Combining Metric Aerial Photography and Near-Infrared Videography to Define Within-Field Soil Sampling Frameworks

G.G. Wright, K.B. Matthews and **J.C. Tapping**
The Macaulay Institute
Craigiebuckler, Aberdeen,
AB15 8QH, United Kingdom
E-mail: k.matthews@mluri.sari.ac.uk

R. Wright
Department of Geography & Environment
University of Aberdeen, Elphinstone Road
Aberdeen, AB24 3UF, United Kingdom
E-mail: r.wright@abdn.ac.uk

Abstract

This paper investigates the combination of metric aerial photography and near-infrared (NIR) videography data to improve the design of field-survey sampling frameworks. Spatial data collection can contribute up to 80% of the cost of deploying a Geographic Information System (GIS) based Decision Support System (DSS). The use of remotely sensed information, field survey using differential Global Positioning System (dGPS) and geostatistical interpolation methods maximises data quality for a given rate of sampling.

Medium-format colour aerial photography and NIR videography were orthorectified to the national map base and mosaiced using ERDAS Imagine. The green and red layers of the aerial photography were combined with the NIR videography to form a false-colour composite image. Two sampling strategies were tested. The first stratified sampling on a per field basis, creating four points per hectare, randomly located within each field. The second strategy used the remotely sensed information to identify within-field variability classes for each field, using red-green difference or normalised difference vegetation index (NDVI) models. These variability classes were used as a sub-stratification framework with each class sampled at the same rate of 4 per hectare. For both strategies the sample points were generated within ESRI ArcView and were located in the field using dGPS. Maps of stone content were created using geostatistical methods and validated against samples collected on a 100 metre grid. It was concluded that combining the two image sources to create a within-field stratification framework improved the precision of the results obtained from field-survey.

Introduction

Decision Support Systems (DSS) have been developed to respond to the increasingly complex financial, social and environmental goals of land managers (Matthews *et al*., 1999). Critical to the credibility and effectiveness of these farm-scale DSS is the availability of accurate site-characterisation data. The cost of collecting such base-line characterisation data, particularly soil profile data collected using ground-survey methods, can outweigh the financial benefits of using the DSS, especially where the land management goals are primarily environmental. It has been reported elsewhere that the accuracy of DSS outputs can be increased by using remotely sensed data (Moran *et al*, 1997) and improves the effectiveness of sampling effort (Stein *et al*., 1998) thus reducing overall costs.

For the purposes of a soil survey there is the recognition that characterisation of within-field variability can be a problem for random, or grid-based sampling frameworks. To address this issue, sampling can be stratified using secondary sources of information such as land use plans, soil map units (Brus, 1994) or remotely-sensed imagery. The utility of land use maps as a stratification framework is, however, reduced if they are not contemporary with the soil survey, since land use boundaries can be subject to significant change. Furthermore for agricultural land planted in monocultures, land-use maps provide a limited basis for within-field stratification. Soil maps, on the other hand, are frequently compiled at scales inappropriate for site-specific analysis and their mapping units may not be a suitable basis for sampling the particular soil properties of interest. Remotely-sensed information is more easily synchronised with field survey and from a light aircraft platform is available at a cost which is being reduced by developments in sensor and image processing technology (Wright *et al*. 2003).

Light aircraft, as a sensor platform to support farm-scale DSS, provide flexibility both in the opportunistic timing of data capture and the scale of the imagery obtained. Although the costs of purchasing and processing satellite imagery are decreasing there remain difficulties of obtaining suitable images for cloud-prone regions such as north-western Europe. In the research reported here, two sensors have been used: medium-format colour aerial photography and NIR videography. The aerial photography, obtained using a calibrated lens and camera, yields high quality imagery suitable for use with digital photogrammetric techniques. The NIR videography provides an additional band of information that when combined with conventional photography allows the use of red/NIR difference indices to characterise within-field variability of vegetated fields.

This paper presents a methodology for defining soil-sampling frameworks based on the integration of medium format colour photography and NIR videography. The paper first outlines the methodology adopted for the preparation and integration of the image data and then details the approach taken to structuring the soil-sampling frameworks using models of within-field variability. Two sampling strategies are compared, one using the field as the sampling unit and the second using variability classes to sub-stratify the sampling. The effectiveness of the two strategies is compared using the prediction accuracy of geostatistically-derived soil property maps.

