Using Advanced Image Analysis to Predict Coal Char Morphology, Structure and Burnout Behaviour

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“Advanced Image Analysis of Coals”

To develop several new image analysis methods to measure coal, char, mineral and ash materials resulting in a simple method that can characterise fuel in a way that enables power generators to understand the consequences of fuel choices

Image Analysis of Coal

International Journal of Coal Geology, 2 (1982) 113—150 113
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APPLICATION OF AUTOMATED IMAGE ANALYSIS TO COAL PETROGRAPHY

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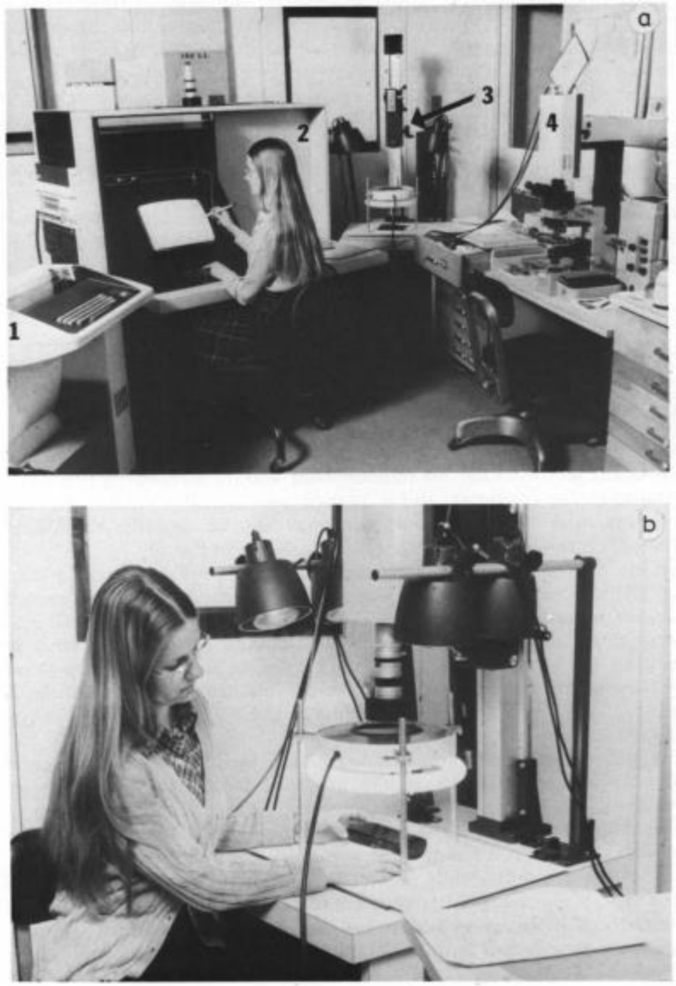
ABSTRACT

Chao, E.C.T., Minkin, J.A. and Thompson, C.L., 1982. Application of automated image analysis to coal petrography. Int. J. Coal Geol., 2:113—150.

The coal petrologist seeks to determine the petrographic characteristics of organic and inorganic coal constituents and their lateral and vertical variations within a single coal bed or different coal beds of a particular coal field. Definitive descriptions of coal characteristics and coal facies provide the basis for interpretation of depositional environments, diagenetic changes, and burial history and determination of the degree of coalification or metamorphism. Numerous coal core or columnar samples must be studied in detail in order to adequately describe and define coal microlithotypes, lithotypes, and lithologic facies and their variations. The large amount of petrographic information required can be obtained rapidly and quantitatively by use of an automated image-analysis system (AIAS).

An AIAS can be used to generate quantitative megascopic and microscopic modal analyses for the lithologic units of an entire columnar section of a coal bed. In our scheme for megascopic analysis, distinctive bands 2 mm or more thick are first demarcated by visual inspection. These bands consist of either nearly pure microlithotypes or lithotypes such as vitrite/vitrain or fusite/fusain, or assemblages of microlithotypes. Megascopic analysis with the aid of the AIAS is next performed to determine volume percentages of vitrite, inertite, minerals, and microlithotype mixtures in bands 0.5 to 2 mm thick. The microlithotype mixtures are analyzed microscopically by use of the AIAS to determine their modal composition in terms of maceral and optically observable mineral components. Megascopic and microscopic data are combined to describe the coal unit quantitatively in terms of (V) for vitrite, (E) for liptite, (I) for inertite or fusite, (M) for mineral components other than iron sulfide, (S) for iron sulfide, and (VEIM) for the composition of the mixed phases (X_i) i = 1,2, etc. in terms of the maceral groups vitrinite V, exinite E, inertinite I, and optically observable mineral content M. The volume percentage of each component present is indicated by a subscript. For example, a lithologic unit was determined megascopically to have the composition $(V)_{13}(I)_1(S)_1(X_1)_{83}(X_2)_2$. After microscopic analysis of the mixed phases, this composition was expressed as $(V)_{13}(I)_1(S)_1(V_{63}E_{19}I_{14}M_4)_{83}(V_{67}E_{11}I_{13}M_9)_2$. Finally, these data were combined in a description of the bulk composition as $V_{67}E_{16}I_{13}M_3S_1$. An AIAS can also analyze textural characteristics and can be used for quick and reliable determination of rank (reflectance).

Our AIAS is completely software based and incorporates a television (TV) camera



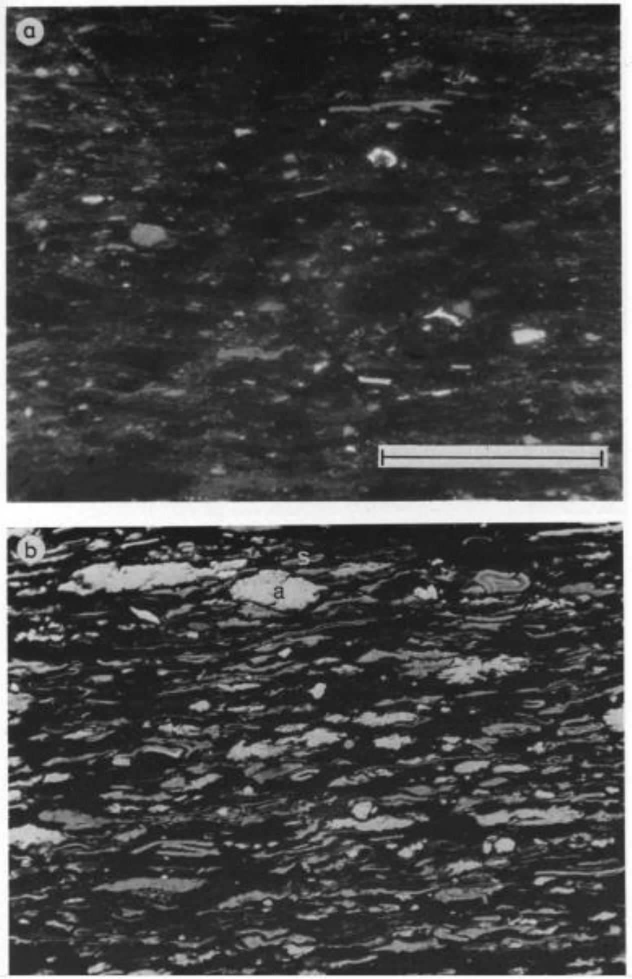
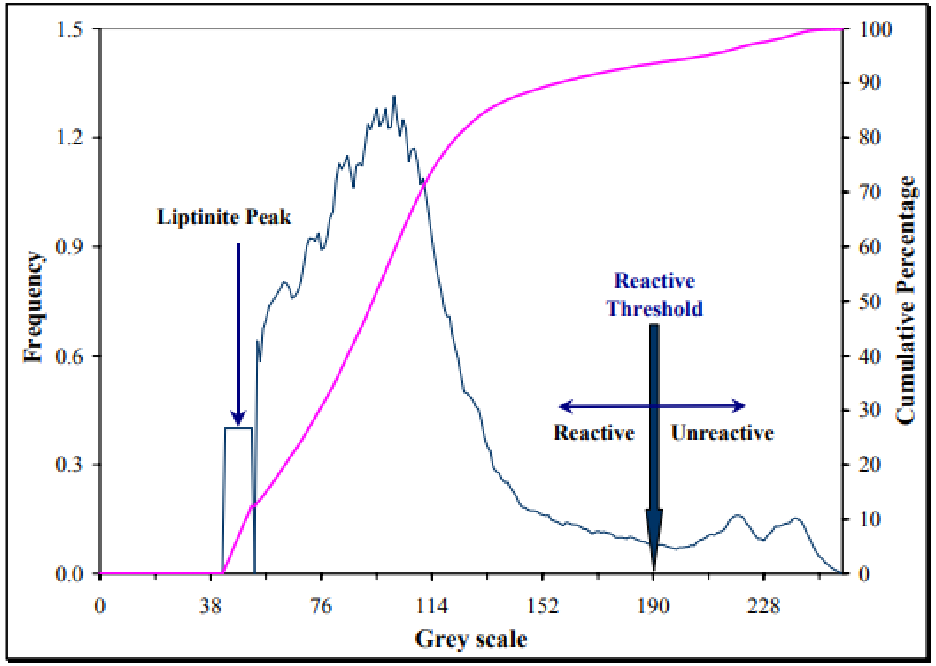


