A generic procedure for automatically segmenting landforms into landform elements using DEMs, heuristic rules and fuzzy logic

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Abstract

A robust new approach for describing and segmenting landforms which is directly applicable to precision farming has been developed in Alberta. The model uses derivatives computed from DEMs and a fuzzy rule base to identify up to 15 morphologically defined landform facets. The procedure adds several measures of relative landform position to the previous classification of Pennock et al. [39, 40]. The original 15 facets can be grouped to reflect differences in complexity of the area or scale of application. Research testing suggests that a consolidation from 15 to 3 or 4 units provides practical, relevant separations at a farm field scale. These units are related to movement and accumulation of water in the landscape and are significantly different in terms of soil characteristics and crop yields. The units provide a base for benchmark soil testing, for applying biological models and for developing agronomic prescriptions and management options.

Key words: Fuzzy logic, automated landform classification, digital elevation models, precision farming, expert heuristics, soil-landscape models, linguistic modeling.

Introduction

There has been increasing interest, in western Canada, and other locales, in developing generic procedures for automatically classifying landscapes into functional landform or soil-landform spatial entities. Motivation for such research includes the need to define effective management units for precision farming and requirements for mechanisms for scaling the results of site specific modeling and analysis up to local and regional scales [40]. In a more general sense, the research may be considered to be aimed at replacing current, expensive manual procedures for delineating and describing soil-landform entities (e.g. soil mapping) with consistent, replicable and cost effective automated procedures.

Automated procedures for segmenting landforms into landform elements or facets have been described by, among others, Pennock et al. [39, 40], Skidmore [44] Skidmore et al. [45], Fels and Matson [13], Irwin et al. [21], MacMillan and Pettapiece [25, 26], Graff and Usery [17], Franklin [14], Zevenbergen and Thorne [49] and Burrough et al. [7].

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Agri-businesses partners in the current research indicated, that to be useful to them, a landform segmentation procedure should ideally meet a number of criteria including:

- The defined units should exhibit meaningful differences in soil properties, moisture regimes and crop performance (yield).
- The procedures should apply to a wide range of types and scales of agricultural landscapes (with an emphasis on glaciated landscapes in the northern Great Plains).
- The procedures should be based on a single model or protocol and should produce simple output consisting of a limited number of landform classes with defined characteristics.
- The landform classes should support a limited number of protocols (varying by ecological region) for assigning standard management prescriptions to each defined landform unit.

Initial efforts utilizing the landform classification procedures of Pennock et al. [39, 40] encountered several key problems, specifically; a) a fragmented or chaotic spatial pattern, b) confusion in differentiating level areas and depressions in upper versus lower landscape positions and c) the inflexibility of fixed, rigid Boolean classification rules that require adjustment for different types and scales of landforms

Our current research has therefore focussed on improving spatial cohesion and reducing confusion by developing explicit measures of relative landform context and by incorporating these, along with other derivatives (e.g. those used by Pennock et al. [39]) into a fuzzy logic rule base that is applicable, without modification, to a wide range of landforms.

Objectives

The overall objective of the project was to develop and evaluate a practical procedure for partitioning soil-landscapes into landform elements or facets that display significant differences with respect to soil properties and to management requirements for precision farming.

The approach taken was to build upon existing models (e.g. Pennock et al. [39, 40]) using techniques first described by MacMillan and Pettapiece [25, 26, 27] to:

- Develop a model that is applicable the wide range of landscapes in the northern Great Plains.
- Incorporate measures of landform context and relative landform position.
- Emphasize the ability to recognize and classify landform facets in lower landform positions.
- Evaluate the model in terms of its ability to explain observed spatial variation in soils, soil properties and crop performance (yield)

Statement of the problem

The problem is essentially one of how to produce a generic classification of landform elements that can be applied automatically, and virtually without alteration, to a wide variety of landscapes.

Opinions vary widely regarding the most efficacious way of producing such a classification. The traditional view [20, 1, 2, 31] is based on acceptance of a soil-landscape paradigm that has long been the basis for soil survey and much applied soil research [20, 18, 19]. This view holds that the distribution of soils in the landscape is predictable and is a function of the five soil forming factors of Jenny with topography often playing a dominant role locally [1, 2, 31]. It results in the recognition of what Burrough et al. [8] refer to as a double crisp model with spatial entities having fixed and uniform conditions within each entity and abrupt boundaries between entities. Typically, application of the soil-landscape paradigm has relied heavily on subjective use of local tacit knowledge that is often inexact and poorly documented [20]. Recent studies have argued for adoption of a model involving continuous variation, quantitative definitions and fuzzy classes [50, 51, 8, 18, 19]. Both approaches, however, acknowledge the existence of fundamental relations among topography, landscape processes and soil properties [21, 35, 5].

The present research assumes that traditional manual procedures for delineating landform or soil-landform units from aerial photos can be approximated, and potentially improved upon, by automated procedures based on computer assisted analysis of digital elevation data (e.g. see [21, 39, 40, 7, 17]).

A human interpreter views and analyzes aerial photographs to delineate repeating soil-landform units in terms of readily visible external landscape attributes such as relative slope position, slope gradient, local surface form (convexities versus concavities), drainage condition and vegetation. Numerous studies have shown that even knowledgeable experts may vary widely in how they interpret any given landscape to produce manually interpreted soil-landform units [4, 22, 23, 21]. With the need for effective delineation of meaningfully different soil-landscape elements increasing and the availability of experienced landscape interpreters decreasing, any procedures for automating the process of landscape segmentation offer the promise of improved consistency and reliability.

The problems inherent in programming a machine to recognize and interpret landform elements in a way that is equivalent to, or superior to, manual interpretation of aerial photographs (API) involves three main challenges.

These are:

1. Selecting and computing an appropriate suite of terrain derivatives from DEM data
2. Identifying an appropriate number of meaningfully different landform classes and describing their salient or defining characteristics

3. Selecting and applying a classification procedure capable of using the available terrain derivatives to produce the required classes

Selecting and computing appropriate terrain derivatives

Fundamental to landform analysis is an interpretation of how shape and relative landform position influence the surface and near-surface movement and accumulation of water (plus energy and material) in landscapes. For automated classification, it is necessary to identify and implement algorithms that can convert raw elevation data into quantitative, numerical measures of those landform attributes. The terrain derivatives and topographic indices most widely used in landform classification to date include slope gradient, profile and plan curvature, slope aspect, solar illumination, wetness index or compound topographic index, slope position and slope length [21]. For landscapes with poorly integrated drainage into closed depressions there is a need for an additional derivative that measures the likelihood of inundation by ponding.

Numerous algorithms exist for computing the most commonly used terrain derivatives, namely slope gradient, aspect, profile and plan curvature [39, 49, 11]. These algorithms typically operate on a local 3x3 roving window and provide no explicit measure of the context of grid cells in terms of their overall landscape position. Recent developments have seen new algorithms proposed for computing other, more contextual, landform attributes including absolute and relative relief [3, 12, 13, 14, 15], slope length and relative slope position [44, 13, 33, 36], relative drainage condition as expressed by the compound topographic index [41, 42] or wetness index [35, 37, 38] and average incoming solar energy [21].

The emergence of suitable algorithms in combination with the increasing availability of high resolution digital elevation data (DEMs) has made developing and applying procedures for automated landform segmentation increasingly feasible and cost effective.

Identifying and defining appropriate landform element classes

The main alternatives for identifying the number and characteristics of functionally different landform units were: a) to use statistically based techniques (e.g. cluster analysis) to analyze the available DEM data to define significantly different classes or b) to accept existing geomorphic descriptions and utilize expert knowledge regarding the characteristics of different landforms. Classification procedures based on statistical analysis and ordination of terrain derivatives and other data for a particular site [21, 7, 8] result in classifications that are optimum for a given site. However, the results are specific to each unique site and cannot be easily generalized. The objective of defining a single classification procedure capable of producing a consistent, repeating set of landform entities for a wide variety of types and scales of landscape argued in favor of adopting a single set of heuristic rules based on expert knowledge and judgement.

Selecting and applying an appropriate classification methodology

Approaches to landform classification can be sub-divided according to whether they produce rigid (e.g. “crisp”) or continuous (e.g. fuzzy) classifications [8]. Each of these classes may be further sub-divided according to whether the classification rules are based on expert judgement (heuristics) or statistical analysis.

Hard or crisp classifiers

The landform classifications of Pennock et al. [39, 40] and Fels and Matson [13] are examples of rigid or “crisp” classifiers based on expert heuristics. They utilize expert knowledge and informed judgement to decide on the appropriate number of landform classes, the central concepts for each class and the values to adopt to define class boundaries.

Crisp classifications can also result from application of a wide variety of numerical classification techniques. Such techniques are usually differentiated according to whether the central concepts and boundaries of classes are defined from manually extracted training data sets (supervised classification) or by numerical procedures designed to identify “natural” clusters or groupings of classes in unbiased sample sets (unsupervised classification). Irwin et al. [21] provide an example of use of the ISODATA unsupervised classification clustering method to define landform elements for a 50 ha study site in Wisconsin.

Continuous or fuzzy classifiers

There is increasing interest in assessing not just a single, most likely, class membership for each grid cell in a raster matrix, but also the strength, or degree, of membership of each cell in each of ***n*** defined classes [28, 29, 10, 8]. McBratney and Odeh [28] refer to this as continuous classification to emphasize the continuity of the classes in attribute space and hopefully also in geographical space.

Again, a distinction can be made between continuous (fuzzy) classifications produced through manually defined rules based on expert judgement [51, 9] and those produced through statistical analysis and ordination of numerical input data.

Statistical classifications based on ordination of numerical data in n-dimensional feature space, such as fuzzy k-means, [21, 7, 8]), can identify the optimum number of natural classes for a given landscape, the central concepts and boundaries for each class and the mathematical rules for assessing the degree of class membership of each cell in a raster data set in each of k classes. Statistically-based classifications have the advantage of defining an optimal number of “natural” classes for a given site. Additionally, the classes so defined are expected to exhibit maximum differences amongst each other with respect to the numerical terrain derivatives used to define them.

The principal drawback of the statistical approach is that the classes and class definitions are optimized for a particular site. The classification rules, and the definitions and attributes of any defined "natural" classes, will never be exactly the same for any two sites. While a standard protocol can be developed for application to each new site, the number, type and characteristics of the resulting classes will always vary for each new site. This raises a number of practical (application) concerns. One is the time and effort required to develop and apply a new statistical classification for each site. Another might be the challenge of developing standard sets of recommendations or prescriptions for precision farming. Standard sets of recommendations are easier to envisage and develop if there is some expectation of a repeating set of classes with a defined and limited range of class attributes.

Expert knowledge and judgement can be codified and applied to produce continuous, fuzzy classifications via development of a semantic import (SI) model [6, 9]. The SI model permits formal recognition and incorporation of the "imprecise and overlapping semantics used to describe or classify data" [21]. In the case of landform facet classification, the SI model permits experts to identify any desired number of conceptual landform elements and to define each element using imprecise semantics (e.g. the class is relatively steep or relatively high in the landscape). Landform elements may be defined as having overlapping characteristics such that two or more elements may both be described as relatively steep but differentiated on the basis of another attribute such as being relatively convex or relatively concave. This approach was selected for the present project due to the flexibility it offered for applying a single set of heuristic concepts to a variety of types and scales of landscape.

Materials and Methods

Description of the study areas

The procedures for landform facet segmentation described here were initially developed and tested at two sites in Alberta with distinctly different glaciated landforms (Table 1).

The digital elevation data for both sites were acquired using a truck mounted differential global positioning system (DGPS) receiver as part of a previous precision farming research project [16]. The initial x, y, z DGPS data were processed into regular raster grids using the thin plate spline interpolation function available in GRASS [32] to produce regular grids with a horizontal grid spacing of 5 m and no missing data. Elevation values were reported with a vertical precision of 0.001 m although the absolute vertical accuracy was no better than 0.20 m. The DEM for the

Hussar site was filtered three times using a 3x3 low pass (averaging) filter. No filtering was applied to the Stettler data set.

