1	Variability in spatial distribution of mineral phases in the Lower Bowland
2	Shale, UK, from the mm- to µm-scale: quantitative characterization and
3	modelling
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31 Abstract

32 The microstructure of a highly laminated Lower Bowland Shale sample is characterized at 33 the micron- to millimeter scale, to investigate how such characterization can be utilized for 34 microstructure-based modelling of the shale's geomechanical behavior. A mosaic of scanning 35 electron microscope (SEM) back-scattered electron (BSE) images was studied. Mineral and organic content and their anisotropy vary between laminae, with a high variability in 36 37 fracturing and multi-micrometer aggregates of feldspars, carbonates, quartz and organics. The 38 different microstructural interface types and heterogeneities were located and quantified, 39 demonstrating the microstructural complexity of the Bowland Shale, and defining possible 40 pathways for fracture propagation. A combination of counting-box, dispersion, covariance 41 and 2D mapping approaches were used to determine that the total surface of each lamina is 3 42 to 11 times larger than the scale of heterogeneities relative to mineral proportion and size. 43 The dispersion approach seems to be the preferential technique for determining the 44 representative elementary area (REA) of phase area fraction for these highly heterogeneous 45 large samples, supported by 2D quantitative mapping of the same parameter. Representative 46 microstructural models were developed using Voronoï tessellation using these characteristic scales. These models encapsulate the microstructural features required to simulate fluid flow 47 48 through these porous Bowland Shales at the mesoscale.

50 Highlights

51	•	The microstructure of the Lower Bowland Shale was studied quantitatively.							
52	•	The presence of multi-scale microstructural interfaces supports hydraulic fracturing							
53		potential in the Bowland Shale.							
54	•	The dispersion approach is the most suitable method to define representative							
55		elementary areas.							
56	٠	2D mapping of phase area fraction supports the dispersion approach.							
57	•	A representative model of the geometry of the microstructure based on Voronoï							
58		tessellation was generated.							

1 1. Introduction

2 Significant shale gas and oil resources are believed to exist in Western Europe (EIA, 2013) 3 and in particular in the UK (EIA, 2015a), such as in Carboniferous and Jurassic-Age shale 4 formations. One example is the Bowland Basin, in the west portion of the Pennine Basin, 5 close to Blackpool, Lancashire, Northern England (EIA, 2015). The Bowland Shale is 6 generally divided into two units: the Upper Bowland Shale composed of thick layers of 7 marine-deposited organic matter-rich mudstone, whilst the Lower Bowland Shale is 8 composed of thinner alternating layers of organic-matter-poor and organic-matter rich 9 mudstone (Andrews, 2013).

10 The Upper Bowland Shale demonstrates similarities to North American shale gas plays, 11 whereas relatively few regions in the Lower part have been identified as potentially 12 productive. The Lower Bowland Shale is still largely undrilled and its geographical extent is 13 currently uncertain (Andrews, 2013). Despite this lack of data, the potential of the Lower 14 Bowland Shale is considered to be important, albeit with a higher uncertainty than the Upper 15 Bowland Shale (Andrews, 2013). Shale gas potential depends on the oil and gas retention 16 capacity of the system, which is directly related to the microstructure: the nature and the 17 specific adsorption of organic and inorganic phases, their structural relationships, and those 18 of the pore and fracture networks. Moreover, quantifying the relationships between porosity, 19 permeability, pore size distribution and brittleness in combination with the mineralogy and 20 rock fabric is essential for the estimation of shale gas potential (Josh et al., 2012). 21 Microstructural heterogeneities such as variations of grain size, shape, mineralogy, elasticity, 22 anisotropy and stiffness, together with preexisting defects can create local stress 23 concentrations. Such stress concentrations influence the initiation and behavior of fractures in shales, such as hydraulic fractures (Keneti and Wong 2010), mechanical fractures (Van de 24

25 Steen et al., 2003) and desiccation fractures (Hedan et al., 2012; Fauchille et al., 2016; Figueroa Pilz et al., 2017) in response to the local stress field. In a general sense, Sone and 26 27 Zoback (2013) and Amann et al., (2014) have shown how significantly the microstructure can 28 impact upon the mechanical properties of shale. As a direct result, the microstructure therefore influences the gas retention process (Bernard et al., 2010). Despite the strong 29 30 interest in the Lower Bowland Shale in the UK, its petrophysical properties and 31 heterogeneities are still poorly understood, but are expected strongly to influence yield during 32 any gas production.

33 Due to the sub-micrometer scale of shale components, scanning electron microscopy (SEM) 34 and transmission electron microscopy (TEM) are often used to characterize the 35 microstructural features of shales (Ma et al., 2017). Houben et al., (2014, 2016) and Klaver et 36 al., (2015) constructed mosaics of high resolution SEM images to quantify the morphology 37 and size distribution of pores, clay and organic matter particles in the Opalinus Clay 38 (Switzerland) and Posidonia Shale (Germany), and the microstructure of European Early 39 Jurassic Shales. However, in light of the well-known heterogeneity of such rocks and the 40 dependence of large-scale features (clay minerals, organics) on the structure of fine-scale features (clusters of inorganic grains, clay phase, fractures), the size of the field of view is 41 42 often limited by the compromise between sample size and spatial resolution. Fracture 43 initiation may depend on heterogeneities down to the nanometer scale if differential stresses 44 are high enough, but fracture propagation is affected by multi-scale heterogeneities (Griffith, 45 1924; Jaeger and Cook, 1976). Consequently, the characterization of "low-scale" (meso- and 46 macro-scales) heterogeneities should be considered in fracture propagation studies.

47 Mechanical behavior of shale at the macroscale is strongly dependent on the behavior at 48 smaller scales, for example due to the primary structure and arrangement of particles 49 (anisotropy), and also to the variability of small scale components such as organic matter, rigid inclusions and clay minerals (Sayers, 1993; Wang, 2012; Wang et al. 2015, Bonnelye et al., 2017 a, b). As a consequence, understanding the microscale structure may aid detailed comprehension of the macroscale behavior and hence bulk constitutive relations. To predict strain location and fracturing behavior at the macroscale, simple models of grain-based microstructure taking into account microstructural parameters such as grain size, shape, proportion, elongation ratio and orientation ratio are required (van den Eijnden et al., 2015, 2016, 2017).

57 This study we investigates the variability of microstructural parameters (phase area fraction, 58 grain size, shape, elongation and orientation) from the mm to μ m scales in a sample of the 59 Lower Bowland Shale, with a millimeter mosaic of SEM images at sub-micrometer 60 resolution where two laminae were identified. The goals of the study are:

- 61 i) to quantitatively characterize the spatial variability of mineral phases of the Lower
 62 Bowland shale;
- 63 ii) to describe the heterogeneity of the microstructure using several methods allowing
 64 quantifications of representative elementary areas;
- 65 iii) to establish a simple representative model of the Lower Bowland shale
 66 microstructure based on the approach of van den Eijnden et al. (2015-2017),
 67 which takes into account (i) and (ii).
- 68 2. Geological Setting and Sampling

The Carboniferous Bowland Shale occurs across the center and north of England. Its occurrence extends from Merseyside to Humberside and Loughborough to Pickering (Andrews, 2013). It is divided into an upper unit with thick and continuous (a few hundreds of meter thick) shale formations, and a lower unit containing shale interbedded with clastic and carbonate deposits, explained by the influence of glacio-eustatic sea levels changes and

74 tectonic events (Gawthorpe, 1987; Andrews, 2013). For this study, one sample of Lower 75 Bowland Shale was collected from the Preese Hall-1 borehole at a depth of 2495.27 meters, supplied by the British Geological Survey (BGS) in Nottingham (UK). The Preese Hall-1 76 borehole was drilled in 2010 on the Fylde coast of NW Lancashire at 53° 49' 19.006"N: 2° 77 78 56'56.576" near to Blackpool, north-west England. Preese Hall-1 was the first dedicated 79 unconventional shale gas borehole drilled in the UK and Europe (de Pater and Baisch, 2011). 80 The sample chosen for this study corresponds to sample B8 in Fauchille et al. (2017). The 81 sample has a laminated microtexture and the mean organic content (TOC) is 1.1 wt %, 82 measured with a Leco carbon analyzer using 100 mg powder samples, at the University of 83 Newcastle (UK). Centimeter-size samples were used for making the powder samples, to 84 ensure several laminae are included in the powder. According to bulk XRD measurements 85 (the accuracy of quantification of XRD results in terms of modal proportions is around 1%), 86 the sample is composed of 51.7 wt% quartz, 18.4 wt% kaolinite, 11.1 wt% ankerite, 8.6 wt% 87 albite, 5.1 wt% muscovite, 3.5 wt% calcite and 1.6 wt% pyrite. The intact sample was 88 vacuum impregnated with low-viscosity epoxy resin (Araldite 2020) at room temperature 89 (20°C) and mechanically polished as a thin section with carbide and diamond products for 90 scanning electron microscopy.

91 **3. Methods Employed**

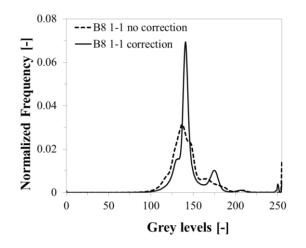
92 **3.1. Scanning electron microscope (SEM) mosaic image acquisition**

A mosaic of 4×11 back-scattered electron (BSE) images each of 1280 × 960 pixels was acquired from the carbon-coated polished specimen at a resolution of 0.4 μ m.pixel⁻¹ (Jeol JSM-6610LV) with 23% overlap (Klaver et al., 2012; Vergès and Morales, 2014; Fauchille, 2015). The mosaic is 4204 × 8128 pixels (8bit) covering 1.68 × 3.25 mm². The working distance (WD) was 10 mm and the beam accelerating voltage was 20 kV. A magnification of

98 250X proved to be a good compromise between spatial resolution, field of view and 99 acquisition time, and minimized drift of the incident electron beam and scanning lens. 100 Contrast and brightness were adjusted to have the organic matter particles in black (0) and the 101 heavy minerals in white (255). The parameters were optimized to obtain a histogram with 102 distinct peaks to facilitate mineral segmentation (Prêt et al., 2010a; Robinet et al., 2012, 103 Fauchille, 2015).

