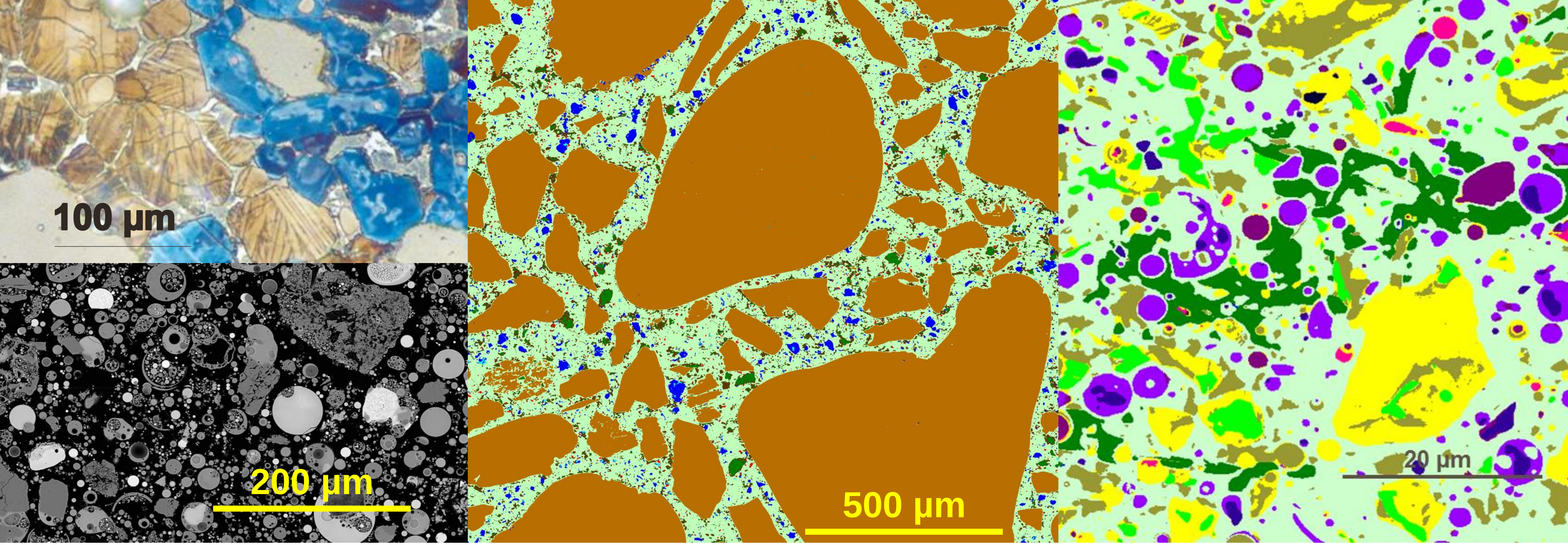


Spectro-Spatial phase analysis applied to S.E.M. X-Ray mappings of building materials

- *Concepts & Cases of applications* -

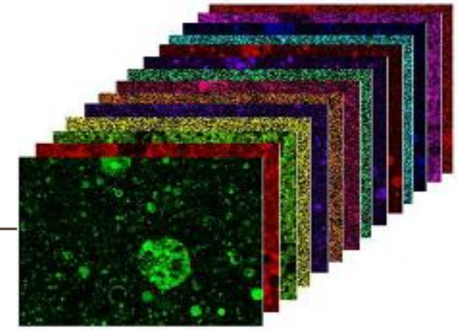
2017 GN-MEBA workshop - *Samuel Meulenyzer*

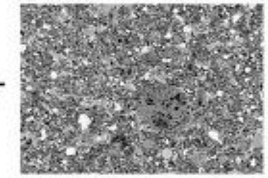
08/ 12 / 2017

GN MEBA

LafargeHolcim

This presentation is about…





Supervised phase clustering of building materials SEM/EDS mappings / microstructures

- From satellite tools to industrial applications:
  - Why ? How does it work ?
- Cases of applications:
  - REACTIVITY • mineral phase quantification of Raw materials
  - KINETIC • Hydration of heterogeneous blended cement & concrete
  - GRADIENT • Sulfate attack of concrete
  - LARGE AREA • Deformulation of concrete

LafargeHolcim

2005: CONTEXT

CLIMATE → CO_2 reduction !
(Total emission of cement = 5 %)

CONCRETE IS ALSO BEAUTIFUL !

Direct CO_2 emissions in Cement Manufacture (critical issue)

In 2014 total world annual production of cement was about 4000 millions T.

CO_2 from Limestone calcination	**≈ 510 kg/t clinker**
(fairly constant from plant to plant)	**+**
CO_2 from fuel combustion	**≈ 315 kg/t clinker**
(larger variations from plant to plant)	**=**
Direct CO_2 emissions for clinker	**≈ 825 kg/t clinker**
	x
Global average PC clinker content in "cementitious materials," due to addition of fillers and SCMs	**75%**
	=
Direct CO_2 emissions for cementitious materials	**≈ 620 kg/t cement**

.62 t/CO_2 X 4 billions T. of cement = 2 billions T. of CO2 *(per year)*

A reminder: What is ordinary portland cement (OPC) and concrete ?

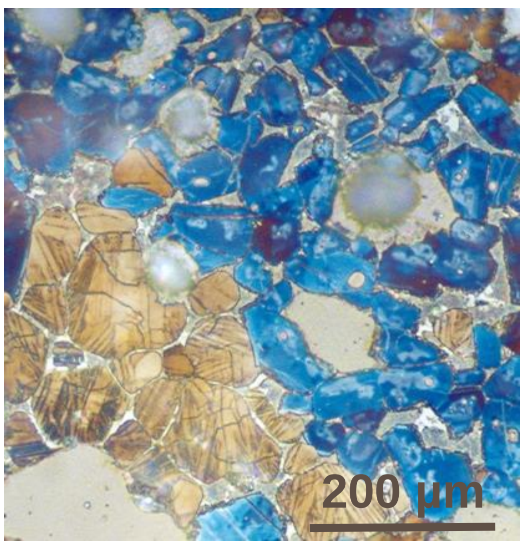
= powder of 4 mineral phases (clinker) and gypsum which react with water

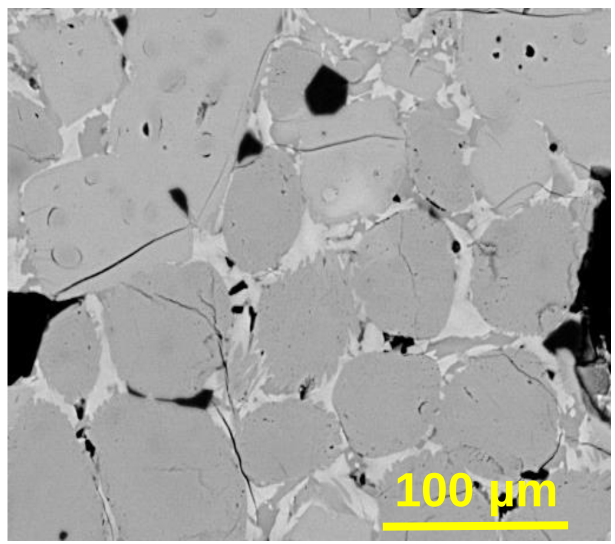
=

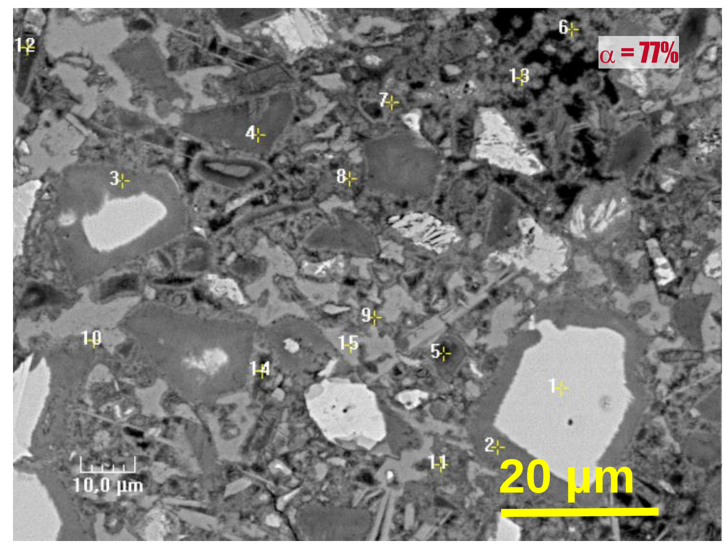
+

+

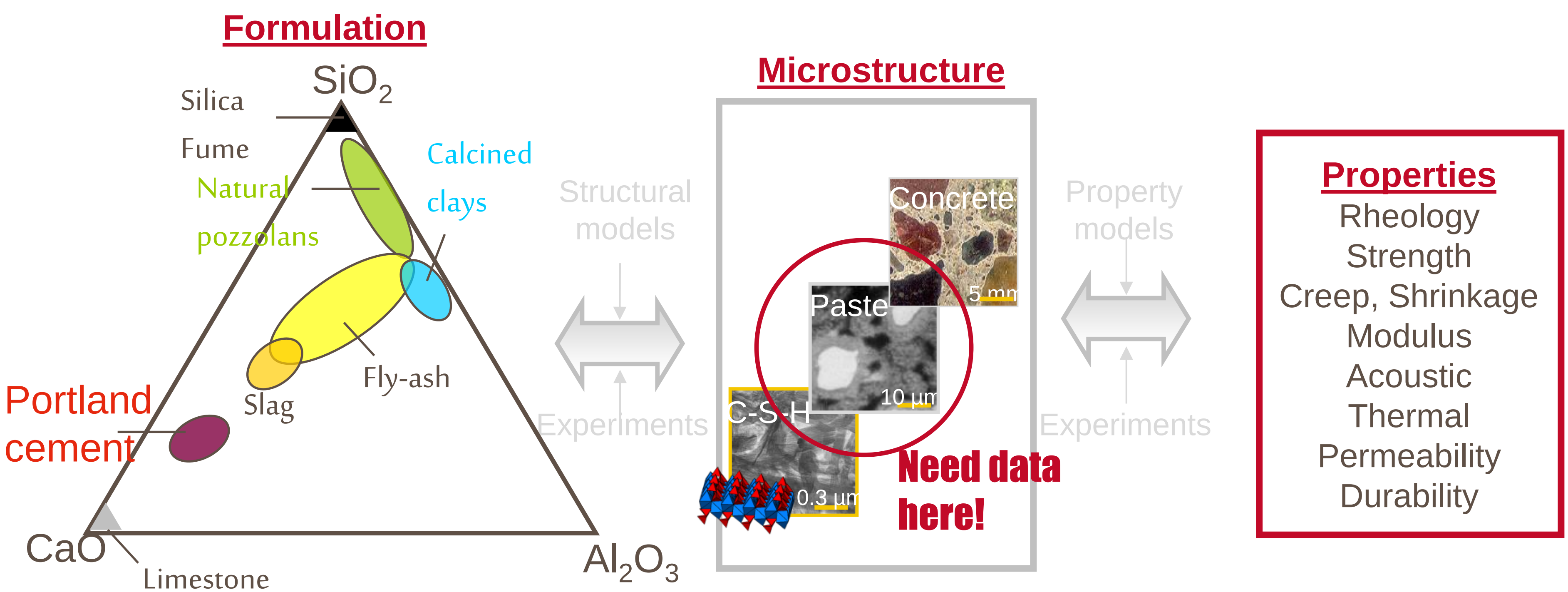
(Concrete)



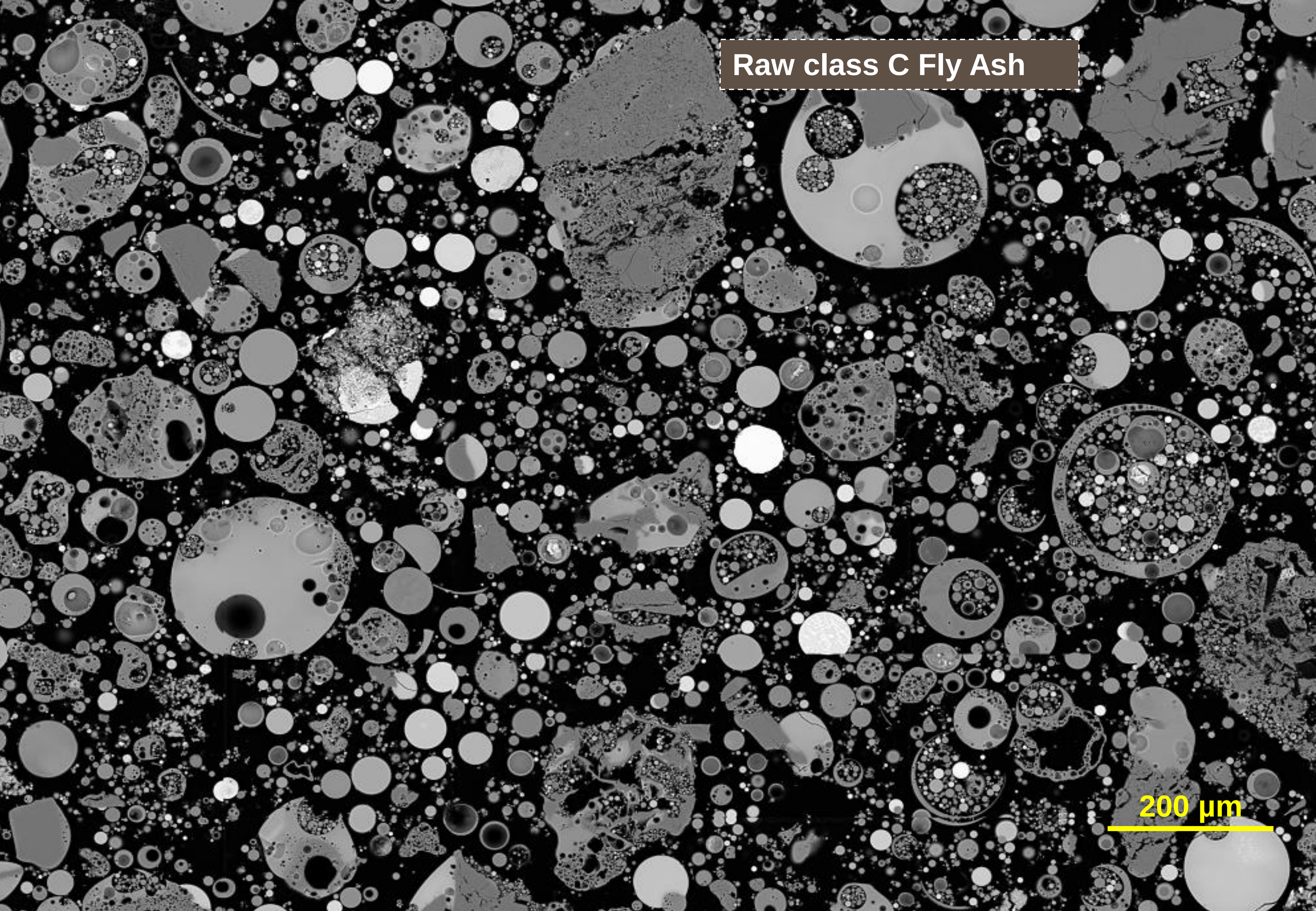


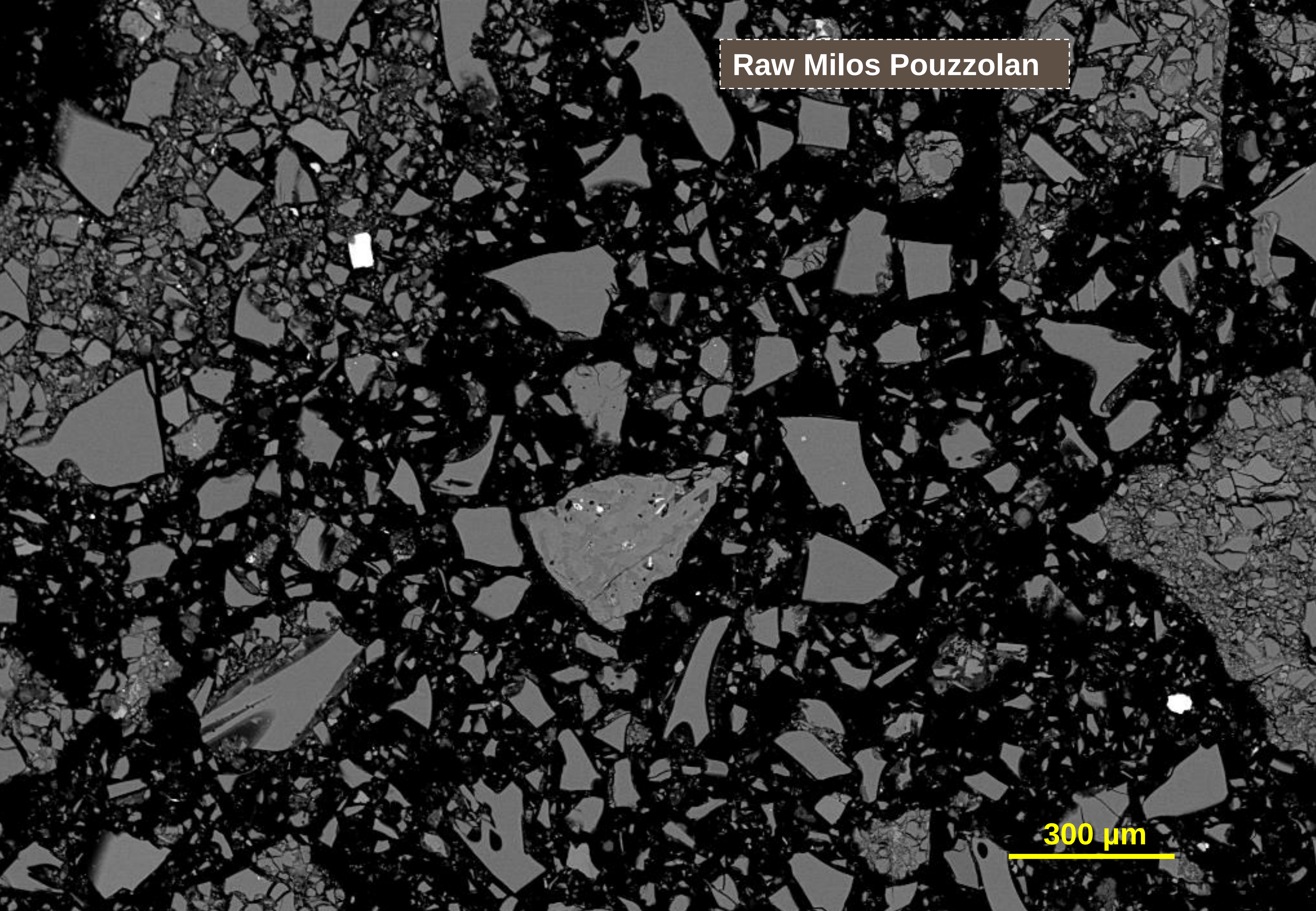


How to reduce OPC in concrete keeping durable prop. ?



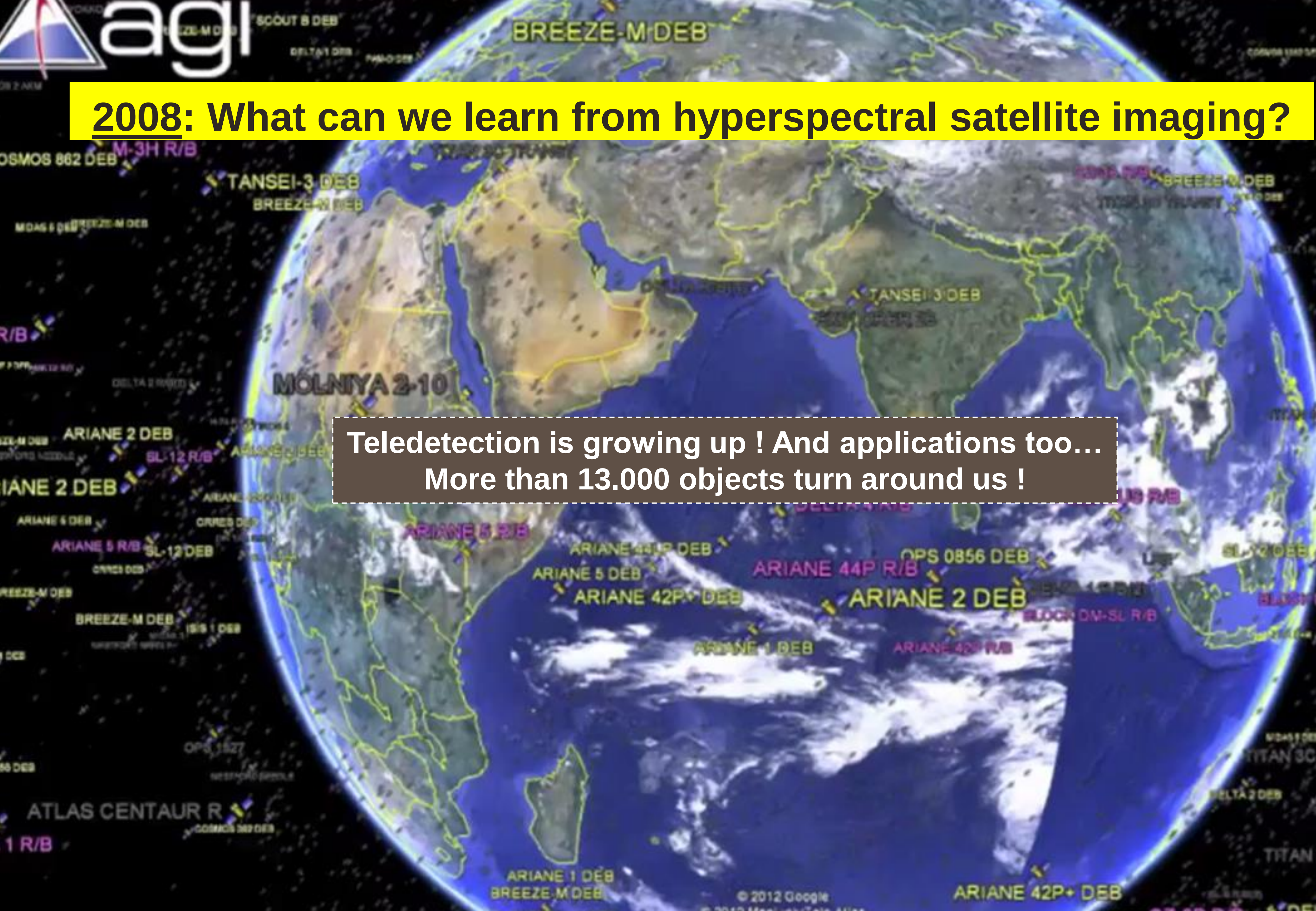
The successful use of SCMs requires that we master the formulation-microstructure-property link


Raw class C Fly Ash
200 µm


Raw Milos Pouzzolan
300 µm

What we want is to measure phase fraction of materials !

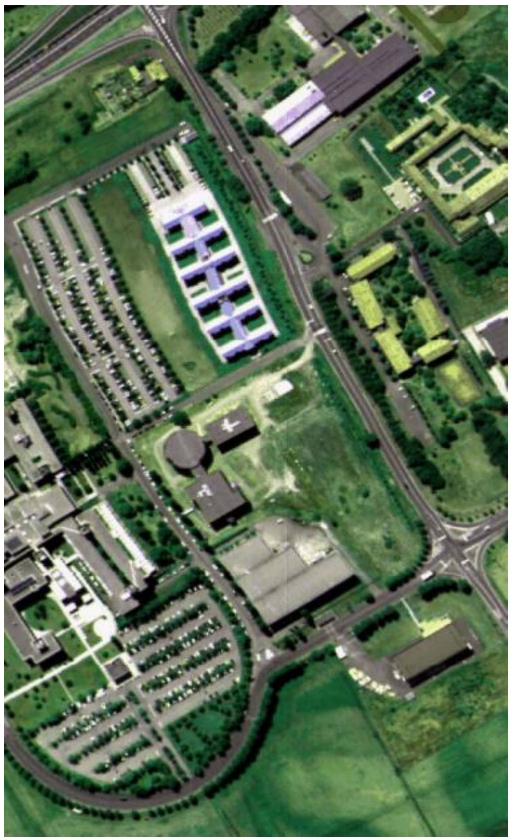
2008: What can we learn from hyperspectral satellite imaging?



Teledetection is growing up ! And applications too…
More than 13.000 objects turn around us !

What can we learn from hyperspectral satellite imaging?

Hypespectral image of Univ Pavia, Italy



Each pixel is a vector containing a reflectance spectrum. (This is a lot of data!)

