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***Abstract*—Today, drought has become part of the identity as well as the fate of many countries. In fact, drought is considered among the most damaging natural disasters. The severe consequences resulting from drought affect the nature and society at different levels. Proper and efficient management is not possible without accurate prediction of drought and the identification of its various aspects. Thus, the existence of a considerable body of literature on drought monitoring. However, significant growth of remote sensing databases as will an increased amount of available data related to drought have been detected. Therefore, a more adequate approach should be developed. During the past decades, Data Mining (DM) methods have been introduced for drought monitoring. According to the best of our knowledge, a review of drought monitoring using remote sensing data and DM methods is lacking. Thereby, the purpose of this paper is to review and discuss the applications of DM methods. This paper consolidates the finding of drought monitoring, models, tasks, and methodologies.**

***Index Terms*—Drought monitoring, drought index, Data Mining, remote sensing, knowledge, prediction**

I. Introduction

Drought is a precarious natural hazard that affects economic, social, and environmental sectors, resulting in significant damages. Thus, four types of droughts have been identified that include hydrological, agricultural, meteorological, and socio-economic droughts [1] [2] [3].Drought is usually quantified using drought indices such as the Standardized Precipitation Index (SPI), Standardized Precipitation Evapotranspiration Index (SPEI) [4] , the Reconnaissance Drought Index (RDI) [5], the Comprehensive Drought Index (CDI) [6], the Surface Water Supply Index (SWSI) [17], the Crop Moisture Index (CMI) [8], the Palmer Drought Severity Index (PDSI) [9]. Some of the most important DIs are developed from remote sensing data such as Normalized Difference Vegetation Index (NDVI). All along with a big remote sensing data set a huge amount of data related to drought are used by decision makers in order to extract time/space characteristics of drought. In fact, one of the main challenges is the inability to predict drought conditions accurately for months or years in advance. To address this issue, many methods has been developed. This paper mainly focuses on drought monitoring using DM methods.

In the literature, several DM-based methodologies have been proposed for drought monitoring (c.f. Section 2). Thus, this paper reviews the related studies reported in the period between 2004 and 2018, with the focus on the use of DM methods for monitoring drought. The main research questions considered in this review paper are:

- Q1: For what purpose has the DM applied in drought monitoring?
- Q2: How have DM methods been applied to drought monitoring using remote sensing data?
- Q3: Which DM methods have been applied?
- Q4: What are the limitations of the current work and future directions?

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II. Data mining methods for drought monitoring

In the last few years, DM methods have been shown to yield high performance in discovering hidden patterns and handling the growing amount of data [10]. In addition, DM methods, aims to generate new knowledge (i.e. models, cart, rules, etc.) that leads to a better understanding and prediction. Figure 1 presents a flowchart of a generic methodology of drought monitoring using DM. The DM methods applied for droughts modelling identified among the reviewed papers are summarized in Table 1.

