THE APPLICATION OF GEOSTATISTICS IN COAL ESTIMATION AND CLASSIFICATION

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A research report submitted to the Faculty of Engineering and the Built Environment, University of the Witwatersrand, Johannesburg, in partial fulfilment of the requirements for the degree of Master of Engineering (Mining)

15 January 2018

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DECLARATION

I Avhurengwi Colbert Nengovhela declare that this Research Report is my own, unaided work. It is being submitted for the Degree of Master of Engineering at the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination at any other University.

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ABSTRACT

This study set out to assess a multiplicity of related questions regarding the applicability of geostatistical principles, practices and techniques to the estimation, classification and reporting of Coal Resources. Two cases, i.e. Case A and B were selected for the study. Both areas are in the Witbank Coalfield. A few exercises were undertaken to investigate whether a technique such as Ordinary Kriging (OK) could be better suited. The second part of the problem statement is to evaluate whether the current drill hole spacing recommended by the SANS 10320:2004 standard is appropriate for the considered cases.

In terms of drill spacing, the South African National Standard (SANS 10320:2004) provides that for a Measured, Indicated and Inferred classification, samples should be spaced at 200 m (minimum of 8 samples), 282 m (minimum of 4 samples) and 564 m (minimum of 1 sample) respectively. By quantifying the precision associated with estimating the two cases at different drill grids, it was shown that for both Cases A and B, a Measured Resource can be classified by using drill holes that are spaced approximately 1000 m apart. It was established that precision results associated with the global estimation variance are only applicable to the area in which the study was undertaken i.e. the findings are not globally applicable although rough approximations can be deduced.

For short-term mine planning purposes, further drilling may and is usually required. The guidelines provided in the SANS standard for separation distances are evidently too stringent for both Cases A and B. Therefore, a drill spacing of 500 m, 1000 m and 4000 m should be considered as being more appropriate than the current overly tight spacing.

With regard to the use of OK, the findings of this study clearly show that the current Growth Algorithm (GA) technique commonly used by South Africa coal estimators is more appropriate than other alternatives as it outperforms both OK and Inverse Distance Weighting (IDW) whether on a global or local scale. The current estimation method used for these cases is therefore appropriate.

The current drill grids are too small for global estimation and reporting and thus there is possible overspending if the required estimation precision is between 5 and 10 %. At the current drill spacing, precision is around 2 % within ‘Measured’ areas, which is more than what is required to produce predictable long-term plans.

DEDICATION

This work is dedicated to my teachers. Bisrat Yibas, Raymond Nii-Armah and Jonathan Kleynhans for showing me how to apply scientific knowledge in practical ways.

Thank you for the lessons that have shaped my work.

ACKNOWLEDGEMENTS

I would like to thank my employer for access to the software, the database and for the financial support.

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Nomenclature

Geostatistics Terminology for Mining Geologists (After Isaaks E.H and Srivastava R.M, 1989)	
Boxplot	A compact graphical summary that focusses on key statistics. The box in the middle of the diagram goes from the 25th percentile to the 75th percentile i.e. it spans half the data, the arms that stick out of the box record the location of the median and the dot records the location of the mean
Coal	A carbonaceous sedimentary rock with an ash content of less than 50% (by mass fraction on a dry basis).
Correlation Coefficient	A number that lies between -1 and +1 and that measures how close the cloud of points comes to falling on a straight line.
Coefficient of Variation (CoV)	This statistic is often used as an alternative to skewness to describe the shape of the distribution. It is used primarily for distributions whose values are all positive and whose skewness is also positive though it can be calculated for other types of distributions. It is defined as the ratio of the standard deviation to the mean. A CoV of greater than one indicates the presence of some erratic high values that may have a significant impact on the final estimates.
Cumulative probability plot	Shows the chance (from 0 to 1) of a data value being lower than any given value on the x-axis
Histogram	Records the number (or percentage) of data values in each class and their spread
Kurtosis	This is a measure of whether the data are peaked or flat relative to a normal distribution. That is, data sets with high kurtosis tend to have a distinct peak near the mean, decline rather rapidly, and have heavy tails. Data sets with low kurtosis tend to have a flat top near the mean rather than a sharp peak. A uniform distribution would be the extreme case. The kurtosis statistic measures concentration of the values in the centre as opposed to the thickness of the tails

Mean	The mean is the arithmetic average of data values. Measures of the centre of the distribution
Mean Squared Error (MSE)	*MSE= mean(Xest-Xtrue)*^{2} As a general approximation, the following relationship can be used to determine if the semivariogram used is optimal; *MSE ~ Kriging variance±10 %*
Scatterplot	Graphical summary commonly used when analysing more than one variable at a time.
Skewness	Skewness is a measure of symmetry, or more precisely, the lack of symmetry. A distribution, or data set, is symmetric if it looks the same to the left and right of the centre point. If skewness is negative, the distribution is negatively skewed, if positive, the distribution if positively skewed and if the skewness is zero, then the distribution is symmetrical. If the data is negatively skewed then there are many high values and a few low values, and if its positively skewed then there are many low values and a few high values
Standard deviation	This is the square root of the variance. It is often used instead of the variance since its units are the same as the units of the variable being discussed.
Variance	The average squared difference of the observed values from their mean. Since it involves squared differences, it is sensitive to erratic high values.
Variance and standard deviation	Measures of spread of the distribution.

1 INTRODUCTION

1.1 Background

The publication of the 2014 Australian Coal Guidelines for the Estimation and Classification of Coal Resources advocates for the introduction of geostatistics as a tool that should be considered during Coal Resource estimation and classification (Coalfields Geology Council of New South Wales and the Queensland Mining Council, 2014). Mineral Resource and Reserve classification is one of the most difficult and challenging responsibilities of Competent Persons. At the same time, it is one of the most important and rewarding jobs, since it requires Competent Persons to make maximum use of their knowledge and experience and to exercise a great deal of professional judgement. Classification directly affects the quantity of Mineral Resources, which can be converted to Ore Reserves. Classification also directly affects the lender's, investor's or company executive's confidence in the Ore Reserves. Since the Ore Reserves are the ultimate basis for a mining project, inappropriate or poorly conceived Mineral Resource/Ore Reserve classification can have a serious effect on the viability of a project (Stephenson and Stoker, 2001).

The introduction of the South African Code for the Reporting of Exploration Results, Mineral Resources and Mineral Reserves (The SAMREC Code) in 2000 led to the development of additional guidelines and parameters for standardized reporting of Coal Resources and Coal Reserves. The aim of this was to meet the coal reporting requirements of both the Johannesburg Securities Exchange (JSE) and the National Coal Inventory in the country. The South African Guide to the Systematic Evaluation of Coal Resources and Coal Reserves was developed under the auspices of the South African Bureau of Standards (SABS). This South African National Standard (SANS) was first published in 2004 and is known as SANS 10320:2004.

The guide provided drill spacing guidelines for Coal Resource confidence classification. The unintended consequence of these guidelines were that the coal mining industry adopted them as prescriptions for classifying Coal Resources regardless of the heterogeneity of the deposit.

The guidelines provided in the standard for the different Coal Resources confidence categories are as follows;

- Inferred Coal Resource is quantified by a minimum of one cored borehole with coal quality data per 100 ha (approximately 1 km spacing) for multiple seam deposit types.
- Indicated Coal Resource is quantified by a minimum of four cored boreholes with coal quality data per 100 ha (approximately 500 m spacing) for multiple seam deposit types.
- Measured Coal Resource is quantified by a minimum of eight cored boreholes with coal quality data per 100 ha (approximately 350 m spacing) for all deposit types.

This practice has led to the standardisation of classification practices across the industry at least on paper, and thus ignoring the potential value and application of geostatistics. The 2014 Australian Coal Guidelines have removed the minimum distance requirements in favour of geostatistical analysis.

Bertoli et al (2013) compared classification and estimation results generated using the Australian Coal Guidelines against results from geostatistical drill hole spacing analysis (DHSA) and found that the non-geostatistical approach leads to levels of uncertainty that do not always agree with the complexity of the geology. They concluded that the use of a 'one size fits all' classification scheme such as the one suggested by the Australian Coal Guidelines for classification of Resources may result in inappropriate Resource classifications.

Detailed analyses required to estimate and classify Coal Resources using geostatistical estimates have not been adequately undertaken and applied in practice in South Africa. In 1992, Mark Noppé completed a Master of Science thesis in Mineral Exploration titled, 'Geological controls for coal exploration and mining' in which he used geostatistics to quantify the estimation error that results when Ordinary Kriging (OK) is used. Prior to his work, Wood (1979) had undertaken a geostatistical evaluation of low-ash Coal Reserves in No. 2 Coal Seam, Witbank Area through the South African Chamber of Mines.

This report presents the application of geostatistics in the classification and estimation of Coal Resources. In order to understand the origins of the drill hole spacing guidelines, an understanding and appreciation of the history of the Australasian and South African Codes, i.e. the JORC Code (2012) and the SAMREC Code (2016) is necessary. Furthermore, an understanding of the history of the respective guidelines both the Australian Coal Guidelines (2014) and SANS 10320:2004 is necessary.

1.1.1 History and Development of the Australian Coal Guidelines

In 1971, the Standing Committee on Coalfield Geology of New South Wales (ratified June 1968), published the First Edition of the Code for Calculating and Reporting Coal Reserves which contained the suggested drill spacing for Coal Reserve classification before Resource classification was introduced. Four categories of Coal Reserves were introduced with < 0.5 mi (0.8 km) as the spacing between points of observation for the Measured category, < 1 mi (1.6 km) for Indicated and < 2 mi (3.2 km) for Assumed with the rest classified as Inferred (Arnott and Reich, 2013). Reference to Coal Reserves in this Code was before the introduction of Coal Resource classification categories.

In 1974, the Second Edition of the Code was published (ratified March 1973) by the same Standing Committee on Coalfield Geology of New South Wales. This version saw the conversion from the Imperial Units to Metric Units. It is not clear what informed the suggested spacings when this new Code was published but it introduced increased spacing for the Measured Reserves class to < 1 km, and the Indicated category to < 2 km, Assumed to < 4 km and Inferred to anything outside these recommended distances i.e. > 4 km. When the Fifth Edition of the Code came out in 1986, the recommended maximum drill hole spacing suggestions remained unchanged. The term Resources was introduced that year which led to the separation between In-situ Resources and Mineable Reserves. In 1989, the first publication of the JORC Code, called the Australian Code for Reporting Identified Coal Resources and Reserves was released by the Joint Ore Reserves Committee of the Australasian Institute of Mining and Metallurgy (JORC) and ten years later a set of Coal guidelines to support the Code were published by The Coalfield Geology Council of New South Wales and the Queensland Mining Council. The 1999 document was called 'The Guidelines for Estimating and Reporting of Australian Black Coal Resources and Reserves' (Arnott and Reich, 2013).

In 1999, the Coalfield Geology Council of New South Wales and the Queensland Mining Council published the Guidelines for the Estimation and Reporting of Australian Black Coal Resources and Coal Reserves. By now, only three Resource classification categories were recognized, Inferred, Indicated and Measured. The drill spacing had changed moderately to Inferred (< 4 km), Indicated (up to 2 km but normally less than 1 km apart) and Measured (up to 1 km but normally less than 500m) leading to an implied tightening of the requirements (Arnott and Reich, 2013).

As has been the case throughout the different changes, a cautionary note has always been included in the Australian Coal Guidelines which states that "for areas where seams are faulted, intruded, split, lenticular or subject to significant variations in thickness or quality, more closely spaced points of observation supported by interpretive results are required". In 2001, the guidelines were updated with all the distance requirements/guidelines retained as per the 1999 version (Coalfields Geology Council of New South Wales and the Queensland Mining Council, 2001). Two years later saw the publication of the 2003 Edition of the Guidelines, for Indicated Coal Resources the < 4 km spacing was retained (Coalfields Geology Council of New South Wales and the Queensland Mining Council, 2003). There was however a subtle difference in phrasing the requirements for the Indicated and Measured categories. For Indicated points, 'normally less than 1km' could be used but they could be extended if there was sufficient technical justification, for example, if supported by geostatistical analysis. The same phrase was used for the Measured category with the distances being 'normally less than 500 m apart' that could be extended if supported by geostatistical analysis. The 2014 Australian Coal Guidelines, almost fifty years after the first Code was published has seen the move from recommended maximum drill hole distances and places the responsibility to classify a Coal Resource squarely on the shoulders of the Competent Person (Coalfields Geology Council of New South Wales and the Queensland Resources Council, 2014).

According to the 2014 Guidelines, the reasoning for excluding the recommended maximum distances is that these were never meant to be used as prescribed distances or distances endorsed by the 2003 Coal Guidelines or prior versions. It was found that there was misinterpretation of the intent of the guidelines and practitioners were using these in a manner that suggested a prescriptive intent regardless of the geological characteristics of the coal being classified.

The First Edition of the SAMREC Code was published in 2000 and was incorporated in Section 12 of the JSE Listing Rules (http://www.samcode.co.za/downloads/SAMCODEpresentation.pdf). This was followed by the release of the SANS 10320:2004 (South African National Standard, 2004) which included recommended maximum distances which were, in general, more closely spaced than the distances recommended by the Australian Guidelines. The SANS 10320:2004 standard had four categories including reconnaissance. The spacing for this category is up to 4 km, for Inferred Coal Resources it is up to 1 km whilst for Indicated and Measured categories the spacings are 500 m and 350 m respectively (Table 1).

Table 1: Comparison between the recommended maximum separation distances

	Australian Guidelines (2003)	South African National Standard SANS 10320:2004 Multiple seams deposit	South African National Standard SANS 10320:2004 Thick interbedded seams
Measured	<500 m	<350 m	<350 m
Indicated	<1000 m	<500 m	<1000 m
Inferred	<4000 m	<1000 m	<3000 m

It is worth highlighting that the coalfields in Australia are different to those in South Africa and that the distances recommended reflect this aspect. The recommended maximum distances stated in Table 1 for multiple seam deposit types e.g. the Witbank Coalfield in the South African context. The updated standard that is yet to be published is likely to retain the recommended maximum distances which is likely to lead to the continuation of this practice going into the near future.

1.2 Problem Statement

South African Coal Resource estimation and classification is carried out in line with the guidelines provided by the South African Guide to the Systematic Evaluation of Coal Resources and Coal Reserves (SANS 10320:2004) (South African National Standard, 2004) which suggests drill hole spacing at certain distances for multi seam deposits. The work done in other parts of the World e.g. Queensland, Australia (Bertoli et al, 2012) showed that reliance on generic Coal Guidelines may be inappropriate.

1.3 Purpose of Study

The purpose of this study is to determine appropriate estimation and classification guidelines based on geostatistical principles instead of relying on the current South African Guide to the Systematic Evaluation of Coal Resources and Coal Reserves for the multi seam coal deposits of the Witbank Coalfields (South African National Standard, 2004).

1.4 Research Aims and Objectives

The objectives of this research are as follows;

- To develop a Witbank Coal Resources classification protocol based on geostatistical methods for the two specific areas
- To test the appropriateness of applying geostatistical methods to the estimation of Coal Resources for two specific sites and two specific seams in identified areas within the Witbank Coalfields

1.5 Research Methods

This work was undertaken as a desktop exercise relying on drill hole data collected from two specific sites across the Witbank Coalfield. The following specific methods were followed in achieving the set objectives;

- Exploratory Data Analysis using Micromine modelling software.
- Geostatistical analysis using Micromine modelling software.
- A comparative analysis of the current practices against the proposed geostatistics based approach.

1.6 Research Motivation

The 2014 Australian Coal Guidelines explicitly encourage the consideration of geostatistical analyses when generating a Coal Resource estimate. This development presents an opportunity to undertake detailed geostatistical analyses of projects across the Witbank Coalfield and come up with different approaches to some existing problems. Currently there are no clearly documented practices on how to apply geostatistics for coal classification and estimation in South Africa. The industry is thus in need of such a practitioner's guide.

In a joint paper by Hancox and Pinheiro (2016), the authors argue that the yet to be published SANS 10320:2016 update could benefit from including the application of geostatistical considerations in the estimation and classification of Coal Resources. They did however, flag the one possible pitfall of applying geostatistical methods i.e. that the generation of a robust semivariogram requires sufficient data-points, which, owing to commonly wide data point spacing, may prove a challenge. This issue is also addressed in this research report.

1.7 Study Locality

The two areas considered in this study are located in Witbank, Mpumalanga Province of South Africa. The topography of the region is typical of the Highveld and is generally around 1,500 meters above mean sea level (mamsl). The undisturbed topography is dominated by rolling grassland with little areas of trees and shrubs. Rehabilitated areas are seeded grasslands, the majority of the un-mined Coal Resource is covered by grasslands while the remaining parts of the resource area are cultivated with crops by surrounding farmers (mostly maize). The two areas are described in more detail below. Figure 1 shows where the two areas are located in relation to each other.

The two areas are Case A and Case B. Case A Colliery is located 40 km Southwest of the town of Witbank and 100 km East of Johannesburg. It commenced as an underground bord and pillar mine in 1984, while its open cut operations started in 1996. A major graben transects the property dividing it into Northern and Southern areas.

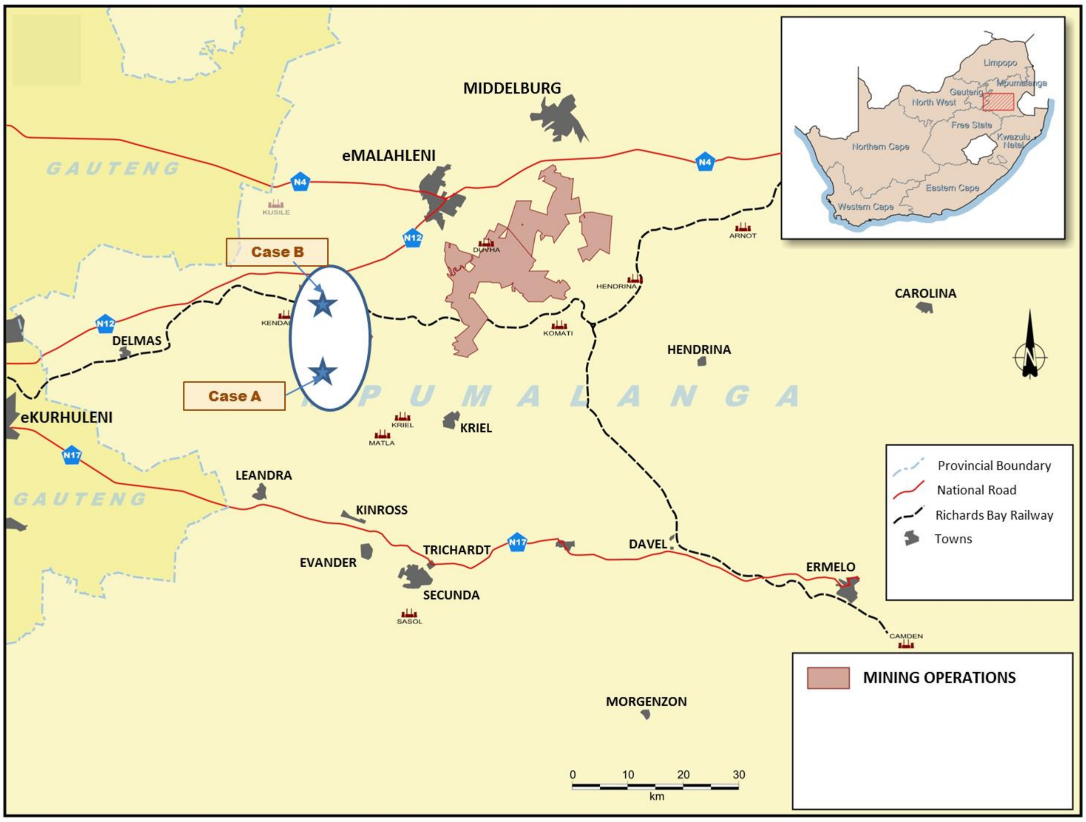

Figure 1: Locality plan for the study areas, Case A and Case B

Case B is a single dragline, multi seam open cut mine with a truck and shovel mini pit. It is located approximately 30 km West of Witbank. The only major structure in the area is the Ogies dyke, which is well understood. Coal seams become increasingly deeper towards the South. The current confidence classification on the Resource and Reserves for both study sites are Measured and Proved respectively.

1.8 Review of the Regional Geological Setting

The two project areas fall within the Witbank Coalfield (Figure 2). According to Hancox and Gotz. 2014, the Witbank Coalfield is situated in the northern part of the Main Karoo Basin (MKB), extending from roughly 25°30′S to 26°30′S by 28°30′E to 30°00′E, and covering an area of over 568,000 ha. It extends some 90 km in a West–East direction, from the towns of Springs in the West to Belfast in the East, and 50 km in a North–South direction, from the town of Middelburg in the North to Rietspruit in the South. The authors also point out that the Coalfield is elongated over a 180 km distance in a West to East direction.

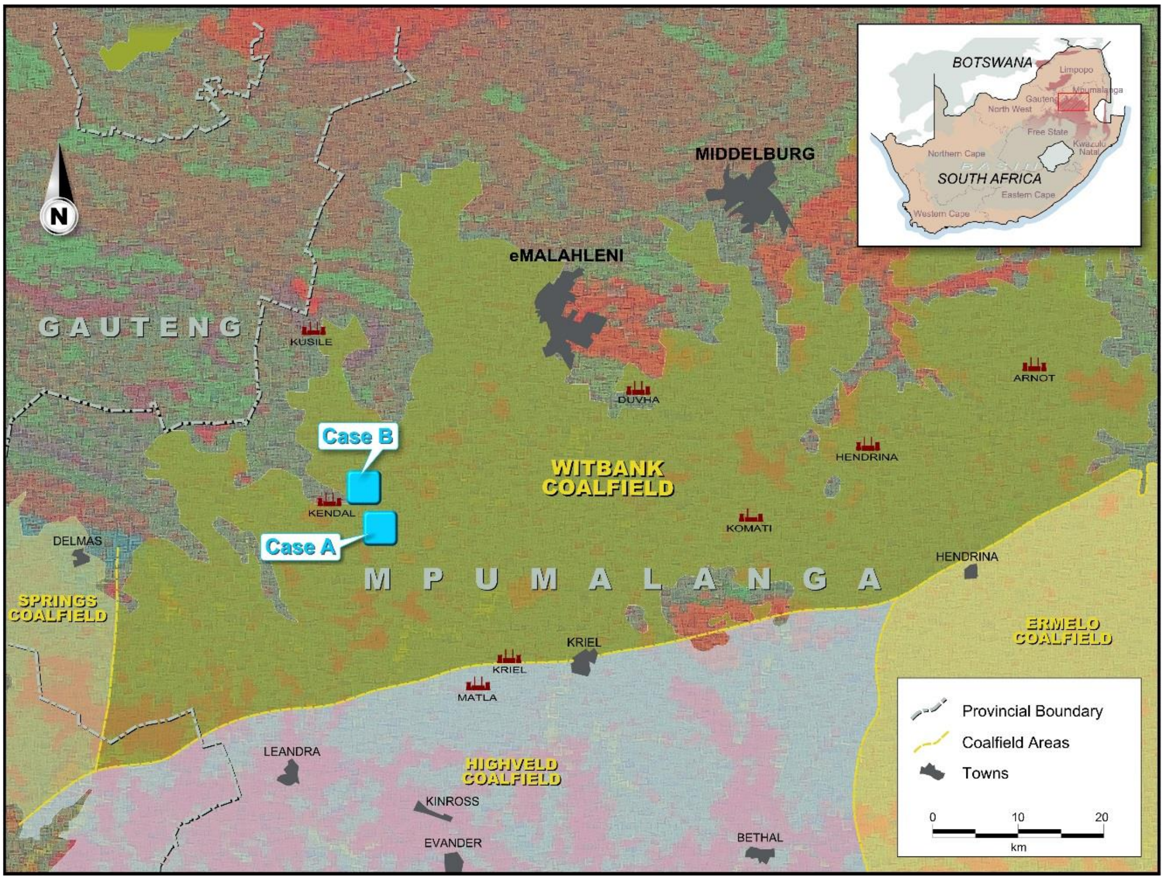

Figure 2: Coalfields of South Africa showing the Witbank Coalfield

Five and sometimes six seams occur within an approximately 70 m thick succession of the Vryheid Formation (Figure 3). They are generally numbered from No.1 Seam at the base of the sequence to No.5 at the top. In places, the No. 2 Seam is split into a No. 2 Lower (2L) and No.2 Upper (2U) by an intra-seam parting of clastic sediments deposited from a braided river system during peat accumulation. In the central sector, there is sometimes an additional intra-seam parting, creating an upper No.2A seam as well. The No.2 Seam averages 6.5 m in thickness in the main central part of the Coalfield and thins to approximately 3 m towards the East. The No. 3 Seam is only poorly developed and when present it is usually less than 0.5 m thick. It is often of good quality coal but it is not generally economically extracted due to its thin development (Hancox and Gotz. 2014).

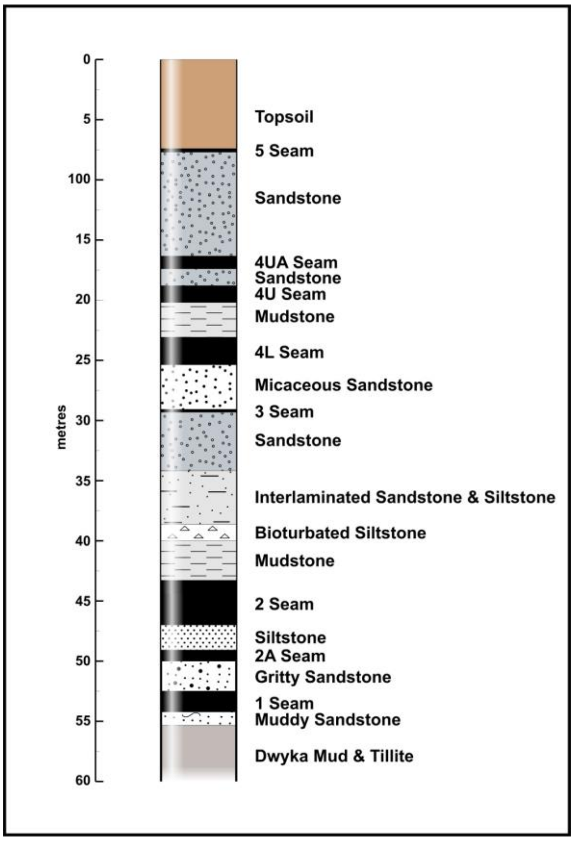

Figure 3: Generalised stratigraphic column of the Witbank Coalfield (South32 Competent Person's Report, 2015)

The No.4 Seam is the second most important source of coal in the Witbank Coalfield and varies in thickness from approximately 2.5 m in the central Witbank Coalfield to around 6.5 m elsewhere. In places, the seam is divided into a No. 4 (No.4L), No.4 Upper (No.4U) and No.4A seams, separated by sandstone and siltstone partings. The No.5 Seam generally lies some 25 m above the No.4 Seam and the base of the No.5 Seam is formed by a thick succession of interbedded sandstones and siltstones. Where present the No.5 Seam has an average thickness of around 1.8 m (Figure 3), being developed between 0.5 and 2 m. In general, the No.5 Seam is of high quality and may be a source of metallurgical coal for both the domestic and export markets, including the ferro-manganese industry (Smith and Whittaker, 1986b). Figure 3 is the generalized stratigraphic column of the Witbank Coalfield.

1.9 Local Geology of Cases A and B

The seams in the Witbank Coalfield are numbered from top (youngest) to bottom (oldest) and in general can be summarized as follows.

- No 5 Seam (S5) (0.5 – 2 m) is the topmost seam and is discontinuous mainly due to weathering and to a lesser extent the palaeo ridges. The relatively thin S5 Coal Seam reveals a short period of peat accumulation in a relatively unstable basin. The seam is of high quality but often friable. The average thickness is mostly between 1.5 and 2.0 m where present. There are only isolated areas at Case B where the S5 seam is adequately developed to be mined, however, at Case A Colliery the S5 is well developed across the Mineral Rights area.

- No 4 Seam (S4U and S4L) (0.5 – 5 m) is present across most of the area and is overlain by one lesser seam, the good quality but thin S4 Upper A (S4UA). The thicker S4 Upper seam (S4U) is only of economic value at the Case A Colliery area but is of thin, sporadic and poor quality at Case B. The S4L follows the S2 seam in economic importance at Case B but is not of economic importance at Case A Colliery. The S4L is mined in all the pits at Case B.
- No 3 Seam (S3) (0.5 – 1 m) is thin and erratically developed as shown in the stratigraphic column of Figure 3. The S3 seam is of high quality but due to its thickness and sporadic development is uneconomic and not mined.
- No 2 Seam (S2) (3 - 8 m) occurs throughout the area with fairly thick average thicknesses. In general, the sediments above the coal seams tend to be fine-grained to argillaceous, somewhat carbonaceous in places, and generally show an upward coarsening texture with increasing distance above the seam. A zone of bioturbated siltstone is present above the S2 seam.
- In some areas, intra seam partings developed in the S2 seam which resulted in the development of the 2 Lower Seam (S2L). The S2 seam has a heterogeneous quality distribution with higher and lower quality zones within the seam.

- No 1 Seam (S1) (0 – 3 m). The S1 seam is the oldest of the coal seams and was deposited on the sedimentary basin floor. The coal is relatively uniform and tends to vary in thickness. The coal is generally dull, with a tendency towards cubic fracture. The diamictite/tillite facies which unconformably overlies the pre-Karoo forms the lowermost sedimentary sequence below S1 seam.

This study focuses on only S4U seam for Case A and S2 seam for Case B.

2 LITERATURE REVIEW

Given that the South African coal industry in general has chosen not to embrace geostatistics there is, as a result, very little written on the subject of geostatistical application in coal. The Australian coal mining industry has in the recent past, published a few papers with Bertoli et al (2013) being the most relevant to this study. These authors compared classification and estimation results done by applying maximum distances recommended by the Australian Coal Guidelines (2003) against results from geostatistical drill hole spacing analysis (DHSA). They found that the non-geostatistical approach leads to a level of uncertainty that does not always agree with the complexity of the geology. Estimation methods such as the Growth Algorithm (GA) commonly used by South African coal geologists generally do not take into account the presence of coal deposit variability when generating an estimate. They concluded that the use of a 'one size fits all' classification scheme such as the one suggested by the 2003 Australian Coal Guidelines for Estimating and Reporting of Inventory Coal, Coal Resources and Coal Reserves may result in inappropriate resource classifications.

In 1979, Wood undertook a geostatistical evaluation of the low ash Coal Reserves of the No. 2 Seam at Greenside Colliery in the Witbank area. He found that the variograms generated from this deposit showed no anisotropy but had a high nugget effect suggesting that samples from neighbouring sites may have substantially different values. The range of the variogram was found to be between 150 m and 320 m, which meant that geostatistics could only be of use to estimate into grids of up to 100 or 200 m. With a drill hole grid of 100 m by 100 m, He found that an estimate of the average yield of a 200 by 200 m block would have a possible error of 1% at the 90% confidence level. It was observed that the size of the blocks should be less than 100 m by 100 m for a 50 by 50 m borehole grid. For a 100 by 100 m grid, this was 150 m by 150 m and lastly for a 200 m by 200 m borehole grid this was 500 m by 500 m. Based on the results, for larger grids, the use of blocks would not be justified. In his conclusions, Wood observed that geostatistics gives the most accurate estimates for the Reserves and further places confidence limits on all the estimates.

In most commodities, guidance for resource classification is provided by the reporting code under which a listed company is regulated. This guidance however tends to be 'loose' as commodities vary in ways that make standardisation impossible. The coal industry has come closest to a form of standardisation particularly following the publication of the South African National Standard (SANS 10320:2004) which provided minimum borehole spacing for each Coal Resource classification category (Figure 4). The standard is the Guide to the systematic evaluation of Coal Resources and

Coal Reserves. The guide provides guidance in terms of the confidence that should be assigned to the different Coal Resource categories as defined in the SAMREC Code (2016).

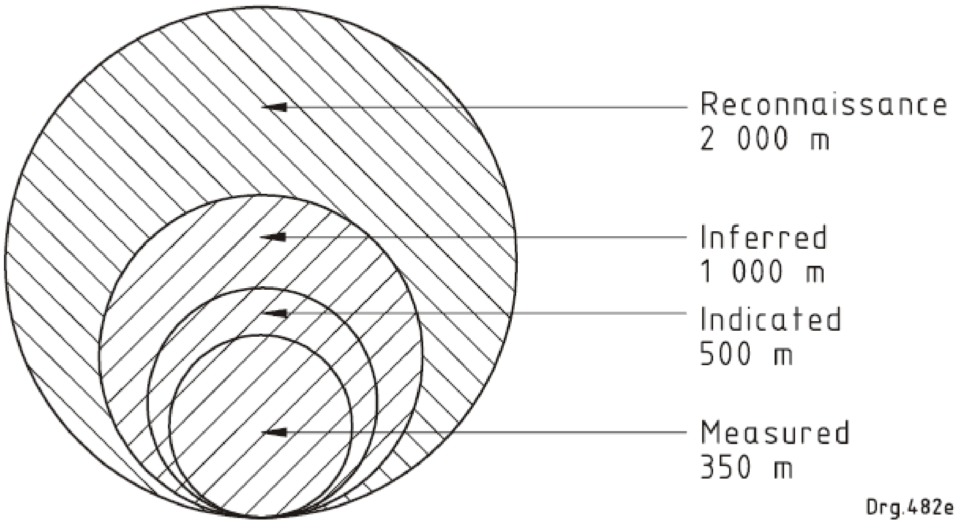

Figure 4: Coal Resources: minimum borehole spacing - schematic diagram to illustrate the minimum borehole spacing for each Coal Resource classification category for multiple seam deposit type Coal Resources (South African National Standard ((SANS 10320:2004), 2004)

The following is a description of the different Coal Resource classification categories according to the SAMREC Code (2016). Figure 5 shows the relationships between the different Resource categories and how they relate to Coal Reserves.

- Coal Resource; is a concentration or occurrence of solid material of economic interest in or on the Earth's crust in such form, grade or quality and quantity that there are reasonable prospects for eventual economic extraction. The location, quantity, grade, continuity and other geological characteristics of a Mineral Resource are known, estimated or interpreted from specific geological evidence and knowledge, including sampling. Coal Resources are sub-divided, in order of increasing geological confidence, into Inferred, Indicated and Measured categories.
- Inferred Coal Resource is that part of a Mineral Resource for which quantity and grade or quality are estimated on the basis of limited geological evidence and sampling. Geological evidence is sufficient to imply but not verify geological and grade or quality continuity. An Inferred Resource has a lower level of confidence than that applying to an Indicated Mineral Resource and must not be converted to a Mineral Reserve. It is reasonably expected that the majority of Inferred Mineral Resources could be upgraded to Indicated Mineral Resources with continued exploration.

- Indicated Coal Resource is that part of a Mineral Resource for which quantity, grade or quality, densities, shape and physical characteristics are estimated with sufficient confidence to allow the application of Modifying Factors in sufficient detail to support mine planning and evaluation of the economic viability of the deposit. Geological evidence is derived from adequately detailed and reliable exploration, sampling and testing and is sufficient to assume geological and grade or quality continuity between points of observation.
- Measured Coal Resource is that part of a Mineral Resource for which quantity, grade or quality, densities, shape, and physical characteristics are estimated with confidence sufficient to allow the application of Modifying Factors to support detailed mine planning and final evaluation of the economic viability of the deposit. Geological evidence is derived from detailed and reliable exploration, sampling and testing and is sufficient to confirm geological and grade or quality continuity between points of observation. A Measured Mineral Resource has a higher level of confidence than that applying to either an Indicated Mineral Resource or an Inferred Mineral Resource. It may be converted to a Proved Mineral Reserve or to a Probable Mineral Reserve.

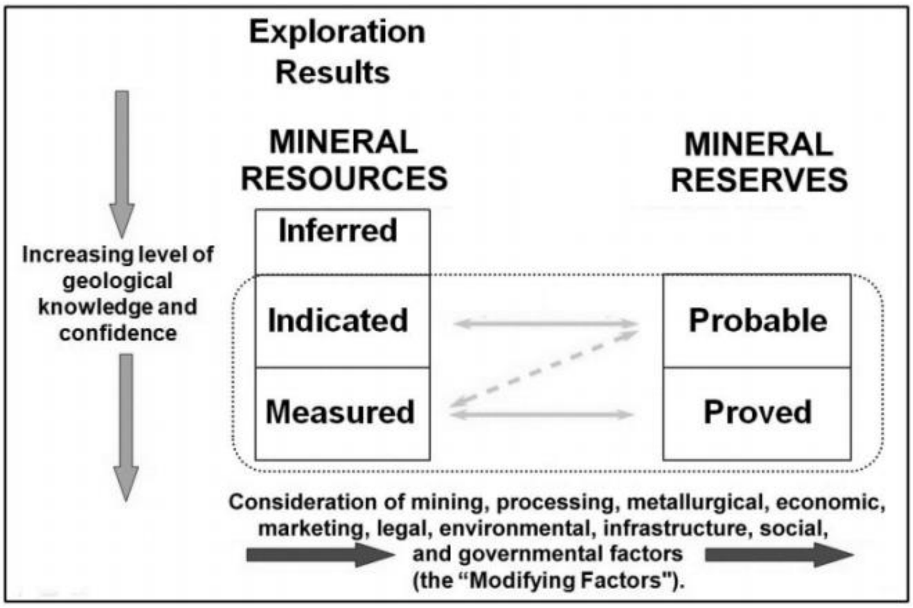

Figure 5: Relationship between Exploration Results, Mineral Resources and Mineral Reserves (SAMREC Code, 2016)

2.1 The JORC Code, SAMREC Code, SANS 10320:2004 Standard and the Australian Coal Guidelines

The Australian Coal Guidelines (2014) expand on the details of how to report and classify Coal Resources by providing recommendations that should be considered if Coal Resources are to be said to be reported in accordance with the requirements of the JORC Code (2012). Part of the scope of the 2014 Australian Coal Guidelines was to include a variety of assessment tools that can be used for the estimation and classification of Coal Resources, to replace the application of suggested maximum distances between points of observation that were included for guidance in previous versions of the document. Furthermore, it is stated in these Coal Guidelines that the document is intended for use in Australian Coalfields but may also provide guidance internationally.

Confidence in classification categories of an estimate can be determined by a variety of methods and criteria. The combination of the most applicable methods and criteria to demonstrate confidence in the estimate should be used to support the classification assigned.

Such methods and criteria as suggested in Table 1 of JORC (2012) include but are not limited to;

- Critical assessment of relevant local, geographical and geological settings
- Identifying critical data
- Data analysis, error and verification
- Domaining
- Statistical analysis
- Geostatistical analysis
- Geological modelling

The SAMREC Code (2016) is not as explicit as the JORC Code (2012) when it comes to the use of geostatistical analysis in estimating a Coal Resource. Although the new Coal Guidelines (2014) no longer have suggestions on minimum separation distances, the practice is still very much in use. In the previous Coal Guidelines (2003), it is stated that Measured Resources may be estimated using data obtained from points of observation usually less than 500 m apart, Indicated Resources from points of observation less than 1000 m apart and Inferred Resources less than 4000 m apart. The guidelines also specify that these separation distances may be extended if there is sufficient technical justification to do so, for example if supported by geostatistical analysis. SANS 10320:2004 is drafted in a similar vein with differences being on the minimum distances stipulated.

