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Automated Mapping of Drumlin Orientation using Object-oriented Approach

Dr. Kakoli Saha[1]
Dr. Mandy Munro-Stasiuk[2]
[1]Department of Planning, School of Planning & Architecture, Bhopal, M. P., India, 462 051
[2]Department of Geography, Kent State University, Ohio, USA, 44242

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Abstract

This paper proposes an automated method for mass scale mapping of drumlin orientation. The drumlins of the Chautauqua Drumlin Field in the upstate New York and Pennsylvania, USA are composed of three major sections: east sloping side, west sloping side and the flat- topped middle portion or MidRidges. Due to their central location, MidRidges reflect exact orientation of individual drumlins. The automated method has been developed using object-oriented classification available through eCognition software. The 30 m resolution National Elevation Dataset (NED) USGS Digital Elevation Model has been used as a source data.

Introduction

The concept of object-based analysis as an alternative to pixel-based analysis emerged as early as the 1970s (De Kok, 1999). The early models of object-based image classification are limited by hardware, software, poor resolution of images, and qualitative interpretation. Since the mid-1990s, hardware capabilities have increased dramatically. The availability of images from high spatial resolution satellite sensors, with increased spectral variability within map-sized objects, has increased the demand for object-oriented techniques (De Kok, 1999). Basically, there are two steps in such classification segmentation and classification. Segmentation involves partitioning the image into contiguous groups of pixels, called object primitive segments (or primitives). Ideally, these segments correspond to the real world objects of interest (Hofmann et al., 2000). Once these are identified in the image, the second step commences with the classification of these objects based on its spectral, texture, shape, and contextual features. Eventually, the use of successfully segmented images leads to improved classification with higher accuracy when compared to pixel-based classification methods (Aplin et al., 1999; Carleer et al., 2004; Janssen et al., 1995). eCognition Developer V.8.7.2, is an image-analysis program from Trimble Germany GmbH, Munich, Germany. It can combine spectral as well as spatial information for each image object, thereby allowing great flexibility in the relatively complicated process of automated extraction of landforms (eCognition Userguide, 2012).

In this particular research 'drumlins' have been chosen to build the technique because they represent a form that is repeated and can be recognized in the landscape, although they represent subtle changes in shape from location to location. Generally, drumlins can be described as subglacially streamlined hills, roughly ovoid in shape, that contain glacial debris or bedrock (Menzies, 1979).

This paper proposes mass scale mapping of drumlin orientation by automated extraction of Midridges. This method was developed using object-oriented analysis via eCognition Developer software package. The advantage of automated method over pixel based method is that object based method eliminates the "salt-and-pepper" effect by reducing the number of units. The proposed method also enables the user to extract morphometric information such as asymmetry, main direction, size for each bedform which are inaccessible even in pixel-by-pixel classifications. Drumlins of the study area (i.e., the Chautauqua drumlin field) are composed of three parts west-side slope, east-side slope, and the flat-topped middle-portion or MidRidge (Saha et al., 2011). Only MidRidges have been selected for automated extraction because of their central location which shows exact orientation of a drumlin. On the other hand, instead of extracting three parts, extracting MidRidges is quicker in terms of processing time as the study area is large.

Study Area

The Chautauqua Drumlin Field is located south of Lake Erie in Pennsylvania and New York State, USA (fig.1). It is approximately 110 km (NESW) by 23 km (NWSE) with an area of more than 2500 km^2. The majority of the drumlins occur on preexisting upland surfaces that range in elevation from 350 to 630m above sea level (Norton et al., 2007). This particular region has been chosen because the drumlins have a strong alignment in one direction which favoured developing the rule-set for automatic extraction easier.

Sources of Data

The data used in this study are the 30-m resolution National Elevation Dataset. '30-m resolution' refers to the area covered on the ground by a single grid cell in the DEM (Maune, 2007). The 30-m NED data are well suited to the size of the drumlins (300m 3000 m long and 138 m 810 m wide) in the Chautauqua drumlin field. In addition to DEMs, Digital Raster Graphics (DRGs) of the topographic maps are also used to generate a base map for comparison. These are obtained through http://data.geocomm.com/drg.

Automated Mapping of Landforms

Researchers have developed routines for automatic landform extraction and classification (for) of a variety of applications. For example, Barbanente et al. (1992) developed routines for automatic identification of ravines and cliffs. Several research groups (Gardner et al., 1990; Graff et al, 1993; Chorowicz et al. 1995) have developed methodologies to extract terrain features from Digital Terrain Models (DTM). Automated extraction became even more popular with the advent of eCognition software because it employs advanced strategies for knowledge representation. Object-based approaches provide finer levels of detail and fuzzy logic facilitates handling of uncertainties.

Automated extraction of information from DEMs using Object Based Image Analysis (OBIA) technique offered by eCognition is a growing field in the study of remote sensing. Dragut et al. (2012) introduced an object-based method to automatically classify topography from Shuttle Radar Topography Mission (SRTM) DEM data for the entire globe. By using the mean values of elevation and standard deviation of elevation they automated the optimization of scale parameter for extracting the image objects. These are then classified into landforms ranging from low mountains, high hills, table lands etc. Camargo et al. (2009) performed object-based semi-automatic geomorphological mapping for the municipality of Sa˜o Jose´ dos Campos at southeastern Brazil. They used Aster DEM to derive morphometric attributes such as slope, curvatures etc Saha et al. (2011) proposed an automated object-oriented approach to map landforms from digital elevation models (DEMs), using the example of drumlins in the Chautauqua drumlin field in NW Pennsylvania and upstate New York.

