Research Article GU J Sci, Part A, 13(3): 1328-1354 (2026) 10.54287/gujsa.1968177

Gazi University
Journal of Science
PART A: ENGINEERING AND INNOVATION
http://dergipark.org.tr/gujsa

Trend Analysis of Road Traffic Accident Injuries and Fatalities Using Nonparametric Statistical Methods: A Temporal and Seasonal Assessment

Ayşe ÜNAL[1*] İslam GÖKALP[2] Serdar EKINCI[3] Muhammet İsmail GÜNGÖR[4] Davut İZCI[4]

[1] Alanya Alaaddin Keykubat University, Rafet Kayış Faculty of Engineering, Department of Civil Engineering, Division of Transportation, 07425, Alanya, Türkiye
[2] Batman University, Engineering and Architecture Faculty, Civil Engineering Department, Division of Transportation, 72000, Batman, Türkiye
[3] Bitlis Eren University, Department of Computer Engineering, Division of Computer Hardware 13100, Bitlis, Türkiye
[4] Bursa Uludağ University, Department of Electrical and Electronics Engineering, Division of Control and Command Systems, 16059, Bursa, Türkiye

Keywords

Innovative Polygon Trend Analysis
Innovative Trend Analysis
Nonparametric Methods Traffic Accidents
Sen Slope Test Method
Mann-Kendall

Abstract

Road traffic accidents remain a major public health concern, requiring systematic analyses of temporal trends to support evidence-based road safety planning. This retrospective longitudinal study analyzes traffic accident-related injuries and fatalities in Diyarbakir Province, Türkiye, based on official records from 2014 to 2023. The study evaluates temporal trends in accident severity and their associations with selected accident-related variables across monthly, seasonal, and annual scales. Four complementary non-parametric trend analysis methods, including Innovative Trend Analysis (ITA), Innovative Polygon Trend Analysis (IPTA), the Sen Slope Test Method (SSTM), and the Mann-Kendall (MK) trend test, were applied to injury and fatality data. Correlation analysis was also performed to examine the associations between 26 accident-related parameters and injury and fatality counts. The results revealed a statistically significant decreasing trend in injury counts, whereas fatalities showed increasing tendencies during specific periods, indicating that reductions in accident frequency were not accompanied by proportional decreases in accident severity. Seasonal analysis showed that injuries occurred more frequently in summer, while fatalities were relatively higher in winter and spring. Correlation analysis identified significant associations between accident outcomes and several traffic-related variables, highlighting the complex temporal characteristics of road traffic accidents. Overall, the findings demonstrate the importance of integrating complementary non-parametric trend analysis methods for evaluating accident severity patterns and supporting regional road safety assessment.

Cite

Ünal, A., Gökalp, İ., Ekinci, S., Güngör, M. İ., & İzci, D. (2026). Trend Analysis of Road Traffic Accident Injuries and Fatalities Using Nonparametric Statistical Methods: A Temporal and Seasonal Assessment. *GU J Sci, Part A*, *13*(3), 1328-1354. doi:10.54287/gujsa.1968177

Author ID (ORCID Number)

0000-0002-3262-135X Ayşe ÜNAL
0000-0003-3198-3508 İslam GÖKALP
0000-0002-7673-2553 Serdar EKINCI
0009-0003-9241-770X Muhammet İsmail GÜNGÖR
0000-0001-8359-0875 Davut İZCI

Article Process

Submission Date **.**.****
Revision Date **.**.****
Accepted Date **.**.****
Published Date **.**.****

1. INTRODUCTION

Road transportation constitutes the backbone of modern mobility, serving as the primary means by which both people and goods are moved across geographies. Among all transport modes, highway systems are by far the most widely used, accounting for nearly 90% of total passenger and freight movement in most countries (WHO, 2023). The accessibility and flexibility that road transport offers connecting origins and destinations with minimal interruption has made it indispensable to everyday life. Yet this same ubiquity carries a profound and persistent cost. The sheer volume of traffic generated by a growing global population has brought with it

*Corresponding Author, e-mail: unal.ayse@alanya.edu.tr

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an alarming incidence of road traf-fic accidents, which are now recognised as one of the leading causes of preventable death and disability worldwide. According to data published by the World Health Organization (WHO) in 2023, approximately 1.19 million people lose their lives annually as a result of road traffic accidents, and between 20 and 50 million others sustain inju-ries of varying severity (WHO, 2023). These figures confirm that road traffic accidents are no longer a concern confined to the domain of transport engineering alone they constitute a serious and multidimensional public health crisis.

The factors that influence the frequency and severity of traffic accidents have been examined extensively in the literature and are broadly grouped into environ-mental and temporal categories. Environmental influences include seasonal variabil-ity, prevailing weather and climate conditions, and the physical characteristics of road infrastructure (Hyodo & Hasegawa, 2021; Sangkharat et al., 2021; Zou et al., 2021; Basagaña & de la Peña-Ramirez, 2023). Temperature extremes, precipitation, and adverse atmospheric conditions have all been shown to affect driver behaviour and vehicle dynamics, thereby contributing to accident risk. At the same time, temporal patterns in traffic flow including the distinction between peak and off-peak hours, differences in acci-dent rates between weekdays and weekends, and elevated risks associated with public holidays and seasonal travel periods have attracted considerable research attention (Adeyemi et al., 2021; Doucette et al., 2021; Macioszek & Kurek, 2021; Zhang et al., 2024). The interplay of these environmental and temporal dimensions underscores the complexity of road accident causation and the difficulty of designing universally effec-tive safety interventions.

The Mann-Kendall test, originally proposed by Mann (1945) and subsequently for-malised by Kendall (1975), is a rank-based nonparametric procedure for detecting mon-otonic trends in time series data. Because it makes no assumption regarding the un-derlying distribution of observations, it is well suited to traffic accident data, which are often skewed or irregularly distributed (Hamed & Ramachandra Rao, 1998). The test has been widely adopted in hy-drology and environmental science, and its application to transportation engineering has grown steadily in recent years (Yue et al., 2002; Şen, 2012). Yue et al. (2002) demonstrated the utility of the MK test in analysing accident trends in conjunction with environmental variables, establishing it as a credible analytical tool in traffic safety research. Its application to road accident data enables the identification of periods in which accident frequencies or fatality rates show statistically significant directional change, thereby informing the temporal targeting of safety interventions. Earlier studies (Shahid et al., 2015; Yasmin & Eluru, 2018) have applied the MK test in traffic safety contexts with varying geographic and regulatory settings, while more focused investigations such as that of Ngwira et al. (2023) in Malawi and Melchor et al. (2015) in Spain have demonstrated that the test is capable of capturing both deteriorating and improving safety trajectories over multi-year periods. These findings highlight the value of the MK test as a diagnostic tool for policy evaluation.

Closely associated with the MK test, the Sen Slope Test Method (SSTM), intro-duced by Sen (1968), provides a nonparametric estimate of the magnitude of a trend in time series data. It computes the median slope across

all possible pairs of observations, thereby yielding a robust estimator that is relatively insensitive to outliers and extreme values a characteristic of particular importance when working with accident counts, which may be heavily influenced by isolated catastrophic events. The SSTM is most commonly applied in conjunction with the MK test (Hirsch et al., 1982), so that the statistical significance of a trend and its quantitative rate of change can be assessed simultane-ously. Within the traffic safety literature, this combined approach has been employed to characterise long-term changes in accident rates across diverse contexts (Yue et al., 2002; Şen, 2012). Shahid et al. (2015) applied the SSTM to accident data in Malaysia, identifying a statisti-cally significant upward trend in accident rates, while Yasmin and Eluru (2018) high-lighted its suitability for regional traffic safety analysis in the United States. The method's resistance to the distorting effects of outlier observations strengthens its credibility when applied to disaggregated temporal datasets.