2.2 Drill Hole Spacing

According to Snowden (1996), the most obvious factor affecting classification is that of drill hole spacing. Most companies strive, for obvious economic reasons, to obtain the maximum benefit at minimum cost, meaning that the number of drill holes must be just sufficient to ensure continuity, without costing more than necessary. The inevitable question that arises is, “what is the optimum drill hole spacing?”. The answer is “it depends!” The level of risk that management is willing to accept determines how rigorous data collection will be at the start of a project as well as during subsequent mine development. The cost of gathering information has to be weighed up against the potential cost of uncertainty. Inferred Resources are estimated “from geological evidence and assumed, but not verified, geological and/or grade continuity”. Sample data for Indicated Resources must be “spaced closely enough for geological and/or grade continuity to be assumed”. Measured Resources are based on data “spaced closely enough to confirm geological and grade continuity”.

Geological controls may or may not be related to mineralisation continuity. It is thus important to establish the relevant geological controls which affect mineralisation in order to quantify spatial continuity within meaningful geological domains. Drill hole spacing needs to be designed with the style of mineralisation in mind (Snowden, 1996).

2.3 Classification Tools in Current Use

There is a need to classify Mineral Resources into different categories. Sections 1 and 2 of the JORC Code, cover the ‘why’ but do not explain ‘how’ one goes about such an undertaking (Snowden, 2001). This question has been answered to a large degree by an array of geological modelling and resource estimation software tools that simplify the assignment of confidence to a resource based on a combination of selected criteria that are applicable to the commodity of interest. The advent of computers for geological modelling and the increased application of geostatistics in estimating Mineral Resources has seen most practitioners limiting the assignment of confidence to the suggestions made by software package algorithms. This has further seen a reduced focus on the impact geology has on the confidence of an estimated block, which is something that industry needs to address. As of the writing of this research report, 2017, the most common tools used for Coal Resource classification are summarised in Table 2;

Table 2: Resource classification tools commonly used for Mineral/Coal Resources (Mwasinga, 2000)

Tool	Drill Hole spacing	Variogram range	Kriging efficiency Ratio	Slope of Regression
Measured	250 m by 250 m	Blocks within sampled area and using range of influence (66 % of the variogram range)	0.5	0.95
Indicated	350 m by 350 m	Blocks within sampled area but beyond range of influence or with one data (34 % of the variogram range)	0.3 – 0.5	0.80 to 0.95
Inferred	500 m by 500 m	Blocks within deposit but remote from data (extrapolated blocks.)	<0.3	<0.80

- The number of points used to estimate grade; the estimation run that successfully informed the cell; kriging variance of the estimate; slope of regression of the true block grade on the estimated block grade; Relative distance from a data point based on the range of a variogram and drill hole spacing.

These parameters are all useful in resource classification. As geostatistics software packages become readily available, there has been an emerging trend, threatening to ignore the role of classical geological interpretation. One of the reasons for this is that the latter is qualitative and as such difficult to analyse in a numeric sense using software. To achieve increased confidence in resource classification it is necessary to add more parameters to the conventional ones. Snowden (2001) suggested some of these;

- *Spatial continuity; Data quality; Potential mining method; Reporting period; Cut-off grade; Geological risk and Reconciliation results*

A reliable estimate of the In-situ Resource depends on an adequate number of reasonably spaced drill holes, representative sampling, reasonable and coherent geological interpretation of the deposit geometry and continuity. The reliability of the estimate increases with the level of geological knowledge of the deposit and depends on the characteristics of the deposit, mineralization style and geological complexity. Resource classification must incorporate all aspects of the geological framework and should always be based on the geologist's best judgement of the true but unknown reality. Other aspects to consider during classification which are provided for by JORC are 'gut feel' and good old-fashioned common sense. These are obviously difficult parameters to model and as such don't reflect in Competent Person's reports but they are just as important as geological interpretation and geostatistical analysis. They must however not be applied in isolation from the available data (Arseneau and Roscoe, 1998).

Another tool that is useful in classifying Mineral and/or Coal Resources is the use of reconciliation results. According to Yeates and Hodson (2006), a Measured Resource should be an estimate of the in-situ geology of the orebody, tonnes, grade/quality and other pertinent characteristics with sufficient confidence that with further mine planning, the Resource can be used to support the prediction of recovered or saleable ore tonnes and grade/quality to within ±10 % on an annual basis.

On a quarterly basis, this number should be within ±15 % with 95 % confidence. An Indicated Resource should be within ±15 % of reconciliation results and Inferred should be within ±25 % on an annual basis (Figure 6). A review conducted by Parker (1998) found that, annual cash flow projections could accommodate a 15 % drop in tonnage, grade (quality) or metal content (recoveries) without severely affecting project viability (Parker, 1998).

Figure 6: Proposed threshold for resource classification (adopted after Gold and Whitehouse, 2013)

Clay et al (2012), proposed the following for quantitative mineral resource classification; that a less than 50 % variance from the mean of all sample parameters is required to achieve the classification threshold to define an Inferred Resource whereas between 10 - 20 % is needed for an Indicated Resource and less than 10 % variance from the mean is needed to declare a Measured Resource.

A reliable estimate of the In-situ Resource depends on an adequate number of reasonably spaced drill holes, representative sampling, reasonable and coherent geological interpretation of the deposit geometry and continuity. The reliability of the estimate increases with the level of geological knowledge of the deposit and depends on the characteristics of the deposit, mineralization style and geological complexity (Arseneau and Roscoe, 1998).

Generally, the closer the holes are to each other the more confidence can be assigned to those areas. If recommended maximum distances between points of observations are to be done away with, the broad concept of geostatistics needs to be supported by practical and easy to implement tools that all Competent Persons can rely on. One such tool is Drill Hole Spacing Analysis (DHSA) which at its core uses the Global Estimation Variance (GEV) to determine estimation precision (Bertoli et al, 2013).

2.4 Drill Hole Density, Number of Samples, Sectors, Maximum Number of Sectors (determined through cross validation)

In his study, Mwasinga (2000), posited that four samples are usually acceptable as the minimum used in geostatistical estimations. The estimator flags the blocks estimated with four samples or more and these become candidates for the Measured and Indicated categories. Blocks estimated with less than four samples are usually only considered for the Inferred category.

In this study, cross validation/jack-knifing tests were carried out by validating the semi-variogram model against the composited input data. To do this, the software removes a known data point from the dataset and uses search neighbourhood parameters entered by the user together with the semi-variogram model to estimate the grade of a known data point. In making the decision, the parameters, which result in the least error statistic and smallest difference between the actual and estimated grades, are accepted as being the most optimal/appropriate and later used during grade interpolation.

2.5 Sample Spacing and Pattern

According to Yeates and Hodson (2006), the drilling and spacing for a Measured Resource should be sufficient to define key geological domain volumes to within ±10 % of the actual realised tonnage. The sample position accuracy should be within 30 % of the smallest SMU[1] dimension. The drilling and sampling method has to be appropriate for the mineralization and situation, the sample volume appropriate and core/sample recovery known and greater than 95 %. More than 3 % of the holes must be twinned and used to verify geostatistical parameters. The rock density and moisture content must be determined for all rock types to within ±7 %. The sample variance needs to have been measured for the key elements of economic importance and this has been used to determine the drill hole spacing and configuration. The spacing should also be close enough to determine the position of key geological boundaries and structural features at the precision required for mine planning with the proposed mining method. Close spaced pattern of sampling (e.g. grade control spacing, bulk sampling or trenching etc.) and testing both geology and grade with drill holes from different angles, completed to determine short-range variograms and nugget/sill ratio.

2.6 Sample Preparation and Analysis

The sample size, preparation, analytical methods, data validation must be checked with a comprehensive quality assurance/quality control (QAQC) program to measure precision and accuracy through each step of the sampling and analysis process. The size of the sample and pulverising efficiency should be appropriate for the material type e.g. use Gy's Theory of Sampling as guide. QAQC should use properly prepared standard samples, blanks, sample duplicates, intra-lab repeat assays, inter-lab repeat assays, with a full audit trail of the data stored in the database. The combined sampling and analytical precision and accuracy need to have been measured and within ±15 % precision (95 % confidence) and ±7 % accuracy. Legacy data should be statistically proven through twinned samples to be within ±7 % accuracy. Areas where the quality of the data is known to be a problem must be clearly demarcated and excluded from the Measured category (Yeates and Hodson, 2006).

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[1] Smallest Mining Unit

2.7 Mining Method and Cut-off Grade

The classification of a Mineral Resource should also be a function of the mining method to be employed for the extraction of the orebody. There are significant differences in resource confidence between open pit and underground mining and for different commodities. The risk is related not only to drill hole spacing and the nature of the mineralization but also the style of mining (Snowden, 1996).

In general, consideration of the mining method when classifying Mineral/Coal Resources should be made as follows;

- Measured Resource: high confidence, no problem areas, and
- Indicated Resource: high confidence, some problem areas with low risk.
- Inferred Resource: some aspects might be of medium to high risk.

Generally, Coal deposits to be mined by underground methods will often have a lower proportion of the Resources and Reserves in the higher classification categories than deposits to be mined by open-pit methods as more parameters such as stope width and geotechnical stability need to be considered for the former (Stephenson and Stoker, 2001).

2.8 Kriging Variance and Kriging Efficiency

Kriging variance represents the expected value of the squared error between the actual grade and the estimated grade. It is independent of the actual grade. It can be used as an objective measure of the geostatistical confidence in a given block with respect to data configuration. Within a given geological domain, a map of kriging variance highlights the relative confidence from block to block and can be used as a drill hole-targeting tool, which exposes locations where infill drilling may be beneficial (Snowden, 2001).

The kriging variance links the drill hole spacing to the semivariogram ranges of influence, and appropriate variances can be chosen to define Mineral Resource confidence categories. The most effective way of doing this is to display the colour-coded variances and drill holes in plan and section in order to define which variance most closely obeys the limits defined by the semivariogram ranges of influence. In applying the classification, there is an automatic distinction made between interpolated blocks (lower variance, more confidence) and extrapolated blocks (higher variance, less confidence). Any volume extrapolated beyond the range of influence is given no more than Inferred status, as there is no geo-spatial correlation between qualities of samples at locations this far apart. In situations of complex nested structures, small-scale structures may account for most of the variability and should be given most weight in defining confidence. Thus, simply having a long-range structure present may not be sufficient to infer a high confidence, if, in addition, small-scale structures are apparent (Snowden, 2001).

Efficiency is a measure of the relative amount of effort to accomplish a task. If a different process can accomplish the same task with less effort, then it is more efficient. For an unbiased estimator, the efficiency is defined as the minimum possible estimation variance divided by the variance of the estimator. The kriging efficiency is expressed as the kriging variance *(σ^2_K)* normalized by the variance of the true blocks (σ^2) as a percentage. A high efficiency means that the kriging variance is low, and the variance of the block estimates is approximately equal to the variance of the true block values. A low efficiency implies a high kriging variance relative to the block variance. The kriging variance varies from block to block, so the kriging efficiency will vary. For perfect evaluations, the efficiency is 100%. If the variance is greater than the true block variance, efficiency can be negative. Kriging efficiency, can be expressed as KE_{DK}, subscripted by Krige's initials (Deutsch et al, 2014).

$$KE_{DK}(\%) = \frac{\sigma^2 - \sigma_K^2}{\sigma^2}$$

Generally, the kriging variance reduces as the number of informing samples increases and/or position of the samples relative to one another and the estimation target becomes more favourable.

For perfect valuations, the kriging variance i.e. error variance of the block estimate must be equal to zero whilst the kriging efficiency must be 100 % (Deutsch et al, 2014).

Krige (1996) suggests the following parameters for Resource and Reserve classification based on the kriging efficiency ratio.

Table 3: Resource/Reserve categories based on the kriging efficiency ratio

Krige's index	**Measured**	(Block variance - kriging variance)/Block Variance > 0.5
	Indicated	(Block variance - kriging variance)/Block Variance > 0.3
	Inferred	(Block variance - kriging variance)/Block Variance < 0.3

A high kriging efficiency means that the kriging variance is low and the variance of the block estimates is approximately equal to the variance of the true block values. A low efficiency implies a high kriging variance relative to the block variance. When the estimation variance exceeds the block variance, Krige deems this a kriging anomaly and states that valuing the block with the mean would be more efficient assuming the mean is known accurately (Deutsch et al, 2014).

2.9 Global Estimation Variance and its application in Drill Hole Spacing

Global estimation variance represents the precision of the overall average grade estimate. The method used to determine estimation variance for use in the assessment of resource estimation confidence is known as Drill Hole Spacing Analysis (DHSA). Journel and Huijberts (1978a) defined the estimation variance or extension variance as the variance associated with using the known average grade for a small volume ‘v’, to estimate the grade for a much larger region ‘V’.

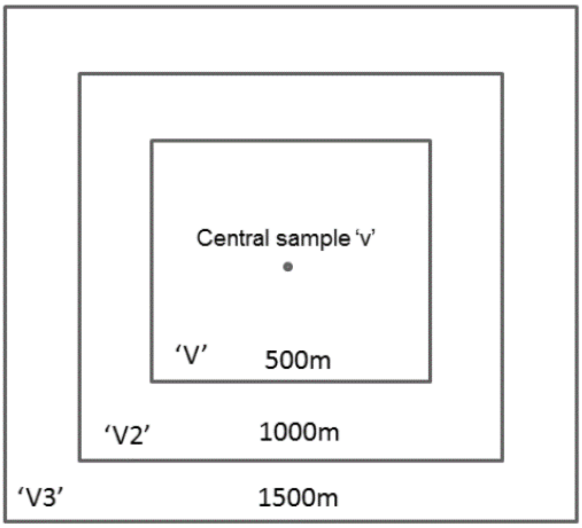


Figure 7: Calculation of estimation variance into a regular square region V, of increasing size V2 and V3 (Image copied from Williams et al, 2015).

To calculate Global Estimation Variance the following approach is undertaken (Global Estimation Variance (GEV), see Journel and Huijbregts, 1978). The methodology followed here uses in-situ Ash content over an area that corresponds to a mining period of 1 year, and characterise the precision of estimation through an estimation variance. This estimation variance depends on:

- The variogram model chosen for the variable, domain and seam being modelled
- The 'geometry of the data' that is, particular data locations used for estimation and
- The block size and geometry (the area to be estimated)

Once a variogram model is available for a given variable (in-situ Ash) the following general methodology can be implemented (after Bertoli et al, 2010):

- Select grid mesh dimensions Easting (X) and Northing (Y) corresponding to the nominal drill spacing being investigated. The range of the variograms should inform the test block sizes used from around 10 % of the maximum range up to between 200 % of the maximum range. It is a good idea to use a regular increment between successive block sizes (Williams, et al, 2015). Note that, because there is one block per sample, the block dimensions are the same as the sampling grid dimensions (Cornah, et al, 2013).
- Calculate the elementary estimation variance σ^2_e when a block size X (m) by Y (m) is estimated using one central sample (using the variogram model established previously). Set the maximum number of samples to one.
- Calculate the number (*N)* of blocks required to cover the area of interest corresponding to the envisaged mining period (this number *N* corresponds to the number of samples required to achieve sampling of the area of interest at the desired drill spacing. N further refers to the number of blocks at the specific test block size that would fit into the area of interest i.e. how many blocks/grids would be required at a specific size to fill up the area of interest. Assuming that a regular grid is used across the area of interest and that the deposit being estimated is only two dimensional, then an approximation can be used for the estimation variance over the area of interest. This is the true meaning of global estimation variance σ^2_E. The higher the value of N, the lower the global estimation variance for the study area. A high value for N can be achieved by reducing the block size (in other words reducing the drill spacing) or by increasing the test size area.
- Calculate the theoretical variance of estimation of the mean in situ Ash value of the entire area as

$$\sigma^2_E = \sigma^2_e/N \text{ (combination of elementary variances)}$$

- Calculate the equivalent standard deviation (square root of the variance calculated above). Then, as a first approximation of relative precision, calculate the ratio of two times this standard deviation to the global mean of *in situ* Ash, i.e. $2\sigma_E/m$, this can also be expressed as;

$$\text{Relative } 95^{th} \text{ \%ile range} \pm 2\sigma_E/m \times 100\%$$

Where σ_E is the standard deviation and m is the mean value.

- Plot this relative precision (expressed in percent) versus the sampling grid defined in Step 1.

This equates to an approximate 95% confidence interval versus a drilling spacing for the corresponding area.

2.9.1 Using the Global Estimation Variance to determine confidence in an estimate

Once the relative percentage errors are plotted against the test block/drilling grid size and the distances at which the 10 %, 20 % and 50 % relative percentage error thresholds are reached, this can be used as resource classification distances for Measured, Indicated and Inferred Resources respectively. It should be noted that it is possible in some cases that a 50 % error will never be reached for attributes with a low population variance. In such cases, there should theoretically be no limit to Inferred Resources within the tenement (apart from the limit imposed by the margin of the drilling) (Williams et al, 2015).

2.10 Slope of Regression

The slope of the regression line, considering the true value and the estimated value, is often used as a diagnostic for conditional bias. Ideally, the slope of this line should be equal to one, which implies conditional unbiasedness.

Figure 8 shows that the mean of the true values Z_V and estimated values Z^*_V are the same; virtually all estimators are globally unbiased. The regression of the true values given the estimates in an indication of conditional bias (Deutsch, 2007).

Mwasinga, (2000) suggests that the use of regression slope in classification be applied as shown in Table 2. When using the 'linear regression' approach values of p (probability density function) could be arbitrarily selected to correspond to the 'Measured, Indicated and Inferred' categories by examining p for the estimated blocks.

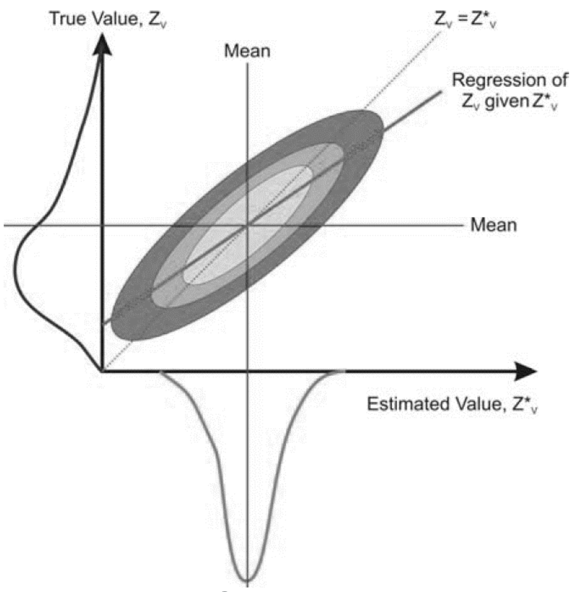


Figure 8: Slope of regression for kriging estimators[2] (Deutsch, 2007)

2.11 Geostatistical Analysis

Geostatistical analysis provides a mechanism to understand and quantify a variable's continuity and the degree to which it is spatially correlated. The process can also provide an evaluation of the sample data geometry, and considers the volume ('support') of the data and the volume or area being estimated. Geostatistics provides a useful measure of the uncertainty of an estimate. Careful consideration of data selection, data validation, domain definition and identification of critical data are required for reliable geostatistical analysis (Coalfields Geology Council of New South Wales and the Queensland Resources Council, 2014).

Because coal represents a heterogeneous mixture of constituents, there is a range of coal quality parameters that should be considered for geostatistical analysis. With multiple variables, consideration of the primary defining drivers in the choice of critical variables is necessary. Continuity for different variables should be considered when determining the maximum range of influence of any data applied in any estimate. When numerous variables are assessed, the critical variable with the highest variability should take precedence in determining this maximum

[2] where Z_V is the unknown true value for volume V at unsampled locations and Z^*_V is the estimate (the independent variable on the X axis because it will be known) (Deutsch, 2007)

influence (Coalfields Geology Council of New South Wales and the Queensland Resources Council, 2014).

Variability when estimated through geostatistical techniques is a function of the dimensions in which variance is reported. Larger volumes will be less variable than smaller ones. When quoting variances, the scale of the estimated blocks should be stated. Geostatistical analysis provides a mechanism to understand and quantify a variable's continuity and the degree to which it is spatially correlated (Coalfields Geology Council of New South Wales and the Queensland Resources Council, 2014).

The use of maximum separation distances in both the South African guide to the systematic evaluation of Coal Resources and Coal Reserves (2004) and the Australian Coal Guidelines (2003) has resulted in estimation and classification of Coal Resources in ways that are not always reflective of expected geological occurrences. In most instances, practitioners end up classifying pockets of resources as Measured or Indicated whilst enveloped by an inferior category. In some instances, an Inferred pocket ends up surrounded by Measured Resources as the software packages used, particularly Minex, which is the most pervasive software package in the South African coal mining industry, are geared to use the minimum separation distances.

Stephenson et al (2006) made a case for the discontinuation of this practice in their paper, 'Mineral Resource Classification – It's time to shoot the 'spotted dog''. The spotted dog effect essentially ignores geological continuity, which perhaps in more than any other commodity is well documented in coal.

Stephenson et al (2006) make the observation that the spotted dog approach fails geologically and does not align with reporting codes and standards in that all the standards advocate for geological continuity when classifying resources, meaning that both the geology and grade/quality are discussed in terms of drill holes in the plural, not around individual drill holes. They also argue against an over reliance on the attributes of each block especially when the blocks are very small in relation to drill hole spacing and lastly they feel that this approach takes no account of uncertainty in the geological interpretation or quality of data.

Stephenson et al (2006) suggested a solution to this problem by advocating for the smoothing of block-by-block resource classifications into 'geological sensible and coherent zones'. The main point was that classification needs to exit the mathematical realm and introduce geological sense by sensibly over-riding what software packages spawn-out.

In their paper of quantitative kriging neighbourhood analysis, Vann et al (2003) address the issue of number of samples as one of the key considerations in resource classification and the determination of the search neighbourhood. As a rule of thumb, they determined that using less than 10 samples to generate a kriged estimate is not recommended. Given the wide separation distances in coal, a minimum of 10 samples represents a considerable area. It should also be stated that this minimum number of samples does not hold in instances where the data is composited across the full seam as the warning applies primarily to instances where individual samples are used.

In 2015, Williams et al, following the release of the 2014 Australian Coal Guidelines undertook work at two operating mines owned and operated by Peabody Energy Australia. In order to undertake the work, they applied a process that has come to be known as DHSA (Drill Hole Spacing Analysis). Their results showed that the main criteria in determining classification distance using DHSA are; population/global variability; spatial continuity, one measure of which is the variogram range; and lastly the size of the study area, which in turn is a function of working section thickness and mining rate.

In their research, the authors selected to undertake the study on two variables, seam thickness and raw ash. The reasons provided for this selection were that seam thickness has a direct influence on coal volume whilst raw ash is indicative of the unwashed, raw coal quality and it is directly related to other critical coal quality variables such as raw coal density and washed coal yield. The selection of both the thickness and the raw ash assists with meeting one of the Australia Coal Guidelines requirements (Section 4.1.3) to use outlines that are determined by merging quantity confidence limits (tonnes) with coal quality confidence limits. It further states that the final confidence limits should be based on the more constrained of the two variables. In modelling the semi-variogram (omni-directional), the authors encountered problems with a noticeable trend in the data and uncertainty around what nugget effect should be used due to the lack of closed spaced drilling.

2.12 General or Growth Algorithm Estimation Method

The growth method is a two-stage process. Stage 1 surrounds the data with four grid mesh points. Stage 2 fills in the remaining mesh points. Stage 1 determines the mesh point values of a square containing one or more data points, the centroid of these data points is first determined. If only one data point falls within a square, the data is the centroid. Next, a plane is established passing through the centroid. To establish this plane, values of surrounding data points are taken into consideration. The technique involves searching out the nearest data point falling within each of eight equal sectors around a centroid. These data points are then used in a least squares fit to determine a plane passing exactly through the centroid. The weighting of the selected data point values is such that the closer the data point to the centroid, the greater the weight in the least squares fit. The value of the plane at each of the four mesh points of the grid square is taken to be the value at that particular mesh point (Barber, 2011).

Stage 1 uses a sextodecimo (16 sectors) search to estimate the nodes. The second stage fills in the remaining mesh points. These are calculated by taking the average of two planes (a "secant plane" and a "tangent plane") calculated at each grid intersection. The secant plane is calculated in a manner analogous to the first stage. The tangent plane is produced by a "first order finite difference equation". This generation proceeds outwards from the known mesh values of stage one. The secant plane is described as interpolation and the tangent plane as extrapolation. Nodes must exist in at least three of the sectors to generate the secant plane. As with stage 1 the weights of the nodes are based on distance to build a least squares plane. However, if there are five or less points available to estimate the secant plane then an inverse distance weighted average estimate is used in lieu of a least squares estimate (Barber, 2011).

As the secants planes bridge across the void between stage 1 nodes, they do not reflect the gradient or trend of the data. This gradient or trend is supplied by the tangent planes. The tangent plane is determined by only using the local nodes. A first order partial differentiation equation is used to determine the tangent value. This is determined from triangles formed at the surrounding four mesh points at the node to be estimated. Within the Minex software, the user is able to control the weight assigned to the extrapolation (tangent) estimate. By default the weighting is 2/3 interpolation or secant and 1/3 extrapolation or tangent. The user can further disable the extrapolation estimate, which tends to flatten the model between data points. Unlike inverse distance methods, the growth algorithm method can generate values that exceed the data values (Barber, 2011).

This occurs for two reasons;

- In stage 1 the plane around each data point is built from the surrounding data and can thus generate a node greater than or less than the data values.
- The tangent plane or extrapolation component of stage 2 as it grows forms a local trend.

2.13 Additivity and Accumulation

Geostatistical methods typically assume that the variables of interest behave additively (i.e. that the mean calculated through a simple linear average is unbiased. Sample assays represent a concentration of an attribute per unit of mass. In coal, attributes are generally measured over varying seam thicknesses, and therefore sample determinations represent variable masses. As such some attributes of interest may be strictly non-additive and an accumulation type approach may be preferable (Bertoli et al. 2003).

Any volumetric grade (e.g. g/t) defined on a constant support (same sample size, constant density) is an additive variable. The same volumetric grade defined on variable supports (unequal sample size, variable density) is no longer an additive variable as the mean grade of two different supports is not the arithmetic mean of their grades. However, certain types of variables may behave non-additively even if measured under uniform support or following an accumulation approach to dealing with variable supports. The accumulation approach as explained in Chapter 3 was used to generate both the variograms and the final estimate.

When undertaking resource estimation on any deposit with layer-like geometry (coal), the variable of interest (quality) is not a suitable variable for direct interpolation. This is because quality of the coal seam is clearly defined on varying supports. However, quality can also be defined as the ratio of two other variables (thickness and accumulation – the product of quality by thickness potentially weighted by bulk density), which are amenable to direct interpolation (Chiles and Delfiner, 1999). There is also an operational issue to consider, because the variables of economic interest, i.e. those upon which economic decisions and optimisations will be made, are actually the projected horizontal thickness (tonnage) and the accumulation (quality content) and not the quality. In these situations, quality is usually of secondary interest (Bertoli et al, 2003).

The appropriateness of a 2D approach, in the interests of avoiding biases due to violation of additivity, is beyond debate. Additivity refers to the following property of a variable: that the linear average of its values will result in a variable with similar physical meaning (see Journel and Huijbregts, 1978 pp 199-200, for discussion of additivity). The definition of the new variables (thickness and accumulation) is straightforward: it simply requires a careful consideration of not only the quality and length of the mineralised intercepts but also their orientation, if a meaningful, appropriate projection is to be decided upon. Once these variables are defined, the tools of linear geostatistics can be deployed at will.

It is worth stating that additional practical problems with 3D approaches when applied to narrow seams and layers arise from the difficulties of dealing with geometry.

Specifically:

- to capture the essential geometry of layers, the block size must be too small (from an estimation variance point of view);
- the alternative of estimating large blocks and using sub-blocking (assigning parent cell grades) or, equivalently, ‘block partials’ (i.e. percentages) is also problematic because the kriging assumes the support of the parent blocks (and in these cases this is generally too large, leading to excessive smoothing); and
- the appropriate composite length to employ for 3D estimation is also problematic: there is no way of correctly and exactly honouring the hangingwall-to-footwall sample dimensions. These problems along with additivity issues are overcome when a 2D approach is adopted (Bertoli et al, 2003).

In order to generate pairwise relative variograms used in this study, this 2D approach was employed at both Case A and Case B.

3 ANALYSIS & DISCUSSION OF RESULTS (CASE A)

3.1 Case A Colliery

3.1.1 Exploratory Data Analysis (EDA)

The data presented in this section includes all the statistical analyses that was carried out during the evaluation process. Statistics were generated on variables including number of samples, mean, minimum values, maximum values, population variance, standard deviation, skewness and kurtosis; in addition, histograms, QQ Plots and box and whisker plots were also plotted. This aligns with the requirements of Table 1 of both SAMREC (2016) and JORC (2012).

For Case A, the economic seams are S4U, S2 and S5. The thicker S4 Upper seam (S4U) is only of economic value at the Case A Colliery area but thin, sporadic and of poor quality in Case B. As a result, statistical analyses and estimation for S4U will only be for Case A, S2 will be assessed for Case B. As of June 2016, Colliery A had 2321 drill holes drilled since the mine started operating. Exploration drilling for the colliery dates back to the 1920s. Of the 2321 holes, 2229 contain lithological information with 1571 of those containing raw quality data. This research report summarizes the quality data contained in the 1571 holes. The data was converted from .csv files to a Micromine Version 15.0.0 format. The same software was used for all analyses from exploratory data analysis through to reporting. The variables that were selected for analyses are thickness, ash and calorific value for both deposits.

3.1.1.1 S4U Raw Uncomposited Basic Statistics (Case A)

For the raw samples, the maximum sample length is 8.8 m. The maximum ash content within the database was capped at 50 % in line with SANS 10320:2004's definition of coal. Its minimum value is 11.2 %Ash with a mean quality/grade of 30.59 %Ash. The mean sample length is 1.03 m, which represents the mean sampling interval. The coefficient of variation (CoV) for ash, which is a measure of spread that describes the amount of variability relative to the mean is 0.31. Owing to the fact that CoV does not have a unit of measure, it can be used instead of the standard deviation to compare the spread of datasets that have different units or different means. In this case, it allows for the comparison of the difference in the spread of thickness and Ash. Mathematically, the CoV is defined as the standard deviation/mean. As a rule, OK performs well in deposits which have a CoV close to (or less than) one. Dominy et al, 1997 and Fytas et al, 1990 stated that for quality distributions with a CoV of less than about 1.5, meaningful variograms can be produced.

For Case A S4U, the CoV of 0.56 for thickness, is higher than that of Ash at 0.31. The implication of this is that during the generation of the kriged estimates in later sections, the latter should in theory, generate better estimates. For calorific value (CV), the minimum value is 10.1 MJ/kg with a maximum of 28.2 MJ/kg and a mean value of 20.35 MJ/kg. Its variance is lower than that of Ash. The kurtosis (peakedness) for CV is normal (Figure 11) whereas for Ash (Figure 9) the distribution is flat. The CoV of CV is a low 0.174 with the population slightly negatively skewed compared to the slightly positive skewed nature of the Ash distribution.

Table 4: Classical uncomposited raw statistics for Case A's S4U seam.

Variable	Minimum	Maximum	No of Points	Mean	Variance	Std Dev	Coeff. of Variation	Skewness	Kurtosis
ASH%	11.2	50	5220	30.59	87.54	9.35616	0.306	0.353	-1.037
THICKNESS (m)	0.08	8.8	5220	1.03	0.33	0.57	0.557	3.579	24.087
CV (MJ/kg)	10.1	28.2	5220	20.35	12.51	3.54	0.174	-0.359	-0.906
RD (g/cm^3)	1.32	2.04	5204	1.63	0.01	0.12	0.071	0.345	-0.657

The range of the distribution of Ash% for the uncomposited data is from 11.2 % to 50 % (Figure 9). There is a noticeable difference between the mean and median i.e. 30.59 %Ash and 28.7 %Ash respectively further confirming the positive skewness of the distribution. There is a hint of tri-modality in the Ash population with three groupings of mean %Ash values of 24 %Ash, 36 %Ash and 44 %Ash roughly. This tri-modal nature of the data is further supported by the histogram of CV with grouped means of 15, 19 and 24 MJ/kg (Figure 11) respectively. This phenomenon was further investigated once the data has been composited across the seam to see if there are distinct domains that should be separated during variogram analysis and estimation. What is clear in Figure 17 is that the tri-modal populations suggested by the histogram of uncomposited data disappear and are replaced by a more uniform and normal distribution for Ash when the data is composited. For this reason, a decision not to domain the population on Ash content was made.

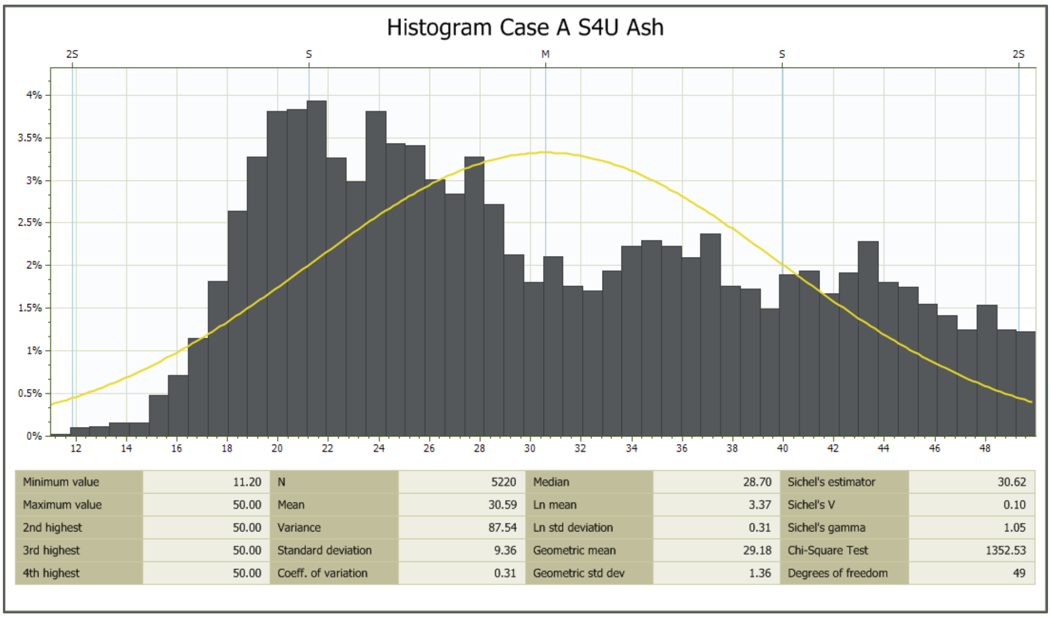


Figure 9: Histogram for Case A S4U %Ash on raw uncomposited samples (A top cut of 50 % was applied)

The box and whisker plot for S4U %Ash (Figure 10) shows a 25th quartile value of 22.6 %Ash with a 75th quartile value of 38.1 %Ash. There are a few outliers, which pull the mean value down. Of interest is the fact that, all the potential outliers show values of between 10 and 15 %Ash.

Calorific value on the other hand has a few outliers above the 75th quartile (Figure 13). The 25th quartile shows a value of 17.6 MJ/kg whilst the 75th quartile has a value of 23.3 MJ/kg. The mean and median CV values are 20.3 vs. 20.96 MJ/kg respectively. When composited, the CV histogram for S4U takes on a more normally distributed shape (Figure 11).

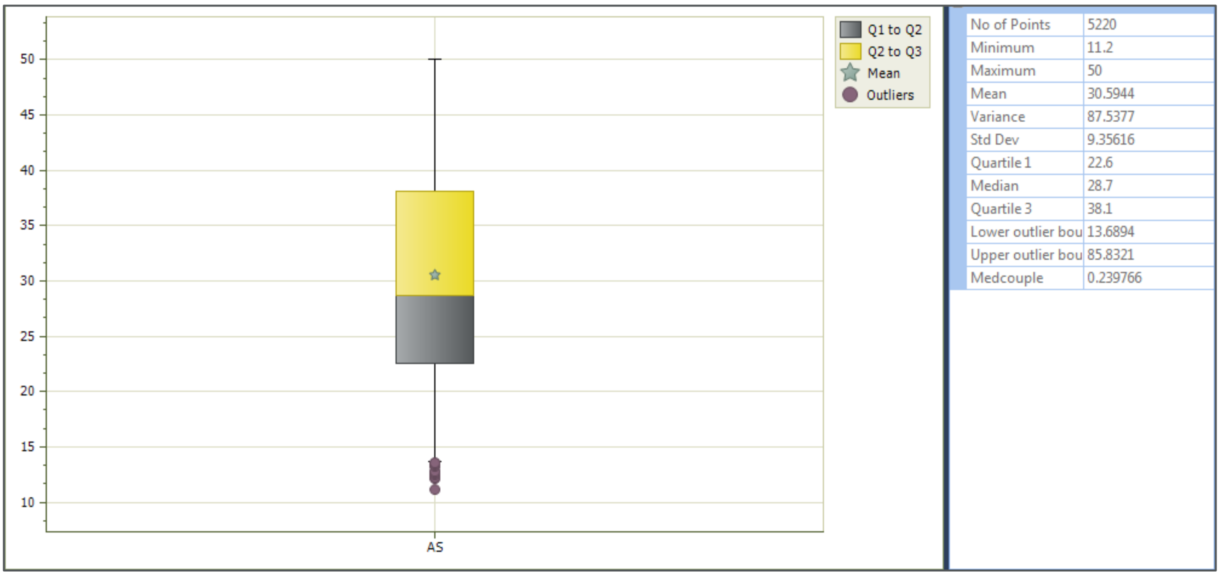
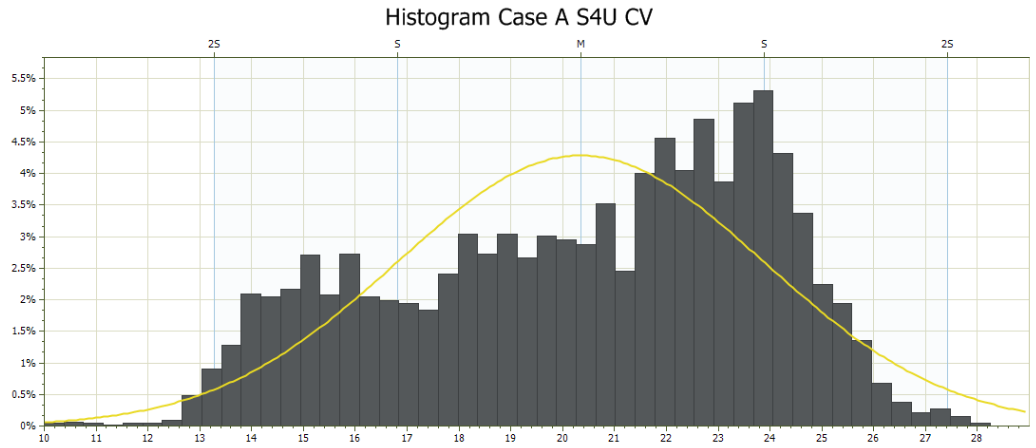


Figure 10: Box plot for Case A S4U %Ash content on raw uncomposited samples



Minimum value	10.10	N	5220	Median	20.96	Sichel's estimator	20.36
Maximum value	28.20	Mean	20.35	Ln mean	3.00	Sichel's V	0.03
2nd highest	27.90	Variance	12.51	Ln std deviation	0.18	Sichel's gamma	1.02
3rd highest	27.80	Standard deviation	3.54	Geometric mean	20.02	Chi-Square Test	1197.34
4th highest	27.80	Coeff. of variation	0.17	Geometric std dev	1.20	Degrees of freedom	49

Figure 11: Histogram for Case A S4U CV on raw uncomposited samples

There is a relatively wide spread in the CV population showing that what the box and whisker plot suggests to be outliers are actually normal data points within the population (Figure 13). There are a few low values contributing in lowering the mean quality to 20.35 MJ/kg. Figure 12 shows the population distribution of RD for the S4U seam. The minimum value is 1.320 with a maximum of 2.040. The mean value is 1.630g/cm^3.