Multi-Spectral Imagery and Soil Mapping

When remotely-sensed imagery is available, useful information may be extracted on the distribution of soil map units or the variability of soil properties. LANDSAT MSS spectral data has been be used to stratify regions into smaller sampling units (di Paolo, 1979; Lund *et al*. 1980; Harrison and Johnson, 1982). This stratification process can increase both the accuracy and efficiency of field surveys. Satellite data, when used as part of an Arizona rangeland soil survey, increased the accuracy of the survey in about 35 percent of the mapping units both for defining mapping-unit boundaries and mapping-unit composition (Roudabush *et al*., 1985). The total cost of the soil survey effort was also reduced by about 33 percent relative to a conventional soil survey in similar areas. Higher spatial-resolution images from satellites such as LANDSAT TM and SPOT have also proved useful for soil mapping applications (Agbu and Frank, 1988; Biswas and Singh, 1991). Leone *et al*. (1995 and 1996) used LANDSAT TM data in the Apennine region of Southern Italy to define the principal geomorphologic units and maps derived from remotely-sensed data were supplied to surveyors as part of the field surveying process.

The use of remotely-sensed imagery for soil survey applications can be broadly categorised into hard copy and image-analysis approaches. Milton and Webb, (1987) conclude that "spectral maps, when used with conventional aerial photographs, form very useful documents for use in the field by soil surveyors to delineate map unit boundaries, allowing large areas to be surveyed rapidly with little reduction in accuracy". The remotely sensed data is used as an additional data source informing the complex field-observation-based assessments conducted by soil surveyors. The approach is one of visual interpretation from hard-copy mapping. Although much information on soil may by gathered from visual interpretation of remotely sensed data, digital processing of image data can provide a significantly greater consistency and repeatability for the classification or modelling of soil properties. The semi-automation of repetitive tasks may also increase efficiency. Digital processing can, however, lack flexibility in evaluating the complex patterns of soils. SPOT or LANDSAT TM imagery has been combined with Digital Elevation Model (DEM) data to identify soils, their boundaries and variation in soil characteristics (Lee *et al*., 1988; Su *et al*., 1989). Results from these studies suggest that high-resolution satellite data can be manipulated to discriminate spectrally parcels of land with which soil-mapping units may be associated. This was seen to improve the accuracy of soil surveys where the dominant land use was rangeland.

Electromagnetic-radiation reflectance can be an important diagnostic property of soils. For visible wavelengths tone or colour has been used as part of soil survey for many years (USDA, 1951). Considering multi-spectral imagery, minimum reflectance occurs in the blue-violet portion of the spectrum, with the green, red and near-infrared regions offering the most favourable areas for a quantitative and qualitative description of soils (Myers *et al*., 1983). As a diagnostic tool, however, reflectance is influenced by a large number of soil characteristics or physio-chemical conditions, for example organic matter, moisture, structure (or surface roughness), texture (particle size) and mineralogy (Bowers and Hanks, 1965; Condit, 1970; Montgomery and Baumgardner, 1974; Stoner *et al*., 1980 and Myers et. al., 1983). The accuracy of estimates of soil properties based on soil colour is poor (da Costa, 1979), indeed many field studies have found no general relationship between reflectance values and dominant soil physical properties (McKeague *et al*., 1970) or low levels of confidence in predictions (Baumgardner *et al*., 1970; Hovaroth *et al*., 1971 and Page, 1974). The uncertainty, in these mainly regional studies, suggests that 'local' factors may overcome any general trend indicating that field-by-field analysis may be necessary.

It may be, therefore, that the best contribution that remotely sensed imaging could make to soil survey is the definition of spatially-explicit variability classes that can be investigated by field-survey. This may help to focus attention on those areas where there are gradients of change or boundaries. Where boundaries are important features and their accurate definition is significant for the application it will be necessary to obtain imagery that has sufficient spatial resolution. Any sensor system for soil survey applications should be capable of capturing broadband information within the green, red and NIR spectral wave bands. Field survey will remain an essential aspect of defining map units when the characteristics of the whole profile must be considered since surface variation may not be indicative of variation at depth. This makes surveys based on remote sensing imagery most relevant to those applications where it is the surface layer that is of greatest significance such as in precision agriculture.

Materials and Methodology

The methodology used to combine photogrammetric camera imagery and NIR videography to define within-field soil sampling frameworks is detailed in Figure 1. The flow-chart shows the steps from image capture through to the validation of the outputs from the two sampling strategies. First the geometry of the raw images is corrected (in this case to the U.K. Ordnance Survey map base), mosaiced and combined in a three-layer image stack. Variability within bare soil and vegetated fields is then characterised using red-green difference and NDVI values respectively (Myers *et al*., 1983). These images are classified and the resulting polygons merged to create sub-stratified sampling units.

