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Araştırma Makalesi Research Article

EFFECT OF THE CURVATURE PARAMETER AND İTS CLASSİFİCATİON ON LANDSLİDES

Seda ÇELLEK[1*],

[1] Kırşehir Ahi Evran Üniversitesi, Mühendislik-Mimarlık Fakültesi, Jeoloji Mühendisliği Bölümü, Kırşehir, Türkiye

Keywords
Landslide Susceptibility, Curvature, Concave, Convex, Parameter.

Abstract
The first question that generally comes to mind about the curvature parameter is whether this parameter is suitable for the study area. This question uses every parameter to be asked, but some effects that are implemented incorrectly, such as curvilinearity, raise question marks. As a result of technical errors and conceptual confusion regarding the parameter, the landslide area defined as concave by one researcher may be defined as convex by another researcher. For this reason, some researchers state that they contradict the literature and produce results contrary to their expectations. Due to such negativities, there is no consensus in the literature regarding curvilinearity parameters. This determination was used for 64 areas selected for curvature parameters in three different classes and the prices of their changes in total. By examining the maximum and minimum distributions in the landslide area, it was investigated what kind of change it caused in concave, convex and flat areas depending on the terrain. As a result of the analysis, it was revealed that class intervals that could not be determined correctly resulted in cracks in the landslide capacity proportional distributions. Thus, the study achieves the main goal that will facilitate the use of the curvature parameter.

EĞRİSELİK PARAMETRESİ VE SINIFLANDIRILMASININ HEYELANLARA ETKİSİ

Anahtar Kelimeler
Heyelan Duyarlılık, Eğrisellik, Konkav, Konveks, Parametre.

Öz
Eğrisellik parametresini seçerken akla gelen ilk soru, bu parametrenin çalışma alanına uygun olup olmadığıdır. Genellikle bu soru kullanılan her parametre için sorulur, ancak eğrisellik gibi uygulama hatası yapılan bazı parametreler soru işaretlerine neden olur. Parametre ile ilgili yapılan teknik hatalar ve kavram karmaşası sonucu, bir araştırmacı tarafından içbükey olarak tanımlanan heyelanlı alan, diğer bir araştırmacı tarafından dış bükey olarak tanımlanabilmektedir. Bu nedenle bazı çalışmalarda, araştırmacılar literatürle çelişmekte ve kendi alanlarının beklentilerinin aksine sonuçlar verdiğini belirtmektedir. Bu gibi olumsuzlular nedeniyle, eğrisellik parametresi konusunda literatürde fikir birliği sağlanamamaktadır. Yapılan bu çalışmada seçilen 64 alan için üç farklı sınıftaki eğrisellik parametresi kullanılmış ve bunların toplamdaki değişimleri incelenmiştir. Heyelanlı alandaki maksimum ve minimum dağılımlar incelenerek bunun araziye göre içbükey, dışbükey ve düz alanlarda nasıl bir değişime neden olduğu araştırılmıştır. Analizler sonucunda, doğru belirlenmeyen sınıf aralıklarının, heyelan alanlarının oransal dağılımlarında farklılıklar çıkarttığı ortaya çıkmıştır. Böylece çalışma ana hedefine ulaşarak, eğrisellik parametresinin kullanımını kolaylaştıracak ip uçları vermiştir.

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[*] İlgili yazar / Corresponding author: sedacellek@ahievran.edu.tr, +90-386-280 38 20

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Seda Çellek[1†],
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Highlights (At least 3 and maxium 4 sentences)

- There is no consensus on the parameter in the literature
- The first question that comes to mind is whether it is suitable for my field of study
- Some researchers use more than one curvature class and create a separate classification
- The most crucial error seen in the studies is encountered even in the most straightforward classification, concave, flat, and convex groupings

Graphical Abstract

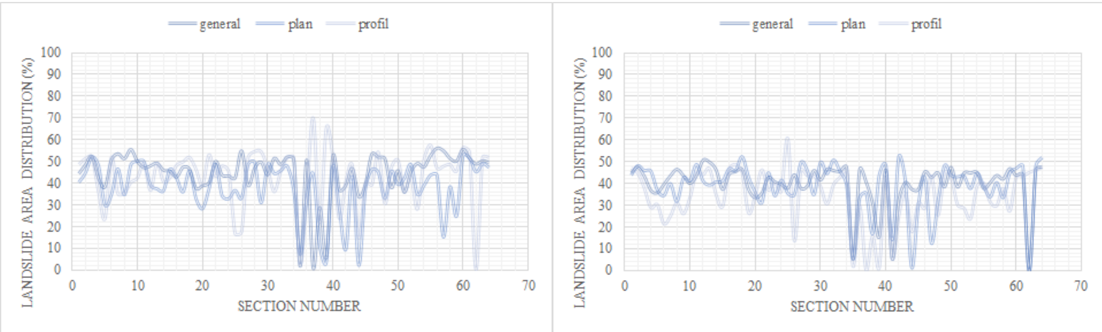

Figure. Perfect Classification and Automatic Classification Cfor % Distribution of Landslide Areas

Purpose and Scope

This study was prepared to find the cause of the problems encountered in the curvature parameter used in landslide susceptibility maps.

Design/methodology/approach

Parameter selection in landslide susceptibility studies is a difficult process. Creating subclasses of the selected parameter is an even more challenging process. The curvilinearity parameter, which has differences in its applications in the literature, was used in this study. In literature research, it has been seen that the parameter has different uses in different studies. For this purpose, 64 landslide maps with a scale of 1,25,000 were selected from Turkey. The program automatically classified and produced a secondary classification that was considered excellent. Error rates between both classifications were determined.

Findings

In the study, it was seen that some studies took the classifications incorrectly and made incorrect mapping as a result of this error.

Research limitations/implications

The study serves as a warning for future studies. It is highly recommended to take this article as a reference when creating subclasses of the curvilinearity parameter.

Practical implications

With this study, an attempt was made to eliminate the conceptual confusion in two of the three subclasses used in the curvilinearity parameter. Correct use of + and - markings in concave and convex classification is given.

Social Implications

In this article, the correct use of the curvilinearity parameter is given. Because there is information pollution in the literature due to incorrect use. As a result of a small number of articles produced with incorrect classification, incorrect map printouts were obtained. Taking this study as a reference will help prevent such mistakes.

