Front. Earth Sci. 2022, 16(2): 352–367
https://doi.org/10.1007/s11707-021-0884-y

REVIEW ARTICLE

Deep learning of DEM image texture for landform classification in the Shandong area, China

Yuexue XU[1], Hongchun ZHU (✉)[1], Changyu HU[1], Haiying LIU[2], Yu CHENG[1]

1 College of Geodesy and Geomatics, Shandong University of Science and Technology, Qingdao 266590, China
2 College of Computer Science and Engineering, Shandong University of Science and Technology, Qingdao 266590, China

Abstract Landforms are an important element of natural geographical environment, and textures are the research basis for the spatial differentiation, evolution features, and analysis rules of the landform. Using the regional difference of texture to describe the spatial distribution pattern of macro landform features is helpful to the landform classification and identification. Digital elevation model (DEM) image texture, which gives full expression to texture difference, is key data source to reflect the surface features and landform classification. Following the texture analysis, landform features analysis is assistant to different landforms classification, even in landform boundary. With the increasing accuracy requirement of landform information acquisition in geomorphic thematic mapping, hierarchical landform classification has become the focus and difficulty in research. Recently, the pattern recognition represented by Convolutional Neural Network has made great achievements in landform research, whose multichannel feature fusion structure satisfies the network structure of different landform classification. In this paper, DEM image texture was taken as the data source, and gray level co-occurrence matrix was applied to extract texture measures. Owing to the similarity of similar landform and the difference of different landform in a certain scale, a comprehensive texture factor reflecting landform features was proposed, and the spatial distribution pattern of landform features was systematically analyzed. On this basis, the coupling relationship between texture and landform type was explored. Thus, the deep learning method of Convolutional Neural Network is used to train the texture features, and the second-class landform classification is carried out through softmax. The classification results in small relief and mid-relief low mountains, overall accuracy are 84.35% and 69.95% respectively, while kappa coefficient are 0.72 and 0.40 respectively, were compared to that of traditional unsupervised landform classification results, and the superiority of Convolutional Neural Network classification was verified, it approximately improved 6% in overall accuracy and 0.4 in kappa coefficient.

Keywords DEM image texture, comprehensive texture factor, texture spatial pattern features, Convolutional Neural Network, landform classification

1 Introduction

Under the comprehensive action of the internal and external forces (Cheng and Zhou, 2014), Shandong area has formed different landform types, such as plain, hill and mountain area, which constructed diverse regional landform types (Xu et al., 2009). Systematic acquisition of regional landform feature objects, analysis of landform feature parameters, and fine classification of landform are the research hotspots in geoscience research. Landform morphology exhibit significant difference reflection in different landform features, and accurate analysis of landform features are key steps to describe the landform classification and to understand internal geomorphologic formation process in a specific region. At present, most of the researches on landform features are terrain factors, which used for excavating the quantization rules of local landform. But the results show that the ability of terrain factors is insufficient to grasp the spatial features of landform, and the accuracy is low in landform type recognition or classification. The complexity of landforms determines that the study of landform occupies an important position in the field of geography. In particular, correctly reflecting the macroscopic landform features is the basis for the accuracy of landform classification.

Early studies on landform classification, combined with the landform information, classification principle, and

Received September 25, 2020; accepted January 26, 2021

E-mail: sdny_xa@163.com

systems, can be traced back to manual and field observation. However, with the development of digital terrain analysis technology, digital elevation model (DEM) plays an import role in landform research (Band, 1986; Zhu et al., 2018a), in which DEM is the vital data source for describing terrain relief (Chen et al., 2014a; Tang et al., 2015) and landform spatial patterns (Chen, 2020) which are the measure for extracting the texture information. Based on the diversity of theoretical research, a variety of landform classification methods are found. Some methods are based on the morphological index (Arrell et al., 2007), that is, threshold classification of terrain factors, such as decision tree method (Iwahashi and Pike, 2007). Other techniques employed supervised (Prima et al., 2006) and unsupervised classification methods (Piloyan and Konečný, 2017) to classify landforms on multiband images that composed of terrain elements, as well as fuzzy C-means algorithm. On the basis of what was aforementioned, scholars have improved the disadvantage of lacking spatial relevance in pixel classification (Bricher et al., 2013). An object-oriented classification method for landform was proposed (Drăguț and Blaschke, 2006; Eisank et al., 2011). Besides, topographical position index was also used for classifying landforms (Mokarram et al., 2015; De Reu et al., 2013; Halls et al., 2018). In addition, considering the structural features of landform surface, many scholars began to carry out landform classification from the perspective of visual perception and quantitative calculation. Texture-based research on the DEM image data is one of major topic in landform classification (Bugnicourt et al., 2018).

For those combined elevation region and varied morphology geomorphologic landscape, the texture features of visual perception mechanism can be used to distinguish the difference of landforms. Since texture is a process of integrated visual perception and the basic feature of image, DEM image texture can reflect the spatial distribution of pixel grayscale pattern and give consideration to the macroscopic and microscopic features, which is an extremely important analysis method for object recognition and image classification (Wang et al., 2015). Applying texture theory, researchers have identified and classified landslide terrain in the DEM image (Chen et al., 2014b; Mezaal and Pradhan, 2018). The properties of DEM image describe the consistency and the difference of the texture gray value in a region. Moreover, in terms of visual perception, texture primitives exhibit the arrangement characteristics of local random and global regular, which determines that statistical texture analysis model is an appropriate analysis model. The most commonly used statistical texture analysis model is gray level co-occurrence matrix (GLCM) method. Based on the texture attributes, some scholars have further applied texture to the study of landform classification, contributions are as follow: the optimal texture feature parameters were calculated and employed to classify landforms using the support vector machine method (Volpi et al., 2013; Zhu et al., 2019). With the breakthrough in the traditional classification method, machine learning methods (i.e., random forest and back propagation neural network) combined with texture feature analysis were obtained good results in different landform classifications (Zhi et al., 2014; Zhao et al., 2017; Franklin and Ahmed, 2017; Liu et al., 2013). Moreover, studies have proved the feasibility when using CNN method to classify landforms (Basu et al., 2018; Shumack et al., 2020; Li et al., 2020). For example, CNN method emphasizes the superiority of texture and color feature, so it can improve the classification accuracy (Ahmed and Ahmed, 2019; Du et al., 2019).

The preceding analysis indicates that some of current studies on landform classification generally rely on terrain factors. However, the quantitative analysis of the macro-morphological features and genetic mechanism in a specific region is difficult to perform. Other studies rely on the texture parameter object to achieve the purpose of landform classification via different methods. Only a few studies have deeply explored the strong coupling relationship between texture and landform type from spatial distribution of texture features. Therefore, to construct quantitative factor and index systems are urgent problems that should be solved. It was designed to reflect macro-landform features and implementing an efficient feature extraction through the DEM image data. Others valuable research topics are: whether the spatial pattern differentiation law of landform features can be quantitatively explored, and whether the coupling relationship between texture and landform types can be achieved by constructing texture factors through DEM image data and texture feature analysis. Given this idea in the DEM data, landform samples in the Shandong area were selected as the analytical data. The texture analytical method of GLCM was adopted to construct the comprehensive texture factor for analyzing macroscopic landform features, and then the differentiation law was analyzed quantitatively based on the spatial distribution pattern of texture features. According to the consistency between the boundary of landform classification and the transition of landform features, the intensity of the coupling relationship between texture and landform type was obtained. Finally, the sample features of texture were trained using CNN method, and hierarchical landform classification was conducted. Compared with the traditional classification method, the accuracy results of landform classification based on CNN method are greatly improved by calculating the texture feature.

2 Materials and methods

2.1 Study area and data

The study area was located in Shandong Province, China, where mountains rise in the central area, plains extend in the southwest and northwest areas, and gentle hills stand in the east region (Mao, 1993). These landforms comprise a complete terrain trend, in which the mountains and hills are considered as framework, and the plains and basins are distributed in a staggered manner (Fu et al., 2018), all of those are conducive to the analysis of landform features in whole Shandong Province. Varying reliefs can create different landform types and map out rich terrain texture thereafter (terrain texture, in a narrow sense, is DEM based terrain texture. That is affiliated with terrain parameters in visual perception, which mainly used to represent the morphological relief of different landforms). The mid-southern mountainous area and eastern hilly area were selected as two typical sample areas according to the altitude and morphological indices of relief, that is, the classification scheme of digital land geomorphology of 1:1000000 in China, (Shi, 2013; Zhou et al., 2009). Given the vastness of China's mountainous area, the classification of mountains should be given substantial attention. To achieve hierarchical landform classification and satisfy the repeatability of the texture primitives and stability of the model, 43 low-mountain samples were selected in the subset area to calculate the GLCM feature parameters. Of these cases, 24 samples with the size of 100 × 100 pixels are described in box A1, and 19 samples are contained in box A2. Thereinto, A1 and A2 were represented by red rectangle in Fig. 1. The location distribution of sample area is shown in Fig. 1(a) and the typical samples are shown in Figs. 1(b)−1(c). The experimental image data was the Advanced Spaceborne Thermal Emission and Reflection

