Application of remote sensing image classification based on adaptive Gaussian mixture model in analysis of mountain environment features

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Abstract
The adaptive Gaussian mixture model is a probability model that can be used to represent the probability distribution of \( K \) in the overall distribution. The mixed model represents the probability distribution of the overall observed data. This is a mixed distribution composed of \( K \) sub-distributions. In the mixed model, in order to calculate the probability of the observation data in the overall distribution, the observation data is not required to provide information about the sub-distribution. The EM algorithm is used to estimate the parameters of a probability model with hidden variables. Large-scale analysis of remote sensing images of various temporal, climate, and terrain types of mountain environmental characteristics is one of the most important issues at present. In this experiment, 6 Landsat TM remote sensing images with different longitudes and latitudes, different land use patterns, different realities, different ranges, different terrains, and different climates were selected as the research objects. Through their comprehensive comparison, the general ones were selected. The supervised classification method (most likelihood method, BP neural network and support vector machine method) classifies Landsat TM remote sensing images. In order to improve the accuracy of remote sensing image classification and the accuracy of land use information extraction, data such as normalized vegetation index and texture features are used to classify the experimental samples. Cluster statistics and filter analysis are used to classify the results. Finally, a confusion matrix is used to evaluate the accuracy of the classification results.

Keywords Adaptive Gaussian mixture model · Remote sensing · Image classification · Mountain environment

Introduction
In the study of the EM algorithm in the Gaussian mixture model, the hybrid model is a widely used model now. Unfortunately, it is not easy to obtain parameter analysis solutions using conventional parameter estimation methods, which is disadvantageous to the development and application of hybrid models (Adam et al. 2014). Over the years, some scholars have proposed to combine the EM algorithm with the parameter estimation of the hybrid model (Al-Mustansiriyah et al. 2018). In this model, Bi Yong, Yang Ming, and Lei Yingji gave the initial iterative values of the parameters based on the empirical distribution. Steven G. conducted a very important research on mixed distributions such as mixed binomial distribution and mixed 0–1 distribution, derived the repetitive formula of parameters, and proposed a general regression method suitable for the overall experimental sample (Amarsaikhan et al. 2012). Usually, the covariance information of each member can be obtained through experiments. Therefore, in order to investigate the relationship between the response and the available covariates, they can be analyzed in stages using regression methods (Ashkan and Najmeh 2012). Ren Dawei studied the EMboost algorithm based on the boosting algorithm. Compared with the previous EM algorithm, the EMboost algorithm is more accurate and more sensitive to the initial value (Badreldin and Goossens 2014). Feng Hang used the clustering method and moment method to overthrow the parameter estimation of various forms of Poisson distribution and performed calculations (Ban et al. 2017). At the same time, the estimated confidence interval was obtained. Due to the development of satellite remote sensing technology, the use of remote
sensing image classification to obtain mountain environmental characteristic analysis information is one of the main contents of LUCC research (Breiman 2001). Remote sensing image processing software can quickly update the analysis of mountain environmental characteristics (Chatziantoniou et al. 2017). Now, remote sensing image classification is mainly used for feature analysis information of the mountain environment, which improves the information extraction of remote sensing images. In related studies in China, the LUCC classification of remote sensing images has gradually improved from statistical-based classification to non-linear classification (Cho et al. 2012). In the field of remote sensing research, the use of remote sensing classification technology to analyze the characteristics of the mountain environment is a hot topic in remote sensing application research (Erinjery et al. 2018). In order to adapt to the rational use of land science, monitoring methods are mainly used to speed up the extraction and development of land (Foody 2002). Therefore, an important issue in remote sensing application research is how to obtain high-precision change information in the analysis of mountain environmental characteristics (Goodman 1963). Moreover, in order to solve the accuracy of mountain environment characteristic analysis, this is also one of the urgent problems that need to be solved (Zhou 2008). This is very important for the analysis of the environmental characteristics of mountains and the optimization of the structure, as well as the comprehensive exercise of the ecological benefits of the analysis and study of the environmental characteristics of the mountains (Hansen and Loveland 2012).

