T.C.

ANTALYA BILIM UNIVERSITY

INSTITUTE OF POSTGRADUATE EDUCATION

DISSERTATION MASTER'S PROGRAM OF ELECTRICAL AND COMPUTER ENGINEERING

METEOROLOGICAL DROUGHT FORECASTING USING DECISION TREE

DISSERTATION

PREPARED BY

ESMA KALE

ANTALYA – 2021

T.C.

ANTALYA BILIM UNIVERSITY

INSTITUTE OF POSTGRADUATE EDUCATION

DISSERTATION MASTER'S PROGRAM OF ELECTRICAL AND COMPUTER ENGINEERING

METEOROLOGICAL DROUGHT FORECASTING USING DECISION TREE

DISSERTATION

PREPARED BY

ESMA KALE

Dissertation Advisor

Prof. Dr. Cafer ÇALIŞKAN

Co-Advisor

Assoc. Prof. Dr. Ali Danandeh MEHR

ANTALYA – 2021

APPROVAL/NOTIFICATION FORM

ANTALYA BILIM UNIVERSITY

INSTITUTE OF POST-GRADUATE EDUCATION

ESMA KALE, a M.Sc. student of Antalya Bilim University, Institute of Post Graduate Education, Electrical and Computer Engineering owning student ID 171222002, successfully defended the thesis/dissertation entitled "METEOROLOGICAL DROUGHT FORECASTING USING DECISION TREE", which he prepared after fulfilling the requirements specified in the associated legislations, before the jury whose signatures are below.

Academic Tittle,	Name-Surname,	Signature
Thesis Advisor	**:** …………………………	
Co advisor	**:**…...................................	
Jury Member	**:** …………………………	
Jury Member	**:** …………………………	
Director of the Institute	**:** ………………………………..	

Date of Submission: …/…/….

Date of Defense: …/…/…

INSTITUTE OF POSTGRADUATE EDUCATION
ELECTRICAL AND COMPUTER ENGINEERING
MASTER OF SCIENCE PROGRAM WITH THESIS

ACADEMIC DECLARATION

I hereby declare that this master's thesis titled "Meteorological Drought Forecasting Using Decision Tree" has been written by myself under the academic rules and ethical conduct of the Antalya Bilim University.

I also declare that the work attached to this declaration complies with the university requirements and is my work.

I also declare that all materials used in this thesis consist of the mentioned resources in the reference list. I verify all these with my honor.

… /…/ ….

Esma Kale

PREFACE

This thesis aims to predict and classify drought in Antalya Region. To this end, firstly a comprehensive literature review was done and literature was investigated. Then, a methodology to predict drought class in a region was presented. I present my graduate to my advisors Prof. Dr. Cafer Çalışkan and Assoc. Prof. Dr. Ali Danandeh Mehr due to their supports on me in this thesis.

ÖZET

KARAR AĞACI KULLANARAK METEOROLOJİK KURAKLIĞIN TAHMİN EDİLMESİ

Kuraklık insan hayatını etkileyen önemli bir doğal fenomendir. Bu nedenle, kuraklık tahmini ve sınıflandırması kuraklık ile ilgili alınacak önlemler için önemli bit yer tutmaktadır. Bu tez kapsamında öncelikle çeşitli makine öğrenmesi metotlarının kuraklık tahmininde kullanılması ile ilgili literatür taranmıştır ve karar ağaçları algoritmasının kuraklık tahmininde kullanımı incelenmiştir. Bu amaçla Antalya ilinde 4 farklı noktada ölçülen Standard Yağış Terleme İndis değerleri elde edilmiştir. Bu değerlerin ortalaması alınarak hedef değerler belirlenmiştir. Ardından bu değerlere göre kuraklık sınıfları belirlenmiştir. Her bir noktada t ayında ölçülen indis değerlerinin girdi parametresi olarak kullanıldığı ve bir ay sonrası (t+1) için kuraklık sınıfı tahmini yapan bir karar ağaçları modeli geliştirilmştir. Veriler eğitim ve test verisi olarak ikiye ayrılmıştır. Tahmin edilen değerler toplam doğruluk, kappa istatistiği ve sınıflandırma hatası yöntemleri kullanılarak karşılaştırılmış ve geliştirlen modelin doğruluğu ölçülmüştür. Sonuçlar, geliştirilen modelin kuraklık sınıflandırmasında kullanılabileceğini göstermiştir. Ayrıca, çalışma alanında son yıllarda kurak dönemlerin sayısında artış meydana geldiği görülmüştür ve bu bölgede iklim değişikliğinin bir göstergesi olarak yorumlanabilir.

Anahtar Kelimeler: Kuraklık, Karar Ağacı, SPEI, Sınıflandırma, Antalya

ABSTRACT

METEOROLOGICAL DROUGHT FORECASTING USING DECISION TREE

Drought is a natural phenomenon that directly affects human life in a region. Therefore, drought classification and prediction models are essential tools for the mitigation of adverse consequences of drought. Beginning with a brief review of different machine learning techniques to predict drought, the applicability of decision tree for drought classification and the prediction was investigated in this thesis. For this aim, quantitative values of Standardized Precipitation Evapotranspiration Index (SPEI) were collected from a global SPEI data repository (grid points across Antalya province) during the period of 1961-2015. A dataset including 659 samples was created and considered as features in this study. The target SPEI values were first calculated by averaging SPEI values of nearby grid points. Then, drought classes for target SPEI values were determined in terms of wet and dry events. It is well documented that negative monthly SPEI values in a region generally represent dry months at the given region. The lower the SPEI, severe the drought. A binary classification decision tree model was presented that uses the SPEI values of each grid point at month *t* as inputs and predicts the drought classes (wet or dry) of Antalya at one month later (i.e., month *t+1*). The dataset was divided into train and validation sets. The predicted and observed values of drought classes were compared using performance evaluation criteria such as total accuracy, kappa statistics, and classification error. It was obtained that a value of 80.63, 19.37, and 0.61 for total accuracy, classification error, and kappa statistics, respectively. This indicated that the presented decision tree model is moderately accurate for drought prediction in the case study region. On the other hand, results showed an increasing trend for dry events in the most recent years that can be considered as the signal for climate variability in the study area.

Index Terms: Drought, Decision Tree, SPEI, Classification, Antalya

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABBREVIATIONS

NASA	National Aeronautics and Space Administration
SPI	Standardized Precipitation Index
SPEI	Standardized Precipitation Evapotranspiration Index
ML	Machine Learning
DT	Decision Tree
PDSI	Palmer’s Drought Severity Index
FL	Fuzzy Logic
ANN	Artificial Neural Networks
ANFIS	Adaptive Neuro Fuzzy Inference System
GP	Genetic Programming
ACP	Atmospheric Circulation Pattern
PMDI	Palmer Modified Drought Index
RMSE	Root Mean Square Error
MSE	Mean Square Error
TA	Total Accuracy
KA	Kappa Statistic
CE	Classification Error
TP	True Positive
TN	True Negative

1. INTRODUCTION

Drought is a natural phenomenon that characterizes a significant reduction in precipitation over a large area for a period. According to National Aeronautics and Space Administration (NASA), drought is defined as extended period of deficient rainfall relative to the average for a region [1]. Climate change resulting from increased population and anthropogenic activities is effective on drought. But climate change is not only reason. Drought is such a complex natural phenomenon that it can not be expressed for a single reason. The cause of the drought is not always the same in all basins. For example, while 2 weeks without precipitation in Western Europe are expressed as drought by people, in desert climate regions such as Arabian Peninsula, the period without the precipitation can be up to a year. Although drought is a natural phenomenon that is difficult to define, its effects are quite clear. It makes a significant impact on the quantity and quality of water resources at local and regional scales which might yield famine and socioeconomic crisis [2]. In addition, drought is one of the major factors that effecting the agricultural production of a region. Drought can be classified as meteorological, hydrological, agricultural, and socioeconomic. There are several indices to measure drought severity for drought classes. From a meteorological drought perspective, variables such as precipitation and temperature are commonly used to calculate drought index [3]. In the literature, Standardized Precipitation Index (SPI) which was presented by McKee et.al [4] is frequently used to measure meteorological drought severity on a region. Also, Standardized Precipitation Evapotranspiration Index (SPEI) which was more recently developed by Vicente_serrano et.al. [5] is another way to measure meteorological drought severity. But, unlike SPI, SPEI is used in also agricultural drought calculation. SPI can be calculated by using historical precipitation data, while SPEI can be calculated by using precipitation and temperature data.

Meteorological drought classification and prediction in a region is extremely significant process to provide sustainable water supply for human life such as agricultural activities, freshwater usage, and even industrial activities. It requires to application of various machine learning (ML) methods by using the historical data such as precipitation and temperature or direct use of drought index values. One of the widely used ML method is decision trees (DT). It is frequently used in solving engineering and earth science related problems based on classification. In addition, decision trees make a grateful contribution to prediction and extract rules that lead the goal.

1.1. Motivation

Antalya province is located on the Mediterranean coast of south-west Turkey. It is fifth most populous city in Turkey with a population of more than 2 million. According to agriculture and forestry directorate of Turkey [6], Antalya is the second ranked city of Turkey in terms of agricultural production values. Also, it is the first ranked city in terms of agricultural production variability. On the other hand, tourism activities of the city are one of the most dominant income sources. It is reported by Turkish Ministry of Tourism and Culture [7], 14.650 million tourists visited the Antalya province in 2019. Both agriculture and tourism activities depend on the sustainable freshwater and domestic water use. Therefore, a long-term or even short-term drought can break the city's development and terminate the income sources such as agriculture and tourism. As we discussed before, drought is directly affecting the socioeconomic wealth and human life in the city. Therefore, the main motivation of this thesis is the develop a DT model that predict the drought classes for one month ahead for Antalya province with using historical monthly SPEI-6 data. The developed model will be beneficial for early warning of drought and taking preventive measurements in the city.

In this thesis, the local monthly SPEI-6 series from four different grid points are collected from the SPEI database [8] for Antalya province. SPEI-6 is the precipitation and temperature conditions over the past 6 months period. The collected time-series includes the period of January 1961 – December 2015. The SPEI data were analyzed and a DT model was developed to classify drought events in the Antalya Basin. Based on the SPEI value, two class of drought was selected. These are wet and dry. Developed DT model can accurately predict the drought classes of future month.

1.2. Contributions

There are three main contributions to this work. Firstly, monthly SPEI-6 data were downloaded from the SPEI database [8] and dataset was created for the period of 1961-2015. The dataset was analyzed statistically. Secondly, the literature was reviewed to determine drought classes. Two drought categories were selected as wet and dry. Although there are more than two categories for drought in the literature, we divided the drought categories into two for easy computation. Thirdly, ML techniques in literature were reviewed and a general aspects of model development was revealed. Then, a DT models was created that has can classify the historical SPEI-6 dataset in terms of drought classes. Developed DT model also revealed that the importance of each grid point contributions to the drought event occurrence.

1.3 Thesis Organization

The paper is organized as follows: The literature review is presented in Chapter 2, while Chapter 3 describes the case study area and used data. The overview of SPEI calculation and background method (Decision Tree and its architecture) that we apply on the proposed system were explained in Chapter 4. In addition, a methodology flowchart was illustrated in Chapter 4. Results of developed DT model were given in Chapter 5. Also, discussion about the results were done in this chapter. Finally, we concluded the thesis and some advices about the future work were given in Chapter 6.

2. LITERATUR REVIEW

Although there is not an exact definition of drought in the literature, it can be defined in basic form as the lack of precipitation in a region over a period. Drought is a universal phenomenon that directly effects the human life. Therefore, drought monitoring, classification and prediction is an essential engineering processes that provide the manage drought and mitigate its effects. However, the science behind the drought must be well-known to demonstrate these processes. To this end, in this chapter a comprehensive literature review was performed. The definition, types, indices, and classes of drought were reviewed in the first part of this chapter. Then, several machine learning applications to classify and predict the drought were mentioned in the second part.

2.1. Drought Types, Indices and Classes

In general, drought is defined as the period during which precipitation, underground or surface water in a region is less than the expected amount (average) in terms of climate [9]. Similar definitions of drought were defined by several researchers [10; 11; 12; 13]. Drought is directly proportional to increase in temperature, inversely proportional to increase in precipitation [14]. It is classified as meteorological, hydrological, agricultural, and socioeconomic. According to Van Lenan and Peters [15], decrease in the precipitation and ground water surface, and also increase in the temperature and evaporation cause meteorological drought. Resulting from these, soil water shortage, and decrease in vegetation occur as agricultural drought. Finally, hydrological drought occurs due to reduction in water resources, and loss of natural areas. Briefly, drought is a process that starts with meteorological drought and ends with famine drought after agricultural and hydrological drought respectively [16]. A drought event cause economic, social, and environmental impacts. Based on the literature, drought types and their impacts can be visualized as in Figure 1.

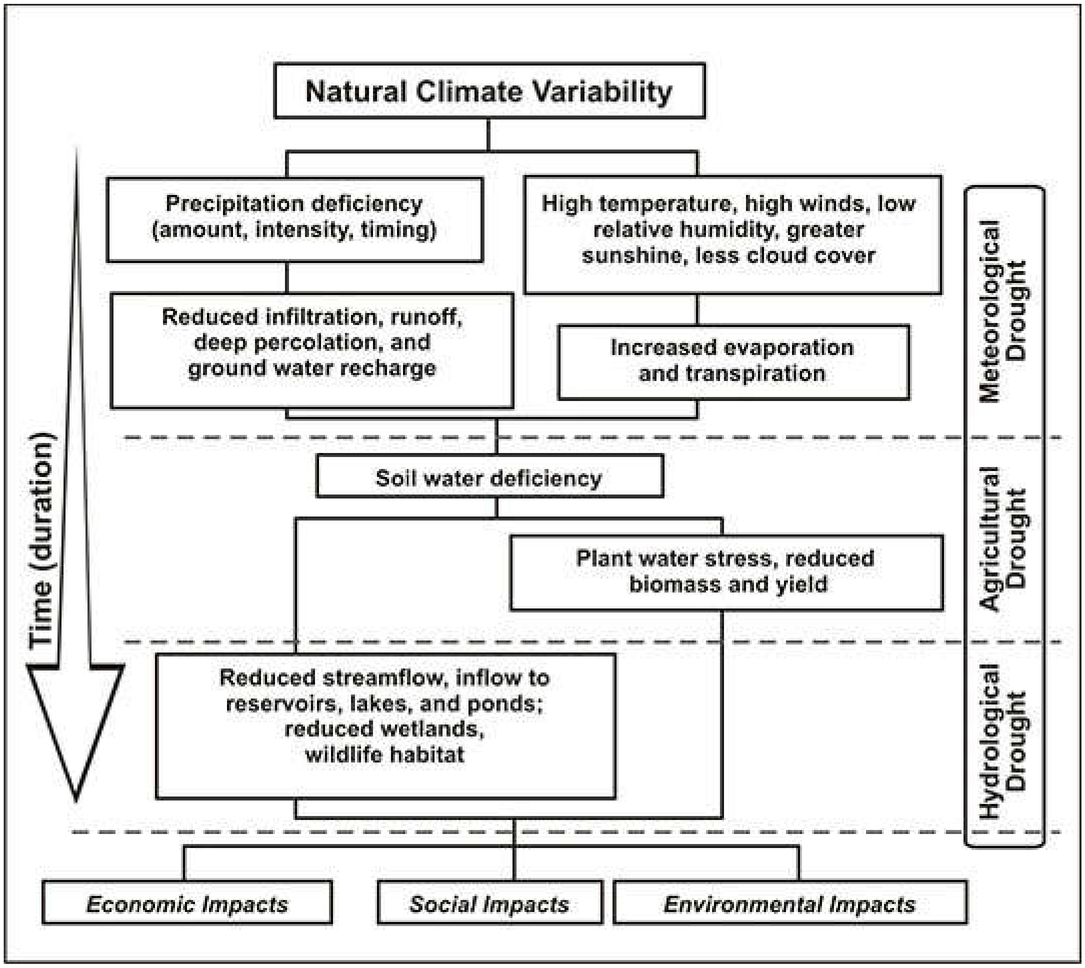

Figure 1. Drought Types and Their Impacts [19]

There are several indices to measure drought severity for drought types. From a meteorological drought perspective, SPI is one of the drought indices that frequently used in literature. It is first introduced by McKee et. al [4]. The calculation of SPI requires fitting and transforming a long-term precipitation record into a normal distribution with respect to the SPI which has zero mean and unit standard deviation [17]. However, the probability distribution function of precipitation sequences does not generally conform to normal distribution [4]. In such cases, the probability distribution functions obtained from precipitation data are transformed into Gamma probability distribution functions. Then, it is converted into "normalized" standard precipitation series by using the inverse standard normal distribution function. Finally, the SPI is obtained by dividing the difference between precipitation and mean precipitation by standard deviation of precipitation.

Palmer's Drought Severity Index (PDSI) and SPEI are another meteorological drought severity index that frequently used in literature. PDSI was first introduced by Palmer [18]. This index is a convenient way to quantify long-term drought. Historical precipitation and temperature data are required to calculate PDSI. Also, SPEI was introduced by Vicente-Serrano et. al. [5]. Similarly, it requires historical precipitation and temperature data for calculation. SPEI is convenient way to measure meteorological and agricultural drought. Comparing with the other indices, SPEI is more recently developed drought severity index. Drought severity indices can be calculated for different time scales (i.e., 1, 3, 6, 9, 12, and 24 months). For example, 6-month SPEI (SPEI-6) compares the precipitation and temperature in that period with the same 6-month period used in the historical record calculation. Despite being a meteorological index, short time scales such as 1-, 3-, and 6-months is used to measure meteorological and agricultural drought analysis, while longer time scales such as 9-, and 12-months is used to measure hydrological drought analysis [3].