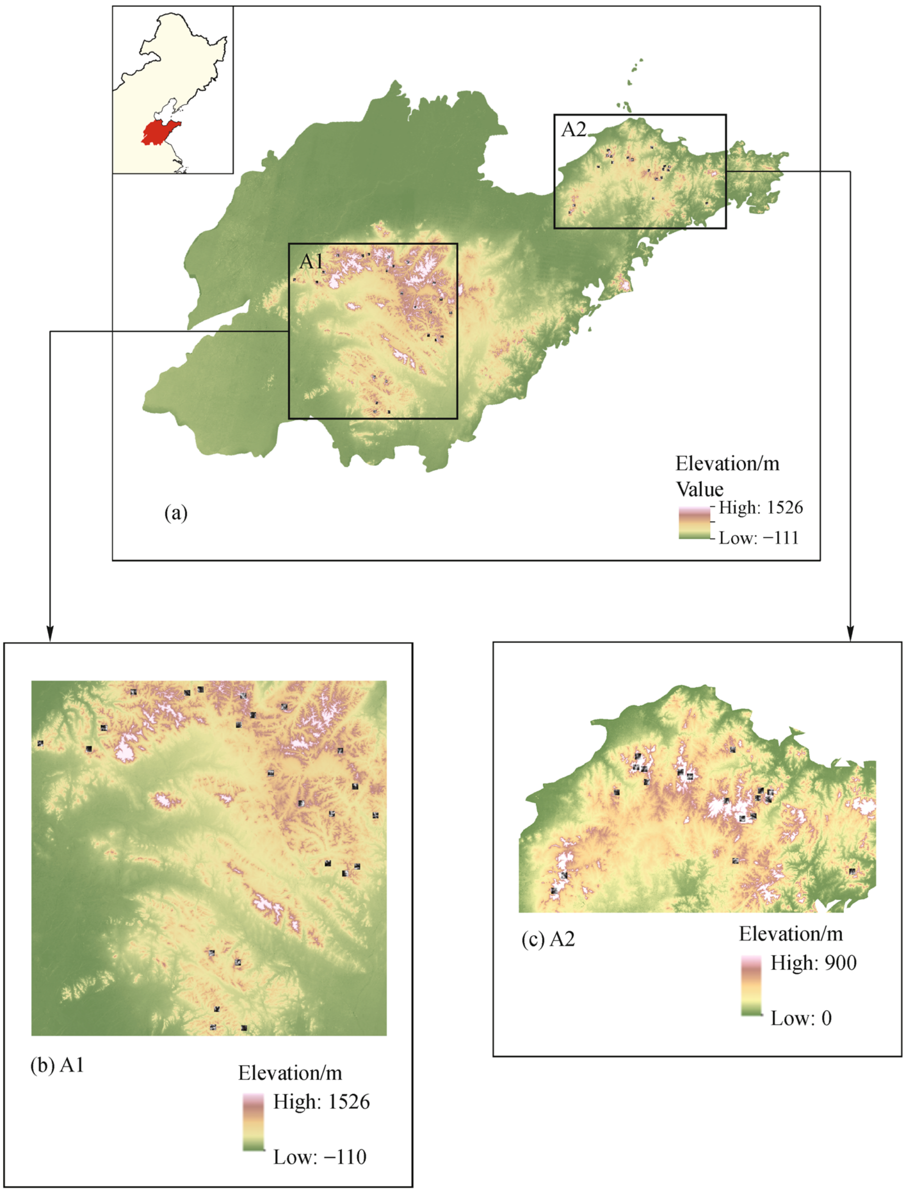


Fig. 1 Distribution of two sample areas in Shandong Province, China. (a) Shandong hilly area; (b) mid-southern mountainous area; (c) eastern hilly area.

Radiometer Global Digital Elevation Model (ASTER GDEM), which provided by the United States Geological Survey and possessed 30 m pixel resolution. The accuracy of the terrain texture expression varies with different analytical scales, thereby inevitably affecting the stability and precision of the analysis results. For large-scale DEM data, 30 m DEMs has high spatial resolution that can mirror the surface relief in detail and meet the needs of hierarchical landform classification.

2.2 Experimental methods

This research aims to classify landforms using DEM image textures. In particular, landforms refer to second-class landform types (Zhao et al., 2019a). Before this, we need to complete the extraction of texture features, analyze the reflective landform features, and achieve the final hierarchical classification via those feature relationship. Thus, GLCM method was used for texture feature extraction, and factor analysis (FA) was applied to feature analysis, as well as CNN in deep learning method was carried out on the selection of landform classification. The classification results were evaluated by the confusion matrix analysis. The detailed technical route (Fig. 2) and method introduction are as follows.

2.2.1 GLCM method

The texture feature value has different forms, such as digital feature value (Roy Chowdhury et al., 2011), image feature value (Puissant et al., 2005), and so on. An appropriate calculation method is the key of texture feature extraction. To date, there is no uniform standard for texture definition, so, scholars put forward many texture analysis methods for study. Primary analytical methods are the statistical method, structural method, model method, and signal method. DEM image texture, from the perspective of structure and perception, which shows the same visual feature attribute in image by mapping the gray level and consists of a series of texture primitive arrangement, is the two-dimensional display of elevation value in DEM data. And DEM image texture belongs to natural texture, whose texture features are random in local and regular in global. From the texture features, we can know that it is difficult to extract natural texture through image processing by

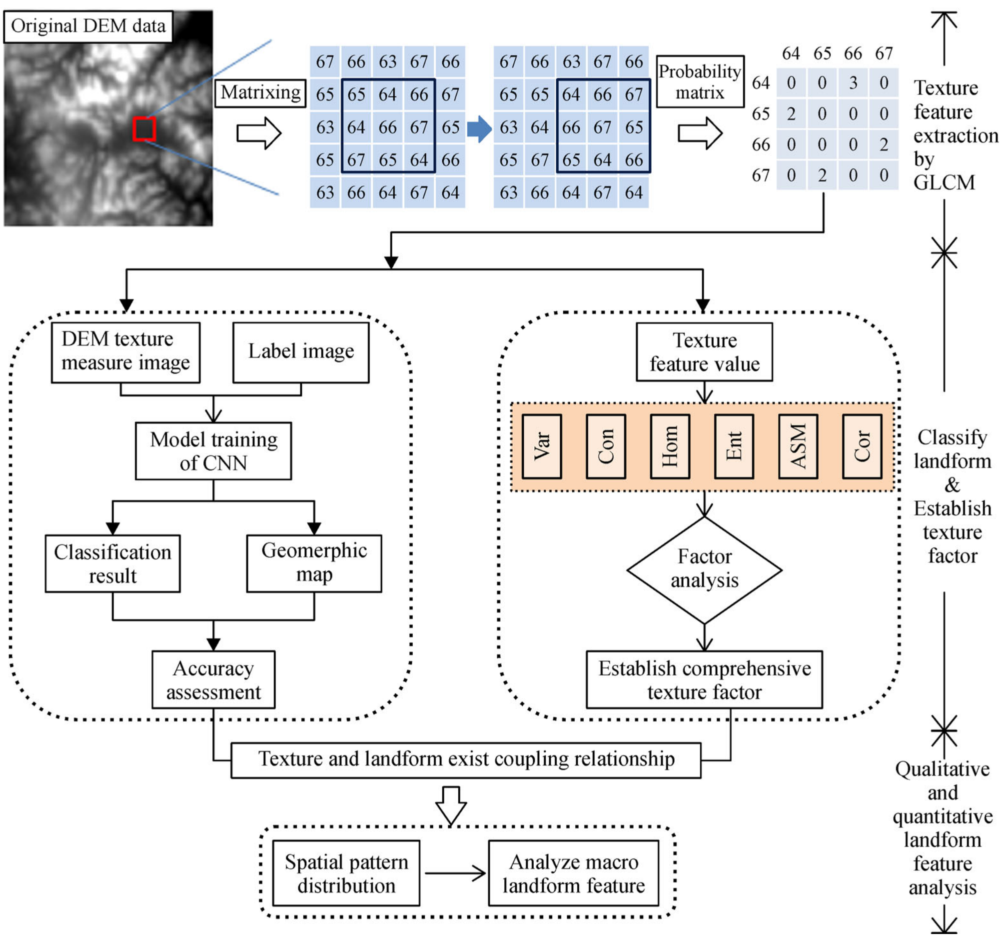


Fig. 2 Flowchart of the technical route.

structural method, solve model coefficient iteration by model method, and acquire local information of image by signal processing. On the contrary, statistical texture analysis method studies the spatial joint probability relationship of gray scale between pixel and its neighborhood pixel. Considering the internal relation between local and global texture, statistical method is more in line with the texture analysis and law exploration in DEM data. GLCM is the most commonly used and typical statistical methods for image texture calculation, and the texture parameters extracted by GLCM method are explained in the literature (Haralick et al., 1973). Besides, the texture image of GLCM plays an important role in geosciences analysis. For instance, improving the display effect of ground objects and enhancing the linear bodies, as well as increasing the classification effect of geosciences target. Each statistical attribute of GLCM can generate a texture image, which not only reflect the significant difference of spatial features of classification categories, but also can achieve landform classification compatible with traditional classification algorithm based on probability model. However, the existing problem of the other statistical methods for texture analysis is how to choose the size of neighborhood, such as the gray difference method. Hence, GLCM method was adapted to extract texture features from the perspective of comprehensive analysis.