Image Capture and Preparation

Colour aerial photography is obtained using a Rolleiflex 6006 metric camera (1) with a Zeiss Planar f2.8/80mm lens. The resulting hardcopy prints are flat-bed scanned to create 24bit TIFF files with a resolution of 600dpi. This imagery is orthorectified with OrthoBASE (2). The calibration information available for the camera, including interior orientation parameters, means that typically only 3 ground control points (GCPs) are required per image. Terrain distortion is removed using a digital elevation model (DEM) derived in ArcInfo (3) from digital contour data. The colour photography is resampled to a resolution of 1m using the nearest-neighbour method. The individual frames are histogram matched to the central image and mosaiced in ERDAS Imagine to create a single image.

The NIR videography is captured using a PULNiX (4) TM765i video camera (2/3 inch CCD array, with 756 x 581 pixels) fitted with a Pentax Cosmicar f1.5/8.5mm lens and filtered using a Kodak Wratten 88a filter. The data is recorded on a Sony GV-S50E portable Video8 recorder. Individual frames with 60% overlap are manually selected and extracted using the SnapMagic frame-grabber.

A module of the OrthoBASE software allows the correction of both metric and non-metric imagery. The NIR video imagery is non-metric since it lacks the fiducial marks of conventional metric photography. The non-metric rectification can, however, make use of lens focal length and radial distortion characteristics and is particularly sensitive to the accurate specification of the video camera's CCD pixel size. Such information is usually found within the technical data sheets available from lens and camera manufacturers. With this data available, 8 GCPs per stereo-model are typically required. Where mapped features are unavailable to act as GCPs additional points are collected using dGPS (using an LR12 Omnistar 3000). This is most often necessary for elevation values that are less commonly mapped in rural areas. The lens and CCD data enables the residuals in the triangulation to be reduced to means of 1.1 m in x and y at the checkpoints. This level of accuracy was sufficient to make the NIR video imagery compatible with the metric aerial photography and the ground survey (Wright *et al*., (2003)).

Deriving the Sub-Stratified Sampling Frameworks

The red and green layers of the colour aerial photography are added to the single layer of the NIR videography, to create a three-layer image stack. The image stack dataset is used to characterise within-field variability. The variability

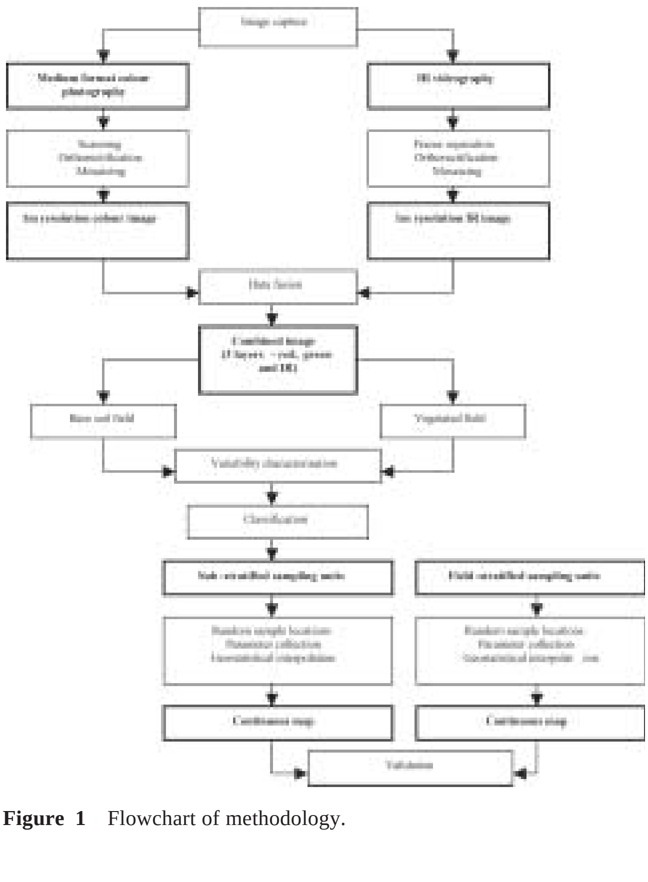

Figure 1 Flowchart of methodology.

(1) RolleiMetric. http://www.rolleimetric.de
(2) Leica Geosystems. http://www.erdas.com
(3) ESRI. http://www.esri.com
(4) PULNiX. http://www.pulnix.com

of bare-soil fields is characterised using a simple soil-model of red band minus green band; higher values indicate darker soil tone that may have higher levels of organic matter. The variability of vegetated fields is characterised using NDVI where high values indicate the presence of more biomass.

Unsupervised classification is employed to derive variability classes using either the red-green difference or the NDVI image. Unsupervised classification is used when no pre-survey ground-truth data is available. Each classified image is then filtered using a 7 x 7 median filter to reduce pixelation and converted into polygon coverages for further analysis within a GIS environment. All polygons with an area less than the minimum sampling unit (MSU) are merged with the largest neighbouring polygon. The MSU is the area for which a single sampling location would be generated. For example a sampling density of 10 per ha would result in a MSU of 1000 m^2.