Drought index values are used to analysis drought in terms of dry/wet conditions. To this end, drought indices have been categorized into several classes using some specific threshold values. For example, McKee et.al [4] categorized the SPI values into eight classes that describes the precipitation range from extreme drought to extreme wet. Similarly, SPEI values are categorized into eight classes (see Table 1). On the other hand, PDSI are categorized into eleven classes in terms of dry/wet condition. These classes are split using threshold values within the range of -4 to +4. Table 2 presents the drought classes in terms of PDSI values. Recently, Danandeh Mehr et. al [21] proposed SPEI thresholds that divided meteorological drought events into five classes. It can be seen in Table 3.

Table 1. SPI / SPEI Drought Classes [4]

SPI Values	**SPEI Values**	**Drought Classes**
SPI ≥ 2.00	SPIE ≥ 2.00	Extremely Wet
1.50 < SPI < 1.99	1.50 < SPIE < 1.99	Severely Wet
1.00 < SPI < 1.49	1.00 < SPIE < 1.49	Moderately Wet
0.00 < SPI < 0.99	0.00 < SPIE < 0.99	Mild Wet
-0.99 < SPI < 0.00	-0.99 < SPIE < 0.00	Mild Drought
-1.49 < SPI < -1.00	-1.49 < SPIE < -1.00	Moderate Drought
-1.99 < SPI < -1.50	-1.99 < SPIE < -1.50	Severe Drought
SPI ≤ -2.00	SPIE ≤ -2.00	Extreme Drought

Table 2. PDSI Drought Classes [20]

SPI Values	**Drought Classes**
PDSI ≥ 4.00	Extremely Wet
3.00 < PDSI < 3.99	Very Wet
2.00 < PDSI < 2.99	Moderately Wet
1.00 < PDSI < 1.99	Slightly Wet
0.50 < PDSI < 0.99	Incipient Wet Spell
0.49 < PDSI < -0.49	Near Normal
-0.50 < PDSI < -0.99	Incipient Drought Spell
-1.00 < PDSI < -1.99	Mild Drought
-2.00 < PDSI < -2.99	Moderate Drought
-3.00 < PDSI < -3.99	Severe Drought
PDSI ≤ -4.00	Extreme Drought

Table 3. SPEI Drought Classes Proposed by Danandeh Mehr [21]

SPIE Values	Drought Classes
SPIE ≥ 1.40	Extremely Wet
0.50 < SPEI < 1.40	Wet
-0.50 < SPEI < 0.50	Near Normal
-1.40 < SPEI < -0.50	Dry
SPEI ≤ -1.4	Extremely Dry

2.2 Machine Learning to Drought Prediction and Classification

Machine learning is an application of data mining that used in several engineering studies including drought classification and prediction. Fuzzy Logic (FL), Artificial Neural Networks (ANN), Adaptive Neuro Fuzzy Inference System (ANFIS), and Genetic Programing (GP) are the most widely used ML techniques in the literature. In this part of the literature review, ML techniques and their applications on the drought classification / prediction were review in an order.

Fuzzy logic approach was developed by Zadeh [22] and is an effective method in branches where dynamic and nonlinear analyzes are performed, such as hydrology and climatology. It enables developing models based on the expert knowledge and expressing complex systems with linguistic rules. Several studies have been performed to forecast regional drought by using FL-based models in literature. For example, Pesti et. al. [23] developed a FL-based model to predict drought in terms of atmospheric circulation patterns (ACP). Atmospheric pressure data and the historical PDSI data from New Mexico were used as the input variables of the model. Triangular membership functions with 16 linguistic fuzzy rules were applied in the study. The presented model linked the relation between drought characteristic and ACP. Pangracz et. al. [24] developed a fuzzy rule-based model to predict regional drought in terms of Palmer Modified Drought Index (PMDI) for Nebraska. El Nino/Southern Oscillation and ACP were used as the input of the model. A comparison was performed between the observed and predicted values. Authors indicates that the fuzzy rule-based model has accurate results to forecast drought. Integrated drought index model for drought assessment was demonstrated by Huang et. al. [25] by using fuzzy set theory. Yellow river basin, China was selected as case study area. Developed integrated method was compared with SPI and Standardized Stream Flow Index which is a hydrology drought assessment index. It was concluded that the developed drought index can be used in drought studies. Recently, a FL-rule based model was presented by Abdourahamane and Acar [26] that can predict SPI-3 of Western Niger. Several meteorological sensor data such as sea surface temperature, humidity, sea level pressure, and Southern Oscillation Index were used as input variables of SPI prediction. The predicted and observed values were statistically evaluated using mean square error (MSE) and Pearson correlation coefficient. The results showed that the developed model may provide accurate drought prediction.

ANN is an another widely used ML technique for drought prediction in literature. For example, Morid et. al. [27] developed an ANN model to predict two different drought index such as SPI and Effective Drought Index. Different combinations of previous precipitation data were used as input variables of the model. Several ANN models were developed for the prediction of drought indices to identify best input combination. Best model was chosen in terms of person correlation coefficient. Authors indicated that the developed model can be used for drought early warning system. Rezaeian and Tabari [28] applied an ANN model including Levenberg-Marquardt algorithm to predict quantitative values of SPI in different climatic regions in Iran. The lagged values of SPI were used to train ANN algorithms. The predicted values were compared with the observed values in terms of root mean square error (RMSE) and Pearson correlation coefficient. It was concluded that the ANN with using Levenberg-Marquardt algorithm has a high prediction accuracy for drought studies. A Multilayer Perceptron ANN model was developed by Zulifqar Ali et. al. [29] to predict different time scales SPEI values (SPEI-1, SPEI-3, SPEI-6, and SPEI-12). The model was created by using 3 layers of input layer, 30 neurons of hidden, and output layer of 8 and 1 neurons. Several ANN models were established. Each of them evaluated by Pearson correlation coefficient and RMSE. Based on the results, authors indicated that the multilayer perceptron ANN model can be used in decision-making process by water management planner.

Another ML techniques that used for drought prediction is ANFIS. Architecture and learning procedure underlying ANFIS were first presented by Jang [30]. It combines the optimization and learning capabilities of neural networks with fuzzy logic linguistic IF-THEN rules which consist of membership functions. The applicability of it in drought studies were investigated by Bacanli and Firat [31]. They developed an ANFIS model to predict SPI values. To this end, the historical precipitation data were collected from 10 different gauging station over the Central Anatolia, Turkey. The lagged values of precipitation and SPI were used as input variables for training. The predicted and observed values were statistically compared and the results pointed out that the ANFIS can be used for drought prediction studies.

Although aforementioned ML techniques are accepted as the efficient way for drought prediction, GP is one other used technique by researchers in this field. It is commonly used to generate high-quality solutions to prediction studies. A recent study presented by Abbasi et. al. [32] showed that the GP is an efficient technique for both drought monitoring and prediction in short and long-term scale. In this study, a GP model was developed to predict future SPEI values. Historical data of the precipitation and temperature were collected from Urmia Station, Iran. The lagged SPEI values of 1 to 5 months were used to feed the model. Different time scales of SPEI were used for prediction. The results showed that the increasing in the time scale of SPEI cause an increase in the model results.

On the other hand, several studies were reported that combination of more than one ML techniques can increase the prediction accuracy of drought studies. These are referred as to hybrid techniques. For example, Özger et. al [35] developed a wavelet-FL model to estimate PDSI values. The model results of proposed hybrid model and classical FL model were compared. Authors indicate that the hybrid model has higher accuracy of estimation. As an improvement of the previous study [35], Özger et. al. [36]

compared the wavelet-FL model with a new wavelet-ANN model. The Nino 3.4 index and PDSI values were used to predict future PDSI values. The results showed that the wavelet-FL model is superior to wavelet-ANN model for drought studies. Similarly, ANFIS-based hybrid models were developed to improve drought prediction accuracy in literature. A wavelet-ANFIS model was developed by Shirmohammadi et. al. [37]. Historical SPI quantitative values that recorded from 1952 to 1992 were used to predict future SPI values. It was observed that proposed hybrid model is an accurate and reliable for drought prediction. A study published by Kisi et. al. [38] terminated the wavelet transform which is frequently used as hybrid model in literature and implemented a new hybrid ML approaches. In this study, ANFIS techniques were combined with several models such as particle swarm optimization, GP, colony algorithm, and butterfly optimization algorithm. All these hybrid techniques were compared with the classical ANFIS technique for prediction of various time scales of SPI values. In a general view, ANFIS-GP technique were selected as the superior techniques comparing with others. Focusing on the GP-based hybrid models, Mehr et. al. [33] presented a new gene-wavelet model for drought forecasting using the NINO 3.4 index and Palmer's Modified Drought Index values as predictors of the future PMDI values (target). The authors developed classical GP model and GP- based model by combining with the wavelet transform concepts that allow to use long-time intervals for low frequency signals. The proposed model was applied to predict drought conditions in Texas State with 3-, 6-, and 12-months lead times. The authors reported that the proposed gene-wavelet model is superior to classical GP for long-term prediction. Recently, a hybrid wavelet packet- GP model was introduced by Danandeh Mehr et. al. [34] for short-term drought prediction. To this end, the historical data were collected from two meteorological stations at Ankara, Turkey. Based on the data, SPEI-3 and SPEI-6 values were calculated. Using wavelet transform, decomposition of the SPEI values was performed. Then, the lagged SPEI quantitative values were used as the input variables of the developed model. It was concluded that the proposed hybrid model is superior to classical GP model for the short-term drought prediction.

Briefly, it can be observed that ML techniques such as FL, ANN, ANFIS, and GP were frequently used by researchers for the prediction of drought indices and pattern of them. However, Danandeh Mehr et.al. [3] reported that a few studies have attempted to model and predict drought classes. In general, tree-based ML techniques such as decision tree (DT) and random forest (RF) is used to classifications problems. These are categorized as supervised learning methods. They are easy to use techniques to predict class label or values such as drought indices. For example, Chen et. al. [39] developed a RF model for prediction of SPI values. Developed model has the ability of the estimate number of dry days in study area. Thus, it was also used to predict wet/dry conditions. The model results were compared with the results gathered from auto regressive integrated moving average method which is the classical time series analysis technique. It was observed that RF has better prediction accuracy. Three different drought monitoring model including RF, boosted regression trees, and Cubist were presented by Park et.al. [40] for monitoring the drought during 2000-2012 in the USA. Several drought indices were used in the study. Model performance analysis showed that the RF outperformed the other approaches. Park et. al. [41] applied RF techniques for short-term drought prediction throughout East Asia. Remote-sensing data and climate variability indices over the study area were used for drought prediction. Three satellite-based drought indices were predicted. It is concluded that the RF can capture sudden changes in drought classes such as from wet to dry or dry to wet. Nourani and Molajo [42] was applied a DT-based hybrid technique to modelling atmospheric and oceanic variables for drought monitoring in Iran. DT was used to identify most dominant parameters. Then, association rules were applied to reveal relationship between drought index (SPI) and atmospheric variables such as sea surface temperature. Recently, Danandeh Mehr et.al. [3] developed a new tree-based model namely Fuzzy Random Forest. This model combined the prediction efficiency of FL with classification success of RF technique. Antalya province was selected as case study area. The corresponding tree-based model were created based on the spatiotemporal relationship between SPEI-6 values of the nearby global grid points and the drought class in the Antalya Basin attained through FL. Then, RF model was used to predict one month ahead drought classes. On the other hand, a fuzzy DT model was used to cross validation. The results showed that developed FL-based RF model (authors referred it to as FRF) superior to FL-based DT model (which is also referred to as FDT).

Based on the reviewed literature, following comments can be mentioned:

- Drought classification and prediction model is required to develop early warning systems. These systems are essential for the drought management and mitigate drought affects.
- Models are developed by using lagged values combination of input parameters such as precipitation or drought indices.
- It is seen that the hybrid techniques increase the model performance accuracy.
- RMSE, Pearson correlation coefficient, and MSE are frequently used in performance evaluation of prediction model, while total accuracy, and Kappa are used for classification models such as DT, and RF.
- SPI is the most dominant drought indices that are used in the literature.

3. STUDY AREA

Antalya province is located on the Mediterranean coast of south-west Turkey. It is fifth most populous city in Turkey with a population of more than 2 million. According to Turkish Ministry of Agriculture and Forestry (Agriculture in Antalya, 2020), Antalya is the second ranked city of Turkey in terms of agricultural production values. Also, it is the first ranked city in terms of agricultural production variability. On the other hand, tourism activities of the city are the most dominant income source. It is reported by Turkish Ministry of Tourism and Culture [7], 14.650 million tourists visited the Antalya province in 2019. The city is in the Mediterranean climate zone, which is expressed as hot and dry in summers, warm and rainy in winters. Its temperature ranges from -4.3 °C to 43.4 °C during a year [3]. The annual average precipitation is about 1070 mm per square meter.

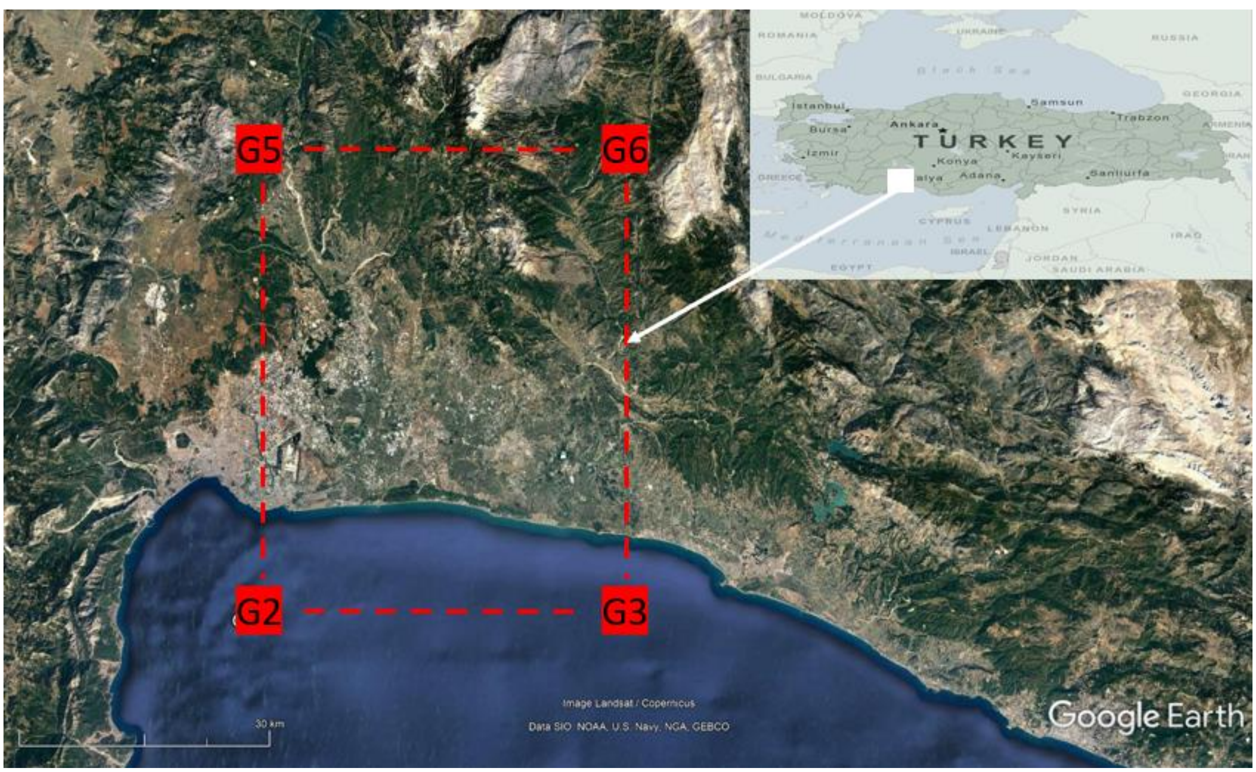

Figure 2: Location of the grid points (G2, G3, G5, G6) and the case study area (red rectangle)

The global SPEI database offers long-time, robust information conditions at the global scale, with a 0.5 degrees spatial resolution and a monthly time resolution [8]. The SPEI time scale values between 1 to 40 months for different spatial locations can be downloaded from the website of SPEI database [8]. In this study, the local monthly SPEI-6 time series (in the period of January 1961 – December 2015) were collected from the SPEI database [8] for four grid points (G2, G3, G5, G6) that located in Antalya province. The location of the city and the four grid points presented in Figure 2. Also, downloaded SPEI-6 time-series (during 1961-2015) for each grid points were presented in Figure 3-6. The created dataset can be found in Appendix A.

