Facies (Rock Type) Modeling Using Inverse Static Model Process from Porosity Distribution, Case from Baturaja Formation*

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Abstract

Reservoir characterizations are intended to transfer geological and geophysical data into digital data, so that the model can reflect the best subsurface condition. Several state of the art geostatistical techniques have recently been used to construct a full field, three-dimensional (3D) models. Constructing reservoir models has become a significant step in resource development as reservoir modeling provides a spot to integrate and compile all available data and geologic concept. The successful application of these reservoir models is used to calculating reserves and input for further process (simulation).

Pyrite Structure is located in the South Sumatera Basin that produces gas and condensate from limestone of Baturaja Formation that has complex and heterogeneous geological and petrophysical characteristics, and exhibit complex porosity-permeability system. This structure provides geophysical and geological data such as acoustic impedance (AI) attributes, log data, and core data as well. An acoustic impedance attribute is commonly used as the trend for the reservoir modeling. The problem rises since the AI trend at this structure cannot directly represent the facies trend. Hence, the inverse modeling process used to determine facies (rock type).

Since AI data has high correlation with porosity and consistent with geological concept, this modeling use inverse modeling process to determine facies (rock type) from porosity model. First approach is to distribute porosity model guided by variogram analysis and AI. Second, after porosity log distributed, probability map from rock type-1, rock type-2 and rock type-3 generated from porosity model. Then the trend modeling for each rock type made and used to guide facies model distribution.

Furthermore, the facies models along with the AI trend are used to create the new porosity distribution model. This porosity model and the permeability-porosity logarithmic correlation equation are used to make the permeability distribution model. At last, by using J-Function and consider the water saturation is the function of depth and rock quality, the water saturation model can be also created using the facies model

and constrained by gas-water contact. Those reservoir properties models provide better depiction of their trend that is fit with AI trend. Those models also can reduce the hesitation in calculating hydrocarbon volumetric.

Introduction

Geologically, the study area is located in South Palembang Sub Basin, South Sumatra Basin, Indonesia. Location of Pyrite Structure is located in the East Prabumulih, working area of Pertamina EP. On this location, several fields have been developed to produce oil, gas or condensate from productive reservoir Baturaja and Talang Akar Formation.

Limestone of the Baturaja Formation is one of the principal reservoirs in Pyrite Structure. The original facies distribution of carbonate reservoir has complex and heterogeneous geological and petrophysical characteristics over short distance, so provide a challenge for reservoir modeling. The porosities and permeabilities values in the formation body can be grouped into some trends that indicate there are some different facies (rock type) that exists in the formation. The proper distribution of the facies becomes the important part in constructing an appropriate reservoir model.

In this case, the Acoustic Impedance (AI) attribute as the continuous data cannot directly represents the facies trend distribution. This paper presents a result of inverse static model process by using together porosity values and AI trend to generate the trend model of the each facies (rock types) distribution.

Methodology and Result

Building 3D reservoir models using stochastic simulation techniques are required to produce more realistic images of reservoir heterogeneity. Reservoir models are represented as static depositional models, which are used to provide a geologic view of reservoir bodies. This study combines all available data including 3D seismic data, core, and logs of three existing wells (PYR-2, PYR-3, and PYR-6) in Pyrite Structure. All those data provided information to build the structural and property model.

Structural Modeling

The structural modeling started with interpretation of top and bottom horizons of the reservoir zone and the fault formed in this structure. The zone of the reservoir body is confined from the top of Baturaja Formation until the base model (± 40 meter below top Baturaja Formation). Afterwards, the horizon and three fault models were built as the structural model framework with grid area size 100 m x 100 m. The reservoir zone is then proportionally divided into eighty-eight layers (Figure 1) as the infill surface in the structural model framework with 0.5 feet minimum thickness of layers. Each layer composing an upscaled porosity log interpolated laterally to obtain a 3D porosity model related to the facies map.

Facies (Rock Type) Modeling: Problem and Solution

Facies (rock type) modeling is used to represent the modeling of geological rock, which can be grouped according to geological facies that represent depositional environment. Rock type is a unit of rock deposited under similar conditions, which experienced similar diagenetic processes resulting in a particular Φ-k relationship and other variables. In carbonate, rock quality is more influenced by diagenetic process that can increase or reduce its quality rather than depositional process.

Petrophysical variables, such as porosity and permeability in reservoir rocks, result from complex geological processes and characterized by heterogeneity in their distribution. The rock types classification was undertaken by making the porosity-permeability and Flow Zone Indicator (FZI)-Sample Number crossplot. The FZI data is derived from core analysis. The crossplots show that the porosity-permeability and FZI values are spread into three trends that represent three different rock types. Rock type-1 has porosity-permeability range 22-23.1% and 67.5-108.58 mD. Rock type-2 has porosity-permeability range 19-21.4% and 15.41-26.41 mD. Rock type-3 has porosity-permeability range less than or equal to 15.6% and 4.416 mD. The FZI range for each Rock Type 1, 2, and 3 are 1.61-2.1, 0.88-1.14, and less than or equal to 0.624 (Figure 2). The carbonate facies patterns in every rock type based on core description were recognized as mudstone, wackstone and packstone but have different porosity-permeability values due to diagenetic process, that can increase or reduce its quality rather than depositional process. However, the higher values of porosity and permeability indicate good reservoir quality while the lower values of porosity and permeability indicate tight carbonate poor reservoir quality

Those three different rock types used to model the facies distribution in the Pyrite Structure. The trend of the facies is guided with Acoustic Impedance attribute trend. An acoustic impedance attribute is commonly used as the trend for the reservoir modeling. The problem occurs when a wide range of AI values as secondary attribute for trend are not working properly to distribute those three of rock types (rock type-1, rock type-2 and rock type-3), so that the AI trend cannot directly represent a proper trend of each rock types (Figure 3).

Since AI data has high correlation with porosity and consistent with geological concept, this modeling use inverse modeling process to determine facies (rock type) from porosity model. First approach is to distribute porosity model guided by variogram analysis and AI. The inverse modeling approach is then used to solve the problem. The initial step of this approach is to distribute the sparse porosity data from logs into the structure using variogram analysis and AI attribute to guide the trend of porosity distribution. Porosity logs are transformed to a normal score to make the porosity values adjusted to have a normal distribution. Sequential Gaussian Simulation (SGS) is used with variogram ranges from AI trend, as the simulation method to propagate porosity in space and it is a stochastic method of interpolation based on kriging, combined by co-kriging with AI from seismic, models of porosity are produced (Figure 4).

Furthermore, the porosity-permeability crossplot is made by using the data to determine the group of rock type. From this crossplot, the new range values for each rock type are obtainable, where rock type-1 has porosity range > 20%, rock type-2 has porosity range 20-16% and rock type-3 has porosity range less than 16% (Figure 5).

The next step is to make probability map with calculator for each rock type (facies) based on porosity distribution that has been guided by AI trend (Figure 6). The new facies model is more appropriate in accordance with the trend of seismic attribute. Then, probability maps for each rock type with trend modeling have been generated to build map, which is more in line with realistic situation (Figure 7).

