Karaelmas Science and Engineering Journal
Journal home page: http://fbd.beun.edu.tr
DOI: 10.7212%2Fzkufbd.v8i1.692

Research Article
Received / Geliş tarihi : 11.11.2016
Accepted / Kabul tarihi : 02.08.2017

Emerging and Vanishing Association Pattern Mining in Hydroclimatic Datasets

Hidroklimatik Veritabanlarında Oluşan ve Kaybolan Birliktelik Örüntülerinin Madenciliği

Mete Çelik[1*], Ahmet Şakir Dokuz[2], Filiz Dadaşer-Çelik[3]

[1]Department of Computer Engineering, Erciyes University, Kayseri, Turkey
[2]Department of Computer Engineering, Niğde Ömer Halisdemir University, Niğde, Turkey
[3]Department of Environmental Engineering, Erciyes University, Kayseri, Turkey

Abstract

Emerging and vanishing association patterns can be defined as association patterns whose frequencies (supports) get stronger and weaker over time, respectively. Discovering these patterns is important for several application domains such as financial and communication services, public health, and hydroclimatic studies. Classical association pattern mining algorithms do not consider how the strengths of association patterns change over time. An association pattern can be defined as an emerging or vanishing pattern when its support measure changes over time. In this paper, we focus on discovery of time evolving association patterns (i.e., emerging and vanishing association patterns) from datasets. To discover such patterns, a novel algorithm, named as Emerging and Vanishing Association Pattern Miner (EVAPMiner) algorithm, was proposed. The proposed algorithm was evaluated using hydroclimatic dataset of Turkey. The analyses showed that the proposed algorithm successfully detects emerging and vanishing association patterns in hydroclimatic datasets.

Keywords: Association pattern mining, Data mining, Emerging patterns, Hydroclimatic data, Vanishing patterns

Öz

Oluşan ve kaybolan birliktelik örüntüleri, frekansları (destekleri) zamanla artan ve azalan birliktelik örüntüleri olarak tanımlanır. Bu örüntülerin keşfedilmesi finans ve haberleşme servisleri, halk sağlığı, ve hidroklimatik çalışmalar gibi uygulama alanları için önemlidir. Klasik birliktelik örüntü madenciliği algoritmaları birliktelik örüntülerinin zamanla nasıl değiştiklerini göz önüne almazlar. Bir birliktelik örüntüsünün destek değeri zamanla değişiyor ise bu örüntü oluşan veya kaybolan örüntü olarak tanımlanabilir. Bu çalışmada, zamanla gelişen birliktelik örüntülerinin (oluşan ve kaybolan biliktelik örüntüleri gibi) veri kümelerinden keşfine odaklanılmıştır. Bu örüntüleri keşfetmek için, Oluşan ve Kaybolan Birliktelik Örüntü Madencisi (EVAPMiner) olarak isimlendirilen özgün bir algoritma önerilmiştir. Önerilen algoritma, Türkiye hidroklimatik verileri üzerinde uygulanmıştır. Analizler, önerilen algoritmanın hidroklimatik veri kümelerindeki oluşan ve kaybolan birliktelik örüntülerinin keşfinde başarılı olduğunu ortaya koymuştur.

Anahtar Kelimeler: Birliktelik örüntü madenciliği, Veri madenciliği, Oluşan örüntüler, Hidroklimatik veri, Kaybolan örüntüler

1. Introduction

Association pattern mining is the task of discovering patterns in the form of A→B that may occur frequently in a dataset, where A and B refer to parameters of an application domain (Han et al. 2011, Tan et al. 2005). Discovering association patterns from a dataset is important for extracting associations between parameters and identifying cause-effect relationships. However, classical association pattern mining algorithms do not consider how the strengths of patterns change over time.

Emerging and vanishing association patterns are association patterns, whose frequencies get stronger and weaker over time, respectively. These patterns provide more information about how the strengths of patterns change in the temporal dimension. Discovering emerging and vanishing patterns is beneficial for time-evolving financial analyses, identification of temporal associations among various parameters related to diseases, or the relationships among hydroclimatic parameters under changing climatic conditions. In this study, we focus on discovering emerging and vanishing association patterns in hydroclimatic datasets.