2.2.2 Classification method of deep learning

Traditional hierarchical classification methods, such as altitude and slope, require high quantization threshold. This defects in the results of manual intervention. With the development of computer technology, automatically learning classification methods in the aspect of landform classification were explored. A series of study found that deep learning network structure is suitable for image features extraction (Shumack et al., 2020; Li et al., 2020). This study adopted CNN method, a quintessential example of deep learning model, to classify landform types in accordance with the DEM image texture. It belongs to pixel-based image processing method that has high research value for fine landform classification (Maggiori et al., 2017). Mapping elevation information of the DEM data into gray scale value, texture represents same morphology appeared in the similar landforms due to pixel value, and the case is contrary to the different landforms. Thus, CNN has the ability of directly convolution, representation learning and shift-invariant classification according to the input image pixels information (Kussul et al., 2017). And it employs local connection, spatial arrangement, and shared weight to improve the efficiency of image feature extraction, reduce the number of parameters, and solve the problem of model overfitting (Chen et al., 2017). This research selected Tensorflow as the framework in machine learning (Wongsuphasawat et al., 2018). First, the original pixel matrix of the DEM image texture is inputted. Second, the convolution layer executes convolution command to extract the texture features, and subsequent convolution layer maps the texture features layer by layer. Lastly, high-level features were formed and transferred to the full connection layer. As for the pooling layer, it was used to reduce the high feature dimension after feature extraction. While the full connection layer aims to output features extracted by nonlinear combination. And the softmax function, which turns the neuron into a probability form, objective to solve multi-class classification problems in neural networks, namely the classification categories are determined by the output probability (Zhao et al., 2019b). The specific parameters are listed in Table 1.

2.2.3 Method of accuracy evaluation

The accuracy results should be evaluated after image classification. Confusion matrix, which is an $n \times n$ matrix calculated from the classification images and reference maps, is commonly used to measure the classifier accuracy (Congalton, 1991). Four indicators, namely, overall accuracy (OA), produce accuracy (PA), user accuracy (UA), and Kappa coefficient, were obtained from the matrix to reflect the classification accuracy in different aspects. The theoretical introduction of the OA, PA, and UA are described in detail in the previous work (Story and Congalton, 1986). However, the disadvantage of using OA, PA, and UA is that small changes in pixel categories may lead to substantial percentage changes. Therefore, the kappa coefficient, which measures the degree of coincidence or accuracy between the two images, is used to compensate for this defect (Rwanga and Ndambuki, 2017). The Eqs. (1)–(4) of four indicators are listed as follows.

$$OA = \frac{\sum_{i=1}^{n} x_{ii}}{N}, \tag{1}$$

$$PA = \frac{x_{ii}}{\sum_{i=1}^{n} x_{+i}}, \tag{2}$$

$$UA = \frac{x_{ii}}{\sum_{i=1}^{n} x_{i+}}, \tag{3}$$

Table 1 Structure parameters of CNN

Input layer	Convolution layer	Poling layer	Strides	Activation function	Padding	Connection layer	Dropout	Classifier
100×100×8	3×3	2×2	2	ReLU	Same	256	0.5	Softmax

$$\text{Kappa} = \frac{N\Sigma_{i=1}^{n}x_{ii} - \Sigma_{i=1}^{n}(x_{i+}x_{+i})}{N^2 - \Sigma_{i=1}^{n}(x_{i+}x_{+i})}, \tag{4}$$

where N is the total number of categories, x_{ii} is the number of properly classified pixels, and x_{i+} and x_{+i} are the total number of pixels in row i and column i, respectively. In this study, the confusion matrix of the landform classification results is calculated, and the existing landform classification maps was used to verify the classification accuracy (Sharma, 2010).

2.2.4 FA

Single texture measure is often utilized to reflect one aspect of landform information in several existing studies (Ding et al., 2018). However, a certain amount of redundant information is reserved among single texture measures. All that hampered the systematic description of landform morphology and spatial feature distribution. Therefore, multiple texture measures should be formed to an organic whole. To improve the efficiency of terrain texture features in quantitative analysis, the core texture measures should be selected to deepen the understanding of landform morphology and spatial differentiation in Shandong area. Compared with the limitation of single texture measure, FA method, which aims to reduce dimensionality and reflect most information in the source data, is proposed to describe the relationship among variables or factors with a few parameters (Meneses et al., 2015). The key issues of FA include constructing, naming, and explaining factor variables. FA steps are as follows in this study (Napitupulu et al., 2017).

1) The original texture variable is confirmed whether it is suitable for FA, including Kaiser-Meyer-Olkin (KMO) and Bartlett's spherical test. Napitupulu et al. (2017) have provided the detailed formula and significance of these two indicators.

2) Factor variables are constructed. According to the cumulative contribution rate (generally above 80%) and characteristic value (above 1), principal component analysis is used as basis in determining the extraction number of factors. Two comprehensive texture factors are eventually determined.

3) The factor variables are made considerably interpretable by applying the rotation method. The main purpose is to ensure that each variable has a large loading only on one common factor and relatively small loading on other common factors. In this study, the factors were rotated using varimax to facilitate the naming of factor variables.

4) The factor variable scores and model forms are acquired. FA specifically aims to reduce the number of variables. When the original variables are replaced with a few factors to participate in data modeling, the linear combination formula of factors can be obtained (Eq. (5)).

$$F_i = a_{ij} \times X_i, \tag{5}$$

where a_{ij} is a factor score coefficient.

3 Results and analysis

3.1 Landform spatial features research based on DEM image texture

3.1.1 Construction of the DEM comprehensive texture factor

In order to supplement the existing defects of landform feature analysis by terrain factors, such as discontinuity of macroscopic features, weak interpretation of single index, and inconsistent of dimensions. The expression of the core factor, that is, the DEM comprehensive texture factor was constructed to analyze the texture spatial pattern on the basis of FA method. In the Shandong area, GLCM method was used to calculate the eight texture measure images, and 300 correspondence points were randomly selected as the research samples. Each point contains eight texture feature values. Through correlation analysis, result indicated that two texture measures, namely, dissimilarity and mean, were excluded owing to the high correlation and parallel texture meaning.

To begin with, KMO and Bartlett's test were used to verify the feasibility of FA (Guvenc et al., 2011). The experimental result shows that the KMO value is 0.703 and the significance probability obtained by Bartlett's test of sphericity is 0.000. In that case, a strong correlation can be inferred among the six texture measure variables, and the precondition of FA is satisfied. Besides, the FA effect must be considered on the basis of the common factor variance. Among the six texture measures, that is, variance (Var), contrast (Con), homogeneity (Hom), entropy (Ent), angular second moment (ASM), and correlation (Cor), the values of common factor variance are 0.785, 0.891, 0.846, 0.910, 0.901, and 0.648. All values are above 0.5, indicating that texture measures can be explained by factors at a high degree, and the analytical effect is distinct. Then, principal component analysis has been used for feature reduction. As stated in Section 2.2.4, the first two common factors are deemed as the appropriate component extraction because the relative integrity of the original texture information can be ensured. The result of total variance is showed in Table 2.

To easily name and explain the factors and highlight their typical representative variables, the varimax rotation's method is adopted (Kaiser, 1958; Ungureanu et al., 2017). The result of rotated composition matrix is illustrated in Table 3. As the table shows, the first principal factor has a large load on Hom, Ent, and ASM, and these three measures usually used to depict the terrain texture uniformity, which is also called as texture uniformity factors. The second factor has a large load on Cor, Var, and Con. Var and Con represent the texture periodicity, while Cor is the directional measure of the terrain texture. Thus, the second principal factor included the texture periodic and directional factor. On the basis of the component score coefficient matrix, as listed in Table 4, the score of each principal factor is calculated using the standardized value of the original index. The DEM comprehensive texture factors are acquired using Eqs. (6) and (7). On the basis of mentioned expression, six indexes of the texture spatial pattern are comprehensively evaluated. And then the change rule of the texture spatial pattern and landform features are discussed.

$$F_1 = -0.065X_1 + 0.265X_2 - 0.117X_3 - 0.29X_4 + 0.319X_5 + 0.210X_6, \tag{6}$$

$$F_2 = -0.438X_1 - 0.015X_2 + 0.37X_3 - 0.07X_4 + 0.238X_5 + 0.566X_6, \tag{7}$$

where X_1, X_2, X_3, X_4, X_5, X_6 stand for Var, Hom, Con, Ent, ASM, Cor, respectively.

3.1.2 The relationship of spatial pattern between the DEM comprehensive texture factor and landform feature

The texture factor scores were calculated with the help of 300 sample points, and the texture factor model was constructed as Section 3.1.1 described. Based on the geostatistical and spatial analysis, the spatial differentiation of the texture pattern was studied in Shandong area. The geostatistical test determined that the spatial point data existed differences when a spatial interpolation method named inverse distance weight was used (Ikechukwu et al., 2017). Figure 3 shows the spatial interpolation results of texture.