Image Analysis of Coal

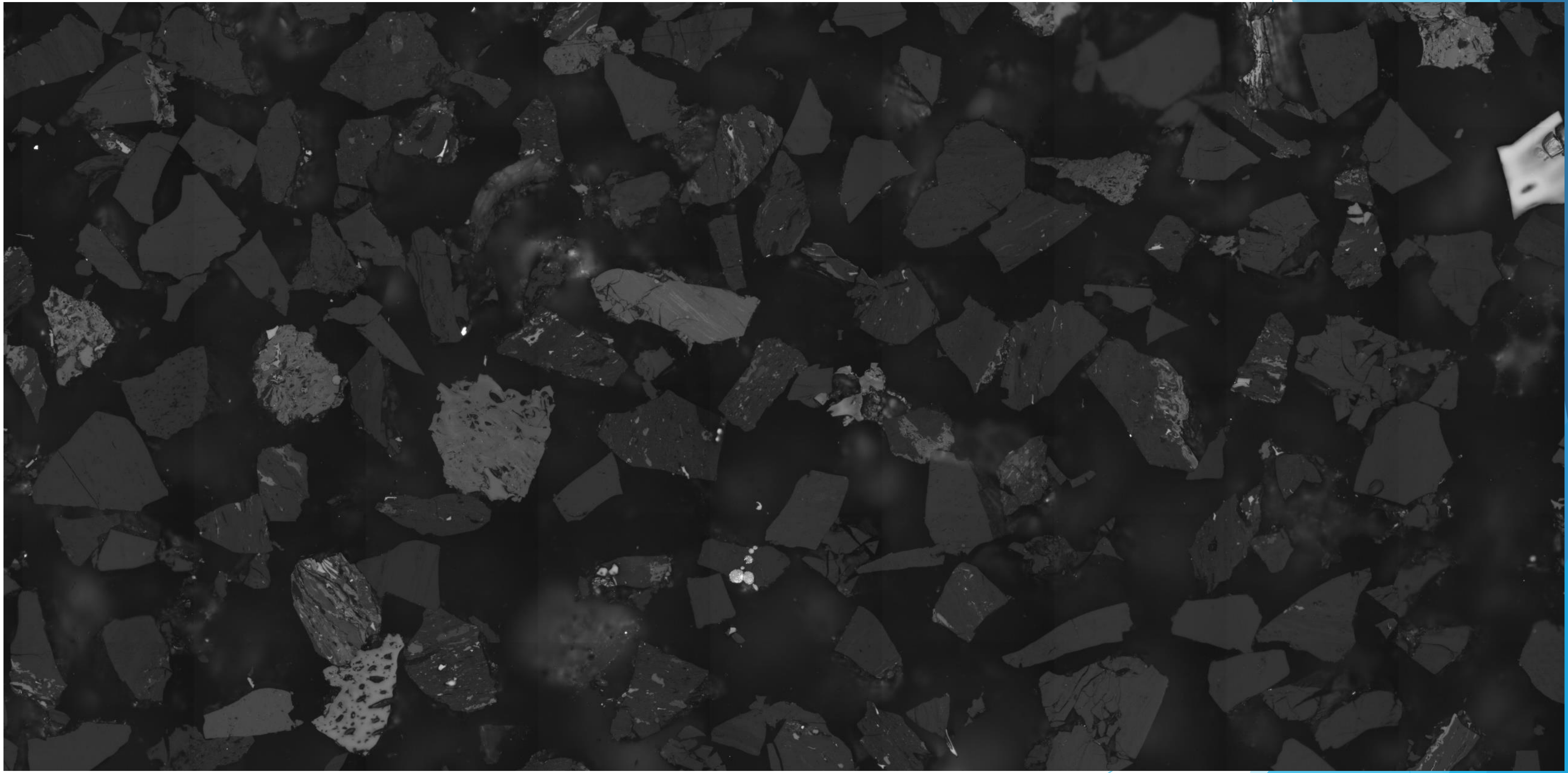
IBAS 2000 Image Analyser

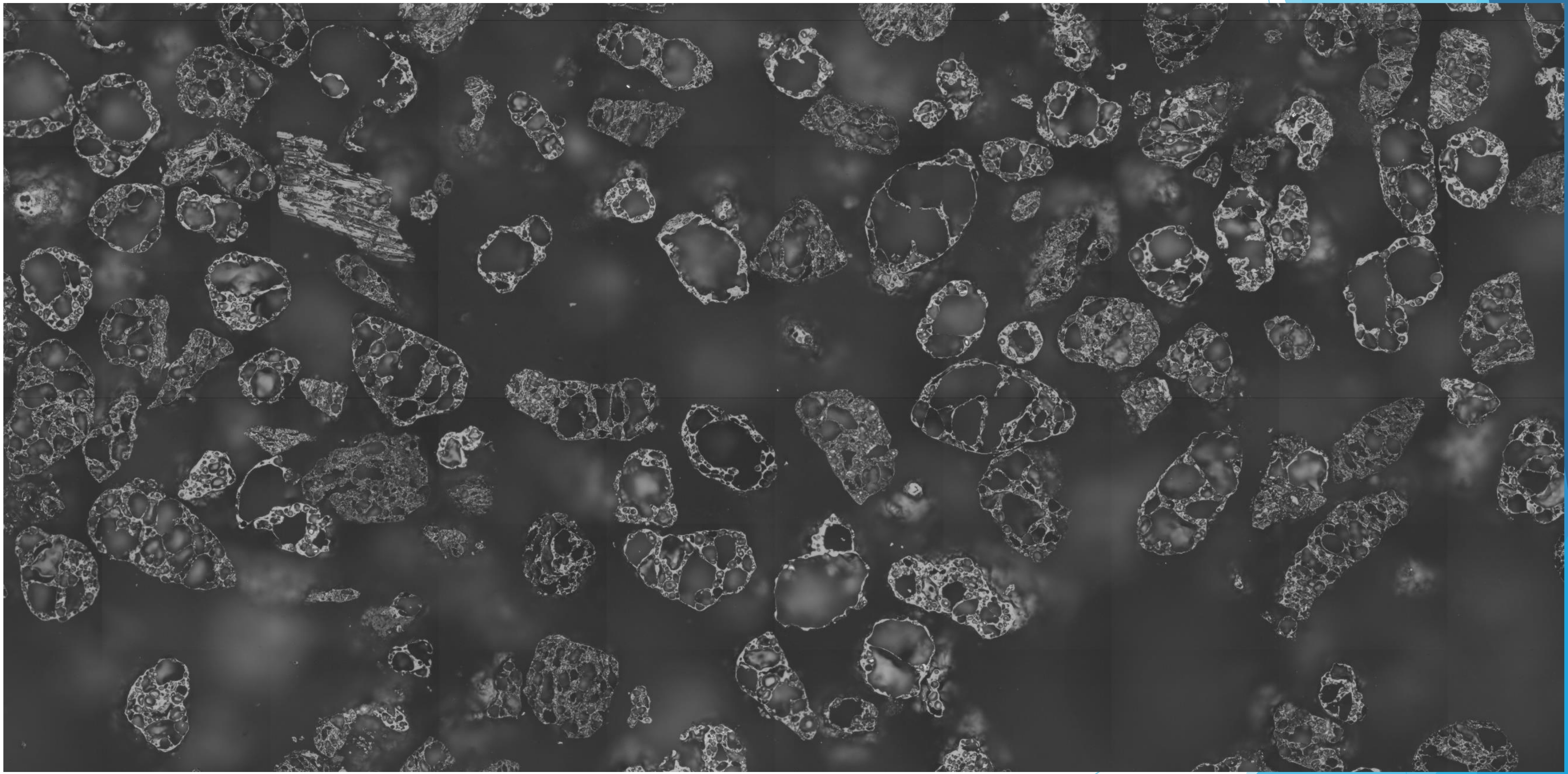


Coal reflectance histogram (RAP)

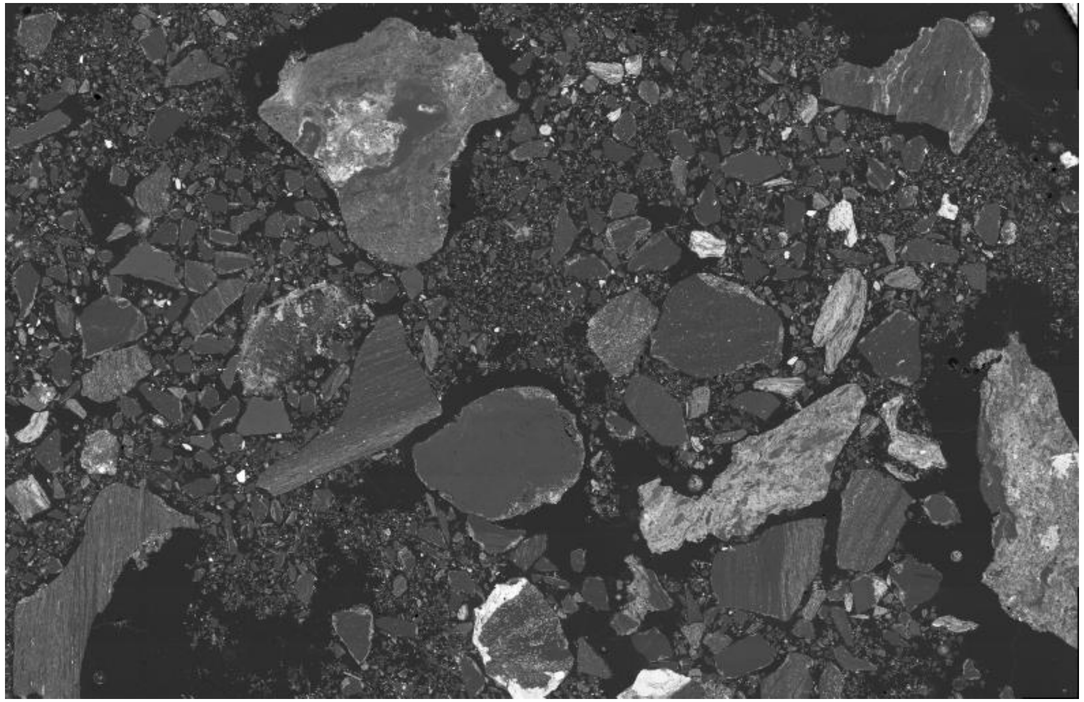
SOURCE: Lester E., Allen M., Cloke M., Miles N.J. (1994a). An automated image analysis system for major maceral group analysis in coals. Fuel 73, 1729- 1734.

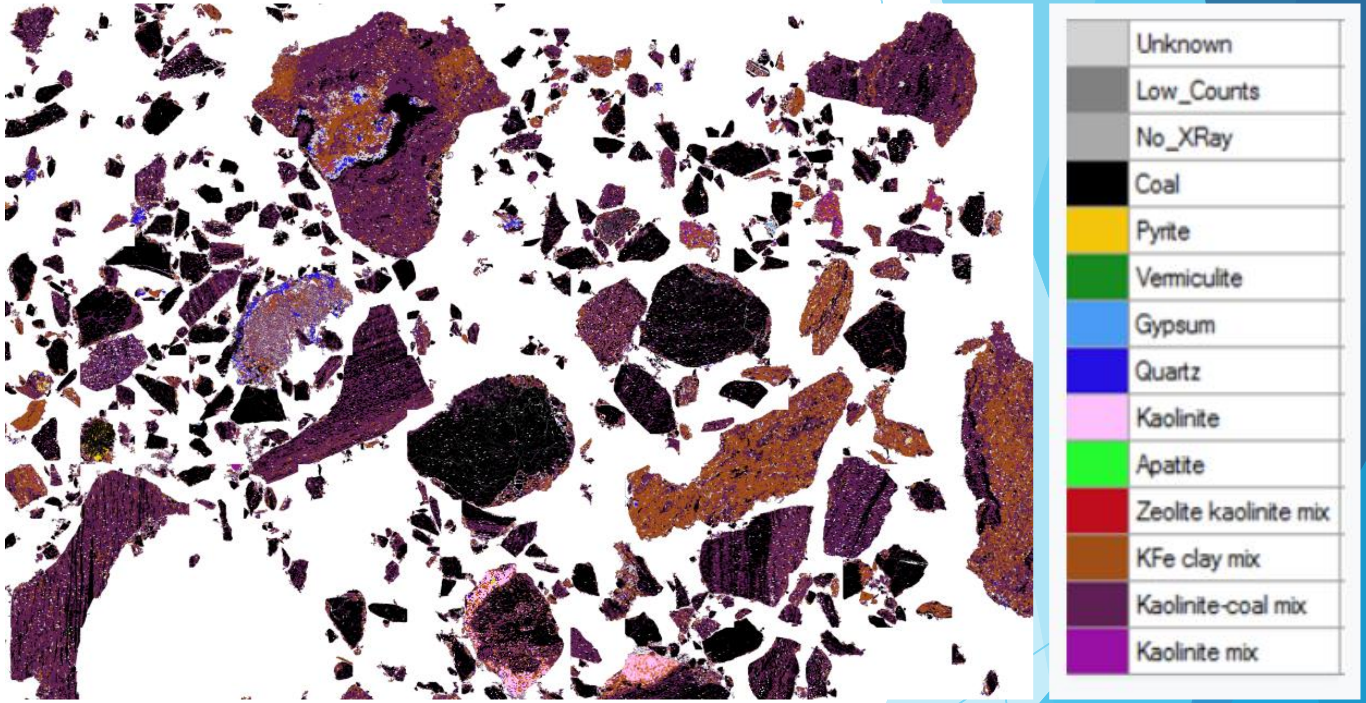
Image Analysis





Mineral Detection – SEM/MLA

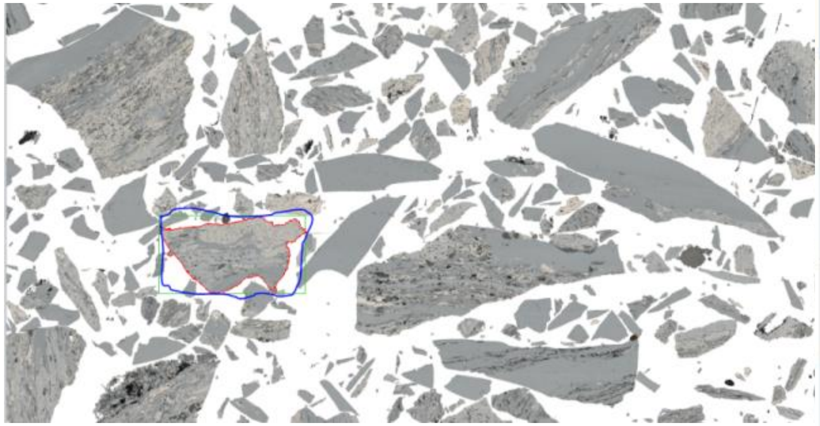




Mineral Detection – Air Objectives

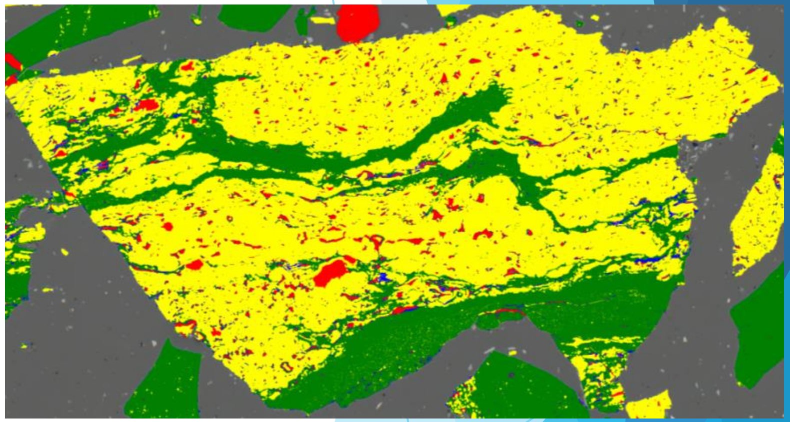
Coal Grain Analysis

	tones per channel per pixel
8 bit	256
10 bit	1,024
12 bit	4,095
14 bit	16,383
16 bit	65,532



Segmented Colour Coal Mosaic

	Dark Mineral
	Liptinite
	Vitrinite
	Inertinite
	Bright Mineral



Characterized Grain

SOURCE: O'Brien G., Jenkins B., and Beath H., 2003b, Coal Grain Analysis, ACARP Project C10053

Image Analysis

- Image Analysis has helped to improve coal and char assessment significantly over the last 20-30 years
- It remains a challenge to combine all the useful characteristics that are measured using EM/OI
- Predicting all major events (boiler performance, slagging and fouling and EP performance) would be a powerful tool for generators

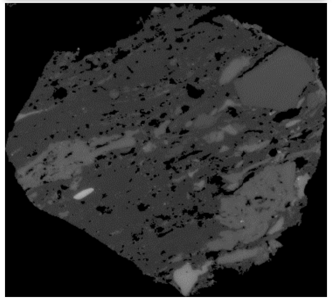
Project Aims

Develop several new image analysis techniques to;

