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Socio-economic factors of soil pollution

László Várallyai*, Szilvia Botos, Ádám Péntek

University of Debrecen, Faculty of Economics and Business, Institute of Applied Informatics and Logistics
H-4032 Debrecen, Böszörményi út 138.

Abstract

Analysing the relationship between agricultural production and the natural environment (soil, water and air) and the unfavourable reactions between them became an important question inthe second half of the 20th century and nowadays both in Hungaryand across Europe. Impairment of the environment is a complex process, it affects all the three basic components of the biosphere (soil, water, air) always at the same time, but the level of the effect is different for each part.
Soils are threatened by two basic dangers: the various soil degradation processes (water and wind erosion, acidification, salinisation, physical and biological degradation, unfavourable changes in the humus content and a decrease in the buffer capacity) as well as pollution. Inspite of all these, quality, functionality and productivity of soils can be preserved and maintained.
Our aim is developing a statistical basedinformation system from the data of the Hungarian Soil Information Monitoring System measured points. We developed a method for estimating element content. To determine the concentration of the elements, we need only the GPS co-ordinates of the place based on the number of nearest neighbouring points. This method does not calculate with spatial circumstances. The other possibility is using the kriging method (spatial interpolation) for estimating more precisely the element content. In this study these two methods are compared.
Building our statistical based information system has to determine the number of nearest neighbouring points to be considered in the case of certain elements.
We discovered thatelements can be ranged only into two groups depending on how many nearest neighbouring diagnostic points were considered to kriging.

- 3 neighbouring diagnostical points: K, P, Sr
- 10 neighbouring diagnostical points: Al, B, Ba, Ca, Co, Cr, Cu, Fe, Mg, Mn, Na, Ni, Pb, S, Ti, V, Y, Zn

Using this method the soil pollution locations and elements and its concentration can be determined.
The other important question is to investigate the socio-economic factors of these soil pollutions. There are a lot of data in the Eurostat database which can show the socio-economic effect of these pollutions.
Based on these data is concluded that usage amount of chemical fertilizer, total population and total grain yield are the three most important socio-economic factors that contribute to soil heavy metal pollution.Enterprise amount, total cultivated area, gross

* Corresponding author. Tel.: +36-52-508393; fax: +36-52-486255.
E-mail address: varallyai.laszlo@econ.unideb.hu

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value of farming, forestry, animal husbandry product as well as total freight amount have less impact on soil heavy metals pollution.Last and least impact factors are GDP and value of industry output in rural area.
This article shows our research results on the field of socio-economic factors of soil pollution used by statistical analyses, based on the Eurostat database in Hungary and across Europe.

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*Keywords:*Digital divide, e-competences, e-skills, skills gap, ICT

1. Soil pollution

The informatics - especially applied informatics - undergone a significant development at the end of XXth century. This is allowed analyzing of soil pollution by computer-controlled systems.The importance of this explains the soil is polluted especially by pesticides, wastes, nitrogen and phosphorus fertilizer, which through plants get into our food direct and indirect way (Rodrigues, 2012). In this way polluted foods can cause ill our vitally important organs. On account of opening of the mentioned pollution we can process the experimental data fast and exactly so we can get such a large number of new information. Being aware of this valuable information we can make indispensable arrangements and we can hinder the impairing micro-elements – other elements as well – segregate in food chain (Raguza et al., 2013).

1.1. Socio-economic factors of the soil pollution

We studied the environmental pollutant affect of the different elements load experiment in Nagyhörcsök Experimental Station (Németh & Kádár, 2005). We analysed the contact between the uptake of different micro-elements and its effect on plant organs (loaf, seed) using by different statistic methods. The study emphasizes the importance of applied informatics because without this method the results wouldn't have been able to analyze exact and effective way (Ráthonyi et al., 2010).

While diffuse soil contamination is difficult to localise, local soil contamination or pointsource problems occur in specific sites. Contaminants related to both diffuse and local soil contamination comprise (heavy metals, organic compounds, etc.) (Patócs, 1990).

