

COLOUR AERIAL PHOTOGRAPHY FOR RIVERBED CLASSIFICATION

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KEYWORDS: Hydrology, Classification, Scale, Texture, Orthoimage, Land Cover, Aerial.

ABSTRACT:

Colour aerial photography has the potential to identify and classify the size characteristics of exposed riverbed sediments over large areas efficiently. This paper describes the findings of a pilot project that sought to assess this potential and consider the impact of photo-scale on the accuracy of classifications obtained.

Colour multi-scale digital imagery was acquired of a test area (120 x 80m) at scales of 10,000, 5,000, 3,000, 2,000 and 1,000 using a helicopter and a hand-held Kodak DCS460 high-resolution digital camera. Intensive ground work obtained conventional grain size parameters (Wolman samples), requiring 15 person days of fieldwork. This was supplemented with the measurement of a 1 and 2 m high resolution digital elevation model (DEM) and photo-control, using a motorised Total Station. Conventional photogrammetric processing and the DEM were then used to create orthophotos of the test area at differing photo-scales. Supervised classification methods were adopted to classify each pixel into one of five classes: sand, sandy gravel, pebble, clean gravel and cobbles. Comparison with the known ground truth achieved a success rate initially of only 38% at 1:5,000 photo-scale, but developments enabled this to be increased to a more encouraging 49%. Similar tests were conducted using orthophotos at other scales (1:3,000 and 1:10,000) and similar improvements were achieved using the approaches developed.

A key parameter that indicates bed roughness and is of significant biological interest, is the percentage content of sand. Further work was carried out to ascertain whether this simple parameter could be extracted from the imagery at differing photo-scales. The dataset derived by the supervised classification procedure was converted to percentage sand using a 5x5 convolution filter. It was hoped to assess the accuracy of the classification by comparing this percentage sand map with a similar map derived from the intensive fieldwork. However, the enormous improvement in spatial resolution demonstrated that the two datasets were not directly comparable. Despite this, it was evident that overall sand distribution was clearly revealed using both the 1:5,000 and 1:10,000 scale imagery. More significantly, it was apparent that significant savings in time and effort would be accrued if the methods developed in the study were to be used to map and classify large areas of dry river-bed using colour aerial photography.

1. INTRODUCTION

Gravel-bed rivers form the upper reaches of virtually all river networks and are ubiquitous across the world. They are a major source of aggregate for construction, support important fisheries, and provide (and frequently threaten) crucial transportation corridors. The sediment particles that make up the surface of a gravel-bed river define hydraulic roughness, control bed material mobility and provide benthic habitat, but accurate characterisation of the surface material is notoriously difficult. Hydraulic sorting produces a patchwork of textures across the channel bed so that a large number of point samples is required to parameterise a reach (Wolcott & Church, 1991). In addition, even homogeneous sedimentary patches known as “facies” can exhibit a range in grain size that spans two or three orders of magnitude, so that precise estimates require many measurements (ISO, 1992). Conventional measurement techniques (Fripp & Diplas, 1993) are extremely labour intensive and sampling is therefore costly. This typically leads to inadequate characterisation of individual sites and to sampling programmes that compromise spatial or temporal representation. Moreover, conventional sampling methods are invasive, destroying the very substrate that is being monitored.

Although aerial photography is widely acquired in river engineering and commonly used for basic mapping, the potential of remotely sensed imagery to provide additional information about river systems has not yet been fully realised (Gilvear, 1999; Lane, 2001). Recent work using Lidar, multi and hyper-spectral data, has focussed on the derivation of high resolution digital elevation models (DEMs), the classification of stream morphology and the estimation of water depth (e.g. Gilvear et al, 1995; Thompson et al, 1998; Marks and Bates, 2000; Wright et al., 2000; Westaway et al., 2001). No published work to date has presented methods for the automated characterisation of river bed material facies from aerial photography, though this has recently been flagged as a key challenge (Gilvear, 2001) and Lane (2001) highlights the relevance of texture operators in this context.

This paper describes a pilot study carried out on the Fraser River, British Columbia, Canada as part of an ongoing research and management project (Church, 2003). The principal aim of this study was to assess the potential of colour aerial photography for riverbed classification. Objectives were to assess the influence of photo-scale upon the classifications and to ascertain whether the large archive of grey scale imagery could be also used for such bed classifications.

