Block model in a multi facies context - Application to a porphyry copper deposit

Serge Antoine Séguret

Block model in a multi facies context - Application to a porphyry copper deposit

Serge Antoine Séguret

Centre of Geosciences / Geostatistics, MINES ParisTech, Fontainebleau, France

ABSTRACT

When a mineral deposit is made of geological bodies such as breccias or lenses that concentrate high grades, and when production blocks contain few such bodies, estimating block grades by ordinary kriging may produce unrealistic spatial continuity. To improve the block model, a usual practice consists in (1) estimating spatial proportions of facies (unit), (2) estimating the grades, facies by facies, and (3) combining the results to obtain the block grades. We show that this practice assumes some links between the geological bodies, which will be verified. Then, we try to answer this general question: Given a set of samples where facies and grades are known, what is the best way to build a block model? We propose a methodological work flow which leads to a cokriging system where facies indicators are used, together with their product with the grade, a method that does not require the previous calculation of the facies proportions, at the scale of the blocks, but is implicitly based on them, at the point-support scale. The method is applied to a porphyry copper deposit located in northern Chile. When compared to a usual kriging without any facies consideration, the improvement of the method is slight because the grade follows the contact hierarchy between facies and also an important part of the spatial variability is purely random. When compared to the traditional approach we notice very poor correlation and this makes perhaps questionable some choices made by the geologists.

For more details on this paper, follow this link:
http://www.geomin.cl/evento2011/index.php?lang=en

INTRODUCTION

In this paper, we try to answer this question: given samples where facies (i.e., a categorical variable) and grade are known, what is the best way to build the block model (i.e., to estimate the average grade at the scale of production block). We show that, contrary to usual practice, it is not necessary to separate facies proportion estimation from grade one and that the useful variable to solve this problem is the grade multiplied by the facies indicator. Then, following an application on a porphyry copper deposit, we show, step by step, how we can characterize the geometry of the facies and we build a cokriging system using indicators and grade. The block model is compared to usual kriging, and to the block model used in the company.

Basic functions used in the following are indicator functions. The probabilistic interpretation of cross, direct, and ratio of indicator variograms is helped by the presentation of Rivoirard [1]. A general overview of all this material is contained in the textbook by Chilès and Delfiner [2].

FORMALIZATION

We consider a block named V within which the ore is classified into n subsets v_i associated with facies (units). V and vi denote the objects and their volumes. We consider that the rock density ρ is constant over V and does not depend on i but it can vary slowly in space. We are interested by Z(V) the average grade of metal over V

$$Z(V)=\frac{1}{V}\int_V Z(x)dx=\frac{Q(V)}{T(V)}=\frac{\text{metal tonnage}}{\text{ore tonnage}} \qquad (1)$$

The problem is: Given the point-support samples, what is the best way to estimate Z(V)?

TRADITIONAL APPROACH

We set

$$Z(V)=\sum_{i=1}^{n}\frac{v_i}{V}\frac{Q(v_i)}{\rho v_i}=\sum_{i=1}^{n}p_i Z(v_i)$$

$Q(v_i)$, quantity of metal contained in v_i

p_i , (volumetric) proportion of unit i in V

$Z(v_i)$, metal grade of subset v_i (2)

A usual practice is

(1) To estimate each p_i and $Z(v_i)$ separately

(2) To estimate p_i by interpolating local proportions or by indicator kriging or by "hand drawing"

(3) To estimate $Z(v_i)$ by kriging, at the scale of V, using the sole samples labeled i

(4) To combine the estimations to obtain the result

We remark that the optimal estimation of a sum of variables is not necessary equal to the sum of optimal estimators, and the same for a product. Questions:

- If the proportions p_i (resp. the grades $Z(v_i)$) are spatially correlated, could it be useful to use cokriging?
- Is it possible to avoid the proportions estimation during the block estimation procedure?
- Why separating p_i from $Z(v_i)$ and not estimating directly the product?
- What is this product?

SIMPLIFICATIONS

We set

$$Z(V)=\sum_{i=1}^{n}\frac{Q_i(V)}{\rho V}=\sum_{i=1}^{n}Z_i(V) \tag{3}$$

We consider that we have as many type of metal as facies. $Q_i(V)$ represents the quantity of metal i contained in V and $Z_i(V)$ the grade of metal i.

