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Uncertainties Related to Scale and Sampling Window Size in Defining Macro Landforms

Makro Yerşekillerinin Tanımlanmasında Ölçek ve Örneklem Pencere Boyutuna İlişkin Belirsizlikler

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ÖZ

Bu çalışma makro yer şekillerinin tanımlanmasında temel alınan pencere örneklem boyutlarının istatistiksel önemi ve tanımlamalarda meydana getirdiği farklılıkların üzerinde durmaktadır. Yerşekillerinin otomatik olarak sınıflandırılmasında, optimum ölçeğin belirlenmesi sorunu önemini korumaktadır. Bu nedenle, ölçek faktörü ile örneklem pencere boyutu arasındaki ilişkiler yer şekillerinin tanımlanmasında dolayısıyla sınıflandırılmasındaki ilk aşamayı oluşturmaktadır. Yapılan değerlendirmeler, farklı çözünürlüklerde sayısal yükseklik modelleri Global Multi-resolution Terrain Elevation Data–GMTED2010 ve Multi-Error-Removed Improved–Terrain DEM kullanarak yapılmıştır. Dağ-plato ve dağ-ova arasındaki sınır belirsizliklerinin farklı ölçek ve analiz pencerelerinde tanımlamalarda getirdiği farklılıklar, UNEP-WCMC 2000 (K1) sınıflama algoritması kullanılarak Türkiye özelinde tartışılmıştır. Bu alanlara ilişkin yükseklik, eğim, topoğrafik röliyef gibi sayısal yükseklik modeli türevleri ve bunlara ait tanımsal istatistikler kullanılarak veri matrisleri oluşturulmuştur. Seçili alanlarda sahayı en iyi temsil eden ölçek ve pencere boyutlarının kombinasyonlarını içeren test sonuçları, pencere boyutunda yapılan değişikliklerle genelleştirme kapasitesi arttıkça tanımlanan makro yer şekli birliğinin farklı bir haritayla sonuçlanabileceğini göstermektedir. Buna göre makro yer şekillerinin tanımlanmasında, çalışmamızda değişen oranlarda yapılan pencere boyutu testlerinde belirlenen 2.5 km'lik komşuluk analiz penceresi boyutu üst sınırı ile daha anlamlı sonuçlar ortaya çıkmıştır. Yerşekli sınıflamasında dağ sınır ilişkilerinin, SYM çözünürlüğünden ziyade komşuluk analiz pencere boyutuna daha duyarlı olduğu görülmüştür.
Anahtar kelimeler: Jeomorfometri, Makro Yer Şekilleri, Dağ Sınıfları, Sayısal Yükseklik Modeli

ABSTRACT

This study focuses on the statistical significance of sampling window sizes, which are used to define macro landforms and the differences they cause in definitions. In the automatic classification of landforms, the problem of determining the optimum scale remains important. Therefore, the relations between the scale factor and the window size constitute the first step, thus classifying landforms. The evaluations were carried out using GMTED2010 and MERIT DEM at different resolutions. The differences in the definitions of different scales and analysis windows caused by the border uncertainties between mountain-plateau and mountain-plain that are specific to Türkiye were discussed using the UNEP-WCMC 2000 classification algorithm. Data matrices were created using DEM derivatives such as elevation, slope, and topographic relief for these areas and their descriptive statistics. The test results, which include the combinations of scale and window sizes that best represent the area in selected fields, indicate that the defined macro landform units can result in a more different map as the generalization capacity increases with the changes made in the window size. More meaningful results emerged with the upper limit of the 2.5 km NAW size determined in our study's window size tests performed at varying rates. In landform classification, mountain boundary relationships were more sensitive to NAW size than DEM resolution.
Keywords: Geomorphometry, Macro Landforms, Mountain Classes, Digital Elevation Model

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1. INTRODUCTION

An important part of geomorphology is the systematic characterization of land parameters, landforms, and topographic structures (Rasemann, Schmidt, Schrott, and Dikau, 2004). Landforms, as a physical feature of the earth's surface that have a characteristic, definable shape and are produced by natural causes, are considered natural objects that divide the land surface into basic spatial entities. The Earth's surface is continuous in most places and the morphological structure differs in various scales and dimensions (Schmidt and Andrew, 2005; MacMillan and Shary, 2009). As a separate discipline, geomorphometry (Dehn, Gartner and Dikau, 2001), dealing with the qualitative and quantitative description and measurement of landforms, uses digital elevation models as a basic data source by representing the continuous variation of relief in space in a regular grid (square) matrix (Szypula, 2017; Pike, Evans and Hengl, 2009). The metric elevation values in grids abstract the real Earth with a mathematical model (Guth et al., 2021) and enable the generation of various morphological variables to describe different topographies (Gallant and Hutchinson, 1997; Shary, Sharaya and Mitusow, 2002; Wang, Laffan, Liu and Wu, 2010). General geomorphometry analyses this continuous field (Evans, 2012). As the scale changes in this continuous field, the perceived image changes. For example, in rough scales, larger forms on the surface are evident. In the space-time hierarchy of geomorphological features (**Figure 1**), geomorphic areas at the macro and meso scale are characterized by tectonic units with a spatial scale of 10^2 - 10^8 km², mountainous areas, and physiographic regions (Slaymaker, 1991). As can be seen in Figure 1, landforms such as mountainous areas are included the area defined by the shortest time and smallest spatial scales. The longest time scales of 100 Ma and 100 M km² are geomorphological zone belts (Slaymaker and Hamann, 2018).

The definition of morphological variables, their features, and the character of landforms are limited by the scale factor. The scale is accepted as a function of the resolution of digital elevation models in which morphological variables are calculated in geomorphometry (Hengl and Evans, 2009; MacMillan and Shary, 2009). The dependence on this resolution of landforms defined in different dimensions in a spatial hierarchy was identified by Evans (1975) as a fundamental problem in geomorphometry.

This variation in spatial scale causes the surface to be perceived differently as a function of the geographical extent and the grain size (pixels) it contains. Thus, as the spatial extent of the elevation matrices, in which morphological variables are calculated, changes, the results also change (Shary et al., 2002), and the fact that the