*Corresponding Author: mcelik@erciyes.edu.tr

Mete Çelik orcid.org/0000-0002-1488-1502
Ahmet Şakir Dokuz orcid.org/0000-0002-1775-0954
Filiz Dadaşer-Çelik orcid.org/0000-0003-3623-7723

Data mining and association pattern mining approaches have been applied for different purposes in hydroclimatic datasets and environmental sciences. These include drought and flood analysis (Dhanya and Nagesh Kumar 2009, Kumar et al. 2009), analysis of oceanic and climatic parameters to extract drought patterns (Tadesse et al. 2004a, Tadesse et al. 2004b), and extracting fuzzy association rules (Shua et al. 2008). However, in the literature, studies are not available for discovering emerging and vanishing patterns among hydroclimatic parameters.

Discovering emerging and vanishing patterns is a challenging task in hydroclimatic datasets for several reasons. First, hydroclimatic parameters are geography-based and have spatial and temporal correlations. Second, outlier instances are common in hydroclimatic datasets. Third, determining antecedents and consequents of association patterns are hard to predict. Fourth, emerging and vanishing patterns add an extra temporal dimension.

In this study, we formulated the problem of discovering emerging and vanishing association pattern mining in hydroclimatic datasets. To extract these patterns, we proposed a novel algorithm which is called Emerging and Vanishing Association Pattern Miner (EVAPMiner) algorithm. We discovered the emerging and vanishing association patterns for 64 streamflow stations of Turkey. In the hydroclimatic data analysis, the main goal was to discover effect of meteorological parameters (such as air temperature and precipitation) onto hydrological parameters (such as streamflow) and how the association among these parameters change over time.

Association pattern mining is first introduced by Agrawal et al. (1993) and Apriori algorithm is first introduced in Agrawal and Srikant (1994). Association pattern mining is applied in several domains, such as finance (Du et al. 2009, Khan et al. 2009), business (Apte et al. 2002, Ngai et al. 2009, Olson and Shi 2005), health and medicine (Nahar et al. 2013, Rajendran and Madheswaran 2010), and bioinformatics (Alves et al. 2009, Creighton and Hanash 2003). However, association pattern mining applications in environmental sciences are rather limited.

Several studies focused on developing association pattern mining and Apriori algorithm. Liu et al. (1999) mined association rules with multiple support values for every parameter in a dataset to solve rare item problem. Li and Zhang (2011) moved association rule mining process into cloud computing by parallelizing Apriori algorithm to achieve faster performance. Yew-Kwong et al. (2001) proposed a fast online dynamic association rule mining algorithm for dynamic e-commerce dataset and outperformed classical Apriori algorithm. In the literature, several online association rule mining techniques were proposed (Hidber 1999, Ölmezoğulları and Ari 2013). These techniques mainly focus on mining streaming data, allow users to adjust the threshold values and generally do not deal with emerging and vanishing characteristics of the rules.

In environmental sciences, data mining techniques and specifically association pattern mining approaches have been used for several purposes. Dhanya and Nagesh Kumar (2009) and Nagesh Kumar et al. (2009) tried to discover association rules for droughts and floods. Tadesse et al. (2004a, 2004b) analyzed oceanic and climatic parameters to extract drought patterns for Nebraska. Shua et al. (2008) extracted fuzzy association rules from climatic datasets. Mishra et al. (2013) analyzed monsoon period for floods using clustering and dynamic time warping. Dadaser-Celik et al. (2012) and Celik et al. (2014) analyzed associations between hydrological and climatic parameters for Turkey. However, none of these studies consider discovering time evolving association patterns (i.e., emerging and vanishing association patterns) from datasets.

In this study, we formulated the problem of emerging and vanishing association pattern mining and proposed a novel algorithm, named as EVAPMiner, based on Apriori algorithm. Using the proposed method, we analyzed hydroclimatic dataset of Turkey for 64 streamflow/meteorology stations for discovering emerging and vanishing association patterns. Experimental results showed that positioning association patterns as emerging and vanishing provides more information about temporal changes in patterns.

2. Materials and Method

2.1. Modeling Emerging and Vanishing Association Patterns

To formulize the problem of emerging and vanishing patterns, we first present several definitions related to classical association pattern mining and, then define emerging and vanishing patterns. Definitions 1-5 are for classical association pattern mining and Definitions 6 and 7 are for emerging and vanishing association patterns. Definition 8 gives the problem definition for discovering emerging and vanishing association patterns.