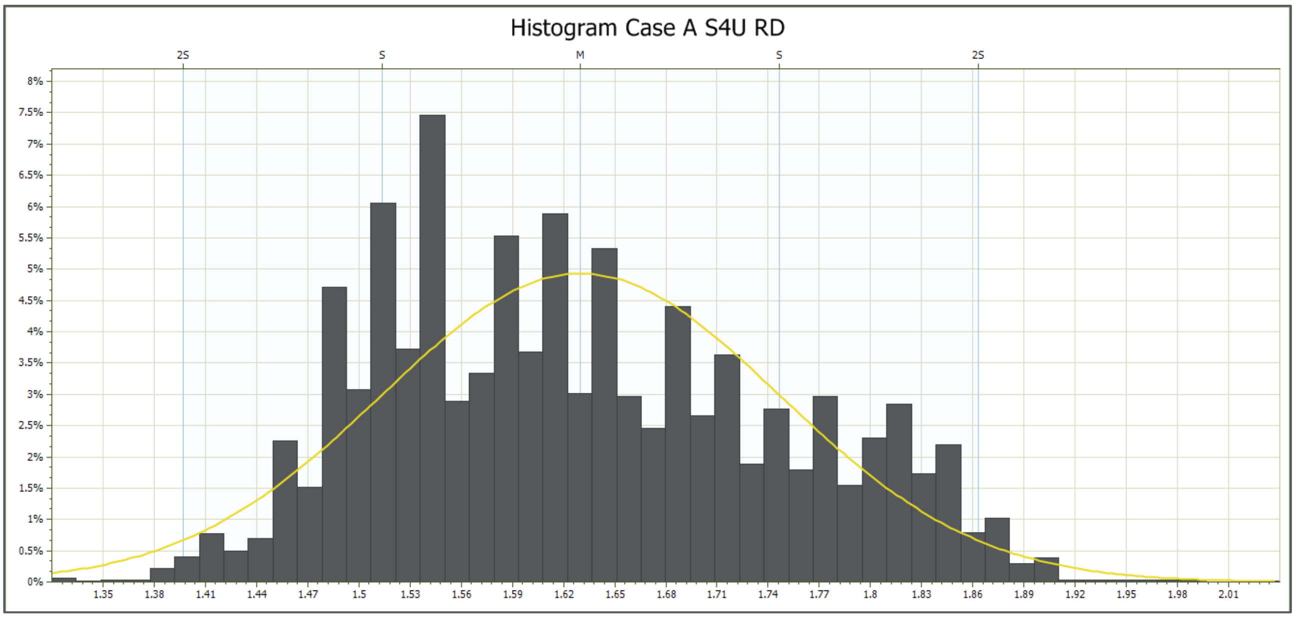


Figure 12: Histogram for Case A S4U RD on raw uncomposited samples

Both the box plot and histograms for ash show that there are hardly if any outliers within the Ash population.

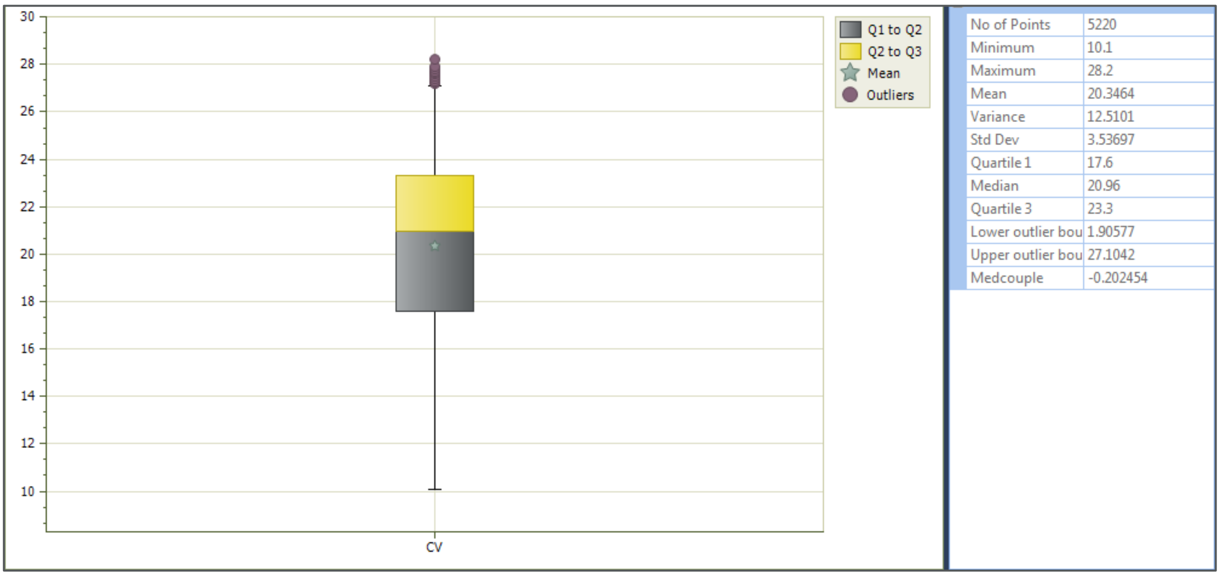


Figure 13: Box plot for Case A S4U CV content on raw uncomposited samples

For thickness, the following plots on composited data will provide information that is more meaningful. There exists an inverse relationship between Ash content and CV. This is further evidenced by the scattergram presented in Figure 14, which shows a high linear correlation coefficient of 0.97 between the two variables.

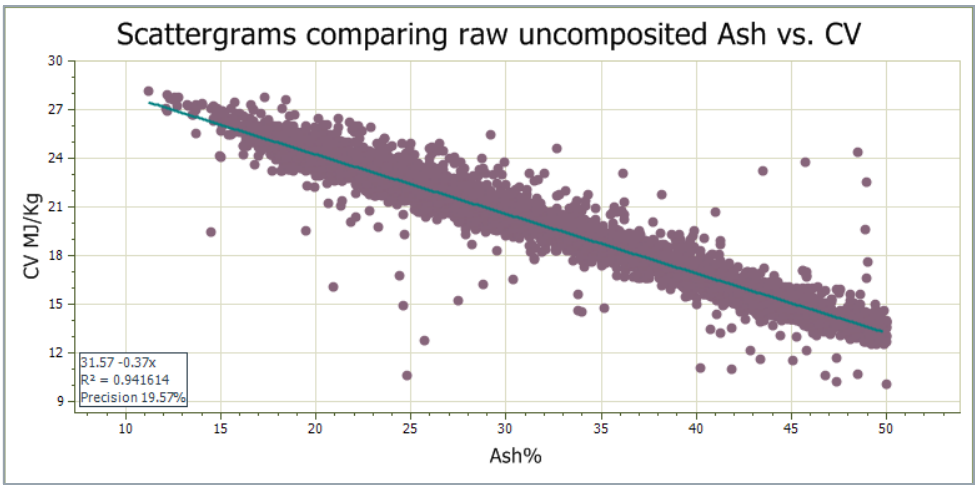


Figure 14: Scattergram for Case A S4U CV vs. Ash on raw uncomposited samples

3.1.1.2 S4U Raw composited basic statistics

Three variables were selected, Ash (%), CV (MJ/kg) and thickness (m). The expected effect of compositing the data is the lowering of variance as the volume increases (change of support (CoS)). Worth highlighting is that the data was composited across the full seam i.e. all the samples that fall within the S4U seam were composited into one sample/data point. From the variance of the raw uncomposited Ash of 87.54 $(\%)^2$ it reduces to a composited value of 16.48 $(\%)^2$ which represents a 19% change of support impact. The CoV values for both cases are low with composited %Ash having a CoV of 0.12 compared to 0.31 for uncomposited data. The CoV for CV is 0.08 for the composited data against a higher CoV of 0.17 for the raw uncomposited data. The CV variance changes from 12.51 $\%^2$ for uncomposited data to 2.49 $\%^2$ for the composited dataset. The impact of change of support is approximately 20% which is similar to that of Ash.

Unlike with the uncomposited data for thickness, compositing this variable provides meaningful information. The mean thickness for S4U for Case A is 5.25 m with min and max values of 0.22 and 8.8 m respectively. The mean value of %Ash increases to 34.7 % when composited compared to the 30.59 % when uncomposited. The composited value is in line with Case A Colliery's production quality. The minimum and maximum values for Ash are 14.91 % and 50 % respectively. The maximum seam thickness remains 8.8 m whilst the mean composited CV drops to a more realistic 18.8 MJ/kg. Compositing also reduces the number of samples from 5220 to 1196. The minimum and maximum CV values are 12.66 and 26.48 MJ/kg respectively. All three variables when composited have relatively high kurtosis. The skewness varies from a moderate skewness for Ash to a strong negative skewness for thickness and a moderate positive skewness for CV.

Table 5: Classical composited statistics for Case A's S4U seam for thickness and Ash.

Variable	Min	Max	No of Points	Mean	Variance	Std Dev	Coeff. of Variation	Skewness	Kurtosis
ASH%	14.91	50	1194	34.709	16.48	4.06	0.117	-0.389	3.144
THICKNESS (m)	0.22	8.8	1194	5.252	1.72	1.31	0.25	-1.218	1.918
CV (MJ/kg)	12.66	26.48	1194	18.841	2.49	1.58	0.084	0.529	2.946
RD (g/cm^3)	1.4	1.883	1194	1.679	0.003	0.06	0.033	-0.410	2.373

The histogram in Figure 15 shows a negative skew distribution of thickness across the Case A Colliery project area. The variance is 1.72 $(m)^2$.

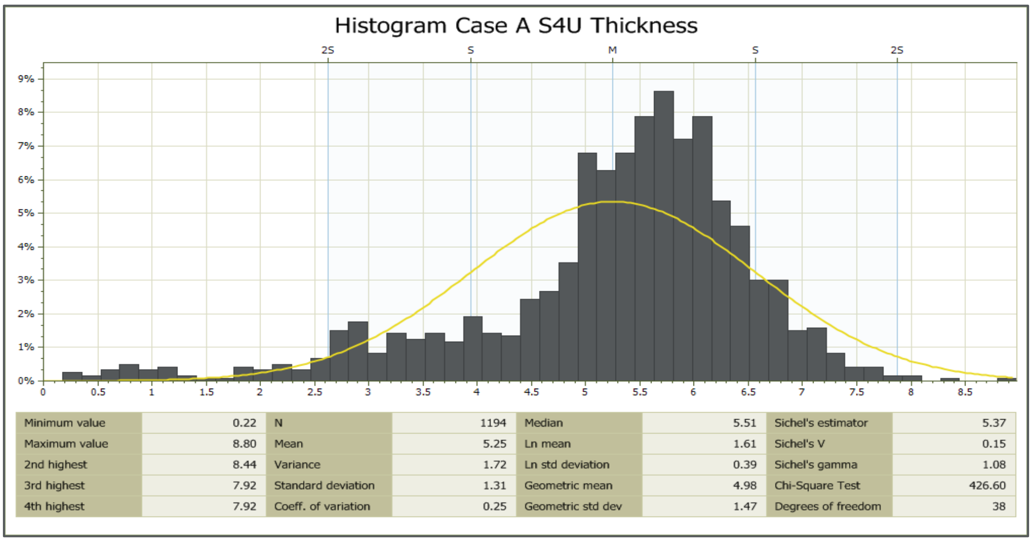


Figure 15: Histogram for Case A S4U thickness on composited samples

The box and whisker plot of seam thickness (Figure 16) shows a value of 4.8 m representing the 25th quartile and 6.07 m representing the value at the 75th quartile. The interquartile range (mid-spread or middle 50 %) is therefore, 1.27 m.

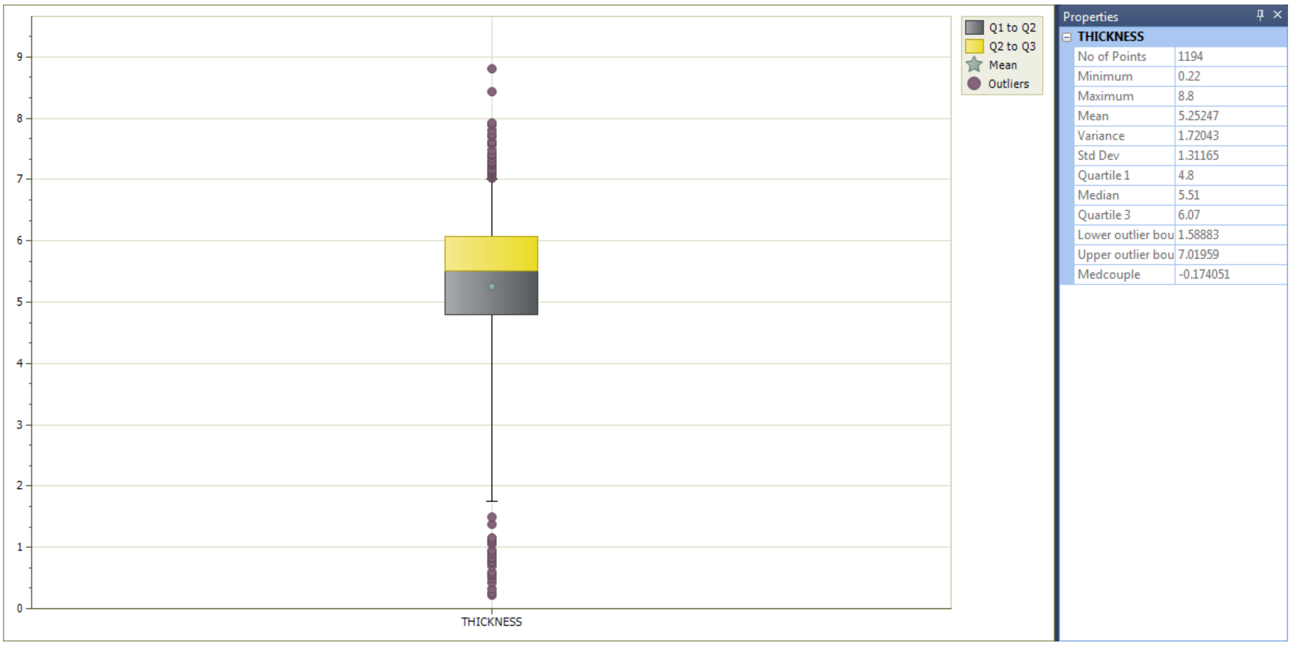
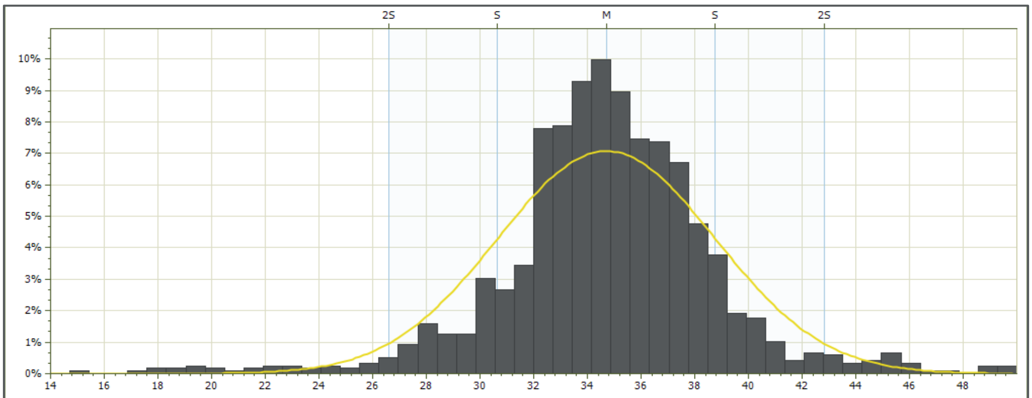


Figure 16: Box plot for Case A S4U thickness on composited samples

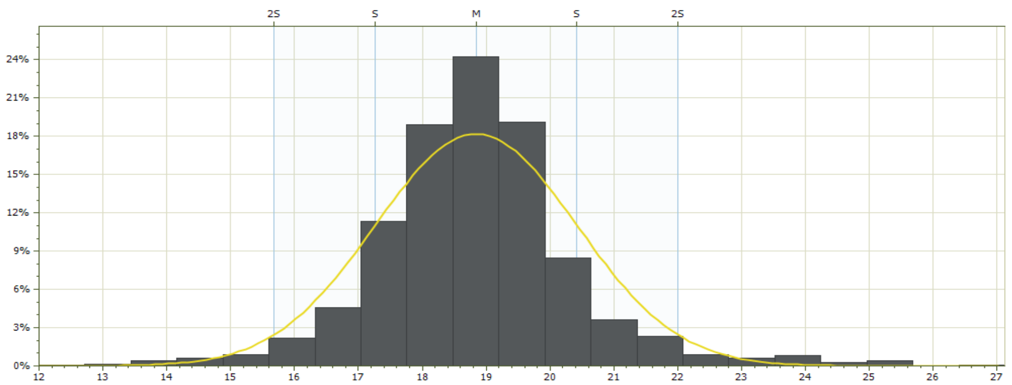
The composited Ash histogram (Figure 17) shows the highest peakedness of the three variables with a variance of 16.47 (%)^2.



Minimum value	14.91	N	1194	Median	34.69	Sichel's estimator	34.72
Maximum value	50.00	Mean	34.71	Ln mean	3.54	Sichel's V	0.02
2nd highest	49.75	Variance	16.49	Ln std deviation	0.13	Sichel's gamma	1.01
3rd highest	49.69	Standard deviation	4.06	Geometric mean	34.45	Chi-Square Test	257.95
4th highest	48.66	Coeff. of variation	0.12	Geometric std dev	1.13	Degrees of freedom	30

Figure 17: Histogram for Case A S4U Ash on composited samples

The histogram of the composited CV shows a variance of 2.49 $(MJ/kg)^2$ (Figure 18) and a very close mean to median relationship (Figure 18) confirming the symmetrical nature of the composited CV population.



Minimum value	12.66	N	1194	Median	18.78	Sichel's estimator	18.84
Maximum value	26.48	Mean	18.84	Ln mean	2.93	Sichel's V	0.01
2nd highest	25.64	Variance	2.49	Ln std deviation	0.08	Sichel's gamma	1.00
3rd highest	25.50	Standard deviation	1.58	Geometric mean	18.78	Chi-Square Test	576.56
4th highest	25.40	Coeff. of variation	0.08	Geometric std dev	1.09	Degrees of freedom	13

Figure 18: Histogram for Case A S4U CV on composited samples

The scattergram in Figure 19 shows a slightly lower correlation coefficient in composited CV vs. Ash i.e. 0.94 compared to 0.97 from the uncomposited data. It is however still a very high negative linear correlation.

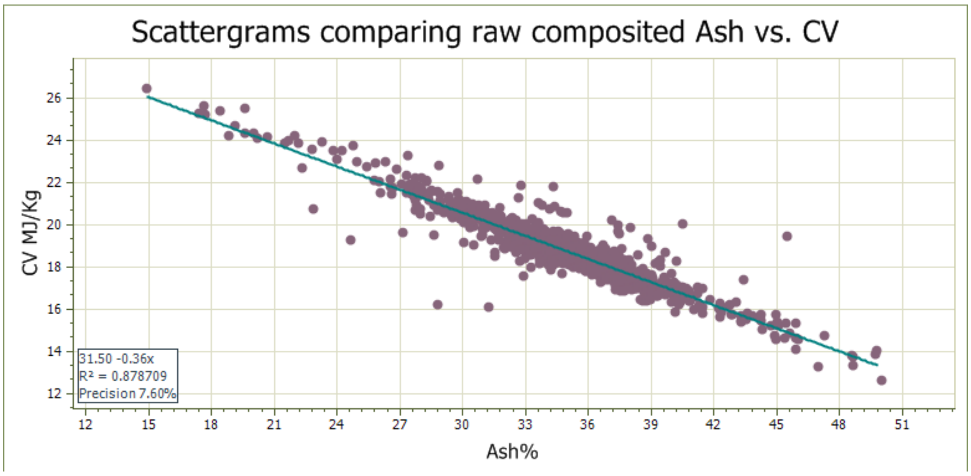


Figure 19: Scattergram for Case A S4U CV vs. Ash on raw composited samples

3.1.1.3 Transforming the composited data to accumulated variables

Several tests carried out on the data regarding its suitability to generate a robust estimate revealed that two transformations needed to be made on the datasets before they could be used to generate useable variograms and resultant estimates. Several trial and error runs on the composited and uncomposited data showed that better variograms result when the data is accumulated per quality variable. The first transformation involves converting the data into accumulated variables. The second 'transformation' was the generation of pairwise relative variograms on the accumulated variables (details below).

In transforming the data through accumulation, the following approach was adopted from an example by Bertoli et al, 2003. According to the authors when dealing with a 2D layer, grade is not a suitable input for direct kriging because it is defined on varying 'support'.

However, the grade can also be defined as the ratio of two variables that are clearly both amenable to direct kriging, namely the thickness and accumulation (grade multiplied by thickness). The problem of 'additivity' is of critical importance and motivates the 2D approach. On variable support, the grade of unequal sample lengths cannot be linearly averaged to obtain a correct result because the outcome of the linear averaging is not a grade. Below is an example used to illustrate how this 2D accumulation method is applied (Table 6). In this example,

- Q is the metal contained in the central area
- T is the corresponding tonnage
- BD is the bulk density
- L denotes thickness (which equates in the example to the length of the interval)
- A is the accumulation (thickness × qualities)

The estimates of T and Q (respectively T*and Q*) are:

$$T^* = BD \text{ x } (L_1+L_2+L_3)/3 \text{ and}$$

$$Q^* = BD \text{ x } (A_1+A_2+A_3)/3$$

Numerically, T* = BD × 5 and Q* = BD × 102.87. The mean CV quality is the ratio Q*/T* and in the example: *m** = 102.87/5 = 20.57 %

Table 6: Characteristics of 2D samples in example

	Thickness (m)	CV (%)	BD (g/cm^3)	Accumulation (m x %)	Accumulation with RD (m x % x BD)
1	L_1=3	19.4	BD_1 = 1.62	A_1 = 58.2	A_{11} = 94.28
2	L_2 = 8	22.3	BD_2 = 1.57	A_2 = 178.4	A_{12} = 280.09
3	L_3 = 4	18.0	BD_3 = 1.43	A_3 = 72	A_{13} = 102.96

The next step is to assume that the density is no longer constant but is correlated to the CV qualities. In this case, the equation becomes;

$$T^* = (BD_1L_1+BD_2L_2+BD_3L_3)/3 \text{ and}$$

$$Q^* = (A_{11}+A_{12}+A_{13})/3$$

In this example, it follows that T* = 7.71 and Q* = 159.1. The resulting CV quality is thus m* = 20.64 %, and this is the average of the CV qualities weighted by length and density of each interval. It is concluded that the absence of proper density weighting in this example induces a relative bias in metal of 0.4 % (globally). Such a bias may be even more pronounced depending on the anisotropy of the variogram models employed. In conclusion, this simple illustrative example highlights the need to properly incorporate density in calculations when density is highly correlated to grade (Bertoli et al, 2003).

Graphics for the histograms for the accumulated variables are included in the appendix section of this report. Care needs to be taken when using different variograms and search strategies for kriging the accumulation and thickness x density products. If variogram properties are roughly proportional i.e. similar nugget, sill and ranges then kriging weights will be distributed similarly for the accumulation and thickness x density product leading to stable block quality back calculation. Caution must be exercised when using 'wildly' different variograms and searches as kriging weights will be vastly different for the accumulation and thickness x density product leading to unstable block grade back-calculation.

3.1.2 Exploratory Data Analysis - Spatial Data Analysis

The red coloured polygon in Figure 20 is an outline of the Mining Right boundary. As was shown in Table 5 the average thickness for the S4U seam is 5.25 m. Figure 16 further shows that most of the thickness data plots between 4.8 and 6.07 m. This becomes increasingly apparent in Figure 20 with the basemap showing a considerable amount of values between 5 and 7 m. The Southwestern part of the property contains data with higher thickness values whilst the Northeastern parts are consistently between 5 and 6 m. Towards the North-North-West section of the property, the average thickness drops to between 1 and 4 m. Towards the East, there is limited information but the seam also shows a gradual thinning.

Composited Ash% averages 34.70 %. There is no discernible concentration of Ash in any specific area as drill holes containing Ash content of between 32 and 37 %Ash occur throughout the project area (Figure 21). What is evident is that the South side contains relatively higher Ash values than the North. Towards the Northern margins of the property, the Ash content rises above 42 % with a few samples showing Ash content of over 45 %. The Eastern section of the property contains significantly lower Ash with values ranging between 15 and 33 %.

The mean CV for the composited data is 18.84 MJ/kg. Relatively higher values are located on the western margins of the property with the Central and South portion tending towards the mean value (Figure 22).

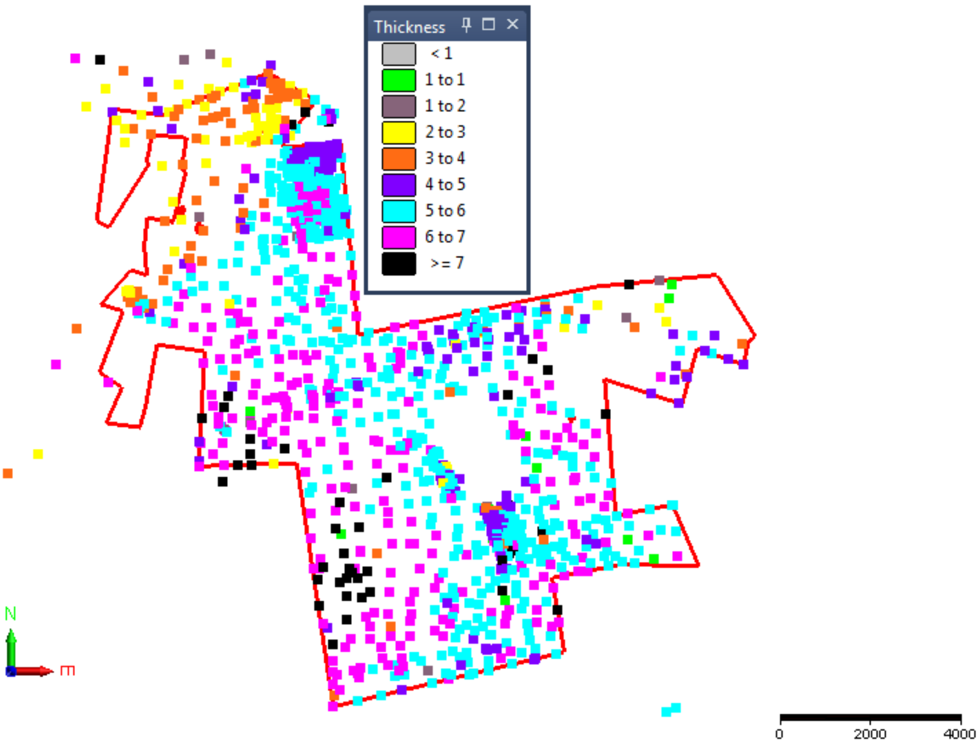
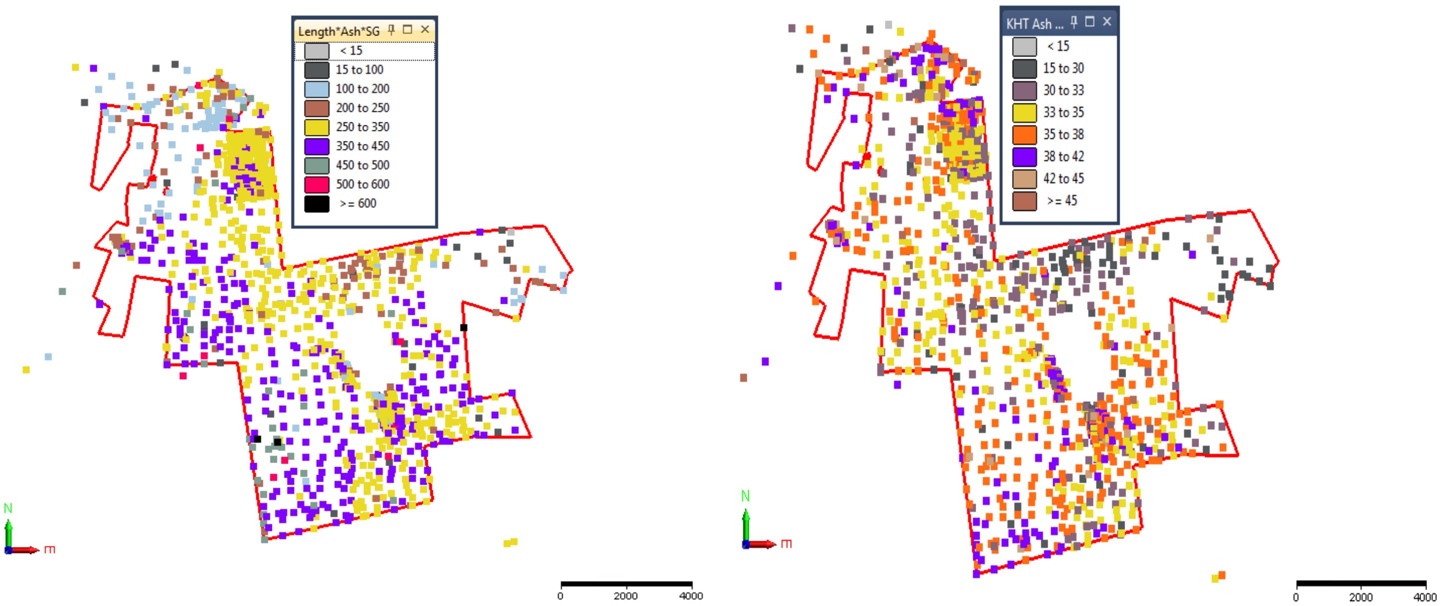
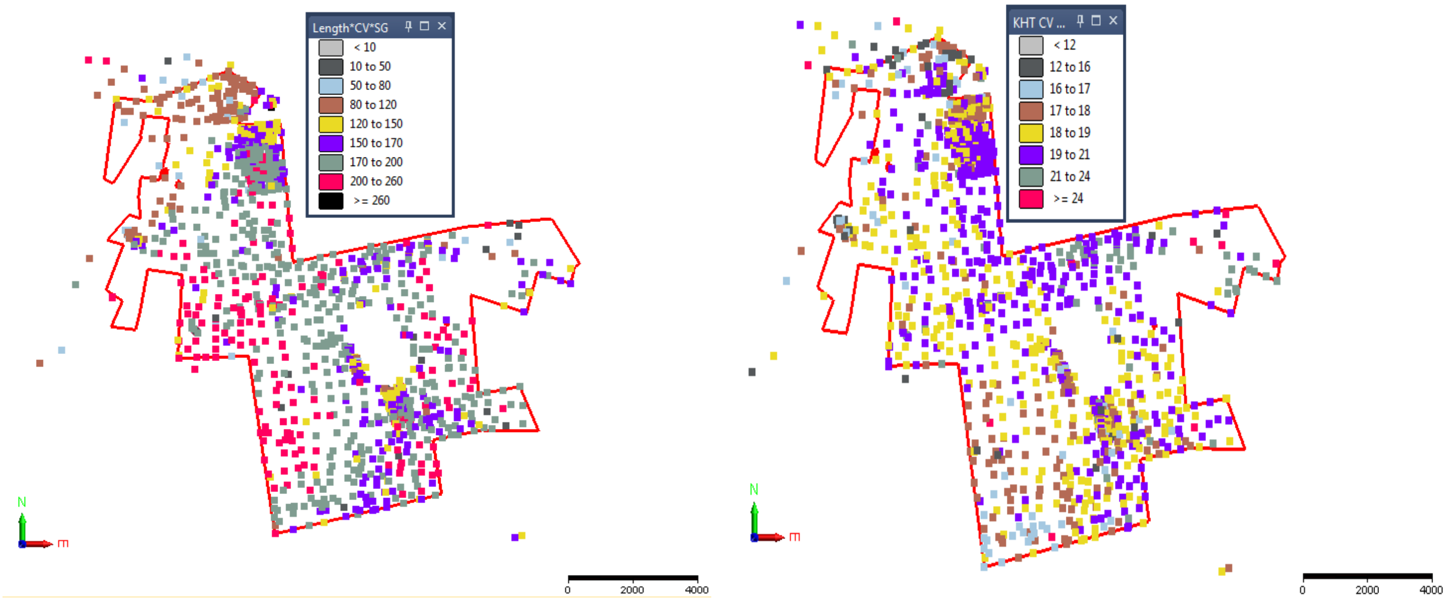


Figure 20: Case A thickness basemap for the composited S4U seam



(a) Case A Length*Ash*SG plot (composited) (b) Case A Ash plot (composited)

Figure 21: Case A Length*Ash*SG plot for the composited S4U seam plotted next to the Ash only plot



(a) Case A Length*CV*SG plot (composited)

(b) Case A CV plot (composited)

Figure 22: Case A Length*CV*SG plot for the composited S4U seam

3.2 Determining Average Drill Hole Spacing

Data or drill hole spacing is often directly related to grade uncertainty, it has been used traditionally as a determinant for resource classification and it can be compared to the dimensions of relevant geological features for defining their continuity. Mory and Deutsch (2006) assert that a more complete criterion for Mineral Resources classification should be one that combines the geometrical features of data, as spacing and density, with different geological considerations, and is supported by probabilistic measures.

The following dimensions define the areal extent of Case A Colliery;

Table 7: Geographic dimensions of Case A Mining Property Rights Boundary

Parameter	NS Length (m)	EW Length (m)	Diagonal Length (m)	Ave DH Spacing (m)	Number of lags (#)	Nominated lag (m)
Case A	14000	15000	20000	200	80	250

The Case A project area is 93 km^2 in areal extent, it contains 1571 drill holes that have assay data. This means that the drill density calculated as number of points/area is 17 drill holes per square kilometre. When using the SANS 10320:2004 South African guide to the systematic evaluation of Coal Resources and Coal Reserves, which proposes a Measured Resource as that part of the Resource which was determined from a minimum of 8 cored drill holes with coal quality data per 100ha or 1 km^2 Case A would require a total of only 744 drill holes assuming a 350 m spacing on an evenly spaced grid. An example to illustrate how the SANS (2004) classification criteria is applied is shown below using an Indicated category.

An Indicated Coal Resource is quantified by a minimum of four cored boreholes with coal quality data per 100 ha (approximately 500 m spacing) for multiple seam deposit types.

$$100 \text{ ha} = 1{,}000 \text{ m} * 1{,}000 \text{ m} = 1{,}000{,}000 \text{ m}^2$$

Therefore, within an area of 1 km x 1 km there needs to be a minimum of four drill holes with coal qualities. However to avoid the effect of clustered information, the four drill holes need to be spaced 500 m apart. Essentially this means drilling on a 500 m x 500 m grid.

From this 500 m x 500 m grid, the radius of the circle is determined so that all four samples can have a relationship (grouping). Using the formula

$$a = \pi * r^2$$

$$(500 \text{ m x } 500 \text{ m}) = 3.14 * (r^2)$$

$$\text{Therefore } r = 282 \text{ m}$$

Therefore, the radius[3] around each of the drill holes for an Indicated Resource is 282 m. Within 1 km x 1 km there must be four samples containing quality data and spaced 500 m apart (i.e. their radii of 282 m must touch). This is illustrated in Figure 23.

[3] The number π is a mathematical constant, the ratio of a circle's circumference to its diameter, approximated as 3.14159

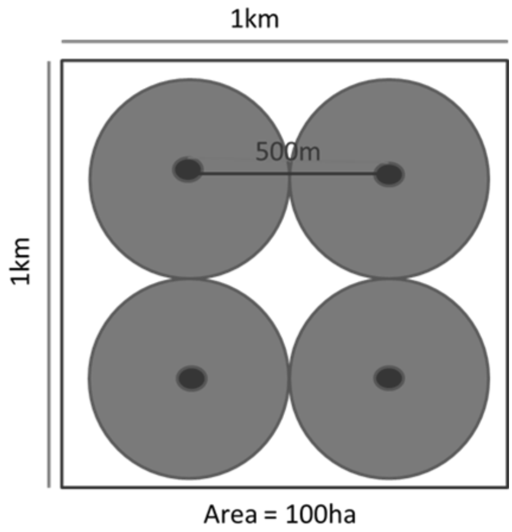


Figure 23: Indicated Resource drill hole spacing in accordance with the guidelines set out in the 2004, SANS 10320:2004 South African guide to the systematic evaluation of Coal Resources and Coal Reserves

3.3 Variography and Kriging Neighbourhood Analysis

Variography is a tool used in geostatistics to analyse the spatial continuity of qualities, thickness and density in a coal deposit. Information that can be extracted from a variogram includes the inherent variability of a sample (nugget effect), the pattern of mineralization, and the extent to which samples are related as well as the maximum variability within all selected samples. It forms the foundation upon which OK is based. The rule of thumb proposed by Snowden (1996) when applying variography to Mineral Resource classification is to have two-thirds of the semi-variogram sill (total variance) (usually represented by the first structure of a double structured semi-variogram) as Measured and the material between the second structure and the sill ($1/3^{rd}$) as Indicated. Anything beyond the range should be considered Inferred. It should be emphasized that this is not a law of geostatistics but merely a rule of thumb/guiding principle.

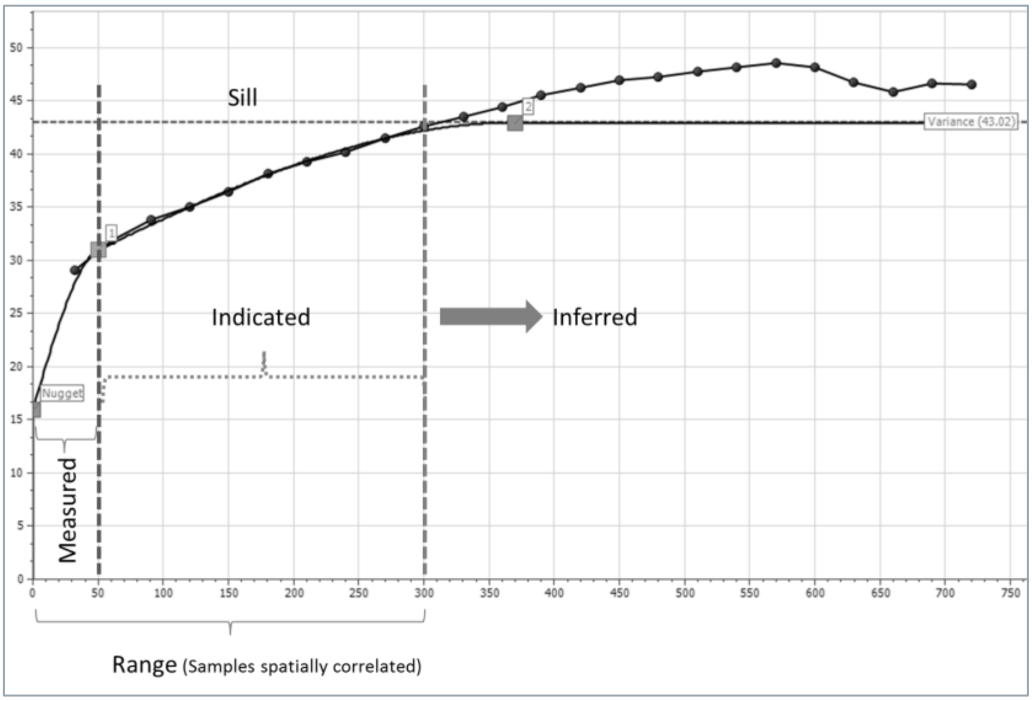


Figure 24: Components of a semivariogram and how the structures are typically used in resource classification decisions (Snowden, 1996)

Geological continuity will not be demonstrated where drill holes are further apart than the range of influence, beyond which the Coal Resource is Inferred. It is more subjective defining drill hole spacing at which the division between Measured and Indicated Resources is made by taking the range at 2/3 of the variability (Snowden, 1996).