Originality

Landslide susceptibility studies are produced in thousands of numbers annually, but studies on parameters are not carried out. It is a first and has a unique value because it is the first analysis study on the curvature parameter.

[†] Corresponding author: sedacellek@ahievran.edu.tr, +90-386-280 38 20

1. Introduction

Curvature, a three-dimensional property of a two-dimensional surface, represents the morphology of the slope. In this way, slope curvatures and slope shapes are revealed (Kornejady et al. 2017). The topography and the slope shape play an influential role in the emergence of landslides. The effect of the parameter on the landslide formation is examined by taking into account the changes in the curvature ratios (concave, convex, flat) and the water and sediment accumulation on the surface, slope, and aspect (Elmacı et al. 2017). These definitions indicate that the parameter has a significant effect on the occurrence of landslides. The confusing question is, why is there no consensus on its use in sensitivity maps when it is such a robust parameter? Or why, while some researchers defend the power of the parameter, some researchers find the parameter inconsistent and useless. In this research, the properties of the parameter were investigated, and a study was conducted on how the parameter could be transformed into a more robust form.

Literature research and application studies have shown that the underlying problem is the lack of understanding of the use of the parameter. Another problem is the errors in the concepts used. In addition, this confusion of the concepts poses a problem at that point when creating parameter classes. While there are class intervals that can be used more standard, confusion and lack of consensus cause chaos on this issue.

The biggest problem in the studies is the chosen curvature class. Again, the literature reveals definition errors in the base classes used. Some researchers confuse plan curvature with a different curvilinearity, and errors occur in the subclasses created. They (He or she) defines the concave area as convex in this way, and the landslide frequency ratios are wrong. Gökçeoğlu and Ercanoğlu (2001) and Özşahin (2015) emphasised that the evaluations regarding the parameter may cause some uncertainties.

Another mistake is in classification. Some researchers, who create three classes with automatic class selection, call these classes outer-inner and flat. This is the basis of the error. In the use of parameters, of course, as in other parameters, the selection of the land and the suitability of the parameter are the most fundamental issues. However, this does not constitute the main subject of errors in using the parameter.

2. Material and Method

2.1. Subclassing The Parameter And Errors Made

Since the parameters are produced directly from the topographic map, the reliability of the data is also sufficient. The main problem in parameters is the preparation of subclasses. Selected grade ranges should reflect terrain conditions as much as possible. The only issue with consensus in the literature on this subject is that the values of zero and around represent flat and near-flat areas. The point of difference of opinions is whether positive and negative values should be considered concave or convex. It is this distinction that is the starting point of errors. Based on this, what kind of curvature is used in the study. Because different curvature values make a different negative and positive classification, most studies use the curvature option of the ArcGIS program produced by ESRI for parameter generation. Plan and profile curvatures can also be made easily by using the same option (ArcGIS). For this reason, the classifications given on the company's page were taken as a basis (Url-1). Table 1 shows which sign is used for which curvature. As known, 0 and close values represent flat and near-flat areas (Figure 1)

When Table 1 is examined, it is seen that the Profile and Longitudinal curvatures have the same marking. It is seen that Plan, Tangential, Cross-Sectional, and General curvatures have opposite markings. Unlike these five curvatures, there is a graded classification from Low to High in total curvature since it is not based on calculation. After choosing the curvature type, classification is started. Classification intervals differ in different studies. In these classifications, especially in rigorous studies, the classifications are restructured and narrowed. The parameter is evaluated gradually in these sensitive studies, and a second classification is made. In such studies, areas without landslides are excluded from the classification.

The literature shows that the parameter is generally evaluated with a triple classification consisting of concave, flat, and convex. For example, in insensitive studies, gaps are reduced to two, and flat areas where landslides are rarely or never seen are excluded from this classification. It is thought that one of the problems encountered in this type of classification is experienced during the determination of the interval values of flat areas with zero values. Here, it is seen that there are differences in taking zero of flat areas, which is thought to be a consensus about the parameter in the literature. For example, El-fengour et al. (2021); used triple classification in the study areas and determined the limit values for flat areas between "-0.05 and 0.05". There are tiny differences in the transitions between "-" and "+" values in the study areas, and the transitions between these values can show vast differences. The transitions between the "-" and "+" values of the land have a significant role in the errors occurring in the class value ranges.

In the literature, there are no four-class classifications. In general, classifications in parameters can be made as single or double. In the literature, at first glance, although it seems that no one uses it in 4-class classifications, as in the dual classification, some people use this classification by reclassifying them.

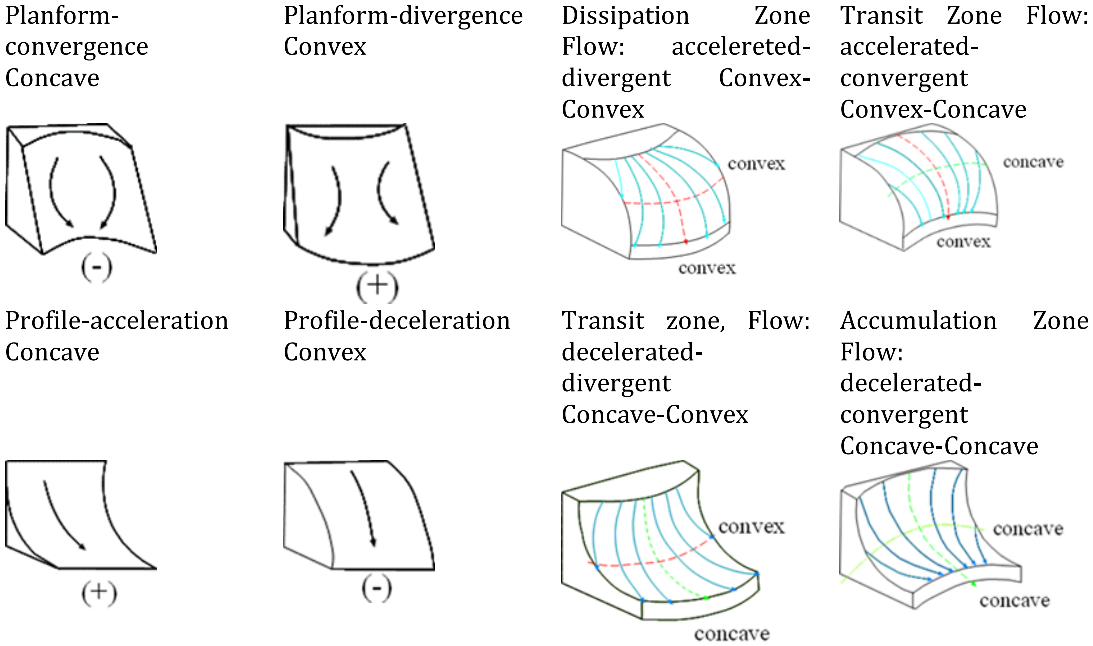

Figure 1. Plan and Profile Curvature

Its use is the same in all curvature classes. Unlike the others, the total curvature does not calculate; it makes the classification in the form of grading, from low to high.