Object-oriented Analysis using eCognition

To have a holistic view of the drumlins of the area under study, first the traditional method was adopted using contour patterns on 1:24000 USGS topographical maps. But, it failed to serve the purpose because of the vastness of the study area. As a result, computer visualization was used for close observation of the drumlins. The elevation information recorded in DEM can be visualized using 3D technique such as relief shading that uses an idealized light source to illuminate the landscape at a user-specific azimuth and elevation (Onorati et al., 1992; Pike, 1992; Smith et al., 2005). Visualization of drumlins through relief-shaded DEM has been done by researchers like Clark and Meehan (2001), Smith and Clark (2005) and Smith et al. (2009). Relief shading has also been performed on 30 m DEM of Chautauqua Drumlin Field (fig.2A) and a close observation reveals the fact that each drumlin has three parts — east-facing slope, westfacing slope and the flat MidRidge (fig.2B).

Relief shading often causes problems of azimuth-biasing (Smith and Clark, 2005), where very slight changes in the azimuth of the light source can greatly affect the visibility of linear landforms, changing them from cryptic to plainly evident or vice versa (Lidmar-Bergström, 1991; Smith et al., 2009). (Hence)Thus, the drumlin parts are reinvestigated by calculating slope and aspect from DEM layer. The attributes of the parameters of elevation, slope and aspect are then merged into the RGB layer (Fig.3A). The Merged Image confirms the fact that drumlins of the study area have three parts. These are labeled as Side A (west-side slope), Side B (east-side slope), and the flat-topped Middle portion (MidRidge, Fig. 3B). These morphometric and morphologic information are then used to develop rule-set for automated extraction. The key to map drumlin orientation automatically is the ability to automate recognition of MidRidges.

Determining the Rule-set for Test Area

The MidRidges are easily identified due to the distinct changes in aspect values on either side of it (fig.3B). To accentuate this edge effect, a Sobel Edge Detection filter has been applied to the aspect layer. This produced a layer with very high pixel values where there is an edge between two objects (fig. 4A). MidRidges and the boundaries of "Side B" have exceptionally high pixel values and therefore stand out on the image. To extract the brighter portions as image objects, the image is segmented using eCognitions' Contrast Split segmentation algorithm, which divides the image into dark and bright regions. The brighter and darker image objects are then classified under 'bright' and 'dark' classes (fig.4B) and only bright classes are exported to the shape file, MidRidge.shp.

This MidRidge.shp (fig. 5A) file is used as a thematic layer for subsequent analysis, i.e., segmentation (fig.5B). MidRidge.shp has boundaries of Side B attached to the MidRidges. To extract the MidRidges, the boundaries of Side B needed to be eliminated. To do this a rule set is developed to extract all objects showing east and west facing slopes (fig.5C). After this, the MidRidge portions are extracted as separate objects using customized relational feature. In eCognition, relational features are used to compare a particular feature of one object to those of related objects of a specific class within a specified distance. Related objects are surrounding objects (neighbors), sub-objects, super-objects, sub-objects of a super-object or a complete image object level (eCognition Userguide, 2012). In this particular case the relational feature is customized to compare X-centered distance between MidRidges and boundaries of side B from Side B itself. The extracted image objects are then classified as the "DrumMid"which represents MidRidges of the Test Area (fig.5D).

Evaluating the Automated Results

The process of accuracy assessment started with building a reference data. Merged image, along with the DRG of the topographic map, is used to produce a reference map. This is done by simple on-screen digitization in eCognition of what qualitatively appears (qualitatively) to represent the drumlin MidRidges on the basis of contour alignment and distinct changes in both slope and aspect (fig. 6A). A total of 155 MidRidge polygons are then digitized and saved in vector format. In order to extract descriptive statistics for the manually mapped MidRidges, the vector layer is used to segment the "Merge Image". In this case, the segmentation process gives maximum weightage to shape for ensuring that the DEM is segmented into shapes that match the predefined MidRidges in the vector layer created by manual digitization. The segmented image (fig. 6B) and objects are then classified (fig. 6C). Morphometric parameters such as length and main direction data are collected and saved as a table of attributes (fig. 6D) for comparison with those derived from automated method.

For further assessment of accuracy, the automatically extracted MidRidges are overlaid on the (top of the) manually digitized MidRidges. Both visual and quantitative comparisons have been done. Fig. 7 shows that the automated method has been able to identify most of the digitized polygons. Statisics reveal that the proposed automated method successfully recognizes 78.71% of the total manually digitized drumlins. Visually it seems that there is a high agreement between these two methods (Table - 1).

eCognition often produces larger 'means' because it tends to include the underlying terrain and the modern gully walls as MidRidges of the drumlins. The significance of the differences between these two sets of result has been evaluated with the MannWhitney Rank-Sum test (Table - 2). The parameters mostly failed normality with respect to skewness, kurtosis, and KolmogorovSmirnov test. Results of the MannWhitney Rank-Sum test shows that parameters measured in the two different methods are statistically identical. The high agreement between these two methods shows the success of the automated method that eventually opened up the scope of application of this method over the entire Chautauqua Drumlin Field.

