

Spatial distribution prediction of agro-ecological parameter using kriging

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Abstract. In modern agroecology, one of the most pressing problems is the problem of spatial data mapping. The development of information technology opens up a wide range of approaches for solving this problem. One of these approaches is based on the use of geostatistical methods. This study was carried out with the aim of developing ideas about the applicability of the ordinary kriging method for predicting the spatial distribution of the agro-ecological indicator with identifying the boundaries of in-field heterogeneity according to remote sensing data. For the model computational experiment, aerial photographs of the agricultural field in the red and near infrared ranges were used, which made it possible to obtain sets of uniformly distributed values of the vegetative index NDVI that were randomly generated. The high spatial resolution of the images allowed us to analyze the observational data for the studied agricultural field.

1 Introduction

In studies aimed at developing a forecast of the spatial distribution of various agro-ecological indicators, mainly methods for processing remote sensing data (RSD) are used, as well as geostatistical methods. Among the methods of image analysis in solving forecasting problems, two main directions are distinguished: the analysis of spectral brightness coefficients (SBC) or color characteristics of the image pixels, as well as image analysis using vegetation indices. At the end of the twentieth century, studies were carried out to assess the state of plants based on an analysis of the spatial distribution of the characteristics of crops using aerial photography [1, 2]. At present, hyperspectral images have begun to be used to solve such problems [3]. One of the new directions in this area is the use of binary regression [4, 5]. More studied areas include geostatistics, which allows

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mapping the nutrient content in the soil and other indicators for optimal farm management [6-8]. It should be noted that the ordinary kriging method is traditionally used from geostatistical tools to predict the spatial distribution of various agro-ecological indicators [9-11]. The purpose of this study is developing the ideas about the applicability of the ordinary kriging method for predicting the spatial distribution of agro-ecological indicators with the identification of the in-field heterogeneity boundaries according to remote sensing data.

2 Materials and methods

2.1 General information about the biofield

An experimental field (biologic polygon) of the Agrophysical Research Institute is located in the southwestern part of the Leningrad Region in the village of Men'kovo (60 km from St. Petersburg). The territory of the biologic polygon belongs to the most common agricultural lands in the North-West Region of Russian Federation in terms of the combination of basic characteristics (agrometeorological indicators, soil, landscape, etc.) [12]. The territory of the Leningrad Region is characterized by excessive moisture and difficult hydrogeological conditions, which, in turn, leads to the soils formation of varying degrees of hydromorphism, that are very different in their hydrophysical properties [13-17]. The land area of the biologic polygon is 538.56 ha, of which agricultural land covers 444.89 ha. The main crops on the landfill are cereals, potatoes and perennial herbs.

2.2 Vegetation Index NDVI (Normalized Difference Vegetation Index)

It is proposed to use the values distribution map of the vegetation index NDVI during the conducting model experiments and analyzing the possibilities of using the kriging method for predicting the spatial distribution of agro-ecological parameters. As the initial data, images of an agricultural field located on the biologic polygon of the Agrophysical Research Institute (field No. 26) are used in red (RED) and near infrared (NIR) ranges. The mapping of the distribution of NDVI values is performed in the QGis program using the Raster Calculator tool according to the Eq.1:

$$\text{NDVI} = (\text{NIR} - \text{RED}) / (\text{NIR} + \text{RED}) \quad (1)$$

2.3 Kriging method

For spatial interpolation of the agro-ecological parameter (in the model examples, the values of the NDVI index), it is proposed to use ordinary kriging as the widely used and studied method of geostatistics [18], which takes into account the spatial statistical structure of the studied parameter.

First of all, using the semivariogram, the spatial correlation of the studied variable is determined, which is estimated on the basis of the experimental sample [19], Eq.2:

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [Z(x_i) - Z(x_i + h)]^2, \quad (2)$$

where $\gamma(h)$ is the value of the variogram at a distance h , $Z(x_i)$ is the value of the studied agro-ecological parameter at location x_i , $N(h)$ is the total number of experimental pairs of points at a distance h . Based on the experimental graphic display, a theoretical variogram model is selected.

The geostatistical methods for estimating the distribution of the parameter are based on the linear regression estimator $Z^*(x)$ [19], Eq.3:

$$Z^*(x) - m(x) = \sum_{i=1}^{n(x)} \lambda_i(x) [Z(x_i) - m(x_i)], \quad (3)$$

where $\lambda_i(x)$ are weights, $m(x)$ and $m(x_i)$ are the mathematical expectations of the random variables $Z^*(x)$ and $Z(x_i)$.

