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Impacts of Climate Variables on Residential Water Consumption in the Czech Republic

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Abstract The paper investigates whether there is a statistically significant impact of short-term climate variables (specifically air temperature and rainfall) on residential water consumption at two selected case sites in the Czech Republic. The analysis is based on a unique time series of daily data from 2004–2009. The statistical methods used are CART methodology and a decomposition of these time series based on a locally weighted regression method. Apart from the data analysis results, the investigation raises several methodological questions regarding the use of daily data and the scope of analysis based on such data sets.

Keywords Water consumption · Climate variables · Drought · Czech Republic

1 Introduction

Residential water consumption is an important parameter of water use and its changes are influenced by many determinants varying from climate, hydrological and technical to socio-economic ones. Within numerous studies, mainly national or regional, scientists have tried to classify these variables and to asses their particular influence on residential water consumption (see Downing et al. 2003; Schleich and Hillenbrand 2008 among others). Extensive attention has been paid to various tariff structures and consumer responses to them (such as

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Arbues et al. 2003; Berger et al. 2007; Barberán and Arbués 2008; Chu et al. 2009 etc.). On the other hand, analyses of climate variable impacts are less frequent (Nieswiadomy and Molina 1989; Hewitt and Hanemann 1995; Renwick and Green 2000).

Therefore, the goal of the paper is to contribute to the knowledge in this area—particularly to test, whether climate variables have a statistically significant impact on residential water consumption. The analysis concentrates on two selected case sites in the Czech Republic.

The growing importance of such an analysis is driven by the findings of climate change studies (Kašpárek et al. 2006) which bring systematic evidence of hydrological regime changes that should intensify in the upcoming decades, such as the redistribution of annual rainfall from the summer to the winter period and the increase of hydrological extremes (specifically rainstorms and droughts). These national findings also correspond with the conclusions of the European Environmental Agency for the Central European region (EEA 2008). Climate variables and their changes could be one of the determinants of residential water consumption which could increase households' demand for the available water resources.

This paper gives a detailed analysis of the impact of rainfall and air temperature. Following the recommendation of Schleich and Hillenbrand (2008), we used local daily data from the years under investigation to see the impact of both variables on daily drinking water consumption in selected case sites. Water consumption is represented by the amount delivered by the public water supply which is the major source of drinking water in the area. Considering data availability and comparability, the period of 2004–2009 is analysed. To construct the drinking water consumption model, the nonparametric classification and regression trees methodology (CART) was used. For the seasonal component investigation, a time series analysis is implied. The decomposition of these time series is based on the locally weighted regression method proposed by Cleveland et al. (1990). A robust statistical analysis of the available data is complemented by interviews with local representatives to assess the potential of individual water supply (through private wells) in the area.

This approach brings a unique insight into the possible dependence of residential water consumption on short-term climate factors (recorded on a daily basis). Moreover, despite the analysis' limited scope at the regional level it brings important findings regarding the possibilities and limitations of further enhancing the analysis (e.g. at the national level).

The paper's structure is as follows: Chapter 1 maps previous studies dealing with determinants of residential water consumption with a special focus on climate variable impacts. Chapter 2 introduces selected case sites and describes the data sources and the method of analysis. In Chapter 3 the main results of the analysis are presented and the context of their relevance and related methodological issues are discussed.

2 Investigations of Climate Variable Impacts on Residential Water Consumption

Schleich and Hillenbrand (2008) cluster determinants of residential water consumption into three main groups—economic, social and environmental, where climate variables are understood as a subgroup of environmental ones. This subgroup usually contains rainfall, air temperature, evapotranspiration, intensity of sunlight and wind speed. The investigators devote great efforts to calculate the separate effect of particular determinants. An overview of the key studies, their approaches and conclusions with a specific focus on environmental factors is given here.

Among the relevant analyses, Nieswiadomy and Molina (1989) and Hewitt and Hanemann (1995) include temperature as a direct determinant of Texan residential water consumption at the micro level (matched to the billing cycle of each consumer). However, the assessment of the climatic variables' impact is simplified by using summer maximums. Further, Renwick and Green (2000) use maximum daily air temperature and monthly cumulative rainfall in their model to evaluate the potential of price and alternative demand-side management policies in California. The results of the analysis indicate that the maximum air temperature variable is statistically significant, suggesting that higher than average maximum daily air temperatures increase the consumption of water. The rainfall variable was statistically insignificant in comparison to seasonal effects. Besides, Miaou (1990) analyses agricultural water consumption in Texas by including the number of rainy days in his model. According to his conclusions, water consumption has different response rates in different seasons under the same air temperature. Rainfall causes a temporary reduction in seasonal use (the higher the seasonal use level prior to the occurrence of rainfall, the more significant the effect is expected).