Alongside these established nonparametric tools, innovative graphical trend analysis methods have emerged as powerful complements for the visual and compara-tive interpretation of temporal patterns. The Innovative Trend Analysis (ITA) method, developed by Şen (2012), offers a distinctive approach by dividing a time series into two equal sub-periods and plotting the first against the second on a Cartesian plane. Departures from the 1:1 line known as the no-trend line provide an immediate and intuitive indication of whether conditions in the more recent period are higher or low-er than in the earlier period. This visual transparency is a significant practical ad-vantage, as it allows trends to be interpreted without requiring prior knowledge of the statistical distribution of the data. The Innovative Polygon Trend Analysis (IPTA), an extension of ITA, introduces polygon-based visualisation to capture the behaviour of the entire time series more comprehensively, and is particularly effective in the pres-ence of noisy or fluctuating data (Mazrekaj et al., 2022). Mazrekaj et al. (2022) demonstrated the applicabil-ity of IPTA to road accident analysis in a case study from Kosovo, while Hossain et al. (2022) showed that the combined use of ITA and the MK test provides a fuller picture of accident dynamics than either method alone. The spatial and temporal dimensions of accident trends have been further examined by Muguro et al. (2020) in Kenya and Kričković et al. (2024) in Serbia, with both studies illustrating how innovative trend methods can reveal distributional patterns that traditional approaches may obscure. Forecasting-oriented approaches, such as the time series model applied by Yousefzadeh-Chabok et al. (2016), complement these descriptive analyses by extending the tem-poral horizon of safety assessments. Although nonparametric trend analysis methods such as MK, SSTM, ITA, and IPTA have been widely applied in hydrology, climatology, and environmental sciences, their application to traffic accident analyses in Türkiye remains very limited. Existing national traffic safety studies have predominantly focused on accident statistics, spatial hotspot identification, roadway characteristics, and conventional statistical analyses rather than integrated nonparametric trend analysis approaches (Çelik, 2013; Yıldırım et al., 2023; Fidan et al., 2024; Kulaç & Arslankaya, 2024; Özçelebi, 2024).

Despite the considerable volume of research on road traffic accident trends, a re-view of the existing literature reveals that the joint application of the MK test, SSTM, ITA, and IPTA within a single, integrated analysis

remains uncommon in the field of transportation. These methods have each been applied in isolation or in partial com-binations, and their individual virtues are well documented. However, a unified ana-lytical framework that simultaneously exploits the distributional robustness of the MK test and SSTM, the graphical transparency of ITA, and the polygon-based comparative depth of IPTA has seldom been brought to bear on traffic accident datasets, particularly at the sub-national level in regions where accident dynamics may differ markedly from national averages. The present study was designed to address this gap. Using a ten-year dataset of traffic accidents recorded in Diyarbakir province, Turkey, between 2014 and 2023, the temporal trends in total injuries and total fatalities are analysed through the combined application of ITA, IPTA, SSTM, and MK test, supplemented by a correlation analysis of 26 accident-influencing parameters. The findings are intended to contribute to a more evidence-based formulation of regional traffic safety policies, and to demonstrate the analytical value of integrating multiple nonparametric trend methods within a single study.

As previously highlighted, road traffic accidents remain a major global public health and socioeconomic concern, despite ongoing improvements in transportation systems and safety measures. Turkey also faces this challenge, with TURKSTAT/TÜİK (2026a) reporting more than 1.5 million traffic accidents in 2025, including 288,321 accidents involving death or injury that resulted in 6,035 fatalities and 403,937 injuries. These figures highlight the considerable burden of traffic accidents in Türkiye and the need for effective, evidence-based road safety strategies.

Within this national context, Diyarbakir Province represents an important regional case study due to its strategic location in southeastern Turkey, a population of approximately 1,8 million, and a heavily used road network. Previous studies have investigated traffic safety conditions in Turkey, particularly in Diyarbakir, to provide scientific support for policymakers and transportation authority's (Erenler & Gümüş, 2019; Kuşkapan et al., 2019; Ersen et al., 2021; Can et al., 2022; Dogrul & Alkan, 2022). According to TURKSTAT/TÜİK (2026b), Diyarbakir recorded more than 16,000 traffic accidents during the most recent reporting year, resulting in 133 fatalities and more than 6,000 injuries. Therefore, this study evaluates temporal trends in traffic accident fatalities and injuries in Diyarbakir during the 2014–2023 period using four nonparametric methods: Innovative Trend Analysis (ITA), Innovative Polygon Trend Analysis (IPTA), the Sen Slope Test Method (SSTM), and the Mann–Kendall (MK) trend test. In addition, it examines the relationships between 26 accident-related variables and accident outcomes to identify the factors associated with accident occurrence and severity.

2. MATERIALS AND METHODS

2.1. Study Area and Data

Diyarbakir province is situated in the Southeastern Anatolia Region of Turkey, at approximately 37°55' north latitude and 40°12' east longitude. It shares borders with Batman and Muş to the east, Mardin to the south, Şanlıurfa, Adıyaman, and Malatya to the west, and Elazığ and Bingöl to the north. Geographically, the province occupies the northern tip of Mesopotamia and rests on an elevated plateau along the banks of the Tigris River,

a location that has historically rendered it a significant centre of commerce and cultural exchange. With a surface area of approximately 15,168 km², Diyarbakir ranks among the largest provinces in Turkey (DG, 2025; DMM, 2025). Its topography is characterised by the Taurus Mountains in the southeastern portion and by comparatively flat terrain toward the interior. In terms of population, the province was home to approximately 1,852,356 residents according to 2025 data, making it the twelfth most populous province in the country (TURKSTAT/TÜİK, 2026c). The geographic position of Diyarbakir within Turkey is illustrated in Figure 1.



Figure 1. *Location of the study area*

The traffic accident data analysed in this study were obtained from the Ministry of Interior, General Directorate of Security, and cover a continuous ten-year period from 2014 to 2023. Descriptive statistics derived from this dataset are presented in Table 1, disaggregated by month, season, and year for both the total number of injured persons and the total number of fatalities.

Turning to the dataset in Table 1, the monthly fatality counts were generally characterised by low absolute values, with the minimum recorded as zero in several months. The single highest monthly maximum was observed in March, at 9 fatalities, although March does not yield the highest monthly mean. The months of August, September, and October recorded the highest mean fatality counts on a monthly basis. At the seasonal level, spring again showed the greatest variability, with the number of fatalities ranging from 0 to 15 and a standard deviation of 4,7, substantially larger than those of the other seasons. Autumn and summer exhibited broadly comparable fatality patterns, while the annual fatality data, ranging from a minimum of 6 to a maximum of 38 with a mean of 18.4, underscore the extent to which seasonal dynamics shape the aggregate yearly outcome. In summary, the descriptive statistics in Table 1 consistently indicate that summer months are associated with higher injury counts attributable in large part to the intensification of human mobility and traffic volume during this period while the variability in both injuries and fatalities is greatest in spring and

summer, suggesting that these seasons are the most analytically consequential for the purposes of trend detection and safety policy.

Table 1. *Descriptive statistics of traffic accident data for Diyarbakir province (2014–2023)*

Variables	Obs.	Number of Injuries				Total Fatalities			
		Minimum	Maximum	Mean	Std. deviation	Minimum	Maximum	Mean	Std. Dev
Jan	10	104.000	221.000	167.400	35.868	0.000	1.000	0.500	0.527
Feb	10	96.000	205.000	133.800	32.758	0.000	4.000	0.900	1.287
Mar	10	113.000	194.000	165.300	25.569	0.000	9.000	1.500	2.759
Apr	10	53.000	241.000	159.200	56.223	0.000	3.000	1.200	1.033
May	10	86.000	208.000	167.300	41.018	0.000	4.000	1.000	1.414
Jun	10	94.000	270.000	180.800	49.868	0.000	5.000	1.700	1.636
Jul	10	134.000	282.000	208.400	45.819	0.000	3.000	1.300	1.059
Aug	10	132.000	268.000	194.000	46.397	1.000	6.000	2.500	1.780
Sep	10	141.000	232.000	184.000	27.341	0.000	5.000	2.300	1.767
Oct	10	139.000	233.000	185.600	34.268	0.000	5.000	2.300	1.567
Nov	10	118.000	251.000	182.600	38.592	0.000	6.000	1.300	1.829
Dec	10	112.000	198.000	167.200	24.380	0.000	5.000	1.900	1.729
Winter	10	369.000	566.000	468.400	68.490	0.000	6.000	3.300	2.111
Spring	10	252.000	619.000	491.800	114.044	0.000	15.000	3.700	4.668
Summer	10	367.000	771.000	583.200	120.888	3.000	11.000	5.500	2.991
Autumn	10	439.000	653.000	552.200	75.909	2.000	13.000	5.900	3.843
Annual	10	1449.000	2561.000	2095.600	330.594	6.000	38.000	18.400	10.058

2.2. Data Analysis Methods

Previous studies have demonstrated that a rigorous statistical framework is essential for detecting and quantifying temporal trends in accident data due to its complex and variable nature. Parametric approaches require distributional assumptions that are often difficult to verify in real-world datasets, whereas nonparametric methods provide a more robust and flexible alternative. Among the widely used approaches are the Mann–Kendall (MK) trend test, the Sen Slope Test Method (SSTM), and innovative trend analysis techniques, including Innovative Trend Analysis (ITA) and Innovative Polygon Trend Analysis (IPTA). Each method provides a distinct perspective on temporal variations, and their combined application enables a comprehensive assessment of accident trends across multiple temporal scales.

