DIRECTORATE OF ADVANCED STUDIES
EVENT CATALOGUE
2021

14TH SEMINAR OF DAS EVENTS CALENDAR – 2021

A PROJECTION OF WHEAT YIELD FOR PAKISTAN BY USING STOCHASTIC MODELLING

ACTIVITIES

Objective

- The objective of the present research is to analyze the structure of Pakistan agriculture subsectors of wheat crop by non-stationary Markov chain. And then to project the agricultural structure by the use of transition probabilities obtained from non-stationary Markov chain analysis.

Variable

A variable X is any characteristics, number, or quantity that can be measured or counted. Age, business income and expenses, country of birth, capital expenditure, class grades, eye color and vehicle type are examples of variables. It is called a variable because the value may vary between data units in a population, and may change in value over time. For example; 'income' is a variable that can vary between data units in a population.

Dependent vs independent variables

Dependent variable X and Y

The variable that depends on other factors that are measured. These variables are expected to change as a result of an experimental manipulation of the independent variable or variables. It is the presumed effect.

(Regression)

Independent variable X and Y

The variable that is stable and unaffected by the other variables you are trying to measure. It refers to the condition of an experiment that is systematically manipulated by the investigator. It is the presumed cause.

(Correlation)

Regression

Regression analysis is a set of statistical methods used for the estimation of relationships between a dependent variable and one or more independent variable. It can be utilized to assess the strength of the relationship between variables and for modeling the future relationship between them. The simple linear model is

$$\mathbf{Y = \alpha + \beta X + \epsilon}$$

Where:

- **Y** – Dependent variable
- **X** – Independent (explanatory) variable
- **α** – Intercept
- **β** – Slope
- **ϵ** – Residual (error)

Regression Analysis – Multiple Linear Regression

Multiple linear regression analysis is essentially similar to the simple linear model, with the exception that multiple independent variables are used in the model. The mathematical representation of multiple linear regression is:

$$Y = a + bX_1 + cX_2 + dX_3 + \epsilon$$

Where:

- **Y** – Dependent(response, Regressand, measured, observed, explained, outcome, experimental) variable
- **X_1, X_2, X_3** – Independent (Regressors, controlled, manipulated ,explanatory, exposure) variables
- **a** – Intercept
- **b, c, d** – Slopes
- **ϵ** – Residual (error)

Stochastic Process

Stochastic is the word that comes from the Greek word which means random process. Stochastic or random process can be characterized as a collection and groups of random variables, that's recorded by some mathematical and numerical set and models that means that every chance of random variable of the stochastic process is related to a component within the set and models. The set used to index the random variables is called the index set. So, the index set is some subset of the important real line, such as the natural numbers giving the index set the interpretation of time. Random variable within the collection takes values from the same mathematical and the identical area known as the state space. Stochastic describes an approach to anything that is based on probability with respect to time. Stochastic process deals with different stochastic model our concerned with diffusion model whereas diffusion shows the variation.

Consider the following SDE which define a continuous-time Ito diffusion model:

$$dX_t = \mu(X_t)dt + \sigma(X_t)dW_t$$

Where

$\mu(X_t)$ drift is function

$\sigma(X_t)$ diffusion function of process

$\{W_t, 0 \leq t \leq T\}$ known as standard Brownian motion.

X_t is one dimensional which is mostly used to define the properties of many underlying economic variables.

Markov Chain

The Markov Chain model is becoming a more popular tool to predict the number and the distribution of a population of agricultural firms. Markov chain is a succession or chain of discrete states in time or space with altered probabilities for the move from one state to a given state in the following stride in the chain. In its simplest form, a Markov chain may be regarded as a series of transitions between diverse states, such that the probabilities connected with every move depend just on the instantly going before state, and not on how the process arrives at that state.

