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Full Length Research Paper

Comparison of automated and manual landform delineation in semi detailed soil survey procedure

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ASTER DEM data was used to automate landform classification during soil survey in the Varamin area. For comparison, manual landform classification was done in the same area. Study area was located at South of Jajrood river watershed, Southeast of Tehran province (Iran). The main purpose of this study was to compare the effect of automated and manual landform classification methods in semi-detailed soil survey procedure. Eight geomorphometric parameters were extracted from DEM using the TAS and DiGem software. The Pearson correlation coefficient analysis elucidated that, the most effective of parameters were: analytical hill-shade, plan and profile curvature, and slope and divergence-convergence index. In addition to these terrain attributes, principal component analyses (PCA) of primary geomorphometric parameters were produced to increase the quality of classification and to reduce modeled data. First three PCAs cover 97% of variance of the data. These PCAs and mentioned terrain parameters were selected for performing of K-means unsupervised landform classification model. Results indicated that unsupervised and manual classification can be complemented, such that conflation of the final maps obtained by these methods can produce a more accurate map. Also, the K-means algorithm with correct iterations, tolerance and suitable number of classes can be used for automated landform classification as well. Hybrid landform classification method is useful for soil survey and soil mapping especially, in watersheds and natural resource fields.

Key words: Hybrid landform classification, geomorphometric parameters, K-means classifier, Pearson correlation coefficient.

INTRODUCTION

Landforms are considered a central concept for soil development. It influences soil distribution, properties and processes that occur in soil pedon and catena. In different parts of the world, many studies have been carried out to show the relationships between landform elements and soil distribution. In soil survey and soil mapping procedures, the geomorphologic processes in delineating the landscape is inferred to find the controller process and cause of different types of soil. Besides, extracting soil-landscape relationships helps surveyors to judge and infer their tacit knowledge into modeling steps. A fundamental objective in geomorphologic clustering is to extract and classify landform units. These units provide primary view about the distribution of soil units. Most of the environmental processes depend on topography (Hugget and Cheesman, 2002) and if topography remains uniform, then the processes affect mostly the earth crust.

There are different approaches to define and describe the landscape divisions (geomorphic units). These terms used in different approaches are more or less the same (Wilson and Gallant, 2000). Landform units are formed due to different geomorphic, hydrologic and pedologic processes in each landscape. Thus, based on the approach of Zink (1988), large areas are divided to

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geomorphologic units such as landscape, landform and geomorphic surfaces. Each of them may be composed of one or several types of soil unit. Contiguous environmental processes make delineation and mapping of geomorphic or soil units difficult. Similarity in geomorphic units indicates uniformity in soil forming processes, therefore, we will be able to delineate uniform soil mapping unit. This induces that mapping topography will help us to delineate the soil units also (Etzelmüller and Sulebak, 2000). Different techniques from automatic (supervised and unsupervised algorithm) to hybrid (semi-automated) classification methods were used in landform classification for modeling of soil characteristics and spatial distribution of types of soils. In this context, improvements in Geographic Information Systems (GIS) and terrain analysis techniques allow developing soil survey models based on different new concepts such as geomorphometry. DEMs are used for analysis of topography, landscapes and landforms and extracting terrain attributes (Bishop and Shroder, 2000; Tucker et al., 2001). Many geomorphometric parameters are derived from DEMs.

These parameters are used for automated landform classification and are more correlated with current digital soil mapping than conventional soil surveying. These morphometric attributes are divided to primary terrain attributes (for example, slope, aspect, elevation, plan curvature, profile curvature, total curvature, tangential curvature, surface curvature index, and shaded relief etc) and compound terrain attributes (for example, topographic wetness index, sediment transport capacity, and composite relief model etc) (Gallant and Wilson, 2000). Both of them can be used to predict surface and sub-surface processes through automated landform classification. Digital soil mapping can be performed in different scales: from large (1:5,000) to small scales (1:500,000) depending on vertical and horizontal resolution of produced DEMs (Gallant and Wilson, 2000). Recently, studies on these topics has increased due to availability of high-resolution DEMs produced by different satellite data and software packages of terrain analysis systems (McMillan et al., 2003; McBratney et al., 2003; Smith et al., 2006). Many studies have shown that changes in goemorphometric parameters can cause intrinsic differences in elucidating the spatial distributions of the landform and soil units (Gallant and Wilson, 2000).

