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Case study

Electrofacies analysis for coal lithotype profiling based on high-resolution wireline log data

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ABSTRACT

The traditional approach to coal lithotype analysis is based on a visual characterisation of coal in core, mine or outcrop exposures. As not all wells are fully cored, the petroleum and coal mining industries increasingly use geophysical wireline logs for lithology interpretation.This study demonstrates a method for interpreting coal lithotypes from geophysical wireline logs, and in particular discriminating between bright or banded, and dull coal at similar densities to a decimetre level. The study explores the optimum combination of geophysical log suites for training the coal electrofacies interpretation, using neural network conception, and then propagating the results to wells with fewer wireline data. This approach is objective and has a recordable reproducibility and rule set.In addition to conventional gamma ray and density logs, laterolog resistivity, microresistivity and PEF data were used in the study. Array resistivity data from a compact micro imager (CMI tool) were processed into a single microresistivity curve and integrated with the conventional resistivity data in the cluster analysis. Microresistivity data were tested in the analysis to test the hypothesis that the improved vertical resolution of microresistivity curve can enhance the accuracy of the clustering analysis. The addition of PEF log allowed discrimination between low density bright to banded coal electrofacies and low density inertinite-rich dull electrofacies.The results of clustering analysis were validated statistically and the results of the electrofacies results were compared to manually derived coal lithotype logs.

1. Introduction

Along with rank and grade, coal organic composition, defined megascopically by lithotype and microscopically by maceral analysis, will control the physical and chemical properties of coal that influence its utilisation and coal seam gas reservoir behaviour. Accordingly, geologists manually log core and use the distribution of lithotypes (Fig. 1) to characterise the coal seams for correlation and sampling for further laboratory analysis. Visual analysis of coal lithotypes can be subjective, and once the coal is sampled, crushed and analysed, its megascopic properties are destroyed. Core is also considered expensive, and as a result, geophysical wireline logs have become an alternative source of information for coal characterisation (Reeves and Muir, 1976; Johnston, 1991; Sutton, 2014). The impetus for this study was that the coal seams in the study area were not contiguously cored, so full seam characterisation was not possible unless we developed a characterisation method based on the wireline logs.

A common approach to coal characterisation using wireline data applies cut-off values on each wireline log measurement (Zhou and Esterle, 2007). Density is used for identification of coal, and gamma ray or sonic values (among others) for interburden lithology. Provided good correlation between sampled core properties and the selected wireline, the approach demonstrates quite good results. This method might produce significant errors if the wrong cut-off values were chosen, or if they vary between different coal seams or formations (Fullagar et al., 2004).

This paper describes a methodology that exploits geostatistical cluster analysis of wireline geophysical data and uses laboratory and visual core logging analysis data for initial control and subsequent validation of the results. It does not require any predefined cut-offs and assumptions about coal quality which potentially makes the method less prone to an interpreter bias and more robust and reproducible. In addition to identification of high or low density coal, the method is interpreted to discriminate inertinite-rich low density dull from mineral-rich dull from higher density or mineral matter rich dull coal and from banded or bright (high vitrinite) low density coal.

2. Methodology

2.1. Background

The application of cluster analysis, often referred to as electrofacies analysis, to identify different lithologies of facies in clastic

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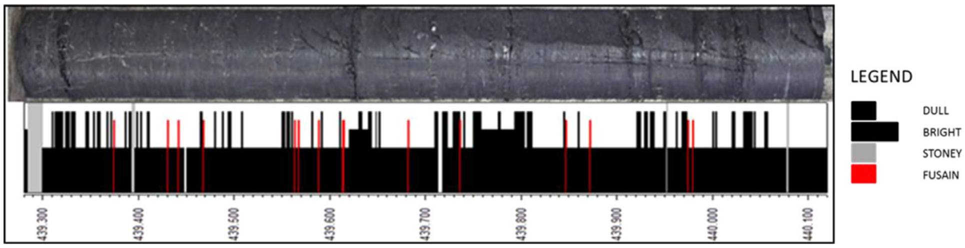

Fig. 1. An example of a manual coal lithotype profile plotted next to coal core for end member coal lithotypes. Core is 80 cm long (image provided by Natalya Taylor, University of Queensland).

sedimentary rocks is common (Ellis and Singer, 2007; Rider and Kennedy, 2013), so a similar approach could be applicable for coal lithologies. The term "electrofacies" refers to a cluster or group with common wireline log signatures or values that distinguishes it from other clusters. Ye and Rabiller (2005) define electrofacies as an element of the N-Dimensional (N being the number of wireline logs considered) data structure created by all petrophysical material available, whose ordering reveals the organised relationship imparted to petrophysical properties of interest by natural geologic systems ordering (Ye and Rabiller, 2005). Electrofacies, in contrast to geological facies, is an interval defined on wireline logs, with consistent or consistently changing wireline log responses and characteristics – sufficiently distinctive to separate it from other electrosequences (Rider and Kennedy, 2013). Electrofacies analysis involves partitioning a set of log data into electrofacies units and presenting them in a manner that is comparable to that used by geologists for interpretation purposes – each electrofacies is assigned a number, or index, which can be plotted against depth or used to control colour coding on displays (Ye and Rabiller, 2005).

Electrofacies ordering can be performed by different algorithms such as genetic algorithms (Goldberg, 1989) and neural networks. Artificial neural networks are computational models inspired by biological neural networks and are used to approximate functions that are generally unknown. There are many types of artificial neural networks and more details can be found in Potvin (1993). The neural-network scheme, first developed by Angeniol et al. (1988) is derived from the Kohonen's Self-Organising Map (SOM). An advantage of the SOM is that the resulting map is automatically ordered in the data space. A self-organising map (SOM) or self-organising feature map (SOFM) is a type of artificial neural network (ANN) that is trained using unsupervised learning to produce a low-dimensional (typically two-dimensional), discretised representation of the input space of the training samples, called a map. Self-organising maps are different from other artificial neural networks in the sense that they use a neighbourhood function to preserve the topological properties of the input space. An SOM performs an ordered mapping from a hyper-dimensional data space onto a lower (one- or two-) dimensional lattice of points (neurons). It can be considered as a non-linear regression of the reference vectors (neurons) through the input data (Ye and Rabiller, 2005).

The SOM network is made up of a specified number of neurons interconnected into a one- or two-dimensional array. This interconnection among neurons is called the lateral relationship. Neurons are initialised randomly. The input data are iteratively presented to the network for a given number of cycles. The convergence is controlled by two learning parameters: the width of the neighbourhood (Gaussian) function and the learning rate. In the neuron-splitting technique, all the input data are presented to the learning mechanism simultaneously instead of successively as in the SOM. Ye and Rabiller (2005) presented a simple and fully automated method based on the neuron-splitting technique using a 1D line-structured SOM. The input data are electrofacies kernels. These could be derived from any method. Multi-Resolution Graph-based Clustering (MRGC) method (Ye and Rabiller, 2000) available within software was used for this coal electrofacies research.