### Materials and methods

#### Data source

The survey area consists of two natural geographic areas: mountains, hilly areas, and centrally inclined plains in the western part of county A. The auxiliary data used includes Google Earth, field surveys, and other auxiliary data. There are various wavelength bands in the OLI image, corresponding to the reflected radiation characteristics of various ground objects in this band, and there are various wavelength ranges, uses, and statistical characteristics (Van 1996).

According to the crop growth period, land use patterns, and remote sensing image quality of the survey area, in the choice of time, the selected seasonal characteristics must be considered, especially whether the forest and the cultivated land are easy to distinguish (Jos’ 2009). The crops in the survey area are mainly winter wheat, and the maturation system is once a year (Joshi et al. 2016). At the time selected in the image data, the growth of wheat in the remote sensing image turns green, and the forest turns red or deep red in the remote sensing image, so the selected remote sensing image can be used for research (Landis and Koch 1977). Table 1 shows the detailed information of the remote sensing image data source of the survey area.

### Analysis of remote sensing image characteristics

Landsat 8 is equipped with two main loads, OLI and TIRS. This research uses Landsat 8OLI remote sensing image data. OLI contains all frequency bands of the ETM+ sensor, and that frequency band is readjusted. The bigger adjustment is OLIBAND5 (0.845–0.885 μm); the water vapor absorption function of 0.825 μm is excluded. In addition, OLI has added two bands, including strong water vapor absorption band 9 (1.360–1.390 μm), which can be used to observe cirrus clouds, as shown in Table 2 and Table 3.

Landsat fully considers the differences in various ground objects such as water, plants, soil, rocks, etc., thereby effectively expanding the application fields of remote sensing image data.

| Band number | Wavelength(μm) | Spectral region | Spatial fraction(m) | Features and uses                                      |
|-------------|----------------|-----------------|---------------------|--------------------------------------------------------|
| 1           | 0.45–0.52      | Blue            | 30                  | Used for water penetration, distinguishing soil vegetation |
| 2           | 0.52–0.60      | Green           | 30                  | Used to distinguish vegetation, with strong penetration into water |
| 3           | 0.63–0.69      | Red             | 30                  | Used to distinguish vegetation type and coverage        |
Remote sensing image classification method

Supervised classification and unsupervised classification are the main methods of traditional computer classification. The result of unsupervised classification is generally not as good as the result of supervised classification. Therefore, in this study, we chose a supervised classification method for classifying remote sensing images based on research needs. Supervised classification is a high-precision general statistical decision classification method, as shown in Fig. 1.

Therefore, this is an important basic task for computers to interpret remote sensing images. According to the methods of artificial visual interpretation and computer screen interpretation, it is possible to intuitively distinguish the characteristics of 5 types of land for construction land, forest, arable land, water, and other land.

In the process of supervised classification, the selection of training samples is especially important. The selected training samples must accurately reflect the spectral characteristics of different categories in the entire region. Different regions were selected, and several sample classification training areas were established, such as cultivated land, forests, construction land, and water areas. The experiment adopts a stratified sampling method, and 2000 sampling points are selected as training and verification samples.

In remote sensing image classification, it is necessary to determine the classifier to be used according to the complexity and accuracy requirements of the classification. At present, in addition to artificial neurons, ENVI’s supervised classification also includes the most widely used minimum distance, fuzzy classification, most likelihood method, spectral angle (SAM), support vector machine, etc. Among them, the network method and the support vector machine classification method are widely used.

Design of adaptive Gaussian mixture model

In the binomial distribution, it can be seen that the optimal group size $k = k(N) = \arg\min \text{MSE}(\hat{p}; l, p_0, N)$ depends on the number of groups and the estimated $P$ mean square error.

