Flood and Drought Prediction Using the Machine Learning Algorithm Support Vector Regression

K. Sangeetha, K. Mohan Kumar

Abstract*: Flood and drought are frequently happening natural disasters in most of the countries. These disasters can cause considerable damage to agriculture, ecology and economy of the country. Mitigating the impacts of flood and drought is a valuable help to the human being. The main cause of these disasters is precipitation. If the past precipitation data are analyzed properly, the future flood and drought events can be easily found. Prediction using the Standard Precipitation Index (SPI) is a way to find the wet or dry condition of a region or country. In this paper the SPI values with different lead times are calculated for a long period of time. These SPI indices are analysed by a predictive model using the machine learning algorithm called Support Vector Regression (SVR) with RBF (Radial Basis Function) kernel. In this model the Grid Search approach is used for optimization. The forecast result of this predictive model shows the predictive skill of the SVR-RBF kernel.

***Keywords* : Flood and drought, Support Vector Regression, SPI**

I. INTRODUCTION

The support vector regression is one of the machine learning algorithms which has the capability to forecast the time series for non linear, non stationary data perfectly. The support vector regression model integrates the various drought indices and builds the SVR model to predict the meteorological drought [1].

Flood and drought are the recurring innate calamities in the World, caused by the high and lack of precipitation and lead direct and indirect economic loses. Flood and drought assessment and consciousness are very important to manage the water resources in future. The flood and drought definitions vary from region to region based on the precipitation. Various indicators are used to asses and predict the flood and drought. Calculating the Standard Precipitation Index (SPI) values for a period and analyzing through SVR model is a way to predict flood and draught events [2].

The foremost objective of this research is to evaluate the performance of the drought indicator Standard Precipitation Index (SPI) in the flood and drought forecasting at different lead time using the SVR with the RBF kernel grid search method. In this paper section II summarize review of the SVR related prediction system. Section III provides the background theory such as SVR, SPI computations. Section IV explains how the algorithm employed in the prediction methodology. Section V includes the result and discussion and section VI gives the conclusion of this work.

II. REVIEW OF RELATED PREDICTION SYSTEM

Many researchers have performed disaster prediction using various machine learning algorithms with drought indicators in different way. The measurement and forecast of drought are based on some models and methods such as hydrological and data-driven [3].

Ganguli.P et al. proposed the Support Vector Machine (SVM) is mainly used for the classification, regression (SVR) in the field of hydrology for the forecasting of drought. In SVR based drought model the prediction system used different SPI lead time [4].

T. B. Trafalis et al. and N. I. Sapankevych et al. explained the Support Vector Regression (SVR) and Least Squares (LS) SVR methodologies to forecast the rainfall with the use of WSR-88D radar data. The polynomial kernel used by LS-SVR give more accurate result when compared to linear regression technique and Gaussian RBF kennel under mean square error [1, 5, 18].

H.prem et al. and N. I. Sapankevych et al. applied Support Vector Regression (SVR) in weather prediction. SVR is compared with other methods, it produce the best forecast with minimum processing time and least network bandwidth [6, 18]. Belayneh. A et.al forecast the drought with SPI using the Support vector Regression, Neural network algorithm such as wavelet Neural Network. Most of the Support Vector Regression (SVR) models used the kernel of Radial Basis Function (RBF) with different parameters based on trial and error procedure [7,17].

Chaitaly Hemant et al. proposed various drought indices used to forecast drought with the use of different machine learning methods and computational models. The appropriate selection of indicators can assist in signifying the aridness more accurately than the usual methods [8]. Zhenchen Liu et.al build the predictor SPI3 relationship with the forecast dataset then simulate and predict seasonal drought process in China [9].

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Sujitha et al suggested Standard Precipitation Index (SPI) is a important tool for measure the spatial inconsistency of aridness and humidity due to its capability to represent rainfall variance. They applied SPI to spot the happening of drought and flood years and to notify the trends of dry and wet condition in Trichy over 30 years and conclude SPI can effectively represent the quantity of precipitation over a given time range[10].

All related prediction systems are using the SVR with various approaches. This research work used the SVR with grid search approach, also developed the flood and drought prediction model based on the precipitation data.