Determining the Rule-set for the Study Area

The contrast split segmentation which is applied in the Test Area cannot be applied in the Study Area because of its irregular shape (fig.1). As the segmentation program includes areas outside the drumlin field boundary ,(which) it prevents from getting the desired result. Due to this reason, the analysis is performed via the “Top Down” approach (fig.8), as follows—

(1) First Level of Segmentation and Classification: Level 3

First, the aspect edge layer is segmented by using the Multi-resolution segmentation which considers each pixel as a separate object (Marangoz et al., 2006). Subsequently, pairs of image objects are merged to form bigger segments. The merging decision is based on local homogeneity criteria (here, gray value is above zero). Thus the area outside the drumlin field boundary is excluded from analysis because the gradient value for aspect is considered to be zero. The segmentation process involves merging of the pixels having similar gray values above zero into smaller image objects (fig. 9A). The size of the image objects can be determined by setting the value for scale. Here, the scale parameter was set to 20 which produced smaller image objects. The image objects with gradient value for aspect higher than 300 are then classified under the class Temp_1. It contains all image objects with higher gray values including MidRidges, boundaries of the east facing slope of drumlins and boundaries of the steep valley walls, where change of aspect is abrupt (fig. 9B). To exclude the valley walls from MidRidges, membership function of main direction is used. From the relief-shaded image, it is observed that MidRidges are aligned from NNW — SSE direction. As a result, the threshold value is set between 120° and 180°. Resultant Temp_2 class contains only MidRidges and boundaries of east facing slope of drumlins (fig. 9C). The next step is to separate boundaries of east facing slope of drumlins from MidRidges.

(2) Second level of Segmentation and Classification: Level 2

To eliminate boundaries of the east facing slope, the aspect layer is added to the already existing gradient layer. Using aspect information, all the objects showing east and west facing slopes are then extracted and separated (fig. 10A). After that, the image objects having relational feature value between 550100 — 550350 are assigned to MidRidge1 class (fig.10B).

(3) Third Level of Segmentation and Classification: Level 1

Ideally, the resultant image (fig.10B) should be the final image showing drumlin MidRidges. Minute observation reveals the fact that some classified objects do not have satisfactory morphometric characteristics. Parameters such as elongation ratio (length/width) and width are used as filters to get rid of non-MidRidge image objects. Fig. 11 shows the final map representing automatically extracted MidRidges.

Accuracy Assessment

Preparing reference data for the area under study is critical considering the amount of MidRidges to be digitized. Even if it is done, it will nullify the main objective of this research which is already providing a better, quicker, more objective and repeatable alternative to fieldwork and manual digitization. As a result, a smaller part of the study such as, the Test Area (fig..1) was chosen for reference area. Manually digitized MidRidge polygons of this area are considered as the reference data.

Visual Comparison

MidRidges of the Study Area falling within the boundary of the Test Area are isolated by overlaying the reference data (fig.12). Thus we will compare the extracted MidRidges not only by two different methods but also at two different scale dimensions. Visual comparison shows that the automated method successfully recognized 80.6% of the total digitized MidRidges, making it better suited for larger areas / datasets.

Statistical Comparison

Two sets of morphometric information including 'main direction' and 'length' extracted in two different methods and spatial scales are statistically compared (Table 3). The mean values for parameters extracted in two different methods are different. To understand the significance of this difference Non-Parametric Mann-Whitney-Rank Sum test is performed (Table - 4). It shows that the automatically derived attributes of the parameters are statistically identical with those manually delineated.

Discussion

The above analysis has been performed in two steps. In the first step, a smaller Test Area was selected and the automated MidRidges extracted through eCognition were compared with manually digitized MidRidges. Both visual and statistical comparison revealed the fact that the automated results using eCognition were identical to results obtained by traditional “expert-judgement” methods. In the second step, the entire Chautauqua Drumlin Field was taken to test the validity of the automated method. With some modifications, the automated set of rules was applied over the area of study and the results confirmed the fact that the method was as successful for the larger Study Area as it was for the smaller Test Area. In fact, visual comparison shows an improvement of automated method in terms of extracting MidRidges when spatial scale becomes larger (fig.13).

Conclusion

The main objective of this paper is the automated mapping of drumlin orientation using object-oriented classification available in eCognition. Drumlins of the study area have distinct flat ridge in the middle, called MidRidges that reflect their exact orientation. Once orientation is mapped, the visualization of the overall drumlin distribution becomes easier. Thus, the proposed method makes efficient mass-scale extraction of drumlins quicker compared to field work or manual digitization. As drumlin orientation reflects the movement of past glaciers, it will also certainly help to reconstruct the glacial history of a particular region. Though the method is tested over drumlins only, it has the potential to be equally applied for all cases of oriented landforms/features with measurable morphology.