Some authors try to predict the impacts of climate change on water consumption in the upcoming decades. Downing et al. (2003) model water consumption scenarios in the UK based on 4 existing climate change scenarios. Residential water consumption seems to be the least vulnerable to climate change—the authors expect it to rise by 1.5–3.0 % by 2020 compared to 2000 (whereas the increase in agriculture is about 26 %). This growth will come due to higher hygiene needs (more showering) and more intensive use of water for gardens and swimming pools. Analogically, Goodchild (2003) analysed future residential water consumption in England under varying climate-change scenarios, which had been produced for 2020. The results suggest an increase in seven-day average residential water consumption of about 3.3 l/day per person in periods with high evapotranspiration, low rainfall (up to 2 mm) and air temperature exceeding 25 °C. In another study from England, Herrington (1996) estimates a residential water consumption increase of 29 % by 2021 (in comparison to 1991), from which 4 % is caused directly by climate change. However, these studies (namely Herrington 1996; Downing et al. 2003) primarily analyze long-term climate change impacts, whereas residential water consumption is also determined by short-term climate variables.

Finally, a complex analysis of all three groups of residential water consumption determinants in Germany is contained in Schleich and Hillenbrand (2008). Using the cumulated rainfall and average air temperature from April to September in 2003, the authors conclude that climate variables do not have a significant impact on residential water consumption, however, the impact of rainfall is more important than that of temperature. Specifically a ten percent decrease in summer rainfall results in an increase in daily water consumption per person by 0.7–1.2 l (according to the type of model used). This relatively small reaction may be rationalized by the small share gardening has on total residential water consumption (only 4 %) in the area. Schleich and Hillenbrand (2008) also point out that for a detailed investigation of climate factors weekly or even daily data of all variables would be necessary.

Within the above studies, it is recognized that residential water consumption significantly differs among particular groups of inhabitants depending e.g. on the type of housing. The consumption of people living in multi-family houses (e.g. blocks of flats) is almost fully dependent on water from the (public) water supply and it is also less vulnerable to climatic factors. On the other hand, people living in single-family houses may use their own well as a complementary source of water which than lowers their recorded water consumption from the water supply by about 1.4 % (Schleich and Hillenbrand 2008). Their water consumption is influenced by gardening and other outdoor activities that can represent up to 10 % of total consumption and will supposedly increase due to climate change in the near future (Downing et al. 2003).

Various determinants of residential water consumption are closely linked and it is difficult to separate them and to evaluate particular impacts. In contrast, to investigate the full range of determinants by using all the relevant detailed data often seems impractical and it leads to the numerous simplifications and assumptions that are necessary to make an analysis manageable. This situation and the cons and pros of both approaches (the complex vs. partial analysis) was taken into account whilst undertaking the research agenda.

Clearly, from the previous literature review, the studies investigating the impacts of climate variables on residential water consumption are rather rare. The other common feature of these studies is the nature of the data used - it rarely uses climate and water consumption data gathered on a daily basis. This is due to the relative difficulty of obtaining such data and the necessity to restrain the analysis to small and well demarcated areas. This approach is unique in this aspect, as it uses detailed daily data of household consumption as well as daily data of the climate variables in question. In the process of acquiring and analyzing these data several methodological issues appeared which seem to be of serious importance for the research and its dissemination might be helpful for other researchers in this field. In further chapters data sources are given, as is the approach to the analysis and the statistical methods used.

3 Characteristics of Case Sites, Data Sources and Methods

For a detailed investigation of the impacts of rainfall and air temperature on residential water consumption, two municipalities located in Central Bohemia—Hradek and Strasice (further referred to as Case site 1 and 2)—were selected as case sites. The localization was strongly determined by the willingness of local water service providers to share specific daily data on water consumption for each case site.

Both selected municipalities own the pipelines and they rent them to the same service provider. Most of the municipalities' socio-economic and environmental characteristics are similar, so the results can be compared (see Table 1).

Both case sites are situated at a central, continental latitude with higher humidity in the highlands. They are only 8 km from each other. Potential climate change threats based on

Table 1 Characteristics of selected case sites in 2009

Characteristics	Case Site 1 (Hradek)	Case Site 2 (Strasice)
No. of inhabitants	3 003	2 436
No. of residencies	514	606
-of which multi-family houses	6 %	4 %
-of which single-family houses	76 %	66 %
-of which seasonally used cottages	18 %	30 %
Average water consumption from public pipeline	106 l/person/day	83 l/person/day
Portion of inhabitants connected to public pipeline	96 %	91 %
Altitude	440 m ASL	498 m ASL
Annual rainfall (1961–1990)	501–600 mm	601–700 mm

Source: Czech Statistical Office (2010), Pšeničková (2006), VOSS, a.s., interviews with mayors regional climate models exist namely in the expected redistribution of annual rainfall from the summer to the winter season (of about 10–20 %) which could increase pressure on water sources during drier summer seasons (Kavan 2010).

