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Secondary iron ion contamination of water in the water supply network

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ABSTRACT

This paper presents the modeling of iron concentration in the water supply network using geographic information systems. The method of ordinary cokriging, which belongs to geostatistical methods of data interpolation, was chosen to estimate the distribution of variation of iron content in the water supply network area. Actual values of iron concentration in tap water were used for the modeling. The tests presents the results of estimating the values of estimated iron ion concentrations over a year. Data input in the model regarded the existing water supply network administered by the Municipal Water Supply and Sewerage Company in the Capital City of Warsaw, Joint Stock Company. Advanced technologies and modern water treatment processes are in many cases insufficient to deliver high quality water to the consumer. The composition of water in a water supply system is altered by physical, chemical and biological processes. Phenomena occurring in water supply networks, plants and equipment cause deterioration of water quality at the stage of water distribution. The results of laboratory tests on the quality of water entering the water supply network from the three water treatment plants and water supply network with control points were presented. The test results showed different concentrations of iron ions in the water supply network control points within the range from 0.012 to 0.85 mg/L. Results of spatial distributions of secondary iron contamination using ordinary cokriging method on the infrastructure map was able to determine the places of iron concentration changes in the water supply network.

Keywords: Water network; Iron contamination; Ordinary cokriging

1. Introduction

In large cities, water from water treatment plants reaches consumers through a pipeline system that can be as long as several thousand kilometers. Distributed structure of the water supply network, variability of the operation parameters with the simultaneous need to make numerous decisions at the same time cause that management of the network infrastructure is a complex process. One of the most significant operational problems are undesirable changes in the technical condition of the water supply network, which causes, among other things, an increase in the content of iron in the distributed water.

Secondary contamination of water in the water supply network as water flows from the treatment location to consumers is a serious problem for the vast majority of water supply companies [1]. A significant deterioration of water quality, both in terms of physical–chemical and microbiological aspects, is caused by the deposition of chemical and biological sludges on the inner surfaces of pipes during many years of use of water supply networks and plants [2]. The vast majority of water supply networks, both nationally and internationally, is characterized by a very heterogeneous material structure. This is particularly evident in large cities where water supply systems have been evolving for decades. A variety of materials are used to construct water supply networks and the proportions of such

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materials each depend on the period of construction. The predominant materials used for constructing water supply networks include gray cast iron, ductile cast iron and steel. In addition to metal alloys, asbestos-cement pipes, reinforced concrete pipes and increasingly thermosetting pipes, that is, made of polyvinyl chloride and polyethylene, are used [3]. The negative effect of sludges formed on the materials used to make water distribution pipes leads to the deterioration of the mechanical and hydraulic properties of these pipes.

In natural freshwater, iron is present in low concentrations [4,5]. In treated tap water, iron occurs as a residue of naturally occurring iron, as a result of the use of iron coagulants, and the release of particles due to corrosion of steel and cast iron water pipes [6–9]. During transport of water from the treatment plant, iron present in tap water precipitates and accumulates as hard or smear-like sludges on the surface of the water supply plant. Sludge in water distribution systems can appear after only a few weeks of use, and the rate of growth depends on the prevailing hydraulic conditions [10–14]. Sludges precipitated from water harden over time and gradually overlapping subsequent layers of such sediments can narrow the clear opening of piping, even closing it completely. Negative effects on the efficiency of the water supply network due to the decreasing cross-sectional area of the pipes are observed in the form of high energy losses necessary for the pumps that convey water. The presence of sludge in the water supply system also causes operational problems in the form of, among others, an increase in the resistance of the water supply network, the risk of bacterial growth in the iron sludge, difficult disinfection, especially when using sodium hypochlorite or free chlorine, the detachment of sludges and an increase in the concentration of iron in the tap water inside the network, despite the low content recorded after treatment [15]. The occurrence of such problems requires an assessment of the hazards associated with indoor water supply systems and an assessment of the hazards associated with products and materials in contact with potable water.

Current national legislation specifies that the maximum allowable concentration of iron in potable water must not exceed the value of 0.2 mg/L, whereas the World Health Organization (WHO) standards provide the permissible limit of iron in potable water of 0.3 mg/L [16]. The conducted observations indicate that already at an iron concentration of 0.05 mg/L in tap water the effect of iron sludge formation on the inner walls of the pipeline can occur [17].

Secondary water contamination in the water supply network can be caused by many factors. Increases in iron concentration in treated water with the composition according to national regulation when injected into the system can occur due to sludge detachment through diversions or varying water flow rates in the water supply system. Sludge accumulation is particularly intense during periods of reduced water demand and, during periods of high water demand, accumulated substances from the accumulated sludges are released into the liquid and transported to consumers [18]. Stagnant water in water pipes is equally dangerous. Increasing the contact time between water and the sludges accumulated in the distribution system creates conditions for equalization of contaminant concentrations in the water-sludge system due to dissolution of sludges, especially in the first intake volume after the stagnation period. The chemical composition of sludge depends on many factors, but usually the main elements are corrosion products in the form of iron compounds [19–21]. In addition, various bacteria grow in the sludge, causing secondary bacteriological water contamination. Secondary water contamination is highly dependent on water pressure and flow velocity [22]. Increases in water flow pressure and sudden changes in water flow rate affect the detachment of sludges from the surface of water pipes and weaken the pipe material.

