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An Improved Spatiotemporal Time Series Modelling Procedure with Application to Forecasting of Solar Radiation

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SUMMARY

The demand for energy and associated services to meet sustainable agricultural and economic growth and improve human health and lifestyle is increasing day by day. Hence, there is a need for systematic and scientific prediction of solar and other renewable sources of energy to meet these requirements. The main purpose of this study is to propose a hybrid Space-Time Autoregressive Moving Average Artificial Neural Network (STARMA-ANN) model for the precise and accurate forecasting of solar radiation for better planning and policy making. This approach has been implemented at seven geographical locations of Bihar in India. Spatial weight matrices have been used to describe all seven geographical locations and incorporated into the STARMA model to reflect the spatial and temporal correlation. To deal with nonlinear dynamics in the spatiotemporal data, ANN technique has been applied on residuals of the fitted STARMA model. The results have demonstrated that the proposed hybrid model performs better prediction accuracy than using conventional STARMA model, especially for spatiotemporal data with nonlinear characteristics of solar radiation.

Keywords: Solar radiation; STARMA; ANN; Hybrid model; Spatial weight matrix; Forecasting.

1. INTRODUCTION

Change of climate and high demand of power supply have led to the requirement of solar and other green and renewable energy recently. The high spatial and temporal variability of Earth's solar radiation is one of the most important challenges for the use of solar energy. The Solar radiation has pivotal role in the agriculture sector that brings energy to the metabolic process of the plants and it is also helpful in the processes of photosynthesis, transpiration, and evaporation. However, in this direction, a need for accurate solar radiation forecasts can play an important role for sustainable agriculture and economic growth.

Several approaches have been developed for the forecast of solar radiation on various time scales. The linear Autoregressive Integrated Moving Average (ARIMA) method has been extensively studied (Alsharif *et al.* 2019, Shadab *et al.* 2019). Concerning the spatio-temporal processes, very few literatures have been proposed to forecasting of weather parameters with incorporation of both spatial and temporal information (Rathod *et al.* 2018; Glasbey and Allcroft, 2008). In real-world phenomena, solar radiation often exhibits spatiotemporal and nonlinear dynamics. Therefore, these two approaches are not suitable if the data exhibits nonlinear patterns. Many researches have been carried out on nonlinear dynamics of solar radiation forecasting (Kumar *et al.* 2016, Sharma *et al.* 2016, Sharma and Kakkar, 2017) but main constraint is that they dealt only with temporal dynamics. Specially in Indian metrological context, very few researches have been carried out in the reference of both spatio-temporal and nonlinear characters in the data set (Saha *et al.* 2020, Kumar *et al.* 2023). Hence, to overcome this limitation, this study has been tried to describe prediction of solar radiation by using a hybrid space-time autoregressive moving average (STARMA) and Artificial neural networks (ANN) approaches

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that is capable to handle the linear, nonlinear and spatiotemporal dynamics in the time series data.

2. MATERIALS AND METHODS

2.1 Study Area and Data

The research study has been focused on agro-climatic Zone-I of Bihar in India. The study areas have been considered for monthly average solar radiation for seven locations, viz. East Champaran (ECH), West Champaran (WCH), Gopalganj (GOP), Muzaffarpur (MUZ), Saran (SAR), Siwan (SIW), and Vaishali (VAI) that are represented in **Fig. 1**. Data have been retrieved from NASA power source (https://power.larc.nasa.gov/) for a period from January, 1984 to December, 2020. The data of solar radiation (MJ/m^2/month) are accessible on a grid of 0.5^o latitude x 0.5^o longitude spatial resolution in all sky insolation incident on a horizontal surface. The whole data has been divided into two parts viz., training data set (January, 1984 to December, 2018) and testing data set (January, 2019 to December, 2020). The graphical trends of monthly average solar radiation is given in **Fig.2**.

2.2 STARMA Model

The STARMA model is defined as a lag spatial operator to express the influence of the nearest neighbours at a certain spatial lag through the use of weights. The equation of STARMA model ($p_{\lambda_1, \lambda_2, \ldots, \lambda_p}$, $q_{m_1, m_2, \ldots, m_q}$) can be expressed as:

$$\boldsymbol{Y}_t = \sum_{k=1}^{p}\sum_{l=0}^{\lambda_\kappa}\phi_{kl}\boldsymbol{W}^l\boldsymbol{Y}_{t-k} - \sum_{k=1}^{q}\sum_{l=0}^{m_\kappa}\theta_{kl}\boldsymbol{W}^l\boldsymbol{\varepsilon}_{t-k} + \boldsymbol{\varepsilon}_t \tag{1}$$

where $\boldsymbol{Y}_t = N\times 1$ vector of observations at time t at the N locations, p = autoregressive order, q = moving average order, λ_κ = spatial order of the k^{th} autoregressive term, m_κ = spatial order of the k^{th} moving average term, ϕ_{kl} =autoregressive parameter at temporal lag k and spatial lag l, θ_{kl} = moving average parameter at temporal lag k and spatial lag l, $\boldsymbol{W}^l$ = $N\times N$ spatial weight matrix with spatial order l, and $\boldsymbol{\varepsilon}_t$ = random disturbances are assumed to be normally distributed with $E[\boldsymbol{\varepsilon}_t]$ = 0; $E[\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}'_{(t+s)}] = \begin{cases}\sigma^2\boldsymbol{I}_N & s=0\\ 0 & s\neq 0\end{cases}$ and $E[\boldsymbol{Y}_t\boldsymbol{\varepsilon}'_{t+s}]$ = 0, for $s>$ 0. The STARMA model

