LOCAL RECOVERABLE ESTIMATION: A CASE STUDY IN UNIFORM CONDITIONING ON THE WANDOO PROJECT FOR BODDINGTON GOLD MINE

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Abstract

A practical case study for estimation of the large, low grade Wandoo deposit at Boddington Gold Mine is presented. This was broken down into seven zones, primarily by geology. One of these zones was a higher grade vein set that could be solid modelled and estimated separately. A geological mineralisation envelope was applied to constrain the estimation. This represented a broad, relatively continuous envelope in keeping with the geology of the orebody and was loosely based on a 0.1 g/t Au cut-off. Data was composited to 9m to reflect the intended mining bench height and the true variability expected from those benches. Waste dykes were only excluded from this compositing if they were considered large enough to be practically avoided when mining. Variograms of the composited data were not particularly clear for either Au or Cu, and a Gaussian transform was applied to help determine a model. Gold and copper do not exhibit the same anisotropy and there is significant variability at less than, or equal to ,the average drill spacing. Tests were conducted to determine the suitability of the Gaussian approach. This approach best represents a "diffusion model" of spatial continuity. These tests indicated that the Gaussian approach was suitable at Wandoo. A global evaluation of resources was carried out using the Discrete Gaussian Model. This was a first quick estimate of resources at cut-off that was useful as an order of magnitude check on the final local estimates. There was a requirement to represent selectivity in mining for a local resource estimate. It was unrealistic to try to achieve this by directly estimating such a small block size taking into consideration the average drillhole spacing. Therefore, the technique of Uniform Conditioning was applied to calculate the expected proportions above a cut-off. Previous experience has shown that this is a relatively robust method.

Key Words: uniform conditioning, non-linear estimation, Discrete Gaussian Model, mining selectivity.

Introduction

Study data are from the Wandoo deposit at Boddington Gold Mine (BGM), located approximately 130 km southeast of Perth, Western Australia. The numbers present have been modified for confidentiality.

Mineralisation is hosted by intermediate volcanic and intrusive rocks of the Archaean Saddleback Greenstone Belt. Unmineralised dolerite dykes transect the sequence. The estimation area has been broken up into seven distinct geological zones. One of these zones consists of two solid modelled, steeply-dipping actinolite veins a few metres wide. These are generally associated with higher grades. The estimation was confined to unoxidised host rocks.

Data

There are 2589 drillholes with over 118000 samples, mostly on 2m lengths, from diamond (DDH) and reverse circulation (RC) drilling (Figure 1). These were coded for rock type and zone. Exploration holes are variously spaced, but average a 25m x 25m spacing, with some zones drilled more sparsely. Inclinations vary from vertical to sub-horizontal. Hole azimuths also vary widely. A 25m x 25m x 9m block model was supplied, defining the geological zones, blocks to be estimated and rock type. This block size was chosen from the data spacing and mining considerations. Smaller blocks could not be used without possibly serious under-estimation of the variability (Vann and Guibal, 1998).

An outer boundary to possible mineralisation was created by BGM geologists at a 0.1 g/t Au cut-off. This boundary was relatively insensitive to increases in cut-off up to approximately 0.5 g/t Au. An advantage of defining the outer boundary at a "geological" cut-off was that it allowed the application of different mining cut-offs within this boundary. Conversely, estimating with a high mining cut-off initially would probably require re-estimation if lower cut-offs were subsequently contemplated.

It is very important in estimation to work with equal support (volume) samples. This is why the data were composited to equal lengths. A bench height of 9m was envisaged, therefore the samples were composited to that length along drillholes within the geological envelope (excluding defined, barren dolerite samples) to best represent real 9m bench variability. For this estimation, some dolerite was considered as unavoidably mined, and included. Dykes that were large enough to be easily excluded when mining, were excluded from compositing and estimation. Not to do so may bias the estimation.

In gold, the effect of outlying values is usually significant and some approach must be taken to account for these. There is no single accepted method for determining "upper cuts" with theoretical justification available, and no strong argument to choose one method over another. A final cut of 40 g/t Au was employed.

