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Route Specific Analysis and Prediction of Road Traffic Accidents in Gombe State Using ARIMA Models

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Abstract. Over the years, road traffic accidents have become a significant concern in both developed and developing nations. Thousands of lives are lost annually, in addition to substantial property damage. In Nigeria, numerous studies have examined road traffic accident data, yet few have focused on the dynamics and contributing factors affecting accident severity in the North East region. This study adopts an autoregressive integrated moving average (ARIMA) approach, building upon the Box-Jenkins methodology, to examine the trends and forecasts of road traffic accidents in Gombe State. A predictive model was developed using ten years of FRSC data for four major routes: Gombe–Alkaleri, Gombe–Darazo, Gombe–Kaltungo, and Gombe–Bajoga. Results show that the Gombe–Alkaleri route has the highest accident rate, highlighting the urgent need for targeted safety interventions. The analysis identified ARIMA (1,0,2) as the optimal model for the Gombe–Darazo and Gombe–Kaltungo routes, while ARIMA (2,0,2) and ARIMA (5,1,1) provided the best fit for the Gombe–Bajoga and Gombe–Alkaleri routes, respectively. Contributing factors to accident occurrence include poor road conditions, speeding violations, and dangerous driving practices. The fitted models demonstrate robust predictive accuracy and provide evidence-based insights into future accident patterns.

Keywords: Traffic accidents, Trends, Forecasting, ARIMA, Gombe State

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1. Introduction

Road traffic accidents (RTAs) are collisions involving road vehicles and other vehicles, pedestrians, animals, road debris, or obstacles. Globally, RTAs claim approximately 1.35 million lives annually and cause 20–50 million non-fatal

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injuries (WHO, 2023). Without significant interventions, fatalities could rise to two million by 2030 (WHO, 2023). Currently, RTAs are the ninth leading cause of death worldwide and are projected to become the third by 2030. Developing countries experience disproportionately higher rates of road crashes compared to developed nations (Odukoya et al., 2024). Africa alone accounts for about 20% of global road deaths, despite having fewer vehicles than Europe and Asia, largely due to poorly maintained roads and weak enforcement of traffic regulations (FRSC, 2020).

Nigeria has one of the highest rates of RTAs globally, with about 1,042 deaths per 100,000 vehicles and economic losses estimated at 80 billion annually (Atubi, 2021). Recent FRSC data reported 5,053 deaths from 9,694 crashes in 2022, slightly down from 5,440 deaths in 2021 (FRSC, 2023). Human factors such as speeding, reckless driving, drink driving, driver fatigue, and dangerous overtaking account for nearly 90% of crashes (Waskito et al., 2024; Zeng et al., 2024). These accidents have severe consequences on quality of life, economic productivity, and national development (Lucky and Ezekiel, 2025). For examples, Immurana et al. (2024) reports that road injuries negatively affect economic growth and labor productivity in Africa. Tandrayen-Ragoobur (2025) notes that road traffic fatalities and injuries increase human capital losses and raise the cost of living for citizens in affected countries. Klaver (2020) discusses the significant economic impact of road crashes in the United States, including costs related to medical care, legal services, emergency response, and property damage. Other studies have examined the relationship between traffic fatalities and injuries with GDP, as well as the short- and long-term impacts of road traffic accidents on victims and their communities (Bayraktar et al., 2025; Chan et al., 2025).

Results from the existing literature show that the main target of road traffic accident study remains to reduce the frequency of occurrence and minimize the severity damage (Zeng et al., 2024). One of the most commonly used approaches used to achieve that is the time series analytical tools. Within the time series, ARIMA model is mostly applied and compared to AR and ARMA.

Recent literature show that ARIMA is widely applied in road traffic accident analysis (Mahmudah et al., 2024; Wei et al., 2025). This is because it captures non stationary, temporal dependence and randomness inherent in road crash data (Balawi and Tenekeci, 2024).