Finally, facies model distribution with more realistic for every rock type has been created (Figure 8), by using probability porosity trend combined with variogram ranges from AI trend (azimuth: N75°E, major direction: 3,500 meter and minor direction: 2,500 meter). So that, the new facies modeling distribution should be appropriate with AI trend although it must pass through several treatments.

Porosity Model

After the new facies model produced, porosity model distribution in Pyrite Structure can be determined by trend of AI attribute and new facies model using SGS technique, which is commonly adopted for simulation of continuous variables such as porosity and permeability. The distribution of porosity shows that in this structure, the highest porosity with the range of 17.5-22.5% are gathered in the middle of the structure with Northeast- Southwest direction, but the low to medium porosity values with the range of 10-17.5 % appear dominantly (Figure 9). Higher porosity distribution is observed at the crestal area, which corresponds to the lower AI value, and vice versa, lowers porosity distribution at the flank regions. The presence of seismic data like AI as a trend and dense data may be expected to improve the quality of reservoir porosity description compared to using the well control only as a sparse data.

Permeability Model

The permeability prediction approach is used to predict permeability at the non-cored wells combines regression analysis and geostatistical simulation. Permeability model distribution in this study derived from equation porosity-permeability relationship. Porosity model based on trend of AI attribute and new facies model using SGS technique, is used as a guidance to produce permeability model distribution. The distribution of permeability shows that in this structure, the highest permeability with the range of 1-100 mD are gathered in the middle of the structure with Northeast- Southwest direction, but the low to medium permeability values (< 1 mD) appear dominantly at flank region (Figure 10).

Water Saturation

The equilibrium method (using either Sw-H or J-Function relationship) to calculate 3D water saturation is better approach as this will be the method used in dynamic modeling. The use of 3D water saturation based on interpolation (simulation) of well logs will produce significant variability of Sw, which is not suitable for flow simulation. Water saturation is function of depth and rock quality, therefore modeling must consider Sw - Depth relationship as well as rock information. Once Sw-H relationship per rock type is known, Sw can be calculated in the 3D model using calculator. Sw-H curves can be generated by convert Capillary Pressure (Pc) into depth (H) directly or digitize Sw-H (per rock type) from Sw log data. The distribution of water saturation shows that in Pyrite Structure, the highest value for water saturation is one where the flank area located below gas water contact (GWC). The range of water saturation value from 0.2-0.7 located at top of the structure, and it is become the best area for hydrocarbon occurrences (Figure 11). Modeling water saturation in this structure involves placing a gas water contact

(GWC) at some specific depth, and the water saturation values below GWC will be used as 100%. Furthermore, by utilizing cross plot between Sw – Depth relationship as an input to calculator, the water saturation model at Pyrite Structure can be generated.

Upscaling

The resolution of production data may be different than the resolution of static data, so that upscaling from static model to dynamic model is required with consequences; preserve the dynamic performance while reducing the number of active grid blocks in static model and able to capture both the current and future dynamic performances. Upscaling in porosity model will reduce layers from 88 to 29, but still honor the data (Figure 12).

Conclusions

1. The three-rock types classification was undertaken by making the porosity-permeability and Flow Zone Indicator (FZI)-Sample Number crossplot.
2. The AI trend cannot directly represent a proper trend of each rock types, so that the inverse modeling approach is then used to solve the problem.
3. Facies modeling distribution which more realistic images for every rock type has been created by using porosity model distribution trend and variogram ranges from AI trend.
4. The highest porosity with the range of 17.5-22.5% are gathered in the middle of the structure with northeast-southwest direction, but the low to medium porosity values with the range of 10-17.5 % appear dominantly at flank region.
5. The highest permeability with the range of 1-100 mD are gathered in the middle of the structure with northeast-southwest direction, but the low to medium permeability values (< 1 mD) appear dominantly at flank region.
6. The range of water saturation value from 0.2-0.7 located at top of the structure, and it is become the best area for hydrocarbon occurrences.

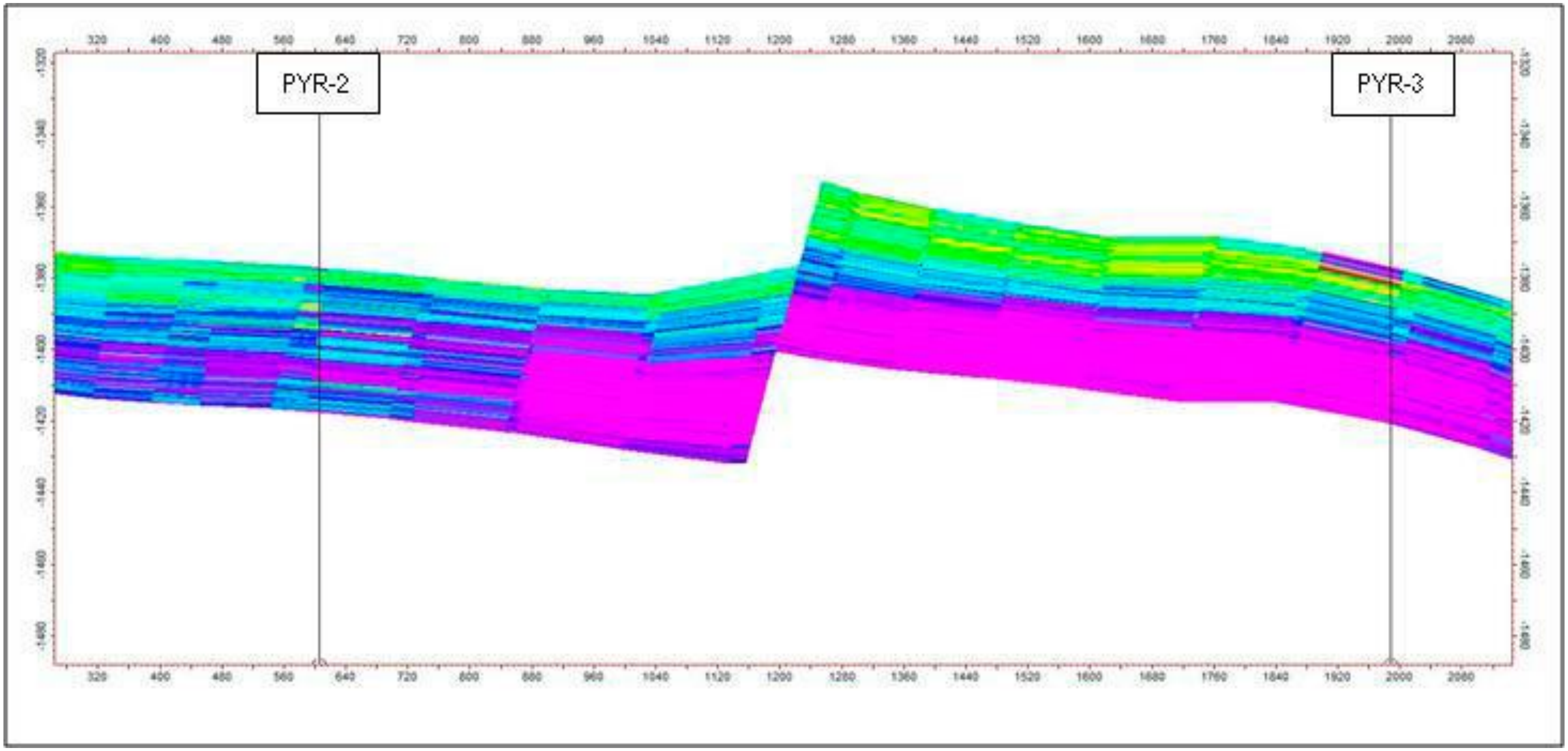


Figure 1. Reservoir zone with eighty-eight layers.

