Mapping of the Late Miocene sandstone facies using indicator kriging

K. Novak Zelenika, T. Malvić and J. Geiger

PRELIMINARY COMMUNICATION

Facies mapping is one of very important tasks in modelling of oil and gas reservoirs. Facies type has direct influence on porosity and permeability values, which eventually influence both the migration and accumulation of hydrocarbons. The most numerous reservoirs in the Croatian part of the Pannonian basin major are in the Late Pannonian and Early Pontian sandstones. Various types of these sandstones were formed in turbiditic depositional environment, which had been periodically activated in relatively calm, deeper (mostly up to 200 meters), brackish lake environment with marl sedimentation over the basin plain. Sandstones form sedimentary bodies that are very elongated in approximately NW-SE direction, with sharp transition toward basin marls in bottom and top. On the contrary, lateral transition is gradual, from the clean, medium-grained sandstones, toward fine-grained sandstones or siltites, silty sandstones, marly sandstones, sandy marls and eventually basin marls. Such lateral facies transition in the Kloštar field was analysed, focusing at the largest sandstone oil reservoir 'T' of Early Pontian age. There were available 19 wells with the newest e-logs and calculated average porosity in reservoirs. With 6 additionally constructed virtual wells using Surfer residual calculation, this made a reliable input dataset. The (litho)facies are analysed through e-logs, porosity map and, eventually, indicator variograms and Indicator Kriging facies map. Transition of porosity values and their probabilities are clearly recognized on the Indicator Kriging maps, and can be correlated with the interpreted depositional environment at the specific well location. This is the first time that Indicator Kriging was applied in Croatian sandstone hydrocarbon reservoirs and result positively confirmed that this interpolation technique is appropriate and useful tool for facies mapping based on subsurface data.

Key words: facies, sandstone, marl, indicator variogram, indicator kriging, Late Miocene, Sava depression, Croatia

1. INTRODUCTION

Mapping of the Upper Miocene depositional facies in the Croatian part of the Pannonian basin is still one of the most important tasks in the Croatian petroleum geology.

Mapping of facies is important for getting insight to sedimentary environments, shapes and boundaries of hydrocarbon reservoirs. It is impossible to show all varieties on one map and that is the reason why several facies mapping methods were developed. One of the well known methods is based on spontaneous potential (SP) and resistivity (R) curve (in Croatia it was represented in works of e.g. refs.[12, 13, 14, 15, 16, 17]

However there is another way for lithofacies interpretation based on subsurface data: if quantitative well-log interpretations of porosity are available, specific porosity intervals can be related to some lithofacies types. That is how by mapping of these intervals the lateral distribution of the corresponding lithofacieses can be predicted. Unfortunately this is burdened with significant uncertainties. On one hand, the calculation of effective porosity from well-logs has uncertainty of its own. Consequently sometimes the meaningful question is not 'What is the porosity at a particular location', but rather 'What is the probability of porosity lying in a particular interval' or 'What is the probability of porosity being smaller/larger than a particular cutoff'. On the other hand, there hasn't been any traditional way to map the lateral distribution of a porosity interval for a long time.

However, by continuous development of geostatistical tools, during the late 80's a special method for kriging was introduced, called Indicator Kriging (IK).[5, 7] This method has already been applied by other authors[2, 3, 4, 7] to address the problems mentioned above. Later, several authors applied this method for a wide variety of problems including mapping of soil types[2] and facies mapping[8] as categorical variables, estimating of geological attributes with great number of extreme values,[9] or mapping of the production data of a hydrocarbon reservoir.[6] By accumulating the practice, several textbooks appeared, summarizing these applications and giving theoretical background of IK.

In this paper certain key questions are summarized concerning the meaningful application with aim to demonstrate the possible application in approaching lithofacies mapping using IK of porosity from well-logs. An old oil field located close to the margin of the Sava depression named Kloštar field is chosen as a suitable study area.

2. THE STUDY AREA

Most of the oil and gas reservoirs in SW corner of the Pannonian basin (i.e. in the Sava, Drava, Slavonia-Srijem and Mura depressions) are in sandstones of Late Pannonian and Early Pontian age (Late Miocene). Depositional model of these sandstones is well interpreted by now.[10, 12, 14, 16, 17] They represent a result of periodical activity of turbiditic currents in calm, brackish, lake environment, where hemipelagic marls were deposited most of the time.

Late Miocene sandstone-prone turbidites entered the structural depressions, located between regional strike-slip faults (mostly like pull-apart basins). Parts of these depressions were later subjected to structural uplifts as a result of the inversion due to transpression resulted from the N-S orientation of the horizontal component of regional stress. Hydrocarbons started to migrate in these traps in Late Pliocene and Early Quaternary, and probably even in Late Miocene (e.g. ref. [1]).

Sedimentation in smaller structural depressions had great influence on facies distribution, as well as on boundaries of the reservoir. Fault planes are also often boundaries between turbiditic sandstone and basin marl. It means that sandstones had been deposited periodically, with marl in their top and base. Lateral facies boundaries are not sharp and there is wide transition zone toward the basin plain. Laterally there is transition from (in axial parts of submarine channels) medium-grained to fine-grained sandstone, marly sandstone, sandy marlstone and finally marl. Also, granulometric composition of sandstones changes in the direction of turbidite current palaeotransport,[10] from medium-grained to fine-grained sandstones.

Kloštar field is located 35 km east of Zagreb on the western slopes of Moslavačka Gora Mountain, with altitude from 110 to 180 m.

