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Fuzzy land element classification from DTMs based on geometry and terrain position

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Abstract

Land elements have been used as basic landform descriptors in many science disciplines, including soil mapping, vegetation mapping, and landscape ecology. We describe an approach in terrain classification, with the objective of deriving a method for classifying land elements from DTMs based on their fundamental characteristics. The methodology for modelling land elements is implemented as a two-step process: first, form elements are classified based on local geometry, and second, land elements are derived by evaluating the form elements in their landscape context. Form elements are derived by fuzzy classification of slope and curvature at a specified global scale (window size). The form elements are reclassified according to their geomorphometric context using a higher scale terrain position index. The resulting land elements are evaluated with respect to their predictive value for modelling soil properties. It is shown that scaling geomorphometric properties is important for applying them to predict soil properties and to model landform units. The presented model, based on scaled geomorphometric properties and geomorphometric context, using a limited number of model parameters, is capable of modelling fundamental land elements that can be utilized in soil–landscape modelling and in other applications in land resource management.
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Keywords: Terrain classification; Land elements; Soil–landscape modelling; Digital elevation models; Fuzzy sets; GIS

1. Introduction

Landform units have been used as basic landform descriptors in soil mapping (Speight, 1990; Milne et al., 1995), vegetation mapping (Whitehouse et al., 1992), and landscape ecology (Zepp and Müller, 1999). Terms like 'ridge', 'hollow', and 'footslope' are used in many mapping legends to describe fundamental terrain units at the hillslope scale ('Microrelief' after Dikau, 1989). However, the rationale behind these land units is only weakly described and/or differs for different legends (Milne et al., 1995). This paper focuses on the issue of modelling land elements. Land elements are defined in the context of the Australian land system classification (Christian and Stewart, 1968) as small areas of land surface that are uniform in geomorphometric parameters, such as slope, surface roughness, contour, and profile curvature (Lynn and Basher, 1994). They therefore roughly correspond with form facets

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as defined by Dikau (1989). Some attempts have been made in recent years to develop automated mapping routines for land elements from digital terrain models (DTMs). Dymond and Harmsworth (1994) presented an approach in modelling terrain units using slope (flow) profile analysis and detection of breaks in gradient. This method is dependent on the methods used for detection of steepest slope and does not recognize two-dimensional surface characteristics, i.e. changes in contour. Dymond et al. (1995) used a combined aspect–slope–elevation classifier to generate land elements. Their algorithm includes an arbitrary classification into nine aspect classes and complex, iterative filtering techniques to remove noise from the dataset. Drawbacks of these approaches are that they only indirectly consider scale and curvature characteristics of landscapes. Fels and Matson (1996) introduced a scalable landscape-position parameter and developed a terrain model based on a combination of slope and landscape position. Here also, curvature as an important landform parameter is not included. Macmillan et al. (2000) developed a complex classification system based on 10 geomorphometric parameters, including curvature and distances to drainage divides, and a fuzzy rule set, resulting in a model of 15 land elements. The model requires a large number of parameters and thresholds to be adjusted. These procedures vary in the types of algorithms, the parameters used, and therefore in format and range of predicted units. Most important, they only partly consider the problem of scale in landforms. The approaches are mostly based on surface derivatives, as gradient, curvature, and flow direction. The problem of incorporating surface roughness is often ignored, as coarse resolutions of available DTMs mostly do not allow the estimation of surface roughness at the required sub-land element scales.

Whereas the discussed studies are based on semantic models of land elements, a different, data-driven approach in landform classification is based on automated classification. Unsupervised classification of terrain parameters using ISODATA and k-means algorithms has been proved to give good results in representing terrain elements (Irvin et al., 1997). Moreover, fuzzy k-means algorithms deliver also uncertainty measures for the delineated land elements (Burrough et al., 2000, 2001). These techniques are based on the fact that the geomorphometric signature of different landform units is related to similar terrain parameters: valley bottoms are low slope, close to thalweg areas, whereas hillslopes are steep areas more distant from thalwegs. Land surface attributes, however, vary continuously over the landscape and do not show clear clusters. Moreover, we do have a priori knowledge about the units we want to derive. It is the purpose of this paper to describe a new method of modelling land elements based on their fundamental properties. First, parameters describing the basic characteristics of land elements are identified, i.e. an attempt at rationalizing land elements is presented. Then, a quantitative method for modelling land elements is described. Finally, the methodology is applied to a study area in New Zealand and evaluated with respect to modelling spatial soil distributions. It is shown that land elements can be applied to derive fundamental land units of steepland country, and that these units correspond with terrain characteristics used in soil (e.g. Milne et al., 1995) and vegetation (e.g. Whitehouse et al., 1992) mapping.

2. Fundamental properties of land elements

Various studies have proposed notations and definitions of land elements (Speight, 1990; Milne et al., 1995). There are no unique and universal definitions of land elements. For example, Speight (1990) describes about 70 different landform elements using the attributes slope, morphological type, dimensions, and geomorphological activity, whereas Milne et al. (1995) describes about 77 land units on different scales.

