PAVEMENT DEPRECIATION RATE ESTIMATION FROM POTHOLE OCCURRENCE AND DEVELOPMENT OF REMEDIAL STRATEGIES

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The management of road infrastructure presents a considerable challenge as rapid road deterioration impacts the transportation of goods and persons. Road administrators must streamline their asset inventory, valuation, and depreciation procedures to establish a shared understanding between road financial management and engineering. This research endeavours to contribute to this ongoing effort by exploring the potential of statistical models to estimate road pavement depreciation. The study developed a model to estimate pothole occurrence to estimate the depreciated value of road pavements through a road accounting system. The frequency of occurrence of potholes can serve as a valuable metric for assessing the rate at which a road surface is degrading. Furthermore, the predictive models developed in this research aim to incorporate a range of relevant predictor variables, such as weather conditions and road usage patterns. By doing so, the accuracy of the model predictions is enhanced. This approach not only aids in predicting pothole occurrence but also assists in identifying road sections that are particularly susceptible to other defects, including in the subsurface layers. The estimated results empower decision-makers to allocate resources more efficiently, prioritising maintenance and rehabilitation activities within constraints, including budgets. Road authorities can optimise inspection procedures and resource allocation by creating and utilising predictive models. By enhancing asset inventory, valuation, and depreciation procedures, road networks can be maintained at a better quality to improve road serviceability and safety. Lastly, the study contains an empirical application and model calibration of Japanese road pavement data for an expressway in Himeji, Japan.

Key Words : *Road asset management; Pavement management; Statistical prediction model; Poisson process; Road accounting process.*

1. INTRODUCTION

In recent decades, data has emerged as the most sought-after and valuable commodity on a global scale. Developed and developing countries emphasise allocating resources to individuals and institutions to create systems that facilitate data correlation. Pursuing enhanced analytics has become the surest way to process data into meaningful knowledge, providing enlightenment and bearing the fruits of wisdom. Simultaneously, the growing spectre of climate change presents new challenges for infrastructure management as extreme weather events, including floods, storms, and heat waves, become more frequent and severe. This confluence of factors requires innovative infrastructure planning and management approaches, particularly in developing countries. Optimal maintenance models have been developed, incorporating Markov decision processes and financial engineering techniques to

address these challenges.

However, road managers often struggle to secure sufficient annual budgets for optimal repair planning, delaying necessary repairs. Changes in economic policies and financial statuses further complicate budget allocations for road pavement repairs. Deferred repairs can lead to a backlog of sections needing maintenance and a decline in overall service levels. Japan has a Pavement Management Accounting system (PMAS) designed for local government road managers seeking rational repair strategies based on asset management information related to road pavement. It comprises two key components: Pavement Management Accounting (PMA), which records changes in the asset price of road pavement and assets (or debts) during the fiscal year, and a Maintenance Management System (MMS), which determines repair strategies based on the execution budget during the fiscal year. The results of repairs in a given fiscal year are used as a basis for managing the budget for repairs in the following fiscal year, ensuring that maintenance activities align with maintaining an appropriate service level.

To improve the reliability of the PMAS application, it is required to develop such a system so the deterioration model can be automatically generated from the inspection data of the road pavement. The deterioration process in this application was deterministic, but it is challenging to predict the future condition state of road pavement due to the uncertainty of pavement deterioration. Using a stochastic deterioration process by considering uncertainty, there is the possibility to estimate the depreciation rate of a road pavement for network-level calculation. This study aims to integrate pothole occurrence estimation models, and PMAS which is essential for optimising infrastructure management, especially in the face of emerging challenges like climate change and rapid urbanisation. The model applies the Poisson model to estimate the occurrence of Potholes, investigate the factors that significantly contribute to the occurrence, and analyse and describe the pavement section's deterioration process. Effective pavement management is vital for road safety, transportation, and economic and environmental sustainability.

2. METHODOLOGY

A study by Jovanis and Chang (1986) demonstrated the significance of utilising generalised linear regression with a Poisson error structure over traditional linear regression when addressing the modelling of count frequencies. This distinction becomes particularly evident when dealing with random, discrete, non-negative, and infrequent events, such as road defects. Jovanis and Chang introduced a Poisson model to establish a connection between accident frequency, traffic patterns, and various environmental factors. Their findings underscored a critical drawback of linear regression: its inability to handle non-negativity and unequal variance in error terms. Notably, in scenarios where the mean count frequency is functionally tied to the variance, as assumed by the Poisson distribution (where the mean equals the variance), linear regression produces unbiased parameter estimates but renders incorrect confidence intervals. Given that regression analysis aims to identify factors significantly influencing accident occurrence, reliance on inaccurate confidence intervals compromises hypothesis testing and parameter significance.