Table 1. Location and general description of the Hussar and Stettler study sites

Description	**Hussar**	**Stettler**
Latitude/Longitude	52E, 11',14"/112E,29',35"	52E, 15',59"/112E,59',56"
Dominant landform	Strongly rolling glacial till overlying bedrock	Hummocky morainal (knob and kettle)
Elevation (min/max in m)	950 - 989 m	817 - 825 m
Maximum Relief (m)	49 m	8 m
Slope gradient (%) (maximum)	15-30 %	9-15 %
Slope gradient (%) (controlling)	10 %	8 %
Slope length (m)	100-300 m	50-100 m
Degree of drainage integration	Well integrated (95% off-site)	Poorly integrated (5% off-site)
Horizontal dimensions	765 m (NS) by 890 m (EW)	455 m (NS) by 830 m (EW)
Area (ha)	68 ha	38 ha
DEM horizontal grid dimensions	5 m by 5 m	5 m by 5 m

Selecting and computing appropriate terrain derivatives

Ten terrain derivatives were computed from the initial raw digital elevation data to act as input variables for automated landform classification (Table 2). The derivatives were selected based on their ability to provide meaningful, quantitative measures of both landform shape and relative location in the landscape, particularly as regards how these measures reflect the movement and accumulation of water in the landscape.

One group of derivatives includes slope gradient, aspect, profile and plan curvature and relative illumination. These describe the local shape and orientation of each grid cell based on calculations within a 3 by 3 window passed over the data set. These three derivatives are generally acknowledged to influence the movement of water and materials over and through the landscape and have been widely adopted as inputs for other landform classifications [21, 7, 39, 40, 49]. They were computed by solution of the numerical finite difference equations of Eyton [11].

Table 2. Terrain derivatives computed and used for the automated landform segmentation

Abbreviation of Terrain Derivative	**Name of Terrain Derivative**	**Description of Terrain Derivative**	**Reference for Method of Calculation**
SLOPE	Slope gradient	Slope gradient in percent (finite difference method)	Eyton, 1991
PROF	Profile Curvature	Rate of change of slope in the down slope direction in degrees per 100 m (finite difference method)	Eyton, 1991
PLAN	Plan Curvature	Rate of change of slope in the across slope direction in degrees per 100 m (finite difference method)	Eyton, 1991
QWETI	Wetness Index	Compound Topographic Index or Wetness Index measures relative likelihood of saturation or wetness	Quinn et al., 1991
PMIN2MAX	Percent Z relative to min & max elevation for the entire study area	Percent height (Z) of each cell above the minimum elevation relative to minimum and maximum elevations for the entire study site area	MacMillan and Pettapiece, 1997 b
PCTZ2TOP	Percent Z relative to top & bottom of each watershed	Percent height (Z) of each cell above the local pit elevation relative to the maximum elevation in each defined watershed	MacMillan and Pettapiece, 1997 b
PCTZ2PIT	Percent Z relative to local pits & peaks	Percent height (Z) of each cell above the local pit elevation relative to the elevation of each local peak in each watershed	MacMillan and Pettapiece, 1997 b
PCTZ2STR	Percent Z relative to nearest stream & divide	Percent height (Z) of each cell above the nearest cell designated as a stream channel cell relative to the nearest cell designated as a local divide (or ridge) cell	MacMillan and Pettapiece, 1997 b
Z2PIT	Absolute height (Z) above the local pit cell	Absolute elevation difference (m) of each grid cell above the local pit cell to which it drains	MacMillan and Pettapiece, 1997 b
PIT2PEAKZ	Absolute maximum pit to peak relief (Z)	Absolute maximum pit to peak elevation difference (Z) for the portion of the local watershed in which a given cell is located	MacMillan and Pettapiece, 1997 b

A multiple flow direction algorithm [41] was used to compute a second set of terrain derivatives, namely a multiple flow upslope area and a relative wetness index, also called a compound topographic index [35, 37, 38, 42]. This derivative provides an improved measure of the spatial pattern associated with redistribution of water and soil materials in the landscape arising from surface and near-surface runoff. We felt it was important to include wetness index in our extended classification due to the primary importance of moisture availability for crop growth in the moisture limited agricultural landscapes of western Canada. Wetness index, or some variation of it, is also increasingly being incorporated into other landform element classifications [21, 35, 7].

The remaining six derivatives listed in Table 2 all represent various measures of absolute relief or of relative slope position expressed in terms of relative relief. These measures were developed in response to one of our primary objectives; namely including an effective measure of relative landform position to help establish the context of each grid cell in the larger landscape.

All these derivatives require prior calculation of hydrological topology as defined by flow paths and watershed delineation. Flow directions were computed using an implementation of the conventional D8 steepest descent algorithm [47] as per the public domain raster GIS PC-RASTER [46]. A key feature of the watershed delineation procedures was the ability to either remove or retain depressions in the DEM. Small pits considered to be artifacts in the DEM were removed but all depressions above minimum threshold values for area, depth, volume or runoff required to fill were retained. Two separate sets of flow paths and watersheds were computed, the first applied to downward flow from each grid cell to a flow terminus at a pit or channel and the second to notional upslope flow paths from each grid cell to an upslope terminus at a local peak or divide. Upward flow was simulated by inverting the original DEM and rerunning the flow path algorithms on the inverted DEM.

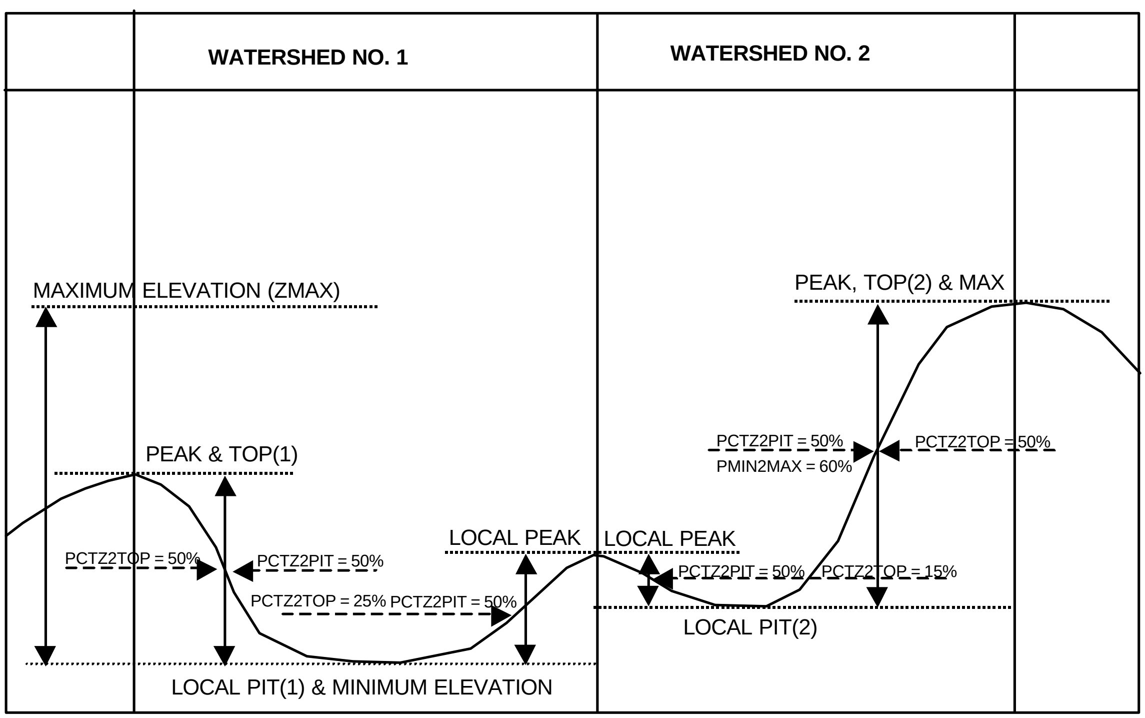


Figure 1. Illustration of the concepts underlying the various measures of relative landscape position

Once both sets of flow patterns were computed and a complementary set of stream channels and ridge lines was defined, it was possible to establish the position and context of every grid cell with respect to a number of significant locations or elevations within the data set (Figure 1). Each cell was evaluated in terms of its absolute difference in elevation (m) and horizontal distance (m) to the nearest divide and channel cells and pit and peak cells to which it is connected by a defined flow path. Relative relief was also evaluated in terms of the highest and lowest elevations in each watershed and in the database as a whole.

Both relative and absolute landform position exercise significant influence over the spatial distribution of soils and soil properties in agricultural landscapes [30, 5]. Much of this influence can be explained in terms of the movement and accumulation of water and sediment in the landscape. Downslope movement of water and sediments in surface and near-surface flow partially determines the locations were soil materials are most likely to be removed, transported and deposited. The redistribution of moisture in the landscape also promotes differential rates of soil development leading to deeper, thicker, more organic rich soils in moister locations and thinner soils with lower levels of organic matter in dryer locations.

These measures of relative and absolute landscape position were included in order to deal explicitly with multiple scales of spatial variation in landscape position. Baldwin et al. [3] demonstrated that the same location could be considered part of a number of different landscape features simultaneously, depending upon the scale and context in which it was viewed (e.g. the grid dimensions and kernel size used to compute the feature). Similarly, Fels and Matson [13] found it necessary to establish the relative landscape context of level areas and terraces by computing a second measure of relative landscape position for a greatly expanded window operating at a much broader scale than that used to define their primary landform elements. Any given location might simultaneously be considered to occupy, for example, both a mid-slope position, in terms of the larger landscape, and a crest or divide position in terms of a local ridge. We wished to be able to capture and express this ambiguity. It was felt that a combination of multiple measures of relative landform position and landform element definitions based on fuzzy logic was required to achieve this goal.

Flow paths for surface water flow, and the local watersheds or catchments defined by these flow paths, were adopted as the unifying features used to define the search areas within which the relative landform position of each cell is evaluated. Most current algorithms [13, 3, 48, 15] evaluate the landform position of each cell based on its relative elevation within a regular i-row by j-column search window. The dimensions of the search window are often meant to approximate the average dimensions of one complete cycle of topographic variation in the landform of interest.

Specification of an appropriate size for a search window is often achieved by trial and error [13], assisted by repeated visualization of the landscape of interest and manual adjustment of window dimensions, until the defined window size is deemed to match the dominant local wavelength of the landscape (e.g. the horizontal distance from crest to crest or trough to trough). We felt that defining local watersheds was a more context sensitive method of establishing the group of cells against which the relative landform position of each included cell could be judged. Each local watershed represents an explicit identification of the local ridge to ridge region within which a cell's landform position is best evaluated. The size of each defined watershed can vary across any given area in response to the actual terrain shape and configuration. This is equivalent to allowing a fixed search window to vary in size in response to varying terrain conditions.

The ability to link each cell in a gridded data set to the closest channel, depression, divide and peak cells to which it is explicitly connected by defined flow paths is fundamental to most of our procedures for computing indices of absolute and relative landform position (see Table 3.).

Table 3. Equations used to compute each of the derivatives measuring relative and absolute relief

	DERIVATIVE & EQUATION	EXPLAINATION OF DERIVATIVE	EQN NO.
a)	$PMIN2MAX = \frac{Z_{CELL} - Z_{MIN}}{Z_{MAX} - Z_{MIN}} * 100$	Percent Elevation relative to Minimum and Maximum Elevations in the data set	1
b	$PCTZ2TOP = \frac{Z_{CELL} - Z_{PIT}}{Z_{TOP} - Z_{PIT}} * 100$	Percent Elevation relative to Watershed Maximum Elevation and Pit Elevation	2
c)	$PCTZ2PIT = \frac{Z_{CELL} - Z_{PIT}}{Z_{PEAK} - Z_{PIT}} * 100$	Percent Elevation relative to Watershed Local Peak Elevation and Pit Elevation	3
d	$PCTZ2STR = \frac{Z_{CELL} - Z_{STR}}{Z_{DIV} - Z_{STR}} * 100$	Percent Elevation relative to closest Divide Cell and Stream Channel Cell	4
e)	$Z2PIT = Z_{CELL} - Z_{PIT}$	Absolute elevation (in m) of a cell above the pit cell to which it is connected by a defined flow path	5

The derivative PMIN2MAX is used to establish the context of each grid cell relative to the cells with the lowest (MIN) and highest (MAX) elevations in the entire data set. It is not significantly different than simply entering elevation as a basic input consideration [7, 21]. Any cell with an elevation midway between that of the maximum and minimum elevations in the data set is considered to be 50% upslope from the minimum elevation cell and to occupy a mid-slope position in this context.