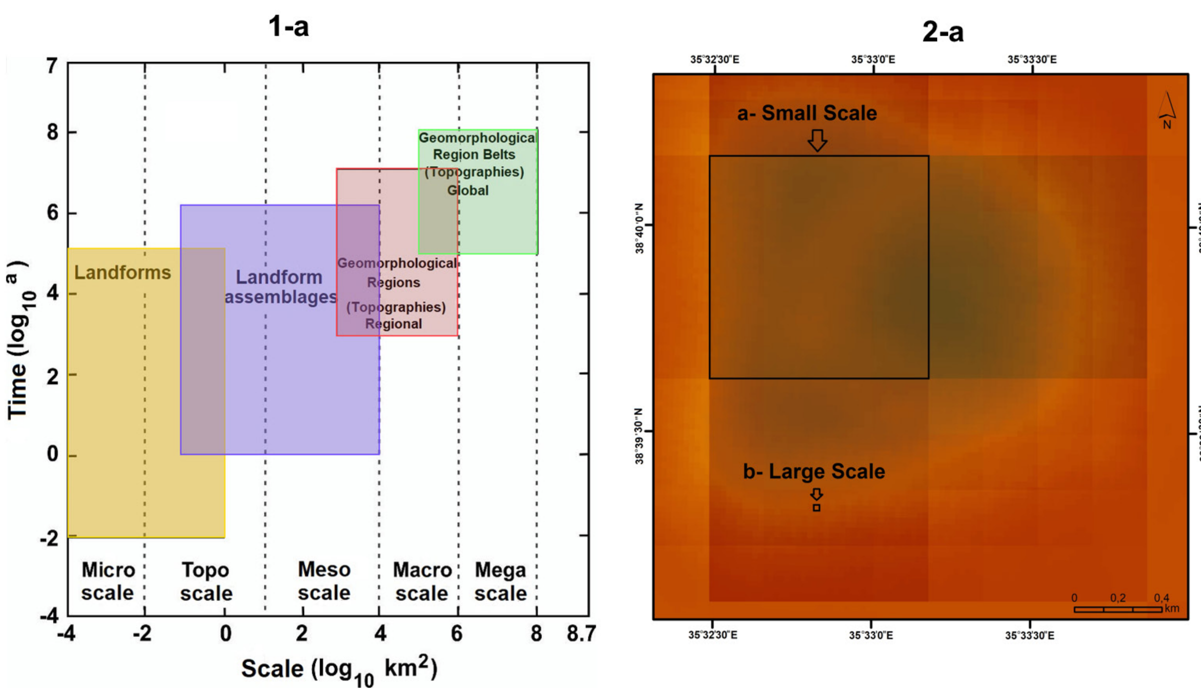

Figure 1: 1-a: Spatio-temporal hierarchy of landforms and geomorphological regions: The spatial scale is plotted on the x-axis and the temporal scale on the y-axis (edited from Slaymaker and Hamanni, 2018). 2-a: Representation of scales in raster data: a-small scale corresponds to a digital elevation model with 1000 m resolution. Higher resolution data (100 m), mostly used for describing micro landforms, has a smaller grid, as in b.

surface and processes observed at a certain scale will change when observed at different scales reveal scale dependence (Marceau, 1999). For instance, the study carried out by Arrell, Fisher, Tate, and Bastin (2007), investigating the effect of morphological variables on scale dependencies and landform classification, revealed that the scale (different resolutions) determines the morphological classes to be defined, and the morphometric classes display resolution dependence in their geographical extent. In a different study, Li (2015) revealed that morphological parameters (e.g., slope) could produce different results (particularly slope parameter) at different resolutions and analysis window sizes. On the other hand, Deng, Wilson, and Bauer (2007) stated that the calculated values of terrain attributes did not change consistently when the resolutions of the digital elevation models used as data sources were changed. This dependence on resolution and sampling window makes an area-data relationship suitable for the purpose of calculations necessary (MacMillan and Shary, 2009). As a result, the accuracy of geomorphometric calculations or the type of landform defined varies as the horizontal and vertical resolution of the digital elevation model and the extent of the sampling (analysis) window change.

1.1. Metric Perception-Scale Problem

The Analysis/Neighborhood (sampling) window defines the frame in which morphological variables are calculated, and the size of the window determines the analysis scale (Zanker, 2016; Zwoliński and Stefańska, 2015). The main difficulty in this part is how to best determine the extent of the search window for calculating morphometric statistics. From this point of view, it is seen that the changes to be made in the window sizes are as important as the parameter selections according to the characteristics of the area. In a selected window, the cell in which variables are calculated is called the processing cell. All cell values in the defined neighborhood (analysis window) are included in the neighborhood statistics calculation. All these cells are used to calculate the value of an output cell. An increase or decrease in window size may result in a different map related to the defined landform (Jasiewicz and Stepinski, 2013).

These problems or dependencies in metric perception in the calculation of morphological variables have become widespread, especially with the emergence of automatic landform classification procedures based on digital elevation models in geomorphology studies (Mark, 1975; Pike, 1988; Skidmore, 1990; Wood, 1996; MacMillan, Pettapiece, Nolan and Goddard, 2000). These procedures extend from the classification of recurring landform types to the classification of more detailed and large-scale landform patterns (Macmillan and Shary, 2009).

However, uncertainties in the representation of the land surface by digital elevation models have led studies to be carried out on the effects of different spatial resolution on the value and accuracy of objects generated from datasets (Sørensen and Seibert, 2007; Schoorl, Sonneveld and Veldkamp, 2000; Florinsky and Kuryakova 2000; Deng et al., 2007; Pain, 2005; Smith, Zhu, Burt and Stiles, 2006, A-Xing, Burt, Smith, Rongxun and Jing, 2008; Shary et al., 2002; Wilson and Gallant, 2000; Thompson, Bell and Butler, 2001). Identification of landforms using automatic algorithms enables the creation of fingerprints of the topography. Thus, the best descriptive measurements that distinguish the landform from other units can be generated with the geometric signature created (Pike, 1988). Algorithms that consider local conditions can increase the accuracy of the signature. This study investigated the effect of different scales and generalization capacities on the definition of macro landforms in an area such as Türkiye where different orogenic phases are observed with complex landforms. When making these definitions, the uncertainties regarding the dimensions of the selected sample window were examined. In the study, some macro landforms with consensus by geomorphologists were selected, and data matrices were created using DEM derivatives such as elevation, slope, topographic relief, and their descriptive statistics. These matrices followed the steps of a global classification procedure (K1).

2. METHODOLOGY

2.1. Motivating hypotheses

Since digital data, which is a representation of the real world, suffers data loss at every stage of morphological analysis, it becomes impossible to have a perfect representation of the surface (Li, Ban, Wechsler and Xu, 2018). For this reason, various researchers have argued that spatial data uncertainty is inevitable in data sets (Goodchild, 2001, Couclelis, 2003). Different studies (Schoorl et al., 2000; Deng et al., 2007; Sørensen and Seibert, 2007; Deng, Wilson and Gallant, 2018; Ehsani, Quiel and Malekion, 2010; Li, 2015) revealed that the values of morphometric elements can change with a variance in DEM resolution and analysis window size. These features are effective in defining landform features, leading to changes in the definition of classes assigned in automatic landform classifications. Accordingly, this study focuses on two questions. What is the effect of DEMs with different resolutions on the definition of macro landforms? What is the response of classifications to change in analysis window size?

