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Short Report

LIFE+ PROJECT NAME: "The impact of geological environment on health status of residents of the Slovak Republic", **Acronym "GEOHEALTH"**

Chemical composition of groundwater and relative mortality for cardiovascular diseases in the Slovak Republic

(Action A4: „Linking of environmental and health indicators")

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Abstract

The study deals with the analysis of relationship between chemical composition of the groundwater / drinking water and the data on relative mortality for cardiovascular diseases (REI) in the Slovak Republic. Primary data consist of the Slovak national database of groundwater analyses (20 339 chemical analyses, 34 chemical elements/compounds) and data on REI collected for the 10 years period (1994-2003). The chemical and health data were unified in the same form and expressed as the mean values for each of 2883 municipalities within the Slovak Republic for further analysis. Artificial neural network was used as mathematic method for model data analysis. The most significant chemical elements having influence on ReI were identified together with their limit values (maximal acceptable, minimal necessary and optimal). Based on the results of calculations, made through the neural networks, the following ten chemical elements/parameters in the groundwater were defined as the most significant for REI: Ca+Mg (mmol l^{-1}), Ca, Mg, TDS, Cl^-, HCO_3^-, SO_4^{2-}, NO_3^-, SiO_2 and PO_4^{3-}.

The obtained results document the highest relationship between REI and the groundwater contents of Ca+Mg (mmol l^{-1}), Ca and Mg. Following limit values were set for the most significant groundwater chemicals/parameters: Ca+Mg 4.4 – 7.6 mmol l^{-1}, Ca > 89.4 mg l^{-1} and Mg 42–78.1 mg l^{-1}. At these concentration ranges the relative mortality for cardiovascular diseases in the Slovak Republic reaches the lowest levels. These limit values are about twice higher than current Slovak valid guideline values for the drinking water.

Key words

Groundwater, cardiovascular disease mortality, neural network, Slovak Republic

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1. INTRODUCTION

The cardiovascular diseases (CVD) became the most common cause of death in Slovakia during the long period. They represent about 50% or more of all causes of death (NCZI 2012, OECD 2013). The main risk factors for CVD encompass the stress, genetic predisposition, overweight, regular smoking, excessive alcohol intake, unhealthy eating habits, as well as environmental factors, where belong the chemical composition, level of the contamination of the groundwater (especially drinking water), soil and air.

The present article discusses the issue of the impact of chemical composition of the groundwater / drinking water to the relative mortality on CVD.

Mortality, or increased incidence of CVD is often associated with an excess or deficit of several chemical elements in the groundwater. Obviously the CVD are most often associated with the deficient content of Ca and Mg, and the low water hardness **(Dawson et al., 1978, Shaper et al., 1980, Rylander et al., 1991, Rahman and Husain 2011**). However, there exist studies not confirming this dependence, e.g. **Maheswaran et al. (1999)**. Numerous other works associate CVD with increased content of potentially toxic elements (PTE) in the groundwater / drinking water, mainly As, Cd, Pb, Sb and Ba **(Schroeder MD and Kraemer 1974, Bhatnagar 2006, Mitchell et al. 2011, Sturchio et al. 2013**). In the present article we deal with the evaluation of the wide range of chemical elements commonly analysed in the groundwater for CVD. Through "the higher statistics" – neural networks – we interconnect the chemical composition of the groundwater with CVD. The main objective of this work is to determine which chemical elements in the groundwater impact most on CVD mortality and simultaneously to determine their limit concentrations (optimum, maximum allowable and minimum required), for which the mortality on CVD is as low as possible.

2. MATERIALS

Chemical composition of the groundwater

The data source on chemical composition of the groundwater encompassed a national environmental-geochemical mapping, mainly that from the *Geochemical Atlas of the Groundwaters* and environmental-geochemical maps of Slovak regions **(Rapant et al, 1999, Vrana et al. 1997).** These were complemented in particular by the data from the national groundwater monitoring, hydrogeochemical maps and other regional and local geochemical works **(SHMU www.shmu.sk/en , Kordík et al. 2000).** Our database includes virtually all sources of the groundwater, used for bulk supply of drinking water. Total number of accumulated chemical analyses of the groundwater was 20 339. There are included chemical analyses of the water since 1991, when the modern environmental-

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geochemical mapping of the Slovak Republic has started *under the IGCP 360 Geochemical Correlation Programme* (**Darnley et al., 1995).** The density of the groundwater samples was about one sample per 2.5 sqkm.

Data on the water chemical composition we have adjusted to such a form that they can be linked with data on CVD mortality. So we had to transform the data on water chemical composition to compatible form with the data on CVD mortality. They represent one number for administrative-territorial units of the Slovak Republic (2883 municipalities). The calculation procedure was as follows. A pixel map of spatial distribution of elements and components was compiled from all the input data for the entire Slovak Republic using the MapInfo Professional 9.0 software. The search factor was 1, function power 2, while anisotropy of the environment was not involved. The basic map cell is a square or a pixel with a one-kilometre side, i.e. a pixel area is 1 sqkm. For each pixel a corresponding average value of element concentration was computed based on inverse distance from the pixel centre to the nearest ten samples. Grid average value of chemicals for specific administration units (villages, districts and Slovak Republic) was then calculated as the arithmetic mean value from the values of the contents for each pixel falling under the administration units. In addition, pixel values concerning the involved administration units were only partially included in the calculation.