In Nigeria, the frequent occurrence of road accidents remains a major social concern, particularly in Gombe State, along Gombe-Kaltungo, Gombe-Darazo, Gombe-Alkaleri, and Gombe-Bajoga highways (FRSC, 2023). On these routes, the major identified contributing factors include inadequate road traffic management, unsafe road conditions, poor enforcement of traffic laws, and driver-related errors (Chan et al., 2025). Despite efforts by the FRSC and other agencies, these problems continue to cause significant human and economic losses (Inah et al., 2025; Tandrayen-Ragoobur, 2025). Our search shows that the majority of ARIMA-based studies on road traffic accident data in Nigeria are state-specific (Ettuk et al., 2019). However, due to geographic variation in road characteristics, environment, and human behavior, it becomes challenging to use a model that has worked well in one location for data collected from a different location. This suggests that the characteristics of accident risk factors in the cited studies may differ from those in Gombe State. In addition, there are fewer studies on road accidents in Gombe State. As a result, statistical analysis of traffic accident data specific to Gombe State is needed to determine the validity and limitations of the current literature on road traffic accidents in Nigeria. Therefore, applying the ARIMA model to address these issues is critically important. Specifically, we examine the influence of road conditions, driver behaviors, vehicle types, and environmental factors on accident prevalence. The contributions of this work include: (1) showcasing the application of the ARIMA model for capturing trend patterns in crash data, (2) developing and validating time series models for road traffic accidents along four major highways in Gombe State, and (3) systematically evaluating the performance of AR, MA, and ARMA models using BIC, AIC, variance, and residual diagnostics before selecting the ARIMA model. Our results and findings will help the managers and users of the four major highways in minimizing road accident occurrences and fatalities in Gombe State. In addition, these results will contribute valuable information to the academic literature on road traffic accidents.

The findings will provide policymakers, law enforcement agencies, and stakeholders with evidence-based insights to design targeted interventions and strengthen road safety strategies in the state. Numerous researchers have investigated road traffic accidents (RTAs), examining their causes, effects, and potential interventions. Studies have focused on diverse aspects such as accident black spots, weather conditions, vehicle maintenance, driver behavior, road design, and environmental factors. Others have developed accident forecasting models and proposed strategies for improving road safety. For instance, Gboyega et al. (2012) identified human error as the leading cause of RTAs in Nigeria, followed by vehicle condition and road/environmental factors. They recommended public awareness campaigns and stricter enforcement of traffic laws as effective countermeasures. Similarly, Ogwude et al. (2025) emphasized the role of driver behavior and road conditions, advocating for enhanced driver training and road maintenance. Research specific to the north east, though limited, shows patterns similar to the national context (Iyanda, 2019). Adamu et al. (2025) highlighted human factors, including speeding and reckless driving, alongside poor road conditions, as primary contributors to accidents. Akande (2021) studied the effect of socio-economic determinants on road accident prevalence in Abuja and Lagos. Several comparative studies in other regions of Nigeria highlight on driver behavior, road conditions, and economic factors (Audu et al., 2021; Okpalaku-Nath et al., 2025). In another research, Uzondu et al. (2022) mentioned that enforcement of restrictions on roadside activities, regular maintenance of traffic control devices, and improved road alignment during construction would enhance safety and significantly reduce RTAs. Bamidele and Baah (2022) Stressed the need for the role of the internet of things technology in reducing the risk of accident. Further, Uzondu (2019) emphasized on role of poor road design, weak enforcement and organization of road safety laws, unsafe road user behavior, and limited research are major obstacles to improving road safety in Nigeria. Abiodun and Jembola (2023); Uhunwagho et al. (2025) further emphasized the role of well-equipped FRSC operations, road repairs, and strengthened driver education. Ajiboye et al. (2022) proposed a comprehensive strategy involving training and licensing programs, road infrastructure improvements, safety legislation, database development, and information sharing for inter-agency collaboration. Although all the articles cited above provide valuable information on the causes and prevention of RTA in Nigeria, significant gaps remain. The search in Gombe state remains limited despite facing a high burden of road accidents. In addition, previous studies focused mainly on human, socio-economic, and infrastructure variables instead of modeling them together.

2. Materials and Method

2.1 *ARIMA Framework*

The ARIMA (p, d, q) model integrates three components: autoregressive (AR), differencing (I for integrated), and moving average (MA). It is widely used for modeling and forecasting time series data that may exhibit non stationarity. The autoregressive process of order p, denoted AR(p), models the current value of a stationary time series as a linear combination of its p past values and a white noise error term:

$$x_t = \phi_1 x_{t-1} + \phi_2 x_{t-2} + \cdots + \phi_p x_{t-p} + w_t, \tag{1}$$

where x_t is a stationary series, ϕ_i are autoregressive parameters, and w_t is white noise with zero mean and variance σ_w^2.