MRGC is a multi-dimensional dot-pattern-recognition method based on non-parametric K-nearest-neighbour and graph data representation (Ye and Rabiller, 2000). The underlying structure of the data is analysed, and natural data groups are formed that may have very different densities, sizes, shapes, and relative separation. MRGC automatically determines the optimum number of clusters, yet allows the geologist to control the level of detail actually needed to define the electrofacies. Some vector analysis programs let the user to decide how many clusters based on a "goodness of fit". In turn, software used for the research offers a number of probability tables to estimate and validate the clustering results. These probability tables were used in this research for validation of the clustering results.

The electrofacies ordering method which was presented by Ye and Rabiller (2005) performs a complete training of the SOM between each splitting process, whereby the newly split neurons are fully trained before being split again. This process was called a Coarse-to-Fine Self-Organising Map (CFSOM), because the electrofacies ordering is made from a low-resolution (coarse) map towards a high-resolution (fine) map. There are no concerns about how many cycles of input data presentation are necessary to split neurons and what the optimal parameters for SOM might be when the data configuration and the size of problem are changed. All that is needed is for the algorithm to add a reasonable number of neurons at each step and re-apply the ordinary SOM algorithm.

2.2. Dataset

The research was focused on the northern Bowen Basin (Fig. 2) and included geophysical wireline logs from wells intersecting three main Late Permian coal measures – Moranbah, Fort Cooper and Rangal. In general, the character of the coals changes stratigraphically up section, with a general increase in inertinite group macerals in the Rangal Coal Measures (Mutton, 2003). That area is also characterised by good collection of high-quality wellbore data and has previous research results that were exploited for validation of the current study.

The dataset included 26 wells which had been geophysically logged and cored. Wireline logs included caliper, gamma ray (GR), laterolog resistivity, density, photo-electric factor (PEF) and thermal neutron porosity; three wells contained sonic data (dt and dipole data). Borehole electrical images were available for 18 of the 26 wells. Of these 26 wells, not all coal seams were fully cored and analysed, making the validation against megascopic description a bit sporadic. The lack of contiguous coring was actually an impetus for this study, so that complete seams might be characterised within the measures. Coal proximate analysis data were available for samples from 23 wells. Visual lithotype logging (using an end member millimetre scale approach (Esterle et al., 2002)), maceral and reflectance analysis data were available for 182 sampled metres of core from 12 wells. The summary of data available for

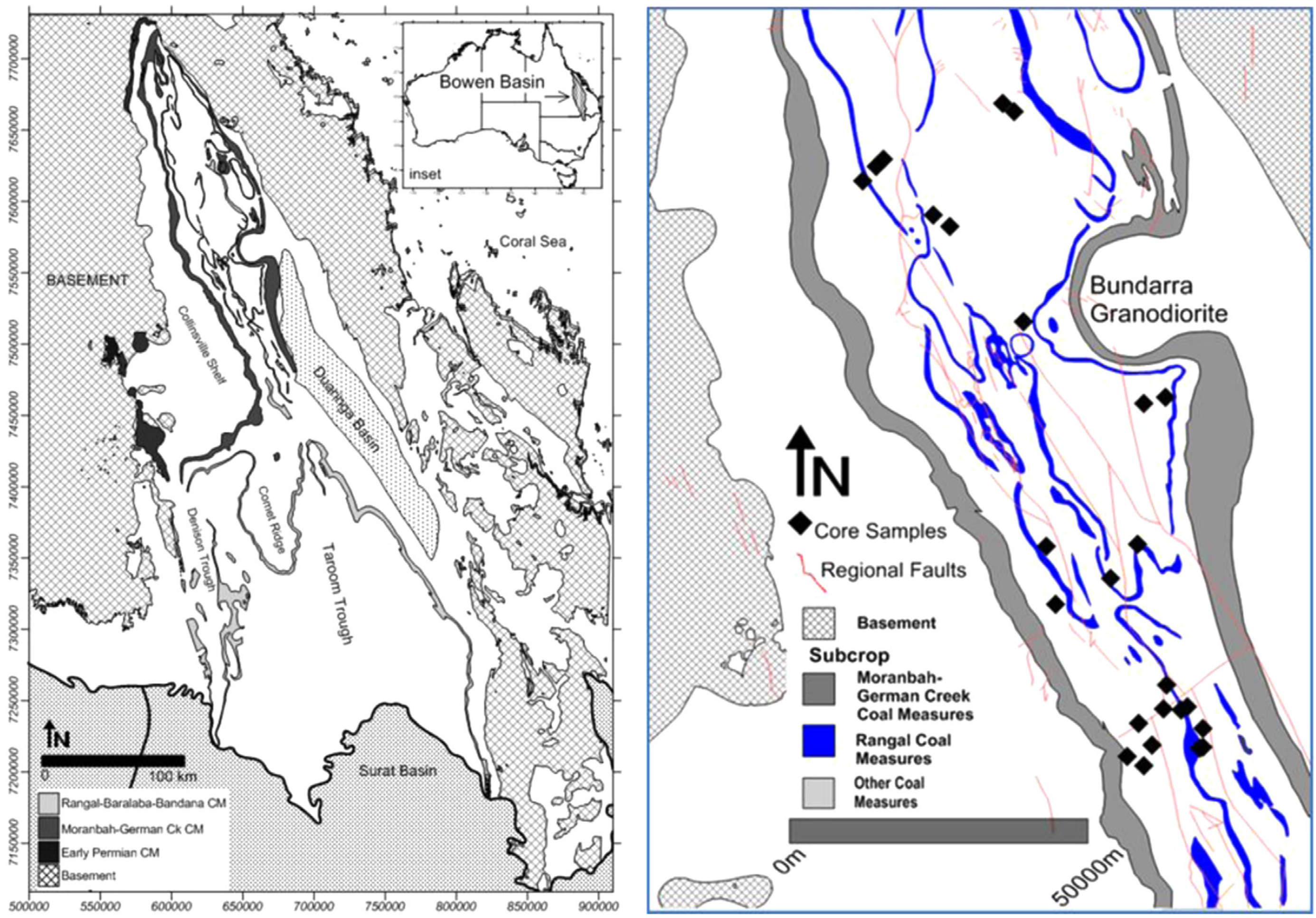

Fig. 2. Location map of the study area within (a) simplified map of economic coal measures in the Bowen Basin, with inset of location within Australia and (b) close up showing location of core samples with wireline logs. Note that the Fort Cooper Coal Measures, which occur between the Moranbah and Rangal coal measures, are not shown. Compiled from IRTM shape files www.irtm.qld.gov.au.

the research is shown in Table 1. The location of these wells is presented in Fig. 4 and discussed below.

