Hierarchical Trend Modeling for Improved Reservoir Characterization

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1. Abstract

Geostatistical tools inherently assume stationarity, that is, statistical homogeneity in the mean and other statistical parameters. Reservoirs often have significant nonstationary features, such as trends in the mean. Methodologies for trend model construction and geostatistical simulation are described that honor trends within hierarchies of nested architectural elements and property constraints. These procedures are demonstrated with a synthetic deepwater reservoir example based on an outcrop study.

2. Introduction

Geostatistical methods are increasingly popular for natural resource characterization. These tools are well documented in fundamental geostatistical texts (Deutsch, 2002; Goovaerts, 1997; Journel and Huijbregts, 1978). These tools, however, rely on invariance of the multivariate distribution function over the domain, that is, stationarity.

Sedimentological processes are not stationary. The result is trends that may be characterized in principle depositional directions such as parallel and transverse with respect to paleoflow and vertical. A further complication is the subjectivity of trend detection and modeling. There is no objective way to determine the existence and form of a trend. Identification of trends depends primarily on the data available and the scale of observation. Trends are often modeled arbitrarily by a decomposition approach:

$$Z(\mathbf{u}) = m(\mathbf{u}) + R(\mathbf{u}) \qquad \textbf{(1)}$$

This paper explains a methodology for the (1) construction of hierarchical trend models and (2) a transformation such that the relationship between the trend and the variable of interest is reproduced. This allows for the integration of small scale geologic trend information and corrects common problems associated with the decomposition of trend and residual. The result is more geologically realistic geostatistical reservoir models. This paper is necessarily abbreviated; greater detail is available in associated references (Pyrcz, 2004; Pyrcz and others, 2005; Leuangthong and Deutsch, 2003 and 2004).

3. Hierarchical Trend Model Construction

The hierarchical trend modeling methodology allows for the construction of trend models that captures the features within a hierarchy of architectural elements (Pyrcz, 2004; Pyrcz and others, 2005). The steps in constructing hierarchical trend models are: (1) calculate the depositional coordinates at each hierarchical order, (2) determine relative trend functions, and (3) combine the trend functions.

For the construction of a hierarchical trend model the location relative to the primary sedimentation axis must be determined for each nested hierarchy and for each location in the model. In the absence of this information, architectural elements may be approximated with connected geo-objects and the axes of flow may be approximated with a skeleton transform, applied to all architectural elements over all hierarchical orders. Quality control will be essential to check these approximations.

Architectural element trends may be quantified with trend functions. The key components of the trend functions are the shape and the magnitude of variability relative to each other. The lower the relative variability the less impact the specific trend function will have on the final composite trend value. Calibration and expert judgment is required to set the relative importance of the directional trends for each order and their associated shapes.

A convenient method for combining trend functions is shown in Equation 2. This method is based on an assumption of independence between the trend functions in each direction and for each hierarchical order.

$$trend(\mathbf{u}) = \bar{\phi} \cdot \prod_{\ell=1}^{L} V^{\ell}(\mathbf{u}) \cdot L^{\ell}(\mathbf{u}) \cdot T^{\ell}(\mathbf{u}) \qquad \textbf{(2)}$$

where L is the number of hierarchical orders considered and $V^{\ell}(\mathbf{u})$, $L^{\ell}(\mathbf{u})$ and $T^{\ell}(\mathbf{u})$ are the local trend multipliers from the trend functions in the vertical, longitudinal and transverse directions for each order, respectively. The trend model may be post processed to honor areal and vertical trends.

Trend modeling is subjective. It represents a model decision and not a hypothesis; therefore, a trend model cannot be validated (Deutsch, 2002). Nevertheless, there are some logical checks that may be applied to judge whether a trend model is reasonable. Some practical checks include (1) reviewing the variance of the trend model relative to the variance of the property and (2) confirming that structures in the trend model agree with the available information and data.

4. Stepwise conditional transformation for modeling in the presence of a trend

The stepwise conditional transformation is a multivariate transform wherein variables are transformed sequentially with increasing conditioning (Leuangthong and Deutsch, 2003; Leuangthong and Deutsch, 2004). It can be applied for modeling in the presence of a trend model. Unlike the conventional approach of modeling the residuals, the idea is to transform the original variable conditional to the trend, that is, the trend is chosen as the primary variable, and the original variable is transformed conditional to probability classes of the trend. This is shown schematically in Fig. 1.

There are two main reasons for choosing to model the original variable instead of the residuals. Firstly, the trend application is simplified by avoiding implementation difficulties associated with working with a residual. The original variable and the trend model are both well understood while the residual is often poorly understood. It should be noted that there is still an implicit decomposition between trend and residual, even though the residual is not explicitly considered. Secondly, the conventional modeling of the residuals and the subsequent addition of the trend provides no assurance that simulated values will be non-negative. The transformation and modeling of the original variable conditioned to the trend ensures that (1) simulated values account for the trend and (2) all model values are non-negative.