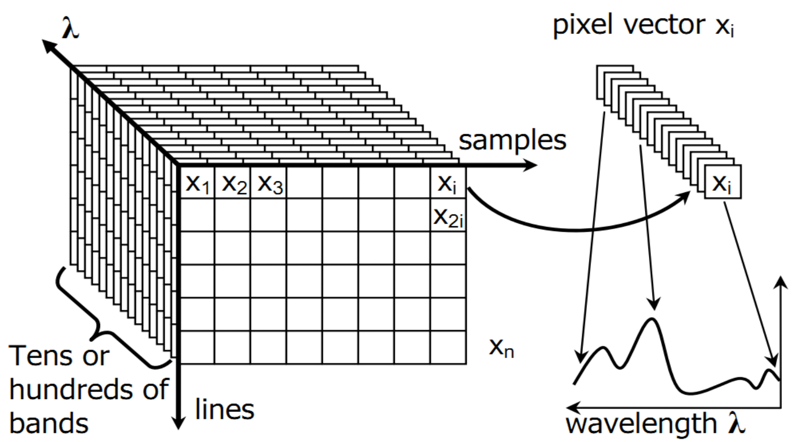
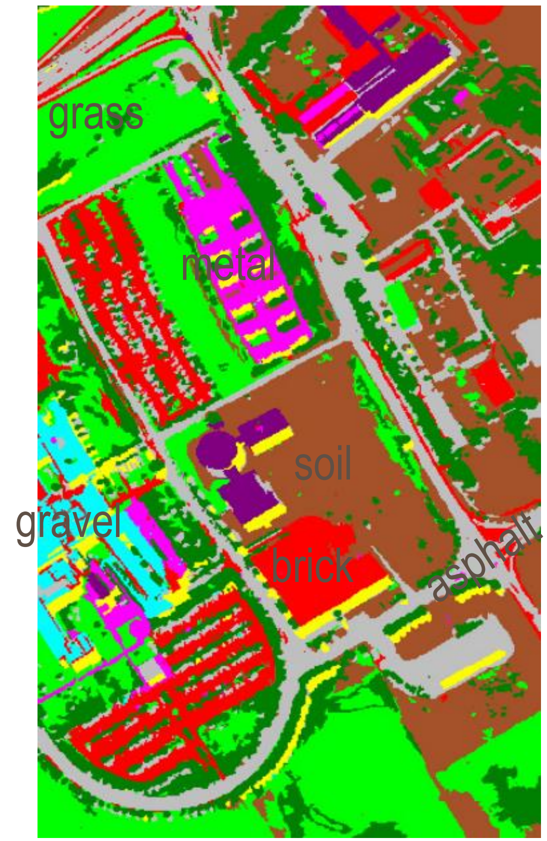


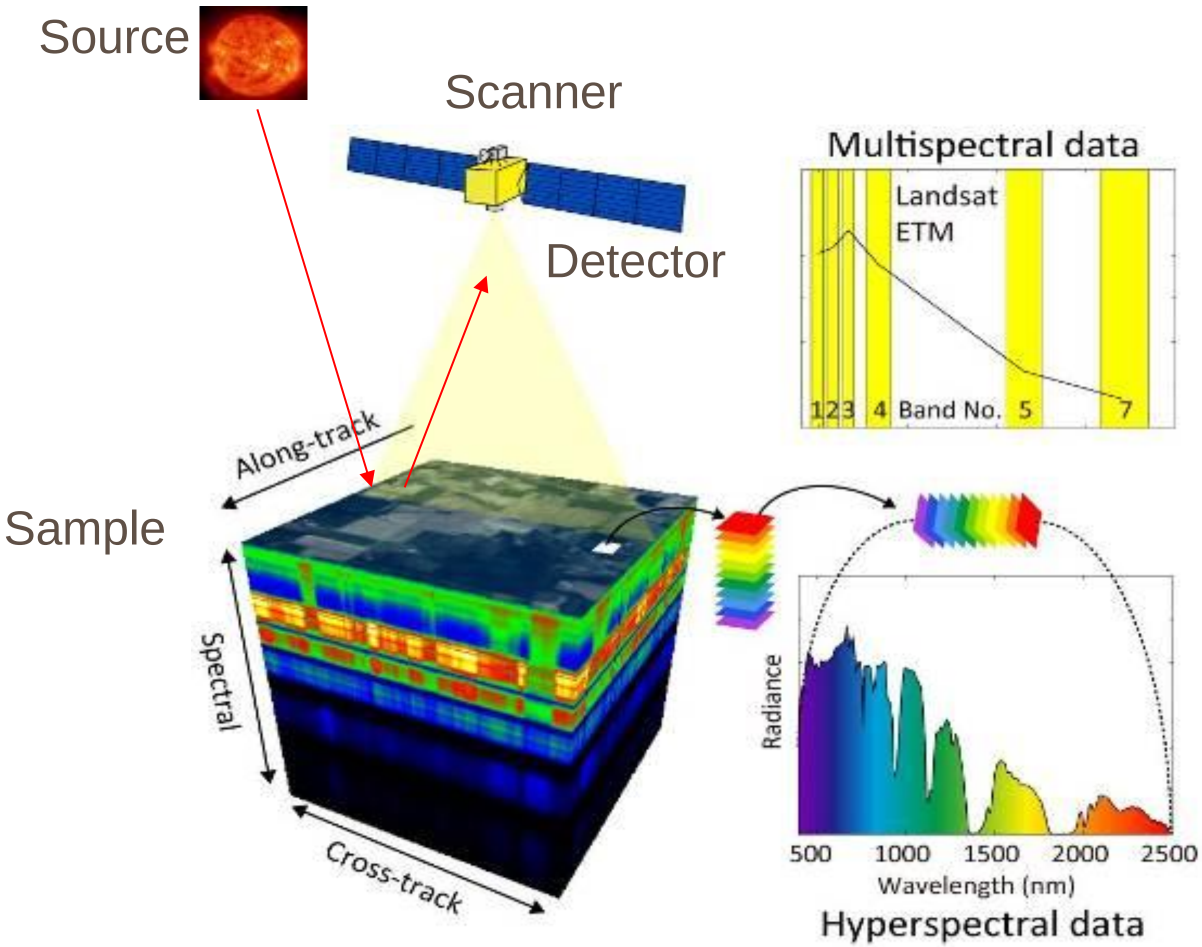
Image processing

Advanced algorithms use spectral + spatial info to classify objects



From Y. Tarabalka PhD, Univ Grenoble, 2010

Could satellite imaging tools inspire us for Building Materials ?



Think about this :

- → 3000 channels Int.+ (x,y) position

⇒3002 octets/pixel

⇒629.146 ko (614Mo) if 2000x2000 pixels for 1 image

- Suppose 1pixel=5m resolution

⇒1image = 100 km²

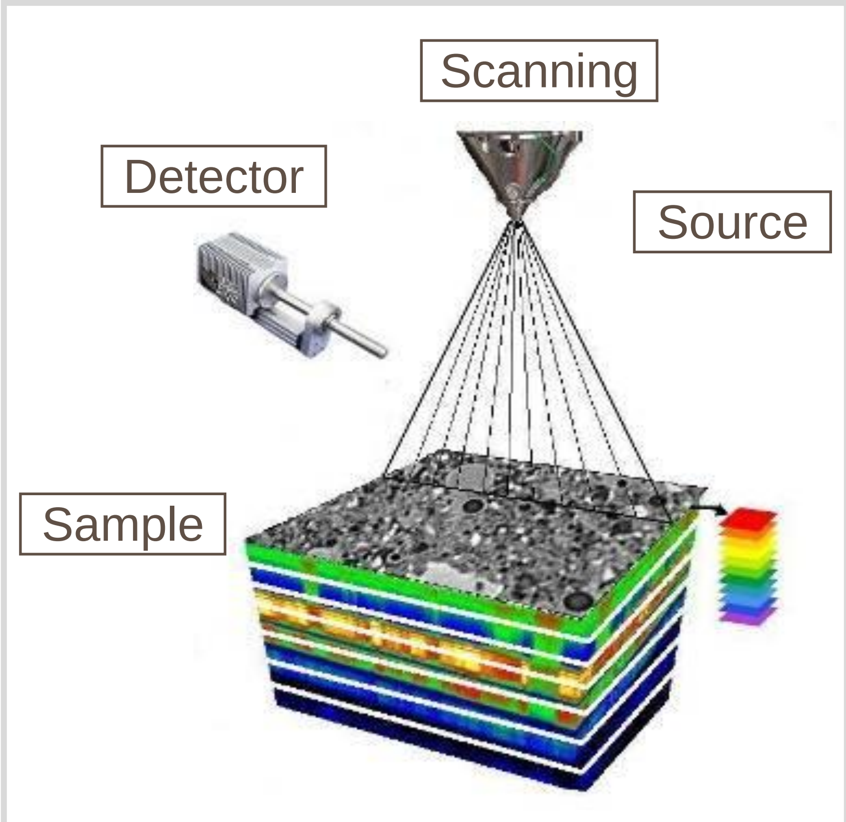
- Paris = 2845 km²

⇒30 images & 17 To of Data !

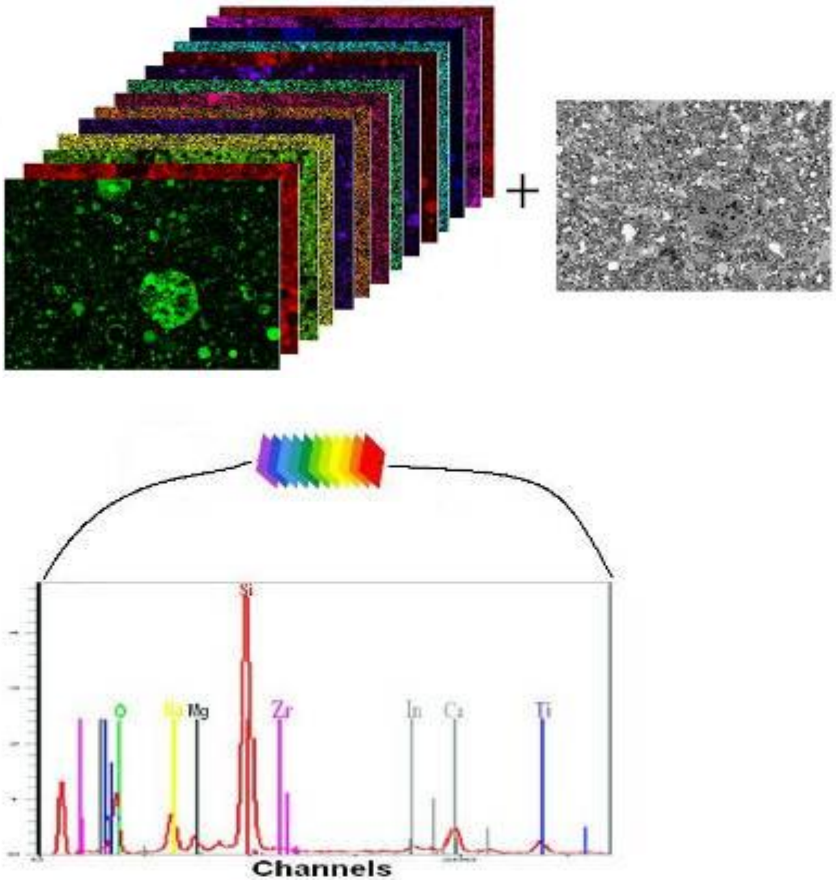
- USA = 10.000.000 km²=6000 To

huge quantity of Data !

Multispectral means a selection of selected channels



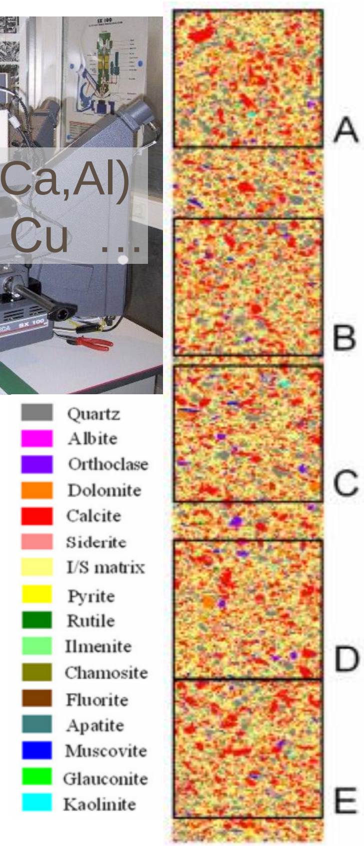
Scanning Electron Microscope



The more simplest way to do phase clustering

How to get phase Id. & clustering from our S.E.M. datasets ?

- By thresholding the grey-level histogram *(ImageJ®, FiJi®)*
  - *Observe your sample in optical microscope before SEM !*
- Full quantitative mappings
  - *If you have (lot of) time and don't need large analyzed area*
- Unsupervised classification *(K-Means, ME, Clara, deep learning, etc…)*
  - *Let's the computer decide for you !*
- By combining BSE image and a selected elemental map
  - *A 'mask' is used to cluster a specific signature*
- Supervised classification ← **The solution we've chosen**
  - *Welcome to the jungle ! Complex field of knowledge but it gives the best robustness !*



LafargeHolcim

**Robinet, J-C., 2008. Minéralogie, porosité et diffusion des solutés dans l'argilite du callovo-oxfordien de Bure (Meuse/Haute-Marne, France) de l'échelle centimétrique à micrométrique, Thèse de l'université de Poitiers, France*

Some free and commercial tools (non exhaustive)

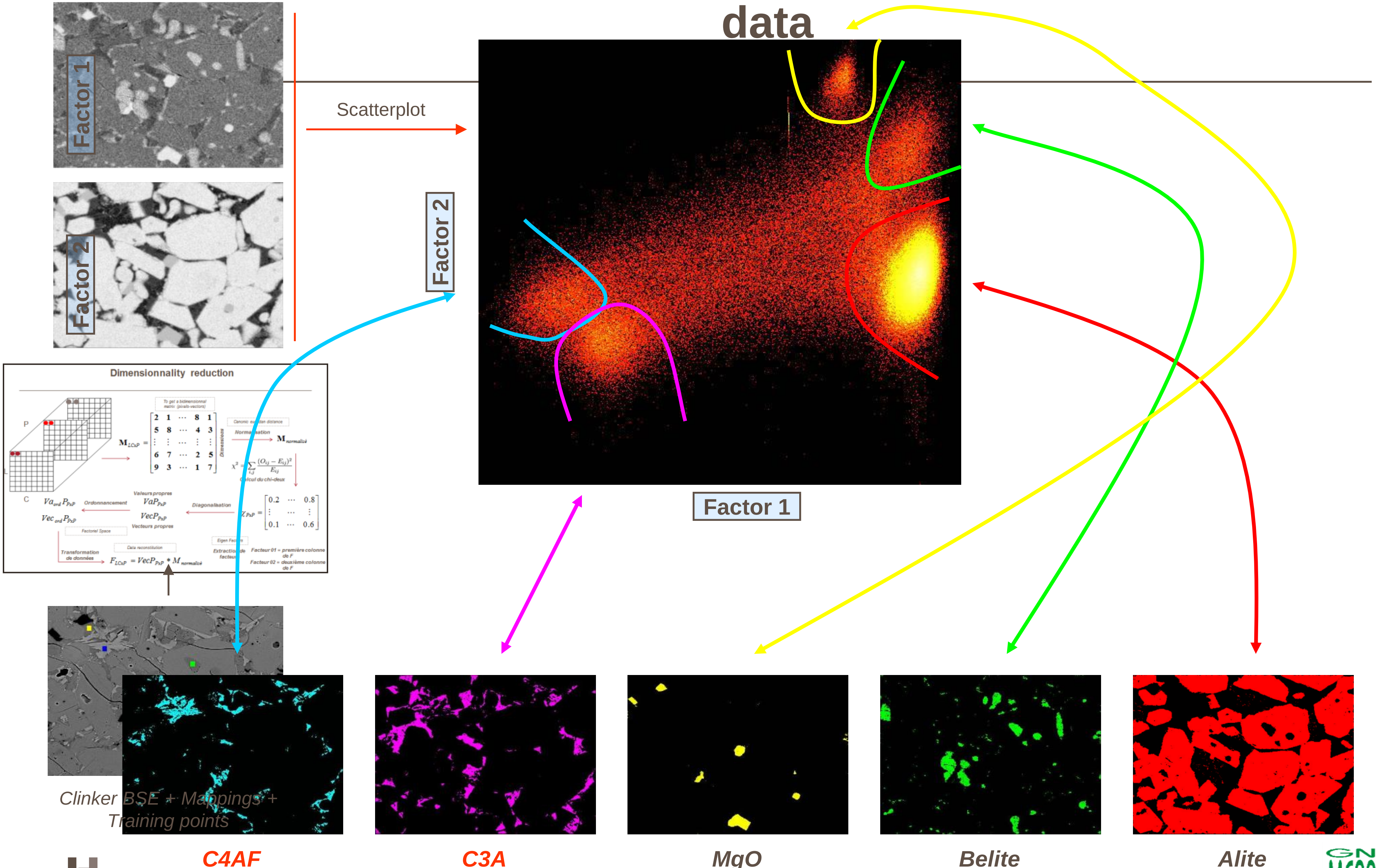
- ImageJ® / FiJi ® - '*Weka*'
- Multispec®
- And all others clustering Algo in the internet ….
  - Python
  - Matlab, etc…

free

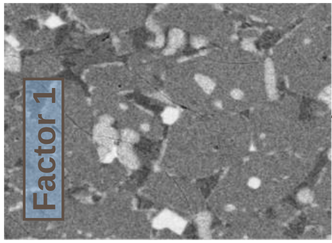
- Phase Cluster Analysis including in EDS soft.
- ENVIE® free soft.
- 'Royce Rolls' = M.L.A. ® *(Mineral Liberation Analysis)*

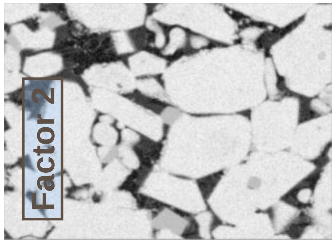
commercial

Starting 2009: Let's apply PCA *('easily')* with SEM clinker data

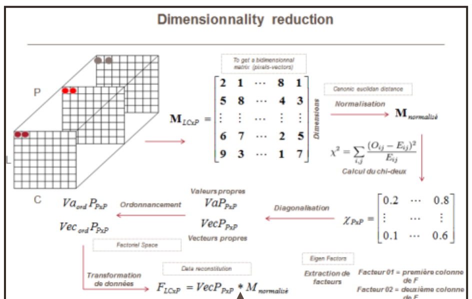


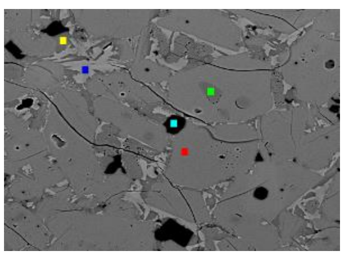
Starting 2009: Let’s apply PCA *(‘easily’)* with SEM clinker data



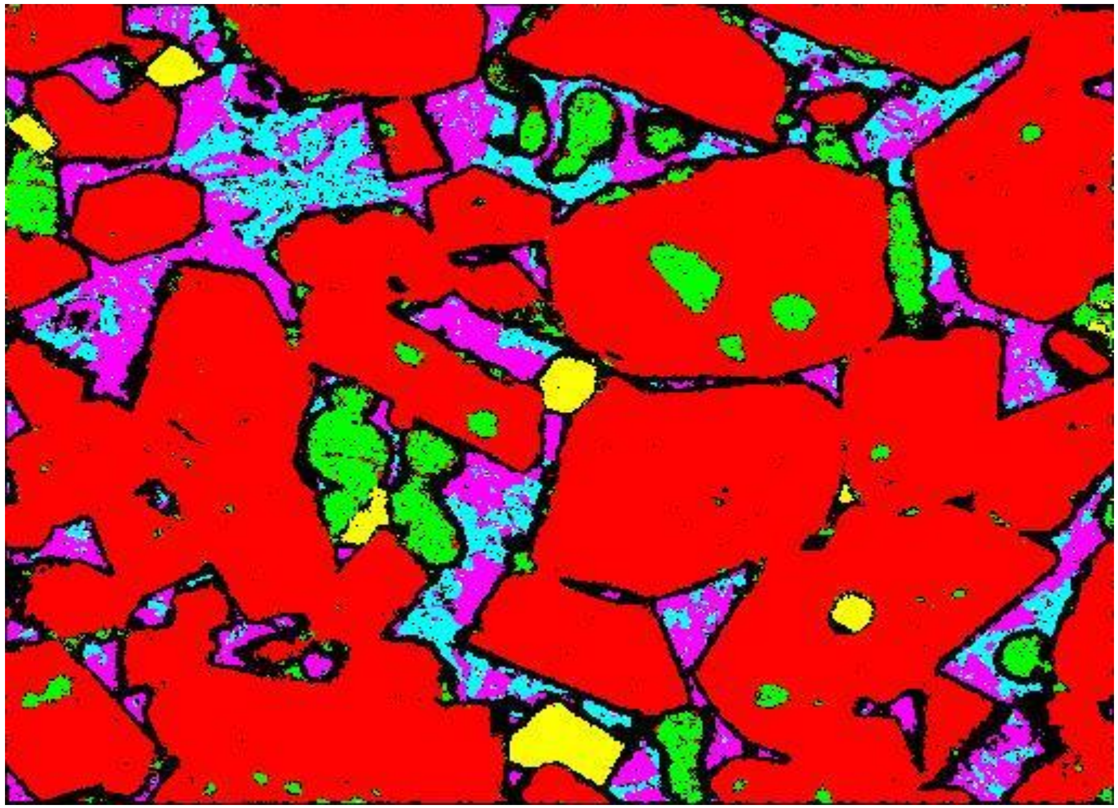


Scatterplot

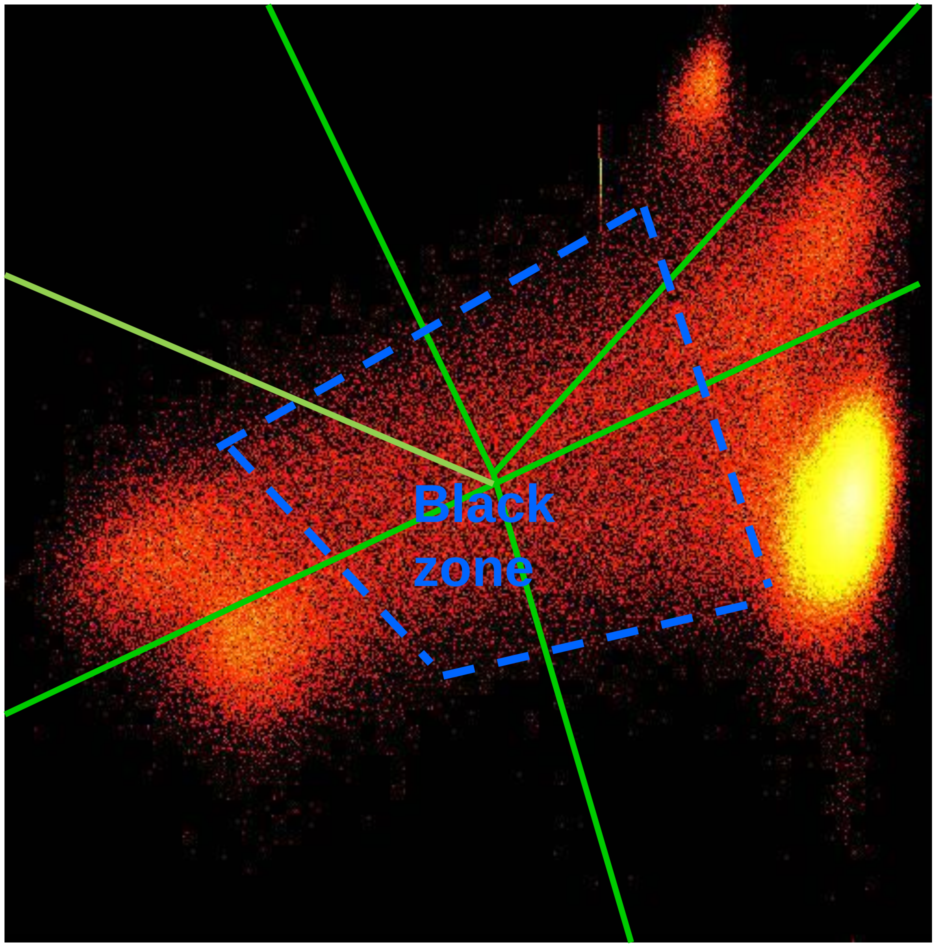


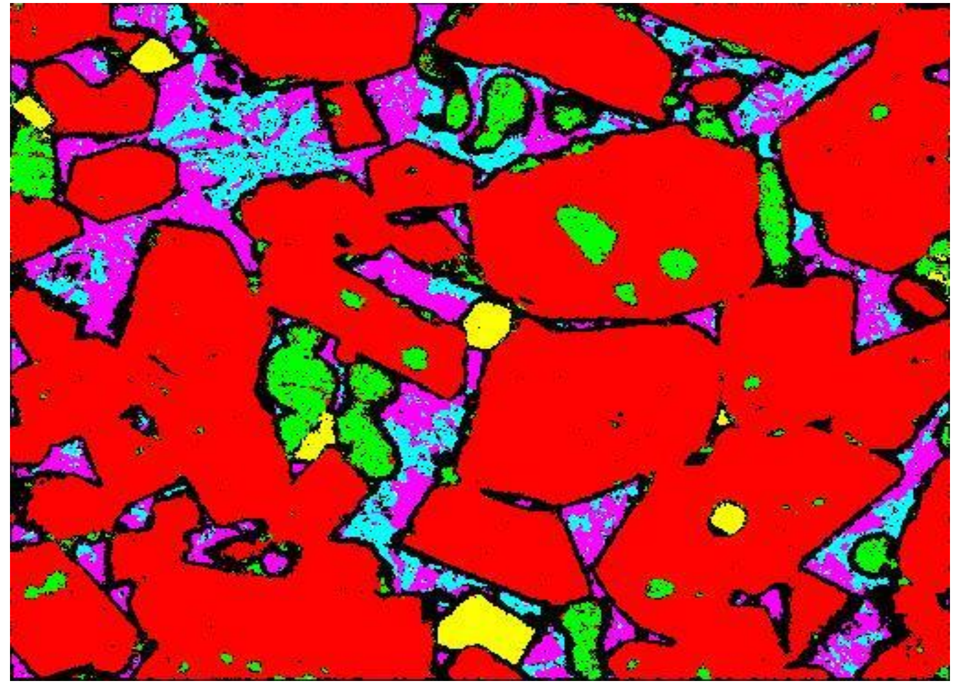


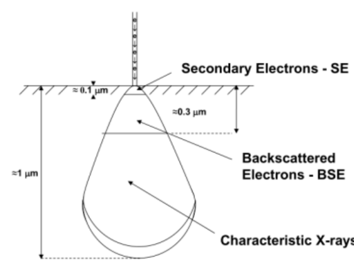
Clinker BSE + Mappings + Training points



What happened near the interface of phases ?



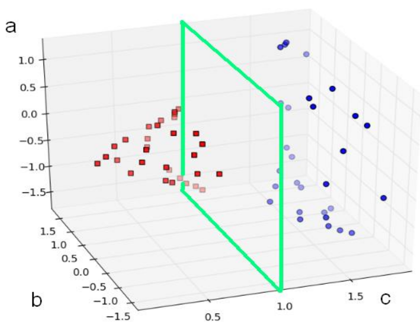




Choosing a classifier: Support Vector Machines (SVM) as a tool to transform hyper-multispectral data into linearly separated set of pixels

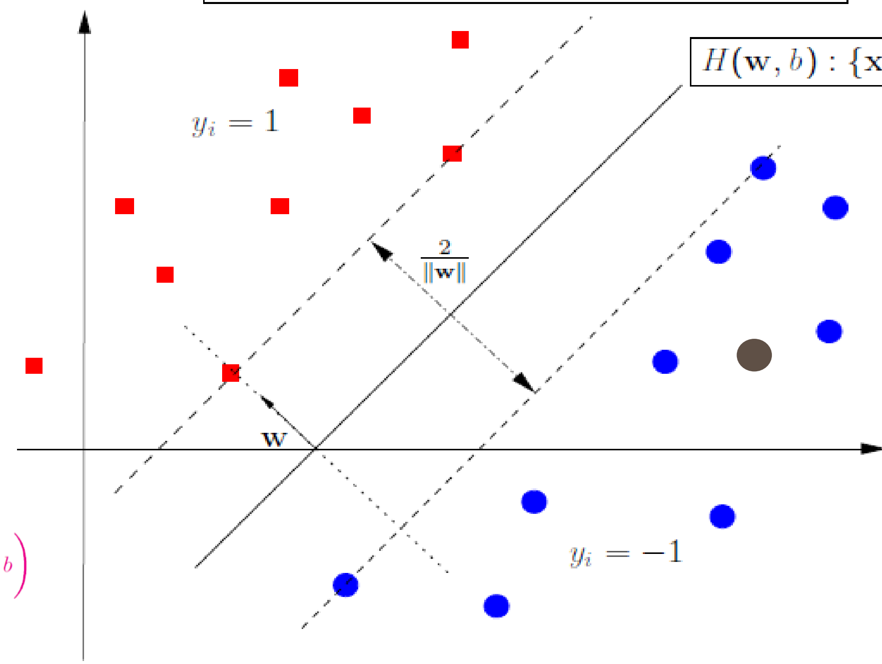
Optimal separating hyperplane [Vapnik-98]:

- Minimize training errors over $\mathcal{S}$
- Maximize the margin $\Longleftrightarrow$ minimize $\|\mathbf{w}\|^2$



$\mathcal{S} = \{(\mathbf{x}^1, y_1), \ldots, (\mathbf{x}^\ell, y_\ell)\} \in \mathbb{R}^n \times \{-1, 1\}$

$H(\mathbf{w}, b) : \{\mathbf{x} | \langle \mathbf{w}, \mathbf{x} \rangle + b = 0\}$



$f(\mathbf{x}) = \langle \mathbf{w}, \mathbf{x} \rangle + b$

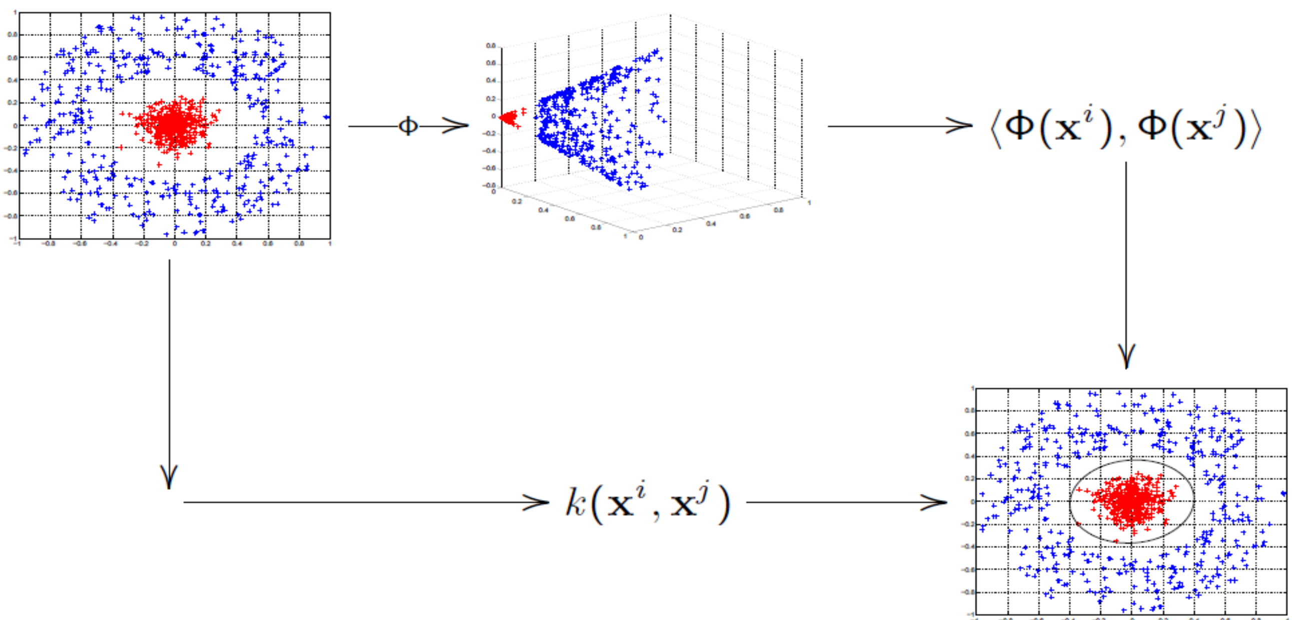
Decision: $g(\mathbf{x}) = \text{sgn}\,(f\,(\mathbf{x})) = \text{sgn}\left(\sum_{i=1}^{\ell} \alpha_i y_i \langle \mathbf{x}^i, \mathbf{x} \rangle + b\right)$

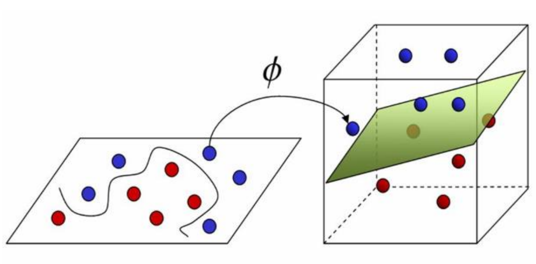
No need to know dimension of working space !