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Table – 1: Comparison of Morphometry for all MidRidges extracted Manually (N=155) and by eCognition (N=168)

Parameter	Tech-nique	Basic Statistics				Normality Statistic		
		Mean	Standard Deviation	Maxi-mum	Mini-mum	Kolm.-Smirnov	Skewness	Kurto-sis
Length (m)	Manual	674.19	331.67	1881.98	235.08	nn	nn	nn
	Auto-mated	693.05	300.24	2206.94	396.05	nn	nn	nn
Main Direction (degrees)	Manual	146.84	9.40	174.98	125.83	G	nn	nnn
	Auto-mated	153.81	11.82	178.85	111.74	nn	nn	nn
The tests for normality are the Kolmogorov-Smirnov test, and tests for non-normality in skewness and kurtosis. G = Gaussian (normal), nn = non-normal, and nnn = nearly non-normal.								

Source: Computed by the authors

Table - 2: Mann–Whitney Rank-Sum Test of Similarity in Means

Parameter	Z score for U score	P diff>0.90	MWW Decision
Length (m)	(-0.948)	0.343	Same
Main Direction (degrees)	(-5.870)	0.000	Same

Source: Computed by the authors

Table - 3: Comparison of Morphometry for all MidRidges extracted Manually (N=155) and Automatically by eCognition (N=176)

Parameter	Area	Basic Statistics				Normality		
		Mean	Standard Deviation	Maxi-mum	Mini-mum	Kolm.-Smirnov	Skew-ness	Kur-tosis
Length (m)	Reference	674.18	331.67	1881.98	235.08	nn	nn	nn
	Study Area	512.24	266.75	1731.81	164.11	nn	nn	nn
Main Direction (degrees)	Reference	146.84	9.40	174.98	125.83	G	nn	nnn
	Study Area	150.20	10.36	178.27	125.32	nn	nn	nn
The tests for normality are the Kolmogorov-Smirnov test, and tests for nonnormality in skewness and kurtosis. G = Gaussian (normal), nn = non-normal, and nnn = nearly non-normal.								

Source: Computed by the authors

Table – 4: Mann–Whitney Rank-Sum Test of Similarity in Means

Parameter	Z score for U score	P diff>0.90	MWW Decision
Length (m)	(-5.35)	0.000	Same
Main Direction (degrees)	(-3.01)	0.003	Same

Source: Computed by the authors

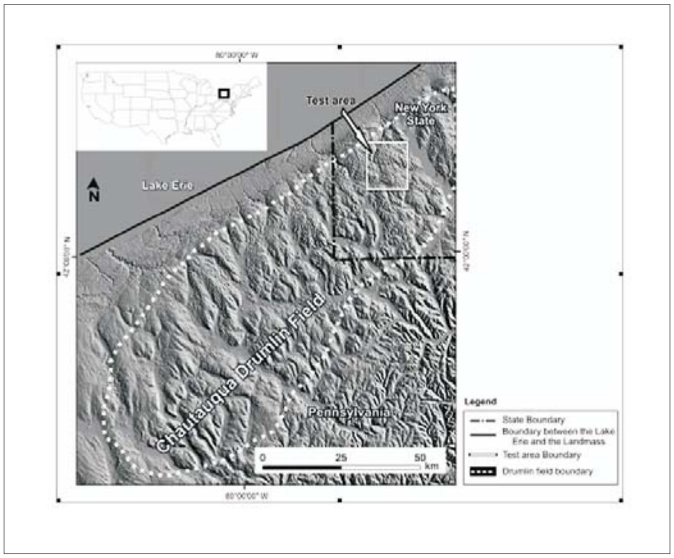

Fig.1: Relief-shaded image of the Study Area (including 'test area')

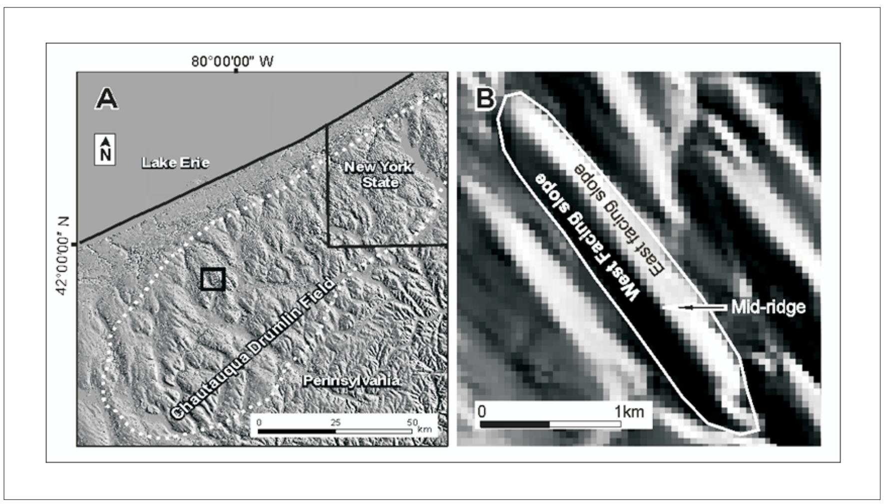

Fig. 2 (A) Relief-shaded Image of entire Chautauqua Drumlin Field
(B) Zoomed-in view showing three parts of a Drumlin

