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Geostatistics applied to cross-well reflection seismic for imaging carbonate aquifers

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ABSTRACT

Cross-well seismic reflection data, acquired from a carbonate aquifer at Port Mayaca test site near the eastern boundary of Lake Okeechobee in Martin County, Florida, are used to delineate flow units in the region intercepted by two wells. The interwell impedance determined by inversion from the seismic reflection data allows us to visualize the major boundaries between the hydraulic units. The hydraulic (flow) unit properties are based on the integration of well logs and the carbonate structure, which consists of isolated vuggy carbonate units and interconnected vug systems within the carbonate matrix. The vuggy and matrix porosity logs based on Formation Micro-Imager (FMI) data provide information about highly permeable conduits at well locations. The integration of the inverted impedance and well logs using geostatistics helps us to assess the resolution of the cross-well seismic method for detecting conduits and to determine whether these conduits are continuous or discontinuous between wells. A productive water zone of the aquifer outlined by the well logs was selected for analysis and interpretation. The ELAN (Elemental Log Analysis) porosity from two wells was selected as primary data and the reflection seismic-based impedance as secondary data. The direct and cross variograms along the vertical wells capture nested structures associated with periodic carbonate units, which correspond to connected flow units between the wells. Alternatively, the horizontal variogram of impedance (secondary data) provides scale lengths that correspond to irregular boundary shapes of flow units. The ELAN porosity image obtained by cokriging exhibits three similar flow units at different depths. These units are thin conduits developed in the first well and, at about the middle of the interwell separation region, these conduits connect to thicker flow units that are intercepted by the second well. In addition, a high impedance zone (low porosity) at a depth of about 275 m, after being converted to ELAN porosity, is characterized as a more confined low porosity structure. This continuous zone corresponds to a permeability barrier in the carbonate aquifer that separates the three connected conduits observed in the cokriging image. In the zones above and below this permeability barrier, the water production is very high, which agrees with water well observations at the Port Mayaca aquifer.

1. Introduction

This study aims to integrate geophysical information to constrain the mapping of conduits in the interwell region of an aquifer test site, located about 48 km west of the Atlantic Ocean and approximately 1.6 km east of the eastern boundary of Lake Okeechobee in Martin County, south Florida. Some of the conduits are so thin that they are observed only in the Formation Micro-Imager (FMI) logs at the well locations (Parra et al., 2009). Thicker conduits are delineated by geophysical data, obtained by ground penetrating radar (GPR) and seismic techniques (Cardimona et al., 1998; Dubreuil-Boisclair et al., 2011; McKenna and Poeter, 1995). In these studies, GPR and seismic measurements are based on cross-well transmission tomography with well separations ≤30 m. Cardimona et al. (1998) compared images of seismic reflections and GPR in a shallow aquifer. The results showed that seismic data imaged clay lenses, whereas low-frequency radar profiles did not provide clear results. In GPR measurements, depth of penetration is limited by the presence of clay minerals or high conductivity pore fluid. GPR waves can reach depths up to 30 m in low conductivity materials such as dry sand or granite. Clays, shale, and other high conductivity materials may attenuate or absorb GPR signals, greatly decreasing the depth of penetration to 1 m or less. In contrast, cross-well reflection seismic measurements can detect heterogeneities and rock physical properties with vertical and horizontal resolutions of 0.6 m and 3 m, respectively, at an interwell distance greater than 365 m (Parra et al., 2009). The goal of this study is to estimate porosity between well locations in order to identify the lateral extents of the rock

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structures and their connectivity, by combining cross-well reflection seismic data and well log data.

The problem with using densely sampled secondary information (such as seismic impedance) in addition to sparsely sampled well-log measurements is a longstanding issue in subsurface mapping applications, especially in oil reservoir modeling (Abrahamsen et al., 1997; Doyen, 1988; Doyen et al., 1996; Dubrule, 1998, 2003). Bayesian approaches, such as Bayesian maximum entropy (Christakos, 1990; Christakos and Li, 1998; Wibrin et al., 2006) and Bayesian data fusion (Bogaert and Fasbender, 2008), offer a flexible solution to account for secondary information and its uncertainty, while they avoid assuming linear relationships between the variables. An alternative way of integrating secondary information without the restriction of linear models is provided by machine learning algorithms, such as artificial neuronal networks, support vector regressions, and genetic algorithms (Besaw and Rizzo, 2007; Kanevski et al., 2003; Leite and Vidal, 2011; Matsoukas et al., 1999).