Kernel methods: Use kernel function k (positive semi-definite)

$$k(\mathbf{x}^i, \mathbf{x}^j) = \langle \Phi(\mathbf{x}^i), \Phi(\mathbf{x}^j) \rangle_{\mathcal{H}}$$

Fauvel et al., 2007*





Some kernels:

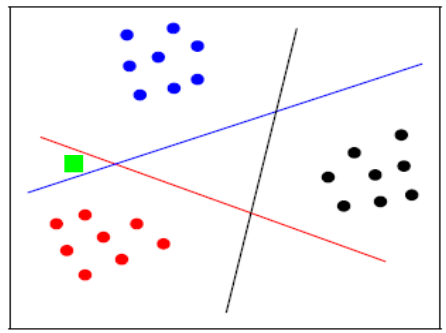
- Polynomial kernel: $k(\mathbf{x}^i, \mathbf{x}^j) = (\langle \mathbf{x}^i, \mathbf{x}^j \rangle + q)^p$
- Gaussian kernel: $k(\mathbf{x}^i, \mathbf{x}^j) = \exp\left(-\frac{\|\mathbf{x}^i - \mathbf{x}^j\|^2}{\gamma^2}\right)$

** Mathieu Fauvel, Jocelyn Chanussot, Jon Atli Benediktsson, Johannes R. Sveinsson: Spectral and spatial classification of hyperspectral data using SVMs and morphological profiles. IGARSS 2007: 4834-4837*

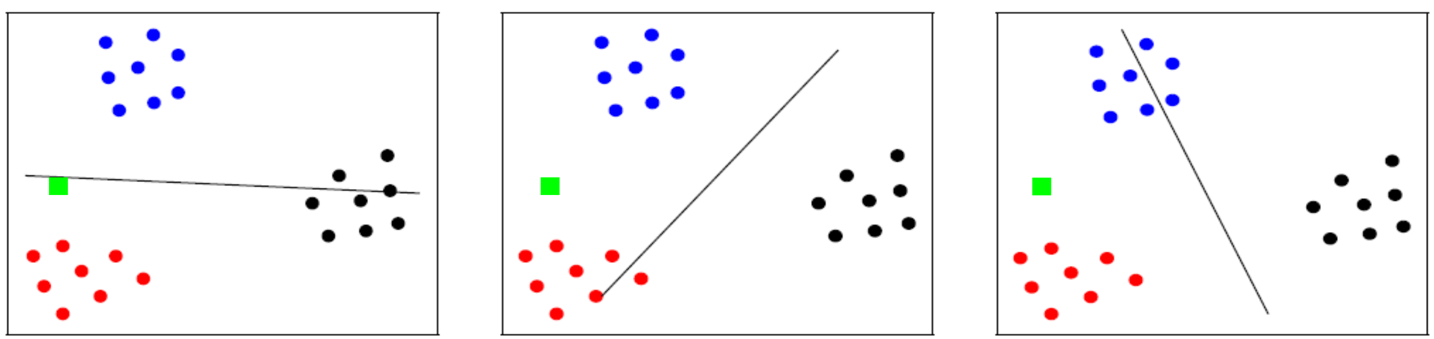
How to separate data in a multiclass problem ?

Multiclass problem: m classes

1. One versus All: m binary classifiers

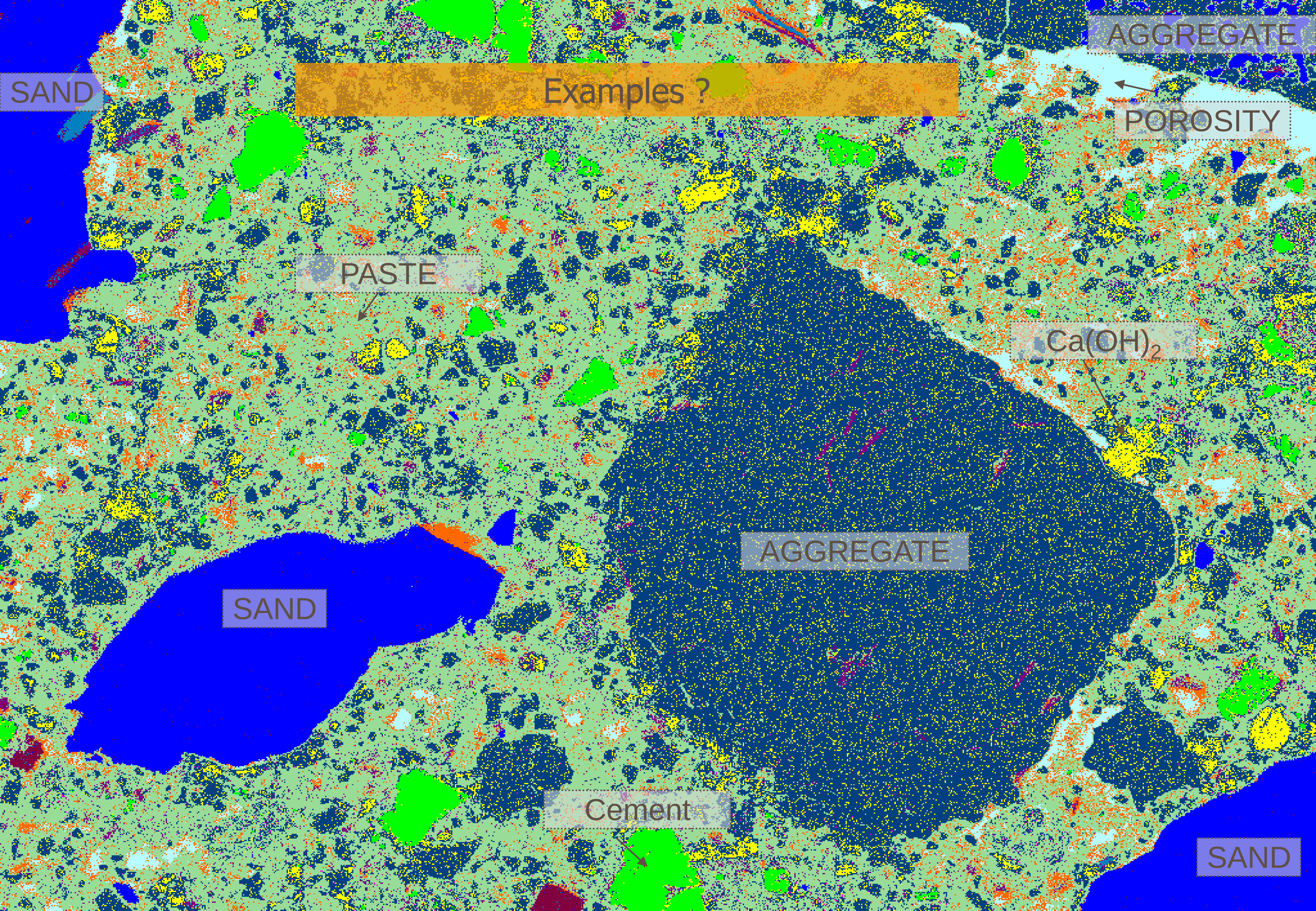


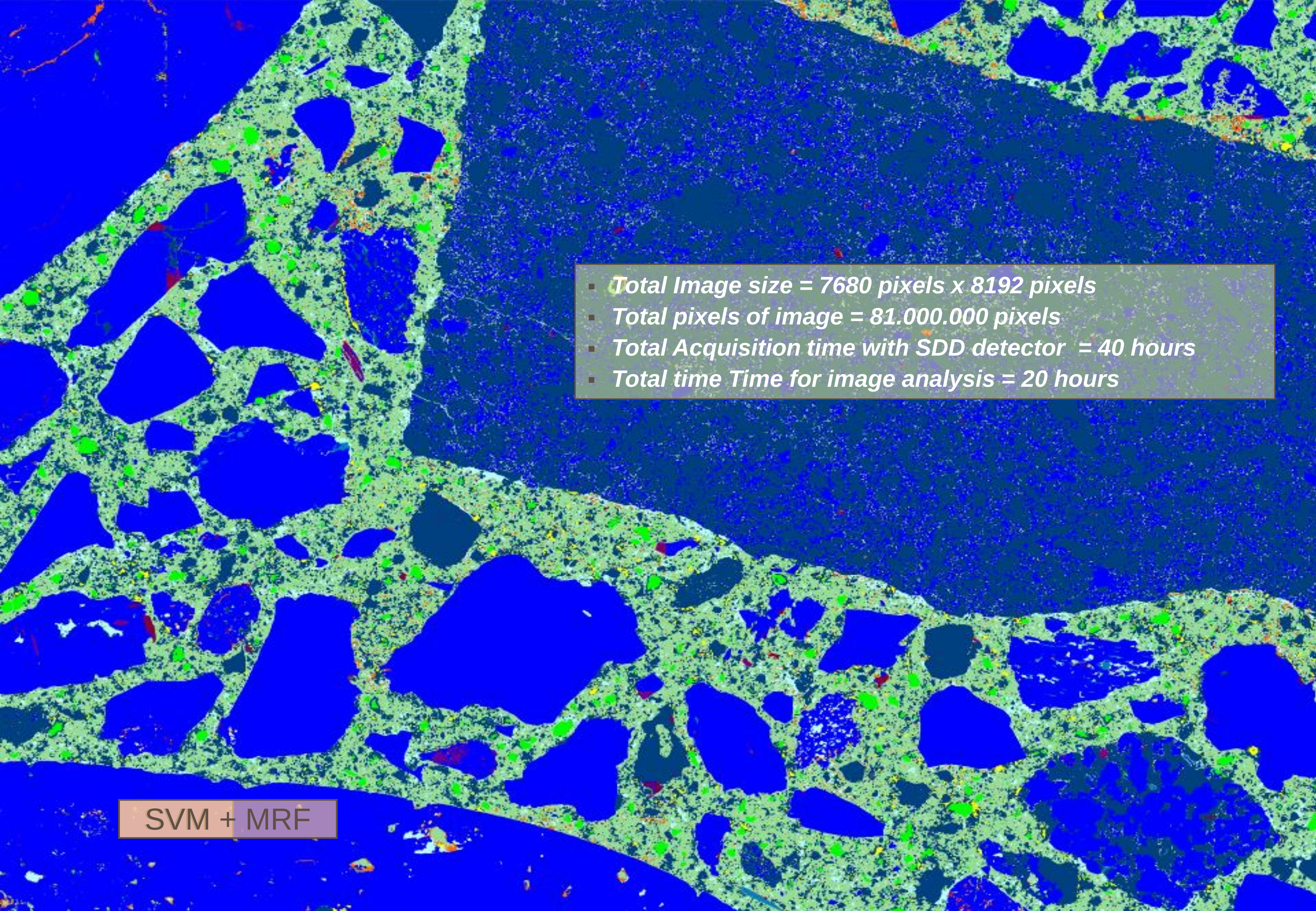
2. One versus One: m(m-1)/2 classifiers

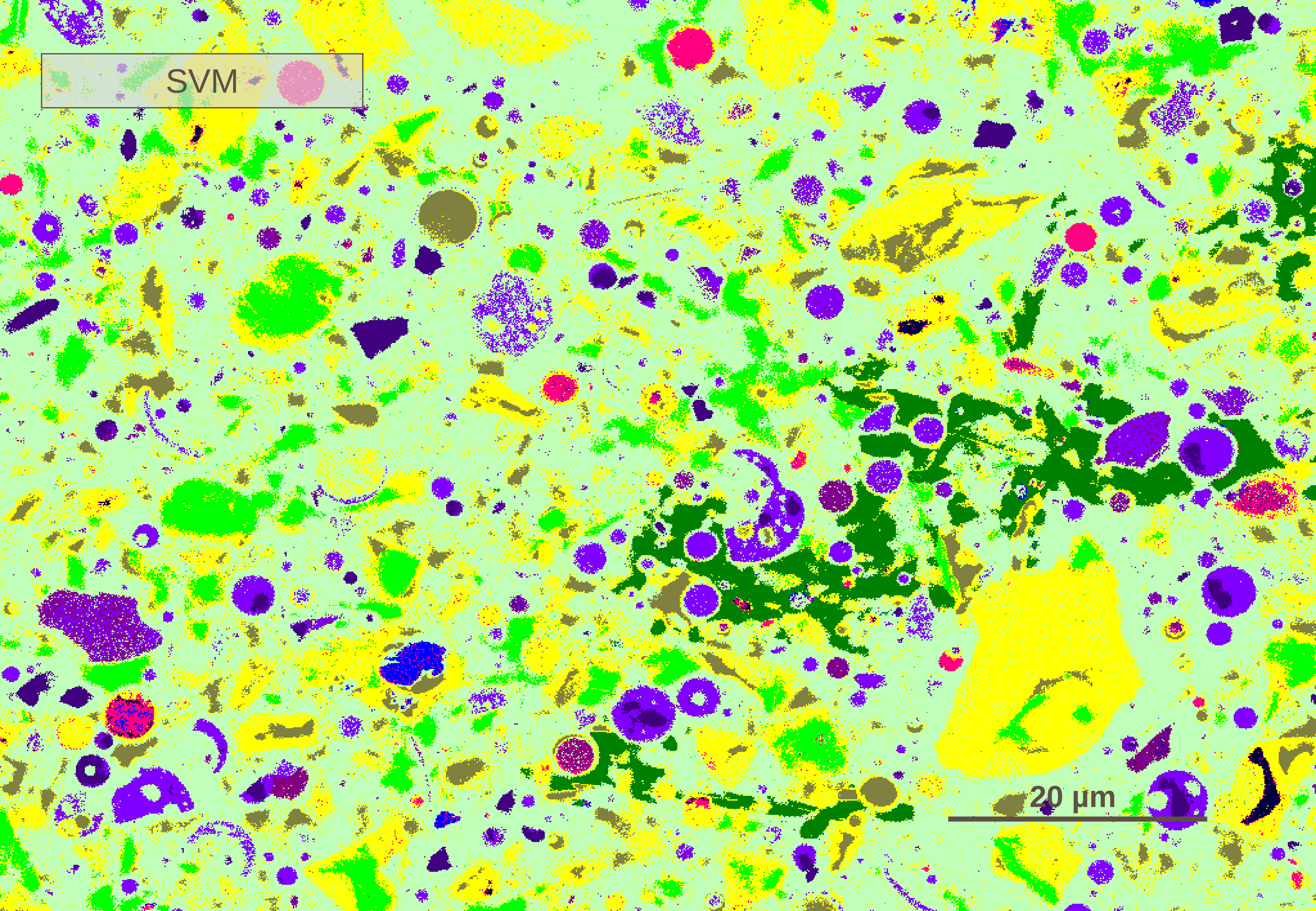


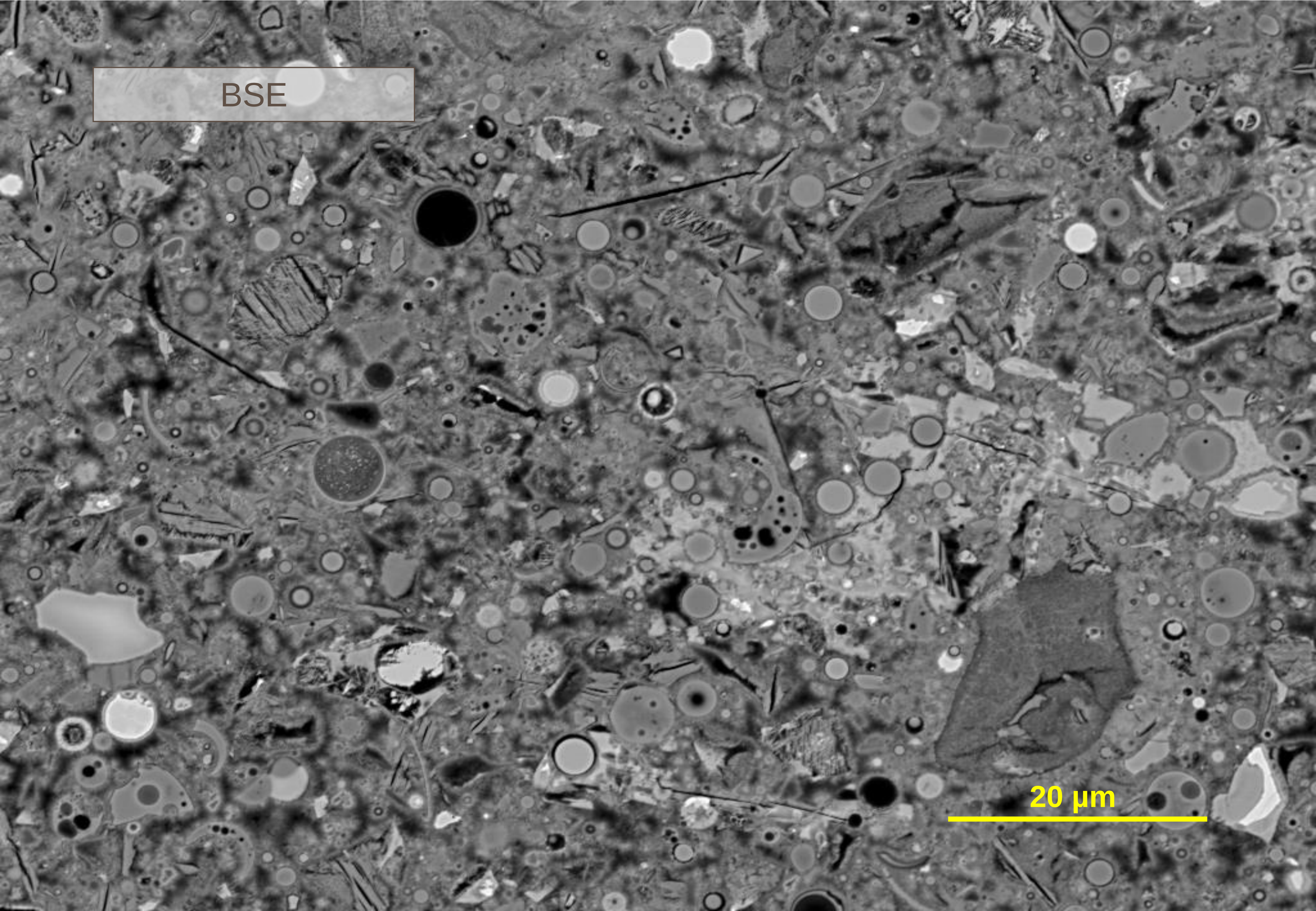
Let’s have a look on ‘Clustering’ applied to building materials

- **1994**: D.P. Bentz & P Stutzman (NIST) combined BSE & X-Ray maps for cement Quant.
- **1997**: Bonnet et al. (Mines Nancy) used PCA as a tool for clustering (rocks)
- **2003**: D.P. Bentz & P Stutzman (NIST) introduced pixel-wize classification
  - Using EDS quantitative maps, applied on clinkers & OPC
- **2003:** Pret et al. (Univ. Poitiers) used WDS quanti mapings for clustering
- **2009**: Kocaba et al. (EPFL) used Mg mapping to measure HD of slag
- **2010**: Ben Haha et al. found a grey level way to quantity fly ashes
- **2010**: Chancey et al. (Austin) used Maps & Multispec® to quantify phases in Anh-FA
- **2013**: Meulenyzer et al. (Lafarge) introduced supervised classification using non quanti mappings of blended pastes
- **2015**: Durdinsky et al. (EPFL) used EDX quantitative maps as input for clustering
- **2015**: Munch et al. (EMPA) combined supervised classification and quanti EDS


Examples ?
AGGREGATE
SAND
POROSITY
PASTE
Ca(OH)2
AGGREGATE
SAND
Cement
SAND


Total Image size = 7680 pixels x 8192 pixels
Total pixels of image = 81.000.000 pixels
Total Acquisition time with SDD detector = 40 hours
Total time Time for image analysis = 20 hours
SVM + MRF


SVM
20 µm

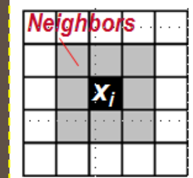

BSE
20 µm

Filtering & spatiality: Need to get info from spatial domain

Boggle effect

NOISE management:
- **Before classification**
- **After classification**

Markov Random Field:
- **'Recuit simulé' based**
- **Reassess classification by taking into account class probabilities of pixel xi and of its neighbors.**
- **Spatial energy minimisation**



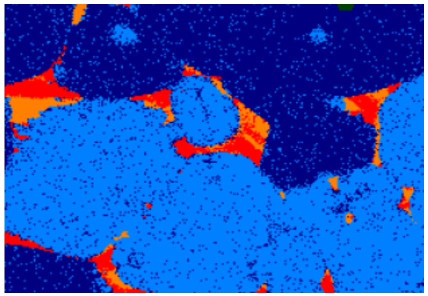
$$U^{E}_{spatial}(\mathbf{x}_i) = \sum_{\mathbf{x}_j \in \mathbf{N}_j} \beta \varepsilon(\mathbf{x}_j)(1-\delta(L_i, L_j)).$$

BM3D [9]:
Estimation of noise variance using Median Absolute Deviation (MAD) **[10]**

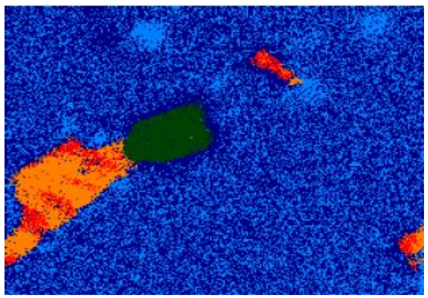
[9] Dabov, K., Foi, A., Katkovnik, V., and Egiazarian, K., "Image denoising by sparse 3D transform-domain collaborative filtering," *IEEE Transactions on Image Processing* **16** (August 2007).

[10] Hoaglin, D., Mosteller, F., and Tukey, J., [*Understanding robust and exploratory data analysis*], vol. 3, Wiley New York (1983).

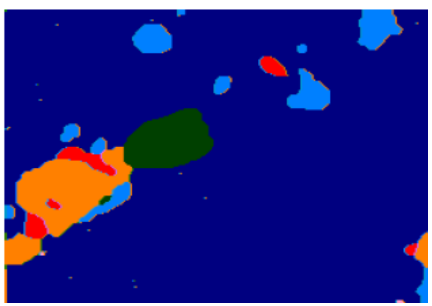
M.R.F.



