Understanding the (Co)Variance in Petrophysical Properties of CO₂ Reservoirs Comprising Sedimentary Architecture

Robert W. Ritzi*

Wright State University, Dept. of Earth and Environmental Sciences

Jared T. Freiburg and Nathan D. Webb

Illinois State Geological Survey, Prairie Research Institute, University of Illinois Urbana-Champaign

*Corresponding Author. Mailing Address: Department of Earth and Environmental Sciences, Wright State University, Dayton, OH, 45435, phone: (937) 775-2201, e-mail:

robert.ritzi@wright.edu

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Abstract

Scientific evaluation of CO₂ geo-sequestration requires fundamentally understanding the processes associated with CO₂ movement and trapping within reservoirs. Fully understanding these processes requires understanding a diverse set of heterogeneous geologic properties that vary at different scales. Establishing basic relationships between the sedimentary architecture in these reservoirs and the variation in petrophysical attributes that can affect plume dynamics and residual trapping is an important step toward understanding reservoir processes. Highly-resolved data sets at well-characterized research sites can be used to establish these basic relationships. In this vein, the sample (co)variance for petrophysical attributes can be quantitatively and deterministically decomposed according to a hierarchy of textural factors that vary among sedimentary facies. A new hierarchical method for the analysis of (co)variance of petrophysical attributes is adapted for this purpose. The results quantify the magnitude that each factor contributes to the (co)variance, and thus clarify their relative contribution within the factor hierarchy. This leads to a basic understanding of how the sample (co)variance arises within the

sedimentary architecture, and of which factors are important in defining it. Such an understanding aids in developing parsimonious reservoir simulation models. The method is illustrated using a highly-resolved data set from the lower Mt. Simon Sandstone reservoir.

Keywords: CO₂ geo-sequestration, reservoir heterogeneity, fluvial architecture, analysis of variance, Mt. Simon Sandstone

1. Introduction

Evaluating the efficacy of geological sequestration of CO₂ requires understanding subsurface flow dynamics, including CO₂ plume migration and trapping, which, in turn, requires understanding a diverse set of geologic properties of a candidate reservoir. For example, there is considerable interest in the post-injection process of residual trapping of CO₂ within reservoirs (occurring far below caprock). Residual trapping occurs because CO₂ is immobilized by snap-off of CO₂ bubbles at the tail of a CO₂ plume as it buoyantly rises and by entry pressure pinning of the plume below areas where capillary entry pressure exceeds buoyant pressure. These trapping processes could immobilize appreciable amounts of CO₂ within the reservoir and add to the overall efficacy of CO₂ storage (e.g., Juanes et al. 2006; Saadatpoor et al. 2009; Zhou et al., 2010; Gershenzon et al., 2015a; Krevor et al., 2015; Bacon et al., 2016). As shown by Gershenzon et al. (2015a), smaller-scale (decimeter to tens of meters) textural differences in reservoir rock, related to sedimentary architecture, can exert strong control on residual trapping and other aspects of CO₂ dynamics because of the variation in petrophysical attributes such as capillary entry pressures, intrinsic permeability, saturation relationships with capillary pressure and relative permeability, and porosity. The focus of this article is on understanding and explaining the variance of an attribute through the sedimentary architecture. A new method of

decomposing the sample variance or covariance (Soltanian and Ritzi, 2015) is adapted for this purpose, which incorporates indicator variables to represent a hierarchy of sedimentary attributes.

Field studies of sedimentary deposits have created a body of literature on the link between sedimentary architecture and heterogeneity in intrinsic permeability and porosity [e.g., Anderson, 1989, 1991a, 1991b; Davis et al., 1993; Davis et al., 1997; Allen-King et al., 1998; Barrash and Clemo, 2002; Divine, 2002; Guad et al., 2004; Biteman et al., 2004; Dai et al., 2005; Ritzi et al., 2013; Allen-King et al., 2015; Soltanian and Ritzi, 2015]. Facies classifications are prevalent in this work. Facies are three-dimensional bodies of sediment whose differentiation provides a useful conceptual framework within which to characterize heterogeneity in attributes of interest within the larger sedimentary deposit. Importantly, facies classifications are not unique. For example, Dai et al. (2005) demonstrated how either depositional sedimentary facies or textural sedimentary facies could be used to represent spatial heterogeneity in permeability arising in alluvial deposits in the Rio Grande Valley. There is no universal answer to questions over how facies should be defined. A classification should be useful and parsimonious, and these both depend upon context. What is most appropriate in one context may not be most appropriate for another. Our interest is in defining facies classifications useful within the workflow for creating interpretive reservoir simulation models.

The idea behind the approach is illustrated here in the context of understanding and modeling the spatial distribution of petrophysical attributes within sedimentary architecture created by fluvial deposition, though the general approach is not limited in applicability to fluvial architecture. A number of candidate reservoirs suitable for CO₂ sequestration have sedimentary architecture reflecting fluvial deposition in at least part of their stratigraphic sections, such as in

the lower Mt. Simon Sandstone (Freiburg et al., 2014); the lower Paaratte Formation (Krevor et al., 2012; Dance et al., 2016); the Victor interval of the Ivishak Formation (Tye et al., 2003), the Morrow Sandstone (Dia et al., 2014; Gallagher, 2014), and the lower Tuscaloosa Formation (Krevor et al., 2012; Lu et al., 2011). These are predominantly composed of sandstone or conglomerate, and their sedimentary architecture comprises multiple scales of heterogeneity ranging from the decimeter to the reservoir scale. The complexity of the sedimentary architecture internal to such reservoirs needs to be included in developing a basic-science understanding of CO₂ injection, migration, and residual trapping.