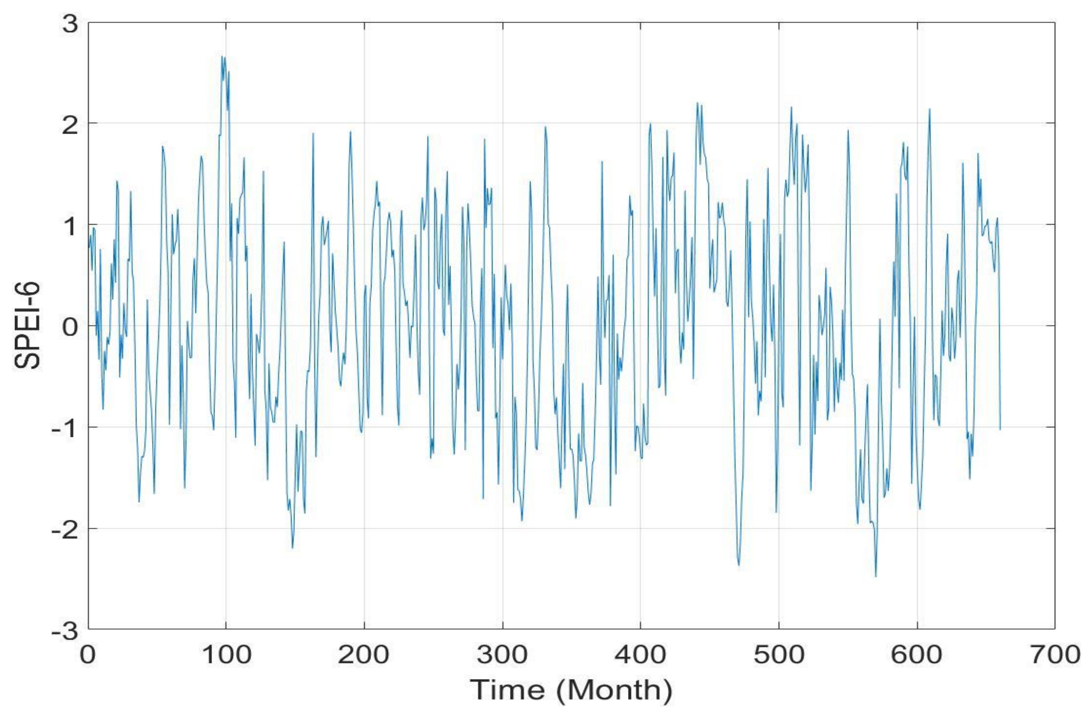

Figure 3. SPEI-6 Time-Series of G2

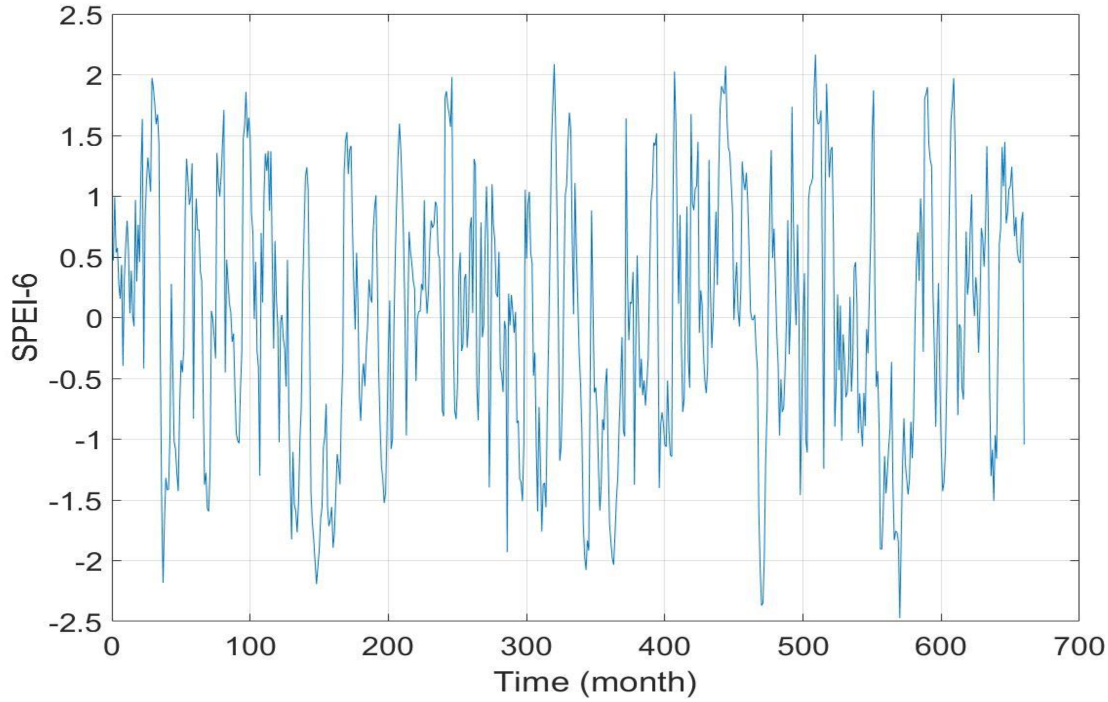

Figure 4. SPEI-6 Time-Series of G3

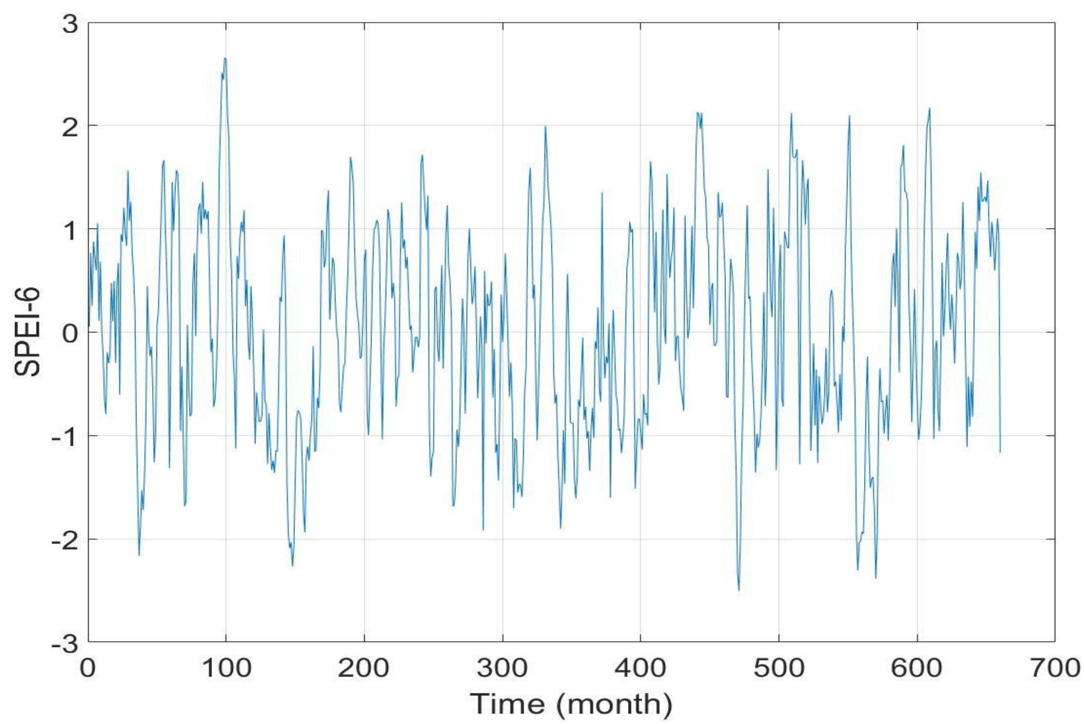

Figure 5. SPEI-6 Time-Series of G5

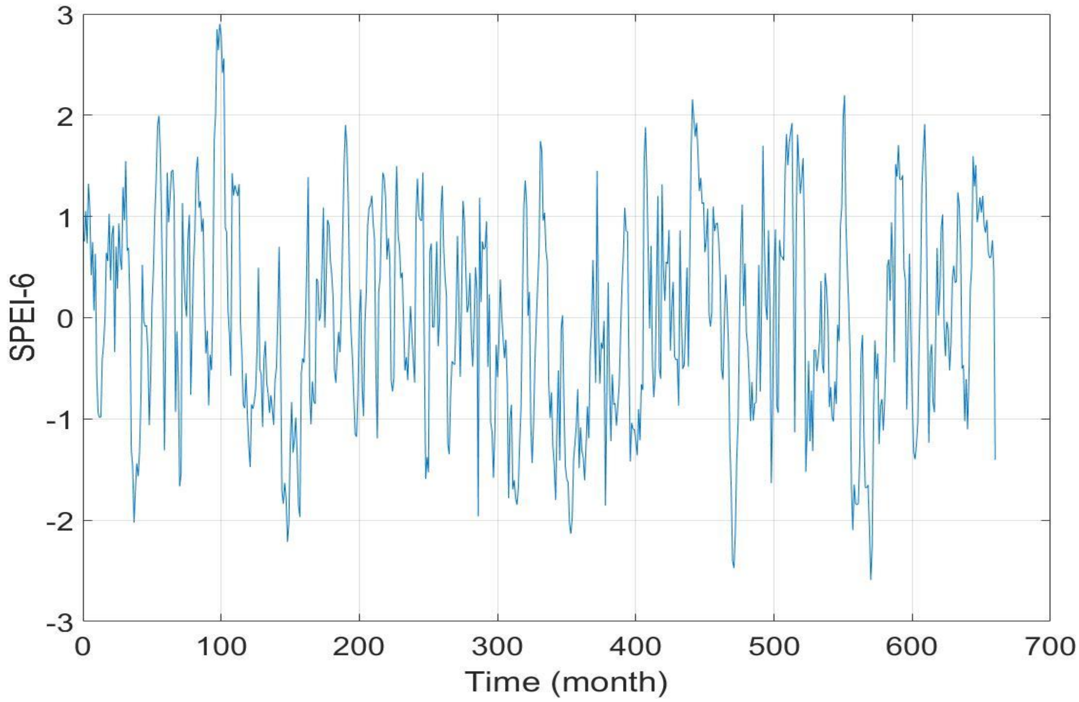

Figure 6. SPEI-6 Time-Series of G6

3.1. Descriptive Statistics

A dataset was created by using the monthly SPEI-6 values of each grid points. Descriptive statistic analysis which is used to explore the statistical characteristics of data by decision-makers was applied to the created dataset. Statistical parameters such as mean, standard deviation, minimum and maximum values are the main components of descriptive statistics. The results presented in Table 4.

Table 4. Descriptive Statistics of SPEI-6 Time-Series

Grid Point	**Latitude**	**Longitude**	**Mean**	**Minimum**	**Maximum**	**Standard Deviation**
G2	36.75	30.75	0.029	-2.483	2.655	1.05
G3	36.75	31.25	0.008	-2.473	2.165	1.03
G5	37.25	30.75	0.035	-2.502	2.657	1.00
G6	37.25	31.25	-0.019	-2.591	2.901	1.02

Based on Table 4, similar mean, minimum and maximum values were observed for all time-series. Also, standard deviation values of each time-series can be interpreted as not a major variance difference observed between the series. It was observed that SPEI-6 values vary in the range of -2.591 and 2.901.

4. METHODS

In this chapter, first an overview of SPEI calculation was presented. Then, the basics of DT was explained. The proposed DT model was presented using a flowchart. Finally, performance evaluation criteria that evaluate the accuracy of the developed model were mentioned.

4.1. Standard Precipitation Evapotranspiration Index (SPEI)

The SPEI was introduced by Vicente-Serrano et.al [5]. It is a simple multi-scalar drought index that combines the effects of precipitation and temperature data for drought monitoring [5]. It can be used to calculate meteorological and agricultural drought severity. Different time scales (i.e., 1-,3, 6-, 9-, 12-, 24-, 48-month) of SPEI can be calculated to analyzed different drought types. Short time scales (i.e., 1-, 3-, 6-month) are used to analyze meteorological and agricultural drought, whereas the longer time scales are proper to analyze hydrological drought.

SPEI can be expressed as the difference between monthly potential evapotranspiration and precipitation.

$$D_i = P_i - PET_i \tag{1}$$

Where, P_i is the precipitation for analyzed month i, PET_i is the potential evapotranspiration for analyzed month i, and D_i is the deficit. PET can be calculated by Thornthwalte method [43] that use the monthly mean temperature, and monthly mean sunshine hours as the key parameters.

$$PET = 16 \left(\frac{N}{12}\right)\left(\frac{m}{30}\right)\left(10\ \frac{T_i}{I}\right)^{a} \tag{2}$$

Where, N is the monthly mean sunshine hour, m is the number of days in a month, T_i is the monthly mean temperature for analyzed month, “a” is a coefficient, and I is the cumulative twelve months thermal index. The calculation of the coefficient, “a” is expressed below:

$$a = 6.75\ x\ 10^{-7} x\ I^3 - 7.71\ x\ I^2 + 1.79\ x\ 10^{-2} x\ I + 0.49 \qquad (3)$$

The calculation of I can be expressed as following:

$$I = \sum_{i=1}^{12} \left(\frac{T_i}{5}\right)^{1.514} \qquad (4)$$

After calculate D_i, its standardized time series must be fitted to a log-logistic probability distribution function. Although some other probability distribution functions can be used, log-logistic function was suggested by the founder of SPEI [5]. Finally, SPEI values can be calculated by using below equations.

$$SPEI_i = \frac{2.515517+0.802853\ Wi+0.010328\ Wi^2}{1+1.432788\ Wi+0.189269\ Wi^2+0.001308\ Wi^3} \qquad (5)$$

W_i can be calculated by following:

$$W_i = \sqrt{-2\ln p}\ \ for\ p \le 0.5 \qquad (6)$$

and

$$W_i = \sqrt{-2\ln p}\ \ for\ p \ge 0.5 \qquad (7)$$

Basically, drought is categorized as dry/wet condition. Dry means the lack of precipitation, while wet means excessive precipitation over a region. The calculated SPEI values determine these dry/wet conditions. If SPEI time-series is plotted, any value higher than the threshold value (dashed line) indicate wet condition (See Figure 7).

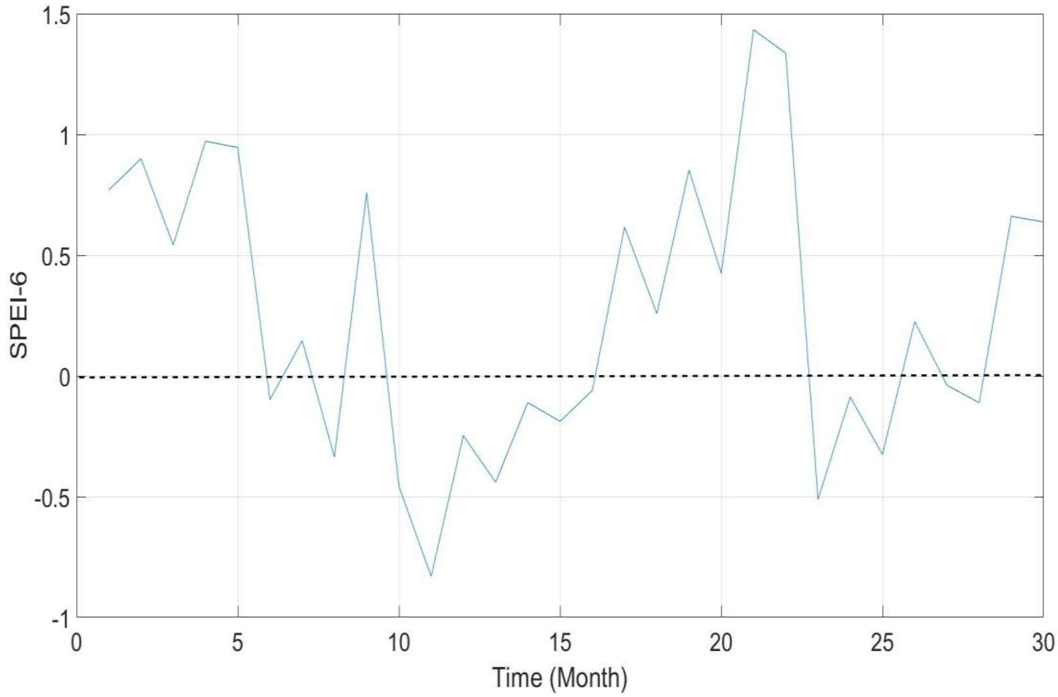

Figure 7. Schematic representation of dry/wet condition

Any values that lower than threshold value (dashed line) indicate dry condition. In mathematical modelling of drought, several threshold values were attained to classify drought classes. Similar SPI threshold values to categorized drought classes (in terms of dry/wet condition) are used for the SPEI values categorization. However, as early mentioned, a recent study that conducted by Danandeh Mehr et.al [21] suggested a drought classification threshold value for SPEI (see Table 3).

4.2. Overview of Decision Tree

DTs are one of the frequently preferred algorithms in clustering and prediction problems. These algorithms present a strategy that advances from top to bottom or from general to specific during training process. In this strategy, which is a kind of flowchart-like tree structure, the attribute value of each node is measured, and branches are formed with the obtained results. A typical decision tree architecture can be shown in Figure 8.