The point-support grade $Z_i(x)$ is defined by

$$Z_i(x)=1_i(x)Z(x) \tag{4}$$

with

$$1_i(x)=1 \text{ if } x\in \text{facies i, 0 if } x \notin \text{ facies i} \tag{5}$$

and we have finally

$$Z_i(V)=\frac{1}{V}\int_V Z_i(x)dx=\frac{1}{V}\int_V 1_i(x)Z(x)dx=p_iZ(v_i) \tag{6}$$

We are in an isotopic situation (the variables are equally sampled) and the cokriging of the sum equals the sum of cokrigings

$$Z(V)^{CK}=\sum_{i=1}^{n} Z_i(V)^{CK} \tag{7}$$

For each grade Z_i, we estimate by cokriging its average over V and we add the estimations.

We have 2n variables to consider for building the cokriging system

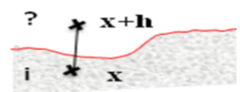
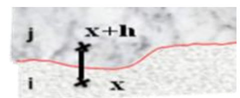
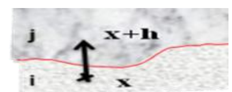
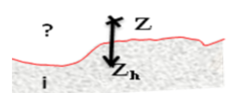
- n facies indicators $1_i(x)$ (introduced for their major influence),
- n grades $Z_i(x)$ (variables of interest).

Depending on the link between these variables, we search if it is necessary or not to split the metal according to the units and if we can regroup some facies.

TOOLS

Indicators define spatial domains so one can say that they set the "geometry" of the problem. For the modelling, it seems natural to start with the indicators then continue with the grades and the way they interact with the indicators. The tool is the variogram interpreted in a probabilistic way (Table 1).

Table 1 Indicator variograms (denoted by Greek letter γ) and their probabilistic interpretation

Calculation	Interpretation	Conceptual illustration
$\gamma_i\ (h)$	$p(x \in i\ ,\ x+h \notin i)$ Probability, for a pair of points separated by h, to overlap 2 facies, one being i	
$\lvert\ \gamma_{ij}\ (h)\ \rvert$	$p(x \in i\ ,\ x+h \in j)$ Probability, for a pair of points separated by h, to overlap facies i and j	
$\left\lvert \frac{\gamma_{ij}\ (h)}{\gamma_i\ (h)} \right\rvert$	$p(x+h \in j / x \in i,\ x+h \notin i)$ Probability to reach j while leaving i	
$\frac{\gamma_{iZ_i}\ (h)}{\gamma_i\ (h)}$	$E[Z(x+h)/x+h \in i,\ x \notin i]$ Average grade when entering in i	

EXPERIMENTATIONS

We study a domain of approximately 400x1500x400 m^3 which contains more than 54000 samples of 1.5 meter length, all informed in copper grade and coded in 4 facies (units) (Table 2). Breccias are mainly located in the centre of the domain and waste to the west. The eastern limit is given by a fault.

Table 2 Main characteristics of the grades

	Abr.	Colour	Proportion %	Mean grade %	Std dev.
All facies			100	0.78	1.54
Waste	W		31.2	0.06	0.17
Low grade	C1		27.5	0.31	0.36
High Grade	C5		31.7	1.16	0.90
Breccias	Bx		9.6	4.27	3.48

General statistics

Average grades present important differences between facies (Table 3). Even poor facies present high grades like 8% of copper for waste for example. These are probably isolated breccias coded as waste (W) because they are not accessible in exploitation.

Table 3 Basic statistics of the grades

Type	Nb. samples	Min %	Max %	Mean %	Std. dev. %
All	54578	0	33	0.88	1.71
W	17022	0	8.1	0.06	0.17
C1	14995	0	7.6	0.31	0.36
C5	17298	0	23.1	1.16	0.9
Bx	5263	0	33	4.27	3.48

All the grade variograms present an important nugget effect. Figure 1 shows omni-directional variograms for clarity. They all look stationary with different ranges: more than 125m for W, 80m for Bx, around 30m for C1 and C5.