Typical landform properties used in describing land elements are local form, form and size (scale), topological/neighborhood attributes, and surface roughness. It is, for example, certainly expected that a hollow is a concave part of the earth surface, whereas a spur generally has a convex form. So, a fundamental property of land elements is related to *local geometry*. Additionally, a *scale* issue is related to the definition of land elements, i.e. the parameterization has to incorporate a specific spatial extent: a ridge is generally a larger land element than a hollow. A basic problem is the quantification of appropriate scales for a local land element, which often is related to the

context. Wood (1996) therefore proposed to use a variety of window sizes (surrogate for spatial scales) and derived the dominant element over all scales as a classifier, whereas Gallant and Dowling (2003) used a multiscale index for modelling valley bottoms. Important characteristics for land elements are derived from the *spatial context*, i.e. neighborhood relationships and landscape position in a higher scale context. For example, a ridge can be defined as a facet on a hill that is surrounded in two opposite directions by shoulders or backslopes. It has to be kept in mind that a unique, nonambiguous classification into land elements will not be possible, as there is a high degree of *uncertainty* inherent in the semantic descriptions of land elements and the descriptor variables used: it is, for example, unclear what a hillslope is in semantic terms (Dehn et al., 2001). If a hillslope is simply defined as a high gradient area, it is still uncertain what 'high gradient' means in quantitative terms. Therefore, there are no clearly defined spatial boundaries, i.e. land elements are 'fuzzy objects' (Macmillan et al., 2000). The aspect of surface roughness is ignored in this paper, as the used DTMs do not allow an estimation of microtopography.

3. Methodology: strategy for land element modelling

From the previous section, it is assumed that two basic properties control the occurrence of land elements: local geometry at specific scales and terrain context. The properties need to be evaluated/classified considering an amount of uncertainty with respect to their role in the definitions of land elements. The factors are included in the modelling strategy (Fig. 1). The individual modelling steps are described in the following paragraphs. Each model step delivers a specific product that is of potential use for land resource modelling. The strategy is realized as a series of grid algebra scripts in the Arc Macro Language (AML) within the Geo-Information system Arc/Info (Table 1).

3.1. Terrain generalization and parameterization by scaled derivatives

Gradient and curvature are the fundamental derivatives describing geometric form at any point of a surface. These derivatives are, however, strongly scale-dependent. Considering complex land surfaces within the context of land element classification, appropriate scales for derivation of the local geometry have to be selected according to the semantic terrain model implied by the application (Schmidt et al., 2003). Fig. 2 shows that the predictive value of profile curvature for estimating soil properties in a regression model varies with the scale (window size) for which profile curvature is calculated. This highlights the importance of scale in the calculation of geomorphometric properties for continuous soil–landscape modelling.

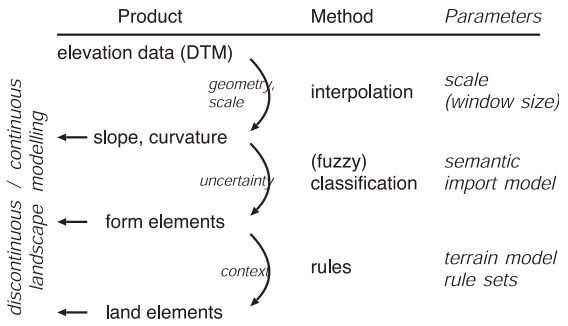

Fig. 1. Strategy for delineation of land elements. Output at different levels can be used in landscape modelling. The final model output is a fuzzy classification into land elements.

Therefore, Wood (1996) proposed to calculate the derivatives at varying window sizes. Here, this approach is used to derive slope and curvature for the subsequent classification at appropriate scales (Table 1). According to the results of Florinsky (1998) and Schmidt et al. (2003), a least-square fit for a quadratic polynomial function after Evans (1980) was chosen as a local interpolator to calculate derivatives [Eq. (1)].

$$\begin{pmatrix} \sum x_i^4 & \sum x_i^2 y_i^2 & 0 & 0 & 0 & \sum x_i^2 \\ \sum x_i^2 y_i^2 & \sum x_i^4 & 0 & 0 & 0 & \sum x_i^2 \\ 0 & 0 & \sum x_i^2 y_i^2 & 0 & 0 & 0 \\ 0 & 0 & 0 & \sum x_i^2 & 0 & 0 \\ 0 & 0 & 0 & 0 & \sum x_i^2 & 0 \\ \sum x_i^2 & 0 & 0 & 0 & 0 & N \end{pmatrix} \begin{pmatrix} a \\ b \\ c \\ d \\ e \\ f \end{pmatrix} = \begin{pmatrix} \sum z_i x_i^2 \\ \sum z_i y_i^2 \\ \sum z_i x_i y_i \\ \sum z_i x_i \\ \sum z_i y_i \\ \sum z_i \end{pmatrix} \quad (1)$$

N is the number of cells for the chosen window size, and the sums are calculated from the cell coordinates (x_i, y_i, z_i). The user has to choose an

Table 1
Technical framework to model land elements (Fig. 1)

Method	Parameters	Output	References
(1) Local polynomial fit on DTM	window size	slope and curvature at specified scale	Evans (1980), Wood (1996)
(2) Fuzzy classification of slope and curvature	semantic import model, fuzzy classification model	fuzzy form element classification	Burrough (1989), Dikau (1989), Wood (1996)
(3) TOPHAT, fuzzy classification	window sizes, elevation threshold	landscape position indexes	Rodriguez et al. (2002)
(4) Fuzzy classification	rules	fuzzy land element classification	

The different algorithms are applied sequentially to derive the final product: the land elements. The algorithms are implemented using the Arc Macro language (AML).

appropriate window size for the derivation of geometric properties that is related to the general landscape character and the scale of the intended application: if fine details of a landscape need to be modelled, a smaller window has to be used. The adjustment has to be done according to the average size of form elements (hollows, spurs, etc.) for the specific study area. The results of this procedure are maps of slope and various curvature measures (Shary et al., 2002; Schmidt et al., 2003) calculated at a specific global (spatially invariant) scale. These maps can be used as predictive variables in land resource mapping, e.g. for continuous soil-landscape modelling (Fig. 1).

