Available online at www.sciencedirect.com
ScienceDirect
Chemometrics and Intelligent Laboratory Systems 88 (2007) 3 – 10
Chemometrics and intelligent laboratory systems
www.elsevier.com/locate/chemolab

Ecological assessment of landfills with multivariate analysis — A feasibility study

E.V. Mikhailov [a,*], O.V. Tupicina [a], D.E. Bykov [a], K.L. Chertes [a], O.Ye. Rodionova [b], A.L. Pomerantsev [b]

[a] *Samara State Technical University, Molodogvardeyskaya Str., 244, Samara, 443100, Russia*
[b] *Institute of Chemical Physics, Kosygin Str. 4, Moscow, 119991, Russia*

Received 3 April 2006; received in revised form 8 November 2006; accepted 13 November 2006
Available online 23 January 2007

Abstract

Methods of multivariate data analysis are applied for ecological monitoring of the landfills. Traditional waste management approach often fails to reveal the specific areas within a landfill due to the complexity of geometrical configuration and variety of degradation processes. The present investigation is based on three different man-caused formations in the Samara region: illegal dump Bezenchuk, poorly run landfill Otradny, and a modern well-run landfill Kinel. Refuse samples are obtained by means of step-by-step drilling. Each sample is characterized by several measured variables such as depth, temperature, humidity, ash content, volumetric weight, and pH. The samples also have a variety of evaluated properties such as age, belonging to a stratum or lens, topsoil, etc., determined by the traditional methods of landfill exploration. Both measured and evaluated data are subjected to PCA and PLS analysis. Chemometric methods give possibility to explore the structure of a landfill, to reveal their specific areas, and to predict evaluated properties using measured data only.

Keywords: PCA; PLS; Landfill

1. Introduction

Numerous illegal garbage dumps appeared around the inhabited localities in Russia in the last decades. These objects are called man-caused formations, or landfills. A typical landfill contains both solid domestic and industrial wastes of all classes of danger. The state of a man-caused formation is formed by the processes of the substances' degradation and their assimilation into the environment. The analysis of these processes aims to predict the current state of a landfill, as well as to work out the proper measures for the landfill reclamation [1].

Landfill evolution passes through different stages. The main way of conversion of wastes into soil is organic substance biodegradation [2]. The intensity of this process depends on various factors: (1) environmental conditions, such as temperature and moisture; (2) formation features, type and volume of refuse and organic composition; (3) ability for biochemical decomposition, etc. [3].

Each landfill consists of various local areas, which cause the heterogeneity of the whole formation. These areas have specific physical and chemical features and create various adverse environmental impacts. Therefore, each area requires special reclamation management actions. The traditional approach used in waste management [1–4] is mainly based on typical univariate kinetic data analysis, where each measured property is considered separately. The conclusions are yielded in comparative exploration, and often intuitively. Such an approach can hardly recognize separated areas in the landfill.

We propose to employ chemometrics based methods for the evaluation of landfill stability expressed in terms of age, or maturity. It is supposed that multivariate approach can provide us with a more efficient data analysis and simplify the areas' separation. The goal of the article is to test the feasibility of multivariate approach in this area. This is reached by the systematic comparison of the results, obtained by traditional methods with those predicted by chemometrics. The analysis is based on the data collected during landfill survey and analytical laboratory measurements.

* Corresponding author.
E-mail address: EvgeniyStat@gmail.com (E.V. Mikhailov).

0169-7439/$ - see front matter © 2006 Elsevier B.V. All rights reserved.
doi:10.1016/j.chemolab.2006.11.006