To enable a comparative evaluation of how accident outcomes have evolved over time, the complete ten-year dataset was partitioned into two consecutive sub-periods of equal length: the first covering 2014–2018 and the second covering 2019–2023, each comprising five years of observations. This division provides the structural basis for the ITA and IPTA analyses, in which the two sub-periods are compared directly to identify short-term and medium-term shifts in accident patterns. The SSTM and MK test are then applied across the full dataset to assess long-term monotonic trends and their statistical significance at monthly, seasonal, and annual resolutions.

In addition to the trend analyses, the relationships between a set of 26 accident-influencing parameters and the two outcome variables total injuries and total fatalities were examined through a comparative correlation analysis, as described in Section 4.5. This supplementary analysis allows the structural and environmental characteristics most strongly associated with accident occurrence and severity to be identified, thereby providing a contextual dimension that reinforces and enriches the temporal trend findings. Taken together, the four trend methods and the correlation analysis form an integrated analytical framework through which the evolution of road traffic accidents in Diyarbakir province is systematically characterised.

2.2.1. Innovative Trend Analysis

The Innovative Trend Analysis (ITA) is a graphical, nonparametric method developed to detect and visualise monotonic or non-monotonic trends in time series data (Şen, 2012; Pastagia & Mehta, 2022). Unlike conventional trend detection approaches (which typically operate on the time series as a whole and may obscure sub-period dynamics) ITA achieves its analytical transparency by partitioning the data into two consecutive and equal sub-periods, which are then compared directly against one another. This structural division allows temporal changes to be rendered immediately observable without requiring prior assumptions about the statistical distribution of the underlying data, making the method particularly well suited to traffic accident records that may exhibit irregular or non-normal behaviour.

In the present study, the complete ten-year accident dataset is divided into two chronologically ordered sub-series of equal length. The first sub-series, denoted $X_1 = \{x_1, x_2, \dots, x_m\}$, encompasses the traffic accident records for the period 2014–2018, while the second sub-series, $X_2 = \{x_{m+1}, x_{m+2}, \dots, x_n\}$, covers the period 2019–2023. The arithmetic means of the two sub-series are then computed according to:

$$\bar{X}_1 = \frac{1}{m}\sum_{i=1}^{m} x_i \tag{1}$$

$$\bar{X}_2 = \frac{1}{m}\sum_{i=m+1}^{n} x_i \tag{2}$$

where $\bar{X}_1$ and $\bar{X}_2$ denote the mean number of accidents in the first and second periods, respectively. These period averages serve as the primary quantities through which temporal change is assessed.

To visualise the trend, the ordered values of the first sub-series are plotted along the horizontal axis against the corresponding values of the second sub-series on the vertical axis. A reference line defined by $Y = X$ (representing a condition of no change between the two periods) is superimposed on this scatter plot. The position of the data points relative to this diagonal line carries direct interpretive meaning: points that fall above the $Y = X$line indicate that the second-period values exceed those of the first period, signifying an increasing trend, whereas points falling below the line reflect a declining trend between the two sub-periods. Points lying on or in close proximity to the diagonal suggest the absence of any meaningful directional change.

This geometric interpretation provides an intuitive and visually accessible basis for trend detection, and its application to the monthly, seasonal, and annual accident data in this study allows both the direction and the relative magnitude of changes in injuries and fatalities to be assessed across multiple temporal scales.

2.2.2. Innovative Polygon Trend Analysis

The Innovative Polygon Trend Analysis (IPTA) is a graphical nonparametric method that extends the analytical framework of ITA by introducing a polygon-based visualisation scheme for the comparison of temporal sub-periods (Şen et al., 2019). While sharing the same foundational logic as ITA namely, the division of a time series into two equal consecutive segments IPTA provides a richer and more structured visual representation that is particularly effective when the data are noisy, oscillatory, or subject to pronounced seasonal fluctuations, as is typically the case with traffic accident records.

Consider a time series of total length n, defined as $X = \{x_1, x_2, \dots, x_n\}$, where Xrepresents the sequence of traffic accident observations. This series is partitioned into two chronologically ordered sub-series of equal length: the first sub-series, $X_A = \{x_1, x_2, \dots, x_m\}$, corresponding to the period 2014–2018, and the second sub-series, $X_B = \{x_{m+1}, x_{m+2}, \dots, x_n\}$, corresponding to the period 2019–2023. The arithmetic means of the two sub-series are computed as:

$$\bar{X}_A = \frac{1}{m}\sum_{i=1}^{m} x_i \tag{3}$$

$$\bar{X}_B = \frac{1}{m}\sum_{i=m+1}^{n} x_i \tag{4}$$

where $\bar{X}_A$and $\bar{X}_B$denote the mean accident counts for the first and second periods, respectively. These period averages constitute the vertices of the IPTA polygon, which is constructed by connecting the paired sub-period means across successive temporal units months or seasons, as applicable to form a closed polygon on the Cartesian plane.

The interpretation of the resulting polygon follows a straightforward geometric logic. When $\bar{X}_B > \bar{X}_A$, the data point associated with that temporal unit lies above the no-trend reference line, indicating that accident counts in the second period exceed those of the first, and therefore reflecting an increasing trend. Conversely, when $\bar{X}_B < \bar{X}_A$, the corresponding point falls below the reference line, indicating a declining trend between the two sub-periods. The shape and area of the polygon as a whole provide an integrated visual summary of how accident dynamics have evolved across all temporal units simultaneously, making it possible to identify not only the direction but also the relative magnitude of change at each point in the annual cycle. In the present study, this method is applied separately to total injury counts and total fatality counts on both a monthly and a seasonal basis, allowing the spatial configuration of the resulting polygons to be compared directly and the differential behaviour of injuries and fatalities to be interpreted within a unified graphical framework.

2.2.3. Sen Slope Test Method

The Sen Slope Test Method (SSTM), originally proposed by Sen (1968), and further developed within the broader framework of nonparametric trend estimation (Theil, 1950), is employed in the present study to quantify the magnitude of temporal trends in traffic accident injury and fatality data over the ten-year observation period from 2014 to 2023. The method is particularly well suited to this context because of its robustness to outliers, a property that arises from its reliance on the median rather than the mean of pairwise slope estimates, and which makes it considerably more reliable than classical linear regression when the data contain extreme or anomalous values (Theil, 1950; Hamed & Ramachandra Rao, 1998; Yue et al., 2002). In recognition of this advantage, the SSTM is applied here in conjunction with the Mann-Kendall trend test, so that the statistical significance of an identified trend and the numerical rate of that trend can be assessed within a unified analytical framework.

Given a temporally ordered dataset $(x_1, x_2, \dots, x_n)$, the method proceeds by computing the slope between every possible pair of distinct observations. For any two time points $i$and $j$satisfying $1 \leq i < j \leq n$, the pairwise slope is defined as:

$$Q_i = \frac{x_j - x_i}{j - i};\ \forall\ 1 \leq i < j \leq n \tag{5}$$

where Q_i represents the rate of change between the observations at positions $i$and $j$in the time series. This calculation is repeated exhaustively across all admissible index pairs, yielding a total of $N = n(n-1)/2$ individual slope estimates. The Sen slope is then taken as the median of this complete set of pairwise slopes $Q_{\text{med}} = \text{median}(Q_1, Q_2, \dots, Q_N)$. The use of the median as the summary statistic is what confers on the SSTM its resistance to the distorting influence of outlying observations, since individual extreme values can affect at most a small fraction of the Npairwise estimates without shifting the median appreciably. The sign and magnitude of Q_{med}carry direct physical meaning within the context of accident trend analysis. A positive value indicates that the time series exhibits an upward trend that is, accident injuries or fatalities have tended to increase over the period examined while a negative value reflects a downward trend. When $Q_{\text{med}}$is close to zero, the data are interpreted as exhibiting no sustained directional change over time (Helsel & Hirsch, 2002). In the present study, the SSTM is applied separately to total injury counts and total fatality counts at monthly, seasonal, and annual temporal resolutions, enabling the rate and direction of change to be characterized with precision across all relevant timescales.

