Nonparametric Regression Estimation of Growth Rate of India's Fish Production and Export

C. G. Joshy^{1*}, N. Balakrishna² and C. N. Ravishankar¹

¹ICAR-Central Institute of Fisheries Technology, Matsyapuri P.O., Cochin - 682 029, India

Abstract

Mechanistic growth models, parametric and non-parametric regression models were used to estimate the trend and growth rate of fish production in India during the period 1980 to 2014 and fish export during the period 1960 to 2014. It was found that parametric and mechanistic growth models produced high R² values and low RMSE, but error terms of fitted models were not independent. The local polynomial regression of order one was fitted to the data and found to be the best model to estimate the trend of fish production and export over the decades. Nonparametric regression approach used to estimate the compound growth rate of fish production and export efficiently compared to parametric and mechanistic growth models.

Keywords: Trend, compound growth rate, fish production and export, mechanistic growth models, parametric and nonparametric regression, local polynomial regression

Introduction

Compound growth rate of a commodity is an important economic factor used for policy implementation and it is widely discussed in the past (Panse, 1964; Dey, 1975). The usual practice to estimate growth rate over a period of time is to formulate a hypothetical function which would estimate the growth curve. Thus, choice of the functional form of the growth curve and estimation of its parameters are two important steps involved in computing growth rate. Reddy (1978) had

Received 04 January 2017; Revised 26 July 2017; Accepted 08 August 2017

*E-mail: cgjoshy@gmail.com

compared in detail various parametric models used for trend analysis and estimation of growth rate. Tornqvist et al. (1985) computed relative growth rate during a period as the logarithm of ratio of values at the two successive time periods of a time series. Lorenzen (1990) introduced an improved method for measuring growth rate using mean-value theorem. Prajneshu & Chandran (2005) used non-linear logistic and gompertz growth models to compute the compound growth rate.

The above discussed methods are not valid when the error terms are not independently and identically distributed. Such situations arise when the relationship between the explanatory variables and the response is not adequately modelled parametrically. In such cases, any degree of model misspecification may result in serious bias of the estimated response. Furthermore, the optimal regressor settings may be miscalculated. To overcome the deficiencies of parametric models, non-parametric regression models are used in place of parametric models by alleviating the sound statistical assumptions. Hardle (1990) used different smoothing techniques to estimate the response function via nonparametric method. Chandran & Prajneshu (2004) used nonparametric approach for computing compound growth rate in agriculture and found it to be superior over the existing parametric models. Rajarathinam & Vinoth (2013) used non-parametric regression with jump points over the parametric models to describe the tobacco production. Aneirosperez et al. (2010) used local linear regression with functional explanatory variable as a functional method for time series prediction and compared it with other functional nonparametric methods. Nonparametric regression requires larger sample sizes than regression based on parametric models because the model structure as well as the model estimates need to be derived from the data.

² Department of Statistics, Cochin University of Science and Technology, Cochin - 682 022, India

India is the second largest producer of fish in the world contributing to 5.43% of global fish production. The marine and inland fish production witnessed increasing growth over the decades. The total fish production from marine and inland sector was 24.42 lakh tonnes in 1980-81 and which increased to 95.82 lakh tonnes in 2013-14. marine and inland fish production was 15.55 and 8.87 lakh tonnes during 1980-81, respectively; which increased to 34.4 and 61.42 lakh tonnes during 2013-14. The inland fish production has attained higher growth compared to marine fish production. India also earns foreign exchange through the export of fresh and processed fishery products. The quantity of fish exported from India in 1980-81 was 74 542 tonnes and which increased to 9 83 756 tonnes in 2013-14. During this period, the annual export showed an increasing trend with nonlinear behaviour.