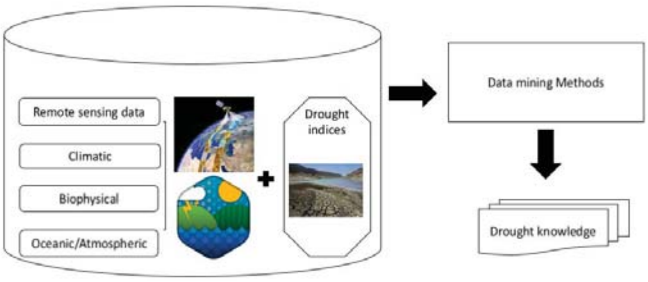

Fig. 1. Flowchart of the drought modelling via data mining methods

A. Association Rules (AR)

AR is a descriptive DM method proposed by Agrawal in 1993 [28]. In fact, AR is defined as the procedure for finding frequent relationships, associations, or correlations between data in databases [28]. As an example Tadesse et al. proposed two-time series DM algorithms, namely the Representative Episodes Association Rules (REAR) and the Minimal Occurrences with Constraints and Time Lags (MOWCATL) [1]. The ARs were generated based on the relationships between climate and oceanic indices (PNA, MEI, NAO, PDO, and SOI) and drought indices (SPI and PDSI) in Nebraska for the period from 1950 to 1999. The REAR algorithm provides a discrete representation of time-series data to identify the episodes that occur together within the same time intervals. This algorithm is based on counting the frequency of episodes where the rules depend on the minimum frequency, the window width, and the minimum confidence values. On the other hand, the MOWCATL algorithm is used to identify the number of minimal occurrences as a support of the episode in the generating rules. It has three window parameters: the time lag, the maximum window width for the antecedent and for the consequent. The implementation of REAR and MOWCATL enhances discovering the relationships between the drought episodes and SOI, MEI and PDO. The REAR algorithm is usually used to identify drought episodes without a time lag, while MOWCATL is designed to identify minimal occurrences of an episode in the existing lag in time between the occurrence of oceanic parameters and drought episodes. Thavorntam et al. analyzed monthly correlation between VCI and SPI to generate the ARs using the A priori algorithm [11]. The objective was to determine drought severity, frequency, and the future drought occurrence. They used rainfall data sets for the period from 1980 to 2009 and NDVI data collected for the period from 2001 to 2009 in the northeastern region of Thailand. For each vegetation cover, VCI was calculated within the extracted SPI values. Results were evaluated, based on confidence, support, and lift; there values indicated the accuracy of the derived rules.

TABLE I
Data mining methods for drought monitoring, Multivariate El Nino and Southern Oscillation Index (MEI), North Atlantic Oscillation index (NAO), Southern Oscillation Index (SOI), Pacific/North American index(PNA), NAO, Principal component analysis (PCA), Pacific Decadal Oscillation (PDO), Seasonal Rainfall Series (SRS), Madden-Julian Oscillation (MJO), Standardized Seasonal Greenness(SSG), Sea Surface Temperature anomalies (SST), Standardized Deviation of Normalized Difference Vegetation Index (SDNDVI), vegetation condition index (VCI), Independent Component Analysis (ICA), Adaptive Neuro-Fuzzy Inference Systems (ANFIS), Support Vector Machine (SVM), and Autoregressive Integrated Moving Average Multivariate time series (ARIMAX).

Article	Inputs	Data mining methods	Output
[1]	SPI, PDSI, SOI, MEI, PNA, MEI, PNA, NAO and PDO.	Association Rules (AR)	Rules
[11]	SPI and VCI.	AR	Rules
[2]	NDVI, SPI, Start of the Season (SOS), Soil moisture and Land Cover.	Regression Trees (RT)	Rules and Maps
[12]	PDSI, SPI, SOI, MEI, PDO, AMO, PNA, NAO, MJO, SST, land cover type, available soil water capacity, percent of irrigated land, ecosystem type and SSG.	RT	Maps
[13]	SPI, Seasonal Rainfall Series and Annual Rainfall Series.	Decision Trees (DT)	Rules
[14]	Precipitation, Wind, Humidity and Temperature.	DT	Rules
[15]	SPI and monthly precipitation.	DT	Tree model
[16]	Precipitation and Temperature.	Artificial Neural Network (ANN)	Knowledge
[?]	SPI, precipitation and monthly rainfalls.	ANN	Model
[25]	SPI, precipitation, temperature (minimum and maximum) and the humidity levels.	MultiLayer Perceptron ANN, ANFIS, SVM, and ARIMAX.	-
[18]	Number of rainy days, Rainfall amount, Average temperature, average soil moisture and average wind speed.	Fuzzy Logic (FL)	Knowledge
[19]	SPI and VCI.	ICA and AR	Rules
[20]	Rainfall and Temperature.	AR and DT	Model
[21]	VCI and NDVI.	Image mining and FL.	Maps
[22]	SEVIRI and NDVI.	Image mining and FL.	Knowledge
[23]	Land cover, SPI, PDO, AMO, NAO, PNA, MEI, DEM and SDNDVI.	ANN and RT	Knowledge, model and cart
[24]	Monthly precipitation and SST	DT and AR	Model
[25]	NDVI and SPI.	Random Forest (RF), BRT and Cubist.	Maps
[27]	NDVI, self-calibrated PDSI, SPI, elevation and land cover.	RT and CART.	Rules

B. Decision trees (DT)/Regression Trees (RT)

DT are often used in classification and prediction as a supervised approach. The DT presents a model that is represented in the form of a tree structure with rules that require human interpretation [29].