The set of evaluated chemicals in the groundwater with respective mean values for the Slovak Republic is reviewed in Tab. 1 (**Rapant et al. 2014**). The example of final interpretation of chemical composition of the groundwater for Slovak Republic is shown in Fig. 1 for Ca+Mg (mmol l^{-1}), presenting the most influential chemical composition of the groundwater in relation to CVD mortality. Other chemicals are available online at www.geology.sk/geohealth.

Table 1: Characteristics of chemical composition of the groundwater in the Slovak Republic (mean values).

GROUNDWATER (n=20 339)												
pH	**T.D.S.**	**COD_{Mn}**	**Ca+Mg**	**Li**	**Na**	**K**	**Ca**	**Mg**	**Sr**	**Fe**	**Mn**	**NH_4**
7.33	629.75	2.18	3.5	0.019	20.34	11.10	93.56	28.29	0.36	0.17	0.12	0.10
F	**Cl**	**SO_4**	**NO_2**	**NO_3**	**PO_4**	**HCO_3**	**SiO_2**	**Cr**	**Cu**	**Zn**	**As**	**Cd**
0.13	32.96	79.32	0.11	38.76	0.20	303.85	18.21	0.0013	0.0026	0.2673	0.0019	0.0010
Se	**Pb**	**Hg**	**Ba**	**Al**	**Sb**		Note: Data except of pH in mg l^{-1}, Ca+Mg in mmol l^{-1}					
0.0010	0.0014	0.0001	0.0747	0.0297	0.0009							

Fig. 1 Ca+Mg (mmol l^{-1}) distribution in the groundwater of the Slovak Republic - municipalities

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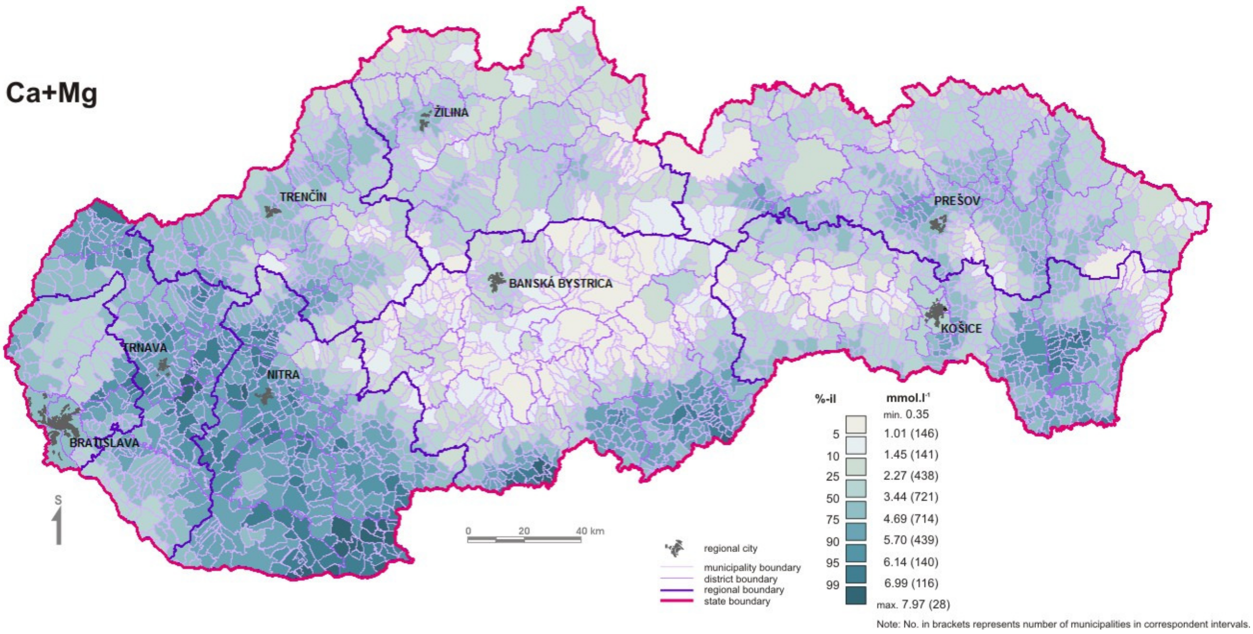

In our work we consider and evaluate groundwater as a drinking one. However, we are aware of some inaccuracies, which may affect or limit our results. But we really deal with a large data base (more than 20 000 chemical analyses, more than 30 set chemicals), thus reducing the uncertainties to a great extent. The groundwater is the most important source of drinking water for most of population in Slovak Republic. We deal with the source of drinking water for approximately 90 % of inhabitants **(Klinda and Lieskovská, 2010).** Approximately 20 % of the Slovak population has been using water from individual wells for drinking and cooking purposes. About 50 % of the population has been supplied with drinking water from the local water companies using local water resources with a low discharge (less than 5 l s^{-1}) captured and distributed to water supply pipes in the vicinity of settlements. Only in southern Slovakia (especially in the Quaternary sediments) the population has been supplied from large water resources distributed distances from 50 to 100 km. Of course, we are not able to assess the proportion of different bottled water that people consume.