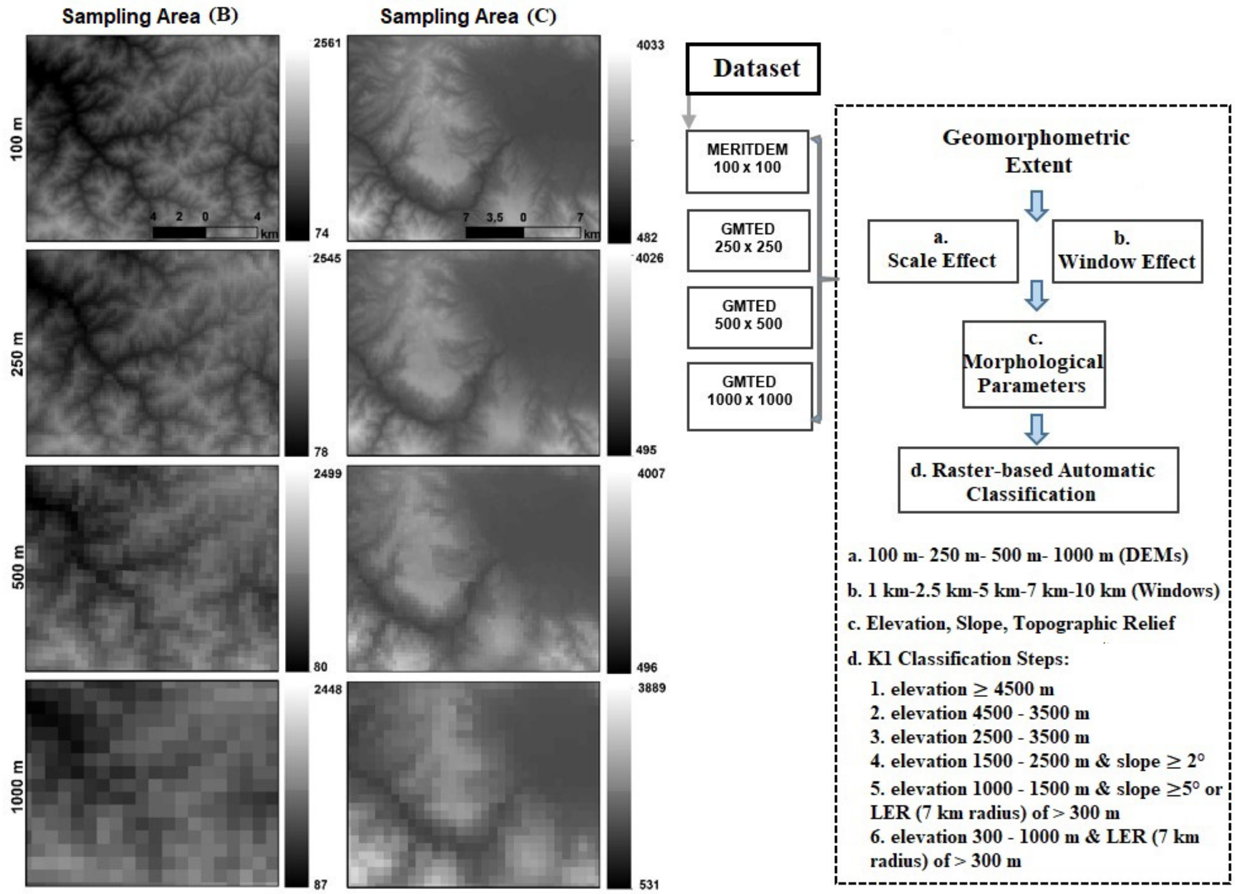

Figure 2: Digital elevation models used for analysis in selected sample areas (B – C) and general procedure of processing steps

In this context, the following arguments will be discussed in this study.

- The values of the morphological features calculated from the DEMs change when the input DEM resolution is changed.
- Landform classes assigned as a result of classification respond to window size change. Thus, as the window size changes, the landform corresponding to the assigned class changes significantly.

2.2. Data Attributes

Few studies classifying macro landforms use global data sets. In this study, analyses to evaluate the effects of resolution of digital elevation models and different neighborhood/analysis (sampling) windows on macro landform classes were performed on four different data sets. These data sets are Global Multi-resolution Terrain Elevation Data (GMTED) 2010 (USGS, 2010) and Multi-Error-Removed Improved –Terrain DEM (MeritDem) (Yamazaki et al., 2019). The GMTED 2010 dataset consists of elevation data of approximately 250 m, 500 m, and 1 km as a refined version of GTOPO30 by the USGS (U.S. Geological Survey) and NGA (National Geospatial-Intelligence Agency) (Danielson and Gesch, 2011). MeritDEM 90 m elevation data is a dataset with 90 m resolution developed by combining the data obtained from SRTM and 30 m resolution ALOS World 3D, to provide digital elevation data with reduced error (Uuemaa et al., 2020). The downloaded datasets were projected in the Lambert Conformal Conic Projection using the ArcGIS Project Raster geoprocessing tool. There was no significant change in the data values and the sum of the values at different resolutions of the GMTED data. MERITDEM data is projected at 100 m resolution as a result of projection transformation. There was no significant change in the values of the GMTED data at different resolutions and the sum of the values. MERITDEM data is projected at 100 m resolution as a result of projection transformation.

Most of the global landform classifications (Kapos, Rhind, Edwards, Price and Ravilious, 2000; Meybeck, Green and Vörösmarty, 2001) used datasets with 1000 m resolution. In these studies, using a rough scale to define mountain and other landforms in terms of macro landform, morphological classes were determined with different analysis windows. However, these classes and the boundaries of macro landforms are

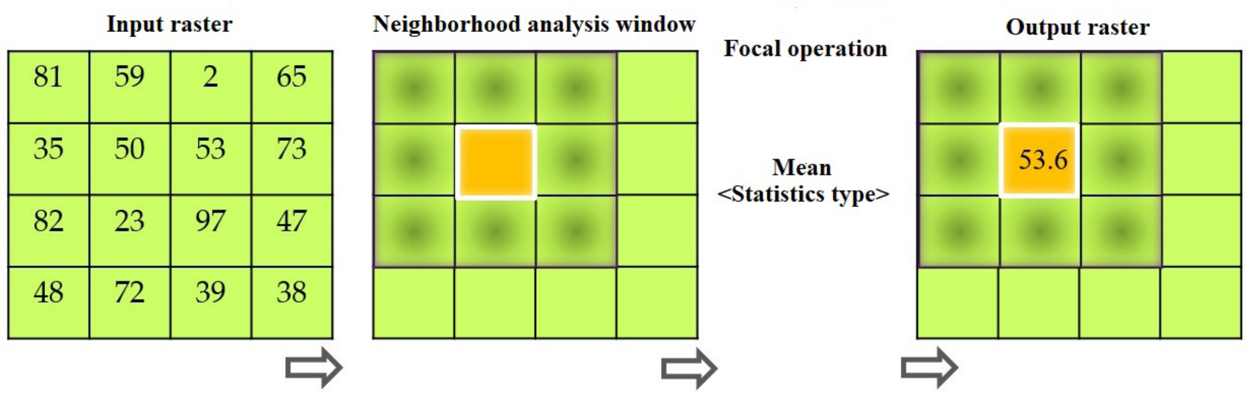

Figure 3: Illustration of calculating a neighborhood statistic "focal - sum." The first figure, from left to right, shows the input raster data. The second figure shows the 3x3 rectangular analysis window, thus the cells included in the process. The box shown in yellow is the processing cell, and after the calculation, it will be the data that takes the average value calculated in the radius, whose size is specified by the user. In the third figure, the same cell in the output scan received the average value of the cells included in the process.

controversial. For this reason, to observe the scale effect on the landform classification selected as an example in this study, first of all, the appropriate scales for the analyses (geographic extent-study areas) were selected, and then analyses were carried out on datasets with different resolutions. In these analyses, morphological parameters were first generated in two different areas with four different resolutions for the scale effect in classification and eight classifications. In the second step, each dataset's classification process was renewed in different analysis windows. In order to evaluate the applied global classification, different window tests were carried out within the scope of the scale used in the classification. These studies were carried out using the ArcMap 10.6 program. The datasets and the selected classification steps are shown in **Figure 2**.