The main difference among case sites consists of the quality and subsequently also the intensity of groundwater abstractions by individual inhabitants. At Case Site 2, there are sufficient sources of potable groundwater. Therefore, most single-family houses own and partly use a private well despite being connected to the public mains. The amount of individual withdrawals from wells is not measured. At Case Site 1, groundwater has lower quality and can only be used as service water. More than half of single-family houses own a water well, although less than in Case site 2.[1] Likewise, the amount of individual withdrawals from wells is not recorded. This matter of fact probably explains the lower than average water consumption from public pipeline per person/day at Case Site 2 (drinking water withdrawals from privately owned wells).

3.1 Hydro-meteorological and Water Consumption Data

As mentioned, the analysis is based on daily records of drinking water consumption from public pipelines in 2004–2009. The data represents the evidence of the private water service provider and it is gathered at two separate extraction sites. Gross daily records of so-called "produced" drinking water (PW) contain water invoiced to customers (IW), water used directly by the service provider (WSP) and water leakages from the pipeline (WL).

$$PW = IW + WSP + WL$$

To calculate invoiced water (IW), recorded WSP and breakdowns of pipelines, which are part of WL (this data is gathered on a daily basis), was deducted. Further, quarterly recorded permanent leakages from the pipelines recalculated to daily leakage and deducted. At both case sites, the IW also included consumption by one large industrial consumer, which is recorded on a monthly basis. At Case Site 2, this industrial consumption showed high stability over the entire observed period (about 20 % of total IW) so its deduction did not cause a distortion in the residential IW. At Case Site 1, the data adjustment was complicated by the significant variability in industrial consumption due to discontinuous production (varying from maximum to zero production). Based on the interviews with the water service provider representative, five different levels of production (and relating water consumptions) were defined and deducted from IW to obtain the water consumed directly by inhabitants.[2] The whole process of the data preparation is further illustrated by diagram 1.

Hydro-meteorological data was provided by the Czech Hydro-meteorological Institute, a government research organization. Specifically, daily rainfalls were measured by a rain-gauge station 5 km from the case sites. Daily average air temperature was measured at a climatological station about 25 km from the case sites. No data adjustment was undertaken.

3.2 Method of Analysis

The statistical analysis of the dependency of residential water consumption on air temperature and rainfall was done separately for both case sites. Model 1 developed included water consumption throughout the whole year. Model 2 focused on water

[1] Information based on interviews with mayors of both municipalities.
[2] Industrial consumers were asked to provide daily water consumption data, but this request was refused.

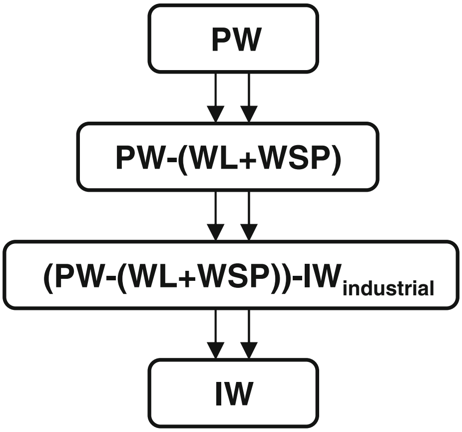

Diagram 1 Data preparation process

consumption recorded in the summer seasons (specifically May–September), i.e. months when periods of drought usually appear.

Before Model 1 was estimated, the normality assumption of the studied variables was checked, i.e. water consumption, rainfall and air temperature in both selected case sites. For this purpose the classical Shapiro-Wilk's W test for normality was used. It was concluded that none of the analyzed variables met the normality assumption due to significant results of the test (p-value<0.001). With respect to the character of the response (water consumption) and the normality assumption violation, we used a nonparametric method for the data analysis. More concretely we decided to choose classification and regression trees methodology (CART) developed by Breiman et al. (1984) instead of the classical regression analysis with dummy variables. The key principle of CART is based on recursively partitioning the sample space into p-dimensional rectangular subspaces. For the regression trees the recursive binary splitting is made in accordance with a squared residuals minimization algorithm which implies that expected sum variances for two resulting nodes should be minimized (see further Breiman et al. 1984). The estimation of the regression model, i.e. the construction of the regression tree is, realized in several steps and could be described shortly as follows:

Firstly, initial or the so called root node of the tree comprises a whole sample. Consequently we have to examine every allowable split on each predictor variable. Secondly, we have to identify and execute (i.e. create left and right) consequent of so called daughter's nodes by splitting antecedent node. The best split or the splitting criterion is determined through the split function $g(s;t)$ that can be evaluated for any split s of node t. In this case the $\underline{t}$ is a node of the tree containing a subsample of observations $\{\mathbf{x}_\mathbf{i}^{'}, \mathbf{y}_\mathbf{i}\}$ xx whereas $\mathbf{x}_\mathbf{i}^{'} = [\mathbf{x}_{\mathbf{i1}}, \mathbf{x}_{\mathbf{i2}}, \cdots, \mathbf{x}_{\mathbf{ip}}]$ and y_i is the ith water consumption. Let n_t be the total number of observations in t and let $\overline{y}_t = (1/n_t)\sum_{i\in t} y_i$ be the response average for node t. Now we can define within-node sum of squares for node $\underline{t}$ as $SS(t) = \sum_{i\in t} [y_i - \overline{y}_t]^2$ and suppose that we split s partitions t into so called left and right daughters nodes (consequents) t_L and t_R. The least-squares split function is defined then as

$$g(s;t) = SS(t) - SS(t_L) - SS(t_R)$$

The optimal—best split s_{best} of node t is the split such that $g(s_{best};t) = \max_{s\in\Omega} g(s,t)$ whereas Ω is the set of all allowable splits s of node t.