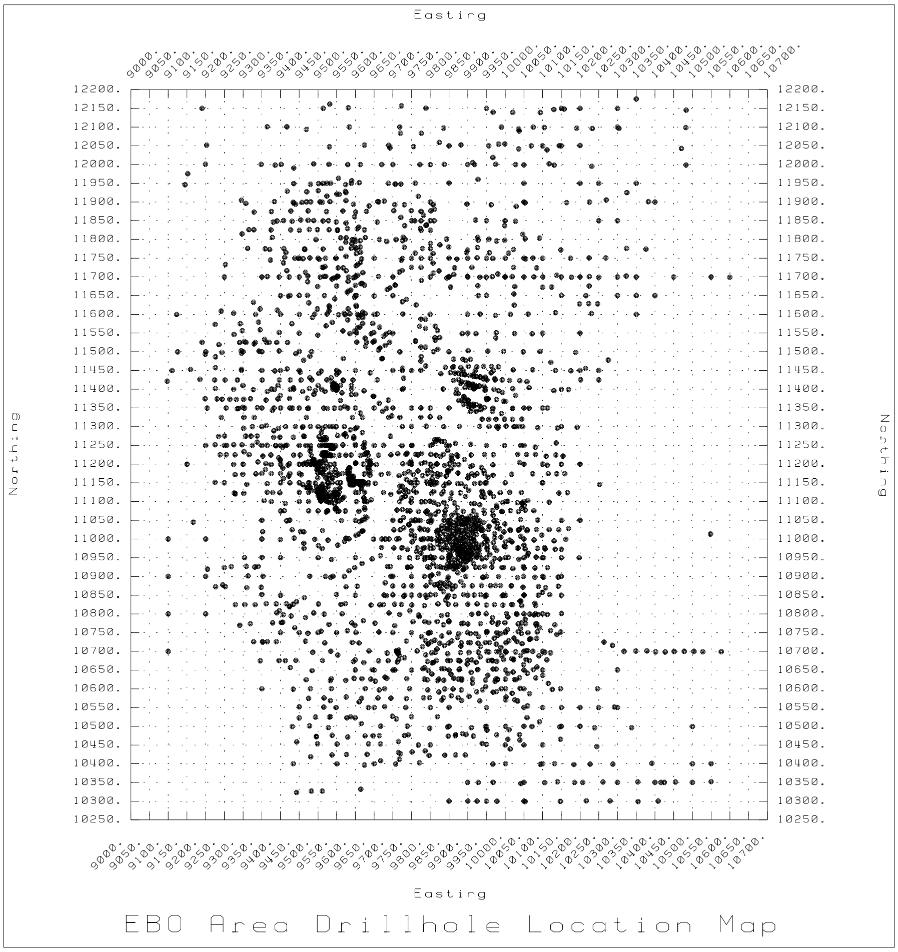

Figure 1 Drillhole Location Map

Two tests for sensitivity of grade variability to cut-off were carried out (Figure 2) in each zone. These showed that (i) "removing" approximately the highest 10 values, and (ii) employing an upper cut of around 40 g/t Au, both reduced the outlier effect significantly.

RC and DDH composites were compared in an area that was adequately covered by both datasets. Tests showed little difference in the statistical characteristics. This, along with the greater volume of RC drilling, led to the decision to keep both sets of data for the estimation. Combining data types should not be an automatic decision, but one consciously made with supporting results.