1.3. Neighborhood Operations and Focal Statistics

Statistically, the concept of "neighborhood" is used to express the spatial extent of the frame in which morphological variables are calculated (Smith et al., 2006; Szypuła, 2017). The principle in neighborhood analysis is to calculate the value of a particular raster cell from the values of its neighboring cells (Grohmann and Riccomini, 2009). Neighborhood statistics operations generate an output raster dataset in which the output value at each cell location is a function of the values of cells in a particular neighborhood around the input value at the same cell location (**Figure 3**). The neighborhood frame in which the calculations will be made may have different geometric shapes (for example, rectangle, circle, annulus, and wedge). The size of the neighborhood is user-defined depending on the nature of the operation to be performed. For instance, as seen in Figure 3, a new value is assigned to the processing cell on the output data according to the "average" statistics type calculated in a rectangular neighborhood window consisting of 3x3 raster cells. At this point, the aim is to make heterogeneous areas more homogeneous (**Figure 4**).

It is necessary to determine the optimum horizontal dimensions for a search window focused on each cell in which statistics for each grid cell in a raster data (DEM) will be calculated. As can be seen in Figure 4, this size was determined as 2 km. In the image resulting from the process, the macro landform (mountains) is more prominent and the morphological elements that could be defined at the micro scale disappeared or lost their clarity. At this point, the focus should be on deciding on the window size that will best define the landform. It has been stated that manually specifying different search window sizes for different parts of an area or for different parameters would be a more successful approach (MacMillan and Shary, 2009).

Macro landforms need an expanded assessment of their details. Although generalization procedures have brought many advantages over manual methods in geographic information systems-based landform classification, issues such as determining the optimum scale may pose the problem of extracting appropriate scale-dependent information from a surface. In this study, a global classification procedure was applied to classify mountainous areas to evaluate the differences brought about by the scale and analysis window in describing macro landforms. This classification is the first pixel-based classification attempt to define mountainous areas globally and was made by the World Conservation Monitoring Center (UNEP-WCMC) (Kapos et al., 2000). This pixel-based classification, whose general steps are given in Figure 2, is based on the combination of three morphological parameters and was made using a DEM with 1000 m resolution. The UNEP-WCMC 2000 global definition method is based on elevation and slope, but does not include elevations below 300 m. The UNEP-

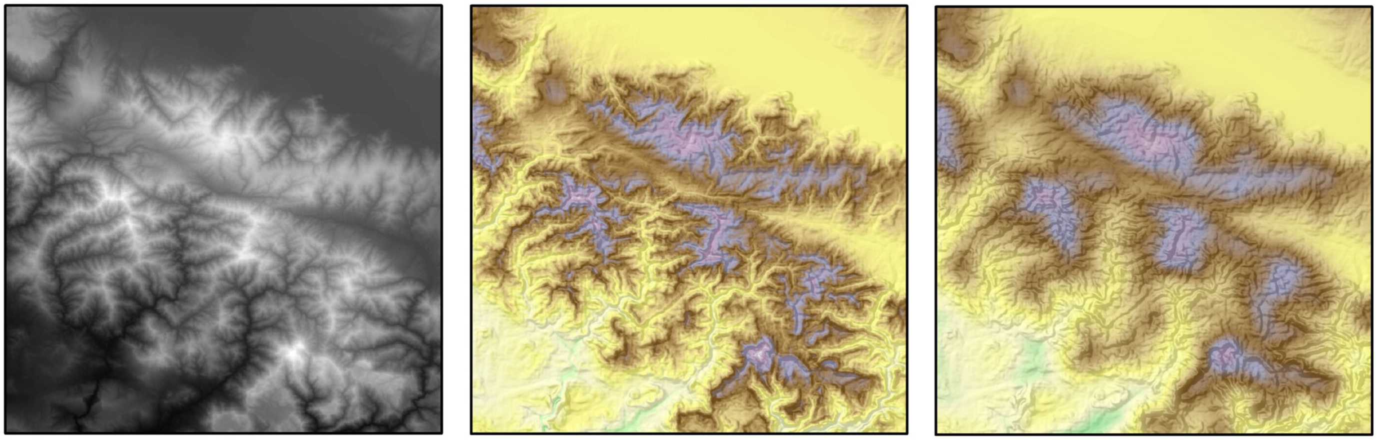

Figure 4: Example of neighborhood statistics. Figure a shows an unprocessed DEM with 100 m resolution (the focal point of geographic extent is south of C, one of the sample areas of this study). The colorized image of the same data is shown in Figure b. In Figure c, an image that results in a new map as a result of a neighborhood statistic is presented. Here is an analysis window process that calculates average values in a radius of 2 km in order to obtain a more homogeneous image.

WCMC approach uses only elevation criteria to define mountain areas above 2500 m and combines elevation and slope criteria to define mountains above 1000 m. To define mountainous areas at lower elevations (300-999 m), an additional criterion based on the local elevation range was used. In this context, morphological parameters were produced for classification and a matrix was formed and classification was made at different scales with four different resolutions (100 m, 250 m, 500 m, and 1000 m). By applying 12 different analysis windows for the "topographic relief," one of the morphological parameters that make up the classification, the difference in defining the landform in the sample area was revealed (**Table 1**). Differences in mountain-plateau and mountain-plain border relations caused by the differences arising from the scale in the sample areas were evaluated with the classifications made within the scope of the analysis window in five different dimensions.

2.4. Determination of Appropriate Scales for Analysis

1.1.1. Sampling Areas

This study focuses on revealing the complex relationship between scale and window size and definitional problems in automatic classifications. Two different fields were selected to reveal these relationships. The area of 55,744.62 km² in the north of the Anatolian plateau, which represents the contrast of the plateau-mountain border relationship, was determined as the first sampling area. The second is the Muş Plain and its surroundings, which reflects the plain-mountain border relationship, with an area of 57,555.56 km² (**Figure 5**; **B-C**). Orogenic movements have a great impact on shaping the Anatolian peninsula (İzbırak, 1983). The Central Anatolian high plateau, in which the first area (B) is located, is bounded by the Pontic mountains in the north and the Taurus mountains in the south (Kuzucuoğlu, Çiner and Kazancı, 2019). High Anatolian orographic margins differ greatly in terms of topographic relief and uplift rate (Görüm, 2019). The area is in the western Pontides, located in the İzmir-Ankara-Erzincan suture zone from the south and the Kırşehir block in the east (Hinsbergen et al., 2016). The second area (C) is the area that covers the Muş basin, extending in the SE-NW direction, which has been under the influence of the uplift and compression regime of Eastern Anatolia. Especially active faults have affected the character of the landforms (Atalay, 1987; Kuzucuoğlu, Çiner and Kazancı, 2019).