The moving average process of order q, MA(q), expresses the current value as a linear combination of the current and past q white noise error terms:

$$x_t = w_t + \theta_1 w_{t-1} + \theta_2 w_{t-2} + \cdots + \theta_q w_{t-q}, \tag{2}$$

where θ_j are the moving average parameters.

The ARMA(p, q) model combines both AR and MA components to capture dependencies on past values and past errors:

$$x_t = \phi_1 x_{t-1} + \cdots + \phi_p x_{t-p} + w_t + \theta_1 w_{t-1} + \cdots + \theta_q w_{t-q}. \tag{3}$$

However, many real-world time series are nonstationary and require differencing to achieve stationarity. The integrated component d denotes the order of differencing. The differencing operator is defined using the lag operator B (also called β) as

$$\nabla^d = (1 - B)^d, \tag{4}$$

where for $d = 1$,

$$\nabla x_t = x_t - x_{t-1}. \tag{5}$$

Thus, the ARIMA (p, d, q) model is generalized from ARMA by applying d-th order differencing to the observed series y_t to yield a stationary series $x_t =$

$\nabla^d y_t$. The model can then be written compactly using the lag operator as:

$$\phi(B)\,\nabla^d y_t = \theta(B)\,w_t, \tag{6}$$

where

$$\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p, \tag{7}$$

$$\theta(B) = 1 + \theta_1 B + \theta_2 B^2 + \cdots + \theta_q B^q, \tag{8}$$

and w_t is white noise. In this work, we adopted a model-building process based on Al Sulaie (2024), who employed the ARIMA model to forecast future trends in crash consequences in Saudi Arabia. The methodological workflow adopted for our analysis is depicted in Figure 1.