Moreover, comparative studies undertaken by Joshua and Gerber (1990) and Miaou and Lum (1993) have corroborated the superiority of the Poisson model over traditional linear regression. In their methodology review, a critique by Lee and Mannering (2002) suggested that categorical modelling techniques like logit models are ill-suited for count data characteristics, which often exhibit non-negative integer counts, as is the case with pothole frequencies. To address these limitations, researchers have adapted generalised linear modelling techniques to implement Poisson models. However, the Poisson distribution's requirement for near equality between variance and mean poses challenges when dealing with pothole frequencies. Typically, the variance significantly exceeds the mean, a phenomenon known as over-dispersion, rendering the Poisson model inadequate.

In response to this challenge, Maher and Summersgill (1996) proposed using both the quasi-Poisson and the negative binomial models. While the quasi-Poisson model might yield inefficient coefficients and biased results, the negative binomial model emerged as a robust solution to mitigate over-dispersion. Extensive empirical studies conducted by the U.K. Transport Research Laboratory have resoundingly endorsed the negative binomial model, particularly when handling large datasets. Recent research endeavours have consistently favoured the negative binomial model as the most suitable methodological approach for modelling count frequencies.

3. ROAD ACCOUNTING SYSTEM

Potholes are often the result of pavement deterioration caused by various factors, and their frequency and severity can serve as a reflection of the

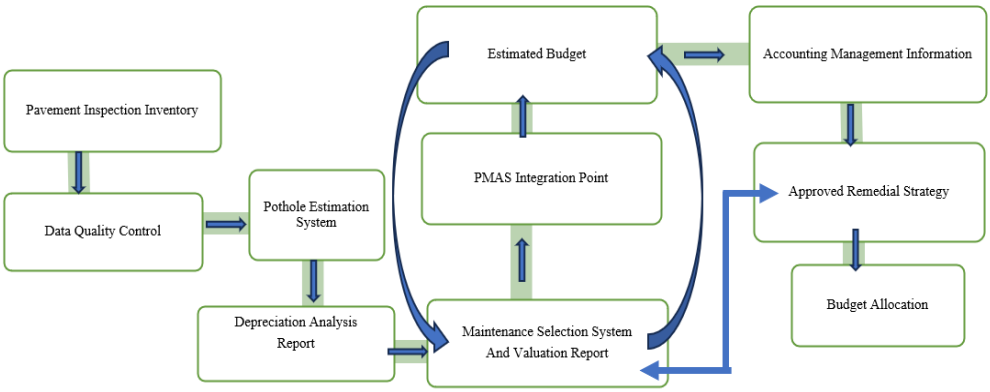


Fig. 1 Overview of the Road Accounting Procedure

pavement's overall condition. By assessing the frequency and severity of potholes, pavement managers can estimate how much of the pavement's service life has been consumed. Potholes are a sign that the pavement is reaching the end of its functional life; however, they hold data that can be used to predict future maintenance needs. For example, when potholes start occurring more frequently, it indicates that significant rehabilitation or resurfacing may be required soon. Resources can be allocated more effectively based on the estimation of pavement depreciation derived from pothole data. Pavement managers can prioritise repairs and maintenance activities in areas where potholes are forming rapidly. The output of this model can be part of stored information about the condition of road pavement, including MCI (Maintenance Criteria Index) values, inspection data, and cost data for various repair methods. It will allow the decision maker to input repair category, pavement repair unit costs and annual repair budgets, which are essential parameters for simulating different repair scenarios. Fig. 1 describes the proposed Road Accounting procedure. The generated output will include a report to help road management agencies make informed decisions about repair priorities and budget allocation. The empirical study by Mitsuru Jido in Mie Prefecture in Japan used the PMAS to analyse road pavement management. The Key findings of the research included calculating the average annual MCI decline quantity and determining a minimum budget necessary to maintain pavement service levels.

