
Importance of Market Intelligence, Price Forecasting and Time Series Analysis in Agriculture

Bibhu Santosh Behera,

Ph.D Research Fellow, OUAT, Bhubaneswar

Anama Charan Behera,

Principal, D. B. College, Turumunga, Keonjhar

Rudra Ashish Behera,

P.G. Student, TTS, Bhubaneswar

Jishnu,

K.J.,P.G. Student, OUAT, Bhubaneswar

Abstract

Agriculture is the backbone of Indian economy. Agriculture, with its allied sectors, is unquestionably the largest livelihood provider in India. The Indian agriculture sector accounts for 14 per cent of India's gross domestic product (GDP) and employs just more than 50 per cent of the country's workforce. It has to support almost 17 per cent of world population from 2.3 per cent of world geographical area and 4.2 per cent of world's water resources .In 2013-14 India achieved a record food grain production of 264 million tonnes , beating the previous year's (2012-13) 257 MT, according to data provided by Department of Economics and Statistics .Amidst in these high potentiality, we are facing lots of challenges in the marketing aspects of agriculture. Better marketing with increased and assured remuneration is the need of the hour to foster and sustain the tempo of rural economic development.

For bettering marketing prospects in agriculture, market intelligence needs to be bettered.

Keywords: Market intelligence, price forecasting

1. Introduction :

Market Intelligence (MI) is knowledge based management system which may be defined as a process primarily based on market information collected over period of time. An analysis based on past information helps to take decision about the future. MI synthesizes information from many diverse sources to form greater insights. It requires sophisticated understanding of strategic trade goals and to widen trade opportunities. It provides diversified avenues to examine the market behaviour of agricultural commodities to facilitate all the stake holders. It is an essential function for the formulation of sound price and trade policy.

Generally, the role of MI can be pointed as follows :

- ♦ Provides better understanding of the forces that are operating in a particular situation as well as anticipating situation.
- ♦ Provides regular and continuous appraisal of market behaviour and of various factors that influences the market behaviour.
- ♦ Offers a solution to the probable behaviour of market and forces that is likely to influence it in the near future.

- ♦ Helps evaluation of the functioning of the marketing organisations with a view to ensuring efficient and effective implementation of agricultural marketing and price policy.
- ♦ Offers proper advice in influencing market players for ensuring remunerative prices to the farmers, supply of commodities and to maintain stability in market prices.
- ♦ Provides the collection of data on prices, arrivals, stocks, release of important agricultural commodities for the selected market centres of the country.
- ♦ The data are reported by technical personnel such as market information inspector, price inspectors, statistical investigators, market secretaries, etc and are posted in the selected markets of the country.

The importance of flow of market information has increased considerably in recent years particularly in case of fruits and vegetables.

2. Methodology :

By reviewing all relevant articles from secondary sources of information, Research data are compiled for

preparation. model is used along with basic statistics. Secondary data of Turmeric from major markets of India are collected from agmarknet.nic.in and Regional Market Centre (RMCs). **Autoregressive integrated moving average (ARIMA) / Seasonal Auto Regressive Integrated Moving Average (SARIMA)** model will be used for forecasting purpose. R software package has been used. Secondary data from Agricultural Marketing Information Centre (AMIC), Kerala Agriculture University (KAU) has been collected.

3. Review of Literature :

Erik Hjalmarsson and Par Osterholm (2007) have investigated the properties of Johansen's (1988, 1991) maximum eigenvalue and trace tests for co integration under the empirically relevant situation of near-integrated variables. Using Monte Carlo techniques, we show that in a system with near-integrated variables, the probability of reaching an erroneous conclusion regarding the co integrating rank of the system is generally substantially higher than the nominal size. The risk of concluding that completely unrelated series are co integrated is therefore non-negligible. The spurious rejection rate can be reduced by performing additional tests of restrictions on the co integrating vector(s), although it is still substantially larger than the nominal size.

