IJBPAS, December, 2021, 10(12): 4508-4520

ISSN: 2277–4998

International Journal of Biology, Pharmacy and Allied Sciences (IJBPAS)
'A Bridge Between Laboratory and Reader'

www.ijbpas.com

GENERALIZED LINEAR MODEL APPROACH FOR ROAD ACCIDENT PATTERNS IN KERALA, INDIA

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Received 20th Feb. 2021; Revised 20th Mar. 2021; Accepted 16th April 2021; Available online 1st Dec. 2021

https://doi.org/10.31032/IJBPAS/2021/10.12.5768

ABSTRACT

India's development over the past few years and an individual's desire to own vehicles has led to increased motorization across different states in India, with Kerala being one among them. In today's competitive world, everyone is in hurry and their impatience has resulted in careless attitudes towards driving, as well as towards vehicle maintenance, which in turn has risen the number of fatalities due to road accidents in Kerala. In this study we have made an effort to determine regions that are at greater risk of fatality and the vehicles that most prominently contribute to such risk using the Generalized Linear Model (GLM) approach. On comparison, Negative Binomial Regression Model (NBRM) showed up to be more appropriate over Poisson Regression Model (PRM). With Wayanadu as the baseline district, Idukki reported the lowest (1.303) incident rate. Among Ernakulam, Kozhikkode and Trivandrum, urban areas were exposed to lower fatality risk as compared to rural areas. Further, 'KSRTC bus', 'Cars & Two-wheelers' were found to cause more fatal accidents with 0.1% and 0.001% increase in deaths for an increment of one case due to each of them respectively. The prediction model adopted, thus yielded convincing results, which can be utilized for improving not only the human but economic and environmental conditions in Kerala.

Keywords: Generalized Linear Model, Negative Binomial Regression Model, Poisson Regression Model, road accidents

1. INTRODUCTION

Accidental deaths on Indian roads have risen alarmingly over the years involving more than 9-fold, from 14,500 in 1970 to 137,400 in 2013 with urban areas suffering less deaths (36.6%) as compared to rural areas (63.4%) in 2011. While fatality rates, have declined over the years from 87.5 in 1970 to 8.6 in 2013, they are still very high compared with developed countries. If no required steps are taken then road accidents in India by 2025 may exceed 0.25 million **[1, 2]**. Accidents are a dynamic multiple cause phenomenon. The analytical factors are categorized into environment and human related factors. The mixed Kerala's topography includes a hot and wet coastal plain rising slowly up to the Western Ghats' high hills and mountains. Currently, increasing population, urbanization, enormous growth of motor equipped as well as non-motorized and para-transit vehicles, the lonely supremacy of the road transport sector over other modes catalyze a number of accidents in Kerala. Of the 15,525 fatal accidents in 2010-2013, 76 percent of the accidents involved a human factor with 20% involving a path factor and only 4 percent involved a factor in automobiles. Heavy vehicles, i.e. Trucks and Buses, were involved in 32 per cent of all fatal incidents, cars / taxi / tempo involving 20 per cent with the highest involvement of two-wheelers **[3]**. In 2015-16, there were 1330 (4 per day) and 3303 (9 per day) accidents due to KSRTC bus against 5686 and due to private bus against 25449 buses respectively. As of March 2017, Kerala has 110.3 lakh motor vehicles registered with 330 vehicles per 1000 population, experiencing a compounded annual growth rate greater than ten percent over past two decades. Bike accidents accounted for 38% and motor cars for 28% of the total registered accidents in the state approximately in the same year **[4]**. Road traffic collisions and injuries are largely preventable as the likelihood of accident injury is relatively predictable and there are several assisting measures that have been shown to be successful. The most successful way of minimizing deaths and injuries will be through an integrated strategy that requires close cooperation between several sectors. Progress is being made in other areas of the world where ambitious multisectoral policies contribute to gradual reductions in the number of traffic deaths and accidents on the path. These approaches focus on four main factors that lead to the likelihood of a road accident – exposure, attitudinal factors, road conditions and vehicle components **[2]**.