Table 3  Landsat8OLI-related parameters

| Band number | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|-------------|---|---|---|---|---|---|---|---|---|
| Band        | Dark blue | Blue | Green | Red | Near infrared | Shortwave infrared | Shortwave infrared | Panchromatic | Cirrus |
| Spatial resolution/m | 30 | 30 | 30 | 30 | 30 | 30 | 30 | 15 | 30 |
| Radiation resolution/bit | 12 | 12 | 12 | 12 | 12 | 12 | 12 | 12 | 12 |

The import of the EM algorithm used to calculate the $P$ estimate is very complicated. Even after the mean square error is calculated, the estimate of $P$ cannot be directly calculated. Therefore, in the Gaussian mixture model, the classical probability idea frequency is introduced to estimate $P$. The number of positive test groups is $Z$, and the critical value of the tested individual’s positive characteristics is $T_0$, sensitivity $Se$, and specificity $Sp$.

\[
\hat{p} = p(I_i = 1) = Se + (1-Se-SP)p\bar{I}_i = 0 \tag{1}
\]

And variance:

\[
\text{Var} (\hat{p}) = \frac{1}{N^2} \left( p(Y_i > T_0) - p^2 (Y_i > T_0) \right) \tag{2}
\]

The estimate of $P$ is thus obtained:

\[
\hat{p} = 1 - \left( \frac{Se - \hat{v}}{r} \right)^{\frac{1}{k}} \tag{3}
\]

The variance of the estimated value of $P$ is calculated according to the Delta rule. In the calculation of the optimal group size, for convenience, the variance is used to replace the mean square error.

\[
\text{Var} (\hat{p}) = \left[ \frac{1}{r k} \left( \frac{Se - \hat{v}}{r} \right)^{\frac{1}{k} - 1} \right]^2 \cdot \frac{1}{N^2} \left( p(Y_i > T_0) - p^2 (Y_i > T_0) \right) \tag{4}
\]

Therefore, the optimal group size for two-step group detection in the Gaussian mixture model is as follows:

\[
k = k(N) = \arg\min \text{Var}(\hat{p}; p_0, N) \tag{5}
\]
Numerical simulation design of mountain wind environment

The SHW observatory is located in 22° 18′ 21″ N, 113° 58′ 45″ E, as shown in Fig. 2 and Fig. 3. The terrain data within a radius of 5 km is selected for modeling. In order to solve the problem of unmatched elevation of the selected terrain boundary, the expansion formula shown in Eq. (6) is used to extend the original terrain outwards a flat terrain with uniform elevation. The altitude of the flat terrain on the outside is set to zero as follows. The enlarged terrain is shown in Fig. 4. Next, combine GAMBIT and ICEMCFD, as shown in Fig. 5.

\[
z_e(x,y) = \begin{cases} 
 0 & 0 \leq \sqrt{x^2 + y^2} \leq R \\
 0 & 0 < \sqrt{x^2 + y^2} \leq 2000 \\
 2000 + R & \sqrt{x^2 + y^2} \leq 2000 + R \\
 0 & \sqrt{x^2 + y^2} > 2000 
\end{cases} 
\]

Here, \( z_e(x,y) \) is the extended terrain coordinates.

Results

Remote sensing image classification and accuracy evaluation of different geomorphological units

In this study, image preprocessing was performed on ENVI5.1 and ArcGIS 10.0 platforms. The vectorized files and SHP files of terrain units were obtained according to the vectorized contours of the survey area, and the vectorized shearing remote sensing image was used for processing. Obtain the boundaries of remote sensing image data under various terrain units throughout the county. Next, the 1:50,000 topographic map is used to interpret the remote sensing image, which is explained by human-computer interaction using auxiliary data such as the terrain and land use map of the survey area.

According to research needs, remote sensing images of western mountains, hills, and central alluvial plains were selected as sample areas, and remote sensing image classification research was implemented. The classification results are shown in Fig. 6 and Fig. 7.

The experiment process is as follows: use MLC, ANN, and SVM classification; the accuracy evaluation results are shown in Table 4.