- Rapidly characterise fuels to predict boiler performance
- Provide plant operators with a fully automated tool
- Analyse both blends and single fuel sources

Approach

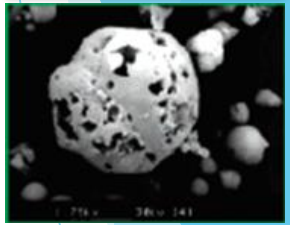
COAL PROPERTIES



Combustion models e.g CBK, CFD

Other combustion predictors (e.g. Rank, % Unreactives)

CARBON IN ASH

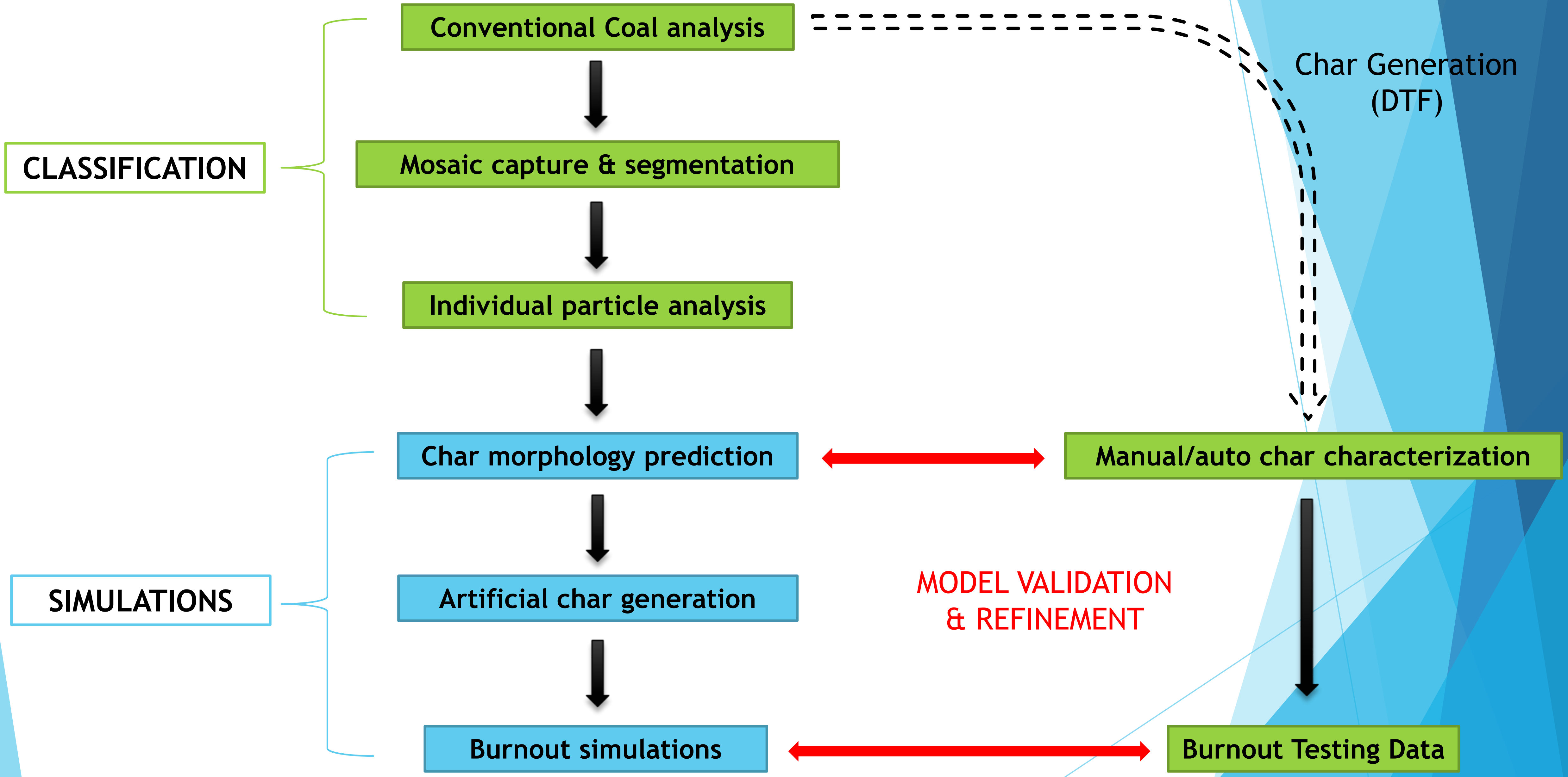


CHAR PREDICTION

High temp rigs
(e.g. DTF)

CHAR MORPHOLOGY

Combustion models



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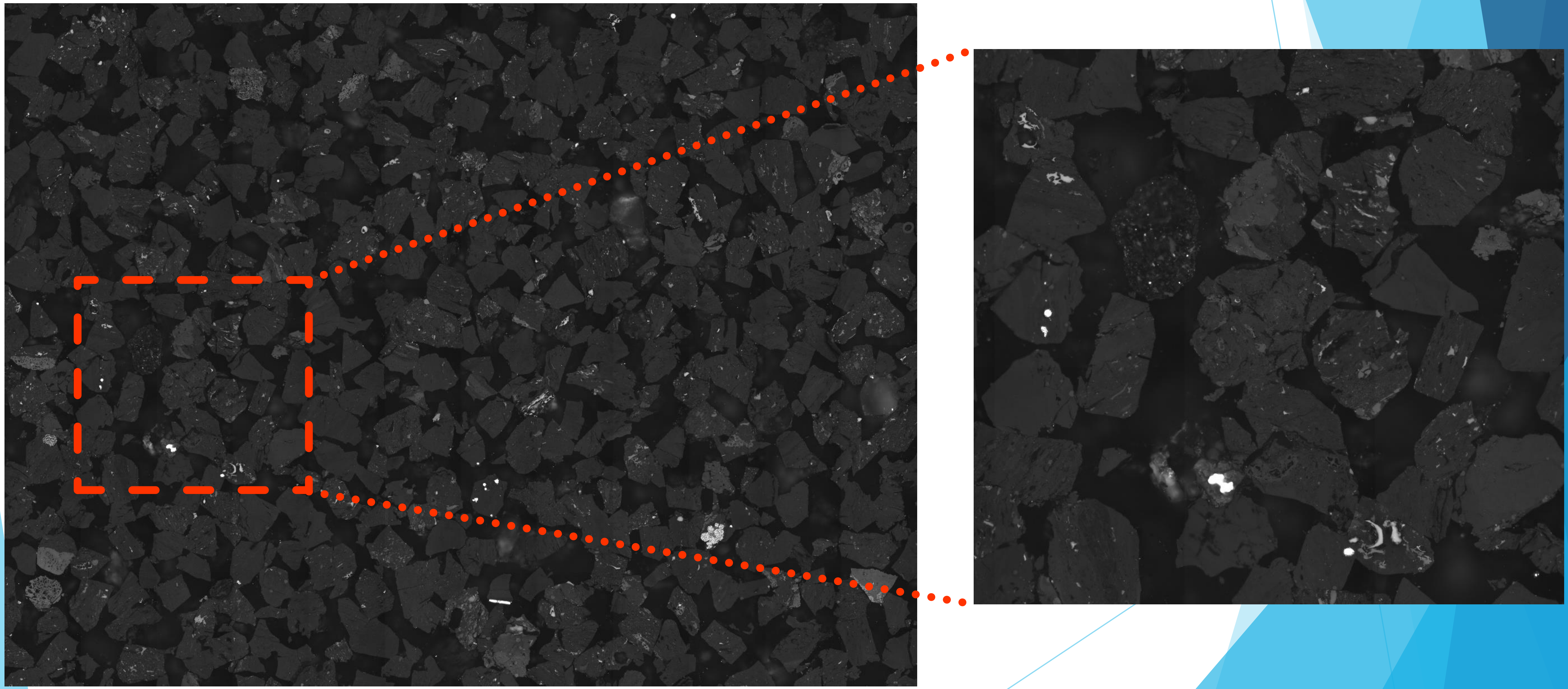
Mosaic capture & segmentation
Individual particle analysis
Char Generation
(DTF)
SIMULATIONS
Char morphology prediction
Artificial char generation
Burnout simulations
Manual/auto char characterization
MODEL VALIDATION
& REFINEMENT
Burnout Testing Data

Part 1 – Carbon Materials, Char Generation & Analysis

Coal	1	2	3	4	5	6	7	8	9	10	11	12
Moisture	0.6	0.7	4.6	0.9	2.3	0.0	2.8	5.4	3.2	2.9	3.9	0.7
Volatiles	28.6	7.5	25.9	7.5	24.4	1.1	35.8	38.4	30.8	34.9	31.1	7.0
Fixed Carbon	59.6	84.7	61.7	66.1	58.4	84.8	53.5	51.2	50.0	53.1	48.5	61.9
Ash	11.2	7.1	7.8	25.4	14.9	14.1	7.9	5.0	16.0	9.1	16.5	30.4
Fuel Ratio	2.1	11.2	2.4	8.8	2.4	75.6	1.5	1.3	1.6	1.5	1.6	8.8

- Pyrolysis using Drop-Tube-Furnace (1300 ^{o}C, 200ms, 1% oxygen)
- Laboratory suite of testing (TGA, Elemental Analysis, Calorific content, Density, BET Surface area)

Part 2 – Image Capture & Segmentation



Part 2 – Image Capture & Segmentation

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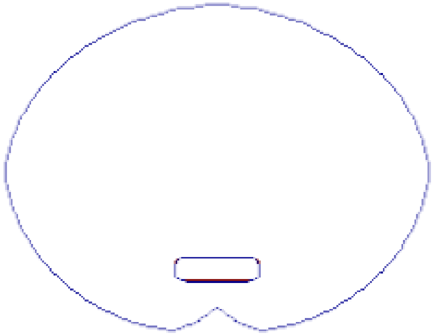
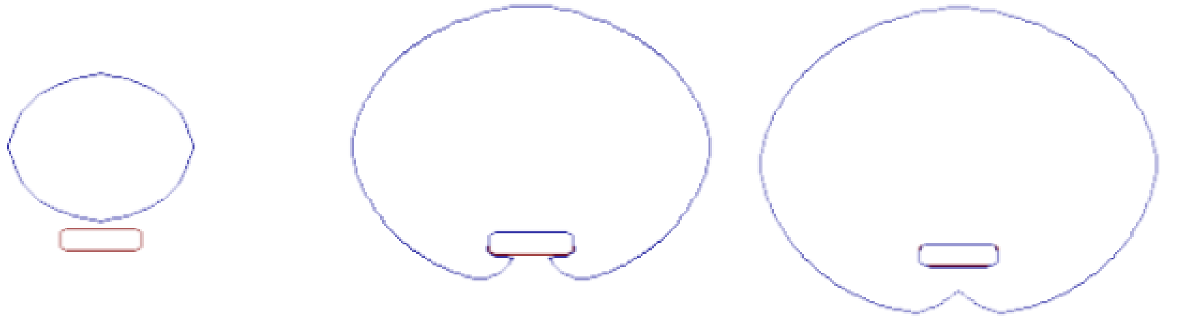


– Image Capture & Segmentation

- Active contours segmentation algorithm
- Does not rely on edge detection, which is susceptible to blemishes
- Iterative, energy minima segmentation method
- Proximity average of foreground and background mean values