Sampling sites are randomly generated within each field or variability-class polygon, using a customised Avenue script in ArcView. This specifies that no points should be within two metres of another sample location, field boundary or variability-class polygon boundary since the accuracy of the dGPS used to locate the sample sites in the field is +/- 1 m.

Testing

A sampling framework, sub-stratified using the remotely sensing imagery, was compared with a field-based sampling stratification for a test site at Newton Rigg in North West England. Field-based stratification was the survey strategy previously employed in previous DSS applications where the goal was the characterisation of individual fields. Imagery was captured in July 2000, at an altitude of 1,740m, with a nominal scale of 1:5,000.

Two fields were used for the testing: Test Field 1, a vegetated field and Test Field 2, a bare soil field. Both fields are used as silage grass leys, with Test Field 2 bare soil as it was undergoing reseeding. In both cases brown earths are the dominant soil type, formed from glaciofluvial drift over boulder clay. The characteristic chosen to compare the two sampling strategies was topsoil stone percentage. This was estimated at each sample site using 1m3 soil-profile inspection pits in accordance with the protocols of the Soil Survey of Scotland (Macaulay Institute, 1984). Since the judgement of the land manager was that both fields were not particularly heterogeneous a sampling density of four points per hectare was used; an MSU of 2500 m2. This was higher that used for previous DSS applications to allow the investigation the trade-off between sampling density and prediction accuracy (outwith the scope of this paper).

Each dataset was evaluated for spatial patterns by computing the omni-directional variogram, directional variogram and anisotropy plots (Kaluzny *et al.*, 1998). Where a trend was present and identified it was removed. The variogram was then computed and modelled. Ordinary kriging was then performed using the variogram results. The outputs of the kriging process were maps of the predicted percentage stone content. Each prediction surface was compared against the validation dataset, collected on a 100x100 m grid basis.

Results

Colour Aerial Photography and NIR Videography Data Fusion

Figure 2 shows an example of orthorectified and mosaiced colour aerial photography for the test site and Figure 3 shows the NIR videography for the same site. Both images are derived from six frames, resampled to 1m using nearest neighbour interpolation. Figure 4 shows a false-colour composite image combining the red and green layers from the colour photography with the NIR video imagery. The match between the two sources of imagery is sufficiently accurate that there is minimal blurring or bleeding of colours at field boundaries.

Figure 5 (a) shows the output of the NDVI model. Variation can be seen within the vegetated fields, including the two test fields, which is not visible in either the colour photography or the NIR videography when viewed individually. Figure 5 (b) displays the red-green difference image. Patterns of surface variation are visible throughout the field. The pattern of variation is typically more heterogeneous than in the NDVI image. Figure 6 shows the variability classes created by (a) the classification, (b) the median filtering and (c) the MMU merging of the NDVI and red-green difference images. It is noticeable that this process of filtering and merging can preserve complex small-scale features but only when they are attached to larger polygons. Contrast the green and blue “finger “ features highlighted in Figure 6 (b) that are lost with the complexity of the orange polygon that is preserved, Figure 6(c).

Comparison of Sampling Frameworks

Figure 7 shows the sample locations stratified by field (field-stratified) or by variability class (sub-stratified). Test Field 1 (Figure 7(a)) has been divided into five classes and Test Field 2 (Figure 7(b)) into four classes. By sub-stratifying samples using these variability classes, the sampling locations are spread across the field (compared to the simple field-stratified samples). The differences are particularly noticeable where the units are complex in shape, for example, the orange unit in Figure 7(a). The complexity of the variability units can, however, also cause problems. Since it was specified that no sample location should be within one metre of another sample location or field boundary, some of the narrow regions of the variability-class polygons have effectively been eliminated from the sampling, for example, the polygon along the outer edge of Test Field 2 (Figure 7(b)).

Geostatistical Interpolation and Validation

Maps of stone percentage for Test Field 1 are shown in Figure 8(a) sub-stratified and Figure 8(b) field-stratified and for Test Field 2 in Figure 9(a) sub-stratified and Figure 9(b) field-stratified. For both test fields, the patterns of stone percentage for the sub-stratified maps are visually different from the variability class polygons. This is not surprising since stone content has a weak effect on the spectral reflectance values used in the classification. The benefit of the sub-stratification is, however, evident when the interpolated maps are tested against the validation samples. The numbers of validation points correctly predicted are shown in Table 1. The validation sites incorrectly predicted are highlighted in red in Figures 8 and 9.

