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The Nature of Reservoir Fracture Heterogeneity: I - A New Conceptual and Computational Model

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ABSTRACT

The ability to quantitatively model geothermal well connectivity in fracture-heterogeneous reservoirs offers the opportunity to mold field data into physically accurate *de facto* models of reservoir-scale flow. Heretofore, however, incorporating fractures in reservoir flow models has tended to be mechanically *ad hoc* and computationally demanding. A large volume of well-log and well-core data points to a physically accurate and computationally tractable basis for simulating fluid flow in fractured reservoirs. Well-log fluctuation power $S(k)$ tends almost universally to scale inversely with spatial frequency k, $S(k) \sim 1/k$, ~1/km < k < ~10^5/km. Such power-law scaling may be understood as long-range spatial correlation of *in situ* grain-scale fracturing of the cemented bonds that characterize most crustal rock. Sequences of porosity φ and permeability κ from hundreds of meters of clastic reservoir well core tend to obey the fluctuation relation $\delta\varphi \approx \delta\log(\kappa)$ at ~85% +/- 8% cross-correlation level. If porosity fluctuations δφ in grain-scale fracture density ν control permeability fluctuations δlog(κ) via permeability proportional to grain-scale fracture connectivity factor ν!, the empirical spatial fluctuation relation is equivalent to the combinatorial identity $\delta\nu \approx \delta\log(\nu!)$. The well-log and well-core reservoir-empirical fluctuation relations for *in situ* fracture systems can be numerically represented in terms of 2D/3D fracture density fields with model realizations of porosity fluctuations scaled as $S(k) \sim 1/k$ and associated permeability given by $\delta\varphi \approx \delta\log(\kappa)$). Fracture-borne fluid flow is efficiently computed with finite-element solvers. Grids of dimension 32x64x64 to 64x128x128 can represent broadband *in situ* fracture heterogeneity to allow rapid quantitative simulation of interwell connectivity systematics.

1. INTRODUCTION

> *One of the most challenging reservoir engineering problems in the design of a geothermal development is the formulation of a strategy for reinjection. Due to the complexities of the geology in most geothermal reservoirs, which are usually found within fractured and heterogeneous volcanic rocks, it is common that injected fluids take apparently surprising paths through the reservoir and often show up rapidly and unexpectedly in production wells. Premature thermal breakthrough is a serious detriment to efficient recovery of the geothermal resource, and unfortunately has been a rather common occurrence in many geothermal fields.* (Horne & Szucs 2007).

> *Many forms of reservoir modeling, such as simulation, decline curve analysis, trace test analysis, well test analysis, material balance analysis, etc., have a central set of physical assumptions explicitly or implicitly included into their underlying models. The predictive effectiveness of the model will be constrained by the accuracy of its assumptions, even if the data are perfectly accurate and even if the model match is precise. One of the principal reasons geothermal reservoir modeling is so difficult is that the reservoir behavior is usually governed in important ways by the location and properties of fractures, neither of which is ever known clearly.*

> *A different philosophical approach is to let the data define the model. Individual wells and their hydraulic neighbors interact throughout their connecting fracture network, in ways that are characteristic of those fractures. Relating the interwell connectivity provide a useful modeling tool for the understanding of at least regional behavior of the reservoir. Often such connectivity interpretations use models and are again constrained by model assumptions. However is also possible….to let the data define the model* (Horne 2008).

These statements clearly and succinctly summarize the importance of, and the uncertainty introduced by, fractures in geothermal reservoir flow structures. The importance of and uncertainty introduced by fractures in reservoir flow are, in fact, common to all crustal reservoirs. They happen to be conspicuous in geothermal reservoirs because no geothermal reservoirs are as big as large-pay oil/gas reservoirs for which poor understanding of reservoir flow structure is routinely ignored because sooner than later even poorly guided drilling produced enough hydrocarbons to be profitable. However, as giant oil/gas fields deplete, it is clear that the problem of poor reservoir flow models besetting geothermal reservoir production is now visiting hydrocarbon reservoirs (not to speak of carbon sequestration programs and attempts to deal with the security of nuclear waste repositories).

This paper and its GWC2010 companion Leary & Malin (2010) seek to 'let the data define the model' in two ways:

- Define *in situ* fracture phenomena based on the near-universal spatial fluctuation properties observed in well logs and well core;
- Define reservoir fracture-borne flow models based on systematic well-connectivity data.

Sections 2-5 illustrate and summarize the empirical view of *in situ* fractures and fracture-borne flow seen in well-log and well-core fluctuation data. Section 6 introduces numerical representation of grain-scale fracture-density as the basis for computing Darcy flow in fracture-heterogeneous reservoirs.

Leary & Malin (2010) presents simulations of fracture-borne flow empirics for application to reservoir-scale flow model building.