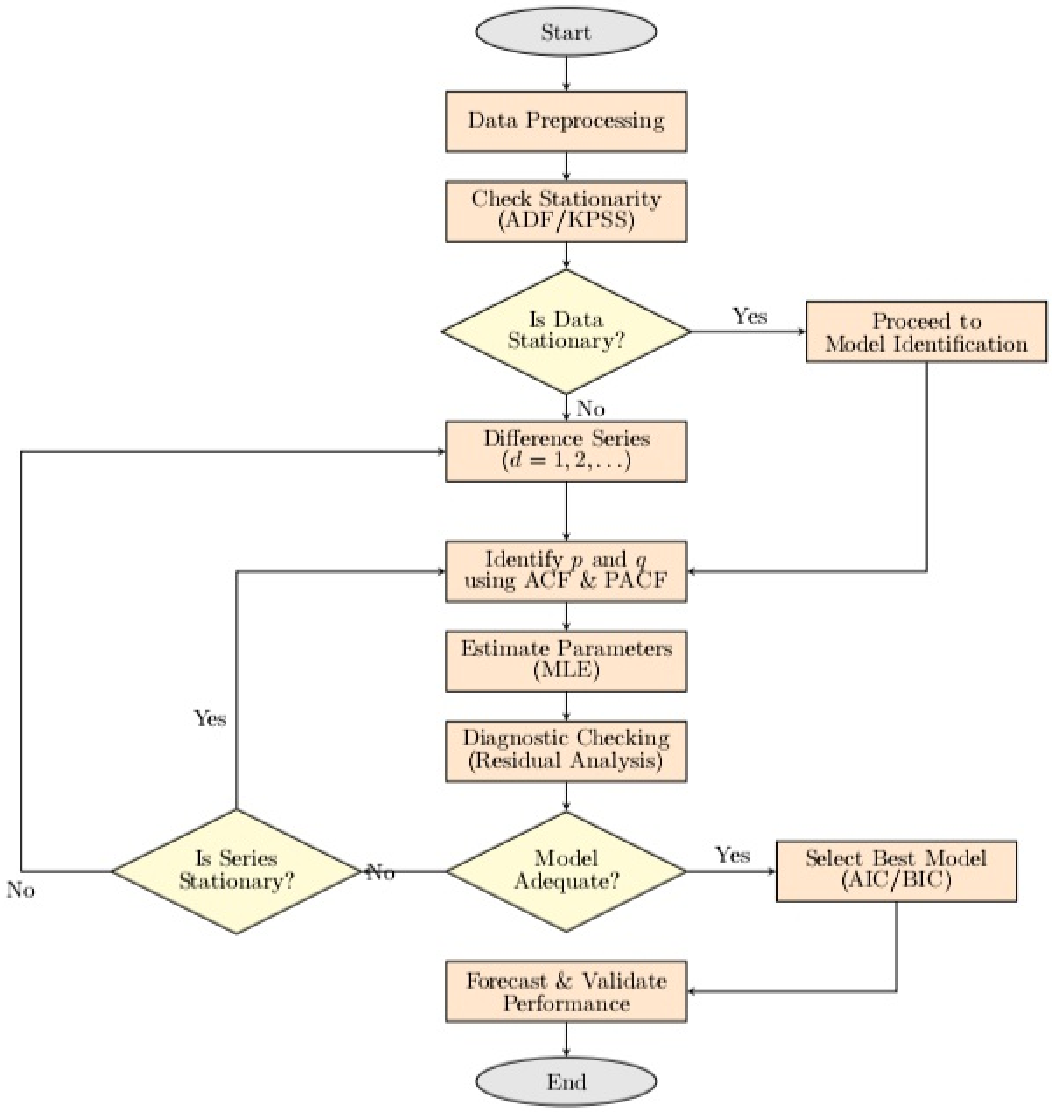

Figure 1: Flowchart of ARIMA time series forecasting using the Box–Jenkin methodology.

To assess predictive performance, we evaluated the ARIMA model alongside related time series forecasting methods in forecasting road traffic accidents across four major routes in Gombe State, with an emphasis on identifying route-specific accident dynamics. After applying the data to the models, the results are presented in the next section.

3. Results and Discussion

This study employed a quantitative research design to develop a time series model capable of capturing the patterns and trends of road traffic accidents (RTAs) in Gombe State, Nigeria. Monthly data covering a ten-year period (2014–2023) were extracted from the official records of the Federal Road Safety Corps (FRSC), which documented the number of reported accidents along four major routes: Gombe–Kaltungo, Gombe–Darazo, Gombe–Alkaleri, and Gombe–Bajoga.

3.1 *Data Analysis*

Time series analysis was applied to examine the trends in RTAs and to build a forecasting model for future occurrences. The analysis was conducted using the R programming environment, with the focus on stochastic models that account for temporal dependence on the data. Specifically, autoregressive integrated moving average (ARIMA) models were considered as the primary modeling framework, given their suitability for univariate time series forecasting (Manikandan et al., 2018; Dutta et al., 2020).
The Augmented Dickey–Fuller (ADF) test Table 1 shows that the time series data for the Gombe–Darazo, Gombe–Kaltungo, and Gombe–Bajoga axes are stationary, as their p-values are all below the 5% significance threshold. Conversely, the Gombe–Alkaleri axis has a p-value of 0.6810 greater than 0.05, indicating non-stationarity. This implies that differencing or transformation is necessary before further modeling of the Alkaleri series.

Table 1: ADF Test Result

Axis	**p-value**
Gombe–Darazo	< 0.0001
Gombe–Kaltungo	< 0.0001
Gombe–Bajoga	< 0.0002
Gombe–Alkaleri	0.6810

Model comparisons for Gombe–Darazo presented in Table 2 indicate that ARMA (1,2) provides the best fit, since it recorded the smallest AIC and BIC. The estimated parameters given in Table 3 show a positive and moderately strong AR (1) term 0.5634, with negative MA1 and MA (2) terms -0.1407 and -0.8593. The non-zero mean 46.86 reflects the long-term level of the series. Small standard errors suggest precise estimates.

Table 2: Gombe–Darazo Model Selection

Model	AIC	BIC	Variance
AR (1)	1187.47	1235.36	0.0000
AR (2)	1171.74	1219.63	0.0000
MA (1)	1161.25	1209.14	0.0000
MA (2)	1160.82	1208.71	0.0000
MA (3)	1147.64	1195.53	0.9487
ARMA (1,1)	1161.37	1209.26	0.0000
ARMA (2,1)	1162.57	1210.46	0.0000
ARMA (1,2)	**1140.14**	**1188.03**	0.9579

Table 3: ARMA (1,2) with Non-Zero Mean (Gombe–Darazo)

	AR1	MA1	MA2	Mean
Estimate	0.5634	-0.1407	-0.8593	46.8645
S.E.	0.0823	0.0664	0.0654	0.2804

For Gombe-Kaltungo, ARMA (1,2) is preferred, see Table 4. Forecasts using an ARIMA (1,0,2) specification displayed in Table 5, show a decreasing trend converging to a steady level near 31, with moderate and relatively stable standard errors across the horizon.