Table 1. Concave and Convex Markings According to Curvature Types

Type	Concave	Convex
Profile	+	-
Plan	-	+
Tangential	-	+
Longitudinal	+	-
Cross-Sectional	-	+
General	-	+
Total	Low-High	

It is used in classifications created by giving value ranges, apart from the classification above. However, some are employed by naming them. In the literature, some studies prepare 5-class classifications using different names. Anis et al. (2019) used plan and profile curvature. He applied the same classification method for both of them separately. They were reclassified using a natural break from Jenks. He expressed the quintuple classification he created with numbers and names (very low, low, moderate, high, very high). Dahal (2014), on the other hand, used a different nomenclature from Anis et al. (2019) (Convex, semi-convex, planar, semi-concave, concave) despite using five classes. In their study, Posner and Georgakakos (2015) created five classes for tangential curvature planar, medium, and high values as positive and negative. Pimiento (2009); profile and plan curvatures are divided into five classes: strongly convex, weakly convex, flat, weakly concave, and strongly concave. However, it was reclassified later and reduced to 3 classes strongly concave, weakly convex, and flat classes.

In studies, concave and convex states can be classified into six classes (Özdemir and Altural 2013; Karaman 2019). Especially in the literature, the 6-class interval is widely used. For example, in Günini (2019), it is used six classes in his study and divided the -1 to 1 into four classes to balance the frequency ratios. He did not calculate the class ranges he changed and flat and near-flat areas (lakes), and he thought that this had a positive effect on the sensitivity map. Some researchers make the classification more precise.

Apart from these, while no study uses seven classifications, studies use 8 and 9 class intervals. For example, Costanzo et al. (2014) used 8-interval classification; Convex/concave, planar/concave, concave/convex, planar/planar, concave/planar, convex/convex, planar/convex, convex/planar. On the other hand, Li et al. (2021) has divided into nine classes for plan and profile curvature, using natural Jenx refraction. The point that draws attention here is that it displays the plan and profile in a different class under a single parameter for those who use multiple classifications.

Another expression used when talking about landslide distribution in studies is balanced distribution. It is seen that this expression is generally used because the two classes are close to each other. Even if one class is slightly more, talking about a balanced distribution is possible. Instead, the expression of homogeneous distribution is frequently used. However, these expressions are commonly used in convex and convex distributions, although very rarely, flat class is also included in some studies. Klose et al. (2014) stated that landslides in the study areas occur in negative or flat areas (-1 to 0) and have a fairly stabilising effect. To stabilise the statistical data, they narrowed the class range in this way. Aras (2021) stated that in the study area, flat areas are more corrugated than others; however, landslides are evenly distributed and even more common on convex slopes. Conforti et al. (2014) determined that the convex and convex slopes are relatively homogeneously distributed in the study areas. Still, the concave (-) slopes' landslide index is higher than the plan curvature. Özşahin and Kaymaz (2013) observed that concave and convex areas are homogeneously distributed in the study areas, but flat areas are more. However, they determined that while flat areas are insensitive to landslides, the highest sensitivity is on convex slopes. In the study of Şahin (2017), landslide areas were sensitive to concave and convex topographies within three factors. After the results are obtained, it is impossible to judge which topographic structure can fully affect landslide susceptibility. For this reason, a more detailed investigation and discussion of the effects of these factors on landslide susceptibility will only be possible after the results of the feature selection algorithms. Çellek (2013), on the other hand, landslides occurring on concave and convex slopes are evaluated together.

Some studies have determined that although a specific class covers more area in the area, it has a low landslide frequency. Eker (2013), on the other hand, found that concave slopes have a higher landslide index, although convex curvature is more in the study area. It is also stated that there are very few flat areas in the study area, but landslides occur in almost all of them and that the landslide index is higher than the convex areas.
The given "+" and "-" values also vary. The "–" value denotes concave in profile curvature, while the "+" value in plan curvature denotes concave. In other words, the first stage of the chain of errors mentioned in the literature occurs here. Likewise, when the general definition is desired, the marking is as in the planform. Unfortunately, some studies ignore this. In general, the approach favours taking the concave as positive and the concave as negative. Kahyan (2021), on the other hand, accepted the opposite, that is, the negative as convex and the positive as concave, without specifying any curvature feature. As a result, he classified the most sensitive areas as convex and the ineffective ones as concave. The higher the negative value, the higher the probability of a landslide occurring. Yüksel (2007) and Taşkanat (2020), on the other hand, approached the subject differently and stated that the degree of saturation increased depending on the surface water drainage. The researcher used general curvature in his study and called (-) values convex. It is a contradictory statement to the general approach.
Another related mistake is that the deceleration-acceleration and divergence-convergence pairs are used for the wrong type of curvature. When the definition of curvature is incorrect, the "+" and "-" values are incorrect, and a researcher who tries to deduce the valley ridge from here interprets the basin entirely incorrectly.

2.2. Effect Of Parameter On Landslide

Slope morphology is one of the most critical factors in landslides. Whether the slope is concave or convex is influential in the formation of landslides (Çil 2009). The parameter controls the state of groundwater and surface waters (Ghobadi et al. 2017). Also, the effect on this hydrological cycle; is the primary determinant of groundwater in the field (Pradhan and Kim 2017), allowing drainage from the slope surface or enabling it to accumulate into the slope, controlling the acceleration or deceleration of the hydrological flow (Çellek 2013).

Irregularities on the slopes affect the stress distributions negatively, and the internal and external stresses of different topographic shapes are also different (Avcı 2016a). In addition, the parameter indirectly affects the geotechnical properties of the material forming the slope.