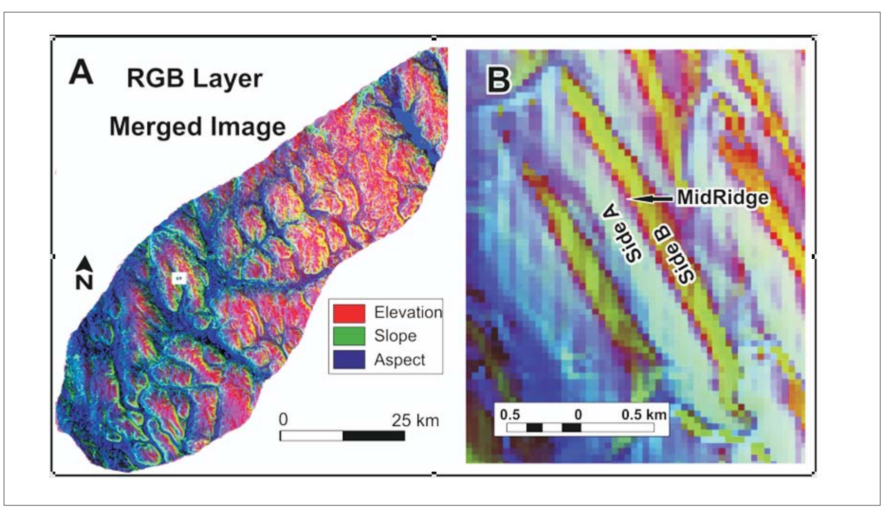

Fig. 3: (A) Layers of Elevation, Slope and Aspect visualized through RGB Channels respectively,
(B) Zoomed-in View of the Merged Image confirming three parts of a Drumlin

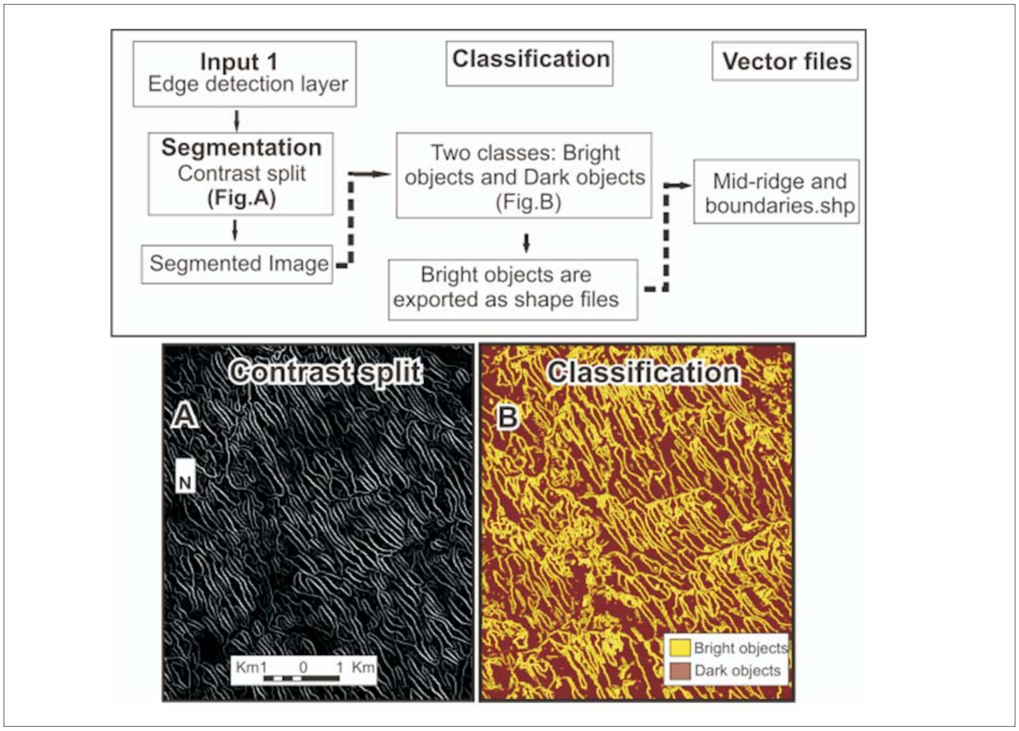

Fig.4. Flowchart and corresponding Images describing the extraction of MidRidges.shp