The main objective of this study is to determine the effect severity of geographic and vehicle types on fatal accidents and thus address the possible underlying reasons by using the appropriate Generalized Linear Model (GLM) that best matches Kerala State's 11-years data from 2007-2017. GLM is a special class of non-linear models where it is assumed that the dependent variable, here the accidental deaths, is a part of the exponential family which encompasses numerous distributions, especially non-normal discrete distributions including Bernoulli, Binomial, and Poisson which can deal with binary and count data. In this retrospective data analysis we come across the two most common models that can be employed comprising of both numerical (automobile types) and categorical (Kerala districts) variables. One being, Poisson Regression Model (PRM) for handling equidispersion data and the other, Negative Binomial Regression Model (NBRM), which is a generalization of Poisson regression and provides flexibility over the restrictive assumption that the variance is equal to the Poisson model mean **[5, 6]**.

2. MATERIALS AND METHODS

2.1. Study area

The total area of Kerala state, 38,863 km^2, is split into fourteen districts which are categorized as North, Central and South Kerala with the entire state population being 33,387,677 as of 2011. Roads cover 1,524 km of National Highways (NH), State Highways (SH) and district roads cover 1,525 km, 4341.6 km and 18,900 km of the roads respectively. Also, an area of 15,577 km^2 of the state belongs to the forest region **[7]**.

2.2. Data collection

2007 to 2017 accidental data, showing regional distribution of fatalities along with the cases due to different types of vehicles and causes were freely available in keralapolice.gov.in, official website of the Kerala police department.

2.3. Generalised Linear Models

Once we begin modelling count data, it is necessary to test the data to see if there are any significant assumption violation on which the fundamental Poisson model is constructed. Any other count model can be considered as its deviation or modification. In addition to the accidental deaths being counts following Poisson distribution with identical mean and variance, they are expected to be non-negative occurring independently and Pearson chi square dispersion statistic nearing to the value 1, indicating that observed and predicted variation in the death occurrence are the same. . In addition to this, the data should also be checked for excess multicollinearity arising due to high correlation (Pearson correlation coefficient, $|r|\geq 0.9$) between some of the explanatory variables **[8, 9]**.

2.3.1. Poisson Regression Model

In this model, death incidence rate, μ is calculated by a set of predictor variables k (the X's), which involves the different types of vehicle cases as the discrete variables and districts representing the various categories. The related quantities can be expressed as,

$$\mu = t\exp(\beta_0 X_0 + \beta_1 X_1 + \ldots\ldots + \beta_k X_k) \quad \ldots\ldots(1)$$

β_0 is the intercept and $X_0=1$. The coefficients of regression, β_0, β_1, β_2 ... β_k are the parameters not known and hence has to be determined from the provided dataset. Accordingly, the basic PRM for death counts (y) reported when the population is exposed to time t in years can be described as

$$\Pr(Y_i = y_i | \mu_i, t_i) = \frac{e^{-\mu_i t_i} (\mu_i t_i)^{y_i}}{y_i!} \quad \ldots\ldots.(2)$$

where, $\mu_i = t_i \mu (X_i' \beta)$

$$= t_i \exp(\beta_0 X_{0i} + \beta_1 X_{1i} + \ldots\ldots + \beta_k X_{ki})$$

(Yang and Berdine, 2015)

2.3.2. Negative Binomial Regression Model

For the death counts following negative binomial distribution, Poisson Regression technique can be extended such that it allows the process variance to surpass the mean. The Negative Binomial Model is derived from the Poisson model by,

$$\ln\lambda_i = X_i\beta + \varepsilon_i \quad \ldots\ldots(3)$$

where λ_i is the mean number of deaths occurring in the ith district; β is the vector representing the parameters to be estimated; X_i is the vector representing ith geographic and corresponding cases due to 8 different automobile categories as the explanatory variables along with the value of X when for the intercept. ε_i is the error term where exp(ε) having 1 as the mean and α2 as the variance belongs to gamma distribution. The consequent probability distribution can be given as,

$$\text{Prob}(n_i|\varepsilon) = \frac{\exp[-\lambda_i \exp(\varepsilon)]\lambda_i^{n_i}}{n_i\,!} \quad \ldots\ldots.(4)$$

where n_i is the number of fatalities for particular districts over time period t. The integration of ε from this expression results in the unconditional distribution of n_i. This distribution is formulated in

$$\text{Prob}(n_i) = \frac{\Gamma(\theta + n_i)}{(\Gamma(\theta) n_i!)} u_i^{\theta} (1 - u_i)^{n_i} \quad \ldots\ldots(5)$$

where $u_i = \theta / (\theta + \lambda_i)$ and $\theta = 1/\alpha$; θ and α being the scale and dispersion parameter respectively.