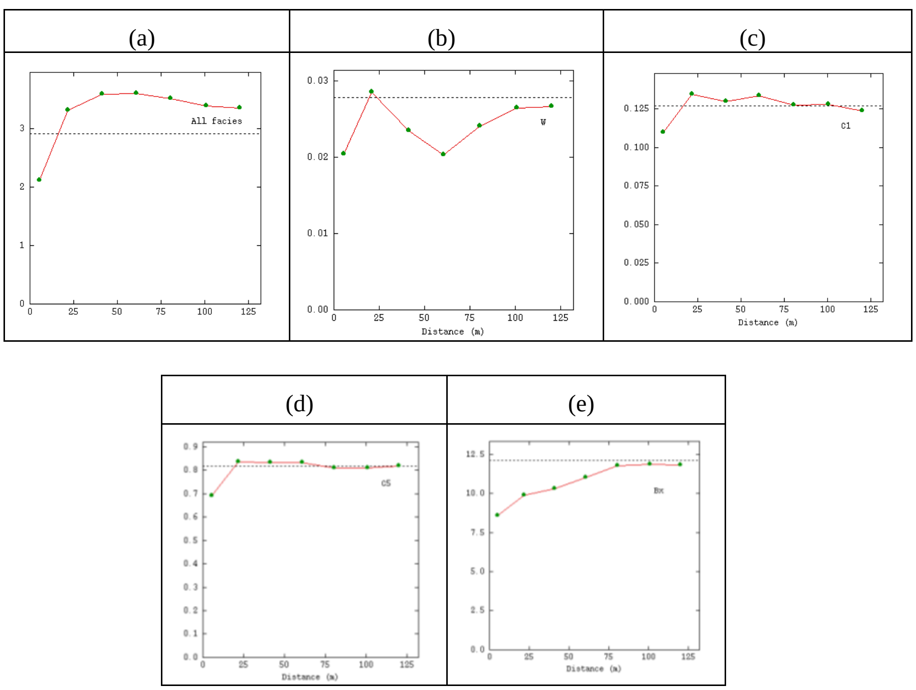


Figure 1 Grade variograms. (a) All facies, (b) Waste, (c) Poor, (d) Rich, (e) Very rich

At this stage, it seems useful to continue considering the four facies for the block modelling, as there are enough differences between them.

Table 4 presents the probability, when leaving a given facies, to encounter another facies. It must be red together with the global proportions of Table 2.

Table 4 Contact probabilities

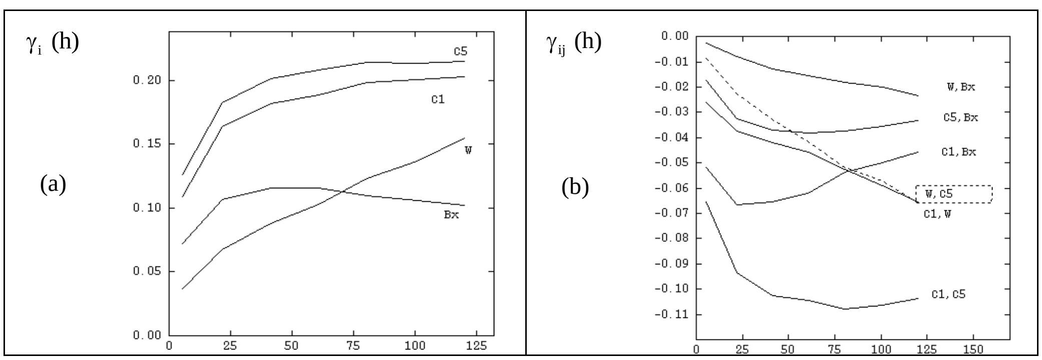
From \ To	**W**	**C1**	**C5**	**Bx**
W		0.8	0.2	0
C1	0.2		0.65	0.15
C5	0.05	0.5		0.45
Bx	0	0.2	0.8	

Main comments are:

- Bx and W are not in contact
- When leaving W, the probability to encounter C1 is 0.8, which is much greater than the global proportion of C1 (less than 30%). So C1 separates W from C5 and Bx
- Same remark for the probability to encounter C5 when leaving Bx: C5 separates Bx from C1 and W
- When leaving C1, one can encounter Bx with a low probability (0.15), while the probability to encounter C5 (0.65) is more important than the global proportion of C5. Same remark when leaving C5 and encountering C1. This shows that C5 tends to surround Bx.

Geometry

Figure 2 shows direct, cross and ratios of indicator variograms.