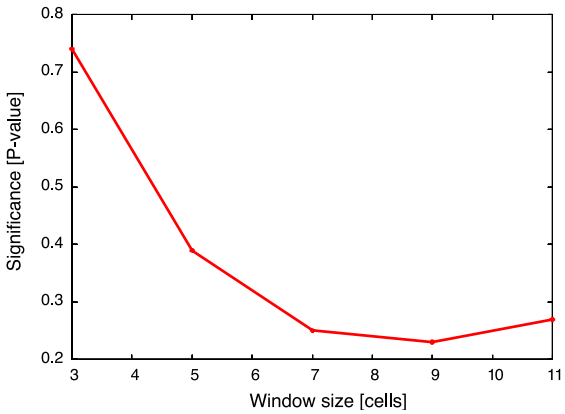

Fig. 2. Profile curvature, calculated at different scales, as an explanatory variable for rooting depth. The explanatory value of profile curvature is very low (high *P*-value: low significance). The significance varies with the scale used for calculation: there is an optimum scale at a neighborhood window of nine cells (135 m).

3.2. Fuzzy classification of local landform geometry

Classifications of curvature and slope have often been applied to land surfaces. Here, a combination of the approaches of Dikau (1989) and Wood (1996) is used: local landform features are individually described by curvature for low-gradient (flat) and for sloping areas (Fig. 3). For flat areas, a definition of a gradient-related curvature makes no sense, so for these areas, maximum and minimum curvatures (Shary et al., 2002) are used to classify six fundamental form facets (Fig. 3, cf. Wood, 1996). For sloping areas, profile curvature and tangential curvature are used to classify nine form elements (Fig. 3 cf. Dikau, 1989). Schmidt et al. (2003) showed that tangential curvature should be preferred to contour curvature for the purpose of classifying form elements. Curvature is classified according to three classes: concave, straight, and convex. The final classification results in 15 elements, which can be attributed by geomorphographic terms as shown in Fig. 3. These elements are called ‘form elements’ as they represent a continuous land surface made up of elements that are homogeneous/similar in their form (geometry).

The definition for ‘flat’ or ‘sloped’ in terms of a specific slope threshold is subject to considerable uncertainty (fuzziness). Likewise, the delineation of straight, convex, and concave curved areas is also uncertain. Different mappers will draw the boundaries differently. Moreover, these thresholds depend on the terrain characteristics. Therefore, it is appropriate to substitute the hard classification thresholds used for form classification (e.g. Dikau, 1989) with fuzzy boundaries, leading to a fuzzy classification of land-

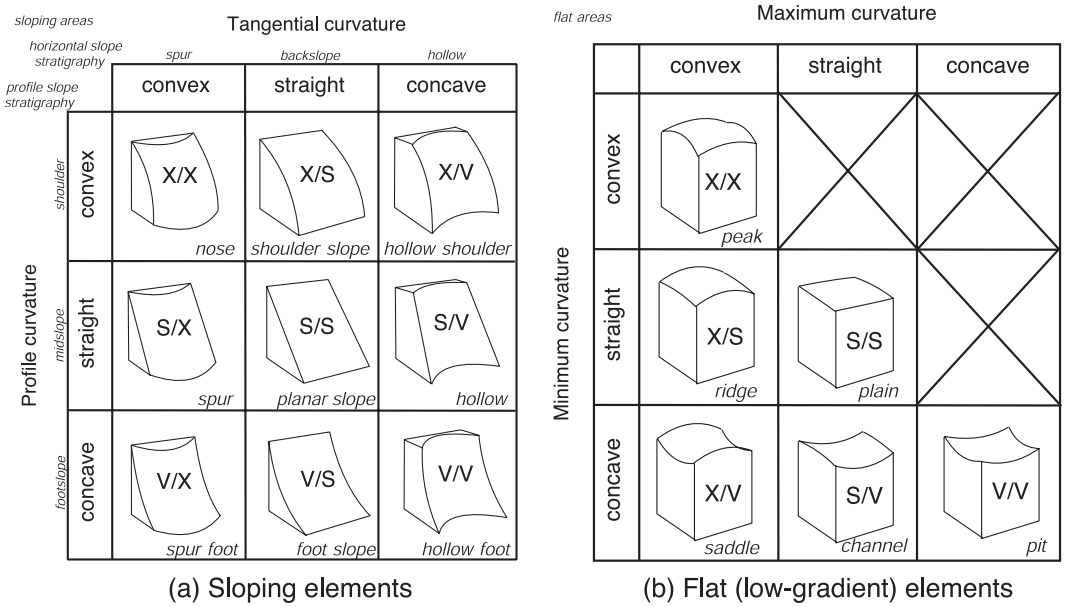

Fig. 3. Fundamental local landform elements: 15 'form elements' based on classification of local slope and curvature.

forms (Fig. 4, Burrough, 1989). Proposed semantic import models for the classification range from simple linear to smooth inverse polynomial functions (Burrough, 1989). Here, a simple linear model with two thresholds was chosen (Fig. 4); as an example, the membership for flatness $m(\text{flat})$ is shown in Eq. (2).

$$\begin{aligned} m(\text{flat}) &= 1, \quad \text{if slope} < s1 \\ &= 0, \quad \text{if slope} > s2 \\ &= \frac{s2 - \text{slope}}{s2 - s1}, \quad \text{if } s1 < \text{slope} < s2. \end{aligned} \tag{2}$$

The rules defining a form element (Fig. 3) can then be implemented on the basis of the semantic import models by applying a fuzzy classification model (Burrough, 1989). Here, a minimum/maximum classifier was used for AND/OR connections. As an example, the calculations for the membership of peaks $m(\text{peak})$ [Eq. (3)] are given.

$$\text{peak} = \text{if}(\text{flat \& maxcurv. convex \& mincurv. convex}) \tag{3}$$

$$m(\text{peak}) = \min(m(\text{flat}), m(\text{maxcurv}_x), m(\text{mincurv}_x)).$$

These algorithms generate membership-value maps for each of the 15 form elements (Fig. 3). The maps can be used to derive a map of form elements from

