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Artificial Intelligence Based Time Series Intervention Models to Assess the Impact of the COVID 19 Pandemic on Cotton Supply and Prices in India

ISABELLA AGARWAL*, RANJIT KUMAR PAUL
ICAR- Central Institute for Cotton Research, Regional Station, Coimbatore - 6410013
**Email : is-agarwalerediffmail.com*

COVID 19 has dramatically impacted nearly every sector of the global economy, and the cotton sector is no exception. Marketing is critical to moving agricultural products from producer to consumer and maintaining price stability. The crisis around COVID 19 pandemic has affected most economic activities across the globe. In the absence of any cure, several countries, including India, opted to go for a general lockdown to contain the faster spreading of the disease. In India, the immediate implications of this lockdown on the agricultural front were witnessed in the form of disruption of activities relating to harvesting and marketing of agricultural crops and commodities.

The COVID 19 crisis has caused significant damage to the national and global economy due to the lockdown measures initiated in March, 2020 in many countries, including India. Due to the imposed lockdown, activities related to supply chains from the agriculture were notably disrupted. Cotton is a crop that is majorly used in textile industries. The global cotton production projected CAGR of 4.1 per cent during forecast period (2021-2026). Due to COVID 19, the demand for cotton decreased by 11 per cent. The imposed global restrictions have resulted in shutting down of ginning mills due to cancellation and suspension of orders by many western clothing brands. This has also affected the cotton production and textile units for Bangladesh and India. Due to economic and logistic factors, the global trade of cotton has taken a downturn. It has affected every link in the global supply chain. Cotton has a complex supply chain that stretch from input suppliers, farmers, traders, ginning factories, spinning mills, textile companies and oil processors. The supply chain is global, spanning from developing countries, where most of the cotton is grown to developed countries where raw cotton is processed into finished products. Global supply chain networks are exposed to a number of risks, ranging from supply delays, supply disruption, price fluctuations, demand fluctuations, to exchange rate fluctuations that may occur at any stage of the flow of seed cotton products. However, it is the disruption due to disasters at the production level that can bring the most significant impact on the whole cotton supply chain. The Indian cotton supply chain is known to be disrupted by lack of irrigation facilities, lack of infrastructure, government cotton policy interventions and competition from other fibres among other factors. Research has shown that disasters have a negative impact on the agricultural sector in general.

However, it remains unclear how exactly these disaster risks influence the survival of cotton industry in India. Following the outbreak of the COVID 19 pandemic, attempts were made to contain the virus and minimize the consequences of the health crisis through various measures, including national lockdowns. However, the mandated lockdowns had a significant impact on the agri sector, delaying the delivery of most inputs (*e.g.*, fertilizers and other agrochemicals), as well as foodstuff on the markets, and imposing significant fluctuations in both their supply and prices.

Pre forecasting and modelling support the formulation of policies required for long term and comprehensive economic development, as well as decision making and efficient scheduling for the national economy. Based on the past time series data under consideration, time series models are used to develop effective forecasting approaches. The autoregressive integrated moving average (ARIMA) model is widely used, due to its statistical capabilities and the well-known Box–Jenkins model-construction process. In many studies, ARIMA models have been successfully applied to forecast the time series of various consumptions and requirements, including the production and exports of different agricultural commodities. In addition, an ARIMA genetic algorithm was recently employed to estimate maize yield and oilseed production in India's agroecosystems. Intervention with the ARIMA time series model developed by Box and Tiao is the most popular method for modelling interrupted time series data. The most popular methods for modelling and forecasting time series data over the years have been Artificial Neural Networks (ANN), which have been successfully applied in different conditions. The ability of Artificial Intelligence (AI) to model nonlinear data, difficult data, and unclear data, without the need for the precise model specification, is its key benefit. Based on the historical time series data, traditional AI algorithms were used to forecast the data, and intervention AI models were used to model the time series data, with the intervention variable considered as an exogeneous variable. However, in general, ANN requires a long time to tweak the model parameters. To determine the impact of agricultural plans or unforeseen changes, prominent classical time series models, such as ARIMA and its intervention models, were used. Earlier, ARIMA modelling with intervention was used in application planning and budgeting issues. Ray and others applied ARIMA intervention model to forecast cotton yield in India; and Ramasubramanian and Ray applied ARIMA intervention model in power computation and they claimed that ARIMA intervention model was superior in performance to classical ARIMA model. Jeffrey and Kyner developed an ARIMA intervention model for forecasting Chinese stock prices. These models are not capable of detecting nonlinear time series data; thus, they have been altered. When the data generation process is highly heterogeneous, nonlinear, and complex, even the parametric nonlinear time series models cannot model the nonlinear, complex and chaotic nature of time series data. The only way to model and predict such time series is by using AI techniques ANN and SVR (Support Vector Regression) have been the most commonly used techniques in modelling and predicting time series data in the last decade. The recent lockdown imposed by the government of India due to the COVID 19 pandemic had an abrupt impact on the supply and prices of agricultural commodities. This study made an effort to assess the effect of the COVID 19 outbreak on prices and arrivals of Indian cotton. This study set out to determine how the COVID 19 lockdown affected cotton arrivals and prices in India.