Fish production and export in the country has undergone structural changes at different time intervals. Parametric models are widely used to capture the structural changes in a given time series. Salazar (1982) examined structural changes in the regression model with auto correlated errors. There have been few studies for describing fish production and export in India. Yogamurthi & Sivashankar (1994) analyzed India's seafood export using polynomial regression methods. Prajneshu & Venugopalan (1997) used polynomial, non-linear mechanistic growth models and ARIMA time-series models for trend evaluation of marine, inland and total fish production in India. They found that ARIMA models are most appropriate compared to other models. Venugopal & Prejneshu (1996) used nonlinear growth models and ARIMA models to forecast India's marine product export and found that ARIMA models best fit. Ravichandran & Prajneshu (2001) used structural time series models for describing all India marine, inland and total fish production which performed better than ARIMA models. Chandran & Prajneshu (2005) used nonparametric regression model with auto correlated errors for describing India's marine fish production and compared with ARIMA method. They found that nonparametric regression is best when error terms are correlated. All these studies were carried out either to forecast or evaluate the trend of fish production in India.

The present study discusses estimation of trend and compound growth rate of India's fish production and export using parametric and non-parametric modelling techniques. The goodness of fit of the fitted models was assessed using appropriate statistics and evaluated merits and demerits of the fitted models. Estimation of trend and growth rate of fish production and export using sound statistical methods will help planners in policy implementation in the harvest and post-harvest sector fisheries.

Materials and Methods

All India fish production data during the period 1980-81 to 2013-14 was collected from the handbook of Department of Animal Husbandry, Dairying and Fisheries (DAHD), Ministry of Agriculture and Farmers Welfare, Govt. of India and fish export data during the period 1960-61 to 2013-14 was collected from Marine Product Export Development Authority (MPEDA), Ministry of Commerce, Govt. of India. The marine, inland and total fish production; and fish export are abbreviated as MFP, IFP, TFP and FE, respectively. Parametric, mechanistic and nonparametric regression models were fitted to the secondary data for computing trend and compound growth rate for marine, inland and total fish production in India and fish export from the country. The functional forms of different models used are described in the following sections.

Parametric Models for Trend and Compound Growth Rate

Consider the standard functional form for computing growth rate as

$$Y_t = f(x_t) + \epsilon_t, t = 1, 2, ..., n,$$
 (1)

where Y_t is observation at time t, $f(x_t)$ is any parametric function relating Y_t and x_t ; and ε_t is independently and identically distributed additive error term. The standard parametric models for computing growth rate takes the functional form of $f(x_t)$ are Malthus model, linearized Malthus model and mechanistic growth models viz., monomolecular, logistic and gompertz model. The functional form of Malthus model is given in equation (2), where Y_0 is the value of Y when t=0 and r is the compound growth rate

$$Y_t = Y_0 (1 + r)^t + \epsilon_t$$
 (2)

Another common procedure is to transform the Equation (2) with multiplicative error term through logarithmic transformation. The parameters of linearized model are estimated by method of least squares.

$$Y_t^* = Y_0^* + Bt$$
, where $Y_t^* = \log(Y_t)$,
 $Y_0^* = \log(Y_0)$ and $B = \log(1 + r)$ (3)

The parameters of the model (2) and (3) may be estimated by the method of ordinary least squares. Thus, the compound growth rate (r) of the linearized model is computed as $r = \exp(B) - 1$

The functional form of mechanistic growth models *viz.*, monomolecular, logistic and gompertz model with 'K' as the carrying capacity of the system and 'r' as the intrinsic growth rate are given in equation (4), (5) and (6), respectively.

$$Y_t = K - (K - Y0) \exp(-r t) + \epsilon_{t'}$$
 (4)

$$Y_t = K / [1 + (KY_0 - 1) \exp(-r t)] + \epsilon_t,$$
 (5)

$$Y_t = K \exp[\log(Y_0K) \exp(-rt)] + \epsilon_t$$
 (6)

The merits and demerits of all the above models are discussed by Prajneshu & Chandran (2005). The parameters are having standard interpretations and nonlinear estimation procedures employed to estimate the parameters using Levenberg-Marquardt algorithm (Seber & Wild, 2003) of NLIN procedure of SAS 9.3. The validity of the fitted model is examined by analysing the residuals. The goodness of fit of the fitted model was assessed based on variance explained (R2) and root mean square error (RMSE). Once the best fitted mechanistic growth model is identified, the next step is to compute the 'Compound Growth Rate (CGR)' for a given set of data. The growth rate for Monomolecular, Logistic and Gompertz models for a period $(t_1, t_{i+1}), i =$ 0,1,2,...,n-1, where n is the total number of data points, is computed as given in Prajneshu & Chandran (2005). The compound growth rate for a given period can be calculated by taking the average of the growth rate during the period. See Seber & Wild (2003) and Prajneshu & Chandran (2005) for more details.