5. Case Study

A synthetic case study was constructed approximately based on Lobe VII of the Cengio Turbidite System (Italy) of the Tertiary Piedmont Basin (Ghosh and Lowe, 1993). Lobe VII is dominated by compensational cycles that constrain the distribution of lithofacies. The subsequent flows event deposits within the lobe may be separated by mudstones from pelagic sediments during hiatus and have persistent internal lithofacies trends. The modeling of hierarchical trends associated with flow event deposits within a reservoir scale turbidite lobe is an important step in assessing the impact on reservoir response of shale baffles and the other related lithofacies trends.

It is assumed that seven vertical wells are available with architectural elements and porosity information, as indicated in Fig. 2. The declustered porosity distribution is shown in Fig. 2. The relative trend functions were quantified based on the available geologic information. The flow event deposits show weak fining upward trends with mud drapes. The longitudinal and transverse trends include fining distal and towards the peripheries.

The depositional coordinates were calculated from surface based model defining the 2nd and 3rd architectural elements (Pyrcz, 2004; Pyrcz and others, 2005). The skeleton transform was applied to approximate the curvilinear primary flow axis for each architectural element. The trend functions were combined by applying Equation 2. The porosity trend model is shown in Fig. 3.

Given the scarcity of data for conditional transformation, a bivariate kernel smoothing algorithm was applied (Leuangthong and Deutsch, 2003). Using this smoothed distribution, the porosity data were then transformed conditional to their corresponding trend values. The resulting relationship between the transformed porosity and the trend model is shown in Fig. 4. It is clear that after transformation, the transformed porosity is Gaussian and uncorrelated with the trend model.

Following transformation, the variogram of the transformed porosity was calculated, and sequential Gaussian simulation was performed. The simulated values were then back transformed conditional to the trend model (see Fig. 3). A comparison to the trend model shows good reproduction of the trend with low porosity values in the northern portion of the long section E-E' and fining upward trends and mud drapes within the 2nd order elements.

Histogram and crossplot reproduction were also checked; Fig. 5 shows this reproduction for the same realization in Fig. 3. Although this shows good reproduction of the statistics, there is some apparent banding in the crossplot of the simulated porosity and the trend model. This banding is due to the tail extrapolation in the transformation table which is based on the input data values. The scarcity of data in this case results in poor inference of the conditional distributions for transformation. Nevertheless, the realizations honor the statistics reasonably well and account for the hierarchical trends in Fig. 3.

6. Discussions and Conclusions

The methodology proposed in this paper allows for the construction of trend models that better integrate geologic information and the improved reproduction of property trend models within a geostatistical workflow. Hierarchical trend models allow for the improved integration of property trends related to nested hierarchies of architectural elements. Hierarchical trend models are constructed based on local data conditioning, analog site information and geologic information related to sedimentary processes.

The stepwise conditional transform ensures that the final model honors property constraints while incorporating property trends specific to the geologic setting. Working with the original variable improves control of variable constraints. Characterization of the bivariate relationship between the original property and property trend may be difficult if there are only a small number of property samples available. Smoothing techniques may improve the results.

7. Acknowledgements

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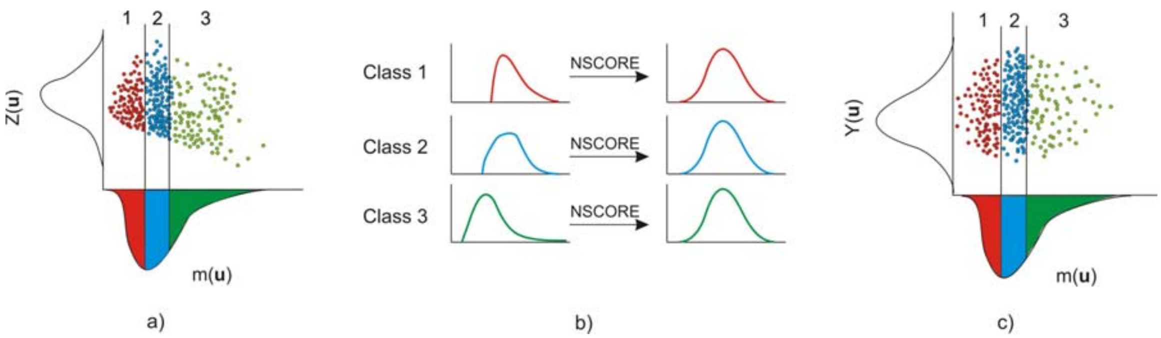

Fig. 1 Schematic illustration of the stepwise conditional transform with the trend model as the primary variable, $m(\mathbf{u})$: (a) partition the original variable, $Z(\mathbf{u})$ into probability classes, (b) subset the secondary data into conditional distributions and normal score transform each class independently, and (c) the resulting transform yields a transformed secondary variable, $Y(\mathbf{u})$, that is both Gaussian and uncorrelated to the trend.

