water demand forecast.

The present work, for the first time, introduces the use of the time-series of the monthly tourists' overnight stays as an additional explanatory variable to model monthly urban water demand, in order to provide knowledge on the combined impacts of climatic and touristic factors.

The case study refers to a set of cities in Italy, where sub-annual analyses are so far not reported in the literature, and in particular to the most economically developed coastal region in the country.

In such and similar contexts, the proposed water demand models may be successively used by water utilities to derive more accurate water demand forecasts based on the available climatic and touristic evolution scenarios.

## 2. Factors driving urban water demand

There is abundant theoretical and empirical literature on urban water demand modelling, at different spatial (household to municipal) and temporal (hourly to multi-yearly) scale: the readers may refer to House-Peters and Chang (2011) or Donkor et al. (2014) for comprehensive reviews of concepts and models.

A variety of determinants (exogenous inputs) may have an impact on water demand and have been considered in the literature, in addition to information on previous consumptions (endogenous input): structural and geographical variables, such as household or building/landscape features, and socio-economic variables, such as population characteristics, water price and consumer income, water use behaviour.

The majority of the above variables are not subject to seasonal fluctuations (or, even when not negligible, such sub-annual fluctuation is generally not recorded) and are considered to change at annual scale, allowing to analyse inter-annual variability only.

For modelling the overall behaviour of the demand over time, it is, instead, necessary to take into account not only factors that change from year to year (interannual), but also the factors that have a seasonal (or monthly) variation, in order to capture also the infra-annual expected variations in the demand, such as climatic variables and tourism.

### *2.1. Influence on water demand of climatic drivers*

When analysing a sub-annual behaviour and the objective is to assess the reasons for seasonal changes in the demand, the main influence is generally attributed to climatic variables (rainfall, temperature, evapotranspiration), as demonstrated by a very large number of studies analysing and modelling the role of such variables (see, among the many others, Zhou et al., 2000; Gutzler and Nims, 2005; Gato et al., 2007; Wong et al., 2010; Bakker et al., 2013, and, in particular, Chang et al., 2014 and Haque et al., 2015a also present excellent reviews on the use of climatic determinants).

It is in fact expected that weather conditions do influence the intensity and/or the frequency of important water-demanding activities, both indoor, such as showers and other personal hygiene practises, and outdoor, such as garden/plants irrigation but also car and street washing, or swimming pool use.

Temperature and rainfall variables are the most frequently adopted in water demand modelling, also due to the good availability of such measures/estimates. On the other hand, derived variables, such as evapotranspiration estimates, are relevant for only a part of the above mentioned water-consuming activities (i.e. irrigation activities for evapotranspiration factors).

Temperature and rainfall can be adopted in several forms in the water demand modelling (see Haque et al., 2015a): temperature indexes may be based on mean values or on daily maxima and minima, or on the numberof days exceeding a certain threshold. In the same way, rainfall indexes may include total rainfall depth, the number of rainy days or rain events or the duration between the events.

Identifying the temperature and rainfall indexes more suitable for each specific water demand modelling analysis is therefore still an open problem and, even more important, the outcomes of previous studies on the impact of climatic variables are not always in agreement.

Some studies found that the demand is both positively related to the temperature and negatively related to the rainfall (Maidment and Miaou, 1986; Lyman, 1992; Corral et al., 1998; Olmstead et al., 2007; Ruijs et al., 2007).

Other authors (Nauges and Thomas, 2000; Martins and Fortunato, 2005; Haque et al., 2015a; 2015b) showed that high temperatures increase the demand, but did not find a significant effect of the precipitation.

On the contrary, in the case studies analysed by Zhou et al. (2000), Klein et al. (2007) and Schleic and Hillenbrand (2009) precipitation was more important than temperature.

In particular, it seems that the touristic vocation of the study area may play an important role in assessing the importance of the meteorological variables and in understanding their influence: in fact, in not touristic cities, rainfall and temperature may do not exert a significant weight on the water demand (see Martinez-Espiñeira, 2002a,b).

Or actually, in some cases it was even found a “wrong” sign, that is a negative correlation, between temperature and consumption: this happened when considering areas that are not highly touristic (or at least not during the summer season), like the city of Zaragoza in Spain (Arbués and Villanua, 2006) or the German areas analysed by Schleic and Hillenbrand (2009): the authors identify as a possible explanation the fact that consumption decreases in summer due to the outflow of residents to holiday destinations.

On the contrary, therefore, we expect, for the reasons stated above, that in coastal touristic regions during the summer climatic variables are especially relevant, due to the specific touristic water uses.

### 2.2. Influence on water demand of touristic drivers

Tourism is strongly dependent on fresh water resources and its contribution to water consumption is expected to rise due to increases in tourists' numbers, in hotel standards and in water-intensity of tourism activities, as highlighted also in the review, at global scale, presented by Gossling et al. (2012). Exacerbating this impact in coastal regions is the fact that the majority of tourists arrive during the above said critical summer season, thus adding considerable strain on available water resources.