Rangsan Nochai and Titida Nochai (2006) This research is a study model of forecasting oil palm price of Thailand in three types as farm price, wholesale price and pure oil price for the period of five years, 2000 – 2004. The objective of the research is to find an appropriate ARIMA Model for forecasting in three types of oil palm price by considering the minimum of mean absolute percentage error (MAPE). The results of forecasting were as follows: ARIMA Model for forecasting farm price of oil palm is ARIMA (2,1,0), ARIMA Model for forecasting wholesale price of oil palm is ARIMA (1,0,1) or ARMA(1,1), and ARIMA Model for forecasting pure oil price of oil palm is ARIMA (3,0,0) or AR(3). In this paper, we developed model for three types of oil palm price, were found to be ARIMA(2,1,0) for the farm price model, ARIMA(1,0,1) for whole sale price, and ARIMA(3,0,0) for pure oil price. Which we can see that the MAPE for each model very small.

Megha Mukim, Karan Singh, A Kanakaraj (2009) they have examined whether the wheat market is integrated across states in India, and concludes that the market is integrated in the long run. This long run integration, however, does not come from the free flow of goods across states in the country, but from the sharing of similar production technologies by farmers across states. The paper also shows that the market for wheat is not integrated in the short run. This implies that at a given time period there exist two prices for the same commodity, since transaction costs are the main barriers to market integration. The paper also estimates such transaction costs using transport and communication infrastructure indices across states, and concludes that

there exist large variations resulting in high transaction costs.

Madhusudan Ghosh (2003) has investigated intra-state and inter-state spatial integration of wheat markets in India. In view of the limitations of the methods used earlier for investigating market integration in Indian agriculture, this study has utilized the ML method of co integration. Intra-state regional integration of wheat markets has been evaluated by testing the linear long-run relationship between the prices of the state-specific variety of wheat quoted in spatially separated locations in five selected states. The co integration results for Bihar and UP indicate that the regional wheat markets were integrated to such an extent that the weak version of the LOP was in operation. The co integration tests also offer evidence for regional wheat market integration in Haryana, Punjab and Rajasthan; but no evidence is found in favour of the LOP for these states. The results for inter-state regional wheat markets represented by five market centres chosen from the five selected states reveal three co integrating vectors and two common stochastic trends. Contrary to Jha *et al.* (1997), we find that though all the prices taken together are integrated, they are not pair-wise co integrated.

Christopher B. Barrett (2005) considered that markets aggregate demand and supply across actors distributed in space. Well-integrated markets play a fundamental role in ensuring that macro level economic policies change the incentives and constraints faced by micro-level decision-makers, in distributing risk and in preserving incentives to adopt improved production technologies. Yet the literature is replete with evidence of forgone arbitrage opportunities in both intra- and international trade. Given limited data and the restrictive assumptions of existing empirical methods, economists still have only a fragile empirical foundation for reaching clear judgements about spatial market integration as a guide for corporate or government policy. The literature on price forecasting has focused on two main classes of linear, single-equation, reduced-form econometric models as well as Time Series models. The first group (Financial Models) includes models which are directly inspired by financial economic theory and based on the market efficiency hypothesis (MHE), while models belonging to the second class (Structural Models) consider the effects of commodity market agents and real variables on commodity prices.

Reza Moghaddasiand and Bitra Rahimi Badr(2008) considered wheat (Bread) is a dominant product in the consumption basket of Iranian households and can be considered as a strategic commodity. In this paper different econometric models including structural and time series models are specified and estimated. The literature on price forecasting has focused on two main classes of linear, single-equation, reduced-form econometric models as well as Time Series models. The first group (Financial Models) includes models which are directly inspired by financial economic theory and based on the market efficiency hypothesis (MHE), while models

