GEOLOGIJA 65/1, 47-57, Ljubljana 2022

https://doi.org/10.5474/geologija.2022.003

Comparison of mapping efficiency for small datasets using inverse distance weighting vs. moving average, Northern Croatia Miocene hydrocarbon reservoir

Primerjava učinkovitosti kartiranja za majhne podatkovne nize z uporabo metode inverzne utežene razdalje in metode drsečega povprečja v miocenskem rezervoarju ogljikovodikov, Severna Hrvaška

Josip IVŠINOVIĆ[1] & Tomislav MALVIĆ[2]

[1]Vodnikova 17, HR-10000 Zagreb, Croatia; e-mail: jivsinovic@gmail.com
[2]Faculty of Mining, Geology and Petroleum Engineering, University of Zagreb, Zagreb, Croatia; e-mail: tomislav.malvic@rgn.unizg.hr

Prejeto / Received 7. 1. 2022; Sprejeto / Accepted 15. 7. 2022; Objavljeno na spletu / Published online 22. 07. 2022

Key words: Sava depression, Croatia, interpolation, hydrocarbon reservoirs, mapping spatial comparison

Abstract

Mapping of geological variables in the Croatian part of the Pannonian Basin System (CPBS) is mostly based on small input datasets. In the case of the analyzed hydrocarbon field "B", reservoir "K", due to the complex geological structure and pronounced tectonics, the interpretations are restricted on several blocks, where each has very limited dataset. The porosity (19 data) and permeability (18 data) variables were analyzed. The applied interpolation methods are the Inverse Distance Weighting (IDW) and the Moving Average (MA). They were compared and analyzed by visual inspection of the obtained maps, comparison of mathematical background and by calculation of cross-validation (CV). The cross-validation value for the porosity of the "K" reservoir in the case of IDW application is 0.0011, and in the case of MA 0.0010; while in the case of permeability the IDW is 480.84, and in the case of MA 1346.41. According to the visual review of maps, the values of descriptive statistics of estimated values and the results of cross-validation, the IDW method is recommended for mapping the porosity and permeability of reservoirs blocks in the Sava Depression.

Izvleček

Kartiranje geoloških spremenljivk v hrvaškem delu Panonskega bazena temelji večinoma na majhnih vhodnih podatkovnih nizih. V primeru preučevanega polja ogljikovodikov »B«, rezervoarja »K« je zaradi kompleksne geološke zgradbe in močno izražene tektonike, interpretacija omejena na nekaj blokov, od katerih ima vsak zelo omejen nabor podatkov. Analizirane spremenljivke so bile poroznost (19 podatkov) in prepustnost (18 podatkov). Kot interpolacijski metodi sta bili uporabljeni metoda inverzne utežene razdalje (IUR) in metoda drsečega povprečja (DP). Metodi smo primerjali in analizirali s pomočjo vizualnega pregleda dobljenih kart, primerjavo matematičnega ozadja in z izračunom navzkrižne validacije. Vrednost navzkrižne validacije za poroznost rezervoarja »K« pri uporabi IDW je 0,0011, v primeru uporabe DP pa 0,0010. Vrednost navzkrižne validacije v primeru prepustnosti pa je bila pri uporabi IDW 480,84 in pri uporabi DP 1346,41. Glede na vizualni pregled kart, vrednosti opisne statistike ocenjenih vrednosti in rezultate navzkrižne validacije, se je metoda IDW izkazala za priporočljivo metodo pri kartiranju poroznosti in prepustnosti rezervoarskih blokov v Savski depresiji.

Introduction

Complex geological structures result in a relatively small volumes and consequently small datasets. The tectonics causes the fragmentation in several block, often separate hydrodynamic units, what negatively affected production. In such complex conditions, it is necessary to set up a reliable spatial model of selected variables. Any successful application of the recommended interpolation method is always welcome because can be repeated in similar geological environments as the best approach. Here are analyzed the porosity and permeability of the Neogene reservoir "K" using Moving Average (MA) and Inverse Distance Weighting (IDW) methods.

The MA method was applied in different research areas: economics (Fan & Wang, 2020; Raudys & Pabarškaitė, 2018), food industry (Kolkova, 2018), medicine (Mustapa et al., 2019), geology (Balić et al., 2008), environment protection (Kumar et al., 2020), agriculture (Hatchett et al., 2009), transportation (Adeniran et al., 2018; Lenkutis et. al., 2021), energy (Alsharif et al., 2019; Xin et al., 2020) etc.

The IDW method is also widely used in various research areas (Achilleos, 2011; Al-Hassan & Adjei, 2015; Moeletsi et al., 2016; Tunçay et al., 2016; Ikechukwu et al., 2017; Maleika, 2020; Liu et al., 2021). In petroleum geology, IDW is used to map a small set of geological variables in the area of the Croatian Pannonian Basin System (CPBS), which has proven to be a reliable interpolation method (Ivšinović, 2018a; Malvić et al., 2019; Malvić et al., 2020; Ivšinović & Malvić, 2020). Also, this could be often applied method in mapping of hydrocarbon reservoirs worldwide (Wenli et al., 2021; Liu et al., 2020; Otchere et al., 2021) or subsurface resource in general (Busygin et al., 2019).

The paper analyzes the possibility of applying the MA on particular subsurface structure in the CPBS, the reservoir "K" of the field "B" located in the western part of the Sava Depression (Fig. 1). The analyzed input data set is less than 20 points, which according to the classification (Malvić et al., 2019) belongs to a small dataset. The mapping can be also done with different hybrid algorithms, no using pure interpolation, but connecting points from the very dense seismic, gravimetric or similar grids (*e.g.,* Vrdoljak et al., 2021; Lemenkova, 2021). As quality check the MA results are compared with the IDW method, which is previously proven as very reliable mapping method in the research area (Malvić et al., 2019; Ivšinović & Malvić, 2020).