Tourism is one of the world's largest industries: according to the World Travel & Tourism Council (WTTC, 2016) the travel and tourism sector accounts for 9.8% of world GDP and for 108 million jobs in 2015, equal to 5% of total employment, that, in line with the positive dynamics of arrivals and revenues, should further increase of 2.6% over the next decade.

Coastal tourism is one of the fastest growing forms of tourism all over the world (Page and Connell, 2006), and in many European, and in particular Italian, regions, it has turned into mass tourism already starting in the 1950s.

On the other hand, tourism is also a massive consumer of natural resources, water included. Tourism has in fact a strong influence on urban water consumption: first, the demand of water for residential uses can be substantially inflated by the presence of tourists to be added to the population to be supplied.

Secondly, tourists' consumption is different from that of residents (see Gossling et al., 2012): a more lavish use, allowed by more leisure time and also related to the fact that water is not included in the hotel or rental bill (and price has therefore no limiting influence) is in particular enhanced in seaside cities by the habit of additional showers after swimming. Also the laundry requirement, due to the much more frequent changes of bed and bath linens that characterizes touristic rather than residential presences, is further increased in seaside resorts by the use of large towels for swimming pools and beach activities.

Thirdly, coastal cities are characterised by the presence of specific activities connected with the tourism economy that may be extremely demanding in terms of water requirements: not only spas and swimming-pools, but also, for example, waterparks (in the study area there are six important waterparks, with around one million visitors per year). Furthermore, more frequent irrigation is needed for hotel and city gardens and landscaping, whose attractiveness is an important asset in a touristic city.

Due to the second and third above points, if we want to fully take into account the tourism impact, the number of tourists cannot be added directly to the number of permanent residents when modelling the change in water demand: not only the water use of holiday-makers is different from that of residents, but an additional complexity lies in the fact that in touristic cities there are water volumes that have to be supplied irrespective of the number of guests (garden irrigation, pools, waterparks).

The literature on the impact of touristic variables on urban water demand is very limited, and at sub-annual scale almost non-existent: the only notable exception, to our knowledge, is the study by Almutaz et al. (2012) that proposes a monthly forecasting model for the city of Mecca, where very large touristic fluctuations are determined by the religious rituals. Such study takes into account, in addition to other determinants, also climatic variables, but the touristic presence is considered only through the probability distribution of the number of tourists expected during the year in agreement with the religious calendar, and not as an explanatory variable, since monthly touristic time-series are not available. On the other hand, it must be underlined that such religious tourism is not directly related to weather conditions, as it happens, instead, in seaside cities as those analysed in the present study.

In light of the above considerations, in a number of increasingly water-scarce and touristically exploited regions, additional research is necessary on the role of tourism as well as meteorological variables as determinants of water consumption, and it is important to carry out such analyses at an appropriate temporal and spatial scale (Gossling et al., 2012).

This study contributes to the advancement of knowledge on determinants of water demand at sub-annual scale by focusing on a Mediterranean highly touristic coastal area and analysing a set of municipalities in a panel data framework.

## 3. Study region and data

### 3.1. Study region

It is worth noting that in the literature on water demand modelling the majority of case studies refer to North America or Australia, with a minority of recently published case studies referring to European countries and in particular there are only a few European studies based on intra-annual data (see Worthington and Hoffmann, 2008). The same unbalanced geographical distribution of the studies was found by Cominola et al. (2015) in their review on the literature on high-resolution water demand modelling and management, where only 13% of the reviewed papers presented studies developed in Europe, but we agree with the authors that driven by the challenges posed by both climatic and anthropogenic factors on urban water supply, increasing attention will be paid to such analyses all over the world.

As far as Italy in particular is concerned, infra-annual water consumption data are generally not available and are often affected by low quality and reliability: the national authorities still do not publish official data and analyses of water consumption in Italy have been so far possible only with the collaboration of one or more water companies.

The research on water demands in Italian cities is mainly based on annual data (Mazzanti and Montini, 2006; Musolesi and Nosvelli, 2007; Statzu and Strazzera; 2009; Romano et al., 2014).

The study area analysed in this work includes all the municipalities on the coastline of the Romagna region, in Northern Italy, which is one of the most economically developed areas in Europe and characterized by an extremely profitable seaside tourist industry. It is in fact one of the most attractive touristic areas in the country, and the national and international tourists spend in the official accommodation facilities of the analysed cities around 27 million of nights every year (mainly concentrated in the summer months), corresponding to 7% of all the overnight stays in Italy over the analysed years.

RomagnaAcque – Società delle Fonti is the regional water supplier and it provides wholesale water to the main retail water company in the three provinces of Ravenna, Forlì-Cesena and Rimini, with a total of more than one million permanent residents.

### 3.2. Monthly water demand data

The water demand data used in the study have been made available by RomagnaAcque, that collects the consumption data at monthly scale for all the towns of the three provinces: since relevant uncertainty characterizes the information referring to many municipalities, we decided to focus only on the coastal towns, where almost half of the permanent residents and the large majority of tourists resides.