III. THEORETICAL CONCEPTS

A. Support Vector Regression(SVR)

By means of Support Vector Regression (SVR) the precipitation data which is given is transferred to an elevated dimensional attribute space through non linear or linear mapping. In the support vector machine (SVM) the application of SVR plays a vital role. The Fig.1 explains the proposal of Support Vector Regression (SVR) on predicting future data. Towards achieving the function $f(x)$ in every training data through ε deviation at the most when compared to y_i actual target value is the main goal for SVR. The equation (1) gives the linear function f. target pairs and input collection takes places in Training data, $\{(x_1, y_1), (x_i, y_i)\} \subset X \times R$.[11]

$$f(x) = (w, x) + b \qquad (1)$$

The function $f(x)$ in the hyper plane is, the symbol (·, ·) comes under the dot product in X and the ε size denotes the margin, where w ϵ X and b ϵ R respectively. The SVR value is taken from the small margin in the hyper plane and it is used for the purpose of findings. With the aid of small margins all the data can be devious till it is possible [11]. The calculation for margin is able to be attained from the equation (2).

Minimize $\frac{1}{2}||w||^2$ Subject to

$$\begin{cases} y_i - (w, x_i) + b \;\; x \leq \varepsilon \\ (w, x_i) + b - y_i \leq \varepsilon \end{cases} \qquad (2)$$

The perfect assumption from equation (2) is as the f function which helps to approximates every target pairs (x_i, y_i) and input with certain accuracy. With the assist of slack variables ξ_i, ξ_i^* the problems that were created can be described as soon as all the data that can't stay within the margin [11] and it is represented in equation (3).

Minimize $\frac{1}{2}||w||^2 + c\sum_{i=1}^{N}(\xi_i + \xi_i^*)$

Subject to $\begin{cases} y_i - (w, x_i) + b \;\; x \leq \varepsilon + \xi_i \\ (w, x_i) + b - y_i \leq \varepsilon + \xi_i \end{cases}$ (3)

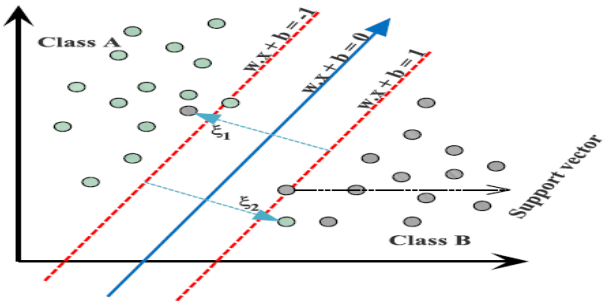

Fig.1. A Support Vector Regression

The kernel selection is one of the important functions in the SVR. The non-stationary and non-linear time series data, the appropriate kernel function for the prediction problem has taken based upon the attributes of the dataset. The different types of the kernels in SVR are Gaussian kernel, linear kernel, Radial Basis Function kernel and polynomial kernel [12].

B. Drought Indicators

Numbers of drought indicators are available in hydrological research papers. They are mostly based on hydrological and meteorological parameters. The selection of an indicator is depends on region, available data and the ability of a method to estimate in the greatest possible way of happening the drought in time and space.

Standard Precipitation Index (SPI): The American scientists Does ken, McKee and Kleist designed the SPI. SPI is dominant, supple index and it is simple to estimate in multiple time scales and also used to find the wet conditions of the region. The precipitation data is the essential input limit for the purpose of evaluating the SPI. Through the software package (SPI_SL_6.exe) the SPI can be estimated. The first step of this calculation is fitting of gamma distribution function with the rainfall data. In the upcoming step the estimated data is changed to normal distribution function in order to obtain mean standard precipitation index as zero [13, 14, 19]. The values of SPI are calculated by means of long-term (12, 18 and 24 months), short-term (1 and 3 months) and medium term (6 and 9 months) using forecasting. Through rainfall record in a specified period for every region the SPI can be calculated. The specified data for rainfall is further inserted into probability distribution function which is the next function. After that to the normal distribution the output is transferred and the mean SPI value in preferred period and region was zero [15].The following Table I represent the SPI drought classes.