Geologically, Kloštar field belongs to the Sava depression. Reservoir rocks are of Miocene age and Palaeozoic age. There are 5 oil and gas prone lithostratigraphic units with altogether 20 reservoirs. Sandstone reservoirs are located in three units. The oldest is named 'Pre-Valencianensis beds' (Early Pannonian) with sandstone lens. Reservoirs of the '2nd sandstone series' and '1st sandstone series' (Early Pontian) have greater lateral extension and contain major hydrocarbon reserves.

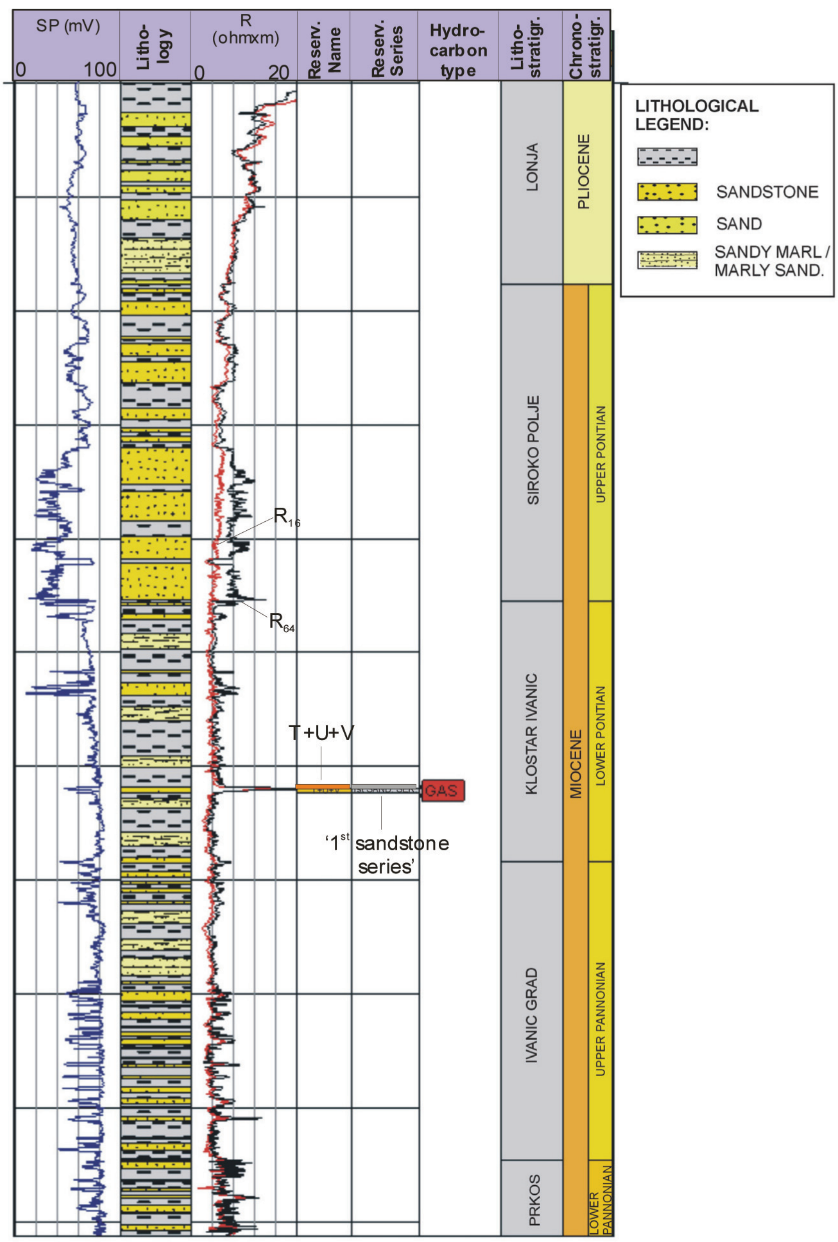

Fig. 1. Composite geological column (including stratigraphy, e-logs and lithology) of the well with minimum average porosity in the analysed sandstone reservoir 'T' (location belongs to sandy marl lithofacies)

Sl. 1. Složeni geološki stup (uključuje stratigrafiju, karotažu i litologiju) kroz bušotinu u kojoj je određena najmanja srednja poroznost u analiziranom ležištu 'T' (lokacija pripada litofacijesu pjeskovitog lapora)

3. DATA SET

The input dataset included porosity data collected in 25 points of Kloštar field, as average value of Lower Pontian oil reservoirs of '1st sandstone series'.

In the analysed reservoir, porosity from wells varies between 13.8 and 23.3%. It is assumed that the lowest value represents marlitic sand, as the transitional facies toward basin marl. On contrary, the maximal value had been measured in the clean sandstone, deposited in the deepest and central part of the transport channel. Of course, the average porosity value of wells strongly depends of their location in depositional environment, and it is represented by geological sections of the two mentioned "extreme" wells shown on Figures 1 and 2.