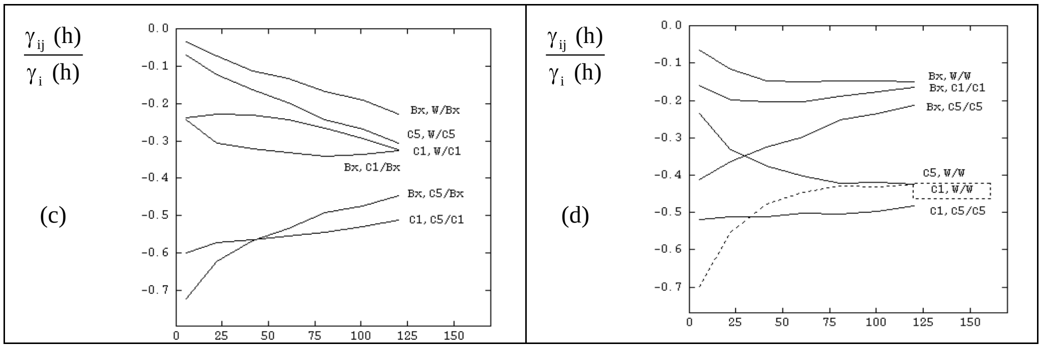


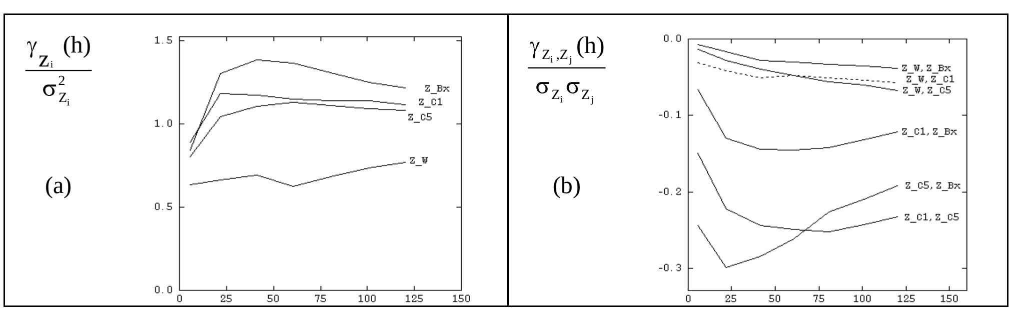
Figure 2 Facies indicator variograms. (a) Direct, (b) Cross, (c, d) Cross divided by direct variograms

Comments:

- Direct indicator variograms (Figure 2a) for C5 and C1 are very close, with a stationary behaviour. W presents increasing probabilities due to the location of waste at the western periphery of the mineral body (non stationary effect). Breccias are thin objects, mainly located in the center of the mineral body, reason why probabilities increase then decrease after 50m.
- Cross variograms between indicators (Figure 2b). The cross variograms between any facies and waste resembles to the variogram of waste indicator (with a negative sign). This is a non stationary effect that masks the other relationships between the facies.
- Cross variograms divided by direct ones (Figures 2c and 2d). Apart one exception, all facies present spatial correlation (due to spatial sequencing W-C1-C5-Bx) and therefore must be estimated together by cokriging if the target is local proportion estimation. Exception is C1 and C5 where the probabilities do not depend on the distance. The frontier between these two facies marks the limit between poor (mainly to the west) and rich to the east.

Geometry and grades

We want to specify the behaviour of the grades when moving away from the frontiers defined by the indicators so we study $Z_i(x)$, the product of the grade by $1_i(x)$. Direct and cross variograms of these quantities have been normalised. Figure 3 just presents the most representative variograms ratios.



