Master Thesis Report

Spatial and temporal relation between drinking water temperature and indicators for microbial water quality in the drinking water distribution system of Amsterdam

Rogier Speksnijder
27th December 2020

Colophon

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Author

Name	R.P. (Rogier Paul) Speksnijder, ing
Student number	4126971
Email	r.p.speksnijder@gmail.com
University	Delft University of Technology
Faculty	Civil Engineering
Department	Water Management

Graduation Committee

Prof. dr. ir J.P. van der Hoek, Delft University of Technology (Chair)
Dr. ir. E. Abraham, Delft University of Technology
Dr. ir. L. Zlatanovic, Delft University of Technology
Dr. ir D.B. Steffelbauer, Delft University of Technology

Daily supervisor

Dr. ir. K.L. Lam, Delft University of Technology

Address

Delft University of Technology
Faculty of Civil Engineering
Stevinweg 1
2628 CN Delft

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Summary

Intensive urbanisation enhances warming of cities' ambient and subsoil environment. The local drinking water distribution system (DWDS) is likewise affected. Hotspots of anthropogenic heating were perceived to influence drinking water temperature and pose a threat for microbial drinking water quality. Information on temporal and spatial relation between drinking water temperature and microbial indicating parameters was however scarce. This is especially the case for a full scale unchlorinated DWDS in a metropolitan area. Therefore, this research aimed to explore the spatial and temporal relation between drinking water temperature and microbial indicating parameters Aeromonas and Heterotrophic Plate count (HPC). Sample data from the DWDS in the metropole of Amsterdam was explored, with the objective to possibly draw conclusions beyond this DWDS. This DWDS consists of two interconnected subsystems (DWDS P1 and DWDS P2). Each subsystem is fed by its own treatment facility.

Data analysis was applied on 11 years of temperature, Aeromonas and HPC samples from the DWDS. Time series analysis was performed on measured parameters to observe the data in time. Heatmaps were prepared for geographic projection of the measurement values throughout the DWDS. Profile plots were introduced to observe the change of temperature and the change of Aeromonas during transport from reservoir to sampled location. A sequence of profile plots was prepared for total observation of the DWDS.

Analysis of measurement data from the DWDS indicated a significant drinking water temperature increase of 0.12 ^{o}C/year among measured time span. The positive correlation between temperature and Aeromonas samples was likewise significant. This correlation was however hardly observed from the heatmaps with absolute sample values. Profile plots indicated drinking water temperature increase during transport in the winter. For some areas this temperature increase was noticeably higher than the average throughout the DWDS. Majority of these areas also showed repetitive occasions of above average Aeromonas increase, during transport in the summer. An indirect causal relation was perceived between drinking water temperature increase during transport in the winter and Aeromonas increase during transport in the summer. This relation seemed stronger for areas on the distributions systems' outskirt than in the central region of the distribution system. Regions on the outskirt of the DWDS were perceived more sensitive for repetitive events of Aeromonas increase during transport. For these outskirt regions was considered that the influence of residence time may have allowed both: temperature increase in the winter, but also excessive Aeromonas increase in summer periods.

Areas with repetitive exceedance of threshold temperature (14 ^{o}C) for accelerating Aeromonas growth, were not inextricably tied to repetitive exceedance of the Aeromonas standard for safe drinking water. Areas with repetitive exceedance of the Aeromonas standard were often linked to prolonged residence time. For regions on the outskirt of observed DWDS it was suggested that the influence of residence time was more important than the absolute water temperature to explain Aeromonas concentrations.

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Glossary

Area, area
With capital letter: Single rectangular field from an imaginary raster overlay, projected on a geographic map. Without capital letter: Geographic region.

Aeromonas value, High
Aeromonas measurement values ≥ 1000 cfu/100ml *(for this report).*

Clean water reservoir
Structure at treatment facility for storage of treated drinking water. A clean water reservoir is in most occasions the final step of a treatment facility before transport pumps and distribution network. Treatment plants have often one or more storage reservoirs. In this report the singular form is used even if more than one reservoir is present at treatment facility.

Drinking Water Distribution System (DWDS), use of acronym
DWDS = singular form
DWDS's = possessive of singular form
DWDSs = plural form
DWDSs' = possessive of plural form
DWDS P1 = DWDS subsystem P1
DWDS P2 = DWDS subsystem P2

Location name
Letter number combination to combine one or more nearby samples. The location name is predefined for each sample in the dataset. Location names have field name 'NM_POINT' in the dataset.

Measurement
Outcome values of (direct) temperature measurement, Aeromonas analysis or HPC analysis.

Profile plot
Scatter plot to observe net change of weekly average Aeromonas value during transport (y-axis), versus net change of weekly average Temperature during transport (x-axis). Three distinctive markers represent absolute sample temperature. Horizontal dotted crosshair divides markers in 4 quadrants, for: Aeromonas increase exceeding absolute limit value at the tap (quadrant I & II) or limited Aeromonas increase (quadrant III & IV). Vertical dotted crosshair divides markers according to net Temperature change during transport. Markers in quadrant I and IV represent a positive net Temperature change during transport. Markers in quadrant II and III represent a negative net Temperature change during transport.

Sample
One or more measurements with common date-time stamp and location name.

STL
Seasonal and Trend decomposition using Loess

Temperature, temperature
With capital letter: Temperature measurement. Without capital letter: Physical quantity.

Time Series analysis (TSA)
Time Series Analysis is a generic term for applied techniques to answer statistical questions while observing data in time.

Significant [parameter] area
Observation circle, or area, on a heatmap with a significantly higher [parameter] measurement mean than the population mean of the observed heatmap (p=0.025).

1 Introduction

1.1 Research context

Human induced climate change is posing increasing pressure on the availability and quality of water resources. Pressure is for example exerted by intensive urbanization which enhances warming in cities and their surroundings. This heat island effect may in turn impose a health risk due to increased microbial activity within the DWDS (Cisneros et al., 2014); (Agudelo-Vera C. M., 2018).

The feed for Dutch drinking water production origins from groundwater sources and surface water sources (ILT, 2019). While the temperature of the groundwater feed is rather stable at about 12 ^{o}C throughout the year, the average annual variation of the surface water feed ranges from 3 to 22 ^{o}C, from winter to summer (Agudelo-Vera C. M., 2018).

From past research it is noted that the maximum surface water temperature is subject to spikes during exceptionally warm summers. Measurements by Van Vliet indicate that the temporal elevated temperature of the river Meuse in 2003, was directly related to the declined discharge of the river (Van Vliet & Zwolsman, 2008). In this period a maximum temperature of 26.9 ^{o}C was measured, resulting in an exceedance of the standard of 25 ^{o}C for drinking water (Drinkwaterbesluit, 2018).

Though the groundwater temperature is considered more stable than surface water, the soil temperature is also subject to the human induced climate change and accelerating urbanization (Agudelo-Vera et al., 2015). As a result from the urbanization in and around the cities, enhanced warming and local 'heat islands' are observed, affecting the soil temperature (Lucon & Ürge-Vorsatz, 2014).

Water temperature is not or negligibly influenced by the drinking water production (KWR, 2020), however it is influenced by the drinking water distribution system (DWDS) and its subsoil environment after treatment. Research by KWR (Agudelo-Vera et al., 2017) indicated that soil temperature locally reached 27 ^{o}C, influencing the temperature of the drinking water distribution system. As a suspect for the elevated soil temperature, the underground expanding grid of electricity transport cables and also the underground distribution network for district heating are named (Van Den Bos, 2020). Aside these anthropogenic heat sources, also the ambient temperature, soil cover type and depth influence soil temperature (Van Den Bos, 2020).

Another possible heat source may be found in the final part of the drinking water transport, the domestic drinking water system (DDWS). Warm environment, combined with longer periods of stagnant water may enable further heating of the drinking water. From recent research it was concluded that both temperature and residence time of drinking water in domestic drinking water systems have a significant impact on the microbial water quality (Zlatanovic et al., 2017).

To maintain and control the water quality, Dutch drinking water companies have the legal obligation to produce and supply safe drinking water. Drinking water companies are also responsible for water quality control, according to the drinking water regulations (Drinkwaterregeling, 2019); (Drinkwaterbesluit, 2018). These regulations specify the minimum frequency and location for sampling and subsequent analysis. Among these mandatory analyses are the microbial indicator parameters 'heterotrophic plate count' (HPC) and Aeromonas. These parameters can act as an indirect indication for the efficiency of measures to limit microbial growth within DWDSs (World Health Organization, 2017).

DWDS are designed for a lifespan of about 30-50 years, depending on the diameter and location of piping sections (Vitens, 2017). Risk management, policy making and planning of infrastructural projects, especially for underground activities in urban areas, require a clear perspective on the long term technical requirements of the DWDS. Modifications or expansion of DWDS should anticipate on the expected change of subsoil environment that might influence drinking water temperature. One example of technical DWDS requirements is the minimum distance from anthropogenic heat sources (Van Den Bos, 2020). This requirement is closely related with network depth and routing. Too strict technical DWDS requirements result in elevated investment costs and more complex decision-making with other stakeholders of subsoil activities. If the technical requirements for DWDSs are insufficient, it might jeopardize drinking water quality.

For this reason, it is important to determine the influence of the rising subsoil temperature on the DWDS temperature and subsequently on the water quality. For this reason Waternet provided laboratory data from tap water samples for research.

Knowledge gap

There is a relatively small body of literature that is concerned with full-scale research on the spatial correlation between drinking water temperature and the influence on the drinking water quality after transport through the DWDS. Especially research on DWDS without added disinfectants is scarce.

The dynamics of bacterial composition and growth within the DWDS are not yet fully understood. Though from recent research on a single branch of a full-scale DWDS it was observed that the water temperature has a significant effect on parameters for bacterial growth (Prest et al., 2016a). The observed pattern was however limited to a time span of maximum two years. Besides, the spatial differences within the DWDS are not yet explored, as past research solely focused on a single sample point.

Research questions and objective

Following research questions are posed in the scope of this thesis:

(1) Is there a spatial and/or temporal correlation between water temperature and microbiological water quality indicators (HPC and Aeromonas) for unchlorinated DWDS in a metropolitan area?
(2) If yes, what conclusions can be drawn from the long term pattern and geographical distribution of correlations?
(3) Can hotspots, potentially caused by anthropogenic heat sources, be identified through long term monitoring of water temperature within the DWDS?
(4) What is the correlation between water temperature and microbiological water quality indicators (HPC and Aeromonas) around these heat hotspots?

1.2 Structure of Thesis

This report is structured according to the stages of research. First, the case study area is outlined (§1.4), followed by methodology for analysis of provided data sets (§2). The results section (§3) is divided in five subsections (Figure 1). In the first subsection statistical characteristics of measurement data were explored (§3.1). The measurements were subsequently approached from spatial point of view by use of heatmaps (§3.2). Exploration of HPC extends up to and including heatmap exploration. Exploration of Temperature and Aeromonas measurements were explored for all named research elements. Focal areas were selected from the heatmaps, for closer observation on spatial differences within measured parameters (§3.3). The change of temperature and Aeromonas during transport was explored for the focal areas (§3.4) and also for the total DWDS (§3.5). Conclusions are presented in §4, followed by recommendations and opportunities for further research in §5.

Figure 1 - Structure of thesis

1.3 Literature review on use of microbial indicating quality parameters within DWDSs

1.3.1 Complexity of bacterial communities in DWDS

Research on the bacterial growth within the DWDS is mainly focused on the composition and distribution of bacterial communities in the DWDS. Research by Liu et al. (2014) pointed at the importance of distinction of the four different phases that the bacteria reside in; (1) bulk water, (2) suspended solids (3) loose deposits and (4) biofilm (Liu et al., 2014). The sum of the bulk water and the suspended solids represent the smallest fraction: <2%. Recent research is ambiguous about the stability of the bacterial composition of the biofilm. Depending on the applied test setup and analysis method, in some studies the composition of the biofilm was stable under changing hydraulic regimes (Douterlo et al., 2013), while in other research the structure of the bacterial community was not stable, but changing in the complex DWDS environment (El Chakhtoura, 2018). Moreover it was considered that the influence of future changes on bacterial communities within DWDS cannot be predicted due to the complexity of this problem (El Chakhtoura, 2018).

1.3.2 Suitability of indicating parameters HPC and Aeromonas

Despite the complexity of the microbial structure within the DWDS, it is required to obtain a reliable indication for the effectiveness of measures taken to limit microbial regrowth. Dutch drinking water companies determine the HPC and the Aeromonas by the standards NEN-EN-ISO 6222 and NEN 6263 respectively (Drinkwaterregeling, 2019), as required by the authorities. Both parameters serve as an indicator for microbial regrowth within the DWDS. Dutch authorities defined the operational limit value for HPC at 100 cfu/ml and the operational limit value for Aeromonas at 1000 cfu/100ml (Drinkwaterbesluit, 2018). Exceedance of HPC does not necessarily pose a direct threat for bacterial safety of drinking water (Hijnen & Van Der Wielen, 2017). Though it serves an indication that operation measures may be required to secure contamination of the DWDS. Aeromonas serves as an indicator for presence of opportunistic pathogens (Hijnen & Van Der Wielen, 2017). Laboratory analysis of HPC and Aeromonas samples is labour intensive and time consuming. The procedure takes a few days, due to the incubation time of 72 hours for the HPC and 24 hours for the Aeromonas (KWR, 2018). From a survey of the KWR (Van Der Wielen et al., 2016), the methods of HPC and Aeromonas were compared with adenosine triphosphate concentration (ATP) analysis and the direct cell count. These two methods take less time and are therefore considered as easier in use. It was however also concluded that ATP and direct cell count are not informative as an indicator for bacterial regrowth within the DWDS. The Aeromonas measurement is preferred to monitor bacterial regrowth in DWDS (Van Der Wielen et al., 2016). HPC analysis was considered a safe indicator for microbial regrowth in DWDS (Gensberger et al., 2015). Though, it was also emphasized that repetitive sampling of HPC is recommended to compare the outcomes, as individual sampling could lead to faulty conclusions.

1.3.3 Examples of critical drinking water temperature in the drinking water distribution systems and domestic distribution systems

Drinking water distribution systems

In 1993 Le Chevallier explored the quality of 31 DWDSs in the United States for a period of 18 months (Le Chevallier et al., 1996). In contrast with Dutch drinking water companies, U.S. drinking water companies in this study were required to monitor coliform bacteria with the colony count method as indicator of bacterial regrowth and indicator of pathogens in the DWDS. The coliform test was considered as a process indicator to determine the effectiveness of the water treatment process with respect to fecal pollution (Ashbolt et al., 2001). Interpretation of coliform test results differs from the HPC method, as coliform bacteria require a higher amount of nutrients for regrowth than heterotrophic bacteria (Le Chevallier et al., 1996). From this study, the critical drinking water temperature for enhanced microbial regrowth of coliform bacteria was defined. A distinction was made between free-chlorinated DWDS (critical T ~ 15 ^{o}C) and chloraminated DWDS (critical T ~ 20 ^{o}C). Despite the clear relation between drinking water temperature and coliform presence, both outcomes were not representative for DWDS without disinfectant added.

Domestic Drinking Water System

From full scale simulation experiments on a domestic drinking water system (DDWS) without disinfectant, it was concluded that the temperature of water supplied from the DWDS has an impact on the microbial growth while the water is stagnant in DDWS (Zlatanovic et al., 2017). The effect was related to the temperature of the supply from the DWDS. Colder water from DWDS resulted in lower HPC after stagnant conditions in DDWS, than colder water from DWDS. It was assumed that this effect results from the amount of nutrients in the colder water from DWDS. From observations of HPC and temperature measurements, the tipping point was determined for heterotrophic bacterial growth. Samples > 16 ^{o}C resulted in elevated HPC values, compared with samples < 16 ^{o}C (Zlatanovic et al., 2017).

1.3.4 Full scale studies on DWDS without disinfectant

In the area of Rotterdam a full scale study was performed by Prest et al. (2016a) on the relation between bacterial growth and the environmental parameters in a disinfectant free DWDS. The bacterial growth (ΔICC[1] and ΔHPC) in the trajectory between drinking water treatment plant (DWTP) effluent and the tap, appeared to be positive related to the drinking water temperature at the tap. The selection of the sample location within the DWDS of Rotterdam was based on the historical data. This data indicated a significant variation of the water characteristics between the DWTP and the sample point. From this perspective it was considered interesting to observe a range of samples among the DWDS trajectory from DWTP to the tap. For another full scale study on a Dutch DWDS without disinfectant, long term laboratory data of water samples was evaluated on the relation between temperature and Aeromonas (Van Der Mark et al., 2011). The positive relation between Aeromonas test results and temperature of the water was determined. The positive relation between temperature and HPC appeared to be different for the two different parts of the DWDS, i.e. the northern part and the southern part. This difference was confirmed to be significant. Several assumptions for this dissimilarity, such as clean water quality, material of network and residence time were named. These assumed causes were however not further investigated.

[1] Intact Cell Concentrations

1.4 Case study area: Amsterdam

Introduction to the distribution networks

Water Cycle Company Waternet is responsible for the production and distribution of unchlorinated drinking water throughout Amsterdam and surrounding municipalities (Waternet, 2020a). Two treatment facilities, Leiduin (P1) and Weesperkarspel (P2), produce about 90 million m^3 drinking water per year (Figure 2).

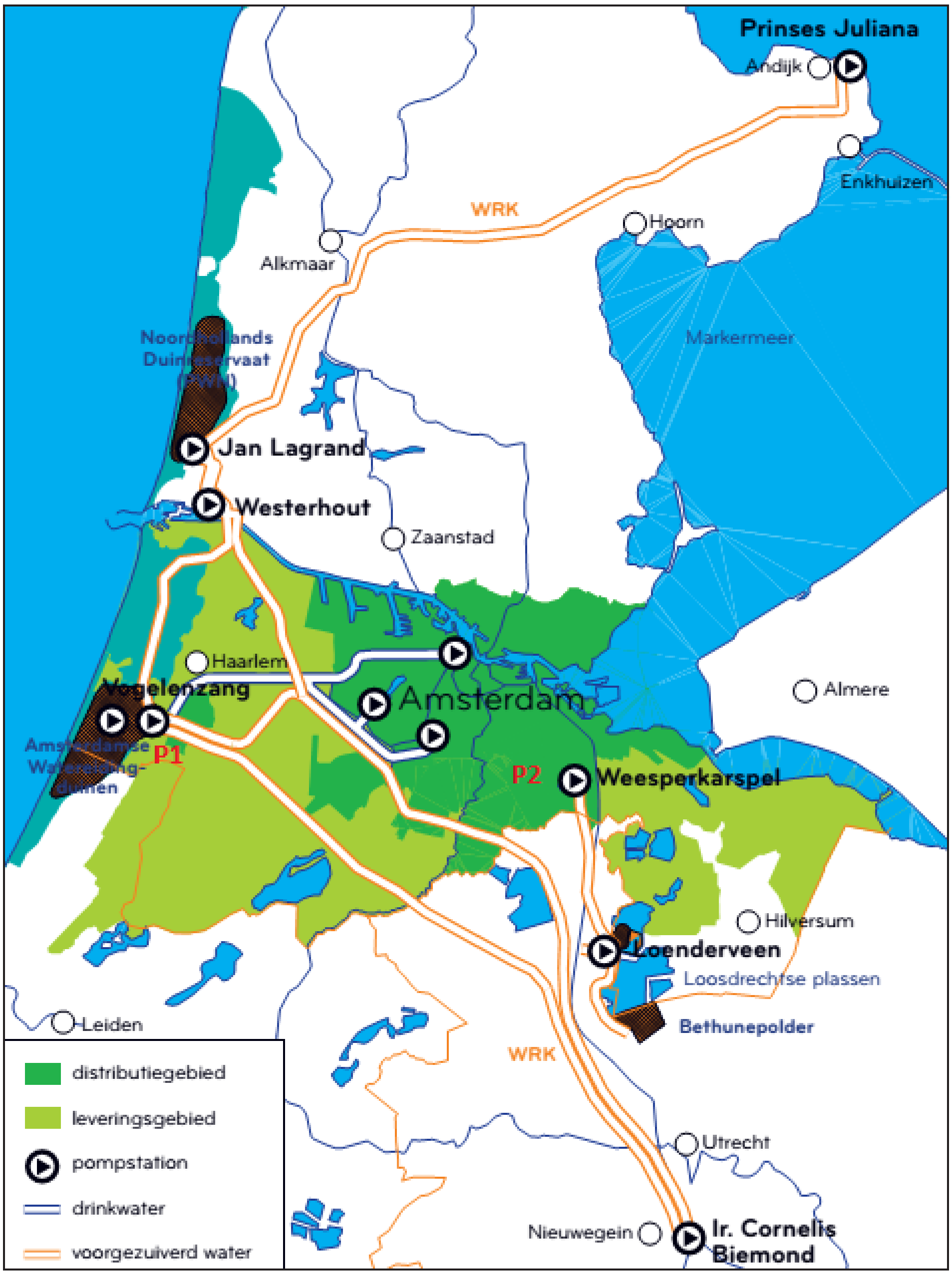


Figure 2 - Location of treatment facilities Leiduin (P1) and Weesperkarspel (P2). Dark green area marks the ditribution area of P1 and P2 (Waternet, 2020a).

Treatment facility P1 is located in the West of Amsterdam, near municipality of Heemstede. Treatment facility P2 is located south-east of Amsterdam. Both treatment facilities provide drinking water for the DWDS of Amsterdam and surrounding municipalities. Treatment facility P1 supplies drinking water for the DWDS subsystem that extends from Heemstede until about the river Amstel, in Amsterdam. In this report DWDS subsystem P1 is abbreviated as 'DWDS P1'.

Treatment facility P2 supplies drinking water for the DWDS subsystem that extends from the River Amstel to Muiderberg. The Northern part of Amsterdam, above the River IJ, is also supplied from Treatment facility P2. In this report DWDS subsystem P2 is abbreviated as 'DWDS P2'. Raw water for treatment facility P1 is drawn from nearby dunes. The larger part of the water in the dunes originates from a pre-treatment facility in Nieuwegein. This pre-treatment includes coagulation, sedimentation and filtration. The treatment facility P1 consists of rapid sand filtration, ozonation, softening, activated carbon, slow sand filtration and clean water storage. The raw water from production P2 is drawn from polder seepage water and from river water (Amsterdam-Rhine Canal). On two successive production locations, the water is treated by coagulation, sedimentation, reservoir storage, rapid sand filtration, ozonation, softening, activated carbon, slow sand filtration and storage (Waternet, 2020a). Detailed information on DWDS P1 and DWDS P2 is subject to secrecy and therefore limited provided for this research. An extensive description of DWDS P1 and DWDS P2 is for this reason not included.

Sampling program

Waternet is also responsible for the monitoring and control drinking water quality. National regulations specify a sampling program with a minimum number of tap water samples per volume and per district (Drinkwaterregeling, 2019). Multiple locations of the network are therefore measured repetitively among the whole time span of 11 years. Other locations are sampled once, or for a shorter time span. These latter locations are presumably sampled as a result of specific events. These events may include: Incidents with risk of contamination, maintenance works or customer complains. At exceedance of the standard for safe drinking water, flushing might be required. After flushing the location is sampled again to verify the effect (ILT, 2019).

1.4.1 Origin of datasets

Waternet provided an extract of their sampling program for this research. This extract exists of three separate datasets for: (1) Temperature, (2) Aeromonas and (3) HPC. The composition of these datasets is clarified in Appendix 1. Temperature was measured at the tap. Samples for Aeromonas and HPC determination were drawn from tap and analysed in laboratory. Storage and analysis of Aeromonas- and HPC samples complied with the protocols in NEN 6263 and NEN-EN-ISO 6222. These protocols are appointed by Dutch authorities (Drinkwaterregeling, 2019). The pipe section from the network to the tap is supposed to be flushed before temperature measurement and sampling to avoid measurement of standing water (Kors, 2020). The samples from the tap were therefore considered as 'samples from the DWDS'. The specific motive behind each specific sample was not known from the provided datasets. Therefore it was considered important to cautiously observe and analyse data within the context (frequency and time span) of measurements at observed location.

Composition of samples

Three datasets with measurements were converted into one dataset, based on original samples. An overview of the composition of samples is presented in Figure 3. The majority of 33.513 samples existed of single temperature measurements (25.998). 4.552 samples were combined measurements of Temperature, Aeromonas and HPC. 1.815 samples combined Temperature and HPC measurements and 369 samples contained Temperature and Aeromonas measurements. A total number of 779 samples did not include a Temperature measurement.

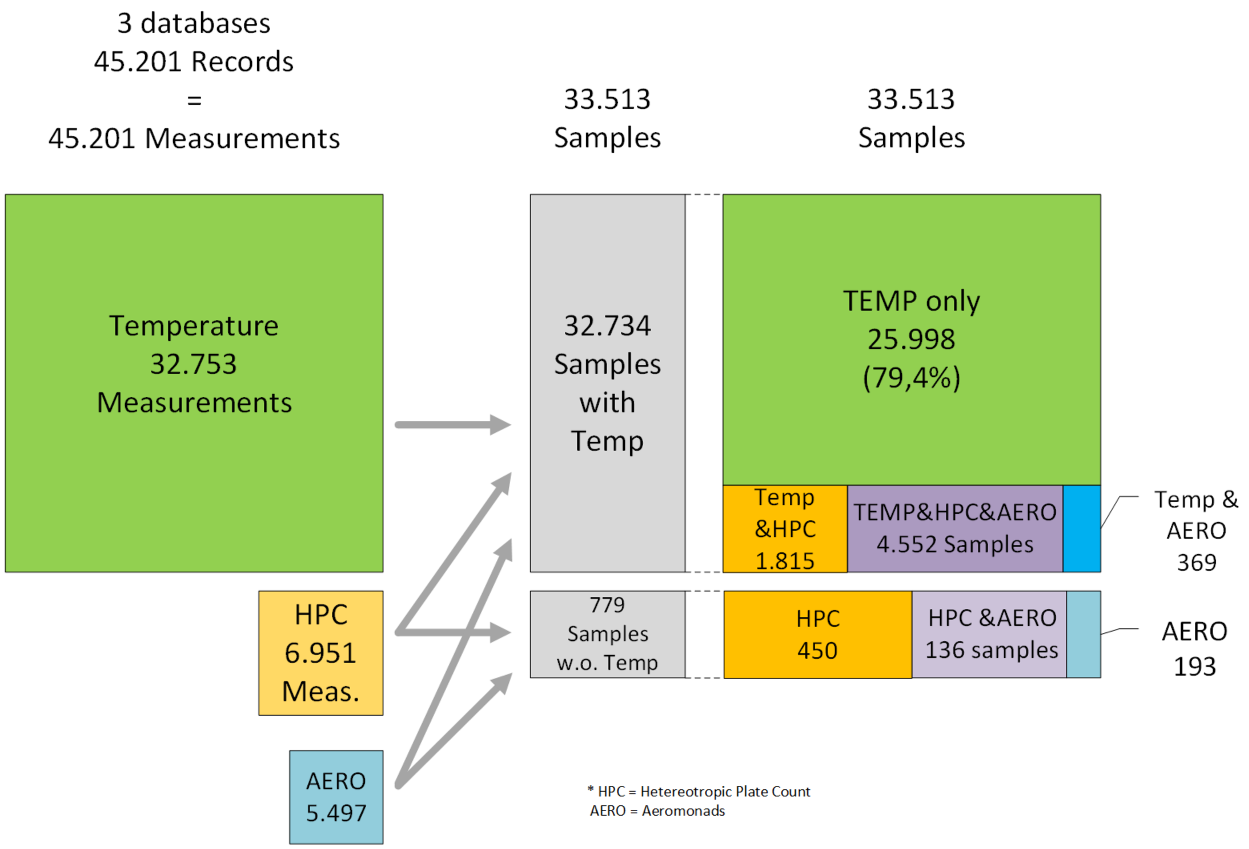


Figure 3 - Composition of samples and measurements from the samples.

Samples excluded from research

Empty data fields were excluded from data analysis and research. Measurements without or with a false GPS location were excluded from research. A small amount of water samples was analysed for Aeromonas at an incubation temperature of 37 °C instead of 30 °C, or was analysed by a different protocol. These samples were also excluded from research. One temperature measurement of 64.3 °C was considered invalid and excluded from research.

Software tools

Only the inventory of sample composition was performed in original Microsoft Excel file format. Data analyses, heat maps, spatial analyses and all other analyses were prepared in Python 3.7.4, within console Spyder Anaconda 3 (Python Software Foundation, 2020).

1.4.2 Geographic characteristics of sample data

Research by Van Der Mark et al. (2011) demonstrated significantly different Aeromonas levels for two production regions within an unchlorinated distribution network. The cause of this difference was not explored in detail, but the influence of a different clean water quality from the two treatment facilities was considered by authors. Therefore two additional datasets from the clean water reservoirs P1 and P2 were explored. From t-tests it was concluded that the Temperature and Aeromonas within the clean water reservoirs P1 and P2 were significantly different. From this perspective it was required to be aware of the possible subsequent effect within the DWDS and distinguish measurement data according to their treatment facility. Therefore is was considered important to know the original treatment facility (P1 or P2) per sample. The measurement datasets did however not contain this information. So the treatment facility was derived indirectly from the geographic projection of DWDS P1 and DWDS P2 (Figure 4b).

(a)

(b)

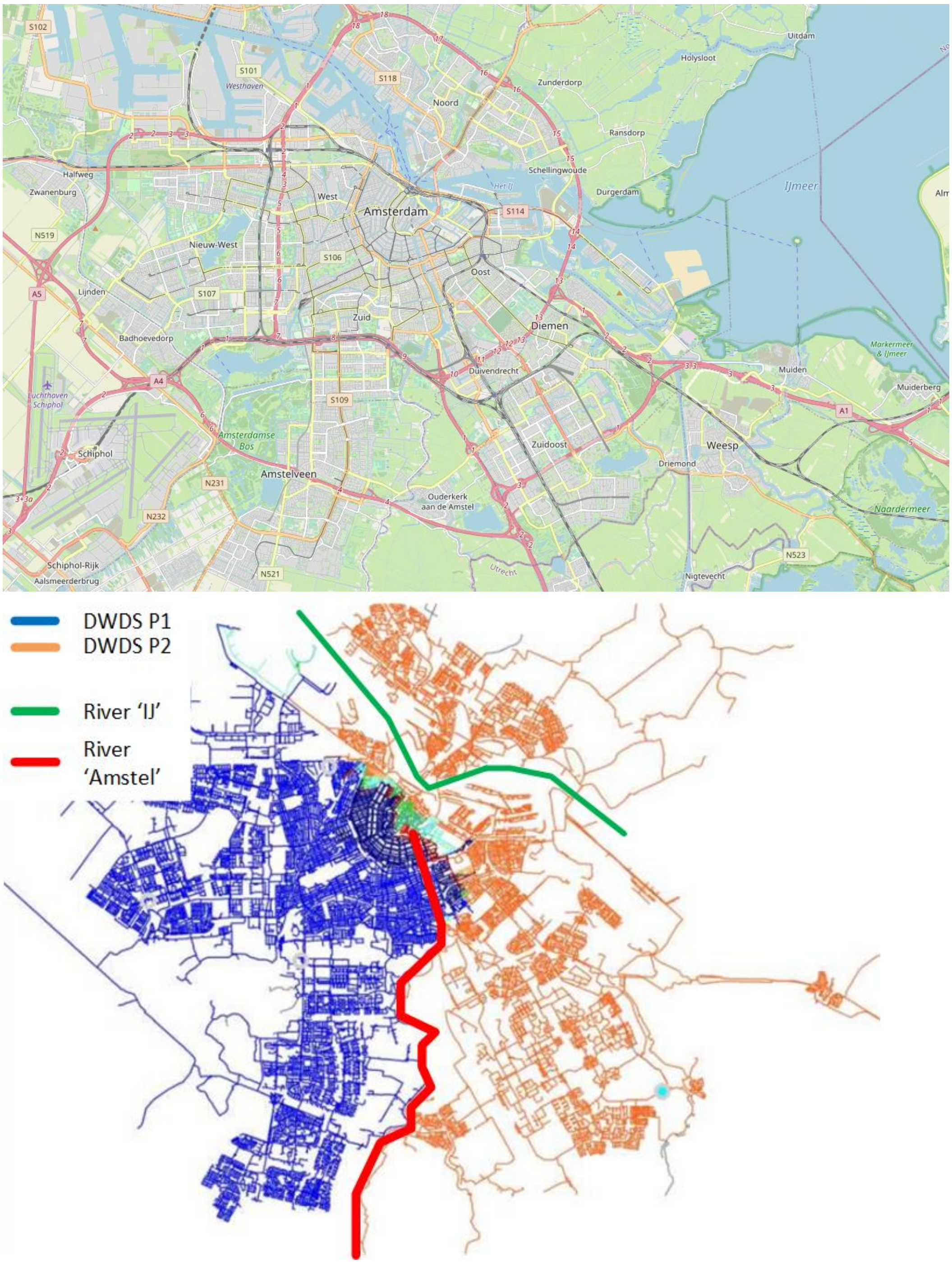


Figure 4 - Geographic map of Amsterdam. Map size: 28 x 17.5 km. (OpenStreetMap Foundation, 2020) (a). Indicative lay-out of DWDS P1 (blue) and DWDS P2 (orange), with River 'IJ' (green) and River 'Amstel' (red) (Waternet, 2020b) (b).

The rivers *'IJ'* and *'Amstel'* were considered approximate natural perimeters of DWDS P1 and P2. From consultation of Waternet (Kors, 2020) it was known that the perimeters of DWDS P1 and P2 are not absolute, in time. Several cross connection valves exist among the common perimeter. These cross connection valves are normally closed. For operational reasons, a cross connection valve is opened for a period of time. This implies there is a mixture of drinking water from both networks in vicinity of the open valve, during opening and after closure of the valve. To trace the production origin of Temperature, Aeromonas and HPC samples it was envisaged to utilize an additional database with sulphate (SO_4) samples. Samples in vicinity of clean water reservoir P1 showed a high sulphate concentration, compared with samples in vicinity of clean water reservoir P2. The different sulphate content within clean water reservoirs P1 and P2 could possibly act as a tracer to pinpoint the original treatment facility of the samples. This method had however some uncertainties. Samples from sulphate database had no time stamp, but only a date stamp. Therefore it was not feasible to relate the sulphate samples to the Temperature, Aeromonas and HPC samples. An indirect connection based on time and GPS-location was considered complex as the available map of the DWDS layout for this research was coarse. On advice by Waternet (Kors, 2020), the production origin of samples were derived by observation of physical perimeters of distribution network P1 and P2.

2 Methodology for Initial analysis

This subsection provides the methodology on the initial statistic analysis of measurement data (§3.1). Methodology for spatial analysis is described in §3.2.1. The methodology for exploration of focal areas within observed DWDS is described in §3.4.1 and §3.5.1.

The initial statistic analysis of measurement data consists of: Regression, Time series analysis (TSA) and T-tests. These are applied to determine the statistic properties of measurement data. This is required for onward exploration of measurement data within the context of time and location within the DWDS. Regression is amongst others used to determine the influence of sample temperature on the Aeromonas and HPC values. Time series analysis is used to observe data in time. With this technique it is possible to observe if there is any trend or seasonal pattern in the measurement data. T-tests are applied to verify if an observed selection from the total dataset is representative (yes or no) for the total dataset. Arguments for selection and suitability of applied methods are explained.

2.1 Correlation test with Ordinary Least Squares regression

A frequently used model for correlation of data is Ordinary Least Squares (OLS) (Fahrmeir et al., 2013a). By this method the influence of explanatory variables on the dependent variable is tested. The method of least squares aims to find the regression line that results in the minimum sum of squared distance between actual data and points on the regression line. The minimum sum of squares is determined by the optimum value for α and β resulting in minimum value for S (Dekking et al., 2005a):

$$S(\alpha,\beta) = \sum_{i=1}^{n}(y_i - \alpha - \beta x_i)^2$$

Estimators for intercept (α) and slope (β) are:

$$\hat{\beta} = \frac{n\sum x_i y_i - (\sum x_i)(\sum y_i)}{n\sum x_i^2 - (\sum x_i)^2}$$

$$\hat{\alpha} = \overline{y_n} - \hat{\beta}\overline{x_n}$$

An argument for the use of OLS regression is the considered reliability of the statistic properties. This reliability does however only apply if the base assumptions are met. Besides is the non-robustness for outliers a known downside of this regression method (Verbeek, 2017). It is therefore important to verify if this method is applicable of the applied data. There are some assumptions for validation and optimum result of OLS (Fahrmeir et al., 2013b). Most important assumptions for OLS regression are:

(1) Known linear relation between explanatory variable and the dependent variable.
(2) Independency between observed explanatory variable and other (not observed) explanatory variables.
(3) Independency between explanatory variables and residuals. This is amongst others observed by testing of residuals on homoscedasticity.
(4) Absence of autocorrelation of residuals.

Assessment of Ordinary Least Squares (OLS) regression assumptions.

For each application of OLS regression, the suitability was determined by verification of above assumptions. This section contains a description of the argumentation or tests that are applied to verify assumptions (1) to (4). The actual verification of these assumptions is provided in the concerning sections where the OLS is applied.

(1) Assumption on known linear relation between explanatory and dependent variable. The assumption on the known linear relation between explanatory variable (for example: Temperature) and dependent variable (for example: Aeromonas) was verified by reference of corresponding research.

(2) Assumption on independency between observed and other (not observed) explanatory variables. This assumption was not tested directly with the application of OLS. However, the influence of other (not observed) variables, or influences, were considered in the conclusions section of this report.

(3) Assumption of homoscedasticity. The variance of error terms of the dependent variable should be independent from the explanatory variable. This assumption is tested by the scatter plot of the residuals versus the explanatory variable. The scatter of the residuals should present a uniform (homoscedastic) pattern (Figure 5a). The homoscedastic pattern may contain errors beyond the uniform pattern (Figure 5b) if these errors can be related to the observed data.

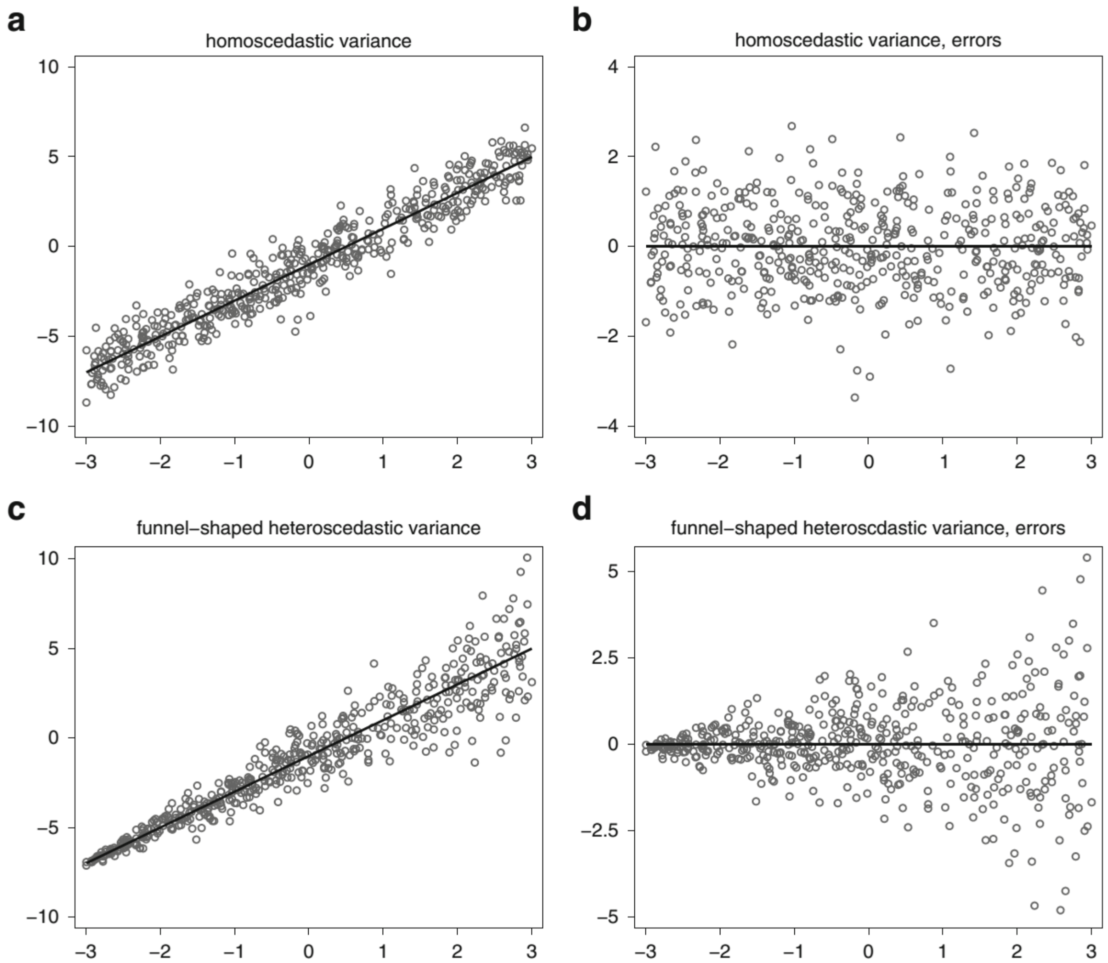


Figure 5 - Examples of homoscedastic and heteroscedastic variances. Homoscedasticity is shown in figure (a). A homoscedastic pattern may contain errors beyond the uniform pattern if related to the observed data (b). Heteroscedasticity is characterized by a 'fan-out' pattern (c and d) (Fahrmeir et al., 2013b).

If the scatter of the residuals should 'fan-out' (Figure 5c & d) without relation of errors in observed data, the assumption of homoscedasticity is violated. (Dekking et al., 2005a); (Verbeek, 2017). Violation of the homoscedasticity assumption may have a negative effect on the accuracy of determined regression coefficient (Fahrmeir et al., 2013b).

(4) Assumption for absence of Autocorrelation – Autocorrelation, or serial correlation, exists if there is a (linear or higher order) relation between two consecutive regression residuals (Fahrmeir et al., 2013c). The Durbin-Watson test was applied to test for autocorrelation of the residuals, with hypotheses:

H_o: residuals are not autocorrelated
H_1: residuals are autocorrelated

The Durbin-Watson variable (d) is defined as:

$$d = \frac{\sum_{i=2}^{n}(\hat{\varepsilon}_i - \hat{\varepsilon}_{i-1})^2}{\sum_{i=1}^{n}\hat{\varepsilon}_i^{\,2}}$$

With: n = number of samples ('samples' as statistic term)

$\hat{\varepsilon}_i$ = residual of i^{th} sample

The value of (d) ranges from 0…4. Values close to d=0 or close to d=4 are a strong indication for autocorrelation of residuals and the null- hypothesis is rejected. The residuals are considered not autocorrelated for values close to d=2 and the null hypothesis is accepted. The interpretation of the Durbin-Watson variable may however be indecisive if the d-value is not close to 0, 2 or 4 (Fahrmeir et al., 2013c). Therefore a rule of thumb was applied for interpretation. The residuals were considered not autocorrelated if variable (d) ranged between 1.5 and 2.5 (University of Texas, 2020). The residuals were considered autocorrelated if variable (d) was close to d=0 or d=4. For other values of (d) the Durbin-Watson test was considered inconclusive. Violation of the autocorrelation assumption may be an indication that the model is not linear. Or it may be an indication that an explanatory variable is missing (Fahrmeir et al., 2013c).

Use of R-squared in this report

R-squared (R^2) defines the fraction of change of the dependent variable (for example: Aeromonas), that can be explained from the change of the explanatory variable (for example: Temperature). R-squared (R^2) is calculated (Montgomery et al., 2012) by:

$$R^2 = 1 - \frac{Sum\ of\ squares\ from\ residual}{Sum\ of\ squares\ (regression + resididual)} =$$

The adjusted R-squared (adj.R^2) is used if multiple explanatory variables are applied. By correction for the degrees of freedom (Df) is possible to select the explanatory variables that result in smallest residual (Montgomery et al., 2012).:

$$adj.R^2 = 1 - \frac{(1-R^2)(Df_{total})}{Df_{residual}} = 1 - \frac{(1-R^2)(n-1)}{(n-k-1)}$$

Where k = degrees of freedom of regression (Df regression) = number of explanatory variables.

By default Python software presents both values in the regression results overview: R-squared (adj.R^2) and adjusted R-squared (R^2). In this research one explanatory variable (Df=1), temperature, is applied for assesment of Aeromonas and HPC. For Time series analysis Aeromonas and HPC are observed for change per 'year' and per 'season'. The OLS results do therefore indicate two separate explanatory variables (Df=2). The data for 'year' and 'season' do however origin from the same data (timestamp of sample). In this report the the value for adjusted R-squared (adj.R^2) will be presented.

2.2 Time series analysis

Several techniques exist to perform time series analysis (TSA). For this research "Seasonal and Trend decomposition using Loess" (STL) was applied. The moving average of measurement data was decomposed into Trend (m), Seasonality (s) and Residual (R) parts. STL was preferred due it its robustness if outliers occur. Besides it was considered suitable if there are variations in the seasonal part (Hyndman & Athanasopoulos, 2020). For correct interpretation the model type was determined first. The performed time series analysis in this study indicated Residuals (R) around zero and no pattern or similarities with the Trend (m). This implied that the additive model was applicable (Dettling, 2020):

$$X_t = m_t + s_t + R_t$$

The STL Python-plugin (version v0.11.1) by Statsmodels was applied for STL on the sample data. Alternative tools, based on the multiplicative model, would require prior transformation of data before use. This tool was by default programmed for an additive model. So prior transformation of data was not required (Seabold et al., 2010). The algorithm of autoregressive moving average (MA) was used for decomposition of data into a seasonal component and averaged trend (Shumway & Stoffer, 2017).

$$X_t = \varphi_1 x_{t-1} + \cdots + \varphi_2 x_{t-2} + \varphi_p x_{t-p} + w_t$$

This algorithm is founded on the assumption that the prediction of actual value (X_t) is based om a number (p) historical values ($X_{t-\ldots}$). The w_t term represents the normal distributed noise (Shumway & Stoffer, 2017). The length of the seasonal period within the dataset (i.e. 12 months) was determined automatically by the applied plugin. This setting was not overruled.

2.3 T-tests

From tests on measurement datasets it was noted that the distribution of Aeromonas and HPC are rather skewed and the Temperature was considered not skewed. The cause and implications of this skewness are discussed later is this report. From statistical point of view it is questionable what methods are legitimate for significance testing of skewed data.

For the Student one-sample t-test the following formula (Dekking et al., 2005b) is applied:

$$t = \frac{\overline{x_n} - \mu_0}{s_n/\sqrt{n}}$$ With null hypothesis H_o: $\mu = \mu_0$

The Student one-sample t-test does however assume a normal distribution (Dekking et al., 2005b). Research from Boneau (1960) does however indicate that the Student one-sample t-test is still applicable under skew conditions if the sample size is large. For comparison of two data sets, the 'Student independent samples t-test' is considered (Dekking et al., 2005b). This test does also assume a normal distribution of data. Non-parametric tests were considered as an alternative. Non-parametric tests are not related to a specific probability distribution. But by (Fagerland, 2012) it was discussed that non-parametric tests should not replace t-tests, for large and highly skewed sample populations. Moreover it was argued that the difference in population size is more important than the inequality variances, for the accuracy of the significance level of the t-test (Zimmerman, 2004). From this last study it was even discouraged to use a selective test in advance of the t-test to check for unequal variances. It was recommended to directly use the Welch's t-test for unequal sized populations. These recommendations were applied for this study. Student t-test was used for equal sized sample populations and Welch's t-test was used for skewed and unequal sample populations. This resulted in a set of rules for t-test selection in this research:

Temperature dataset & comparing dataset with equal population → Student's t-test

Temperature dataset & comparing dataset with unequal population → Welch's t-test
Aeromonas data or HPC data is (almost) always askew → Welch's t-test

For the Student independent samples t-test the following formula (Dekking et al., 2005b) is applied:

$$t = \frac{\overline{x_n} - \overline{y_m}}{S_p} \qquad \text{With } S_p = \sqrt{\frac{(n-1)S_x^2 + (m-1)S_y^2}{n+m-2}\left(\frac{1}{n} + \frac{1}{m}\right)} \quad \text{and null hypothesis } H_o\text{: } \mu_1 = \mu_2$$

For the Welch's independent samples t-test the following formula (Dekking et al., 2005b); (Derrick et al., 2016) is applied:

$$t = \frac{\overline{x_n} - \overline{y_m}}{S_d} \qquad \text{With } S_d = \sqrt{\frac{S_x^2}{n} + \frac{S_y^2}{m}} \quad \text{and null hypothesis } H_o\text{: } \mu_1 = \mu_2$$

2.4 Outlier analysis

Analysis of outlier values in data is required to determine whether or not a perceived extreme value in the dataset should be excluded for further analysis. Data in this research is tested for outliers with the Tukey outlier test (Aggarwal, 2017). This test is analogue with the key components for the Tukey box plot. The upper and lower boundary for determination corresponds with the whiskers in the box plot. The upper and lower boundary for outliers are therefore defined by:

$$Lower\ boundary = q1 - k * (q3 - q1) = \ q1 - k * IQR$$

$$Upper\ boundary = q3 + k * (q3 - q1) = \ q3 + k * IQR$$

With: q1 = quartile 1
q3 = quartile 3
IRQ = Inter-quartile range
k = factor for whisker range

For uniform distributions k=1.5. The allocation of whiskers is however arbitrary (Aggarwal, 2017). Higher values for k are applied to observe skewed datasets (Songwon, 2006).

3 Results

The results section consists of five subsections for: Initial data analysis (§3.1); Initial spatial analysis (§3.2); Focal Areas observations (§3.3); Observation of net Temperature and Aeromonas change during transport, for the focal Areas (§3.4) and Observation of net Temperature and Aeromonas change during transport, for the total DWDS (§3.5).

