Lithology Intelligent Analysis in Three Gorges Based on Remote Sensing Image

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***Abstract*—In the south area of China, there covers thick soil and flourish vegetation on the top of the rocks, so there is little research on lithology analysis by remote sensing in the south area, and there is also no mature methods on this aspect. Three Gorges are the south area which is thickly covered by soil and flourish vegetation and the lithology analysis is very difficult. Three Gorges possess the characters of complicated terrain, frequent geologic disasters and full-grown vegetation and soil, so it is very important to make lithology analysis in the area. In the paper we made analysis of lithology with remote sensing images focusing on the area of Three Gorges, adopted the idea of oriented-object, built three sorts of guideline sets of spectrum, texture and vegetation covering, made quantification of the guideline sets and based on the algorithm of concept grid mined the association rules of the lithology in the stratums of Three Gorges: Jia Second and Third Sections Jia Ling River Group T_1j^2 and T_1j^3, Ba First and Second Sections Ba Dong GroupT_2b^1 and T_2b^2, and Da Ye Group T_1d.**

***Index Terms*—data mining, remote sensing, lithology, knowledge discovery**

I. Introduction

In a remote sensing image, there truly records the spectral radiancy and formal characters of the lithology. In different areas, the geologic background conditions and lithology weathering and covering degrees are different from each other, so the spectral and formal characters are also different. So lithology analysis is a research area of Remote Sensing Geology which is important but very difficult. Lithology analysis by remote sensing possesses the virtues of short period, small human and material resources and galactic extending and application values. Three Gorges possess the characters of complicated terrain and frequent geologic disasters, so it is very important to make lithology analysis in the area.

At the present, international research on lithology analysis by remote sensing mostly concentrates in the regions of exiguous vegetation, weak human influence and high rock bareness rate, and researchers has proposed some mature lithology extracting methods by multi-spectral and hyper-spectral remote sensing images. But there is little research on lithology analysis in the regions of thickly-covering vegetation and soil and few bare rocks[1-2]. Because for such regions, in the remote sensing image, there often presents the information of soil and vegetation, and little information about the rocks, which brings much difficulty to lithology analysis by remote sensing images.Three Gorges belong to the south region with flourish vegetation, in which lithology analysis is very difficult. And the authors almost didn't find the reports on lithology analysis in Three Gorges. The key of lithology analysis in Three Gorges is to search for a method which can eliminate the influence of the top soil and vegetation to extract the lithology information.

In the recent years, there appeared some methods of lithology information extraction[1-5], for example, Mixed Spectrum Decomposition, NAPC (Noise-adjust Principle Components Transform), Corresponding Analysis Based on Principle Components, Spectrum Angle Drawing, Matched Filtering, Absorbing Depth Analysis of Related Spectra. And some methods also introduced some new methods of Neural Network, Wavelet Transform, fractal and so on. Mars[3] adopted absorbing depth analysis of the related spectra and according to the characters of the spectra of strong absorbability in 2.20 μm and 2.33 μm to recognize the minerals of clay, carbonate and Mg-OH. Lawrence [4] adopted the spectra from visible-light to NIR (Near Infrared Ray) and the spectra in SWIR (Short Wavelet Infrared Ray) of ASTER data and made matched filtering to recognize limestone and dolostone. He also recognized quartzite and carbonate by the spectrum of Thermal Infrared Ray. Lawrence also utilized standard multicolor technique to fuse ASTER data and RADARSAT data. In the fused image, there at the same time included both the spectral information from ASTER data the hypsography characters from RADARSAT data, and enhanced the ability of lithology mapping. Lawrence adopted ASTER data and DEM to produce the 3-dimension remote sensing image which can effectively recognize the lithology unit in Nile gorge. Huang [5] made use of the classical variation function to compute the textural information of 6 spectra of TM image which was combined with multi-spectra to make classification. The classification precision was increased from 40.16% obtained only by the multi-spectra to 72.66%. Zhao [6] obtained good classification effect of the rocks based on

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fractal analysis of the textural information. Ma [7] made use of the data from multiple origins to extract the lithology information in the area thickly covered by vegetation. He firstly found the relation of the microelements of different vegetation and spectral responses, combined remote sensing images with none remote sensing data to build the association between rock components and spectra, lastly made lithology classification by the method of remote sensing poor information extraction, and obtained a good effect.

However at the present most of the methods of lithology analysis by remote sensing images possess poor intelligence, primarily depend on visual interpreting to analyze and extract the lithology information, and don't combine with the experts' knowledge and data mining methods.

Formal concept analysis, namely concept grid theory, is a set theory model which reflects the process of human to form a concept by mathematical formal language. It is very suitable to find the potential concepts hidden in the data, so it is very fit to act as the basal data structure of rule discovery and can make a good explanation to the knowledge and rules mined from the remote sensing image. However at the present, there is little international research on spatial data mining by formal concept analysis [8-10]. And the research didn't combine the characters of the spatial data.