Let stochastic process $\{Y_m : m \geq 0\}$ is known as a Markov chain if for all times $m \geq 0$ and all states $i_0, \ldots, I, j \in S$,

$$P(Y_{m+1} = j \mid Y_m = i, Y_{m-1} = i_{m-1}, \ldots, Y_o = i_o) = P(Y_{m+1} = j \mid Y_m = i)$$
$$= P_{ij}$$

P_{ij} is the notation of transition probability, whenever in regime *i*, moves next into regime *j*, and is known as a one-step moving probability. The square matrix $\prod = (P_{ij}),\ i, j \in S$ is called the transition probability matrix, and whenever the chain leaves regime *i* it must have to shift to the next regime *j* ∈ *S*. For each regime *I*

$$\sum_{j \in S} P_{ij} = 1 \ \ and \ \ i, j \in S$$

Markov Chain Model following the publication of Hallberg (1969) and Ethridge (1985) has been applied in the analysis and projection of future structural change within the agricultural industry by many authors see, e.g., Disney (1988), Zepeda (1995), Gillespie (2001), Singh (2012) and reference there in.

It is helpful to accept that Markov transition matrix are the after effects of procedures that are stationary in time or space, i.e. that the move probabilities don't shift with either time or space. Such Markov Chains are called stationary Markov Chains (Disney 1988). In such type of chains;

$$P_{ij} = P(Y_1 = j \mid Y_0 = i)$$
$$P_{ij(t)} = P_{ij} \quad \forall t = 1, 2, \ldots, T$$

Non-stationary Markov approach, which has been proven particularly useful to describe the structural changes over time, is used to model the effects of factors influencing the numbers and the sizes of the farms. In response to this Hallberg (1969) presented probabilities that were a component of exogenous elements that could change all through the arrangement of investigations. In such cases one has to use non-stationary Markov chains.

$$P_{ij(t)} \neq P_{ij} \quad \forall t = 1, 2, \ldots, T$$

A wide range of researches have been done in the field of non-stationary Markov chain models and their application in the field of agriculture to project the future structure of agriculture sector. Singh (2012) inspected the auxiliary changes in area usage and moving of range among distinctive area utilization classes in India by using a Markov chain analysis.

The Markov chain models are frequently utilized as the stochastic model with which to project the future time path of such variables. Projection is the procedure of making expectations without bounds taking into account at various times information and examination of patterns. Following the Projections of the structure for n years the transition probability matrix is multiplied with itself n times.

$$P\left(P_{ij(t)}\right) = \left(P_{ij}\right)^n$$

MARKOV CHAIN MODEL AND ASSUMPTIONS

The Markov Switching model is an outstanding amongst the most famous linear time arrangement models in the literature. This model includes various structures (comparisons) that can represent the time arrangement practices in different regimes. By allowing changes between these structures, this model has the capacity to catch more unpredictable element designs. If there are only two regimes, then by following Font decaba (2009) the two Markovian Switching model would be estimated which can be written as;

$$
\begin{aligned}
&Y_{i,t}^{(1)} = \lambda_{1,t}^{(1)} X_{1,t} + \ldots + \lambda_{k,t}^{(1)} X_{k,t} + \lambda_{k+1,t}^{(1)} X_{k+1,t} + \ldots + \lambda_{i,t}^{(1)} X_{i,t} + e_{t,1} \\
&R_t = 1 \\
&Y_{i,t}^{(2)} = \lambda_{2,t}^{(2)} X_{2,t} + \ldots + \lambda_{k,t}^{(2)} X_{k,t} + \lambda_{k+1,t}^{(2)} X_{k+1,t} + \ldots + \lambda_{i,t}^{(2)} X_{i,t} + e_{t,1} \\
&R_t = 2
\end{aligned}
$$

Where X_i's are independent variables.

As there are only two regimes, so the number of parameters to be estimated is

Deviations of the states: $\left(\sigma^{(1)}, \sigma^{(2)}\right)$

Coefficients of the regression with switching effect: $\left(\lambda_{1,\ldots,k}^{(1)} : \lambda_{1,\ldots,k}^{(2)}\right)$

Coefficients of the regression without switching effect: $\left(\lambda_{k+1}, \ldots, \lambda_{t}\right)$

Transition probabilities $\left(P_{11}, P_{12}, P_{21}, P_{22}\right)$

Projected Transition probabilities

$$\left((P_{11})^{n}, (P_{12})^{n}, (P_{21})^{n}, (P_{22})^{n}\right)$$

The model parameters can also be written as:

$$\theta = \left(\lambda, \sigma, \prod, \prod^{n}\right)$$

Here Π represents the transition probability matrix and Π^{n} represents the projected transition probability matrix. To know the significance of the independent variables the basic assumptions of OLS that are Linearity, Normality, Multicollinearity and Autocorrelation are checked for possible violation. After detecting the presence of multicollinearity, it is removed by using Ridge regression.

