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Object-oriented spatial-temporal association rules mining on ocean remote sensing imagery

CJ XUE, Q DONG, WX MA

Key Laboratory of Digital Earth, Center for Earth Observation and Digital Earth,
Chinese Academy of Sciences. Beijing, 100094, China

Email: cjxue@ceode.ac.cn

Abstract. Using the long term marine remote sensing imagery, we develop an object-oriented spatial-temporal association rules mining framework to explore the association rules mining among marine environmental elements. Within the framework, two key issues are addressed. They are how to effectively deal with the related lattices and how to reduce the related dimensions? To deal with the first key issues, this paper develops an object-oriented method for abstracting marine sensitive objects from raster pixels and for representing them with a quadruple. To deal with the second key issues, by embedding the mutual information theory, we construct the direct association pattern tree to reduce the related elements at the first step, and then the Apriori algorithm is used to discover the spatio-temporal associated rules. Finally, Pacific Ocean is taken as a research area and multi-marine remote sensing imagery in recent three decades is used as a case study. The results show that the object-oriented spatio-temporal association rules mining can acquire the associated relationships not only among marine environmental elements in same region, also among the different regions. In addition, the information from association rules mining is much more expressive and informative in space and time than traditional spatio-temporal analysis.

1. Introduction

In recent three decades, advanced earth-observing technologies make it possible to acquire long time series of marine bio-optical parameters and dynamic elements from multi-remote sensing imagery, and the inter-annual, intra-annual variations and spatial distribution of marine environmental elements are studied by means of mathematical statistics and empirical orthogonal functions (EOF), i.e. spatio-temporal variation of sea surface temperature (SST)[1], spatial distribution and annual, seasonal and monthly properties of sea surface chlorophyll-a concentration and marine primitive productivity [2], spatio-temporal characteristics of sea surface precipitation [3]. Moreover, many algorithms are developed to extract these characteristic parameters from remote sensing imagery, such as ENSO indices, western Pacific warm pool, cold tongue of SST, oceanic rain pool, oceanic desert [4]. To the best of our knowledge, the spatio-temporal variation of marine environmental elements is a complicated system. Usually the inter-annual variability of marine environmental elements is driven by ENSO events, and on the contrary, it can intensify or weaken ENSO events [5-6]. So far few studies are carried on investigating the associated relationship among three or more elements, especially at macroscale using remote sensing imagery.

Geographical spatio-temporal association rules mining is a novel data-driven methodology in spatio-temporal analysis, derived from geography, information science and computer technology [7-8].
This method aims at discovering non-trivial, implicit, previous unknown and potentially useful knowledge among attributes or objects from large datasets. Since the mining association rules problem was presented in 1994 [9], there have been many documents focusing on mining algorithms, rules evaluation, visualization. As for the condition of global change, many applications focus on earth science datasets for better understanding how the earth is varying, for determining which factors cause these changes, and for predicting future change. For example, Zhang et al discussed the association patterns of the fraction of photosynthetic active radiation (FPAR) and net primitive productivity (NPP) at global scale by using remote sensing imagery and historical records [10]; Huang et al extracted the informative salinity and SST patterns around Taiwan Island by analyzing ARGO drifting buoys data [11]; Mennis and Liu mined the spatio-temporal association rules between socioeconomic and land cover change [12]; and Zhang et al investigated the process-oriented association patterns between SST in the Pacific Ocean and precipitation in the southeast coast of China by applying the remote sensing imagery and in situ data [13], and so on. However, with regard to marine environmental elements, there remain a few challenges in applying the long time series of remote sensing imagery to discover their spatio-temporal association patterns. They are how to effectively deal with the related lattices and how to reduce the association dimensions of marine environmental elements.

The purpose of our study is to design the spatio-temporal association rules mining framework on the basis of the long time series of remote sensing imagery, and to deal with two key issues within the framework. This paper is organized as follows. In Section 2, the object-oriented spatio-temporal association rules mining framework is designed on the basis of long term remote sensing imagery and some basic concepts are introduced. Section 3 gives the extraction workflow of marine sensitive regions and marine objects representation, which are responsible for dealing with the related lattices. Section 4 puts forward the association rules mining algorithm on the basis of mutual information theory, and discusses some key steps, which are up to reduce association dimensions and improve the algorithm’s efficiency. A case study of spatio-temporal association analysis among marine environmental elements of the Pacific Ocean is carried out in Section 5. And Section 6 is a summary of the results and conclusions.