Now we can say that regression tree is constructed by recursively splitting nodes to maximize the aboveg function (Everitt and Rabe-Hesketh 2001). After growing the large (in terms of node number) tree we have to drop e.g. snip off the least important splits. The importance of a sub-tree is assessed by the measure of within-node homogeneity or cost and pruning is accomplished using a cost-complexity algorithm. Details of this algorithm are beyond the scope of this paper and could be found in Breiman et al. (1984).

We grow a large tree by setting the so called complexity parameter (cp) to a small number. In our case we set $cp=0.001$. Such a setting of the complexity parameter *cp* led to a "large and rich" regression tree. This rich tree was consequently pruned according to different values of cp. We obtained the sequence of sub-trees (one tree for each value of the *cp* parameter). From this set of trees an optimal one was chosen—it was the smallest tree of which the sum of squares was close to the minimum. Because no validation set was available, we based our calculation on the cross-validation approach (for details see Everitt and Rabe-Hesketh 2001).

For the seasonal component analysis of water consumption in both case sites a time series analysis was carried out. For this analysis total month water consumption was used. The time series was broken down into three parts - trend, seasonal component and residual component. Such a break down was carried out through a seasonal and trend break down procedure based on the locally weighted regression proposed by Cleveland et al. (1990).

As already mentioned, Model 2 focused on water consumption recorded in the summer seasons (specifically May–September). In this analysis the approach using CART methodology was again applied. The results are presented further in the paper.

In order to analyze water consumption in drought periods in more detail further analysis of these seasons was done. Thirteen periods of drought (from 2004–2009) were identified. Such a small number of observations only enabled a simple comparative analysis of water consumption averages (for the definition of the period of drought see chapter 3.3) to be made.

Finally, a statistical evaluation of quantitative data was supplemented by interviews with local key stakeholders. In particular both mayors, two local water service provider representatives and 11 local households were interviewed. The purpose of the interviews was mainly to gather additional information about the intensity of individual groundwater consumption.

4 Interpretation of Results and Discussion

The results for the Model 1 (whole-year data), Model 2 (May–September period) and for drought season are presented separately.

4.1 Model 1: Impact Analysis Containing Data for the Entire Year

For Case Site 1 56 different regression sub-trees were derived according to different values of the complexity parameter (cp). The overview of sub-trees is contained in Table 2. It can be concluded that the minimal cross-validation error was attained in the case of model no. 5 with the cp equal to 0.006466. The regression tree with 5 nodes reduced the residual sum of squares by 8.95 %.

There were 48 regression sub-trees derived for Case Site 2,. The minimal cross-validation error was attained in the case of model no. 2 and no. 5 with cp=0.0062 respectively cp=

Table 2 Basic statistics for regression sub-trees for Case site 1 (Model 1)

Model No.	Complexity parameter (*cp*)	No. of nodes	Error relatively to root node error=RSS_{null}/RSS_{model}	10-fold cross validation error	Standard deviation for 10-fold cross validation error
1	0.059296	0	1.0000	1.0016	0.0309
2	0.016948	1	0.9407	0.9461	0.0289
3	0.011323	2	0.9238	0.9348	0.0293
4	0.010213	4	0.9011	0.9313	0.0293
5	0.006466	5	0.8909	0.9105	0.0288
6	0.00594	6	0.8844	0.9138	0.0289
7	0.005372	7	0.8785	0.9130	0.0289
8	0.005021	8	0.8731	0.9184	0.0294
9	0.004836	9	0.8681	0.9160	0.0295
10	0.004682	10	0.8633	0.9174	0.0297
11	0.00398	12	0.8539	0.9144	0.0297
12	0.00377	15	0.8420	0.9214	0.0303
13	0.003187	17	0.8344	0.9207	0.0304
14	0.003132	19	0.8280	0.9193	0.0305
15	0.002906	22	0.8184	0.9253	0.0308
16	0.002655	23	0.8155	0.9271	0.0305
17	0.002562	25	0.8102	0.9351	0.0310
18	0.0023	27	0.8050	0.9351	0.0309
19	0.002237	30	0.7981	0.9474	0.0315
20	0.002205	31	0.7959	0.9496	0.0317
21	0.002157	32	0.7937	0.9484	0.0317
22	0.002139	36	0.7851	0.9510	0.0318
23	0.002098	37	0.7829	0.9527	0.0319
24	0.002043	39	0.7787	0.9556	0.0319
25	0.002032	40	0.7767	0.9533	0.0317
26	0.001951	43	0.7706	0.9528	0.0318
27	0.00188	45	0.7667	0.9534	0.0319
28	0.001688	46	0.7648	0.9655	0.0326
29	0.001665	48	0.7614	0.9663	0.0326
30	0.001661	54	0.7512	0.9665	0.0326
31	0.001574	55	0.7495	0.9675	0.0327
32	0.00154	57	0.7464	0.9672	0.0326
33	0.001538	58	0.7448	0.9674	0.0327
34	0.001476	61	0.7402	0.9687	0.0328
35	0.001428	62	0.7387	0.9672	0.0326
36	0.001424	64	0.7359	0.9682	0.0327
37	0.001414	65	0.7345	0.9679	0.0327
38	0.001323	66	0.7330	0.9735	0.0328
39	0.001298	69	0.7291	0.9707	0.0329
40	0.001282	70	0.7278	0.9705	0.0329
41	0.001269	71	0.7265	0.9709	0.0329
42	0.001268	72	0.7252	0.9709	0.0329
43	0.001216	73	0.7240	0.9722	0.0329