2.3. Methodology workflow

The automatic algorithm which was implemented for coal lithotype profiling is performed in three steps: (1) data preparation; (2) electrofacies analysis; (3) model propagation. Interpretation of log data was based on statistical and neural network methods following Ye and Rabiller (2000). Parameters which were used in the study are shown in the Appendix.

2.3.1. Data preparation

The first step of the workflow is data preparation and includes three basic procedures: data collection, data organisation and data analysis (Fig. 3). The following geophysical data were chosen for analysis: gamma ray, density, PEF and laterolog resistivity and microresistivity from borehole electrical images. This particular choice of wireline measurements is explained by the relationship between those measurements and coal properties which, in turn, reflect coal lithotype and grade.

All wells are organised into two datasets: reference and application. The former is used to generate the model which would be further applied on all wells which form the application dataset. The reference dataset ideally includes the deepest wells which have a full collection of data (wireline logs, core data, etc.) and characterise the whole geological profile. For this study, the reference set contained 16 wells and the application set included 10 wells (see Table 1) which were equally spread over the study area (Fig. 4).

Finally, all data was analysed and prepared for modelling so that for all wells all measurements have the same sample rates and measurement units, each measurement is on an appropriate scale and erroneous values (such as resistivity values in casing) are excluded from the data range. Data were prepared in the following way: gamma ray was plotted on a linear scale between 0 and 200 GAPI; density on linear scale between 1 and 3 g/cc; laterolog resistivity and microresistivity were both on logarithmic scale between 0.5 and 50 OHHM (for microresistivity) and between 0.02 and 2000 OHHM (for laterolog resistivity); PEF was on a linear scale between 0 and 4 B/E (Fig. 5). Data were reprocessed to start just below the casing shoe and have a sample rate 0.025 m.

Some notes should be made about log normalisation. For this research, authors worked with modern logs and normalisation was not required. The problem of log normalisation was studied while working with another data set (not for this research). That dataset consisted of vintage and modern log curves. Two approaches were used for that data: (1) all logs were normalised and then electrofacies analysis was performed; (2) all wells were divided into three groups and analysed separately. After clustering, the same pattern of electrofacies distribution was observed in all three groups, so while labelling, corresponding electrofacies were named similarly and the results of analysis with normalisation and without normalisation were compared. The comparison

Table 1
Data available for the study.

Well	Wireline geophysical logs						Borehole electrical images	Coal proximate analysis	Maceral analysis data	Millimetre scale coal logging data	Reference or application set?
	GR	Density	PEF	Neutron	Resistivity	Sonic					
W1	Yes	Yes	Yes	Yes	Yes	No	No	No	Yes	Yes	Application
W2	Yes	Yes	Yes	Yes	Yes	No	Yes	No	Yes	Yes	Reference
W3	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Reference
W4	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Reference
W5	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Reference
W6	Yes	Yes	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Application
W7	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Reference
W8	Yes	Yes	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Application
W9	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Reference
W10	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Reference
W11	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Reference
W12	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Reference
W13	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Application
W14	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Application
W15	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Reference
W16	Yes	Yes	Yes	Yes	Yes	No	No	Yes	No	Yes	Application
W17	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Reference
W18	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Reference
W19	Yes	Yes	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Application
W20	Yes	Yes	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Application
W21	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Reference
W22	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No	Application
W23	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	Reference
W24	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Reference
W25	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Reference
W26	Yes	Yes	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Application

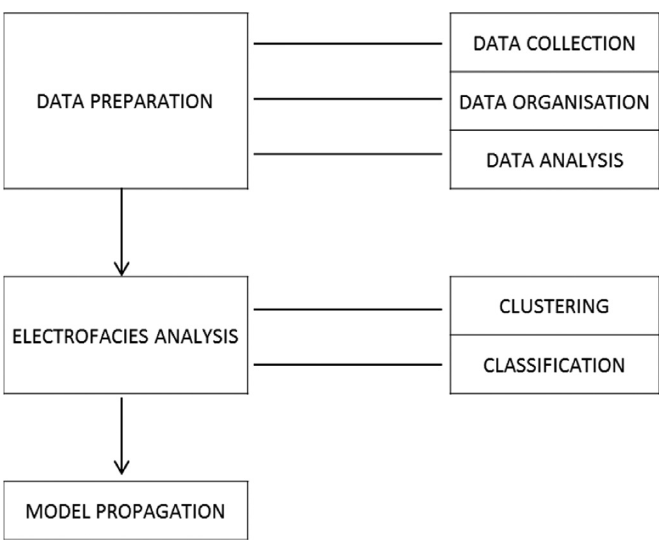

Fig. 3. Methodology workflow.

demonstrated that the discrepancy between two approaches is negligible. (it has been added in response to the reviewers' comment).

2.3.2. Electrofacies analysis

The second step of the workflow is the electrofacies analysis. Electrofacies analysis is performed by two successive procedures: clustering which assumes partitioning the set of data into clusters (or electrofacies units) and classification which involves assigning geological meaning to each electrofacies unit.

2.3.2.1. Clustering. Clustering can be explained as a grouping of all data into smaller groups based on their similarity or close proximity in N-dimensional space. A classic approach to facies analysis, automatic clustering, requires an a priori estimate of the number of clusters, which can force or skew the results (Ye and Rabiller, 2000). Performing this task manually in high-dimensional space (when the amount of logs is higher than 3) is still difficult, slow, somewhat subjective and requires a skill or expertise that is not always readily available.

The MRGC chosen in this study does not require the user to determine a number of clusters before starting the analysis. Instead, MRGC proposes to the user several optimum numbers of clusters corresponding to different resolutions. The user is able to compare several results and choose the most appropriate one. In addition, the results of MRGC are organised in hierarchical way so that the clusters of higher resolutions are always sub-clusters of the lower-resolution clusters (Ye and Rabiller, 2000).

Clustering was performed three times with different input wireline logs (“methods” 1–3 in Table 3). Different types of resistivities were tried in order to investigate the influence of vertical resolution of resistivity tools on the result of electrofacies analysis, and PEF was added to the dataset to check the hypothesis that PEF might help determine a presence of inertinite matter in dull but low density coal. MRGC input parameters are shown on Table 2.