Generally speaking, the classification results of the above three classification methods are that, based on the geological form of the western mountains and hills, ANN and SVM are both effective in the western mountains and hills and the central alluvial plain area. Compared with the previous classification method MLC, it shows superior advantages. However, from the perspective of overall classification, the classification
of remote sensing images in western mountainous and hilly areas is more susceptible to natural factors and more complex influences. Therefore, the classification accuracy of western mountainous and hilly areas is lower than that of central alluvial plain areas.

Analysis of mountain wind environment simulation

Before the numerical simulation of complex terrain, the self-maintenance of inlet wind distribution is the prerequisite to ensure the accuracy and reliability of numerical simulation of complex terrain before reaching the complex terrain. Therefore, before the numerical calculation, the average wind speed and turbulent energy distribution from the entrance to 3000 m, 6000 m, 9000 m, and 11,580 m are extracted, and the wind speed distribution and turbulent energy distribution at the entrance are extracted. The result is shown in Fig. 8. As shown in Table 5, the wind speed distribution and turbulent energy distribution from the entrance of the complex terrain to 11,580 m are selected for error analysis. The maximum error of the inlet average wind speed distribution map is 10.93% at a height of 5 m, and the average error is about 1.44%. The maximum error of turbulent energy distribution is 7.69%, and the average error is about 1.54%. The error is mainly due to the lower boundary conditions of the calculation area, and the influence range is within 10 m near the wall. The overall self-maintaining effect of the inflow state is good.

Use FLUENT’s software to perform numerical calculations of the flow field under various working conditions. As shown in Fig. 9, the velocity cloud graph with the height of the calculation area less than 200 m under the typical inlet wind direction angle of 0° is truncated. It can be seen from the figure that the flow direction of the flow field starts from the right. The distance from the entrance to the terrain boundary is sufficient to fully develop the inflow conditions and reduce the influence of the inflow field boundary. When the flow field flows in a complex terrain area, a wake will be generated under the influence of the terrain. Since the size of the calculation field is sufficient, in order to avoid the adverse effect of the back flow on the flow field in the mountainous area, the back flow can be fully eliminated. The lateral boundary and upper boundary of the calculation area are far enough away

![Fig. 4 Overall and local topography after expansion](image1)

![Fig. 5 Computational domain of 3D complex terrain](image2)

![Fig. 6 Remote sensing image of mountain and hills](image3)
from the terrain area, and the boundary conditions have no obvious influence on the internal flow field. As shown in Fig. 10 and Fig. 11, the average wind speed distribution of less than 600 m will be reduced to varying degrees due to the influence of complex terrain.

At the inlet wind angle of 225° on land, the average wind speed distribution near the surface is most obviously reduced. As shown in Fig. 12, the flow field under the wind profile of the observatory (SHW) at this time was analyzed. The reason for the decrease in the average wind speed curve of SHW is that SHW is in the leeward upstream area, and the velocity on the side of the flow field is greatly reduced.

With an inlet wind direction angle of 292.5° under the marine site classification, the average wind speed distribution near the surface is greatly reduced. As shown in Fig. 13, the flow field of the wind profile of the observatory (SHW) was analyzed. The decrease of the average wind speed curve of SHW is hindered by the location of SHW on the leeward side of the flow field and the complicated terrain.

### Table 4: SVM classification accuracy evaluation

| Category         | Arable land | Woodland | Construction land | Other | Drawing accuracy | Omission error |
|------------------|-------------|----------|------------------|-------|-----------------|----------------|
| Arable land      | 91.37%      | 1.25%    | 4.61%            | 4.37% | 91.38%          | 8.62%          |
| Woodland         | 3.93%       | 97.58%   | 8.16%            | 2.87% | 97.59%          | 2.41%          |
| Construction land| 4.65%       | 1.15%    | 86.47%           | 18.46%| 86.48%          | 13.52%         |
| Other            | 0.05%       | 0.02%    | 0.76%            | 74.28%| 74.27%          | 25.73%         |
| Misclassification error | 6.13% | 3.03% | 16.07% | 12.93% | Kappa coefficient | 0.8963 |
windward side gradually increases with the rise of the slope, and the calculation area determines the terrain characteristics of the actual terrain according to the terrain. This is because topography is the main reason that affects the characteristics of the flow field. Therefore, the flow field characteristics of these two calculation fields are closer to the original topography.