Table 2 (continued)

Model No.	Complexity parameter (*cp*)	No. of nodes	Error relatively to root node error=RSS_{null}/RSS_{model}	10-fold cross validation error	Standard deviation for 10-fold cross validation error
44	0.001194	74	0.7227	0.9724	0.0329
45	0.001193	75	0.7216	0.9726	0.0329
46	0.001184	78	0.7180	0.9737	0.0330
47	0.001142	79	0.7168	0.9731	0.0330
48	0.001141	80	0.7156	0.9742	0.0330
49	0.001125	82	0.7134	0.9736	0.0330
50	0.001096	83	0.7122	0.9736	0.0331
51	0.001085	87	0.7079	0.9740	0.0331
52	0.001045	92	0.7023	0.9751	0.0330
53	0.001031	93	0.7013	0.9739	0.0331
54	0.001018	94	0.7003	0.9741	0.0331
55	0.001006	95	0.6993	0.9760	0.0331
56	0.001	97	0.6972	0.9761	0.0331

Source: authors

0.003987. The cross-validation error attained values of 0.986 and 0.996 respectively. As can be seen, the regression tree with 2 nodes decreased the residual sum of squares by about 1.36 % and the regression tree with 5 nodes by about 0.3 %.

From these calculations, two key observations result: Firstly, the predictive ability of models in both case sites is very low. At Case Site 1, the regression tree reduced the variability of water consumption based on air temperature and rainfall by 8.95 % (at Case Site 2 only by 1.36 or 0.3 %). However, the predictive ability of the model is considered positive when explaining that the variables determine at least 40–50 % of the variability. Therefore it was concluded that a) residential water consumption at both case sites is primarily influenced by other determinants/variables than climate factors under investigation; b) the "rainfall" variable was almost insignificant (i.e. it had almost negligible influence on the estimated results). To sum, air temperature and the season of the year are more relevant determinants for residential consumption variability.

Despite these insignificant results an increase in water consumptions with the higher/lower than average temperatures was observed (the minimum water consumption for both case sites was around the temperatures of 10–15 °C and maximum water consumption at 21 °C and higher and 0 °C or lower). Therefore, the water consumption is represented by the parabolic function as shown in diagram 2. However, differences in water consumption among the temperature intervals are low - they vary between 4–8 % of total consumption.

To verify the seasonal impact the seasonal component of the residential water consumption was analyzed. The results of the analysis for the particular month are displayed in diagram 3. The time series break down implies lower water consumption in autumn and higher in summer. At Case Site 1, residential water consumption shows a decreasing trend over the years with a seasonal maximum in June and a minimum in September. At Case Site 2, the trend in water consumption is stable with regular seasonal increase during June–August and decline during September–November.

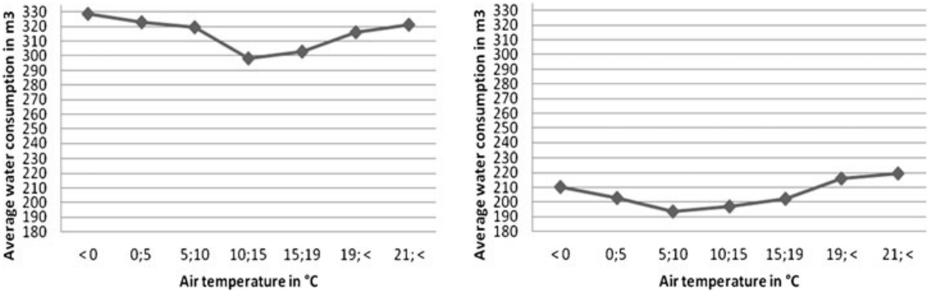

Diagram 2 Average water consumption depending on air temperature (Case site 1 and 2). Source: authors

4.2 Model 2: Impact Analysis Focused on the Period May–September

Due to the low predictive ability of the Model 1, it was decided to focus on the particular part of the year in which higher dependence of water consumption on climate determinants can be expected. This is mainly due to higher temperatures, but also due to less frequent rainfall. Czech climate characteristics refer to a "warm" season considering the period from April to September. For the purpose of this analysis, this period has been shortened to May–September due to average air temperatures in every month being significantly higher than in April (long term April average temperature is 7.7 °C, whereas in other months it exceeds 12 °C). The results of the model are presented in Table 3.