MRGC offered three different levels of detail. Thus, for method #1 software produced: (1) fourteen clusters; (2) twelve clusters; (3) nine clusters (Table 3). Probability tables were used for validation of clustering analysis (see Appendix). How the validation was done for clustering results is explained in the next section.

2.3.2.2. Electrofacies classification

The next step of electrofacies analysis is electrofacies classification in order to assign proper geological meaning to each electrofacies unit (or cluster). This procedure is performed manually by labelling each cluster according to the interpretation of wireline log characteristics of each electrofacies and the detailed description is given in the next section.

Clustering resulted in a number of clusters (electrofacies), each with a statistical distribution (range, mean, standard deviation), for which an example from Method #2 is shown in Table 3.

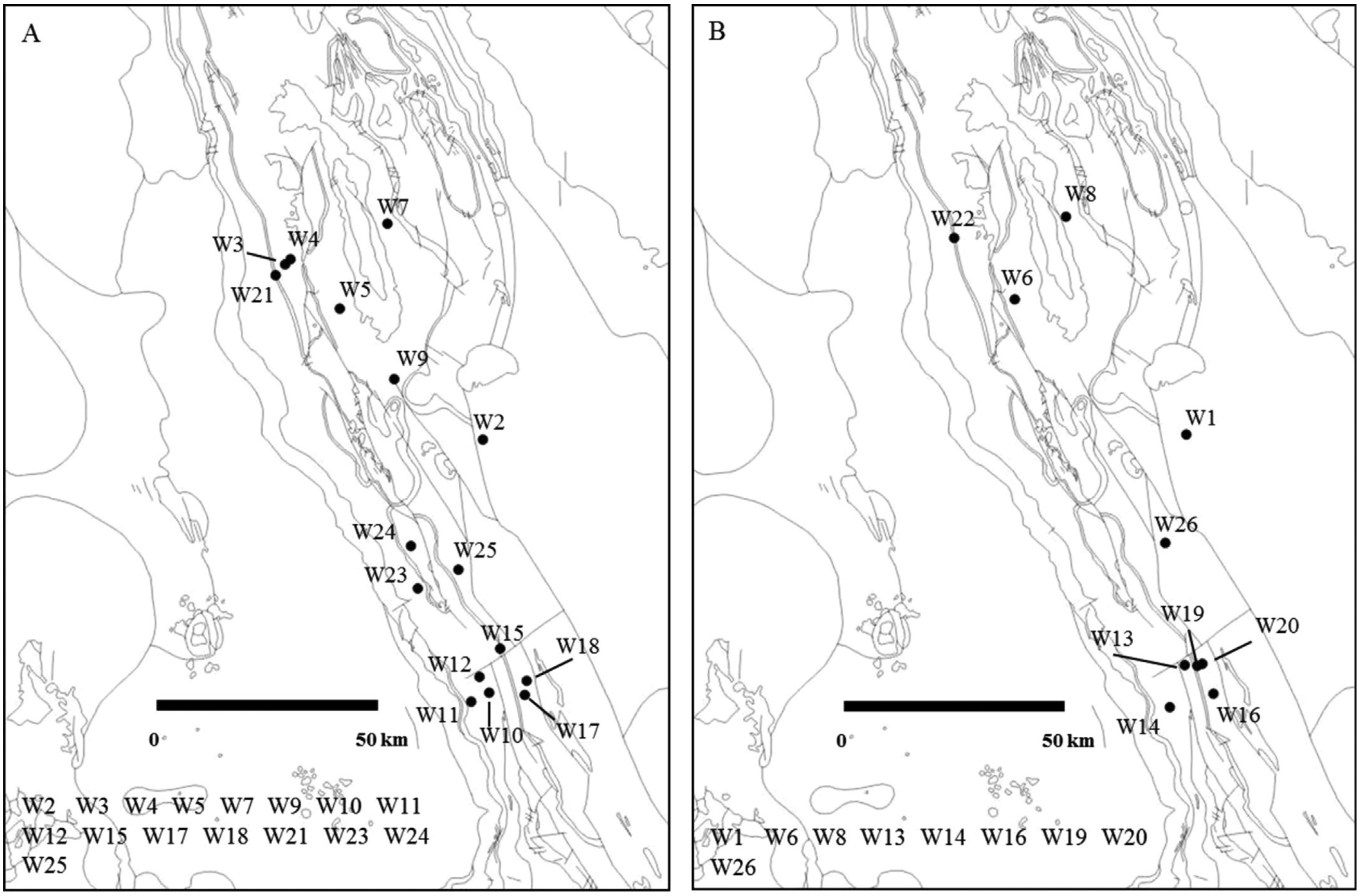

Fig. 4. Distribution of wells in the study area: (A) reference dataset; (B) application dataset. (distance scale has been added in response to the reviewers' comment).

In Table 4, these electrofacies were organised according to an increase of density and gamma ray values. This trend was then examined against fixed carbon and ash yield to perform the classification of these electrofacies.

Looking at the trends in distribution of wireline logs values and the statistics of the distribution, all clusters were classified according to the understanding of properties of dull mineral matter rich coal, dull inertinite-rich coal etc. Some clustered were classified similarly (Fig. 6 and Appendix A) as the authors did not see significant difference (in terms of statistical distribution of wireline logs values) between them and these clusters were merged together. Those clusters which were classified similarly then, were merged together. The validation at this stage was performed in software by the analysis of the contingency tables (see below).

Initially, it was assumed that the increase of density and gamma ray values correlated to the corresponding decrease of fixed carbon and increase of ash yield which generally reflects an increase in coal dullness (provided that rank is held constant). If coal lithotypes were only based on density, then all bright and banded coal would be low and all dull coals would be high density. But density/gamma ray and fixed carbon/ash trends were also compared to the distribution of resistivity and PEF curve values and the following observations were made:

- heat affected (heated and coked coal) coal electrofacies was interpreted based on the distribution of resistivity values and comparison to core descriptions;
- mineral matter rich dull coal electrofacies was distinguished by an increase of gamma ray and density and corresponding increase of ash yield;
- bright and banded coal electrofacies was determined by a decrease of gamma ray and density which is correlated to a decrease of ash yield;
- inertinite-rich dull coal electrofacies was distinguished from low density bright coals by the distribution of PEF values, as its gamma ray and density distribution was similar to bright and banded coal electrofacies.