Table 1: Different neighborhood window sizes calculated for topographic relief

NAW ID	I	I	III	IV	V	VI	VII	VIII	IX	X	XI	XII
NAW (r) (pixels)	2	4	8	10	12	16	20	24	28	32	36	40
NAW (r) (km)	0.5	1	2	2.5	3	4	5	6	7	8	9	10
NAW (r) area (km²)	3.14	6.28	12.56	15.7	18.84	25.13	31.41	37.69	43.98	50.26	56.54	62.83

NAW: Neighborhood Analysis Window; r: radius

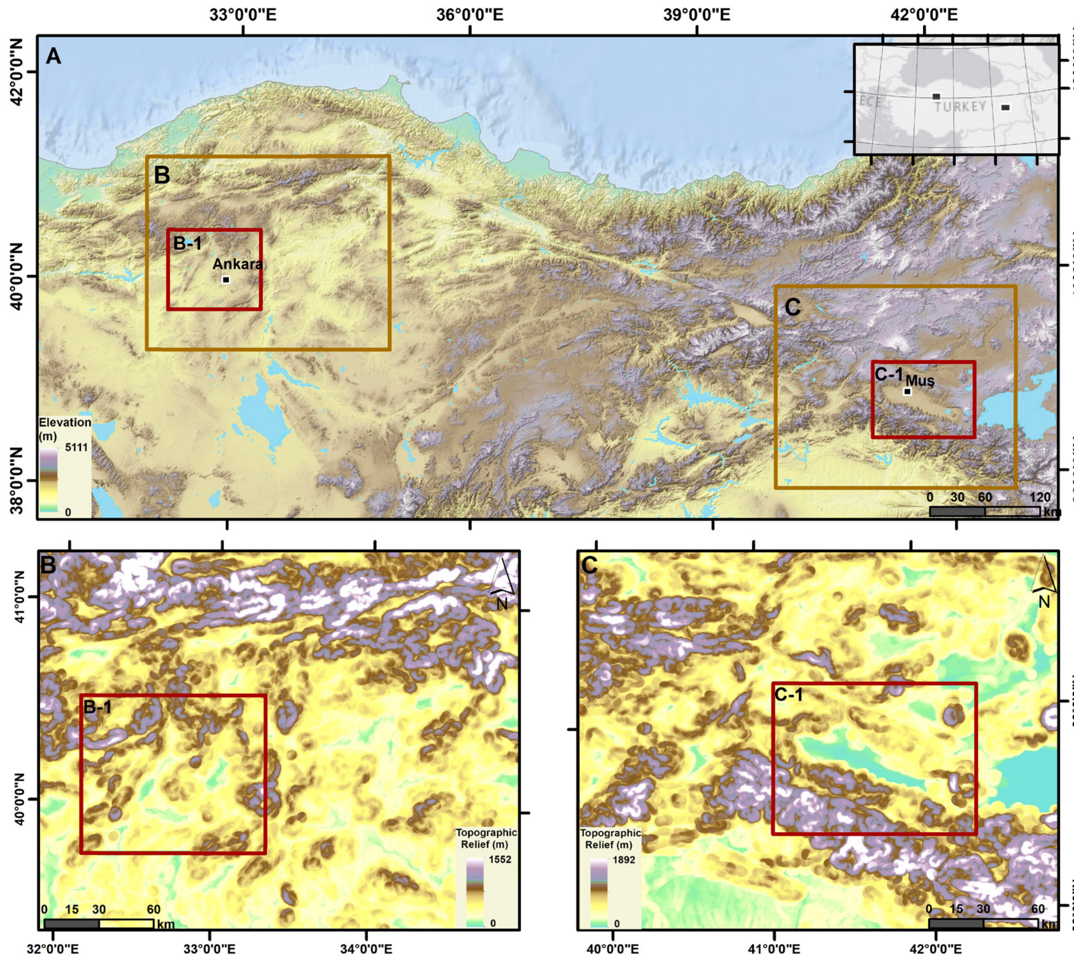

Figure 5: A: The analysis window scale of the parameters used for automatic classifications is the Turkish borders. After the main matrix was created, two main frames were determined (B-C). Additional focus has been placed on areas B-1 and C-1 to illustrate macro landform class relationships.

The basin is located on the Taurus-Zagros orogenic belt. The eastern Anatolian flysch zone is located in the north of the basin and the Bitlis massif in the south (Hinsbergen et al., 2016). The area where the effects of active tectonism are observed in its formation and development is an orogenic basin. The mountains surrounding the basin from the south and north caused it to be limited as a product of high relief. Analysis results are given in B, B1-C, and C1 frames. Since the calculations are affected by the neighborhood relationship, classification steps were applied after the parameters were generated at the Turkish scale (**Figure 1-A**).

2. FINDINGS AND DISCUSSION

1.1. What is the effect of DEMs with different resolutions on the definition of macro landforms?

In order to apply the UNEP-WCMC classification, slope, topographic relief, and elevation parameters in the classification procedure were applied to different digital elevation models in the study, and some of the minimum, maximum, mean, and standard deviation values of these were calculated to understand the data distribution. It has been stated that many morphological parameters will show different properties when derived from DEMs of different resolutions (Kienzle, 2004). As can be seen in Table 2, there is a tendency to decrease in slope, topographic relief (calculation was made within the 7 km radius used in classification), and elevation values from 100 m resolution (scale) to 1000 m resolution. Therefore, the first effect of DEMs with different resolutions on landform definition was on the values of morphological variables. The image variance of each parameter was affected by the DEM resolution. For example, between 1000 m and 100 m resolution, the most affected parameter was topographic relief. As the resolution decreases in digital elevation models, the total number of pixels decreases and the generalization capacity increases. Therefore, the values of the morphological parameters decreased in both areas (B-C). The question to be asked at this stage is how this change toward decrease will affect the classification and the final map.

Table 2: Statistical values regarding the parameters used in classifications

Morphological Parameters								
DEM	**Area B**	**Slope (°)**	**Topographic Relief**	**Elevation**	**Area C**	**Slope (°)**	**Topographic Relief**	**Elevation**
100 m	Min.	0	120	74	Min.	0	0	482
	Max.	64	1851	2561	Max.	65	2322	4033
	Mean	8	697	1074	Mean	10	895	1646
	Std.	7	307	307	Std.	9	426	523
250 m	Min.	0	118	78	Min.	0	0	495
	Max.	47	1836	2545	Max.	51	2277	4026
	Mean	6	680	1075	Mean	8	870	1646
	Std.	5	304	308	Std.	7	416	523
500 m	Min.	0	29	80	Min.	0	0	496
	Max.	38	1778	2499	Max.	39	2244	4007
	Mean	5	643	1076	Ort.	6	812	1645
	Std.	4	298	307	Std.	5	405	522
1000 m	Min.	0	70	87	Min.	0	0	531
	Max.	24	1745	2448	Max.	26	2186	3889
	Mean	4	600	1075	Ort.	5	759	1645
	Std.	3	281	305	Std.	4	375	522

In the classification rules used in this study, areas higher than 2500 m were accepted as mountainous areas without requiring any other additional conditions. There is a slope condition of ≥ 2° in the range of 2500-1500 m and ≥ 5° in the range of 1500-1000 m. In addition, there is a 300 m topographic relief condition for elevations in the range of 1000-1500 m and 1000-300 m. In this classification, 1000 m resolution is used. The basic logic for this selection is that the cell resolution should be lowered in order to classify topographic surfaces dominated by macro landforms such as mountains in horizontal and vertical resolution. For example, if a land surface depicted using a cell resolution of 500 to 1000 m is imaged, only the largest and most prominent macro-scale features of the Earth's surface can be captured and defined (MacMillan and Shary, 2009). However, as can be seen in **Table 2**, as the thresholds of the parameters that make up the classification change according to the resolution, the morphological unit to be defined and its boundaries will also change, moving away from reflecting the reality. At the same time, the standard deviation of parameters moving away from the mean non-regularly disproves the idea that low resolution would be more suitable in describing macro landforms. In this case, creating a classification without data loss in the values of morphological features needs to be done. At this stage, we can say that the analysis window size that will most accurately reflect the definition-boundary relationships should be applied to relatively high-resolution data.