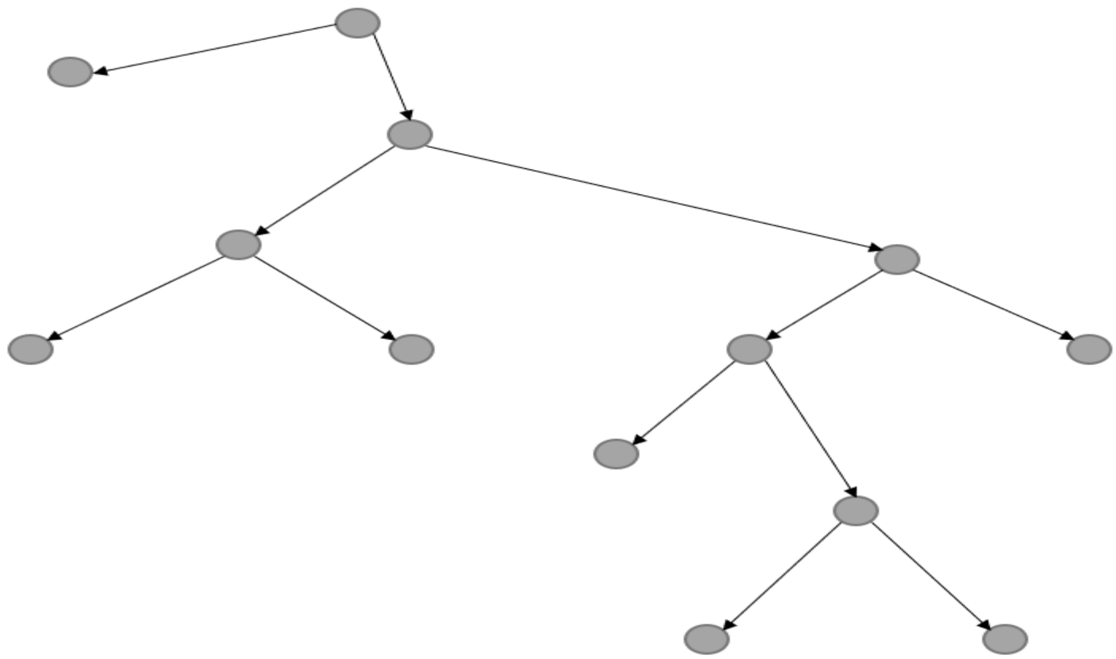

Figure 8. A Typical Decision Tree Architecture

DTs are start with a root node, accompanied by separation criteria such as information gain. According to selected criteria, this root node is divided into branches. This separation continues until terminated by leaf nodes. In this structure, the path followed by the data progresses with the answer given in binary (yes/no), categorical (dry/wet), numerical (SPEI>1.50) distinctions depending on if-then-else algorithms. Tree contains all trained cases in the root node and check for clustering. If all cases in the root node coincidence with a single cluster, the solution is achieved. Otherwise, the root node is divided into branches and repeated until the branch is simple enough to decide directly. Based on the size of the dataset, branches of tree can be a difficult task. To prevent overfitting, pruning algorithms are used, which refers to removing leaf nodes containing a small number of objects from the decision tree.

DT algorithm starts with the calculation of expected information, in other words it is referred as Entropy. Entropy theory is used to measure of uncertainty associated with a random variable. In DT modeling, it can be used to decomposing the tree branches and nodes. It provides to characterize impurity in a data set. Higher entropy means higher uncertainty, while lower entropy means lower uncertainty. To give an example, consider T is an attribute, and D is a label. From the perspective of binary progress (yes/no) the entropy can be expressed as following:

$$Entropy\ (D) = -p_{yes}\left(log_2 p_{yes}\right) - p_n(log_2 p_{no}) \tag{8}$$

Where, p_{yes} is the proportion of yes answers for the attribute, and p_{no} is the proportion of the no answers for the attribute. Then, information that required to classify attribute T into v partitions in label D can be calculated as the weighted summation of entropies in the subsets. Information calculations is expressed as follows:

$$Info_T(D) = \sum_{i=1}^{v} \frac{D_i}{D} Entropy(D_i) \tag{9}$$

Finally, information gain by branching on attribute T can be calculated by using:

$$Gain\ (T) = Entropy(D) - Info_T(D) \tag{10}$$

Then, the attributes with the highest information gain are selected to construct a tree model in a top-down recursive divide and conquer manner. The existing data set is divided into two parts as training and test sets to create a model. DT algorithms extracts the if-then rules using training sets. Then, extracted rules are applied to test sets and statistical evaluation is performed to validate test results.

4.3. Developed Decision Tree Model

In this study, a DT model for meteorological drought classification and prediction was developed. As illustrated in Figure 9, developed model consist of five steps: collection of SPEI global repository vector data, calculation of SPEI-6 target values, DT application, model performance evaluation, and decision of SPEI classes.

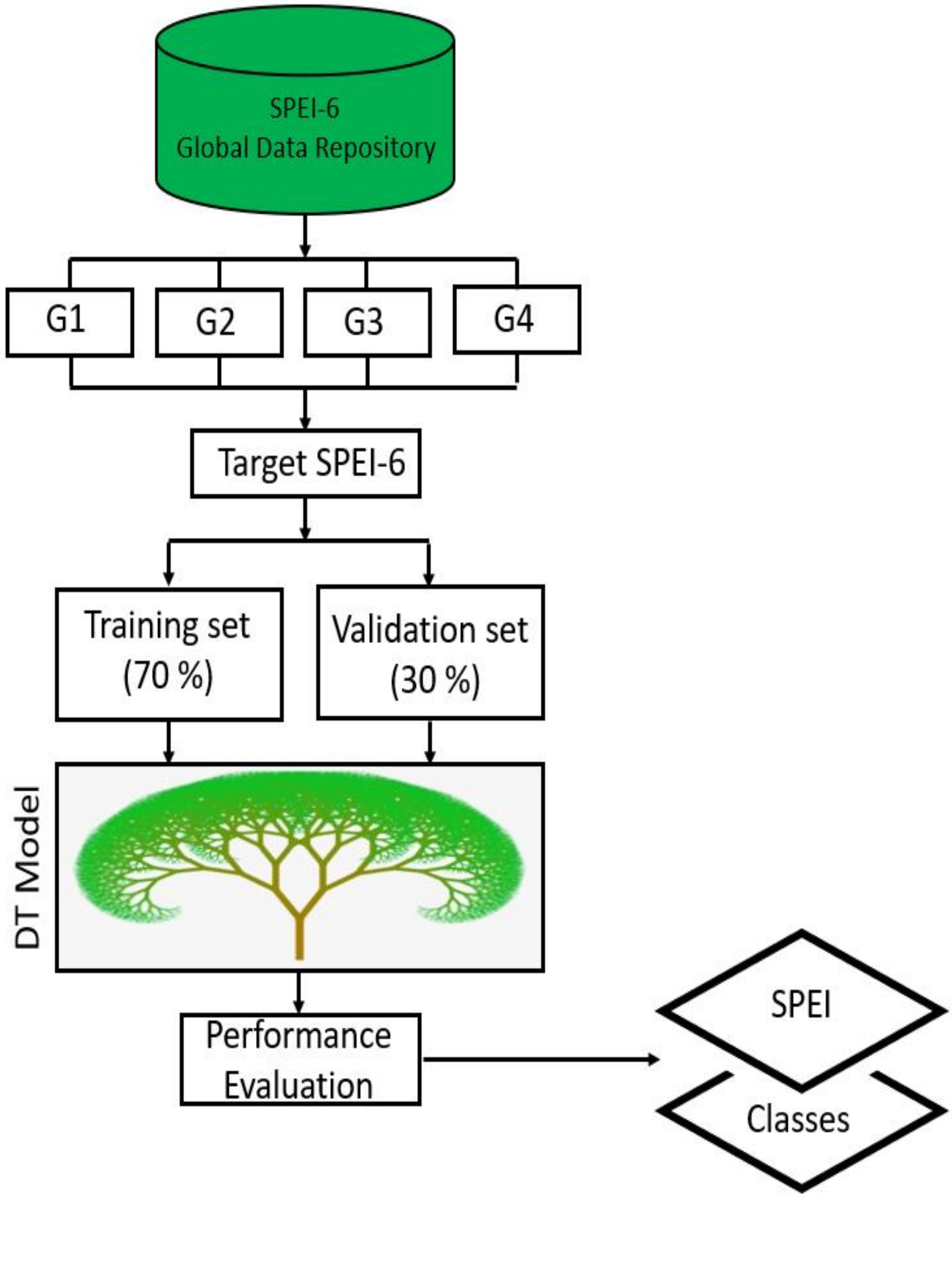

Figure 9. Methodology Flowchart of the Developed DT Model in This Thesis

In the first step, we selected four grid points (G2, G3, G5, G6) around the study area (Antalya Province). Then, we collected the monthly SPEI-6 values for specified grid points. In the next step, we calculated the target SPEI-6 values by taking the average of four grid points. Thus, 659 samples of SPEI-6 target values were added to dataset. A sample of data set including target values presented in Table 5.

Table 5. Sample of Data Sets Extracted From Global SPEI Data Repository

Month	**G1**	**G2**	**G3**	**G4**	**Target SPEI-6**
Jan. 2014	-1,048	-1,086	-0,430	-0,469	-0,758
Feb.2014	-1,519	-1,508	-0,913	-1,023	-1,241
March 2014	-1,068	-0,968	-0,479	-0,608	-0,781
April 2014	-1,292	-1,161	-0,819	-1,103	-1,094
May 2014	-0,900	-0,268	-0,002	-0,585	-0,439
June 2014	-0,040	0,604	0,972	0,284	0,455
July 2014	0,316	0,741	0,613	0,509	0,545
Aug. 2014	1,707	1,404	1,408	1,597	1,529
Sep. 2014	1,176	1,082	1,076	1,296	1,157
Oct. 2014	1,452	1,447	1,546	1,508	1,488
Nov. 2014	0,885	0,777	1,262	0,941	0,966
Dec.2014	0,908	0,869	1,277	1,048	1,026

It was observed that target SPEI-6 values vary in the range of -2.48 and 2.47. They were categorized into two classes as dry and wet. Categorization of target values were done based on a threshold value of 0. The values higher than zero were accepted as wet condition, while values lower than zero were accepted as dry condition. The absolute count and fraction of the observed target values of each class presented in Table 6.

Table 6. Absolute Counts and Fractions of Drought based on the Target SPEI-6

Drought Class	Absolute Count	Fraction
Wet	333	0.51
Dry	326	0.49

Target SPEI-6 values were split into train and validation sets with a percentage of 70% and 30% respectively. DT model was developed using the training set and if-then rules are extracted. Finally, the developed model was tested using validation set and model performance was evaluated by various statistical parameters.

4.4 Performance Measurement

After developing a prediction model, the predicted values must be evaluated to identify the model accuracy. To this end, several performance measurement parameters can be used. For example, Total accuracy (TA), Kappa (KA), and Classification Error (CE) are some of specific performance measurement parameters that can be measured using confusion matrix of the model's outputs. These methods are commonly used for DT with binary target variables, and a specified target including various combinations of True Positive (TP) and True Negative (TN) values [44]. Basically, a confusion matrix is a table that shows the True and False predictions in an order. It is an N x N matrix, where N is the total number of target classes (i.e., dry, wet). In addition, it was defined by Ting [45] as a matrix that summarizes the classification performance of a classifier with respect to some validation data.

TA is the averaged value of True Positive and True Negative class predictions based on the confusion matrix. It can be expressed in following form:

$$TA = \frac{TP+TN}{N}\ x\ 100 \tag{11}$$

In the equation, N is the total number of samples. TP is true positive predictions, while TN is true negative predictions.

Cohen's [46] KA parameters is a statistical method that measures the reliability of the comparative agreement between two classifiers. It is calculated in the range of 0 to 1 where 1 indicates a perfect agreement, while 0 indicates no agreement. It can be expressed in following form:

$$KA = \frac{\Pr(o) - \Pr(e)}{1 - \Pr(e)} \tag{12}$$

Where, Pr(o) is observed agreement, and Pr(e) is expected agreement. For example, if we have a 2 x 2 confusion matrix with True Positive and True Negative values of a prediction (see Figure 10), the corresponding Pr (o), and Pr (e) values can be calculated as following procedure:

$$\Pr(o) = \frac{60+15}{100} \tag{13}$$

$$\Pr(e) = \left[\frac{70}{100}\ x\ \frac{75}{100}\right] + \left[\frac{30}{100}\ x\ \frac{25}{100}\right] \tag{14}$$

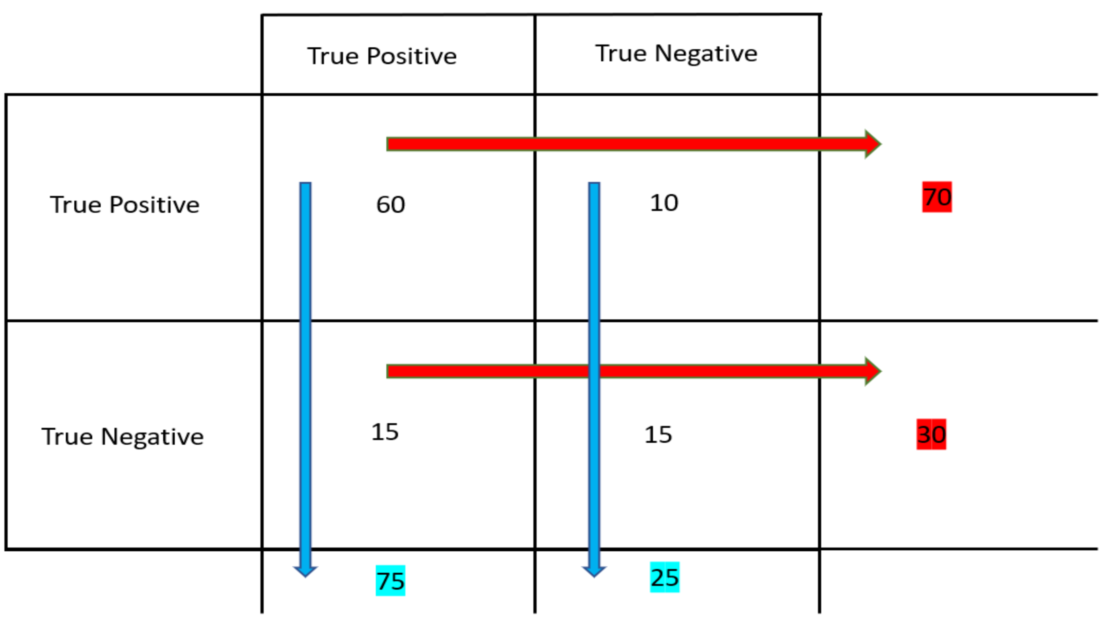

Figure 10. Example Confusion Matrix

Finally, CE and accuracy rate (AC) are can be calculated using Eq 15 and 16, respectively.

$$CE = 100 - AC \tag{15}$$

Where, AC is the accuracy rate and can be expressed as:

$$AC = \frac{TP}{N} \tag{16}$$

As a final sentence to this part, all the above performance measurement parameters are calculated using confusion matrix values such as TP, and TN.

5. RESULTS AND DISCUSSION

In this study, a DT model was developed to predict drought classes over the lead time of one month. To this end, firstly SPEI-6 global vector data were downloaded from the Global SPEI database. These data include SPEI-6 values of four different grid points (mentioned before) that surrounded the Antalya Province (see Figure 2). Then, target SPEI-6 values were calculated by averaging the SPEI-6 values of four grid points. After this calculation, each target SPEI-6 values were categorized into two class of drought (i.e., dry, and wet) based on a threshold value of zero. It was observed that 326 samples categorize as dry condition, while 333 samples categorize as wet condition (see Table 6). Then, the target SPEI-6 values were divided into train and validation sets with a percentage of 70%, and 30%, respectively. Features of the train and validation sets presented in Table 7.

Table 7. Features of Train and Validation Sets

		Train				**Test**			
		Mean	**Standard Deviation**	**Minimum**	**Maximum**	**Mean**	**Standard Deviation**	**Minimum**	**Maximum**
Inputs	G2	0.073	1.019	-2.201	2.665	-0.075	1.142	-2.483	2.164
	G3	0.015	1.023	-2.193	2.087	-0.001	1.066	-2.472	2.165
	G5	0.033	0.970	-2.267	2.657	0.046	1.078	-2.502	2.174
	G6	-0.012	1.008	-2.215	2.901	-0.029	1.068	-2.591	2.199

In the next step, a DT model was developed that use the SPEI-6 values of four different stations as input and predict the one month ahead drought condition. DT model was created using RapidMiner Studio version 9.8 [47]. It is an open-source, free project implemented in Java [48]. Several implementations of RapidMiner Studio have been reported by researchers in literature [49; 50]. The developed DT model that evolved one month ahead drought condition was illustrated in Figure 11.

