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# High Variation Topsoil Pollution Forecasting in the Russian Subarctic: Using Artificial Neural Networks Combined with Residual Kriging

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**Abstract.** The work deals with the application of artificial neural networks combined with residual kriging (ANNRK) to the spatial prediction of the anomaly distributed chemical element Chromium (*Cr*). In the work, we examined and compared two neural networks: generalized regression neural network (GRNN) and multi-layer perceptron (MLP) as well as two combined techniques: generalized regression neural network residual kriging (GRNNRK) and multi-layer perceptron residual kriging (MLPRK). The case study is based on the real measurements of surface contamination by *Cr* in subarctic city *Novy Urengoy, Russia*. The networks structures have been chosen during a computer simulation based on a minimization of the root mean square error (RMSE). Different prediction approaches are compared by a Spearman's rank correlation coefficient, the mean absolute error (MAE), and RMSE. MLPRK and GRNNRK show the best predictive accuracy comparing to kriging and even to MLP and GRNN, that is hybrid models are more accurate than solo models. The most significant improvement in RMSE (15.5% compared to kriging) is observed in the MLPRK model. The proposed hybrid approach improves the high variation topsoil spatial pollution forecasting, which might be utilized in the environmental modeling.

**Keywords:** Chromium, Artificial Neural Networks, Combined modeling, GRNNRK, MLPRK

## 1. INTRODUCTION

Rapid industrialization over the last decades has significantly contributed to the environmental contamination in Arctic and Subarctic regions of Russia. The environment components such as air, snow, water, soil, biota, bottom sediment etc. are considered as recipients of large amount of contaminants from the multiple sources and, thus, might be used for studying the nature and features of the pollution (Saet et al., 1990). Soil pollution, particularly at urban locations, is considered as an important risk factor due to the health and environment hazards. Studies on the impact of urban environment on the soil pollution in the Arctic and Subarctic became important field of geochemical researches. A significant heterogeneity of spatial distributions of geochemical spectra has been detected in preliminary analysis of empirical data for the various functional and geographic areas (Chukanov et al., 2006). The data being obtained in monitoring of urban territories strongly depend on relative position and intensity of emission sources as well as on building features, meteorological and hydrological conditions, climate variability and other factors. These processes and factors may cause the spatial heterogeneity and sometimes anomalies of the pollution and contaminants distributions (Zhang et al., 2008; Sergeev et al., 2010; Guo et al., 2012; Sergeev et al., 2015).

It is essential to have a model that is able to precisely predict the distribution of pollutants within analyzed territory. Modelling facilitates the localization and delineation the pollution sources. Interpolation is one of the most widely used modeling methods. Generally, there are two main types of spatial interpolation methods in use:

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