This research is continuation of analyses of different mathematical interpolation algorithms application in the Miocene reservoirs of the CPBS. This task is important, not only for better knowing of the geological subsurface of this part of the PBS, but also because such algorithm is mostly applied in hydrocarbon reservoirs, still in production, and results have also economic value. The testing of different mathematical interpolation algorithms extensively started in this part more than decade ago *(e.g.,* Balić, et al., 2008; Malvić, 2008), where some of the knowing algorithms had been compared regarding their efficiency in mapping of geological variables collected in Miocene of the CPBS. So, Balić et al., (2008) compared also in the Sava Depression, in the Kloštar Field, four interpolations, namely: Inverse Distance Weighting, Nearest Neighborhood, Moving Average and Kriging, using 20 porosity values from Upper Miocene reservoir. Interestingly, cross validation/mean square errors formula resulted in very similar values, orderly: Kriging 366.93, Moving Average 369.26, Inverse Distance Weighting 371.97, Nearest Neighborhood 389.00. It was concluded that limited dataset influenced variogram model as well as successfulness of exact interpolators like (Ordinary Kriging or IDW, especially because distribution could not be concluded. Authors pointed out that calculation of residual map can help in the interpretation of zones with higher uncertainty. Simultaneously, Malvić (2008) performed comparison between three geostatistical approaches – Kriging, CoKriging and stochastical simulation (i.e., deterministic vs. stochastic) for datasets taken in the Drava Depression (also in the CPBS). The analysis was done with only 14 data points, so the application of geostatistics strongly depended on assumption of normal distribution (the 2nd order stationarity assumption for Kriging and related methods). The simulations are described as the most descriptive approach, where zones of errors are the easiest recognizable.

In analysis presented here, the input datasets are not characterized with normal distribution as well as the entire dataset can be set up in only three classes, so distribution cannot be examined with any statistical formal test for normality like Shapiro-Wilk, Kolmogorov-Smirnov, Lilliefors and Anderson-Darling (Razali & Wah, 2011). To bypass the normality condition, we selected two methods where such distribution is not strong condition, namely Inverse Distance Weighting and Moving Average, to improve conclusions obtained in earlier publications, especially in (*e.g.,* Balić et al., 2008).

Geological settings of analyzed area

Analyzed oil reservoir is part of the typical hydrocarbon field in the CPBS. The geographical position of the analyzed field "B" is shown in Figure 1.

The reservoir is composed of medium to fine-grained sandstone, altered with marls. The age is Upper Miocene. A typical geological column of the western part of the Sava Depression is shown in Figure 2.

The reservoir had been formed by the deposition of turbidities originating from the eastern part of the Alps. A schematic representation of the sedimentary environment during the Upper Pannonian and Lower Pontian is shown in Figure 3.

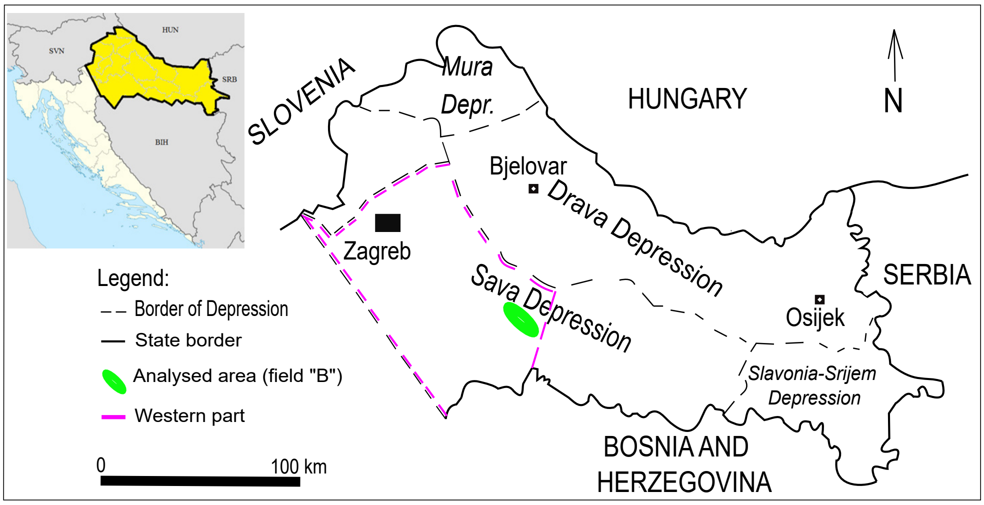

Fig. 1. Geographical position of the western part of the Sava Depression and field "B" (Ivšinović et al., 2020).

