The Pharma Innovation Journal 2023; 12(8): 1675-1681

www.ThePharmaJournal.com

The Pharma Innovation

ISSN (E): 2277-7695
ISSN (P): 2349-8242
NAAS Rating: 5.23
TPI 2023; 12(8): 1675-1681

www.thepharmajournal.com
Received: 15-04-2023
Accepted: 20-05-2023

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Predicting area, production and productivity of sapota in Gujarat-an application of GARCH, eGARCH and TAR models

Prity Kumari, DJ Parmar and Sathish Kumar M

Abstract
A GARCH, eGARCH, and TAR model was used in this study to forecast sapota area, production and productivity in Gujarat. Secondary data on sapota area, production and productivity for the period 1991–1992 to 2016–17 was provided by the Directorate of Horticulture in Gujarat. For the years 1958–1959 to 2016–2017, time series secondary data on the area, production and productivity of sapota were gathered. Software called R Studio (version 3.5.2) was used to analyze the collected data. For the estimation of the area, production, and productivity of sapota in Gujarat, different models such as GARCH, eGARCH, and TAR were employed. The study found that the GARCH model, with a forecast value of 30.02 ('000' Ha) for 2017–18, best explained the area of the sapota. The TAR model provided the best explanation for the production and productivity of sapota, with anticipated values of 327.33 ('000' MT) and 11.15 (MT/ha), respectively.

Keywords: Forecasting, area, production, productivity, sapota, ARCH model, eGARCH model and TAR model

Introduction
Horticulture crops are essential to India's food, nutritional and economic security. The production of diverse fruits is led by India, which is the world's second-largest producer of horticulture crops. Horticulture produce currently outpaces food grain production in India. From a significantly smaller area of 25.66 million hectares, India produced 320.48 million tons of horticulture produce. India leads the globe in sapota production and produces 10% of the global fruit production. Sapota was produced in India in total in 11,56,060 tons from 2017 to 2018. Gujarat is the leader in sapota production, having produced 3,26,360 tonnes of the crop in 2017–18, accounting for 28.19 percent of all sapota output in India (National Horticulture Board, 2017–18). The use of statistical forecasting enables us to develop future plans and decisions that will significantly contribute to the expansion of our nation's economy. In statistical forecasting, there are primarily two methods: i) Extrapolation method, which anticipates present series based on historical past behavior over a period of time. ii) The explanatory method entails anticipating future phenomena by taking into account variables that will have an impact on them (Diebold and Lopez, 1996). The study was done to estimate and predict the area, production, and productivity of sapota fruit in Gujarat state in light of the aforementioned information. The data were analyzed using the ARCH model, eGARCH model and TAR models.

Methodology
Source of data
From 1991-1992 to 2016-17, secondary data was collected from the Government of Gujarat's Directorate of Horticulture regarding sapota production, productivity, and area. Data were collected from 1958-1959 to 2016-2017 on the production, productivity and area of sapota.

Autoregressive Conditional Heteroscedastic (ARCH) Model
ARCH models that depend on the variance of the error term at time t are derived from past squared error term values. This model is specified as follows:

$$y_t = u_t$$

$$u_t \sim N(0, h_t)$$

$$h_t = \alpha_0 + \sum_{t=1}^{q} \alpha_j u_{t-i}^2$$

Model ARCH(q), in which q is the order of the lagged squared returns. Assuming ARCH (1) model, this would be

$$h_t = \alpha_0 + \alpha_1 u_{t-1}^2$$

As a conditional variance, its value must always be positive; it would be meaningless if it were negative at any given time. It is usually required that all coefficients in the conditional variance be non-negative in order to obtain a positive estimate of conditional variance. In this regard, coefficients must be satisfied $\alpha_0 > 0$ and $\alpha_1 \geq 0$.