Table 4: Gombe–Kaltungo Model Selection

Model	AIC	BIC	Variance
AR (1)	1174.66	1222.55	0.0000
AR (2)	1162.52	1210.41	0.0000
MA (1)	1156.01	1203.90	0.0000
MA (2)	1153.97	1201.86	0.0000
ARMA (1,1)	1154.46	1202.35	0.0000
ARMA (2,1)	1156.28	1204.17	0.0000
ARMA (1,2)	**1133.80**	**1181.69**	0.0000

Table 5: Forecasted Values using ARIMA (1,0,2) (Gombe–Kaltungo)

Forecasted Value	Standard Error
93.1356941	25.77217
-0.1076953	27.82444
14.0800730	32.03770
21.9045726	33.21333
26.2197540	33.56272
28.5995600	33.66827
29.9120138	33.67543
30.6358270	33.71005
31.0350072	33.71301
31.2551536	33.71391
31.3765634	33.71418
31.4435205	33.71427

Displayed in Table 7 indicate strong persistence AR1 with mean-reversion negative AR2, and MA terms capturing short-run shocks. Twelve-month forecasts presented in Table 8 show an early decline followed by stabilization around 29–31.

Table 6: Gombe–Bajoga Model Selection

Model	AIC	BIC	Variance
AR (1)	1147.05	1194.94	0.0000
AR (2)	1136.30	1184.19	0.0000
MA (1)	1134.81	1182.70	0.0000
MA (2)	1135.62	1183.51	0.0000
ARMA (1,1)	1135.82	1183.71	0.0000
ARMA (2,1)	1137.71	1185.60	0.0000
ARMA (1,2)	1114.12	1162.01	0.0000
ARMA (2,2)	**1112.38**	**1160.27**	0.0000

Table 7: ARMA (2,2): Coefficients and Fit Statistics (Gombe–Bajoga)

Parameter	Estimate	S.E.
AR1	0.9502	0.2235
AR2	−0.3878	0.1917
MA1	−0.6582	0.2677
MA2	−0.3418	0.2669
Mean	29.1440	0.1836
Model Fit Statistics		
Variance	566.2	–
Log Likelihood	−550.19	–
AIC	1112.38	–
AICc	1113.12	–
BIC	1129.11	–

Table 8: Forecasts for Next 12 Months using ARIMA (2,0,2) (Gombe–Bajoga)

Period	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
1	73.88150	43.90842	103.85458	28.04163	119.72137
2	31.86123	0.56838	63.15409	−15.99706	79.71953
3	14.37747	−19.59855	48.35348	−37.58436	66.33930
4	14.05904	−23.52362	51.64171	−43.41869	71.53677
5	20.53638	−18.38833	59.46110	−38.99383	80.06660
6	26.81468	−12.25810	65.88746	−32.94198	86.57134
7	30.26855	−8.81048	69.34759	−29.49768	90.03478
8	31.11583	−8.01349	70.24515	−28.72730	90.95896
9	30.58156	−8.58099	69.74410	−29.31239	90.47550
10	29.74533	−9.42465	68.91532	−30.15999	89.65066
11	29.15793	−10.01219	68.32804	−30.74759	89.06345
12	28.92404	−10.24659	68.09468	−30.98227	88.83036

For Gombe-Darazo road, forecasts from ARIMA (1,0,2) (Table 9) show an initial sharp decline from 110 in January to 39 in February, followed by stabilization between 46 and 47 for the remainder of the year. Early confidence intervals are wider and narrow later, indicating improved reliability.

We also include a broader model screen used in cross-axis comparisons as displayed in Table 10.

Table 9: Forecasted Values for the Next 12 Months using ARIMA (1,0,2) (Gombe–Darazo)

Month	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
Jan	110	75.79482	144.76241	57.54020	163.01703
Feb	39	1.88185	76.97359	−17.99374	96.84917
Mar	43	−0.35725	85.70588	−23.13679	108.48541
Apr	45	−0.12872	89.13587	−23.75564	112.76278
May	46	0.40565	90.66285	−23.48400	114.55249
Jun	46	0.82995	91.40000	−23.14249	115.37244
Jul	46	1.10761	91.77675	−22.89106	115.77542
Aug	47	1.27625	91.97682	−22.73074	115.98381
Sep	47	1.37514	92.08569	−22.63449	116.09532
Oct	47	1.43208	92.14580	−22.57839	116.15627
Nov	47	1.46456	92.17928	−22.54618	116.19001
Dec	47	1.48298	92.19802	−22.52784	116.20884