104 **3.2. Correction and segmentation of images**

105 All images were drift-corrected to produce a homogeneous histogram across all images of the 106 mosaic. A linear gray level drift was observed in the *x* direction (horizontal) on each image, 107 due to slight shadowing of the incident beam caused by the low-vacuum aperture of the pole-108 piece. Images were corrected in vertical sections of 30×960 pixels to balance the gray 109 levels, producing consistent histograms with well-separated peaks (see Fig. 1). No significant 110 shift was detected in the *z* direction (vertical).



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Fig. 1. Gray level histogram of the first image of mosaic B8 1-1 (this image corresponds to the first column and first line of the mosaic) before and after drift correction.

114 The mineral phases were segmented on the BSE images using a combination of filters and 115 gray level thresholding using in-house codes written for Visual Studio, Matlab and ImageJ 116 (Peters, 2009; Prêt et al., 2010a,b; Robinet et al., 2012; Khan et al., 2014). The organic matter 117 and fractures (om+fractures), feldspars (felds), ankerite, calcite (carb) and heavy minerals (h-118 min) were only segmented by gray levels with ImageJ. The gray levels used for thresholding 119 were: 0 to 64 for organic matter and fractures, 65 to 133 for clays and quartz cement, 134 to 120 147 for quartz inclusions, 148 to 163 for micas, 164 to 192 for feldspars and ankerite, 193 to 121 218 for calcite and 219 to 255 for heavy minerals. Due to their similar silica contents, the 122 segmentation of quartz and micas was performed using the gray level histogram and a local 123 variance filter (Prêt et al., 2010a, Robinet et al., 2012). In ImageJ software, the value of the 124 variance was chosen at 10 to detect the homogenous areas of quartz, according to the BSE 125 images. Owing to the small size of kaolinite particles and their silica content being close to 126 the background, clays were removed in the same phase as the quartz cement to form the 127 "binder" of the sample. To improve the segmentation of individual grains, the 1-pixel 128 boundaries of quartz and feldspars grains, were moved to the background. This implies that 129 the segmentation of grains may be underestimated but better separated for calculating 130 morphological parameters. The segmentation, shown in Fig. 2 takes into account the 131 separation between the large grains of quartz and the cement, but cannot differentiate 132 between organic matter particles and fractures, both of which present the same gray scale 133 value (black) on BSE images. The fractures segmented on the mosaic are filled by organic 134 matter or empty. Fractures can be generated by pore fluid overpressuring through organic 135 decomposition and petroleum generation, by the late migration of organic matter. Open 136 cracks can be produced as a result of sample depressurization during recovery and during the sample preparation (Fauchille et al., 2017). There is a fracture filled by ankerite (top right 137 138 part in Figure 2), which was therefore segmented as ankerite minerals (carbonates).

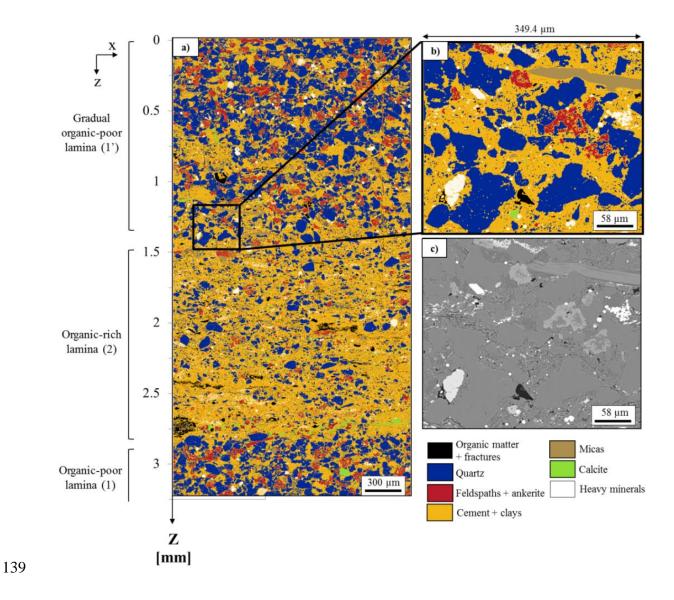


Fig. 2. (a) Mineral phase segmentation on the whole mosaic of SEM-BSE images of the
Bowland Shale sample. (b) Magnified view of a region of (a). (c) Original
(unsegmented) back-scattered electron image corresponding to (b).

- 143 **3.4. Image analysis**
- 144 Microstructural parameters

The anisotropy of the microstructure was studied using the 2D microstructural parameters used on shale (Robinet et al., 2012; Fauchille et al., 2014, 2016). These are the area fraction (ratio between the number of pixels of a grain type and the total number of pixels in the

148 calculation window), the grain size (number of pixels in one grain), the elongation ratio and 149 the orientation, calculated with the ellipsoid plugin in ImageJ software. The ellipsoid axial 150 ratio and orientation of each grain with respect to the reference horizontal axis was 151 calculated, but only for grains larger than 10 pixels, in order to avoid any resolution artefacts.

152 **Determination of correlation lengths of the microstructure**

153 The estimation of a representative elementary area (REA) (also called homogenization 154 surface) of a material for a specific property, scale and resolution (Bear, 1972; Bear and 155 Bachmat, 1984; Grolier et al., 1991; Al-Raoush et al., 2010), can be problematic in shales due 156 their well-known multi-scale and multi-modal heterogeneities. However, the to characterization of heterogeneities and the identification of REAs are crucial for upscaling 157 158 and modelling studies. In theory, a surface is representative of a parameter at a specified scale when this parameter becomes independent of the size of the field of view, including 159 160 statistically all types of structural heterogeneities (Bear, 1972; Kanit et al., 2003; Al-Raoush 161 et al., 2010). In this paper, three methods were used and compared to estimate representative 162 elementary surfaces of the microstructure and to identify its heterogeneities: (i) the counting-163 box method, (ii) the dispersion approach, and (iii) the covariance. All calculations were 164 performed with in-house codes in Visual-Studio (C) and Matlab. Other methods and parameters were used to extract correlation lengths from an image, such as the entropy 165 166 method (Boger et al., 1992) and the percolation method (Cosenza et al., 2015), but they are 167 not taken into account in this paper.

168 *Counting box method*

A simple way to approximate the REA is the "counting-box method", that considers a succession of increasing-size domains until the parameter measured is constant (VandenByggaart and Protz, 1999; Kameda et al., 2006; Houben et al., 2014), plus or minus a

defined confidence limit which was chosen to be 10% in our case, consistent with previous studies on geological materials (VandenByggaart and Protz, 1999; Houben et al., 2014; Vik et al., 2014). In this study, each lamina was defined over an area of 4404 × 3302 pixels (1.76 × 1.32 mm), and the domains between 10 × 10 pixels (4 × 4 μ m) to 3302 × 3302 pixels (1.32 × 1.32 mm) were used for this method. The first domain was chosen in the center of each lamina, in order to have the maximum number of possible domains.

178 Dispersion approach

The dispersion approach was introduced by Kanit et al., (2003). Applied to a 2D image, it involves dividing the image into equal subsamples, in which a chosen parameter is calculated. The goal of this approach is to determine the number of subsamples needed limit to an acceptable level the relative error of this parameter for the set of subsamples.

183 The mosaic of BSE images was divided into independent square domains D from 10×10 to 1876×1876 pixels (4 × 4 and 750 × 750 μ m², respectively) (Kanit et al., 2003; Keller et al., 184 185 2013). Kanit et al., (2003) used this approach to divide random and Voronoï mosaics into a finite number of cells. In this paper, the domains D are the finite square cells of the 186 187 experimental mosaic. This mosaic cannot be extended therefore the number of D decreases as 188 their size increases. Each domain is thus a subsample of the mosaic and contains a finite 189 number of grains. The pixels of the domains are independent from one domain to another, but 190 it is possible that long or large grains (such as micas, Fig. 2b) can be included in multiple neighboring domains. The standard deviation, σ_{D_i} of the phase area fraction $P_D(x, z)$ on each 191 192 lamina as a function of domain size D was used to quantify the heterogeneity of the 193 microstructure (Equations 1 and 2) with a statistical approach.

$$P_D(x,z) = \frac{1}{D} \sum_{n=x-\frac{D-1}{2}}^{n=x+\frac{D-1}{2}} \sum_{m=z-\frac{D-1}{2}}^{m=z+\frac{D-1}{2}} G_{(n,m)}$$
(1)

194 $P_D(x, z)$ is the area fraction of a defined phase (examples: carbonates, quartz, 195 cement/clays...) in a domain, *D*, centered at (x,z). P(x,z) varies between 0 and 1. *D* is the 196 size of the domain in pixels (and is always an odd number). *G* is a binary function (0 or 1). *G* 197 = 1 when the pixel (n, m) corresponds to the chosen phase, and 0 when the pixel corresponds 198 to a different phase. For example, when the area fraction of calcite is calculated: $G_{(n,m)} = 1$ if 199 the pixel (n, m) corresponds to calcite, and 0 if the mineral is not calcite.

To have a whole view of the dispersion of area fraction values, $P_D(x, z)$ was mapped in 2D increments by 1 pixel in the *x* and *z* directions over the mosaic. The standard deviation σ_P of $P_D(x, z)$ was then calculated as a function of domain size (Equation 2):

$$\sigma_P = \sqrt{\frac{\sum (P_D(x,z) - \overline{\overline{P}_D})^2}{N_D}}$$
(2)

203 \overline{P}_D is the mean value of the phase area fraction in all domains *D* and *N*_D is the number of 204 domains D.

This dispersion approach allows us: (i) to identify the minimum size of a representative area of area fraction with $\sigma_P < 0.1$; (ii) to map in 2D the area fraction to present a direct visualization of microstructural variability and its multi-scale heterogeneities; and (iii) to investigate the evolution of the variance σ_P^2 as a function of *D* in order to estimate the effect of the randomness of the microstructure on the whole mosaic. The characterization of

heterogeneities and REAs will be used for microstructural modelling afterwards. Other
parameters of grains, such as the size, the representative ellipse axial ratio or its long axis
orientation can be investigated to map the spatial variability of microstructure, but the area
fraction was chosen here as a good indicator of the microstructure, and it is commonly used
in 2D and 3D texture analysis (VandenByggart et al., 1999; Madi et al., 2005; Houben et al.,
2014; Fauchille, 2015; Klaver et al., 2015).