2. PRACTICAL WORK

2.1 Fieldwork

The Fraser River drains 250,000 km² of western Canada, rising in the Coast, Columbia and Rocky Mountains and flowing 1,300 km to the Fraser delta in the vicinity of Vancouver, British Columbia. The river regime is typified by both high and low flows created by annual snow melt cycles. Chilliwack is a small town located 100 miles east of Vancouver where the river is both an important habitat for salmon and a resource for aggregate extraction for the construction industry. Several field sites close to Chilliwack have been studied intensively by the research centre at The Department of Geography, University of British Columbia (Church, 2004) and one of these field sites, known as “Queens Bar”, was selected for this particular study, (Figure 1)



Figure 1- Queens Bar, British Columbia, Canada

Fieldwork at the Queens site was carried out in March and April 2002, before the spring melt and during a period when river flows were at their seasonal lowest. An area of exposed river bed that occupied an area 120 x 80 metres was selected. Criteria for selection included the presence of a range of sub-regions occupied by particle mixtures with differing size distributions (facies). Intensive fieldwork was carried out on site during a two week period and generated the following data sets:

1. A high resolution digital elevation model (DEM) covering the entire study area. Two resolutions of DEM were measured: 1 m resolution DEM within a small central portion (60 by 40 m) and; a 2 m resolution DEM for the remaining part of the 120 x 80 m study area;
2. Conventional grain-size parameters were obtained within 96 sampling units covering the entire test area, each being 10x10 m (Figure 2).
3. Ground observations identified the boundaries of fifteen sub-areas which could be classified as type sites using descriptive terminology (i.e. sand, sandy gravel, pebble, clean gravel, cobble).

Both the 1 and 2 m resolution DEMs (Dataset 1) were measured using a motorised Total Station (Leica TCA1105), complete with the remote control unit (RCS1100). The DEMs at the two resolutions consisted of approximately 3,000 points. The plan view of the test area (Figure 2) includes each data point measured and demonstrates the difficulty of measuring points along what is perceived to be a straight line in the field.

The bed characteristics were measured within the 96 10 x 10m blocks, using conventional Wolman (1954) sampling techniques

(Dataset 2). This laborious work entails identifying 100 particles randomly within each quadrat and manually measuring the “b” axis by passing the pebble through a sizing sieve. This was a large undertaking, requiring the assistance of fifteen field workers for a whole day. A clear weakness with this sampling strategy was the transgression of sediment type boundaries (facies) by the rigid 10 m quadrat boundaries. In an attempt to overcome this weakness the irregular boundaries between a series of facies types were measured and digitised using the motorised Total Station also (Dataset 3). The sediment characteristics within each sub area were determined also.

Additional surveying was carried out to determine the positions of 20 photo-control targets distributed across the test area. These targets were constructed locally by laminating a simple black and white target design printed on a standard A4 laser printer. Two sizes of target were used, 110 x 110mm and 180 x 180 mm. Angles and distances were measured to each target using the Leica TCA1105 located at two survey stations. These data were combined in a least squares “variation of coordinates” estimation to derive the best coordinate estimates for these targeted points.

Multi-scale digital imagery was acquired from a helicopter using a Kodak DCS460 hand-held 35mm digital camera, with a resolution of 3060 x 2048 pixels. Unfortunately weather conditions were marginal during photo-acquisition, with low cloud and light drizzle creating poor lighting conditions. Imagery was acquired at 1:10,000, 1:5,000 and 1:3,000 photo-scales using a 24mm lens and 1:2,000 and 1:1,000 photo-scales using an 85mm lens. At such a diverse range of scales, stereo coverage could be achieved using a varied number of frames ranging between 2 images through to a block consisting of 24 images. The latter proved to be un-achievable because of the time required to store each frame on the PCMCIA card, but sufficient imagery was acquired at all scales except 1:2,000, to provide coverage of one area of the site. Most of the 1:2,000 scale images were blurred, arising from long exposure times caused by the poor lighting conditions. Additional oblique imagery proved valuable in maintaining coverage at other scales, image redundancy originally acquired for purpose of camera calibration.