Ventura and Irvin (2000) classified landform by applying the iso-clustering unsupervised classification method using six geomorphometric parameters. Their study showed that automated segmentation landform can separate units more detail than the conventional method. Moreno et al. (2005) also classified landscape automatically using GIS into landform elements based on geomorphometry. The results indicated that it is less time consuming with a rewarding conclusion compared to manual methods.

Mousavi et al. (2007) assessed in their studies the extracted geomorphometric parameters from ASTER DEM with PCI GEOMATICA software in Damavand region (Iran). They derived five parameters which are useful in identifying and describing process and geomorphologic units: height, slop, aspect, vertical curvature and tangential curvature. These researchers concluded that ASTER DEM data, according to their technical specification and features, are appropriate for interpretation and production of geomorphic data in macro and meso scales, and only provide the possibility of topography in medium scales (1:100000 and 1:50000). Barka et al. (2011) used landform classification in predictive soil mapping at the forest area in Slovakia. Their evaluation indicated that terrain classification is one of the methods which can be used suitably in delineation of pedological and forestry units. Hengl and Rossiter (2003) used maximum likelihood classifier for landform classification to enhance the process and replace aerial photo interpretation in semi-detailed soil surveys. They used nine geomorphometric parameters extracted from DEM with a 10 m cell size to model landform classification. The result indicated that their methodology can be applied to update current maps and to enhance or replace aerial photo interpretation for new surveys.

Umali et al. (2010) used a simple method to predict spatial pattern of soil organic carbon (SOC) using a substitute variable, soil color and digital terrain analysis in East of Adelaide, South Australia. They derived seven geomorphometric parameters from the DEMs (specific catchment area, profile curvature, wetness index, slope, plan curvature, sediment transport capacity index and tangential curvature). Also, they identified one hundred random points across the study area and value component of soil color was obtained. Spearman rank correlation analysis showed that elevation, specific catchment area, profile curvature and wetness index affects value component of soil color. They also found that the application of logicalness algorithms to DEMs derived from contour line maps produced better correlation coefficients as compared to unsmooth DEMs.

With this background, it is assumed that quantitative geomorphology can be used for delineating landform units within a soil surveying procedure. Thus, the objectives of this study are: 1) to what extent the geomorphometric parameters and automated landform classification method can be used to replace physiographic classification method traditionally used for Iranian soil survey and soil mapping? 2) to what extent can satellite data from Google Earth replace aerial photo interpretations in soil survey and geomorphological studies?

MATERIALS AND METHODS

Condition of study area

The study area is located on the Southern slopes of Alborz range, 40 km South-east of Tehran (Figure 1). It is part of the major alluvial