Generalized Autoregressive Conditional Heteroscedastic (GARCH) Model:
GARCH (p, q) is a model developed by Bollerslev and Taylor (1986). In this model, the conditional variance of the variable is calculated according to historical lags; the first lag is derived from the squared residual from the means equation and the second lag is derived from the volatility from the previous period:

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i u_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i}$$

GARCH (1,1) is the most commonly used and most simple model in the literature. It can be expressed as follows:

$$h_t = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta_1 h_{t-1}$$

By using the unconditional expectation of the above equation, it is possible to find the unconditional variance h_t under the hypothesis of covariance stationarity. $h = \alpha_0 + \alpha_1 h + \beta_1 h$

$$h = \frac{\alpha_0}{1 - \alpha_1 - \beta_1}$$

As a condition to the existence of this unconditional variance, it must be the case that $\alpha_1 + \beta_1 < 1$ and for it to be positive, we require that $\alpha_0 > 0$.

Exponential Generalized Autoregressive Conditional Heteroscedastic (eGARCH) Model
EGARCH (Exponential GARCH) is a model developed by Nelson (1991) that incorporates leverage effects in its equation. Conditional covariance is specified in the EGARCH model by the following formula:

$$\log(h_t) = \alpha_0 + \sum_{j=1}^{q} \beta_j \log(h_{t-j}) + \sum_{i=1}^{p} \alpha_i \left| \frac{u_{t=i}}{\sqrt{h_{t=i}}} \right| + \sum_{k=1}^{r} \gamma_k \frac{u_{t-k}}{\sqrt{h_{t-k}}}$$

The EGARCH formulation has two advantages over the pure GARCH specification, as even negative parameters will be positive when log (h_t) is used and asymmetries will be allowed.

Asymmetry in the model is attributed to leverage effects γ_k in the equation. As opposed to the basic GARCH model, the EGARCH model allows the variance to be estimated without restrictions.

If $\gamma_k < 0$ it indicates leverage effect exist and if $\gamma_k \neq 0$ impact is asymmetric. The meaning of leverage effect bad news increase volatility.
It has been observed that GARCH residuals are often heavy tailed when applied to series resulting from GARCH models. Instead of using the normal distribution for students' ts and GEDs, ARCH/GARCH models are employed to accommodate this.

Threshold Autoregressive (TAR) Model
Generally, when a variable's values exceed a certain threshold, a process may behave differently. The model may be different if values exceed a threshold compared to those below the threshold, i.e. when values exceed a threshold, a different model may be applied. As defined by the dependent variable, AR models are estimated separately in two or more intervals of values. These AR models may or may not be in the same order.
In the Threshold Autoregressive model, the parameter values change according to the value of an exogenous threshold variable. Therefore, the model can be considered as an extension of autoregressive models. Self-Exciting Threshold Autoregressive Model (SETAR) is known if it is substituted by the past value of the time series itself.

TAR model

$$y_t = \begin{cases} \beta_{10} + \beta_{11} y_{t-1} + u_{1t} & \textit{if } s_{t-d} < r \\ \beta_{20} + \beta_{21} y_{t-1} + u_{2t} & \textit{if } s_{t-d} \geq r \end{cases}$$

SETAR model:

$$y_t = \begin{cases} \beta_{10} + \beta_{11} y_{t-1} + u_{1t} & \textit{if } y_{t-d} < r \\ \beta_{20} + \beta_{21} y_{t-1} + u_{2t} & \textit{if } y_{t-d} \geq r \end{cases}$$

In this example, d is the delay parameter that triggers the change between two different regimes. It is possible to apply these models to time series data that exhibits regime switching characteristics. This model, however, has a discontinuous threshold value. The Smooth Transition Autoregressive (STAR) model can be generalized from the TAR model by replacing the threshold value with a smooth transition function.

Results and Discussion
Prediction of Sapota's area, production and productivity
Sapota area forecasting
Figure 1 depicts a series of charts for the sapota area dataset from 1991-1992 to 2016-17. Furthermore, Table 1 provides information regarding the characteristics (Basic statistics) of the data set used.