belonging to the second class (Structural Models) consider the effects of commodity market agents and real variables on commodity prices. Then forecasting performance of these models are evaluated and compared by using common criteria such as: root mean square error, mean absolute error, mean absolute percentage error and the inequality coefficient. The data used in this study include annual farm and guaranteed prices of wheat and rice (as a competitive product) and wheat stock for 1966 to 2006. Main findings reveal the superiority of time series models (unit root and ARIMA(3,2,5)) for forecasting of wheat price. ARIMA annual models outperformed the structural model in predicting the price of wheat for the period 1966-2006. The unit root and ARIMA models were also constructed using only the information provided by the historical time series of the variable being forecast; hence the amount of information required to develop these models was considered to be less than those employed in formulating the structural models. Likewise the costs involved in developing the econometric structure forecasting models were considered to be more than the cost associated in developing time series models. It is difficult to conclude about the adequacy of the forecasts derived from the selected models, since it largely depends on the particular use to which the price predictions are to be employed.

Chakriya Bowman and Aasim M. Husain (2004) in their paper aim to assess the accuracy of alternative price forecasts for 15 primary Commodities over the past decade. A number of alternate measures of forecast performance, having to do with statistical as well as directional accuracy, are employed. The analysis indicates that although judgmental forecasts tend to outperform the model-based forecasts over short horizons of one quarter for several commodities, models incorporating futures prices generally yield superior forecasts over horizons of one year or longer. Spot and futures prices were generally found to be non stationary and, in most cases, spot and futures prices appear to be co integrated. Although there is considerable co movement between spot and futures prices, futures prices tend to exhibit less variability than spot prices. Hence, futures prices tend to act as an anchor for spot prices, and error-correction models that exploit the long-run co integrating relationship provide better forecasts of future spot-price developments. When evaluating the *ex-post* effectiveness of forecasts, standard statistical measures are commonly used. Mean pricing error, mean absolute pricing error, mean absolute relative pricing error (*MARPE*), median absolute relative pricing error and root mean squared error (*RMSE*) are typically calculated and the results used to generate conclusions about the accuracy of forecasts. This research will focus primarily on *RMSE*, which gives a measure of the magnitude of the average forecast error, as an effectiveness measure. The ECM forecasts outperform the other types of forecasts for eight of the fifteen commodities at the eight quarter horizon. In some of these cases, the ECM forecast performance is superior in both statistical and directional terms (wheat, soybeans, and soybean meal), although for several commodities the

ECM yields significantly better directional accuracy at the expense of somewhat lower statistical accuracy (aluminum, lead, nickel, zinc, and maize). For another four commodities (tin, soybean oil, sugar, and cotton), the ECM performs about as well as judgment at the eight-quarter horizon, and both perform better than the best unit root/ARMA forecasts.

Padhan, P.C., (2012) considered that forecasting of any issues, events or variables requires an in-depth understanding of the underlying factors affecting it. Such is the case for forecasting annual productivity of agricultural crops. Agricultural productivity, in the context of India, extensively depends upon numerous factors namely: good rainfall, timely use of appropriate fertilizer and pesticides, favorable climate and environments, agricultural subsidies given to farmers etc. Therefore, forecasting productivity of agricultural crops is not only tedious but also indispensable, as large chunk of people depends on agriculture for their livelihood. Various univariate and multi-variate time series techniques can be applied for forecasting such variables. In this paper, ARIMA model has been applied to forecast annual productivity of selected agricultural product. For empirical analysis a set of 34 different products has been considered, contingent upon availability of required data. Applying annual data from 1950 to 2010, forecasted values has been obtained for another 5 years since 2011. The validity of the model is verified with various model selection criteria such as Adj R², minimum of AIC and lowest MAPE values. Among the selected crops, tea provides the lowest MAPE values, whereas cardamom provides lowest AIC values.