Some of such municipalities are very close to each other and the same junction of the water supply network may serve more than one municipal administration: in such cases (S. Mauro and Riccione, denoted with an asterisk in the map in Fig. 1), more municipalities have been aggregated based on 'hydraulic boundaries'.

The final list of municipalities (or grouped municipalities) includes, from North to South: Ravenna, Cervia, Cesenatico, S. Mauro (including also Savignano, Gatteo and Gambettola), Bellaria, Rimini and Riccione (including also Misano and Cattolica): the municipalities boundaries are shown in Fig. 1.

The dependent variable used in the analysis is the monthly average consumption (WDem) per town, collected for the period (7 years) from 2009 to 2015 and expressed in cubic meters per month, then transformed in an average daily volume ($m^3$/day) for that month.

Due to the crucial importance of the volumes supplied during the summer touristic season, when it is also much more important the influence of the climatic (see also Gutzler and Nims, 2005) and touristic drivers, the analysis considers only the five months from May to September; Fig. 2 shows the water demands during all the summer months of the observation period for the seven municipalities.

### 3.3. Monthly tourists' presence data

In Italy there is a monthly census of the guests hosted in the official touristic accommodation facilities, such as hotels, bed and breakfast, etc. (the establishment owners are asked to provide such data in real time, along with the billing documents). This data are aggregated (for privacy reasons) at municipal level and then published in provincial level (NUTS 3) databases.

Such data report the number of monthly overnight stays, but only in official accommodation facilities. The tourism statistics in fact do not include any information on the occupancy of second homes (holiday homes) and not even on the majority of rental homes, of which only a very small percentage is officially registered.

As far as the towns of the Emilia-Romagna are concerned, Guizzardi (2005) proposed an indirect estimation of the touristic presence in holiday homes, based on the measurements of electric power consumption in households that were not officially occupied by permanent residents. Based on his assessment, at annual level, of the total number of nightstays in each municipality, we have estimated the second-homes occupancy for each month assuming that the tourists lodged in unofficial accommodation facilities vary proportionally to the monthly presences in official structures, even if we acknowledge the high uncertainty of such assumption.

Including both official and not official tourists' overnights, the total population to be supplied in the summer months increases of additional 228000 people on average. Considering the peak month, in every day of August the tourists to be added to the around 492000 permanent residents varies from 373000 to 391000 over the observation years (+ 78% on average).


**Fig. 1.** Study area: coastal municipalities of the Romagna region.

### 3.4. Monthly rainfall and temperature data

The climate on the Romagna coast is warm and temperate, with annual rainfall between 550 and 750 mm and a mean annual temperature between 12 and 14 °C. Summer months are warm but not necessarily dry.

For the observations period (2009–2015) we have collected daily rainfall and temperature data in the weather stations owned and managed by the regional Meteorological and Hydrological Service (ARPAE-SIMC).

The point measurements were spatially averaged with an inverse distance weighting approach, thus obtaining, for each municipality: 1) monthly rainfall depths; 2) number of rainy (> 1 mm) days, 3) monthly average of maximum daily temperatures, 4) monthly average of minimum daily temperatures.

Such climatic variables have been chosen based on the literature results that highlight the importance of the rainy days occurrence. In fact, there is general agreement on the usefulness of considering not only the total rainfall depths but also the number of rainy days, that was found by many authors (Maidment and Miaou, 1986; Martınez-Espiñeira, 2002; Schleich and Hillenbrand, 2009) to be a better explanatory variable than the total rainfall amount.

Other studies highlight, instead, the possible influence of both day (maximum) and night (minimum) temperature data (see

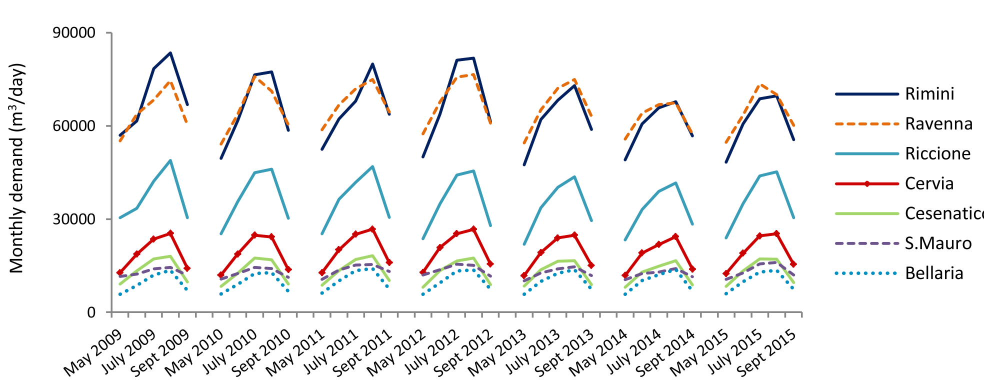


**Fig. 2.** Monthly (daily average for the month) water demand ($m^3$/day) for each municipality during the summer months.