Tadesse et al. [2] presented a rule-based RT model as an application of DM. Cubist DM Software was used to generate models of vegetation stress due to drought in Nebraska and South Dakota. Rule-based RT models were generated to identify relationships between the input data. the historical data integrated satellite, climate, and biophysical data from 1989 to 2002. For the climate data, the authors used SPI, PDSI and self-calibrated PDSI, while the PASG represented the satellite data calculated based on seasonal greenness (start and end of the season) and temporal NDVI. On the other hand, the land-cover type, available soil water capacity, percent of irrigated farm land, and ecological type represented the biophysical data. In this study, the rule-based models were generated, based on the absence or presence of a time lag (e.g. 2, 4, and 6 weeks), and reported the average error of the prediction and correlation coefficient values between the given parameters. According to Tadesse et al, RT used based on historical data from 1989 to 2005 [12]. The RT is available in the Cubist DM software. The aim of this paper was to identify temporal and spatial relationships among the historical data. In this study, the Vegetation Outlook (VegOut) model was used to generate rules based on climate, oceanic, biophysical, and satellite data. The authors used monthly climatic data as PDSI and SPI values. As satellite based data, the SSG was calculated from NDVI values using the seasonal greenness data. On the other hand, eight oceanic/climatic indices (SOI, MEI, PDO, AMO, PNA, NAO, MJO, and SST) were also used in modeling. This study used the VegOut to provide a future prediction of the SSG based on earlier conditions. The aim of using RT was to analyze the input data and generate rules at different 3 time intervals (i.e., 2, 4, and 6 weeks). The study could detect a higher prediction accuracy ($R^2 > 0.90$) for the three periods (2-, 4-, 6-week predictions).

In the Cekerek watershed, Turkey Yurekli et al. applied the DT on the SPI to predict drought constituted from a series of rainfall [13]. The main objective was to predict drought categories for each region by applying the DT rules obtained from the training phase of the k-reference periods for the rainfall data sets. The results revealed that there was no significant difference between drought categories calculated from the SPI algorithm and DT approaches. Further, the accuracy of prediction by the DM was greater than 94% k-reference periods.

Another use of DT recorded by Sattari et al. [14]. The DT used Based on the use of precipitation, wind, humidity, and temperature data taken from 18 meteorological stations in the Ankara region between 1926 and 2006. In this study, the SPI values were used with statistical attributes (mean (mm), standard error, standard deviation, kurtosis, skewness, maximum (mm) and minimum (mm)). The rules were created in the form of "if-then" to provide reliable predictions for drought. According to the training and test results, the decrease in the quantity of data could lead to a decrease in the performance of modeling. For the first time for drought prediction the Sattari et al. [15] applied the M5 rule tree model using the data from the Maragheh region located in the southwest of East Azarbaijan Province, Iran. The M5 rule tree model used monthly precipitation data from 1965 to 1989 to calculate SPI-6 values. Therefore, this article showed the efficiency of the M5 rule tree model for drought prediction. The proposed solution was evaluated, based on performance measurements such as correlation coefficient R and the Root Mean Square Error (RMSE). The proposed solution was based on previously taken decisions using a linear regression equation. The M5 model has a tree structure with roots, branches, nodes, and leaves. The tree was built in two steps. The first step consisted of data splitting. Hence, the standard deviation of the data must be reduced in the child nodes. However, in the case that the standard deviation could not be reduced. The M5 selected the branches with the least expected error from the accurate branches resulting via the branching process in the child nodes. On the other hand, the second step consisted of using Weka software to create the tree model using linear regression functions. Overall, this article highlighted the ability of the M5 tree model in predicting drought and making decisions.

