M.Sc. Agriculture Analytics

Risk Analysis & Modeling

Project Title:

Application of ML Techniques for Drought Forecasting

Submitted To:

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CONTENT

Abstract:

This report outlines a comprehensive approach to forecasting Standardized Precipitation Index (SPI) values and predicting meteorological droughts in six districts of Gujarat, India. The project employs time series models (ARIMA, SARIMA, SARIMAX) and machine learning algorithms (Random Forest, Gradient Boosting Regression, Support Vector Regression) to forecast SPI values. Forecasted SPI values are utilized to identify drought-prone areas, defined as locations with SPI values below -1. ArcGIS Pro is used to generate maps depicting drought-prone and wet regions across the six districts. SPI values are interpolated for 5 representative points within each district to enhance spatial representation. Drought and wet regions are categorized based on SPI ranges.

Introduction:

One of the major challenges of agricultural systems is how to mitigate the impacts of droughts. Droughts impact agricultural systems economically as well as environmentally. With respect to economic impacts, droughts damage agricultural production, and can cause economic damage to industries connected to agricultural production, in addition to causing unemployment as a result of reduced production. From an environmental perspective, droughts can deprive crops and soils of essential precipitation as well as increase the salt content in soils and irrigation systems. Globally, 22% of the economic damage caused by natural disasters and 33% of the damage in terms of the number of persons affected can be attributed to drought **[Keshavarz et al., 2013].** To mitigate the impacts of drought an effective and timely monitoring system is required. Effective monitoring of droughts can aid in developing an early warning system. An objective evaluation of the drought condition in a particular area is the first step for planning water resources in order to prevent and mitigate the impacts of future occurrences of drought. The evaluation and forecasting of drought is made possible by the use of drought indices. The Standardized Precipitation Index (SPI) is a widely used drought indicator that quantifies precipitation deficits over various time scales

Importance of Drought Forecasting and Mapping:

- **Early Warning and Preparedness**: Accurate drought forecasts provide timely information to prepare for potential water shortages, agricultural losses, and ecological impacts.

- **Water Resource Management:** Drought maps help water managers optimize water allocation, prioritize conservation efforts, and plan for potential disruptions to water supply systems.
- **Agricultural Planning**: Farmers can utilize drought forecasts and maps to adjust planting schedules, irrigation practices, and crop selection to minimize drought-induced losses.
- **Ecosystem Protection:** Drought maps can inform conservation efforts to protect drought-sensitive ecosystems and wildlife habitats.
- **Policymaking and Decision-Making**: Drought forecasts and maps support informed decision-making by policymakers and stakeholders at various levels.

Drought forecasting and mapping play a vital role in reducing the adverse impacts of drought on human societies and the environment. By providing valuable insights into drought patterns and severity, these tools contribute to sustainable resource management and resilient communities.

Literature Review:

Drought forecasting is crucial for mitigating the adverse impacts of drought on agriculture, water resources, and ecosystems. Various methods have been developed to forecast drought, ranging from traditional statistical techniques to advanced machine learning algorithms. There are several drought indices that are commonly used, such as the Palmer Index, the Crop Moisture Index and the Standardized Precipitation Index (SPI). The Palmer Index and the SPI are traditionally the most popular indices for forecasting drought due to their standardization. For the purposes of comparing drought conditions from different areas, which often have different hydrological balances, the most important characteristic of a drought index is its standardization **[BONNACCORSO et al. 2003].** Standardization of a drought index ensures independence from geographical position as the index in question is calculated with respect to the average precipitation in the same place **[CACCIAMANI et al. 2007].**

One of the differences between the Palmer Index and the SPI is that the characteristics of the Palmer Index vary from site to site while those of the SPI do not. Another difference is the Palmer Index has a complex structure with a very long memory, while the SPI is an easily interpreted, simple moving average process **[TSAKIRIS, VANGELIS 2004].** This characteristic makes the SPI useful as the primary drought index because it is simple, spatially invariant in its interpretation and probabilistic, allowing it to be used in risk and decision making analysis. The SPI is also more representative of short-term precipitation than the Palmer Index and is thus a better indicator for soil moisture variation and soil wetness **[MISHRA, SINGH 2010].**

Data & Methodology:

The provided was a time series data of monthly data of SPI and SPEI values of 5 grid areas in Gujarat which are partially falling in six districts i.e. Anand, Vadodra, Panchmahal, Chhota Udepur, Bharuch, and Narmada.

SPI Values: Jan 1986 – Dec 2015

SPEI Values: Jan 1986 – Dec 2000

Grid Code	Lat (°N)	Long (°E)
	From - To	From - To
AE01	22.00-22.25	72.50-72.75
AE02	22.00-22.25	72.75-73.00
AE03	22.00-22.25	73.00-73.25
AE04	22.00-22.25	73.25-73.50
AE05	22.00-22.25	73.50-73.75

Methodology:

1. Data Collection: Gather historical SPI and SPEI data and location data of study area.
2. Data Preprocessing: Handle missing values, outliers, and data inconsistencies to ensure data quality.
3. Model Development:

- Time Series Models: Develop ARIMA, SARIMA, and SARIMAX models to forecast future SPI values.
- Machine Learning Models: Train Random Forest, Gradient Boosting Regression, and Support Vector Regression models for SPI forecasting.

4. Model Evaluation: Assess the performance of each model using appropriate metrics (e.g., mean absolute error, root mean squared error) and select the best-performing model.

5. Drought Prediction: Identify drought-prone areas based on forecasted SPI values (SPI < -1).
6. ArcGIS Pro Mapping: Generate maps visualizing drought-prone and wet regions across the six districts.
7. SPI Interpolation: Interpolate SPI values for 5 representative points within each district to enhance spatial representation.
8. Drought Categorization: Classify drought and wet regions based on SPI ranges.

Time Series Models:

ARIMA:

The ARIMA model is a statistical model that can be used to forecast future values of a time series based on its past values. The ARIMA model is a combination of three models:

- Autoregressive (AR): The AR model predicts the future value of a time series based on its past values.
- Integrated (I):The I model transforms a non-stationary time series into a stationary time series.
- Moving average (MA): The MA model predicts the future value of a time series based on its past errors.

ARIMAX:

The ARIMAX model is a generalization of the ARIMA model that can include exogenous variables in the prediction process. Exogenous variables are variables that are outside of the system being modeled, but that may influence the behavior of the system.

SARIMA:

SARIMA (Seasonal Autoregressive Integrated Moving Average) is a statistical technique used for forecasting time series data, a series of observations recorded at regular intervals over time. SARIMA models are a combination of autoregressive (AR) models, moving average (MA) models, and differencing.

Machine Learning Models:

Random Forest:

Random Forest is an ensemble learning algorithm that combines multiple decision trees to make predictions. Decision trees are simple tree-like structures that make predictions by recursively splitting the data into smaller and smaller subsets. Random Forest averages the predictions of the individual decision trees to reduce variance and improve accuracy.

Gradient Boosting Regression:

Gradient Boosting Regression is another ensemble learning algorithm that combines multiple trees in a sequential manner. Each tree is built to minimize the error of the previous tree. This process is repeated until the desired level of accuracy is reached. Gradient Boosting Regression is often more accurate than Random Forest, but it can also be more computationally expensive.

Support Vector Regression:

Support Vector Regression is a non-parametric algorithm that finds a hyperplane that minimizes the total error. The hyperplane is a decision boundary that separates the data into two classes. Support Vector Regression is often used for regression tasks because it is robust to outliers and can handle non-linear relationships between the data.

Result:

The result shows SARIMA and SVR model has performed best among the used models and forecasted values from SVR model is used for interpolation and map generation using ArcGIS Pro.

		AIC	BIC	MSE	RMSE	RMSE%	R2
A1	ARIMA	808.73	835.45	1.3456	1.16	22.73	-
	SARIMA	688.88	719.42	0.8649	0.93	18.16	-
	SARIMAX	688.88	719.42	0.8649	0.93	18.16	-
	ARCH	823.78	839.05	1.3225	1.15	22.44	-
	RF	-	-	0.9604	0.98	20.22	0.26
	GBR	-	-	0.9801	0.99	19.4	0.24
	SVR	-	-	0.8836	0.94	18.49	0.31

		AIC	BIC	MSE	RMSE	RMSE%	R2
A2	ARIMA	795.71	818.61	1.3689	1.17	24.25	-
	SARIMA	654.89	681.61	0.7921	0.89	18.71	-
	SARIMAX	654.89	681.61	0.7921	0.89	18.71	-
	ARCH	850.16	865.43	1.3924	1.18	24.59	-
	RF	-	-	0.6084	0.78	16.02	0.54
	GBR	-	-	0.5929	0.77	15.95	0.55
	SVR	-	-	0.5625	0.75	15.52	0.57

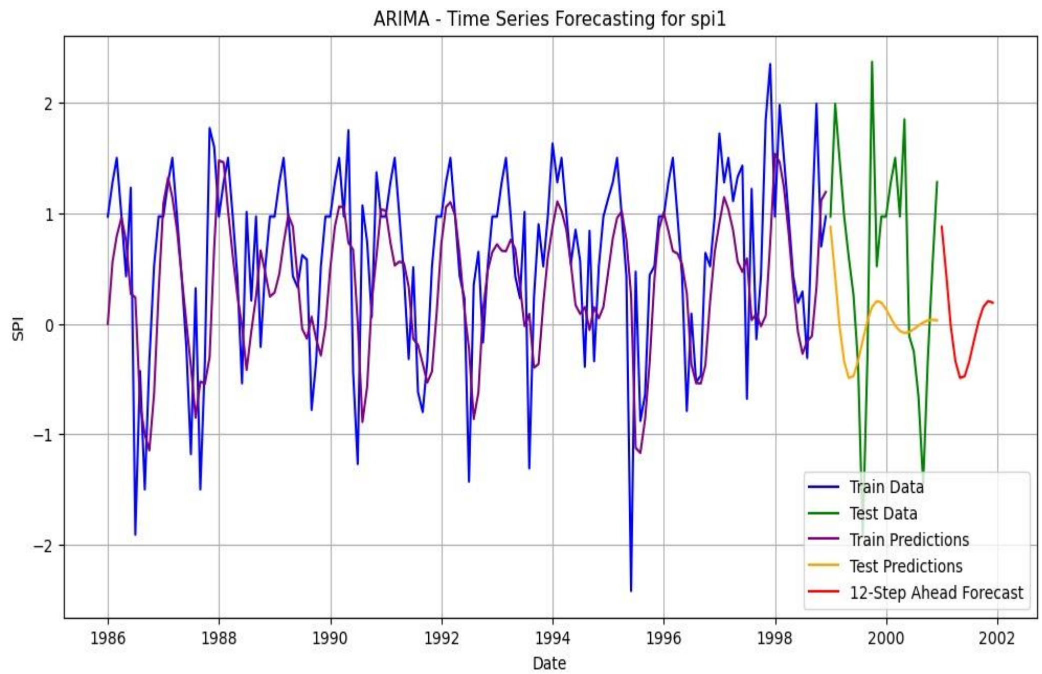
		AIC	BIC	MSE	RMSE	RMSE%	R2
A3	ARIMA	730.12	764.47	0.9216	0.96	21.03	-
	SARIMA	708.45	742.8	0.5929	0.77	16.82	-
	SARIMAX	708.45	742.8	0.5929	0.77	16.82	-
	ARCH	868.58	883.85	1.2321	1.11	24.21	-
	RF	-	-	0.5329	0.73	15.18	0.54
	GBR	-	-	0.5329	0.73	16.02	0.54
	SVR	-	-	0.4624	0.68	14.95	0.6

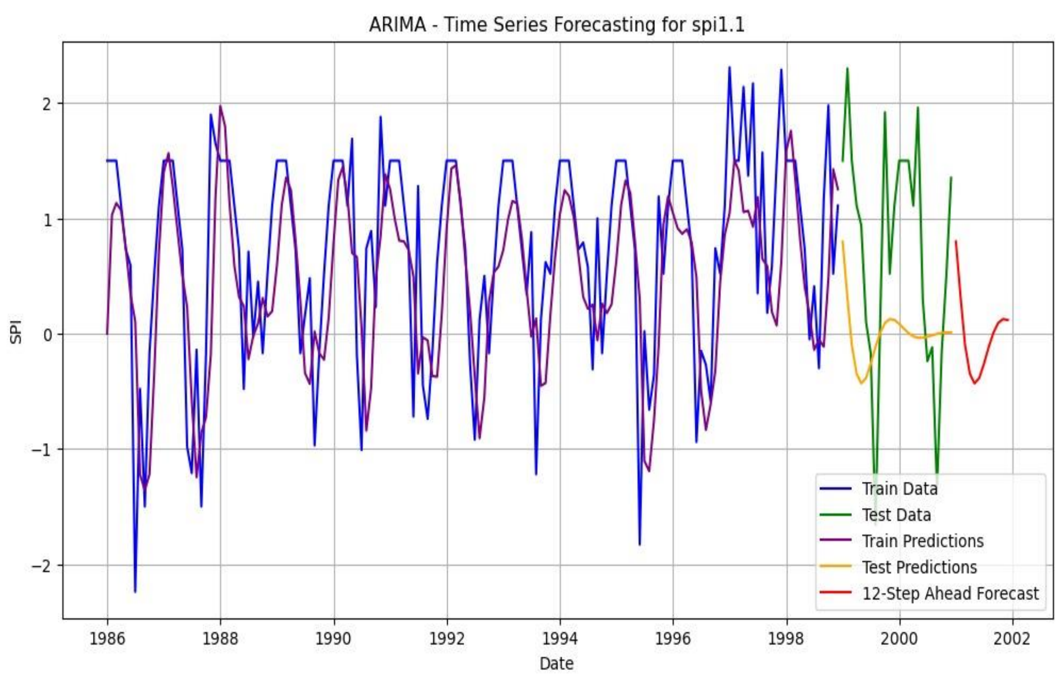
		AIC	BIC	MSE	RMSE	RMSE%	R2
A4	ARIMA	718.18	752.53	1.0816	1.04	21.26	-
	SARIMA	702.23	732.76	0.7225	0.85	17.52	-
	SARIMAX	702.23	732.76	0.7225	0.85	17.52	-
	ARCH	817.08	832.35	1.3456	1.16	23.92	-
	RF	-	-	0.6561	0.81	16.83	0.47
	GBR	-	-	0.7744	0.88	18.17	0.37
	SVR	-	-	0.7569	0.87	17.76	0.4

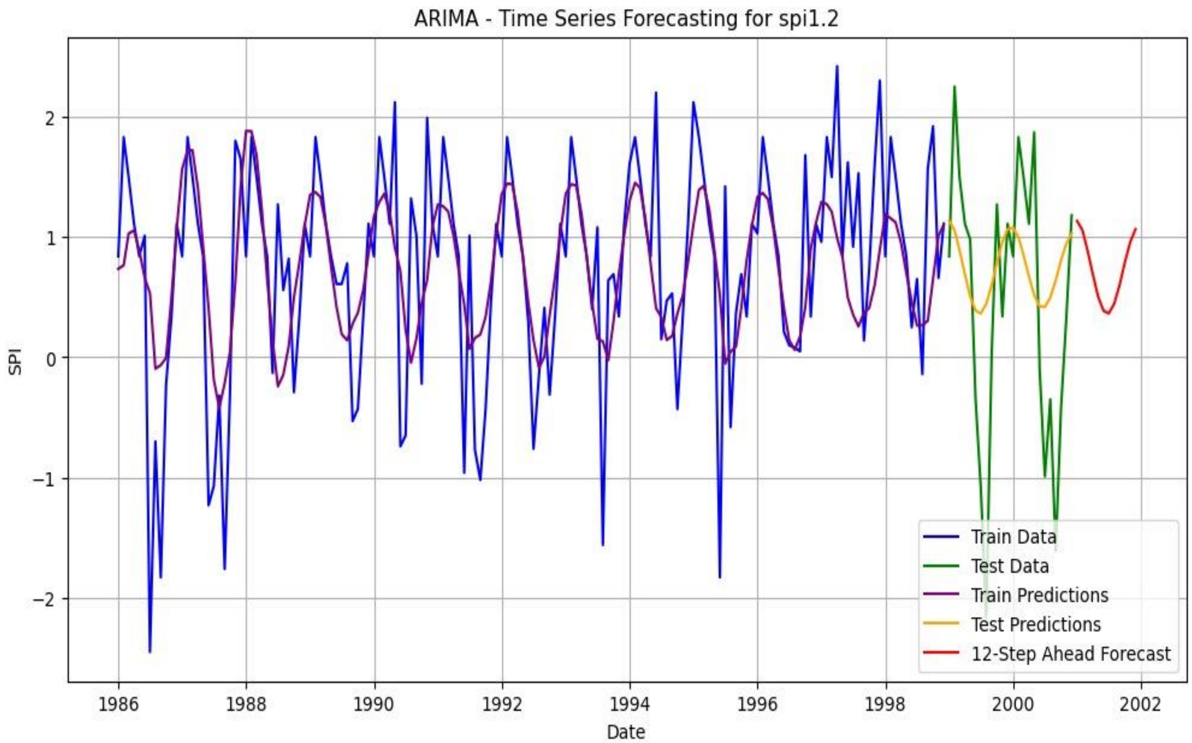
		AIC	BIC	MSE	RMSE	RMSE%	R2
A5	ARIMA	824.39	847.29	1.2996	1.14	23.58	-
	SARIMA	705.94	728.85	0.7225	0.85	17.65	-
	SARIMAX	705.94	728.85	0.7225	0.85	17.65	-
	ARCH	837.96	853.23	1.2996	1.14	23.49	-
	RF	-	-	0.81	0.9	18.75	0.32
	GBR	-	-	0.7225	0.85	17.55	0.41
	SVR	-	-	0.7569	0.87	18.03	0.38

The above Tables shows accuracy, error values and different scores for different grid area (A1, A2, A3, A4 and A5) for different time series and machine learning models as well.