Guhathakurta and Gober, 2007; Praskievicz and Chang, 2009).

### 3.5. Annually varying factors: number of residents and water price data

For each Italian municipality the data on permanent residents are updated and published every year (and in the study municipalities there is a slight population increase over the years).

As far as water price is concerned, even if water may be considered an ordinary good (its demand is expected to decrease when price increases), its price elasticity can be very low, especially for higher income countries (Dalhuisen et al., 2003; Statzu and Strazzera; 2009; Romano et al., 2014).

On the other hand, García-Valiñas (2005) observed higher price elasticity in peak (summer) than in off-peak periods (all other seasons).

The Italian water price, as in many countries, is based on a complex increasing-blocks tariff structure: the problem of how to estimate the price elasticity in presence of complex tariff structures is still open in the literature and we decided to use as proxy for water tariff the volumetric price (euro for cubic meter) of the central block of the tariff structure (there are three blocks for residential use), that generally includes the large majority of the consumers' volumes, representing the "core" of the tariff policy.

Overall, our data base includes the variables listed in Table 1, whose mean values are reported in Table 2. Climatic and touristic variables have seasonal, i.e. monthly, fluctuations (like the water demand), whereas number of residents and tariff change at yearly scale and are therefore constant for all the months of the same year.

The variables WDem, Tour, RainD and RDays, corresponding to monthly cumulative totals, are divided by the number of days in each month, so to make all the determinants independent of the length of the different months, and the data thus represent the values for an average day in the considered month, t.

**Table 1**
Definition of predictand and predictors.

| Variable | Description and unit |
|---|---|
| $WDem_t$ | Water demand: mean daily volume in month t) ($m^3$/day) |
| $Tour_t$ | Tourists: mean daily presences in month t |
| $RainD_t$ | Rainfall depth: mean daily depth in month t (mm/day) |
| $RDays_t$ | Rainy days: days with rainfall > 1 mm (% of the month t) |
| $TMax_t$ | Maximum temperature: mean max daily temperature in month t (°C) |
| $TMin_t$ | Maximum temperature: mean min daily temperature in month t (°C) |
| $Res_t$ | Permanent residents in month t (change at annual scale), constant for the 12 t of the same year |
| $Tar_t$ | Tariff: base component of the first block in month t (euro/$m^3$), constant for the 12 t of the same year |

## 4. Methodology and results

### 4.1. Correlation analysis

In order to investigate the drivers of the seasonal fluctuations of the water demand, we analyse, for each municipality, the correlation existing between the water demand in the five summer months and the seasonally-varying predictors.

Table 3 shows the ranges (maximum and minimum values obtained for the different municipalities) of the correlation coefficients (and corresponding p-values) obtained relating the predictand (WDem) with Tour, RainD, RDays, TMax and TMin.

All the predictors, for all the municipalities, are significantly correlated with water demand. The number of tourists is, as expected, strongly positively related with the consumption.

The temperatures are also very highly correlated with a positive sign, thus showing that, in a coastal touristic area (where residents do not leave the city in the hottest months), an increase in temperature causes an increase in the water volumes (differently from the case studies analysed by Arbues and Villanua (2006); for the city of Zaragoza, by Schleic and Hillenbrand (2009); for a set of German supply areas, and by Romano et al. (2014); for the main Italian chief towns).

Also both the variables describing the rainfall (total rainfall depth and number of rainy days) have a correlation, in this case of negative sign, indicating a reduction of consumptions with increasing rain, but the correlation of the total rainfall depth (RainD) is less significant than for the other seasonal variables, with a p-value larger than 1% for four over seven cities.

On the other hand, also the seasonal variables are highly intercorrelated: Table 4 shows the maximum and minimum values, over all the municipalities set, of the correlation coefficients computed between each couple of seasonally varying predictors.

Since the explanatory variables are intercorrelated, some of them might not contribute with additional information content to the determination of the demand: we will therefore explore their role through the application of the panel-data modelling, carrying out an input saliency analysis.

### 4.2. Panel-data model structure

The studies that present water demand models at monthly or

**Table 2**
Top: Mean values of the water demand (mean on all summer months and monthly mean); Bottom: mean values of explanatory variables.