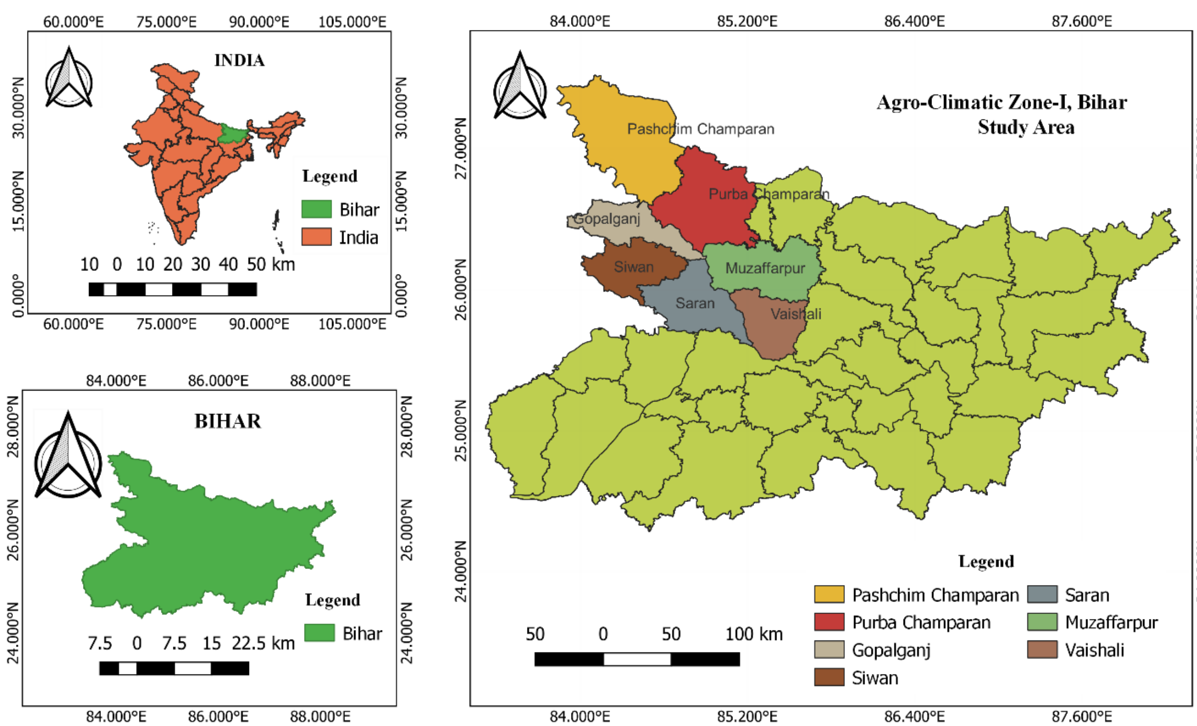

Fig. 1. Geographical Map of Bihar

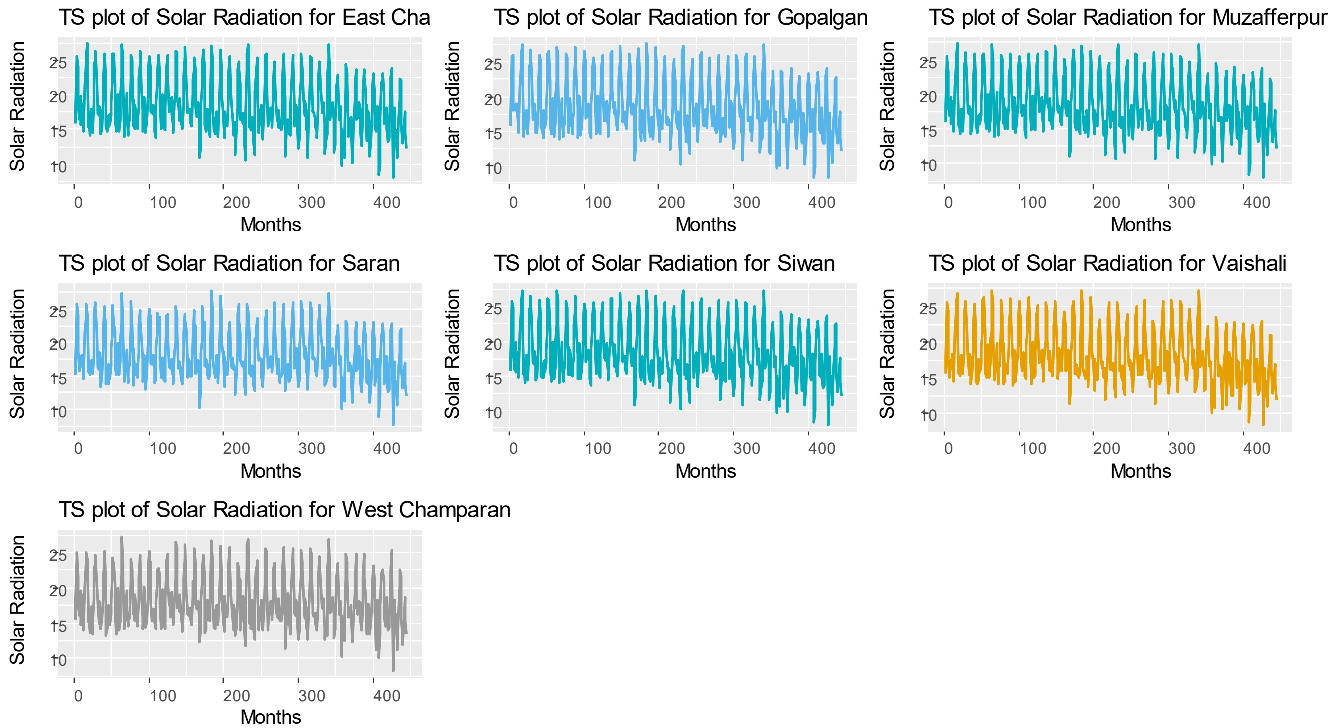

Fig. 2. Graphical trend plots of monthly average solar radiation

($p_{\lambda_1, \lambda_2, \ldots, \lambda_p}$, $q_{m_1, m_2, \ldots, m_q}$) becomes a STAR model ($p_{\lambda_1, \lambda_2, \ldots, \lambda_p}$) when $q = 0$, which is expressed as:

$$\boldsymbol{Y}_t = \sum_{k=1}^{p}\sum_{l=0}^{\lambda_\kappa}\phi_{kl}\boldsymbol{W}^l\boldsymbol{Y}_{t-k} + \boldsymbol{\varepsilon}_t \quad (2)$$

when $p = 0$, it becomes a STMA model ($q_{m_1, m_2 \ldots m_q}$) which is expressed as:

$$\boldsymbol{Y}_t = \boldsymbol{\varepsilon}_t - \sum_{k=1}^{q}\sum_{l=0}^{m_\kappa}\theta_{kl}\boldsymbol{W}^l\boldsymbol{\varepsilon}_{t-k} \quad (3)$$

The modelling procedure of STARMA model is the similar to univariate ARIMA (Box and Jenkins, 1976) methodology viz. identification of model, estimation of the parameters, and validation of the fitted model (Pfeifer and Deutsch, 1980; 1981).

2.2.1. Model identification

In this step, tentative orders of STAR and STMA models are selected on the basis of significant spike of the sample space-time autocorrelation (ST-ACF) and space-time partial autocorrelation functions (ST-PACF) plots.

2.2.2. Parameter estimation

After selection of best fitted orders, linear coefficients of the model are estimated through conditional maximum likelihood estimates (Pfeifer and Deutsch, 1980b, 1980c). To do with maximum likelihood estimates, the residuals are assumed to be normally distributed. The parameters are estimated using the conditional maximum likelihood method.