2. SPATIAL CORRELATION SYSTEMATICS OF GEOPHYSICAL PROPERTIES IN CRUSTAL ROCK

Figures 1-2 illustrate the broadband nature of *in situ* physical property fluctuations measured in well log data.

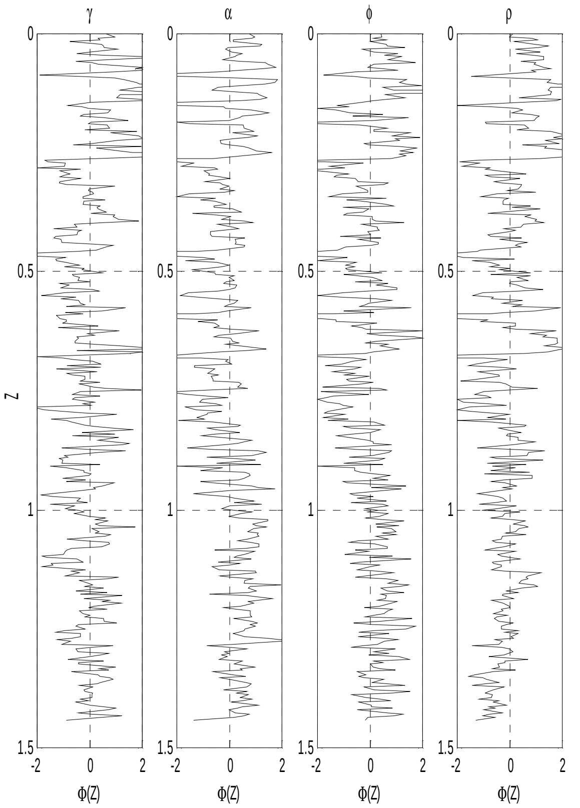

Figure 1 – Normalized 1.5km well-log fluctuation sequences for, left to right, gamma ray activity, sonic velocity, neutron porosity and mass density; traces are normalized to zero-mean and unit variance.

Figure 1 shows well-logs for four physical properties (gamma ray activity, sonic velocity, neutron porosity and mass density) from a 1.5km interval of a North Sea gas-sands reservoir. For ease of comparison the logs are treated as statistical fluctuation sequences normalized to zero-mean and unit-variance. Figure 2 shows synthetic fluctuation sequences for four types of spatial correlation. From left to right the spatial correlation types are: a 'geologically smoothed' version of the *in situ* logs attempting to identify significant mean-value components of log sequence; uncorrelated or white/Gaussian-noise random numbers with Fourier power spectrum $S(k) \sim 1/k^0$; correlated random numbers with 1/*f*-noise power spectrum $S(k) \sim 1/k^1$; and correlated random numbers with Brownian-noise power spectrum $S(k) \sim 1/k^2$.

Three conclusions emerge from comparing Figure 1 *in situ* fluctuations with Figure 2 synthetic noise types:

- Highly correlated Brownian noise fluctuation sequences resemble only block-like interpretations of *in situ* fluctuations; Brownian noise is dominated by step-like interfaces as might occur between different rock types if no other significant geophysical property fluctuations occur *in situ* to obscure the significance of interfaces.
- Uncorrelated random numbers have too much short-term fluctuation tendency to resemble *in situ* fluctuations; standard 'white-noise randomness' is not a good statistical model for crustal rock.
- The 1/*f*-noise sequence most resembles *in situ* fluctuations; rock properties have a significant degree of spatial correlation and cannot be effectively modeled by mean/average values and their standard deviations, but neither are they well defined by step-like changes or interfaces between formations.

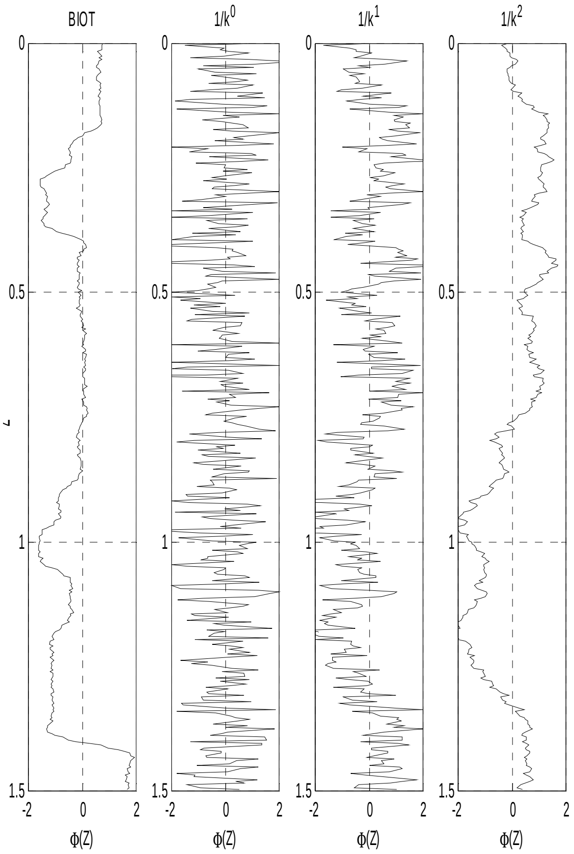

Figure 2 -- Normalized synthetic fluctuation sequences for, left to right, composite block-filtered well-logs, uncorrelated random noise, 1/*f*-noise, and Brownian noise.