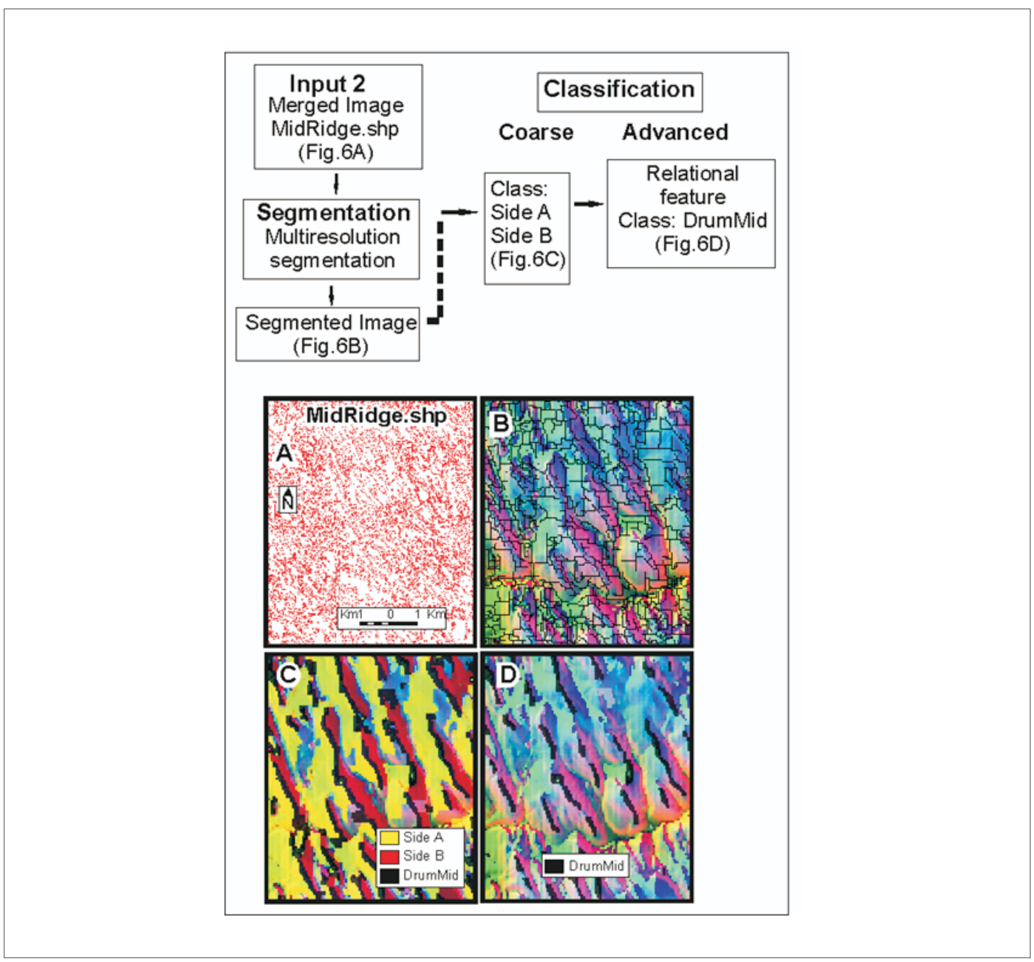

Fig. 5: Flowchart describing Separation of Drumlin Boundaries from MidRidges with Images showing Intermediate Outputs

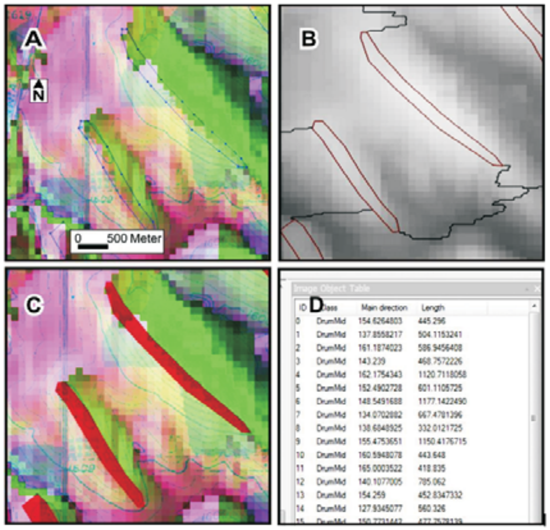

Fig. 6: Preparation of reference data:
(A) Merged Image placed on the top of DRG; drumlin polygons are digitized using contour alignment, elevation, slope, and aspect
(B) The digitized layer is used to segment the DEM
(C) The MidRidge image objects are classified under MidRidge class
(D) Morphological parameters are obtained for each MidRidge polygon

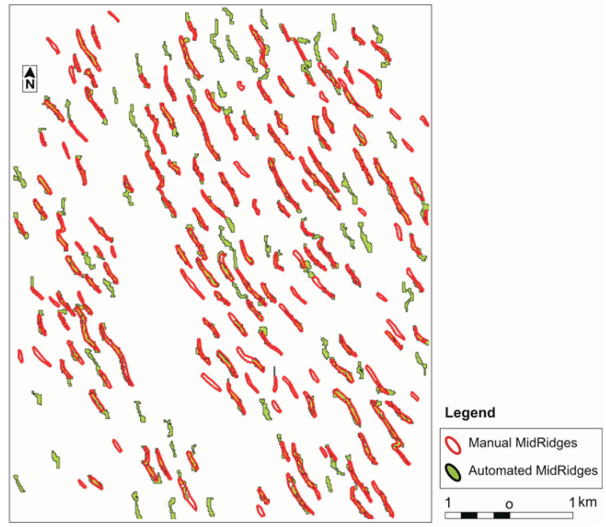

Fig. 7: Visual Comparison between Automated and Manually extracted MidRidges for the Test Area