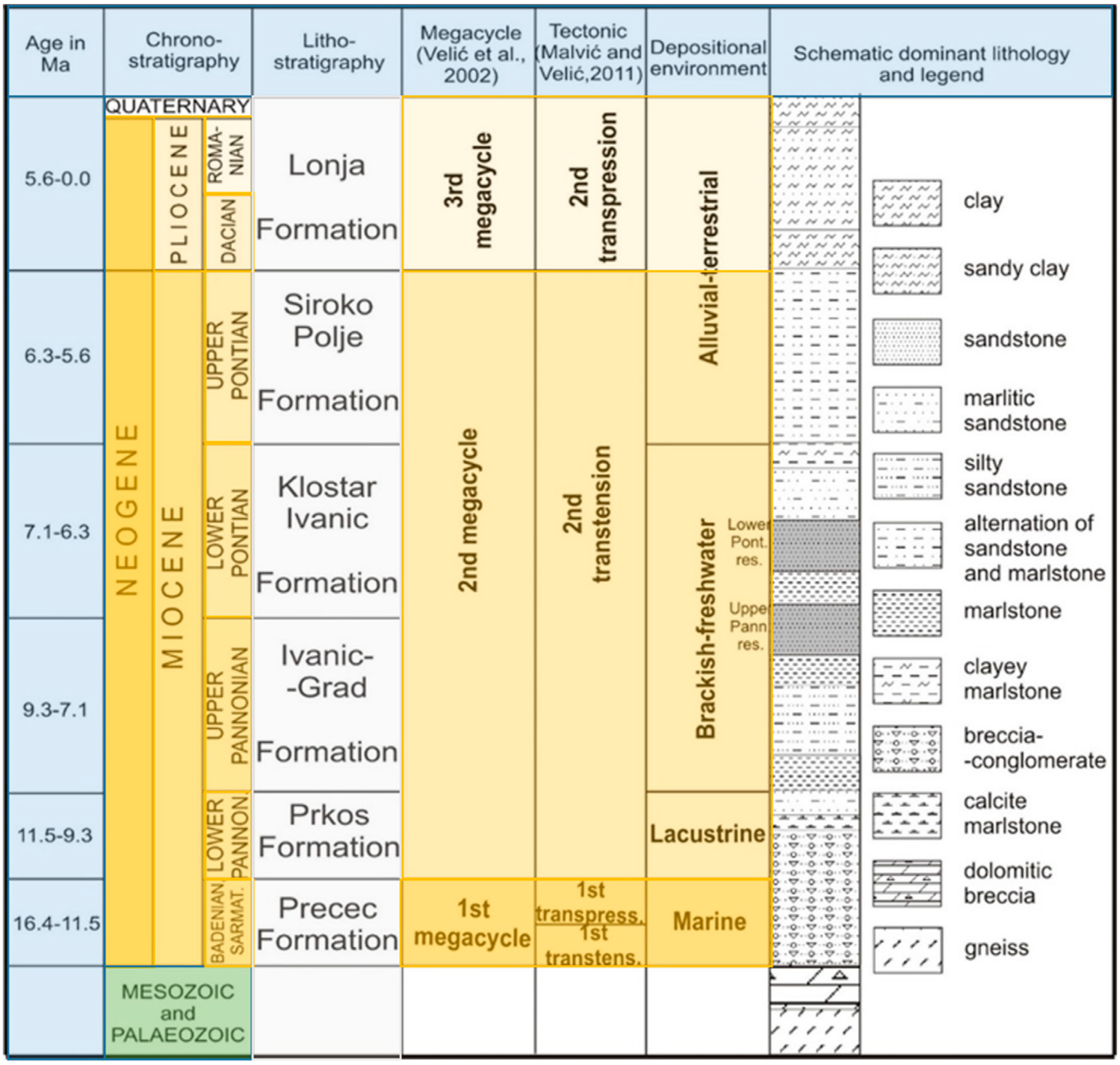

Fig. 2. Typical geological column of the Sava Depression (e.g., Novak Zelenika, 2013; Novak Zelenika et al., 2018).

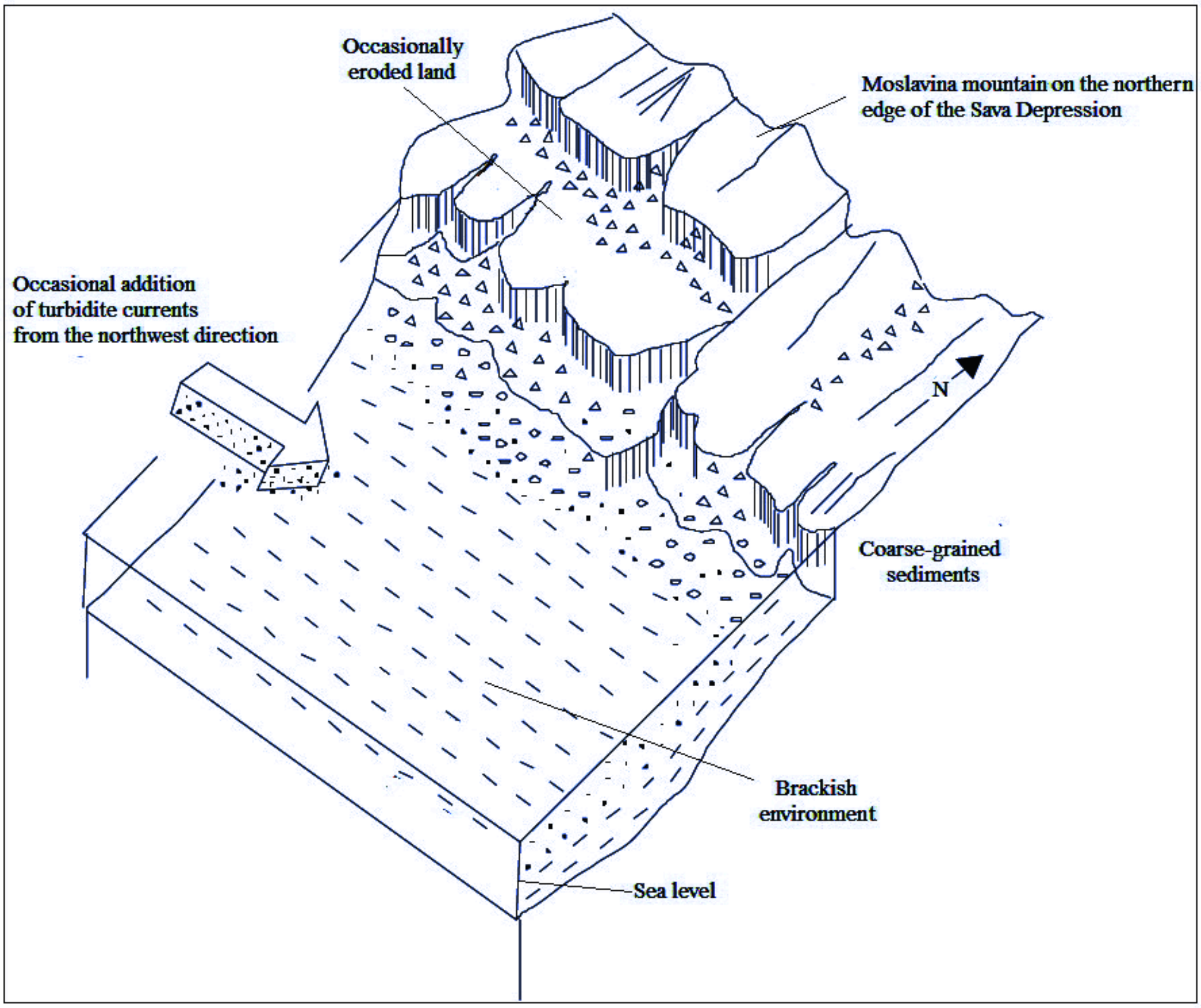

Fig. 3. Sedimentary environment during the Upper Pannonian and Lower Pontian western part of the Sava Depression (Ivšinović et al., 2021).