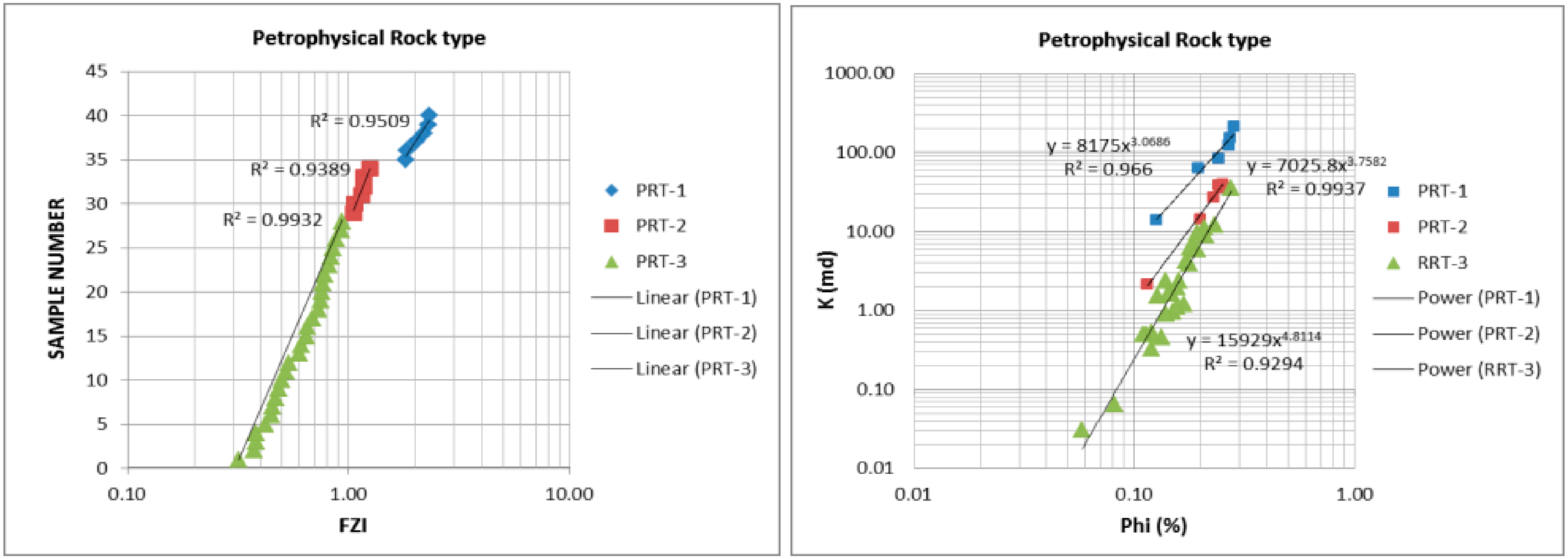


Figure 2. Three different rock types in Pyrite Structure.

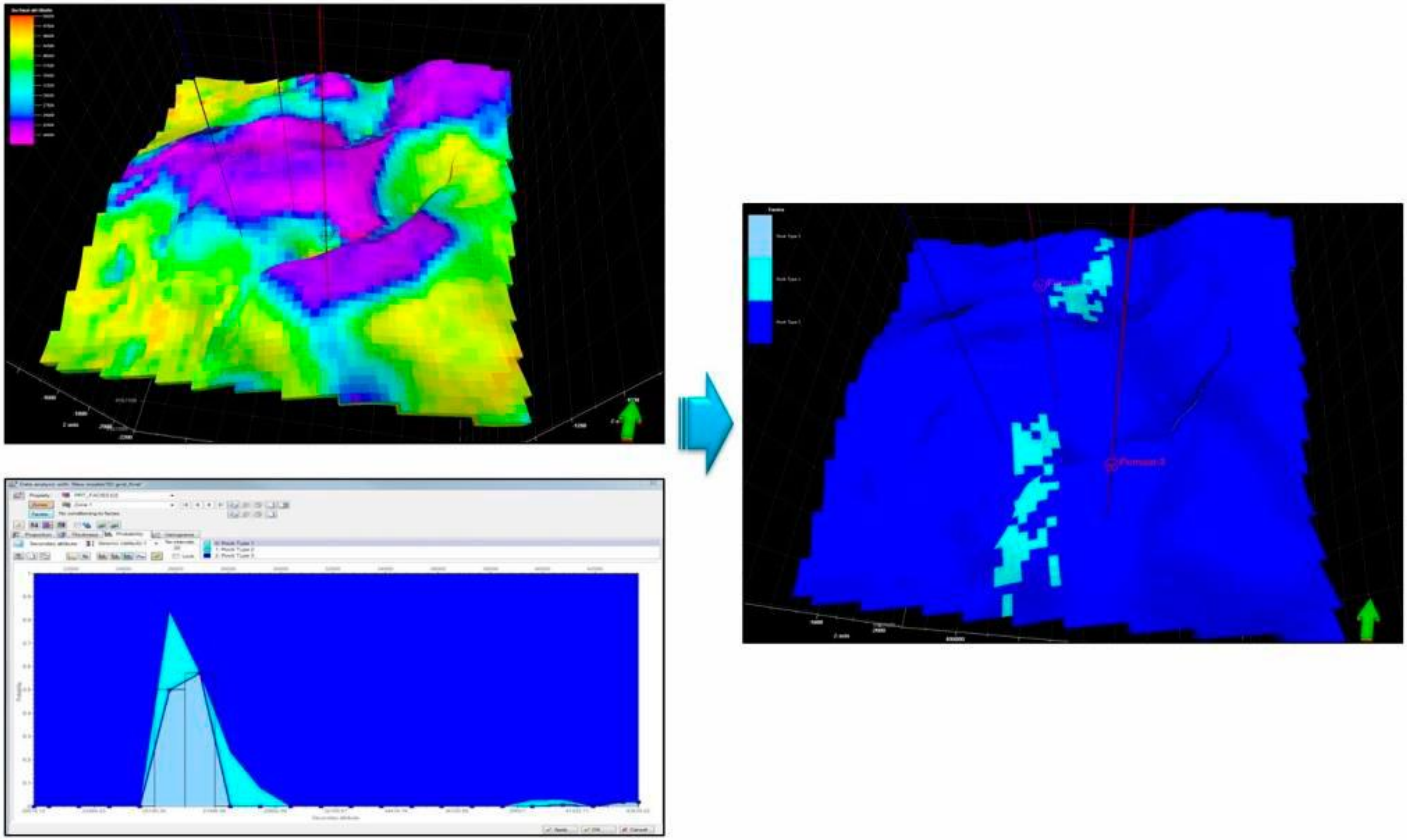


Figure 3. Facies (rock type) modeling distribution with AI trend.