1.2. Multiscale description of macro landforms

The resolution of digital elevation models and the analysis window size plays a vital role on morphological variables and in defining morphometric features depending on terrain features (Ehsani et al., 2010). In this study, the definitional and spatial differences of different sizes of analysis windows and DEM resolutions on macro landform classification were examined in a combination of three morphological parameters. Among these, the topographic relief parameter is the most important feature used to define mountainous areas compared to others. Mountains are a product of topographic relief and the threshold value of the parameter and the window size to be selected affect accuracy in determining boundary relationships in mountain definitions. As a result of the analyses carried out, multi-scale and multidimensional window analyses in the selected areas in **Figure 6** clearly show the change in boundary relations in terms of topographic relief. The second effect (for the same NAW size) of DEMs with different resolutions on landform definition is on the boundaries, which become more unstable as the resolution decreases. We see this with the gradual decrease of the plain area in Figure 6. This effect multiplies as the NAW size increases. In order to understand the window size that will define the mountainous area optimally and have the best border relations, maps were produced in 20 different analysis windows, and as can be seen in Figure 6, different resolution samples are given for five different window sizes. Muş plain and its surroundings can be seen in the zoomed in images of area C. With the help of the hillshade map, the plain border was drawn to draw attention to the deterioration in border relations.

It is clearly understood from the maps that the increase in the analysis window size from 1 km to 10 km, regardless of resolution, disrupts the plain-mountain border relationship

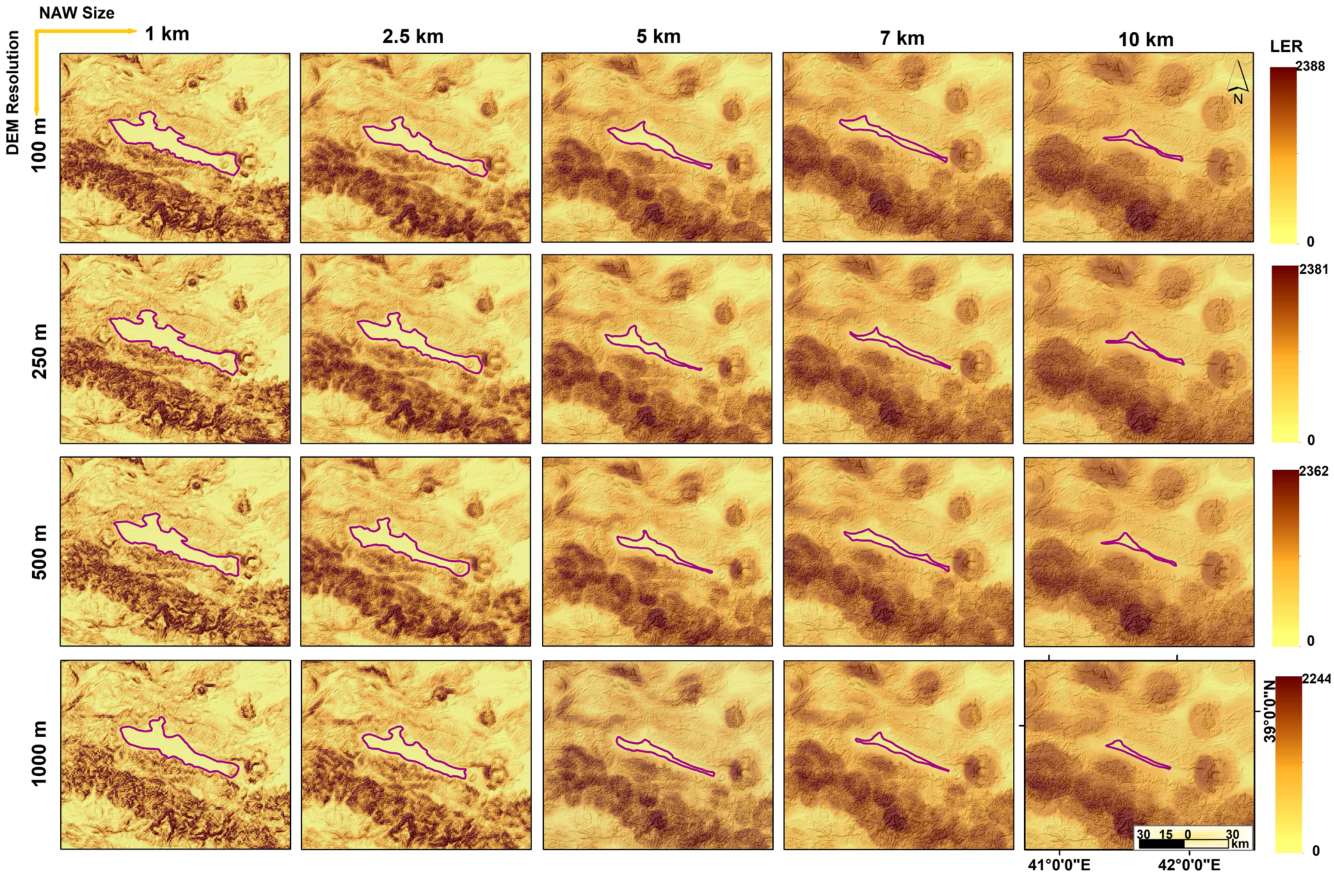

Figure 6: Calculated maps of the topographic relief parameter at different resolutions and different analysis window sizes for the selected area C (NAW: Neighborhood Analysis Window, LER: Local Elevation Range)

(**Figure 6**). The distortions at the boundaries increased significantly after the 5 km analysis window. According to the calculations, while the rate of change between 1 km and 2.5 km window sizes in the topographic relief parameter produced at the same resolution (100 m DEM) was 26%, the rate of change from 1 km to 10 km increased to 87% (the rate of change between 2.5 km and 5 km was 59%, between 5 km and 7 km was 30%, and between 7 km and 10 km was 53%). Considering the DEM resolution only, the rate of change between 100 m and 1000 m resolution is only 14.5% at the 1 km analysis window size (the rate of change between 100 m and 250 m resolution was 0.2%, between 250 m and 500 m was 6%, and between 500 m and 1000 m was 10%). Calculations and maps revealed that the change between mountain-plain boundary relations is more affected by the selected analysis window size rather than the resolution of the digital elevation model. In this context, it is necessary to emphasize two important features of the window size. When the scatter plots of the standard deviation values for the same parameter are examined, it is seen that there is a linear relationship between the increase in the window size and the standard deviation (**Figure 7-8**).

As can be seen in Figures 7 and 8, the increasing window size results in the standard deviation being far from the mean. Thus, we can say that the data are distributed far from the mean, and the smaller standard deviation provides a closer distribution of the data to the mean with the relatively small window size. Likewise, STD+1 and STD-1 values, which we associate with the mean value, also support this interpretation.