ARIMA



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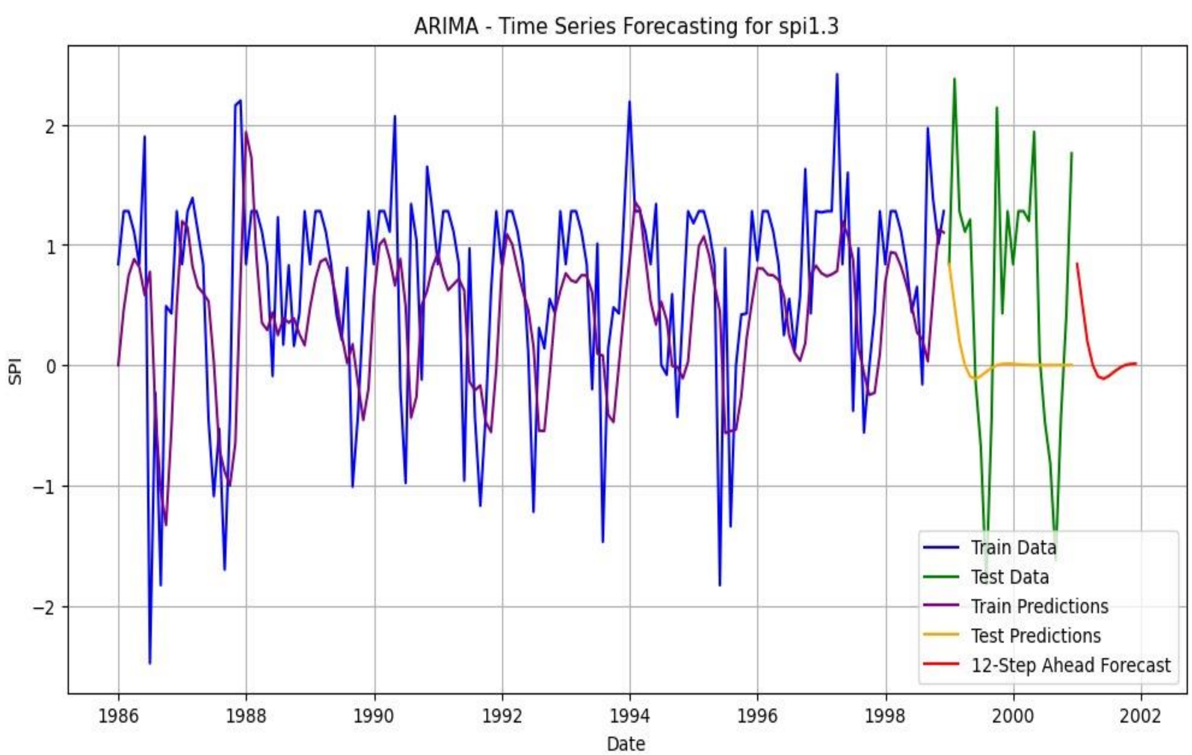
SPI
Date
Train Data
Test Data
Train Predictions
Test Predictions
12-Step Ahead Forecast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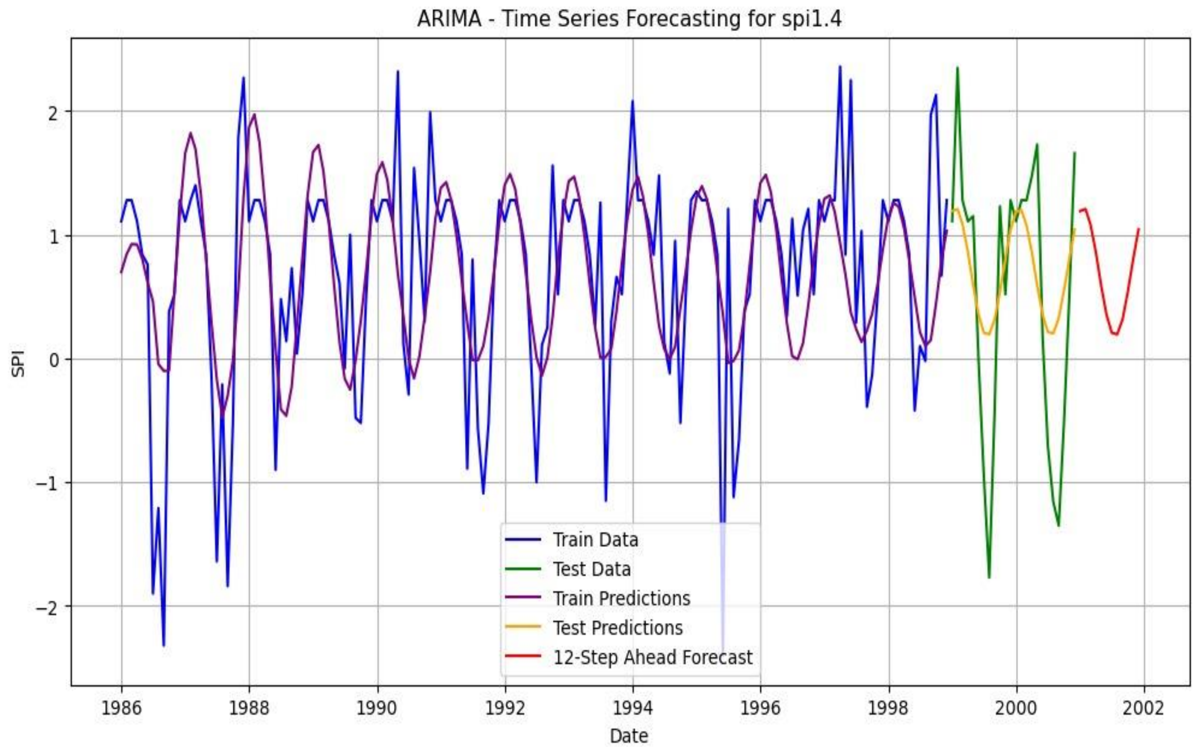
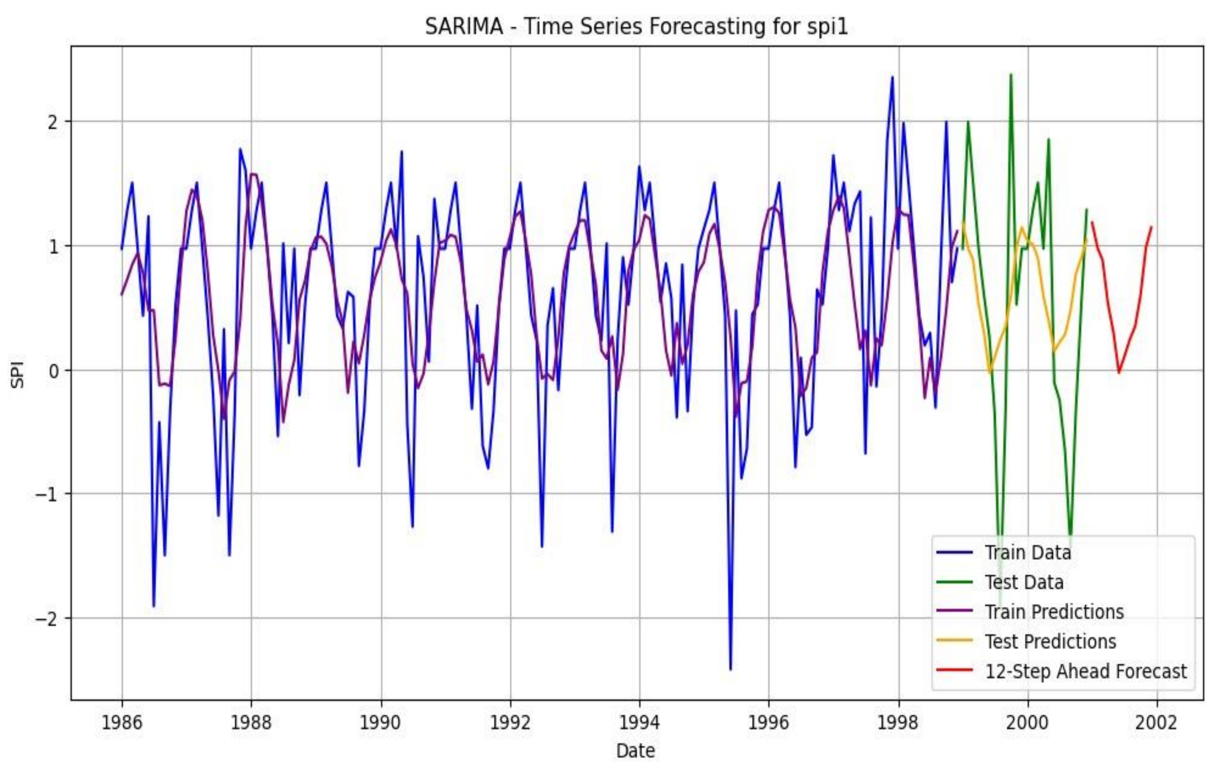
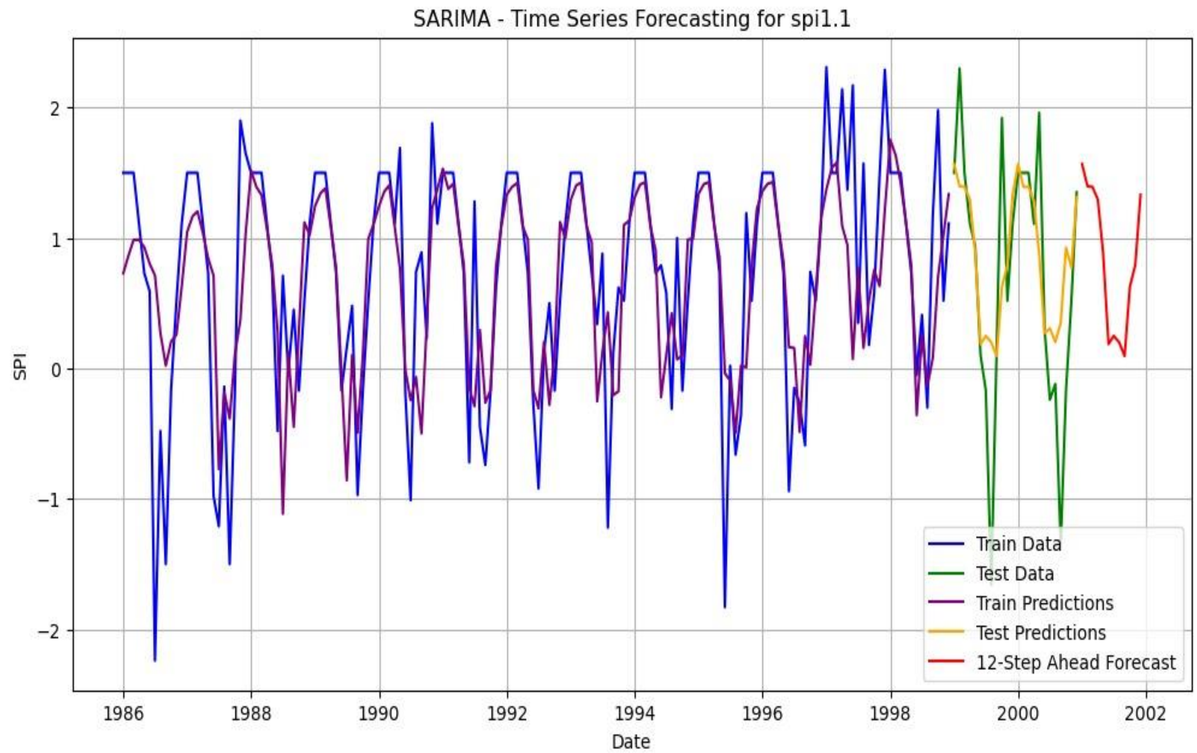
SPI
Date
Train Data
Test Data
Train Predictions
Test Predictions
12-Step Ahead Forecast

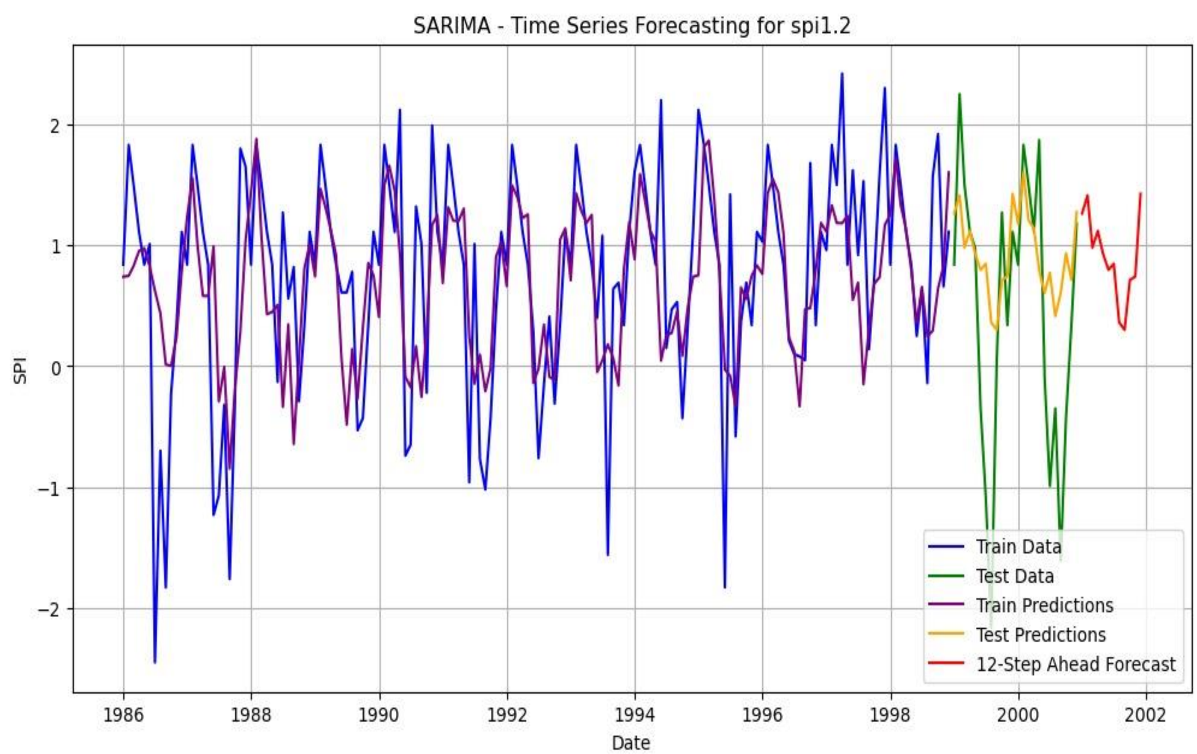


SARIMA and SARIMAX





SARIMA - Time Series Forecasting for spi1.1
SPI
Date
Train Data
Test Data
Train Predictions
Test Predictions
12-Step Ahead Forecast