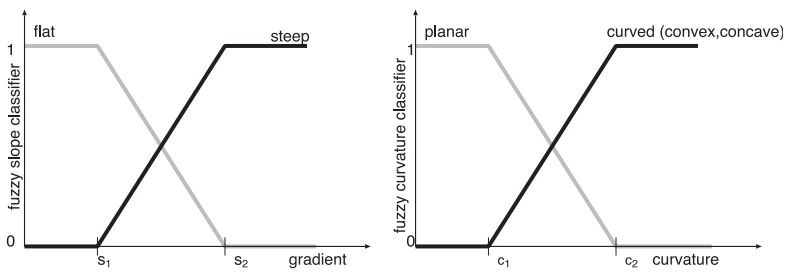

Fig. 4. Semantic import models for slope and curvature: fuzzy classifier for slope and curvature tendency.

the highest membership value for each cell. Additionally, uncertainty in the classification can be quantified by the derived maximum membership value, the 'confusion index' (Burrough and van Gaans, 1997), or entropy values (Wood, 1996). These maps express the uncertainty of the classification for each classified unit (e.g. raster cell).

3.3. Modelling terrain context

The classification procedure leads to a fuzzy model of form elements, which is based on fuzzy local curvature and gradient characteristics for a specific scale. It is important to include the terrain context in the classification procedure (Fig. 1, cf. Wood, 1998). Therefore, a model for terrain position was implemented based on a second, higher scale landform classification. The TOP HAT approach (Rodriguez et al., 2002) was extended by a fuzzy classification (Fig. 5), producing membership values for grid cells in the DTM, which are a measure for landscape position. The algorithm requires three global (spatially homogeneous) parameters: two window sizes identifying the horizontal spatial scales of valleys and hills and an elevation threshold defining the minimum magnitude for valleys and hills, i.e. how much hills/valleys are exposed-above/submerged-below the surrounding area. These measures can be estimated from the DTM used.

3.4. Reclassification including terrain context

The higher scale landscape position model was combined with the form element model using a set of

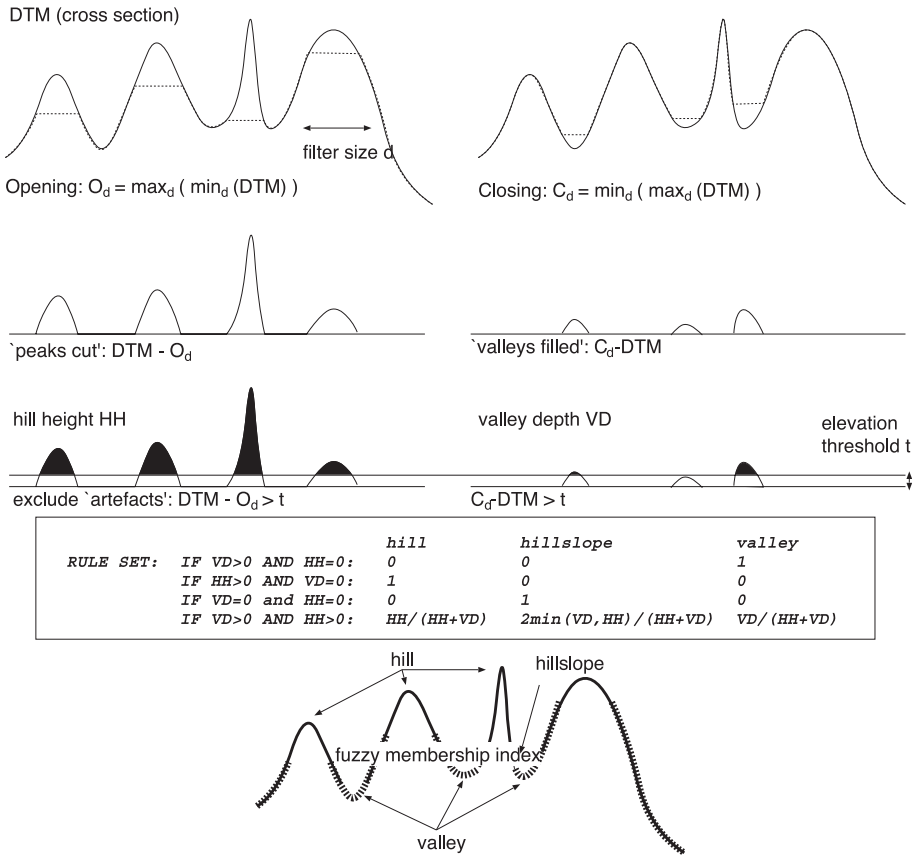

Fig. 5. Fuzzy valley/hill classification using the TOP HAT approach. The original method (Rodriguez et al., 2002) was extended to a fuzzy index for valleys and hills.

Table 2
Modelling land elements by topological rules

Terrain	Form (Fig. 3)	Element
Hill	peak or plain or ridge or spur or saddle	ridge
Hill	shoulder or hollow shoulder or spur shoulder	shoulder
Hillslope	backslope	backslope
Hillslope	hollow or channel or hollow shoulder or hollow foot	hollow
Hillslope	spur or ridge or spur shoulder or spur foot	spur
Hillslope	plain or footslope or shoulder	terrace
Valley	footslope or hollow foot or spur foot	footslope
Valley	pit or plain or channel or hollow or saddle	valley bottom

Some examples for rules used. Inputs are the two terrain classifications: the form element classification (form) and the valley/hill classification (terrain). The output is a land element classification (element). The rules are implemented as a fuzzy classification (compare Table 1).

rules (Table 2) to address the following major problems in the form classification. Planar, flat land elements can occur on ridges, backslopes (as terraces), and in valley bottoms (both as valley bottom and as pronounced terraces). These significantly different landscape units are not distinguished by the form element model. The solution lies in the consideration of a higher scale landscape context: a flat, planar area on a hilltop, for example, would be a ridge. Therefore, it is necessary to include context information in the model.