MATERIALS AND METHODS

Data description

Marketwise daily arrivals and price (minimum, maximum and modal) data of five major cotton markets of India *viz.*, Rajasthan from North zone, Gujarat and Maharashtra from Central zone, Karnataka and Telengana from South zone were collected for the period from 1st January '2020 to 31st December '2021. In total, 1220 and 1310 cotton markets during 2020 and 2021, respectively, were taken up for the study. The secondary data on cotton prices and arrivals were collected from the website https://agmarknet.gov.in. The Government of India announced a nationwide lockdown from 23rd March 2020 to 30th June 2020; In this study, 1st Jan to 24th March '2020 was considered as pre intervention period, 23rd March to 30th June '2020 as Intervention period and 1st July to 31st Dec. '2020 as post intervention period. During the year 2021, COVID spread peaked during mid April to June during which time full and partial lockdown in almost all the States were implemented. Accordingly, 1st Jan to 15th April '2021was considered as pre intervention period, 16th Apr. to 30th June '2021 as Intervention period and 1st July to 31st Dec. '2021 as post intervention period.

ARIMA Model

The Box Jenkins ARIMA is the most commonly used model in forecasting time series data. When the time series Yt is non stationary or integrated, this procedure is an amalgamation of the ARMA process. To build the ARMA model in the case, the series must be differenced to make it stationary, and this differenced series, which is now stationary, must be subjected to ARIMA model fitting. This procedure is known as ARIMA (p,d,q), where p and q denote the number of AR and MA terms, respectively, and d denotes the order of differencing required to make the series stationary. An ARIMA model is expressed by the following expression:

$$Ø(B)\ (1 – B)\ dYt = q(B)\#t \qquad \ldots (1)$$

where:

$$Ø(B) = 1 – Ø1B1 – Ø2B2 - \ldots - Øp\ BP$$

(autoregressive parameter)

$$Ø(B) = 1 - Ø1B1 - Ø2B2 - \ldots - Øp\ Bq$$

(Moving average parameter)

where *d* = differencing term, *B* = backshift operator, *i.e.*, BaYt = Yt-a#t = white noise or error term. The ARIMA methodology is conducted in three steps, namely identification, estimation and diagnostic checking. For diagnostic checking, the Box Pierce non correlation test is most commonly used.

ARIMA Intervention Model

ARIMA intervention analysis [10] is a time series analysis technique that uses modelling approaches to incorporate the effect of exogenous forces or interventions. Government policies, strikes, earthquakes, price shifts, folds, pandemic, and other unforeseen catastrophes are all examples of interventions. It produces unexpected shifts in time series. Simply put, intervention analysis in time series refers to the study of how a series mean level changes as a result of an intervention.

$$Yt = \frac{\omega(B)}{\delta(B)} B^{b} I_{t} + \frac{\theta(B)}{\varphi(B)} \varepsilon t \qquad \ldots(2)$$

In this, the dependent variable is *Yt*, indicator variable. It = indicator variable coded according to the type of intervention (step, pulse/point, and impulse). Here, d(B) = 1 + d1 B + … dr Br is the slope parameter, (B) =w0 + w1 B + … ws Bs is the impact parameter, j(B) = 1 - j1 B - j2B2 - … - jp Bp is the autoregressive parameter, q(B) = 1 - q1 B - q2B2- … - qqBq is the moving average parameter, b is the delay parameter, B is the backshift operator, *i.e.*, *BaYt* = *Yt*-a, "t is the white noise or error term. The step intervention occurs at a specific point in time and persist over successive time periods. The impact of the step intervention may be stable over time, or it may rise or diminish. The indicator variable is coded as follows since the occurrence of COVID 19 is a step intervention type, It = 0, t < T0 and 1, t = T0. The COVID 19 intervention, which was classified as a lockdown, began on March 25, 2020 and was later extended in multiple phases. As a result, the indicator variable It was given a value of 0 before intervention period and one during the intervention period.

