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Progress in Soil-landscape Modelling and Spatial Prediction of Soil Attributes for Environmental Models

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Abstract

This paper summarizes progress and new work for the quantitative spatial prediction of soil attributes. An example spatial prediction of the soil profile carbon pool is presented for a study area in Australia. New methods integrating soil layer models and a hillslope profile sampling procedure are demonstrated for development of spatially-averaged hillslope models for three study areas. Visualizations of convergent and divergent hillslope soil layer cross-sections for each study area are presented with interpretations of landscape function.

1. Introduction

In Gessler et al. (1995) we reported on the development of generic soil-landscape modelling methods to provide explicit and quantitative spatial predictions of soil attributes that may be used in other, more comprehensive, environmental models. These methods build on the work of Moore et al. (1993), McKenzie and Austin (1994), McSweeney et al. (1994) and others. This paper provides: (i) a brief summary of the methods; (ii) discussion of progress and experiences in applying the methods over the last two years; (iii) an implemented example; (iv) a presentation of new work integrating the methods for development of hillslope models; and (v) a critical evaluation of the overall approach and requirements for additional components.

1.1 Summary of Methods

The approach outlined in Gessler et al. (1995) assumed that local terrain modifies climate and parent materials and therefore served as a simple surrogate integrating many landscape processes that influence soil patterns. Spatial analysis of a digital terrain attribute, the compound topographic index (cti), was used to define the local catenary/landscape population and catenary environmental gradients for allocating field sample locations. The assumption was that the stratifying variable, cti, captured the range and relative distribution of variation in the landscape for the attributes of interest. This was an attempt to explicitly quantify the implicit process often used in traditional soil survey. The strategy could be altered and adapted in many ways depending on the requirements of a particular project and availability of prior information.

After collection of field data, exploratory data analysis (Cleveland 1993) was used to search for correlations between the soil attribute being modelled and environmental attributes that were simpler to measure and available in a spatially continuous manner. Useful relationships were then confirmed and defined by statistical models. The statistical models were evaluated and improved by: (i) analysis of residuals; (ii) visualization of a spatial implementation of the model; and (iii) field verification. Generalized linear models (McCullagh and Nelder 1989) were used for spatial prediction of basic soil layer patterns (A horizon depth, E horizon presence/absence, Solum depth).

The first objective of the modelling was to develop empirically-based spatial predictions. The second objective was to interpret useful environmental correlations discovered in the modelling process for elucidation of underlying landscape processes responsible for the patterns.

1.2 Progress and Experiences in Application

The first study area (Griggward) was expanded and two additional study areas (Ladysmith, Brucedale) were sampled in the same manner described in Gessler et al. (1995). A broad range of soil attributes (physical, chemical and morphological) were modelled using a common set of procedures. Additional environmental variables (e.g. climatic, geochemical, digital imagery) were acquired over the study areas and sampled for use in predictive modelling. An example is presented below and comprehensive reporting of the study findings will be presented elsewhere.

The process used to develop statistical models described in Gessler et al. (1995) was improved using tools available in the S-PLUS (Statistical Sciences 1993) statistical computing package. For each individual soil attribute, plots of the univariate sample distribution and bi-variate relationships with sample depth and soil layer or horizon factor were produced. These indicated whether: (i) data transformation for normalization was warranted; (ii) if the soil attribute varied systematically or smoothly with depth in the soil profile; or (iii) if morphologically described soil layers strongly partitioned the variation suggesting modelling by individual soil layers. Conditioning plots or co-plots (Cleveland 1993) were routinely used to search for conditional relationships in terrain attribute space. Regression tree models (Breiman et al. 1984, Clark and Pregibon 1992) were also used to explore for possible conditional or complex nonlinear relationships in the data (landscape) that may be missed by other data exploration and model fitting criteria. A comprehensive stepwise exploration of both linear and nonlinear fits of all potential explanatory variables was conducted using the Akaike Information Criterion (Akaike 1974). This provided an objective numerical assessment that balanced the reduction in residual deviance with complexity of the model as defined by the degrees of freedom consumed (e.g. parameters fitted). Generalized additive models (Hastie and Tibshirani 1990) with scatterplot smoothers were routinely used for nonlinear fitting. If model residual patterns showed non-normal characteristics the "quasi" family was used in generalized linear or generalized additive models to allow use of stabilizing link and variance functions and relaxation of assumptions about the data distribution (McCullagh and Nelder 1989, Hastie and Tibshirani 1990).