Clinker with alite / belite

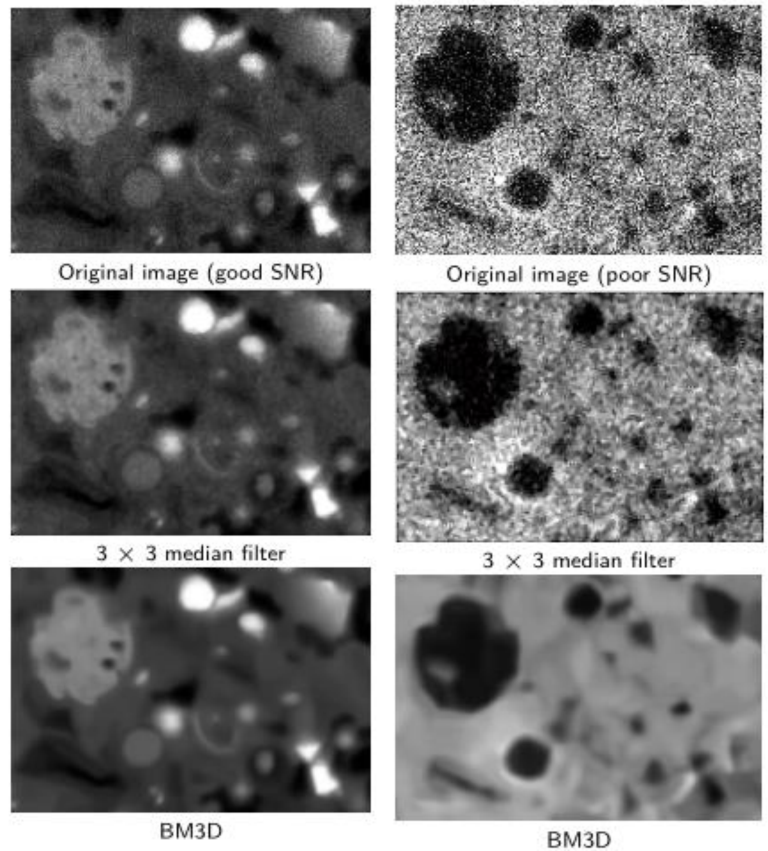


Clinker with alite (SVM)



Clinker with alite (SVM + MRF)

BM3D



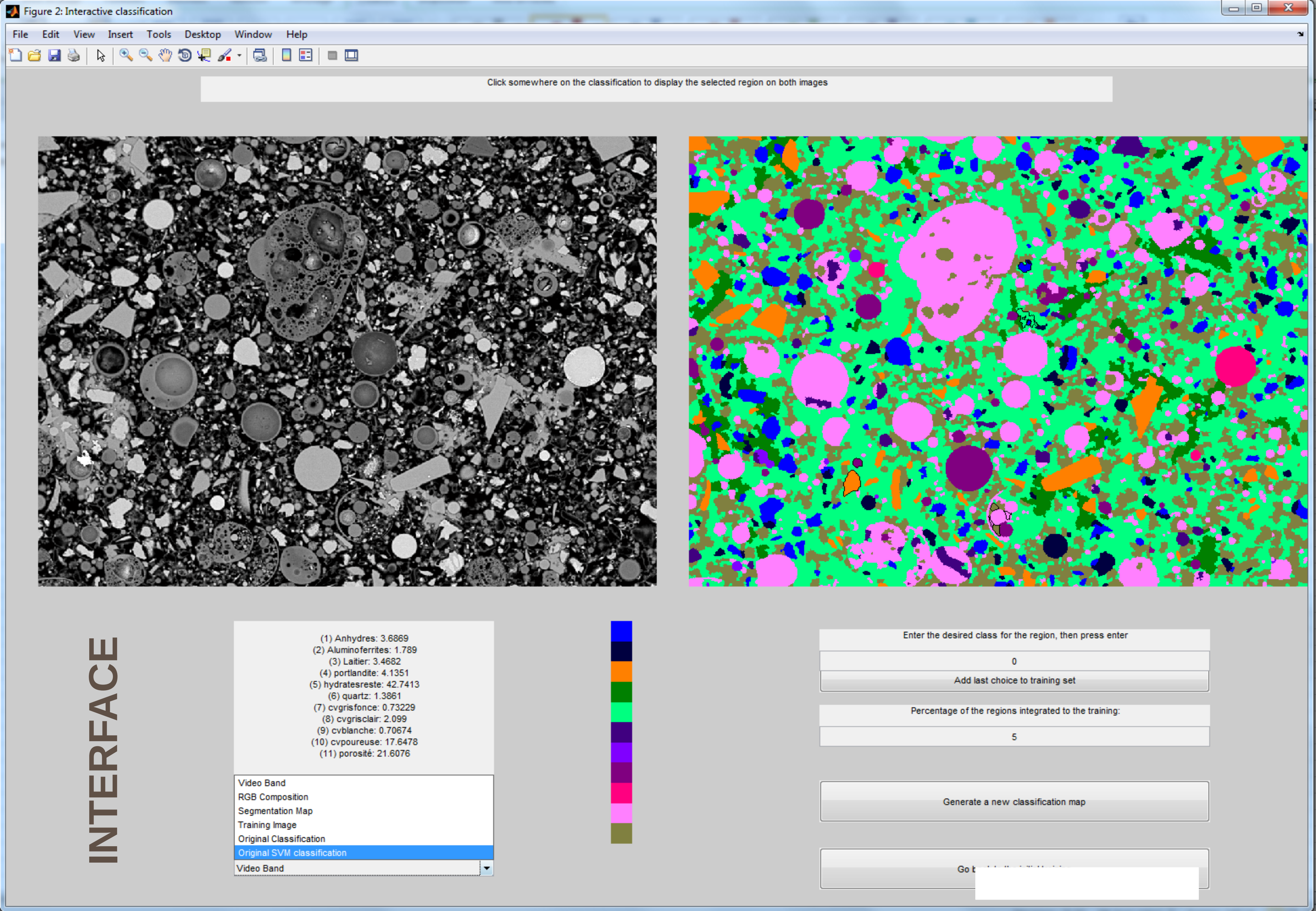
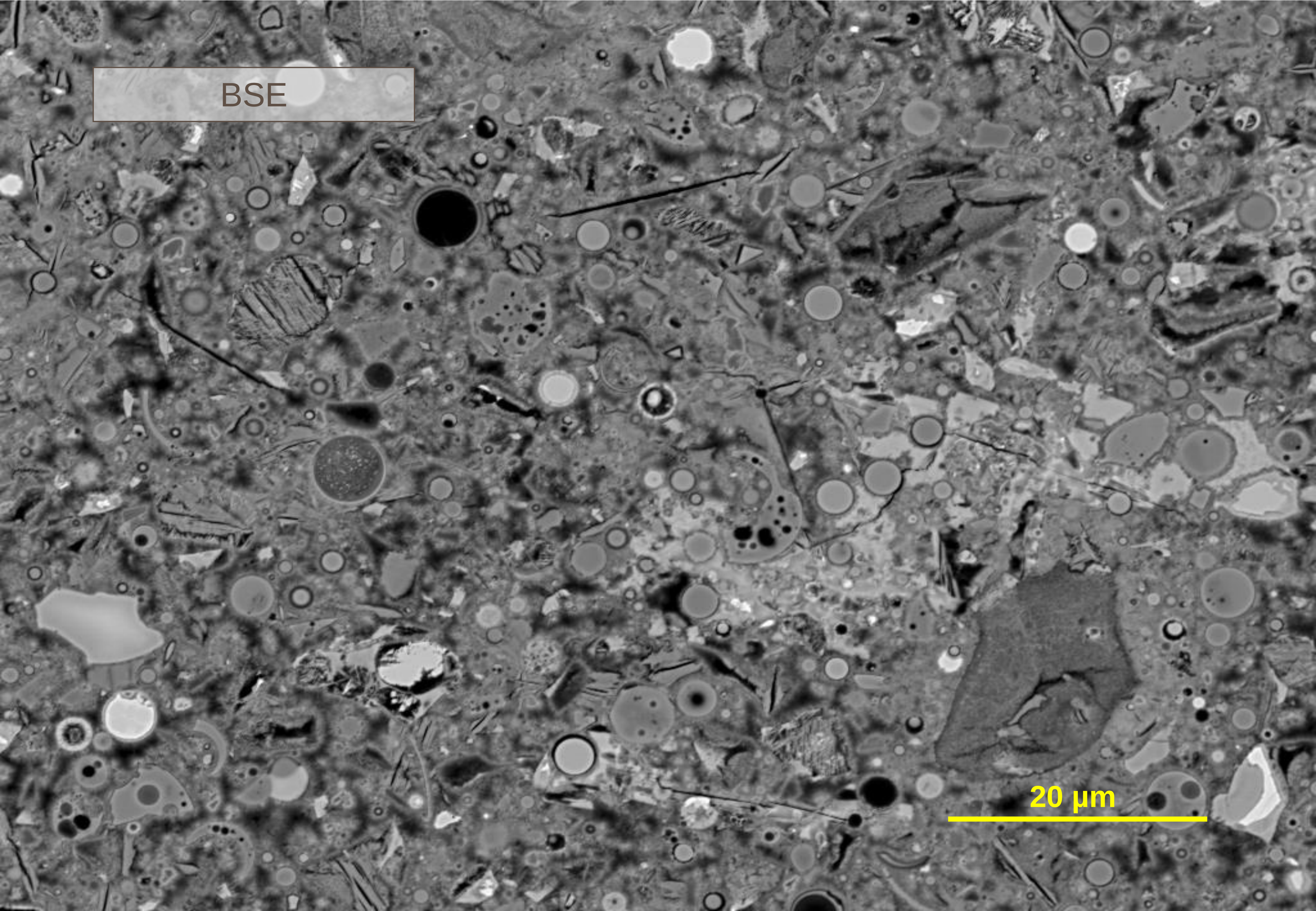
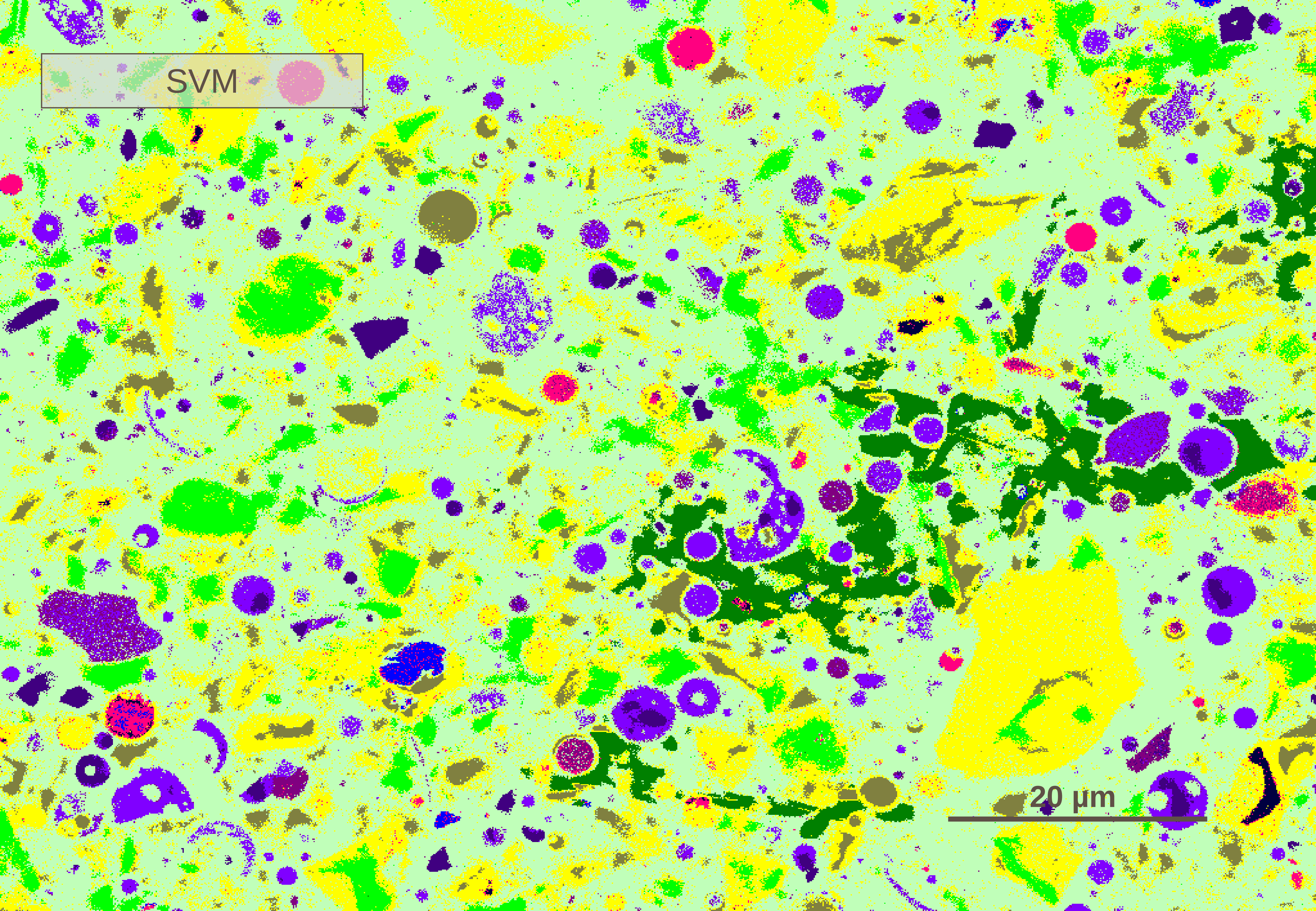
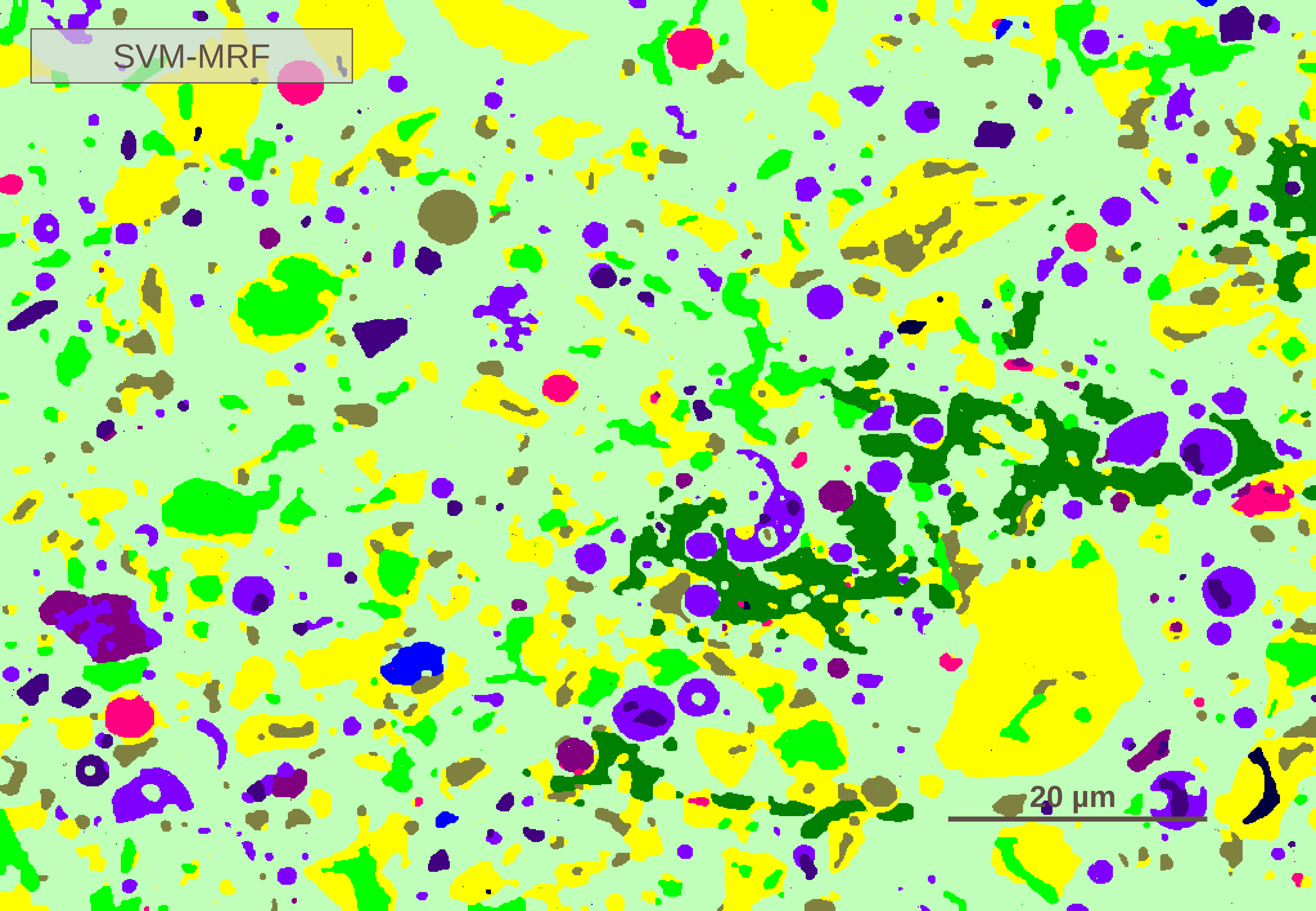
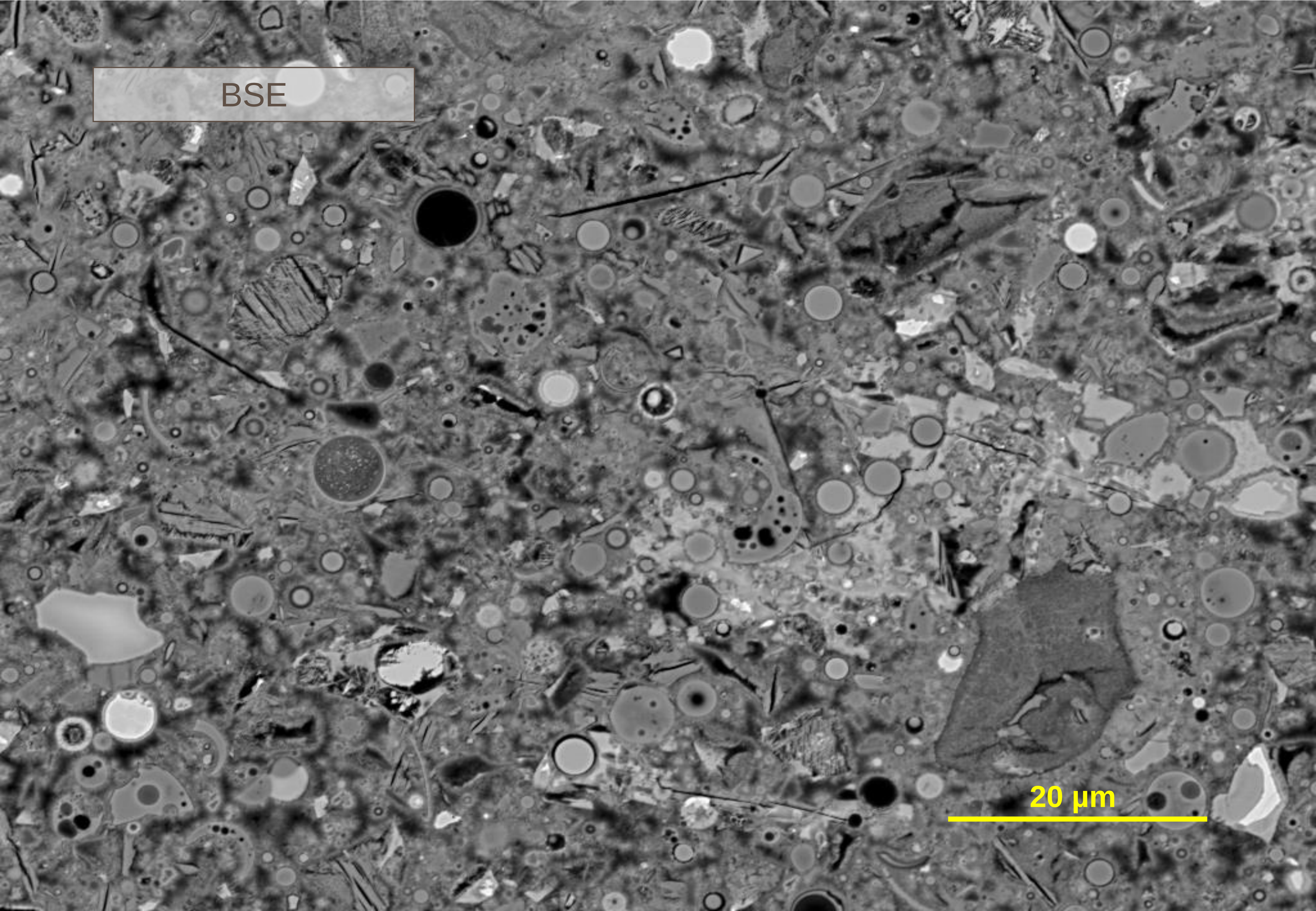


Figure 2: Interactive classification
File Edit View Insert Tools Desktop Window Help
Click somewhere on the classification to display the selected region on both images
INTERFACE
(1) Anhydres: 3.6869
(2) Aluminoferrites: 1.789
(3) Laitier: 3.4682
(4) portlandite: 4.1351
(5) hydratesreste: 42.7413
(6) quartz: 1.3861
(7) cvgrisfonce: 0.73229
(8) cvgrisclair: 2.099
(9) cvblanche: 0.70674
(10) cvpoureuse: 17.6478
(11) porosité: 21.6076
Video Band
RGB Composition
Segmentation Map
Training Image
Original Classification
Original SVM classification
Video Band
Enter the desired class for the region, then press enter
0
Add last choice to training set
Percentage of the regions integrated to the training:
5
Generate a new classification map
Go b

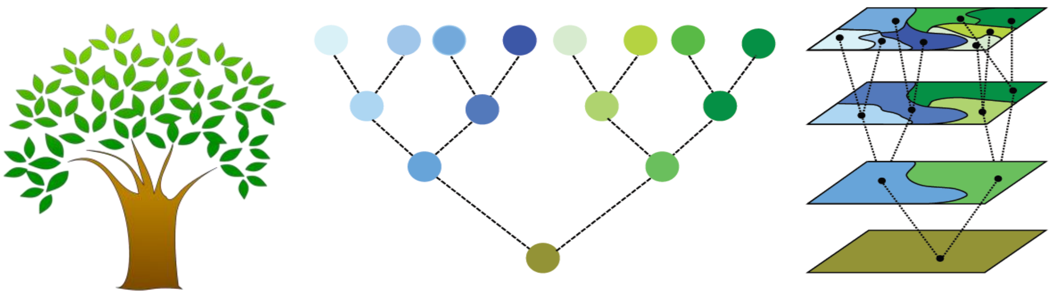

BSE
20 μm


SVM
20 µm


SVM-MRF
20 µm

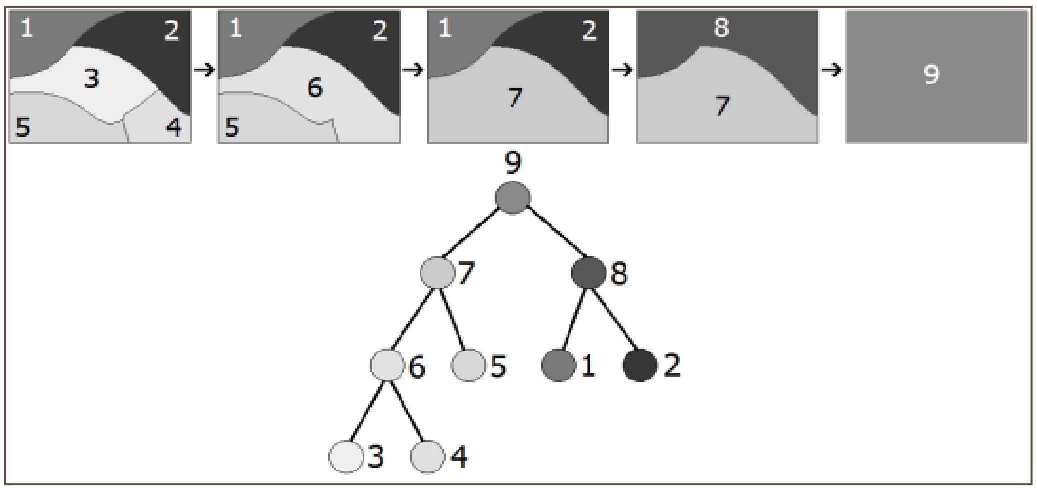

BSE
20 µm

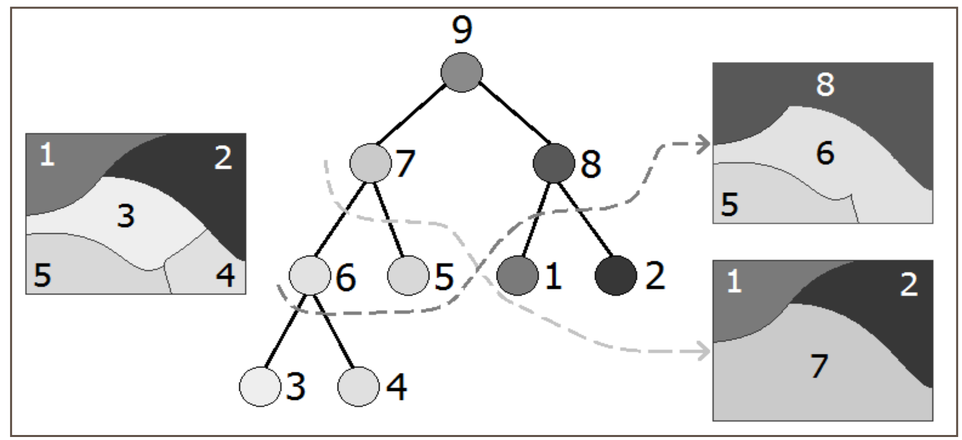
Supervision of the supervisation: Binary of Partition Tree



All pixels are separate regions

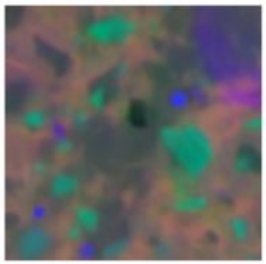
All pixels are merge into 1 region (= the image)



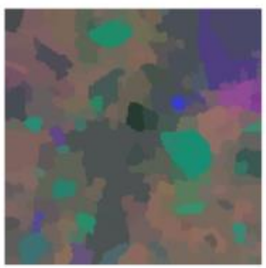


BPT with our eyes

(a) Video band.

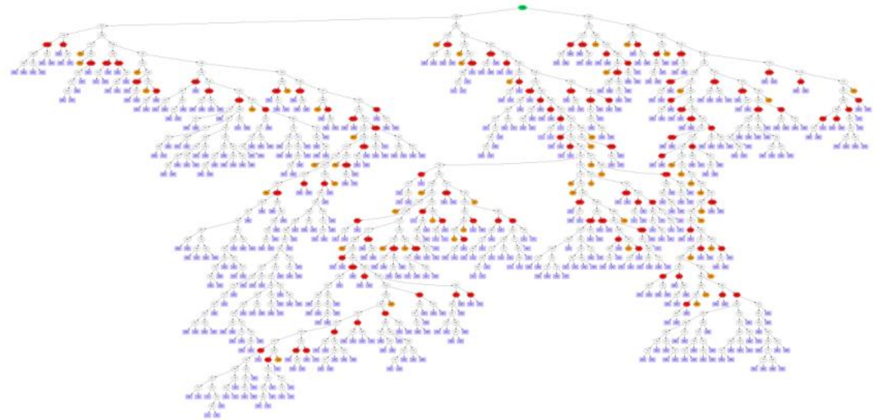


(b) RGB composition (first three bands of a PCA on the denoised data).

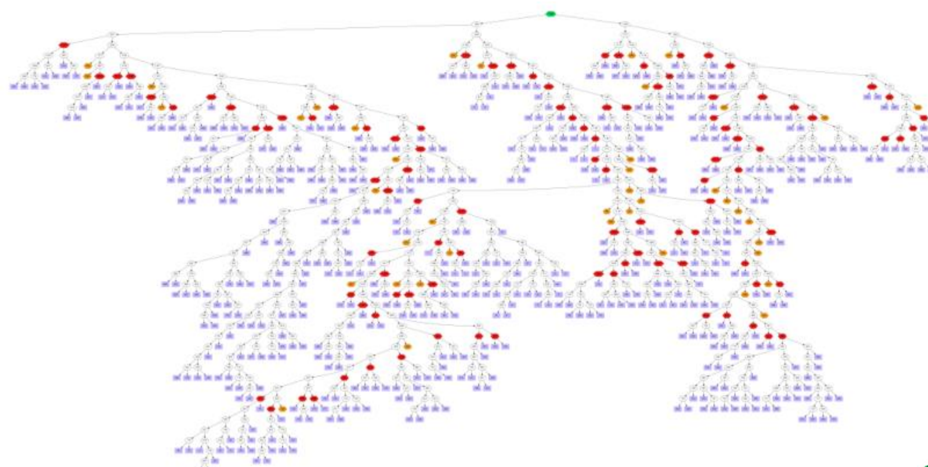


(c) Automatic segmentation with our method (threshold on SAM: 0.2 rad, threshold on size: 10 pixels).

(d) Correction of the automatic segmentation with the interface.