These features of *in situ* geophysical property fluctuations have direct impact on reservoir modeling. The underlying assumption of most reservoir models is that geological formations can be described in terms of "effective medium properties". On this assumption, it is supposed that a suitable small scale length ξ exists such that on scales $r > \xi$ reservoir physical property variations tend to average out around a mean or "effective" value. It is further supposed that the "effective" properties of reservoir geological formations are adequately determined by a few small-scale samples from, say, well logs and/or well core.

Figures 1-2 show that neither feature of the "effective medium" hypothesis works for *in situ* geophysical properties. The rapid fluctuations are not rapid enough to be averaged over so that the scale length ξ does not appear in the well-log data. And the fluctuations are too rapid and vigorous to be blocked into a sequence of 'geologically smooth' partitions. Figure 1 thus eliminates the two spectral noise types $S(k) \sim 1/k^0$ and $S(k) \sim 1/k^2$. It does not, however, eliminate the spectral noise type $S(k) \sim 1/k^1$.

Failure of the "effective medium" procedure of producing reservoir models by averaging and/or sampling *in situ* data can be stated mathematically. The "effective medium" approximation is valid only if the spatial fluctuations of reservoir properties are uncorrelated above the scale length ξ. The necessary and sufficient condition for spatially uncorrelated fluctuations in rock volume physical properties is a constant (white) fluctuation Fourier power-spectrum in spatial frequency k, $S(k) \sim 1/k^0$. *In situ* geophysical fluctuations are thus subject to some form of spatial correlation, but not the degree of spatial correlation enforced by Brownian noise spectrum $S(k) \sim 1/k^2$. The *in situ* degree of spatial correlation $S(k) \sim 1/k^1$ lies mid-way between the two extremes of zero correlation, $S(k) \sim 1/k^0$, and block-like correlation, $S(k) \sim 1/k^2$.

3. WELL-LOG EMPIRICS IN CRUSTAL ROCK: 1/*F*-NOISE SPATIAL FLUCTUATIONS

Figures 3-4 show examples of well-log power-spectra for data recorded in both reservoir and associated sedimentary rock drilled by the hydrocarbon industry, and in a range of crystalline rock drilled for scientific purposes worldwide (Leary 2002; Goff & Holliger 2002).

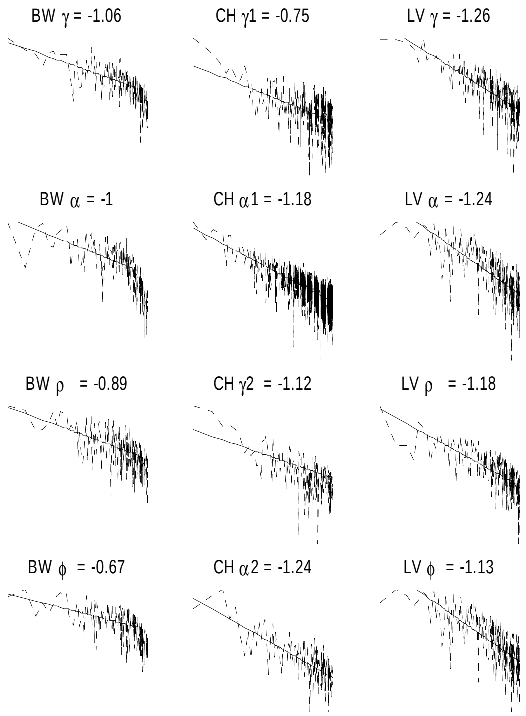

Figure 3 – Well-log power-spectra power-law scaling for three geological terrains: (left) Bierwang gas field, Germany; (centre) western Colorado tight gas field; (right) Long Valley CA tuff /crystalline basement; log types are γ = gamma ray activity, α = sonic velocity, ρ = mass density and ϕ = neutron porosity; power-spectral exponents given above each plot; spatial frequencies range from ~1/km to ~1000/km.