After a previous emergency water stagnation, a sharp increase in iron concentration is observed at the customers' premises, many times exceeding acceptable standards, and an increase in turbidity and color. Increasing iron concentrations in the water supply network can also occur due to dissolution of iron compounds. Iron sludge is a stabilized chemical compound that will not secondarily dissolve in water unless external factors and varying oxidizing and reducing conditions are present [23,24]. The form of iron(III) that is difficult to dissolve enters the water. The release of substances causing dissolution of iron sludges into the water in the form of acidifying substances or occurrence of reducing conditions in the water supply network, in which the reaction of reduction of iron(III) into iron(II) will take place, will directly affect the deterioration of chemical conditions of treated water [25].

The objective of the tests was to evaluate changes in tap water quality due to varying iron concentrations in tap water as it flows from the treatment location to consumers as a function of residence time in the distribution system, water pressure and flow velocity, as well as the annual water intake cycle.

2. Material and methods

2.1. Object description

The plant used for the capital city of Warsaw, a large urban agglomeration, was chosen as an example water supply network for tests. The main sources of water supply for Warsaw are the Vistula River and a reservoir – Zegrzyńskie Lake. The northern part of the city is supplied with water taken directly from Zegrzyńskie Lake through shore type intakes. The main source of raw water for the southern and central parts of Warsaw is the Vistula River. The water taken from the Vistula River covers about 70% of the city's demand. The river intake complex consists of a primary intake and six secondary intakes located on both banks of the river. All intakes operate below the river bed based on the principle of infiltration. Water is taken using a system of drains from the sandy layer of soil beneath the river bed. The drainage system consists of 300–400 mm dia. and 100–400 m long pipes laid 4 m to 7 m below the bed and covered with a natural sand filtration layer.

The city's water supply system is divided into three zones: the Northern Plant (ZP) supplying the northern part of the city, the "Filtry" Central Plant (ZCF) supplying the central part of the city and the "Praga" Central Plant (ZCP) supplying the southern part of the city. The division, related to the altitude system of the city, is maintained by a fixed amount of pressure at the exit of each station into two pressure zones. The border of the division runs along the Vistula Escarpment – the upper city and the lower city, marking the division between the zone of ZCF and ZCP. The division of the Warsaw agglomeration into water supply zones is shown in Fig. 1. The range of operation of individual plants is not constant and varies depending on the pressure system and water demand in different parts of the city. Depending on the needs, also waterworks can complement each other and replace each other in the water supply system.

The material structure of the water supply network in Warsaw has been changing systematically over the years. Last studies show that despite intensive extension and replacement of old pipelines into pipes made of new materials, the material structure of the analyzed water supply networks still features large quantities of grey cast iron (56.54%), ductile cast iron (21.45%) and steel (12.35%). The material structure includes a small share of plastic pipes which comprise approximately 5.01% (PVC) and 0.22% (PE) of the length of analyzed water supply networks, respectively. The asbestos cement pipelines (4.43%) have been undergoing systematical replacement into pipes made of new materials such as PE and ductile cast iron. In general, one may conclude that the water supply networks are constructed mainly using grey cast iron, steel, PVC and PE pipes – the pipelines made of these materials comprise 74% of length of the analyzed networks.

2.2. Sampling methodology

In order to trace changes in water quality during its flow from supplier to consumers, water samples for testing were collected for testing from characteristic points of the water supply system, that is, from 3 water treatment plants immediately downstream water treatment upstream the process of supply into the network and at control points located within the water supply network throughout the city. Within the water supply network, 20 measurement stations for the ZP area, 31 measurement stations for the ZCF area and 8 measurement stations for the ZCP area were selected. The layout of the control stations is shown in Fig. 2. Water samples from the selected stations were collected once a month for a period of 1 y. Total iron concentration was determined in the collected water samples.

Additionally, during the research period, measurements of the dissolved oxygen content were carried out at selected stations for ZP-5, ZCF-4 and ZCP-1 measurements. The tested water was characterized by the oxygen content ranging from 1.7 to 15.4 mg/L, the median and the mean were respectively 9.15 and 9.40 mg/L.

Laboratory tests of iron concentration were carried out using the spectrophotometric method (in the range of 0.020 to 5.0 mg/L) according to the methodology indicated in the testing laboratory accreditation No. AB 811 (PN-ISO 6332:2001).

2.3. Methods of the analysis

Cokriging is a geostatistical technique that is used to interpolate a surface from a scattered set of known points in which a continuous surface of values can be predicted between the known locations. Cokriging uses autocorrelation and cross-correlation to create an interpolated surface that predicts values at unmeasured locations. Additionally, cokriging includes a secondary variable in the interpolation model [27], and assumes that some autocorrelation exists between a primary and secondary variable; stronger the autocorrelation among the multivariates results in greater accuracy for the prediction of the primary variable in the cokriging model [28,29]. Cokriging methods in which more than one variable is used for estimation are particularly useful when the main variable is sparsely sampled and the secondary variable is densely or even over-sampled.

