

An Object-Based Workflow to Extract Landforms at Multiple Scales From Two Distinct Data Types

S. d'Oleire-Oltmanns, C. Eisank, L. Drăgut, and T. Blaschke

Abstract—Landform mapping is more important than ever before, yet the automatic recognition of specific landforms remains difficult. Object-based image analysis (OBIA) steps out as one of the most promising techniques for tackling this issue. Using the OBIA approach, in this study, a multiscale mapping workflow is developed and applied to two different input data sets: aerial photographs and digital elevation models. Optical data are used for gully mapping on a very local scale, while terrain data are employed for drumlin mapping on a slightly broader scale. After a multiresolution segmentation, a knowledge-based classification approach was developed for the multiscale mapping of targeted landforms. To identify well-suited scale levels for data segmentation, the estimation-of-scale-parameter tool was applied. Contrast information and shape properties of segments were implemented for gully classification. Contextual and shape information was utilized for mapping drumlins. An accuracy assessment was performed by comparing classification results with independent reference data sets that were delineated manually from the input data. We achieved satisfactory agreements between mapped and reference landforms. Knowledge-based identification of segment features improves both accuracy and transferability of the classification system.

Index Terms—Drumlin, estimation of scale parameter (ESP), gully, landform classification, multiscale, object-based image analysis (OBIA), segmentation, unmanned aerial vehicle (UAV).

I. INTRODUCTION

DIGITAL landform mapping is the process of deriving landform information from digital data such as digital elevation models (DEMs), satellite images, and aerial photographs [1]. Due to the ever increasing spatial resolutions, too much detail may be represented in the data [2], which results in noise at the landform scale. Therefore, researchers began to think

Manuscript received November 28, 2012; revised March 5, 2013; accepted March 6, 2013. This work was supported in part by the research project “AGASouss—Assessment of gully erosion in agro-industrial landscapes of the Souss Basin (Morocco),” granted by the German Research Foundation (DFG) under Research Contracts MA 2549/3 and Ri 835/5 and in part by the Austrian Science Fund (FWF) through the Doctoral College GIScience under Grant DK W 1237-N23 and through the project “KnowLand—Knowledge and Semantics in Landform Classification” under Grant P23818-N23.

S. d'Oleire-Oltmanns is with the Remote Sensing and GIS Working Group, Goethe University Frankfurt am Main, 60438 Frankfurt am Main, Germany, and also with the Doctoral College GIScience, University of Salzburg, 5020 Salzburg, Austria (e-mail: doleire@em.uni-frankfurt.de).

C. Eisank is with the Department of Geoinformatics (Z_GIS) and the Doctoral College GIScience, University of Salzburg, 5020 Salzburg, Austria (e-mail: clemens.eisank@sbg.ac.at).

L. Drăgut is with the Department of Geography, West University of Timisoara, 300223 Timisoara, Romania (e-mail: lucian.dragut@cbg.uvt.ro).

T. Blaschke is with the Department of Geoinformatics (Z_GIS), University of Salzburg, 5020 Salzburg, Austria (e-mail: thomas.blaschke@sbg.ac.at).

Color versions of one or more of the figures in this paper are available online at <http://ieeexplore.ieee.org>.

Digital Object Identifier 10.1109/LGRS.2013.2254465

about redefining the basic spatial unit for landform modeling from cells to segments (or objects), particularly for DEM-based studies [3]–[5].

Assuming that landforms can be associated with segments as collections of adjacent cells with similar values, object-based image analysis (OBIA) becomes a valuable approach to their mapping [6]. Generally, OBIA involves two steps: segmentation and classification. A widely used algorithm for deriving homogeneous segments from input scenes is multiresolution segmentation (MRS) [7], [8]. The resulting segments present more realistic processing units than cells and can be created in a multiscale structure. Once the segments are delineated, classification rules are applied to map each segment to the landform concept to which it comes closest [5], [9].

In OBIA, knowledge-based landform classifications have been employed on DEMs [10], satellite images [11], and combinations of the two [1]. Recently, Kim *et al.* [12] have utilized OBIA for mapping vegetation, channels, and bare mud from very high spatial resolution images.