Relative mortality on cardiovascular diseases – ReI

According to International Classification of Diseases (ICD, 10th revision, www.who.int/classifications/icd/en), the CVD include diseases of circulatory system, diagnosis I.00-I.99. These include hypertension, coronary heart disease (heart attacks), cerebrovascular diseases, diseases of the arteries, veins and other non-specified diseases of circulatory system. All these diseases bear conventional name the cardiovascular diseases. Relative value of mortality on CVD –

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ReI is calculated as number of death from CVD divided by number of person–years and multiplied by 100,000 inhabitants.

The ReI data used in this paper represent average values for the period 1994–2003, and thus they represent the average ReI values for each municipality of the Slovak Republic (2,883 municipalities). The ReI data were received from the database of the Statistical Office of the Slovak Republic (www.statistics.sk). We used only the data describing the mortality for CVD. The data evaluating the incidence of CVD are not available. The number of cases of deaths from the CVD represents the sum of all cases of deaths for the evaluated diagnosis, recorded by Statistical Office of the Slovak Republic within the monitoring of death causes in the period of years 1993-2004.

The number of person-years is defined as the sum of all residents in each municipality by 31st December of the related year. It varies every year since people are born, dying and moving, so that is why it is not a simple number of residents. The number of person-years represents the basis that the value of relative mortality is related to. The evaluated diagnosis is well recognized only after one hundred thousand-fold increase, recalculated for 100,000 inhabitants. The calculation was performed for each municipality with attributed statistical code for the evaluated period of years. Altogether, the analysis of ReI comprises 2,883 studied municipalities. Military districts (4), where values of health indicators are skewed, were discarded.

The average ReI value for 2,883 municipalities of SR is 765. The distribution of ReI in the Slovak municipalities for the evaluated period is shown in Fig. 2. Approximately half of the municipalities (1,440) has a value close to the average value of the interval 554–887. In evaluated period, not one municipality was registered with a zero ReI value. Only 28 municipalities (app. 1 %) are characterized by the ReI value three times higher than national average.

Fig. 2 Relative mortality on cardiovascular diseases in Slovak municipalities

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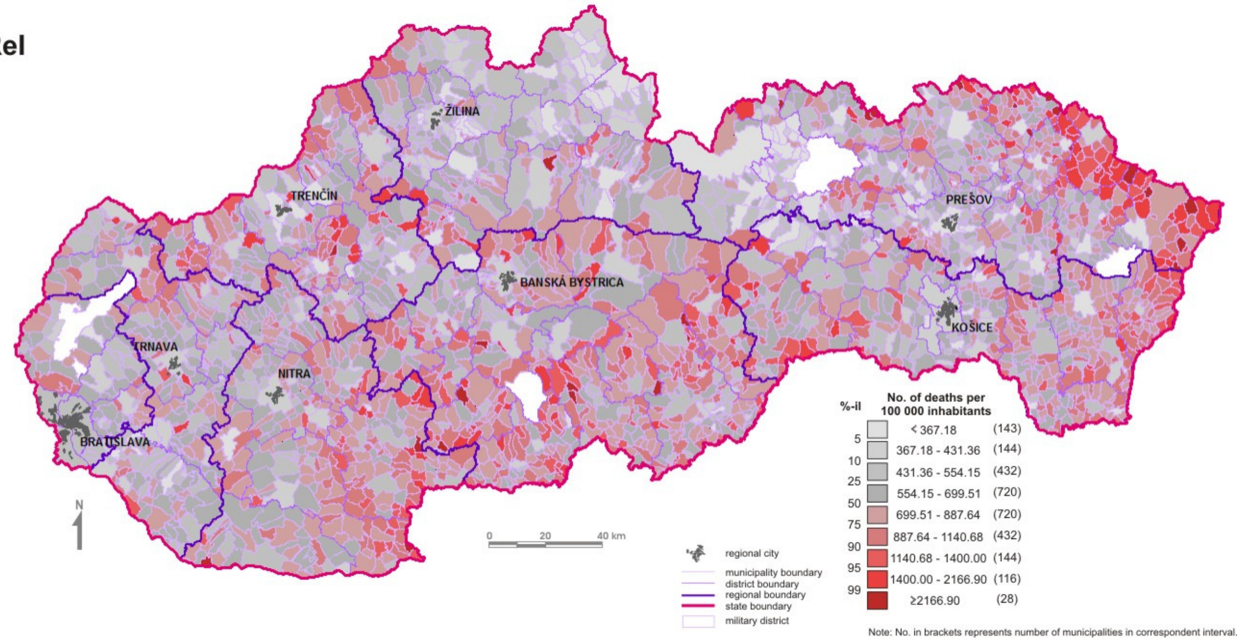
ReI



3. METHODS

Investigation of relationships between two different variables is the domain of statistics. However, the selection of appropriate statistical methods to link two databases requires a very correct approach to obtain relevant dependency relations. Correlation coefficients are used for expressing the intensity of stochastic dependence between two variables, demonstrating the dependence relationships between surveyed attributes. Classical Pearson correlation coefficients express the degree of simple linear dependence of two variables. Spearman correlation coefficients are a measure of monotonous dependence. Our data do not have a normal distribution, are unevenly distributed, and often vitiated with an error, incomplete and exhibit high variability. They have all attributes of the daily life, particularly biological research, where we operate. Therefore it would be incorrect to assume the existence of a functional relationship such in physics. Using classical methods of regression analysis could lead to wrong conclusions. Therefore, for the analysis of relationships between chemical composition of the groundwater and ReI we use artificial intelligence - the artificial neural networks (ANN).