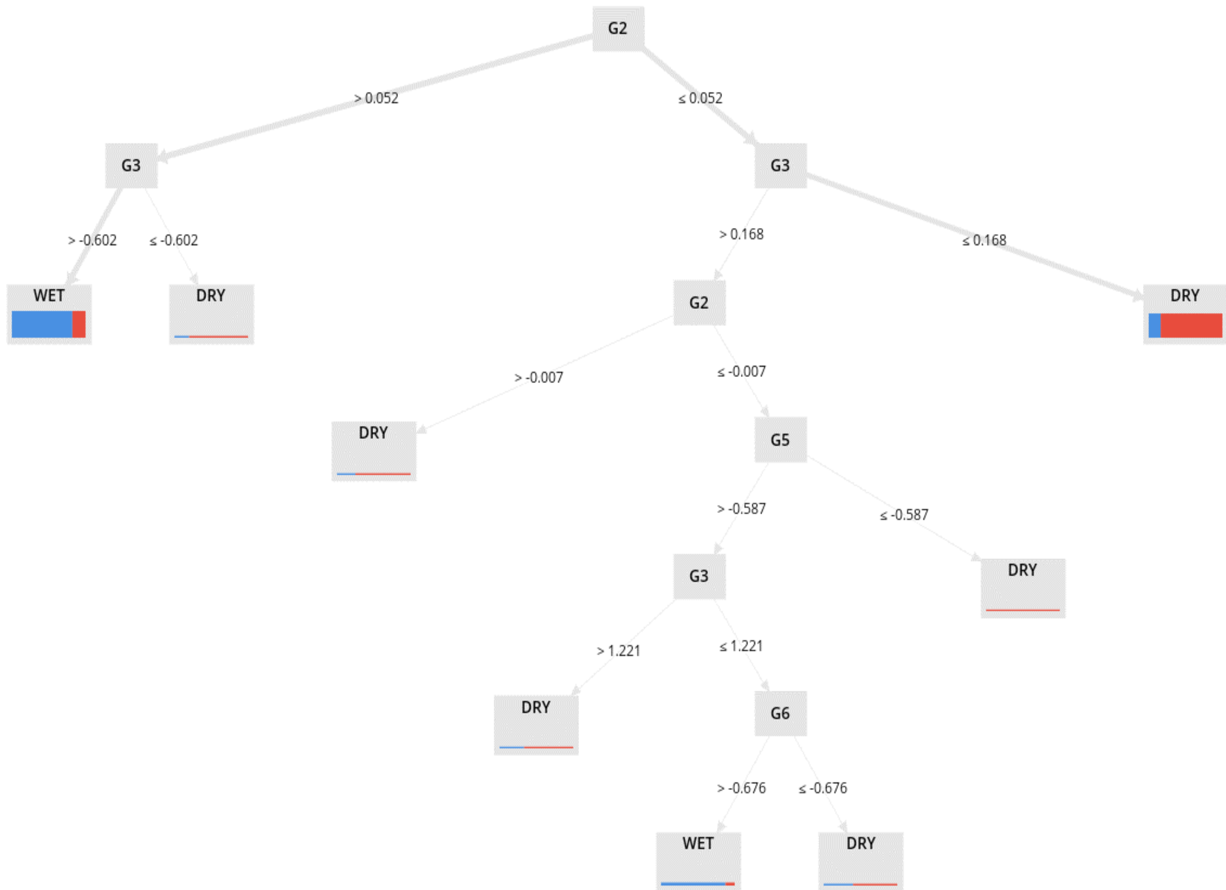

Figure 11. DT Model Evolved for One-Month Ahead Drought Classification at Antalya

In the model, the most important input variable was found as G2 based on information gain calculations. It was followed by G3, G5, and G6. Based on the Figure 11, it was observed that a threshold value of 0.052 was selected by the tree algorithm to split the first branches. The main mechanism behind the DT is if-then algorithm. This algorithm follows a path in a binary manner. The extracted rules for corresponding DT model were presented below.

G2 > 0.052

| G3 > -0.502: THEN → WET

| G3 ≤ -0.502: THEN → DRY

G2 ≤ 0.052

| G3 > 0.168

| | G2 > -0.007: THEN → DRY

| | G2 ≤ -0.007

| | | G5 > -0.587

| | | | G3 > 1.221: THEN → DRY

| | | | G3 ≤ 1.221

| | | | | G6 > -0.676: THEN → WET

| | | | | G6 ≤ -0.676: THEN → DRY

| | | G5 ≤ -0.587: THEN → DRY

| G3 ≤ 0.168: THEN → DRY

Based on the presented rules, an example to read the decision tree can be expressed as following:

"IF" SPEI value of G2 is "greater than 0.052", there are two condition to check. First, "IF" SPEI value of G3 is "greater than -0.052", the drought can be classified as "WET". "Else", it can be classified as "DRY".

Confusion matrix that shows predicted drought classes at the training and validation sets presented in Table 8 and 9, respectively. In other words, it is the matrix that presents the TP, and TN values of outputs. Also, the model results were presented in Appendix A.

Table 8. Prediction Results of Train Set

Train	True Wet	True Dry
# of Samples (N=468)		
Predicted Wet	201	44
Predicted Dry	38	185

Table 9. Prediction Results of Validation Set

Validation	True Wet	True Dry
# of Samples (N=191)		
Predicted Wet	76	20
Predicted Dry	17	78

On the Table 8, and 9, each row shows predicted drought classes, while each column shows the observed drought classes. The diagonal interception of rows and columns shows the success of the model that predicted accurately. Others are accepted as errors that predicted inaccurately. It was observed that developed model truly predicted 201 wet condition out of 239 and truly predicted 185 dry condition out of 229 in the training. For validation set (see Table 9), it was observed that developed model truly predicted 76 wet condition out of 93 and truly predicted 78 dry condition out of 98. The overall accuracy rates that is the ratio of true prediction in whole sample were found as 82.48%, and 80.63% for train, and validation sets, respectively.

To measure the model performance, TA, KA, and CE values were calculated using Eq 11, 12, and 15 depending on the confusion matrix (Table 8, and 9). Results presented in table below.

Table 10. Performance Evaluation of DT Model

Train			**Validation**		
TA (%)	CE (%)	KA (%)	TA (%)	CE (%)	KA (%)
82.48	17.52	0.72	80.63	19.37	0.61

It is seen from the table TA, CE, and KA values of 80.63, 19.37, and 0.61 were found for validation sets. McHugh [51] interprets the KA values in six level as none, minimal, weak, moderate, strong, and almost perfect. The ranges of each level presented in Table 11.

Table 11. Interpreted KA Values [51]

Kappa Value	**Levels**
0.00 – 0.20	None
0.21 – 0.39	Minimal
0.40 – 0.59	Weak
0.60 – 0.79	Moderate
0.80 – 0.90	Strong
≥ 0.91	Almost Perfect

Based on the Table 11, KA value found in this study are interpreted as moderate and substantially satisfactory classifiers in this study. Figure 12, and 13 shows the comparison between the observed and predicted values in the training and validation periods, respectively.

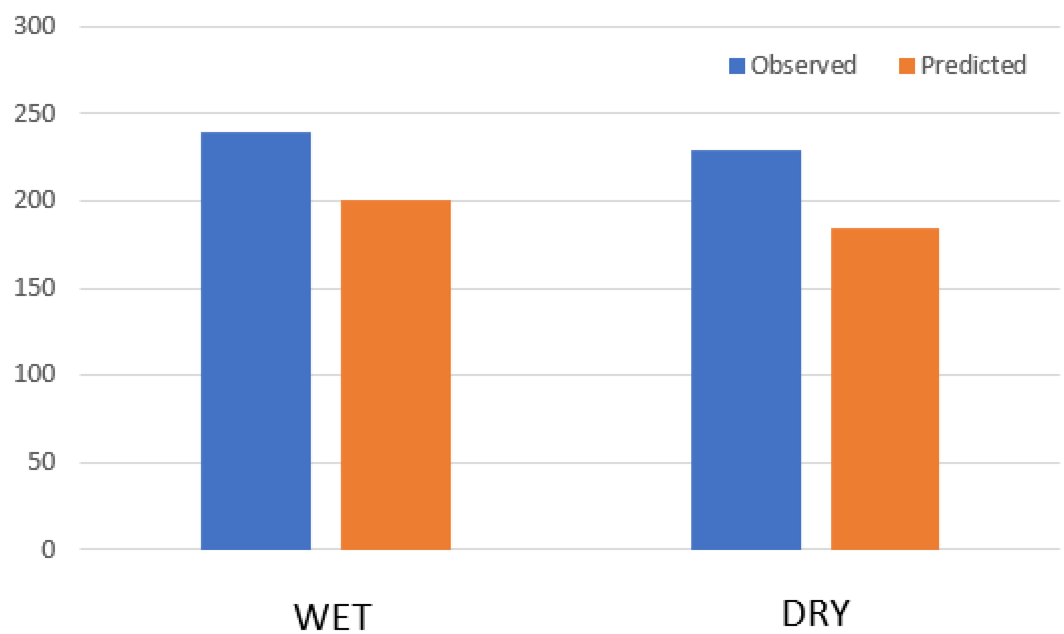

Figure 12. The Observed and Predicted Drought Classes in Training

Based on the Figure 12, the study area has experienced 239 wet event, and 229 dry events during the training period. However, developed model accurately predicted the 201 wet event, and 185 dry events. The study area has faced more wet event than dry events in the training period.

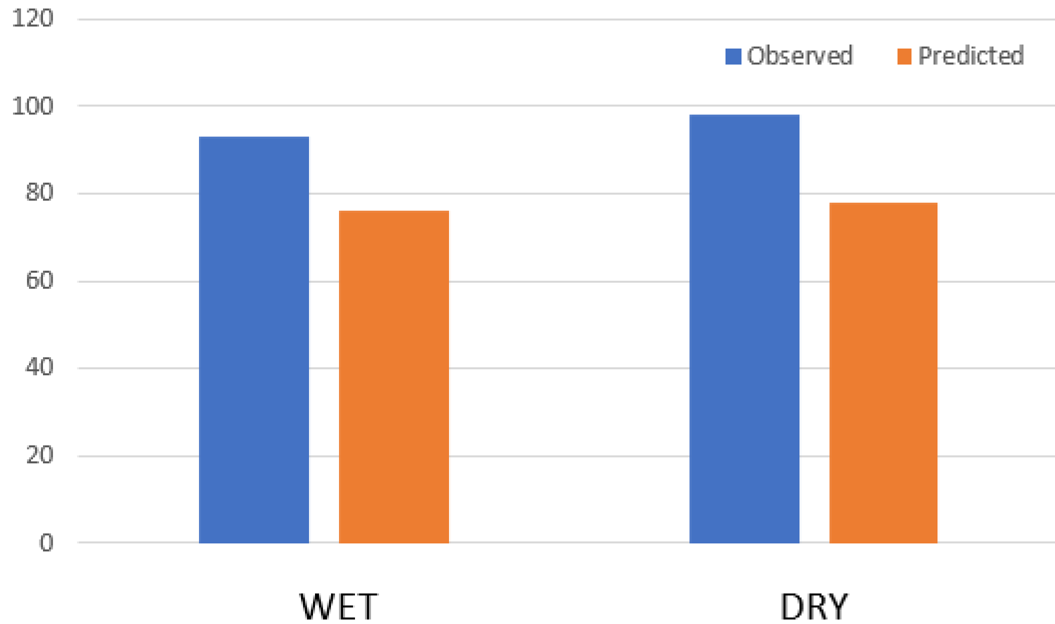

Figure 13. The Observed and Predicted Drought Classes in Validation

On the other hand, Figure 13 showed that the study area has experienced 93 wet event, and 98 dry events during the validation period. However, developed model accurately predicted the 76 wet event, and 78 dry events. The study area has faced more dry event than wet events in the validation period. Also, developed model underestimate the wet and dry events in both training and validation periods. As training set include more former years (1961 - 2000), and validation set include more recent years (2000 - 2015), increasing trend for dry events in the most recent years can be considered as the signal for climate variability in the study area.

6. CONCLUSION

Drought is a natural phenomenon that causes social, economic, and environmental impacts in a region. Therefore, drought classification and prediction have a paramount importance for drought management. It is a challenging engineering task due to stochastic features of drought classification indices. Most of the studies attempted to model temporal variation of drought indices using station-based historical data, while in this thesis the contribution of remote sensed/global observatory meteorological data was considered to develop a prediction model. A DT model was developed to predict drought classes. To this end, firstly, SPEI values of four nearby grid points were averaged to obtain target SPEI values. Two class of drought were selected based on a threshold value of zero. The target SPEI values which is higher than zero were categorized as wet class, while values that are lower than zero were categorized as dry class. It was observed that the developed DT model can accurately classify and predict one month ahead drought events in the study area. Historical SPEI-6 values of each grid were used as the input of the model. The results showed that a trend of increasing dry events can be observed for the case study area. The model performance was evaluated using statistical parameters such as TA, KA, and CE. It was observed that developed model can moderately accurate to predict drought classes for one month ahead with a KA value of 0.61. On the other hand, TA value was evaluated as 80.63 for the validation sets. This showed that the developed model has a strong accuracy for drought prediction. In total, it can be concluded as the developed model is accurate enough to prediction.

The developed DT model was limited to a short-term (one month ahead) classification/prediction. Developing drought classification model with higher lead times to predict long-term drought condition would be beneficial for drought management and mitigation in the case study area. In addition, further studies are required to multiclass drouth classification and prediction.

We would like to express some issue about the work done in this study. A binary logic based (yes/no) DT model was developed using just early mentioned two drought classes as dry and wet. Although there are more than two drought classes such as multi drought classes, due to its easy calculation and considering that the hybrid models are more proper to classify multi classes of drought, therefore, just two class of drought was used in the developed model. The developed DT model was limited to a short-term (one month ahead) classification. Developing drought classification model with higher lead times to predict long-term drought condition would be beneficial for drought management and mitigation in the case study area.

On the other hand, random forest is another tree-based method that frequently used in the literature for classification or prediction studies. However, in this study only DT based model was developed and therefore the capabilities and accuracy of random forest method could not be investigated. For future studies, it is recommended that the using of random forest model for drought classification studies could be beneficial for the researchers to identify and compare the accuracy of random forest method with DT method.

7. REFERENCES

[1] Drought. Web 05 Dec. 2020, https://earthdata.nasa.gov/earth-observation-data/nearreal-time/hazards-and-disasters/drought

[2] Danandeh Mehr, A. Vaheddoost, B. and Mohammadi, B. (2020a). ENN-SA: A novel neuro-annealing model for multi-station drought prediction. Computer & Geosciences, 145, 104622. doi: 10.1016/j.cageo.2020.104622

[3] Danandeh Mehr, A. Tur, R. Çalışkan, C. and Tas, E. (2020b). A Novel Fuzzy Random Forest Model for Meteorological Drought Classification and Prediction in Ungauged Catchments. Pure and Applied Geophysics. doi: 10.1007/s00024-020-026097

[4] McKee, T. B. Doesken, N. J. and Kleist, J. (1993). The relationship of drought

frequency and duration to time scales. In Proceedings of the International 8 th Conference on Applied Climatology, American Meteorology Society, Anaheim, CA, USA, 17-22 January, 179-184.

[5] Vicente-Serrano, S. M. Begueria, S. and Lopez-Moreno, J. I. (2010). A multiscalar drought index sensitive to global warming: The standardized precipitation evapotranspiration index. Journla of Climate, 23(7), 1696-1718. Doi: 10.1175/2009jCLI2909.1

[6] Agriculture in Antalya. 01 Dec. 2020. https://antalya.tarimorman.gov.tr/Menu/75/Antalyada-Tarim

[7] Turizm ve Kültür Bakanlığı. (2019). Turizm İstatistikleri. https://yigm.ktb.gov.tr/Eklenti/69320,turizmistatistikleri2019-4pdf.pdf?0 (01 Dec. 2020)

[8] Global SPEI Database. 25 Nov. 2020. https://spei.csic.es/database.html

[9] Bakanoğulları, F. (2020). Kırsal Havzalarda Kuraklığın İki Yöntem (SPEI ve SPI) Kullanılarak Belirlenmesi: Kumdere Havzası Örneği. Türk Tarım ve Doğa Bilimleri Dergisi, 7(1), 146-156.

[10] Wilhite, D. A. and Glantz, M. H. (1985). Understanding the Drought Phenomenon: The Role of Definitions. Water International, 10(3), 111-120. Doi:

10.1080/02508068508686328

[11] Dai, A. (2011). Drought Under Global Warming: A Review. Wiley

Interdisciplinary Reviews: Climate Change 2, 45-65. Doi:10.1002/wcc.81

[12] Türkeş, M., Akgündüz, A. S., ve Demirörs, Z. (2009). Palmer Kuraklık İndisi’ne Göre İç Anadolu Bölgesi’nin Konya Bölümü’ndeki Kurak Dönemler ve Kuraklık Şiddeti. Çoğrafi Bilimler Dergisi, 7(2), 129-144.

[13] Fung, K. F., Huang and Soh, Y. W. (2019). Drought Forecasting: A Review of Modelling Approaches 2007-2017. Journal of Water and Climate Change, 11(3). Doi: 10.2166/wcc.2019.236.

[14] Çaldağ, B. Şaylan, L. Toros, H. ve Bakanoğulları, F. (2004). Drought analysis in north-west Turkey. Agroenvironment, 20-24 October, Udine, Italy, 169-179.

[15] Van Lenan, H. A. J. and Peters, E. (2000). Definitions, Effects and Assessment of Groundwater Droughts. Dordrecht: Kluwer Academic Publishers.

[16] Öz, A. (2020). Farklı Kuraklık İndisleri Kullanılarak Van Gölü Havzası Kuraklık Analizi. Yayınlanmış Yüksek Lisans Tezi, Van Yüzüncü Yıl Üniversitesi, Van.

[17] Dai, A. (2010). Drought under global warming: a review. Wiley Interdisciplinary Reviews: Climate Change, 2(1), 45-65. Doi: 10.1002/wcc.81

[18] Palmer, W. C. (1965). Meteorological Drought, Weather Bureau Research Paper No. 45, U.S. Department of Commerce, Washington D.C.