216 Covariance

The covariance approach is commonly used to determine characteristic scales and to quantify the anisotropy of 2D microstructure (Berryman and Blair, 1986; Stoyan et al., 1995; Jeulin, 2001; Kanit et al., 2003; Degallaix and Ilschner, 2007; Rolland du Roscoat et al., 2007; Rudge et al., 2008; Gaboreau et al., 2016). The principle of covariance is the measurement of how well one image matches a spatially shifted copy of itself. The covariogram C(X, h) measures the intersection of a 2D image X and the translated image of X by a distance h (Kanit et al., 2003) (Equation 3):

$$C(X,h) = \int c(x)c(x+h) \, dx \tag{3}$$

224 where c(x) is the phase detection function, defined by :

$$c(x) = \begin{cases} 1 \ if \ x \in X \\ 0 \ else \end{cases}$$

The dispersion of the state of two points x_1 and x_2 between the image X and the image X translated by *h* can therefore be quantified (Kanit et al., 2003). For a non-periodic microstructure, correlations between points decrease with increasing *h*. When *h* is sufficiently large, there is no correlation anymore between the points of the two images. Consequently, C(X, h) describes an asymptotic behaviour limited at the mean phase

proportion, \overline{P}^2 , of the whole image. When the asymptote is not reached, the points included in the image are partially correlated, and therefore the image size is not considered to be representative of its content. The distance *h* corresponding to the scale beyond which the asymptote matches will be therefore considered as an indicator for defining an adequate scale of microstructure. The covariograms of the parts corresponding to each lamina (independent areas of 4404 × 3302 pixels) were calculated. All phases were first considered independently in the calculation.

3.5. Numerical model for microstructure and mineral geometry

238 A simple model for convex grains, based on Voronoï diagrams (Sellers and Napier, 1997; 239 Fan et al., 2004; van den Eijnden et al., 2015, 2017) is used to reproduce the microstructure. 240 Previously this model has been used to generate simple microstructures in a periodic representative elementary volume with straightforward finite element discretization (van den 241 242 Eijnden, 2015), and to model the microstructure of a Callovo-Oxfordian claystone (van den 243 Eijnden et al. 2017). Here, the model is used to investigate microstructures with geometrical 244 properties matching those of the different laminae of the studied Bowland shale. The model 245 applies Voronoï tessellation on a set of randomly generated sites and uses the resulting 246 diagram as a geometrical model of the microstructure. Preferred orientations and grain elongation are introduced by stretching the domain during tessellation by an amount ξ which 247 248 thereby becomes a model parameter for the grain shape contribution to total anisotropy. The 249 model calibration is by a minimization of the root-mean-square error between the model 250 distributions and experimental distributions of total grain elongation L and orientation β (see 251 Fig. 6). As the model is based on Voronoï tessellation, there is little flexibility in the grain 252 size distribution without a strong distortion of the grain geometry distributions. For this 253 reason, no attempt was made to reproduce the grain size distributions, and the emphasis here 254 is on reproducing the correct distributions of (1) elongation (also called length ratio), (2)

grain orientation and (3) area fraction of all mineral groups (including organic matter and fractures). Calibration of the model has indicated that grain circularity corrections, as part of the model in van den Eijnden et al., (2017), are not needed to capture the grain geometry distributions of the shale.

Distributions of grain orientation and elongation for the different mineral types can be reproduced reasonably well using simple Voronoï tessellation while slight manipulation of the sites and stretching of the domain is applied during the tessellation operation. Based on the parameter distributions and area fractions of the different mineral types, mineral properties can be assigned. Their parameter distributions are then approached in the model.

The distributions of orientation and elongation are matched in an average distribution of all phases combined (quartz, carbonates, feldspars, micas, heavy minerals, organics and fractures). In the microstructure model, the phases are scattered as a function of their experimental area fraction. The cement and clays were first divided into random cells but their boundaries were then merged to form a unique phase. van den Eijnden et al., (2017) provide further details on the method of developing the microstructure model.

According to the experimentally determined area fraction of mineral phases, the mineral types were assigned following the conditional probability $P_M(m_i|L,\beta)$ to meet specified orientation and elongation properties, matching the distributions in Fig. 11. m_i is the type of mineral phase, *L* the elongation and β the orientation, which is the direct application of Bayes' theorem to derive a conditional probability, with an additional correction factor to account for grain-size dependency of the model (Bernardo and Smith, 2001; Berger, 2013). This probability is defined by Equation 4:

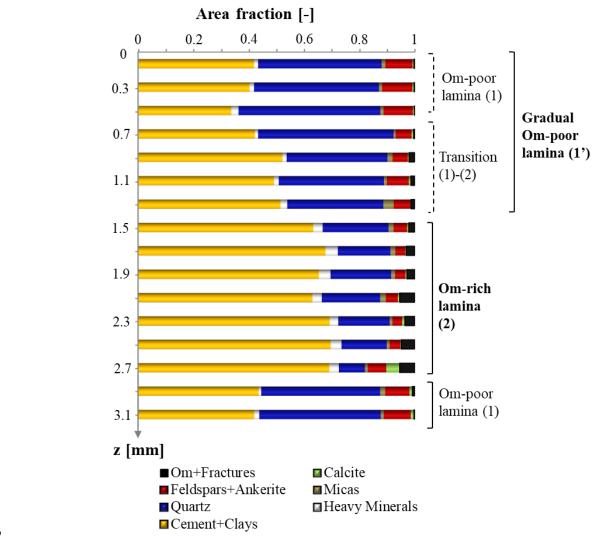
$$P_{M}^{N}(m_{i}|L,\beta) = \frac{q_{D}^{N}(L,\beta|m_{i})f_{D}^{S}(m_{i})}{q_{M}^{N}(L,\beta)}c_{i}$$
(4)

with $f_D^S(m_i)$ being the area fraction of mineral phase m_i (following Table 1), $q_D^N(L,\beta|m_i)$ is 277 the bivariate distribution of L and β in the data for phase type m_i and $q_M^N(L,\beta)$ is the 278 279 bivariate distribution of L and β of all phases in the model. c_i is a ratio to correct for the 280 influence of the correlation between grain size and grain geometry in the model on the final 281 area fractions of the minerals. The values of c_i are defined theoretically as the ratio of the resulting model area fraction over the expected area fraction of the assigned materials, and 282 283 requires the distribution of model grain size as a function of L and β . However, here the 284 ratios c_i have been determined based on the resulting area fractions of the model and updated iteratively to obtain the required area fractions. Values for c_i range between 0.6 and 1.25. 285

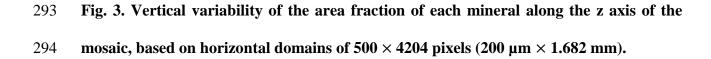
286 **4. Results**

287 **4.1. Vertical variability of phase content**

Fig. 3 shows the vertical variation of all area fractions, for independent horizontal domains of 289 200 μ m × 1.682 mm. A width of 200 μ m was chosen as a good compromise to show 290 quantitatively the vertical variability of area fractions including different types of 291 microstructural heterogeneities.







295 Three different regions were identified:

(1) Organic-poor laminae (z = 0.0.80 mm and z = 2.8-3.25 mm). These laminae are characterized by an area fraction of cement and clays lower than 50 % with a near zero content of organics and fractures. The detrital quartz grains represent 40 to 50 % of area, and heavy minerals (mostly pyrite), micas and calcite are on the order of a few percent. The proportion of feldspars and ankerite is around 8-10 %.

301 (2) Organic-rich lamina (z = 1.4-2.8 mm). This lamina is 1.4 mm thick, and composed of 302 60 to 70 % of area as cement and clays with a higher organic and fracture content between 303 1.7 to 7 %. The proportion of detrital quartz is between 10 and 30 %. The heavy mineral 304 content is also higher than in the organic-matter poor lamina with variable proportions between 2 and 5 %. Feldspars and ankerite are less common with area fractions between 2 305 306 and 6 %. Calcite and micas are still scarce, although peaks of micas and calcite were detected 307 due to very large micas at z = 1.2 mm and the presence of an horizontal calcite vein at z =308 2.7 mm.

309 **Transition** (1)-(2): This is the transition between organic-poor and organic-rich laminae 310 (z=0.80-1.4 mm). It is marked by a progressive increase in cement and clay area content 311 from 40 to 62 %, and a decreasing proportion of detrital quartz grains from 50 to 30 %. 312 Feldspars/ankerite variability is less marked at between 6 and 2 %. The proportion of heavy 313 minerals increases from 2 to 5 %. However, the transition between the organic-poor and the 314 organic-rich laminae around z = 2.8 mm is very abrupt with sharp jumps in cement/clays, organic-matter/fractures, quartz and heavy mineral proportions. The proportion of 315 cement/clays falls from 70 to 38 % over 240 μ m (between z = 2.68 to 2.92 mm), while quartz 316 content dramatically increases from 9 to 49 % in 220 μ m (between z = 2.76 to 2.92 mm). 317

In order to ensure a sufficient dataset for statistics in sections 4.3 to 4.5 below, the organicpoor and one part of the transition (z = 0-1.28 mm) zones were taken together to form a gradual organic-poor lamina (1'), in order to compare its microstructure with the that of the organic-rich lamina (2) (z = 1.48-2.76 mm).

322 **4.2. Spatial variability of phase content**

2D maps of *P* are shown as Fig. 4 for cement and clays, quartz, feldspars and carbonates, and 324 organics and fractures for N = 200, 500, 1250 and 1876 pixels, i.e. for, 80, 200, 500 and 750

325 μ m respectively (Fig. 4). P = 1 means that the domain *D* consists 100 % of the phase 326 considered whereas 0 (purple) means it is completely absent.

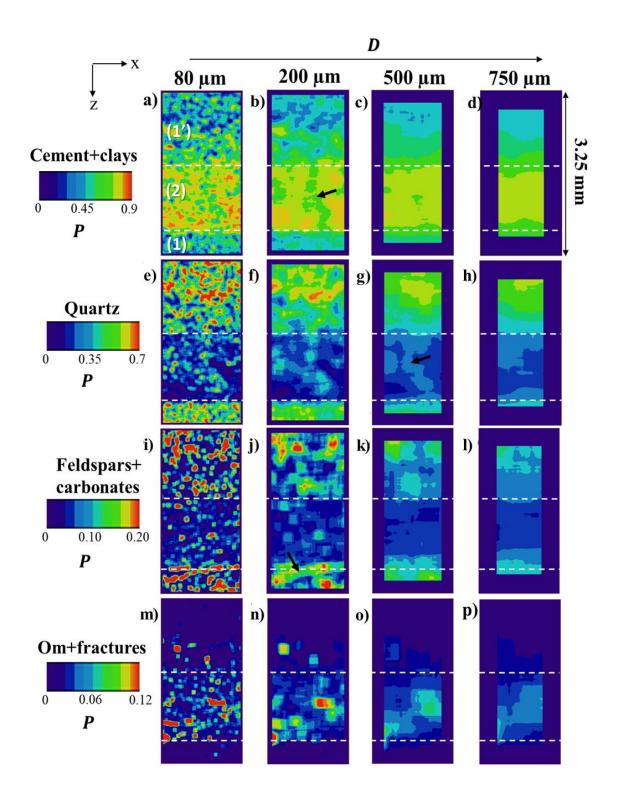


Fig. 4. 2D maps of phase area fractions with variable domain sizes for: (a-d) cement+clays, (e-h) quartz, (i-l) feldspars+carbonates, (m-p) Om+fractures. [Each of

the three laminae [(1) organic-poor lamina, (1') gradual organic-poor lamina, (2) organic-rich lamina] are labelled on (a).