Table- I: Drought classification based on SPI [13]

SPI VALUES	CLASS
>2	Extremely wet
1.5 to 1.99	Very wet
1.0 to 1.49	Moderately wet
-0.99 to 0.99	Near normal
-1 to -1.49	Moderately dry
-1.5 to -1.99	Very dry
< -2	Extremely dry

IV. PREDICTION METHODOLOGIES

This section explains how the SVR prediction model perform with the Standard Precipitation Index (SPI) values are calculated from the past precipitation data of India with different lead time and forecast the SPI for future.SVR Grid search approach is used for optimization. These concepts are implemented via PYTHON coding.

A. Precipitation Data and Study Area

Through Indian Institute of Tropical Meteorology (IITM) the data for monthly rainfall in India was obtained. Data base consists of the region wise precipitation data which includes south peninsular India, central India, Northwest India and Northeast India. The data set for the regions of period 1900 to 2016 is taken for the prediction process [16]. The following Table II shows the rainfall data of central India. Table III shows the SPI values of central India computed using the data in Table II.

Table- II: Central India Rainfall (mm)

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	DEC
1900	42	8	6	24	43	154	263	308	313	64	0	19
1901	57	47	10	16	40	44	242	351	180	27	31	2
1902	4	2	10	31	41	69	394	237	246	20	4	8
1903	14	7	4	15	36	114	205	312	217	229	9	3
1904	5	7	20	5	72	236	371	335	124	58	9	13
1905	25	28	40	22	52	41	316	301	261	13	0	2
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2013	7	41	3	27	46	274	270	258	149	236	1	2
2014	27	39	19	5	67	83	314	245	169	68	1	6
2015	23	4	35	40	23	154	262	222	104	16	2	8
2016	6	6	11	3	61	119	329	254	216	53	4	0

Table- III: SPI values - Central India

Year	Month	SPI 1	SPI 3	SPI 6	SPI 12
1900	1	1.59	-99	-99	-99
1900	2	-0.57	-99	-99	-99
1900	3	-0.48	0.4	-99	-99
1900	4	0.76	-0.33	-99	-99
1900	5	0.3	0.18	-99	-99
1900	6	0.11	0.23	0.29	-99
1900	7	-0.75	-0.49	-0.61	-99
1900	8	0.01	-0.51	-0.45	-99
1900	9	1.77	0.54	0.51	-99
1900	10	0.08	0.99	0.36	-99
1900	11	-1.4	1.03	0.24	-99
1900	12	1.51	0.03	0.39	0.45
1901	1	2.12	1.61	1.35	0.54
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.
2010	12	1.28	0.4	-0.76	-1.43

The following Table IV shows the rainfall data of Northeast India. Table V shows the SPI values of Northeast India computed using the data in Table IV.

Table- IV: Northeast India Rainfall (mm)

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	DEC
1900	7	42	83	164	200	345	389	227	298	66	5	6
1901	25	27	20	148	130	381	331	366	283	143	87	1
1902	3	5	60	227	204	407	387	368	363	96	9	5
1903	14	28	84	62	131	435	275	409	286	165	42	0
1904	5	43	40	273	247	330	404	367	228	93	47	3
1905	17	31	146	129	199	311	438	532	270	179	7	16
.	.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.	.
2013	1	12	31	110	339	281	321	332	257	193	1	1
2014	1	31	25	37	231	306	288	378	304	44	2	0
2015	14	13	31	201	209	383	370	410	239	59	8	9
2016	14	28	53	185	241	294	370	266	260	105	40	3

Table- V: SPI values - Northeast India

Year	Month	SPI 1	SPI 3	SPI 6	SPI 12
1900	1	-0.42	-99	-99	-99
1900	2	0.82	-99	-99	-99
1900	3	0.8	0.78	-99	-99
1900	4	0.72	1.07	-99	-99
1900	5	-0.5	0.34	-99	-99
1900	6	-0.5	-0.31	-0.01	-99
1900	7	-0.14	-0.7	-0.05	-99
1900	8	-2.37	-1.6	-1.02	-99
1900	9	0.46	-1.15	-1.02	-99
1900	10	-1.4	-2.07	-1.68	-99
1900	11	-1.13	-0.92	-1.81	-99
1900	12	0.07	-1.77	-1.81	-1.3
1901	1	0.99	-0.4	-2.09	-1.18
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.
2010	12	1.36	-0.15	-1.36	-0.28

The following Table VI shows the rainfall data of Northwest India. Table VII shows the SPI values of Northwest India computed using the data in Table VI.