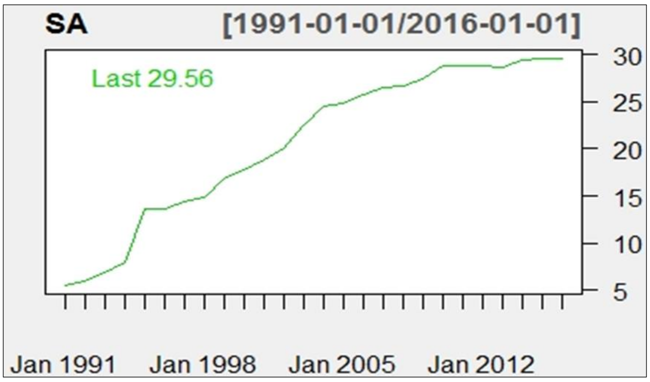

Fig 1: Area under sapota in Gujarat (In ' 000 Hectare)

Table 1: Statistic summary for the Sapota area

Total observations	26
Min	5.5
Max	29.55
Mean	20.71
Median	23.56
Std	8.16
Sem	1.60
Variance	66.60
Skewness	-0.53
Kurtosis	-1.17

Testing of ARCH Effect
Based on the Box-Jenkins method, the residuals are assumed to remain constant over time. In order to determine whether residuals remain constant after fitting the ARIMA model on all the series, the ARCH - Lagrange multiplier (LM) test was performed on the square of the residuals obtained after fitting the ARIMA model on all the series. A positive ARCH effect was found for the present series as a result of the test. Statistical results of the Lagrange-Multiplier (LM) test for autocorrelation of squared residuals up to lag four where significant results were observed.

Autoregressive conditional heteroscedastic (ARCH) model/ Generalized ARCH (GARCH)
In case of fitting GARCH (ARCH) model, out of various parametric combination of GARCH model arma (1,1) + garch (1, 0) was found to be the best. The results were given in Table 3.

Table 2: Arma (1,1) + garch (1, 0) model parameters for area of sapota

Model	Parameter estimation	
Arma (1,1) + garch (1, 0)	Estimate (S.E.)	Sig.
Mu	11.13 (0.51)	<0.01
ma1	0.92 (0.02)	<0.01
ma2	-0.41 (0.08)	<0.01
Omega	0.37 (0.14)	<0.01
alpha1	0.26 (0.16)	NS
Forecast Value 2017-18 (C.I.)	30.02 (29.21 to 30.63)	
Fit Statistics		
AIC	Box-Ljungtestresid fit p value	
61.04	0.97	
Lagrange-Multiplier test:		
order	LM test statistics	p. value
6	0.13	0.0004

According to Table 2, all parameters with the exception of alpha1 of the Garch model were found to be statistically significant. A Box-Ljung test for residual autocorrelation resulted in a probability value of 0.97. Also, the forecasted value of sapota area in Gujarat for the year 2017-18 by arma (1,1) + garch (1, 0) was obtained as 30.02 ('000' Hectares) with confidence interval 29.21 to 30.63. Also, Lagrange-Multiplier (LM) test statistics for autocorrelation of squared residual of this model was found to be non-significant up to the lag 6.

Exponential Generalized ARCH (eGARCH)
Among various parametric combinations of the eGARCH model, arma (1,1) + eGARCH (1, 1) was identified as the best combination for fitting eGARCH models. Table 4 summarizes the results.

Table 3: Arma (1,1) + egarch (1, 1) model parameters for area of sapota

Model	Parameter estimation	
Arma (1,1) + egarch (1, 1)	Estimate (S.E.)	Sig.
Mu	4.46 (0.0008)	<0.01
AR1	1.00 (0.0002)	<0.01
MA1	0.06 (0.00002)	<0.01
Omega	-1.44 (0.0003)	<0.01
alpha1	1.09 (0.0003)	<0.01
beta1	-0.76 (0.0001)	<0.01
Forecast Value 2017-18 (C.I.)	29.56 (28.01 to 30.95)	
Fit Statistics		
AIC	Box-Ljungtestresid fit p value	
63.06	0.53	
Lagrange-Multiplier test:		
order	LM test statistics	p. value
7	0.80	NS

Statistical significance was found for all parameters as shown in Table 3. A Box-Ljung test statistical probability value of 0.53 indicated that residual autocorrelation was not significant. According to arma (1,1) + egarch (1,1), the forecasted value for the sapota area in Gujarat for 2017-18 is 29.56 ('000' Hectares) with a confidence interval of 28.01 to 30.95. Also, Lagrange-Multiplier (LM) test statistics for autocorrelation of squared residual of this model was found to be non-significant up to the lag 7.