In the end, our preference was to use simple models with linear terms if possible. There are several reasons for this. First, our longer term intention is to integrate the models for understanding pattern/process relationships within and between study areas. Secondly, subsequent work will investigate how we attempt to incorporate and account for estimations of error entered at various steps. Thirdly, we hypothesized that the further we push the models to fit the sample data by adding additional explanatory variables and higher order fits, the more local the model becomes and therefore less useful for prediction at regional scales. This will be tested in subsequent work.

The concept of a soil "type" was disregarded in this research. Instead, we focussed on the collection of useful datasets that can be continually analyzed as methods and our understanding develop. We explicitly stated the measurement methods, sample size and scale of each soil attribute and environmental variable (meta-data) realizing that they are taken over a range of different scales. Our spatial predictions assume the quantified relationships can be applied in the broader spatial context defined by explicit physiographic domains. Classification and imposition of traditional soil types or taxonomic classifications are not precluded in this approach, but our research focusses on the development of quantitative and continuous predictions of individual attributes with defined confidence and uncertainty based on collected sample evidence.

This approach enabled the development of a broad range of different models for individual soil attributes using a broad range of explanatory environmental variables and statistical modelling tools. Regression tree models often provided the largest reductions in residual deviance, but often produce stepped (e.g. non-continuous) prediction surfaces unsupported by field investigation. Soil layers proved very useful in partitioning the variation for many soil attributes, and hence supported the concept of a building block approach where soil layers were used to aggregate or disaggregate soil attribute data for modelling and spatial prediction where appropriate. Reductions in residual deviance ranged from 10 (A horizon exchangeable sodium percentage) to 90 (solum depth) percent, indicating the span of prediction certainty for different attributes that should be an explicit part of model implementation.

1.3 Example Integration of Models for Spatial Prediction

Total carbon was one of the soil chemical attributes measured in this study. In soils where negligible calcium carbonate is present, as was the case here, total carbon provides a measure of organic carbon held in the soil relating to biomass (e.g. microbial, macrobial, humus, plant material). The amount of carbon in the soil pool is an important component of the carbon cycle and knowledge of it is useful for broader biosphere modelling.

A plot of the bivariate relationship between total carbon and sample depth showed a very smooth relationship where percentage total carbon declined rapidly with soil depth. Conditioning plots using the compound topographic index as the conditioning variable showed that this relationship was invariant with landscape position. This indicated that a generalized additive model with a scatterplot smoothing spline could be used to model carbon over the landscape as a function of soil depth.

By combining models previously developed for solum depth and A horizon depth (incorporating E or A2 horizons) with the spline profile total carbon model and assumptions about soil bulk density, we developed a spatial prediction of the soil profile total carbon pool across the landscape. Bulk density was not measured as part of this work, but a recent survey (Geeves et al. 1995) encompassing the study area provided a regional mean A horizon bulk density (rhob) of 1.5 Mg m-3 of soil and a regional mean B horizon bulk density (rhob) of 1.6 Mg m-3. Using these, a predictive equation was constructed as follows:

Soil Profile Total Carbon =

$$\int_0^{adep} f(Totc.gam(s(dep))d(x) * \rho_b(Ahor) + \int_{adep}^{soldep} f(Totc.gam(s(dep))d(x) * \rho_b(Bhor) \qquad (1)$$