For the two test fields, the sub-stratified sampling strategy is a significant improvement on using field-stratified sampling (p=0.007 for a Fisher exact probability test). Table 1 shows that for Test Field 1 the surface generated from the sub-stratified dataset matched at seven out of the eight validation points, whereas the surface from the field-stratified sampling matched only three points. The one validation point that did not match with the predictions had a percentage stone value of 10%, whereas the predicted surface assigned it a value of 15%. The differences between the field-stratified surface and the validation points were

Table 2 Validation of the interpolated maps.

Test Field 1			**Test Field 2**		
Strategy	Correct	Incorrect	Strategy	Correct	Incorrect
Sub-stratified	7	1	Sub-sdtratified	7	0
Field-stratified	3	5	Field-sdtratified	4	3

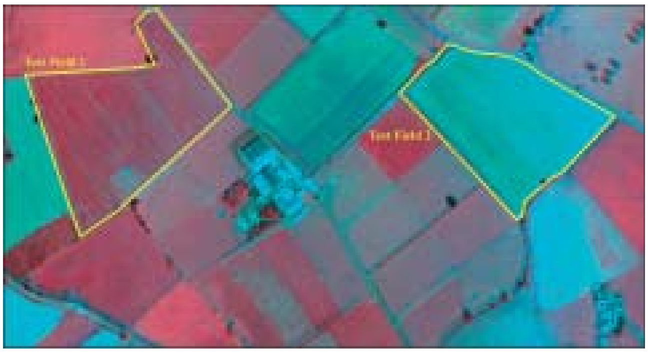

Figure 4 Green, red and NIR false colour composite image with the test fields identified.

Figure 2 Orthorectified and mosaiced colour aerial photography.

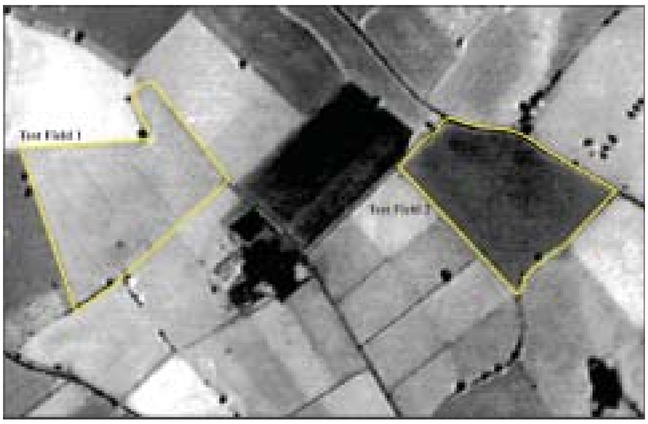

Figure 3 Orthorectified and mosaiced NIR videography.

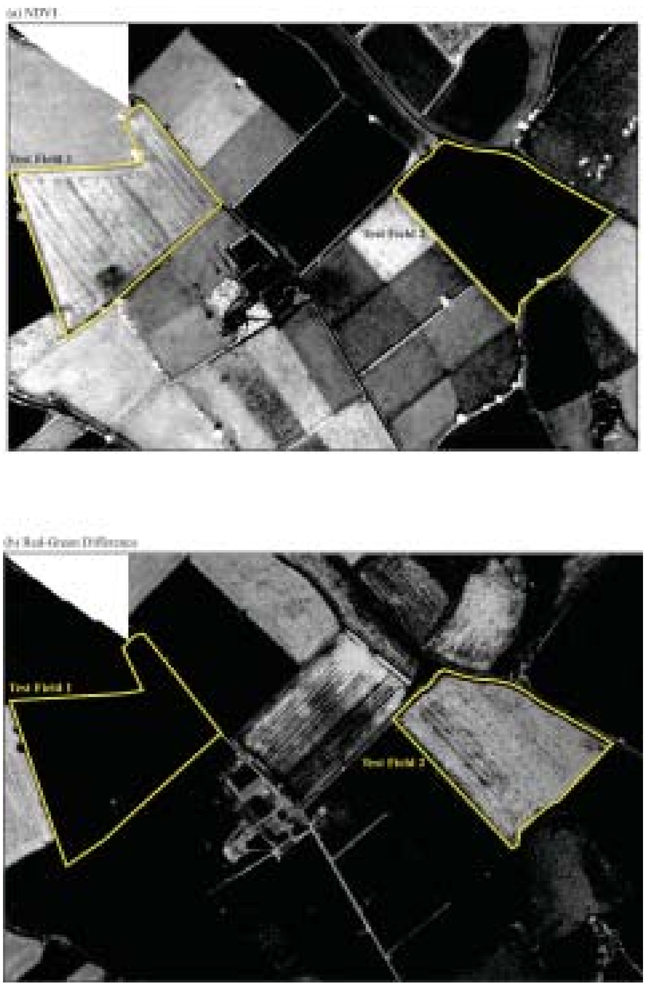

Figure 5 The NDVI image (a) and the Red-Green difference image (b).