C. Artificial Neural Network (ANN)

The ANN is classified under the discovery-driven techniques. ANN is considered as a prediction model which has been widely used for time-series forecasting. As a classification technique, the ANN has also been used to deal with complicated or imprecise data to identify involved hidden patterns [30]. The study of Razmkhah et al. used ANN to model drought using SPI as a commonly used drought index and the data between 1999 and 2009 for Kohgilooyeh-and-Boyer Ahmad Province, Iran [16]. The objective was to control the frequency of dry period based on time scales and to find an NN model to monitor drought. The areas, altitudes, temperature, and precipitation were used as input data. They used the MultiLayer Feed-Forword-Back Propagation (MLFF-BP) as the most commonly used ANN algorithms. To develop the NN models, the data was normalized for the training process. In this study, the authors tested three different training algorithms, the Levenberg-Marquardt algorithm, BP with Steepest Descent, Conjugate Gradient Descent and Quasi-Newton, described by Haykin. Based on the results, the Quasi-Newton training algorithm was the best for SPI3 and 6, while for SPI 1, 9, 12, 24 and 48, Levenberg-Marquardt led to better results. The effect of hidden node number was also investigated in the study.

Other use of ANN in Karaman, Iran by Sattari et al. [**?**]. This study used the FFBPANN to train the ANN based on the monthly rainfall data and the SPI values collected from 1975 to 2009. Based on the historical precipitation data, the ANN model was able to reliably provide future SPI for different time periods. In other words, the ANN model was trained to be able to make decisions for future conditions. The training of networks was repeated until the relationship between the input variables from earlier examples of the ANN and the predicted variables was revealed. The momentum training rule and activation function hyperbolic within -1 and +1 tangent function was used for the training input data, while the back-spread algorithm was used to reduce the error between computed and observed values. The learning process performed the adjustment of weights and bias to generate an efficient estimation, based on the efficiency criterion.

Based on SPI, Jalalkamali et al. compared the MLP-NN to three models, namely ANFIS, SVM, and ARIMAX to monitor meteorological drought [25]. In fact, the authors used precipitation and temperature time-series for the period between 1961 and 2012 from the Yazd synoptic station in Iran. In addition, the humidity levels were calculated using SPI for two different periods: short-term (3 and 6 months) and long-term (9, 12, 18, and 24 months). Results showed that the ARIMAX was better performed compared to the SVM, ANFIS, and MLP models.

D. Fuzzy Logic (FL)

Zandvakili et al. used the fuzzy system to monitor drought in Iran [18]. This kind of DM method was applied, based on the SPI index and other related data. The fuzzy systems were used to handle certain types of data, such as vague, imprecise and qualitative data. For this purpose, they used the open method to provide an acceptable accuracy of the resulting models. In addition, this article used the number of rainy days, rainfall amount, temperature, soil moisture, and wind speed as data collected from the meteorological stations from 1961 to 2005. The first step in the fuzzy process was to extract and calculate the dominant parameters from the available data. Then, the authors used the extracted 18 rules obtained from the output of the SPI in the proposed system. The output of the fuzzy system and the output of the SPI were the same. The third step was to identify the type, range of changes, and the numbers of fuzzy member functions for each input parameter. The final step consisted of evaluating and validating the model. Thus, the results of this analysis led to using the rainfall amount or rainy days as input in the proposed model due to their association with drought. The presented model was able to produce reliable output with acceptable accuracy.

E. Hybrid methodologies

Several studies presented hybrid approaches for increasing the efficiency of drought monitoring systems taking the advantage of the fusion between different techniques.