The integrals of total carbon for the A and B (B equals solum depth minus A horizon depth) horizons as predicted by the GAM model, computed on a one centimeter depth increment, is multiplied by the bulk density for the A and B horizons. Assuming that this model was valid across the area encompassed by a 400m2 grid cell, a spatial prediction was computed. Figure 1 shows a color coded spatial implementation of the modelled variation of the profile total carbon pool for the Griggward study area. A histogram equalized stretch was applied to enhance visual display, therefore the color legend does not have equal intervals of tons/hectare carbon. The total carbon GAM model provides a percentage reduction in residual deviance of 84%. The A horizon depth and Solum depth GLM models provide 78% and 77% reductions in residual deviance. This indicates that each of these component models can be predicted with a high level of certainty.

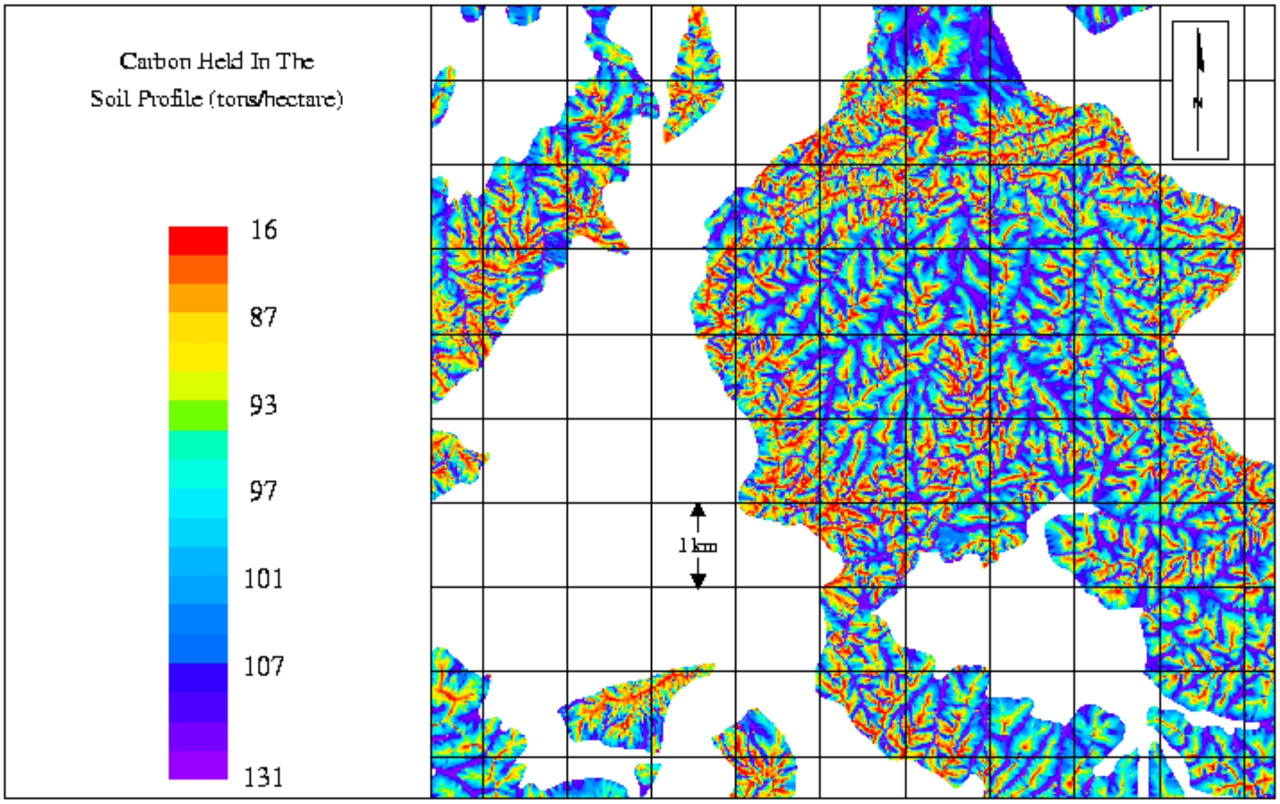

Figure 1. Predicted Soil Profile Carbon Pool (Griggward Study Area)