![Figure 1. Object-oriented spatio-temporal association rules mining framework based on remote sensing imagery](image-url)
2. Object-oriented spatio-temporal association rules mining framework

2.1. Mining framework

Using the long term marine remote sensing imagery, the object-oriented spatio-temporal association rules mining consists of three parts. Firstly, this paper extracts marine objects from marine remote sensing imagery, and uses the marine objects to construct spatio-temporal mining transaction table; secondly, based on the table and marine objects' attributes, we implement the spatio-temporal association rules mining algorithms and discover the association relationships among marine objects. Finally, strong associated rules are examined and discriminated, and the pso-rules are removed. The framework of object-oriented spatio-temporal association rules mining based on the marine remote sensing imagery is shown in figure.1.

2.2. Some basic concepts

To mine association rules from long term remote sensing imagery, some basic concepts need to be considered, they are:

2.2.1. Quantitative association rules mining (QARM). Quantitative association rule mining has served as a useful tool to discover association relationships among sets of attributes in business and scientific domains [14]. When implementing QARM, attributes are quantitative numeric values not boolean one, so the quantitative association rules are far more expressive and informative than boolean association rules [15]. The continuous value in remote sensing imagery is discretized into five continuous levels which represent seven changes, slight changes and no changes.

2.2.2. Object mutual information (OMI). Object mutual information describes how much information one object tells about another one, the idea comes from the information theory, and the object in this paper refers to the same change region of marine bio-optical and dynamic elements. Given the objects x and y, the OMI of them is defined as,

\[
I(x; y) = - \sum_{v_x \in \text{dom}(x)} \sum_{v_y \in \text{dom}(y)} p(v_x, v_y) \log p(v_x, v_y)
\]

(1)

Where, \( p(v_x, v_y) \) is joint probability density between the objects x and y.

2.2.3. Normalized object mutual information (NOMI). The normalized mutual information of two objects x and y, is defined as

\[
\tilde{I}(x; y) = \frac{I(x; y)}{I(x; x)}
\]

(2)

The NOMI can get rid of the localness and make the normalized mutual information a global measure [15].

2.3. Evaluation indices

In addition the above concepts, several evaluation indices are also needed to address, they are,

2.3.1. Support. Support describes the co-occurrence probability of object A and B in the dataset, which is defined as

\[
s(AB) = \frac{n(AB)}{N} \times 100\
\]

(3)

Where, \( n(AB) \) is the record of the co-occurrence of A and B, and the N is the record of the dataset.

2.3.2. Confidence. Confidence describes the object B occurrence probability on the condition of object A happening, defined as the following formula.
\[ c(AB) = \frac{s(AB)}{s(A)} \times 100\% = \frac{n(AB)}{n(A)} \times 100\% \] (4)

2.3.3. Lift. Lift depicts the impacts on object B on the condition of object A occurrence, that is to say, once object A has occurred, how much does the occurrence probability of object B change? The Lift is defined as

\[ l(AB) = \frac{c}{e} = \frac{n(AB)}{n(A)} \times \left(\frac{n(B)}{N}\right)^{-1} = \frac{n(AB) \times N}{n(A) n(B)} \] (5)

2.3.4. Min support, min confidence, min lift. They are used as criterion thresholds to discover the interesting relationships between objects. And the values of them are customized before carrying out the mining algorithms.

3. Two key issues of the spatio-temporal association rules mining framework

To carry out figure 1, two key issues need to be paid more attentions. They are how to effectively deal with the related lattices and how to reduce the associated dimensions? As all known, large neighbor lattices in remote sensing imagery are also related, one or several lattices may be represent the related group pixels, how to transform them. On the other hand, the complexities of Apriori algorithm are related with the attribute dimension. And the marine bio-optical and dynamic parameters contain chlorophyll-a, marine primitive product, sea surface temperature, sea surface precipitation, sea level anomalies, sea surface wind, sea surface current, and so on. In one lattice, not all attributes are related. And in one lattice, even some attributes are related, while in another lattice, they are not. Thus, the Apriori algorithm should not take all marine elements as input parameters. How to identify the related elements in each lattice needs to process before carrying out the mining algorithm.