332 The organic-rich lamina 2 is clay and cement-rich, and detrital quartz, feldspar and 333 carbonate-poor (Fig. 4 a-l). The organic-matter and fractures are heterogeneously distributed 334 due to the variable sizes of particles and fractures (Fig. 4 m-p). The organics and fractures are 335 nearly absent in the organic-poor lamina (1) (Fig. 4 m-p). The gradual organic-poor lamina 1' is quartz, feldspar and carbonate-rich (Fig. 4 e-l). The heterogeneities relative to P are 336 337 defined by local higher or lower phase area fraction than the mean phase area fraction of each 338 map (local concentration of red or blue colors for example). For all phases and D sizes, the 339 area fraction is spatially heterogeneous in x (horizontal) and z (vertical) directions on the 340 whole mosaic, mainly due to the presence of a sedimentary lamination (Fig. 2a), but also to a 341 heterogeneous distribution of mineral phases inside each lamina.

For $D = 80 \,\mu\text{m}$, local high concentrations of quartz, feldspars, carbonates and organics (red 342 343 areas in Fig. 4 e,i,m, first column) defined the grain shapes visible on the mosaic in Fig. 2. 344 The phase heterogeneities are thus relative to the grain-size scale for $D = 80 \,\mu\text{m}$, due to the 345 small value of D including a low number of grains. Therefore this scale shows interfaces between relatively large grains and the phase including cement and clays. For $D = 200 \ \mu m$, 346 347 the organic-rich lamina contains circular clay and cement-rich areas and a discontinuous 348 vertical line with a lower concentration (Fig. 4b), mainly due to the presence of quartz (Fig. 349 4f). Scattered feldspar and carbonate-rich areas were detected in the gradual organic-poor 350 lamina with a concentration gap around 0.15-0.20 with respect to the background. However, 351 the organic-poor lamina contains a continuous line with a higher concentration of feldspars 352 and carbonates (P > 0.15), mainly due to the presence of calcite veining (black arrow in Fig. 353 4j). This scale highlights the areas rich in large particles of organics and large fractures in the organic-rich lamina (Fig. 4n). The maps show these interfaces between clusters and grain-354

355 poor areas with the background at the scale of $D = 200 \ \mu\text{m}$. For $D = 500 \ \mu\text{m}$, cement and 356 clay proportion heterogeneities are averaged, reducing their surface fractions in both laminae (Fig. 4c), whereas larger clusters of feldspars, carbonates, and quartz are highlighted (Fig. 4 357 358 g, k). A continuous vertical line of quartz (P > 0.25) is present in the organic-rich lamina (black arrow in Fig. 4g). The organics and fractures are divided in two separate clusters with 359 360 P > 0.06 in the organic-rich lamina (Fig. 4o). For $D = 500 \mu m$, the domains D contain thus 361 more grains and average the phase area fraction and their heterogeneities relative to 362 individual and clusters of grains at larger scales than $D < 500 \ \mu\text{m}$. For $D = 750 \ \mu\text{m}$, phase 363 area fraction maps show the progressive and abrupt transitions between the different laminae 364 (Fig. 4 d, h, l, p, last column). They highlight the interfaces between sedimentary laminae, 365 and the maps for D = 500 show heterogeneities for extended clusters and the beginning of the detection of laminae at an intermediate scale between D = 200 and 750 µm. 366

The multi-scale mapping of phase area fractions shows three different types of microstructural heterogeneities relative to three different scales: (i) the interfaces between rigid inclusions (quartz, feldspars, carbonates, organics) and the phase cement/clays, (ii) the interfaces between clusters of rigid inclusions and the background and (iii) the interfaces between laminae. These maps highlight the high multi-scale variability of microstructure, based on the area fraction parameter.

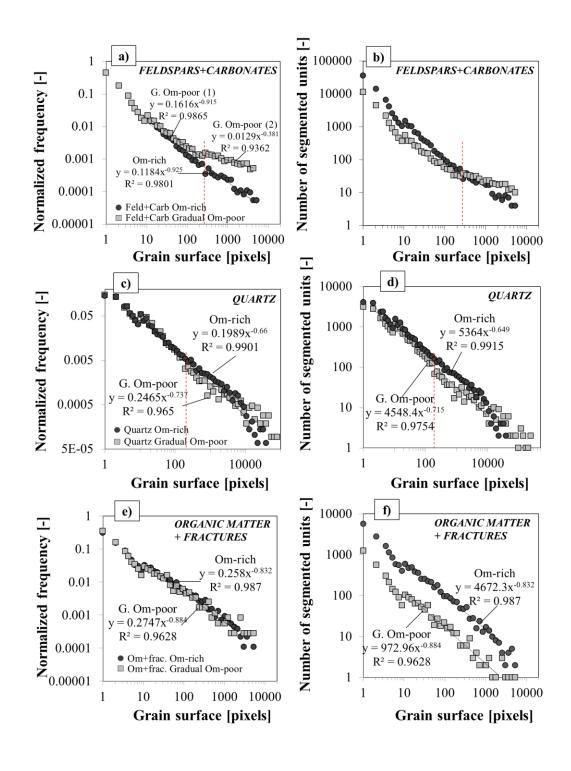
4.3. Variability of microstructural parameters

The grain size, grain number per size, length ratio and orientation of grains were calculated for each of laminae 1' and 2 (labelled on Fig. 4a) in independent areas of 4204×3200 pixels (1.682 × 1.280 mm²) (Fig. 5).

377 Variability of grain size

378 The grain size distribution (GSD) is an important parameter to help understand the 379 sedimentation conditions. As expected in shale, the grain size distributions (Fig. 5 a, b, c), 380 follow a power-law for both laminae for quartz, feldspars, carbonates, organic matter and 381 fractures, micas and heavy minerals (not shown). Their fractal dimensions on the studied 382 areas are shown. In both laminae 1' and 2, the GSD of feldspars, carbonates and quartz are 383 similar for grain surfaces below 200 pixels (Fig 5 a, c) and differ significantly above 200 and 384 300 pixels respectively, especially for feldspars and carbonates (Fig. 5a). This difference is 385 interpreted as a result of a large proportion of large grains (surface above 200 pixels) of 386 feldspars and carbonates in the organic-poor lamina (Fig. 5b) alongside the presence of grain 387 clusters (aggregates of grains, red grains in Fig. 2a). The GSD for feldspars and carbonates 388 describes a dual power law, thus large grains and clusters contribute heavily to the total phase 389 proportion of the gradual organic-poor lamina. Quartz GSD differ for grains larger than 200 390 pixels but the effect is less pronounced than in feldspars and carbonates (Fig. 5c), whereas 391 quartz clusters are more easily visible in Fig. 2 (blue grains). The number of independent 392 quartz segments is fewer by 18 % in the gradual organic-poor lamina 1' than the organic-rich 393 lamina 2 (Fig. 5d), despite Fig. 2a suggesting the opposite. This can be explained by the fact 394 that the quartz clusters are significantly larger than the feldspar and carbonate clusters, hence 395 their number and frequency are consequently much lower. In the gradual organic-poor lamina 396 1', quartz regions are relatively small and independent, whereas they are larger and arranged 397 in clusters in the organic-rich lamina 2. The clusters decrease the number of individual quartz 398 segments, which minimize their impact on the GSD (Fig. 5 c,d).

Organic matter and fractures show very close GSD for both laminae 1' and 2 (Fig. 5 e) but
the number of segmented features is until 4.8 times higher in the organic-rich lamina 2 than
the gradual organic-poor lamina 1' (Fig. 5 d).





403 Fig. 5. Grain size and grain number distributions for each of laminae 1' (gradual om404 poor) and 2 (om-rich).

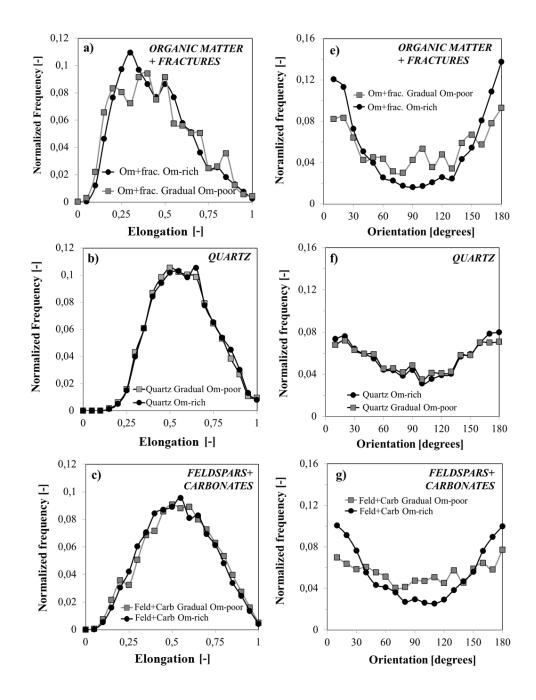


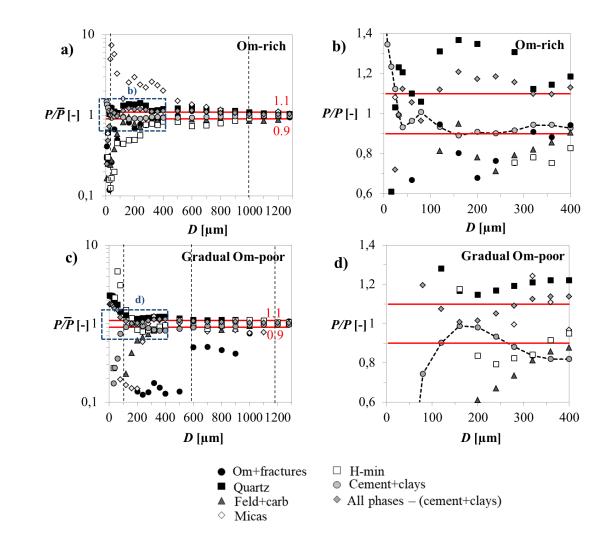
Fig. 6. Elongation and orientation distributions for a), b) organic matter particles and fractures, c), d) quartz, e), f) feldspars and carbonates, on the organic-rich (black plots) and the gradual organic-poor (gray plots) laminae 2 and 1' respectively. Only grains larger than 10 pixels were considered.