In the paper, we make lithology analysis focusing on the region of Three Gorges. We adopt the object-oriented idea, built three sorts of guideline sets respectively reflecting the characters of spectra, texture and vegetation coverage, quantified the guideline sets and based on the concept grid algorithm to realize the lithology analysis and association rule extraction in the stratums of Three Gorges: Jia Second and Third Sections Jia Ling River Group T_1j^2 and T_1j^3, Ba First and Second Sections Ba Dong GroupT_2b^1 and T_2b^2, and Da Ye Group T_1d.

II. OBJECT-ORIENTED IDEA

The lithology distribution is sequential, so pixel-oriented idea of data mining is not suitable for litholgy analysis. And a remote sensing image generally possesses a large data amount, so in the paper, unlike some algorithms of remote sensing data mining and knowledge discovery which were based on the pixel process, we adopted the object-oriented idea, namely making data mining focusing on the pixel sets, which can effectively increase the algorithm efficiency and decrease the time complexity. The chosen of the size of the pixel set is the key of the idea. If the window size is chosen too small, it cannot adequately extract the spatial information reflecting the lithology characters. On the contrary, if the window size is chosen too big, it will cover up the difference between two different lithology and extract the wrong spatial information. In the paper, we adopted *VC* (Variation Coefficient) to establish the pixel sets of stable quality. The definition of *VC* is as follows:

$$VC = S / \overline{X} . \tag{1}$$

in which S is the standard deviation, and $\overline{X}$ is the mean value, namely

$$S = \sqrt{\frac{\sum x^2 - \frac{\sum x^2}{n}}{n-1}} \tag{2}$$

$$\overline{X} = \frac{1}{n}\sum_1^n x_n \tag{3}$$

If *VC* is big, it illuminates that the variation amplitude is big, and the orderliness and stability is poor. If *VC* is small, it illuminates that the variation amplitude is small, and the orderliness and stability is good. By experiment, we choose the window size 9×9 of the *VC* going steady as the best size of the pixel set.

III. FORMAL BACKGROUND ESTABLISHING

The key of establishing the formal background is the choice and quantification of the guideline sets.

A Choice of Guideline Sets

The spectral and textural information of different lithology (stratums) in a remote sensing image are different. For example, in the remote sensing image, conglomerate often takes on the shapes of speckles and blocks and the asymmetric and fuscous hue. Shale often takes on dark and gray blocks or zonary texture and limestone and dolomite often present the alveolate shapes. On different rocks, the vegetation coverage is also different. On some rocks, the vegetation is very flourish; but on some rocks, the vegetation is exiguous, even no vegetation coverage. And on different rocks, the vegetation species are also different. So in the paper, we choose the three sorts of guideline sets of spectra, texture and vegetation coverage of different lithology to establish the formal background.

In Three Gorges, there covers thick soil and flourish vegetation and the bare rocks are few, so in the remote sensing image, there often presents the information of soil and vegetation on the earth's surface, and little information about the rocks. In the remote sensing image, the information of rocks cannot be directly reflected or the characters of the rocks reflected from the remote sensing image is quite different from the experts' experience as the above. Therefore it is the key of lithology analysis by remote sensing how to cancel the influence of the vegetation and soil information and extract the bottom rock information.

In the paper, we make lithology analysis by TM multi-spectral remote sensing images in Three Gorge. We analyze the seven spectra of TM images and discover the spectrum information of TM5 image can best reflect the lithology information, so we choose the mean, standard deviation and entropy of the pixel values of each pixel set in TM5 image as the candidate spectral guideline sets.

Gray level co-occurrence matrix describes the spatial distribution and structural characters of various pixels in a image and possesses the predominance in improving geological object classification by the textural characters in a remote sensing image. Gray level co-occurrence matrix provides some textural feature values which describe the textural characters of a image from various aspects. By analysis, we choose the following 4 textural feature values to make lithology analysis.

a. Contrast

$$CON = \sum_{i=1}^{n}\sum_{j=1}^{n} p(i,j)^2 \times (i-j)^2 \quad (4)$$

b. Correlation

$$CON = [\sum_{i=1}^{n}\sum_{j=1}^{n} p(i,j)\times(i-n)\times(j-n)]/(\sqrt{i-n^2}\times\sqrt{j-n^2}) \quad (5)$$

c. Energy

$$ASM = \sum_{i=1}^{n}\sum_{j=1}^{n} p(i,j)^2 \quad (6)$$

d. Entropy

$$ENT = -\sum_{i=1}^{n}\sum_{j=1}^{n} p(i,j)\times \lg^{p(i,j)} \quad (7)$$

in which $p(i,j)$ is the element value of the position (i,j) in gray level co-occurrence matrix.

Because the division between two spectra can effectively restrain some needless information and give prominence to the key information, we make division between the spectra which can effectively restrain the vegetation information and give prominence to the lithology information. In the paper, we choose to divide spectrum TM3 by spectrum TM1. We called the image produced by the division as 3/1 image. Then the candidate texture guideline sets are chosen as the contrast, correlation, energy and entropy of the gray level co-occurrence matrix of each pixel set in 3/1image and TM5 image.