2.3.3. Model propagation

The final step of electrofacies analysis is model propagation. Data clustering and electrofacies classification based on the reference set data are procedures which are required to "teach" neural network, or build a model, how to recognise electrofacies in a *N*-dimensional space; in turn, propagation is used to apply the obtained model on all application set data. Electrofacies propagation is achieved by KNN (K-nearest neighbour) method. It means that in order to assign value for any application set point, distance-weighted average of K nearest (in *N*-dimensional log space) values of reference data set are used. FNN propagation method assumes that the first nearest value is taken for propagation. This method has been chosen because FNN method applies no smoothing to the results and can capture heterogeneity. FNN propagation was performed for 10 wells from application set.

3. Validation

In order to validate clustering results, software produces a number of contingency tables to evaluate the amount of samples dropped to each particular cluster, or electrofacies, and their probabilities (see Appendix). A probability of 100% means that all

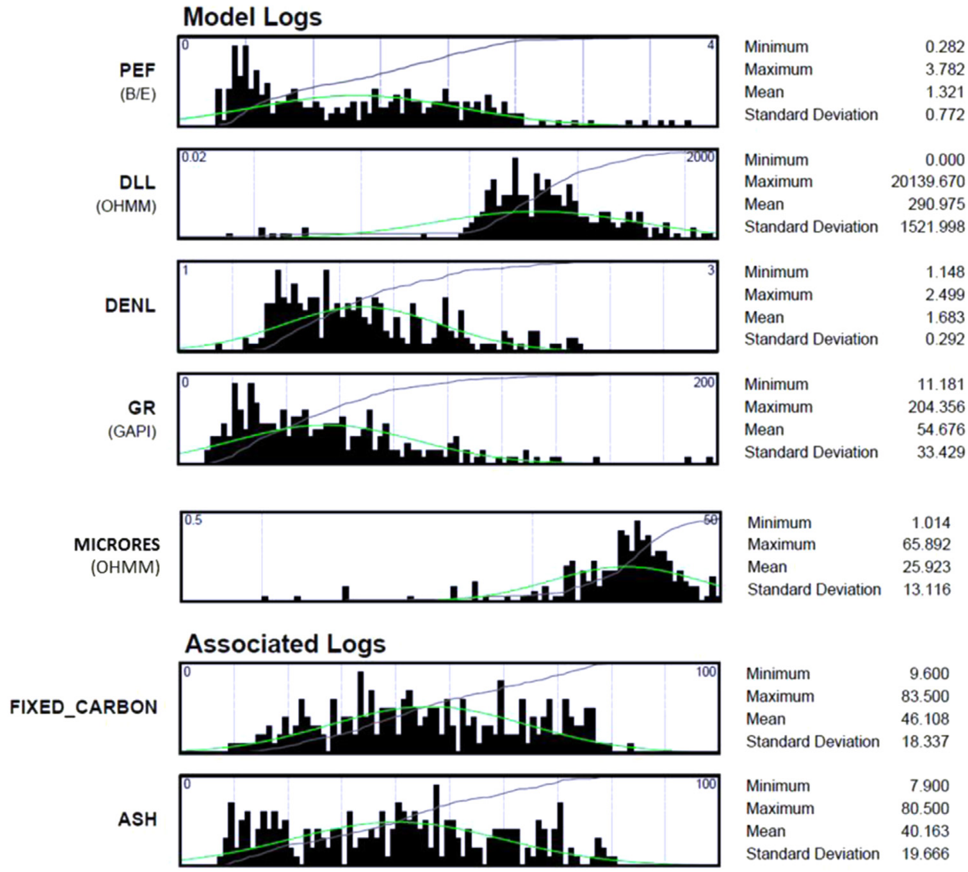

Fig. 5. Input wireline logs statistics. (microresistivity has been added in response to the reviewers' comments).

Table 2
MRGC input parameters.

Normalize Using	Plot Range
Minimum Number of Electrofacies	8
Maximum Number of Electrofacies	35
Number of Optimal Models	5
Initial Neurons for CFSOM	4

Table 3
Input data for three different clustering methods.

METHOD	INPUT DATA	Number of clusters		
		Cluster Set #1	Cluster Set #2	Cluster Set #3
METHOD #1	GR, DENSITY, DEEP LATEROLOG RESISTIVITY, MICRORESISTIVITY	14	12	9
METHOD #2	GR, DENSITY, DEEP LATEROLOG RESISTIVITY, PEF	14	11	8
METHOD #3	GR, DENSITY, MICRORESISTIVITY, PEF	15	12	10
METHOD #4	VALIDATION SET (MILLIMETRE SCALE LOGGING RESULTS)			

samples belong only to that electrofacies; probability other than 100% means that those samples can also belong to another facies. The probability reflects the degree of uncertainty of clustering results. The higher the probability, the better is the result of clustering.

Comparing different contingency tables for the different methods (refer Table 2), it was observed that the probability is the highest for 14 (or 15 in case of method #3) clusters (see Appendix). Contingency tables for all three different "methods" were compared and the highest probabilities were observed for method #2. This method was regarded as the most reliable one. The input set for method #2 included gamma ray, density, laterolog resistivity and PEF. As method #2 shows better results than method #3 (where laterolog resistivity was replaced by microresistivity), this suggests that microresistivity data (i.e. the image logs) does not improve clustering results. However, the PEF log does improve the electrofacies analysis more than method #1 or #3, as it can discriminate another low density facies that is interpreted as high inertinite dull rather than bright coal. This conclusion is demonstrated by contingency tables (see Appendix).

4. Field example

The results of the electrofacies coal lithotype characterisation were compared to the coal lithotype profiling results obtained by millimetre scale logging. It was done by comparison of the weighted average proportion of each electrofacies to the weighted average proportion of corresponding coal lithotypes obtained by millimetre scale logging results. The results of the analysis of 26 wells were summarised in tables and presented in a number of charts for comparison. Two wells (W2 and W21) were selected as examples. These wells were chosen as they represent almost the whole geological profile and major coal seams (it has been changed in response to the reviewers'comment).

4.1. Coal lithotype study

Charts on Fig. 7 shows the overall distribution of dull, banded and bright coal electrofacies plotted together with corresponding coal lithotypes obtained from millimetre scale logging

Table 4
Statistics for electrofacies clustering results (method #2).