Liew Khim Sen, Mahendran Shitan and Huzaimi Hussain (2007) It is important to forecast price, as this could help the policy makers in coming up with production and marketing plan to improve the Sarawak's economy as well as the farmers' welfare. In this paper, we take up time series modelling and forecasting of the Sarawak black pepper price. Our empirical results show that Autoregressive Moving Average (ARMA) time series models fit the price series well and they have correctly predicted the future trend of the price series within the sample period of study. Amongst a group of 25 fitted models, ARMA (1, 0) model is selected based on post-sample forecast criteria.

4. Price Forecasting :

Price forecasting plays an important role in augmenting the growth of agricultural sector at the zenith level. Forecasting is the process of making statements about events whose actual outcomes (typically) have not yet been observed. A common place example might be estimation of some variable of interest at some specified future date.

Price is the primary mechanism by which various levels of the market are linked. The extent of adjustment and speed with which shocks are transmitted among producer, wholesale, and retail market prices is an important factor reflecting the actions of market

participants at different levels. Price forecasting has been very important in decision making at all levels and sectors of the economy. In agriculture, where the decision environment is characterized by risks and uncertainty largely due to uncertain yields and relatively low price elasticity of demand of the most commodities, decision makers require some information about the future and the likelihood of the possible future outcomes. Price forecasts are critical to market participant making production and marketing decisions and to policy makers

who administer commodity programs and assess the market impacts of domestic or international events. Therefore commodity price movements have a major impact on overall macroeconomic performance. Hence, commodity price forecasts are a key input to macroeconomic policy planning and formulation.

An Example for the Analysis of Price Forecasting of Turmeric in Odisha Using R Software (weekly data from January 2004 to august 3rd week 2014) ARIMA MODEL (2,1,2) (courtesy AGMARK net , OUAT BBSR)

```

RGui (32-bit)
File Edit View Misc Packages Windows Help
R
Untitled - R Editor
#EXAMINE VISUALLY IF THE SERIES HAS A TREND
plot(turmeric@turmeric)
plot(diff(turmeric@turmeric))

#PLOT THE ACF AND PACF AFTER APPROPRIATE DIFFERENCING
par(mfrow=c(2,1))
pacf(diff(turmeric@turmeric))
acf(diff(turmeric@turmeric))

par(mfrow=c(2,1))
pacf(diff(diff(turmeric@turmeric)),4)
acf(diff(diff(turmeric@turmeric)),4)

#INVOKER THE PROGRAMME TO RUN SARIMA
library(astsa)
#ESTIMATING ARIMA AND FORECASTING
fitturmeric <- sarima(turmeric@turmeric, 2,1,1, P=2, D=1, Q=2, S=4)
forecastturmeric <- sarima.for(turmeric@turmeric,12, 2,1,1,2,1,2,4)

#TO OBTAIN NUMERICAL VALUES OF THE FORECAST
forecastturmeric

# FORECASTING VARIANCE USING ARCH AND GARCH MODELS

#INVOKING THE GARCH MODULES
library(fgarch)
library(rugarch)

attach(turmeric)
#FOR GARCH FITTING AND FORECASTING

spec <- ugarchspec()
fit1 <- ugarchfit(data = turmeric[,2], spec = spec)
fore <- ugarchforecast(fit1, n.ahead=12)
fore
<
R Console
final value 7.163296
converged
initial value 7.163642
iter 2 value 7.163568
iter 3 value 7.163547
iter 4 value 7.163523
iter 5 value 7.163475
iter 6 value 7.163432
iter 7 value 7.163410
iter 8 value 7.163403
iter 9 value 7.163400
iter 10 value 7.163400
iter 11 value 7.163399
iter 11 value 7.163399
iter 11 value 7.163399
final value 7.163399
converged
> forecastturmeric <- sarima.for(turmeric@turmeric,12, 2,1,1,2,1,2,4)
> forecastturmeric
$pred
Time Series:
Start = 511
End = 522
Frequency = 1
[1] 3518.386 3524.360 4719.295 4061.509 3694.564 3840.176 3895.498 3663.694
[9] 3587.714 3675.951 4128.195 3954.289

$se
Time Series:
Start = 511
End = 522
Frequency = 1
[1] 1279.687 1476.094 1557.468 1625.581 1675.423 1731.787 1789.657 1846.096
[9] 1881.450 1923.678 1968.468 2012.716
> |