3.3.1 Calculating the nugget effect

In theory, the semivariogram value at the origin (0 lag) should be zero. If it is significantly different from zero for lags very close to zero, then this semivariogram value is referred to as the nugget. The nugget represents variability at distances smaller than the typical sample spacing, including measurement error. The nugget model represents the discontinuity at the origin due to small-scale variation. On its own, it represents a purely random variable, with no spatial correlation.

The nugget effect is based on the closest spaced data, usually the downhole direction. It describes the expected difference between samples when the separation distance is almost negligible. The nugget effect encompasses both the inherent small-scale variability (precision) and any errors due to the sampling process.

To determine the appropriate nugget effect for the S4U, downhole variograms were generated for Ash and CV. For thickness, there is no point in generating the downhole variograms as the variable being analysed is an artefact i.e. 'man-made' sample length. Case A's downhole variogram for Ash (Figure 25) shows that there is no spatial correlation when searching for data downhole (Along the vertical plane). The results of this exercise were thus, not used in deciding the appropriate nugget value for Ash. The downhole variogram for CV (Figure 26) is also irregular and thus not modelled to determine the downhole nugget. Due to this, the nugget effect was determined from omnidirectional planar experimental semivariograms as shown in Figure 27 through to Figure 36.

The nugget effect is important for determining estimation variances for point-estimates, but is less important when estimating block means (Noppé, 1994). The latter is particularly valid if the nugget effect is small compared to the sill (David, 1977).

The structure of the Ash and CV downhole variograms are effectively invalid for use to determine the nugget. All the variogram pairs except for three towards the end plot above the population variance. The only viable solution to determining the nugget when comparing data points along a horizontal dimension is to ignore the down hole comparisons and focus on comparing samples across drill holes for horizontal continuity, and estimating the nugget effect from it.

The following section summarizes the results from ash, CV and thickness variograms by comparing composited samples across drill holes. This is done by generating directional variograms across the S4U seam using the variogram parameters shown in Table 8. Deciding on the lag distance and tolerance was done after calculating the appropriate parameters for the size of the area (Table 8). The data was analysed in both uncomposited and composited forms. The first test was to check if there is any zonal or geometric anisotropy and determine the direction of greatest continuity.

Table 8: Setting the lag distance and tolerance for CASE A S4U used for both CV and Ash

Area	93188719 m^2
N	1571
SQRT (Area/N)	243 m

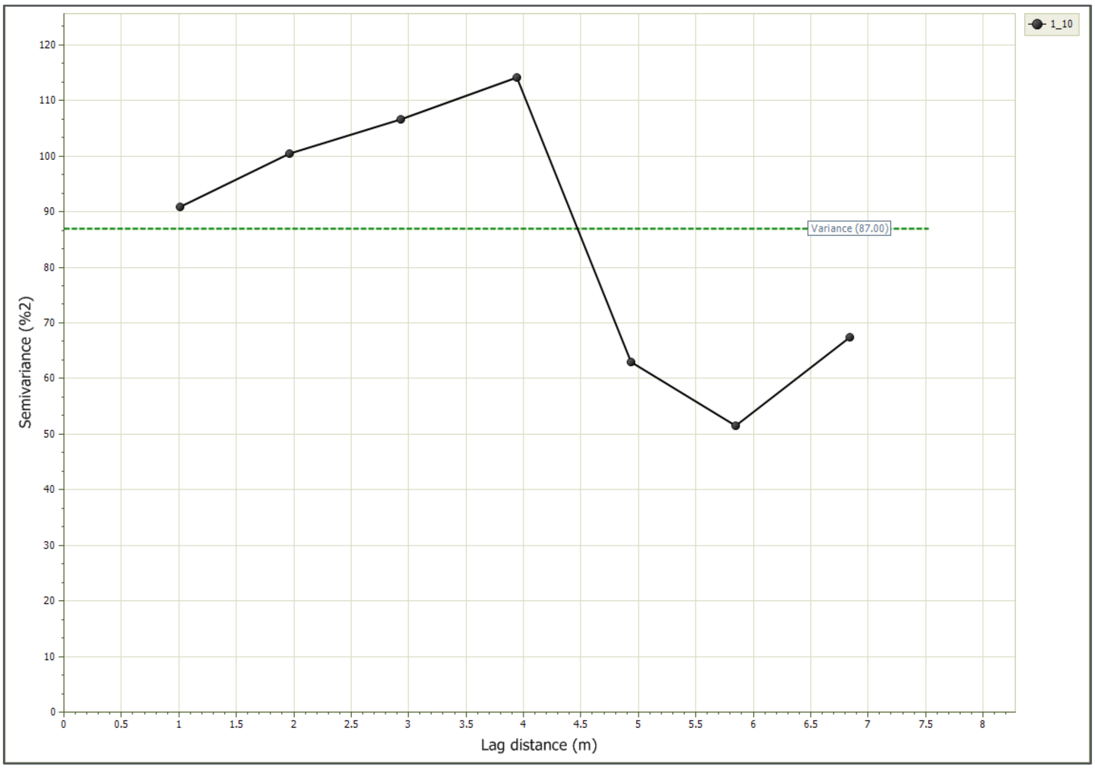


Figure 25: Ash downhole variogram CASE A S4U to determine the nugget effect (uncomposited data).

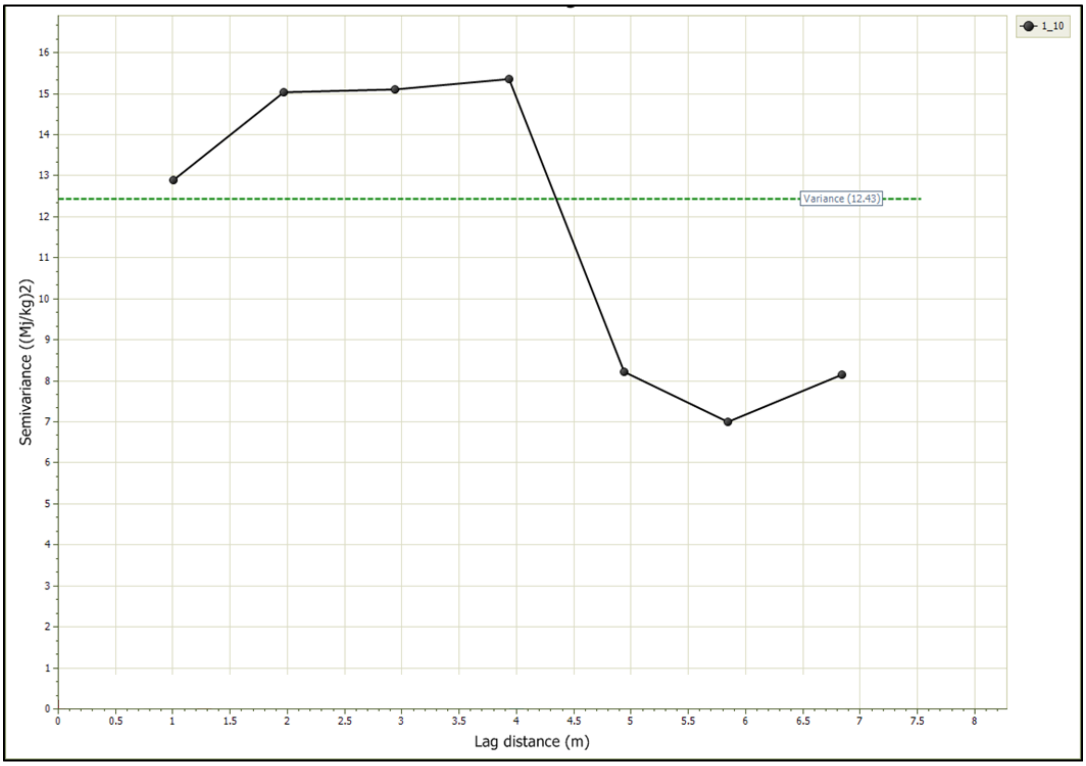


Figure 26: CV downhole variogram CASE A S4U to determine the nugget effect (uncomposited data).

Table 9: Directional variogram parameters for Case A S4U used for both CV and Ash

Azimuth Tolerance Bandwidth			Plunge Tolerance Bandwidth			Lag	
Angle	Tolerance	Bandwidth	Angle	Tolerance	Bandwidth	Interval	#Intervals
30	15	500	0	0	0	250	23
60	15	500	0	0	0	250	23
90	15	500	0	0	0	250	23
120	15	500	0	0	0	250	23
150	15	500	0	0	0	250	23
180	15	500	0	0	0	250	23

The results of this exercise show that the CV variogram along the 90 degrees direction has the shortest continuity with a range of 1250 m for the composited data. The direction of longest continuity is along the 180 degrees with a range of 2800 m (Figure 27).

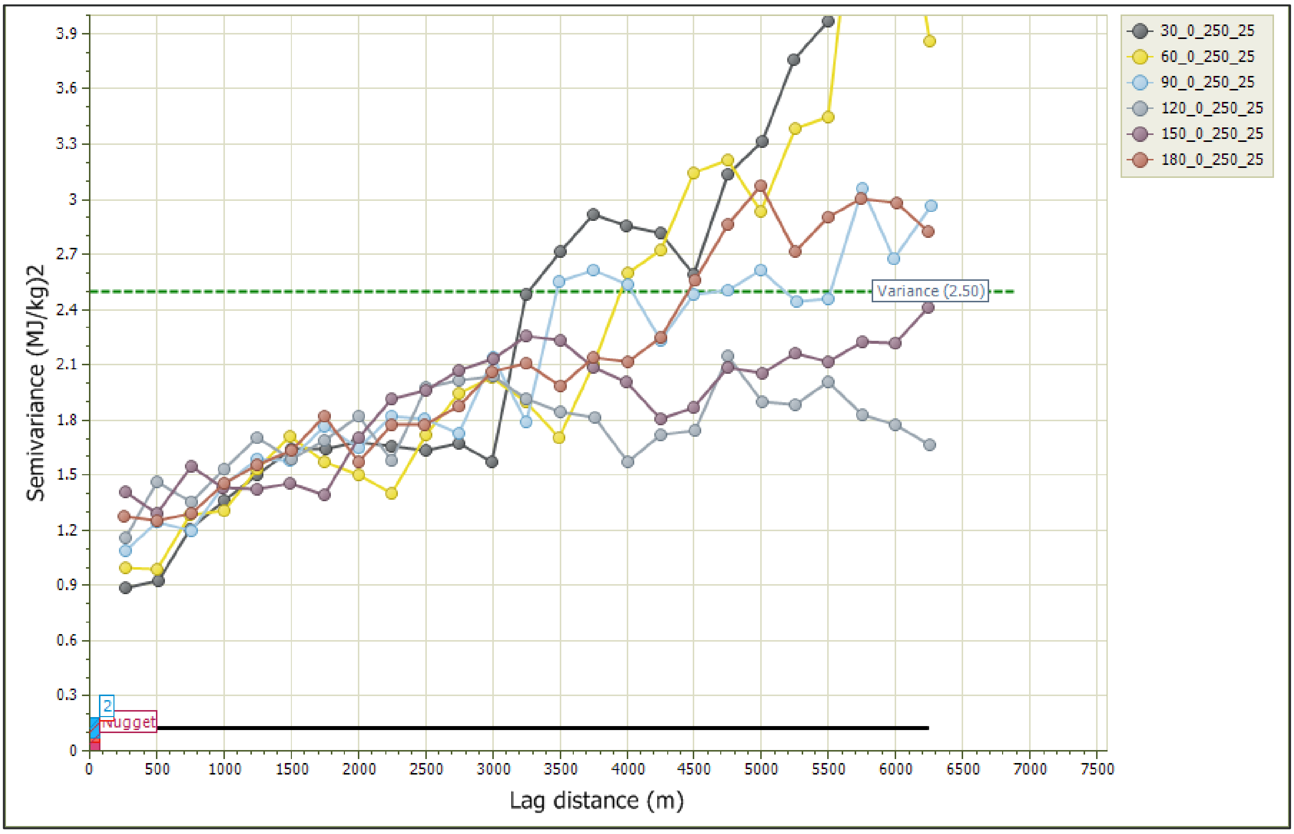


Figure 27: Planar CV variograms in 6 directions (composited data).

Before proceeding with the analyses of the variograms, it is important to outline the two different types of anisotropy, i.e. zonal and geometric anisotropy. Geometric anisotropy occurs when the range, but not the sill, of the semivariogram changes in different directions. Zonal anisotropy on the other hand exists when the sill of the semi-variogram changes with direction. Geometric anisotropy means that the correlation is stronger in one direction than it is in the other directions (Budrikaite and Ducinskas, 2005).

Based on this definition, the data for Case A shows a strong presence of zonal anisotropy in the sense that for most of the variograms the sill appears to be around 12.51 for thickness. In order to build a 3D variogram, the direction of longest continuity for CV is 180 degrees. The variogram perpendicular to this is along the 90-degree direction. The direction of longest continuity for Ash is along the 180^{o} direction with 90^{o} representing the direction of shortest continuity with a range of 1250 m compared to 2400 m for the direction of longest continuity.

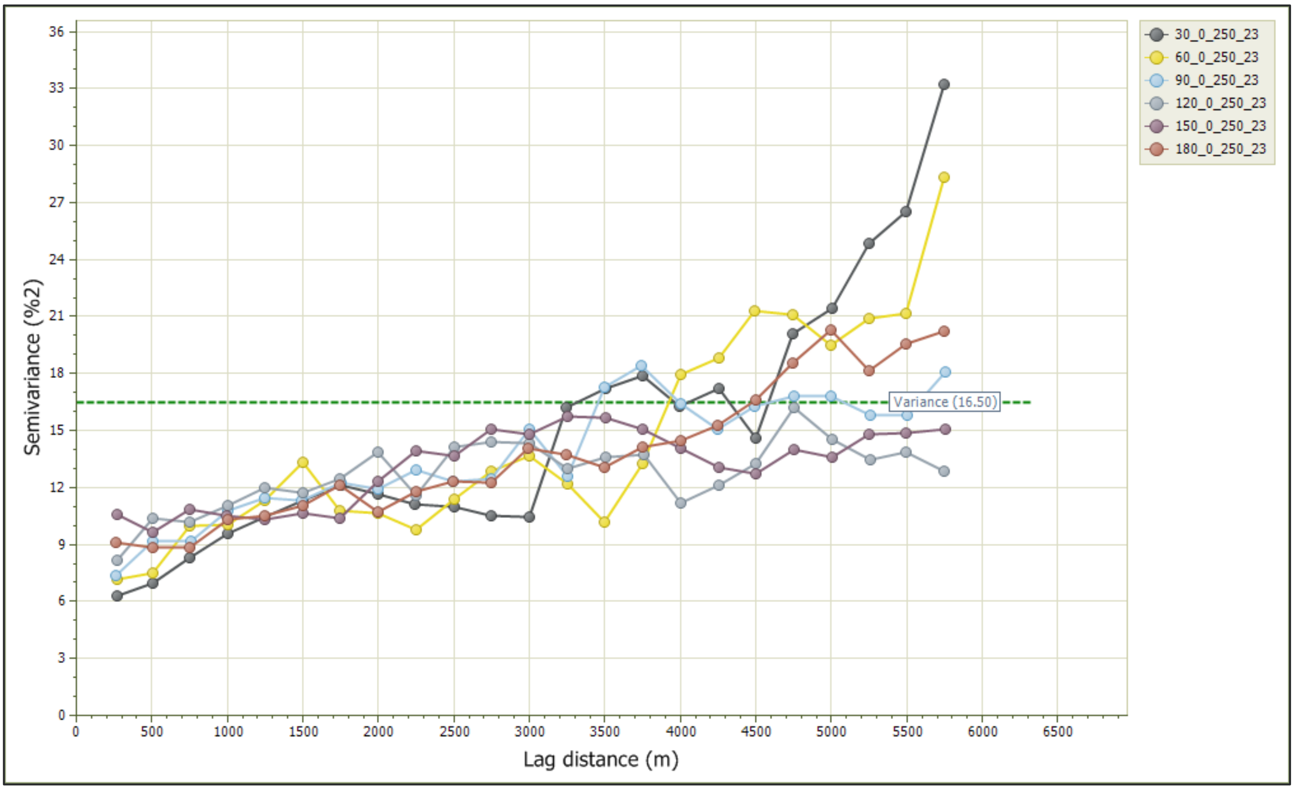


Figure 28: Ash horizontal experimental variogram for CASE A S4U along 6 directions (composited data).

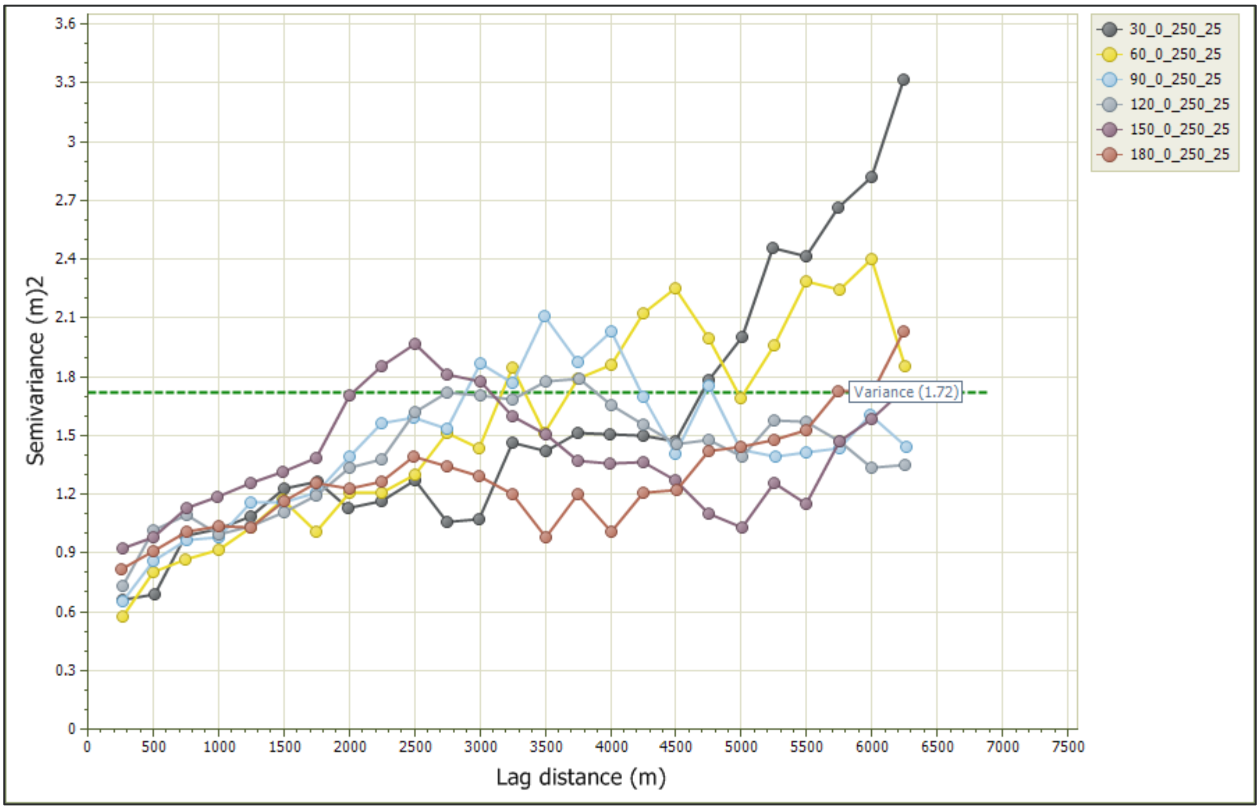


Figure 29: Thickness directional experimental variogram for CASE A S4U (composited data).

For thickness, directions 150° and 60° represent the directions of shortest and longest continuity respectively for this variable. The direction of longest continuity is not clearly distinguishable along one direction as a result; the selection of one direction in favour of another may lead to misleading results.

In order to validate the selected directions of longest continuity and the direction perpendicular to that, omnidirectional variograms were plotted for the S4U thickness, Ash and CV in terms of the interval length and the number of intervals i.e. 250 m and 30 respectively.

The thickness omni-directional variogram model in Figure 30 shows a modelled sill of 1.56 m^2. This is somewhat short of the population variance of 1.72. The range of the first structure is 600 m with a partial sill of 0.3133. The range of the second structure is 3500 m. The modelled nugget is 0.4, which results in a model to sill ratio of 26 %.

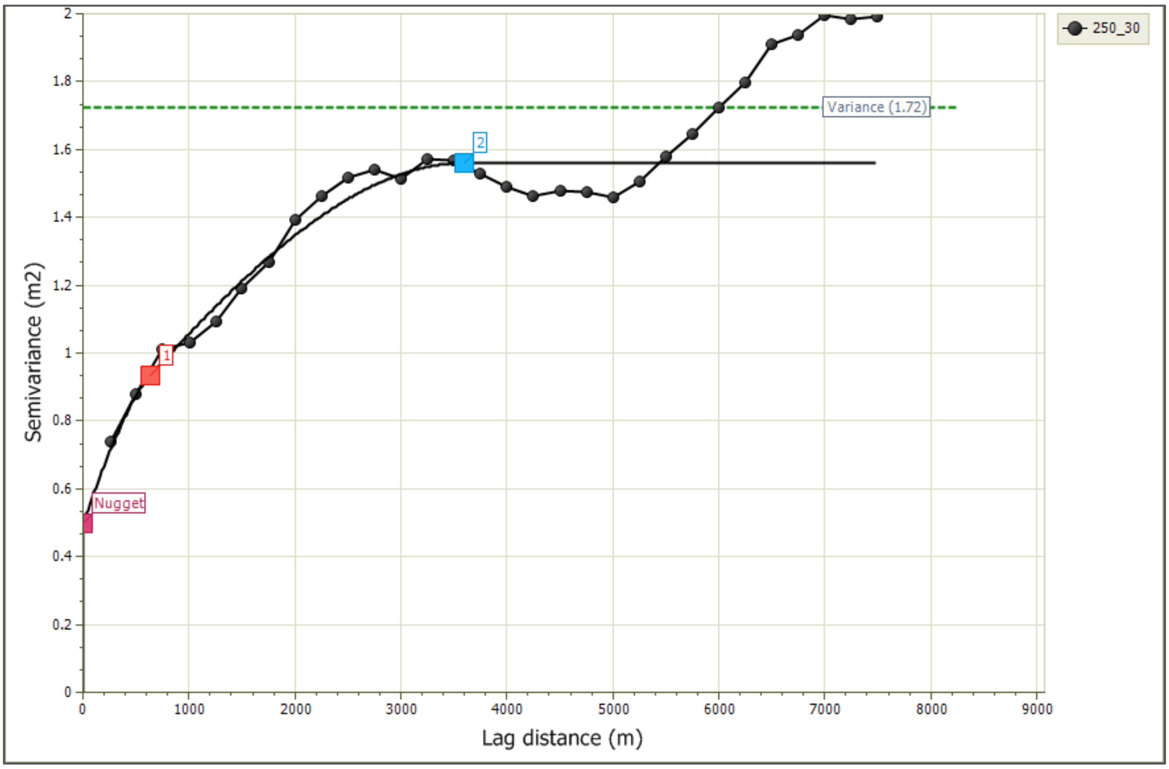


Figure 30: Omnidirectional modelled semivariogram for Case A S4U (composited data) – Thickness (m)

The shape of the omnidirectional experimental variogram compares favourably with that along the direction of longest continuity i.e. along 180^{o}. Generally, it can be shown that the range of an omnidirectional variogram is the same as the average range of the maximum and minimum axis of continuity in a deposit that exhibits directional anisotropy. As a result, whether a single omnidirectional or two anisotropic variograms are used, the estimation variance calculated for a square block is the same. Secondly, in coal deposits, there is often a shortage of valid data points for variograms analyses, particularly in the down dip direction, which often corresponds to the direction of minimum continuity. Use of an omnidirectional variogram allows pairs to be identified in all directions, thereby making maximum use of available data (Williams et al, 2015).

The result for the Ash omnidirectional semivariogram is shown in Figure 31. This semivariogram has a nugget of 3.6. The ranges of the first and second structures are 600 m and 6300 m respectively with partial sill values of 4.01 and 8.42 respectively.

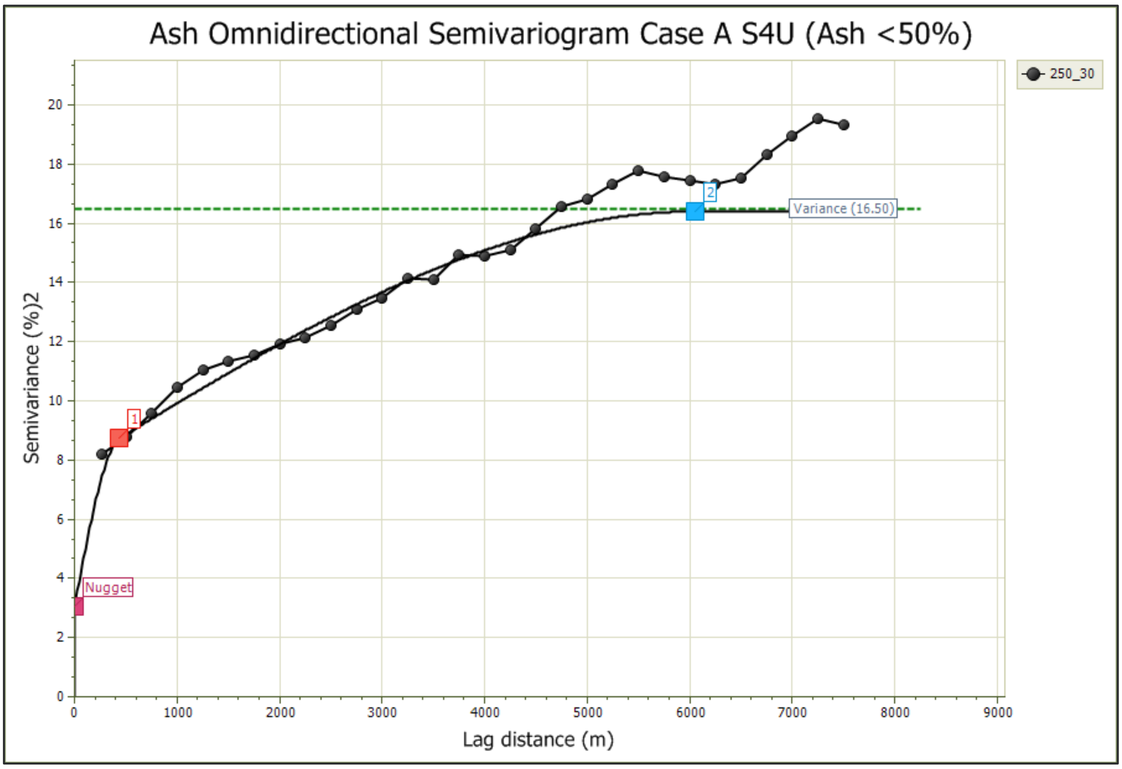


Figure 31: Omnidirectional semivariogram for Case A S4U Ash% (composited data)

Williams et al, 2015 notes that when in doubt as to where to set the nugget effect, experience gained from modelling variograms for a large number of coal deposits has shown that a nugget of around 10 % of the sill value is a good approximation.

The range of the CV omnidirectional semivariogram model is 4500 m (Figure 32). The range of the first structure is 600 m. The sill is 2.5 $(MJ/kg)^2$ which reflects the population variance with a nugget of 0.8 $(MJ/kg)^2$. From this, a nugget/sill ratio of 32 % is calculated.

Work undertaken by Noppé, 1994 on No. 4 Seam of the Highveld Coalfield using 172 samples over a 2 x 4 km area showed ranges of up to 750 m. Wood (1979) found ranges between 150 m and 320 m using the Spherical variogram. For the three variables analysed for Case A, the ranges for thickness, Ash and CV are 3000 m, 4500 m and 4500 m respectively.

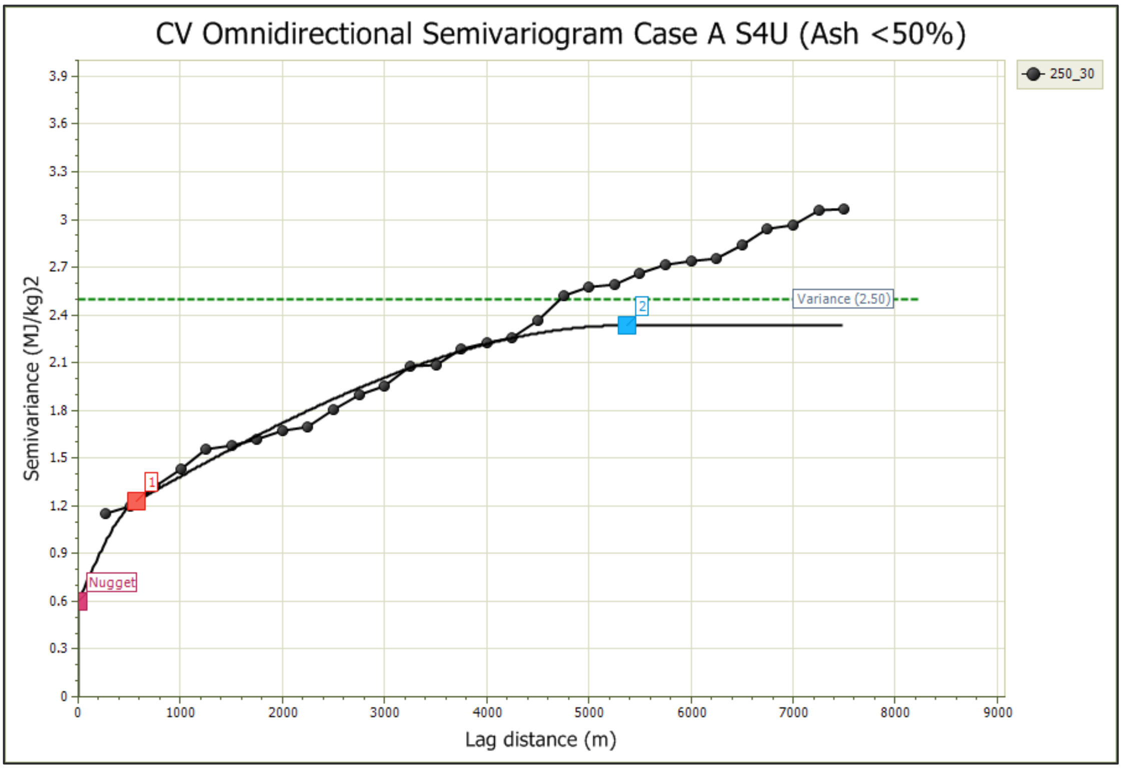


Figure 32: Omnidirectional semivariogram for Case A S4U -CV $(MJ/kg)^2$ (composited data)

From the data presented above there is clearly a need to re-evaluate the type of variogram modelling technique applied to align the findings with what is expected of a coal deposit. There is a case of data trend, drift or lack of geostatistical stationarity that appears apparent. To re-evaluate requires the introduction of two concepts; proportional effect and pairwise relative variograms. The results from the re-evaluation are presented in section 3.3.2.

3.3.2 Proportional effect and relative variograms

Most regionalized variables exhibit a proportional effect, that is, increased variability in high valued areas (Manchuk et al, 2007). Essentially, the meaning of proportional effect is that variability is sometimes higher in areas with high average values than in areas with low average values. The improvements in the results (when using the proportional effect) is quite remarkable. If a proportional effect exists, it must be taken into account when assessing local uncertainty. By rescaling the variogram to a sill of one and locally correcting the relative kriging variance, confidence intervals can be built that reflect conditions (Isaaks and Srivastava, 1989). The proportional effect is referred to in two distinct contexts: (1) a large-scale relationship between the local mean and the local standard deviation and (2) a dependency of the variance of local distributions on the local mean.

In variography, the proportional effect is commonly described in the context of the variogram being different in different areas. In practice, it was observed that the variograms could be made equal by dividing by a function of the experimental mean. The proportional effect is primarily due to skewness in the histogram. Symmetric distributions show little proportional effect. Positively skewed variables show increasing variability with increasing mean. Negatively skewed variables show decreasing variability with increasing mean (Manchuk et al, 2007).

A variogram may become difficult to interpret when proportional effect is present. The geologists' preference for sampling high grade more densely than low grades (i.e. clustering of data) usually results in high-grade samples contributing heavily as short lags. As the lag increases, the contributing data becomes more representative, and the lag mean and variance decrease as a result. This adversely affects the experimental variogram by overestimating the relative nugget. In some datasets, the values at small lags may appear larger than those at larger lag distances, giving a false impression that the data is spatially unstructured. Pairwise relative variograms adjust the variogram calculation by the squared mean. This adjustment is done separately for each pair of sample values, using the average of the two values as the local mean (www.acsu.buffalo.edu/~lbian/ch7.ppt).

To test for proportional effect, several variograms were generated across the property boundary. The structures revealed by the variograms were significantly different from the combined data. As a result, a decision was made to use pairwise relative variograms on accumulated data for both Case A and B.

Micromine works with relative values whenever a relative variogram is modelled. However, it back transforms the values during kriging. The existence of grade/quality variable trends in the data manifest themselves as pairwise relative semivariograms (Figure 33). The nugget is 0.03 with ranges of 300 m and 1050 m for the first and second structure.

The Length*RD omnidirectional pairwise relative semivariogram (Figure 33) for Case A S4U shows a range of 1050 m with the range of the first structure at 300 m. Its nugget to sill ratio is 42 %. The ranges for the accumulated Ash (Figure 34) and CV (Figure 35) are 1120 and 1200 m respectively.

This shows that transforming the data into accumulated variables and generating pairwise relative variograms generates usable results. Noteworthy are the relatively high nugget to sill ratios for all variables. A maximum search distance of 1000 m was used in generating the estimates for Case A.

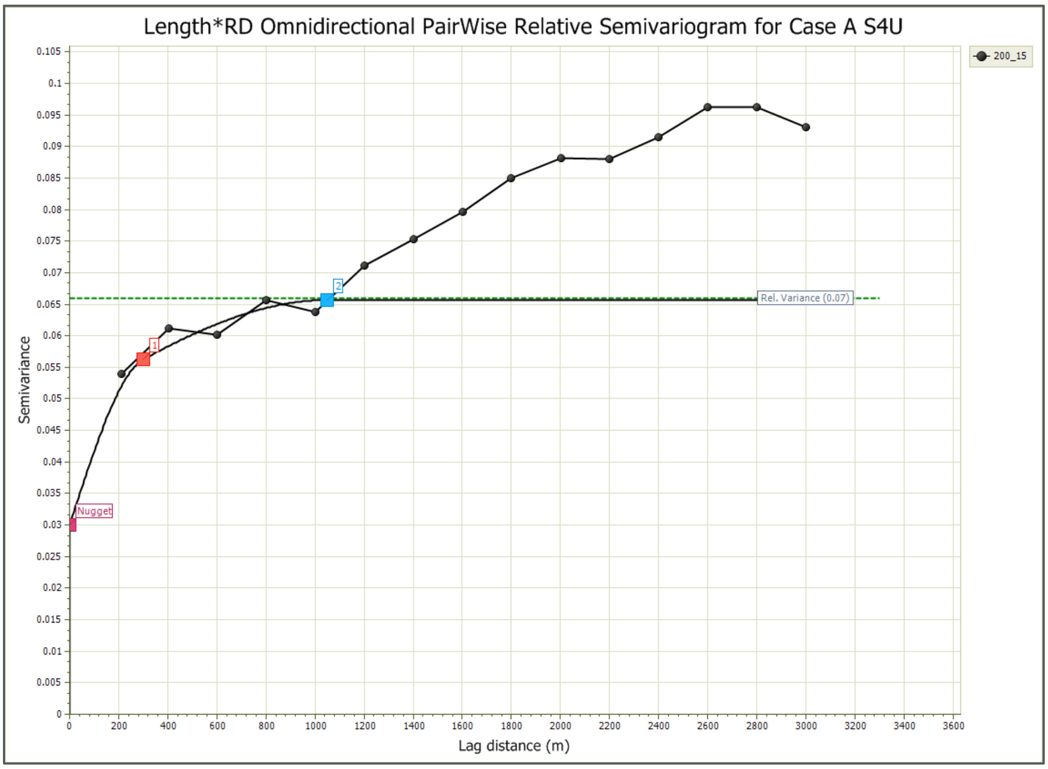


Figure 33: Pairwise Omnidirectional Relative Semivariogram for CASE A S4U for LengthxRD

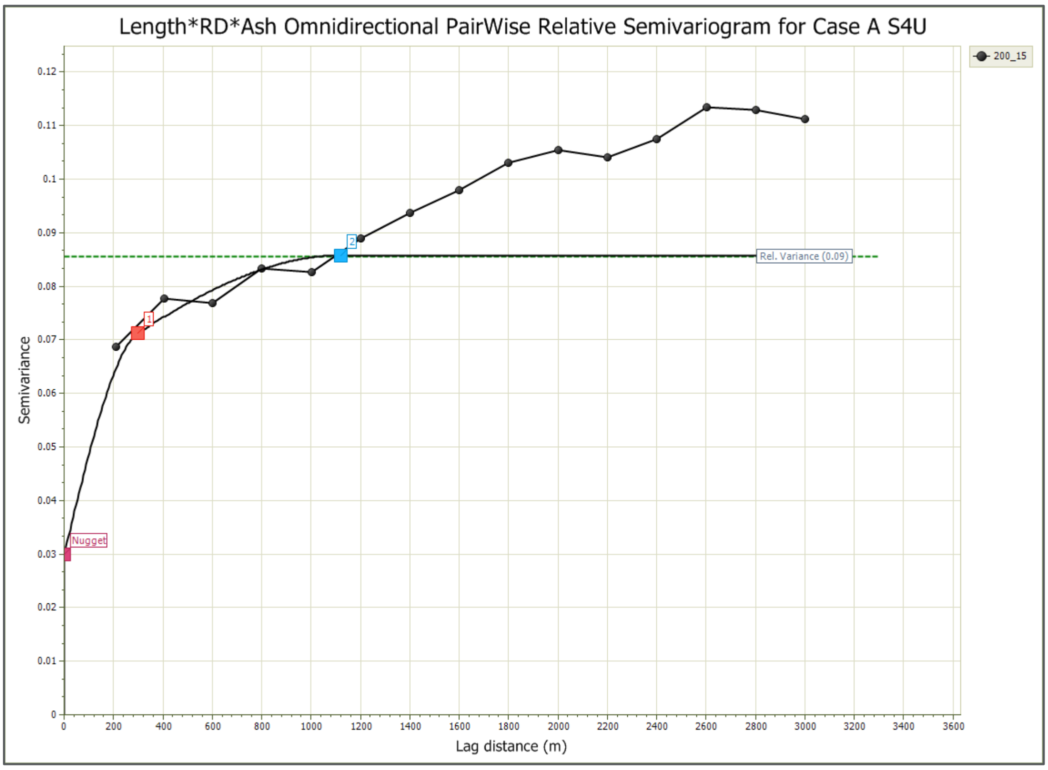


Figure 34: Pairwise Omnidirectional Relative Semivariogram for CASE A S4U for Length x RD x Ash

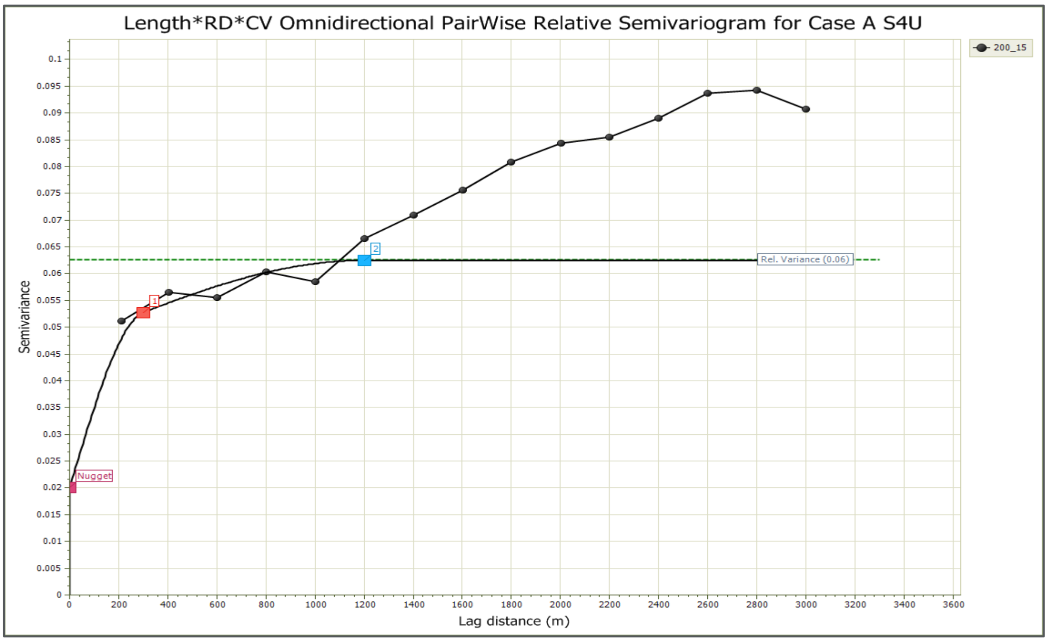


Figure 35: Pairwise Omnidirectional Relative Semivariogram for CASE A S4U for Length x RD x CV

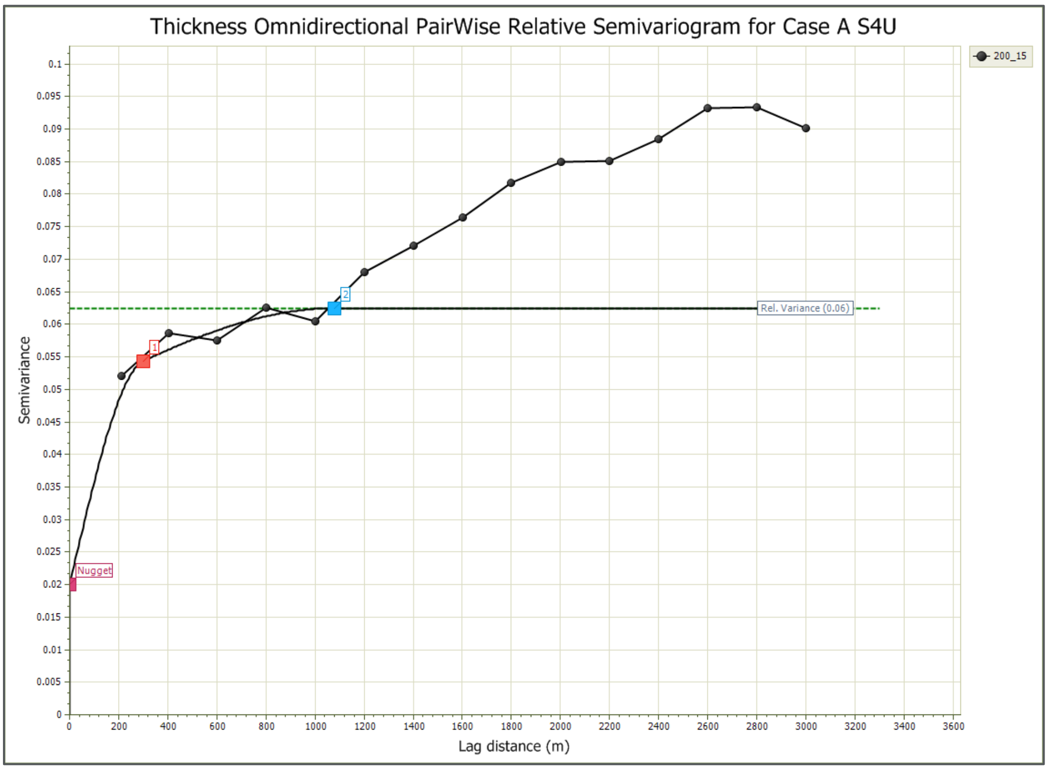


Figure 36: Pairwise Omnidirectional Relative Semivariogram for CASE A S4U for Thickness

3.4 Stationarity/Homoscedasticity[4]

Geostatistics is based on fundamental assumptions required by regionalized variable theory and its modifications and extensions. One of the key assumptions is that of stationarity or homoscedasticity. Mean stationarity is when it is assumed that the mean is constant between samples and is independent of location. The second type of stationarity is called second-order stationarity for covariance and intrinsic stationarity for semivariograms. Second-order stationarity is the assumption that the covariance is the same between any two points that are at the same distance and direction apart no matter which two points you choose. The covariance is dependent on the distance between any two values and not on their locations. For semivariograms, intrinsic stationarity is the assumption that the variance of the difference is the same between any two points that are at the same distance and direction apart no matter which two points you choose (Henley, 2001).