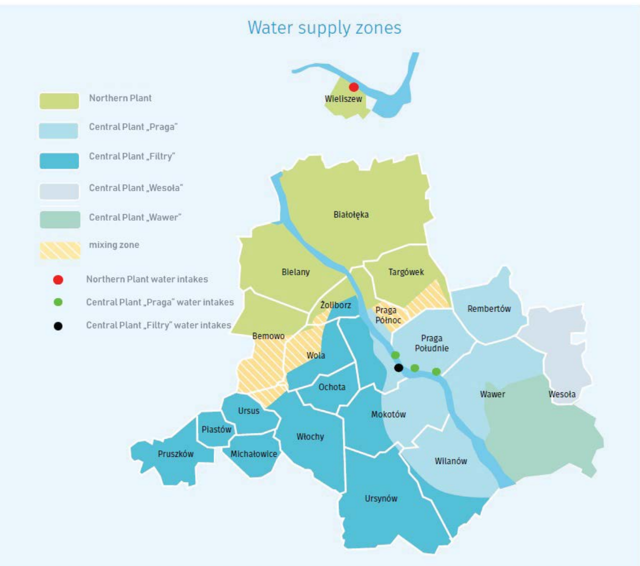

Fig. 1. Water supply zones with marked water intakes [26].

Fig. 2. Diagram of the water supply network model with control points.

Using two or more variables, cokriging produces the best model based on eliminating bias between the estimated value and the true value and minimizing the variance among estimations [30]. Using cokriging, the accuracy of the interpolated surface can be increased when compared to univariate kriging by as much as several dozen percent.

Cokriging is the best known geostatistical method for integrating measurement data. The estimated value is a linear combination of both the value of the main variable and the value of the secondary variable and takes the following form (Eq. 1):

$$\hat{U}(x_0)=\sum_{i=1}^{n}a_i(x_i)U_i(x_i)+\sum_{j=1}^{m}b_j(x_j)V_j(x_j) \quad (1)$$

where $\hat{U}(x_0)$ – U variable estimator at position x_0; $U_1, \ldots, U_n$ – measurement values of the main variable at points x_i; $V_1, \ldots, V_m$ – measurement values of the secondary variable at points x_j; $a_1, \ldots, a_n$ and $b_1, \ldots, b_m$ – position-dependent cokriging weights.

The estimation error R of the main variable U can be written in the following form [Eq. (2)]:

$$R=\hat{U}_0-U_0=\sum_{i=1}^{n}a_iU_i+\sum_{j=1}^{m}b_jV_j-U_0 \quad (2)$$

where $U_1, \ldots, U_n$ – values of random variables at points x_i; $V_1, \ldots, V_m$ – values of random variables at points x_j. Finding the cokriging weights $a_1, \ldots, a_n$ and $b_1, \ldots, b_n$ requires minimizing the variance of the estimation error Var(R) depending on these weights and on the covariance between the random variables U and V.

To ensure that the estimated values are unbiased, it is necessary to make assumptions about the cokriging weights. Non-bias is obtained by equating the weights a_i to unity (Eq. 3) and the sum of the weights b_j to zero [Eq. (4)]. The cokriging weights are calculated by minimizing the variance and solving a system of cokriging equations. In the system of cokriging equations, it is necessary to use Lagrange multipliers μ_1 and μ_2 so as to ensure that the estimated values are unbiased [Eqs. (5) and (6)] [31]:

$$\sum_{i=1}^{n}a_i=1 \quad (3)$$

$$\sum_{j=1}^{m}b_j=0 \quad (4)$$

$$\sum_{i=1}^{n}a_i\operatorname{cov}(U_iU_j)+\sum_{j=1}^{m}b_i\operatorname{cov}(V_iU_j)+\mu_1=\operatorname{cov}(U_0U_j) \quad (5)$$

$$\sum_{i=1}^{n}a_i\operatorname{cov}(U_iV_j)+\sum_{j=1}^{m}b_i\operatorname{cov}(V_iV_j)+\mu_2=\operatorname{cov}(U_0U_j) \quad (6)$$

By calculating the cokriging weights, the minimum error variance can be determined using the equation [Eq. (7)] [32]:

$$\operatorname{Var}(R)=\operatorname{cov}(U_0U_0)+\mu_1-\sum_{i=1}^{n}a_i\operatorname{cov}(U_iU_0)-\sum_{j=1}^{m}b_j\operatorname{cov}(V_jU_0) \quad (7)$$

The system of cokriging equations can also be written in terms of cross-semivariances, using the equality that combines covariance with semivariance [Eq. (8)]:

$$\gamma_{UV}(h)=C_{UV}(0)-C_{UV}(h) \quad (8)$$

where h – separation vector.

The existence of a solution to a system of cokriging equations is conditional on a positively defined set of auto semivariances and cross-semivariances occurring in that system [33].

The true prediction accuracy of the prediction methods was evaluated by the difference between the observations and the predictions at the validation sites and was expressed by the following terms.