1.4 Hillslope Models of Soil-landscape Structure

The work presented thus far has focussed on the development of quantitative models for predicting soil-landscape patterns. The intention is to provide a good base from which to build an understanding of landscape processes to facilitate simulation of landscape dynamics. Forman and Godron (1986) and Turner and Gardner (1991) state that three important landscape characteristics are structure, function and change. Our work follows these concepts by first developing quantitative models describing the soil-landscape structure as defined by soil layer patterns. The soil layers, as discussed in McSweeney et al. (1994) and Gessler et al. (1995), are a result of pedo-geomorphic and hydrological processes and therefore can be used as a link or pointer to material and energy flow processes and pathways in landscapes.

In undulating landscapes with open drainage, the catchment or watershed is an important spatial area for understanding flow connectivity and flow accumulation that can be approximated using digital terrain attributes (Moore et al. 1993). The watershed is comprised, at a more local level, of a continuum of converging and diverging hillslopes (Carson and Kirkby 1972). In the past, hillslope block diagrams displaying soil layers have been a useful technique for visualizing hillslope patterns and flow pathways (Gerrard 1981, Walker and Butler 1983, Buol et al. 1989). However, these visualizations are often idealized two-dimensional hillslopes and not based on quantitative models developed over the three-dimensional soil-landscape continuum.

In reality, there is a complex mixture of landform curvatures causing flow to converge and diverge. Conceptually, the two end-members of this continuum would be hillslopes that continuously converge from summit to base and those that continuously diverge from summit to base. Everything else falls in-between as a mixture of converging and diverging hillslope elements. Therefore developing visualizations of these two end-members using quantitative models will be useful for interpreting landscape function and comparison of hillslope patterns between different study areas. The following sections describe methods and preliminary results for visualizing hillslope patterns for interpretation of material and energy flow processes in landscapes.

2. Material & Methods

2.1 Study Area Environmental Characterization

Three study areas were selected to cross a regional climatic gradient on two different parent materials. Detailed environmental characterizations of each area in the form of climatic, geologic, geomorphometric and airborne gamma radiometric spatial characterizations (e.g. summary statistics) have been created for each area and Table 1 presents six study area means indicative of basic physiographic differences. The climatic variables were developed using the ANUCLIM software (McMahon et al. 1995) output to a grid node spacing of approximately 245m. The geomorphometric variables were developed using the methods described in Moore et al. (1993) and Gessler et al. (1995) computed from a 20m grid node spacing digital elevation model (DEM) derived from a 1:25 000 topographic map source (10m contours).

Table 1. Study Area Spatial Mean Environmental Characterizations

Study Area	Climate			Geomorphometry		
	mean annual temp. (°C)	total annual precip. (mm)	mean annual radiation (mJ/m^2/day)	mean elevation (meters)	mean slope (percent)	mean compound topographic index
Brucedale	15.53	509	17.78	235	3.48	9.35
Ladysmith	15.11	575	17.61	259	8.68	7.75
Griggward	13.98	709	17.18	383	11.42	7.16

The Brucedale study area is 9 500 hectares in size (centered on: 147�25�E, 35�05�S) and situated on very gently undulating granitic parent materials covered by a thick mantle of aeolian clay. The dominant land uses are cereal cropping and pastoral grazing. The Ladysmith study area is 5 800 hectares in size (centered on: 147�29�E, 35�13�S) situated on gently undulating hills of Ordovician metasediments dominated by slightly metamorphosed shales and sandstones of marine origin. The dominant land use is pastoral grazing. The Griggward study area (centered on: 147�27�E, 35�24�S) is 5 300 hectares in size situated on rolling hills of Ordovician metasediment parent materials. The dominant land use is pastoral grazing.