In Three Gorges, there grows flourish vegetation. On different kinds of rocks, there grows different kinds of vegetation, and the vegetation coverage degrees are also different. For the region of flourish vegetation, vegetation index is an effective classification factor. Vegetation index is a kind of value about the vegetation circumstances on the earth's surface extracted from multi-spectral remote sensing data. It can illuminate the vegetation coverage circumstance on the earth's surface. The normalized vegetation index NDVI possesses the virtues of wide inspecting amplitude of vegetation coverage degree and good adaptability in phase and space. Therefore the candidate vegetation coverage guideline sets are chosen as the mean, stand deviation and entropy of each pixel set in the NDVI image.

We make a large amount of statistical analysis of the swatch images of various lithology in the remote sensing images and discover that the following guidelines of the textural contrast in 3/1 image, the mean in NDVI image, the spectral mean in TM5 image, the textural correlation in TM5 image and the textural energy in TM5 image can commendably reflect the characters of the lithology and distinguish various lithology, so we choose them as the final guideline sets.

B Guideline Set Quantification

By analyzing various lithology, we divide each guideline set into several intervals, which can to a good degree distinguish various lithology and reflect the characters of each lithology, so the formal background and the lithology rules to be mined are both quantified. By a large amount of statistical analysis, the quantificational intervals of various guideline sets are shown as Table Ⅰ.

TABLE I. GUIDELINE SET QUANTIFYING

Guideline sets	Quantification
3/1 textural contrast	[-,2]e+003, [2,3]e+003, [3,4]e+003, [4,5]e+003, [5,8]e+003, [8,-]e+003
TM5 textural correlation	[-, 0.2], [0.2, 0.7], [0.7, 0.8], [0.8, -]
NDVI mean	[-,110], [110,140],[140,180], [180,-]
TM5 spectral mean	[-,60], [60,100], [100,170], [170,180], [180,-]
TM5 textural energy	[-,0.01], [0.01,0.011], [0.011,0.015], [0.015,-]

Ⅳ. CONCEPT GRID ALGORITHM

In the paper we adopt the incremental algorithm to build the concept grid. The incremental concept grid algorithm [10] scans only once the database, inserts the new affair T into the old concept grid L, and produces the new grid L'. Incrementally building of concept grid is to educe the new concept grid $L^* = (CS(K^*), \leq)$ corresponding to the new formal background $K^* = (O \cup \{o^*\}, A, R^*)$ based on the initial concept grid $L = (CS(K), \leq)$ corresponding to the original concept background $K = (O, A, R)$ and the new object o^*. The incremental concept grid algorithm formally defines the types of the grid nodes according to the relations between each node in the initial concept grid and the new object.

a. Invariable node

If the grid node C accords with the condition $Intent(C) \cap f(o^*) = \phi$, in which $Intent(C)$ is the intension of the grid C, and $f(o^*)$ is the attribute set of the new object o^*, C is an invariable node. The invariable nodes are the ones the new grid L^* retains from the old grid L, and their intensions and extensions are both not changed.

b. Renewed node

If the grid node C accords with the condition $Intent(C) \subseteq f(o^*)$, C is a renewed node. The intention of the renewed node doesn't change, and the extension increases: $Extent(C) = Extent(C) + 1$.

c. Producing-seed node

If the grid node $C=(O,A)$ accords with the following two conditions, *C* is the producing-seed node.

(a) Suppose $Inter\sec tion = Intent(C) \cap f(o^*)$. In the grid *L*, there doesn't exist another node C1 which contents $Intent(C1) = Inter\sec tion$;

(b) In the grid L, if the node C2 possesses the relation of partial ordering with the node *C*, $Intent(C_2) \cap f(o^*) \neq Inter\sec tion$.

d. New node

If in the old grid *L*, there doesn't exist the node *C*1 which contents the condition $Intent(C1) = Intent(C)$, in which *C* is any node in the new grid L^*, *C* is called as the new node.

The incrementally building algorithm of concept grid produces an affair set *T* while it reads a note from the database. It begins to search from the top node of the concept grid *L*, makes comparisons and set operations of the affair set *T* and the nodes in the grid *L* according to the descending order of the number of the layers in the grid, dynamically produces and inserts the new nodes, and at the same time renews the father-parent relationships of the nodes.

Ⅴ. LITHOLOGY RULE MINING FROM REMOTE SENSING IMAGE IN THREE GORGES

The lithology rules adopt the format of production rule $A \Rightarrow B$, in which *A* and *B* are both attribute sets. The meaning of the rule is in the database, if an object possesses the attribute *A*, it maybe also possesses the attribute *B*. And each rule possesses two parameters: support and confidence.

A. Searching for the Frequent Close Item Sets

If a close item set contents the minimum support threshold, it is a frequent close item set [10]. If a grid node contents the minimum support threshold, it is a frequent grid node. The intention of a frequent grid node is a frequent close item set.

B Production of the Producing-Seed of A Frequent Close Item Set

The rules are produced according to the producing-seeds of the frequent close item sets. The producing-see can be taken as the one which reflects the essential attribute of the concept corresponding to the concept grid node.