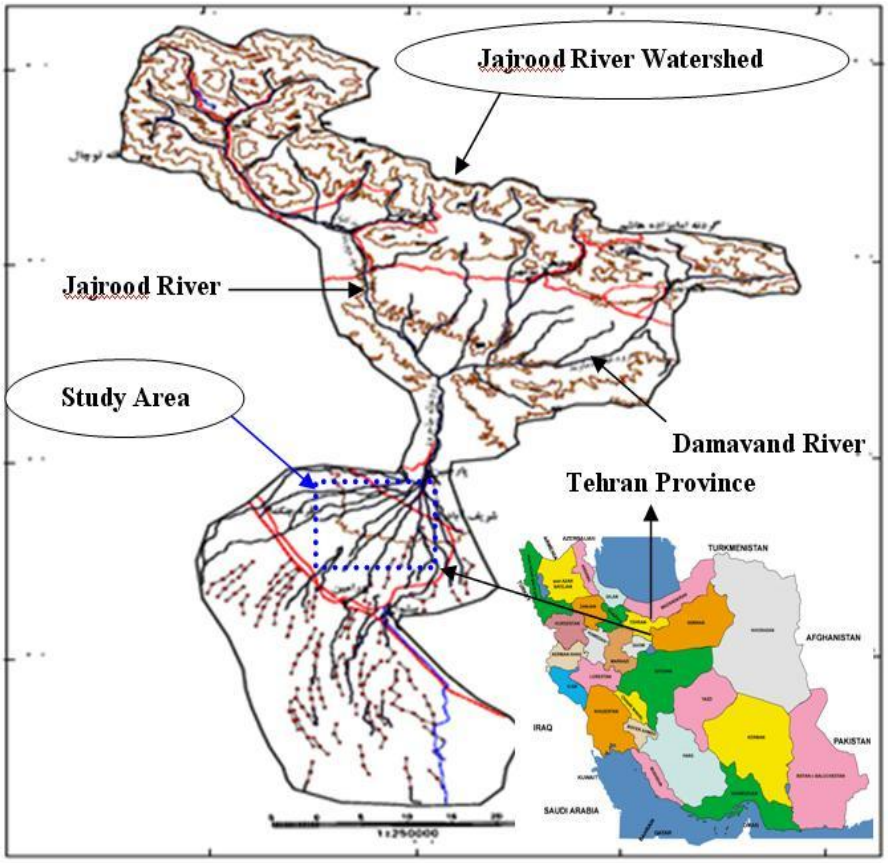

Figure 1. Location of the study area in Southeast of Tehran province, Iran.

fan formed by Jajrood river watershed between 35˚20´26˝ and 35˚31´09˝ N latitude and 51˚41´52˝ and 51˚52´32˝ E longitude. Mean elevation of region is 1250 m above sea level (1463 to 950M). Variations of elevation were represented by Hypsometric map (Figure 2). Soil moisture and temperature regimes are weak aridic and thermic respectively. Topography of such regions is predominantly flat with the exception of the Northern part. General slope of the area runs from North to South. Soils of the region are generally classified (Moravej et al., 2003) in two orders of Entisols and Aridisols (USDA, 2010). The Varamin plain represents an inter-mountain basin that is bounded on the North by Alburz mountain range and on the South by Siah kuh range. Study area consists of Paleozoic and Mesozoic sediments and Eocene volcanic, which are covered with young Tertiary and Quaternary deposits of the Jajrood river. The river deposits, mainly from Pleistocene Epoch, are more than 300 m thick in some places and, through their sandy nature, represent an important reservoir of good quality groundwater. At the apex of the alluvial fan, the Jajrood river diverges into a large number of branches and its sediment-carrying capacity thus diminishes. Coarse and very coarse sediments therefore, occur at the apex; while farther downstream the sediments gradually becomes finer, passing into loam and silt in the lower parts of the fan.

AUTOMATED LANDFORM CLASSIFICATION METHOD

Pre-processing of the DEM

The DEM of study area was downloaded form the ASTER GDEM web site. There are different acceptable procedures for producing, editing and correcting of DEM before starting the extraction of goemorphometric parameters (Lindsay, 2005; Liu et al., 2006). Improving methods more or less depends on the way the DEM is extracted (satellite data or contour lines). The procedures used in this research to increase the quality of DEM before extraction of geomorphometric parameters were: re-sampling of the ASTER DEM to 14 m to exploit full ortho image resolution. Then, DEM data was searched for sink. 9010 sinks were detected that filled by DiGem software to improve the quality of the DEM. Flat area drainage enforce command was performed to the DEM by TAS software. Without this, flow routing algorithms are unable to identify down slope neighbors in these areas and flow routing ceases. This command adds very small elevation adjustments to flat areas (that is, cells where the lowest neighbors have equal elevation) from the 'pour point' backwards, so that flow routing algorithms can work properly. The algorithm used in this module is taken from Jenson and Dominique (1988). The study area is mostly flat to gently sloping except in the Northern part. So, it was important to know what the variation in elevation is within a grid cell size distance from the centre cell in a window. Consequently, a circular shaped window with 5 × 5 size was used for mean filtering of the raster DEM. A circular shape window seems more suitable than a square because the boundary of a circle will always be of equal distance to the focal point (Brabyn, 1998).

