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Article

Spatiotemporal Dynamics of Water Quality: Long-Term Assessment Using Water Quality Indices and GIS

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Abstract: The severe contamination of groundwater supplies in rural areas is a global problem that requires strict environmental measures. Related to this, one of the most important challenges at present is the elimination of local sources of pollution. Therefore, this research examined the local water quality changes following the construction of the sewerage network, under the framework of long-term monitoring (2011–2022) in Báránd, Hungary, using water quality indices and GIS (Geographic Information System) techniques. In order to understand the purification processes and spatial and temporal changes, three periods were determined: the pre-sewerage period (2011–2014), the transitional period (2015–2018), and the post-sewerage period (2019–2022). Forty monitoring wells were included in the study, ensuring complete coverage of the municipality. The results revealed a high level of pollution in the area in the pre-sewerage period. Based on the calculated indices, an average of 80% of the wells were ranked in categories 4–5, indicating poor water quality, while less than 8% were classified in categories 1–2, indicating good water quality. No significant purification process was detected in the transitional period. However, marked changes were observed in the post-sewerage period as a result of the elimination of local sources of pollution. In the post-sewerage period, the number of monitoring wells ranked as excellent and good increased significantly. Additionally, the number of wells assigned to category 5 decreased markedly, compared to the reference period. The significant difference between the three periods was confirmed by the Wilcoxon test as well ($p < 0.05$). Based on interpolated maps, it was found that, in the post-sewerage period, an increasing section of the settlement had good or excellent water quality. In addition to an assessment of long-term tendencies, the annual fluctuations in the water quality of the wells were also examined. This showed that the purification processes do not occur in a linear pattern but are influenced by various factors (e.g., precipitation). Our results highlight the importance of protecting and improving groundwater resources in municipal areas and the relevance of long-term monitoring of water adequate management policy.

Keywords: water quality index; groundwater contamination; geostatistical analysis; sewerage network; GIS

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1. Introduction

Over the past 30 years, the area of rural settlements has increased in parallel with urbanization, which has also entailed an increase in anthropogenic activities. As a result of intense anthropogenic activity, the environment, including groundwater and soil, has already been irreversibly damaged in many settlements [1]; these settlement-specific effects have considerably transformed the groundwater system. Therefore, there is a need to identify, prevent, and, if still possible, reverse pollution and further harmful effects [2].

Due to its proximity to the surface, groundwater is the most sensitive of subsurface waters to external pollution, as a result of which groundwater quality has now deteriorated severely worldwide [3], making it a high priority in environmental research [4–7].

Over the past decade, several international studies have confirmed that environmental problems caused by urban waste water remain unresolved, especially in rural areas [8–12]. In municipalities where wastewater treatment systems are not installed, wastewater enters groundwater, resulting in a sharp deterioration in groundwater quality [13–16]. Although case studies have been published on the contamination of groundwater and the deterioration of water quality caused by point sources of pollution in settlements, long-term research based on monitoring data has not been the focus of research so far. Another obstacle is that, to assess the spatiotemporal characteristic in the water quality of a settlement, in addition to knowing the reference status, time-series monitoring geodatabases covering the whole municipality are also needed. However, the lack of this makes it difficult to investigate the dynamics of decontamination processes and the detection of contaminated sites [17,18].

In addition to geostatistical and GIS analyses, various water quality indices (WQIs) have been widely used in water quality assessment, with increasing emphasis in recent years. WQIs are useful tools that combine complex environmental data into a single value, providing an overall picture of water quality [19]. Due to their fast, effective, and reliable characteristics, a number of indices have been developed for different purposes, including irrigation, industrial, and drinking water quality evaluation. Index-based methods such as the water quality index (WQI), overall index of pollution (OIP), and synthetic pollution index (SPI) have been used to assess the suitability of groundwater for domestic use [20–22]. By integrating the water quality information generated from WQI values into cloud-based WebGIS systems and supporting with interactive data visualization tools, researchers can further assist decision-makers in monitoring water quality changes and thus in taking rapid and even immediate water management measures [23,24].

The collection of monitoring data is essential for assessing and describing a municipality's water quality conditions [25–29]. Thus, the joint evaluation of water quality parameters (e.g., pH, electrical conductivity(EC), nitrate, phosphate) derived from long-term monitoring data can be expressed based on water quality indicators. The combination of overlapping techniques and geographic information systems (GIS) to evaluate water quality helps scientists monitor changes in different water quality indices over spatio-temporal scales that are only sometimes readily apparent from in situ measurements [30]. In recent years, several freely available, open-source, and GIS-based tools have been designed to support groundwater management. Therefore, novel GIS-based and open-source software should enable the complex management, visualization, interpretation, and sharing of water quality data [31–33]. Among others, the AkvaGIS tool (Version 1.0) is a user-friendly, free, and open-source GIS-based package integrated into the FREEWAT platform [34].

The primary goal of our research was to obtain a comprehensive picture of the contamination status of groundwater wells in the studied settlements using an 11-year water quality database. A further goal was to compare the groundwater quality of the settlement from the point of view of whether the positive effects of the sewerage network can be detected in different water quality indices. Our goals also included the exploration of pollution foci within the settlements and the spatial and temporal changes in pollution.

The novelty of our study is, among other things, the fact that, based on 11 years of water quality monitoring carried out in a Hungarian settlement, it is the first to present the long-term effects of the construction of a sewerage network on groundwater quality, with special regard to changes according to spatial and temporal dimensions. While using different water quality indices in groundwater assessment is widespread, the use of water quality indices combined with GIS techniques in long-term monitoring studies is less common [35–37]. This research is of paramount importance, as it provides a detailed methodological approach for exploring the temporal dynamics and spatial patterns of local water quality changes. This new approach offers a new perspective for monitoring groundwater pollution and improvement, which could be a further link for similar international research. Due to current global environmental challenges, assessing the efficiency of wastewater treatment is essential; therefore, our study can make a significant contribution to a new science-based approach to assessing and improving water quality.

2. Materials and Methods

2.1. Study Area

The study area is located in the eastern part of Hungary in Europe (Figure 1). According to the Hungarian Central Statistical Office, Báránd is a middle-sized settlement with a population of 2426 [38]. The municipality is situated in the eastern part of the Great Hungarian Plain, in the Nagy-Sárrét region. The altitude of the area is generally between 85 and 89 m above sea level, and it is characterized as a flat plain with a relative relief of 0–3 m/km^2. The direction of regional groundwater flow is directed from north to south. The groundwater level is close to the surface, typically at a depth of 1 to 5 m, which leads to the formation of different soil types influenced by water [39]. The predominant soil types within the study area include Solonetz, Vertisols, Castanozems, and Chernozems, while anthropogenic influences have resulted in the formation of Anthrosols and Technosols in the populated area. The settlement area is characterized by significant anthropogenic activities. According to the CORINE (Co-ordination of Information on the Environment) Land Cover (CLC) classification, the area is classified as "111": continuous urban fabric [40]. This indicates a densely built-up area with a predominance of impervious surfaces such as housing and infrastructure.