Figure 6 Classified (a) filtered (b) and aggregated (c) images for the test fields.

larger, for example 30% compared to a predicted value of 10%. For Test Field 2 the sub-stratified surface matched at all of the validation points. For the field-stratified dataset, only four out of the seven validation points matched with the predicted values. Differences between the actual values and predicted values, however, were not as striking as in Test Field 1.

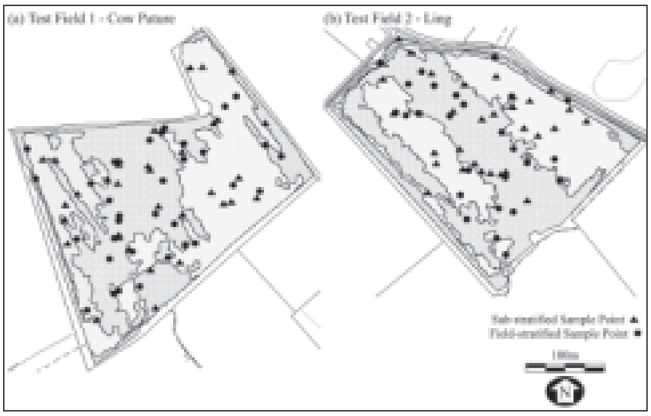

Figure 7 The field-stratified and sub-stratified sampling frameworks within (a) Test Field 1 and (b) Test Field 2.

Conclusions

This paper has presented a methodology to assist in the process of site characterisation, a crucial step in the application of computer-based DSS to land management problems. The methodology combines of aerial photography and NIR videography to define within-field sampling frameworks for soil survey, with the goal of improving the accuracy achieved for a given density of sampling sites.

The use of light aircraft mounted sensors enables four-bands of imagery (Blue, Green, Red and NIR) to be captured at a reduced cost, opportunistically and with higher spatial resolution compared to satellite imagery. Difficulties in creating survey coverage from video images have previously been reported but advances in image processing software means that the problems of image rectification and mosaicing can now be overcome (Wright *et al*. 2003). The successful rectification of the video imagery does, however, require significantly greater levels of ground control but this can be met without making excessive labour demands. The four-band imagery created has a wide range of possible applications in site characterisation, but is particularly useful in assisting the characterisation of soil properties.

Within-field spectral reflectance variation was characterised by classifying NDVI or red-green difference images. More patterns of spatial variability were apparent using the composite imagery than was visible in the imagery from the individual sensors. The soil property maps created using the within-field sampling stratification were more accurate than those of using field stratification. Increasing the accuracy of such base-line datasets ensures that the simulation models within the DSS have the best possible initialisation for a given level of sampling. No matter how sophisticated the DSS, it cannot overcome errors introduced by initialisation of site characteristics. Conversely improved initialisation will significantly enhance the DSS' ability to accurately represent the land management unit being simulated.

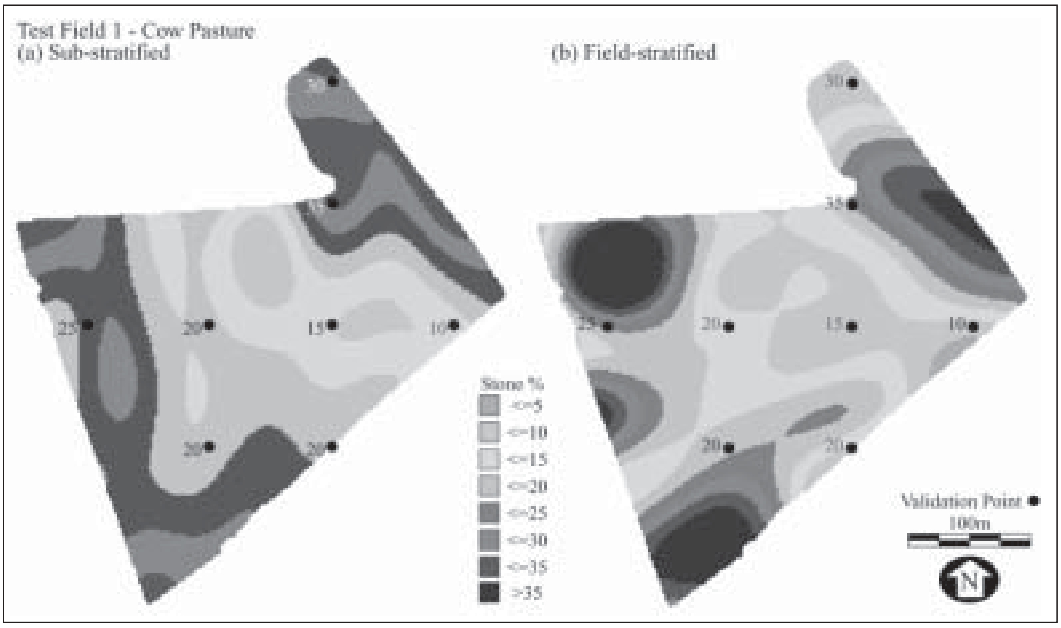

Figure 8 Geostatistical interpolation of the sub-stratified (a) and field-stratified (b) datasets for Test Field 1, overlain with the grid based validation samples.