3.1 Results from initial data analysis

In this sub-section most relevant findings from initial data exploration are outlined. §3.1.1 contains a brief look on the distribution of data. §3.1.2 presents the analysis on correlation between Temperature and quality indicating parameters for both DWDSs. Based on the correlation results, the measurement values were observed in time by time series analysis (§3.1.3).

3.1.1 Data distribution and outliers

For correct interpretation of results a statistical inventory was done on measurement data. All measurements were included regardless the composition of samples. (For clarification on composition on samples refer to §1.4.1 and Figure 3.) Cumulative distribution functions of Aeromonas and HPC (Figure 6 & Appendix 1) indicated a very small fraction of samples in exceedance of national drinking water standards.

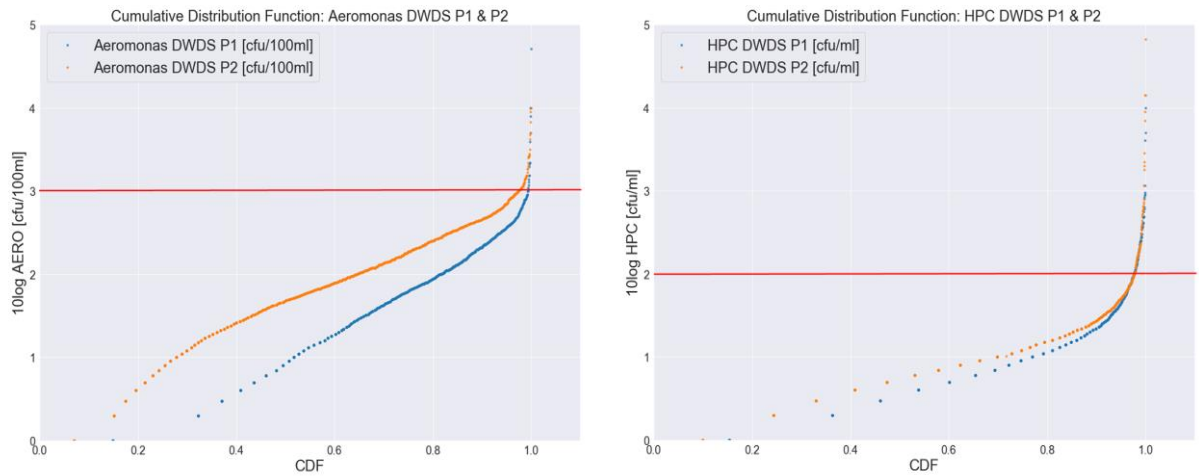


Figure 6 - Cumulative distribution function of Aeromonas (cfu/100ml) samples of DWDS P1 and P2 (left). Cumulative distribution function of HPC (cfu/ml) samples of DWDS P1 and DWDS P2 (right). Red line indicates drinking water standard for Aeromonas and HPC.

From Figure 6 it was also observed that Aeromonas measurement values ranged from 0 to 52000 cfu/100ml. While about 80% of the measurement values was lower than ~300 cfu/100ml. HPC measurement values ranged from 0 to 67200 cfu/ml. While about 80% of the measurement values was lower than ~16 cfu/100ml. The distribution of Aeromonas and HPC measurement values is therefore not symmetric but rather skew (Dean & Illowsky, 2013). Temperature, Aeromonas and HPC measurements were tested for outliers with the Tukey outlier test. This test is described in §2.4. Due to the skew distribution of Aeromonas and HPC values, the Tukey outlier test is performed with k=3. This resulted in a wider range between the upper and lower boundary for outliers. Despite this adaption, still a large number of outliers resided within the acceptance limits of Dutch regulations. These outlier values were however considered plausible for DWDS samples. Especially considering the release of loose deposits from the piping (Liu et al., 2017); (ILT, 2019). Besides, the outlier values did not exceed the maximum measurement range of laboratory analysis and counting methods (KWR, 2018); (Hallas & Monis, 2015). Outlier values were therefore not excluded before analysis. A single extreme high Aeromonas and HPC value might not be accurate, but does provide a possible clue for extra attention. Concluding, it was considered important to handle data with care and observe extreme values in context of time and space to avoid erroneous conclusions (Gensberger et al., 2015).

3.1.2 Correlation between Temperature and Quality indicating parameters within both DWDSs

Note:
The denotation and use of adjusted R^2 (adj.R^2) is explained in §2.1.

Temperature and Aeromonas DWDS samples.
OLS regression tests on from DWDS P1 indicated a significant correlation between all Temperature and Aeromonas measurements (*adj.R^2=0.732; p=0.000*) (Figure 7, left & Appendix 3). This significant correlation was also observed when the test was restricted to the samples with combined Temperature and Aeromonas measurements (*adj.R^2=0.751; p=0.000*).

OLS regression tests on from DWDS P2 indicated a significant correlation between all Temperature and Aeromonas measurements (*adj.R^2=0.785; p=0.000*) (Figure 7, right & Appendix 3). This significant correlation was also observed when the test was restricted to the samples with combined Temperature and Aeromonas measurements (*adj.R^2=0.756; p=0.000*).

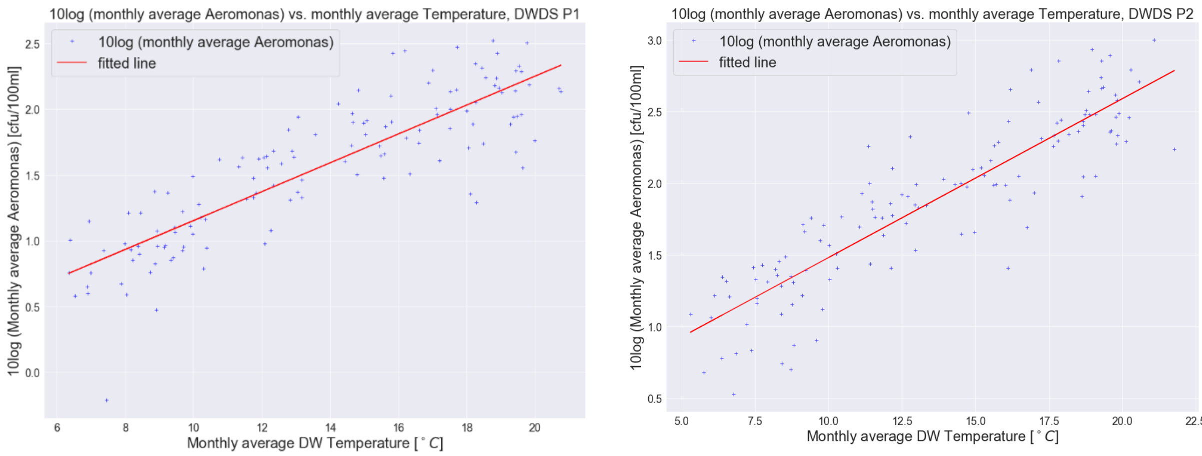


Figure 7 - Correlation between ^{10}log (monthly average Aeromonas) (cfu/100ml) and monthly average Temperature (°C) of all samples from DWDS P1 (left) and DWDS P2 (right).

OLS assumptions.
The OLS regression results for correlation between Temperature and Aeromonas measurements from DWDS P1 and DWDS P2 are presented in Appendix 3. Validation tests for OLS regression assumptions are described in §2.1. Both residual plots (Figure 45 and Figure 48, 'residuals versus x') indicated a homoscedastic pattern. The assumption of homoscedasticity was therefore confirmed. The Durbin-Watson test was used to verify the absence of autocorrelation of residuals (Figure 44 and Figure 47). The outcome of this test was however inconclusive for DWDS P1 (d = 1.233) and for DWDS P2 (d = 1.008). Autocorrelation of residuals was therefore not confirmed or ruled out. A possible violation of the autocorrelation assumption may be an indication that the model is not linear. Or it may be an indication that an explanatory variable is missing (Fahrmeir et al., 2013c).

Results for Ordinary Least Squares on Temperature and HPC DWDS samples.

OLS regression tests on from DWDS P1 indicated a significant correlation between all Temperature and HPC measurements. (*adj.*R^2*=0.091; p=0.000*) (Figure 8, left & Appendix 4). This significant correlation was also observed when the test was restricted to the samples with combined Temperature and HPC measurements (*adj.*R^2*=0.083; p=0.000*).

OLS regression tests on from DWDS P2 indicated a significant correlation between all Temperature and HPC measurements (*adj.*R^2*=0.102; p=0.000)* (Figure 8, right & Appendix 4). This significant correlation was also observed when the test was restricted to the samples with combined Temperature and HPC measurements (*adj.*R^2*=0.103; p=0.000*).

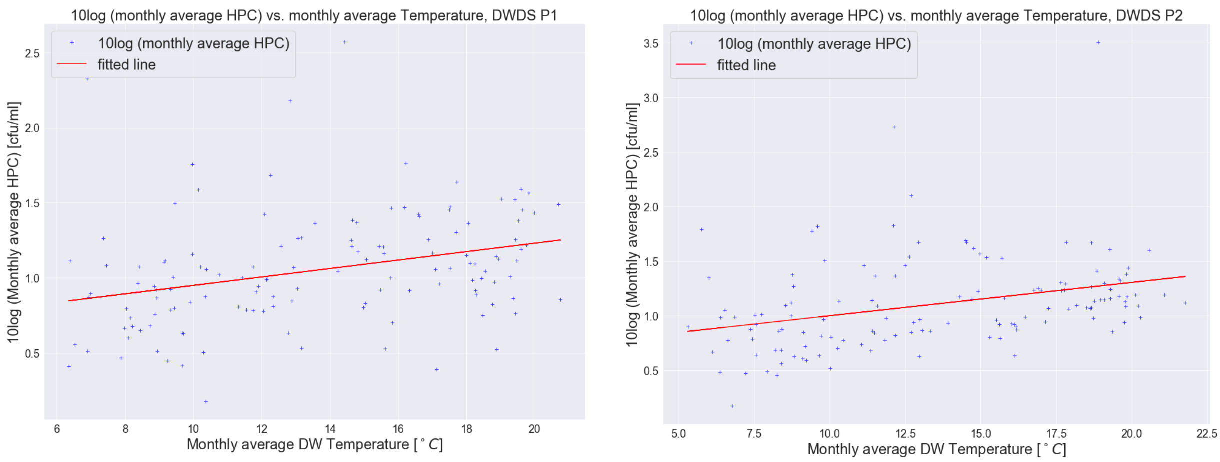


Figure 8 - Correlation between 10log (monthly average HPC) (cfu/ml) and monthly average Temperature (°C) of all samples from DWDS P1 (left) and DWDS P2 (right).

OLS assumptions.

The OLS regression results for correlation between Temperature and HPC measurements from DWDS P1 and DWDS P2 are presented in Appendix 4. Validation tests for OLS regression assumptions are described in §2.1. Both residual plots (Figure 51 and Figure 54, 'residuals versus x') indicated a homoscedastic pattern. The assumption of homoscedasticity was therefore confirmed. The Durbin-Watson test was used to verify the absence of autocorrelation of residuals (Figure 50 and Figure 53). This test indicated the absence of autocorrelation for DWDS P1 (d = 1.534) and for DWDS P2 (d = 1.774). The assumption on the absence of autocorrelation of residuals was therefore confirmed.

Discussion on correlation of Temperature with Aeromonas and HPC DWDS samples.

Caution was considered for interpretation of observed correlation. The correlation model did not include other explanatory variables influencing microbial growth, such as: Network material, deposits from biofilm dynamics or residence time (Prest et al., 2016b). Besides, the Aeromonas and HPC measurements showed a very skew distribution. These arguments supported the assumption that the true origin behind the correlation between Temperature and quality indicating parameters of DWDS measurements was not fully understood.

From comparison of OLS results, it was observed that the adj.R^2 for HPC is much lower than for Aeromonas. This implied that, compared with Aeromonas, a much smaller fraction of the HPC values can be explained from corresponding temperature values. The linear coefficient value for temperature variable is presented in the OLS regression results as: 'coef' for variable 'x' (Appendix 3 and Appendix 4). This value indicated a smaller influence of Temperature on HPC DWDS measurements than on Aeromonas DWDS measurements. Comparison of OLS results for DWDS P1 and DWDS P2 showed no major difference of correlation between DWDS Temperature and indicating parameters. Due to mentioned arguments for caution on interpretation were the correlations between DWDS Temperature and indicating parameters interpreted as coarse estimates. The skew distribution of samples did suggest temporal and spatial influences.

3.1.3 Time series analysis on Temperature and Quality indicating parameters

Correlations between DWDS Temperature and indicating parameters (§3.1.2) indicated a skew distribution of Aeromonas and HPC DWDS samples. As explained by Liu et al. (2016) indicating parameters of DWDS samples are not constant in time and also dependent on position within the DWDS (Liu et al., 2016). This could be a possible reason for the observed skew distribution within this research. Therefore the temporal and spatial effects were explored first. This paragraph will focus on the time series analysis, i.e. change of temperature and indicating parameters in time.

3.1.3.1 Time series analysis on Temperature

Time series analysis for Temperature of reservoirs P1 and P2.

Time series analyses on Temperature measurements from clean water reservoirs P1 and P2 are shown in Figure 9. Full details for this time series are presented in Appendix 5.

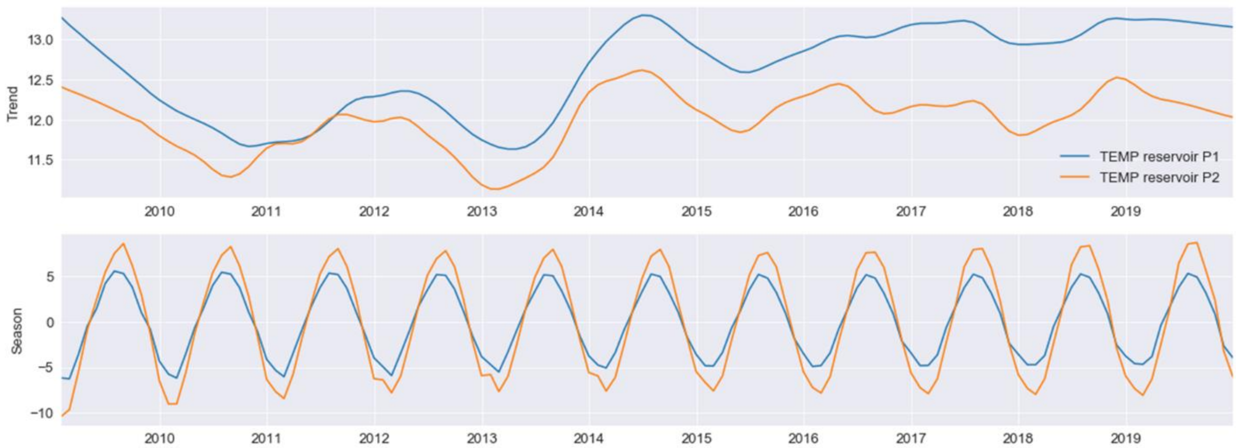


Figure 9 - Time series analysis for Temperature (°C) of clean water in reservoirs of treatment facilities P1 (blue) and P2 (orange). With: Trend components (upper plot) and Seasonal components (lower plot).

Trend lines (upper plot of Figure 9) indicate the change of long term mean temperature for reservoirs P1 and P2. The seasonal plot (lower plot of Figure 9) indicates the monthly change within the seasonal temperature patterns for reservoirs P1 and P2. The seasonal plot represents the monthly change around the mean, as if the trend component is removed from original data. OLS results indicated a significant temperature increase within samples from clean water reservoir P1 (+0.12 +/- (1.96*0.021) °C/year, *p=0.000*). Temperature increase within samples from clean water reservoir P2 was not significant (*p=0.061*).

From the Welch's t-test on actual Temperature measurements from clean water reservoirs P1 and P2, it was observed that the average clean water temperature of reservoirs P1 and P2 were significantly different (p=0.024). From the Student's t-test on monthly average of Temperature measurements from clean water reservoirs P1 and P2, it was observed that the average clean water temperature of reservoirs P1 and P2 were not significantly different (p= 0.295).

OLS assumptions.

The OLS regression results are presented in Appendix 5. Validation tests for OLS regression assumptions are described in §2.1. The residual plots (Figure 56 and Figure 57, 'residuals versus year' and 'season') indicated a homoscedastic pattern. The assumption of homoscedasticity was therefore confirmed. The Durbin-Watson test was used to verify the absence of autocorrelation of residuals. The outcome of this test was however inconclusive for reservoir P1 (d = 1.246) and reservoir P2 (d = 1.159). Autocorrelation of residuals was therefore not confirmed or ruled out.

Time series analysis for Temperature of DWDS P1 and P2.

Time series analyses on Temperature measurements from DWDS P1 and P2 are shown in Figure 10. Full details for this time series are presented in Appendix 6.

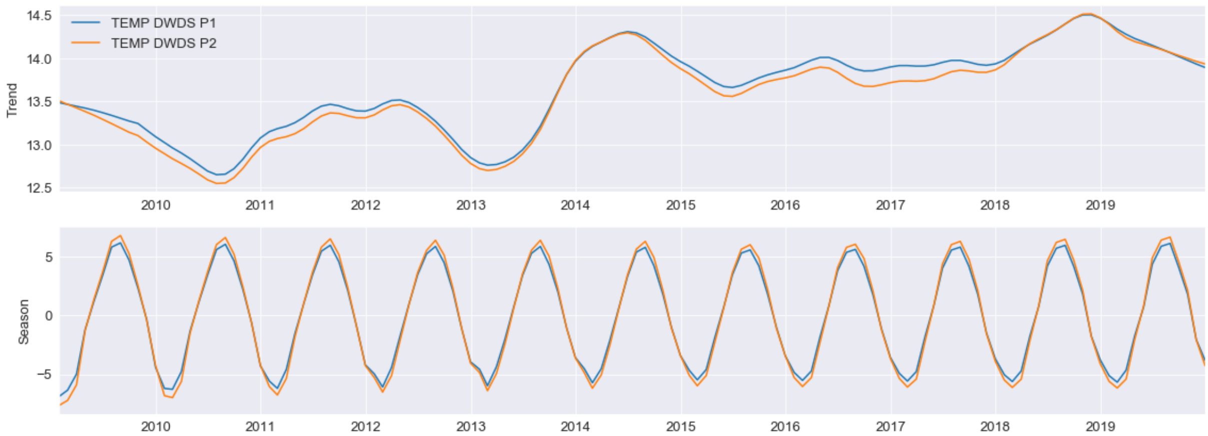


Figure 10 - Time series analysis for Temperature (°C) of DWDS P1 (blue) and DWDS P2 (orange). With: Trend components (upper plot) and Seasonal components (lower plot).

Trend lines (upper plot of Figure 10) indicate the change of long term mean temperature for DWDS P1 and P2. The seasonal plot (lower plot of Figure 10) indicates the monthly change within the seasonal temperature patterns for DWDS P1 and P2. The seasonal plot represents the monthly change around the mean, as if the trend component is removed from original data. OLS results indicated a significant Temperature increase within samples from DWDS P1 (+0.12 +/- (1.96*0.02) °C/year, *p=0.000)*. Temperature increase within samples from DWDS P2 was also significant. (+0.13 +/- (1.96*0.022) °C/year, *p=0.000*).

From the Welch's t-test on actual Temperature measurements from DWDS P1 and P2, it was observed that the average water temperature within DWDS P1 and P2 were not significantly different (*p= 0.108*). From the Student's t-test on monthly average Temperature measurements from DWDS P1 and P2, it was also observed that the average water temperature within DWDS P1 and P2 were not significantly different (*p= 0.885*).

OLS assumptions.

The OLS regression results are presented in Appendix 6. Validation tests for OLS regression assumptions are described in §2.1. The residual plots (Figure 59 and Figure 60, 'residuals versus year' and 'season') indicated a homoscedastic pattern. The assumption of homoscedasticity was therefore confirmed. The Durbin-Watson test was used to verify the absence of autocorrelation of residuals. The outcome of this test was however inconclusive for DWDS P1 (d = 1.135) and DWDS P2 (d = 1.087). Autocorrelation of residuals was therefore not confirmed or ruled out.

Discussion on time series analysis for Temperature

Among the span of 11 years drinking water temperature in the clean water reservoirs and within the DWDSs is gradually increasing. The average increase is 0.12 to 0.13 °C/year. This increase was significant for clean water reservoir P1, DWDS P1 and DWDS P2. The increase was not constant in time. The trend lines of reservoir Temperature for both treatment facilities follow a similar pattern. The mutual distance between Temperature trend lines seems to narrow in after distribution. This does correspond with research that showed that the drinking water adopts the soil temperature during transport (Agudelo-Vera et al., 2015).

3.1.3.2 Time series analysis on Aeromonas

Time series analysis on Aeromonas samples from clean water reservoirs P1 and P2.

Time series analyses on Aeromonas measurements from clean water reservoirs P1 and P2 are shown in Figure 11. Full details for this time series are presented in Appendix 7.

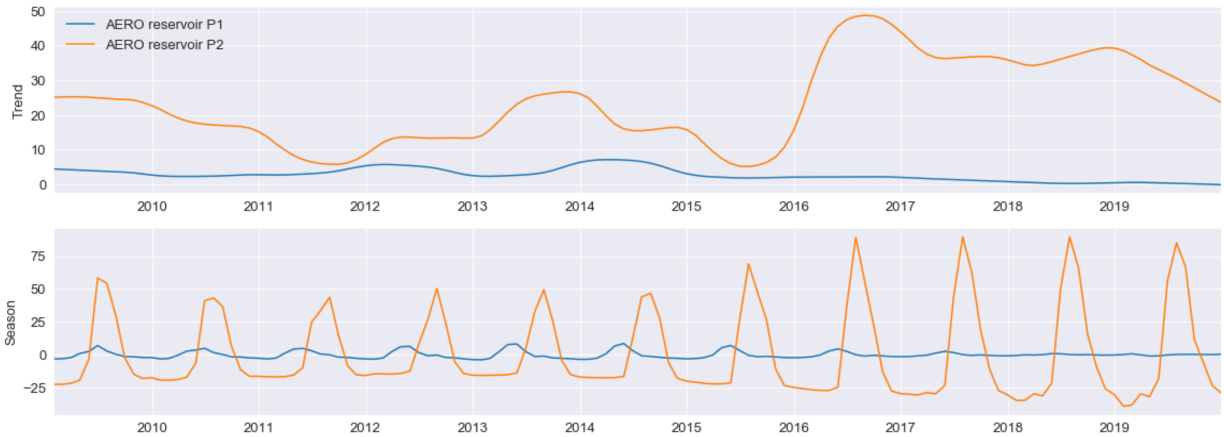


Figure 11 - Time series analysis for Aeromonas (cfu/100ml) of clean water in reservoirs of treatment facilities P1 (blue) and P2 (orange). With: Trend components (upper plot) and Seasonal components (lower plot).

Trend lines (upper plot of Figure 11) indicate the change of long term mean Aeromonas value in reservoirs P1 and P2. The seasonal plot (lower plot of Figure 11) indicates the monthly change within the seasonal patterns for mean Aeromonas value in reservoirs P1 and P2. The seasonal plot represents the monthly change around the mean, as if the trend component is removed from original data.

From the Welch's t-test on actual Aeromonas measurements from clean water reservoirs P1 and P2, it was observed that the average Aeromonas values within clean water reservoir P2 was significantly higher than reservoir P1 (*p=0.000*). From the Student's t-test on monthly average of Aeromonas measurements from clean water reservoirs P1 and P2, it was also observed that the average Aeromonas values within clean water reservoir P2 was significantly higher than reservoir P1 (*p= 0.000*).

OLS assumptions.

The OLS regression results are presented in Appendix 7. Validation tests for OLS regression assumptions are described in §2.1. The residual plots (Figure 62 and Figure 63, 'residuals versus year' and 'season') indicated a homoscedastic pattern, with errors related to the observed data. The assumption of homoscedasticity was therefore confirmed. The Durbin-Watson test was used to verify the absence of autocorrelation of residuals. The outcome of this test indicated at a strong suspicion for autocorrelation of residuals for: Reservoir P1 (d = 0.679) and reservoir P2 (d = 0.845). The assumption for absence of autocorrelation of residuals is therefore violated. Violation of the autocorrelation assumption may be an indication that the model is not linear. Or it may be an indication that an explanatory variable is missing

(Fahrmeir et al., 2013c). The OLS regression results from Aeromonas measurements from clean water reservoirs P1 and P2 are therefore considered not accurate and not further evaluated.

Time series analysis on Aeromonas samples from DWDS P1 and P2.

Time series analyses on Aeromonas measurements from DWDS P1 and P2 are shown in Figure 12. Full details for this time series are presented in Appendix 8.

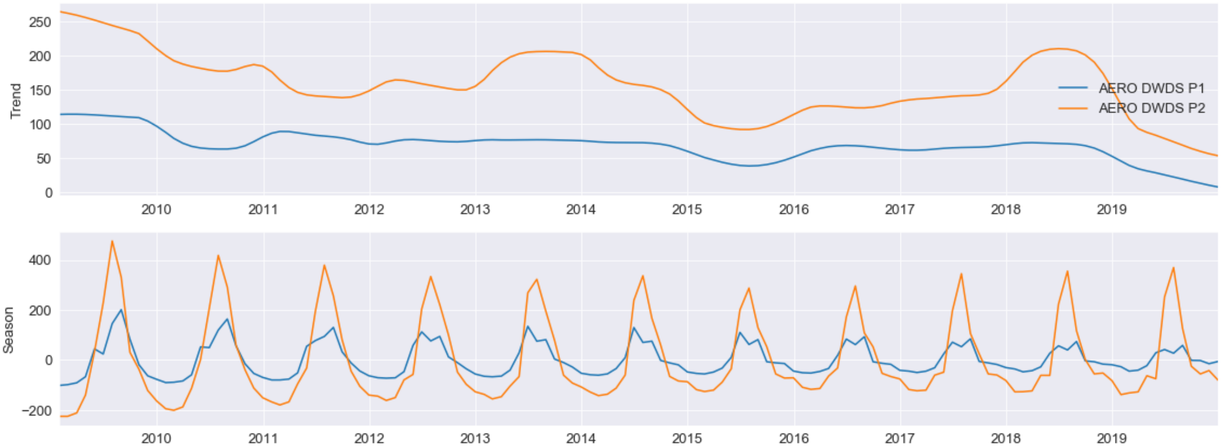


Figure 12 - Time series analysis for Aeromonas (cfu/100ml) of DWDS P1 (blue) and DWDS P2 (orange). With: Trend components (upper plot) and Seasonal components (lower plot).

Trend lines (upper plot of Figure 12) indicate the change of long term mean Aeromonas value in DWDS P1 and P2. The seasonal plot (lower plot of Figure 12) indicates the monthly change within the seasonal patterns for mean Aeromonas value in DWDS P1 and P2. The seasonal plot represents the monthly change around the mean, as if the trend component is removed from original data. OLS results indicated a significant Aeromonas decrease within samples from DWDS P1 (-5 +/- (1.96*1.192) cfu/100ml/year, *p=0.000*). Aeromonas decrease within samples from DWDS P2 was also significant (-8 +/- (1.96*2.957) cfu/100ml/year, *p=0.000*).

From the Welch's t-test on actual Aeromonas measurements from DWDS P1 and P2, it was observed that the average Aeromonas value of DWDS P2 was significantly higher than DWDS P1 (*p=0.000*). From the Student's t-test on monthly average of Aeromonas measurements from DWDS P1 and P2, it was also observed that the average Aeromonas value of DWDS P2 was significantly higher than DWDS P1 (*p= 0.000*).

OLS assumptions.

The OLS regression results are presented in Appendix 8. Validation tests for OLS regression assumptions are described in §2.1. The residual plots (Figure 66 and Figure 67, 'residuals versus year' and 'season') indicated a homoscedastic pattern, with errors related to the observed data. The assumption of homoscedasticity was therefore confirmed. The Durbin-Watson test was used to verify the absence of autocorrelation of residuals. The outcome of this test was however inconclusive for DWDS P1 (d = 1.395) and DWDS P2 (d = 1.394). Autocorrelation of residuals was therefore not confirmed or ruled out.

Discussion on time series analysis for Aeromonas

The seasonal part of Aeromonas time series indicated a clear yearly pattern of yearly maxima in the summer and yearly minima during winter. This seasonality of Aeromonas concentrations corresponds previous research on Dutch DWDS's (Holmes et al., 1996). Both trend lines for Aeromonas of reservoirs P1 and P2 were rather flat. The average Aeromonas value was of reservoir P2 was significantly higher than reservoir P1. The average Aeromonas value was of DWDS P2 was also significantly higher than DWDS P1. In addition showed both DWDSs a significant decline of average Aeromonas values. The presence of a sudden change in the trend would have been an indication for possible changing dependency, in time (Dettling, 2020). The trend of Aeromonas value was varying in time, but a structural break or change in the trend was not observed. Therefore it was considered that the skew distribution of Aeromonas samples did not seem to be related to a structural change among the observed time span of 11 years.

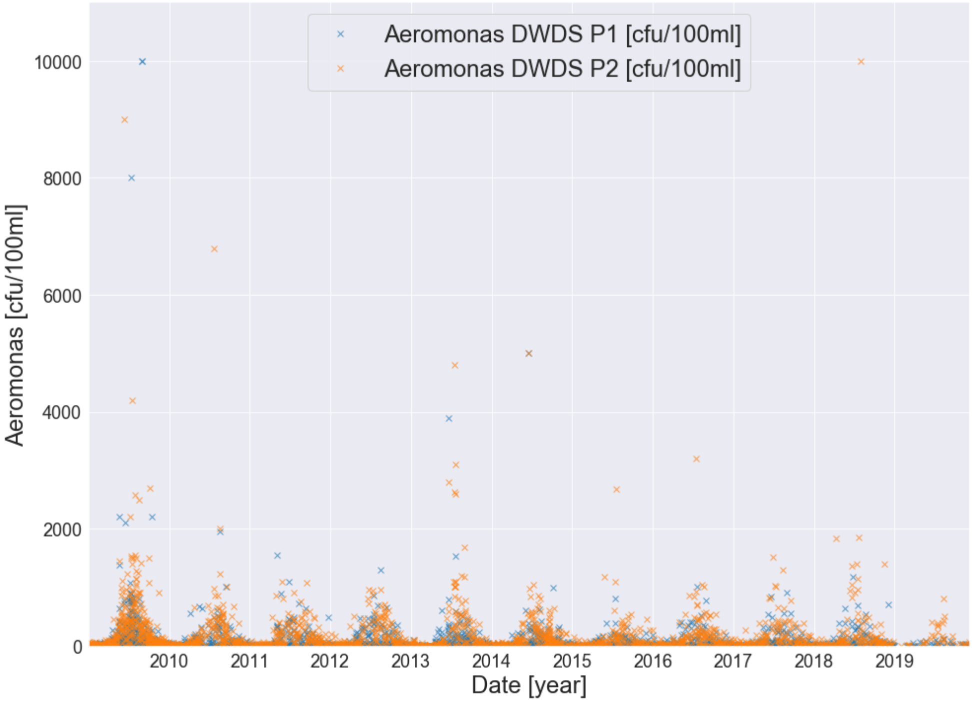


Figure 13 - Aeromonas (cfu/100ml) samples of DWDS P1 (blue) and P2 (orange)[2].

From combined projection of Aeromonas samples values for DWDS P1 and DWDS P2, the skew distribution of Aeromonas samples seemed to be related to the elevated samples values in the summer periods (Figure 13). It is however considered that further spatial observations are required in attempt to trace for the origin or cause of elevated Aeromonas values.

[2] One DWDS sample with Aeromonas = 50000 cfu/100ml is removed from plot.

3.1.3.3 Time series analysis on HPC

Time series analysis on HPC samples from clean water reservoirs P1 and P2.

Time series analyses on HPC measurements from clean water reservoirs P1 and P2 are shown in Figure 14. Full details for this time series are presented in Appendix 9.

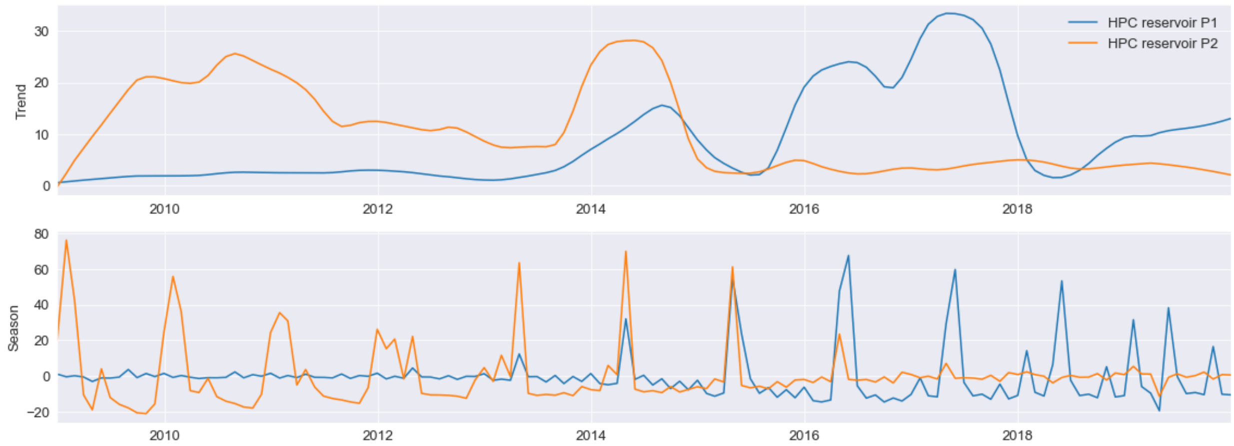


Figure 14 - Time series analysis for HPC (cfu/ml) of clean water in reservoirs of treatment facilities P1 (blue) and P2 (orange). With: Trend components (upper plot) and Seasonal components (lower plot).

Trend lines (upper plot of Figure 14) indicate the change of long term mean HPC value in reservoirs P1 and P2. The seasonal plot (lower plot of Figure 14) indicates the monthly change within the seasonal patterns for mean HPC value in reservoirs P1 and P2. The seasonal plot represents the monthly change around the mean, as if the trend component is removed from original data. OLS results indicated a not significant yearly change of HPC value within samples from clean water reservoir P1 (*p=0.091*). The HPC decrease within samples from reservoir P2 was significant (-1.9 +/- (1.96*0.802) cfu/ml/year, *p=0.018*).

From the Welch's t-test on actual HPC measurements of clean water reservoirs P1 and P2, it was observed that the average HPC values within clean water reservoirs P1 and P2 were not significantly different (*p=0.185*). From the Student's t-test on monthly average of HPC measurements from clean water reservoirs P1 and P2, it was observed that the average HPC values within clean water reservoirs P1 and P2 were also not significantly different (*p= 0.524*).

OLS assumptions.

The OLS regression results are presented in Appendix 9. Validation tests for OLS regression assumptions are described in §2.1. The residual plots (Figure 69 and Figure 70, 'residuals versus year' and 'season') indicated a homoscedastic pattern. The assumption of homoscedasticity was therefore confirmed. The Durbin-Watson test was used to verify the absence of autocorrelation of residuals. This test indicated the absence of autocorrelation for Reservoir P1 (d = 2.086) and Reservoir P2 (d = 1.850). The assumption on the absence of autocorrelation of residuals was therefore confirmed.

Time series analysis on HPC samples from DWDS P1 and P2.

Time series analyses on HPC measurements from DWDS P1 and P2 are shown in Figure 15. Full details for this time series are presented in Appendix 10.

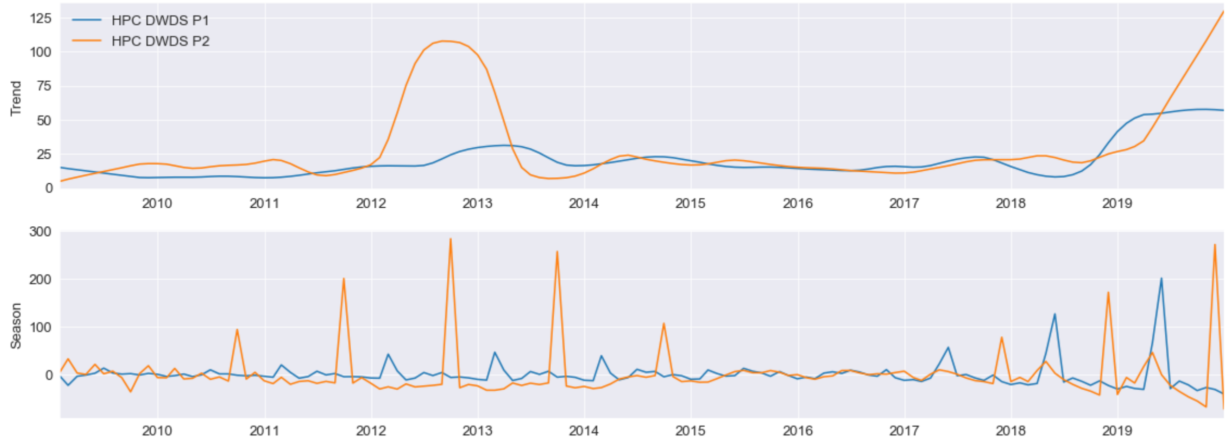


Figure 15 - Time series analysis for HPC (cfu/ml) of DWDS P1 (blue) and DWDS P2 (orange). With: Trend components (upper plot) and Seasonal components (lower plot).

Trend lines (upper plot of Figure 15) indicate the change of long term mean HPC value in DWDS P1 and P2. The seasonal plot (lower plot of Figure 15) indicates the monthly change within the seasonal patterns for mean HPC value in DWDS P1 and P2. The seasonal plot represents the monthly change around the mean, as if the trend component is removed from original data. OLS results indicated a significant yearly increase of HPC value within samples from clean water DWDS P1 (2 +/- (1.96*1.024) cfu/ml/year, *p=0.028*). The HPC change within samples from DWDS P2 was not significant. (*p=0.683*).

From the Welch's t-test on actual HPC measurements from DWDS P1 and P2, it was observed that the average HPC values within DWDS P1 and P2 were not significantly different (*p=0.100*). From the Student's t-test on monthly average of HPC measurements from DWDS P1 and P2, it was observed that the average HPC values within DWDS P1 and P2 were also not significantly different (*p= 0.318*).

OLS assumptions.

The OLS regression results are presented in Appendix 10. Validation tests for OLS regression assumptions are described in §2.1. The residual plots (Figure 73 and Figure 74, 'residuals versus year' and 'season') indicated a homoscedastic pattern. The assumption of homoscedasticity was therefore confirmed. The Durbin-Watson test was used to verify the absence of autocorrelation of residuals. This test indicated the absence of autocorrelation for Reservoir P1 (d = 1.609) and Reservoir P2 (d = 2.019). The assumption on the absence of autocorrelation of residuals was therefore confirmed.

Discussion on time series analysis for HPC

Analysis of HPC values in time did not provide a clear trend or seasonal pattern. The adj.R^2 values for HPC in the DWDS (adj.$R^2 < 0.1$) are considered low in comparison with adj.R^2 values for Aeromonas in the DWDS (adj.R^2 ~0.6 … 0.7). The contribution of drinking water Temperature change to the change of HPC value in the DWDS is therefore considered smaller in comparison with contribution of the change of Aeromonas value in the DWDS.

The small seasonal variation of HPC value corresponds with observations from chlorinated DWDS's in Poland (Siedlecka et al., 2020). Better comparison with an unchlorinated DWDS is sought but not found. In contradiction with time series observations on Aeromonas, there was no possible clue for observed skew distribution of HPC values within DWDSs. Elevated HPC values (HPC > 100 cfu/ml) were not restricted or focussed on a period in the observed time span of 11 years.

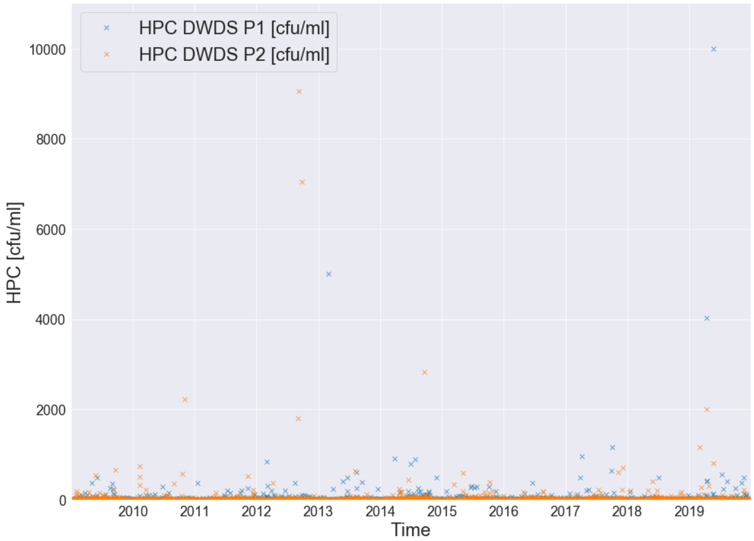


Figure 16 - HPC (cfu/ml) samples of DWDS P1 (blue) and DWDS P2 (orange)[3] *.*

Moreover, from combined projection of HPC samples values of DWDS P1 and DWDS P2 no clear relation between the HPC values and seasonal changes was observed (Figure 16). In contrast with Aeromonas the elevated HPC values occurred throughout the year. This did correspond with the observation on weak correlation between HPC and Temperature. Spatial observations were considered to possibly trace the origin or a cause for the elevated HPC values.

[3] Three DWDS samples with HPC > 10000 cfu/ml are removed from plot. Argumentation for removal is presented in Appendix 10.

3.1.3.4 Time Series Analysis summary of results.

A summary of the results from §3.1.3.1 to 3.1.3.3 is presented in Table 1.

Table 1 - Summary of time series analyses.

Parameter	Compare P1 and P2	Trend coefficient (95% CI)	p-value (95%)[*1]
Temperature			
Reservoir P1 & P2	N.S. different		p = 0.295
Reservoir P1		+0.12 (+/- 1.96*0.021) °C/year	p = 0.000
Reservoir P2		N.S.	p = 0.061
DWDS P1 & P2	N.S. different		p = 0.885
DWDS P1		+0.12 (+/- 1.96*0.020) °C/year	p = 0.000
DWDS P2		+0.13 (+/- 1.96*0.022) °C/year	p = 0.000
Aeromonas			
Reservoir P1 & P2	Significantly different (P2>P1)		p = 0000
Reservoir P1		Invalid due to violation of OLS assumptions	
Reservoir P2		Invalid due to violation of OLS assumptions	
DWDS P1 & P2	Significantly different (P2>P1)		p = 0.000
DWDS P1		-5 (+/- 1.96*1.192) cfu/100ml/year	p = 0.000
DWDS P2		-8 (+/- 1.96*2.957) cfu/100ml/year	p = 0.000
HPC			
Reservoir P1 & P2	N.S. different		p = 0.524
Reservoir P1		N.S.	p = 0.091
Reservoir P2		-1.9 (+/- 1.96*0.802) cfu/ml/year	p = 0.018
DWDS P1 & P2	N.S. different		p = 0.318
DWDS P1		+2 (+/- 1.96*1.024) cfu/ml/year	p = 0.028
DWDS P2		N.S.	p = 0.683

1) Two sided p-value

3.2 Initial Spatial Analysis

For spatial analysis, the measurement data for Temperature, Aeromonas and HPC were projected on heatmaps. A heatmap is a tool to observe data from a dataset in context of the geographic origin of data. A heatmap may be an assist to observe spatial differences in observed dataset. The heatmaps in this section are prepared for visualisation of spatial differences or similarities among measurements. In §3.2.1 the applied method is explained along with its advantages and options for improvement. Paragraph §3.2.1.2 contains an explanatory on how the optimum balance between resolution and suitability for analysis was explored.

3.2.1 Methodology Initial Spatial Analysis

In this part of spatial analysis heatmaps are constructed from a similar principle as recently used by Laurens Van Den Bos (2020). A heatmap was constructed based on measurements within overlapping geographical circles. This principle was adapted to better suit with the dataset. Additionally, significant data was projected on a geographic map for better interpretation of results. In later phase of this thesis a variation on this method was required. Therefore an alternative method was explored and applied in §3.5.1.

3.2.1.1 Original circular method

In the original circular method (Van Den Bos, 2020) a geographic frame was made (in Python) between south-west and north-east extend of observed measurements. In addition to the original method, the frame was made adjustable to focus on the sample locations of interest (Figure 17). Circular areas were defined within the geographic frame. Mutual orthogonal distance of two adjacent circle-centres was equal to the radius of the circles (Figure 18).

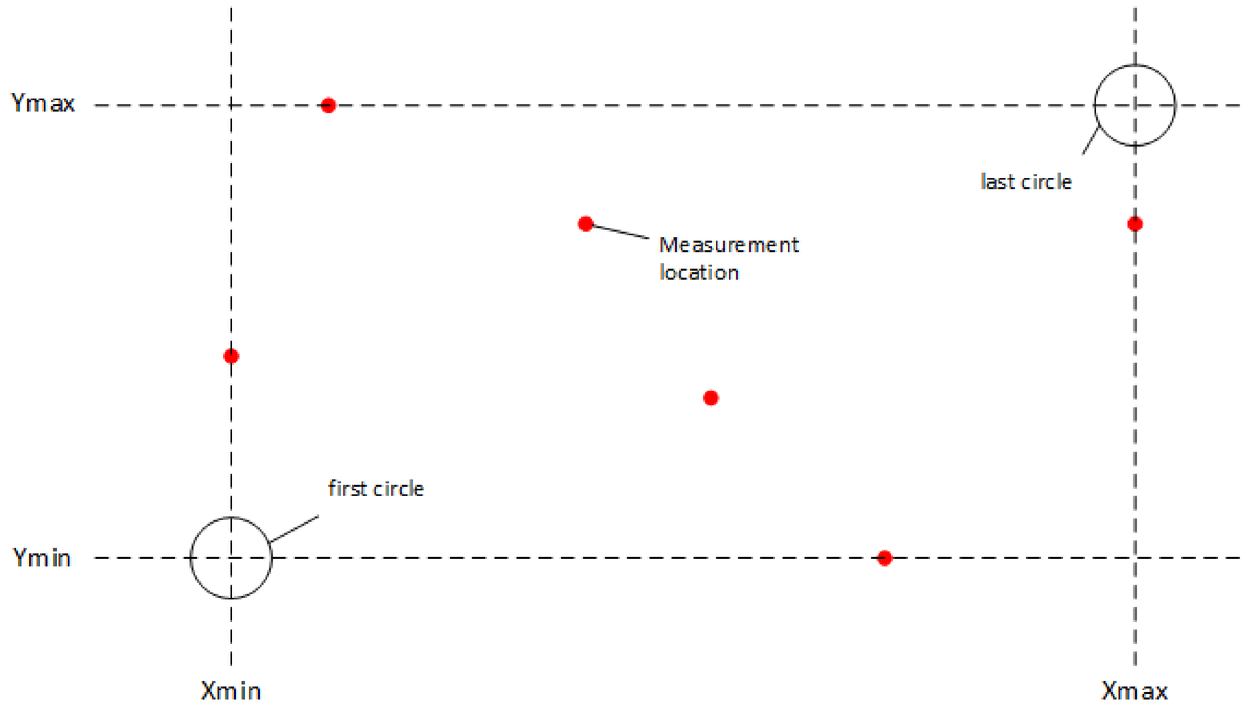


Figure 17 – Sketch: Geographic frame for construction of heatmaps with circular method.

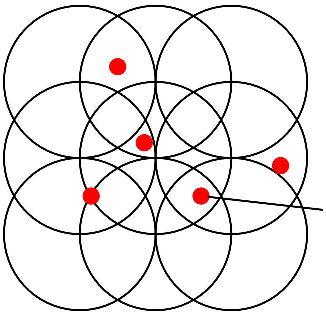


Figure 18 - Sketch: Measurement locations within framework of observation circles.

Adjustment of circle radius influenced both resolution of the heatmap and number of measurements within each circle. A new matrix was constructed from the (average, min, max or 'other characteristic') of measurement values within each circle. From this matrix of circle-values the heatmap was built. So, the circular method resulted in a heatmap with squared pixels. The x- and y- coordinates of the heatmap were non-informative as it represented the number of pixels in x- and y- direction. Therefore an overlay was provided for indicative projection of data. Depending on the observation window, heatmaps might contain 'gaps' if corresponding pixels contained no information. Gaps exist if (1) DWDS was out of range, or (2) in absence of measurements within observed time span, or if (3) set threshold value for minimum number of measurements per observation circle was not reached.

One sample t-test

The one-sample t-test is applied according to clarification in §2.3. With this t-test the following null-hypothesis was tested: 'The mean of measurements within each observation circle is equal with the mean of all measurements on the heatmap'. Both positive and negative differences were considered. A 'significant marker (x)' was added to the observation circle (or pixel) if the null-hypothesis proved to be false ($p<.05$) and $t > 0$.

Caution for diplopia of significant markers

The method of overlapping circles was beneficial for a smooth colour transition of adjacent pixels of a heatmap. This method did however include drawback for interpretation. Multiple occasions of diplopia, or double vision, of 'significant markers' were encountered. Depending on the position of an individual measurement, two, three or even four overlapping circle values were influenced (Figure 18). If the t-test on the data within these observation circles indicated a significantly higher value than the population mean, multiple markers were placed on the heatmap. This might suggest that a group of elevated locations existed, while it was actually only one location with (an) elevated value(s). On the other hand there might actually have been a group of nearby elevated values, which should not be neglected from assumed diplopia. Therefore it was important to focus on the measurement data behind the markers, and not focus on the number of adjacent markers. For aid of observations, the original method was extended with generated tables for additional measurement data behind the heatmap.