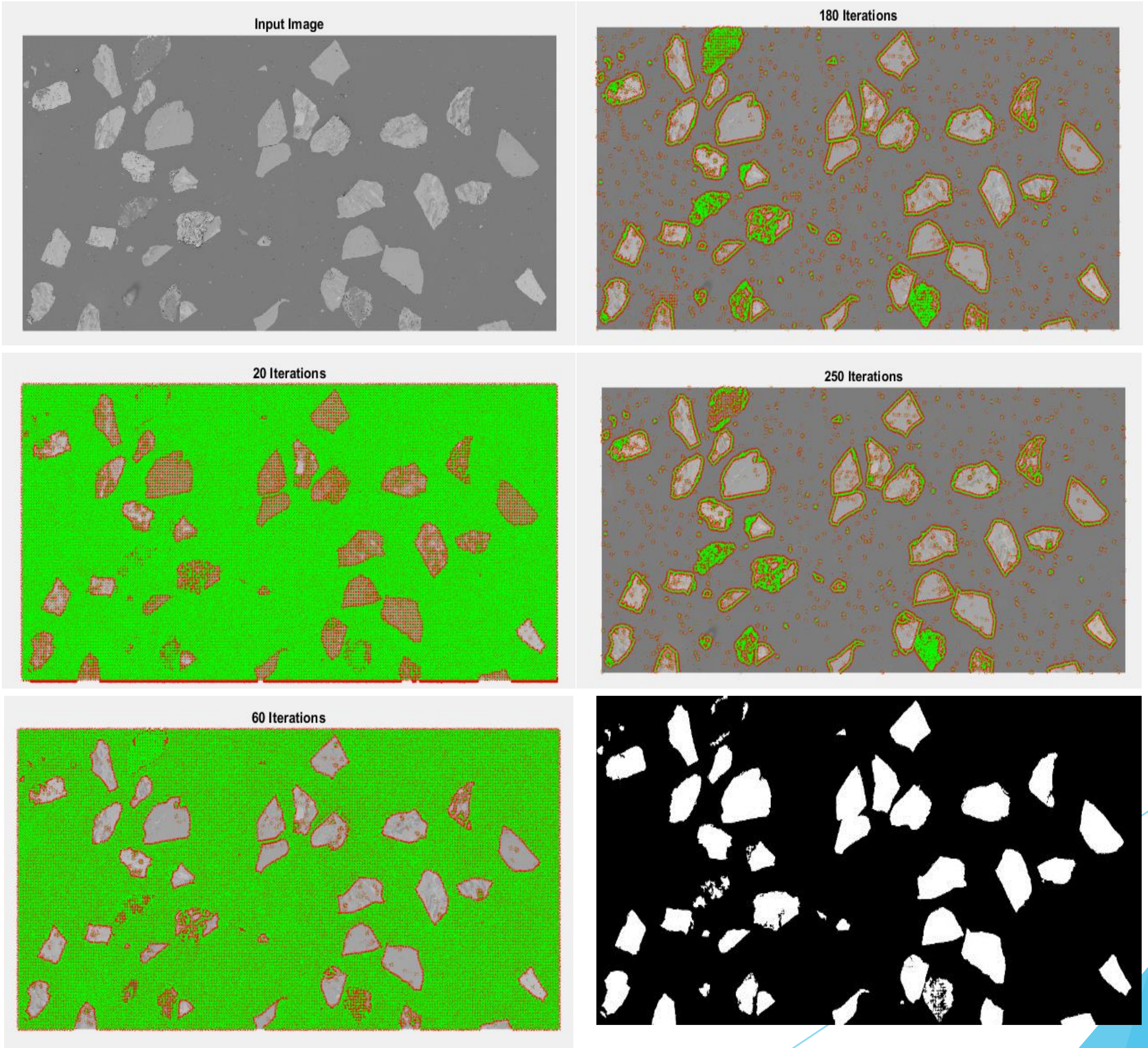


a) Initial contour

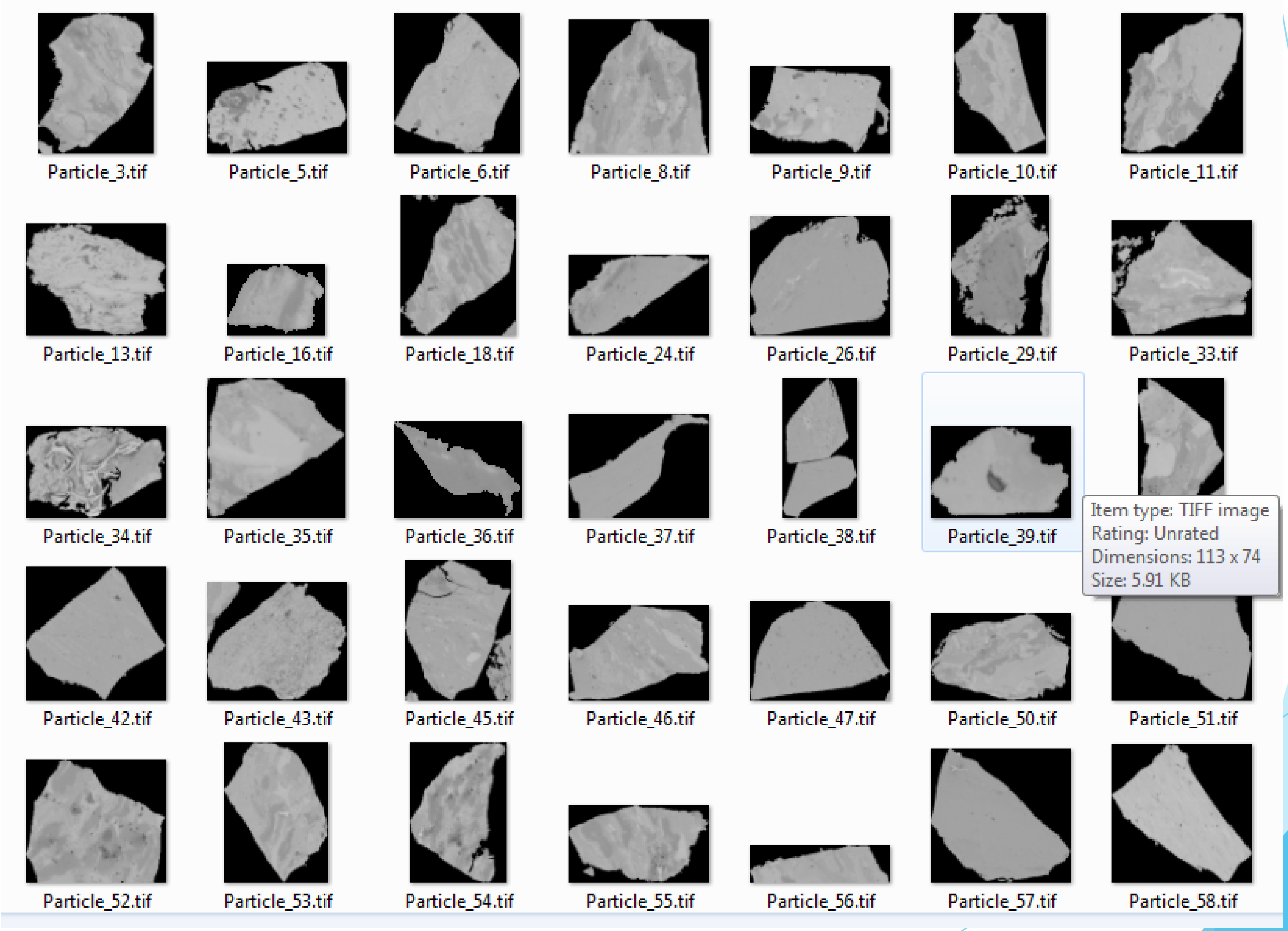
b) Stopped by an obstacle

c) Later perturbation

Part 2 – Image Capture & Segmentation

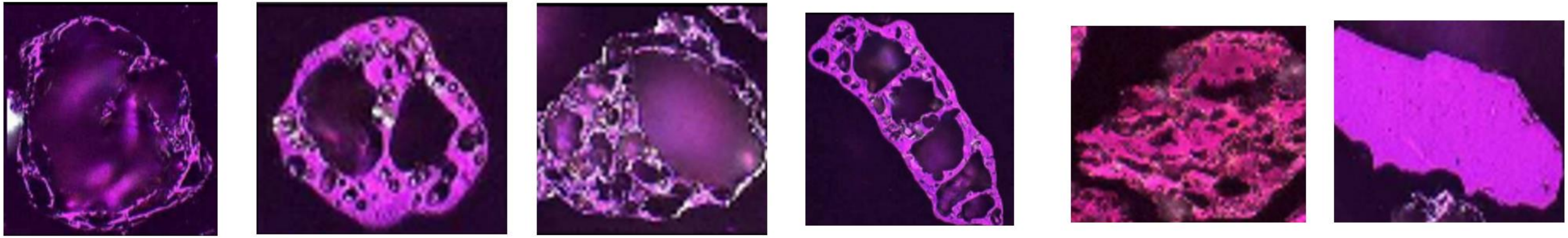


Part 3 - Individual Particle Analysis



Coal Chars – ICCP Atlas Classification

- *Char Wall Thickness*
- *Char Voidage and Porosity*
- *Fused and Unfused Structures*

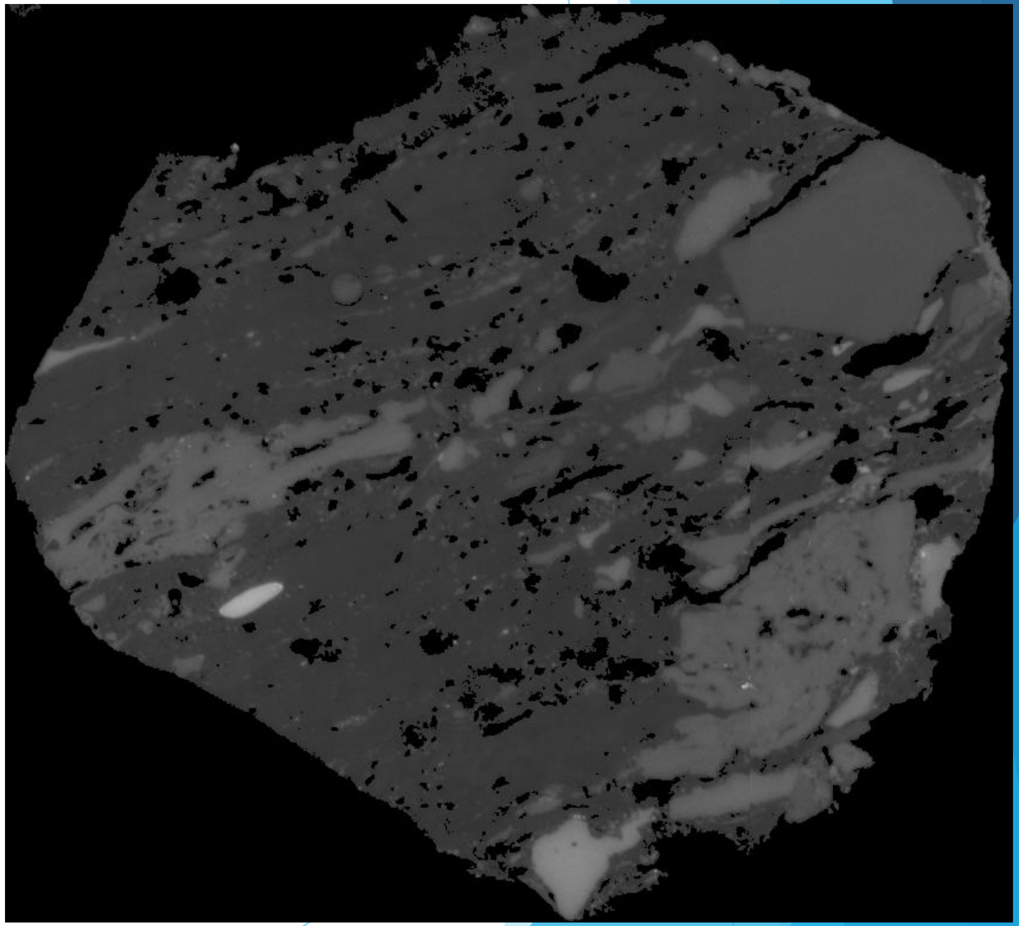


Tenuisphere | Crassisphere | Tenuinetwork | Crassinetwork | Inertoid | Fusinoid/Solid

SOURCE: Alvarez, D., Lester, E.: Atlas of char occurrences. combustion working group, commission iii. In: International Conference on Coal Petrology, ICCP (2001)

Part 3 – Individual Particle Analysis

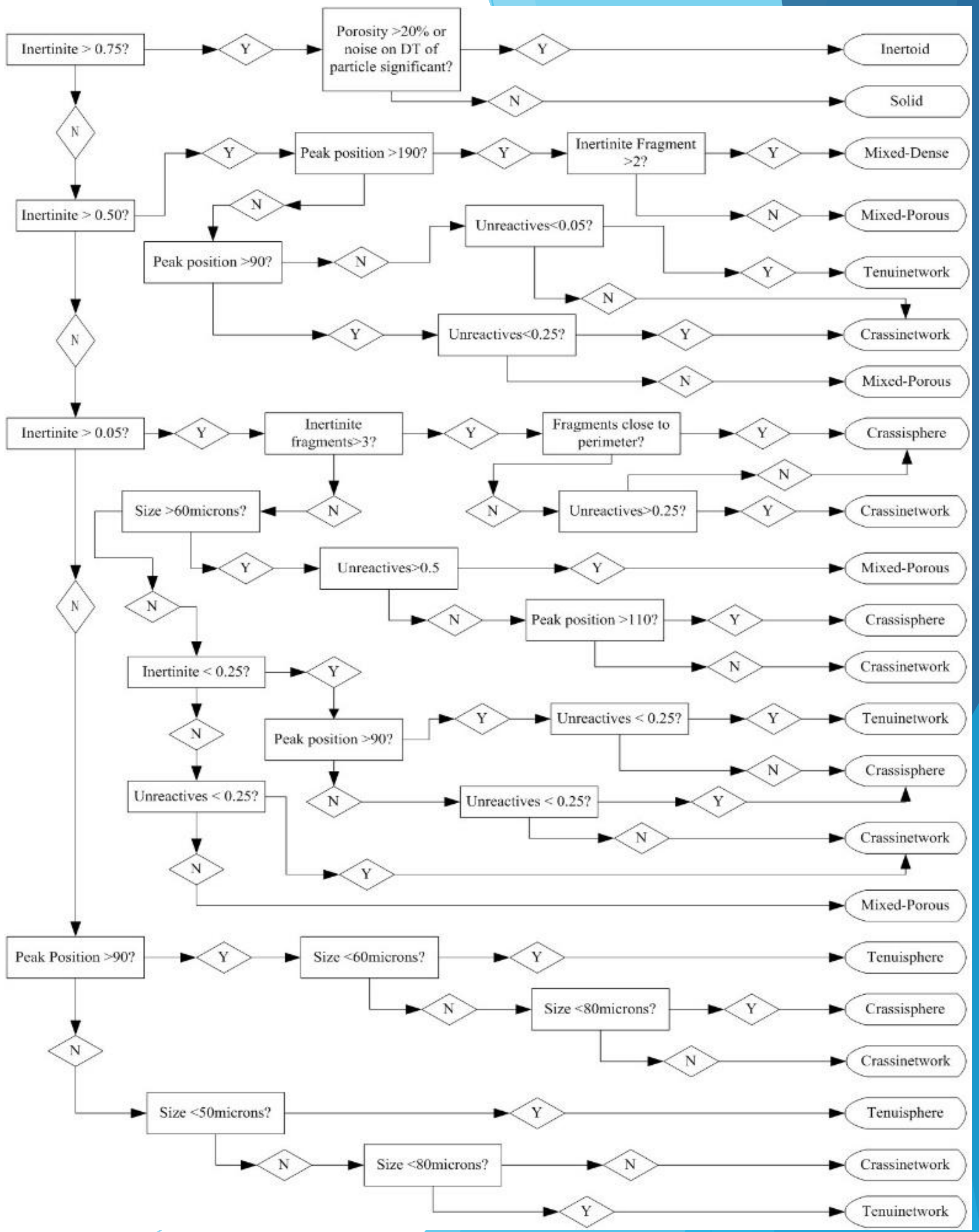
1. Maceral content
2. Inertinite fragment count
3. Inertinite proximity to particle boundary
4. %Unreactives
5. Reflectance histogram mean peak value
6. Particle size