The contamination sites can be divided in two groups:

- Potentially contaminated site, where an activity has been operated that may have caused soil contamination.
- Contaminated site, where site with confirmed presence of dangerous substances caused by man.

Soil contamination is one of the most widespread types of soil degradation in Europe: 180million ha are affected by pesticides; 170 million ha by nitrates and phosphates; and 85million ha by acidification (EEA, 1995). These sources concentrate mainly on Central and Eastern European countries. According to them, acidification is the most widespread type of soil contamination in Poland (10 million ha, including natural acidification). A high concentration of heavy metals is estimated in Lithuania (nearly 3 million ha). Contamination by pesticides is also common in Romania (more than 4 million ha).The data on local soil contamination are incomplete due to the various classification systems used in different countries.

The causes of soil contamination are varied. Hazardous substances are emitted at all stages of the product chain, from the raw material and the production processes, from the use of products and from the handling of products as waste. Emissions can arise from:

Point sources, like industrial installations; industrial plants, which are no longer in operation; storage installations; industrial accidents; improper industrial and municipal waste disposal; and mines. Due to the large variety of influencing activities, different pollutants might cause contamination in different countries or regions.

Diffuse sources, like agriculture, atmospheric deposition and consumer products. The pollutants can reach the soil via dry or wet deposition, such as atmospheric deposition of acidifying and eutrophying compounds (Draaijers et al,, 1989); potentially harmful chemicals; deposition of contaminants from flowing water or eroded soil itself; or via waste disposal. The pollutants can reach the soil also via the direct application of substances such as plant protection agents (pesticides), fertilisers (farmyard manure, mineral fertilisers), the spreading of sewage sludge and compost. Fertilisers and sewage sludge can also contaminate soil with heavy metals.

1.2. Impact and indicators of soil pollution

Due to the wide variety of soil pollutants and concentrations, as well as natural factors such as soil type and climate conditions, the impacts of soil contamination may be extremely varied. In general, soil contamination affects both the soil itself and the other media (Burges et al., 2015). The direct impacts include:

- Soil contamination restricts buffering and substance conversion capacities of soil.
- The contamination of soil causes the uptake of contaminants by soil biota.
- In terms of the effects on other media, soil contamination primarily affects groundwater.
- However, ecosystems and human health, are also strongly affected by soil contamination:
- The contamination of soil leads to the leaching of pollutants, especially nitrate (due tointensive application of fertilisers), into the ground- and surface water.
- The contaminated soils remove greater amounts of nitrogen from the soil back into the atmosphere as nitrous oxide through the denitrification process than would occur naturally. Nitrous oxide, as one of the greenhouse gases, consequently influences the climate change process.
- The contamination of soil and groundwater causes the uptake of contaminants by plants.
- The contaminated soil itself, as well its effects on other media, affects public health (ingestion by children in playgrounds) and thereby restricts potential uses of the soil.

The following could serve as main indicators to quantify soil contamination.

- Area affected by contamination (ha);
- Number and average size (ha) of sites in different impact categories;
- Heavy metal content of soil (mg/kg dry soil material);
- Organic pollutant contents of soils (μg or mg/kg dry soil material);

2. The Soil Information Monitoring System

A large amount of soil information are available in Hungary as a result of long-term observations, various soil survey, analyses and mapping activities on national (1:500.000), regional (1:100.000), farm (1:10.000-1:25.000) and field level (1:5.000-1:10.000) during the last sixty years. Thematic soil maps are available for the whole country in the scale of 1:25.000 and for 70% of the agricultural area in the scale of 1:10.000.

There are at least three reasons why this rich soil database has been developed (Várallyai, 1993):

- the small size of the country (93.000 km²)
- the great importance of agriculture and soils in the national economy
- the historically "soil loving" character of the Hungarian people, and particularly the Hungarian farmers.