Spatial pattern is an abstract conception in representing the spatial distribution and allocation of geographical elements, this paper used it to study the spatial pattern relationship between texture factors and landform types. From the macro-overview, the spatial pattern of the texture factor has clear hierarchy with polycentric diffusion type. Noting that the feature value is relatively regular, which is shown as in Fig. 4, the original landform classification map is superimposed with the texture factor spatial pattern map for 3D visualization. In Fig. 4(a), the top map is a stretched texture spatial pattern, the bottom is the existing second-class landform classification map, and the black line symbolizes texture spatial pattern through vector form. The same is true of Fig. 4(b). Relationship in Fig.4 demonstrates that the variation trend of the comprehensive texture factor is similar to that of the landform type. In general, the differentiation of landform type is usually explained by the landform features, such as relief, roughness, periodicity, and directivity. Referring to the DEM comprehensive texture factors, the different landform features are quantitatively analyzed.

Uniformity, which describes a uniform texture property with less mutation, is the similarity of similar landform. As can be seen in Fig. 4(a), the high values of the texture uniformity factor appeared in the northwest and Jiaolai

Table 2 Explanation of total variance

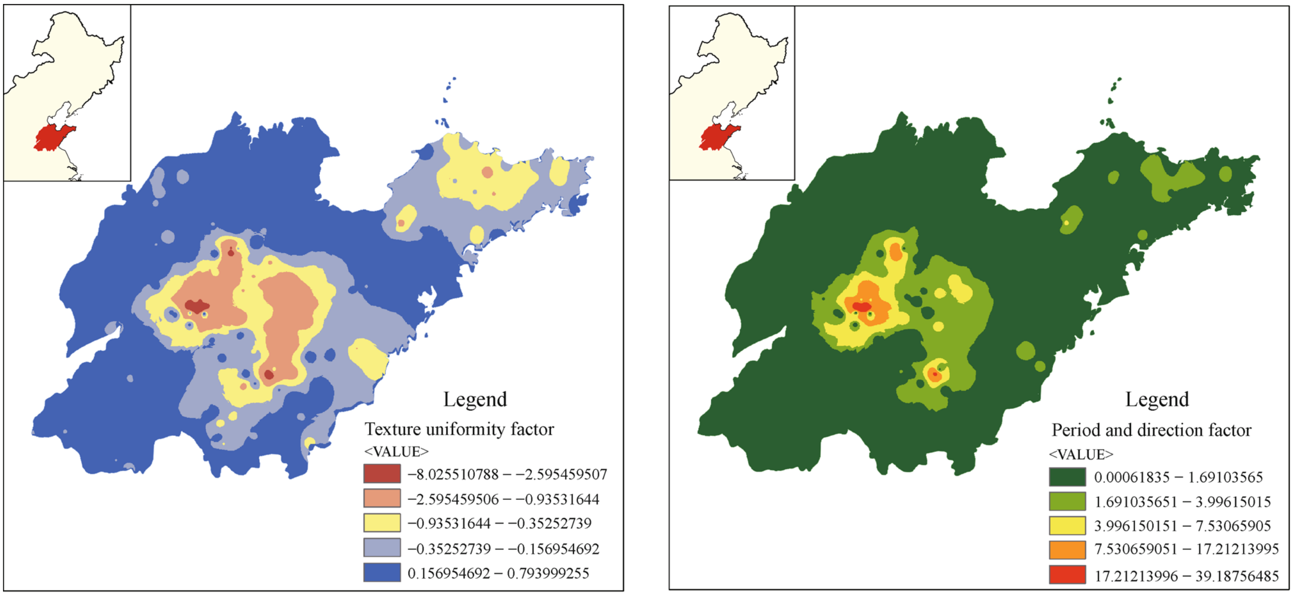
Component	Initial eigenvalue of variance/%	Cumulative/%	Total	Extracting load squared of variance/%	Cumulative/%	Total	Rotating load squared % of variance	Cumulative/%	Total
1	60.964	60.964	3.658	60.964	60.964	3.658	57.388	57.388	3.443
2	22.054	83.019	1.323	22.054	83.019	1.323	25.631	83.019	1.538
3	11.594	94.613	0.696						
4	3.226	97.839	0.194						
5	1.619	99.459	0.097						
6	0.541	100.000	0.032						

Table 3 The rotated composition matrix

	Var	Hom	Con	Ent	ASM	Cor
1	−0.520	0.922	−0.653	−0.950	0.937	0.341
2	0.718	−0.202	0.648	0.087	0.152	0.729

Table 4 Component score coefficient matrix

	Var	Hom	Con	Ent	ASM	Cor
F1	−0.065	0.265	−0.117	−0.290	0.319	0.210
F2	0.438	−0.015	0.370	−0.070	0.238	0.566



(a) (b)

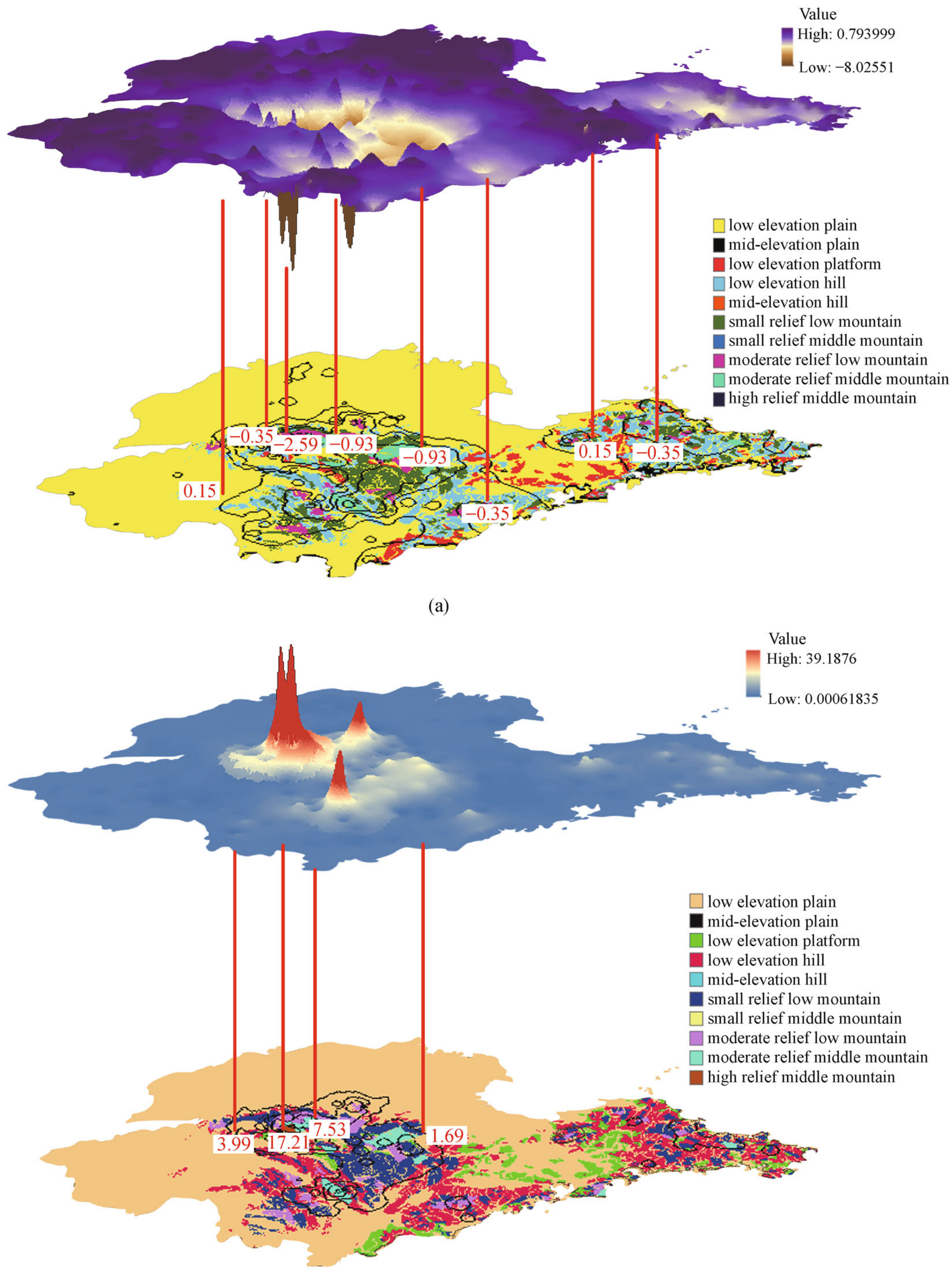
Fig. 3 The spatial interpolation results of texture. (a) Uniformity factor; (b) periodic and directional factor.

plain of China, the other values gradually decreased to the middle mountainous area and eastern hilly area. The boundary line of the texture factor spatial pattern basically conforms to the transition among landform types. When the value of the uniformity factor is above 0.15, the landform types are low elevation plain and platform; when the factor value is from −0.35 to −0.15, the corresponding landforms are low elevation plain, platform, and hill, and small relief low mountain; when the factor value is from −0.93 to −0.35, many landform types, including low elevation hills, mid-elevation plains and hills, and small relief low mountains, are displayed; when the factor value is between −2.59 and −0.93, mid-elevation plain, small and moderate relief low and middle mountain could be classified; and when the factor value is below −2.59, the landform of high relief middle mountain could be classified. With the decrease of the texture factor uniformity, the second-class landforms change from low elevation plains and platform to low elevation hills, small relief low mountain, mid-elevation plains and hills, moderate relief low mountain, small relief middle mountain, moderate relief middle mountain, and finally transition to the high relief middle mountain, that is, as relief increases, the landform types change from low elevation to high layer by layer. The results show that the uniformity factor of texture is positively correlated with the relief and landform development. Such a finding, to a certain degree, can be adopted to reflect the landform relief and the characteristics of landform developmental stage.