Self-Exciting Threshold Auto Regressive (SETAR) models
According to the results of fitting SETAR model, the SETAR (2, 1, 1) model with delay = 0 was the best out of various parametric combinations. Table 4 presents the results.

Table 4: SETAR (2, 1, 1) delay = 0model parameters for area of sapota

Model	Parameter estimation	
SETAR (2, 2, 1) delay = 0	Estimate (S.E.)	Sig.
Lower Regime estimate		
Intercept	2.94 (1.60)	NS
Lag1	0.88 (0.11)	<0.01
Upper Regime estimate		
Intercept	6.93(1.27)	<0.01
Lag1	0.76 (0.04)	<0.01
Forecast Value 2017-18 (C.I.)	29.53 (28.56 to 30.46)	
Fit Statistics		
AIC	Box-Ljungtestresid fit p value	
62.76	0.24	

The estimates of all parameters were significant except for the intercept at the lower regime, as shown in Table 4. As indicated by the Box-Ljung test statistics probability value of 0.24, residual autocorrelation was not significant. With SETAR (2, 1, 1) delay = 0 and a confidence interval of 28.56 to 30.46, the forecasted sapota area for Gujarat for the year 2017-18 is 29.53 ('000' Hectares).
Also, Chow test was done in order to know the structural breakpoint in the data series. An obvious candidate for a breakpoint estimate is the year that yields the largest value of the Chow test sequence. In the present study, delay = 0 was found to be the best value with minimum AIC out of all.

Forecasting the production of sapota

According to Figure 2, the production dataset for sapota has been charted from 1991-92 to 2016-17. A summary of the characteristics (basic statistics) of the data set was also provided in Table 5.

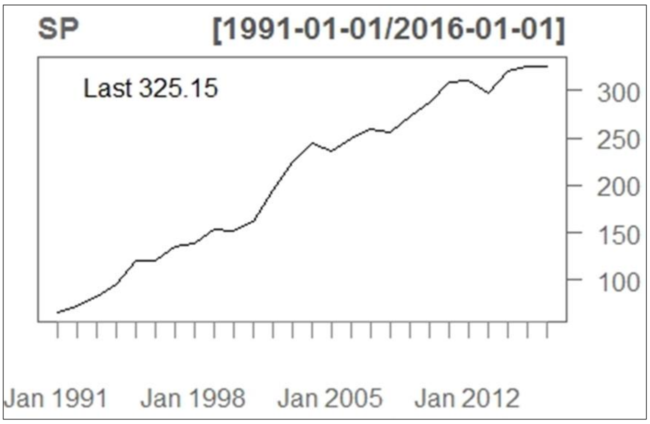

Fig 2: Production (In '000 MT) under sapota in Gujarat

Table 5: Summary statistics of sapota production

Total observations	26
Min	65
Max	325.17
Mean	208.14
Median	229.75
Std	86.93
Sem	17.06
Variance	7558.88
Skewness	-0.17
Kurtosis	-1.48

Testing of ARCH Effect

Based on the Box-Jenkins approach, the residuals are assumed to remain constant over time. To determine whether residuals are constant after fitting the ARIMA model to all the series, the ARCH-Lagrange multiplier (LM) test was conducted on the square of residuals obtained after fitting the ARIMA model to all the series. The LM test found no significance in the present data series, which indicates that there is no nonlinearity present.

Autoregressive conditional heteroscedastic (ARCH) model/Generalized ARCH (GARCH)

Among the various parametric combinations of the GARCH (ARCH) model, the best fit was found to be by combining arma (1, 1) with garch (1, 0). Table 7 shows the results.