According to the FEP method, the numerical simulation of the downward flow field of the flowing wind is implemented, and the simulation results are compared with the wind tunnel test results or the field measurement data, and satisfactory results are obtained. As shown in Fig. 18, the numerical simulation results are consistent with the actual observable data, so it can better simulate the actual wind field of complex terrain.

Discussion

The relationship between mountain topography and soil environment

Terrain and small field environment

The research on the microclimate system of China’s topography began in 1956 on the microclimate of various topographies of the plateau. In the mountainous area, due to the difference in the direction of inclination and the angle of inclination, the influence on the amount of sunshine, sunshine time, and wind is also different, so the microclimate of the slope is formed (Leinenkugel et al. 2014).

The “Small Network Method” is used to correct the temperature and precipitation field under the complex terrain of the mountainous area (Lin et al. 2010). The results show that the temperature contours of the average temperature zone from May to August basically follow the contours, and the precipitation contours basically follow the contours. According to research, the increase in altitude, the decrease in temperature, atmospheric pressure, CO2 partial pressure, and the increase in light intensity are due to the insignificant “siesta” phenomenon of crops on the plateau (Mahboob Iqbal et al. 2013). The speed of photosynthesis at noon has been reduced due to the proper local temperature and the larger coefficient of air pressure.

Terrain and soil environment

The existence of the International Soil Moisture Monitoring Network (ISMN) highlights that soil moisture research has become one of the popular areas of the international scientific community. Global soil moisture data sharing also provides...
new methods and ideas in the field of soil moisture research. The soil moisture content on the surface changes drastically, which is not only affected by the input of precipitation, but also affected by the micro-topography (de Markus 2009).

Now, there are many reports on the dynamic changes of soil nutrients and water rules and the response to rainfall, mainly focusing on all types of vegetation and soil. For example, Azuma believes that P. Chino’s growth path can be activated in areas where the bottom of the slope is stable. Wangyq et al. studied the depth of water consumption by vegetation and the characteristics of soil dryness in the Loess Plateau. Wangs et al. pointed out that the soil moisture content varies greatly among different vegetation types on the Loess Plateau. In the study of Gao Fu et al., the surface soil moisture content of forest clusters is highest in the upper part of the slope, second in the lower part of the slope, and lower in the center of the slope. And as time changes, the surface soil water content of the slope shows a decreasing trend.

In the change of small terrain, few studies on soil moisture content such as dryness and slopes have become news. The order of topography and soil moisture is as follows: cutting of grooves, slow inclination, truncation of trenches, and steep, steep inclination. The order of soil moisture on the micro-topography of the semi-sun slope is as follows: slow slope, shallow trench, steep slope, and very steep slope. Under the various terrains of the Ordos Plateau, soil moisture has various spatial fluctuation characteristics. Ma Yingbin et al. studied the dynamic fluctuation characteristics of water in different soil layers on both sides of different slope cracks after rainfall. There is no report on the difference in soil moisture content of different crops on the micro-topography. Due to the inhomogeneity of the soil, the soil moisture has a large spatial variation. Soil also has a great influence on the growth and quality of crops. In order to form high-quality crops, the soil needs to supply enough nitrogen in the early stage to ensure the good growth of the crops, so that the crop metabolism can transition from the active state from protein synthesis to starch accumulation in time, and the nitrogen supply level should be appropriately reduced. The soil of flat land is mainly light loam, and the soil of hilly land is clay (Mohammed Noori et al. 2018).