411 For both laminae, the microstructure of the Bowland Shale sample is anisotropic due to 412 horizontally-elongated quartz, feldspars, carbonates, organic matter particles and fractures 413 (Fig 6 a-g). The elongation distributions of quartz, feldspars, carbonates, organics and 414 fractures do not change significantly between the gradual organic-poor and the organic-rich 415 laminae (Fig. 6 a,b,c). However, the orientation distribution of organics, fractures, feldspars 416 and carbonates differ between the organic-rich lamina to the gradual organic-poor lamina 417 (Fig. 6 e,g). Organics, fractures, feldspars and carbonates are more elongated horizontally 418 (long-axis highest orientations at 0 and 180 degrees, i.e. parallel to the trace of bedding) in 419 the organic-rich lamina contrary to detrital quartz minerals which do not show any variation 420 of orientation between the two laminae (Fig. 6f). Based on these two criteria, the variation of 421 anisotropy is mainly due to a variation of orientation of fractures and feldspars, carbonates, 422 organic matter particles and fractures. Note that this measure of anisotropy ignores 423 contributions from any preferred crystallographic orientation of grains (other than micas) that 424 might exist and oriented cracks smaller than microscopic resolution.

425 **4.4. Quantitative description of the microstructure**

Figs. 3 to 6 have shown that the microstructure is spatially variable. However, even if the 426 427 microstructure is variable, microstructure modelling is required to predict strain localisation 428 and potential sites of fracture initiation in rocks (Lan et al., 2012; van den Eijnden et al., 429 2016). In this section, three methods are used to quantify representative elementary areas of 430 the measured microstructure, based on the surface proportion of phases, and as applied to 431 polycrystalline and heterogeneous materials (Kanit et al., 2006; Madi et al., 2005) and rocks 432 (Klaver et al., 2012; Houben et al., 2014; Vik et al., 2014). These methods can quantify how 433 representative are the microstructural models generated from the microstructural parameters 434 of the mosaic.

435 *Counting-box approach*



437 Fig.7. (a and b) Ratio between the local phase area fraction *P* and the mean phase area 438 fraction \overline{P} as a function of the size of calculation domain *D* for the *organic-rich lamina* 439 where b) is a magnified view of the dashed-line box in a) for $D \leq 400 \mu m$. (c and d) show 440 similar features for the *gradual organic-poor* lamina, where d) is a magnified view of the 441 dashed-line box in c) for $D \leq 400 \mu m$.

The starting point of the counting box method is the center of each lamina image, in order to take into account the maximum number of different *D* values. *P* is the mean area fraction of the phase in *D* and \overline{P} is the mean phase area fraction in the whole image of the lamina. In the organic-rich lamina, the ratios P/\overline{P} for cement-clays (gray circles in Fig. 7 a,b) and all rigid inclusions (gray diamonds in Fig. 7a,b) start to oscillate at 1±0.10 for *D* close to 50 µm and

320 µm, respectively. However, the ratio P/\overline{P} of all phases separately considered is stable at 447 1±0.10 for $D \ge 1$ mm. This result is interpreted as being a balance effect between the 448 449 different mineral phase fractions. In the gradual organic-poor lamina 1' (Fig. 7 c, d), P/\bar{P} varies at 1±0.10 for $D \ge 120 \ \mu m$ for the cement-clays (oscillation around 0.9) and the overall 450 451 grain phase (oscillation around 1.1). However, all phase area fractions taken independently are stable for $D \ge 600 \ \mu\text{m}$, except organics and fractures at $D \ge 1.1 \ \text{mm}$ due to small and 452 elongated units (Fig. 5f, 6d) and a low mean area fraction on the whole image. Consequently, 453 P/\bar{P} reaches 1±0.10 for $D \ge 1.2$ mm for all phases separately considered. The 454 homogenization areas are larger for the gradual organic-poor lamina than the organic-rich 455 lamina due to higher grain sizes and larger clusters, and the scattering of small and low 456 frequency phases such as organics and fractures. 457

458 Dispersion of phase proportion

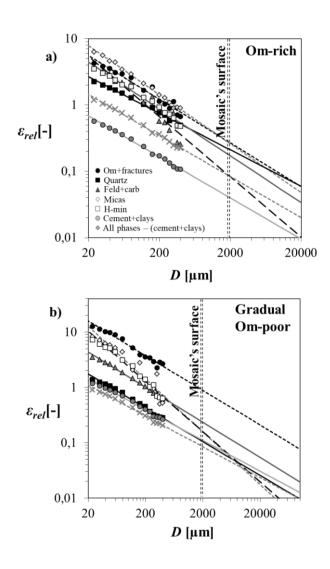
Each lamina was divided into a number, *N*, of independent domains, *D*, to calculate the standard deviation $\sigma_P(D)$, variance $\sigma_P^2(D)$ and relative error $\varepsilon_{rel}(D)$ (Fig. 8) of each phase area fraction *P* as a function of *D* (Kanit et al., 2003) (Equation 5, Fig. 8, Tables 1,2). :

$$\varepsilon_{rel}(D) = \frac{2\sigma_P(D)}{\bar{P}\sqrt{N}} \tag{5}$$

462 with \overline{P} the mean phase area fraction between 0 and 1.

In Kanit et al., (2003), *N* is the number of cells on theoretical Voronoï mosaics. In this study, *N* is the number of cells, called domains, of the experimental mosaic. A domain can therefore be considered as a 2D rock subsample of the whole mosaic of the Bowland Shale. The experimental mosaic has a limited size, so the number of domains is also limited to a finite value.

The fitting of relative uncertainty ε_{rel} by a power law $\varepsilon_{rel} = a.D^{-b}$ (Table 1) allows the 468 quantification of ε_{rel} for the surface corresponding to each type of lamina (Fig. 8, table 1). 469 470 On each lamina, the number of calculation domains as a function of the domain's size follows the law: $N = 2.10^{6} D^{-b}$ with b = 2.05 (r² = 0.9993) for D between 10 and 1250 pixels (4 and 471 472 500 µm respectively). Data with fewer than 10 domains were not considered (Kanit et al., 473 2003), i.e domains above 400 μ m. As expected, the dispersion of P decreases when the size of D increases for phases segmented. The relative errors of all phase area fractions were 474 475 calculated as a function of D for both laminae according to equation 5 (see Figure 8).



477 Fig. 8. Relative uncertainty, ε_{rel} , of area fraction as a function of *D* for a) the organic-

478 rich lamina and b) the gradual organic-poor lamina, for N=1.

479	Considering all phases combined together in both laminae, $\varepsilon_{rel} = 0.11$ and 0.09 for square
480	domains of $1.32 \times 1.32 \text{ mm}^2$ and $1.76 \times 1.76 \text{ mm}^2$ respectively (gray crosses in Fig. 8),
481	whereas $\varepsilon_{rel} \gg 0.1$ for the phases segmented independently for same <i>D</i> . Based on the surface
482	proportion, the areas used to characterize the lamina's microstructures are representative with
483	a ε_{rel} around 10% when all mineral phases are considered together in a unique phase, but not
484	separately, at the study resolution.

Gradual Om-poor	a	b	\mathbf{R}^2
Om+fractures	103	0.626	0.97
All grains	5.80	0.556	0.99
Cement+clays	7.54	0.556	0.99
Quartz	10.8	0.610	0.99
Feldpars+Carbonates	29.1	0.635	0.99
Heavy minerals	154	0.906	0.98
Micas	218	0.952	0.90
<u>Om-rich</u>			
Om+fractures	39.8	0.658	0.95
All grains	9.19	0.619	0.99
Cement+clays	4.39	0.619	0.99
Quartz	13.9	0.551	0.99
Feldpars+Carbonates	81.9	0.908	0.91
Heavy minerals	36.6	0.706	0.99
Micas	71.3	0.738	0.99

486 Table 1. Parameters of the power law fitting, ε_{rel} , as a function of *D* corresponding to

both laminae.

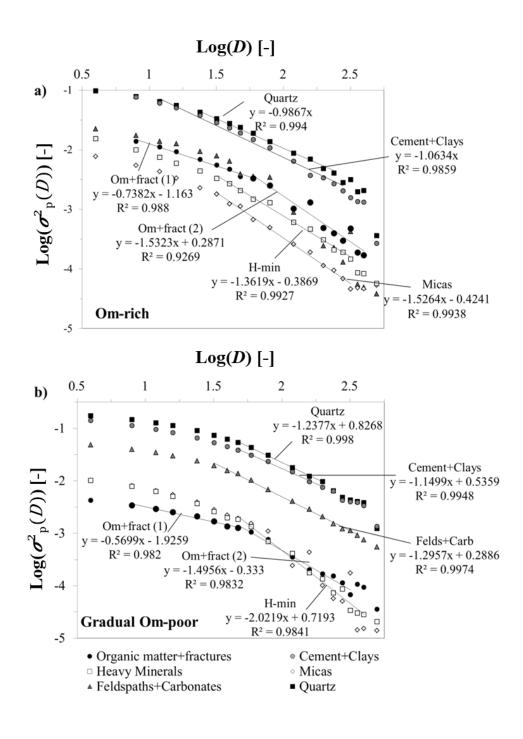
		REA [mm]								
			N=1			N=5			N=10	
	E _{rel}	0.15	0.1	0.05	0.15	0.1	0.05	0.15	0.1	0.05
	Cement+clays	0.233	0.449	1.38	0.063	0.122	0.375	0.036	0.070	0.214
ch	Grains	0.746	1.44	4.40	0.203	0.391	1.20	0.116	0.223	0.685
-i,	Quartz	3.71	7.75	27.2	0.861	1.80	6.33	0.459	0.959	3.37
nic	Feld+Carb	1.03	1.62	20.4	0.426	0.666	1.43	0.291	0.455	0.975
Organic-rich	H-min	2.41	4.28	11.4	0.771	1.37	3.65	0.472	0.838	2.24
õ	Om+fractures	4.83	8.94	25.6	1.42	2.63	7.55	0.839	1.55	4.46
	Micas	4.24	7.35	18.8	1.42	2.47	6.32	0.892	1.54	3.95
	Cement+clays	1.15	2.38	8.28	0.270	0.560	1.95	0.145	0.300	1.04
0C	Grains	0.715	1.482	5.16	0.168	0.349	1.21	0.090	0.187	0.650
Gradual ganic-poor	Quartz	1.10	2.14	6.68	0.295	0.573	1.79	0.167	0.325	1.01
adı nic	Feld+Carb	4.02	7.61	22.7	1.13	2.14	6.38	0.655	1.24	3.70
Gr	H-min	2.12	3.32	7.14	0.874	1.37	2.94	0.596	0.932	2.03
° Č	Om+fractures	33.8	64.7	196	9.36	17.9	54.1	5.38	10.3	31.1
	Micas	2.10	3.21	6.66	0.901	1.38	2.86	0.626	0.959	1.97

Table 2. REA values in mm, calculated for different number of domains and for the phases of each lamina.