Mean prediction error (ME) – is a measure of estimator bias, the average value from the differences between measured and estimated values [34,35]. The value of this error should be as low as possible and is expressed in the same units as the estimated values [Eq. (9)].

$$\text{ME}=\bar{r}=\frac{1}{n}\sum_{i=1}^{n}r_i \quad (9)$$

Mean standardized prediction error (SEM) – is the standard deviation of the sample-mean's estimate of a population mean. The error value should be as close to zero as possible and is a dimensionless quantity [Eq. (10)].

$$\text{SEM}=\frac{s}{\sqrt{n}} \quad (10)$$

Mean squared prediction error (MSE) is the sum of the squares of the differences between the actual and predicted values [36] [Eq. (11)].

$$\text{MSE}=\frac{1}{n}\sum_{i=1}^{n}r_i^2 \quad (11)$$

Root mean square prediction error (RMSE) is a frequently used measure of the difference between values predicted by a model and the values actually observed from the environment that is being modelled. These individual differences are also called residuals, and the RMSE serves to aggregate them into a single measure of predictive power [37–40]. Lower values of RMSE indicate better fit [28] [Eq. (12)].

$$\text{RMSE}=\sqrt{\frac{1}{n}\sum_{i=1}^{n}r_i^2} \quad (12)$$

Prediction quality statistics which take into consideration both the dispersion and bias of error distribution are, among others, MSE and RMSE [41].

3. Results

The results of laboratory tests on the quality of water entering the water supply network from the three water treatment plants are presented in Table 1. The water contained iron concentrations of less than 0.02 mg/L at all treatment plants.

The results obtained from testing water from the water supply network in each test area differed significantly from the plant water quality. In ZP area, the range of iron concentrations was 0.01–0.85 mg/L; the mean value and median for the Northern Plant were 0.06 and 0.04 mg/L, respectively. For ZCF, the Fe concentration range was 0.01–0.40 mg/L; the mean value was 0.07 mg/L, and the median was 0.06 mg/L. For ZCP, the Fe concentration range was 0.01–0.29 mg/L; the mean Fe concentration was 0.05 mg/L, and the median was 0.03 mg/L. The results of iron concentration in the water supply network show a high variability at the control stations and over the annual cycle as shown in Figs. 3–5.

Based on the test results obtained for water at the control points, estimations of iron content in the city area were carried out with the ordinary cokriging method using geostatistical software. The estimation results of iron concentrations in the tested area are shown in Figs. 6 and 7. The presented figures show the spatial distributions of secondary iron contamination of tap water in the water supply network according to time distribution of 1 y. The water leaving the water treatment plant had very low

Table 1
Physical–chemical quality of abstracted water

Month	Iron content in treated tap water (mg/L)					
	ZCF		ZCP		ZP	
	Mean value	Maximum value	Mean value	Maximum value	Mean value	Maximum value
January	<0.020	<0.020	<0.020	<0.020	<0.012	<0.012
February	<0.020	<0.020	<0.020	<0.020	<0.012	0.014
March	<0.020	<0.020	<0.020	<0.020	<0.012	0.016
April	<0.020	<0.020	<0.020	<0.020	0.014	0.025
May	<0.020	<0.020	<0.020	<0.020	<0.012	0.015
June	<0.020	<0.020	<0.020	<0.020	<0.012	0.013
July	<0.020	<0.020	<0.020	<0.020	<0.012	0.012
August	<0.020	<0.020	<0.020	<0.020	<0.012	<0.012
September	<0.020	<0.020	<0.020	<0.020	<0.012	<0.012
October	<0.020	<0.020	<0.020	<0.020	<0.012	<0.012
November	<0.020	0.026	<0.020	<0.020	<0.012	<0.012
December	<0.020	0.026	<0.020	0.036	<0.012	<0.012

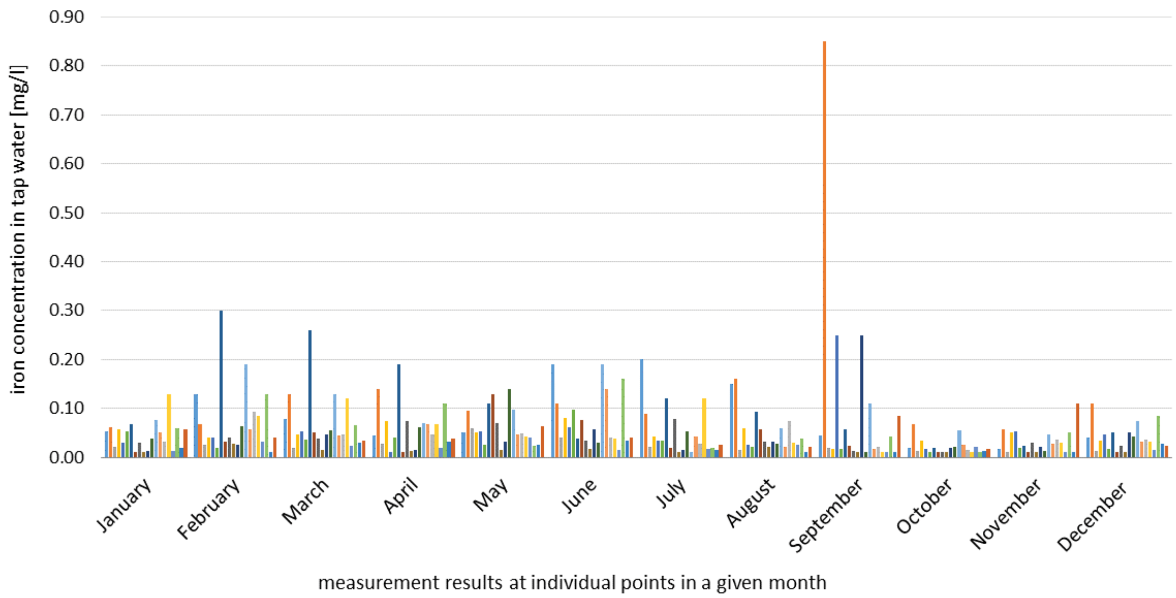

Fig. 3. Change in iron concentration in water within the network supplied by ZP (mg/L).