The study also highlights the importance of developing automated deterioration models, addressing uncertainty in pavement deterioration, improving system usability, and integrating geographical information systems (GIS) for a more comprehensive road management approach. Integrating a pothole estimation model can be into the PMAS, predicting their formation can help plan repair activities more proactively (Mitsuru et al.). The pothole estimation model can use weather conditions, traffic volume, road material quality, and historical occurrences to predict where and when potholes might appear. The proposed estimation model could offer additional insights into the road pavement condition, allowing for more targeted repairs and budget allocation. By integrating this predictive model into the PMAS, road managers can make data-driven decisions and plan for pothole repairs more effectively, ultimately reducing maintenance costs and improving the overall service level of road pavement.

4. DATA AND PREPROCESSING

The dataset employed in this study comprises monitoring data related to potholes on Japanese national roads. Japan's distinct four seasons: winter, spring, summer, and fall, render its road pavements susceptible to various road defects. The dataset used in this research constitutes a subset of the monitoring and maintenance data by the Yaka National Highway Branch Office. To incorporate an environmental aspect into the dataset, we included monthly total precipitation data recorded by the Japan Meteorological Agency station close to the study location (see Table 1). The records encompass the period from 2007 to 2009, with 236 observations collected. These observations represent an average sectional length of 100 meters, and it's worth noting that any identified potholes were promptly repaired upon discovery. In Fig. 2, we present the number of observed potholes and the total area affected by potholes for each year. The data for 2007 spans six calendar months, 2008 covers twelve calendar months, and 2009 spans only two. This discrepancy explains why 2008 exhibits the highest number of observed potholes. However, it's intriguing that 2009 recorded the second-highest number of observed potholes and the largest total

Table 1 Japan Meteorological Agency – Monthly Total Precipitation station records close to the study area.

WAKKANAI WMO Station ID:47401 Lat 45o24.9'N Lon 141o40.7'E			
Toyooka Wmo station ID: 47747			
Year	2007	2008	2009
Jan	35	77.5	71
Feb	70.5	40	147
Mar	36	26.5	68.5
Apr	22.5	22	34
May	85.5	89	57
Jun	16	52.5	161.5
Jul	30	53.5	121.5
Aug	214.5	62.5	99.5
Sep	159.5	80	44.5
Oct	74	101.5	96.5
Nov	77.5	79	135.5
Dec	84.5	111.5	134.5
Annual	905.5	795.5	1171

pothole area despite the relatively shorter observation period than the other two years. This observation may be attributed to the high precipitation conditions experienced in 2009, as shown by the frequency of potholes identified within a defined period. One crucial assumption for the regression model is that the relationship between the independent variables and the expected value of the count variable should be linear.

It's important to emphasise that the collected observations provide information about the location, area, shape, and depth of potholes but do not yield an actual count. In many studies, the count variable used for modelling is often the number of observed potholes grouped by time, day, month, or year of occurrence. However, this approach assumes that all potholes have the same area, which is not valid in practical scenarios.

Fig. 3 illustrates the plot of the pothole area against Average Daily Traffic(ADT), indicating no significant correlation. Similarly, Fig. 4 displays the plot of the pothole area against Monthly Precipitation, again showing no apparent correlation. Fig. 5 represents the plot of the pothole area against the Longitudinal slope, failing to reveal any notable correlation. These initial findings may appear counterintuitive.

Based on engineering judgment, we derived the relative pothole count using the following equation: In this study, we have selected the Relative Area of potholes (y) as the count variable, as shown by equation 1. To model this, we have considered three explanatory variables: Average Daily Traffic (ADT), categorised into 11 sections representing traffic volume for all vehicle types (see Table 2), Total Monthly Precipitation, and the Longitudinal slope at the pothole's location. Other influencing factors were not considered.

$$\frac{A_i}{A_{min}} = [y] \tag{1}$$

$$A_i = Area\ of\ Observed\ pothole$$
$$A_{min} = Minimum\ Area\ in\ Data\ set$$
$$[y] = Relative\ Pothole\ Count$$

Fig.6 shows that the plot of Relative Pothole Count $[y]$ against Average Daily traffic has a normal distribution. The peak Pothole count between 3000 – 3200 ADT can be explained, considering this section is the longest of the 11 characterised sections. Fig. 7 is the plot of the Relative Pothole Count $[y]$ against Monthly Precipitation, which shows the highest occurrence of potholes between 15mm and 55mm, which can be associated with Japan's winter period. It also depicts a decrease in pothole occurrence with increased precipitation, which indicates that the winter period has a more significant influence on deterioration than rain. Fig.8 is the plot of Pothole Count $[y]$ against the Longitudinal slope, which shows two peaks of pothole occurrence between 0-2.5 gradients, indicating that as the inclination increases, the pothole occurrence reduces.