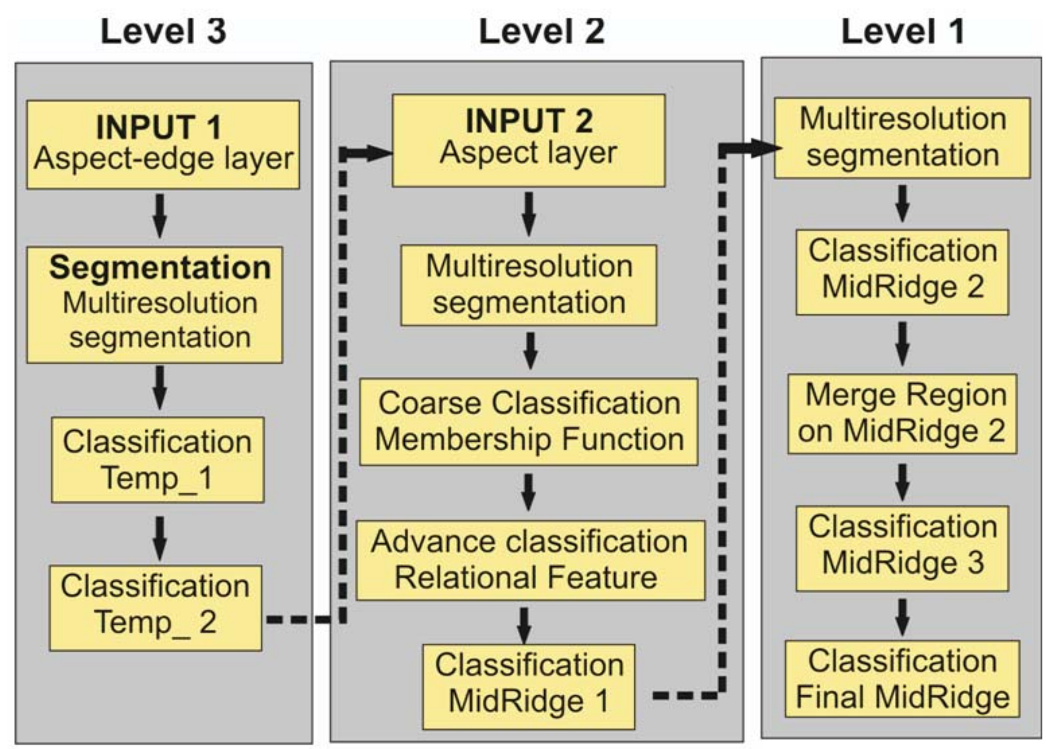

Fig. 8: Flowchart showing Methodology for extracting Drumlin MidRidges for the Study Area

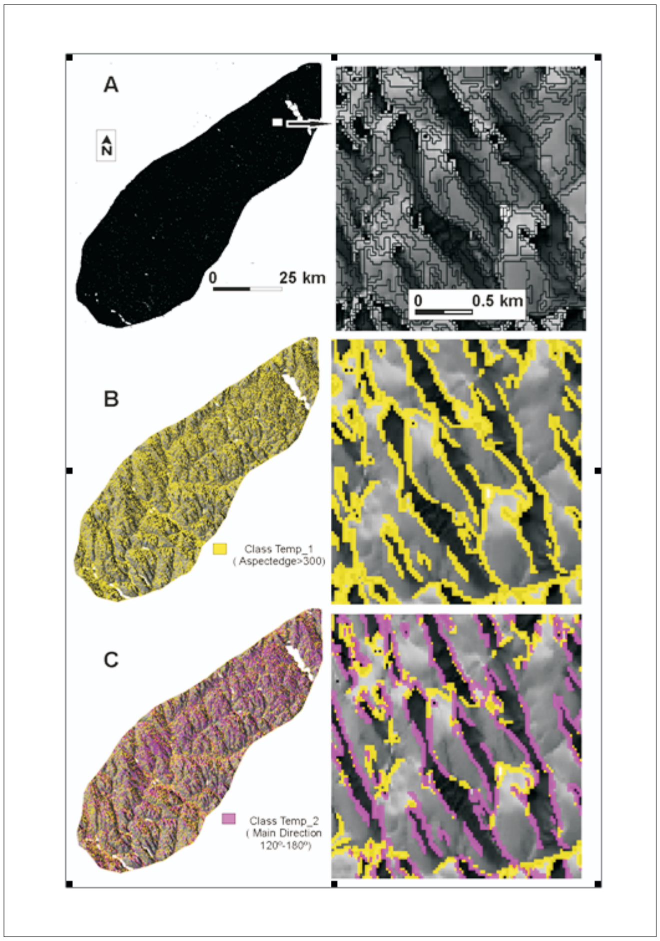

Fig. 9: (A) First Level of Analysis on the Chautauqua Drumlin Field and their corresponding Zoomed-in view