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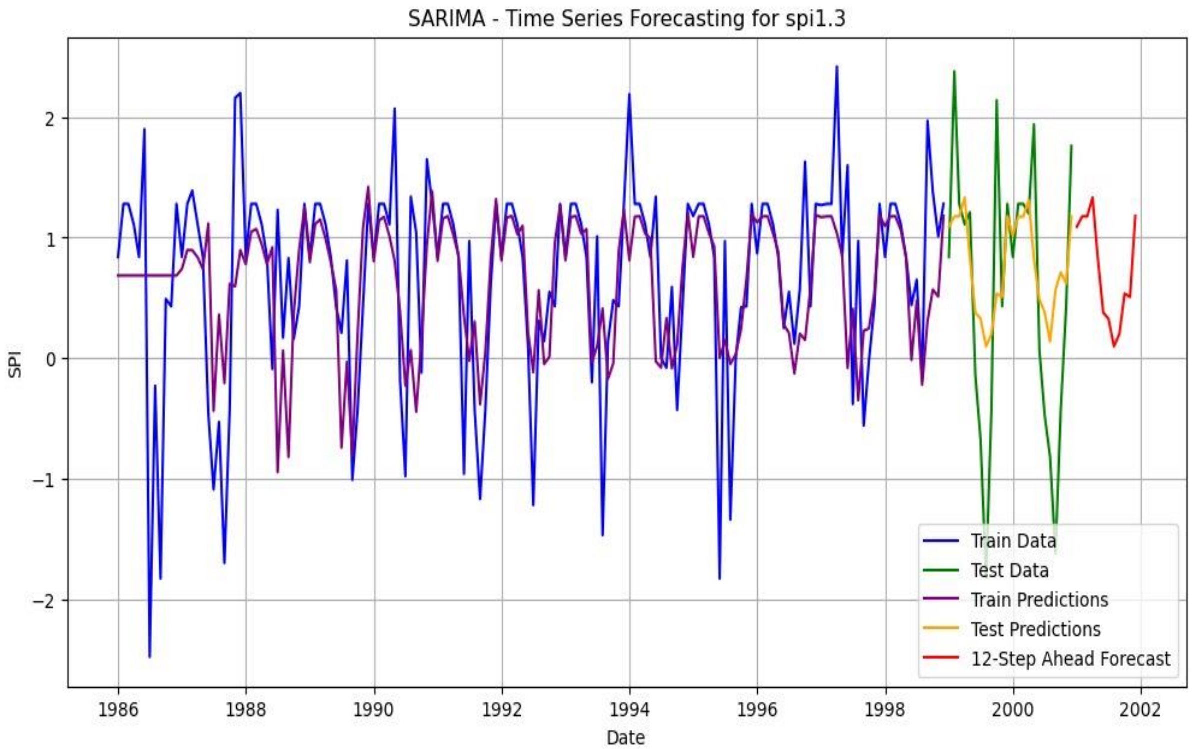
SPI
Date
Train Data
Test Data
Train Predictions
Test Predictions
12-Step Ahead Forecast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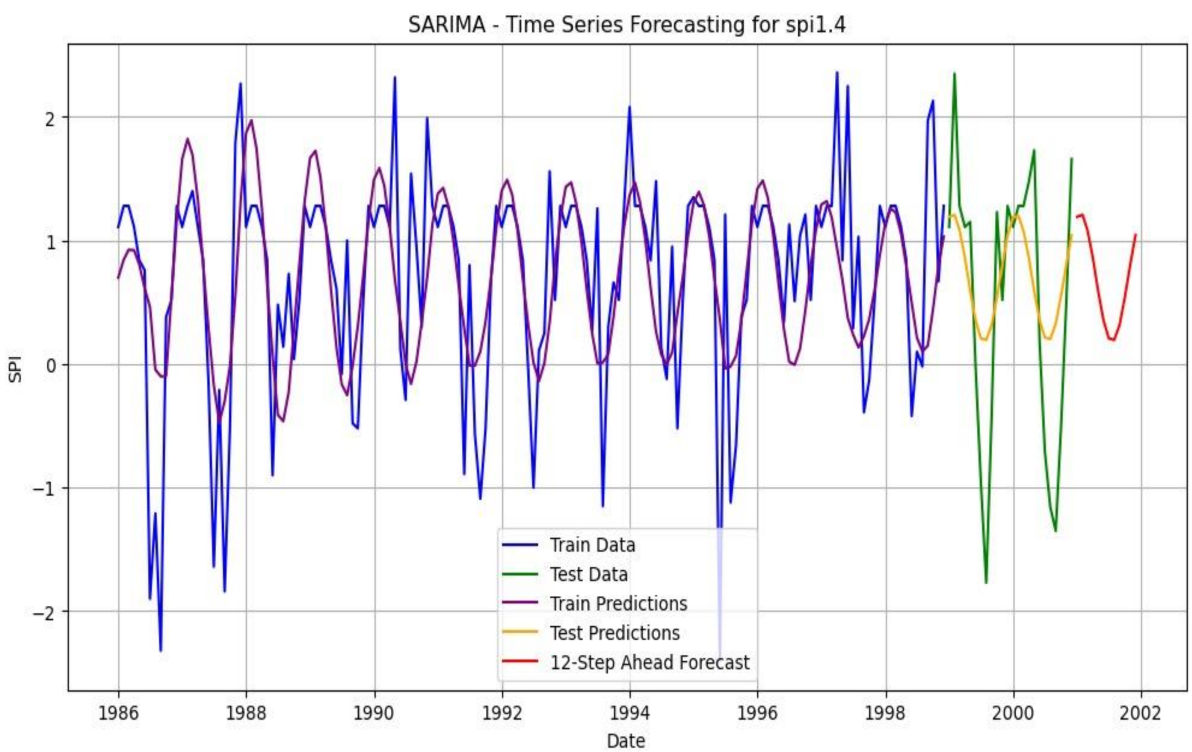
SPI
Date
Train Data
Test Data
Train Predictions
Test Predictions
12-Step Ahead Forecast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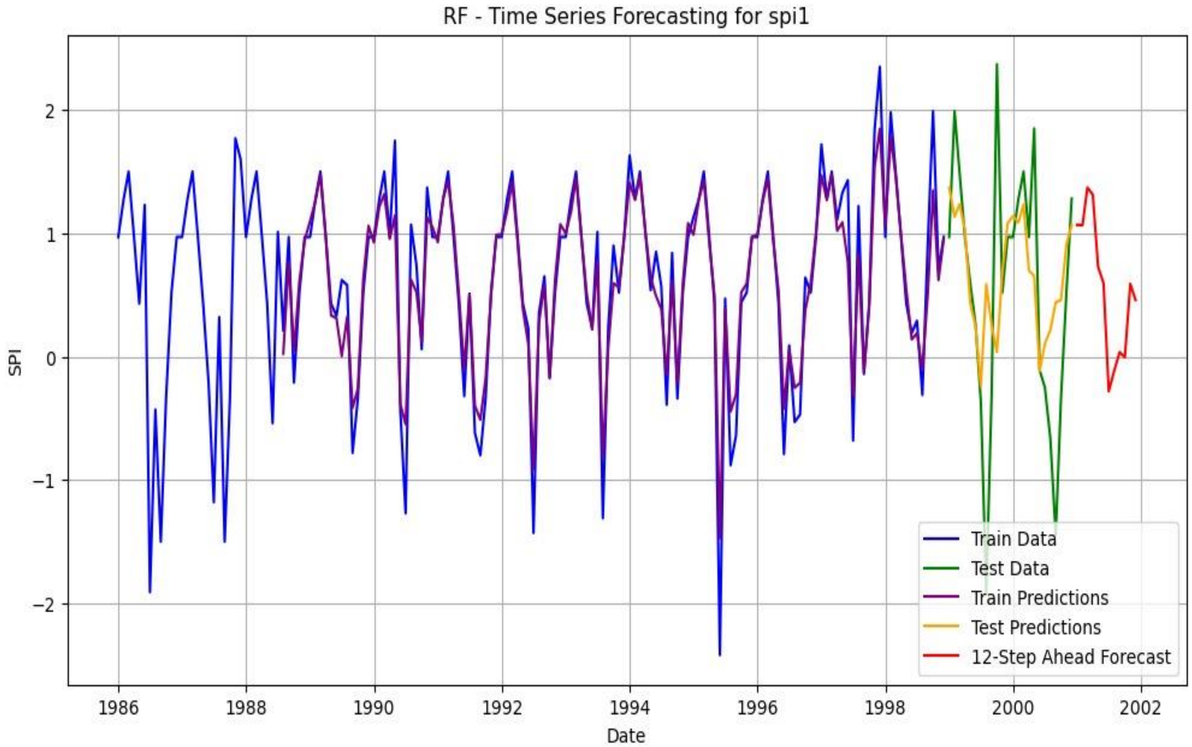
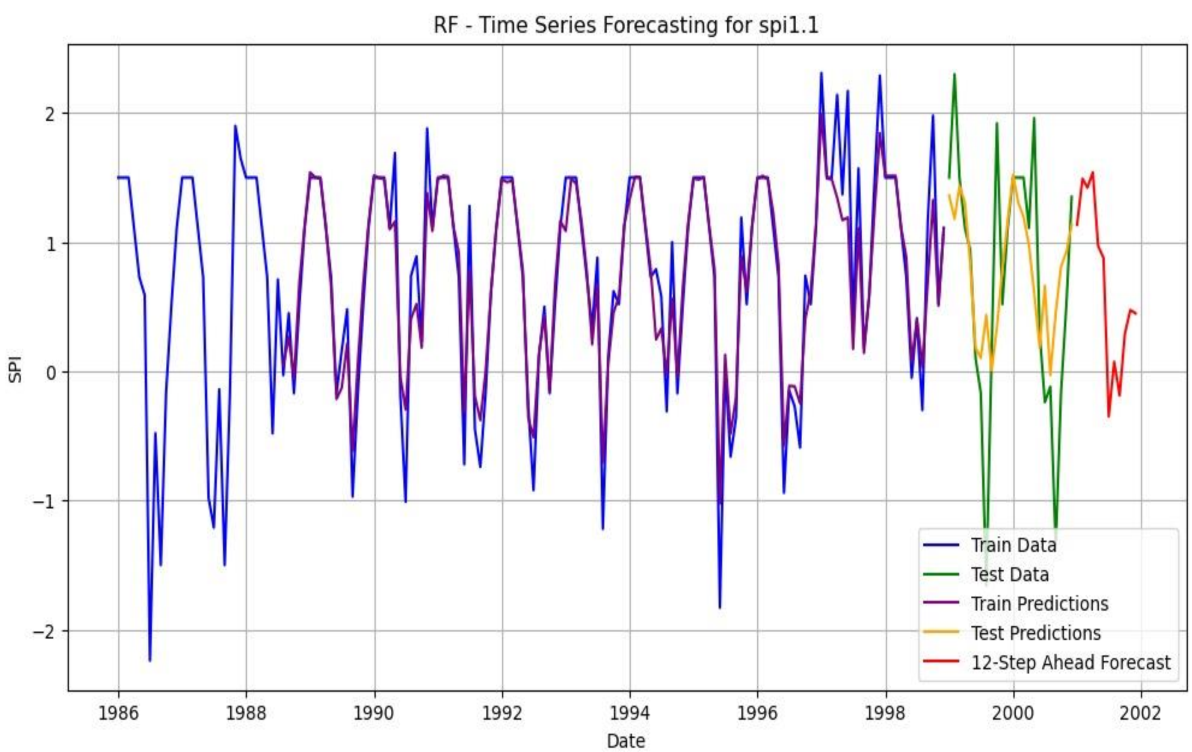
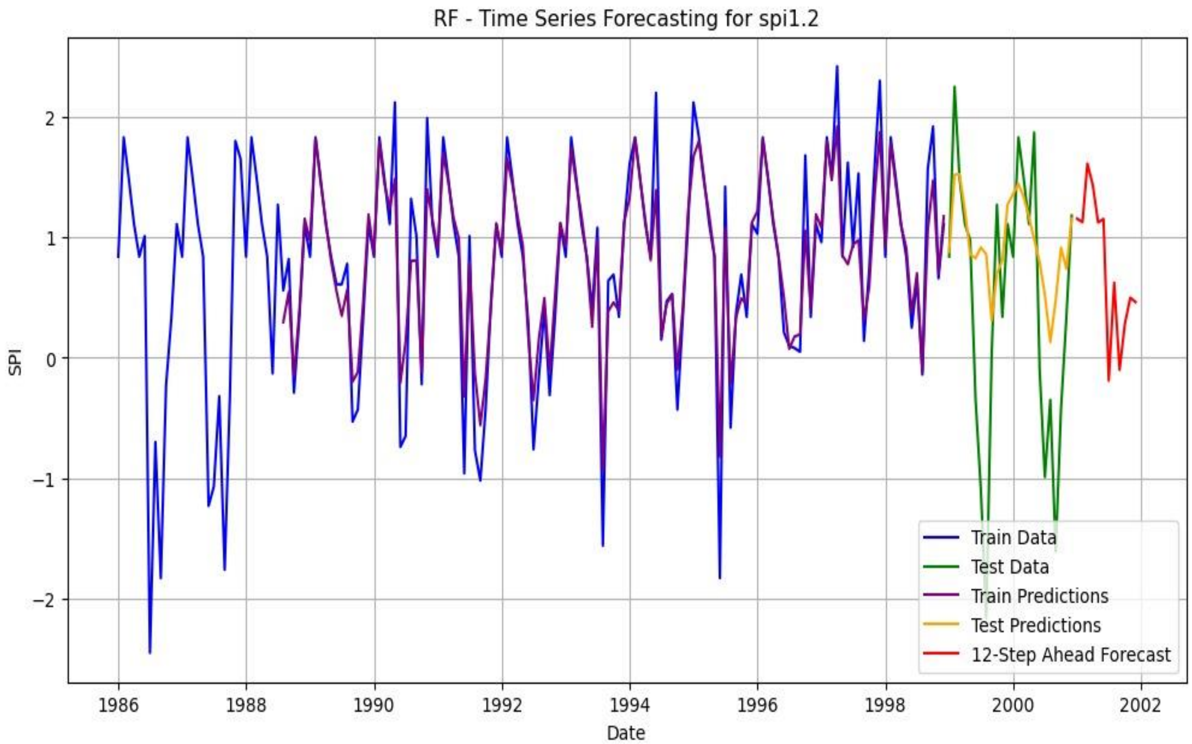
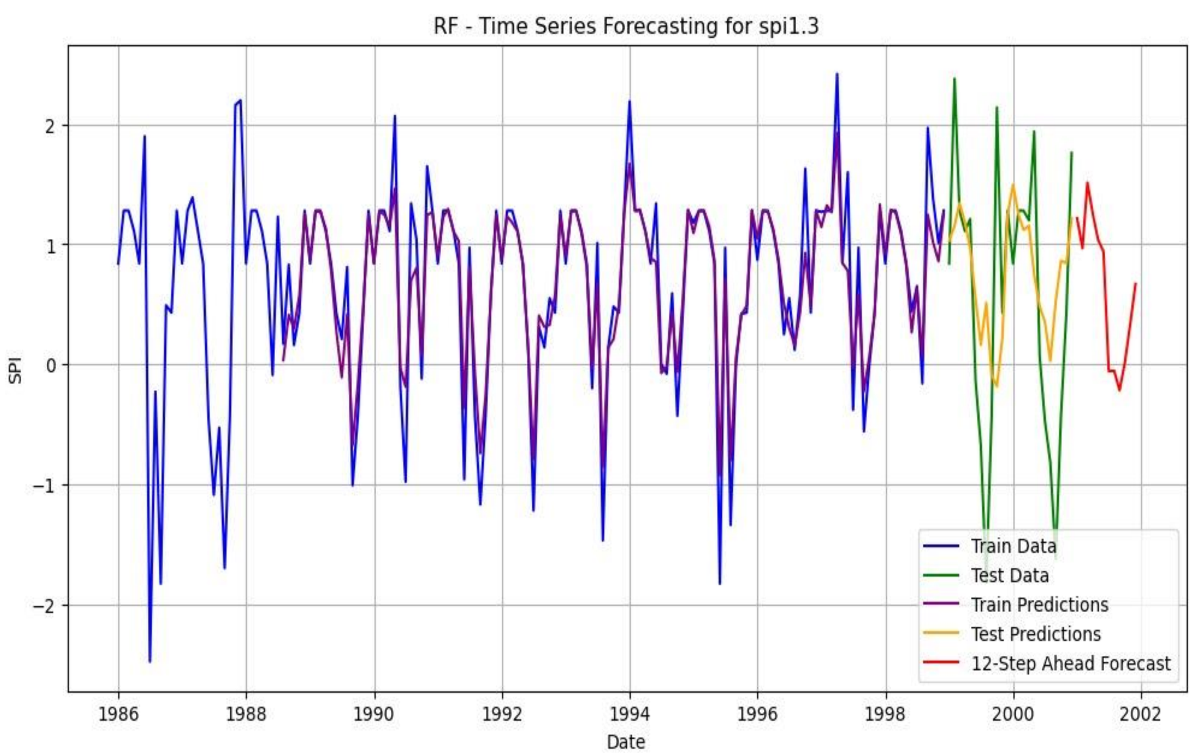
SPI
Date
Train Data
Test Data
Train Predictions
Test Predictions
12-Step Ahead Forecast

RANDOM FOREST






RF - Time Series Forecasting for spi1.2
SPI
Date
Train Data
Test Data
Train Predictions
Test Predictions
12-Step Ahead Forecast


RF - Time Series Forecasting for spi1.3
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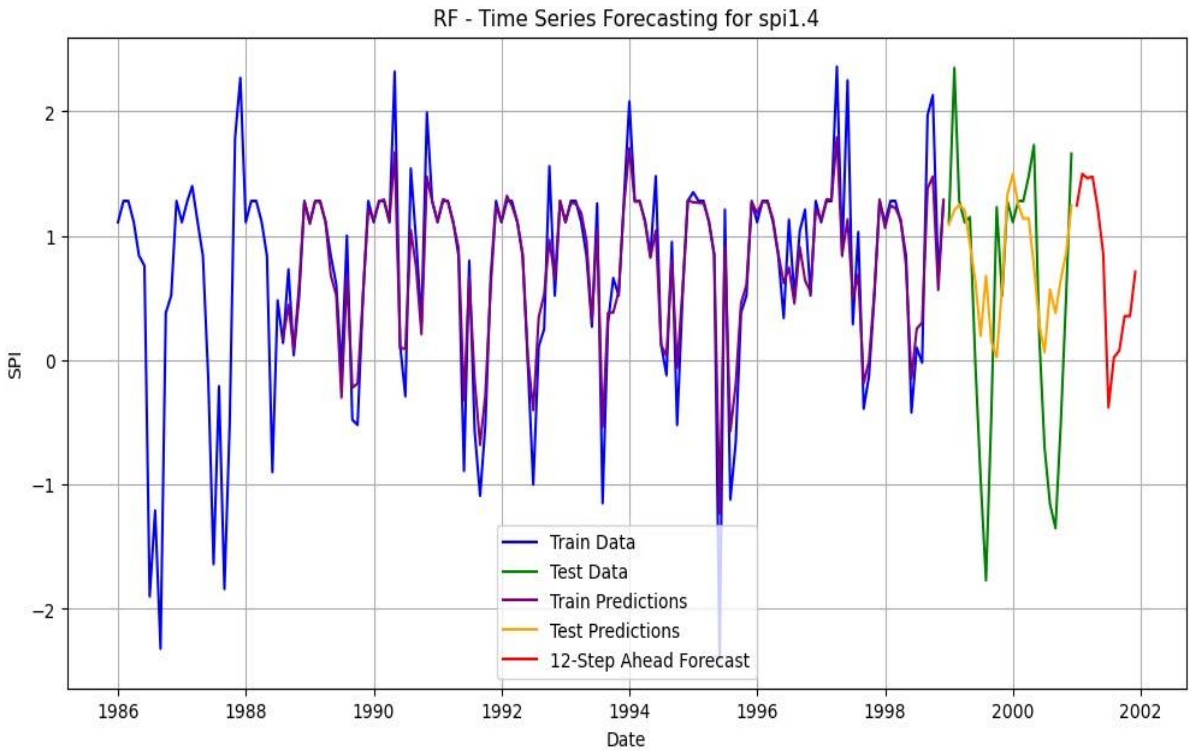
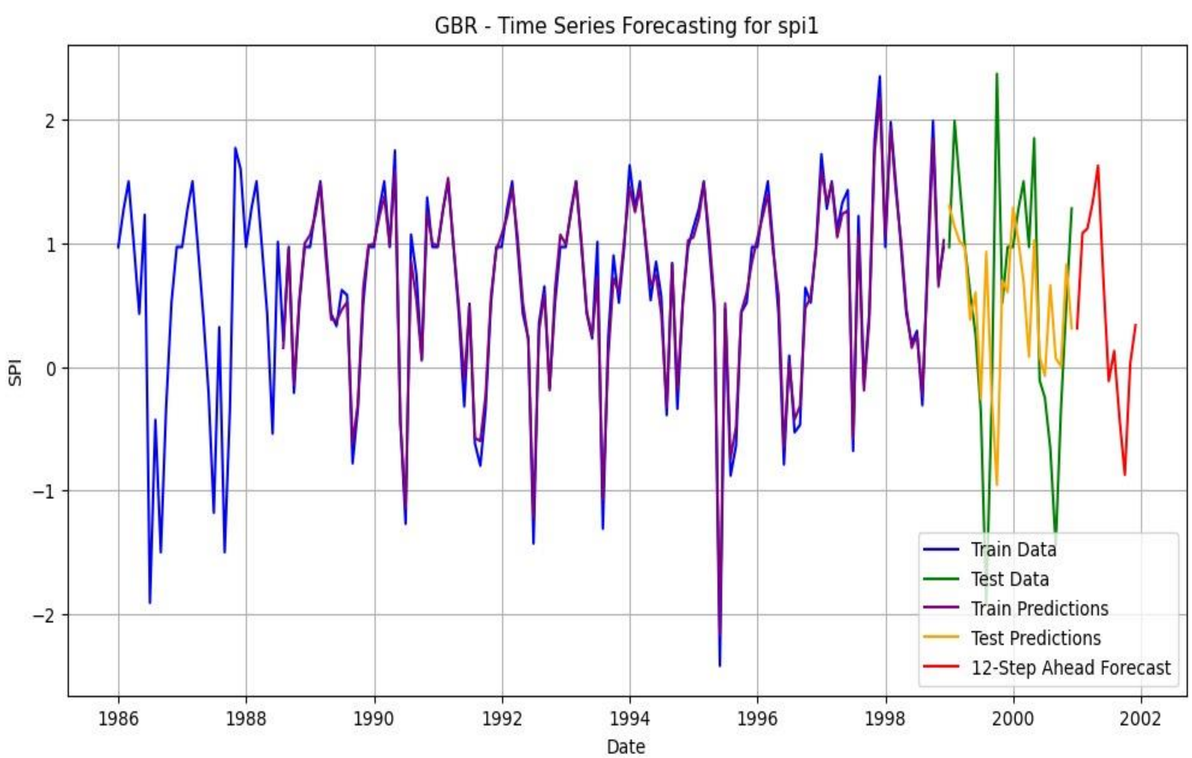
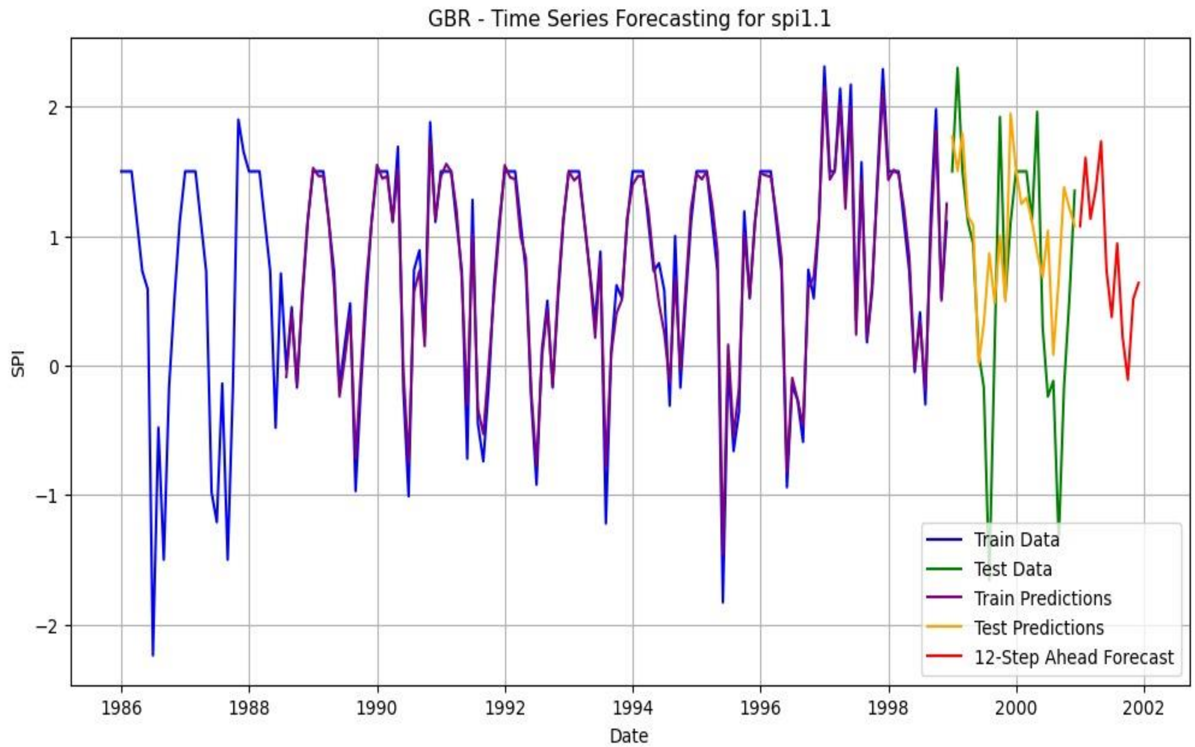
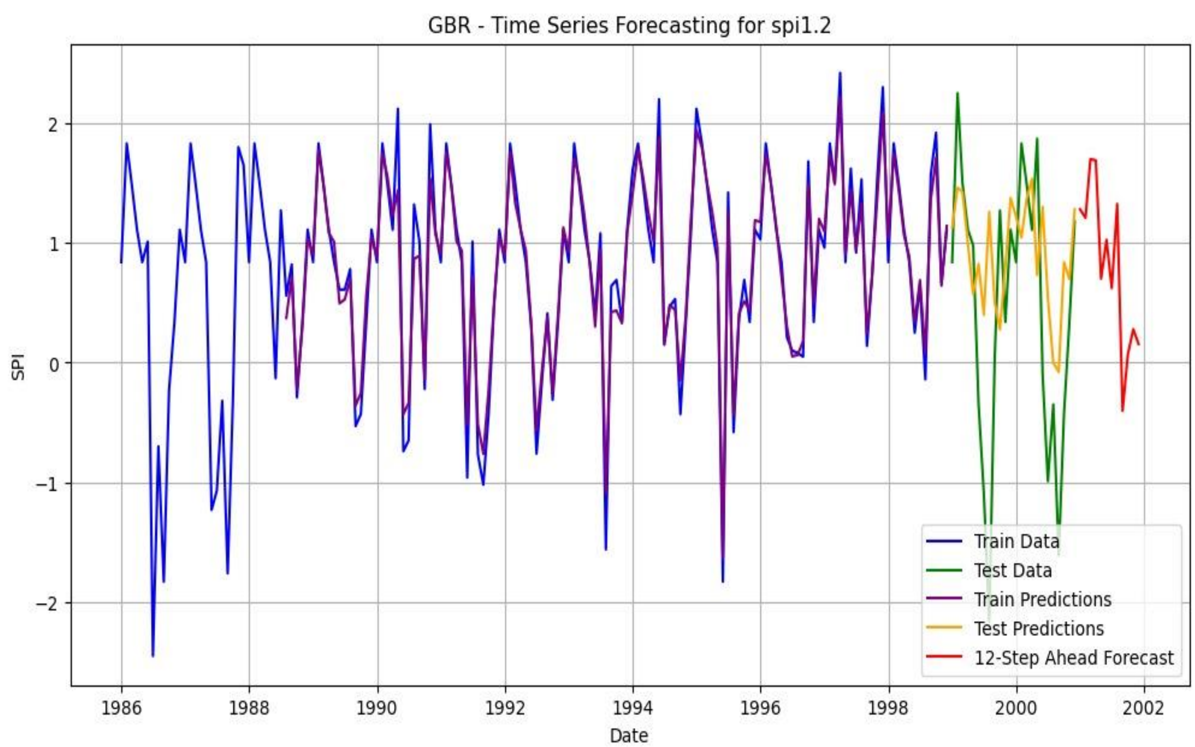
Test Data
Train Predictions
Test Predictions
12-Step Ahead Forecast