Support Vector Regression (SVR) Model

The SVR model was basically developed for classification problem, later adopted to regression problem by adding "-insensitive loss function [32]. The main concept behind SVR is to solve a nonlinear regression in a linear manner by transferring nonlinear input data from a lower dimensional feature space to a higher dimensional feature space.

The SVR estimation function is written as follows:

$$f(x) = \theta^T \varphi(X)+b \quad \ldots(3)$$

where ϕ (.) stands for a nonlinear space transformation, is the weight vector, and b stands for the bias. By further introducing a kernel function, θ is no longer needed to be given explicitly in the SVR estimation function, which becomes:

$$f(x)=\sum_{i=1}^{n}(ai-ai^*)\ k\ (x,xi)+b \quad \ldots(4)$$

where k (x, xi) = φ (xi)T φ (xi) is the kernel function. The radial basis function (RBF) kernel function is the most commonly used kernel function in SVR and is represented as follows:

$$(x, xi) = \exp(-\gamma \|x - xi\|^2) \quad \ldots(5)$$

The coefficients *W* and *b* are estimated from data by minimizing the following regularized risk function.

$$R(\theta) = \tfrac{1}{2}\|\varpi\|^2 + C[1/N\sum_{i=1}^{N}L\varepsilon\ (y_i, f\ (x_i))] \quad \ldots(6)$$

This regularized risk function minimizes both the empirical error and regularized term simultaneously, which helps in avoiding both under- and over fitting of the model. In Equation (6), the first term $\tfrac{1}{2}\|\varpi\|^2$ is called the 'regularized term', which measures the flatness of the function. Minimizing $\tfrac{1}{2}\|\varpi\|^2$ will make a function as flat as possible. The second term $1/N\sum^N L\varepsilon\ (y_i, f\ (x_i))]$ is called 'empirical error', which was estimated by the Vapnik e-insensitive loss function as follows:

$$L\varepsilon\ (y_i, f\ (x_i)) = f\ (x) = \begin{cases} |y_i, f\ (x_i) - \varepsilon|; & |y_i - f\ (x_i)| \geq \varepsilon, \\ 0 & |y_i - f\ (x_i)| < \varepsilon, \end{cases} \quad \ldots(7)$$

The performance of the RBF kernel function requires the optimization of two hyper-parameters: regularization parameter C, which balances the complexity and approximation accuracy of the model; and Kernel bandwidth parameter γ, which represents the variance of the RBF kernel function

Artificial Neural Network (ANN) Model

The ANN is the most widely used AI technique in the last three decades in time series modelling and prediction. In the field of time series modelling, ANN is commonly referred to as an autoregressive neural network because it considers time lags as inputs.

The time series framework for ANN can be mathematically modelled using a neural network with implicit functional representation of time. The general expression for the final output Y of a multilayer autoregressive neural network with feedforward is expressed as follows:

$$Y_t = \alpha_0+\sum_{j=1}^{q}\alpha_j\ g(\beta 0_j + \sum_{i=1}^{p}\beta_{ij}\ Y_t\ p) + \varepsilon t \quad \ldots(8)$$

where a_j (j = 0, 1, 2, ... , q) and β_{ij} (i = 0, 1, 2,..., p, j = 0, 1,2, ... , q) are the model parameters, also called the synopsis weights; *p* is the number of input nodes; *q* is the number of hidden nodes; and g is the activation function. The training part in ANN minimizes the error function between actual and predicted values. The error function of autoregressive ANN is expressed as follows:

$$E=1/N\sum_{t=1}^{N}(e_t)^2 =1/N\sum_{t=1}^{N}(Xt-(w_0+(\sum_{j=1}^{Q} w_{Jg}(w_{oj}+i\sum_{i=1}^{P}w_{ij}\ X_{t-i}))))^2 \quad \ldots(9)$$

where N is the total number of error terms. The parameters of the neural network *wij* are changed by a number of changes in Δw_{ij} as $\Delta w_{ij} = -\eta\ \partial E/\partial w_{ij}$, where η is the learning rate.

The schematic representation of neural network structure is depicted in Figure I.