Derivation of geomorphometric parameters

All the important primary and secondary terrain attributes were

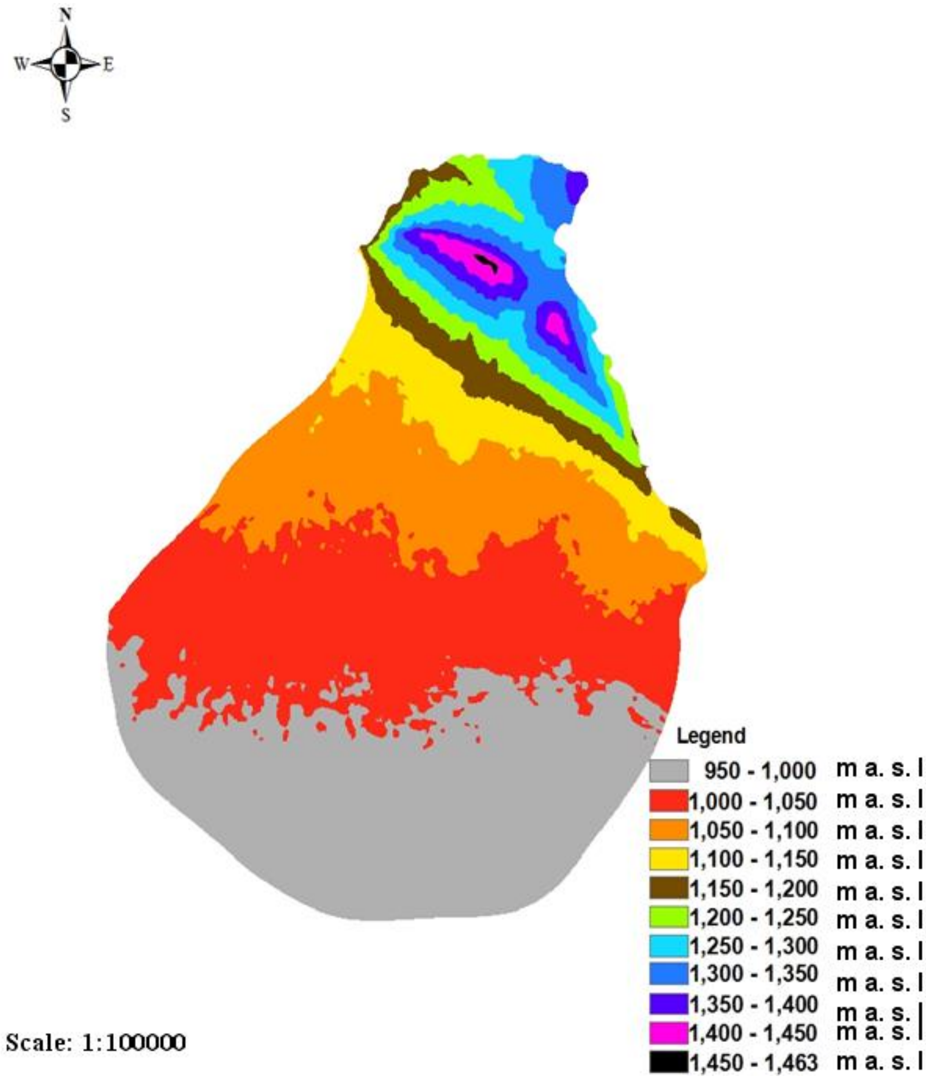

Figure 2. Hypsometric map of the study area.

extracted using TAS Version 2.0.9 (Terrain Analysis Systems), a Software called White box GAT (Geospatial Analysis Tools) developed by Lindsay (2005) and DiGem software produced by Conrad (2002) of the Gottingen University. The extracted parameters which have been mapped separately are: Aspect, slope, curvature, Maximum Down Slope (MDS), Sediment Transport Capacity Index (STCI), Shaded Relief (SHR), Wetness Index (WI) or Topographic Index, Analytical Hill shade (AH), Divergence-Convergence Index (DCI), Plan Curvature (PL.C) and Profile Curvature (PR.C).

