Interpretation and Research On Landuse Based On Landsat 7 ETM Plus Remote Sensing Data

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Abstract. The change of landuse is very important factor in environmental. For example, it has significant relationship with the natural disaster such as landslide. With the development of technology about GIS and RS, the interpretation of landuse become easy and accuracy. This paper based on Landsat 7 ETM + data, combined Xiushui County, Jiangxi Province of geographic information base data using maximum likelihood classification method however, the minimum distance, secession law, ISODATA so on Xiushui county land use remote sensing interpretation. The results show that the maximum likelihood classification accuracy of the overall evaluation of the maximum likelihood method is to examine the method best suited to the region. The result of this study was the use of land may be provided to decision makers and land-use planning.

1. Introduction
Since the 20th century, due to the rapid population growth, and the use of land resources is relatively less and less, so LAND USE gradually attracted attention around the world, [1, 2]. The urban concentration is of population trends and the growing area of the city, [3, 4]. With the continuous development of science and technology, land use accuracy and scalability of the increasingly high demand. Based on this problem, scientists all over the world work together to explore different data and different classification methods, [5, 6]. Land use classification is to distinguish between the processes of land use spatial geographical composition unit, [7]. This spatial unit area of land use is a combination of geographical units, the performance of human impact on land use, the transformation of the way and the results reflect the land use form and use function, [8]. In recent years, with the development of remote sensing technology and the emergence of various types of high-precision digital remote sensing image data, land use provides high accuracy guarantee, [4, 9, 10]. Many remote sensing classification methods, mainly: classification based on traditional methods of statistical analysis, neural network classification methods, fuzzy classification method, decision tree classification methods, expert system classification, [9, 11, 12, 13]. In addition, data now can be a very
accessible, such as the US landsat satellite data, modis satellite data, and so on. The data for the researchers provide a good data supporting platform, [14, 15, 16]. In recent years, many scholars are engaged in land use interpretation work.

In the study area, based on landsat 7 ETM + satellite image data, using a variety of classification methods, the use Arcgis and ENVI software for land use interpretation in Jiangxi Province, the results show that Maximum likelihood is the best classification in land use. The results obtained can be applied to land use management, geological disaster risk assessment and zoning of the underlying database. These are the local government decision-makers and residents to provide scientific data management and support.

2. Study area and data
Xiushui County is belonging to Jiujiang City, in Jiangxi Province, it is located in the northwest of Jiangxi Province, Xiushui upstream. It is located in the Mufu and Jiuling Mountain, the highest point above sea level 171.55 meters. Annual average temperature of Xiushui area is 16.5 degrees, and annual rainfall of is 1580 mm, and the average annual sunshine hours is 1629 hours. The Landsat 7 ETM’ is come from U.S. Geological Survey [17].

3. Methods
3.1. Maximum likelihood method
Maximum likelihood method (Maximum Likelihood, ML), is known as maximum likelihood estimation, also known as maximum likelihood estimation, and it is a kind of theoretical point estimation method [18]. The basic idea of this method is: when random from the overall model after the group n sample observations. The most reasonable parameter estimator should be such that the probability of drawing the sample set of n observations of the maximum from the model [19], rather than least squares estimation method is designed to obtain such a model that best fits the sample data parameter estimator [20]. The formula is as follows:

\[
D = \ln(a_C) - 0.5 \ln(\text{Cov}_C) = \left[0.5(X - M_C)\right]^T (\text{Cov}_C^{-1}) (X - M_C) \tag{1}
\]

where: \( D \) - Right from the (possibility); \( C \) – is a feature types; \( X \)- pixel measurement vector; \( M_C \) - sample mean vector type \( C \); \( a_C \) - any percentage probability that a pixel belongs to type (default is 1.0, according to the first or knowledge test input) \( C \); \( \text{Cov}_C \) - the sample of the type of the covariance matrix of pixels \( C \); \( |\text{Cov}_C| \) determinant; \( \text{Cov}_C^{-1} \) - an inverse matrix; \( T \) - transpose function.