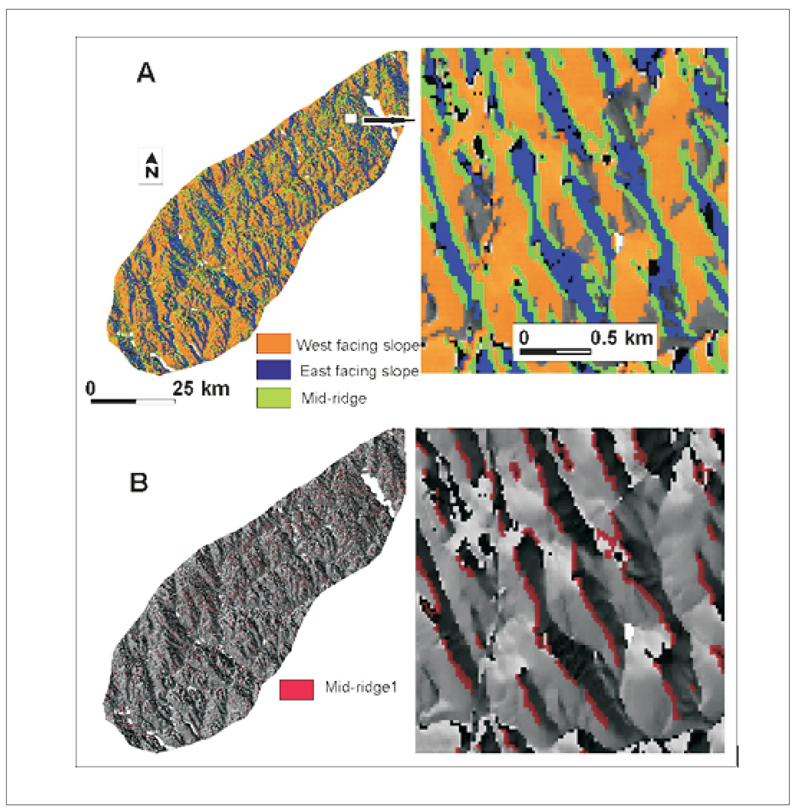

Fig.10: Second level of Analysis on the Chautauqua Drumlin Field and Zoomed-in view

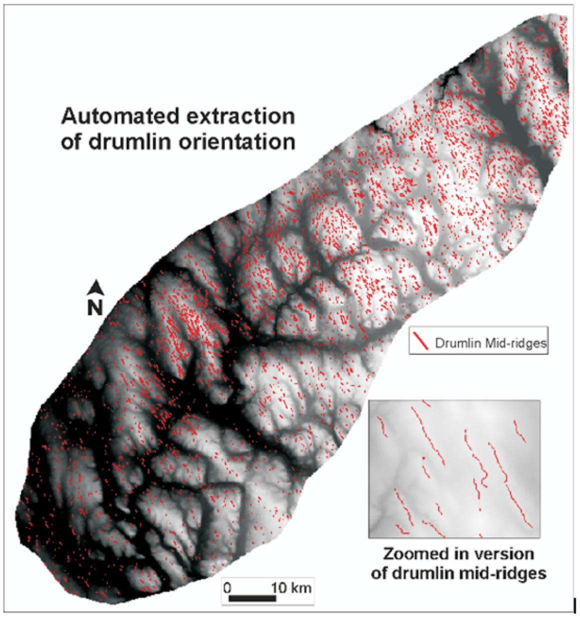

Fig. 11: Automated extraction of Drumlin Mid-ridges of the Chautauqua Drumlin Field

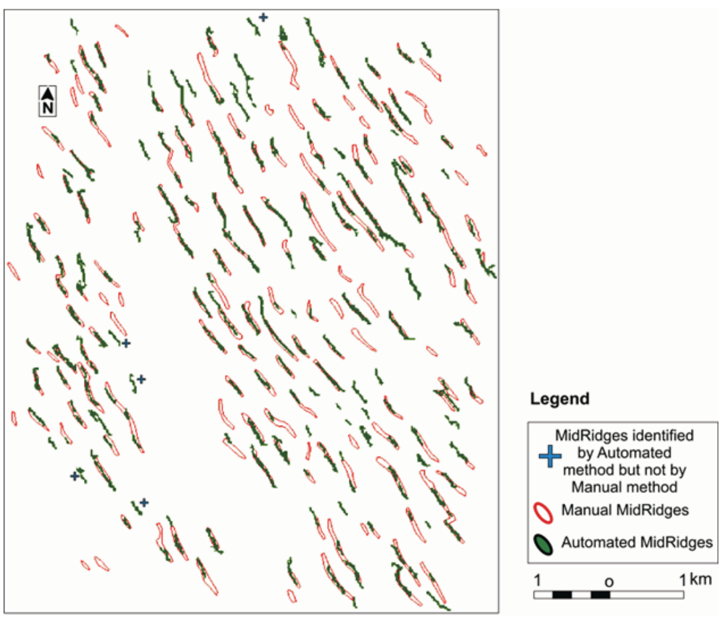

Fig. 12: A Visual Comparison between MidRidges extracted by two different Methods and at two different Scales

Dr. Kakoli Saha
Post Doctoral Research Fellow
School of Planning and Architecture, Bhopal
Madhya Pradesh, India
kakolisaha@spabhopal.ac.in

Dr. Mandy Munro-Stasiuk
Department of Geography,
Kent State University,
Kent, Ohio, USA, 44242
mmunrost@kent.edu