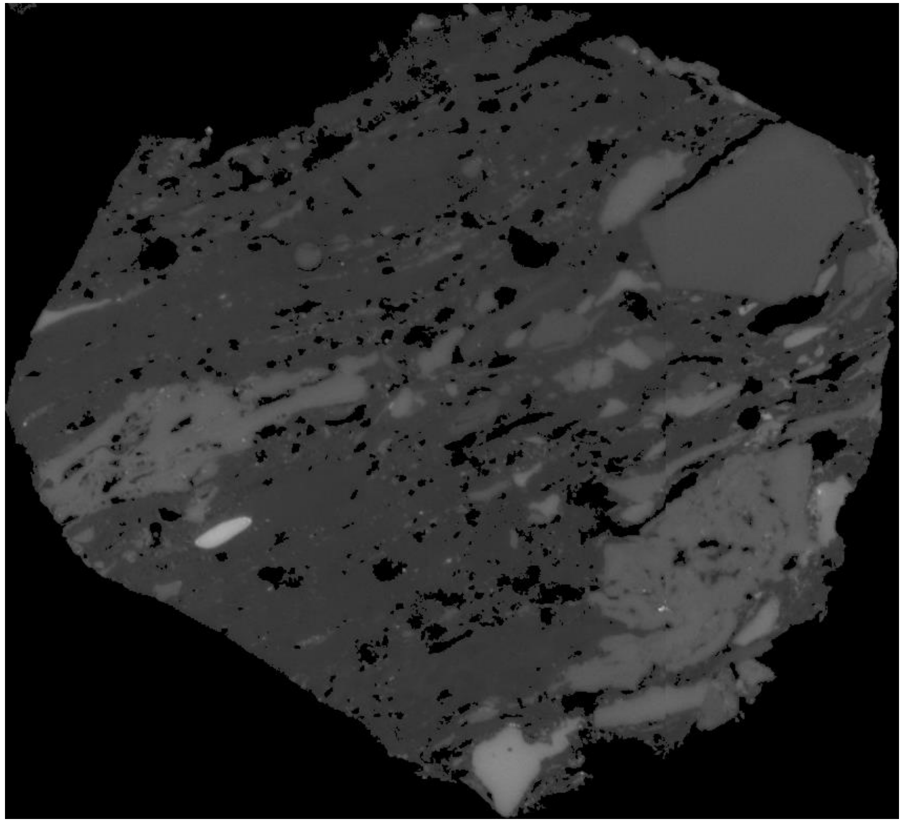
Part 4 – Char Morphology Prediction

- Maceral content
- Maceral fragment count
- Fragment Proximity
- % Unreactives
- Reflectance histogram peak value
- Size

Decision Tree Skeleton - 6000 initial data points

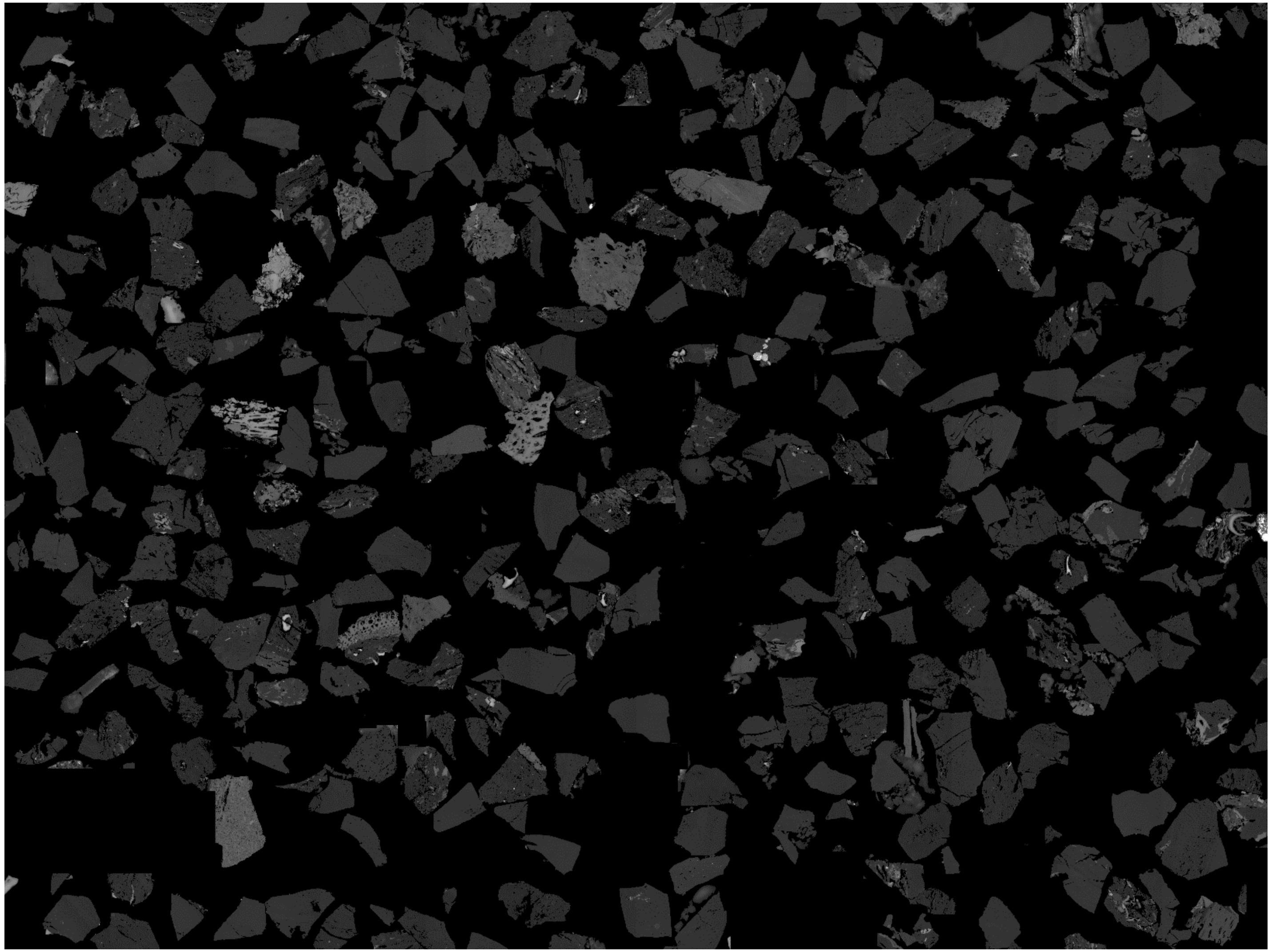


Part 4 – Char Morphology Prediction



Particle Size	111.2 microns
Inertinite Content	56.2 %
%Unreactives	24.6 %
Inertinite Fragments	70
Fragment proximity Mean	0.3372 microns
Grayscale Peak	107
Porosity	7.4313
PREDICTED CHAR MORPHOLOGY	**CRASSISPHERE**

Part 4 – Char Morphology Prediction



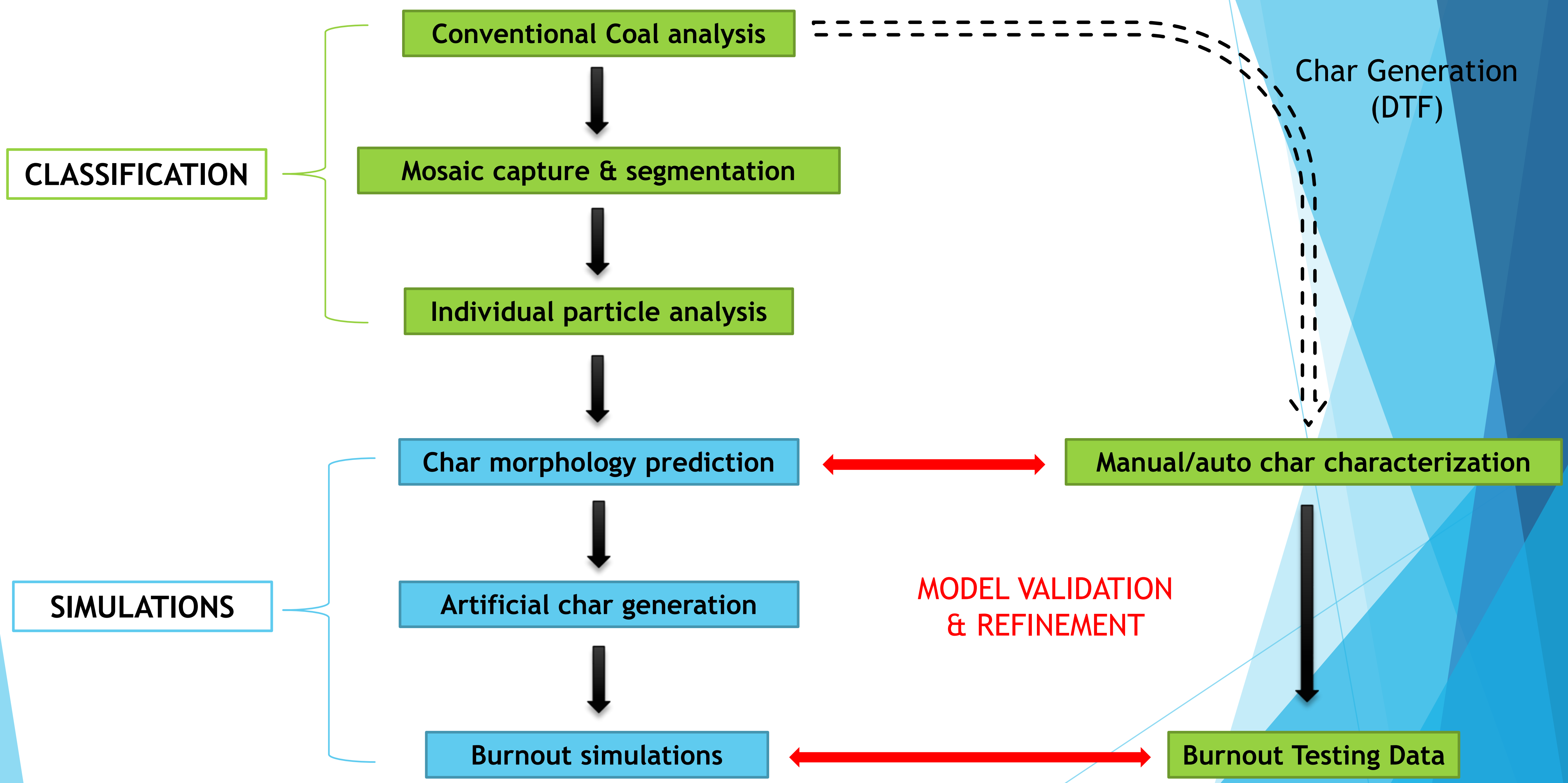
MORPHOLOGY	PREDICTED %	MANUAL %
TENUISPHERE	16	21.0
TENUINETWORK	40	40.0
CRASSISPHERE	26	26.0
CRASSINETWORK	8	6.0
FUSINOID	2	4.0
SOLID	8	2.0