CLUSTER	PHOTOELECTRIC EFFECT				DEEP LATEROLOG RESISTIVITY				BULK DENSITY				GAMMA RAY			
	MINIMUM	MAXIMUM	MEAN	STANDARD DEVIATION	MINIMUM	MAXIMUM	MEAN	STANDARD DEVIATION	MINIMUM	MAXIMUM	MEAN	STANDARD DEVIATION	MINIMUM	MAXIMUM	MEAN	STANDARD DEVIATION
ELECTROFACIES_1	0.37	2.37	0.82	0.67	0	856.11	77.92	258.1	1.34	2.3	1.76	0.24	19.14	103.85	46.17	27.23
ELECTROFACIES_2	1.96	3.64	2.46	0.44	0.15	41.11	15.44	8.95	1.88	2.5	2.27	0.16	50.08	196.83	106.81	35.9
ELECTROFACIES_3	0.83	3.58	2.22	0.74	14.92	75.62	28.44	16.44	1.66	2.09	1.93	0.15	46.6	110.03	70.27	19.45
ELECTROFACIES_4	0.47	2.48	1.95	0.43	11.36	368.07	48.9	76.82	1.33	2.06	1.81	0.19	22.04	155.94	90.16	32.02
ELECTROFACIES_5	1.25	1.94	1.7	0.2	13.86	41.08	22.87	8.8	1.81	2.07	1.94	0.08	60.46	85.14	70.24	7.39
ELECTROFACIES_6	0.48	3.78	1.71	0.56	12.74	7871.58	351.52	1359.08	1.44	2.34	1.68	0.17	26.98	83.72	50.47	12.34
ELECTROFACIES_7	0.43	1.56	0.95	0.31	10.2	1158.39	282.95	273.75	1.25	1.57	1.43	0.08	11.18	40.73	23.86	7.94
ELECTROFACIES_8	0.51	1.98	0.81	0.49	8.79	68.87	30.95	21.47	1.46	1.81	1.62	0.11	24.82	95.04	48.5	20.95
ELECTROFACIES_9	0.59	1.47	1.25	0.26	28.74	216.48	78.73	55.21	1.15	1.72	1.51	0.15	30.95	55.27	43.01	7.48
ELECTROFACIES_10	0.36	1.77	1	0.46	0.12	275.53	56.94	65.47	1.35	1.99	1.7	0.2	22.42	96.51	65.14	19.86
ELECTROFACIES_11	0.28	2.81	0.78	0.67	20.87	198.95	81.23	43.69	1.31	1.99	1.47	0.18	14.58	71.11	31.18	13.85
ELECTROFACIES_12	0.45	1.49	0.92	0.24	25.77	183.63	76.92	44.3	1.38	1.73	1.58	0.09	29.17	76.88	56.43	11.81
ELECTROFACIES_13	0.4	0.8	0.5	0.13	67.82	315.59	182.12	64.95	1.33	1.51	1.39	0.05	12.39	30.47	18.44	4.76
ELECTROFACIES_14	0.31	0.87	0.52	0.19	0	20139.67	2414.15	5029.54	1.24	1.62	1.42	0.11	16.32	39.3	27.24	6.75

results. The results of four different methods are presented in the chart:

- method #1 involves electrofacies analysis based on gamma ray, density, laterolog and microresistivity;
- method #2 includes gamma ray, density, laterolog and PEF;
- method #3 involves gamma ray, density, microresistivity and PEF;
- method #4 is the millimetre scale coal lithotype profiling which is based on visual characterisation of coal lithotypes in core samples.

Some observation can be made based on the charts. First of all, it can be seen that there is a good correlation between electrofacies analysis results and millimetre scale logging results, although some discrepancy exists (Fig. 7). In most cases the quantitative difference between electrofacies results and manual coal lithotype profiling does not exceed 20% (Fig. 7). Method #2 which was regarded as the best method among all three electrofacies analysis methods shows the results that are close to those used for validation apart from only one exception which is consistent in all wells. The Vermont Upper seam (VU1) demonstrates higher percentage of bright coal electrofacies compared to millimetre scale logging results. The authors do not have a sufficient explanation of that phenomenon but it can possibly be explained by the constitution of Vermont Upper coal. The possible explanation is that the mineral constituent of the seam affect the wireline response which was not taken into account in the research and a subject for further study.

Fig. 8 demonstrates the comparison of brightness profile obtained from millimetre scale logging which data were used for the validation and electrofacies analysis results – both with PEF and without PEF.

One can observe that there is a similarity between the outcomes of different electrofacies analysis methods. Both methods seem to recognise dull and bright+banded coal but when PEF data are not involved, the analysis mistakenly determines dull inertinite-rich coal as bright coal, because it also has low density. Especially, it is observed for LU1 (Leichhardt Upper main seam) coal seam (Fig. 8B).

A very good correlation is observed between millimetre scale logging data and electrofacies results. Thus, brightness profile of sample 1 (Fig. 8A) demonstrates (from the top to the bottom) that bright and bright banded coal is followed by dull coal and then changes to bright and banded coal again. Electrofacies analysis (method which involves PEF data) results shows exactly the same distribution of dull and bright+banded coal.

4.2. *Inertinite-rich coal study results*

The weighted average proportion of inertinite-rich electrofacies was compared to the results of petrographic analysis data.

The results of inertinite-rich coal electrofacies analysis results were summarised and presented in a number of charts for comparison to maceral analysis data and for stratigraphic trends analysis. Chart demonstrates an increase of the amount of inertinite-rich dull coal electrofacies from the FCCM towards the top of RCM (the Leichhardt Upper seam) which corresponds to an increase of total inertinite observed from maceral analysis data (Fig. 9). On a global scale, Leichhardt Upper is known as the coal seam which is rich in inertinite matter (Hunt, 1989), that is also in conjunction to the observations of this study.

5. Conclusions

The methodology developed in this study was in response to a need to characterise coal seams in the absence of complete and