Correlation among the geomorphometric parameters

Some geomorphometric parameters have some correlation and contain similar information. When two parameters have positive correlation (between 0 to +1) it shows that increase in one parameter resulted from the increase in another one, and vice versa. Also, it shows that the presence of high correlated coefficient between two parameters means that there are some similarities in the data. To ordinate the geomorphometric parameters, the Pearson product-moment correlation coefficient (*r*) was computed between these parameters by White box GAT software. The primary correlation coefficients among mentioned extracted parameters vary from -0.09 to 0.99. So, high positive correlated parameters were omitted including: Curvature, MDS, and SHR. Pearson correlation coefficient was computed between the remained parameters [Aspect, Slope, Sediment Transport Capacity Index (STCI), Wetness Index (WI) or Topographic Index, Analytical Hill shade (AH), Divergence-Convergence Index (DCI), Plan Curvature (PL.C) and Profile Curvature (PR.C)]. For the second time (Table 1). As can be seen in this table, *r* varies from -0.291 to 0.55.

Principal components analysis (PCAs) of eight geomorphometric parameters was extracted to increase the quality of classification and to reduce the data. The outputs of correlation matrix extracted by PCA and Pearson Correlation Coefficient (*r*) are exactly similar. So, principal components analysis was done for producing images that had maximum variance data. Subsequently, three parameters that had relatively high correlation with other parameters (STCI, WI, Aspect) were omitted and replaced by $PCA_{1,2,3}$ that had the highest information variance (97% approximately).

Table 1. The Pearson correlation coefficient (*r*) matrix.

Parameter	Aspect	AH	DCI	PL.C	PR.C	Slope	STCI	WI
Aspect	1	-0.291	0.210	0.051	0.036	0.357	0.209	0.550
AH		1	0.037	0.029	0.008	0.261	0.177	0.219
DCI			1	0.519	0.572	0.181	0.005	0.146
PL.C				1	0.463	0.123	-0.069	0.113
PR.C					1	0.035	-0.096	-0.002
Slope						1	0.736	0.470
STCI							1	0.384
WI								1

AH: Analytical hill shade, DCI: divergence-convergence index, PL.C: plan curvature, PR.C: profile curvature.

Table 2. Geomorphic legend showing automated landform classification.

Landscape	Relief	Lithology	Landform	Code
Alluvial fan	Low	Coarse alluvial sediments over red marl with intercalations of well bedded sandstone.	Upper alluvial fan	Af 111
		Middle-texture alluvial sediments over old gravel fan quaternary.	Middle alluvial fan	Af 121
	Very low	Fine alluvial sediments.	Lower alluvial fan	Af 211
Hill land	Low rolling hills	Gray conglomerate with marl cement.	Complex facet hillside	Hi 111
		Light gray to light red alternation of conglomerate, sandstone with silt.	Complex facet hillside	Hi 121
	Moderate (steeply dissected)	Gray conglomerate with marl cement.	Steeply dissected hillside	Hi 211
			Moderately steep slope hillside	Hi 212

Automated landform classification

Selected terrain parameters (analytical hillshade, plan and profile curvature, slope and divergence-convergence index) and $PCA_{1, 2, 3}$ were treated as a single band images and using a K-mean unsupervised algorithm, the landforms were classified. This method finds statistically similar groups in multi spectral space during its analysis. The algorithm starts by randomly locating *k* clusters in spectral space. Each pixel in the input image group is then assigned to the nearest cluster centre and the cluster centre locations are moved to the average of their class values. This classification is then repeated until a stopping condition is reached. The stopping condition may either be a maximum number of iterations or a tolerance threshold which designates the smallest possible distance to move cluster centers before stopping the iterative process. In this approach, the determinative parameters were 10, 15 and 5 respectively, for the number of predictive class, maximum iteration and change tolerance. Post processing of this primary classification was done in ArcGIS software. Process was consisted of performance majority filtering and other cartographic rules.

Manual landform classification

Manual landform classification was done using Google Earth images, Geological maps (scale: 1:100000) and field works. To delineate the landforms and description of each unit, we have used the categories presented by Zink (1988) which clearly relates landforms to soil units. Legend of the delineated landforms is also defined. The primary map was exported to ArcGIS using KLM extension and final map was edited.