Artificial Intelligence (AI)-Based Intervention

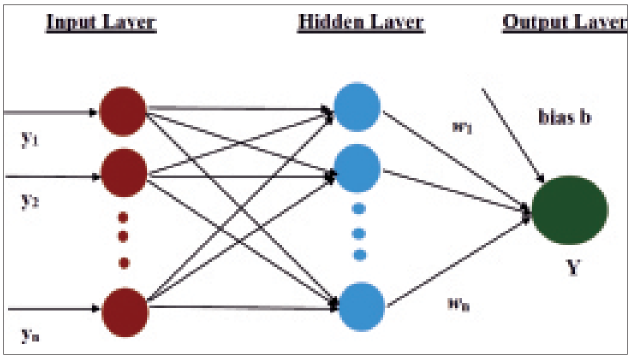


Fig. I. Model structure of the artificial neural network

Models

The traditional artificial intelligence approach allows for forecasting based solely on the past values of the forecast variables. The model assumes that the future values of a variable are determined by its previous values as a well as the values of exogenous variable in the past. The artificial intelligence intervention model is a modified version of the artificial intelligence model that adds an additional independent variable called the intervention variables; this model is also referred to as the vector artificial intelligence model. The artificial intelligence forecasting models typically assume that each observed value is an unknown nonlinear function F of clags $t_1, t_2, \ldots, t_c$, for a given univariate time series $\{x_t, t = 1, 2, \ldots, n\}$, where $x_t eR$

$$x_t = F(x_{t-t1}, x_{t-t2}, \ldots, x_{t-tc}) + \varepsilon_t \qquad \ldots(10)$$

where the error ε_t is error of zero mean. Next, we assume that m interventions have been observed throughout time periods $r_1, r_2, \ldots, r_m$. Depending on the nature of the interventions, we define m auxiliary variables $\delta_1^t, \delta_2^t, \ldots, \delta_m^t$. As a result, we can have a nonlinear forecasting model with clags $t_1, t_2, \ldots, t_c$ and m interventions

$$x_t = F(x_{t-t1}, x_{t-t2}, \ldots, x_{t-tc}, \delta_1^t, \delta_2^t, \ldots, \delta_m^t) + \varepsilon_t \qquad \ldots(11)$$

In this article, two AI-based intervention models, namely SVR and ANN intervention models, were developed by the intervention concept explained in this section. Finally, the mean absolute percentage error (*MAPE*) is the most commonly used measure for forecasting error.

$$\text{MAPE} = \left|\frac{1}{N}\right|\frac{A-F}{A} \times 100 \qquad \ldots(12)$$

where A is the actual value, F is forecast or predicted value, and N is the number of observations.

RESULTS AND DISCUSSION

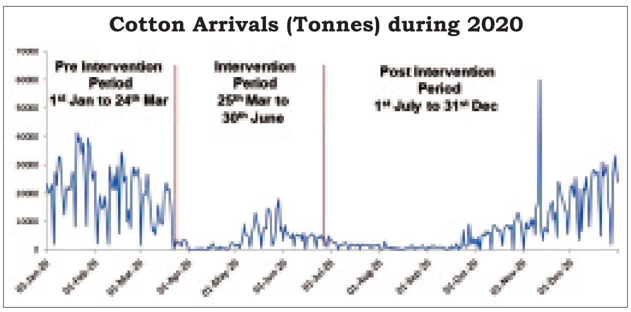
Fig. II shows the time series of supplies, maximum price, minimum price, and modal price in the cotton market, where the whole study period has been seggregated as pre intervention, intervention and post intervention period during the years 2020 and 2021, respectively.

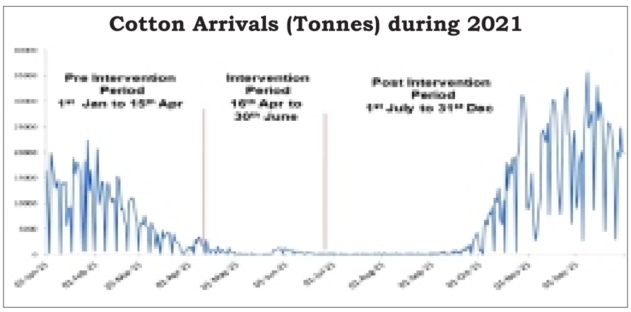
Table 1. shows the descriptive statistics for all four series of the cotton markets from five major States during 2020 and 2021. The arrival price series are positively skewed and leptokurtic. The coefficient of variation were 94 and 98 per cent for arrivals and 7 to 19 per cent for maximum price, minimum price, and modal price, respectively during 2020 and 2021.

Results of ARIMA Model

The parameters of the models were estimated using the maximum likelihood method.

Diagnostic testing of the residuals was





performed using the Box Pierce non correlation test for residuals and the results show that the residuals are not autocorrelated and random as the probability values of significance were less than one for the arrivals, minimum price, maximum price and modal price, respectively for the years 2020 and 2021.