Neural networks represent one of the techniques of the data mining. A detailed overview of the history of origin and development of neural networks is given **Kriesel (2007).** ANN is one of the most widely used modeling techniques used in many areas of research. The most significant feature of neural networks is that they are universal function approximator. Universality of neural networks as approximators has been mathematically proven **(Hornik et al., 1989).** The advantage of ANN

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consists in depiction of a complex nonlinear relations. The ANN disadvantage is that we do not know the mechanism of action of various factors values on the output parameter. The equivalent of regression equation known from regression analysis is absenting.

Each of practiced networks represents a unique result, which is uniquely defined only by the network topology and vector of synaptic weights. The global sensitivity analysis of neural networks, however, provides knowledge about the importance of particuliar input variable in practiced network. **Kovalishyn et al. (1998)** and **Zurada et al. (1995)** submitted several methods of measuring of the sensitivity of ANN input variables. **Gevrey et al. (2003)** presented and compared seven methods of measuring the importance of input variables ANN. When the s_r for a given input variable is less than one, we can assume that its exclusion will not lower, but contrary, it will increase the network efficiency **(StatSoft, 1999).**

The quality of the neural network can be evaluated using several metrics. The value of the correlation coefficient R is the most widely used, determining the relationship between outputs and objectives, i.e. estimated values and the values of output variable. A value of 1 means the close dependence and the 0 means no dependence.

Applying ANN, the order of effects of chemical elements in the water on ReI was determined together with the limit values (maximum allowable or minimal required) and optimum range for the groundwater contents of chemicals. The order of effects of chemicals in groundwater on ReI was determined based on the value of sensitivity coefficient s_r. ReI is influenced by those chemical elements in the water, for which the average sensitivity coefficient is greater than one and the impact is by this way higher.

Table 2. Created neural networks and their characteristics

Indicator	**Selection of influential elements**	**Researching ReI dependence on the elements in the water**									
		Ca+Mg	**Ca**	**Mg**	**T.D.S.**	**Cl**	**HCO_3**	**SO_4**	**NO_3**	**SiO_2**	**PO_4**
Number of neural networks	100	29	29	29	29	29	29	29	29	29	29
highest R value	0.3001	0.1509	0.1447	0.1671	0.1504	0.1485	0.1472	0.1682	0.1296	0.1210	0.1129
Order of the best neural networks	85	21	25	22	22	26	19	23	29	12	1
median value R	0.2264	0.1066	0.0962	0.0653	0.0799	0.0650	0.0755	0.0738	0.0287	0.1197	0.0824

In order to identify the important parameters of the chemical composition of the groundwater, 100 networks were created. Selected number 100 networks has proven to be fully satisfactory, because for next networks the value of correlation coefficient do not increase, but stagnated or declined. The

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best performance had the network No. 85 having 32 input variables (chemical composition of the water), seven neurons in the hidden layer and one output variable (ReI) – with the value of the correlation coefficient R=0.3001 (level of significance P< 0,01).

Despite the performance (reliability) of the network was satisfactory, the impact of various environmental indicators was relatively low and was for each created network different. Therefore the most influential chemicals were ordered based on median values of s_r of all 100 calculated networks. This approach was used e.g. by **Opitz and Shavlik (1996), Han et al. (2011), Kourentzes et al. (2014).**

Based on median sensitivity calculated for each of evaluated chemicals we can assume that the most influential chemicals are those with s_r >1.1. The chemicals characterized as medium influential are those with s_r within the range 1.1 – 1.01. Other chemicals determined as non influential on ReI are those with $s_{r<}$ 1.

The performance of networks for studying ReI dependence on the contents of chemical elements in water (for the derivation of limit values) is relatively low (Tab. 2). This is a consequence of a very large range of values of investigated indicator ReI for individual values of elements contents in the water. As an example we state the ReI dependence on the content of Ca + Mg in the water (Fig. 3). In the case of Ca + Mg contents in the water there were constructed 100 networks.

With an increase of the number of networks, the value of the correlation coefficient has not increased significantly. Networks with the highest correlation coefficient do not always proved to be best. In several cases they were not monotonous, but this contradicts the logic of the studied relation. We searched for the optimum number of networks that showed good performance (the highest value of R) and simultaneously they were monotonous (not curled). For the 10 most influential elements, the number of 29 networks proved to be optimal, and therefore we used this number to derive the limit contents of the 10 most influential elements. Procedure for determining the limit contents was as follows. For each value of examined content of chemical elements in the water we assigned median of aligned ReI values, obtained using 29 neural networks. Through these values, we have put the regression curve (parabola or straight line). Its position is statistically highly significant – the determination index reaches values higher than 0.9, in some cases even 0.99. This allows us to consider the procedure as appropriate and number 29 ANN for each element (for deriving the limit contents) as sufficient.

Another method we used to analyse dependence of ReI on the content of elements in the water, was as follows. The range of values of investigated element content we divided into deciles. In the next step we found the locus of points, which x-coordinate belonged into individual deciles.