| | Ravenna | Cervia | Cesenatico | S.Mauro | Rimini | Bellaria | Riccione |
|---|---|---|---|---|---|---|---|
| Mean value of water demand | | | | | | | |
| WDem (all summer months) | 65′292 | 19′200 | 12′981 | 12′968 | 64′211 | 9′768 | 35′337 |
| WDem May | 55′754 | 12′333 | 8′427 | 10′853 | 50′525 | 5′875 | 24′808 |
| WDem Jun | 64′940 | 19′368 | 13′232 | 12′832 | 61′802 | 9′590 | 34′557 |
| WDem Jul | 72′035 | 24′142 | 16′663 | 14′513 | 72′368 | 12′672 | 42′284 |
| WDem Aug | 72′792 | 25′350 | 17′273 | 14′791 | 76′148 | 13′543 | 45′405 |
| WDem Sep | 60′938 | 14′807 | 9′312 | 11′853 | 60′209 | 7′161 | 29′630 |
| Mean value of explanatory variables | | | | | | | |
| Tour | 36′168 | 39′249 | 29′149 | 12′040 | 43′446 | 17′387 | 51′138 |
| RainD | 1.5 | 1.7 | 1.8 | 2.0 | 2.0 | 1.9 | 1.9 |
| Rdays | 16% | 17% | 17% | 18% | 17% | 17% | 17% |
| TMax | 27.1 | 27.9 | 28.0 | 27.5 | 25.9 | 27.6 | 27.3 |
| TMin | 17.9 | 17.3 | 17.7 | 17.2 | 18.3 | 17.5 | 17.1 |
| Res | 158′647 | 29′023 | 25′766 | 48′559 | 145′312 | 19′406 | 64′991 |
| Tar | 1.09 | 1.07 | 1.33 | 1.33 | 1.22 | 1.22 | 1.19 |

**Table 3**
Ranges (in the municipalities set) of the correlation coefficients between water demand and each seasonal explanatory variable (and corresponding p-values).

| | *WDem/Tour* | *WDem/RainD* | *WDem/RDays* | *WDem/TMax* | *WDem/TMin* |
|---|---|---|---|---|---|
| Correlation coefficients | 0.89/0.99 | −0.56/−0.36 | −0.58/−0.47 | 0.89/0.94 | 0.85/0.93 |
| p-values | All<0.001 | 0.001/0.034 | 0.001/0.004 | All <0.001 | All <0.001 |

**Table 4**
Ranges (in the municipalities set) of the correlation coefficients among the seasonal explanatory variables (and corresponding p-values).

| | Tour/RainD | Tour/RDays | Tour/TMax | Tour/TMin | TMax/TMin |
|---|---|---|---|---|---|
| Correlation coefficients | −0.48/−0.19 | −0.45/−0.39 | 0.83/0.91 | 0.84/0.90 | 0.92/0.98 |
| p-values | 0.003/0.27 | 0.007/0.020 | <0.001 | <0.001 | <0.001 |
| | RainD/RDays | RainD/TMax | RainD/TMin | RDays/TMax | RDays/TMin |
| Correlation coefficients | 0.64/0.79 | −0.64/−0.41 | −0.58/−0.40 | −0.71/−0.60 | −0.65/−0.59 |
| p-values | <0.001 | 0.001/0.015 | 0.001/0.016 | <0.001 | <0.001 |

sub-monthly scale usually refer to a single spatial entity (metropolitan area, city or district). In econometrics water consumption studies, generally developed at annual scale, it is instead frequent using a cross-section of entities (cities), taking into account the socioeconomic characteristics of the different cities measured at the same time instant (and assumed to be time-invariant), and the elasticities (i.e. the responsiveness of the predictand to a change in the value of the explanatory variables or determinants) are supposed to represent their long-term value.

Panel data or "pooled" or Time-Series Cross-Section (TSCS) analysis combines time series for several cross-sections. Pooled data are characterized by having repeated observations (more years) on fixed units (municipalities). This increases the number of observations, enhancing the quality and quantity of data, and this is especially needed when, as in the present case study, the number of observation years is unfortunately limited: additional, more informative data help to overcome problems of multicollinearity, to control for unobservable heterogeneity of the cross-sectional units and to estimate more reliable parameters (Arbues et al., 2003; Gujarati, 2004).

To the Authors' knowledge, a part from the study based on linear regression analysis by Martinez-Espineira (2002a,b), there is no literature on the use of a panel-data approach, that models urban water demand at subannual (monthly) scale, in reference to a set of cities (cross-section analysis).

The data analysed in this work has a balanced panel structure and the model can be written as:

$$Y_{i,t} = f(X_{i,t},\ Z_i) + \varepsilon_{i,t} \tag{1}$$

where $i$ indexes individual municipalities and $t$ indexes time periods (months): $Y_{i,t}$ is the dependent variable (water demand in the summer month, t), $X_{i,t}$ is a vector of time varying regressors (cross-sectional time-series variables), changing in time and in space, $Z_{i,}$ is a vector of time invariant regressors (cross sectional time-invariant variables) and $\varepsilon_{i,t}$ is the error term.

Time invariant variables ($Z_i$) may be very important to explain the specificity of each entity: the municipalities of our study area are extremely different not only in relation to the time-varying variables we are considering as predictors, but in many physical and socio-economic features that we here assume to be time invariant.

We hypothesise that such specificity is fully captured by one variable only, $MeanM_i$, i.e. the mean value of the demands in the same month in the available years (excepting the year over which we are modelling the demand in the split-sample validation approach described later on), for the given city:

$$\begin{aligned} Z_i = MeanM_i = & \sum_{t=1,N-1} WDem_{t,i}(t \\ & = month\ M\ of\ other\ years)/N-1 \end{aligned} \tag{2}$$

Such value represents also the best information available, in the operational practice, for the water company to model the expected monthly demands.