The sedimentary architecture created by fluvial deposition has recently been described and quantified in three-dimensional models (e.g., Lunt, 2002; Lunt et al., 2004; Bridge, 2006; Ramanathan et al., 2010; Guin et al., 2010). As shown in Figure 1, channel-belt deposits are characterized by a large volume fraction of convex-up compound-bar deposits formed within channels, which comprise unit-bar deposits which, in turn, comprise mostly sets of cross-beds (cross-sets hereafter) formed by migrating dune bedforms, creating a hierarchy of stratification in preserved deposits. Unit bar deposits may also comprise planar- and ripple-laminated strata. When channels are abandoned and filled, concave-up, channel fills are formed comprising finer-grained sediment. This sedimentary architecture is found in modern fluvial settings and in ancient fluvial reservoirs that range in mean grain size from sand (e.g., lower Mt. Simon Sandstone) to gravel (e.g., the Ivishak Formation conglomerate). Importantly, these deposits and reservoirs are dominated by an assemblage of finer- and coarser-grained cross-sets, as illustrated in Figure 1. Those finer- and courser-grained sedimentary textures can be a primary factor influencing the variance of a petrophysical attribute such as permeability, and depositional

architecture can explain the spatial organization of textural facies that are indeed of primary importance.

Well-developed, digital, geocellular models exist for simulating the depositional architecture of fluvial deposits (e.g., Ramanathan et al., 2010; Hassanpour et al., 2013; Gershenzon et al., 2015a). Because the size of the depositional units scale together with the width of the active channels in which they form (Bridge, 2006), it is possible to adapt these general models to specific deposits. The model units can be scaled to the length scales quantified for a specific reservoir. The grid cells of the different sedimentary units in the digital model can be populated with values for attributes, such as intrinsic permeability, based on a quantification of their statistical distributions specific to the textures of the units (e.g., finer-grained vs. coarser-grained cross-sets) found in a specific reservoir. The workflow in creating a CO₂ simulation model for a specific reservoir might proceed with 1) evaluating reservoir data to define textural facies based on grain size, bedding, and other factors, 2) defining statistical distributions for petrophysical attributes per each of the textural facies, and 3) mapping values for the attributes from these distributions into the digital geocellular model for sedimentary architecture and using the geocellular model in reservoir simulations (e.g. Gershenzon et al., 2014, 2015a,b).

This article addresses steps 1 and 2 using deterministic statistics (*sensu* Issaks and Srivastava, 1988). In this approach, highly-resolved data sets are used to compute sample statistics within a deterministic framework. The general goal is to study real, highly-resolved, sample statistics when well-quantified in naturally-occurring reservoirs, and to understand how the sample statistics are influenced by attributes of the sedimentary architecture. Thus, this area of statistics can be distinguished from other areas that focus on estimation or uncertainty. Here

we undertake a deterministic analysis of the sample variance of intrinsic permeability and porosity, and their sample covariance, in a reservoir with highly resolved data, to see how the sample statistics are controlled by a hierarchy of attributes including sedimentary grain size and bedding, and also vertical position and diagenetic alteration, and to use that knowledge to create a parsimonious set of textural facies types and statistical distributions for the populations of petrophysical properties that occur within them. These could then be used in the third step of the workflow outlined above (the third step is outside the scope of this article).

To accomplish the deterministic analysis of the sample variance, we use a newer hierarchical approach described below. We illustrate the methodology using a rich data set from the lower Mt. Simon Sandstone, a target CO₂ storage reservoir in the Illinois Basin, USA. The methodology is presented as adapted to a hierarchy of factors defined by this example, and therefore the hierarchy of factors used for study of the lower Mt. Simon are first described.

2. Lower Mt. Simon Sandstone

The Middle Cambrian Mt. Simon Sandstone is a permeable and porous formation that is used for the Illinois Basin Decatur Project (IBDP), a 1 million metric-ton carbon capture and storage demonstration project located in Macon County, Illinois (Finley, 2014). The IBDP began injecting CO₂ in November 2011 into the lower Mt. Simon Sandstone (Figure 2) below a depth of 2000 m.

Within the scope of IBDP research, the Mt. Simon Sandstone has been rigorously characterized (Leetaru and Freiburg, 2014; Freiburg et al., 2014). The highest quality reservoir rock is in the lower Mt. Simon, designated as Unit A (Figure 2a). Unit A can be divided into upper A and lower A, which include braided-fluvial and other sandstone deposits, and which are

separated by a thin (~1 m) mudstone that creates a pressure baffle between them (Senel et al., 2014). Our interest has been in characterizing the relatively more permeable upper and lower A units, and not in the mudstone itself. Therefore, we have not included the mudstone in the example analysis below, though it could be included if desired.

A highly resolved data set, used here, comes from a relatively continuous core (vertical interval represented by an ochre stripe in Figure 2) taken during the drilling of well VW#1, located 300 m from the injection well. From analyses of this core, Freiburg et al. (2014) provided a highly-resolved textural description of the rock. Related laboratory analyses of 10-cm diameter whole-core samples provided intrinsic permeability and porosity data with 0.3 m (on average) vertical resolution. Capillary entry pressures and other attributes are also important to developing reservoir simulation models; however, data for these attributes do not exist in numbers sufficient for an analysis of their variance. The method we present could be applied in the future if sufficient numbers of data were developed.