Definition 1. An **association rule** is defined as follows: Let $I = \{i_1, i_2, \ldots, i_n\}$ be a set of n binary attributes called items. Let $D = \{t_1, t_2, \ldots, t_m\}$ be a set of records called the database. Each record in D has a unique record ID and contains a subset of the items in I. A rule is defined as an implication of the form $A \rightarrow B$, where $A; B \subseteq I$ and $A \cap B = \varnothing$. The sets of items (for short itemsets) A and B are called the antecedent and consequent of the rule, respectively. A pattern P is defined as set of $\{A, B\}$.

Definition 2. Given a pattern P and a station S, the **support** of pattern P in station S is the fraction of the number of records containing P to the total number of records of the station S. Support of pattern P at station S can be formulized as shown in equation (1):

$$support(P, S) = \frac{(number\ of\ records\ containing\ P)}{(number\ of\ all\ records\ station\ S)} \quad (1)$$

Definition 3. Pattern P is **frequent** (support prevalent) if its support is equal to or greater than a user-defined support threshold, *min_sup*.

Definition 4. Given a rule $A \rightarrow B$ (where $P = \{A, B\}$), the **confidence** of rule $A \rightarrow B$ determines how frequently the parameters in B appear in the records that contain A parameters and is formulized as shown in equation (2):

$$confidence(A \rightarrow B) = \frac{support(A \cup B)}{support(\mathrm{A})} \quad (2)$$

Definition 5. A rule is called as **meaningful pattern** if its confidence value satisfies the minimum confidence threshold *min_conf*.

Definition 6. Given a meaningful pattern P and its support values for each time slot ti of a time period $T=[t1,t2...,tn]$, if trend of supports of pattern P in time period T increasing over time, then P is an **emerging association pattern**.

Definition 7. Given a meaningful pattern P and its support values for each time slot ti of time period $T=[t1,t2...,tn]$, if trend of supports of pattern P in time period T decreasing over time, then P is an **vanishing association pattern**.

Based on these definitions, emerging and vanishing association pattern mining problem can be formulized as follows:

Definition 8. Given a dataset D, *min_sup* and *min_conf* thresholds, a time period T, generated pattern P in meaningful patterns set R is identified as emerging or vanishing association pattern with respect to Definition 6 and 7 (equation (3)).

$$Pattern\ P\ in\ R\ is \begin{cases} emerging\ if\ satisfies\ Definition\ 6 \\ vanishing\ if\ satisfies\ Definition\ 7 \end{cases} \quad (3)$$

2.2. EVAPMiner Algorithm

We proposed a novel algorithm for discovering emerging or vanishing association patterns from hydroclimatic datasets, named as **E**merging or **V**anishing **A**ssociation **P**attern **Miner**, EVAPMiner, based on classical Apriori algorithm. Algorithm 1 presents pseudo code for EVAPMiner algorithm based on the definitions given in Section 3.

Algorithm 1. EVAPMiner algorithm pseudo code

Inputs:
min_sup: Minimum support threshold
min_conf: Minimum confidence threshold
T: Time period
D: Dataset (e.g. Hydroclimatic) dataset
Output: Emerging or vanishing association patterns which satisfy *min_sup* and *min_conf* thresholds in time period T.

```
Initialization; k = 0; C_0 = 0
C_0 = generate-candidates(D)
C_k = calculate-support(C_0, D)
for every time slot ti in time period T do {
    while(not empty C_k){
    L_k(ti) = prune-candidates(C_k(ti), min_sup)
    C_k+1(ti) = generate-candidates(L_k(ti))
    C_k+1(ti) = calculate-support (C_k+1(ti), D)
    k = k + 1
    }
}
L = calculate-confidence(L, min_conf)
if L >= min_conf
    add(L_rule, L)
L_emerging_vanishing=determine-emerging-vanishing-
patterns(L_rule)
return L_emerging_vanishing
```

The inputs of EVAPMiner algorithm are minimum support threshold *min_sup*, minimum confidence threshold *min_conf*, time period T and Dataset D and the output of the algorithm is emerging or vanishing association patterns that satisfy user-given thresholds and time period. The values of minimum support threshold *min_sup*, minimum confidence threshold *min_conf* and time period T are user given and so these values should be determined by the user a priori. EVAPMiner algorithm, first, discovers patterns for each time slot of given time period, and support values for these rules are calculated. Then, the rules are generated if they satisfy the minimum confidence threshold. Last, the rules are identified as emerging if trend of their support values increase over time and as vanishing if trend of their support values decrease over time.