3.2. The minimum distance method
The minimum distance classification is based on a representative sample from the model and all kinds of pattern classification of a statistical recognition method [21]. In this method, the distance to your pattern is recognized mode with the minimum sample category, [22]. And \( x \) is the distance \( R_i \) \((i = 1, 2, \ldots, c) \) between \( c \) category representation model assumes that the feature vector with R1, ..., Re represents, \( x \) is the feature vector recognition mode, \( |x-R_i| \).

If \( |x-R_i| \) is minimum, then is put \( x \) into class \( i \). It can be used a representative sample of all types of collections in a more complex situation, rather than just using a sample as the minimum distance classification basis (see Nearest neighbour classification, [23]). Minimum distance classifier performed first to determine its representative feature vector mode for each category, which is classified in this way be good and bad effects of the key [24]. Various types of representative feature vector may be determined mechanism of physical, chemical, biological and other aspects of the study, [25, 26]. According to the commonly used method is to collect all kinds of samples with various types of sample mean vector feature vector as a feature vector representative of all kinds of patterns, [27, 28]. Second, we must choose a determined distance metrics to calculate distance recognition mode with various representative’s pattern feature vectors are [27, 29]. There are commonly used Euclidean distances from the absolute distance. The following equation is applicable:
\[
d(x, M_i) = \left[ \sum_{k=1}^{n} (x_k - m_{ik})^2 \right]^{1/2}
\]  

(2)

Where, \( n \): number (dimension) bands; \( k \): a characteristic band; \( i \): a cluster centres; \( M_i \) sample mean of class \( i \); \( m_{ik} \) class \( i \) k pixel value of the center bottom band; \( d (x, M_i) \): x pixels to class \( i \) to M center distance.

3.3. Mixing distance classification

Mixed distance classification is an system clustering method, [30, 31]. In contrast, at the beginning of all the pixels as a class, find the variables mean and standard deviation, the centre calculated after splitting two categories according to a certain formula and then calculates each pixel to cluster these two types of centres will be integrated into the cell from the nearest to the kind of form two new classes. then for each new class classification, as long as there is a band of mean square error is greater than a predetermined threshold value, a new class division is necessary, [32].

3.4. Iterative Self organizing Data Analysis Techniques Algorithm

Iterative Self organizing Data Analysis Techniques Algorithm, is known as the Mixed distance classification method, which method and system clustering [33]. In contrast, at the beginning of all the pixels as a class, find the variables mean and standard deviation, the centre calculated after splitting two categories, [34]. According to a certain formula and then calculates each pixel to cluster these two types of centres will be integrated into the cell from the nearest to the kind of form two new classes [35]. Then for each new class classification, as long as there is a band of mean square error is greater than a predetermined threshold value, a new class division is necessary, [36].

4. Results and Discussions

The overall classification accuracy (Overall Accuracy) equal to the sum of correctly classified pixels is divided by the total number of pixels, the real image surface or surface area defining a real interest in the real pixel classification. Correctly classified pixels along the diagonal of the confusion matrix distribution, which shows the number of pixels are classified to the correct classification of the real surface. Total classification is as equal to the sum of all the surface of the cell's classification. Table 1 shows the four kinds of classification results of an evaluation by the overall classification accuracy.

**Table 1. The overall classification accuracy of evaluation results**

| Time | Maximum likelihood [%] | Minimum distance [%] | Mixing distance [%] | ISODATA [%] |
|------|------------------------|----------------------|---------------------|-------------|
| 2010 | 94.6                   | 91.4                 | 93.4                | 89.33       |
| 2012 | 93.4                   | 92.3                 | 90.9                | 91.2        |
| 2013 | 92.8                   | 91.7                 | 92.1                | 90.2        |

5. Conclusions

The paper dealt about various data using and combining. On the example of Landsat 7 ETM + data combined with data of Xiushui County, Jiangxi Province, which are geographic information base data, by using of maximum likelihood classification method, minimum distance, mixing distance and ISODATA. The results show that the maximum likelihood classification accuracy of the overall evaluation was examined the best method suited to the region. The result of this study was the evaluate classification method suitable for land evaluation, which will be provided for decision making process and land-use planning.
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