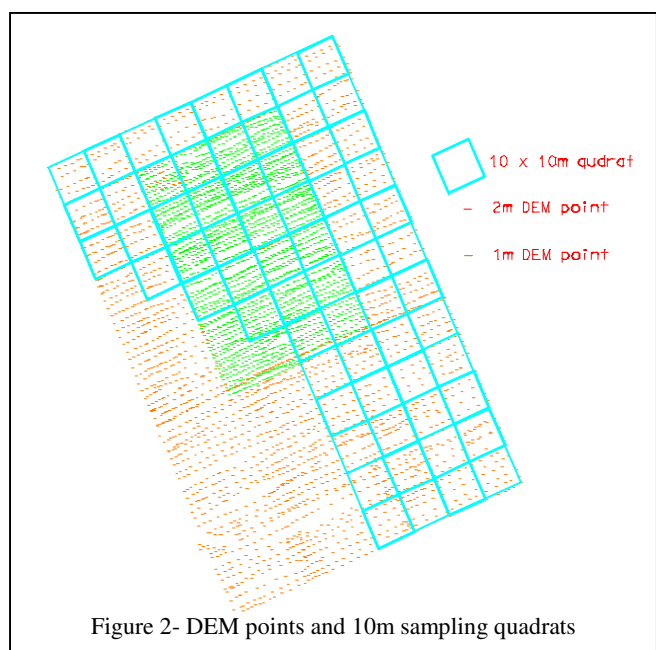


Figure 2- DEM points and 10m sampling quadrats

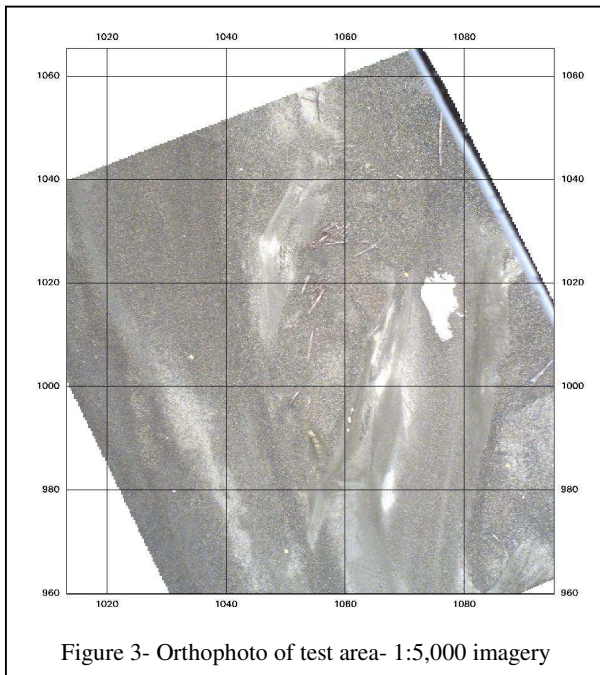


Figure 3- Orthophoto of test area- 1:5,000 imagery

2.2 Initial photogrammetric processing

Once images were downloaded it was possible to use conventional photogrammetric methods to derive colour orthophotographs for the 120 x 80m test area. This was achieved using Erdas Imagine OrthoBase (©Erdas LLC), following an “in-situ” calibration of the camera using an off-line self-calibrating bundle adjustment (Chandler et al., 2001). Automated DEM extraction methods were capable of generating a DEM, but orthophotos were derived using the more accurate DEMs measured in the field. All available imagery was processed and full orthophoto coverage was achieved at the 1:10,000 and 1:5,000 photo-scales (Figure 3). The central area was derived at 1:3,000 and finally a small area within this was achieved at 1:1,000.