```

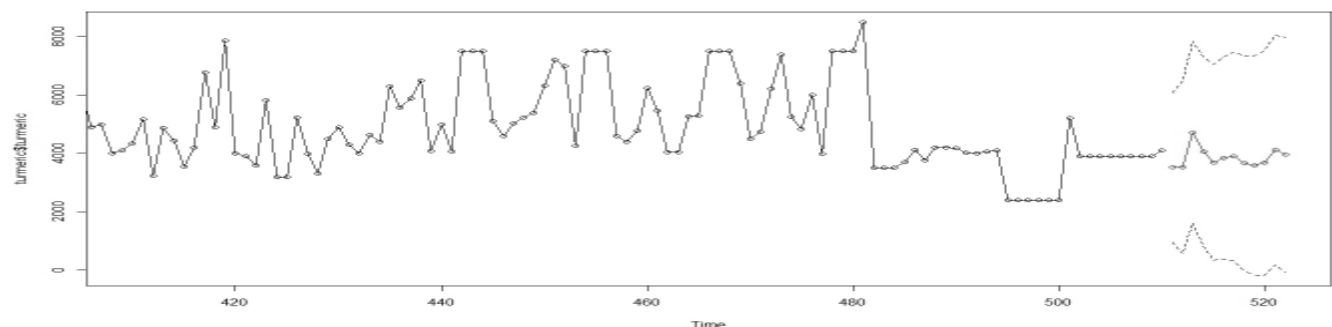
Forecasted Price Values of Turmeric for Next Two Months

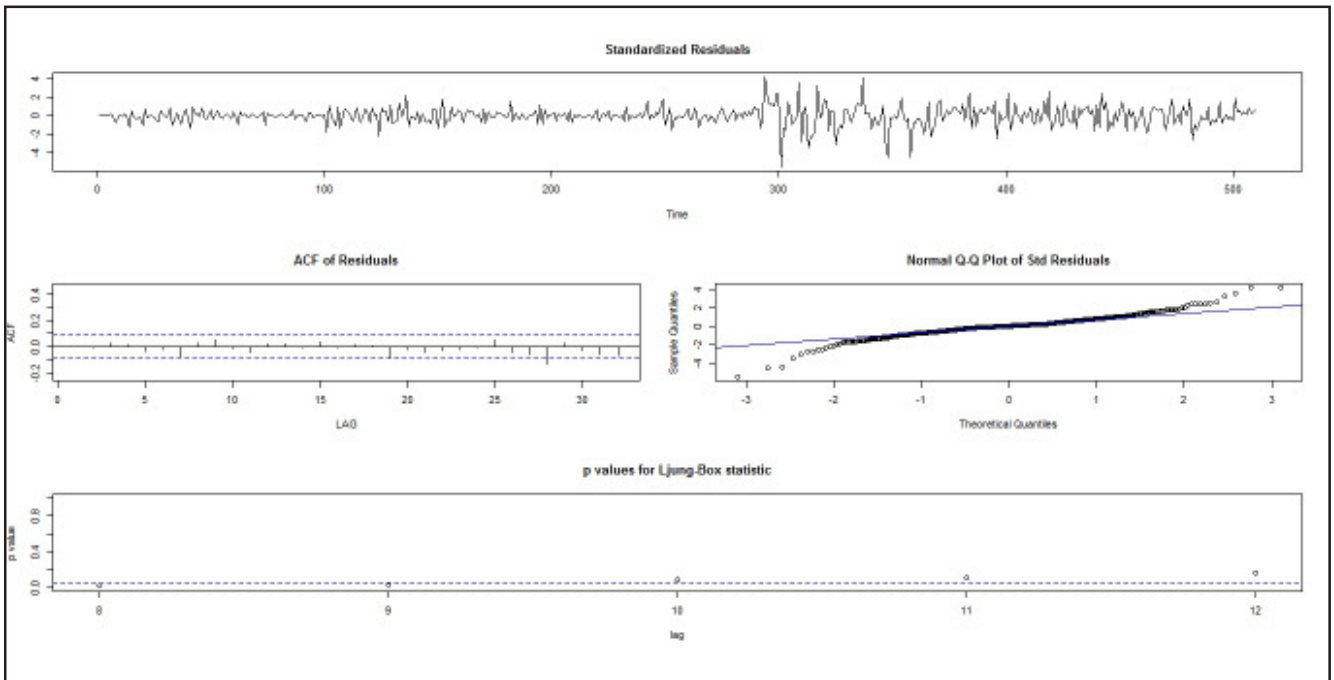
```

converged
> forecastturmeric <- sarima.for(turmeric@turmeric,12, 2,1,1,2,1,2,4)
> forecastturmeric
$pred
Time Series:
Start = 511
End = 522
Frequency = 1
[1] 3518.386 3524.360 4719.295 4061.509 3694.564 3840.176 3895.498 3663.694
[9] 3587.714 3675.951 4128.195 3954.289