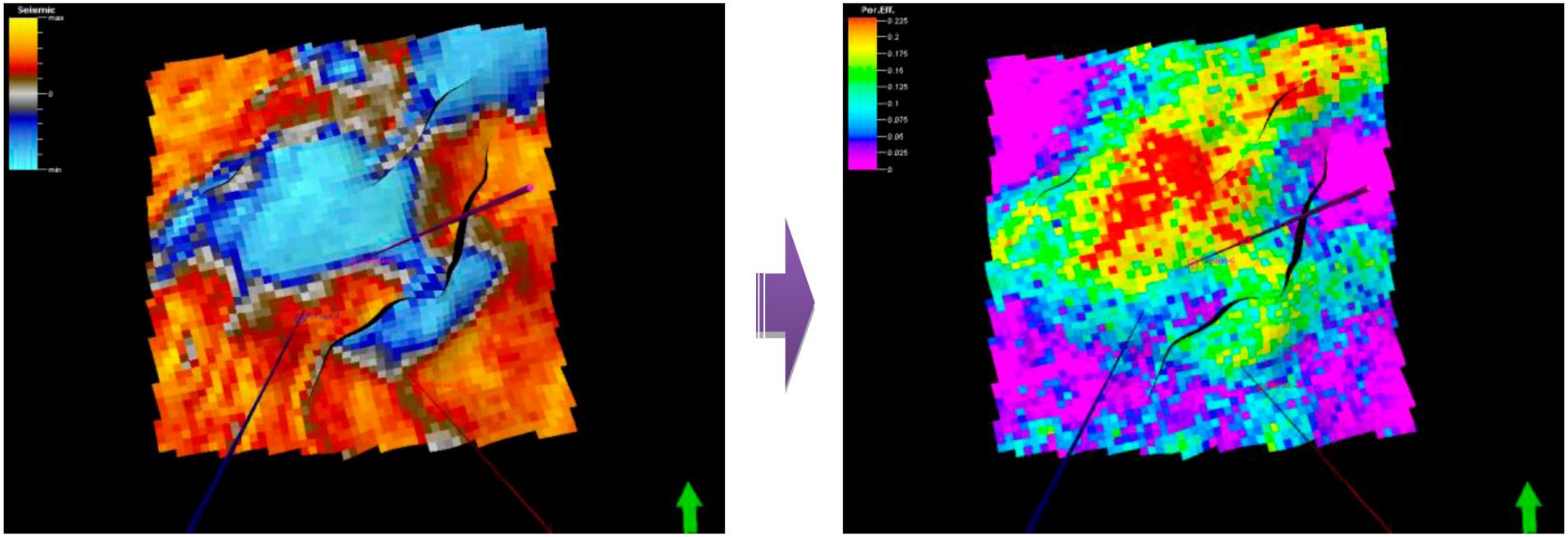


Figure 4. Porosity model guided by variogram analysis and AI from seismic.

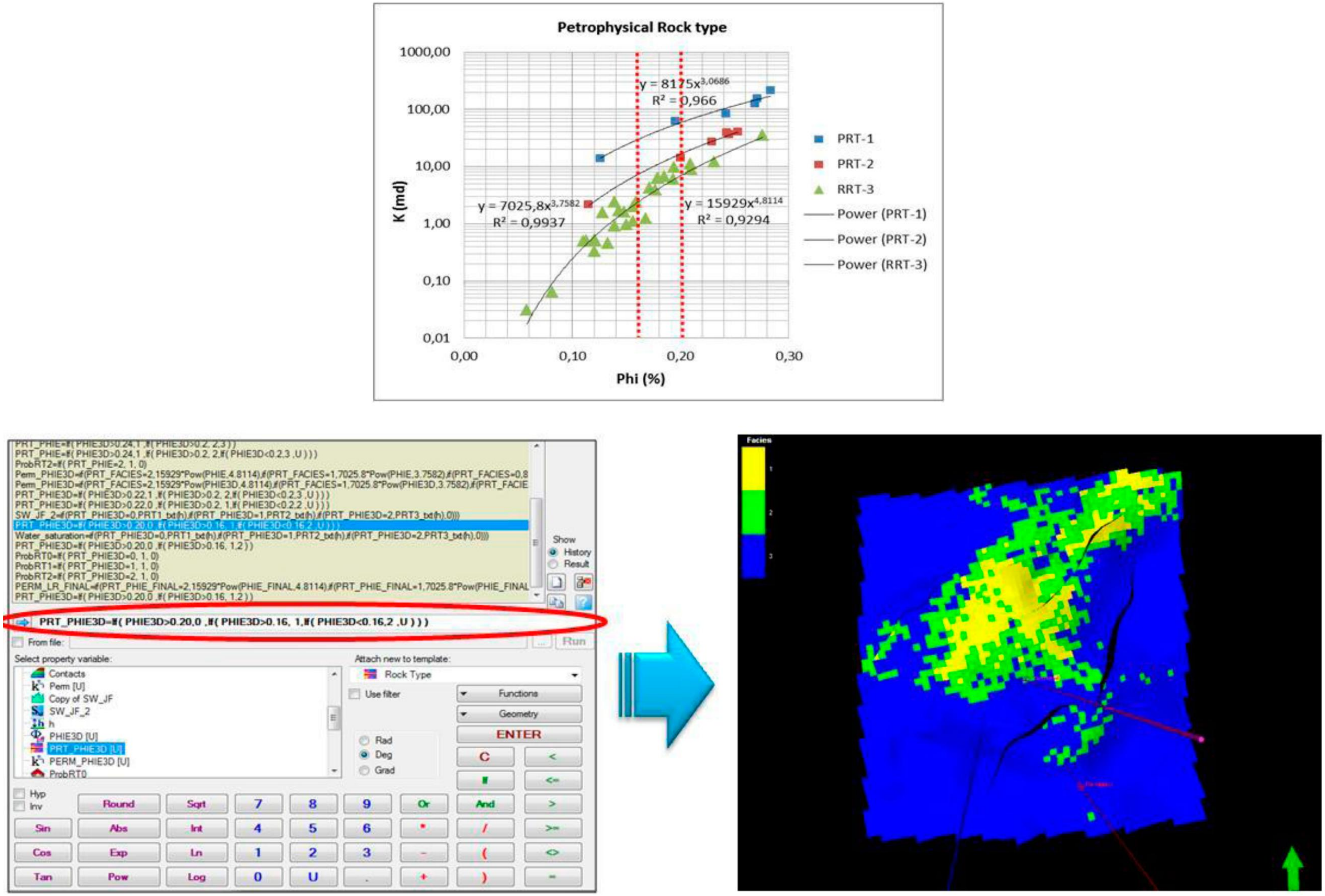


Figure 5. Facies model from calculator (based on porosity model).