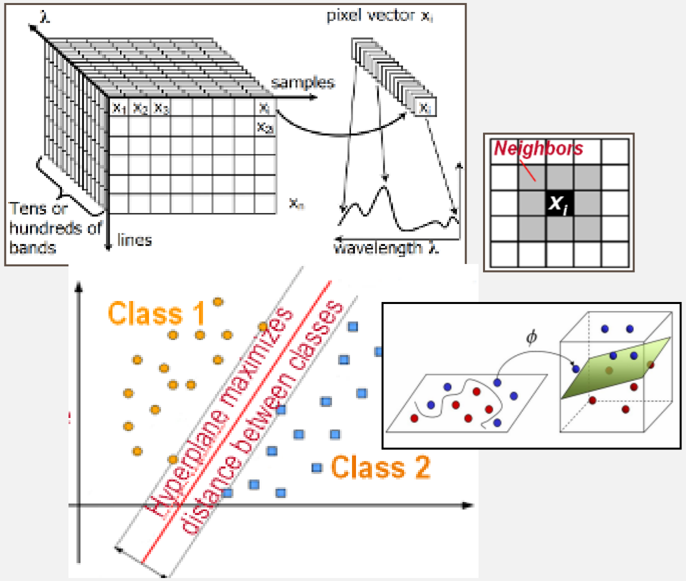
(a) BPT corresponding to the automatic segmentatior



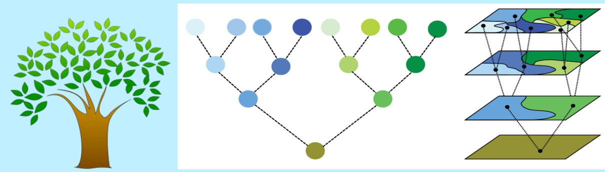
(b) BPT corresponding to the corrected segmentation

LafargeHolcim

Supervised classification: a classifier, a filtering process <u>and an idea to improve final results</u>

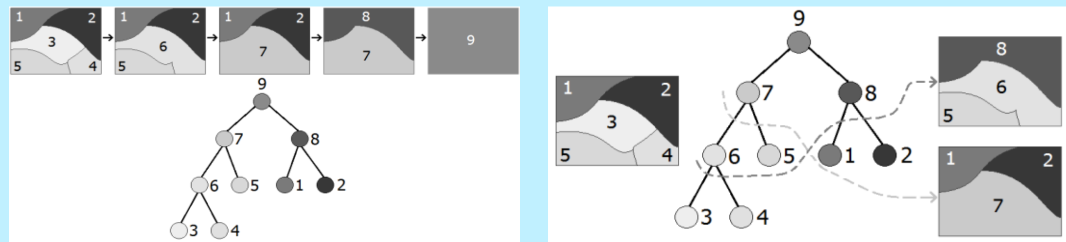


- **Multispect. image (= BSE+X-Ray Maps) is dimensionally <u>reduced</u>**
- **Expert assign some of chosen pixel to a known class → SVM is performing on training data set (= a class has now a specified signature)**
- **SVM is performed on the entire dataset →each new unknown pixel is assigned to a class according its probability of belonging**
- **A filter is applied in order to get more spatiality in images (alone pixels)**
- **Final result is the classified image : all classes are now separated**

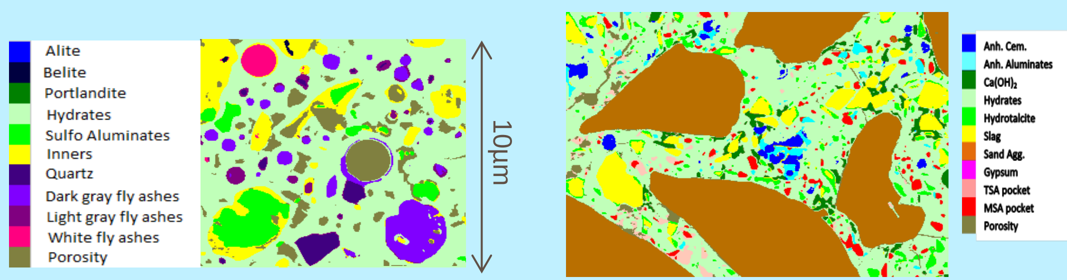


All pixels are separate regions

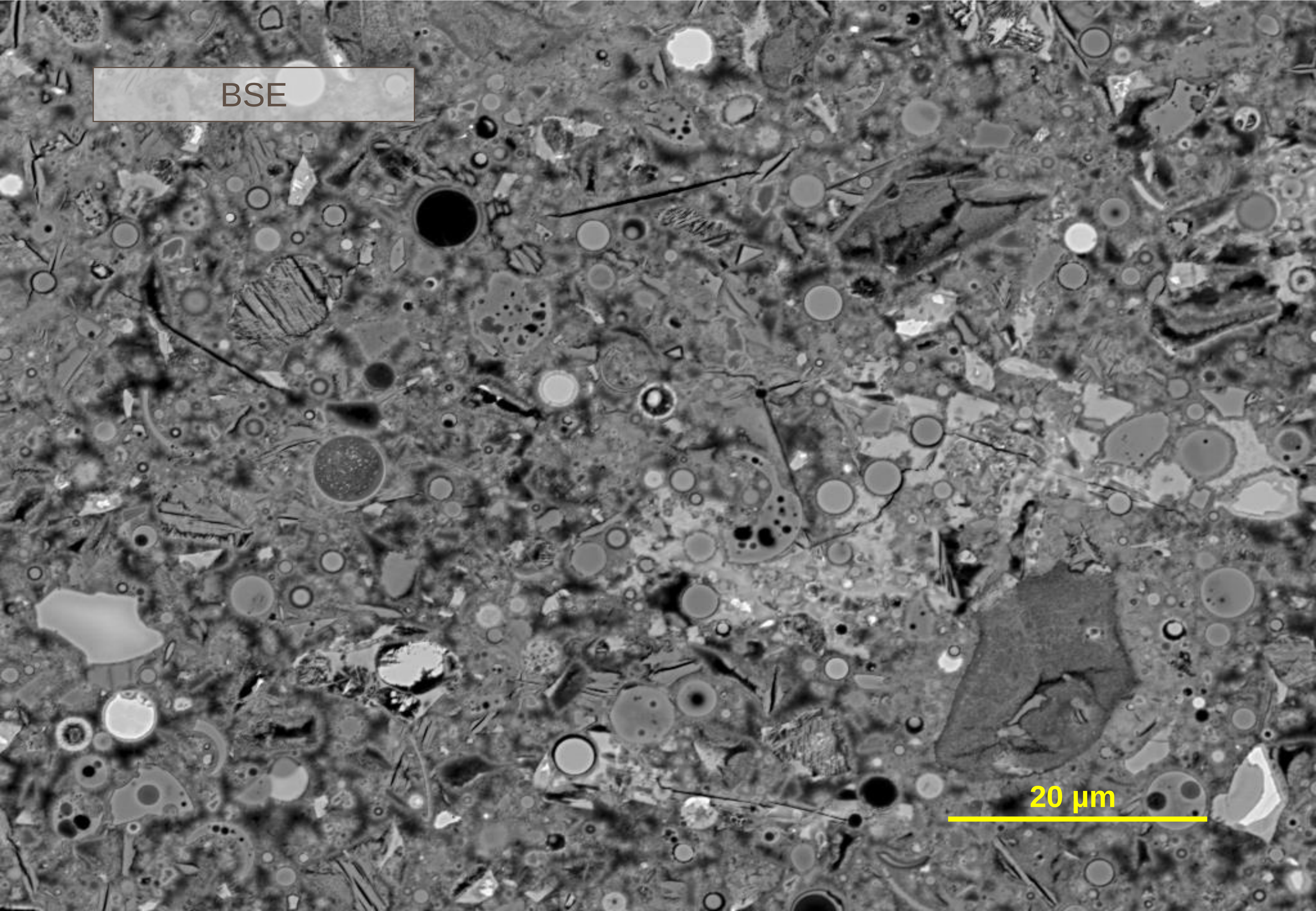
All pixels are merge into 1 region (= the image)

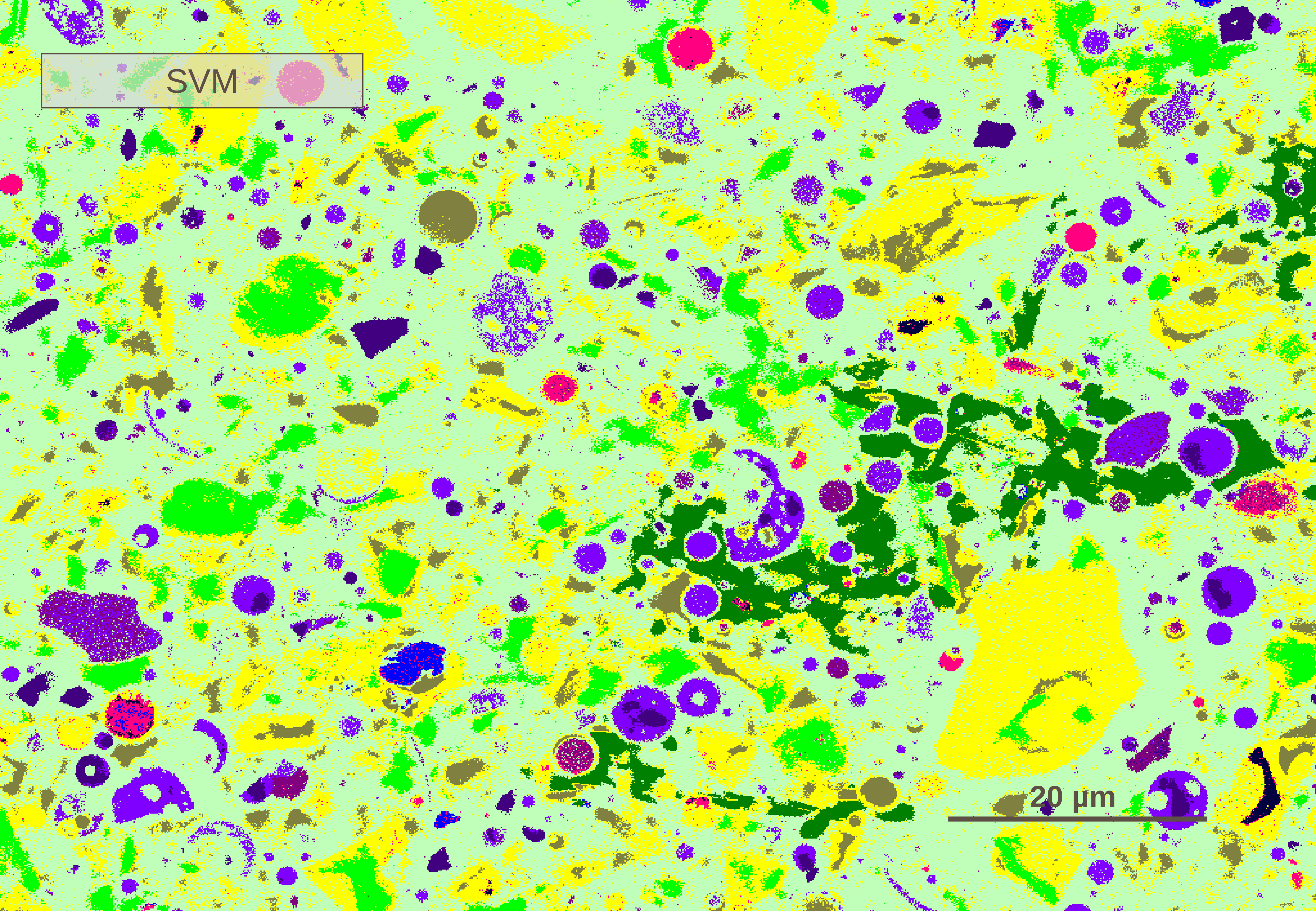


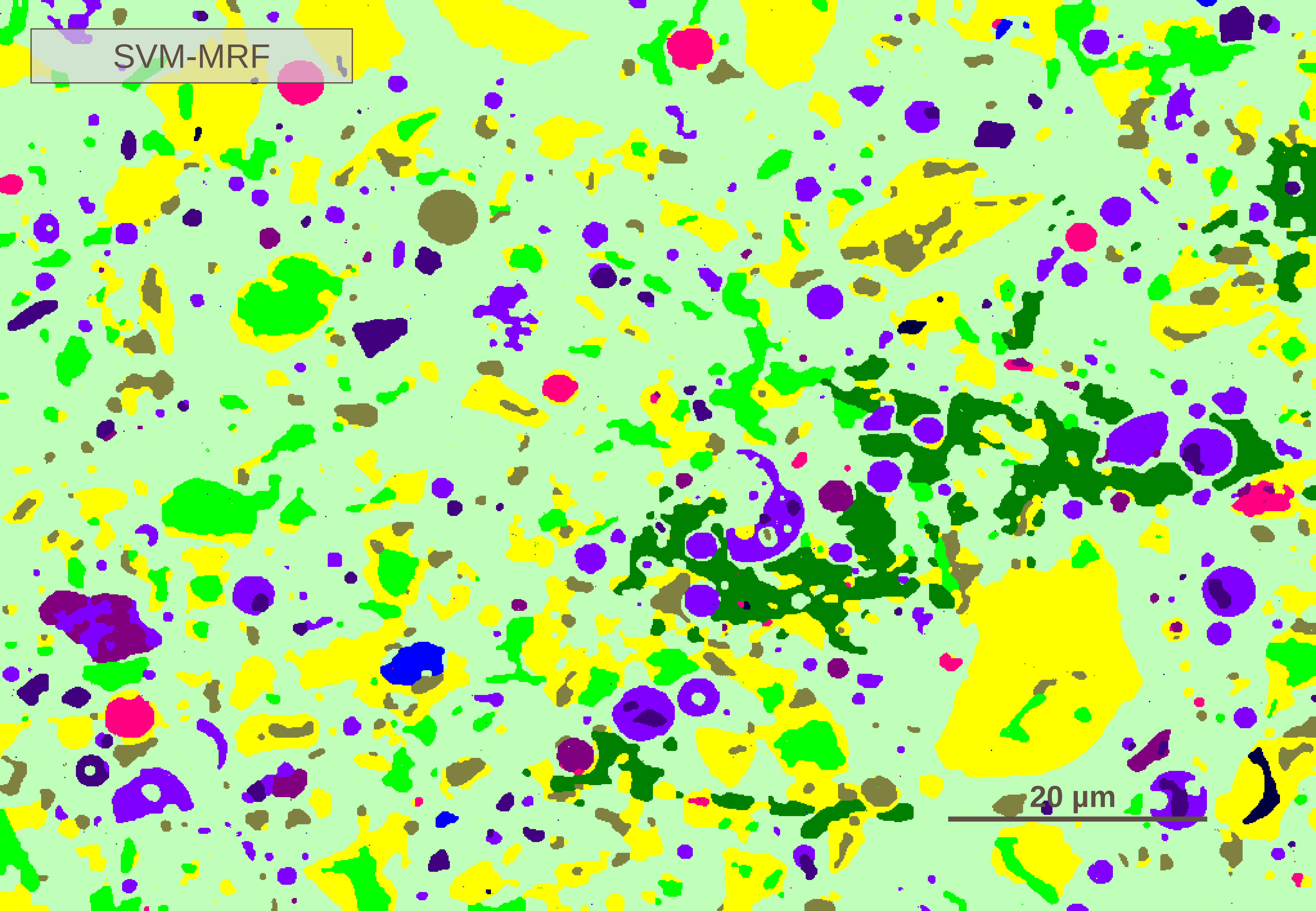
- **BPTs are a <u>region-based</u> hierarchical representation of an image** *[Salembier & Garrido, 2000]*
- **A BPT is built using <u>denoised</u> data using initial SVM partition**
- **An user can interact with classification using <u>pruning</u> process keeping only certain nodes of the tree. A new class can e.g. be created. Then the modified training set provide new classified image**

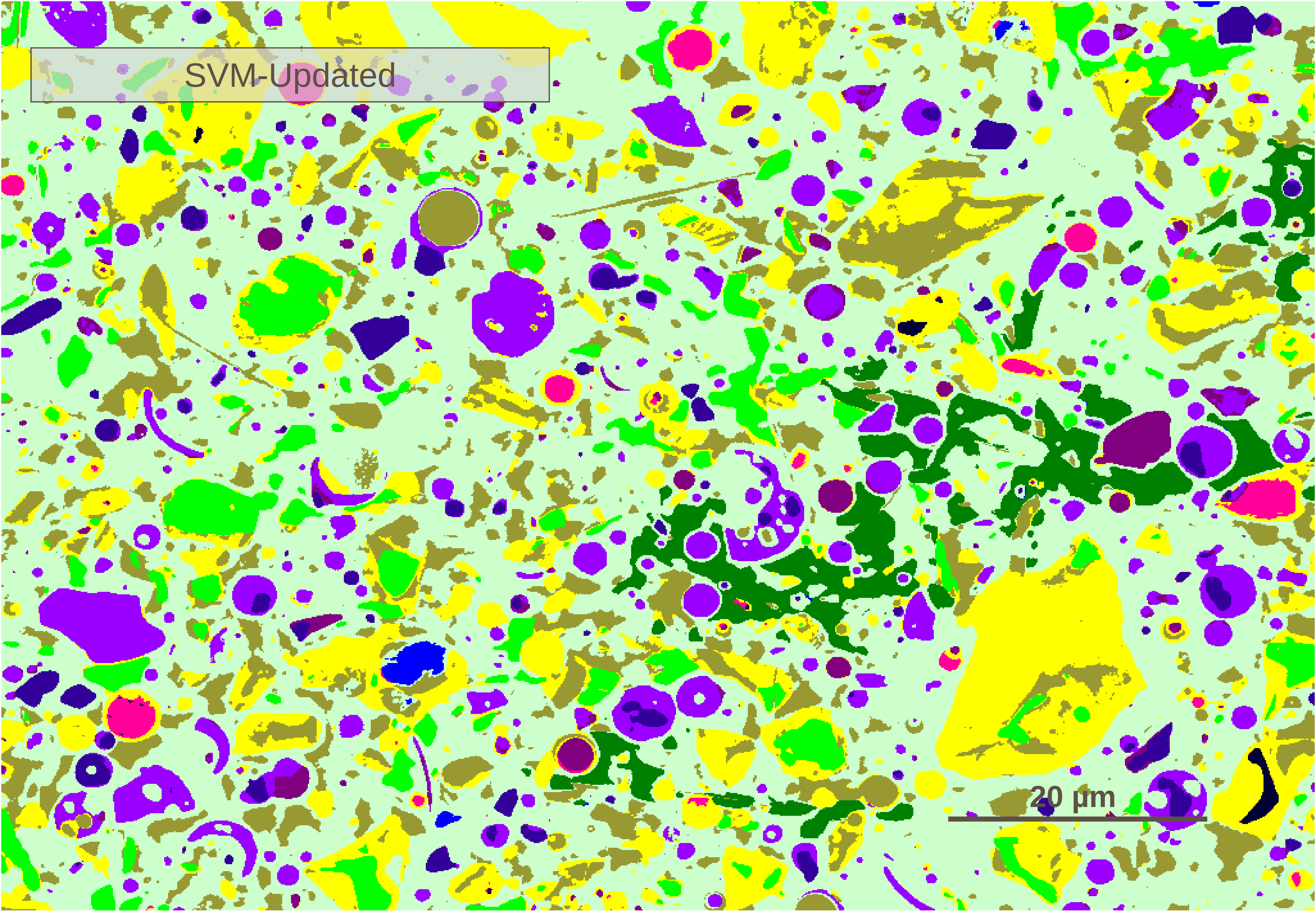


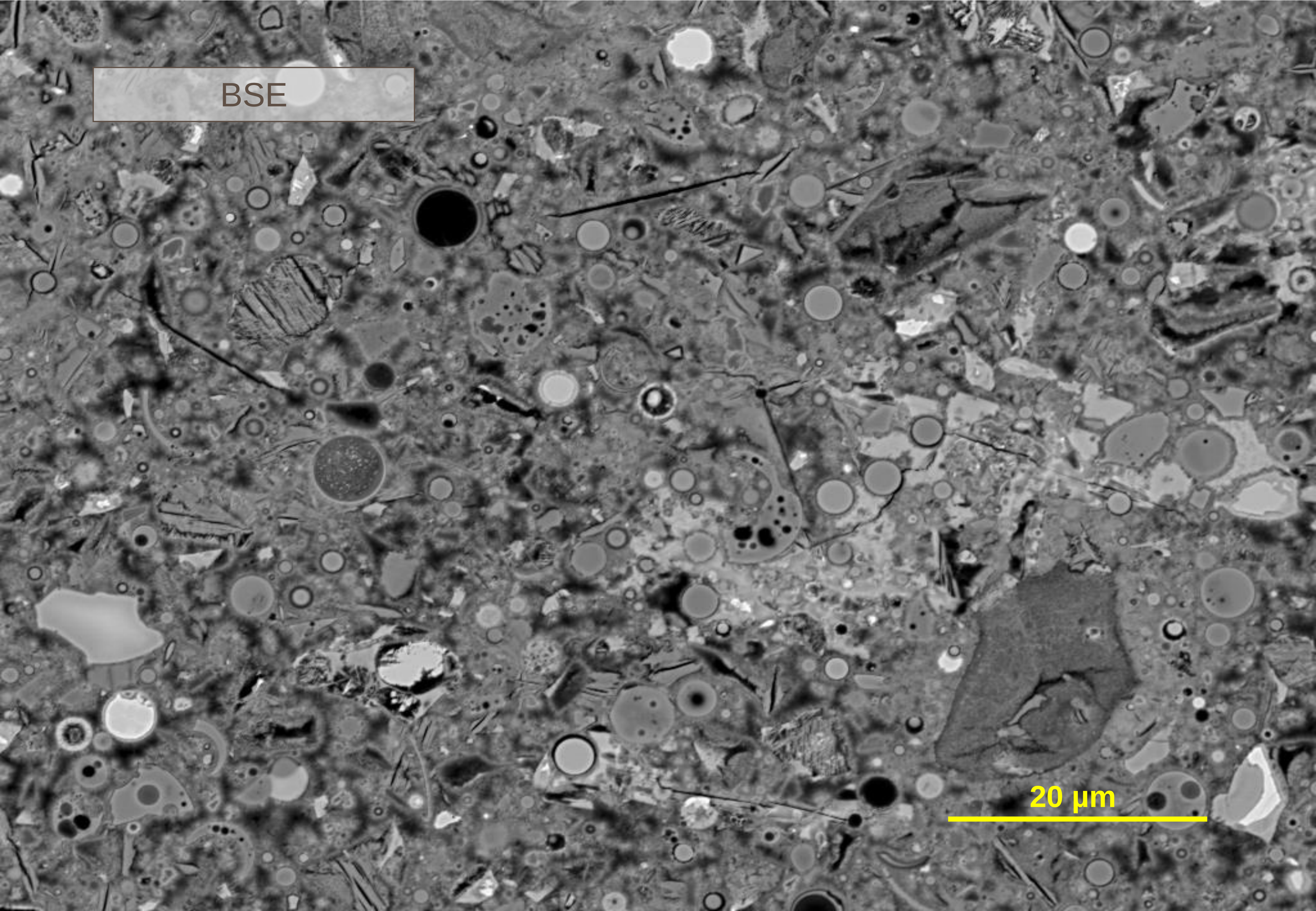
L. Drumetz ; M. Dalla Mura ; S. Meulenyzer ; S. Lombard ; J. Chanussot; ***Semi-automatic classification of cementitious materials using scanning electron microscope images.*** Proc. SPIE 9534, Twelfth International Conference on Quality Control by Artificial Vision 2015, 953403 (April 30, 2015) doi:10.1117/12.2182762.


BSE
20 µm


SVM
20 µm


SVM-MRF
20 µm

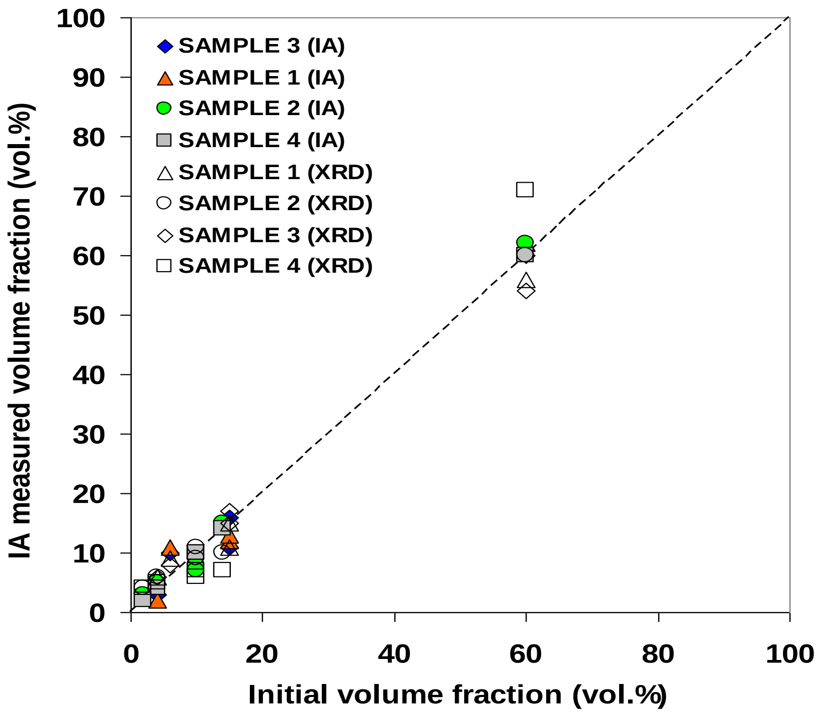

SVM-Updated
20 µm

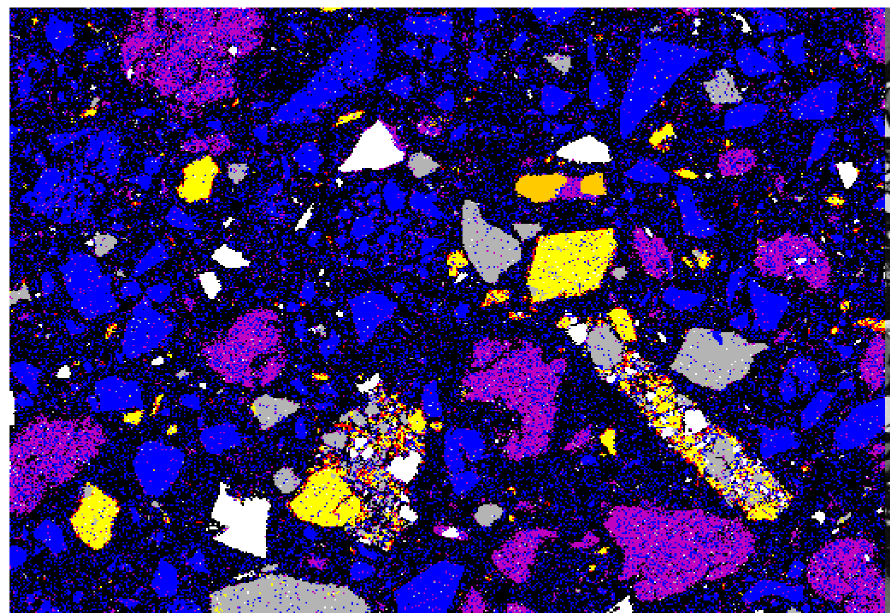

BSE
20 µm

CASE 1: Measuring the amorphous fraction of Pouzz.