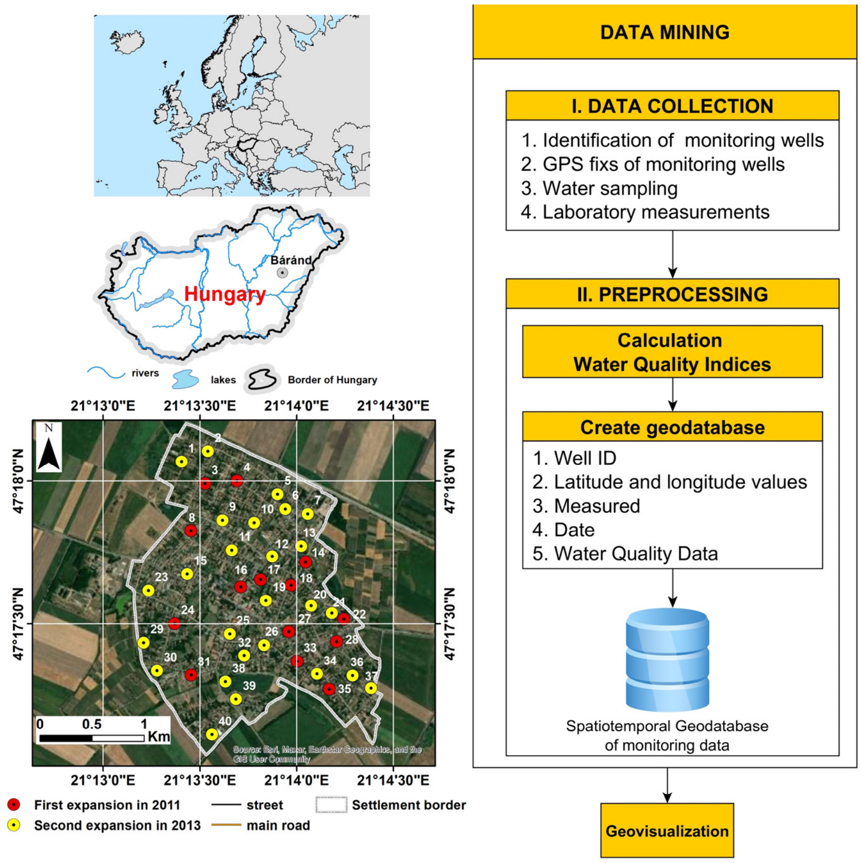

Figure 1. The study area, water sampling sites, and the process of data collection and preprocessing.

Late Holocene and Lace Pleistocene sediments are dominant in the study area and all deposits are of fluvial origin, while the texture is predominantly clay and silt; however, alluvial sand layers can be observed as well [41].

The sewerage network in the settlement was completed in 2014. By 2024, more than 80% of the dwellings had been connected to the sewer network. Prior to construction, wastewater from households was stored in inadequately insulated septic tanks, which leached into the soil and resulted in severe pollution of the municipal environment.

2.2. Data Collection and Analysis

Using the groundwater wells dug in the settlement, a monitoring network was established in order to explore and evaluate changes in groundwater quality over time and space. When designating the monitoring wells, one of the most important aspects was to cover the entire settlement evenly. In the first year of the study (2011), only 14 dug wells, with depths of 5–6 m, could be included in the study. The number of dug wells was expanded in 2013, 2017, and 2022 to determine water quality and pollution. Since there were years when it was not possible to sample certain wells, the analysis in this study was only performed on wells that were not missing any data. The number of wells used, starting in 2011, was 14, followed by 13 in 2012, then 40 in 2013, 13 in 2014, 13 in 2015, 13 in 2016, 40 in 2017, 40 in 2018, 40 in 2019, 0 in 2020, 37 in 2021, and finally 34 in 2022. The zero in 2020 was due to no sampling being allowed under COVID-19 restrictions.

The geographical positions of the monitoring wells were recorded with a high-precision GPS (Global Positioning System) device. In the course of regular sampling and laboratory tests, the characteristic pollutants of municipal wastewater (electrical conductivity (EC), pH, chemical oxygen demand (COD), sodium (Na^+), phosphate (PO_4^{3-}), ammonium (NH_4^+), nitrite (NO_2^-), and nitrate (NO_3^-)) were determined according to the Hungarian standards in force [42–44]. Since the data on the chemical and physical parameters of the water in the monitoring wells and the water quality indices calculated from them were recorded together with coordinates in a table, it was possible to create a time-series dataset for later mapping. The municipality Báránd, which is being investigated by our research team, has been subject to regular groundwater quality studies since 2011; therefore, several studies have been published on the subject, but the combined assessment of long-term monitoring data and the identification of local level water quality changes has not yet been carried out [31,35,45].

2.3. Evaluation of Water Quality According to Indices

Water quality indices are valuable for determining groundwater quality and localization in a contaminated area [16,30,46,47]. Moreover, amalgamating intricate information and formulating a rating system to describe the water quality condition is a user-friendly and straightforward approach for policymakers to attain a more profound insight into surface and groundwater resources [4,48–51]. In the present study, two different water quality indices have been applied. The water quality index (WQI), developed by Brown et al. [46], and the contamination degree (Cd), created by Backman et al. [49], are widely used methods for determining the water quality of the monitoring data (Appendix A). Samples were ranked based on their quality on a five-point scale, with 5 representing the worst rating and 1 representing the best (Table 1).

Table 1. Evaluation and ranking of water quality based on water quality index and contamination degree.

Rank	WQI	Water Quality Status (WQS)	Cd	Cd Status
R1 (Rank 1)	0–25	Excellent water quality	0	Non contaminated
R2 (Rank 2)	26–50	Good water quality	<1	Low contamination
R3(Rank 3)	51–75	Poor water quality	3–1	Medium contamination
R4 (Rank 4)	76–100	Very poor water quality	6–3	High contamination
R5 (Rank 5)	Above 100	Unsuitable for any use	>6	Very High contamination

2.4. Assessing Changes in Water Quality in Spatial and Temporal Dimensions

To evaluate the changes in water quality in the monitoring wells between two consecutive sampling years, 3 groups were created based on the water quality rank of each index: 0 = no change in water quality rank, 1, 2, 3, 4 = positive water quality rank change indicating an improvement in water quality status, −1, −2, −3, −4 = negative water quality rank change indicating a deterioration in water quality status.

For all possible changes in groups, both the initial and final water quality ranks were classified according to the group they belonged to, based on their WQI and Cd results (Table 2). Thus, the process of change could also be evaluated from the point of view of changes in water quality statuses.

Table 2. Evaluation matrix of groundwater quality changes between two consecutive years.