The present study aims at assessing the potential of exploiting additional information in order to improve such 'standard of reference' estimate.

Our models have therefore the following form:

$$\begin{aligned} WDem_{i,t} = & f\big(\big[RainD_{i,t},\ RDays_{i,t},\ TMax_{i,t},\ TMin_{i,t}, Tour_{i,t}, \\ & Res_{i,t}, Tar_{i,t}, MeanM_i\big]\big) + \varepsilon_{i,t} \end{aligned} \tag{3}$$

In the panel-data framework, all the data (predictors and predictand) referring to the seven municipalities are merged in an unique data set, that is thus formed by a number of records equal to 7 times the number of records available for each city.

All models are applied in a cross-validation procedure, with a rigorously independent calibration and test data set, i.e. test data are not used for estimating the parameters of the models.

Given the limited number of observation years, we have applied a leave-one-out split-sample calibration procedure where, for modelling the water demand in the five summer months of one year, all the data referring to such year (test year) for all the municipalities are removed from the calibration set used to parameterise the model. The calibration period is thus formed by the data of all the remaining years: the calibrated model is successively applied over the independent test year to assess its performance in validation. The procedure is repeated using every year, one at a time, as independent test period.

### 4.3. Linear models: stepwise regression

The first implemented model is a multiple linear one (like, for example, in Haque et al., 2015a) with a stepwise regression approach where regressors are added or removed one at a time until no additional regressor can be added to improve the model: the model is assessed based on the sum of squared errors criterion, with p-values of the F-statistics used to decide if adding or removing a predictor equal corresponding to 0.05 and 0.1 respectively.

The final selected linear model structure (denoted in the following as SWRM) excludes the following variables: permanent residents (Res), rainfall depth (RainD) and both the temperatures

(TMax and TMin), including instead the other four input variables: Tar, Tour, RDays, MeanM, with the last one as the most significant one (and first to be included in the stepwise procedure). It appears, therefore, that, when modelling the water demand with a linear regression, the role of the number of residents, of the rainfall depth and, more surprisingly, also that of the temperature, are already included in the values of the mean demand, rainy days, tariff and presence of tourists.

On the other hand, the relation among water demand and the explanatory variable (function f of equation (3)) is not necessarily linear (on the contrary, we do expect a non-linear influences of the climatic variables, see Maidment and Miaou, 1986 or Miaou, 1990) and this also affects the relative influence of the explanatory variables.

### *4.4. Non-linear models (artificial neural networks): input saliency analysis*

Non-linear models, based on artificial neural network (ANN) architectures, were tested to model the water demand in the five summer months. Numerous studies have successfully applied ANN in water demand modelling in the recent years (among others: Grino et al., 1992; Jain et al., 2001; Jain and Ormsbee, 2002; Liu et al., 2003; Bougadis et al., 2005; Adamowski, 2008; Ghiassi et al., 2008; Firat et al., 2009; Adamowski and Karapataki, 2010; Adamowski et al., 2012; Babel et al., 2014).

Artificial neural networks are massively parallel and distributed information processing systems, composed of nodes, arranged in layers, which are able to infer a non-linear input–output relationship. ANN, in particular feedforward networks, have been widely used in many hydrological and water resources applications (see for example the recent review papers by Maier et al., 2010; by Abrahart et al., 2012) and the readers may refer to the abundant literature for details on their characteristics and implementation.

The models applied here are networks formed by one hidden layer, with tan-sigmoid activation functions, and a single output node (corresponding to the $WDem_{t,l}$ to be estimated), with a linear activation function. The training algorithm, minimizing a learning function expressing the closeness between observations and ANN outputs (in the present case the mean squared error) is the Newton Levenberg–Marquardt BackPropagation algorithm. In order to avoid overfitting, which degrades the generalization ability of the model, a Bayesian regularization of the learning function (Foresee and Hagan, 1997) was applied.

Also the panel-data (regional) ANNs were implemented in a fully independent cross-validation leave-one-out procedure: for each year (or better, for each summer season) to be modeled, the data of the months of the other summer seasons are used for the training.

For each validation year, the ANN is trained starting from 10 different initial networks, randomly initialized; each one of the trained networks (provided their performance over the calibration data is considered acceptable, i.e. with a coefficient of determination greater than 0.9) is then fed by the input variables, for each of the municipality, of the test year (independent data) and the water demand of the test year is finally obtained averaging the resulting ANN outputs.

The first implemented ANN model has in input all the predictors of Eq. (3) ("ANN all inputs"). Successively, since the stepwise linear regression procedure indicated that number of residents (Res), rainfall depth (RainD) and both the temperature indexes (TMax and TMin) appeared to be redundant, we have carried out an input saliency analysis, testing other networks where such input variables are removed one at a time (denoted as ANN M1 to M4).