Topography is also directly related to changes in soil properties. Because topography affects the redistribution of soil-
forming substances and hot water conditions, the characteristics of the soil vary according to the location of the soil shape. Wang Yongwang’s research results show that topography has a great influence on the available water and soil fertility, and the characteristics of the soil have similar tendencies in the same place on the slope. Sun Bo et al. pointed out that under the same soil base material, climate, and land use pattern, topography determines the spatial correlation interval of soil characteristics. In certain areas, altitude even directly affects the yield and quality of crops. Mu Biao et al. analyzed the chemical composition of crops at different altitudes in terms of climatic ecology for 3 years, and found that the total scores of appearance quality score, internal quality score, color, and aroma of crops all decreased with the increase in altitude. The overall quality has declined. They believe that altitude is the main comprehensive ecological factor that affects the chemical composition of crops, and altitude is significantly related to many major chemical components of crops.

Dai Changming analyzed 200 crop soil samples collected based on mountainous areas, terrain, and soil conditions. The results showed that the average soil organic matter content of crops is 27.70 g/kg, which is generally an appropriate level. The pH value is partly acid, the available nitrogen content is high, the available P content is small, and the available K content is generally abundant. The average content of water-soluble chlorine in the soil is 158.42 mg/kg.

**Terrain and plant growth and development**

The functional characteristics of plants are the connection between the plant and its environment. It is the morphological, biological seasonal and physiological properties formed during the long-term adaptation of the plant to the environment, which can maximize the use of various external resources. These attributes will affect the process and structural functions of the ecosystem, and can objectively reflect the ability of plants to adapt to the environment and the balance and evolution of various functions within plants.

Changes in topography will lead to spatial inhomogeneity of the environment and climate and affect changes in the functional characteristics of plants. The results show that there are significant differences in the phosphorus content and specific leaf area of plants in different oblique directions. Generally speaking, the phosphorus content of the shaded slope is higher than that of the slope with good sunlight. On the other hand, the main environmental factors that affect the morphology of plants are different under different terrain conditions.
The terrain helps explain the volatility of red grass biomass and corn yield. Kumhalova et al. used land statistics to study the relationship between yield and topographic attributes. Kumhalova et al. studied the influence of terrain on soil nutrient content and yield. The aboveground biomass of different site types is the highest at the bottom of the ditch, followed by...

Fig. 13 SHW downwind cross-sectional velocity and turbulent kinetic energy cloud diagram and streamline diagram at 292.5° wind direction

Fig. 14 Velocity clouds at different heights in the first-scale computing domain
Fig. 15  Velocity clouds at different heights in the second-scale computing domain
the slope of the ditch slope toward the sun, and the slope of the ditch slope toward the sun has the lowest aboveground biomass.

Main features of mountain landscape environment

Multi-level and three-dimensional spatial characteristics of mountain landscape

Multi-level overall space The height of the mountain is different, and flexible and diverse landscapes can be set up in multi-layer combination and free style. The shape comes from the terrain and the original environment, and has an irregular nature. Mountain roads play the role of connecting all nodes, with twists, turns, rich layers, and multi-functional characteristics.

Three-dimensional overall image People’s knowledge of things is 85% visually. People’s perception of the impression of residential areas comes from the experience of the environment. Therefore, the landscape structure has a clear priority, which can improve people’s environmental experience. The characteristic of the mountain space is that the vertical direction changes greatly, and the audience experiences the environment from a three-dimensional perspective, which provides help for a more comprehensive perspective understanding of the residential land as a whole.

The decisive node The landscape nodes of the mountain residential area are generally set at the two ends of the tour route, stopping points, and branch points, which are places for residents’ activities, leisure, and communication. Only clear node images can allow residents to have an obvious spatial position during walking. The most important image of the node is the visual stay. The clear image, unique spatial form, and concentrated activity space clearly define the nodes of the scenery. Among them, the complete spatial image is the most important element. The three-dimensional and hierarchical nature of the mountain space can produce strong spatial points and weak spatial points. People can experience various landscape images at various heights and produce various audio-visual experiences.