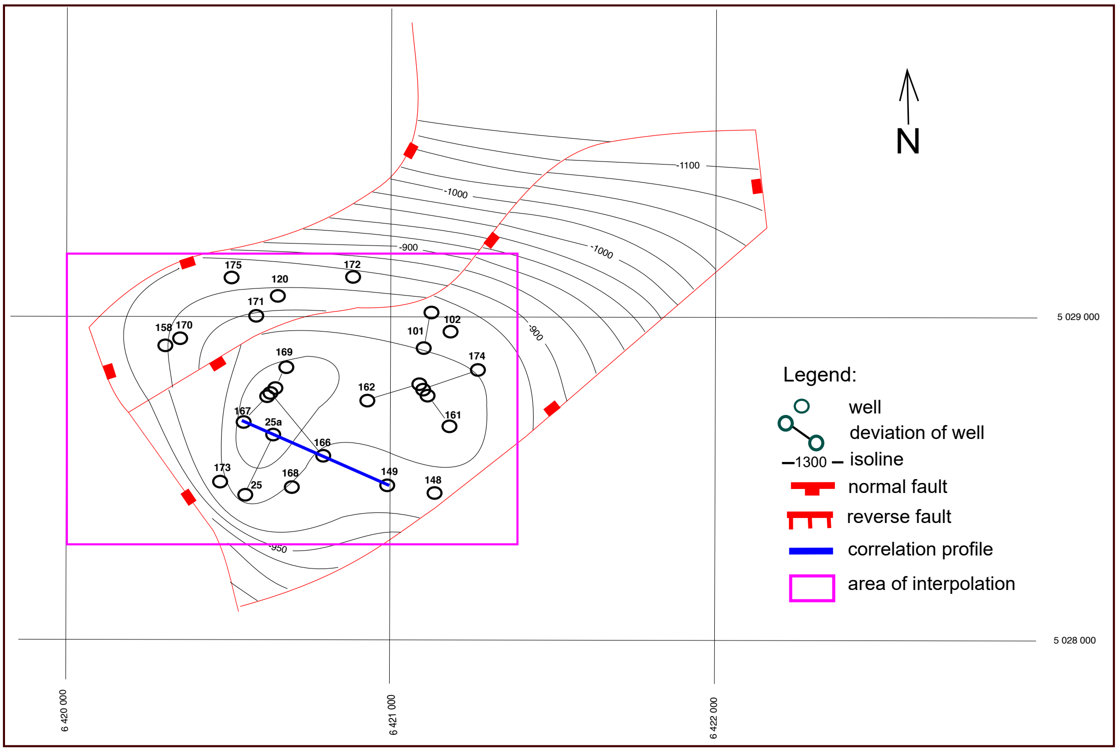

Fig. 4. Structural map of reservoir "K" (Malvić et al., 2020).

Reservoir hydrodynamics is defined by faults, which created several blocks with different permeabilities. In the beginning the contact oil-water was unique for entire reservoir, i.e., reservoir was single hydrodynamic unit. However, after some recovery period, parts are characterized with larger permeability caused that that fluids faster moving upward as well as contact, and consequently larger portion of water in produced fluid, until the production was not ceased. The structural map of the analyzed deposit "K" of the field "B" is shown in Figure 4. The reservoir is classified as layer type or with structural-stratigraphic trap.

Simultaneously, reservoir pressure was dropped, but also minor communication of fluids had happened through fault zones.

Methodology

The applied interpolations were Moving Average (MA), and Inverse Distance Weighting (IDW). Their results had been compared visually, numerically and theoretically.

Moving Average (MA)

The MA method (Eq. 1) assigns values to spatial points by determining the mean value of measured data located within a particular area around the grid node (un-known value that is estimated by MA). The minimum (sometimes also maximum) amount of analyzed data should be defined. The value calculated in each grid node is equal to the arithmetic mean of the measured data located within the defined range of spatial dependence. The mathematical equation for calculating the moving average value is (*e.g.,* Johnston et al., 1999; Ekhosuehi & Omorogbe Dickson, 2016; Rusdiana et al., 2020):

$$y_{i,\mathrm{j}} = \frac{1}{n}\sum_{k=1}^{n} x_{i,j-k} \tag{1}$$

where: $y_{i,j}$-interpolated value of moving average method; n- number of data set; $x_{i,j-k}$- input data.

Inverse Distance Weighting (IDW)

The IDW method is based on the distance (ponder with exponent, mostly second power) between the measured data and the location where unknown value is estimated. Such values are in grid nodes. The measured data included in calculation are values inside the searching radius/radii, i.e. inside circle/ellipsoid of spatial dependence. The mathematical expression for inverse distance estimation (*e.g.*, Setianto & Triandini, 2013; Ivšinović, 2018b) is:

$$z_{IU} = \frac{\dfrac{z_1}{d_1^p} + \dfrac{z_2}{d_2^p} + \dots \dfrac{z_n}{d_n^p}}{\dfrac{1}{d_1^p} + \dfrac{1}{d_2^p} + \dots \dfrac{1}{d_n^p}} \tag{2}$$

where: z_{iu}-estimated value; d_i-distance to "i-th" location; p-power of distance; z_i-measured values at "i-th" location.

The result of IDW interpolation depends on the value of the exponent p, which is obtained experimentally and has a different value in different fields of science. In subsurface mapping, for the CPBS, the proposed value exponent "p" is 2.

Cross-validation (CV)

Cross-validation (CV) or out-of-sample testing is a method of assessing the quality of a map obtained by implemented an interpolation method. It is based on the re-placement of the any measured (original) data(s) from an entire measured dataset and is replaced by a new value(s) estimating from the existing data set. In geology the most often is applied "p=1", i.e., leaving-one-out CV. Differences between measured and estimated value on the same location is error. The very often such error are calculated using mean square error algorithm (MSE). The mathematical formula for calculating MSE is (*e.g.*, Malvić & Novak Zelenika, 2013):

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(\text{measured} - \text{estimated})^2 \tag{3}$$

where: MSE- mean square error; measured-known value at location "i"; estimated- unknown value (deleted) at location "i"; n - number of locations.