Fig. 3 shows the performances, in terms of both MAE (mean absolute error) and RMSE (root mean square error) of the stepwise regression model (SWRM) and of the ANN models.

As a term of reference, the figure shows also the errors of the naïve model that assumes that the water demands for a given month of the test year is equal to the mean of the monthly demands of the remaining (calibration) years (MeanM).

The MAE and RMSE indicate that only the removal of the rainfall depth (M1, no RainD) improves the performance of the non-linear models, whereas removing the values of Res, TMin and, above all, TMax actually deteriorates the performance in validation.

This finding, in line with the result on the significance of RainD vs WDem obtained in the correlation analysis, confirms what emerged also in other studies, that is, that the total rainfall depth has not a significant impact on water consumption, which is instead more affected by rainfall occurrence (RDays). Also the important role of both mean day and night temperatures is confirmed as far as our case study is concerned.

As an additional test, the removal not only of RainD but also of each one of other three predictors was tested, but there was no additional improvement in the modelling performance in validation in respect to model ANN M1.

The figure also highlights that the ANN non-linear models (with the exception of the one that does not include TMax) outperform both the naïve Mean M and the linear regression approach and that, in turn, SWRM is better than MeanM, thus demonstrating i) the importance of including the influence of both weather and touristic explanatory variables for estimating the water demand and ii) that such relation appears to be better captured by a non-linear model.

In order to better analyse the modelling capability of the implemented approaches, Fig. 4 shows the disaggregation of the mean absolute error over the different municipalities (left panel) and over the different months (right panel), comparing the MeanM, the linear regression model and the best performing ANN.

The right-hand panel of Fig. 4 indicates that there is a gain allowed by the inclusion of the time-varying predictors for every month of the season: such gain is the highest for the critical August month, whereas it's hardly noticeable for June, that appears to be less fluctuating over the years.

The left panel of Fig. 4 shows that the highest benefit from the inclusion of the time-varying explanatory variables ($X_{t,i}$) is obtained for the city of Rimini (one of the most important touristic city in Italy), whose estimates are shown in Fig. 5, and secondarily for the municipalities of Ravenna and Riccione.

On the other hand, for two municipalities (Bellaria and Cesenatico), the left-hand panel of Fig. 4 shows that assuming a water demand equal to the mean on the remaining years (MeanM) would be better than the application of the proposed models (and for S.Mauro the improvement is negligible). In these cities, the smallest of the set, the water demand is the less fluctuating from one year to the other and the demands over the different years have the lowest discrepancy from the mean values so that the influence of the time-varying determinants is limited.

Since the approach is a panel one, each one of the "pooled" models attempts to mimic simultaneously, in addition to the behaviour of such relatively stable municipalities, also the behaviour of all the other cities, where the monthly water demand fluctuations are much stronger, as may be seen, for example, for the city of Rimini. It follows that the ANN (and the SWRM) model tends to assign, also over the less fluctuating municipalities, an over-estimated influence of the variations in the seasonal predictors, thus resulting in a deterioration in comparison with the use of MeanM alone for Bellaria and Cesenatico.

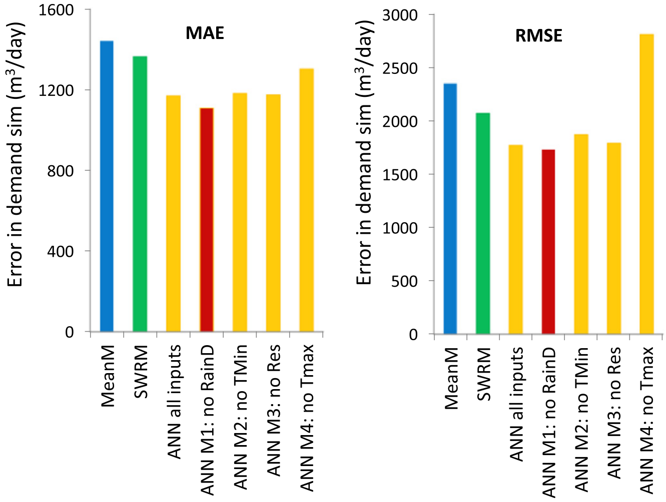


**Fig. 3.** Mean absolute and square errors over the independent test set (leave-one year –out framework).

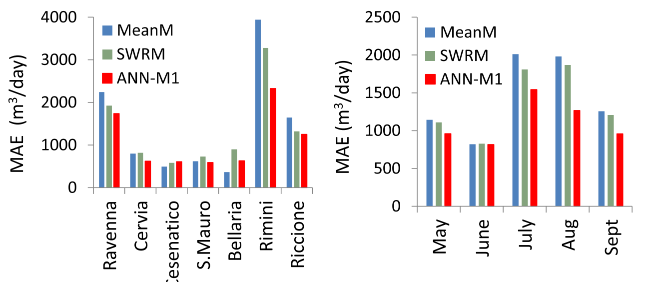


**Fig. 4.** Mean absolute errors (in validation) over the municipalities (left panel) and the months (right panel).

## 5. Conclusions

The study has analysed the monthly residential water demand referred the municipalities of one of the most important touristic areas in Europe, where it is extremely important to assess the significance of the water use drivers, in particular during the critical summer season.