491 REA were calculated for a number of samples of 1, 5 and 10 and for $\varepsilon_{rel} = 0.05, 0.1$ and 0.15 492 (Table 2) according to Table 1 and Fig. 8. For $\varepsilon_{rel} \ll 0.05$, unrealistically high values of 493 REA were found, significantly greater than lamina width. Therefore, these values were not 494 considered to be realistic. The REA calculated for $\varepsilon_{rel} = 0.1$ and N = 1 are millimetric 495 surfaces. However, the maximum possible lamina width used to calculate the microstructural 496 parameters is only 1.5 mm due to natural sedimentary structure (Fig 2). As such, the 497 calculations for N = 10 and $\varepsilon_{rel} = 0.1$ are more realistic than for N = 1 or 5 because the REA 498 are below 1.5 mm for all phases, except organics and fractures in the gradual organic-matter 499 poor lamina owing to their small quantities and scattered structure.

500 Randomness of phase distribution

501 The variance of phase area fraction describes a log-linear law as a function of D for both 502 laminae (Fig. 9, equation 6).



504 Fig. 9. Fitting of Log ($\sigma^2(D)$) as a function of Log (*D*) for the mineral phases of a) the 505 organic-rich lamina and b) the gradual organic-poor lamina.

$$Log(\sigma_P^2) = -\alpha Log(D) + k$$

(6)

506 α in Equation 6 is an indicator of the randomness of the distribution of the physical parameter 507 studied, which is *P* in this study (Cailletaud et al., 1994; Kanit et al., 2003;). According to 508 these authors, *P* was considered to be randomly distributed for $\alpha = 1\pm 0.15$. $\alpha > 1$ means that 509 the variance increases rapidly with increasing domain, *D*, whereas $\alpha < 1$ when the variance 510 decreases with increasing domain, *D*.

511 In the organic-rich lamina, the proportions of quartz and cement-clays are distributed 512 randomly enough for D = 24 to 400 µm (log(D)=1.38 to 2.6) and D = 12 to 400 µm 513 $(\log(D)=1 \text{ to } 2.6)$ respectively, unlike the other phases (Fig. 9a). In the gradual organic-poor 514 lamina, only the fraction of cement-clays is randomly distributed for D = 48 to 200 µm $(\log(D)=1.68 \text{ to } 2.3)$ whereas all other phases are heterogeneously scattered, with $\alpha >> 1$ for 515 516 a domain larger than 48 μ m. For all phases, the coefficients α are higher in the gradual 517 organic-matter poor lamina than in the organic-matter rich lamina. Therefore, the variance of 518 their fractions increases more rapidly with increasing D in the gradual organic-poor lamina 519 than in the organic-rich lamina. The gradual organic-matter poor lamina contains more large 520 grains and clusters (especially quartz, feldspars and carbonates), and consequently, their 521 number per domain is lower than if they were smaller grains. It thus requires a larger domain, 522 D, to generate a homogeneous phase area fraction on a finite surface. In the whole range of 523 D, $\log(\sigma^2)$ of area fraction for all phases show affine laws in both laminae, especially visible 524 in the gradual-organic matter poor lamina. An example is given for the organics and fractures 525 (Fig. 9 a, b). For organics and fractures, $\alpha \ll 1$ for $D \leq 60 \mu m (\log(D)=1.78)$, while $\alpha \gg 1$ 526 for $D > 60 \,\mu\text{m}$. For $D \le 60 \,\mu\text{m}$, the resolution is not sufficient to capture the different sizes of 527 organics and fractures. However, domains larger than 60 µm include various sizes of particles 528 heterogeneously scattered and/or with insufficient mean fraction to cause a sharp increase of 529 variance as a function of D. The log-linear law is divided in two slopes, caused by a scaling 530 effect due to various particle sizes, but a fixed resolution.

531 Covariance

- 532 In order to compare the different covariograms, they are plotted minus the square of the mean
- 533 phase area fraction in each lamina in Figure 10.

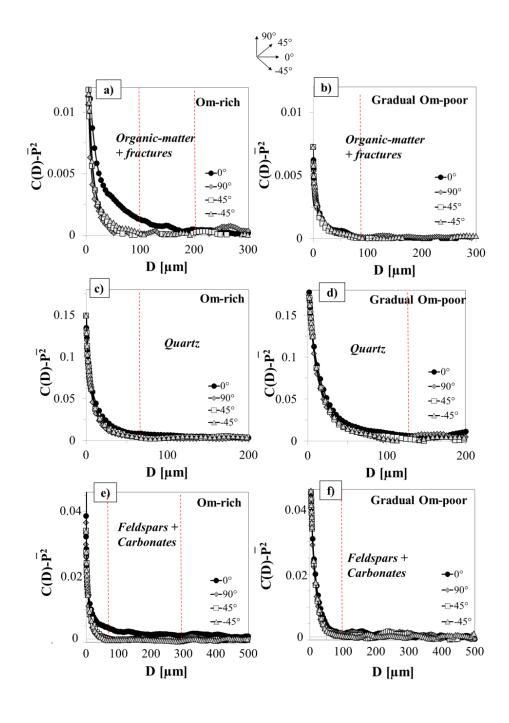


Fig. 10. Covariograms of a) organic-matter and fractures in the Om-rich lamina; b)
organic-matter and fractures in the gradual Om-poor lamina; c) quartz in the Om-rich

lamina; d) quartz in the gradual Om-poor lamina; e) feldspars and carbonates in the
gradual Om-poor lamina; and f) feldspars and carbonates in the Om-rich lamina.

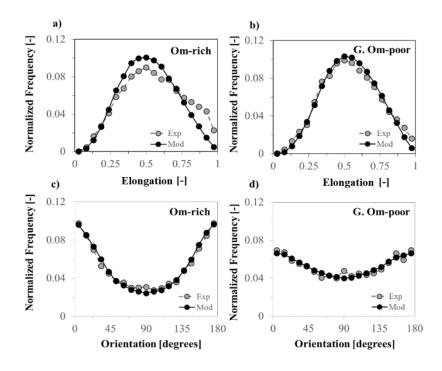
539 Organic-matter and fractures become homogeneously scattered for $D \ge 100 \,\mu\text{m}$, except in the 0° orientation with $D \ge 200 \ \mu m$, due to horizontal fractures and elongated particles of 540 541 organics in the organic-matter rich lamina (Fig. 10a, b). Under the study conditions, domains 542 smaller than 100 µm can be considered as heterogeneous scales for the organic-poor lamina, and 200 µm for the organic-rich lamina. The covariograms of quartz reach the asymptote for 543 544 domains $D \ge 75 \ \mu m$ in the organic-matter rich lamina and 120 μm in the gradual organic-545 poor lamina (Fig. 10 c, e). The higher heterogeneous scale relative to quartz in the gradual organic-poor lamina is mainly due to the presence of aggregates which contribute towards an 546 547 increase in the size of quartz heterogeneities.

548 In the gradual organic-poor lamina, the covariograms of feldspars and carbonate reach the 549 asymptote for D close to 100 μ m in all directions, showing a microstructure close to isotropic 550 for these phases at the resolution of the study. However, this is not the case for the organic-551 rich lamina. The asymptote is reached for $D=300 \ \mu m$ in the horizontal direction (0°) contrary 552 to the other directions (asymptotes at 75 µm), due to smaller, more elongate and horizontally-553 elongate feldspars, as well as horizontal calcite grains within a vein in the organic-rich lamina 554 (bottom part of the lamina, Fig. 2). Therefore, the laminae have different scales of textural 555 heterogeneities. For the microstructure models, the parameters are calculated over a surface of $1.32 \times 1.76 \text{ mm}^2$; at least 3 to 11 times the size of the minimal homogeneous surfaces 556 557 determined by the covariograms (considering all directions). In the sample of Lower 558 Bowland Shale used here, the variability of microstructure thus causes a variability of the 559 minimum size of the homogeneous scale. Covariograms also indicate that the anisotropy of the microstructure is mainly caused by the organic-matter particles, fractures, feldspars and 560

561 carbonates in the organic-rich lamina (Fig. 10 a, c, e). The microstructure is more isotropic in
562 the gradual organic-poor lamina (Fig. 10 b, d, f).

563 5. Microstructural modelling

564 The total grain geometry of the model was calibrated against the geometry of all mineral types combined. This calibration, performed against distributions of elongation ratio and 565 566 orientation, leads to the total distribution of all phases in the model, including the ones that eventually make up the cement and clays. Results of this first step are given in Fig. 11. The 567 568 overall properties are calibrated at $\xi = 1.3$ in the organic-rich lamina and $\xi = 1.1$ in the 569 gradual organic-poor lamina. ξ is higher for the organic-rich lamina because of particles that 570 are more horizontally-elongated in the organic-rich lamina which therefore cause a greater 571 stretching of the modelled microstructure.

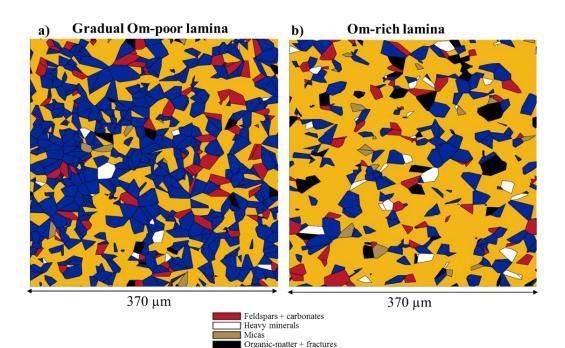


573 Fig. 11. Result of the model calibration of all model grains against the data of all phase 574 units combined [quartz + (feldspars,carbonates) + micas + heavy-minerals + 575 (organics,fractures)]: a) elongation distributions of the organic-rich lamina; b)

elongation distribution of the gradual organic-poor lamina; c) orientation distribution
of the organic-rich lamina; and d) orientation distribution of the gradual organic-poor
lamina.