In the field of geostatistics, a secondary variable that is exhaustively known in space can be used to define a trend model for the variable of interest (also called the primary variable). To this end, one can combine spatial prediction and regression techniques, leading to the so-called "kriging with a trend model", i.e., the guess field model (Chilès and Delfiner, 2012), regression kriging (Hengl et al., 2007) and external drift kriging (Goovaerts, 1997; Hudson and Wackernagel, 1994). The underlying trend model is that the primary variable has been generated by a spatial random field Z_1 such that, at each location $\mathbf{x}$, one has:

$$E\{Z_1(\mathbf{x})\} = a + bZ_2(\mathbf{x}), \tag{1}$$

where a and b are numerical coefficients, Z_2 denotes the secondary variable, and $E\{.\}$ stands for the mathematical expectation. The differences between the aforementioned approaches lie in how the regression model is calibrated and whether or not the regression coefficients (a and b) are known. From Eq. (1), it is seen that the dependence between the primary (Z_1) and secondary (Z_2) variables is essentially a functional dependence and that the secondary variable is considered as a deterministic field.

An alternative to kriging with a trend model is cokriging, which allows one to predict a variable of interest at a given location from data on this variable as well as on one or several covariates (Goovaerts, 1997; Wackernagel, 2003; Wackernagel et al., 2002). Here, all the variables are viewed as outcomes of spatial random fields, commonly with the assumption that their expected values are constant in space or, at least, constant at a local scale. In such a case, the relationship between the primary and secondary variables is reduced to a stochastic dependence, controlled by cross-correlation between the random fields. Cokriging variants include simple cokriging, in which the mean values of the random fields are assumed known, and ordinary cokriging, in which the mean values are unknown. The former implies little flexibility, as no uncertainty in the means can be taken into account (a reason global means are usually considered), while the latter often gives little importance to the secondary variable, as the weights assigned to secondary data sum to zero (Goovaerts, 1997). Several studies have compared the performance of kriging with a trend predictors and cokriging predictors (Asli and Marcotte, 1995; Goovaerts, 2000; Juang and Lee, 1998; Pardo-Igúzquiza, 1998), but no clear conclusion can be drawn as to which is better. The main characteristics of the predictors are listed in Table 1.

For this study, we combined the advantages of cokriging and kriging with a trend model, by considering both a functional dependence and a stochastic dependence between the primary and secondary variables. These variables are considered as outcomes of cross-correlated random fields (as in simple or ordinary cokriging), but with the following additional restriction that modifies Eq. (1):

$$E\{Z_1(\mathbf{x})\} = a + bE\{Z_2(\mathbf{x})\}, \tag{2}$$

where the coefficients a and b are assumed known, while the expected values of Z_1 and Z_2 are unknown but locally constant in space. This way, the relationships between the primary and secondary variables stem not only from the correlation (second-order moment) between the associated random fields, but also from the functional dependence between their expected values (first-order moments). This variant is suitable when the variables are linearly related, which is the case for impedance and porosity.

For completeness, the stochastic simulation approach is considered as an alternative for incorporating data from different sources. Many algorithms have been proposed, based on Gaussian or indicator transforms, simulated annealing, or Bayesian models, among others (Dafflon et al., 2009; Deutsch and Cockerham, 1994; Dubreuil-Boisclair et al., 2011; Goovaerts, 1997; Pebesma, 2004). Simulation allows one to assess spatial uncertainty through the construction of multiple outcomes that reproduce the spatial variability of the true unknown fields, but none of these outcomes is a good local predictor of the true fields. Simulation is out of the scope of this work, which aims at mapping porosity rather than constructing multiple outcomes of it.

2. Data acquisition and processing

A cross-well survey was conducted at the Port Mayaca test site, Florida. This site is located about 48 km west of the Atlantic Ocean and approximately 1.6 km east of the eastern boundary of Lake Okeechobee in Martin County, south Florida. The measurements were taken between monitoring wells MF-37 and EXPM-1 (located at east coordinates 0 and 382.6 m, respectively), using a Z-Seis piezoceramic X series source and a 10-level hydrophone system (Parra et al., 2003, 2006, 2009). Multiple source and detector measurements were taken in the depth interval from 121.9 to 518.2 m. The objectives of the survey were to map the flow unit variability in the region between the two wells, to assess whether the high-resolution seismic survey could resolve and detect zones of high water production, and to map the matrix porosity and permeability. In this study, we consider the porosity logs from wells MF-37 and EXPM-1 and the P-wave impedance data obtained by inverting the cross-well reflection seismic measurements,

Table 1
Main characteristics of kriging and cokriging predictors.

Kriging with a trend	Simple cokriging	Ordinary cokriging
Linear functional dependence between primary and secondary variables (trend model)	No functional dependence between primary and secondary variables	No functional dependence between primary and secondary variables
No stochastic dependence between primary and secondary variables	Linear stochastic dependence (correlation) between primary and secondary variables	Linear stochastic dependence (correlation) between primary and secondary variables
Secondary variable exhaustively known	Secondary variable may be partially known	Secondary variable may be partially known
Implementation in a local neighborhood when too many primary data points are available	Implementation in a local neighborhood when too many primary or secondary data points are available	Implementation in a local neighborhood when too many primary or secondary data points are available
	No uncertainty in the mean values, generally taken as constant in space	Total uncertainty in the mean values, which are constant at the neighborhood scale
Need for the variogram of the primary variable only	Need for a coregionalization model (direct and cross variograms)	Need for a coregionalization model (direct and cross variograms)