Table 2 Eleven sections representing traffic volume for all vehicle types

No.	Route No.	Chainage Start	Chainage End	Average Daily Traffic
1	9	106+820	111+665	4000
2	9	111+665	114+200	4619
3	9	114+200	123+640	3592
4	9	123+640	127+500	3183
5	9	127+500	131+800	3740
6	9	131+800	140+400	3416
7	9	140+400	147+400	3013
8	9	147+400	158+200	3341
9	9	158+200	175+000	2866
10	9	175+000	182+200	3035
11	9	182+200	183+940	2667



Fig. 2 Route -9 Number of Observations and Total Pothole Area from 2007 -2009

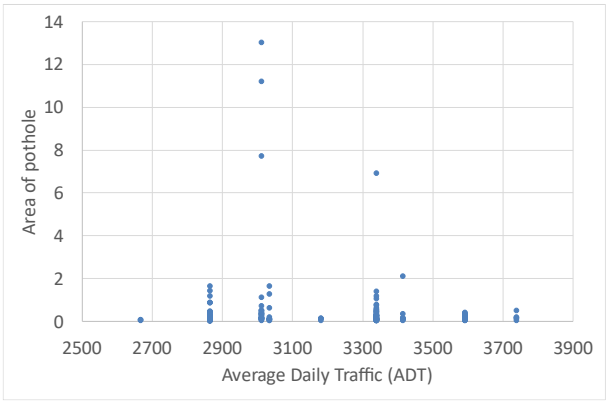


Fig. 3: Plot of Area of Pothole(m^2) against Average Daily Traffic shows no correlation.

Analysing the area of the pothole as the Pothole count further provides the opportunity to understand the influence of the explanatory variables on the two pavement types: Impermeable pavement (Type A) and Permeable pavement type (Type B). In Fig. 9, the Relative Pothole Count (RPC) graph observed for Impermeable pavement (Type A) against the ADT shows a normal distribution with large counts similar to all. The ADT between 2600-2800 and 3400-3600 showed the most minor counts. This can be explained by those sections being pavement Type B. In Fig.10, the graph of the Relative Pothole Count for Permeable pavement type (Type B) against the ADT shows a right-skewed distribution. The ADT between 2600-2800 and 3000-3200 showed no counts. This can be explained by those sections being pavement Type A. In Fig. 11, the graph of the Relative Pothole Count observed for Impermeable pavement (Type A) against the Longitudinal slope shows a distribution slightly skewed to the left. Longitudinal slopes between 2-3, 6-7 degrees and above showed the lowest counts. This can be explained by the fact that the length of those sections is relatively shorter than the other sections. In Fig. 12, the graph of the Relative Pothole Count observed for Permeable pavement (Type B) against the Longitudinal slope shows a left-skewed distribution. Longitudinal slopes between 7-degree slopes and above showed the lowest counts. This can be explained by the fact that the length of those sections is relatively shorter than the other sections. In Fig.13, the graph of the Relative Pothole Count observed for Impermeable pavement (Type A) against the Monthly Precipitation shows a distribution skewed to the right. The plot shows that the relative pothole count decreases with an increase in Monthly Precipitation, inferring that the count increases during the winter period in Japan. The values between 55-95mm and 175-215 mm showed the lowest counts, and this can be explained by the fact that the summer periods in Japan have little influence on the occurrence of potholes in Type A. Pavements. In Fig.14, the graph of the relative Pothole Count observed for Permeable pavement

Table 2 List of Dependent and Independent variables

Count Variable [y] = Relative Pothole Count				
No.	Independent Variables	Description	Correlation with Count Variable	P-Value
1	x1	Average Daily Traffic (ADT)	-0.0800206	0.220674
2	x2	Monthly Precipitation (mm)	-0.0796432	0.222866
3	x3	Longitudinal Slope (Degrees)	0.05745765	0.379553