The type of evaluator depends on the model of the random function $Z(x)$. It can always be decomposed into two components: the deterministic trend $m(x)$ and the random residual $R(x)$, Eq.4:

$$Z(x) = m(x) + R(x). \quad (4)$$

The residual component $R(x)$ is modeled as a stationary random function with zero mathematical expectation $mR(x)$ and covariance $CR(h)$, Eq.5:

$$E\{R(x)\} = 0, \quad Cov\{R(x), R(x+h)\} = E\{R(x)R(x+h)\} = CR(h). \quad (5)$$

The mathematical expectation of the spatial variable Z at point x is thus equal to the trend value, Eq.6:

$$E\{Z(x)\} = m(x). \quad (6)$$

In ordinary kriging, it is assumed that the mean $m(x)$ is constant and known in the field of study.

3 Results and discussion

For the analysis, aerial photographs of the agricultural field were used on the biofield of the Agrophysical Research Institute in the red and near infrared ranges (shooting date 05/17/2019). Figure 1 shows a map of the distribution of the NDVI vegetation index. This map has a high spatial resolution (3 cm per 1 pixel), which also allows to analyze the optimal number of observation points. For further processing, the SAGA GIS program was used. Random sets of evenly distributed points of different volumes are generated on the same map. Accordingly, six data sets were obtained from 726, 364, 216, 147, 109 and 69 points.

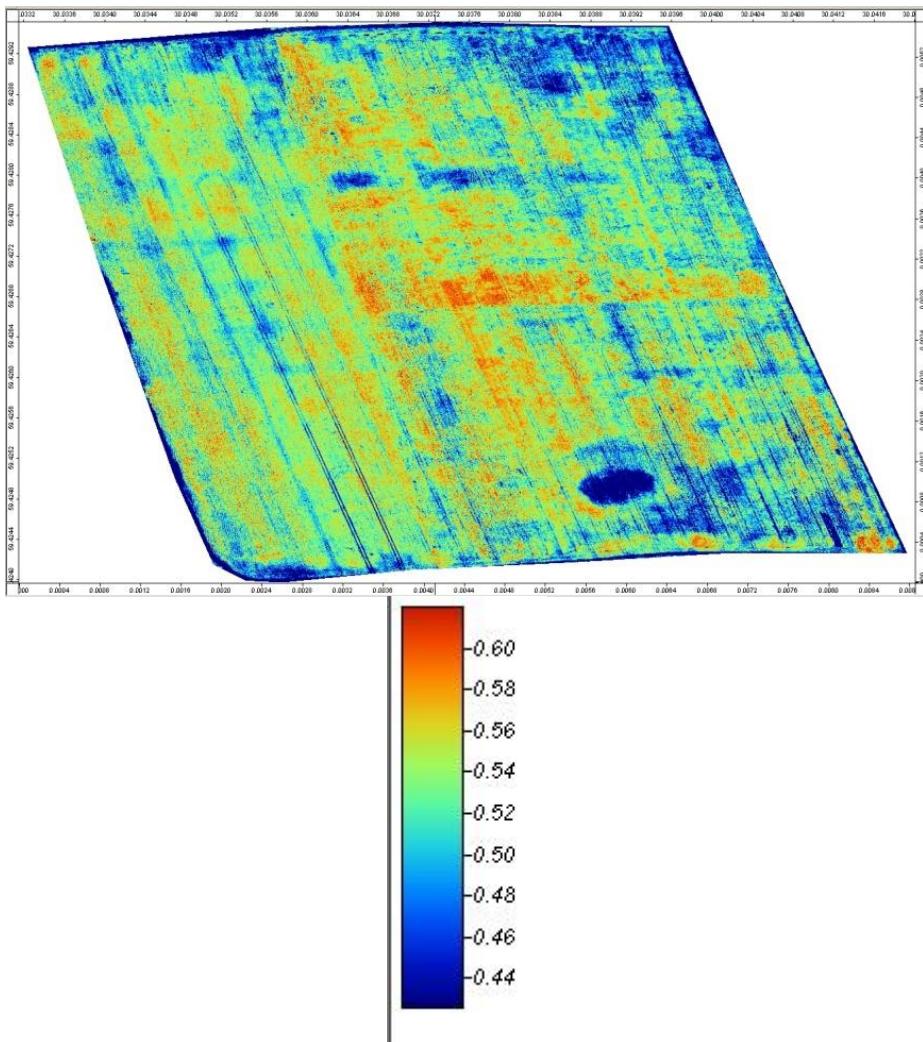


Fig. 1. The constructed distribution map of NDVI.