The quantization results of the periodic and directional factor shows an increasing trend in Fig. 4(b). The landform type is high relief middle mountain when the value of periodic and directional factor is above 17.21. When the factor value of periodic and directional factor is from 7.53 to 17.21, the corresponding landforms are moderate relief low and middle mountains; when the factor value of periodic and directional factor is from 3.99 to 7.53, the corresponding landforms are mid-elevation hill, moderate relief low mountain, and small relief low and middle mountains; when the factor value of periodic and directional factor is from 1.69 to 3.99, the landform types are mid-elevation plain, low elevation and mid-elevation hills, small relief low mountain, and moderate relief low and middle mountains. When the factor value of periodic and directional factor is below 1.69, the corresponding landforms are low elevation plain, hill, platform, as well as small and moderate relief low mountains. As the periodic and directional factor decreases, the second-class landforms change from the high relief middle mountain to the moderate relief low and middle mountains, small relief low and middle mountains, and mid-elevation hill. Then, the types gradually transit to the mid-elevation plain, low elevation plain, mid-elevation hill, and low elevation plain and platform. In summary, the periodic and directional factor is closely related to the landform's complexity, which can completely reflect the landform features and evolution.

3.1.3 Analysis of the landform spatial features based on DEM comprehensive texture factor

The DEM texture analysis enhances the reliability of the macro landform spatial features, thereby providing a solid scientific basis for the positioning, qualitative, and



(a)

(b)

Fig. 4 Relationship between the DEM comprehensive texture factor and landform. (a) Uniformity texture factor; (b) periodic and directional texture factor.

quantitative research. From the perspective of spatial distribution pattern, the DEM comprehensive texture factor presents an aggregation distribution tendency in Shandong area. Such distribution tendency manifested in radially decrease or increase from Mount Tai to all sides. The detail analysis of landform features are as follows.

The uniformity feature values gradually decrease along the low–middle–high elevation (low–moderate–high relief). The plain areas occupy the majority of the landform type. Especially, the low elevation of surface relief dominates the top place. With the increase of the elevation and relief, the effect of uniformity goes from bad to worse.

This pattern is caused by the internal forces of the Earth. In a strict sense, the uniformity distribution tendency is elliptic and circular, which centered on the mid-south mountainous area and its northwest area, as well as the eastern hilly area. The complete landform type has been formed in the northwest of the mid-south mountainous area due to the action of Mount Tai. With regard to the texture uniformity of the other two regions, where textures are situated on the transition zone of mountain valley and basin, nearly all uniformity features are extended along the river. Moreover, the extension direction varies with the landform changes. From the genetic mechanism aspect, the northwest plain belongs to the flood plain because of the differential tectonic subsidence, and the format of flat terrain was resulted. The texture uniformity in the Jiaodong Peninsula is lower than that in Jiaolai Basin of China. Mainly reason lie in the development of Yishu Fault Belt when the Pacific plate subducted westward toward the Eurasian plate. This pattern gave rise to the towering mountains. When the fault belt strongly moved to the left, the north of Jiaobei Plain of China was uplifted, and the Jiaolai Basin sagged. Therefore, texture uniformity is a description of landform relief and developmental stage.

Semantic depiction is insufficient when describing the directional features. Quantitative analysis can embody the terrain transition trend and landform features in a numerical form. The texture factor value from the highest to the lowest is Mount Tai, mid-southern, and southeast as the contour line shows (Fig.4 black line). Thus, the terrain alignment of mountainous area can be judged as northwest–southeast. On the basis of the periodic and directional rules, the second-class landforms decrease from the central mountainous area to the northwest plain area, that is, the periodicity and directionality features from evident gully structure change to weak and smooth landform features. A large number of intermountain basins and plains are scattered between low mountains and hills due to the water erosion and accumulation. Such a phenomenon is the reason for the significant horizontal differentiation. Thus, the complex and varied features of the Shandong area was expressed according to the texture periodicity and directionality.

The landform distribution features changed with elevation and relief. In summary, the spatial pattern generates two features: horizontal ring and vertical zonal features. The texture can map the difference of landform by shading. Meanwhile, the different features, such as uniformity, periodicity, and directionality, also can be mirrored by the diverse landform types in the Shandong area equally. The experiments show that these two texture factors are correlated and supplemented to map landform features. Consequently, the land use spatial pattern can be simultaneously optimized and adjusted according to the spatial differentiation law of the texture factor. In conclusion, the texture spatial pattern that relied on the DEM comprehensive texture factor has reinforced geospatial cognition in this study.

3.2 Deep learning classification of landform based on DEM image texture

3.2.1 Landform classification using CNN method

As CNN can learn the image features step by step, a higher level of semantic features were formed through statistical description, coding or kernel, resulting in a fine accuracy of landform classification. Hence, DEM data in two sample areas is taken as texture feature extraction based on the GLCM method, and the second-class landforms are classified using CNN method according to the differences in texture feature values. The specific classification steps are displayed in Fig. 5 and CNN parameters are described in Section 2.2.2. Beyond that, after several experiments, the learning rate is set up for 0.001.

In the whole Shandong area, the small relief and mid-relief low mountains were determined as classification targets with the selection principles in Section 2.1. Adopting the visual interpretation method and referring to previous data images, 23 and 18 training samples and 1 test sample image of A1 and A2 were selected for landform classification. Owing to a small part of the low elevation plains existed in the testing mid-southern mountainous area, the low elevation plains were masked before the experiment to prevent their inclusion in the classification. For CNN method has a strong dependence on the sample features and quantity, eight texture feature images were extracted without removing the redundant information. Details of sample selection are provided as follows.

1) On the multi-band DEM texture images, the corresponding small relief and mid-relief low mountains are selected according to prior knowledge, and the selection principle is to keep the uniform distribution as far as possible. As for the number, it is determined in this paper based on the actual size of the study area, with no less than 3000 feature vectors for each category;

2) Make labels of different landform types, in which the label of small relief low mountains is set as 0 and the label of mid-relief low mountains is set as 1, and then match the feature vector with the label one to one;

3) Using CNN to train features and labels, softmax classifier was adopted to automatically output the landform classification results on the computer. Classification results show in Figs. 6(a)–6(b). In Fig. 6(a), the geographical location of the test area is in the west of mid-southern mountain area, the latitude and longitude are 36°16′–36°17′30″N, 116°52′–116°54′E. In Fig. 6(b), the geographical location of the test area is in the east of the whole Shandong Province, the latitude and longitude are 37°30′30″–37°32′N, 120°27′30″–120°29′30″E.

