Geoderma Regional 22 (2020) e00291

Contents lists available at ScienceDirect

Geoderma Regional

journal homepage: www.elsevier.com/locate/geodrs

Multi-resolution soil-landscape characterisation in KwaZulu Natal: Using geomorphons to classify local soilscapes for improved digital geomorphological modelling

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ARTICLE INFO

Article history:
Received 31 January 2020
Received in revised form 28 April 2020
Accepted 30 April 2020

Keywords:
Gleysols
Geomorphon
SRTM
Ferralsols

ABSTRACT

Continual advances in quantitative modelling of surface processes, combined with new spatio-temporal and geo-computational algorithms, have revolutionised the auto-classification and mapping of landform components through the automated analysis of high-quality digital elevation models (DEMs). Digital geomorphic mapping (DGM) approaches that can simplify and translate the inclusion of "human knowledge" to automatic terrain classification across a broader spectrum of terrain morphological units as well as a range of spatial scales, therefore, offer great potential for improved topographic and landscape analysis. One such approach is the mapping of landform elements using the concept of the Geomorphon (geomorphological phonotypes). The output of the geomorphon approach is the stratification of the landscape into ten unique but recognisable landform elements: peak, ridge, shoulder, spur, and slope, hollow, foot slope, valley, depression and flat. Equally appealing is the way the model self-adapts to local topography using a line-of-sight principle enabling better matching of landform elements to computational spatial scale. The purpose of this paper is to observe the effects that different pixel resolution (grain size) and digital elevation model source (DEM) would have on the replication of observed geomorphic spatial patterns and representation of terrain selected parameters within the landscape. This paper provides a comprehensive exploratory assessment of digital terrain representation and relief classification using an automated geomorphometric mapping approach, by evaluating three different digital surface models (SUDEM, SRTM, ASTER GDEM2) and different spatial resolution (30 m & 90 m) for an 11,200 ha catchment in KwaZulu-Natal, South Africa. To test the self-adapting ability of the geomorphon approach under regional conditions, we use 4750 gridded terrain samples to quantitatively analyse how the choice of terrain model and scale influence the extraction, generalisation and representation of digitally-derived terrain attributes such as slope, elevation and terrain unit feature extent. We further show how the variation in resulting terrain unit representation is limited by spatial resolution discontinuities of selected elementary soil association distribution, soil texture and soil depth. We also introduce the results of a Similarity Index used to gauge the degree of recall and precision between the different geomorphic landscape features. Finally, the findings of the regional geomorphon-soil relationships are presented in a readily interpretable and qualitative manner, providing a "quasi-landscape signature" for potential localised geomorphons. The application of the study findings may be beneficial to practitioners looking to align or refine modelled terrain classification approaches with expert perception and formalised heuristic approaches.

1. Introduction

Digital terrain representation techniques have been developed since the middle of the 20th century, relying heavily on developments in geocomputational technology, modern mathematics and computer graphical operations. The last decade has seen renewed interest in pushing the boundaries of topographic quantification and geomorphic regionalisation of land surfaces within a GIS environment (Bishop et al., 2012; Florinsky, 2012). Over this period, land-surface analyses and classification have seen rapid improvements in both the rate and quality of geomorphometric computational approaches, a key factor for the utility of digital geomorphic mapping (DGM) (Bishop et al., 2012; Rigol-Sanchez et al., 2015). DGM has provided users with a new set of tools with which to explore the conceptual issues of simulating single or even multi-landscape level functional and structural processes

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https://doi.org/10.1016/j.geodrs.2020.e00291

and hierarchical organisation of heterogeneous surface composition or character (Bishop et al., 2003; Tate and Atkinson, 2001; Walsh et al., 1997).

Importantly, DGM has provided an outlet for users to transcend beyond traditional humanistic and deterministic approaches to spatial organisation and visualisation of landscape phenomena. While conventional methods offer a high degree of regional or site-specific accuracy driven by expert input; replication, analytical reasoning and standardisation of procedures are often inhibited by human error, subjectivity and biases typically characterised by qualitative geomorphological and physiographic terrain analysis (Baker, 1986). Incidentally, with advanced DGM approaches, users are now able to better quantify and represent landscape morphology (Pike, 2000; Reuter et al., 2009), disaggregate terrain morphological units for farm-scale applications (Flynn et al., 2019); evaluate surface-biophysical associations (Florinsky, 1998; Gregory and Goudie, 2011; Liang, 2007; Smith and Pain, 2009; Tarolli et al., 2009) and implicitly explore spatial landscape complexity (Papadimitriou, 2009) through a broad suite of diversity and contagion indices of landscape heterogeneity (Li and Reynolds, 1993). Current international literature on landform classification and soil-landscape analysis using DGM is extensive (Libohova et al., 2016).

However, the specific application of DGM is yet to be fully explored under Southern Hemisphere conditions where a variety of landscape pattern-process functions inevitably influence a unique-set of soil-landscape and pedo-hydro-geomorphic processes (Grab and Knight, 2015; Holmes et al., 2016; Partridge et al., 2010). There is an immense opportunity to further examine the effectiveness of geospatial tools in understanding the scale-dependency of landscape pattern-process assemblages and calibrate model predictions to local geographical settings (Van Zijl and Le Roux, 2014). With regards to the pioneering of geomorphological studies, that now form the baseline for many DGM principles, the authors acknowledge that much work has already been done with regards to exposing the geomorphic principles that resonate in today's diverse South African Landscape and landforms. At a national scale, the work by Lester King (King, 1967) in delineating 18 geomorphic provinces for Southern Africa based on geomorphic history, geological structure, climate location and altitude provides a departure point in assessing how far the discipline of geomorphological mapping has progressed in South Africa. Recently, Partridge et al. (2010) were able to refine the concept by identifying 34 geomorphic provinces and 12 sub-provinces relating to drainage structure and slope by combining macro-reach descriptors, statistical analyses and digital terrain derived data (Holmes et al., 2016). These studies have contributed much towards outlining the contemporary challenges of landscape classification and landform discretisation studies in South Africa. However, these terrain categories remain limited to macro-scale geomorphic classification and offer a minimal contribution to the representation of distinct, local-scale (*meso*) geomorphic sub-regions (Schumann et al., 2011).

Arguably the most prevalent representation of landscape pattern-process for South Africa must be the National Land Type Database (ARC, 1972). A Land Type Unit represents a delineated area at a map scale of 1:250,000, displaying marked uniformity with regards to terrain form, soil pattern and climate (Schoeman et al., 2013) resulting in a homogenous distribution of soil properties across the landscape. Soil attributes are represented by a probabilistic organisation and symmetry of soil property associations and topographic processes known as a toposequence (Bushnell, 1943), or terrain morphological unit (TMU) linked to the following five terrain units: Crest (TMU 1), Scarp (TMU 2), Mid Slope (TMU 3), Foot Slope (TMU 4) and Valley Bottom (TMU 5). In the absence of readily accessible conventional or semi-detailed soil survey data for a vast majority of South Africa, local context studies still rely on the Land Type Survey database for describing a variety of process-pattern interactions within the landscape. Incidentally, the pursuit of a universally acceptable domain ontology for defining a framework in landform characterisation, particularly in South Africa, remains ever elusive given the fugacious nature, regionality, scale-dependency and preference of geospatial technologies in addressing geomorphological problems (Cavazzi et al., 2013).

Oddly, DGM technologies remain a source of *Felix culpa* to the end-user. That is, a major caveat of using DGM technologies for landscape analysis is the abundance of empirical black-box toolsets currently available to the general end-user. DGM technologies provide an objective and repeatable definition for geomorphological mapping of elementary terrain forms. However, many users are not adequately prepared for the technical-rigour required to define and translate the scientific underpinnings of geomorphological concepts into a GIS environment to accurately parameterise or regionalise these terrain models; leaving the end-user often undecided or unconvinced of the resulting modelled landform representations. Concomitantly, users are now called upon to a have a generalised understanding of the practical as well as empirical underpinnings of key discipline-specific concepts. Many considerations now exist before a terrain map can even be derived. So, while current DGM software/tool technologies expose a younger, more technocratic generation to the appreciation for quantitative evolutionary assessment of terrain features, so too does it prejudice more traditionalist-geoscientists reluctant, intimidated and disinterested in exploring these new avenues of research (Bishop et al., 2012). DGM approaches that can both simplify and translate the inclusion of "human-knowledge" to automatic terrain classification, therefore, offer great potential for improved landscape analysis. A design that has attracted attention in the field of DGM, internationally, is that of Geomorphon mapping created by Jasiewicz and Stepinski (2013). Geomorphons represent the fundamental micro-structures within a landscape and simultaneously represent terrain attributes and landform types (Jasiewicz and Stepinski, 2013). Geomorphons are analogous to textons (Julesz, 1981) of a landscape and their extraction from a DEM comes at a small computational cost considering that they simultaneously represent quantitative and stratified terrain attributes and landform types. The product of the geomorphon approach is the stratification of the landscape into ten unique but recognisable landform elements: Peak, Ridge, Shoulder, Spur, and Slope, Hollow, Footslope, Valley, Pit and Flat (Jasiewicz and Stepinski, 2013).

Two important concepts truly distinguish the geomorphon approach apart from its contemporaries. First, is that landform discretisation is not based only on geomorphometric variables, but rather on the complete topographic pattern corresponding to specific landform elements. Applying tools of computer vision rather than simply tools of differential geometry in an attempt to replicate the level of classification performed by human analysts (Silva et al., 2016a). Secondly, is the ability of geomorphons to determine a local pattern from a DEM using a neighbourhood approach with size and shape that self-adapts to the local topography using the line-of-sight principle (Lee, 1991; Nagy, 1991; Yokoyama et al., 2002) enabling better matching of landform elements to the appropriate spatial scale. This aspect in itself is a revolutionary advantage to end-users not sufficiently skilled in the concept of DGM scale-dependency (how patterns change with scale) which is pivotal in feature selection and terrain generalisation (Cavazzi et al., 2013). No *consensus omnium* yet exists for defining the optimal grain size for environmental factors to use in terrain analysis and scale-dependency in soil-landscape analyses is still mostly unresolved with minimal empirical guidelines available (Bishop et al., 2012). The main reason for this is that the determination of an optimal grid size for classifying terrain heterogeneity is highly dependent on issues such as terrain provenance, terrain complexity, observed terrain phenomena, neighbourhood size and DEM generalisation approach (Wu, 2004). Thereby limiting direct applicability of most DGM approaches and models of soil-landscape studies to other regions (Quinn et al., 1991; Vaze et al., 2010). The main challenges with DEM pixel resolution are that firstly at finer resolutions the terrain variables contain too much unnecessary detail or "noise" that may lead to poorer modelled accuracies. Secondly, at coarse resolutions, terrain variables may show too much generalisation or "smoothing" and not adequately represent terrain attributes or the land surface, ultimately limiting the predictive capacity and accuracy of soil-landscape models (Cavazzi et al., 2013). The utility of superior DGM tools, such as the geomorphon approach, in simplifying the spatial definition and classification of terrain morphology within complex soils-landscape systems necessitates further review in a local context. It's against this backdrop that the authors contend, supported by others (Malan, 2016; Mashimbye et al., 2014; Miller and Schaetzl, 2016; Smith and Hudson, 2002; Van Niekerk, 2010; Zerizghy et al., 2013), that geomorphic classification and delineation need to be better represented in discrete landform mapping endeavours in South Africa. Central to this directive is the shift away from an ad-hoc to a more formal and systematic approach to landscape character assessment (Wascher, 2005) across a range of DEM pixel resolutions, using modern geographic technologies and incorporating better base maps of topography into the landform mapping process (Miller and Schaetzl, 2014). Here landscape character is defined as the distinct, recognisable and consistent pattern of elements in the landscape that distinguish one landscape from another (Swanwick, 2002). This definition, therefore, underlines the explicit recognition of individual landscape elements, that constitute the landscape, and therefore allow for a systematic comparison of areas based on their landscape character (Galatowitsch et al., 2009). On this basis, the authors believe that the present study approach offers great potential to not only improve landform classification but so too terrain-unit discretisation at a local to semi-regional scale in South Africa. This study was carried out in response to the need to explicitly investigate how DEM spatial variations and geomorphon parameterisation influence the geomorphic terrain characterisation for soil-landscape feature extraction. In this study, we investigate how robust the geomorphon approach is at characterizing terrain features from three different derived DEM models, namely the SUDEM, SRTM and ASTER GDEM2 datasets calculated at two distinctive, and operationally-relevant, pixel resolutions, 30 m and 90 m. Two key objectives were outlined for this study: 1) to qualitatively assess, using a single set of model optimisation criteria, the similarity in terrain representation and selected soil-landscape covariate extraction between four geomorphon surfaces derived at different spatial resolutions in a mountainous region in Central KwaZulu-Natal. 2) to evaluate how well aligned these derived geomorphon surfaces and their (scale-dependent) topographic properties are to the heuristic underpinnings of accepted, operative soil-landscape relationships for the study region.