3. RESULTS

3.1 Bed classification

Once orthophotos had been generated a conventional “supervised classification” procedure was used to categorise

Classified\Truth	Sand	Sand gravel	Clean gravel	Cobble	Pebble
Sand	13	24	1	0	n/a
Sand gravel	16	23	8	1	n/a
Clean gravel	25	25	27	9	n/a
Cobble	20	8	62	90	n/a
Pebble	25	20	3	0	n/a

Table 1, 1:5,000- Percentages classified from three colour bands

Classified\Truth	Sand	Sand gravel	Clean gravel	Cobble	Pebble
Sand	39	6	0	0	n/a
Sand gravel	12	43	8	0	n/a
Clean gravel	4	16	32	18	n/a
Cobble	18	9	59	81	n/a
Pebble	28	26	1	0	n/a

Table 2- 1:5,000- Percentages classified from three colour bands + texture layer

each pixel in the orthophotos into one of five classes: sand, sandy gravel, pebble, clean gravel, and cobble (Figure 4). Type signatures, initially based on three colour bands, were derived from five of the fifteen classified sub-areas and located by ground survey (Dataset 3). The true accuracy of the classification was then assessed by comparing the classification in the remaining sub-areas with their known bed material categorisation. It is important to stress that these areas were determined on the ground but were **not** used during signature derivation, which contrasts to the dubious practice of deriving “accuracy” statistics from the same areas used to create signatures. Results are presented in the form of an accuracy or

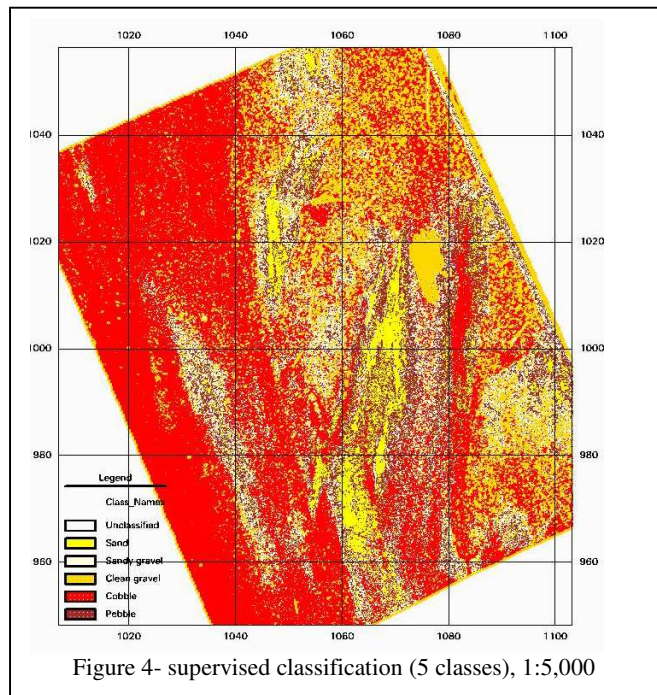


Figure 4- supervised classification (5 classes), 1:5,000

contingency matrix in which the columns represent each of the test areas (truth), whilst rows indicate the percentages of pixels classified into each of the 5 classes. The initial results were disappointing (Table 1- average success rate 38%), with only Cobble areas being identified with a high success rate (90%). Both Atkinson and Lewis (2000) and Lane (2001) recommend the addition of a “texture” layer to enhance spectral classification. An initial and simple texture layer was derived using a 3x3 variance convolution filter, which enabled localised

variability in the image to be represented. This simple addition improved accuracies radically (Table 2). The average success rate improved overall to 49%, with Sand exhibiting an accuracy improvement of 26%.

One additional test that was carried out was to assess the significance of the three colour bands compared with simple grey-scale image representation combined with texture.

The overall average success rate was lower (44%) but accuracy was better than may have been expected and is of particular significance. There are many large collections of black and white vertical aerial photography of gravelly river channels and significantly, these record changes that have taken place over many decades. The spectral qualities of these archives have been largely unused and the simple techniques described could be used to obtain informative long-term records.