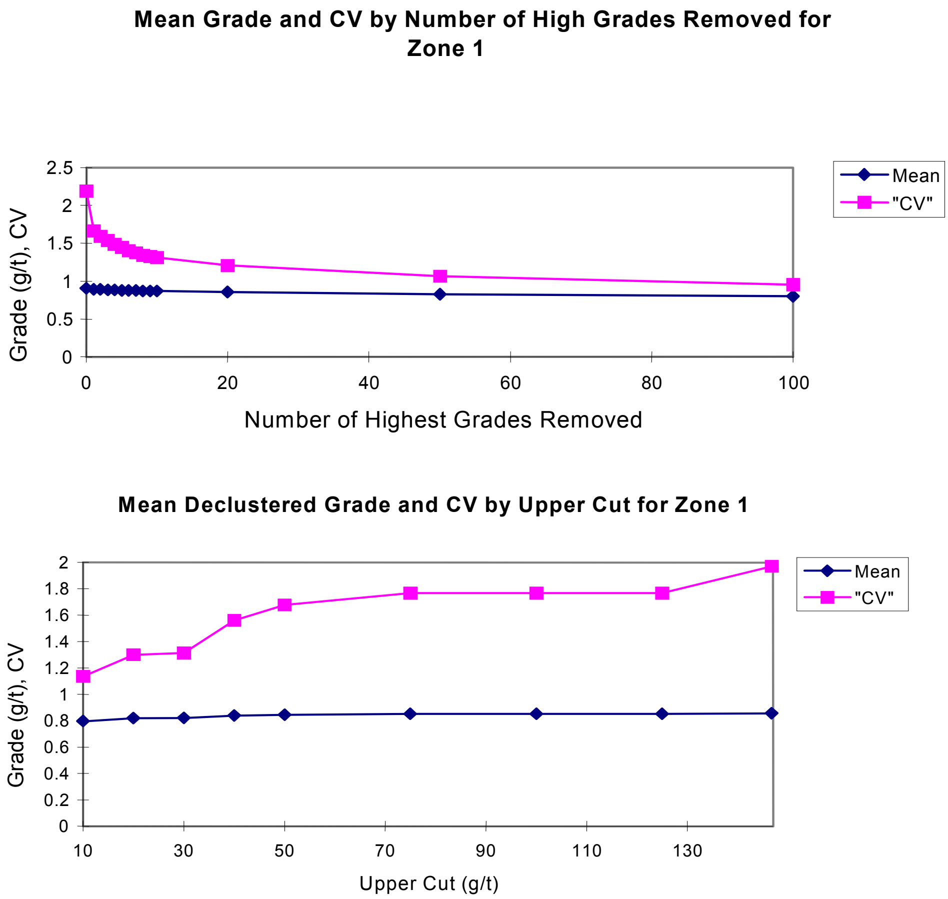

Figure 2 Sensitivity tests to cut-off grade

The spatial distribution of data is not uniform due to an irregular drilling grid, varied length and inclination of holes. There fore we used a Declustering (weighting) procedure so that statistics were not biased by preferential spatial position (eg many close-spaced holes in a high grade area). This does not decrease the number of composites used, but simply weights the histogram to produce an unbiased mean and variance. A simple Declustering usees the number of points in a block but we required the more accurate method using kriging weights – which is far more time consuming. Table 1 shows the weighted means and variances compared to the original statistics. The weighted variances and means are generally lower than the unweighted statistics.

Au	**Zone 1**	**Zone 2**	**Zone 3**	**Zone 4**	**Zone 5**	**Zone 6**	**Zone 7**
Number	8460	4240	3339	1178	2078	776	129
Mean	1.14	0.64	0.88	0.48	1.21	1.20	10.17
Variance	2.82	0.79	4.06	0.54	4.14	11.22	168.7
Weighted Mean	1.07	0.64	0.66	0.43	0.91	0.87	8.78
Weighted Variance	2.15	1.30	2.02	0.32	2.21	3.35	134.9
Cu	**Zone 1**	**Zone 2**	**Zone 3**	**Zone 4**	**Zone 5**	**Zone 6**	**Zone 7**
Mean	1416.2	1650.9	1057.9	646.5	503.1	1556.9	2234.6
Variance	1546842	1572393	1256807	272742	318646	1233720	3177538
Weighted Mean	1472.1	1599.7	939.9	645.1	511.0	1409.3	1905.5
Weighted Variance	1536447	1592774	921811	297998	265296	1100511	2766932

Variograms were then calculated for Au and Cu in each of the zones on the 9m composites. These were not particularly clear and a Gaussian transform was employed to help define the underlying structure. Calculation of the Gaussian transform utilised the Declustering weights previously discussed. Variograms of the Gaussian transformed data presented clearer structures and were more easily modelled. Models were fitted in consultation with BGM geologists taking into account the known geological and mineralisation trends (see Figures 3 and 4). Models for the Gaussian variables were then transformed back to models on the raw data which will now reflect the declustered 3D spatial variability.

The Gaussian transform is very powerful, and is part of the Discrete Gaussian method (diffusion methods). It is the only method having a built-in change of support to reflect a deskewing of the histogram for different volumes (eg samples versus blocks).

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Three tests were conducted to see whether the Discrete Gaussian Model was applicable at Wandoo as follows:

1. checking indicator residuals (see Rivoirard, 1994, for example). If these show some spatial correlation (as seen in cross variograms) then a Gaussian approach is justified.