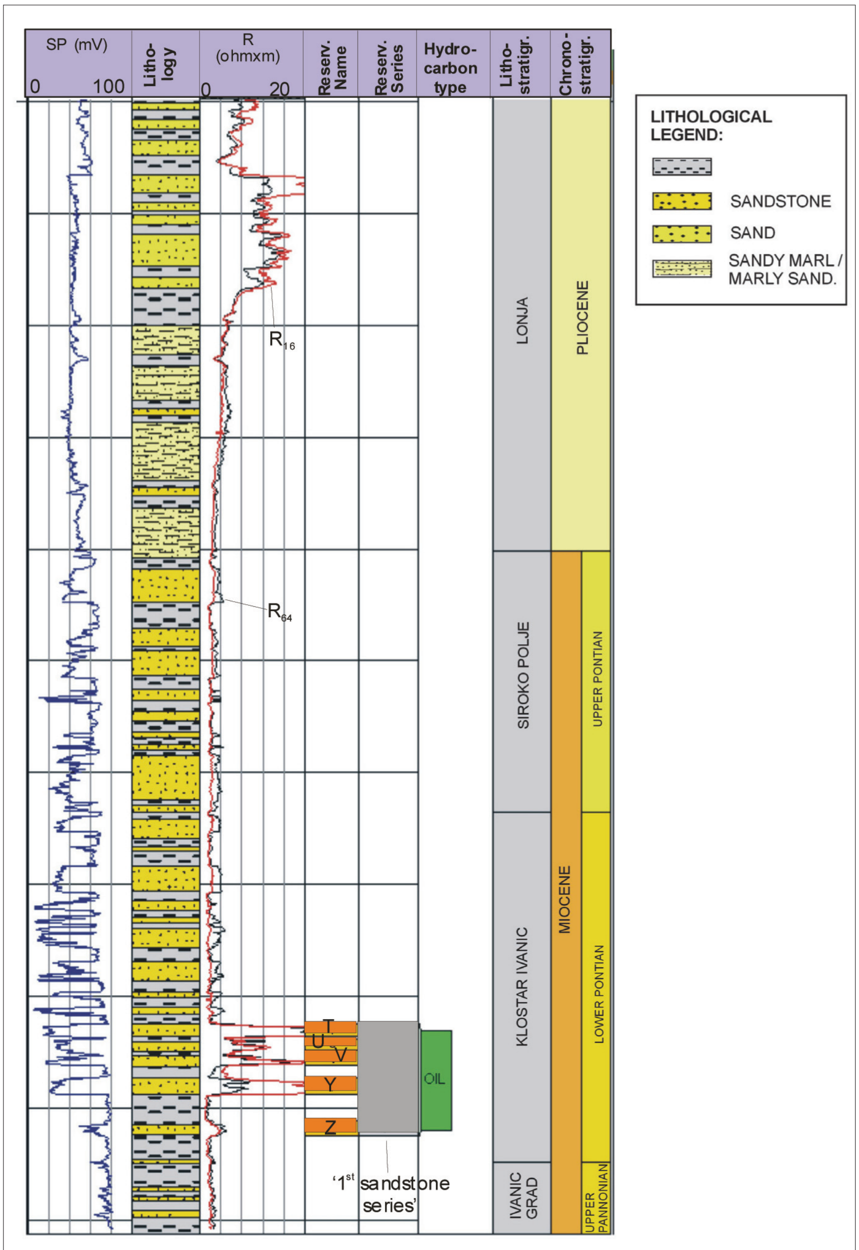

Fig. 2. **Composite geological column (including stratigraphy, e-logs and lithology) of the well with maximum average porosity in the analysed sandstone reservoir 'T' (location belongs to medium grained sandstones lithofacies)**

Sl. 2. Složeni geološki stup (uključuje stratigrafiju, karotažu i litologiju) kroz bušotinu u kojoj je određena najveća srednja poroznost u analiziranom ležištu 'T' (lokacija pripada litofacijesu srednjozrnatih pješčenjaka)

4. INDICATOR KRIGING (IK)

The following brief review on indicator formalism and Indicator Kriging technique are based on the works of refs. [3, 4, 5, 6, 7]

4.1. Indicator formalism and some consequences

Within an uncored region, one of the most frequently used method for facies identification is the usage of porosity cutoffs. More precisely, if a particular facies can be recognized by a ícutoff, and if the presence of this facies is assigned with 1 and absence with 0 respectively, one can introduce a so-called indicator variable (like in Figure 3) with the following form:

$$I(x)=\begin{cases}1 \text{ if } z(x)\le v_{cutoff}\\ 0 \text{ if } z(x)>v_{cutoff}\end{cases} \qquad (4.1)$$

where:

$I(x)$ is the indicator variable;

$z(x)$ is originally measured value;

v_{cutoff} is cutoff value.

Let's assume that instead of a single threshold ícutoff, l cutoffs íl are applied to the observed data, such that

$$I(x,v_l)=\begin{cases}1 \text{ if } z(x)\le v_{l\ cutoff}\\ 0 \text{ if } z(x)>v_{l\ cutoff}\end{cases} \qquad (4.2)$$

where $z(x)$ is the value of a regionalized variable such as porosity at location x.

Thus, raw data are transformed into l new variables, each taking on the value of 0 or 1. Note, that by selecting v_l cutoffs the main purpose is to obtain a reasonable picture of the frequency of wells or reservoir sections above or below each cutoff. It can be shown, that the probability of porosity $z(x)$ below a cutoff íl within an area A equals

$$P(A;z)=\frac{1}{A}\int_A i(x,v_l)\,dx \qquad (4.3)$$

With knowledge of $P(A, v)$, one can derive the probability of wells with porosity above cutoff v_l:

$$P(z(x)>v_l)=1-P(A,v) \qquad (4.4)$$

This probability can be estimated directly from n observed values of $z(x)$:

$$P^*(A,v)=\sum_{i=1}^{n}\lambda_i(v_l)\,i(x_k,x_l) \qquad (4.5)$$

where λ_i ($i=1, 2, \ldots, n$) are n weights being calculated from a kriging system through calculation of residual indicator data $[i(x_k, v)\text{-}F^*(z)]$.[7] In this latter expression $F^*(z)$ is an unbiased estimate of frequency, $F(z)$:

$$F(z)=E\{P(A,v)\} \qquad (4.6)$$

One of the most impressive consequences of the above derivations is that the aim of the indicator formalism for continuous variables is to directly estimate the distribution of uncertainty at unsampled location. The global probability distribution function of the input data set also then can be estimated at a series of threshold values.