Table 10: Model Selection Screen (Another Axis)

Model	AIC	BIC	Variance
AR1	1195.964	1243.854	0.0000
AR2	1179.216	1227.106	0.0000
AR3	1181.215	1229.105	0.0000
MA1	1178.377	1226.267	0.0000
MA2	1177.931	1225.821	0.0000
MA3	1159.814	1207.704	0.0000
ARMA (1,0,1)	1178.516	1226.406	0.0000
ARMA (2,0,1)	1180.177	1228.067	0.0000
ARMA (1,0,2)	1154.161	1202.051	0.0000
ARMA (2,0,2)	**1153.596**	**1201.486**	0.0000
ARIMA (1,1,1)	1190.922	1238.812	0.0000
ARIMA (2,1,1)	1174.968	1222.858	0.0000
ARIMA (1,1,2)	1173.703	1221.593	0.0000
ARIMA (2,1,2)	1175.468	1223.358	0.0000

Figures 2–5 present trend analyses from 2014 to 2023 for all axes. Seasonal patterns with regular peaks and troughs are evident in Darazo, Kaltungo, and Bajoga, confirming strong cyclical influences. The Alkaleri axis shows more irregular fluctuations, consistent with the ADF result. Forecast plots (Figures 6–9) show that Darazo and Kaltungo stabilize after initial fluctuations, Bajoga shows similar stabilization with declining volatility, while Alkaleri remains unstable and may require more complex modeling or structural interventions.