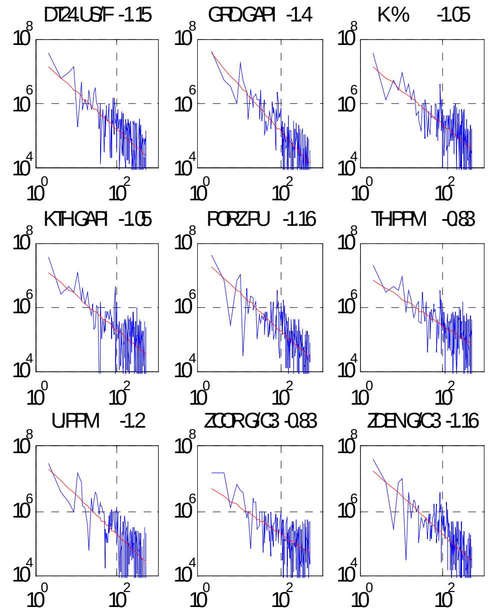

Figure 4 – Power-spectra log-log scaling for well-log suite in Lewis Formation sand/shale reservoir analogue outcrop; log types include sonic velocity, gamma activity, mass density, neutron porosity, and chemical abundances; power-spectral exponents given above each spectral plot; spatial frequencies range from ~3/km to ~500/km.

The well-log spatial fluctuations have power-spectra scaling inversely with spatial frequency k, $S(k) \sim 1/k^1$, over five decades of scale length, 1/km < k < 1/cm. Not only are material property fluctuations in crustal rock systematically spatially correlated at scale lengths from grain-size to reservoir-size, but a single spatial correlation process appears to apply to essentially all crustal rock. The following two sections discuss a unifying spatial correlation process and how this process controls the flow properties of crustal rock.

4. FRACTURE EMPIRICS: GRAIN-SCALE FRACTURE DENSITY IN CRUSTAL ROCK

The existence of power-laws in general, and of a single power-law in particular, is observed to occur in physical systems in transition between two spatial-organization states (Binney et al 1995). Such a transition state occurs in percolation systems at a critical density of percolation defects (Stauffer & Aharony 1994). At the percolation-defect critical density, system-wide spatially-correlated fracture pathways permit fluids to traverse the rock system. That is, at the critical percolation defect density a transition occurs from a non-conducting rock volume to a conducting rock volume. Well-log power-law-scaling fluctuation spectra arise in crustal rock at the defect critical density for 'phase transition' from non-through-conducting to through-conducting states.

Well-log power-law-scaling spatial fluctuations indicate that rock can be conceptually idealized as a binary population of non-percolating intact cemented grain-grain bonds and percolating grain-size defects at which the grain-grain cement bond has fractured (Leary 2002). Grain-scale defect populations are created in rock in the course of finite-strain damage sustained during tectonic deformation. With increasing deformation, the grain-scale fracture density (number of grain-grain cement bond fractures per unit volume) reaches a 'critical density' of defects, at which density the existence of through-going percolation pathways become inevitable and the near-universal broadband statistically intractable reservoir fracture complexity is born.

Well-log fluctuations thus naturally characterize fractures in terms of observable well-connectivity. *In situ* fractures no longer need to be seen as mechanically distinct from otherwise quasi-uniform intact rock, and we may abandon the assumption-rich/observation-poor struggle to assign flow properties to *in situ* fractures and fracture sets. Rather *in situ* fluctuation systematics show that fractures appear at all scale lengths as elements of a continuum of critical-state long-range spatially-correlated grain-scale-fracture density fluctuations. The critical-state nature of percolating grain-scale fracture density is consistent with evidence of crustal rock being in a state of near-failure attested by earthquakes occurring virtually everywhere within the continental landmass, and by earthquakes induced by low stress dam-impounded groundwater loading.

5. PERCOLATION EMPIRICS: WELL-CORE FLUCTUATIONS & GRAIN-SCALE FRACTURE CONNECTIVITY

Well-core porosity-permeability data from oil-field clastic reservoirs provide direct evidence that grain-scale fractures control geofluid flow via percolation networks. Figures 4-9 illustrate the strong spatial correlation of well-core plug laboratory measurements of porosity φ and permeability κ. When reduced to zero-mean unit-variance form, porosity and log(permeability) sequences for a given reservoir interval obey the fluctuation relation $\delta\varphi \approx \delta\log(\kappa)$ with mean cross-correlation 85% +/- 8%.

The empirical well-core poroperm fluctuation relation $\delta\varphi \approx \delta\log(\kappa)$ is conceptually equivalent to the mathematical identity $\delta\nu \approx \delta\log(\nu!)$ if porosity is proportional to number of grain scale fractures ν in a volume and the permeability of that volume is proportional to the multiplicative term $\nu!$, representing the number of ways ν grain-scale fractures can be combined to produce a percolation pathway. In fluctuation terms, if a rock volume has ν grain-scale fractures per unit volume at location (x,y,z) and $\nu+\delta\nu$ grain-scale fractures at location $(x,y,z)+(\delta x,\delta y,\delta z)$, then percolation-related permeability in the two volumes can be expected to vary as the combinatorial terms $\nu!$ and $(\nu+\delta\nu)!$. Stirling's formula for the factorial term, $\nu! \approx (\nu+ ½)\log(\nu) - \nu$, applied to the two fracture connectivity expressions reduces the fluctuation expression to $\delta\nu \approx \delta\log(\nu!)$ as the grain-scale fracture density percolation model for the empirical well-core poroperm fluctuation relation $\delta\varphi \approx \delta\log(\kappa)$.