	Status in the Following Year				
Status in the Baseline Year	**R1 (Rank 1)**	**R2 (Rank 2)**	**R3 (Rank 3)**	**R4 (Rank 4)**	**R5 (Rank 5)**
R1 (Rank 1)	0	−1	−2	−3	−4
R2 (Rank 2)	1	0	−1	−2	−3
R3 (Rank 3)	2	1	0	−1	−2
R4 (Rank 4)	3	2	1	0	−1
R5 (Rank 5)	4	3	2	1	0

Considering changes in water quality, conversions where the water quality status belonged to the same group were classified in the unchanged water quality. A deterioration in water quality status was assumed during the change if the former water quality rank and the latter category belonged to different groups and if the latter belonged to the group with higher water quality status, i.e., it moved up between the groups in Table 2. An improvement in water quality status was assumed if the former water quality category and the latter category belonged to different groups and the latter belonged to the group with a lower water quality status, i.e., it moved down between the groups in Table 2.

2.5. GIS Methods and Statistical Analysis

The geoinformatic processing and thematic mapping of the time-series monitoring data was performed using ESRI ArcGIS version 10.4.1 and Surfer software version 22 [52,53]. To explore the spatiotemporal trends of the water quality, we plotted the individual indices and the types of water quality change during the studied periods on point maps. Furthermore, from the data of the water quality statuses, we prepared the distribution and difference maps of the area for all 11 sampling times using kriging interpolation.

The statistical processing of the data and the visualization of the results were carried out using IBM SPSS (International Business Machines Corporation Statistical Product and Service Solutions) 22 and Tableau 2022 software [54,55]. The time-series water quality database was divided into 3 periods: the pre-sewerage period (2011–2014), the transitional period (2015–2018), and the post-sewerage period (2019–2022). Data from consecutive years were also examined to detect positive or negative changes in the water quality. The differences in the data series for different time periods were investigated using a Wilcoxon test. The test can be used to determine whether differences in water quality status are random or shaped by a background process [56].

3. Results and Discussion

3.1. Spatial and Temporal Distribution of Applied Indices

The annual variation in water quality index values between 2011 and 2022 is shown in Figure 2 and in the Supplementary Materials (Tables S1 and S2). The heavy contamination of the settlement's groundwater resources can be seen in both its WQI and Cd values. For the WQI, both median (115–133) and upper quartile values (143–180) were classified in the worst category (category 5) in the pre-sewerage period (2011–2014). Groundwater can also be considered extremely polluted based on the Cd index; the upper quartile values (10.08–15.9) significantly exceed the value 6, which indicates the lower limit of the most polluted category, and even the lower quartile values approach 6 for several years (namely 2011, 2012, and 2014).

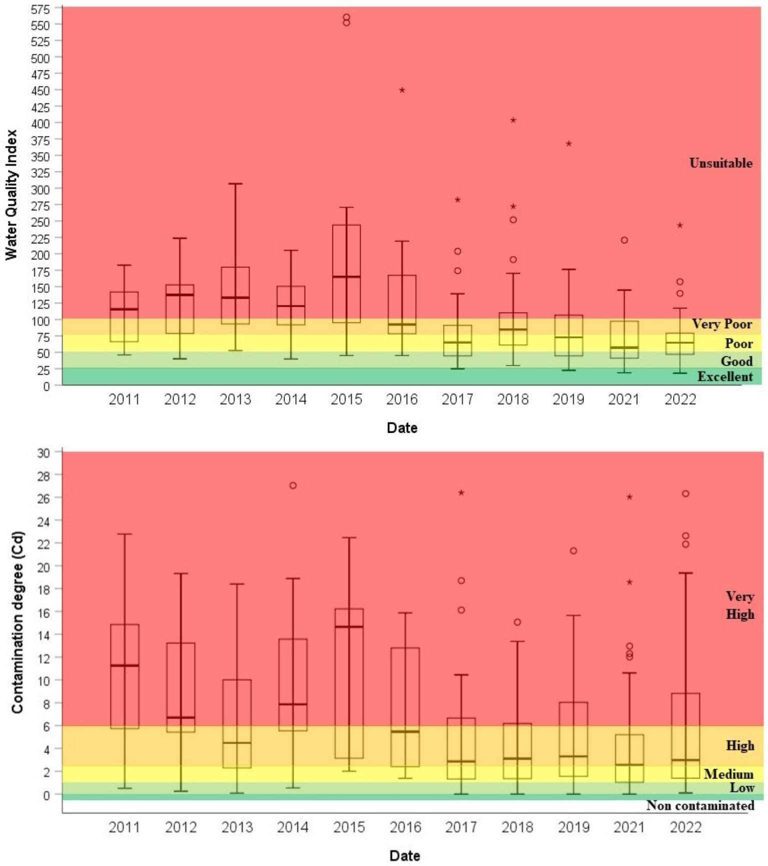

Figure 2. WQI and Cd index values between 2011 and 2022.

In the two transitional years (2015 and 2016), no decreasing values were detected, and the highest average value for the WQI (209.87) for the entire study period was found for 2015. In the case of the Cd index, the highest upper quartile value (16.42) was found for 2015. Since there were no outlier weather data, it is likely that large-scale pumping and changes in water flow conditions in order to reduce water levels during the construction may be the reason for these outliers. By 2016, the outliers were significantly reduced, which indicates the start of groundwater purification.

However, the values of the post-sewerage period between 2017 and 2022 show significant differences compared to the values in the pre-sewerage period. Significant decreasing values indicate the start of the groundwater purification processes. For WQI, the median values no longer reach category 5 in any of the years, varying typically in category 3, except for 2018, when they are in category 4. The upper quartile values show a sharp decrease, from an average value of 157.84 in the pre-sewerage period to 98.08, indicating intensive purification processes. The lower quartile values show a smaller decrease, but, except for 2018, they are in category 2 (“Good”). Similar trends can be observed in the case of the Cd index; the average of the upper quartile values decreased from 13.63 in the pre-sewerage period to 7.32 in the post-sewerage period. There were differences between the two indices in the lower categories, with the Cd index typically ranking the samples one category worse: in the post-sewerage period, the median values were in category 4 (“Poor”) in each year, while the lower quartile values were in category 3 (“Medium”).

Monitoring wells were evaluated according to their quality and contamination on a five-point scale (Figure 3). The results of the rating are presented in the Supplementary Materials (Tables S1 and S2). The substantial contamination is proved by the fact that, based on the WQI 80.72% of the monitoring wells were rated in categories R5 and R4 (“Unsuitable for any usage, Very Poor” and “High, Very High”). Based on both WQI and Cd, no monitoring wells were rated as R1 (“Excellent”, “Non-contaminated”) between 2011 and 2014.

There were only four wells in category R2 (“Good”, “Low”), indicating good water quality and low contamination, based on the WQI, and six water samples rated as category R2 based on the WQI.