3.2.1.2 Heatmap customizations to suit context of observed data

Heatmaps were composed from a matrix of data, corresponding with an artificial grid of a geographic map. Each field in the matrix contained an operation (average, minimum, maximum, etc.) of the original data, corresponding with observed time span and geographic part of the plot. Each field was subsequently converted to a pixel on the heatmap. Resolution of the heatmap was determined by the size of the surface area that is represented by one pixel. High resolutions provided more information, but the number of measurements per pixel was lower.

Resolution and context of samples

DWDS measurements were not uniformly distributed in time and space. Some locations were frequently sampled as part of the regular sample program. Other locations were sampled less frequently or appending maintenance activities, calamities or customers complains. Careful adjustment of heatmap resolution was therefore important.

Resolution controlling parameters

Three settings were available to customize resolution of heatmaps and control the number of measurements per observation circle.

(1) The resolution of the heatmap was determined by adjustment of circle-radius.

(2) A threshold value was set to specify the minimum number of measurements per observation circle. Observation circles with less measurements than set threshold value were discarded. Corresponding pixels contained no information.

(3) The observed time span influenced the heatmap resolution in a different way. In general a wider time span allowed a higher resolution as the observation circles contained more measurements than a short time span. A heatmap with a wide time span was however less accurate for interpretation.

Comparison of heatmaps

This last drawback was addressed from multiple tests on the heatmaps. In exploration phase, a series of experiments was done to observe the number of measurements by adjustment of observed area and time span. The relatively high number of Temperature measurements in measurement dataset allowed a higher resolution for a Temperature heatmap than for a HPC heatmap, with a lower number of measurements in the dataset. Heatmaps with mutually different resolution were however poorly comparable. Therefore an optimum balance was sought to compare heatmaps.

Colour scale

A clear description of applied colour scale was essential for correct interpretation of heatmaps. Upper and lower values of a colour scale were adjusted to represent the minimum and maximum value on the heatmap. This was particularly the case if the observed heatmap was an extract of a collection of heatmaps with appending time frames. This was an addition to the original method of van den Bos (2020).

Time lapse framework

The heatmaps of this research were prepared and arranged in a time lapse framework for mutual comparison. The arrangement is shown in Figure 19.

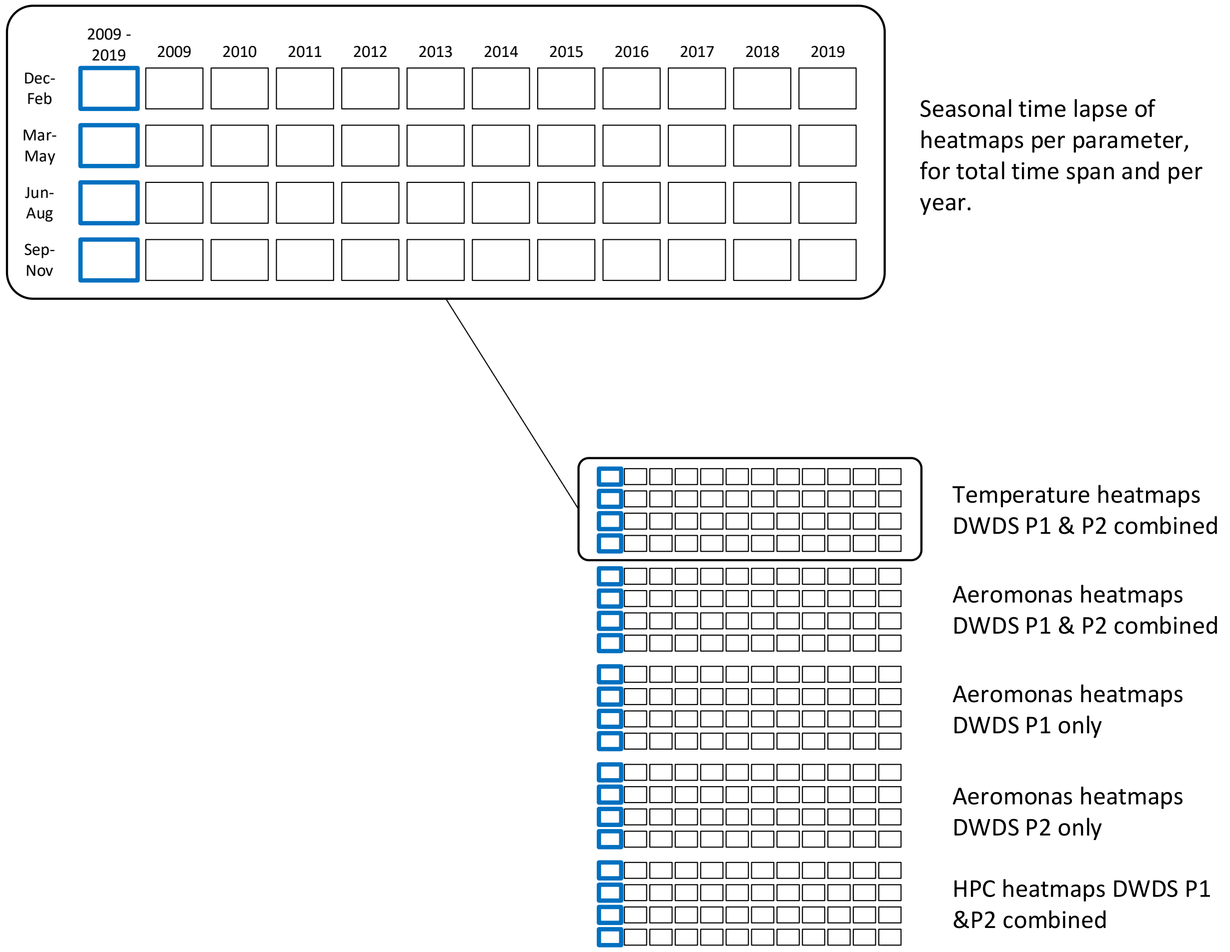


Figure 19 – Schematic overview of time-frames for heatmaps, per parameter: Temperature, Aeromonas and HPC. The population mean of Aeromonas measurements in DWDS P2 was significantly higher than DWDS P1. Therefore, this scheme was applied twice for Aeromonas.

In column 2 to 12 the parameters Temperature, Aeromonas and HPC were observed for its yearly seasons. In the first column the measurements from the single seasons were combined in one seasonally heatmap for 2009 to 2019. Per heatmap the population mean was calculated for aforementioned t-test. The population mean of Aeromonas measurements in DWDS P1 and DWDS P2 were however significantly different (§3.1.3.2). The heatmaps for Aeromonas measurements were therefore also individually observed for DWDS P1 and DWDS P2. This resulted in a total of (3+2) parameters x (11 yearly + 1 total) time span x 4 seasons = 240 heatmaps. Circle radius and threshold values were adjusted for optimum compare.

The paper format of this report does not allow to present all heatmaps. Full set of heatmaps (according to Figure 19 arrangement) is therefore available in the digital appendices file of this report.

3.2.2 Results from spatial analysis

Note on results:

Full set of heatmaps according to Figure 19 arrangement is available in the digital appendices file of this report.

Notes for readability:

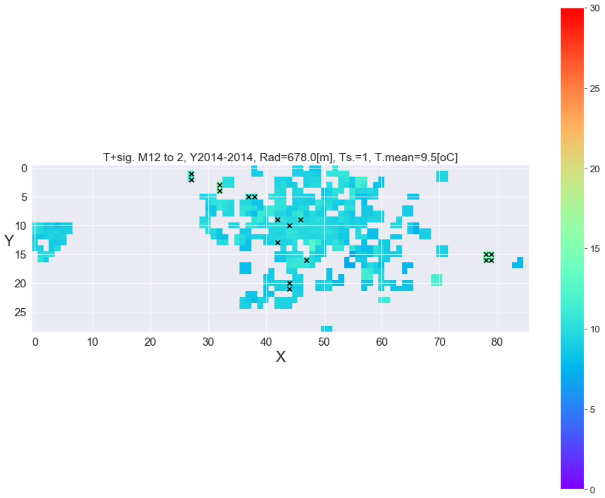
The term 'Significant [parameter] area' is defined as: 'Area on a heatmap with a significantly higher [parameter] sample mean than the population mean of the observed heatmap (p=.025).'

The word '*significant*' is occasionally placed between () brackets to include areas with a sample mean, which is not significantly higher than the population mean. Argument for the '(significant)' notation is the automatic exclusion from t-test of observation circles with only one measurement.

3.2.2.1 Spatial observation from DWDS Temperature measurements

Significant Temperature areas were predominantly observed in summer and winter periods. These areas were however not repetitive for same seasons through the individual years. Besides showed the summer and winter heatmaps different significant areas. Several heatmaps suggested that significant Temperature areas predominantly occurred in far end DWDS P1. An example heatmap of winter 2014 is shown in Figure 20 (For original size, refer to Figure 75 & Figure 76 in Appendix 11.)

(a)



(b)

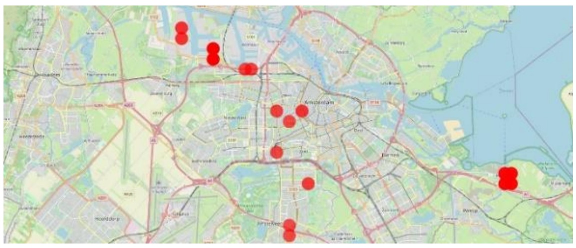


Figure 20 – Heatmap example with markers (x) for areas with significant elevated average drinking water Temperature °C, (p<.025). Time frame: 1 Dec 2013 … 28 Feb 2014. Radius of observation circle = 678 m. Heatmap colour bar represents average of measurements within observation circle. X and Y-axis values are not related to geographic map (a).
Projection of significant areas from Figure 20a. Areas with significant elevated average drinking water Temperature are represented by red markers (p<.025). Markers have no colour bar definition. Projected map covers markers in DWDS P1 (centre of map) and the map covers markers in DWDS P2 (east). Map size: 36.2 x 15.7 km (b).

3.2.2.2 Spatial observation from DWDS Aeromonas measurements

Significant Aeromonas areas were predominantly observed in summer, into lesser extend in the autumn and sparsely in winter and spring. An example heatmap of autumn 2009-2019 is shown in Figure 21. For original size, refer to Appendix 11.

(a) (b)

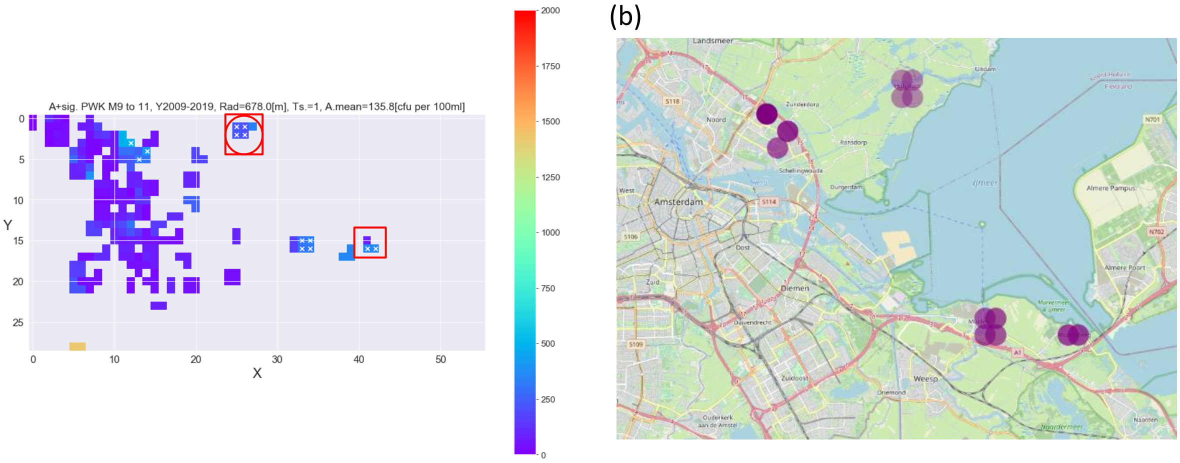


Figure 21 – Heatmap overlay with markers (x) for areas with significant elevated average Aeromonas measurement values cfu/100ml from DWDS P2 (p<.025). Time frame: 1 Sep - 30 Nov of 2009-2019. Radius of observation circle = 678 m. Heatmap colour bar represents average of measurements within observation circle. X and Y-axis values are not related to geographic map. Circle highlights markers with multiple reoccurrence in same seasons of individual years. Squares highlight multiple reoccurrence in different seasons in total time span (a).
Projection of significant areas from Figure 21a. Areas with significant elevated average Aeromonas measurement values are represented by purple markers (p<.025). Markers have no colour bar definition. Projected map covers markers of DWDS P2 only. Map size: 21.8 x 15.5 km (b).

Significant Aeromonas areas were characterized by (1) multiple occurrences on summer heatmaps for individual years (Figure 21a, highlighted by circle). Other significant Aeromonas areas were characterized by (2) multiple occurrences on the combined seasonal heatmaps for total time span (Figure 21a, highlighted by squares). Some locations combined characterisation (1) and (2). Finally were significant Aeromonas areas also characterized by (3) absence of a clear pattern of occurrence. Besides it was noted that a number of (significant) Aeromonas areas reside nearby the far end of DWDS (i.e. at the far end from the treatment facility). Examples are shown on Figure 21b nearby municipalities *'Holysloot'* and *'Muiderberg'*, respectively *centre-north* and *south-east* on the map.

3.2.2.3 Spatial observation from DWDS HPC measurements

Significant HPC areas were scarce and seasonally re-occurrence is not observed.

3.2.3 Conclusions from spatial analysis

Temperature versus Aeromonas and HPC

From time lapse of heatmaps there was no clear spatial relation observed between Temperature, Aeromonas and HPC. Significant Temperature areas did only occasionally correspond with Significant Aeromonas areas. The marginal variation among seasonal HPC heatmaps was in line with observations of HPC time series analysis (§3.1.3.3). No relation was observed between HPC heatmaps and Temperature heatmaps. The indicating parameter HPC was therefore not further explored.

Aeromonas

Seasonal patterns from time series analysis on Aeromonas in DWDSs (§3.1.3.2) were clearly visible from time lapse of Aeromonas heatmaps. The elevated population means for summer Aeromonas heatmaps were also as expected from Aeromonas time series analysis. The significant difference between average Aeromonas values in DWDS P1 and DWDS P2 was however hardly distinguishable from Aeromonas heatmaps of DWDS P1 and DWDS P2.

Limits for interpretation

Heatmap observations did provide some additional information on the time series analyses. Besides, it did provide some insight on the spatial and temporal aspects of the skew distribution of Aeromonas measurements. Though solid clues on the origin of the skew distribution were not considered due to the complexity of DWDSs. A number of known influencing factors for Aeromonas and HPC measurements from the DWDSs were still unobserved. Some factors are directly related to the DWDSs and its' daily use, such as: Piping material, network age, distance to treatment plant, flow velocity (Liu et al., 2016) and periods of stagnant water (Zlatanovic et al., 2017). Other factors, related to operation of DWDSs, are: Incidents, maintenance and construction works (El Chakhtoura, 2018). Heatmap observations are therefore only considered as indicative.

Connection with next phase

Despite its restrictions, heatmaps may provide a possible connection for further research from the re-occurrence of significant Aeromonas areas. In §3.3 a distinct section of DWDS P2 is further explored.

3.3 Focal Areas – Observations on absolute Temperature and Aeromonas

Repetitive high Aeromonas measurements (in this report: ≥ 1000 cfu/100ml) from the DWDS pose a concern for drinking water companies as Aeromonas is an operational indicator for increased microbial regrowth (Hijnen & Van Der Wielen, 2017). From the prepared heatmaps it was possible to allocate some suspect locations of concern, in time and space. These heatmaps were however too coarse for comparison with local characteristics of the direct environment of DWDS P1 and P2. The primary goal for observation of focal areas was not the exploration of this particular this case study. The primary goal was to possibly find more universal causalities for high Aeromonas values from a focus on a number of areas within this case study. A secondary goal was to explore methods to trace locations that are prone to repetitive high Aeromonas values. In this chapter a part of DWDS P2 is observed, with particular focus on a number of areas within their demographic characteristics. Six focus Areas were selected within DWDS P2. Arguments for selection are supported with demographic information in §3.3.1. In §3.3.2 the results are presented and discussed.

3.3.1 DWDS selection

The northern section of DWDS P2 was selected for (1) its observed presence of repetitive high Aeromonas measurements and for (2) concerns by the drinking water company about this section (Kors, 2020). Northern and southern section of DWDS P2 are separated by the *'River IJ'*. Three main pipe lines connect the northern section of DWDS P2 with the treatment facility in the south (Figure 22).

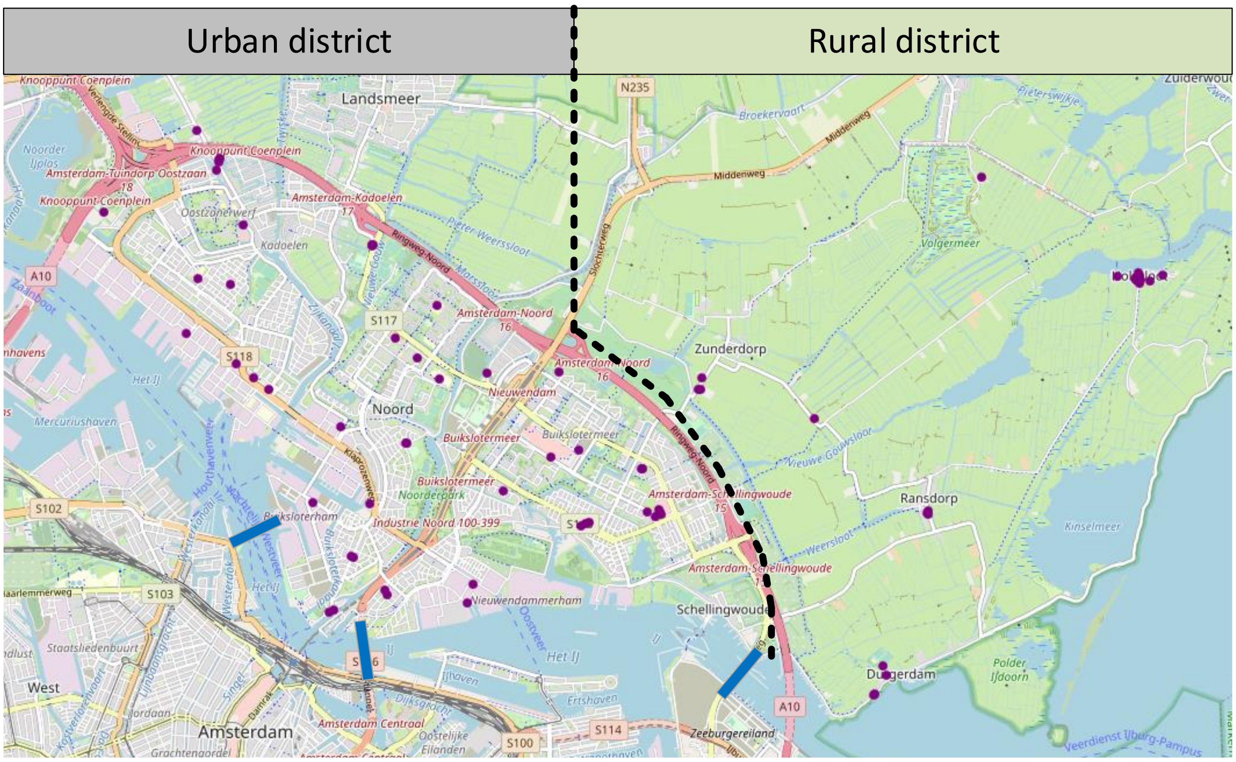


Figure 22 - Northern section of DWDS P2, located north of 'River IJ' or 'Het IJ'. Connections with treatment facility P2 in South of Amsterdam are marked in blue. Purple dots mark Aeromonas sample locations (2009-2019). Map size: 12.3 x 6.8 km.

By reference of demographic data, an apparent geographic division was observed among Aeromonas sample locations within this DWDS section. The western district was considered 'urban' and the eastern district was considered 'rural'. The urban district was characterized by a population density of 7856 p/km^2, large share of multi-family houses and a typical city subsurface infrastructure with district heating and metro lines. The rural district was characterized with a much lower population density (93 p/km^2), mainly single family houses, no district heating and no metro network (Gemeente Amsterdam, 2020) (Van Bijsterveld, 2020). The artificial perimeter between urban and rural districts is indicated with dotted line (Figure 22).

Considered influence of suburban heat island effect

From an early study the effect of a densely populated city in general was already linked to an increased surface air temperature, in comparison with rural areas (Oke, 1973). In appending studies the complex dynamics of cities were highlighted and further explored for its influence on both surface air temperature (SAT) and ground water temperature (GWT) (Menberg et al., 2012). Recently a study was conducted to the subsurface urban heat island (SUHI) effect in Amsterdam (Visser et al, 2020). From measurements in this study it was known that the average annual groundwater temperature (at depth of 20 m below ground level) in 'our' observed urban district ranged between 12.1 and 13 °C. The average annual groundwater temperature in rural district ranged between 10.8 and 12.0 °C. Though it is important to bear in mind that a single known variable is not representative for the diverse subsoil conditions of an urban district (Menberg et al., 2012).

3.3.2 Areas of interest within selected DWDS

From results of the initial heatmap analyses (significant) Aeromonas areas were selected within the perimeter of the considered urban and rural districts. These areas of interest are labelled 'Area 1' to 'Area 6' (Figure 23).

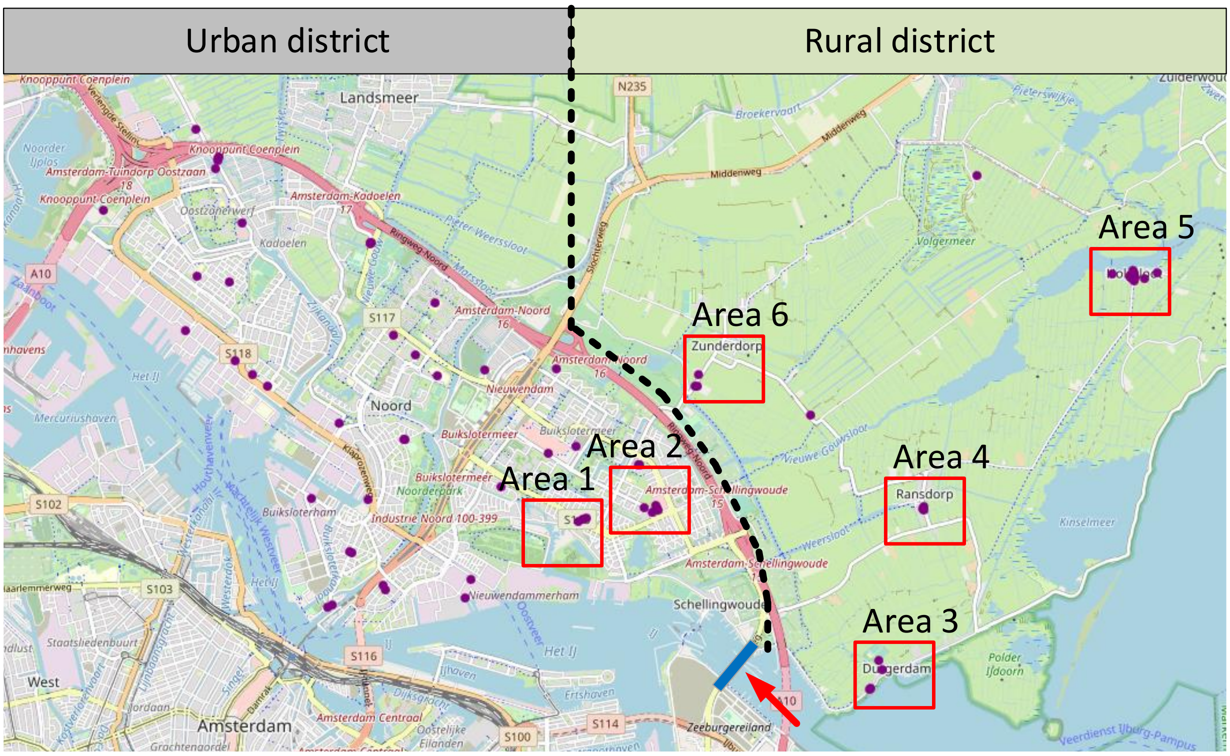


Figure 23 - Demarcation of urban and rural districts within Northern section of DWDS P2. Red squares mark 6 Areas of interest. Common connection of 'Schellingwouderbrug' is indicated with red arrow. Map size: 12.3 x 6.8 km.

Area 1 and 2 were located within in the urban district. Area 3 to 6 were located in the rural district. Aeromonas measurements and Temperature measurements from Area 1 to 6 were explored. These Areas were selected for its geographic position within the urban and rural area. Area 1 to Area 6 received water from the same treatment facility P2, moreover was the water supplied via the common traverse under the 'River IJ'. This traverse was located at the considered border between the urban and rural districts (marked by red arrow on Figure 23). Initial clean water quality was therefor considered comparable among Area 1 to Area 6.

3.3.2.1 Observations for Area 1 to 6

Paragraphs 3.3.2.1 to 3.3.2.3 include a selection of plots from observation of Area 1 to Area 6. Full details are presented in Appendix 12.

Area 1

Aeromonas sample values of urban Area 1 indicated a rather constant Aeromonas quality, with only two exceedances of upper drinking water standard of 1000 cfu/100ml. Summer peak values were observed, but not giving rise to concern as the frequency was low (Figure 24). Aeromonas sample values from Area 2 showed a similar pattern.

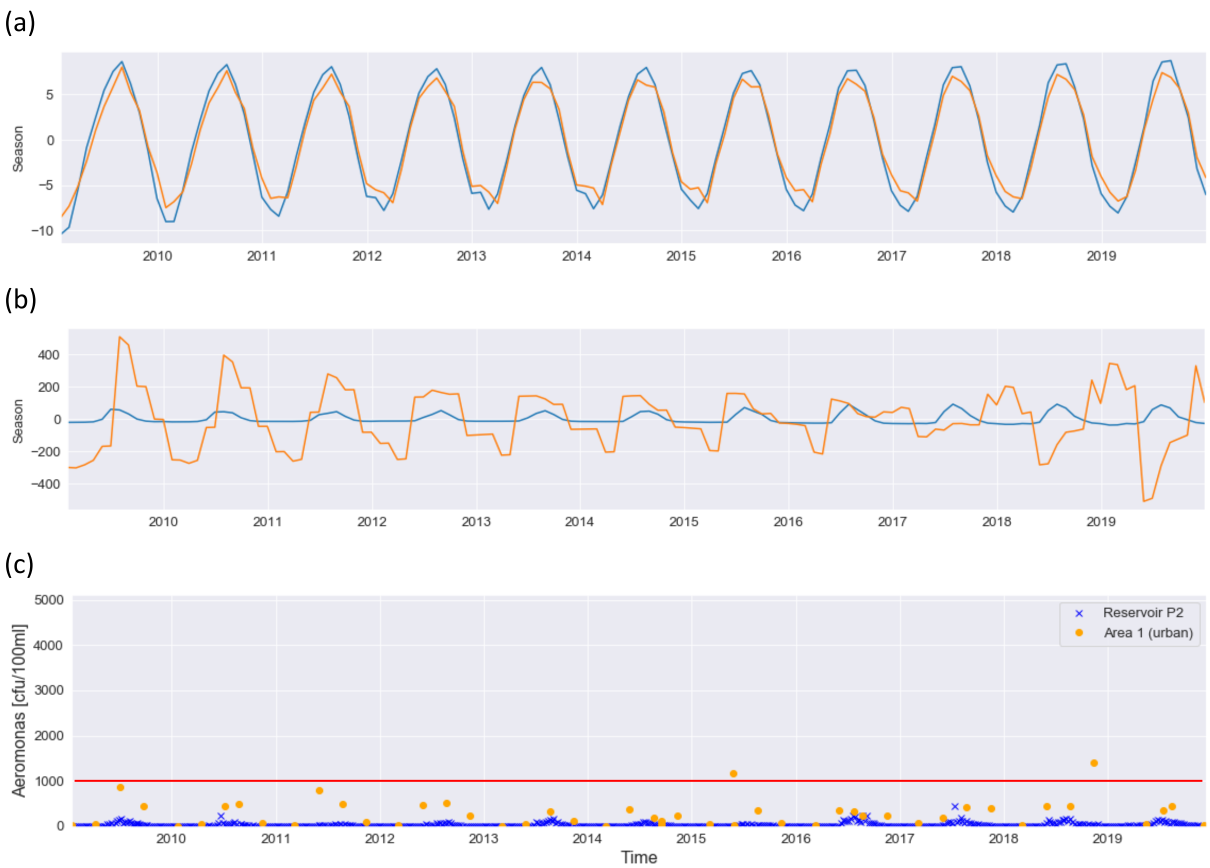


Figure 24 - Area 1 (urban) with Seasonal pattern of absolute sample temperature (°C) (a) and seasonal pattern of Aeromonas samples (cfu/100ml) (b). Aeromonas sample values (cfu/100ml) for Area 1 (orange), reservoir P2 (blue) and drinking water standard (red) (c).

The seasonal plots (Figure 24a and b) represent the monthly change around the mean, as if the trend component is removed from original data.

Area 3, 4 & 6

Plots of rural Areas 3, 4 and 6 indicated a constant water quality with respect to the Aeromonas indicating parameter. Exceedance of Aeromonas legal standard were observed sporadically. The Aeromonas sample values of Area 4 even suggested a declining trend (Figure 25). Plots of Area 3 and Area 6 are included in Appendix 12 for reason of overview.

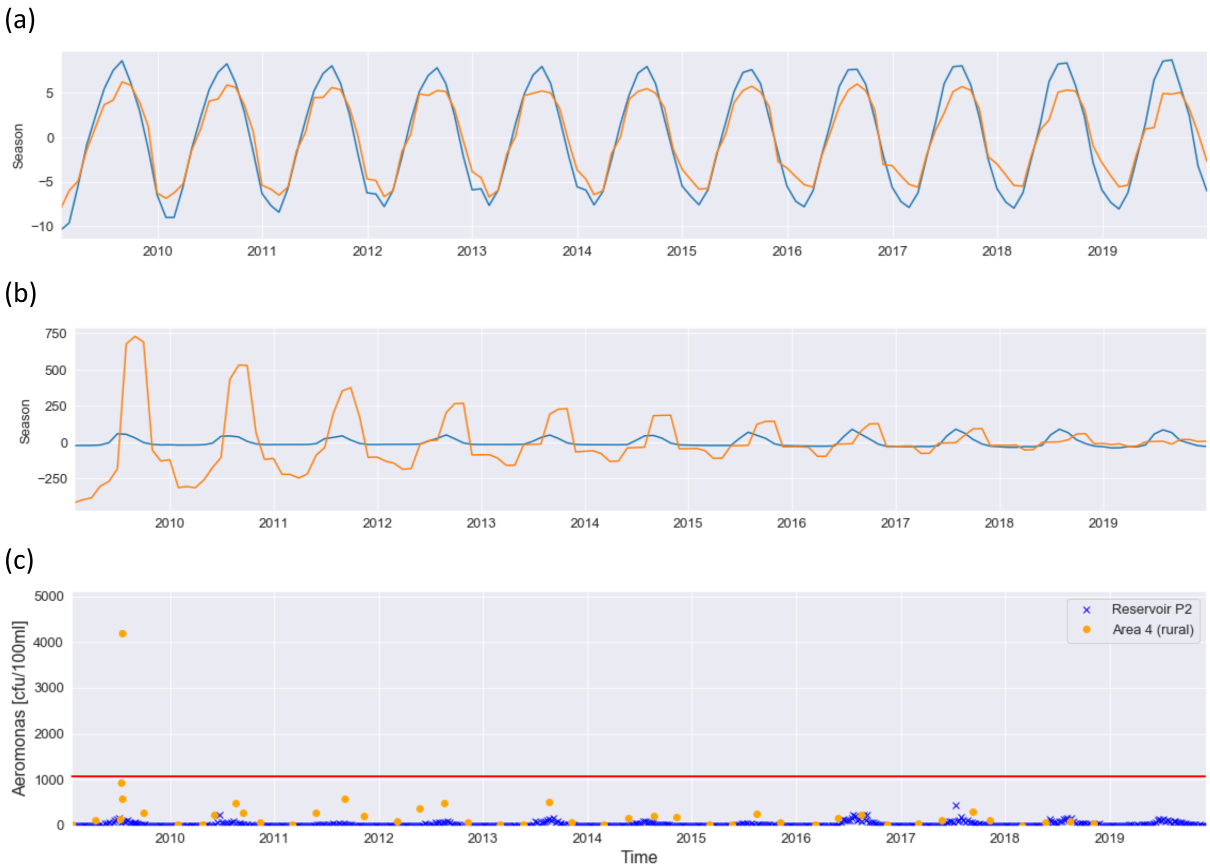


Figure 25 - Area 4 (rural) with Seasonal pattern of absolute sample temperature (°C) (a) and seasonal pattern of Aeromonas samples (cfu/100ml) (b). Aeromonas sample values (cfu/100ml) for Area 4 (orange), reservoir P2 (blue) and drinking water standard (red) (c).

The seasonal plots (Figure 25a and b) represent the monthly change around the mean, as if the trend component is removed from original data.

Area 5

The Aeromonas measurements values of Area 5 (Figure 26) showed however a more perturbing pattern. This pattern was considered perturbing due to repetitive occasions of high Aeromonas values (in this report >1000 cfu/100ml). Besides, summer peaks of Aeromonas sample values were higher and the number of high Aeromonas values was larger than Area 1 to Area 4 and Area 6. Repetitive occasions of high Aeromonas measurements from the DWDS pose a concern for drinking water companies as Aeromonas is an operational indicator for increased microbial regrowth (Hijnen & Van Der Wielen, 2017). It was also noted that Area 5 contained a higher number of Aeromonas samples than the other Areas. This might have been caused by the fact that Area 5 was subject to a more intense surveillance due to known concerns on drinking water quality (Kors, 2020).

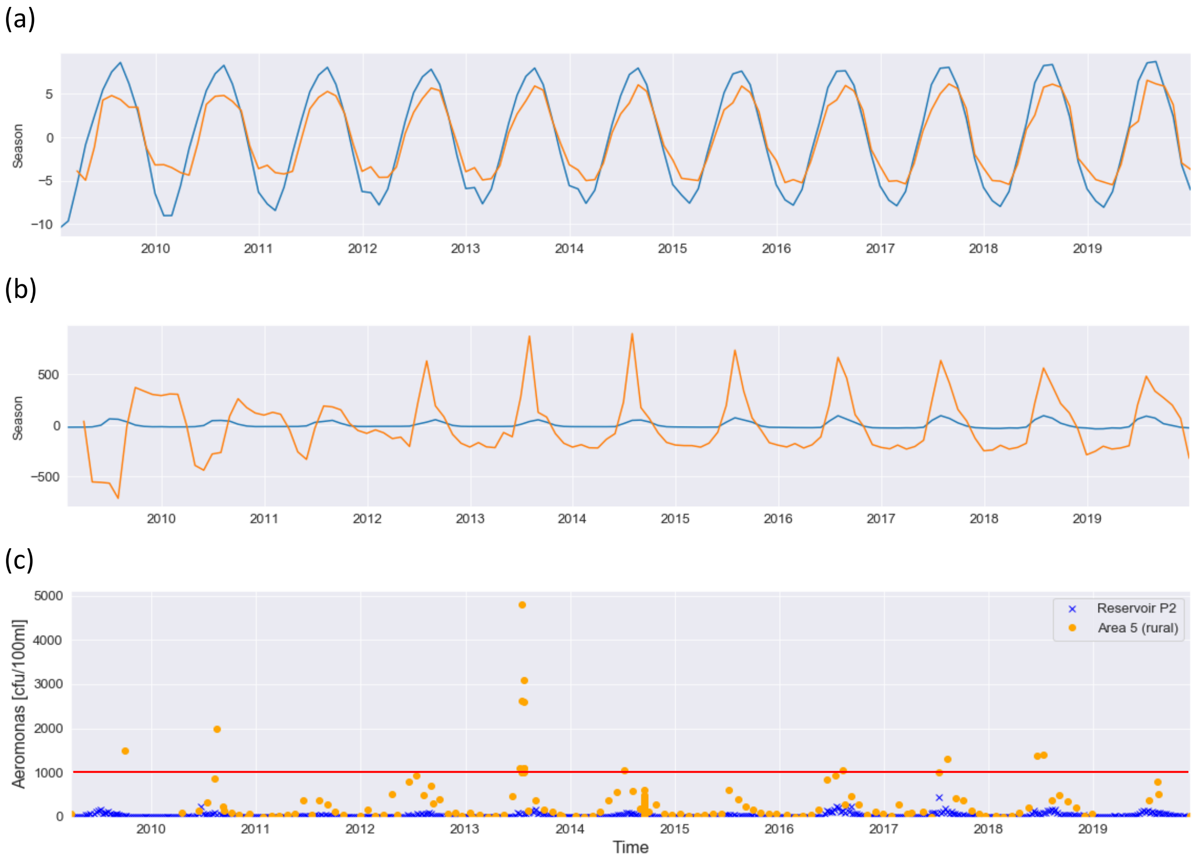


Figure 26 - Area 5 (rural) with Seasonal pattern of absolute sample temperature (°C) (a) and seasonal pattern of Aeromonas samples (cfu/100ml) (b). Aeromonas sample values (cfu/100ml) for Area 5 (orange), reservoir P2 (blue) and drinking water standard (red) (c).

The seasonal plots (Figure 26a and b) represent the monthly change around the mean, as if the trend component is removed from original data.

3.3.2.2 Closer look at Aeromonas measurements of Area 5

Measured Aeromonas concentration in Area 5 seemed not solely related to the Temperature of corresponding samples. Figure 27 shows combined Aeromonas and temperature samples for Area 5. Majority of samples with Aeromonas measurements > 500 cfu/100ml were linked to a sample Temperature > 15 °C. Occasionally a sample with Aeromonas measurements > 500 cfu/100ml was linked to a lower sample Temperature (9 °C). Maximum registered sample Temperature for Area 5 was 21.8 °C.

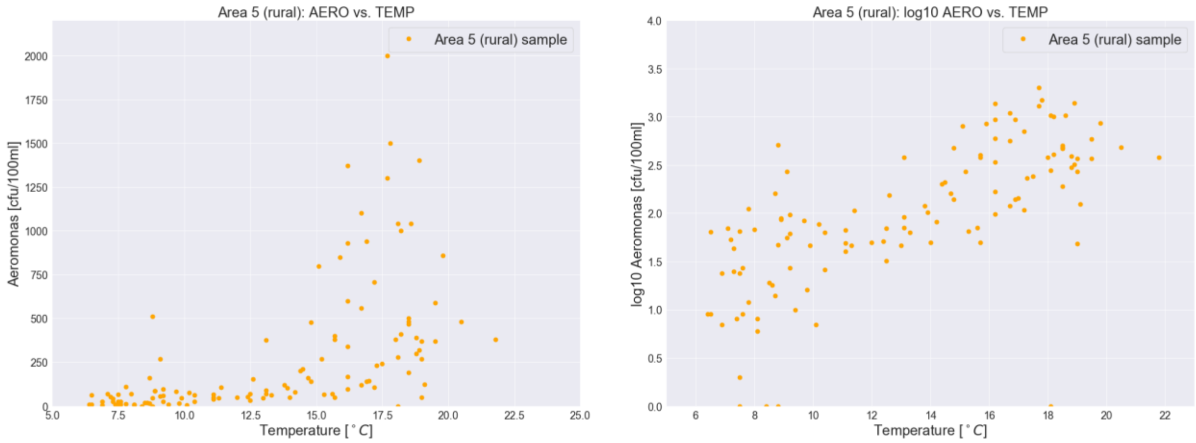


Figure 27 – Plot of samples from Area 5. For combined Temperature (°C) and Aeromonas (cfu/100ml) measurements (left). For combined log10 Temperature (°C) and Aeromonas (cfu/100ml) measurements (right). Time span 2009-2019.

Another possible reason for the disturbing Aeromonas pattern of Area 5 is the distal position from the network traverse under the 'River IJ', compared with other observed Areas (Figure 23). A visually longer travel distance may imply a longer residence time and deterioration of microbial water quality. Visual estimates are however no good indication for residence time. Waternet provided a map with simulated residence time (in hours) from clean water reservoir to the projected location within the DWDS (Waternet, 2020c). This map contains an indication of simulated average residence time within observed DWDS. Simulation was based on SIMDEUM model (SIMulation of water Demand, and End-Use Model) and field tests were performed to verify model for residence time (De Groot, 2020); (Blokker et al., 2017).

Area 1 to 6 were projected on the map with simulated residence time (Figure 28a). For reference the network map of DWDS P1 (partly) and DWDS P2 was added (Figure 28b) (Waternet, 2020d). This projection seemed to support the assumed argument for residence time. Area 5 contains only dark blue indicators, representing an average residence time > 50 hours. Area 1 to 4 and Areas 6 contain green, light blue and dark blue indicators. These colours represent an average residence time ranging from 20 to >50 hours. For interpretation of this map it is important to consider that the accuracy of residence time depends on the location within the DWDS. Aforementioned field tests indicated that the simulated residence time proved to be more accurate for the larger transport sections than for the distribution branches to (groups of) consumers (De Groot, 2020).

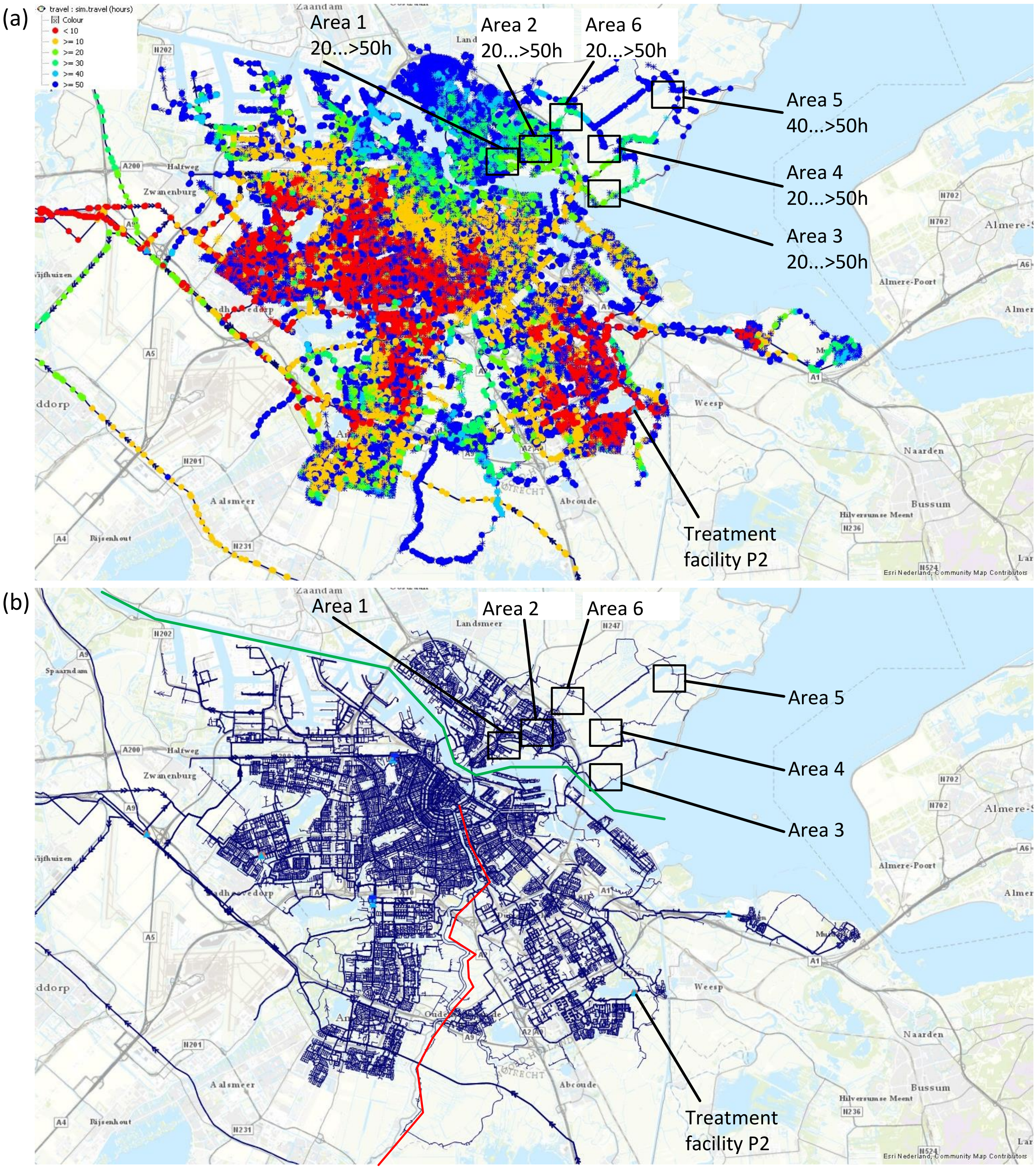


Figure 28 - Geographic map with simulated residence time (hours) from clean water reservoir to location within DWDS. Colour of indicators (dots) represent average residence time. Red: <10h, orange: 10-20h, green: 20-40h, light blue: 40-50h, dark blue: >50h (Waternet, 2020c) (a). Network layout covering DWDS P1 (partially) and DWDS P2, with River 'IJ' (green) and River 'Amstel' (red) (Waternet, 2020d) (b). Location of Area 1 to 6 are added for reference. Map size: 37.5 x 21.9 km.

3.3.2.3 Comparison of Areas in context of urban and rural character

In another try to get a grip on the high Aeromonas measurements, the seasonal temperature patterns from time series analysis of Area 1-6 were prepared (Figure 29a to f).

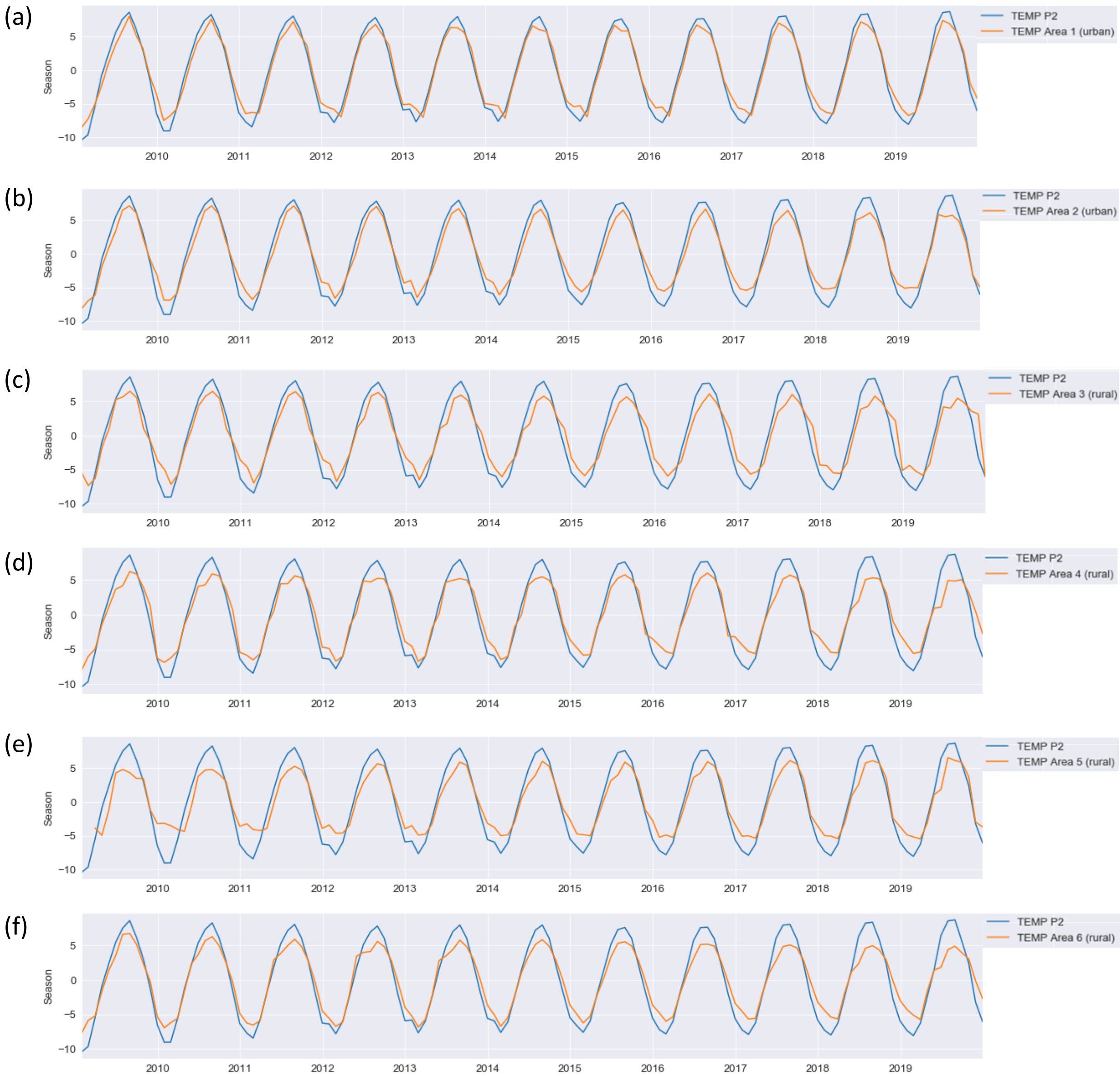


Figure 29 –Seasonal Temperature plot for sample values for Area 1 to Area 6, combined with corresponding Temperature of reservoir P2 (a to f).

Gaps were identified between the blue (reservoir) lines and orange (Areas) lines. These gaps suggested a net temperature decline during transport in the summer and a net temperature increase during transport in winter periods. Moreover it was suggested from these plots that the gaps between the blue (reservoir) lines and orange (Areas) lines were somewhat larger for the rural Areas, compared with the urban Areas.