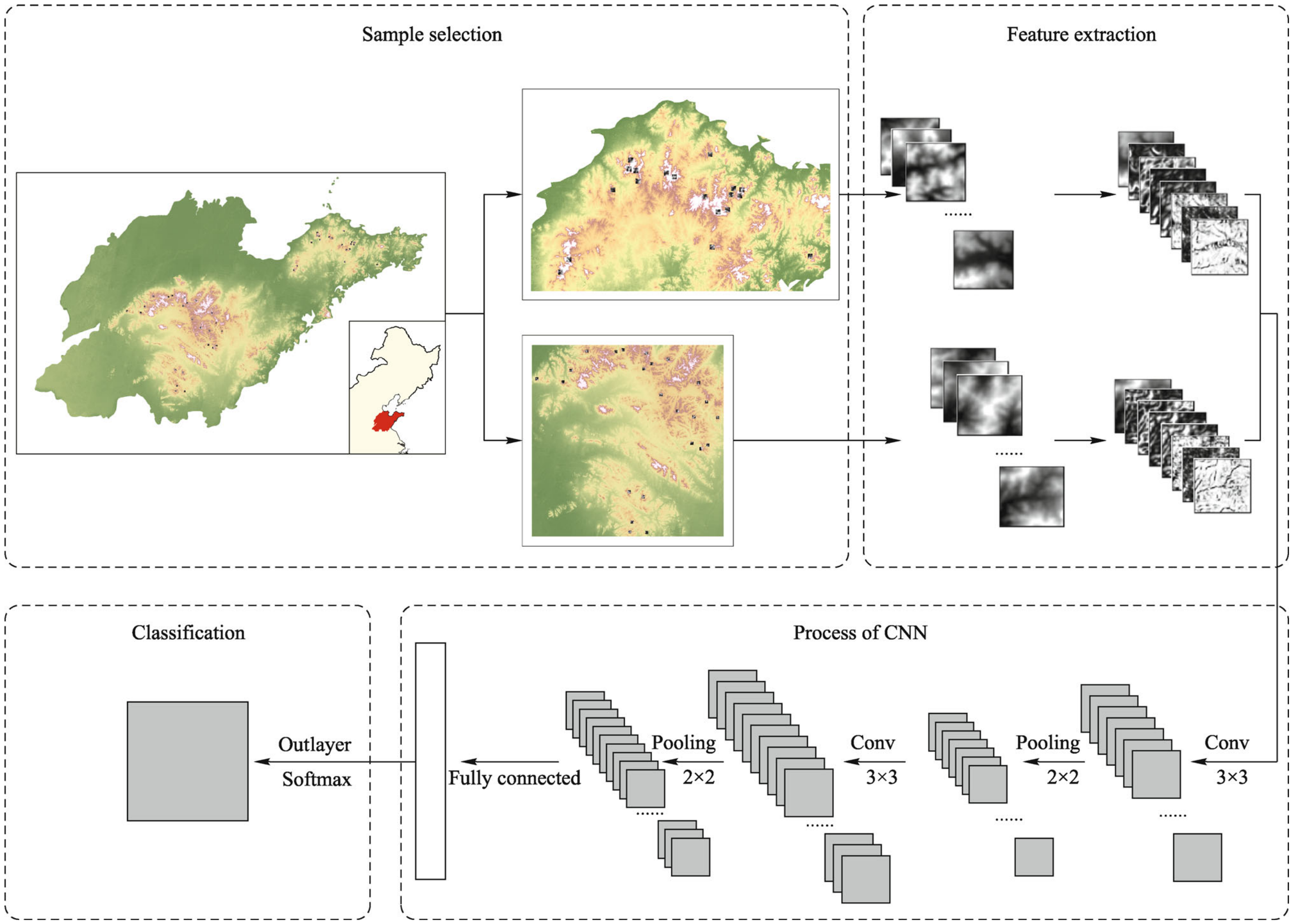


Fig. 5 Landform classification process of CNN.

3.2.2 Analysis of the strong coupling relationship between terrain texture and landform type

Depending on the confusion matrix theory, OA and kappa coefficient were adopted as accuracy evaluation principles in the Shandong areas (Zhu et al., 2019). And Shandong areas were divided into first- and second-class landform regions, the latter region consists of the mid-southern mountainous and eastern hilly areas. If the classification accuracy is high, the texture can considerably aggregate the same and distinguish the different landform types. The strong coupling relationship, which is between terrain texture and landform unit, can be obtained via gray scale mapping. As can be seen in Table 5, OA in the first-class landform types, such as plains, hills, and mountains, is over 95%. This finding shows that the properly classified pixels occupy 95% of the entire image. kappa coefficient is 0.91, thereby indicating that the texture classification results are highly consistent with the reference landform map. In the second-class landforms (i.e., mid-southern mountainous and eastern hilly areas), the OA are 84% and 69%, and the kappa coefficient are 0.72 and 0.40, respectively. The properly classified texture pixels are above 60%, and kappa coefficient is above 0.4. All the classification results fitted well with the reference map. These two indicators completely demonstrate the results reliability of the second-class landform classification. Regardless of the landform classification (e.g., rough or fine), texture is an effective means to achieve hierarchical landform classification. In the accuracy evaluation, the classification accuracy of landform based on texture is in the high level. The majority of the landform units, which are mapped by pixel gray of texture, are correctly classified. This finding verifies a strong coupling relationship between terrain texture and landform type.

4 Discussion

4.1 The effect enhancing analysis of landform spatial pattern using comprehensive texture factors

In this study, an establishment method of comprehensive texture factor is proposed to analyze the spatial pattern of landform features. Comparing to other correlation analysis in regard to landform features, for example, the land use

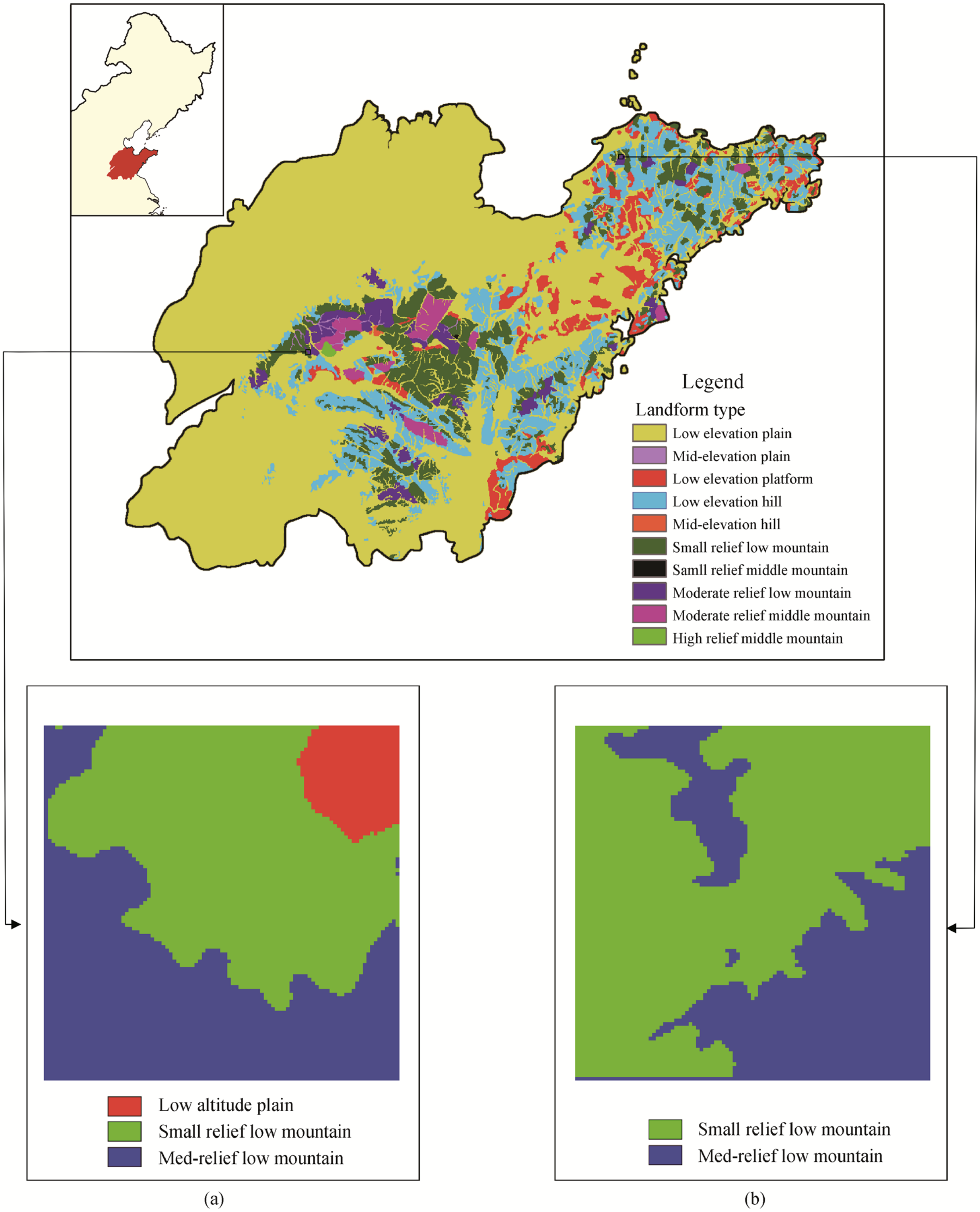


Fig. 6 Result of landform classification. (a) Mid-southern mountainous area; (b) eastern hilly area.

Table 5 Classification accuracy of hierarchical landform types

First-class landform types in Shangdong area	Second-class landform types in mid-southern mountainous area	Second-class landform types in eastern hilly area
Plain	low altitude plain	
Hill	small relief low mountain	small relief low mountain
Mountain	med-relief low mountain	med-relief low mountain
OA: 95.48 Kappa: 0.91	OA: 84.35 Kappa: 0.72	OA: 69.95 Kappa: 0.40

and morphology (Sahu et al., 2014), the loess geomorphology and terrain factors (Li et al., 2019), as well as the landform evolution and hypsometric integral (Zhu et al., 2018b), it has the benefits of establishing relationship between comprehensive texture factors and landform types. Using comprehensive texture factors, to a large extent, the means of landform spatial pattern analysis was further improved. On the one hand, when the spatial pattern map of texture factors are superimposed on the landform type map, the coupling relationship can be qualitatively or quantitatively analyzed (Fig. 4). On the other hand, comprehensive texture factors have dealt with the problem that single parameter tends to be one-sided in discussing landform feature. Besides, the aggregation and dispersion of landform spatial feature can be explored in macroscopic view. The construction of DEM comprehensive texture factor that characterized by synthesizing the directionality and periodicity of surface relief highlights the structural features of the landform, which can study the texture distribution features that unable to be directly determined in visual perception. In comparison with conventional contour line, the comprehensive texture factor quantitative exhibit trends of regional geographical elements, such as river. Besides, the landform type effect effectively enhanced by the 3D display of texture factors through vertical down alignment, indicating that texture information fusion is the further development of digital terrain analytical technology.