2.2 Soil layer modelling

Approximately 80 locations were sampled in each study area following the methods described in Gessler et al. (1995). A broad range of GLM, GAM and TREE soil layer models were developed using the procedures described above for A horizon depth, probability of E horizon presence/absence, E horizon depth and solum depth. These are the basic functional soil layers from which more detailed work may proceed. The Brucedale study area showed only two occurrences of E horizons, therefore E horizon models were not developed for this study area.

The best model for each soil layer attribute was selected based on reduction in residual deviance, degrees of freedom consumed and type of model. The general order of preference for model type was GLM, GAM and TREE. The selected soil layer models were implemented as spatial prediction surfaces using map algebra tools.

2.3 Hillslope Profile Sampling

The intention of the hillslope profile sampling was to develop a visualization of the average convergent and divergent hillslopes in each study area. This involved four steps of: (i) developing a quantitative definition of a hillslope; (ii) developing a sampling strategy to provide convergent and divergent hillslope datasets; (iii) editing and averaging the data in hillslope distance space; and (iv) developing display graphics.

A hillslope was defined as a spatial object that maintains flow connectivity from summit (hillslope initiation) to base (hillslope conclusion). Following empirical experimentation with digital terrain attributes, hillslope initiation cells were defined as those cells with less than two DEM grid nodes flowing into them. Hillslope conclusion cells were defined as cells with greater than 100 DEM grid nodes flowing into them. These usually corresponded with streamlines defined on digital 1:25 000 topographic map sheets for the area. Convergent and divergent hillslope components were then defined as the remaining cells with plan curvature greater than zero (convergent) and plan curvature less than zero (divergent). A convergent hillslope is therefore a hillslope that starts at an initiation cell and flows continuously through convergent cells downslope to a hillslope conclusion cell; and vice versa for a divergent hillslope. Using these principles, a visual display was created that showed the four-class grid overlaid with flow vector arrows and a 1:25 000 contour map (10m contour interval). Convergent and divergent hillslopes could then be traced to sample along the hillslope profile from each predicted soil layer surface.

Ten convergent and ten divergent hillslopes were sampled in each study area. A one by one kilometer line coverage was placed over each study area and each 1 km2 cell numbered sequentially. A random number vector was developed and sampled to randomly select ten 1 km2 subareas for hillslope sampling in each study area. This ensured no bias for any part of the three study areas. The data files generated were then edited to ensure that the hillslope distance intervals were identical for averaging. The average of all hillslope vectors was taken for each convergent and divergent sample in each study area to provide a mean hillslope vector. The average length of the ten hillslopes was used to determine the average hillslope length.

Data files were set up using the Splus language (Statistical Sciences 1993) for graphic creation. The E horizon probability data was used to filter the E horizon depth so that E horizon depths are only displayed for those hillslope distance vectors where the probability of an E horizon is greater than 0.5. Approximate colors were used that closely match the true soil colors as determined from the sample data. The graphical axes (x = hillslope distance, y= hillslope height) were established to fit all of the convergent or divergent hillslope model displays to highlight relative differences. The layer depths have been multiplied by a factor of ten to enhance cross-section display, and the ordinate extended to negative hillslope heights to fit the entire soil layer extents onto the display.

3. Results and Discussion

Figure 2 displays the convergent hillslope models and Figure 3 the divergent hillslope models. The relative differences in basic hillslope structure for each study area are readily apparent from the graphics. The soil layers may now be used to interpret and compare how these landscapes function with respect to material and energy pathways and flows.