Figure 5 shows the spatial correlation of zero-mean unit-variance fluctuations of well-core porosity and permeability ('poroperm') data from a shallow reservoir-analogue sand/shale outcrop in the Lewis Formation, Wyoming, USA (Figure 4 well-log spectra are from the same unit).

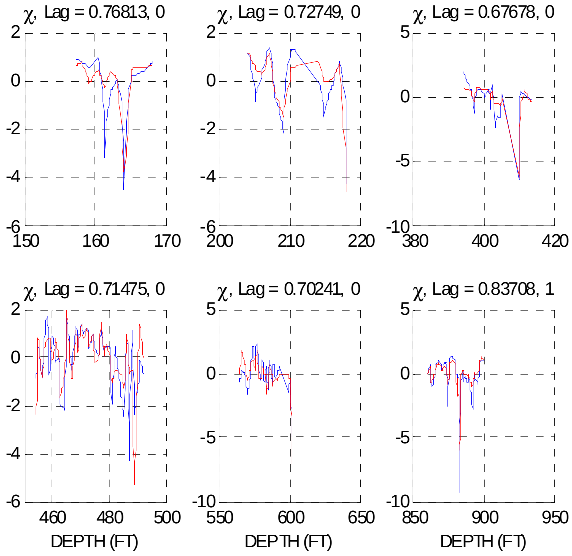

Figure 5 – Poroperm spatial correlation data for well-core suite in Lewis Formation sand/shale reservoir analogue outcrop in Wyoming USA; blue = zero-mean unit variance porosity sequence; red = zero-mean unit-variance log(permeability) sequence; cross-correlations given above each plot.

Figures 6-8 illustrate the same degree of cross-correlation for a suites of poroperm data from North Sea gas sands and tight-gas sands in South Australia.

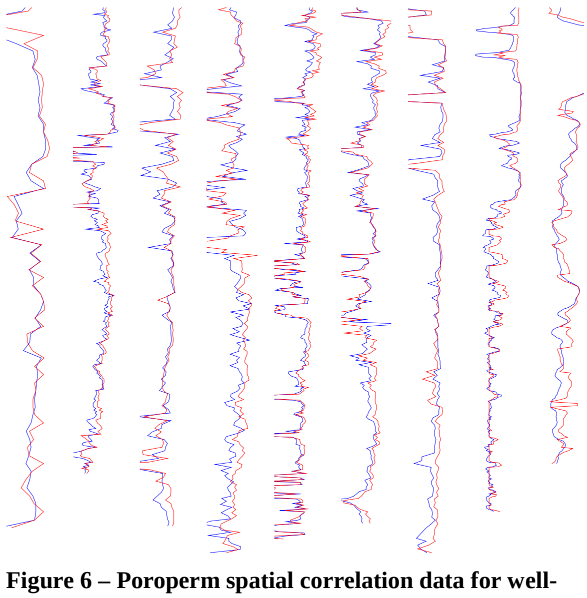

Figure 6 – Poroperm spatial correlation data for well-core suite from gas reservoir in Germany; blue = zero-mean unit variance porosity sequence; red = zero-mean unit-variance log(permeability) sequence.

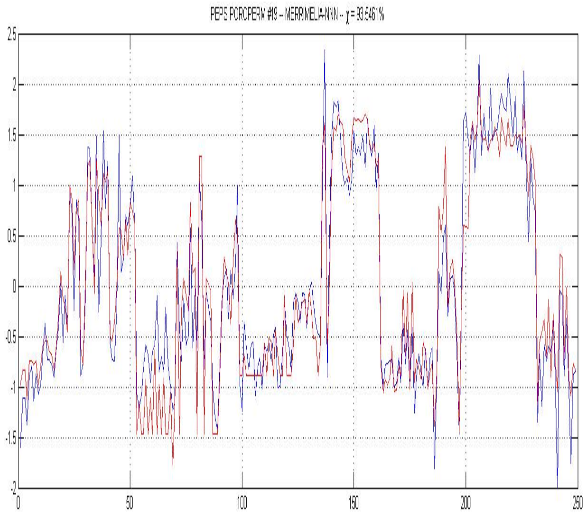

Figure 7 – Poroperm spatial correlation data for well-core suite from Otway Basin, South Australia; blue = zero-mean unit variance porosity sequence; red = zero-mean unit-variance log(permeability) sequence. For these tight gas sands, poroperm fluctuations hold across formation boundaries.