In the last years all existing soil data were organized into a computerized geographic soil information system, which consists of two main parts:

- The soil data bank, including 3 different types of information:
    - basic topographic information (geodetic data standards)
    - point information (measured, calculated, estimated or coded data on the various characteristics of soil profiles)
    - territorial information (1:25.000 scale thematic maps) and soil properties.
- The information system, including models on moisture and plant nutrient regimes of soils; susceptibility of soils to various soil degradation processes, etc.

In consequence of the EU accession, the particular and objective survey of current soil condition is a very important question, which can be the beginning of the implementation of the modern agro-environmental management program. This survey is not useable if the change of condition cannot be investigated continuously in systematic interval.

The Soil Information and Monitoring System (SIM) – this was the first working subsystem - is an independent part of the integrated Environmental Information and Monitoring System (EIMS) (Soil Information Monitoring Professional Committee, 1995).

The Soil Information Monitoring System (SIM) covers the whole country and provides opportunity to create similar information systems for the natural resources (atmosphere, supply of water, flora and biological resources etc.). The aim is to relate these databases.

The SIM territorial measuring grid consists of 1236 measuring points (selected exactly defined by geographical coordinates using GPS). These points are representatives. Distribution of the points by soil types represents the variety of soil types of the country.There were 865 points on agricultural land, 183 points in forests and 189 points in environmentally threatened "hot spot" regions. The latter represented 12 different types of environmental hazards or particularly sensitive areas such as: degraded soils, ameliorated soils, drinking water supply areas, watersheds of important lakes and reservoirs, protected areas with particularly sensitive ecosystems, "hot spots" of industrial, agricultural, urban and transport pollution, military fields, areas affected by (surface) mining, waste (water) disposal affected spots.

3. Applied methods

3.1. Calculating method of distance, element content, relative error and confidence interval

After converting and rounding the measured data of the available SIM samples we carried out further calculations in order to determine the distance between the points, their element contents, their relative errors and confidence intervals. For the calculations we used the following connections:

The program calculates the distances by using the Pythagorean Theorem:

$$Z = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \tag{1}$$

where x_1, y_1 are the coordinates of the known point, x_2, y_2 are the coordinates of the unknown point.

The software determines the calculated figure of chemical element content in case of 10 nearest neighbouring points by using the following connection:

$$C_x = \frac{1/Z_1 * C_1 + 1/Z_2 * C_2 + ... + 1/Z_{10} * C_{10}}{1/Z_1 + 1/Z_2 + ... + 1/Z_{10}} \tag{2}$$

where $Z_1, Z_2, \ldots Z_{10}$ are the distances of the known points correlated to the basis profile number,

$C_1, C_2, \ldots C_{10}$ measured chemical element content in the known points.

The program calculates the percentage deviation – relative error – on the basis of the following formula:

$$Deviation = ABS\left(100 * \left(\frac{Sz - M}{M}\right)\right)[\%] \tag{3}$$

where ABS is the absolute value function, „Sz" means the element content calculated by us, „M" means the measured element content.

The program invokes two Excel functions to calculate the confidence interval, one of them calculates the standard deviation (σ), and the other one calculates the confidence interval.

To calculate the confidence interval, it calculates the standard deviation first (σ):

$$\sigma = \sqrt{\sum_{i=1}^{n} \frac{(x_i - \overline{x})^2}{n-1}} \tag{4}$$

Formula of the confidence interval:

$$\overline{x} \pm 1{,}96 \left(\frac{\sigma}{\sqrt{n}} \right) \tag{5}$$

3.2. Kriging method

Kriging (Yang et al., 2015) is an interpolation method that predicts unknown values of a random process. More precisely, a Kriging prediction is a weighted linear combination of all output values already observed. These weights depend on the distances between the input for which the output is to be predicted and the inputs already simulated. Kriging assumes that the closer the inputs are, the more positively correlated the outputs are. This assumption is modelled through the correlogram or the related variogram, discussed below (Alsamamra et.al., 2009).