Results of ARIMA Intervention Models

Like the ARIMA model, the ARIMA intervention models were built for all four time series dates. The parameters estimated using maximum likelihood estimation techniques are shown in Table 2.

The intervention parameters (impact(ω)) for arrivals in the States under study show cased negative impact as -504.44, -362.61, -1012.39, -795.53 and -3116.53, respectively, during 2020 while during 2021 it was positive impact in Gujarat, Karnataka, Maharashtra and Telengana excepting in case of Rajasthan (-6.93). The results show that the lockdown had a negative impact on cotton arrivals which means there was a shortage of 500 to 3000 qtls of cotton per day during 2020. The impact on minimum, maximum and modal price were mixed in all the States during both the pandemic periods under consideration. The results showed that there was decrease in the average price in the cotton markets of Gujarat and Karnataka during both the years and Maharashtra during 2021. In general, there was no significant impact on price as the demand was low though supply was also less.

The fitted models were appropriate as the Box–Pierce non-correlation test for the residuals is not autocorrelated and random as the average probability values of significance are 0.84, 0.61 for arrivals, 0.60 for minimum price, 0.66 and 0.56 for maximum price and 0.67, 0.76 for modal price, respectively during the years 2020 and 2021.

Results of SVR and SVR Intervention Models

Based on the required user defined parameters, the SVR model and SVR intervention models (Table 4) were constructed. The radial basis function (RBF) is used as the kernel function.

The number of support vectors obtained at optimal level was 100(79), 90(86), 87(71) and 82(74) for arrival series, minimum, maximum and modal prices, respectively during the pandemic years 2020 (2021). For the support vector regression with intervention model, the number of support vectors obtained at the optimal level was 100(73), 92(98), 86(75) and 81(75) for the arrival series, minimum maximum and modal prices, respectively during the same periods

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Results of ANN and ANN Intervention Model

The sigmoidal activation function was used in the input to the hidden layer and the linear activation function from the hidden to

Table 1. Descriptive statistics of cotton markets

Statistic	2020				2021			
	Arrivals (t)	Min (Rs./q)	Max (Rs./q)	Modal (Rs./q)	Arrivals (t)	Min (Rs./q)	Max (Rs./q)	Modal (Rs./q)
Count	1309.00	1309.00	1309.00	1309.00	1220.00	1220.00	1220.00	1220.00
Mean	**2815.06**	**4436.18**	**5132.65**	**4889.52**	**2504.65**	**5680.31**	**6976.72**	**6583.71**
Median	1928.43	4453.13	5172.78	4916.06	929.72	5352.46	6515.72	6118.57
Mode	1612.23	4766.10	5343.10	5233.09	8.26	5245.00	5761.00	5680.00
Std Deviation	2654.11	462.40	354.40	379.78	2445.16	1066.87	1261.23	1167.13
Minimum	1.50	3361.06	4162.18	3835.82	0.96	1778.66	5006.24	3801.40
Maximum	18495.74	5351.46	6362.51	5550.20	10435.75	8072.24	10862.10	8968.61
Kurtosis	12.88	-0.59	0.95	0.20	1.06	0.44	-0.81	-0.51
Skewness	2.02	-0.14	-0.31	-0.60	1.29	0.18	0.51	0.31
CV (%)	94.28	10.42	6.90	7.77	97.63	18.78	18.08	17.73