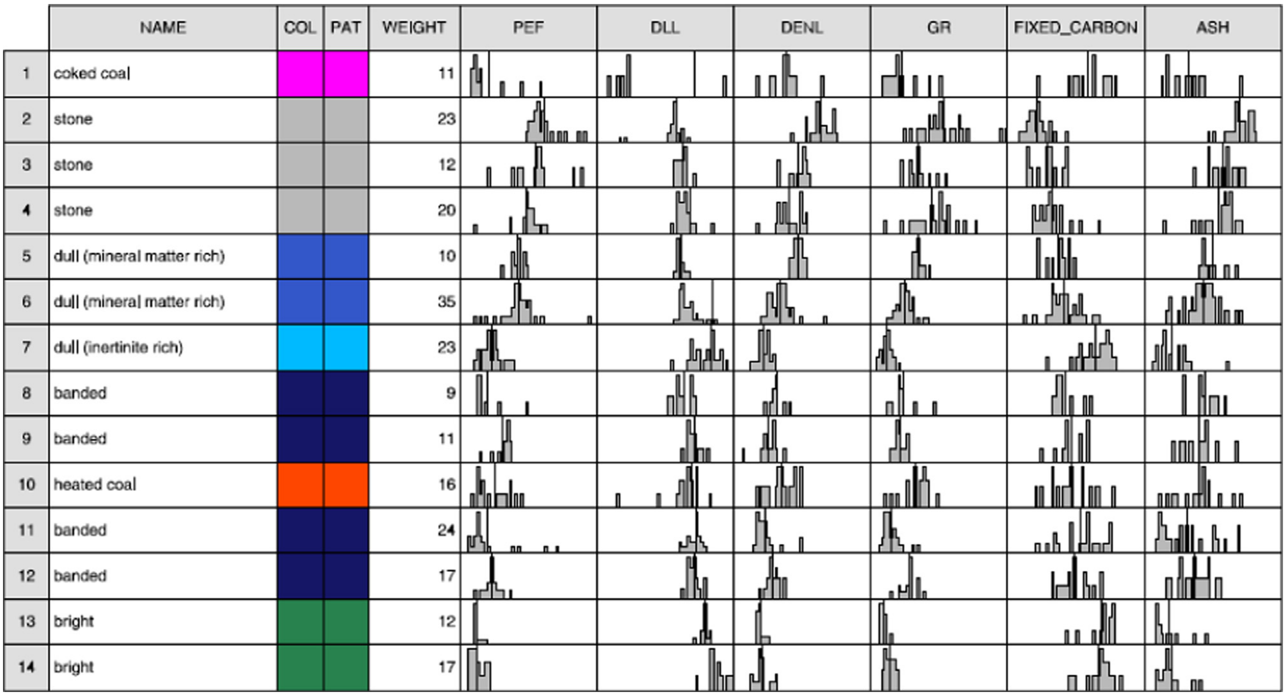

Fig. 6. Interpreted electrofacies units and the distribution of wireline logs values presented as histograms. PEF=photoelectric effect factor; DLL=deep laterolog resistivity; DENL=bulk density; GR=gamma ray; FIXED_CARBON=fixed carbon content; ASH=ash yield.

contiguous coring, beyond the assumption that high density coal is dull and low density coal is bright and banded. The author's initial view was that image logs were required, but it was not the case. Three different sets of input data were used during the study:

1) Gamma ray, density, laterolog and microresistivity;
2) Gamma ray, density, laterolog and PEF;
3) Gamma ray, density, microresistivity and PEF.

When clustering is performed on these combinations of wireline logs, the objective is to group all data points into clusters based on proximity in N-dimensional data space, which in each of these cases $N=4$. The number of mathematical output clusters is based only on proximity or similarity of wireline log values, without any regard to geological meaning. The labelling or geological interpretation of the clusters usually results in the further grouping, which in this case was focussed on recognition end member coal lithotypes. The grouping and interpretation into these lithotypes were validated by the contingency tables and by comparison to millimetre scale logging data. The contingency tables were used as a measure of the goodness of fit, or the probability that all data points belongs to that particular lithotype or group.

It was observed that the second method provides the best clustering results and demonstrates the best match between electrofacies analysis data and millimetre scale logging results. This method might be suggested for further use to perform coal

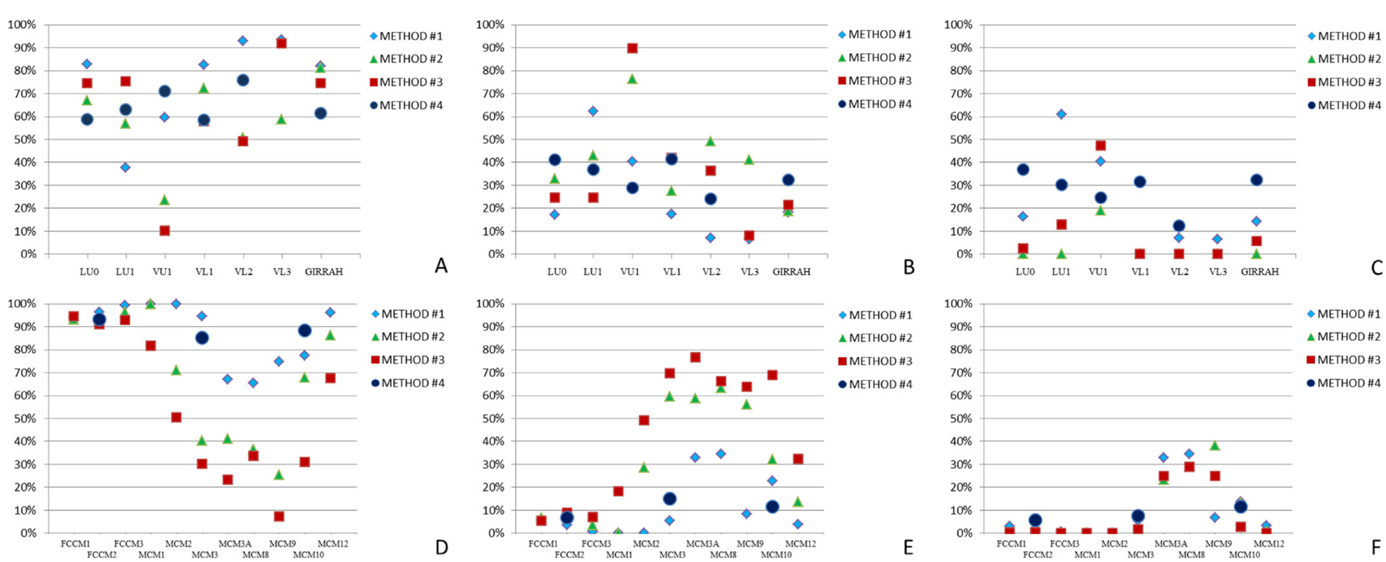

Fig. 7. Proportion of different coal lithotypes obtained by different methods: horizontal axis shows coal seam; vertical axis represents the percentage of a given coal electrofacies for methods #1, #2 and #3, and coal lithotype for method #4; Horizontal scale: LU=Leichhardt Upper; VU=Vermont Upper; VL=Vermont Lower; FCCM=Fort Cooper Coal Measures; MCM=Moranbah Coal Measures (A–C) Well W2: (A) Dull coal; (B) Bright+banded coal; (C) Bright coal; (D–F) Well W21: (D) Dull coal; (E) Bright+banded coal; (F) Bright coal.