One main issue in OBIA is to transfer the implicit knowledge of an expert into machine-understandable classification rules [2]. This also applies to landform mapping as a particular case of OBIA. Due to a lack of comprehensive knowledge models, the current strategies (e.g., those in [10] and [11]) for defining the landform classification rules are still quite subjective and mainly based on trial and error. Thus, the classification process is time consuming, and the rules are tailored to the underlying data.

This letter presents a methodology that allows for a more objective and faster mapping of landforms with OBIA. The methodology combines a statistical procedure to make multiscale segmentation self-adaptive to the input data and a knowledge-based selection of the most transferable properties to be used in the classification. The method is applied to two distinct cases: mapping gullies from aerial photographs and drumlins from DEMs.

II. METHODOLOGY

The general approach for mapping gullies and drumlins comprises three steps: 1) statistical optimization of MRS; 2) knowledge-based classification; and 3) accuracy assessment.

First, MRS was applied in order to partition the input scenes into segments that could be directly related to targeted landforms in terms of size and shape. Due to size variations of the target landforms, one cannot expect their accurate delineation as single objects at only one segmentation scale. Therefore, multiple segmentation levels were generated for a specific

scene with the estimation-of-scale-parameter (ESP) tool [13]. The resulting local variance graphs indicated the statistically significant scales for MRS. Once segmentation was optimized, knowledge-based rules were employed to classify the resulting segments into targeted landforms. The classification results were quantitatively compared with independent reference data.

The two case studies for mapping drumlins from DEMs and gullies from aerial photographs are described in detail in the following sections.

A. Drumlins

The central part of the “Eberfinger Drumlinfield,” situated in Bavaria, Germany, was chosen as the test area for automated drumlin delimitation. The selected site is 5.2×7.8 km in size and contains 114 drumlins. The interplay of erosion and accumulation processes during the Last Glacial Maximum led to the formation of the drumlin field [14]. Ideally, a drumlin exhibits elliptical shape in planar view and Gaussian shape in profile view [15]. However, due to postglacial overprinting, some drumlins show significant deviations from the ideal form.

DEMs have been reported to be the most valuable database for the digital mapping of drumlins [16]. Ideally, the spatial resolution of the DEM should be at least 10 m or finer [17]. For the present study, a LiDAR-derived DEM at a spatial resolution of 5 m was utilized. The LiDAR data were acquired with a mean point density of $1.29/\text{m}^2$ during flight campaigns between November 2009 and April 2010. To produce the gridded 5-m DEM, the elevations of the true ground points were interpolated by using a method that adapts to terrain type, as implemented in the software SCOP++.

To select well-suited input layers for segmentation, we checked the literature for terrain layers that have successfully been used in manual approaches [18], [19]. One of the few reported options was a normalized relative elevation layer that was calculated from a procedure known as “residual relief separation” [20]. Residual relief separation involves several DEM filtering steps to increase local contrasts in elevation and thus emphasizes drumlin topographies. Values range from zero to one, whereby higher values indicate high local elevation differences, which can be associated with drumlins. More details are provided in [20].

Application of the ESP tool to the relative elevation layer yielded four significant segmentation levels at scales 6, 9, 12, and 15. These levels provided the basic segments for the subsequent knowledge-based classification of drumlins. Therefore, qualitative descriptions and definitions of the term “drumlin” were transferred into machine-understandable rules. For instance, drumlins were described as “multiconvex units that have an elliptic and elongated planar shape” [15]. These properties were modeled in an OBIA environment by positive values in “mean curvature” of segments, as well as by high segment values of “elliptic fit” and “elongation.” In addition, a contextual feature, ensuring that the drumlin segment was higher than its neighbor segments, was implemented. The same class system was then employed to each of the four detected segmentation levels of the relative elevation layer. The four individual classifications were merged at the finest level to

produce the final map of drumlins. Since the classified segments systematically underestimated the size of the actual drumlins, a resizing operation was performed. Grid cells that were adjacent to a segment classified as drumlin and with a slope value above 6° were added to the respective segment.

B. Gullies

Aerial photographs were used as input data. The acquisition of the aerial photographs (RGB color) has been taking place annually during several field campaigns in the Souss Basin, Morocco, since autumn 2010 [21].

The image mosaic was generated from data acquired in autumn 2010. For data acquisition, a calibrated digital system camera was utilized. Aerotriangulation using bundle block adjustment of these annually acquired very high resolution aerial photographs (i.e., around $0.03 \text{ m} \times 0.03 \text{ m}$) delivers image block bonds which are used for creating image mosaics as well as for extracting precise DEMs as described in [22].