2.2.4. Mann-Kendall Trend Analysis

The Mann-Kendall (MK) trend test is a rank-based nonparametric statistical procedure used to assess whether a time series exhibits a statistically significant monotonic trend over time (Mann, 1945; Kendall, 1975). In the present study, it is applied to the annual traffic accident data for Diyarbakir province to determine whether injury and fatality counts have followed a consistent directional trajectory over the 2014–2023 observation

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period. Because the test operates on the ranks of observations rather than their actual values, it does not require the data to conform to any particular distributional form, making it well suited to accident datasets that may deviate substantially from normality. The results obtained from the MK test are intended to complement the magnitude estimates provided by the SSTM, together identifying both the direction and the statistical credibility of the trends detected (Helsel, & Hirsch, 2002).

For a temporally ordered dataset $x_1, x_2, \ldots, x_n$, the test is built around the Sstatistic, which accumulates the signs of all pairwise differences between observations:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \text{sgn}(x_j - x_i) \tag{6}$$

where the sign function is defined as:

$$\text{sgn}(x_j - x_i) = \begin{cases} +1, & \text{if } x_j > x_i \\ \pm 0, & \text{if } x_j = x_i \\ -1, & \text{if } x_j < x_i \end{cases} \tag{7}$$

The S statistic therefore summarises the net balance between concordant and discordant pairs across the entire series. A positive value of Sindicates that later observations tend to exceed earlier ones, reflecting an upward trend, whereas a negative value signals a prevailing downward tendency. A value near zero suggests the absence of any systematic directional change.

To establish whether the identified trend direction is statistically significant, the Sstatistic is standardised by approximating its distribution to the standard normal, yielding the test statistic Z:

$$Z = \begin{cases} \dfrac{S-1}{\sigma_S}, & S > 0 \\ \pm 0, & S = 0 \\ \dfrac{S+1}{\sigma_S}, & S < 0 \end{cases} \tag{8}$$

where the continuity correction of $\pm 1$is applied to account for the discrete nature of the Sstatistic, and $\sigma_S$denotes its standard deviation, computed under the assumption of no ties as:

$$\sigma_S = \sqrt{\frac{n(n-1)(2n+5)}{18}} \tag{9}$$

The standardised Z value is then compared against critical thresholds corresponding to a pre-specified significance level typically 95% or 99% confidence to reach a conclusion regarding trend significance. If $|Z| > Z_{\text{critical}}$, the null hypothesis $H_0$of no trend is rejected, and it is concluded that the time series exhibits a statistically significant monotonic trend (Helsel, & Hirsch, 2002). In the present study, this decision criterion

is applied separately to total injury counts and total fatality counts, providing a rigorous statistical basis for the directional conclusions drawn from the ITA, IPTA, and SSTM analyses.

2.2.5. Comparative Statistical Analysis

To complement the trend analyses described in the preceding sections, a comparative statistical analysis was conducted to examine the relationships between a comprehensive set of accident-related parameters and the two primary outcome variables of this study the total number of injuries and the total number of fatalities. This analysis was carried out using the Pearson correlation coefficient, which quantifies the strength and direction of the linear association between each parameter and the outcome variables, and provides a basis for identifying which accident-influencing factors are most closely associated with injury and fatality counts in Diyarbakir province.

The dataset supplied by the Ministry of Interior, General Directorate of Security, includes 26 accident-characterising parameters recorded alongside each accident event. These parameters, together with their designated labels used throughout the analysis, are as follows: Road Type (P1), Road Pavement (P2), Road Legal Speed Limit (P3), Number of Lanes (P4), Horizontal Geometry (P5), Vertical Geometry (P6), Intersection Geometry (P7), Geometric Crossing (P8), Other Road Geometry (P9), Day Condition (P10), Road Surface (P11), Accident First Aid Type (P12), Accident Occurrence Type (P13), Number of Vehicles Involved (P14), First Collision Location (P15), Accident Road Defect (P16), Presence of Guardrail (P17), Presence of Footpath (P18), Presence of Safety Lane (P19), Road Lane Line (P20), Presence of Traffic Sign (P21), Presence of Traffic Light (P22), Lighting (P23), Presence of Obstruction to Visibility (P24), Damaged Element (P25), and Working on the Road (P26).

This parameter set spans a broad range of road geometric, environmental, infrastructural, and operational attributes, reflecting the multifactorial nature of traffic accident causation. By assessing the pairwise correlation of each of these 26 parameters with total injuries and total fatalities individually, it becomes possible to identify which categories of road and traffic characteristics exhibit the strongest associations with accident outcomes, and to evaluate the degree to which the parameters inter-correlate with one another. The results of this analysis are presented in the form of Pearson correlation matrices (Supplementary S1 and S2) and are discussed in conjunction with the Kendall's tau coefficients and Sen slope estimates reported in Table 2, thereby situating the correlation findings within the broader trend-analytical context of the study.

3. RESULTS AND DISCUSSION

3.1. Innovative Trend Analysis Results

The results of the ITA were analyzed for two periods, 2014-2018 and 2019-2023, based on the total numbers of fatalities and injuries resulting from traffic accidents in Diyarbakir Province. The analysis was conducted to examine changes in the numbers of fatalities and injuries at monthly, seasonal, and annual scales, as presented in Supplementary S3.

As shown in Supplementary S3 the total number of injuries exhibits a decreasing trend, as all data points remain below the diagonal line. In contrast, the data points for fatalities are generally above the reference line, indicating an increasing trend. Although the number of injuries decreased, traffic fatalities showed the opposite pattern. However, the variations observed in some months, such as June, may reflect the influence of seasonal and structural factors on fatality trends.

At the seasonal scale, all data points for injuries are below the baseline, indicating a general downward trend during 2019-2023. The summer season also shows a decreasing pattern, although some fluctuations are observed in certain periods. The highest number of injuries occurred in autumn, whereas the lowest level was observed in winter. For fatalities, winter and spring show data points above the baseline, indicating an increase during these seasons. In summer, fatalities decreased, while autumn showed mixed patterns, suggesting that variations were influenced by multiple factors rather than a consistent trend.

The annual trend analysis shows that injury counts remain below the diagonal line, indicating a decreasing trend. However, a clear increasing or decreasing trend cannot be established for fatalities. Overall, fatalities show an increasing tendency, although temporary declines were observed in some years due to various influencing factors.