Estimation of the NBRM can be done by using conventional maximum likelihood methods. The function in correspondence to this is,

$$L(\lambda_i) = \prod_{i=1}^{N} \frac{\Gamma(\theta + n_i)}{\Gamma(\theta) n_i!} u_i^{\theta} (1 - u_i)^{n_i} \quad \ldots\ldots(6)$$

where N represents the total number of districts. Maximizing the above function, estimates for the β and α coefficients can be obtained. There is an ancillary parameter in this model, in comparison to the Poisson model, so that,

$$\text{Var}\,[n_i] = \text{E}\,[n_i]\,\{1+\alpha\text{E}\,[n_i]\} \quad \ldots\ldots(7)$$

The choice between the two models can be understood clearly by using the estimated coefficient, α, and the Goodness of fit test. A α value of 0 or very close to it condenses the Negative Binomial Model to Poisson **[9, 11-13]**.

Wald Chi-squared test

The Wald test known as the Wald Chi-Squared Test is an approach to figure out if the regressors in a model are meaningful, implying addition of something to the model. Variables that make no difference can be removed without creating significant affect to the model. The Wald test is generally told in terms of chi-squared, as we are aware of the distribution of samples (as n tends to infinity) The Wald statistic can be expressed as, **[14]**.

$$W_T = \frac{[\hat{\theta}-\theta_0]^2}{1/I_n(\hat{\theta})} = I_n(\hat{\theta})\,[\hat{\theta}-\theta_0]^2 \quad \ldots\ldots(8)$$

where $\hat{\theta}$ being the Maximum Likelihood Estimator and $I_n(\hat{\theta})$, the expected Fisher information.

Goodness of fit

Among a family of models under competition, with different parameter quantities, Akaike's Information Criterion (AIC) and Bayesian Information Criterion (BIC) helps to recognize the model with the most resemblance. AIC and BIC can be defined as follows:

$$\text{AIC} = -2*\text{ML} + 2*k \quad \ldots\ldots(9)$$

$$\text{BIC} = -2L + k\ln(n) \quad \ldots\ldots(10)$$

with ML representing the maximum L(β)and k is the number of the model variables, and n is the model observations. The model with the smaller values of AIC and BIC can be considered the better fit one.

The deviance value 2(LL (β)-LL (0)) which follows a chi-square distribution was used to calculate the overall goodness-of-fit statistics. The log-likelihood ratio of the model described as ρ^2=1-LL (β)/LL (0)), is an indicator of the additional variance in accident deaths explained by the model obtained to the constant term **[9, 15]**.

2.4. Statistical methods

The statistical softwares, Excel 2013 and SPSS Statistics 22 (IBM corp.) served useful in the application of the multivariate techniques adopted in this study to determine the best prediction model. Level of significance was set to 0.05.

3. RESULTS

3.1. Descriptive analysis

There is a clear rise and fall in both the number of cases and deaths over the eleven years. Even though highest number of cases (39917) were recorded in the year 2007, deaths were found to maximum (4287) in the year 2016. This makes it clear that, accidents have shown a dreadful impact on the public which requires an immediate remedy **(Figure 1)**.

From the **Table 1** observations we can say that cases due to cars and two wheelers have shown an overall increase from one year to the next year with the total reported cases during the interval being 113833 and 289684 respectively. Further, comparatively, accident occurrences were very high due to these two vehicles. However, remaining vehicles exhibited ups and downs in their distributions. In addition to this, on comparison, incidences due to unknown vehicles and Kbus were found to be minimum.

Each district faced adverse suffering mainly due to the driver's attitude toward driving with Eranakulam, Trivandrum and Trissur being the most effected while least effecting Wayanadu and Kasarakodu regions.