In Algorithm 1 in step 2, *generate-candidates* function generates all possible size-1 pattern candidates, and in step 3, *calculate-support* function calculates support values for these candidates. Steps 4-11 discovers frequent rules for each time slot *ti*. Steps 4-11 prune candidates, generates size-k+1 candidate patterns from size-k prevalent patterns and calculate support values for newly generated candidates. The function of *prune-candidates* prunes support non-prevalent candidate patterns and support prevalent patterns are assigned to *L* matrix. The function of *generate-candidates* generates size-k+1 candidate patterns from *L*, and support values for these candidates are calculated by *calculate-support* function. Step 12 calculates confidence values for extracted patterns with *calculate-confidence* function. Step 13-15 selects patterns which satisfy *min_conf* threshold. In step 15, *determine-emerging-vanishing-patterns* function discovers emerging and vanishing patterns by analyzing trends of selected patterns' support values. Lastly, step 16 returns discovered emerging and vanishing association patterns.

3. Results and Discussion

The experiments were conducted for discovering emerging and vanishing association patterns in hydroclimatic dataset of Turkey. Streamflow data from 64 streamflow gauging stations and meteorological data were analyzed and the association patterns and the patterns change over time for these parameters were extracted. Also, these patterns were analyzed based on stations emerging or vanishing properties.

3.1. Dataset

The dataset contains data for precipitation, air temperature, and streamflow parameters from 64 locations over Turkey for the time period of 1975-2000. Data for all parameters from all stations were originally daily observed values. Original daily data were converted to monthly values by calculating the average for air temperature and stream flow, and sum for precipitation. Streamflow data were obtained from 64 gauging stations. These 64 stations were previously selected from more than 300 stations, based on their completeness, homogeneity, and length (Kahya and Karabork 2001). The meteorological data (precipitation and air temperature parameters) were obtained from a meteorology station in the same river basin with the stream flow gauging stations (Figure 1). The homogeneity of the meteorological data were tested to ensure data quality (Dadaser-Celik and Cengiz 2012). If there were more than one meteorology stations in a river basin, we selected the meteorology station whose data had the highest correlation with the stream flow data. In the experiments for every 2 year rules were generated and then emerging and vanishing association patterns were discovered. Because of that reason our dataset includes 12 time periods.

The data contained continuous numerical values and should be converted to discrete format for the algorithm. We discretized the data into three groups by using their statistical properties (i.e., mean (μ) and standard deviation (σ)). The data were named as "Medium (M)" if they were between "μ - 0.5σ" and "μ + 0.5 σ". The data were named as "Low (L)" if they were "smaller than μ - 0.5σ", and "High (H)" if they were "higher than "μ + 0.5σ". An example data discretization for stream flow of a station can be seen in Figure 2.

3.2. Example Emerging and Vanishing Patterns of Hydroclimatic Dataset

In this experiment, we analyzed our hydroclimatic dataset for emerging and vanishing association patterns. The minimum support threshold *min_sup*, minimum confidence threshold

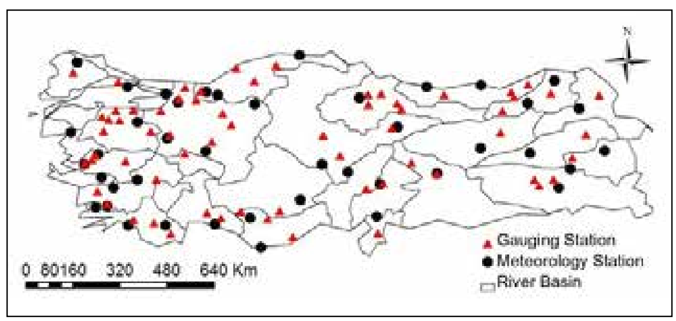

Figure 1. The locations of the stream flow gauging stations and meteorology stations.

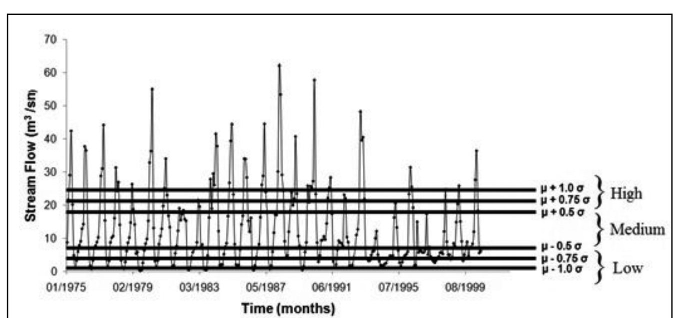

Figure 2. An example of data discretization for streamflow data from a gauging station.