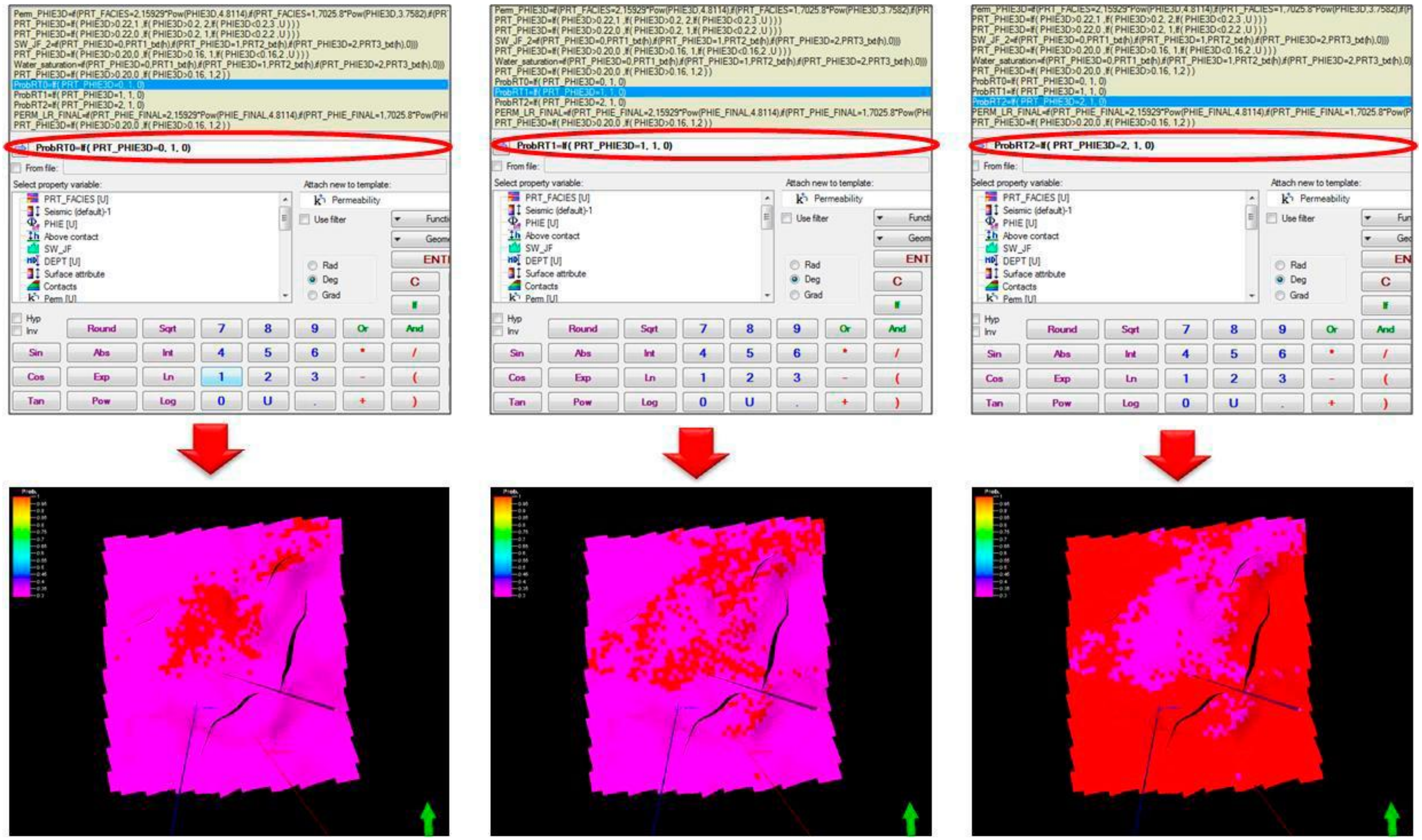


Figure 6. Probability map of facies model for each rock type.

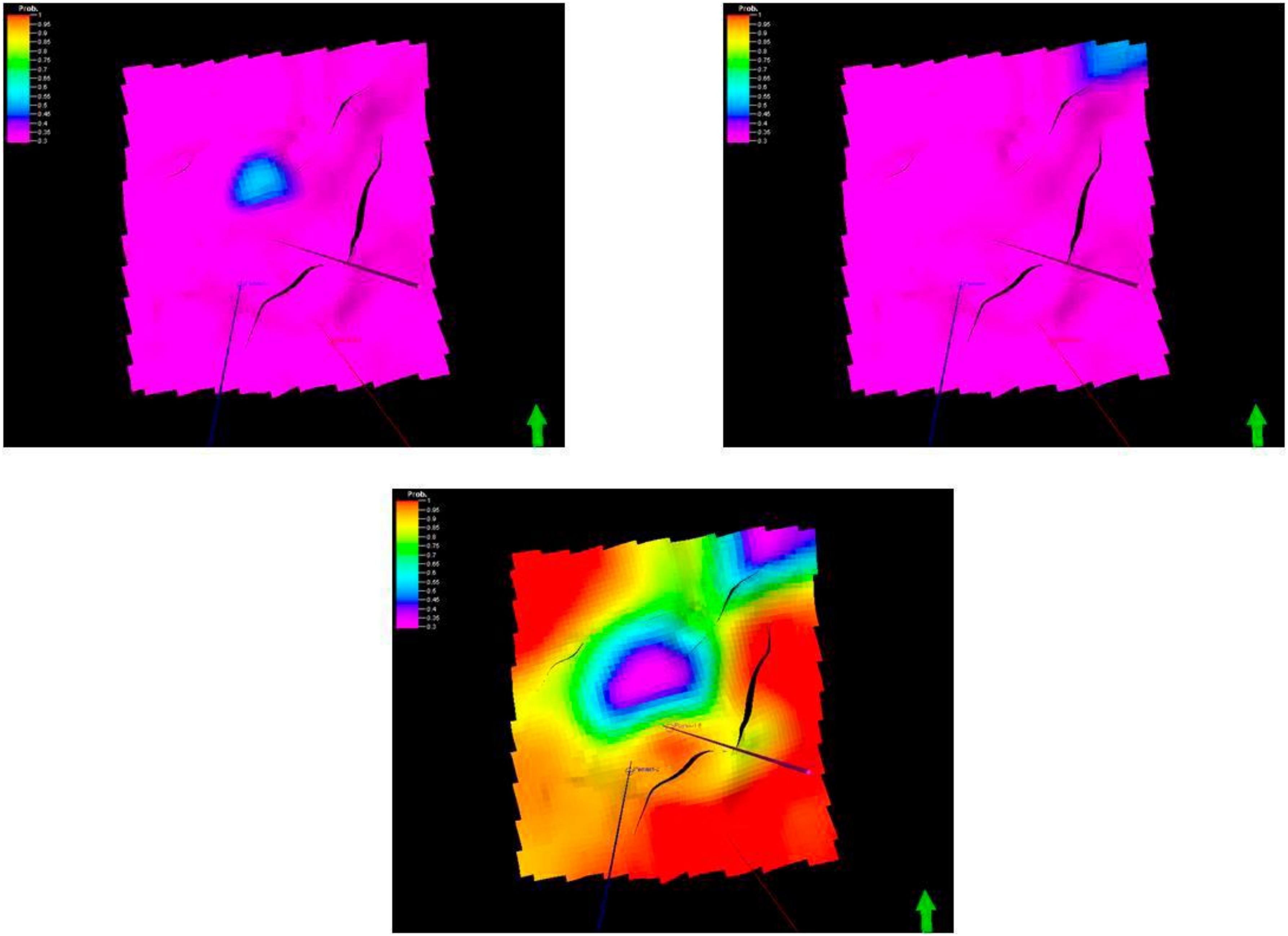


Figure 7. Probability map rock type after trend modeling.