3.2. Poisson and Negative Binomial Regression analysis

3.2.1. Assumption testing

The endogenous variable considered for the study (deaths) is certainly discrete non-negative counts having independent occurrence. In order to remove extreme multicollinearity, resulting due to highly correlated variables ($|r|\geq 0.9$) and to obtain more accurate meaningful results, we combined car and two wheeler cases together ('Cars & Two-wheelers') as well as incidences due to jeep and others ('Others') **(Table 3)**.

Tests conducted to check whether the death occurrences follow normal or Poisson distribution, yielded highly significant p-values (<0.05), which is an indication that neither of the distributions best fit the data. Further, greater value of variance than the mean, is in implication that NBRM is the more appropriate model. Also, this becomes more evident once we look into the goodness of fit statistics comparing the two models, given in **Table 4**.

The high significance (p-value<0.005) of omnibus test for both the models states that inclusion of predictors provides more efficient results than the one involving only intercept. The ancillary parameter value approaching 0 for the Negative Binomial Regression Model (0.0045), creates a confusion as to which model to choose, which can be cleared comparing the other model statistics. According to the aforementioned criteria, as compared to the PRM, NBRM has lower AIC and BIC values with deviance statistic approaching 1 (0.915), whereas for Poisson model the value exceeds 1. Therefore we can conclude that Negative Binomial model is comparatively best fit to the dataset providing predicted death counts close to the observed ones and we continue to work with the model to obtain further results.

3.2.2. Estimation and Prediction

The p-value obtained from the Wald's chi square test is highly significant (p-value<0.05) for all the Kerala districts. The Negative Binomial Model considers one of them as the reference category with respect to which all the other regions can be compared. B column provides the parameter coefficients which can be explained as the decrease or increase of the expected log of deaths in a particular region with comparison to the baseline district (here, Wayanadu with B=0 and Exp (B) = 1) depending on whether they take negative or positive values. Exp (B) also called the exponentiated regression coefficient gives the incident rate ratio (IRR), defined as the ratio of incident rate (IR) of the given place to that of Wayanadu. We mainly focus on IRR to interpret our results. We can clearly observe that incident rates of every district is corresponding Exp (B) times greater than that of the reference region with other variables held constant. Idukki was found to be having the lowest rate of death incidence, that is, 1.303 times more than Wayanadu's IR respectively. Moreover, rural areas of Ernakulam, Kozhikkode and Trivandrum were at substantial risks than their urban areas. Among the covariates, Wald's test showed significance only for accident cases due to KSRTC bus (p-value = 0.008) and 'Cars&Two-wheelers' (p-value = 0.000), which is an evidence that they are the considerable contributors of death prediction in each Kerala district whereas the left over vehicle types were found to be insignificant (p-value≥0.05) predictors. Further, with every unit increase in 'Kbus' and 'Cars&Two-wheelers' cases, expected log count of people dying increases by 0.001 and 0.0001 every year respectively. In other words, we can say that as the Kbus instances rises by 1, the death occurrences for the given year rises by 0.1 % [(1.001-1)*100] of the total deaths occurred in the previous year. Similarly, a single increment of accident incidence due to cars and two wheelers kills about an extra 0.01% [(1.0001-1)*100] people. All the parameter coefficients had low standard error values and their exponentiated values lay within the 95% confidence interval **(Table 5)**.

On the basis of the above parameter estimation results, NBRM estimates the average deaths occurring in each district for the values of all the covariates fixed by the model given by, Kbus = 75, Pbus = 223, Lorry = 132, Mini = 116, Auto = 394, Cars&Two-wheelers = 2158, Others = 169, Unknown = 20. The mean values are displayed in the **Table 6**. The predicted model equation for the first district (Alappuzha) is given by

λ_1 = exp (4.045 + 1.318 + Kbus * 0.001 + Pbus * 0.0001 + Lorry * 0.0001 + Mini * 0.0001 + Auto * 0.0001 + Cars&Two-

wheelers * 0.0001 + Others * 0.0001 + Unknown * 0.0001) with $\lambda_1$representing the average deaths in Alappuzha for a particular year and vehicle names denote respective cases corresponding to the region. All the vehicle parameters were included in the model as they had a B value not equal to 0 in the model. Similar equations can be framed for the different regions. Dispersion parameter was not considered during the estimation as it does not affect the values predicted. However, year-wise observed and predicted deaths in Kerala as a whole is shown in the **Table 7** with their graphical representation in **Figure 2**. The number of deaths estimated using the model were found to be close to the actual values with no unacceptable variations.