Myers (1989), stated that stationarity is a property of the random function, not of the data. Simply put, stationarity means that things i.e. mean and variance are the same everywhere. Henley (2001) defines strong stationarity as requiring that the distribution of the regionalized variable Z(x) is independent of location x. This implies that the mean, variance and all other distribution parameters are the same everywhere i.e. across the project area/deposit. Second order stationarity requires that the expected value (i.e. the mean) is the same everywhere and that the spatial covariance function (hence, also the semivariogram for each lag h) is also the same everywhere.

Where there is a lack of homoscedasticity, geostatisticians have tried to avoid this problem by definition of ever smaller ‘homogenous’ zones. This, of course, often leads them into the trap of identifying zones which contain too little data from which useful statistics of any kind may be derived. Because there is just one realization, multiple replicate experiments cannot be carried out to obtain different versions of the same deposit. Another approach to the problem, however, would be to view stationarity (of any form) as an unlikely property of a model suitable for fitting data which quite clearly vary in both expected value and variance from one place to another, and to seek an alternative model which does not require any such assumptions (Henley, 2001).

[4] The variance does not change with location

To test for stationarity across the Case A deposit, 6 areas, each 10 km^2 in areal extent were ‘domained’ and experimental semivariograms generated (Figure 38). The domaining did not consider spatial correlation but was purely a size consideration. There remains room for further, more considered domaining based on isopachs etc.

Table 9 show that depending on the area selected to undertake geostatistical analyses, the variance and mean quality of Ash differ quite substantially. There is no correlation between the mean and variance for this test. The range can be anything from 650 m to 1800 m. The spread of the variance is from 7 to 22 (%)^2 with the mean quality ranging between 32.28 to 36.21 %. This strongly suggests lack of stationarity across the deposit. In other words, the Case A deposit is not uniform across the property.

Figure 38 (a-f) show that when the Case A area is divided into Areas 1 to 6 i.e. domained, the shape of the experimental semivariograms for Ash improves significantly. In Area 1, the range of the semivariogram goes up to 1100 m with a variance of 12.18 (%)$_2$ and a mean Ash value of 35.29 %. The shortest range is in Area 3 (650 m) with comparable variance and mean values. Area 2 shows the longest range (1800 m) with the highest variance of 22 (%)^2 and lowest mean Ash value of 32.28 %.

Figure 37: Areas selected across the Case A deposit (Ash%) to demonstrate stationarity/non-stationarity

Figure 38: Comparing the variogram ranges for Case A area on a domain by domain basis (composited data)

Table 10: A comparison of the variance, mean and ranges from the 6 different areas across Case A using normal omnidirectional variograms

Area	**Variogram Range(m)**	**Ash Variance (%)^2**	**Mean Ash (%)**
Total Mining Right Area	4500	16.50	34.71
Area 1	1100	12.18	35.29
Area 2	1800	22.00	32.28
Area 3	650	11.78	36.21
Area 4	2200	8.26	34.38
Area 5	1400	10.51	34.18
Area 6	1200	10.43	35.32

3.5 Kriging Neighbourhood Analysis (KNA)

This section is a fundamental part required prior to undertaking more advanced resource estimation work. This helps with the determination of the number of samples required for a representative mean of a regularized block. This ensures that an optimal number of samples is determined leading to a more representative localized mean of the area in question. The amount of samples required in order to obtain a representative mean depends on the size of the area in question (Vann et al, 2003).

The procedure for determining the appropriate number of samples also depends on the sample density of the area. For Case A, the data is densely spaced in a relative sense and as a result, the method of determining the number of samples is different from areas that for example use widely spaced grids.

In determining the minimum number of samples to be used for the global and local mean estimation for the S4U seam, consideration was given to the fact that the drill hole data has been composited. As a rule of thumb for coal, four samples (drill hole intersections) around a point to be estimated provide a good estimate. The compositing of the data means that every drill hole with assay data represents one sample. Micromine's '*Cross Validation'* tool was used to undertake what is essentially a kriging neighbourhood analysis exercise. The process compares the measured value for a point with that estimated for the same location after trends have been removed and a variogram model fitted. This process is also known as "jack-knifing". The difference between the estimated value and the actual value is used to calculate the standard error and the error statistic. The programme calculates the ratio of the actual error (actual value-estimated value) to the kriging standard deviation to obtain the standard error. If the basic assumptions have been satisfied and the correct variogram model has been chosen, the average should be zero and the standard deviation of the error statistic, one (Micromine, 2013).

According to Vann et al, 2003, when defining a neighbourhood, caution must be exercised to ensure that the defined neighbourhood is not too restrictive. The authors further make the point that there is a widely held misconception that searching to the range of the variogram is a good strategy for defining the neighbourhood. The choice of neighbourhood should be influenced more by the slope of the variogram model at short lags and the relative nugget effect (i.e. the ratio of the nugget variance to the total variance, expressed as a percentage) than by the ranges per se. As the range of a variogram approaches zero it can be shown that the neighbourhood required for good estimation will progressively get larger. In the case of pure nugget, correlation between any two points in a domain is zero. Therefore, samples located within any limited search neighbourhood will be uncorrelated to the true grade of the block. In other words, local estimation is risky and will be increasingly riskier as progressively smaller neighbourhoods are defined. In the case of pure nugget, the most reliable estimate will be made with the largest number of samples. In fact in this case, searching the whole domain will be the minimum estimation variance solution (Vann et al, 2003).

Table 11: Kriging Neighbourhood Analysis test results for Case A S4U accumulated Ash%

Min N	Max N	Sectors	Actual Value	Estimated Value	Standard Error	Standard Deviation Estimated	Actual error	Error Statistic	Search Distance
8	60	1	308.96	309.25	0.25412	58.959	-0.094%	2.5339	1000
16	60	1	308.96	312	0.25241	55.107	-0.984%	3.8926	1000
4	60	1	308.96	307.68	0.25466	60.578	0.414%	2.7018	1000
1	60	1	308.96	307.57	0.25533	61.079	0.450%	3.268	1000
1	60	16	308.96	307.67	0.25532	61.059	0.418%	2.871	1000
2	60	8	308.96	307.44	0.25487	60.82	0.492%	2.8855	1000
1	60	8	308.96	307.67	0.25532	61.059	0.418%	2.871	1000
4	60	4	308.96	307.77	0.25465	60.551	0.385%	2.3073	1000
2	60	4	308.96	307.44	0.25487	60.814	0.492%	2.8917	1000
1	60	4	308.96	307.66	0.25532	61.054	0.421%	2.8772	1000
8	100	1	308.96	309.32	0.25411	58.927	-0.117%	2.2401	1000
8	80	1	308.96	309.29	0.25411	58.924	-0.107%	2.3324	1000
8	40	1	308.96	309.2	0.25415	59.051	-0.078%	2.7191	1000
8	**30**	**1**	**308.96**	**309.14**	**0.25421**	**59.228**	**-0.058%**	**2.9549**	**1000**
8	20	1	308.96	308.91	0.25444	59.482	0.016%	3.8339	1000
8	16	1	308.96	308.95	0.25472	59.913	0.003%	3.73444	1000

The exercise for Case A to determine the optimal number of samples and search neighbourhood for Ash, CV and Thickness resulted in the results shown in Table 11. This is an iterative process of cross-validation and parameter refinement until the model provides the best results according to a few checks (Noppé, 1994). Some of these checks are;

- Good graphical fit to experimental data points
- Actual error of estimation of the variable close to zero
- Minimum standard deviation of the error statistics

Table 11 shows the results of Micromine's Cross Validation process used to determine the appropriate number of samples, number of sectors and the search distance that should be used to estimate the mean quality of a block leading to the least error statistic. According to Micromine (2013), the average error statistic should be close to zero. A poor result may suggest that the variograms do not represent the data and should be remodelled. Each estimate is calculated using the variograms with the original assay temporarily removed.

The selected appropriate combination of sectors, range and number of samples is shown in Table 12. The same parameters generated for Ash were used for thickness and CV. Table 12 summarises the selected parameters used for the estimation of all three variables.

Table 12: Kriging Neighbourhood Analysis selected parameters results for estimating Case A's S4U accumulated Ash (composited data).

	Min N	Max N	Sectors	Search Distance	% Negative weights	Pass
Parameters	8	30	1	1000 m	0.727	First
Parameters	4	60	1	1000 m	2.374	Second

After running a few iterations using the different combinations of search neighbourhood parameters, a scattergram plotting the input data accumulated ash against the output model accumulated ash was generated (Figure 39). Based on the results of the kriging neighbourhood analysis, it is fair to expect these results to be the most optimal.

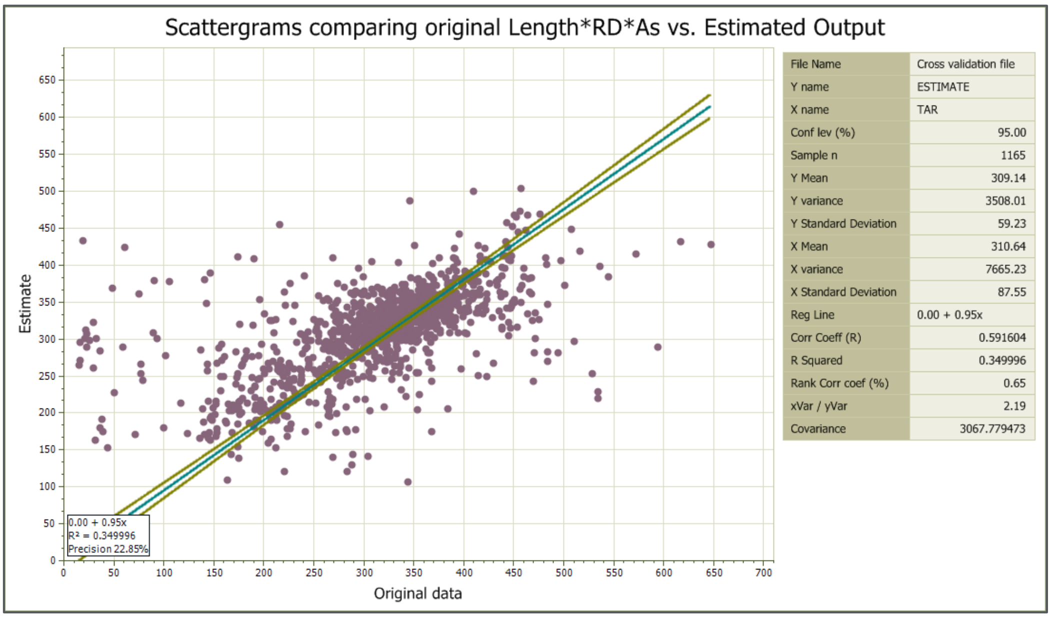


Figure 39: Scattergram for Case A S4U accumulated Ash vs. Estimated Accumulated Ash on composited samples using the selected search neighbourhood parameters

3.6 Negative Kriging Weights

Negative kriging weights in OK arise when data close to the location being estimated screen outlying data. When applied to high data values they may lead to negative estimates (Deutsch, 1995). When searching to the range 1000 m of the Ash variogram using the neighbourhood parameters shown in Table 11, the percentage of negative kriging weights is a mean of 4.9 %. At a search distance of 2000 m, this increases to 34 %. When the range of the second structure (6000 m), the mean percentage of negative weights rises to 45 %. As a rule of thumb, anything above 5 % is undesirable and leads to sub-optimal estimates. This demonstrates that searching beyond a 6000 m range yields sub-optimal results for this deposit. At a 600 m range and a minimum of 2 samples per sector (4 sectors used), the slope of regression is a mean of 0.94 with a mean kriging efficiency of 0.68 and a mean kriging variance of 0.37.

3.7 Selecting Block Size

According to Vann et al, 2003, the selection of a block size is critical in all cases where a cut-off will be applied to an estimate. As a general summary, the block size needs to increase as the nugget (and other short scale discontinuities) increases. It is unusual for blocks appreciably smaller than half the drilling grid dimensions to yield acceptable QKNA results, unless the grade continuity is very high (i.e. very low nugget and long ranges). For Case A, a block size of 100 m x 100 m was selected as representing approximately half the average drill spacing. This block size mimics the block size used for long term mine planning. The average search distance per block is 400 m. The use of small blocks typically less than 1/3rd the drill spacing is strongly discouraged in the case of OK. This may pose a problem in the case of coal quality with typically widely spaced data.

3.8 Estimation Results for Ordinary Kriging vs. other Estimation Methods

For the kriged estimate at Case A, two runs were generated using the search parameters listed in Table 12. The results of these estimates were that no blocks were estimated using the second pass i.e. all blocks were estimated using the search parameters of the first pass.

For Case A, on a global mean basis, the GA technique performs better than both OK and IDW in estimating both Ash and CV. IDW outperforms OK in terms of the actual error between the input data and the estimated global mean. This is further illustrated in Figure 40.

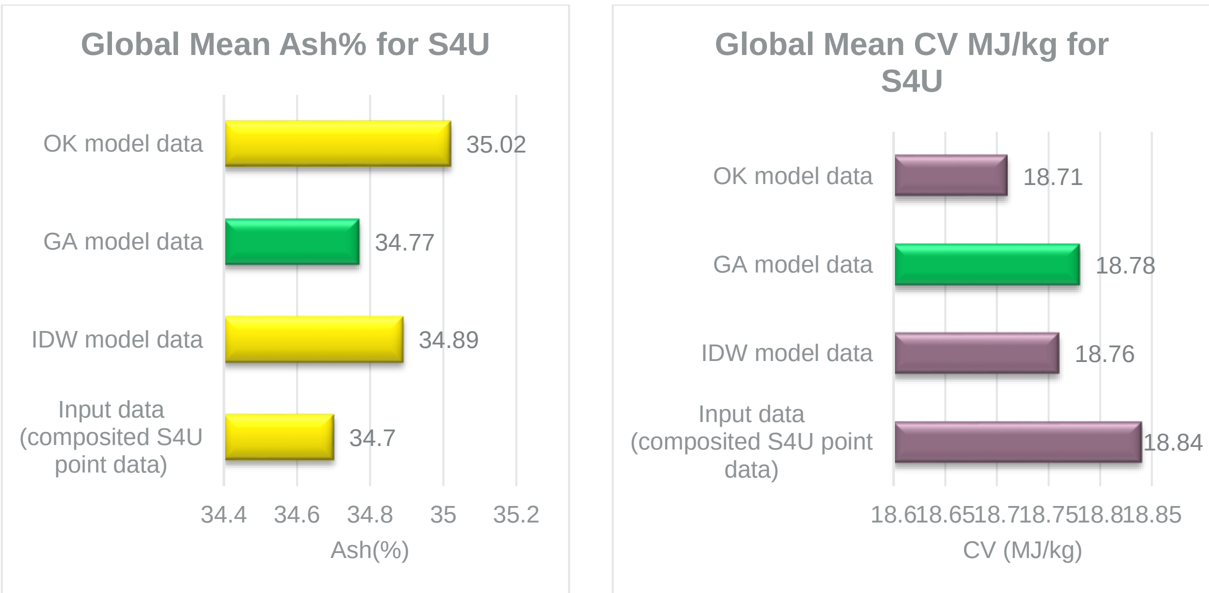


Figure 40: A comparison between the input composited data against OK, IDW and GA estimates for Case A.

For the OK estimates, the mean slope is 0.83 with a very low kriging efficiency of 0.23 and a kriging variance of 0.04 for all three variables. The closest search distance is 185 m with a global average of 606 m. In terms of efficiency, the desired result is a number close to 1, which would represent perfect valuations.

A QQ plot was generated to compare OK against IDW results in order to assess whether there was a difference in the accuracy of the two techniques (Figure 41). The correlation coefficient is 1.007 between IDW and OK when using QQ plots with 100 quantiles for Ash. The Spearman's rank Correlation Coefficient for this comparison is a perfect +1. There is a perfect linear relationship between the results of the two models/techniques. This shows that there is no tangible difference between the distributions of the IDW estimates and OK estimates for Ash. The effort and technical complexity that accompanies the choice of OK as an estimation technique may not be worth the result. IDW is a far easier and repeatable technique than OK, which means that the choice of a more complex technique, in this case, OK may not be justifiable. The same pattern is repeated for calorific value estimates.

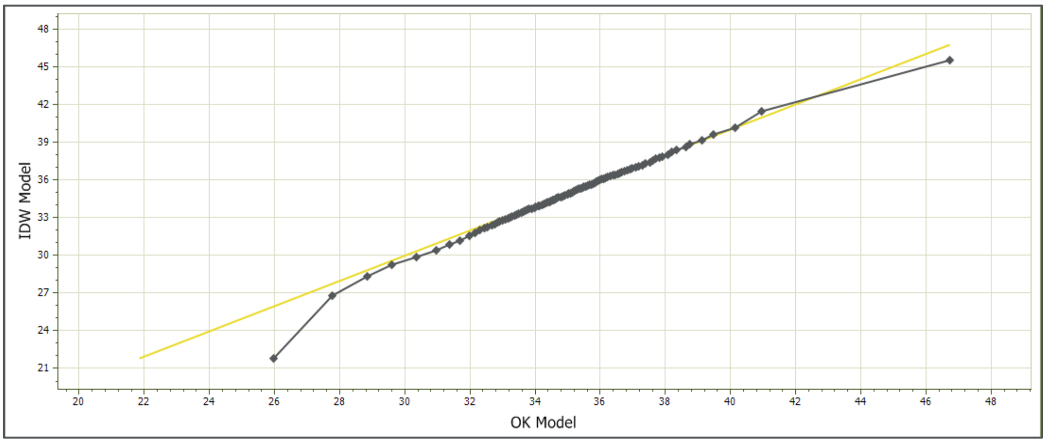


Figure 41: A QQ plot for IDW Model vs. OK Model for Case A (Ash)

In order to compare the results of OK to GA, a Minex grid originally created on a 20 x 20 m grid was re-blocked using Micromine to a 100 x 100 m grid to allow for direct comparison. In undertaking this process, the original file was modified (change of support) resulting in a slight drop in the mean Ash quality from 34.77 to 34.24 %Ash (1.5% percentage drop in mean grade). This is a classic case of the volume variance effect and conditional bias. The comparison between the GA method of interpolation generated in Minex against OK shows a correlation coefficient of close to 1 with a rank correlation of exactly 1. The comparison between GA and OK for CV is less optimal than that for Ash with a 2.6 % reduction in CV.

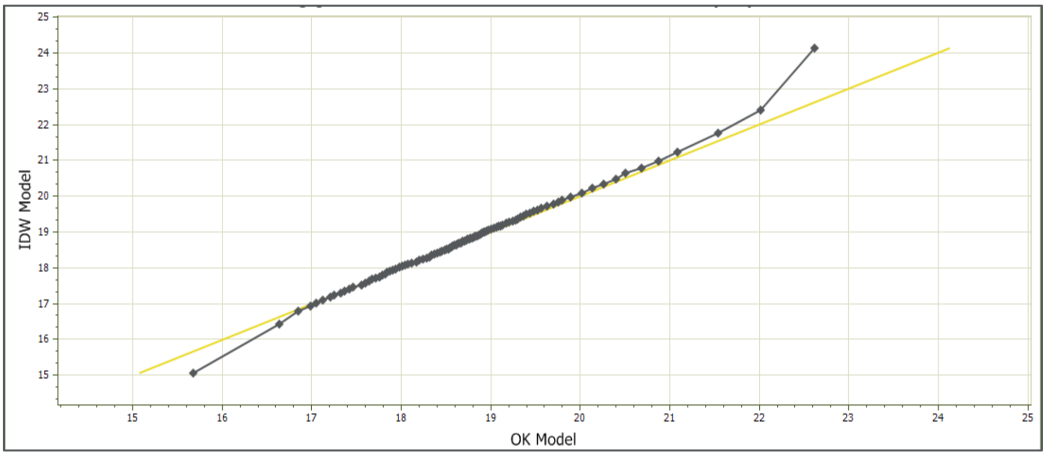


Figure 42: A QQ plot for IDW Model vs. OK Model for Case A (CV)

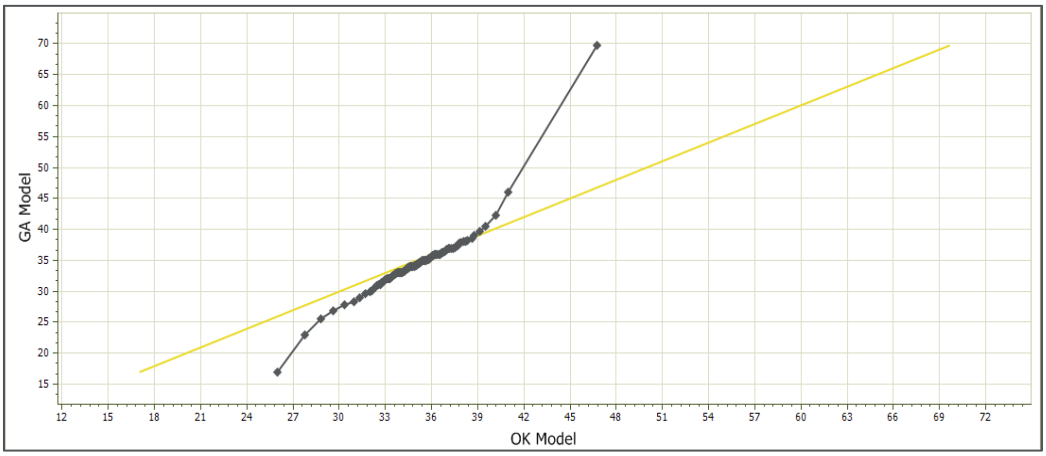


Figure 43: A QQ plot for IDW Model vs. OK Model for Case A (CV)

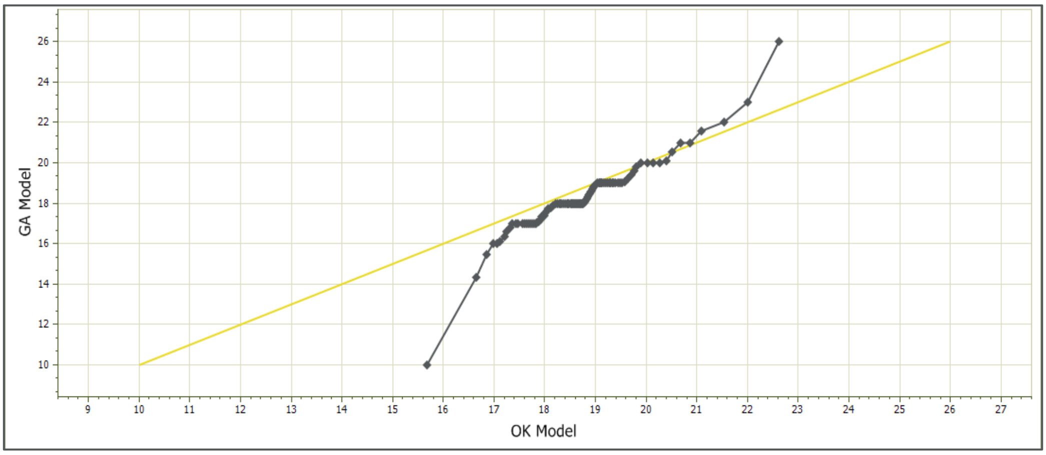


Figure 44: Impact of change of support in re-blocking the GA model from the original 20 x 20 m grid to the 100 x 100 m grid (CV).

3.9 Using the Global Estimation Variance to carry out Drill Hole Spacing Analysis

The SANS 10320:2004 classification guidelines recommends the following search neighbourhood for classifying South Africa coal deposits;

- 8 boreholes with wash data per 100 ha for Measured Resource (0 - 199 m wash data radius),
- 4 boreholes with wash data per 100 ha for Indicated Resource (199 - 282 m wash data radius),
- 1 boreholes per 100 ha for Inferred Resource (282 – 564 m wash data radius) and,
- 0.25 wash data per 100 ha (> 546 m wash data radius) for reconnaissance class occurrence (NOT DECLARED).

The Global Estimation Variance method as described in Chapter 2 was applied to determine the appropriate drill spacing for the Case A deposit.

New semivariograms (Figure 45 & Figure 46) over localised areas were generated for the Global Estimation Variance exercise. This led to new search parameters, range, nugget and sill. Over smaller areas, (Figure 47) spherical semivariograms can be modelled compared to generating semivariograms over the entire deposit. The separation of the project area into the two smaller areas (GEV Area A and GEV Area B) resulted in sills and ranges that are within the norm i.e. it allowed for stationarity to be clearly captured and thus pairwise relative variograms were not used once the area was divided into domain or areas. This is true for both Case A and Case B. For GEV Area A, the range of the experimental semivariogram is 700 m with a sill value of 2.48 $(\%)^2$ Ash. For GEV Area B, these values are 650 m and 2.86 respectively. These results are comparable to those found by Wood (1979) and Noppé (1992).

Results of a global estimation variance are sensitive to locality and size of the property that is being assessed hence its adoption comes with the following caveats. The global precisions;

- Apply only to the deposit, seam, domain and variable considered
- Can only be used to assign a precision to estimation of the mean of an attribute of interest for a global area equivalent to a certain production period, assuming fixed mining rate and
- Are not applicable to any other area than the one implicit in the calculations and, in particular, are not suited to assigning local confidence intervals.

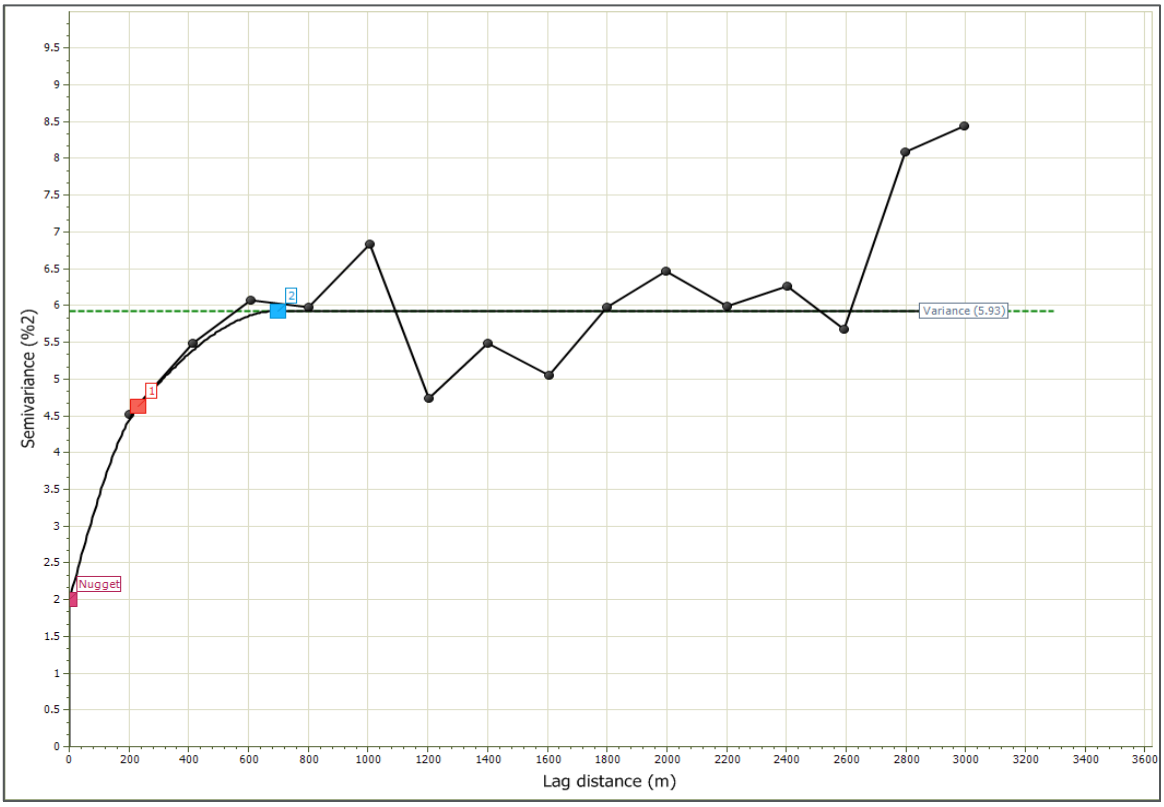


Figure 45: Semivariogram - GEV Area A - Ash

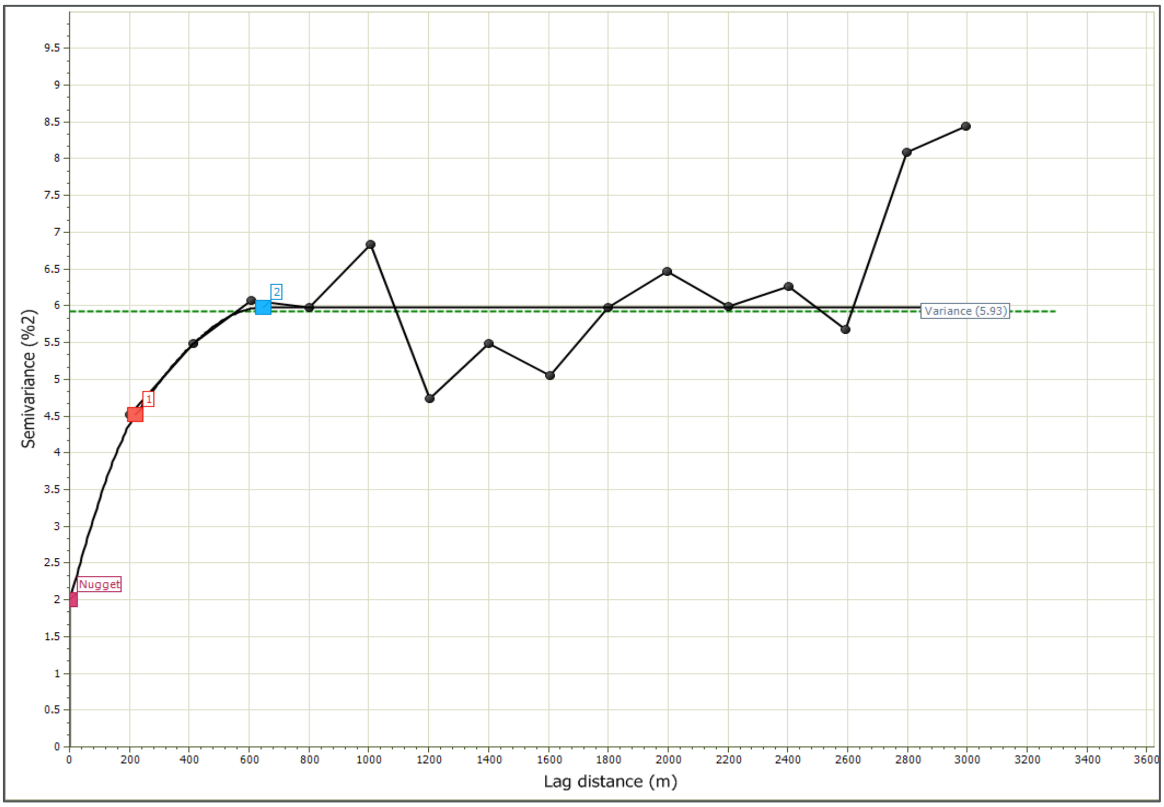


Figure 46: Semivariogram - GEV Area B – Ash

For Case A, two areas of roughly 10 km^2 each were selected to run the exercise. It is worth reemphasizing that the results are only valid for these areas and cannot be applied anywhere else. The results are plotted as relative precision versus the sampling grid.

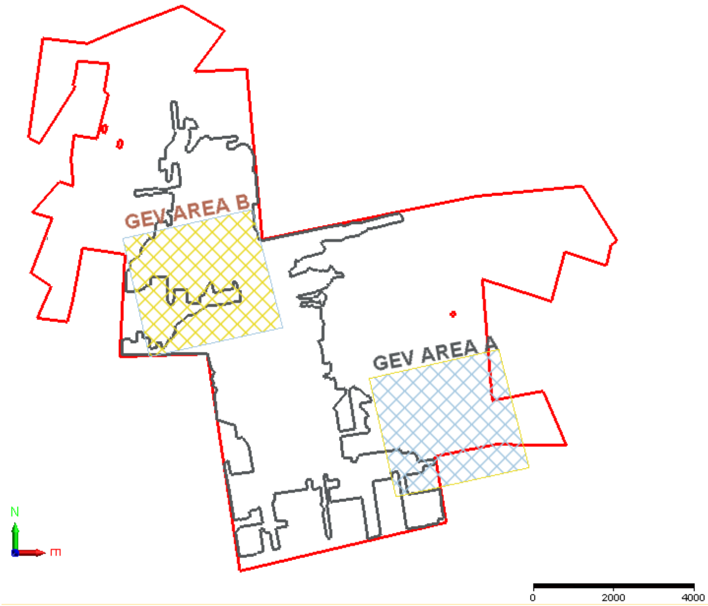


Figure 47: Global estimation variance calculation areas to determine drill hole spacing for Case A S4U. The black line represents the mined-out areas i.e. GEV Area B is inside the mined-out areas whilst GEV Area A is on virgin coal. The red line is the Mining Right Boundary.

For Areas A and B, the estimation precision remains under 10 % up to 1200 m and 2000 m respectively. This means that for Area A, drill holes that are spaced 1200 m apart can estimate the quality variable of a block to within 10 % of the actual value. If the desired precision is 5 % then for Area A, holes can be spaced 800 m apart and yield this result (Figure 48). For Area B, the spacing can go up to 1100 m and still yield results that are within 5 % (Figure 49). The precision values calculated are quite sensitive to the size of the area as the number of blocks (N) is used as a denominator in determining the values. In a global sense, the current SANS 10320:2004 recommended guidelines on spacing would appear to be overly conservative for these two areas i.e. the standard recommends a spacing of 350 m for Measured and 500 m for Indicated. The results presented here show that for Areas A and B this can go up to 2000 m.