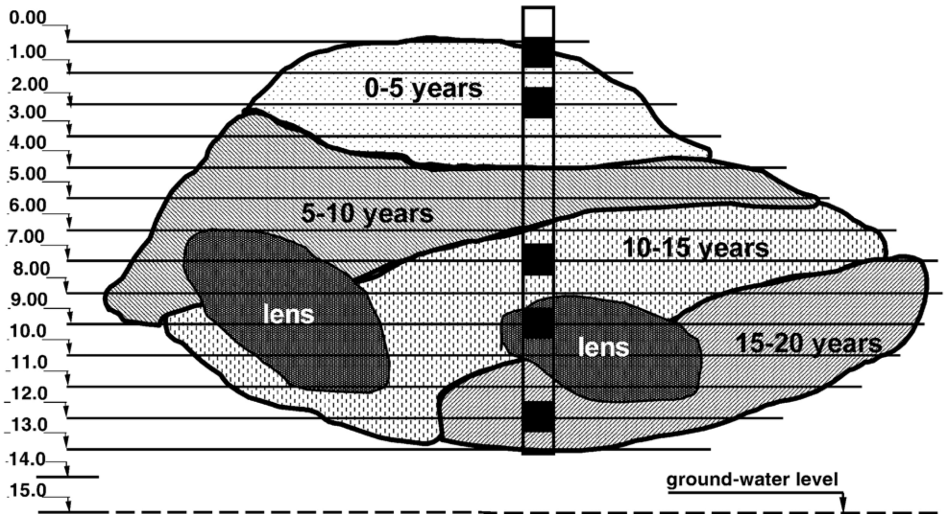

Fig. 1. Vertical section of Bezenchuk landfill with age evaluation. Sewage sludge lenses are highlighted. Drilling hole with samples presented in Fig. 2 is shown.

A landfill study is carried out in several stages. At first, the geodesic survey is performed to obtain the overall object features and properties, such as size, volume, layers, etc. This is called the explorative step, when the initial information is collected. The results of these surveys are presented in Section 2.1. Three totally different man-caused formations are investigated. They form a representative set of various objects, including an illegal dump, an old poorly run dump, and a modern well-run landfill.

During the second stage, the waste substance is explored by the drillhole tests, sampling, and laboratory testing. Physical and chemical properties are measured for the samples collected at different depths. These properties include ash content, humidity, acidity, etc. The data collection technique is presented in Section 2.2.

Experimental data are then analyzed using traditional waste management methods [4,9]. They are based on the waste composting followed by kinetic analysis. Each landfill is separated into specific areas such as sludge lenses, industrial and domestic wastes localities, etc. The approximate value of samples' age is also determined. The traditional kinetic approach is presented in Section 3.1.

Multivariate data analysis is used to explore data structure with PCA and PLS methods [5–7]. The details are described in Section 3.2. Section 4 presents the results and discussion of different case studies.

2. Experimental

2.1. Landfills

The objects under investigation are an illegal dump Bezenchuk, a poorly run landfill Otradny, and a modern well-run landfill Kinel. These three man-caused formations present the most typical landfill types in the Samara region.

Bezenchuk dump is about 25 years old. The field reconnaissance revealed two large sources of wastes in this region, a poultry farm and a granary. In addition to regular domestic refuse, the agricultural and industrial wastes were disposed illegally in this dump. They form two sewage sludge lenses that are shown in Fig. 1. This landfill is located on the flat relief without any isolation layer or consolidation. The loose organo-mineral wastes are subjected to a rather rapid aerobic degradation even before self-consolidation and anaerobiosis. The temperature of the bulk mass is variable due to rapid heating in summer and freezing in winter.

Kinel represents an example of a modern, well-run landfill, in which both the domestic and industrial wastes are disposed. It is formed by well separated parts and layers. The domestic wastes are placed in the compacted layers which have similar depth in the landfill plan. These layers are covered by industrial wastes (oil polluted soil, sewage sludge, etc) pretreated to reduce the environmental impact. At present, the landfill is filled only partly. Its total depth is less than 10 m, and the area is about 260 thousand square meters. The bulk consists of four condensed layers; with the depth of 2–2.5 m each.

Otradny landfill is about 45 years old. During its exploitation the types and amounts of disposed wastes, as well as the technology of disposition permanently changed. This results in high heterogeneity of the waste mass.

The main characteristics of the investigated landfills are collected in Table 1. They were evaluated by the methods of engineering geodesy and geology [8].

Table 1
Landfills under study

Object name	Type of management	Age	Protection system	Type of wastes	Waste volume $\times 10^3$ m^3	Area, $\times 10^3$ m^2	Number of samples
Bezenchuk	Illegal dump	25	No	Municipal, agricultural industrial	90	60	123
Kinel	Modern well-run landfill	15	Yes	Municipal, industrial	960	260	105
Otradny	Poorly run landfill	45	No	Municipal	300	86	84

2.2. Sampling and measurements

Landfills were sampled, and refuse was collected and shipped to the Samara State Technical University for analysis. Waste samples were collected from the landfills during 2000–2004 years employing traditionally used procedures [4]. Samples of the waste bulk and topsoil were gathered by means of the step-by-step bore-hole drilling consequently from various depths. The drilling depth step is equal to 1 m.

Gadding in Otradny and Kinel landfills was carried out during the warm seasons, while at Bezenchuk dump some additional sampling was performed in winter in order to measure the waste bulk temperature. The depth of each hole was determined at drilling. This allowed us to assess the borders of the landfills and their depths. The drilling depth ranged within the following limits: Bezenchuk — 0.3–13.0 m; Otradniy — 0.3–7.0 m; Kinel — 0.5–10.0 m. Refuse samples were obtained both as the unbroken and arenaceous cores with the mass of 1.5–3.0 kg. Sample temperature was measured in the field, while other properties such as ash content, humidity, and volumetric weight were measured in a laboratory using standard analytical methods [9]. For Otradny landfill acidity (pH) was additionally obtained from the aqueous extract.