The quality of the map obtained by the interpolation method is based on the numerical value of the MSE, the lower the value of the MSE the better the applied interpolation method.

Mathematical differences in MA and IDW and reflections of searching radius

Basically, both methods are considered as mathematically simpler interpolation methods, that highly depend on number of input data. However, both use so called searching radius or radii. If anisotropy could be recognized and quantitatively described, two axes/ellipsoid of dependency are defined, if not – the circle outlined area with hard data included in calculation. The small datasets (n<20) hardly allow unambiguous recognition of anisotropy, even with lot of qualitative geological data, so the most often MA or IDW works with searching radius or circle (of spatial dependance), without any further separation of circle in quadrants or octants, because most of them would be without single hard value, i.e., would be empty.

Definition of searching radius is much more important in MA then IDW, because MA does not honor distances among unknown value/location and known, measured, hard data. However, one of the geological axioms is that if what two measurements are more distant in space, the difference must be larger. It is valid for any geological variable, like thickness, granulometry, porosity, permeability, depths etc., simply because any geological value is result of particular geological environment, limited in space and time. Consequently, the equally weighting of each measured value (MA) inside searching radius surely does not honor such rule (Equation 1), especially because area of spatial dependance has to cover large part or entire analyzed area to include at least one measured value.

Oppositely, the IDW honor the distances among estimated and measured values, equally for any direction (Equation 2). Even for single reservoir this could be crucial advantage, because reservoir's lithofacies is not homogeneous and will gradually change from the center of structure, especially if depocenter remained in the current structure top, toward the reservoir margins. This presumption has been tested in this work and elaborated with results, discussion and conclusions.

Results and discussion

The analyzed variables were obtained from laboratory measurements of well cores and logging measurements. Data from reservoir "K" are shown in Figure 5.

The analyzed porosity (19 data) and permeability (18 data) belong to a small datasets. They are characterized by intervallic grouped data - in the case of permeability two, and in the case of porosity three groups, which is results of analytical approximation and reservoir heterogeneity. However, the problem is what the formal normality tests cannot be applied, and empirical Q-Q plot cannot be calculated. It is why those two interpolation algorithms, where normal distribution is not strong condition for their application, had been selected.

Based on selected area and structural axes, the searching radius was in both algorithms set on 628 m. It is done using the "rule of the thumb" that if data do not allow create reliable spatial model, omnidirectional or anisotropic, for searching radius is recommended to use structural or depositional axes and their ration (if exists). So, 628 m is about half of the quadrat used to border researched area and is used for omnidirectional/circle searching radius. The research area is

Well	Surface X	Surface Y	Porosity (part of units)
J-101	6421096	5028877	0.217
J-120	6420658	5029068	0.272
J-161	6420957	5028870	0.217
J-162	6421034	5028593	0.217
J-167	6420529	5028674	0.217
J-168	6420699	5028475	0.315
J-169	6420724	5028825	0.217
J-170	6420349	5028926	0.223
J-174	6421298	5028863	0.217
J-175	6420475	5029136	0.223
J-158	6420303	5028910	0.223
J-171	6420576	5028970	0.223
J-172	6420928	5029147	0.223
J-102	6421208	5028926	0.217
J-148	6421126	5028437	0.217
J-149	6420959	5028501	0.217
J-166	6420771	5028650	0.217
J-25	6420546	5028460	0.315
J-173	6420539	5028382	0.217

Fig. 5. Raw data set of porosity and permeability of reservoir "K" (Malvić et al., 2020).

Table 1. Cross-validation values and descriptive statistics of estimated values for IDW and MA methods for geological variables porosity and permeability of reservoir "K".

Variable	Method	Cross-validation (MSE)	Min	Max	Mean	Standard deviation
Porosity	IDW	0.0011	0.219	0.293	0.232	0.016
Porosity	MA	0.0010	0.217	0.243	0.231	0.006
Permeability	IDW	480.84	36.33	115.97	90.97	28.97
Permeability	MA	1346.41	63.95	121.20	93.06	13.34

42.3 km^2. Obtained permeability and porosity interpolations by IDW and MA methods are shown in Figure 6, while the results of cross-validation and descriptive statistics are shown in Table 1.

The results given on Figure 6 are influenced with, and reflected in, the complexity of the geological structure, and especially depositional environments that are responsible for clastic types and their petrophysics. Here is also included the problem of measurement errors and consequently fitting of measured values into classes. It is well known that laboratory and logging results can differ, even for an order of magnitude, so sometimes they are not directly comparable or have to be used jointly only with caution. The step of caution had been selection of values in group, decreasing influence of measurement error, but also decreasing data spectrum, what made interpolation significantly less representative, especially on smaller scales of changes.

The IDW porosity map (Fig. 6, a) shown many outliners of individual points resulted in so-called bull-eyes and even on NW part butterfly effects. That was expected due to the distances of measured data, applied power exponent and values of minimum and maximum. According to Table 1 IDW porosity values have standard deviation of 0.016 and MSE 0.0011.

The MA porosity map (Fig. 6, b) is more uniformly shaped at first glance. No butterfly or bull-