$$S(\phi, \theta) = \sum_{t=1}^{T}\boldsymbol{\varepsilon}_t^{'}\boldsymbol{\varepsilon}_t, \quad (4)$$

where,

$$\boldsymbol{\varepsilon}_t = \boldsymbol{Y}_t - \sum_{k=1}^{p}\sum_{l=0}^{\lambda_\kappa}\phi_{kl}\boldsymbol{W}^l\boldsymbol{Y}_{t-k} + \sum_{k=1}^{q}\sum_{l=0}^{m_\kappa}\theta_{kl}\boldsymbol{W}^l\boldsymbol{\varepsilon}_{t-k}, \quad (5)$$

for $t = 1, 2, \ldots T$, while setting $\boldsymbol{\varepsilon}_t$ and $\boldsymbol{Y}_t$ equal to zero for $t < 1$. The corresponding estimate of σ^2 is

$$\sigma^2 = \frac{S_*\left(\hat{\phi}, \hat{\theta}\right)}{TN} \quad (6)$$

2.2.3. Validation

Finally, to verify the acceptability of the selected model, in this investigation, multivariate Box-Pierce non-correlation test and BDS test (Brock, Dechert and Scheinkman, 1987, Brock, Dechert, Scheinkman and LeBaron, 1996) have been employed for checking the simple space-time autocorrelations and non-linear patterns within model residuals respectively. The Multivariate Box-Pierce non-correlation test has been employed to check the adequacy of the model. It is an extended version of the Box-Pierce test which applies to spatio-temporal data. Because space is involved, the residuals are tested for both temporal and spatial lags. The following are the test hypotheses:

Null hypothesis (H_0): Residuals are uncorrelated

Alternative hypothesis (H_1): Residuals are auto correlated

Test statistic:

$$N\sum\left(T-S\right)\hat{\rho}_{l0}\left(s\right)^2 \sim \chi^2\left(slag \times tlag\right). \tag{7}$$

where $\hat{\rho}_{l0(s)}$ is the spatio-temporal autocorrelation function of residuals.