Preliminary explanatory analysis of various sample properties has shown that changes in ash content, volumetric weight and temperature are the most significant characteristics of the landfill state in comparison to other features.

3. Methods

Two different methods are used in the investigation. They are the traditional kinetic and new chemometric approaches to the waste management. Both methods provide similar results, so the chemometrics approach allows us to confirm the results obtained by the traditional approach and also make the whole investigation procedure clearer and simpler.

3.1. Traditional kinetic approach

There are no analytical methods for direct evaluation of the refuse age. The traditional solution of this problem is based on the kinetic investigations, in which samples are subjected to accelerated aging (composting) [9]. The experiment is performed on the surface of an open experimental ground, protected from atmospheric perspirations. Each sample is subjected to the aerobic composting for 4–5 months, starting in May. During this period, the special conditions that are auspicious for the aerobic biochemical degradation are provided. Namely, sample humidity is kept within the range 60–70% by repeated wetting. To maintain the suitable aeration conditions, each sample is intermixed two times a week. Every 10 days the composted mass is sampled and analyzed for the organic content.

Some results of these aging tests are shown in Fig. 2, in which both experimental (dots) and fitted (curves) values are presented. All these samples were taken from the same drillhole at various depths. The consumption of the organic content during composting can be modeled by the first order reaction, i.e.

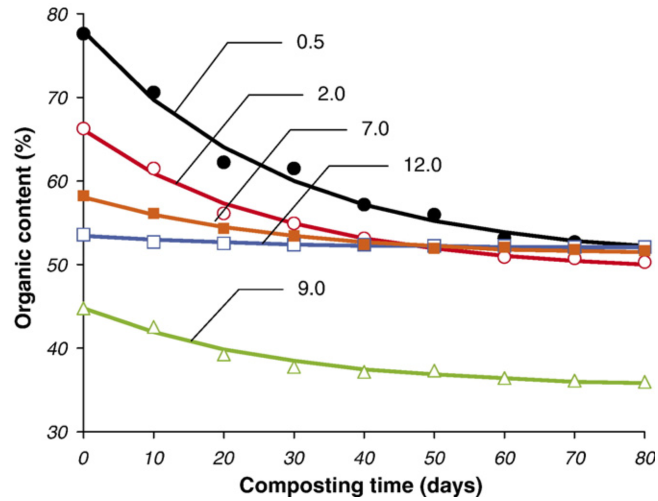

Fig. 2. Composting test. Experimental and fitted values. Number represents the depth, from which the sample was taken.

$$C = (C_0\text{-}B_0)\exp(\text{-}kt) + B_0 \tag{1}$$

The constant rate, k, can be estimated as a common parameter for all samples. This agrees with the basic concept that biodegradation is a thermo-oxidation process. Both C_0 and B_0 parameters, representing the initial and equilibrium values of organic content, are specific for each sample. Model (1) has been estimated using the Fitter software [10]. The results are shown in Fig. 2.

To evaluate the sample age the following assumptions should be made. Firstly, it may be supposed that the waste degradation in a landfill also follows the first order reaction, i.e.

$$A = (A_0\text{-}B_0)\exp(\text{-}Kt) + B_0, \tag{2}$$

where A is the organic content during the natural degradation and A_0 is the initial value of the organic content at the landfill. The constant rate, K, in Eq. (2) differs from the constant rate k in Eq. (1). Secondly, it may be assumed that the equilibrium values of the organic content in Eq. (1) and Eq. (2) have the same value, B_0. Applying these considerations we obtain the following equation

$$C_0 = (A_0\text{-}B_0)\exp(\text{-}KT) + B_0, \tag{3}$$

that connects the sample initial organic content C_0 with the sample age T. This equation can be solved with respect to T

$$T\frac{1}{K}\ln\left(\frac{A_0\text{-}B_0}{C_0\text{-}B_0}\right) \tag{4}$$

Then, supposing that the initial organic content in the landfill, A_0, is known, it is possible to calculate the ratios T_1/T_2 for each pair of samples using the estimated values of C_0 and B_0. At last, it is necessary to have a “standard sample”, which age is known, say T=1. Thus, we can evaluate all other sample ages. Ages of the samples shown in Fig. 2 were estimated as 1, 5, 10, 10, 20 years (in depth order).