Then Markov Switching Model is applied to the data. The two regimes can be defined as two states separated by the average value of the dependent variable. If the values of dependent variable in response to the independent variables are less than or equal to the average value of dependent variable then it goes in regime-I. On the other hand if it is greater than the average value it goes into regime-II.

The above Markov Switching Model related to present research can be written as:

$$P^{(1)}_{i,t(yield)} = \lambda^{(1)}_{0} + \lambda^{(1)}_{fertilizer,t} + \lambda^{(1)}_{pesticides,t} + \lambda^{(1)}_{tractors,t} + \lambda^{(1)}_{tubewells,t} +$$

$$\lambda^{(1)}_{electricity,t} + \lambda^{(1)}_{agri.credit,t} + \lambda^{(1)}_{rain\,fall,t} + \lambda^{(1)}_{wheat\,price,t} + e^{(1)}_{t}$$

$$R_t = 1$$

$$P^{(2)}_{i,t(yield)} = \lambda^{(2)}_{0} + \lambda^{(2)}_{fertilizer,t} + \lambda^{(2)}_{pesticides,t} + \lambda^{(2)}_{tractors,t} + \lambda^{(2)}_{tubewells,t} +$$

$$\lambda^{(2)}_{electricity,t} + \lambda^{(2)}_{agri.credit,t} + \lambda^{(2)}_{rain\,fall,t} + \lambda^{(2)}_{wheat\,price,t} + e^{(2)}_{t}$$

$$R_t = 2$$

The aim of this study is to analyze wheat yield data of four provinces of Pakistan by using the Markov Switching models. Markov Switching models results showed that Markov models are much better forecasting technique as it yielded much lesser values of residual standard error and also produced higher values of R^2. The wheat yield is projected to the next ten years in terms of transition probabilities. These Markov Switching Models are helpful for the practitioners and agriculturists because it yields better forecasts in terms of probabilities.

EMPERICAL RESULTS

To analyze Pakistan agriculture structure (main focus on wheat crop) by using non stationary Markov models, data is taken for wheat yield along with other independent factors. The data set used for analysis is related to Wheat crop yield and taken from the Agricultural Statistics of Pakistan 2010 – 2011, Government of Pakistan Statistics Division; Pakistan Bureau of Statistics has made this survey. The data set is a panel data consisting of 17 years.

The basic assumptions of OLS (Linearity, Normality, Multicollinearity and Autocorrelation) are checked for possible violation. After detecting the presence of multicollinearity, it is removed by using Ridge regression; then Markov Switching Model is applied to the data. The Markov Switching Model results for each province for wheat yield are summarized in the given tables. Markov Switching model fits separate model for each regime. The results showed that by using Markov switching models, the R^2 increased and the residual standard reduced greatly. These regime switching models are then used in finding the transition probabilities of the two state Markov Chains.

Table 1: Markov Switching Model Results of Punjab Wheat Yield

3	Regime 1				Regime 2			
Coefficients	**Est. Values**	**St. Error**	**T-values**	**P-values**	**Est. Values**	**St Error**	**T-values**	**P-values**
Intercept	712.867	120.902	5.8962	3.720e-9	2189.75	135.823	16.1221	2.2e-16
Fertilizer	0.9248	0.0522	17.7165	2.2e-16	0.7162	0.0584	12.2637	2.2e-16
Elec.cons	0.0319	0.0076	4.1974	2.700e-05	-0.2733	0.0176	-15.5284	2.2e-16
Cre. inst.	-0.0012	0.0002	-6.0000	1.973e-09	0.0020	0.0003	6.6667	2.616e-11
Rainfall	-0.7327	0.0353	-20.7564	2.2e-16	0.8553	0.0964	8.8724	2.2e-16
Model Sum.	Residual standard error: 8.346859 R-squared: 0.9985				Residual standard error: 32.62988 R-squared: 0.9811			

23

The significant variables for Punjab wheat data are Fertilizer, Electricity consumption, credit by institutions and rainfall. Regime-1 is lower yield regime while regime-2 shows high yield regime. The estimated values of the coefficients are interpreted as that one unit increase in fertilizer brings on average 0.9248 units increase in wheat yield while the yield is in lower regime. The other independent variables are interpreted in the same way.