The computing method of a producing-seed is as follows:

a. Computing all the non-void subsets of the intention of each frequent close grid node. If a subset is the subset of the intention of one of its parent nodes, delete it;

b. For each subset, if there exists another subset to be the proper subset of it, delete it.

After the above processing, the remained are the producing-seed of the frequent close node. And the association rules can be produced according to those producing-seeds.

C Production of Lithology Rules

The lithology rules are produced by analyzing the relation of inclusion between two gird nodes. In the concept grid, we compute from the top down and obtain the lithology rules according to the frequent close item sets and their producing-seeds corresponding to the frequent close node pairs of the relationship of parent-child. For a pair of frequent close nodes of the relation of parent-child, the frequent close item set and the producing-seed of the parent node are f_1 and G_{f1}, and the ones of the child node are f_2 and G_{f2}, so the produced rule is $r: g \Rightarrow (f_2 - g) | g \in G_{f1}$.

Ⅵ. EXPERIMENTS

In the paper we adopt a TM sub-image (411×340) in Badong county, Engshi city, Hubei province in Three Gorges as the experimental remote sensing image which is shown in Fig. 1 (a). The image which stacks the TM sub-image with the geological graph is shown in Fig. 1 (b), in which the stratum recorded by the fuchsia lines and appearing alveolate is T1j2, which is mostly composed of limestone, dolostone and breccic. The stratum recorded by the white lines is Jia Third Section Jia Ling River Group T_1j^3, which is mostly composed of calcareous marl containing dolostone, limestone and in the central section contains chert conglomeration. The stratum of T_1j^3 partly appears vermiform and banded. The stratum recorded by the red lines is Ba Second Section Ba Dong Group T_2b^2. The upside of the stratum are fuchsia shale, arenaceous shale containing thin-middle or thick quartzose sandstone and appears interlaced. The underside are arenaceous clay stone containing a middle or thick calcium layer, quartzose sandstone cemented with calcareous marl, calcareous marl and sandstone containing cuprum. The stratum illuminated by the yellow lines is First Section Da Ye Group T_1d, which is composed of the yellow or yellow-gray calcareous shale containing a thin-middle or thick calcareous marl layer. In the paper, we adopt the incremental concept grid algorithm and the guideline images are shown in Fig.1 (c)-(e). From the NDVI image we can see the vegetation on the limestone and dolostone in T1j2 is more flourish than the one on other stratums.

In the paper we produce the formal background and build the concept grids by adopting 31, 10, 33, 39 and 8 objects (pixel sets) respectively in the stratums of T_1j^2, T_1j^3, T_2b^1, T_2b^2 and T_1d. The built concept grids are shown in Fig. 2. Suppose the minimum support threshold be minsupport=0.3 and the minimum confidence threshold be minconfidence=0.5, then we mine 18, 9, 62, 20 and 7 lithology association rules respectively in T_1j^2, T_1j^3, T_2b^1, T_2b^2 and T_1d. Because of the space limit, we only give part of the experimental results, which are shown in Fig.3.

From the experimental results, we can see that in each produced 2-dimension concept grid, each concept is expressed by a grid node and realizes the formal expression. In the produced concept grids, the extensive or special relations between two concepts are clearly denoted, which reflects the relations between the concepts hidden in the data. The minded rules possess the high confidence and accord with the practical condition, so they provide a large amount of important transcendental knowledge for intelligent classification and interpreting of lithology.

Because of the space restriction, we only interpreted some of the mined rules.

Rule1: the association rule on Jia Second Section Jia Ling River Group T_1j^2: TM5 mean value [100, 170] $\Rightarrow$ NDVI mean value [0, 140]. The connotation is for the lithology in Jia Second Section Jia Ling River Group T_1j^2, if the mean value of the pixel sets in TM5 image is in [100, 170], it can be deduced the mean value of the object in NDVI image must be in [0, 140].

Rule2: the association rule on Ba First Section Ba Dong Group T_1b^1: 3/1 Textural contrast [5, 8]e+003 $\Rightarrow$ TM5 Textural correlation [0.2, 0.7]. The connotation is for the lithology in Ba First Section Ba Dong Group T_1b^1, if the textural contrast of the research object in TM3/TM1 image is in [5e+003, 8e+003], it can be deduced that the textural correlation of the object in TM5 image must be in [0.2, 0.7].

Rule 3: the association rule on Jia Third Section Jia Ling River Group T_1j^3: TM5 Spectral mean [100, 170], TM5 textural energy [-∞,0.01] $\Rightarrow$ NDVI Spectral mean [140, 180]. The connotation is for the lithology in Jia Third Section Jia Ling River Group T_1j^3, if the spectral mean and textural energy of the research object in TM5 image are respectively in [100, 170] and [-∞,0.01], it can be deduced that the spectral mean value of the object in NDVI image must be in [140, 180].

Other rules can be connoted according to the above.

The mined rules quantitively express the relations and inner rules among various guideline factors of the lithology in each stratum, accord with the practical conditions, and provide important criterion for the intelligent classification and interpreting of the lithology.