Table- VI: Northwest India Rainfall (mm)

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	DEC
1900	5	1	1	12	12	9	133	290	161	1	2	10
1901	14	9	4	1	9	15	131	108	9	5	0	1
1902	1	0	1	2	8	37	131	125	130	7	0	2
1903	4	1	7	0	9	12	249	141	106	6	0	1
1904	5	5	27	0	16	29	126	100	56	2	5	10
1905	11	9	4	2	1	11	174	19	64	0	0	2
.	.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.	.
2013	8	23	4	11	4	112	239	203	147	25	1	1
2014	14	7	8	8	14	19	161	129	125	3	1	3
2015	7	4	38	18	8	86	252	72	52	3	0	0
2016	1	1	8	0	8	43	177	238	38	28	0	0

Table- VII: SPI values – Northwest India

Year	Month	SPI 1	SPI 3	SPI 6	SPI 12
1900	1	-0.03	-99	-99	-99
1900	2	-0.83	-99	-99	-99
1900	3	-0.66	-1.06	-99	-99
1900	4	1.47	-0.04	-99	-99
1900	5	0.44	0.51	-99	-99
1900	6	-1.96	-1.08	-1.46	-99
1900	7	-0.6	-1.35	-1.41	-99
1900	8	1.52	0.31	0.35	-99
1900	9	1.21	1.14	0.84	-99
1900	10	-0.77	1.61	0.7	-99
1900	11	0.17	0.98	0.68	-99
1900	12	1.2	-0.16	1.05	0.68
1901	1	1.19	0.98	1.7	0.76
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.
2010	12	0.82	1.61	1.69	1.47

The following Table VIII shows the rainfall data of South peninsular India. Table IX shows the SPI values of South peninsular India computed using the data in Table VIII.

Table- VIII: South peninsular India Rainfall (mm)

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	DEC
1900	8	1	1	76	49	175	226	128	167	142	57	32
1901	14	55	10	35	67	178	157	114	149	138	181	56
1902	23	4	15	27	64	129	231	147	190	265	110	97
1903	12	3	0	14	124	160	254	182	220	170	222	85
1904	20	0	5	22	125	204	186	85	95	175	10	23
1905	3	10	19	35	84	171	113	180	86	204	54	2
.	.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.	.
2013	4	27	20	24	64	215	206	151	179	191	86	18
2014	4	4	12	24	119	111	182	215	136	195	67	33
2015	4	1	21	86	94	181	107	134	154	121	269	62
2016	3	2	5	7	107	197	157	94	103	52	23	43

Table- IX: SPI values – South peninsular India

Year	Month	SPI 1	SPI 3	SPI 6	SPI 12
1900	1	0	-99	-99	-99
1900	2	-0.8	-99	-99	-99
1900	3	-1.5	-1.14	-99	-99
1900	4	1.64	0.63	-99	-99
1900	5	-0.91	-0.21	-99	-99
1900	6	0.4	0.24	-0.21	-99
1900	7	0.76	0.14	0.34	-99
1900	8	-0.68	0.22	0.02	-99
1900	9	0.49	0.28	0.33	-99
1900	10	-0.58	-0.6	-0.37	-99
1900	11	-1.01	-0.96	-0.62	-99
1900	12	-0.03	-1.34	-0.81	-0.88
1901	1	0.45	-1.01	-1.23	-0.81
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.
2010	12	1.09	2.06	2.66	2.82

The following Fig.2 depicts step-by-step process of the proposed predictive model. The Region wise precipitation data was preprocessed and calculate the SPI values. All the values should be calibrated and validated using model performance measures and finally select the suitable prediction model.