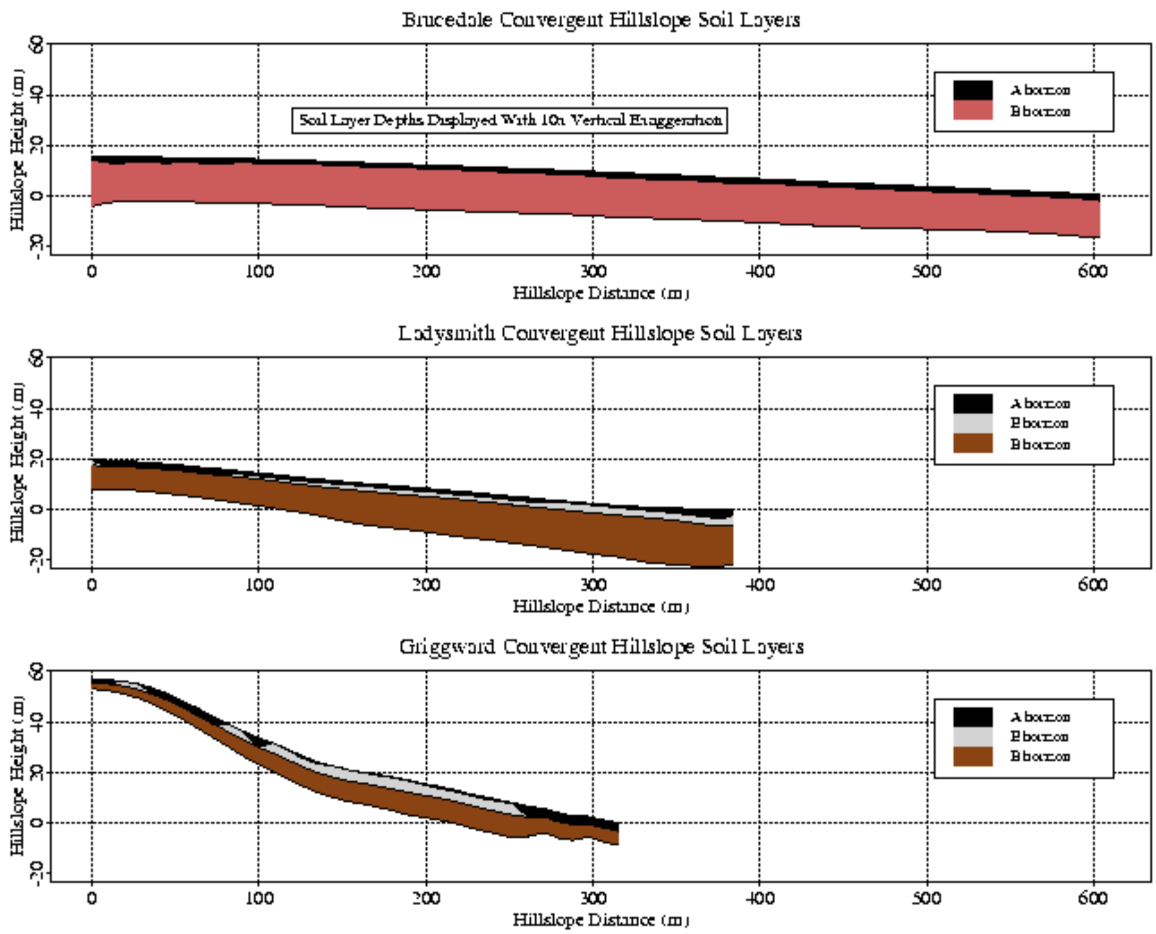

Figure 2. Study Area Mean Convergent Hillslope Models

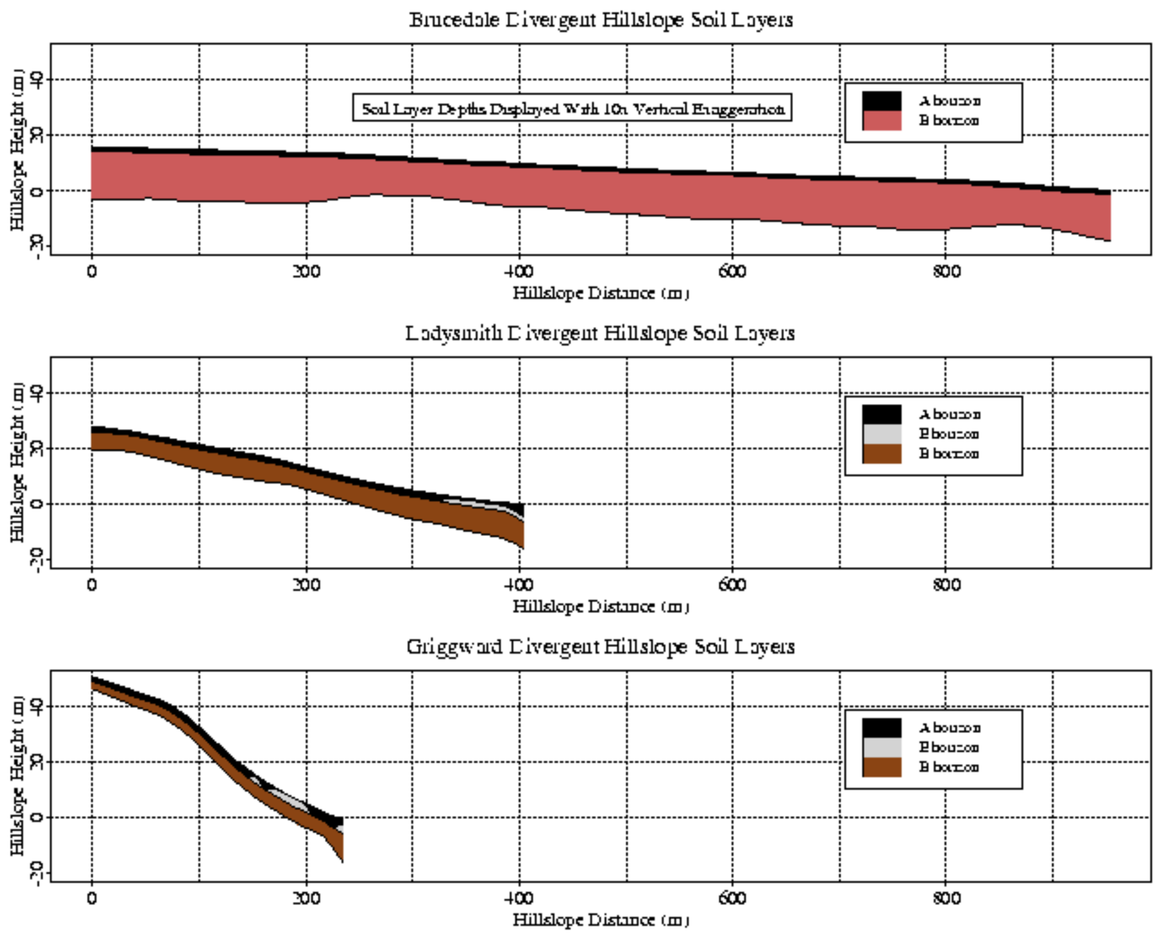

Figure 3. Study Area Mean Divergent Hillslope Models

3.1 Brucedale Hillslope Models

The A horizon depths are slightly greater and the solum depth less variable on the Brucedale mean convergent hillslope, but the overall difference between convergent and divergent hillslopes is small. The consistent nature of the A horizon depth may be influenced by the widespread cereal cropping landuse in this study area where cultivation maintains a plow layer A horizon (Ap). Soil texture does not strongly contrast between the A horizon (clay loam) and B horizon (light clay). Field samples also indicated that the B horizons are well structured. These factors coupled with the dryer and warmer climate and gently inclining topography indicate that very little surface or subsurface lateral flow occurs in these landscapes. This suggests that the principal material and energy flow pathway in this landscape is in-situ vertical infiltration of water where it is either used by plants or lost to deep percolation.