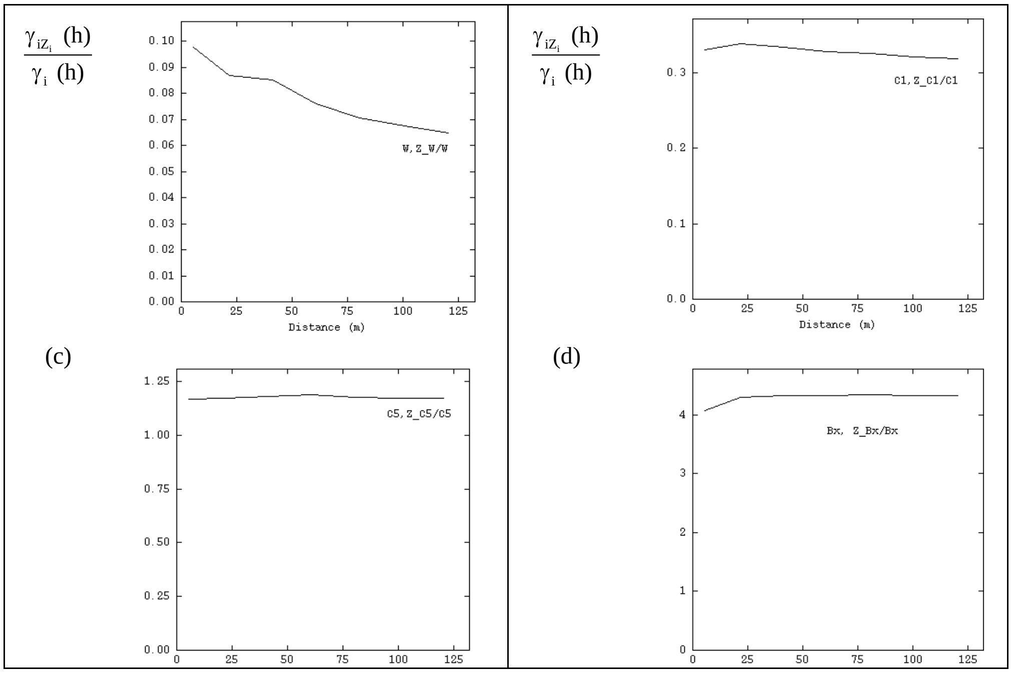


Figure 3 (a) Grades variograms divided by grade variances, (b) Cross variograms between grades, (c, d) Cross variograms between grades and facies indicators divided by direct variograms

Comments:

- Variogram of Z_{Bx} (Figure 3a) is very close to Z variogram (Figure 1a) while breccias represent just 10% of the data. The contrast of Bx grades with the other grades is so important that the non breccias grades play the role of the zero introduced in the Z_{Bx} calculation. All over the deposit, most of the variance is due to breccias.
- The cross variograms between the grades Z_i (Figure 3b) are all very close to their facies indicator homolog (Figure 2b). Considering the grades does not give knowledge on the mutual behaviour of the facies. This is linked to the important nugget effect encountered on the grade variograms calculated facies by facies (Figures 1b to 1e) and also to the lack of dependency between grades from neighbouring facies.
- There are border effects for each facies (Figures 3c and 3d), but the magnitude is not important. For example, the copper grade decreases when moving inside W (impoverishment of the mineral body envelop when one goes away from the mineral body), but only 0.05% after 150m. The most important gradient is linked to Bx, the average grade gains 0.4% after 150m.

Globally, one can consider that the behaviour of the grades inside the facies is minor compared to the mutual behaviour of the facies.

Cokriging

As the facies partition the domain, just three out of four indicators must be used, otherwise the cokriging system would be singular. We built a multivariate model and cokriging is done using a small moving neighbourhood to follow the non stationarity (maximum distance 60m). It contains more than 30 data points on average. We also fit the variogram of Z (without distinction of the facies) in order to compare cokriging with common kriging.

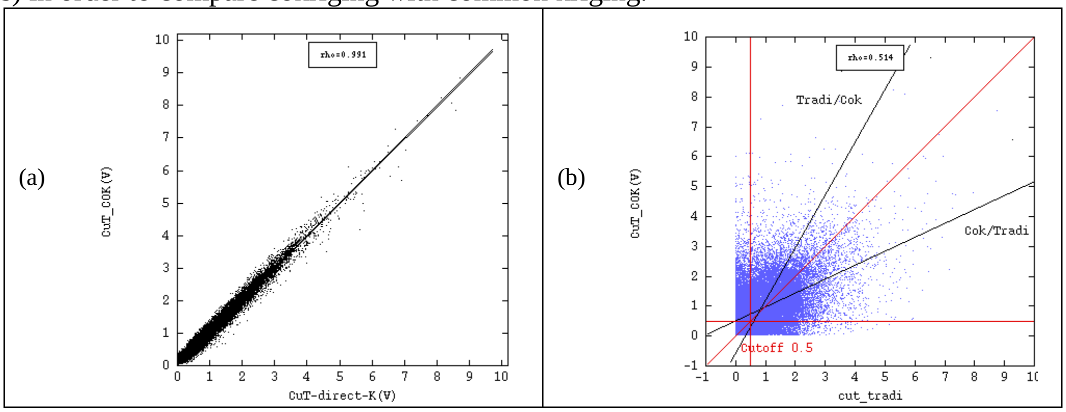


Figure 4 Scatter diagrams. (a) Cokriging versus usual kriging, (b) Cokriging versus traditional method