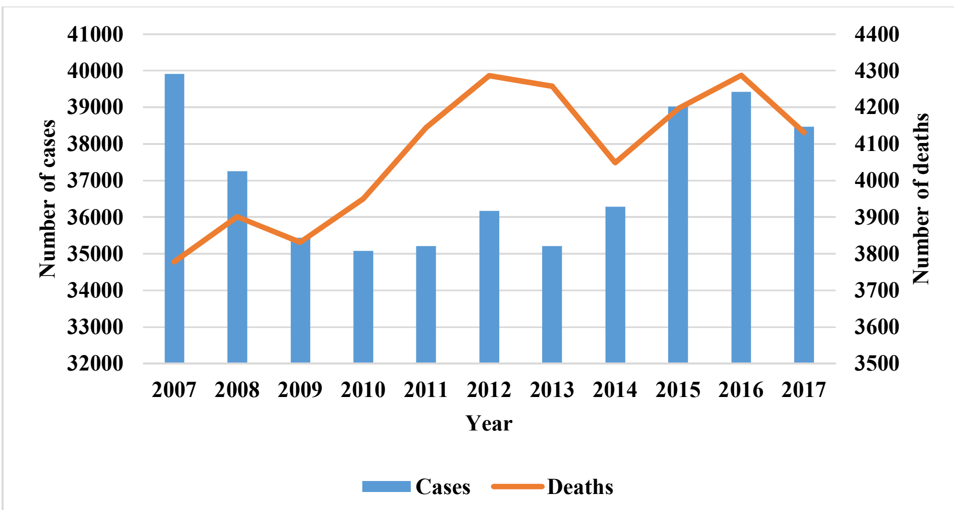

Figure 1: Distribution of cases and deaths from 2007 to 2017

Table 1: Distribution of accident cases due to different vehicles during the years 2007-2017

Vehicles	Year											Total
	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	
Kbus	1052	1208	1269	1286	1368	1435	1332	1200	1321	1270	1252	13993
Pbus	4502	4598	4362	4177	4003	3819	3523	3208	3293	3292	2971	41748
Lorry	3010	2655	2245	2248	2194	2072	1967	2174	2275	1956	1840	24636
Car	8149	9121	9406	9616	9871	10365	10344	10731	11641	12294	12295	113833
Mini	2507	2424	2183	2027	1997	1967	1624	1632	1673	1892	1725	21651
Jeep	1585	1521	1411	1298	1096	1019	883	897	800	730	618	11858
Auto	6961	7598	6967	6996	6920	7222	6711	6477	6381	5761	5651	73645
Two wheelers	18449	23193	23161	23057	23637	25445	26236	28546	31614	32812	33534	289684
Others	720	2275	1781	1827	1908	1841	1861	1702	1577	2249	1918	19659
Unknown	1042	345	324	370	313	252	270	249	210	229	165	3769
Kbus: KSRTC bus. Pbus: Private bus												

Table 2: Eleven years average incidences due to different factors for each district in Kerala

Districts	Causes		
	Rash driving	Drunk and drive	Others
Trivandrum city	1884	29	66
Trivandrum rural	2670	1	101
Kollam	2883	1	81
Pathanamthitta	1436	1	40
Alappuzha	3015	0	62
Kottayam	2581	2	51
Eranakulam city	2240	8	60
Eranakulam rural	3432	1	50
Idukki	1033	0	17
Trissur	4056	2	53
Palakkad	2221	1	32
Malappuram	2658	1	24
Kozhikkode city	1393	9	21
Kozhikkode rural	1566	0	15
Wayanadu	612	1	7
Kannur	1768	1	20
Kasarakodu	829	0	8