2.3 Spatial weight matrix

Prior to STARMA modelling, choice of the spatial weight matrix is very important because different spatial weights matrices often lead to different results. The spatial weights are expressed as a hierarchical ordering of spatial neighbours of each site. In this study, spatial weights matrix has been constructed by assigning equal weight of each neighbours. For example, for location East Champaran (ECH), the first order neighbours are Gopalganj (GOP), Muzaffarpur (MUZ), and West Champaran (WCH) and the second order neighbours are Siwan (SIW), Saran (SAR), and Vaishali (VAI). In a similar way, all the seven locations have been created in **Table 1.** After row normalization (all rows total to one) of each location, spatial weight matrices of order first ($\boldsymbol{W}^1$) and second ($\boldsymbol{W}^2$) have been created (**Tables 2** and **3**). In addition, each space unit is defined as its zero spatial order neighbour and the zero order spatial weight matrix ($\boldsymbol{W}^0$) can be defined as unit matrix (**Table 4**).

Table 1. Spatial order for each location

Location	Spatial orders	
	1st order neighbour	2nd order neighbour
East Champaran	GOP, MUZ, WCH	SIW, SAR, VAI
Gopalgang	SIW, WCH, SAR, ECH	MUZ, VAI
Muzaffarpur	ECH, SAR, VAI	SIW, GOP, WCH
Saran	SIW, GOP, VAI, MUZ	ECH, WCH
Siwan	GOP, SAR	WCH, ECH, VAI, MUZ
Vaishali	MUZ, SAR	SIW, ECH, GOP
West Champaran	ECH, GOP	SIW, SAR, MUZ

Table 2. Row normalized first order spatial weight matrix ($\boldsymbol{W}^1$)

Location	1st Order						
	ECH	GOP	MUZ	SAR	SIW	VAI	WCH
ECH	0.00	0.33	0.33	0.00	0.00	0.00	0.33
GOP	0.25	0.00	0.00	0.25	0.25	0.00	0.25
MUZ	0.33	0.00	0.00	0.33	0.00	0.33	0.00
SAR	0.00	0.25	0.25	0.00	0.25	0.25	0.00
SIW	0.00	0.50	0.00	0.50	0.00	0.00	0.00
VAI	0.00	0.00	0.50	0.50	0.00	0.00	0.00
WCH	0.50	0.50	0.00	0.00	0.00	0.00	0.00

Table 3. Row normalized second order spatial weight matrix ($\boldsymbol{W}^2$)

Location	2nd Order						
	ECH	GOP	MUZ	SAR	SIW	VAI	WCH
ECH	0.00	0.00	0.00	0.33	0.33	0.33	0.00
GOP	0.00	0.00	0.50	0.00	0.00	0.50	0.00
MUZ	0.00	0.33	0.00	0.00	0.33	0.00	0.33
SAR	0.50	0.00	0.00	0.00	0.00	0.00	0.50
SIW	0.25	0.00	0.25	0.00	0.00	0.25	0.25
VAI	0.33	0.33	0.00	0.00	0.33	0.00	0.00
WCH	0.00	0.00	0.33	0.33	0.33	0.00	0.00

Table 4. Row normalized zero order spatial weight matrix ($\boldsymbol{W}^0$)

Location		Zero Order					
	ECH	GOP	MUZ	SAR	SIW	VAI	WCH
ECH	1	0	0	0	0	0	0
GOP	0	1	0	0	0	0	0
MUZ	0	0	1	0	0	0	0
SAR	0	0	0	1	0	0	0
SIW	0	0	0	0	1	0	0
VAI	0	0	0	0	0	1	0
WCH	0	0	0	0	0	0	1

2.4 Artificial Neural Networks

A neural network is a made up of simple processing units called neurons that behave like to human brains. It is capable to model nonlinear systems by using an input layer, hidden layer, and an output layer. Several authors (Warner and Misra, 1996, Cheng and Titterington, 1994) have provided an general idea of various aspects of the ANN model. Rajendra *et al.* (2019) has successfully carried out the prediction of meteorological data using ANN models.