The distributions for elongation and orientation of the microstructure model match well the experimentally observed distributions in the case of all phases combined (Fig. 11). Only the distribution of the elongation of the grains in the organic-rich lamina appears poorly calibrated (Fig. 11a), but this can be corrected for in the model through proportionally assigning mineral properties.

Figure 12 shows two resulting periodic microstructures, reproducing the distributions of elongation, orientation and surface fractions of the gradual organic-matter poor lamina (Fig. 12a) and the organic-matter rich lamina (Fig. 12b). Other periodic microstructures are given in Appendix 1 and the distributions of elongation ratio and orientation for each mineral type are shown in Appendix 2.



Quartz Cement + clays

589

Fig. 12. Geometrical microstructure models of a) the gradual organic-poor lamina, b)
the organic-rich lamina. The models were generated from 1000 cells of all phases
combined.

593 In a numerical sense, a scale bar should not be displayed with the microstructure model. 594 However, shales are multi-scale materials with components and properties varying over this 595 same range of scales. The scale is therefore important in order to determine which 596 phenomena can be studied with these models, because in shale materials phenomena 597 associated with one scale can exhibit controls over behaviors on larger scales. The models 598 presented here are at the mesoscopic scale, effectively micrometric rigid inclusions within a 599 "binder" composed of clays and quartz cement. A scale was qualitatively calculated for the 600 microstructure models in Fig. 12. Considering the mean cell size for each phase and 1000 601 cells in total, the scale value suggested and shown on Fig. 12 is around 370 µm for both 602 laminae.

603 6. Discussion

604 6.1. Variability of interfaces relative to phase area fraction, from the μm to 605 mm scale

Microstructural defects influence the initiation, propagation and aperture of fractures within shales (Montes et al., 2002; Hedan et al., 2012; Fauchille et al., 2014, 2016; Wei et al., 2016). The maps of phase area fractions highlight the location of three types of interface: the limits between (1) individual grains and the cement and clay phases (micrometer scale), (2) discontinuous phase aggregates and the background (several tens of micrometer scale), and (3) the transitions between laminae (millimeter scale). These interfaces are detected as a function of the size of the calculation domain, which is directly correlated to the scale investigated. The capture of these different interfaces is only possible with a large mosaic of
images in high resolution, which allows a multi-scale investigation of the microstructure.
Multi-scale 2D mapping allows the detection of heterogeneities and interfaces which may not
be obvious when only examining at the initial mosaic, especially for aggregate boundaries.

The Lower Bowland Shale has a complex and multi-scale natural fracture network (Fauchille et al., 2017). The Lower Bowland Shale sample studied here may have also an interesting potential for "artificial" (such as hydraulic simulation) fracture propagation in multiple directions, due to the variability of interfaces relative to the microstructure.

The transport properties of shales are controlled by the structure and arrangement of potential transport pathways (Keller et al., 2011), particularly at the nanoscale (McKernan et al., 2017). Microcrack location and properties are important for any bottom-up prediction of the transport properties of shales. The quantification of strain concentrations at specific interfaces using digital image or volume correlation may present an interesting way forward in the development of predictive models of fracture initiation and propagation, and in the understanding of scale factors controlling the fracture mechanisms.

628 6.2. Contrasting vertical microstructural properties in the Lower Bowland 629 Shale, from the µm to mm scale

According to previous studies, the qualitative variability of microtexture of Bowland Shale from Preese-Hall-1 lies at the borehole scale with various microtexture types (Andrews, 2013; Fauchille et al., 2017). Here, we demonstrate quantitatively that it is also variable at the sample scale, from the mm to the μ m at the resolution used. The alternation of mineralogically and texturally variable laminae indicates periodic changes of depositional controls during the sedimentation process. 636 With different mineral content, grain properties and anisotropy, the laminae may have 637 markedly different mechanical properties and fracturing behavior, both within each layer, but 638 perhaps particularly at their transitions, which are smooth or abrupt, but necessarily 639 elastically contrasting. These different properties and behavior could influence the production 640 and orientation of microcracks that are likely to control permeability and contribute 641 significantly to anisotropy (McKernan et al., 2017). The organic-poor lamina is quartz-rich 642 (detrital quartz and cement), unlike the organic-rich lamina. A relatively low proportion of 643 clay minerals (<35%) (Andrews, 2013) and high proportion of non-swelling minerals is 644 considered to be favorable for hydraulic fracturing cutting across the layering (Jarvie, 2012, 645 2014), depending on the in-situ stress state, and hence for potential gas extraction. High 646 proportions of quartz or carbonates that are contiguous limit ductility and enhance the 647 brittleness of the rock (Jarvie 2014; Raji et al., 2015). Microtextural changes across layers 648 induce discontinuities and weak regions, producing localized stresses, and strain 649 incompatibilities under mechanical simulations (Lan et al., 2010; Amann et al., 2011) which 650 aid in the development of pathways for fracture growth.

651 However, the presence of a laminated structure can act to limit the vertical extent of fractures 652 by blunting cracks propagating across the layering. Ease of formation of shear steps parallel to laminae further acts to inhibit vertical fracture growth by blocking upward flow paths for 653 654 hydraulic fracture fluid (Rutter and Mecklenburgh, 2017). The presence of rather thin 655 laminae increases the number of interfaces relative to thick beds, and thereby improves the 656 number of potential pathways for fracturing. At such larger scales, in the Austin Chalk for 657 example, the vertical connectivity of fractures is controlled by the vertical alternation of chalk 658 and shale layers due to different microstructure (grain size), fracture toughness and maximum 659 compressive stress (Warpinski and Teufel, 1989; Rijken and Cooke, 2001). According to 660 previous studies, the Bowland Shale contains laminated and interlaminated microtexture

types with laminae less than millimeter-thick. Note that the thickness of laminae is much smaller and periodic in the interlaminated microtexture than the laminated microtexture. Thinner shale layers have lower resistance to fracturing compared to thick beds (Rijken and Cooke, 2001). The characterization of the mechanical behavior of each type of lamina will aid understanding of the impact of the lamination on the vertical propagation of hydraulic fractures in the Bowland Shale.

667 6.3. Comparison of various methods for estimating the homogeneous scales 668 of the Bowland Shale microstructure

669 The counting-box and the covariance methods are easier and faster to perform than the 2D 670 mapping and dispersion approaches of Kanit et al., (2003) which are more time-consuming due to the requirement for incremental calculations on millions of pixels. Even if the center of 671 672 the first domain can be chosen randomly, the counting-box method gives a local 673 approximation of the representative area of the total surface investigated, for specific physical 674 parameters, scale and resolution. Nevertheless, the results depend strongly on the final 675 surface because the comparative surfaces overlap. For example, the domains of 1 and 1.2 mm 676 have an overlap of 83.3% ($100 \times 1/1.2 = 83.3$ %). As the calculation domain becomes closer to the final surface (i.e. 1.76×1.32 mm in this case), the probability that the physical 677 parameter (area fraction here) measured on the subsurface is close to the mean parameter of 678 679 the entire surface increases and reaches 1.

In the dispersion approach, or mosaic scattering, the mosaic is divided into tens to several thousands of independent domains which give a sufficient set of data for statistical interpretation. The domains are compared to each other, rather than to a mean parameter measured over the whole surface. However, the requirement for this substantial number of subareas does not allow the use of areas larger than 400 \times 400 μ m in our case, whereas calculations are performed for millimeter-scale areas in the counting-box and covariance
approaches. The dispersion approach therefore limits the maximum size of the subareas used.
The representative areas are thus determined by extrapolation using a power law and not
directly from experimental data.

689 For each phase unit considered independently from the others, the homogeneous surfaces of 690 phase area fraction are obtained at 1-1.2 mm with a relative error of 10% with the counting 691 box, whereas they are 7 to 9 mm with the dispersion approach. For all phase units combined, 692 the homogeneous areas are much smaller due to a balance effect caused by the mixing of low 693 proportion phases. REA are in the range of 150-350 µm with the counting box method, 694 whereas they are around 1.44 mm with the dispersion approach for all phases combined to 695 form a single phase. As per previously, the REA are up to 9 times larger with the dispersion 696 approach than with the counting box. The 2D quantitative maps (Figure 4, Appendix A) 697 confirm that the homogeneous surfaces are larger than $500 \times 500 \ \mu m$ for the organic-rich 698 lamina, and larger than $750 \times 750 \,\mu\text{m}$ for the organic-poor lamina, which support using the 699 dispersion approach to estimate the REA. The counting box was found to underestimate the 700 size of the representative elementary surface. The 2D mapping of phase area fraction 701 provides a direct method of viewing the parameter under consideration, therefore is useful in 702 the comparison of methods.

The homogeneous surfaces determined by the covariance approach are much smaller than those obtained by the counting box and dispersion methods (Rolland du Roscat et al., 2007,). Indeed, the covariance is used to define homogeneity relative to the size of objects compriing the image (Fig. 2b), i.e., the characteristic length of heterogeneities, in addition to their area fraction. The size of the homogeneous scales determined by the dispersion approach appears proportional to the number of heterogeneities, with a characteristic length determined by the covariance (Rolland du Roscat et al., 2007). Therefore, we recommend using the dispersion approach when the surface is large enough to have several sizes of subareas, in order to extrapolate REAs at different relative errors. This is supported by the 2D quantitative maps showing that the counting box and the covariance approaches are not sufficient to define a homogeneous scale of the area fraction on a large surface. The covariance gives a minimum size of homogeneous scale which is important in the case that a larger surface cannot be investigated.

The counting-box and covariance methods are widely used in image analysis, and geoscience generally. On the other hand, the dispersion method introduced by Kanit et al., (2003) has not been very commonly applied in geoscience, and particularly to shales, except for recent studies from Klaver et al., (2012), Keller et al., (2013) and Houben et al., (2014). The results previously explained have shown that this method is robust enough to be applied to a natural and complex material such as shale, and can be applied to numerical and artificial materials as well as natural materials.