In the state of Karnataka in India, the AR and the Independent ICA used as a spatio-temporal process to find hidden patterns and relationships in temporal NDVI and rainfall datasets [19]. Three categories of data were used for this study, rainfall data for the period of 1970 to 2004, NOAA-AVHRR NDVI for the period of 1981 to 2003 as a satellite data set, and the field data. In the study area, the SPI indices were used at time-scales 1 and 2 to monitor the occurrence of drought. The first technique was an A priori DM algorithm used to generate AR and identify the relationship between SPI and VCI. Five steps were required as pre-processing of the time series. Discretizing the data was the first step. The second step was to formulate target episodes. Step three was to identify the minimum confidence and support as a criterion of selection in an A priori analysis. Step 4 was to generate the AR. Finally, step five consisted of selecting the best rules using the goodness of the rules measure. The second technique, ICA, was used to analyze the output of the PCA technique in the spatio-temporal process. In this technique, PC1 and PC2 were applied to the pre-processed VCI images to identify spatial and temporal components. The algorithm Natural Gradient Flexible -ICA was executed two times to observe the performance of ICA generated from the three leading PCs.

Rajput developed a DM technique for drought monitoring by combining climatic and meteorological parameters [20]. The study presented a hybrid method to take advantage of DT as a classification technique and the AR mining to discover the patterns involved in the databases. In the AR, the Apriori algorithm was used to find a frequent item set. The author used rainfall and temperature data from Sagar District in India for 1997-2010. In the study, two examinations were performed after data pre-processing. The first examination was made to generate AR from the data set, while the second examination was made for the DT. The generated tree from Weka was the base for decision making. To build the DT, the J48 was used and the results were compared with the ID3 results.

In two studies, Rulinda used remote sensing data, image mining and fuzzy classification as a DM technique [21] [22]. In the first study, Rulinda used 18 NDVI images to produce deviation maps collected in East Africa from December 2005 to February 2006. In this research, the fuzzy classification was used to solve the mixed pixel problem. In fact, author developed a framework that uses image mining techniques to monitor drought by considering both vegetation stress intensity and duration. A selected function was then used to characterize drought.

Rulinda applied a membership function to Meteosat SEVIRI images for the months of September to December between 2005 and 2007 in eight crop field locations in drought prone areas of eastern Africa [22]. Like in the 2007 research the DM was used to handle a large amount of data and the Fuzzy theory to handle the uncertainties of drought effect on vegetation [21]. Rulinda suggested the use of an object-oriented approach for drought monitoring. The author improved modeling using the space-time drought object on the basis of a group of pixels instead of individual pixels. The idea that drought can be seen as a spatial object was suggested in 2010 by Rulinda and explored in 2013 [23].

Berhan et al. developed a new approach that can be used for identifying and predicting drought using satellite images in Ethiopia [23]. In fact, the authors applied ANN and RT with the fuzzy segmentation approach. In this research, the drought was presented as a spatial object that was identified and evaluated using DM techniques and remote sensing imaginary. Accordingly, 11 attributes of the drought object were used: the soil water holding capacity, land cover and ecological regions (ecosystems of Ethiopia presented by veg-Ethiopia) as biophysical parameters, the SPI (3-month SPI) with teleconnections, and climatic/oceanic indices such as the PDO, AMO, NAO, PNA and MEI, DEM as climate data and the SDNDVI images from the NOAA AVHRR satellite for 1983 to 2006. In the DM step, the ANN was used for predicting 1 to 4 months of the SDNDVI values using the identified 11 key attributes. Then, the required rules were developed and tested using the cubist RT DM technique. After creating the network object, it was trained to learn the relationship between independent attributes and dependent inputs using the NN Toolbox. To validate the drought object-ANN model, a comparison was performed between the predictions and the target data. In the RT modeling, the RT (CART) algorithm was used in Cubist software. The output was visualized as an image, named drought map. To evaluate the model, the average error, relative error, and correlation coefficients were calculated and compared. According to the results, the low-resolution data led to uncertainties in the models and prediction maps. This study indicated the potential of using either ANN or RT for the prediction of future drought events (prediction horizon of 4 months).