Table 3: Distribution fit test

Dependent variable	Mean	Variance	Tests for normality (p-value)		Test for Poisson distribution fit (p-value)
			Kolmogorov-Smirnov	Shapiro-Wilk	One-sample Kolmogorov-Smirnov
Deaths	240	13962	0.0001	0.0001	0.0001

Table 4: Goodness of fit statistics

Models	Deviance (Value/df)	AIC	BIC	Ancillary parameter	Omnibus test (p-value)
Poisson	1.857	1692.32	1773.095	0	0.0001
Negative binomial	0.915	1666.27	1747.052	0.0045	0.0001
df-degrees of freedom					

Table 5: Parameter estimation

Parameters		B	Std.error	Wald test (p-value)	Exp (B)	95% confidence interval for Exp (B)	
						Lower bound	Upper bound
	Intercept	4.045	0.0535	0.0001	57.103	51.421	63.413
Districts	Alappuzha	1.318	0.1195	0.0001	3.736	2.955	4.723
	Ernakulam city	0.575	0.1045	0.0001	1.777	1.448	2.181
	Ernakulam rural	1.179	0.1368	0.0001	3.251	2.486	4.251
	Idukki	0.264	0.0632	0.0001	1.303	1.151	1.474
	Kannur	0.945	0.0802	0.0001	2.572	2.198	3.01
	Kasarakodu	0.428	0.0578	0.0001	1.533	1.369	1.717
	Kollam	1.321	0.122	0.0001	3.746	2.95	4.758
	Kottayam	0.978	0.1062	0.0001	2.66	3.16	3.275
	Kozhikkode city	0.796	0.0861	0.0001	2.217	1.873	2.825
	Kozhikkode rural	0.893	0.0725	0.0001	2.443	2.12	2.816
	Malappuram	1.282	0.12	0.0001	3.605	2.849	4.561
	Palakkad	1.436	0.0929	0.0001	4.205	3.504	5.045
	Pathanamthitta	0.591	0.0679	0.0001	1.806	1.581	2.063
	Trissur	1.314	0.1638	0.0001	3.72	2.699	5.129
	Trivandrum city	0.594	0.0876	0.0001	1.811	1.525	2.15
	Trivandrum rural	1.174	0.1201	0.0001	3.236	2.558	4.095
	Wayanadu	0			1		
Vehicles	Kbus	0.001	0.0005	0.008	1.001	1.000	1.002
	Pbus	0.0001	0.0003	0.933	1.0001	0.999	1.001
	Lorry	0.0001	0.0003	0.212	1.0001	1.000	1.001
	Mini	0.0001	0.0003	0.51	1.0001	0.999	1.000
	Auto	0.0001	0.0002	0.345	1.0001	1.000	1.001
	Cars&Two-wheelers	0.0001	0.00002	0.000	1.0001	1.000	1.0001
	Others	0.0001	0.0002	0.396	1.0001	0.999	1.000
	Unknown	0.0001	0.0004	0.542	1.0001	0.999	1.001
Kbus: KSRTC bus, Pbus: Private bus							

Table 6: Estimated marginal means

Districts	Mean deaths	95% Wald Confidence Interval	
		Lower	Upper
Alappuzha	320	288	357
Ernakulam city	152	138	169
Ernakulam rural	279	246	316
Idukki	112	98	127
Kannur	220	204	239
Kasarakodu	131	114	151
Kollam	321	288	358
Kottayam	228	212	245
Kozhikkode city	190	165	218
Kozhikkode rural	209	191	229
Malappuram	309	278	343
Palakkad	360	335	388
Pathanamthitta	155	141	170
Trissur	319	267	381
Trivandrum city	155	141	171
Trivandrum rural	277	244	315
Wayanadu	86	73	101

Table 7: Year-wise prediction of Kerala deaths

Year	Observed	Predicted
2007	3778	3850
2008	3901	3949
2009	3831	3943
2010	3950	3977
2011	4145	4041
2012	4286	4132
2013	4258	4090
2014	4049	4126
2015	4196	4291
2016	4287	4187
2017	4131	4223