4.2 Accuracy comparison of the different landform classification methods

CNN is a supervised classification method under the condition that the sample categories are known. This study utilizes the ISO Cluster Unsupervised Classification method for contrastive analysis (Wieczorek and Migoń, 2014), with no need for priori knowledge and sample set, only the category of final output should to be determined. The computer will automatically cluster features according to the similarity between landforms, then iterate and classify them with high computational efficiency. The data sources used in the unsupervised classification are multi-band images, which are composed of elevation, slope, relief, and elevation variation coefficient. The optimal analytical window of the relief and elevation variation coefficient is calculated by mean change point method. Such window of mid-southern mountainous area is 17 $\times$ 17, while that in the eastern hilly area is 15 $\times$ 15. Verification was carried out in accordance with the existing classification map. The four indicators in Section 2.2.4 were used to comprehensively evaluate the landform classification results. Table 6 shows the detailed classification accuracy results. The result indicates that the classification method based on CNN can improve the landform classification accuracy.

As for small relief low mountain area in mid-southern mountainous area, accuracy in Table 3 demonstrates that PA of CNN method is 4.43% higher than that of the ISO Cluster Unsupervised Classification method, and UA increased by 12.05%. In the medium relief low mountain, PA increased by 16.23%, and UA increased by 5.92%. In general, OA increases by 10.4% and the kappa coefficient increases by 0.17. For the small relief low mountain area in the eastern hilly area, PA of the CNN method is 6.54% higher than that of the ISO Cluster Unsupervised Classification method, and UA increased by 4.94%. In the medium relief low mountain, PA increased by 6.39% and UA increased by 9.32%. In general, OA increases by 6.46% and the kappa coefficient is augmented by 0.12. The experimental results show that the detailed landform classification by CNN method is valuable. Moreover, PA of the CNN method has a high recognition rate for medium relief low mountains in the mid-southern mountainous area, while a high recognition rate for small relief low mountain area has revealed in the eastern hilly area. Such findings correlate with the landform features in these two areas. That is because mountains occupy a vast portion in the mid-southern mountainous area and hills occupy a vast portion in the eastern hilly area. Thus, the CNN method, which is supported by the texture measure, can accurately classify landforms, increase the classification accuracy, and improve the correct recognition rate of landforms in different areas. The landform surface is a field model for combining gradient and mutation characteristics, while the continuity and transitional characteristics of the landforms can be formed using CNN method. In contrast with the

Table 6 Landform classification accuracy using different method

Sample area		Mid-Southern mountainous area				Eastern hilly area			
Method		CNN		ISO		CNN		ISO	
Accuracy assessment		PA	UA	PA	UA	PA	UA	PA	UA
Landform types	plain	100	100	100	100				
	small relief low mountain	93.80	73.39	89.37	61.34	85.55	64.95	79.01	60.01
	medium relief low mountain	75.28	94.35	59.05	88.43	54.63	79.36	48.24	70.04
Total	OA	84.3554		73.9505		69.9543		63.4924	
	Kappa coefficient	0.7266		0.5528		0.4007		0.2718	

object-oriented method, the classification accuracy of small and moderate relief low mountains cannot reach a high level in the transitional boundary of the landform types, especially regions with uncertain landform boundaries. Consequently, the misclassification rate of landform types is high. In summary, hierarchical classification result exhibit several advantages compared with the previous classification result of the 500 m DEM data (Table 5) (Zhu, et al., 2019). The reason lies in that the 500 m DEM data can only complete the first-class macro classification. By contrast, this study can achieve the second-class landform classification with relatively high precision and dissect landform features in 30 m DEM data.

5 Conclusions

Texture measure is a crucial basis for terrain texture expression. The DEM data are key means of terrain texture visualization and data source for landform classification. As the development of digital terrain analysis technology, scientific and effective regional landform classification system should be noticed in essential research topics, this study performs a preliminary exploration of expert experience transformation and knowledge rule setting. The main results and conclusions are as follows.

1) Landform types are mirrored by the gray scale of texture, and the macro landform features are illustrated by the terrain texture. On the basis of the texture feature points, the DEM comprehensive texture factor used for interpreting the spatial pattern is established with six texture measures. And the inverse distance weight interpolation macroscopically displayed the spatial pattern of the texture factors. Thereafter, quantitative expressions of the macro landform features, qualitative analysis of landform pattern and spatial differentiation are achieved. These aspects substantially enriched the contents of the macro landform analysis in the Shandong areas.

2) The coupling relationship between terrain texture and landform type was discovered. According to the DEM comprehensive texture factor, macro landform features and spatial pattern differentiation rules was further quantitatively analyzed. Superimposed texture spatial pattern map and landform classification map, we found that the boundary line has the similar variation tendency between terrain texture and landform type. With the strong coupling relationship, the mapping mechanism between texture and landform is obtained. Therefore, the method of texture analysis is suitable for landform classification.

3) Fine classification of the second-class landform types was carried out on the basis of the 30 m DEM texture feature images. A pixel-based classification method (i.e., CNN) is adopted, and the visual interpretation criteria are used to create feature labels thereafter. At last, the landform classification images are outputted by the softmax classifier. Fewer pattern spots of the landform classifications are acquired compared with the traditional classification method, and continuous landforms are completed with CNN method. High accuracy was observed in the evaluation results of the confusion matrix. This finding indicates that texture can effectively identify different landform types.

The existing landform classification acquired is mainly based on the qualitative analysis, such as geometrical morphology, elevation, and relief. Nevertheless, this network has difficulty in providing the precise indicators to distinguish the morphological characteristics, resulting in incorrectly landform classification. Despite CNN method considers the differences between pixels for samples training, CNN network is unable to consider the geomorphic cause. Thus, the classification results showed the fuzzy border among different landforms. Furthermore, the boundary issue is one of the important factors affecting the landform classification. Future research should explore this problem. And if the CNN method is extended to classify landforms in the plain and hilly areas, the gradual elevation change will weaken the texture difference and recognition ability of the landforms. Single landform classification principle may be incapable of ensuring the integrity and diversity of the geomorphic classification. Therefore, the hierarchical classification of landform types relatively entails the radar DEM data for the experimental data to extract the feature information of landform surface.

Acknowledgements This work was supported by the auspices of the National Natural Science Foundation of China (Grant Nos. 41930102, and 41971339) and SDUST Research Fund (No. 2019TDJH103).

References

Ahmed J, Ahmed H (2019). Assessing performance of convolutional features for terrain classification using remote sensing data. In: 2019 2nd International Conference on Communication, Computing and Digital systems (C-CODE). IEEE, 2019: 178–183

Arrell K E, Fisher P F, Tate N J, Bastin L (2007). A fuzzy c-means classification of elevation derivatives to extract the morphometric classification of landforms in Snowdonia, Wales. Comput Geosci, 33 (10): 1366–1381

Band L E (1986). Topographic partition of watersheds with digital elevation models. Water Resour Res, 22(1): 15–24

Basu S, Mukhopadhyay S, Karki M, DiBiano R, Ganguly S, Nemani R, Gayaka S (2018). Deep neural networks for texture classification—A theoretical analysis. Neural Netw, 97: 173–182

Bricher P K, Lucieer A, Shaw J, Terauds A, Bergstrom D M (2013). Mapping sub-antarctic cushion plants using random forests to combine very high resolution satellite imagery and terrain modelling. PLoS One, 8(8): e72093

Bugnicourt P, Guitet S, Santos V F, Blanc L, Sotta E D, Barbier N, Couteron P (2018). Using textural analysis for regional landform and landscape mapping, Eastern Guiana Shield. Geomorphology, 317: 23–44

Chen N (2020). Spectra method for revealing relations between slope and possible sunshine duration in China. Earth Sci Inform, 13(3): 695–707

Chen N, Tang G A, Guo D S, Chen C C (2014a). Influence of DEM orientation on the error of slope calculation. Earth Sci Inform, 7(4): 277–285

Chen W T, Li X J, Wang Y X, Chen G, Liu S W (2014b). Forested landslide detection using LiDAR data and the random forest algorithm: a case study of the Three Gorges, China. Remote Sens Environ, 152: 291–301

Chen Y S, Zhu L, Ghamisi P, Jia X P, Li G Y, Tang L (2017). Hyperspectral images classification with Gabor filtering and convolutional neural network. IEEE Geosci Remote Sens Lett, 14 (12): 2355–2359

Cheng W M, Zhou C H (2014). Methodology on hierarchical classification of multi-scale digital geomorphology. Prog Geogr, 33 (1): 23–33

Congalton R G (1991). A review of assessing the accuracy of classifications of remotely sensed data. Remote Sens Environ, 37 (1): 35–46

De Reu J, Bourgeois J, Bats M, Zwertvaegher A, Gelorini V, De Smedt P, Chu W, Antrop M, De Maeyer P, Finke P, Van Meirvenne M, Verniers J, Crombé P (2013). Application of the topographic position index to heterogeneous landscapes. Geomorphology, 186: 39–49

Ding H, Na J M, Huang X L, Tang G A, Liu K (2018). Stability analysis unit and spatial distribution pattern of the terrain texture in the northern Shaanxi Loess Plateau. J Mt Sci, 15(3): 577–589