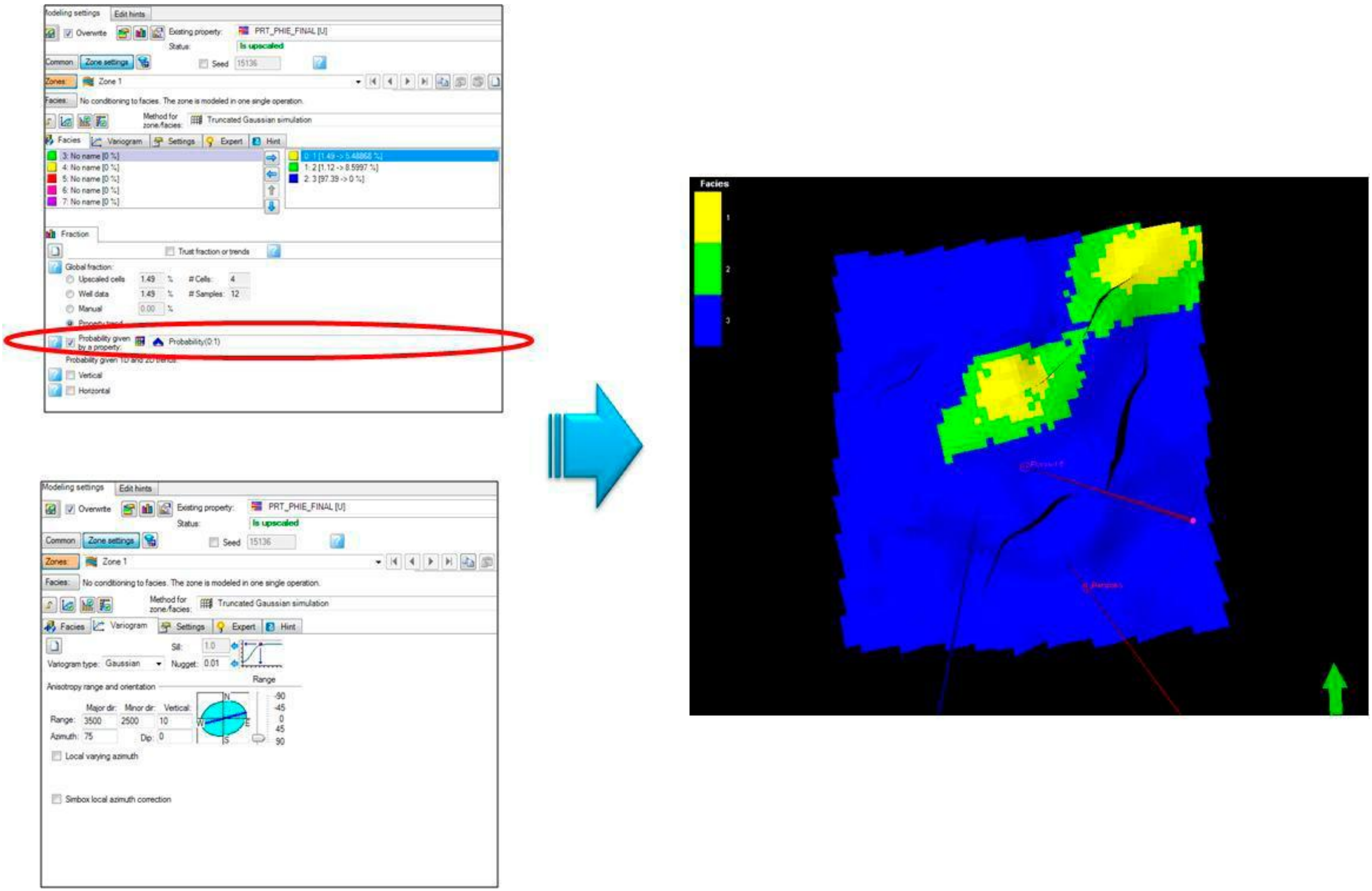


Figure 8. Facies model distribution for rock type with trend modeling.

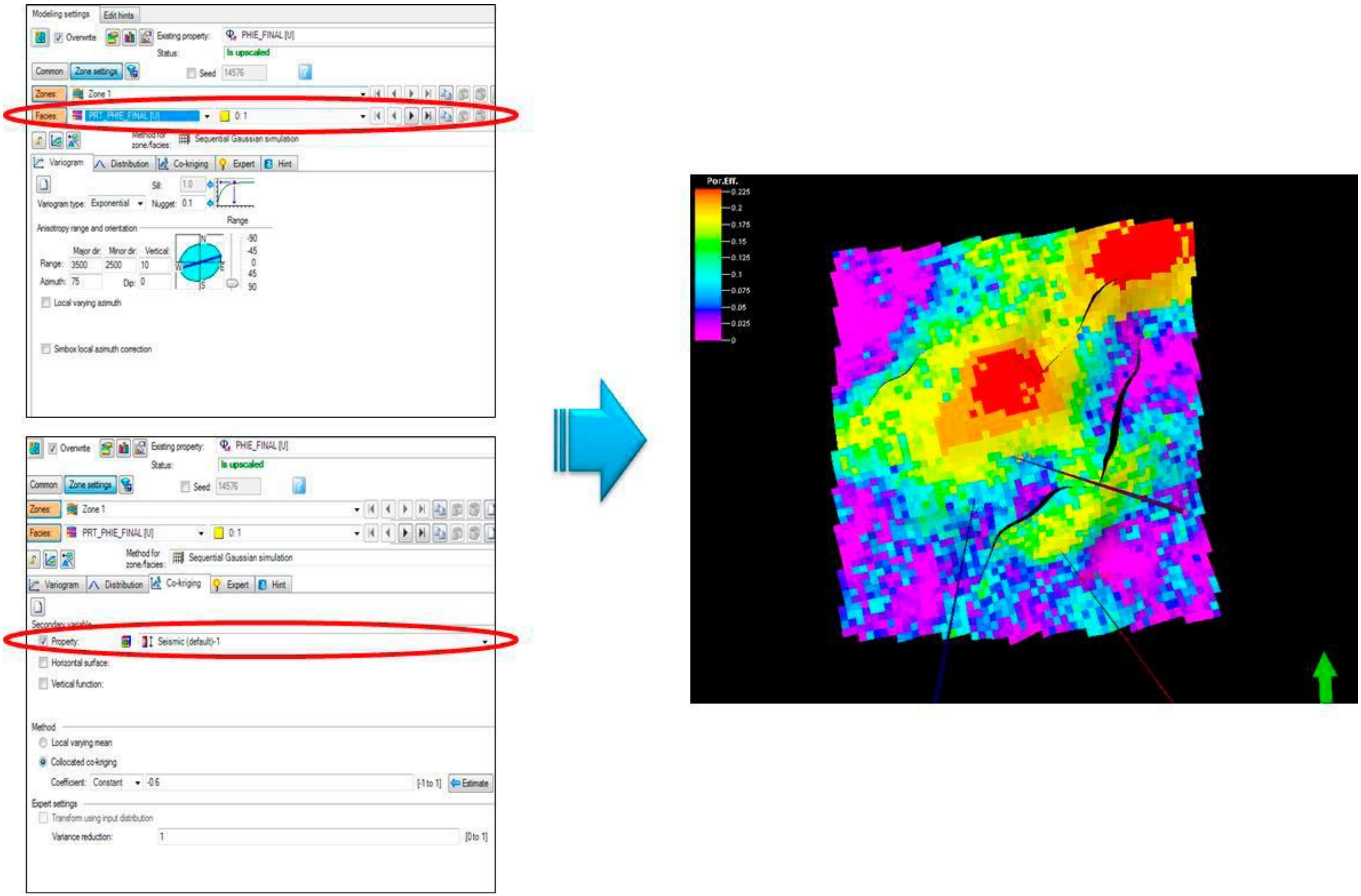


Figure 9. Porosity model with trend from facies model and AI.