3.2. Innovative Polygon Trend Analysis Results

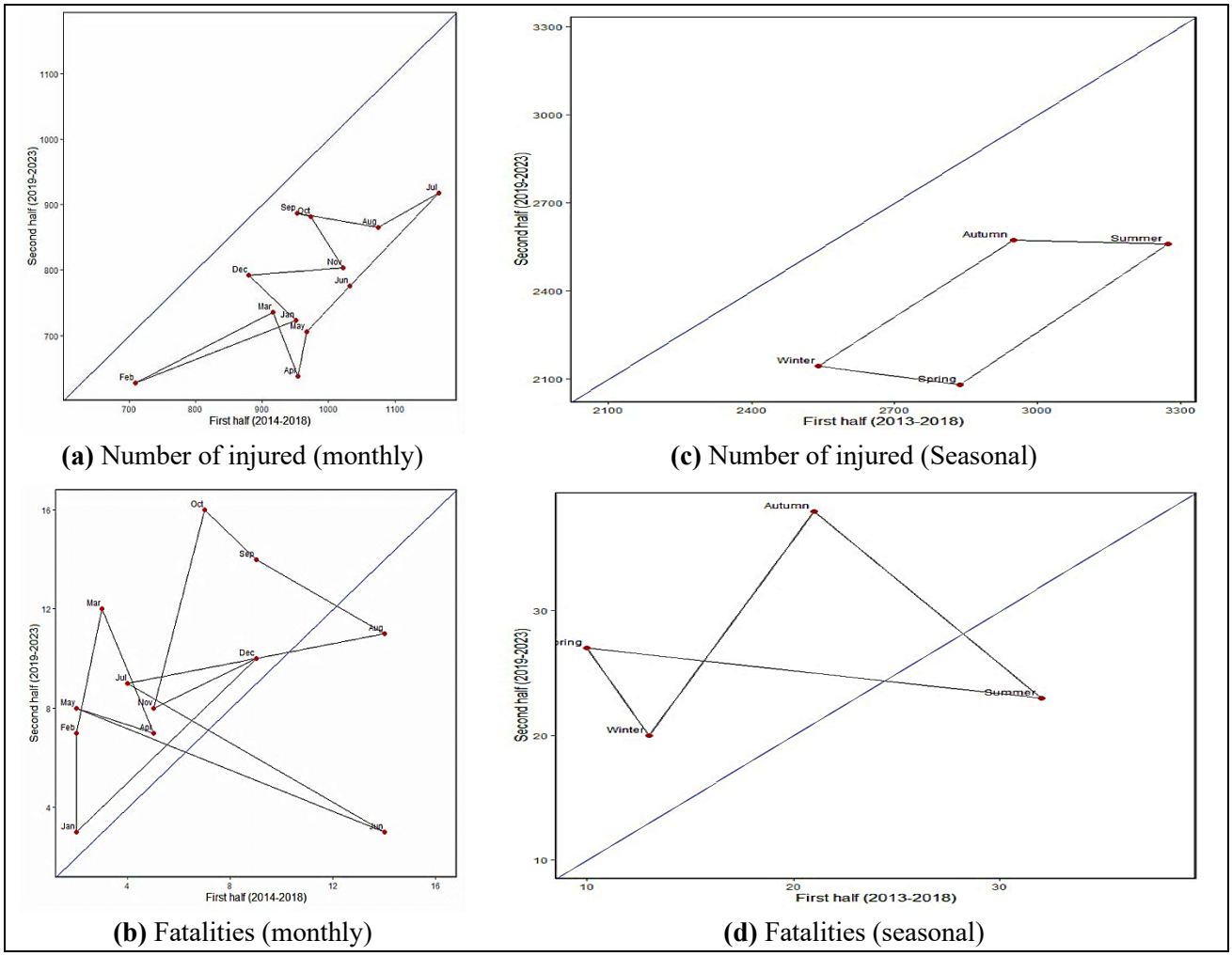
Total fatality and injury data were analyzed at monthly and seasonal scales for both periods (2014-2018 and 2019-2023) using IPTA for Diyarbakir Province. The results are presented in Figure 2.

As shown in Figure 2, the monthly trends of total injuries and fatalities in Diyarbakir are compared between the periods 2014-2018 and 2019-2023. The monthly IPTA results indicate a decreasing trend in the number of injuries, with the highest values observed in July and the lowest in February. The number of injuries reached peak levels during July, August, September, and October. The lower values observed in February may be associated with weather conditions, transportation dynamics, or other external factors.

For fatalities, the monthly IPTA results show an increasing trend, as most data points are located above the diagonal line. A noticeable increase is observed during the autumn months, particularly in September and October, whereas relatively smaller changes occur during the winter months, especially in January and February. Spring and summer months show considerable variability, indicating an irregular pattern in fatality trends.

At the seasonal scale, all injury data points remain below the diagonal line, indicating a decreasing trend. The lowest injury counts occur in winter, while the highest values are observed in summer. Winter shows the most pronounced decline, whereas spring and autumn exhibit similar patterns. In contrast, seasonal fatality analysis shows an increasing trend, as most data points are above the reference line. Fatalities reach their highest levels

in autumn, while winter and spring values are relatively similar. A decreasing trend is observed during the summer season.



(a) Number of injured (monthly) **(c)** Number of injured (Seasonal)

(b) Fatalities (monthly) **(d)** Fatalities (seasonal)

Figure 2. *Total number of injured and killed people in traffic accidents by IPTA*

3.3. Sen Slope Test Method Results

The graphs presented in Supplementary S4 and Supplementary S5 were obtained using the SSTM and were evaluated according to whether the trend line exhibited a decreasing or increasing slope. The figures show the monthly trends in the total number of injured people obtained using the Sen's slope method. For example, when we look at January, the trend line generally has a negative slope. This indicates a general decreasing trend in the total number of injuries in January over the analyzed period. Although the general trend is in the direction of decrease, fluctuations are observed between individual years. In particular, there was a significant decline in 2015-2016, but a relatively stable trend was observed in the following years. After 2020, a significant decrease is observed again.

In general, a decreasing slope is observed in all months except October. However, temporary increases are observed in some periods. These variations are thought to be due to reasons such as increased traffic safety measures, changes due to weather conditions, improved access to health services and increased use of public

transportation. The SSTM trend line for October has a positive slope, indicating that there is a long-term upward trend in the total number of casualties in October. In other words, injuries in October have generally been on an upward trend over the time period analyzed. Although the trend is in the direction of increase, it is noteworthy that there are sharp increases in 2015 and 2017, a relative decrease in the period 2019-2021, and an increase again in 2022-2023.

The reasons behind this upward trend can be considered to be; increased traffic density due to the opening of schools and tourism mobility, seasonal reasons, inade-quacies in traffic safety measures. Moreover, the monthly SSTM graphs of the total number of fatalities. Looking at the graph trends, the slope of January, February, No-vember and December is zero. This indicates that there is no clear upward or downward trend in the analyzed time series. In other words, the data follow a constant course over time or show random fluctuations. There is no clear long-term trend. There may be small increases and decreases, but in general there is no permanent change in direction in the data. There is an increasing trend in March, April, May, July, Septem-ber and October. During these months, an increase in the number of fatalities resulting from traffic accidents is observed. The largest increases were observed in May and September. It can be seen from the graphs that there is a decreasing trend in June and August.

There is a decreasing trend in all seasons when looking at the seasonal change in the total number of injured. The highest decrease is in the summer season. It can be in-terpreted that there is a decrease in accidents due to the decrease in traffic volume and good weather conditions as schools are on vacation in the summer season. The second decreasing trend belongs to the spring season. It is thought that weather conditions have an important effect on traffic accidents. The seasonal variation in the number of fatalities indicates an increasing trend in the SSTM slopes, except during the summer season. The highest increase is in the fall season. In summer, the trend is zero, indicating no clear increase or decrease over the analyzed period.

On the other hand, the annual graph of the Sen's Slope value of the total number of injured is given show that, the negative Sen's slope value suggests that there is a sig-nificant downward trend in the number of injured in the long term. However, the in-crease in 2022-2023 indicates that there may be short-term fluctuations and the downward trend may be interrupted. The annual trend in total fatalities shows a positive slope. The positive Sen's slope value indicates a long-term upward tendency in the annual number of fatalities. Even though there are short-term decreases, the general trend is upward. The number of injured between 2014 and 2023 follows a wavy course. After reaching the lowest level in 2020, a significant increase was observed especially from 2021 onwards and it reached its highest level in 2023.

3.4. Comparative Statistical Analysis

Pearson correlation coefficient is used to measure the linear relationship between two variables. This analysis expresses how the variables change together. Supplementary S1 and Supplementary S2 were prepared for total

injuries and fatalities respectively. Table 2 shows the comparative statistical results based on Kendal, p-value and Sen slope.0

From the Supplementary S1 the parameters P3 (0.159), P18 (0.103) and P14 (0.134) have a weak positive correla-tion on the total number of injuries. This indicates that increases in these variables are associated with slight increases in the total number of injuries. However, since the values are less than 0.2, a strong relationship cannot be mentioned. There is a weak negative correlation with the parameters P13(-0.101), P25(-0.103). However, since these values are also small, their effects are not strong. There is a very strong negative correlation between the parame-ters P13 and P14 (-0.796). When P13 increases, P14 decreases significantly and vice versa. There is a moderate positive correlation between P19 and P20 (0.434), indicating that the two parameters increase together. Similarly, there is a moderately strong posi-tive correlation between P3 and P18 (0.448). Thus, increases in P3 are associated with increases in P18.