Hollows and channels are distinguished by a slope threshold. This can lead to a repeating pattern of hollow-channel sequences in the valleys because of steps in the valley/hollow floor. Similarly, ridges and spurs are distinguished by a slope threshold, leading to sequential occurrence of ridges/spurs. These problems are related to a generalization problem: an 'optimal' land element map would generalize those fine-scale details, so that a continuous ridge- and channel-network is mapped, and no hollows would occur directly below channels or ridges directly below spurs. The rule sets (Table 2) partly remove those unwanted patterns.

4. Study area

The developed approach was applied to a variety of different landscapes of the South Island of New Zealand. Here, results from hill country south of Nelson underlain by Moutere gravels are presented (Fig. 6). The lithology consists of Pliocene/Pleistocene greywacke gravel. A series of different soil sets are mapped in the area, related to increasing relief and rainfall. A DTM of 15-m grid size was created using the Arc/Info routine TOPOGRID, based on

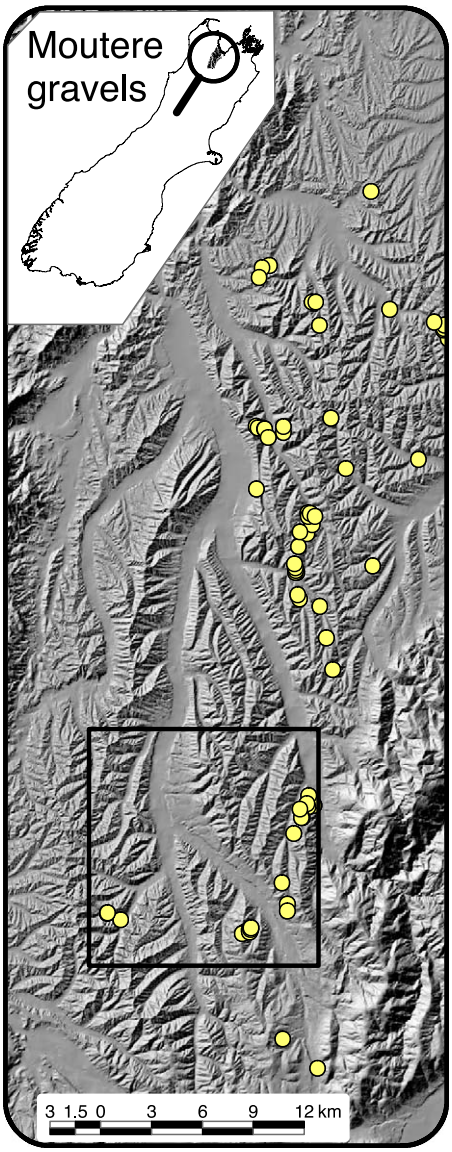

Fig. 6. Study area: Moutere gravels, South Island, New Zealand. Dots indicate locations of soil profiles used in this study. The box indicates the study window for Figs. 7, 9 and 10.

the ANUDEM interpolation procedure (Hutchinson, 1996). The base data used are 20-m contour lines and spot heights from 1:50,000 topographic map sheets (Land Information New Zealand 260 Series). Accordingly, the quality of the generated DTM will vary over the landscape. The extended flat valley bottoms with low information density will have high uncertainty as the interpolated distances often reach kilometers. On the steeper hillslopes, however, the horizontal distance of the contours will be in the range of several tens of meters. As the major aim of this study is to model hillslope elements, a spatial grid resolution of 15 m was chosen, which is adequate to represent hillslope structures, but may overestimate accuracy in flat areas. A series of soil profiles (71 soil descriptions) was described for the area (Fig. 6), which were sampled over a range of different parts of the landscape and landscape components. These soil profiles are used to show the utility of the model approach presented in this paper for soil-landscape modelling.

5. Results

Fig. 7 shows results of the form element model applied to the study area. The membership maps display membership values for the individual form elements. The higher the membership value, the higher the probability that a specific point in the landscape can be characterized as that form element. The figures show the general landform character, i.e. the basic landscape stratigraphy is emphasized by the model. However, the results also show the problems of a landform description based on local geometry only: plain areas on ridges are not classified as ridges, misclassification of channels/hollows occurs in valleys, and of spurs/ridges on hilltops (Fig. 8).

The final land element model is derived by combining the form classification with the higher scale terrain classification. The terrain classification for the study area is shown in Fig. 9. The parameters reflect the general, higher scale, landscape position for the study area.