2. Materials and methods

2.1. Site description

This study was carried out in a 16 km × 11 km area (11,200 ha) located near the town of Bergville in the Central Drakensberg Region, KwaZulu-Natal (Fig. 1). The study area, which extends from 28° 38′ 13.17″S to 28° 38′ 56.99″S and from 29° 0′ 57.01″E and 29° 17′ 11.28″ E was selected as it provided a suitable range of terrain types from moderate to steep sloping hills to open and incised valleys showing evidence of anastomosing channels formed by old stream meltwaters. Moreover, regional-scale digital elevation models show these rolling hills as distinct, recognisable features of the landscape. Changes in elevation from the lower-lying troughs to hillslope highs are approximately 45 m, and distances between these features are about 150 m.

The primary geological material across the site is of the Karoo Systems' Beaufort Series. The lithology consists mainly of blue, green, red, or even purple mudstones and shales alternating with yellow, fine-to medium-grained feldspathic sandstones (Van der Eyk et al., 1969). The most distinctive landscape element in the study area is the noticeable presence of a table-topped hill (mesa) feature with well-defined scarp slopes extending to lower ranging hillslopes and finally an alluvial toe slope at the base of Woodstock Dam (Ruhe, 1960). The less dominant terrain features are characterised by moderate to steep undulating sandstone deposits through the site. The elevation ranges from 1164 m above sea level in the east to 1472 m in the centre of the study area with an average altitude of 1318 m. Mean annual temperature is in the region of 18.4 °C with temperatures dropping as low as 1.2 °C between June and July and reaching 31.1 °C during the summer months of December to January. Median annual rainfall for the region is 820 mm with a higher concentration from December to February (Camp, 1995). The dominant land use in the area is natural grassland and veld (6387 ha) with other prominent land uses including extensive commercial arable and livestock agriculture (3961 ha), woodland and open bushland (153 ha) and water bodies (453 ha) with Woodstock Dam occupying 373 ha of the total catchment impoundment footprint. Most of the urban villages and settlements (32 ha) are limited to the lower-lying regions while surface erosional features (55 ha) such as channelled gullies and "dongas" prevail in the moderate to lower surface gradient regions (GeoTerraImage, 2015).

2.2. Data acquisition and analysis

2.2.1. Sample data points

To characterise landscape homogeneity, its spatial heterogeneity must first be appropriately described. Using the definition by Kolasa and Rollo (1991), a surface property is heterogeneous, if its measurements vary in space. A more thorough description is that spatial heterogeneity in categorical landscape maps is defined as the complexity for both the composition (diversity) and configuration (spatial arrangement) of a particular land feature (Lausch, 2015). Landscape composition accounts for the types of categories that are present, including how many of these groups are present while ignoring the specific spatial arrangement of these classes on the landscape. In this study, spatial configuration refers to the particular spatial arrangement of the different cover types on a landscape (Wang et al., 2017). Characterizing the spatial heterogeneity of geomorphons derived under a set of controlled parameters may help in designing the spatial resolution for future earth observing missions, *vis-à-vis,* under local settings (Morisette et al., 2002). In this study, spatial heterogeneity has been defined through two components, namely: the *spatial variability* (DEM derivative variability) of the surface property over the observed study area; and the *spatial structure* (Geomorphon variability) or landscape objects or patches that represent themselves independently and repeatedly within the study site at a characteristic length scale (spatial scale) (Garrigues et al., 2006).

The study adopted a purposive grid sampling approach (Aguilar et al., 2005; George et al., 2018; Nanni et al., 2011) using a 150 × 150 m ground-sampling grid resulting in a total of 4750 derived gridded sample-point locations for the entire 11,200 ha site. The choice of this sampling design is based on two fundamental research-specific considerations: 1) foremost, the design is intended to capture as much surface heterogeneity from the DEM-resulting geomorphon surface derivatives as possible by exhaustively surveying the entire study region using all 4750 point samples. This systematic gridded sample approach proved most optimal in comprehensively accounting for the terrain feature variation within the study site, limiting minimum biased feature extractions and resulting in higher reliability of final results in comparison with other possible sampling techniques, i.e. stratified cluster sampling or Conditioned Latin-hypercube Sampling (George et al., 2018). Furthermore, the applied sampling approach would not only limit the possibility of drawing an unrepresentative sample of terrain features but also enable the second-order geographical variance: global variance and spatial structure to be better represented (Wang et al., 2010). The choice of the sample-grid resolution (150 × 150 m) was selected by design to corroborate derived computational results with in-field applications to soil and landscape assessments in the Province of KZN where this grid resolution is the de facto grid resolution for field-based surveys (Smith, 2006). Incidentally, a review of the model proposed by (Hengl, 2006) to determine maximum location accuracy (MLA) or average size area (ASA), the 150 × 150 m gridded approach applied in this

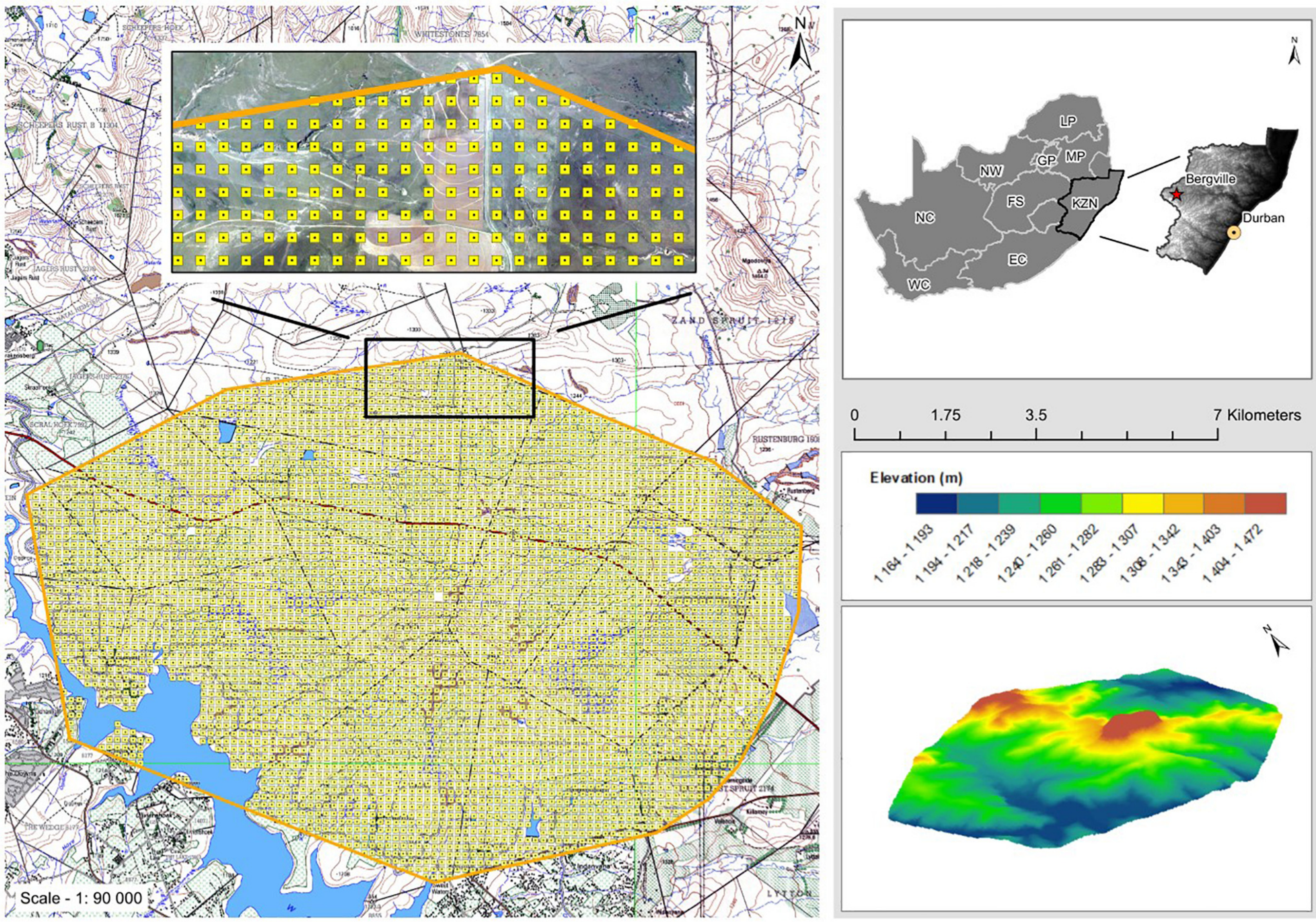

Fig. 1. Bergville area - (a) Location of study site showing stratified sample observations (b) geographical overview of the study site (c) DEM delineated catchment area.

study was found to be appropriate to describe the landscape with reported results correlated well to similar pixel resolutions for the 30 and 90 m resolution DEM datasets used in the study.

2.2.2. Digital elevation data

DEM choice generally contains tradeoffs between cost, accuracy, spatial coverage and grid size as well as the way they are prepared and corrected (Robinson et al., 2014). However, the quality of the DEM ultimately determines the accuracy and reliability of the spatial geomorphometric analysis. For this study, four DEM surfaces were analyzed: a locally derived 30 m and 90 m (generalised from 5 m DEM surface) Stellenbosch University Digital Elevation Model (SUDEM) (Van Niekerk, 2014; Van Niekerk, 2016) as well as the readily available C-Band, 90 m Shuttle Radar Topography Mission (SRTM) and 30 m Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) Global Digital Elevation Model V2 surface models. The high-resolution SUDEM terrain products are gaining in popularity in a variety of terrain analysis, digital-soil mapping and hydrological modelling applications. The SUDEM is perhaps the most accurate and readily available localised high-resolution DEM for South Africa. SUDEMs are offered as a series of products developed by the Centre for Geographic Analysis (CGA) situated at Stellenbosch University, South Africa. By processing large scale contours and spot heights with local interpolation approaches, DEM products are offered at four different processed levels: level 1, 2 3 and 4 (Van Niekerk, 2012). Selected regional studies have shown that the SUDEM products, even when generalised to lower resolutions, are able to yield as accurate terrain feature representations when compared to using higher-resolution products such as LiDAR generalised to the same resolutions (Atkinson et al., 2017). The SUDEM is an appealing option in terrain surface analysis in South Africa as it's both cost-effective and retains high feature quality. While there are spurious issues relating to contour and spot height estimations in the data, many of these errors (gaps) do not feature in the final interpolated product(s). The baseline level 2b product used in this study offered far superior data accuracy and image quality than other readily available primary surface models obtained from public-sector data custodians such as the South African Chief Directorate National Geospatial Information. The SRTM and ASTER GDEM2 remain the most widely applied satellite-derived, near-global and high-resolution DEM data sets and were selected due to their reputable operational application and general ease of open-access to the end-user (Gesch et al., 2012). The SRTM is reported to have an absolute vertical (orthometric) accuracy of 16 m or less, a relative vertical accuracy of 10 m or better and an absolute horizontal accuracy of better than 20 m (Rexer and Hirt, 2014; Jarihani et al., 2015; Sharma and Tiwari, 2014). While the ASTER GDEM2, released in October 2011, has an improved vertical accuracy (orthometric) of 17 m, and absolute horizontal accuracy of ±30 m (Gesch et al., 2012; Jarihani et al., 2015; Meyer, 2011) For a full comparative review of the sensor and surface products used in this studies, readers are referred to the study by Atkinson et al. (2017).

To examine the applicability of DEMs for geomorphon feature detection, digital analyses with ArcGIS® (ArcMap™, Version 10.5) had to be performed for further data interpretation. All DEM products were re-projected to meters from a Geographic Coordinate System to the Universal Transverse Mercator (UTM) projection (Zone 36S) before analysis. Minimal post-processing procedures were applied to the DEM models (versions) used in this study as the products were already suitably post-processed by the vendors with image enhancements including the elimination of voids, spike and pit removal, water body levelling with overall improved surface accuracy and height validation (Tachikawa et al., 2011; Yang et al., 2011). Postprocessing of the primary-derived geomorphon products using both the with majority-filtering and mean-filtering algorithms ensured that outlier pixels and anomalies within classes were removed before the final reclassification of the geomorphon raster surfaces into the ten discrete categories. While pre-processing is vital for model accuracy, DEM preparation can impact other components of model performance (Callowa et al., 2007).