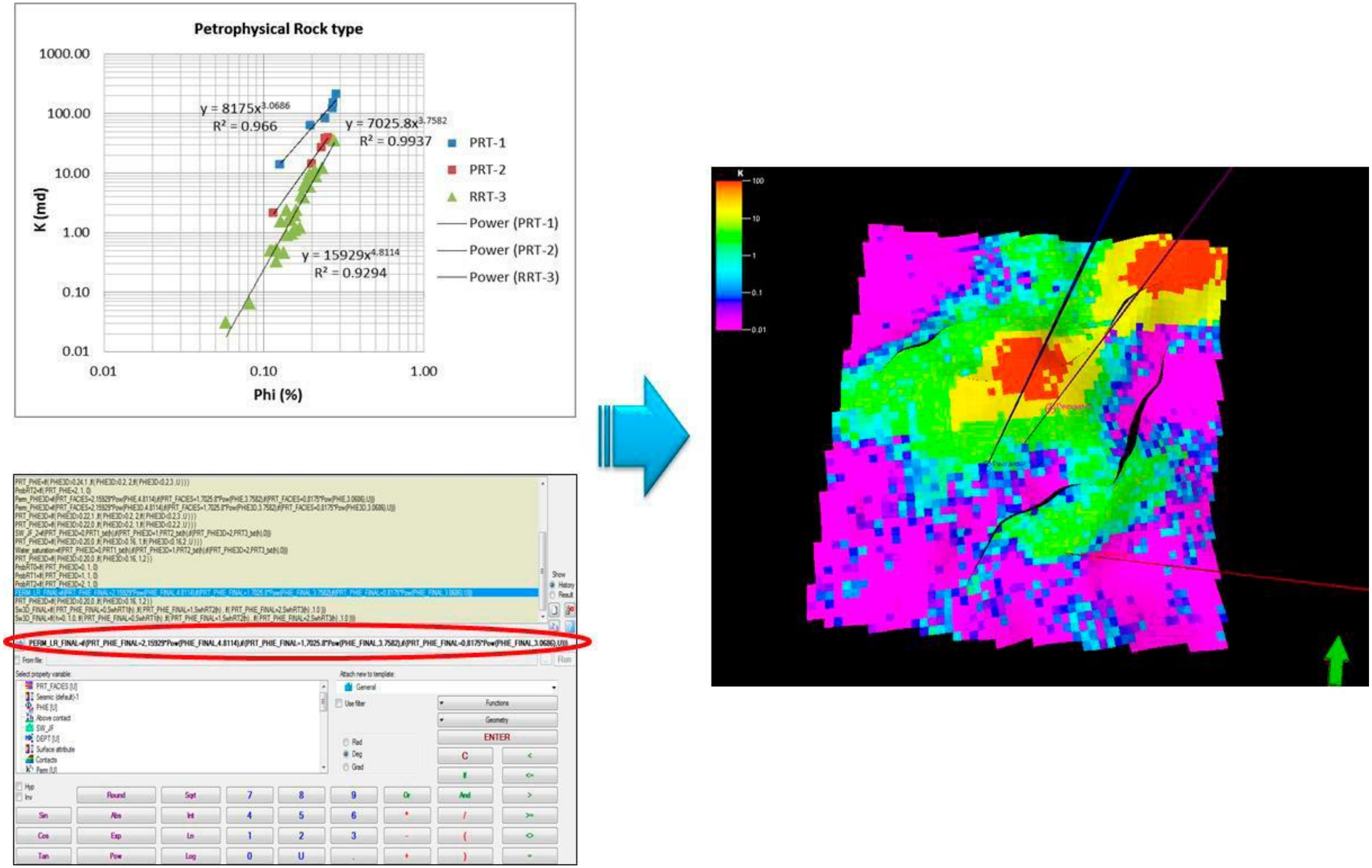


Figure 10. Permeability model from equation poro-perm relationship.