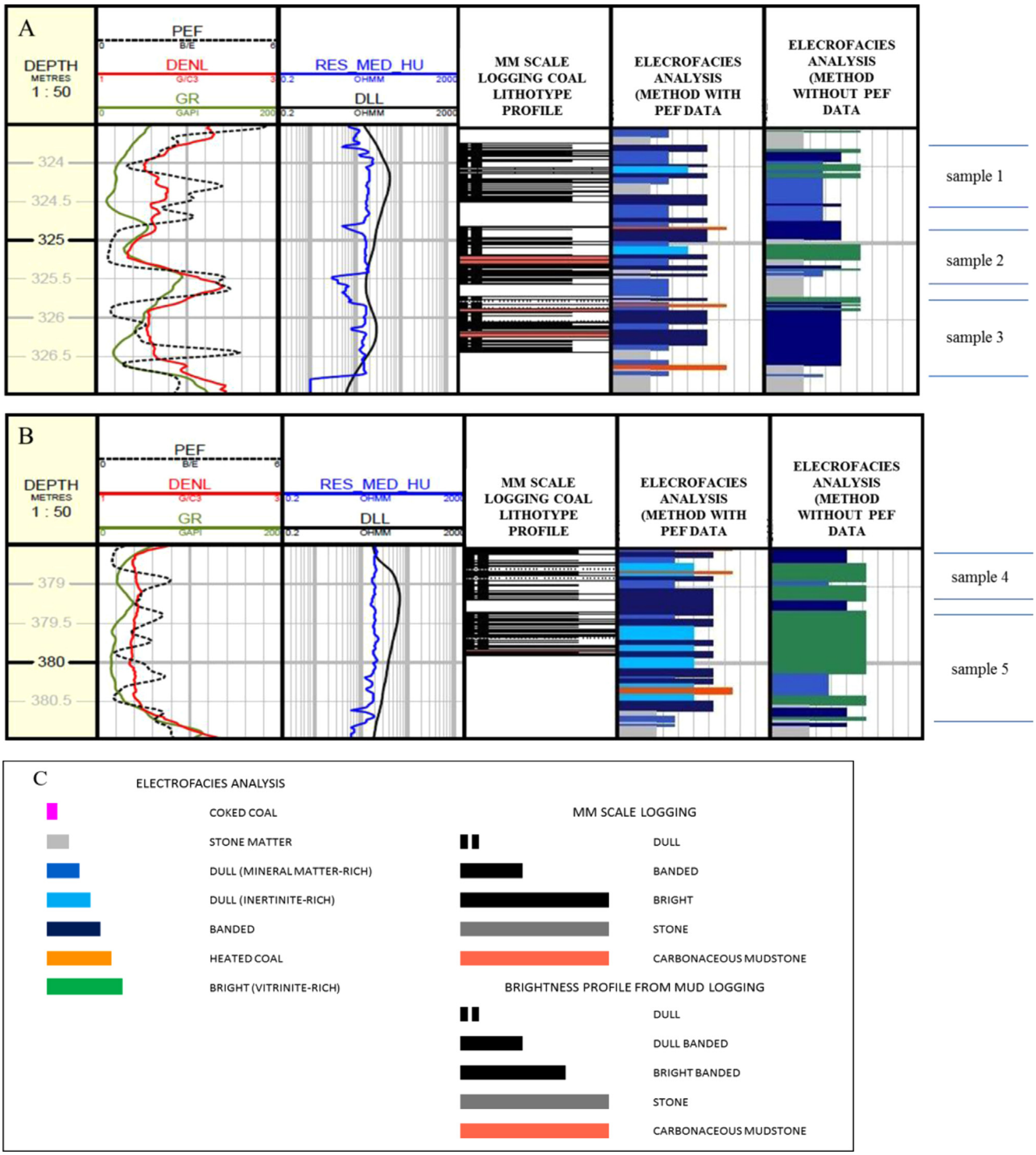

Fig. 8. The comparison of coal lithotype profiling obtained by different methods: (A, B) the measured depth presented on Track 1; Track 2 shows density and gamma ray; millimetre scale logging coal lithotype profile is plotted on Track 3 and Facimage results are on Track 4 (PEF, gamma ray, density, laterolog were used as the input data) and Track 5 (gamma ray, density, laterolog, microresistivity were used as the input data). Some depth shift exists for manual logging data. Picture A shows LU0 (Leichhardt Upper rider seam) Picture B shows LU1 (Leichhardt Upper main seam) The legend is shown on picture C.

lithotype profiling of coal. Two hypotheses were tested in the course of research:

1) Microresistivity data can improve the electrofacies analysis results; and
2) PEF data can help to distinguish dull inertinite-rich coal.

The first hypothesis was rejected, while the second one was proved that is supported by contingency tables (see Appendix).

Based on the analysis and comparison of the results, a number of conclusions were made:

1) The most reliable method of coal lithotype profiling using electrofacies analysis amongst tested involves gamma ray, density, laterolog resistivity and PEF;
2) PEF can help recognise inertinite-rich coal and this fact is proved by analysis of contingency tables, millimetre scale logging results and maceral analysis data;

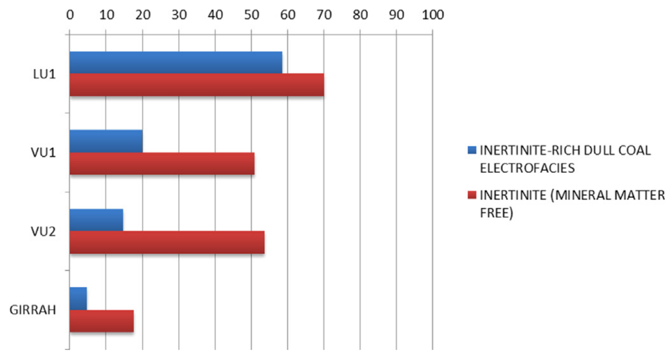

Fig. 9. The comparison of inertinite-rich dull coal electrofacies (from electrofacies analysis) and inertinite mineral matter free (from maceral analysis) for well W15. LU=Leichhardt Upper; VU=Vermont Upper.

3) Being included into input dataset, microresistivity does not significantly improve the results of electrofacies analysis;
4) Coked coal is very well recognised by all electrofacies methods;
5) Vermont Upper coal seam demonstrates a discrepancy between electrofacies analysis and millimetre scale logging results. The discrepancy was explained by the mineral matter composition of the coal seam which was not taken into account in this research.

The coal rank study is an interesting problem and can potentially be solved by exploitation of sonic data. This problem left out of focus of this research due to a lack of sonic data.

To sum all, in this paper an automated coal lithotypes profiling algorithm has been presented. This method is based on wireline geophysical logs data and does not require any predefined cut-offs or assumptions, it's based on raw data analysis only and, thus, it's immune to interpreter bias. The results of automated coal lithotype profiling were validated by millimetre scale logging data and analysed. Some recommendations were made about which wireline log data are appropriate for coal lithotype profiling. The problem of inertinite-rich dull coal was also successfully solved during the course of the research and the solution is explained in the paper.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found in the online version at http://dx.doi.org/10.1016/j.cageo.2016.03.006.

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