The parameter controls the state of the superficial materials. Controlling the water cycle increases microclimatic conditions and soil properties and affects the transport of sediments on the slope (Özşahin 2015). It is a very useful parameter in distinguishing the erosion and deposition sections of the land (Wilson and Gallanat 2000).

In the relationship between landslide occurrence and curvature, the more positive or negative a value is, the higher the probability of a landslide occurring. It was mentioned that landslides in 46 studies were concave, 24 studies convex, and 7 studies flat. Although landslides can be seen more frequently in an area other than today, it is generally said to be inhomogeneous mountains in seven studies. In these 75 studies, it can be said that landslides are more intense in two of some classes.

There are studies stating what type of landslides they encountered in which class in the studies reviewed. Table 2 was created with these data (Url-2).

Table 2. Landslides by Curvature Classes

	Flow	Slide	Circular	Rotary	Complex	Rockfall	Debris
Plan concave	X	X	X				
Profile convex	X						
Concav	X		X	X	X		X
Convex	X	X		X		X	
Flat	X	X					
Plan convex	X						

1. Flow, 2. Slide, 3. Circular, 4. Rotary, 5. Complex, 6. Rockfall, 7. Debris

When Table 2 is examined, it is seen that there are researchers who encounter flow-type movements in all kinds of slopes and all situations. Rockfall-like movements are seen primarily on convex slopes. Again, sliding-style movement can be seen in all three slope classes.

Since the morphology that develops after a landslide is concave, as, in every landslide mass, there is a general tendency that convex slopes are more prone to landslides than concave slopes (Hoek and Bray 1977; Jakob 2000). On the contrary, some argue that concave slopes are more susceptible to landslides (Görüm 2006; Çil 2009). Despite these two contrasting examples, many researchers used these parameters in their studies (Mazman 2005). For General and Plan Curvature, Negative values indicate concavity, and the more negative the value, the higher the probability of a landslide (Moradi and Rezaei, 2014). Özşahin (2015) determined that the frequency ratio of the slope shape is higher on concave slopes in the study area. Still, in some studies in the literature, he stated that convex slopes are more suitable for landslide.

For this reason, to eliminate the uncertainty, the Analytical Hierarchy Process (AHP) values of the parameter were assigned according to the frequency ratio result. On the contrary, Chen et al. (2017) and Hong et al. (2017), on the other hand, encountered landslides on convex slopes in the study area while expecting landslides to be on concave slopes and supporting this with literature and flow regime. Kayhan (2021), on the other hand, argues that the researchers do not have a complete consensus on the effect of the curvature parameter on the landslide, as in the same aspect map.

2.3. Landslides Occurring On Concave Slopes Effect Of Concave Slopes On Landslide

The main reason why more landslides are seen on concave slopes is that the morphology that develops after the landslide is concave, as in every landslide mass. The conditions before this landslide affected the concave old landslides in their renewed movement (Görüm, 2006).

In general, concave slopes are most sensitive as they relate to surface and subsurface flow (Zêzere et al. 2007). Many researchers explain this situation (slopes with concave upward surfaces) by retaining more and longer slope rainwater on slopes (Lee and Min 2001; Dai and Lee 2002). After a rain, ground cover on a concave slope can contain more water and retain it longer than on a convex slope (Jakob 2000; Moradi and Rezaei 2014). This process is known as runoff accumulation. Curvature is a measure of the area ofland that contributes surface water to an area where water can accumulate on the surface. Therefore, water is more likely to seep into the slopes and thus trigger landslides (Dahal 2014). Poor drainage causes leakage in front of the ponding and accumulation zone on backward or concave slopes (Lee et al. 2003a). In general, concave slopes are potentially unstable as they concentrate water at the lowest point and contribute to adverse hydrostatic pressure developments (Kayastha 2015). Pore pressure can rise rapidly at the deposition point (Meinhardt et al. 2015). It increases the concentration (pressure) of the pore water (space water) and thus the saturation of the material (Komac 2006). Therefore, water overloads the slope, affecting shear stress (Chena et al. 2017). They are effective on landslides by affecting the groundwater conditions more or less at the rate of permeability of the ground (Görüm, 2006).

It is understood that the erosion power is much higher on concave slopes since the currents will move in the direction of approaching each other (Pradhan and Kim 2017). Therefore, material accumulates as unconsolidated colluvium at the base of the slope, making these areas highly susceptible to erosion and gully formation. This finding was corroborated in a study by Kakembo (1997), in which GIS applications showed that troughs and their debris cut approximately 85% of the accumulated colloid in the study. These areas are more susceptible to landslides since the surface waters on concave slopes have higher carving ratios than on convex slopes. (Çellek 2013). The concave portion of the slope will be susceptible to the accumulation of abrasive material. The deposition of slope materials from debris flows and shallow landslides indicates that transport is faster on concave slopes than on linear slopes (Afungang et al. 2017).

2.4. Effect of convex slopes on landslide

Flow-type landslides are more likely to develop on convex slopes (Harrison et al. 2008). The main reason here is the presence of a free surface in front of it and the potential for more effortless movement (Biber 2019). Since there is no obstacle to holding the material piled up on convex slopes due to gravity, excessive rain, slope, and other factors, it is thought that the accumulated material will gain momentum with these factors (Biber 2019). The velocity varies according to the amount of sediment transported and the linear structure of the slope where they are collected. However, the highest velocity was recorded with rockfalls on convex slopes (Afungang et al. 2017). Ermini et al. (2005) emphasised that slips on convex slopes were observed in the lower and middle parts of the heel. The heel part where the material accumulates (Ermini et al. 2005) and the part where the material breaks (Avcı, 2016b) show a convex profile.

The convex part of the slope is more susceptible to erosion with varying topographic slopes. In heavily drained areas, the landslide mass curves outward. Mostly convex slope-shaped, rough surface topography and flow channel accumulation zone are evident (Aksoy 2010). In many places, convex slopes mark outcrops of strong bedrock in loose rock. (Moradi and Rezaei, 2014).

There are also studies stating that convex slopes are stable against landslides. For upwardly convex sloping faces, the situation will be the opposite of concave sloping (Ahmed et al. 2014). After precipitation events, water flows through areas of convex curvature and accumulates in areas of concave curvature. On the contrary, studies state that such slopes are more consistent. For example, convex slopes are more inclined than concave slopes. Therefore, soil moisture is relatively low on convex slopes due to the rapid movement of water. Convex slopes are more stable as they distribute the current more evenly (Kayastha 2015). Convex slopes allow drainage of surface waters. The convex disperses water better to neighbouring regions, resulting in a more consistent pore water pressure distribution (Meinhardt et al. 2015).