3.2 Ladysmith and Griggward Hillslope Models

The A horizon depths are deeper and more variable in the Ordovician metasediment landscapes. The A horizon depths for Griggward are deeper than Ladysmith and occupy a larger proportion of the solum. The soil texture contrasts more markedly in the solum derived from the Ordovician metasediments parent materials compared to the Brucedale setting. The A horizons are typically sandy loams and the B horizons, light clay to clay textures. This texture contrast provides greater impedance to vertical conductance of water from the A to B horizons. This factor coupled with the steeper slopes and relatively cooler and moister conditions compared with Brucedale favors development of distinct E horizons where lateral throughflow of water is an important process.

As expected, the E horizons occur much higher on the convergent hillslopes for both study areas with the Ladysmith landscapes showing a more systematic E horizon development and increase in depth transcending the hillslope. Both convergent and divergent hillslopes for Griggward show a more probabilistically variable occurrence of E horizons. This suggests that the moister, cooler and higher energy Griggward landscapes exhibit a more dynamic mixture of processes including overland flow, material movement by surface erosion and subsurface flow.

Lack of E horizons just below the hillslope summit on the Griggward convergent hillslope may indicate an area of active colluvial processes not stable enough for E horizon development to occur. E horizon absence at the hillslope base may indicate an active area of alluvial processes as the hillslope connects to the broader, higher energy watershed system. The area in between where deep E horizons occur may be a region of seasonal waterlogging.

3.3 Regional Interpretations

Over the climatic gradient in the direction of increasing rainfall and cooler temperatures, A horizon depths increase and solum depths decrease. This is echoed by an increase in the A horizon mean total carbon percentages (Brucedale: 1.3, Ladysmith: 2.27; Griggward: 2.58) indicating increased soil biological activity. Hence, a more favorable annual water balance, less prevalent dry and hot organic matter oxidizing conditions and less frequent soil cultivation likely contribute to this. The Brucedale soils exhibit slightly higher cation exchange capacity's and higher pH's than the Ladysmith and Griggward soils. This suggests conditions more favorable to leaching and solute transport in the Ordovician metasediment study areas reflected by the E horizon presence. The descreased solum depths on the Ordovician metasediments suggest that erosional processes are more common as a result of soil layer, geomorphometric and climatic conditions. These indicate that lateral surface and subsurface flow pathways are much more prevalent in the Ordovician metasediment landscapes.

4. Conclusions

This paper presents a summary of our progress in soil-landscape modelling research and briefly demonstrates new work that integrates developing methods. The intention is to demonstrate quantitative methods that place soil-landscape modelling on a scientific foundation for continual evaluation and improvement. In many hydrological and environmental models, the soil component is incorporated in a very simplistic way, if at all. The methods discussed here aim to provide continuous spatial predictions with known levels of confidence based on the sample evidence collected. The integration of models to develop hillslope soil layer visualizations is simple in concept, yet provides an explicit and quantitative base from which to build better models and understanding of landscape processes and dynamics. The models behind the visualizations may also be used to rapidly generate automated maps for landscape management.

4.1 Critical Appraisal of Approach

Several general areas are in need of further conceptual development and empirical testing. At the broad regional scale, we have developed and characterized three study areas using prior information about geology and climate. More research is required to determine how to best define physiographic domains and place them in a broader spatial context to extrapolate developed models. At the more local catchment and hillslope scales, we have used a simple environmental gradient, based on the compound topographic index terrain attribute, to allocate and spread samples in both environmental attribute and geographic space. More research is required to define basic concepts to guide this process. These are difficult challenges for general purpose natural resource inventory intended to build various models of different attributes from a single sampling. Iterative and nested approaches for sampling and data analysis may be more appropriate, but are not always logistically feasible.

We have maintained information that could be used to account for and model error propagation through the modelling process, but we have not attempted to explicitly incorporate it. It is likely that this should be planned from the beginning. Tools to do this need to be developed.

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