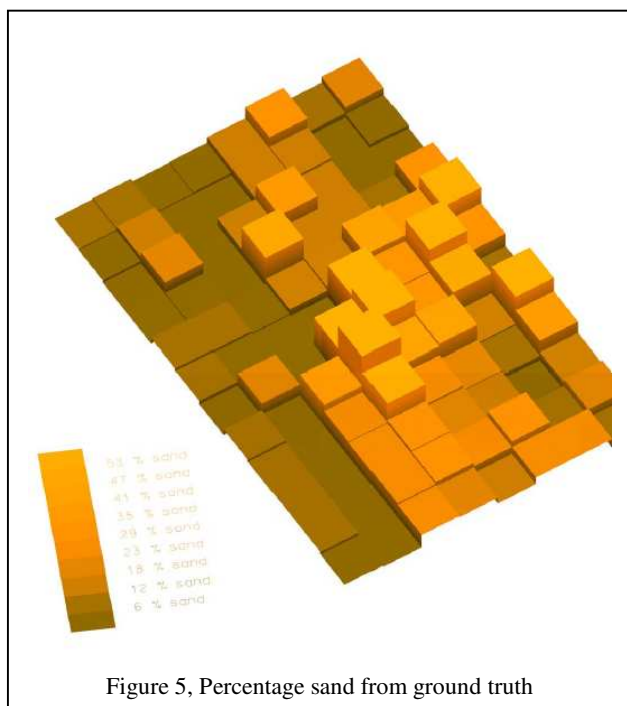


Figure 5, Percentage sand from ground truth

3.2 Percentage Sand

Percentage sand is increasingly recognised as a key parameter in defining hydraulic and transport characteristics in gravel-bed rivers and the ability to generate just percentage sand from aerial imagery is significant.

The Wolman data from 10 x 10m sampling units (Dataset 2) were manipulated to yield percentage sand values across the full 120 x 80m test area (Figure 5). It must be remembered that the sampling effort involved in obtaining this map (for a relatively small part of the river bed) was great, yet resolution is coarse and inevitably key facies boundaries are transgressed. The classified image derived using the 1:5,000 orthophotograph and signatures based on three colours bands and the texture layer was then used to create an alternative percentage sand map. This was achieved by plotting the proportion of pixels classified as sand within a five by five pixel moving window (Figure 6).

If figures 5 and 6 are compared there is clearly a significant improvement in the information provided. Facies units in the image have shapes and orientations that closely resemble their true nature and are clearly not influenced by the artificial blocks created by the conventional sampling strategy. Moreover, the automated classification procedure broadly mirrors that achieved by the ground fieldwork in terms of the estimation of percentage sand across the entire surface.

This is further demonstrated if the ground and aerial estimates of percentages are superimposed (Figure 7), where it is clear that localised peaks are smoothed by the coarse ground based

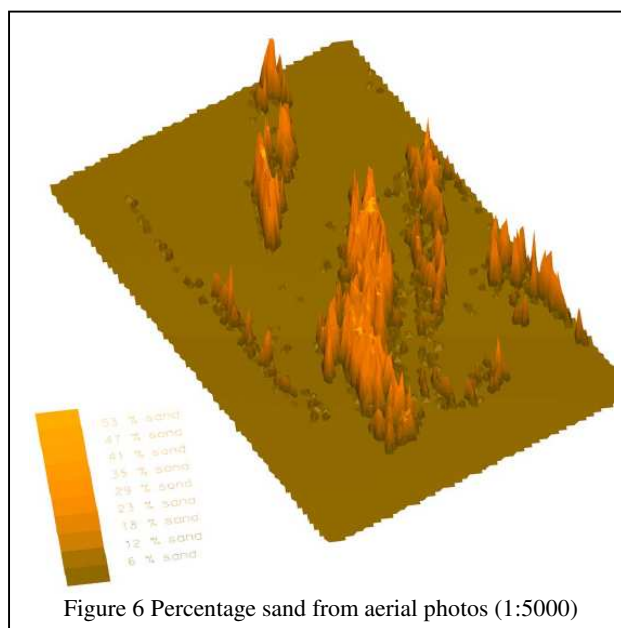


Figure 6 Percentage sand from aerial photos (1:5000)

methods. It had been hoped to derive quantitative data to demonstrate the accuracy of the image based approach. However, the contrast in resolution prevents an objective and quantitative assessment being made.

The automated aerial classification procedure was carried out also using the 1:10,000 orthophoto. A very similar result was achieved, and only a slight smoothing effect was apparent when compared to the 1:5,000 percentage sand map (Figure 6).