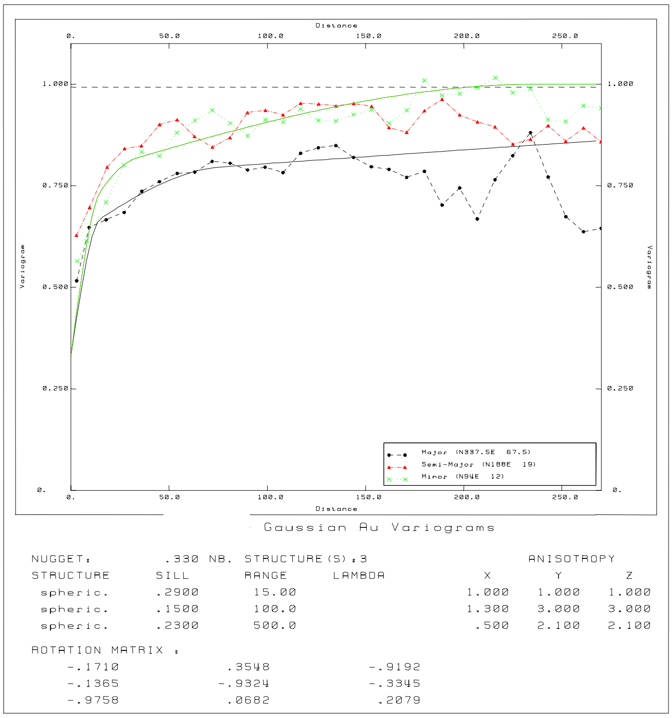
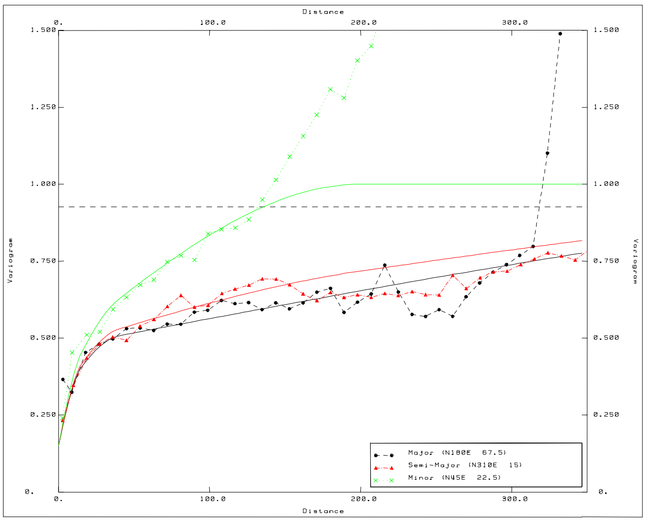


Figure 3 Zone 1 Gaussian Au Variograms



: Gaussian Cu Variograms

NUGGET, .150 NB. STRUCTURE(S), 4

STRUCTURE	SILL	RANGE	LAMBDA	ANISOTROPY X	Y	Z
spheric.	.1500	15.00		1.000	1.000	1.000
spheric.	.1700	40.00		1.000	1.000	1.000
spheric.	.1000	300.0		.350	1.500	1.500
spheric.	.4300	300.0		.350	.350	1.500

ROTATION MATRIX :

.0203	-.3931	-.9193
.7332	-.6192	.2810
-.6797	-.6797	.2756

Figure 4 Zone 1 Gaussian Cu Variograms

2. Using the Deutsch and Lewis normalised indicator approach. If the Gaussian reconstructed indicator variograms are the same as those calculated immediately from the data, then the Gaussian approach is justified (see Figure 5).
3. Checking ratios of indicator variograms. If the ratio of cross variogram to variogram increases with distance, then a diffusion or Discrete Gaussian Model is applicable (see Figure 6).

All these conditions were satisfied (see Figures 5 and 6).

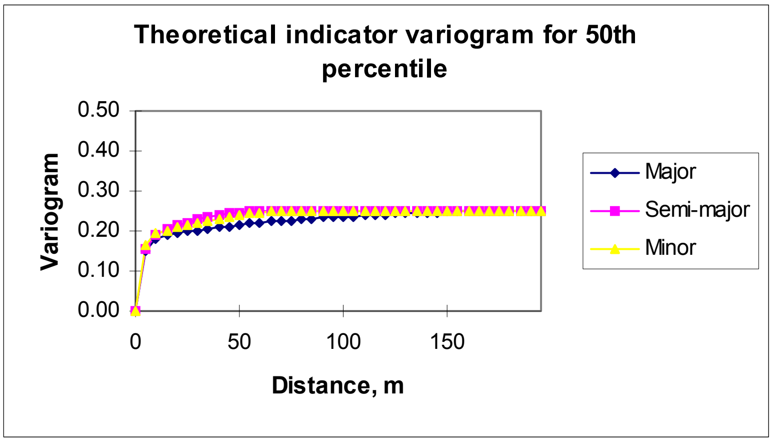


Figure 5a Gaussian reconstructed indicator variograms (test 2)