Temperature change and Aeromonas change during transport from reservoir to urban and rural districts.
From t-tests (Appendix 13) it was observed that the weekly average Temperature change of samples from urban district was higher than the samples from the rural district (*p=.000*). The weekly average Aeromonas change of samples from the urban district was significantly lower than in the samples from the rural district (*p=.000*).

Comparison of absolute Temperature and absolute Aeromonas values for urban and rural districts.
Similar observations were done for the weekly average absolute Temperature and Aeromonas measurement values: The weekly average absolute sample Temperature of urban district was significantly higher than the samples from the rural district (*p=.006*). The weekly average absolute Aeromonas value of the samples from urban district was significantly lower than in the samples from the rural district (*p=.000*).

Discussion on urban and rural character of observed districts
Before discussion, it is important to mention that an individual test or comparison is not explanatory for DWDSs beyond this case study area. Besides, a single known variable is not representative for the complexity of subsoil conditions (Menberg et al., 2012).

The higher average absolute sample Temperature (and higher Temperature change) in the urban district corresponded with expectations, because the average ground water temperature of the urban district was also higher than in the rural district (Visser et al., 2020). The outcome on the test was however somewhat suspicious for the comparison of absolute Aeromonas levels within urban and rural districts. This was suspicious because a positive correlation was observed between absolute Temperature and Aeromonas within DWDS P2 (§3.1.2). So, from the higher average absolute sample Temperature in the urban district, a corresponding higher average absolute Aeromonas value was expected. Though the average absolute Aeromonas value was higher in the rural district. A hint from work of El-Chakhtoura provided the inspiration for further exploration:

> Quote: *"Most studies reported long-term effects to be more significant than spatial variations, although distribution network samples were rarely compared to the original treatment plant samples."* (El Chakhtoura, 2018, p. 84)

A closer look at the change of Temperature and change of Aeromonas during transport was therefore considered. This topic is further explored in §3.4.

3.4 Net Temperature change and Aeromonas change during transport

The results of §3.3 suggest further exploration of Temperature change and Aeromonas change during transport. Therefore a new 'profile plot' was prepared. This profile plot aims to observe if there is any relation between:

(1) Net change of Temperature during transport
(2) Net change of Aeromonas during transport
(3) Absolute sample Temperature

Section §3.4.1 contains a description of the methodology to construct the profile plot. In section §3.4.2 the profile plots are applied to explore for Area 1 to 6.

3.4.1 Methodology

Data from Area 1 (§3.3.2) was picked for example. The weekly average Aeromonas change (cfu/100ml) during transport, is plotted against the weekly average Temperature (°C) change during transport (Figure 30).

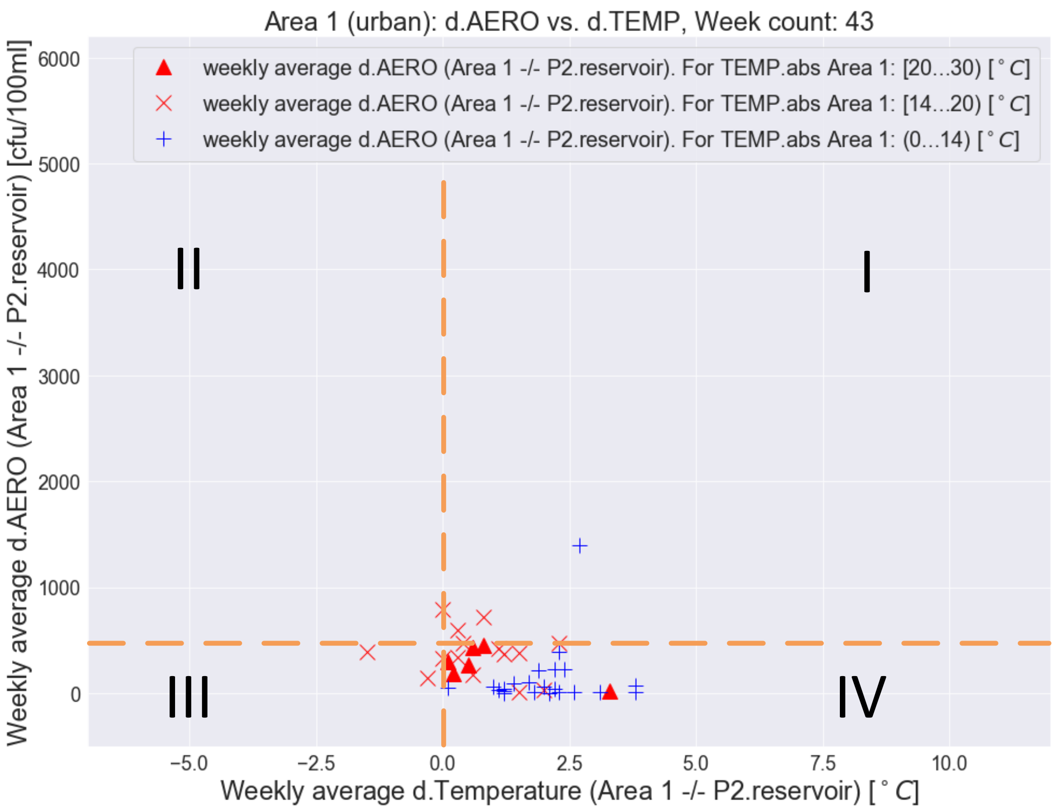


Figure 30 – Example: Net weekly average Aeromonas change (Area 1 -/- P2 reservoir) versus net weekly average Temperature change (Area 1 -/- P2 reservoir). Period 2009-2019.

Methodology - Markers

The markers on the profile plot represent weekly average sample Temperature in observed Area. So, in the example of Figure 30 every marker represents a weekly average sample Temperature, in Area 1. Three temperature ranges are distinguished:

+	Cold	weekly average sample temperature: 0…13.9 °C
X	Warm	weekly average sample temperature: 14…19.9 °C
▲	Hot	weekly average sample temperature: 20…30 °C

The lower temperature range of '*warm samples*' (14 ^{o}C) corresponds with the observed threshold value for enhanced Aeromonas growth in an unchlorinated DWDS (Van Der Mark et al., 2011). The authors used specifically the word 'growth'. Initially was the split between '*warm markers*' and '*hot markers*' defined at 25 ^{o}C instead of 20 ^{o}C to correspond with the Dutch drinking water guidelines for Temperature. But consequently no 'hot markers' appeared on any of the plots.

Methodology - Quadrants

The plotted area is divided in four quadrants (Figure 30). A division is made for the net Temperature change during transport. This division is made by the vertical dotted line between quadrant I,IV and quadrant II,III. Markers in quadrant I and IV represent a positive net Temperature change during transport. Reversely, represent the markers in quadrant II and III a negative net Temperature change during transport. Likewise a division is made for the Aeromonas change during transport. This division is made by the horizontal dotted line between quadrant I,II and quadrant III,IV. The level of this line represents the 'maximum Aeromonas increase during transport' before the samples value will exceed Dutch drinking water standard for Aeromonas at the tap, of 1000 cfu/100ml (Drinkwaterbesluit, 2018). From the dataset is observed that the maximum Aeromonas value in clean water reservoir P2 was: 434 cfu/100ml. For ease of observation the level of the horizontal dotted line is rounded to 500 cfu/100ml. Markers in quadrant I and II indicate a net Aeromonas change of ≥ 500 cfu/100ml, during transport from clean water reservoir to observed Area. Markers in quadrant III and IV indicate a net Aeromonas change of < 500 cfu/100ml, during transport from clean water reservoir to observed Area.

Methodology – Note on the net change of Temperature and Aeromonas during transport

For all observations with these profile plots was important to bear in mind that a change of Temperature and/or Aeromonas only reflected on the net difference between the observed Area and the reservoir:

- The profile plots contain no information on the fluctuation of these parameters *during* transport. Observations and conclusions from the profile plots may therefore never suggest a linear relation or single direction of change. Temperature or Aeromonas change may have been induced gradually in time and space, or at a specific location or time span. From research by Van Den Bos (2020) on the DWDS in the metropolitan of Rotterdam the local influence of anthropogenic heating was explored. Anthropogenic heating was therefore also considered plausible for the DWDS of Amsterdam. The subsoil environment of the DWDS of Rotterdam and Amsterdam are however not fully comparable. Rotterdam is built on heavy clay, while Amsterdam is built on peat soil (Klok et al., 2012). The soil type is a co-determent factor for heat transfer between soil and the DWDS (Agudelo-Vera et al., 2017). The DWDS of Rotterdam and Amsterdam were therefore not fully comparable for the aspect of heat transfer. Although not fully comparable, it was considered plausible that the drinking water within the DWDS of Amsterdam may have been subject to anthropogenic heating and temperature fluctuations during transport. The subsoil temperature at DWDS depth was rather stable through the year and ranging from 10 ^{o}C in winter to about 13 ^{o}C in the summer period (Veenman, 2020). The reservoir temperature was subject to seasonal variations (Figure 9). The temperature difference between water from the reservoir and the subsoil DWDS conditions is the driving force for heat transfer and subsequent temperature fluctuations of drinking water along DWDS trajectory.

- From research on DWDSs it was known that Aeromonas values may also vary during transport. Release of deposits from pipe wall (Liu et al., 2017), residence time (Van Der Kooij et al., 1981) and drinking water temperature (Van Der Mark et al., 2011) are known causes for peak values from microbial measurements in DWDSs.

- The observed Temperature change and Aeromonas change were net changes of the weekly average sample value, minus the measured value in the reservoir for corresponding week. The provided measurement data of Temperature and Aeromonas samples from clean water reservoir P2 had an interval of one week. The transport (residence) time, from the reservoir to the sampled Area, ranged from about one hour to up to four or five days (Kors, 2020). Therefore it was important to realize that the weekly average value of the sample might have been related with the reservoir measurement of the week before.

3.4.2 Net change of Temperature & Aeromonas during transport for Area 1-6

In this paragraph the net change of Temperature and Aeromonas is explored for Area 1 to 6 (Figure 23). Profile plots for Area 1 to 6 are projected in Figure 31a to f.

Legend:			
	+	Cold	weekly average sample temperature: 0…13.9 °C
	X	Warm	weekly average sample temperature: 14…19.9 °C
	▲	Hot	weekly average sample temperature: 20…30 °C

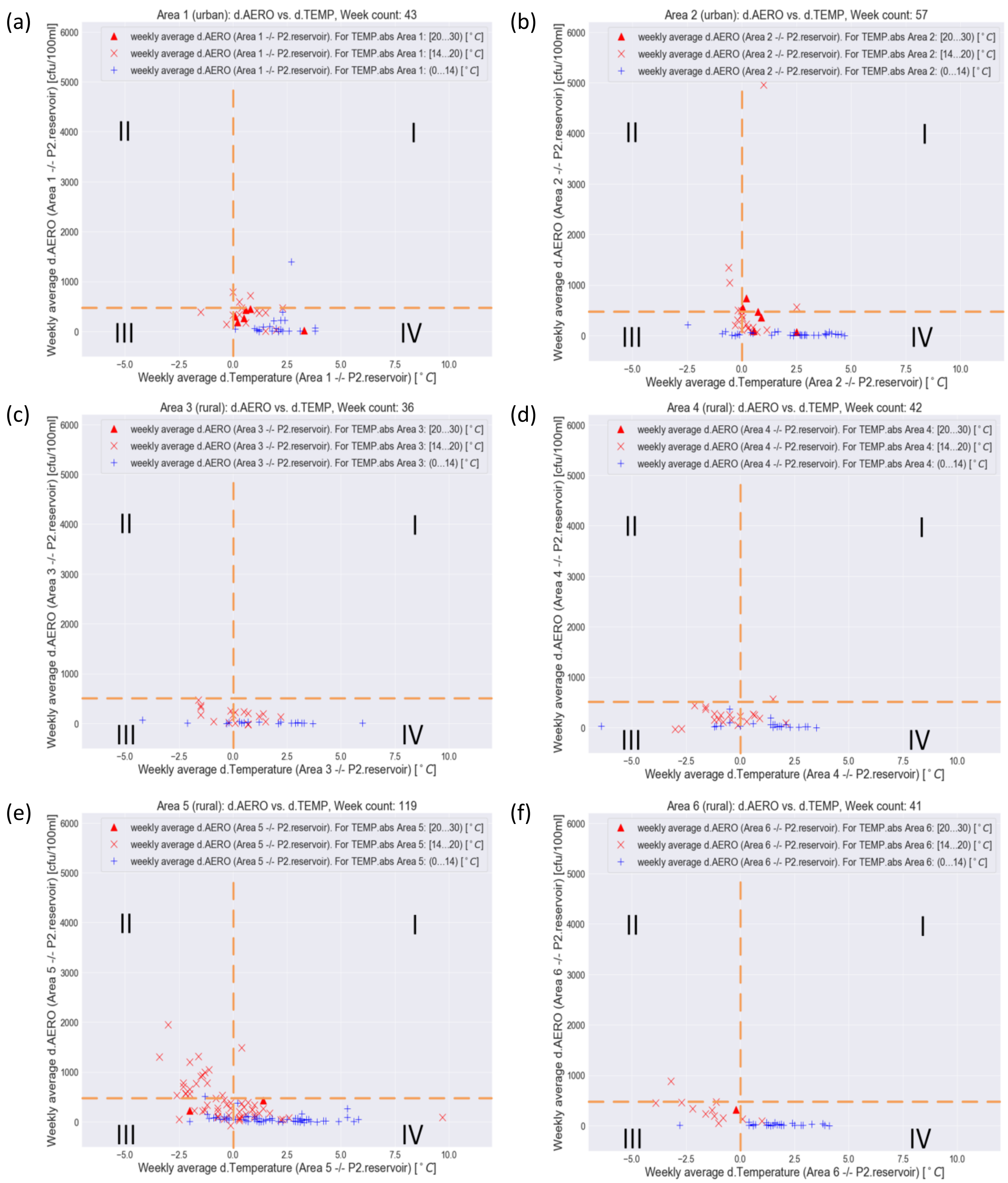


Figure 31 – Profile plots of Area 1 to 6 (a-f), with net weekly average Aeromonas change (Area -/- P2 reservoir) (cfu/100ml), versus net weekly average Temperature change (Area -/- P2 reservoir) (°C). Period 2009-2019.

Area 1 (urban)

The presence of blue 'cold' markers[4] in quartile IV of Area 1 (Figure 31a) implied cold reservoir water warmed up during transport. The majority of the blue 'cold' markers indicated limited Aeromonas increase. Only one marker was located in quarter I, representing an elevated Aeromonas increase. The 'warm' markers indicated occurrences of both temperature rise and decline. The Aeromonas change of 'hot' markers was not perturbing and did not exceed the Aeromonas change of 'cold' and 'warm' markers.

Area 2 (urban)

The range of blue 'cold' markers within Area 2 (Figure 31b) pointed at a slightly higher temperature increase than Area 1. In addition to Area 1 a temperature decline was observed for the 'cold' markers. This decline was traced back to measurements in the months March to May of several years. 'Cold' markers were concentrated near the bottom section of the plot. This inferred a low Aeromonas change during transport. The distribution of 'warm' and 'hot' markers was comparable with the scatter of 'warm' and 'hot' markers of Area 1. One extreme high Aeromonas change was traced back to a single 'warm' measurement. Some 'hot' markers of Area 2 show a potential disturbing Aeromonas increase, though there was no inseparable causal connection between 'hot' markers and disturbing Aeromonas increase.

Area 3 (rural)

The temperature change of the blue 'cold' markers on Area 3 (Figure 31c) exhibited a wider spread, compared with the 'cold' markers within the urban areas. The high and low values of this scatter could however be interpreted as outliers. From this point of view the pattern of cold markers were similar to Area 1 and 2, with a hint of elevated temperature change. The 'warm' markers did represent a higher Aeromonas increase than the 'cold' markers, though safe within the limits of drinking water standard. 'Hot' markers are non-existent in Area 3 and almost all markers resided in quadrant III and IV.

Area 4 and 6 (rural)

The plots for Area 3 and Area 4 (Figure 31c and Figure 31d) were rather similar. The temperature change of the blue 'cold' markers in Area 6 (Figure 31f) was almost completely positive, except for one marker. Corresponding Aeromonas changes are likewise low. Warm markers of Area 4 and 6 were only occasionally linked to Aeromonas change during transport of > 500 cfu/100ml. Only a single hot marker was observed for Area 6 and not related to noteworthy Aeromonas change.

Area 5 (rural)

The plot of Area 5 (Figure 31e) was considered dissonant, compared with the plots of Area 1 to 4 and Area 6. Observation of 'warm' markers within Area 5 was however puzzling for three reasons: (1) Area 5 exhibits the widest range of repetitive blue 'cold' markers. Corresponding Aeromonas increase of the 'cold' markers was however similar to Area 1 to 4 and Area 6. (2) The number of markers in quadrant II exceeded Area 1 to 4, 6 by far. From the positive correlation between Temperature and Aeromonas (§3.1.2), it was expected that (3) the 'hot' markers would also reside in quadrant I or II.

---

[4] Reference for markers:

	+	Cold	weekly average sample temperature: 0…13.9 °C
	X	Warm	weekly average sample temperature: 14…19.9 °C
	▲	Hot	weekly average sample temperature: 20…30 °C

3.4.3 Discussion on Net change during transport for Area 1-6

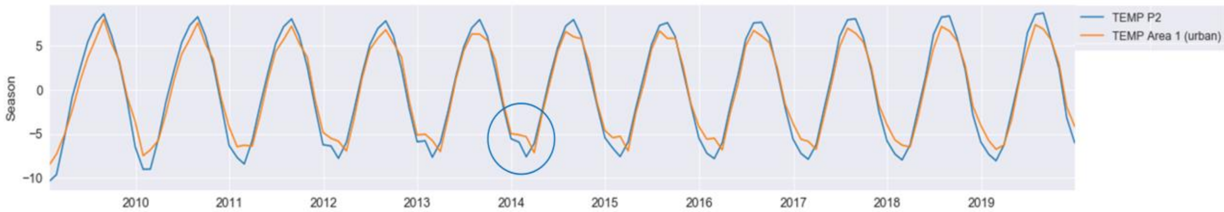
A common aspect for plots of Area 1 to 6 was the limited Aeromonas increase among the 'cold' markers. Virtually all 'cold' markers resided in quadrant III and IV. There was no inextricably causal connection between 'warm' or 'hot' markers and disturbing Aeromonas increase. The majority of the 'hot' markers resided in quartile III and IV. And 'warm' markers did sporadically result in repetitive occasions of perturbing Aeromonas increase, if Area 5 is disregarded.

Assumed common cause

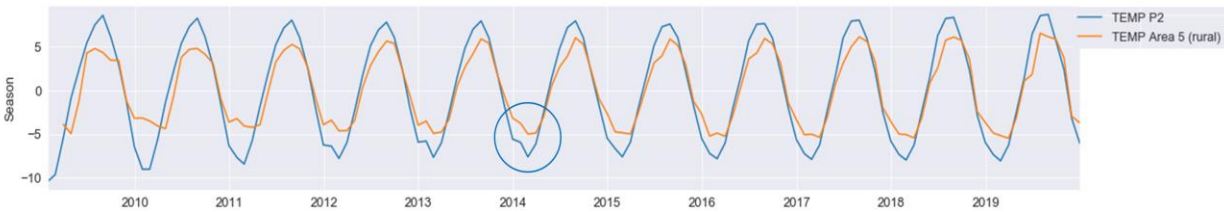
A direct relation between net Temperature change during transport and net Aeromonas change was not observed. An indirect relation was however suggested from comparison of plots for Area 1 and Area 5 in Figure 32.

<u>Legend:</u>			
	+	Cold	weekly average sample temperature: 0…13.9 °C
	X	Warm	weekly average sample temperature: 14…19.9 °C
	▲	Hot	weekly average sample temperature: 20…30 °C

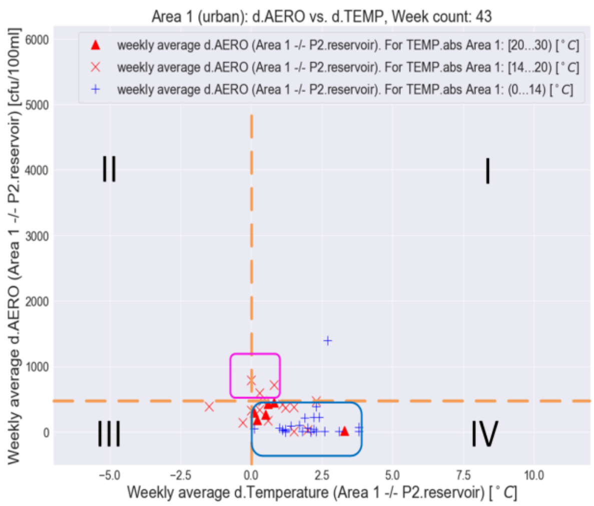
(a)



(b)



(c)



(d)

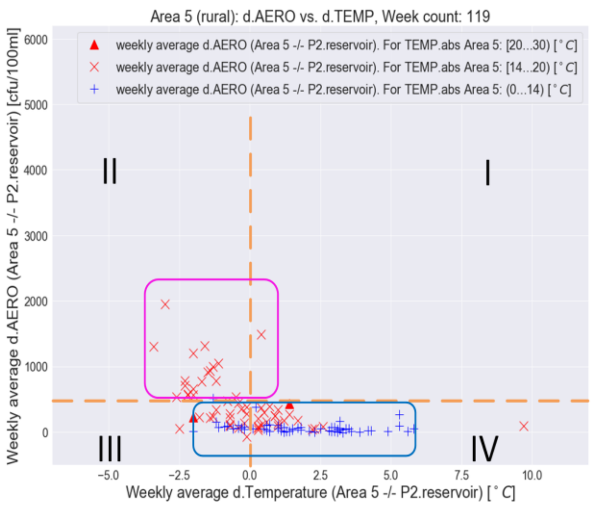


Figure 32 – Time series analysis shows an apparent different drinking water temperature change during transport for Area 1 and Area 5, marked with blue circles (a and b). Profile plots show different Temperature change patterns for 'cold' markers of Area 1 and 'cold' markers of Area 5, indicated with blue squares (c and d). Profile plots also show a different Aeromonas change for 'warm' markers of Area 1 and 'warm' markers of Area 5, indicated with magenta squares (c and d).

Elevated DWDS temperature increase (beyond maximum of other observed Areas) in the winter (blue markers within blue square) seemed somehow related to enhanced Aeromonas increase in the summer (markers in magenta square). It was assumed that an underlying common cause may have allowed both: Temperature increase in the winter, but also allowed excessive Aeromonas increase in summer periods. From experiments by Zlatanovic et al. (2017) it was shown that prolonged residence time within Domestic Drinking Water Systems (DDWSs) may result in a higher absolute water temperature and support enhanced microbial growth above threshold temperature.

Bridge to explore full DWDS P2

So far only a limited number of areas within DWDS P2 are observed. And there were no clues yet beyond observed Areas 1 to 6. Questions that rose were amongst others: What was the quality and age of the DWDS nearby Area 5? From personnel of Waternet it is understood that this part of the network was under extra surveillance due to its repetitive high Aeromonas values. Though the quality and age of this part of the network was not different from its direct surrounding areas (Kors, 2020). Besides it was questioned if Area 5 was an exception within this DWDS? Was there an (unknown) source of contamination nearby or upstream in Area 5's DWDS? Did the distal location of Area 5 influence the Aeromonas quality so badly or was this just a matter of coincidence?

In answer to these questions and for possible onward conclusions beyond this particular DWDS, more analysis was required beyond the restricted selection of Areas in this chapter. Therefore the total DWDS P2 was explored (§3.5.2). Though for sake of efficiency a sequenced version of the profiling plots was prepared first. This method is explained in §3.5.1.

3.5 Sequenced Area profiling

From discussion on net change of Temperature and Aeromonas values during transport (§3.4.3), it was wished to explore a wider part of the DWDS. Not for exploration of this particular DWDS, but to answer the question if the observations for Area 5 (§3.4.2) were an exception and should be neglected for conclusions beyond this case study. Therefore it was attempted to scan a total DWDS for the relation between: (1) the net change of Temperature during transport, (2) net change of Aeromonas during transport and the (3) absolute sample Temperature. The aim of such a scan was to create a profile for the DWDS and to observe above parameters spatially.

Preparation of individual profiling plots per Area (as in chapter 3.4) was rather labour intensive. Besides, without prior exploration DWDS there was no foreknowledge of what location to observe. Therefore a new automated sequence was proposed to apply the principle of the profiling plots on the total DWDS, instead of directly on a particular Area. This method is clarified in §3.5.1 and applied for DWDS P2 in §3.5.2.

3.5.1 Methodology for sequenced Area profiling

Elements of this profiling method corresponded with the circular method from §3.2.1.1. The basis was however different and the data input was new. The adapted basis is depicted below and the new methodology for data input are described in this section.

Methodology - Different basis

The DWDS was automatically divided in Areas by use of a geographic squared raster overlay. Every square on the raster represented one Area. Overlapping circles were beneficial for a smooth heatmap, though confusing for interpretation. Due to this overlap individual measurements may be observed up to four times (§3.2.1.1). By use of adjacent squares all measurements were processed only once. This principle is depicted in Figure 33.

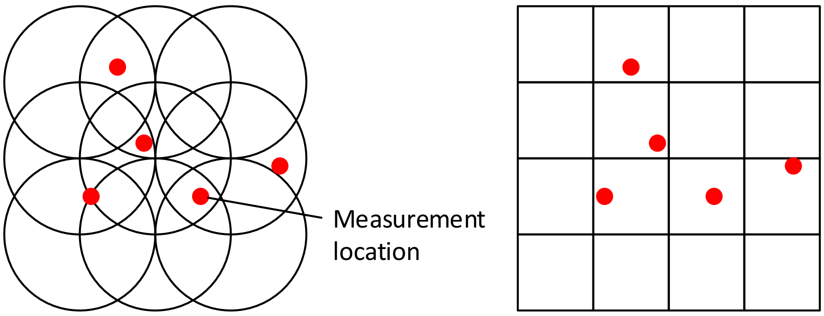


Figure 33 – Profiling of Areas alternative geographic is prepared. Existing overlapping circles (left) and new adjacent squares (right).

Methodology - Applied steps for sequenced Area profiling

In order to apply the principle of the profiling plots on the total DWDS following a Python script was written to automatically run through a sequence of steps. These steps are schematically shown in Figure 34.

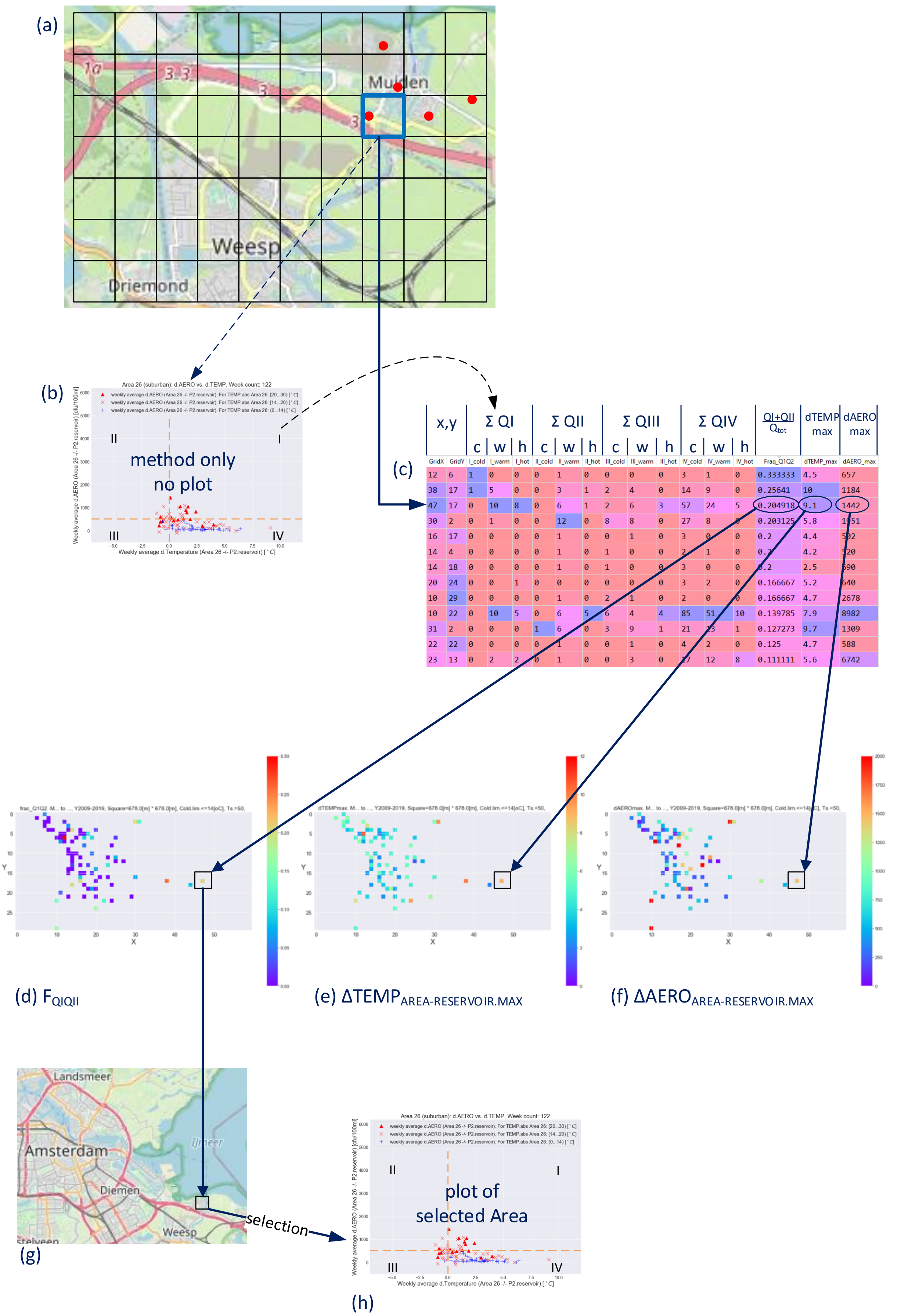


Figure 34 – Example of steps applied for Area profiling. From a squared raster (a) the method of profile plots (b) was applied. All Areas were sequenced into a single dataset (c). The dataset was prepared for: Fraction of all markers per Area with potential perturbing Aeromonas increase (d), maximum Temperature increase per Area (e) and Maximum Aeromonas increase per Area (f). Projection on geographic map (g) for orientation. Profile plots (h) for selected Areas of interest.

Methodology - Applied steps for sequenced Area profiling (continued)

For every Area within the squared raster (Figure 34a) the same data handling was applied as for the profiling plots of Area 1 to 6 (Figure 31). The result was however not directly presented as a profile plot per area (Figure 34b), but as one dataset per DWDS (Figure 34c). Markers[5] on the scatter plot were summed according to the corresponding quartile and temperature designation as-if a plot was prepared. Resulting dataset contains one record per area on the DWDS raster. From this profiling dataset it was possible to compose multiple types of heatmaps. For this research three heatmaps were selected from the profiling dataset:

Figure 34d) Heatmap for F_{QIQII}

$$F_{QIQII} = \frac{(\sum QI + \sum QII)}{\sum Qall}$$

Definition:

F_{QIQII} is the fraction of sampled weeks that the 'average Aeromonas change during transport' potentially results in exceedance of drinking water standard for Aeromonas at the tap.

Figure 34e) Heatmap for marker with maximum Temperature increase: $\Delta TEMP_{AREA\text{-}RESERVOIR.MAX}$

(This is the description of methodology. Figures are shown in application (§3.5.2)

Figure 34f) Heatmap for marker with maximum Aeromonas increase: $\Delta AERO_{AREA\text{-}RESERVOIR.MAX}$

(This is the description of methodology. Figures are shown in application (§3.5.2)

Note the explicit different denotation of 'increase' instead of 'change' for ΔTEMP and ΔAERO on heatmaps (Figure 34e and f). From heatmap (d) the areas with critical Aeromonas increase are observed. These areas were subsequently compared with high temperature increase on heatmap (e). Heatmap (d) did intentionally not provide information on the level of Aeromonas increase to avoid overexposure of handful of extreme values. Heatmap (f) was added for backup reference only on maximum Aeromonas increase per Area. Areas of interest were subsequently projected on geographic map (Figure 34g) and individual profile plot (Figure 34h).

[5] Reference for markers:

	+	Cold	weekly average sample temperature: 0…13.9 °C
	X	Warm	weekly average sample temperature: 14…19.9 °C
	▲	Hot	weekly average sample temperature: 20…30 °C

3.5.2 Observations from sequenced profiling of P2 DWDS.

Following on discussion of Area 1 to 6 (§3.4.3) the full DWDS P2 was observed. This section aims to compare the deviating results from Area 5 within the context of the total DWDS. Moreover it was intended to look for causal relations between Temperature and Aeromonas that are applicable beyond this particular DWDS. In addition, the sequenced profiling method (§3.5.1) was evaluated for its ability to trace Areas with raised suspicion for influence of anthropogenic heating.

3.5.2.1 Parameters

For Profiling of DWDS P2 the following parameters were applied:

- Area Size: 678 m * 678 m
- Minimum sample size, or: samples per Area = 50
- Minimum week count, or: markers per Area = 15
- F_{QIQII} > 0.1

Week count minimum limit was set to exclude areas with high number of measurements within very short time span. These Areas were possibly measured due to construction works or incidents. The week count limit was only applied for interpretation of heatmaps. Areas with week count smaller than set limit value were still projected on the heatmap, though deselected for Area selection. The fraction of all markers per Area with potential perturbing Aeromonas increase (F_{QIQII}) was set at a threshold value of F_{QIQI} > 0.1. This value is arbitrary and considered specific per DWDS.

3.5.2.2 Procedure and observations on DWDS P2

Procedure steps in this section are numbered (1 to 7) and observations are marked by bullets (•).

1. A heatmap was prepared for repetitive occasions of Aeromonas increase during transport, based on F_{QIQII} factor[6] per Area. Areas with $F_{QIQII} > 0.1$ were labelled with a square (Figure 35a). Areas with limited timespan (week count < 15) of measurements were removed from selection. Remaining Areas were numbered Area 21 to Area 26 (Figure 35a). Note that the Area 23 and 24 correspond with Area 5 from Figure 23.

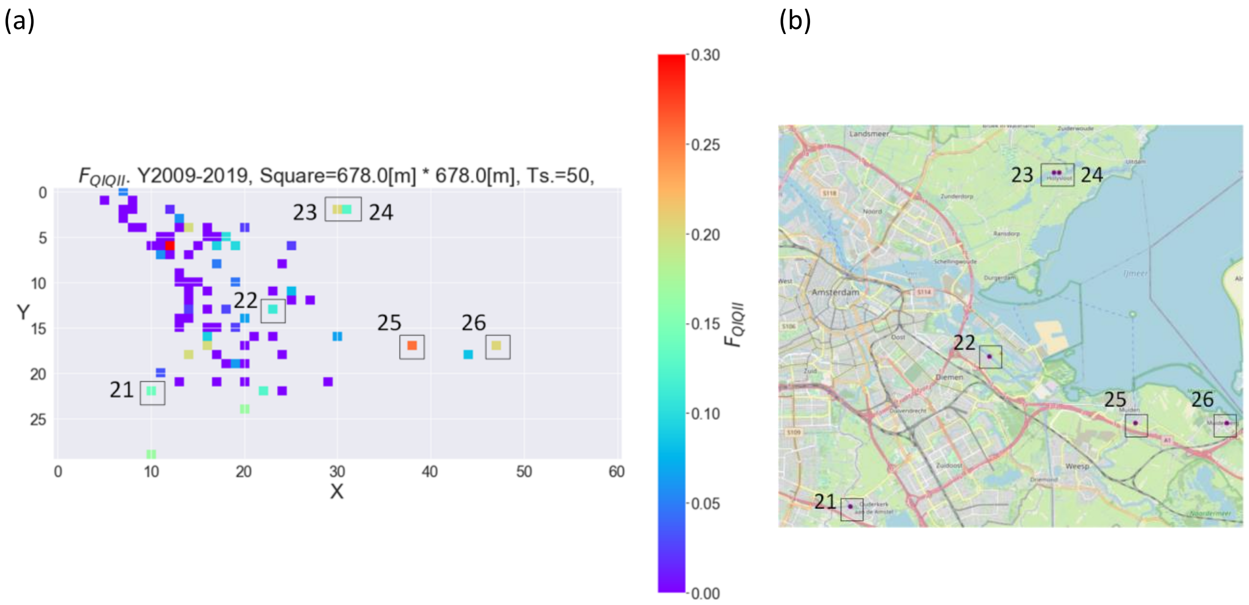


Figure 35 - DWDS P2 Profile plot with fraction of all markers per Area with potential perturbing Aeromonas increase. Areas with $F_{QIQII} > 0.1$ and measurement time span > 15 weeks were numbered Area 21 to Area 26 (a). Area 21 to Area 26 projected on Geographic plot (b). Map size: 18.8 x 15.7 km

- After exclusion of Areas with a limited timespan six Areas appeared with perturbing Aeromonas increase of $F_{QIQII} > 0.1$. These Areas 21 to 26 showed the highest ratio of markers in the QI and QII quadrants of the profiling plots. Which implies that these areas were subject to repetitive weeks with potentially exceedance of drinking water standard for Aeromonas.

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[6] $F_{QIQII} = \frac{(\sum QI + \sum QII)}{\sum Qall}$

F_{QIQII} is the fraction of sampled weeks that the 'average Aeromonas change during transport' potentially results in exceedance of drinking water standard for Aeromonas at the tap.

2. The squares of Area 21 to 26 were subsequently projected on the Heatmap for maximum Temperature increase during transport (Figure 36a). This projection was compared with Top-6 Areas (circles) for 'maximum Temperature increase during transport' (Figure 36b).

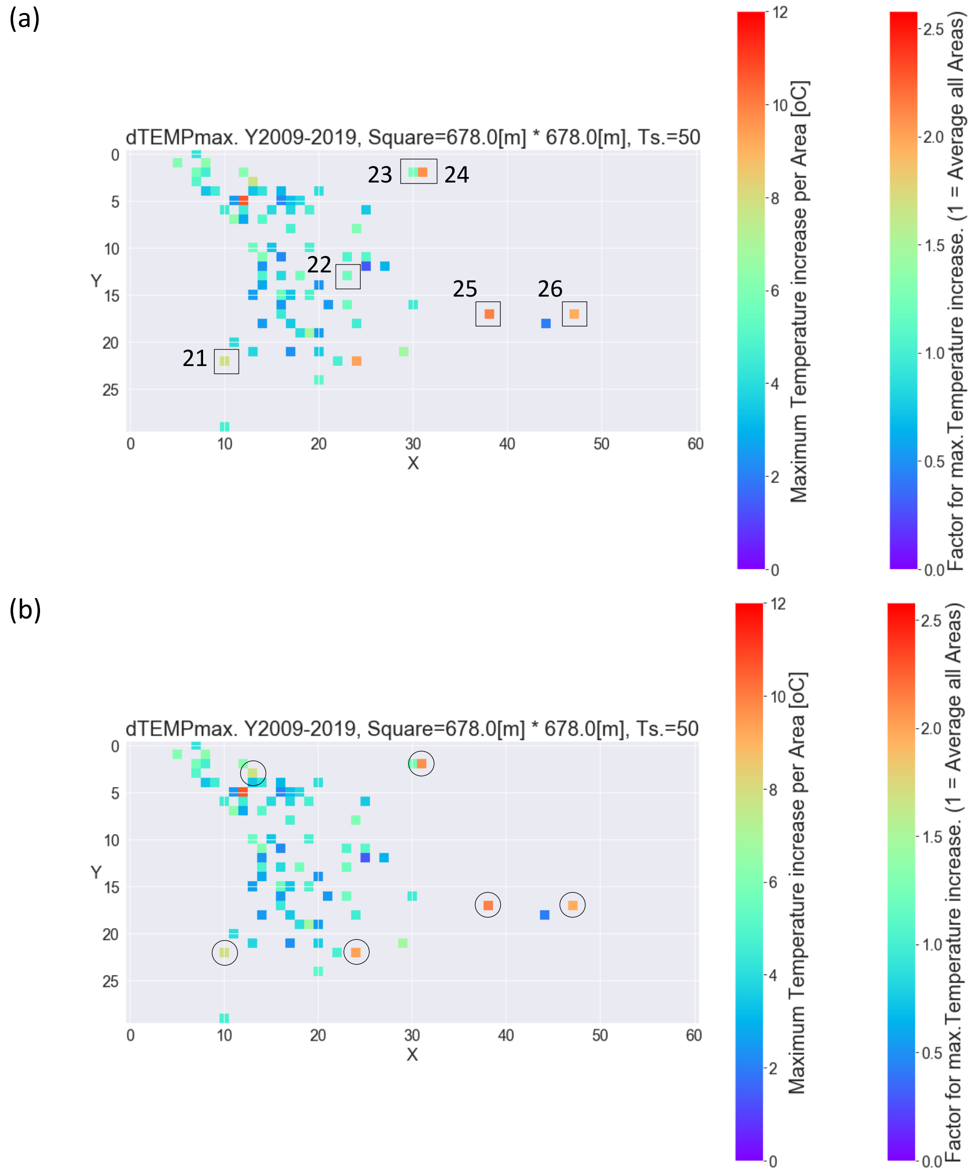
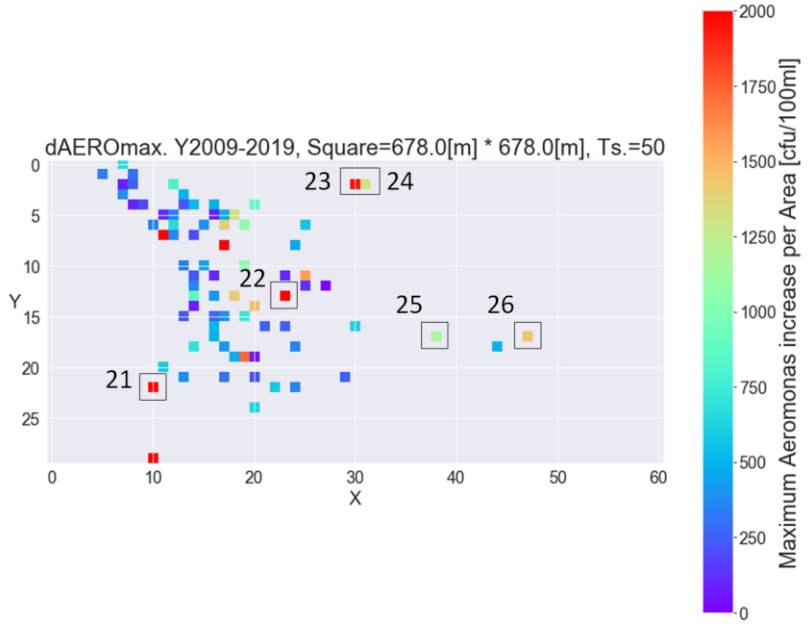


Figure 36 - Projection of Area21 to Are 26 on heatmap for maximum Temperature change (°C) during transport (a). Top-6 Areas (circles) for maximum Temperature change (°C) during transport (b).

- Area 21 to 26 matched with 4 Areas from the Top-6 Areas for 'maximum Temperature increase during transport'. The allocation of this Top-6 also seemed to suggest that the Areas with highest 'maximum temperature increase' were located on the outskirt of the DWDS.

3. The squares of Area 21 to Area 26 were additionally compared projected on the heatmap with Top-6 Areas for 'maximum Aeromonas increase during transport' (Figure 37a). This projection was compared with Top-6 Areas (circles) for 'maximum Aeromonas increase during transport' (Figure 37b).

(a)



(b)

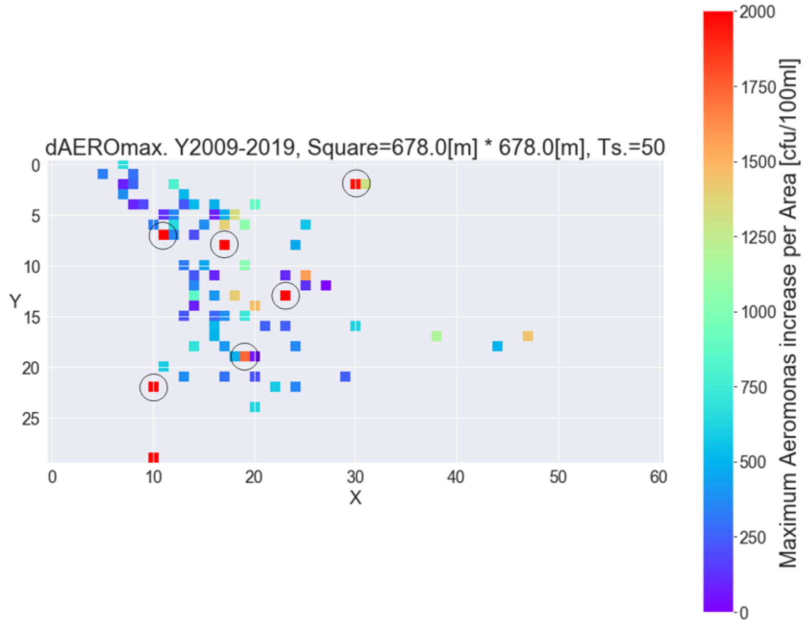


Figure 37 - Projection of Area 21 to Area 26 projected on heatmap for maximum Aeromonas increase (cfu/100ml) during transport (a). Top 6 Areas (circles) for maximum Aeromonas increase (cfu/100ml) during transport (b).

- Only two Areas from the Top-6 of 'maximum Aeromonas increase' were located on the outskirt of the DWDS.
- Only three areas from the Top-6 of maximum Aeromonas increase corresponded with Areas of perturbing Aeromonas increase.

4. In the next stage, profiling plots for Area 21 to Area 26 were prepared (Figure 38a to Figure 38f).

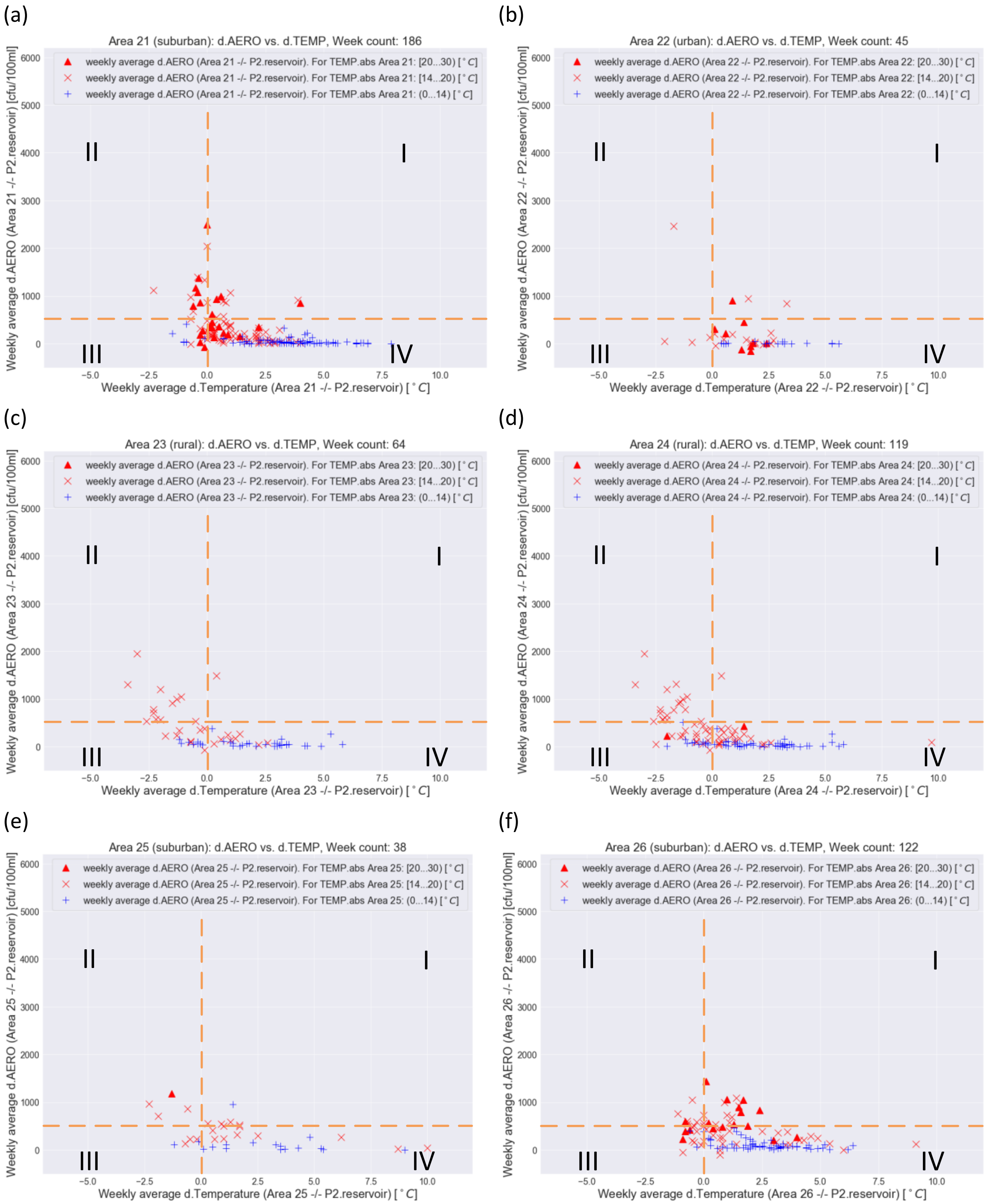


Figure 38 – Profile plots for Area 21 to2 6 (a-f) with net weekly average Aeromonas change (Area -/- P2 reservoir) versus net weekly average Temperature change (Area -/- P2 reservoir). Period 2009-2019.