Gradient Boosting Regression




GBR - Time Series Forecasting for spi1.1
SPI
Date
Train Data
Test Data
Train Predictions
Test Predictions
12-Step Ahead Forecast


GBR - Time Series Forecasting for spi1.2
SPI
Date
Train Data
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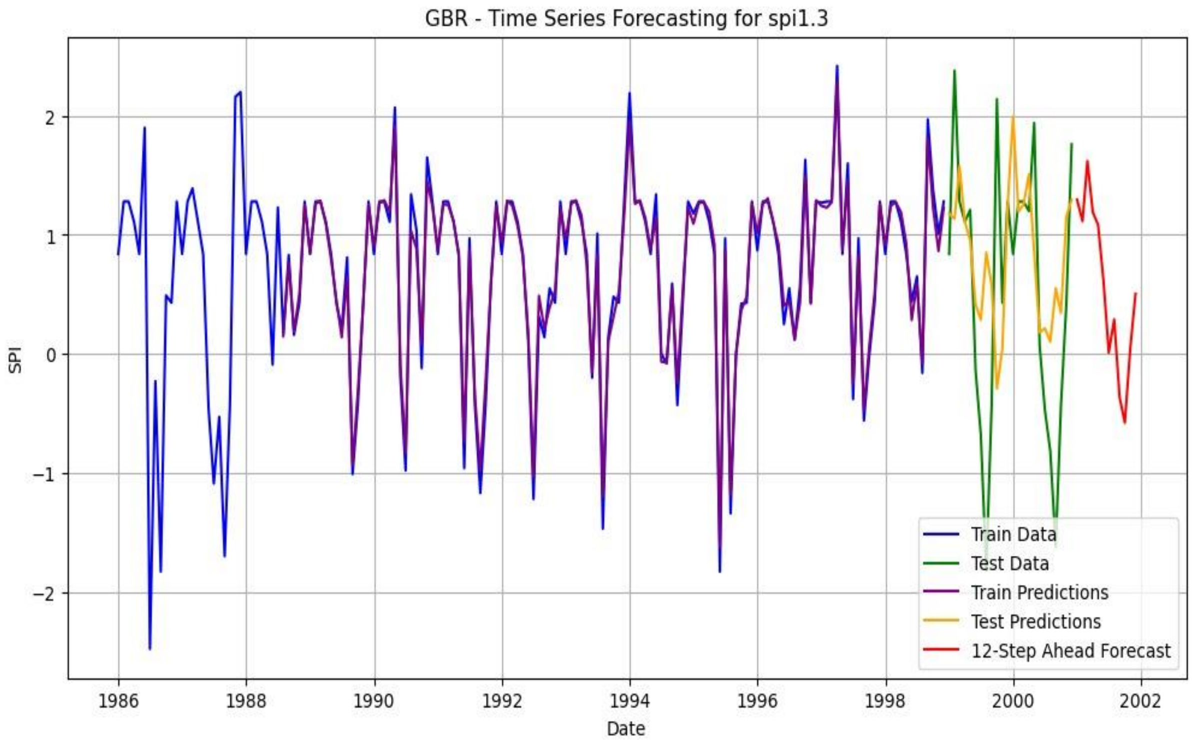
Train Predictions
Test Predictions
12-Step Ahead Forecast


GBR - Time Series Forecasting for spi1.3
SPI
Date
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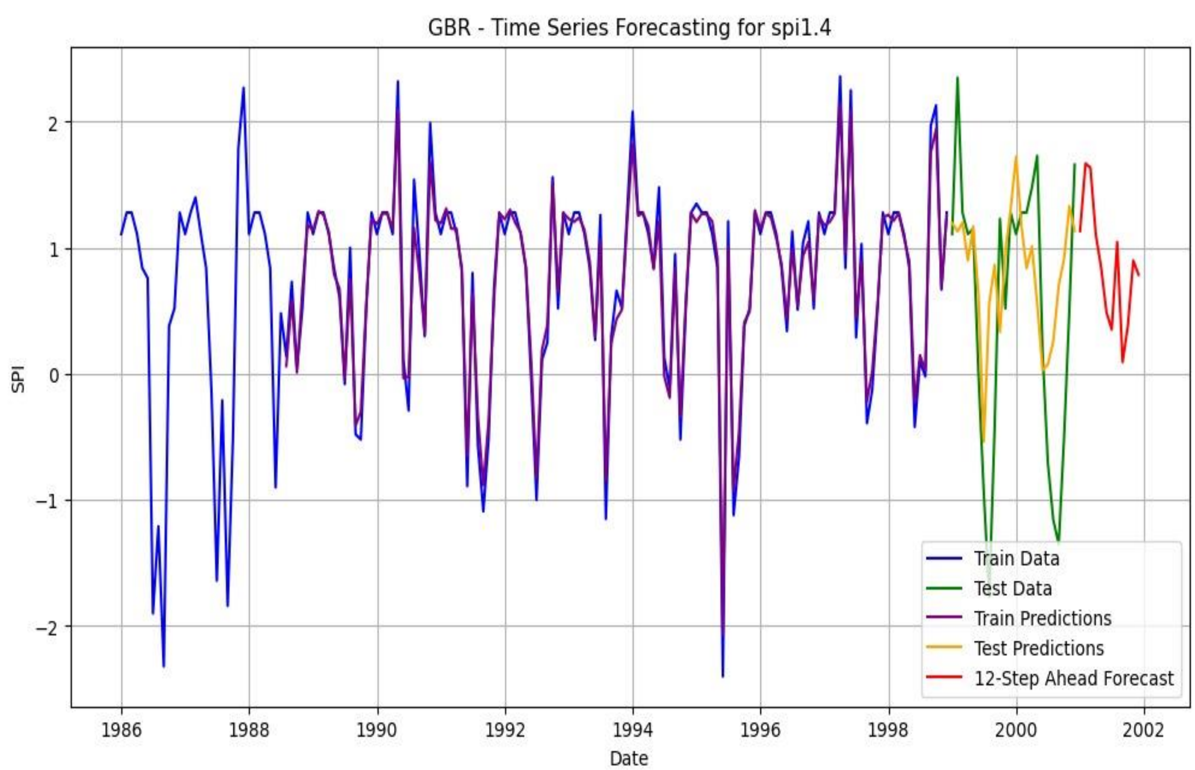
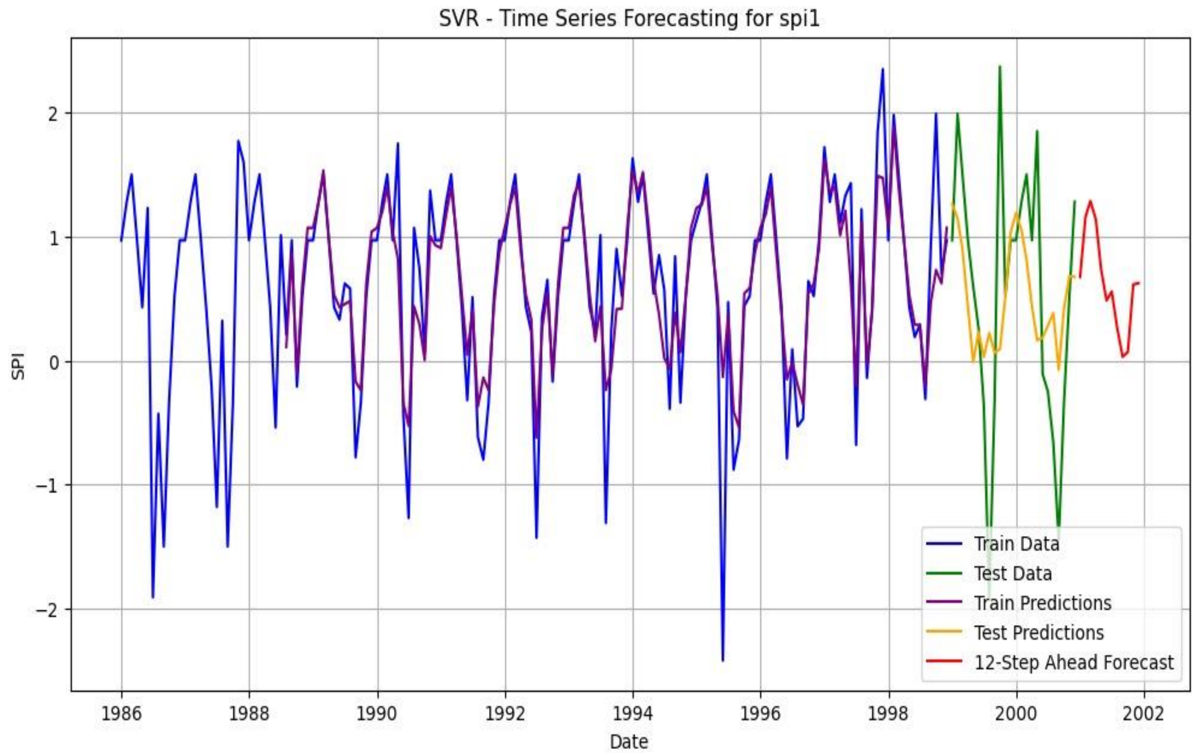
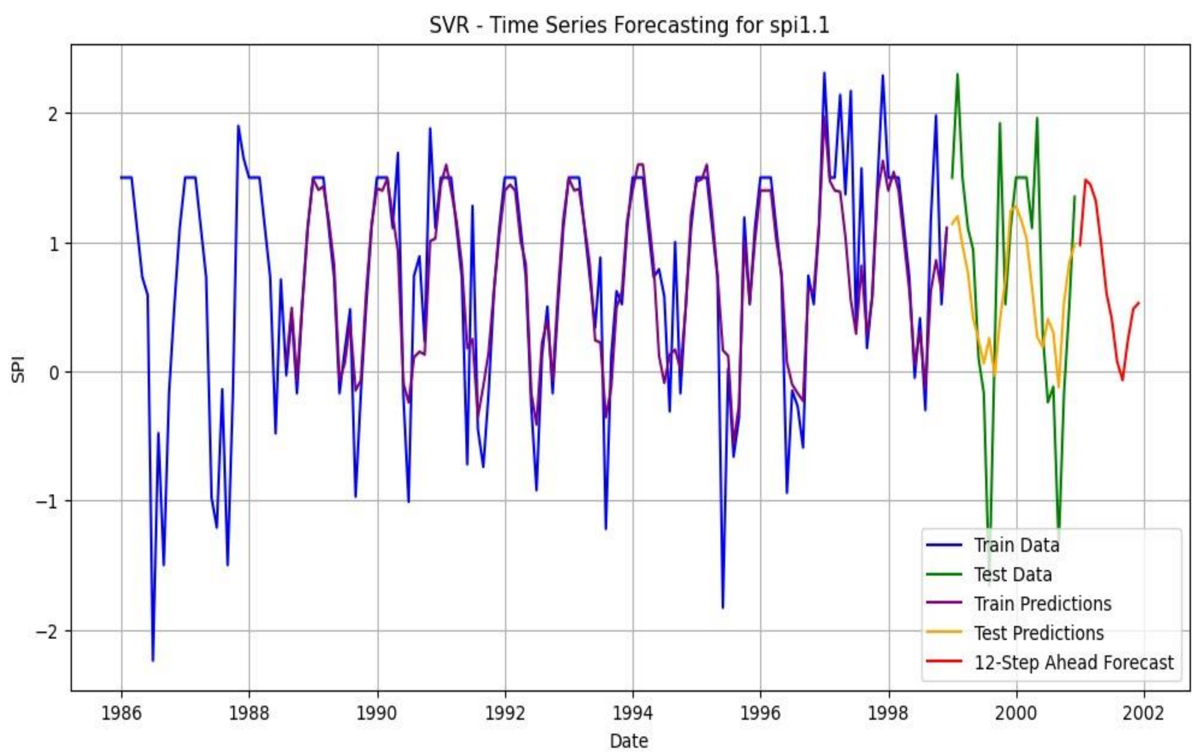
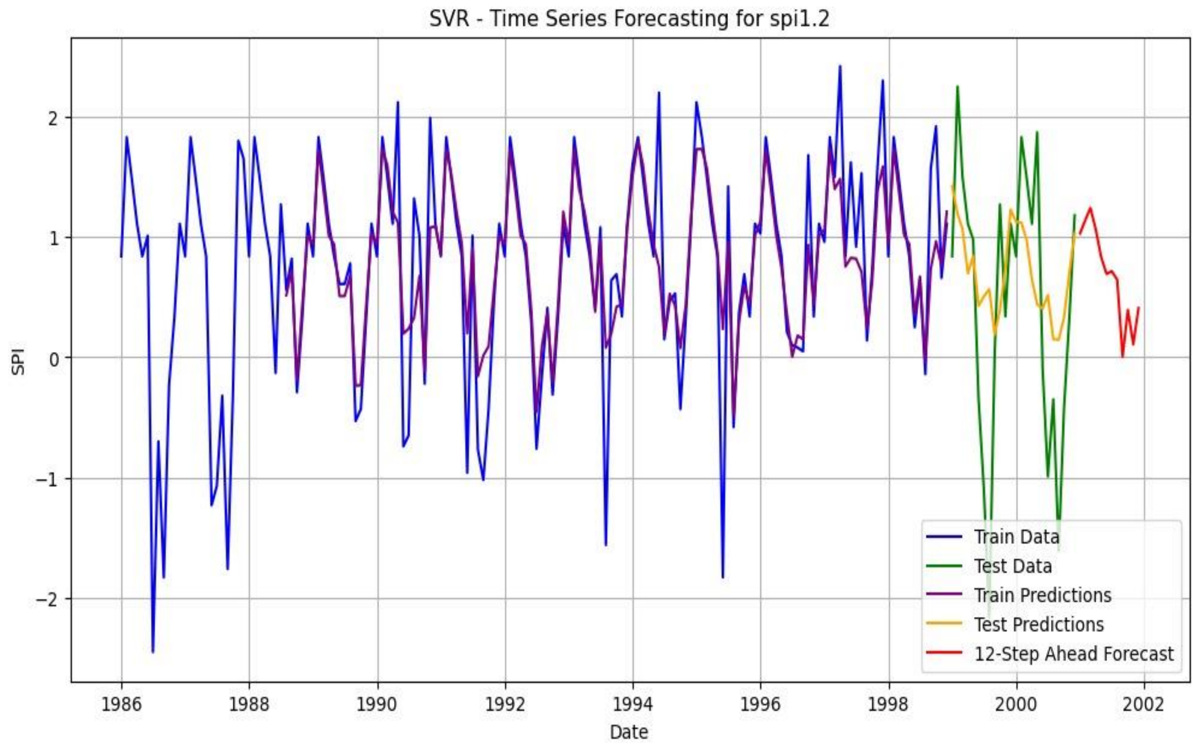
Test Data
Train Predictions
Test Predictions
12-Step Ahead Forecast

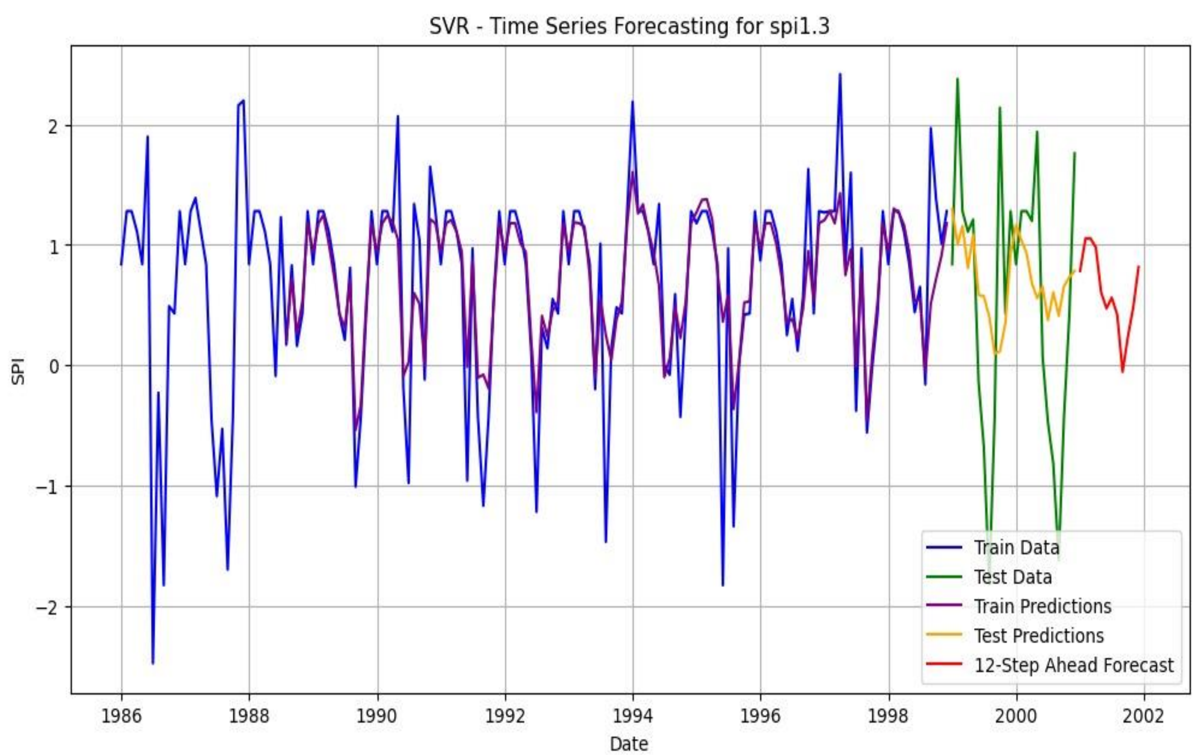

GBR - Time Series Forecasting for spi1.4
SPI
Date
Train Data
Test Data
Train Predictions
Test Predictions
12-Step Ahead Forecast