ANN is defined as a system or mathematical model consists of non-linear artificial neurons running in parallel that are structured in one or more layers.

$$y_t = \alpha_0 + \sum_{j=1}^{q} \alpha_j g\left(\beta_{0j} + \sum_{i=1}^{p} \beta_{ij} y_{t-1} \right) + \varepsilon_t \,, \tag{8}$$

where, α_j ($j = 0, 1, 2, ..., q$) and β_{ij} ($i = 0, 1, 2, ..., p$; $j = 1, 2, ..., q$) are the parameters of the model, p = number of input nodes and q = number of hidden nodes. Among the various transfer functions, the logistic function is often used as the hidden layer transfer function:

$$g(x) = \frac{1}{1+e^{-x}} \,, \tag{9}$$

Equation (8) attempts to map with a non-linear function to the future observation (y_t) from the previous observations $(y_{t-1}, y_{t-2}, \dots y_{t-p})$ i.e.,

$$y_t = f\left(y_{t-1}, y_{t-2}, \dots y_{t-p}, \boldsymbol{w}\right) + \varepsilon_t \,, \tag{10}$$

where, $\boldsymbol{w}$ = vector of all parameters and f = function determined by the network structure and connection weights. **Fig.3**, show the generalized structure of the neural network consisting of neurons, input layer, hidden layer, an output layer, and bias.

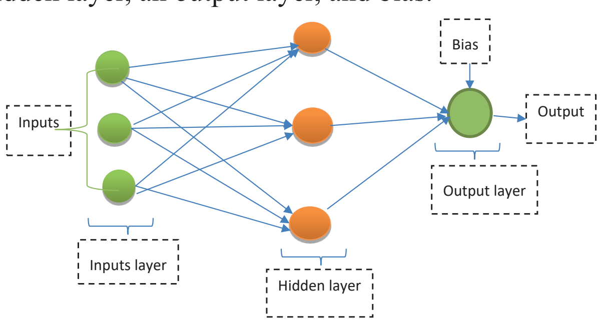

Fig. 3. Structure of multilayer perceptron artificial neural network

2.5 Hybrid STARMA-ANN model

The real world time series data may contain both linear and nonlinear components, so a hybrid approach that has both linear and nonlinear modelling abilities is a good alternative for forecasting and performs in two steps. In the first step, the STARMA model is applied to the data to fit the linear component and in the second step, the residuals of STARMA model as using in neural network if the residuals test depicts presence of nonlinear and mixture of linear and nonlinear patterns (Rathod *et al.*2021, Saha *et al.* 2020). The proposed hybrid model has been graphically portrayed in **Fig. 4**.

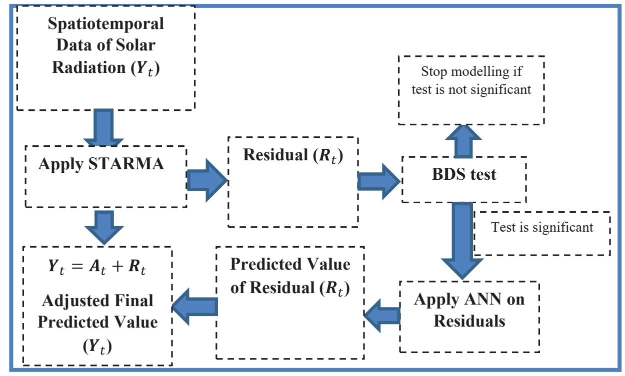

Fig. 4. Flow chart of hybrid STARMA-ANN model

2.6 Forecast Evaluation

To evaluate the forecast efficiency, mean absolute percentage error (MAPE) has been used. The formula is given below:

$$\text{MAPE} = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i} \right| \times 100, \tag{11}$$

where, n = total numbers of predicted value, y_i = actual value at time t, and $\hat{y}_i$ = corresponding predicted value.

2.7 Computation work

In this study, the proposed approach has been implemented on R software (R version 4.1.2). For stationarity check, *adf.test()* function under tseries package is used, for STARMA modelling, *stacf (), stpacf ()* and *starma()*functions under starmapackage are used, for BDS test, *bds.test ()* function under t series package is used and for ANN model fitting, *nnetar ()* under forecast package is used.

3. RESULTS AND DISCUSSION

3.1 STARMA Modelling

In this section, the monthly average solar radiation is estimated by the application of STARMA approach. The MAPE has been used as the performance evaluators for the proposed approach. Before proceeding to the modelling processes, first, checked the stationarity and spatiotemporal correlation of the space-time series. Augmented Dickey–Fuller (ADF) test (Dickey and Fuller, 1981) has been employed to check the stationarity and results showed that space-time data are stationary for all seven locations (**Table 5**). The space-time series plots of each locations indicates presence of seasonality. Therefore, seasonally adjustment has been made to the space-time series to eliminate the influence of seasonality by seasonal differencing with period 12. The Multivariate Box-Pierce non-correlation test has been used to conformation of spatiotemporal correlation in time series data and result (Chi Square = 219501.9, p value = <0.001) shows that presence of spatiotemporal correlations in space-time series. Prior to STARMA modelling, spatial weight matrices up to 2nd orders have been incorporated into the space-time data set to reflect the spatial and temporal correlation of each location. As explained in methodology section, the STARMA modelling procedure occurs in three stages. In the first step, tentative model orders have been selected on the basis of significant spike of ST-ACF and ST-PACF plots (**Figs. 5** and **6**) and final suitable orders of $\text{STAR}(2)$ and $\text{STMA}(0)$ are selected. In the second stages of the modelling process, parameters of the fitted $\text{STARMA}(2_2, 0, 0)$ model has been estimated by Conditional Maximum Likelihood method. According to estimated results of the parameters, spatial-temoral orders of 0 and 2 showed statistically significant, whereas order 1 showed non significant which are represented in **Table 6.** The estimated model can be expressible as following equation:

$$\widehat{\boldsymbol{Y}}_t = 0.3128\ \boldsymbol{W}^0\boldsymbol{Y}_{t-1} + 0.0576\boldsymbol{W}^1\boldsymbol{Y}_{t-1} + 0.2115\ \boldsymbol{W}^2\boldsymbol{Y}_{t-1} + 0.1793\boldsymbol{W}^0\boldsymbol{Y}_{t-2} + 0.0540\boldsymbol{W}^1\boldsymbol{Y}_{t-2} + 0.1839\boldsymbol{W}^2\boldsymbol{Y}_{t-2} \quad (12)$$

After the parameters estimate, last and third stages of the STARMA modelling is the diagnostic checking of the fitted STARMA model. Multivariate Box-pierce non-correlation test has been used and result (Chi Square = 598.9744, p value = 0.001) revealed the presence of spatiotemporal correlations within the residuals that means the fitted model residuals are not white noise. In the next step, BDS test has been performed to check the presence or absence of linearity and nonlinearity patterns in fitted residuals. The test confirmed that the presence of strong nonlinearity patterns within residuals because null hypothesis of identically and independent distribution is rejected for all locations (**Table 7**). Therefore, to deal with nonlinear patterns, a hybrid technique has been used for better modelling and forecasting accuracy.

Table 5. ADF test results for original and seasonally adjusted data series

Location	Test Statistic	Test Statistic (with seasonally adjusted)	*P*-Value
ECH	-20.38	-7.16	<0.001**
GOP	-19.39	-7.17	<0.001**
MUZ	-20.63	-7.43	<0.001**
SAR	-16.26	-5.50	<0.001**
SIW	-19.93	-6.89	<0.001**
VAI	-16.81	-5.53	<0.001**
WCH	-21.71	-9.89	<0.001**

** indicate the significant at 1% level of significance

Table 7. BDS test results for residuals

Dimensions		2				3			
Location		eps(1)	eps(2)	eps(3)	eps(4)	eps(1)	eps(2)	eps(3)	eps(4)
ECH	Statistic	3.219	3.080	3.348	5.355	6.906	5.643	5.211	6.534
	Probability	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
GOP	Statistic	2.923	2.759	3.509	4.905	4.023	4.017	4.517	5.569
	Probability	0.003	0.005	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
MUZ	Statistic	3.233	3.966	3.885	5.717	6.709	6.273	5.837	6.692
	Probability	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
SAR	Statistic	3.728	4.132	4.302	5.293	5.634	6.022	5.610	6.211
	Probability	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
SIW	Statistic	3.189	2.712	2.545	4.954	6.054	4.955	4.221	5.950
	Probability	<0.001	0.006	0.010	<0.001	<0.001	<0.001	<0.001	<0.001
VAI	Statistic	4.089	3.740	4.532	6.503	5.482	5.225	5.683	6.849
	Probability	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
WCH	Statistic	4.965	4.556	4.165	5.721	5.173	5.384	4.930	6.261
	Probability	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001

Table 6. Parameters estimate for $\text{STARMA}\left(2_2,\ 0,\ 0\right)$ model

Spatial lag	0		1		2	
	AR					
	Φ10	***Φ20***	***Φ11***	***Φ21***	***Φ12***	***Φ22***
Parameters	0.3128	0.1793	0.0576	0.0540	0.2115	0.1839
Standard Error	0.0566	0.0567	0.0803	0.0801	0.0749	0.0751
Probability	<0.001**	<0.001**	0.473	0.500	0.004**	0.014*

*&** indicated the significant at 5% and 1% level of significance respectively.