Table 7: Arma (1, 1) + garch (1, 0) model parameters for production of sapota

Model	Parameter estimation	
arma (1, 1) + garch (1, 0)	Estimate (S.E.)	Sig.
Mu	399.79 (99.47)	<0.01
AR1	0.94 (0.02)	<0.01
MA1	0.03 (0.03)	NS
Omega	126.11 (35.10)	<0.01
alpha1	0.000 (0.001)	<0.01
Forecast Value 2017-18 (C.I.)	328.93 (317.00 to 339.94)	
Fit Statistics		
AIC	Box-Ljungtestresid fit p value	
339.13	0.89	
Lagrange-Multiplier test:		
order	LM test statistics	p. value
6	0.10	NS

According to Table 7, all parameters except MA1 were found to be significant. The residual autocorrelation was also found to be non-significant according to the Box-Ljung test statistical probability value of 0.89. In Gujarat for the year 2017-18, the forecasted value of sapota production was determined by arma (1, 1) + garch (1, 0), with a confidence interval of 317.00 to 339.94. Also, Lagrange-Multiplier (LM) test statistics for autocorrelation of squared residual of this model was found to be non-significant up to the lag 6.

Exponential Generalized ARCH (eGARCH)

The best parameter combination of eGARCH model was arma (1, 1) + egarch (1, 1) when fitting eGARCH model. In Table 8, the results are presented.

Table 8: Arma (1, 1) + egarch (1, 1) model parameters for production of sapota

Model	Parameter estimation	
Arma (1, 1) + egarch (1, 1)	Estimate (S.E.)	Sig.
Mu	676.32 (0.17)	<0.01
AR1	0.98 (0.004)	<0.01
MA1	0.008 (0.0003)	<0.01
Omega	2.87 (0.001)	<0.01
alpha1	0.65 (0.002)	<0.01
beta1	0.40 (0.0002)	<0.01
Forecast Value 2017-18 (C.I.)	331.50 (319.51 to 343.50)	
Fit Statistics		
AIC	Box-Ljungtestresid fit p value	
338.51	0.97	
Lagrange-Multiplier test:		
order	LM test statistics	p. value
3	0.89	NS

The results shown in Table 8 indicate that all parameters were significant. As well, residual autocorrelation was non-significant as demonstrated by the probability value of 0.89 in the Box-Ljung test statistics. According to arma (1, 1) + egarch (1, 1), the estimated production of sapota in Gujarat for the year 2017-18 was 331.50 ('000' MT), with a confidence interval of 319.51 to 343.50. Lagrange-Multiplier (LM) test statistics for autocorrelation of squared residual of this model was found to be non-significant upto the lag 3.

Self-Exciting Threshold Auto Regressive (SETAR) models

For fitting the SETAR model, out of various parametric combinations, SETAR (2, 1, 1) model delay = 0 was found to be the most effective. In Table 9, the results are presented.

Table 9: SETAR (2,1,1) delay = 0model parameters for production of sapota

Model	Parameter estimation	
SETAR (2,1,1) delay = 0	Estimate (S.E.)	Sig.
Lower Regime estimate		
Intercept	25.35 (17.82)	NS
Lag1	0.91(0.11)	<0.01
Upper Regime estimate		
Intercept	53.46(26.36)	<0.05
Lag1	0.84 (0.09)	<0.01
Forecast Value 2017-18 (C.I.)	327.33(306.52to 347.81)	
Fit Statistics		
AIC	Box-Ljungtestresid fit p value	
198.2	0.60	

As shown in Table 9, all parameters were significantly estimated except for the intercept at the lower regime. A probability value of 0.60 was obtained from the Box-Ljung test statistics for residual autocorrelation. For the year 2017-18, the SETAR (2, 1, 1) delay = 0 forecasted value for sapota production in Gujarat was 327.33('000' MT) with a confidence interval of 306.52 to 347.81.
Also, Chow test was done in order to know the structural breakpoint in the data series. An obvious candidate for a breakpoint estimate is the year that yields the largest value of the Chow test sequence. In the present study, delay = 0 was found to be the best value with minimum AIC out of all.