For each data set, experimental semivariograms with approximating theoretical models were constructed; in each case, the logarithmic model turned out to be the closest. As a result of these constructions, the greatest accuracy (92.28%) was achieved with the maximum number of points (726), and the least accuracy (43.45%) was achieved with the least number of points (69). As an optimum, it is proposed to adopt a set of 216 points, where the accuracy of construction was 72.19%.

Using the ordinary kriging method, the spatial distribution of the studied NDVI parameter was predicted for each set of points. If we take as a reference the map obtained for a set of 726 points, then just as in the construction of semivariograms, we can take a set of 216 points as optimal.

Having taken 200-250 values as the optimal number of points, similar constructions were performed for Sentinel-2 satellite images (L2A processing level, shooting date is the same - 05/17/2019) in the same agricultural territory. Using images in the 4th and 8th channels, the NDVI map was built in the QGis program. It should be noted that in this case,

a direct comparison of the constructed maps based on aerial and satellite imagery is not correct, however, it is assumed that the optimal number of starting points coincides.

A set of observations was generated based on the obtained optimal value for this field. A set of 232 points was obtained (Fig. 2). Next, an experimental semivariogram and its theoretical model are constructed. As with constructions using aerial photography, the logarithmic model turned out to be the closest (Fig. 3).

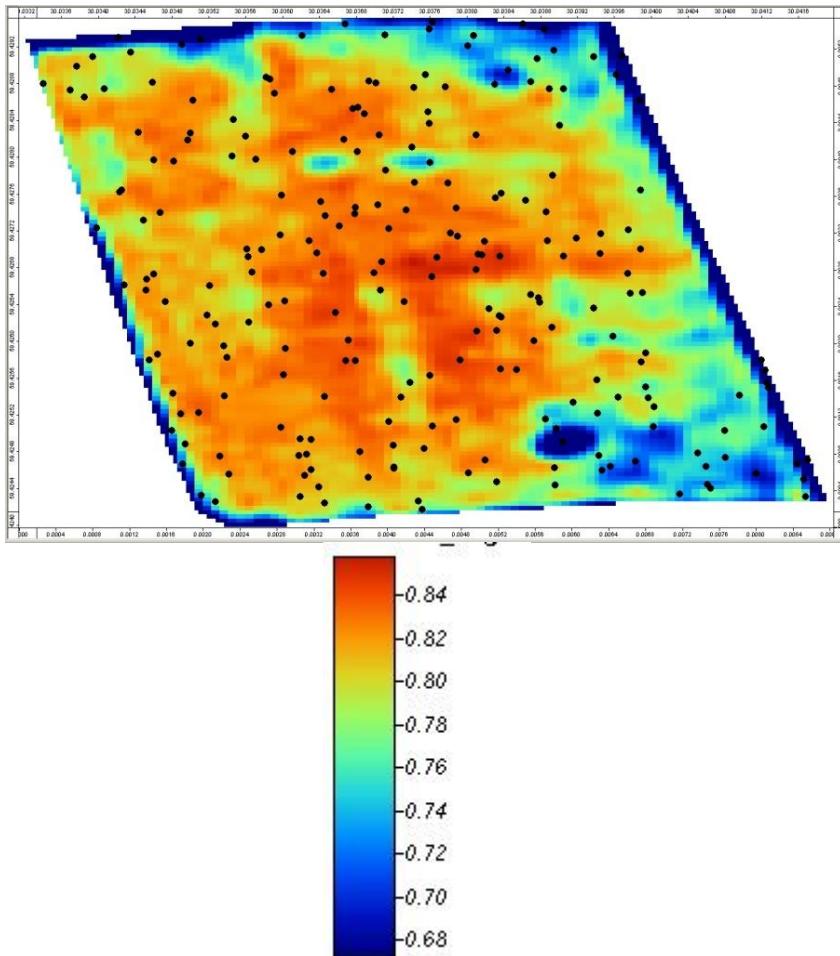


Fig. 2. A map of the distribution of NDVI values based on satellite imagery, indicating a randomly generated set of uniformly distributed points.