Ⅶ. CONCLUSIONS

In the paper, we make lithology analysis focusing on the region of Three Gorges which possess the characters of complicated terrain, frequent geologic disasters and full-grown vegetation and soil. We adopt the object-oriented idea, built three sorts of guideline sets respectively reflecting the characters of spectra, texture and vegetation coverage, quantified the guideline sets and based on the concept grid algorithm to realize the lithology analysis and association rule extraction in the stratums of Three Gorges: Jia Second Section Jia Ling River Group T_1j^2, Jia Third Section Jia Ling River Group T_1j^3, Ba First Section Ba Dong GroupT_2b^1, Ba Second Section Ba Dong GroupT_2b^2 and Da Ye Group T_1d. And the minded rules provide important criterion and transcendental knowledge for the intelligent classification and interpreting of the lithology. Next we will be engaged in the research on rule application, namely applying the mined rules to lithology intelligent classification and interpreting.

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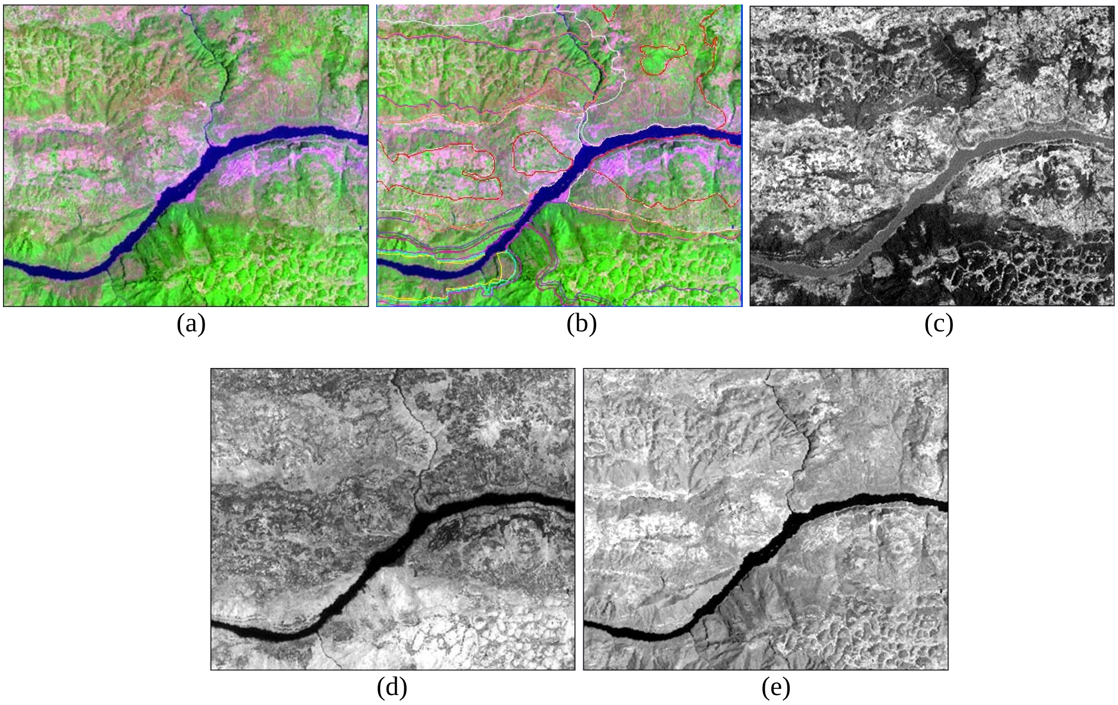

Figure 1. Remote sensing images and index images in THREE GORGES: (a) this is TM743 stacking image. (b) this is geological graph. (c) this is 3/1 image. (d) this is NDVI image. (e) this is TM5 image