```

Forecasted Graph of Turmeric Price Data





The graph and forecasted values shows that price remains in between Rs 3500-4700 per quintal in the next two month. So the farmers can take steps in marketing during the peak price season.

5. Time Series Analysis :

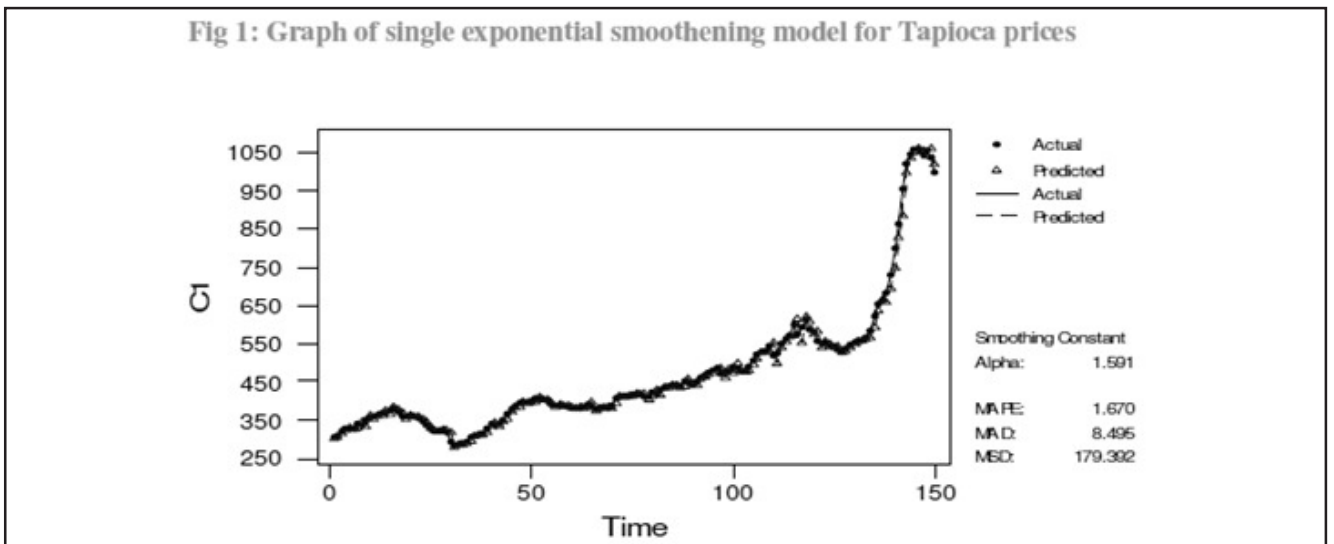
We separately study the nature and behaviour of various components of prices and other time series variables in the time series analysis. To analyse the nature of inter temporal behaviour of prices we require time series data on prices for various agricultural commodities over time and space.