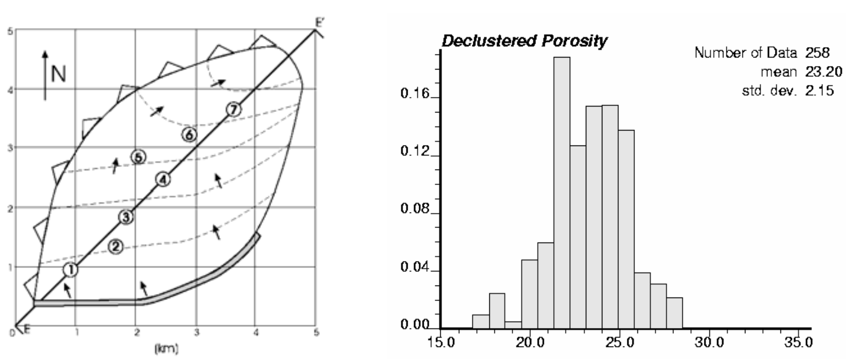

Fig. 2 *Left* - A schematic of the initial bathymetry loosely based on a study of Cengio turbidite system Italy (Cazzolo and others, 1985). The fan lobe onlaps a mudstone slope along the west, northwest and north. The vertical well locations and the paleocurrents are indicated. *Right* - The declustered porosity distribution (% porosity).

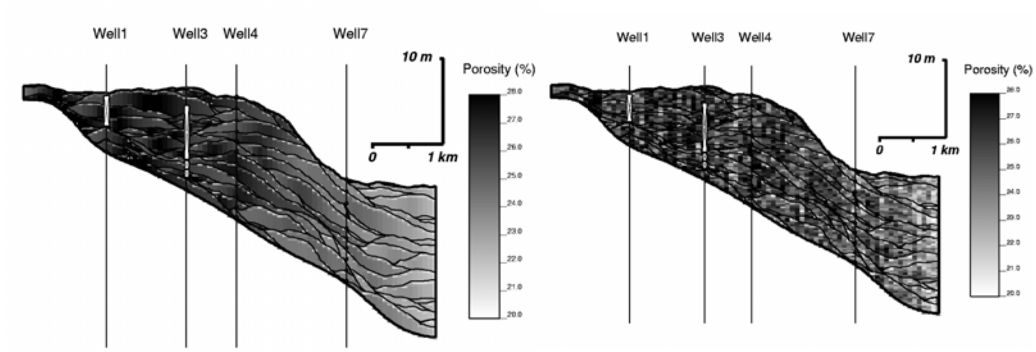

Fig. 3 Long section E-E' with well contacts and 2^{nd} order flow event deposits within a 3^{rd} order turbidite lobe. One simulated realization shown along section E-E' with well contacts.

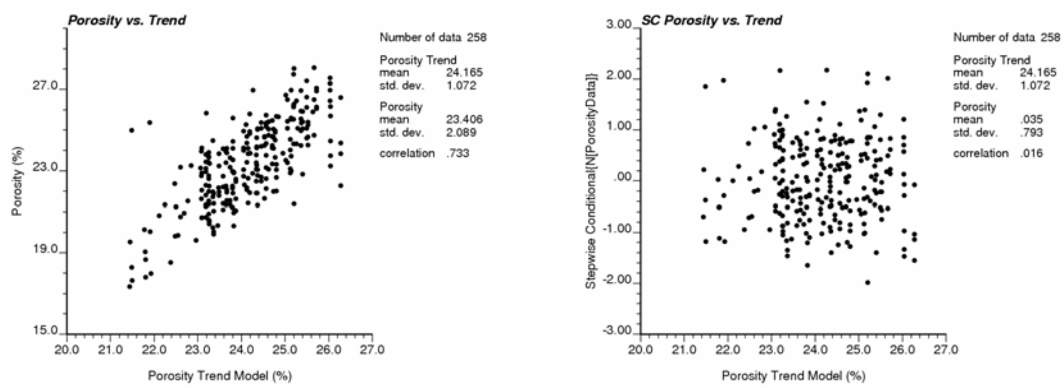

Fig. 4 The crossplot of the trend and porosity (left) and the transformed porosity and the trend (all in porosity %).

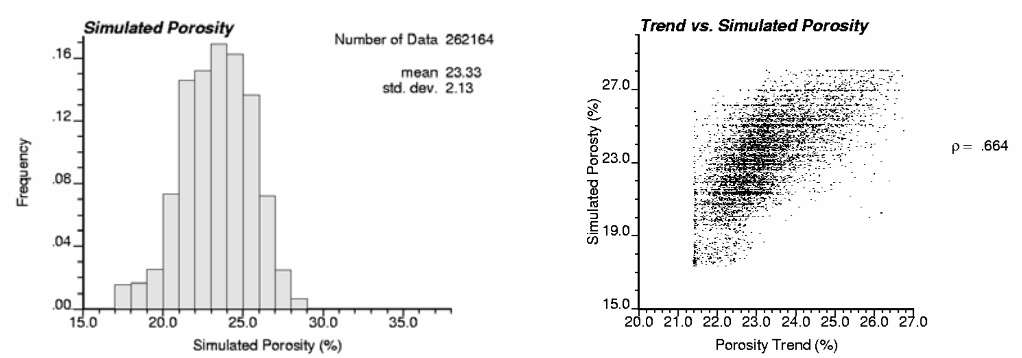

Fig. 5 Histogram of the simulated porosity and the crossplot of simulated porosity and the trend model (all in porosity %).