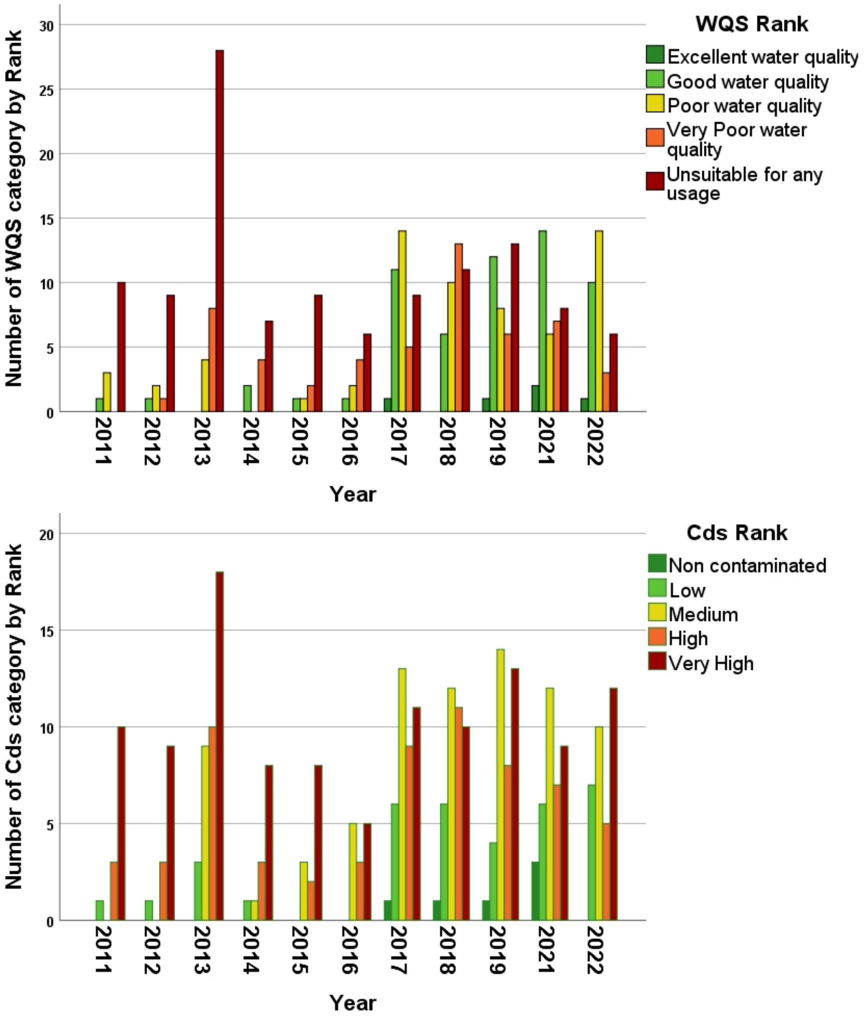

Figure 3. Number of categories according to WQI and Cd.

In the transitional period (2015–2018), considerable changes were identified. The number of wells in categories R5 and R4 decreased, and the number of wells in categories R2 and R3 increased significantly, compared to the previous period. In addition, one monitoring well for each index was classified in the best (R1) category in 2017.

In the post-sewerage period (2019–2022), the number of monitoring wells rated as R1 and R2 increased, based on the WQI. For the Cd index, the change was much more moderate. In addition, the number of wells in category R5, which indicates the most contaminated samples, continued to decrease, compared to those detected in the reference period, with the exception of 2019.

Improvements in the variation in index values were evident during the aforementioned four- and three-year periods; however, the index values in the post-sewerage period still showed a stronger correlation with the transitional period data (Figure 4). The positive changes in the index values of water quality indicators were confirmed using Wilcoxon signed-rank tests. The analysis of the three periods revealed significant differences for both water quality indices, which can be attributed to the impact of the sewerage network construction. The strongest significance ($p = 0.00$) was observed for $\mathrm{WQI}_{\text{Pre-sewerage}} - \mathrm{WQI}_{\text{Transitional}}$ and $\mathrm{Cd}_{\text{Pre-sewerage}} - \mathrm{Cd}_{\text{Post-sewerage}}$, the Z-values for which were -3.29 and -3.722, respectively (Table 3).

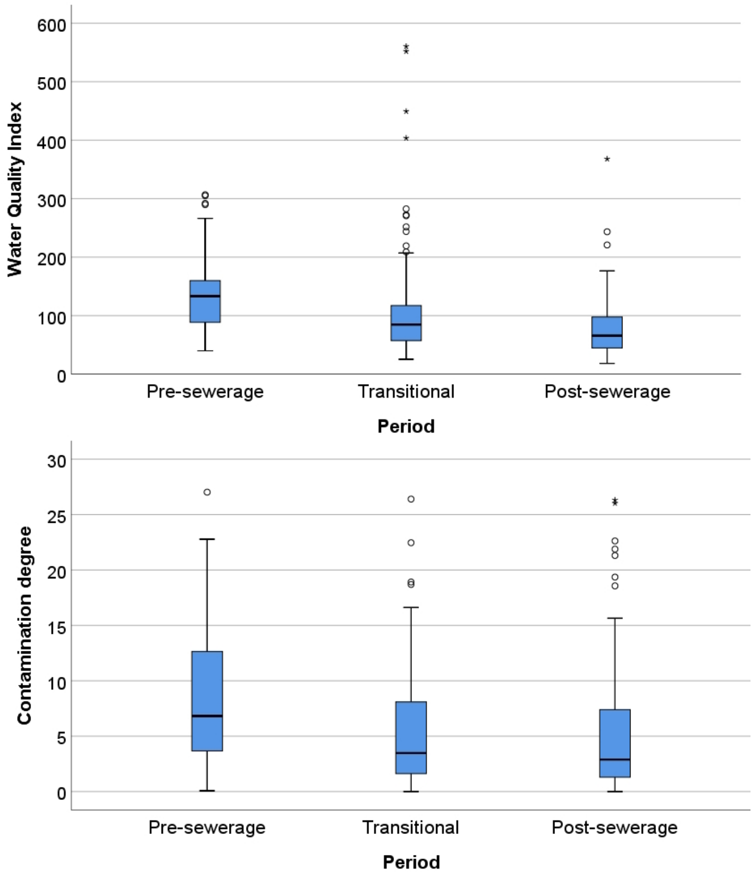

Figure 4. Index values in the investigated periods.

Table 3. Results of Wilcoxon signed-rank test (based on negative ranks).

	$WQI_{Pre\text{-}sewerage} - WQI_{Transitional}$	$WQI_{Transitional} - WQI_{Post\text{-}sewerage}$	$WQI_{Pre\text{-}sewerage} - WQI_{Post\text{-}sewerage}$	$Cd_{Pre\text{-}sewerage} - Cd_{Transitional}$	$Cd_{Transitional} - Cd_{Post\text{-}sewerage}$	$Cd_{Pre\text{-}sewerage} - Cd_{Post\text{-}sewerage}$
Z	-3.290 [b]	-2.785 [b]	-5.962 [b]	-2.451 [b]	-0.727 [b]	-3.722 [b]
Asymp. Sig. (2-tailed)	**0.001**	**0.005**	**0.000**	**0.014**	0.467	**0.000**

The Z-value indicates the extent to which changes in each water quality index differs between the periods compared. In the analysis, Z-scores with a negative sign ("b") refer to cases where the data measured later are lower than in the earlier period. Z-scores are used to decide whether changes are significant between periods, indicated by the semi-circular highlighting of p-values ($p < 0.05$) (Table 3).