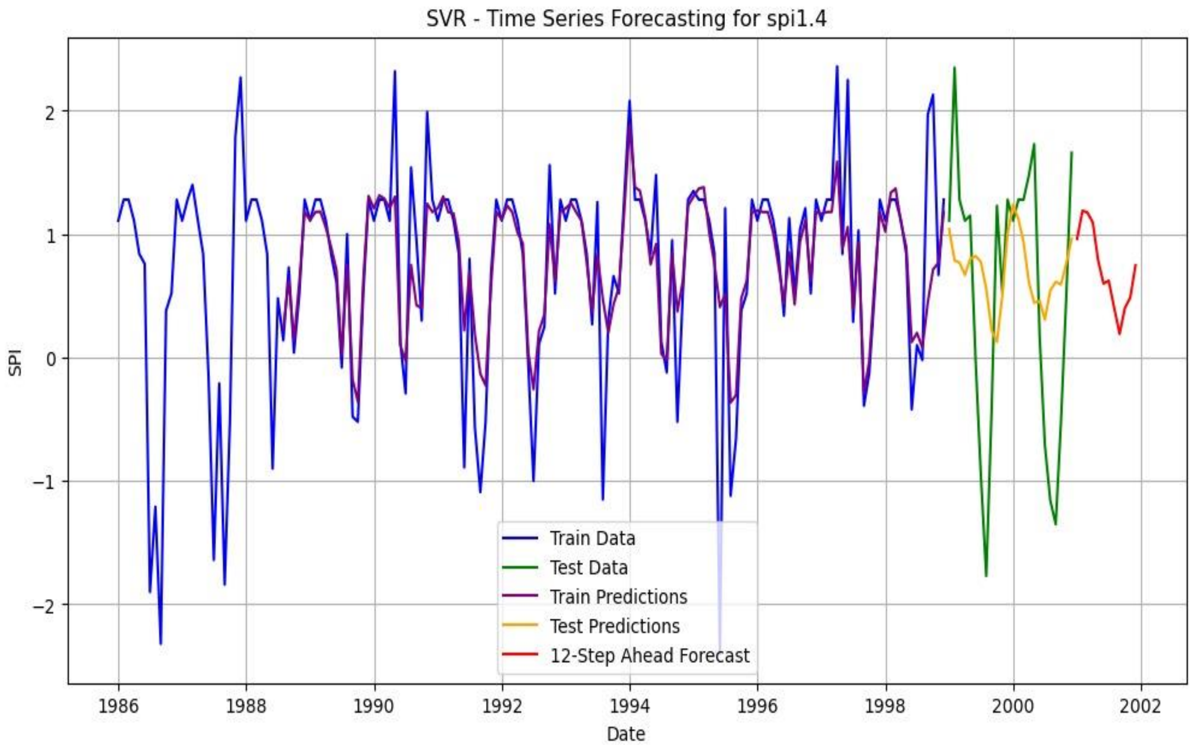
Support Vector Regressor





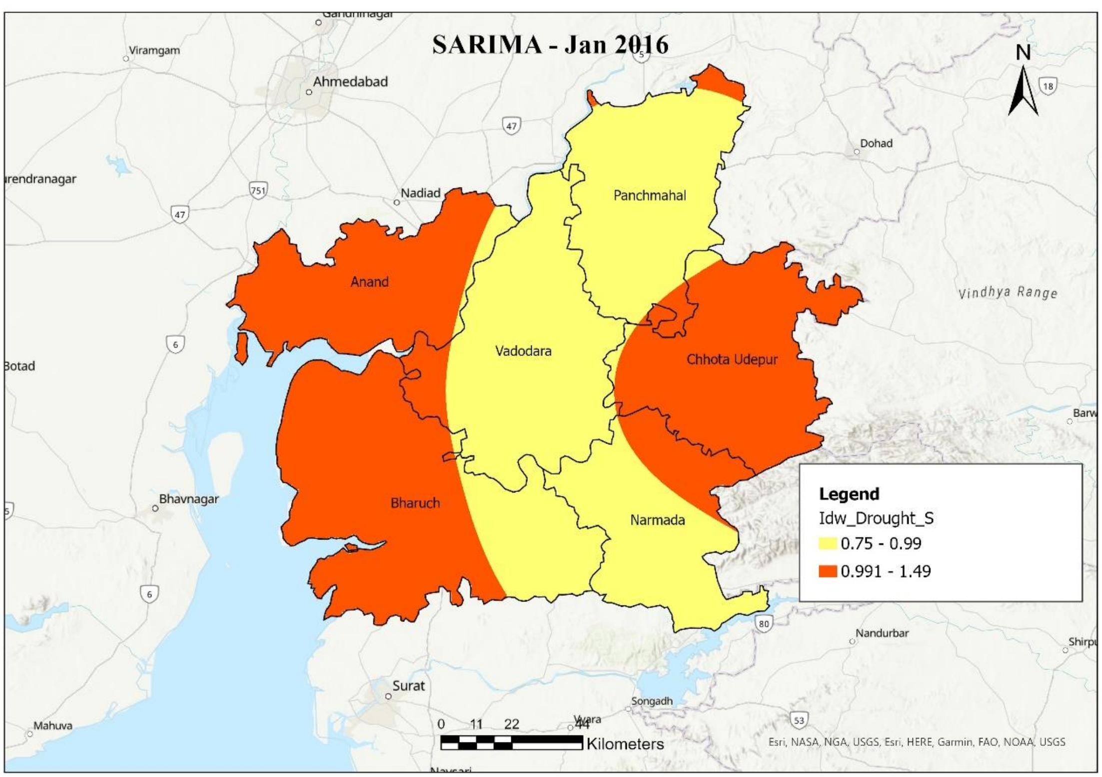

SVR - Time Series Forecasting for spi1.2
SPI
Date
Train Data
Test Data
Train Predictions
Test Predictions
12-Step Ahead Forecast

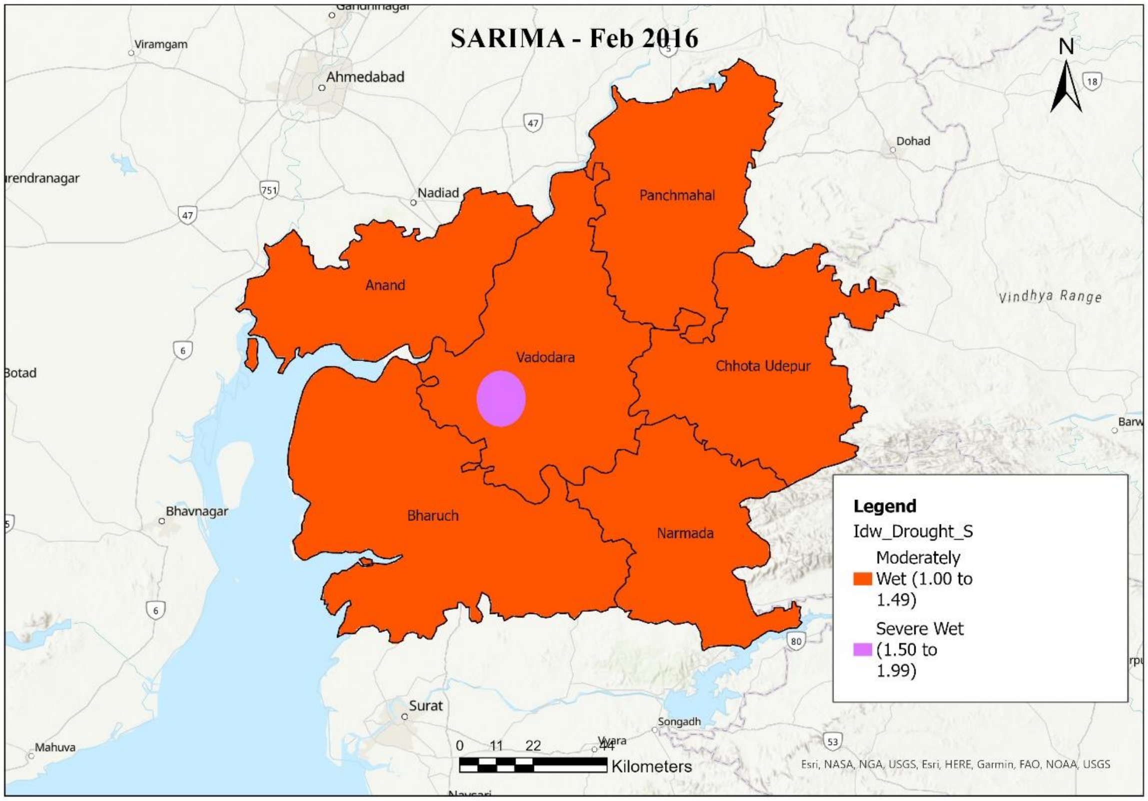

SVR - Time Series Forecasting for spi1.3
SPI
Date
Train Data
Test Data
Train Predictions
Test Predictions
12-Step Ahead Forecast

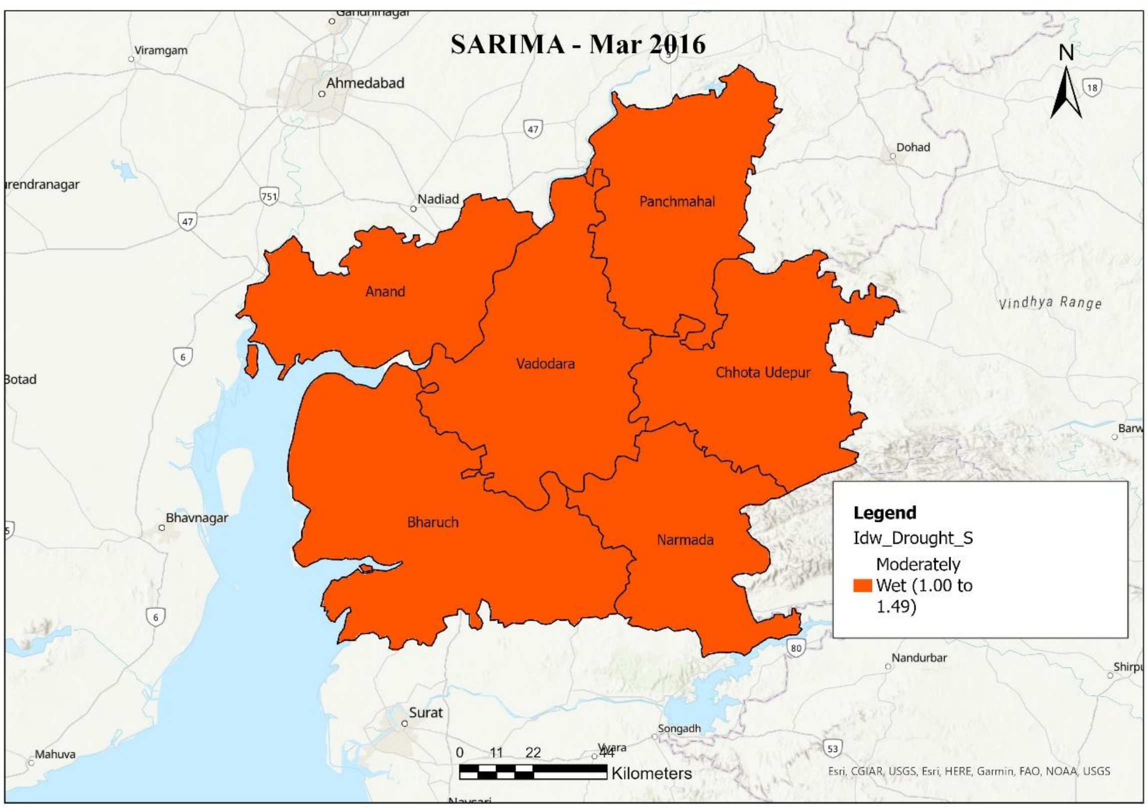


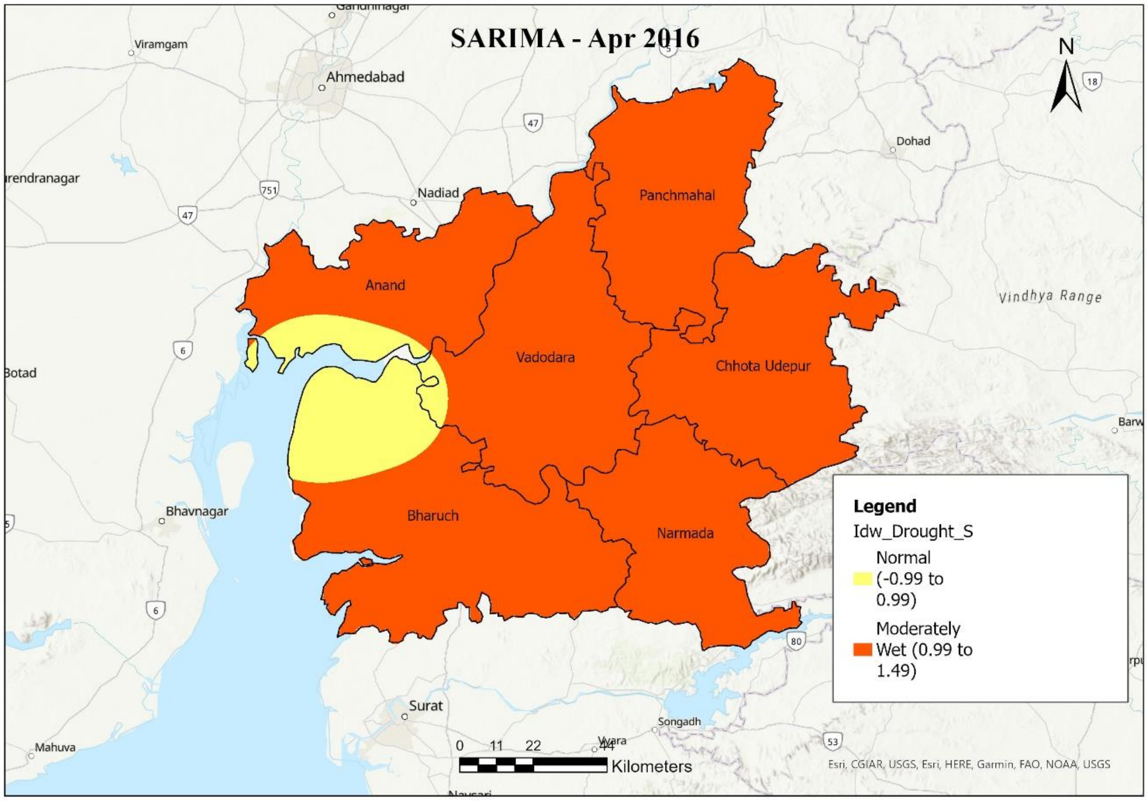
Maps

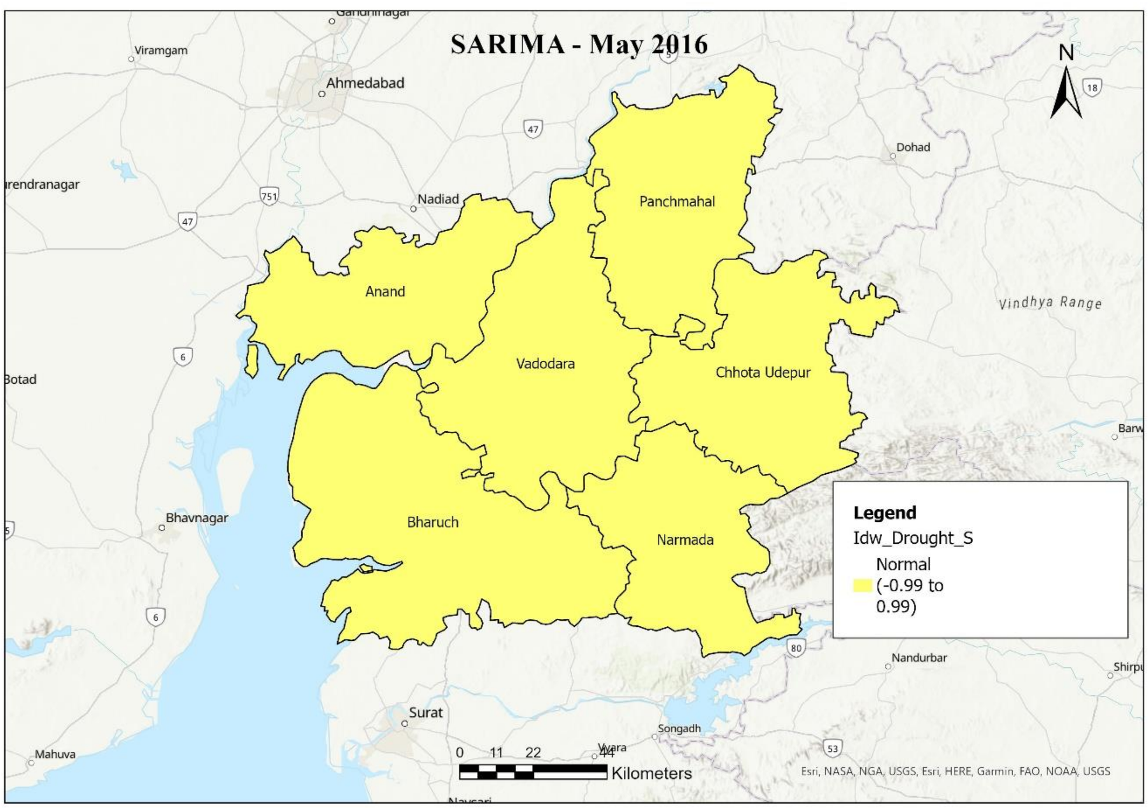
SARIMA and SARIMAX:

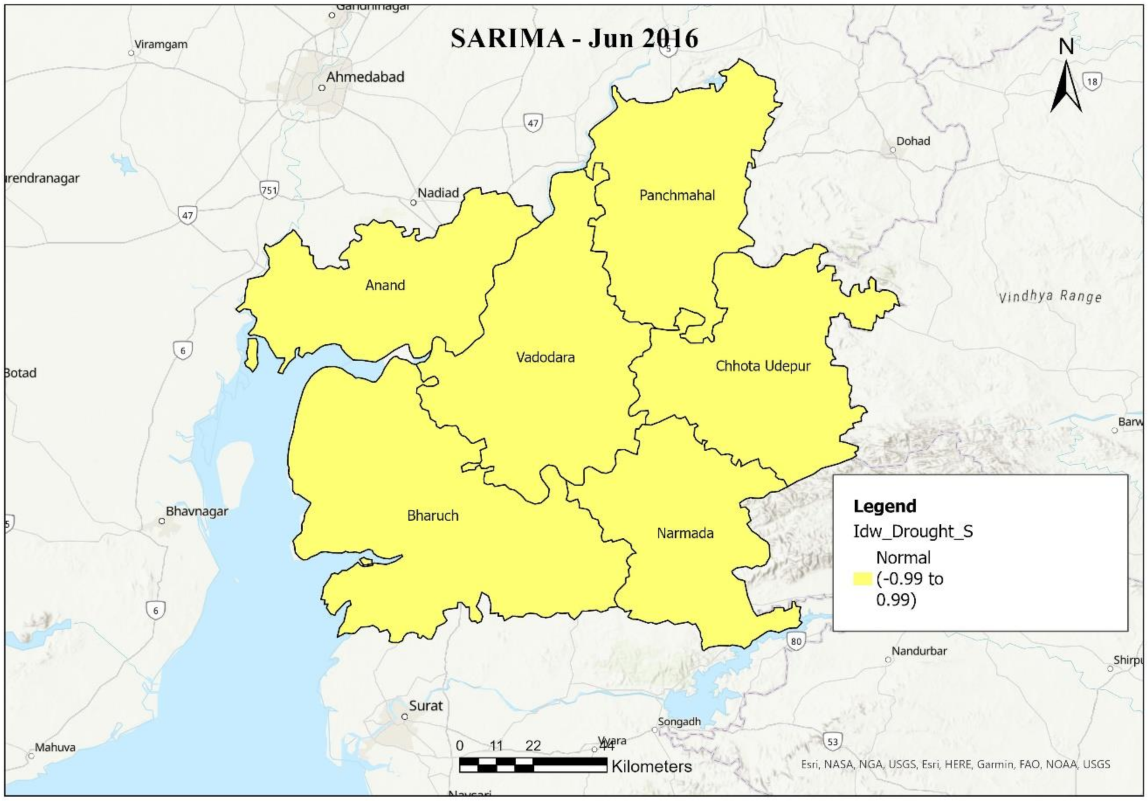


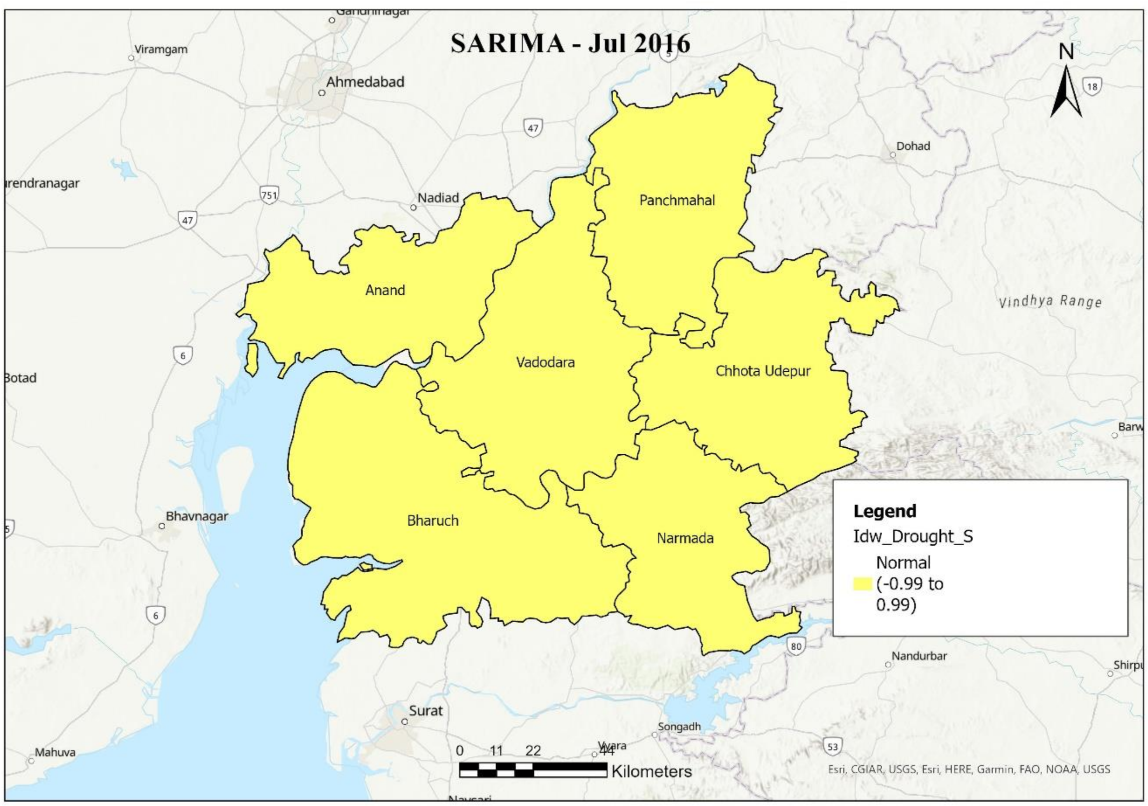

SARIMA - Feb 2016
Viramgam
Ahmedabad
Nadiad
Dohad
Panchmahal
Anand
Vadodara
Chhota Udepur
Vindhya Range
Bharuch
Narmada
Botad
Bhavnagar
Surat
Songadh
Mahuva
Legend
Idw_Drought_S
Moderately Wet (1.00 to 1.49)
Severe Wet (1.50 to 1.99)
0 11 22 44
Kilometers
Esri, NASA, NGA, USGS, Esri, HERE, Garmin, FAO, NOAA, USGS