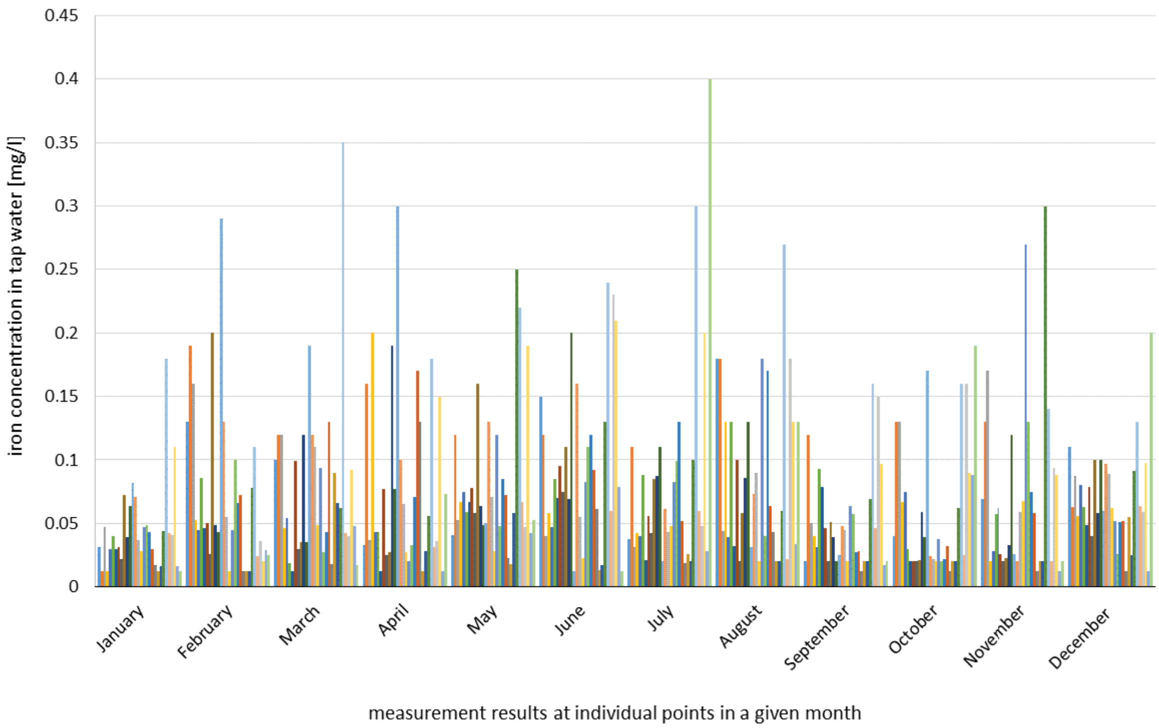

Fig. 4. Change in iron concentration in water within the network supplied by ZCF (mg/L).

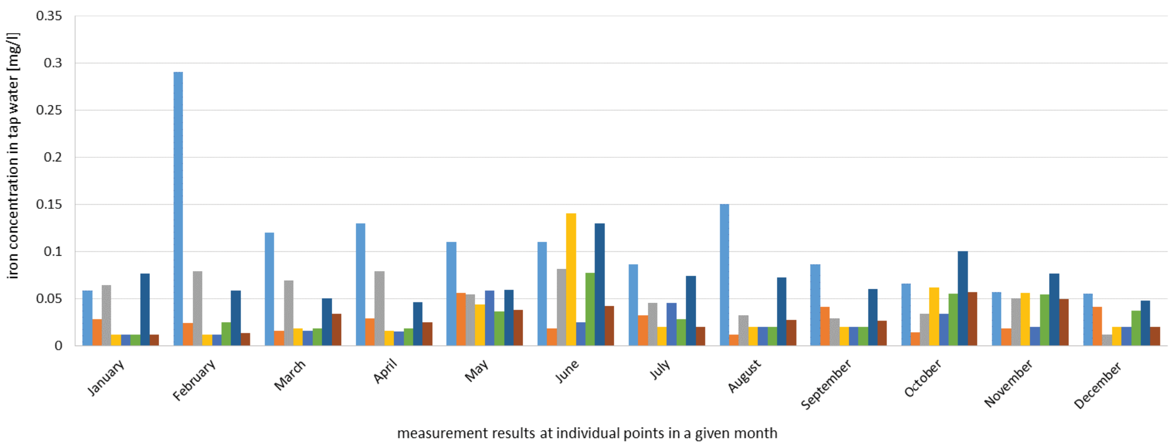

Fig. 5. Change in iron concentration in water within the network supplied by ZCP (mg/L).

iron concentration values (Table 1) compared to the water within the water supply networks (Figs. 3–5).There was an increase in Fe concentration as a result of the water coming into contact with the pipeline material transporting water to consumers.