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Subsequently we put polynomial of the second degree, the straight line through the cores of 2 to 9 decile. The conformity for the very influential elements was excellent. In the decline elements influence the consensus exists, but the similarity decreases (Fig. 4).

Another possibility to obtain dependence consisted of using the quantile regression. Because the results were nearly identical, we do not state them.

Fig. 3. Dependence ReI from Ca + Mg content in water - the original data, the median value of data obtained by neural networks and parabola through the median values

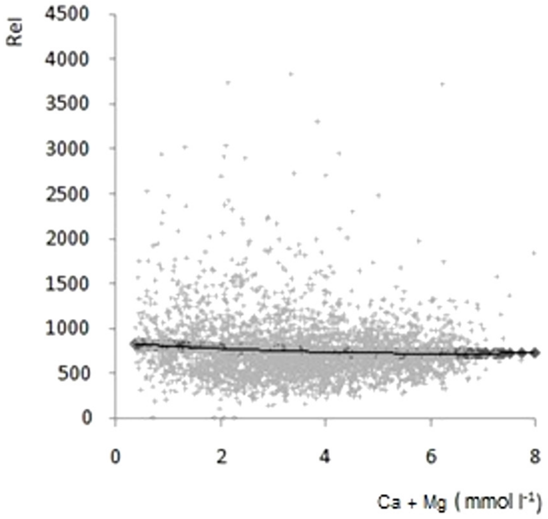
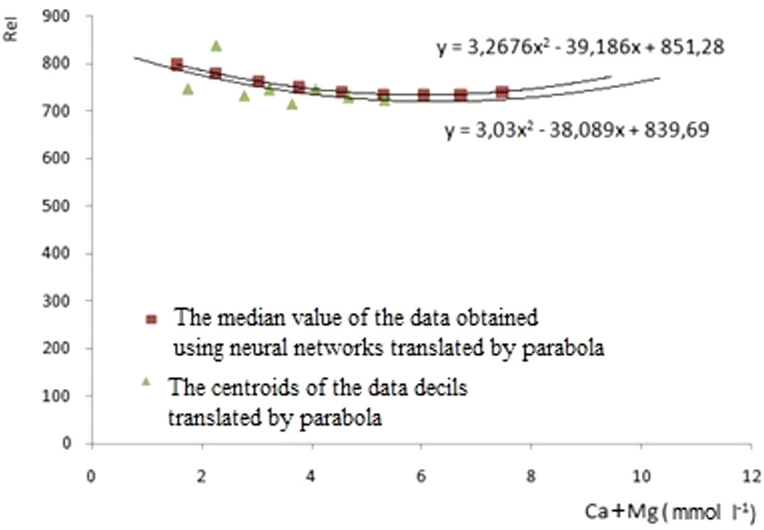


Fig. 4 Dependence ReI from Ca + Mg content in water - median values of the data obtained by neural networks translated by parabola and centroids of the decils translated by parabola



The approach at the derivation of the limiting and optimum values for the most influential elements was as follows. In the plot of relations between the chemical elements in the waters and ReI (Fig. 5) we supposed as limiting values those, where the curve, or straight line intersects the average

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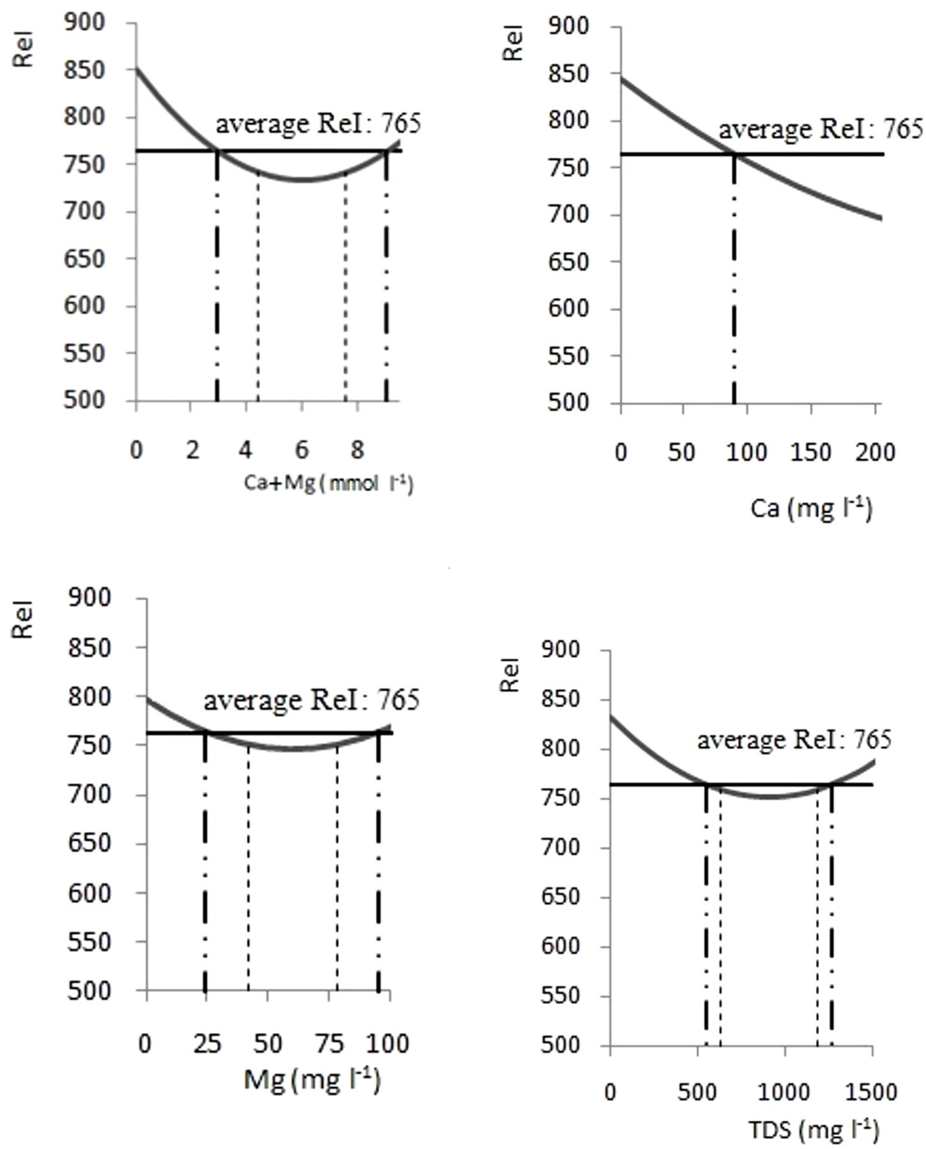
ReI value, calculated as the average of all ReI values REI for 2,879 municipalities of the Slovak Republic (the number of municipalities is 2,883, but 4 military districts were omitted), i.e. 765. Thus, we were able to allocate the maximum allowable and minimum required contents. In the case when the curve was a convex parabola, we have determined the optimum contents-peak of the parabola ± standard deviation. The derivation of limit values for the groundwater contents of chemicals in relation to ReI (critical as well as optimum) is clearly figured on Fig. 5.