Table 2: Transition Probability Matrix for Punjab Wheat

Trans. Prob.	Regime-1	Regime-2
Regime-1	0.2454224	0.7545776
Regime-2	0.5407882	0.4592118

This transition probability matrix shows that the wheat yield for Punjab data has a greater chance of shifting from lower yield regime to higher yield regime. For Punjab data these transition probabilities are quite not persistent as the yield is transitioning between lower yield regime and higher yield regime.

Table 3: Markov Switching Model Results of Sindh Wheat Yield

	Regime 1				Regime 2			
Coefficients	Est. Values	St. Error	T-values	P-values	Est. Values	St. Error	T-values	P-values
Intercept	2065.732	394.216	5.2401	1.60e-07	1900.950	45.719	41.578	2.2e-16
Fertilizers	-0.8167	0.8366	-0.976	0.3290	2.1090	0.0759	27.787	2.2e-16
Elec. cons.	0.0589	0.0104	5.6635	1.48e-08	-0.2112	0.0037	-57.08	2.2e-16
Tube wells	0.0030	0.0010	3.0000	0.0027	-0.0036	0.0002	-18.00	2.2e-16
Cred. inst.	-0.0002	0.0040	-0.050	0.9601	0.0081	0.0001	81.000	2.2e-16
Rainfall	-0.9902	0.1374	-7.206	5.73e-13	1.1804	0.0297	39.744	2.2e-16
Wheat Price	0.9997	1.6908	0.5913	0.5543	-0.7366	0.0277	-26.59	2.2e-16
Model Summary	**Residual standard error**: 16.31819 **R-squared**: 0.9978				**Residual standard error**: 6.013305 **R-squared**: 0.9998			

The significant variables for Sindh wheat data are Fertilizer, Electricity consumption, Tube wells, Credit by institutions, rainfall and wheat price. The estimated values of the coefficients are interpreted as that one unit increase in fertilizer brings on average 0.8167 units decrease in wheat yield while the yield is in lower regime. The other independent variables are interpreted in the same way.

Table 4: Transition Probability Matrix for Sindh Wheat

Trans. Prob.	Regime-1	Regime-2
Regime-1	0.3141598	0.6858402
Regime-2	0.4954637	0.5045363

This transition probability matrix shows that the wheat yield for Sindh data has a greater chance of being in higher yield regime and has also a greater probability of shifting from lower yield regime to higher yield regime.

Table 5: Markov Switching Model Results of KPK Wheat Yield

	Regime 1				Regime 2			
Coefficients	Est. Values	St. Error	T-values	P-values	Est. Values	St Error	T-values	P-values
Intercept	1097.9333	26.8762	40.852	2e-16	554.2947	68.2375	8.1230	4.441e-16
Fertilizer	0.0523	0.0050	10.460	2e-16	0.0713	0.0103	6.9223	4.444e-12
Elec.cons	0.0332	0.0335	0.991	0.3217	0.4945	0.0732	6.7555	1.423e-11
Model Sum.	**Residual standard error**: 14.77629 **R-squared**: 0.9707				**Residual standard error**: 39.55631 **R-squared**: 0.9438			

The significant variables for KPK wheat data are Electricity consumption and rainfall. Regime-1 is lower yield regime while regime-2 shows high yield regime. The estimated values of the coefficients are interpreted as that one unit increase in electricity consumption brings on average 0.0523 units increase in wheat yield while the yield is in lower regime. The other independent variable is interpreted in the same way.

Table 6: Transition Probability Matrix for KPK Wheat

Trans. Prob.	Regime-1	Regime-2
Regime-1	0.3867135	0.6132865
Regime-2	0.5005085	0.4994915

This transition probability matrix shows that the wheat yield for KPK data has a greater chance of transitioning between these two regimes. That shows that for KPK data the two regimes are quite not persistent.