Nonparametric Model for Trend and Compound Growth Rate

Nonparametric regression captures structure in the data. The nonparametric functional form for an equi-spaced time series data to describe the relationship between the dependent and explanatory variables is given as

$$Y_i = m(t_i) + \epsilon_{i'}, i = 1, 2, ..., n,$$
 (7)

where Y_i is the value of Y at ith time period, m(.) is assumed to have an unknown but reasonably

smooth form (Cleveland, 1979) and ϵ_i are errors with zero mean and constant variance. Similar to parametric regression, the estimator is a linear combination of the values of the dependent variable, but assigns more weight to observations closest to the point of prediction. The nonparametric fit is more flexible than the parametric fit as it is not confined to the user's specified form.

Several fitting techniques have been proposed in the nonparametric regression literature. Some of these are kernel regression (Nadaraya, 1964; Watson, 1964; Priestley & Chao, 1972; Gasser & MÄuller,1984), local polynomial models (Fan & Gijbels, 1996 and Fan & Gijbels, 2000), spline-based smoothers and series-based smoothers (Ruppert et al., 2003). Kernel regression is an intuitive approach to estimation; however, it inherently has a boundary bias problem when symmetric kernel functions, such as the Gaussian, are used. For example, if the observations follow a concave down trend, the kernel estimates at the first and nth order statistics of the regress or are weighted averages of values larger than the observed values at t_1 and $t_{n'}$ respectively. Thus, the estimates at t₁ and t_n will most likely be biased. Local polynomial regression (LPR) is a smoothing technique that is robust to biased estimates at the boundary of the independent variables. Originally proposed by Cleveland (1979), LPR is a weighted least squares problem where the weights are given by a kernel function.

A local polynomial equation m (t,t^*) of degree 'p', when the value of the predictor (t) is close to (t^*) , is given by

$$m(t, t^*) = a_0(t^*) + \sum_{j=1}^p a_j(t^*)(t - t^*)$$
 (8)

The parameters a_j (t*), j = 0,1,...,p are derived by minimizing

$$E_{local}(t^*) = \sum_{i=1}^{n} \left[w \left(\frac{t_i - t^*}{h} \right) (Y_i - m(t_i, t^*))^2 \right]$$

$$= \sum_{i=1}^{n} w \left(\frac{t_i - t^*}{h} \right) \left(Y_i - a_0(t^*) - \sum_{j=1}^{p} a_j(t^*)(t - t^*)^{j} \right)^2 ,$$

where, $w\left(\frac{t_i - t^*}{h}\right)$ is a kernel function and h is the

bandwidth. We used tri-cube weight function (Takezawa, 2006) defined by

$$w\left(\frac{t_{i}-t^{*}}{h}\right) = \begin{cases} \left[1-\left(\frac{\left|t_{i}-t^{*}\right|}{h}\right)^{3}\right] & if \left(\frac{\left|t_{i}-t^{*}\right|}{h}\right)^{3} \leq 1\\ 0 & if \left(\frac{\left|t_{i}-t^{*}\right|}{h}\right)^{3} > 1 \end{cases}$$