Table 2. Parameter estimation of ARIMA intervention mode

Model	Model fitting		Box–Pierce Non-Correlation Test			Model	Model fitting		Box–Pierce Non-Correlation Test		
	Log likelihood	AIC	BIC	Original	Residual		Log likelihood	AIC	BIC	Original	Residual
Gujarat 2020						Gujarat 2021					
ARIMA(1,0,2)	-2264.29	4536.58	4550.78	92.245 p=0)	0.0074 (p= 0.931)	ARIMA(0,0,1)	-2177.92	4359.83	4366.82	87.78 (p=0)	0.746(p= 0.3876)
ARIMA(1,0,1)	-1870.32	3746.63	3757.28	169.97 p=0)	1.207(p= 0.272)	ARIMA(1,0,2)	-1682.67	3373.34	3387.31	113.85 (p=0)	0.293 (p= 0.588)
ARIMA(0,0,1)	-1897.58	3799.16	3806.26	99.738 =0)	0.0182 (p= 0.893)	ARIMA(0,0,1)	-1836.97	3677.95	3684.94	118.39 (p=0)	0.212 (p= 0.6452)
ARIMA(0,0,1)	-1866.46	3736.91	3744.01	147.17(p=0)	0.0244 (p= 0.876)	ARIMA(0,0,1)	-1765.97	3535.94	3542.92	119.09 (p=0)	0.105 (p= 0.7453)
Karnataka 2020						Karnataka 2021					
ARIMA(2,0,2)	-2182.56	4375.12	4393.15	48.73 (p=0)	0.0084 (p= 0.9271)	ARIMA(1,0,1)	-1692.8	3391.61	3402.03	10.86(p=0.001)	0.014 (p= 0.9046)
ARIMA(0,0,2)	-1913.04	3832.08	3842.90	145.52 p=0)	0.0551 (p= 0.8144)	ARIMA(1,0,1)	-1692.8	3391.60	3402.03	1.10(p=0.293)	1.103 (p= 0.2935)
ARIMA(2,0,2)	-1819.75	3649.49	3667.52	218.39 p=0)	0.0009 (p= 0.9765)	ARIMA(1,0,2)	-1993.38	3994.75	4008.65	84.73 (p=0)	0.475 (p= 0.4907)
ARIMA(1,0,3)	-1784.03	3578.05	3596.08	227.92 p=0)	0.0221 (p= 0.8818)	ARIMA(1,0,2)	-1880.51	3769.02	3782.92	131.31 (p=0)	0.169 (p= 0.6829)
Maharashtra 2020						Maharashtra 2021					
ARIMA(0,0,4)	-2017.54	4045.08	4062.10	119.04 p=0)	0.1169 (p= 0.7324)	ARIMA(2,0,3)	-1544.49	3100.98	3120.17	59.071 (p=0)	135 (p= 0.2437)
ARIMA()	-2017.54	4045.08	4062.10	202.18 p=0)	1.2692 (p= 0.2599)	ARIMA(0,0,2)	-1374.26	2754.52	2764.11	109.99 (p=0)	0.0000 (p= 0.9961)
ARIMA(2,0,2)	-1358.11	2726.21	2743.23	148.92 p=0)	0.0617 (p= 0.8038)	ARIMA(0,1)	-1364.72	2733.43	2739.82	102.11 (p=0)	0.109 (p= 0.7404)
ARIMA(0,0,2)	-1241.25	2488.493	2498.701	200.52 p=0)	0.0665 (p= 0.7964)	ARIMA(0,2)	-1367.98	2741.95	2751.54	147.17 (p=0)	0.0244 (p= 0.876)
Rajasthan 2020						Rajasthan 2021					
ARIMA(1,0,1)	-1464.78	2935.566	2944.92	63.441(p=0)	0.0008 (p= 0.9778)	ARIMA(0,0,1)	-1502.64	3009.277	3015.663	66.539 (p=0)	0.0007 (p= 0.9334)
ARIMA(1,0,0)	-978.589	1961.178	1967.414	147.48 p=0)	0.0561 (p= 0.8128)	ARIMA(0,0,1)	-1284	2572.008	2578.394	144.47 (p=0)	0.4713 (p= 0.4924)
ARIMA(1,0,0)	-978.589	1961.178	1967.414	149.02 p=0)	3.3643 (p= 0.0666)	ARIMA(0,0,1)	-1137.46	2278.911	2285.296	171.91 (p=0)	0.7762 (p= 0.3783)
ARIMA(1,0,1)	-906.612	1819.224	1828.578	149.57 p=0)	1.6835 (p= 0.1945)	ARIMA(0,0,1)	-1165.66	2335.324	2341.71	169.11 (p=0)	0.1241 (p= 0.7246)
Telengana 2020						Telengana 2021 *					
ARIMA(0,0,2)	-1196.47	2398.937	2407.469	34.072(p=0)	0.0074 (p= .9332)	ARIMA(1,0,1)	-1164.78	2435.566	3946.92	83.441(p=0)	0.0008 (p= 0.7778)
ARIMA(2,0,1)	-965.312	1940.624	1954.845	38.677 p=0)	0.0494 (p= .8242)	ARIMA(2,0,1)	-1065.34	2140.644	2954.85	138.677 p=0)	0.0494 (p= .8242)
ARIMA(0,0,2)	-837.757	1681.515	1690.047	35.2 (p=0)	0.0293 (p= .8642)	ARIMA(0,0,2)	-1241.25	2488.493	2498.701	200.52 p=0)	0.6665 (p= 0.7964)
ARIMA(1,0,0)	-896.232	1798.463	1806.996	34.5848(p=0)	0.0711 (p= 0.6791)	ARIMA(1,0,1)	-1692.81	3391.61	3102.03	110.86(p=0.001)	0.1014 (p= 0.904)

Table 3. Parameter estimation of ARIMA intervention model.

