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PREDICTING THE YIELD PROMISING RICE VARIETIES THROUGH STRUCTURAL TIME-SERIES MODELS IN CHHATTISGARH

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ABSTRACT

The enterprise of modeling is most productive, when the reasons underlying a model adequacy, and possibility its superiority to others model to understand. The emphasis is on the time domain representation, for which the season is at the core of the modelling effort, rather than on the frequency domain, although the relationships between the two approaches will also be discussed. Structural time series model is formulated in such a way that their components are stochastic, i.e. they are regarded as being driven by random disturbances. The study mainly confined to secondary collected for a period 2009-10 to 2014-15 data of promising varieties of rice yield. As these techniques, it may be mentioned that models are fitted to the data and coefficient parameter values obtained on the basis of the model are compared with the actual observation for assessing the accuracy of the fitted model. Structural time series models are a flexible approach to time series analysis. Trend information was provided on the basis of least standard error for Swarna (0.001), MTU-1010 (0.001) and Mahamaya (0.002) varieties. The rice varieties BPT-5204 (3.984), Karmamasuri (2.186) and Bamleshwari (1.170) showed a decreased trend.

KEYWORDS: AIC, BIC, Goodness of fit, Forecasting and Structural time series model

INTRODUCTION

Agriculture will be faced with major challenges in the next few decades. We chose rice as the crop for this analysis, because rice is an important cereal crop and because rice yield time series show a great diversity of trends (increasing, plateauing, and decreasing). Rice is an economically important food crop in both developed and developing countries. India ranks 2^{nd} largest country in the world in production of rice, after China.

Structural time series models are used not only for providing a description of the salient features of the series, but also for forecasting its future values. Forecasting provides the means of projecting the past into the future by attaching suitable weights for the past and current observations of the variable under investigation. Harvey *et al.* (1990) studied univariate structural time series models based on the traditional decomposition into trend, seasonal and irregular components. A number of methods of computing maximum likelihood estimators were considered. These include direct maximization of various time domain likelihood functions. Rivera (1990) studied multivariate structural time series models, analysis and modeling of cross-sections of time series.

As far as the former is concerned, linear univariate structural models have a reduced form ARIMA representation, but the latter is subject to restrictions on the parameter space, which play a relevant role for forecasting and signal extraction, providing a sensible way of weighting the available information (Tommaso, 1991). A thorough presentation of the main ideas and methodological aspects underlying structural time series models is contained in Harvey (1989); other important references are West and Harrison (1997) and Kitagawa and Gersch (1996). Once a model is estimated, its suitability can be assessed using goodness fit statistics. The Structural Time-Series Model (STM) is a recently developed statistical method that can be used to estimate past trends and to predict future trends in time series. It has been applied in diverse domains, such as Econometrics, signal processing, genetics yield forecasting, and population dynamics (Petris et al 2009; Prado, 2010). Statistical modelling of time-series data in Agriculture is usually carried out by employing an ARIMA methodology (Brock well and Davis, 1991). An alternative mechanistic approach, which is quite promising, is the "Structural time series modeling (Harvey, 1996)".

Statistical methods other than regression models have been used to predict future yield trends. Exponential smoothing has been shown to perform well in a large range of applications. (Kumar and Haque, 2013; Brock well and Davis, 2002), but Kumar (2000) showed that the lowest mean square error (MSE) for yield predictions was obtained with the quadratic regression model. However, this result was obtained with a small data set: yield predictions were assessed for three years at a specific location in Chhattisgarh. The aim of this study: to the performance of statistical models for analyzing yield time series and predicting yield trends. Harvey *et al.* (1986) studied the intervention analysis based on structural time series modelling which differ from the standard intervention analysis based on ARIMA modelling. The relative merits of the two approaches were compared.

Prajneshu, *et al.* (2000) compared structural time series modelling with corresponding analogue from ARIMA family. The advantages of "Structural time-series modelling" approach over well known "Auto Regressive Integrated Moving Average" (ARIMA) methodology were highlighted. Various types of models, which were capable of explaining "cyclical fluctuations" discussed. As an illustration, all-India lac production data, which had prominent cycles, was modelled. Ravichandran *et al.* (2001) used Box-Jenkins Autoregressive Integrated Moving Average (ARIMA) procedure for analyzing time-series data. They studied another approach, which is quite promising, *viz.* State space modelling approach using Kalman filtering technique. The advantage of this technique was that it could take into account the time dependency of the underlying parameters. Ravichandran *et al.* (2002) compared ARIMA with two new promising time series model. ARIMA methodology quite often is not applicable the series under consideration was not stationary and could not be made so by differencing or de-trending. Two new promising approaches, viz., "Bayesian Analysis of Time-Series" (BATS) and "Structural Time-series Modelling" (STM) were discussed. India's food grain production and forecasts for the year 2020, on the basis of these two models were discussed. Scott and Varian, 2013 describes a system for short term forecasting based on an ensemble prediction that averages over different combinations of predictors.