3.1. Marine sensitive region extraction from remote sensing imagery

From long term remote sensing imagery, many documents have investigated to analyze the spatio-temporal variation of marine environmental elements with the regional and time-delay properties, such as, western Pacific warm pool, eastern Pacific cold tongue, oceanic rain pool, and oceanic deserts and sensitive change region of oceanic color as well [16-20]. The regional and time-delay properties of marine elements are denoted as marine sensitive region and time phase, which mostly are related with global changes. How to apply the object-oriented technology to represent them has been the hot and difficult issue in marine information domain [21-25].

Object-oriented technology is an imagery analysis method that groups neighbor pixels into meaningful areas and tracks these areas as objects according to their shape, texture, and spectral information. In this paper, marine change sensitive regions are treated as marine objects represented by a quadruple with object ID, geometry, time and attributes. As the dominant spatial components extracting from empirical orthogonal function have the same variation in time series, the EOF is used to identify the sensitive region.

The data processing for extracting the sensitive region and representing the marine object is as following: (1) Calculate anomaly marine elements per month by subtracting monthly averaged value for each pixel; (2) Identify the sensitive region from the EOF’s spatial components; (3) Abstract the related pixels covered by the sensitive region into a marine object; (4) Represent the marine object with a quadruple.

3.2. Data mining algorithm based on mutual information theory

From Equations (1) and (2), the OMI tells the information from object A to object B is equal with the information from object B to object A, while the NOMI presents the different information from object A to object B and object B to object A. In marine information domain, the NOMI is more suitable for addressing the association relationships among marine environmental elements. For example, the
abnormal increase of SST over one region may drive the rain drops in another region, vice versa, the rain variation may not drive the SST change.

On the basis of NOMI, the workflow of spatio-temporal association rules mining algorithm is given in figure 2.

Figure 2. Algorithm workflow of spatio-temporal association rules mining based on the NOMI

In the above workflow, four key steps need to address. They are which discretization strategy is used, how to determine the optimal threshold to identify association objects, how to construct the direct association pattern tree (APT) and which mining algorithm is selected to discover association relationships.

3.2.1. Discretization strategy. Discretization is a pretreatment in quantitative association rules mining, which aims to map a large number of distinct values of a quantitative attribute to a smaller set of intervals to deal with the continuous domain and to speed up the mining efficiency. There are many discretization strategies, such as, cluster-based, equal-density, equal-areas or equal-depths method and so on. And each discretization method is suitable to certain domain. The purpose of this paper is to discover the association relationships among marine environmental elements on the condition of global change, and try to address the responding or driven mechanism to global change. So this paper uses objects’ statistical characteristics to select the discretization strategy. The attributes are levelled into five ranks from -2 to 2 with continuous interval by standard deviation. And the five ranks stand for severe negative changes, slight negative changes, no changes, slight positive changes and severe positive changes, respectively.

3.2.2. Optimal threshold. Optimal threshold determines how many objects are related. The large value of threshold, the related objects is small, and the association relationship between marine environmental elements is less, that is to say, some interesting rules may lose, and vice versa. This paper combines the mean and standard deviation of the objects’ attributes to determine the threshold, and auto- changes the value according to the specific application and objects’ characteristics.

3.2.3. Association pattern tree construction. The construction of APT is a core step to discover meaningful relationships, which is a foundation to implement the association rules mining algorithm. Since the mutual information table is a asymmetry, the association pattern is a direct tree, that is to say, even if SSTA→CHLA (s%, c%, 1%) is true, the CHLA→SSTA (s%, c%, 1%) may be not. According to the transitive property of association rules mining, i.e. if m dimension attributes are not frequent, the m+1 dimension attributes must not be frequent, this paper adopts the recursion method to construct the APT, the implementation is as following: (i) Use the optimal threshold to determine two-dimension association pattern by looking through the normalized mutual information table; (ii) Construct three-dimension association pattern by joining the two-dimension association pattern; (iii) And according to the transitive property, prune the three-dimension association pattern; (iv) Repeat the (ii) and (iii) to construct the m-dimension (m>3) APT based on the (m-1)-dimension.

3.2.4. Association rules mining algorithm. Since all the meaningful relationships originating from the constructed APTs, the association rules mining algorithm in this paper discovers the two-dimension
association relationships followed by popular Apriori. When dealing with m-dimension (m \(\geq 3\)), the algorithm adopts the recursion to discovering interesting relationships. That is, the preceding (m-1) dimension attributes are denoted as an antecedent, and the m\textsuperscript{th} item is a consequent.