Again, the results of the CART methodology indicate that residential water consumption in the selected period is not significantly determined by air temperature or rainfall (the variable "rainfall" did not apply in the analysis). Again, the total predictive ability of estimated models is very low. From partial results from the regression trees only fragmental information can be obtained, e.g. lower temperatures during the summer season (especially July) resulted in a decrease in water consumption at both case sites etc.

4.3 Drought Season Analysis

A period of drought can be characterized as "the deficit that results when soil moisture is insufficient to meet the demands of soil potential evapotranspiration" (Critchfield 1984:

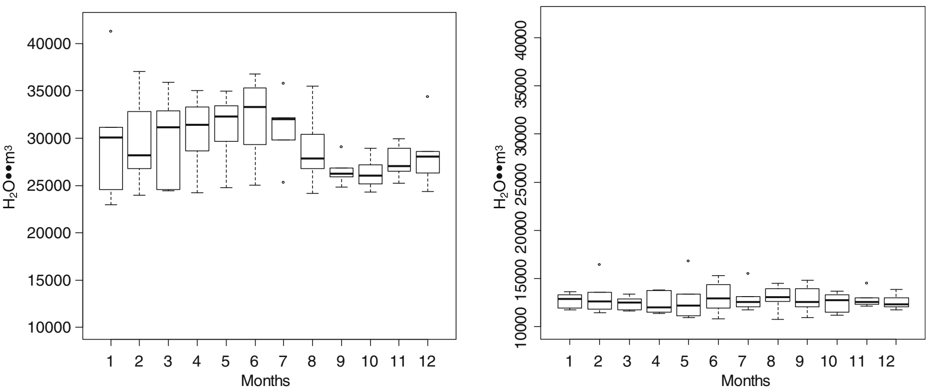

Diagram 3 Box-Whiskers' diagrams for residential water consumption from 2004–2009 at Case Site 1 and Case Site 2. Source: authors

Table 3 Summary of results of Model 2

Parameter	Case Site 1	Case Site 2
No. of sub-trees	39	35
CP in the selected model	0.012336	0.011563
Cross-validation error in selected model	0.8963	0.963
Reduction of residual sum of squares by	10.34 %	3.7 %

309). To determine such periods, meteorologists use various indexes. E.g. Blumenstock's index defines drought as a period without rainfall which ends with rainfall exceeding 2.54 mm in the last 48 h (Heim 2002). Potop and Turkott (2007) define drought as a period without rainfall (or with negligible rainfall up to 1 mm) that lasts at least 10 days, within which total rainfall did not exceed 5 mm during 5 consecutive days. For the purpose of this supplementary analysis, the following criteria has been used to identify drought periods:

a) average rainfall for the period did not exceed 1 mm/day and single rainfall exceeding 6 mm did not appear in any day of the period,
b) the period without rainfall lasted at least 10 consecutive days and
c) air temperature within the period was above the long-term monthly average.

Based on these criteria 13 periods of drought were identified. Subsequently there was an investigation as to whether there are any discrepancies in water consumption compared to average water consumption in the period May–September of the relevant year. As mentioned above, the number of observations did not allow a robust statistical evaluation to be applied, so the conclusions are based on comparison of averages as recorded in the following table.

By calculating total averages from Table 4, it was concluded that the increase in water consumption is a prevalent feature during drought periods. This increase was 10.7 % at Case site 1 and 7.4 % at Case site 2. When considering only the last third of the period, within which the water stress should culminate, the water consumption increased by 16.9 %, resp. by 11.8 %. It is apparent that water consumption from mains water at Case site 2 is less vulnerable to air temperature. This is due to more extensive use of individual wells (the next chapter will deal with this issue).

However, comparing each drought period separately, the trend for an increase in water consumption is not absolute (periods with a decrease in water consumption are marked in grey in Table 4). On the other hand, in the majority of situations (68 % of observations), there was an increase in water consumption. Therefore, the supplementary analysis focusing on drought periods brought ambivalent results. For further investigation, the redefinition of the drought season would be plausible (see section 4.4 below).