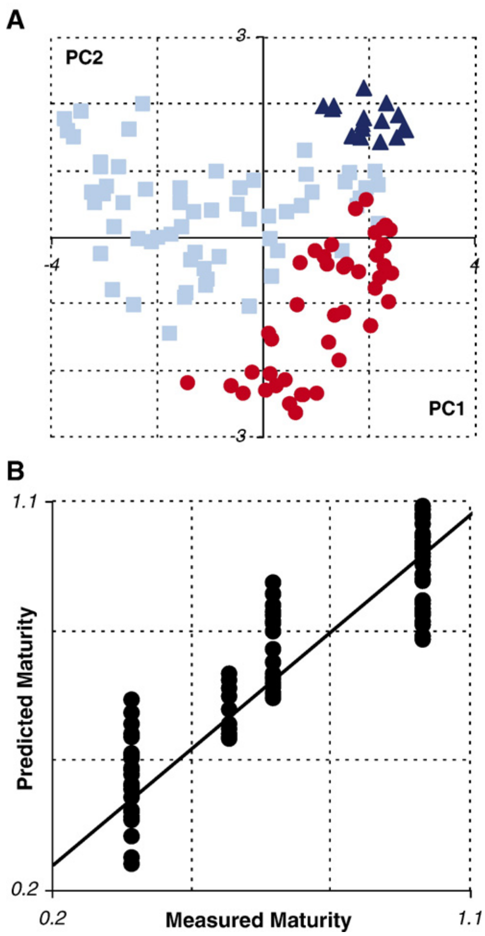

Fig. 3. Bezenchuk data. PCA scores plot (▲) — sewage sludge samples, (●) — topsoil samples, (■) — refuse samples. Short PLS model with 2 components. Predicted vs. measured. Y-maturity value.

The weakest point of the kinetic method is evaluating of the initial organic content A_0. It is clear that A_0 cannot be less than C_0 for the object sampled from the depth = 0.5 m, and at the same time it cannot exceed 100%. The value of A_0 equal to 82% was used for the age evaluation. It is important that initial organic content may occasionally vary in some specific areas of the landfill, e.g., in the sewage sludge lenses. Such a case is observed in Fig. 2, for the series of data obtained at the depth of 9.0 m. This kinetics demonstrates irregular behavior with respect to other curves presented in the plot. Therefore, it may be supposed that this sample was taken from a lens, in which the initial organic content was relatively higher. Taking this into account, the sample age can be evaluated as 15 years. Simultaneously, the position of the lens is revealed.

Fig. 1 shows a vertical profile of Bezenchuk landfill and the drilling hole where the samples were collected from. Highlighted areas were derived from the analysis of composting tests with subsequent kinetic modeling [11]. One can see that the sample taken from the depth of 9.0 m belongs to the lens. As accuracy of this method is about 5 years, only averaged aging areas are delimited.

In this section we presented just a brief overview of the kinetic approach. A more detailed description will be given in a new paper, which is at the moment in progress. However, it may be concluded that the traditional kinetic approach to the landfill exploration is labor intensive and not economical. Using doubtful assumptions the method has a low accuracy.

3.2. Chemometric approach

For the chemometric approach the feature matrix **X** is formed for each landfill. The number of **X** rows is equal to the number of samples obtained at a landfill. The matrix columns correspond to the measured and evaluated sample properties. The first X-block, termed as **X1**, comprises the measured properties, which are ash content, temperature, volumetric weight, pH, humidity, and depth. The second block termed as **X2**, includes the features evaluated by the traditional methods, explained in Section 3.1. They are presented as indices marking that a sample belongs to some ground stratum such as lens, layer, topsoil, etc.

Another evaluated property is sample age. This, however, is an ambiguous value, which can be considered for the waste only, not for topsoil. Therefore, it is proposed to replace the age with another characteristic called *the maturity*, which is calculated as follows

$$M_1 = 1\text{-exp}(-mT_1), \tag{5}$$

where M_i is the maturity of sample i, T_i is the age of sample i, and m is the constant. Such a transformation could be considered as a data pre-treatment procedure, in which variable T is replaced with variable M. In this case, constant m should be obtained as the value that gives the best linearization (the t–u relationship) in PLS modelling. On the other hand, constant m is naturally connected to the degradation rate constant K introduced in the previous section. These considerations will be presented in detail in a new paper that is in preparation. For the moment, we just claim that this constant equals $m=1/15$ for Bezenchuk, and $m=1/5$ for Otradny.