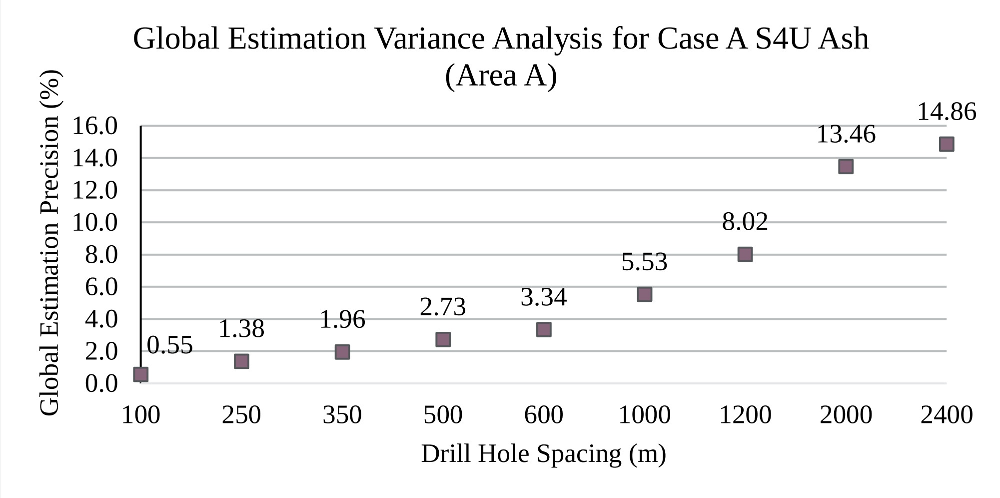


Figure 48: DHSA results for CASE A S4U Ash – Area A

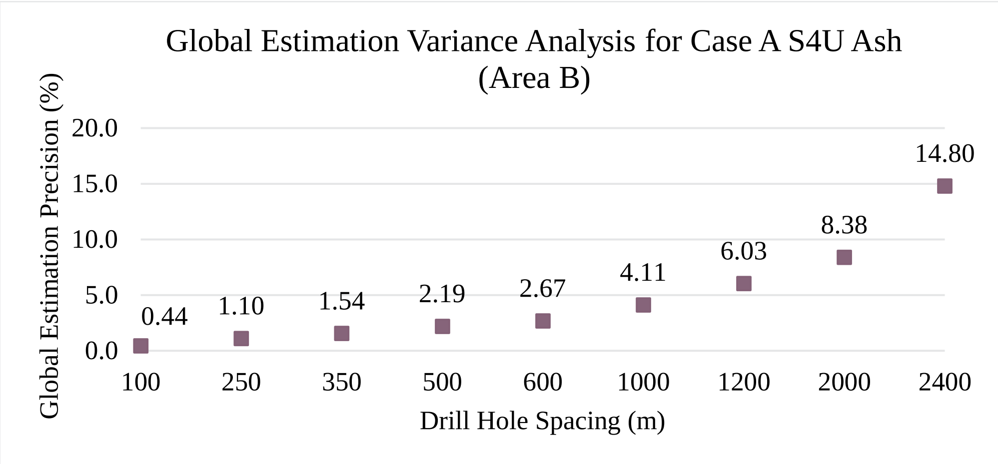


Figure 49: DHSA results for CASE A S4U Ash – Area B

The result equates to an approximate 95 % confidence interval versus a drilling spacing for the corresponding area. It is worth emphasizing that DHSA merely provides an additional tool to allow the Competent Person to make classification decisions using a quantitative tool. The Competent Person must still make the classification decision taking into account not only DHSA results but also, all other geological and economic considerations for the deposit. Given the low kriging efficiency and the fact that the GA method outperforms OK for this deposit, these DHSA results should always be applied in the correct context.

The results presented here are not dissimilar to what Bertoli, et al, (2013) found in the Bowen Basin, Queensland. Operations/Deposits that yielded precisions of <10 % which represents a Measured Category included Caval Ride (800 m), Crinum M Block (1100 m), Gregory Crinum (1100 m), Norwich (750 m), Peak Downs (700 m and 850 m) and Saraji (750 m). These results are considerably different from what the Australian Coal Guidelines (2003) recommend. In the South African context, the guidelines are even more stringent compared to Bertoli et al, (2013)'s findings. The rest of Bertoli et al (2013)'s results are summarised in Table 13.

Table 13: DHSA spacings in metres (m) for various BHP Billiton Mitsubishi Alliance (BMA) coal projects

operation	Measured (±10 %)	Indicated (±20 %)	Inferred (±50 %)
Blackwater (TK, RA)	550	1050	2100
Caval Ridge (RA)	800	1400	2800
Caval Ridge (TK)	500	1000	2450
Crinum M Block (RA)	1100	1900	3600
Daunia (RA)	650	1250	2800
Goonyella Riverside (TK)	650	1250	3150
Gregory Crinum (RA)	1100	1900	3600
Lotus North (TK core)	350	700	1850
Norwich Park (TK)	750	1450	3550
Peak Downs (TK)	700	1300	2600
Peak Downs (TK)	850	1700	4200
Poitrel (TK)	400	750	1800
Saraji (TK)	750	1400	2500
South Walker Creek (TK)	250	500	1000
Coal guidelines	500	1000	4000

The geostatistical analyses undertaken in these areas indicated that the characterisation of spatial continuity of thickness and Ash for the major tonnage contributors can lead to a variation of the proposed spacings for the different categories (Bertoli et al, 2003). South Walker, Poitrel, Blackwater and Daunia return spacings for the Measured category around 500 m or below, for Indicated typically at 1000 m or below and for Inferred, less than 2000 m between points of observations. Goonyella, Riverside, Caval Ridge, Peak Downs, Norwich Park and Saraji return spacings for the Measured category around 750 m, for the Indicated typically at 1250 - 1500 m and for Inferred around 2500 m. Lastly, Gregory Crinum and M-Block return spacing for the Measured category of 1000 m, for Indicated, 2000 m and for Inferred, 3500 m.

3.10 Testing the 10% Precision Hypothesis using Jack-knifing

In order to test whether the 10 % precision rule holds true for Case A, the CV and Ash content were estimated using IDW by using neighbouring holes that are 600 to 1100 m away. The estimated drill hole was 'masked out' of the database to see if the result would be within 10 % or less (Figure 50).

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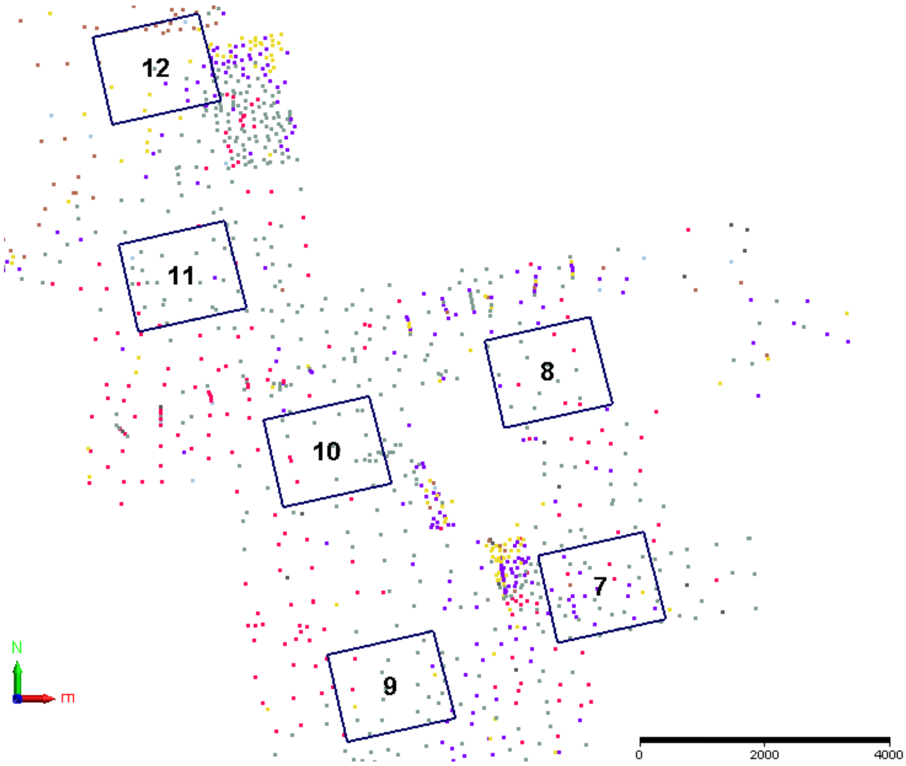


Figure 50: Areas selected for jack-knifing to test the 10 % precision theory

Table 14: Manual jack-knifing results for Case A using IDW

	Drill hole value (CV)	Nearest block value (CV)	%age difference (CV)	Drill hole value (Ash)	Nearest drill hole value (Ash)	%age difference (Ash)
Block 7	17.87	18.40	-3%	37.72	36.18	4%
Block 8	18.65	18.99	-2%	36.40	34.41	6%
Block 9	17.75	17.38	2%	37.85	37.34	1%
Block 10	18.45	19.20	-4%	35.87	33.68	6%
Block 11	18.61	19.32	-4%	34.16	33.22	3%
Block 12	15.37	18.34	-18%	45.05	35.84	23%

The results show that if the widely accepted 10 % and 15 % (Yeates and Hodson, 2006) rules are used to separate Measured[5] from Indicated Coal Resources respectively, for Case A, the separation distances suggested by GEV/DHSA should hold. This means that the deposit can have holes spaced 1000 m apart and still be within the Measured category. Once again it should be noted that the purpose of the geological model is always worth considering i.e. local variability may negatively impact short term planning but may have no effect on long term planning and resource declaration.

3.11 Resource Classification Matrix/Criteria

The following classification matrix is applicable to the Case A deposit based on work that was undertaken by Mwasinga (2000), Vann et al (2003) and Bertoli (2013). The slope of regression numbers for the deposit are fair but the kriging efficiency scores are too low for resource classification consideration. The low kriging efficiencies challenge the applicability of the OK technique to the evaluation of coal qualities for the deposit. In terms of number of samples and estimation precision, the matrix provides guidance to the Competent Person. The results of the performance of the estimation exercise in relation to the classification matrix are presented in Table 15.

When looking at the number of samples in isolation, every block for Case A is estimated using a minimum of 8 samples making the entire deposit a Measured Resource. This is true whether the SANS 10320:2004 guidelines are applied or if kriging neighbourhood analysis results are applied. About 40 % of the area has a slope of regression of > 0.9 with the other 40 % being greater than 0.8 (Figure 51).

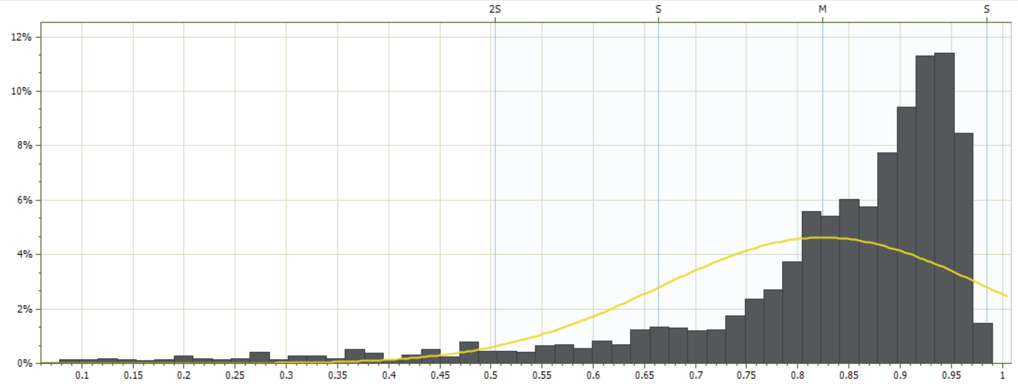
Table 15: Proposed classification matrix for Case A

	Measured	**Indicated**	**Inferred**	
Regression Slope	>0.9	>0.8	<0.8	Used
Kriging efficiency	>0.5	>0.3	<0.3	Too low
Number of samples	≥8	≥4	≥1	Used
Estimation Precision	10%	10-20%	20%	Suggested

[5] Measured – Drill spacing should be enough to determine the limits of the deposit and close enough to give reasonable interpretation of the position of geological boundaries to give volumes to within 10% accuracy

Indicated – The spacing should also be close enough to give reasonable interpretation of the position of geological boundaries to give volumes to within 15% accuracy

Inferred – Sufficient to define extent or limits of the drilled mineralized resource and estimate mineralized volume to within 25%



Minimum value	0.066	N	2168	Median	0.878	Sichel's estimator	0.834
Maximum value	0.984	Mean	0.825	Ln mean	-0.225	Sichel's V	0.087
2nd highest	0.983	Variance	0.026	Ln std deviation	0.296	Sichel's gamma	1.045
3rd highest	0.982	Standard deviation	0.160	Geometric mean	0.799	Chi-Square Test	2372.429
4th highest	0.981	Coeff. of variation	0.194	Geometric std dev	1.344	Degrees of freedom	34

Figure 51: Histogram of slope of regression for Case A estimates.

“In classical statistics, a 'best fit' line can be fitted through the points to find the slope of the line that 'best' fits the points. In least squares regression (LS), the 'best' line is that which minimizes the difference between the true average block value and the value that would be estimated using the regression line. This slope is calculated by:

$$\frac{\text{Covariance between estimated and actual value}}{\text{Variance of estimated values}}$$

and the intercept on the line is determined by making sure that the line passes through the average value of all the points for each variable. According to stated theory, application of these regression factors to the estimates produces a new estimate of the form:

$$\text{Intercept} + \text{slope} \times \text{kriged estimate}$$

which should 'correct' for the regression effect and produce estimates that lie around the 45° line (Clark, 2015).”

The same results are presented differently in Figure 52 and Figure 53 where the slope of regression is mostly above 0.8. Virtually all blocks were estimated using more than the minimum number of samples of eight (8) for a Measured category. For Case A, it is clearly that for all practical purposes, all blocks are classified as Measured.

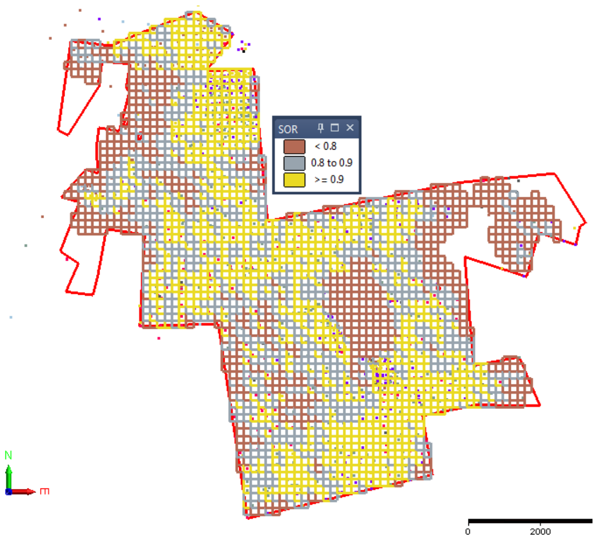


Figure 52: Slope of regression resulting from estimating the different block

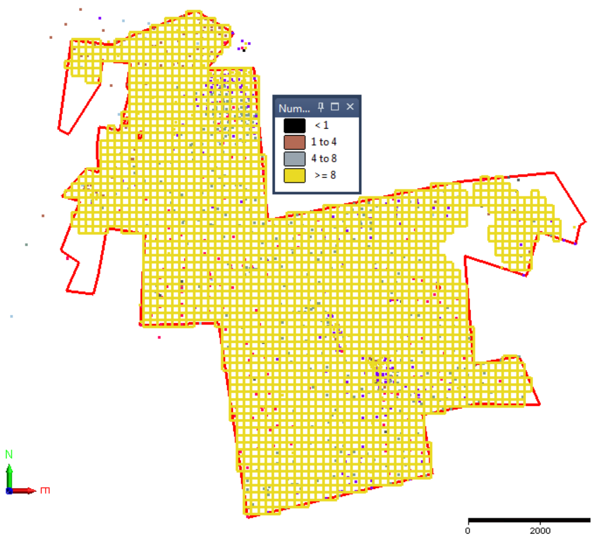


Figure 53: Number of samples used to estimate a block

The following aspects of estimation arise from the analysis of Case A;

- For this deposit, the Growth Algorithm method performed better than both OK and IDW over the global area when looking at the mean CV, Ash and thickness of the estimate against the average of the input data.
- There is no discernible difference between IDW and OK and thus, IDW should be the preferred option over OK due to its relative simplicity
- Case A's deposit is all Measured and arguably over drilled for global estimation and reporting purposes.
- The size of the property i.e. 93 km^2 introduces issues of data stationarity. As a result, generating spherical variograms becomes a challenge unless the area is domained into smaller areas. Geostatistics can be used over smaller areas. Without domaining the property, a different estimation technique needs to be considered.

4 ANALYSIS & DISCUSSION OF RESULTS (CASE B)

4.1 CASE B Colliery

At CASE B, the selected economic seam is S2. The property is comprised of 1361 drill holes drilled since the mine started operating in 2011. Of these drill holes, 1234 contain assay information. For S2, 1199 drill holes intersected the seam and there were assay for qualities.

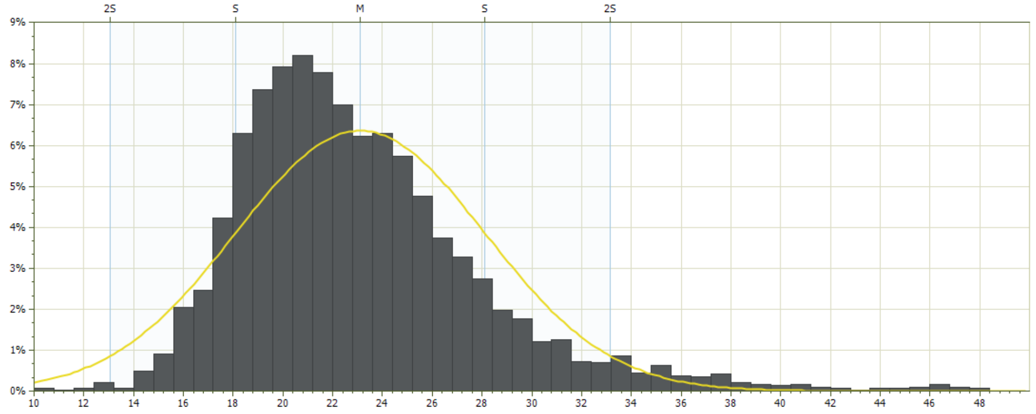
4.2 Exploratory Data Analysis – Basic Statistics

4.2.1 S2 Raw uncomposited basic statistics

For the raw samples the maximum sample length is 6.61 m. The maximum Ash content within the database was reduced to 50 % in line with SANS 10320:2004's definition of coal. Its minimum value is 10.32 % with a mean value of 23.10 %. The mean sample length is 2.09 m, which represents the global mean sampling interval. The CoV for Ash, which is a measure of spread that describes the amount of variability relative to the mean is 0.22 (Table 16). For the raw uncomposited database, thickness and Ash show a strong positive skewness of 1.19 and 1.31 respectively with CV showing a strong negative skewness of -1.27 (Figure 54 & Figure 55). With regard to kurtosis, all three variables show a peaked population distribution. The population variances for Ash and CV are 25.18 $(\%)^2$ and 4.16 MJ/kg^2 respectively. Skewness of data plays a role on whether proportional effect exists within a population or not which then influences the selection of the search neighbourhood parameters as well as the type of variogram modelled.

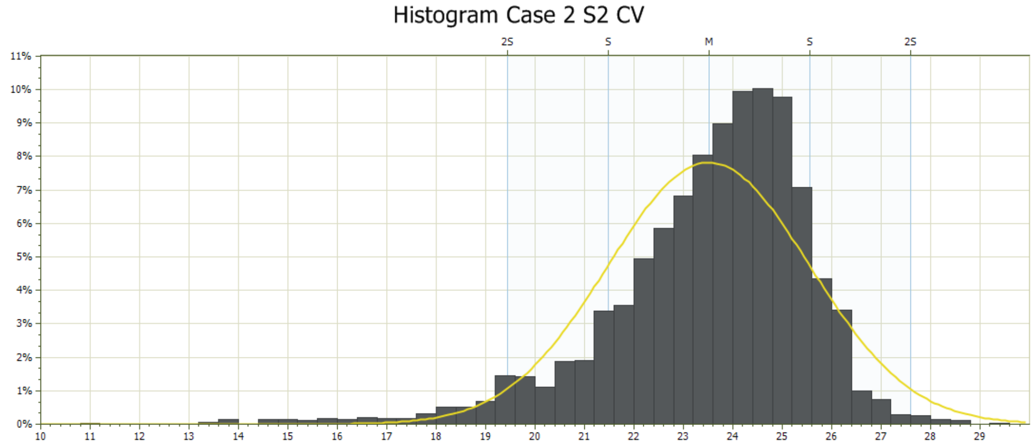
Table 16: Classical uncomposited raw statistics for Case B S2 seam.

Variable	Min	Max	No of Points	Mean	Variance	Std Dev	Coeff. of Variation	Skewness	Kurtosis
THICKNESS (m)	0.24	6.61	2893	2.089	0.98	0.99	0.473	1.195	2.163
ASH%	10.32	48.02	2893	23.103	25.18	5.02	0.217	1.309	2.987
CV (MJ/kg)	10.91	29.36	2893	23.512	4.16	2.04	0.087	-1.269	3.018
RD (g/cm^3)	1.33	1.86	2884	1.537	0.003	0.06	0.039	1.101	2.516



Minimum value	10.320	N	2893	Median	22.232	Sichel's estimator	23.086
Maximum value	48.019	Mean	23.103	Ln mean	3.119	Sichel's V	0.041
2nd highest	47.700	Variance	25.176	Ln std deviation	0.203	Sichel's gamma	1.021
3rd highest	47.523	Standard deviation	5.018	Geometric mean	22.614	Chi-Square Test	1038.710
4th highest	47.281	Coeff. of variation	0.217	Geometric std dev	1.225	Degrees of freedom	34

Figure 54: Histogram for Case A S4U Ash on raw uncomposited samples



Minimum value	10.910	N	2893	Median	23.874	Sichel's estimator	23.517
Maximum value	29.362	Mean	23.512	Ln mean	3.153	Sichel's V	0.009
2nd highest	28.687	Variance	4.159	Ln std deviation	0.094	Sichel's gamma	1.004
3rd highest	28.477	Standard deviation	2.039	Geometric mean	23.414	Chi-Square Test	781.458
4th highest	28.447	Coeff. of variation	0.087	Geometric std dev	1.098	Degrees of freedom	31

Figure 55: Histogram for Case B S2 CV on raw uncomposited samples

As expected, the negative correlation between Ash and CV (Figure 57) is strong showing a correlation coefficient of -0.94, which is comparable to that of Case A (-0.97). For RD, the minimum value is 1.330 with a maximum of 1.860 g/cm^3. The mean of this dataset is 1.537 g/cm^3.

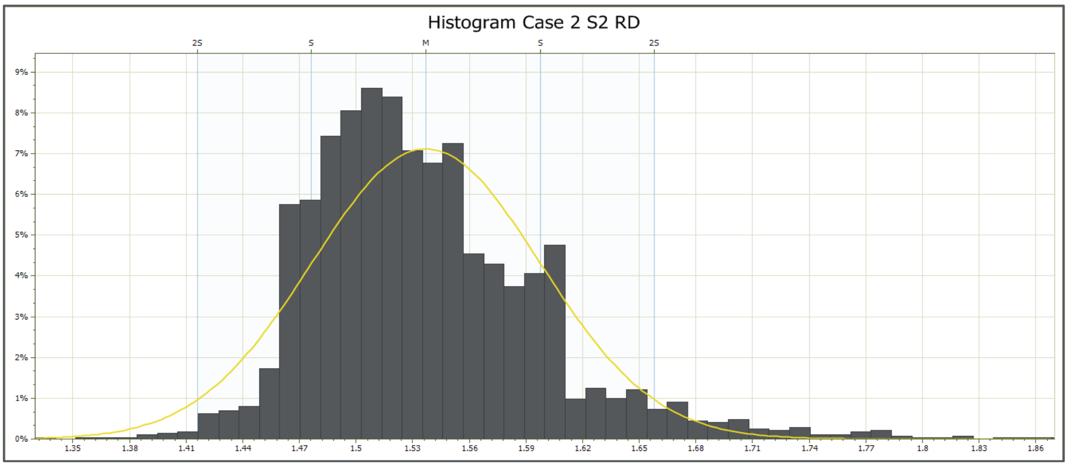


Figure 56: Histogram for Case B RD on raw uncomposited samples

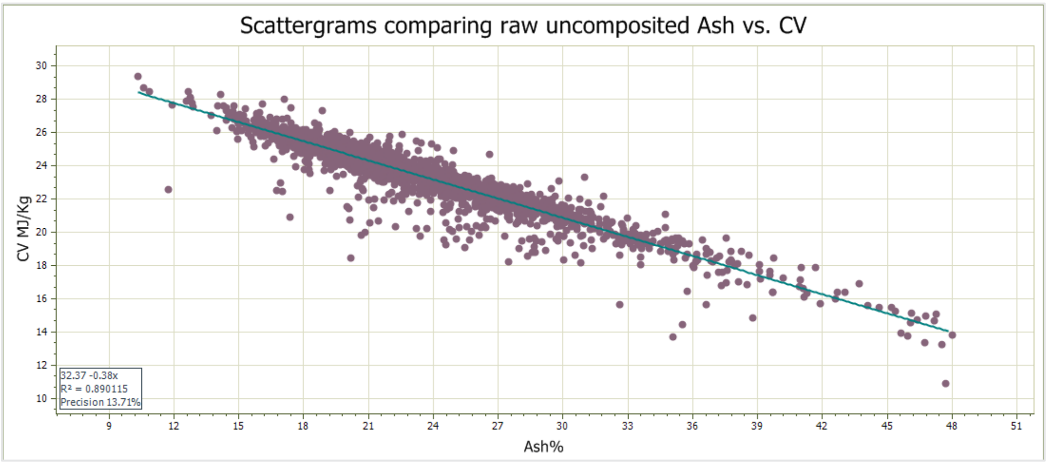


Figure 57: Scattergram for Case B CV vs. Ash on raw uncomposited samples

4.2.2 S2 Raw composited basic statistics

The expected effect of compositing the data is the lowering of variance as the volume increases (change of support). During compositing the variance of Ash drops from 25.18 $(\%)^2$ to 12.83 $(\%)^2$ to illustrate the effect of change of support. The CoV numbers for both variables are also low with the composited Ash having a CoV of 0.16 compared to 0.22 when uncomposited. The CoV for CV is 0.06 for the composited data against a higher CoV of 0.09 for raw uncomposited data (Table 17).

Unlike with the uncomposited thickness data, compositing this variable provides meaningful information. The mean thickness for S2 for Case B is 5.06 m with min and max values of 0.30 and 7.5 m respectively. The mean value of Ash increases slightly to 23.17 % when composited compared to the 23.10 % when uncomposited. This is in line with Case B Colliery's production mean quality. The minimum and maximum values for Ash are 16.04 % and 46.14 % respectively. The maximum seam thickness remains 7.5 m whilst the maximum composited CV drops marginally to 23.49 MJ/kg. Compositing also reduces the number of samples from 2893 to 1199. The 1199 represents one sample per drill hole. The minimum and maximum CV values are 13.73 and 27.69 MJ/kg respectively. All three variables when composited have relatively high kurtosis . The skewness for thickness is strongly negative (3.52). Ash and CV inversely show a strong positive skewness (2.37) and strong negative skewness (-2.06) respectively.

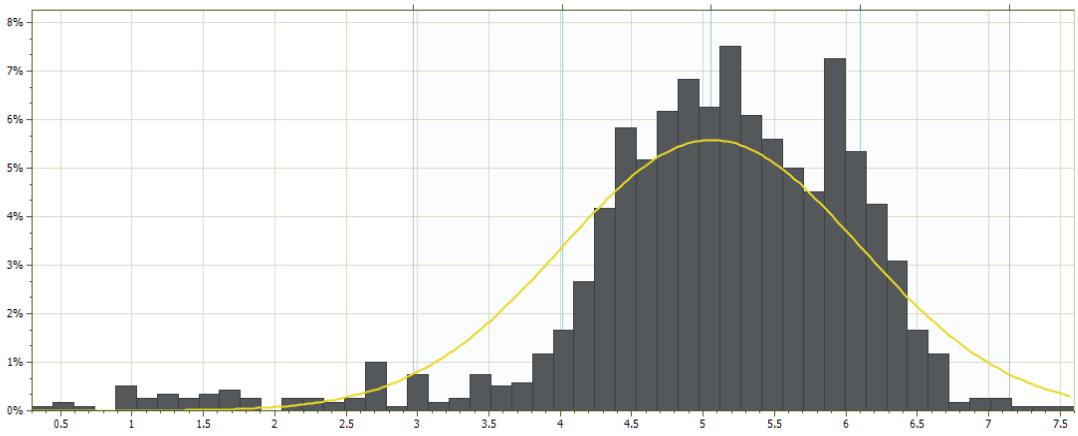
Table 17: Classical composited statistics for Case B seam for thickness, CV and Ash.

Variable	**Min**	**Max**	**No of Points**	**Mean**	**Variance**	**Std Dev**	**Coeff. of Variation**	**Skewness**	**Kurtosis**
THICKNESS (m)	0.3	7.5	1199	5.06	1.09	1.04	0.206	-1.449	3.527
ASH%	16.037	46.14	1199	23.17	12.83	3.58	0.155	2.367	8.578
CV (MJ/kg)	13.733	27.69	1199	23.46	2.23	1.49	0.064	-2.058	6.95
RD (g/cm^3)	1.38	1.79	1195	1.54	0.002	0.04	0.029	1.666	6.235

The histogram in Figure 58 shows a good distribution of thickness across Case B Colliery. The variance is 1.09 m^2. Figure 59 on the other hand shows the distribution on composited Ash using a variogram. To a degree, the Ash histogram is positively skewed.

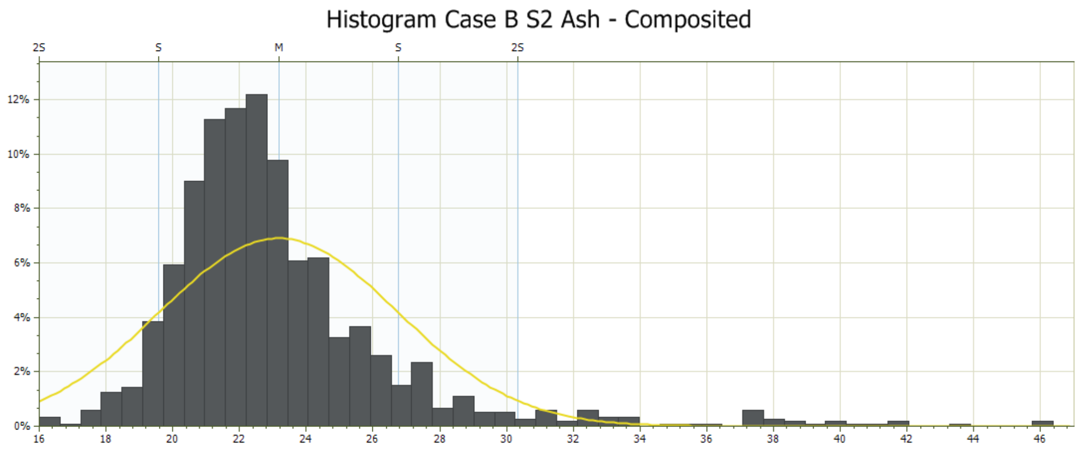
The Ash histogram further shows the highest peakedness (8.57) of the three variables with a variance of 12.83 $(\%)^2$. CV's negative skewness is displayed in Figure 60.

The scattergram in Figure 61 shows a slightly lower correlation coefficient in composited CV vs. Ash i.e. -0.93 compared to -0.94 from the uncomposited data. It is however still a high negative correlation.



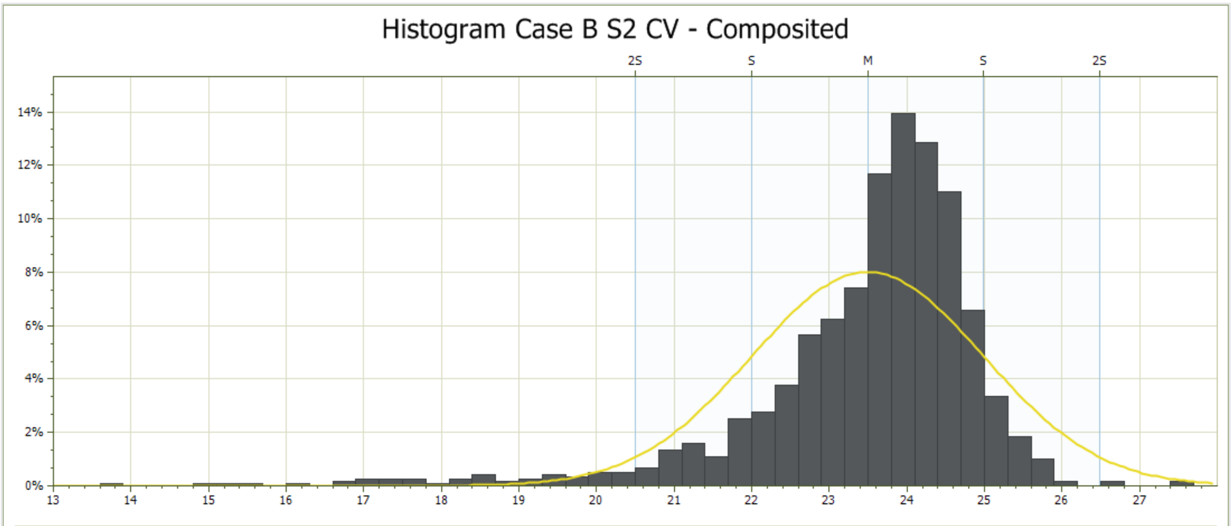
Minimum value	0.30	N	1199	Median	5.17	Sichel's estimator	5.12
Maximum value	7.50	Mean	5.06	Ln mean	1.59	Sichel's V	0.09
2nd highest	7.40	Variance	1.09	Ln std deviation	0.30	Sichel's gamma	1.05
3rd highest	7.18	Standard deviation	1.04	Geometric mean	4.89	Chi-Square Test	424.21
4th highest	7.15	Coeff. of variation	0.21	Geometric std dev	1.36	Degrees of freedom	36

Figure 58: Histogram for Case B S2 thickness on composited samples



Minimum value	16.037	N	1199	Median	22.409	Sichel's estimator	23.156
Maximum value	46.138	Mean	23.172	Ln mean	3.133	Sichel's V	0.019
2nd highest	45.947	Variance	12.833	Ln std deviation	0.137	Sichel's gamma	1.009
3rd highest	43.452	Standard deviation	3.582	Geometric mean	22.939	Chi-Square Test	661.038
4th highest	41.945	Coeff. of variation	0.155	Geometric std dev	1.147	Degrees of freedom	26

Figure 59: Histogram for Case B S4U Ash on composited samples



Minimum value	13.733	N	1199	Median	23.824	Sichel's estimator	23.498
Maximum value	27.698	Mean	23.495	Ln mean	3.155	Sichel's V	0.005
2nd highest	27.638	Variance	2.233	Ln std deviation	0.069	Sichel's gamma	1.002
3rd highest	26.659	Standard deviation	1.494	Geometric mean	23.442	Chi-Square Test	564.753
4th highest	26.601	Coeff. of variation	0.064	Geometric std dev	1.072	Degrees of freedom	27

Figure 60: Histogram for Case B S2 CV on composited samples

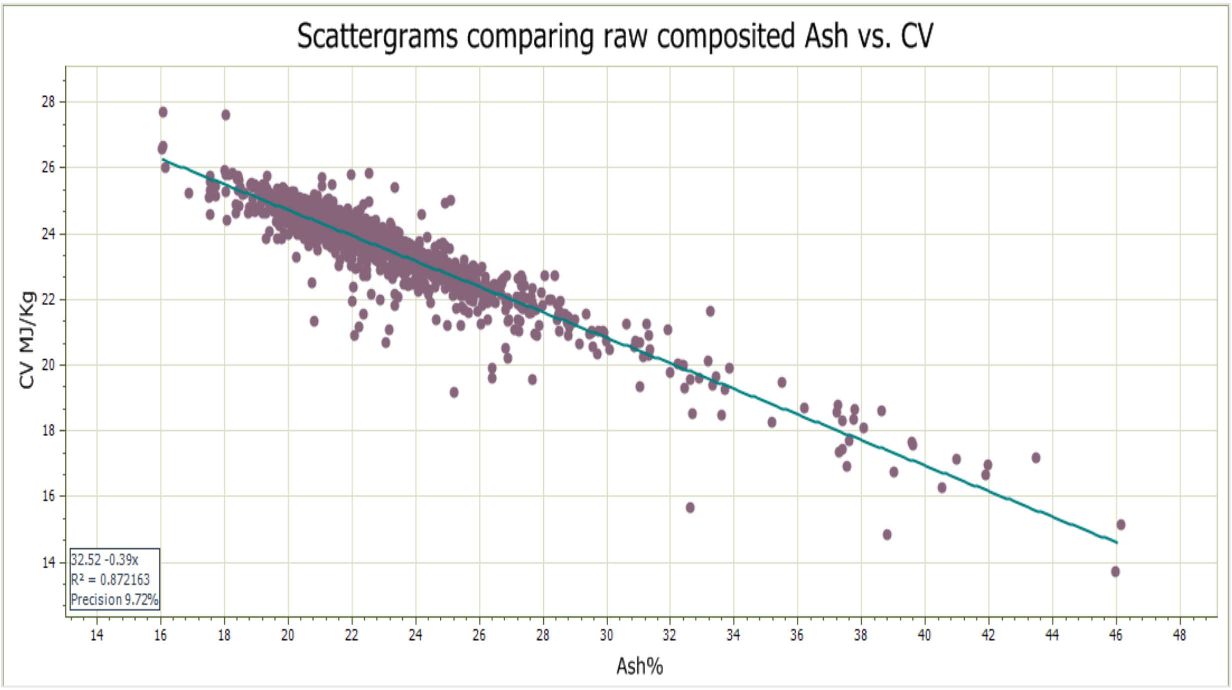


Figure 61: Scattergram for Case B S2 CV vs. Ash on raw composited samples

4.3 Exploratory Data Analysis - Spatial Data Analysis

The yellow coloured polygon in Figure 62 is an outline of the project area (Case B). As was shown in Table 17, the average thickness for the S2 seam is 5.06 m. This becomes increasingly apparent in Figure 62 with the base map showing a considerable amount of values between 4 and 6 m.

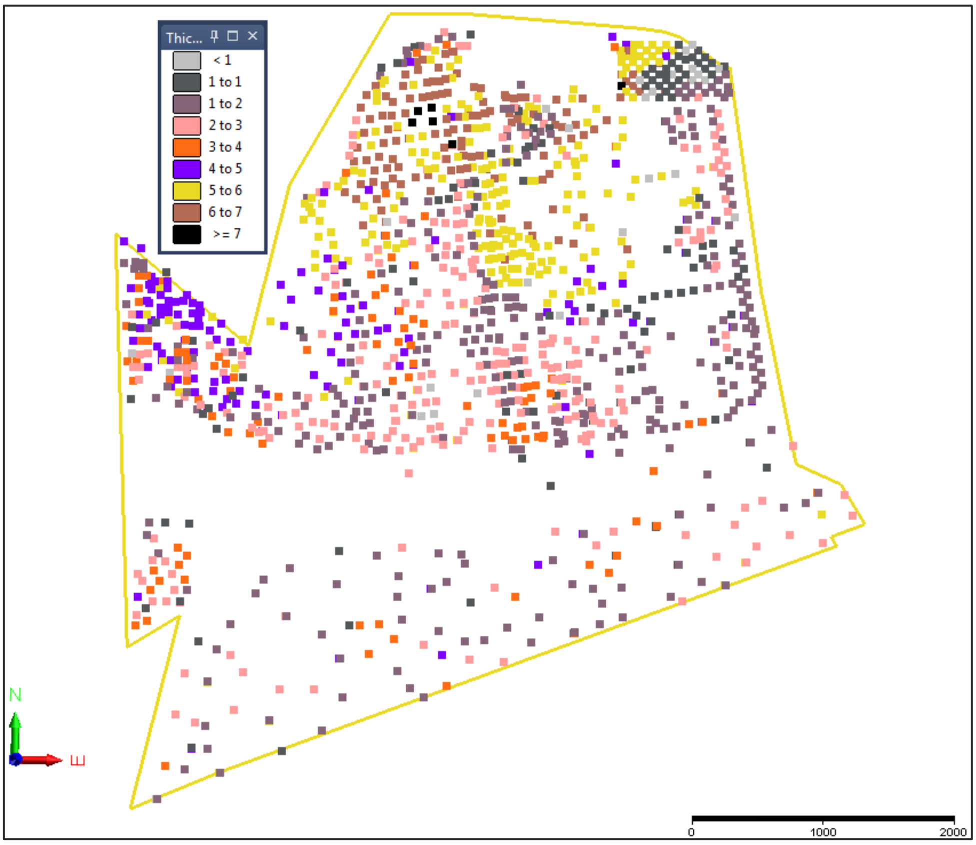


Figure 62: Case B thickness basemap for the composited S2 seam

The Southwestern part of the property contains data with higher thickness values whilst the Northern parts are consistently between 5 and 6 m as well as 6 to 7 m. Towards the centre of the property, the average thickness drops to between 4 and 5 meters. Towards the West, there is less information but the seam shows a gradual thinning.