5. Observations from profile plots (Figure 38a to Figure 38f).
    - The scatter of 'blue' markers on profiling plots of Area 21, 25 and 26 showed similarities with Area 5 (i.e. Area 23 and 24). The 'blue' markers represented a ΔTemperature range between -2 and +7 ^{o}C. Besides were almost all 'cold' markers located in quadrants III and IV. Not completely similar, though notable was the ΔTemperature range of markers in quadrants QI and QII, among observed Areas on the outskirt of DWDS (Area 21, 23, 24, and 26).
    - Quadrant I was well-nigh vacant for the plots for Area 23 and 24. While the plots for Area 21 and 26 indicate multiple 'warm' markers in quadrant I. A possible relation with the rural characteristics of Area 23 & 24, and suburban characteristics of Area 21 and 26 was considered. Though the restricted number of observed Areas was a feeble base for conclusions. Additional comparison of Areas for their profiling plots and their demographic characteristics is therefore advised.
    - The pattern for Area 22 was unlike the pattern of Areas 21, 23, 24, 25 and 26. Area 22 deviated from these areas by the lowest fraction of perturbing Aeromonas increase (F_{QIQII} = 0.11) combined with the smallest range for the Temperature change of 'blue' markers.
    - Concluding showed the profiling plots of Area 21, 25 and 26 both similarities ánd differences with the plot of Area 5 (Figure 32d). The Profiling plot of Area 22 was rather comparable with Area 1 (Figure 32c).
    - From the 6 selected Areas only Area 22 and 25 were nót located on the outskirts of the DWDS (Figure 35). Albeit, these areas were considered different for their profiling plots. The profiling plot of Area 25 showed more similarities with Areas 21, 23, 24, and 26 on the outskirt of the DWDS. Possible influence of high residence time was therefore considered.

6. The squares of Area 21 to Area 26 were projected on the map with simulated residence time (Figure 39a).
   - Areas 21, 23, 24, and 26 corresponded with an average residence time ranging from 40 to >50 hours. Area 22 and Area 25 corresponded with a much wider range for the average residence time: 10 to >50 hours. This comparison confirmed the suspicion of high residence time at the outskirt Areas 21, 23, 24 and 26.

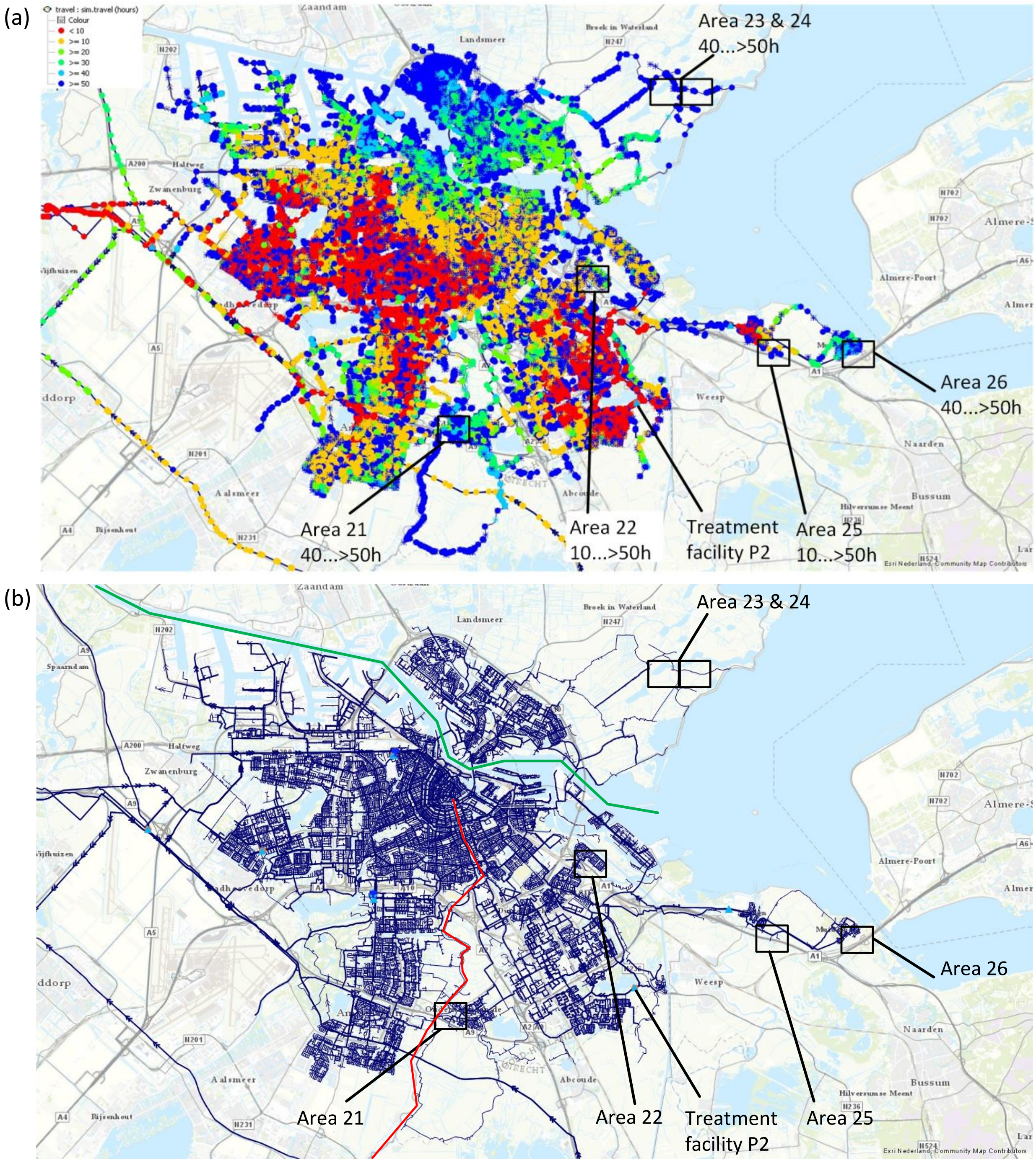


Figure 39 - Geographic map with simulated residence time (hours) from clean water reservoir to location within DWDS. Colour of indicators (dots) represent average residence time. Red: <10h, orange: 10-20h, green: 20-40h, light blue: 40-50h, dark blue: >50h (Waternet, 2020c) (a). Network layout covering DWDS P1 (partially) and DWDS P2, with River 'IJ' (green) and River 'Amstel' (red) (Waternet, 2020d) (b). Location of Area 21 to 26 are added for reference. Map size: 37.5 x 21.9 km.

- Prolonged residence seemed therefore related to repetitive exceedance for Aeromonas drinking water standard at the outskirt Areas 21, 23, 24 and 26. This relation was however not inextricably linked or absolute for all outskirt Areas. A comparison of Figure 35a and Figure 39a also presented some Areas (For example coordinates [x=8, y=1]) on the outskirt of the DWDS with long residence time (>50h), though without repetitive exceedance for Aeromonas drinking water standard.
- Another comparison was made for the combination of Area 4 & 5 (Figure 28b) and combination of Area 25 & 26 (Figure 39b). The Areas within these combinations are serially interconnected on an isolated branch to the outskirt of a DWDS. Remarkably seems Area 4 not adversely affected by the end-of-line position of Area 5. Although, a closer look at the network topology learned that the network topology of Area 4 & 5 differed from Area 25 & 26. The network connection from Area 4 to Area 5 was not isolated (dead-end) but circular connected with another part of the DWDS.
- The possible influence of different demographic characteristics of Area 4 & 5 (both rural) and Area 25 & 26 (both suburban) was considered. For a substantiated comparison additional information was required, such as: The DWDS routing, age, material and sizing. This information was not available during this research stage and therefore not further explored.

7. Per observed Area (Area 21 to 26) two scatter plots were prepared for correct interpretation of profile plots: (1) Temperature change during transport, in time. (2) Aeromonas change during transport, in time. These plots were excluded from report for the argument of overview.
   - Both plots showed a rather constant seasonally pattern for Aeromonas change, among six observed areas. Extreme high (> 2000 cfu/100ml) absolute Aeromonas values are identified, though did not occur on regular or repetitive basis.
   - It was perceived that a sudden trend break for 'seasonal Temperature change during transport', might have been an indication of anthropogenic heating along DWDS trajectory. Construction of trend lines was unfortunately not possible due to limited number of weekly observations per Area. Observed scatter plots did however suggest a horizontal trend for Temperature change during transport, among measured time span.

8. Closer look at profiling data-set for all Areas (example: Figure 34c).
   - 34 Areas were distilled from the total DWDS (with a week count ≥ 15). For every of these Areas held that the majority of 'warm' markers resided in quadrants QIII and QIV.
   - The same held true for the 'hot' markers, with the sole exceptions of Area 25 and 26. Within these two Areas the majority of the 'hot' markers were located in quadrants I and II.
   - The Area with coordinates [x=24, y=22] (Figure 35a) was of interest for: (1) Its proximity to the treatment facility (straight line distance = 1.8 km); (2) Its occasions of above-average Temperature change; (3) Its vacant quadrants I and II and (4) its hot markers in quadrant IV. The week count for this Area of 46 was rather low, but time series plots indicated continuous measurements over full time span. Future research is advised to explore if this Area, or the DWDS trajectory to this Area, is subject to short periods of anthropogenic heating.
   - The Area with coordinates [x=13, y=3] (Figure 35a) was of interest for: (1) Its distal position from the treatment facility (straight line distance = 13.2 km), its (2) occasions of above-average Temperature change and (3) its neigh vacant quadrants QI and QII. This Area was not suspicious for repetitive occasions of perturbing Aeromonas increase ($F_{QIQII} < 0.06$), but its direct surrounding seems more affected (Figure 35a). The limited 'week count' of 17 raised suspicious for observation of incidental measurements. This is confirmed as time series plots demonstrated a discontinuous

sample sequence in 2009, 2010 and 2014. From this Area it was considered that the cause for a divergent profile plot of one particular Area might be better observed in its vicinity than within the same particular Area.

3.5.2.3 Brief test for sequenced profiling of DWDS P1

Sequenced profiling was also applied as a test on DWDS P1, based on same parameters as for DWDS P2. This brief test was performed as a trial, so plots and graphs are not included in this report.

- Area size: 678 m * 678 m
- Minimum sample size, or: samples per Area = 50
- Minimum week count, or: markers per Area = 15
- Criteria for Area selection (F_{QIQII} [7]): $F_{QIQII} > 0.1$

These parameters did however result in zero selected areas. For illustration: The DWDS P1 Area top-6 for F_{QIQII} factor ranged between 0.05 … 0.08. This was considered low compared with the DWDS P2 top-6 for F_{QIQII} factor (0.11…0.25). Experiments with an alternative ‘area size’, ‘minimum sample size’ or ‘minimum week count’ did not change this outcome. The average Aeromonas quality indicating parameter of DWDS P1 was therefore considered significantly better than DWDS P2. This finding was based on the independent samples t-test on F_{QIQII} for all Areas (Minimum week count ≥15) of DWDS P1 and DWDS P2 (p<.005).

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[7] $F_{QIQII} = \frac{(\sum QI + \sum QII)}{\sum Qall}$

F_{QIQII} is the fraction of sampled weeks that the ‘average Aeromonas change during transport’ potentially results in exceedance of drinking water standard for Aeromonas at the tap.

3.5.3 Conclusions from observation of DWDS P2

In §3.5.2 DWDS P2 was scanned and examined for similarities that could imply or explain a spatial connection between Temperature and Aeromonas. Most important disclaimer for this chapter comes from the observation of net changes during transport. The net change did not reflect on the changes or influences along the way. From literature it was known that the DWDS status, age, material, microbial fouling and subsoil characteristics influence water quality during transport. These influences were not included in this study.

- The location of Areas with recurring perturbing Aeromonas increase suggested that the Areas on the outskirt of DWDS were sensitive to repetitive exceedance of Dutch drinking water standard of 1000 cfu/100ml. Areas on a non-circular (dead-end) branch in direction of DWDS outskirt seemed to be equally prone to repetitive exceedance of Aeromonas standard for safe drinking water. Further exploration with accurate network topology map is however advised.
- All observed profile plots from DWDS P2 outskirt Areas demonstrated recurring perturbing Aeromonas increase recurring for warm markers, combined with above-average temperature increase for cold markers. A direct causal relation between Temperature change and Aeromonas change during transport was not observed from literature and was not suggested from this research. Albeit, an indirect common cause by means of 'residence time' was considered plausible.
- There was no observed inextricably causal connection between 'hot' markers and disturbing Aeromonas increase. 'Warm' and 'hot' markers were predominantly related to limited Aeromonas increase, resulting in Aeromonas measurements within the standard for safe drinking water. From observation of Area profile plots it was perceived that 'Warm' and 'hot' markers were not or incidentally related to perturbing Aeromonas increase, unless the Area was located on the outskirt of the DWDS.
- A correlation or similarity between the demographic characterisation (urban, suburban and rural) of selected Areas and its Aeromonas change or Temperature change was explored, but not observed. A more specific research with additional information on network topology could possibly relate demographic Area characteristics with Temperature and Aeromonas observations.
- 'Maximum Temperature increase during transport' seemed a better indicator for 'recurring perturbing Aeromonas increase' than 'maximum Aeromonas increase during transport'.

3.5.4 Discussion on limitations

In preceding sections measurement data from DWDS samples were explored spatially and in time. So far, the reliability and accuracy of the measurement values were not put into question. It was however considered that a number of factors might have influenced the applied measurement procedures and its outcome. The considered influences are discussed in this section.

- Local differences within subsoil temperature. - Local subsoil temperature differences are demonstrated by Visser et al. (2020). The possible effect of these differences are not structurally explored and related to the spatial observations.
- Changing subsoil conditions. - Static and changing subsoil conditions affect the thermal resistance of the soil around a DWDS (Agudelo-Vera et al., 2015); (Klok et al., 2012). This is effect is not explored.
- Operational interventions on DWDS. - From Waternet personnel it was known that the DWDS routing from reservoir to a specific sample location may have changed during time span of observations (De Groot, 2020). It was perceived that a route change might have influenced microbial water quality and/or Temperature at the sampled location. These events are not retrieved or explored.
- Moment of sample taking. - It was also suggested that the moment (time) of sampling might be related to the age of the drinking water sample. Flow through a DWDS pipe section is amongst others related to the diurnal demand patterns. Early morning samples might have been subject to longer residence time than samples retrieved at noon or afternoon. This influence was tested by inclusion and exclusion of samples according to its sample time. Only minor changes were observed on individual profile plots and heatmap projections of profile plots.
- Flush of standing water from DWDS to tap. - All drinking water samples were considered samples from within the DWDS. This assumption is however only valid if the standing water in the piping section between DWDS and tap was sufficiently flushed. Waternet technicians are well trained and received specific instructions on this matter (Kors, 2020). However, occasions of inadequate flushing cannot be ruled out.
- Deduction of Aeromonas and Temperature change during transport. – The deduction of net Aeromonas and Temperature change during transport, from reservoir to DWDS sample location, included an uncertainty. Net change during transport was based on the calculated difference between samples with equal calendar week (date stamp). This deduction was however not accurate for sample locations with a long residence time (i.e. >50h). For these samples, the net change during transport should in fact have been calculated from samples with two consecutive calendar weeks (date stamp).
- Unequal distribution of samples. – The sample locations in this case study were not equally distributed through the geographic extend of the DWDSs. Furthermore, the sample frequency was not equal but varied among the sampled locations. It was therefore considered that mutual comparison of equally sized Areas might be inaccurate as the number of measurements per area might be very different. On the other hand it is also informative. For example: The blue markers on the profile plot of Area 1 (Figure 32c) exhibit a very limited scatter compared with Area 25 (Figure 38e). Despite their identical observation window and comparable week count.
- Residence time estimates - A geographic map with estimates of average residence time was applied for comparison with the profile plots of 12 observed Areas. This map was based on combined simulations and field tests. These field tests indicated that the simulated residence time proved to be more accurate for the larger transport sections (piping) than for the distribution branches to (groups of) consumers (De Groot, 2020). The 'residence time range' was therefore considered reliable for the main lines within observed Areas.

4 Conclusions

Short summary

The aim for this research was the exploration of spatial and temporal relation between drinking water temperature and microbial quality indicating parameters within a DWDS. Past research on unchlorinated DWDSs pointed at the influence of temperature on indicating parameters for microbial growth. Spatial and temporal effects throughout the DWDS remained however underexposed. To maintain and control the drinking water quality until the tap, it was required to obtain a better understanding of the relation between drinking water temperature and microbial quality indicating parameters.

DWDSs were considered complex and its physical and microbial processes are under influence of changing subsoil conditions. Clear findings or strong conclusions, for this DWDS or beyond, were therefore presumed inappropriate. Salient similarities between Areas within observed DWDS were however explored and highlighted.

Two treatment facilities with distinct raw water sources produce drinking water for the city of Amsterdam and its surrounding municipalities. The drinking water was transported from the two treatment facilities to the customers through two adjacent subsystems, DWDS P1 and DWDS P2. The clean water temperature of reservoir P1 was significantly higher than reservoir P2. Though within the service area it seemed as if both systems adopt the same DWDS temperature. The drinking water temperature within DWDS P1 and DWDS P2 was subject to a slight, though significant, temperature increase of 0.12…0.13 °C/year. DWDS P1 and DWDS P2 displayed a significant Aeromonas decrease among observed time span (-4…-8 cfu/100ml/year). Both networks were well operated, maintained and monitored, according to strict national regulations.

4.1 Conclusions on spatial and temporal analysis

- A clear correlation between Temperature and Aeromonas was observed. This was consistent with literature. The correlation between Temperature and HPC was however very weak. While the Aeromonas time series indicated a clear repetitive seasonal pattern, there was no discernible seasonal pattern for HPC at all.
- Spatial variations of Temperature and Aeromonas measurements were most distinct in the summer. This was evident from the time lapse of heatmaps with absolute Temperature and Aeromonas measurements. The seasonal pattern was visible from some locations with elevated absolute Temperature or Aeromonas values.
- Incidental extreme high Aeromonas values defined the maximum value for the heatmap colour scheme. This effect hindered heatmap observations for lower Aeromonas values. Local differences became indiscernible because different Aeromonas values were projected by the same colour.
- Areas with elevated Temperature and Aeromonas did occasionally correspond in time and space.

4.2 Conclusions on focal area analysis

- From the initial heatmap series six Areas of interest were selected with one common network connection, residing within a distinctive urban district and rural district.
- From time series analysis on these six Areas a seasonal pattern of warming and cooling of DWDS was noted. The visually small differences within cooling and warming patterns, appeared to be significantly different for the observed urban and rural district. The weekly average absolute sample Temperature of the urban district was significantly higher than the weekly average absolute sample Temperature of the rural district. It was not possible to repeat or compare this

observation for the total DWDS. The unique setup with one common main connection split into two distinctive demographic areas (urban versus rural) was not available elsewhere in the DWDS.

- A new plot was prepared to observe a possible relation between (1) the net change of Temperature during transport, (2) net change of Aeromonas during transport and the (3) absolute sample Temperature.
- Preparation of individual profiling plots per Area was rather labour intensive. Besides, without prior exploration the DWDS there was no foreknowledge of what location to observe. Therefore a new automated sequence was proposed to apply the principle of the profiling plots on the total DWDS, instead of directly on a particular Area.
- The method of sequenced profiling plots was applied to observe the DWDS P2. From this method new heatmaps are prepared. Though, to prevent the overbearing influence of extreme high Aeromonas values, absolute Aeromonas measurements are replaced by the fraction of weeks that the Aeromonas standard is surpassed. This factor is used for the new heatmap. The heatmap is visually coarser than the initial produced maps. Though multiple evaluation of same data was averted, so heatmap observations became easier backwards related to original data source.
- Profiling plots from Areas on the outskirts of observed DWDS appeared to be visually dissimilar from plots of Areas away from the DWDS's outskirts. Plots on the outskirts combined elevated DWDS temperature increase in the winter with enhanced Aeromonas increase in the summer. Areas in the centre of observed DWDS were not located in proximity of the treatment facility, nor in proximity of DWDS's outskirt. Most profiling plots of centrally located Areas, combined a restricted temperature increase of cold markers with no or a few exceedances of Aeromonas drinking water standard at sampled location. Prolonged, or restricted 'residence time' was a suspected common cause. This presumption was confirmed from consultation of the map with simulation of average residence time within observed DWDS. Average residence time on observed outskirt Areas was higher than average residence time for observed Areas away from DWDS's outskirt.
- The location of Areas with highest fraction of Aeromonas standard exceedance showed similarities with location of Areas with highest temperature increase during transport.
- The location of Areas with maximum Aeromonas change seemed less similar with the allocation of Areas with highest temperature increase.
- These combined observations pointed at the influence of residence time. Repetitive exceedance for Aeromonas drinking water standard at the DWDS's outskirt Areas were related to prolonged residence time. This relation was however not inextricably linked for all outskirt Areas. Nor was this relation reversible. Some Areas on the outskirt of the DWDS showed prolonged residence time (>50h), though without repetitive exceedance of Aeromonas drinking water standard.

4.3 Conclusions related to research questions

In context of research objectives and in respond to the research questions, following conclusions were drawn.

1. Is there a spatial and/or temporal correlation between water temperature and microbiological water quality indicators (HPC and Aeromonas) in the DWDS?

The direct relation between Temperature and Aeromonas was observed. Temporal correlation was strong according to the time series analysis of Temperature and Aeromonas. The spatial aspect of this relation was however not clearly discernible from the initial series of heatmaps. Information on the residence time throughout the DWDS was considered essential for assessment of correlation between Temperature and Aeromonas. Spatial relation between Temperature and HPC was not observed.

2. What conclusions can be drawn from the long term pattern and geographical distribution of local correlations?

The initial series of heatmaps, based on absolute values, predominantly highlighted areas with high Aeromonas samples values or areas with a reduced time span. Combined observation of Temperature and Aeromonas changes during transport, resulted in a more nuanced heatmap. The outskirts of explored DWDS seemed sensitive for repetitive exceedance of Aeromonas standard. Areas with repetitive exceedance of threshold temperature for accelerating Aeromonas growth (14 ^{o}C), were however not inextricably tied to repetitive exceedance of Aeromonas standard. Areas with repetitive exceedance of Aeromonas standard showed a strong indication of prolonged residence time. For this particular DWDS, it was therefore suggested that the influence of residence time is more important than the absolute sample temperature, for the spatial assessment of Aeromonas quality parameter. It was however unknown if this suggestion holds for other DWDSs beyond this case study area. Additional research is considered essential. Especially on individual network branches to the outskirt of DWDSs.

3. Can hotspots, potentially caused by anthropogenic heat sources, be identified through long term monitoring of water temperature within the DWDS?
4. What is the correlation between water temperature and microbiological water quality indicators (HPC and Aeromonas) around these heat hotspots in Amsterdam?

Research questions 3 and 4 implicitly suggest that the observed correlation between absolute Temperature and absolute Aeromonas values, holds for spatial observations. The DWDS was however complex and from literature it was known that microbial processes within DWDSs are dynamic. The initial time lapse series of heatmaps was explored extensively to possibly answer these research questions. It became however clear that it was hard to discern direct similarities between absolute drinking water Temperature and Aeromonas. The profiling plots of explored DWDS did indicate very limited arguments for local causality between absolute temperature samples and absolute Aeromonas values. However, if the research question is perceived for 'temperature change', instead of 'absolute temperature', a reply is possible. Two areas of interest were indeed identified from sequenced profiling of observed DWDS. Both areas showed a suspicious above-average temperature change. One Area was selected for its proximity to the treatment facility. Another Area was selected for is distal position from the treatment facility. Further investigation on these two Areas was considered required for correct interpretation of findings.

5 Limitations, Recommendations and Opportunities for future research

Limitations

From this research the spatial and temporal relations between drinking water temperature and two quality indicating parameters for microbial regrowth were explored within an unchlorinated DWDS. From the results of this particular DWDS, the focus shifted from absolute measurements to the net change of parameters during transport. The pattern of change during transport was however not explored. It was considered that information on Temperature and Aeromonas change along trajectory, could provide additional information on the origin of perturbing Aeromonas increase. Another limitation of this research was related to the direct comparison of weekly reservoir samples and average Area samples of the same week. Comparison of Areas with short residence time with Areas of long residence time could have been inaccurate.

Recommendations

To address both limitations and improve understanding of spatial and temporal relations between temperature and Aeromonas some recommendations are suggested.

- It is strongly recommended to explore the change of Aeromonas and Temperature along is trajectory from reservoir to tap. The presence of repetitive elevated Aeromonas change was considered more informative than sporadic occasions of (extreme) high Aeromonas change.
- Therefore it is considered essential to combine heatmap observations with corresponding time series analysis. These may indicate the presence of a trend break or extreme values in time. It is likewise recommended to scan for Areas with a short time span of measurements. These Areas might have been subject to non-reoccurring measurements after construction works or incidents.
- For future research on this topic disclosure of network topology is considered essential.
- Heatmaps based on the circles method provide a smooth picture with the circled raster method. If the spatial observation is applied to allocate areas of interest (or concern), it is advised to prepare heatmaps with the 'squares method' instead. By preparation of heatmaps with the 'squares method' double evaluation of same sample data is averted. Heatmap observations become directly relatable to original sample data.

Opportunities for future research

From the recommendations it would be very interesting to optimize the profiling method by additional information on the network characteristics.

With additional information on DWDS routing, a series of profile plots can be prepared along trajectory from reservoir to tap. This could provide information on a particular DWDS, but also contribute to more universal knowledge on the causal relation between temperature, residence time and quality indicating parameters in DWDSs. Specific focus on network branches to the DWDS outskirt is advised.

Mutual comparison of separate DWDSs by the sequenced profiling method may likewise contribute to better understanding of DWDSs and the possible effect of its demographic characteristics.

References

Aggarwal, C. C. (2017). Visualizing Extreme Values with Box Plots. In C. C. Aggarwal, *Analysis* (Second Edition ed., pp. 45-46). Cham: Springer. ISBN 978-3-319-47578-3. doi:DOI 10.1007/978-3-319-47578-3

Agudelo-Vera, C. M. (2018). *Aanpak om de hotspots in het leidingnet terug te dringen (BTO 2018.024).* Nieuwegein: KWR. Retrieved January 12, 2020, from https://library.kwrwater.nl/publication/55650341/

Agudelo-Vera, C. M., Blokker, M., De Kater, H., & Lafort, R. (2017). Identifying (subsurface) Anthropogenic Heat Sources that Influence Temperature in the Drinking Water Distribution System. *Drinking Water Engineering Science, 10*, 83-91. doi:https://doi.org/10.5194/dwes-10-83-2017-supplement

Agudelo-Vera, C. M., Blokker, M., Van Der Wielen, P., & Raterman, B. (2015). *Drinking water temperature in future urban areas (BTO 2015.012).* Nieuwegein: KWR. Retrieved February 1, 2020, from https://library.wur.nl/WebQuery/hydrotheek/2163979

Ashbolt, N. J., Grabow, W. O., & Snozzi, M. (2001). Indicators of microbial water quality. In WHO, L. Fewtrell, & J. Bartram (Eds.), *Water Quality: Guidelines, Standards and Health* (pp. 289-316). London, United Kingdom: IWA Publishing, ISBN: 1900222280.

Blokker, M., Agudelo-Vera, C., Moerman, A., Van Thienen, P., & Pieterse-Quirijns, I. (2017). Review of applications for SIMDEUM, a stochastic drinking water demand model with a small temporal and spatial scale. *Drinking Water Engineering and Science*(10), 1-12. doi:doi:10.5194/dwes-10-1-2017

Boneau, C. A. (1960). The Effect of Violations of the Assumptions Underlying the T test. *Psychological Bulletin, 57*(1), 49-64. Retrieved July 22, 2020, from https://psycnet.apa.org/record/1960-06756-001

Cisneros, J. B., Oki, T., Arnwell, N. W., Benito, G., Cogley, J. G., Döll, P., . . . Mwakila, S. S. (2014). Freshwater resources. In *Climate chanage 2014: Impacts, Adaption and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the 5th Assesment Report of IPCC* (pp. 229-269). Cambridge: Cambridge University Press. Retrieved January 11, 2020, from https://www.ipcc.ch/site/assets/uploads/2018/02/WGIIAR5-Chap3_FINAL.pdf

De Groot, R. (2020). Specialist hydraulic analyses at Waternet. (R. P. Speksnijder, Interviewer) Retrieved November 23, 2020

Dean, S., & Illowsky, B. (2013). Descriptive Statistics: Skewness and the Mean, Median, and Mode. In K. Chu, S. Dean, B. Illowsky, D. Lane, T. Short, & T. Short (Ed.), *Collaborative Statistics (Custom Online Version Modified by T. Short)* (pp. 81-82). Houston: Rice Univerity. Retrieved December 7, 2020, from http://cnx.org/content/col11476/1.5

Dekking, F. M., Kraaikamp, C., Lopuhaä, H. P., & Meester, L. E. (2005a). The Method of Least Squares. In F. M. Dekking, C. Kraaikamp, H. P. Lopuhaä, & L. E. Meester, *A Modern Introduction to Probability and Statistics* (2005 ed., pp. 329-337). London: Springer. ISBN 1852338962. Retrieved August 26, 2020

Dekking, F. M., Kraaikamp, C., Lopuhaä, H. P., & Meester, L. E. (2005b). The t-test. In F. M. Dekking, C. Kraaikamp, H. P. Lopuhaä, & L. E. Meester, *A Modern Introduction to Probability and Statistics* (2005 ed., pp. 399-413). London: Springer. ISBN 1852338962. Retrieved September 10, 2020

Derrick, B., Toher, D., & White, P. (2016). Why Whelch's test is Type I error robust. *The Quantitative Methods for Psychology, 12*(1), 30-38. doi:DOI: 10.20982/tqmp.12.1.p030

Dettling, M. (2020). *Applied Time Series Analysis.* Winterthur: Institute for Data Analysis and Process Design, Zurich University of Applied Sciences.

Douterlo, I., Sharpe, R. L., & Boxall, J. B. (2013). Influence of hydraulic regimes on bacterial community structure and composition in an experimental drinking water distribution system. *Water Research*, 503-516.

Drinkwaterbesluit. (2018, July 1). Retrieved from Overheid.nl: https://wetten.overheid.nl/BWBR0030111/2018-07-01/0/

Drinkwaterregeling. (2019, June 28). Retrieved from Overheid.nl: https://wetten.overheid.nl/BWBR0030152/2019-06-28

El Chakhtoura, J. (2018). *Drinking Water Microbial Communities.* Delft: Delft University of Technology.

Fagerland, M. W. (2012). t-tests, non-parametric tests, and large studies - a paradox of statistical practice? *Medical Research Methodology, 12*(78), 1-7. doi:doi:10.1186/1471-2288-12-78

Fahrmeir, L., Kneib, T., Lang, S., & Marx, B. (2013a). Extensions of the Classical Linear Model. In L. Fahrmeir, T. Kneib, S. Lang, & B. Marx, *Regression Models, Methods and Applications* (pp. 177-267). Berlin: Springer. ISBN 978-3-642-34333-9. doi:DOI 10.1007/978-3-642-34333-9_4

Fahrmeir, L., Kneib, T., Lang, S., & Marx, B. (2013b). Discussion of Model Assumptions. In L. Fahrmeir, T. Kneib, S. Lang, & B. Marx, *Regression Models, Methods and Applications* (pp. 78-80). Berlin: Springer. ISBN 978-3-642-34333-9. doi:DOI 10.1007/978-3-642-34333-9_3

Fahrmeir, L., Kneib, T., Lang, S., & Marx, B. (2013c). Extensions of the Classical Linear Model. In L. Fahrmeir, T. Kneib, S. Lang, & B. Marx, *Regression Models, Methods and Applications* (pp. 191-201). Berlin: Springer. ISBN 978-3-642-34333-9. doi:DOI 10.1007/978-3-642-34333-9_4

Fahrmeir, L., Kneib, T., Lang, S., & Marx, B. (2013d). Parameter Estimation. In L. Fahrmeir, T. Kneib, S. Lang, & B. Marx, *Regression Models, Methods and Applications* (pp. 104-124). Berlin: Springer. ISBN 978-3-642-34333-9. doi:DOI 10.1007/978-3-642-34333-9_4

Gemeente Amsterdam. (2020). *Data en informatie.* Retrieved September 3, 2020, from Dataset Bevolking Buurten 2019: https://api.data.amsterdam.nl/dcatd/datasets/9Ib177KQQ4UgMA/purls/1

Gensberger, E. T., Gössl, E. M., Antonielli, L., Sessitsch, A., & Kostic, T. (2015). Efect of different heterotrophic plate count methods on the estimation of the composition of the culturable microbial community. *PeerJ*. doi:10.7717/peerj.862

Hallas, G., & Monis, P. (2015). Evaluation of Heteroptrophic Plate and Chromogenic Agar Colony Counting in Water Quality Laboratories. *MethodsX, 2*, 415-422. doi:http://dx.doi.org/10.1016/j.mex.2015.10.003

Hijnen, W., & Van Der Wielen, P. (2017). *Biologische stabiliteit en nagroei: definities en positiebepaling van de bedrijfstak anno 2016 (BTO 2017.068).* Nieuwegein: KWR. Retrieved November 22, 2020, from https://library.kwrwater.nl/publication/55383235/

Holmes, P., Niccolls, L. M., & Sartory, D. P. (1996). The Ecology of Mesophilic Aeromonas in the aquatic Environment. In B. Austin, M. Altwegg, P. J. Gosling, & S. Joseph, *The genus Aeromonas* (pp. 127-150). ChiChester: John Wiley & Sons. ISBN 9780471967415.

Hyndman, R. J., & Athanasopoulos, G. (2020). *STL decomposition*. (A. Monash University, Editor) Retrieved August 11, 2020, from Forecasting: Principles and Practice: https://otexts.com/fpp2/stl.html

ILT. (2019). *Drinkwaterkwaliteit 2018.* Den Haag: Inspectie Leefomgeving en Transport, Ministerie van Infrastructuur en Waterstaat.

Klok, E. J., Schaminée, S., Duyzer, J., & Steeneveld, G. J. (2012). *De Stedelijke hitte-eilanden van Nederland in kaart gebracht met satellietbeelden.* Utrecht: TNO. TNO-060-UT-2012-01117. Retrieved February 7, 2020, from http://publications.tno.nl/publication/102466/AipebS/TNO-060-UT-2012-01117.pdf

Kors, L. (2020). Teamleader Process at Waternet. (R. P. Speksnijder, Interviewer) Retrieved June 17, 2020

KWR. (2018). *Laboratoriumanalyses LMB 2018 - Achtergronden, beschrijving van de uitvoering en prestatiekenmerken.* Nieuwegein: KWR.

KWR. (2020). *Climate-proof drinking water, now and in the future*. Retrieved from KWR water: https://www.kwrwater.nl/en/projecten/climate-proof-drinking-water-now-and-in-the-future/

Le Chevallier, M. W., Welch, N. J., & Smith, D. B. (1996). Full-Scale Study of Factors Related to Coliform Regrowth in Drinking Water. *Applied and Environmental Microbioly*, 2201-2211.

Liu, G., Bakker, G. L., Li, S., Vreeburg, J. H., Verberk, J. Q., Medema, G. J., . . . Van Dijk, J. C. (2014). Pyrosequencing Reveals Bacterial Communities in Unchlorinated Drinking Water Distribution System: An Integral Study of Bulk Water, Suspended Solids, Loose Deposits, and Pipe Wall Biofilm. *Environmental Science and Technology*, 5467-5476. doi:dx.doi.org/10.1021/es5009467

Liu, G., Zang, Y., Lut, M., Knibbe, W. J., Van Der Wielen, P., Wentso, L., . . . Van Der Meer, W. (2017). Hotspots for Selected Metal Elements and Microbes Accumulation and the Corresponding Water Quality Deterioration Potential in an Unchlorinated Drinking water Distribution System. *Wate Research*, 435-445. doi:http://dx.doi.org/10.1016/j.watres.2017.08.002

Liu, S., Gunawan, C., Barraud, N., Rice, S. A., Harry, E. J., & Amal, R. (2016). Understanding, Monitoring, and Controlling Biofilm Growth in Drinking Water Distribution Systems. *Environmental Science and Technology*, pp. 8954-8976. doi:10.1021/acs.est.6b00835

Lucon, O., & Ürge-Vorsatz, D. (2014). Infrastructure and systemic perspectives. In IPCC, O. Edenhofer, & R. Pichs-Madruga (Eds.), *Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the IPCC* (pp. 696-697). Cambridge: Cambridge University Press. ISBN 978-1-107-05821-7. Retrieved from https://www.ipcc.ch/report/ar5/wg3/

Menberg, K., Bayer, P., Zosseder, K., Rumohr, S., & Blum, P. (2012). Subsurface urban heat islands in German cities. *Science of the Total Environment*, 1223-133. doi:http://dx.doi.org/10.1016/j.scitotenv.2012.10.043

Montgomery, D. C., Peck, E. A., & Vining, G. G. (2012). Multiple Linear Regression. In D. C. Montgomery, E. A. Peck, & G. G. Vining, *Introduction to Linear Regression Analysis* (pp. 67-128). John Wiley. ISBN 9781118627365.

Oke, T. R. (1973). City size and the urban heat island. *Atmospheric Environment, 7*, 769-779.

OpenStreetMap Foundation. (2020, June 17). *OpenStreetMap*. Retrieved June 17, 2020, from OpenStreetMap.org: https://www.openstreetmap.org/#map=12/52.3516/4.9397

Prest, E. I., Hammes, F., Vrouwenvelder, J. S., & Van Loosdrecht, M. C. (2016b, February 1). Biological Stability of Drinking Water: Controlling Factors, Methods, and Challenges. *7*, 1-24. doi:10.3389/fmicb.2016.00045

Prest, E. I., Weissbrodt, D. G., Hammes, F., Loosdrecht, M. C., & Vrouwenvelder, J. S. (2016a). Long-Term Bacterial Dynamics in a Full-Scale Drinking Water Distribution System. *PLOS ONE*, 1-20. doi:DOI:10.1371/journal.pone.0164445

Python Software Foundation. (2020). Retrieved from Python: https://www.python.org

Seabold, Skipper, & Perktold, J. (2010). Statsmodels: Econometric and Statistical Modeling with Python. *Proceedings of the 9th Python in Science Conference.*

Shumway, R. H., & Stoffer, D. S. (2017). ARIMA Models. In R. H. Shumway, D. S. Stoffer, R. DeVeaux, S. E. Fienberg, & I. Olkin (Eds.), *Time Series analysis and Its Applications* (Fourth Edition ed., pp. 75-88). Cham, Switserland: Springer. ISBN 978-3-319-52451-1. doi:DOI 10.1007/978-3-319-52452-8

Siedlecka, A., Wolf-Baca, M., & Piekarska, K. (2020). Spatiotemporal Changes of Antibiotic Resistance and Bacterial Communities in Drinking Water Distribution System in Wrocław, Poland. *MDPI Water, 12*`(2601), 1-17. doi:doi:10.3390/w12092601

Songwon, S. (2006). *A Review and Comparison of Methods for Detecting Outliers in Univariate Data Sets.* MSc thesis defence, University of Pitsburg, Department of Biostatistics. Retrieved December 06, 2020

University of Texas. (2020). *Strategy for Complete Regression Analysis - Presentation for course SW388R7.* Retrieved 11 08, 2020, from Slideplayer: https://slideplayer.com/slide/5773353/

Van Bijsterveld, W. (2020). *AlleCijfers.nl*. Retrieved September 5, 2020, from Informatie wijk Waterland 2019: https://allecijfers.nl/wijk/waterland-amsterdam/

Van Den Bos, L. (2020). *Quantifying the effects of anthropogenic heat sources on the water temperature in the drinking water distribution system.* Delft: Delft University of Technology.

Van Der Kooij, D., Hijnen, W. A., & Oranje, J. P. (1981). Vermeerdering van Bacterien in Drinkwater. *H2O*, 317-323.

Van Der Mark, E., Roman, F., Zandvliet, L., & Ramaker, T. (2011). Ruim tien jaar wateronderzoek: Een statistische goudmijn. *H2O, 18 - 2011*, 34-36.

Van Der Wielen, P. W., Bakker, G., Atsma, A., Lut, M., Roeselers, G., & Van der Graaf, B. (2016). A survey of indicator parameters to monitor regrowth in unchlorinated drinking water. *Environmental Science Water Research & Technology*, 683-692. doi:10.1039/c6ew00007j

Van Vliet, M. H., & Zwolsman, J. J. (2008). Impact of Summer Droughts on the Water Quality. *Journal of Hydrolgy*, 1-17. doi:doi:10.1016/j.jhydrol.2008.01.001

Veenman, K. (2020). *Opwarming van het freatisch grondwater in Amsterdam, een modeleerstudie.* Retrieved September 10, 2020, from Cruxbv.nl: https://www.cruxbv.nl/artikel/opwarming-van-het-freatisch-grondwater-in-amsterdam-een-modeleerstudie

Verbeek, M. (2017). Using linear regression to establish empirical relationships. *IZA World of Labor, 336*, 1-11. doi:10.15185/izawol.336

Visser, P. W., Kooi, H., Bense, V., & Boerma, E. (2020). Impacts of progressive urban expansion on subsurface temperatures in the city of Amsterdam (The Netherlands). *Hydrogeology Journal*. doi:10.1007/s10040-020-02150-w

Vitens. (2017). *Vitens Jaarverslag 2017.* Zwolle: Vitens.

Waternet. (2020a). *Waternet.* Retrieved August 3, 2020, from Waternet Folder Drinkwaterproces: https://www.waternet.nl/contentassets/e3c8a4e0e4c24601a74678d85ad17194/0165-waternet-folder-drinkwaterproces-1000-x-210mm.pdf

Waternet. (2020b). Waar komt uw water vandaan - (distributie PWK PLD.jpg). (L. Kors, Ed.) Amsterdam. Retrieved June 7, 2020

Waternet. (2020c). Simulated Water Age DWDS Amsterdam - (water_age.jpg). (R. De Groot, Ed.) Amsterdam: Waternet. Retrieved November 24, 2020

Waternet. (2020d). Distribution network Amsterdam - (distribution_network.jpg). (R. De Groot, Ed.) Amsterdam. Retrieved November 24, 2020

World Health Organization. (2017). Microbial fact sheets. In WHO, *Guidelines for drinking-water quality: fourth edition incorporating the first addendum.* (Fourth ed., pp. 231-306). Geneva: World Health Organization. ISBN 978-92-4-154995-0. Retrieved November 22, 2020, from https://www.who.int/publications/i/item/9789241549950

Zimmerman, D. W. (2004). A note on preliminary tests of equality of variances. *British Journal of Mathematical and Statistical Psychology, 57*, 173-181.

Zlatanovic, L., Van Der Hoek, J. P., & Vreeburg, J. G. (2017). An experimental study on the influence of water stagnation and temperature change on water quality in a full-scale domestic drinking water system. *Water Research*, 761-772. doi:http://dx.doi.org/10.1016/j.watres.2017.07.019

6 Statement of independent work

Although my profession is in the field of drinking water, there is no incentive or entanglement that might influence objectiveness of observations and/or conclusions. All data is provided under condition of non-disclosure.

Appendix 1 Composition of datasets

Each record in within the three datasets represents one measurement on one location. Each record consists of: location name (*NM_POINT*), date-time stamp (*DT_SAMPLE*), measured parameter (*CD_TPANA*), units (*CD_UNIT*), measured value (*DC_SAMVAL*) and GPS coordinates (*NR_X* and *NR_Y*). The format of database field names are presented in Table 2.

Table 2 - Format of datasets with measurement data.

Field	Description of Field	Format of Field
NM_POINT	Location name of sample	-
DT_SAMPLE	Date-Time stamp of sample	DD-DD-YYYY hh:mm:ss
CD_TPANA	Measured parameter	TEMP / AERO-30 / KG-22 *1)
CD_UNIT	Unit of measured value	^{o}C; cfu/100ml; cfu/ml
DC_SAMVAL	Measured value	
NR_X	GPS X-coordinate	Decimal degrees (4- 13 digits)
NR_Y	GPS Y-coordinate	Decimal degrees (4- 13 digits)

1) Aero-30 = Aeromonas value, with incubation at 30 ^{o}C
KG-22 = Kolonie Getal bij 20 ^{o}C = Heterotrophic Plate Count at 22 ^{o}C

Location names were used to combine groups of nearby samples. The geographic extend of a location name was not pre-defined. In general, unique name/number combinations were used for location name. It was however occasionally observed that the same group name was used for two distinct locations. Sample selection by location names was therefore avoided. Date-time stamps ranged from January 1st 2009 to December 31st 2019. Unique combinations of date-time stamp ánd location name identify which measurements originated from the same sample.

Appendix 2 **Analysis on Sample data distribution network**

Temperature

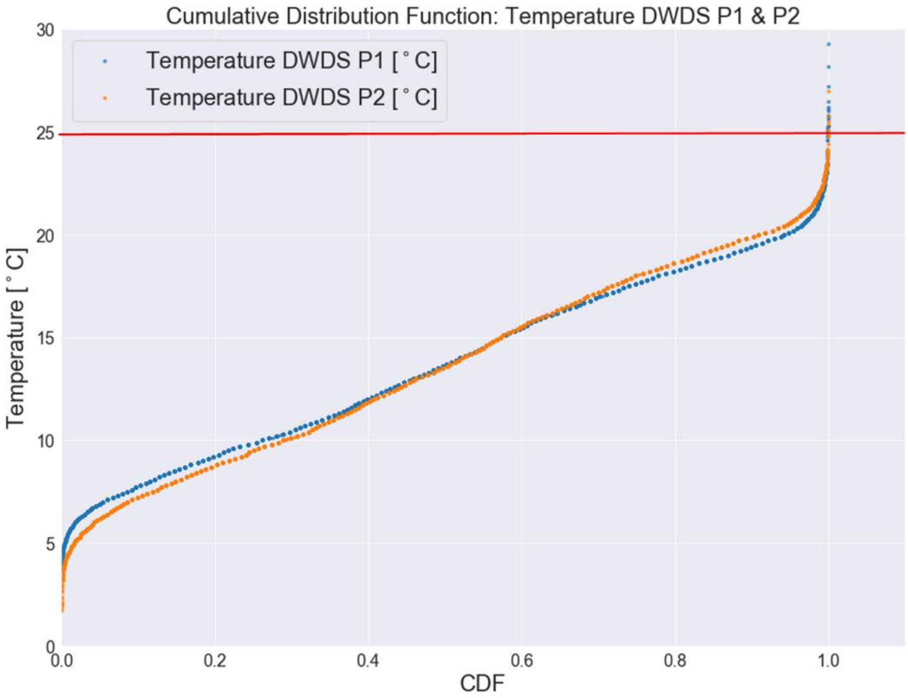


Figure 40 - Cumulative distribution function for sample Temperature (°C) of DWDS P1 (blue) and P2 (orange). Red line indicates Dutch standard for drinking water temperature.

Aeromonas

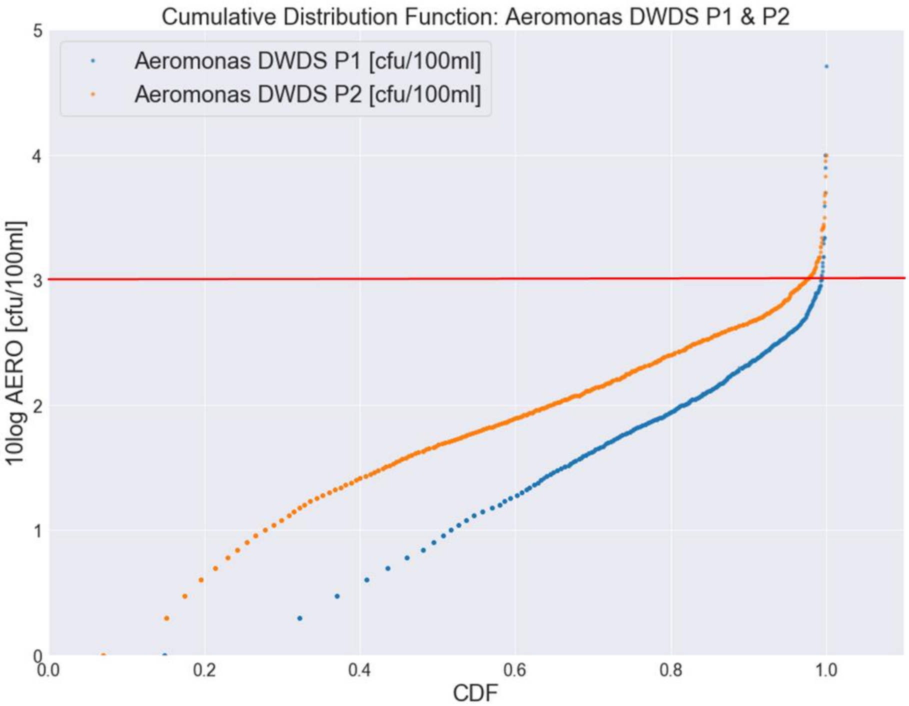


Figure 41 - Cumulative distribution function of Aeromonas (cfu/100ml) samples of DWDS P1 (blue) and P2 (orange). Red line indicates Dutch drinking water standard for Aeromonas.