One can see that the maturity of topsoil is equal to one, while the maturity of new refuse equals zero. The maturity feature is used in Bezenchuk and Otradny datasets, because these objects have no environmental protection systems, and the samples collected at such landfills may have been originated not only from the waste bulk, but from topsoil as well. On the contrary, Kinel landfill has a protection system; the waste layers are sandwiched with clay layers. There is also a plastic liner on the bottom of the landfill, so all samples from Kinel can be featured by the age, and no maturity transformation

Table 2
Short and full PLS model for Bezenchuk

PC	Short model			Full model		
	RMSEC	RMSEP	cor(t,u)	RMSEC	RMSEP	cor(t,u)
1	0.155	0.159	0.87	0.096	0.098	0.99
2	0.122	0.126	0.62	0.074	0.076	0.65
3	0.109	0.115	0.43	0.061	0.064	0.57
4	0.108	0.115	0.11	0.058	0.062	0.25

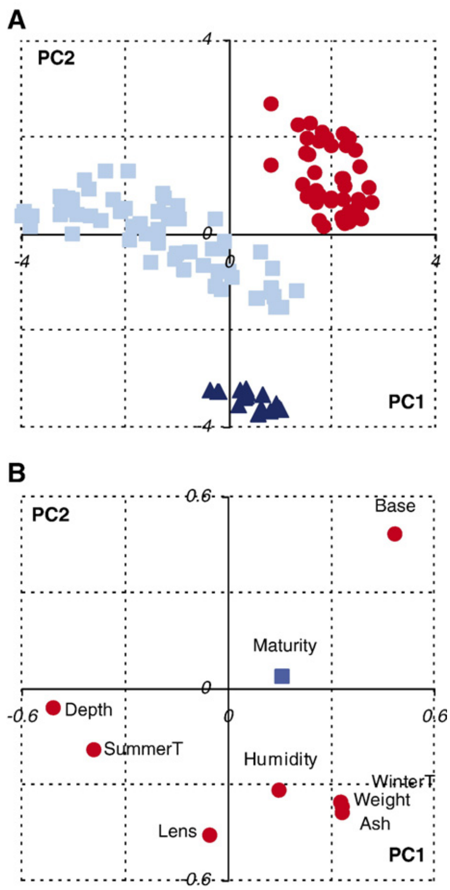

Fig. 4. Bezenchuk data. Full PLS model. Scores (A) and loading weights (B) plots PC1 vs.PC2. (▲) — sewage sludge samples, (●) — topsoil samples, (■) — refuse samples.

is needed. For PLS modeling, the age or maturity is treated as the response variable **Y**.

Before processing, the standard data pretreatments are carried out including column-wise centering and scaling to unit variance.

Each data set is analyzed in two stages. At first, the PCA model is constructed using **X1** block only. This model is employed to reveal the sample groupings and patterns, which may be connected with **X2** block of evaluated variables. At the second stage two PLS regressions are built to predict the sample age, or the maturity. The short PLS model is constructed using block **X1** as predictors. The expanded **X** matrix (**X1**, **X2**) is used to obtain the full PLS model. Comparing the results obtained with both PLS models it is possible to understand the necessity of the additional evaluated variables, such as stratum indices collected in **X2** block.

The PCA and PLS scores plots are used to distinguish different areas inside each landfill graphically. Joint analysis of scores and loadings plots helps to reveal the influence of different variables on sample grouping and age prediction. The aim of the paper is to explore the possibility to use the multivariate data analysis for the landfills management. Therefore all models are validated with the random 10% out cross-validation. For model evaluation and comparison we use the coefficient of correlation between the *t*- and *u*- PLS scores, the root-mean square error of calibration (RMSEC), and the root-mean square error of prediction (RMSEP), which is calculated by cross-validation [5].

4. Results and discussion

4.1. Case study 1. Bezenchuk

Bezenchuk data set includes 123 samples. The **X1** block comprises six analytical variables. They are depth, ash content, volumetric weight, humidity, refuse temperature in summer (indicated as Summer T), and refuse temperature in winter (indicated as Winter T). The **X2** block includes two variables, which are the topsoil and the sewage sludge lenses indices. The PCA model with two PCs built using **X1** block explains 88% of the total variance.

The first goal of this study is to reveal the specific areas such as the sewage sludge and topsoil using only measured variables. Corresponding sample groupings can be clearly seen in scores plot in Fig. 3A, where the sewage sludge (triangles) and topsoil (circle) samples are highlighted.

Thus PCA detects specific areas inside the landfill using only objective information and confirms inferences that have been drawn by the traditional analysis.

Two PLS models are used for the maturity evaluation. The first one, termed as the short model, uses **X1** block (123 × 6) as predictors and the maturity **Y** as a response. In the full model the predictor matrix is expanded by the evaluated variables, i.e. by block **X2**. Both regressions employ three PLS components. This model complexity can clearly be seen from Table 2 in which some essential regression characteristics are presented.