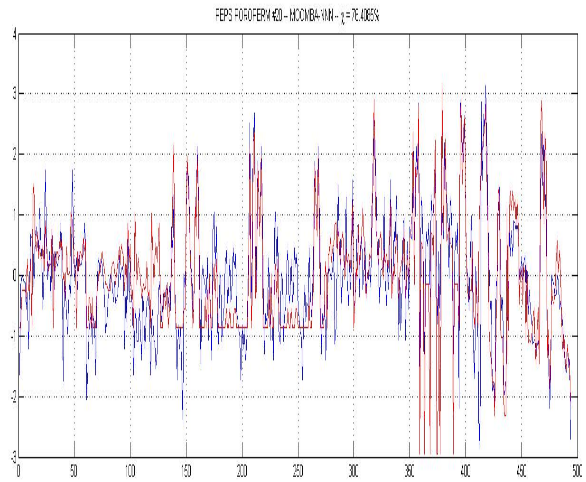

Figure 8 – Poroperm spatial correlation data for well-core suite from Cooper Basin, South Australia; blue = zero-mean unit variance porosity sequence; red = zero-mean unit-variance log(permeability) sequence. For low permeability core samples, laborary permeability reading are given as a minimum value; when such samples are given enough time to register an accurate permeability reading, the correlation is improved.

Figure 9 illustrates the how a dense sequence of well-core poroperm data from a tight-gas sand formation (leftmost five logs) can be spatially correlated with suitably smoothed well-log data from the same formation (rightmost two logs).

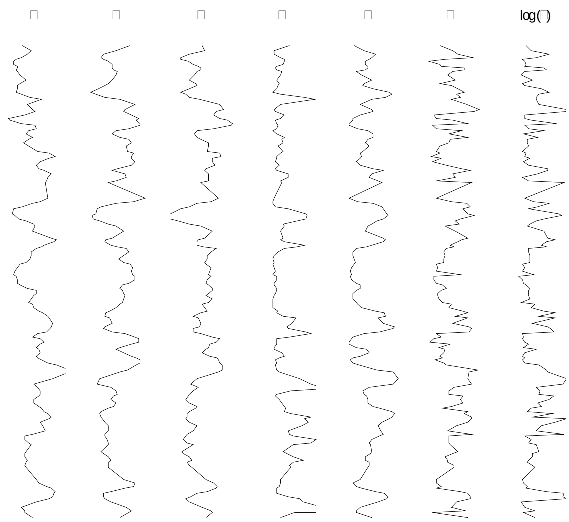

Figure 9 – Well-log and well-core fluctuation data from western Colorado tight gas sands formation; five well logs (left) suitably filtered to remove high frequency fluctuations compare well with a dense sequence of well-core poroperm spatial fluctuations (right). Traces are reduced to zero-mean unit-variance. Well interval is 100m. Log types are γ = gamma ray activity, α = sonic velocity, ϕ = neutron porosity, Ω = resistivity, and ρ = mass density.

6. NUMERICAL REALIZATION OF $S(K) \sim 1/K^1$ AND $\delta\varphi \approx \delta$LOG($\kappa$)

Well-logs give evidence for power-law scaling spatial fluctuations based on the scale-independent interactions of grain-scale-fracture density in crustal rock. Well-core poroperm data give evidence for critical-density grain-scale-fracture density percolation connectivity control of fluid flow in crustal rock. Together these suites of evidence indicate that the fracture phenomenology of crustal rock can be simulated by a numerical scheme based on the spatial distribution of a scalar grain-scale-fracture density parameter. Figures 10-13 illustrate the numerical realization of the 2D reservoir-section fracture-heterogeneity models derived from well-log and well-core data.

Figure 10 displays a 'standard model' of reservoir structure derived from crosswell seismic velocity tomography. Each side of the 200m-wide by 700m-deep reservoir section is constrained by layer-blocked well-log gamma ray activity measurements converted to acoustic velocity. Crosswell seismic tomography travel-time data are interpreted in terms of the displayed velocity distribution (red ~ higher velocities and blues ~ lower velocities).

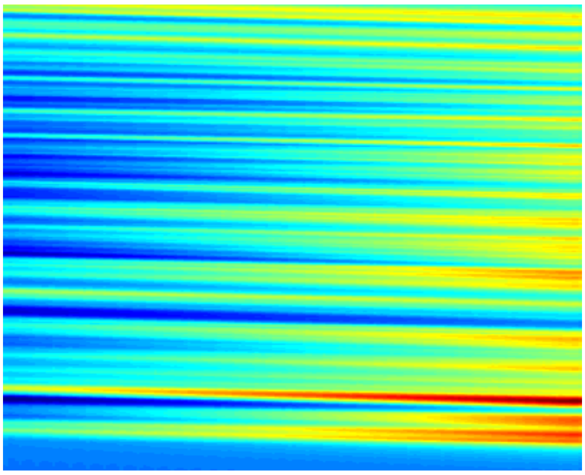

Figure 10 – Crosswell seismic velocity tomographic section acquired between two 700m well sections at 200m offset; inferred well-velocity data constrain the tomographic inversion; higher velocities ~ red, lower velocities ~ blue.