Thematic point maps and interpolated time-series distribution maps of the settlement were prepared to map the spatiotemporal distribution of water quality and pollution (Figures 5 and 6). However, it should be noted that the number of monitoring wells on which interpolation was based differed in each sampling year. In the pre-sewerage period, with the exception of the northern parts of the study area, significant levels of pollution were identified, the extent of which remained unchanged until the transitional period. In the transitional period, these significant pollution levels gradually decreased, and similar spatial trends were found both in the state of water quality and in the degree of contamination. In the central part of the study area, the degree of contamination and the state of water quality decreased to categories 3 and 4. In the case of the WQI and the Cd, a category 2 ("Good", "Low", respectively) water quality status could be identified to varying extents in the northern and central parts of the study area, as well as in the southern areas, in the case of WQI. The spatial extent of these categories is significantly greater in terms of water quality than in terms of degree of pollution. This difference is also noticeable in the state of water quality in the southern part of the city.

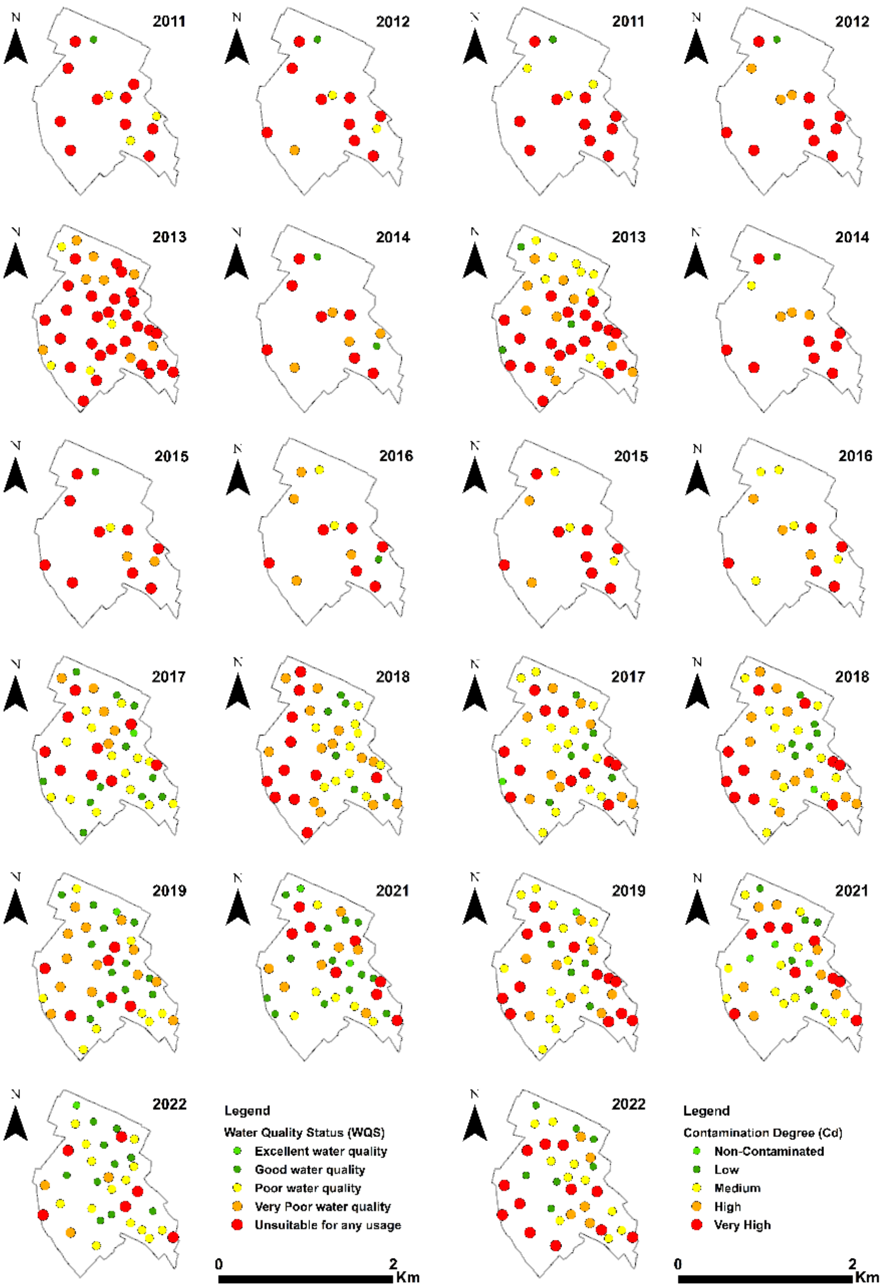

Figure 5. Thematic point map of the spatial distribution of WQI and Cd between 2011 and 2022.

In the post-sewerage period, pollution in the settlement continued to decrease compared to the reference period, while improving water quality became more and more evident, starting from the central and north-eastern parts of the study area. The spatial distribution of the parts of the areas with high pollution from north to south, which had been typical in previous years, decreased further. The extent of "Good" and "Excellent" water quality statuses continued to vary in the settlement. Nonetheless, the spatial distribution of these settlement zones exhibited greater continuity for WQI than in Cd.

Interpolated difference maps of the WQI and Cd indices were created to represent the spatial variations resulting from the different calculation methodologies (Figure 7). Areas where both indices ranked the same are coloured in grey. The smallest difference was detected in the sampling years of 2015 and 2016, and then the difference increased gradually over the years. However, it should be noted that the number of monitoring wells on which interpolation was based was different in certain sampling years.