Time Series	2020				2021			
	Estimation	Z value	p value	Residual	Estimation	Z value	p value	Residual
Gujarat								
Arrivals	-504.4498	0.692665	0.2445	p= 0.929	377.072	0.4473	0.3275	p= 0.3767
Min Price	-64.01617	0.320663	0.3743	p= 0.272	-110.007	0.8858	0.1883	p= 0.5907
Max Price	-257.5791	1.066496	0.1436	p= 0.849	-10.569	0.0451	0.4820	p= 0.6466
Modal Price	-204.4969	0.86778	0.1931	p= 0.902	-8.818	0.0476	0.4810	p= 0.7454
Karnataka								
Arrivals	-362.6009	1.586864	0.0568	p= 0.9726	22.172	0.2624	0.3966	p= 0.9041
Min Price	18.94962	0.127824	0.4491	p= 0.8127	-74.073	0.4558	0.0983	p= 0.5072
Max Price	-231.8159	1.936343	0.0269	p= 0.7236	-235.807	0.5671	0.2856	p= 0.4873
Modal Price	-104.843	1.001492	0.1587	p= 0.881	-171.590	0.5971	0.2755	p= 0.6863
Maharashtra								
Arrivals	-1012.388	0.965286	0.16774	p= 0.7026	19.7590	0.0316	0.4874	p= 0.2441
Min Price	7.89951	0.120544	0.4520	p= 0.4438	-247.224	0.9182	0.1799	p= 0.9458
Max Price	9.213614	0.137154	0.4455	p= 0.7975	-18.9668	0.0820	0.4674	p= 0.7412
Modal Price	36.98304	0.79733	0.2130	p= 0.8049	-247.007	0.9778	0.1648	p= 0.8971
Rajasthan								
Arrivals	-795.5318	1.118532	0.1324	p= 0.9465	-46.5936	0.0830	0.4670	p= 0.9324
Min Price	90.49839	1.543813	0.0622	p= 0.7534	73.4707	0.4455	0.3283	p= 0.5156
Max Price	28.94962	0.427427	0.3497	p= 0.0512	39.8225	0.4332	0.3327	p= 0.3799
Modal Price	65.4724	1.649478	0.0504	p= 0.1027	14.5360	0.1423	0.4435	p= 0.7244
Telengana								
Arrivals	-3116.426	3.148979	0.0010	p= 0.665	159.0214	0.1476	0.5214	p= 0.3197
Min Price	374.5151	2.925367	0.0020	p= 0.7599	-62.1607	0.375	0.1273	p= 0.5713
Max Price	17.86704	0.224247	0.4114	p= 0.8683	-31.8525	0.4032	0.3927	p= 0.2099
Modal Price	-6.41455	0.067812	0.4730	p= 0.6785	-57.9180	0.5423	0.4435	p= 0.6184

output layer. The residual values of all four series of the cotton markets are shown in Table 5 indicating that the residuals are not autocorrelated or random in nature.

Based on the MAPE values obtained (Table 4), the ARIMA intervention model outperformed the ANN and other models in both model building and validation data sets for arrivals and ANN intervention model for price time series during 2020 whereas for the year 2021, ANN intervention model performed better than ANN and the other models in both the training and test data sets for the arrivals and price series. The predicted values of the ARIMA and ARIMA intervention models, as well as the SVR models, produced the same predicted values

Table 4. Parameter specification of SVR and SVR intervention model 2020 (2021)

Parameters	Arrivals		Minimum price		Maximum price		Modal price	
	SVR	SVR intervention	SVR	SVR intervention	SVR	SVR intervention	SVR intervention	SVR
Kernel function	Radial							
No. of SVs	100 (79)	100 (73)	90 (96)	92 (98)	87 (71)	86 (75)	82 (74)	81 (75)
Cost	1(1)	1(1)	1(1)	1(1)	1(1)	1(1)	1(1)	1(1)
Gamma	0.04 (0.05)	0.04 (0.05)	0.04 (0.05)	0.04 (0.05)	0.04 (0.05)	0.04 (0.05)	0.04 (0.05)	0.04 (0.05)
Epsilon	0.1(0.1)	0.1(0.1)	0.1(0.1)	0.1(0.1)	0.1(0.1)	0.1(0.1)	0.1(0.1)	0.1(0.1)
Box–Pierce Non-Correlation Test	17.638 (1.658)	16.479 (1.702)	13.823 (2.337)	10.922 (1.959)	24.272 (2.428)	20.911 (3.019)	20.097 (2.688)	16.763 (2.247)
p value	0.027 (0.217)	0.031 (0.207)	0.015 (0.373)	0.013 (0.390)	0.022 (0.452)	0.031 (0.484)	0.001 (0.261)	0.002 (0.298)