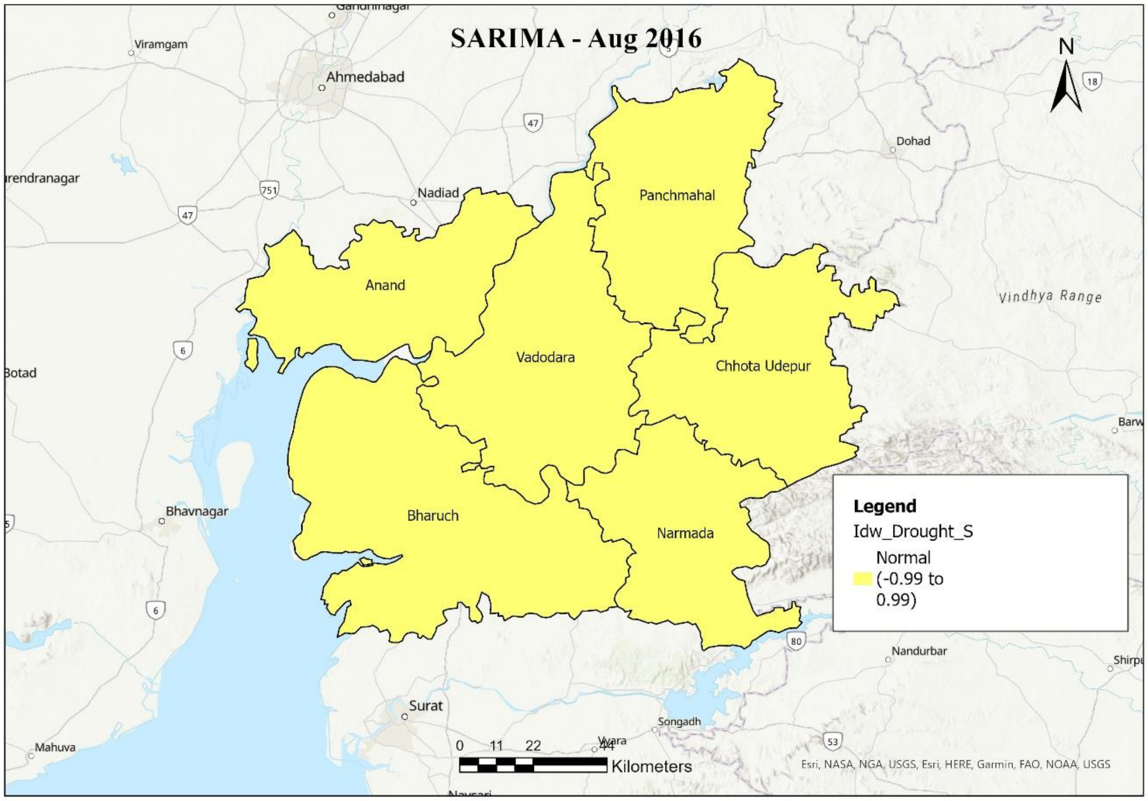

SARIMA - Mar 2016
Viramgam
Ahmedabad
Nadiad
Dohad
Panchmahal
Anand
Vadodara
Chhota Udepur
Vindhya Range
Bharuch
Narmada
Botad
Bhavnagar
Nandurbar
Surat
Songadh
Mahuva
Legend
Idw_Drought_S
Moderately Wet (1.00 to 1.49)
0 11 22 44
Kilometers
Esri, CGIAR, USGS, Esri, HERE, Garmin, FAO, NOAA, USGS

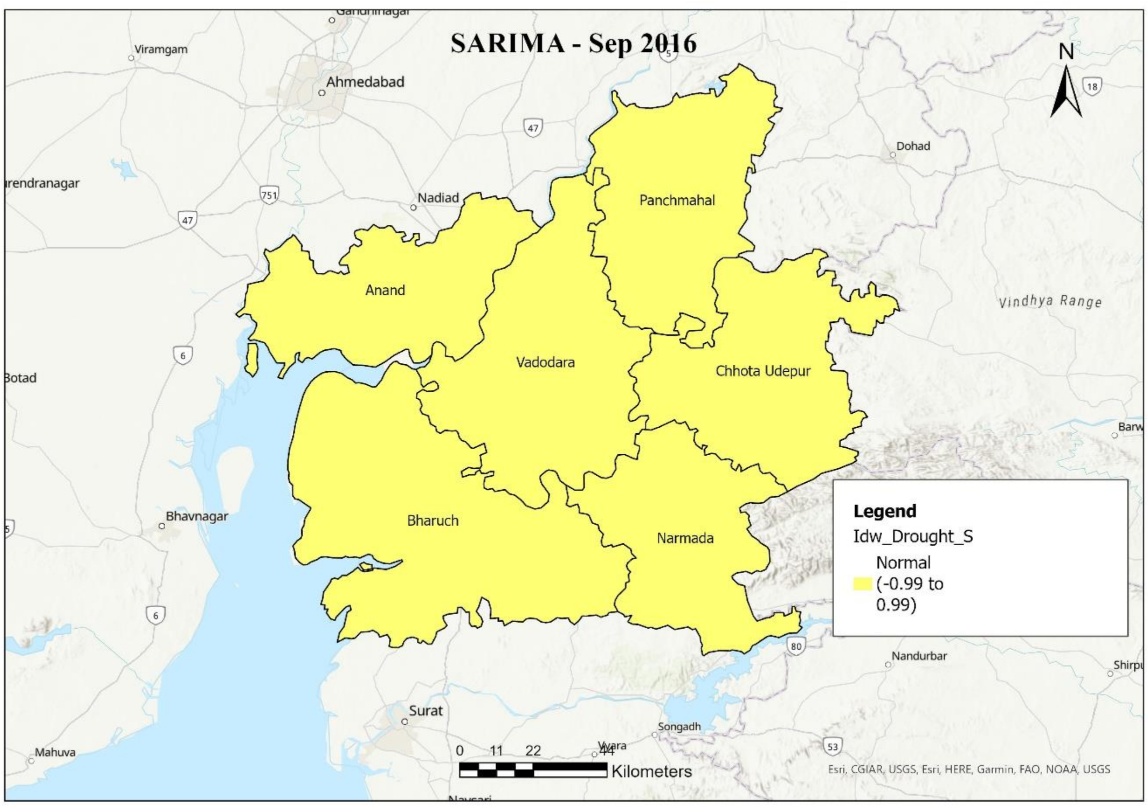

SARIMA - Apr 2016
Viramgam
Ahmedabad
Dohad
Nadiad
Panchmahal
Anand
Vindhya Range
Vadodara
Chhota Udepur
Botad
Bhavnagar
Bharuch
Narmada
Legend
Idw_Drought_S
Normal (-0.99 to 0.99)
Moderately Wet (0.99 to 1.49)
Surat
Songadh
Mahuva
0 11 22 44
Kilometers
Esri, CGIAR, USGS, Esri, HERE, Garmin, FAO, NOAA, USGS

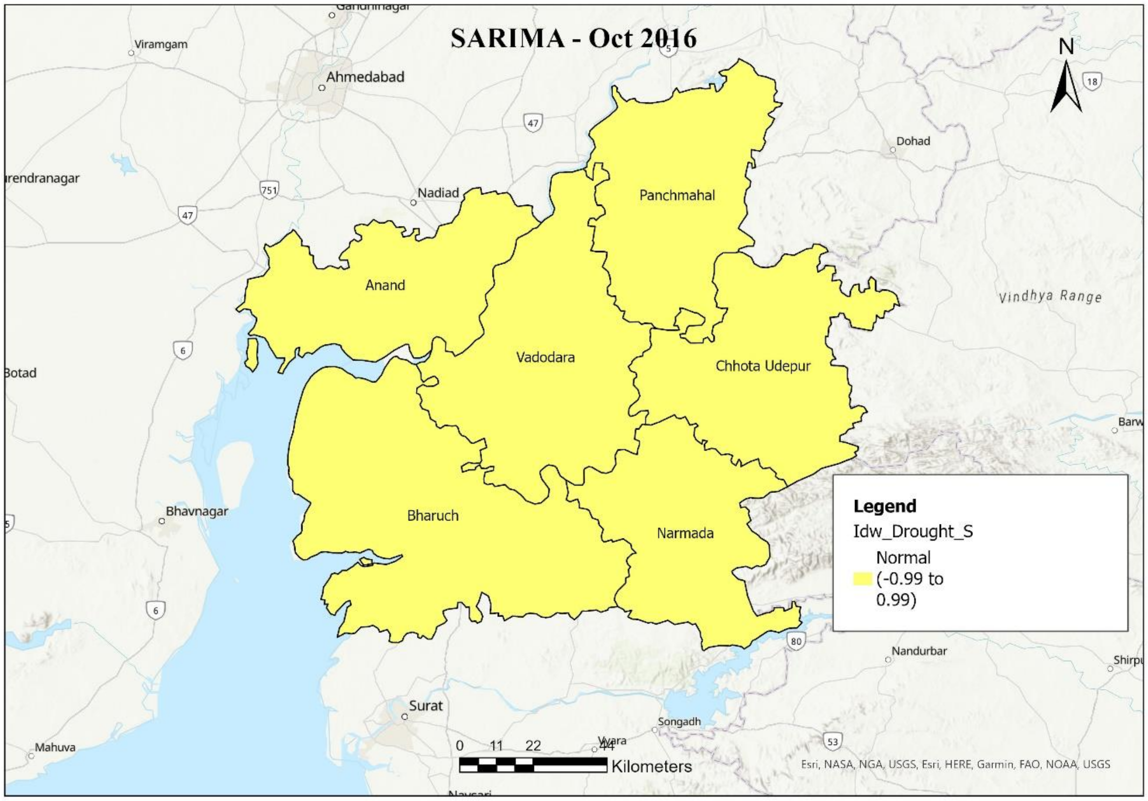

SARIMA - May 2016
Viramgam
Ahmedabad
Dohad
Nadiad
Panchmahal
Anand
Vindhya Range
Vadodara
Chhota Udepur
Botad
Bhavnagar
Bharuch
Narmada
Legend
Idw_Drought_S
Normal (-0.99 to 0.99)
Nandurbar
Surat
Songadh
Mahuva
0 11 22 44
Kilometers
Esri, NASA, NGA, USGS, Esri, HERE, Garmin, FAO, NOAA, USGS

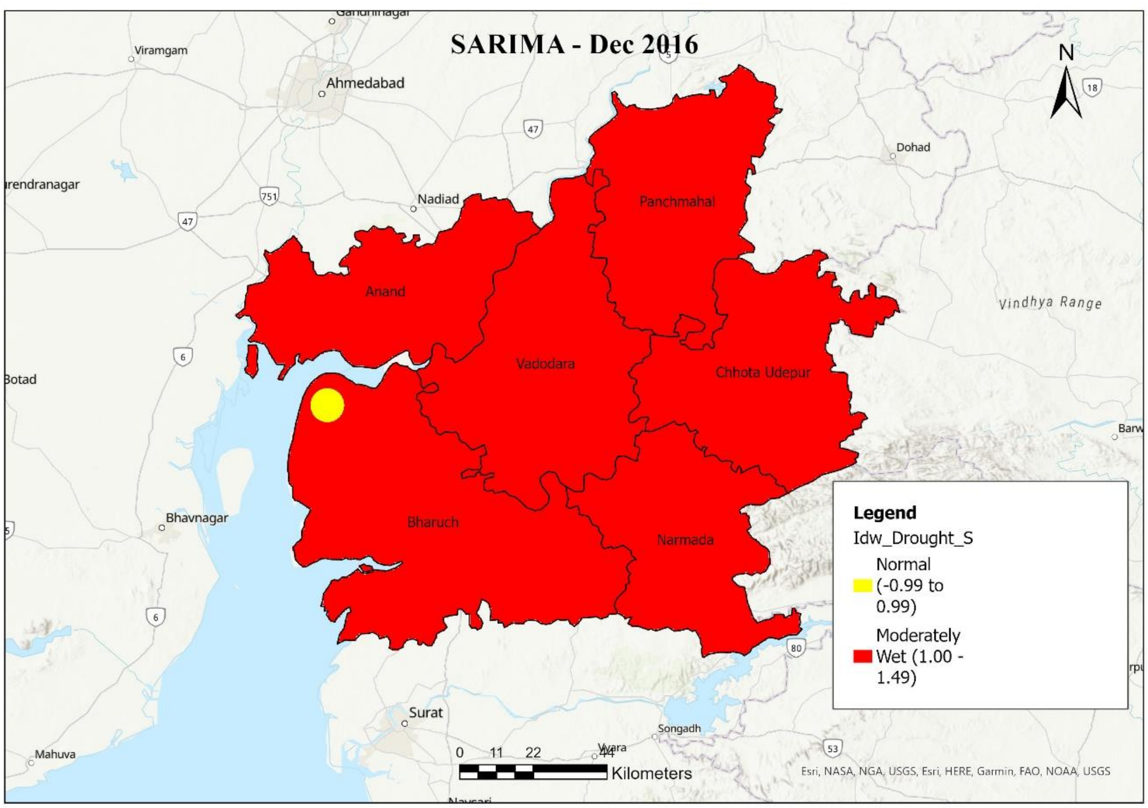

SARIMA - Jun 2016
Legend
Idw_Drought_S
Normal (-0.99 to 0.99)
Panchmahal
Anand
Vadodara
Chhota Udepur
Bharuch
Narmada
Ahmedabad
Viramgam
Nadiad
Dohad
Vindhya Range
Botad
Bhavnagar
Surat
Mahuva
Nandurbar
Songadh
0 11 22 44
Kilometers
Esri, NASA, NGA, USGS, Esri, HERE, Garmin, FAO, NOAA, USGS

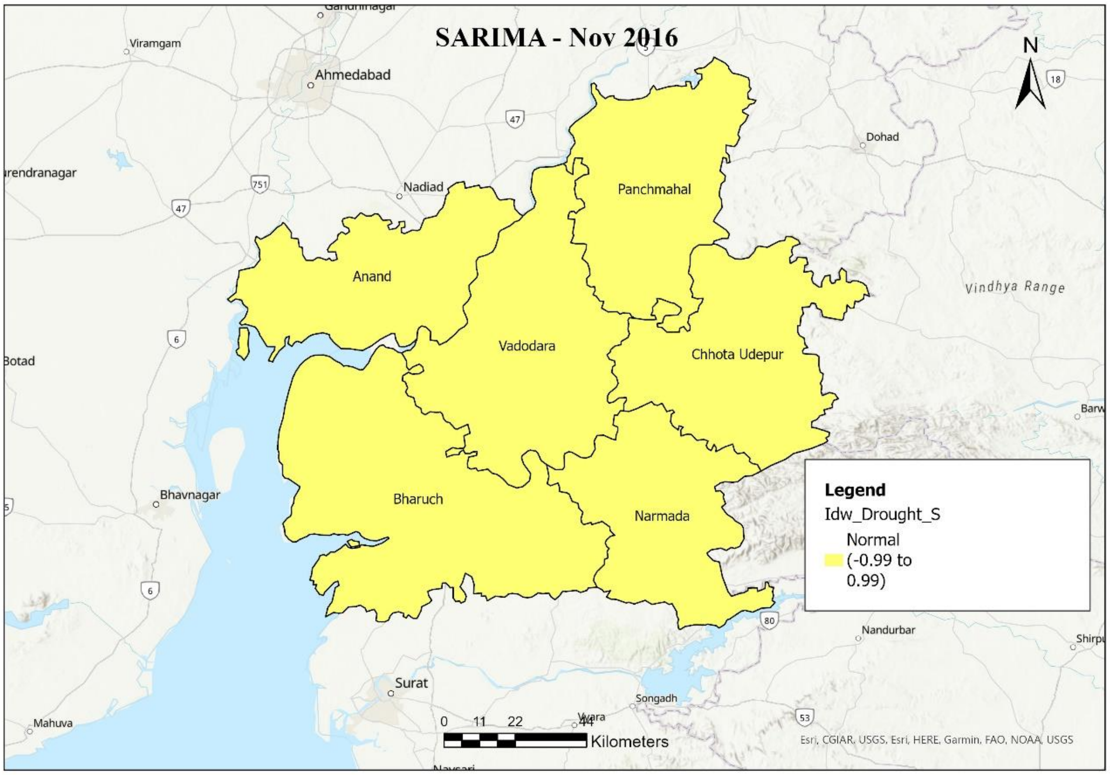

SARIMA - Jul 2016
Legend
Idw_Drought_S
Normal (-0.99 to 0.99)
Panchmahal
Anand
Vadodara
Chhota Udepur
Bharuch
Narmada
Ahmedabad
Viramgam
Nadiad
Dohad
Vindhya Range
Botad
Bhavnagar
Surat
Mahuva
Nandurbar
Songadh
0 11 22 44
Kilometers
Esri, CGIAR, USGS, Esri, HERE, Garmin, FAO, NOAA, USGS


SARIMA - Aug 2016
Viramgam
Ahmedabad
Nadiad
Dohad
Panchmahal
Anand
Vadodara
Chhota Udepur
Vindhya Range
Botad
Bharuch
Narmada
Bhavnagar
Nandurbar
Surat
Songadh
Mahuva
Vyara
Legend
Idw_Drought_S
Normal (-0.99 to 0.99)
0 11 22 44 Kilometers
Esri, NASA, NGA, USGS, Esri, HERE, Garmin, FAO, NOAA, USGS

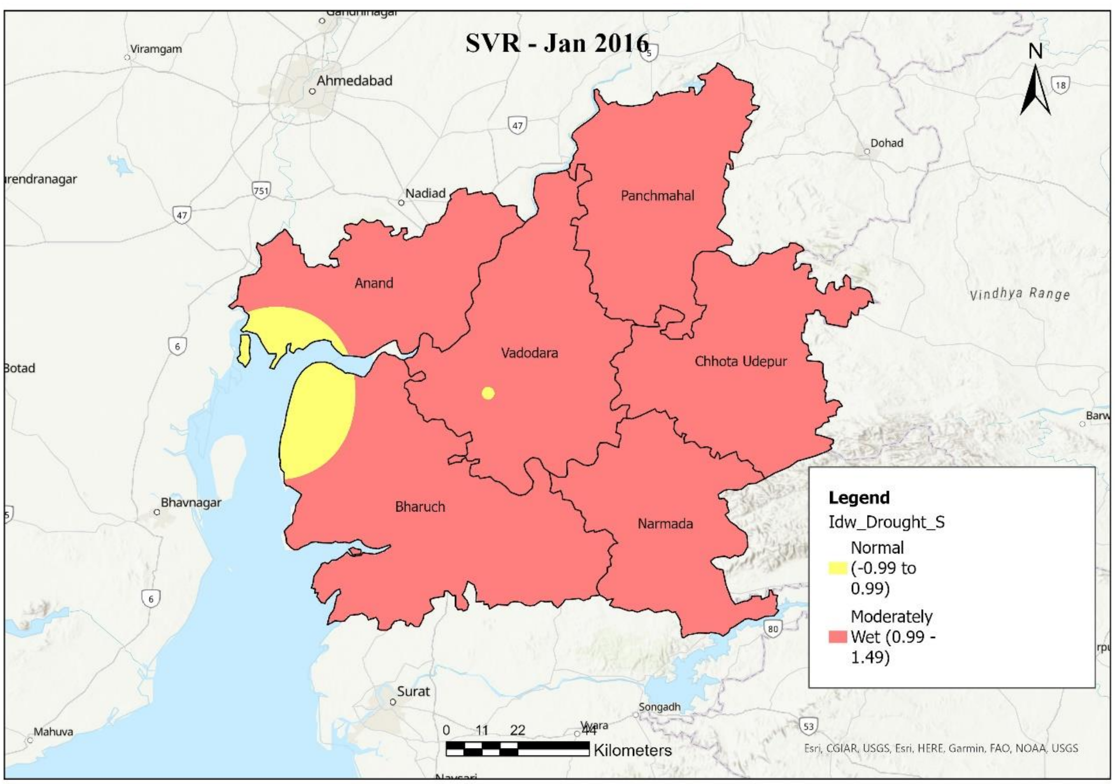

SARIMA - Sep 2016
Viramgam
Ahmedabad
Nadiad
Dohad
Panchmahal
Anand
Vadodara
Chhota Udepur
Vindhya Range
Botad
Bharuch
Narmada
Bhavnagar
Nandurbar
Surat
Songadh
Mahuva
Vyara
Legend
Idw_Drought_S
Normal (-0.99 to 0.99)
0 11 22 44 Kilometers
Esri, CGIAR, USGS, Esri, HERE, Garmin, FAO, NOAA, USGS