The Mt. Simon Unit A deposits are maroon to tan-white sandstones classified as subarkose arenite (between 5% to 25% total feldspar), with minor sublithic arenite, arkose arenite, and arkose wacke. Dark maroon mudstones are rare, with a thin zone creating the pressure baffle in Unit A as noted above. The arenites generally have abundantly preserved primary framework porosity, and secondary porosity due to potassium feldspar dissolution. Some porosity loss due to compaction is common, and porosity loss due to cementation (cementation as authigenic quartz where present) is less common. The general lack of authigenic quartz cementation is attributed to feldspar alteration to authigenic illite, which subsequently coats quartz grains and prevents quartz overgrowths (Freiburg et al., 2014). Intervals with

inferred iron reduction or bleaching have little to no authigenic clay and thus more authigenic quartz cementation and are generally more consolidated and compacted.

Figure 3 shows five 0.3 m sections of core. The red arrows designate the piece of core used for intrinsic whole-core permeability and porosity measurement. Intrinsic permeability was measured in two orthogonal horizontal directions and in the vertical direction on each piece. The larger and the smaller of the two horizontal-direction measurements are herein referred to as “max” and “min.” (Note that these are not necessarily the principle directions of horizontal anisotropy.) Summary sample statistics for the intrinsic permeability and porosity data are given in Table 1. Intrinsic permeability, k , ranges over more than three orders of magnitude in the horizontal and in the vertical directions, indicating an analysis of log-transformed data, $Y=\ln(k)$, is appropriate. The geometric means are similar between measurements made in the two orthogonal horizontal directions (31.3 mD in the horizontal max direction vs. 26.3 mD in the horizontal min direction), suggesting little horizontal anisotropy at the scale of the core samples. Horizontal to vertical anisotropy is indicated to be on the order of 4:1. The sample variance in porosity, ϕ , is quite small relative to the sample variance in permeability, and log-transformation is contraindicated.

The Y and ϕ data were subdivided into a hierarchy of subpopulations according to categories within identifiable physical factors available from Freiburg et al. (2014), which were expected to affect the variability in those attributes (Table 2). The data were first divided into subpopulations based on location in the upper vs. lower Unit A (Figure 2). Though the upper and lower zones of Unit A appear similar, defining the data subpopulations allows formally quantifying to what extent any differences contribute to the sample variance in the sample statistics of the attributes. These subpopulations were each further subdivided into five

subpopulations based on a factor to represent grain-size differences. The core samples shown in Figure 3 illustrate each of these five categories defined for the grain-size factor. The grain-size factor was expected to be especially significant in explaining the sample variance for Y . These subpopulations were each further subdivided into two subpopulations according to whether or not the sample exhibited cross-bedding (Table 2, Figure 4). Most samples (74%) have cross-bedding/lamination. Some other bedding textures are shown in Figure 4. Soltanian and Ritzi (2015) found that presence of bedding/lamination was negligible in explaining the sample variance of a highly-resolved data set for Y measured in an unconsolidated sand deposit. Nevertheless, a bedding factor is included here for completeness. Finally, these subpopulations were each further divided according to presence or absence of bleached alteration, as in Figure 5. Bleaching alteration is common to red-bed deposits, with crosscutting geometries and petrophysical studies of paragenesis indicating that the red color predates the white bleached zone (e.g., Beitler et al., 2003). Bleaching has been attributed to various causes, including the migration of hydrocarbons (Beitler et al., 2003). The cause of bleaching found in the lower Mt. Simon Sandstone has not been identified; however, indigenous populations of iron-reducing bacteria have been described and perhaps play a role (Dong et al., 2014). The effect of this alteration is a reduction in pore space, as evident in Figure 6. The focus of this article is not on the cause of the bleaching alteration, but rather on the effect and its contribution to the sample variance in Y and ϕ , and their covariance. Four categories were used to represent the bleaching factor (Table 2, Figure 5). Bleached intervals occur fairly regularly with depth (Figure 7).

Conventional analysis of variance or covariance (ANOVA/ANCOVA) methods have been used in a number of studies to quantify facies contributions to the sample variance of Y in sedimentary deposits (e.g., Allen-King et al., 2015). The factors considered for the lower Mt.

Simon have a hierarchical relationship. Both the upper and lower Unit A data subpopulations include sediments in all of the grain-size categories. Each of these subpopulations include samples with presence or absence of cross-bedding/lamination. Samples in each of these bedding-factor subpopulations can have bleached alteration. A hierarchical analysis of sample variance allows representation of the nesting of data subpopulations and thus, importantly, facilitates studying how the nested factors affect the sample variance in highly resolved data sets. Here we adapt the hierarchical analysis of variance method for a deterministic study of the sample variance in Y and ϕ , and their covariance, in the lower Mt. Simon Sandstone. Note that the factors and categories being used in the lower Mt. Simon illustration are what are available from the existing core data and are not meant to be exclusive. If other factors were identified and quantified at the support scale of the Y and ϕ measurements, they could also be included in the analysis.