Overall, none of the 26 investigated parameters showed a significant relationship with the total number of injuries. As shown in Supplementary S2, the correlation coefficients between total fatalities and the examined variables ranged approximately from −0.1 to 0.1, indicating weak associations. Although P3 and P13 exhibited slight positive correlations, these relationships were not statistically significant.

Table 2. *Comparative statistical results based on methods*

Series\Test	Total Injuries			Total Fatalities		
	Kendall's tau	p-value	Sen's slope	Kendall's tau	p-value	Sen's slope
Jan	-0,539	0,039	-9,500	0,328	0,296	0,000
Feb	-0,200	0,474	-2,200	0,316	0,282	0,000
Mar	-0,467	0,074	-5,167	0,441	0,121	0,250
Apr	-0,244	0,371	-6,500	0,248	0,399	0,111
May	-0,200	0,474	-5,500	0,527	0,063	0,333
Jun	-0,270	0,323	-5,143	-0,466	0,092	-0,250
Jul	-0,333	0,210	-7,500	0,389	0,175	0,125
Aug	-0,289	0,283	-4,800	-0,221	0,454	-0,143
Sep	-0,111	0,721	-2,333	0,358	0,198	0,333
Oct	0,067	0,858	2,200	0,471	0,102	0,167
Nov	-0,111	0,721	-2,500	0,227	0,449	0,000
Dec	-0,022	1,000	-0,250	-0,026	1,000	0,000
Winter	-0,378	0,152	-12,250	0,210	0,467	0,333
Spring	-0,467	0,074	-15,000	0,414	0,124	0,833
Summer	-0,289	0,283	-19,429	-0,097	0,781	0,000
Autumn	-0,090	0,788	-5,857	0,460	0,085	1,000
Annual	-0,200	0,474	-52,000	0,333	0,210	2,200

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Table 2 shows that, for total injuries, Kendall's tau values are negative, indicating a decreasing tendency, except in October. The strongest negative correlation is in January with Kendall's tau -0.539 and a statistically significant decrease with p = 0.039. The largest decrease is observed in spring, with a Sen's slope of −15.000 and a Kendall's tau of −0.467. For the annual trend, Kendall's tau is −0.200 (p = 0.474), indicating a negative but statistically non-significant tendency. Although the trends are not statistically significant in most months, the overall pattern indicates a downward tendency in the number of injuries, with more pronounced decreases in January and spring. The results for fatalities show that Kendall's tau values are generally positive, indicating an overall increasing tendency in fatalities. The strongest increasing trend is observed in May with Kendall's tau values of 0.527 and p 0.063 (marginal statistical evidence) (Altman & Krzywinski, 2024). he strongest positive Kendall's tau is observed in May ($\tau = 0.527$; $p = 0.063$); however, this relationship is not statistically significant at the 0.05 level (Altman & Krzywinski, 2024). The autumn season shows a positive Kendall's tau value ($\tau = 0.460$; $p = 0.085$), indicating an increasing tendency; however, this relationship is not statistically significant. The annual Kendall's tau is 0.333; however, the trend is not statistically significant ($p = 0.210$). In summary, although fatalities show an overall increasing tendency, particularly in May and autumn, most of these trends are not statistically significant.

For a general discussion it can said that traffic accidents are a critical public health and engineering problem for the transportation safety of cities. As a result of trend analysis, it was found that while there was a general downward trend in the number of injuries, fatal accidents increased in certain periods. These findings show similar trends when compared to previous studies. For example, in their study on traf-fic accidents in India, Manikandan et al. (2018) stated that although there are fluctua-tions in the total number of accidents over time, fatalities tend to increase in certain periods. Similarly, Weast (2018) in his analysis in the US, emphasized that seasonal ef-fects shape the fluctuations in traffic accidents to a great extent. When seasonal changes are analyzed, it is observed that fatalities increase in winter and spring months, while they tend to decrease in summer months. This result is in line with the findings of its study on traffic accidents in the USA, DeGroat (2009), states that fatal traf-fic accidents are highest in the fall season. The results of this study also conclude that fatal accidents increase the most in the fall season. Another important finding of this study is that traffic safety measures have been effective in reducing the number of in-juries in recent years. Sümer and Kaygısız (2015), revealed in their study, that traffic safety policies play a critical role in reducing the number of fatalities and injuries in accidents and emphasized that factors such as lowering speed limits, seat belt control and in-creasing traffic inspections reduce accident rates.

4. CONCLUSION

This study investigated the temporal trends in road traffic accident injuries and fatalities across Diyarbakir province, Turkey, over the ten-year period from 2014 to 2023. Four complementary nonparametric statistical methods Innovative Trend Analysis (ITA), Innovative Polygon Trend Analysis (IPTA), the Sen Slope Test Method (SSTM), and the Mann-Kendall (MK) trend test were applied at monthly, seasonal, and annual scales

to characterise both short- and long-term patterns in accident out-comes. A correlation analysis involving 26 accident-related parameters was addition-ally performed to explore the nature and strength of relationships between these vari-ables and the observed injury and fatality counts. The overall picture that emerges from the combined analyses is one of diverging trajectories between injury and fatality trends. A general and consistent decline in the total number of injured persons was observed across the study period, most pronounced during the 2019–2023 sub-period relative to 2014–2018. At the seasonal level, injury counts were highest during summer months and lowest in winter, reflecting the well-documented influence of seasonal mobility patterns on accident exposure. Fatalities, however, followed a markedly dif-ferent course. Despite the reduction in total injuries, fatalities attributable to traffic acci-dents showed an upward tendency during certain periods, particularly in winter and spring, with a decrease observed in summer. This divergence between injury and fatal-ity trends is a finding of considerable significance: it indicates that while enforcement measures and awareness campaigns may have been effective in reducing the overall number of accidents, the lethal severity of those accidents that do occur has not di-minished at a commensurate rate. The role of weather conditions, road surface char-acteristics, and seasonal variations in driving behaviour appears central to this pat-tern, and warrants deliberate attention in the formulation of safety policy.

The decline in injury counts observed during 2019–2023 is attributable to a con-vergence of several concurrent factors. Progressively strengthened traffic safety regu-lations and their enforcement, together with improvements in emergency medical re-sponse infrastructure, have likely reduced the downstream consequences of accidents. The marked reduction in vehicular mobility during the COVID-19 pandemic years of 2020 and 2021 further contributed to the observed decrease in accident exposure dur-ing this period. Additionally, broadened public awareness initiatives and the wider dissemination of safe driving education appear to have had a measurable, if partial, effect on driver behaviour.

It should be acknowledged that the present study was focused specifically on trend quantification and did not extend to a detailed causal investigation of the factors underlying the observed patterns. The dataset, while comprehensive in its temporal coverage and the breadth of its 26 parameters, did not permit a systematic disaggrega-tion of accident causes or a thorough examination of the demographic and infrastruc-tural dimensions of accident risk. Future research would benefit from incorporating such variables including road geometry, vehicle fleet characteristics, land use pat-terns, and socio-demographic profiles of accident-involved drivers so that the de-terminants of both accident occurrence and accident severity can be more precisely identified. Spatial analysis techniques capable of pinpointing high-risk corridors and intersections within the province would further strengthen the practical utility of such work.

Taken together, the findings of this study offer a substantive empirical basis for regional traffic safety planning in Diyarbakir. The seasonal and temporal patterns identified through the integrated application of ITA, IPTA, SSTM, and MK provide ac-tionable insight into the periods and conditions that demand heightened intervention. From the perspective of urban planning and traffic engineering, a targeted allocation of resources

toward the risk periods identified particularly the winter and spring seasons in which fatality rates are most elevated alongside continued investment in infrastructure quality, emergency response capacity, and public education, offers the most promising pathway toward a sustainable reduction in the human cost of road traffic accidents at the regional level.

AUTHOR CONTRIBUTIONS

AU: Writing – Original Draft, Conceptualization, Methodology, Investigation, Formal analysis; **IG**: Research, Writing – Original Draft, Formal analysis; **MIG**: Validation, Visualization; **SE**: Supervision, Review & Editing; **DI**: Supervision, Review & Editing.

AI Exclusion: AI tools are strictly prohibited from being listed as authors.