HPC

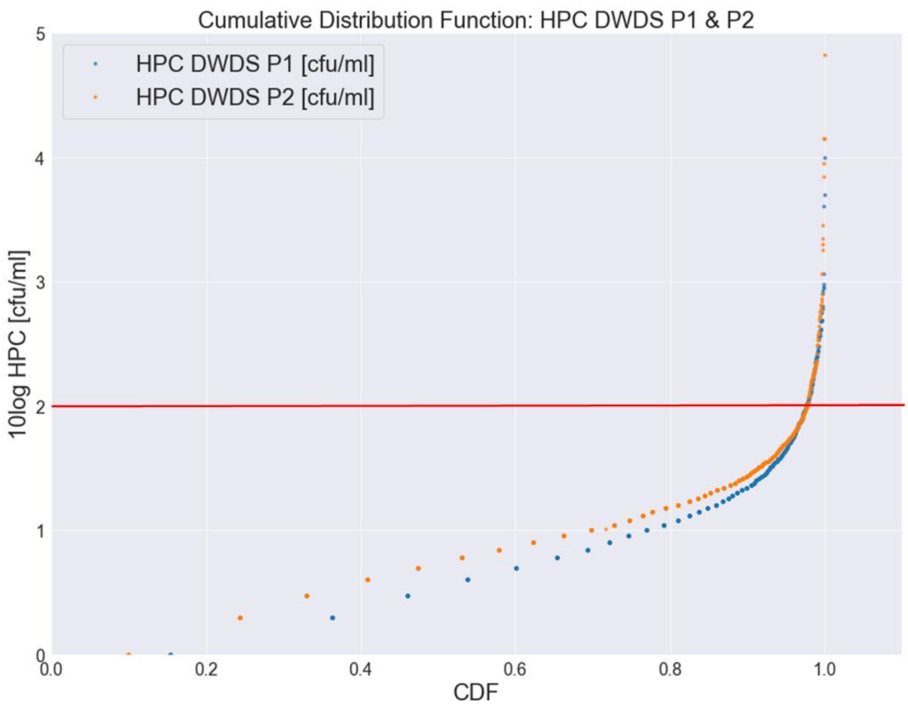


Figure 42 - Cumulative distribution function of HPC (cfu/ml) samples of DWDS P1 (blue) and P2 (orange). Red line indicates Dutch drinking water standard for HPC.

Appendix 3 **Correlation of Aeromonas and Temperature**

DWDS P1

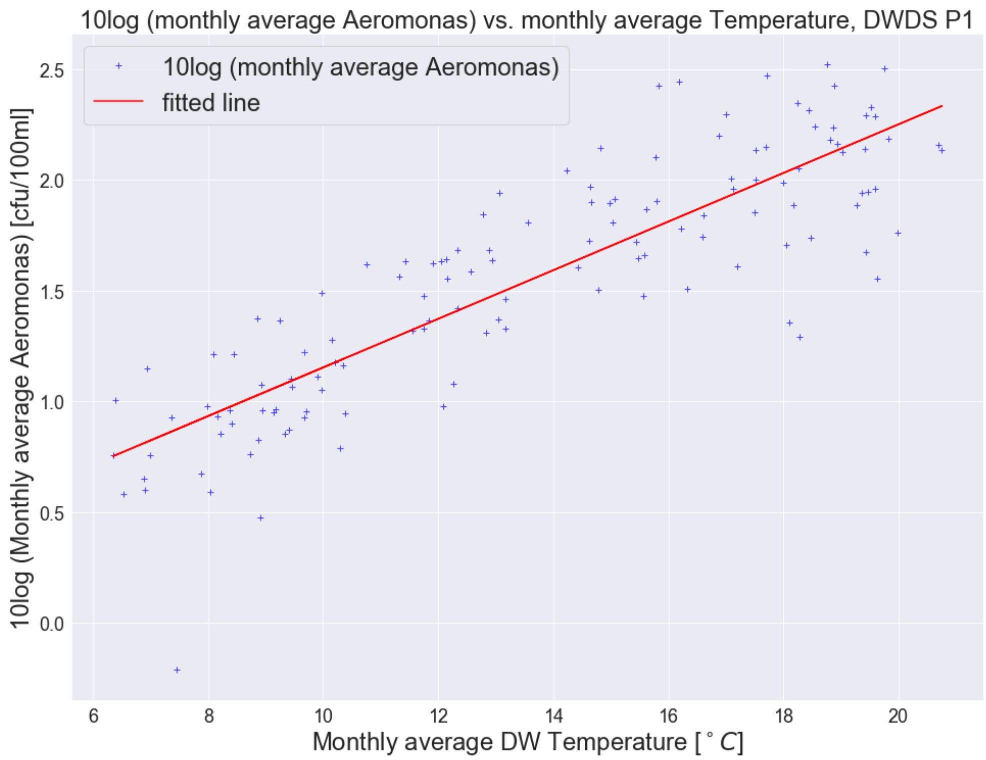


Figure 43 - Correlation between ^{10}log (monthly average Aeromonas) (cfu/100ml) and monthly average Temperature (°C) of all samples from DWDS P1 (adj.R^2=0.732; p=0.000).

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.735
Model:                            OLS   Adj. R-squared:                  0.732
Method:                 Least Squares   F-statistic:                     356.9
Date:                Fri, 11 Dec 2020   Prob (F-statistic):           5.79e-39
Time:                        08:49:16   Log-Likelihood:                -17.644
No. Observations:                 131   AIC:                             39.29
Df Residuals:                     129   BIC:                             45.04
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0552      0.083      0.665      0.508      -0.109       0.220
x              0.1098      0.006     18.892      0.000       0.098       0.121
==============================================================================
Omnibus:                       13.324   Durbin-Watson:                   1.233
Prob(Omnibus):                  0.001   Jarque-Bera (JB):               16.575
Skew:                          -0.607   Prob(JB):                     0.000252
Kurtosis:                       4.251   Cond. No.                         49.0
==============================================================================
```

Figure 44 - OLS regression results for ^{10}log (monthly average Aeromonas) (cfu/100ml) and monthly average Temperature (°C) of all samples from DWDS P1.

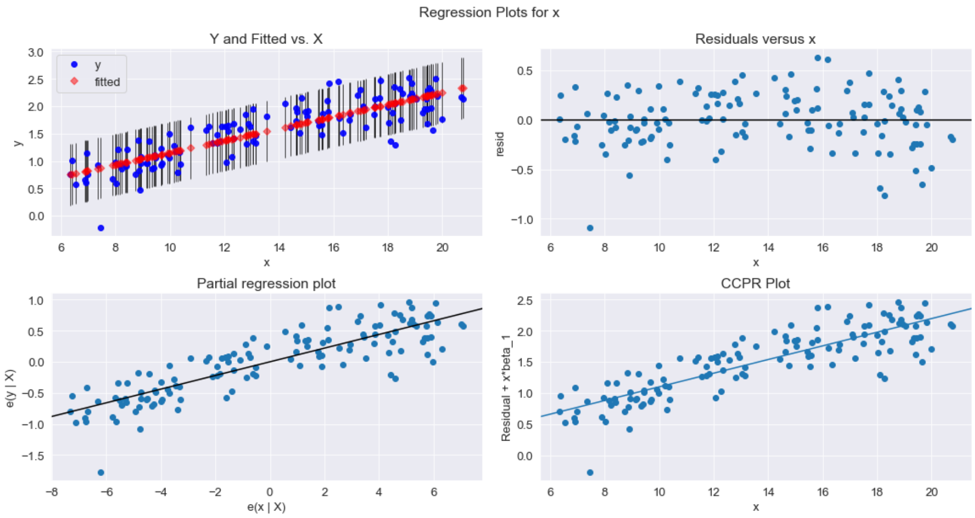


Figure 45 – Residual plots for OLS regression on ^{10}log (monthly average Aeromonas) (cfu/100ml) and monthly average Temperature (^{o}C) of all samples from DWDS P1.

DWDS P2

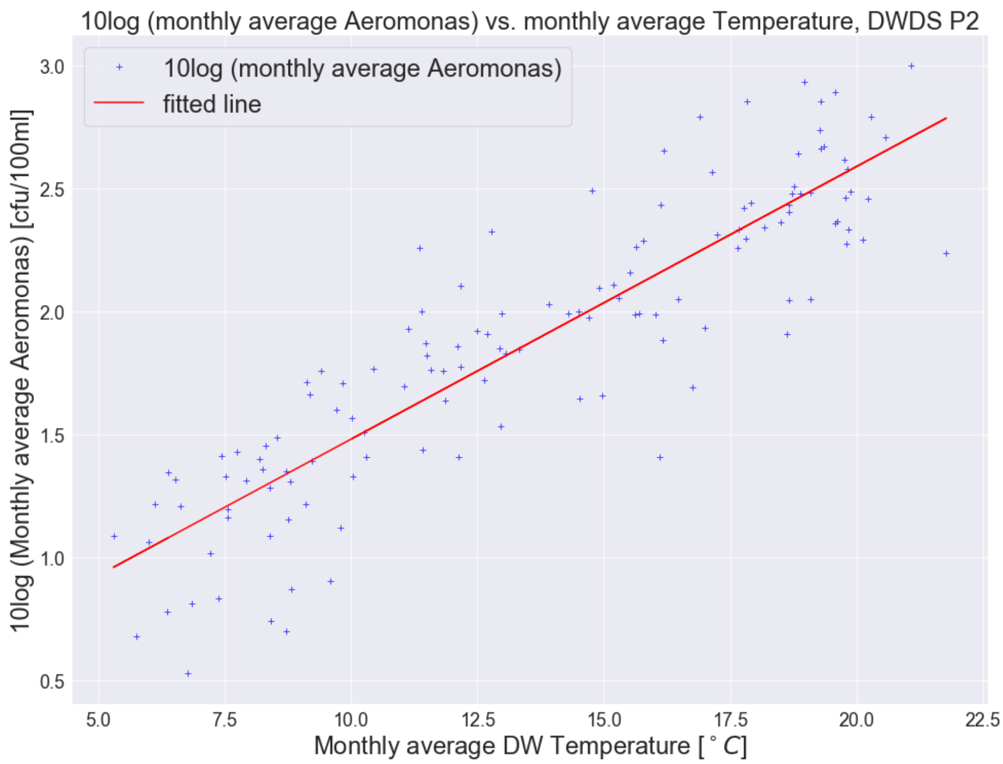


Figure 46 - Correlation between ^{10}log (monthly average Aeromonas) (cfu/100ml) and monthly average Temperature (°C) of all samples from DWDS P2 (adj.R²=0.785; p=0.000).

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.786
Model:                            OLS   Adj. R-squared:                  0.785
Method:                 Least Squares   F-statistic:                     474.8
Date:                Fri, 11 Dec 2020   Prob (F-statistic):           4.61e-45
Time:                        10:54:45   Log-Likelihood:                -12.284
No. Observations:                 131   AIC:                             28.57
Df Residuals:                     129   BIC:                             34.32
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.3718      0.073      5.102      0.000       0.228       0.516
x              0.1109      0.005     21.789      0.000       0.101       0.121
==============================================================================
Omnibus:                        3.111   Durbin-Watson:                   1.008
Prob(Omnibus):                  0.211   Jarque-Bera (JB):                2.750
Skew:                          -0.351   Prob(JB):                        0.253
Kurtosis:                       3.102   Cond. No.                         44.8
==============================================================================
```

Figure 47 - OLS regression results for ^{10}log (monthly average Aeromonas) (cfu/100ml) and monthly average Temperature (°C) of all samples from DWDS P2.

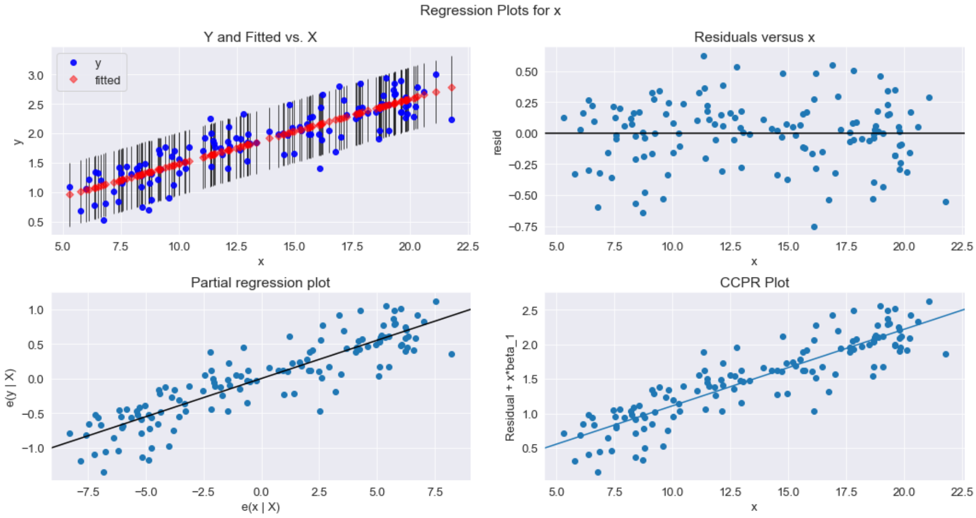


Figure 48 - Residual plots for OLS regression on ^{10}log (monthly average Aeromonas) (cfu/100ml) and monthly average Temperature (^{o}C) of all samples from DWDS P2.

Appendix 4 **Correlation of HPC and Temperature**

DWDS P1

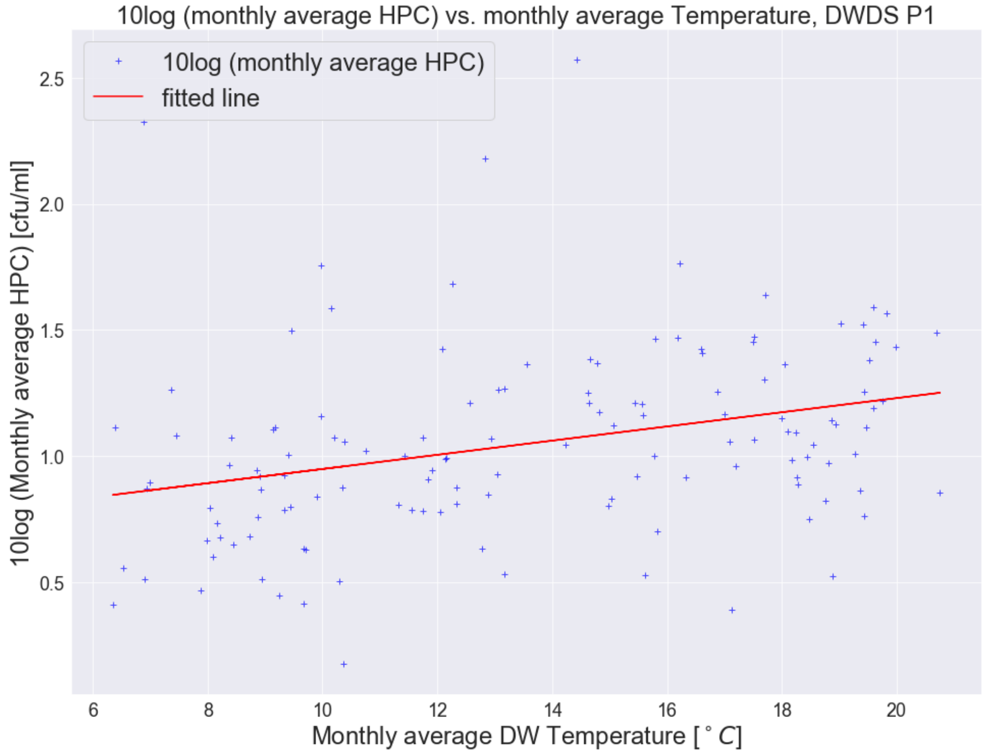


Figure 49 - Correlation between ^{10}log (monthly average HPC) (cfu/ml) and monthly average Temperature (^oC) of all samples from DWDS P1 (adj.R^2=0.091; p=0.000).

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.098
Model:                            OLS   Adj. R-squared:                  0.091
Method:                 Least Squares   F-statistic:                     14.23
Date:                Fri, 11 Dec 2020   Prob (F-statistic):           0.000244
Time:                        11:00:09   Log-Likelihood:                -51.905
No. Observations:                 133   AIC:                             107.8
Df Residuals:                     131   BIC:                             113.6
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.6670      0.106      6.281      0.000       0.457       0.877
x              0.0281      0.007      3.772      0.000       0.013       0.043
==============================================================================
Omnibus:                       41.317   Durbin-Watson:                   1.534
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              106.111
Skew:                           1.214   Prob(JB):                     9.09e-24
Kurtosis:                       6.640   Cond. No.                         48.6
==============================================================================
```

Figure 50 - OLS regression results for ^{10}log (monthly average HPC) (cfu/ml) and monthly average Temperature (^oC) of all samples from DWDS P1.

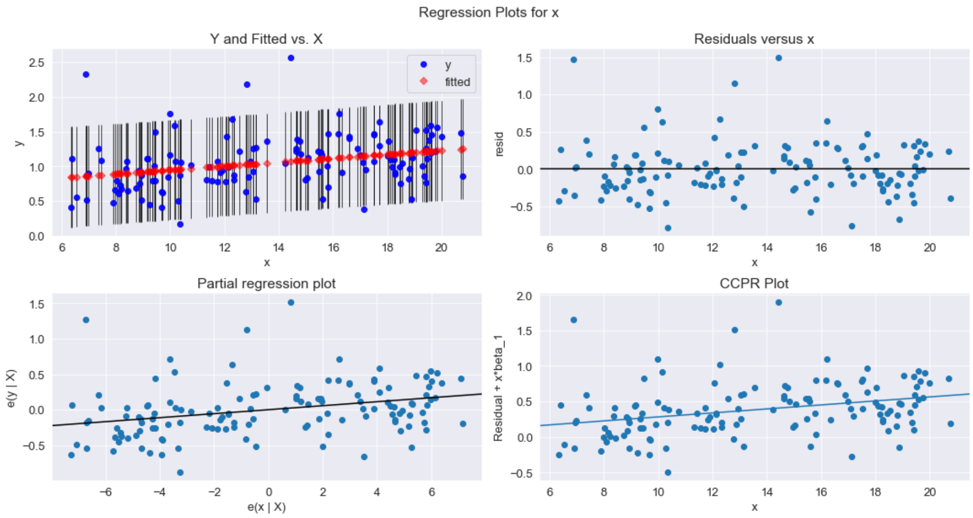


Figure 51 - Residual plots for OLS regression on ^{10}log (monthly average HPC) (cfu/ml) and monthly average Temperature (^oC) of all samples from DWDS P1.

DWDS P2

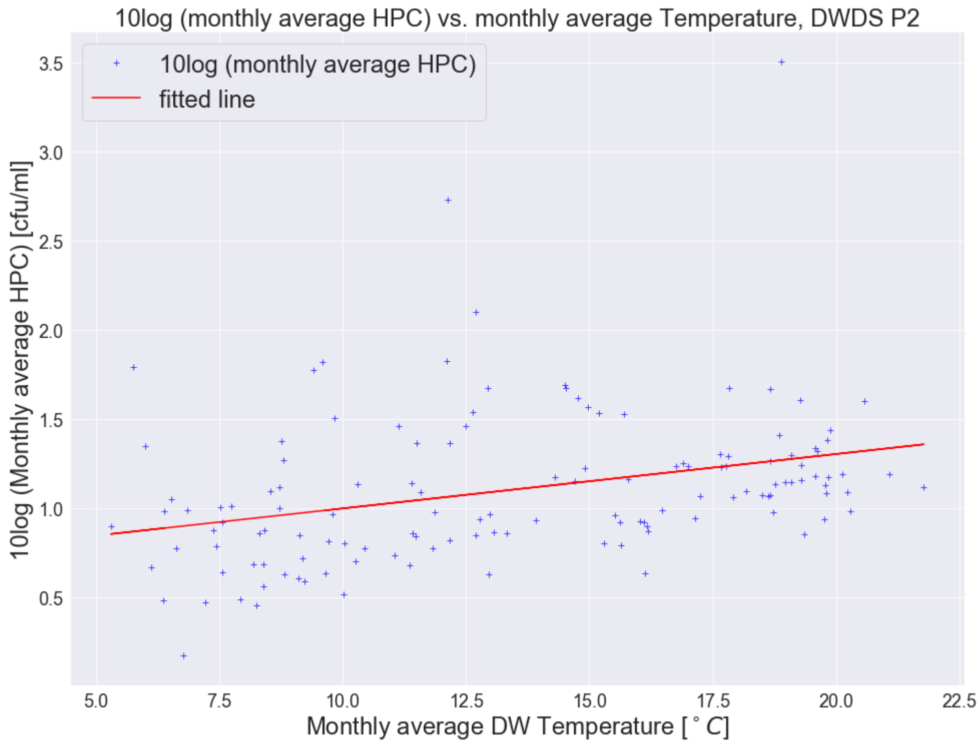


Figure 52 - Correlation between ^{10}log (monthly average HPC) (cfu/ml) and monthly average Temperature (^oC) of all samples from DWDS P2 (adj.R^2=0.109; p=0.000).

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.109
Model:                            OLS   Adj. R-squared:                  0.102
Method:                 Least Squares   F-statistic:                     16.00
Date:                Fri, 11 Dec 2020   Prob (F-statistic):           0.000105
Time:                        10:57:57   Log-Likelihood:                -66.744
No. Observations:                 133   AIC:                             137.5
Df Residuals:                     131   BIC:                             143.3
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.6949      0.109      6.377      0.000       0.479       0.911
x              0.0305      0.008      4.000      0.000       0.015       0.046
==============================================================================
Omnibus:                       82.821   Durbin-Watson:                   1.774
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              465.191
Skew:                           2.196   Prob(JB):                    9.66e-102
Kurtosis:                      11.040   Cond. No.                         44.8
==============================================================================
```

Figure 53 - OLS regression results for ^{10}log (monthly average HPC) (cfu/ml) and monthly average Temperature (^oC) of all samples from DWDS P2.

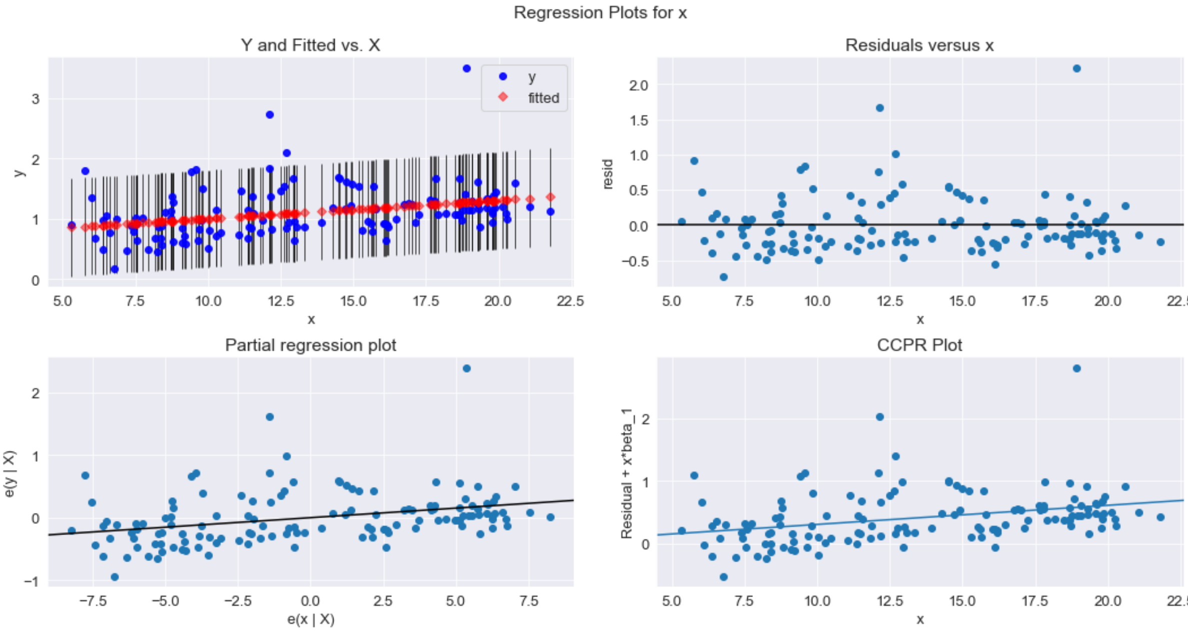


Figure 54 - Residual plots for OLS regression on [10]log (monthly average HPC) (cfu/ml) and monthly average Temperature (°C) of all samples from DWDS P2.

Appendix 5 TSA on Temperature samples from clean water reservoirs P1 and P2

Temperature Reservoir P1 and Reservoir P2

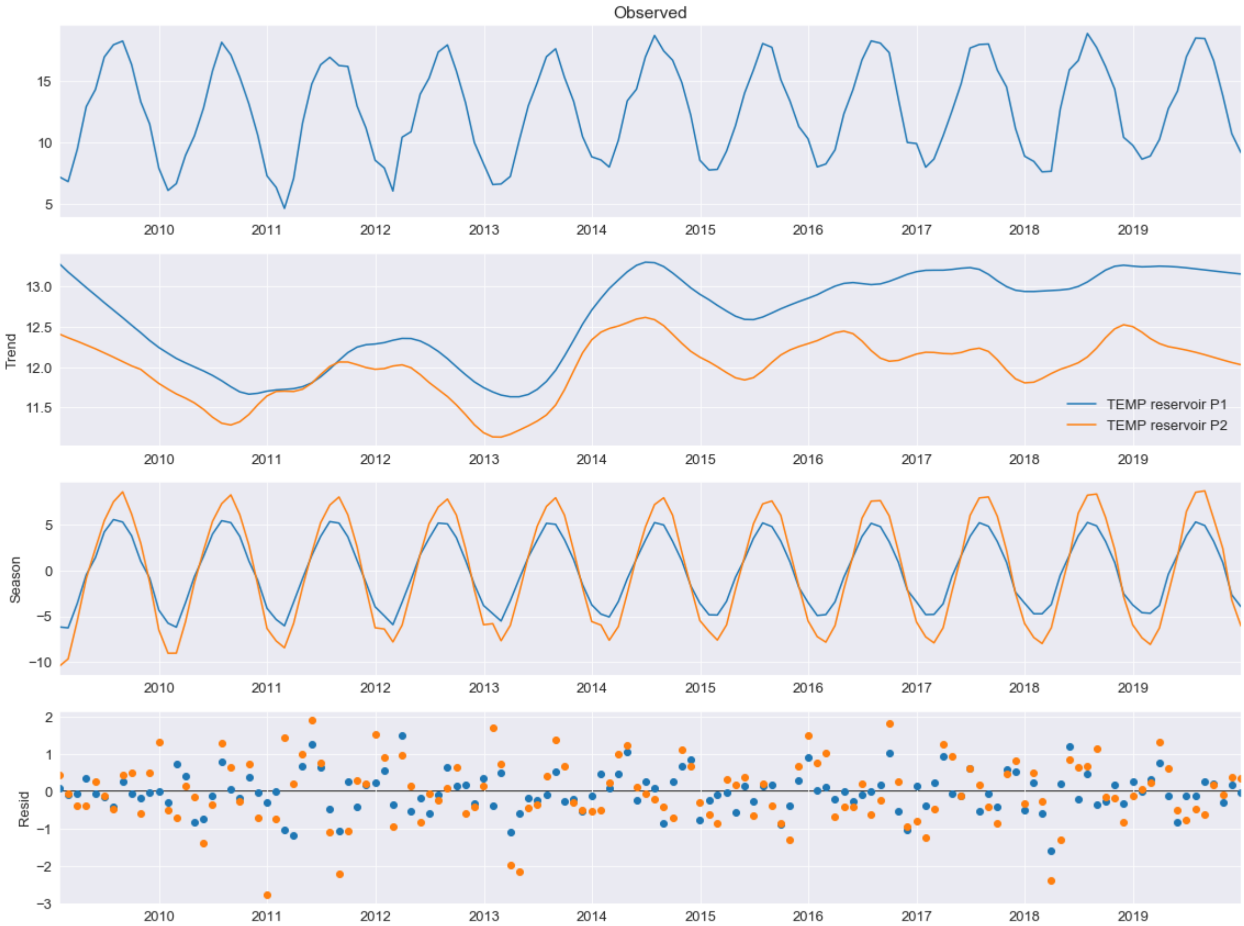


Figure 55 - Time series analysis for Temperature (°C) of clean water in reservoirs of treatment facilities P1 (blue) and P2 (orange).

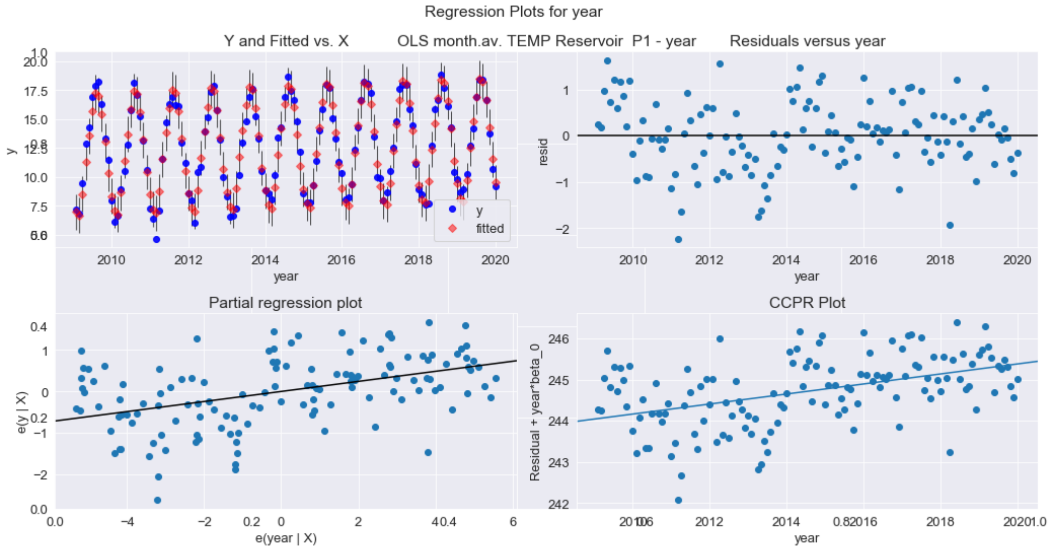
Difference between DW Temperature within Reservoir P1 and P2

Null-hypothesis: Based on actual samples, is the average Temperature of reservoir P1 equal to the average Temperature of reservoir P2.
Independent Samples Welchs t-test.
t= 2.267
two-sided p value= 0.024

Null-hypothesis: Based on monthly average of samples, is the average Temperature of reservoir P1 equal to the average Temperature of reservoir P2.
Independent Samples Student t-test.
t= 1.05
two-sided p value= 0.295

Regression on time series Temperature Reservoir P1

```
OLS on monthly average Temperature samples from Reservoir  P1
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.961
Model:                            OLS   Adj. R-squared:                  0.961
Method:                 Least Squares   F-statistic:                     1596.
Date:                Sun, 23 Aug 2020   Prob (F-statistic):           1.03e-91
Time:                        16:41:22   Log-Likelihood:                -149.34
No. Observations:                 132   AIC:                             304.7
Df Residuals:                     129   BIC:                             313.3
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
year           0.1215      0.021      5.838      0.000       0.080       0.163
constant    -244.6727     41.914     -5.838      0.000    -327.600    -161.745
season         0.9966      0.018     55.974      0.000       0.961       1.032
==============================================================================
Omnibus:                        1.627   Durbin-Watson:                   1.246
Prob(Omnibus):                  0.443   Jarque-Bera (JB):                1.410
Skew:                          -0.253   Prob(JB):                        0.494
Kurtosis:                       3.022   Cond. No.                     1.28e+06
==============================================================================
```



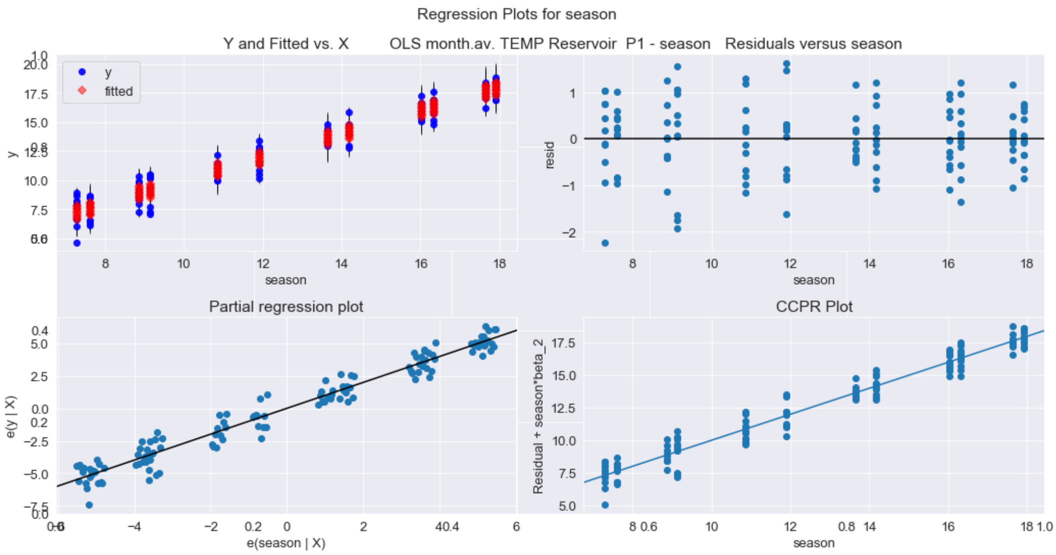


Figure 56 - OLS on TSA for Temperature (°C) of P1 Reservoir samples.

Regression on time series Temperature Reservoir P2

```
OLS on regression of monthly average Temperature samples from reservoir P2
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.965
Model:                            OLS   Adj. R-squared:                  0.965
Method:                 Least Squares   F-statistic:                     1797.
Date:                Sun, 23 Aug 2020   Prob (F-statistic):           6.50e-95
Time:                        16:41:23   Log-Likelihood:                -197.98
No. Observations:                 132   AIC:                             402.0
Df Residuals:                     129   BIC:                             410.6
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
year           0.0568      0.030      1.888      0.061      -0.003       0.116
constant    -114.3845     60.597     -1.888      0.061    -234.276       5.507
season         0.9989      0.017     59.811      0.000       0.966       1.032
==============================================================================
Omnibus:                        8.287   Durbin-Watson:                   1.159
Prob(Omnibus):                  0.016   Jarque-Bera (JB):                8.087
Skew:                          -0.530   Prob(JB):                       0.0175
Kurtosis:                       3.589   Cond. No.                     1.28e+06
==============================================================================
```

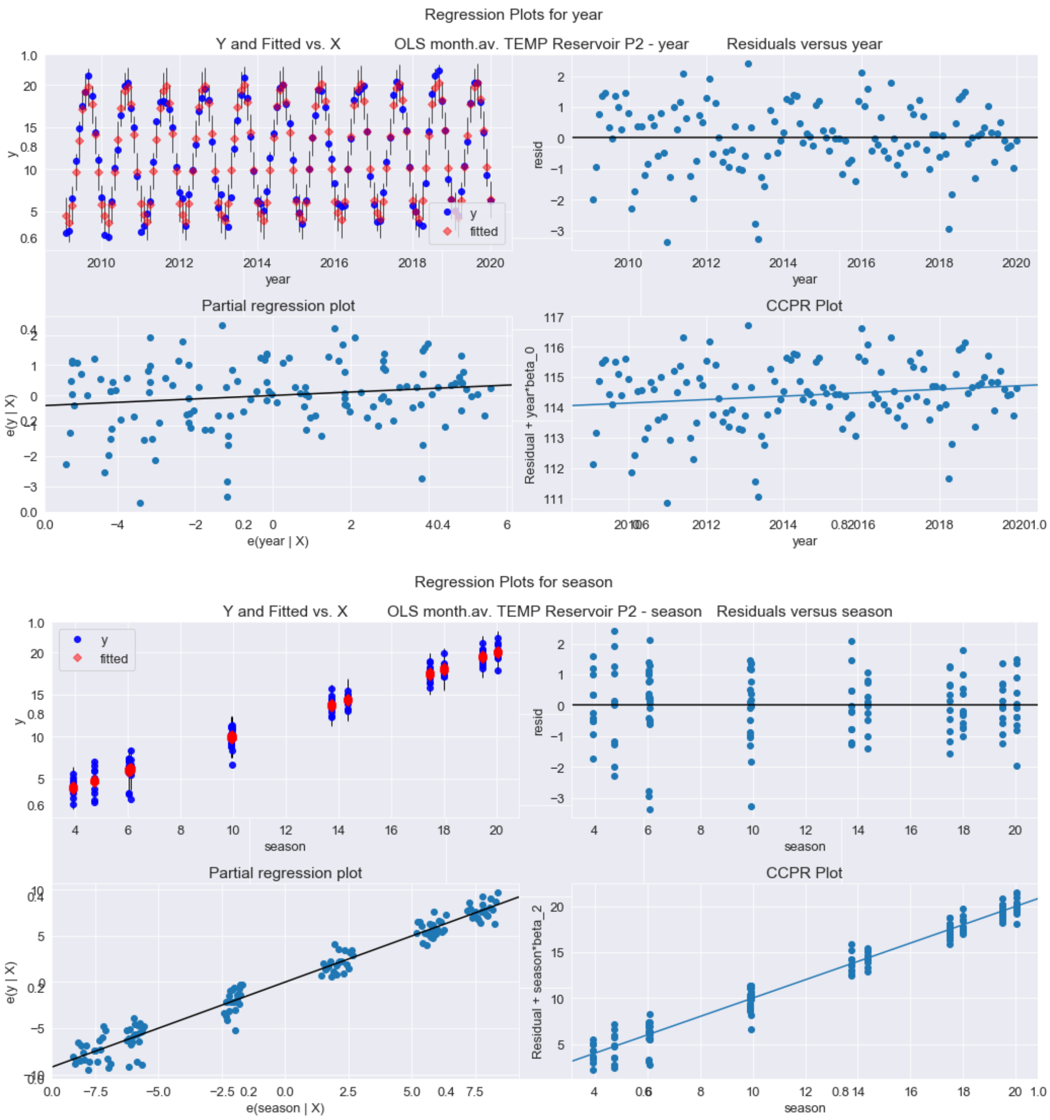


Figure 57 - OLS on TSA for Temperature (°C) of P2 Reservoir samples.

Appendix 6 **TSA on Temperature samples from DWDS P1 and P2**

Temperature DWDS P1 and DWDS P2

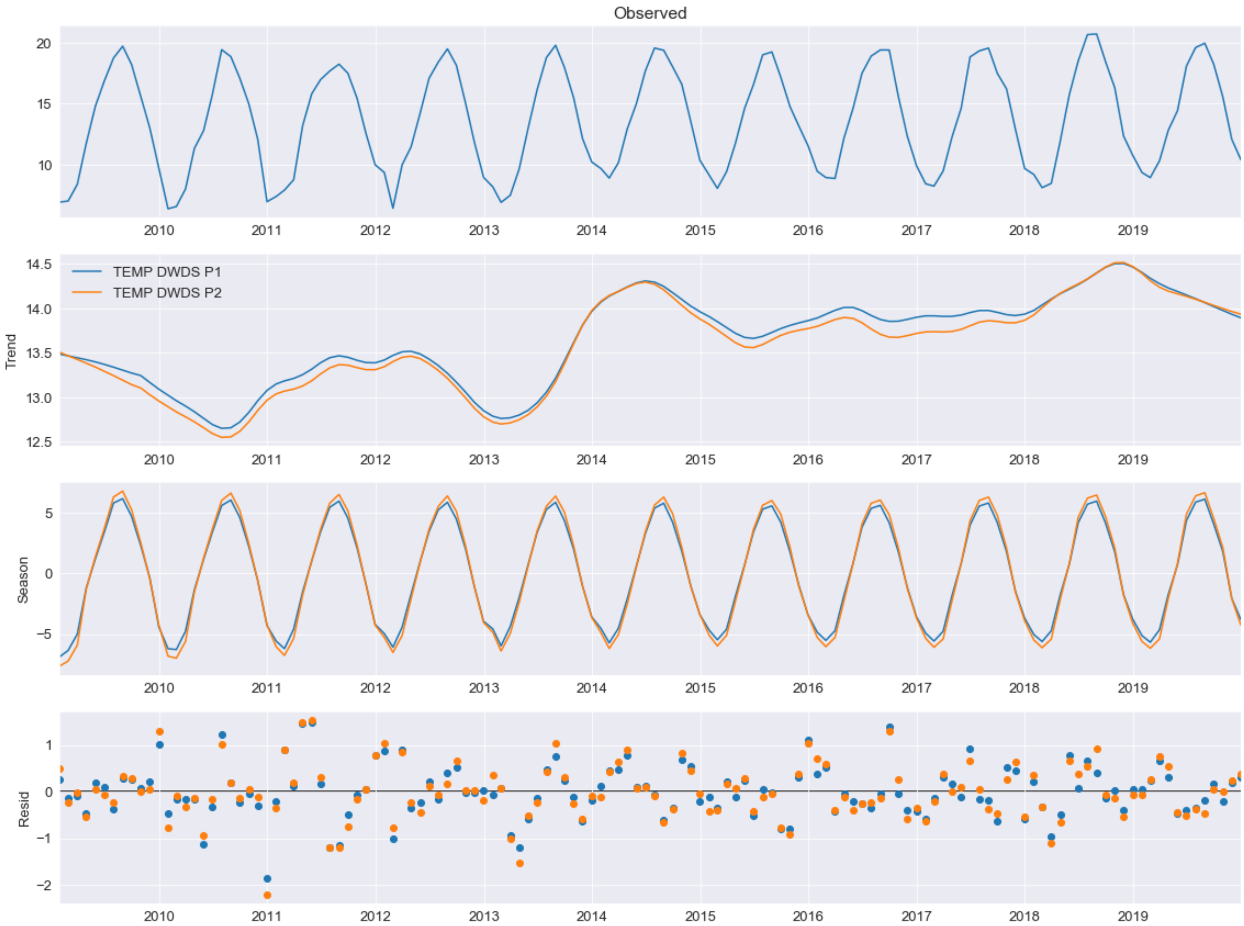


Figure 58 - Time series analysis for Temperature (°C) of DWDS of P1 (blue) and DWDS P2 (orange).

Difference between DW Temperature within DWDS P1 and DWDS P2

Null-hypothesis: Based on actual samples, is the average Temperature of DWDS P1 equal to the average Temperature of DWDS P2.
Independent Samples Welchs t-test.
t= 1.608
two-sided p value= 0.108

Null-hypothesis: Based on monthly average of samples, is the average Temperature of DWDS P1 equal to the average Temperature of DWDS P2.
Independent Samples Student t-test.
t= 0.145
two-sided p value= 0.885

Regression time series Temperature DWDS P1

```
OLS on monthly average Temperature samples from DWDS P1
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.969
Model:                            OLS   Adj. R-squared:                  0.969
Method:                 Least Squares   F-statistic:                     2036.
Date:                Sun, 23 Aug 2020   Prob (F-statistic):           2.63e-98
Time:                        13:04:27   Log-Likelihood:                -146.57
No. Observations:                 132   AIC:                             299.1
Df Residuals:                     129   BIC:                             307.8
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
year           0.1268      0.020      6.219      0.000       0.086       0.167
constant    -255.3259     41.054     -6.219      0.000    -336.553    -174.099
season         0.9961      0.016     63.214      0.000       0.965       1.027
==============================================================================
Omnibus:                        3.683   Durbin-Watson:                   1.135
Prob(Omnibus):                  0.159   Jarque-Bera (JB):                3.198
Skew:                          -0.287   Prob(JB):                        0.202
Kurtosis:                       3.503   Cond. No.                     1.28e+06
==============================================================================
```

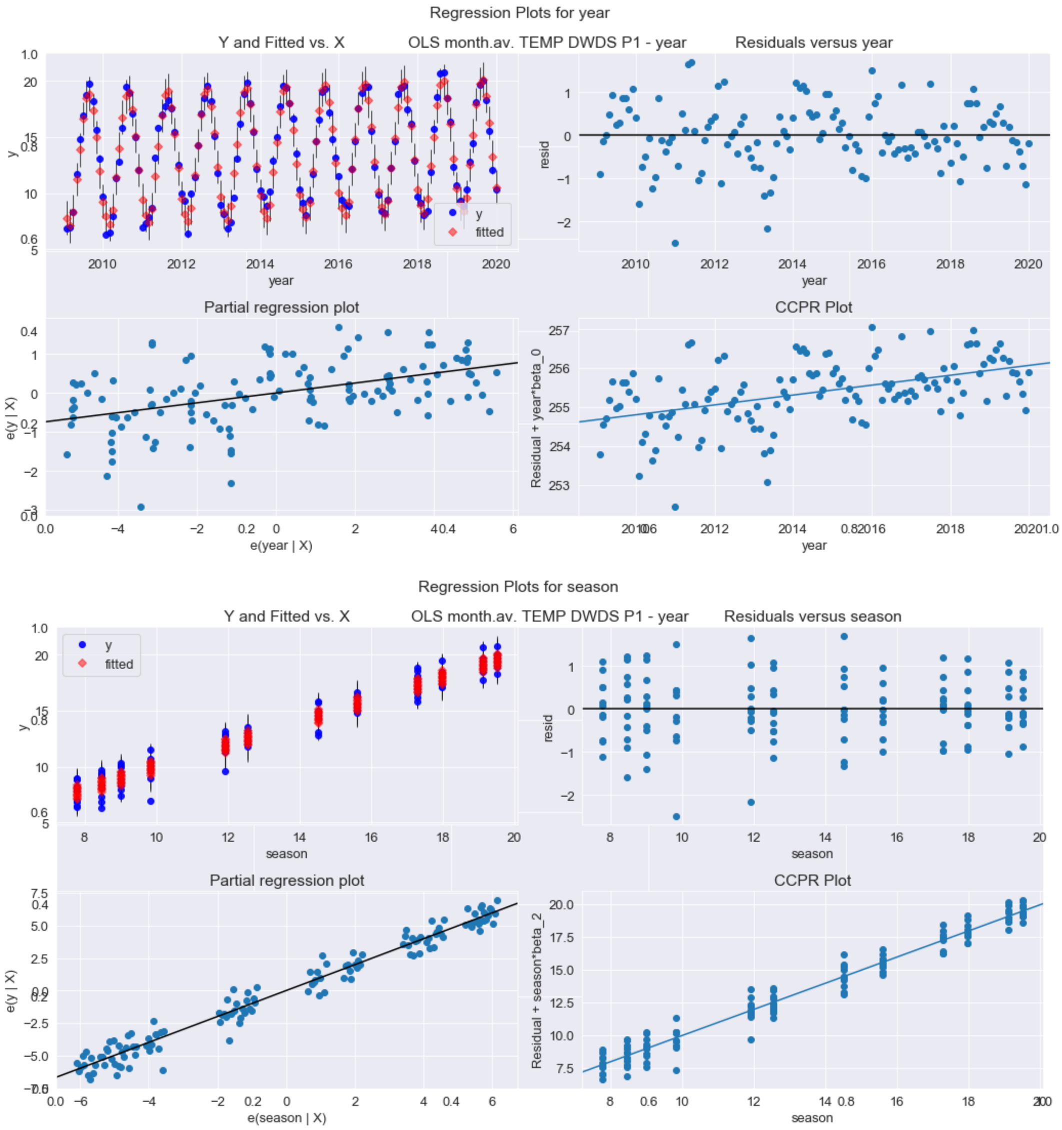


Figure 59 - OLS on TSA for Temperature (°C) of P1 DWDS samples.

Regression time series Temperature DWDS P2

```
OLS on regression of monthly average Temperature samples from DWDS P2
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.969
Model:                            OLS   Adj. R-squared:                  0.969
Method:                 Least Squares   F-statistic:                     2047.
Date:                Sun, 23 Aug 2020   Prob (F-statistic):           1.93e-98
Time:                        13:12:42   Log-Likelihood:                -158.01
No. Observations:                 132   AIC:                             322.0
Df Residuals:                     129   BIC:                             330.7
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
year           0.1325      0.022      5.963      0.000       0.089       0.177
constant    -266.9635     44.772     -5.963      0.000    -355.547    -178.380
season         0.9961      0.016     63.393      0.000       0.965       1.027
==============================================================================
Omnibus:                        4.751   Durbin-Watson:                   1.087
Prob(Omnibus):                  0.093   Jarque-Bera (JB):                4.468
Skew:                          -0.317   Prob(JB):                        0.107
Kurtosis:                       3.640   Cond. No.                     1.28e+06
==============================================================================
```

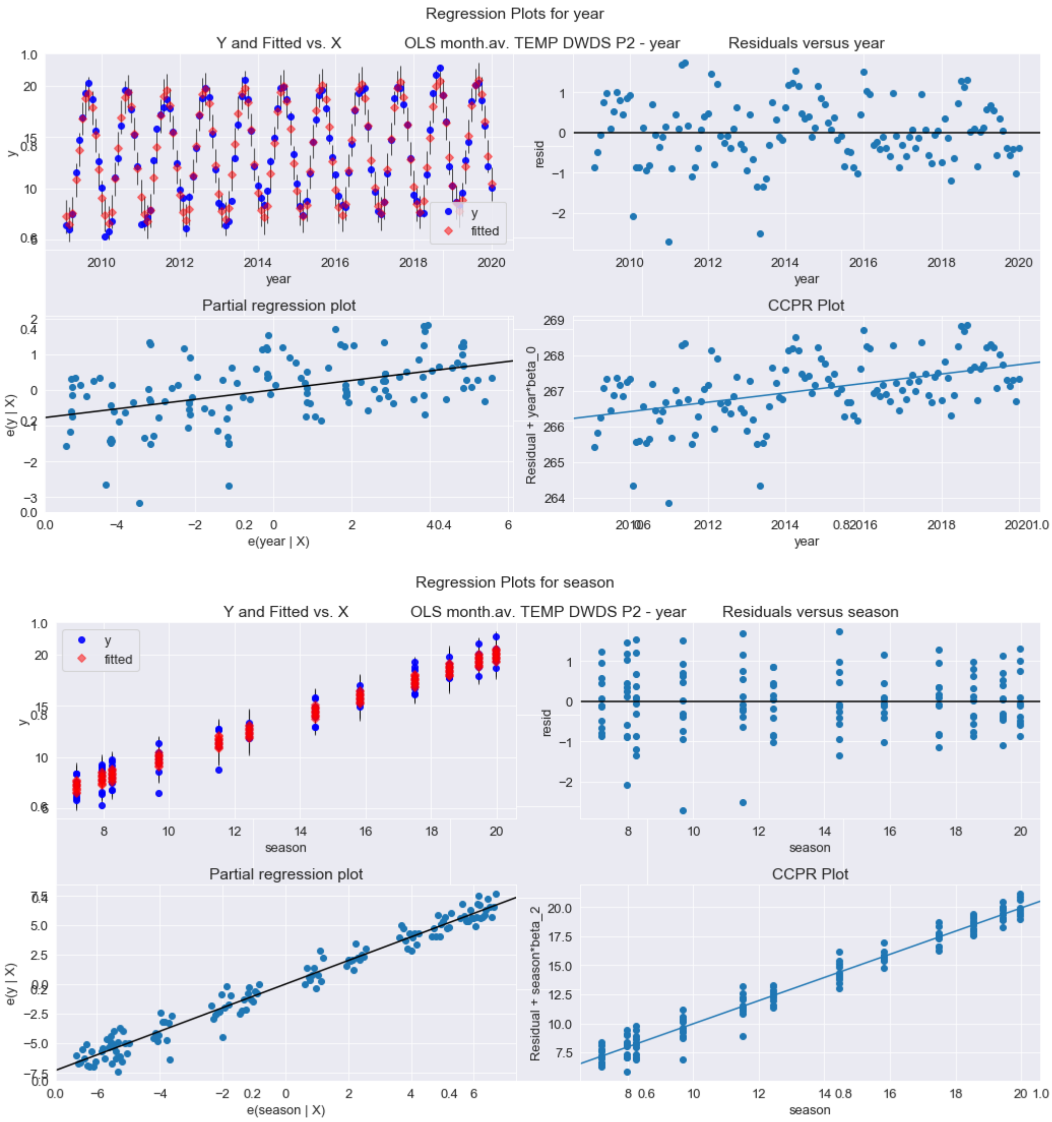


Figure 60 - OLS on TSA for Temperature (°C) of P2 DWDS samples.