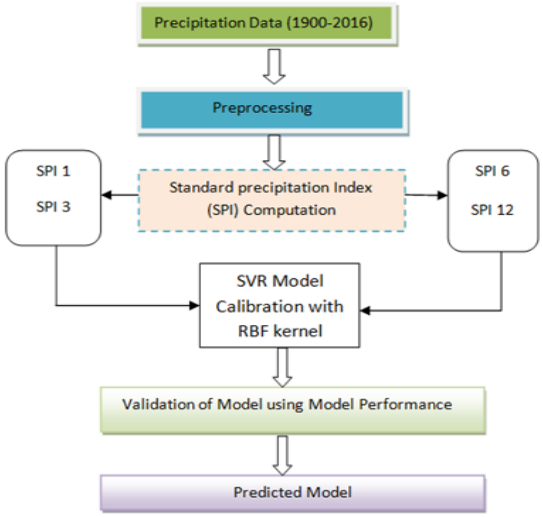

Fig. 2.Prediction Process Model

B. SVR-RBF Kernel

Support Vector Regression (SVR) comes under the kernel functions which are nonlinear radical basis function (RBF) kernel. In the SVR model the three parameters are contained which is defined as epsilon (ε), gamma (ɤ) and cost (C). The Parameter tuning is one of the important aspects in grid search approach which produce the model with each combination of the algorithm parameters. The ε parameter was constant which helps in result complexity and diminishes the model space. Cost C denotes the positive constant and as well as referred to a capacity control parameter. The loss function is represented as gamma (ɤ). It also explains every input data which is regression vector limited. By means of trial and error method the three parameters were chosen. The parameters are grouped and the parameter that gains the least MSE values in calibration data set is chosen as the prediction model. [7, 17].

C. Performance Measures

The evaluation of the performance and accuracy of the prediction system is one of the important things.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(\overline{y_i} - y_i)^2 \qquad (4)$$

Where, MSE denotes mean squared error, N denotes the number of samples, y_i denotes the observed value, and $\overline{y_i}$ denotes the forecasted value. This performance trial provides necessary information regarding the prediction accuracy of the prediction system.

V. RESULTS AND DISCUSSION

Under the section, the results of forecast for the accurate prediction models at each Indian region are presented. In this research to build the SVR model using the grid search approach for the various C and ɤ values with three RBF kernels such as RBF 1, RBF 2 and RBF 3.Value of ε is constantly taken as 0.1. The best combination of the C and ɤ parameter values which can generate the least MSE value is chosen to set the drought prediction model. The prediction model should be developed using the drought indicator SPI 12, SPI 6, SPI 3, and SPI 1 are

trained with different C and ɤ values. The Table X, below summarize the best c, ɤ, ε values which give the minimum MSE value for each region with different RBF kernels.

Table- X:
performance measures with best c, ɤ, ε parameters with RBF 1

Region	Drought Indicators	c	ɤ	ε	MSE
Central India	SPI 1	0.92	0.0094	0.1	0.94
Northeast India		0.9	0.00831	0.1	0.96
Northwest India		0.91	0.0072	0.1	0.93
South Peninsular India		0.9	0.0028	0.1	0.99
Central India	SPI 3	0.9	0.00098	0.1	**0.93**
Northeast India		0.9	0.0021	0.1	0.96
Northwest India		0.91	0.0002	0.1	**0.90**
South Peninsular India		0.9	0.0028	0.1	0.99
Central India	SPI 6	1.07	0.003	0.1	0.96
Northeast India		0.9	0.00091	0.1	1.02
Northwest India		0.91	0.0046	0.1	0.98
South Peninsular India		0.9	0.0009	0.1	**0.94**
Central India	SPI 12	1.01	0.004	0.1	0.96
Northeast India		0.91	0.0009	0.1	**0.93**
Northwest India		0.92	0.0031	0.1	0.95
South Peninsular India		0.9	0.0008	0.1	0.97

In the above Table X, some least MSE values are highlighted based on the accuracy of SPI indicators compare with the four regions. The forecast results show that the MSE values of SPI 3(0.93 &0.90) are notably better than SPI1, SPI 6 and SPI 12 indicators in the central India and northwest Indian region. The following Fig.3 and Fig.4 illustrate the prediction results of central India and Northwest India in near future using the SPI indicator with 3 month lead time. The Figure 3 shows that the SPI values above the 0, represents the wet level and below 0, represents the dry climate level of central India. The severity of flood and drought is recognized on the basics of values of SPI given in Table I. RBF 1 prediction produces the accurate result in central India and Northwest India. The Fig. 3 showed the Prediction result of Central India and Fig. 4 shown the Prediction result of Northwest India. These figures show the prediction of flood in 2019 accurately.