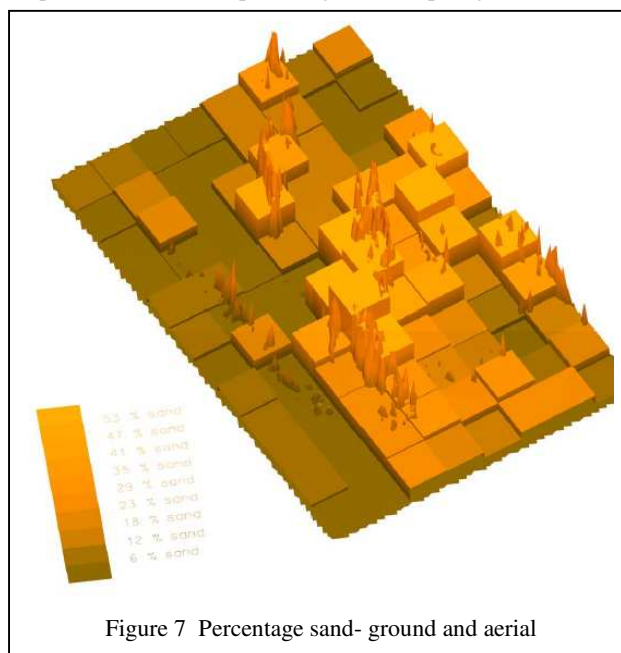


Figure 7 Percentage sand- ground and aerial

4. DISCUSSION

The classification accuracies achieved in this pilot project, are not as high as many published in the remote sensing literature, with the highest average accuracy achieved being just 49%. There are perhaps three factors that need to be considered. It should be remembered that sample sub-areas used to create signatures were not homogeneous, with many individual particles being outside the size range of the field identified type. In such inhomogeneous areas, a per-pixel classification will

Classified\Truth	Sand	Sand gravel	Clean gravel	Cobble	Pebble
Sand	42	3	0	0	n/a
Sand gravel	10	45	5	0	n/a
Clean gravel	5	21	43	27	n/a
Cobble	8	9	52	73	n/a
Pebble	35	22	0	0	n/a

Table 3 Percentages classified from three colour bands, texture + “similarity index”

inevitably yield a range of particle types and hence, during accuracy assessment many pixels will be identified as erroneous, when they actually represent valid particles. In addition, it should be recognised that **true** accuracies have been derived by comparing classified data with test areas **not** used for signature generation. Finally, the imagery was acquired in poor and overcast lighting conditions during light drizzle. In brighter weather, improved results may be obtainable; at least conditions were typical of mountainous environments!

It is clear that a supervised classification based upon the three colour bands is inadequate, particularly for a five-fold classification. A three-fold classification into just sand, pebble and cobble was more successful (56%) but the more ambitious target was pursued. The classification is significantly enhanced by adding a “texture” layer, which implies that the spatial variability of signal response, rather than simply the colour characteristics of the pixels is important. An interesting variable in this context is the lithotype mix represented in the sediments with colour variation between clasts being important. It would be necessary to examine other field sites before this influence can be examined fully. The criticality of texture was expected given the relative roughness and hence shading-induced intensity variability of different bed material textures. Other authors have noted the significance of texture in related work, with Atkinson and Lewis (2000) reviewing “geostatistical” methods for classification and describing various alternative measures of “texture”. These range from the statistics derived from the simple variance (Section 3.1) through to spatial auto-correlation (Section 4.1) and semi-variograms (Section 4.2) which were investigated in this study briefly.

4.1 Texture via spatial auto-correlation

An additional avenue explored was the use of spatial auto-correlation to assist in the bed classification procedure. Rubin (2004) used spatial auto-correlation to derive correlation profiles between an original greyscale image of borehole-sand sections and the same image displaced by one, two, three and four, etc. pixels. The basic idea being that large particles exhibit high correlations for initial displacements, while smaller particles generate low correlations for all pixel displacements. These basic differences generate contrasting correlation profiles which then vary spatially. Rubin (2004) then develops an empirical calibration function between measured sand grain size distributions and the correlation profiles that, it is claimed, can be used to identify sand grain size distributions for borehole-sand sections.