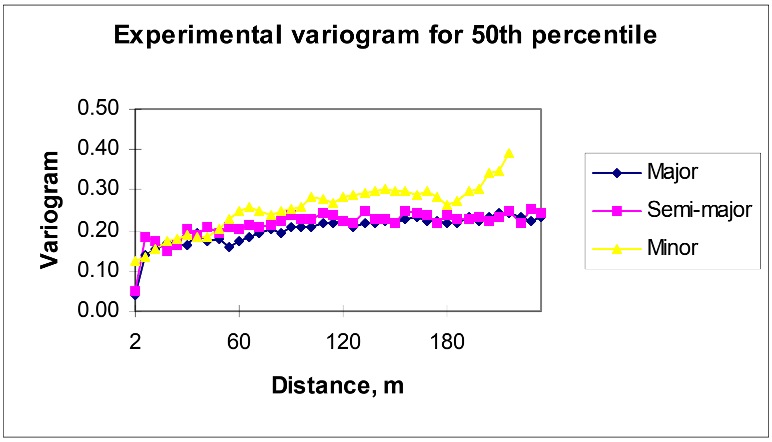


Figure 5b Indicator variograms (test 2)

Figure 6 Indicator variogram ratio test for Zone 3 (test 3)

Knowing that the Discrete Gaussian Model was applicable a global estimate was made (see also Vann and Sans, 1995 or Guibal, 1987). By modelling the composite histogram and knowing the Gaussian transform function, the histogram of any size block that we want to consider for estimation can be obtained. This gives a prediction of the global tonnes and grade above a cut-off and is a good first pass approximation to a local result.

The last step before local estimation is to test the estimation/neighbourhood parameters. This is important and is all too rarely performed. A consequence of not testing and using too small a neighbourhood would be a biased, poor quality and badly representative estimate. Many different configurations were tested and results compared for estimation variance, bias (slope of the regression of true value with the estimated value) and weight of the mean (a measure of the need for closer spaced and/or more data in the neighbourhood). For further discussion see Armstrong and Champigny (1989), Krige (1994, 1996a, 1996b and 1997), Ravenscroft and Armstrong (1990) and Royle (1979).

Examining the kriging weights can also help determine if large negative weights or other possible problems exists. Table 2 shows some results. It is desirable that the weight of the mean is below 10%, the slope of the regression is close to 1.0 (above 0.9 is preferable) and that estimation variance is minimised.

Table 2 Kriging Neighbourhood Test Results for Zone 1

Sample grid	25 x 25 x 9	25 x 25 x 9	25 x 25 x 9	25 x 25 x 9	25 x 25 x 9	25 x 25 x 9	25 x 25 x 9	25 x 25 x 9
No. of informing composites	3 x 3 x 5	3 x 3 x 7	3 x 3 x 9	3 x 3 x 11	3 x 5 x 5	3 x 5 x 7	3 x 5 x 9	3 x 5 x 11
Estimated block size	25 x 25 x 9	25 x 25 x 9	25 x 25 x 9	25 x 25 x 9	25 x 25 x 9	25 x 25 x 9	25 x 25 x 9	25 x 25 x 9
Ordinary kriging result								
Estimation variance	0.0971	0.0911	0.0886	0.0874	0.0937	0.0893	0.0874	0.0866
Slope of the regression Z/ZE	0.9029	0.9382	0.9580	0.9701	0.9524	0.9745	0.9862	0.9931
Simple kriging result								
Weight assigned to the mean	0.1179	0.0773	0.0539	0.0393	0.0647	0.0361	0.0201	0.0104

Sample grid	25 x 25 x 9	25 x 25 x 9	25 x 25 x 9	25 x 25 x 9	25 x 25 x 9	25 x 25 x 9	25 x 25 x 9
No. of informing composites	5 x 5 x 5	5 x 5 x 7	5 x 5 x 9	5 x 5 x 11	5 x 7 x 11	5 x 7 x 13	9 x 9 x 13
Estimated block size	25 x 25 x 6	25 x 25 x 6	25 x 25 x 6	25 x 25 x 6	25 x 25 x 6	25 x 25 x 6	25 x 25 x 6
Ordinary kriging result							
Estimation variance	0.0920	0.0884	0.0869	0.0862	0.0862	0.0859	0.0858
Slope of the regression Z/ZE	0.9877	0.9989	1.0042	1.0071	1.0090	1.0093	1.0024
Simple kriging result							
Weight assigned to the mean	0.0190	0.0018	-0.0072	-0.0125	-0.0188	-0.0203	-0.0122

The Gaussian model, the variograms and the results of neighbourhood testing provide the parameters necessary for the kriging estimation and the non-linear local estimation by Uniform Conditioning.