Consequently, none of the DEM models were further modified to generate hydrologically-conditioned DEM surfaces. This was a necessary and deliberate consideration since the study required the identification of certain discontinuous terrain features such as pits (Geomorphon Unit 10) and hollows (Geomorphon Unit 7) within the landscape. Furthermore, Atkinson et al. (2017) reported that the use of hydrologically corrected DEMs to derive selected surface parameters was not found to be reliable for the extraction of selected terrain variable estimates across a range of pixel resolutions.

To ensure DEM comparability, all DEMs were processed to equal spatial resolutions of analysis of 30 and 90 m, respectively (Bubenzer and Bolten, 2008). While both the ASTER GDEM2 and SRTM DEMs were used in their native resolutions of 30 and 90 m respectively, the 30 m and 90 m SUDEM DEM models were derived from a high-resolution 5 m SUDEM using the nearest neighbour generalisation approach outlined by (Atkinson et al., 2017). Having been derived directly from the 5 m DEM, and therefore assuming the highest elevation accuracy, the 30 m SUDEM was used as the reference DEM to evaluate the accuracy of the geomorphon surfaces and associated terrain variables from the other DEM sources. A vital part of this research involved the identification of the relationship between geomorphon surfaces and terrain character and the similarities in terrain products across these scale-specific geomorphon surfaces. It is however beyond the scope of this paper to explicitly address all the issues of DEM error assessment in a single paper and readers are referred to the work of (Atkinson et al., 2017; Florinsky, 1998; Prasannakumar et al., 2011; Shafique et al., 2011; Sørensen and Seibert, 2007; Thompson et al., 2001).

2.3. Geomorphon pattern characterisation

For the creation of the 2D geomorphon models, the DEMs were input to GRASS GIS (v 7.4.1) (Neteler and Mitasova, 2007) with the workflow making use of the *r.geomorphon* extension. The raster-based *r. geomorphon* delineates the ten most universally accepted landform units by applying a pattern recognition algorithm that is based on 3 × 3 local neighbourhood search radius from a central focal point (Jasiewicz and Stepinski, 2013). Each Geomorphon coincides with the most common slope positions used to describe landscape features. A vital function of the *r.geomorphon* extension is the ability to process extensive DEM datasets through optimal memory management (Jasiewicz and Stepinski, 2013). It does this by limiting geomorphon calculations to a local, user-defined neighbourhood extent (line of sight) thereby ensuring that only a relevant, small portion of the entire DEM is read to the computer memory during processing. A key consideration in the generation of geomorphic surfaces is *a posterior* selection of window size and length-scale (Wood, 2002). The *r.geomorphon* algorithm can analyse the extent and shape of the featured neighbourhood to classify the landform elements by automatically self-adjusting/adapting to the geometry of the local terrain derived from the DEM surface. Notably, model optimisation depends on three core parameters: *maximum search radius* (lookup distance), *flatness threshold* (*t*-degrees) and *Skip radius* (cells). A key consideration is the search radius (*L-cells)* which represents the maximum distance for line-of-sight (LOS) calculations for each pixel. To evaluate, how well the *r.geomorphon* tool can adapt to feature scale recognition and consistently detect similar local terrain features its essential that landform feature resolution is relative to DEM spatial (pixel) resolution. Users can therefore systematically and iteratively, *albeit* on a trial-and-error basis, calibrate the geomorphon model inputs with parameters such as search and skip radii values to determine the appropriate scale of analysis for the study. By adjusting these parameters, user's can effectively skip small terrain variations to capture more massive landforms and uniformly optimise the final geomorphon surface outputs. For this study, the optimisation approach enabled the researchers to determine whether geomorphic features detected at 30 m are diligently represented at 90 m and vice versa across different DEM surfaces.

In this study, the authors adopted a similar approach to Luo and Liu (2018) and Gruber et al. (2015) by iteratively selecting model parameters that offered a reasonable balance between the accuracy of capturing landform elements and model computational cost. Applying a constant outer search radius of 30 cells across all DEM surfaces allowed the authors to control the classification outputs by solely observing surface variation resulting from pixel resolution and not the line of sight variations as well (Libohova et al., 2016). The following optimisation parameters best represented the Geomorphon surfaces across all DEM surfaces (Table 1).

The table shows that a constant outer search radius of 30 cells was used to map the Geomorphon features between the DEM surfaces. The 30-cell search radius is equal to search distances of between 900 and 2700 m for the 30 and 90 m DEM surfaces respectively. The *r. geomorphon* tool allows the user to model both inner and outer search radii using either cell number or ground distance (m) depending on user preference (Jasiewicz and Stepinski, 2013). Finally, the flatness threshold of 1.2° used in this study corresponded well with similar studies by Luo and Liu (2018) and Trentin and Robaina (2016) who settled on a maximum search radius of 2500 m and 1800 m and flatness threshold of 1° and 2° respectively. The SUDEM 30 m and 90 m, as well as the SRTM DEM, identified nine geomorphic features while the Aster GDEM2 identified all ten geomorphic features including the "Pit" terrain feature.

2.4. Extracting the primary topographic covariates

All geomorphon features were assessed against two primary compound terrain attributes namely *altitude (DEM height) and slope gradient*. These indices were selected since they are readily extractable in a GIS environment, are simple to interpret and compare across datasets, can be analyzed using descriptive or non-parametric statistical approaches and are regularly used as input variable parameters in similar landscape assessment studies (Kumar, 2013). Many studies still rely on local elevation and slope as easily interpretable parameters to identify and compare landform types (Saadat et al., 2008). Slope, represented as percentage values, were extracted using the slope tool in the Earth Science Research Institutes ArcGIS® (ArcMap™, Version 10.5) Spatial Analyst suite of tools.

Table 1
Distance parameters (search, skip, flat distances) used in r.geomorphon for computational optimisation of multi-resolution DEMs.

DEM Source	Resolution	Outer Search Radius		Inner Search Radius		Flatness Threshold	Flatness Distance
		Cells	Distance	Cells	Distance		
SUDEM	30 m	30	900 m	6	180 m	1.2°	0
SUDEM	90 m	30	2700 m	6	540 m	1.2°	0
ASTER GDEM	30 m	30	900 m	6	180 m	1.2°	0
SRTM	90 m	30	2700 m	6	540 m	1.2°	0

2.5. Extracting legacy soil data: Tugela Basin database

In this study, the primary source of synoptic soil information that provided reasonable coverage of the area was obtained from the semi-detailed survey of the Soils of the Tugela Basin. It was Van der Eyk et al. (1969) who first produced a compilation of hardcopy soil maps at a scale of 1:50,000 for the Three Rivers Area (Umvoti, Umgeni and Illovo) and 1:18,000 topographic coverage for the Tugela Basin, in which the study area resides. The purpose of the survey was, however, not to provide a blueprint for detailed land use planning, and the data do not show the distribution of individual soil series or phases of series for the region. Instead, the data reveals the broad zonal arrangements in the distribution of the soil series with each mapping unit potentially comprising as many as several associated series (Van der Eyk et al., 1969). For this study, a digital version of the Tugela survey data was used. The data was initially acquired in a vector format but later rasterized for ease of automated overlay analysis with the other covariate terrain datasets. In the absence of readily interpretable taxonomic criteria, the study applied categorical properties (as defined in the original attribute space of the soil dataset) associated with soil taxa such as dominant soil complex, dominant clay content and dominant soil depth class. The authors acknowledge that while these indicators do not provide an utterly definitive definition for taxonomic classification by modern standards or approaches, they do however enable a “coarse” first approximation and departure point to assess the soil-landscape component between derived geomorphon surfaces.

2.6. Data analysis and measures used for map comparisons

The 4750 sample data points were used to extract the raster values from each of the geomorphon, elevation, slope, soil complex, clay percentage and soil depth data sets respectively in ArcGIS 10.5 using the extract to multipoint feature. The data were then imported to *STATISTICA* 13.2 for statistical and exploratory data analysis. Data analysis for similarity assessment of geomorphon features between DEMs was primarily limited to simple quantitative assessment metrics of central tendency and variance around the mean. Each geomorphon surface feature was classified according to *count, trimmed mean,* min, max, *standard deviation, coefficient of variation and standard error* values for elevation and slope respectively.

Further to this, data for *elevation, slope, soil complex, clay content and soil depth* were categorically classified for comparison of dominant soil-landscape features across each geomorphon surface. Finally, to independently evaluate the accuracy and similarity of the predicted geomorphon surface products, the resulting maps (90 m SUDEM, 90 m SRTM and 30 m ASTER GDEM2) were compared to the reference DEM surface (30 m SUDEM). A cell-by-cell comparison of raster values for each of the geomorphon surface layers and each of the derived datasets using measures of recall and precision were used to analyse feature similarity. Specifically, the novel application of a composite measure (BK) (Leifman et al., 2003) to evaluate geomorphon classification similarity (Smirnoff et al., 2008) was used in this study. The BK metric (normalised between −1 and 1 but typically reported as n × 100%) has been used in other studies to evaluate the accuracy of different classification methods and has an advantage of being readily produced from a confusion matrix (Sharifzadeh et al., 2005) of predicted vs observed observations. Geomorphon feature similarity was then assessed by the following: *Recall* = *Cells of Unit X placed as X on resulting map/All cells of Unit X on the original map* then (1- *Recall) which is* considered an indication of the classification of false negatives. Similarly, the *Precision* = *Cells of Unit X placed as X on resulting map/All cells of Unit X on the resulting map* represents the portion of cells rightfully placed in the units of the resulting map with (1-*Precision)* representing the so-called false positives (Smirnoff et al., 2008).

A significant advantage of using the composite BK approach is that it allows two or more generalised maps to be compared, regardless of spatial resolution differences, with either of them serving as a reference map. The observed BK values then represent the degree of similarity/dissimilarity between two or more maps. The high-resolution SUDEM 30 m, including all associated derived products, was used as reference (observed) map while the other DEM surfaces and their related products served as the predicted (produced) surface(s). By combining the recall and precision, the BK = *Recall* + *Precision – 1* score can be calculated with the range of the composite values represented between −1 and 1 with higher similarity tending towards more positive values approaching 1.

3. Results and discussion

3.1. Geomorphon similarity, cross-tabulation and BK composite measure

The overall similarity results of the unsupervised surface classification for the BK composite comparison are presented both graphically and through a confusion matrix (Tables 2a–2c). The results reflect the geomorphon feature comparison of the SUDEM 90 m (Fig. 2b), SRTM 90 m (Fig. 2c) and ASTER GDEM2 (Fig. 2d) to the reference SUDEM 30 m surface (Fig. 2a). Visual inspection of the geomorphon surfaces reveals that the reference 30 m SUDEM exhibits the most surface detail, while the 90 m geomorphon surfaces depict a relatively smooth, generalised landscape with geomorphon features still distinctive and most surface-feature patterns well aligned with those represented in the 30 m SUDEM. In contrast, the 30 m GDEM2 surface displayed a noisy and incoherent geomorphon surface with minimal feature characterisation largely attributed to the “fractured” nature of the DEM surface. Admittedly, the GDEM2 coverage for the study site is inherently poorly represented with high intra-class fragmentation and heterogeneity of surface elevation. In this instance, the overall poor performance of the GDEM2 Geomorphon classification is predominantly a manifestation of the sub-optimal quality of the DEM surface. The ASTER GDEM2 surface product(s) have noticeably improved quality compared to its predecessor, ASTER GDEM1, attributed to reduced artefact incidence and improve spatial resolution and the accuracy of water masking (Rexer and Hirt, 2014). Despite the overall improved image quality, the GDEM2 dataset remains beset with region/scene-specific anomalies and artefacts that require processing and removal before use, particularity at higher latitudes (>60 N) and lower latitudes (<60 S) (Robinson et al., 2014). Furthermore, improvement in both vertical and horizontal accuracy has come at the cost of increased noise in the datasets as well as reflectance-bias to land cover and reflective surfaces with accuracy measurement being lower for forested areas, buildings etc. compared to bare surface areas (Gesch et al., 2012; Meyer, 2011).

Considering these first-approximation visual comparisons, we can conclude that while the reference 30 m SUDEM surface may contain detailed geomorphon detail, particularly with the representation of discrete features, such as ridges, slopes and valleys, the 90 m geomorphon surface products were able to graphically represent similar morphon features perhaps not in extent but at least in terrain position. This result was not entirely unexpected, given how spatially autocorrelated all the DEM surfaces were within the study area (Tables 3a–3d). Nonetheless, the result remains positive in the context of this study given that the consensus is that as pixel resolution of the DEM surface decreases slope values are underestimated typically leading to a misrepresentation of terrain features at coarser resolutions (Warren et al., 2004).