Singh *et al.* (2015) used structural time series model for secondary time series yield data and forecasted potato production in India. He observed that structural time series models fitted better for potato production based on the various Goodness of Fit statistics *viz.* Akaike information criterion (AIC) and Schwartz-Bayesian information criterion (BIC or SBC) were used for assessing the overall model fit. It could be seen that the productions were likely to be increased in the next five years with slow rate. Forecasting Yield of Promising Varieties of various Crop in Chhattisgarh through Structural Time-Series Models (Bharadwaj *et al*, 2015 a&b; Bhardwaj *et al.*, 2016).

MATERIALS AND METHODS

We assessed the suitability of statistical models for analyzing yield time series. The models were first fitted to the time series included in our datasets and their qualities of fit for analysis. Structural time series model adopted for forecasting purpose is given below. The accuracy of the yield predictions obtained with the models was then assessed by cross-validation. Secondary data have been collected from Deptt. of Agriculture (CG) in the year from 2009-10 to 2014-15 of rice yield in different varieties.

Structural time series models are formulated directly in terms of components of interest, that is, trend, seasonal, and error components, plus other relevant terms. This approach is strongly opposed to the philosophy of ARIMA models, where the series are differences prior to any type of analysis, in order to remove trend and seasonal. Hence, time series modelling is often more straightforward in an STS framework as compared to ARIMA approach. In this part, we shall present the structural time series models.

Basic Structural Time Series Model

A Structural time-series model was set up in terms of its various components, like trend, cyclical fluctuations, and seasonal variations, i.e.,

$$Y_t = T_t + C_t + S_t + \varepsilon_t \quad \textbf{(a)}$$

Where; Y_t the observed time-series at time't' is, $T_t, C_t, S_t, \varepsilon_t$ were the trend, cyclical, seasonal and irregular components.

Local Level Model (LLM)

In the absence of seasonal and cyclical components, eq. (a) reduces to (b)

$$Y_t = \mu_t + \varepsilon_t;\ \varepsilon_t \sim N(0, \sigma_\varepsilon^2)\ t=1, 2,\ldots, T. \quad \textbf{(b)}$$

When the trend component (μ_t) does not show a steady upward or downward movement, it becomes a permanent component called "level". Sometimes, it is assumed to vary according to a random walk, i.e.

$$\mu_t = \mu_{t-1} + \eta_t\ \eta_t \sim N(0, \sigma_\eta^2) \quad \textbf{(c)}$$

Eqs. (b) and (c) together form the LLM. It may be noted that these equations were already in state space form. However, level μ_t was not directly observable but could be estimated. When $\sigma_\varepsilon^2 = 0$, forecast is just the last observation and when $\sigma_\eta^2 = 0$, level was constant and the best forecast was sample mean. Level of time series varied over time depending on signal to noise ratio $q = \sigma_\eta^2/\sigma_\varepsilon^2$. Estimation of μ_t , conditional on σ_ε^2 and σ_η^2, was done recursively using Kalman filter and smoother (Harvey, 1996). The parameters σ_ε^2 and σ_η^2 was unknown and were treated as hyperparameters. Likelihood function could be evaluated by Kalman filtering via prediction error decomposition (Shum way and Stoffer, 2000). Once σ_ε^2 and σ_η^2 were known, one-step-ahead prediction of level, i.e. estimator of μ_{t+1} given

$Y_t = \{Y1, Y_2, \ldots, Y_t\}$, viz.

$$a_{t+1} = E(\mu_{t+1} / Y_t), \quad \textbf{(d)}$$

Was evaluated recursively by Kalman filter. Prediction error variance

$P_{t+1} = Var(\mu_{t+1} / Y_t) = Var(a_{t+1})$ **(e)**

Was also obtained recursively. Reduced form of LLM is ARIMA (0, 1, 1) model.