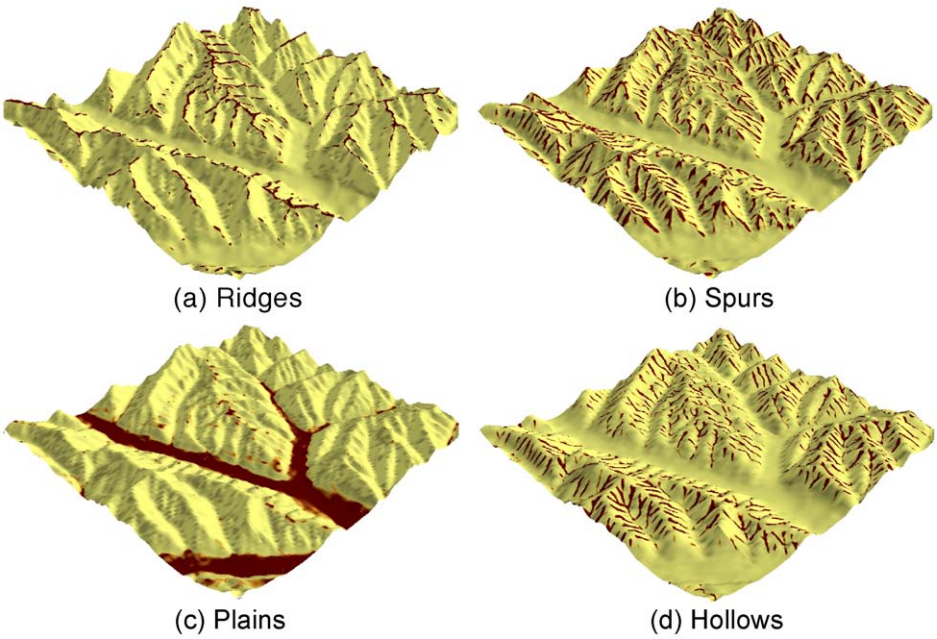

Fig. 7. Form element classification for an area of Moutere gravels (see Fig. 6). Extent is approximately 15×15 km^2, elevation ranges from 300 to 800 m. Shown are membership values for some form elements. Refer to Fig. 3 for explanation of the terms. Dark areas denote high membership values, and bright areas denote low membership. Model parameters: window size: 135 m, slope thresholds: 2–10°, curvature thresholds: 1/500–1/200 1/m.

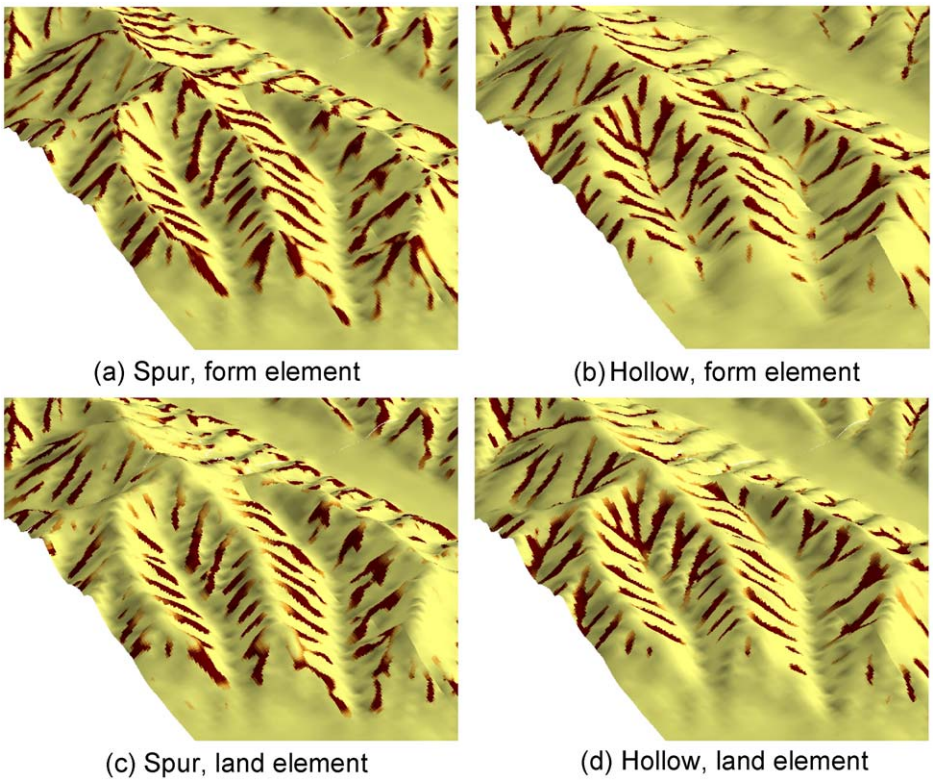

Fig. 8. Problems of landform description based on local geometry. Spurs extend to ridges (a), hollows to valleys (b). Including landscape position partly solves these problems (c, d). Note the differences between (a) and (c) on the ridges, and between (b) and (d) in valley bottoms.

By combining the form element model and landscape position model, the final land element model is derived. As Figs. 8 and 10 show, some of the problems of the pure form classification are resolved: ridges, spurs, and hollows occur as more continuous units. Planar, flat landform elements on ridges are reclassified as ridges, and plains in the valleys are classified as valley bottoms.

The model results were tested for their relationship to soil attributes of the Moutere gravels. Rooting

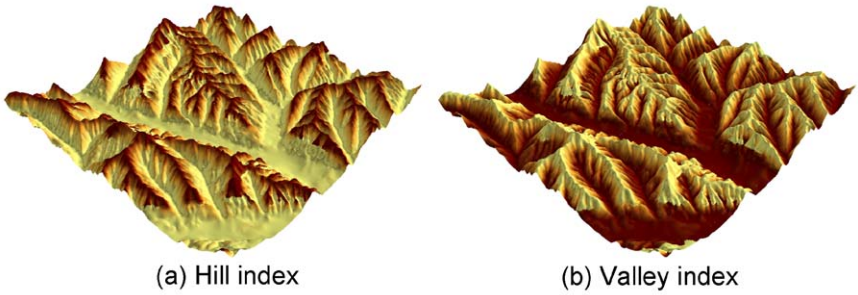

Fig. 9. Terrain position classification for an area of Moutere gravels (see Fig. 6). The valley/hill terrain indices indicate membership values for valleys and hills, based on TOP HAT approach (Rodriguez et al., 2002). Dark areas relate to high membership values for hills/valleys; bright areas indicate low membership values.