Table 7: Markov Switching Model Results of Balochistan Wheat Yield

	Regime 1				Regime 2			
Coefficients	Est. Values	St. Error	T-values	P-values	Est. Values	St Error	T-values	P-values
Intercept	4751.2804	64.4881	73.677	2.2e-16	3173.4028	560.5797	5.6609	1.506e-08
Tractors	-0.0399	0.0009	-44.333	2.2e-16	-0.0196	0.0095	-2.0632	0.03909
Tube wells	-0.0883	0.0029	30.448	2.2e-16	-0.0300	0.0334	0.8982	0.36908
Credit. inst.	0.0188	0.0004	47.000	2.2e-16	0.0071	0.0038	1.8684	0.06171
Price	-1.7681	0.0138	-128.123	2.2e-16	-0.4150	0.9400	-0.4415	0.65885
Model Summary	**Residual standard error:** 15.97573 **R-squared:** 0.9974				**Residual standard error:** 119.2361 **R-squared:** 0.4607			

The significant variables for Baluchistan wheat data are Tractors, Tube wells, Credit by institutions and wheat price. The estimated values of the coefficients are interpreted as that one unit increase in tractors brings on average 0.0523 units decrease in wheat yield while the yield is in lower regime. The other independent variable is interpreted in the same way.

Table 8: Transition Probability Matrix for Baluchistan Wheat

Trans. Prob.	Regime-1	Regime-2
Regime-1	0.5722393	0.4277607
Regime-2	0.5139176	0.4860824

This transition probability matrix shows that the wheat yield for Baluchistan data has a greater chance of being in lower regime and has also a greater chance of transitioning from higher yield to lower yield.

Table 9: Projection of Transition Probabilities

	Projected Transition Probabilities (n=1)				
Data Set	Provinc e	P_{11}	P_{12}	P_{21}	P_{22}
Wheat	Punjab	0.2454224	0.7545776	0.5407882	0.4592118
	Sindh	0.3141598	0.6858402	0.4954637	0.5045363
	KPK	0.3867135	0.6132865	0.5005085	0.4994915
	Baluchistan	0.5722393	0.4277607	0.5139176	0.4860824

These are the one step projected transition probabilities which shows that for Punjab, Sindh and KPK province there is a high chance of wheat yield for next year to transition from lower yield state to higher yield state. But for Baluchistan province the chance of being in lower yield state or transitioning from higher yield state to lower yield state is high.

	Projected Transition Probabilities (n=2)				
Data Set	Province	P_{11}	P_{12}	P_{21}	P_{22}
Wheat	Punjab	0.468299	0.531701	0.381058	0.618942
	Sindh	0.438505	0.561495	0.405634	0.594366
	KPK	0.456502	0.543498	0.443553	0.556447
	Baluchistan	0.547292	0.452708	0.543890	0.456110

These are the two years ahead projected transition probabilities which shows that for Punjab, Sindh and KPK province there is a high chance of wheat yield after two years to remain in higher yield state or transitioning from lower yield state to higher yield state. But for Baluchistan province the chance of being in lower yield state or transitioning from higher yield state to lower yield state is high.

	Projected Transition Probabilities (n=3)				
Data Set	Province	P_{11}	P_{12}	P_{21}	P_{22}
Wheat	Punjab	0.402489	0.597531	0.428237	0.571763
	Sindh	0.415961	0.584039	0.421921	0.578079
	KPK	0.448561	0.551439	0.450034	0.549966
	Baluchistan	0.545837	0.454163	0.545638	0.454362

These are the three years ahead projected transition probabilities which shows that for Punjab, Sindh and KPK province there is a high chance of wheat yield to be in higher yield state. But for Baluchistan province the chance of being in lower yield state or transitioning from higher yield state to lower yield state is high.

	Projected Transition Probabilities (n=5)				
Data Set	Province	P_{11}	P_{12}	P_{21}	P_{22}
Wheat	Punjab	0.421913	0.578087	0.414302	0.585698
	Sindh	0.420048	0.579952	0.418968	0.581032
	KPK	0.449465	0.550535	0.449297	0.550703
	Baluchistan	0.545752	0.454248	0.545740	0.454260

These are the four years ahead projected transition probabilities which shows that for Punjab, Sindh and KPK province there is a high chance of wheat yield to be in higher yield state. But for Baluchistan province the chance of being in lower yield state or transitioning from higher yield state to lower yield state is high.