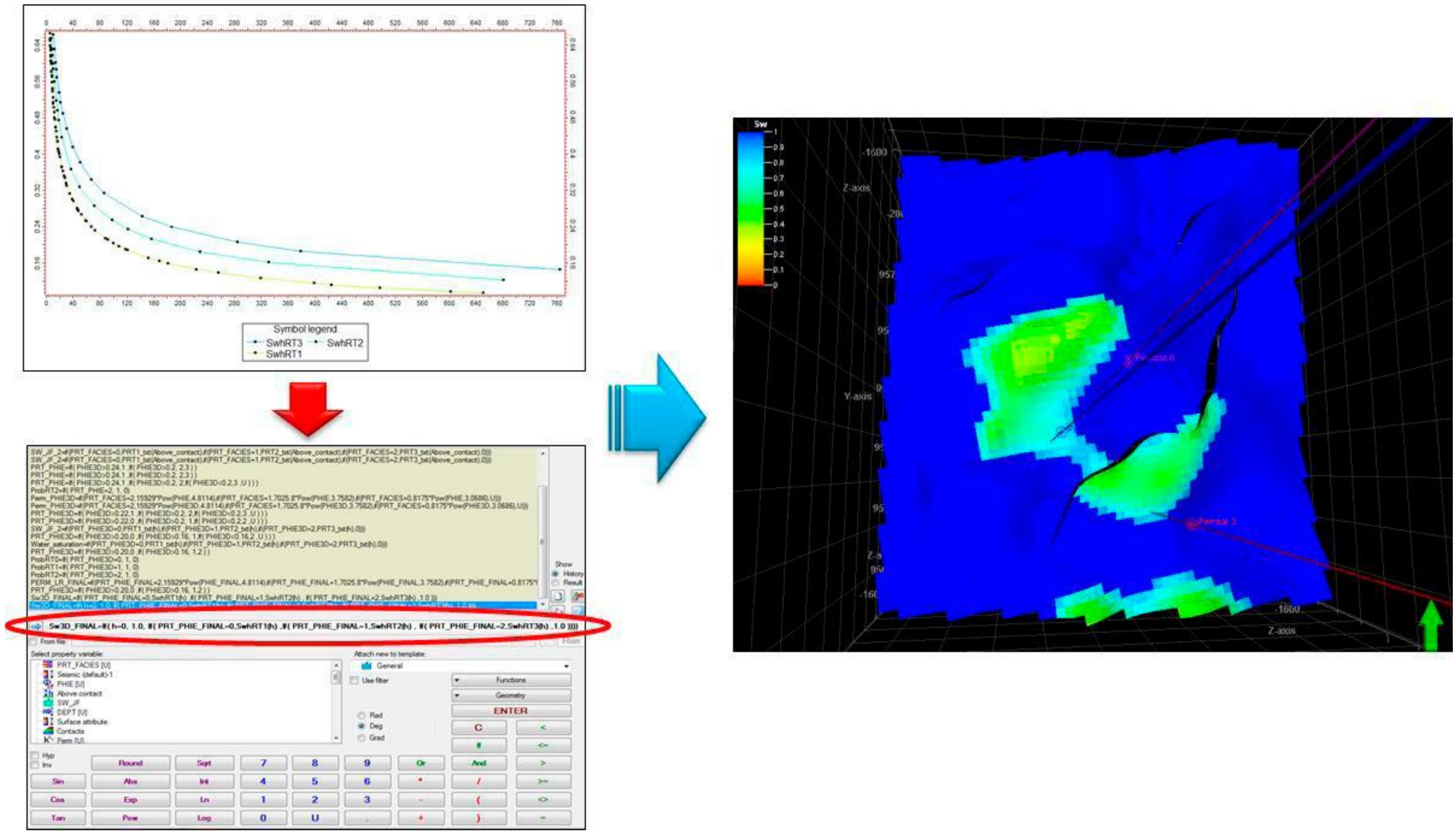
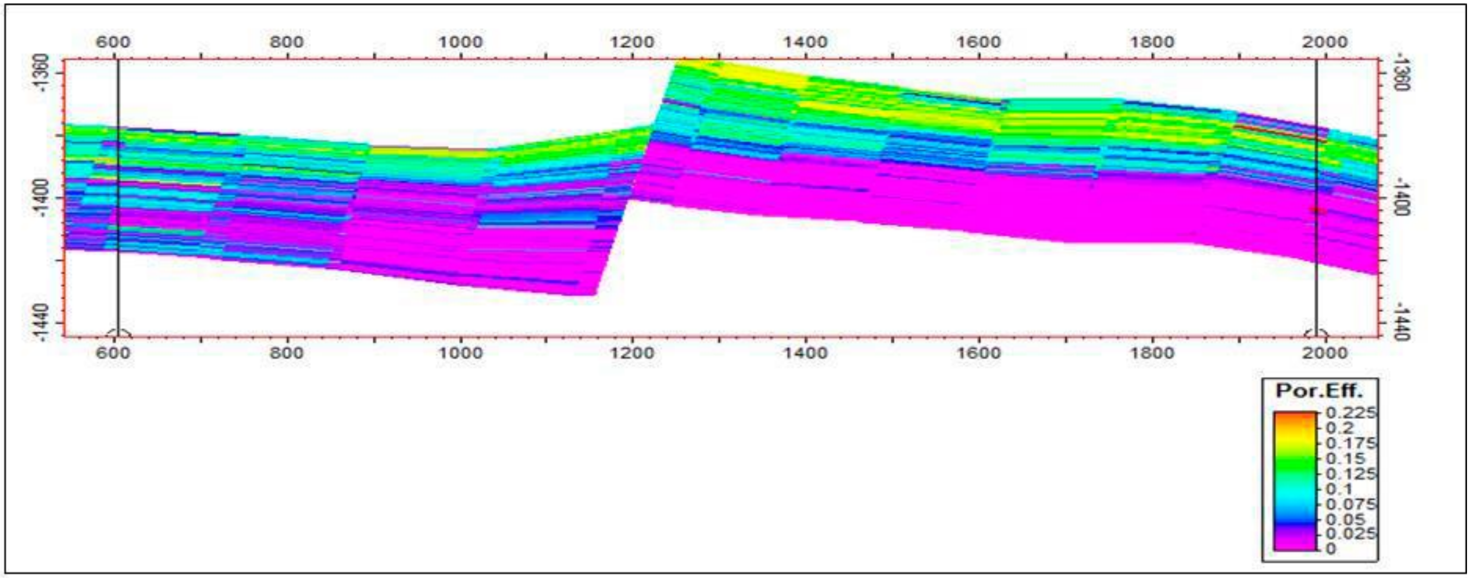
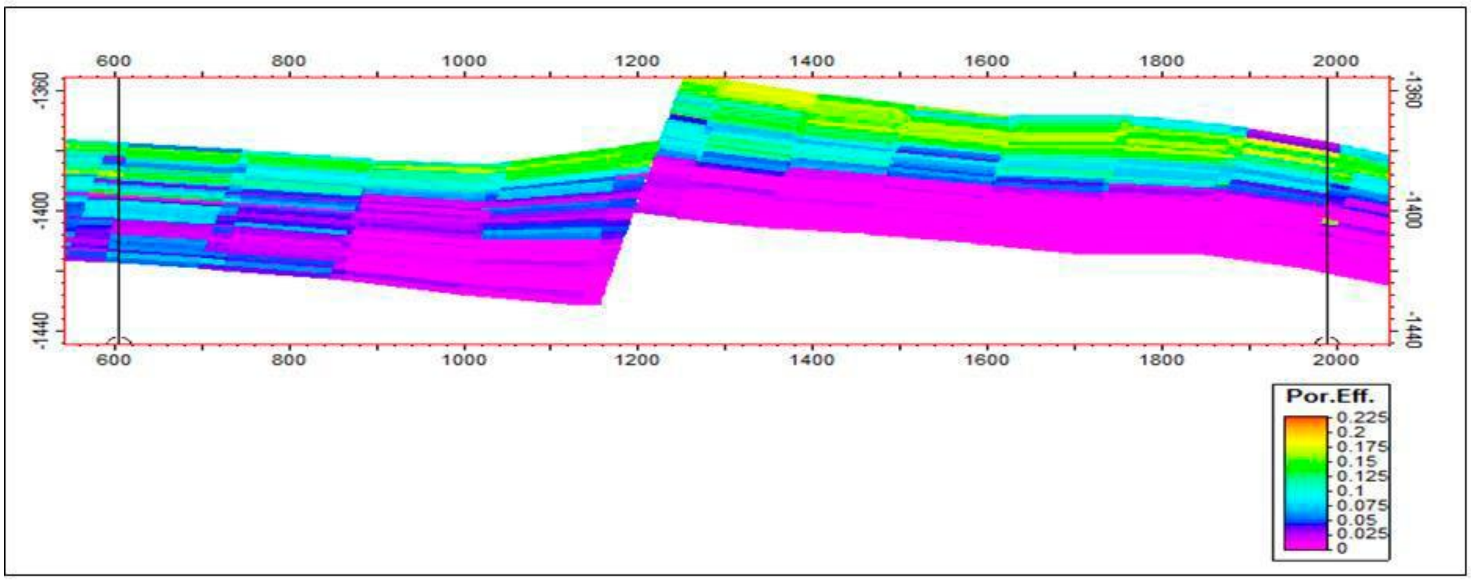


Figure 11. Sw model from Sw-depth relationship.



Porosity Model Intersection Fine Model – 88 layer



Porosity Model Intersection Coarse Model – 29 layer

Figure 12. Comparison of coarse model with fine model.