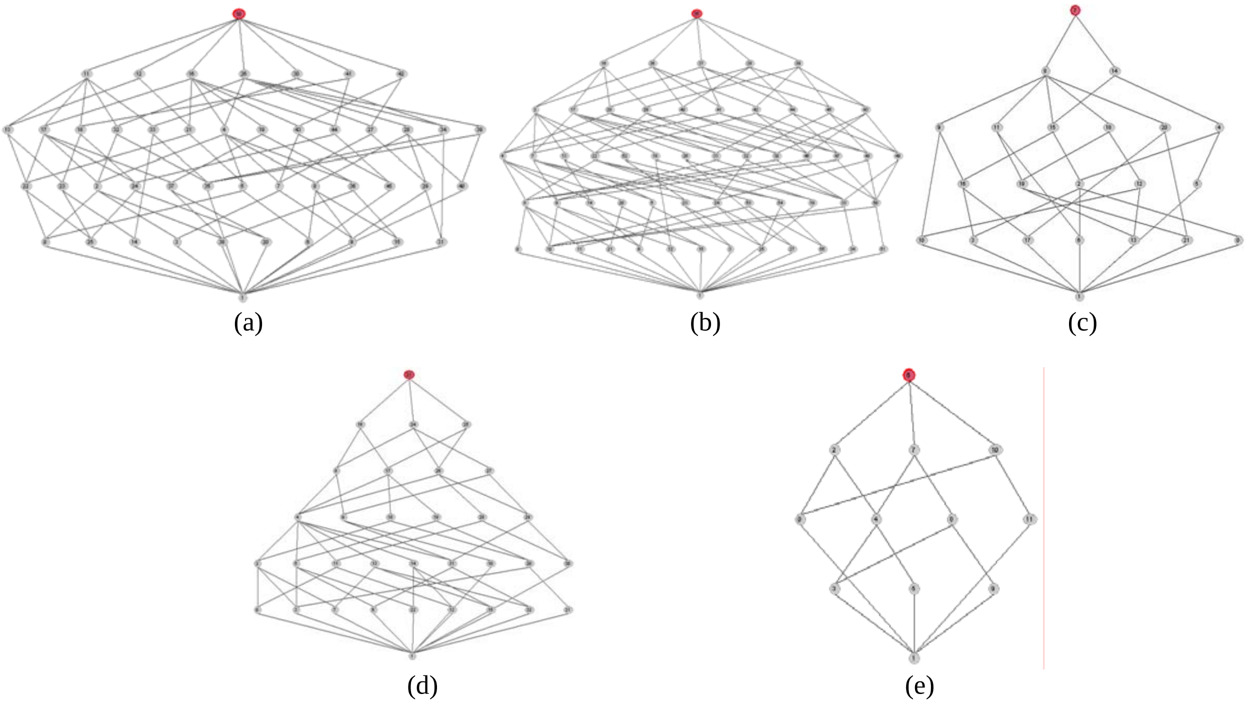

Figure 2. Built concept grid: (a) this is the cocept grid in the stratum T1j2. (b) this is the cocept grid in the stratum T2b1. (c) this is the cocept grid in the stratum T1j3. (d) this is the cocept grid in the stratum T2b2. (e) this is the cocept grid in the stratum T1d1

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Premise	Consequence	Support	Confidence
[TM5 textural correlation[0.2,0.7]]	[TM5 spectral mean [100,170]]	0.94	0.97
[TM5 textural correlation[0.2,0.7]]	[TM5 textural energy [-,0.01]]	0.94	0.97
[TM5 spectral mean [100,170]]	[TM5 textural correlation[0.2,0.7]]	0.94	0.97
[TM5 spectral mean [100,170]]	[TM5 textural energy [-,0.01]]	0.94	0.97
[TM5 textural energy [-,0.01]]	[TM5 textural correlation[0.2,0.7]]	0.94	0.97
[TM5 textural energy [-,0.01]]	[TM5 spectral mean [100,170]]	0.94	0.97
[TM5 spectral mean [100,170], TM5 textural correlation[0.2,0.7]]	[TM5 textural energy [-,0.01]]	0.92	0.97
[TM5 textural correlation[0.2,0.7], TM5 textural energy [-,0.01]]	[TM5 spectral mean [100,170]]	0.92	0.97
[TM5 textural correlation[0.2,0.7], TM5 textural energy [-,0.01]]	[NDVI mean[110,140]]	0.71	0.75
[TM5 textural correlation[0.2,0.7], TM5 textural energy [-,0.01]]	[3/1 textural contrast [5,8]e+003]	0.58	0.62
[TM5 spectral mean [100,170], TM5 textural energy [-,0.01]]	[TM5 textural correlation[0.2,0.7]]	0.92	0.97
[TM5 spectral mean [100,170], TM5 textural correlation[0.2,0.7], TM5 textural energy [-,0.01]]	[NDVI mean[110,140]]	0.69	0.75
[TM5 spectral mean [100,170], TM5 textural correlation[0.2,0.7], TM5 textural energy [-,0.01]]	[3/1 textural contrast [5,8]e+003]	0.56	0.61
[NDVI mean[110,140], TM5 textural correlation[0.2,0.7], TM5 textural energy [-,0.01]]	[TM5 spectral mean [100,170]]	0.69	0.96
[NDVI mean[110,140], TM5 textural correlation[0.2,0.7], TM5 textural energy [-,0.01]]	[3/1 textural contrast [5,8]e+003]	0.48	0.67
[3/1 textural contrast [5,8]e+003, TM5 textural correlation[0.2,0.7], TM5 textural energy [-,0.01]]	[TM5 spectral mean [100,170]]	0.56	0.95
[3/1 textural contrast [5,8]e+003, TM5 textural correlation[0.2,0.7], TM5 textural energy [-,0.01]]	[NDVI mean[110,140]]	0.48	0.82
[NDVI mean[110,140], TM5 spectral mean [100,170], TM5 textural correlation[0.2,0.7], TM5 textural energy [-,0.01]]	[3/1 textural contrast [5,8]e+003]	0.46	0.66
[3/1 textural contrast [5,8]e+003, TM5 spectral mean [100,170], TM5 textural correlation[0.2,0.7], TM5 textural energy [-,0.01]]	[NDVI mean[110,140]]	0.46	0.81
[3/1 textural contrast [5,8]e+003, NDVI mean[110,140], TM5 textural correlation[0.2,0.7], TM5 textural energy [-,0.01]]	[TM5 spectral mean [100,170]]	0.46	0.94