However, deferring to the quantitative result comparisons for the overall similarity performance, i.e. the BK composite results, between the predicted and reference surfaces are not particularly promising. The performance described here refers to the quality of the classifier (predicted surface) and its usefulness for automatic mapping of the “true surface” or some permutation thereof (Jasiewicz et al., 2015). The low BK values displayed in Tables 2a–2c show that a majority of the predicted geomorphon units are statistically dissimilar to their

Table 2a
BK similarity comparison of geomorphometric features between the reference SUDEM 30 m and SUDEM 90 m DEM surface.

ACTUAL (30 m SUDEM)	PREDICTED (90 m SUDEM)											SIMILARITY		
	FLAT	SUMMIT	RIDGE	SHOULDER	SPUR	SLOPE	HOLLOW	FOOTSLOPE	VALLEY	DEPRESSION	TOTAL	RECALL	PRECISION	BK
FLAT	16	0	0	2	0	0	0	45	2	0	65	0.25	0.16	−0.59
SUMMIT	0	19	11	0	0	0	0	0	0	0	30	0.63	0.28	−0.09
RIDGE	5	42	429	41	89	33	1	4	1	0	645	0.67	0.55	0.21
SHOULDER	5	0	27	36	14	35	15	30	6	0	168	0.21	0.15	−0.63
SPUR	6	5	192	50	224	194	27	36	18	0	752	0.30	0.36	−0.34
SLOPE	35	2	111	88	257	607	168	207	123	0	1598	0.38	0.53	−0.10
HOLLOW	2	1	13	11	30	205	155	73	119	0	609	0.25	0.34	−0.40
FOOTSLOPE	28	0	0	5	5	18	7	150	135	0	348	0.43	0.24	−0.33
VALLEY	1	0	4	1	4	64	80	83	297	0	534	0.56	0.42	−0.02
	98	69	787	234	623	1156	453	628	701	0	4749			

Table 2b
BK similarity comparison of geomorphometric features between the reference SUDEM 30 m and SRTM 90 m DEM surface.

ACTUAL (30 m SUDEM)	PREDICTED (90 m SRTM)											SIMILARITY		
	FLAT	SUMMIT	RIDGE	SHOULDER	SPUR	SLOPE	HOLLOW	FOOTSLOPE	VALLEY	DEPRESSION	TOTAL	RECALL	PRECISION	BK
FLAT	6	0	0	0	2	1	2	44	10	0	65	0.09	0.29	−0.62
SUMMIT	0	22	8	0	0	0	0	0	0	0	30	0.73	0.28	0.01
RIDGE	1	48	433	18	102	30	3	8	2	0	645	0.67	0.52	0.19
SHOULDER	1	0	37	22	21	32	14	34	7	0	168	0.13	0.20	−0.67
SPUR	1	8	207	28	221	213	30	16	28	0	752	0.29	0.34	−0.37
SLOPE	6	1	125	35	257	651	219	151	153	0	1598	0.41	0.54	−0.05
HOLLOW	0	0	13	7	36	205	157	41	150	0	609	0.26	0.30	−0.44
FOOTSLOPE	6	0	0	2	8	25	9	149	149	0	348	0.43	0.31	−0.26
VALLEY	0	0	5	0	6	52	87	42	342	0	534	0.64	0.41	0.05
	21	79	828	112	653	1209	521	485	841	0	4749			

Table 2c
BK similarity comparison of geomorphometric features between the reference SUDEM 30 m and ASTER GDEM2 30 m DEM surface.

ACTUAL (30 m SUDEM)	PREDICTED (30 m ASTER GDEM2)											SIMILARITY		
	FLAT	SUMMIT	RIDGE	SHOULDER	SPUR	SLOPE	HOLLOW	FOOTSLOPE	VALLEY	DEPRESSION	TOTAL	RECALL	PRECISION	BK
FLAT	0	1	4	5	7	16	4	5	15	8	65	0.00	0.00	−1.00
SUMMIT	0	17	11	2	0	0	0	0	0	0	30	0.57	0.13	−0.30
RIDGE	0	79	364	17	111	53	11	1	7	2	645	0.56	0.44	0.00
SHOULDER	0	6	61	4	31	35	16	0	14	1	168	0.02	0.06	−0.92
SPUR	0	10	199	8	269	178	50	15	22	1	752	0.36	0.35	−0.30
SLOPE	0	11	150	22	295	702	237	19	154	8	1598	0.44	0.55	−0.01
HOLLOW	0	0	13	5	32	147	210	18	178	6	609	0.34	0.32	−0.34
FOOTSLOPE	1	2	24	3	26	86	54	8	122	22	348	0.02	0.08	−0.90
VALLEY	1	0	5	2	7	54	82	36	318	29	534	0.60	0.38	−0.02

reference geomorphon counterpart. In particular, the predicted geomorphon features that showed the lowest similarity in both 90 m DEM products were the flat, shoulder, spur and footslope terrain features. Coincidently, the same geomorphon features also exhibited higher slope gradient standard deviations to the SUDEM 30 m surface (Tables 3a–3c). Interestingly, a study conducted by Gruber et al. (2017) similarly found that features such as shoulders, foot slopes, and localised flat regions were poorly mapped despite applying best parameter settings for each topographic position with only minor gains in accuracy related to scale variation. In contrast, the results for the 30 m GDEM2 displayed lower similarity to the reference 30 m SUDEM surface than the 90 m products with almost all morphon features displaying lower BK values with features such as flat, shoulder and footslope BK scores even approaching −1.00 suggesting complete dissimilarity with the reference surface. Conventionally, these results would not be expected given the fine-scale resolution of the 30 m GDEM2 surface coinciding with the resolution of the reference 30 m SUDEM.

Before simply ignoring the extraneous predicted surface similarity results to the reference surface as ineffectual for terrain characterisation, based solely on the poor BK values, we need to also consider two additional measures of model effectiveness, i.e. model recall (*producer accuracy*) defined as the proportion of relevant material actually retrieved and model precision (*user accuracy*) representing the proportion of correlated material actually appropriate (Leifman et al., 2003). Furthermore, the BK approach used in this study was adapted from Smirnoff et al. (2008) who applied the metric as means of comparing the results obtained from surface generalisation using a cellular automata algorithm on a cell-by-cell basis. While novel when applied to this study, our application of discrete point feature comparisons may have led to a far more restrictive sample-space analysis of results if compared to a complete pixel-based grid comparison of datasets. This may have in part contributed to the overall poor BK results and moderately acceptable precision and recall results between the predicted and actual geomorphon surfaces. Further investigation into the selection of a robust and suitable "benchmark" assessment for similarity assessment between geomorphon surfaces may yet need to be further defined for future applications in terrain analyses.

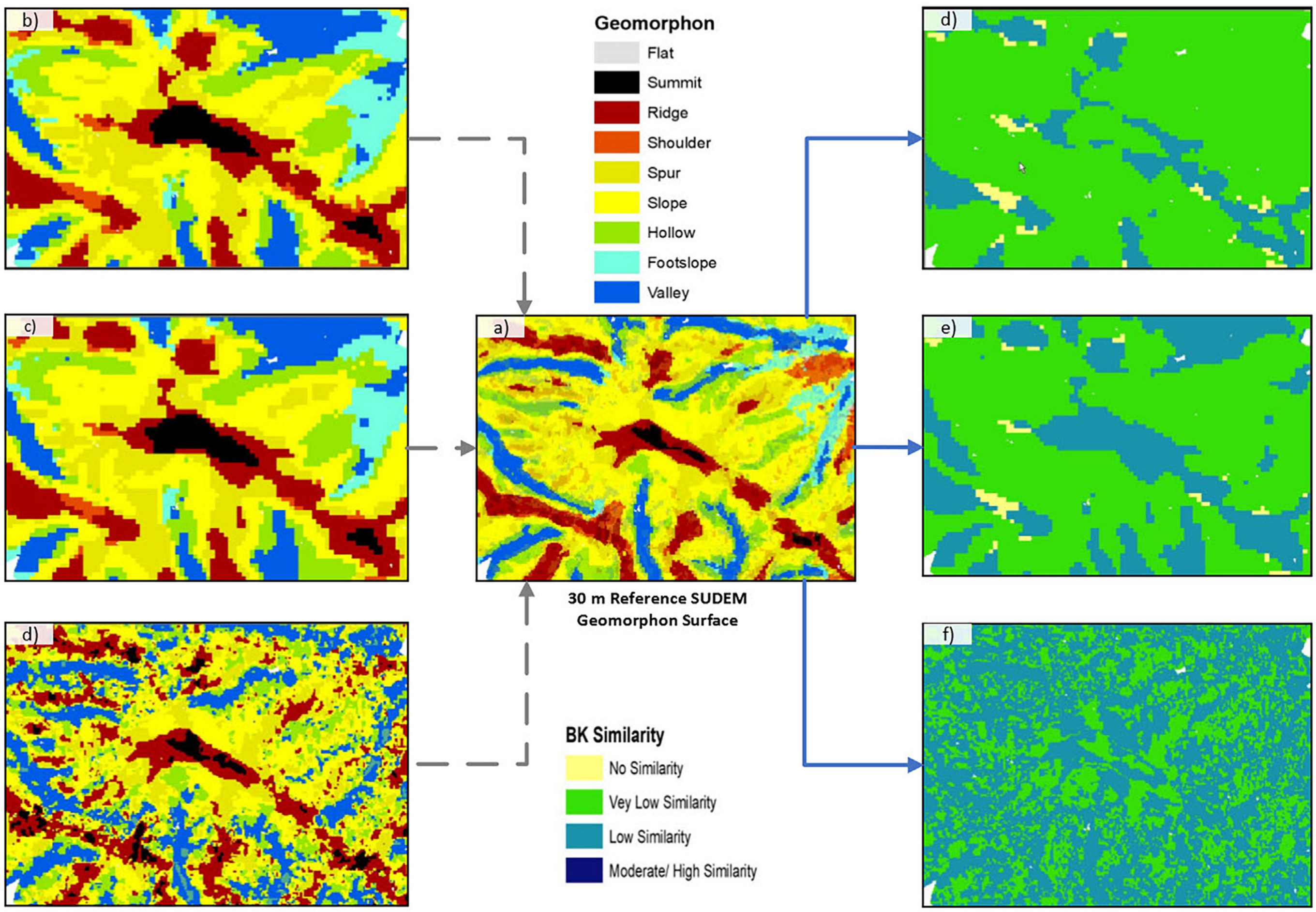

Fig. 2. Overview of a centrally located Sub-AOI showing a 2-D comparison of (a) reference SUDEM 30 m geomorphon surface with (b) SUDEM 90 m surface (c) SRTM 90 m surface and (d) GDEM2 30 m geomorphon surface. Figures (e-f) showing results of the BK similarity for the SUDEM 90 m, SRTM 90 m and 30 m GDEM2 respectively.

Table 3a
Descriptive statistics for DEM elevation, slope and feature area for the 30 m SUDEM reference Geomorphon surface.

	SUDEM 30	Height						Slope						Area
	Count	Min	Max	Mean	SD	CV	SE	Min	Max	Mean	SD	CV	SE	Ha
Flat	65	1169	1255	1181	16	1	2	0	6	2	2	65	0	145
Summit	30	1244	1472	1379	81	6	15	0	19	6	4	68	1	70
Ridge	645	1182	1462	1278	57	4	2	0	55	7	7	101	0	1450
Shoulder	168	1176	1292	1225	32	3	2	0	15	3	2	53	0	392
Spur	752	1178	1445	1259	44	4	2	0	60	9	8	88	0	1670
Slope	1598	1172	1417	1247	40	3	1	0	55	8	5	73	0	3600
Hollow	609	1178	1375	1246	31	2	1	1	52	7	4	58	0	1359
Foot	348	1168	1292	1201	27	2	1	0	11	3	2	62	0	796
Valley	534	1169	1335	1230	33	3	1	0	20	6	4	62	0	1233
Pit	0	0	0	0	0	0	0	0	0	0	0	0	0	0

In all three predicted surfaces, the summits, ridges, slopes and valleys show relatively high values of either recall or precision accuracy concerning the SUDEM surface. For instance, while the 90 m SRTM surface yielded low overall BK values, the recall accuracies – that a mapped geomorphon was predicted – were high with 73%, 67% and 64% for the summit, ridges and valleys respectively. Interestingly, even the ASTER GDEM2, despite the low similarity in the BK metrics, was able to map 57% and 56% of the summit and ridges in the reference surface 30 m SUDEM surface. These results indicate that some replication between the predicted and reference surfaces, albeit at a specific morphon feature and not complete landscape level, is possible even with coarse DEM resolutions of 90 m and despite inherent artifactual inconsistencies in selected DEM surfaces.