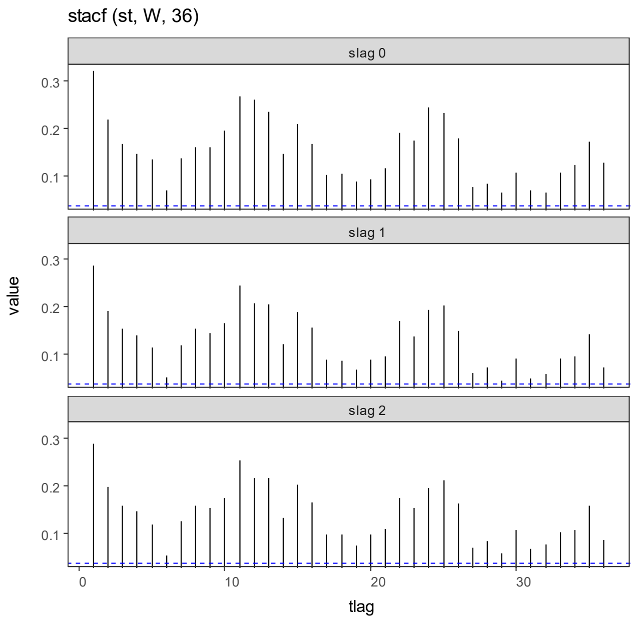

Fig. 5. ST-ACF plots for seasonality adjusted data series of solar radiation

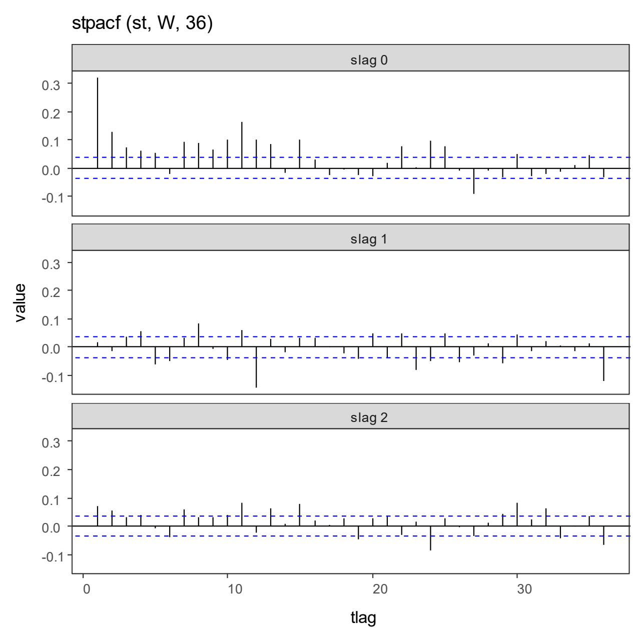

Fig. 6. ST-PACF plots for seasonality adjusted data series of solar radiation

3.2 ANN Modelling

After diagnostic checking of residuals, the existence of nonlinear patterns that indicate for ANN model fitting on STARMA residuals. The proposed ANN model is based on Levenberg–Marquardt (LM) algorithm using logistic activation function in input to hidden layer and identity function in hidden to output layer. To train the neural network model, neural network auto regression model (NNAR (p, q)) estimation methodology has been used. The fitted NNAR model is reported in **Table 8** where numbers of input neurons (p) varies from 2 to 6 and hidden neurons (q) varies from 2 to 4 with single hidden layer. After fitting of ANN model, a diagnostic check has been done using Box-Pierce non-correlation test and results satisfied the model assumptions.

Table 8. ANN model fitting

Location	ANN model	Weight
ECH	NNAR(2, 2)	9
GOP	NNAR(2, 2)	9
MUZ	NNAR(4, 2)	13
SAR	NNAR(2, 2)	9
SIW	NNAR(2, 2)	9
VAI	NNAR(6, 4)	33
WCH	NNAR(2, 2)	9

3.3 Comparison of Models Performance

A comparison of results obtained by STARMA model with those of the hybrid STARMA-ANN model reveals improvement in results by using hybrid model. To evaluate the modelling and prediction accuracy, mean absolute percentage error (MAPE) has been computed for both the training and testing datasets which is reported in **Table 9**. According to the results of MAPE, the hybrid model has lowest mean absolute percentage errors as compared to STARMA model for all seven locations. Further model validation, forecasts have been carried out for all seven locations. From **Fig. 7**, it can be observed that the forecast results of the hybrid model have lowest forecast errors and forecast values are very close to out sample values (testing data) for all seven locations. Therefore, it can say that the fitted hybrid model has better forecasting accuracy as compare to the conventional STARMA model. The possible reasons for better forecasting accuracy of hybrid model could be due to its capability of capture both spatial and nonlinear information in the space-time series of solar radiation.