Analyzing the spatial distributions presented, one can notice varying iron concentrations. Variations that occur may be due to flow rates and water intake, varying aerobic and oxidation–reduction conditions prevailing in the water supply system. The test results obtained for water downstream the water treatment process differ significantly from the values achieved for the water collected at the control points. In the northern part of the city supplied with water from Zegrzyńskie Lake through shore type intakes (ZP), iron concentration is similar to the results obtained during the tests at the water treatment plant. For water treatment plants supplied from the Vistula River by infiltration shore type intakes, concentration deterioration occurs when water is pumped into the network. The highest concentrations occur at the furthest sections of the network in the south-western area. These results were confirmed to be repeatable in each of the months studied. In January, February, July, November and December, the iron content was stabilized in the tested area. In April, May, August, September and October, point increases in concentrations as high as 0.85 mg/L were found.

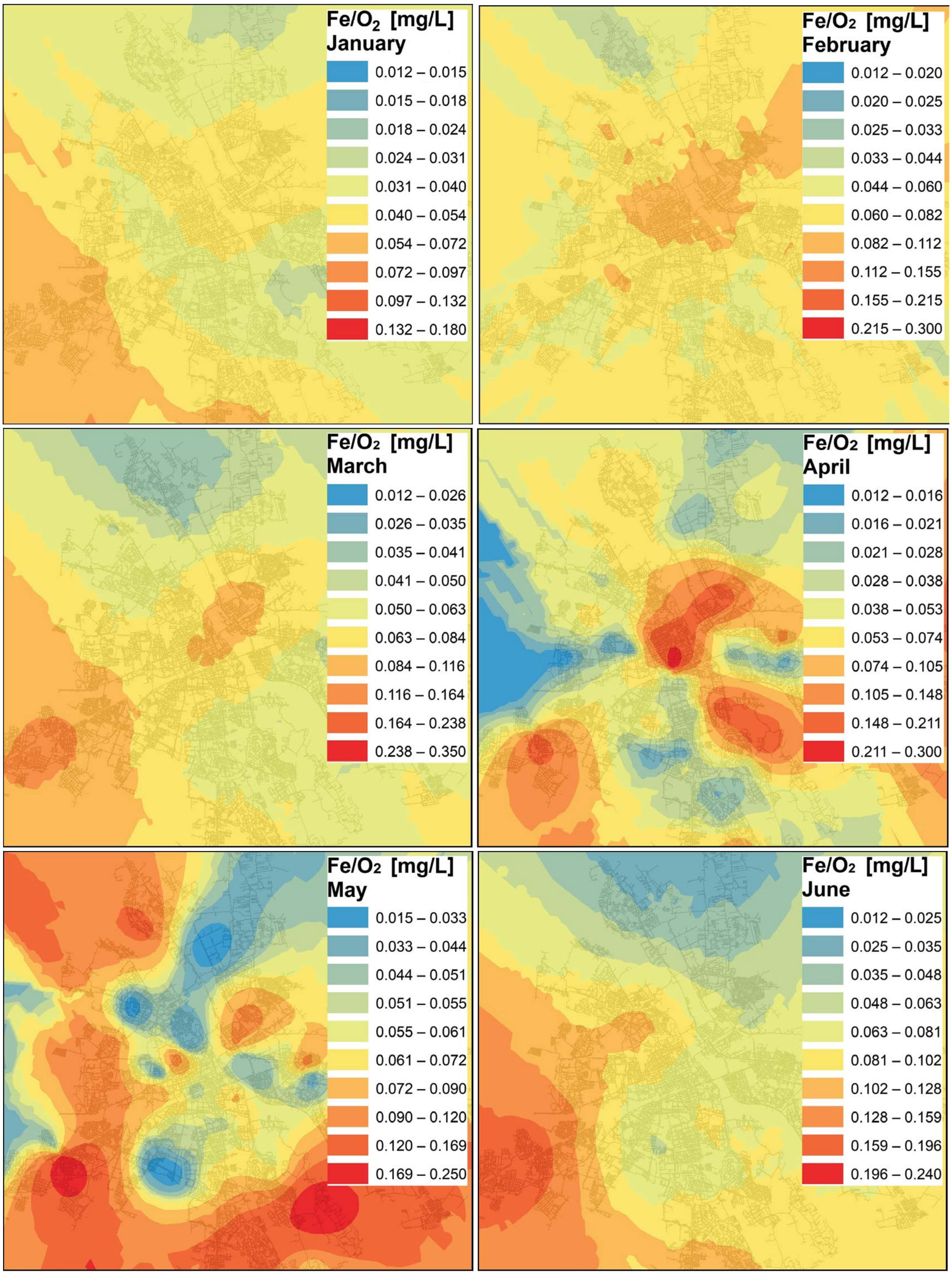

Fig. 6. Spatial distributions of secondary iron contamination in the water supply network by month (January–June).

Prediction errors for individual spatial distributions performed using ordinary cokriging are found in Table 2.