These results present both advantages and drawbacks for future terrain characterisation analysis with varying DEM surfaces using geomorphons. Firstly, the application of coarse resolution DEMs to geomorphon feature discretisation holds promise for soilscape studies in South Africa, particularly in regions where open-source global DEM datasets such as SRTM are still a primary source of terrain data. However, the fact that the GDEM2 was able to comparatively represent approximately 60% of the reference geomorphon features despite the mediocre DEM surface begs the question: how much of the model

Table 3b
Descriptive statistics for DEM elevation, slope and feature area for the 30 m GDEM2 predicted Geomorphon surface.

	GDEM2	Height						Slope						Area
	Count	Min	Max	Mean	SD	CV	SE	Min	Max	Mean	SD	CV	SE	Ha
Flat	2	1170	1176	1173	4	0	3	9	29	19	14	74	10	4
Summit	126	1173	1470	1287	67	5	6	1	47	14	9	64	1	270
Ridge	831	1168	1469	1266	56	4	2	0	86	13	10	77	0	1885
Shoulder	68	1164	1386	1242	51	4	6	1	47	14	8	54	1	144
Spur	778	1164	1432	1256	48	4	2	0	87	14	10	70	0	1770
Slope	1271	1159	1436	1248	44	4	1	0	66	13	8	64	0	2839
Hollow	664	1163	1367	1240	36	3	1	1	61	12	8	62	0	1480
Foot	102	1161	1313	1222	31	3	3	1	33	12	7	57	1	240
Valley	830	1150	1328	1225	34	3	1	0	50	12	7	58	0	1928
Pit	77	1154	1267	1197	29	2	3	2	33	13	8	58	1	155

Table 3c
Descriptive statistics for DEM elevation, slope and feature area for the 90 m SRTM predicated Geomorphon surface.

	SRTM 90	Height						Slope						Area
	Count	Min	Max	Mean	SD	CV	SE	Min	Max	Mean	SD	CV	SE	Ha
Flat	21	1172	1213	1183	11	1	2	0	10	4	2	64	1	44
Summit	79	1295	1476	1416	57	4	6	0	45	16	14	88	2	172
Ridge	828	1194	1419	1277	42	3	1	0	58	8	7	96	0	1887
Shoulder	112	1188	1302	1243	32	3	3	1	16	5	3	50	0	242
Spur	653	1197	1420	1268	37	3	1	0	47	8	6	77	0	1489
Slope	1209	1184	1398	1250	34	3	1	1	51	7	4	59	0	2705
Hollow	521	1190	1317	1246	25	2	1	1	20	6	3	47	0	1156
Foot	485	1166	1288	1199	24	2	1	0	25	5	3	64	0	1082
Valley	841	1168	1323	1223	30	2	1	0	18	5	3	60	0	1938
Pit	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 3d
Descriptive statistics for DEM elevation, slope and feature area for the 90 m SUDEM predicated Geomorphon surface.

	SUDEM 90	Height						Slope						Area
	Count	Min	Max	Mean	SD	CV	SE	Min	Max	Mean	SD	CV	SE	Ha
Flat	98	1169	1250	1185	15	1	1	1	14	4	2	58	0	228
Summit	69	1296	1472	1418	59	4	7	0	45	16	14	84	2	155
Ridge	787	1193	1426	1278	46	4	2	0	52	8	8	99	0	1776
Shoulder	234	1187	1346	1241	31	2	2	0	21	6	3	60	0	557
Spur	623	1193	1387	1270	34	3	1	0	41	8	6	72	0	1362
Slope	1156	1185	1357	1249	32	3	1	1	36	7	4	54	0	2614
Hollow	453	1191	1324	1248	26	2	1	2	17	6	2	41	0	1020
Foot	628	1168	1288	1204	25	2	1	0	24	5	3	61	0	1417
Valley	701	1170	1300	1221	27	2	1	0	21	5	3	56	0	1586
Pit	0	0	0	0	0	0	0	0	0	0	0	0	0	0

precision in the output predicted geomorphon surfaces is a result of statistical or spatial chance or even endogenous error.

Indeed, the intelligible multi-scale format of the geomorphon approach may appear to wholly endogenize the otherwise complicated inputs of other pixel-based terrain models; however, MacMillan and Shary (2009) concluded that it would be near impossible and impractical for any terrain model using any fixed dimension of search radius to perfectly capture the variation of landform features of interests in any given area. With the geomorphon approach, this expectation is not without a valid reason. By users specifying an infinitely large search radius (L) and low flatness threshold (t) when trying to define geomorphons in the landscape, the vision-based model should, in theory, identify all possible landform elements within a particular landscape (Jasiewicz and Stepinski, 2013). However, shorter (L) values will attempt to register surface microfeatures while applying larger (L) values will result in smaller features lumped into other more common landforms with the apparent implication of false-positive morphon classifications. Incidentally, the monologue by (Levin, 1992) states that *"scale represents the window of perception, the filter or the measuring tool through which a landscape may be viewed or perceived"*. Unambiguously then, the most critical consideration for users of geomorphons (and their success after that) is that firstly the geomorphometric application and interpretation must still be governed by primary geomorphological factors such as the characterisation of either localised or regional landforms in the landscape (Pike, 2000). It's incumbent upon users to, therefore, invest adequate time in pre-planning and troubleshooting the optimal synergies between DEM quality and geomorphon parametrisation before their strategic and operational uptake in terrain or soil-landscape based studies.

Given the undulating terrain for this study site combined with the low frequency of "narrow" and "finer" resolution features such as flats, shoulders and summits (Fig. 3) it would not be surprising if many of these smaller features were grouped with the more extensive and more frequently occurring elements such as slopes and valleys and ridges in the 90 m DEM surfaces. In fact, (Luo and Liu, 2018) found that geomorphon maps created using different search radii converge yield no significant comparisons as the maximum search radius increased to a threshold of zero variance. In this study, a similar trend

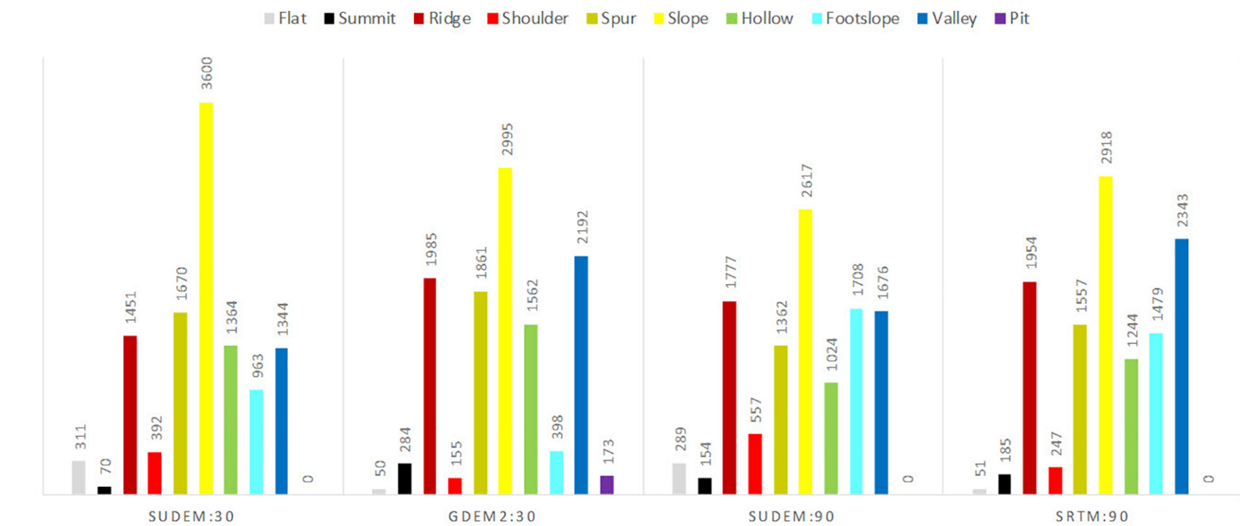

Fig. 3. Histogram of geomorphon frequency for the SUDEM 30, GDEM2 30, SUDEM 90 and SRTM 90 DEM with feature area (ha) indicated for each Geomorphon feature.

was observed between the 30 m and 90 m SUDEM surface products where, despite the difference in pixel resolution, the threshold values set in Table 1 resulted in similar features detected across the landscape albeit in different extent, abundance and detail (Fig. 3a–f). Evidently, selected findings from our study on this particular aspect were corroborated by (Libohova et al., 2016) who also reported little to no significant difference between geomorphon products with a different line of sight within the same pixel resolution. Consequently, the line of sight threshold(s) evaluated in this study would then be considered consistent and applicable for mapping most terrain features across that landscape across the observed DEM resolutions. Our findings gain further momentum, given the detailed comparison of automated landform detection by Gruber et al. (2015). Their study concluded that there was no significant difference between terrain features characterised at *meso* (50–100 m) and macro (250–400 m) extents when uniform *(L)* values were tested with the only important consideration that at a mesoscale level some terrain classes were not reliably detectable. While not much new evidence has been generated by this study at a global scale, what is encouraging is that our results are inline with reviews of a similar localised nature, specifically that of Libohova et al. (2016); Gruber et al. (2015) and Trentin and Robaina (2016).

Adjacent to the discussion on optimal pixel resolution Liang et al. (2004) observed impacts of different spatial resolutions on modelling surface runoff and concluded that the resolution could be improved only to a critical level after which no substantial improvements on

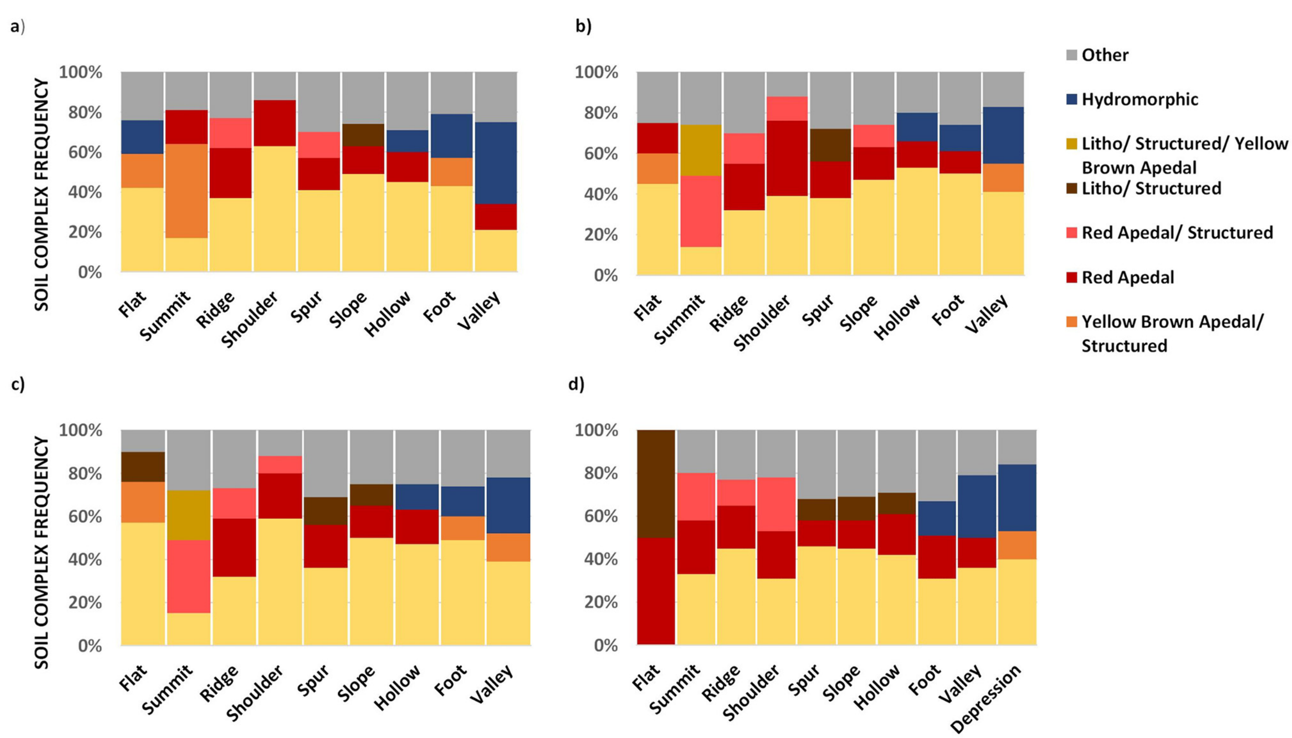

Fig. 4. Histogram showing percent soil complex cover and geomorphon frequency for a) 30 m SUDEM b) 90 m SUDEM c) 90 SRTM d) and 30 m ASTER GDEM2.

model performance will be observed. So, while grid resolution plays a vital role in the efficiency of the mapping geomorphons, its contribution can only be optimised to a certain level to satisfy both processing capabilities and representation of spatial variability. Further, regarding the parametrisation of geomorphons, specifically the choice and refinement of optimal *LOS* values, Silva et al. (2016a) were able to highlight that pixel size alone and not threshold *LOS* values had a more considerable influence on the Chi-squared values of geomorphon surfaces and soil type phenomena. (Hengl, 2006) corroborated this pixel-specific concept with similar findings suggesting that the choice of optimal pixel size may need to differ according to different target terrain variables investigated.