3. Methodology

Let $\xi(i)$ be a sample of an attribute such as Y or ϕ . The data for that attribute are divided into a hierarchy of subpopulations defined in Table 2 with, from the highest level to the lowest level, subset ξ_r containing samples from within category r , $r=[\text{UA}, \text{LA}]$, ξ_{ro} containing samples from within category o , $o=[\text{SLT-VFS}, \text{FS}, \text{MS}, \text{CS}, \text{VCS-CLG}]$ within the category r , and ξ_{roj} containing samples from within category j , $j=[\text{XB}, \text{NXB}]$, within category o within category r , and $\xi_{roj p}$ containing samples from category p , $p=[\text{UB}, \text{BB}, \text{BM}, \text{BS}]$, within category j within category o within category r .

Let $I_r(i)$ be an indicator variable that takes on the value of 1 if sample number i is within category r and the value of 0 otherwise. In the same vein, indicator variable $I_{ro}(i)$ takes on a

230 value of 1 if that sample is in category o , and $I_{roj}(i)$ takes on a value of 1 if in category j , and I_{roj}
 231 (i) takes on a value of 1 if in category p , and they take on the value of 0 otherwise.

232 The sample proportions of the unit types from lowest to highest level are:

$$233 \quad \hat{P}_{roj} = \frac{1}{N_t} \sum_{i=1}^{N_t} I_{roj}(i) = \frac{N_{roj}}{N_t} \quad (1)$$

$$234 \quad \hat{P}_{roj} = \frac{1}{N_t} \sum_{i=1}^{N_t} I_{roj}(i) = \frac{N_{roj}}{N_t} \quad (2)$$

$$235 \quad \hat{P}_{ro} = \frac{1}{N_t} \sum_{i=1}^{N_t} I_{ro}(i) = \frac{N_{ro}}{N_t} \quad (3)$$

$$236 \quad \hat{P}_r = \frac{1}{N_t} \sum_{i=1}^{N_t} I_r(i) = \frac{N_r}{N_t} \quad (4)$$

237 The sample means for the subpopulations defined at each level are:

$$238 \quad \hat{m}_{\xi_{roj}} = \frac{1}{N_{roj}} \sum_{i=1}^{N_{roj}} \xi_{roj}(i) \quad (4)$$

$$239 \quad \hat{m}_{\xi_{roj}} = \frac{1}{N_{roj}} \sum_{i=1}^{N_{roj}} \xi_{roj}(i) = \sum_{p \in j} \left[\frac{1}{N_{roj}} \sum_{i=1}^{N_{roj}} \xi_{roj}(i) \right] \frac{N_{roj}}{N_{roj}} = \sum_{p \in j} \hat{m}_{\xi_{roj}} \frac{\hat{P}_{roj}}{\hat{P}_{roj}} \quad (5)$$

$$240 \quad \hat{m}_{\xi_{ro}} = \frac{1}{N_{ro}} \sum_{i=1}^{N_{ro}} \xi_{ro}(i) = \sum_{j \in o} \hat{m}_{\xi_{roj}} \frac{\hat{P}_{roj}}{\hat{P}_{ro}} \quad (6)$$

$$241 \quad \hat{m}_{\xi_r} = \frac{1}{N_r} \sum_{i=1}^{N_r} \xi_r(i) = \sum_{o \in r} \hat{m}_{\xi_{ro}} \frac{\hat{P}_{ro}}{\hat{P}_r} \quad (7)$$

242 and for the composite data set:

$$243 \quad \hat{m}_{\xi} = \frac{1}{N_t} \sum_{i=1}^{N_t} \xi(i) = \sum_r \hat{m}_{\xi_r} \hat{P}_r \quad (8)$$

244 The corresponding non-centered sample covariances are:

$$245 \quad \hat{K}_{\xi_{roj\hat{p}}\xi_{roj\hat{p}}} = \frac{1}{N_{roj\hat{p}}} \sum_{i=1}^{N_{roj\hat{p}}} \xi_{roj\hat{p}}^2(i) \quad (9)$$

$$246 \quad \hat{K}_{\xi_{roj}\xi_{roj}} = \frac{1}{N_{roj}} \sum_{i=1}^{N_{roj}} \xi_{roj}^2(i) = \sum_{p \in j} \hat{K}_{\xi_{roj\hat{p}}\xi_{roj\hat{p}}} \frac{\hat{P}_{roj\hat{p}}}{\hat{P}_{roj}} \quad (10)$$

$$247 \quad \hat{K}_{\xi_{ro}\xi_{ro}} = \frac{1}{N_{ro}} \sum_{i=1}^{N_{ro}} \xi_{ro}^2(i) = \sum_{j \in o} \hat{K}_{\xi_{roj}\xi_{roj}} \frac{\hat{P}_{roj}}{\hat{P}_{ro}} \quad (11)$$

$$248 \quad \hat{K}_{\xi_r\xi_r} = \frac{1}{N_r} \sum_{i=1}^{N_r} \xi_r^2(i) = \sum_{o \in r} \hat{K}_{\xi_{ro}\xi_{ro}} \frac{\hat{P}_{ro}}{\hat{P}_r} \quad (12)$$

$$249 \quad \hat{K}_{\xi\xi} = \frac{1}{N_t} \sum_{i=1}^{N_t} \xi^2(i) = \sum_r \hat{K}_{\xi_r\xi_r} \hat{P}_r \quad (13)$$