The local linear regression fit at the prediction point $t' = (t_1, t_2, \dots, t_n)$ to predict $y' = (y_1, y_2, \dots, y_n)$ is given by

$$y^{LPR} = t'(t'Wt)^{-1}t'Wy = Ly,$$
 (9)

where, W is a n x n diagonal matrix containing the kernel weights associated with t,

$$\mathbf{W} = \begin{pmatrix} w \bigg(\frac{t_1 - t^*}{h} \bigg) & 0 & 0 & \cdots & 0 \\ 0 & w \bigg(\frac{t_2 - t^*}{h} \bigg) & 0 & \cdots & 0 \\ \\ 0 & 0 & w \bigg(\frac{t_3 - t^*}{h} \bigg) & \cdots & 0 \\ \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & w \bigg(\frac{t_n - t^*}{h} \bigg) \end{pmatrix}$$

and L is the local linear HAT or smoother matrix defined as,

$$L = \begin{bmatrix} h_1^{(LPR)'} \\ h_2^{(LPR)'} \\ h_n^{(LPR)'} \end{bmatrix}, \text{ where } h_i^{LPR} = t'(t'Wt)^{-1}t'W$$

Since the LPR estimates are dependent on the kernel weights, bandwidth selection remains important. For more details on local polynomial regression, see Fan & Gijbels (1996) and Fan & Gijbels (2000). The selection of optimum smoothing parameter was done based on the values of generalized cross validation (GCV) (Takezawa, 2006). The goodness of fit of the model was assessed by AICC and the independence of error terms were examined by run test.

Estimation of Growth Rate

Suppose the change in Y_t per unit time is measured by $r_{t'}$ the value of Y_{t+1} can be considered as

$$\begin{aligned} Y_{t+1} &= Y_t + r_t Y_t = b_t Y_t \\ &\text{or} \quad \frac{Y_{t+1}}{Y_t} &= b_t \Rightarrow Z_t = b_t \end{aligned}$$

We now assume that Z_t is a smooth function over the time interval (t, t+1) and it can be written as

$$Z_t = m(t) + \epsilon t, \tag{10}$$

where $E(Z_t) = m(t)$ and ε_t follows normal distribution with mean zero and constant variance $\sigma^2 < \infty$. The function m(t) can be estimated using nonparametric method as given in the previous section.

$$\hat{\mathbf{m}}(t) = \mathbf{t}'(\mathbf{t}'\mathbf{W}\mathbf{t})^{-1}\mathbf{t}'\mathbf{W}\mathbf{Z}_{\mathbf{t}} = \mathbf{L}\mathbf{Z}_{\mathbf{t}}$$
(11)

Thus, the relative growth r_t for a given time period t can be computed from the estimated values of nonparametric function as

$$\hat{\mathbf{r}}_{t} = \hat{\mathbf{m}}(t) - 1 \tag{12}$$

Here, relative growth is computed non-parametrically from a smooth function and the growth rate is computed at each time point. Growth rate for a given time interval can be computed as the average of the individual growth rates during that period.

Results and Discussion

Secondary data on all India marine, inland and total fish production measured in lakh tonnes during the period 1980-81 to 2013-14 and fish export data during the period 1960-61 to 2013-14 were used for the study. Nonlinear functional form of equation (2) with additive error term was fitted to the data using Levenberg-Marquardt method by writing programme in SAS 9.3. The model explained 85, 99 and 98.5% of the total variability in the data for marine, inland and total fish production, respectively with RMSE of 2.52, 0.78 and 2.64, respectively. The R² and RMSE values for fish export data were 0.98 and 0.378. The parameters along with the standard error of the fitted model are given in Table 1.

The estimated compound growth (r) based on this model was 2.3 %, 5.9% and 4.1% for marine, inland and total fish production, respectively and 7.4 % for fish export. The result of run test rejected the null hypothesis of independence of error terms (p<0.05) and the authenticity of the fitted model. Therefore, the model under consideration is not good enough to compute the growth rate of fish production and export.

Log linearized functional form of Equation (2) was also fitted to the data using simple linear regression procedure (Prajneshu & Chandran, 2005). The results of the fitted model along with R² and RMSE values are given in Table 2.