In fact, Gruber et al. (2015) explicitly outlined the need to adapt model thresholds or membership functions according to topographic detail of an area for better terrain differentiation. A key finding from their study encapsulates the dichotomy and complexity of terrain detail vs membership function vs pixel resolution considerations: their study found that in general, macro-scale terrain classification maps were able to replicate a larger number of topographic position classes (*quantitative*) whereas the meso-scale models contained fewer classes but were more similar (*qualitative*) to a reference surface.

3.2. Geomorphon area frequency distribution by DEM surface

The ability to quantify the overall similarity between different landscapes by merely evaluating the descriptive data of the associated and derived surfaces is a critical element of our methodology. Jasiewicz et al. (2014) recommend the use of a histogram as an option for rapidly assessing the terrain-pattern "primitive feature" signature because of its rotational invariance, i.e. two patterns rotated in respect to each other will be identical. Fig. 4 shows the histogram of geomorphon terrain features vs feature area for each of the DEM surfaces. Tables 3a–3d show the detailed results for the respective geomorphon surface products, including the summary statistics for elevation, slope and geomorphon area. Firstly, comparing the point-sample count for each geomorphon surface, interpreted here as a quasi-indicator for in-field sample survey frequency, it was observed that the dominant (count) and largest (area) terrain feature identified in all geomorphon surfaces were slope features. A key observation was that for selected geomorphon features, the areas derived from the coarser-resolution 90 m SUDEM and 90 m SRTM surfaces were consistently higher for the same Geomorphon features derived from the reference 30 m SUDEM surface. Furthermore, the results depict a higher intra-class similarity of geomorphon properties within, rather than between surface resolution, *vis a vie*, geomorphon feature properties derived from the 90 m SUDEM and 90 m SRTM DEM surfaces were more similar to the geomorphons derived from the reference surface (30 m SUDEM) than the 30 m ASTER GDEM2 surface.

These trends are evident in both the lower-lying terrain features such as foot slopes and valley bottoms as well as certain higher altitude features such as summits, ridges and shoulders. These results are surprising, considering that higher resolution DEMs have typically shown to be better suited for the detection of finer resolution terrain features (Cavazzi et al., 2013). Interestingly, similar results were observed in separate studies by Libohova et al. (2016) and Silva et al. (2016b). The work by Jasiewicz et al. (2014) provides the necessary context for the observed trends in this study relating these observations to the computational efficiency (or rather limitations) of the geomorphon approach to ternary pattern characterisation. While the final geomorphon model-output represents the ten most common and recognisable terrain features; there are more ternary elements and associated patterns that are calculated within a given feature space with as many as 500 geomorphon patterns identified in some studies (Jasiewicz and Stepinski, 2013). There is no ideal or utterly optimal classification approach to accomplish the decomposition of so many terrain morphologies into ten, unique classes. Similarly, there are multiple terrain features that may systematically be assigned to one of the archetypical ten unique geomorphon classes, and therefore the Type II error misclassification of cells can be expected. Moreover, it is possible to have multiple ternary elements and different ternary patterns that represent different instances of the same morphon class, i.e. slope; valley etc. within and between locations (Jasiewicz and Stepinski, 2013). The less constrained the rule-criteria are for the allocation of the ternary patterns to the morphon instances (combinations) and the more uniform the landscape is, the higher the frequency of features assigned to a typical class and higher the likelihood of Type II errors (false positives). In contrast, the accurate detection of specific (and less common when compared to slopes and valleys) landform features such as pits/depressions and summits/peaks require a single exact geomorphon to be allocated to the final 10 class classified map. So typically there are fewer instances or interpretations of these less-common ternary patterns before final classification, generally resulting in a far lower computational frequency of these features within the final 10-class geomorphon surfaces.

Analysing the histogram patterns (landscape signature) for each of the DEMs we observe that the reference SUDEM 30 m is the only geomorphon surface that is dominated by a slope-spur-ridge-hollow pattern. The remaining DEM surfaces all display similar patterns with minor variations. The SRTM 90 m: slope-valley-ridge-spur, SUDEM 90 m: slope-ridge-valley-footslope and the GDEM2 30 m: slope-valley-ridge-spur. Despite these sequential variations between the DEM surfaces, the histogram results imply that all geomorphon surfaces were still able to broadly define the "character" of the landscape as a composite of higher altitudes, i.e. ridges; spurs as well as lower lying features, i.e. valleys; foot slopes albeit in varying extent and frequency of occurrence. Surprisingly, despite being derived from the same 5 m DSM, the two SUDEM surfaces do not show as much geomorphon feature similarity as would have been expected. This is evident by the fact that almost 3500 ha of slope feature area was classified in the 30 m SUDEM surface in contrast to the 2500 ha in the 90 m SUDEM product reaffirming that the influence of pixel resolution and pixel generalisation on the detection and classification of certain features in the landscape must still be acknowledged in geomorphon surface analysis (Atkinson et al., 2017; Thompson et al., 2001). Astonishingly, the GDEM2 geomorphon surface results were more comparable to the SRTM 90 surface than the SUDEM 30 m surface. However, the GDEM2 histogram also revealed certain trends in the geomorphon surface that suggested the presence of inherent spurious anomalies in the DEM surface as previously observed with the BK similarity results. For instance, the GDEM2 was the only surface that had identified approximately 200 ha of pit features while only classifying 50 ha as flat areas and further classifying approximately 2200 ha of valley features in the study site. As a baseline visual approximation of the geomorphon surfaces, the histogram plot provides the basic synoptic overview to establish that the quality of the GDEM2 for this region may inherently be compromised for terrain-based assessments and feature extraction.

The slope gradient is more sensitive than elevation to local and global terrain variation (Atkinson et al., 2017). From the results in Table 3a–3d, we see that slope gradient values do show more variability than elevation between the four DEM surfaces. Importantly, the derived slope values for the three DEM surfaces were well aligned to widely accepted conceptualisations of slope values for the actual landscape features for the region (Smith, 2006). These findings are positive as they suggest the categorisation of the modelled geomorphic features by slope gradient remains consistent despite the difference in pixel resolution (grain size) of the DEM surface and choice of DEM sensor platform. The exception to this appears to manifest with a higher altitude, complex terrain features such as ridges, spurs and summits which consequently indicated higher slope SDs for the SUDEM 30 m, SUDEM 90 m and SRTM 90 DEMs respectively.

Notwithstanding, to further endorse the spurious findings of the GDEM2 elevation data, the higher than expected mean slope and SD values observed in selected GDEM2 geomorphons confirms the likelihood of contemporaneous DEM error present in the surface model. Notably, all GDEM2-identified flat features were reported to have a mean slope of 19% and a maximum slope of 29% at low altitudes (1173 m).

Likewise, typically steep terrain features such as spurs; slopes and ridges all displayed relatively small mean slope values of approximately 13% (1266 m) at higher altitudes (1266 m). These summary results for the GDEM2 presented in Table 3d are not indicative to the topographic patterns for the region which may present a challenge in defining the utility of the GDEM2 product for further geomorphon soilscape applications in KZN. Slope gradient and soil properties are strongly correlated (Gerrard, 1981) and Landscape configuration features can be readily defined by contemporary geomorphological and pedogenic processes. Topo-sequence properties further represent a composite of terrain characteristics, i.e., profile curvature, slope gradient and relative elevation that allow experts to develop a mental, albeit subjectively, the model of soil patterns in the landscape to synthesise complex soilscape relationships in-field "on-the-fly". It is therefore crucial that when calibrating the geomorphic/topo-sequence heterogeneity of derived models, that these generalised soil-landscape relationships correspond with well-defined, and widely accepted interpretive catenary delineations, aligned with knowledge-driven expressions of qualitative mental models of pedogenesis, whether explicit (soil properties) or implicit (soil classes), particularly for South African conditions (Van den Bergh et al., 2009). Understanding the contemporaneous erosional and hydrological succession of soil properties down the slope is necessary for guiding the description and segmentation of the geomorphon soilscape "fingerprint" for each DEM surface. Constraints on accurate surface representation using the GDEM2 naturally pose challenges to the credibility of any derived geomorphon to predict soil-landscape properties across the study site. These findings corroborate well with work by (Rexer and Hirt, 2014) who found similar results when conducting accuracy assessment studies of the GDEM2 and SRTM products in Australia. Their findings reported that the major drawback of ASTER for landscape analysis is that as an optical sensor, data collection may be impaired by cloud cover over certain areas leading to data anomalies such as voids (holes) or artefacts in the GDEM2. To evaluate the utility and scale-sensitivity of geomorphons for soil-landscape assessments the authors aimed to further assess how predicted geomorphon terrain features measured against specific qualitative descriptions for well-accepted soil-landscape relationships and terrain properties for the study region.

3.3. Geomorphon character assessment: generalised soil-landscape properties

The interaction between soils and topography and perhaps, more importantly, soil-landscape pattern-process relationships can be treated on several levels. For the purposes of this study, the results of the geomorphon contribution to the soil-landscape pattern-process interaction for the study region have therefore been limited to a "black-box" assessment approach whereby the whole system is regarded as a collection of sub-units with no consideration of the dynamics of the internal structure, i.e. no attempt has been made to account for the flux of materials and/or energy through the pedo-transfer system or the consideration of the balance between inputs or outputs directly relating to soil genesis in the landscape (Gerrard, 1981). Instead, similar to the work by (Strand, 2011) the results are intended to highlight how soil pattern-processes within geomorphons may contribute to the concept of landscape character assessment (Wascher, 2005), i.e. the distinct, recognisable and consistent pattern of elements in the landscape that differentiates one landscape from another (Swanwick, 2002). This approach attempts to emphasize the recognition of individual components that constitute the geomorphic landscape for the Bergville region. The soil properties for each geomorphon unit may then be used as a basis to establish a systematic approach to formal and parametrised soil-landscape mapping (Mücher et al., 2010) providing a rapid comparison of regions in terms of their landscape character (Galatowitsch et al., 2009). The generalised classification of soil properties into the geomorphon classes across the different DEM surface resolutions yielded exciting results for the selected soil covariates. These soil covariates were selected based on their comprehensive representation of the Tugela Basin soil survey and their ability to represent the basic soil-landscape characteristics of the region.

3.4. Geomorphons and soil complex

Each geomorphon surface was sampled using the terrain attributes intended to capture the maximum variation in generalised soil-landscape properties for the region. Histogram modifications were performed on the attribute maps to highlight essential features in each resulting geomorphon surface (Jasiewicz and Stepinski, 2012). The observed soil complex properties characterised in the geomorphon classes are presented in Fig. 4a–d. The results show the relationship between each DEM specific geomorphon feature and soil complex presented as percentages (cumulative) based on the frequency of extracted gridded soils points per landscape feature within the geomorphon surface(s). Table 4 provides an overview of the Tugela soil complex descriptions with reference to the major World Reference Base (WRB) Classification system (Tóth et al., 2008).

A high degree of variability was observed between the four DEM surfaces and the legacy soil complex distribution both in the percentage composition of soil complex and in the extent of occurrence for each geomorphon feature. The only two DEM datasets that showed overall generalised soil-geomorphon similarity were the two 90 m DEM surfaces. This result was, however, expected given the prior findings of the analysis, which showed that these two datasets were highly correlated on pixel resolution alone. Interestingly, the hollow, ridge and shoulder geomorphons for all modelled surfaces, including the ASTER GDEM2, were highly similar both in composition and extent of the specific soil complexes, *vis a vie*, hydromorphic and well-drained apedal soils respectively. Accurately, the hollow feature for all DEM surfaces represented the dominant soil complexes as 45–55% yellow-brown

Table 4
Soil complex descriptions used in this study correlated with WRB soil groups.

