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Spatial modeling of lignite energy reserves for exploitation planning and quality control

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ABSTRACT

Energy resources are distributed in space. Models of spatial variability thus greatly contribute to the optimal exploitation of such resources. This paper concentrates on modeling the spatial distribution of energy content based on geostatistical interpolation and simulation methods. We focus on lignite, a fossil fuel which plays a key role in the energy budget in several parts of the world. Nonetheless, geostatistical tools are also relevant for the analysis of renewable and other fossil-based energy resources. Quantitative understanding of the spatial variability of lignite energy reserves helps to optimize mine exploitation and to reduce fluctuations in the quality of the fuel supplied to power plants. We also introduce the spatial profitability index as an analytical tool for the design and medium-term exploitation of multiseam mines. Based on this index we propose an empirical equation which allows fast and practical estimation of changes in energy reserves due to variations in expected costs or revenues. We illustrate the proposed modeling framework using lignite data from the Mavropigi mine in Northern Greece.

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1. Introduction

In spite of environmental concerns related to fossil fuels, coal remains an important energy resource which contributes to the energy independence of countries poor in other energy resources. Currently, approximately 30% of the electricity generation in the European Union is coal-based, while the coal industry contributed ≈240,000 jobs in 2012 [1].

Both fossil-based and renewable energy resources are distributed in space (renewable resources in addition have temporal dependence). A quantitative understanding of the spatial variations is necessary to optimize exploitation plans, correctly assess investment risks, and timely compensate for local fluctuations in the quality of the energy product. This paper shows that geostatistical tools [2,3] can be used to efficiently analyze the spatial variability, estimate uncertainties, and address economic questions, environmental concerns, as well as issues related to mine exploitation. Geostatistical methods are sufficiently general to handle spatial variability and exploitation strategies for diverse energy sources.

Coal exploitation presents several environmental challenges due to release of CO_2, toxic hydrogen sulfide (H_2S), deposition of large quantities of waste, and production of fly ash, bottom ash and sludge [4]. However, the environmental problems can be at least partially mitigated [5]: filters can capture and neutralize fly ash and harmful gases, while planning strategies allow for waste disposal in exploited parts of the mine. Lignite is considered to be low-quality coal based on its low calorific value and content of volatiles. The world-wide lignite production in 2012 was 0.9 billion tonnes whereas 3% of the global power generation was lignite-based.

1.1. Background on lignite mining

Many lignite mines exploit multiseam geological structures in which lignite seams alternate with other formations [6]. There are, however, no universal criteria for geologically classifying a seam as lignite [1]. Herein, a seam is considered as lignite if its *lower calorific value (LCV)* exceeds 900 kcal/kg and the sum of CO_2 and ash content

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is less than 50%. Intercalated seams refer to non-profitable soil or rock that is extracted with the lignite: *overburden* lies above the first lignite seam, while *interburden* refers to material that lies between ore seams in multiseam deposits.

The terminal depth in open pit lignite mines is measured by the *pit bottom elevation* [6]. *Long-term planning* refers to exploitation for periods that usually exceed five years, e.g. to the planning of large mine sectors. *Medium-term* planning refers to periods that are typically less than five years.

1.2. Economic indices

Engineers use several indices that help to optimize lignite production under specified economic and environmental constraints. Profitability is commonly measured by means of the *discounted cash flow* method (DCF) which is based on the equation

$$\mathrm{NPV} = -C_0 + \sum_{i=1}^{T} \frac{\Pi_i (P_i - C_i)}{(1+r)^T}, \quad i = 1, \ldots, T. \tag{1}$$

In the above, NPV is the net present value of the mine, C_0 is the investment cost, T is the expected life of the mine in years, i is the time period (measured in years), Π_i is the annual production, P_i is the price per unit tonne, C_i is the production cost per unit tonne, and r incorporates discount effects and risk factors [[6], p. 51], [7]. DCF provides a global estimate of economic profit but does not resolve local variations across the mine or the interchange of ore and intercalated seams in the vertical direction.

The *profitability index* (revenue to investment ratio), is defined by

$$\mathrm{PIR} = \frac{PV}{C_0}. \tag{2}$$

PV is the present value of the mine. PIR > 1 denotes a potentially profitable investment, whereas PIR < 1 implies that the required costs exceed the expected payoff. PIR also lacks the ability to account for local variations and individual seams.

The *stripping ratio* (R) is the volume of intercalated material that must be disposed per tonne of ore recovered [[6], p. 389]. The marginal stripping ratio is the critical threshold above which exploitation becomes unprofitable. The stripping ratio is evaluated for different mine sectors and helps to define the pit limits via comparison with the marginal stripping ratio. Hence, the stripping ratio incorporates spatial variability but does not account for the profitability of individual seams.