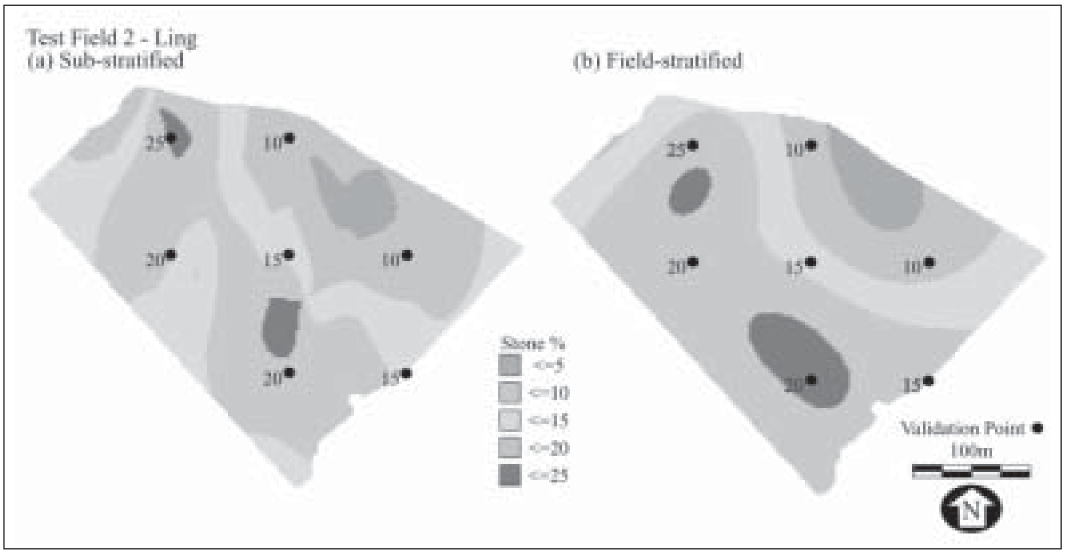

Figure 9 Geostatistical interpolation of the sub-stratified (a) and field-stratified (b) datasets for Test Field 2, overlain with the grid based validation samples.

Acknowledgements

The research for this paper is funded by grant-in-aid from the Scottish Executive Environment and Rural Affairs Department and the Macaulay Development Trust. The authors also acknowledge the assistance provided by M. Jones, H. Martin, W.H. Ekin and D. Riley, PULNiX (UK), and Pentax (UK). Ordnance Survey materials © Crown copyright 2002 - GD27237X 2002.

References

Agbu P.A. and Frank T.D., (1988). Assessing the improvement in soil mapping using spot HVR over LANDSAT MSS imagery. Technical Papers, American Society for Photogrammetry and Remote Sensing. Annual Convention, St. Louis. 4:191-197

Baumgardner, M.F., Kristof, S., Johannsen, C.J. And Zachary, A., (1970). Effects of organic matter on the multispectral properties of soils. LARS Information Note 030570, Purdue University, West Lafayette, Indiana.

Biswas R.R., and Singh C.P., (1991). Capability of TM data for evaluation of soil and land resources in the Malwa plateau (Chambal and Mahi catchments) in Madhaya Pradesh. *International Journal of Remote Sensing*, 12, 1905-1913.

Bowers, S.A. and Hanks, R.J., (1965). Reflectance of radiant energy from soils. *Soil Science*, 100, 130-138.

Brus, D.J. (1994). Improving design-based estimation of spatial means by soil map stratification. A case study of phosphate saturation. *Geoderma*, 62:233-246.

Condit H. R., (1970). The spectral reflectance of American soils. *Photogrammetric Engineering and Remote Sensing*, 36: 995-966.

Da Costa, L.M., (1979). Surface soil colour and reflectance as related to physiochemical and mineralogical soil properties. PhD Dissertation, University of Missouri, Columbia.

Di Paolo W.D., (1979). *An analysis of LANDSAT data for soil investigation on federal land in southern Idaho*. LARS Contract Report. 082879. Laboratory for Applications of Remote Sensing, Purdue University, West Lafayette, Indiana.