4. Case studies: Spatio-temporal association analysis of marine environmental elements in the over Pacific Ocean

4.1. Data
This paper applies sea surface temperature (SST), sea surface chlorophyll-a (CHLA) concentration, sea surface precipitation (RAIN), sea surface wind speed (U-component, and V-component), sea surface height (SSH) and ENSO indices to analyze their spatio-temporal association relationships. Table1 shows the space and time information about the available multi-remote sensing imagery. The monthly anomalies of them are denoted as SST\textsubscript{a}, CHLA\textsubscript{a}, RAIN\textsubscript{a}, SSH\textsubscript{a}, UW\textsubscript{a} and V\textsubscript{a}, respectively.

| Element | Sensor | Time span         | Temporal resolution | Space cover | Spatial resolution |
|---------|--------|-------------------|---------------------|-------------|-------------------|
| SST     | NOAA ERSST | 1981.12-2012.02 | Monthly             | Global      | 4km (Grid)        |
| CHL     | SeaWIFS MODIS | 1997.09-2010.11 | Monthly             | Global      | 9km (Grid)        |
| RAIN    | TRMM   | 1998.01-2011.06  | Monthly             | Global      | 4km (Grid)        |
| Wind    | CCMP   | 1987.07-2010.12  | Monthly             | Global      | 0.25° (Grid)      |
| SSH     | AVISO  | 1992.12-2010.12  | Monthly             | Global      | 1/3° (Mercator projection) |
| ENSO    | MEI    | 1950.01-2012.03  | Monthly             | -           | -                |

4.2. Extraction and representation of marine object
The time span from Jan. 1998 to Dec. 2010 is selected and the Pacific Ocean covering 100°E-60°W and 50°S-50°N is used. We first transform the long term remote sensing imagery into the uniform datasets with spatial resolution of 1° in grid projection and with temporal resolution of a month. Then the monthly anomalies of these elements are calculated and the EOF analysis is conducted to decompose the spatio-temporal co-variability of these elements in the Pacific Ocean. Finally the zones of abnormal change spatially are grouped into uniform ones, and abstracted into objects, denoted as CHLObj\textsubscript{1}, CHLObj\textsubscript{2}, SSTObj\textsubscript{1}, SSTObj\textsubscript{2}, and so on, respectively. The uniform zones extracted from CHLA\textsubscript{a}, SST\textsubscript{a}, RAIN\textsubscript{a} and SSH\textsubscript{a} of long term remote sensing imagery are shown in figure 3. And the abstracted objects are shown in Table 2.
Figure 3. Abnormal change zones from long term remote sensing imagery (The background is first EOF mode of CHLAa, RAINa, SSTa, SSHa, and the white rectangles are extracted marine objects)

Table 2. Extracted marine objects and their representation information

| Uniform zone | Object name | Object ID | Object spatial range |
|--------------|-------------|-----------|----------------------|
| CHLZone1     | ChlObj1     | 10001     | 26N-35N, 180-159W    |
| CHLZone2     | ChlObj2     | 10002     | 1N-15N, 132E-155E    |
| ...          |             |           |                      |
| SSTZone1     | SSTObj1     | 40001     | 0-18N, 133E-153E     |
| SSTZone2     | SSTObj2     | 40002     | 22S-36S, 157W-178W   |
| ...          |             |           |                      |
| SSHZone1     | SLAObj1     | 50001     | 10S-15N, 120E-160E   |
| SSHZone2     | SLAObj2     | 50002     | 12S-5N, 157W-88W     |
| ...          |             |           |                      |
| RainZone1    | RainObj1    | 30001     | 10S-10N, 120E-140E   |
| RainZone2    | RainObj2    | 30002     | 8N-5N, 160E-160W     |
| ...          |             |           |                      |

4.3. Case 1: Extraction of spatio-temporal association within an object

This case study intends to demonstrate the spatio-temporal association relationship among marine environmental elements within an object. SSTa, CHLAa, SSHa, RAINa and the U/V-component of wind speed anomaly in Zone CHLObj1 and ENSO indices are applied. The normalized mutual information among these elements is shown in Table 3, which beyond the threshold is tagged with green color. In this case, we define the optimal threshold as the mean value plus the half standard deviation (0.169).