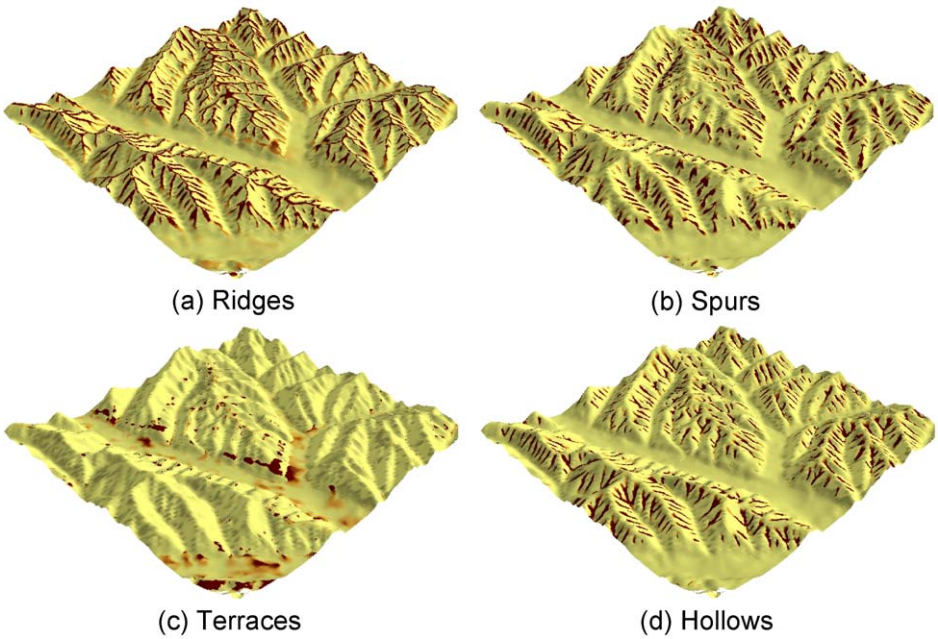

Fig. 10. Final land element classification for an area of Moutere gravels (see Fig. 6). Dark areas denote high membership values; bright areas denote low membership.

depth from the sampled soil profile description was related to the modelled land elements (discontinuous soil–landscape model, Fig. 11). The rooting depth shows distinct relationships with modelled land components (Fig. 11). Therefore, the derived landform model can be used as a predictor variable for modelling soil landscapes in the Moutere gravels. Moreover, the statistics also allow a prediction of the means and the variability of soil parameters for the land elements (Fig. 11).

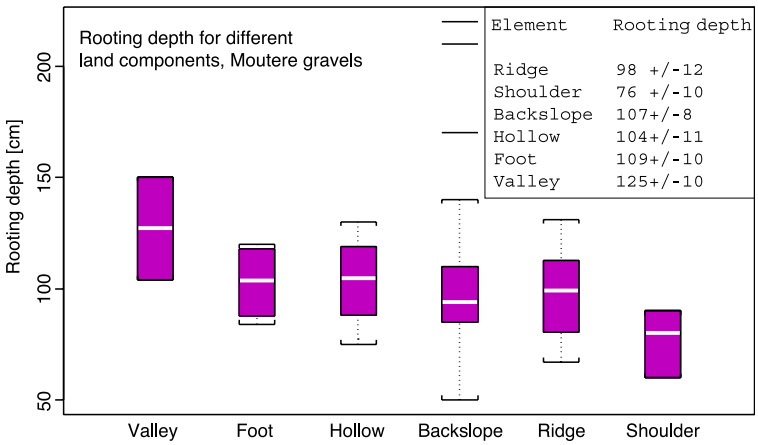

Fig. 11. Modelled land components as explanatory variables for rooting depth. The figure shows boxplots for distribution of rooting depth within the modelled land components. The relationship shows the expected trend: higher rooting depth on footslopes and in valleys, lower rooting depth for shoulders (significant at 90% level).

6. Discussion

A methodology has been presented for calculating land elements from DTMs, based on geometry, scale, context, and uncertainty. The methodology was used to derive land elements for a steepland area in New Zealand. The resulting maps reflect the general topography and landform character. They are therefore useful in mapping the fundamental land components of a land system that are dominantly explained by landform characteristics. However, the advantage of the technique is that it not only produces a landform classification, but the membership maps can also be used to measure the uncertainty in the classification. The method is simple with respect to computational and parameter requirements and is therefore easy to apply.

The modelled land elements were used to give spatial estimates of soil properties (Fig. 11). Different methodologies can be used to model soil landscapes (Fig. 12). The model presented here is based on a heuristic landform model and soil property statistics with respect to the defined landform elements (Fig. 12). As discussed by Macmillan et al. (2000), heuristic approaches take advantage of a priori expert knowledge about landform structure and related landform processes. Automatic classifications have the advantage of more objectivity (Burrough et al., 2001), but the disadvantage of a subsequent semantic interpretation of the automatic defined classes, and they are less transferable than heuristic approaches (Macmillan et al., 2000). The advantage of discontinuous soil-landscape models as defined by land elements in comparison to continuous soil-landscape models (Fig. 13) lies in an intuitive landscape model, which is easily understandable (i.e. the semantics of the term 'hollow' is common knowledge) and spatially applicable (i.e. I am on a shoulder, therefore I expect a rooting depth of XX). Therefore, discontinuous soil-landscape models are more desirable in an applied sense, whereas continuous soil-landscape models might be suitable as a model component (e.g. in hydrological modelling), where distributed parameter input is required.

A series of issues have been identified that could be used to improve the methodology, including (a) spatially variable scale, (b) locally adaptive thresholds, (c) improved modelling of landscape position, (d) better rules describing neighborhood relationships and geomorphometric context, and (e) the form and connectivity constraints of land elements. These issues are discussed in the following paragraphs.