It should be also mentioned that the supplement of the evaluated properties (**X2** block) to the predictor matrix does not give an essential gain in the prediction accuracy. The maturity prediction with the short model is presented in Fig. 3B.

The results of the PLS analysis for the full model help in a more detailed investigation of the interdependence of various properties. The scores and loading weights plots are presented in Fig. 4. Simultaneous analyses of the two plots reveal that such variables as humidity and summer temperature have a principal influence on the lens grouping. The maturity value mainly correlates with depth, base index, and summer temperature.

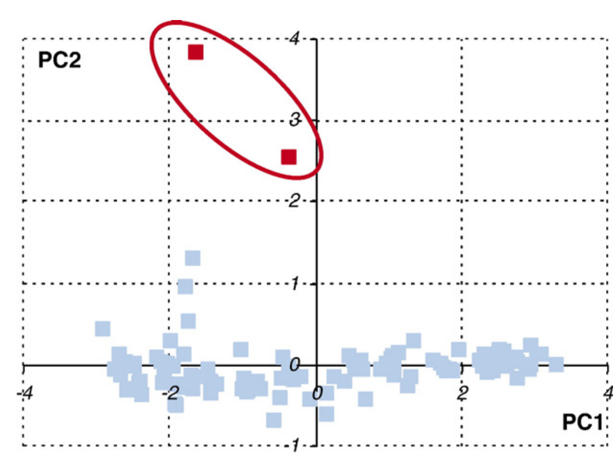

Fig. 5. Kinel data. PCA analysis on **X1** block. Scores plot PC1 vs. PC2. Two outliers are marked.

Table 3
Short and full PLS model for Kinel

PC	Short model			Full model		
	RMSEC	RMSEP	cor(t,u)	RMSEC	RMSEP	cor(t,u)
1	0.088	0.090	0.96	0.069	0.070	0.98
2	0.081	0.085	0.41	0.041	0.043	0.80
3	0.079	0.083	0.17	0.035	0.037	0.53
4	0.079	0.083	0.01	0.033	0.035	0.33

Table 4
Short and full PLS model for Otradny

PC	Short model			Full model		
	RMSEC	RMSEP	cor(t,u)	RMSEC	RMSEP	cor(t,u)
1	0.107	0.111	0.90	0.115	0.120	0.88
2	0.098	0.104	0.41	0.097	0.104	0.53
3	0.097	0.105	0.14	0.094	0.105	0.26
4	0.097	0.105	0.01	0.093	0.104	0.11

Thus, it can be seen that the PCA modeling can reveal the lens and topsoil groups using only measured variables (block **X1**), and that the PLS regression based on **X1** block provides the acceptable prediction of maturity only.

4.2. Case study 2. Kinel

Kinel data set consists of 105 samples. The **X1** block (105×4) comprises the following variables: ash content, volumetric weight, refuse temperature (in summer), and depth. Block **X2** consists only of one variable, which indicates the affiliation of a sample with one of four waste layers. We term this variable as the layer index. As Kinel is a well-run landfill, the depth values and the number of layers are known a priori from the records kept for this landfill. Thus the layer index is not an evaluated variable as in the previous case. Due to the same reasons, there is no need for age/maturity variable transformation, so the response variable **Y** is age.

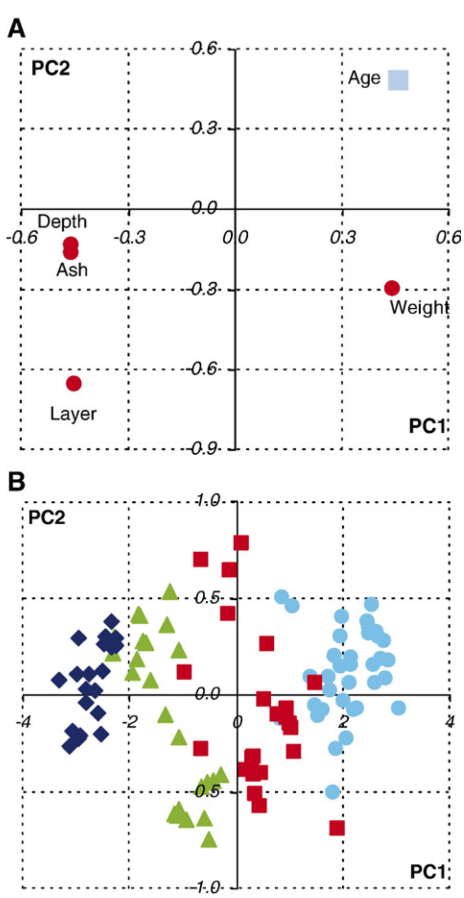

Fig. 6. Kinel data. Full PLS model. X- and Y weight loading plot. Short PLS model. Scores plot Four sample groups represent different layers.