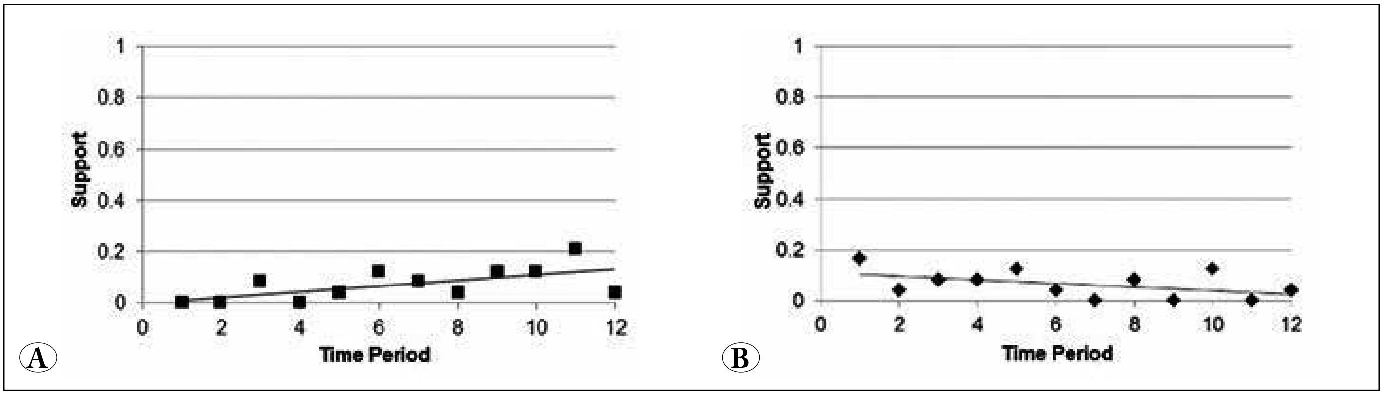

Figure 3. An example **A)** emerging and **B)** vanishing association patterns.

min_conf, and time period T of the algorithm were set as 0.001, 0.5, and 1975-2000, respectively. Many association patterns were extracted, but two of them are presented here, one for each pattern. Figure 3 presents these patterns.

Figure 3a presents an emerging association pattern as its trend of support value increases over time, and and Figure 3b presents a vanishing association pattern as its trend of support value decreases over time. For emerging association pattern in Figure 3a, the parameters are {Temperature-Low, Precipitation-High} → {Stream Flow-High}. This means that, this pattern more frequently occurs over time. For vanishing association pattern in Figure 3b, the parameters are {Temperature-High, Precipitation-Low} → {Stream Flow-Low}. This means that, this pattern was more frequent, but vanishes over time.

3.3. Mining Emerging and Vanishing Association Patterns in Hydroclimatic Dataset

Data from 64 streamflow gauging stations were analyzed for emerging and vanishing association patterns. The results were extracted for every station and selected patterns were presented here due to the space limitation. For every station-level pattern, emerging and vanishing association patterns were discovered and presented. The minimum support threshold *min_sup*, minimum confidence threshold *min_conf*, and time period T of the algorithm were set as 0.001, 0.5, and 1975-2000, respectively. Figure 4 shows selected patterns and their station-level positions. The patterns whose trends do not change over time also marked in Figure 4.

Figure 4A and 4B show selected patterns and their station-level positions in our hydroclimatic dataset of 64 stations. Figure 4a presents patterns of Stream Flow-Low. {Temperature-High} → {Stream Flow-Low} is an emerging pattern for most of the stations. Contrarily, {Precipitation-Low} → {Stream Flow-Low} is a vanishing pattern for most of the stations. These patterns show us that low stream flow was more associated with low precipitation at earlier times but it is associated with high temperature over time. {Temperature-High, Precipitation-Low} → {Stream Flow-Low} pattern is an emerging pattern for west half of Turkey, while this pattern is a vanishing pattern for east half of Turkey.