The basic correlation algorithm was implemented in Matlab but tests revealed some concerns, particularly whether spatial auto-correlation can provide a good basis for measuring texture. An alternative approach was developed based upon the reciprocal of the summed variances between a 5x5 image patch and the same patch displaced by one pixel. This was adopted for bed classification using the 1:5000 orthophotos (converted to

greyscale) and used as an additional layer to the three colour bands and the texture layer used prior. Results indicated only a modest improvement (Table 3, average success rate 51%), implying

that very little new information was being added to the classification process and that the original texture layer was sufficient.

4.2 Texture via the semi-variogram

Another approach investigated was the use of semi-variograms to perhaps provide an alternative measure of “texture”. Work conducted by Atkinson & Lewis (2000) and particularly Chica-Olmo and Abarca-Hernandez (2000) advocated this geostatistical method most strongly. Their field of application was quite different, and involved the classification of Quaternary deposits using Landsat 5 imagery (Chica-Olmo & Abarca-Hernandez, 2000). Their results indicated an accuracy improvement of approximately 20% and the approach appeared promising.

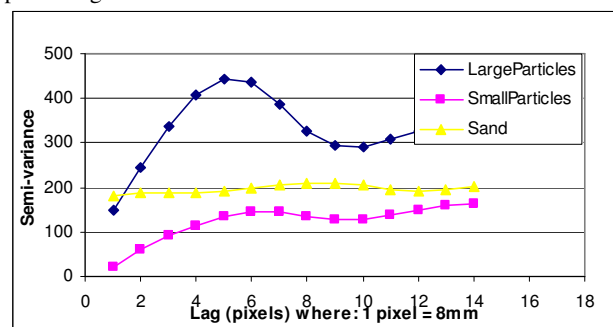


Figure 8- semi-variogram, 1:1,000, (NS)

To investigate the technique semi-variograms were computed for three of the sub-areas (Dataset 3) labelled in the field as Sand, Gravel and Cobble. (Figure 8). This plot certainly suggests that production of a semi-variogram could provide useful information for bed classification, with contrasting profiles being generated for the differing bed materials.

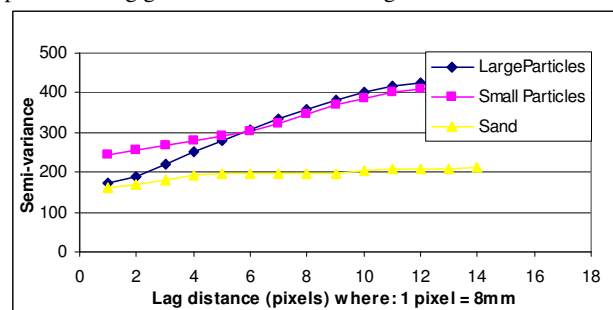


Figure 9- semi-variogram, 1:1,000, (EW)

However, Figure 8 represents a North-South section through the semi-variogram surface, whilst Figure 9 represents an East-West section through the same surface. In this case there is not such a clear distinction in the profiles, particularly between the Gravel and Cobble sediment types. It is clear that semi-variogram direction is a critical controlling parameter with such an

anisotropic field. The anisotropy being a function of sediment preferred orientation arising from water flow direction.

There are other problems with using a semi-variogram approach, as indicated by Atkinson & Lewis (2000). Homogenous regions of varying texture must be large enough to allow computation of the semi-variogram with a reasonable number of lags. In many cases, areas of interest are too small relative to the spatial resolution of the imagery. Computation of the semi-variogram is also intensive, particularly if the full variogram surface is generated. A consequent problem is how this surface is represented and stored to a precision sufficient for the classification process. For each desired profile direction, a minimum of three parameters is necessary and these results suggest that storing both downstream and cross-stream parameters would be essential.

Despite these drawbacks it is believed that additional texture layers represented by either variance or semi-variograms could provide additional information necessary for bed-classification and the derivation of grain-scale data from aerial imagery.