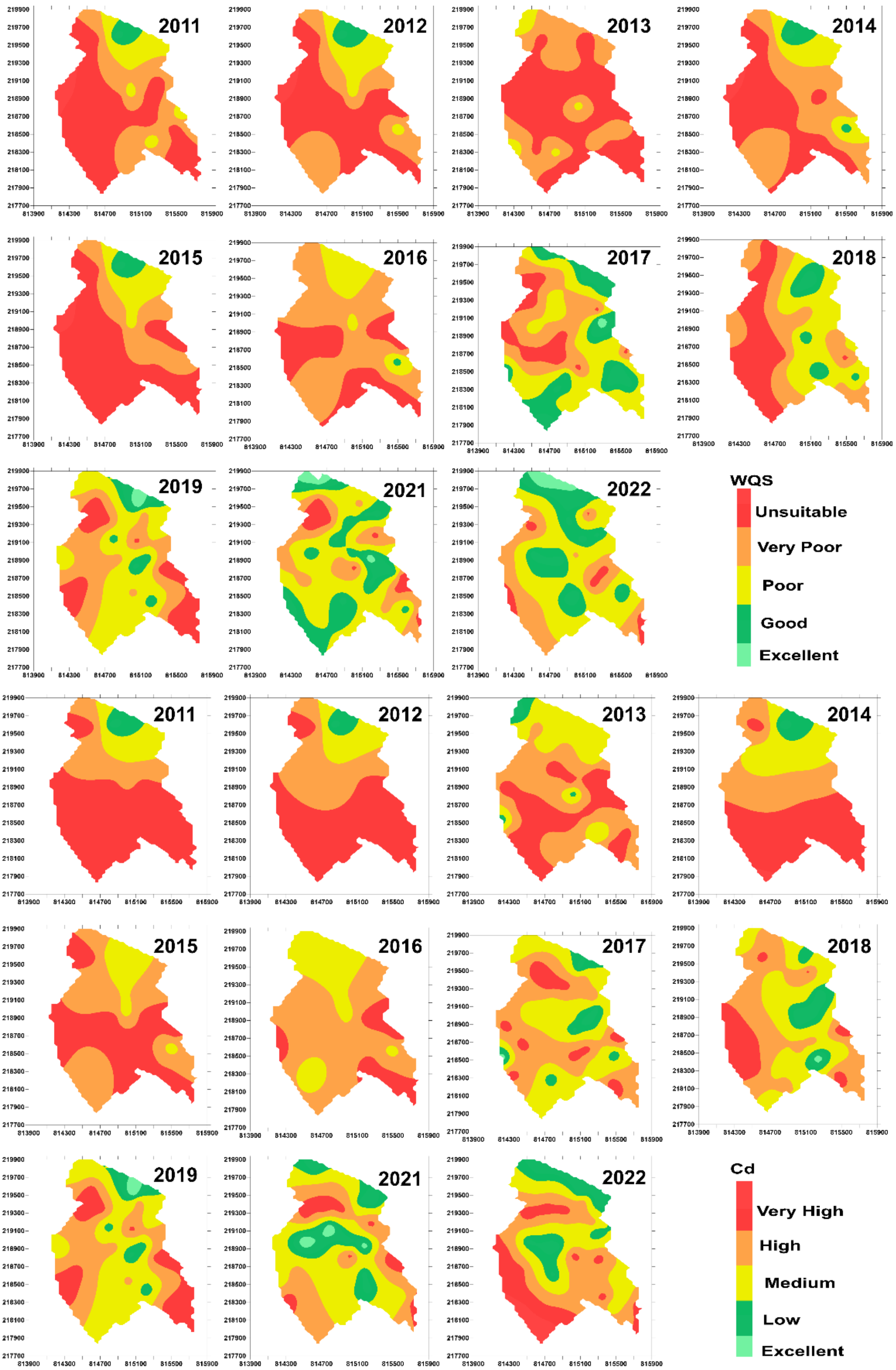

Figure 6. Time-series map of the spatial distribution of WQI and Cd in the investigated periods (2011–2022).

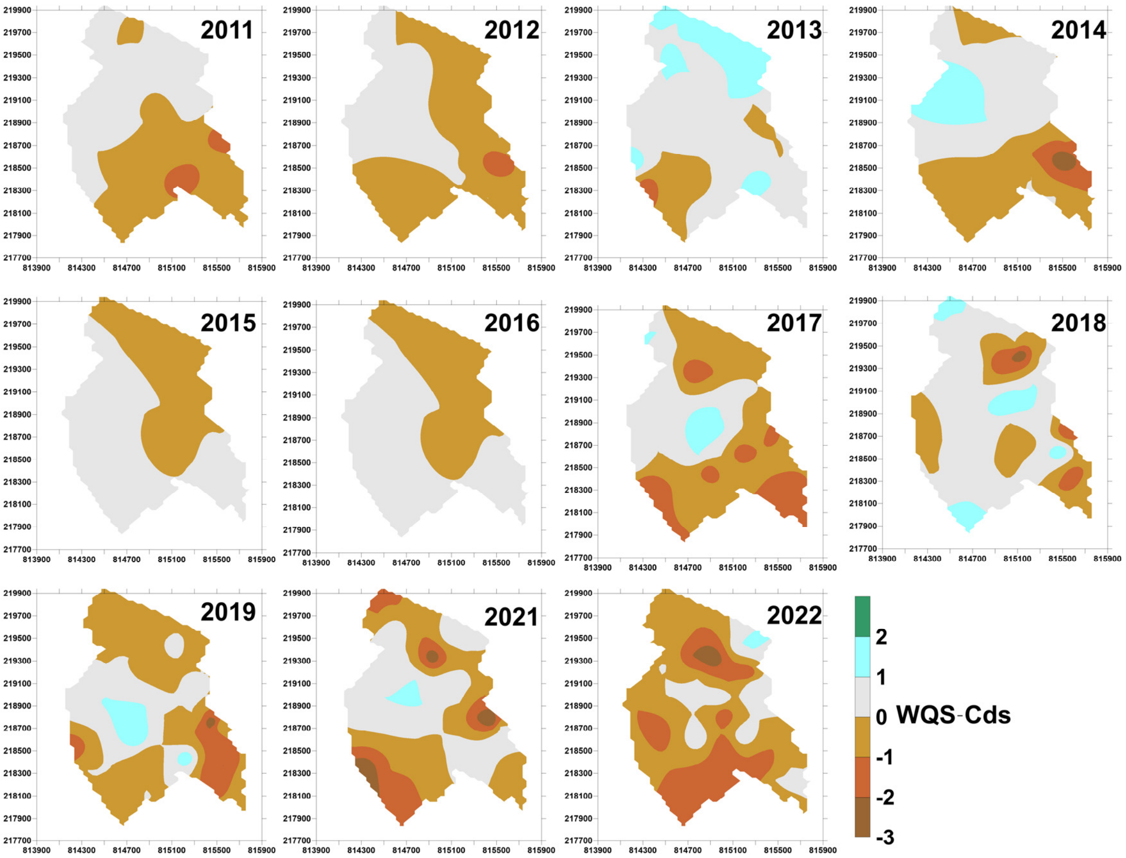

Figure 7. Difference rank maps of the indices (WQS and Cd) between 2011 and 2022.

In the sampling years of 2013 and 2014, the WQI rank indicated higher contamination than the Cd rank by +1 in the northern part of the settlement; these differences disappeared by 2017 and then reappeared in the central areas. The −2-rank differences between WQI and Cd gradually appeared in a higher proportion throughout the municipality from 2014 onwards. The largest difference of −3 was first detected in 2014 in the south-western part of the settlement, which gradually decreased until 2019. In 2021, three new hotspots emerged in the northern, central, and southern areas, which, although decreased and fragmented by the following year, remained mosaic.

One contributing factor to the regional differences is the weighting applied to the WQI, which renders it more responsive to variations in specific water chemical parameters, such as ammonium and phosphate levels, than the Cd index. Additionally, the WQI shows reduced sensitivity to fluctuations in nitrate levels, which are more heavily weighted in the Cd index. Furthermore, the Cd index does not account for parameters below the threshold value, even if they are very close to it [35,45]. These results highlight the fact that, based on the same input data, indices with different priorities can indicate significant differences in water quality.