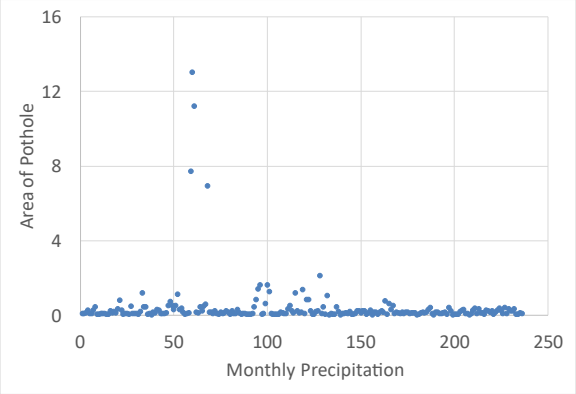


Fig. 4: Plot of Area of Pothole(m^2) against Monthly Precipitation shows no correlation.

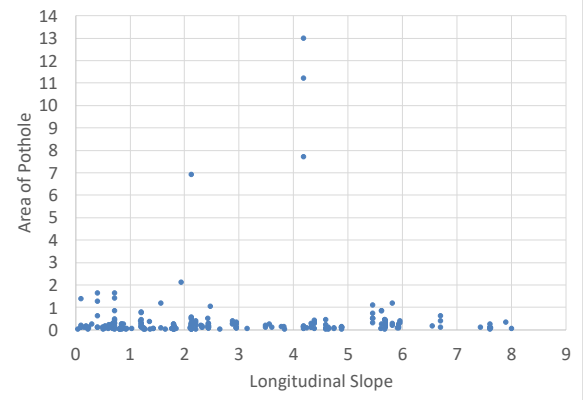


Fig. 5: Plot of Area of Pothole(m^2) against Longitudinal Slope.

(Type B) against the Monthly Precipitation shows a left-skewed distribution.

The values between 175-215mm and above recorded no counts, showing the highest counts between 15-55mm values. This can be explained by the fact that the influence of pothole occurrence on permeable pavement is significant in winter compared to early summer rain, called plum rain in Japan.

(4.1) Model forms

The Relative Area of the potholes was utilised as the count variable in our analysis. We considered three explanatory variables: Average Daily Traffic (ADT), Total Monthly Precipitation, and the Longitudinal slope at the pothole's location. Table 2 summarises the statistics for these variables used in constructing our models. The initial Pearson correlation between each independent variable and the count variable revealed some interesting insights. Firstly, it showed that the Relative pothole Count increases as Average Daily Traffic (ADT) decreases, resulting in a negative correlation coefficient. This finding may appear counterintuitive.

Additionally, it indicated that the Relative pothole Count rises with a decrease in Monthly precipitation, which might also seem counterintuitive. However, it's worth noting that some regions in Japan experience low precipitation even during winter. Lastly, the correlation analysis suggested that the Relative pothole Count increases with an increase in slope, which might be counterintuitive. Regarding the p-values for all three variables, they generally exceed 0.05. However, it's worth noting that explanatory variables x_1 and x_2 are relatively significant in explaining the variation in the Relative pothole count.

Three regression models were considered for the research: Poisson, Negative Binomial and Poisson-Gamma regression.

All three regressions are typically expressed as:

$$\ln(\mu) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots \beta_p x_p \qquad (2)$$

Where:

- $\ln(\mu)$ Is the natural logarithm of the mean count μ
- β_0 is the intercept.
- $\beta_1, \beta_2 \ldots\ldots \beta_p$ are the regression coefficients associated with the predictor variable $x_1, x_2, \ldots\ldots x_p$

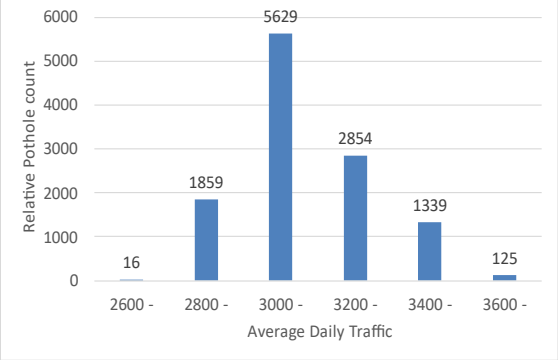


Fig. 6: Plot of Relative Pothole Count against ADT shows a normal distribution.