A fixed, spatially invariant window size (scale) is used to calculate slope and curvature for the form element classification. It is clear, however, that scale properties of landscapes vary spatially and, additionally, are dependent on the modelled landform feature. For example, ridges have considerably different scale properties than alluvial plains. Additionally, anisotropy issues arise, i.e. spatial scales can depend on the direction. Therefore, a spatially adaptive scaling approach is needed. This could be accomplished by (a) defining scale specifically to each feature and/or (b) using a more complex filter approach to determine and optimize scale properties of landscape based on local terrain characteristics. Similarly, the slope and curvature thresholds used in the form element classification would be spatially variant, as landscape character changes continuously, and the local characteristics depend on the context. For example, slope thresholds, subdividing backslope units from ridges and valleys, depend on the local characteristics of the landform, i.e. the gradient of the slopes and valleys. Global thresholds, as used in the presented technique,

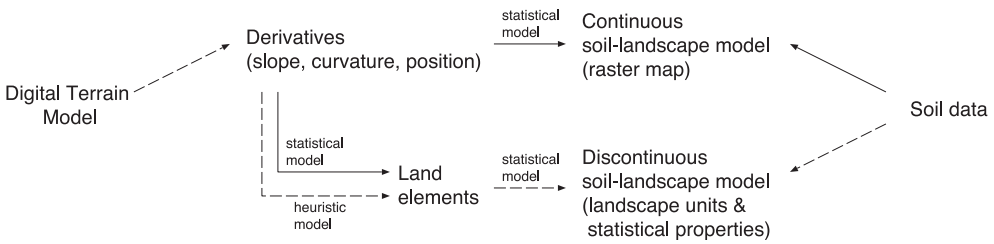

Fig. 12. Different methodologies in soil-landscape modelling. Dashed arrows indicate the path taken in this study.

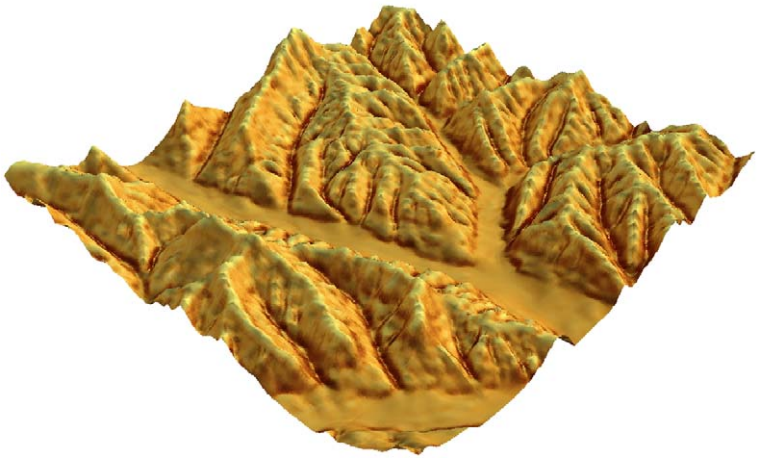

Fig. 13. Continuous soil-landscape model predicting rooting depth for the research area (dark areas: deep soils). Multivariate regression model of rooting depth in relation to the used input parameters for the soil-landscape model. The model shows generally shallower soils on ridges and fine-scale spatial variability, which is hard to interpret.

are regarded as producing poor results. It is therefore a research question to extend the methodology to spatially variant thresholds, based on an analysis of local geometrical constraints.

The higher scale landscape position model used in this study is based on a fixed-scale approach. There exist a variety of different models describing landscape position, also including variable scaling issues (e.g. Gallant and Dowling, 2003). This study did not evaluate how a landscape-position model for valleys/hills could be optimized. Related issues include the technology used, the parameters, and spatially variable, adaptive scales, and thresholds.

The model used to derive land elements is based on rules combining local form properties and general landscape position. The rule set used comprises only a few very simple rules, and there is a need to improve these rules. In this respect, it would be useful to evaluate the geomorphometric signature of the individual land elements considered in relation to important landform properties. In addition, following on from this, to the question whether it is enough to use local geometry and landscape position to model land elements, are there other explanatory landform parameters? Which combinations of relevant landform properties determine the spatial occurrence of a land element? Moreover, many land elements are inherently constrained by form and connectivity characteristics. For example, ridges are narrow areas that tend to form networks. Spurs normally connect to ridges. Shoulders occur in a variety of landscape positions, but normally between an upslope spur/ridge area and a lower backslope. Including these connectivity problems into a land element model would require vectorization of features into networks and/or directional/graph-oriented searching algorithms (e.g. Wood, 2000).

It was shown that the mapped land elements are related to soil characteristics. In particular, scaling geomorphometric parameters (here profile curvature) is of high relevance for their application in soil-landscape modelling and derivation of land elements. Land elements can therefore be used as input parameters for soil-landscape modelling. The model also produces uncertainty maps, and these can be applied to model uncertainty in the soil-landscape context. The technique developed is a stepwise technique

Table 3
Complete set of eight parameters required for the land element model

Parameter	Model input
Scale of form elements	one global window size
Fuzzy model for sloped/none-sloped areas	two slope thresholds
Fuzzy model for curved/none-curved areas	two curvature thresholds
Scale of terrain units: valley/hills	two window sizes
Relative relief of valley/hills	one elevation threshold

producing outputs at different levels of complexity, including scaled primary geomorphometric parameters, form elements, landscape position, and land elements. These different outputs can be utilized independently in land resource mapping.

7. Conclusions

The results show that it is possible to derive land elements for steepland areas based on geometry and landscape context using a relatively simple model. The model emphasizes the use of scaled geomorphometric parameters for terrain classification. The advantage of the model is that it requires a relatively limited set of parameters (degrees of freedom). The parameters are intuitive, i.e. they are directly related to landform features (Table 3). It was shown that the modelled land elements are related to soil properties. Therefore, they can be applied in the context of soil-landscape modelling. As the land elements model is based on a generic algorithm and fundamental terrain features, the derived units can be applied for other purposes in land resource management including, for example, vegetation mapping and identifying sediment storages.

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