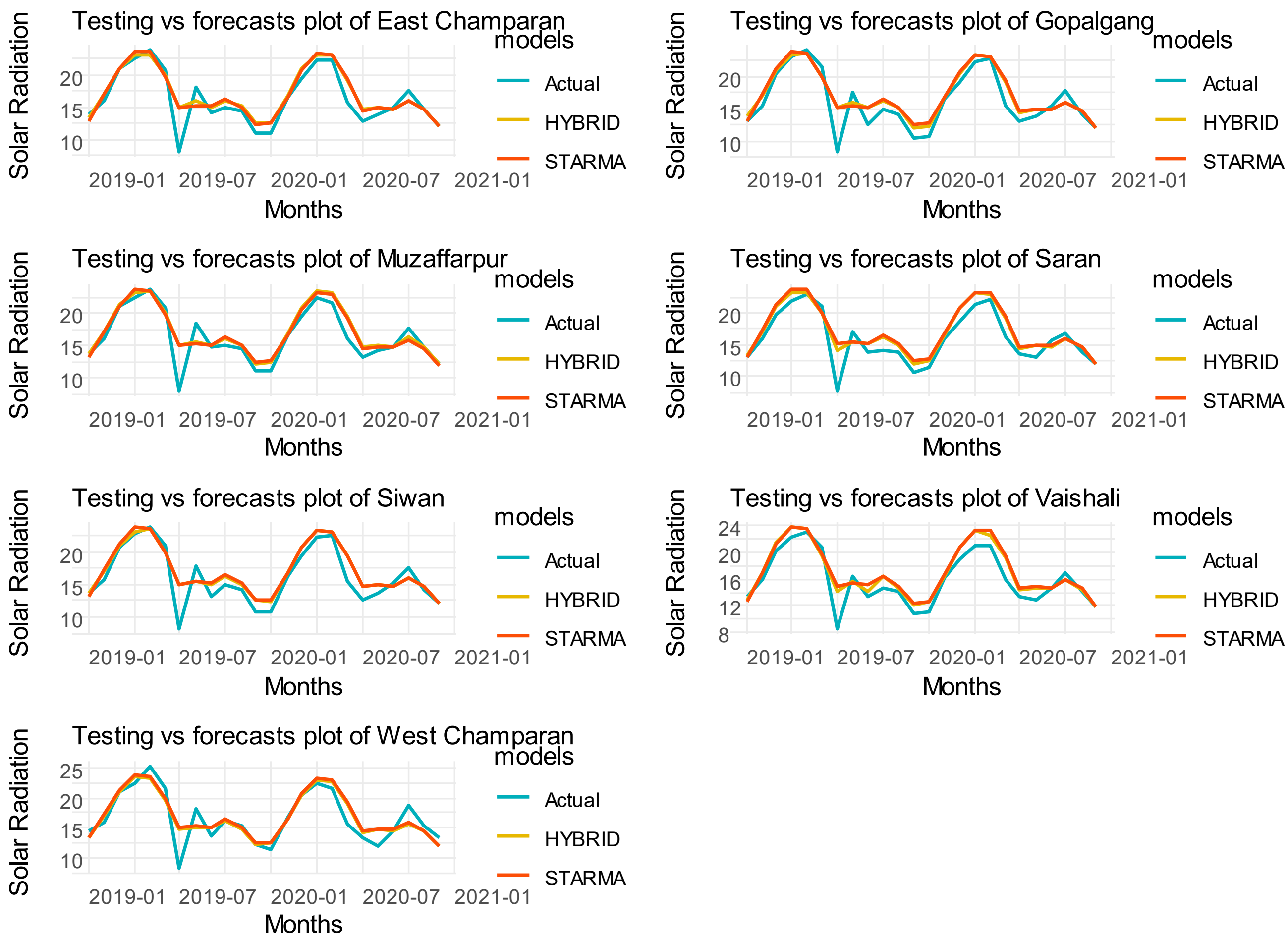

Fig. 7. Graphical representation of the forecast results

Table 9. Performance of the fitted STARMA and hybrid STARMA-ANN models

Location	Training Data	Testing Data		
	MAPE			
	STARMA Model	Hybrid STARMA-ANN Model	STARMA Model	Hybrid STARMA-ANN Model
ECH	7.8624	6.9151	10.2283	9.8657
GOP	8.2630	7.3868	11.9132	10.8768
MUZ	7.8380	6.7401	9.7924	9.27040
SAR	7.7554	6.9191	12.1314	10.8662
SIW	8.0472	7.1333	11.3265	10.6768
VAI	8.0573	6.1299	10.8454	9.46042
WCH	8.1224	7.2741	11.9132	10.6112

4. CONCLUSION

In this paper, a hybrid model has been developed for the predication of the monthly average solar radiation exhibiting strong spatial and/or temporal nonlinear patterns. The hybrid model combining the STARMA and ANN techniques have been employed to deal with spatial and temporal nonlinear data set. The modelling procedure has been started from model identification involving spatial and autoregressive orders determination. In the application of STARMA modelling, spatial weight matrices up to second orders are incorporated into the time series data and based on ST-ACF and ST-PACF plots the best fitted $\text{STARMA}\left(2_2,\ 0,\ 0\right)$ model has been identified. The fitted model parameters estimated by Conditional Maximum Likelihood method. After diagnostic checking, residuals of the fitted model have found that presence of strong nonlinear patterns. Therefore, to deal with nonlinear patterns, ANN technique has been used on residuals of the STARMA model. The proposed hybrid model has lower MAPE values as compared to conventional STARMA model for both the training and testing data sets. Therefore, this investigation concludes that the fitted hybrid model would be able to give useful forecasts if the time series data possess both spatiotemporal correlation and strong nonlinear patterns. In future research, the proposed hybrid model could be applied to other fields where the time series data set exhibits spatiotemporal patterns.

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