2.5.Effect Of Flat Areas On Landslide

There are very few studies that have encountered landslides in flat areas (Yüksel 2007; Ohlmacher 2007; Akıncı et al. 2010; Avcı 2016b). Çelebi (2021), on the other hand, used the plan curvature and detected the landslides in the straight section. Again, Abe and Ziemer (1991) and Altürk (2019) detected landslides in flat and concave areas.

2.6.Negatives İn Using Parameters

Some studies argue that the parameter is ineffective alone and will be more meaningful if used with specific parameters. This parameter is mainly evaluated with ground and surface waters. There are even studies that associate it with precipitation. In their research, Chena et al. (2017) recommend studying the soil texture parameter and this parameter. This is because the parameter does not come out in the expected values.

On the other hand, inclination angle and aspect effectively produce the parameter. It is thought to be associated with these parameters, albeit indirectly. It is even possible to think that the height can be effective in the material transport distance. The landslide susceptibility is high in concave and convex areas and is evaluated as the slope rather than the slope shape.

In some studies, the parameter was found to be ineffective, and it was stated with which parameters it was ineffective. Dai and Lee (2002) found that slope shape and proximity to drainage parameters were not influential in forming landslides in the study area (Yüksel, 2007). Altural (2012), it is evaluated that the slope rather than the slope shape is more effective in the high landslide susceptibility in concave and convex areas in the study area. Şahin (2017), in his study, determined that the plan and profile curvature and the drainage density factors were the minor weighty factors. The same feature draws attention in these two studies. Water is also ineffective in areas where the curvature is not effective either.

One of the most interesting details about the use of the parameter is the scale used. Although the parameter is not suitable for small scales, it provides more accurate results at large scales. In short, the parameter is more useful in high-scale field studies. Booth et al. (2009), in the study area, it is expected that irregularities in the landslide area, especially in the crown, wings, and accumulation zone, will be observed. Accordingly, concave and convex-shaped slope views will emerge. However, these changes are not distinctive for small-sized landslides and landslides that lose their shape over time (Aksoy 2010). This suggests that the smallest-scale variations of these parameters do not represent well the physical processes of landslide triggering, as indicated in some previous studies Freer et al. 2002; Tarolli and Tarboton 2006; Paudel et al. 2016).

Another issue is the naming of the parameter. Slope curvature can be included in the classification as slope geometry. This slope shape also includes curvature and length parameters (Hasekioğulları 2010). However, the correctest name for the parameter among these is slope curvature.

Again, one of the biggest problems with the parameter is the lack of a standard for the curvature parameter among researchers and other parameters (Başara 2021). The most significant limitation of the parameter is the absence of a generalisation to be used in classification. In the studies that do not pay attention to the curvature used, the subject is carried in different directions, creating an ineffective impression of the landslide. Although the slope shape parameter is not widely used in landslide susceptibility assessments, it is considered in some studies (Yüksel, 2007). Although there is a tendency in the literature that convex slopes are more susceptible to landslides than concave slopes, there are opinions on the contrary which argue that concave slopes are more susceptible to landslides. Başara (2021), in his study, showed that the curvature parameter was not suitable for the study area since all the methods he created were close to each other in the curvature classes.

Another difficulty encountered in the use of this parameter is that it becomes difficult to collect statistical data on this parameter because of the shape of the slopes changes after the landslide (Gökçeoğlu and Ercanoğlu 2001).
In the literature, it is seen that some curvatures are mismarked. For example, studies use the phrase that positive values in plan and profile curvatures indicate that the slope surface is convex (convex, peak), negative values indicate that the surface is concave (concave, pit), and a zero value indicates that the surface is linear. This contrasts with the program's markup because plan and profile Curvatures have opposite markings.
In order to examine the errors in the parameter classes in the study, parameter maps of general, plan, and profile curvature were created on 64 randomly selected landslide maps. The results are analysed comparatively. The study formed classification groups consisting of concave, convex, and flat.
According to the general plan and profile curvature, class ranges were prepared for 64 study areas. First, three classes were selected, and the graphs of the values prepared according to the automatic assignment were drawn. Next, these 3 class ranges are split into – and + values. The zero value is reduced to the most sensitive value possible. This new classification is called perfect classification. The ideal classification was prepared in the same way for the other groups created. The original and ideal classification for all fields is given in Figure 2.

When Figure 1 is examined, the percentage distributions of all areas show homogeneity in the flat area, while it shows different distributions for concave and convex. The differences in the distribution are due to the profile curvature. While the distribution for the general and plan curvatures shows similar characteristics, the profile curvatures are distributed on the opposite side of them. The biggest reason for this is that the plan and the general have the same marking, while the profile curvature has a different marking. There is a more homogeneous distribution than automatic in the percentages of distribution prepared for perfection. The classes showed close distribution in all curvatures according to the other classification. The values of all three classes show settlement in a particular area. If an evaluation is made between the original class and the perfect class, all classes have a different distribution. Percentage distribution changes in concave, flat, and convex areas presented remarkable differences. These class changes were clearly seen in all three curvatures.

In concave areas, the plan curvature has a distribution of around 50%, while this value has changed to values ranging from 0 to 60% for perfect classification. General and plan curvatures have lower and scattered values compared to the profile. In perfect classification, an increase is observed in the percentage values of these two curvatures.

When the distribution of flat areas according to curvature is examined, it is seen that they have an approximately homogeneous distribution according to all three curvature types within specific limit values, except for exceptional plots. However, when examined in perfect classification, there is a severe change in the % distribution of all areas. Areas with an overall distribution of between 20% and 60% were severely dispersed, and values ranged from 0 to 100.

Convex areas show an opposite distribution of convex areas. While the plan and general curvature were together again, they were located on the opposite side of the profile. Compared to the other two of the profile curvature, the result of the significant difference is also evident here. However, in the perfect classification, these contrasts disappeared, and a more homogeneous distribution was achieved in all three curvatures.

Concave areas showed a distribution as in all area % distribution charts. The profile curvature gave distributions on the opposite side to the plan and overall curvature, that is, at high values.