- Artificial mixing :

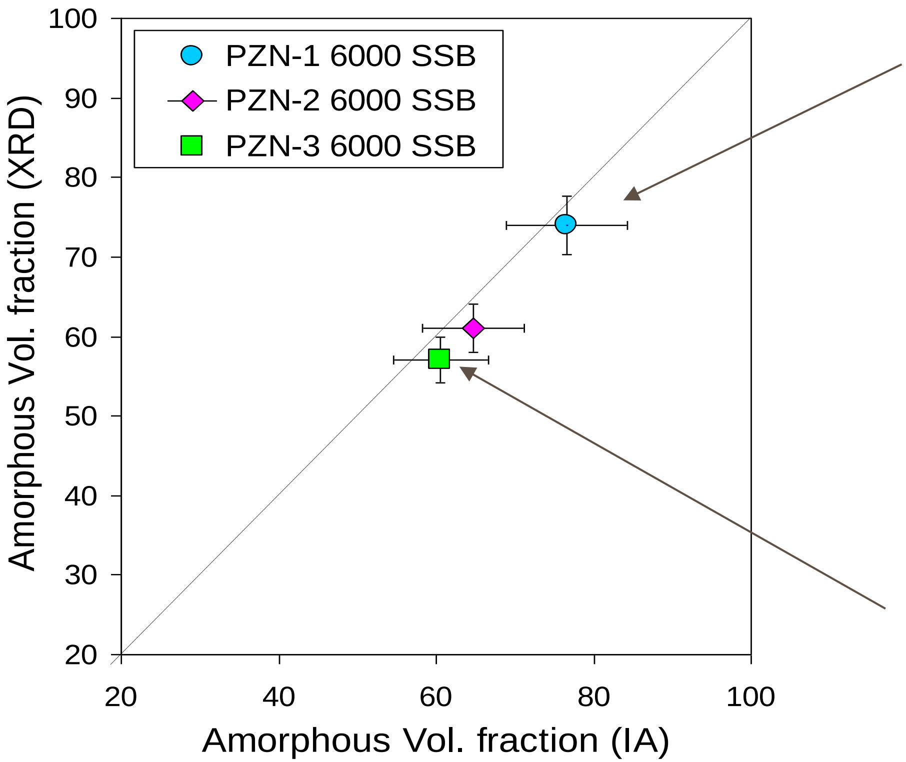
	Glass	Feldspar	augite	clay	dolomite	calcite	quartz	forsterite	magnesite	Edenite	titanite	Magnetite
PZN1	76.8	8.7	0.3	1.1	6	3.5	2.3	-	-	1.3	-	-
PZN2	53.1	14.3	8.1	2.8	-	2	0.2	16.9	--	0.2	-	2.3
PZN3	47	32.1	5.2	1.3	-	0.4	-	9.4	1.4	0.3	1.4	1.5
PZN4	64.5	26.8	0.1	5.6	-	0.5	2.2	-	-	-	-	0.28

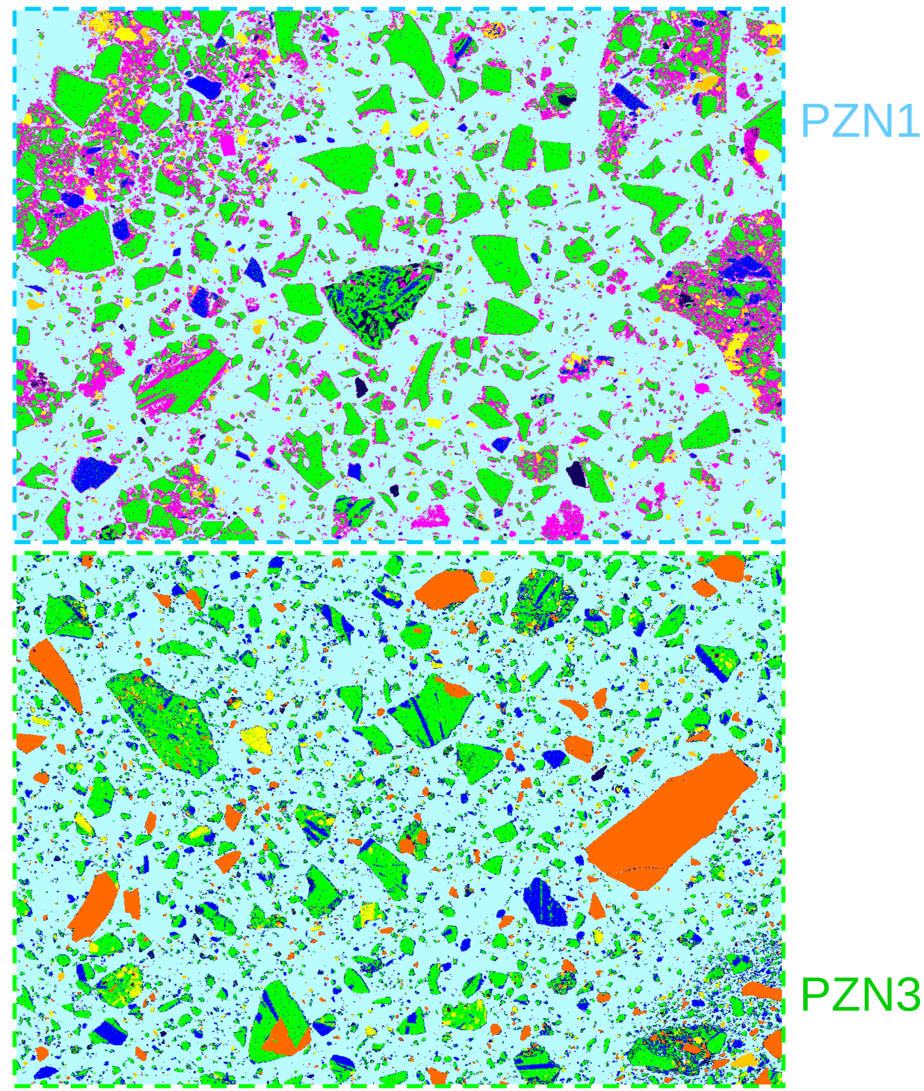




CASE 1: Measuring the amorphous fraction of rocks

- Natural pouzzolana :





Amorphous

CASE 2: Validating SVM-MRF-BPT on reference mix design

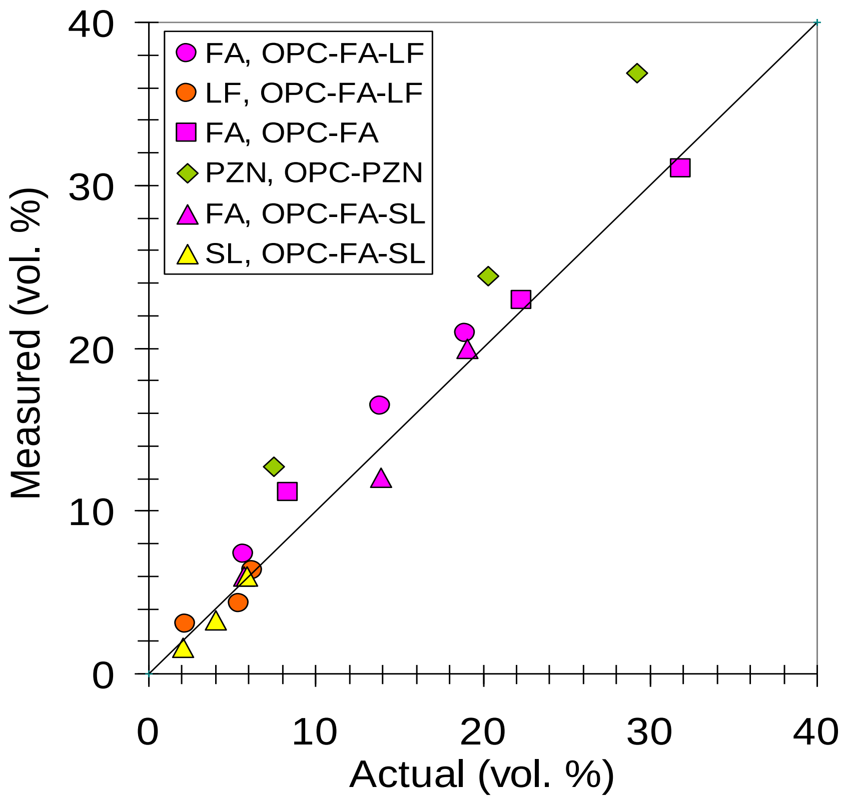
- 1d-stopped blended pastes:

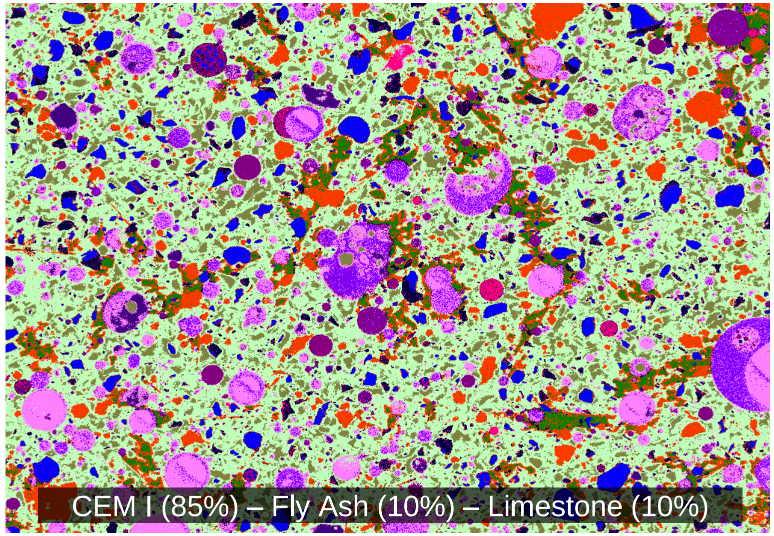
	System	Series	Sample designation	Micronized-OPC (20µm)	Fly Ash	Limestone Filler	Slag	Pozzolan
			µOPC-FA1-1	38	62			
		1	µOPC-FA1-2	58	42	-	-	-
			µOPC-FA1-3	85	15			
	Binary		µOPC-PZN-1	38				62
		2	µOPC-PZN-2	58	-	-	-	42
			µOPC-PZN-3	85				15
1 day			µOPC-FA1-LF-1	50	35	15		
		3	µOPC-FA1-LF-2	65	25	10	-	-
			µOPC-FA1-LF-3	85	10	05		
	Ternary		µOPC-FA1-SLAG-1	50	35		15	
		4	µOPC-FA1-SLAG-2	65	25	-	10	-
			µOPC-FA1-SLAG-3	85	10		05	

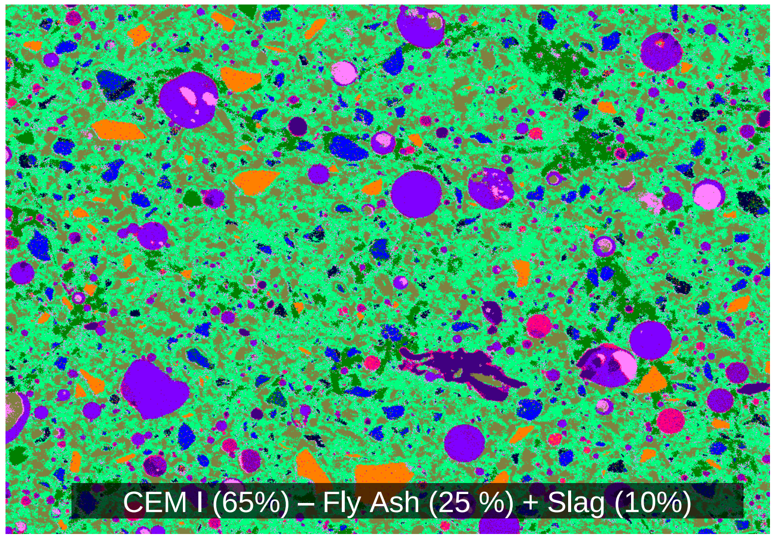
- 91 d stopped mature pastes:

	Sample designation	Regular-OPC	Slag	Fly Ash	PZN1	PZN2	PZN3
	OPC	100					
	OPC-SLAG	55	45				
	OPC-FA1	55		45			
91 d	OPC-PZN1	55			45		
	OPC-PZN2	55				45	
	OPC-PZN3	55					45
	OPC-SLAG-FA1	55	10	35			

CASE 2: 1d-stopped blended pastes

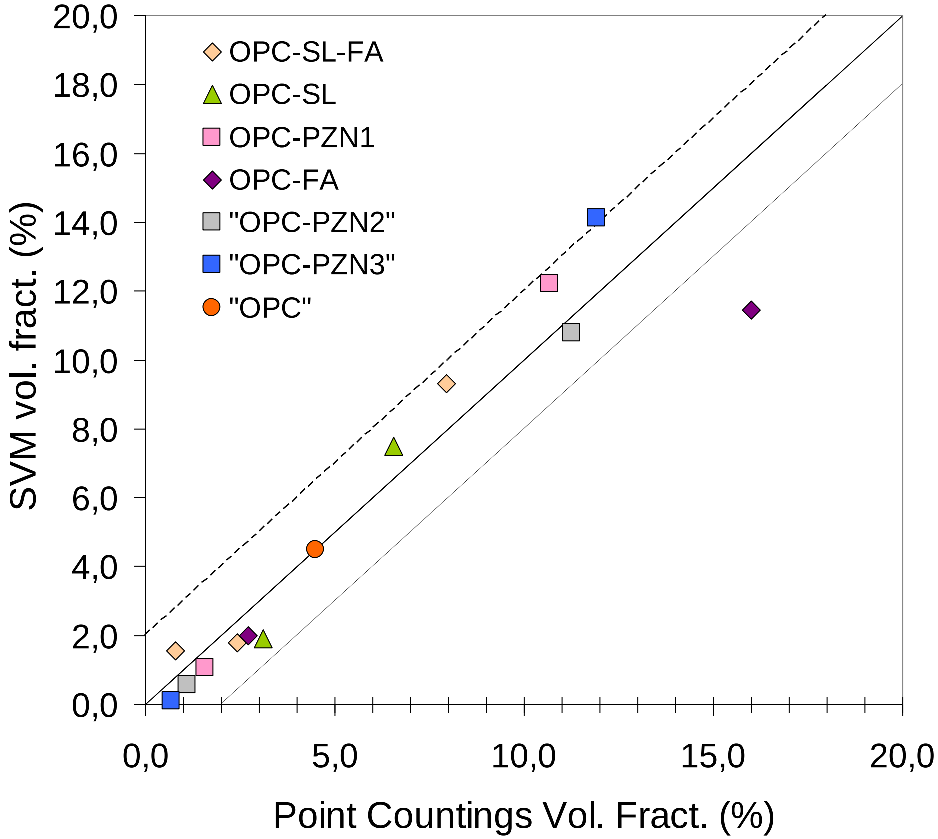


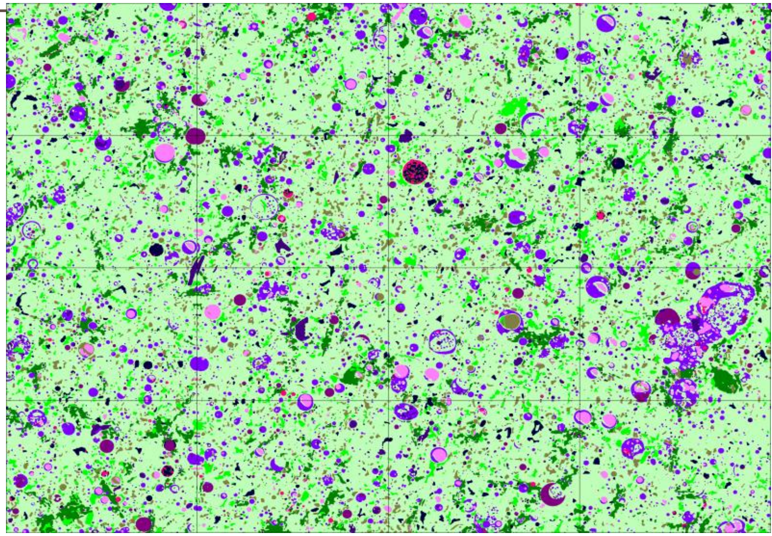


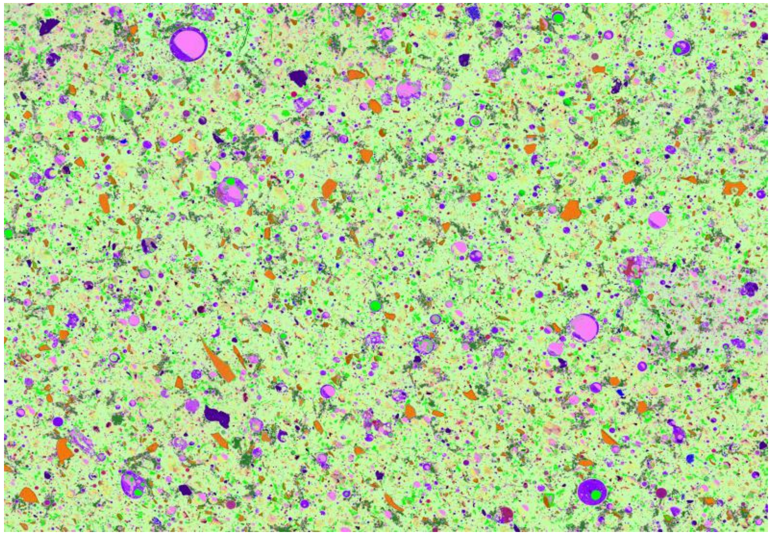


Method shows excellent results on fly-ash, limestone, slag. Discrepancy on pozzolan due to clay impurities.

CASE 2: 91d-stopped mature blended pastes







LafargeHolcim

CASE 3: Connecting binders formulation to sulfate resistance

Marchand, J., Odler, I., Skalny, J.P., « Sulfate Attack on Concrete », Spoon Press, 2001

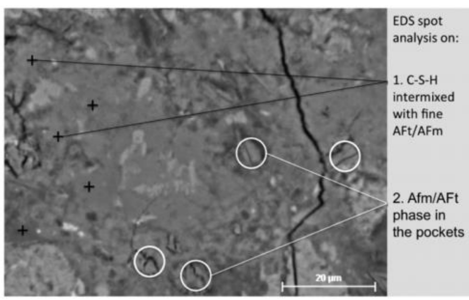
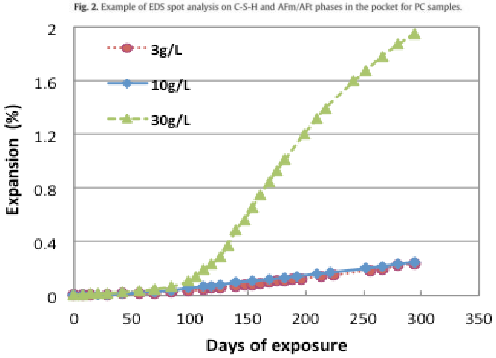


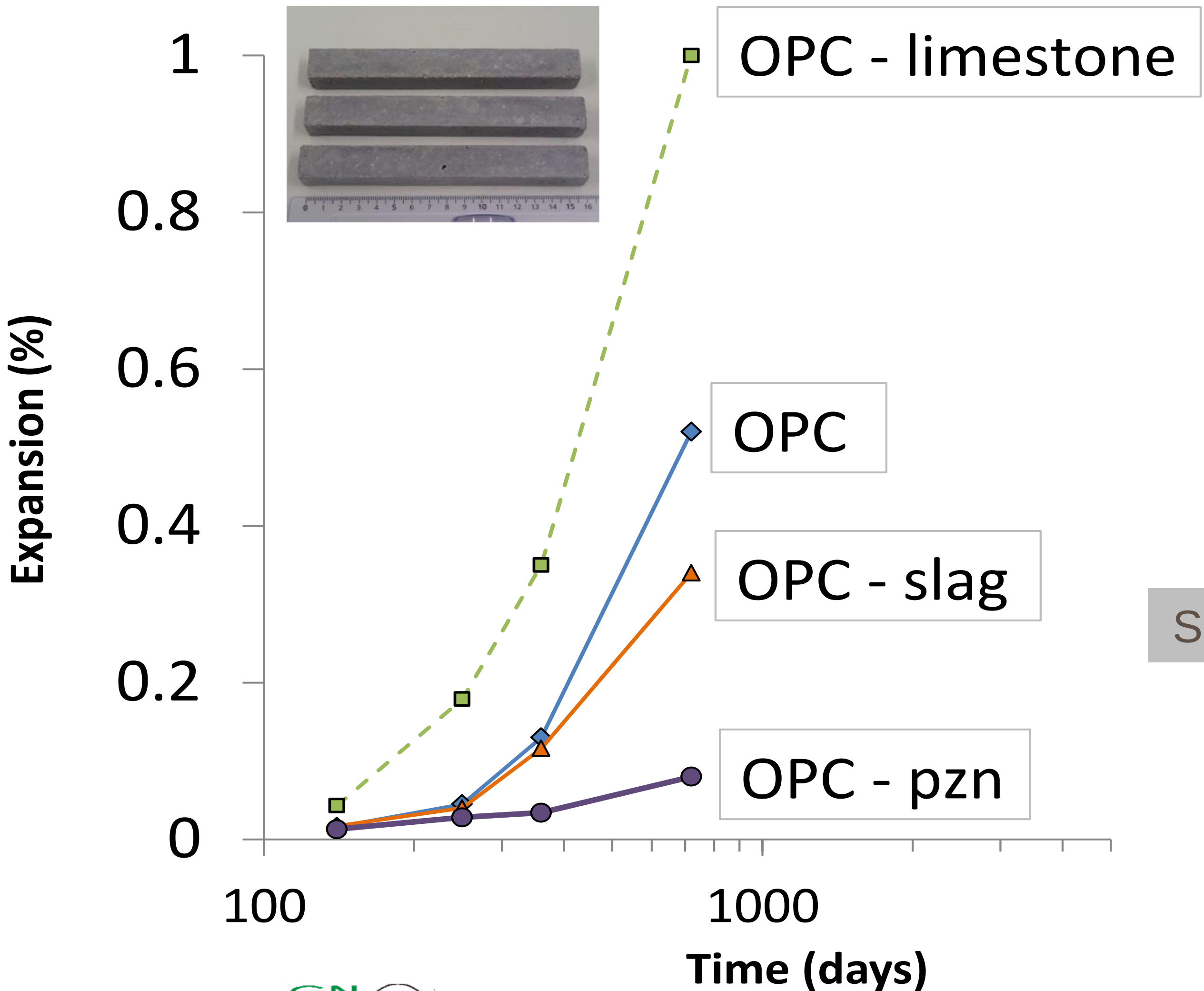
Fig. 2. Example of EDS spot analysis on C-S-H and AFm/AFt phases in the pocket for PC samples.

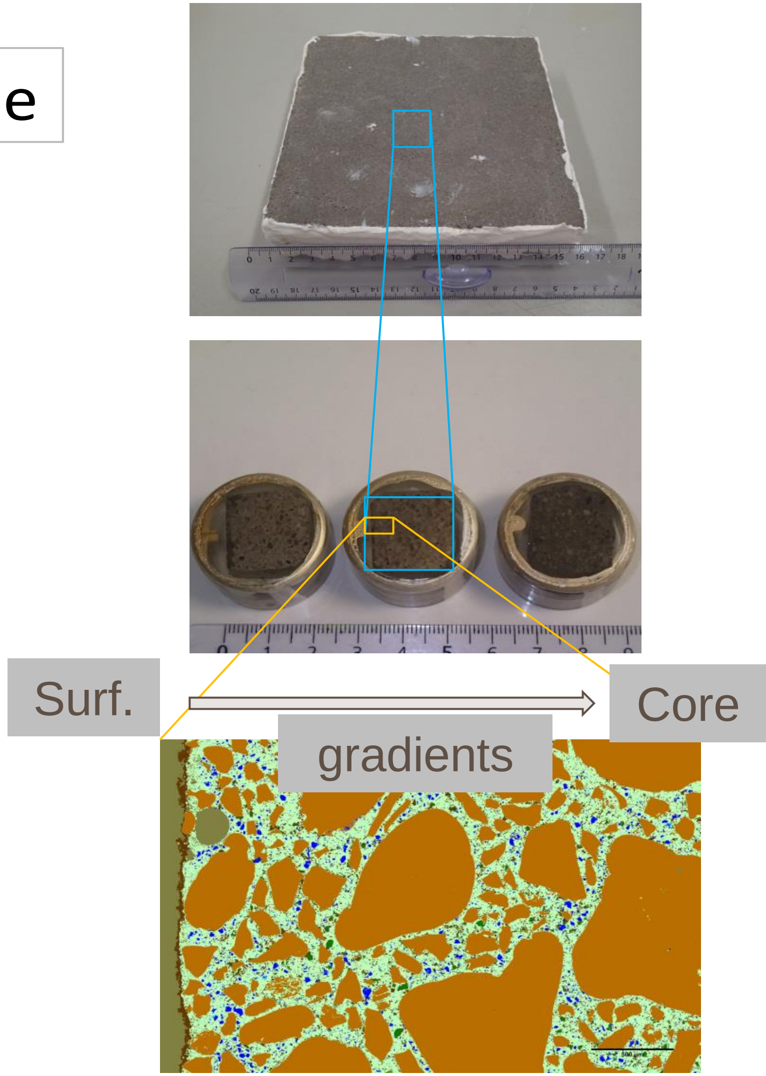


[Yu & Scrivener, 2013]

- Mechanisms understanding is needed to produce new binders or new concretes
- It is widely recognized that Ettringite and (probably) Gypsum (sulfate containing phases) cause damage due to expansion
- Recent studies (e.g. Scrivener, 2013) have shown that pocket of MSA could act as a buffer
- Recent IA development (like supervised spectral classification, *Meulenyzer, EMABM 2013*) have shown potential to quantify these pockets
- We've taken opportunity to study 4 mortars through industrial project
    - **OPC**
    - **OPC-Limestone Filler**
    - **OPC-Slag**
    - **OPC-Pzn**

Expansion strongly depends on binder composition

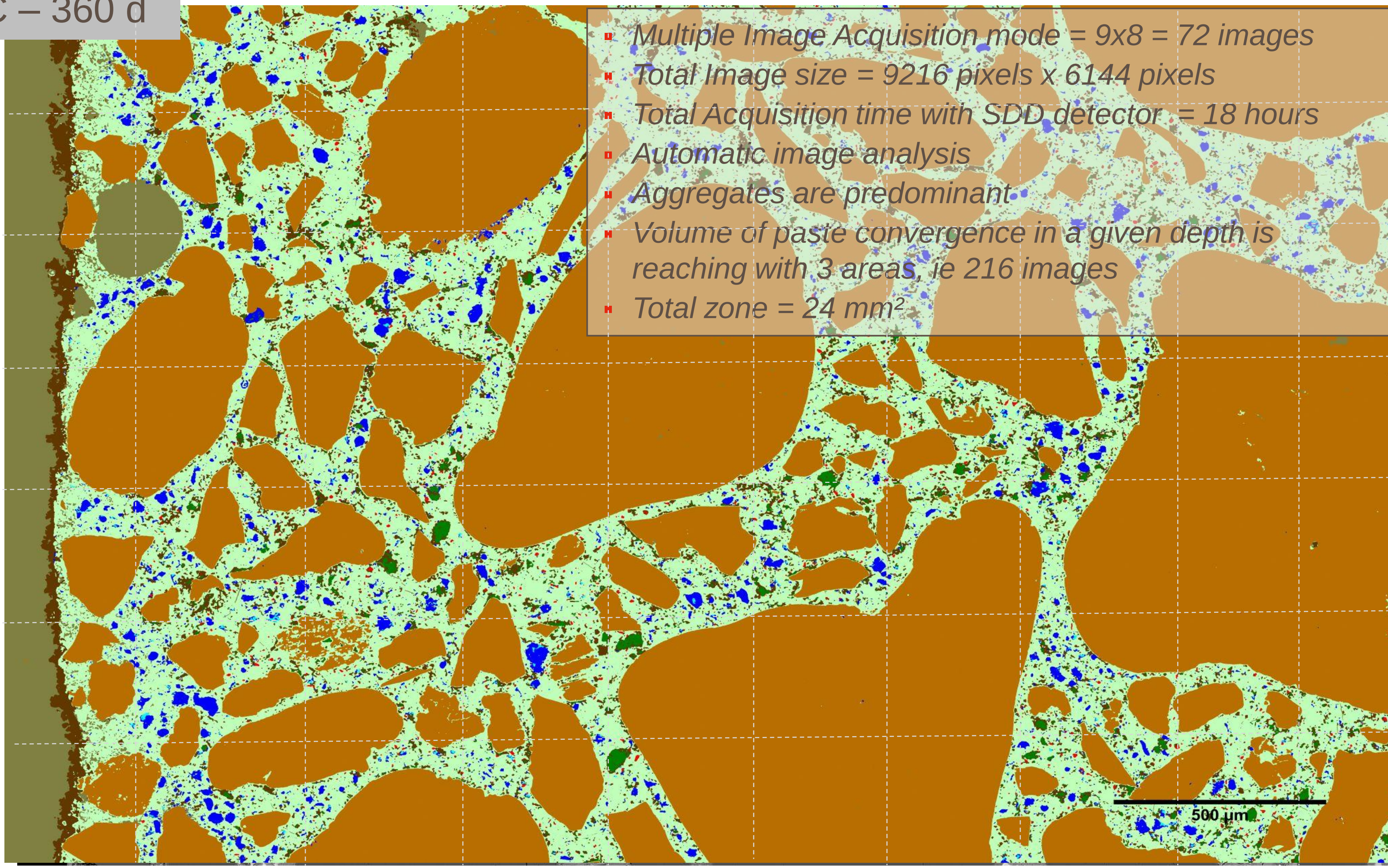




LafargeHolcim

What are good conditions to be representative ?