Evaluation

Classification algorithms can be evaluated by different methods. The most common methods are cross tabulation and error matrix analysis. The outputs of these tables are Kappa index, Chi square, Crammers V, Overall accuracy and etc. evaluation process was used to compare the frequency of cells belonging to all landform units within manual and automated landform classifications and for the purpose of accuracy assessment.

RESULTS

An automated landform classification map was produced at a scale of 1:50000. The result was a map with seven classes (Figure 3). Table 2 shows hierarchical landform

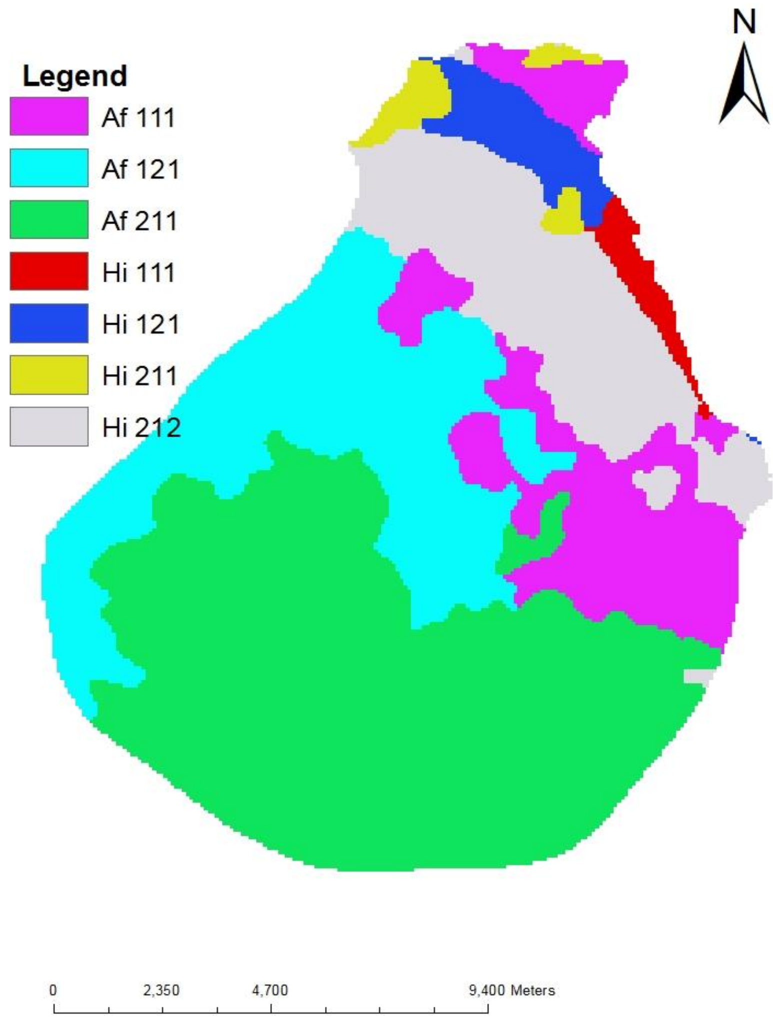

Figure 3. Automated landform classification of study area.

classification based on Zink method. The results indicated that diverged landforms mostly vary by variation of only two geomorphometric parameters (slope and hill shade). Although, some other parameters have more influence than others in different parts of the study area. For example, Af 121, Af 211 and Af 111 units were mostly separated by slope and partly hill shade factor in alluvial fan landscape. But, all of the used terrain parameters simultaneously affect the separation of landform units in hilly landscape with different intensities. Although, Analytical hill shade parameter has more influence in some landform units located in hilly landscape.