The values of ME and SEM being close to zero, indicates that the predicted values are unbiased. The mean error is the average of all the cross-validation errors. A positive error means that the predicted value is larger than the true value, and a negative error means that the predicted value is less than the true value. For unbiased models, the underpredictions should cancel out the overpredictions on average, and the mean error should be close to zero. SEM values are lower than RMSE shows that chosen model slightly under-estimates the variability of iron contamination. RMSE was used to check whether the prediction is close to the measured values. It is a measure of the error that occurs

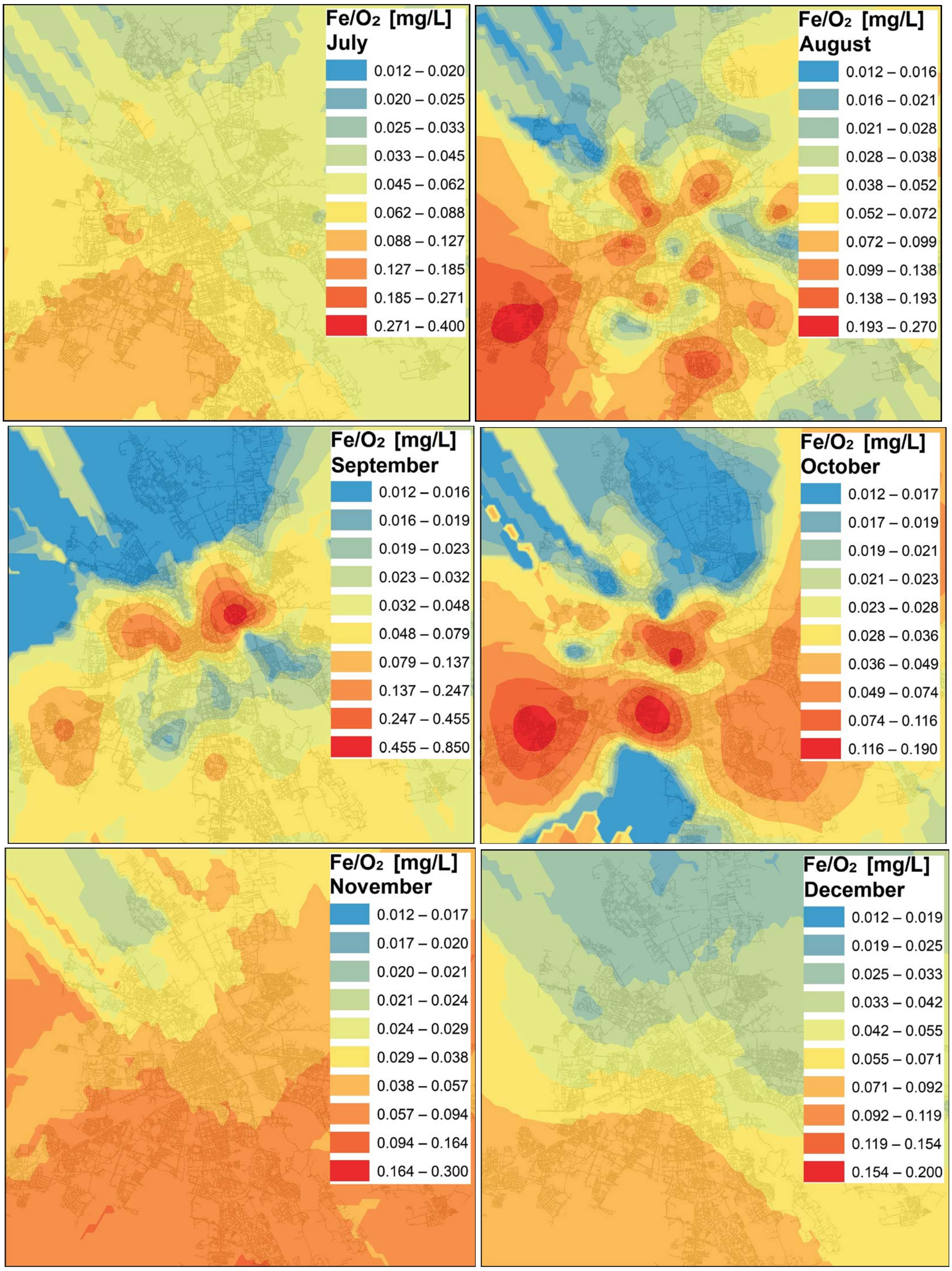

Fig. 7. Spatial distributions of secondary iron contamination in the water supply network by month (July–December).

when predicting data from point observations and provides the means for deriving confidence intervals for the predictions. The smaller the RMSE value, the closer the prediction is to the measured value.

4. Discussion

The results of iron concentrations in treated water, taken at the point of entry into the distribution network, allow us to assess the effectiveness of the technology used for water treatment. Despite the differences in the process lines of the three water treatment plants, the results of iron content were repeatable and at a similar level. This indicates that the treatment processes are carried out properly. The completed tests show that water quality deterioration due to iron content occurs in the network when water is transported. While the quality of water fed into the water supply network complied with the applicable national standards

Table 2
Prediction errors of ordinary cokriging for iron contamination in water network

Month	Prediction error value			
	ME	SEM	MSE	RMSE
January	–0.0001	–0.0052	0.0010	0.0318
February	–0.0018	–0.0239	0.0053	0.0729
March	–0.0002	–0.0031	0.0039	0.0627
April	0.0009	0.0246	0.0051	0.0717
May	0.0003	0.0015	0.0026	0.0514
June	0.0002	0.0012	0.0026	0.0511
July	0.0011	0.0149	0.0048	0.0692
August	0.0012	0.0148	0.0042	0.0649
September	0.0053	0.0345	0.0233	0.1527
October	0.0038	0.0858	0.0023	0.0487
November	–0.0004	–0.0074	0.0034	0.0586
December	–0.0003	–0.0069	0.0009	0.0315

and WHO recommendations, the water taken by consumers does not meet these standards and recommendations in extreme cases.