OPC – 360 d



- *Multiple Image Acquisition mode = 9x8 = 72 images*
- *Total Image size = 9216 pixels x 6144 pixels*
- *Total Acquisition time with SDD detector = 18 hours*
- *Automatic image analysis*
- *Aggregates are predominant*
- *Volume of paste convergence in a given depth is reaching with 3 areas, ie 216 images*
- *Total zone = 24 mm²*

Huge Image acquisition program…

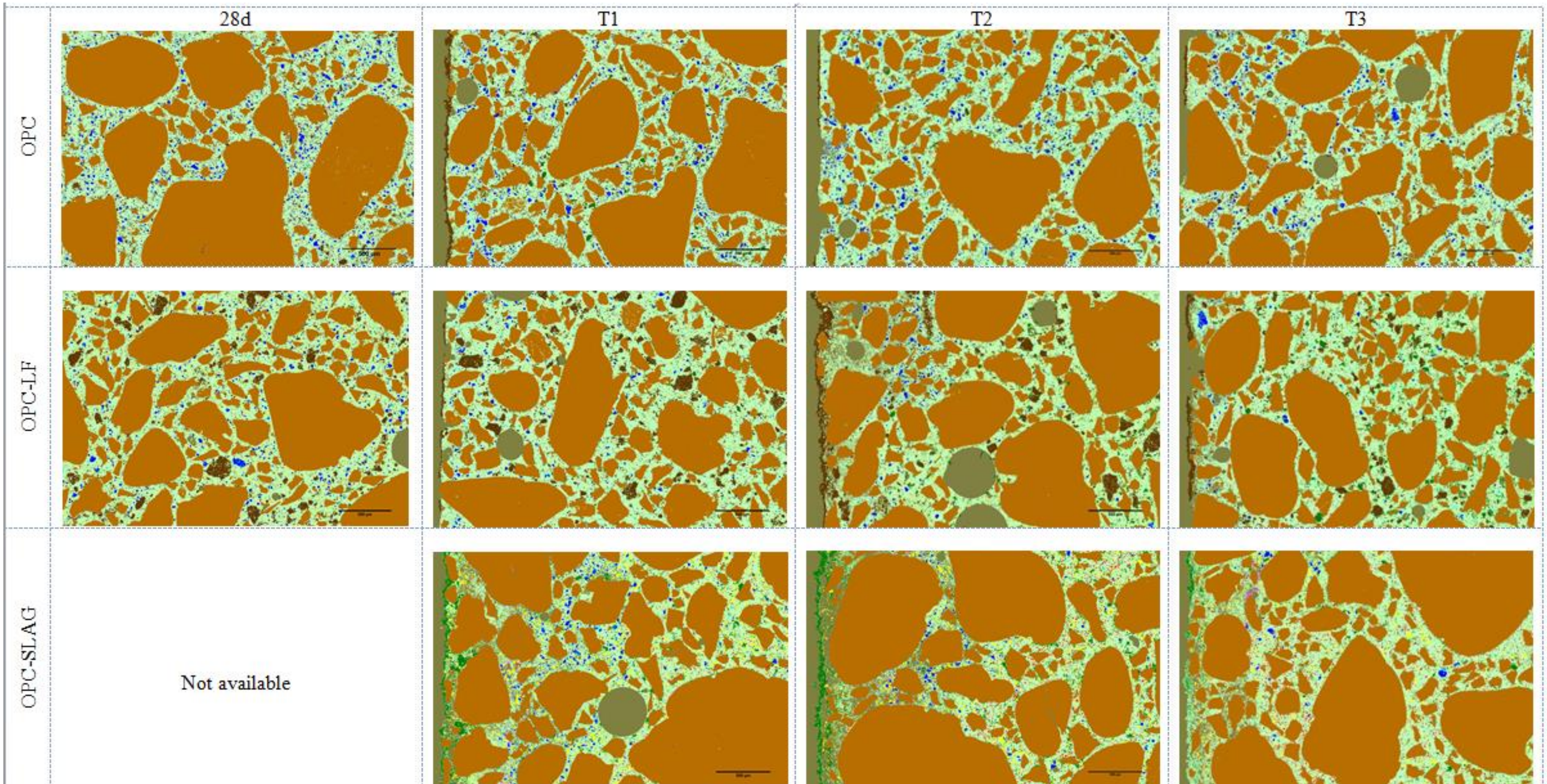
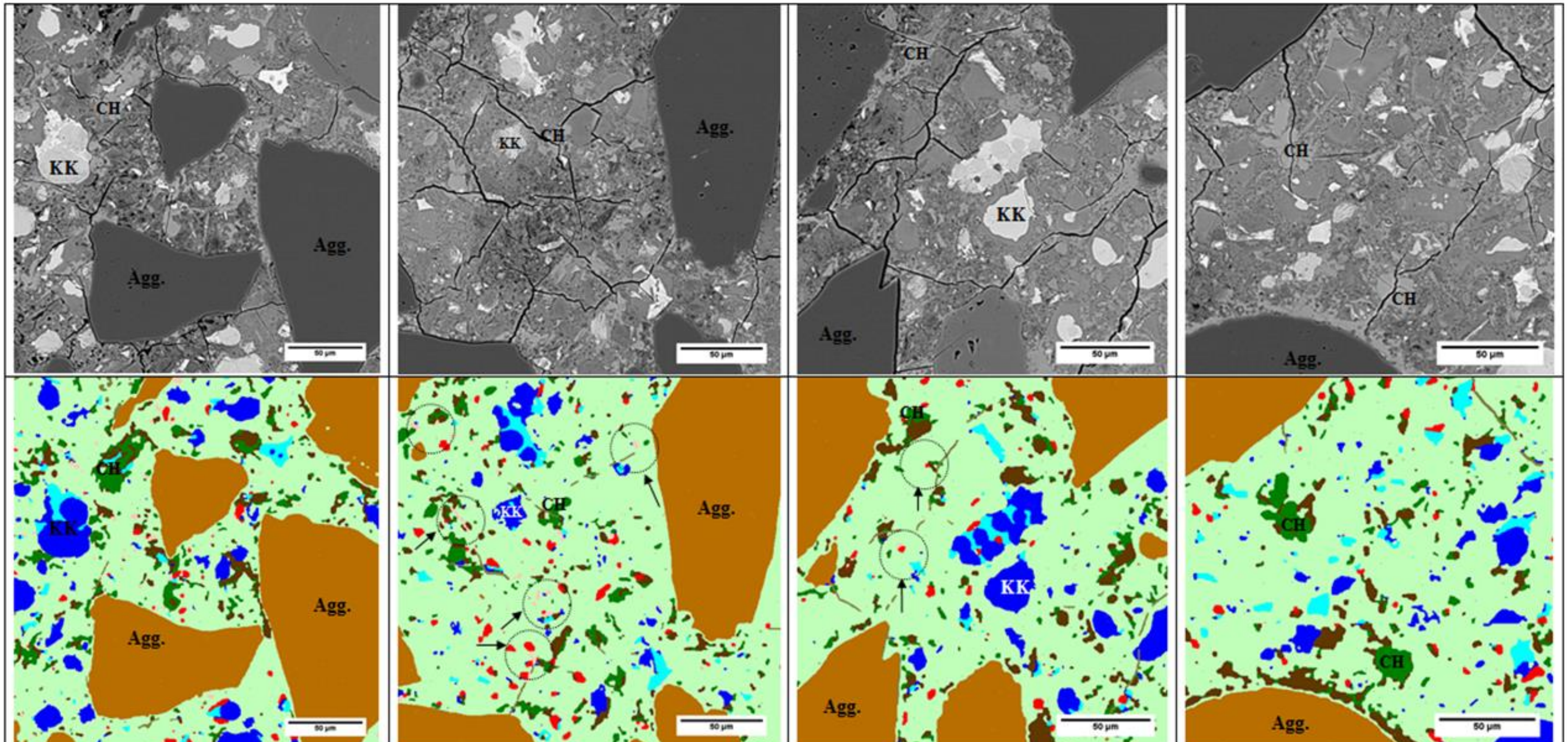


Figure 5: Classified images of OPC, OPC-LF (Limstone Filler) and OPC-Slag at 28, 250, 350 and 720 days, corresponding to previous BSE images (Figure 3).
Scale bar is 0.5 mm. The code of colors are: Sand (Orange), Porosity (light brawn), Porlandite and/or calcite in OPc and OPC-Slag mortars (dark green), 'Outers' (light green), C3S C2S silicates (light and dark blue), Slag (Yellow), monosulfoaluminates grains (red), trisulfoaluminate coarser phases (rose), limestone filler (dark brawn).

OPC T2 (1-year) local gradient evolution

3.3.1 Microstructural évolution of OPC-T2 mortar

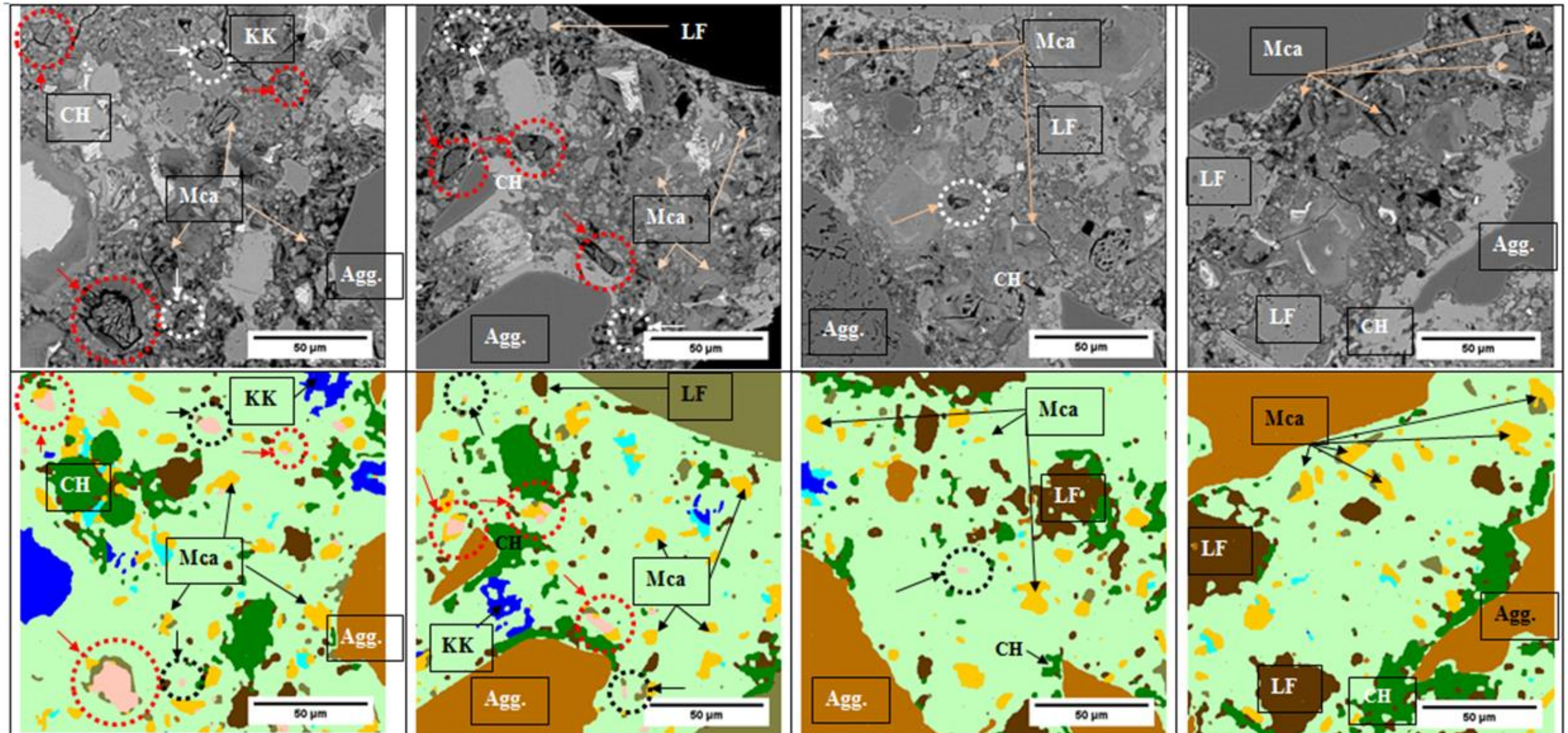


Near the surface *HFW =160 µm* *Msa grains seem coexisted with Tsa grains.*	*1.25 mm from surface* *HFW =160 µm* *As sulfate concentration is smaller than in the surface. TSA are found (pink) but seem more 'thinner' than in the surface.*	*1.98 mm from surface* *HFW =160 µm* *TSA (pink color) starts to appear (pointed circle) in place where monosulfoaluminate grains (red) have been dissolved...*	*2.84 mm from surface* *HFW =160 µm* *Sulfates haven't penetrated yet. Red grains are monosulfoaluminate (confirmed by EDS). No TSA grains.*

Figure 7: Microstructural phase evolution at local scale from surface (left) to core of mortar (OPC). KK=clinker; Agg.=Aggregates; CH=portlandite;

OPC-LF T2 (1 year) local gradient evolution

3.3.2 Microstructural évolution of OPC–Limestone filler–T2 mortar

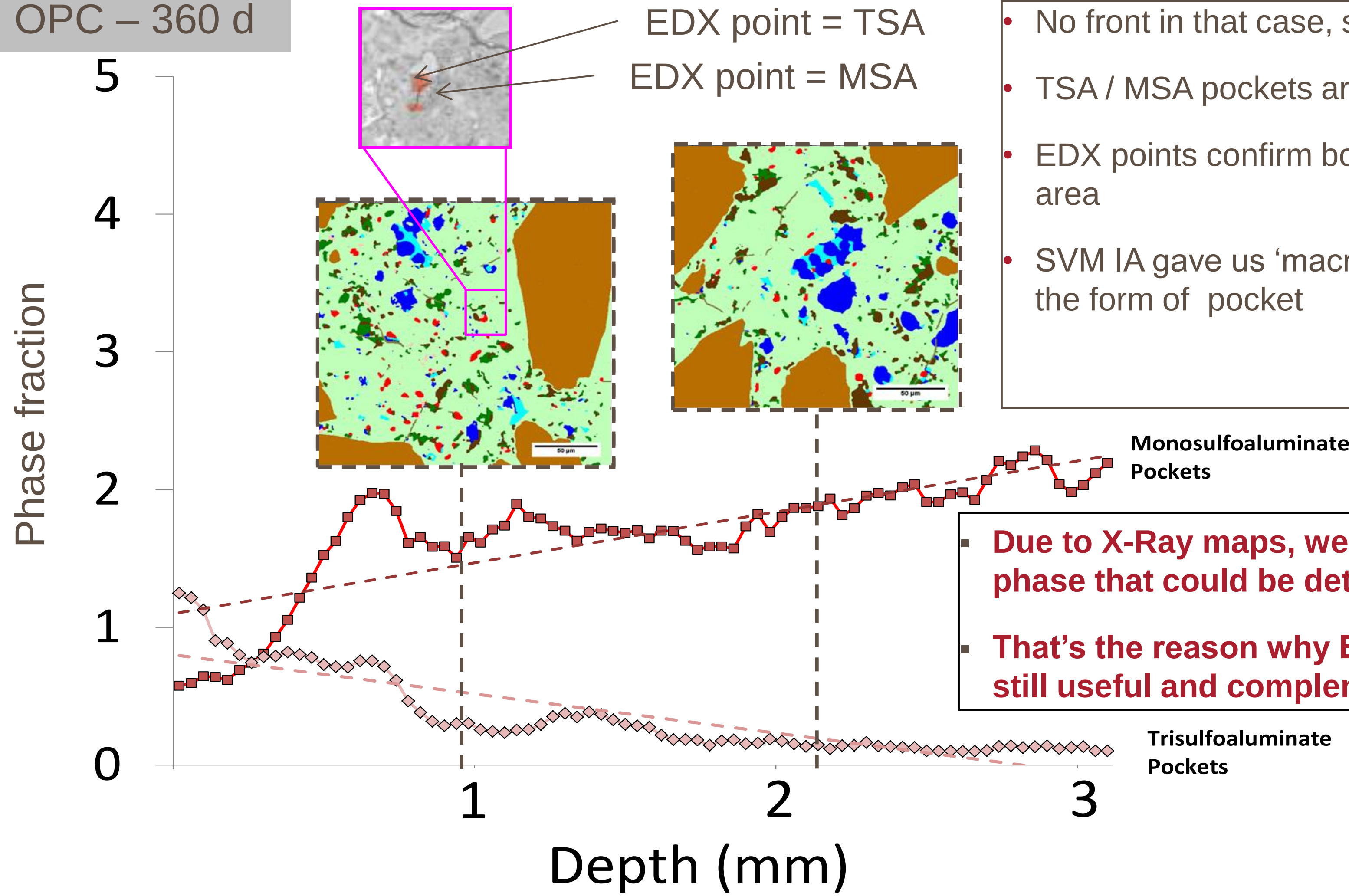


0.87 mm from surface *HFW=160µm* *'Massive' TSA grains can be found. Also many TSA grains are in formation.*	*1.25 mm from surface* *HFW =160 µm* *As sulfate concentration is higher more TSA are found. Some Mca grains seem going to be 'transformed' in TSA (red circles)…*	*1.98 mm from surface* *HFW =160 µm* *TSA starts to appear (pointed circle) in place where Mca grains have been dissolved…*	*2.84 mm from surface* *HFW =160 µm* *Sulfates haven't penetrated yet. No TSA grains.*

Figure 8: Microstructural phase evolution at local scale from surface (left) to core of mortar (OPC-LF). KK=clinker; Agg.=Aggregates; CH=portlandite; LF=Limestone Filler; Mca= Monocarboaluminate

MSA / TSA Pockets gradients get quantified

OPC – 360 d

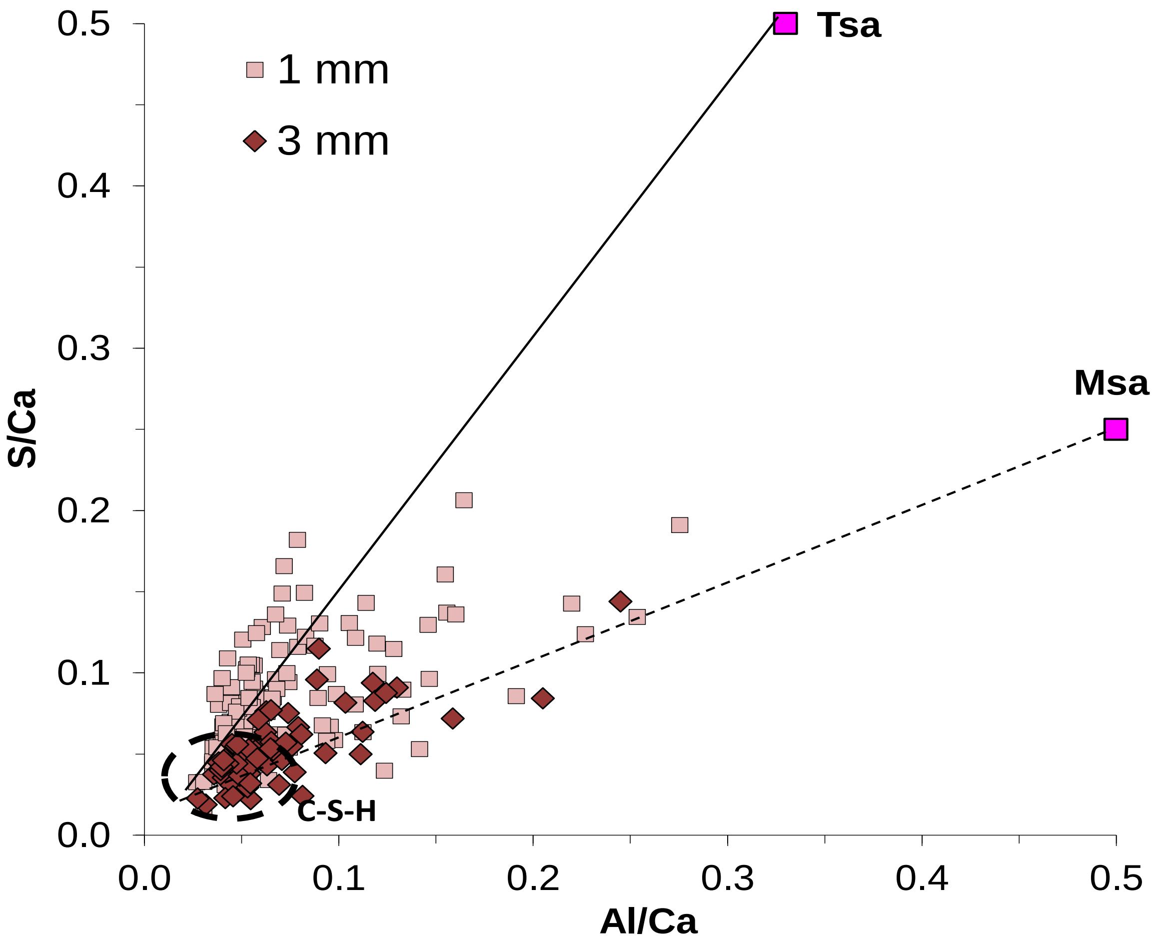


- No front in that case, surprising
- TSA / MSA pockets are sometimes coexisting
- EDX points confirm both MSA / TSA in a same area
- SVM IA gave us ‘macro’ vision of TSA / MSA, in the form of pocket

- **Due to X-Ray maps, we are limiting by size of phase that could be detected, ie few µm**
- **That’s the reason why EDX analyses in CSH are still useful and complementary**

EDX on CSH show evolution from MSA to TSA

OPC – 360 d



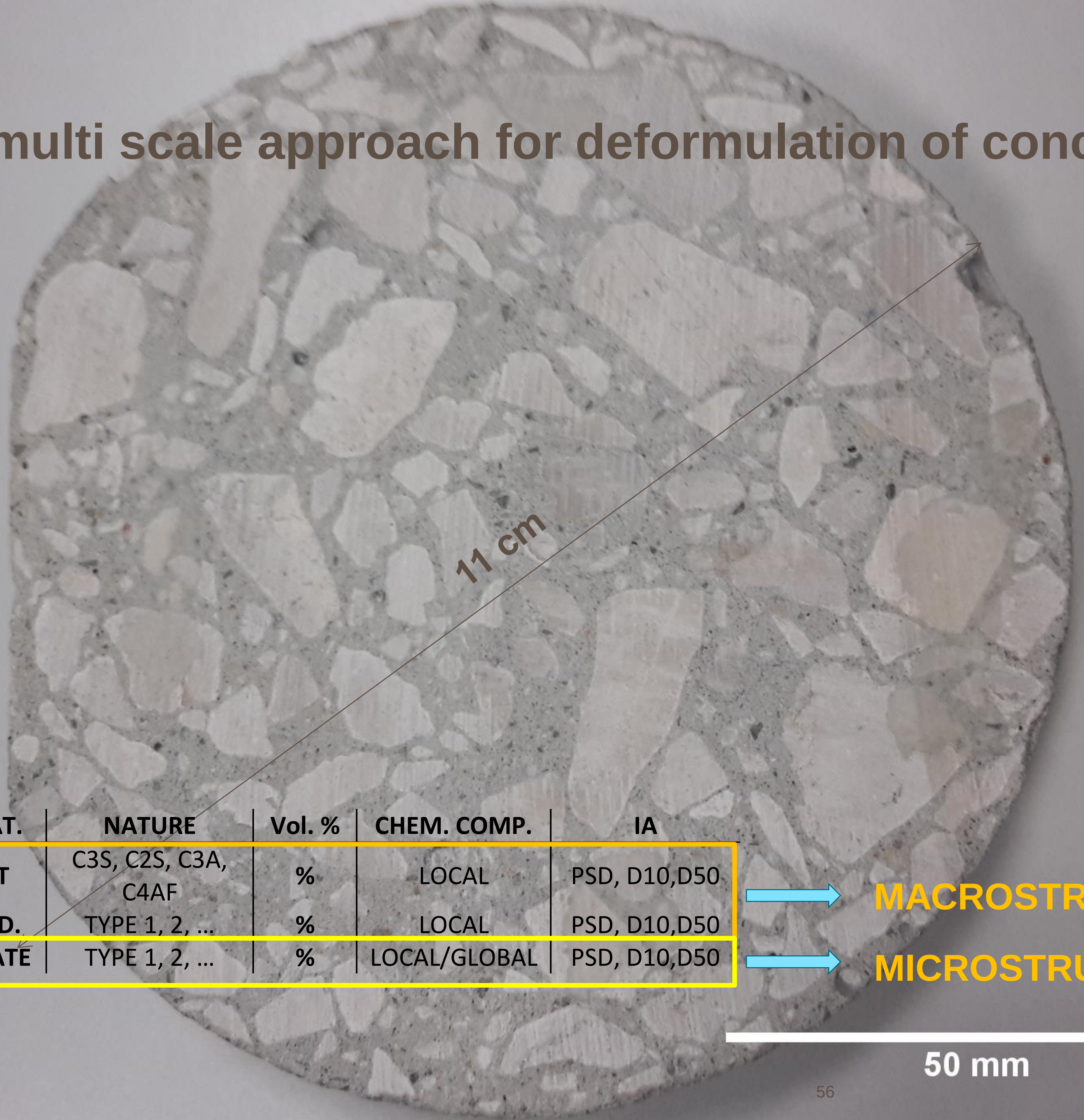
- Classical EDX quantifications have been operated in function of depth
- In theory, pocket of Msa should have a buffering effect with sulfates before creating TSA in CSH (smallest pores…)
- IA combined to EDX clearly show that both phenomena seem coexist…

CASE 4: multi scale approach for deformulation of concrete

UNKNOWN

↓

INFOS ?