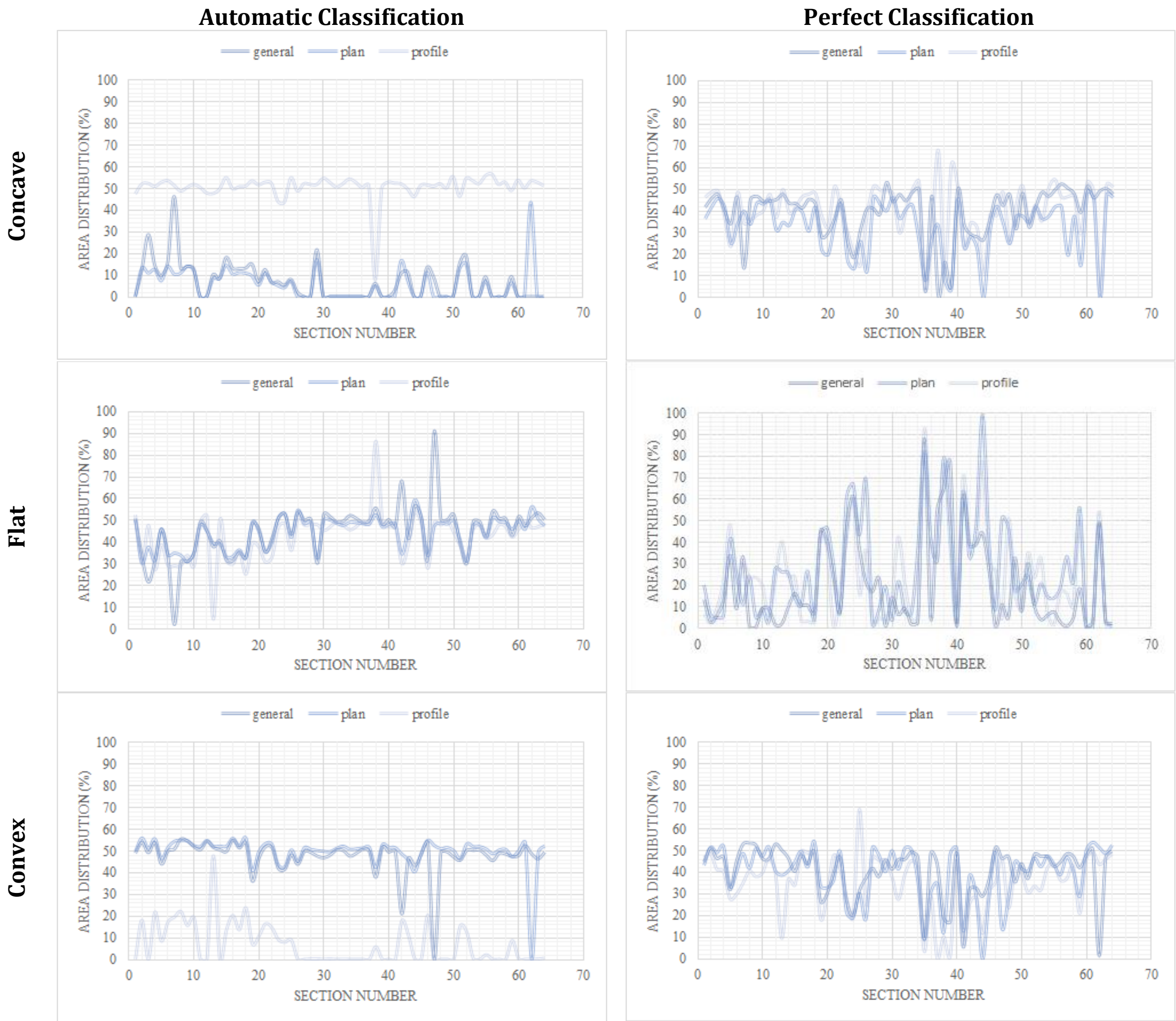

Figure 2. Perfect Classification and Automatic Classification Prepared for % Distributions of all Area

Strategy and general curvature values share lower percentage values. In concavity, which shows a homogeneous distribution in perfect curvature, the profile curvature, albeit slightly, gives slightly higher percentage values than the others.

When the distributions for flat areas are examined, the values varying between 30 and 60% show an approximately homogeneous distribution for all curvatures when the exceptions are ignored. In perfect classification, on the other hand, these values show a near homogeneous distribution in a different area between 0 and 50.

Finally, when the convex values are examined, it is seen that they have the opposite distribution of the concave. When the exceptional layouts are ignored, the distributions are around 50% in the plan and general curvature. When the profile curvature is examined, it is seen that these values are distributed around 10%. When the distributions for perfect classification are examined, it is seen that it gains homogeneity again. Still, half of this distribution is between 55% and 25%, and the other half has values ranging from 60% to 0%.

Landslide densities were calculated using the formula given below for the study area.

$$Landslide\ Area\ Density\ (\%) = \frac{Landslide\ Area\ of\ Parameter\ Subclass\ (km^2)}{Landslide\ Area\ (km^2)} \qquad (1)$$

In Figure 3 the % distribution created for landslide areas is seen. Likewise, the original and perfect classifications were prepared within this group, and the opportunity for comparison was provided.

The most crucial issue for the studies already done is their distribution according to the landslide frequency, according to concave, flat, and convex areas. In Figure 4, distributions according to landslide densities are given.

While the % distributions prepared according to the concave slopes show a nearly homogeneous distribution in all three curvature types, the landslide distributions give a higher rate in the parameter of the general curvature.

Figure 3. Perfect Classification and Automatic Classification for Percent Distribution of Landslide Areas

These rates take values ranging from 0 to 90%. When we look at the distributions in perfect classification, the distributions again show homogeneity. Similarly, high values give general curvature. However, except for a few areas, it is seen that the distributions take values varying between 10% and 50%.

When the landslide densities for flat areas are examined, it has been determined that these values vary between 10 and 60%, except for exceptional values, according to the automatic classification. Here again, it is seen that the general curvature gives the greatest concave values—this homogeneous distribution distortion between general and profiles curvature in perfect classification. In general, it is seen that the distribution takes values varying between 10 and 50%.