Fig. 5 ReI dependence on the content of the influential elements in the water



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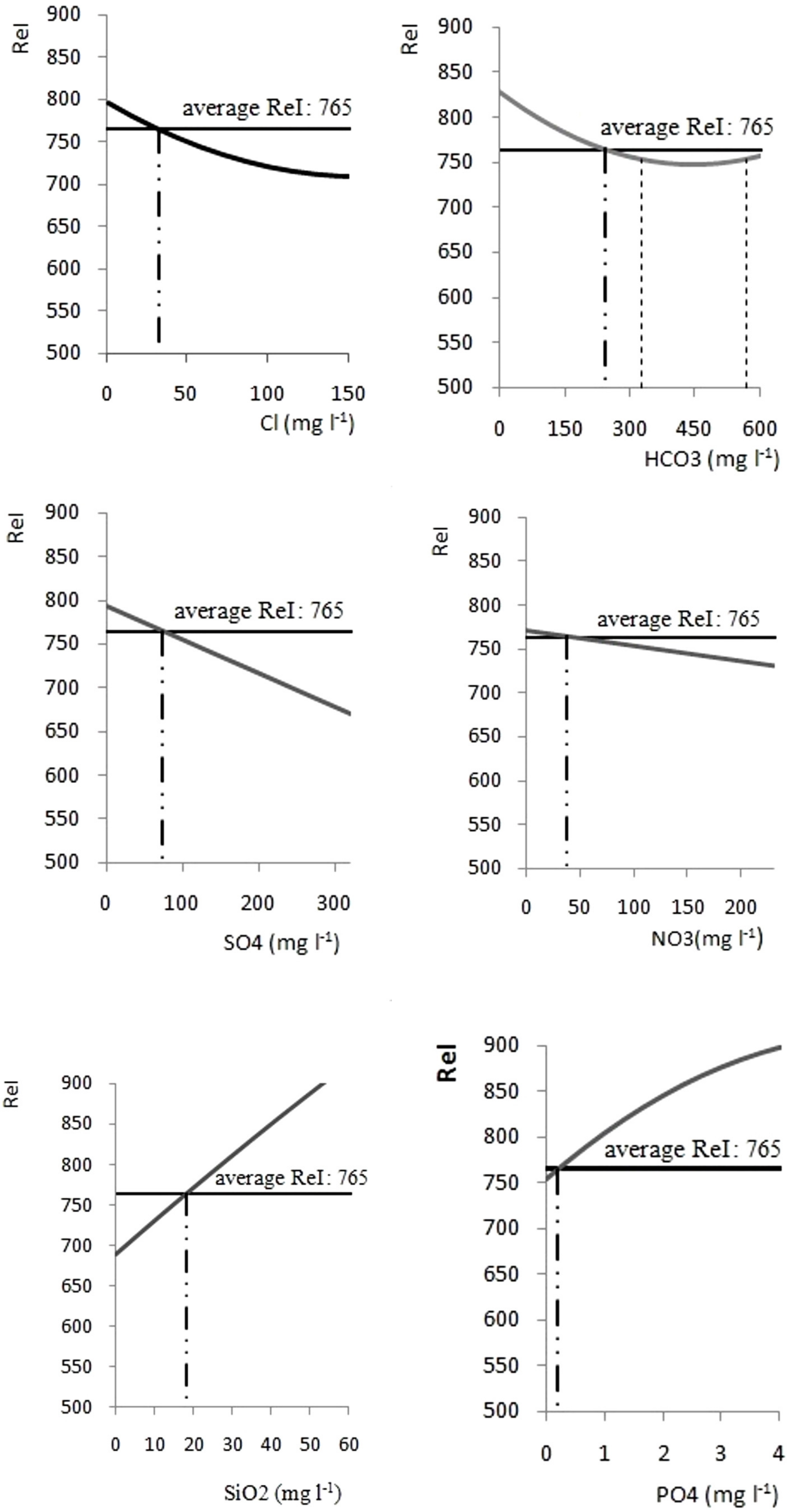