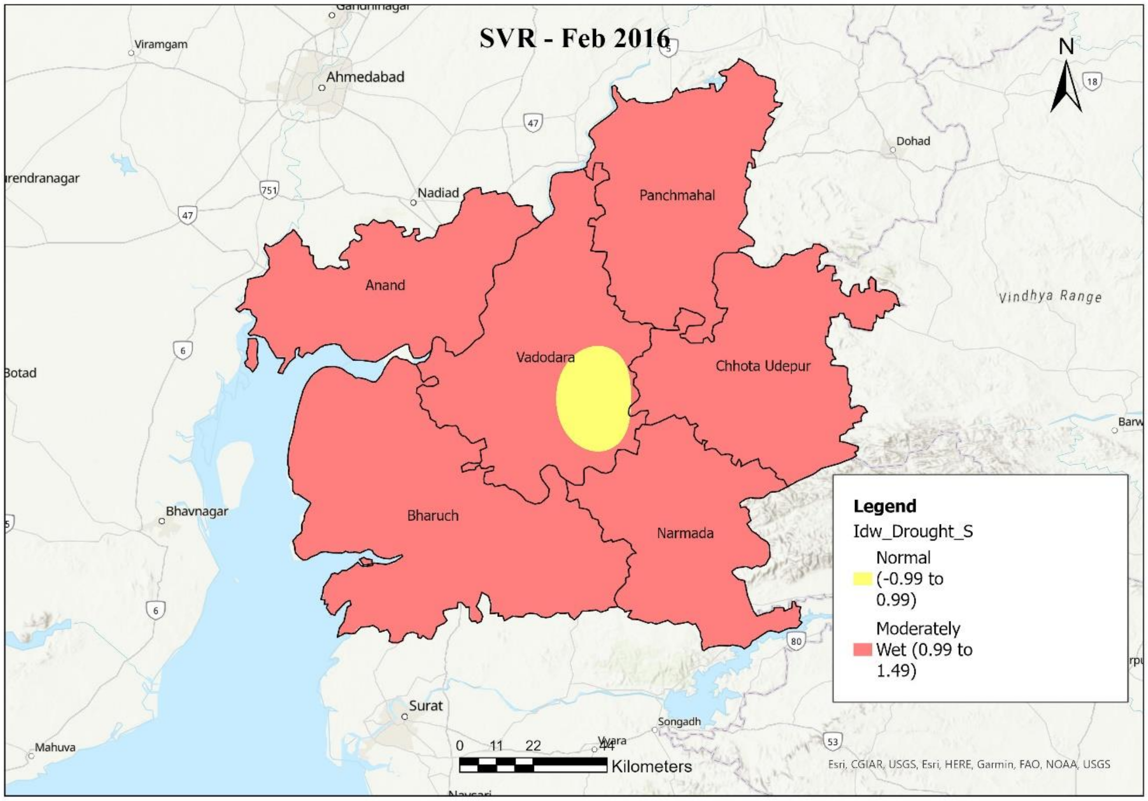

SARIMA - Oct 2016
Ahmedabad
Viramgam
Nadiad
Dohad
Panchmahal
Anand
Vadodara
Chhota Udepur
Bharuch
Narmada
Bhavnagar
Botad
Vindhya Range
Surat
Songadh
Nandurbar
Mahuva
Legend
Idw_Drought_S
Normal (-0.99 to 0.99)
0 11 22 44
Kilometers
Esri, NASA, NGA, USGS, Esri, HERE, Garmin, FAO, NOAA, USGS

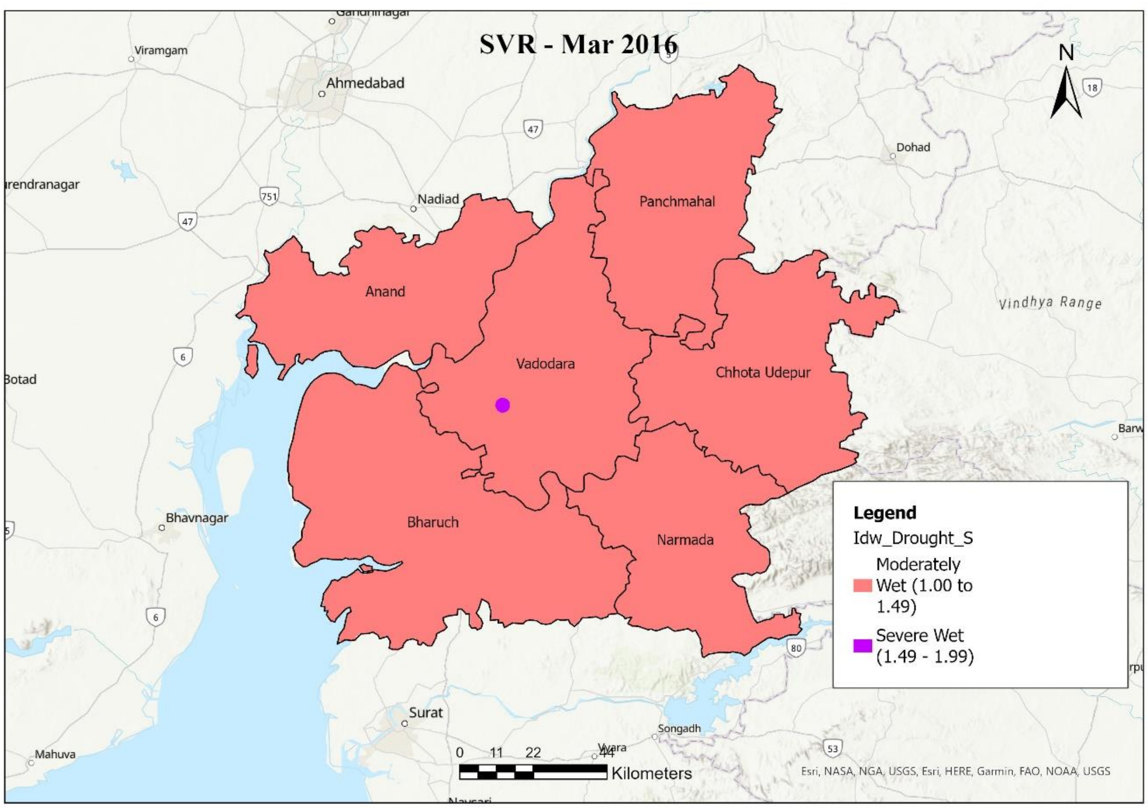

SARIMA - Dec 2016
Ahmedabad
Viramgam
Nadiad
Dohad
Panchmahal
Anand
Vadodara
Chhota Udepur
Bharuch
Narmada
Bhavnagar
Botad
Vindhya Range
Surat
Songadh
Mahuva
Legend
Idw_Drought_S
Normal (-0.99 to 0.99)
Moderately Wet (1.00 - 1.49)
0 11 22 44
Kilometers
Esri, NASA, NGA, USGS, Esri, HERE, Garmin, FAO, NOAA, USGS

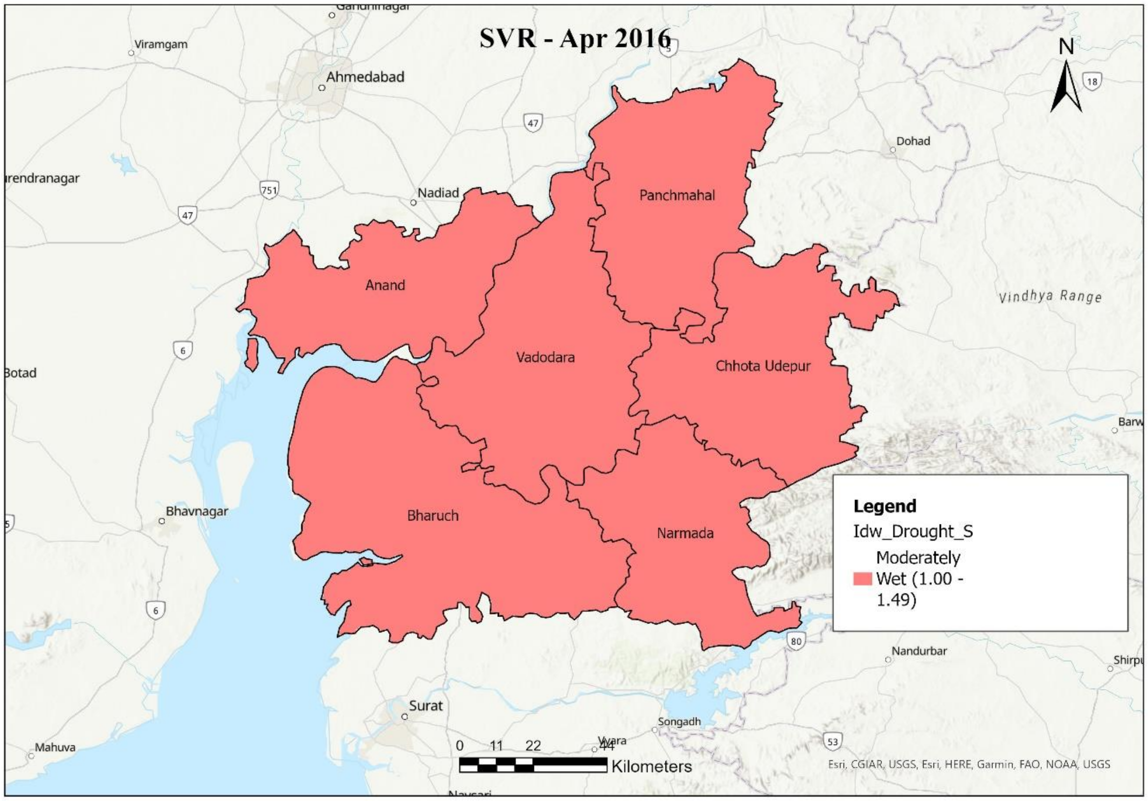


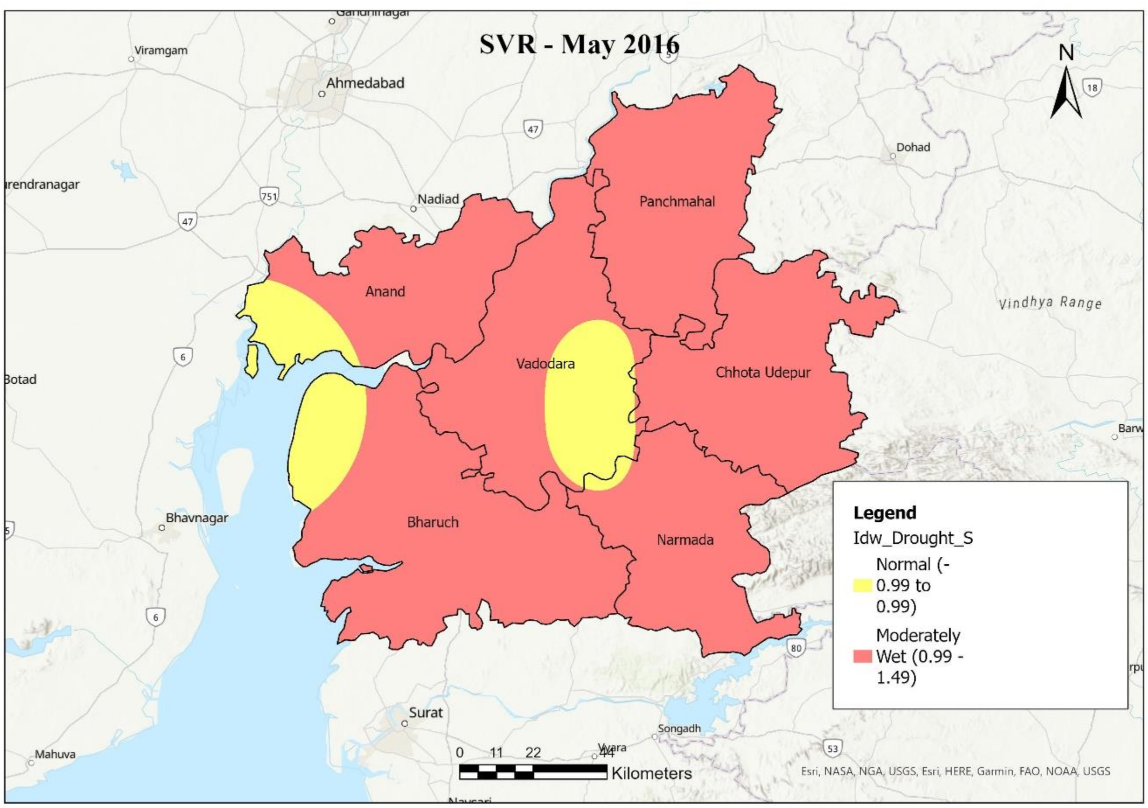
Support Vector Regressor:

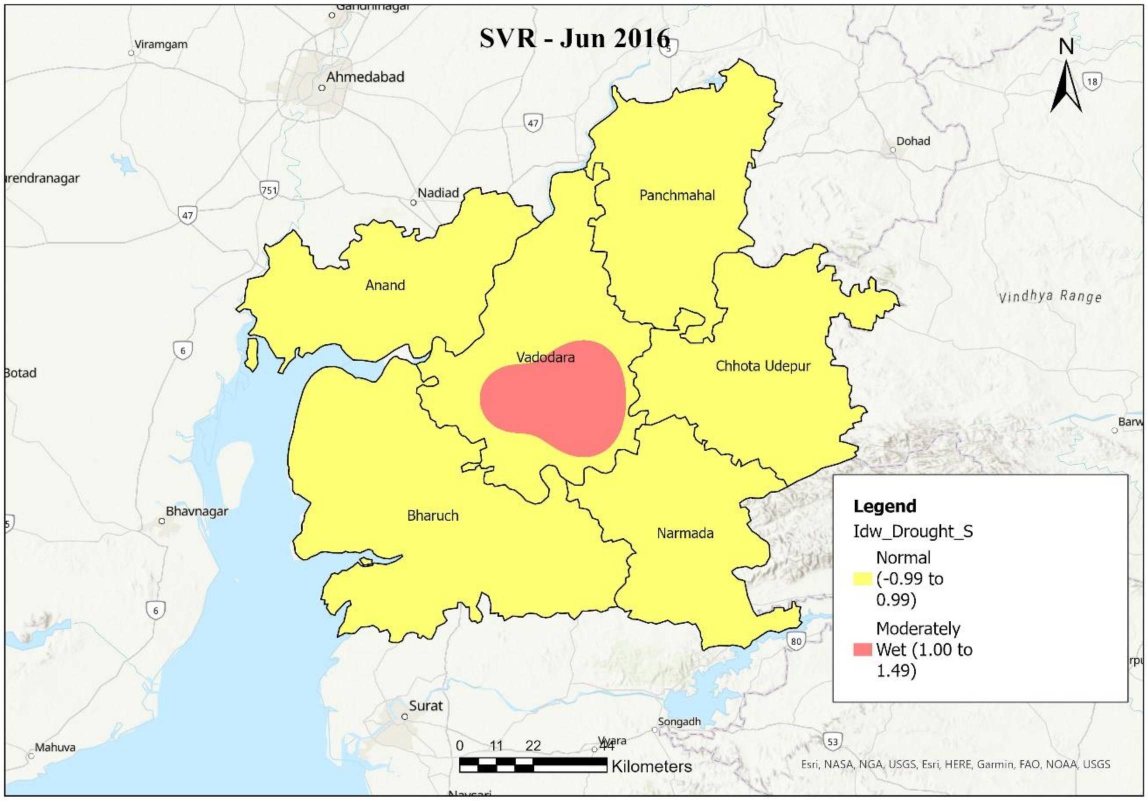


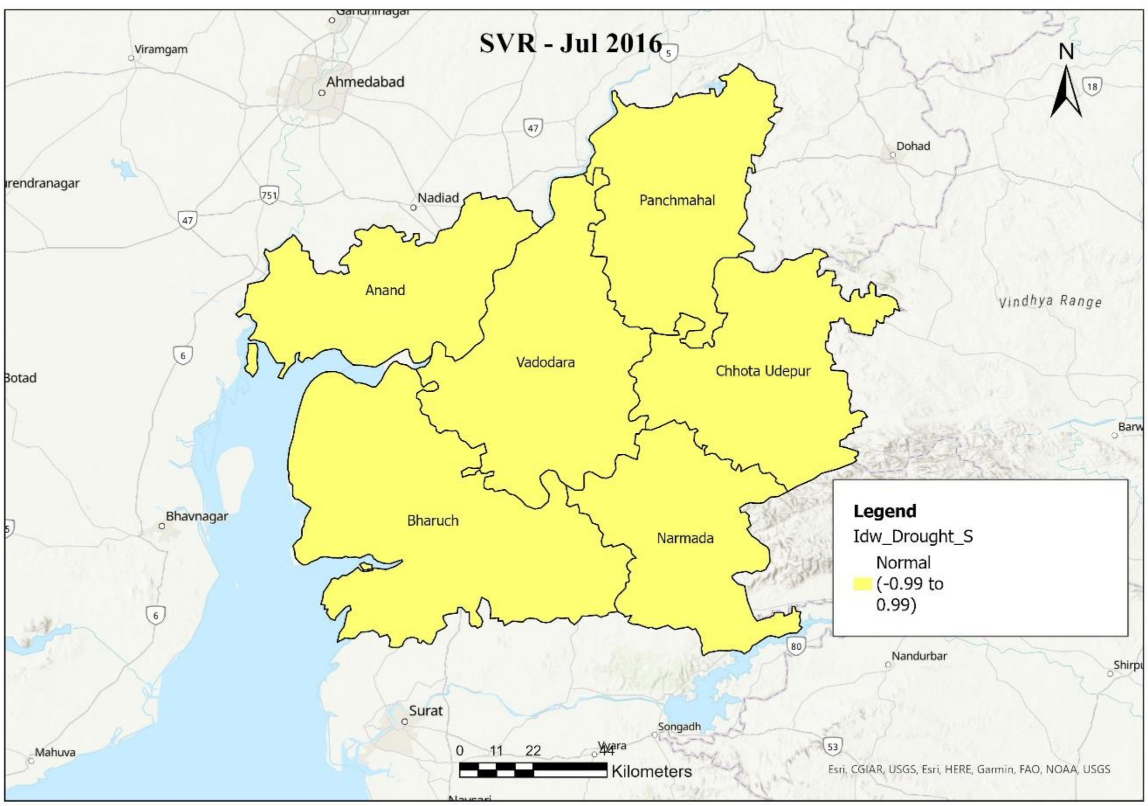

SVR - Feb 2016
N
Gandhinagar
Viramgam
Ahmedabad
Dohad
Surendranagar
Nadiad
Panchmahal
Anand
Vadodara
Chhota Udepur
Vindhya Range
Botad
Bharuch
Narmada
Bhavnagar
Surat
Songadh
Mahuva
Vyara
Navsari
Legend
Idw_Drought_S
Normal (-0.99 to 0.99)
Moderately Wet (0.99 to 1.49)
0 11 22 44
Kilometers
Esri, CGIAR, USGS, Esri, HERE, Garmin, FAO, NOAA, USGS