Beyond the explanatory variables proposed in the past literature, including climatic drivers, the work has introduced tourism as an important factor that may affect water consumption: such factor has been, so far, neglected in urban water models and its influence is not well documented, yet, also due to the lack of information at sub-annual scale.

The correlation analysis carried out for all the study cities between the water demand in the summer months and the seasonally-varying predictors, in order to understand their influence, showed that the consumption indeed increases very much with the number of tourists. Furthermore, differently from other non-touristic areas, in a coastal area, where residents do not leave the city in the hot summer months, an increase in temperature always causes a significant growth in the water volumes.

On the other hand, the rainfall occurrence (number of rainy days) has an highly significant negative correlation for all the municipalities, while the total rainfall depth does not always exert an equally strong significant effect on the demand, in line with similar results obtained in the literature.

The panel-data water demand modelling demonstrates the added value of the inclusion of the determinants analysed in the study, if compared with the monthly estimate given solely by the mean value of the demand over the same month of the other years, that is the estimate currently used by the water company, and that implicitly ignores the influence of the changing climatic, economic and societal conditions on the demand.

In a panel-data approach, there is not a different model tuned to fit each single city, but only one model that simulates the water demand (aggregated at municipal scale) for all the cities included in the panel: the model may therefore be used to simulate also the demand for a city that is not included in the set of cities used to parameterised it, provided that such demand is guided by the same underlying causal relationships.

When comparing the modelling approaches, the results show that the non-linear model (based on an artificial neural network architecture) outperforms the linear regression indicating that the influence of the identified predictors appears to be better captured by non-linear causal relationships.

The input saliency analysis for the non-linear models has shown that the best performances are obtained when the following exogenous variables are added in input to the model: residents, tariff, number of tourists, both day and night temperatures, and number of rainy days. Instead, the total rainfall depth is not included in the set of significant drivers identified by the input saliency analysis, confirming the results of the correlation analysis.

In light of the above considerations and of the promising results, we believe that additional research on the role of tourism in addition to meteorological variables as determinants of water consumption at seasonal and finer time scale is useful and necessary.

Lack of data currently hinders the development of such analyses and the number of available data is also one of the main limitations of the present study: in Italy and in many other countries infra-annual water consumption data are generally not accessible and often affected by low quality and reliability.

More complete information is especially needed on water uses by tourists and by specific touristic activities. In particular, more detailed data on the number of tourists lodged out of official accommodation facilities would be required to fully capture such important phenomenon.

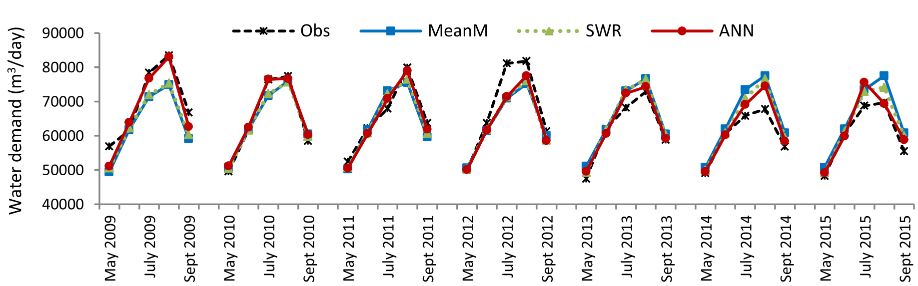


**Fig. 5.** Estimates for the city of Rimini, obtained by the proposed models in the independent test set (leave-one year –out framework).

Additional knowledge on the sub-annual determinants will help to better understand and model the expected consumption. Such improved models may be of great help to water utilities to forecast water demand when factoring in the possible evolution of the explanatory variables (through climate/meteorological and tourism forecast scenarios), in order to improve the water supply management policies and practices: possible future research stemming from this study includes: i) exploring the use of numerical weather predictions and of tourism forecasting models for weekly to seasonal urban water demand forecasts over the study area and ii) investigating urban water security under changing long-term climate and tourism projections. Such analyses may be needed at aggregated scale, for forecasting the need of all the cities supplied by the same water sources, or at local scale, for planning the evolution and management of the distribution network.

This kind of analyses, in addition to being needed by the water managers, may also help to increase the resilience of tourism business to water-scarcity risks, thus allowing a long-term sustainability of mass and quality tourism in the Romagna seaside cities and in other highly developed coastal areas (Eurostat, 2009).

## Software/data availability

The analyses have been developed within the MATLAB® (MathWorks) software development platform: the scripts are available upon request from the first author.

The information on tourists' overnight stays and the rainfall and temperature data are public, and the data set used in the study are available upon request from the first author, whereas the data on water consumptions are based on measurements that are not public and have been provided by Romagna-Acque Società delle Fonti SpA.

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