The image mosaic is 220 m long and 170 m wide, resulting in coverage of 3.74 ha. It contains two ephemeral gullies which are located next to a settlement area. Details on the study area in Morocco as well as further technical details are given in [21].

The delineation of gullies is challenging due to their heterogeneous morphologic characteristics [23]. Hence, the high level of detail present within the aerial photographs is considered to be valuable and necessary for an OBIA approach to gully mapping.

Two main scale levels, 500 and 100, were identified after the image mosaic was analyzed with the ESP tool. Initially, the larger scale parameter was applied to the mosaic to follow the principles of a top-down approach. Parameter values for the MRS were set to 0.1 for shape and 0.5 for compactness. These settings prioritize color over shape.

For the knowledge-based classification, a rule set was developed using features which were—in the ideal case—independent from the location of the input data. The main features used for a coarse classification at level 500 were “border contrast” and “edge contrast of neighbor pixels.” Both features were combined to a *contrast feature* (CF). The CF builds the sum of the squared value of “edge contrast of neighbor pixels” and the square root of “border contrast” and is denoted as

$$CF = \sqrt{\text{border contrast} + (\text{edge contrast of neighbor pixels})^2}$$

This index supports separation between plane areas and gullies by high differences in CF values. The coarse classification was then segmented with a lower scale value of 100. In addition to CF, “segment size” and “roundness” were chosen to refine the gully classification at this more detailed level. The final gully map was generated by intersecting the coarse and detailed gully classifications.

C. Accuracy Assessment

For both input data sets, independent reference data sets were created. Outlines of the drumlins were delineated manually on a

shaded relief layer that combined four different directions [19], thus providing the digital reference map.

The extents of gullies were digitized based on a slope layer and the image mosaic. The slope layer was computed from a photogrammetrically derived DSM.

For both case studies, gullies and drumlins, the accuracy assessment was based on the following three measures:

- 1) *user's accuracy (UA)*, the percentage of correctly classified area from the total classified area;
- 2) *producer's accuracy (PA)*, the percentage of correctly classified area from the total reference;
- 3) *detection rate*, the percentage of reference data that have been detected by the classification (also including partial detection).

III. RESULTS

The two landform mapping efforts showed acceptable results. However, the ideal case where landforms correspond to single segments was hard to achieve, particularly in cases where landform boundaries were obscured in the data (e.g., by vegetation).

A. Drumlins

Segmentation levels at the four ESP-detected scales included terrain segments with varying degrees of homogeneity in relative elevation. As the scale increased, more heterogeneity in relative elevation was added to the segments. Thus, terrain segments at the scale of 15 were far larger than segments at scale 6. When aiming at delineating target features as individual segments, this is an important property, particularly when target landforms are largely variable in size, as it is the case for the observed drumlins in our test area. A visual check proved that, at each scale, a group of similar-sized drumlins was approximated by individual segments. Those segments could therefore also be addressed by shape features such as “elongation” and “elliptic fit” in the classification. At each of the four levels, different drumlins—depending on their size—were classified. The merged drumlin classification map is displayed in Fig. 1. As illustrated by the three color-coded insets, the spatial extents of individual segments and reference drumlins matched well (green) in several cases. However, there were also some cases where the classified drumlin segments either overrepresented (red) or underrepresented (yellow) the extents of reference drumlins.

B. Gullies

Results are illustrated in Fig. 2. The left image illustrates the classification results (pink polygons) as well as the reference polygon data (black outlines) with the image mosaic as a base layer. The three color-coded insets on the right present some examples of good matches, as well as over- and underestimations. Most parts of the two main gully systems were classified. Furthermore, numerous lateral rills were mapped. The green inset shows a good match between classified gully segments and the reference polygon data. In the figure, the