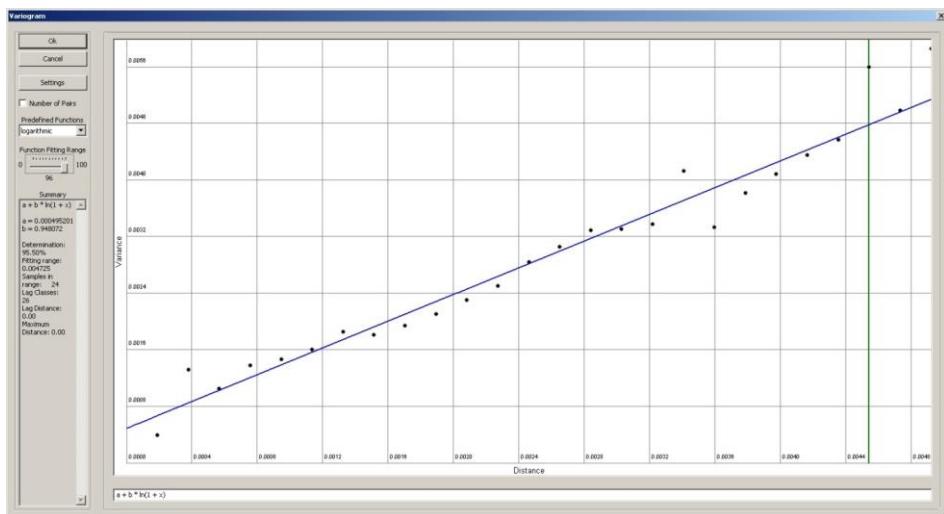


Fig. 3. The result of constructing an experimental semivariogram with approximation by a theoretical model based on an analysis of satellite images.

As it can be seen from the results of the analysis, the accuracy of the construction of the semivariogram was 95.5%, which is a fairly high indicator. Based on the obtained theoretical approximation of the semivariogram, the spatial distribution of NDVI can be predicted using the ordinary kriging method (Fig. 4).

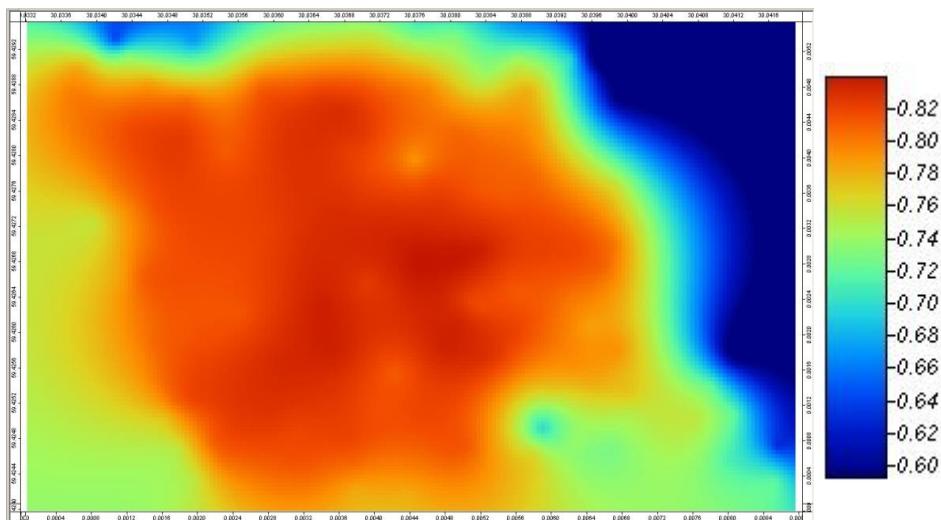


Fig. 4. Prediction of the spatial distribution of NDVI values using the ordinary kriging method based on satellite imagery analysis.

4 Conclusions

The method of ordinary kriging allows you to accurately predict the spatial distribution of the studied agro-ecological indicator on the agricultural field. However, it should be borne in mind that this task, as a rule, is applied when it is necessary to map a certain indicator

based on ground-based measurements. Therefore, special attention should be paid to the development of a sampling plan: the optimal number of measurement points for a given field, taking into accounts the further application of geostatistical methods, as well as their spatial location.

As one of the areas for further research on the possibilities of geostatistical methods in precision farming problems, it is advisable to pay attention to the ordinary cokriging method. The high efficiency of the ordinary cokriging method in solving problems using remote sensing has been proved in comparison with alternative methods. This method allows increasing the efficiency of the analysis of the studied indicator (ground based measurements) due to the information obtained using remote sensing, and this may be several sets of optical data that correlate with the studied indicator [20-22].

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