As was the case with Ash and CV for Case A, the statistical analysis, variography and estimation for Case B was undertaken on accumulated variables (Figure 63 and Figure 64). Before this decision was made several tests were undertaken to ensure that the deposit behaviour replicated that of Case A. Only once this was established was a decision made to use the accumulation approach. The results of the tests are not presented in this text as they are deemed redundant i.e. the only serve to confirm that Cases A and B are similar in terms of statistical behaviour.

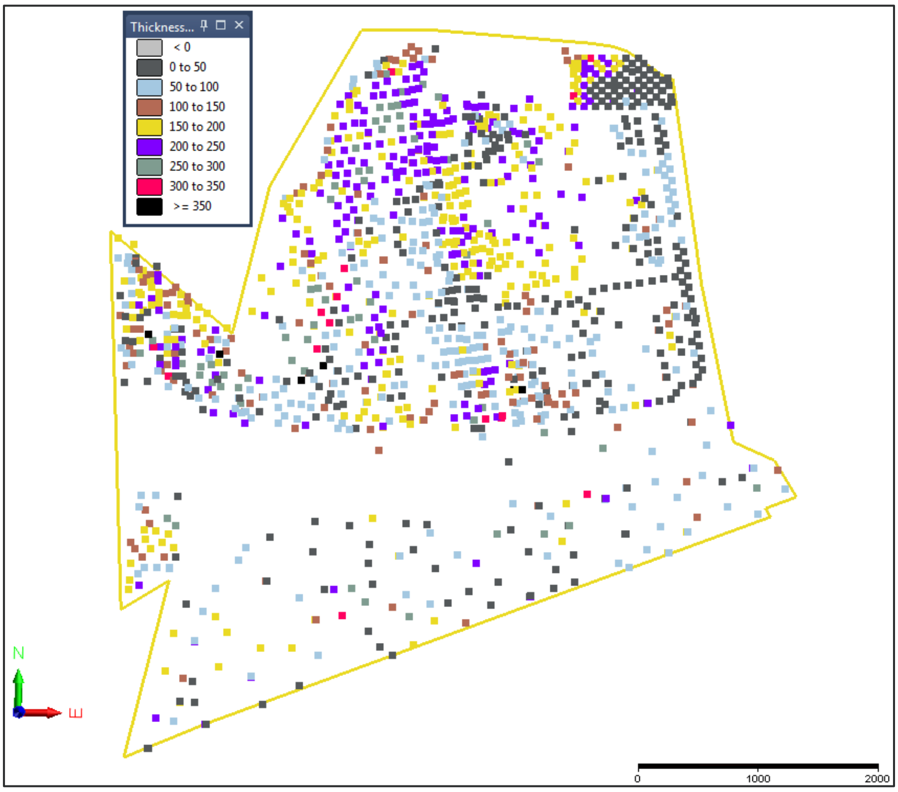


Figure 63: Case B Length*Ash*SG plot for the composited S2 seam

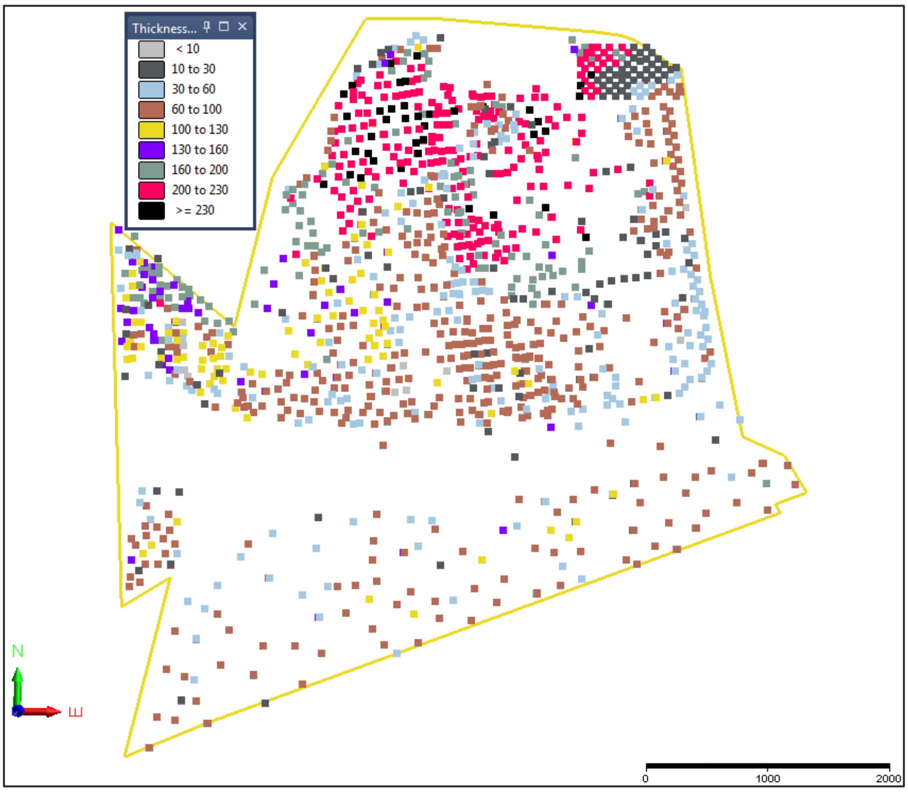


Figure 64: Case B Length*CV*SG plot for the composited S2 seam

There is no discernible concentration of high or low Ash values in any particular areas although globally speaking the West side of the property has relatively higher Ash content. The mean CV for the composited data is 23.49 MJ/kg.

4.4 Determining Average Drill Hole Spacing

The areal extent of Case B as defined by the parameters in Table 18 is 21.8 km^2. There are roughly 56 drill holes per km^2.

Table 18: Geographic dimensions of Case B Boundary

Parameter	NS Length (m)	EW Length (m)	Diagonal Length (m)	Ave DH Spacing (m)	Number of lags	Nominated lag (m)
	6200	5700	7150	132	15	150

The Case B project area is 22 km^2 in areal extent. It contains 1199 drill holes that contain assay data for S2. This means that the drill density calculated as number of points/area is 55 drill holes per km^2.

4.5 Variography and Kriging Neighbourhood Analysis

The following section summarizes the results from Ash, CV and thickness variograms generated through correlating composited samples across drill holes. The following parameters were used in calculating the omnidirectional pairwise experimental variograms.

Table 19: Setting the lag distance and tolerance for CASE B S2

Area	21787615 m^2
N	1199
SQRT (Area/N)	135 m

The pairwise relative semivariogram model for thickness (Figure 65) shows a range of 1130 m a nugget to sill ratio of 25 %. The range of the first structure is 150 m with a C0+C1 value of 0.02 representing 50 % of the population variance. This shows that within the property, there is spatial correlation between samples that are located 1100 m apart (on thickness).

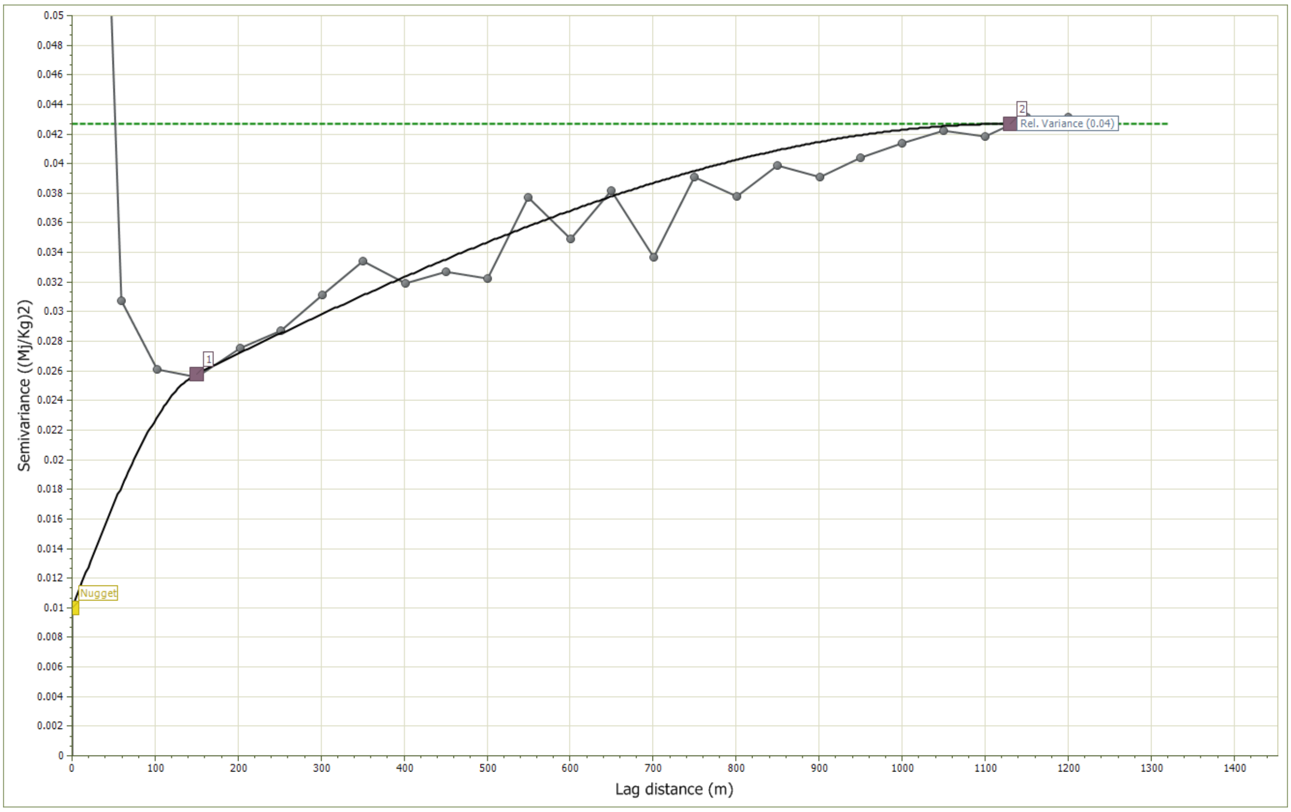


Figure 65: Pairwise omnidirectional semivariogram for Case B S2 – Thickness (composited data)

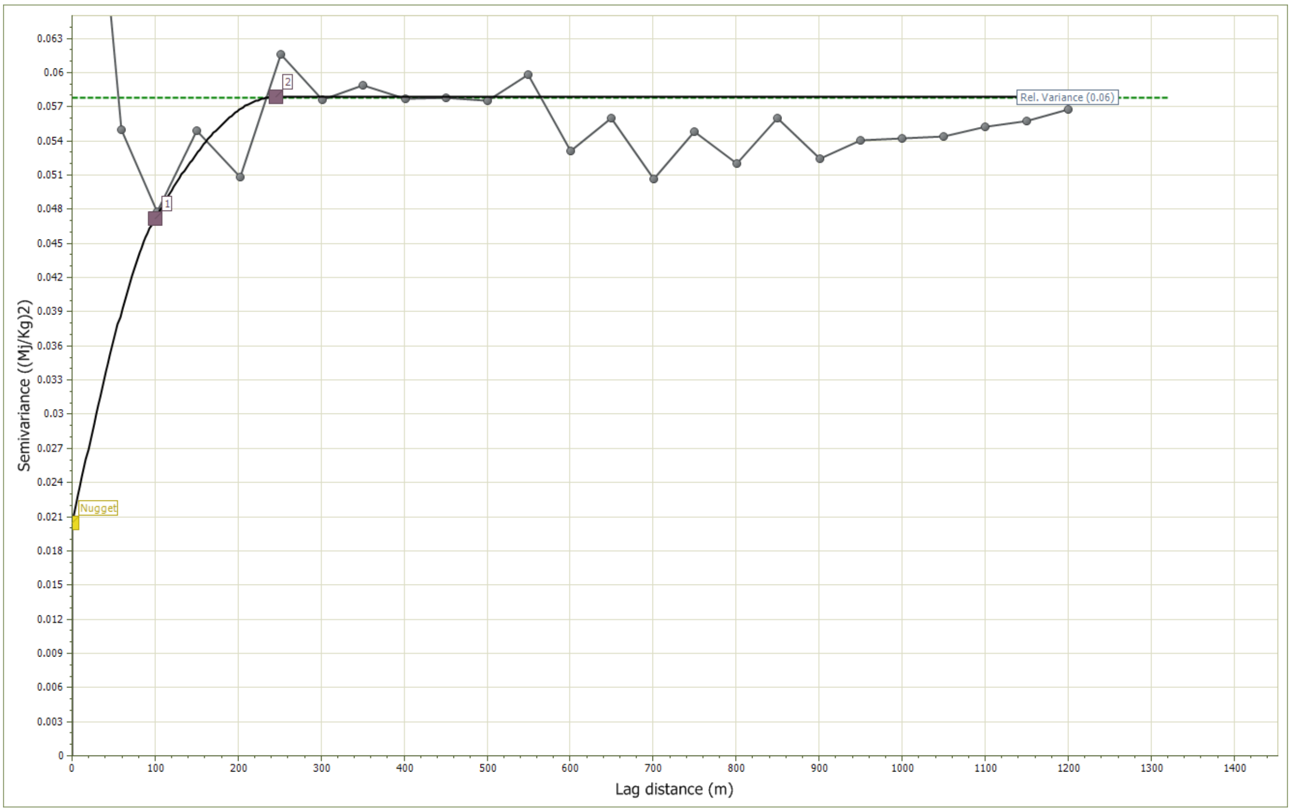
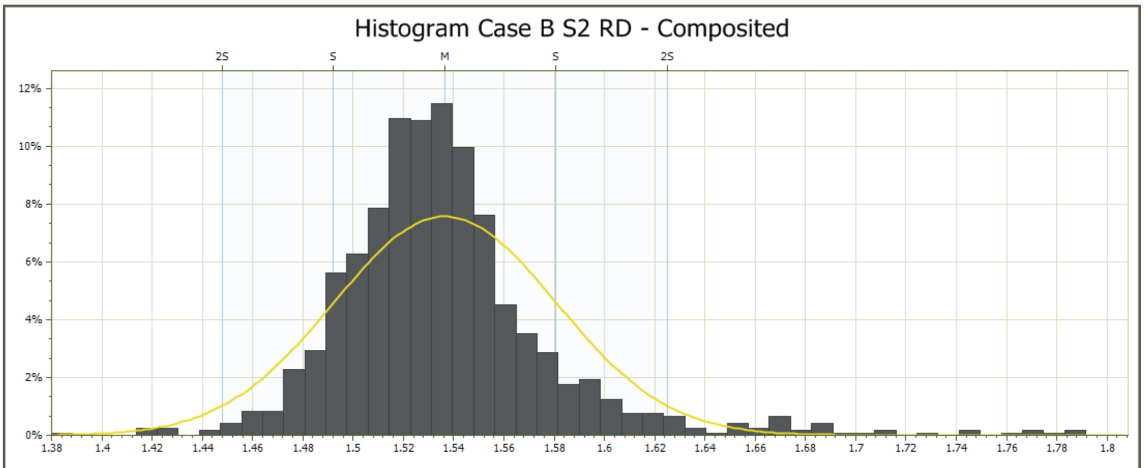


Figure 66: Pairwise omnidirectional semivariogram for Case B S2 (Length*Ash*RD) (composited data)

The range of the accumulated Ash variable is 250 m (Figure 66). The range of the first structure is 100 m with a nugget to sill ratio of 40 %. The same pattern is repeated for the CV pairwise relative variogram showing a range of 234 m and a nugget to sill ratio of 20 % (Figure 68). The relative density of coal within Case B shows some variability (Figure 67) with a statistical range of 0.41 and slight positive skewness.



Minimum value	1.380	N	1195	Median	1.532	Sichel's estimator	1.536
Maximum value	1.790	Mean	1.537	Ln mean	0.429	Sichel's V	0.001
2nd highest	1.788	Variance	0.002	Ln std deviation	0.028	Sichel's gamma	1.000
3rd highest	1.780	Standard deviation	0.044	Geometric mean	1.536	Chi-Square Test	588.444
4th highest	1.772	Coeff. of variation	0.029	Geometric std dev	1.029	Degrees of freedom	29

Figure 67: Variability of relative density for Case B S2 (composited data)

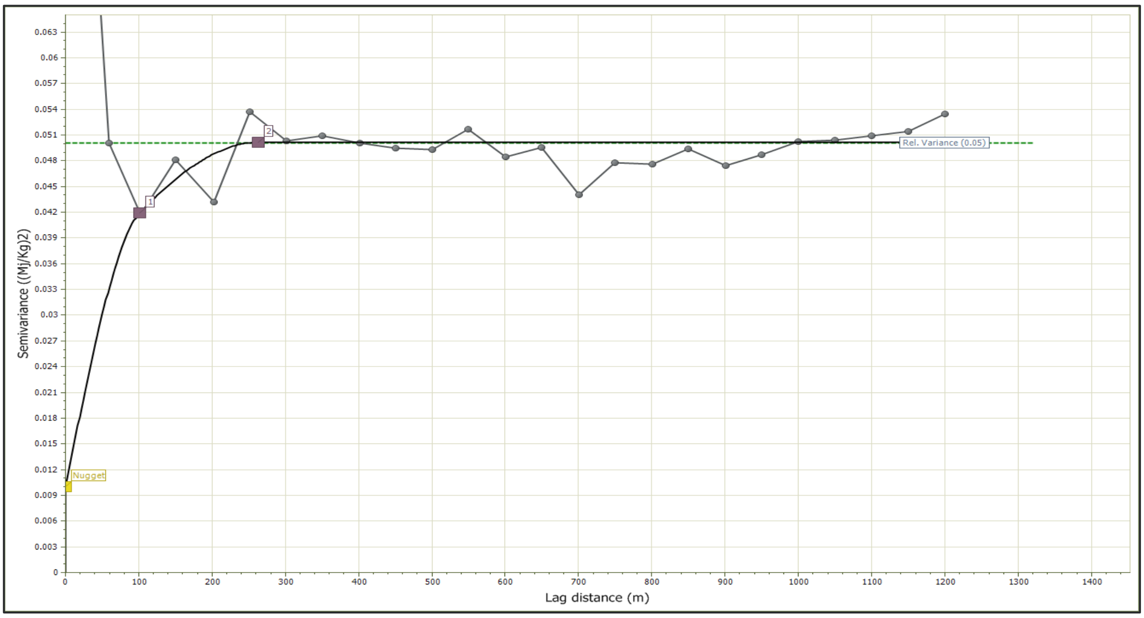


Figure 68: Omnidirectional semivariogram for Case B S2 accumulated CV (composited data)

4.6 Kriging Neighbourhood Analysis (KNA)

This section is a fundamental part required prior to undertaking more advanced resource estimation work. For Case B, the same exercise undertaken for Case A was followed. Table 21 provides a summary of the kriging neighbourhood results (see section 3.5 for details). The parameters that were used are presented in (Table 20). The resultant search parameters, i.e. a search distance of 250 m and four sectors are used by the Micromine software as shown in Figure 69.

Table 20: Number of samples to define the optimal search neighbourhood for Ash, CV and Thickness for Case B S2

	Min N	Max N	Sectors	Search Distance	% Negative weights	Pass
Parameters	2	60	4	250 m	0.317	First
Parameters	1	60	4	250 m	0.295	Second

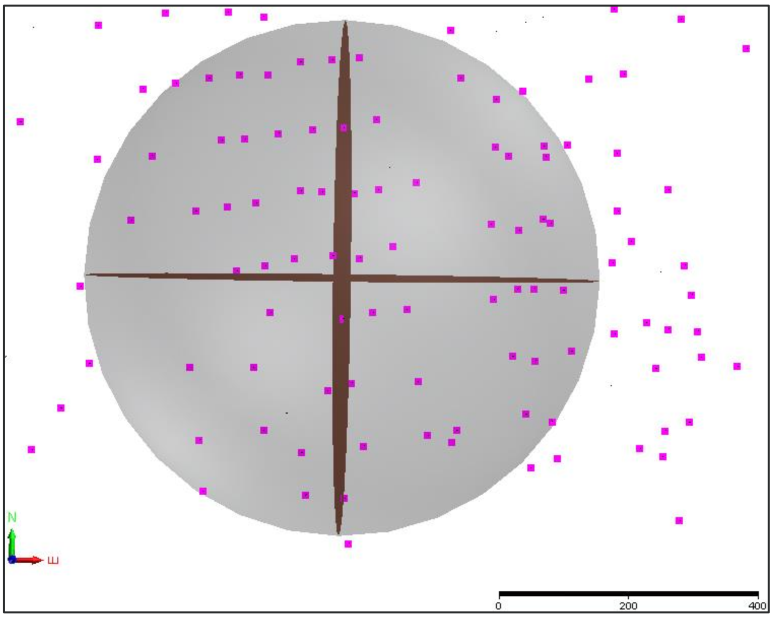


Figure 69: Visual display of the search parameters (4 sectors and 250 m radius) used in generating estimates for both Ordinary Kriging (OK) and Inverse Distance Weighting (IDW) for Case B.

Table 21: Kriging neighbourhood Analysis test results for Case B S2 accumulated Ash%.

Min N	Max N	Sectors	Actual Value	Estimated Value	Standard Error	Standard Deviation Estimated	Actual error	Error Statistic	Search Distance
8	60	1	177.75	179.14	0.2169	27.66	-0.782%	-1.5149	250
16	60	1	177.75	183.54	0.21274	28.955	-3.257%	3.4897	250
4	60	1	177.75	178.38	0.21873	28.592	-0.354%	-1.893	250
1	60	1	177.75	177.82	0.22371	29.622	-0.039%	-0.37477	250
1	60	16	177.75	177.82	0.22371	29.622	-0.039%	-0.37477	250
2	60	8	177.75	177.62	0.22182	29.202	0.073%	-0.97767	250
1	60	8	177.75	177.82	0.22371	29.622	-0.039%	-0.37477	250
4	60	4	177.75	178.38	0.21873	28.592	-0.354%	-1.893	250
2	**60**	**4**	**177.75**	**177.62**	**0.22182**	**29.202**	**0.073%**	**-0.97767**	250
1	**60**	**4**	**177.75**	**177.82**	**0.22371**	**29.622**	**-0.039%**	**-0.37477**	250
8	100	1	177.75	179.14	0.2169	27.66	-0.782%	-1.5149	250
8	80	1	177.75	179.14	0.2169	27.66	-0.782%	-1.5149	250
8	40	1	177.75	179.14	0.2169	27.66	-0.782%	-1.5155	250
8	30	1	177.75	179.14	0.2169	27.661	-0.782%	-1.5415	250
8	20	1	177.75	179.14	0.21691	27.676	-0.782%	-1.531	250
8	16	1	177.75	179.12	0.21694	27.719	-0.771%	-1.4194	250

Micromine uses sector declustering to divide the search neighbourhood into radial sectors and allow each sector to independently search for input data to avoid introducing bias presented by preferential sampling.

4.7 Selecting Block Size

For Case B a block size of 100 m x 100 m was selected as representing 2/3^{rds} the average drill spacing.

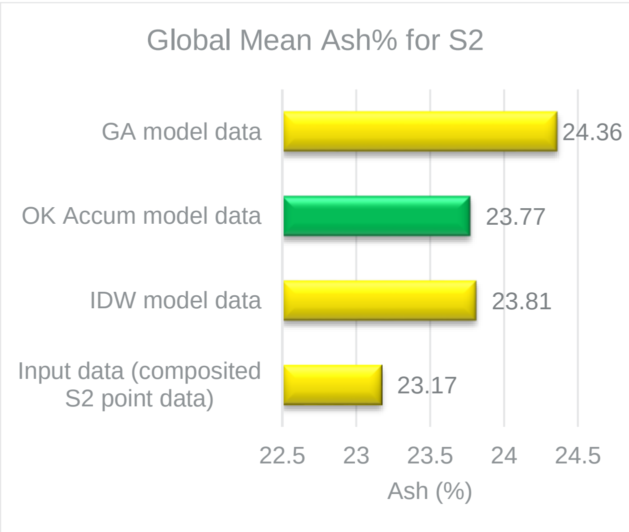
4.8 Estimation Results for Ordinary Kriging vs. other Estimation Methods

For the kriged estimate at Case B, two runs were generated using the search parameters listed in Table 20. The results of these estimates were that, no blocks were estimated using the second pass i.e. all blocks were estimated using the search parameters of the first pass. The results yielded by the IDW and OK techniques, globally compare favourably to the input composited data (Figure 70). The estimates generated by the GA method are inferior.

Although the OK estimates appear favourable, key kriging metrics such as the kriging efficiency (-0.104) and slope of regression (0.416) raises challenges with the confidence that can be assigned to this technique for this deposit. In recognizing that the 250 m search distance may be creating a search neighbourhood that may be too restrictive, the same exercise was repeated using different ranges.

When a range of 1000 m was used, in line with Case B's neighbourhood, the resultant kriging efficiency and slope of regression were 0.049 and 0.568 respectively. At a range of 750 m, these numbers become 0.036 and 0.530 respectively. When using 2000 m as the search radius, the kriging efficiency values improves to 0.058 with the slope of regression also improving to 0.625. Although increasing the search distance leads to incremental improvements on the efficiency and slope of regression numbers, the results still do not meet the generally accepted minimum requirements for confidence classification. The large search distances are also not in line with the results of the pairwise relative semivariograms.

It is worth pointing out here again that there is a widely held misconception that searching to the range of the variogram is a good strategy for defining neighbourhood. The choice of neighbourhood should be influenced more by the slope of the variogram model at short lags and the relative nugget effect than the ranges per se (Vann et al, 2003). In instances were kriging efficiency is negative, the valuations are practically worthless.



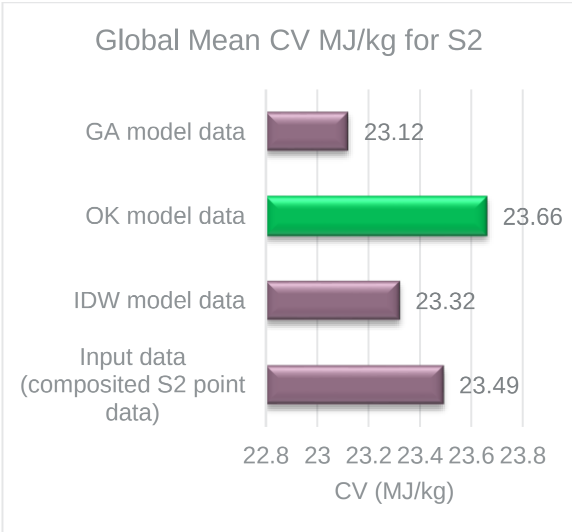


Figure 70: Comparing the input composited data against OK, IDW and GA estimates for Case B

To check whether the poor performance of kriging at this site was due to the search parameters as well as non-stationarity, new variograms over smaller areas were generated and new estimation carried out. Four areas were domained as shown in Figure 71 below.

The results of the subdomains show that on average the range of the experimental semivariogram within this area when using Ash is between 250 m and 600 m. Area 2 shows the longest continuity

(750 m) whilst Area 4 shows the shortest continuity and the highest variance (15.31 $(\%)^2$). The lowest variance (2.86 $(\%)^2$) is present within Area 3.

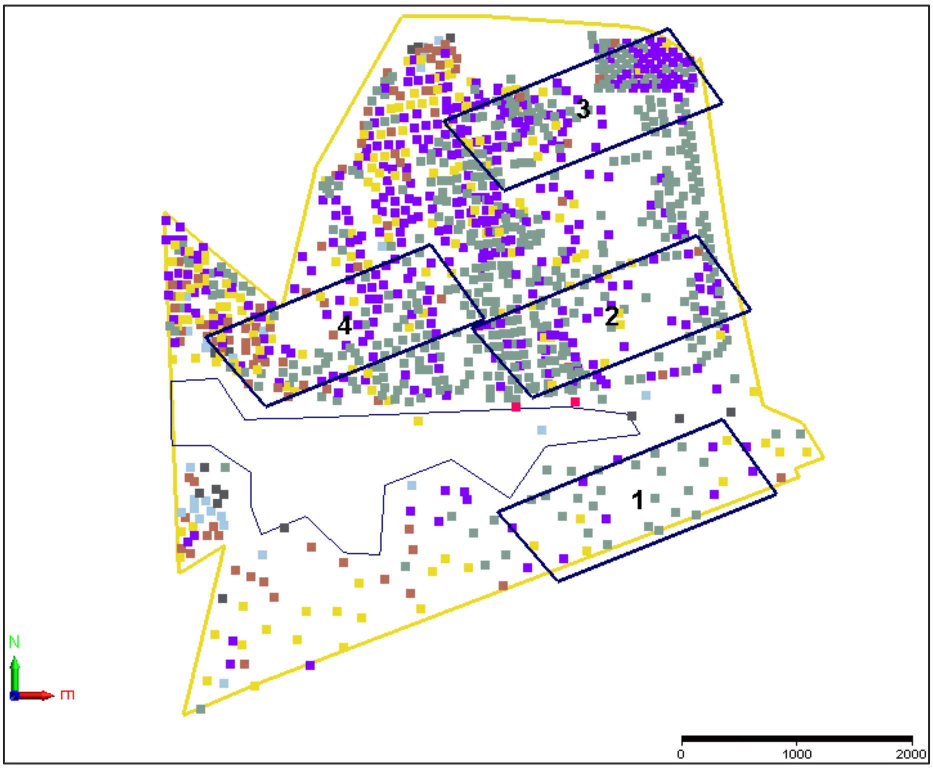


Figure 71: Areas selected for testing stationarity and validating variograms (search parameters)

From the domained variograms, the selected range used for the estimates per area is 600 m. For purposes of simplicity, this was applied across all four areas in order to generate a fair comparison. It is also worth noting that the range is somewhat similar to Case A's. There is no geostatistically valid reason to search beyond 600 m, as this would be incongruent with what the data suggests. The results of the mini-models are presented in Table 22. When the area is sub-domained, it is clear that the results generated from the GA method are superior in terms of estimating the global mean. The slope of regression is greatly improved by reducing the area of estimation and increasing the range in line with the variogram range. The percentage of negative weights is over the acceptable 5% range. Limiting the search neighbourhood and generating new variograms significantly improves the kriging efficiencies. For a Measured category, a minimum kriging efficiency rating of 0.5 is acceptable. Anything between 0.3 and 0.4 is generally classified as Indicated with blocks below 0.3 classified as Inferred (Krige, 1996). Valuations subject to conditional biases result in lower efficiencies and higher error variances and, if used directly for selective mining decisions, can led to serious biases in quality, tonnage and profit estimates (Krige, 1996).

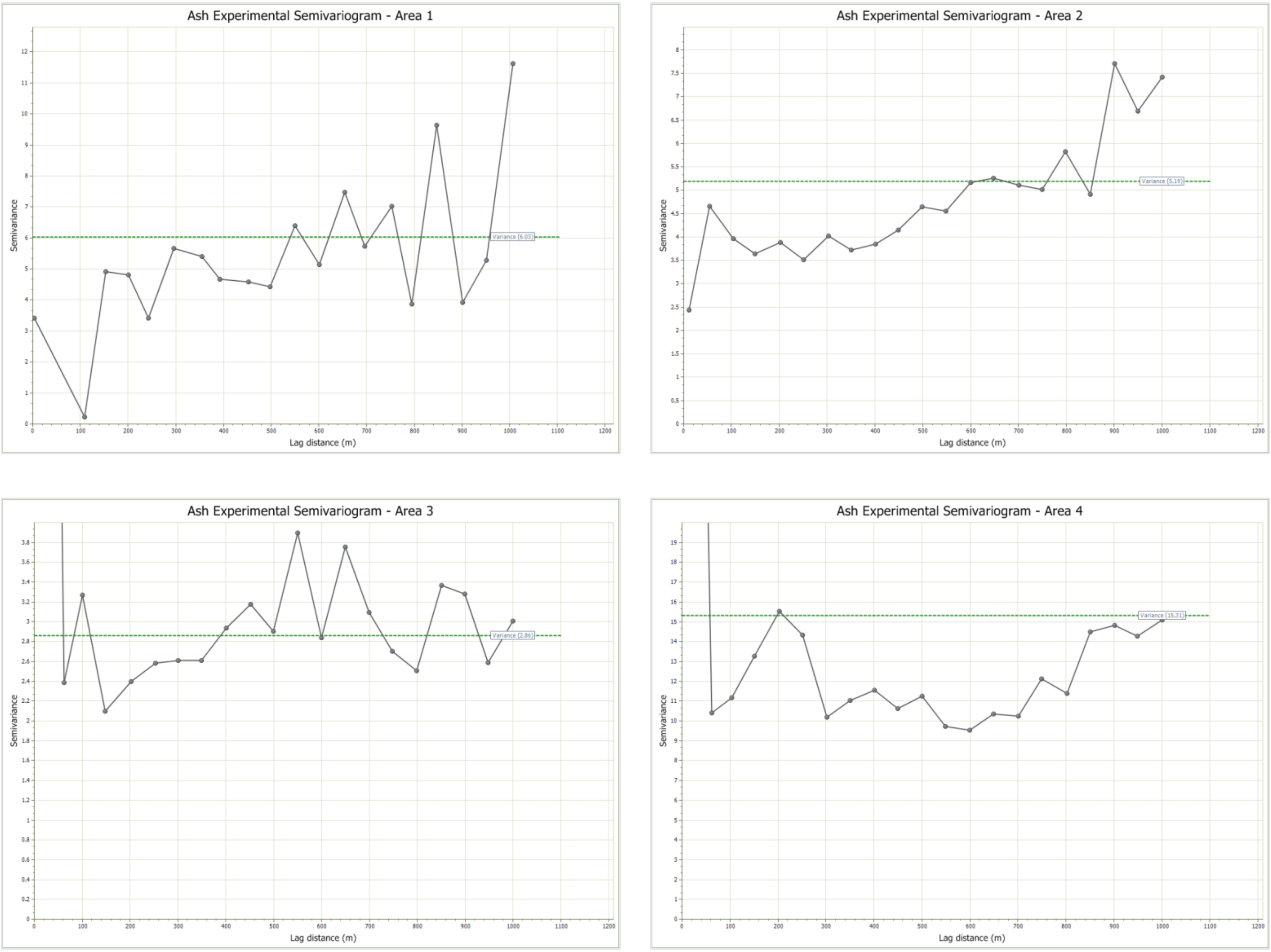


Figure 72: Comparing the range, variances and mean over the whole of Case B area on domain by domain basis (composited data)

Table 22: Range, mean and sill (variance) after domaining the data into 4 areas to test the kriging performance

Areas	N	Variance	Data Mean	Range	Estimated Mean (GA)	Estimated Mean (OK)	Slope	%neg weights	Kriging efficiency
Area 1	32	6.03	22.27	550	22.62	22.25	0.91	31.00	0.46
Area 2	130	5.19	21.41	600	21.77	21.98	0.96	25.88	0.49
Area 3	190	2.86	22.44	400	22.43	22.34	0.94	27.97	0.45
Area 4	126	15.31	23.89	200	23.90	23.50	0.82	9.25	0.13

The final global kriged estimates were generated using a range of 600 m as this improves the kriging efficiency from negative to positive. This changed the kriging efficiency to 0.059. The slope pf regression also improved to 0.637 with the percentage of negative kriging weights remaining below 5 %. The estimated mean Ash% when these parameters are used is 24.07 %, which represents a 1.26 % deterioration in the quality of the global mean estimate. Greater efficiencies correlate positively with the slope of regression. Poor efficiencies correspond to poor spatial structures and low numbers of data accessed. As the structures strengthen and more data is used the results move up along the curve to higher levels of efficiencies (Figure 73).

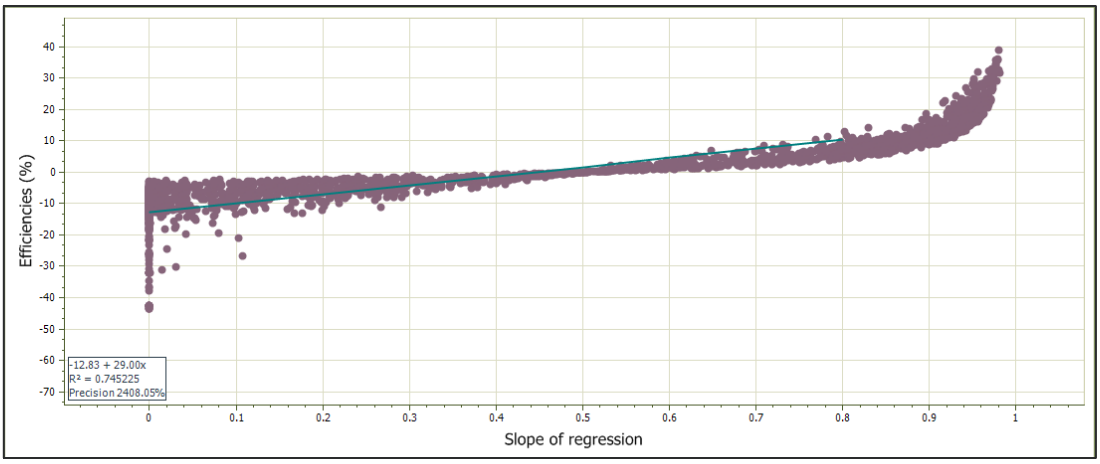


Figure 73: Showing correlation between efficiencies of estimated blocks and regression slopes

4.8.1 Comparing IDW to Ordinary Kriging results

The correlation between IDW and OK when using QQ plots with 10 quantiles is shown in Figure 74. The correlation coefficient between the two models shows an almost perfect correlation. The estimated global means for Ash are 24.13 % and 24.07 % for IDW and OK respectively.