Table 1. Estimated parameters of the Malthus model

		Y	Estimate	Std Error	95% Confid	lence Limits	R ²	RMSE
Parameter		TFP	24.38	0.61	23.14	25.61	0.98	2.64
	Y_0	MFP	16.79	0.71	15.36	18.24	0.85	2.52
		IFP	8.61	0.14	8.32	8.89	0.99	0.78
		FE	0.170	0.018	0.133	0.207	0.98	0.378
		TFP	0.041	0.001	0.0385	0.0426		
		MFP	0.023	0.002	0.019	0.026		
	r	IFP	0.059	0.0006	0.057	0.060		
		FE	0.079	0.003	0.074	0.084		

Table 2. Estimated parameters of log-linearized model

		Y	Estimate	Std Error	95% Confid	lence Limits	R2	RMSE
		TFP	1.37	0.0095	1.35	1.39	0.97	0.027
	Y ₀ *	MFP	1.20	0.012	1.16	1.23	0.84	0.053
Parameter		IFP	0.918	0.006	0.91	0.93	0.99	0.016
		FE	-0.855	0.022	-0.899	-0.811	0.97	0.079
	В	TFP	0.018	0.0005	0.017	0.019		
		MFP	0.011	0.0008	0.092	0.013		
		IFP	0.025	0.0002	0.024	0.026		
		FE	0.035	0.0007	0.034	0.037		

MFP IFP and TFP are marine, inland and total fish production; FE - fish export

The estimated compound growth rate (r) based on log linearized model is 1.11, 2.53 and 2.01% for marine, inland and total fish production, respectively and 3.57% for fish export. The run test of residual terms rejected the null hypothesis (p<0.05) and so the assumption of the error terms are violated. Thus the model was not selected.

Nonlinear growth models *viz.*, Monomolecular, Logistic and Gompertz were fitted to the secondary data on fish production and export as a function of time using Levenberg-Marquardt method. The parameters of the fitted model along with goodness of fit of the model are given in Table 3.

The fitted monomolecular model was found unrealistic as its estimated value of carrying capacity (K) and standard error is very high. Thus, monomolecular model was not good enough to explain the given data set. Logistic and Gompertz models fitted with

similar efficiency to the data set as can be seen in Table 3. The randomness of error terms of the fitted models were tested by performing run test and the bad part was that none of the so called best fitted models could produce independent error terms, thus rejected the null hypothesis of error terms (p<0.05). So that, both the models can't be used to estimate the growth rate as they failed to produce independent error terms.

Local polynomial regression (LPR) of degree one was fitted to the marine, inland, total fish production and fish export data. The assumed model could estimate the trend of fish production and export with higher accuracy compared to the parametric models. The estimated values of smoothing parameter along with GCV and residual sum of square (RSS) are given in Table 4. The number of points in the local neighbourhood was 5 for total and marine fish production; 6 for inland fish production and 10

Table 3. Estimated parameters of Mechanistic growth models

Model	Parameter	Y	Estimate	Std Error	95% Confidence Limits		R2	RMSE
	K	TFP	8250.30	202950	0	422169		
		MFP	38.78	3.53	31.58	45.99		
ar		IFP	12407	974431	0	1999768		
Monomolecular		FE	8235.2	4687870	-9407629	9424100		
mole	Y_0	TFP	16.21	1.78	12.58	19.85	0.97	3.26
ono	· ·	MFP	11.5	1.21	9.04	13.99	0.92	1.82
\geq		IFP	1.28	1.9	-2.5	5.15	0.95	3.48
		FE	-1.66	0.52	-2.71	-0.63	0.80	1.21
	r	TFP	0.0003	0.006	-0.013	0.013		
		MFP	0.047	0.013	0.021	0.073		
		IFP	0.0001	0.009	-0.019	0.019		
		FE	0.00002	0.011	-0.021	0.021		
	K	TFP	238.9	78.32	79.12	398.60		
		MFP	33.72	1.25	31.16	36.28		
		IFP	346	130.7	80.01	613.2		
υ.		FE	227.6	978.1	0	2192.1		
Logistic	Y_0	TFP	9.52	3.13	3.13	15.91	0.98	2.50
Log	Ü	MFP	1.75	0.17	1.41	2.09	0.92	1.81
		IFP	41.39	15.09	10.61	72.18	0.99	0.732
		FE	1393.6	5728.9	-10113.2	12900.5	0.98	0.382
	r	TFP	0.052	0.006	0.041	0.063		
		MFP	0.113	0.015	0.08	0.146		
		IFP	0.063	0.003	0.057	0.068		
		FE	0.078	0.007	0.063	0.092		
	K	TFP	919.1	905.2	0	2765.2		
		MFP	35.34	1.85	31.56	39.12		
		IFP	346	130	78	610		
Ę		FE	7904.8	33499.4	0	75190.4		
Gompertz	Y_0	TFP	3.73	0.95	1.79	5.67	0.98	2.4
Som	Ü	MFP	1.08	0.068	0.95	1.22	0.92	1.80
)		IFP	40.29	15.08	12.28	68.18	0.99	0.721
		FE	11.43	3.80	3.79	19.06	0.98	0.384
	r	TFP	0.014	0.005	0.004	0.024		
		MFP	0.079	0.014	0.051	0.108		
		IFP	0.06	0.003	0.056	0.067		
		FE	0.009	0.006	-0.001	0.021		