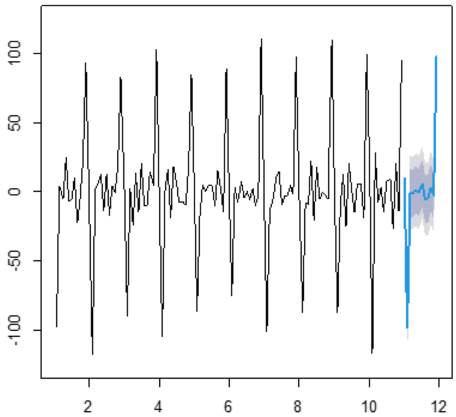

Figure 2: Forecasted trend for Gombe to Alkaleri axis

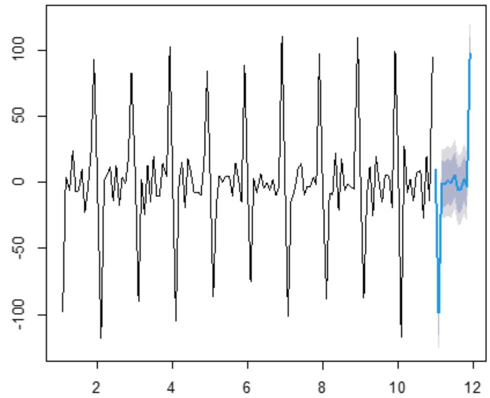

Figure 3: Forecasted trend for Gombe to Bajoga axis

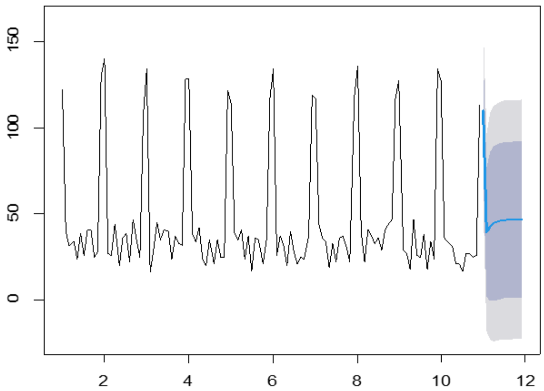

Figure 4: Forecasted trend from ARIMA(1,0,2) for Gombe to Darazo

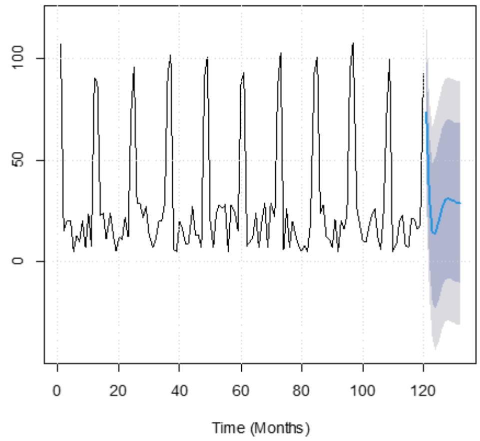

Figure 5: Forecasted trend from ARIMA (2,0,2) for Gombe to Kaltungo

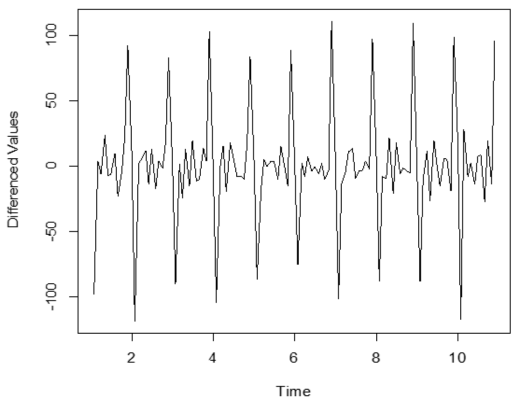

Figure 6: Gombe to Alkaleri axis (2014-2023)

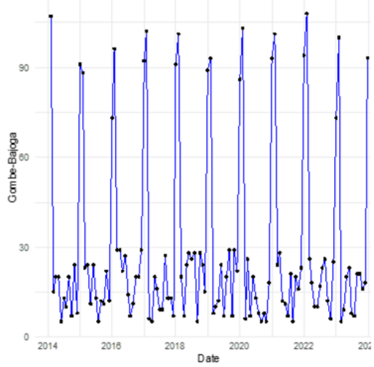

Figure 7: Gombe to Bajoga (2014-2023) Trend analysis

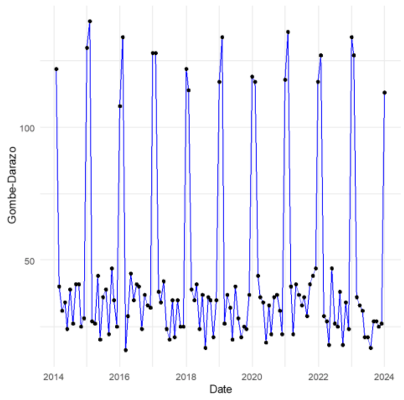

Figure 8: Gombe to Darazo (2014-2023) Trend analysis

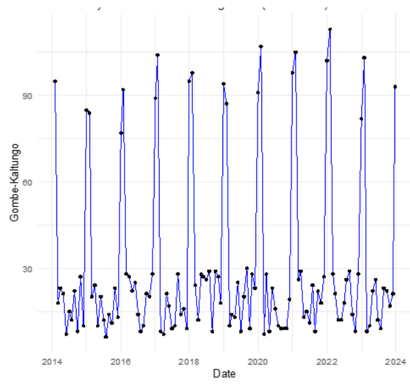

Figure 9: Gombe to Kaltungo (2014-2023) Trend analysis

Complementary to the time series forecasts, Table 11 highlights respondents' perceptions of silent causes of road accidents across Gombe State. Road environment (10.2%), bad roads (9.9%), speed violations (9.5%), and dangerous driving (8.1%) are the leading factors, underscoring how infrastructure and driver behavior affect transportation flow and accident risks.

Table 11: Perception of Respondents on Silent Causes of Road Accidents in Gombe State

Cause	**Frequency**	**Percent**	**Percentage of Cases**
Speed violation	175	9.5	87.5
Loss of control	72	3.9	36.0
Dangerous driving	150	8.1	75.0
Wrongful overtaking	89	4.8	44.5
Route violation	49	2.6	24.5
Dangerous overtaking	122	6.6	61.0
Overloading	103	5.6	51.5
Sleeping on steering	63	3.4	31.5
Driver under alcohol/drug	89	4.8	44.5
Use of phone while driving	92	5.0	46.0
Fatigue	31	1.7	15.5
Road environment	189	10.2	94.5
Bad road	183	9.9	91.5
Road obstruction violation	49	2.6	24.5
Poor weather	117	6.3	58.5
Sign light violation	37	2.0	18.5
Vehicle	144	7.8	72.0
Tyre burst	29	1.6	14.5
Brake failure	56	3.0	28.0
Mechanically defective vehicle	12	0.6	6.0
Total	1851	100.0	925.5

Consistent with the ADF result, the Gombe-Alkaleri series requires differencing to achieve stationarity. The selected specification, presented in Table 12, is

ARIMA (5,1,1), with multi-month forecasts and uncertainty intervals shown in Table 13. The profile includes sizable swings notably a deep negative estimate in February and a sharp increase in December— signaling heightened volatility and potential sensitivity to exogenous shocks. Planning for this axis should remain adaptive, with emphasis on monitoring and intervention readiness.