Appendix 7 TSA on Aeromonas samples from clean water reservoirs P1 and P2

Aeromonas Reservoir P1 and Reservoir P2

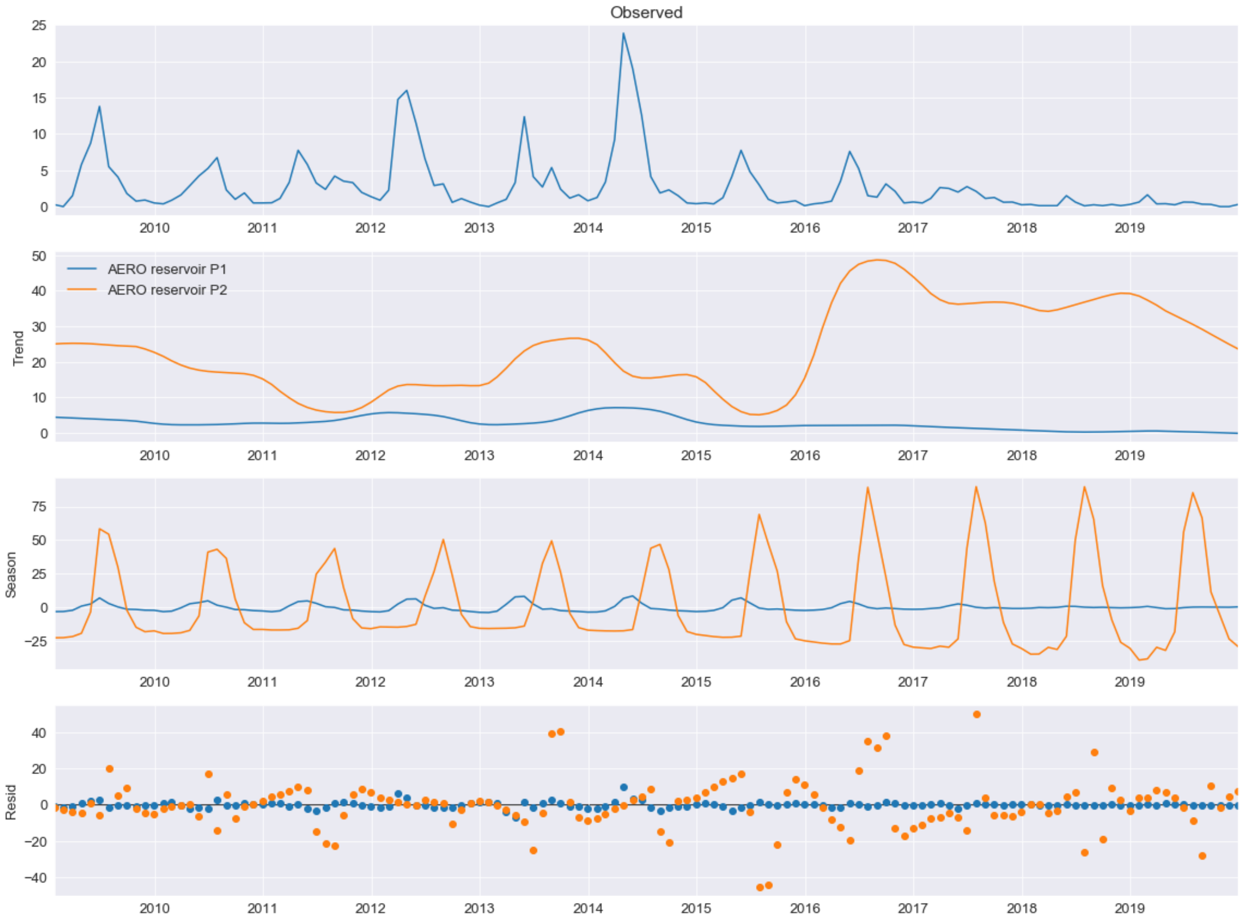


Figure 61 - Time series analysis for Aeromonas (cfu/100ml) of clean water in reservoirs of treatment facilities P1 (blue) and P2 (orange).

Difference between Aeromonas values within reservoir P1 and P2

Null-hypothesis: Based on actual samples, is the average Aeromonas value of reservoir P1 equal to the average Aeromonas value of reservoir P2.
Independent Samples Welchs t-test.
t= -11.768
two-sided p value= 0.0

Null-hypothesis: Based on monthly average of samples, is the average Aeromonas value of reservoir P1 equal to the average Aeromonas value of reservoir P2.
Independent Samples Student t-test.
t= -6.353
two-sided p value= 0.0

Regression on time series for Aeromonas of reservoir P1

```
OLS on monthly average of Aeromonas samples from Reservoir  P1
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.410
Model:                            OLS   Adj. R-squared:                  0.401
Method:                 Least Squares   F-statistic:                     44.88
Date:                Mon, 24 Aug 2020   Prob (F-statistic):           1.60e-15
Time:                        11:16:53   Log-Likelihood:                -332.50
No. Observations:                 132   AIC:                             671.0
Df Residuals:                     129   BIC:                             679.7
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
year          -0.3218      0.083     -3.861      0.000      -0.487      -0.157
constant     648.2196    167.891      3.861      0.000     316.043     980.396
season         0.9872      0.116      8.537      0.000       0.758       1.216
==============================================================================
Omnibus:                       94.221   Durbin-Watson:                   0.679
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              715.006
Skew:                           2.463   Prob(JB):                    5.48e-156
Kurtosis:                      13.282   Cond. No.                     1.28e+06
==============================================================================
```

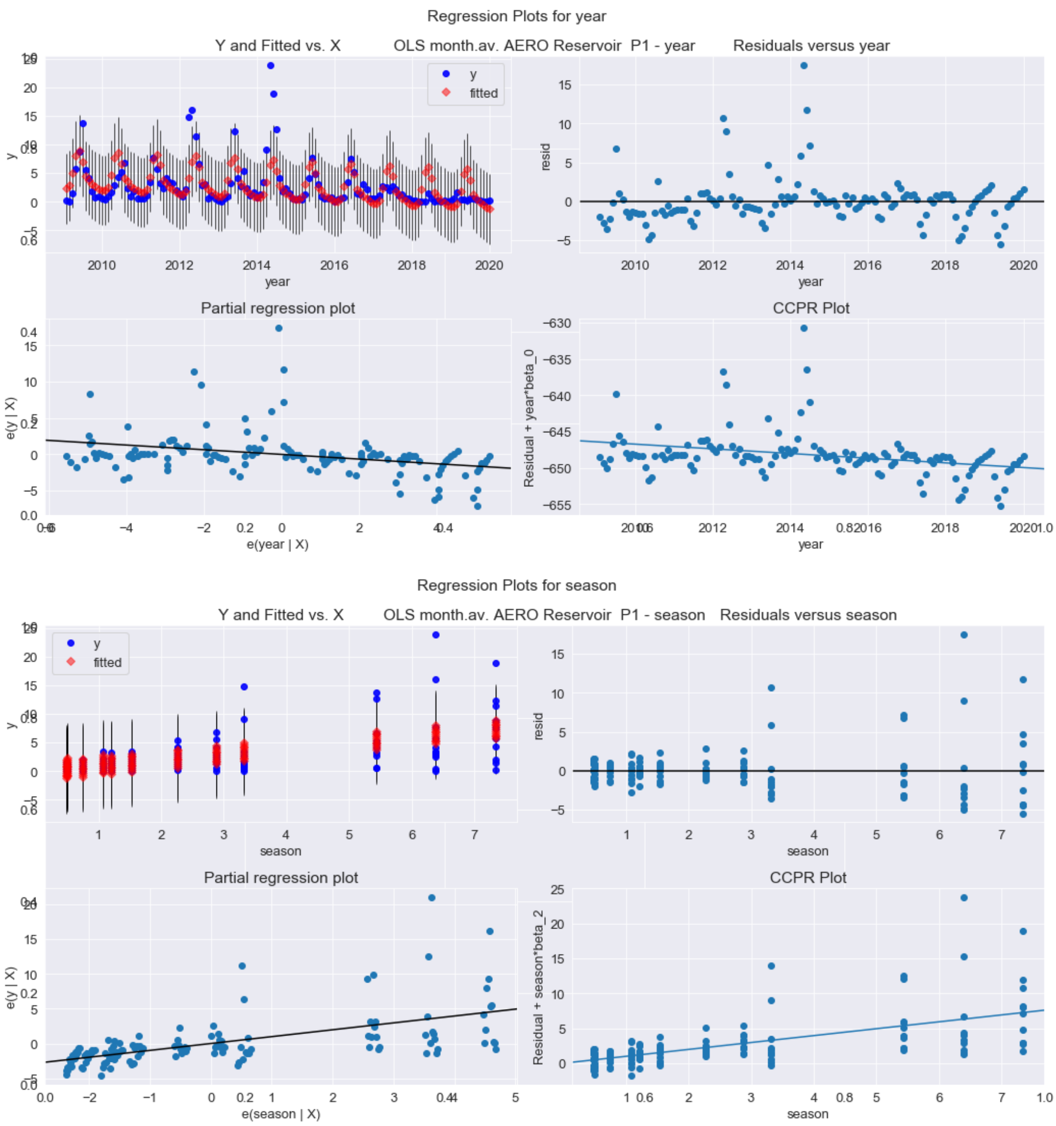
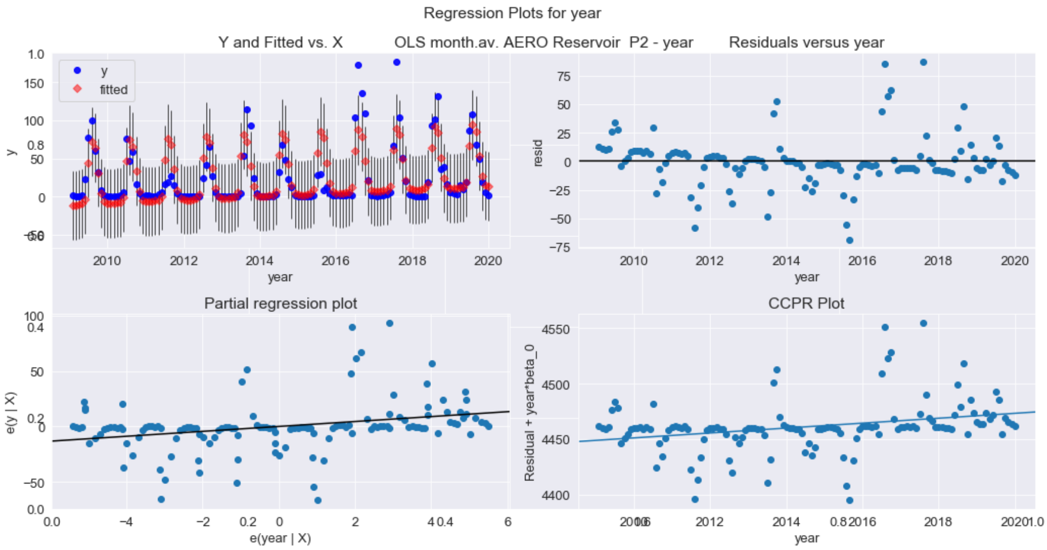


Figure 62 - OLS on TSA for Aeromonas (cfu/100ml) of P1 Reservoir samples.

Regression on time series for Aeromonas of reservoir P2

```
OLS on monthly average of Aeromonas samples from Reservoir  P2
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.657
Model:                            OLS   Adj. R-squared:                  0.652
Method:                 Least Squares   F-statistic:                     123.7
Date:                Mon, 24 Aug 2020   Prob (F-statistic):           1.00e-30
Time:                        11:52:06   Log-Likelihood:                -596.43
No. Observations:                 132   AIC:                             1199.
Df Residuals:                     129   BIC:                             1208.
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
year           2.2145      0.615      3.599      0.000       0.997       3.432
constant   -4461.1473   1239.499     -3.599      0.000   -6913.527   -2008.767
season         0.9953      0.065     15.238      0.000       0.866       1.125
==============================================================================
Omnibus:                       30.332   Durbin-Watson:                   0.845
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               96.174
Skew:                           0.788   Prob(JB):                     1.31e-21
Kurtosis:                       6.873   Cond. No.                     1.28e+06
==============================================================================
```



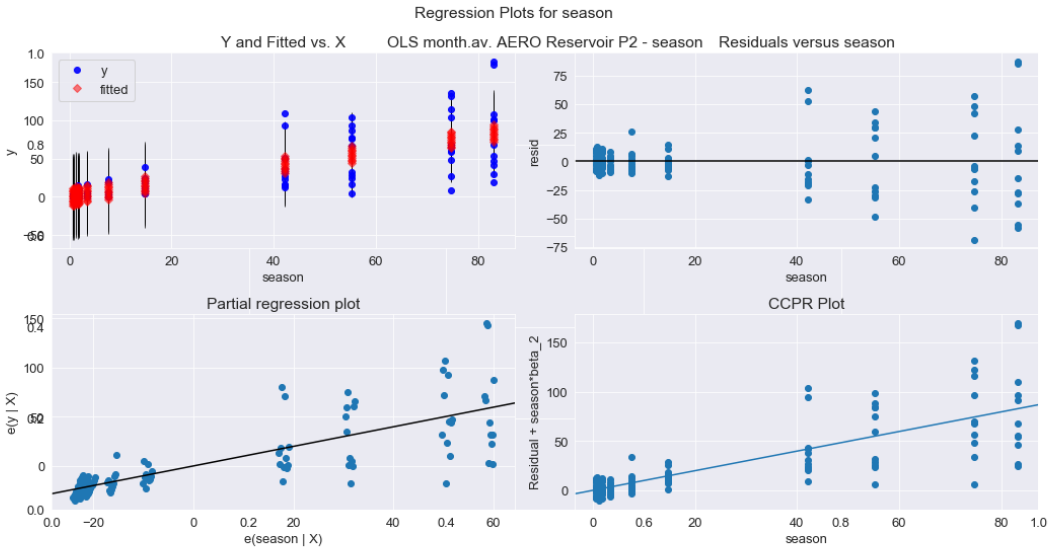


Figure 63 - OLS on TSA for Aeromonas (cfu/100ml) of P2 Reservoir samples.

Appendix 8 TSA on Aeromonas samples from DWDS P1 and P2

Notes:

1) Data filler is added due to missing AERO value **for DWDSS P1 only**, in January of 2019:
   DATA_AERO_DWDS_P1_MAV = DATA_AERO_DWDS_P1.resample('M').mean()**.ffill()**
2) One Aeromonas measurement of 50000 cfu/100ml is excluded from OLS regression analysis. Otherwise the TSA is totally flat with few very small yearly spikes.
3) Removal of more high AERO measurements (up to AEROmax < 10000 cfu/100ml = 10xAERO.legal.limit), results in same outcome as removing of only AERO=50000 cfu/ml. In other words: Removing more AERO values is like peak shaving. Elevated AERO peaks in the years 2009 and 2013 and 2018 remain visible. Change in OLS results are marginally. This is therefore not further explored. AERO=50000 cfu/ml is removed for reason mentioned above.

Aeromonas[8,9] DWDS P1 and DWDS P2

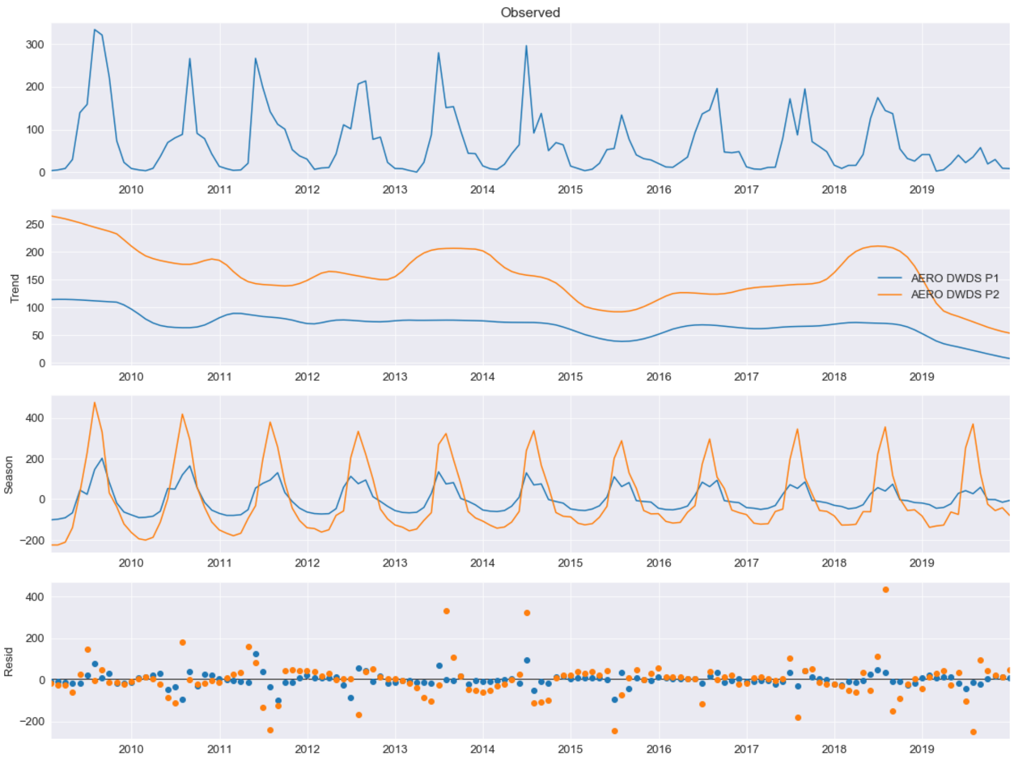


Figure 64 - Time series analysis for Aeromonas (cfu/100ml) of DWDS P1 (blue) and DWDS P2 (orange).

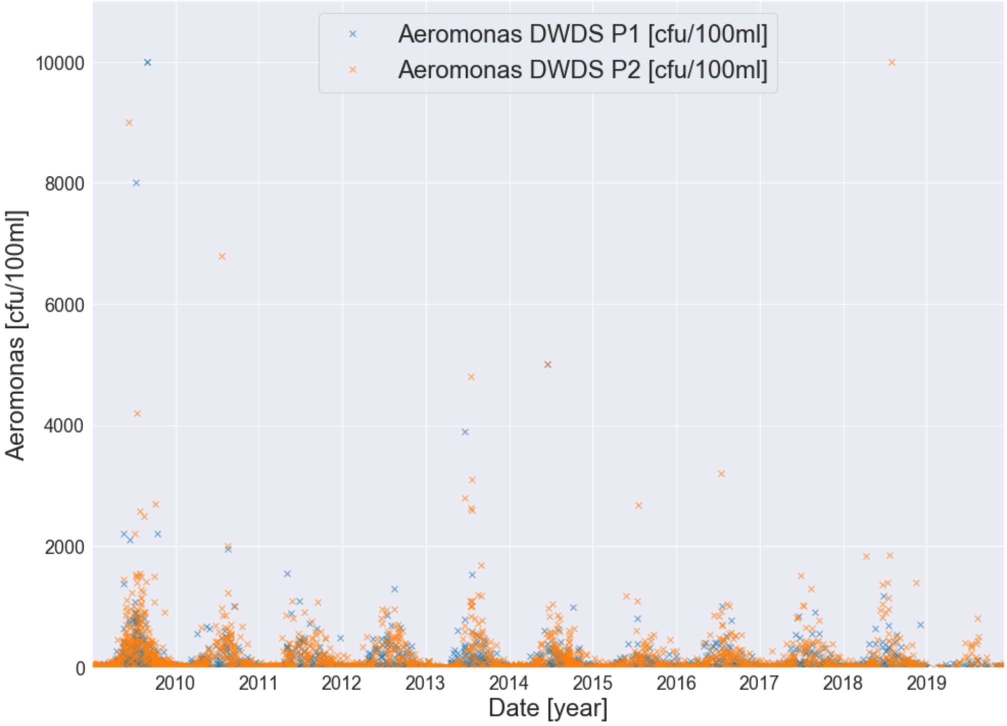


Figure 65 – Aeromonas (cfu/100ml) samples of DWDS P1 (blue) and DWDS P2 (orange)[10].

Difference between Aeromonas values within DWDS P1 and P2

Null-hypothesis: Based on actual samples, is the average Aeromonas value of DWDS P1 equal to the average Aeromonas value of DWDS P2.
Independent Samples Welchs t-test.
t= -8.103
two-sided p value= 0.0

Null-hypothesis: Based on monthly average of samples, is the average Aeromonas value of DWDS P1 equal to the average Aeromonas value of DWDS P2.
Independent Samples Student t-test.
t= -4.96
two-sided p value= 0.0

[10] One DWDS sample with Aeromonas = 50000 cfu/100ml is removed from plot

Regression time series Aeromonas DWDS P1

```
OLS on monthly average Aeromonas samples from DWDS P1
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.656
Model:                            OLS   Adj. R-squared:                  0.650
Method:                 Least Squares   F-statistic:                     122.9
Date:                Tue, 25 Aug 2020   Prob (F-statistic):           1.33e-30
Time:                        09:35:47   Log-Likelihood:                -683.77
No. Observations:                 132   AIC:                             1374.
Df Residuals:                     129   BIC:                             1382.
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
year          -4.7117      1.192     -3.951      0.000      -7.071      -2.352
constant    9491.5972   2402.223      3.951      0.000    4738.741    1.42e+04
season         1.0053      0.066     15.250      0.000       0.875       1.136
==============================================================================
Omnibus:                       37.131   Durbin-Watson:                   1.395
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               98.591
Skew:                           1.073   Prob(JB):                     3.90e-22
Kurtosis:                       6.650   Cond. No.                     1.28e+06
==============================================================================
```

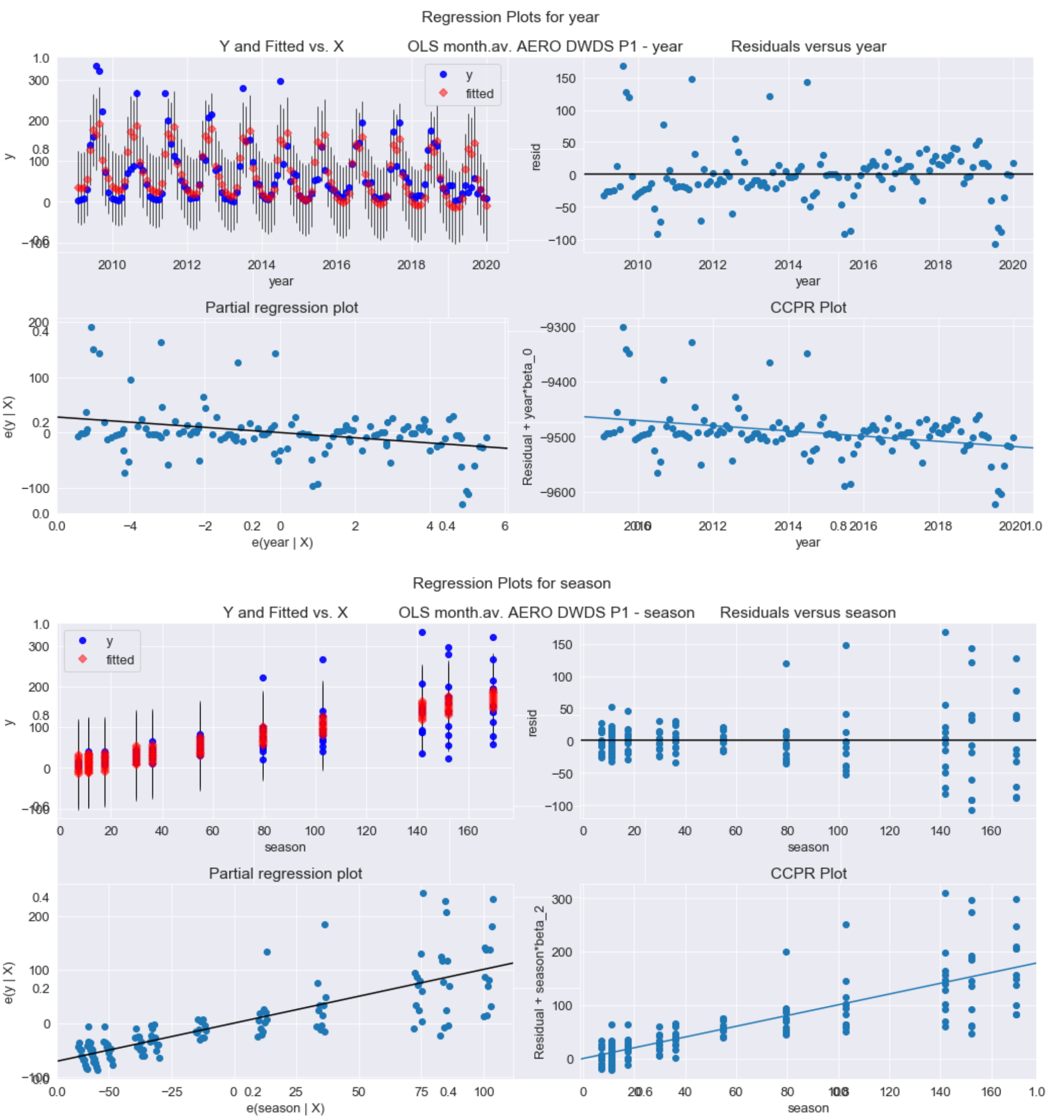


Figure 66 - OLS on TSA for Aeromonas (cfu/100ml) of P1 DWDS samples.

Regression time series Aeromonas DWDS P2

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.690
Model:                            OLS   Adj. R-squared:                  0.685
Method:                 Least Squares   F-statistic:                     143.6
Date:                Tue, 25 Aug 2020   Prob (F-statistic):           1.53e-33
Time:                        09:35:48   Log-Likelihood:                -803.64
No. Observations:                 132   AIC:                             1613.
Df Residuals:                     129   BIC:                             1622.
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
year          -8.3097      2.957     -2.810      0.006     -14.160      -2.459
constant    1.674e+04   5956.602      2.810      0.006    4954.467    2.85e+04
season         1.0032      0.060     16.765      0.000       0.885       1.122
==============================================================================
Omnibus:                       44.126   Durbin-Watson:                   1.394
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              191.613
Skew:                           1.081   Prob(JB):                     2.46e-42
Kurtosis:                       8.492   Cond. No.                     1.28e+06
==============================================================================
```

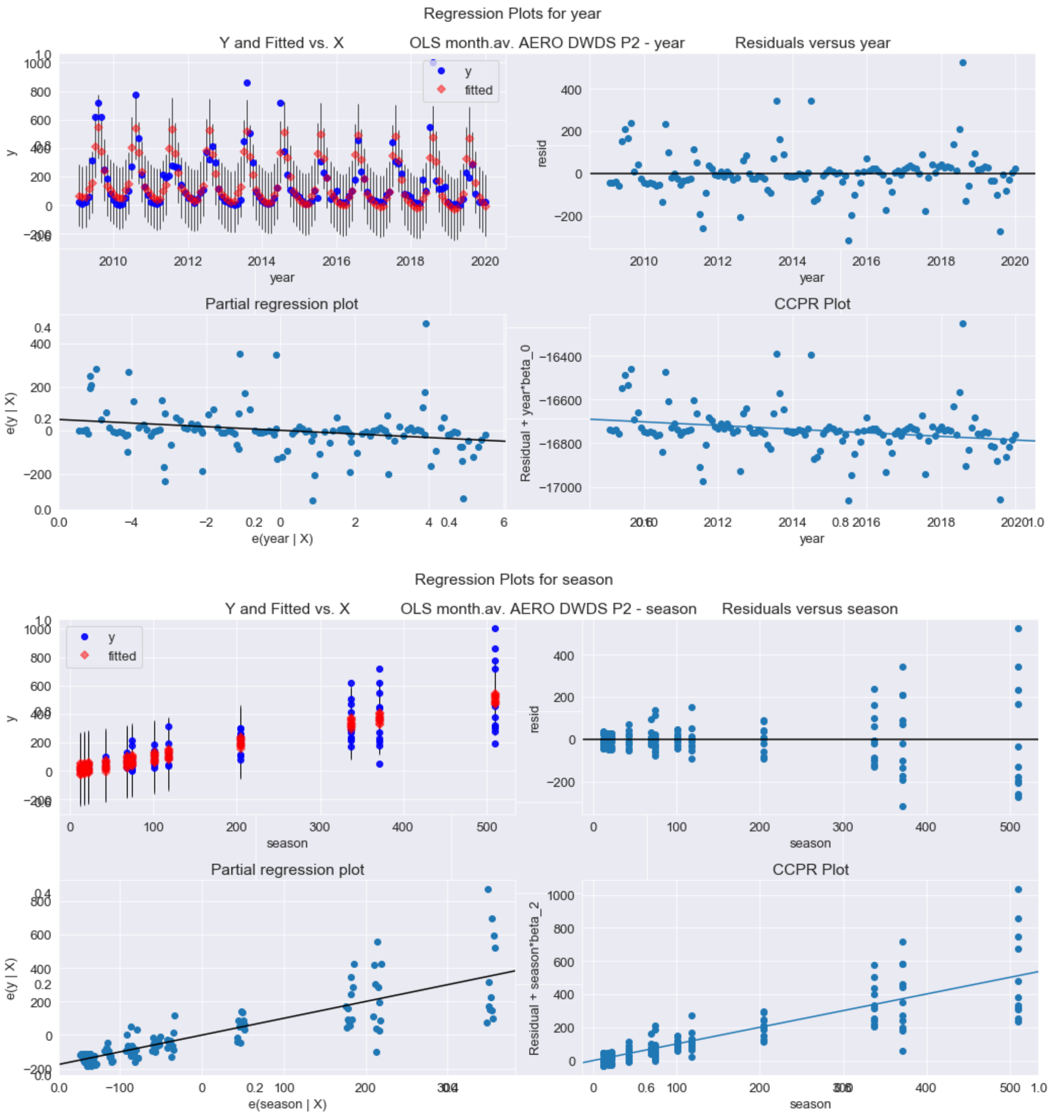


Figure 67 - OLS on TSA for Aeromonas (cfu/100ml) of P2 DWDS samples.

Appendix 9 TSA on HPC samples from clean water reservoirs P1 and P2

HPC Reservoir P1 and Reservoir P2

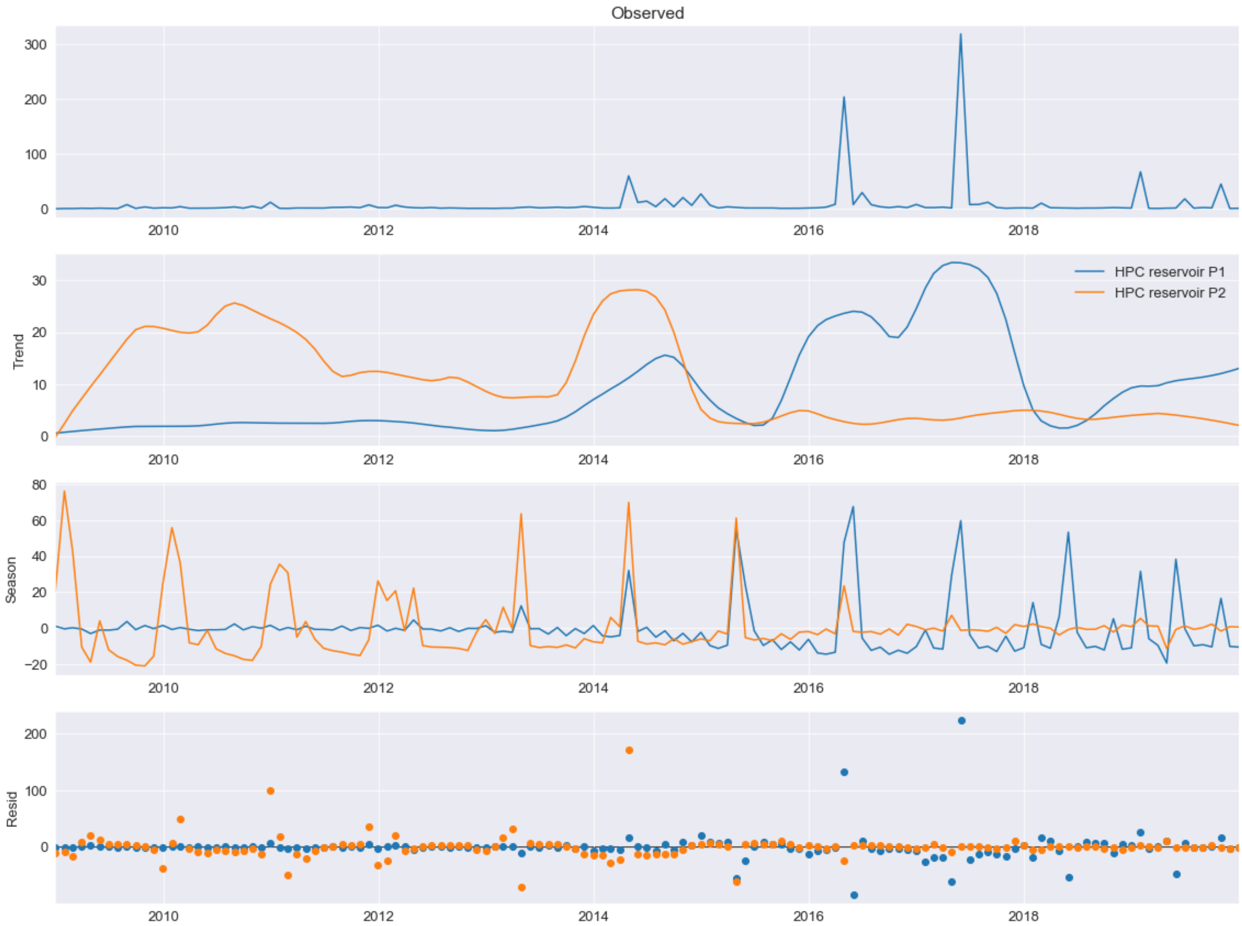


Figure 68 - Time series analysis for HPC (cfu/ml) of clean water in reservoirs of treatment facilities P1 (blue) and P2 (orange).

Difference between HPC values within reservoir P1 and P2

Null-hypothesis: Based on actual samples, is the average HPC value of reservoir P1 equal to the average HPC value of reservoir P2.
Independent Samples Welchs t-test.
t= -1.325
two-sided p value= 0.185

Null-hypothesis: Based on monthly average of samples, is the average HPC value of reservoir P1 equal to the average HPC value of reservoir P2.
Independent Samples Student t-test.
t= -0.638
two-sided p value= 0.524

Regression on time series for HPC of reservoir P1

```
OLS on monthly average of HPC samples from Reservoir  P1
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.032
Model:                            OLS   Adj. R-squared:                  0.017
Method:                 Least Squares   F-statistic:                     2.138
Date:                Wed, 26 Aug 2020   Prob (F-statistic):              0.122
Time:                        11:47:28   Log-Likelihood:                -652.74
No. Observations:                 133   AIC:                             1311.
Df Residuals:                     130   BIC:                             1320.
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
year           1.5306      0.898      1.704      0.091      -0.246       3.307
constant   -3078.0881   1809.097     -1.701      0.091   -6657.171     500.994
season         0.3776      0.312      1.212      0.228      -0.239       0.994
==============================================================================
Omnibus:                      226.219   Durbin-Watson:                   2.086
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            22093.729
Skew:                           7.452   Prob(JB):                         0.00
Kurtosis:                      64.357   Cond. No.                     1.27e+06
==============================================================================
```

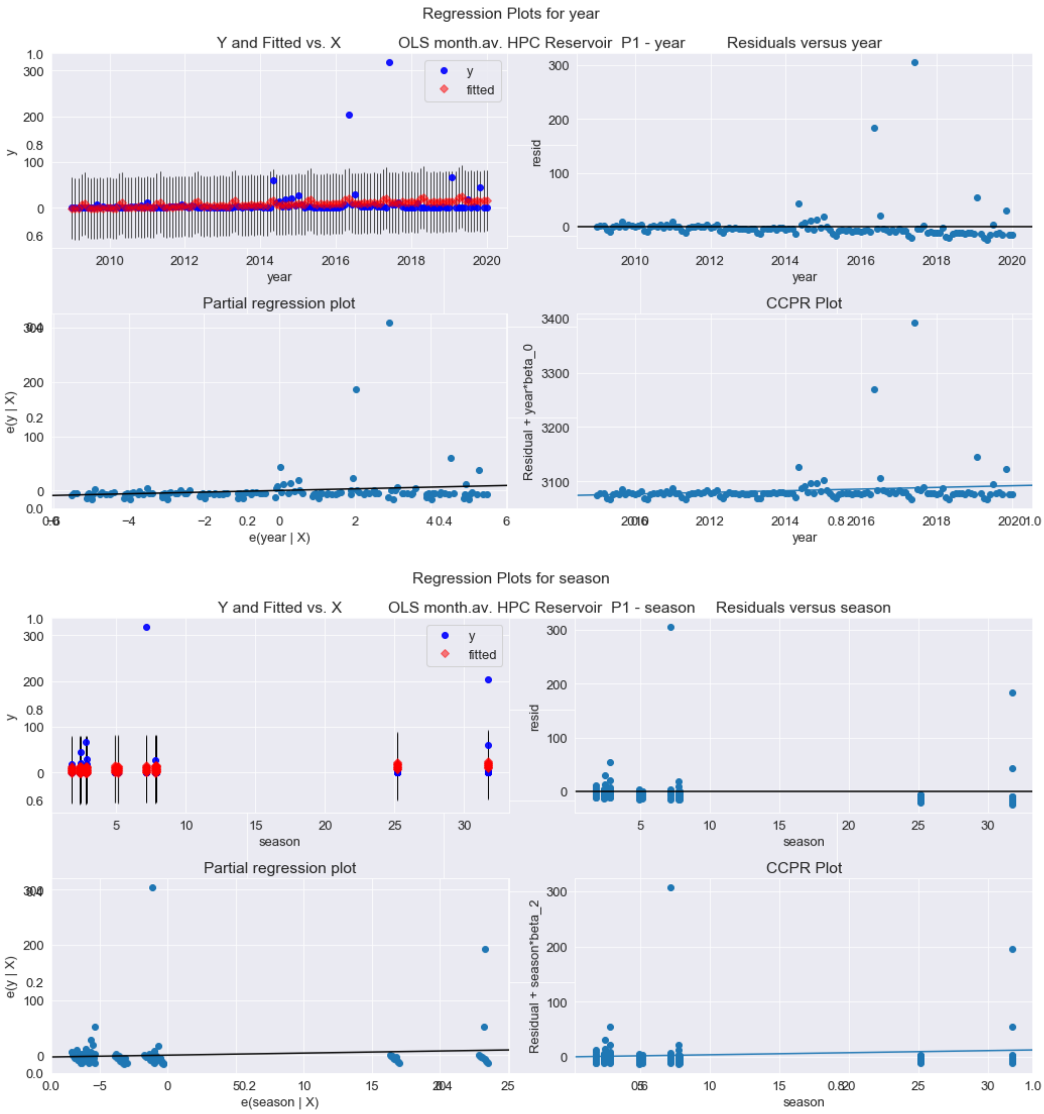


Figure 69 - OLS on TSA for HPC (cfu/ml) of P1 Reservoir samples.

Regression on time series for HPC of Reservoir P2

```
OLS on monthly average of HPC samples from Reservoir  P2
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.052
Model:                            OLS   Adj. R-squared:                  0.038
Method:                 Least Squares   F-statistic:                     3.594
Date:                Wed, 26 Aug 2020   Prob (F-statistic):             0.0302
Time:                        11:47:29   Log-Likelihood:                -637.74
No. Observations:                 133   AIC:                             1281.
Df Residuals:                     130   BIC:                             1290.
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
year          -1.9308      0.802     -2.407      0.018      -3.518      -0.344
constant    3897.2589   1616.340      2.411      0.017     699.524    7094.993
season         0.2983      0.268      1.114      0.267      -0.231       0.828
==============================================================================
Omnibus:                      202.316   Durbin-Watson:                   1.850
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            13326.348
Skew:                           6.210   Prob(JB):                         0.00
Kurtosis:                      50.439   Cond. No.                     1.27e+06
==============================================================================
```

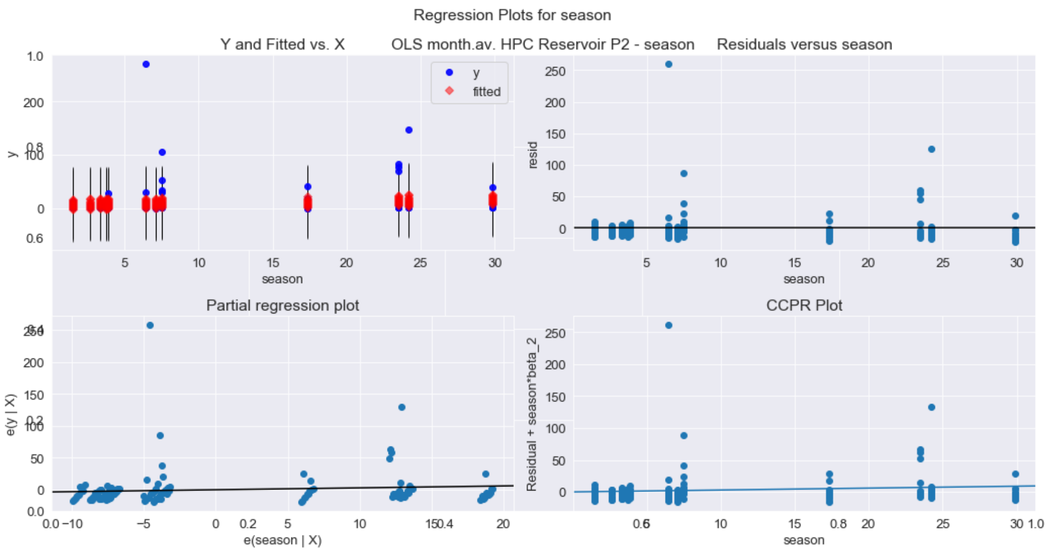


Figure 70 - OLS on TSA for HPC (cfu/ml) of P2 Reservoir samples.

Appendix 10 TSA on HPC samples from DWDS P1 and P2

Notes:

4) One HPC measurement of 67200 cfu/ml is excluded from OLS regression analysis. Otherwise the TSA is totally flat with few very small yearly spikes.
5) Removal of more high HPC measurements (up to HPCmax < 1000 cfu/ml = 10xHPC.legal.limit), results in same outcome as removing of only HPC=67200 cfu/ml. In other words: Removing more HPC values is like peak shaving. Elevated HPC peaks in the years 2012 and 2019 remain visible. Change in OLS results are marginally. This is therefore not further explored. Only HPC=67200 cfu/ml is removed for reason mentioned above.

HPC DWDS P1 and DWDS P2

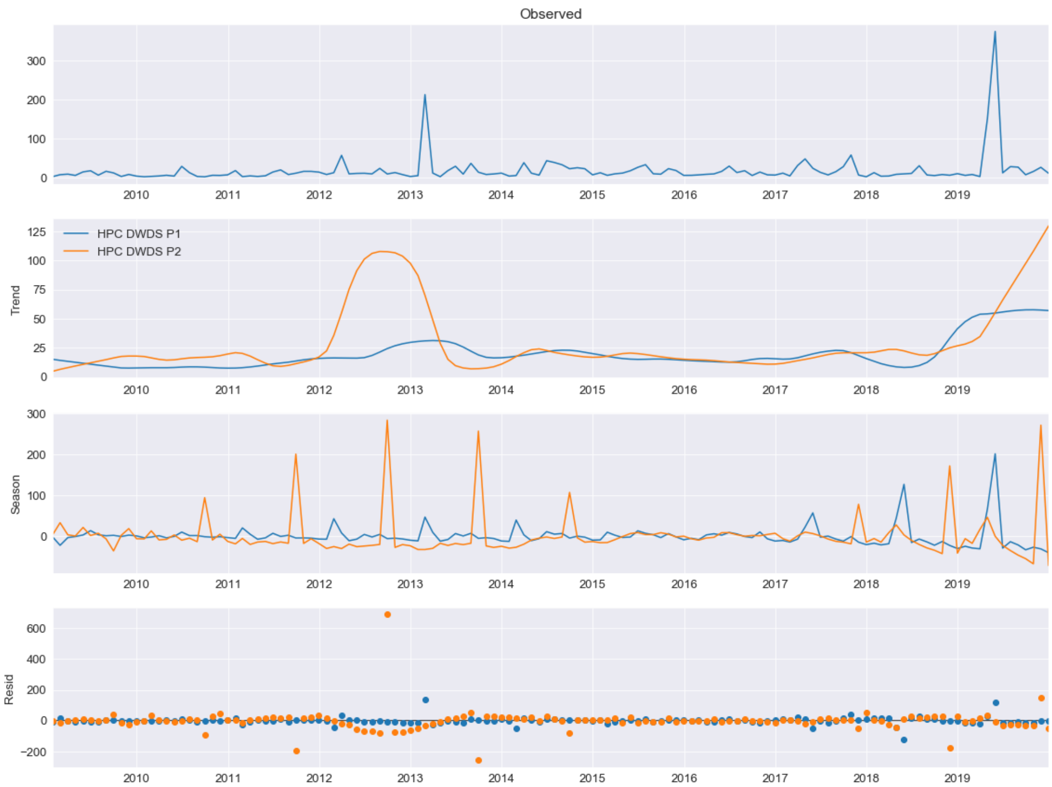


Figure 71 - Time series analysis for HPC (cfu/ml) of DWDS P1 (blue) and DWDS P2 (orange).

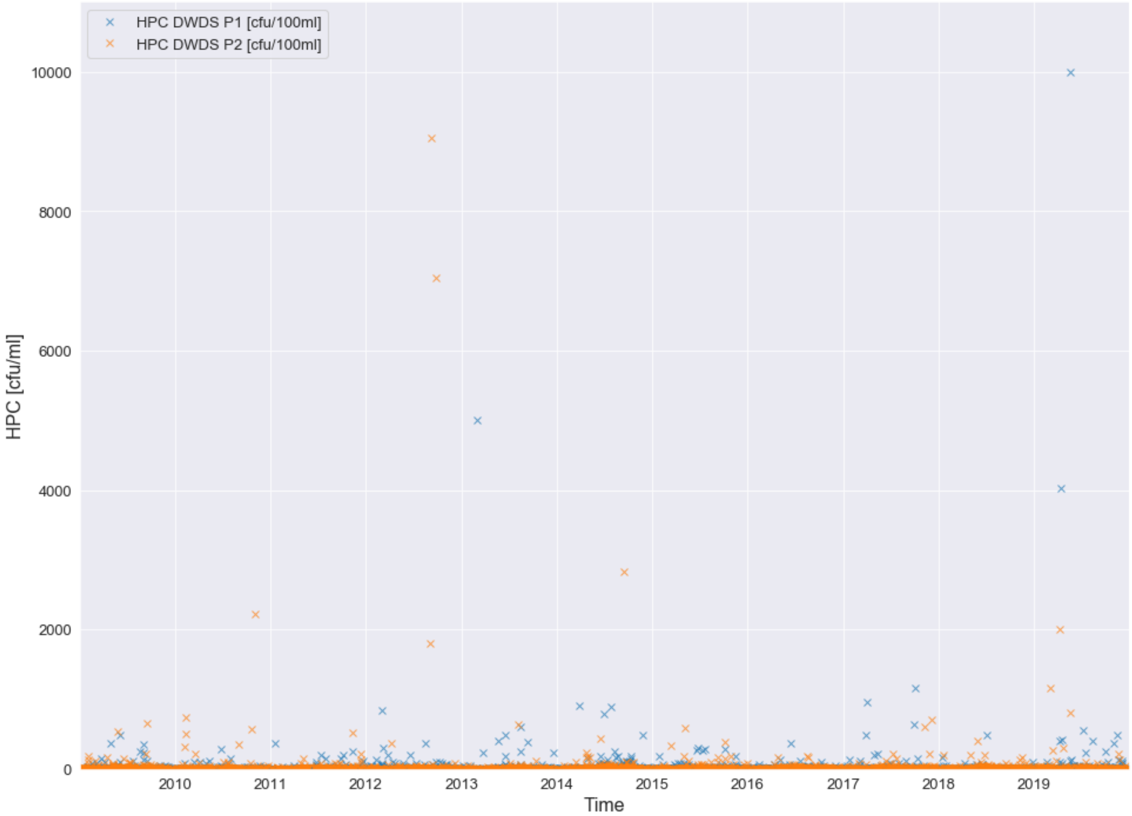


Figure 72 - HPC (cfu/ml) samples of DWDS P1 (blue) and DWDS P2 (orange)[11] .

Difference between HPC values within DWDS P1 and P2

Null-hypothesis: Based on actual samples, is the average HPC value of DWDS P1 equal to the average HPC value of DWDS P2.
Independent Samples Welchs t-test.
t= -1.645
two-sided p value= 0.1

Null-hypothesis: Based on monthly average of samples, is the average HPC value of DWDS P1 equal to the average HPC value of DWDS P2.
Independent Samples Student t-test.
t= -1.001
two-sided p value= 0.318

[11] Three DWDS samples with HPC > 10000 (cfu/ml) are removed from plot

Regression time series HPC DWDS P1