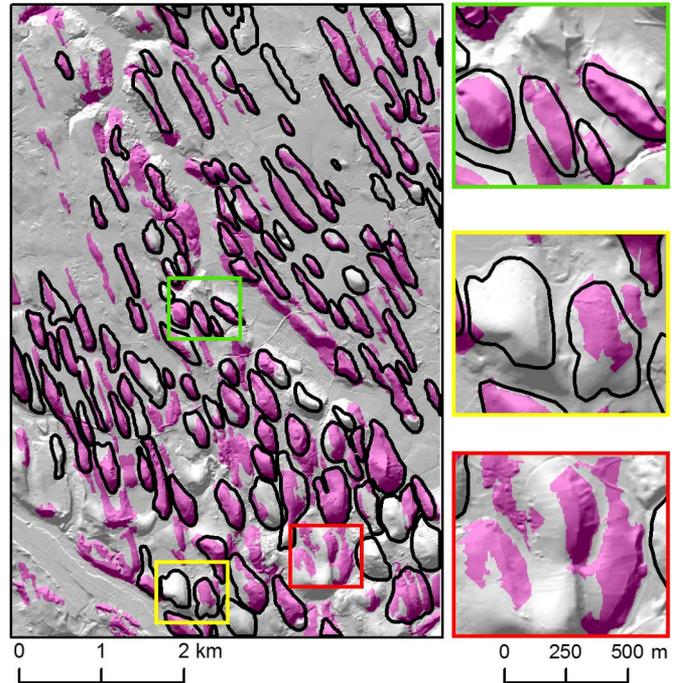


Fig. 1. Classification results for (pink polygons) drumlins and (black outlines) the reference drumlin polygons are illustrated. A shaded relief layer is displayed in the background. Three color-coded insets show examples of (green) good matches between classification and reference, (yellow) underestimations of reference, and (red) overestimations of reference.

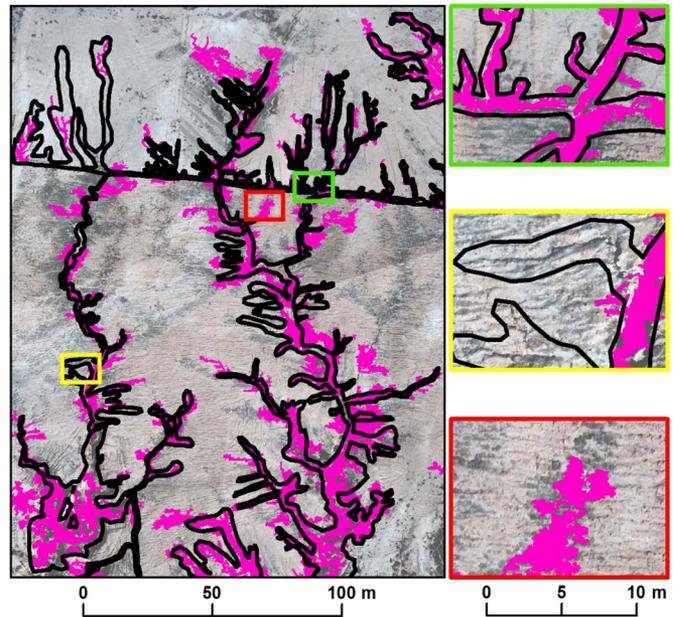


Fig. 2. Classification results for (pink polygons) gullies and (black) the reference polygon data are illustrated. The image mosaic is displayed in the background. Three color-coded insets show (green) a good match between classification and reference, (yellow) underestimation of reference, and (red) overestimation of reference.

yellow inset illustrates a case of underrepresentation of gully classification, and finally, the red inset depicts an example where the classification overestimated the reference polygon data. Visual comparison of segments at the two chosen scale levels confirmed that, on the lower scale level, the gully shape

TABLE I
ACCURACY VALUES OF BOTH MAPPING APPROACHES

Accuracy measure	Calculation	Drumlins [%]	Gullies [%]
User's accuracy	(Overlap area / classified area) * 100	58.33	57.08
Producer's accuracy	(Overlap area / reference) * 100	61.14	38.94
Detection rate	Amount of classified reference / Total reference	87.72	67.15

was delineated more precisely observe the surrounding plane surfaces.

C. Accuracy Assessment

The values of classification accuracies are given in Table I. For each mapping approach, the UA, PA, and detection rate were calculated.

A quantitative comparison to the reference map showed that, from the 114 reference drumlins, 100 were at least partially extracted by the multiscale OBIA classification, resulting in a detection rate of 87.7%. PA for the drumlin classification was calculated with 61.1%. UA issued a value of 58.3%.

Comparing the gully mapping results with the reference data set, UA amounted to 57.1%. PA reached 38.9%. The overall detection rate resulted in a value of 67.2%.