The derivative PCTZ2TOP is used to establish the context of each grid cell relative to the cells with the lowest (PIT) and highest (TOP) elevations in the local watershed to which the cell belongs. A cell at an elevation ½ way between that of the cell that acts as the sink point for the local depression and the cell with the highest elevation in the watershed is considered to be 50% upslope from the depression centre. This is an excellent measure of relative relief and would be sufficient for most uses if not for complications arising from asymmetry in the elevations of local peaks within given watersheds and from a need to recognize landform positions that vary within the scale of a local watershed.

The derivative PCTZ2PIT is used to establish the context of each grid cell relative to the local pit cell (PIT) and the single local peak cell (PEAK) to which it is explicitly connected via a defined flow path. This derivative permits recognition of a cell at a local peak within a watershed as being 100% upslope relative to a pit to peak flow path. It is not uncommon to find several local peaks or mounds within a defined local watershed. Field experience has shown that these local mounds can resemble upslope crests if they are at a sufficient elevation above the local water table (approximated by the elevation of the pit centre). In other instances, mounds that are less than 2-3 m above a local base level may behave more like lower slope positions, with the exception that they often have a very low upslope contributing area and receive little moisture or sediment from above.

The derivative PCTZ2STR is used to establish the context of each grid cell relative to the closest divide cell (DIV) and channel cell (STR) to which it is explicitly connected via hydrological flow paths. In some instances, it is preferable to consider relative slope position in terms of a cell's location with respect to the nearest stream channel and local divide to which it is hydrologically connected. Thus, a cell located at the top of a local divide might only be considered to be in a midslope position (50% upslope) relative to the watershed depression cell (PIT) and either the maximum watershed elevation (TOP) or the local peak (PEAK). Even though it is considered to be only 50% upslope in this context, it is clearly 100% upslope in the context of a local divide. It has no cells upslope of it from which it can receive water or sediment and it should not be compared with a cell 50% upslope from the pit centre that is part of a continuous flow path from the top of the watershed to the depression center.

The derivative Z2PIT provides a measure of absolute relief (in m) for each cell in a watershed relative to the lowest cell in the watershed, designated as the pit cell (PIT). This measure of absolute relief was included in order to provide a means of distinguishing between local peaks and divides that are well above the local base level for a watershed (usually 2-3 m) and those that are closer to the local base level and may be influenced by moisture rising from near-surface water tables.

This combination of measures of absolute and relative landform position were developed and implemented in favor of other individual alternatives [44, 13, 3, 15]. We felt this series of measures provided a more comprehensive assessment of landform position than any of the alternatives.

Identifying and defining appropriate landform element classes

An important consideration was to decide upon the number of landform element classes that were to be defined and to devise an appropriate semantic description for each landform element.

The decision was made to use expert judgement and local knowledge to identify the number of landform classes to create and to describe the defining characteristics of each class. This was, in part, a response to requests from our commercial sponsors for a single model possessed of a fixed number of classes with a consistent suite of defining characteristics. It also acknowledged the existence of a considerable body of heuristic knowledge regarding the main kinds of landform features in glaciated terrain and of well-established relationships among topography, water flow, soil properties and crop management factors.

A review of pertinent literature was conducted to identify the numbers and types of landform elements that had previously been found useful for describing and classifying landforms. This resulted in nomination of an initial suite of 15 landform element classes judged to be potentially useful (Table 4).

The list of 15 proposed landform classes included conceptual entities similar to 6 of the original 7 landform units of Pennock et al. [39]. The original level class of Pennock was replaced with 6 separate units to differentiate level areas and depressions in upper, mid and lower landscape positions respectively. An extra unit was added in both the mid-slope (BSL) and lower-slope (TSL) landscape positions that was neither markedly convex nor concave, but rather planar in the across-slope direction. One final addition was included to recognize what we termed a lower-slope mound (LSM), which essentially meets all of the shape criteria for classification as a divergent shoulder (DSH) but is located in relatively low-lying landscape positions in close spatial association with foot-slopes and toe-slopes.

The defining characteristics of each of the 15 proposed classes were assigned using expert judgement. Previously existing criteria, (e.g. those adopted by Pennock et al. [39]), were used wherever possible to establish the central characteristics and boundary definitions for each of the 15 classes, with boundaries initially defined using Boolean logic (Table 4). These fixed boundary definitions were subsequently modified and expressed as a series of semantic constructs such as relatively steep, or relatively convex in profile.

The 15 proposed classes were intended to express properties indicative of systematic and meaningful variation in local surface shape (measured by gradient and curvature), moisture conditions (measured by wetness index and height above base level) and relative and absolute landform position (measured by a series of indices of relative relief). All of these measures influence the distribution and redistribution of moisture, energy and matter in landscapes. Classes within the upper, mid and lower groupings (Table 4) were differentiated primarily on the basis of slope gradient (level versus sloping) and plan curvature (convex = water shedding, concave = water accumulating and planar = water neutral). It was hoped that each of the classes would differ from all others in some way, but it was never anticipated that, at all locations, all classes would differ significantly with respect to all features of interest.

Table 4. Initial guidelines proposed for the 15 unit landform classification rule base

Landform Category	Landform Element (also called Landform Facet)				Slope (%)	Slope Curvature (deg/100 m)	
	no	name	abbr.	comments	slope	Profile	Plan
Upper Slope	1	Level crest	LCR	level area in upper slope	0 - 2	+10 to -10	-
	2	Divergent shoulder	DSH	convex upper, water shedding element	> 2	>+10	-
	3	Upper depression	UDE	depression in upper slope position	0 - 2	< -10	< -10
Mid-slope	4	Backslope	BSL	rectilinear transition mid-slope segment	> 2	+10 to -10	+10 to -10
	5	Divergent backslope	DBS	Sloping 'ridge'	> 2	+10 to -10	> +10
	6	Convergent backslope	CBS	Sloping 'trough'	> 2	+10 to -10	< -10
	7	Terrace	TER	level mid-slope > 2m above base level	0 - 2	+10 to -10	na
	8	Saddle[2]	SAD	special case of a divergent footslope	na	< -10	> 10
	9	Midslope depression	MDE	depression in midslope position	0 - 2	< -10	< -10
Lower Slope	10	Footslope	FSL	concave, water receiving element	> 2	< -10	na
	11	Toeslope	TSL	rectilinear in lower slope > 20% of low slope	> 2	+10 to -10	+10 to -10
	12	Fan	FAN	special case of a divergent toeslope	> 2	+10 to 10	> +10
	13	Lower slope mound	LSM	crown in lower slope < 2m above base level.	> 2	>+10	>+10 ?
	14	Level lower slope	LLS	level in lower slope, > 20% of low slope	0 - 2	+10 to -10	+10 to -10
	15	Depression	DEP	concave element in lowest landform pos.	0 - 2	< -10	<0

Selecting and applying an appropriate classification methodology

Landform classification was achieved through development and application of a fuzzy semantic import (SI) model [6, 9] based on expert knowledge and judgement.

Development and application of the SI model involved the following steps:

1. Convert each of the terrain derivatives into continuous values scaled from 0 – 100 which express landform attributes in terms of fuzzy semantic constructs such as the degree to which a site (or grid cell) is considered to be nearly level or near a mid-slope.

    a) Construct a SI model rule base to define the rules by which data for each of the 9 selected terrain derivatives are converted into values for the fuzzy possibility that a particular grid cell displays a particular fuzzy landform attribute.

    b) Apply the SI rule base to the computed terrain derivatives to convert the original terrain derivative data sets into fuzzy landform attributes scaled from 0 – 100

2. Convert individual fuzzy landform attribute values into continuous numbers scaled from 0-100 which express the likelihood that a given cell or site belongs to each of ***n*** defined landform element classes

    a) Construct a set of rules for calculating Joint Membership Functions (JMF) for the selected set of landform elements by defining each landform element in terms of a weighted linear combination of the individual fuzzy landform attribute values

    b) Apply the rule base to the data set of individual fuzzy landform attributes to compute values for each grid cell for the JMF for each of the ***n*** landform element classes to be defined.

    c) Harden the fuzzy classification by determining the landform element class with the largest JMF value for each grid cell and assigning each cell to this class.

Converting terrain derivatives into fuzzy landform attributes

Nine of the computed terrain derivatives were used to define 20 fuzzy landform attributes (Table 5). Each fuzzy landform attribute represents an attempt to quantify a fuzzy semantic construct such as relative likelihood of being steep or convex in plan by expressing the concept in terms of the degree of membership of the terrain derivative value in a fuzzy landform attribute class with degree of membership (MF) expressed in terms of a continuous integer number ranging from 0 to 100.

Table 5. Heuristic rule base for converting initial terrain derivatives into fuzzy landform attributes

No.	Input Terrain Derivative	Output Fuzzy Landform Attribute	Description of Fuzzy Landform Attribute	Model No.	Standard Index (***b***)	Dispersion Index (***d***)
1	PROF	CONVEX_D	Relatively convex in profile (down)	4	10.0	5.0
2	PROF	CONCAVE_D	Relatively concave in profile (down)	5	-10.0	5.0
3	PROF	PLANAR_D	Relatively planar in profile (down)	1	0.0	5.0
4	PLAN	CONVEX_A	Relatively convex in plan (across)	4	10.0	5.0
5	PLAN	CONCAVE_A	Relatively concave in profile (across)	5	-10.0	5.0
6	PLAN	PLANAR_A	Relatively planar in profile (across)	1	0.0	5.0
7	SLOPE	NEAR_LEVEL	Nearly level slope gradient	5	1.0	2.0
8	SLOPE	REL_STEEP	Relatively steep slope gradient	4	5.0	2.0
9	QWETI	HIGH_WI	Relatively high wetness index	4	7.0	3.0
10	QWETI	LOW_WI	Relatively low wetness index	5	0.5	3.0
11	PMIN2MAX	NEAR_MAX	Relatively near maximum elevation	4	90.0	15.0
12	PCTZ2TOP	NEAR_TOP	Relatively near top of the watershed	4	90.0	15.0
13	PCTZ2ST	NEAR_DIV	Relatively near to a local divide cell	4	90.0	15.0
14	PCTZ2PIT	NEAR_PEAK	Relatively near to a local peak cell	4	90.0	15.0
15	PCTZ2PIT	NEAR_MID	Relatively near pit to peak mid-slope	1	50.0	25.0
16	PCTZ2PIT	NEAR_PIT	Relatively near to pit relative to peak	5	10.0	15.0
17	Z2PIT	HI_ABOVE	Relatively high above a pit cell (in m)	4	6.0	3.0
18	PMIN2MAX	NEAR_MIN	Relatively near to minimum elevation	5	10.0	15.0
19	PCTZ2TOP	NEAR_BOT	Relatively near to pit relative to the maximum elevation in the watershed	5	10.0	15.0
20	PLAN PROF	PLANAR_2X	Relatively planar in profile and plan	NA	NA	NA

Scaling of the fuzzy landform attribute values from 0 to 100 was accomplished by selecting an appropriate model and applying appropriate values for the boundary value or central concept value (***b***) and the dispersion index (***d***) for each terrain derivative as per Burrough et al.[9].

Of the five distinct model types available for conversion of terrain derivatives into fuzzy landform attributes [9], types one, four and five were used in this project (Figure 2). Model 1 (Figure 2 a) was used for computing attributes such as relative likelihood of being close to a mid-slope landscape position in which the central concept for mid-slope was taken to be a value of 50% for landscape position computed relative to the closest local pit and peak cells. In this model, the relative likelihood of occupying a mid-slope landscape position diminishes in a symmetrical manner as one progresses outwards in both directions (up and down) from the modal value. Model 4 (Figure 2 b) was applied for attributes such as relatively convex (in profile or plan) or relatively steep slope in which all values of the input terrain derivative greater then the specified upper boundary value (***b***) were considered to fully satisfy the requirements for class membership (MF = 100). Similarly, model 5 (Figure 2 c) was applied for all attributes for which some minimum value of input terrain derivative existed below which all values were considered to fully satisfy the criteria for class membership.