Table 4. Fitting summary of nonparametric regression

Y Smoothing Parameter		RSS	GCV	AICC	
TFP	0.16	12.29	0.034	1.87	
MFP	0.16	9.06	0.025	1.57	
IFP	0.2	6.34	0.011	0.41	
FE	0.2	4.04	0.0022	-1.05	

for fish export. The predicted and residual values were computed from the fitted model. The independence of error terms are tested at 5% level of significance by run test and did not reject the null hypothesis (p>0.05) of error terms for marine, inland, total fish production and fish export. Therefore, nonparametric regression model was found suitable to predict marine, inland and total fish production as well as fish export. The predicted values along with observed values are given in Fig. 1 and 2 for fish production and export.

The structural change in fish production and export was very well estimated by nonparametric regression approach and it is shown in Fig. 1 and 2. The results of run test revealed that error terms are independently and identically distributed with constant variance. The marine, inland and total fish production during 2014-15 were 34.9, 65.7 and 100.6 lakh tonnes, respectively and the corresponding predicted values were 34.5, 65.2 and 100.1 lakh tonnes. The fish export during 2014-15 and 2015-16 was 10.51 and 9.46 lakh tonnes, respectively; the predicted

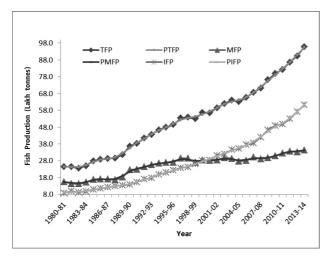


Fig. 1. Nonparametric regression fit to fish production

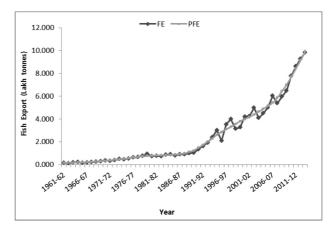


Fig. 2. Nonparametric regression fit to fish export

values based on the fitted nonparametric regression were 10.01 and 9.71 lakh tonnes, respectively.

Once the nonparametric model was found suitable to predict the fish production and export, it was used for computing compound growth rate for fish production and export during 1980-81 to 2013-14 as discussed in the methodology. Based on the nonparametric regression method, the average compound growth rate for marine, inland and total fish production was 2.71, 6.02 and 4.24%, respectively. The average compound growth rate of fish export was 6.83%. The year wise growth rate was computed using the formula $r_t = m(t)-1$ with predicted values of Zt and it is given in the Table 5. The non-parametric regression method can be used in place of parametric and mechanistic growth models for computing compound growth rate of fish production and export at the cost of sound statistical assumptions and parametric interpretation of the estimated regression coefficients.