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Results

The results of the calculations of neural networks (the median sensitivity coefficients of 100 neural networks, limit and optimum levels of the chemical composition of the groundwater) are presented in Tab. 3. The table below presents the results for the 10 most influential components of the groundwater, the most influencing the ReI incidence. As more influential elements for ReI there were determined also Na (sensitivity = 1.0021), F (1.0015), K (1.0013), pH (1.0012), Ba (1.0010), Mn (1.0008), Rn^{222} (1.0004), Ra226 (1.0004), Zn (1.0004), Cu (1.0003), NO_2 (1.0002), Sb (1.0002), Fe (1.0002), COD_{Mn} (1.00003), As (1.00003), NH_4 (1.00003) and Hg (1.00001). Other elements are not affected: Cr (0.99996), Cd (0.9999), Al (0.9999), Se (0.9999) and Pb (0.9999).

Tab. 3 The results of calculations of neural networks between REI and 10 the most influential elements in the water.

Order	Element	S_r	R^2	Limit content	Optimum content	Evaluation of function dependency
1	Ca+Mg	1.37	0.992	2.9- 9.1	4.4-7.6	convex parabola
2	Ca	1.211	0.999	Less than 89.4	Non-existing	convex parabola
3	Mg	1.15	0.986	24.3-95.8	42.0-78.1	convex parabola
4	T.D.S.	1.053	0.960	553.1-1263.2	629.4-1186.8	convex parabola
5	Cl	1.027	0.988	Less than 31.8	Non-existing	convex parabola
6	HCO_3	1.026	0.979	Less than 241.9	326.1-567.9	convex parabola
7	SO_4	1.009	0.961	Less than 73.3	Non-existing	line with negative slope
8	NO_3	1.004	0.939	Less than 37.6	Non-existing	line with negative slope
9	SiO_2	1.003	0.999	More than 18.2	Non-existing	concave parabola
10	PO_4	1.002	0.919	More than 0.2	Non-existing	concave parabola

The network quality is average (correlation coefficient is 0.3001). Though, the calculated results can be considered as sufficiently proven. It is indicated by values of the determination coefficients R^2, which are in the range 0.919 to 0.999, so we can consider the achieved results as statistically significant. Unambiguously the highest weight (Tab. 3) in the chemical composition of the water with respect to ReI there have Ca, Mg, and Ca + Mg parameter (mmol l^{-1}), which expresses the approximate water hardness. In terms of ReI, these three parameters are the most influential. The medium influence can be allocated to TDS, Cl and HCO_3 with a sensitivity of 1.053–1.026. Other parameters we consider as the least influential and their sensitivity is less than 1.01. As elements non-influencing ReI, there were determined Cr, Cd, Al, Se and Pb with a sensitivity less than 1.

The derivation of content limits (critical and optimum) is shown in Fig. 5. The limit values for the 10 chemical elements in water having the highest influence on ReI are presented in Tab. 3.

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When defining the limit contents, in the case of Mg + Ca, Mg, TDS and HCO_3 we were able to determine the limit values (minimum required and maximum allowable) as well as optimum range (Tab. 3, Fig. 5), where the ReI incidence was below the average ReI level in Slovakia, below 765, or as low as possible. In the case of Ca, Cl, SO_4, NO_3, SiO_2 and PO_4 we were able to identify only limit risk value of their contents. The optimum value of their concentration range could not be determined. The determination of limit values has followed the function dependencies of ReI values from individual components of chemical composition of the water.

Discussion

From any mathematical and statistical processing of different variables almost always we get some correlation dependencies. However, the most difficult part is to determine, whether it is a causal relationship or just stochastic. Chemical elements in relation to health indicators were divided into three groups, namely: the causal elements, indicative elements and elements without effect **(Rapant et al., 2010, Rapant et al., 2014).**

As causal chemical elements we understand those elements for which many case studies have demonstrated a relationship to human health and which statistically significant dependence on health indicators has been registered. The indicative elements are defined as the elements with still not proven or well described relationship to human health by the case studies. However, they show statistically significant stochastic relationship to health indicators, related mainly to their geochemical associations to causal elements. They accompany causal elements and their contents reflect the rock environment, where the groundwater formed. They may not have and is unlikely they have any effects on human health.

Among the elements without health effects we include those elements which causal or indicative character was not proven and for which we do not observe any significant statistical relationship with health indicators. In the case of Slovak Republic, these are mainly chemical elements occurring in low concentration levels without notable health effects.