The exploratory data analysis of block **X1** by PCA method reveals two evident outliers (Fig. 5). In section 2.1 it was mentioned that this landfill contains layers of industrial wastes, and these two samples belong to one of them. So, PCA allows us to distinguish between the industrial and domestic wastes in this example. Kinel data are further explored without these outliers.

To investigate the interference between various variables, a PLS2 model with **X1** block as predictors and **X2** block as response is established. Two PLS2 components explain 97% of **X1**-variance and 91% of **X2**-variance. Joint **X1**- and **X2**- loading weights plot shows that the layer index highly correlates with the ash content and depth.

To predict age **Y** two PLS models are built. The short model uses **X1** as predictors and the full model employs joint matrices **X1** and **X2**.

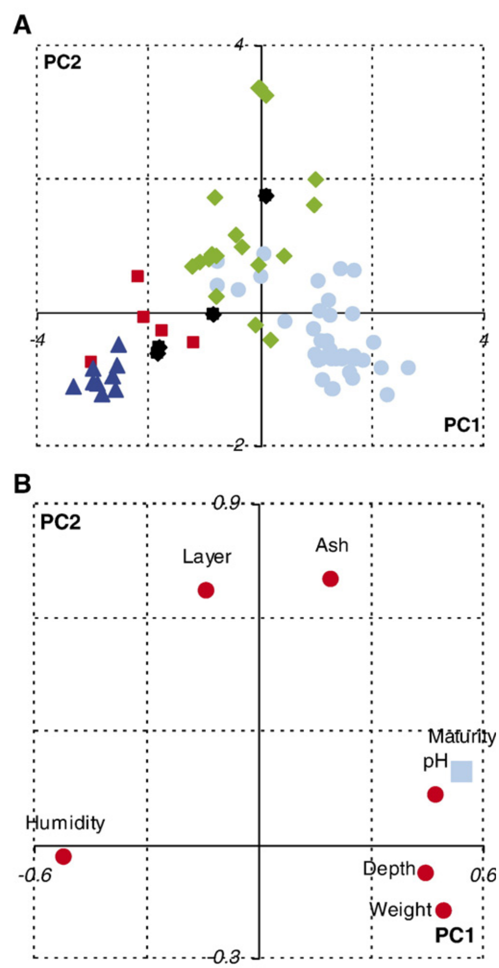

Fig. 7. Otradny case. Full PLS model. PLS score plot with layers highlighted. PLS loading weights.

Table 5
Overall comparison of PLS models

	Based on X1 variables		Based on X1+X2 variables	
	RMSEC	RMSEP	RMSEC	RMSEP
Bezenchuk	0.109	0.115	0.061	0.064
Kinel	0.081	0.085	0.041	0.043
Otradniy	0.098	0.104	0.097	0.104

Both regression models employ two PLS components. This complexity can be drawn from Table 3 in which essential regression properties are shown.

In the previous case we predicted the maturity value that naturally changes between 0 and 1. To facilitate the comparison between these two cases we also scaled the Kinel age variable within the same range. Such a comparison reveals no evident advantages in the age prediction of a well-run Kinel over illegal Bezenchuk dump. It can be also seen that the supplement variable, layer index, essentially improves the age prediction. There is a high negative correlation between variables 'Age' and 'Layer' (see Fig. 6A). This can easily be explained as Kinel is a landfill with the clearly vertical layer structure that was systematically generated in a regular way. Four groups of samples corresponding to different layers are also revealed by the short PLS model where the layer index is not used. Scores plot (PC1-PC2) shows this sample grouping (Fig. 6B).

The age prediction seems to be needless for the well-run landfills when the terms of formation are known a priori. On the other hand, due to the heterogeneity of the domestic waste composition, biodegradation processes may proceed irregularly [3]. The examination of the relationships between age and the measured properties gives a possibility to specify the stability status and thus helps in further landfill management.

4.3. Case study 3. Otradny

Otradny data set includes 84 samples. The **X1** (84×5) block variables are: ash content, volumetric weight, depth, humidity, and pH. The estimated features are the layer index (block **X2**), and age (block **Y**). This landfill has an irregular structure since it was formed and filled disorderly for a long time. Therefore, the layer index can not be trusted enough. PCA based on block **X1** confirms this claim, as there is no clear layer's separation in the scores plot. PLS2 modeling **X1** → **X2** that was very useful in Kinel case also yields no interesting results.