5. CONCLUSION

This project has demonstrated that it is possible to derive a five-fold bed classification to a **true** accuracy of 49% using just the three original colour bands and 1:5,000 scale photography. It has to be recognised that this was achieved using a “per-pixel” classification within non-homogeneous bed material. If material had been homogeneous, accuracies would have been higher. It was found necessary to create an additional “texture” layer using a 3x3 variance convolution filter. It was found that classification accuracy was not affected greatly by varying the photo-scale, with 1:10,000 scale imagery also yielding a valid classification. Significantly, it was found that simple grey-scale imagery could yield useful classifications, provided a texture layer was generated and used. Alternative methods of deriving a texture layer were investigated. Autocorrelation yielded only a modest improvement to 51%. The semi-variogram could provide the basis for useful measures of bed texture and may improve the classification accuracies further but efficient storage of semi-variogram data is required.

Once a classified image had been generated from the aerial imagery it was simple to derive a percentage sand map. Comparison between this and traditional ground-based methods requiring intensive fieldwork, highlighted the potential for significant savings in time and effort if aerial imagery is acquired. More detailed examination of the optimal photo-scale for identifying sand patches remains an area for further development.

ACKNOWLEDGEMENTS

The authors gratefully acknowledge the financial support provided by the Natural Science and Engineering Research Council of Canada (NSERC) for fieldwork support and helicopter hire.

REFERENCES

Atkinson, P.M. and Lewis, P., 2000. Geostatistical classification for remote sensing: an introduction. *Computers and Geosciences*, 26, pp. 361-371.

Chandler, J.H., Shiono, K., Rameshwaren, P. and Lane, S.N. 2001. Measuring flume surfaces for hydraulics research using a Kodak DCS460, *Photogrammetric Record*, 17(97), pp. 39-61.

Chica-Olmo, M. and Abarca-Hernandez, F., 2000. Computing geostatistical image texture for remotely sensed data classification, *Computers and Geosciences*, 26, pp. 373-383.

Church, 2004. Fraser River Gravel Reach Studies <http://www.geog.ubc.ca/fraser/river/> (accessed: 4 March, 2004)

Fripp, J. B., and Diplas, P. 1993. Surface sampling in gravel streams. *American Society of Civil Engineers, Journal of Hydraulic Engineering*, 119, pp. 473-490.

Gilvear D.J., Waters, T.M., and Milner, A.M., 1995. Image analysis of aerial photography to quantify changes in channel morphology and instream habitat following place mining in interior Alaska. *Freshwater Biology*, 34, pp.389-398.

Gilvear DJ, 1999. Fluvial geomorphology and river engineering: future roles utilizing a fluvial hydrosystems framework. *Geomorphology*, 31 (1-4), pp. 229-245.

Gilvear DJ, 2001. Discussion of: Lane, S.N., 2001. The measurement of gravel-bed river morphology, in “Gravel Bed Rivers V”, Mosley, M.P., (ed). NZ Hydrology Society, Wellington, pp. 323-324.

ISO, 1992. *Liquid flow measurement in open channels - sampling and analysis of gravel-bed material* International Organisation of Standardization, Publication 9195, pp. 9.

Lane, S.N., 2001. The measurement of gravel-bed river morphology, in “Gravel Bed Rivers V”, Mosley, M.P., (ed). NZ Hydrology Society, Wellington, pp. 323-324.

Marks K, Bates P, 2000. Integration of high-resolution topographic data with floodplain flow models. *Hydrological Processes*, 14 (11-12), pp. 2109-2122.

Rubin, DM, (2004). A simple auto-correlation algorithm for determining grain size from digital images of sediment. *Journal of Sedimentary Research*, 74 (1) pp. 160-165.

Thomson AG, Fuller RM, Eastwood JA, 1998. Supervised versus unsupervised methods for classification of coasts and river corridors from airborne remote sensing. *International Journal of Remote Sensing*, 19(17), pp. 3423-3431.

Wolcott, J. F., and Church, M. 1991. Strategies for sampling spatially heterogeneous phenomena: the example of river gravels. *Journal of Sedimentary Petrology*, 61, pp. 534-543.

Wolman MG, 1954. A method of sampling coarse river-bed material. *American Geophysical Union Transactions*, 35, pp. 951-956.

Wright A, Marcus WA, Aspinall R, 2000. Evaluation of multispectral, fine scale digital imagery as a tool for mapping stream morphology. *Geomorphology*, 33(1-2), pp. 107-120.