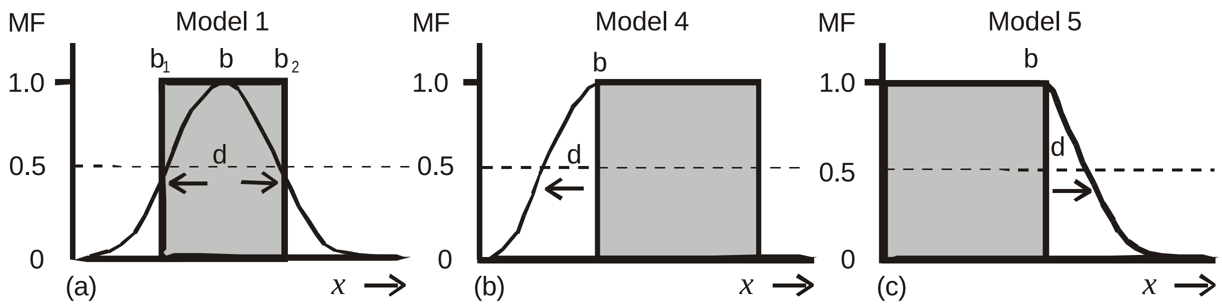


Figure 2. Illustration of the fuzzy Semantic Import (SI) models used to convert terrain derivatives into fuzzy landform attributes (after Burrough et al., 1992)

The values for ***b*** and ***d*** selected for each of the 20 fuzzy landform attributes (Table 5) were substituted into equation 6 [9] to compute the degree of membership (MF_x) of each terrain derivative value (x) in its corresponding fuzzy landform attribute class.

$$MF_x = \frac{1}{\left[1+\left(\frac{x-b}{d}\right)^2\right]} * 100 \ldots\ldots\ldots \textit{for} \ldots 0 \le x \le P \qquad \textbf{(6)}$$

Expert judgement was used to select appropriate values for ***b*** and ***d*** for each fuzzy terrain attribute. Where applicable, values selected for boundaries, central concepts (***b***) and dispersion indices (***d***) were selected from the literature. Thus all cells with curvatures greater than 10° /100 m were considered to fully meet the criteria for classification as convex in either profile or plan (MF = 100) and all cells with curvatures less than –10.0° /100 m were considered concave (MF = 100). We relaxed the slope gradient criteria of Pennock et al. [39] considerably from the original value of 3° to a value of 1% below which a cell was considered to have a membership value of 100 in the fuzzy landform class of nearly level. The selected dispersion index of 2% meant that the cross-over point at which a cell was considered to have a 50% likelihood of being nearly level was a slope gradient of 3%. Cells with a slope gradient greater than 3% are more likely to be considered relatively steep until the threshold value of 5% is reached, beyond which all slopes are considered to have a membership value of 100 in the fuzzy landform attribute class, relatively steep.

The derivative of Wetness Index (WI) was used to define 2 fuzzy landform attributes representing the fuzzy possibility of a cell being relatively wet (having a high wetness index) or dry (having a low wetness index). Cells with a WI < 0.5 were considered to have a 100% likelihood of being relatively dry (belonging to the class LOW_WI) and cells with a WI > 7.0 were considered to have a 100% likelihood of being relatively wet (belonging to the class HIGH_WI). The cross-over point was selected at a WI of 3.5 such that values of WI > 3.5 were more likely to belong to the relatively wet class (HIGH_WI) than to the relatively dry class (LOW_WI).

Fuzzy landform attributes 11 through 20 are all measures of relative likelihood of a cell occupying a specified position in the landscape. The class NEAR_MAX provides a measure of the likelihood that the elevation of a given cell is close to that of the maximum elevation for the entire data set of current interest. All cells with an elevation greater than that of a cell at 90% of the vertical elevation difference between the lowest and highest cell in the entire watershed are considered to have a 100% likelihood of belonging to the class NEAR_MAX. All cells with a value for PMIN2MAX > 75% have a likelihood of belonging to the class NEAR_MAX that is > 50.

The classes NEAR_TOP, NEAR_PEAK and NEAR_DIV reflect the relative likelihood of a cell occurring in the top 25% of cells relative to (a) the maximum elevation of a watershed in comparison to the minimum (PIT) elevation of a watershed (TOP2PIT), (b) the elevation of each local peak in comparison to the elevation of the local pit for the watershed (PIT2PEAK) and (c) the elevation of the closest local divide relative to the elevation of the closest local channel (STR2DIV).

The class NEAR_MID evaluates the likelihood that a cell occupies a mid-slope landform position where mid-slope is defined as occurring at 50% of the vertical elevation difference between the lowest cell in each watershed (the PIT cell) and one of any number of local peak cells in the watershed (but specifically the closest PEAK cell to which a given cell is connected via a defined upslope hydrological flow path).

Converting fuzzy landform attributes into fuzzy landform elements (facets)

Each of the 15 proposed classes of landform element was described in terms of a convex combination of fuzzy landform attributes expressed as semantic constructs (Table 6). Thus, for example, a level crest (LCR) was described as nearly level, relatively near the top of the local watershed, relatively near to a local divide, relatively planar in both plan and profile, relatively dry (LOW_WI) and relatively high above the local base level (PIT elevation) for the watershed in which it was located. These definitions embodied the fuzziness or uncertainty present in the semantics used by an expert to describe and define a series of notional landform element types.

Table 6. . Rule base for defining the Joint Membership Functions for the 15 fuzzy landform element classes

FACET NAME	CODE	FUZZY ATTRIBUTE	WT	FACET NAME	CODE	FUZZY ATTRIBUTE	WT
Level Crest	LCR	NEAR-LEVEL	20	Saddle	SAD	CONCAVE_D	20
	LCR	NEAR_TOP	20		SAD	CONVEX_A	20
	LCR	NEAR_DIV	10		SAD	NEAR_MID	20
	LCR	PLANAR_2X	5		SAD	HI_ABOVE	10
	LCR	LOW_WI	5		SAD	HIGH_WI	5
	LCR	HIGH_ABOVE	5	Mid-slope	MDE	NEAR_MID	20
Divergent	DSH	CONVEX_D	20	Depression	MDE	CONCAVE_D	10
Shoulder	DSH	CONVEX_A	20		MDE	CONCAVE_A	10
	DSH	NEAR_DIV	10		MDE	HIGH_WI	20
	DSH	NEAR_TOP	10		MDE	NEAR_LEVEL	20
	DSH	HI_ABOVE	5		MDE	HIGH_ABOVE	5
	DSH	LOW_WI	5	Foot-slope	FSL	NEAR_BOT	20
Upper	UDE	NEAR_TOP	20		FSL	CONCAVE_D	20
Depression	UDE	NEAR_MAX	10		FSL	HIGH_WI	20
	UDE	HIGH_WI	10		FSL	CONCAVE_A	10
	UDE	CONCAVE_D	10		FSL	REL_STEEP	5
	UDE	CONCAVE_A	10	Toe-slope	TSL	PLANAR_A	20
	UDE	NEAR_LEVEL	10		TSL	NEAR_BOT	20
	UDE	HI_ABOVE	5		TSL	REL_STEEP	10
Back-slope	BSL	PLANAR_D	20		TSL	PLANAR_D	10
	BSL	PLANAR_A	20	Lower-slope Fan	FAN	NEAR_BOT	20
	BSL	NEAR_MID	20		FAN	PLANAR_D	20
	BSL	REL_STEEP	10		FAN	CONVEX_A	20
	BSL	HI_ABOVE	5		FAN	REL_STEEP	10
Divergent	DBS	PLANAR_D	20	Lower-slope	LSM	CONVEX_D	20
Back-slope	DBS	CONVEX_A	20	Mound	LSM	CONVEX_A	20
	DBS	NEAR_MID	20		LSM	REL_STEEP	20
	DBS	REL_STEEP	10		LSM	NEAR_BOT	20
	DBS	HI_ABOVE	5		LSM	LOW_WI	10
	DBS	LOW-WI	5		LSM	NEAR_DIV	10
Convergent	CBS	CONCAVE_A	20	Level	LLS	NEAR_BOT	20
Back-slope	CBS	PLANAR_D	20	Lower-slope	LLS	NEAR_LEVEL	20
	CBS	NEAR_MID	20		LLS	NEAR_PIT	10
	CBS	REL_STEEP	10		LLS	PLANAR_D	5
	CBS	HIGH_WI	5		LLS	PLANER_A	5
	CBS	HI_ABOVE	5		LLS	HIGH_WI	5
Mid-slope	TER	NEAR_LEVEL	20	Lower-slope	DEP	NEAR_PIT	20
Terrace	TER	NEAR_MID	20	Depression	DEP	CONCAVE_A	10
	TER	PLANAR_D	10		DEP	CONCAVE_D	10
	TER	PLANAR_A	10		DEP	NEAR_LEVEL	10
	TER	HI_ABOVE	5		DEP	NEAR_BOT	10
					DEP	HIGH_WI	10

A Joint Membership Function (JMF) was computed for each of the 15 defined landform element classes to express the overall likelihood of a given cell belonging to each specific landform class. A common approach for determining JMF values is to apply a fuzzy minimum function and assign each cell a JMF equivalent to the lowest of the individual MFs used as input [51, 6, 9]. We elected instead to compute the JMF as a weighted linear average, defined by Burrough [6] as a convex combination of $A_1 \ldots A_k$ fuzzy sets. Each input fuzzy subset (MF) was multiplied by an assigned weight, where the combined weights summed to one.

The Joint Membership Function (JMF_A) for each of the 15 defined landform element classes was computed as the weighted linear average of the individual Membership Functions (MF_{Aj}) of the fuzzy landform attributes used to describe a given class multiplied by the relative weighting factor (W_j) assigned to each fuzzy landform attribute (equation 7).

$$JMF_A = \sum_{j=1}^{k} W_j * MF_{Aj} \ldots\ldots where \ldots \sum_{j=1}^{k} W_j = 1, \ldots\ldots W_j > 0 \quad \textbf{(7)}$$

Application of the heuristic SI rule base via equation 7 resulted in calculation of 15 different JMF values, one for each of the 15 different landform elements, for every grid cell in the raster DEM. Weights were selected to emphasize factors from the original 7 unit classification of Pennock et al. [39]. Consequently, fuzzy landform attributes derived from slope gradient, profile and plan curvature were consistently assigned the highest relative weights (Table 5). This allowed the criteria of the original Pennock model to dominate our classification so that most cells were placed into classes similar to those of the Pennock classification. Fuzzy landform attributes based on wetness index and relative or absolute relief were generally assigned lower weights and acted as modifiers to adjust the original Pennock classification mainly in cases where the relative landform position of the cell was at variance with the expected landform position inferred by the Pennock model.

A single landform element classification was then assigned to each cell by identifying which of the 15 classes of defined landform element had the maximum JMF value for each grid cell.

Model evaluation

A series of linear transects were laid out oriented perpendicular to trends in the landscape at both study sites (and at others not reported on here). Soil profile observations were recorded at regular intervals of 20 m (1/20 of the slope length) along each transect. Soils were sampled by horizon at every second site and samples analyzed for organic carbon, pH, bulk density and available nutrients. Yields at each transect point were measured from areas approximately 1.5 by 3 m in size using a plot combine. All site locations were established accurately using DGPS.

The landform element classification was determined for each transect site. The distribution of soil classes (Subgroup phases), soil properties (organic carbon, pH, thickness of topsoil, depth of profile) and yield was determined for each of the 15 original landform classes. Summary statistics were computed to determine the mean and variance for soil properties and yield by landform element class.

The SAS [43] General Linear Model (GLM) procedure was used to perform a one way analysis of variance on results for depth of A horizon (topsoil thickness), depth to carbonates (solum thickness), and crop yields for 1996 and 1997. The PDIFF option [43], which adjusts for unequal sample sizes was used to determine the significance of the least square means.

Results

Applying the landform segmentation model at the two study sites

Calculating and interpreting the required terrain derivatives

The terrain derivatives computed for the Hussar site (Figure 3) can all be interpreted in terms of the pattern of distribution and redistribution of water and energy in the landscape and the logical reflection of these patterns in soils and soil properties.

Steeper slope gradients (Figure 3 a) are associated with backslopes or shoulders in which one would anticipate rapid runoff, removal of topsoil by erosion and thinner soils. Profile curvature (Figure 3 b) can be interpreted in terms of rapid runoff, erosion and development of thin soils in convex areas, decelerating runoff, deposition and development of thicker soils in concave areas and neutral or modal conditions in areas that are planar in the downslope direction. Plan curvature (Figure 3 c) provides an indication of the pattern of redistribution of surface water and soil materials in the across slope direction. One would expect flow divergence away from areas with a high plan convexity and flow convergence in areas of high plan concavity. It is expected that soils in convex, divergent areas will be more prone to wind or mechanical/implement erosion, have thinner solums, thinner topsoil horizons and less available moisture than soils in concave areas of convergent flow. The wetness index derivative (Figure 3 d) integrates the information contained in the individual derivatives of slope gradient, profile and plan curvature into a single measure of the relative likelihood that a cell will experience wetness due to runoff or accumulation of surface or near surface flow. Areas with a high wetness index may be expected to have, on average, higher available moisture and to develop soils with thicker topsoil horizons and deeper solums than areas with a lower wetness index.