THIN	57	62
THICK	33	32
SOLID	10	6

Part 4 – Char Morphology Prediction

ANALYSIS	IMPORT COAL 1	IMPORT COAL 2	COKE
MOISTURE	3.9	2.9	0.0
VOLATILES	31.1	34.9	1.1
FIXED CARBON	48.5	53.1	84.8
ASH	16.5	9.1	14.1
FUEL RATIO	1.6	1.5	75.6
V. REFLECTANCE	0.54	0.54	7.0

MORPHOLOGY	PREDICTED %	MANUAL %	PREDICTED %	MANUAL %	PREDICTED %	MANUAL %
TENUISPHERE	16	21	12	14	0	0
TENUINETWORK	40	40	14	14	0	0
CRASSISPHERE	26	26	12	40	0	0
CRASSINETWORK	8	6	46	14	7	10
FUSINOID	2	4	1	12	3	25
SOLID	8	2	15	6	90	58
THIN	56	62	26	27	0	0
THICK	33	32	58	55	7	10
SOLID	11	6	16	18	93	90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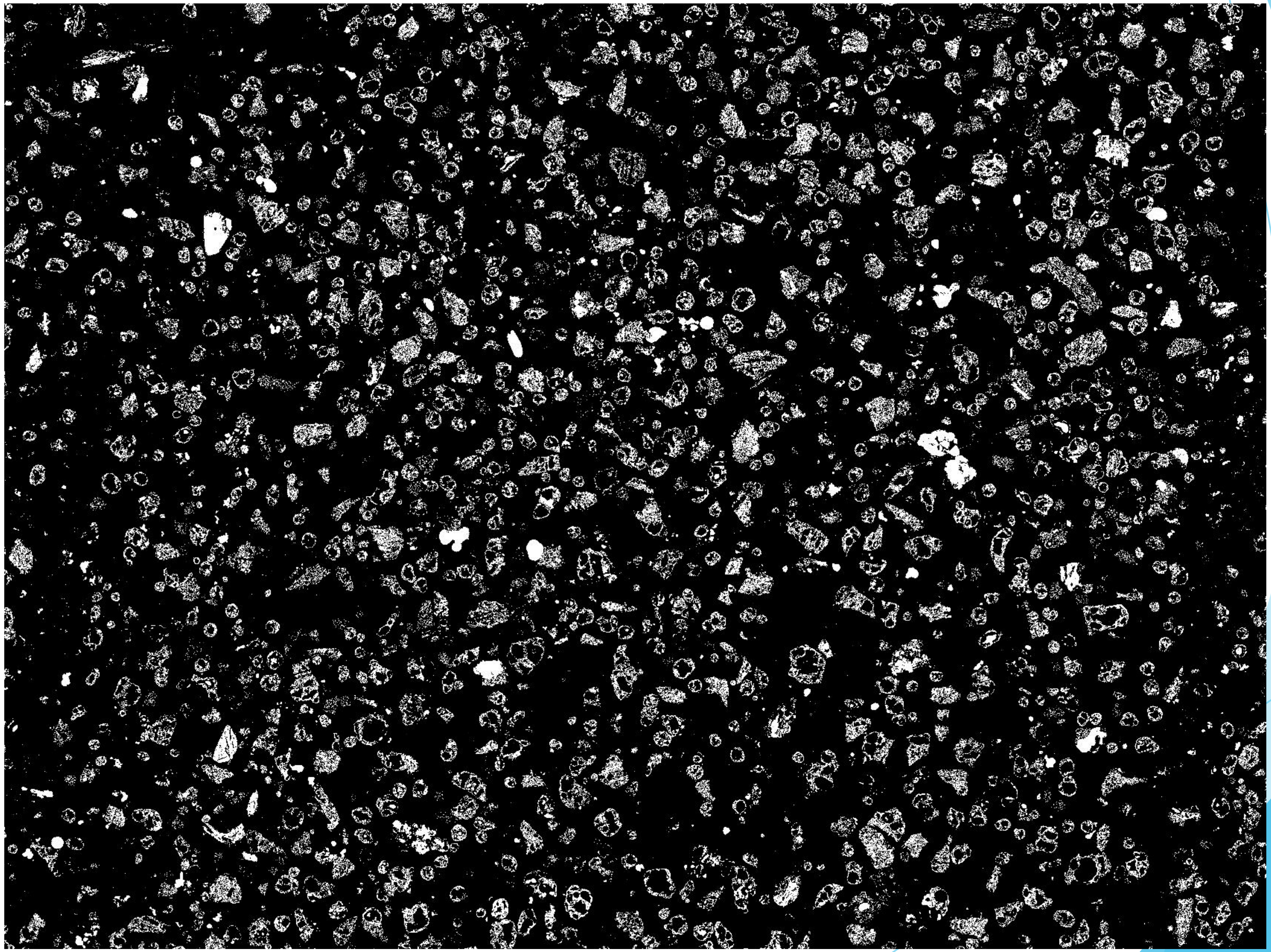
Part 6 – Char Burnout Simulations



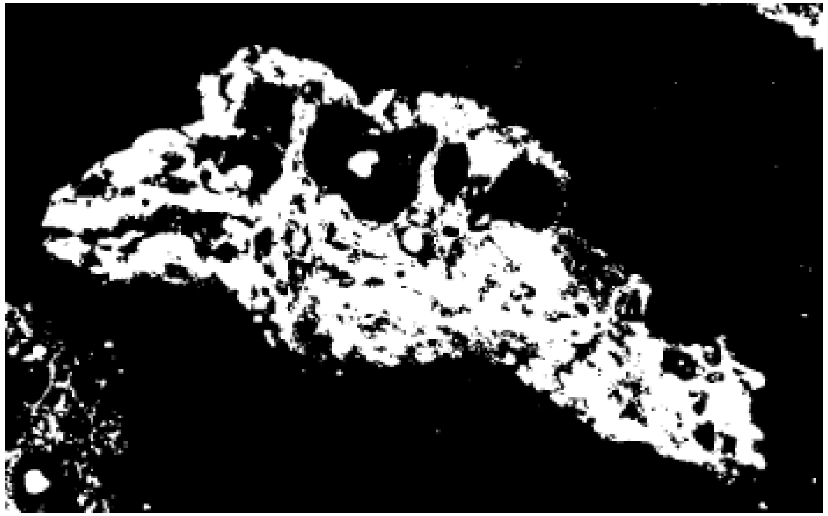
Part 6 – Char Burnout Simulations

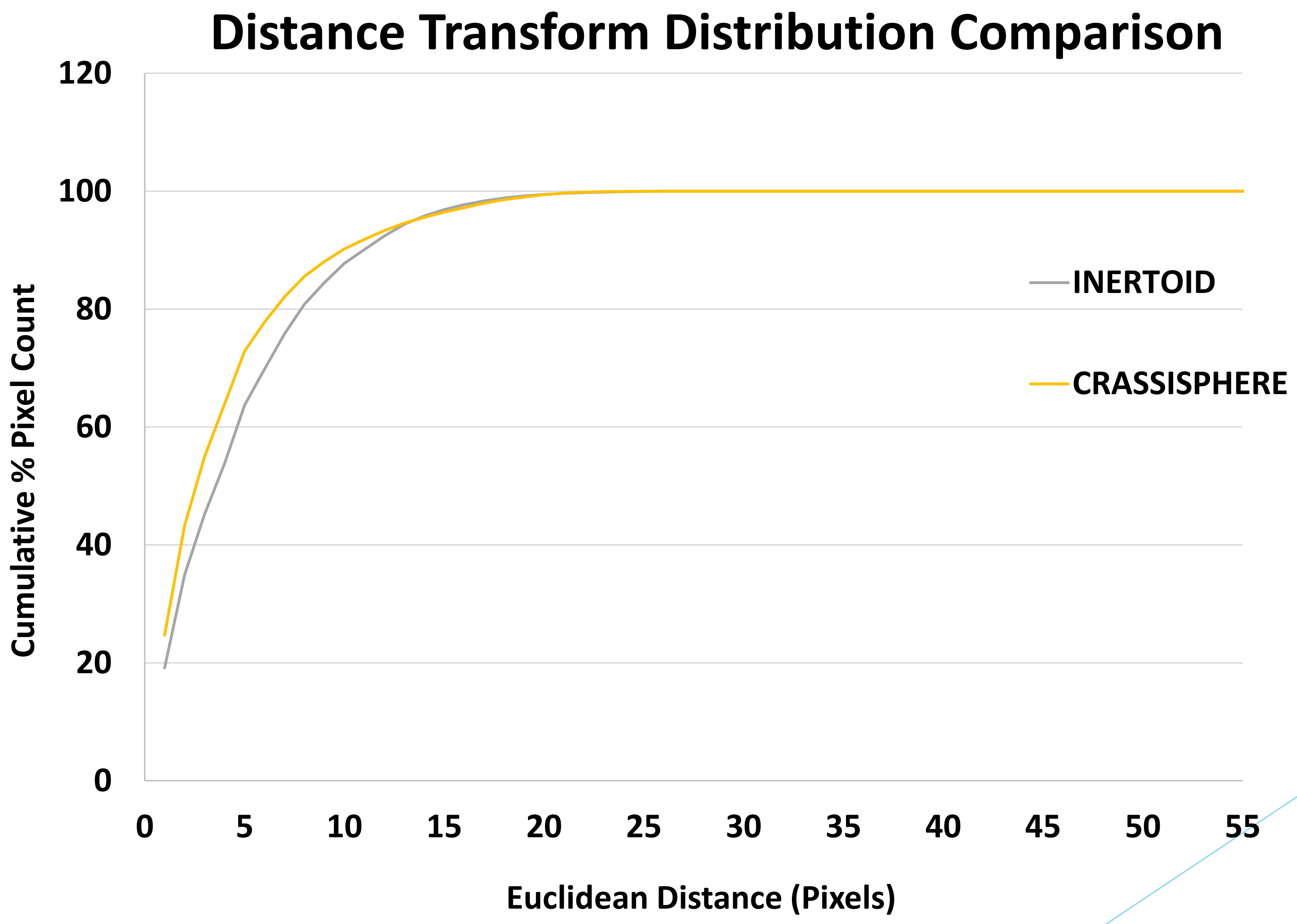
- Thicker chars burn slower and thinner chars burn quicker…
- Previous methods, such as Euclidean Distance Transform can suffer from poor resolution

0	0	0	0	0	0	0	0
0	1	1	1	1	1	1	0
0	1	1	1	1	1	1	0
0	1	1	1	1	1	1	0
0	1	1	1	1	1	1	0
0	1	1	1	1	1	1	0
0	0	0	0	0	0	0	0

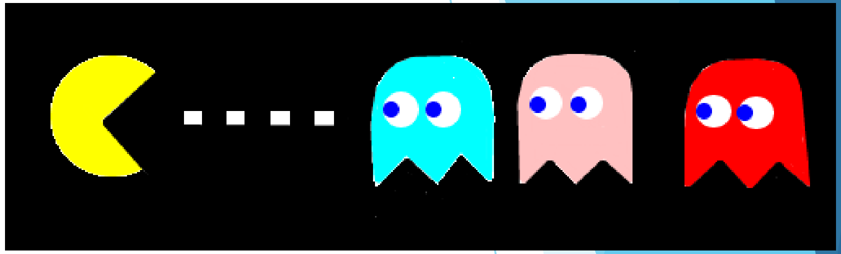
→

0	0	0	0	0	0	0	0
0	1	1	1	1	1	1	0
0	1	2	2	2	2	1	0
0	1	2	3	3	2	1	0
0	1	2	2	2	2	1	0
0	1	1	1	1	1	1	0
0	0	0	0	0	0	0	0