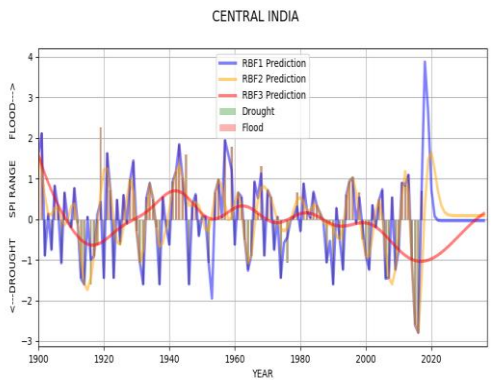

Fig. 3.Prediction result of Central India

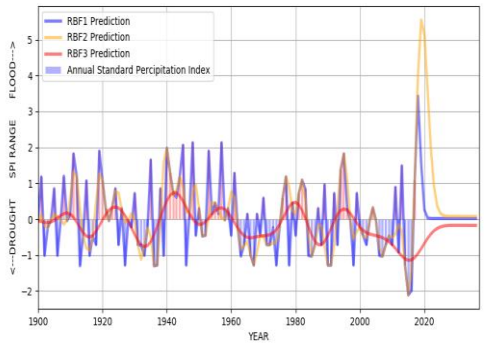

Fig. 4. Prediction result of Northwest India

From the Table X the forecast result of SPI 6 gives the least MSE values in South Peninsular region that is 0.94. The following Fig. 5 illustrates the prediction results of South Peninsular region in near future using the SPI indicator with 6 month lead time. The RBF kernel 1 produces the most accurate prediction level of this region.

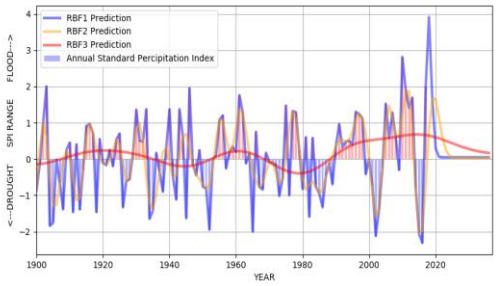

Fig. 5. Prediction result of south peninsular India

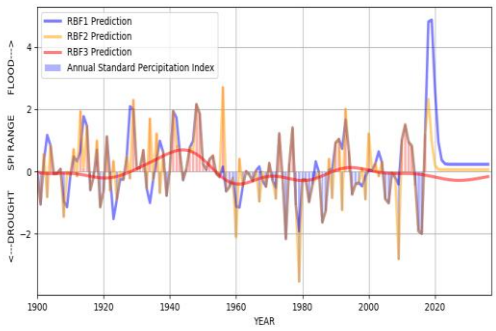

Fig. 6.Prediction result of Northeast India

In Northeast India SPI with 12 month lead time gives the minimum MSE value of 0.93. The Fig.6 shows the prediction result of Northeast India. Prediction results based on the Fig.6 shows the flood level in 2019 accurately and also shows the flood levels in near future.

VI. CONCLUSION

Flood and drought forecasting is a most important activity to regulate water management. In this research work a prediction model is constructed using SVR with RBF kernel. The results of this model show that the predictable data is in non-linear form. The Standard Precipitation Index (SPI) with different lead time gives more accurate result for the flood and drought prediction of various Indian regions using precipitation data. The results show that the grid search approach of SVR model is an effective and flexible approach in flood and drought prediction.