Legal Consent: All human authors confirm they have reviewed and legally accepted the final version under the **CC BY-SA 4.0** framework.

ACKNOWLEDGEMENT

The author gratefully acknowledges the Ministry of Interior, General Directorate of Security for providing the traffic accident data used in this study. The views and conclusions expressed in this paper are those of the author and do not necessarily reflect the official policies or positions of the data provider.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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Supplementary S1. Pearson matrix results for total injured

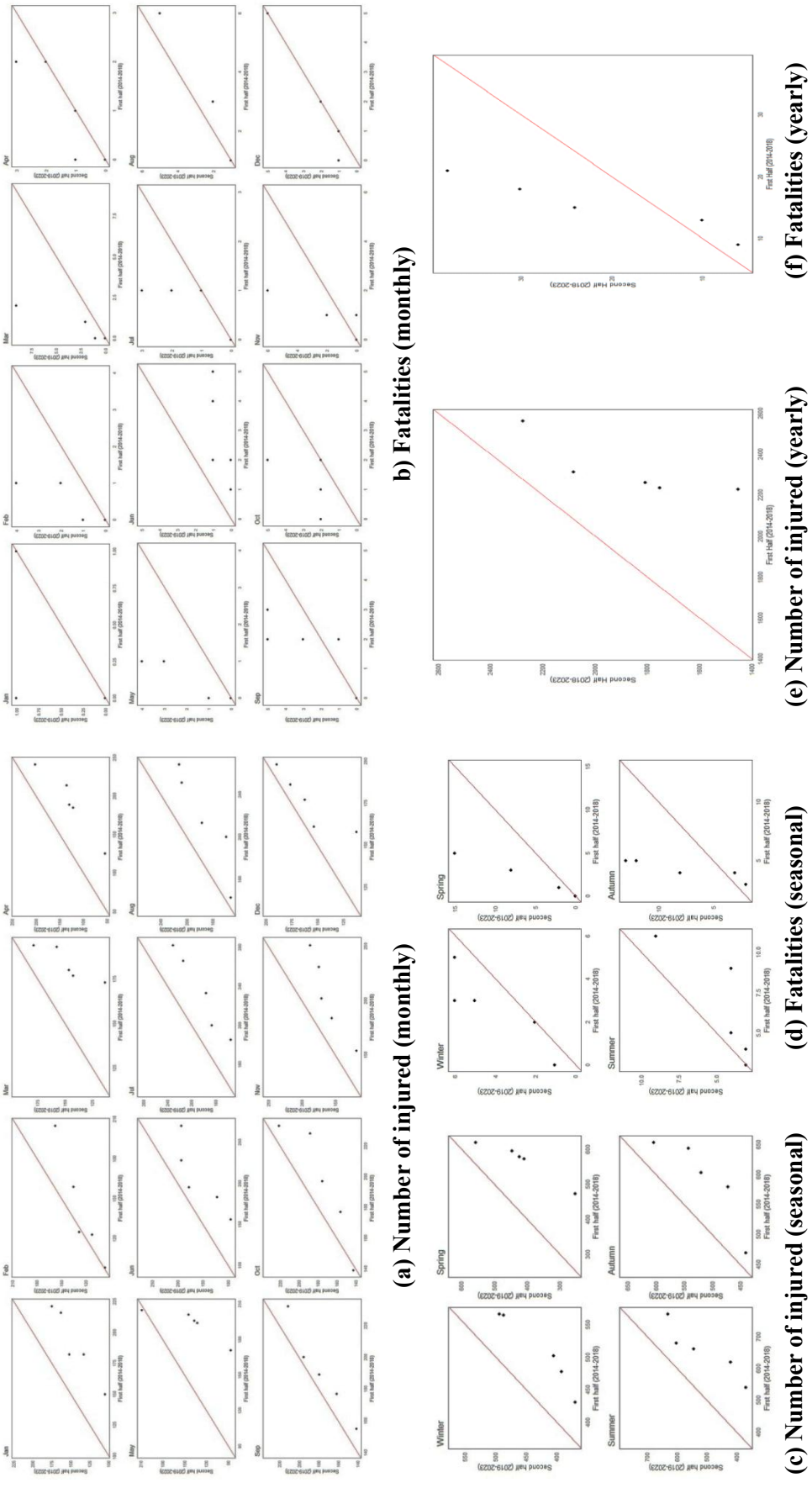
Variables	Total Injuries	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14	P15	P16	P17	P18	P19	P20	P21	P22	P23	P24	P25	P26
Total Injuries	1	-0,038	-0,021	0,159	-0,001	0,019	0,043	0,008	0,04	-0,001	0,038	0,042	-0,047	-0,101	0,134	0,019	-0,005	-0,022	0,103	-0,05	-0,061	-0,039	-0,007	0,083	0	-0,103	-0,016
P1	-0,038	1	0,167	-0,254	-0,274	-0,016	-0,025	-0,133	0,139	-0,013	-0,052	-0,013	0,033	-0,104	0,071	-0,092	0,005	0,117	-0,077	0,253	0,445	0,154	0,174	0,097	-0,017	0,109	-0,071
P2	-0,021	0,167	1	-0,062	-0,111	-0,009	0,011	0,034	0,033	-0,047	-0,019	0,026	0,03	0,052	-0,058	0,017	-0,024	0,025	0,06	0,114	0,195	0,074	0,061	0,07	-0,013	0,005	-0,025
P3	0,159	-0,254	-0,062	1	-0,004	-0,007	0,154	0,3	0,154	-0,004	-0,006	0,049	-0,008	0,161	-0,075	0,163	0,004	-0,184	0,448	-0,21	-0,219	0,085	0,13	0,329	0,026	-0,109	-0,019
P4	-0,001	-0,274	-0,111	-0,004	1	-0,033	-0,038	0,036	-0,091	0,009	0,069	-0,018	-0,045	-0,016	0,016	0,021	0,011	-0,043	-0,085	-0,123	-0,28	-0,103	-0,089	-0,155	0,016	-0,054	0,024
P5	0,019	-0,016	-0,009	-0,007	-0,033	1	0,227	0,049	0,01	-0,056	0,013	0,028	-0,006	0,152	-0,133	0,1	-0,025	-0,055	0,104	0	-0,008	-0,077	0,013	0,037	-0,001	-0,089	-0,003
P6	0,043	-0,025	0,011	0,154	-0,038	0,227	1	0,073	0,039	-0,102	0,003	0,033	0,015	0,053	-0,03	0,075	-0,012	-0,099	0,141	0	-0,027	-0,014	0,06	0,104	-0,007	-0,083	-0,049
P7	0,008	-0,133	0,034	0,3	0,036	0,049	0,073	1	0,088	-0,041	-0,01	0,02	0,013	0,218	-0,144	0,1	0	-0,101	0,186	-0,074	-0,112	0,112	0,192	0,12	0,004	-0,02	-0,056
P8	0,04	0,139	0,033	0,154	-0,091	0,01	0,039	0,088	1	0,129	0,003	0,005	0	-0,004	0,038	0,011	0,002	-0,027	0,148	0,061	0,105	0,24	0,245	0,115	0,009	-0,016	-0,034
P9	-0,001	-0,013	-0,047	-0,004	0,009	-0,056	-0,102	-0,041	0,129	1	-0,007	-0,047	-0,016	-0,009	0,01	-0,016	0,023	0,108	-0,035	-0,054	-0,006	-0,009	0,011	-0,018	0,005	0,026	0,034
P10	0,038	-0,052	-0,019	-0,006	0,069	0,013	0,003	-0,01	0,003	-0,007	1	0,063	-0,016	0,019	-0,01	0,051	-0,008	-0,01	-0,004	-0,008	-0,043	-0,014	-0,042	-0,136	0,016	-0,1	-0,03
P11	0,042	-0,013	0,026	0,049	-0,018	0,028	0,033	0,02	0,005	-0,047	0,063	1	0,042	0,031	-0,015	0,039	-0,066	-0,049	0,031	0,002	-0,004	0,005	0,011	0,024	0,013	-0,055	-0,016
P12	-0,047	0,033	0,03	-0,008	-0,045	-0,006	0,015	0,013	0	-0,016	-0,016	0,042	1	0,042	-0,047	0,013	0,003	-0,001	-0,006	0,029	0,039	0,013	0,007	0,02	-0,028	0,012	0,005
P13	-0,101	-0,104	0,052	0,161	-0,016	0,152	0,053	0,218	-0,004	-0,009	0,019	0,031	0,042	1	-0,796	0,277	-0,04	-0,045	0,144	-0,096	-0,044	0,017	0,106	0,097	-0,017	-0,138	-0,026
P14	0,134	0,071	-0,058	-0,075	0,016	-0,133	-0,03	-0,144	0,038	0,01	-0,01	-0,015	-0,047	-0,796	1	-0,212	0,029	0,034	-0,093	0,061	0,026	0,025	-0,081	-0,08	0,023	0,135	0,03
P15	0,019	-0,092	0,017	0,163	0,021	0,1	0,075	0,1	0,011	-0,016	0,051	0,039	0,013	0,277	-0,212	1	-0,034	-0,063	0,135	-0,122	-0,074	-0,01	0,051	0,073	0,02	-0,199	-0,004
P16	-0,005	0,005	-0,024	0,004	0,011	-0,025	-0,012	0	0,002	0,023	-0,008	-0,066	0,003	-0,04	0,029	-0,034	1	0,014	-0,033	0,01	-0,008	0,013	-0,005	-0,032	0,013	0,007	0,06
P17	-0,022	0,117	0,025	-0,184	-0,043	-0,055	-0,099	-0,101	-0,027	0,108	-0,01	-0,049	-0,001	-0,045	0,034	-0,063	0,014	1	-0,118	0,051	0,133	0,021	-0,032	-0,024	-0,011	0,114	-0,009
P18	0,103	-0,077	0,06	0,448	-0,085	0,104	0,141	0,186	0,148	-0,035	-0,004	0,031	-0,006	0,144	-0,093	0,135	-0,033	-0,118	1	-0,036	-0,025	0,063	0,07	0,304	0,025	-0,083	-0,096
P19	-0,05	0,253	0,114	-0,21	-0,123	0	0	-0,074	0,061	-0,054	-0,008	0,002	0,029	-0,096	0,061	-0,122	0,01	0,051	-0,036	1	0,434	0,138	-0,001	-0,024	-0,014	0,037	-0,012
P20	-0,061	0,445	0,195	-0,219	-0,28	-0,008	-0,027	-0,112	0,105	-0,006	-0,043	-0,004	0,039	-0,044	0,026	-0,074	-0,008	0,133	-0,025	0,434	1	0,208	0,069	0,078	-0,023	0,079	-0,009
P21	-0,039	0,154	0,074	0,085	-0,103	-0,077	-0,014	0,112	0,24	-0,009	-0,014	0,005	0,013	0,017	0,025	-0,01	0,013	0,021	0,063	0,138	0,208	1	0,14	0,089	0,004	0,091	0,049
P22	-0,007	0,174	0,061	0,13	-0,089	0,013	0,06	0,192	0,245	0,011	-0,042	0,011	0,007	0,106	-0,081	0,051	-0,005	-0,032	0,07	-0,001	0,069	0,14	1	0,187	-0,002	0,019	-0,036
P23	0,083	0,097	0,07	0,329	-0,155	0,037	0,104	0,12	0,115	-0,018	-0,136	0,024	0,02	0,097	-0,08	0,073	-0,032	-0,024	0,304	-0,024	0,078	0,089	0,187	1	0,012	-0,007	-0,087
P24	0	-0,017	-0,013	0,026	0,016	-0,001	-0,007	0,004	0,009	0,005	0,016	0,013	-0,028	-0,017	0,023	0,02	0,013	-0,011	0,025	-0,014	-0,023	0,004	-0,002	0,012	1	-0,013	0,02
P25	-0,103	0,109	0,005	-0,109	-0,054	-0,089	-0,083	-0,02	-0,016	0,026	-0,1	-0,055	0,012	-0,138	0,135	-0,199	0,007	0,114	-0,083	0,037	0,079	0,091	0,019	-0,007	-0,013	1	0,03
P26	-0,016	-0,071	-0,025	-0,019	0,024	-0,003	-0,049	-0,056	-0,034	0,034	-0,03	-0,016	0,005	-0,026	0,03	-0,004	0,06	-0,009	-0,096	-0,012	-0,009	0,049	-0,036	-0,087	0,02	0,03	1