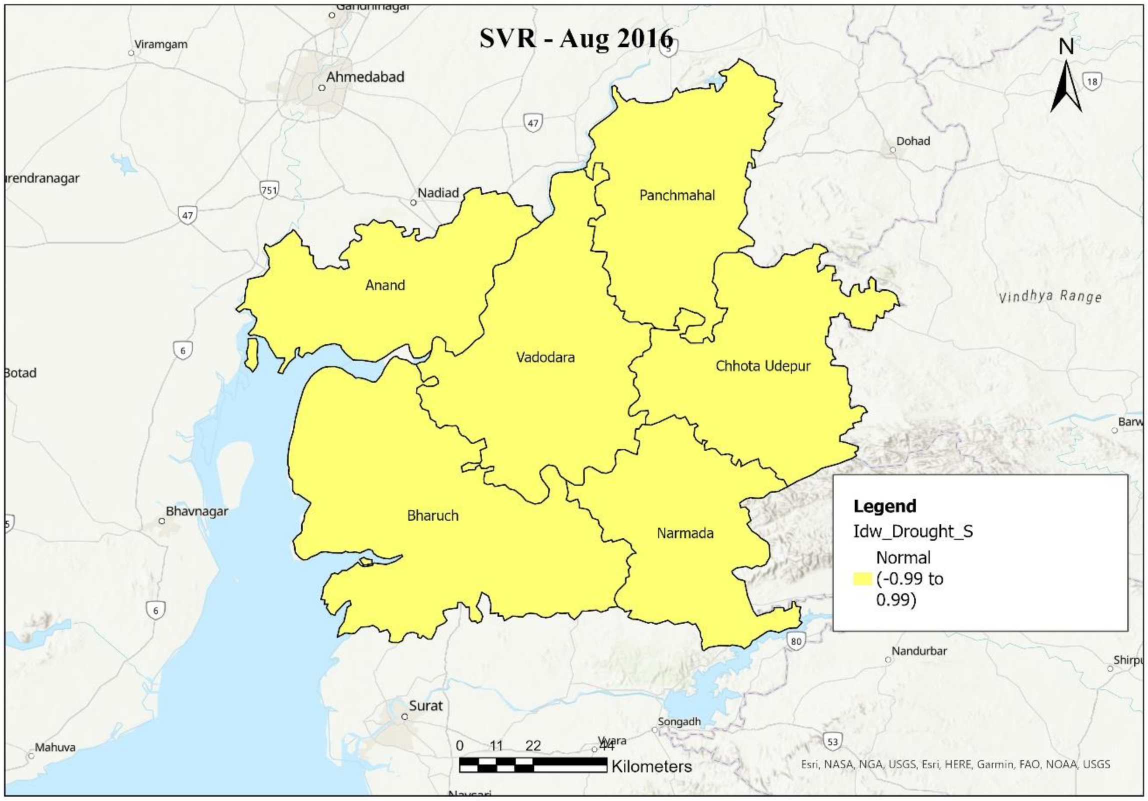

SVR - Mar 2016
N
Gandhinagar
Viramgam
Ahmedabad
Dohad
Surendranagar
Nadiad
Panchmahal
Anand
Vadodara
Chhota Udepur
Vindhya Range
Botad
Bharuch
Narmada
Bhavnagar
Surat
Songadh
Mahuva
Vyara
Navsari
Legend
Idw_Drought_S
Moderately Wet (1.00 to 1.49)
Severe Wet (1.49 - 1.99)
0 11 22 44
Kilometers
Esri, NASA, NGA, USGS, Esri, HERE, Garmin, FAO, NOAA, USGS

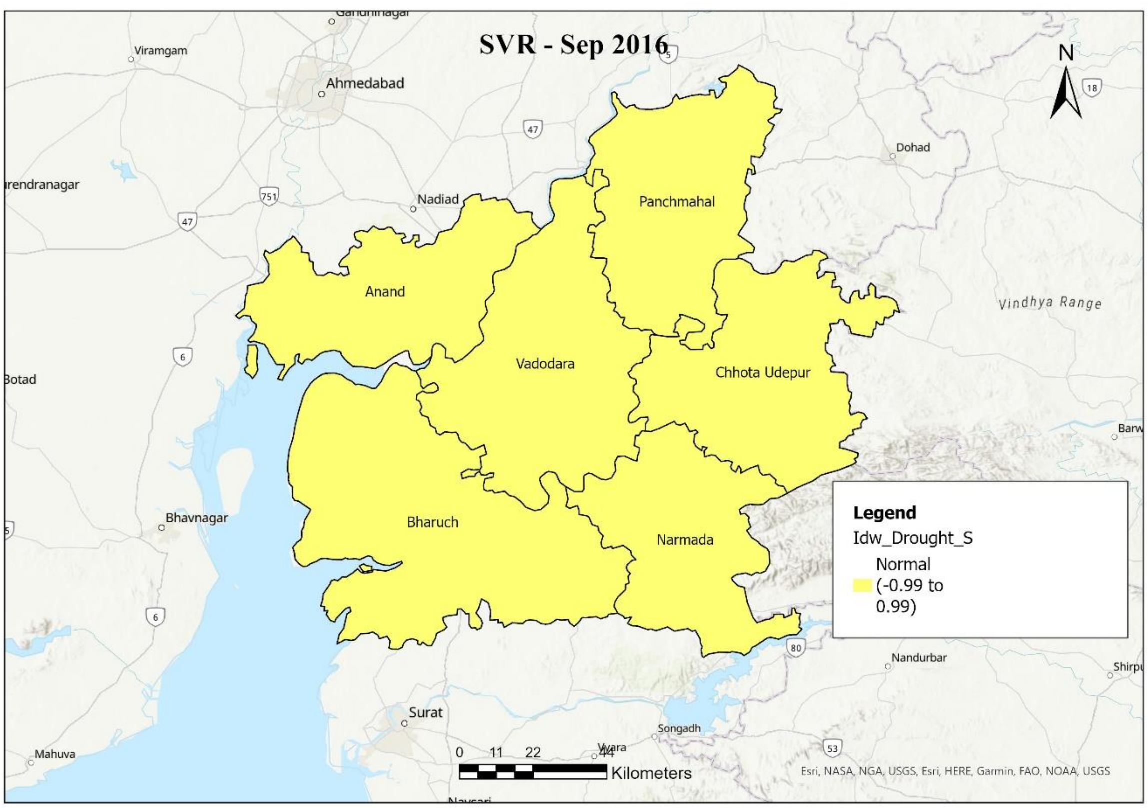

SVR - Apr 2016
N
Viramgam
Ahmedabad
Dohad
Nadiad
Panchmahal
Anand
Vadodara
Chhota Udepur
Vindhya Range
Botad
Bharuch
Narmada
Bhavnagar
Legend
Idw_Drought_S
Moderately Wet (1.00 - 1.49)
Nandurbar
Surat
Songadh
Mahuva
0 11 22 44
Kilometers
Esri, CGIAR, USGS, Esri, HERE, Garmin, FAO, NOAA, USGS

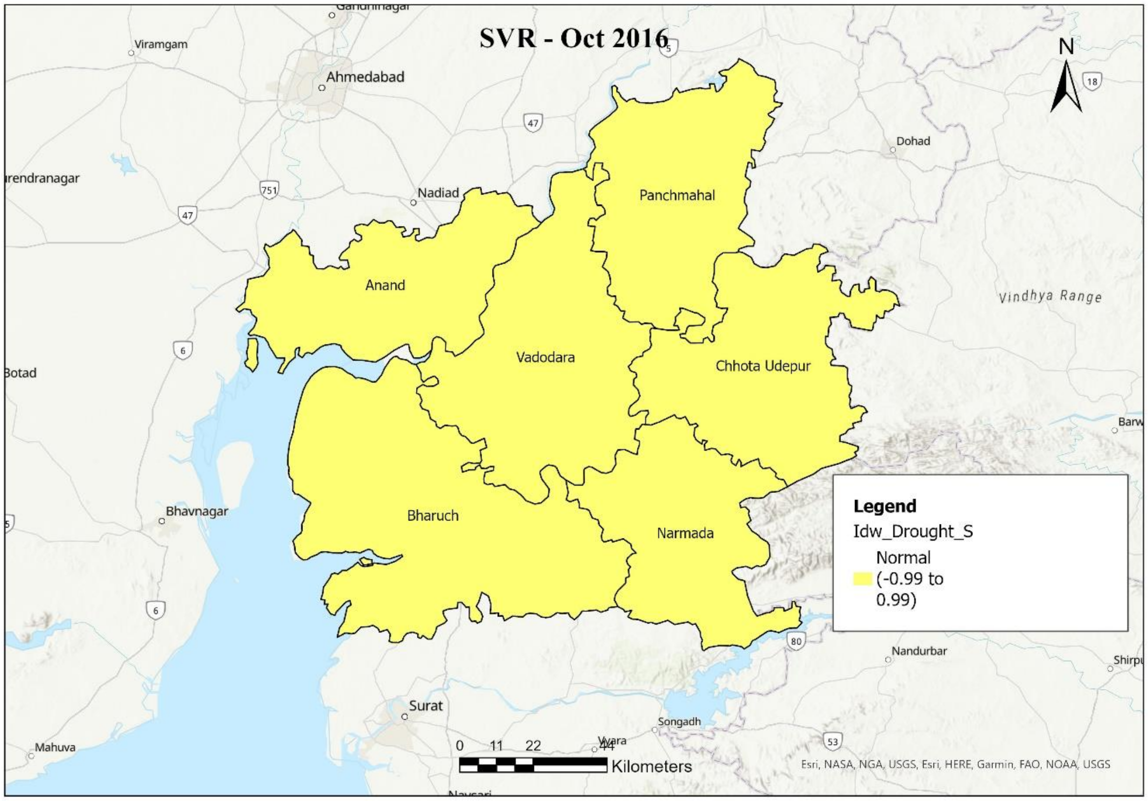

SVR - May 2016
N
Viramgam
Ahmedabad
Dohad
Nadiad
Panchmahal
Anand
Vadodara
Chhota Udepur
Vindhya Range
Botad
Bharuch
Narmada
Bhavnagar
Legend
Idw_Drought_S
Normal (-0.99 to 0.99)
Moderately Wet (0.99 - 1.49)
Surat
Songadh
Mahuva
0 11 22 44
Kilometers
Esri, NASA, NGA, USGS, Esri, HERE, Garmin, FAO, NOAA, USGS

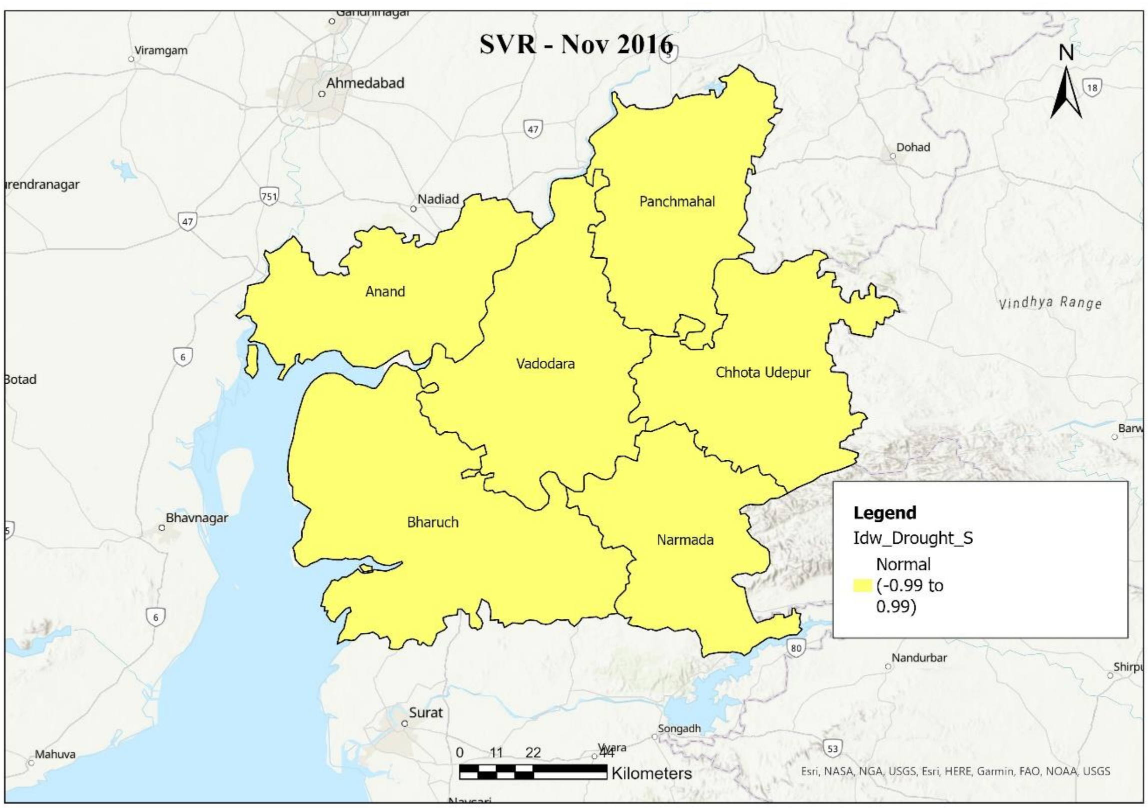

SVR - Jun 2016
N
Viramgam
Ahmedabad
Dohad
Nadiad
Panchmahal
Anand
Vadodara
Chhota Udepur
Vindhya Range
Botad
Bharuch
Narmada
Bhavnagar
Surat
Songadh
Mahuva
Vyara
0 11 22 44
Kilometers
Esri, NASA, NGA, USGS, Esri, HERE, Garmin, FAO, NOAA, USGS
Legend
Idw_Drought_S
Normal (-0.99 to 0.99)
Moderately Wet (1.00 to 1.49)

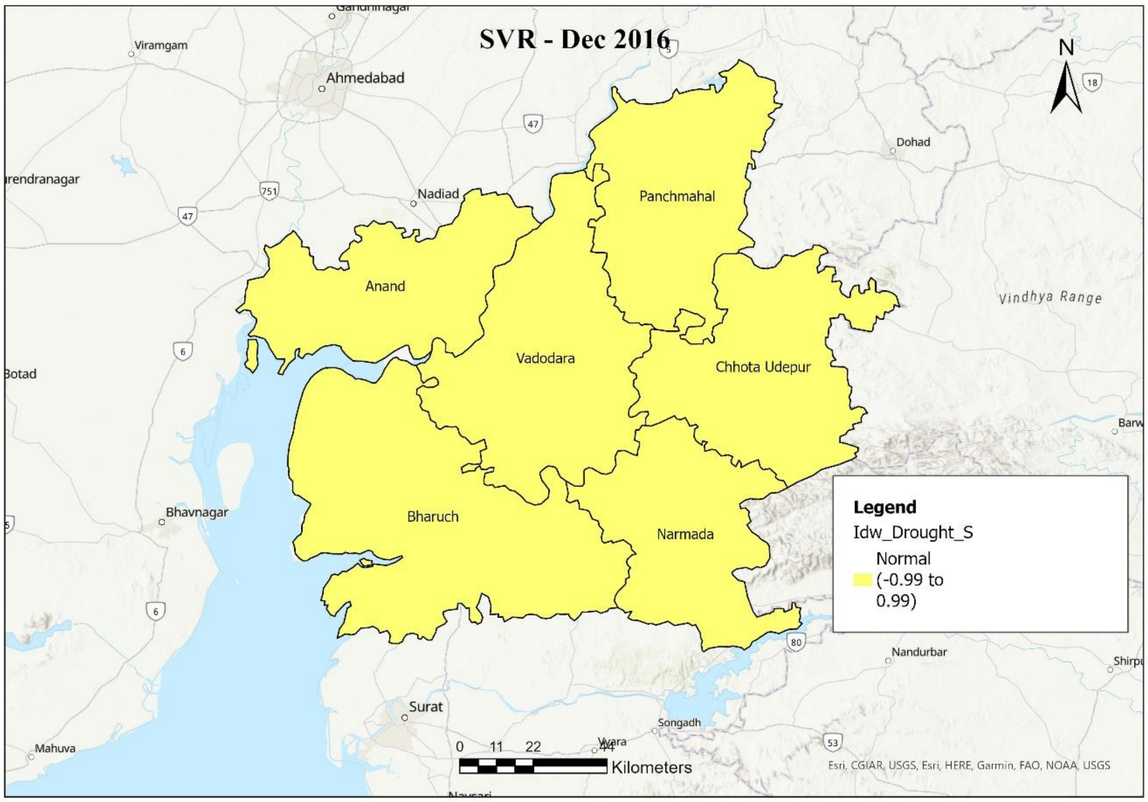

SVR - Jul 2016
N
Viramgam
Ahmedabad
Dohad
Nadiad
Panchmahal
Anand
Vadodara
Chhota Udepur
Vindhya Range
Botad
Bharuch
Narmada
Bhavnagar
Nandurbar
Surat
Songadh
Mahuva
Vyara
0 11 22 44
Kilometers
Esri, CGIAR, USGS, Esri, HERE, Garmin, FAO, NOAA, USGS
Legend
Idw_Drought_S
Normal (-0.99 to 0.99)


SVR - Aug 2016
N
Legend
Idw_Drought_S
Normal
(-0.99 to
0.99)
Panchmahal
Anand
Vadodara
Chhota Udepur
Bharuch
Narmada
Ahmedabad
Nadiad
Dohad
Viramgam
Botad
Bhavnagar
Surat
Mahuva
Songadh
Nandurbar
Vindhya Range
0 11 22 44
Kilometers
Esri, NASA, NGA, USGS, Esri, HERE, Garmin, FAO, NOAA, USGS


SVR - Sep 2016
N
Legend
Idw_Drought_S
Normal
(-0.99 to
0.99)
Panchmahal
Anand
Vadodara
Chhota Udepur
Bharuch
Narmada
Ahmedabad
Nadiad
Dohad
Viramgam
Botad
Bhavnagar
Surat
Mahuva
Songadh
Nandurbar
Vindhya Range
0 11 22 44
Kilometers
Esri, NASA, NGA, USGS, Esri, HERE, Garmin, FAO, NOAA, USGS


SVR - Oct 2016
N
Viramgam
Ahmedabad
Dohad
Nadiad
Panchmahal
Anand
Vadodara
Chhota Udepur
Vindhya Range
Botad
Bharuch
Narmada
Bhavnagar
Nandurbar
Surat
Songadh
Mahuva
Vyara
Legend
Idw_Drought_S
Normal (-0.99 to 0.99)
0 11 22 44
Kilometers
Esri, NASA, NGA, USGS, Esri, HERE, Garmin, FAO, NOAA, USGS


SVR - Nov 2016
N
Viramgam
Ahmedabad
Dohad
Nadiad
Panchmahal
Anand
Vadodara
Chhota Udepur
Vindhya Range
Botad
Bharuch
Narmada
Bhavnagar
Nandurbar
Surat
Songadh
Mahuva
Vyara
Legend
Idw_Drought_S
Normal (-0.99 to 0.99)
0 11 22 44
Kilometers
Esri, NASA, NGA, USGS, Esri, HERE, Garmin, FAO, NOAA, USGS



Area-wise Model Comparison:

Area A1:

- SARIMA and SARIMAX outperform other models in terms of RMSE.
- Random Forest and Gradient Boosting Regressor have similar performance but relatively lower R2 compared to SARIMA.

Area A2:

- SARIMA and SARIMAX exhibit the lowest RMSE.
- Random Forest and Gradient Boosting Regressor again show similar performance, with higher R2 compared to SARIMA.

Area A3:

- SARIMA and SARIMAX demonstrate the lowest RMSE.
- Support Vector Regressor has the highest R2 among the models.

Area A4:

- SARIMA and SARIMAX have the lowest RMSE.

- Random Forest outperforms Gradient Boosting Regressor in terms of RMSE and R2.

Area A5:

- SARIMA, SARIMAX, and Random Forest have competitive RMSE values.
- Gradient Boosting Regressor shows slightly better performance compared to Support Vector Regressor.

Conclusion:

To mitigate economic and environmental implications, it is important to have effective drought monitoring and mapping systems in place. In this project, we used a combination of time series models and machine learning algorithms to predict droughts in six districts of Gujarat in India. The study followed an elaborate methodology that involved data preprocessing, model development as well as GIS mapping; the study found that of all the possible **SARIMA** time series model performed the best while **SVR** was found to be the most accurate forecasting Standardized Precipitation Index (SPI) values using machine learning. The findings highlight the importance of early warning systems for water resources management, agricultural plans and policy formulation. Continuous model monitoring is one of the recommendations while future research could consider investigating other factors for better precision. This study provides valuable inputs on how to tackle sustainable drought disaster risks in the area under analysis.

Reference:

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3. **MISHRA A.K., SINGH V.P. 2010.** A review of drought concepts. Journal of Hydrology. Vol. 391. Iss. 1–2 p. 202– 216.
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5. **Keshavarz, M., Karami, E., & Vanclay, F. (2013, January 1).** *The social experience of drought in rural Iran*. Land Use Policy. https://doi.org/10.1016/j.landusepol.2012.03.00