Sapota productivity forecasting
A chart series representing Sapota's productivity between 1991-1992 and 2016-17 can be found in Figure 3. The data set is also summarized in Table 10 (Basic statistics).

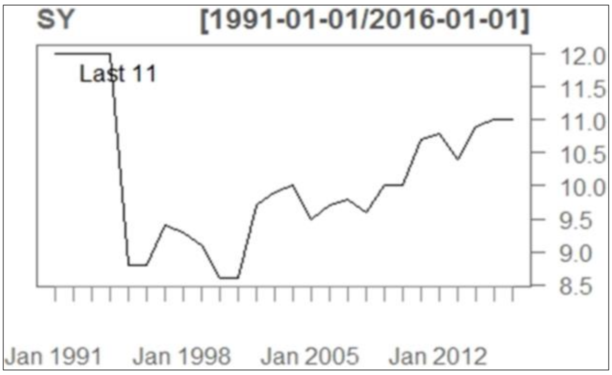

Fig 3: Productivity (In MT/Ha.) under sapota in Gujarat

Table 10: Summary statistics of sapota productivity

Total observations	26
Min	8.7
Max	12
Mean	10.15
Median	9.96
Std	1.06
Sem	0.22
Variance	1.16
Skewness	0.42
Kurtosis	-0.98

Testing of ARCH Effect: According to Box-Jenkins, a fundamental assumption is that residuals will remain constant over the course of time as a function of time. An ARCH-Lagrange multiplier (LM) test was conducted on the square of residuals obtained after fitting the ARIMA model to all series in order to determine whether residuals remain constant after fitting the ARIMA model. A test conducted on the present series revealed that ARCH effect is present. Lagrange-Multiplier (LM) test statistics for autocorrelation of squared residual was found to be significant up to the lag 4.

Autoregressive conditional heteroscedastic (ARCH) model/ Generalized ARCH (GARCH): In case of fitting GARCH (ARCH) model, out of various parametric combination of GARCH model arma (1, 1) + garch (0, 1) was found to be the best. The results were given in Table 12.

Table 12: Arma (1, 1) + garch (0, 1) model parameters for productivity of sapota

Model	Parameter estimation	
Arma (1,1) + garch (0, 1)	Estimate (S.E.)	Sig.
Mu	10.67 (0.71)	<0.01
AR1	0.77 (0.22)	<0.01
MA1	0.07 (0.30)	NS
Omega	0.001 (0.003)	NS
beta1	0.93 (0.02)	<0.01
Forecast Value 2017-18 (C.I.)	10.93 (8.65 to 12.53)	
Fit Statistics		
AIC	Box-Ljungtestresid fit p value	
52.29	0.90	
Lagrange-Multiplier test:		
order	LM test statistics	p. value
6	0.57	NS

It can be seen from Table 12 that all of the parameters, except MA1 of the arma model and constant of the garch model, were significant. Additionally, residual autocorrelation was non-significant as determined by the Box-Ljung test statistics probability value of 0.90. As a result of arma (1, 1) + garch (1, 0), sapota productivity was forecasted to be 10.93 (MT/Ha.) with confidence intervals ranging from 8.65 to 12.53 for the year 2017-18 in Gujarat. Also, Lagrange-Multiplier (LM) test statistics for autocorrelation of squared residual of this model was found to be non-significant up to the lag 6.

Exponential Generalized ARCH (eGARCH): In order to fit an eGARCH model, it was found that arma (1, 1) + eGARCH (1, 1) was the most appropriate parametric combination. The results presented in Table 13.