Drăguţ L, Blaschke T (2006). Automated classification of landform elements using object-based image analysis. Geomorphology, 81(3–4): 330–344

Du L, You X, Li K, Meng L Q, Cheng G, Xiong L Y, Wang G X (2019). Multi-modal deep learning for landform recognition. ISPRS J Photogramm Remote Sens, 158: 63–75

Eisank C, Drăguţ L, Blaschke T (2011). A generic procedure for semantics-oriented landform classification using object-based image analysis. Geomorphometry, 2011: 125–128

Franklin S E, Ahmed O S (2017). Object-based wetland characterization using RADARSAT-2 quad-polarimetric SAR data, Landsat-8 OLI imagery, and airborne LiDAR-derived geomorphometric variables. Photogramm Eng Remote Sensing, 83(1): 27–36

Fu J D, Zhang G C, Wang L, Xia N (2018). Geomorphology classification of Shandong Province based on digital elevation model in the 1 Arc-second format of shuttle radar topography mission data. IOP Conf Ser Earth Environ Sci, 108(3): 032025

Guvenc G, Akyuz A, Açikel C H (2011). Health belief model scale for cervical cancer and Pap smear test: psychometric testing. J Adv Nurs, 67(2): 428–437

Halls J N, Frishman M A, Hawkes A D (2018). An automated model to classify barrier island geomorphology using lidar data and change analysis (1998–2014). Remote Sens, 10(7): 1109

Haralick R M, Shanmugam K, Dinstein I H (1973). Textural features for image classification. IEEE Trans Syst Man Cybern, SMC-3(6): 610–621

Ikechukwu M N, Ebinne E, Idorenyin U, Raphael N I (2017). Accuracy assessment and comparative analysis of IDW, spline and kriging in spatial interpolation of landform (Topography): an experimental study. J Geogr Inf Syst, 9(3): 354–371

Iwahashi J, Pike R J (2007). Automated classifications of topography from DEMs by an unsupervised nested-means algorithm and a three-part geometric signature. Geomorphology, 86(3-4): 409–440

Kaiser H F (1958). The varimax criterion for analytic rotation in factor analysis. Psychometrika, 23(3): 187–200

Kussul N, Lavreniuk M, Skakun S, Shelestov A (2017). Deep learning classification of land cover and crop types using remote sensing data. IEEE Geosci Remote Sens Lett, 14(5): 778–782

Li S J, Xiong L Y, Tang G A, Strobl J (2020). Deep learning-based approach for landform classification from integrated data sources of digital elevation model and imagery. Geomorphology, 354: 107045

Li Y, Zhou Y, Lei X, Li P L, Liang C X (2019). Simulation of quantitative relationship between positive and negative topographic factors of loess based on catchment unit. J Arid Land Res Env, 33 (07): 78–84 (in Chinese)

Liu K, Tang G A, Jiang S (2013). Research on the classification of terrain texture from DEMs based on BP neural network. Geomorphometry: 1–4

Maggiori E, Tarabalka Y, Charpiat G, Alliez P (2017). Convolutional neural networks for large-scale remote-sensing image classification. IEEE Trans Geosci Remote Sens, 55(2): 645–657

Mao M K (1993). A study on regional structure of landforms in Shandong Province. Sci Geogr Sin, 13(1): 26–33

Meneses B M, Reis R, Vale M J, Saraiva R (2015). Land use and land cover changes in Zêzere watershed (Portugal)—water quality implications. Sci Total Environ, 527-528: 439–447

Mezaal M R, Pradhan B (2018). An improved algorithm for identifying shallow and deep-seated landslides in dense tropical forest from airborne laser scanning data. Catena, 167: 147–159

Mokarram M, Roshan G, Negahban S (2015). Landform classification using topography position index (case study: salt dome of Korsia-Darab plain, Iran). Model Earth Syst Environ, 1(4): 40

Napitupulu D, Kadar J A, Jati R K (2017). Validity testing of technology acceptance model based on factor analysis approach. Indonesian J Electrical Eng Comput Sci, 5(3): 697–704

Piloyan A, Konečný M (2017). Semi-automated classification of landform elements in Armenia based on SRTM DEM using *k*-means unsupervised classification. Quaest Geogr, 36(1): 93–103

Prima O D A, Echigo A, Yokoyama R, Yoshida T (2006). Supervised landform classification of Northeast Honshu from DEM-derived thematic maps. Geomorphology, 78(3–4): 373–386

Puissant A, Hirsch J, Weber C (2005). The utility of texture analysis to improve per-pixel classification for high to very high spatial resolution imagery. Int J Remote Sens, 26(4): 733–745

Roy Chowdhury P, Deshmukh B, Goswami A K, Prasad S S (2011). Neural network based dunal landform mapping from multispectral images using texture features. IEEE J Sel Top Appl Earth Obs Remote Sens, 4(1): 171–184

Rwanga S S, Ndambuki J M (2017). Accuracy assessment of land use/land cover classification using remote sensing and GIS. Int J Geosci, 8(04): 611–622

Sahu N, Obireddy G P, Kumar N, Nagaraju M S S, Srivastava R A J E E V, Singhm S K (2014). Characterization of landforms and land use/land cover in basaltic terrain using IRS-P6 LISS-IV and Cartosat-1 DEM data: a case study. Agropedology (Nagpur), 24(2): 166–178

Sharma A (2010). Integrating terrain and vegetation indices for identifying potential soil erosion risk area. Geo Spat Inf Sci, 13(3): 201–209

Shi B H (2013). Influence of the hydrologic and geomorphic conditions upon the location of settlements in the Jiaodong Peninsula. Huaxia Archaeol, 04: 34–45

Shumack S, Hesse P, Farebrother W (2020). Deep learning for dune pattern mapping with the AW3D30 global surface model. Earth Surf Process Landf, 45(11): 2417–2431

Story M, Congalton R G (1986). Accuracy assessment: a user's perspective. Photogramm Eng Remote Sensing, 52(3): 397–399

Tang G A, Song X O, Li F Y, Zhang Y, Xiong L Y (2015). Slope spectrum critical area and its spatial variation in the loess plateau of China. J Geogr Sci, 25(12): 1452–1466

Ungureanu T, Iancu G O, Pintilei M, Chicoș M M (2017). Spatial distribution and geochemistry of heavy metals in soils: a case study from the NE area of Vaslui county, Romania. J Geochem Explor, 176: 20–32

Volpi M, Tuia D, Bovolo F, Kanevski M, Bruzzone L (2013). Supervised change detection in VHR images using contextual information and support vector machines. Int J Appl Earth Obs Geoinf, 20: 77–85

Wang C Z, Tang G A, Yuan S, Sun J W, Liu K (2015). A method for identifying the lunar morphology based on texture from DEMs. Journal of Geo-Information Science, 17(1): 45–53

Wieczorek M, Migoń P (2014). Automatic relief classification versus expert and field based landform classification for the medium-altitude mountain range, the Sudetes, SW Poland. Geomorphology, 206: 133–146

Wongsuphasawat K, Smilkov D, Wexler J, Wilson J, Mané D, Fritz D, Krishnan D, Viégas F B, Wattenberg M (2018). Visualizing dataflow graphs of deep learning models in tensorflow. IEEE Trans Vis Comput Graph, 24(1): 1–12

Xu J X, Li B Y, Yang X P, Zhou L P, Shi C X, Gao S, Zheng X M, Xiong K N, Zhu B Q, Wang Y P, Zhou L M (2009). Recent progress in geomorphology and quaternary geology in China and some perspectives. Acta Geogr Sin, 64(11): 1375–1393

Zhao R, Cheng W M, Liu J P, Dong C, Yu R H, Yin H M (2019a). Accurate division of geomorphological types in China. Sci Surv Mapp, 44(06): 248–255

Zhao W D, Li S S, Li A, Zhang B, Li Y (2019b). Hyperspectral images classification with convolutional neural network and textural feature using limited training samples. Remote Sens Lett, 10(5): 449–458

Zhao W F, Xiong L Y, Ding H, Tang G A (2017). Automatic recognition of loess landforms using Random Forest method. J Mt Sci, 14(5): 885–897

Zhi H, Siwabessy J, Nichol S L, Brooke B P (2014). Predictive mapping of seabed substrata using high-resolution multibeam sonar data: a case study from a shelf with complex geomorphology. Mar Geol, 357: 37–52

Zhou C H, Cheng W M, Qian J K, Li B Y, Zhang B P (2009). Research on the classification system of digital land geomorphology of 1:1000000 in China. J Geo-Infor Sci, 11(06): 707–724

Zhu H C, Xu Y X, Cheng Y, Liu H Y, Zhao Y P (2019). Landform classification based on optimal texture feature extraction from DEM data in Shandong Hilly Area, China. Front Earth Sci, 13(3): 641–655

Zhu H C, Zhao Y P, Liu H Y (2018a). Scale characters analysis for gully structure in the watersheds of loess landforms based on digital elevation models. Front Earth Sci, 12(2): 431–443

Zhu H C, Zhao Y P, Xu Y X, Liu H Y (2018b). Hierarchy structure characteristics analysis for the China Loess watersheds based on gully node calibration. J Mt Sci, 15(12): 2637–2650