The highly complex nature of the land surface indicates that it is mappable down to the molecular level (Goodchild, 2011). This complexity creates uncertainty and makes it difficult to meaningfully define morphological units in terms of their spatial dimensions and boundaries (Fisher, Wood and Cheng, 2004). For example, the definition of a mountain and its boundary features may seem simple at first glance to those who define it only by height. However, it is difficult to give a definite and consistent answer as to what a mountain is or is not (Fisher, 2000). The fact that the features that define the mountain are different in the classifications (for example, boundary conditions) and the uncertainties in the geographical extent show us that the class assigned as a mountain may change according to the perception. This uncertainty leads us to an ambiguity known as the “Sorites

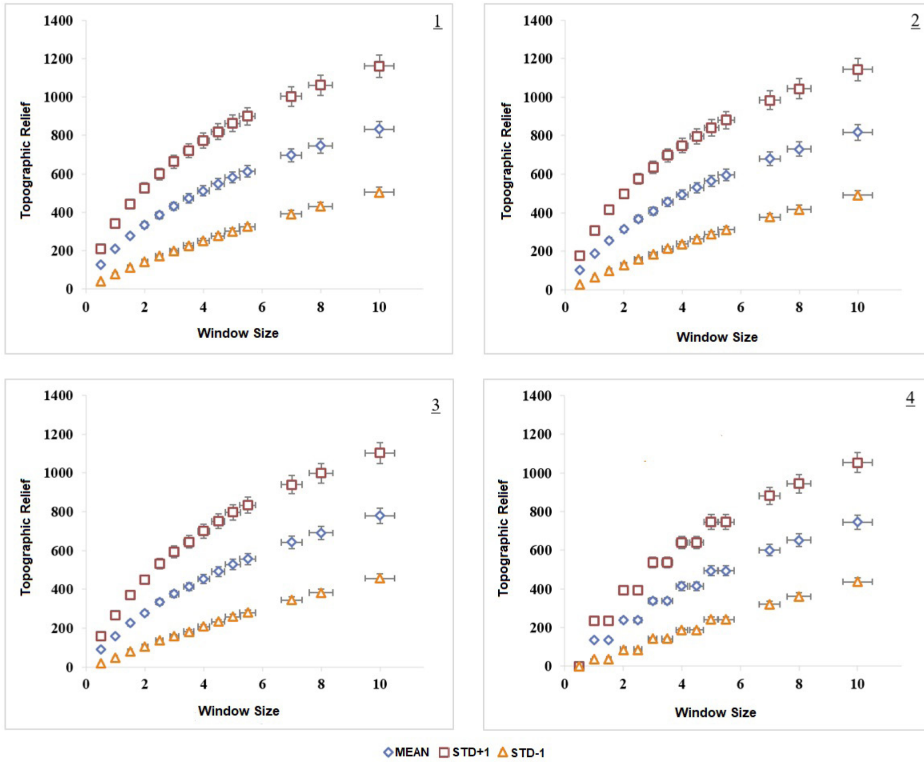

Figure 7: Standard deviation variation of the topographic relief parameter at different window sizes for the selected area B (1st, 2nd, 3rd, and 4th graphs were calculated over DEMs with 100 m, 250 m, 500 m, and 1000 m resolutions, respectively).

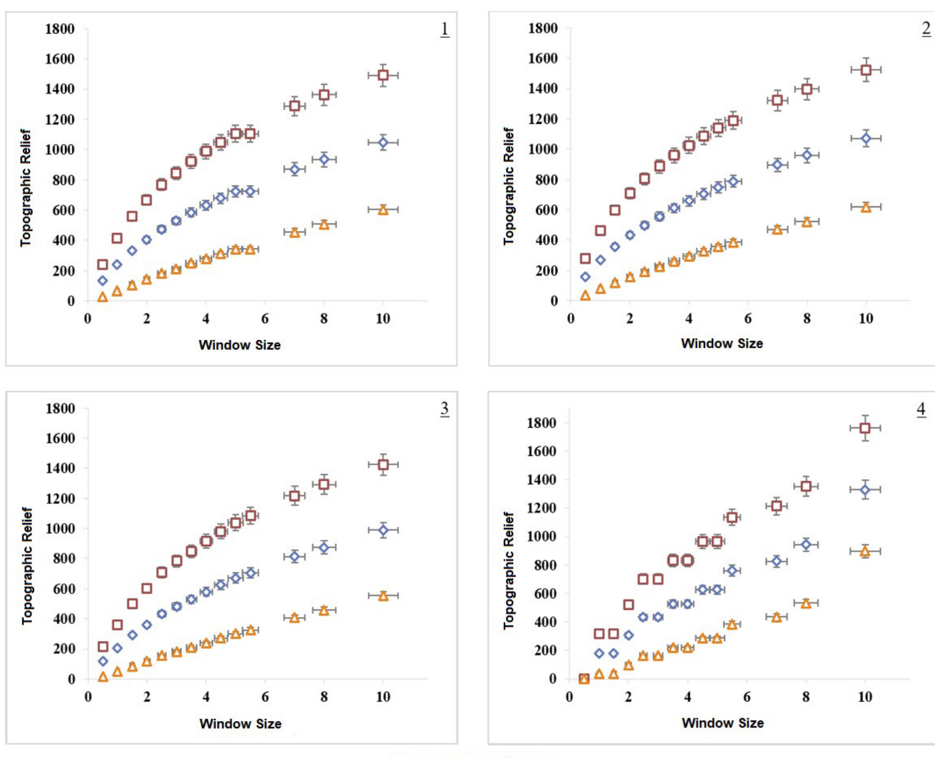

Figure 8: Standard deviation variation of the topographic relief parameter at different window sizes for the selected area C (1st, 2nd, 3rd, and 4th graph were calculated over DEMs with 100 m, 250 m, 500 m, and 1000 m resolutions respectively).

paradox" (Fisher et al., 2004). This concept refers to the complexity associated with analysis scales (Couclelis, 2013). This complexity in the paradox exemplifies the uncertainty that pervades geospatial information by discussing at what scale a heap of sand is still a heap (Fisher, 2000). Landforms are rarely clearly defined due to effects such as the "Sorites paradox," resulting in blurred distinctions between landforms at different scales, such as peaks, hills, and mountains (Sainsbury, 1995). For these reasons, researchers have discussed the fact that it is difficult to define geographical natural objects meaningfully in terms of their spatial dimensions (Wood, 1996, Fisher and Wood, 1998).

2.3. What is the response of macro landform classification to the change of analysis window size?

When we examine the K1 mountain classification maps created with the produced parameters, it is revealed that the mountain-plateau and mountain-plain boundary relations are sensitive to window change, and as the window size increases, there is an increase in the rate of change and the boundary relations deteriorate (**Figures 9** and **10**). DEM with 1000 m resolution was used for classification. Since a resolution of 1000 m was used in the original version of the classification, this resolution was kept constant so that the response to the window change could be well revealed. For example, as a result of the NAW size of 10 km used for area B in Figure 9, almost all of the plateau area is defined as mountain. Likewise, as a result of the NAW size used as 10 km for area C in Figure 10, the plain area (Muş plain) has completely disappeared and is defined as a mountainous area.

It is clearly seen in mountain classification maps that in automatic classifications using DEM, the analysis window must be set to the optimum size for the parameters to correctly define a morphological structure. Otherwise, even the plains in the area indicated by the window size of 10 km can be classified as a mountain (**Figure 10**).

In the evaluation made in this context, it is necessary to emphasize three important features of the window size. These are:

1. As the radius of the window size decreases, the plains come to the fore in the landform that we have determined to be mountains, and it may come to the point where we cannot define it as a mountain (e.g., as in sampling area B with a 1 km search radius in Figure 9).
2. As the window size increases, the plain or flat areas at the front of the mountain begin engaging with this area and the flat areas become defined as mountains (e.g., for sampling area C with 5 km, 7 km, and 10 km search radiuses in Figure 10).
3. Since the generalization has affected the mountain boundary and neighboring areas, optimizing the generalization capacity and, therefore, the window sampling size is necessary. These problems arise in generalization; hence, the window sampling size greatly influences the delimitation of mountainous areas.