5.1 Components of Time Series :

5.1.1 Trend Factor

These are those which reflect movement in the economic variable over time. If the Time series data is collected over different years, then we can analyse the trend factor and measure the growth or recession of the variable over several years. The prices of the commodities, production of goods and services etc can be measured through this.

Example- Tapioca price in kerala(courtesy-AMIC , KAU)



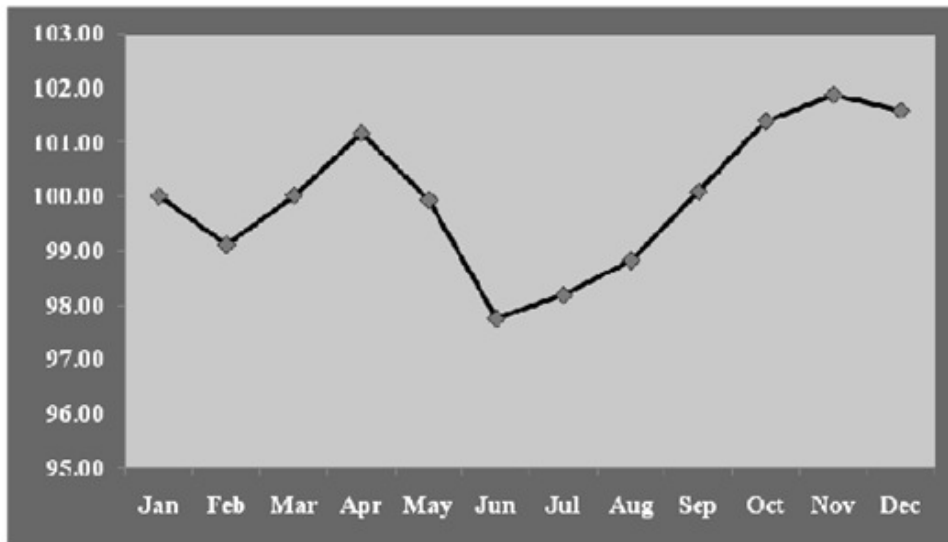
5.1.2 Seasonal Factor

Almost all businesses tend to have recurring seasonal patterns. It relates to specific season of the year or month. If the Time series data are available over seasons of the year or months, we can separate Seasonal factor and measure the seasonal component for making appropriate decisions regarding seasonal variations. The seasonal variations refer to systematic though not

necessarily regular intra-year movements in a time series. Seasonal indices were worked out to capture the seasonal patterns in the price data. The seasonal index showed a declining trend for prices during the harvest period when market arrivals are maximum. The consumption of meat, chicken, eggs etc undergoes variation over different season or months.

Example- Tapioca price in kerala(courtesy-AMIC , KAU)