4.4 Discussion and Conclusions

Overall, the daily data analysis did not bring any significant evidence of a relationship between climate variables and water consumption. The CART methodology results showed that water consumption is, to some extent, influenced by air temperature (a rise in temperature causes a slight increase in water consumption), but the predictive ability of the model is very low. In the case of rainfall, almost no impact was found. Supplementary drought season analysis revealed average water consumption increase in selected periods, although this relation does not have absolute validity and was not tested statistically. In this context we emphasize that drought periods were identified according to both criteria—low rainfalls (or

Table 4 Characteristics of selected drought seasons

Period No.	Date DD/MM	Duration (days)	Average daily rainfall (mm)	Average temperature (°C)		Average water consumption (m^3/day)		Average daily water consumption (m^3/day)	
						CASE SITE 1		CASE SITE 2	
				In the period	Monthly	In the period	May–Sept	In the period	May–Sept
1	30.7.–17.8.	19	0.55	21.3	17.3	288	208	–[a]	–[a]
2	24.5.–3.6.	11	0.46	19.5	13.6	426	356	187	186
3	15.6.–24.6.	10	0.42	20.5	15.9	432	356	164	186
4	23.8.–9.9.	18	0.30	18.6	15.2	316	356	208	186
5	1.6.–15.6.	15	0.27	16.2	15.9	286	303	215	212
6	1.7.–30.7.	30	0.40	23.7	17.5	327	303	236	212
7	4.9.–18.9.	15	0.09	18.0	13.3	329	303	222	212
8	11.7.–20.7.	10	0.65	22.5	17.5	318	265	202	188
9	21.5.–2.6.	13	0.20	17.8	13.2	269	293	293	185
10	25.7.–6.8.	13	0.26	23.0	17.5	363	293	212	185
11	23.8.–2.9.	11	0.12	17.5	16.3	373	293	169	185
12	26.7.–9.8.	15	0.56	20.0	17.2	356	357	224	244
13	13.8.–30.9.	49	0.37	17.4	14.7	348	357	260	244

[a] Consumption not recorded

Source: authors

the total absence of rainfalls) and high temperatures. Following these criteria, all periods fall into the interval from May to September.

As pointed out,[3] the analysis neglected other factors influencing the residential water consumption, such as population changes, price level as well as other external conditions relevant for the water scarcity and the purchasing power of inhabitants. We excluded such variables from constructed models for two specific reasons:

a) municipalities in the given period (6 years) did not experience significant external shocks —specifically the population was stable (plus/minus 0.5 % in comparison to the six-year average) and the water prices slowly increased together with inflation and wages,
b) the approximation of monthly or even annual regional and national data in order to get the daily effects on consumption at the municipal level would, according to our opinion, cause larger distortion than the exclusion of mentioned factors from the analysis. Therefore, we have assumed their effect as non-significant.

After the ambitious and time demanding analysis built on daily data, several methodological difficulties identified by the research must be pointed out.

First, residential water consumption on a European scale usually consists of two parts: the consumption of drinking water from public pipelines and groundwater consumption from individual wells. Acquiring data from both sources to get comprehensive short-term water

[3] We give thanks to the anonymous reviewer for this important comment.

consumption series can be very difficult if not impossible; the reason is usually the lack of abstraction monitoring from the individual wells. The case sites analysis supports this thesis—the lower predictive ability of Model 1 and Model 2 appeared in Case site 2, where less inhabitants are connected to public pipeline, more households own a well and where groundwater quality is higher. Also the drought season analysis revealed less significant changes in water consumption from the public pipeline in this locality. In interviews,[4] the individual supply was estimated at 2–5 % of the public supply. It is assumed that the objection due to insufficient monitoring, could be partly overcome by an extensive survey with well owners. Such an additional survey would have to focus on the individual patterns of behaviour under different weather or seasonal situations. In urban areas where individual water supply is not easily accessible, the mentioned data distortion would almost disappear. On the other hand, we would assume potential lower dependence among residential water consumption and climate variables due to the absence of gardening, private outdoor bathing, etc.

Second, the data gathered on water consumption from public pipelines needed adjusting, even though the access to primary data sources was rather exclusive. In particular, the daily records of the water service provider contained continuous water leakages as well as emergency water leakages. Some produced water was consumed directly by the service provider and some was delivered to industrial users whose consumption is affected by different variables than residential consumption. Unfortunately, not all of the necessary time series were gathered on a daily basis. This adjustment could have brought some distortions to the models. On the other hand, such effects exist and must be dealt with somehow. The analysis contains the maximal specification of particular factors considering the given institutional setting and the infrastructural organization. It reveals, to some extent, the unpreparedness of service providers to supply researchers with the specific data. It is assumed that, in particular, data on industrial water consumption could often be unavailable or, better said, can be considered as confidential by the owners. The elimination of the problem could be reached by selecting case sites without industrial users connected.

Third, the question arises if the results would be different or at least more conclusive if the study had been conducted in areas with higher pressure on water resource usage. This is not, fortunately, the case of the Czech Republic. In this respect, the following analyses would have to have been done in other countries satisfying this criterion. In this paper an attempt was made to highlight the aspect of water pressure by conducting the drought season analysis separately. As already discussed the results were rather ambivalent.

However, the drought season analysis led to another important methodological issue: there is a wide variety of drought season definitions, so which drought season should be analyzed? For further investigation, a redefinition of the drought season would be possible. Or even better, the definition of the period could be derived from climatic conditions which significantly influence water consumption.