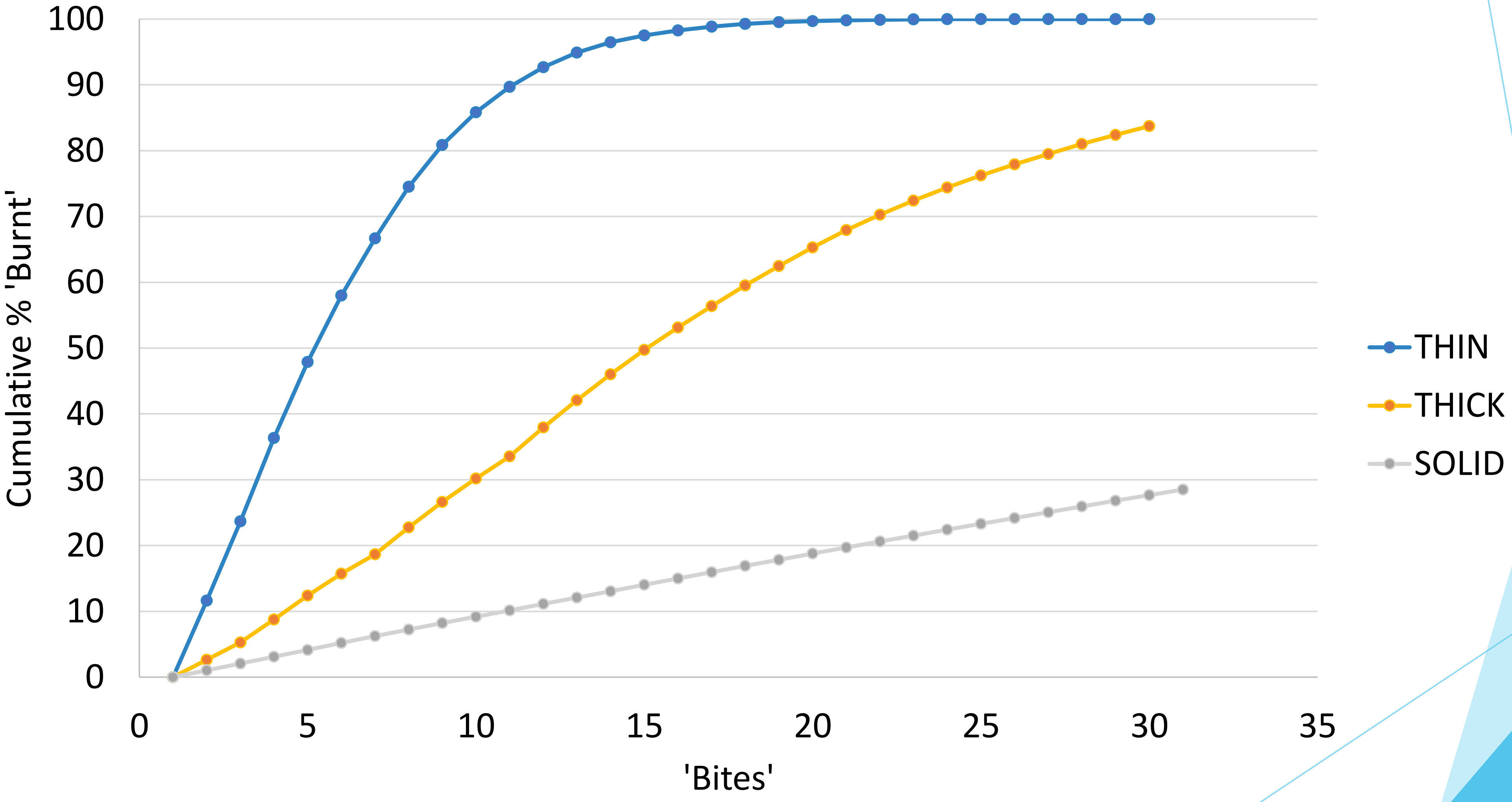

Distance Transform Distribution Comparison
120
100
80
60
40
20
0
Cumulative % Pixel Count
0
5
10
15
20
25
30
35
40
45
50
55
Euclidean Distance (Pixels)
INERTOID
CRASSISPHERE

Part 6 – Char Burnout Simulations ‘Pacman’

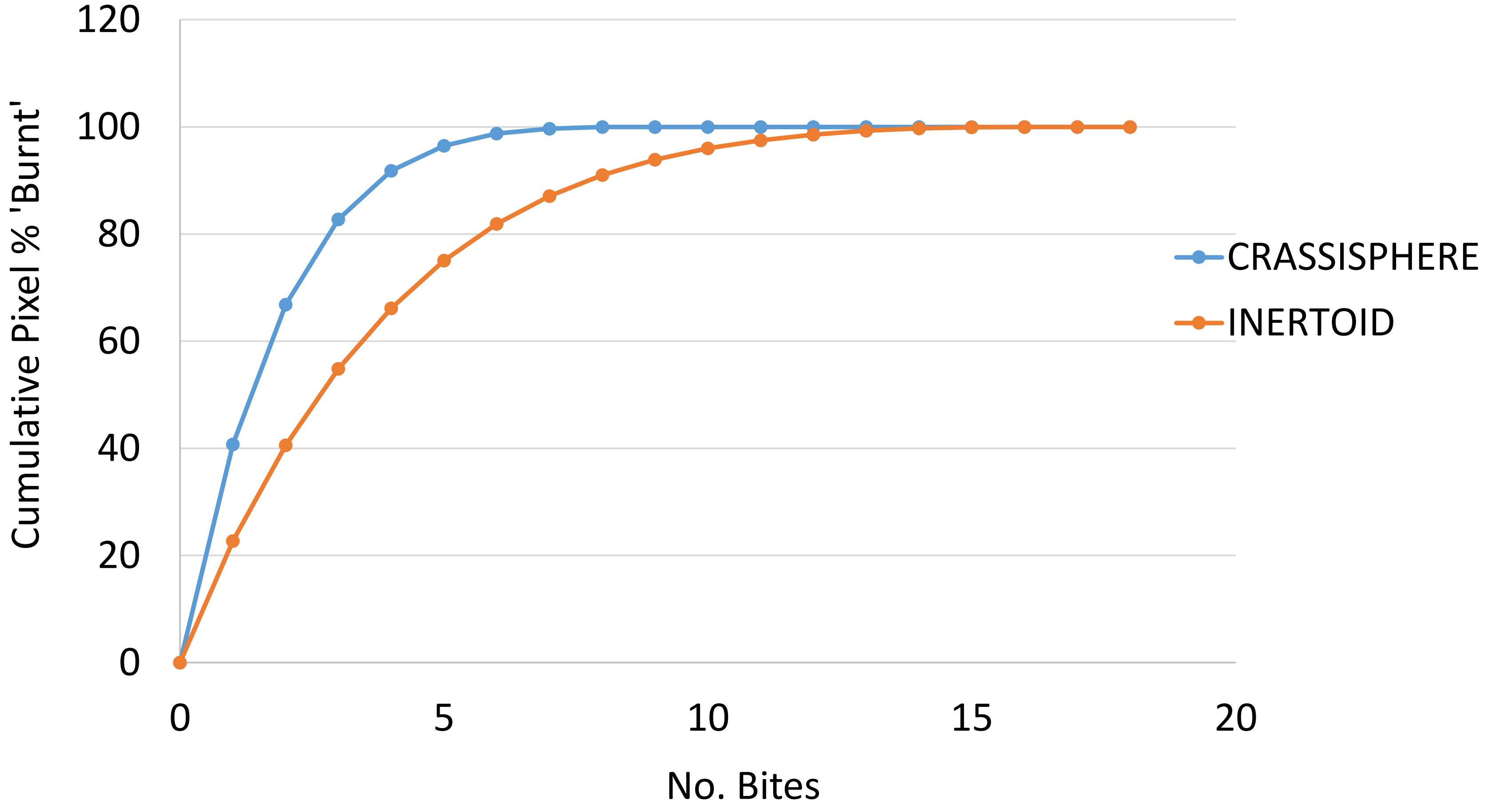


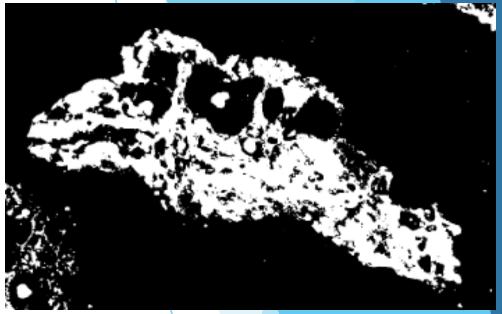
- Iterative, 1x directional ‘eating’ process (1 x pixel bites)
- Available exposed surface