(a)

[NDVI mean[110,140], TM5 spectral mean[100,170]]	[TM5 textural correlation[0.2,0.7]]	0.6	0.95
[NDVI mean[110,140], TM5 spectral mean[100,170]]	[TM5 textural energy[-,0.01]]	0.45	0.71
[NDVI mean[110,140], TM5 spectral mean[100,170]]	[3/1 textural contrast[5,8]e+003]	0.42	0.66
[NDVI mean[110,140], TM5 textural energy[-,0.01]]	[TM5 textural correlation[0.2,0.7]]	0.45	0.93
[NDVI mean[110,140], TM5 textural energy[-,0.01]]	[TM5 spectral mean[100,170]]	0.45	0.93
[NDVI mean[110,140], TM5 textural energy[-,0.01]]	[3/1 textural contrast[5,8]e+003]	0.3	0.62
[3/1 textural contrast[5,8]e+003, TM5 textural energy[-,0.01]]	[TM5 textural correlation[0.2,0.7]]	0.48	0.94
[3/1 textural contrast[5,8]e+003, TM5 textural energy[-,0.01]]	[TM5 spectral mean[100,170]]	0.48	0.94
[3/1 textural contrast[5,8]e+003, TM5 textural energy[-,0.01]]	[NDVI mean[110,140]]	0.3	0.58
[3/1 textural contrast[5,8]e+003, NDVI mean[110,140]]	[TM5 textural correlation[0.2,0.7]]	0.42	0.93
[3/1 textural contrast[5,8]e+003, NDVI mean[110,140]]	[TM5 spectral mean[100,170]]	0.42	0.93
[3/1 textural contrast[5,8]e+003, NDVI mean[110,140]]	[TM5 textural energy[-,0.01]]	0.3	0.66
[TM5 spectral mean[100,170], TM5 textural correlation[0.2,0.7], TM5 textural energy[-,0.01]]	[NDVI mean[110,140]]	0.42	0.63
[TM5 spectral mean[100,170], TM5 textural correlation[0.2,0.7], TM5 textural energy[-,0.01]]	[3/1 textural contrast[5,8]e+003]	0.45	0.68
[3/1 textural contrast[5,8]e+003, TM5 spectral mean[100,170], TM5 textural correlation[0.2,0.7]]	[TM5 textural energy[-,0.01]]	0.45	0.71
[3/1 textural contrast[5,8]e+003, TM5 spectral mean[100,170], TM5 textural correlation[0.2,0.7]]	[NDVI mean[110,140]]	0.39	0.61
[NDVI mean[110,140], TM5 spectral mean[100,170], TM5 textural correlation[0.2,0.7]]	[TM5 textural energy[-,0.01]]	0.42	0.69
[NDVI mean[110,140], TM5 spectral mean[100,170], TM5 textural correlation[0.2,0.7]]	[3/1 textural contrast[5,8]e+003]	0.39	0.64
[NDVI mean[110,140], TM5 textural correlation[0.2,0.7], TM5 textural energy[-,0.01]]	[TM5 spectral mean[100,170]]	0.42	0.93
[3/1 textural contrast[5,8]e+003, TM5 textural correlation[0.2,0.7], TM5 textural energy[-,0.01]]	[TM5 spectral mean[100,170]]	0.45	0.93
[3/1 textural contrast[5,8]e+003, NDVI mean[110,140], TM5 textural correlation[0.2,0.7]]	[TM5 spectral mean[100,170]]	0.39	0.92
[NDVI mean[110,140], TM5 spectral mean[100,170], TM5 textural energy[-,0.01]]	[TM5 textural correlation[0.2,0.7]]	0.42	0.93
[3/1 textural contrast[5,8]e+003, TM5 spectral mean[100,170], TM5 textural energy[-,0.01]]	[TM5 textural correlation[0.2,0.7]]	0.45	0.93
[3/1 textural contrast[5,8]e+003, NDVI mean[110,140], TM5 spectral mean[100,170]]	[TM5 textural correlation[0.2,0.7]]	0.39	0.92

(b)