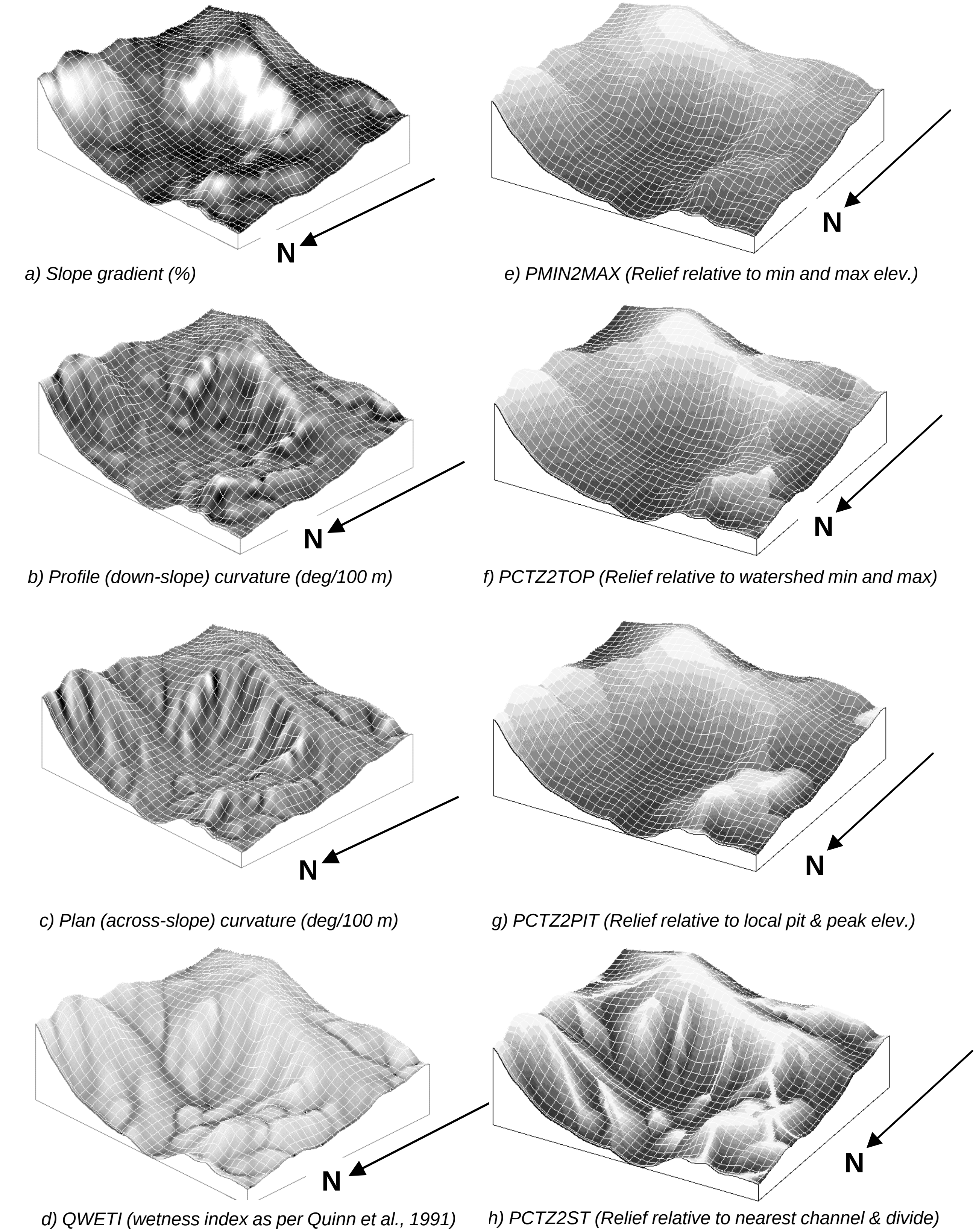


Figure 3. 3D illustrations of 8 of the terrain derivatives used in the fuzzy landform classification (Hussar site)

The four measures of relative relief provide different indications of the landform context of each cell (Fig. 3 e-h). These measures of context are important for differentiating landform entities that may have common characteristics in terms of the previously discussed terrain derivatives (slope gradient, profile and plan curvature and wetness index) but which are expected to behave differently because of their contextual position. For example, a cell with a high wetness index, strong plan convexity and relatively steep slope gradient located high up in the landscape might exhibit more erosion and thinner soils than a similar cell lower in the landscape where deposition may be more prominent. Similarly, a cell with a low wetness index, strong plan convexity and steep gradient that is located in a midslope position, as measured by the index PCTZ2PIT (Figure 3 f) is likely to behave differently and require a different classification than a similar cell located near to a local peak.

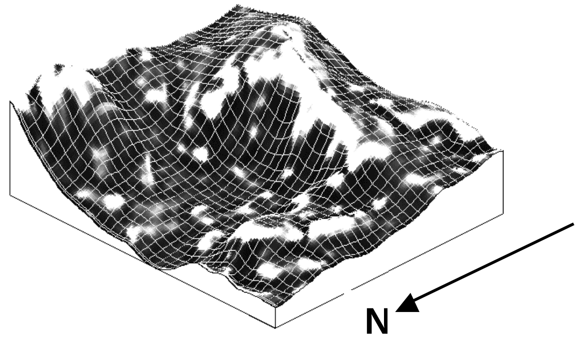
Since they vary more or less continuously across the landscape between widely separated tie points, the measures of relative relief also act as a glue, promoting greater spatial coherence and contiguity in classification than would otherwise be obtained from derivatives based on a local 3x3 window. Cells that are close together in the landscape are more likely to be classified into the same landform element class, based on the relative relief indices, unless they exhibit strong differences in local surface form as measured by gradient and curvature. The relative relief indices focus on measuring the dominant long range signal in the landscape in preference to local short range noise.

Converting terrain derivatives into fuzzy landform attributes

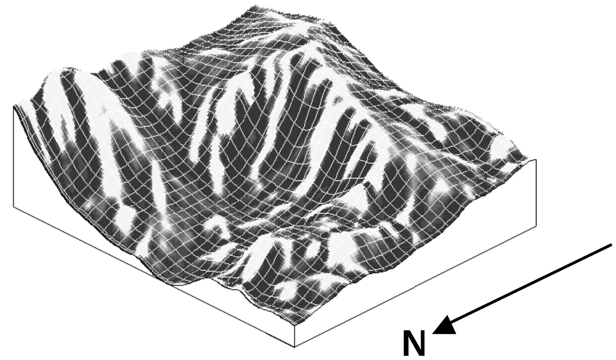
The fuzzy landform attributes computed from each of the initial terrain derivatives (Figures 4 & 5) express the degree to which a particular value of a given terrain derivative reflects the semantic construct associated with a given fuzzy landform attribute.

For example, three of the fuzzy landform attributes considered in the semantic import model are the degree to which each grid cell can be considered to be strongly concave in profile (Figure 4 c) and the degree to which a cell is located relatively close to a midslope (Figure 5 d) or a divide (Figure 5 e). High likelihood of being planar is associated with apparent lines of inflection, or slope breaks, in the downslope (Figure 4 e) and across slope (Figure 4 f) directions.

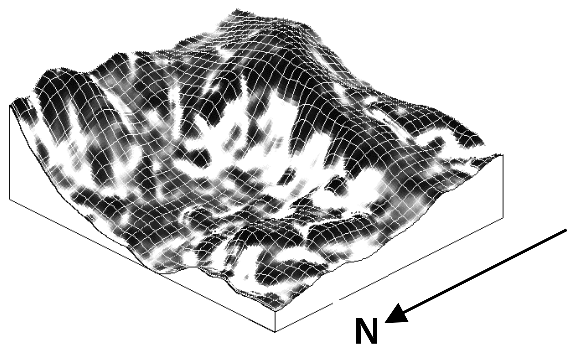
Conversion of absolute values for terrain derivatives into relative values for fuzzy landform attributes scaled from 0-100 is a key element in the classification. The scaled fuzzy attributes permit description of the landscapes in terms of fuzzy semantic constructs such as nearly level and near the top (for a level crest) or steeply sloping and near a mid slope (for a backslope). This facilitates application of a single rule base to a variety of scales and types of landform.



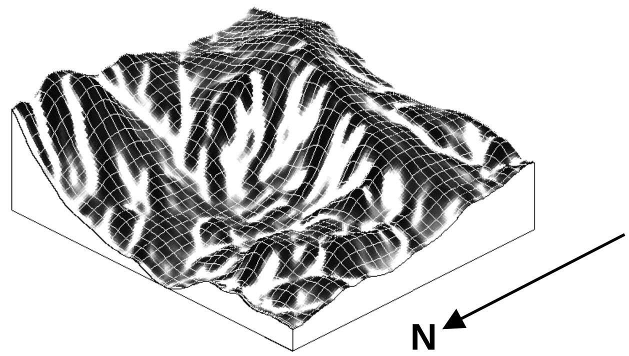
a) Likelihood of being convex in profile (CONVEX_D)



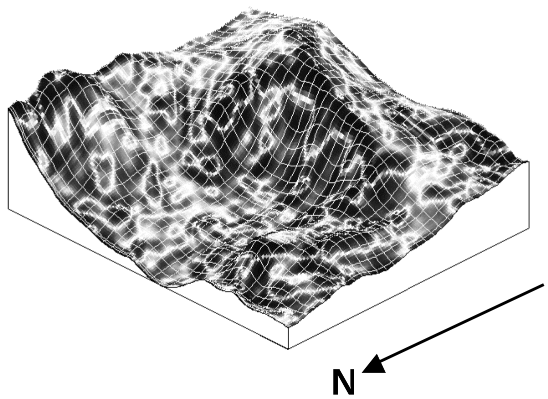
b) Likelihood of being convex in plan (CONVEX_A)



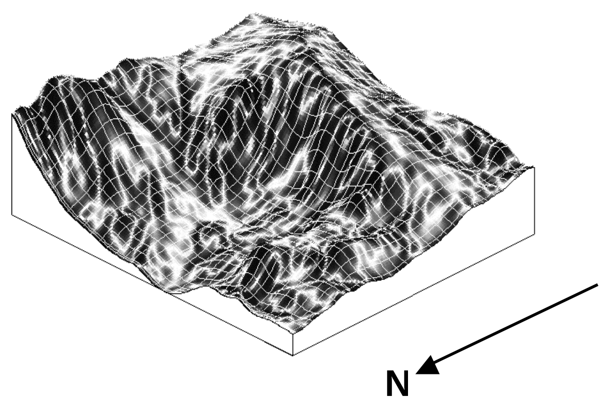
c) Likelihood of being concave in profile (CONCAVE_D)



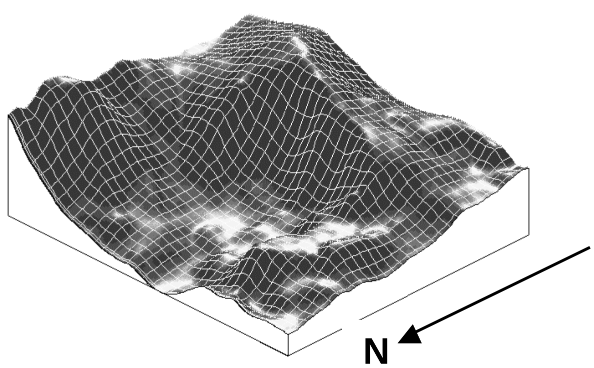
d) Likelihood of being concave in plan (CONCAVE_A)