The results of water tests on the water supply network in individual research areas significantly differed from the quality of water from the water treatment plant. The value deteriorates when the treated water is pumped into the water supply system. The average values of iron concentration for treated tap water at the water treatment plant after the technological process were respectively for: ZP – 0.012 mg/L and increased to 0.06 mg/L at the control points on the network, for ZCF – 0.02 mg/L and increased to 0.07 mg/L, while for ZCP – 0.02 mg/L and increased to 0.05 mg/L. The maximum values obtained in the checkpoints were for ZP – 0.85 mg/L, ZCF – 0.40 mg/L, and for ZCP – 0.29 mg/L. The analysis of the tested samples taken from control points located on the water supply system shows a significant deterioration in the quality of the supplied water. The average values of iron concentration at the control points on the water supply network in relation to the value measured in the water treatment plant were: for ZP – an increase by 400%, for ZCF – an increase by 250%, and for ZCP – an increase by 150%.

Water with elevated iron concentrations in the water supply network will also not meet biological stability criteria. Thus, the adverse phenomenon of secondary iron contamination of water can be noted, with the degree of this contamination varying depending on the conditions – physical (flow rates and water intake) and chemical (oxygen content and oxidation–reduction conditions) – in the water supply system. The released ions are either oxidized and re-bonded in the sludge layer or released from sludge into the water. Ensuring the chemical and biological stability of water entering the system results in limiting undesirable changes in water quality during transport to consumers. Achieving iron concentrations that comply with regulations and do not exceed the parametric value is important to ensure the acceptability of water to consumers and to prevent undesirable changes in the technical condition of the distribution network. Sludges contribute to the deterioration of installation materials, increasing the failure rate of the water distribution system, and flushing and mechanical cleaning of pipelines increases water supply system operating costs and water losses. Removing all causes of secondary water contamination in distribution systems is very difficult but necessary and is the primary task of the water treatment plant and the distribution system operator. The spatial estimation method used allowed values at non-sampled locations to be estimated based on values measured at adjacent measurement points. Ordinary cokriging is used in areas where expensive or difficult measurements are required. In many cases, this technique improves the estimation significantly and reduces the variance of the estimation errors. By using spatial correlations of the secondary variable and cross-correlations between the main variable and the secondary variable, an increased estimation accuracy is obtained. The results of the calculations are maps of spatial distributions of secondary iron contamination in the analyzed water supply network. Determination of areas of an increased iron ion concentration and analysis of the migration of these contaminants over the test period is useful in determining the causes within the operation process of the water supply system. The evaluation of the dynamics of water quality changes and the correlation of iron concentration values with the corresponding results of hydraulic simulations allows the creation of a model of water quality changes, which enables the simulation of the impact of countermeasures taken to minimize the effects of secondary water contamination in the distribution system. Reducing the occurrence of conditions posing a risk to normal operation of the water supply system and ensuring the improvement of its efficiency contributes to reducing the operating costs of water supply systems, increasing the efficiency of company management and supporting the investment project process.

5. Conclusions

The quality of water entering the water supply system and the physical, chemical and biological processes occurring within the network itself have a tremendous impact on secondary contamination of water previously treated and transported to consumers. Proper operation of the system and ensuring the chemical and biological stability of the water entering the distribution network prevents the formation and accumulation of sludges creating a deposit of secondary contaminants. The degree to which these contaminants are released into the flowing water is highly dependent on the hydraulic conditions in the system.

The obtained research results confirm the possibility of applying the proposed geostatistical method in practice. It can be successfully used in water supply companies to analyze the water supply network and as a preliminary research to build numerical models, however, it still requires verification and tests on other real objects. The ordinary cokriging method allowed for the estimation of values in non-sampled locations on the basis of values measured at adjacent measurement points. It allows to a preliminary estimate of the spatial distribution of pollutant concentration, with an accuracy corresponding to the number and location of measuring points. It can serve as a first approximation to the assessment of this spatial distribution. The reliability of the obtained estimation results increases as the number of control points increases.

Distributed structure of the water supply network, variability of the operation parameters with the simultaneous need to make numerous decisions at the same time cause that management of such infrastructure is a complex process. This difficult decision-making process can be supported by geoinformation systems, which are also being developed for managing water distribution systems and are used to collect, store, analyze and visualize this type of data. Modeling of the parameters of water supply networks and the subsequent forecasting of water quality is an essential element for making optimum decisions in the process of management and operation of the water supply networks. The use of GIS software for quantitative spatial analysis is becoming an increasingly important and ubiquitous component in estimating water quality indicators in urban water supply systems.

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