In the manual method, eight soil-landscape units (three in the piedmont area and five in the hilly landscape) were identified using the Zink method (Figure 4 and Table 3). Cross tabulation was used for accuracy analysis and evaluation of manual and unsupervised classification (Table 4). Comparison of these methods indicates that: 1) Af 211 unit in manual method is divided into three different landform units (Af 111, Af 121 and Af 211) in the automated classification; 2) Hi 211 unit in unsupervised landform classification was not separated in the manual segmentation; 3) Hi 121 and Hi 212 units were delineated with relatively good accuracy in manual and automated methods, respectively; 4) Hi 211 and Hi 212 in the manual method were integrated to Hi 121 and Hi 111 in automated method, respectively; 5) Hi 111 unit in the manual method is divided into two units (Hi 111 and Hi 121) in the automated classification mainly by differences in analytical hill shade parameter; 6) Af 111 unit in automated segmentation was divided to unit (Af 111 and Af 121) in manual segmentation. Although, Af 111 and Af 121 are similar in terrain parameters, but they are different in evolution processes and it is better that they are separated. Important point to consider in comparing the two methods is manual and unsupervised classification can be used complementally for areas that are unavailable or study was limited point of cost and time.

Table 3. Geomorphic legend showing manual landform classification.

Landscape	Relief	Lithology	Landform	Code
Alluvial fan	Low	Coarse alluvial sediments over red marl with intercalations of well bedded sandstone.	Upper alluvial fan	Af 111
		Very coarse-texture alluvial sediments over young gravel fan quaternary.	Young alluvial fan	Af 121
	Very low	Middle and fine alluvial sediments.	Lower alluvial fan	Af 211
Hill land	Low rolling hills	Gray conglomerate with marl cement.	Complex facet hillside	Hi 111
		Light gray to light red alternation of conglomerate, sandstone with silt.	Complex facet hillside	Hi 121
	Moderate (steeply dissected)	Gray conglomerate with marl cement.	Steeply dissected hillside	Hi 211
			Steeply dissected hillside	Hi 212

Table 4. Cross-tabulation for manual and automated landform classification.

Unsupervised classification	Manual classification							Total
	Af 111	Af 211	Af 121	Hi 211	Hi 121	Hi 111	Hi 212	
Af 111	345	1353	1086	0	9	40	0	3563
Af 211	0	13144	116	0	0	0	0	11260
Af 121	0	3702	730	0	0	0	0	5702
Hi 211	35	0	0	0	142	85	0	333
Hi 121	0	0	0	71	908	290	14	147
Hi 111	0	0	291	140	54	309	84	3962
Hi 212	1	2071	0	0	794	4	0	852
Total	381	20270	2224	211	1907	728	98	25819

Kappa index: 0.507, overall accuracy: 0.596, Crammer's V: 0.7205.

DISCUSSION

It is logical to assume that increases of one geomorphometric parameter can cause a decrease or increase in other parameters; especially, compound terrain attributes that are extracted from primary terrain attributes. Some of these parameters correlate with each other and have positive or negative co-relationships. At the same time, some geomorphometric parameters have the same basic mathematical formulas which describe relationships between them. It is clear that, correlation between some geomorphometric parameters in one area can not be used for other areas (Debella-Gilo et al., 2007). Thus, in each area, depending on the natural dominant process, one can find different relationships between geomorphometric parameters.

The ASTER DEM data is a suitable source for derivation of geomorphometric parameters (Kamp et al., 2003), automated landform classification and soil survey at a medium scale (1:50000) or order 3 to 4 and smaller scale soil surveys (Soil Survey Division Staff, 1993, Tables 2 and 1). However, in areas with less relief or flat topography, in addition to ASTER DEM, use of other data is suggested, such as remote sensing data and their indexes for increasing the accuracy of outputs. In this study, the accuracy of landform map decreases with reduction of relief. In order to obtain better results, field observations, consumption of more time and money is essential. The ASTER DEM data are available freely for many parts of the world including Iran.

The Google Earth images have many advantages for landform classification as compared with traditional aerial photos: 1) its images are colored instead of black and white photos and as such, interpretation of landform data is easier; 2) Google earth images have more temporal resolution than aerial photos; 3) the images and its related data are available everywhere and every time; 4) it has capability link to ArcGIS software easily and produced layers that have coordinate system in Lat/Long and UTM format; 5) some of primary cartographic errors