In deterministic simulation, Kriging (Shi, 2014) has an important advantage over regression analysis: Kriging is an exact interpolator; that is, predicted values at observed input values are exactly equal to the observed (simulated) output values. In random simulation, however, the observed output values are only estimates of the true values, so exact interpolation loses its intuitive appeal. Therefore regression uses OLS, which minimizes the residuals-squared and summed over all observations (Tugrul & Polat, 2014).

Effectively, geostatistical models directly estimate the variance-covariance matrix. Geostatistical techniques, such as Kriging rely upon an estimated variance-covariance matrix, followed by EGLS (estimated generalized least squares) (Brus & de Gruijter, 2011), and BLUP (best linear unbiased prediction) (Liu et al., 2008). The simplest case assumes one can specify correctly the variance-covariance matrix as a function of distance only (Stein et.al, 2003). The most typical application involves the smooth interpolation of a surface at points other than those measured. Usually, the method assumes errors are 0 at the measured points but modifications allow for measurement errors at the measured points (Guntaka & Myler, 2014).

The first step in most geostatistical models (Zhong et al., 2014) is to estimate the variance-covariance matrix (Ungaro et al., 2014). While techniques exist to perform this directly, the most common technique involves the intermediate stage of computing the variogram (Bates et.al., 1996)

The empirical variogram begins with the pair-wise squared differences among all errors (or sometimes a sample of errors for large data sets) plotted against the distance between the elements of the pair. Positively correlated errors will show small pair-wise squared differences while almost independent errors will show larger differences. For positively correlated residuals, the empirical variogram tends to start off low at small distances and rise with distance up to a point where it levels off (Calder& Cressie, 2009). From the variogram one can estimate the parameters of fitted variogram functions. If the process is stationary, equivalence exists between the fitted variogram functions and fitted covariance functions (Legendre & Legendre, 2012). Only a relatively small number of valid covariance functions exist which yield guaranteed positive definite estimated variance-covariance matrix (Bailey and Gatrell, 1995).

Calculation the concentration of the elements (by using Eq. 6) weighted average mathematical method (Korpás, 1996). The sum of the weighting factors must be 0.

$$Z^*(x) = \sum_{i=1}^{n} a_i Z(x_i) \tag{6}$$

where $Z^*(x)$ the given concentration estimated value, a_i the weighted factor of the observed point
The weighting factors are inverse ratio to distance of the estimated locations (Bodrog, 2001).

$$a_i = \frac{\dfrac{1}{c + d_i^{\omega}}}{\sum_{i=1}^{n} \dfrac{1}{c + d_i^{\omega}}} \tag{7}$$

where d_i is the distance of the estimated location and the i-point,c is constant and ω power (usually $1 < \omega < 3$)
We have to calculate the absolute error from the difference of the measured and estimated concentration value, and the relative error, which give the ratio of the measured and real concentration value (Young, 1986).

4. Results

Building our statistical based information system has to determine the number of nearest neighbouring points to be considered in the case of certain elements. We have to determine the minimums of the average values of relative error for elements. In this point we have got the viewing neighbouring point number for all measured elements.

4.1. Using statistical method

The distance between the known points (K) and the point considered as unknown (U) can be calculated by using the Pythagorean Theorem (Eq. 1). When we determined the distance between all the ten known and “unknown” points, we had ten distance data z_1, z_2, z_3,…..,z_{10}, from which with linear estimation (by using Eq. 2), concentration (c_x) of the certain element can be estimated even in those places where there is no SIM diagnostic point.If we calculate the concentration (c_x) of the certain element for the unknown point, we can compare it with the measured data by ICP-OES spectrometer for the certain element and we can determine the relative standard deviation (Eq. 3).
These steps have to be done first for the same point regarding the other elements which quantities exceed the demonstration line. After that, these steps have to be done again for each available SIM diagnostic point, considering that they are the unknown points in the experiment. After this, we will have the concentration value and its relative standard deviation for each measurable element above the demonstration line for each diagnostic point.
We applied two Excel functions to calculate the confidence interval, one of them (Eq. 4) calculates the standard deviation (σ) and the other calculates the confidence interval (Eq. 5).
We discovered when studying different numbers (1, 2, 3, 4, 5, 6, 7, 10, 15, 20, 25 and 30 in order) of nearest neighbouring diagnostic points within the aggregation, the minimums of the relative error values are different. Elements can be ranged into three groups depending on how many nearest neighbouring diagnostic points were considered when we received the minimum value.