Finally, changes in convex areas were investigated. It is also seen here, although not as concave between the two classifications. When the automatic classification is examined, it is seen that the distribution is close to homogeneous, while the concave distribution is more in the curvature of the profile. The distribution percentages generally vary between 10 and 50% in convex areas of landslide densities. When their places in perfect classification are examined, it is seen that concave curvature values in a distribution close to homogeneous give greater results in profile curvature. Distributions are seen between 20% and 50%.

In the study, the % distributions of the total areas were also prepared for automatic sum and perfect classification. For this purpose, all concave, flat, and convex areas in 64 areas were collected (Figure 5).

For concave values, when viewed in automatic classification, plan and profile have the same percentage distribution, while overall curvature takes a smaller value. For perfect classification, this distribution changes completely. Plan curvature has a greater value even if the profile and overall curvature are close. The most striking aspect of this classification is that the profile curvature takes its value in the lowest %.

The distribution for flat areas lost its homogeneity in automatic classification and gave the highest overall and lowest profile curvature values. In perfect classification, the distribution showed a different distribution. Profile curvature has the highest value, while plan curvature has the lowest value.

Finally, the classification for convex areas is examined. It gave the same percentage distribution as the concave for automatic classification. The distribution was realised as the opposite of concave when evaluated for perfect classification. Plane and overall curvatures have the same percentage but show a similar but larger percentage distribution in the profile.

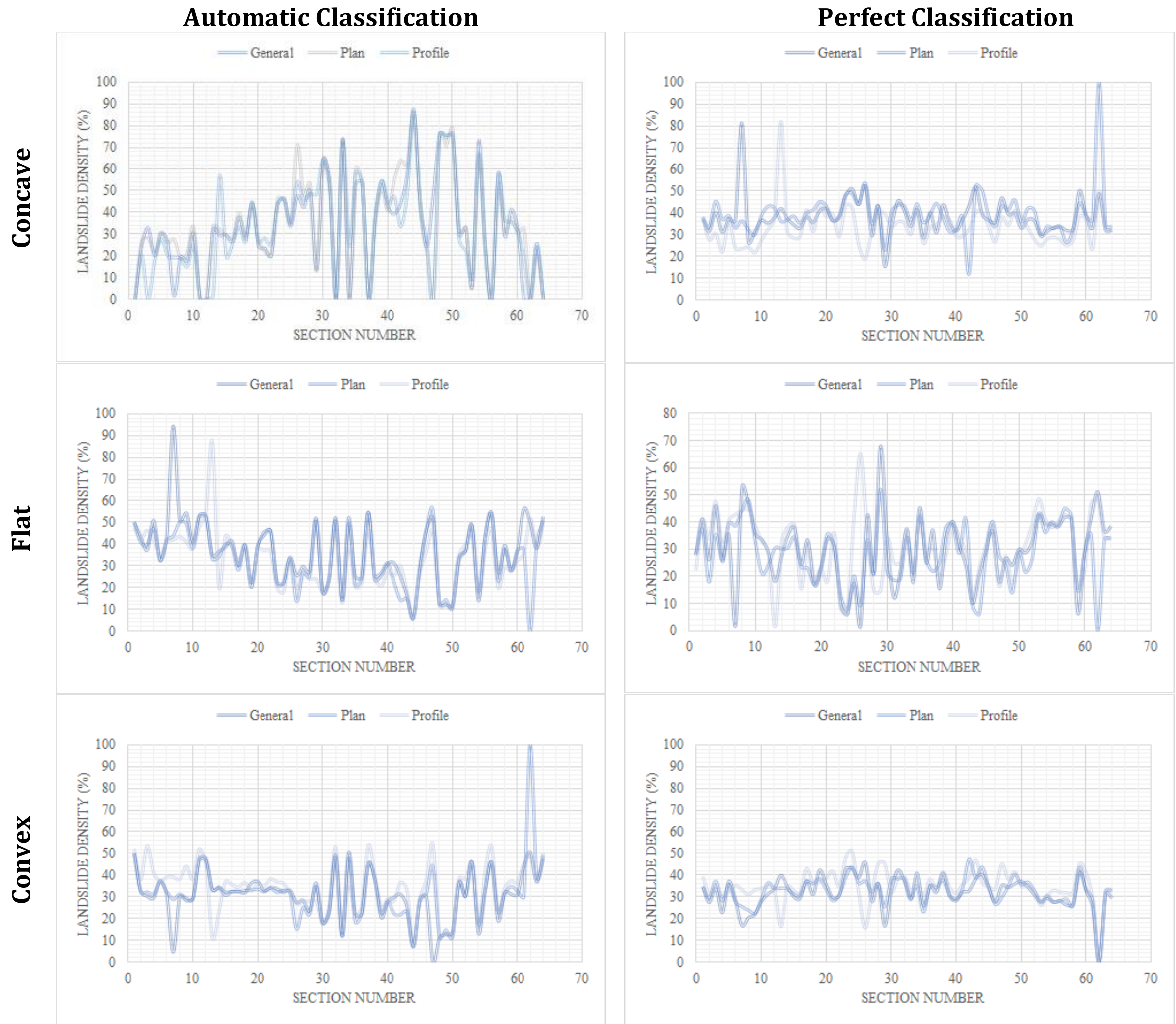

Figure 4. Perfect Classification and Automatic Classification Prepared for Percent distributions of Landslide Densities

3. Results

In the literature search, it was understood that the biggest problem experienced in not assigning subclasses of the parameter came from the marking. Differences in markings have led to different interpretations in studies. In A parameter that is easy to use and simple to implement has been tried by some researchers to make it more complex and incomprehensible by evaluating it from different perspectives.

On the other hand, some researchers misused the parameter, making it even more straightforward than it was. Few researchers have determined the type of curvature suitable for the study area and used it in its application. In addition, they approached the classification of the parameter more sensitively and found correct classification intervals by trial. On the other hand, many researchers use the parameter in the literature with hearsay information and quotations. A group of researchers, who analysed only through the program, ignored the classification parameters, found contradictory results, and contributed to the information pollution in the literature.

The basis of these errors is not based on the primary articles that reveal the use of the parameter but inspired by the researchers that used it in their studies. These main articles, which are constantly in circulation from one language to another, evolve into a completely different article each time with the participating interpretation. After a while, the subject is assimilated and misinterpreted differently by some researchers

Again, one of the biggest mistakes encountered in the literature is the misidentification of "+" and "-" values. This definition also causes incorrect creation in prepared classes. Insufficient research or misinterpretation of the literature causes the areas that should be considered concave in some studies to be evaluated as convex areas.