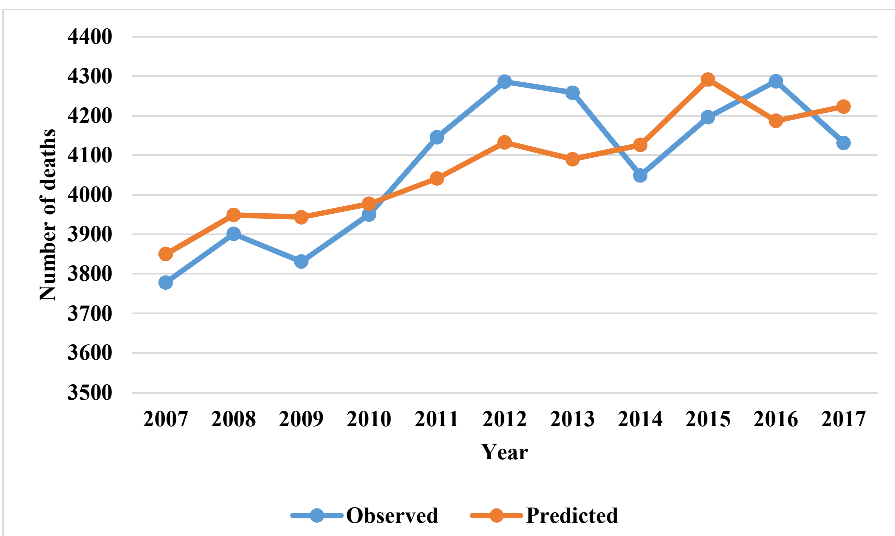

Figure 2: Comparison of observed and predicted deaths over a span of 11 years

4. DISCUSSION

Since 2013, Ernakulam followed by Trivandrum have reported the highest vehicle population, with the least recordings in Wayanadu. Every year, personal vehicles were found to report a faster growth rate in the entire state with higher risks due to multivehicle interactions and insufficient space **[4]**. Districts of Trivandrum, Ernakulam, and Trissur have high health care facilities, where urbanization, industrialization, and population growth play a supreme role in the provision of health care services **[14]**. Emergency response times are a crucial factor deciding the risk of fatality during a road accident. Many of the road collision victims die because the rescue teams arrive late at the location. It is quite obvious that urban areas records lower deaths as more number of hospitals are located at a lesser distance and transfer of victims is possible in a shorter period. As per the data, since the accident cases also appeared higher in number in rural regions, improper road maintenance can be thought of as the reason. Kannur, Kottayam, Kozhikode and Alappuzha stand second in the health care facility order with tourism being predominant in Alappuzha. Such districts do have good accessibility and connectivity to the transport. In the border districts of Pathanamthitta, Idukki, Kasarakodu, Palakkad and Wayanadu comparatively less developed health care facilities are observed. These districts are situated in the Kerala highland zone. Such districts are characterized by low density, composed of more SC / ST and rural communities. More than 35% of the geographic areas of Pathanamthitta (59%), Idukki (47%) and Wayanadu (37%) are covered by forests in the highland regions. There are also not very busy road networks and most importantly, vehicles are not permitted to cross this area during the night by passage and forest area, it is limited there, this is why it plays a very important role in lower accident rates and its deaths. Thus rise in particular vehicle type either due to an individual's desire or due to the regional restrictions can be considered as the main cause behind the increase in specific automobile cases **[16, 18]**.

Over the years, an individual's desire or regional restrictions can be considered as the main cause behind the huge rise in specific automobiles and their movements, such as two wheelers and cars in Kerala, thereby exposing them more to the accidents as compared to the remaining vehicles. However, it is important to note that, vehicles like bus expose large number of passengers while when two-wheelers and cars are considered, lesser number are exposed to accidents. Therefore, lower incidences of Kbus with more deaths and increased car and two-wheeler cases with lesser deaths are equally dreadful. As a result, since rash driving is a major reason behind the accidents, as obtained from our data, proper advisory methods should be adopted by the respective authorities to bring about changes in the driver's behaviour. Although other factors such as road structures, overloading of passengers, effects of bad weather, defect in the automobiles, and fault of the pedestrians may be minor contributors, concentrating on their control and preventive measures such as education in road safety for different types of road users, rectification of road design, shortcomings in the inclusion of road safety issues of road construction planning and operating stages are the key facts to be taken up which can be very useful in reducing accident severity. In addition to this, more attention should be drawn towards the maintenance of accidental reports as in our study there were presence of some cases due to unknown vehicles and a knowledge about them could have altered the results. Also, the results were obtained considering equal exposure of the population towards accidents in each district **[4]**.