3.2. Evaluation of Water Quality Changes

For all possible types of change, the water quality status detected for each sampling time was evaluated, according to which group it belonged to of the two indices. For this reason, the process of change could also be evaluated in terms of changes in water quality statuses. In order to examine the temporal distribution of changes, heat maps visualizing the extent of the change in each monitoring well were prepared for all ten periods examined. Based on the quality/contamination of the water, conversions where the water quality/pollution status belonged to the same group were classified into unchanged types. The deterioration of the water quality status was assumed during the change if the earlier water quality/contamination category and the latter category belonged to different groups and the latter category represented the higher water quality status. Furthermore, an improvement in water quality status was assumed if the former water quality/contamination category and the latter category belonged to different groups and the latter category represented the lower water quality status.

The following groups were identified, based on WQI and Cd ranks, regarding water quality status:

1. Positive changes in water quality;
2. Negative changes in water quality;
3. Unchanged water quality.

Based on the indices, a total of 225 types of water quality status change conversions occurred in the ten periods, of which 76, according to WQI, and 66, according to the Cd, were associated with an improvement in water quality based on the above classification. For 61 and 54 conversion types, water quality deterioration occurred, and 88 and 105 conversion types reported no change in water quality. There were significant differences between the periods, in that the changes in water quality/contamination pointed primarily towards improving or deteriorating effects. However, it can be stated that conversions indicating improvement dominated in six periods based on WQI and in five periods based on Cd (Figure 8, Tables S3 and S4).

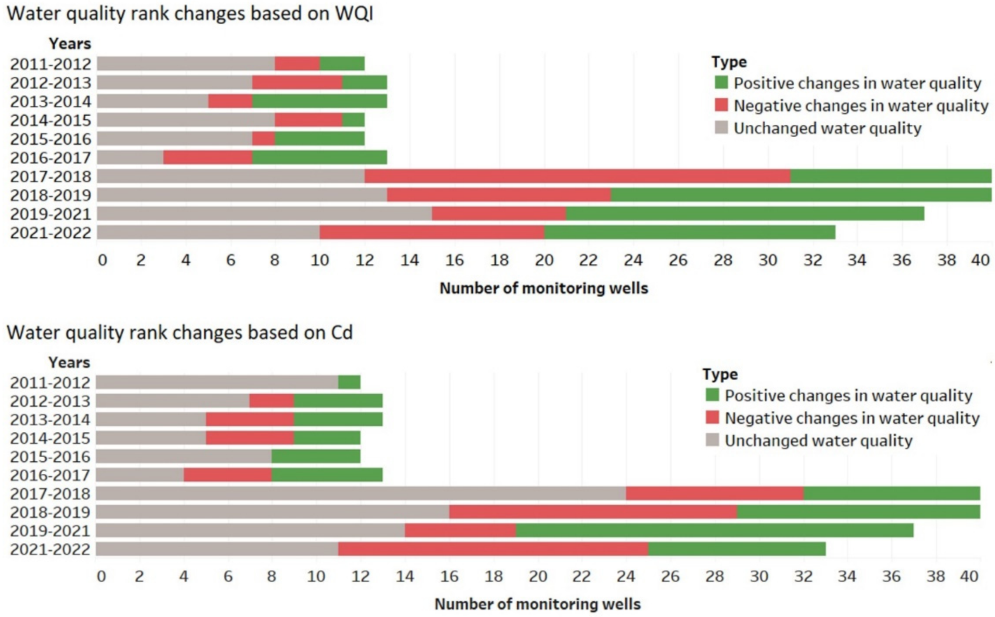

Figure 8. Water quality rank changes based on WQI and Cd ranks of the monitoring wells.

The water quality rank changes of the monitoring wells are shown in Figures 9 and 10. The highest possible rank change was ±3 for WQI and ±4 for Cd during the studied periods. The rate of positive or negative changes did not linearly increase or decrease for either type; in many cases, improvement was followed by deterioration. In the 10 periods examined, neutral conversions dominated, in terms of changes in water quality/contamination; there were also significant differences between monitoring wells, in terms of whether the rank changes pointed in the direction of improvement or deterioration. However, based on the results, it can be concluded that the annual changes alone were not sufficient to prove the dynamics of the purification processes, since the evolution of the chemical parameters of the shallow groundwater is not only influenced by anthropogenic effects but also by, among others, meteorological factors. This draws attention to the fact that, when assessing water quality and the associated changes in water quality, not only the anthropogenic impact prevailing in the given areas has to be taken into account.

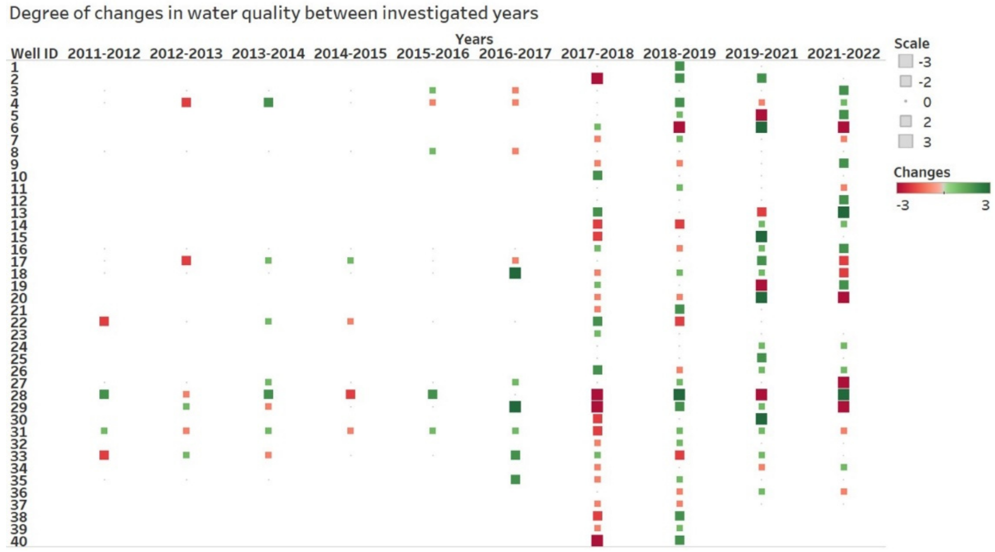

Figure 9. Water quality rank changes, based on WQI, in the monitoring wells between 2011 and 2022.

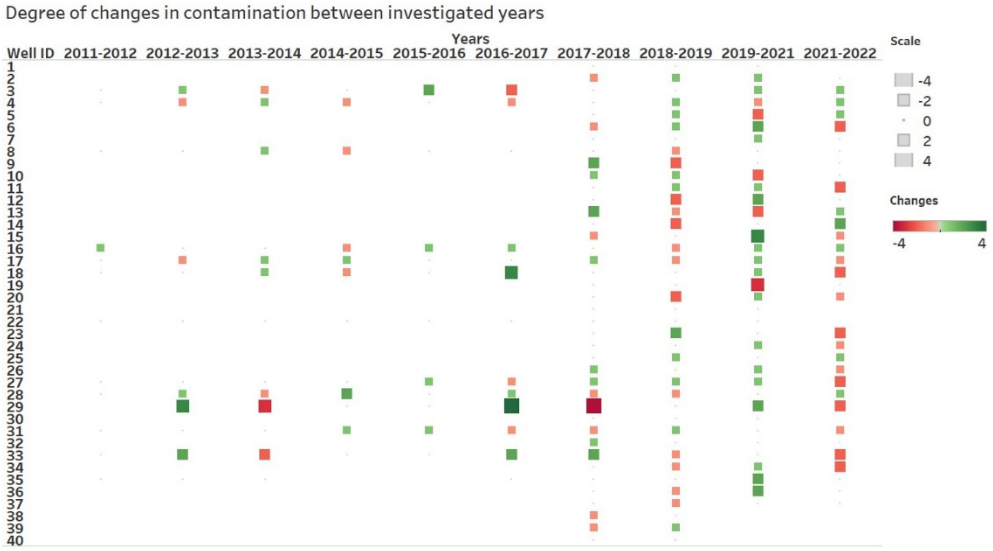

Figure 10. Water quality rank changes, based on Cd, in the monitoring wells between 2011 and 2022.