Figure 11 shows in blue a velocity log for the centre of the model velocity block and in red a velocity log acquired in a neighboring well in the surveyed reservoir formations. Figure 12 shows in blue the spectrum of the model velocity log and the spectrum of the *in situ* velocity log. Unsurprisingly, neither the inferred well-log nor the inferred log spectrum resembles *in situ* data. The well log is blocky with its spectrum having a scaling exponent dominated by interfaces rather than by internal property fluctuations.

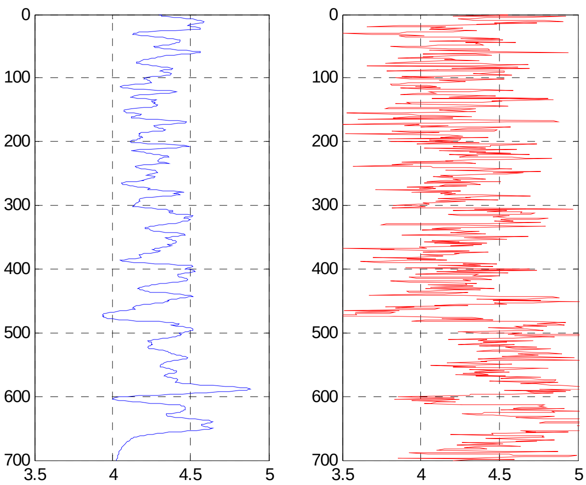

Figure 11 – Blue trace = velocity 'well log' for Figure 10 section; red trace = *in situ* acoustic velocity log recorded elsewhere in surveyed reservoir formation.

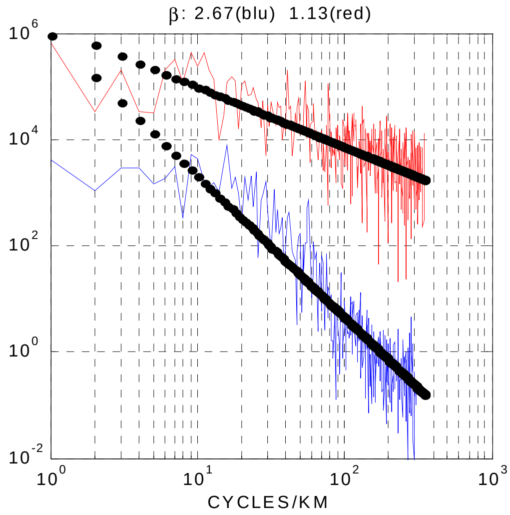

Figure 12 – Blue trace = power-spectrum of Figure 11 blue trace log; red trace = power-spectrum of Figure 11 red trace log. Figure 10 velocity section bears little physical relation to *in situ* reality.

Figures 13-14 show a pair of 2D numerical realisations of the Figure 10 velocity section that are consistent with *in situ* property fluctuations. Logs through the Figure 13 velocity section have spectral scaling exponents ~1.13, and logs through the Figure 14 velocity section have spectral scaling exponents ~1.06. Both velocity sections preserve the geological stratification of the rock section but clearly indicate that, in a statistical sense, the geological layering is broached by geophysical property fluctuations. If the geological property fluctuations are intepreted in terms of grain-scale fracture density fluctuations (as well-log and well-core systemtics suggest), then geofluid flow computed for the Figure 13-14 sections is vastly more realistic than flow computed for the Figure 10 'geologically layered' section (Leary & Walter 2008).

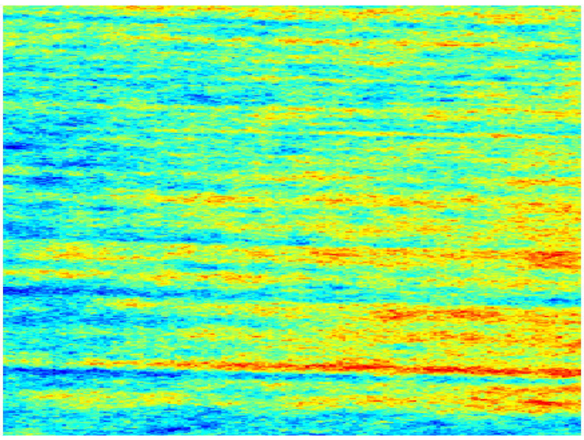

Figure 13 – Figure 10 velocity section with superimposed 1/*f*–noise velocity fluctuations to meet *in situ* spectral scaling conditions; well-logs through the model have power-spectral exponent ~ 1.13.