Figure 4b presents patterns of Stream Flow-High. {Temperature-Low} → {Stream Flow-High} is an emerging pattern for most of the stations. Contrarily, {Precipitation-High} → {Stream Flow-High} is a vanishing pattern for most of the stations. These patterns show us that high stream flow was more associated with high precipitation at earlier times, but it is associated with low temperature over time. {Temperature-Low, Precipitation-High} → {Stream Flow-High} pattern is both emerging and vanishing association pattern.

3.4. Evaluation of Results

The results of the study were evaluated based on the previous literature to determine if they are correct and intereting. In general, the results found in this study were consistent with many other studies that showed that high stream flows are related to high precipitation and low air temperatures and low stream flows are related to low precipitation and high air temperatures (e.g., Changnon and Kunkel 1995, Cayan et al. 1993). For Turkey, Dadaser-Celik and Cengiz (2012) showed that the correlations between stream flow and precipitation and air temperatures are strong over Turkey. Celik et al. (2014) also showed that there is a strong relationship between stream flow and precipitation and air temperature, particularly for low stream flows in Turkey. This

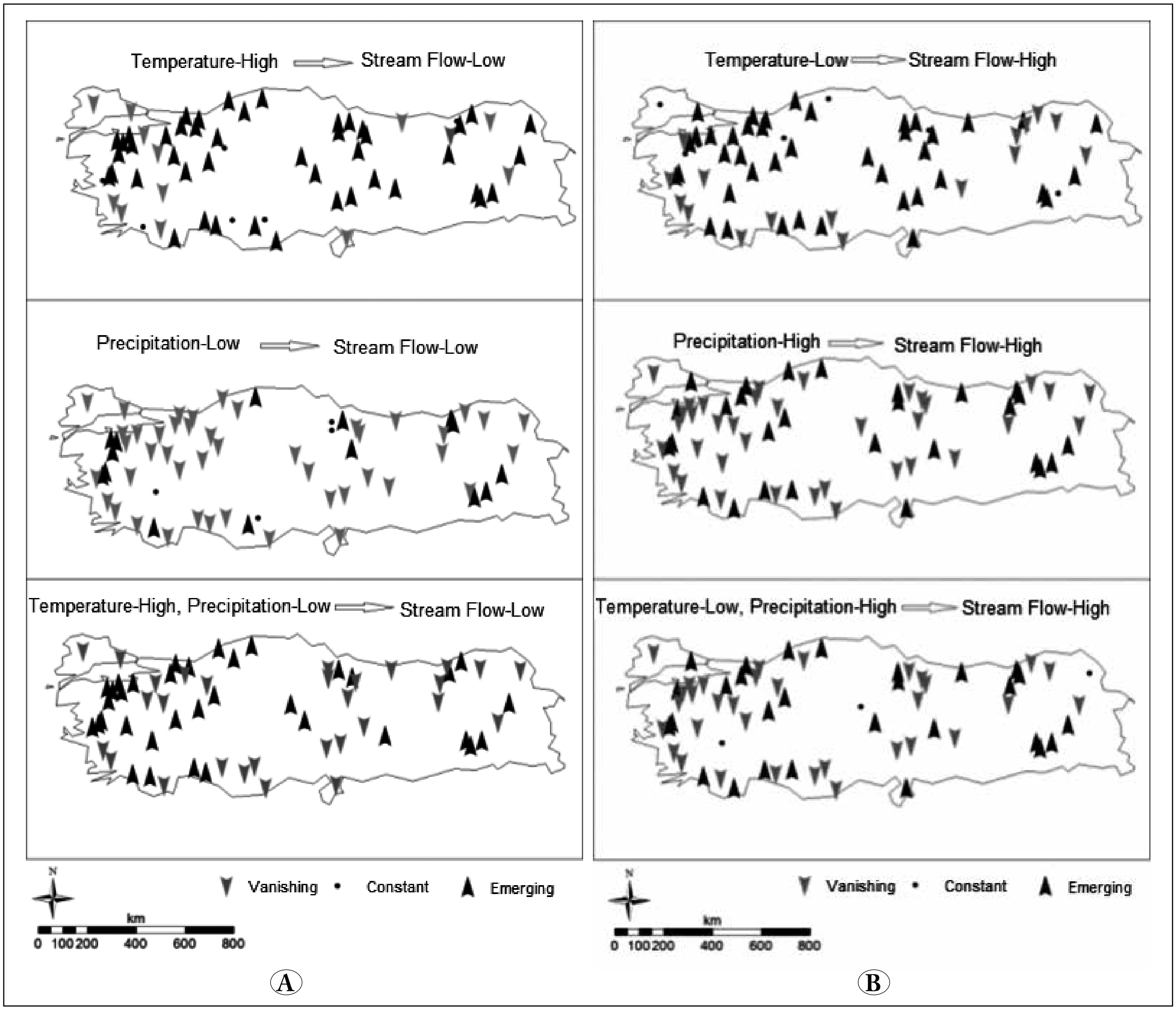

Figure 4. Selected patterns and their station-level positions.