IV. DISCUSSION

Digital landform mapping can be conducted on different data. Optical data such as satellite images and aerial photographs often contain varying (spectral) values for different scenes due to differences in the lighting situation and, therefore, larger or smaller differences in contrasts. DEMs are less affected by such variations and are thus more comparable across scenes (at least for similar spatial resolutions). This may be helpful for developing a solution to the existing demand for reproducible digital mapping approaches to establish standards that subsequently support the progress of geomorphological mapping [24]. Therefore, a main goal in landform classification using OBIA is to transfer and optimize the objectlike perception of human recognition into segmentation algorithms and further into classification rules.

In terms of segmentation, this means to produce single segments within the limits of physical landforms, a procedure that is known as "landform delimitation" [25]. This is relatively difficult to achieve when using the MRS algorithm. In the case of drumlins, despite the knowledge-based selection of an optimal segmentation layer, i.e., relative elevation, the MRS results demonstrate the difficulty in detecting the exact limits of drumlins. Only sometimes, segments approximate reference drumlins quite well. Also, the rather complex shape of gullies is only partially matched by single segments, whereas a group of smaller segments better fits the shape of gullies. The ESP tool supports the detection of the statistically most significant segmentation scales for the underlying data. This does not

imply that the resulting segments correspond to the size and shape of the actual landforms. Only recently, a supervised approach for optimizing MRS has been proposed which determines the best fitting terrain segments for selected reference geomorphological units based on the similarity of frequency distributions [26].

In terms of landform classification, distinct operational definitions that mainly include absolute statements, i.e., statements that can consistently be applied in practice, are required in order to increase the quality of the resulting maps [25]. In particular, statements about the shape and spatial context (neighbor and hierarchical relations) seem to be better suited, rather than spectral or morphometric information [9]. Shape and context features were thus the first choice for developing our knowledge-based landform classification routines in OBIA. Regardless of the underlying data type, namely, aerial photographs or DEMs, we reached reasonable accuracies for the resulting landform maps.

The achieved accuracy values indicate that the two different data types are not equally suited for landform mapping. UA and PA of the drumlin map indicate that a similar amount of over- and underestimations was generated by the knowledge-based classification system. However, 87.72% of drumlins have been at least partially detected by the classification. This is a similar percentage as obtained in [27] in their study on drumlin mapping with OBIA. In contrast to our unsupervised method, the approach in [27] is rather manual, as statistics on reference drumlins were manually analyzed to find the optimal features and thresholds for informing the class system. Thus, we consider our approach to be much faster and more transferable. For gullies, the resulting value of UA of 57.08% is similar to the resulting UA of 67% for channels in [12]. This indicates also the amount of overestimation. The value obtained for the PA is 38.94%. The detection rate is at 67.15%. The existing imbalance of over- and underestimations may be explained by two points: On the one hand, numerous anthropogenic rills appeared in addition to the gullies within the chosen study area which makes a complete differentiation of these two types of incisions almost impossible, and on the other hand, several gullies were obscured by vegetation. These gullies were hard to interpret visually and were not included in the manual reference. The reference therefore clearly underestimated the real gully extents. This issue has been acknowledged to challenge the validation of gullies. However, better transferability is ensured by a certain degree of underestimation [28].

Applying the presented workflow to larger areas would still deliver suitable results. The ESP tool for optimizing segmentation is flexible not only against data type but also against data scales. However, for the classification, it might be necessary to define additional rules, since the probability of class ambiguities is higher when larger areas are analyzed. For instance, the rules for classifying drumlins might be also fulfilled by similarly shaped landforms like ridges.

Recently, the definition of semantic models has been proposed to make landform knowledge explicit, thus supporting the selection of input data and classification features for landform mapping in OBIA [29]. However, the vagueness of some landform terms is problematic and hinders their exact

specification [10]. Moreover, some landforms cannot be precisely defined at a given point in time. For instance, the extents of gullies constantly change due to ongoing erosive processes. Therefore, attempts of semiautomated mapping landforms such as gullies and drumlins are still rare. This letter presents only the second approach to drumlin classification using OBIA (next to [27]) and the very first attempt of gully mapping on aerial photographs using OBIA.