Fig.2. Seasonal variations of monthly state average Tapioca prices



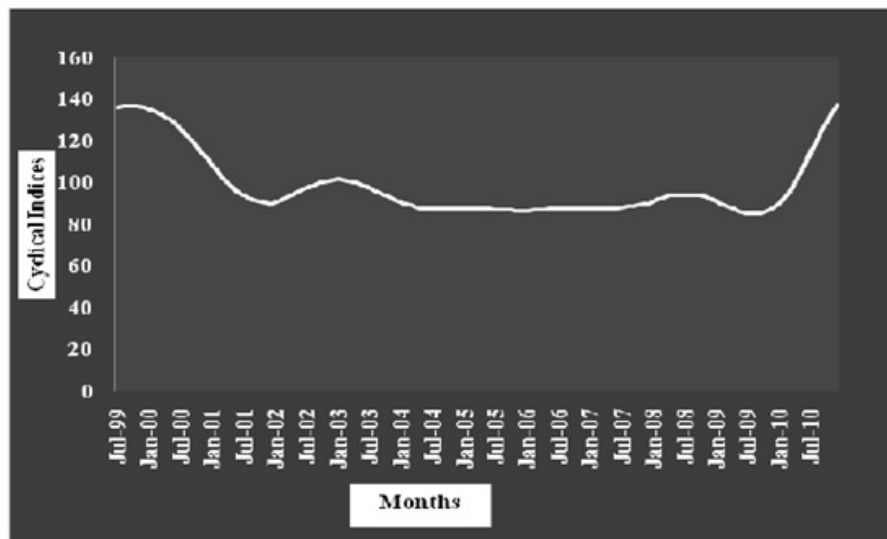
5.1.3 Cyclical Factor

These are long term fluctuations and we require very large Time series data to analyse the cyclical component. A typical business cycle consists of a period of prosperity followed by periods of recession, depression, and then recovery with no fixed duration of the cycle. Cobweb theorem is used to study the cyclical component. According to this the effect of price change on production

of commodity is felt with one time lag. So in Agriculture the existence of time lag is due to the inherent characteristics of the crop. For dryland agriculture, time lag is 1 year, for irrigated crop the time lag may be one season, for livestock and orchard the time lag is still longer.

Example- Tapioca price in kerala (courtesy-AMIC , KAU)

Fig.3. Cyclical variations in the monthly state average prices of Tapioca



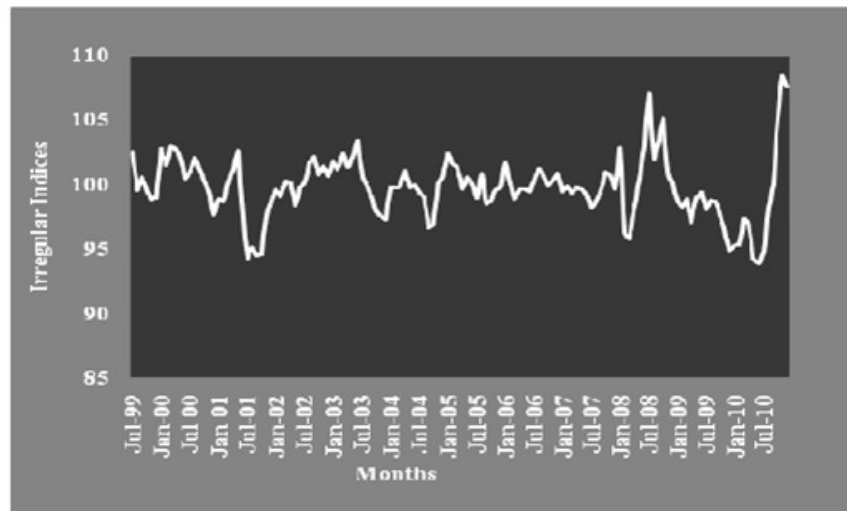
5.1.4 Irregular Factor

The random component is an unpredictable component as a result of unforeseen situations like weather related production problems or demand or supply uncertainties due to a host of factors or due to speculative activities. The indices of irregular variations have been worked out

to capture the random effect. This includes all other omitted factors which influence the value and magnitude of economic variable, changes in tastes and preference which are not specifically related to passage of time/ trend.

Example- Tapioca price in kerala (courtesy-AMIC , KAU)

Fig.4. Irregular variations in the monthly state average prices of Tapioca



So in general Market Intelligence, Price forecasting and Time series analysis play vital role in the keeping the pace of Agricultural sector. They help in taking policy making decisions to cop up with facing challenges.

6. Conclusion :

By using intelligence we can be able to check the malpractice and irregular practice of mintroduction and price spread.

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