250

251 The composite (centered) sample variance is defined by:

$$252 \quad \hat{\sigma}_{\xi\xi} = \hat{K}_{\xi\xi} - \hat{m}_{\xi}^2 \quad (14)$$

253 Recursive substitution of the above equations gives the following useful equality:

$$254 \quad \hat{\sigma}_{\xi\xi} = \alpha + \beta + \chi + \delta + \varepsilon \quad (15)$$

255 Where

$$256 \quad \alpha = \sum_r \hat{m}_{\xi_r}^2 \hat{P}_r - \hat{m}_{\xi}^2 \quad (16)$$

$$257 \quad \beta = \sum_r \sum_o \hat{m}_{\xi_{ro}}^2 \hat{P}_{ro} - \sum_r \hat{m}_{\xi_r}^2 \hat{P}_r \quad (17)$$

$$258 \quad \chi = \sum_r \sum_o \sum_j \hat{m}_{\xi_{roj}}^2 \hat{P}_{roj} - \sum_r \sum_o \hat{m}_{\xi_{ro}}^2 \hat{P}_{ro} \quad (18)$$

$$259 \quad \delta = \sum_r \sum_o \sum_j \sum_p \hat{m}_{\xi_{roj\hat{p}}}^2 \hat{P}_{roj\hat{p}} - \sum_r \sum_o \sum_j \hat{m}_{\xi_{roj}}^2 \hat{P}_{roj} \quad (19)$$

$$260 \quad \varepsilon = \sum_r \sum_o \sum_j \sum_p \hat{\sigma}_{\xi_{roj\hat{p}}\xi_{roj\hat{p}}} \hat{P}_{roj\hat{p}} \quad (20)$$

The relevance of each term with respect to its contribution to the total sample variance can be explained in terms of the factors and categories in Table 2. The α term gives the contribution arising from the contrast in the sample means of the upper or lower Unit A subpopulations. The β term gives the contribution arising from the contrast in the sample means among the grain-size categories. The χ term gives the contribution arising from the contrast in the sample means of the cross-bedded and non-cross-bedded categories. The δ term gives the contribution arising from the contrast in the sample means among the bleaching categories. The ε term gives the contribution to the total sample variance arising from the base-level variability within the smallest subdivisions considered here. Thus, the ε term represents the sample variance undifferentiated and unexplained by the factors and categories considered here.

Following the same threads of the derivation above, the sample point covariance between two different attributes ξ and ζ is given by:

$$\begin{aligned} \hat{\sigma}_{\xi\zeta} = & \sum_r \sum_o \sum_j \sum_p \hat{\sigma}_{\xi_{roj}\zeta_{roj}} \hat{P}_{roj} + \\ & \sum_r \sum_o \sum_j \sum_p \hat{m}_{\xi_{roj}} \hat{m}_{\zeta_{roj}} \hat{P}_{roj} - \sum_r \sum_o \sum_j \hat{m}_{\xi_{roj}} \hat{m}_{\zeta_{roj}} \hat{P}_{roj} + \\ & \sum_r \sum_o \sum_j \hat{m}_{\xi_{roj}} \hat{m}_{\zeta_{roj}} \hat{P}_{roj} - \sum_r \sum_o \hat{m}_{\xi_{roj}} \hat{m}_{\zeta_{roj}} \hat{P}_{roj} + \\ & \sum_r \sum_o \hat{m}_{\xi_{roj}} \hat{m}_{\zeta_{roj}} \hat{P}_{roj} - \sum_r \hat{m}_{\xi_r} \hat{m}_{\zeta_r} \hat{P}_r + \\ & \sum_r \hat{m}_{\xi_r} \hat{m}_{\zeta_r} \hat{P}_r - \hat{m}_{\xi} \hat{m}_{\zeta} \end{aligned} \quad (21)$$

with each of the terms on the right-hand side having clear correspondence with the α , β , χ , δ and ε contributions described above.

The analysis is conducted by computing cursory univariate sample statistics for each category in each factor (sample proportion, sample mean, and sample variance), substituting them into equations 16-20, and evaluating the relative contribution of each term to the total sum

in equation 15 (or equation 21 for the covariance). Factors with categories having larger contrasts in the sample means and having larger sample proportions will contribute most to explaining the composite sample variance statistic.

4. Results

4.1. Analysis of $\hat{\sigma}_{yy}$ in data measured in horizontal directions

The results of computing the terms of equations 15-20 for the analysis of $\hat{\sigma}_{yy}$ in data measured in the horizontal directions are given in the first two columns of Table 3. The results are essentially the same for the horizontal max and horizontal min groupings from the two orthogonal horizontal sets of measurements, and so the results in these two columns are discussed together. The results are given in terms of the relative contribution (as a percentage) of a factor to the total sample variance. The grain-size factor makes the biggest contribution (39%) to the sample variance among the factors considered. This was mostly due to differences between samples from fine-sand size or finer and samples from medium-sand size or coarser grain-size categories (analyzed further below). The second largest contribution was from the bleaching (22-23%) factor, mostly due to differences between samples that were bleached vs. unbleached. The grain size of a sample and whether or not it is bleached explain the majority of the sample variance in horizontally measured Y .