< 80 µm

> 80 µm

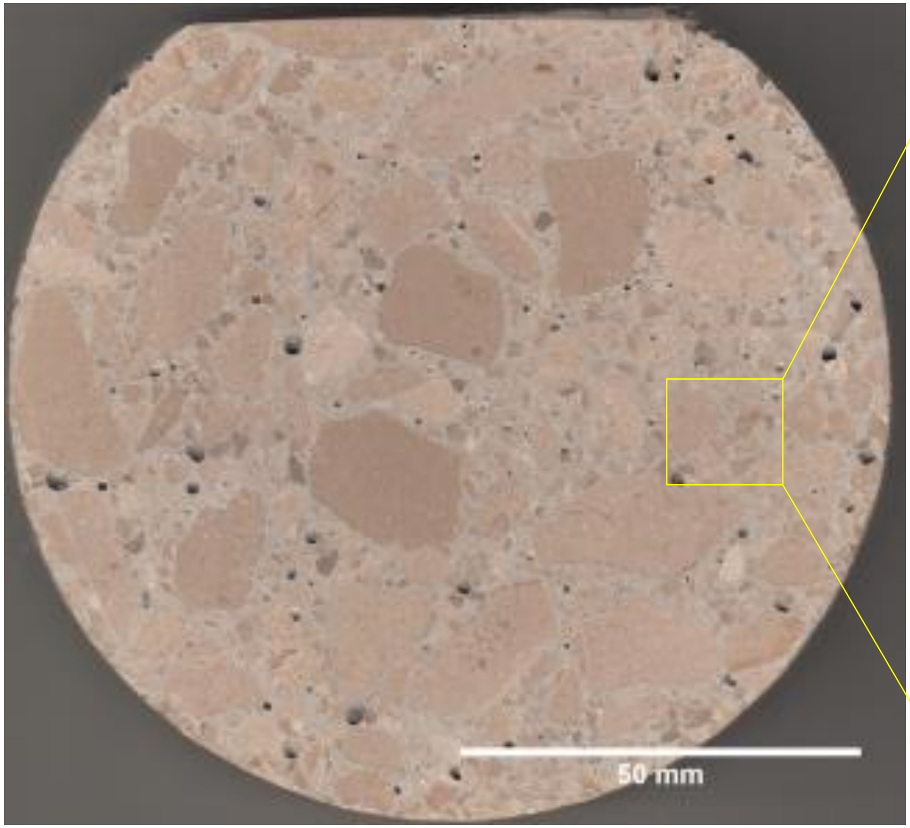
RAW MAT.	NATURE	Vol. %	CHEM. COMP.	IA
CEMENT	C3S, C2S, C3A, C4AF	%	LOCAL	PSD, D10,D50
MIN. ADD.	TYPE 1, 2, …	%	LOCAL	PSD, D10,D50
AGGREGATE	TYPE 1, 2, …	%	LOCAL/GLOBAL	PSD, D10,D50

→ **MACROSTRUCTURE**

→ **MICROSTRUCTURE**

CASE 4: multi scale approach for deformulation of concrete

MACROSTRUCTURE | **MICROSTRUCTURE**

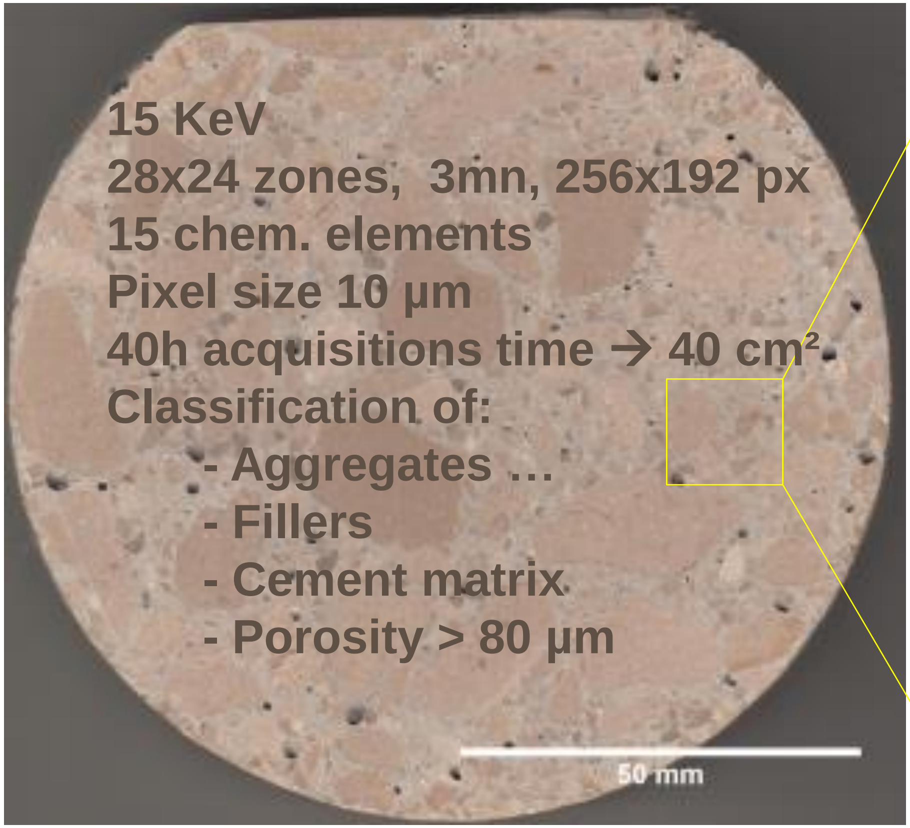


- No impregnation, fast polishing **3 µm** (1h)
- BSE & X-RAY MAPS in Low-Vacc
- EDS: ‘rough’ chemistry of phases

- Impregnation, slow polishing **¼ µm** (1 week)
- BSE & X-RAY MAPS in Hi-Vacc
- EDS: quanti. of small phases

CASE 4: multi scale approach for deformulation of concrete

MACROSTRUCTURE



- No impregnation, fast polishing **3 µm** (1h)
- BSE & X-RAY MAPS in Low-Vacc
- EDS: 'rough' chemistry of phases

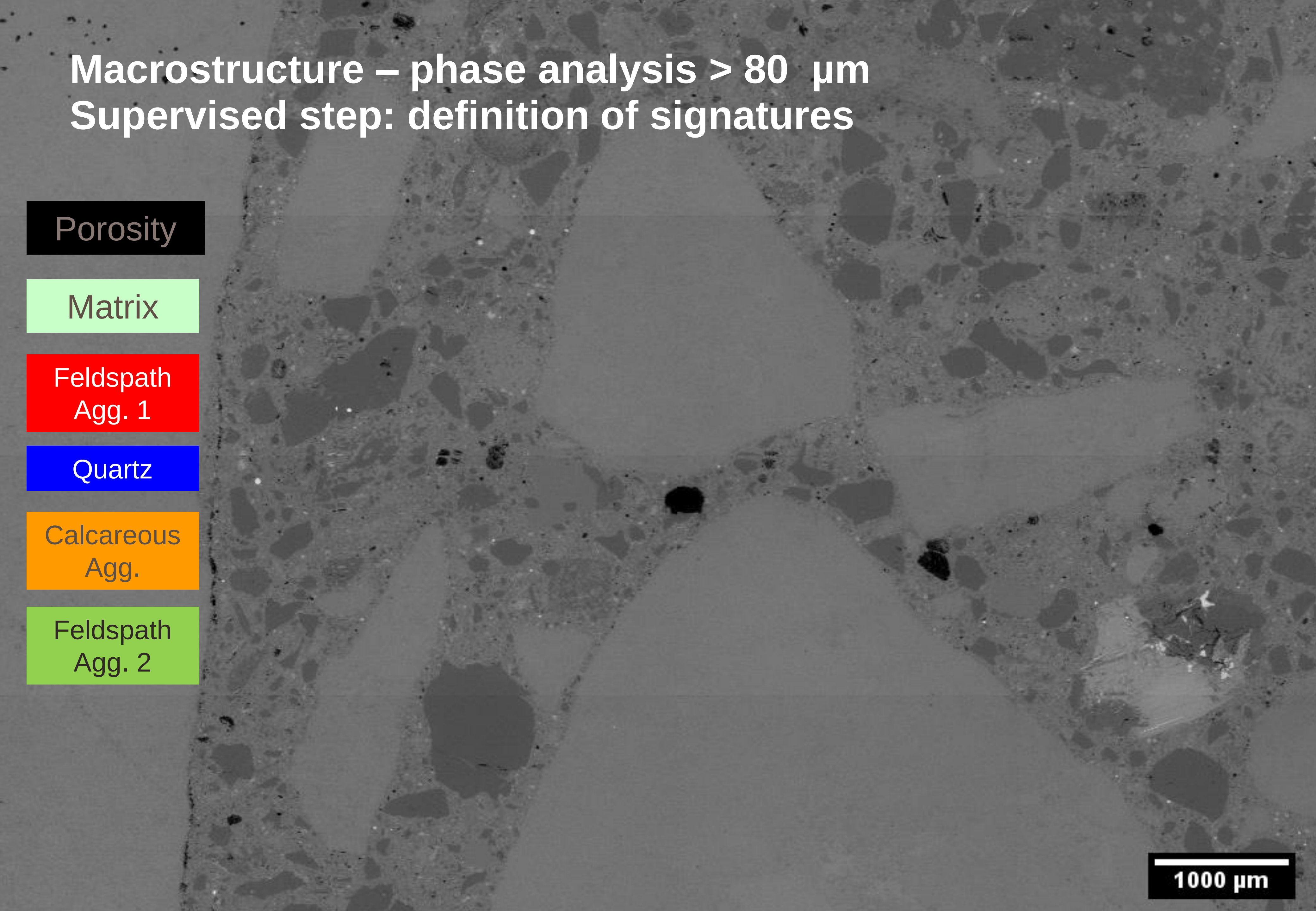
MICROSTRUCTURE

- Impregnation, slow polishing **¼ µm** (1 week)
- BSE & X-RAY MAPS in Hi-Vacc
- EDS: quanti. of small phases

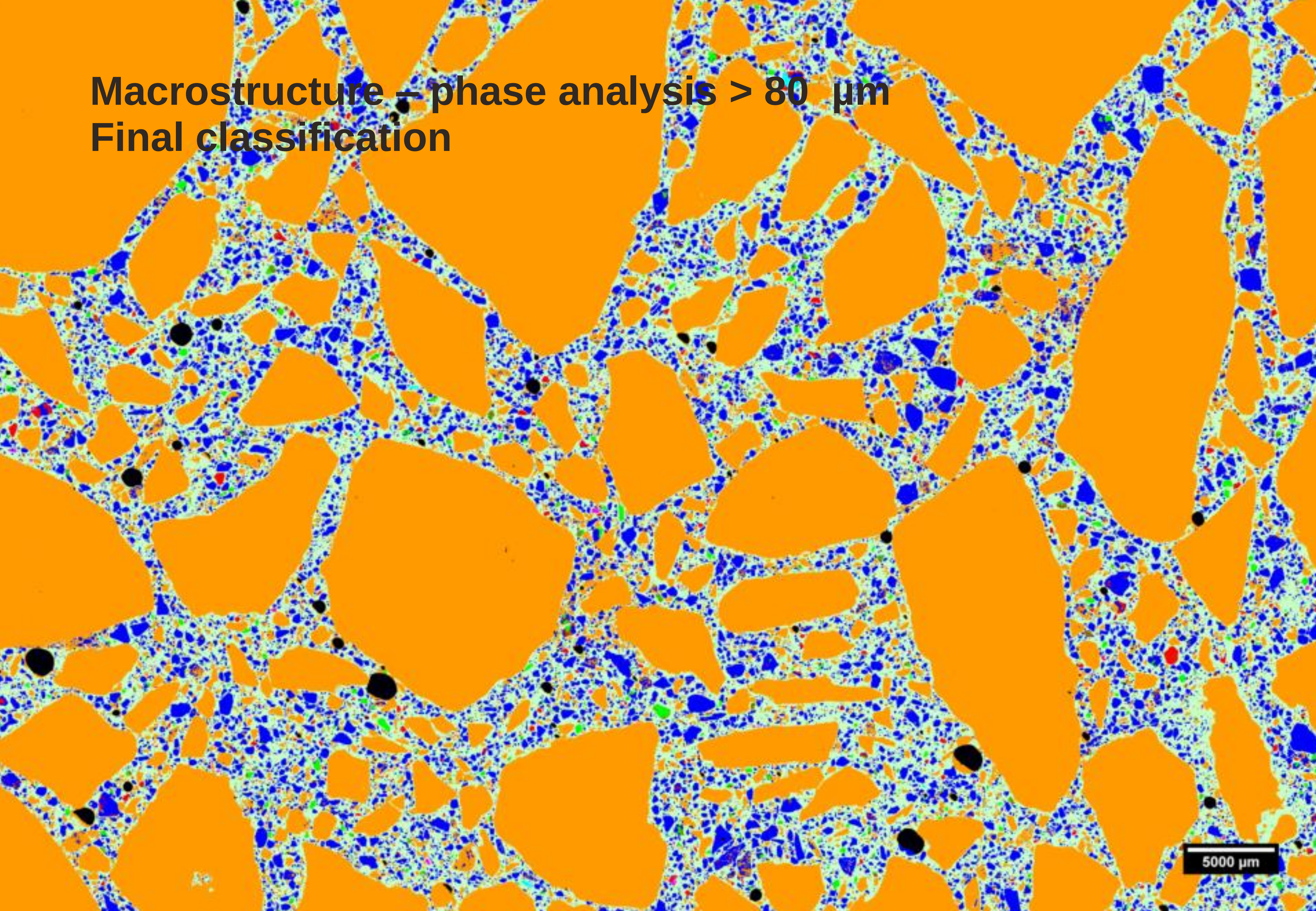
LafargeHolcim

GN MEBA

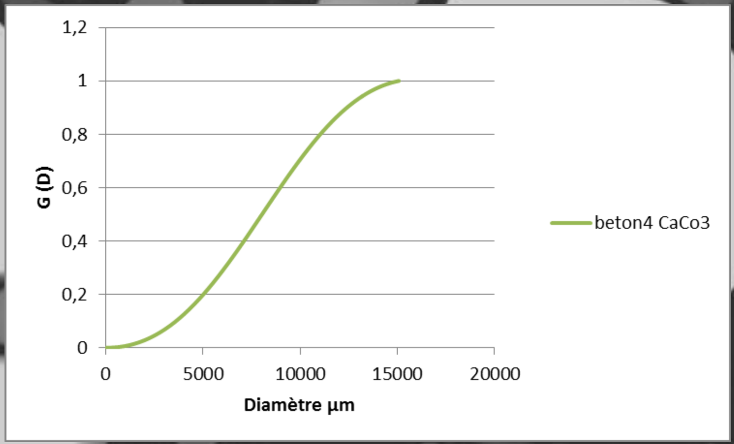
Macrostructure – phase analysis > 80 µm
Supervised step: definition of signatures



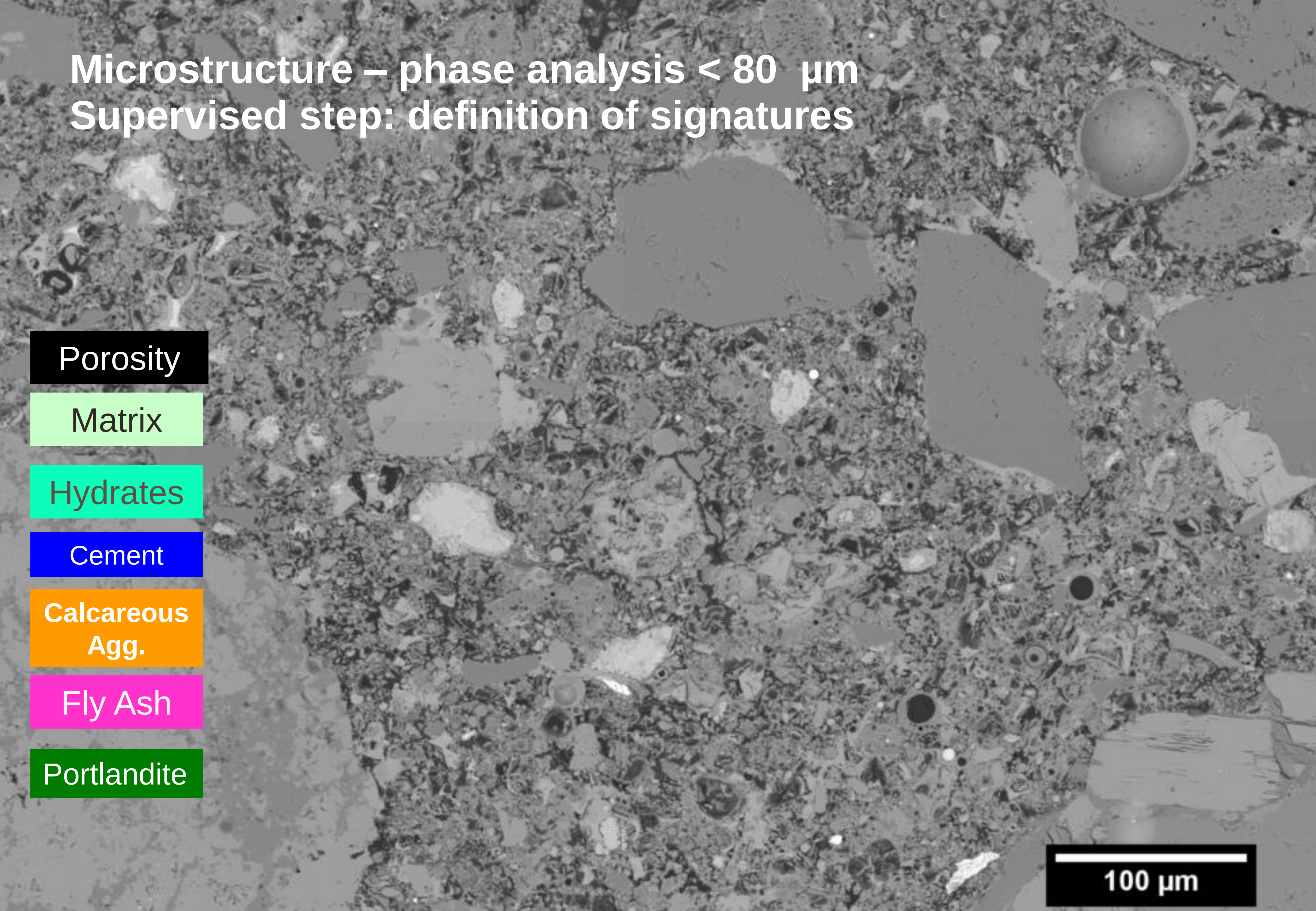
Macrostructure – phase analysis > 80 µm
Final classification

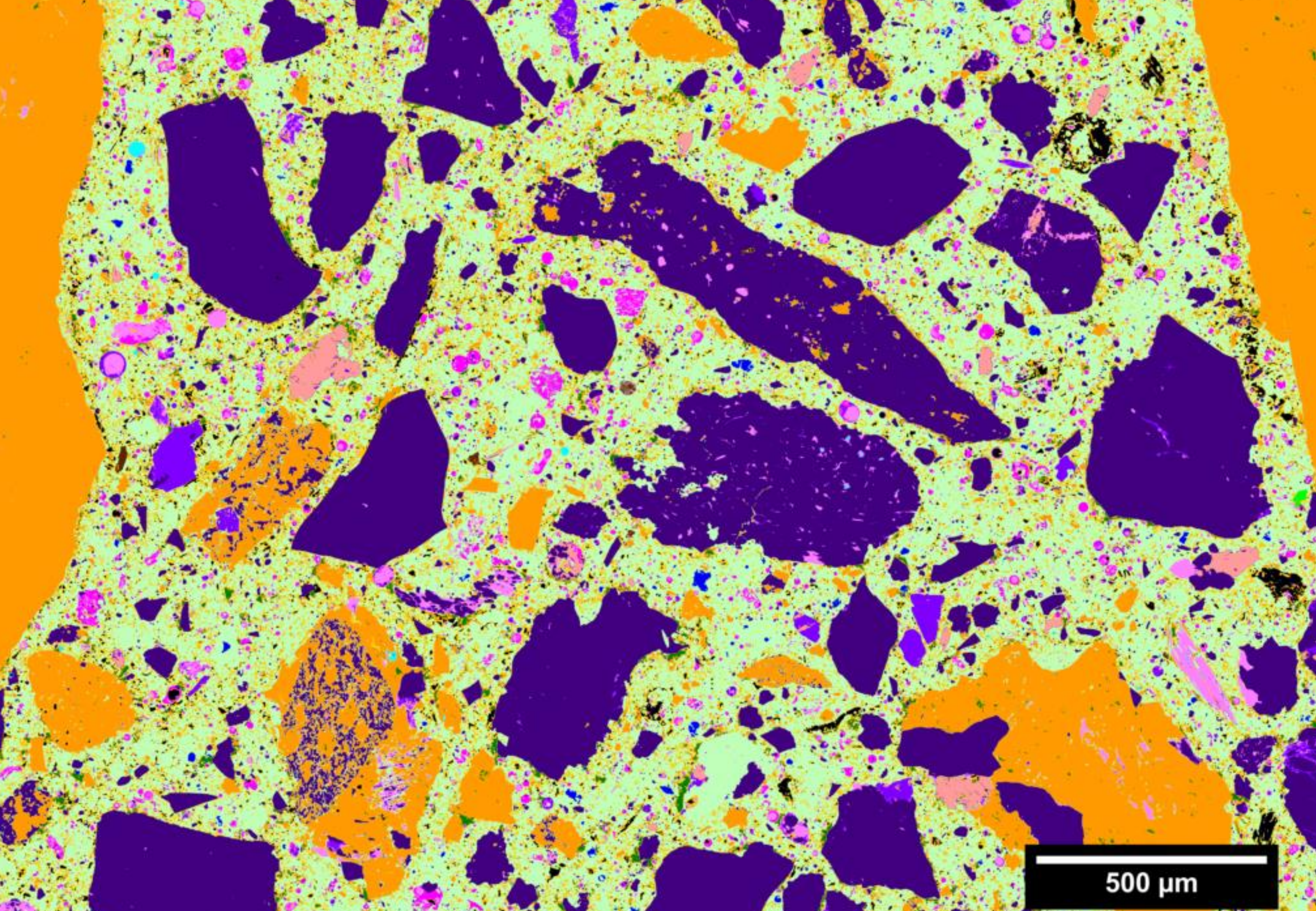


Open granulometry



Microstructure – phase analysis < 80 µm
Supervised step: definition of signatures




500 µm

Complete deformulation example

matière 1ère	Nature	Mass %	Composition chimique (masse oxyde %)					Répartition granulométrique		
			siO2	CaO	Al2O3	Fe2O3	mineurs	D10 mm	D50 mm	D90 mm
Cem		11,3								
SCM	Cendre Volante	1,7	45	3,9	28	16,5	6,6			
Granulats	Calcaire	70,4	7	88	1	2,5	1,5	3,6	8,0	12,4
	Siliceux	12,8	89,9	6,5	1,5		2,1	0,1	0,3	0,6
	Autres	1,8								
	Squelette Granu	**1,8**	**19,2**	**75,7**	**1,4**	**2,3**	**1,9**			
Eau de gâchée		7,3								

Complete deformulation validation…

Approches complémentaires avec données MEB pour granulats

Approche 2 bis			
	Mesure	**Théorie**	*écart*
%liant	11.90	12.4	*-0.50*
%GraSi	13.95	22.8	*-8.85*
%GraCa	65.97	56.8	*9.17*
%eau	8.02	8.1	*-0.08*
kg/m3 béton	**Mesure**	**Théorie**	*écart*
Mliant	282.44	290.00	*-7.56*
MgraSi	331.07	534.00	*-202.93*
MgraCa	1565.55	1334.00	*231.55*
Meau	190.31	189.00	*1.31*

Observation : Bon calcul pour le ciment, résultats ok pour somme des granulats (mais pas bon pour granulats séparé)

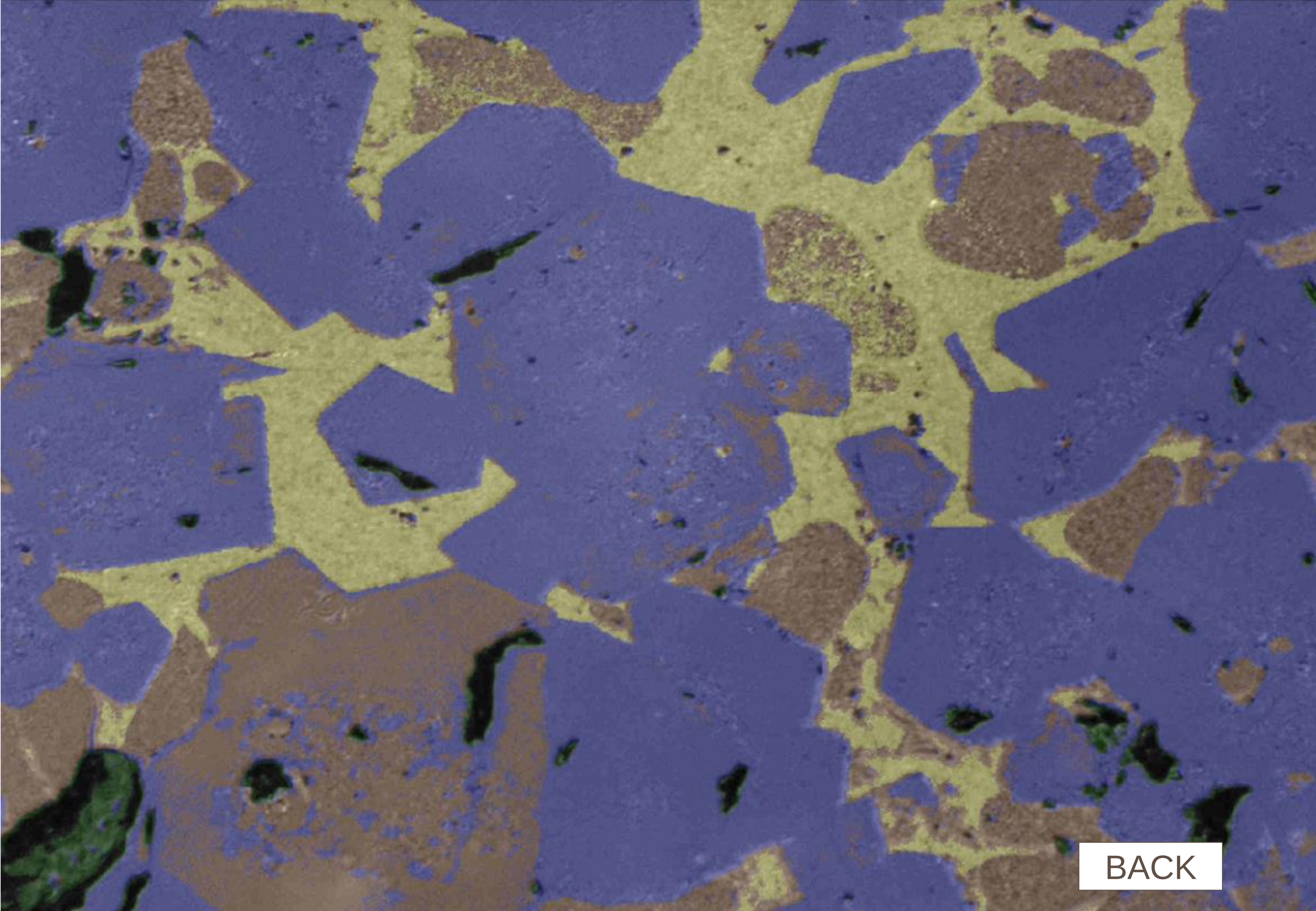
Approche 5			
	Mesure	**Théorie**	*écart*
%liant	12.24	12.4	*-0.16*
%GraSi	10.33	22.8	*-12.47*
%GraCa	69.41	56.8	*12.61*
%eau	8.02	8.1	*-0.08*
kg/m3 béton	**Mesure**	**Théorie**	*écart*
Mliant	290.53	290.00	*0.53*
MgraSi	245.16	534.00	*-288.84*
MgraCa	1646.99	1334.00	*312.99*
Meau	190.31	189.00	*1.31*

Observation : Bon calcul pour le ciment, résultats ok pour somme des granulats

Key messages

- Multispectral imaging / classification of phases
  - several **tools** (free, commercial, home-made), **strategies**: supervised / unsupervised
  - Several raw data **quality**: quali/ semi-quanti/ quantitative
- Multi-scale/Heterogeneous materials→representativity→large areas
- High number of phases→robustness needed !
  - Choice of **SVM**-**MRF**-**BPT** approach:
    - **SVM** (Support Vector Machine) as a robust classifier in any situation
    - **MRF** (Markov Random Filter) as spatial filtering process
    - **BPT** (Binary Partition Tree) as decision improvement tool
- Supervised strategy→ expertise of microstructures is kept in the learning step !
  - Computer is not deciding for you.
- Demonstrated the application of the SVM-MRF classification on SEM multispectral image datasets of blended cement and blended cement paste
  - Good agreement,results and **validation** with reference samples. Measurement on selected SCMs / natural pozzolans and pastes are quite good.
- Fast growing of these techniques, applicable to any signals ! (Optical ?)
  - Tomorrow in your EDX software !


Thank you for your attention !



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