	Projected Transition Probabilities (n=5)				
Data Set	Province	P_{11}	P_{12}	P_{21}	P_{22}
Wheat	Punjab	0.416170	0.583830	0.418418	0.581582
	Sindh	0.419307	0.580693	0.419503	0.580497
	KPK	0.449362	0.550638	0.449381	0.550619
	Baluchistan	0.545747	0.454253	0.545746	0.454254

These are the five years ahead projected transition probabilities which shows that for Punjab, Sindh and KPK province there is a high chance of wheat yield to be in higher yield state. But for Baluchistan province the chance of being in lower yield state or transitioning from higher yield state to lower yield state is high.

According to Pegg Jr (2015) powers of the transition probability matrix can be used to compute the long term probabilities of the system being in either of the two states. As the power grows, the entries in the first row will approach to the long term probability. Devika Subramanian (2008) showed that independent of start time, the Markov process converges to a stationary distribution as N increases. Lidya Zepeda (1995) analyzed that given the current transition probabilities, the probability of finding the farm in a particular state at any point in time can be obtained from steady state probabilities.

The present projected transition probabilities also converge to steady state probabilities as seen in literature. As N increases the projected transition probabilities turns to be long term projected transition probabilities.

	Projected Transition Probabilities (n=6)				
Data Set	Province	P_{11}	P_{12}	P_{21}	P_{22}
Wheat	Punjab	0.417866	0.582134	0.417202	0.582798
	Sindh	0.419442	0.580558	0.419406	0.580594
	KPK	0.449373	0.550627	0.449371	0.550629
	Baluchistan	0.545746	0.454254	0.545746	0.454254

	Projected Transition Probabilities (n=7)				
Data Set	Province	P_{11}	P_{12}	P_{21}	P_{22}
Wheat	Punjab	0.417365	0.582635	0.417561	0.582439
	Sindh	0.419417	0.580583	0.419424	0.580576
	KPK	0.449373	0.550628	0.449372	0.550628
	Baluchistan	0.545746	0.454254	0.545746	0.454254

	Projected Transition Probabilities (n=8)				
Data Set	Province	P_{11}	P_{12}	P_{21}	P_{22}
Wheat	Punjab	0.417513	0.582487	0.417455	0.582545
	Sindh	0.419422	0.580578	0.419421	0.580579
	KPK	0.449372	0.550628	0.449372	0.550628
	Baluchistan	0.545746	0.454254	0.545746	0.454254

	Projected Transition Probabilities (n=9)				
Data Set	Province	P_{11}	P_{12}	P_{21}	P_{22}
Wheat	Punjab	0.417469	0.582531	0.417486	0.582514
	Sindh	0.419421	0.580579	0.419421	0.580579
	KPK	0.449372	0.550628	0.449372	0.550628
	Baluchistan	0.545746	0.454254	0.545746	0.454254

	Projected Transition Probabilities (n=10)				
Data Set	Province	P_{11}	P_{12}	P_{21}	P_{22}
Wheat	Punjab	0.417482	0.582518	0.417477	0.582523
	Sindh	0.419421	0.580579	0.419421	0.580579
	KPK	0.449372	0.550628	0.449372	0.550628
	Baluchistan	0.545746	0.454254	0.545746	0.454254

These steady state probabilities are very useful in projecting the wheat yield. According to these projected transition probabilities the Punjab and Sindh province has a 41% chance of wheat yield to be in lower yield state while there is a 58% chance for wheat to be in higher yield state. For KPK Province there is a 45% chance for wheat yield to be in lower yield state while there is a 55% chance for wheat to be in higher yield state. For Baluchistan Province there is a 54% chance for wheat yield to be in lower yield state while there is a 45% chance for wheat to be in higher yield state.

The three years projected transition probabilities are cross checked with the real data of 2013-2014 and has been found to be verified. On the basis of these transition probabilities, we can project the wheat yield structure after ten years. These projected transition probabilities showed, after 10 years, Punjab, Sindh and KPK would have greater probability of being in higher yield state and also a great probability of going from lower yield state to higher yield state. From these transition probabilities the agriculturists will infer that the next ten years would be satisfactory in terms of high yields and the farmers would be capable of satisfying the high demands of wheat. But for Baluchistan, the projected transition probability showed that after 10 years the Baluchistan province would have high probability of being in lower yield state and would also have a greater probability of shifting from high yield regime to lower yield regime. The transition probabilities for Baluchistan province would lead the farmers in a position to struggle coming future 10 years to increase their yield to higher levels.