The contributions to the sample variance from the vertical position factor and the bedding factor are each small and are each less than 3% of $\hat{\sigma}_{yy}$. Thus, these two terms make relatively small contributions, and thus differences in the sample means among categories defined for these factors are relatively unimportant in explaining the composite sample variance. The physical meaning of this is that it is relatively unimportant to distinguish whether a location is above or

below the pressure baffle, or whether or not samples have internal cross-bedding, in explaining the univariate sample variance among horizontal measurements of permeability. Accordingly, one could choose to do away with defining differences in vertical position and bedding, because the delineation of these factors does not contribute much to understanding the sample variance at this resolution.

The amount of the sample variance among horizontal measurements not differentiated and thus not explained by the factors considered here is 34% and 35% for the max and min subpopulations respectively. This amount of base-level variability is not surprising. Permeability is proportional to the square of the pore openings (e.g., Chapuis, 2004; Kamann et al., 2007). This sensitivity gives rise to a large range in permeability even within a single grain-size category. There are other factors such as compaction, cementation, and clay content that are not quantified and available for this analysis and could be contributing to the base-level variability. The bleaching factor represents some of the differential compaction and cementation, in that bleached samples generally exhibit more compaction and cementation relative to unbleached samples as discussed above, and these results point toward future work that could quantify and represent those factors more directly. However, even well-sorted and unconsolidated beach sand deposits can have permeability ranging over an order of magnitude or more within a single grain-size category (e.g., Ritzi et al., 2013; Soltanian and Ritzi, 2015), without cementation or significant compaction. Thus, we should expect and accept a significant amount of base-level (ε term contribution) variability with the decimeter measurement support scale being used here, as indeed is observed in these results.

Note that the analysis was also done with different orders to the hierarchy of data subpopulations (e.g., dividing the upper and lower Unit A subpopulations into subpopulations

first by bedding categories, and then by grain-size categories), with negligible effect on the results, and therefore those additional results are not presented. Furthermore, Palkovic and Frailey (unpublished report) proposed a correction factor to the horizontal permeability data to account for possible influence of drilling fluid alteration on the outer skin of the core samples used in this analysis. Using those data gives the same results as in Table 3 (see supplemental material).

4.2. Analysis of $\hat{\sigma}_{YY}$ in data measured in the vertical direction

The results for the analysis of $\hat{\sigma}_{YY}$ in data measured in the vertical direction are given in the third column of Table 3, and are generally similar to results of analysis of horizontal measurements. The grain-size and bleaching factors make the largest contributions (24% and 27% respectively) to the sample variance among the factors considered. As expected, the bedding factor contributes a bit more to the sample variance (7%) of permeability data measured in the vertical direction, as compared to when measured in the horizontal but is still small relative to the grain-size and bleaching factors. Again, the contribution to $\hat{\sigma}_{YY}$ from the vertical position factor is small, at 3%. As expected, again, base-level variability within categories was significant (39%) for reasons discussed above.

4.3. Analysis of $\hat{\sigma}_{\phi\phi}$

The results for the analysis of $\hat{\sigma}_{\phi\phi}$ are given in the fourth column of Table 3. The results should be viewed from the perspective that the composite $\hat{\sigma}_{\phi\phi}$ is small relative to $\hat{\sigma}_{YY}$. Porosity in the whole sample population varies within a single order of magnitude, and thus the sample coefficient of variation for porosity data is small (Table 1), even without log transformation of

the variable, relative to permeability data. Porosity is a relative rather than absolute measure of void space, and thus is less related to absolute pore/grain size than it is to the degree of sorting and to the packing of finer grains into coarser pores (e.g., Kamann et al., 2007). Indeed, the contribution from the grain-size factor to $\hat{\sigma}_{\phi\phi}$ is less than it is for $\hat{\sigma}_{YY}$. The sample variance is explained to a larger degree by the presence or absence of bleaching. As with $\hat{\sigma}_{YY}$, the contributions to $\hat{\sigma}_{\phi\phi}$ from the vertical position and bedding factors are negligible.

4.4. Analysis of $\hat{\sigma}_{Y\phi}$

The sample point covariance between horizontal intrinsic permeability (max) and porosity is 0.04, giving a point correlation coefficient (R value) of only 0.39. Thus, these attributes are only weakly correlated. The results for the analysis of $\hat{\sigma}_{Y\phi}$ are given in the fourth column of Table 3, showing that the weak sample correlation between Y and ϕ arises mostly from the presence or absence of bleaching. Bleaching reduces both permeability and porosity, as analyzed further in the next section.

5. Discussion and Conclusions

To summarize the results, the factors contributing most to differences in intrinsic permeability as measured in vertical and horizontal directions, and hence contributing most to the sample variance, are the grain-size factor (SLT-VFS, FS, MS, CS, and VCS-CLG) and the bleaching factor (UB, BB, BM, and BS). The bleaching factor most explains the sample variance in porosity, and the sample covariance between permeability and porosity.

The vertical position (UA and LA) and bedding (XB and NXB) factors add relatively little to explaining the sample variances for intrinsic permeability and porosity, or their sample covariance. The fact that vertical position is not a significant factor supports modeling the variability in intrinsic permeability and porosity based on a textural facies classification without regard to vertical position. The fact that bedding is not a significant factor supports modeling the variability in intrinsic permeability and porosity with textural facies based on grain-size and bleaching factors alone. As stated in the introduction, facies classifications are not unique. What is most appropriate in one context may not be most appropriate for another. The results presented here could lead to a number of different textural facies classifications and models.