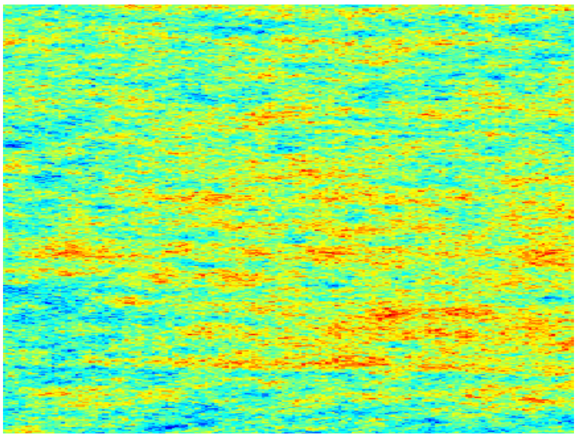

Figure 14 – Figure 10 velocity section with superimposed 1/*f*–noise velocity fluctuations to meet *in situ* spectral scaling conditions; well-logs through the model have power-spectral exponent ~ 1.06.

Figures 15-16 illustrates in 3D the reservoir flow model dichotomy seen for 2D in Figures 10-14. The Figure 15 data volume represents 3D 1/*f*-noise spatial correlation that can be assigned to grain-scale fracture density and/or porosity. The data volume in Figure 16 represents Brownian noise spatial correlation. Data cube permeability is spatially distributed according to the well-core relation $\delta\varphi \approx \delta\log(\kappa)$. Flow simulations for the Figure 15-16 reservoir volumes are presented in Leary & Malin 2010.

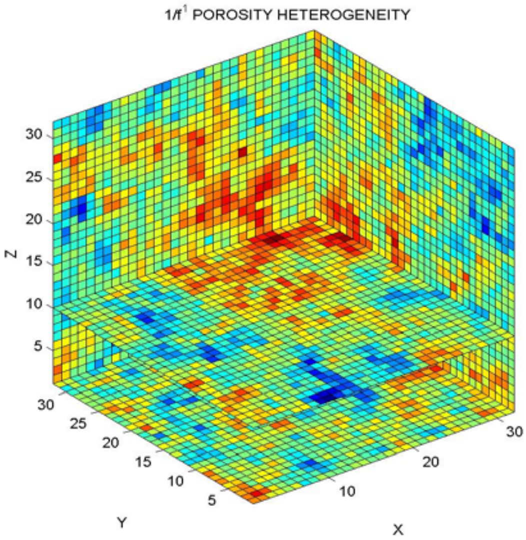

Figure 15 – 3D 1/*f*–noise spatial porosity fluctuations consistent with *in situ* well-log spectra.

7. CONCLUSIONS

The pervasive systematics of well-log spectra power-law scaling $S(k)$~$1/k$ and well-core poroperm fluctuation relation $\delta\varphi\approx\delta\log(\kappa)$) point to an underlying unity of fracture phenomenology in crustal rock. The fracture phenomenology centers on long-range scale-independent spatial interaction of percolating grain-scale fracture density fluctuations that allows *in situ* fractures and fracture-borne geofluid flow to be conceptually and numerically modeled in terms of crustal volumes of intense spatial clusters of grain-scale fractures occurring at all scale lengths. The generalized description of *in situ* fractures and fracture conductivity is easily simulated by numerical distributions and admit of rapid Darcy flow simulation by standard finite-element solvers.

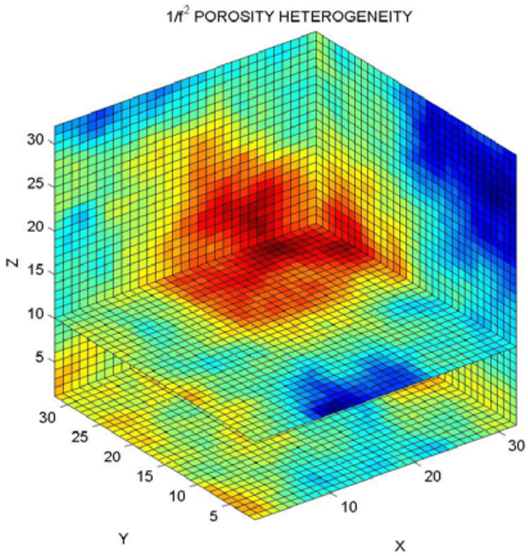

Figure 16 – Brownian–noise porosity fluctuations. This distribution shows how strong spatial correlation leads to block-like partitioning of geophysical properties. In the absence of geological structures of like spatial partitioning, there is no evidence that fracture *in situ* fracture phenomena are spatially distributed in this manner.

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