Local Linear Trend Model (LLTM)

As described by Harvey (1996), LLTM is given by eq. (j) along with the following two equations:

$$\mu_t = \mu_{t-1} + \beta_{t-1} + \eta_t \quad \textbf{(f)}$$

$$\beta_t = \beta_{t-1} + \xi_t, \; t = \ldots,-1,0,1,\ldots.., \quad \textbf{(g)}$$

Where; $\eta_t \sim N(0, \sigma_\eta^2)$ and $\xi_t \sim N(0, \sigma_\xi^2)$. It may be mentioned that; η_t, ξ_t and ε_t are independent of one another. If $\sigma_\eta^2 = \sigma_\xi^2 = 0$, eqs. (f) and (g) collapse to

$$\mu_t = \mu_{t-1} + \beta, t = 1, 2, ..., T, \quad \textbf{(h)}$$

which can equivalently be written as,

$$\mu_t = \alpha + \beta t, \; t = 1, 2, ..., T, \quad \textbf{(i)}$$

Showing that the deterministic linear trend is a limiting case

LLTM is in state space form with state vector $\alpha_t = (\mu_t, \beta_t)$. Updating and prediction is carried out using Kalman filter by assuming that $\sigma_\varepsilon^2, \sigma_\eta^2$ and σ_ξ^2 are known. Otherwise, these can be estimated using maximum likelihood method for state space models (De-Jong, 1988; Koopman and Shephard, 1992).

Local Linear Trend Model with Intervention Effect (LLTMI)

Analysis was connected with making inference about effects of known events. These effects are measured by including intervention, or dummy variables in a dynamic model (Harvey and Durbin, 1986). LLTMI is described by the following equations:

$$Y_t = \mu_t + \lambda w_t + \varepsilon_t \quad \textbf{(j)}$$

$$\mu_t = \mu_{t-1} + \beta_{t-1} + \lambda w_t + \eta_t \quad \textbf{(k)}$$

$$\beta_t = \beta_{t-1} + \lambda w_t + \xi_t \quad \textbf{(l)}$$

Where, w_t was intervention variable and $'\lambda'$ is its coefficient. The quantity w_t depends on the form, which intervention is assumed to take. As for LLTM, estimation of state vector $\alpha_t = (\mu_t, \beta_t)$ for LLTMI is similarly carried out by putting the model in state space form and applying Kalman filter recursively by treating w_t as an explanatory variable. Ravichandran and Prajneshu (2002) utilised this model for sunflower yield forecasting.

Various Goodness of Fit of STM

Goodness of fit statistics is used for assessing the overall model fit. A basic measure of goodness of fit in time-series models is prediction error variance. Model selection criteria the principle;

Criterion = Goodness of fit + Model complexity

Akaike Information Criterion (AIC)

The Akaike information criterion (AIC) was developed by Akaike (1974) to estimate the expected Kullback-Leibler (1951) discrepancy between the model generating the data and a fitted contender model. In another setting, AIC may be characterized by a large negative bias, which limits its effectiveness as a model selection criterion. Comparison of goodness of fit between different models is based on AIC.

$$AIC = -2 \log L + 2n$$

Where, L is the likelihood function, which is expressed in terms of estimated one-step-ahead prediction $\hat{v}_t = Y_t - \hat{Y}_{\frac{t}{t-1}}$ errors. Here n is the number of hyper-parameters estimated from the model.

Corrected Criterion AIC (CAIC)

It could be argued that a good model selection criterion should work even if the user tries a "bad" (e.g., over-parameterized) model: If the model is bad, the criterion should be able to detect this. In this regard, AIC fails. In order to remove this deficiency, the normal multiple regression model for small samples, we can define the finite sample corrected AIC, namely, originally proposed by Sugiura (1978) and later used Hurvich and Tsai (1989) introduced a corrected version, CAIC, defined by

$$CAIC = n \log(2\pi) + n \log\left(\hat{\sigma}^2\right) + n + 2\frac{n(k+1)}{n-k-2},$$

Consistent AIC (AICC)

We recommend the use of the AIC and not the AICC for analysis and inference from capture-recapture data sets. It is proposed by Bozdogan (1987) and represented by

$$AICC = -2\log L + n((\log T) + 1)$$

The lower values of these statistics, better is the fitted model.

Schwartz-Bayesian Information Criterion

(SBC, Schwartz, 1978) is also used as a measure of goodness of fit which is given as,

$$SBC (BIC) = -2 \log L + n \log T,$$

Where, T is the total number of observations.

Hannan–Quinn Information Criterion (HQIC)

The Hannan–Quinn (1979) information criterion (HQIC) is a criterion for model selection. It is an alternative to Akaike information criterion (AIC) and Bayesian information criterion (BIC). It is given as,

$$HQIC = -2L_{max} + 2k \log(\log n)$$

Software for STM Model

STM models can be fitted to the data using Structural Time-series Analyser, Modeller and Predictor (STAMP) (Koopman et al., 2000) or by using SsfPack 2.2 (Koopman et al., 1999) software package or by SAS (Statistical Analysis System), Version 9.2 software packages.

The use of STAMP (Structural Time Series Analyser, Modeler and Predictor) for modeling time series data using state-space methods with un-observed components

RESULTS AND DISCUSSIONS

Modeling Yield Trends through Structural Time Series (STM) for Major Crops

Structural time series model was fitted for trend information and yield forecast of rice, wheat and chickpea. To judge the forecasting ability of the fitted model, important measures of the three year forecast were computed.