study also shows that the {Temperature-High} → {Stream Flow-Low} and {Temperature-Low} → {Stream Flow-High} patterns are getting stronger all over Turkey, which is an expected finding under changing climatic conditions. Several studies detected downward trends in streamflows and upward trends in air temperatures in recent decades (Dadaser-Celik and Cengiz 2014, Kahya and Karabörk 2001).

4. Conclusions

In this study, we defined emerging and vanishing pattern mining problem and proposed a novel algorithm, named as EVAPMiner algorithm. We analyzed hydroclimatic dataset of Turkey using proposed algorithm to discover emerging and vanishing patterns over time. Discovering emerging and vanishing patterns is important for extracting more information than classical association patterns in the context of patterns' temporal variation. Experimental results showed that our proposed algorithm could successfully discover emerging and vanishing patterns and could detect temporal shifts in strengths of these patterns. The results showed us that when association patterns are temporally detailed and positioned as emerging and vanishing, the associations between parameters change over time. The main change for stream flow shifted from precipitation to air temperature. Stream flow was more associated with precipitation at earlier times of dataset but when the time comes recently it is associated with air temperature. Also, spatial analyses of patterns are done based on station-level pattern changes.

In the future, we are planning to extend this work with more hydrological and climatic parameters. Also, our algorithm could be extended to discover patterns quicker. Our proposed algorithm could be used in several application domains that have dynamic characteristics.

5. Acknowledgments

This study was partially supported by the Scientific and Technological Research Council of Turkey (TUBITAK), Project Number: CAYDAG 110Y110 and the Research Fund of the Erciyes University, Project Number: FBA-09-866.

6. References

Agrawal, R., Imielinski, T., Swami, A. 1993. Mining Association Rules between Sets of Items in Large Databases. *In the Proceedings of the 1993 ACM SIGMOD International Conference on Management of Data,* pp: 207 - 216.

Agrawal, R., Srikant, R. 1994. Fast Algorithms for Mining Association Rules. *In the Proceedings of the 1994 International Conference on Very Large Databases,* pp: 487-499.

Alves, R., Rodriguez-Baena, D.S., Aguilar-Ruiz, J.S. 2009. Gene Association Analysis: A Survey of Frequent Pattern Mining from Gene Expression Data, *Brief. in Bioinfor.,* 11: 210-224.

Apte, C., Liu, B., Pednault, E.P.D., Smyth, P. 2002. Business Applications of Data Mining, *Commun. of the ACM,* 45 (8): 49-53.

Cayan, D. R., Riddle, L. G., Aguado, E. 1993. The Influence of Precipitation and Temperature on Seasonal Streamflow in California. *Water Res. Rese.*, 29: 1127–1140.

Celik, M., Dadaser-Celik, F., Dokuz, A.S. 2014. Discovery of Hydrometeorological Patterns. *Turk. J. Electric. Engin. Comput. Sci.,* 22: 840-857.

Changnon, S. A., Kunkel, K. E. 1995. Climate-related fluctuations in Midwestern Floods During 1921-1985. *J. Water Res. Plan. Manag.*, 121: 326-334.

Creighton, C., Hanash, S. 2003. Mining Gene Expression Databases for Association Rules, *Bioinfor.,* 19 (1): 79-86.

Dadaser-Celik F, Cengiz, E. 2014. Wind speed trends over Turkey from 1975 to 2006. *Int. J. Climat.*, 34: 1913-1927.

Dadaser-Celik, F., Celik, M., Dokuz, A.S. 2012. Associations between Stream Flow and Climatic Variables at Kızılırmak River Basin in Turkey. *Glob. Nest J.,* 14 (3): 354-361.

Dadaser-Celik, F., Cengiz, E. 2012. Correlations of Stream Flow and Climatic Variables in Turkey. *In the BALWOIS,* pp: 1-1.