Nourani et al. suggest another hybrid application contain DT and AR using SPI values (from Tabriz and Kermanshah synoptic stations) and de-trend TSST data (from the Black, Mediterranean and Red Seas) [24]. The method followed some major steps, such as data classification and dominant input selection. As an advance for the presented hybrid DM method, this study demonstrated a capacity in grouping the input data with flexible bounds. While in other studies, the classification had been made within rigid and fix bounds. The first step in the data pre-processing was to discretize the monthly de-trended SST data using a DT algorithm. The second step was to discretize the monthly SPI. In the third step, the C4.5 DT algorithm was used to select the most effective groups of SST data for each sea and for different lag times. The fourth step was to extract AR based on the SST and SPI values. The proposed DM process can help discover the hidden information involved in the huge amount of data. A high confidence was demonstrated between the monthly SPI values and the SST of the seas for the stations used. This might be related to the existence of a relative correlation between the Mediterranean, Black, and the Red SST data and drought. In another study the same data were used via a threshold-based DM technique for precipitation forecasting.

In order to monitor meteorological (1-month to 12-month SPI index) and agricultural (e.g. Corn and soybean) droughts, Park et al. proposed the use of DM techniques [26]. The RT was implemented based on the collected data from MODIS and TRMM satellite sensors in the arid, humid, and combined regions in the USA between 2000 and 2012. For regression tasks, RF, BRT and Cubist were used as machine learning approaches. The modeling result was presented as maps showing the drought distribution over the region. The RF was created, based on classification and RT, to produce a CART using out-of-bag (OOB) in selecting data implemented in R software. The BRT also produced cart, but using the entire training samples with a combination of two algorithms of RT and boosting. On the other hand, the Cubist is a DM software that operates, based on a modified RT to produce the rules. The results proved that the RF results were better than the results of other approaches. The LST, ET, NMDI, NDVI, and NDWI) as dominant variables were identified by RF and were used in the modeling in terms of 3- month SPI and crop yield. Their weighted combinations were used as drought indicators.

The VegDRI-SKorea proposed by Nam et al. [27] utilizes the classification and RT (CART) modelling approach in South Korea from 2001 to 2013. A collection of remote-sensing data sets was used as input data in the model (e.g. NDVI, Climate data of SPI, Self-calibrated PDSI and biophysical data of DEM, Soil AWC, Ecological regions ECO). The VegDRI-SKorea modeling was started by assembling a training database from the used data set from each station for 13 years. Then the VegDRI-SKorea model was generated using an RT analysis. The authors used the CART to generate a series of rule, while each rule was included in a corresponding linear regression to produce the values of the models, thus to categorize the values into one of seven drought severity classes. According to this article, thirteen VegDRI-SKorea maps were produced using MapCubist. The maps were produced by applying the rule sets from the Cubist model to the gridded image. The proposed DM model provided more spatially detailed drought patterns.

III. Discussion

Our review paper illustrates that a wide variety of DM algorithms have been applied to drought monitoring using remote sensing data. Following an in-depth research, we are able to present a list of DM techniques applied at present for drought monitoring. However, the extracted knowledge is vastly dependent on several parameters (e.g. the study area, the data sets, the data size, etc.). Some of the important indexes are developed from remote sensing data such as the NDVI, which highlights the importance of remote sensing data in drought forecasting. Thus, the importance of combining remote sensing data to another type of data collected from the study area location and which are in relation to drought. That implies a high heterogeneity among the drought monitoring data sets. This data sets characteristic detected through the previous works listed above. Figure 2 presents a classification of those input data (i.e. remote sensing, climatic, biophysical, oceanic, and atmospheric data.).