Soil complex	Soil set	WRB reference
Hydromorphic	Groundwater affected soils	Gleysols;
	Alternating wet-dry conditions, rich in swelling clays	Vertisols
	Accumulation of Fe under hydromorphic conditions	Plinthosols
Litho/structured/yellow brown apedal	Soils with clay enriched-subsoil	Alisols; Acrisols; Lixisols
	Relatively young soils or soils with little or no profile development	Arenosols; Cambisols
Litho/structured	Soils with limited rooting	Leptosols
	Soils with clay enriched-subsoil	Acrisols
	Relatively young soils or soils with little or no profile development	Cambisols
	Abrupt textural discontinuity	Planosols
	Structural textural discontinuity	Stagnosols
Red apedal/structured	Soils with clay enriched-subsoil	Luvisols; Lixisols
	Relatively young soils or soils with little or no profile development	Ferralsols, Arenosols; Cambisols
Red apedal	Relatively young soils or soils with little or no profile development	Ferralsols, Arenosols; Cambisols
Yellow Brown apedal/structured	Relatively young soils or soils with little or no profile development	Ferralsols, Arenosols; Cambisols
	Soils with clay enriched-subsoil	Alisols; Acrisols; Lixisols

apedal soils, 10–12% red apedal soils and 10–15% hydromorphic soils while the ridge features were consistently associated with 30–40% yellow-brown apedal, 20–25% red apedal and 10–15% red structured soils.

Notable findings from the analysis include the results for soil complex distribution per geomorphons for the 30 and 90 m SUDEM surfaces. The similarity in soil complex distribution between the 30 and 90 m resolution DEMs suggests that the soil-landscape characterisation, and the scale of actual and predicted topographic features present in the study site and were well represented by the *Line of sight* optimisation parameters used to model the geomorphons between the 30 or 90 m SUDEM. However, the 30 m SUDEM was able to better characterise the valley bottom features as being dominated by hydromorphic soils, as expected by the topo-sequence for the region, as well as yellow-brown apedal soils typical of lower, permanently and seasonally wet areas in the landscape. In contrast, while hydromorphic soils were at least represented by valley-bottom regions in both the 90 m SUDEM and SRTM geomorphon surfaces at 26 and 28% respectively, they were not identified as the dominant soil complex. Given the definitive and known hydrography of the study site, these valley-bottom features should undoubtedly be dominated by hydromorphic soils. A similar result was observed in several other geomorphon features where the SUDEM 30 m surface presented a more "analogous" soil-landscape pattern for the region, able to characterise the summit features as being dominated by yellow-brown and structured soil complexes while the flat areas of the study site were indicated to contain approximately 17% hydromorphic soils. Which, given the natural physiographic composition of the study site and the degree of seasonal saturation suggests that these soil-landscape associations are most probable.

To further analyse the degree of soil-geomorphon similarity, a Chi-square contingency test was used to explore any significant relationship between geomorphon features and the soil complex covariates under the different DEM surface models. The Chi-square test is an aspatial goodness of fit test used to assess whether or not the predicted distribution differs from the actual observed distribution H_o: *was defined as no association between Geomorphon features and soil complex and* H_1: *defined as the alternate hypothesis as significantly different at the 5% significance level.*

$$X^2 = \frac{\Sigma(o-e)^2}{e} \tag{1}$$

The given model is represented by Eq. (1) where $\underline{o}$ represents the observed area of each combination between geomorphon feature and soil complex while $\underline{e}$ denotes the expected area of each combination. The higher the calculated value (X^2) above the critical value (X^2 critical) as determined by a chi-square table, the closer the relationship between soil complexes characterised by geomorphons at different DEM resolutions (Silva et al., 2016b). The test was performed at a 95% confidence level, where $\alpha = 0.05$ and df = n-1. Where the predicted surface is not statistically different from the observed surface (30 m SUDEM), then the DEM datasets are assumed to represent the geomorphon/soil covariate pattern-process. The Chi-square test was used to compare the geomorphon surfaces association firstly between the SUDEM 30 m and SRTM 90 m DEMS, then the SUDEM 30 m and GDEM2 and finally the SUDEM 90 m and the SRTM 90 m for the soil complex. The results for the 2-way cross-tabulation are presented in (Table 5) showing the best Chi-square value (X^2) as well as the asymptotic significance for soil complex. The X^2 results for soil complex and geomorphon feature between the predicted and observed datasets show better than expected levels of association considering the marginal performance results from the BK geomorphon similarity analysis. Most of the distributions for the soil geomorphon and soil complex relationships failed to model the observed surfaces with the results found to be statistically significant in favour of H_a. However, there were selected geomorphon features that did show positive soil complex associations between the different DEM datasets with features such as summits, ridges, spurs, foot slopes and valley bottoms all showing some degree of similarity between the predicted and observed surfaces. Specifically, the soil complex/geomorphon association was most notable for the ridge and hollow features showing similarity across all DEM resolutions. These results hold promise for soil-landscape studies exploring the interoperability and utility of the SUDEM and open-source DEM datasets for multi-resolution soil-landscape applications.

Interestingly, the Chi-square results, including the 90 m datasets, show a definite pattern of similarity in soil complex and high altitude, narrow and higher slope gradient geomorphon features. Indeed, while higher resolution DEM surfaces are perhaps more suited to detecting subtle terrain discontinuities, the association presented here also relates to the unique arrangement of soil complex to a specific geomorphon. The more unique/specific the soil complex within the landscape and the smaller the area of the geomorphon then the higher the association of the geomorphic soil complex patterns. This is supported by the fact that flat features, with higher variability of well-drained apedal soil complex combinations, showed no association between the DEM surfaces while hollows, characteristically dominated by hydromorphic soils showed a better association between the DEM surfaces. Equally surprising is the predominance of geomorphon dissimilarity between the 90 m SUDEM and 90 m SRTM DEM datasets given that these two datasets have the same spatial resolution, and therefore would be expected to perform similarly when compared to the reference 30 m SUDEM. These findings, in conjunction with the positive X^2 results between the 30 and 90 m SUDEM selected geomorphons, suggest that the quality of the DEM, and not only the resolution, is a major contributing factor to geomorphon applications in soil-landscape analyses. Given these findings, there may be merit in further exploring the influence that finer spatial resolutions and quantitatively-based statistical DSM approaches (McBratney et al., 2011), as well as detailed soil form and even modal soil type data instead of broad, generalised soil complex representations, could have on geomorphon based soil-landscape associations, (Zerizghy et al., 2013). Our results were able to show that regardless of DEM scale and even inner search radius permutations all DEM surfaces, with the exceptions of the GDEM2, were able to depict the probable and expected soil complex, and thereby toposequence, within the landscape that best represented the synthesised interpretation of composite terrain characteristics for the study site.

3.5. Geomorphons and clay content

The results for clay content exhibit a general degree of uniformity across all DEM surfaces with most geomorphon features characterised by medium to high percentage clay textured soils. The clay content and geomorphon analyses have been presented as a histogram indicating frequency class and ordinal clay content category with this study adopting the same clay content class-breaks for analysis as (Van den Bergh et al., 2009) (Fig. 5a–d). A major shortcoming in using the clay content reported in the Tugela Basin study relates to how the clay content was estimated. Much of the soil texture (clay fraction) was estimated in-field and then "binned" into broad, predefined texture categories (Smith, 2006; Van der Eyk et al., 1969). Secondly, the soils in this region are typically highly weathered, dystrophic and characterised by higher than the average accumulation of clay minerals within 80 cm rooting depth. Furthermore, the dominance of secondary minerals such as Goethite (α-FeOOH) and Hematite (α -Fe2O3), giving rise to the prominent reddish-brown hue down the soil profile, has been shown to mislead the in-field estimation of clay content especially in highly weather and soils (Smith, 2006). These results suggest that the use of legacy categorical data (and associated analyses) for geomorphon characterisation and comparisons for soil-landscape analysis must explicitly consider the scale of measurement as well as the method of clay content analysis, i.e. categorical in-field estimations vs actual clay percentage obtained through wet chemistry approaches.

Table 5
Chi-squared (X^2) goodness of fit analysis of Geomorphon similarity by soil association distribution by comparing the 30 m SUDEM and 90 m SRTM, the 30 m SUDEM and 30 m GDEM2 and, the 90 m SUDEM and 90 m SRTM surface models.

Geomorphon	Flat			Summit			Ridge		
	Value	df	Asymp. Sig.	Value	df	Asymp. Sig.	Value	df	Asymp. Sig.
30 m SUDEM vs 90 m SRTM	38.934	4	0.001	122.848	5	0.001	0.794[a]	3	0.851
30 m SUDEM vs 30 m GDEM2	200	4	0.001	75.669	4	0.001	1.669[a]	3	0.644
90 m SUDEM vs 90 m SRTM	37.311	4	0.001	0,206[a]	3	0.977[a]	0.512[a]	3	0.916
Geomorphon	**Shoulder**			**Spur**			**Slope**		
	Value	df	Asymp. Sig.	Value	df	Asymp. Sig.	Value	df	Asymp. Sig.
30 m SUDEM vs 90 m SRTM	8.257	3	0.041	26.134	3	0.001	24.377	4	0.001
30 m SUDEM vs 30 m GDEM2	38.226	3	0.001	22.253	3	0.001	24.513	4	0.001
90 m SUDEM vs 90 m SRTM	9.295	3	0.260	0.622[a]	3	0.891[a]	21.145	4	0.001
Geomorphon	**Hollow**			**Footslope**			**Valley bottom**		
	Value	df	Asymp. Sig.	Value	df	Asymp. Sig.	Value	df	Asymp. Sig.
30 m SUDEM vs 90 m SRTM	0.416[a]	3	0.937	3.061	3	0.382	34.95[a]	4	0.001
30 m SUDEM vs 30 m GDEM2	21.574	4	0.001	39.56[a]	4	0.940	239.94[a]	3	0.001
90 m SUDEM vs 90 m SRTM	1.38[a]	3	0.710	22.047	4	0.001	0.802[a]	3	0.849

[a] Denotes geomorphon features where Ho is not rejected: terrain features are similar across observed DEM surfaces.

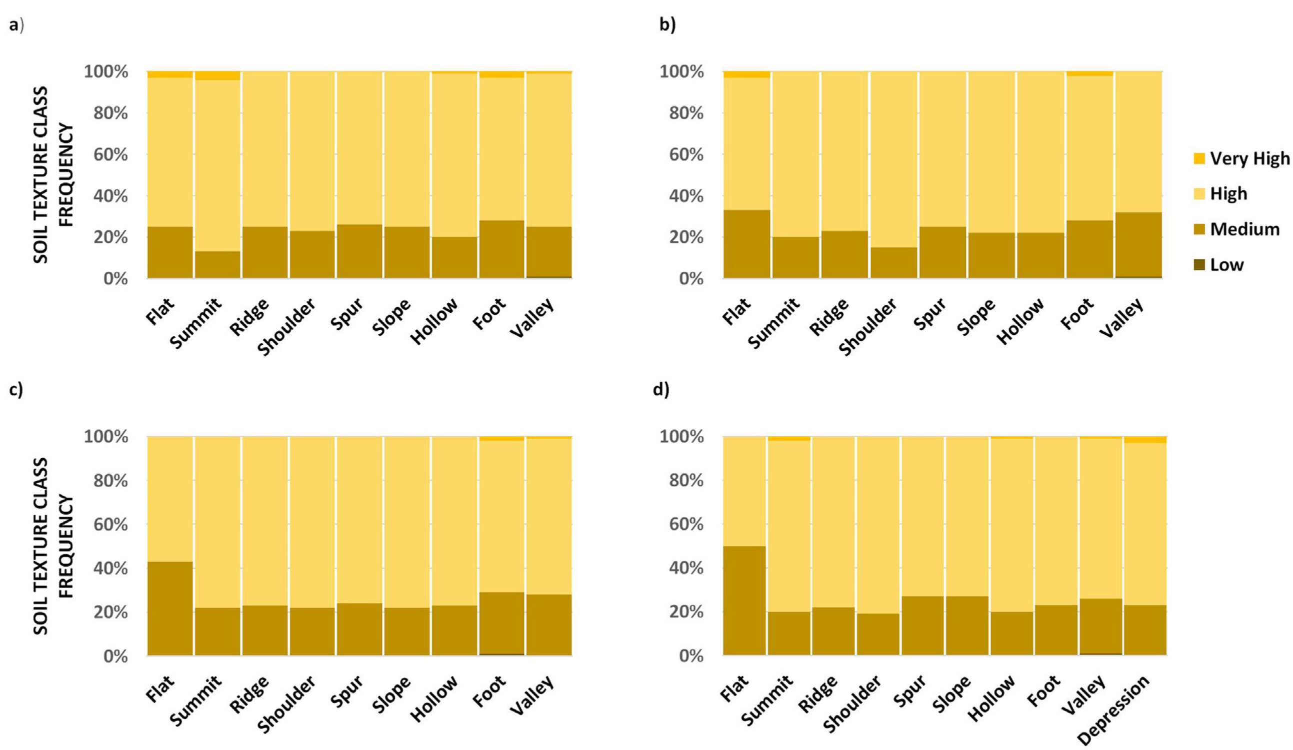

Fig. 5. Histogram showing frequency and pattern of clay content (clay %) for each geomorphon feature in the a) 30 m SUDEM b) 90 m SUDEM c) 90 m SRTM d) and 30 m ASTER GDEM2.