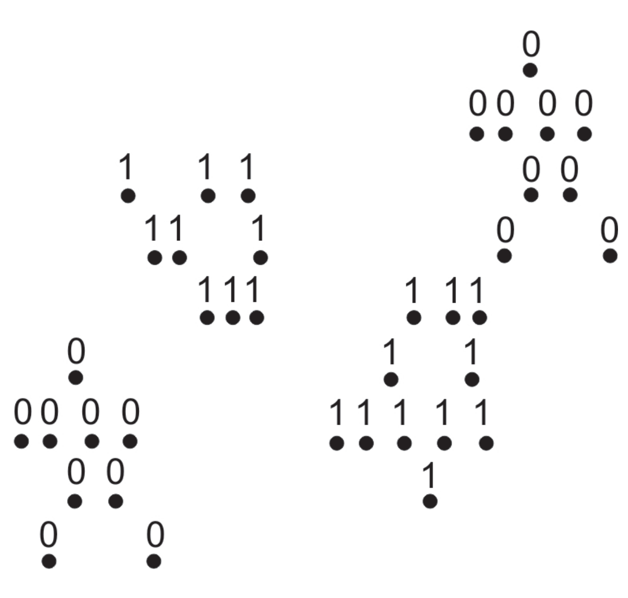

Fig. 3. Expression of 35 imaginary values where '1' used for sandstone locations and '0' for non-sandstone locations

Sl. 3. Skupina od 35 zamišljenih podataka gdje'1' predstavlja lokacije pješčenjaka, a '0' lokacije ostalih litofacijesa

4.2. Brief summary of Indicator Kriging (IK)

If data are not clustered spatially, the estimate of $F^*(z)$ can be done from the histogram of all data available. In the case of Simple Kriging estimator, the residual $[P^*(A, v_l)-F^*(v_l)]$ is used to derive as follows:

$$P^*(A,v_l) - F^*(v_l) = \sum_{i=1}^{n} \lambda_i(v_l)\left[i(x_i,v_l) - F^*(v_l)\right] \qquad (4.7)$$

where $\lambda_i(v_l)$ is the k-th weight for cutoff v_l.

Note, the simple kriging estimator differs from the Ordinary Kriging approach by not requiring the sum of weights to equal one. The Simple Kriging system of equation can be given as:

$$\sum_{k=1}^{n} \lambda_k(v_l)\gamma_i(x_i - x_m; v_l) = \bar{\gamma}(x_k; x_{k+h}, v_l),\ k = 1,2,\ldots,n \qquad (4.8)$$

In the above equation $\gamma_i(x_i - x_m; v_l)$ are the indicator semivariogram values for the distance x_i-x_m at cutoff v_l, and the terms $\bar{\gamma}(x_k, x_{k+h}; v_l)$ are average indicator semivariogram values between location x_k and x_{k+h} at cutoff v_l.

The IK process is repeated for all l cutoff (threshold) values, which discretize the interval of variability of the continuous attribute z. The distribution of uncertainty, built from assembling the l indicator kriging estimates, represents a probabilistic model for the uncertainty about the unsampled value $z(u)$. Obviously this Indicator Kriging procedure requires a variogram measure of correlation corresponding to each threshold.

It is important to note, that correct selection of the l cutoffs is essential for Indicator Kriging, In case of too many cutoffs the computation time increase drastically, but with too few cutoffs one can lose some important details of the distribution.[3] In general the number of cutoffs should be between 5 and 11.

Kriging of an indicator variable does not result only in values 0 and 1, but rather estimates along a continuous scale in the [0,1] interval. Thus Indicator Kriging yields probabilities (or relative frequencies) of the $\{z(x) < v_l\}$ events. Assuming that rank-ordered cutoffs are ($v_1 < v_2 < \ldots < v_n$), it is obvious that the estimated probabilities must obey the relations:

$$P^*(z(x); v_l) \le P^*(z(x); v_{l+1}) \text{ for all } l \qquad (4.9)$$

Linear estimation of probabilities belonging to l cutoffs permits one to draw several types of maps. For each cutoff, e.g. a map of the probabilities of not exceeding cutoff (i.e. $P^*(z(x), v_l)$), or the probabilities of exceeding v_l: $(1-P^*(z(x), v_l)$ can be evidently drawn. It is also evident that the estimated mean can be calculated through a discrete sum:

$$q^*(A;0) = \sum_{i=1}^{L} v_l^*\left\{P(A; v_{l-1}) - P^*(A; v_l)\right\} \qquad (4.10)$$

where v_l^* is the central value of the interval $\left[v_{l-1}; v_l\right]$.

Isoquantile maps can be drawn from the conditional distribution function fitted at each grid node. For instance, the median can be found by interpolation between v_{max} and v_{max-1}, where $P^*(A;v_{max})$ is the highest value of $P^*(A;v) \le 0.5$. The same procedure yields quantiles for any value of p, allowing one to map confidence intervals around a mean or median. The estimated confidence intervals can be calculated directly from the conditional distribution and do not need any assumption of the type of distribution of estimation variance.