[19] Jamal, R. (2019). Trend Analysis of the Drought Over Turkey. Yayınlanmış Yüksek Lisans Tezi, Anadolu University, Eskişehir.

[20] Janssen, M. (2010). Population Aggregation in Ancient Arid Environments. Ecology and Society, 15(2). Doi:10.5751/ES-03376-150219

[21] Danandeh Mehr, A. Sorman. A. U. Kahya, E. and Hesami Afshar, M. (2020c). Climate change impacts on meteorological drought using SPI and SPEI: Case study of Ankara, Turkey. Hydrological Sciences Journal, 65(2), 254-268.

[22] Zadeh, L.A. (1965). Fuzzy Sets. Information and Control, 8(3), 338-353. Doi: 10.1016/S0019-9958(65)90241-X.

[23] Pesti, G., Shrestha, B. P., Duckstein, L., and Bogardi, I. (1996). A Fuzzy RuleBased Approach to Drought Assessment. Water Resourches Research, 32(6), 1741-1747. Doi: 10.1029/96WR00271.

[24] Pongracz, R., Bogardi, I., and Duckstein, L. (1999). Application of Fuzzy Rule-Based Modeling Tecnique to Regional Drought. Journal of Hydrology, 3(4), 100-114. Doi: 10.1016/S0022-1694(99)00131-6.

[25] Huang, S., Chang, J., Leng, G., and Huang, Q. (2015). Integrated Index for Drought Assessment Based on Variable Fuzzy Set Theory: A Case Study in the Yellow River Basin, China. Journal of Hydrology, 527, 608-618. Doi: 10.1016/j.hydrol.2015.05.032.

[26] Abdourahamane, Z. S., and Acar, R. (2019). Fuzzy Rule-Based Forecast of Meteorological Drought in Western Niger. Theoretical and Applied Climatology. 135, 157-168. Doi: 10.1002/joc.1832.

[27] Morid, S., Smakhtin, V., and Bagherzadeh, K. (2007). Drought Forecasting Using Artificial Neural Networks and Time Series of Drought Indices. International Journal of Climatology. 27, 2103-2111. Doi: 10.1012/joc.1498.

[28] Rezaeian-Zadeh, M., and Tabari, H. (2012). MLP-based Drought Forecasting in Different Climatic Regions. Theoretical and Applied Climatology, 109, 407-414. Doi: 10.1017/s00704-012-0592-3.

[29] Zulifgar, A., Hussain, I., Faisal, M., Nazir, H. M., Hussain, T., Shad, M. Y., Shourky, A. M., and Gani, S. H. (2017). Forecasting Drought Using Multilayer Percptron Artificial Neural Network Model. Advances in Meteorology, Vol.2017, 5681308. Doi: 10.1155/2017/5681308.

[30] Jang, S. R. (1993). ANFIS: Adaptive Network Based Fuzzy Inference System. IEEE Transactions on Systems, Man, and Cybernetics, 23(3), 665-685. Doi: 10.1109/21.256541.

[31] Bacanli, U. G., and First, M. (2009). Adaptive Neuro-Fuzzy Inference System for Drought Forecasting. Stochastic Environmental Research and Risk Assessment, 23, 1143-1154. Doi: 10.1007/s00477-008-0288-5.

[32] Abbasi, A., Khalili, K., Behmanesh, J., and Shirzad, A. (2019). Drought Monitoring and Prediction Using SPEI index and Gene Expression Programming Model in the West Urmia Lake. Theoretical and Applied Climatology, 138, 553-567. Doi: 10.1007/s00704-019-02825-9.

[33] Mehr, A. D., Kahya, E., and Özger, M. (2014). A Gene-wavelet Model for Long Lead Time Drought Forecasting. Journal of Hydrology, 517, 691-699. Doi: 10.1016/j.hydrol.2014.06.012.

[34] Danandeh Mehr, A., Safari, M. J. S., and Nourani, V. (2021). Wavelet PacketGenetic Programming: A New Model for Meteorological Drought Hindcasting. Teknik Dergi, 32(4). Doi: 10.18400/tekderg.605453.

[35] Ozger, M., Mishra, A. K., and Singh, V. P. (2011). Estimating Palmer Drought Severity Index Using a Wavelet Fuzzy Logic Model based on Meteorological Variables. International Journal of Meteorology, 31, 2021-2032. Doi: 10.1002/joc.2215.

[36] Ozger, M., Mishra, A. K., and Singh, V. P. (2012). Long Lead Time Drought Forecasting Using a Wavelet and Fuzzy Logic Combination Model: A Case Study in Texas. Journal of Hydrometeorology, 13(1), 284-297. Doi: 10.1175/JHM-D-10- 05007.1.

[37] Shirmohammadi, B., Moradi, H., Moosavi, V., Semiromi, M. T., and Zeinali, A. (2013). Forecasting of Meteorological Drought Using Wavelet-ANFIS model for different time steps (case study: southeastern part of east Azerbaijan province, Iran). Natural Hazards, 69, 389-402. Doi: 10.1007/s11069-013-0716-9.

[38] Kisi, O., Gorgij, A. D., Zounemat-Kermani, M., Mahdavi-Meymand, A., and Kim, S. (2019). Drought Forecasting Using Novel Heuristic Methods in a Semi arid Environment. Journal of Hydrology, 578, 124053. Doi: 10.1016/j.hydrol.2019.124053.

[39] Chen, J., Li, M., and Wang, W. (2012). Statistical Uncertainty Estimation Using Random Forests and Its Application to Drought Forecast. Mathematical Problems in Engineering, Vol. 2012, 915053. Doi: 10.1155/2012/915053.

[40] Park, S., Im, J., Jang, E., and 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, 216, 157-169. Doi: 10.1016/j.agrformet.2015.10.011.

[41] Park, S., Seo, E., Kang, D., Im, J., and Lee, M. (2018). Prediction of Drought on Pentad Scale Using Remote Sensing Data and MJO Index through Random Forest over East Asia. Remote Sensing, 10(11), 1811. Doi: 10.3390/rs10111811.

[42] Nourani, V., and Molajou, A. (2017). Application of a Hybrid Association Rules/Decision Tree Model for Drought Monitoring. Global and Planetary Change, 159, 37-45. Doi: 10.1016/j.gloplacha.2017.10.008.

[43] Thorntwalte, C. W. (1948). An Approach Toward a Rational Classification of Climate. Geographical Review, 38(1), 55-94. Doi: 10.2307/210739.

[44] Muata, K., and Bryson, O. (2004). Evaluation of Decision Trees: A MultiCriteria Approach. Computers & Operation Research, 31(11), 1933-1945. Doi: 10.1016/S0305-0548(03)00156-4.

[45] Ting, K. M. (2011). Confusion Matrix. In: Sammut C., Webb G. I. (eds) Encylopedia of Machine Learning, Springer, Boston, MA. Doi: 10.1007/978-0-387- 30164-8_157

[46] Cohen, J. (1960). A Coefficient of Agreement for Nominal Scales. Educational and Psychological Measurement, XX (1), 37-46.

[47] https://rapidminer.com/

[48] Graczyk, M., Lasota, T., and Trawinski, B. (2009). Comparative Analysis of Premises Valuation Models Using KEEL, RapidMiner, and WEKA. International Conference of Collective Intelligence, Berlin, Germany, 2009, 800-812. Doi: 10.1007/978-3-642-04441-0_70.

[49] Ristoski, P., Bizer, C., and Paulheim, H. (2015). Mining the Web of Linked Data with RapidMiner. Web Semantics: Science, Services and Agents on the World Wide Web, 35(3), 142-151. Doi: 10.1016/j.websem.2015.06.004

[50] Naik, A., and Samani, L. (2016). Correlation of Classification Algorithm Using Data Mining Tool: WEKA, RapidMiner, Tanagra, Orange and Knime. Procedia Computer Science, 85, 662-668. Doi: 10.1016/j.procs.2016.05.251.

[51] McHugh, M. L. (2012). Interrater Reliability: The Kappa Statistic. Biochemia Medica, 22(3), 276-282.

8. APPENDIX A

The train set including SPEI values of G2, G3, G4, G5, observed and predicted one month ahead drought classes were presented in Table below.

Table 12. Train Data Set Including Inputs and Outputs

# of Sample	G2	G3	G5	G6	Observed Class	Predicted Class
1	0,770	0,469	0,054	0,754	WET	WET
2	0,899	0,993	0,770	1,054	WET	WET
3	0,542	0,536	0,256	0,733	WET	WET
4	0,972	0,574	0,879	1,324	WET	WET
5	0,946	0,272	0,723	1,071	WET	WET
6	-0,098	0,156	0,599	0,419	WET	DRY
7	0,146	0,435	1,055	0,747	DRY	WET
8	-0,336	-0,397	0,109	0,071	WET	DRY
9	0,758	0,324	0,684	0,631	DRY	WET
10	-0,457	0,601	0,012	-0,565	DRY	WET
11	-0,830	0,799	-0,217	-0,940	DRY	DRY
12	-0,247	0,548	-0,648	-0,988	DRY	DRY
13	-0,440	0,035	-0,793	-0,978	DRY	DRY
14	-0,111	0,388	-0,194	-0,412	DRY	WET
15	-0,188	0,021	-0,299	-0,263	DRY	DRY
16	-0,060	-0,072	-0,203	0,002	WET	DRY
17	0,617	0,969	0,477	0,642	WET	WET
18	0,258	0,298	0,109	0,560	WET	WET
19	0,852	0,765	0,495	1,027	WET	WET
20	0,425	0,459	-0,297	0,368	WET	WET
21	1,434	1,195	0,455	0,813	WET	WET
22	1,336	1,637	0,670	0,911	DRY	WET
23	-0,512	-0,418	-0,605	-0,340	WET	DRY
24	-0,087	0,825	0,949	0,704	WET	WET
25	-0,325	1,120	0,876	0,287	WET	WET
26	0,225	1,319	1,205	0,932	WET	WET
27	-0,038	1,188	0,957	0,588	WET	WET
28	-0,111	1,036	0,835	0,472	WET	WET
29	0,661	1,974	1,566	1,289	WET	WET
30	0,637	1,892	1,080	0,962	WET	WET
31	1,329	1,759	1,263	1,546	WET	WET
32	0,536	1,593	0,782	0,662	WET	WET
33	0,431	1,674	0,579	0,690	WET	WET
34	-0,196	1,437	0,209	0,157	DRY	DRY
35	-0,978	-0,261	-0,894	-1,302	DRY	DRY

36	-1,224	-1,527	-1,535	-1,477	DRY	DRY
37	-1,744	-2,182	-2,163	-2,024	DRY	DRY
38	-1,454	-1,685	-1,868	-1,684	DRY	DRY
39	-1,290	-1,317	-1,529	-1,438	DRY	DRY
40	-1,300	-1,419	-1,720	-1,566	DRY	DRY
41	-1,235	-1,413	-1,376	-1,321	DRY	DRY
42	-1,025	-0,980	-0,815	-0,788	WET	DRY
43	0,260	0,278	0,444	0,522	DRY	WET
44	-0,444	-0,390	-0,047	-0,026	DRY	DRY
45	-0,644	-1,017	-0,234	-0,087	DRY	DRY
46	-0,831	-1,081	-0,140	-0,075	DRY	DRY
47	-1,176	-1,279	-0,576	-0,330	DRY	DRY
48	-1,662	-1,428	-1,259	-1,062	DRY	DRY
49	-0,854	-0,749	-0,973	-0,619	DRY	DRY
50	-0,442	-0,348	0,065	0,137	WET	DRY
51	-0,161	-0,451	0,205	0,467	WET	DRY
52	0,194	-0,262	0,685	1,003	WET	WET
53	0,787	0,860	1,114	1,368	WET	WET
54	1,776	1,310	1,609	1,891	WET	WET
55	1,706	1,125	1,665	1,995	WET	WET
56	1,547	0,929	1,019	1,639	WET	WET
57	0,842	0,993	0,582	0,883	WET	WET
58	0,522	1,270	0,104	-0,001	DRY	WET
59	-0,980	-0,830	-1,317	-1,310	WET	DRY
60	0,184	0,615	-0,144	0,016	WET	WET
61	1,101	0,981	1,453	1,432	WET	WET
62	0,706	0,718	0,976	0,942	WET	WET
63	0,795	0,726	1,355	1,176	WET	WET
64	0,847	0,379	1,565	1,441	WET	WET
65	1,153	0,303	1,536	1,462	WET	WET
66	0,789	-0,603	1,167	1,196	DRY	DRY
67	-1,021	-1,375	-0,957	-0,931	DRY	DRY
68	-0,194	-1,277	-0,332	-0,135	DRY	DRY
69	-0,689	-1,567	-1,018	-0,601	DRY	DRY
70	-1,607	-1,595	-1,683	-1,667	DRY	DRY
71	-1,113	-1,256	-1,631	-1,539	WET	DRY
72	0,047	0,057	0,075	1,133	DRY	DRY
73	-0,181	-0,014	-0,523	0,507	DRY	DRY
74	-0,319	-0,152	-0,813	0,156	DRY	DRY
75	-0,315	-0,337	-0,785	0,009	WET	DRY
76	0,452	1,357	0,480	0,784	WET	WET
77	0,668	1,113	0,768	1,016	WET	WET
78	0,122	0,996	-0,036	-0,760	WET	WET
79	0,653	1,170	0,840	-0,152	WET	WET
80	1,230	1,428	1,195	0,508	WET	WET

81	1,494	1,711	1,248	0,851	WET	WET
82	1,678	-0,451	0,953	1,438	WET	WET
83	1,607	0,477	1,456	1,591	WET	WET
84	1,054	0,303	1,092	1,086	WET	WET
85	0,700	0,119	1,188	1,152	WET	WET
86	0,420	0,047	1,088	0,848	WET	WET
87	0,323	-0,199	1,174	0,979	WET	WET
88	-0,371	-0,131	0,507	0,111	DRY	DRY
89	-0,857	-0,583	-0,193	-0,354	DRY	DRY
90	-0,889	-0,957	-0,061	-0,129	DRY	DRY
91	-1,033	-1,013	-0,724	-0,867	DRY	DRY
92	-0,515	-1,034	-0,643	-0,366	DRY	DRY
93	0,162	-0,591	-0,361	-0,517	WET	WET
94	0,795	-0,276	0,155	0,126	WET	WET
95	1,885	1,473	1,574	1,758	WET	WET
96	1,877	1,575	2,019	2,009	WET	WET
97	2,665	1,860	2,511	2,850	WET	WET
98	2,417	1,479	2,443	2,643	WET	WET
99	2,654	1,648	2,657	2,901	WET	WET
100	2,502	1,487	2,636	2,790	WET	WET
101	2,122	0,854	2,098	2,418	WET	WET
102	2,513	0,700	1,878	2,560	WET	WET
103	0,639	-0,012	0,862	0,893	WET	WET
104	1,208	0,461	0,555	0,847	DRY	WET
105	-0,320	-0,273	-0,194	0,069	DRY	DRY
106	-0,572	-0,408	-0,459	-0,162	DRY	DRY
107	-1,108	-1,301	-1,126	-0,574	WET	DRY
108	1,064	0,698	0,736	1,429	WET	WET
109	0,909	0,125	0,518	1,208	WET	WET
110	1,252	1,005	0,912	1,309	WET	WET
111	1,291	1,352	1,067	1,253	WET	WET
112	1,318	1,208	0,970	1,202	WET	WET
113	1,664	1,373	1,183	1,320	WET	WET
114	0,636	0,881	0,252	-0,052	WET	WET
115	0,790	1,371	0,508	-0,347	DRY	WET
116	-0,269	0,483	-0,089	-0,859	DRY	DRY
117	-0,724	-0,254	-0,267	-0,894	WET	DRY
118	0,314	0,630	0,447	-0,548	DRY	WET
119	-0,427	0,157	0,110	-0,970	DRY	DRY
120	-0,819	-0,064	-0,381	-1,268	DRY	DRY
121	-1,184	-1,025	-1,080	-1,475	DRY	DRY
122	-0,080	-0,030	-0,582	-0,856	DRY	DRY
123	-0,162	0,023	-0,756	-0,899	DRY	DRY
124	-0,274	-0,175	-0,867	-0,830	DRY	DRY
125	-0,049	-0,254	-0,862	-0,701	DRY	DRY