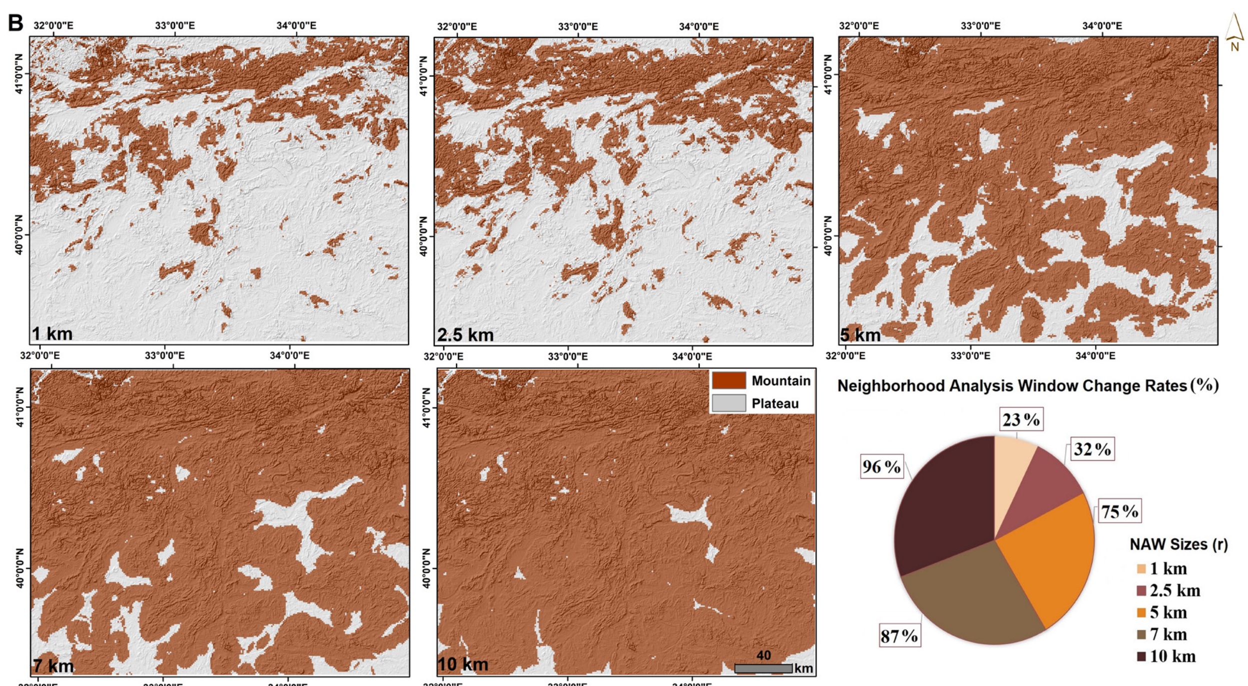

Figure 9: For the selected area B, the mountain-plateau boundary separation and the areal change of the mountainous area at different window sizes

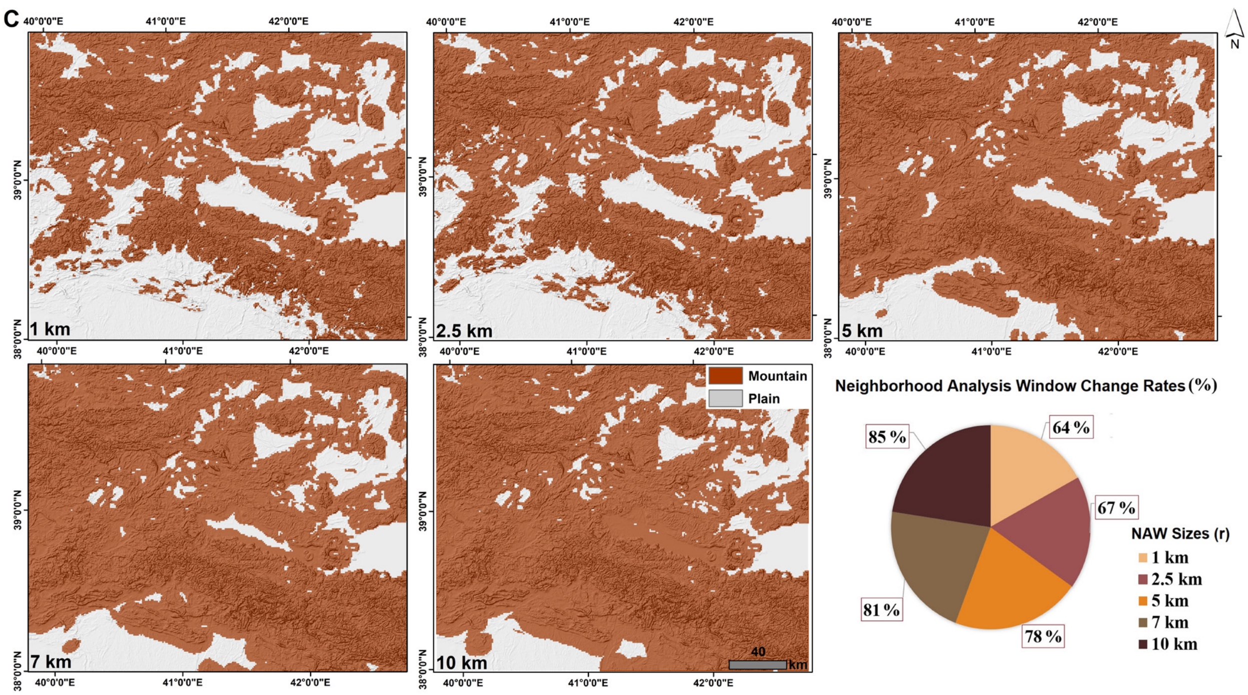

Figure 10: For the selected sample area C, the clarification of mountain-plain boundaries and areal change of the mountainous area at different window sizes.

4. CONCLUSION

In this study, the effect of neighborhood window size and scale on the determination of macro-morphological boundaries calculated from DEMs and on the accuracy of mountain boundaries in mountain definition was investigated. Although the study was carried out in different morphological areas and the relationship between mountain-plateau and mountain-plain border was sampled, similar findings were obtained. First, topographic relief is more sensitive to neighborhood size than elevation and slope. When we compare DEMs with different resolutions within the classification parameters, it has been determined that the topographic relief (the ratio of the maximum elevation to the minimum elevation) is more sensitive than the others and the differences between the coefficients of variance are more pronounced. In landform classification, mountain boundary relationships are more sensitive to analysis window size than DEM resolution. While the difference between the rates of change in macro landform boundary relationships defined from DEMs with different resolutions in the same analysis window is small, the difference in different window sizes calculated on the same DEMs is more significant. The effect of DEM resolution on accuracy in mountain definition and boundary relations is on the data values of the parameters. Data losses increase in DEMs with lower resolution where parameters are calculated. Accordingly, classifications should be made by determining the optimal neighborhood size on relatively high-resolution data, where data losses will be less. The test results, which include combinations of appropriate classification, scale and window sizes for the most accurate descriptions of the selected areas, show that the defined macro landform unity becomes more homogeneous as the generalization capacity increases with the changes made in the window size. In future global studies, higher resolution data and optimum window size combinations will provide a more accurate description of macro landforms.

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