4. Discussion

Water quality assessment based on monitoring data plays a key role in the design of ecosystem services and environmental measures [57]. The careful application of water quality indices can therefore be useful for the objective evaluation of data [58]. By including several indices, a more complex picture can be obtained of the state of water quality, which increases the diversity, robustness, and reliability of the assessment process [59]. At the same time, Yang et al. (2022) drew attention to the numerous challenges (e.g., sample size, coverage, parameters used) that may emerge, in addition to the advantages of the multi-index approach, which need to be carefully addressed in order to accurately assess water quality. By applying water quality indices, we can thus significantly reduce the amount of data and simplify the expression of water quality/contamination status. However, these indices are not suitable for a comprehensive analysis that includes analyzing relationships between the applied physicochemical–biological parameters or identifying the natural or anthropogenic origin of the relationships between parameters affecting water quality [47,48].

Our results are strongly supported by case studies that have found similar improving trends in water quality following the construction of sewerage networks. For example, in India, a study by Adimalla (2021) showed that the construction of sewage treatment systems significantly reduced nitrate pollution in groundwater, consistent with the positive water quality changes detected in our research [8]. In Brazil, Franz et al. (2022) found that shallow groundwater quality improved significantly due to wastewater treatment measures, which our studies in Hungary confirmed [60]. A survey by Sindane and Modley (2023) highlighted that improvements in wastewater treatment significantly reduced pollution in rural areas [11].

Although the analysis of our monitoring data has shown significant results regarding the long-term assessment of the impact of the sewerage network, it is important to note the limiting factors that may affect the interpretability of the results. Firstly, changes in weather conditions between sampling dates (e.g., rainfall, temperature fluctuations, groundwater level changes) may have affected water quality, which cannot be fully isolated from the effects of the sewerage network. Furthermore, the density of the sampling network was not uniform over the sampling years, especially during the COVID-19 pandemic in 2020 when we were not able to collect samples, which thus led to data loss. Finally, adding additional water chemistry parameters is necessary to monitor and sustain the improvements in the study area after the construction of the sewerage.

Since the long-term effects of environmental investments in municipalities, such as the construction of sewerage networks, are rarely monitored, our research provides valuable information for municipalities and the general public. As studies at a municipal level are limited nationally and internationally, we consider it a priority to continue our studies in the future, collecting field information that can serve as a basis for more accurate regional models and forecasts.

5. Conclusions

The long-term monitoring of water resources can provide valuable insights for identifying trends resulting from and the impacts of human activity. This study aimed to evaluate the spatial and temporal changes in groundwater quality resulting from the establishment of a sewerage network in a Hungarian settlement between 2011 and 2022 using water quality indices, GIS, and statistical analysis. Based on the results for the pre-sewerage period (2011–2014), heavy pollution of the shallow groundwater resources was detected. The high level of contamination results from the fact that, until the municipal sewerage network was built in 2014, the population stored the wastewater in inadequately insulated septic tanks, from which large volumes of wastewater leached into the soil. In the transitional (2015–2018) and post-sewerage periods (2019–2022), a clear improvement in groundwater quality was found, which was the result of the elimination of local sources of pollution. During these periods, an increasing proportion of areas were shown to have adequate or good water quality. The significant differences between the three periods examined were also confirmed using a Wilcoxon signed-ranks test. In addition to an assessment of long-term tendencies, the annual fluctuations in the water quality were also examined. It can be stated that the purification processes do not occur in a linear pattern but are influenced by various factors (e.g., precipitation). This highlights the importance of considering anthropogenic impacts and natural factors when assessing water quality and its changes. Furthermore, it highlights the need for long-term monitoring as well.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/ijgi13110408/s1, Table S1: Descriptive statistic of water quality indices; Table S2: Number of the monitoring wells with different indices in the investigated periods (2011–2022); Table S3: Water quality rank changes based on WQI ranks; Table S4: Water quality rank changes based on Cd ranks.

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Emőke Kiss; visualization: Dániel Balla, Emőke Kiss, and Marianna Zichar; supervision: Dániel Balla and Tamás Mester. All authors have read and agreed to the published version of the manuscript.

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Appendix A

The following eight parameters (pH, EC, NH_4^+, NO_2^-, NO_3^-, PO_4^{3-}, COD, Na^+) were used to calculate the water quality index (WQI), the Canadian Council of Ministers of the Environment water quality index (CCME WQI), and contamination degree (C_d).

Water quality index (WQI)

The calculation of the WQI was carried out following the 'weighted arithmetic index method', using the following equation [46]:

$$WQI = \sum Q_n W_n / \sum W_n \quad \text{(A1)}$$

where Q_n is the quality rating of the nth water quality parameter and W_n is the unit weight of the nth water quality parameter. The quality rating Q_n is calculated as follows:

$$Q_n = 100[(V_n - V_i)/(V_s - V_i)] \quad \text{(A2)}$$

where V_n is the actual amount of the nth parameter present, V_i is the ideal value of the parameter [V_i = 0, except for pH (V_i = 7)], and V_s is the standard permissible value for the nth water quality parameter. The unit weight (W_n) is calculated using the following formula:

$$W_n = k/V_s \quad \text{(A3)}$$

where k is the constant of proportionality and is calculated using the following equation:

$$k = \left[1/\sum 1/V_s = 1,\ 2, \ldots, n\right] \quad \text{(A4)}$$

Contamination degree (C_d)

The calculation of the contamination degree, C_d, is made separately for each sample of water analyzed, as a sum of the contamination factors of individual components exceeding the upper permissible value. Hence, the contamination index summarizes the combined effects of several quality parameters considered harmful to household water.

The scheme for the calculation of C_d is as follows [49,51]:

$$C_d = \sum_{i=1}^{n} C_{fi} \quad \text{(A5)}$$

where the following is true:

$$C_{fi} = \frac{C_{Ai}}{C_{Ni}} - 1 \quad \text{(A6)}$$

where C_{fi} is the contamination factor for the ith component, C_{Ai} is the analytical value of the ith component, and C_{Ni} is the upper permissible concentration of the ith component (N denotes the "normative" value).

The elements and ionic species with analytical values below the upper permissible concentration values are not taken into consideration.

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