126	0,412	-0,567	-0,799	-0,311	WET	WET
127	1,531	0,476	0,028	0,495	DRY	WET
128	-0,637	-0,770	-0,661	-0,508	DRY	DRY
129	-0,839	-1,309	-0,703	-0,561	DRY	DRY
130	-1,527	-1,824	-1,277	-1,079	DRY	DRY
131	-0,372	-1,105	-0,784	-0,411	DRY	DRY
132	-0,801	-1,539	-1,115	-0,230	DRY	DRY
133	-0,856	-1,590	-1,332	-0,646	DRY	DRY
134	-0,954	-1,767	-1,244	-0,750	DRY	DRY
135	-0,955	-1,526	-1,362	-0,941	DRY	DRY
136	-0,701	-1,003	-1,144	-0,765	DRY	DRY
137	-0,805	-0,730	-1,155	-0,899	DRY	DRY
138	-0,483	0,226	-0,526	-1,059	WET	DRY
139	-0,225	0,708	0,339	-0,624	WET	WET
140	0,145	1,159	0,295	-0,502	WET	WET
141	0,508	1,239	0,745	0,006	WET	WET
142	0,832	1,044	0,938	0,701	DRY	WET
143	-0,548	-0,033	0,270	-0,323	DRY	DRY
144	-1,654	-1,441	-1,470	-1,715	DRY	DRY
145	-1,824	-1,685	-1,946	-1,836	DRY	DRY
146	-1,709	-1,825	-2,091	-1,630	DRY	DRY
147	-1,877	-2,015	-2,034	-1,785	DRY	DRY
148	-2,202	-2,193	-2,267	-2,215	DRY	DRY
149	-2,031	-2,051	-2,069	-2,031	DRY	DRY
150	-1,441	-1,911	-1,409	-1,258	DRY	DRY
151	-0,974	-1,656	-0,826	-0,833	DRY	DRY
152	-1,639	-1,561	-0,756	-1,332	DRY	DRY
153	-1,334	-1,061	-0,777	-1,206	DRY	DRY
154	-1,038	-0,982	-0,835	-0,985	DRY	DRY
155	-1,052	-0,708	-1,225	-1,347	DRY	DRY
156	-1,715	-1,558	-1,754	-1,856	DRY	DRY
157	-1,855	-1,717	-1,936	-1,969	DRY	DRY
158	-0,639	-1,663	-1,215	-0,552	DRY	DRY
159	-0,441	-1,558	-1,106	-0,402	DRY	DRY
160	-0,455	-1,894	-1,246	-0,443	DRY	DRY
161	-0,211	-1,769	-0,981	-0,071	DRY	DRY
162	0,778	-1,446	-0,847	0,510	WET	DRY
163	1,904	-1,122	-0,134	1,390	DRY	DRY
164	-0,326	-1,218	-1,155	-0,730	DRY	DRY
165	-1,299	-1,371	-1,141	-1,054	DRY	DRY
166	-0,473	-0,752	-0,634	-0,629	DRY	DRY
167	0,094	-0,413	-0,734	-0,827	WET	WET
168	0,317	1,192	-0,335	-0,851	WET	WET
169	0,966	1,451	0,986	0,385	WET	WET
170	1,080	1,528	0,979	0,363	WET	WET

171	0,796	1,181	0,626	-0,030	WET	WET
172	0,866	1,380	0,709	0,037	WET	WET
173	0,943	1,416	1,149	0,513	WET	WET
174	1,035	0,757	1,371	1,087	WET	WET
175	-0,021	0,273	0,122	-0,098	WET	WET
176	-0,263	-0,097	0,421	0,377	WET	DRY
177	0,716	0,536	0,723	0,968	WET	WET
178	0,431	0,114	0,668	0,916	WET	WET
179	0,138	-0,641	0,276	0,572	DRY	DRY
180	-0,028	-0,849	0,014	0,426	DRY	DRY
181	-0,218	-0,509	-0,082	0,194	DRY	DRY
182	-0,535	-0,377	-0,682	-0,511	DRY	DRY
183	-0,599	-0,564	-0,775	-0,643	DRY	DRY
184	-0,386	-0,267	-0,531	-0,359	DRY	DRY
185	-0,266	-0,061	-0,334	-0,141	DRY	DRY
186	-0,380	0,316	-0,295	-0,340	WET	WET
187	0,023	0,174	0,208	0,132	WET	DRY
188	0,712	0,124	0,559	0,858	WET	WET
189	1,573	0,713	1,085	1,527	WET	WET
190	1,921	0,898	1,696	1,904	WET	WET
191	1,544	1,008	1,593	1,684	WET	WET
192	1,005	0,340	1,435	1,140	WET	WET
193	0,409	-0,436	0,788	0,294	DRY	WET
194	-0,060	-0,886	0,330	-0,145	DRY	DRY
195	-0,277	-1,221	0,170	-0,399	DRY	DRY
196	-0,652	-1,328	0,068	-0,794	DRY	DRY
197	-1,016	-1,525	-0,256	-1,156	DRY	DRY
198	-1,058	-1,442	-0,231	-1,175	DRY	DRY
199	-0,858	-0,945	0,126	-0,754	WET	DRY
200	0,290	-0,284	0,691	-0,006	WET	WET
201	0,402	0,144	0,801	0,279	DRY	WET
202	-0,716	-1,081	-0,766	-0,687	DRY	DRY
203	-0,917	-1,001	-0,998	-0,972	DRY	DRY
204	0,215	-0,095	-0,519	-0,057	WET	WET
205	0,392	0,506	-0,074	0,261	WET	WET
206	0,938	0,957	0,609	0,914	WET	WET
207	1,103	1,335	0,992	1,082	WET	WET
208	1,204	1,599	1,017	1,115	WET	WET
209	1,430	1,378	1,086	1,205	WET	WET
210	1,178	1,055	1,049	0,932	WET	WET
211	1,226	0,647	0,776	0,766	DRY	WET
212	0,049	0,017	-0,177	-0,549	DRY	DRY
213	-0,885	-0,970	-1,038	-1,192	WET	DRY
214	0,401	-0,058	-0,170	0,249	WET	WET
215	0,485	0,707	0,125	0,394	WET	WET

216	0,746	0,541	0,581	0,956	WET	WET
217	1,015	0,447	1,188	1,432	WET	WET
218	1,120	0,305	1,110	1,380	WET	WET
219	1,023	0,234	0,883	1,175	WET	WET
220	0,675	-0,521	0,327	0,575	WET	WET
221	0,751	-0,011	0,477	0,785	WET	WET
222	0,541	0,054	0,288	0,586	DRY	WET
223	-0,203	0,053	-0,721	-0,613	DRY	DRY
224	-0,802	0,279	-0,454	-0,728	DRY	DRY
225	-0,986	0,227	-0,412	-0,591	WET	WET
226	0,905	0,968	0,711	0,955	WET	WET
227	1,140	0,252	1,255	1,497	WET	WET
228	0,410	0,032	0,808	0,823	WET	WET
229	0,328	0,207	0,897	0,703	WET	WET
230	0,195	0,615	0,617	0,391	WET	WET
231	0,247	0,801	0,727	0,445	WET	WET
232	0,009	0,740	0,359	-0,026	DRY	DRY
233	-0,318	0,770	0,024	-0,522	WET	WET
234	0,000	0,954	0,063	-0,388	DRY	DRY
235	-0,015	0,919	-0,389	-0,618	WET	WET
236	0,379	0,530	-0,207	-0,191	WET	WET
237	0,901	0,485	-0,047	0,116	DRY	WET
238	0,046	-0,033	-0,048	-0,176	DRY	DRY
239	-0,439	-0,763	-0,146	-0,402	DRY	DRY
240	-0,683	-0,812	-0,048	-0,642	WET	DRY
241	1,051	1,811	1,626	0,991	WET	WET
242	1,265	1,865	1,718	1,373	WET	WET
243	0,945	1,740	1,424	1,015	WET	WET
244	1,010	1,677	1,168	0,968	WET	WET
245	1,223	1,570	0,989	0,956	WET	WET
246	1,871	1,981	1,322	1,434	DRY	WET
247	-0,173	-0,166	-0,912	-0,312	DRY	DRY
248	-1,314	-0,763	-1,395	-1,592	DRY	DRY
249	-1,111	-0,836	-1,219	-1,376	DRY	DRY
250	-1,264	-0,565	-1,155	-1,528	WET	DRY
251	1,366	0,352	0,416	0,652	WET	WET
252	1,237	0,537	0,443	0,733	DRY	WET
253	0,423	-0,275	-0,140	-0,093	DRY	WET
254	0,358	-0,215	-0,285	-0,094	WET	WET
255	0,856	0,312	0,203	0,300	WET	WET
256	1,104	0,362	0,650	0,754	DRY	WET
257	-0,042	-0,246	-0,353	-0,282	WET	DRY
258	-0,098	-0,045	0,276	-0,006	WET	DRY
259	1,117	0,723	0,940	1,040	WET	WET
260	1,527	0,826	1,227	1,303	WET	WET

261	0,205	0,038	0,643	0,682	WET	WET
262	0,591	1,307	0,481	0,396	WET	WET
263	-0,086	1,254	0,127	0,218	DRY	DRY
264	-1,020	-0,562	-1,681	-1,249	DRY	DRY
265	-1,272	-0,844	-1,675	-1,349	DRY	DRY
266	-0,913	-0,217	-1,445	-0,766	DRY	DRY
267	-0,376	0,784	-0,940	-0,431	DRY	DRY
268	-0,630	-0,161	-1,109	-0,452	DRY	DRY
269	-0,406	-0,061	-0,879	-0,464	WET	DRY
270	0,131	0,614	-0,264	0,034	WET	WET
271	1,176	1,081	0,329	0,808	WET	WET
272	0,807	0,610	0,014	0,143	DRY	WET
273	-1,230	-1,398	-0,790	-0,585	WET	DRY
274	0,747	-0,602	0,060	0,255	WET	WET
275	1,208	1,099	0,716	1,155	WET	WET
276	0,945	0,760	1,003	0,961	WET	WET
277	0,603	0,642	0,612	0,476	WET	WET
278	0,199	0,200	0,271	0,051	WET	WET
279	0,087	0,169	0,363	0,123	WET	WET
280	0,016	0,543	0,636	0,443	DRY	DRY
281	-0,511	-0,404	0,074	-0,193	DRY	DRY
282	-0,841	-0,468	-0,638	-0,485	DRY	DRY
283	-0,840	-0,613	-0,281	-0,072	WET	DRY
284	0,167	-0,027	0,153	0,499	WET	WET
285	0,570	-0,099	-0,152	0,275	DRY	WET
286	-1,713	-1,931	-1,920	-1,962	WET	DRY
287	1,847	0,199	0,592	1,187	WET	WET
288	0,965	-0,064	-0,110	0,154	WET	WET
289	1,358	0,188	0,372	0,753	WET	WET
290	1,194	0,050	0,253	0,676	WET	WET
291	1,202	-0,124	0,277	0,693	WET	WET
292	1,362	0,048	0,491	0,952	DRY	WET
293	-0,223	-0,868	-0,632	-0,487	DRY	DRY
294	0,512	-0,847	-0,163	0,232	DRY	DRY
295	-0,916	-1,326	-1,167	-1,035	DRY	DRY
296	-0,855	-1,349	-1,083	-1,127	DRY	DRY
297	-1,570	-1,510	-1,435	-1,582	DRY	DRY
298	-0,738	-1,054	-0,651	-1,127	WET	DRY
299	0,281	1,054	0,365	-0,268	DRY	WET
300	-0,333	0,486	-0,096	-0,588	WET	WET
301	0,123	0,929	0,160	-0,216	WET	WET
302	0,604	1,036	0,764	0,379	WET	WET
303	0,294	0,530	0,365	0,022	WET	WET
304	0,209	0,449	-0,120	-0,207	DRY	WET
305	-0,042	-0,479	-0,625	-0,400	DRY	DRY

306	0,416	-0,286	-0,293	-0,217	DRY	WET
307	-0,173	-1,061	-0,692	-0,649	DRY	DRY
308	-1,750	-1,595	-1,703	-1,782	DRY	DRY
309	-0,703	-0,735	-1,027	-0,997	DRY	DRY
310	-0,869	-1,185	-1,052	-0,859	DRY	DRY
311	-1,620	-1,760	-1,552	-1,696	DRY	DRY
312	-1,628	-1,375	-1,469	-1,605	DRY	DRY
313	-1,711	-1,358	-1,481	-1,775	DRY	DRY
314	-1,932	-1,561	-1,597	-1,849	DRY	DRY
315	-1,700	-0,745	-1,209	-1,687	DRY	DRY
316	-1,369	-0,147	-0,585	-1,230	DRY	DRY
317	-0,957	0,594	-0,346	-0,873	WET	DRY
318	-0,288	1,428	0,817	0,168	WET	DRY
319	0,601	1,770	1,376	1,096	WET	WET
320	1,427	2,088	1,589	1,356	WET	WET
321	1,115	1,578	1,154	1,111	WET	WET
322	-0,356	0,843	0,323	0,018	WET	WET
323	-0,637	-0,020	0,461	0,255	DRY	DRY
324	-1,203	-1,178	-0,415	-1,041	DRY	DRY
325	-1,225	-1,053	-1,048	-1,436	DRY	DRY
326	-0,838	-0,607	-0,519	-1,055	DRY	DRY
327	-0,295	0,290	0,016	-0,447	WET	WET
328	0,055	1,010	0,568	-0,039	WET	WET
329	0,521	1,094	1,071	0,315	WET	WET
330	1,155	1,456	1,258	0,662	WET	WET
331	1,970	1,689	1,996	1,744	WET	WET
332	1,823	1,542	1,767	1,651	WET	WET
333	1,003	0,674	1,386	0,959	WET	WET
334	0,967	0,027	1,235	1,036	WET	WET
335	0,545	1,109	1,025	0,665	WET	WET
336	0,230	0,569	0,639	0,548	DRY	WET
337	-0,634	0,162	-0,390	-0,637	DRY	DRY
338	-0,876	-0,273	-0,692	-0,993	DRY	DRY
339	-0,707	-0,531	-0,600	-0,739	DRY	DRY
340	-1,068	-0,941	-1,200	-1,266	DRY	DRY
341	-1,326	-1,691	-1,513	-1,456	DRY	DRY
342	-1,607	-1,967	-1,903	-1,800	DRY	DRY
343	-0,933	-2,078	-1,492	-1,084	DRY	DRY
344	-0,375	-1,834	-0,949	-0,520	DRY	DRY
345	-1,417	-1,917	-1,467	-1,411	DRY	DRY
346	-0,082	-0,537	-0,055	-0,104	WET	DRY
347	0,407	0,883	0,565	0,025	DRY	WET
348	-0,602	0,118	-0,122	-0,846	DRY	DRY
349	-1,223	-0,617	-0,869	-1,471	DRY	DRY
350	-1,217	-0,575	-0,880	-1,592	DRY	DRY

351	-1,283	-0,787	-0,878	-1,626	DRY	DRY
352	-1,541	-1,240	-1,417	-2,029	DRY	DRY
353	-1,904	-1,588	-1,609	-2,135	DRY	DRY
354	-1,687	-1,375	-1,400	-1,974	DRY	DRY
355	-1,063	-0,835	-0,652	-1,401	DRY	DRY
356	-1,333	-0,924	-0,722	-1,237	DRY	DRY
357	-1,339	-0,560	-0,400	-1,054	DRY	DRY
358	-0,565	-0,416	-0,050	-0,706	DRY	DRY
359	-1,195	-1,125	-0,847	-1,485	DRY	DRY
360	-1,275	-1,696	-0,722	-1,084	DRY	DRY
361	-1,439	-1,847	-1,029	-1,313	DRY	DRY
362	-1,648	-1,978	-0,956	-1,386	DRY	DRY
363	-1,768	-2,033	-1,341	-1,606	DRY	DRY
364	-1,653	-1,775	-0,956	-1,269	DRY	DRY
365	-1,367	-1,496	-0,732	-0,874	DRY	DRY
366	-1,319	-1,305	-1,023	-1,191	DRY	DRY
367	-0,860	-0,878	-0,088	-0,342	DRY	DRY
368	-0,296	-0,564	-0,162	-0,067	WET	DRY
369	0,486	-0,160	0,240	0,570	DRY	WET
370	-0,270	-0,930	-0,547	-0,064	DRY	DRY
371	-0,584	-0,978	-0,675	-0,643	WET	DRY
372	1,625	1,641	1,353	1,451	WET	WET
373	0,357	0,313	-0,080	-0,077	DRY	WET
374	-0,122	-0,186	-0,447	-0,652	DRY	DRY
375	0,251	0,129	-0,235	-0,247	DRY	WET
376	0,256	0,117	-0,302	-0,308	WET	WET
377	0,501	0,377	0,087	-0,032	DRY	WET
378	-1,782	-1,375	-1,601	-1,857	DRY	DRY
379	-0,558	-0,188	-0,341	-0,725	WET	DRY
380	0,702	0,512	0,214	0,349	DRY	WET
381	-0,717	-0,018	-0,171	-0,671	DRY	DRY
382	-1,470	-0,578	-0,599	-1,220	DRY	DRY
383	-0,076	-0,338	-0,678	-0,559	DRY	DRY
384	-0,533	-0,638	-0,951	-0,860	DRY	DRY
385	-0,313	-0,516	-0,936	-0,844	DRY	DRY
386	-0,452	-0,725	-1,169	-1,066	DRY	DRY
387	-0,275	-0,540	-1,019	-0,872	DRY	DRY
388	-0,035	-0,324	-0,817	-0,659	WET	DRY
389	0,087	0,351	0,015	-0,145	WET	WET
390	0,650	0,952	0,623	0,313	WET	WET
391	0,703	1,073	0,734	0,619	WET	WET
392	1,286	1,441	1,067	1,086	WET	WET
393	1,085	1,417	0,964	0,857	WET	WET
394	1,141	1,517	0,998	0,850	DRY	WET
395	-0,141	0,114	-0,162	-0,371	DRY	DRY