Table 12: Fitted ARIMA (5,1,1) (Gombe–Alkaleri)

Coefficient	**Estimate**	**S.E.**
AR1	-0.8523	0.0959
AR2	-0.6587	0.1222
AR3	-0.5130	0.1285
AR4	-0.3846	0.1252
AR5	-0.1611	0.1035
SMA1	-0.8548	0.1539
σ^2	101.1	–
Log Likelihood	-403.85	–
AIC	821.69	–
AICc	822.82	–
BIC	840.40	–

Table 13: Forecasted Values for Next 12 Months using ARIMA (5,1,1) (Gombe–Alkaleri)

Month	**Point Forecast**	**Lo 80**	**Hi 80**	**Lo 95**	**Hi 95**
Jan	10.0617	-2.9177	23.0411	-9.7886	29.9119
Feb	-98.5959	-115.6344	-81.5575	-124.6540	-72.5379
Mar	-0.6434	-17.7043	16.4174	-26.7357	25.4489
Apr	-1.3079	-18.3692	15.7534	-27.4009	24.7850
May	1.4562	-15.6063	18.5187	-24.6387	27.5510
Jun	-0.7369	-17.8751	16.4014	-26.9476	25.4739
Jul	5.9450	-11.1932	23.0831	-20.2656	32.1555
Aug	-5.4809	-22.6650	11.7032	-31.7617	20.7999
Sep	-4.9709	-22.1558	12.2140	-31.2529	21.3111
Oct	2.9846	-14.2003	20.1695	-23.2974	29.2666
Nov	-2.7714	-19.9581	14.4153	-29.0562	23.5133
Dec	97.8715	80.6842	115.0589	71.5857	124.1573

Overall, the ARMA (1,2) and ARIMA (2,0,2) models provide robust forecasts for Darazo, Kaltungo, and Bajoga, as evidenced by low AIC and BIC values and white-noise residuals. The consistent convergence of forecasts around stable means suggests that transport flows along these routes follow regular seasonal cycles with predictable long-run equilibria, supporting parsimonious ARMA and ARIMA choices under stable conditions. By contrast, the Alkaleri axis presents volatility and unpredictability; large forecast intervals imply that resource allocation and safety planning should be flexible and adaptive. The prominence of road environment and road quality in the perception data aligns with the volatility observed on Alkaleri. Infrastructure investment and enforcement on speed control may not only improve safety outcomes but also stabilize demand patterns. These findings align with prior research where ARMA and ARIMA perform well for short term transport forecasting under stable regimes. Under strong external shocks or irregularities, hybrid approaches such as SARIMA, ARIMAX, state space, GARCH, or machine learning methods can be considered to improve accuracy.

4. Conclusion

This study analyzed used data from Federal Road Safety Corps (FRSC) records to model and forecast road traffic accidents (RTAs) across four major routes in Gombe State. It main objective is to identify route-specific accident dynamics and provide better forecasts to inform targeted safety interventions. Our findings show that the Gombe–Alkaleri route records the highest accident burden. Model selection favored ARMA (1,2) for Gombe–Darazo and Gombe–Kaltungo and ARMA (2,2) for Gombe–Bajoga, with model forecasts producing ARIMA (1,0,2) for Darazo and Kaltungo and ARIMA (2,0,2) for Bajoga, while Gombe–Alkaleri shown as the best ARIMA (5,1,1) after differencing. Across routes, poor road environment and pavement condition, speed violations, and dangerous driving are identified risk factors of road traffic accident. Our results also show that route-level evidence that ARMA and ARIMA models can capture short-term accident dynamics with reliable predictive accuracy. Policy implications may include prioritizing road rehabilitation and speed management on Gombe–Alkaleri and sustaining routine enforcement on the more stable routes. The limitations include the use of secondary data and the absence of exogenous covariates. Future work may incorporate traffic counts, weather, and engineering predictors based on SARIMA and ARIMAX and compare performance with machine-learning techniques. This study provides an evidence-based route-specific road traffic accident in Gombe State via ARMA and ARIMA and provide insight and actionable results for professionals and policy makers not only in gombe state but nationally and globally.

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