OPTIMUM SAMPLING SCHEME FOR CHARACTERIZATION OF MINE TAILINGS

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1. BACKGROUND AND OBJECTIVE

Mine wastes contain very high concentrations of metals, which could be leached and thus contaminating the nearby ecosystems. Geochemical characterization of mine waste impoundments is thus important for rehabilitation, or for remediation, to protect the surrounding environment. Such geochemical characterization would entail surface (to subsurface) sampling, which could be labor or cost intensive, especially if not properly planned.

Metals in mine waste impoundments are usually hosted by acid-generating sulphide-rich minerals, for e.g., pyrite, pyrrhotite, or adsorb onto surfaces of weathering products of such sulphide-rich minerals. Unfortunately, such minerals are difficult to detect or identify by using current remote sensing techniques using multispectral or even hyperspectral data. It has been shown, however, that certain sulphide-rich minerals, particularly pyrite, weathers to a series of iron-bearing sulfates, hydroxides and oxides [1]. Such secondary iron-bearing sulfates/hydroxides/oxides have diagnostic spectral features [2], which enable their detection or identification with analytical techniques using hyperspectral data. In a previous work [3], the potential of using hyperspectral data to estimate abundances of spectrally similar iron-bearing sulfates/hydroxides/oxides was demonstrated. It has also been shown that heavy metal contamination in soils can be quantified using reflectance spectroscopy [4]. Thus, remote sensing technology potentially provides an indirect tool for surface characterization of mine waste impoundments with oxidizing sulphide-rich materials; namely, for mapping spatial distributions of secondary iron-bearing sulfates/hydroxides/oxides and heavy metals.

Certain groups of metals could be spatially associated with secondary iron-bearing oxides/hydroxides depending on geochemical conditions in a given environment [5, 6]. Given a model of spatial distribution of secondary iron-bearing oxides/hydroxides, the problem is how to design a sampling scheme that would adequately capture the spatial distribution of certain groups of metals.

In a recent paper, Diggle and Lophaven [7] discuss a retrospective sampling design, which sequentially removes, from a sampling design, samples that contribute least to a Bayesian prediction of a response. They do, however, state that this is not the optimal design. In this paper, an adaptation of the retrospective sampling methodology by Diggle and Lophaven [7] is demonstrated, not through the same Bayesian approach but by incorporation of covariates in a conventional kriging with external drift model. In addition, a prospective sampling scheme is derived for nearby unsampled areas based on variogram model of the adjacent sampled area. The present case study area is in the Recsk-Lahóca copper mining area in Hungary.

2. METHODOLOGY

The study presented in this paper attempts to model spatial relationships between a multi-element signature and abundance estimates of secondary iron-bearing minerals in mine tailings dumps. The multi-element signature, on one hand, was modeled through factor analysis of element contents of mine tailings samples, which were measured in a laboratory. Abundances of secondary iron-bearing minerals, on the other hand, were estimated by the method demonstrated by Debba et. al. [3].

Derivation of an optimal sampling scheme makes use of covariates of the spatial variable of interest, which are readily but less accurately obtainable by using airborne hyperspectral data. The covariates are abundances of secondary iron-bearing minerals estimated through spectral unmixing. Spatial relationships between a multi-element signature and abundance estimates of secondary iron-bearing minerals were modeled through conventional kriging with external drift. Derived spatial relationship models are then used for sampling scheme optimization, by means of simulated annealing, for surface characterization of the mine tailings dumps.

Via simulated annealing, an optimal retrospective sampling scheme for a previously sampled area is derived having fewer samples but having almost equal mean kriging prediction error as the original ground samples. Via simulated annealing, an optimal prospective sampling scheme for a new unvisited area is derived based on the variogram model of a previously sampled area.

3. CONCLUSIONS

This study demonstrates that designing sampling schemes using simulated annealing results in much better selection of samples from an existing scheme in terms of prediction accuracy. The use of secondary information in designing optimal sampling schemes was also illustrated. Often these secondary information can be achieved at a relatively low cost and available over a greater region. These are the primary reasons for incorporating this information into the sampling design. Optimized sampling schemes using the mean kriging with external drift variance will result in sampling schemes that explicitly take into account the nature of spatial dependency of the data and together with hyperspectral data can be used to design sampling schemes in nearby unexplored areas.

4. REFERENCES

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