The growth rate for a given time interval can be obtained by taking the average of the individual growth rate during that time period. It could be inferred from the Table 5 that marine fish production is showing lower growth rate compared to inland fish production. The growth rate of total fish production showed an increasing trend. The predicted growth rate based on the fitted nonparametric method was 1.93, 7.15 and 5.33% respectively for marine, inland and total fish production during 2014-15. The predicted growth rate of fish export during the period 2014-15 and 2015-16 was 0.9 and 7.2%, respectively. The low growth rate in capture fishery might have attributed the negative growth rate for fish export.

Table 5. Computed growth rate (CGR) for TFP, MFP, IFP and FE

Year	CGRTFP	CGRMFP	CGRIFP	CGRFE	Year	CGRTFP	CGRMFP	CGRIFP	CGRFE
1982-83	1.25	-0.72	5.11	1.56	1998-99	2.31	-2.19	5.42	-8.41
1983-84	4.17	5.77	4.73	4.04	1999-00	2.14	-0.38	5.59	5.15
1984-85	5.49	7.19	6.00	4.15	2000-01	3.33	1.26	5.89	7.10
1985-86	5.02	3.79	7.12	-2.63	2001-02	3.52	1.53	5.36	6.38
1986-87	3.32	-0.69	5.98	1.11	2002-03	3.18	2.18	5.56	5.66
1987-88	4.36	1.32	4.89	3.10	2003-04	2.55	-0.63	5.04	-5.35
1988-89	6.95	10.40	5.09	8.54	2004-05	2.35	-2.44	4.72	5.05
1989-90	8.46	13.83	6.28	13.98	2005-06	2.69	1.10	4.71	6.53
1990-91	8.81	9.52	7.66	18.87	2006-07	3.88	2.53	6.00	8.02
1991-92	7.10	4.57	8.54	23.76	2007-08	4.81	1.19	6.96	-7.16
1992-93	5.96	4.90	8.64	19.81	2008-09	4.86	1.06	7.07	8.50
1993-94	5.09	3.17	7.61	15.85	2009-10	4.93	3.46	6.44	9.83
1994-95	4.70	1.66	7.26	16.88	2010-11	4.68	4.20	5.19	11.41
1995-96	4.54	3.46	6.27	-16.18	2011-12	4.66	4.03	5.08	10.48
1996-97	3.51	4.10	5.35	15.47	2012-13	5.03	3.87	5.73	9.56
1997-98	2.90	0.03	5.54	11.67	2013-14	5.40	3.68	6.40	5.85

Conclusion

The merits and demerits of different regression methods for estimating trend and growth rate of fish production and export are discussed in detail. The parametric models viz., Malthus and linearized Malthus models were used to estimate the compound growth rate of fish production and export with high R² value and small RMSE value. But, both models treated the compound growth rate constant instead of a stochastic parameter and also the error terms failed to uphold the independence. Mechanistic growth models viz., Logistic and Gompertz models estimated the trend of the data by treating the growth rate as a stochastic process by computing it at a given time period by using predicted values of dependent variable and the estimated parameters. The error terms of both the models showed significant dependencies as the run test rejected the null hypothesis of independence of error terms. Local polynomial regression of order one was found to be the best model to estimate the trend of fish production and export over the decades. The error terms of nonparametric regression for fish production and export was identically and independently distributed as the run test failed to reject the null hypothesis. Thus, nonparametric regression approach used to estimate the compound growth rate of fish production and export efficiently compared to parametric and mechanistic growth models. The computed compound growth rate for marine, inland and total fish production was 2.71, 6.02 and 4.24%, respectively. The fish export registered a compound growth rate of 6.83% over the decades. The growth rate for a given time interval can be obtained by taking the average of the individual growth rate during that time period.