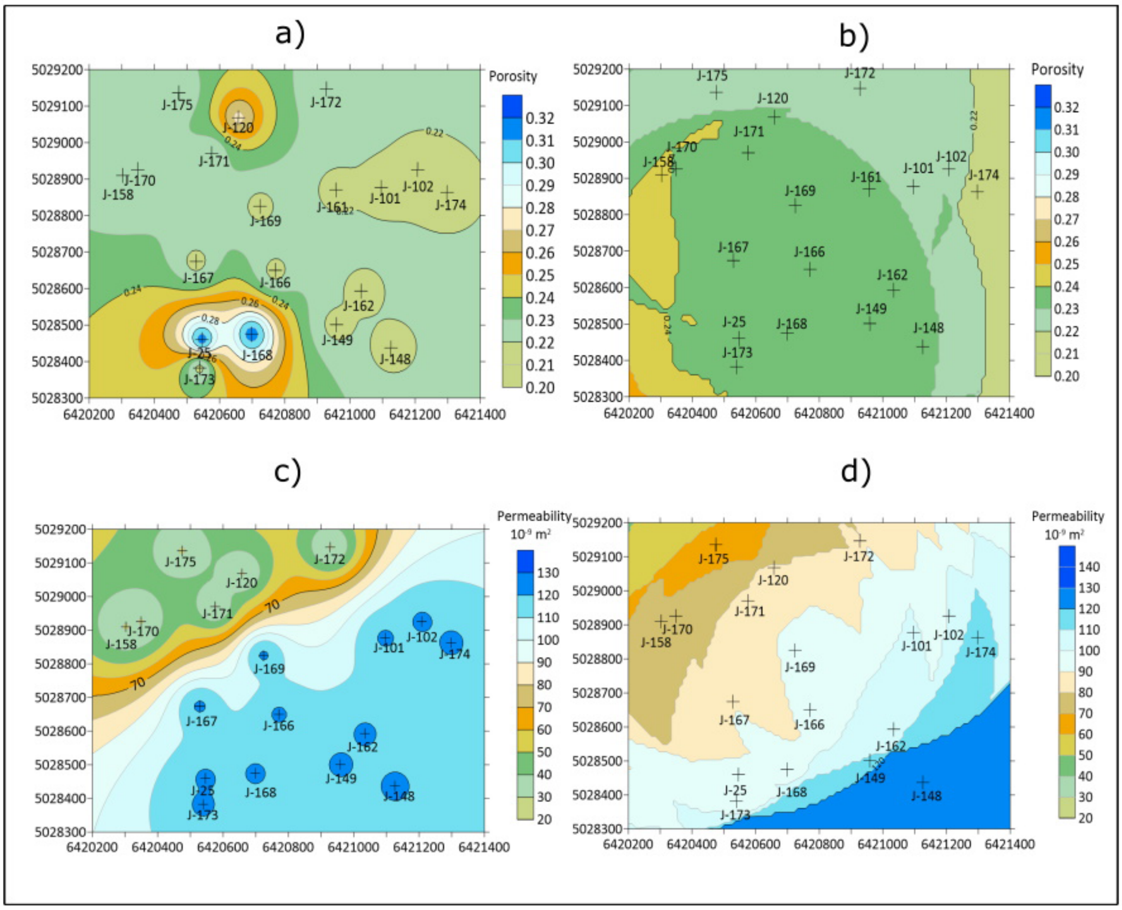

Fig. 6. Maps of reservoir "K" obtained by interpolation methods: (a) Porosity (IDW); (b) Porosity (MA); (c) Permeability (IDW); (d) Permeability (MA).

eyes are pronounced, which is understandable because it is a local calculation of the mean value around the estimated data, i.e., in the searching radius. So, if averaging is dominant, and total number of data is small, the consequence is that many estimations will be averaged with the same values. Furthermore, it means that complex shapes like butterfly of bull-eye effects will not be developed. Moreover, the transition area between the data is not emphasized, but island-like irregularities are formed in this area (between wells J-170 and J-175 or J-162 and J-174. Due to the data averaging, the usual butterfly or bull-eyes effects cannot occur, as in the IDW method. That is clearly seen by the circular appearance of the "green" surface in the center of Figures 6, b. Comparing the data of descriptive statistics (Table 1) the values of standard deviation (0.006) and MSE (0.0010) are slightly smaller than in the IDW.

The IDW permeability map (Fig. 6, c) emphasized the butterfly or bull-eyes effects. In the northwestern part of the reservoir, it is less pronounced, while in the southeastern more. Fig. 6, c clearly shows the zone of abrupt changes between wells J-169 and J-171 or J-167 and J-158. The transition zone between the zone of higher reservoir permeability and lower reservoir permeability can be follow along entire map and correspond to fault zone shown on structural map (Fig. 4). The data of the descriptive statistics from Table 1 showed relatively small standard deviation (28.97) and high MSE (480.84).

On the MA permeability map (Fig. 6, d) is clearly seen no uniform transition zone between the different permeability values. This can be seen in Figure 6, d through the peninsula-like shape between wells J-166 and J-167 or J-101 and J-102. The values are averaged as seen from the descriptive statistics in Table 1 and although standard deviation is smaller than by IDW (13.34) the MSE is extremely high (1346.41). The difference between the original and estimated data (MSE) is twice as large in the case of the min values of the set. This can be seen from the interpolated map (Fig. 6, d) that the permeability values of wells J-167 and J-169 differ significantly, and the measured values are the same ($121.2 \cdot 10^{-9}$ m^2). Regarding large difference between MSE(IDW) and MSE (MA), here 480.84 vs. 1346.41, the range of permeability is much higher than of porosity, so consequently any estimation will varies significantly depending on applied mathematical algorithm, like it is shown in results.

As can be seen from Table 1, the cross-validation/MSE value has a lower value of MA than IDW in the case of porosity, while in the case of throughput it is the reverse case. The difference in cross-validation in bandwidth between the MA and IDW methods is 0.0001. This difference can be ignored due to the other results of the descriptive statistics in Table 1. It can be observed that the coverage of the estimated values in the IDW method is much more realistic than in the case of the MA method. In such cases, the rule of accepting the interpolation method to the amount of the lower CV value can be deviated from. Most importantly, the estimated values obtained by interpolation methods must be an approximate reflection of the measured data.

Conclusions

Here is solved one local problem of selection the appropriate interpolation algorithm for small datasets of petrophysics measured in the subsurface Miocene hydrocarbon reservoirs in the Northern Croatia (CPBS). So, the results are of interest for researchers engaged in the studying of such reservoirs in the Sava Depression as well as in all other depressions in the CPBS. However, all researching that included interpolation of small geological datasets (n<=20 points) could find those achievements and conclusions worth of testing in their own explorations, whatever the data are collected from surface or subsurface. The specific outcomes obtained with this analysis are:

- Visual inspection of the obtained interpolated maps revealed that the maps obtained by the IDW method are more acceptable for interpretation of reservoir petrophysics compared to the MA method.
- The permeability map of the "K" reservoir obtained by the MA method can be described with mosaic effect, with sharply wavy, peninsular, and island shapes, which is not an unusual case in mapping of small datasets, but cannot be interpreted with sense. This is characterized by a high value of cross-validation.
- Descriptive statistics, histograms and maps showed that the values obtained by the IDW method are closer to the ranges of original datasets. The differences between IDW and MA are about 25 % for porosity and more than 200 % for permeability.
- The calculated cross-validation/MSE for the MA method in the case of porosity is 0.0010, and permeability is 1346.41 for reservoir "K". In the case of the IDW method the MSE for porosity is 0.0011, while for permeability 480.84. The difference between the MSE values for porosity can

be neglected with respect to the results of descriptive statistics and visual inspection of the obtained maps.