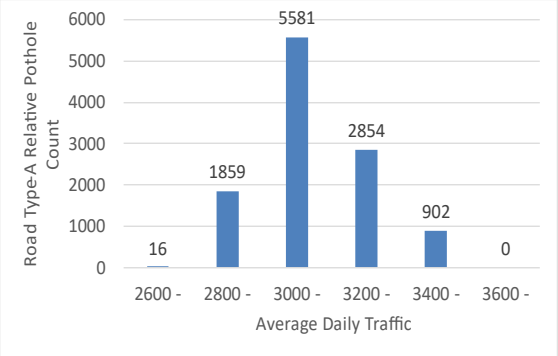


Fig. 9: The plot of Road Type – A RPC against Average Daily Traffic shows normal distribution slightly skewed right.

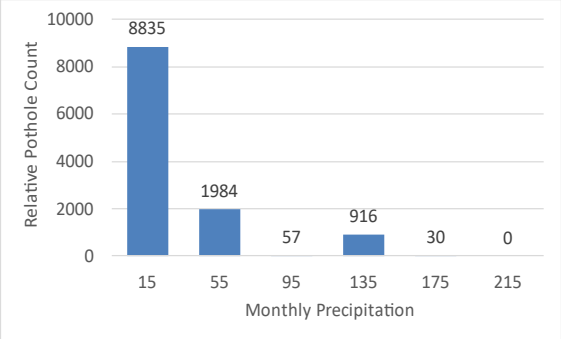


Fig.7: Plot of Relative Pothole Count against Monthly Precipitation shows right-tail

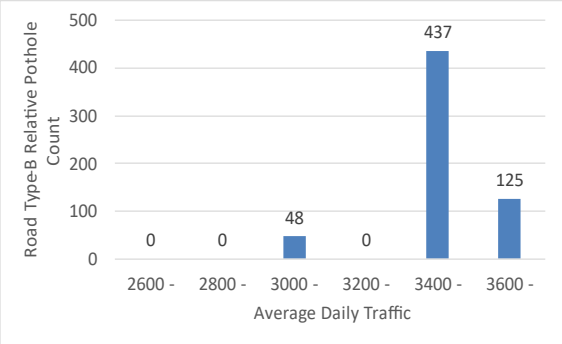


Fig. 10: The plot of Road Type – B RPC against Average Daily Traffic shows normal distribution slightly skewed right.

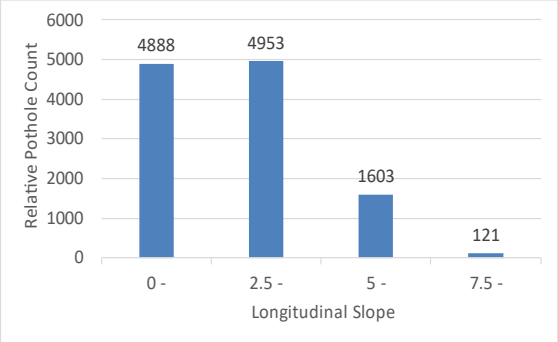


Fig. 8: Plot of Relative Pothole Count against Longitudinal Slope.

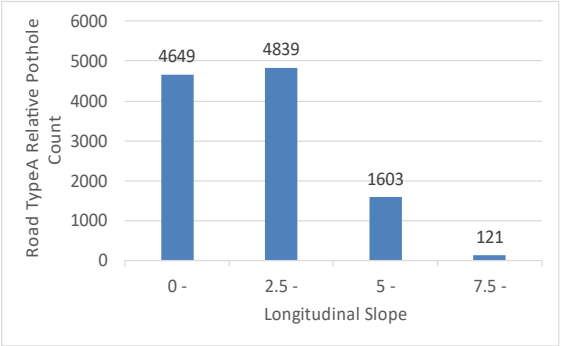


Fig. 11: The plot of Road Type – A RPC against Longitudinal Slope shows a right-skewed distribution.