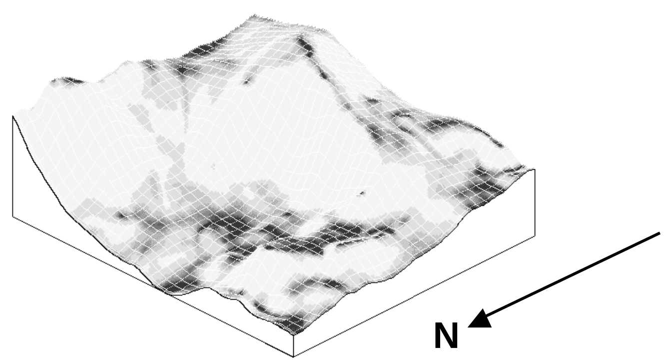
e) Likelihood of being planar in profile (PLANAR_D)



f) Likelihood of being planar in plan (PLANAR_A)

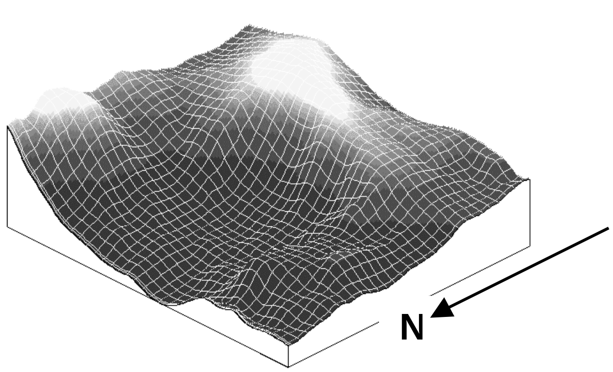


g) Likelihood of being nearly-level (NEAR_LEVEL)

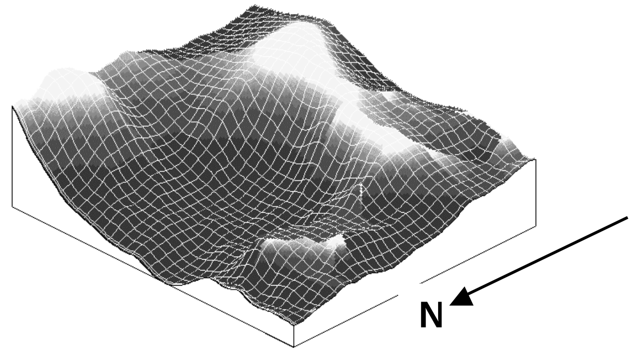


h) Likelihood of being relatively steep (REL_STEEP)

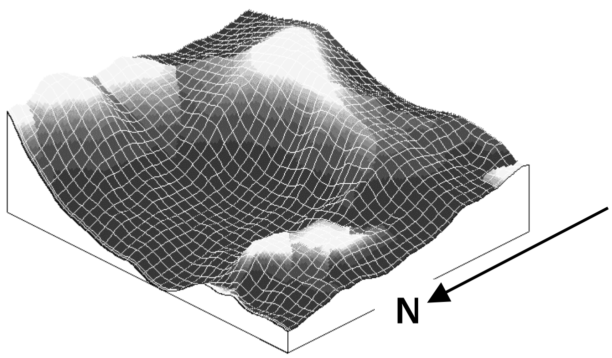
Figure 4. 3D illustrations of fuzzy terrain attributes based on curvature in profile and plan and slope gradient



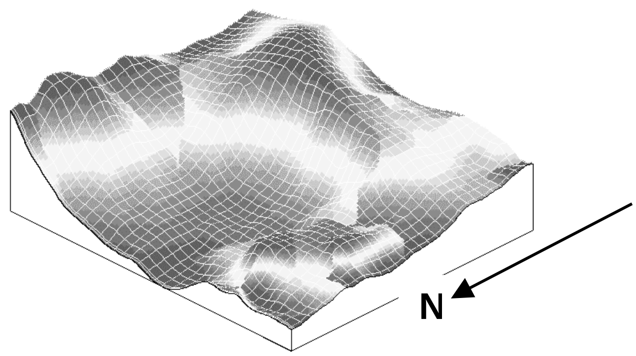
a) Likelihood of being near max elev. (NEAR_MAX)



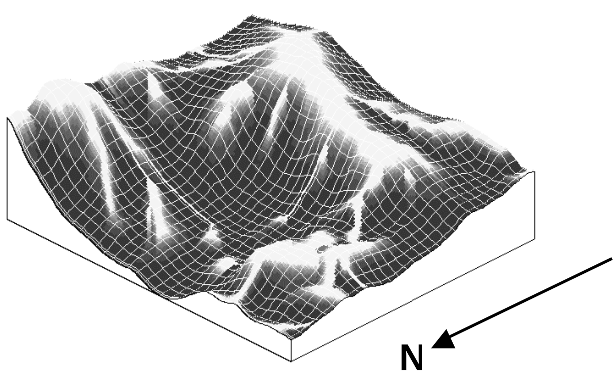
b) Likelihood of being near the top (NEAR_TOP)



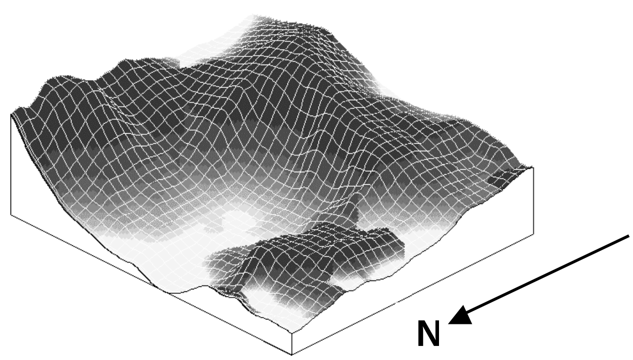
c) Likelihood of being near a peak (NEAR_PEAK)



d) Likelihood of being near a midslope (NEAR_MID)



e) Likelihood of being near a divide (NEAR_DIV)



f) Likelihood of being near a depression (NEAR_PIT)

Figure 5. 3D illustrations of fuzzy terrain attributes based on various indices of relative landscape position

Converting fuzzy landform attributes into fuzzy landform classifications

Every grid cell in a raster DEM has an associated value for the likelihood that it belongs to each of the 15 defined landform element classes.

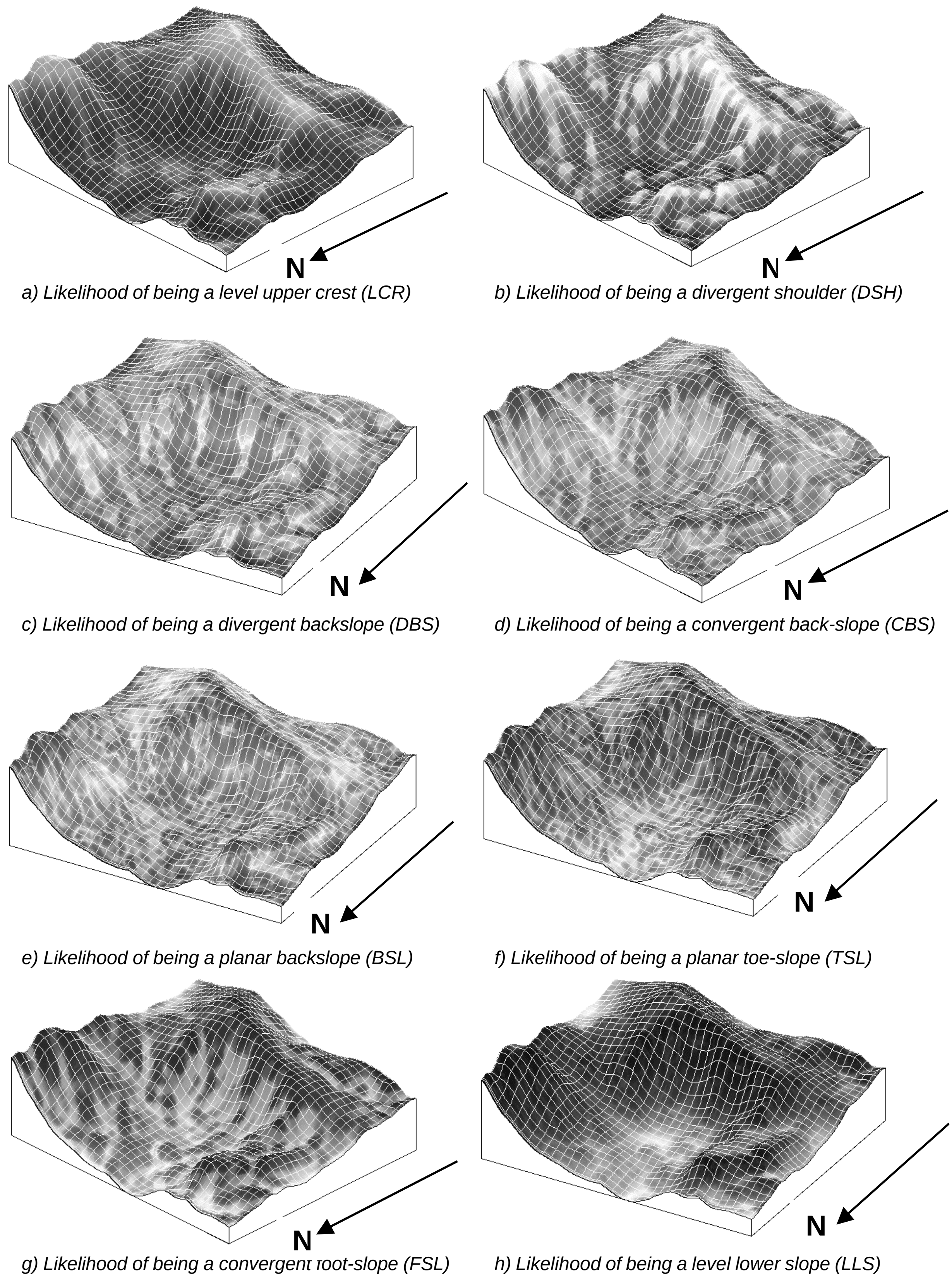
Visual examination of the examples provided (Figure 6) confirms that the likelihood of belonging to a given class ranges from very high (white) to very low (black) in a manner that is consistent with the shape and relative position in the landscape of a grid cell at any given location. Thus divergent shoulders (Figure 6 b) occur mostly in upper landform positions and have strong convexity in both profile and plan, while toe slopes (Figure 6 f) occur mostly in lower landscape positions and are relatively planar in both profile and plan. Similarly, level crests (Figure 6 a) are distinguished from the very similar level lower slopes (Figure 6 h) based on landscape position.

Considerable opportunity exists for overlap or confusion between classes, due to the large number of classes that share similar attributes. For example, both backslopes (Figure 6 e) and toe slopes (Figure 6 f) are defined as relatively steeply sloping and relatively planar in both profile and plan curvature. The main difference between them is their relative position in the landscape as defined by the attributes NEAR_BOT and NEAR_MID. One would expect cells with values for slope gradient, profile and plan curvature similar to those defined for backslopes and toe slopes to exhibit similar values for fuzzy likelihood of belonging to both of the classes back slope and toe slope. Indeed, using the approach of Pennock et al. [39, 40] it would be impossible to differentiate them and both would be classified as backslopes. The values for the attributes of landform context (NEAR_BOT, NEAR_MID) permit subtle distinctions to be made that allow for differentiation of cells with similar shape and local morphology on the basis of their overall landform context.

Assigning the most likely landform element classification to each grid cell

Each cell was assigned to the landform element class with the largest JMF for that cell.