Table 13: Arma (1,1) + egarch (1, 1) model parameters for productivity of sapota

Model	Parameter estimation	
arma (1, 1) + egarch (1, 1)	Estimate (S.E.)	Sig.
Mu	11.00 (0.002)	<0.01
AR1	0.92 (0.02)	<0.01
MA1	0.05 (0.01)	<0.01
Omega	-2.65 (0.06)	<0.01
alpha1	-1.27 (0.004)	<0.01
Beta 1	-4.43 (0.001)	<0.01
Forecast Value 2017-18 (C.I.)	11.06 (10.03 to 12.06)	
Fit Statistics		
AIC	Box-Ljungtestresid fit p value	
50.06	0.54	
Lagrange-Multiplier test:		
order	LM test statistics	p.value
6	1.43	NS

According to Table 13, all parameters were significant. A Box-Ljung test statistical probability value of 0.54 indicated that residual autocorrelation was non-significant. Sapota productivity was forecasted to be 11.06 ('000' MT/Ha.) in Gujarat for 2017-18 by arma (1, 1) + egarch (1, 1). The confidence interval for the forecast was 10.03 to 12.06. Lagrange-Multiplier (LM) test statistics for autocorrelation of squared residual of this model was found to be non-significant up to the lag 6.

Self-Exciting Threshold Autoregressive (SETAR) models
In case of fitting SETAR model, out of various parametric combination, SETAR (2, 1, 0) model delay =1 was found to be the best. The results were given in Table 15.

Table 15: SETAR (2,1,0) delay = 1model parameters for productivity of sapota

Model	**Parameter estimation**	
SETAR (2, 1, 0) delay =1	Estimate (S.E.)	Sig.
Lower Regime estimate		
Intercept	1.59 (1.45)	NS
Lag1	0.84 (0.15)	<0.01
Upper Regime estimate		
Intercept	11.13 (0.50)	<0.01
Forecast Value 2017-18 (C.I.)	11.15 (8.61 to 13.57)	
Fit Statistics		
AIC	Box-Ljungtestresid fit p value	
44.46	0.34	

In Table 15, all parameters except the intercept of the lower regime were found to be significant. According to Box-Ljung test statistics, residual autocorrelation was non-significant with probability value 0.34. By using SETAR (2,1,0) delay = 1, the forecasted value of sapota productivity in Gujarat for the year 2017-18 was 11.15 (MT/Ha.).

Also, Chow test was done in order to know the structural breakpoint in the data series. An obvious candidate for a breakpoint estimate is the year that yields the largest value of the Chow test sequence. In the present study, delay = 1 was found to be the best value with minimum AIC out of all.

Table 16: Performance of different models for sapota

Forecasting model for Sapota		**Area**	**Production**	**Productivity**
GARCH (ARCH)	Model	**arma (1,1) + garch (1, 0)**	arma (1,1) + garch (1, 0)	arma (1,1) + garch (0, 1)
	AIC	**61.04**	339.13	52.29
	Forecast	30.02	328.93	10.93
	C.I.	29.21 to 30.63	339.94 to 317.00	8.65 to 12.53
eGARCH	Model	arma (1, 1) + egarch (1, 1)	arma (1,1) + egarch (1, 1)	arma (1, 1) + egarch (1, 1)
	AIC	63.06	338.51	50.06
	Forecast	29.56	331.50	11.06
	C.I.	28.01 to 30.95	343.50 to 319.51	10.03 to 12.06
TAR	Model	SETAR (2, 1, 1) delay = 0	SETAR (2, 1, 1) delay = 0	SETAR (2, 1, 0) delay = 1
	AIC	62.76	198.2	44.46
	Forecast	29.53	327.33	11.15
	C.I.	28.56 to 30.46	306.52 to 347.81	8.61 to 13.57

According to Table 16, the GARCH model best explained the area of sapota in 2017-18 with a forecasted value of 30.02 ('000' ha). The TAR model was best suited to model production of this crop with a forecasted value of 327.33 ('000' MT) and the TAR model was best suited to model productivity with a forecasted value of 11.15 (MT/Ha).

Conclusion
GARCH, eGARCH and TAR were found to be quite effective statistical models compared to classical time series models in the study. GARCH model was found to be the best for forecasting the sapota area in Gujarat. TAR was considered to be the most effective way of anticipating sapota production and productivity. This will help farmers and policy makers to make effective decisions in advance by using the GARCH and TAR models to forecast agricultural and horticultural crops.

Acknowledgements
Author thankful to College of Horticulture, Anand Agricultural University, Anand 388110, Gujarat, India

Conflict of interest: None declared

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