In this case the maturity variable, given by Eq. (5), should be used again. Two PLS regressions, which are the short model (using block **X1**) and the full model (using block **X1**, **X2**), are established for this purpose. Both models employ two PLS components. The details are presented in Table 4.

Both models explain the equal rate of 75% in the predictor blocks, and the same variation of 84% in **Y** block. The RMSEP and RMSEC values are also similar.

In Fig. 7, the results for the full PLS model are presented. In the loading weights plot (b) the evident orthogonality between the maturity variable and the layer index is observed. This explains why the short and full models are so similar. No clear separation of sample layers can be seen in PLS score plot that is shown in Fig. 7A.

Concluding this case study it may be claimed that for a poorly run landfills the prior authorized information regarding its structure, properties, and age could be confusing and misleading. To get reliable information regarding a landfill status, the objective instrumental data should be thoroughly collected and analyzed.

5. Conclusions

Landfill stabilization is a long process. Moreover, the point at which waste is completely degraded and the landfill becomes stable still has not been clearly defined. The possibility of the detailed landfill exploration and monitoring is especially important in the light of new technology that increases the rate of biological activity and helps to shorten the term of landfill stabilization. Analytical and kinetic methods based upon the univariate data analysis help to determine the landfill waste composition and to evaluate its degree of degradation. Nevertheless, there are no strict rules and such an approach is mainly based on the researcher's experience and intuition. It is also very time and labor consuming.

The exploration of three landfills of different types confirms the appropriateness of the multivariate data analysis for the ecological monitoring. Chemometric methods give a possibility to explore the structure of waste fields, reveal the specific areas and strata and predict evaluated properties using measured data only. Score and loading plots help to reveal the important patterns and interesting structures. The sample stability, or maturity, has been predicted by PLS regression. The obtained results in most cases agree with traditional methods of landfill exploration.

The additionally estimated information termed block **X2** in all the abovementioned examples requires a special comment. Due to the general chemometric concept any prior knowledge that helps to understand the data structure and process under consideration should be taken into account. On the other hand, this information should be used with care. In the first example, the conclusions regarding the dump structure and the lenses positions were conformed by the PCA results. However, this additional information gives a small gain in prediction of the landfill maturity (Table 2). The same situation may be observed in the third example. This is the case mainly due to the fact that poorly run landfills have no regular structure, layers of different ages are mixed and the discovery of separate areas as in Bezenchuk example may be considered to be mere luck. For a well-run formation additional information significantly improves the prediction ability of the model. Table 5 provides the overall comparison of the PLS models based on different predictor variables.

Though each sample is characterized only by 5–6 variables, they are highly correlated, thus the multivariate data analysis provides interesting information. On the other hand in the future more analytical parameters [1] should be measured for a detailed study of refuse properties. Therefore, the general finding of this research is that chemometric based approach is undoubtedly helpful for landfill exploration and such an approach deserves further investigation.

References

[1] R.J. Kelly, B.D. Shearer, J. Kim, C.D. Goldsmith, G.R. Hater, J.T. Novak, Relationships between analytical methods utilized as tools in the evaluation of landfill waste stability, Waste Management 26 (2006) 1349–1356.

[2] R.K. Ham, M.R. Norman, P.R. Fritschel, Chemical characterization of fresh kills landfill and refuse, Journal of Environmental Engineering, ASCE 119 (6) (1993) 1176–1195.

[3] W.E. Eleazer, W.S. Odle III, Y. Wang, M.A. Barlaz, Biodegradability of municipal solid waste components in laboratory-scale landfills, Environmental Science and Technology 31 (3) (1997) 911–917.
[4] A.G. Shmal, Russian Echological Bulletin, vol. 5, 2001, pp. 47–54 (in Russian).
[5] H. Martens, T. Naes, Multivariate Calibration, Wiley, New York, 1998.
[6] A. Höskuldsson, Prediction Methods in Science and Technology, Thor Publishing, Copenhagen, Denmark, 1996.
[7] K.H. Esbensen, Multivariate Data Analysis — In Practice, 4-th Ed, CAMO, 2000.
[8] Russian State Standard, GOST 17.4.4.02–84.
[9] K.L. Chertes, D.E. Bykov, O.V. Tupicina, N.N. Enduraeva, Russian Ecology and Industry, vol. 9, 2002, pp. 18–19 (in Russian).
[10] Fitter Add-In., http://polycert.chph.ras.ru/fitter.htm [1 May 2006].
[11] O.V. Tupicina, PhD Thesis, Samara State University, 2006 (in Russian).