4.3. Advantages and side effects

Using Indicator Kriging does not require stationarity assumption, or multivariate normality. One of the most important advantages is its robustness in respect to the extreme (outlier) values. Another important fact arises from the indicator formalism. By indicator cutoffs the originally continuous distribution is discretized. From this point the analysis runs on interval data rather than crisp data. That is, the preciseness of the input data is not necessarily required. It is enough to know that at a particular location the porosity lies in a particular interval. If this meets with one of the initially defined cutoff pairs, the input data set can be extended by adding this information. This is the property which we used in this work to make the input data set denser.

5. ADDING OF THE NEW "HARD" DATA AND VARIOGRAM ANALYSIS OF INDICATOR SET

The input dataset included porosity data collected in 19 wells from the reservoir 'T'. The very densely vertically spaced porosity values were averaged well by well for the whole reservoir interval. The minimum of 5.448% has been excluded from further analysis because it was recognised as outlier.

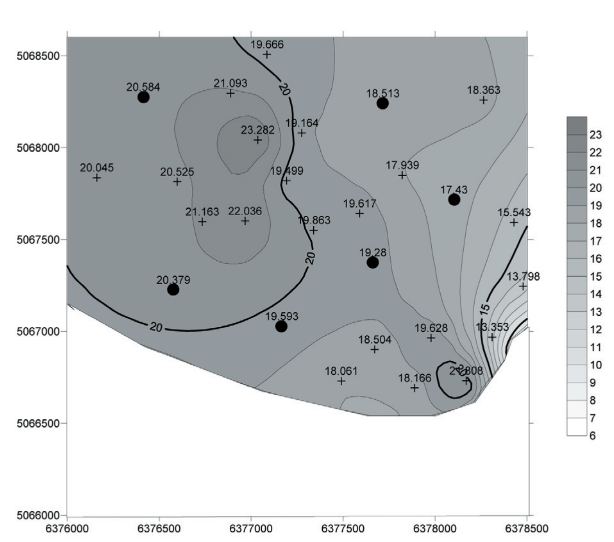

Fig. 4. Porosity distribution based on hard data derived from wells (+) and additional artificial hard data (?) with porosity estimated using Surfer™

Sl. 4. Distribucija poroziteta na temelju čvrstih bušotinskih podataka (+) i dodatno konstruiranih točaka (?) u kojima je poroznost procijenjena Surferom™

The wells are very irregularly spaced, with large areas of missing information (Fig. 4). To avoid this problem, six additional points (A, B, C, D, E and F) were set to the locations with lack of data. Their porosity values were estimated from the neighbouring wells using a linear variogram model. Additional hard data, their estimated porosity and X, Y locations are visible also in Figure 4 and in Table 1.

The presumption was that porosity values indicate different sandstone facies (i.e. marly sand, fine-grained and medium-grained sandstones). It is why porosity dataset had been transformed in the 6 indicator dataset, based on following (Table 1) cutoffs: 14, 18, 19, 20, 22 and 24%.

For each of the cutoffs, the corresponding indicator variogram was calculated using Variowin 2.21.[11]

The variogram models to be used in indicator kriging algorithm must obey the following criteria:[3]

- The theoretical (model) function must be the same (spherical is used here)
- The sill must be identical (standardized variogram)
- The nugget effect must be the same (it is zero here)
- Only the range can change for different indicator variables (all ranges were relatively low).

For keeping the simplicity all the experimental indicator variograms are considered as omnidirectional (Fig. 5). For each of the six variables, the starting lag spacing was set to 250 m.

6. INDICATOR KRIGING MAPPING USING PROGRAM 'WINGSLIB'

Indicator Kriging (abbr. 'IK') in WinGslib™ package is primarily used to generate conditional probabilities

Table 1. Indicator transformations of porosity based on different cutoffs. Coordinates are in Gauss-Krueger system in zone 5 (E13°30' - E16°30) with latitude of origin 0° and longitude of origin 15°.

X	Y	Por (%)	14%	18%	19%	20%	22%	24%
6376161.26	5067837.14	20.045	0	0	0	0	1	1
6376598.12	5067814.56	20.525	0	0	0	0	1	1
6376734.51	5067596.74	21.163	0	0	0	0	1	1
6376888.03	5068296.06	21.093	0	0	0	0	1	1
6377036.31	5068042.44	23.282	0	0	0	0	0	1
6376967.36	5067600.97	22.036	0	0	0	0	0	1
6377085.97	5068506.80	19.666	0	0	0	1	1	1
6377275.39	5068080.14	19.164	0	0	0	1	1	1
6377192.49	5067820.25	19.499	0	0	0	1	1	1
6377340.05	5067550.55	19.863	0	0	0	1	1	1
6377490.35	5066730.24	18.061	0	0	1	1	1	1
6377589.91	5067642.00	19.617	0	0	0	1	1	1
6377672.02	5066901.68	18.504	0	0	1	1	1	1
6377888.33	5066692.16	18.166	0	0	1	1	1	1
6377821.07	5067850.14	17.939	0	1	1	1	1	1
6377977.74	5066964.14	19.628	0	0	0	1	1	1
6378168.97	5066731.69	21.808	0	0	0	0	1	1
6378263.31	5068258.95	18.363	0	0	1	1	1	1
6378478.38	5067245.16	13.798	1	1	1	1	1	1
6376413.48	5068275.11	20.584	0	0	0	0	1	1
6376576.83	5067225.75	20.379	0	0	0	0	1	1
6377165.85	5067027.76	19.593	0	0	0	1	1	1
6377660.83	5067374.25	19.280	0	0	0	1	1	1
6378101.37	5067715.78	17.430	0	1	1	1	1	1
6377715.28	5068240.46	18.513	0	0	1	1	1	1