This review highlight many advantages of DM methods: Identifying the relationships between parameters that occur together or with time lags. In fact, DM methods are not aected by errors associated with the physical relationships of parameters. DM methods could provide a high efficiency and scalability in data pre-processing. After a training phase,

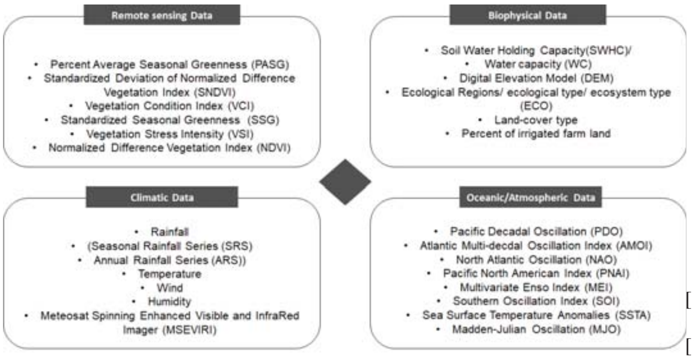

Fig. 2. The input data classification for a drought monitoring system

DM methods provide drought estimates almost extremely and immediate, thereby efficient for near real-time applications.

IV. Conclusion and Future Directions

This paper identifies the strengths and weaknesses of the most relevant works in the area of drought forecasting using DM methods and remote sensing published from 2004 to 2018. In fact, after selecting different existing works, each study is classified according to the DM methods used (e.g. AR, DT, ANN, FL and Hybrid solution). Then, a summary of each DM method is provided by explaining the objectives of each research work, data used, revealed steps, and experiments. However, in recent years, significant advances have been made in recording various meteorological parameters and climatic data. In addition, as the remote sensing technology makes more and more progress, with the development of GIS and GPS, the real-time monitoring droughts over larger areas can be achieved. These recent advances in data gathering can help provide large data warehouses, related to weather, climate, soil parameters, and long-term memory of drought phenomena. On matter of facts, detecting the limits of those earlier studies could create new horizons for the new researches. Therefore, the reductions of drought crises.

References

[1] Tadesse, T., Wilhite, D. A., Harms, S. K., Hayes, M. J., Goddard, S. (2004). Drought monitoring using data mining techniques: A case study for Nebraska, USA. Natural Hazards.

[2] Tadesse, T., Brown, J. F., Hayes, M. J. (2005). A new approach for predicting drought-related vegetation stress: Integrating satellite, climate, and biophysical data over the US central plains. ISPRS Journal of Photogrammetry and Remote Sensing.

[3] Kreyling, J., Khan, M. A. A., Sultana, F., Babel, W., Beierkuhnlein, C., Foken, T., ... Jentsch, A. (2017). Drought effects in climate change manipulation experiments: quantifying the influence of ambient weather conditions and rain-out shelter artifacts. Ecosystems.

[4] Beguería, S., Vicente-Serrano, S. M., Reig, F., Latorre, B. (2014). SPEI revisited: parameter fitting, evapotranspiration models, tools, datasets and drought monitoring. International Journal of Climatology.

[5] Zarch, M. A. A., Sivakumar, B., Sharma, A. (2015). Droughts in a warming climate: A global assessment of SPI and RDI. Journal of Hydrology.

[6] Esfahanian, E., Nejadhashemi, A. P., Abouali, M., Adhikari, U., Zhang, Z., Daneshvar, F., Herman, M. R. (2017). Development and evaluation of a comprehensive drought index. Journal of environmental management.

[7] Moorhead, J. E., Gowda, P. H., Singh, V. P., Porter, D. O., Marek, T. H., Howell, T. A., Stewart, B. A. (2015). Identifying and evaluating a suitable index for agricultural drought monitoring in the Texas high plains. JAWRA Journal of the American Water Resources Association.

[8] Martínez-Fernández, J., González-Zamora, A., Sánchez, N., Pablos, M. (2017, July). CCI soil moisture for long-term agricultural drought monitoring: A case study in Spain. In 2017 IEEE International Geoscience and Remote Sensing Symposium (IGARSS) IEEE.