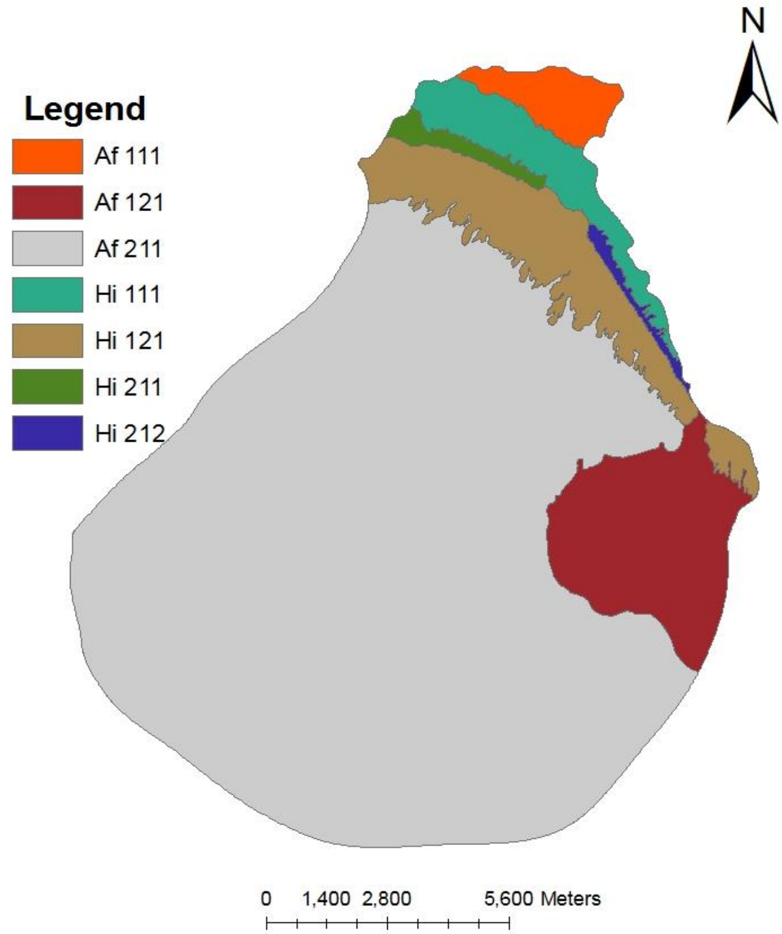

Figure 4. Landform classification map using the manual method.

can be corrected for these images; 6) no stereoscope is needed for a 3D-View; 7) it is more economical, low cost and saves time as compared with aerial photos. Hengl and Rossiter (2003) used aerial photo interpretation for supervised landform classification. They gave some limitations and ways to overcome them.

The advantages of the automated landform classification (Dikau et al., 1991) as compared with the manual method are: 1) it can provide a more detail geomorphic map, soil survey and soil classification if the data and parameters used for the classification are accurate and proportional to topographic variations of the study area; 2) if suitable algorithm classification was selected, classification can result in more accurate output; 3) it can be used for quantitative studies of the relationship between geomorphometric parameters and surface processes; 4) it can easily be processed into different GIS softwares, and it is easily exportable, importable and interpretable. Unfortunately, the terrain attributes to be used as parameters for the supervised and unsupervised classification do not have the capability for standardization for everywhere. So, the validity of the classification is dependent on its ability in showing the changes in geomorphic (Debella-Gilo et al., 2007); 5) automated landform classification and selected terrain parameters can be easily tested to other areas that have similar topography and geomorphology (Brabyn, 1998).

Unsupervised classification algorithms without field observations cannot always result in correct classifications. The best method is to use the manual and unsupervised classification together (Hybrid classification). Hybrid landform classification method and use of Google Earth data as a color composite image of geomorphometric parameters are very useful for soil survey and soil mapping, especially, for developing countries. Automated classification makes more detailed output than traditional semi detailed survey. Some of the Iranian soil maps are old and they need to be updated, so that use of such methods can be very useful and economical.

For many years, delineation of physiographic units has been the basis for soil survey in Iran. In such delineations, less attention is being paid to geomorphic landforms and processes. Geomorphologic studies are very important and it is essential that soil scientists are aware of geomorphic relations to soil formations and distributions (Alavipanah et al., 2009). Geomorphometric parameters can be used successfully for soil survey and results can be more accurate if they were used in association with geomorphologic studies.

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