Although complex, the 15 unit classification (Figure 7a) appeared to be both logical and intuitively reasonable. The procedures produced spatial entities that were relatively large, compact and continuous. Visual interpretation suggested that these entities effectively separated upper, mid and lower slope units (Figure 7 b, c) as well as level areas and depressions in upper, mid and lower landform positions. Within the larger groupings of upper, mid, lower and depression, divergence and convergence of flow was strongly evident in landform facets designed to reflect differences in potential moisture status and erosion arising from lateral differences in plan curvature and across slope flow regimes. Even landform elements that were relatively difficult to conceptualize and define (such as saddles or passes) were recognized in appropriate locations.



a) Likelihood of being a level upper crest (LCR)

b) Likelihood of being a divergent shoulder (DSH)

c) Likelihood of being a divergent backslope (DBS)

d) Likelihood of being a convergent back-slope (CBS)

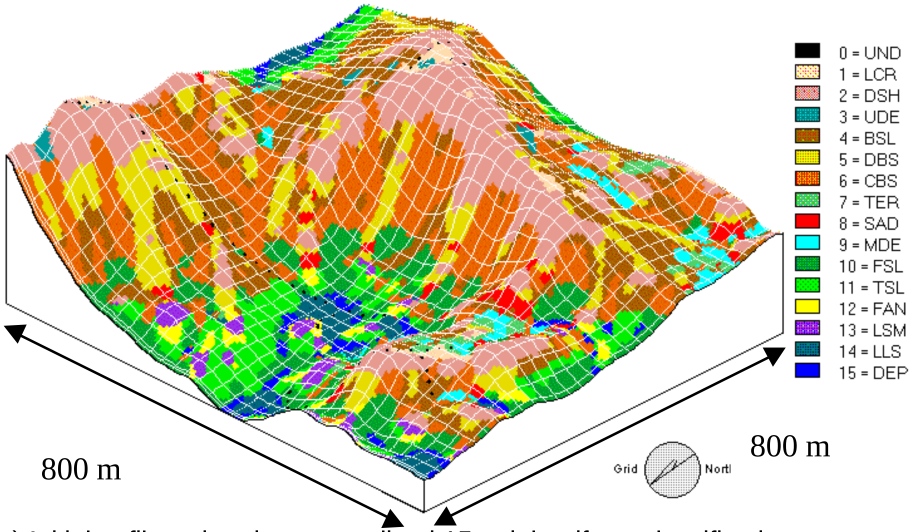
e) Likelihood of being a planar backslope (BSL)

f) Likelihood of being a planar toe-slope (TSL)

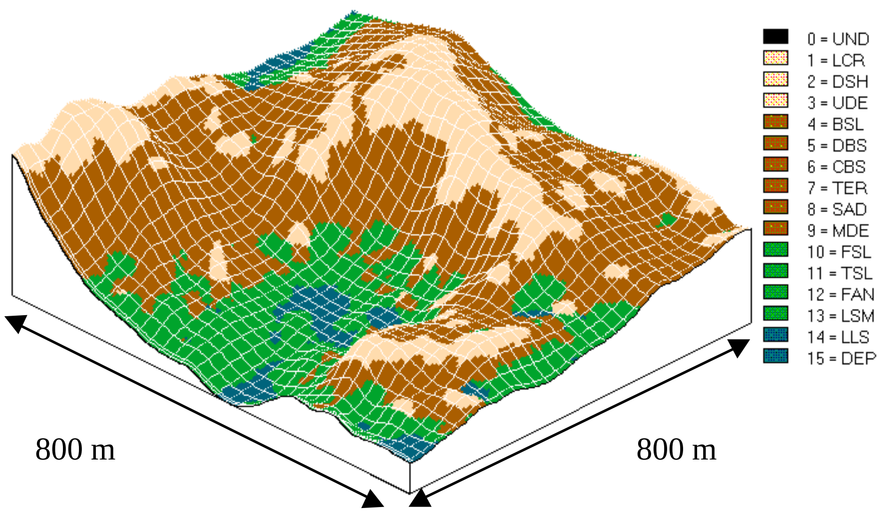
g) Likelihood of being a convergent foot-slope (FSL)

h) Likelihood of being a level lower slope (LLS)

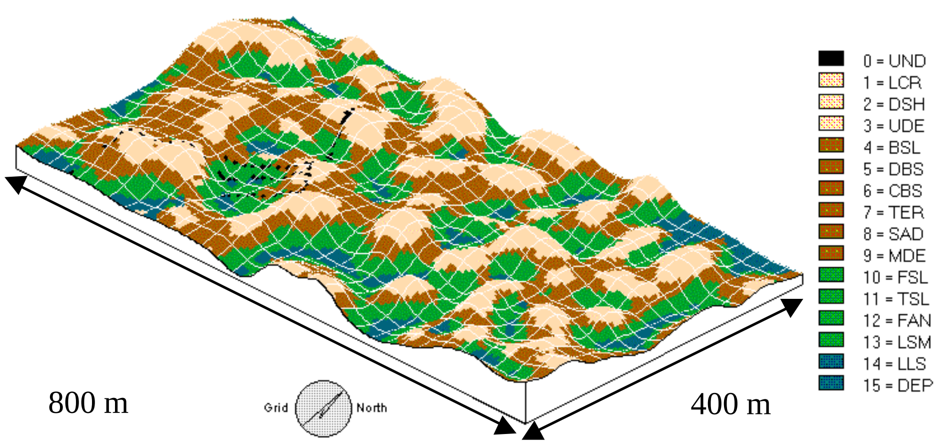
Figure 6. 3D illustrations of fuzzy landform element classifications for selected landform elements



a) Initial unfiltered and ungeneralized 15 unit landform classification



b) Simplified 4 unit landform classification after a 3x3 modal filter



c) Simplified 4 unit landform classification for Stettler after a 3x3 modal filter

Figure 7. 3D views illustrating the initial and generalized landform classifications at two study sites (a, b = Hussar and c = Stettler)

Generalizing the initial 15 unit landform classification

The initial 15 unit landform element classification was judged to contain an undesirable level of complexity and spatial fragmentation for simple applications (Figure 7 a). It was always anticipated that some form of simplification through generalization would be required to reduce the initial 15 classes to a smaller, more manageable number and larger physical size, more appropriate for certain land management activities. The initial 15 classes were therefore grouped into fewer classes (3-4) in several different ways and the efficacy of these groupings was evaluated in terms of their relative abilities to explain the observed differences in yield and soil properties at the study sites.

One approach to simplification involved grouping the initial 15 classes based primarily on relative landscape position (Figure 7 b, c). In this approach, four generalized classes were recognized, namely upper, mid, lower and depressions. All cells in upper landform element classes (LCR, DSH, UDE) were grouped into the upper class. Similarly cells in any of the mid slope classes in the initial 15 unit classification (BSL, DBS, CBS, TER, SAD, MDE) were grouped into the mid class. The lower slope grouping consisted of the classes FSL, TSL, FAN, and LSM while the depression class contained LLS and DEP.

Alternative groupings (not illustrated) were also examined including one based primarily on the behaviour of the facets with respect to the flow of surface water. This 4 class generalization recognized divergent, water shedding, landform facets (DSH, DBS, FAN, LSM), convergent, water receiving, landform facets (CBS, FSL), planar, water neutral facets (LCR, BSL, TER, SAD, TSL) and all depressions (UDE, MDE, LLS, DEP) regardless of their relative landscape position.

The generalized and simplified groupings (Figure 7 b & c) reduce spatial fragmentation considerably and produce large, coherent spatial entities that are easy to visualize and are of appropriate size for application of differing management strategies.

Evaluating the utility and efficacy of the landform classification model

Interpreting the general pattern of soils and soil properties by landform class

While not always statistically significant, the general patterns of spatial distribution of mean soil properties relative to landform classification were consistent with expectations based on local knowledge of soil-landform relationships (Tables 7 & 8). For the larger categories of upper, mid and lower a consistent pattern was evident in which thickness of the A horizons, depth to carbonate, percent organic matter and yield all exhibited a general increase in progressing from upper, divergent portions of the landscape to lower convergent portions and depressions. Upper, generally convex, “water shedding” facets had the thinnest soils (Table 8) and lowest yields

(Table 7) while lower, generally concave or level, “water receiving” facets had thicker soils and higher yields. The “water neutral” mid-slopes exhibited intermediate or average conditions.

Table 7. Soil characteristics and yields for landform categories at the Hussar site

Landform facet Category	**Facet**	**depth of Ah (cm)**		**depth to Ca (cm)[1]**		**Org Mat %[1]**		**pH**		**1996 yield ($g/2m^2$)**	
	(# sites)	ave	(cv)	ave	(cv)	ave	(cv)	ave	(cv)	ave	(cv)
Upper slope	LCR(1)	16		58		5.3		6.3		419	
	DSH(12)	8		17		4.1		7.1		339	
	UDE(0)										
	all (13)	8	31	20	99	4.2	20	6.7	13	345	27
Mid slope	BSL(8)	9		62		5.3		5.9		435	
	DBS(4)	9		23		3.1		7.2		447	
	CBS(5)	20		76		6.9		6.3		437	
	TER(2)	8		42						455	
	SAD(1)	13		60						447	
	MDE(0)										
	all (20)	12	79	56	63	5.5	42	6.2	9	440	16
Lower slope	FSL(8)	24		79		8.0		6.4		563	
	TSL(8)	24		85		6.1		6.1		518	
	FAN(2)	8		38		6.8		5.5		521	
	LSM(1)	28		79						291	
	LLS(3)	28		92		9.4		5.9		587	
	DEP(2)	41		100						570	
	all (23)	25	55	81	35	7.7	19	6.0	7	538	14

[1] As not all sites were sampled, there were a total of 22 analysis for OM and pH.

Patterns displayed by the initial 15 unit classifications within these larger categories were also logical when analyzed in terms of local knowledge. Landform elements defined as divergent with respect to across-slope curvature and flow (DBS, FAN) tended to exhibit thinner A horizons and solum depths than their associated convergent landform elements (CBS, FSL). The transitional planar backslopes (BSL) exhibited deep solums similar to convergent backslopes (CBS) but had thin A horizons similar to divergent backslopes (DBS). Planar toe-slopes (TSL), however, displayed no noticeable differences in A horizon thickness or solum depth compared to the spatially associated convergent foot-slopes (FSL) suggesting that relatively high available moisture and accumulation of soil materials occurs in both lower slope elements (TSL, FSL) at this site regardless of differences in across slope curvature and attendant water flow.

The observed agreement between soil properties (Table 7), soil classifications (Table 8) and landform element classification suggests that the proposed landform segmentation model may prove useful as a component of automated procedures for high resolution soil mapping.

Table 8. Number of soil profiles of each soil type within three generalized landform categories at the Hussar site.

Landform element groupings	**Canadian System of Soil Classification soil types (phases of Subgroups)**[1]						
	REG	RDB	ODB _er	ODB	EDB _tk[2]	SOL	Totals by class
water shedding -upper slopes[3]	5	3	3	1			12
water neutral -mid-slopes [3]		3	4	11	6		24
water receiving -lower slopes[3]			2	3	13	6	24
Totals by soil type	5	6	9	15	19	6	60

[1] REG = Regosol; RDB = Rego Dark Brown; ODB_er = Orthic Dark Brown (Ah<10cm)
ODB = Orthic Dark Brown (Ah 10-15 cm); EDB_tk = Eluviated Dark Brown (Ah >15cm)
[2] EDB_tk includes all soils developed on > 50 cm of slope wash (some ODB and Sz DB) and having > 15 cm Ah.
[3] Upper slopes includes DSH; mid-slopes includes BSL, DBS, CBS, TER, SAD, LCR, LSM, UDE; Lower slopes includes FSL, TSL, FAN, LLS, DEP.

Evaluating the statistical significance of the landform classification

Not all of the 15 landform element classes separated soil properties and yield at a significant level (Table 9), though this may be partly due to the low number of observations in some of the class categories. However, classes with a larger number of observations were significantly different from one another at the Hussar site. When the 15 units were generalized into three categories based on relative landform position (upper, mid and lower) significant differences were observed in both soil properties and 1996 yield of canola but not in 1997 wheat yield (Table 10).

The 15 unit and generalized 3 unit models accounted for a significant amount of the variation (up to 60%) in the depth of A horizon, depth to carbonates and 1996 yield at the Hussar site (Table 11). It is still unclear why the models explained the variation in yield well for 1996 canola but much less well for 1997 wheat. It may be that wheat is less sensitive to spatial variations in soil and moisture conditions than canola or it may be that the variation in soil moisture was less pronounced in 1997 and had less of an effect on yield. Both years were drier than normal (75% of normal) but precipitation during the critical months of April, May and June was 80% of normal in 1997 but only 60% of normal in 1996.

Soil properties such as thickness of Ah, solum depth, percent organic matter and pH may be taken to reflect an integration of climate and growth conditions over a long period of time at any given location. In this sense, they may be assumed to reflect long term average conditions for crop growth which may mask out much of the short term variation inherent in year to year crop yields. The fact that the 15 unit model was able to explain a significant proportion of the variation in these relatively stable soil properties at both the Hussar (Table 11) and Stettler sites (not shown) is encouraging.