```
OLS on monthly average HPC samples from DWDS P1
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.097
Model:                            OLS   Adj. R-squared:                  0.083
Method:                 Least Squares   F-statistic:                     6.903
Date:                Wed, 26 Aug 2020   Prob (F-statistic):            0.00142
Time:                        12:35:29   Log-Likelihood:                -663.69
No. Observations:                 132   AIC:                             1333.
Df Residuals:                     129   BIC:                             1342.
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
year           2.2762      1.024      2.222      0.028       0.249       4.303
constant   -4585.9388   2063.877     -2.222      0.028   -8669.371    -502.507
season         1.0221      0.336      3.042      0.003       0.357       1.687
==============================================================================
Omnibus:                      195.470   Durbin-Watson:                   1.609
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            11335.601
Skew:                           5.956   Prob(JB):                         0.00
Kurtosis:                      46.808   Cond. No.                     1.28e+06
==============================================================================
```

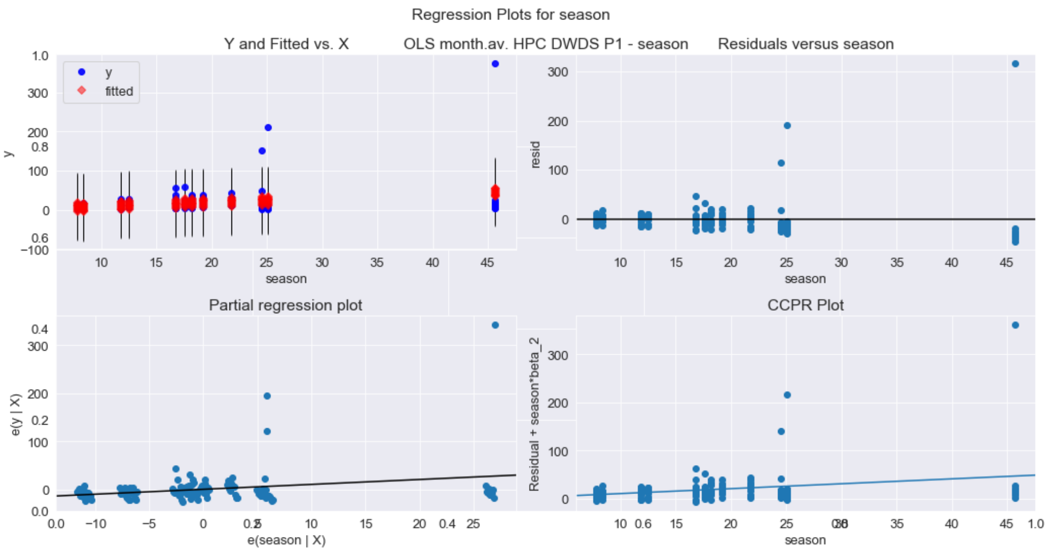


Figure 73 - OLS on TSA for HPC (cfu/ml) of P1 DWDS samples.

Regression time series HPC DWDS P2

```
OLS on regression of monthly average HPC samples from DWDS P2
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.084
Model:                            OLS   Adj. R-squared:                  0.070
Method:                 Least Squares   F-statistic:                     5.896
Date:                Wed, 26 Aug 2020   Prob (F-statistic):            0.00355
Time:                        12:35:30   Log-Likelihood:                -794.31
No. Observations:                 132   AIC:                             1595.
Df Residuals:                     129   BIC:                             1603.
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
year           1.1282      2.757      0.409      0.683      -4.326       6.582
constant   -2272.7328   5552.811     -0.409      0.683   -1.33e+04    8713.640
season         0.9955      0.294      3.392      0.001       0.415       1.576
==============================================================================
Omnibus:                      230.872   Durbin-Watson:                   2.019
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            27535.064
Skew:                           7.716   Prob(JB):                         0.00
Kurtosis:                      72.052   Cond. No.                     1.28e+06
==============================================================================
```

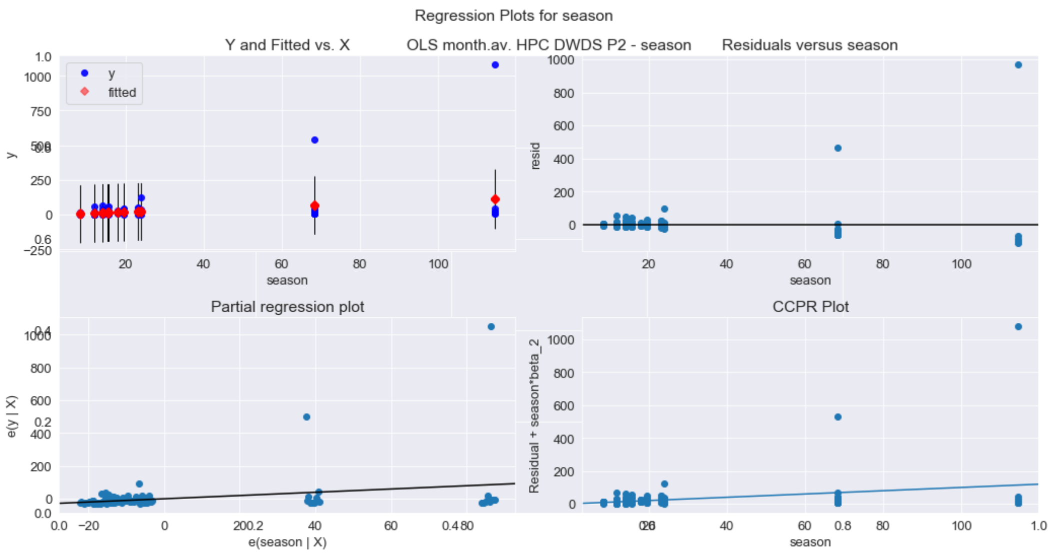


Figure 74 - OLS on TSA for HPC (cfu/ml) of P2 DWDS samples.

Appendix 11 Initial heatmap observations

(This appendix contains a small selection of total series of 240 heatmaps. Total series is available in full appendix of report.)

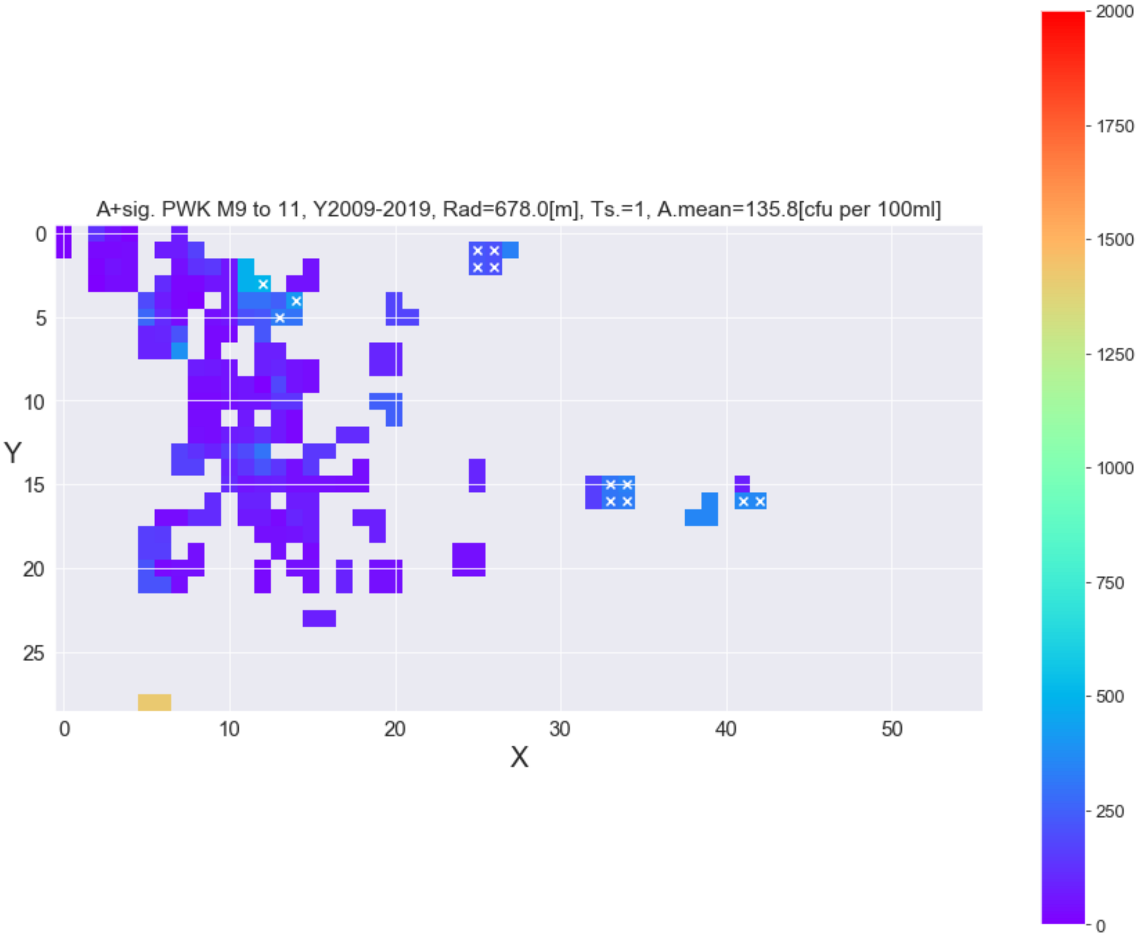


Figure 75 - Heatmap overlay with markers (x) for areas with significant elevated average drinking water Temperature (°C), (p<.025). Time frame: Time frame: 1 Dec 2013 … 28 Feb 2014. Radius of observation circle = 678 m. Heatmap colour bar represents average of measurements within observation circle. X and Y-axis values are not related to geographic map.

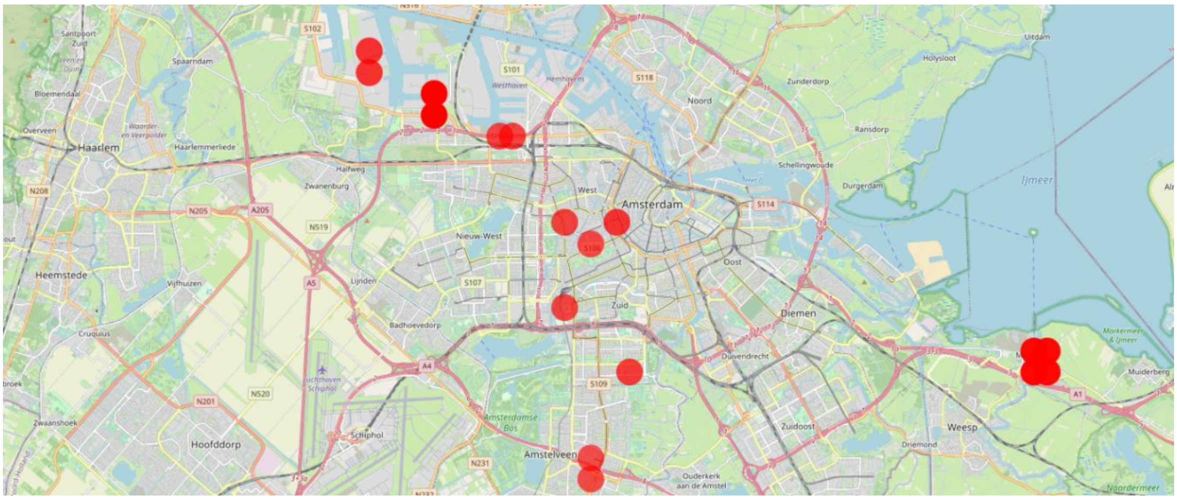


Figure 76 - Projection of significant areas from Figure 75. Areas with significant elevated average drinking water Temperature are represented by red markers (p<.025). Markers have no colour bar definition. Time frame: 1 Dec 2013 … 28 Feb 2014. Projected map covers markers in DWDS P1 (centre of map) and the map covers markers in DWDS P2 (east). Map size: 36.2 x 15.7 km.

Figure 77 - Heatmap overlay with markers (x) for areas with significant elevated average Aeromonas measurement values (cfu/100ml) from DWDS P2 (p<.025). Time frame: 1 Sep - 30 Nov of 2009-2019. Radius of observation circle = 678 m. Heatmap colour bar represents average of measurements within observation circle. X and Y-axis values are not related to geographic map. Circle added to highlight markers with multiple reoccurrence in same seasons of individual years. Squares added to highlight multiple reoccurrence in different seasons in total time span observation.

Figure 78 - Projection of significant areas from Figure 77. Areas with significant elevated average Aeromonas measurement values are represented by purple markers (p<.025). Markers have no colour bar definition. Projected map covers markers of DWDS P2 only. Time frame: 1 Sep - 30 Nov of 2009-2019. Map size: 21.8 x 15.5 km.

Appendix 12 Regional observations

Analysis of Aeromonas samples from Area 1 (urban)

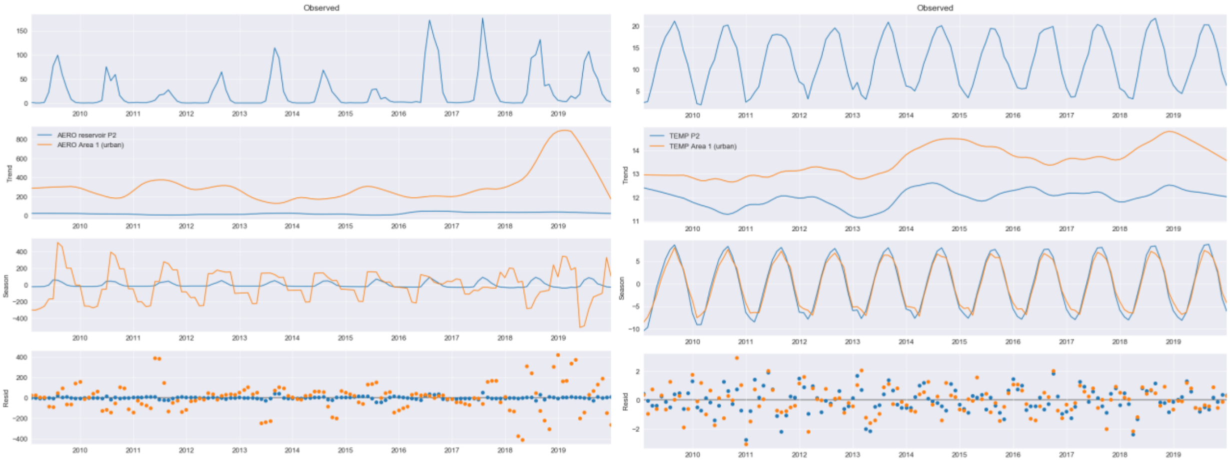


Figure 79 - Time series analysis on Aeromonas sample values (left) and Temperature (right) for Area 1 and reservoir P2.

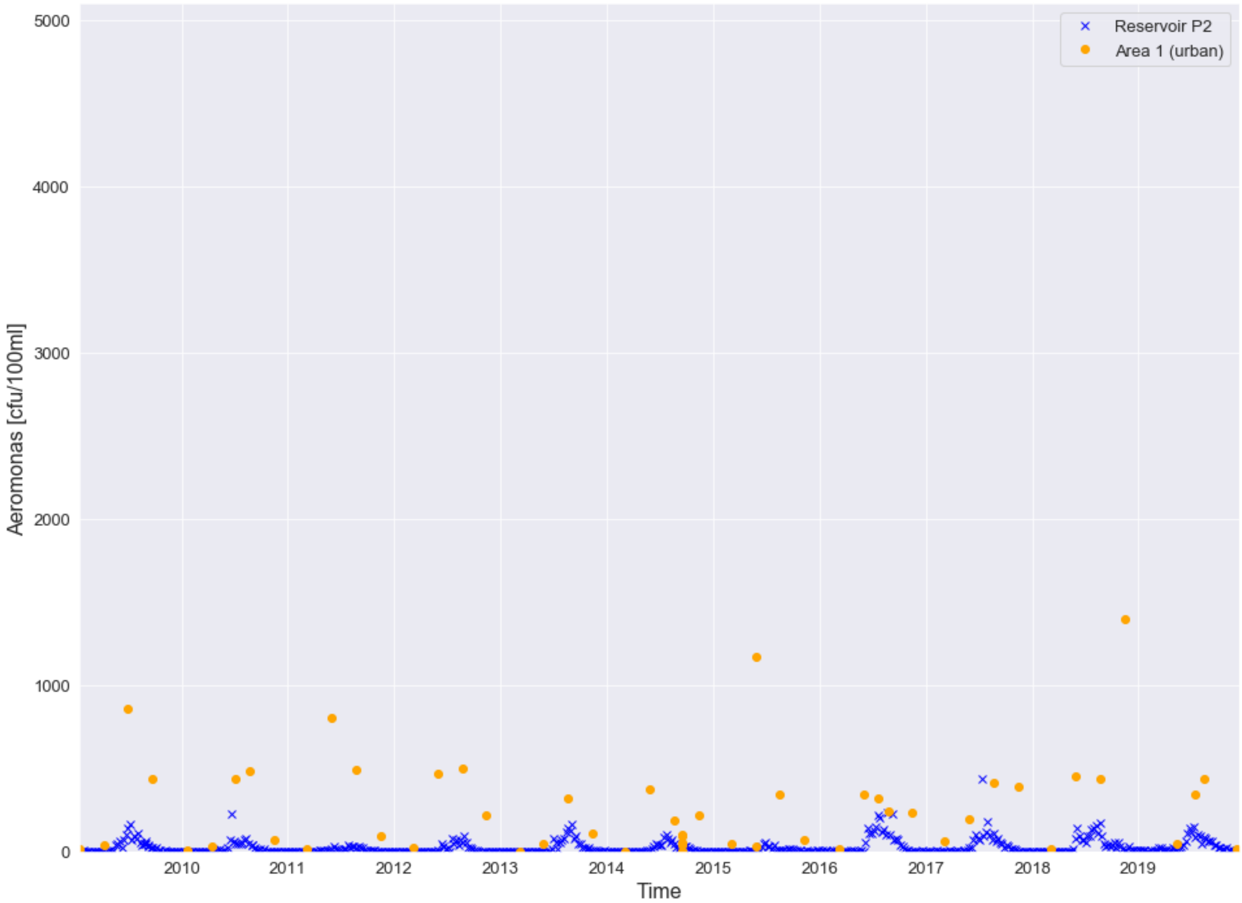


Figure 80 – Aeromonas sample values of Area 1 and reservoir P2.

Analysis of Aeromonas samples from Area 2 (urban)

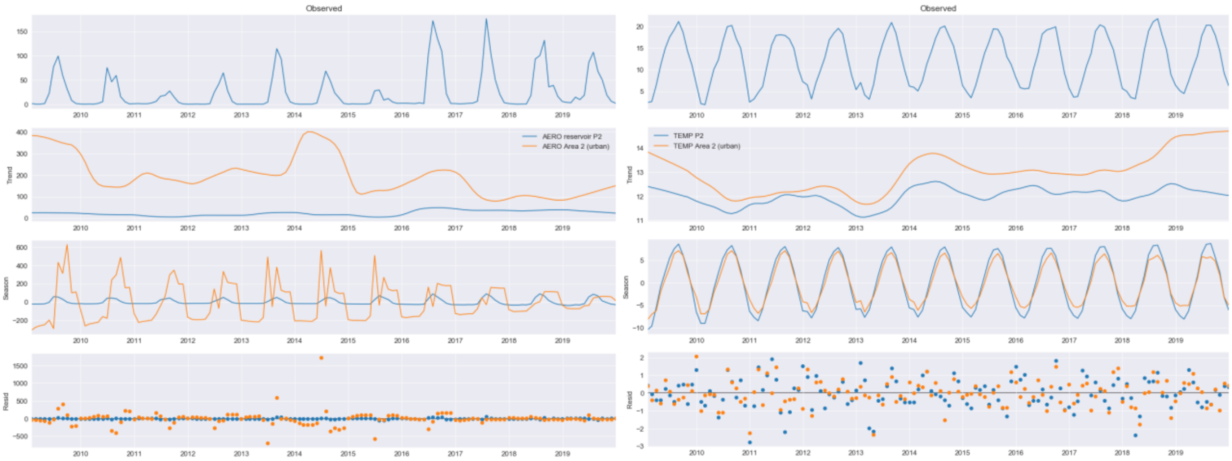


Figure 81 - Time series analysis on Aeromonas sample values (left) and Temperature (right) for Area 2 and reservoir P2.

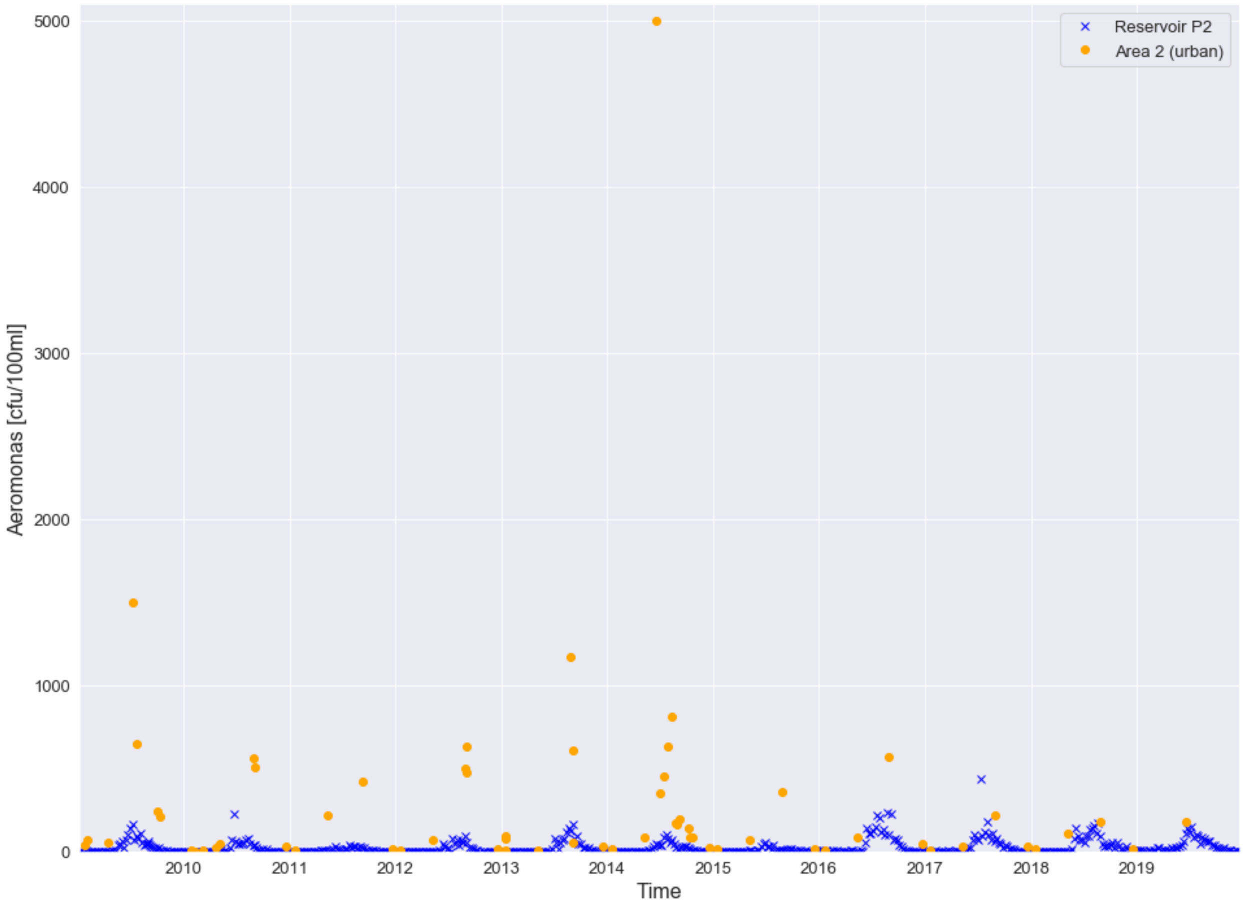


Figure 82 - Aeromonas sample values of Area 2 and reservoir P2.

Analysis of Aeromonas samples from Area 3 (rural)

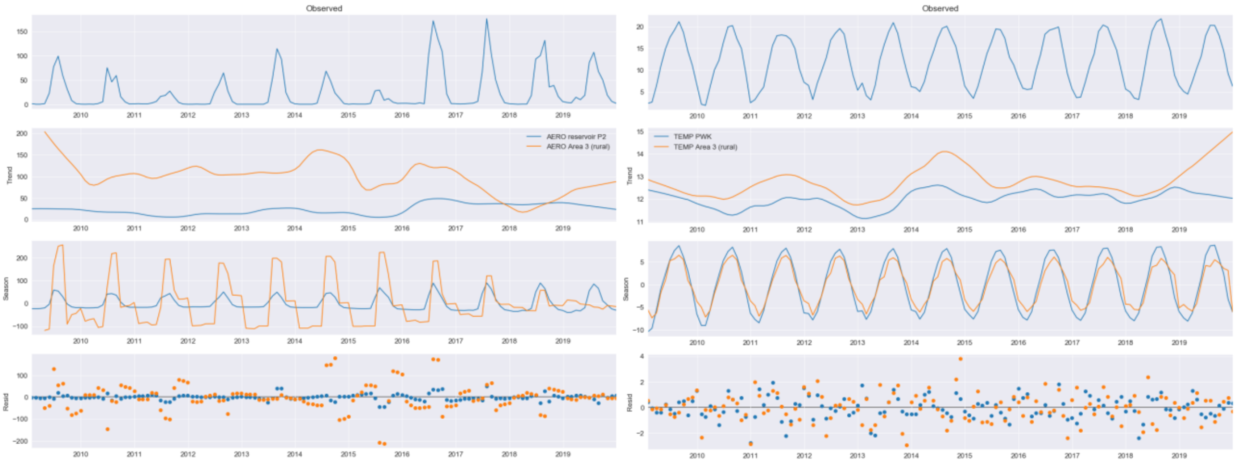


Figure 83 - Time series analysis on Aeromonas sample values (left) and Temperature (right) for Area 3 and reservoir P2.

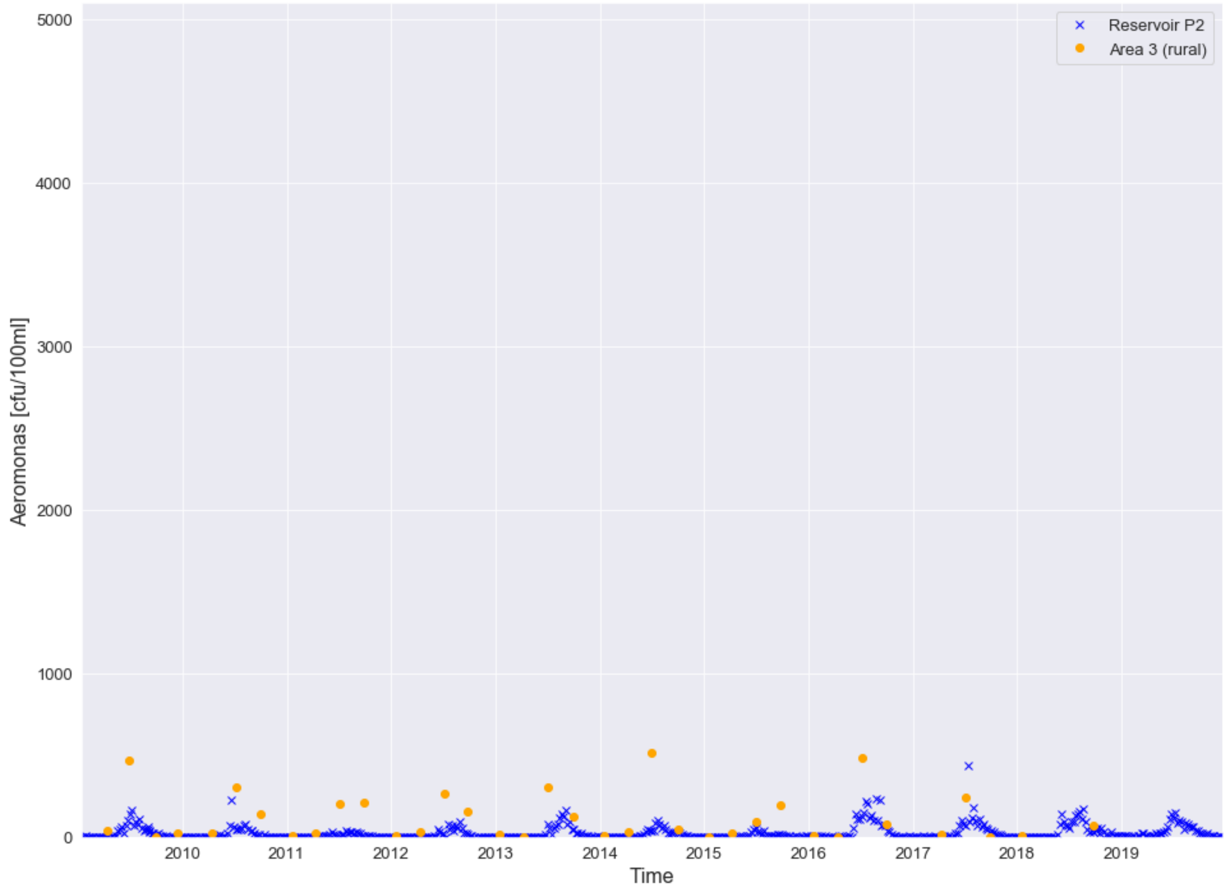


Figure 84 - Aeromonas sample values of Area 3 and reservoir P2.

Analysis of Aeromonas samples from Area 4 (rural)

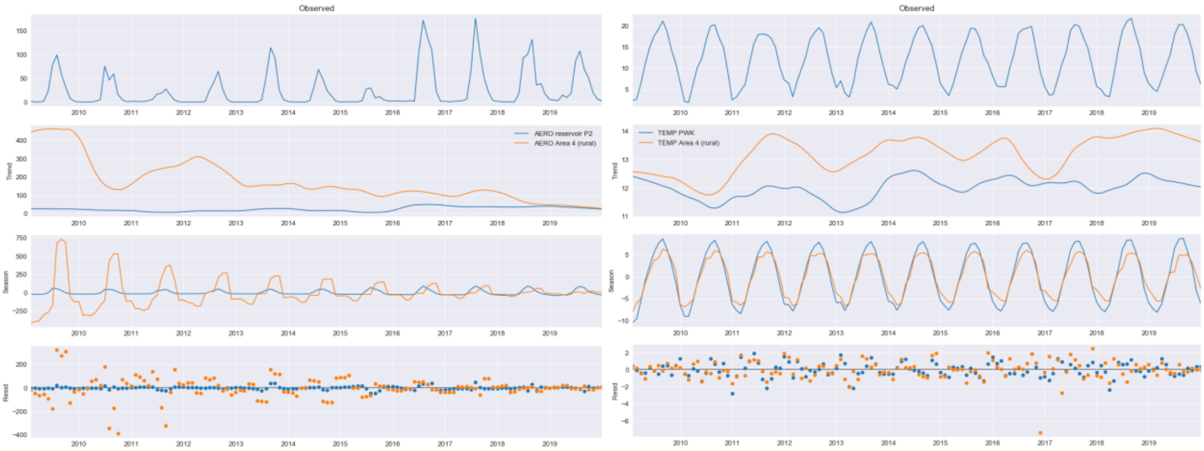


Figure 85 - Time series analysis on Aeromonas sample values (left) and Temperature (right) for Area 4 and reservoir P2.

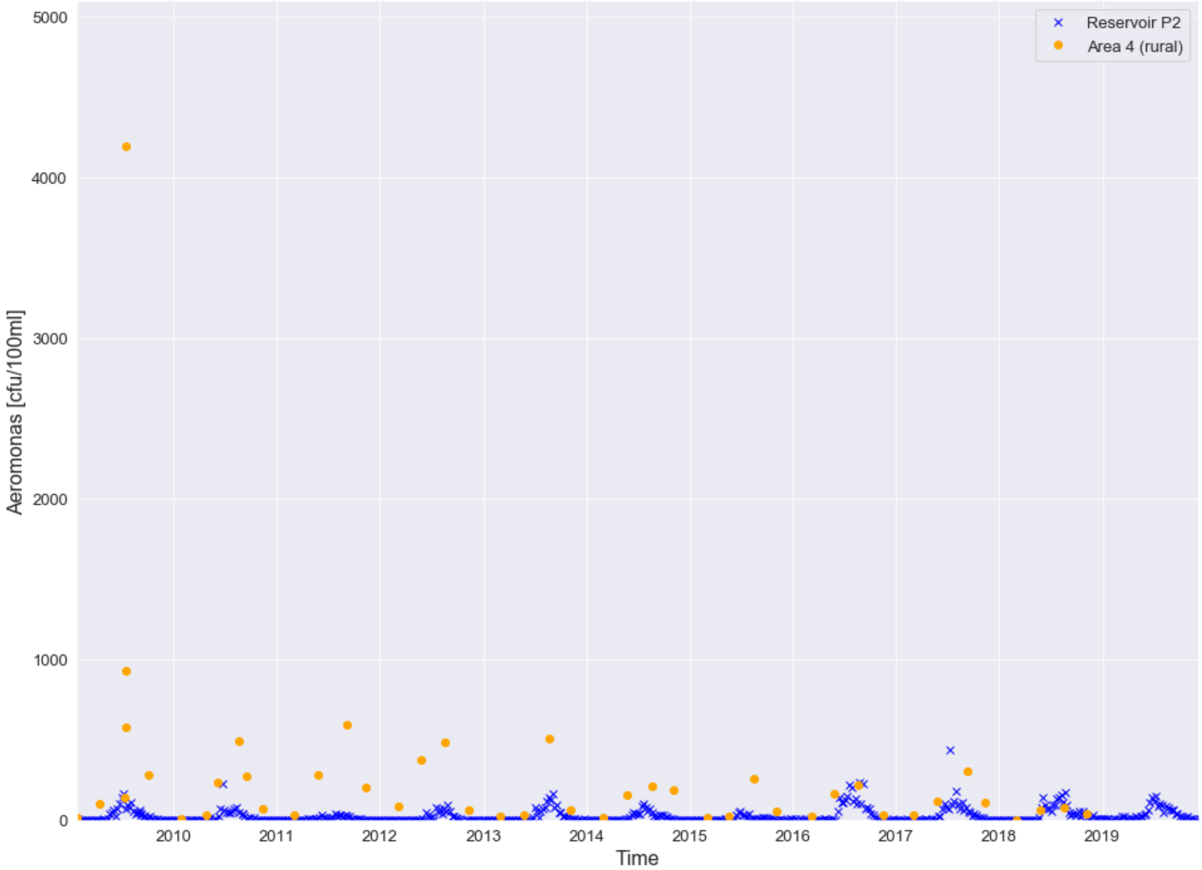


Figure 86 - Aeromonas sample values of Area 4 and reservoir P2.

Analysis of Aeromonas samples from Area 5 (rural)

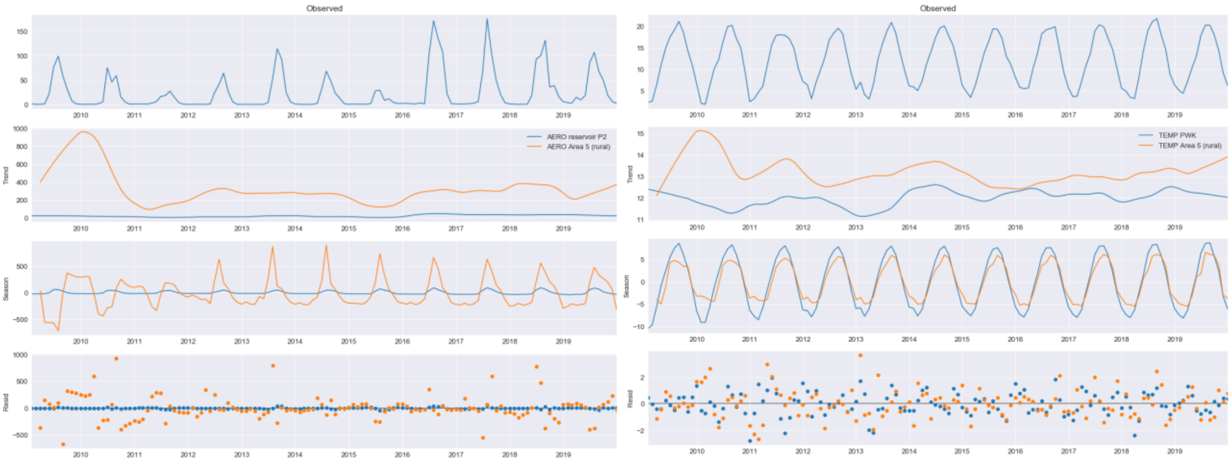


Figure 87 - Time series analysis on Aeromonas sample values (left) and Temperature (right) for Area 5 and reservoir P2.

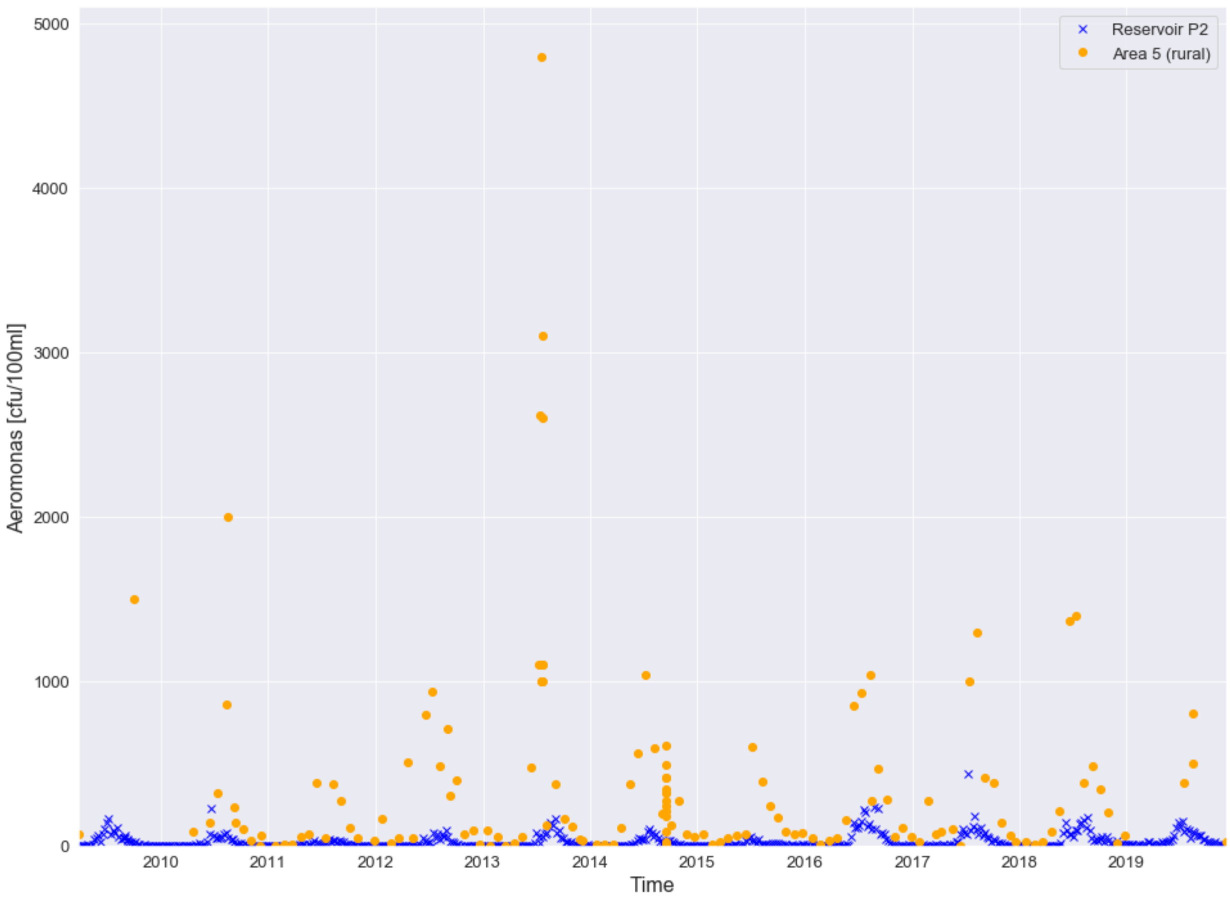


Figure 88 - Aeromonas sample values of Area 5 and reservoir P2.

Analysis of Aeromonas samples from Area 6 (rural)

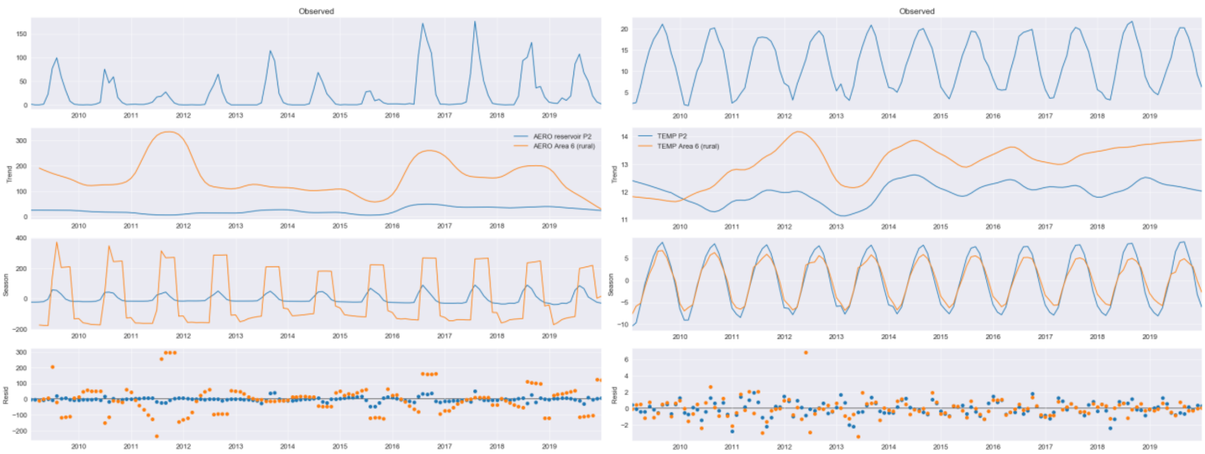


Figure 89 - Time series analysis on Aeromonas sample values (left) and Temperature (right) for Area 6 and reservoir P2.

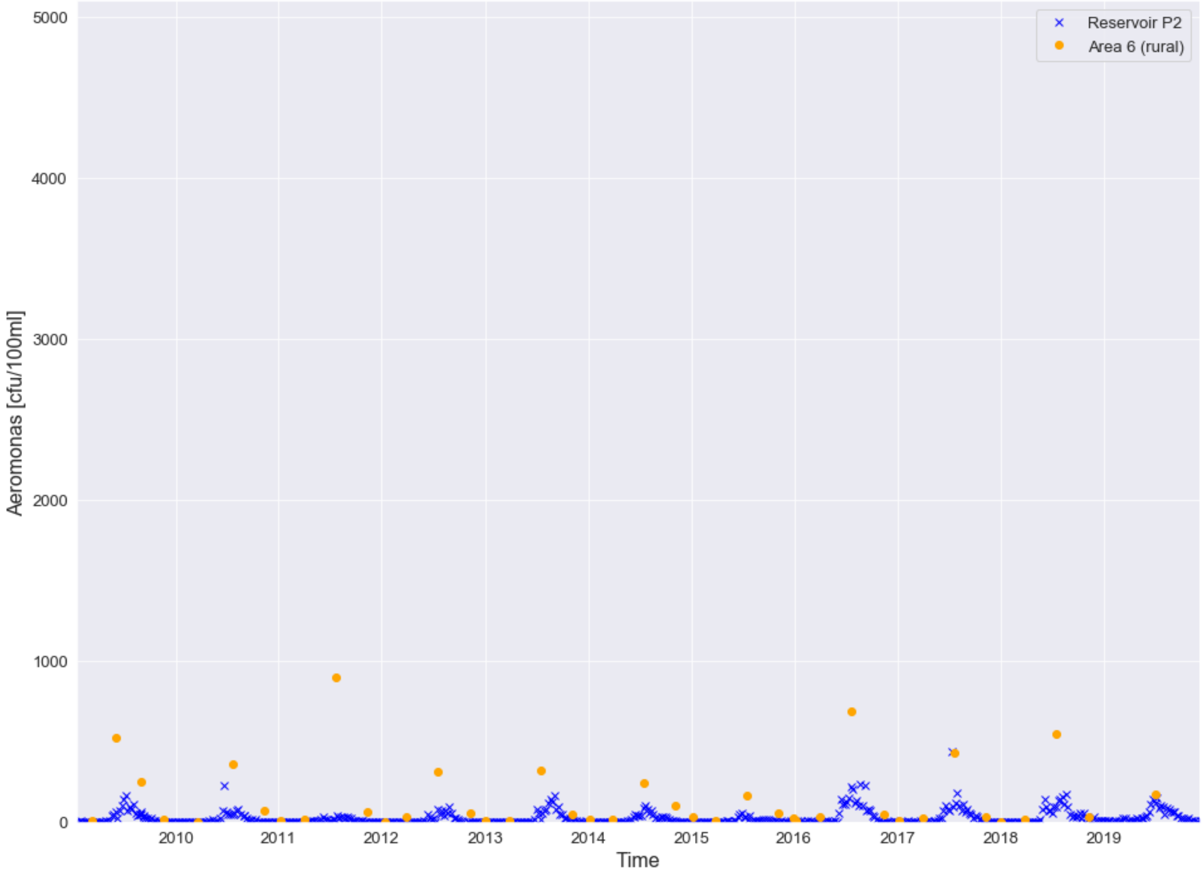


Figure 90 - Aeromonas ample values of Area 6 and reservoir P2.

Appendix 13 T-tests on comparison of Urban and Rural district.

Null-hypothesis on ΔT:

Weekly average Temperature change ($\Delta TEMP_{AREA\text{-}RESERVOIR}$) in the samples of "urban district" and the samples of "rural district" were not significantly different.

T-test:

Independent Samples Welch's t-test between weekly average Temperature change ($\Delta TEMP_{AREA\text{-}RESERVOIR}$) in samples of "urban district", versus Temperature change in samples of "rural district".

t= 5.646

two-sided p value= 0.0

one-sided p value= 0.0

Conclusion:

Null-hypothesis was rejected. Weekly average Temperature change ($\Delta TEMP_{AREA\text{-}RESERVOIR}$) in samples of "urban district" was significantly higher than the Temperature change in samples of "rural district".

Null-hypothesis on ΔAERO:

Weekly average Aeromonas change ($\Delta AERO_{AREA\text{-}RESERVOIR}$) in the samples of "urban district" and the samples of "rural district" were not significantly different.

T-test:

Independent Samples Welchs t-test between weekly average Aeromonas change ($\Delta AERO_{AREA\text{-}RESERVOIR}$) in samples of "urban district", versus Aeromonas change in samples of "rural district".

t= -3.408

two-sided p value= 0.001

one-sided p value= 0.0

Conclusion:

Null-hypothesis was rejected. Weekly average Aeromonas change ($\Delta AERO_{AREA\text{-}RESERVOIR}$) in the samples of "urban district" was statistic significantly lower than the Aeromonas change in samples of "rural district".

Null-hypothesis *on T.abs*:

Weekly average Absolute sample Temperature of "urban district" and absolute sample Temperature of "rural district" were not significantly different.

T-test:

Independent Samples Welch's t-test between weekly average absolute sample Temperature of "urban district", versus absolute sample Temperature of "rural district".

t= 2.535

two-sided p value= 0.011

one-sided p value= 0.006

Conclusion:

Null-hypothesis was rejected. Weekly average Absolute sample Temperature of "urban district" was significantly higher than the absolute sample Temperature of "rural district".

Null-hypothesis *on AERO.abs*:

Weekly average Absolute Aeromonas values of the samples from "urban district" and absolute Aeromonas values of the samples from "rural district" were not significantly different.

T-test:

Independent Samples Welch's t-test between weekly average absolute Aeromonas values of the samples from "urban district", versus absolute Aeromonas values of the samples from "rural district".

t= -3.516

two-sided p value= 0.001

one-sided p value= 0.0

Conclusion:

Null-hypothesis was rejected. Weekly average Absolute Aeromonas values of the samples from "urban district" were significantly lower than the absolute Aeromonas values of the samples from "rural district".

For these tests it is important to note that the number of samples for the urban and rural networks was different, but the distance between the common DWDS feed line to the outskirts of both districts was equal.

--- Final page ---