(4.2) Poisson Regression

This model assumes that the count variable $\boldsymbol{Y}$ follows a Poisson distribution with mean $\boldsymbol{\mu}$. The Probability Mass Function (PMF) of the Poisson distribution is given by:

$$\boldsymbol{P(Y = y) = \frac{e^{-u}\mu^{y}}{y!}} \qquad (3)$$

So, if we consider the probability ($\boldsymbol{P}$) of a random event ($\boldsymbol{Y}$) taking on a specific value ($\boldsymbol{y}$), for the Poisson distribution, it would be the exponential of the negative of the mean $\boldsymbol{\mu}$ multiplied by $\boldsymbol{\mu}$, raised to the power $\boldsymbol{y}$, divided by $\boldsymbol{y}$ factorial to account for the different ways this outcome can occur.

Table 3 Output of regression models.

Poisson Model Output									
Dep. Variable:	Pothole_Number No. Observations:	236							
Model:	GLM Df Residuals:	232		**coef**	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
Model Family:	Poisson Df Model:	3	**Intercept**	4.4774	0.028	160.762	0.000	4.423	4.532
Link Function:	Log Scale:	1.00	**Average Daily Traffic**	-0.8157	0.037	-22.082	0.000	-0.888	0.743
Method:	IRLS Log-Likelihood:	-15701	**Monthly Precipitation**	-1.6844	0.062	-27.096	0.000	-1.806	-1.563
	Deviance:	30274	**Longitudinal slope**	0.4982	0.035	14.215	0.000	0.429	0.567
	Pearson chi2:	9.68E+04	**Aplha = 0.05**						
No. Iterations: 6	Pseudo R-squ. (CS):	0.9996	**AIC: 31,410.85**						
Negative Binomial Model Output									
Dep. Variable:	Pothole_Number No. Observations:	236							
Model:	GLM Df Residuals:	232		**coef**	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
Model Family:	Negative Binomial Df Model:	3	**Intercept**	4.446	0.053	84.241	0.000	4.343	4.550
Link Function:	Log Scale:	1.00	**Average Daily Traffic**	-0.932	0.068	-13.682	0.000	-1.065	-0.798
Method:	IRLS Log-Likelihood:	-3431.7	**Monthly Precipitation**	-1.322	0.099	-13.381	0.000	-1.515	-1.128
	Deviance:	5544.5	**Longitudinal slope**	0.518	0.068	7.568	0.000	0.384	0.653
	Pearson chi2:	2.39E+04	**Aplha = 0.05**						
No. Iterations: 10	Pseudo R-squ. (CS):	0.8993	**AIC: 6,871.36**						
Poisson Gamma Model Output									
Dep. Variable:	Pothole_Number No. Observations:	236							
Model:	GLM Df Residuals:	232		**coef**	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
Model Family:	Negative Binomial Df Model:	3	**Intercept**	4.455	0.525	8.840	0.000	3.425	5.485
Link Function:	Log Scale:	7.0928	**Average Daily Traffic**	-1.004	0.670	-1.500	0.134	-2.317	0.308
Method:	IRLS Log-Likelihood:	-1267.2	**Monthly Precipitation**	-1.140	0.899	-1.267	0.205	-2.902	0.623
	Deviance:	424.88	**Longitudinal slope**	0.481	0.692	0.695	0.487	-0.876	1.838
	Pearson chi2:	1.65E+03	**Aplha = 0.05**						
No. Iterations: 19	Pseudo R-squ. (CS):	0.02267	**AIC: 2,542.41**						

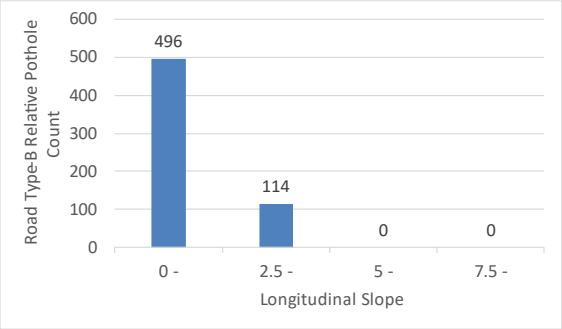


Fig. 12: The plot of Road Type – B RPC against the Longitudinal Slope shows a right-skewed distribution.