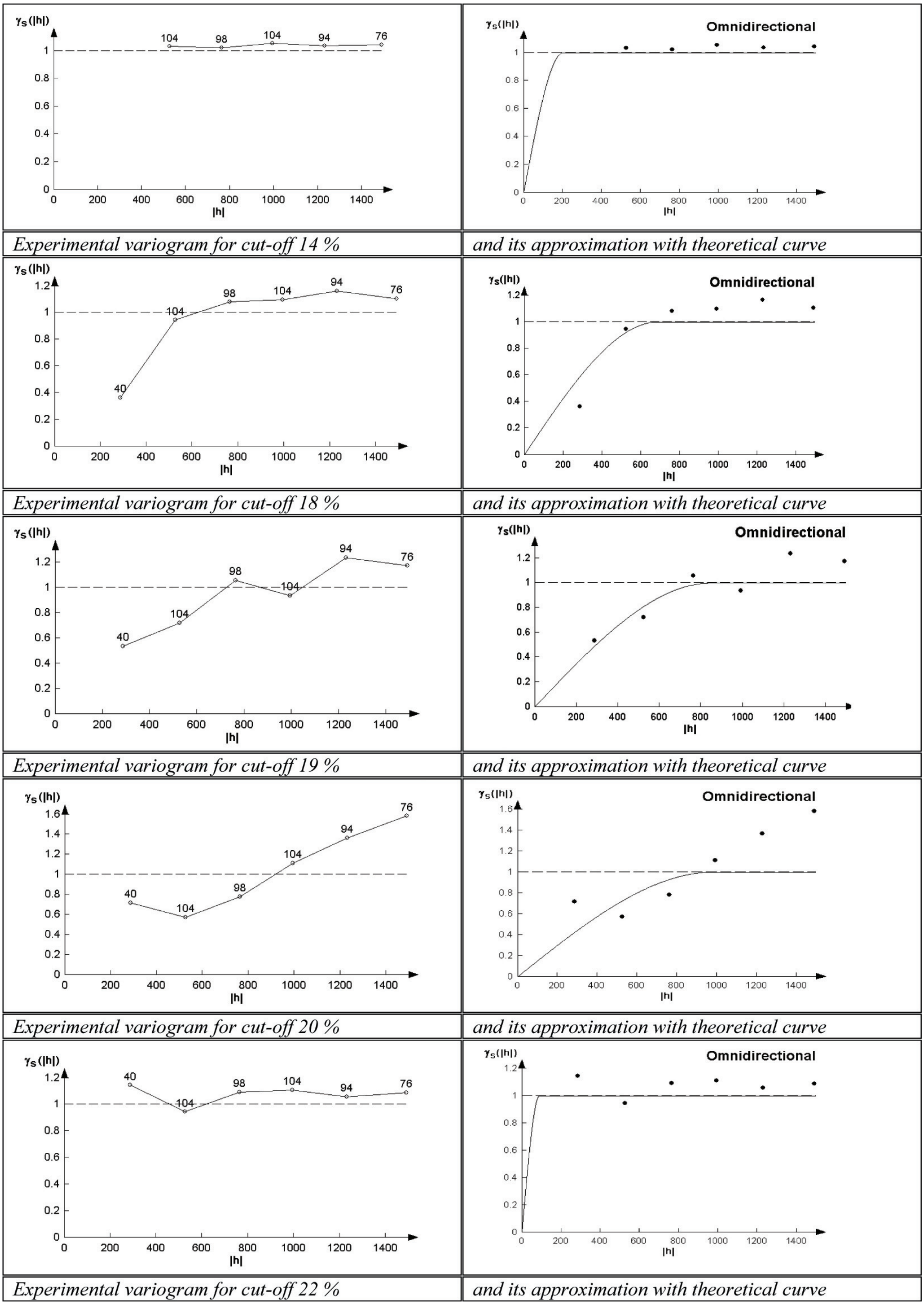

Fig. 5 **Experimental variograms for different cut-offs (left) and their approximations with theoretical curves (right)**
Sl. 5 Eksperimentalni variogrami za različite granične vrijednosti (lijevo) i njihova teorijska aproksimacija (desno)

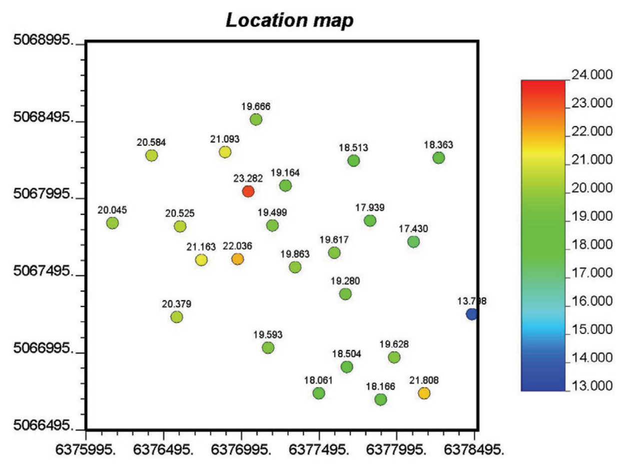

Fig. 6. Hard-data value map of 19 wells in Kloštar field with porosity value on each well, as well as 6 additional artificial hard data

Sl. 6. Položajna karta "čvrstih" (mjerenih) vrijednosti poroznosti u 19 bušotina na polju Kloštar, kao i 6 dodatno konstruiranih točaka

within the 'sisim' stochastic simulation program. Moreover 'ik3d' is program for simply and ordinary Indicator Kriging for categorical variables or cumulative indicators calculated for continuous variable. In the case of continuous variable, the Indicator Kriging algorithm provides independent discrete models (discrete probabilities) for the various cutoffs.