V. CONCLUSION

In this study, a three-step methodology was applied in OBIA to map two distinct types of landforms in remote sensing data: gullies in unmanned-aerial-vehicle-derived aerial images and drumlins in DEMs. The methodology consists of the following: 1) a statistical optimization of MRS; 2) knowledge-based classification; and 3) accuracy assessment against a reference map. The approach turned out to be more objective and faster than previous ones.

For both data types, the application of the ESP tool proved to provide good segmentation scales, although individual segments only sometimes matched the size of targeted landforms. Accuracy values suggest that landform classification systems which predominantly rely on shape and context criteria deliver satisfactory results, independent of the underlying data. Most gullies and drumlins were at least partially mapped. For drumlins, similar amounts of over- and underestimated areas were observed. For gullies, the overestimated area was smaller than the underestimated one.

ACKNOWLEDGMENT

The authors would like to thank two anonymous reviewers for their constructive inputs. Reworking criticized points improved the quality of this letter.

REFERENCES

- [1] F. Camargo, C. Almeida, T. Florenzano, C. Heipke, R. Feitosa, and G. Costa, "ASTER/Terra imagery and a multilevel semantic network for semi-automated classification of landforms in a subtropical area," *Photogramm. Eng. Remote Sens.*, vol. 77, no. 6, pp. 619–629, Jun. 2011.
- [2] S. Lang, "Object-based image analysis for remote sensing applications: Modeling reality-dealing with complexity," in *Object-Based Image Analysis*, T. Blaschke, S. Lang, and G. Hay, Eds. Berlin, Germany: Springer-Verlag, 2008, pp. 3–27.
- [3] B. Romstad and B. Etzelmuller, "Mean-curvature watersheds: A simple method for segmentation of a digital elevation model into terrain units," *Geomorphology*, vol. 139/140, pp. 293–302, Feb. 15, 2012.
- [4] J. Strobl, "Segmentation-based terrain classification," in *Advances in Digital Terrain Analysis*, Q. Zhou, B. Lees, and G.-A. Tang, Eds. Berlin, Germany: Springer-Verlag, 2008, pp. 125–139.
- [5] J. Minar and I. S. Evans, "Elementary forms for land surface segmentation: The theoretical basis of terrain analysis and geomorphological mapping," *Geomorphology*, vol. 95, no. 3/4, pp. 236–259, Mar. 2008.
- [6] L. Dragut and C. Eisank, "Object representations at multiple scales from digital elevation models," *Geomorphology*, vol. 129, no. 3/4, pp. 183–189, Jun. 2011.
- [7] M. Baatz and A. Schäpe, "Multiresolution segmentation—An optimization approach for high quality multi-scale image segmentation," in *Angewandte Geographische Informationsverarbeitung*, J. Strobl, T. Blaschke, and G. Griesebner, Eds. Heidelberg, Germany: Wichmann-Verlag, 2000, pp. 12–23.
- [8] U. C. Benz, P. Hofmann, G. Willhauck, I. Lingenfelder, and M. Heynen, "Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information," *ISPRS J. Photogramm. Remote Sens.*, vol. 58, no. 3/4, pp. 239–258, Jan. 2004.
- [9] R. A. MacMillan, R. K. Jones, and D. H. McNabb, "Defining a hierarchy of spatial entities for environmental analysis and modeling using digital elevation models (DEMs)," *Comput., Environ. Urban Syst.*, vol. 28, no. 3, pp. 175–200, May 2004.
- [10] S. van Asselen and A. C. Seijmonsbergen, "Expert-driven semi-automated geomorphological mapping for a mountainous area using a laser DTM," *Geomorphology*, vol. 78, no. 3/4, pp. 309–320, Aug. 2006.
- [11] N. J. Schneevogt, S. van der Linden, H.-P. Thamm, and L. Schrott, "Detecting Alpine landforms from remotely sensed imagery. A pilot study in the Bavarian Alps," *Geomorphology*, vol. 93, no. 1/2, pp. 104–119, Jan. 2008.