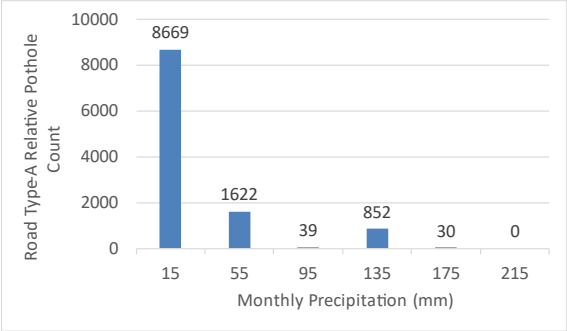


Fig. 13: The plot of Road Type – A RPC against Monthly Precipitation shows a right-skewed distribution.

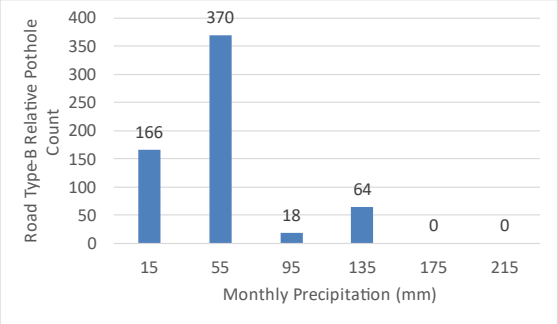


Fig. 14: The plot of Road Type – B RPC against Monthly Precipitation shows a left-skewed distribution.

(4.3) Negative Binomial

This model assumes that the count variable $\boldsymbol{Y}$ follows a negative binomial distribution with mean $\boldsymbol{\mu}$ Mass Function (PMF) of the Negative Binomial distribution**:**

$$P(Y = y) = \frac{\Gamma(y+k)}{y!\Gamma(k)}\left(\frac{\mu}{k+\mu}\right)^{y}\left(\frac{k}{k+\mu}\right)^{k} \quad (4)$$

In the case of the negative binomial regression, the probability of a random event "$\boldsymbol{Y}$" taking on a specific value "$\boldsymbol{y}$" in a binomial distribution is calculated by considering the average rate $\boldsymbol{\mu}$, the specific count $\boldsymbol{k}$, and using these parameters to compute the likelihood of "$\boldsymbol{y}$" events occurring.

(1.3) Poisson - Gamma

This model assumes that the mean $\boldsymbol{\mu}$ follows a Gamma distribution with shape parameter $\boldsymbol{\alpha}$ and rate parameter $\boldsymbol{\beta}$**.** The Probability Mass Function (PMF) of the Gamma distribution is given by**:**

$$f(\mu;\alpha,\beta) = \frac{\beta^{\alpha}}{\Gamma(\alpha)}\mu^{\alpha-1}e^{-\beta\mu} \quad (5)$$

The gamma distribution calculates the likelihood of observing a specific value $\boldsymbol{\mu}$ in a distribution considering how $\boldsymbol{\mu}$ is related to $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$. $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ control the shape and spread of the distribution.

5. RESULTS OF REGRESSION MODELS.

Table 4 displays the output of all three regression models. In each of these models, the regression coefficient for ADT and Monthly Precipitation consistently appears negative, while the coefficient for Longitudinal slope consistently appears positive. We find that they are statistically significant when we compare the p-values to the z-statistic values for these explanatory variables in all three models. Additionally, there is no overlap in the confidence intervals for each explanatory variable, reinforcing that these chosen variables are statistically distinct.

The results further indicate that the Pearson chi-squared statistic (χ^2) for the Poisson regression is the highest, followed by the negative binomial regression, with the Poisson-Gamma model ranking third. On the other hand, when considering the Akaike Information Criterion (AIC), the Poisson-Gamma model records the lowest value, followed by the negative binomial regression, with the Poisson regression ranking third. Considering the Pearson chi-squared statistic (χ^2) and AIC, the negative binomial regression emerges as the best model among the three.

5. CONCLUSIONS

The analysis underscores the importance of selecting the appropriate model for any given dataset. In conclusion, the results suggest that the highest occurrence of potholes, ranging between 15mm and 55mm, is associated with Japan's winter period, characterised by Monthly Precipitation. The relationship between Relative Pothole Count and Longitudinal slope reveals two peaks in pothole occurrence within gradients of 0-2.5, indicating that as the slope increases, pothole occurrence decreases.

The peak Relative Pothole count occurring between 3000 and 3200 ADT is expected, given that this section is the longest among the 11 characterised sections.

Utilising the Relative Pothole count provides a more intuitive dataset for analysis. Based on these findings, the Negative Binomial model best fits the dataset.

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