Here we illustrate how one such textural facies classification and model might be defined in the context of developing a reservoir model, in which the variability of an attribute is modeled by the spatial arrangement of textural facies within the sedimentary architecture (e.g., Ramanathan et al., 2010; Hassanpour et al., 2013; Gershenson et al., 2015a). Our longer-term interest is in developing interpretive simulation models for the study of how smaller-scale sedimentary architecture affects residual trapping of injected CO₂, in the vein of Gershenson et al. (2015a). We are guided by the principle of parsimony, and would like to minimize the number of textural facies needed to represent the variability in the attributes. We first consider how many textural facies types are needed to represent grain-size differences, and then consider bleaching. Table 4A presents the geometric mean and sample variance in intrinsic permeability for unbleached samples only. The difference in the geometric mean values of intrinsic permeability between the MS and CS grain-size categories is relatively small, and the VCS-CGL category is a fairly small percentage (7.3%) of the rock. This suggests that these categories might be combined as in Table 4B, to create two unbleached textural facies categories. The

distributions of horizontal max intrinsic permeability for these combined categories are plotted in Figure 8. Table 4C defines a simple model for unbleached textural facies based on these combinations. The unbleached coarser-grained textural facies could be represented by a horizontal intrinsic permeability subpopulation with a geometric mean around 100 mD and a coefficient of variation around unity. The unbleached finer-grained textural facies would be represented by an intrinsic permeability subpopulation with a geometric mean intrinsic permeability on the order of 10 mD and a coefficient of variation around unity. Horizontal to vertical anisotropy could be represented as 6:1.

The bleaching factor is considered next in defining the textural facies types, and the following additional information about bleached samples is useful. Table 5 shows that the bleached samples have a proportion in each grain-size category close to the proportion all samples have in each grain-size category. This correspondence is especially true for the grain-size categories with significant numbers of samples (i.e., FS, MS, and CS categories) and thus especially true when sample statistics are better supported. This correspondence suggests that the bleaching overprint on the reservoir occurred indiscriminately, rather than occurring preferentially in finer- vs. coarser-grained rock. As shown in Tables 6 and 7, bleaching reduces permeability by about 75% and porosity by about 25% (or by 5% porosity). Based on similar mean values among BB, BM, and BS subpopulations, they could be combined in a simple model. A parsimonious approach might be to define two bleached textural facies, bleached finer and bleached coarser grained. The distributions of horizontal max intrinsic permeability data for these combined categories are plotted in Figure 8. The unbleached finer-grained and bleached coarser-grained facies have similar sample distributions, but would be mapped into different depositional units as illustrated in Figure 9. The sample coefficient of variation for permeability

in bleached zones is of the order of 2, higher than in unbleached intervals. As shown in Table 8, bleached intervals have an average thickness of 0.23 m, with a relatively large variance in thickness.

In this context, we could define four textural facies in a simple model, as defined in Table 9 and illustrated in Figure 9. In addition to the two permeability populations defined for the two unbleached textural facies, a parsimonious model might have a bleached finer-grained textural facies with geometric mean permeability of 2.5 mD, CV of 2, and porosity of 15%, and a bleached coarser-grained textural facies with a geometric mean permeability of 25 mD, CV of 2 and porosity of 15%. Figure 9 illustrates how the four textural facies would be spatially distributed within cross-sets occurring within a compound bar deposit. Importantly, given that the type of bedding was not a significant factor contributing to variation in permeability or porosity, the four textural facies categories (defined on grain size and bleaching alone) and their statistical distributions for permeability and porosity are applicable to all the depositional units within the lower Mt Simon, not only the fluvial cross-sets. Again, facies models are not unique, and choices depend on context. This serves as an illustration of one that would be useful for creating interpretive simulation models for study of CO₂ trapping, in the vein of Gershenzon et al (2015a), who have shown that residual capillary trapping of CO₂ in fluvial reservoirs can be strongly controlled by the juxtaposition of smaller-scale textural units having different grain size. The results presented here, that define the factors controlling the variance in permeability and porosity in the lower Mt. Simon reservoir, show that, in addition to grain size, the bleaching is a significant factor and thus suggest that the juxtaposition of bleached and unbleached textural units at a relatively small scale will have a significant effect on residual trapping of CO₂ in that reservoir.

In conclusion, the hierarchical analysis of factors affecting the sample variance of petrophysical attributes allows for a useful, simple, and straightforward quantitative description of how the sample (co)variance arises from a hierarchy of textural attributes of the reservoir rock. This was illustrated using the lower Mt. Simon Sandstone reservoir as an example. The sample (co)variances of intrinsic permeability and porosity were decomposed according to contributions from a hierarchy of factors, including vertical position, grain size, bedding, and bleaching alteration. The relative contribution to the sample (co)variance arising from each of these factors was quantified in the hierarchical analysis of the sample (co)variance. In the lower Mt. Simon Sandstone reservoir, the most important among these factors were grain size and bleaching. The quantitative analysis of their contributions to the sample variance aids in the development of a parsimonious textural-facies based system for modeling petrophysical attributes within the reservoir modeling workflow, as illustrated in the example.

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Figure captions:

Figure 1. Fluvial deposition, and internal architecture of fluvial deposits. a) A modern fluvial channel-belt system comprising active channels and compound bars. The compound bars, in turn, comprise unit bars. From Sambrook Smith et al. (2006). b) Conceptual diagram of a compound bar with unit bars outlined in green. c) Cross section through (b) showing that unit bar deposits comprise sets of cross strata with different textures. Ideas for (b) and (c) adapted from Lunt et al., (2004).