- [12] M. Kim, T. A. Warner, M. Madden, and D. S. Atkinson, "Multi-scale GEOBIA with very high spatial resolution digital aerial imagery: Scale, texture and image objects," *Int. J. Remote Sens.*, vol. 32, no. 10, pp. 2825–2850, May 2011.
- [13] L. Dragut, D. Tiede, and S. Levick, "ESP: A tool to estimate scale parameters for multiresolution image segmentation of remotely sensed data," *Int. J. Geograph. Inf. Sci.*, vol. 24, no. 6, pp. 859–871, Jun. 2010.
- [14] M. Petermüller-Strobl and H. Heuberger, *Erläuterungen zur Geomorphologischen Karte 1:25 000 der Bundesrepublik Deutschland - GMK 25 Blatt 26, 8133 Seeshaupt*. Berlin, Germany: Dt. Forschungsgemeinschaft, 1985.
- [15] J. Menzies, "Drumlin," in *Encyclopedia of Geomorphology*, A. S. Goudie, Ed. London, U.K.: Routledge, 2004, pp. 282–284.
- [16] M. J. Smith, J. Rose, and S. Booth, "Geomorphological mapping of glacial landforms from remotely sensed data: An evaluation of the principal data sources and an assessment of their quality," *Geomorphology*, vol. 76, no. 1/2, pp. 148–165, Jun. 2006.
- [17] J. Napieralski and N. Nalepa, "The application of control charts to determine the effect of grid cell size on landform morphometry," *Comput. Geosci.*, vol. 36, no. 2, pp. 222–230, Feb. 2010.
- [18] C. D. Clark, A. L. C. Hughes, S. L. Greenwood, M. Spagnolo, and F. S. L. Ng, "Size and shape characteristics of drumlins, derived from a large sample, and associated scaling laws," *Quaternary Sci. Rev.*, vol. 28, no. 7/8, pp. 677–692, Apr. 2009.
- [19] M. J. Smith and C. D. Clark, "Methods for the visualization of digital elevation models for landform mapping," *Earth Surf. Process. Landforms*, vol. 30, no. 7, pp. 885–900, Jul. 2005.
- [20] J. Hillier and M. Smith, "Residual relief separation: Digital elevation model enhancement for geomorphological mapping," *Earth Surf. Process. Landforms*, vol. 33, no. 14, pp. 2266–2276, Dec. 2008.
- [21] S. d'Oleire-Oltmanns, I. Marzloff, K. D. Peter, and J. B. Ries, "Unmanned aerial vehicle (UAV) for monitoring soil erosion in Morocco," *Remote Sens.*, vol. 4, no. 11, pp. 3390–3416, Nov. 2012.
- [22] I. Marzloff and J. Poesen, "The potential of 3D gully monitoring with GIS using high-resolution aerial photography and a digital photogrammetry system," *Geomorphology*, vol. 111, no. 1/2, pp. 48–60, Oct. 2009.
- [23] J. Poesen, J. Nachtergaele, G. Verstraeten, and C. Valentin, "Gully erosion and environmental change: Importance and research needs," *CATENA*, vol. 50, no. 2/4, pp. 91–133, Jan. 2003.
- [24] A. C. Seijmonsbergen, T. Hengl, and N. S. Anders, "Semi-automated identification and extraction of geomorphological features using digital elevation data," in *Geomorphological Mapping*, M. J. Smith, P. Paron, and J. Griffiths, Eds., 1st ed. Oxford, U.K.: Elsevier, 2011, pp. 297–335.
- [25] I. S. Evans, "Geomorphometry and landform mapping: What is a landform?" *Geomorphology*, vol. 137, no. 1, pp. 94–106, Jan. 2012.
- [26] N. S. Anders, A. C. Seijmonsbergen, and W. Bouten, "Segmentation optimization and stratified object-based analysis for semi-automated geomorphological mapping," *Remote Sens. Environ.*, vol. 115, no. 12, pp. 2976–2985, Dec. 2011.
- [27] K. Saha, N. A. Wells, and M. Munro-Stasiuk, "An object-oriented approach to automated landform mapping: A case study of drumlins," *Comput. Geosci.*, vol. 37, no. 9, pp. 1324–1336, Sep. 2011.
- [28] R. B. V. Shrutli, N. Kerle, and V. Jetten, "Object-based gully feature extraction using high spatial resolution imagery," *Geomorphology*, vol. 134, no. 3/4, pp. 260–268, Nov. 2011.
- [29] C. Eisank, L. Dragut, and T. Blaschke, "A generic procedure for semantics-oriented landform classification using object-based image analysis," in *Proc. Geomorphometry*, Hengl, Evans, Wilson, and Gould, Eds., Redlands, CA, 2011, pp. 125–128.