396	-1,240	-1,401	-1,515	-1,421	DRY	DRY
397	-0,988	-0,884	-1,120	-1,040	DRY	DRY
398	-1,001	-0,779	-0,839	-1,101	DRY	DRY
399	-1,100	-0,873	-0,841	-1,105	DRY	DRY
400	-1,298	-1,044	-0,978	-1,219	DRY	DRY
401	-1,316	-1,063	-1,136	-1,360	DRY	DRY
402	-0,769	-0,518	-0,599	-0,905	DRY	DRY
403	-1,095	-0,939	-0,797	-1,210	DRY	DRY
404	-1,182	-1,132	-0,783	-0,657	DRY	DRY
405	-1,161	-1,143	-0,903	-0,715	WET	DRY
406	1,874	1,044	1,068	1,545	WET	WET
407	2,000	2,026	1,654	1,883	WET	WET
408	1,567	1,602	1,467	1,361	WET	WET
409	0,813	0,749	0,898	0,611	WET	WET
410	0,287	0,115	0,190	-0,108	WET	WET
411	0,962	0,846	0,970	0,709	DRY	WET
412	0,017	-0,226	-0,078	-0,417	DRY	DRY
413	-0,617	-0,777	-0,507	-0,786	DRY	DRY
414	-0,587	-0,664	-0,314	-0,564	WET	DRY
415	0,455	0,078	0,552	0,306	WET	WET
416	1,667	0,915	1,186	1,201	DRY	WET
417	-0,291	-0,345	0,049	-0,503	DRY	DRY
418	-0,692	-0,578	-0,113	-0,603	WET	DRY
419	1,933	1,676	1,533	1,318	WET	WET
420	1,397	0,944	0,901	0,484	WET	WET
421	1,233	0,885	0,526	0,166	WET	WET
422	1,465	1,063	0,723	0,551	WET	WET
423	1,484	1,081	0,800	0,532	WET	WET
424	1,711	1,448	1,206	0,867	DRY	WET
425	0,320	-0,125	-0,279	-0,326	WET	WET
426	0,727	0,226	-0,048	0,099	WET	WET
427	0,758	0,113	-0,034	0,355	DRY	WET
428	-0,143	-0,293	-0,350	-0,381	DRY	DRY
429	-0,374	-0,520	-0,549	-0,417	DRY	DRY
430	-0,065	-0,621	-0,626	-0,408	DRY	DRY
431	-0,238	-0,410	-0,761	-0,869	WET	DRY
432	1,336	1,299	1,129	0,862	WET	WET
433	0,434	0,231	0,394	-0,036	DRY	WET
434	0,041	-0,249	-0,063	-0,507	DRY	DRY
435	0,236	0,008	0,031	-0,463	WET	WET
436	0,486	0,470	0,468	-0,052	WET	WET
437	0,875	0,874	1,028	0,496	DRY	WET
438	-0,528	0,268	0,231	-0,485	WET	WET
439	0,761	1,203	0,997	0,536	WET	WET
440	1,825	1,720	1,771	1,632	WET	WET

441	2,206	1,907	2,127	2,157	WET	WET
442	2,020	1,871	2,104	1,954	WET	WET
443	1,589	1,843	1,966	1,788	WET	WET
444	2,181	2,073	2,124	1,924	WET	WET
445	1,819	1,623	1,751	1,616	WET	WET
446	1,690	1,398	1,391	1,250	WET	WET
447	1,657	1,359	1,299	1,381	WET	WET
448	1,450	1,121	0,903	1,125	WET	WET
449	1,406	0,877	0,836	1,139	WET	WET
450	0,367	-0,017	0,069	0,646	WET	WET
451	0,667	0,262	0,414	0,771	WET	WET
452	0,853	0,457	0,475	1,076	WET	WET
453	0,327	0,056	-0,128	0,034	WET	WET
454	0,393	-0,074	-0,129	-0,089	WET	WET
455	0,455	0,234	-0,083	0,054	WET	WET
456	1,222	1,286	1,355	1,098	WET	WET
457	1,060	1,124	1,112	0,854	WET	WET
458	1,084	1,050	1,125	0,926	WET	WET
459	1,216	1,194	1,252	0,937	WET	WET
460	1,040	0,957	0,874	0,754	WET	WET
461	0,963	0,549	0,535	0,414	DRY	WET
462	0,241	0,051	-0,619	-0,501	DRY	WET
463	0,186	-0,015	-0,634	-0,612	WET	WET
464	0,400	-0,016	0,234	-0,069	WET	WET
465	0,746	0,025	0,712	0,427	WET	WET
466	0,155	-0,255	0,583	0,124	DRY	WET
467	-0,560	-0,421	0,384	-0,243	DRY	DRY
468	-1,277	-1,591	-0,847	-1,223	DRY	DRY

The validation set including SPEI values of G2, G3, G4, G5, observed and predicted one month ahead drought classes were presented in Table below.

Table 13. Validation Data Set Including Inputs and Outputs

# of Sample	G2	G3	G5	G6	Observed Class	Predicted Class
1	-1,786	-2,068	-1,369	-1,678	DRY	DRY
2	-2,288	-2,369	-2,321	-2,401	DRY	DRY
3	-2,370	-2,349	-2,502	-2,473	DRY	DRY
4	-2,153	-1,955	-2,051	-2,117	DRY	DRY
5	-1,696	-1,146	-1,155	-1,399	DRY	DRY
6	-1,452	-0,762	-0,710	-1,039	DRY	DRY
7	-0,411	0,264	0,119	-0,072	WET	WET
8	0,892	0,949	0,741	0,726	WET	WET
9	1,447	1,380	1,229	1,116	WET	WET
10	0,083	0,491	0,322	0,113	WET	WET
11	1,029	0,734	0,348	0,537	WET	WET
12	0,234	0,301	-0,158	-0,153	DRY	WET
13	0,083	-0,129	-0,482	-0,279	DRY	WET
14	-0,184	-0,398	-0,806	-0,599	DRY	DRY
15	-0,573	-0,971	-1,357	-1,022	DRY	DRY
16	-0,153	-0,507	-0,982	-0,634	DRY	DRY
17	-0,886	-0,776	-1,118	-1,016	DRY	DRY
18	-0,643	-0,739	-1,049	-0,845	DRY	DRY
19	-0,749	-0,442	-0,781	-0,837	DRY	DRY
20	-0,089	-0,023	-0,303	-0,248	WET	DRY
21	1,053	0,803	0,386	0,522	DRY	WET
22	-0,511	-0,302	-0,715	-0,730	WET	DRY
23	0,662	0,044	-0,248	0,170	WET	WET
24	1,559	1,737	1,579	1,699	WET	WET
25	0,593	0,804	0,829	0,734	WET	WET
26	0,024	0,224	0,312	0,119	DRY	DRY
27	-0,156	-0,061	0,147	-0,022	WET	DRY
28	0,408	0,767	1,203	0,864	WET	WET
29	-0,309	0,052	0,416	0,120	DRY	DRY
30	-1,848	-1,460	-1,335	-1,634	DRY	DRY
31	-1,183	-0,798	-0,518	-0,843	WET	DRY
32	0,222	-0,031	0,490	0,452	WET	WET
33	0,907	0,366	0,848	0,874	DRY	WET
34	-0,664	-1,007	-0,637	-0,873	DRY	DRY

35	-0,806	-1,110	-0,719	-0,938	WET	DRY
36	1,259	0,977	0,974	0,768	WET	WET
37	1,443	1,082	0,902	0,610	WET	WET
38	1,272	1,104	0,824	0,598	WET	WET
39	1,333	1,152	0,813	0,564	WET	WET
40	1,779	1,876	1,767	1,419	WET	WET
41	2,164	2,165	2,120	1,814	WET	WET
42	1,651	1,643	1,700	1,505	WET	WET
43	1,392	1,593	1,687	1,730	WET	WET
44	1,852	1,607	1,700	1,830	WET	WET
45	1,996	1,706	1,772	1,924	WET	WET
46	0,103	0,406	0,207	0,489	DRY	WET
47	-1,184	-1,245	-1,278	-1,132	WET	DRY
48	1,025	0,992	1,006	0,821	WET	WET
49	1,887	1,926	1,664	1,809	WET	WET
50	1,551	1,549	1,432	1,500	WET	WET
51	1,318	1,154	1,041	1,225	WET	WET
52	1,486	1,377	1,372	1,390	WET	WET
53	1,790	1,405	1,486	1,575	WET	WET
54	0,932	0,706	0,362	0,789	DRY	WET
55	-1,631	-0,897	-1,148	-1,522	DRY	DRY
56	-1,141	-0,526	-0,699	-1,078	DRY	DRY
57	-0,287	0,193	-0,107	-0,428	DRY	WET
58	-1,075	-0,432	-0,903	-1,222	DRY	DRY
59	-0,356	0,101	-0,361	-0,719	DRY	DRY
60	-0,743	-1,014	-1,267	-1,318	DRY	DRY
61	0,302	-0,138	-0,426	-0,320	DRY	WET
62	0,156	-0,328	-0,664	-0,317	DRY	WET
63	-0,094	-0,654	-0,889	-0,528	DRY	DRY
64	-0,017	-0,614	-0,821	-0,388	DRY	DRY
65	0,108	-0,382	-0,619	-0,218	WET	WET
66	0,572	0,171	-0,154	0,362	DRY	WET
67	-0,937	-0,609	-0,775	-0,464	DRY	DRY
68	-0,819	-0,337	-0,574	-0,547	WET	DRY
69	0,386	0,412	0,327	0,441	WET	WET
70	0,225	0,458	0,409	0,284	WET	WET
71	-0,092	0,117	0,315	-0,022	DRY	DRY
72	-0,852	-0,950	-0,524	-0,882	DRY	DRY
73	-0,316	-0,623	-0,478	-0,684	DRY	DRY
74	-0,613	-0,894	-0,686	-0,985	DRY	DRY

75	-0,760	-1,059	-0,970	-1,024	DRY	DRY
76	-0,366	-0,619	-0,407	-0,630	DRY	DRY
77	-0,535	-0,891	-0,859	-0,852	WET	DRY
78	0,157	-0,093	0,059	-0,069	DRY	WET
79	-0,546	-0,294	-0,095	-0,233	WET	DRY
80	0,524	0,208	0,791	0,904	WET	WET
81	1,213	0,670	1,247	1,090	WET	WET
82	1,933	1,509	1,808	1,968	WET	WET
83	1,528	1,872	2,099	2,199	WET	WET
84	0,125	0,173	0,927	0,940	DRY	WET
85	-0,477	-0,569	0,347	0,499	DRY	DRY
86	-0,528	-0,439	-0,099	0,127	DRY	DRY
87	-0,867	-0,886	-0,679	-0,364	DRY	DRY
88	-1,756	-1,906	-1,952	-1,654	DRY	DRY
89	-1,958	-1,905	-2,307	-2,099	DRY	DRY
90	-1,535	-1,594	-2,037	-1,648	DRY	DRY
91	-1,221	-1,140	-2,017	-1,837	DRY	DRY
92	-1,711	-1,446	-1,932	-1,847	DRY	DRY
93	-1,759	-1,273	-1,950	-1,836	DRY	DRY
94	-1,248	-1,059	-1,499	-1,389	DRY	DRY
95	-0,896	-0,908	-0,680	-0,359	DRY	DRY
96	-0,578	-0,364	-0,234	-0,171	DRY	DRY
97	-1,440	-1,366	-1,045	-1,134	DRY	DRY
98	-1,951	-1,831	-1,508	-1,679	DRY	DRY
99	-1,929	-1,756	-1,421	-1,679	DRY	DRY
100	-1,947	-1,765	-1,400	-1,652	DRY	DRY
101	-2,015	-1,849	-1,742	-2,070	DRY	DRY
102	-2,483	-2,473	-2,384	-2,591	DRY	DRY
103	-2,046	-1,839	-1,972	-2,264	DRY	DRY
104	-0,925	-1,202	-0,866	-0,953	DRY	DRY
105	0,070	-0,827	-0,348	-0,223	DRY	DRY
106	-0,712	-1,199	-0,674	-0,604	DRY	DRY
107	-1,115	-1,330	-0,662	-0,353	DRY	DRY
108	-1,700	-1,456	-0,982	-1,249	DRY	DRY
109	-1,655	-1,335	-0,757	-0,868	DRY	DRY
110	-1,407	-0,855	-0,607	-0,803	DRY	DRY
111	-1,632	-1,156	-1,047	-1,114	DRY	DRY
112	-1,409	-0,809	-0,589	-0,835	DRY	DRY
113	-0,877	-0,051	0,212	-0,341	WET	DRY
114	-0,072	0,445	0,645	0,512	WET	WET

115	0,635	0,703	0,767	0,576	WET	WET
116	0,089	0,302	0,244	0,167	WET	WET
117	1,306	0,982	1,007	0,944	WET	WET
118	0,822	0,741	0,508	0,518	DRY	WET
119	-0,619	-0,281	-0,390	-0,442	WET	DRY
120	1,555	1,805	1,601	1,516	WET	WET
121	1,606	1,839	1,621	1,394	WET	WET
122	1,814	1,899	1,811	1,706	WET	WET
123	1,489	1,434	1,365	1,367	WET	WET
124	1,437	1,301	1,356	1,361	WET	WET
125	1,771	1,248	1,266	1,408	WET	WET
126	0,615	0,215	0,285	0,489	DRY	WET
127	-0,023	-0,260	-0,108	0,367	DRY	DRY
128	-1,562	-0,897	-0,871	-0,907	DRY	DRY
129	-0,613	-0,171	-0,253	-0,095	WET	DRY
130	0,089	0,284	0,415	0,632	DRY	WET
131	-1,046	-0,525	-0,214	-0,149	DRY	DRY
132	-1,413	-1,070	-0,688	-0,823	DRY	DRY
133	-1,717	-1,428	-1,041	-1,330	DRY	DRY
134	-1,819	-1,358	-0,907	-1,398	DRY	DRY
135	-1,574	-1,103	-0,621	-1,254	DRY	DRY
136	-1,286	-0,519	-0,028	-1,041	WET	DRY
137	-0,629	0,347	0,916	-0,253	WET	WET
138	-0,035	1,014	1,549	0,341	WET	WET
139	1,239	1,623	1,983	1,309	WET	WET
140	1,780	1,765	2,055	1,634	WET	WET
141	2,146	1,972	2,174	1,913	WET	WET
142	1,319	1,396	1,513	1,273	WET	WET
143	-0,122	0,430	0,463	-0,054	DRY	WET
144	-0,934	-0,802	-1,034	-1,234	DRY	DRY
145	-0,482	-0,052	-0,183	-0,374	DRY	DRY
146	-0,504	-0,080	-0,079	-0,262	DRY	DRY
147	-0,917	-0,576	-0,737	-0,830	DRY	DRY
148	-0,993	-0,674	-0,959	-0,934	DRY	DRY
149	-0,478	-0,018	-0,206	-0,112	WET	DRY
150	0,150	0,709	0,672	0,689	DRY	WET
151	-0,299	0,190	-0,039	0,021	WET	WET
152	-0,079	0,321	0,220	0,260	WET	WET
153	0,596	0,729	0,648	0,890	WET	WET
154	0,909	1,016	0,959	1,020	WET	WET

155	-0,293	0,228	0,289	-0,052	DRY	WET
156	-0,353	0,013	0,025	-0,380	WET	DRY
157	0,181	0,333	0,365	-0,040	WET	WET
158	0,029	0,155	0,114	-0,115	DRY	DRY
159	-0,326	-0,288	-0,303	-0,519	DRY	DRY
160	-0,139	0,083	0,141	-0,247	WET	DRY
161	0,436	0,738	0,768	0,378	WET	WET
162	0,549	0,656	0,692	0,516	WET	WET
163	-0,119	0,419	0,413	0,345	WET	WET
164	0,313	0,721	0,530	0,360	WET	WET
165	1,609	1,411	1,261	1,239	WET	WET
166	0,977	0,808	0,634	1,113	DRY	WET
167	-0,018	-0,586	-0,261	0,677	DRY	DRY
168	-1,120	-1,304	-1,110	-0,501	DRY	DRY
169	-1,048	-1,086	-0,430	-0,469	DRY	DRY
170	-1,519	-1,508	-0,913	-1,023	DRY	DRY
171	-1,068	-0,968	-0,479	-0,608	DRY	DRY
172	-1,292	-1,161	-0,819	-1,103	DRY	DRY
173	-0,900	-0,268	-0,002	-0,585	WET	DRY
174	-0,040	0,604	0,972	0,284	WET	WET
175	0,316	0,741	0,613	0,509	WET	WET
176	1,707	1,404	1,408	1,597	WET	WET
177	1,176	1,082	1,076	1,296	WET	WET
178	1,452	1,447	1,546	1,508	WET	WET
179	0,885	0,777	1,262	0,941	WET	WET
180	0,908	0,869	1,277	1,048	WET	WET
181	0,984	1,062	1,312	1,189	WET	WET
182	0,990	1,083	1,256	1,038	WET	WET
183	1,054	1,243	1,468	1,203	WET	WET
184	0,845	0,945	0,998	0,913	WET	WET
185	0,811	0,671	0,728	0,839	WET	WET
186	0,834	0,828	1,067	0,967	WET	WET
187	0,628	0,548	0,907	0,644	WET	WET
188	0,528	0,470	0,595	0,589	WET	WET
189	0,966	0,450	0,826	0,606	WET	WET
190	1,069	0,786	1,102	0,765	WET	WET
191	0,672	0,871	0,940	0,464	DRY	WET