723 The comparison of the phase area fractions for various sizes of domain can also be compared 724 with XRD results, to quantify if the mesoscale can be representative of the macroscale. XRD 725 analyses are performed on a 100 mg powder, but the powder comes from a centimeter-size 726 sample in order to represent as well as possible the macroscale. Area fractions from SEM 727 images represent the mesoscale. However, to compare weight and volume data from XRD 728 with area fractions from SEM images, an accurate 3D characterization of the microstructural 729 anisotropy is ideally required. 3D microstructural data are poorly documented at the 730 mesoscopic scale for the Bowland Shale, despite recent work at the microscale (Ma et al., 731 2016). This comparison was not possible in this case.

732 **6.4. Using the geometrical microstructure models**

733 The geometrical models generated in this study represent the mesoscale of two laminae of a 734 sample of the Lower Bowland Shale, in which inclusions of quartz, feldspars, carbonates, 735 micas, heavy minerals, organic matter and fractures are embedded in a clay matrix and quartz 736 cement. The cement, clays, organics and microfractures define a porous network which 737 provides potential pathways for gas transport following fracturing stimulation. Frey et al., 738 (2012) and van den Eijnden et al., (2016, 2017) use such microstructures to model the micro and macroscale hydro-mechanical behavior of shale in a finite element squared (FE^2) model, 739 attributing mechanical and petrophysical properties (e.g. stiffness, hydraulic conductivity) to 740 741 each phase. With microstructural parameters, Houben et al. (2014), Lan et al., (2010) and 742 Guo et al., (2013) also modeled the microstructure of shales and brittle rocks, by quantitative 743 approaches or by using a distinct element code to generate a deformable microstructure.

The model of microstructure of the Bowland Shale presented here can potentially act as a basis for similar hydraulic transfer modeling in the Bowland Shale at the mesoscopic scale. It can be used to upscale the hydromechanical behavior from the microstructure scale to the macroscale taking into account the anisotropy of the small components of the shale material.

Moreover, the geometry of the microstructural model includes two scales: the scale relative to individual grains and the scale of grain aggregates. It can therefore be used with whole representative images or divided in small subareas (smaller "REA") to study the influence of microstructural heterogeneities (aggregates, individual grains in the cement, grains of feldspars and quartz stacked together...) on the hydromechanical behavior of the material.

6.5. Potential of image mosaics and representative microstructure models for upscaling

Microstructural data are collected at an infinitesimally smaller scale than the size of theBowland Basin, qualitatively estimated at the kilometer scale (Andrews, 2013). It is mainly

757 due to the fact that microstructural features are currently visible with high resolution 758 techniques such as microscopy and tomography, which do not allow the observation of larger 759 samples than the centimeter-size. However, numerical models for hydraulic fracturing require 760 representative microstructural data from the pore scale to hundreds of meters, which makes upscaling a real challenge. Averages of microstructural parameters at a defined scale can be 761 762 calculated on representative areas of smaller scales and implemented into numerical calculations at a larger scale (e.g. Wen and Jaime Gomez-Hernandez, 1996; Zhang et al., 763 764 2012; Peng et al, 2015). Different methods such as homogenization or multiscale asymptotics 765 can be applied during the approach of upscaling (Khalili et al., 2012; Kazemi et al., 2012; 766 Davit et al., 2013). The geometrical models of the microstructure determined from 767 representative experimental areas have the same area fraction and the same distributions for 768 grain elongation ratio and orientation. However, they do not have the same grain structure 769 (layout). The dispersion method could therefore provide the quantification of the variability 770 of grain layout in those REAs. A standard deviation of particle layout could be used to define 771 a standard of deviation of the upscaled data resulted from these models. A few example 772 geometrical models are given in Appendix.

773 **7. Conclusions**

The microstructure of a laminated sample of Lower Bowland Shale from the Preese-Hall 1 borehole was mapped using a mosaic of 2D-SEM images at the mesoscopic scale. The quantitative characterization of the sample's microstructure demonstrates a high vertical variability of mineral content, grain properties and grain shape anisotropy at the millimeter scale from a gradual organic-matter poor lamina to an organic-rich lamina. Quartz, feldspars and carbonate aggregates act to increase the spatial variability inside each lamina. The multiscale 2D mapping of phase area fraction highlights multi-scale interfaces of area fractions, 781 which are potentially of importance to the understanding of fracture initiation and 782 propagation. The Lower Bowland Shale sample chosen here might have potential for multiple 783 direction fracture propagation due to the high variability of microstructure heterogeneities 784 and interfaces (subject to the anisotropy of the ambient stress field), in addition to a complex 785 natural fracture network that might be re-stimulated.

786 The counting-box, dispersion, covariance and 2D mapping approaches were compared to 787 estimate the representativeness of the microstructure of each lamina, based on the phase area 788 fraction parameter. 2D phase mapping supports the use of the dispersion approach to 789 calculate the REA in such heterogeneous rock on a large surface. Nevertheless the covariance 790 allows the quantification of a minimum homogeneous surface relative to the size of particles. 791 The models of the geometry of the microstructure were built with parameters calculated from thousands of grains on a surface of $1.280 \times 1.682 \text{ mm}^2$, which is 3 to 11 times larger than the 792 793 maximum size of microstructural heterogeneities according to the four methods. This 794 microstructure model has been shown to be as representative as is possible from a sample of 795 this scale, and could be used as a starting point in the improvement of our understanding of 796 fluid flow through the porous phase in the Bowland Shale at the mesoscopic scale.

797

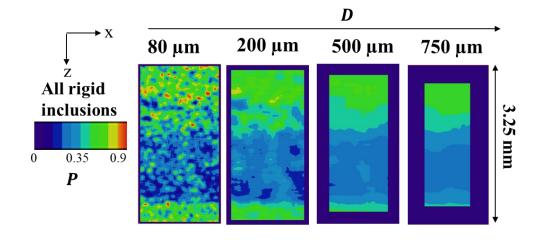
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806 reasonable request.

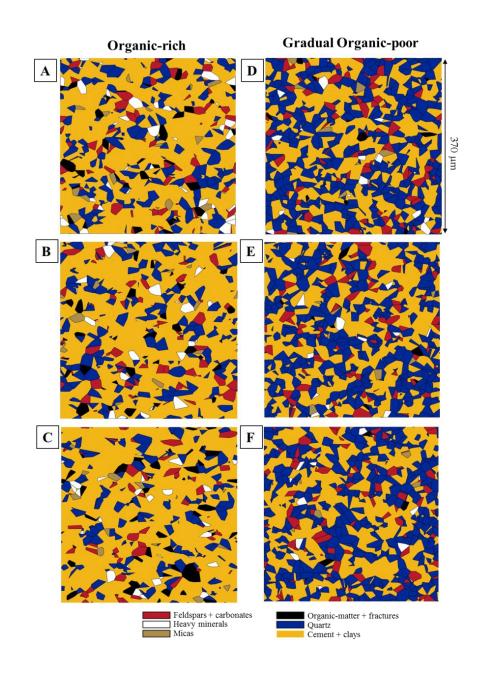
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808 Appendices:



809

Appendix 1 : Quantitative maps of the local area fraction for all rigid inclusions in the cement
(quartz+carbonates+feldspars+micas+heavy minerals+organics+fractures), as a function of the size of the
calculation domain D.



813

Appendix 2 : Example models of the geometry of the microstructure in the Lower Bowland Shale: A,B,C are random
microstructures for the organic-rich lamina and D,E,F for the organic-poor lamina.

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1035 Fig. 1. Gray level histogram of the first image of mosaic B8 1-1 (this image corresponds to 1036 1037 Fig. 2. (a) Mineral phase segmentation on the whole mosaic of SEM-BSE images of the 1038 Bowland Shale sample. (b) Magnified view of a region of (a). (c) Original (unsegmented) 1039 back-scattered electron image corresponding to (b).10 Fig. 3. Vertical variability of the area fraction of each mineral along the z axis of the mosaic, 1040 1041 1042 Fig. 4. 2D maps of phase area fractions with variable domain sizes for: (a-d) cement+clays, 1043 (e-h) quartz, (i-l) feldspars+carbonates, (m-p) Om+fractures. [Each of the three laminae [(1) 1044 organic-poor lamina, (1') gradual organic-poor lamina, (2) organic-rich lamina] are labelled 1045 Fig. 5. Grain size and grain number distributions for each of laminae 1' (gradual om-poor) 1046 1047 1048 Fig. 6. Elongation and orientation distributions for a), b) organic matter particles and fractures, c), d) quartz, e), f) feldspars and carbonates, on the organic-rich (black plots) and 1049 1050 the gradual organic-poor (gray plots) laminae 2 and 1' respectively. Only grains larger than 1051 1052 Fig.7. (a and b) Ratio between the local phase area fraction P and the mean phase area 1053 fraction P as a function of the size of calculation domain D for the organic-rich lamina 1054 where b) is a magnified view of the dashed-line box in a) for $D \leq 400 \mu m$. (c and d) show 1055 similar features for the gradual organic-poor lamina, where d) is a magnified view of the dashed-line box in c) for D \leq 400µm.....27 1056 Fig. 8. Relative uncertainty, *erel*, of area fraction as a function of **D** for a) the organic-rich 1057 1058 Fig. 9. Fitting of Log $(\sigma^2(D))$ as a function of Log (D) for the mineral phases of a) the 1059 1060 1061 Fig. 10. Covariograms of a) organic-matter and fractures in the Om-rich lamina; b) organic-1062 matter and fractures in the gradual Om-poor lamina; c) quartz in the Om-rich lamina; d) 1063 quartz in the gradual Om-poor lamina; e) feldspars and carbonates in the gradual Om-poor 1064 1065 Fig. 11. Result of the model calibration of all model grains against the data of all phase units 1066 combined [quartz + (feldspars, carbonates) + micas + heavy-minerals + (organics, fractures)]: 1067 a) elongation distributions of the organic-rich lamina; b) elongation distribution of the gradual organic-poor lamina; c) orientation distribution of the organic-rich lamina; and d) 1068 1069 1070 Fig. 12. Geometrical microstructure models of a) the gradual organic-poor lamina, b) the 1071 organic-rich lamina. The models were generated from 1000 cells of all phases combined. ...38 1072

1073 **Table captions**

1074	Table 1 : Parameters of the power law fitting, ε rel, as a function of D corresponding to both
1075	laminae
1076	Table 2 : REA values in mm, calculated for different number of domains and for the phases
1077	of each lamina
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