Fig. in parantheses refers to the year 2021

Table 5. Parameter specification of ANN and ANN intervention model

Parameters	Arrivals		Minimum price		Maximum price		Modal price	
	ANN	ANN intervention	ANN	ANN intervention	ANN	ANN intervention	ANN	ANN intervention
Input lag	20	20	20	20	20	20	20	20
Dependent/ output var	1	1	1	1	1	1	1	1
Hidden layers	1	1	1	1	1	1	1	1
Hidden nodes	22	17	22	17	22	17	22	17
Exogenous var	NA	1	NA	1	NA	1	NA	1
Box–Pierce Non-Correlation	46.494	55.09	120.8	122.69	117.24	113.09	128.7	132
Test for residuals (2020)	46.49	28.05	120.80	61.84	117.24	57.04	128.70	66.50
(2021)								

The forecasting performance of the six selected models—ARIMA, ARIMA intervention, SVR, SVR intervention, ANN, and ANN intervention—was evaluated for their forecasting ability based on model errors in both training and test data sets.

Table 6. Comparison of model performance in terms of MAPE in training sets Time serie

	ARIMA		ARIMA Intervention		ANN		ANN Intervention		SVR		SVR Intervention	
	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test
2020												
Arrivals	67.56	164.37	66.56	194.98	85.25	101.60	79.48	117.83	39.52	48.07	29.04	45.53
Min price	4.60	12.52	4.66	12.79	8.74	12.56	8.60	13.00	1.01	4.03	1.01	3.87
Max price	1.90	7.33	1.90	7.34	4.33	7.74	4.24	7.99	0.45	3.37	0.44	3.26
Modal price	2.91	7.93	2.92	7.52	5.94	10.64	6.02	10.80	0.71	4.16	0.71	4.10
2021												
Arrivals	79.62	70.73	79.93	71.02	95.98	370.73	96.58	328.49	35.61	82.62	39.49	82.51
Min price	6.79	14.44	6.83	11.94	10.85	30.74	10.77	30.35	1.93	17.55	1.90	17.36
Max price	4.45	5.28	4.46	7.06	11.81	28.79	11.94	25.02	1.38	7.21	1.41	7.21
Modal price	3.78	6.51	3.80	6.52	11.67	30.27	11.66	29.58	1.35	8.52	1.33	8.52

for all days, implying that the model does not have the generalization ability to provide different predicted values compared to the ANN intervention models. In this study, the developed AI models outperformed the classic ARIMA and ARIMA intervention models.

Among the AI models, the ANN and ANN intervention models performed better than all other models in both training and test data sets. The performance hierarchy of the cotton markets in the training and testing datasets is ANN, ANN intervention, SVR, SVR intervention, ARIMA intervention and ARIMA in all arrivals and datasets.

The empirical results show the superiority of the ANN intervention model over the other models examined in this study. The superiority of the ANN intervention model may be due to its ability to mimic the nonlinear and detailed nature of the data while allowing for an external intervention variable, making it very useful in explaining the dynamics of the impact of the COVID 19 pandemic on cotton arrivals and price fluctuations in the market.

CONCLUSIONS

The present study was undertaken to investigate the impact of the COVID-19 lockdown on the arrivals and prices of cotton in the markets of Gujarat, Karnataka, Maharashtra, Rajasthan and Telengana. The ARIMA intervention model significantly confirmed that the lockdown had a negative impact on cotton arrivals. The impact on minimum, maximum and modal price were mixed in all the States during both the pandemic periods under consideration. The results showed that there was decrease in the average price in the cotton markets of Gujarat and Karnataka during both the years and Maharashtra during 2021. In general, there was no significant impact on price as the demand was low though supply was also less. The classical times series models such as ARIMA and ARIMA intervention models were used in analyzing the impact of policies or sudden changes in agricultural impact studies. These models fail to capture the nonlinear structure present in data sets. To overcome this problem, we have developed ANN and SVR based intervention models by incorporating the intervention variable as an exogenous variable in the input layer. AI-based model was applied in this study to capture the nonlinear and complex nature of the data. The ANN intervention model outperformed all other models for modelling and predicting arrivals and price series of cotton; thus, it can be used to study the nonlinear complex nature of data under intervention in other time series data. The AI-based intervention models developed in this study can be used to evaluate the potential effects of government policies and programmes. The model has a wider scope to study the impact of interventions in agriculture.

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