Char Erosion Profiles - 30 Bites



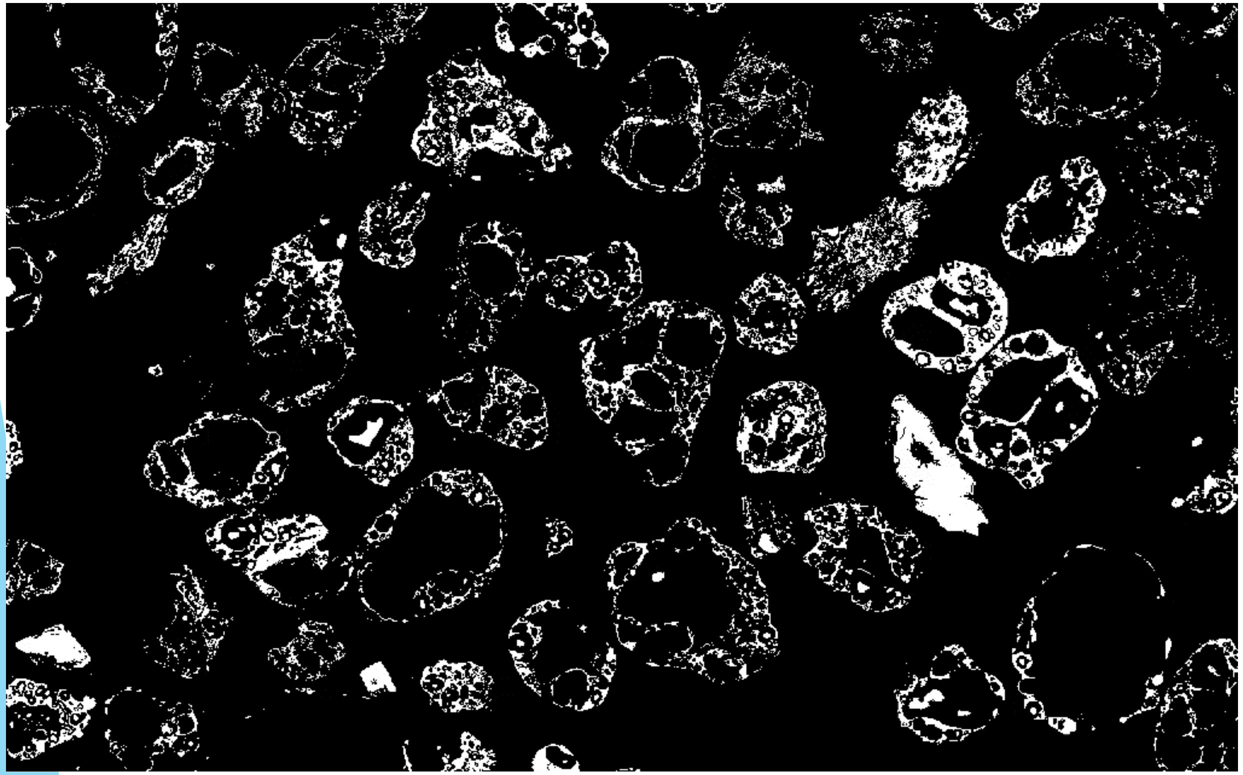
Pacman Erosion Method Comparison

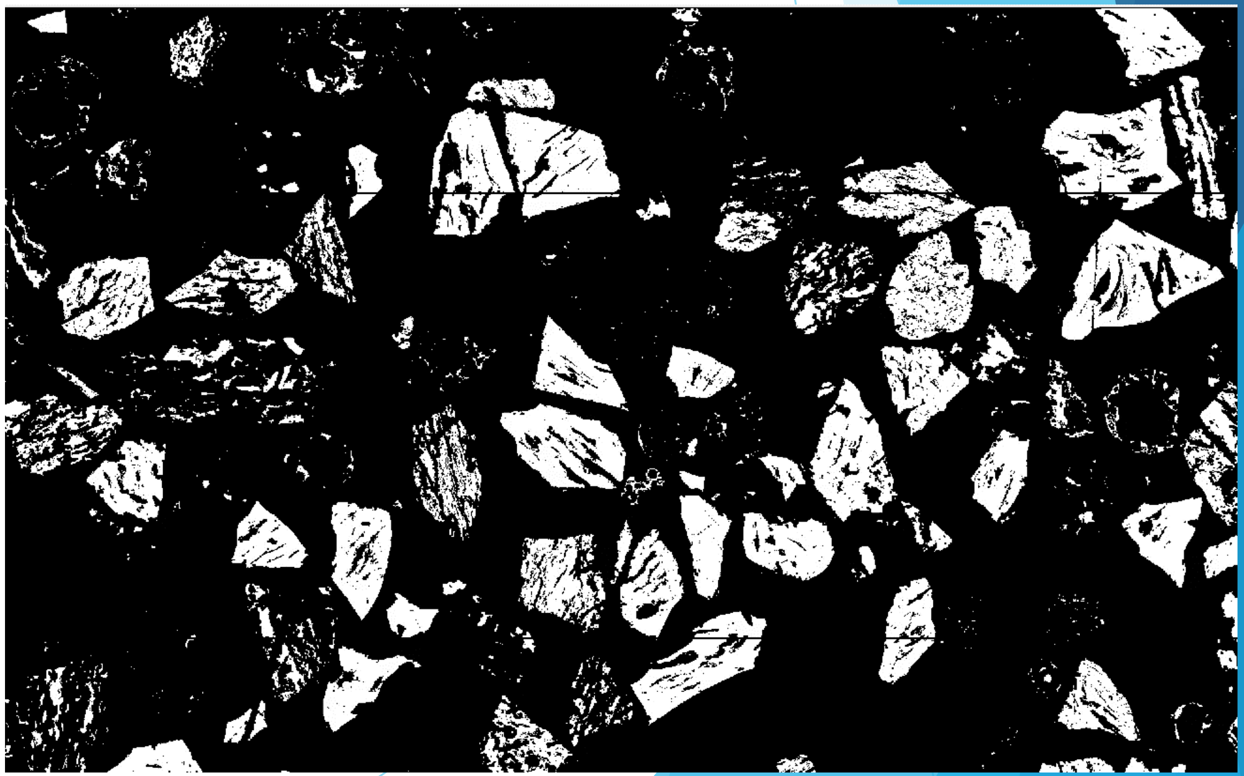


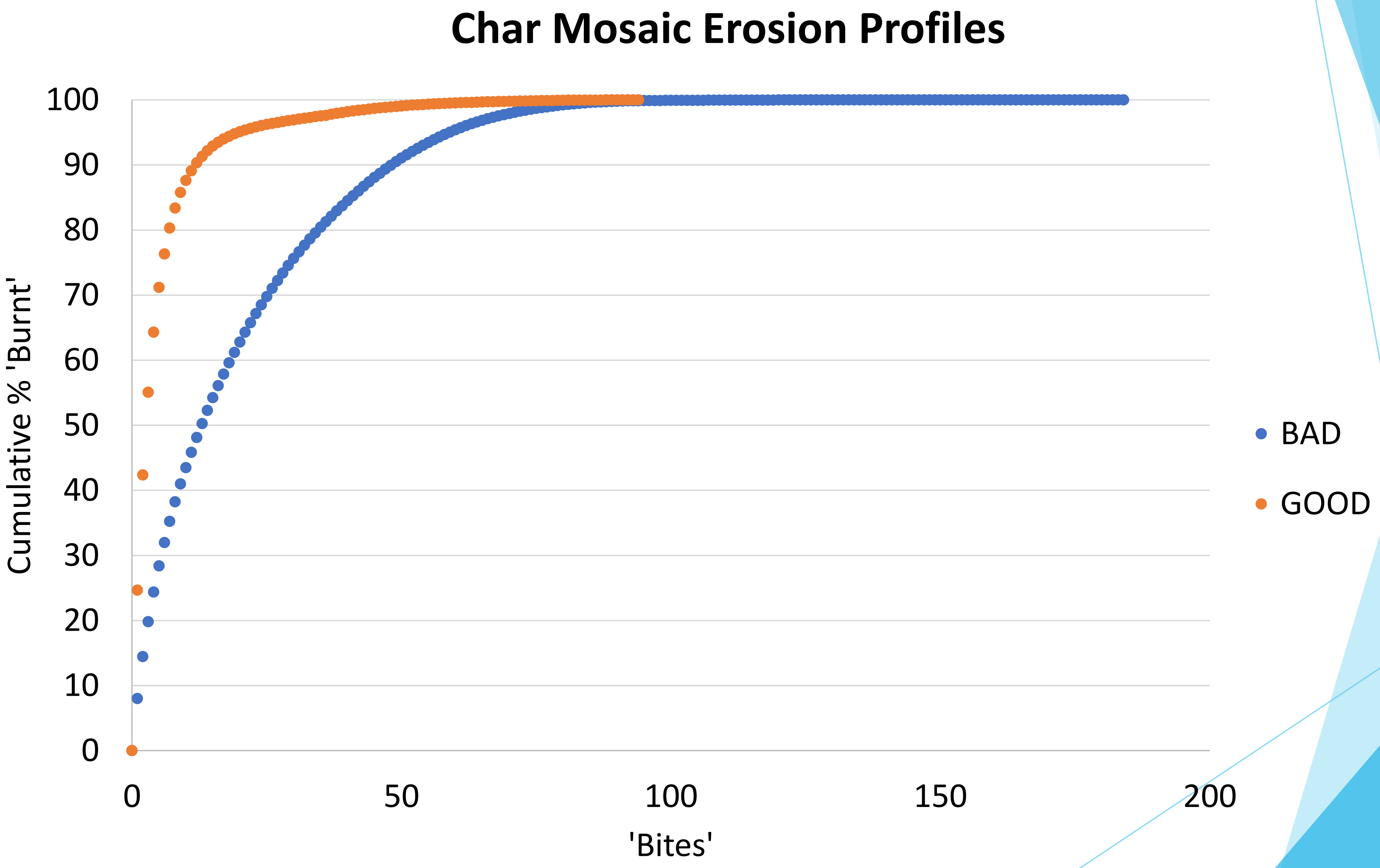


Part 6 – Char Burnout Simulations 'Pacman'

- Can be applied to whole images to indicate sample burnout behaviour







Char Mosaic Erosion Profiles
Cumulative % 'Burnt'
100
90
80
70
60
50
40
30
20
10
0
0
50
100
150
200
'Bites'
BAD
GOOD

Part 6 – Char Burnout Simulations Continued ('Pacman 2.0')

- Controllable, circular active contour method
- Char pixels ('combustion surface') in contact with contour after each (x) iterations are eaten

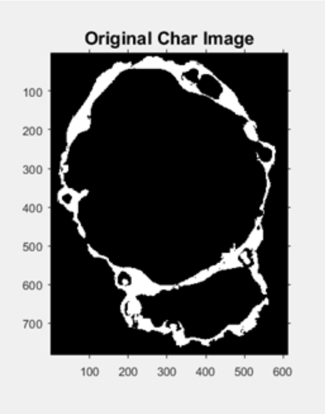
Variables

- Number of iterations – *Combustion duration*
- Contraction bias – *Pore availability for combustion*
- 'Viscosity' – *Degree of propagation per iteration*

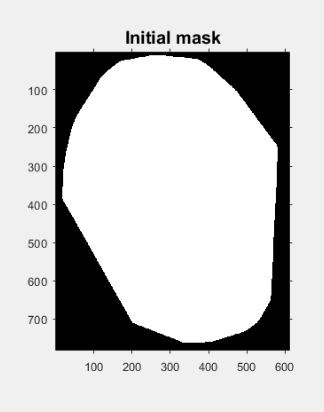
Part 6 – ‘Pacman’ 2.0

Variables

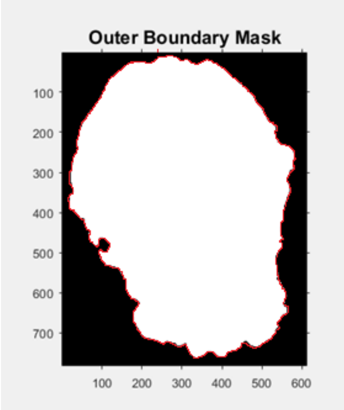
- Number of iterations – *Combustion duration*
- Contraction bias – *Exposed pore resolution*
- ‘Viscosity’ – *Degree of propagation per iteration*



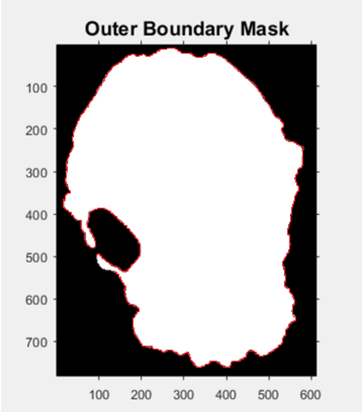
Char Particle



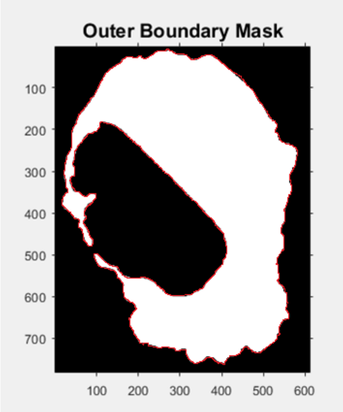
Contour starting point



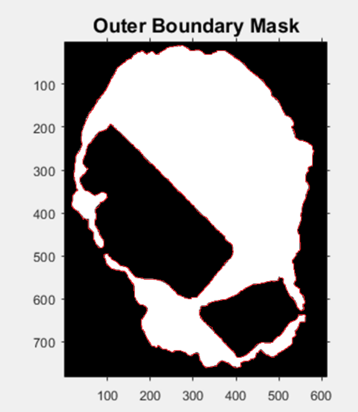
Initial ‘combustion Surface’



Increased viscosity



Increased viscosity further

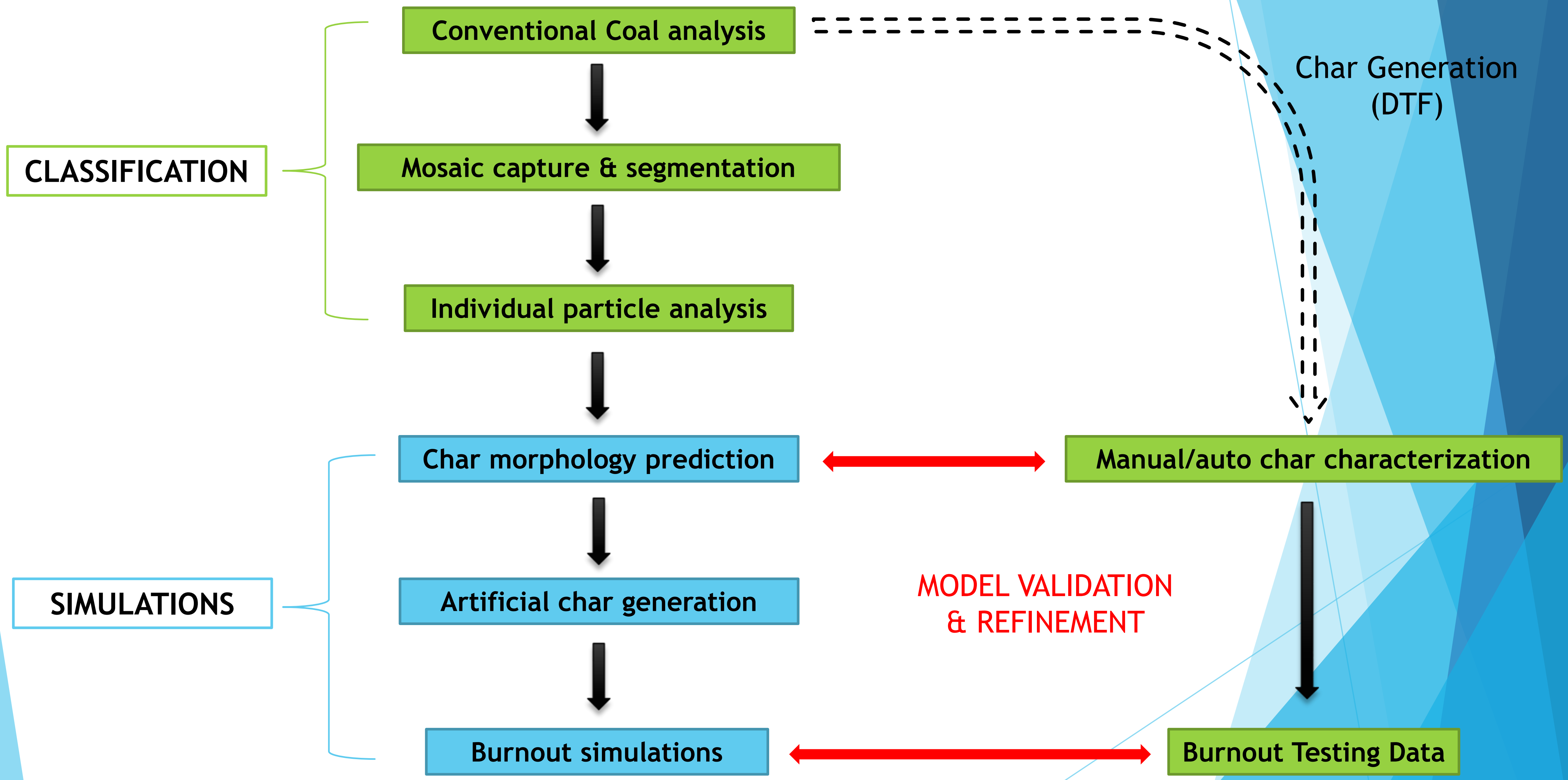


Increased contraction bias

Part 6 – Char Burnout Simulations Continued (Pacman 2.0)

- Generate combustion intermediates to train combustion model
- 5 Coals
  - Pyrolysis in drop tube furnace (DTF) at 1300 degrees, 1% Oxygen , 200ms
  - Refire char samples at 200, 400, 600 ms (1300 degree, 5% Oxygen)

- Train Pacman 2.0 variables to recreate char structures at each residence time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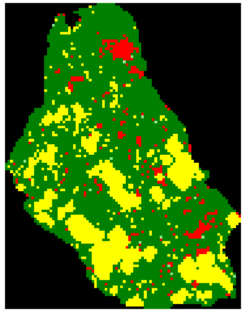
Part 5 – 'Morphing' Linker Step & Predictions

COAL IMAGE



CLASSIFIED IMAGE 'CRASSISPHERE'

ARTIFICAL CHAR

BURNOUT SIMULATION

PREDICTED CARBON IN ASH & % ASH CONTENT

COAL COMPOSITION

BURNOUT PREDICTION

ASH CONTENT

OVERALL

Conclusions & Further Work

- Image analysis is a powerful tool for understanding the characteristics of a coal fuel
- Predicted char morphology can be derived from single coal particle images
- One-click process providing fast & relevant information to a power generator
- Opportunities to relate combustion kinetics to char erosion methods

Further Work

- Work to refine Pacman 2.0 to kinetic characteristics of the fuels
- Morphing linker step