Harrison W.D., and Johnson M.E. (1982). Improving mapping unit delineation accuracy using LANDSAT MSS spectral maps. Proceedings of the western region technical work planning conference. Soil Conservation Service, Washinghton, D.C., 95-98.

Hovaroth, E., Montgomery, O. and Van Zile, B., (1971). The effects of altitude on the multispectral mapping of soil organic matter. *Proceedings of the Indiana Academy of Sciences*, 80, 476.

Kaluzny, S.P., Vega, S.C., Cardoso, T.P. and Shelly, A.A., (1998). S+ Spatial Stats: User's Manual for Windows® and Unix®. Mathsoft, Inc., Seattle.

Lee K.S., Lee G.B. and Tyler E.J., (1988). Determination of soil characteristics from Thematic Mapper data of cropped organic-inorganic soil landscape. *American Journal of Soil Science*, 52, 1100-1104

Leone A.P., Tedeschi P. and Wright G.G., (1996). LANDSAT satellite data for soil investigations in an Apennines region of Southern Italy. *Geografia Fisica E Dinamica Quaternaria*, 19, 371-380.

Leone A.P., Wright G.G., and Corves C., (1995). The application of satellite remote sensing for soil studies in upland areas of Southern Italy. *International Journal of Remote Sensing*, 16, 1087-1105.

Lund L.J, Harrison W.D., Johonson M.E., Wiismiller R.A., and Kristof S.J., (1980) Utilization of LANDSAT data in mapping soils of the Big Desert area, Idaho. Agronomy Absteracts, 212.

Macaulay Institute. (1984). Organisation and Methods of the 1:250,000 Soil Survey of Scotland. Macaulay Land Use Research Institute (formerly the Macaulay Institute for Soil Research), Aberdeen, U.K.

Matthews, K.B., Sibbald, A.R. and Craw, S. (1999). Implementation of a spatial decision support system for rural land use planning: Integrating GIS and environmental models with search and optimisation algorithms. *Computers and Electronics in Agriculture,* 23:9-26.

McKeague, J.A., Day, J.H. and Shields, J.A., (1971). evaluating relationships among soil properties by computer analysis. *Canadian Journal of Soil Science*, 51, 105-111.

Milton, E.J. And Webb, J.P., (1987). Ground radiometry and airborne multispectral survey of bare soils. *International Journal of Remote Sensing*, 8, 3-14.

Montgomery, O. L., and Baumgardner, M. F., (1974). Laboratory applications of remote sensing. Technical Report 112674, Purdue University, West Lafayette, Indiana.

Moran, M.S., Inoue, Y. and Barnes, E.M. (1997). Opportunities and limitations for image-based remote sensing in precision crop management. *Remote Sensing of the Environment*, 61:319-346.

Myers, V.I. and others, (1983). Remote sensing applications in agriculture. In: J.E. Estes and G.A. Thorley, (eds.), Manual of Remote Sensing, Volume 2. American Society of Photogrammetry, Mcgraw-Hill Inc., New York, 2111-2228.

Page N.R., (1974). Establishing of organic matter in Atlantic coastal soils with a colour-difference meter. *Agronomy Journal*, 66, 652-653.

Roudabush R., Herrinam R.C., Barmore R.L., and Schellentrager G.W., (1985). Use Of LANDSAT Multispectral Scanning data for soil survey on Arizona rangeland. *Journal of Soil and Water Conservation*, 40, 242-245.

Stein, A., Bastiaanssen, W.G.M., De Bruin, S., Cracknell, A.P., Curran, P.J., Fabbri, A.G., Gorte, B.G.H., Van Groenigen, J.W., Van Der Meer, F.D. and SaldaÒa, A., (1998). Integrating spatial statistics and remote sensing. *International Journal of Remote Sensing*, 19(9),1793-1814.

Stoner, E.R., Baumgardner, M.F., Weismiller, R.A., Biehl, L.L. and Robinson, B.F., (1980). extension of laboratory-measured soil spectra to field conditions. *Journal of the American Society for Soil Science*, 44, 572-574.

Su H., Ransom M.D., and Kanemasu E.T., (1989). Detecting soil information on a native prairie using LANDSAT TM And SPOT satellite data. *Journal of the American Society for Soil Science*, 53,1479-1483

USDA, (1951). Soil Survey Manual. Handbook No. 18, United States Department of Agriculture, Government Printing Office, Washington.

Wright, G.G., Matthews, K.B., Cadell W.M. and Milne, R., (2003). Reducing the cost of multi-spectral remote sensing: Combining near-infrared video imagery with colour aerial photography. *Computers and Electronics in Agriculture*, 38, 175-198.