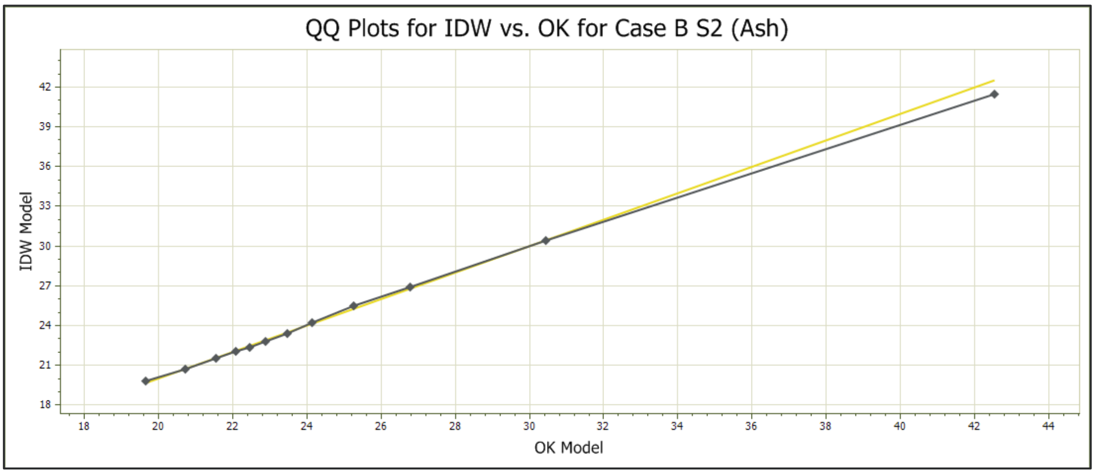


Figure 74: A QQ plot for IDW model vs. OK model for Case B (Ash)

The results for CV are similar to Ash. The two methods are highly comparable at the different qualities.

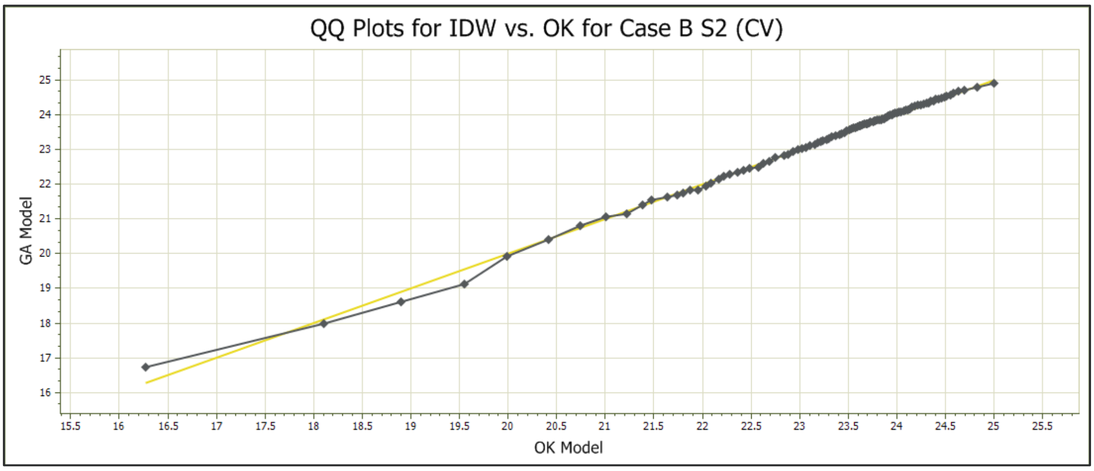


Figure 75: A QQ plot for IDW model vs. OK model for Case B (CV)

In order to compare the results of OK to GA, a Minex grid originally created on a 20 m x 20 m grid was re-blocked using Micromine to a 100 m x 100 m grid to allow for direct comparison. In undertaking this process, the original file was modified (change of support) resulting in a slight drop in the mean quality value from 34.77 % to 34.24 % (1.5 % percentage drop in mean grade). The comparison between the GA method of interpolation generated in Minex against OK (Micromine generated) shows a correlation coefficient of close to 1 with a rank correlation of exactly 1 (Figure 76). Overall, OK better reflects the original data by relatively fine margins. The comparison between GA and OK for CV is less optimal than that of Ash with a 2.6 % reduction (Figure 77).

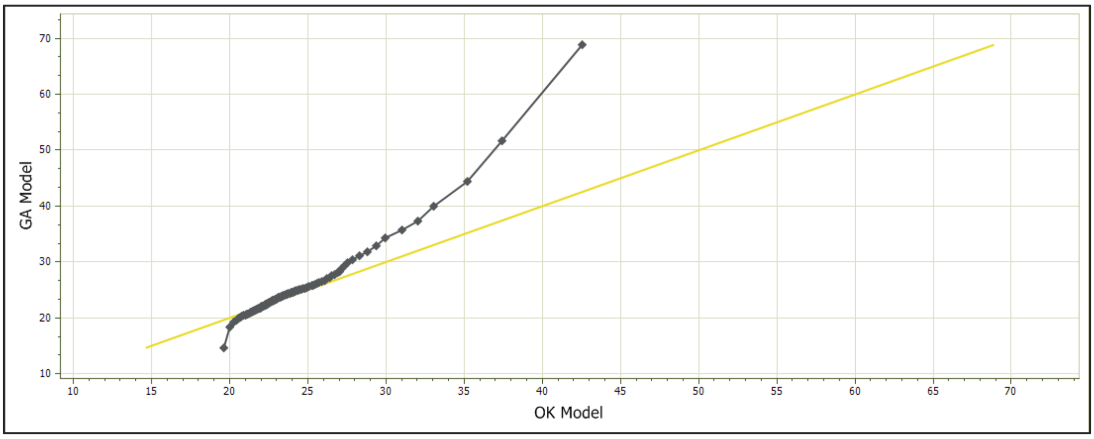


Figure 76: A QQ plot for GA model vs. OK model for Case B (Ash)

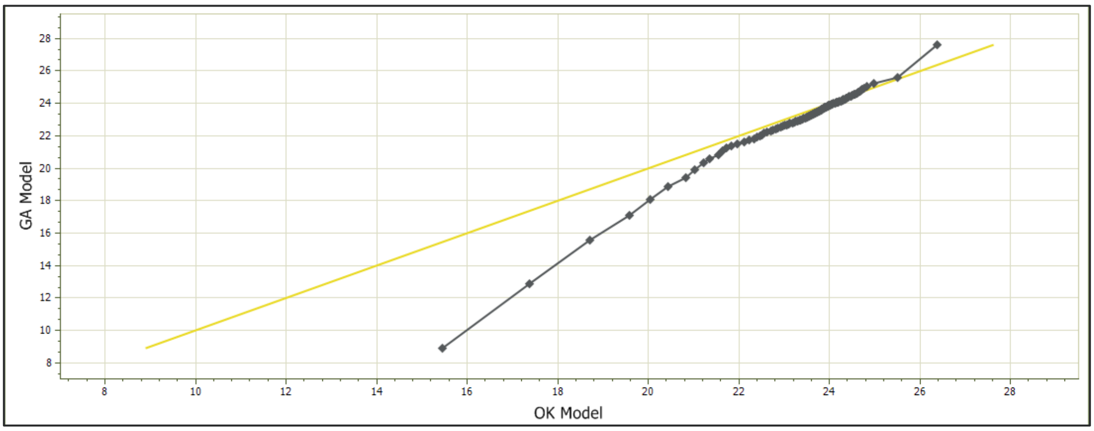


Figure 77: A QQ plot for IDW model vs. OK model for Case B (CV)

4.9 Using the Global Estimation Variance to undertake Drill Hole Spacing Analysis

New semivariograms were generated for the Global Estimation Variance exercise as shown in Figure 78 & Figure 79. The ranges of the two areas are 500 m and 650 m, which align with the results presented above. It is further demonstrated that the range of geological continuity at Case B is around 600 m.

The results of this exercise show that for Areas A and B, the estimation precisions remain within 10 % when drill holes are spaced 1400 m and 1000 m respectively (Figure 81 and Figure 82). For a 5 % precision estimate the spacing needs to be at 600 m and 400 m respectively. What this shows is that both Cases A and B show similar patterns of estimation precision. Whilst the first case used Ash as the variable of interest, Case B uses CV but still yields comparable results.

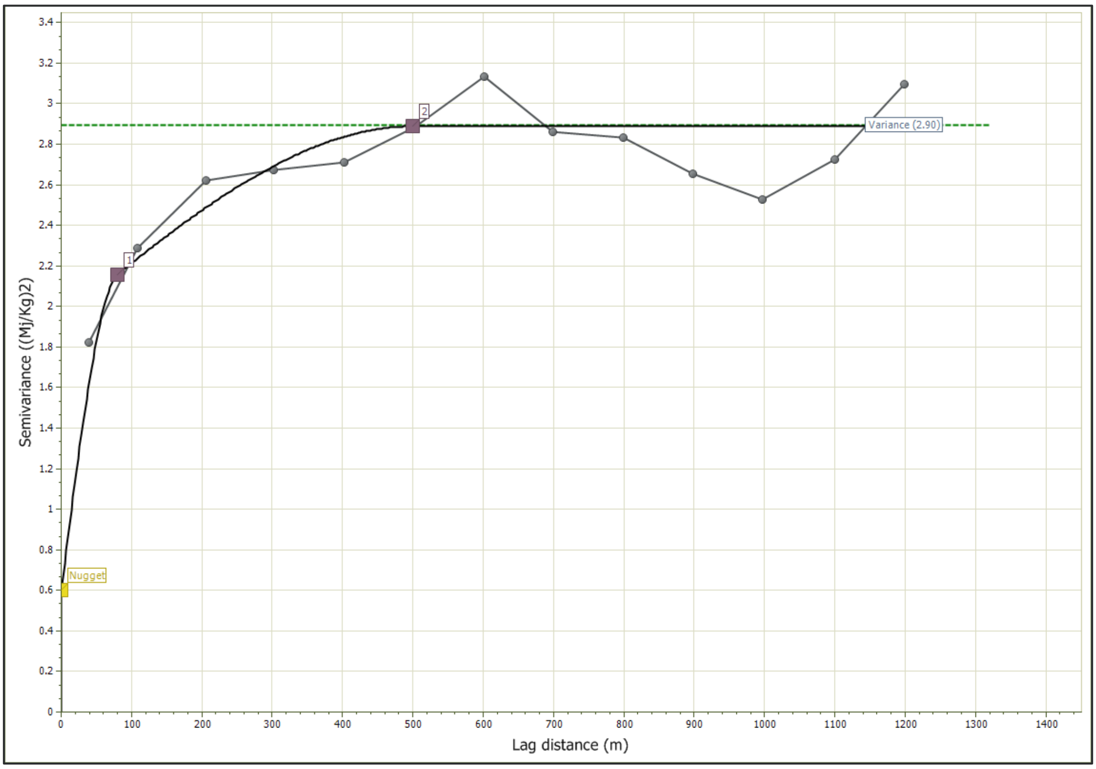


Figure 78: Semivariogram - GEV Area B – CV (composited data)

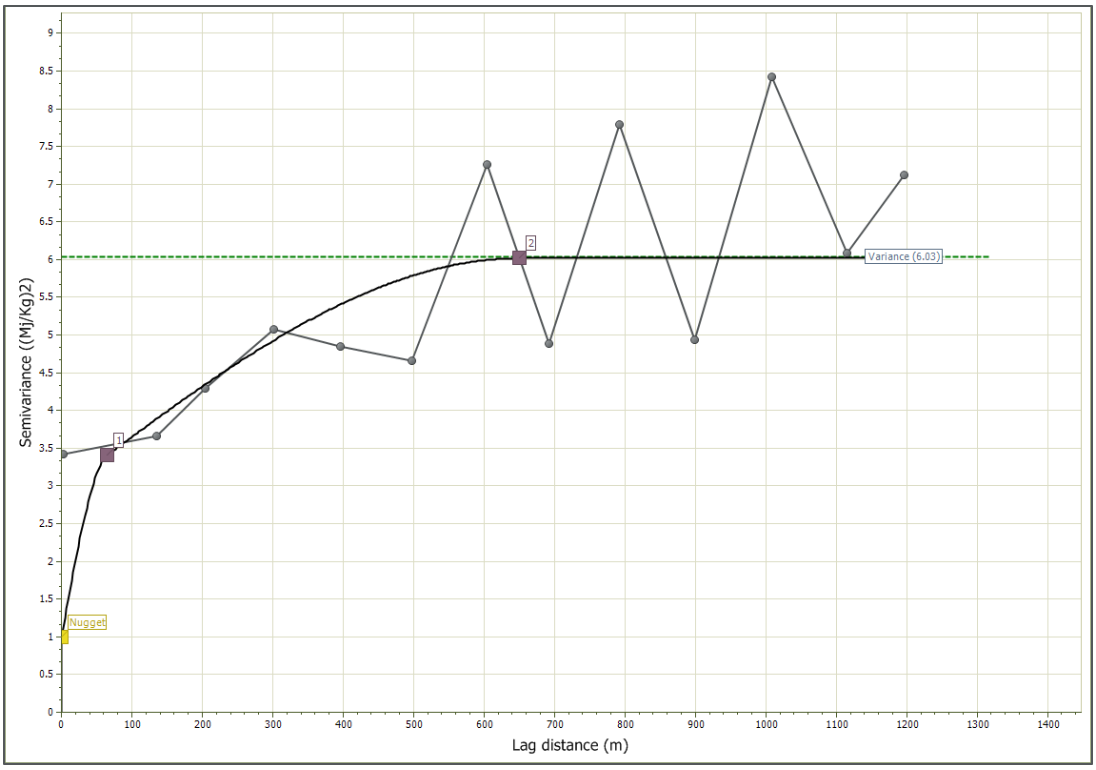


Figure 79: Semivariogram - GEV Area B – CV (composited data)

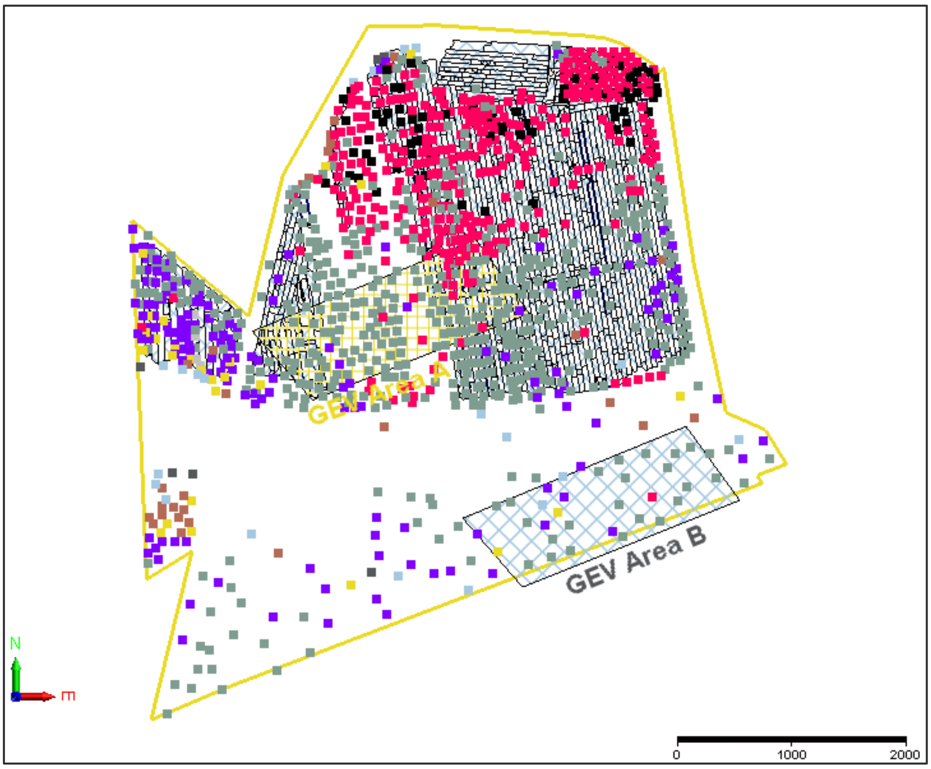


Figure 80: Global Estimation Variance calculation areas to determine drill hole spacing for Case B S2

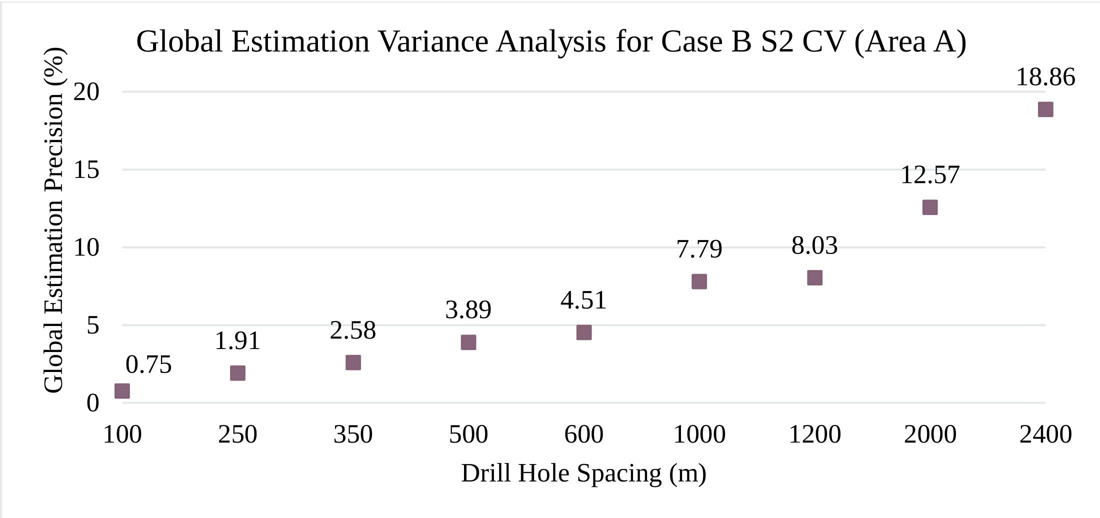


Figure 81: DHSA results for CASE B S2 CV – Area A

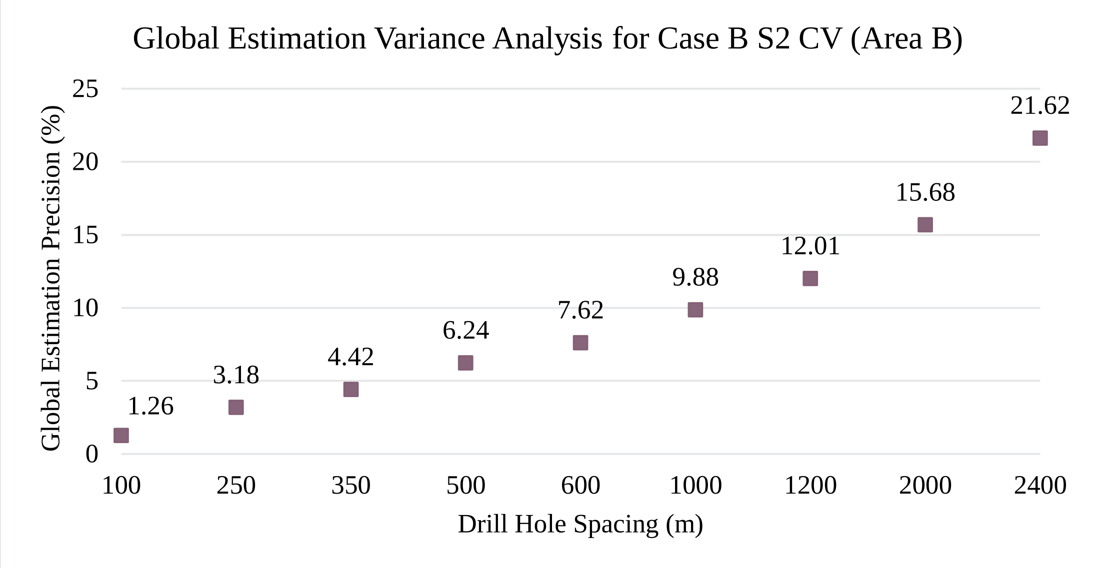


Figure 82: DHSA results for CASE B S2 CV – Area B

The result equates to an approximate 95 % confidence interval versus a drilling spacing for the corresponding area.

4.10 Resource Classification Matrix/Criteria

Similar to Case A, the following matrix was developed for the classification of the Case B deposit (Table 23).

Table 23: Proposed classification matrix for Case B

	Measured	Indicated	Inferred	
Regression Slope	>0.9	>0.8	<0.8	Used
Kriging efficiency	>0.5	>0.3	<0.3	Too low
Number of samples	≥8	≥4	≥1	Used
Estimation Precision	10 %	10 - 20 %	20 %	Suggested

The mean kriging efficiency for Case B is 0.016 (Figure 83) with a relatively low maximum of 0.388. The mean slope of regression is 0.5. This is further illustrated in Figure 84. When using a search radius of 600 m (Figure 85) almost all of Case B uses greater or equal to eight samples per block.

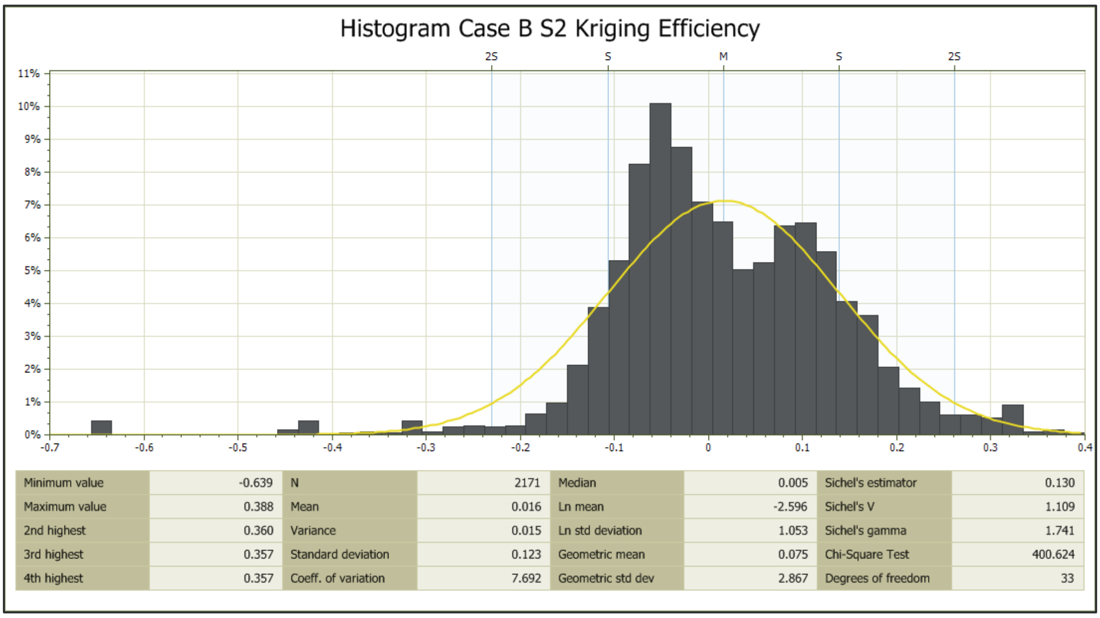
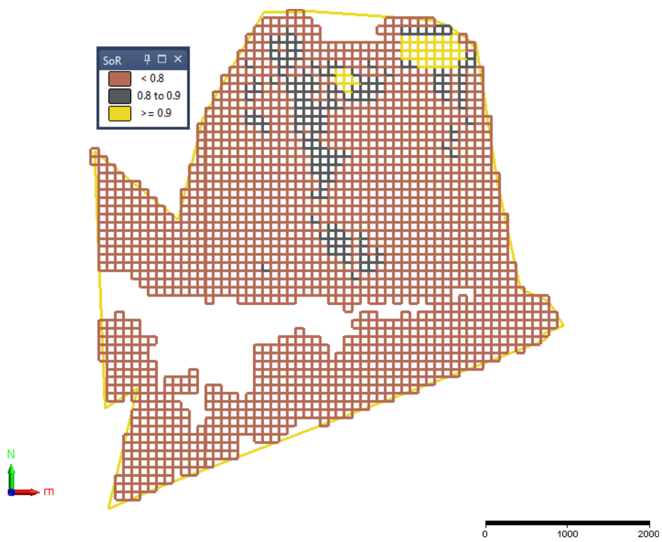


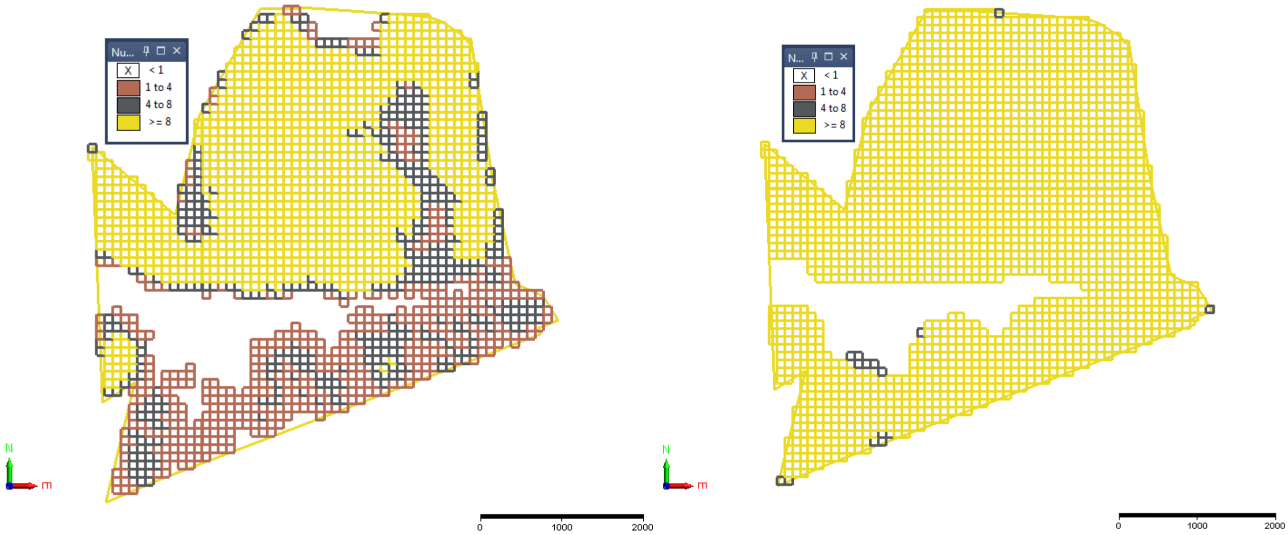
Figure 83: Histogram of kriging efficiency for S2 OK Model



(a) Slope of regression when using a search radius of 250 m

(b) Slope of regression when using a search radius of 600 m

Figure 84: Slope of regression plot for S2 Case B



(a) Number of points used per block when using a search radius of 250 m

(b) Number of points used per block when using a search radius of 600 m

Figure 85: Number of samples used to estimate a block

The following aspects of estimation arise from the analysis of Case B;

- For this deposit, the Growth Algorithm method performed better than both OK and IDW over the global area when looking at the mean CV, Ash and thickness of the estimate against the average of the input data.
- There is no discernible difference between IDW and OK and thus, IDW should be the preferred option over OK.
- The kriging efficiencies scores for the entire deposit are low, i.e. averaging 0.016, which makes the use of OK challenging.
- Case B's deposit is mostly Measured (when looking at number of samples in isolation) and arguably over drilled for global estimation and reporting purposes. When looking at the slope of regression performance, it is clear that towards the South of the property, more drill holes would help in improving the results.
- The size of the property i.e. 22 km^2 introduces issues of data stationarity. As a result, generating spherical variograms becomes a challenge unless the area is domained into smaller areas. Geostatistics can be used over smaller areas. Without domaining the property, a different estimation technique needs to be considered.

5 CONCLUSIONS

This study set out to assess a multiplicity of related questions regarding the applicability of geostatistical principles, practices and techniques to the estimation, classification and reporting of Coal Resources. For the considered cases, in the recent past, Coal Resources have always been estimated using the GA technique primarily in the Minex software. A few exercises have in the past been undertaken to investigate whether a technique such as OK could be applied. Most practitioners hold the 'belief' that OK is always a superior estimation method by definition. The other factor, which contributes to this assertion and rightfully so, is that through OK, errors associated with estimating the grade or quality of a block can be quantified. Other techniques such as IDW and in the case of coal the GA are generally good estimators but they fail to provide useful additional information such as kriging efficiency, slope of regression, estimation error and precision.

The second part of the problem statement was to evaluate whether the current drill hole spacing recommended by the SANS 10320:2004 standard is appropriate for the considered cases. To answer this question, global estimation variances (estimation precision) per drill grid were calculated. SANS 10320:2004 provides that for a Measured, Indicated and Inferred classification, samples should be spaced at 200 m (minimum of 8 samples), 282 m (minimum of 4 samples) and 564 m (minimum of 1 sample) apart respectively. By quantifying the precision associated with estimating the two cases at different drill grids, it was shown that for both Cases A and B, a Measured Resource can be classified by using drill holes that are spaced approximately 1000 m apart. This assumes that the accepted tolerance on coal qualities for an estimated block is ±10 %. If however the desired precision is 5% then a spacing of between 600 m and 800 m would achieve the result. It was established that precision results associated with the global estimation variance are only applicable to the area in which the study was undertaken i.e. the findings are not globally applicable although rough approximations can be deduced.

When the drill hole spacing analysis (DHSA) technique was trialled in the Bowen Basin, Queensland, similar results were obtained. It is worth noting that the spacings determined through geostatistical means are sufficient for global estimation and reporting purposes. For short-term mine planning purposes, further drilling may and is usually required. The guidelines provided in the SANS 10320:2004 standard are evidently too stringent for both Cases A and B. The recommendations made in the Australian Coal Guidelines (2003) which have always been viewed in the South African context as being too 'lenient' are closer to the findings from this study. Therefore, a drill spacing of 500 m, 1000 m and 4000 m should be considered as being more appropriate than the current overly tight spacing, for the two cases considered.

With regard to the use of OK, the findings of this study clearly show that the current GA technique is more appropriate than other alternatives i.e. OK or IDW as it outperformed both whether on a global or local scale. The value of using OK lies in its ability to determine an appropriate search neighbourhood. The complexity that the technique introduces to an estimate far outweighs any potential benefits. For Case B in particular, with different kriging neighbourhoods, the resultant kriging efficiencies and other kriging metrics were considerably poorer. IDW is a far easier and reproducible technique to use and has a 1:1 correlation to OK and thus should always be considered first before OK, as it is less onerous and more reproducible.

Coal deposits tend to be expansive in nature as is the case for both study areas. As a result, achieving homogeneity across an entire deposit is demonstrably difficult. One of the fundamental requirements before OK can be considered is that the regionalized variables must be stationary. Generating one experimental variogram across an entire mine/project boundary shows that the deposit as a whole has a non-stationarity problem, which renders the application of geostatistics pointless. The only way to get around this is to divide the area into domains and estimate them as sub-domains. This was done for Case B with the result still inferior to that achieved by the GA technique. Domaining did however achieve some level of stationarity with ranges up to 600 m and slope of regression of above 0.9. Some of the reasons why the GA technique should be retained in favour of OK are;

- It is fairly quick and easy to set up the estimation parameters with no need for elaborate kriging neighbourhood analysis.
- Like IDW, the results are more repeatable whereas the potentially subjective nature of variogram modelling in kriging means that results may vary.
- The level of knowledge required in modelling variograms and setting up kriging parameters introduces risk in that if the practitioner is not well skilled and experienced, could cause bias to the estimates.
- The selection of the appropriate block size to be estimated is an important consideration in OK; GA is not sensitive to this making the estimates more robust and repeatable.

- Non-stationarity of the data over large study areas means that there are considerable limitations to the application of Geostatistical methods.
- Given that the use of the GA method does not promote robust statistical analysis and QKNA, coal Competent Persons would benefit from applying geostatistical methods in their analyses and using other methods of estimation in addition to the GA method. Furthermore, due consideration should be given to clearly marking different geological domains to further improve estimation results for OK and GA,

The current estimation method used for the considered cases is appropriate i.e. Minex's GA outperforms both OK and IDW. The current drill grids are too small for global estimation and reporting and thus the organization is possibly overspending if the required estimation precision is between 5 and 10 %. At the current drill spacing, precision is around 2 % within 'Measured' areas, which is more than what is required to produce predictable long-term plans.

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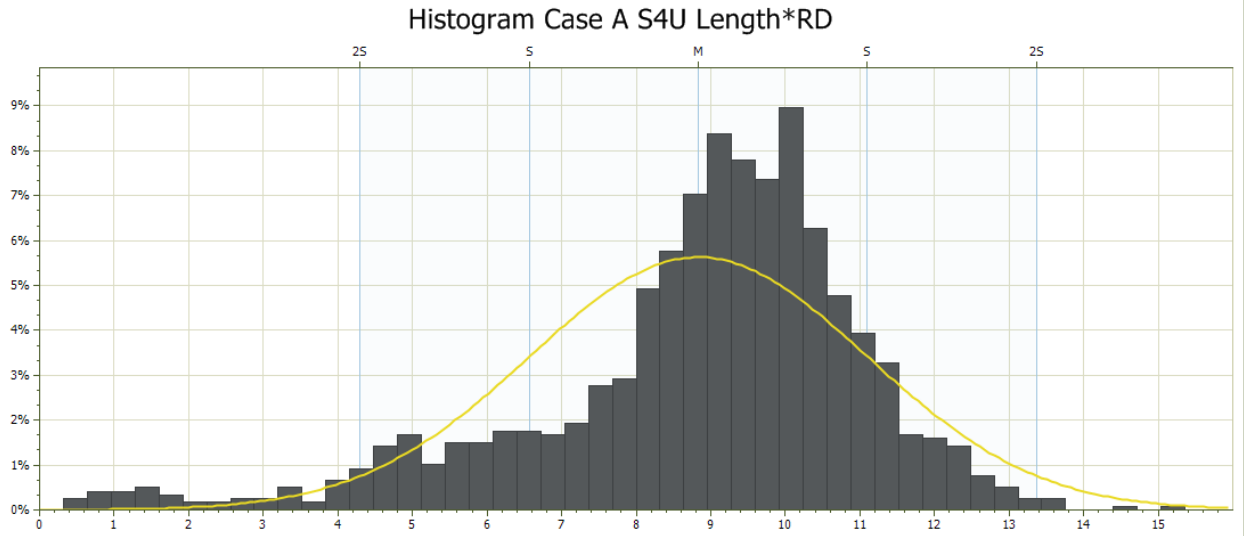
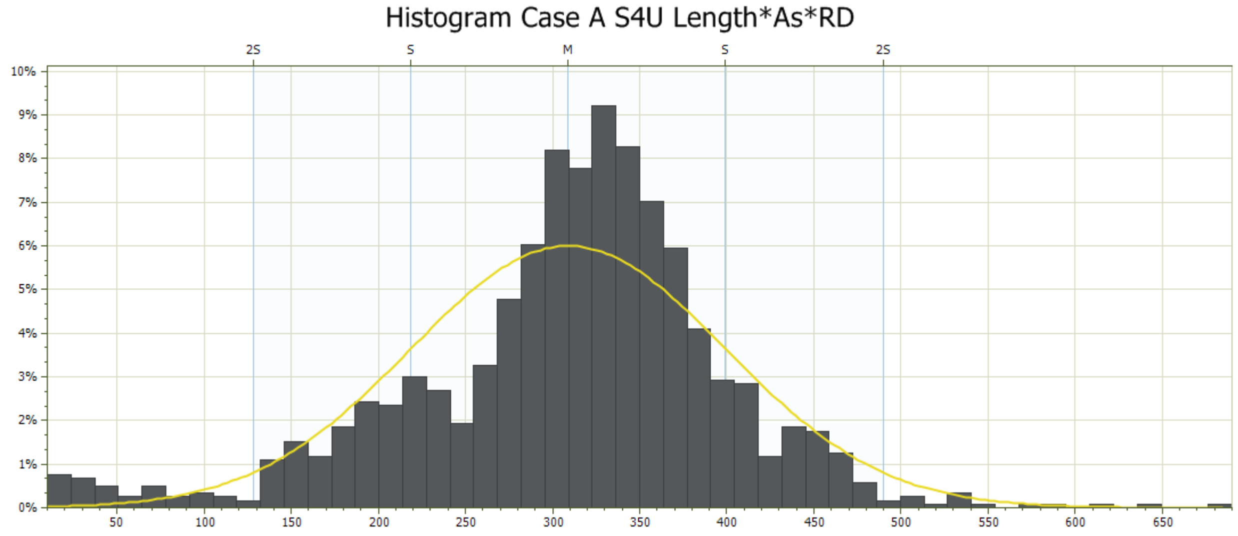
7 APPENDIX

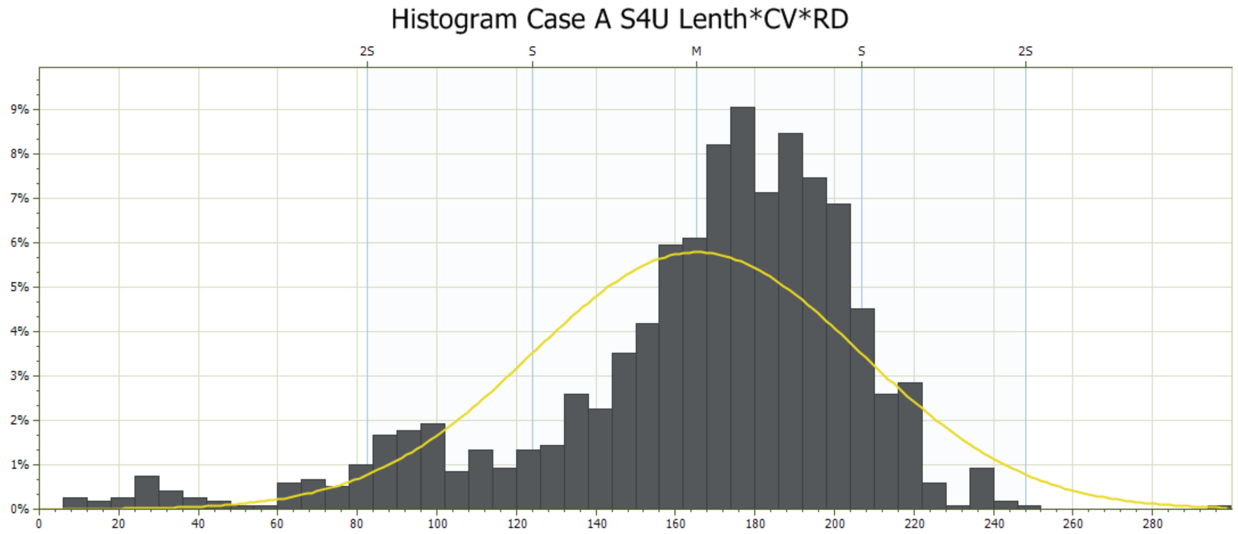
Appendix 1: Basic Statistical analysis of the Accumulated Ash and CV variables for Case A



Minimum value	0.370	N	1195	Median	9.242	Sichel's estimator	9.048
Maximum value	15.142	Mean	8.835	Ln mean	2.124	Sichel's V	0.158
2nd highest	14.412	Variance	5.138	Ln std deviation	0.398	Sichel's gamma	1.082
3rd highest	13.728	Standard deviation	2.267	Geometric mean	8.360	Chi-Square Test	361.955
4th highest	13.717	Coeff. of variation	0.257	Geometric std dev	1.488	Degrees of freedom	37



Minimum value	14.406	N	1195	Median	320.233	Sichel's estimator	319.116
Maximum value	680.841	Mean	308.960	Ln mean	5.663	Sichel's V	0.205
2nd highest	646.898	Variance	8164.720	Ln std deviation	0.453	Sichel's gamma	1.108
3rd highest	617.098	Standard deviation	90.359	Geometric mean	288.015	Chi-Square Test	267.341
4th highest	594.524	Coeff. of variation	0.292	Geometric std dev	1.573	Degrees of freedom	34



Minimum value	6.350	N	1195	Median	174.600	Sichel's estimator	168.974
Maximum value	296.799	Mean	165.376	Ln mean	5.056	Sichel's V	0.147
2nd highest	249.213	Variance	1712.321	Ln std deviation	0.384	Sichel's gamma	1.076
3rd highest	244.810	Standard deviation	41.380	Geometric mean	156.981	Chi-Square Test	501.314
4th highest	242.557	Coeff. of variation	0.250	Geometric std dev	1.468	Degrees of freedom	36