5. CONCLUSION

For a developing state like Kerala, giving importance to even minute factors that brings down the population density is very much necessary. Road accident is one such disaster that, not only kills people but pushes many of them into grievous suffering as a consequence of the damages or loss faced by the society. The affected regions will have to confront with greater economy and environmental hardships. In our study, the application of Negative Binomial Regression Model served useful to a great extent in determining the high risk regions and vehicles related to the road accidents in Kerala. Although rash driving appears to be the most prominent reasons, attention should also be drawn towards the other causes by the management. In addition to this we as individuals should take responsibility to prevent self-deprivation and deprivation to the environment in which we are living, by adopting precautionary measures, most important being, following traffic rules and regulations.

Conflict of interest

The authors do not have any conflict of interest with other entities or researchers.

Acknowledgement

The authors sincerely thank Head of the Department, Department of Water and Health, JSS Academy of Higher Education and Research, Mysore, for having granted the use of SPSS software for performing the statistical analysis.

REFERENCES

[1] Ruikar M. National statistics of road traffic accidents in India. Journal of Orthopedics, Traumatology and Rehabilitation. 2013; 6(1): 1-6.

[2] Singh S. K. Road traffic accidents in India: issues and challenges. Transportation research procedia. 2017; 25: 4712-4723.

[3] Vigneshkumar C, Arichandran R. Fatal road accidents in Kerala (India):

characteristics, causes and remedial measures. International Journal of Research. 2015; 4(4): 4-5.

[4] ENVIS Centre: Kerala, State of Environment and Related Issues.http://www.kerenvis.nic.in/Database/INFRASTRUCTURE_812.aspx

[5] Muller M. Generalized Linear Models. 2004. DOI: 10.1007/978-3- 642-21551-3_24.

[6] Famoye F, Wulu JT, Singh KP. On the generalized Poisson regression model with an application to accident data. Journal of data science. 2004; 2(2004): 287-95.

[7] Kerala. https://en.wikipedia.org/wiki/Keral

[8] Joseph M Hilbe, Modelling count data, http://dx.doi.org/10.1017/CBO9781139236065.003.

[9] Abdel-Aty MA, Radwan AE. Modeling traffic accident occurrence and involvement. Accident Analysis & Prevention. 2000; 32(5): 633-42.

[10] Yang S, Berdine G. Poisson Regression. The Southwest Respiratory and Critical Care Chronicles. 2015; 3(9): 61-64.

[11] Joseph M Hilbe, Negative Binomial Regression (2nd Edition, 2011).

[12] Oyedepo JO, Etu JE. Poisson and Negative Binomial Regression Models Application to Model the Factors of Car Ownership in Akure, South West, Nigeria. Journal of Applied Science & Process Engineering. 2016 Sep 30; 3(2): 72-82.

[13] Ye X, Wang K, Zou Y, Lord D. A semi-nonparametric Poisson regression model for analyzing motor vehicle crash data. PloS one. 2018; 13(5).

[14] Wald test. https://www.statisticshowto.com/wald-test/

[15] Razali MS, Zamzuri ZH. Modeling motorcycle road accidents with traffic offenses at several potential locations using negative binomial regression model in Malaysia. International Journal of Applied Mathematics and Statistics. 2016; 54(3): 104-114.

[16] Koley S, Srivastava S, Ghosal P. Correlating Fatality Rate to Road Accidents in India: A Case Study Using Big Data. In2018 IEEE International Symposium on Smart Electronic Systems (iSES) (Formerly iNiS) 2018 (pp.171- 176). IEEE.

[17] Nair MN, Thangamani V. An Analysis of Spatialy Explicit Scenario of Road Traffic Accidents in Kerala Using GIS. International Journal of Science and Research. 2015: 4(10): 356-359.

[18] Spatial distribution of health care services and facilities in Kerala state. http://shodhganga.inflibnet.ac.in/jspui/bitstream/10603/133267/9/09_chapter%203.pdf.