References

Aneiros-perez, G., Cao, R. and Vilar-Fernandez, J.M. (2010) Functional Methods for time series prediction: A nonparametric approach. J. Forecasting, DOI: 10.1002/for.1169

Box, G.E.P., Jenkins, G.M. and Reinsel, G.C., (1994) Time series analysis: Forecasting and control, 3rd edn., Prentice Hall, New Jersey

Chandran, K.P. and Prajneshu (2005) Nonparametric regression with auto-correlated errors methodology for describing India's marine fish production data. Indian J. Fish., 52(2), 151-158

Chandran, K. P. and Prajneshu (2004) Computation of growth rates in agriculture: nonparametric regression approach. J. Indian Soc. Agricult. Stat. 57: 382-392

- Cleveland, W.S. (1979) Robust locally weighted regression and smoothing scatterplots. J. Am. Stat. Assoc. 74: 829-836
- Dey, A. K. (1975) Rates of growth of agriculture and industry. Econ. Polit. Wkly. 10, June, 21-28
- Fan, J. and Gijbels, I. (1996) Local Polynomial Modeling and Its Applications. Chapman and Hall, London
- Fan, J. and Gijbels, I. (2000) Local polynomial fitting. In: Smoothing and Regression: Approaches, Computation and Application (Schimek, M. G., Ed)Wiley and Sons, New York, pp 229-276
- Fan, J. (1992) Design adaptive nonparametric regression. J. Am. Stat. Assoc. 87: 998-1004
- Fan, J. (1992) Design adaptive nonparametric regression. J. Am. Stat. Assoc. 87: 998-1004
- Gasser, T. and Muller, H.G. (1984) Estimating regression functions and their derivatives by the kernel method. Scand. J. Stat. 11: 171-185
- Hardle, W. (1990) Applied nonparametric regression. Cambridge University Press, UK
- Lorenzen, G. (1990) A unified approach to the calculation of growth rates. Am. statistician, 44: 148-150
- Nadaraya, E. (1964) On estimating regression. Theory Probab. Appl. 9: 141-142
- Panse, V. G. (1964) Yield trends of rice and wheat in first two five year plans in India. J. Indian Soc. Agric. Stat. 16: 1-50
- Prajneshu (2005) Statistical modelling in fisheries: A review. Indian J. Ani. Sci. 75(8): 1008-1012
- Prajneshu and Chandran, K. P. (2005) Computation of growth rates in agriculture: revisted. Agric. Econ. Res. Rev. 18: 317-324
- Prajneshu and Venugopalan, R. (1997) Statistical modelling for describing fish production in India. Indian J. Anim. Sci. 67(5): 452-456

- Priestley, M.B. and Chao, M.T. (1972) Non-parametric function fitting. J. R. Stat. Soc. Series B Stat. Methodol. 34: 385-392
- Rajarathinam, A. and Vinoth, B. (2013) Computations of Jump Points in Tobacco (*Nicotiana Tabacum*) Crop Production. Int. J. Prob. Stat. 2(2) 13-20
- Reddy, V.N. (1978) Growth rates. Econ. Polit. Wkly. 13(19): 806-812
- Rlvichandran, S. and Prajneshu (2001) Structural timeseries model ling for, describing fish productian. Indian J. Anim. Sci. 71: 499-50
- Ruppert, D., Wand, M.P. and Carroll, R.J. (2003) Semiparametric Regression. Cambridge University Press, Cambridge
- Salazar, G. (1982) Structural changes in time series models. J. Econom. 19: 147-163
- SAS Institute Inc. (2011) Base SAS® 9.3 Procedures Guide. Cary, NC: SAS Institute Inc.
- Seber, G.A.F. and Wild, C.J. (2003) Nonlinear Regression. Hoboken, N. J. Wiley-Interscience, Inc., New Jersey
- Takezawa, K. (2006) Introduction to Nonparametric Regression. John wiley and sons. Inc., New Jersey, 568p
- Tornqvist, L., Varita, P. and Varita, Y.O. (1985) How should relative rates be measured? Am. Stat. 39: 43-46
- Vilar-Fernandez, J.M. and Cao, R. (2007) Nonparametric forecasting in time series- A comparative study. Commun. Stat. Simul. C. 36: 311-334
- Watson, G. (1964) Smoothing regression analysis. Sankhya. 26: 359-372
- Yogamoorthi, A. and Sivashankar, A. (1994) India's seafood export trends and its future prospects by 2000 A.D. Seafood Export J. 26:19-34