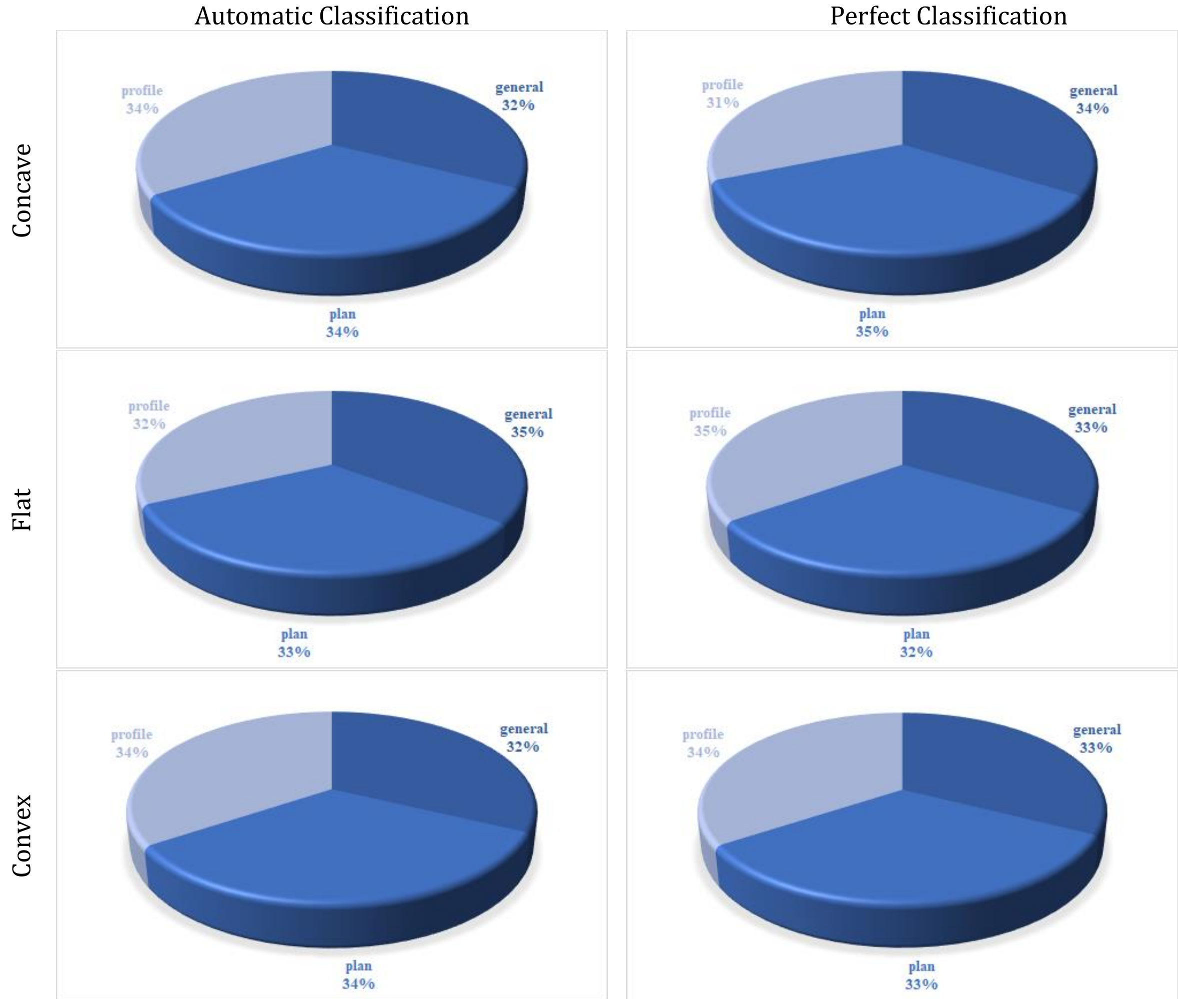

Figure 5. Representation of Percent Distribution Changes According to Total Areas in Original and Perfect Classification

4. Discussion And Conclusions

In the study, a detailed literature study was conducted to understand the cause of the problems experienced in the slope curvature parameter. An application was made on 64 selected landslide maps to reinforce this. In this study, which is the second part of the twin articles, the problems encountered in the subclasses of the parameter were examined.

The most crucial error seen in the studies is encountered even in the most straightforward classification, concave, flat, and convex groupings. The software makes assignments according to the desired class groups. Although this process differs for each land, it gives tremendous differences in areas with a high difference between "+" and "-" values. Even in such studies, there is no standard in limit values for flat areas, and areas considered concave or convex are still included in flat areas.

Again, the other issue that does not reach the standard value for the parameter or does not make any suggestions or recommendations is the class interval numbers. These numbers vary between 2 and 9. Some researchers use more than one curvature class and create a separate classification. Some researchers collect all of them under a single parameter and increase the number of classes. While some researchers prefer a graded classification, others increase the number of classes in the - or + direction, depending on the condition of the land. While some researchers take this approach as if the land is homogeneous, some researchers consider the difference between + and - values and create classification groups accordingly. Another approach encountered in class ranges is double classification. Insensitive classifications, while some researchers eliminate areas that cannot be landslides with the second classification, some researchers narrow the range values and increase the frequency value in the resulting map.

As a result, there is no consensus on the parameter in the literature. In this study, it is revealed in this research that the issue of whether landslides should occur most frequently on concave or convex slopes is in vain trying to set a standard. It has been revealed that this parameter, like other parameters, has its values and that none of its steps can bring it to the standard. In conclusion, this is the place of the famous expression put forward in landslide susceptibility maps. Each study area has its characteristics. However, of course, the knowledge of the literature should be able to put us in expectations for some fields of study.

Practical studies have shown that if enough sensitivity is not shown in the selection of class ranges, changes occur in the results. Again, studies conducted for 64 fields indicate that the parameter does not have a standard. It is not helpful for every field, and the parameter does not mean that it is meaningless in different fields. With the twin studies, the intense information about the parameter in the literature was compiled and tried to be presented more straightforwardly and accurately as possible.

Declarations

This article does not contain any studies with human participants performed by any of the authors beyond that which is described in the text.

Conflict of interest

The author declares no competing interests.

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