Table 3. Asymmetric mutual information of marine environmental elements in Zone CHLObj1.

|        | SSTA | CHLA | SSHA | RAINa | UWNDA | ENSO |
|--------|------|------|------|-------|-------|------|
| SSTA   | 1.000| 0.116| 0.081| 0.083 | 0.128 | 0.094|
| CHLA   | 0.113| 1.000| 0.112| 0.268 | 0.068 | 0.018|
| SSHA   | 0.082| 0.118| 1.000| 0.139 | 0.123 | 0.126|
| RAINa  | 0.086| 0.286| 0.141| 1.000 | 0.141 | 0.375|
| UWNDA  | 0.126| 0.070| 0.121| 0.136 | 1.000 | 0.149|
| ENSO   | 0.091| 0.214| 0.119| 0.358 | 0.143 | 1.000|

According to the workflow of APT construction and Table 3, the constructed direct APT is shown in figure 4, including 2- and 3-dimensional association relationship.
On the basis of the direct APT and the classical Apriori algorithm, we have found the 51 pieces of spatio-temporal association rules, and extracted the 12 pieces of interesting association knowledge, which are shown in Table 4.

Table 4. Spatio-temporal association knowledge among marine environmental elements in Zone CHLObj1

| Association knowledge | Support(%) | Confidence(%) | Lift |
|-----------------------|------------|---------------|------|
| CHLA [-2,0] -> RAINA[2, (-1,3)] | 13.58 | 79.20 | 2.26 |
| RAINA[-2,0] -> CHLA [2,(-2,1)] | 6.32 | 89.67 | 5.58 |
| RAINA[-2,0] -> ENSO[2,(0,2)] | 6.12 | 81.82 | 5.01 |
| ENSO[-2,0] -> RAINA[2,(-2,5)] | 12.23 | 88.75 | 2.53 |
| RAINA[-2,0] -> CHLA[2,-2] -> ENSO[2,(-1,1)] | 3.50 | 88.28 | 5.28 |
| RAINA[-2,0] -> CHLA[2,-1] -> ENSO[2,(-1,2)] | 4.84 | 88.34 | 5.33 |
| RAINA[-2,0] -> CHLA[2,0] -> ENSO[2,(0,2)] | 5.80 | 81.82 | 5.29 |
| RAINA[-2,0] -> ENSO[2,0] -> CHLA[2,(-3,1)] | 5.16 | 80.15 | 5.17 |
| RAINA[-2,0] -> ENSO[2,1] -> CHLA[2,(2,2)] | 4.78 | 94.44 | 6.14 |
| RAINA[-2,0] -> ENSO[2,2] -> CHLA[2,(-2,2)] | 4.98 | 90.48 | 5.98 |
| ENSO[-2,0] -> RAINA[2,-1] -> CHLA[2,0] | 8.97 | 77.78 | 3.91 |

Table 4 demonstrates that sea surface chlorophyll-a concentration and precipitation are related with ENSO in this zone exclusively. The first four rules are two-dimensional association relationships between two of ENSO, chlorophyll-a concentration anomaly and precipitation anomaly. Rule 1 shows that if the sea surface chlorophyll-a concentration drops abnormally in this zone, the sea surface precipitation rises up from 1-month ahead to 3-month retardation abnormally with a support of 13.58%, a confidence of 79.2%, and a lift of 2.26, which means their co-occurrence possibility is 13.58%, on the condition of the former happening, the possibility of the latter occurrence is up to 79.2%, and the former’s occurrence can be 2.26 times of the promotion of the latter’s happening. Rules 5-12 show three-dimensional relationships. The last knowledge in Table 4 (Rule 12) shows that the sea surface precipitation decreases abnormally one month ahead in this zone with La Nina events, and on the condition of their co-occurrence, the sea surface chlorophyll-a concentration within this zone decreases abnormally simultaneously. This information has a support of 8.97%, a confidence of 77.78%, and a lift of 3.91, respectively.

4.4. Case 2: Spatio-temporal association extraction from different objects
The purpose of this case study is to address the spatio-temporal association relationships of marine environmental elements, denoted as marine objects in this paper, in different zones. CHLA\textsubscript{a} of CHLObj\textsubscript{1}, SST\textsubscript{a} of SSTObj\textsubscript{1}, RAIN\textsubscript{a} of RainObj\textsubscript{4}, SSH\textsubscript{a} of SSHObj\textsubscript{2} and ENSO indices are selected. Their asymmetric mutual information are calculated, and shown in Table 5. The optimal threshold, which is defined as the mean value plus half of standard deviation, is 0.232 in this case, to construct the direct-association tree. The values of mutual information greater than the threshold are tagged with green color in Table 5, and the direct association tree is shown in figure 4.