The filtered probabilities graphs show the patterns of the data in terms of probabilities over seventeen years of time span. Fig. 1 illustrates that Punjab wheat data is transitioning between lower yield regime and higher yield regime but for the years 2004-07 the yield was continuously in higher yield regime. For Sindh the yield is constantly in lower regime 1996-98 while for the years 2004-07 the yield is constantly in higher yield regime. Yield of KPK province is in higher yield regime for 1994-96 but is in lower yield regime for 1997-99. The yield of Baluchistan province is in lower yield regime 1999-02 and again in the period of 2007-09. The period of higher yield for Baluchistan province is 2003-06.

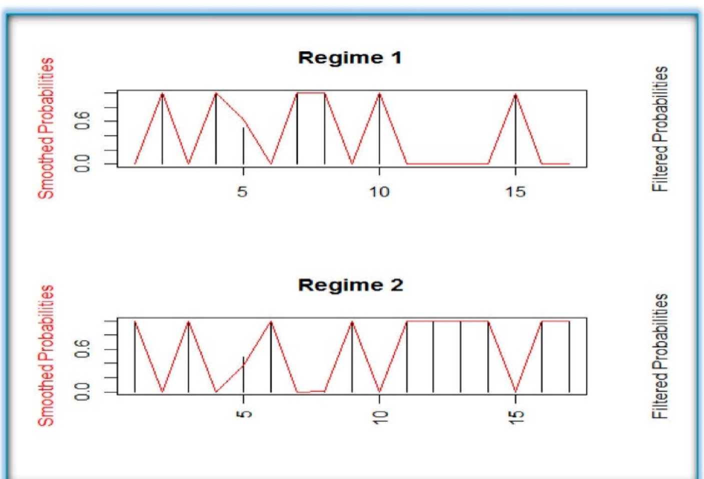

Fig.1: Filtered Probabilities for Punjab Wheat Data

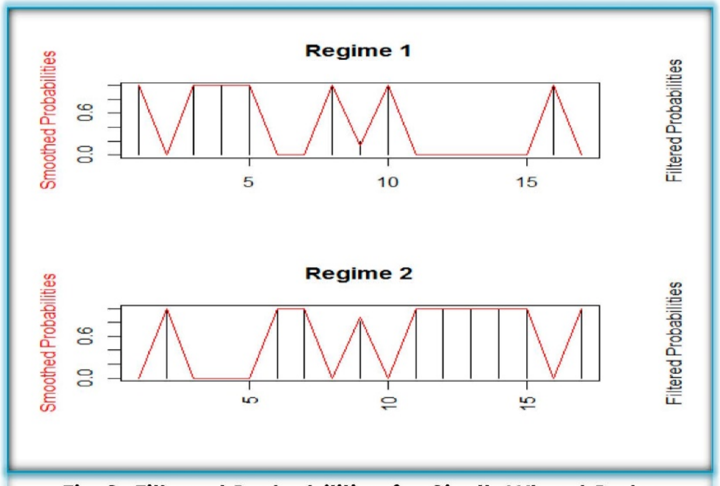

Fig.2: Filtered Probabilities for Sindh Wheat Data

55

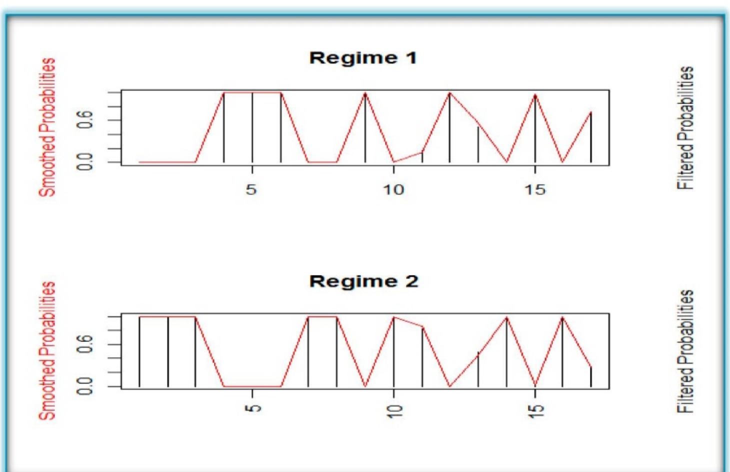

Fig. 3: Filtered Probabilities for KPK Wheat Data

56

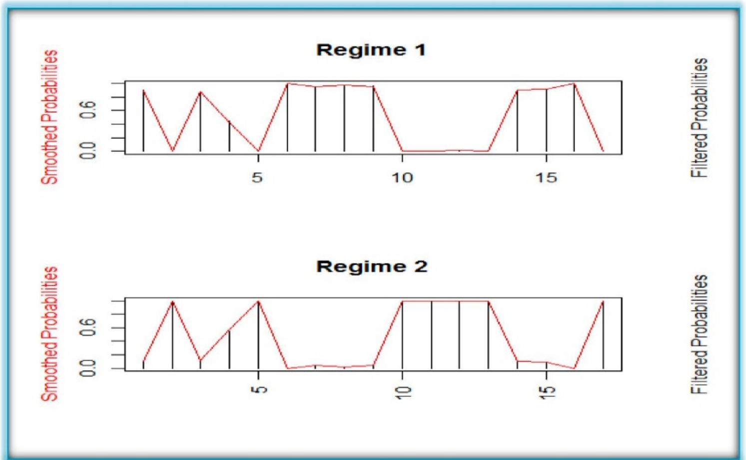

Fig. 4: Filtered Probabilities for Baluchistan Wheat Data

Conclusion

The Markov Switching Model to project structural change in the Pakistan agriculture sector. A non-stationary Markov Chain Model is used and transition probabilities are obtained and which are used for projection of next ten years. The projected pattern of structural changes showed a continuous increase in the wheat yield in three provinces except Baluchistan which shows a traditional decline that probably reflects the unsatisfactory economic and weather conditions of the province.

REFRENCES

Draper, N. and H. Smith. 1981. Applied Regression Analysis. (2nd ed.), *John Wiley and Sons,* Inc., New York.