- 3 neighbouring diagnostical points: K, P, Sr, Ni, Cu, B, Co, Ti
- 5 neighbouring diagnostical points: Al, Fe, Ca, Mg, Mn, S, Ba, Cr, V, Pb, Y, Zn
- 10 neighbouring diagnostical points: Na

It means that in case of a sample originating from a genuinely unknown diagnostic point, for elements in the first column 3, for elements in the second column 5, while for Sodium 10 nearest neighbouring points have to be considered in order to estimate the element content with the smallest error.

4.2. Using by Kriging method

Building our statistical based information system has to determine the number of nearest neighbouring points to be considered in the case of certain elements.

We discovered that elements can be ranged only into two groups depending on how many nearest neighbouring diagnostic points were considered to kriging.

- 3 neighbouring diagnostical points: K, P, Sr

- 10 neighbouring diagnostical points: Al, B, Ba, Ca, Co, Cr, Cu, Fe, Mg, Mn, Na, Ni, Pb, S, Ti, V, Y, Zn

It means that using of kriging method in case of the most elements we need 10 nearest neighbouring points have to be considered in order to estimate the element content with the smallest error. It is interesting, in case of K, P and Sr the results were the same (10 nearest neighbouring points) in case of developed statistical method.

4.3. The Internet-based program

We developed a newer internet-based program that makes it possible to reach the objectives through arranging the results of analyses into a database and developing an authorisation system (Fig. 1.). When developing the newer software, our objective was to create a dynamic website for users which together with the GPS coordinates only of the certain point could provide the estimated element content for the measured chemical elements also in such points where no samples had been taken and thus measured data were not available. The relative error and the confidence interval must be provided for each element content value, since they orientate the users into which range the quantity of the certain chemical element at the given diagnostic point can fall (Dunlap, 2006).

We provided access to the database through internet-based technology. With the help of the database-based server-side script language (PHP) (Andress &Linn, 2012) we planned and developed the user interface, through which the user can communicate with the program (Helderich et al., 2011).