REFERENCES

1. Nicholas I.Saankevych, Ravi Sankar, "Time Seies Prediction Using Support Vector Machines:A Survey",IEEE Computational Intelligence Magazine, pp. 25-38, May 2009.
2. L.Shah, T.M.V.Suryanarayana, F.P.Parekh "Use of SPI and Rainfall Deciles for Drought Assessment", International Journal for Scientific Research & Development , Vol. 5, No. 2, pp. 1378-1382, 2017.
3. Ye Tian,Yue-Ping XU,Guoqing Wang, "Agricultural Drought Prediction Using Climate indices based on Regression in Xiangjiang River basin", Science of Total Environment622-623,Elesvier , pp. 710-720, 2018.
4. Ganguli.P,Reddy.M, "Ensemble prediction of regional droughts using climate inputs and the SVM-coupla approach",Hydrol.process28(19), pp. 4989-5009, 2014.
5. T. B. Trafalis, B. Santosa, and M. B. Richman, "Prediction of rainfall from WSR88D radar using kernel-based methods," Int. J. Smart Eng. Syst. Design, vol. 5, no. 4, pp. 429–438, Oct.–Dec. 2003.
6. H. Prem and N. R. Srinivasa Raghavan, "A support vector machine based approach for forecasting of network weather services," J. Grid Computing, vol. 4, no. 1, pp. 89–114, Mar. 2006.
7. Belayneh A, Adamowski J, "Standard Precipitation Index drought forecasting using neural networks, wavelet neural networks, and support vector regression", Applied Computational Intelligence and Soft Computing, Article ID 794061,(13 pages) ,2012.
8. Chaitaly Hemant Joshi, Seema Jagtap, "Calculation of Drought Index for Drought Forecasting", International Journal of Advances in Engineering & Technology, vol. 5, no. 3, pp. 25–28, 2017.
9. ZhenchenLiu,GuihuaLu,HaiHe1,ZhiyongWu,and jianHe, " A conceptual prediction model for seasonal drought processes using atmospheric and oceanic standardized anomalies: application to regional drought process in China", Hydrology and Earth System Science, vol. 22, pp. 529–546, 2018.
10. Sujitha E and Shanmugasundaram K, "Analysis of dry/wet conditions using the Standardized Precipitation Index and its potential usefulness for drought /flood monitoring in the regions of Trichy" , Journal of Pharmacognosy and Phytochemistry 2017; 6(4): 452-457
11. Ratiporn Chanklan, Nuntawut Kaoungku, Keerachart Suksut, Kittisak Kerdprasop, and Nittaya Kerdprasop, "Runoff Prediction with a Combined Artificial Neural Network and Support Vector Regression", International Journal of Machine Learning and Computing, Vol. 8, No. 1, pp. 39-43,2018.
12. Sathish T., "GAC-ANN Technique for Prediction of Spring Back Effect in Wipe Bending Process of Sheet Metal", Materials Today: Proceedings 2018; 5 (6): 14448 -14457.
13. T. B. McKee, N. J. Doesken, and J. Kleist, "The relationship of drought frequency and duration to time scales," In:cProceedings of the 8th Conference on Applied Climatology, American Meteorological Society, Anaheim, California, USA, pp. 179-184,1993.
14. Standardized Precipitation Index User Guide, World Meteorological Organization, pp.1-24, 2012.
15. Edwards, D. C. and T. B. McKee, " Characteristics of 20th century drought in the United States at multiple time scales". Climatology Report 97-2, Department of Atmospheric Science, Colorado State University, Fort Collins, Colorado,1997.
16. https://tropmet.res.in
17. A. Belayneh, J. Adamowski, B. Khalil, "Short-term SPI drought forecasting in the Awash River Basin in Ethiopia using wavelet transforms and machine learning methods", Sustain. Water Resour. Manag. , Vol 2, pp. 87–101, 2016.
18. N. I. Sapankevych and R. Sankar, "Time Series Prediction Using Support Vector Machines: A Survey," in IEEE Computational Intelligence Magazine, vol. 4, no. 2, pp. 24-38, May 2009. doi: 10.1109/MCI.2009.932254
19. Raphael M. Wambua, Benedict M. Mutua, James M. Raude, 2014, Perf ormance of Standardized Precipitation Index (SPI) and Effective Drought Index (EDI) in Drought forecasting using Artificial Neural Networks (ANNs) for upper Tana River basin, Kenya, INTERNATIONAL JOURNAL OF ENGINEERING RESEARCH & TECHNOLOGY (IJERT) Volume 03, Issue 11 (November 2014).

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