Figure 2. a) Wire-line log through the Middle Cambrian lower Mt. Simon Sandstone Unit A taken at the Illinois Basin-Decatur Project site (Freiburg et al., 2014). Porosity log on right is shaded red where exceeding 10%. Ochre stripe indicates interval of relatively continuous core sampling. b) Exposure of Cambrian sandstone at the southern edge of the Illinois Basin, showing fluvial architecture as in Figure (1). (The larger demarcations on the scale staff are 0.5 m intervals. Blue and green lines are as in Figure 1)

Figure 3. Samples from the lower Mt. Simon core VW1 representing each grain-size category in Table 2. The red arrows indicate the piece used for measurement of intrinsic permeability. Samples from left to right: 1) Very-fine-grained sandstone, $k_{\text{hor max}} = 0.2$ mD, $k_{\text{vert}} =$ below detect, porosity = 9%, 2081.78-2082.09 m (6830-6831 ft) depth. 2) Fine-grained sandstone, $k_{\text{hor max}} = 50$ mD, $k_{\text{vert}} = 6$ mD, porosity = 23%, 2055.27-2055.57 m (6743-6744 ft) depth, 3) Medium-grained sandstone, $k_{\text{hor max}} = 151$ mD, $k_{\text{vert}} = 5$ mD, porosity = 21%, 2129.33-2129.64 m (6986-6987 ft) depth, 4) Coarse-grained sandstone, $k_{\text{hor max}} = 144$ mD, $k_{\text{vert}} = 121$ mD, porosity = 19%, 2116.53-2116.84 m (6944-6945 ft) depth, 5) Conglomerate, $k_{\text{hor max}} = 185$ mD, $k_{\text{vert}} = 85$ mD, porosity = 18%, 2118.66-2118.97 m (6951-6952ft) depth.

Figure 4. Samples from the lower Mt. Simon core VW1 showing different bedding textures. Note that unweathered cross-sets photographed at the scale of core samples (left-most sample) do not stand out as clearly as those exposed to long-term weathering and photographed in outcrop as in Figure 2b. Samples from left to right: 1) Cross-bedded medium-grained sandstone, $k_{\text{hor max}} = 151$ mD, $k_{\text{vert}} = 5$ mD, porosity = 21%, 2129.33-2129.64 m (6986-6987) ft depth, 2) Planar-bedded medium grained sandstone, $k_{\text{hor max}} = 68$ mD, $k_{\text{vert}} = 1$ mD, porosity = 19%, 2086.66-2086.81 m (6846-6846.5 ft) depth, 3) Ripple laminated very-fine grained sandstone, $k_{\text{hor max}} = 0.2$ mD, $k_{\text{vert}} =$ below detect, porosity = 9%, 2081.78-2082.09 m (6830-6831 ft) depth, 4) Massive (not bedded) conglomerate, $k_{\text{hor max}} = 127$ mD, porosity = 18%, 2120.80-2121.10 m (6958-6959 ft) depth.

Figure 5. Samples from the lower Mt. Simon core VW1 showing different categories of bleached alteration, relative to an unbleached sample. Samples from left to right: 1) Unbleached sandstone, $k_{\text{hor max}} = 151$ mD, $k_{\text{vert}} = 5$ mD, porosity = 21%, 2129.33-2129.64 m (6986-6987 ft) depth, 2) Bleached bed in cross-bedded medium-grained sandstone, $k_{\text{hor max}} = 10$ mD, $k_{\text{vert}} = 0.04$ mD, porosity = 14%, 2083.61-2083.92 m (6836-6837 ft) depth, 3) Mottled bleaching in a cross-bedded medium-grained sandstone, $k_{\text{hor max}} = 4$ mD, $k_{\text{vert}} = 0.04$, porosity = 12%, 2101.29-2101.60 m (6894-6895 ft) depth, 4) Bleach speckles in a cross-bedded medium-grained sandstone, $k_{\text{hor max}} = 13$ mD, $k_{\text{vert}} = 0.18$ mD, porosity = 15%, 2104.03-2104.34 m (6903-6904 ft) depth.

Figure 6. Photomicrographs of thin sections from proximal samples taken from a cross-bedded fine-grained sandstone a) unbleached, 2042.4 m depth, $k_{horiz\ max} = 72$ mD, $k_{vert} = 77$ mD, porosity = 26.6; and b) adjacent sample with bleached alteration at 2042.65 m depth, $k_{horiz\ max} = 31$ mD, $k_{vert} = 34$ mD, porosity = 23.2.

Figure 7. Distribution of bleached intervals with depth.

Figure 8. Distributions of the $k_{hor\ max}$ data grouped according to four textural facies. The unbleached finer-grained and bleached coarser-grained facies have similar sample distributions, but would be mapped into different depositional units as illustrated in Figure 9 and thus are kept separate when defining textural facies models.

Figure 9. Conceptual model for four textural facies as assigned within depositional units including cross-sets and cross bar fills.

Caption for Supplemental File:

Supplemental Table 1. Tabulation of the numbers used in the computation of equations 15-21.

Figure 1

Figure 2

Figure 3

Figure 4

Figure 5

Figure 6

Figure 7

Figure 8

Figure 9