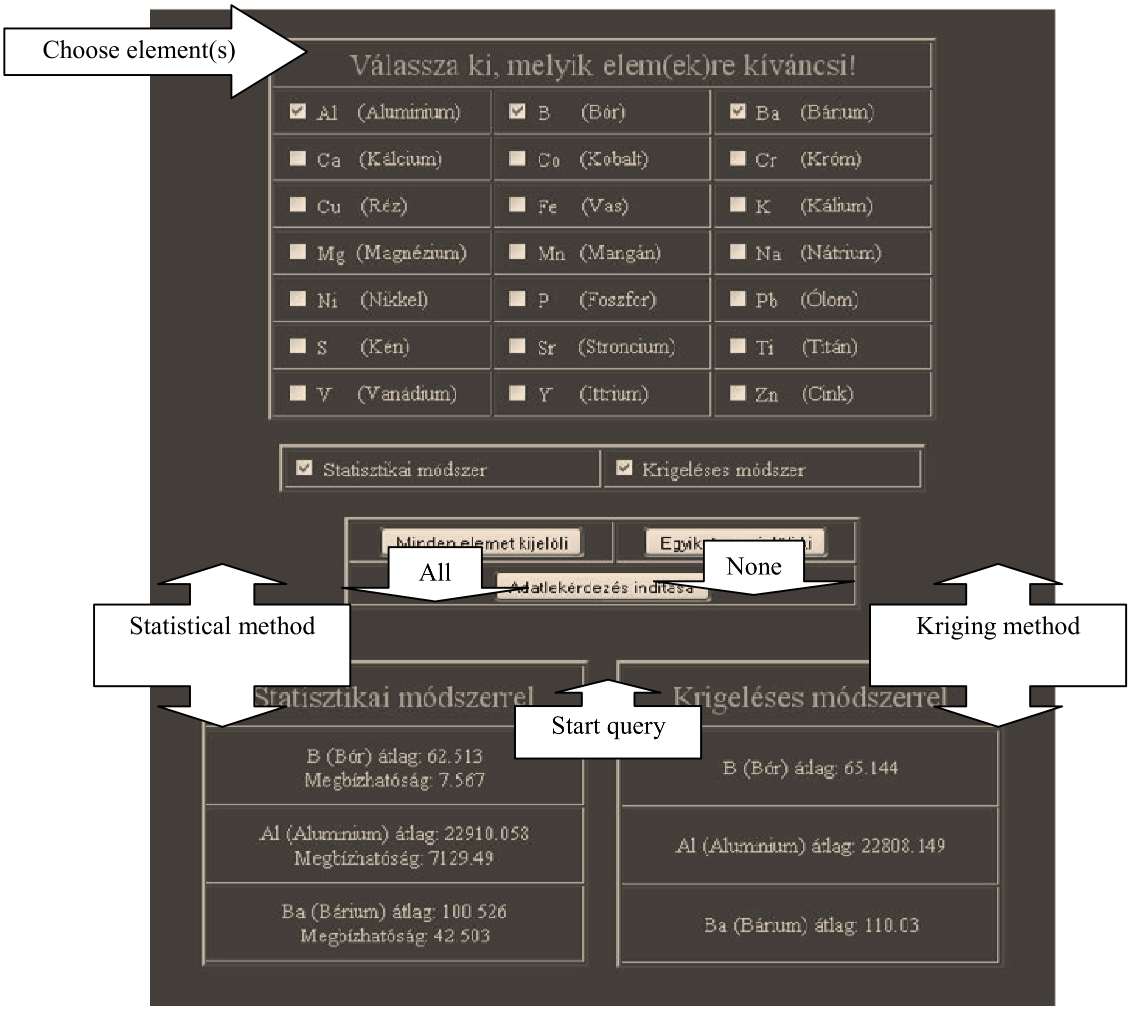

Fig. 1. PHP form to evaluate the concentrations and reliability of the chosen elements based on the GPS-co-ordinates

4.4. Environmental protection expenditure in Europe and Hungary

Environmental protection is defined as all activities directly aimed at the prevention, reduction and elimination of pollution or any other degradation of the environment. Unfortunately we could not find direct data about soil protection, so we could review the environmental protection expenditure. Statistics on environmental protection expenditure present data on the economic resources devoted by resident units to environmental protection. The data cover private and public specialised producers of EP services, the business sector, the general government sector and the household sector. The business sector is further broken down by economic activities. The data are cross-classified by EP classes (e.g. for wastewater management, waste management, protection of biodiversity and landscapes) following the Classification of Environmental Protection Activities.In terms of economic transactions, the following variables are presented: total expenditure, total investments, pollution treatment investments, pollution prevention investments, total current expenditure, internal current expenditure, fees and purchases, receipts from by-products, subsidies/transfers and revenues.

On the Fig. 2 can be seen, that Hungary (black bar) is 7th in the rank from behind the environmental protection expenditure EUR/habitant at the year 2013. We cannot be proud of this result. The three best countries are the following in this order: Norway, Netherlands, and Luxembourg. We can highlight France and Germany, what are 10th and 14th in the rank with not too many environmental protection expenditure.