Ethridge, D. E., K. R. Sujit and W. M. David. 1985. A Markov Chain Analysis Of Structural Changes In The Texas Idgh Plains Cotton Ginning Industry. *J. Southern Agri. Econo.,* 11-19.

Gaffney, P. 2002. A Projection of Irish Agricultural Structure Using Markov Analysis. (Unpublished) CAPRI, Univ. Galway: 22 pp.

Gillespie, J. M. and J. R. Fulton. 2001. A Markov Chain Analysis of the size of Hog production Firm in the United States. *J. Agribusiness,* **17(4):** 557-570.

Hallberg, M. C. 1969. Projecting the Size Distribution of Agricultural Firms- An Application of a Markov Process with Non-Stationary Transition Probabilities. *Am. J. Agri. Econ.*, **51:** 289-302.

Harris, G. R. 1999. Markov Chain Monte Carlo Simulation of Regime switching vector auto regressions. ASIIN BULLETIN, 29(1): 47-79.

Kidwell, J. S. and L. H. Brown. 1982. Ridge Regression as a Technique for Analyzing Models with Multicollinearity. *J. Marriage Fam.*, **44(2):** 287-299.

Krenz, R.D. 1964. Projection of farm numbers for North Dakota with Markov chains. *J. Agri. Econ. Res.*, **16:** 77-83.

Piet, L. 2008. The evolution of farm size distribution: Revisiting the Markov Chain Model. 12th congress of the European Associated of Agricultural Economists: pp. 10.

Singh, M. 2012. Projection of Land use pattern in India: A Markov Chain approach. *J. Ann. Agric. Res.*, **33(2):** 69-78.

Storm , H., T. Heckelei and R. C. Mittel hammer. 2011. Bayesian estimation of non-stationary Markov models combining micro and macro Data. (Discussion Paper), Univ. of Bonn, Institute for Food and Resource Economics, Bonn, Germany.

Zepeda, L. 1995a. Asymmetry and Non-stationarity in the Farm Size Distribution of Wisconsin Milk Producers: An Aggregate Analysis. *Am. J. Agri. Econ.*, **77:** 837-852.