Characteristics of traffic organization in mountainous landscape

Mountainous areas have more characteristic traffic patterns than plains, such as horizontal traffic characteristics and vertical traffic characteristics. The traffic volume in the horizontal direction includes the width of the road, the width of the curve, the radius of the curve, and so on. Vertical traffic includes the vertical and horizontal slopes, curves, and altitudes of roads. Mountain residential areas need to rationally use the natural terrain to design roads, reduce the amount of engineering, and reduce natural damage while considering beauty.

The visual characteristics of the mountain landscape with variable perspectives

The combination of movement and stillness is the best way to appreciate the scenery. First, configure multiple landscape nodes on the main viewing route, and set up rest tables and seats on important landscape nodes, allowing visitors to sit and stand to watch the scenery in a static state. Visitors need a more exquisite scenery and environment when they are still, for more detailed observation.

Differential environmental planting design for different parts of the mountain

In the mountain area, plants from various places in the mountains are naturally arranged. The density is neat; there are voids and solids, as well as a combination of ups and downs. According to the different seasons, there are flowers in three seasons and green effects in four seasons. According to the terrain, slope; choose various slopes and suitable plant varieties, so that they are planted in the right place. Generally speaking, the distribution principles of mountain plants are as follows:
Follow mountain terrain and protect native tree species

The mountainous area, as a treasure house for residential landscape construction, is rich in native plants. Unfortunately, this natural resource is often overlooked by developers and designers, and has brought damage to the original mountain vegetation. In mountain landscape design, it is necessary to protect the original vegetation and natural topography to the utmost extent, skillfully use the weak geological zone and construction surplus land for plant design, and use the natural mountain landscape to divide the area. Moreover, it is necessary to create a characteristic flora, so that they have a rich and diverse landscape.

Pay attention to levels and develop three-dimensional greening

Respect nature, try our best to maintain natural green texture, and attach importance to three-dimensional greening and multi-level greening. According to the types and characteristics of plants, cleverly combine plants, vines, shrubs, and trees to increase the greening rate and improve the ecological environment. Three-dimensional greening is a gardening technique using plant landscapes. Please choose green plants on the roof, window sides, balconies, walls, and building surfaces. It can not only increase the greening rate of the community, but also increase the green space in the city.

Adjust measures to local conditions and reflect local characteristics

The topography of the mountain residential area is the foundation of the entire community for afforestation. According to the mountain environment, various tree species need to be planted. Plant strong tree species in the shade and plant species that love light on sunny slopes. In landscape design, in order to achieve the maximum ecological effect, local design must be paid attention to. In the selection of artificial tree species, local seeds must be selected first. The selected plant varieties will produce delicate changes under the principle of uniform distribution, so that characteristic tree populations such as Ginkgo Road, Cherry Blossom Road, and Magnolia Road can be created, which will defend against the invasion of foreign plants and also protect the ecology.

A variety of flowers and trees, considering seasonal changes

Houses and roads in residential areas in mountainous areas are suitable for planting flowers and trees, leafy trees, tall trees, and evergreen trees near the mountains. The layout reflects the wild atmosphere and harmonizes with the natural environment in a natural way. The change of seasons makes people feel the charm of the plant season. People living in cities can also feel the beauty of seasonal changes and improve their quality of life.

Conclusion

In the specific research of modern statistical science, the application of remote sensing image classification based on the adaptive Gaussian mixture model to analyze the environmental characteristics of mountains is a very wide application and one of the focuses of future research. Moreover, in the application of statistics, the idea of group detection is also applicable to many fields, especially the biological and medical fields such as epidemiological examination and genetic screening, and it is also applicable to the fields of computer and communication engineering such as signal detection. In the hybrid model parameter estimation of group detection, not only can the application of hybrid models in various fields be improved, but also better results can be obtained in practical applications. Based on the research of the latest trends in remote sensing classification at home and abroad, this paper uses remote sensing images of mountain environment analysis as the data source; uses remote sensing and geographic information system technology, mathematical statistics, and other
methods; and uses the maximum likelihood method (MVC) to analyze the mountains. The characteristics of the environment are compared with the classification results to improve the classification accuracy of remote sensing images.

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Declarations

Conflict of interest The author declares no competing interests.

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