5 Conclusions

In the research focused on climate change mitigation provisions the possible influence of short-term climate variables on residential water consumption was tested. Based on the literature review a lack of studies building their analysis on detailed daily climate and water consumption data was identified. This investigative gap was also pointed out in some of the

[4] interviews with mayors (15th October, 2010).

papers reviewed. Building on these findings and the research topic carrying out such an analysis was found to be challenging.

Whether air temperature and rainfall have a statistically significant impact on residential water consumption was tested at two selected case sites in the Czech Republic. The results did not bring any significant evidence that climate variables have an impact on water consumption. Based on all the estimated and discussed models it was concluded that the variable "rainfall" did not have any influence in comparison to the variable "air temperature" both of which appeared to be insignificant for explaining water consumption variability. The question remains whether selected climate variables are really insignificant or whether there are distortions in the daily data analysis due to the discussed factors (individual wells, data adjustment or an incorrect definition of the drought season).

References

Arbues F, Garcia-Valinas MA, Martinez-Espineira R (2003) Estimation of residential water demand: a state-of-the-art review. The J of Socio-Economics 32:81–102. doi:10.1016/S1053-5357(03)00005-2

Barberán R, Arbués F (2008) Equity in domestic water rates design. Water Resour Manag 23(10):2101–2118. doi:10.1007/s11269-008-9372-3

Berger T, Birner R, McCarthy N, Diaz J, Wittmer H (2007) Capturing the complexity of water uses and water users within a multi-agent framework. Water Resour Manag 21(1):129–148. doi:10.1007/s11269-006-9045-z

Breiman L, Friedman J, Olshen R, Stone C (1984) Classification and regression trees. Chapman & Hall

Chu J, Wang C, Chen J, Wang H (2009) Agent-Based Residential Water Use Behavior Simulation and Policy Implications: A Case-Study in Beijing City. Water Resour Manag 23(15):3267–3295. doi:10.1007/s11269-009-9433-2

Cleveland RB, Cleveland WS, McRae JE, Terpenning I (1990) STL: A Seasonal-Trend Decomposition Procedure Based on Loess. J of Official Statistics 6:7–73

Critchfield HJ (1984) General Climatology. Prentice-Hall, Englewood Cliffs, NJ

Czech Statistical Office (2010) http://www.czso.cz/csu/redakce.nsf/i/regiony_mesta_obce_souhrn. Accessed: 10 November 2010

Downing et al. (2003) Climate change and the demand for water. CPM Report No.: CPM-03-107, Stockholm Environment Institute Oxford Office, Oxford

EEA (2008) Impacts of Europe's changing climate—2008 indicator-based assessment. Joint EEA-JRC-WHO report No. 4/2008 http://www.eea.europa.eu/publications/eea_report_2008_4/pp1-19_CC2008Executive_Summary.pdf. Accessed: 2 January 2011

Everitt B, Rabe-Hesketh S (2001) Analyzing medical data using S-PLUS. Springer, New York

Goodchild CW (2003) Modelling the impact of climate change on domestic water demand. Water and Environ J 17(1):8–12. doi:10.1111/j.1747-6593.2003.tb00423.x

Heim RR (2002) A review of twentieth-century drought indices used in the United States. Bull Am Meteorol Soc 83(8):1167–1179

Herrington P (1996) Climate change and the demand for water. Stationery Office Books, London

Hewitt JA, Hanemann MW (1995) A Discrete/Continuous Choice Approach to Residential Water Demand under Block Rate Pricing. Land Econ 71:173–192

Kašpárek L, Novický O, Peláková M (2006) Climate change and water regime in the Czech Republic. VÚV T.G.M, Prague

Kavan J (2010) Vyhodnocení dopadů změny klimatu na vodní režim a zdroje v povodí Saxony a Vltavy. Dissertation. Charles University in Prague

Miaou JH (1990) A Class of Time Series Urban Water Demand Models With Nonlinear Climatic Effects. Water Resour Res 26(2):169–78

Nieswiadomy ML, Molina DJ (1989) Comparing residential water demand estimates under decreasing and increasing block rates using household data. Land Econ 65:280–289

Potop V, Turkott L (2007) Hodnocení sucha a suchých období v agrometeorologickém roce 2005/2006 v České republice. International Scientific Conference. http://www.cbks.cz/SbornikPolana07/pdf/Potop_Turkott.pdf. Accessed: 21st January 2011.

Pšeničková P (2006) Porovnání klimatické regionalizace ČR Kurpelové a Končeka. ČZU, Prague
Renwick ME, Green RD (2000) Do Residential Water Demand Side Management Policies Measure Up? An Analysis of Eight California Water Agencies. J Environ Econ Manag 40:37–55. doi:10.1006/jeem.1999.1102
Schleich J, Hillenbrand T (2008) Determinants of residential water demand in Germany. Ecol Econ 68:1756–1769. doi:10.1016/j.ecolecon.2008.11.012