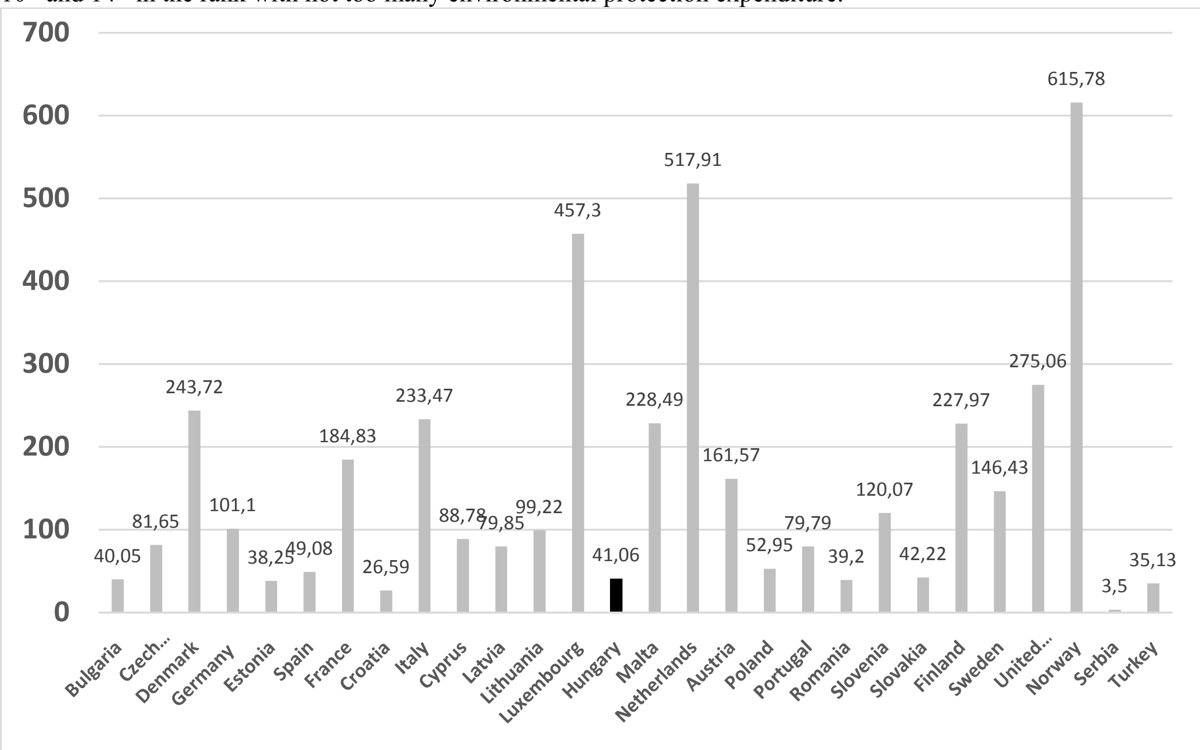

Fig. 2. Environmental protection expenditure in Europe - 2013 (EUR/habitant)

On the Fig. 3 we would like to show how has changed the percentage of GDP for environmental protection expenditure in Hungary between 2004 and 2013.

During the economic crisis, the percentage of GDP for environmental protection expenditure decreased about by half. In 2008 started to increase to 40-45%, but till 2013 have not reached the level of pre-crisis economic level. It seems from the data the Hungarian government has not strategic question the environmental protection.