Premise	Consequence	Support	Confidence
[TM5 spectral mean[100,170]]	[NDVI mean[0,140]]	0.54	0.54
[TM5 spectral mean[100,170]]	[TM5 textural energy[0,0.01]]	0.8	0.8
[TM5 spectral mean[100,170]]	[TM5 textural correlation [0,0.7]]	0.83	0.83
[NDVI mean[0,140], TM5 spectral mean[100,170]]	[TM5 textural energy[0,0.01]]	0.45	0.82
[NDVI mean[0,140], TM5 spectral mean[100,170]]	[TM5 textural correlation [0,0.7]]	0.41	0.76
[3/1 textural contrast [5,8]e+003, TM5 spectral mean[100,170]]	[TM5 textural energy[0,0.01]]	0.45	0.93
[TM5 spectral mean[100,170], TM5 textural energy[0,0.01]]	[TM5 textural correlation [0,0.7]]	0.67	0.84
[TM5 spectral mean[100,170], TM5 textural energy[0,0.01]]	[NDVI mean[0,140]]	0.45	0.56
[TM5 spectral mean[100,170], TM5 textural energy[0,0.01]]	[3/1 textural contrast [5,8]e+003]	0.45	0.56
[TM5 spectral mean[100,170], TM5 textural correlation [0,0.7]]	[TM5 textural energy[0,0.01]]	0.67	0.8
[TM5 spectral mean[100,170], TM5 textural correlation [0,0.7]]	[NDVI mean[140,180]]	0.41	0.5
[TM5 spectral mean[100,170], TM5 textural correlation [0,0.7]]	[NDVI mean[0,140]]	0.41	0.5
[TM5 spectral mean[100,170], TM5 textural correlation [0,0.7], TM5 textural energy[0,0.01]]	[NDVI mean[0,140]]	0.35	0.52
[TM5 spectral mean[100,170], TM5 textural correlation [0,0.7], TM5 textural energy[0,0.01]]	[3/1 textural contrast [5,8]e+003]	0.41	0.61
[NDVI mean[0,140], TM5 spectral mean[100,170], TM5 textural energy[0,0.01]]	[TM5 textural correlation [0,0.7]]	0.35	0.78
[3/1 textural contrast [5,8]e+003, TM5 spectral mean[100,170], TM5 textural energy[0,0.01]]	[TM5 textural correlation [0,0.7]]	0.41	0.92
[NDVI mean[140,180], TM5 spectral mean[100,170], TM5 textural correlation [0,0.7]]	[TM5 textural energy[0,0.01]]	0.32	0.76
[NDVI mean[0,140], TM5 spectral mean[100,170], TM5 textural correlation [0,0.7]]	[TM5 textural energy[0,0.01]]	0.35	0.84

(c)

Premise	Consequence	Support	Confidence
[TM5 spectral mean[100,170]]	[TM5 textural correlation[0.2,0.7]]	0.89	0.89
[TM5 spectral mean[100,170]]	[TM5 textural energy[-,0.01]]	0.69	0.69
[TM5 spectral mean[100,170], TM5 textural correlation[0.2,0.7]]	[TM5 textural energy[-,0.01]]	0.6	0.66
[TM5 spectral mean[100,170], TM5 textural energy[-,0.01]]	[NDVI mean[140,180]]	0.6	0.85
[TM5 spectral mean[100,170], TM5 textural energy[-,0.01]]	[TM5 textural correlation[0.2,0.7]]	0.6	0.85
[NDVI mean[140,180], TM5 spectral mean[100,170], TM5 textural energy[-,0.01]]	[TM5 textural correlation[0.2,0.7]]	0.5	0.83
[3/1textural contrast[4,5], TM5 spectral mean[100,170], TM5 textural correlation[0.2,0.7]]	[TM5 textural energy[-,0.01]]	0.3	0.75
[TM5 spectral mean[100,170], TM5 textural correlation[0.2,0.7], TM5 textural energy[-,0.01]]	[NDVI mean[140,180]]	0.5	0.83
[TM5 spectral mean[100,170], TM5 textural correlation[0.2,0.7], TM5 textural energy[-,0.01]]	[3/1textural contrast[4,5]]	0.3	0.5

(d)

Premise	Consequence	Support	Confidence
[TM5 spectral mean [100,170], TM5 textural correlation [0.2,0.7]]	[TM5 textural energy [-,0.01]]	0.75	0.75
[TM5 spectral mean [100,170], TM5 textural correlation [0.2,0.7]]	[NDVI mean [110,140]]	0.62	0.62
[TM5 spectral mean [100,170], TM5 textural correlation [0.2,0.7], TM5 textural energy [-,0.01]]	[NDVI mean [110,140]]	0.5	0.66
[NDVI mean [110,140], TM5 spectral mean [100,170], TM5 textural correlation [0.2,0.7]]	[TM5 textural energy [-,0.01]]	0.5	0.8
[NDVI mean [110,140], TM5 spectral mean [100,170], TM5 textural correlation [0.2,0.7]]	[3/1 textural contrast [5,8]]	0.5	0.8
[NDVI mean [110,140], TM5 spectral mean [100,170], TM5 textural correlation [0.2,0.7], TM5 textural energy [-,0.01]]	[3/1 textural contrast [5,8]]	0.37	0.75
[3/1 textural contrast [5,8], NDVI mean [110,140], TM5 spectral mean [100,170], TM5 textural correlation [0.2,0.7]]	[TM5 textural energy [-,0.01]]	0.37	0.75

(e)

Figure 3. Association rules of lithology: (a) this is the association rules in the stratum T_2b^2. (b) this is the association rules in the stratum T_2b^1. (c) this is the association rules in the stratum T_1j^2. (d) this is the association rules in the stratum T_1j^3. (e) this is the association rules in the stratum T_1d

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