The scatter diagram between direct kriging and cokriging (Figure 4a) shows an important correlation. The standard deviation of the residual around the regression of cokriging estimator against direct kriging one is 0.1. Both estimators give similar results. Three reasons can be pointed out:

- The grades follow the sequence W-C1-C5-Bx which leads the mutual organization of the facies. When we estimate Z directly, we take into account this sequence naturally as low grades mainly concern W and high grades Bx.
- When one looks to the previous scatter diagram (Figure 4a), it seems that the dispersion is more important for the low grades than for the high ones. This could be due to the fact that rich blocks are those containing breccias and that the Z_{Bx} variogram is similar to the Z one. It is probably for low and intermediate grades that cokriging improves the results.
- All the variograms contain more than 50% of nugget effect and this reduces the impact of the method quality on the result as an important part of the calculation is just a local average. We repeat both calculations without any nugget effect (for cokriging, but also for direct kriging) and the comparison of both results indicates more differences between the approaches. The standard deviation of the residuals around the regression line then equals 0.3%.

Second comparison concerns the model actually used where facies limits are hand drawn by the geologists (Figure 4b). The scatter diagram presents an important dispersion. The standard deviation of the residuals of the linear regression of cokriging against traditional is 0.5, same for the standard deviation of the residuals of the linear regression of traditional against cokriging. At the cutoff 0.5, 13% of the blocks would be rejected by traditional method (but taken by cokriging), and 7% of the blocks would be rejected by cokriging and taken by traditional method.

Where is the truth? Probably between both approaches and the aim here is not to replace the knowledge of the geologists, but to give them tools to quantify their intuition.

CONCLUSIONS

Basic arithmetic considerations show that estimating average grade Z(V), at the scale of block V, using facies indicators $1_i(x)$ and $Z_i(x)$ (their product with the grade Z(x)), does not require *a priori* a first estimate of local facies proportions. The calculation can be made once using cokriging.

Then, we study a complex data set of a porphyry copper deposit. The probabilistic interpretation of $1_i(x)$ and $Z_i(x)$ variograms show that the indicators are spatially linked and their knowledge is mandatory, the grades $Z_i(x)$ being of secondary importance.

Finally, we compared the results of cokriging to direct kriging (without facies consideration) and we noticed very few differences. Reversely, there are important differences when compared to the practice consisting in drawing by hand the geological structures, intersecting them with the blocks and obtaining by this way local proportions.

The poor improvement of cokriging here is due to the important nugget effect of the variograms and the natural ordering of the facies contacts followed by a same ordering of the grades.

So finally, the interest of this presentation is not located in the results themselves, but on the methodological sequence that leads to them, giving the calculation priorities. For example in the present data set, one must focus *a fortiori* on the proportions estimation by block, and one can affect to each facies an average grade for all the blocks, the results will not change a lot.

Second lesson is that the variability of the breccias is so important in this deposit that one would require much more data to obtain a substantial improvement in the proportion calculation. This explains why, finally, the requirement of geologist knowledge is necessary to feed the gaps. But one must not forget then that the resulting proportions are calculated by hand.

ACKNOWLEDGEMENTS

Applications have been done using the Isatis software. The author would like to acknowledge Mr. Julio Beniscelli, Manager of Technical Services, CODELCO Chile, and his company, for their strong support in the implementation of good geostatistical practices along the copper business value chain. As well we would like to thanks an anonymous reviewer for his / her excellent work. This work has been initiated by Pedro Carrasco, may it honour the memory of this eminent colleague and great friend.

REFERENCES

Rivoirard, J. (1994) *Introduction to Disjunctive Kriging and Non-Linear Geostatistics*, Oxford University Press, Oxford; 180p. [1]

Chilès, J.P., Delfiner, P. (1999), *Geostatistics. Modeling Spatial Uncertainty*, Wiley; 703 p. [2]