Structural Time Series Model for Rice Crop

Likelihood statistics, i.e., Akaike's information criterion (AIC), corrected criterion (AICC), consistent AIC (CAIC), Bayesian information criterion (BIC) and Hannon-Quinn's information criterion (HQIC), were calculated for various varieties of rice crop. Its Smallest values were found in varying, Swarna among all varieties, followed by MTU-1001 and MTU-1010 (Table 1). Trend information was provided on the basis of least standard error for Swarna (0.001), MTU-1010 (0.001) and Mahamaya (0.002) varieties. The rice varieties BPT-5204 (3.984), Karmamasuri (2.186) and Bamleshwari (1.170) showed decreased trend (Table 2). Forecasts of various varieties of rice yield (q/ha) in Chhattisgarh state, yield of Swarna obtained consistent performance for the next three years (2015-16 to 2017-18), followed by MTU-1010, IR36, IR-64, Mahamaya, Karmamasuri, Bamleswari, PKV-HMT and BPT-5204 also shown yield in increasing trend. Only rice variety MTU-1001 showed decreasing yield (Table 3) (Bharadwaj *et al.*, 2015 a & b; Bhardwaj *et al.*, 2016).

Table 1: Likelihood Based Fit Statistics for Major Varieties of Rice Crop

Varieties	AIC	BIC	AICC	HQIC	CAIC
Swarna	17.39	15.55	35.39	13.35	18.55
MTU- 1010	19.33	17.49	37.33	15.29	20.49
MTU -1001	18.48	16.63	36.48	14.43	19.63
IR -36	29.37	27.53	47.37	25.33	30.53
IR -64	31.09	29.25	49.09	27.05	32.25
Mahamaya	29.59	27.75	47.59	25.55	30.75
Karmamasuri	30.85	29.00	48.85	26.81	32.00
Bamleswari	25.84	24.00	43.84	21.80	27.00
PKV -HMT	27.07	25.23	45.07	23.03	28.23
BPT -5204	35.65	33.80	53.65	31.61	36.80

Smaller is better for AIC, BIC, AICC, HQIC and CAIC

Table 2: Trend Information (Based on the Final State) for Different Varieties of Rice Crop

Varieties	Components			
	Level		Slope	
	Estimate	Standard Error	Estimate	Standard Error
Swarna	49.81	0.001	0.164	0.367
MTU -1010	37.33	0.001	0.222	0.468
MTU -1001	45.01	0.465	-0.073	0.153
IR- 36	38.69	0.158	1.225	1.644
IR -64	48.84	0.023	0.366	2.037
Mahamaya	47.38	0.002	0.356	1.689
Karmamasuri	41.78	2.186	0.713	0.722
Bamleswari	42.58	1.170	0.309	0.386
PKV- HMT	33.55	0.008	0.079	1.232
BPT -5204	41.92	3.984	0.816	1.315

Table 3: Forecast of Yield (q/ha) of Rice Varieties from 2015-16 to 2017-18 in Chhattisgarh State

Years	2015-16		2016-17		2017-18	
Varieties	Forecast	Standard Error	Forecast	Standard Error	Forecast	Standard Error
Sawarna	49.98	0.90	50.14	1.37	50.31	1.80
MTU-1010	37.55	1.14	37.77	1.75	37.99	2.29
MTU-1001	44.94	0.87	44.87	0.98	44.79	1.09
IR-36	39.91	4.02	41.14	6.15	42.36	8.05
IR-64	43.21	4.99	43.58	7.62	43.94	9.98
Mahamaya	47.73	4.13	48.09	6.32	48.44	8.27
Karmamasuri	42.50	4.12	43.21	4.60	43.92	5.14
Bamleshwari	42.89	2.20	43.20	2.464	43.51	2.75
PKV-HMT	33.63	3.01	33.71	4.61	33.79	6.03
BPT-5204	42.74	7.52	43.56	8.39	44.37	9.36

CONCLUSIONS

Overall, the class of models proposed introduces periodicity without affecting the possibility of extracting signals that are an expression the long run behavior. Therefore, they furnish a reasonable compromise between increasing model complexity in the presence of strong seasonal effects, and preserving the decomposability of the time series. In our study, the structural time-series model developed for rice yield comparison of the state yield showed that the yield of promising varieties is much higher (39 %) than the state yield of rice, since last 16 years after making new state. This indicates that the promotion of high yielding varieties can be made for improving the overall productivity of the state. Different promising varieties of rice in Chhattisgarh showed that forecasted yield increases the next three years for the lead periods and shows that there is a small change in the forecasts yield.

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