- This researching showed that mapping the porosity and permeability of Neogene reservoir in the CPBS highly depends on the experience of the interpreter in the application of different mathematical methods and geological under-standing of spatial distribution of selected variables. The MA showed one large disadvantages – in the case of small datasets there is not enough measured values inside searching radius for reliable calculation of average. So, the "distance weighting" approach of the IDW is far better approach for mapping of reservoirs in such case.

Acknowledgment

This work has been supported in part under the project "Mathematical researching in geology VII (led by T. Malvić), at the University of Zagreb, Faculty of Mining, Geology and Petroleum Engineering.

References

Achilleos, G.A. 2011: The Inverse Distance Weighted interpolation method and error propagation mechanism – creating a DEM from an analogue topographical map. Journal of Spatial Science, 56/2: 283–304. https://doi.org/10.1080/14498596.2011.623348

Adeniran, A., Kanyio, O. & Adelanke Samuel, O. 2018: Forecasting Methods for Domestic Air Passenger Demand in Nigeria. J. Appl. Res. Ind. Eng., 5: 146–155. https://doi.org/10.22105/jarie.2018.133561.1038

Al-Hassan S. & Adjei, D. 2015: Competitiveness of Inverse Distance Weighting Method for the Evaluation of Gold Resources in Flu-vial Sedimentary Deposits: A Case Study. Journal of Geosciences and Geomatics, 3/5: 122-127. https://doi.org/10.12691/jgg-3-5-2

Alsharif, M.H., Younes, M.K. & Kim, J. 2019: Time Series ARIMA Model for Prediction of Daily and Monthly Average Global Solar Radiation: The Case Study of Seoul, South Korea. Symmetry, 11/2: 240. https://doi.org/10.3390/sym11020240

Balić, D., Velić, J. & Malvić, T. 2008: Selection of the most appropriate interpolation method for sandstone reservoirs in the Kloštar oil and gas field. Geologia Croatica, 61: 27-35.

Busygin, B., S. Nikulin, S. & Sergieieva, K. 2019: Solving the tasks of subsurface resources management in gis rapid environment. Mining of Mineral Deposits, 13/3: 49-57. https://doi.org/10.33271/mining13.03.049

Ekhosuehi, N. & Omorogbe Dickson, E. A. 2016: On Forecast Performance Using a Class of Weighted Moving Average Processes for Time Series. Journal of Natural Sciences Research, 6: 87-92.

Fan, Q. & Wang, F. 2020: Detrending-moving-average-based bivariate regression estimator. Phys. Rev. E 102. https://doi.org/10.1103/PhysRevE.102.012218

Hatchett, R. B., Brorsen, B. W., K. B. & Anderson, K. B. 2009: Optimal Length of Moving Average to Forecast Futures Basis. Proceedings of the NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management, St. Louis, U.S.A., 20-21 April 2009.

Ikechukwu, M., Ebinne, E., Idorenyin, U. & Raphael, N. 2017: Accuracy Assessment and Comparative Analysis of IDW, Spline and Kriging in Spatial Interpolation of Landform (Topography): An Experimental Study. Journal of Geographic Information System, 9/3: 354-371. https://doi.org/10.4236/jgis.2017.93022

Ivšinović, J. & Malvić, T. 2020: Application of the radial basis function interpolation method in selected reservoirs of the Croatian part of the Pannonian Basin System. Mining of mineral deposits, 14: 37-42. https://doi.org/10.33271/mining14.03.037

Ivšinović, J. 2018a: The relationship between sandstone depositional environment and water injection system, a case study from the Upper Miocene hydrocarbon reservoir in northern Croatia. In Proceedings of the 2nd Croatian scientific congress from geomathematics and terminology in geology, Zagreb, Croatia, 6 October 2018.

Ivšinović, J. 2018b: Deep mapping of hydrocarbon reservoirs in the case of a small number of data using the example of the Lower Pontian reservoirs of the western part of the Sava Depression. In Proceedings of the 2nd Croatian scientific congress from geo-mathematics and terminology in geology, Zagreb, Croatia, 6 October 2018.

Ivšinović, J., Pimenta Dinis, M., Malvić, T. & Pleše, D 2021: Application of the bootstrap method in low-sampled Upper Miocene sandstone hydrocarbon reservoirs: a case study. Energy sources part A-recovery utilization and environmental effects, 43. https://doi.org/10.1080/15567036.2021.1883773

Ivšinović, J., Malvić, T., Velić, J. & Sremac, J. 2020: Geological Probability of Success (POS), case study in the Late Miocene structures of the western part of the Sava Depression, Croatia. Arabian Journal of Geosciences, 13: 1-12. https://doi.org/10.1007/s12517-020-05640-z

Johnston, F. R., Boyland, J. E., Meadows, M. & Shale, E. 1999: Some properties of a simple moving average when applied to forecasting a time series. Journal of the Operational Research Society, 50: 1267-1271.