1.3. Spatial analysis

Spatial analysis can resolve variations of various properties at different scales and identify potentially useful correlations between variables. Therefore, it finds applications in energy resources exploitation [8–10], earth sciences [11,12], meteorology [13,14] and agriculture [15] among other fields. There are different mathematical frameworks for conducting spatial analysis including machine learning methods, radial basis functions, and geostatistics. The geostatistical viewpoint [2] offers a good balance between flexibility and ease of use. In contrast with the simpler distance-based methods (e.g., Shepard's inverse distance weighting), geostatistical methods provide quantitative uncertainty measures. In addition, they account for spatial correlations, different probability distributions, geological discontinuities, and the extent of the deposit [16].

This work focuses on the geostatistical analysis of lignite energy resources. We use spatial interpolation to estimate the energy content locally and conditional simulations to quantify the uncertainty of the estimates. The *Spatial Profitability Index (SPI)* is introduced as a novel tool for evaluating the profitability of individual seams in open pit multiseam mines. It allows investigating the impact of economic factors (e.g., market price fluctuations, costs of environmental regulations) on the estimated reserves and to better assess the costs and revenues of different exploitation scenarios. The SPI also helps to effectively design the final open pit bottom elevations. With regard to medium-term planning, SPI analysis helps to investigate the economic impact of options such as canceling the exploitation of certain benches or extraction using non-continuous mining methods which involve asynchronous extraction and transportation of the ore. We also derive a semi-empirical, explicit, SPI equation that compactly captures the relation between changes of the estimated reserves and economic scenarios.

2. Methods

2.1. Overview of geostatistical analysis

In the following we assume that the energy area density is modeled as a spatial random fields $\mathscr{E}(\mathbf{s})$, where $\mathbf{s}$ is the position vector [11,2].

2.1.1. Variogram models

Geostatistical analysis is based on the *variogram function* $\gamma(\mathbf{s},\mathbf{s}+\mathbf{r})$, where $\mathbf{r}$ is the lag (distance) vector. The variogram describes the spatial correlations of the spatial random field $\mathscr{E}(\mathbf{s})$. It is defined by means of the following equation, in which $\mathbb{E}[\cdot]$ denotes the expectation over the ensemble of the random field states [17].

$$\gamma(\mathbf{r}) = \frac{1}{2}\mathbb{E}\Big[\{\mathscr{E}(\mathbf{s}) - \mathscr{E}(\mathbf{s}+\mathbf{r})\}^2\Big]. \tag{3}$$

In (3) it is assumed that $\mathscr{E}(\mathbf{s})$ is either statistically stationary or that it has stationary increments, so that $\gamma(\mathbf{r})$ depends only on $\mathbf{r}$ and not on $\mathbf{s}$. If $\mathscr{E}(\mathbf{s})$ is stationary, $\gamma(\mathbf{r})$ is connected to the covariance $C(\mathbf{r})$ as follows

$$\gamma(\mathbf{r}) = C(0) - C(\mathbf{r}). \tag{4}$$

It follows from (4) that $\gamma(0) = 0$. In practice, the empirical variogram, which is estimated from the data, may show a *discontinuity* C_0 at the origin. C_0 is known as the nugget variance and represents unresolvable fluctuations or measurement errors [9].

The Spartan Spatial Random Field (SSRF) covariance model is used in the geostatistical analysis below. In three spatial dimensions the Spartan model is given by Ref. [18,19]

$$C(\mathbf{r}) = \begin{cases} \dfrac{\eta_0}{2\pi\Delta} e^{-\frac{|\mathbf{r}|}{\xi}\beta_2} \left(\dfrac{\sin\left(\frac{|\mathbf{r}|}{\xi}\beta_1\right)}{\frac{|\mathbf{r}|}{\xi}} \right) & |\eta_1| < 2, \\ \dfrac{\eta_0}{8\pi} e^{-\frac{|\mathbf{r}|}{\xi}} & \eta_1 = 2, \\ \dfrac{\eta_0}{4\pi\Delta} \left(e^{-\frac{|\mathbf{r}|}{\xi}\omega_1} - e^{-\frac{|\mathbf{r}|}{\xi}\omega_2} \right) \dfrac{1}{\frac{|\mathbf{r}|}{\xi}} & \eta_1 > 2. \end{cases} \tag{5}$$

In Equation (5), η_0 is the scale factor that determines the magnitude of the fluctuations, η_1 is the rigidity coefficient, and ξ is the characteristic length that determines the range of spatial correlations. The remaining coefficients are given by $\beta_{1,2} = |2 \mp \eta_1|^{1/2}$,

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