Table 5. Asymmetric mutual information among marine environmental elements in different zones

|                | CHLObj\textsubscript{1}.CHLA | RAINObj\textsubscript{4}.RAIN\textsubscript{A} | SSHObj\textsubscript{2}.SSHA | SSTObj\textsubscript{1}.SSTA | ENSO indices |
|----------------|-------------------------------|-----------------------------------------------|-------------------------------|--------------------------|---------------|
| CHLObj\textsubscript{1}.CHLA | 1.000                         | 0.050                                         | 0.079                         | 0.079                    | 0.106         |
| RAINObj\textsubscript{4}.RAIN\textsubscript{A} | 0.049                         | 1.000                                         | 0.068                         | 0.058                    | 0.057         |
| SSHObj\textsubscript{2}.SSHA | 0.075                         | 0.065                                         | 1.000                         | 0.339                    | 0.247         |
| SSTObj\textsubscript{1}.SSTA | 0.077                         | 0.058                                         | 0.248                         | 1.000                    | 0.766         |
| ENSO indices | 0.102                         | 0.055                                         | 0.248                         | 0.766                    | 1.000         |

Figure 5. Direct APT of marine environmental elements in different regions

Applying the above direct APT and the Apriori algorithm, this paper has found 23 association rules, and distinguished and extracted 5 pieces of meaningful association knowledge, which are shown in Table 6.

Table 6. Spatio-temporal association knowledge among marine elements in different zones

| Association knowledge | Support(%) | Confidence(%) | Lift |
|-----------------------|------------|---------------|------|
| SSHObj\textsubscript{2}.SSHA[-2,0] -> SSTObj\textsubscript{1}.SSTA[-2,(-5,3)] | 14.52       | 81.20         | 3.47 |
| SSTObj\textsubscript{1}.SSTA [2,0] -> ENSO[2,(0,1)] | 11.90       | 84.90         | 5.34 |
| ENSO[-2,0] -> SSTObj\textsubscript{1}.SSTA [-2,(-3,5)] | 15.10       | 91.60         | 3.58 |
| ENSO[2,0] -> SSTObj\textsubscript{1}.SSTA [2,-1] | 12.26       | 79.17         | 4.29 |
| ENSO[-2,0] -> SSTObj\textsubscript{1}.SSTA [-2,5] -> SSHObj\textsubscript{2}.SSHA [-2,(1,3)] | 9.03        | 76.47         | 4.23 |

Table 6 shows the associating relationships among the SST in zone SSTZone\textsubscript{1}, SSH in zone SSHZone\textsubscript{2} and ENSO events. Rules 1-4 are two-dimensional associating relationships and Rule 5 is a three-dimensional relationship. The last knowledge in Table 6 reveals that when La Nina occurs, the SST decreases abnormally in zone SSTZone\textsubscript{1} after 5 months, and on the condition of their co-occurrence, SSH drops abnormally in zone SSHZone\textsubscript{2} during the period of one-month ahead to 3-month retardation, with a support of 9.03\%, a confidence of 76.47\%, and a lift of 4.23, respectively.
5. Discussion and conclusion
The object-oriented spatio-temporal association rules mining framework based on long time series of remote sensing imagery is designed to discover the association relationships among marine environmental elements. Within the framework, the main works are summarized as follows. (1) Several marine sensitive zones are extracted from long time series of remote sensing imagery by means of EOF, and are abstracted as marine objects, representing with a quadruple by using object-oriented technologies; (2) By means of embedding into the mutual information theory, this paper constructs the direct APT and then develops the spatio-temporal association rules mining algorithm; (3) Taking the Pacific Ocean as a case, this paper investigates the spatio-temporal association relationships among the marine environmental elements and ENSO both in one zone and among different zones.

Compared with traditionally spatio-temporal analysis, we believe that the information achieved from the association rules mining is much expressive and informative in space and time, and is helpful to better understand how/when/where the marine environmental elements in different zones co-drive the others variations. While this research shows the proposed object-oriented association rules mining to be a promising analytical tool for spatio-temporal analysis of remote sensing imagery, lots of works need further study, such as the discretization strategies of quantify attributes, the optimal threshold of constructing direct association tree, and the minimum support and confidence of discovering the association rules, i.e. How to define the attributes ranks, objectively or subjectively? The optimal threshold is suitable or not? And the minimum support is dynamic according to the quantitative levels or static during the whole implementation? All of them play important roles on the discovering association knowledge.

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