From influential chemical elements determined by us, Ca + Mg, Ca and Mg can be explicitly singled out as causal. These three parameters of the groundwater chemical composition have demonstrated the highest statistical dependence with the CVD mortality (REI). Several case studies have proved their effect (deficit) for CVD (**Pocock et al. 1980, Sauvant et al. 2000, Ferrándiz et al. 2004, Yang et al. 2006, Kousa et al. 2006, Leurs et al. 2010**). These three parameters have significant effects on the CVD mortality in Slovakia in terms of the groundwater / drinking water. The values to TDS and

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HCO_3 we can as indicative elements assign to them. Anion HCO_3 represents in the ionic composition of the groundwater in SR the major (the most-represented) anion and its content is associated mainly with Ca and Mg cations (mineralization process of carbonates dissolution). Similarly, the TDS values depend mainly on the Ca and Mg contents (the most-represented cations) and HCO_3 content, which is the most-represented anion in the groundwater (**Rapant et al., 1996**).

A classic example of indicative element (without causal relationships) can be provided by SiO_2. It is usually increased in silicatogenic (volcanites, granites, crystalline schists) groundwaters of SR, though they manifest the lowermost values of Ca, Mg and the water hardness (**Rapant et al., 1996**). Therefore, we observe a statistical dependence between the SiO_2 and ReI contents. It represents geochemically conditioned stochastic dependence, not causal. The higher is SiO_2 content, the higher is the value of ReI. However, the higher content of SiO_2 causes the lower contents of causal elements (Ca, Mg, Ca + Mg) and therefore the higher ReI values. The SiO_2 content therefore does not have a causal relationship with ReI, this dependence is only stochastic.

Another group of influential elements is represented by the contents of Cl, SO_4 and NO_3. These parameters (mainly NO_3 and Cl) represent classic indicators of anthropogenic contamination in the groundwater of SR. In all three cases, the higher contents of these elements cause lower ReI contents. However, the increased levels of NO_3, SO_4 and Cl in the groundwater are always accompanied with an increased content of particular cations Ca and Mg, which reduce the incidence of cardiovascular diseases. The limit values of these components of the groundwater, being determined by us, are in all three cases mostly significantly lower than the limit values in the Slovak drinking water standard. Therefore, we do not consider these three components of the groundwater to be causal concerning ReI occurrence, also in terms of their order of magnitude lower sensitivity compared with the sensitivity of Ca, Mg, Ca + Mg. All other analysed groundwater components, in particular all potentially toxic elements are assessed as elements without the health effects on ReI occurrence. It can really be a fact that all these elements do not affect ReI, or preferably the fact that their content is so low that at these low levels they cannot affect ReI.

The achieved results demonstrate that from a relatively wide range of analysed elements in the groundwater, the contents of Ca + Mg, Ca and Mg have a determining influence on CVD mortality. Calcium and magnesium are important intracellular cations and their importance for the proper functioning of the heart has been described several times in the world literature **(Bencko et al., 2011, Kožíšek 2003, 2004, Rubenowitz-Lundin and Hiscock, 2005, Cotruvo and Bartram, 2009).** In several works for the occurrence of CVD a great importance of optimum Mg content is often

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emphasized, which affects mainly the hypertension (**Yang 1998, Catling et al. 2005, Monarca et al. 2006, Rosanoff, A. 2013).**

Tab. 4 presents the limits for Ca + Mg, Ca and Mg, according to Slovak standards for drinking water (they are limited as an approximate value, which is not mandatory), being compared with the limit values derived by us. As can be seen from Tab. 4, the limit values derived by us are significantly higher - more than app. 2 to 3 times - than the limit values of the Slovak drinking water standard. At these "increased" contents of Ca, Mg, Ca + Mg, the level of mortality from CVD in Slovakia is significantly lower than the national average.

Tab. 4 Calculated limits of 3 most important elements in the groundwater compared with the Slovak drinking water standards

Chemical element/parameter	Drinking Water Standard*	Limit value	Optimum value
Ca+Mg (mmol l^{-1})	1.1 – 5.0	2.9 – 9.1	4.4 – 7.6
Ca (mg l^{-1})	more than 30	more than 89.4	-
Mg (mg l^{-1})	10 - 30	24.3 – 95.8	42 – 78.1

*Anon (2010)

Conclusion

The achieved results allow us to present the following conclusions: the CVD mortality in the Slovak Republic is from the chemical composition of the groundwater mainly influenced by following elements identified as being the most influential: Ca, Mg and their summary assessment Ca+Mg (mmol l^{-1}). The optimum contents, when the CVD mortality is significantly lower than the national average, are as follows: Ca more than 89.4 mg l^{-1}, Mg in interval 42–78.1 mg l^{-1} and for Ca+Mg interval 4.4–7.6 mmol l^{-1}. These levels, being determined by us, are about 2-3 times higher than the limit levels of the drinking water standards in Slovakia. Therefore we recommend increasing them. The definite limit values will be determined after a comprehensive treatment of the chemical composition of the groundwater with respect to wide spectra of health indicators (especially oncological diseases, diseases of digestive system, respiratory system and endocrine secretion).

WHO in various materials highlights the importance of Ca and Mg on CVD (**Cotruvo J. and Bartram J. eds., 2009, WHO 2009).** Though, the contents of Ca, Mg, and the water hardness are

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not limited by the WHO drinking standards. We recommend adding the limited content of Ca and Mg into WHO drinking standards.

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