[9] Osborn, T., Barichivich, J., Harris, I., Van Der Schrier, G., Jones, P. (2016). Monitoring global drought using the self-calibrating Palmer Drought Severity Index. Bulletin of the American Meteorological Society, 97, S32-S36.

[10] Hao, Z., Singh, V. P. (2015). Drought characterization from a multivariate perspective: A review. Journal of Hydrology.

[11] Thavorntam, W., Tantemsapya, N., Armstrong, L. (2015). A combination of meteorological and satellite-based drought indices in a better drought assessment and forecasting in Northeast Thailand. Natural Hazards.

[12] Tadesse, T., Wardlow, B. (2007, October). The vegetation outlook (VegOut): a new tool for providing outlooks of general vegetation conditions using data mining techniques. In Seventh IEEE International Conference on Data Mining Workshops (ICDMW 2007).

[13] Yurekli, K., Taghi Sattari, M., Anli, A. S., Hinis, M. A. (2012). Seasonal and annual regional drought prediction by using data-mining approach. Atmósfera.

[14] Taghi Sattari, M., Anli, A. S., Apaydin, H., Kodal, S. (2012). Decision trees to determine the possible drought periods in Ankara.

[15] Sattari, M. T., Sureh, F. S. Drought Prediction Based on Standardized Precipitation-Evaporation Index by using M5 tree model(2016).

[16] Homa, Razmkhah and Eshagh Rostami and Mohammad Hadi Fattahi (2015).Drought forecasting using ANN; Case study: Kohgilooye and Boyer Ahmad.Arabian Journal of Geosciences.

[17] Sattari, M. T., YüreklÍ, K., Ünlükara, A. (2011). Drought prediction by using ANN approach in Karaman Province. TABAD, Tarım Bilimleri Araştırma Dergisi.

[18] Aboozar Zandvakili, Vajihe Shahsavari and Ashraf Mandani (2015).Design of the new smart system for drought monitoring Adv. Environ. Biol.Advances in Environmental Biology.

[19] Sharma, A. (2006, January). Spatial data mining for drought monitoring: an approach using temporal NDVI and rainfall relationship. ITC.

[20] Rajput, A., Soni, R., Aharwal, R. P., Sharma, R. (2011). Impact of data mining in drought monitoring. International Journal of Computer Science Issues (IJCSI).

[21] Coco, M. R. (2007). Mining Drought from Remote Sensing Images. International Institute for Geo-Information Science and Earth Observation, The Netherlands.

[22] Rulinda, C. M., Bijker, W., Stein, A. (2010). Image mining for drought monitoring in eastern Africa using Meteosat SEVIRI data. International Journal of Applied Earth Observation and Geoinformation.

[23] Berhan, G., Hovav, A., Atnafu, S. (2010). Knowledge Discovery from Satellite Images for Drought Monitoring in Food Insecure Areas.

[24] Nourani, V., Sattari, M. T., Molajou, A. (2017). Threshold-based hybrid data mining method for long-term maximum precipitation forecasting. Water Resources Management.

[25] Jalalkamali, A., Moradi, M., Moradi, N. (2015). Application of several artificial intelligence models and ARIMAX model for forecasting drought using the SPI. International journal of environmental science and technology.

[26] Park, S., Im, J., Jang, E., Rhee, J. (2016). Drought assessment and monitoring through blending of multi-sensor indices using machine learning approaches for different climate regions. Agricultural and forest meteorology.

[27] Nam, W. H., Tadesse, T., Wardlow, B. D., Hayes, M. J., Svoboda, M. D., Hong, E. M., ... Jang, M. W. (2018). Developing the vegetation drought response index for South Korea (VegDRI-SKorea) to assess the vegetation condition during drought events. International journal of remote sensing.

[28] Agrawal, R., Imieliński, T., Swami, A. (1993, June). Mining AR between sets of items in large databases. In Acm sigmod record.

[29] Quinlan, J. R. (1986). Induction of decision trees. Machine learning, 1(1), 81-106.

[30] Abraham, A. (2005). Artificial neural networks. Handbook of measuring system design.