Despite the poor characterisation of clay content, the results were still able to detect a generalised catenary association/similarity for selected geomorphon features. Footslopes typically accepted to represented zones of colluvial material accumulation characterised by increased clay content were segmented by approximately 28% medium, 70% high and 3% very high clay content in the SUDEM 30 m, SUDEM 90 m and SRTM 90 m respectively. It seems likely that these results could prove to be useful to land use and natural resource planning functions for regional agronomic assessments still relying on the Tugela Basin data. Firstly, land planning practitioners can be assured that the choice of DEM source, and consequently, the resolution between 30 and 90 m, should not significantly influence the representation of clay content across geomorphic features. Secondly, considering that much of the Land Type survey data for this region was derived from the Tugela Basin study (Paterson et al., 2015), similar results could be expected when disaggregating the Land Type data by geomorphic features. Finally, the correct representation of medium to very high textured soils in lower altitude features such as foot slopes, valley bottom and flat features typically characterised by higher textured soils, assure that the relationship between the estimated clay content for the area and modelled geomorphic landscape features are aligned with knowledge-based conceptual models of soil-landscape patterns for the region. Despite the glaring radiometric deficiencies highlighted earlier in this study, the clay content results for the GDEM2 geomorphons were represented as being positively related to the other geomorphon DEM surfaces (Type II error). The endogenous error of the ASTER GDEM2 highlighted previously has shown that the GDEM2 is not suited to DGM for the region. However, these anomalies have not been detected in the clay content representation given the use of historical broad clay content categories despite the poor DEM surface.

3.6. Geomorphons and soil depth

Similar to clay content, diagnostic soil depth (max 120 cm) for the study region was represented as a histogram indicating geomorphon class and ordinal soil depth classified into broad categorical classes derived from the infield depth estimations (Van der Eyk et al., 1969). Geomorphon features were then characterised by the frequency of gridded sample points per depth class (Van den Bergh et al., 2009). Soil depth values were categorised as follows: 0–44 cm: *shallow*; 45–84 cm: *medium*; 85–120 cm: *deep* (Fig. 6a–d).

Despite the use of broad, functional categories to represent geomorphon soil depth character, unlike clay content and soil depth showed better variability between geomorphon features. The results for both 90 m DEM surfaces were almost identical in their representation of soil depth across similar geomorphon features within the study site and the relationship between soil depth and typically shallow-soil terrain features such as summits; ridges; and spurs were accurately represented within DEM surfaces. Interestingly, the 90 m DEM surfaces were able to represent the steeper, shallower terrain features better than even the SUDEM 30 m surface, with the latter showing more refined representations of the flatter, narrower and in-depth features such as the valley bottoms and hollows. Of particular interest, the summits modelled with the SUDEM 30 m were able to represent 7% of the area as deep soils, suggesting that the use of fine-resolution DEMs with coarse resolution soil covariate datasets such as the Tugela soil depth are still able to better represent selected soil-landscape relationships of narrow terrain features than their coarse 90 m counterparts. These soil depth results, when overlaid with soil texture, could be most beneficial to functional land use planning from an agronomic perspective. Superimposing the soil-covariate datasets with the geomorphon features may provide a better representation of soil-landscape composition and information. Moreover, regional adaptations must be incorporated into developed models to better represent soil variability and geometric signatures in the specific area of interest (Silva et al., 2016b). The results from this study have shown that, as a first approach, regional soil depth estimations can be successfully stratified by geomorphons into functional landscape unit's characteristic of typical soil-landscape relationships.

4. Conclusion

Much reliance has been placed on pattern recognition for terrain discontinuity segmentation, classification and mapping. It's further supposed that geomorphological maps that can better define soil-landscape relationship can be improved using the medium to high-resolution DEM datasets. Terrain classification by geomorphons has shown to be a practical approach to significantly enhance soil-landscape characterisation in the Drakensberg interior region. In this study, the use of high-resolution DEMs, GIS and open-source geomorphon approach has shown to be fast, feasible and user-friendly for landform classification in the highland region of the Central Drakensberg.

This paper provides an appealing outlook of geomorphon characterisation across varying DEM resolutions with the intention of highlighting how different DEM source and resolutions, influence the representation of soil-landscape pattern and processes phenomena. A significant part of this research involved the identification of the relationship between geomorphon terrain character and the similarities in derived terrain products across these scale-specific geomorphon surfaces. The study further tested the notional scale-independence property of the geomorphon approach for selected soil (soil complex, soil depth and soil texture) and terrain parameters (elevation, slope) with varying DEM resolution. What is promising for the representation of

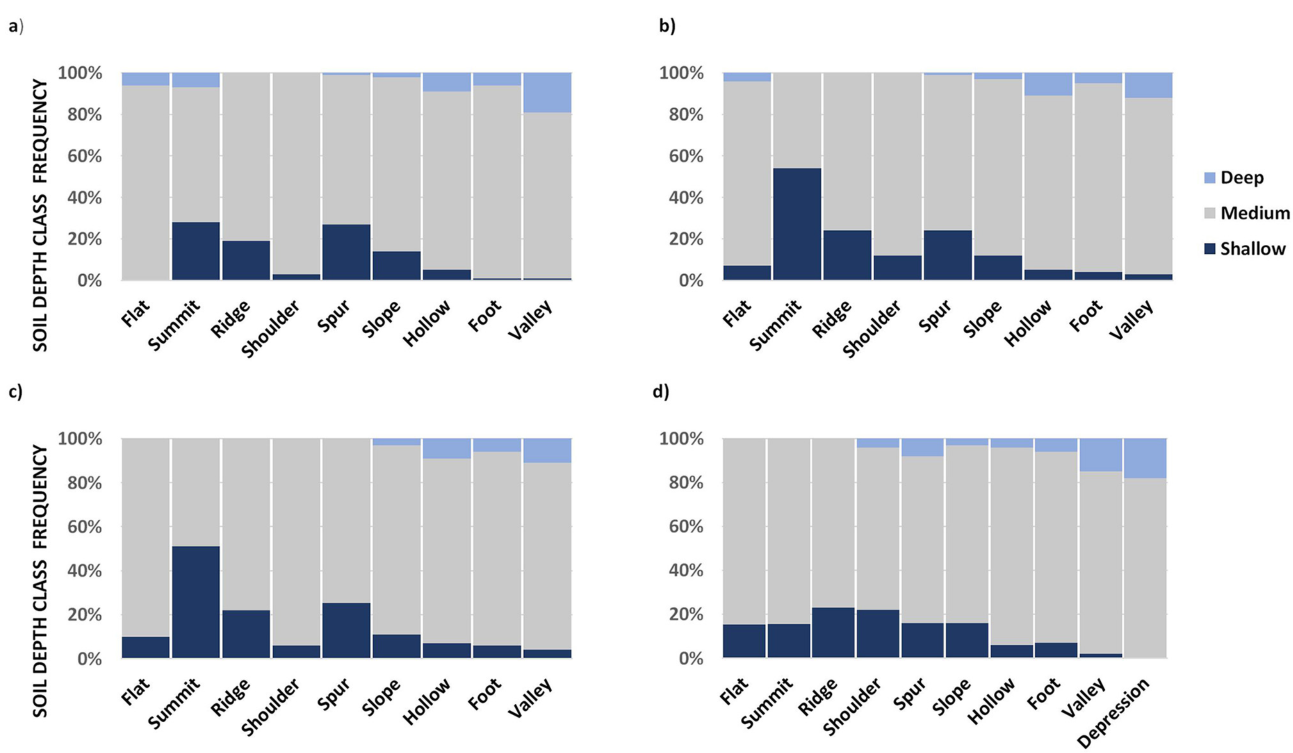

Fig. 6. Histogram showing frequency and pattern of soil depth for each geomorphon feature in the a) 30 m SUDEM b) 90 m SUDEM c) 90 m SRTM d) and 30 m ASTER GDEM2.

geomorphic features and to soil properties is that the presentation of the soil texture, soil depth and terrain classification of the Tugela Basin survey, were well aligned to the known catenary soil-landscape trends for the region with the exception of the ASTER GDEM2 surface products. Our study has reiterated that the quality of DEMs ultimately determines the accuracy and reliability of the spatial geomorphometric analysis. DGM practitioners should, therefore, be aware of the implication to land use planning when integrating elevation datasets of known inherent data deficiencies for soil-landscape and digital soil mapping analysis, especially under South African conditions. The SUDEM is perhaps the most accurate and readily available localised high-resolution DEM for South Africa, and the study has shown why it remains a popular choice for a variety of terrain analysis, digital-soil mapping and hydrological modelling applications.

A key finding of the study relates to the scale-utility- of geomorphons for soil-landscape applications with associations of soil complex, clay content and soil depth to geomorphon all suggesting that geomorphons may well have suitable application at a landscape and regional level rather than a local, farm level. The study has shown that while geomorphon features are detectable across most DEM surfaces of varying resolution, the accuracy of the geomorphon characterisation is not linearly correlated with pixel resolution, i.e. finer resolution DEMs do not necessarily produce "improved" geomorphon surfaces. Mainly because improved geomorphon representation may not translate into enhanced soil-landscape applications; instead, geomorphon surfaces should be applied and interpreted with the conditions of the area under observation and the objectives of the analyses in question.

Reflecting on the collective findings of the study, the authors are compelled to raise an indispensable question regarding the future utility of the geomorphon approach in similar regional environments: *is the Geomorphon approach truly as scale-independent as initially anticipated?* The answer is perhaps more polarised and less anecdotal than initially expected. The application of "machine vision" or "visual perception" to identify terrain-feature patterns, whilst immensely contemporary and efficient, should signal to users that DEM parametrisation inputs and landform relevant outputs can be infinitely more complicated to define and interpret by end-users with extreme subjectivity and variance in surface outputs both within and between DEM scale. For geomorphons to then be functionally relevant, it's necessary to reconcile the choice of optimal scale for simple static terrain visualisation versus the representation of spatial features and associated environmental phenomena or process across the landscape.

The presented results and discussion are based on the comparison of the modelled geomorphons surfaces, i.e. 30 m ASTER GDEM2, 90 m SUDEM and 90 m SRTM DEM to a reference 30 m DEM derived from high a resolution 5 m SUDEM, digital terrain model. Specifically, the main findings of the study are:

- The application of medium and coarse resolution DEMs for geomorphon feature discretisation holds promise for regional soilscape studies in South Africa, particularly in the central regions where open-source DEM datasets such as SUDEM and SRTM are still a primary source of quality terrain data.
- Modelled geomorphic features were able to represent altitudinal and slope gradient of terrain features characterised by higher altitudes, i.e. ridges, spurs as well as lower lying features, i.e. valleys, foot slopes albeit in varying extent and frequency of occurrence across all DEM surfaces.
- Broad-based assessment studies such as ours are necessary to qualitatively inform the generalised representation of soil pattern characterisation within topographic features, in this case, geomorphic features for a large-scale region.
- Geomorphon feature relevance for defining landscape structure and terrain spatial heterogeneity must be framed in the context of landscape or terrain detail, soil covariate membership, DEM pixel resolution and user preference.
- While the ASTER GDEM2 may be a suitable option for selective visualisation of a three-dimensional surface, it is not an appropriate option for the analysis of derived terrain attributes particularly in mountainous regions of the South African interior.

Information and methods discussed in this paper will be valuable for landscape and suitability studies, especially at the regional level. The ability to quantify the overall similarity between different landscapes by merely evaluating the descriptive data of the associated and derived geomorphon surfaces is a critical element of our methodology. Furthermore, the accurate representation of the contemporaneous soil and terrain properties within the study site provides a first approximation for guiding the description and segmentation of the geomorphon "fingerprint" for each DEM surface evaluated for this study. The ease of automation, swift replication and acceptable representation of an expanded set of morphometric classes using geomorphons have shown to be a suitable alternative to the basic 5-class Land Type discrete relief models for South Africa. These geomorphons coincide well with actual terrain geomorphological entities and present better opportunities for soil-landscape characterisation and topographic quantification with considerable potential for future digital geomorphological applications for the central regions of KwaZulu Natal.

Acknowledgements

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

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