Ordinary kriging was performed but this could not be used to give a resource reflecting the real mining selectivity. Kriging of smaller blocks would seriously understate the true variability. Therefore, Uniform Conditioning was applied to obtain a more realistic resource estimate corresponding to the intended mining selectivity. A selective mining unit (SMU) of 8.3 x 8.3 x 9m was used as the minimum basis for determining ore or waste parcels.

Uniform Conditioning (Rivoirard, 1994) takes the locally estimated ordinary kriging result and applies a change of support to calculate the expected histogram of grades for that 25 x 25 x 9m block based on an SMU of 8.3 x 8.3 x 9m. Results are then reported for each large block as the proportion of the block above cut-off and the grade above cut-off from that expected SMU histogram, knowing the estimated grade of the entire block. Histograms comparing composites, kriged 25 x 25 x 9m blocks and SMU results are given in Figure 7. These show the expected deskewing effect of larger block sizes. The Discrete Gaussian Method is one of the few approaches that takes this important deskewing into account. Affine corrections do not for example.

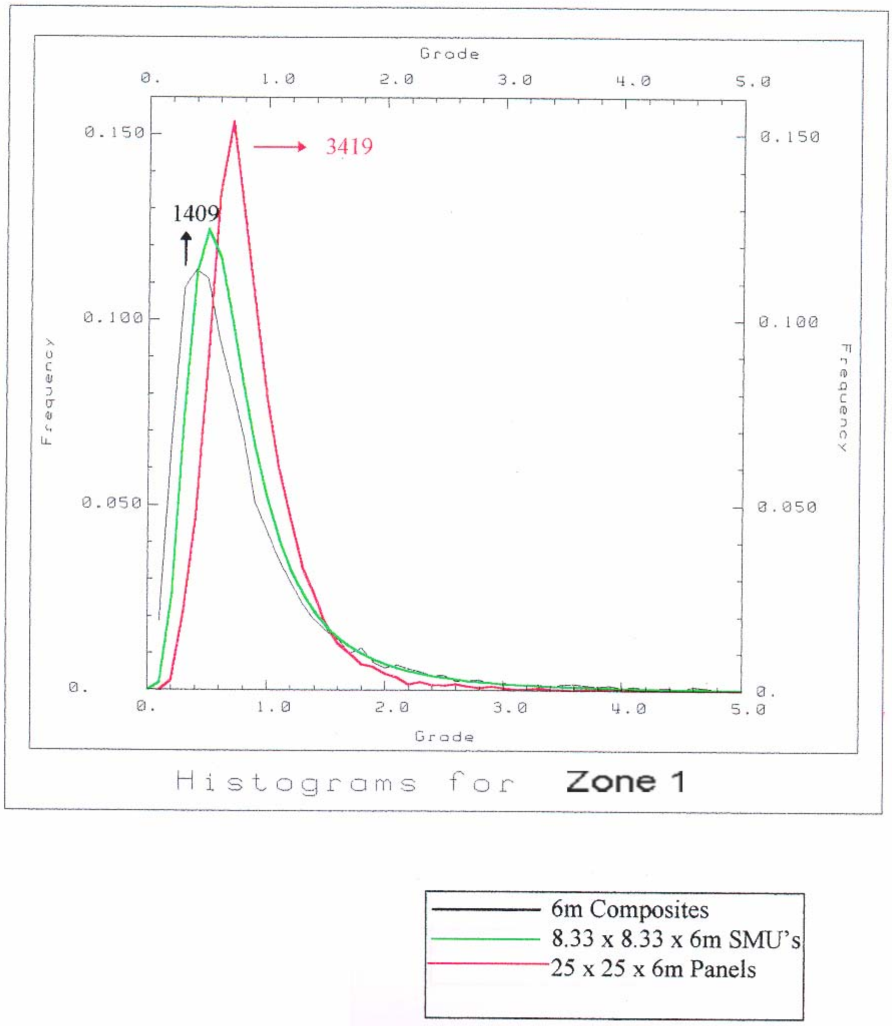


Figure 7 Comparing Histograms for Different Supports

The global results obtained previously can be used as an order of magnitude check for the Uniform Conditioning local results. In this study, agreement between global and local results was good. If alternative cut-offs are required then it is simply a matter of running only the Uniform Conditioning step with the new cut-offs – no other work need be re-done.

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