Dhanya, C.T., Nagesh Kumar, D. 2009. Data Mining for Evolution of Association Rules for Droughts and Floods in India Using Climate Inputs. *J. Geophy. Res.: Atmosph.,* 114 (D2): D02102.

Du, X., Jin, R., Ding, L., Lee, V.E., John H. Thornton, J. 2009. Migration Motif: A Spatial - Temporal Pattern Mining Approach for Financial Markets. *In the Proceedings of the 15th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining,* pp: 1135-1144.

Han, J., Kamber, M., Pei, J. 2011. Data Mining: Concepts and Techniques, 3rd Edition, Morgan Kaufmann Publishers Inc., San Fransisco, 744pp.

Hidber, C. 1999. Online Association Rule Mining. *Proceedings of the 1999 SIGMOD Inernational Conference on Management of Data*, pp:145-156.

Kahya, E., Karabork, M.C. 2001. The Analysis of El Nino and La Nina Signals in Streamflows of Turkey, *Int. J. of Climato.,* 21 (10): 1231-1250.

Khan, A., Khan, K., Baharudin, B.B. 2009. Frequent Patterns Minning of Stock Data Using Hybrid Clustering Association Algorithm. *In the Proceedings of the International Conference on Information Management and Engineering, ICIME '09.*, pp: 667-671.

Kumar, D.N., Ish, M., Dhanya, C.T. 2009. Data Mining and It's Applications for Modelling Rainfall Extremes, *J. of Hydra. Eng.,* 15 (SP.1): 25-51.

Li, L., Zhang, M. 2011. The Strategy of Mining Association Rule Based on Cloud Computing. *In the Proceedings of the 2011 International Conference on Business Computing and Global Informatization,* pp: 475-478.

Liu, B., Hsu, W., Ma, Y. 1999. Mining Association Rules with Multiple Minimum Supports. *In the Proceedings of the Fifth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining,* pp: 337-341.

Mishra, S., Dwivedi, V.K., Saravanan, C., Pathak, K.K. 2013. Pattern Discovery in Hydrological Time Series Data Mining During the Monsoon Period of the High Flood Years in Brahmaputra River Basin. *Int. J. Comput. Appl.,* 67 (6): 7-14.

Nahar, J., Imam, T., Tickle, K.S., Chen, Y.-P.P. 2013. Association Rule Mining to Detect Factors Which Contribute to Heart Disease in Males and Females, *Exp. Syst. with Appl.,* 40 (4): 1086-1093.

Ngai, E.W.T., Xiu, L., Chau, D.C.K. 2009. Application of Data Mining Techniques in Customer Relationship Management: A Literature Review and Classification. *Exp. Syst. with Appl.,* 36 (2, Part 2): 2592-2602.

Olson, D., Shi, Y. 2005. Introduction to Business Data Mining, McGraw-Hill/Irwin, 288 pp.

Ölmezoğulları, E., Ari, I. 2013. Online Association Rule Mining over Fast Data. *IEEE International Congress on Big Data*, pp:110-117.

Rajendran, P., Madheswaran, M. 2010. Hybrid Medical Image Classification Using Association Rule Mining with Decision Tree Algorithm. *J. Comput.*, 2 (1): 127-136.

Shua, H., Zhub, X., Da, S. 2008. Mining Association Rules in Geographical Spatio-Temporal Data. *The Int. Arch. of the Photog., Rem. Sens. and Spat. Inf. Sci.*, 37: 225-228.

Tadesse, T., Wilhite, D., Harms, S., Hayes, M., Goddard, S. 2004a. Drought Monitoring Using Data Mining Techniques: A Case Study for Nebraska, USA, *Natu. Hazar.*, 33 (1): 137-159.

Tadesse, T., Wilhite, D.A., Hayes, M.J. 2004b. Discovering Associations between Climatic and Oceanic Parameters to Monitor Drought in Nebraska Using Data-Mining Techniques, *J. of Clima.*, 18: 1541-1549.

Tan, P.N., Steinbach, M., Kumar, V. 2005. Introduction to Data Mining, Addison-Wesley, Boston, 769 pp.

Yew-Kwong, W., Wee-Keong, N., Das, A. 2001. Fast Online Dynamic Association Rule Mining. *In the Proceedings of the Second International Conference on Web Information Systems Engineering*, pp: 278-287.