The flexibility of the IK approach comes from modelling the various probabilities with different variogram distances. Program 'ik3d' provides the necessary statistics, but with two constraints. The first is related to the estimated value $F\left(u;z_k(n)\right)$ to the bound 0 or 1, if originally valued outside the interval [0, 1]. The second constraint involves 'k' separate kriging results and it is harder condition than the first one. These constraints can help with negative indicator kriging weights or lack of data. Figure 6 is a map showing well locations and values. All maps in paper are created with program WinGslib™.

Cumulative probability distribution curve is obligatory input for indicator mapping. On Figure 7 'X' axis represents classes and 'Y' probabilities (in percentages).

Lots of input parameters had to be defined using 'ik3d'. Within the WinGslib system, the executables are parameterized by a special parameter file (abbr. 'par'). The procedure needs to be repetitive and that is why the main parameters of 'ik3d' program are listed here.

A 'Full IK" approach was used with 'Simple Kriging' estimation. This technique was chosen because it is based on global mean, and input dataset is small to take locally varying mean into consideration. In 'Grid definition' the number of cells both in X and Y directions was 251. The final model contains 63 001 cells.

As for cutoffs, six porosity values were selected: 14, 18, 19, 20, 22 and 24%. The corresponding cumulative probabilities were 0.08, 0.17, 0.36, 0.66 and 0.92 respectively.

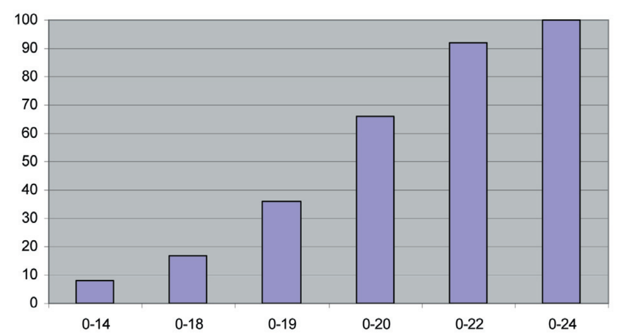

Fig. 7. Cumulative probability distribution for 8 porosity classes (Axes: X are porosity classes, Y is cumulative probability in %)

Sl. 7. Krivulja kumulativne vjerojatnosti prikazana kroz 8 razreda poroznosti (na osi X su vrijednosti razreda, na osi Y kumulativne vjerojatnosti u %)

The so called "E-type estimation" of porosity averaged for the whole reservoir interval is shown in Figure 8. This shows the most probable porosity value in the formation analysed.

Finally, the interpolated probability maps, for each of the selected cutoffs are shown in Figure 9.

Lateral distribution of the all mentioned facies (sandstone, marly sandstone, sandy marlstone and marl) across the analysed reservoir can be observed. Of course, such distribution depends on the selected cutoffs. In this case, the lowest porosities came from the part of reservoir with low oil saturation, close to the oil-water contact. The highest porosities correspond to the best part of the reservoir, i.e. these values are measured in the middle of the sandstone body.

The probability maps (Figure 9) have coloured legend. The blue colour means that there is no probability that

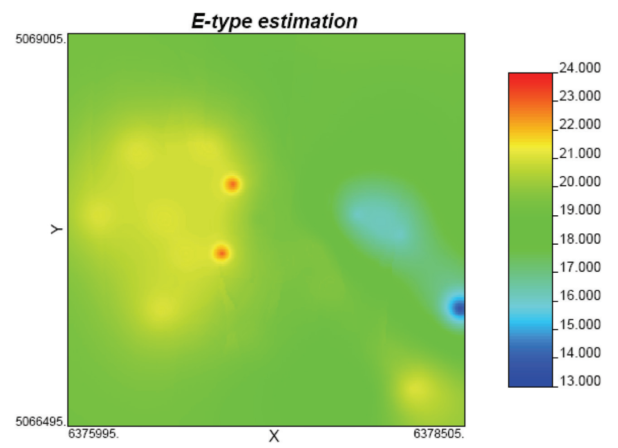

Fig. 8. E-type estimation of porosity derived from IK estimations of 5 cut-offs (14%, 18%, 19%, 20%, 22%)

Sl. 8. E-tip procjena poroznosti izračunata iz karata IK za 5 graničnih vrijednosti (14%, 18%, 19%, 20%, 22%)