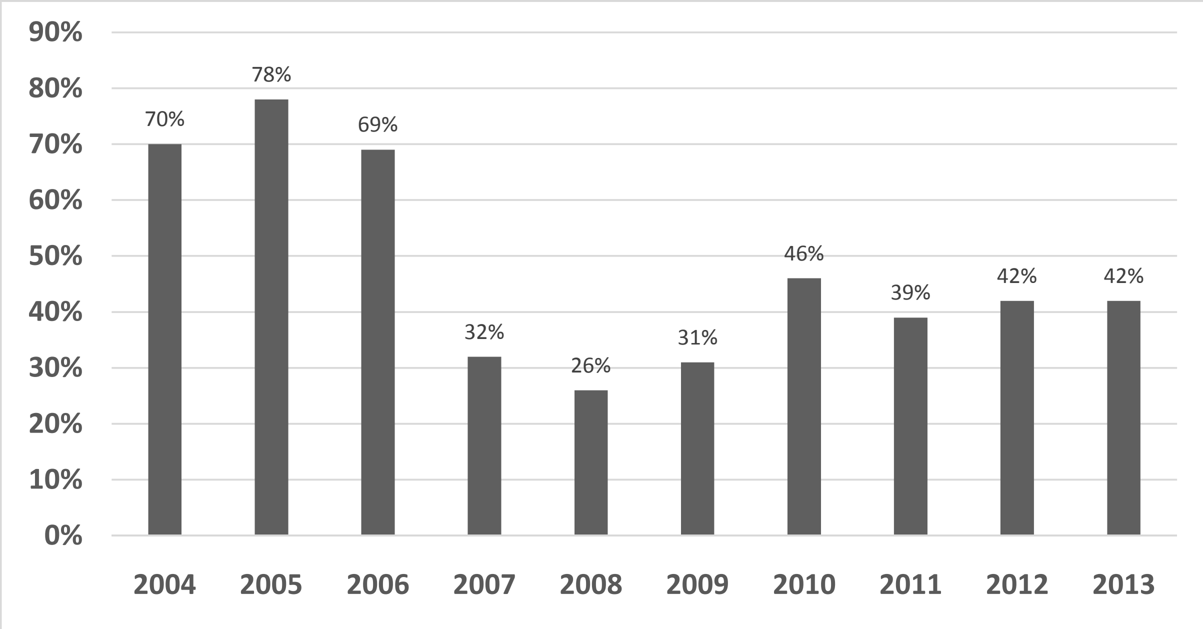

Fig. 3. Percentage of GDP for environmental protection expenditure in Hungary

5. Conclusion

Soil contamination is one of the most widespread types of soil degradation in Europe: 180million ha are affected by pesticides; 170 million ha by nitrates and phosphates; and 85million ha by acidification. These sources concentrate mainly on Central and Eastern European countries.The causes of soil contamination are varied. Hazardous substances are emitted at all stages of the product chain, from the raw material and the production processes, from the use of products and from the handling of products as waste. Emissions can arise from point (industrial) and diffuse (agricultural) sources. The pollutants can reach the soil via dry or wet deposition and direct application of substances such as plant protection agents (pesticides), fertilisers (farmyard manure, mineral fertilisers), the spreading of sewage sludge and compost. Fertilisers and sewage sludge can also contaminate soil with heavy metals.

The Soil Information Monitoring territorial measuring grid consists of 1236 measuring points (selected exactly defined by geographical coordinates using GPS). These points are representatives. Distribution of the points by soil types represents the variety of soil types of the country.There were 865 points on agricultural land, 183 points in forests and 189 points in environmentally threatened "hot spot" regions. We get information only from 1236 points in Hungary that is why important to develop a statistical based soil information monitoring system, where can be estimated the concentration of specific elements in the soil profile based on the given number of neighbouring points and confidence.

The system developed on statistical data could be suitable information system for the management for determine the element concentrations in a well-defined precision. To determine the concentration of the elements, only the GPS coordinates of the place are needed.

Based on the available data, the developed program makes it possible to estimate element content at a certain diagnostic point with some statistical errors; it can also be applied in analyzing effects of environmental pollution. Using by kriging method in the case of the most elements we need 10 nearest neighbouring points have to be considered in order to estimate the element content with the smallest error. It is interesting, in the case of K, P and Sr the results were the same (10 nearest neighbouring points) in the case of the developed statistical method.

After the development of the information system was reviewed how much is spent on environmental protection some European countries. We could not find data about directly soil protection in the Eurostat database, but we thought it is possible deduce for this based on the environmental protection spent.

Based on the Eurostat data Hungary is 7th in the rank from behind the environmental protection expenditure EUR/habitant at the year 2013. We cannot be proud of this result. The three best countries are the following in this order: Norway, Netherlands, and Luxembourg. We can highlight France and Germany, what are 10th and 14th in the rank with not too much environmental protection expenditure.

During the economic crisis, the percentage of GDP for environmental protection expenditure decreased about by half. In 2008 started to increase to 40-45%, but till 2013 have not reached the level of pre-crisis economic level.

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