Liu, H., Chen, S., Hou, M. & He, L. 2020: Improved inverse distance weighting method application considering spatial autocorrelation in 3D geological modeling. Earth Sci Inform 13, 619–632. https://doi.org/10.1007/s12145-019-00436-6

Kolkova, A. 2018: Indicators of Technical Analysis on the Basis of Moving Averages as Prognostic Methods in the Food Industry. Journal of Competitiveness, 10: 102–119. https://doi.org/10.7441/joc.2018.04.07

Kumar, A. K., Lakshmi, A. S. & Nivas Rao, P. J. 2020: Moving average method based air pollution monitoring system using IoT plat-form. In Proceedings of the First International Conference on Advances in Physical Sciences and Materials, Coimbatore, India, 13-14 August 2020. https://doi.org/10.1088/1742-6596/1706/1/012078

Lemenkova, P. 2021: Submarine tectonic geomorphology of the Pliny and Hellenic Trenches reflecting geologic evolution of the southern Greece. Rudarsko-geološko-naftni Zbornik (The Mining-Geological-Petroleum Bulletin), 36/4: 33-48 https://doi.org/10.17794/rgn.2021.4.4

Lenkutis, T., Čerškus, A., Šešok, N., Dzedzickis, A. & Bučinskas, V. 2021: Road Surface Profile Synthesis: Assessment of Suitability for Simulation. Symmetry, 13/1: 68. https://doi.org/10.3390/sym13010068

Liu, Z., Zhang, Z., Zhou, C., Ming, W. & Du, Z. 2021: An Adaptive Inverse-Distance Weighting Interpolation Method Considering Spatial Differentiation in 3D Geological Modeling. Geosciences, 11: 51. https://doi.org/10.3390/geosciences11020051

Maleika, W. 2020: Inverse distance weighting method optimization in the process of digital terrain model creation based on data collected from a multibeam echosounder. Appl Geomat, 12: 397–407. https://doi.org/10.1007/s12518-020-00307-6

Malvić, T. & Novak Zelenika, K. 2013: Hrvatski rječnik odabranih geostatističkih pojmova. Rudarsko-geološko-naftni zbornik, 26: 1-9.

Malvić, T. 2008: Kriging, cokriging or stochastical simulations, and the choice between deterministic or sequential approaches. Geologia Croatica, 61: 37-47.

Malvić, T., Ivšinović, J., Velić, J. & Rajić, R. 2019: Interpolation of Small Datasets in the Sandstone Hydrocarbon Reservoirs, Case Study of the Sava Depression, Croatia. Geosciences, 9: 201. https://doi.org/10.3390/geosciences9050201

Malvić, T., Ivšinović, J., Velić, J., Sremac, J. & Barudžija, U. 2020: Application of the Modified Shepard's Method (MSM): A Case Study with the Interpolation of Neogene Reservoir Variables in Northern Croatia. Stats, 3/1: 68-83. https://doi.org/10.3390/stats3010007

Moeletsi, M., Shabalala, Z., Nysschen, G. & Walker, S. 2016: Evaluation of an inverse distance weighting method for patching daily and dekadal rainfall over the Free State Province, South Africa. Water SA, 42: 466-474. https://doi.org/10.4314/wsa.v42i3.12

Mustapa, R., Latief, M. & Rohandi, M. 2019: Double moving average method for predicting the number of patients with dengue fe-ver in Gorontalo City. Global Conferences Series: Sciences and Technology (GCSST), 2: 332-337. https://doi.org/10.32698//tech1315168

Novak Zelenika, K. 2013: Lithofacies definition based on cut-offs in Indicator Kriging mapping, case study Lower Pontian reser-voir, Sava Depression. Nafta, 64: 39-44.

Novak Zelenika, K., Novak Mavar, K. & Brnada, S. 2018: Comparison of the Sweetness Seismic Attribute and Porosity–Thickness Maps, Sava Depression, Croatia. Geosciences, 8/11: 426. https://doi.org/10.3390/geosciences8110426

Otchere, D. A., Hodgetts, D., Ganat, T. A. O., Ullah, N. & Alidu R. 2021: Static Reservoir Modeling Comparing Inverse Distance Weighting to Kriging Interpolation Algorithm in Volumetric Estimation. Case Study: Gullfaks Field. In Proceedings of the Offshore Technology Conference, Virtual and Houston, USA, 16-19 August 2021. https://doi.org/10.4043/30919-MS

Raudys, A. & Pabarškaitė, Ž. 2018: Optimising the smoothness and accuracy of moving average for stock price data. Technological and Economic Development of Economy, 24: 984-1003. https://doi.org/10.3846/20294913.2016.1216906

Razali, N., M. & Wah, Y., B. 2011: Power comparisons of Shapiro-Wilk, Kolmogorov-Smirnov, Lilliefors and Anderson-Darling tests. Journal of Statistical Modeling and Analytics, 2: 21-33.

Rusdiana, S., Yuni, S. M. & Khairunnisa, D. 2020: Comparison of Rainfall Forecasting in Simple Moving Average (SMA) and Weighted Moving Average (WMA) Methods (Case Study at Village of Gampong Blang Bintang, Big Aceh District-Sumatera-Indonesia. Journal of Research in Mathematics Trends and Technology, 2/1: 21-27. https://doi.org/10.32734/jormtt.v2i1.3753

Setianto, A. & Triandini, T. J. 2013: Comparison of Kriging and Inverse Distance Weighted (IDW) interpolation methods in lineament extraction and analysis. Journal of Applied Geology, 5: 21–29. https://doi.org/10.22146/jag.7204

Tunçay, T., Bayramin, İ., Atalay, F. & Ünver, İ. 2016: Assessment of Inverse Distance Weighting IDW Interpolation on Spatial Var-iability of Selected Soil Properties in the Cukurova Plain. Journal of Agricultural Sciences, 22/3: 377-384. https://doi.org/10.1501/Tarimbil_0000001396

Vrdoljak, L., Režić, M. & Petričević, I. 2021: Bathymetric and Geological Properties of the Adriatic Sea. Rudarsko-geološko-naftni Zbornik = The Mining-Geological-Petroleum Bulletin, 36/2: 93–107. https://doi.org/10.17794/rgn.2021.2.9

Xin, P., Liu, Y., Yang, N., Song, X. & Huang, Y. 2020: Probability distribution of wind power volatility based on the moving average method and improved nonparametric kernel density estimation. Global Energy Interconnection, 3/3: 247–258. https://doi.org/10.1016/j.gloei.2020.07.006

Wenli H., Xiankang X., Xinbo Z., Li L., Shengli N., Qingquan L., Gaoming Y. & Li W. 2021: Application of production splitting method based on inverse distance weighted interpolation in X Oilfield. Energy Reports, 7/7: 850-855 https://doi.org/10.1016/j.egyr.2021.09.189