Table 9. Adjusted least squares, yield, and soil characteristics at transect points within 15 classes

Landscape Facet	Number of Observations	Canola '96 Yield (bu/ac)	Wheat '97 Yield (bu/ac)	Depth A (cm)	Depth Ca (cm)
DSH	14	15.7 c ^{z}	39.5 b	8.0 b	21.8 b
LCR	1	18.6 bc	50.0 ab	16.0 ab	58.0 ab
DBS	5	20.6 b	41.4 ab	7.2 b	18.4 b
CBS	2	18.8 bc	52.3 a	8.0 b	46.0 b
BSL	4	18.2 bc	47.6 ab	9.5 b	61.3 a
SAD	2	19.5 bc	39.3 ab	12.0 b	59.0 a
LSM	3	19.9 b	35.5 b	15.3 b	71.0 a
FAN	1	25.0 ab	46.2 ab	9.0 b	47.0 ab
TSL	9	23.5 ab	42.1 ab	23.4 a	85.9 a
FSL	13	24.8 a	42.2 ab	27.5 a	87.2 a
DEP	1	27.1 a	30.5 b	25.0 ab	100.0 a

^{z} same letters within a column are not significantly different at $P < 0.05$

Table 10. Adjusted least squares, yield, and soil characteristics at transect points within the generalised 15 classes.

Landscape Segment	Number of Observations	Canola '96 Yield (bu/ac)	Wheat '97 Yield (bu/ac)	Depth A (cm)	Depth Ca (cm)
U	15	15.9 c ^{z}	40.2 a	8.5 b	24.2 c
M	13	19.4 b	44.6 a	8.8 b	42.1 b
L	27	23.9 a	41.2 a	24.0 a	84.0 a

^{z} same letters within a column are not significantly different at $P < 0.05$

Table 11. Comparison of landscape classification methods for transect points at Hussar and Stettler.

Classification Method	**'96 Yield**	**'97 Yield**	**Depth A**	**Depth Ca**
			r^2	
Hussar	*n = 56*	*n = 56*	*n = 56*	*n = 56*
Pennock's generalised 5 class	0.28*	0.04	0.21	0.31*
15 class	0.60**	0.16	0.48*	0.61**
Generalised 15 class (to U, M, L)	0.52**	0.03	0.39**	0.50**
Elevation based UML-elev	0.45**	0.11	0.28**	0.38**
Pit to peak ratio UML-relz	0.40**	0.05	0.45**	0.53**

Significant at **P 0.0001; * Significant at P 0.001; ++ Significant at P 0.01
+ Significant at P 0.1; ^ Significant at P 0.2

Comparisons with other methods of classifying landforms

The Hussar site was segmented into 3 simple units of upper mid and lower based solely on elevation (UML-elev) and again based on relative relief as computed by the derivative PCTZ2PIT (UML-relz). In addition, the Hussar site was re- classified using a generalized version of the model of Pennock et al. [39]. In this application of the Pennock model, the landscape was first divided into the seven classes of convergent and divergent shoulders (CSH, DSH), backslopes (CBS, DBS) and footslopes (CFS, DFS) and level areas (L). Convergent and divergent elements were then amalgamated into combined shoulder, backslope and footslope classes. The level class was separated into upper and lower level elements using absolute elevation. This produced a final total of five classes based on the Pennock model.

These classifications were then compared to the 15 and 3 unit results produced by our proposed methodology to determine whether the proposed model offered any improvements relative to the existing model of Pennock or to a straightforward segmentation based on elevation alone.

For the Hussar site, at least, the 15 unit model and its 3 unit generalization consistently explained about two to three times as much of the observed variation as was explained by Pennock's model (Table 11). The 15 class model also explained slightly more of the observed variation in soil properties and yield than either of the re-classifications based solely on elevation or relative relief. The 3 class generalization of the 15 unit model was comparable to, but still slightly better than, the two re-classifications based on elevation and relief. This was not unexpected, as the 3 class generalization is effectively based on relative relief. This implies that, at least for this site, relative landscape position, as determined by indices of relative relief, exerts a greater influence on variation in soil properties and yield than does surface shape, which is the differentiating factor in the Pennock model.

Simplifying the 15 unit model into 3 to 4 generalized classes

It was always intended that the original 15 units could be simplified or generalized into fewer, more spatially compact and simpler to use units in response to differences in either the scale of the landscape at a given site or the requirements of the intended applications.

Grouping by relative landscape position produced somewhat larger, more continuous and coherent spatial entities than grouping by shape and water flow (not illustrated). Given the relatively small differences between the two grouping strategies with respect to the relative amounts of variation in soil properties and yield explained by each, grouping by relative landscape position was identified as the preferred strategy. This approach ensures that land managers are presented with a simple, cognitive classification of 3 to 4 units which is easy to understand, easy to visualize and for which it is relatively easy to devise and implement differing management strategies (see Figure 7 b, c).

It should be noted that the Hussar site represented a large rolling landscape with integrated drainage and very few closed depressions. Other landscapes, such as the Stettler site, which have a greater extent of closed depressions, require recognition of a fourth generalized class, namely closed depressions.

Discussion

Heuristic versus statistically based classification models

The proposed landform segmentation model (LSM) used heuristics based on expert knowledge and judgement to define 15 conceptual landform entities which were subsequently generalized into 3 to 4 simplified classes. Use of expert knowledge, rather than statistical analysis, to define the landform elements permitted definition of a standard set of conceptual spatial entities which are expected to exhibit similar properties and predictable behaviors with respect to water availability and crop performance at all sites at which the classification is applied.

Use of heuristics accepts that a body of knowledge exists which provides some degree of comprehension of, and explanation for, the variation in space and time of soil properties and crop performance. Ultimately, definition of landform entities based on this heuristic knowledge benefits from the understanding of the relationship of process to form inherent in the classification. One is better able to provide explanations for observed differences in soil properties or crop performance because of knowledge of how the basic spatial entities behave with respect to the movement and accumulation of water and energy in the landscape. Heuristic models may also offer advantages in terms of shorter development times, lower costs and broader applicability.

Conversely, use of statistically based classifications accepts that little is known or understood, *a priori*, about the interactions among topography, water flow , soil properties and vegetative growth. Statistically based procedures give rise to classifications that are unique and specific to the site which provided the data used to generate the classification. As such, while the classification procedures are transferable from one site to another, the actual classified entities will differ for each new classified site. This is not a particularly desirable situation from the point of view of businesses wishing to interpret the landform classes and to provide standardized sets of prescriptions regarding management strategies tied to standardized sets of spatial landform entities.

A common theme at conferences on precision agriculture is the proliferation of data generated by the technology and the corresponding lack of understanding regarding how to best interpret and use the masses of data. It may be argued that a heuristic approach to landform classification at least introduces the possibility of intelligent interpretation and understanding of the causal relationships among crop performance, soil properties and topographical controls. The ability to understand and explain why soils are deeper or moister or why yields are elevated or depressed by interpreting landform elements in terms of the movement and availability of water, energy and nutrients might go a long way towards adding knowledge to the large volumes of data presently generated for precision agriculture applications.

Absolute versus relative classification models

During initial conceptual analysis of the problem of how to define a single model and modeling strategy that could be applied to virtually any agricultural landscape in western Canada, one recurring consideration was how to deal with differing types and scales of landscapes. Perception of the abstract qualities of semantic constructs such as "relatively steep" or "relatively convex" is fundamentally scale dependent. For example, a definition or perception of what constitutes a level landform element is different in mountainous versus hilly terrain and is again different in a very low relief glacial lacustrine landscape.

One solution to this problem was to use fuzzy logic, rather than discrete Boolean logic, to define and describe the desired landform entities. By adopting continuous definitions of fuzzy semantic constructs such as "relatively steep" and "relatively convex" a single set of heuristic rules was able to be applied more broadly and to a wider variety of landscapes than an equivalent set of crisp Boolean rules. We encountered less need to adjust the class definitions and class boundaries for each new type and scale of landscape.

Future developments and applications

The initial fuzzy classification rule base was less successful than desired when applied to sites with gently undulating landscapes characterized by low slope gradients, low terrain curvatures and low relief.

One solution, that has been assessed at several sites with low relief and undulating topography, was to computationally re-scale these landscapes. Re-scaling was accomplished by means of an equation in which all elevation values were recomputed such that the minimum elevation in the data set was assigned an elevation of zero (0 m), the highest cell was assigned an elevation of fifteen (15 m) and all other cells were assigned elevations scaled between 0 and 15 m. This process is analogous to applying a large vertical exaggeration factor to a cross section produced for an area of low relief, in order to exaggerate the relief for illustration purposes. In effect, the process re-scales the vertical dimension of the original, low relief, landscape so that it becomes comparable in scale (approximately 15 m of relief) to the landforms for which the heuristic rule base was initially developed and tested and for which reasonable classifications were obtained. Initial results from sites with low relief in the province of Quebec and in Alberta have been encouraging. The re-scaling process is equally applicable to high relief landscapes.

The need to make the initial 15 unit model more applicable to landscapes with low slope gradients and low terrain curvatures also led to a revision of the initial rule bases used to define the fuzzy landform attributes based on slope and curvature. The new criteria used lower values to separate level from sloping elements (1% versus 3%) and planar from convex or concave elements (5 deg/100 m versus 10 deg/100 m).

The computer programs for running the model have been distributed to researchers in four other provinces across Canada. Several ongoing projects are evaluating the utility of the model to explain observed variations in yield and soil properties at additional sites in all four provinces.

Efforts are underway to improve the classification of depressions achieved by the model. A new terrain derivative has been conceptualized that estimates the number of mm of surface runoff required to first inundate every cell within every true closed depression in a DEM. This mm-to-flood derivative can be interpreted to produce a fuzzy terrain attribute called likelihood of inundation by surface ponding which can define depressions more explicitly .

The landform segmentation model has also been used to classify and provide quantitative morphometric descriptions for a number of sites taken as representative of type landscapes used to describe polygons in the digital soils database available for the province of Alberta. This project [24] produced a digital database of classifications and descriptive statistics for each of 10 major landform types. This can assist in the scaling up of results of site models to larger mapped areas and indeed may provide conditional input data to support the application of detailed site models to individual soil database polygons.

The landform segmentation model procedures are generic enough to support a variety of potential applications in addition to defining spatial management units for precision agriculture. They may prove useful for any number of detailed site characterizations as in site descriptions for environmental site assessments or reports on remediation of disturbed or contaminated areas. With modifications to include vegetation preference factors they could conceivably support automated forest site index or range land classification. In many ways the procedures replicate and systematize the processes followed by an expert when interpreting stereo aerial photographs to define morphologically and hydrologically different landform elements.

Conclusions

- A new landform segmentation methodology has been developed that can be applied to a wide variety of agricultural landscapes and generalized according to the magnitude and scale of the landscape and data.
- Inclusion of several measures of relative and absolute landform position resulted in improvements relative to previous models, specifically:

  - spatial fragmentation was reduced, producing larger more spatially continuous areas
  - misallocation of cells into classes at variance with the relative slope position was reduced (e.g. cells in upper landform positions were not classed as footslopes based on shape alone)
- Use of fuzzy definitions, re-scaling and dimensionless measures of relative landform position raises the possibility that a single model with a single set of rules can be applied to most agricultural landscapes of interest.
- The fuzzy procedures supported abstraction and explicit linguistic expression of the imprecise semantics required to define an abstract set of soil-landform entities [20].
- All 15 landform elements were not individually or exclusively different in terms of the selected soil attributes, soil classification or yields. However, several groups related to general landform position and downslope or profile curvature exhibited distinct, quantifiable differences in soil attributes and yields.
- The recommended 3 or 4 class grouping offers an optimum combination of simplicity, spatial coherence and meaningful differences in soil properties and crop yields.
- These spatial entities appear particularly well suited for defining management units for precision farming or for locating benchmark soil sampling (test) sites.

Acknowledgements

This project benefited from the guidance and financial support of a number of industry partners including: Westco Ltd. (John Harapiak), Norwest Research Ltd. (Jean Crepin) and Agrium (Doug Beever). Funding was also provided by Agriculture and Agri-Food Canada (Matching Investment Initiative Program). The DEM and DGPS were provided by Alberta Agriculture Food and Rural Development. Field support and assistance with data management and statistical analysis were contributed by Kelsey Spicer, Germar Lohstraeter and Annette Svederus (AAFRD) and Don Watson (Agriculture and Agri-Food Canada). The authors wish to thank the reviewers for their suggestions on useful and necessary improvements to the original manuscript. P. A. Burrough and P. F. M. van Gaans are thanked for suggesting that the initial manuscript be submitted for publication and for contributing suggestions for strengthening the paper.

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