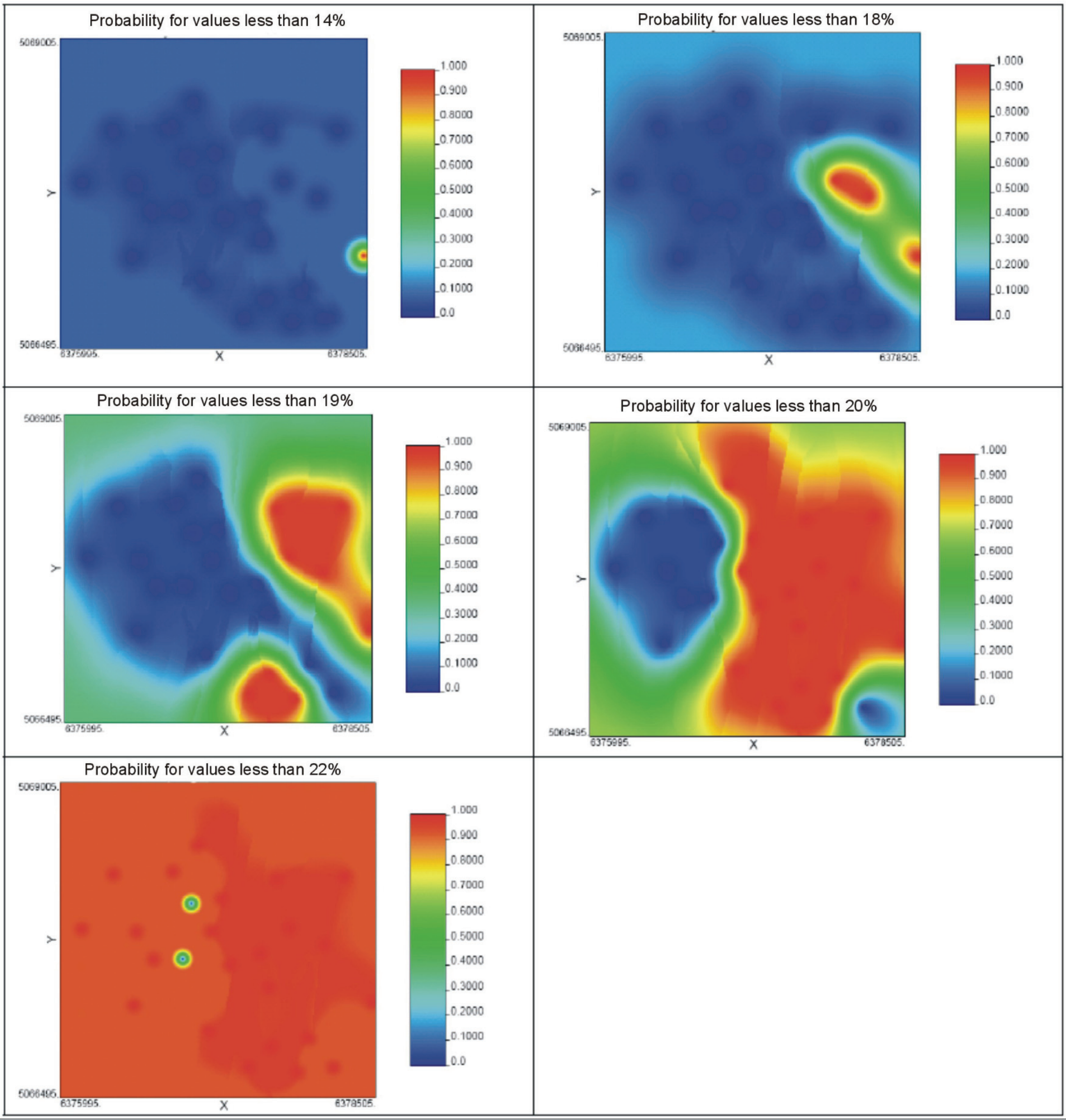

Fig. 9. Probability maps for porosity cutoffs. Probability '1' means for sure that value of cell will be lesser than selected cut-off
Sl. 9. Karte vjerojatnosti za granične vrijednosti poroznosti. Vjerojatnost '1' znači kako je sigurno da će vrijednost ćelije biti manja od odabrane granične vrijednosti

the cell value will be less than selected cutoff ($p = 0$). The red colour shows that cell value is for sure lower than selected cutoff ($p = 1$).

For example, for the cutoff = 14% (Figure 9) only the cells being in the SE corner of the study area can have (with some probability) porosities lower than 14%. The probability of finding such a low porosity values is 0 for all the other parts of the map.

On contrary, the map for cutoff=22% (Figure 9) is almost entirely in red colour (except the two central locations). It means that almost all cells will surely ($p = 1$) have the values lower than 22%. This is the way how to read this set of probability maps (Figure 9).

7. DISCUSSION

The Indicator Kriging is a specific geostatistical technique for spatial phenomena with weak stationarity. In fact, this kriging technique is weaker than any other kriging approximation. However, this technique is designed for estimating lateral uncertainty rather than 'crisp' values. It means that this approach estimates the local probability distributions on grid cells. IK works with interval data discretized form of the originally continuous distribution of a regionalized variable. That is why this method can be used at any case when data are too noisy, or when the 'exact' value is not known, but one can reliably estimate its interval (range of values).

Looking again at stationarity, there are three level of this condition. The first-order stationarity (which is invariant for any translation) is very strict requirement that cannot be satisfied using natural dataset. The weaker form is so called second-order stationarity which requires that the expected value must be independent on locations, and needs that the covariance is dependent only on the separation vector between any two locations. The third form is the so called intrinsic hypothesis which expects the mean to be independent and the existence of semivariogram. Just this third-order stationarity is assumed, because the decision to use variogram model means only the intrinsic hypothesis is expected as the minimum that the dataset has to satisfy (disregarding the nugget model).

Most of the kriging techniques are linear, but some of them are not. In fact, these are linear techniques applied on some non-linear transformation of the data. Indicator transformation (like in Equation 4.4) presented in analysis is one of such non-linear transformation and Indicator Kriging is non-linear technique as well. Such application in this analysis resulted in indicator variograms for different porosity cutoffs and, more important, in set of probability maps for such cutoffs. Using of these maps revealed the areal extension of porosity probability below defined cutoff.

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