Supplementary S2. Pearson matrix results for total fatalities

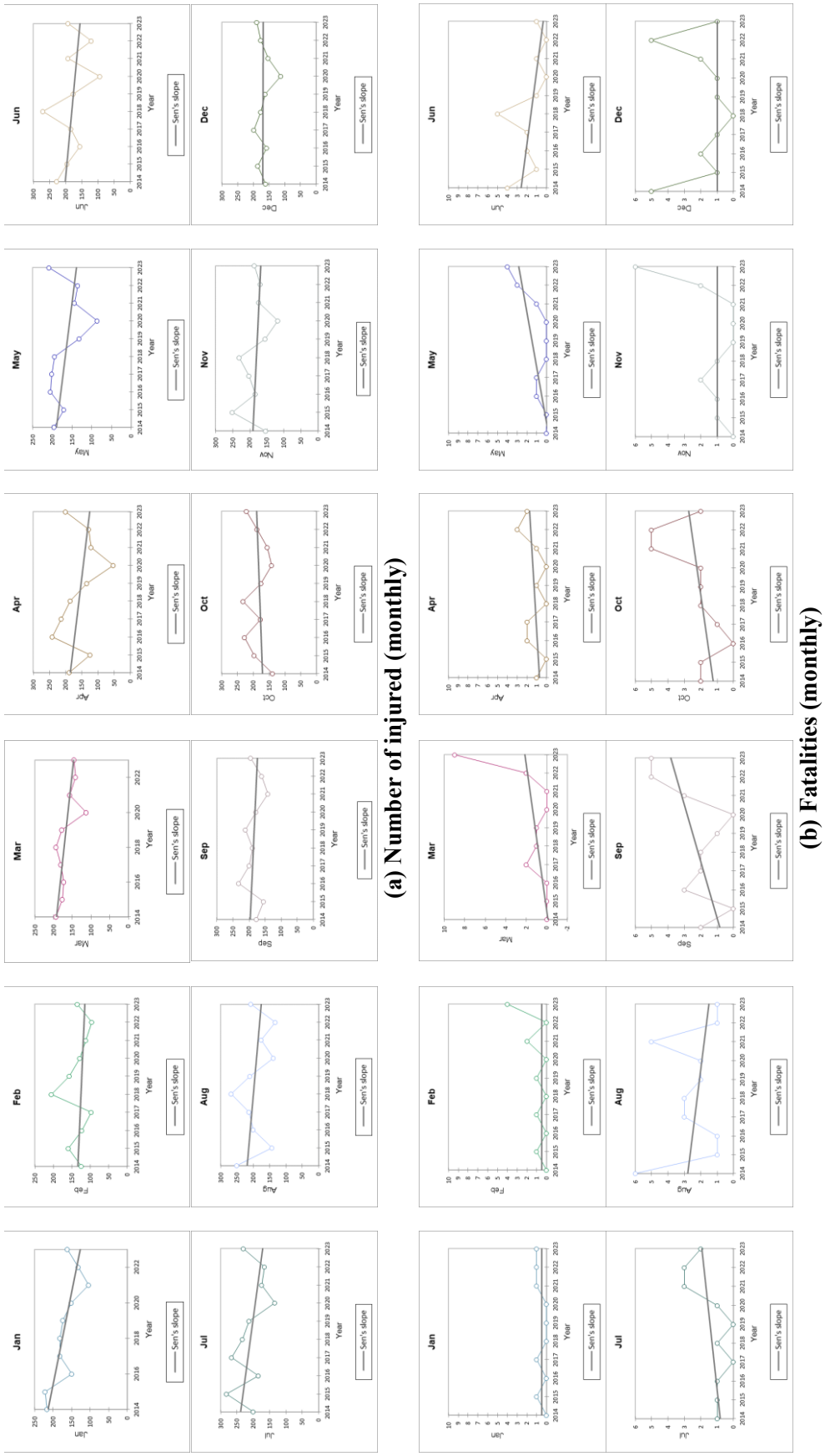
Variables	Total Deaths	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14	P15	P16	P17	P18	P19	P20	P21	P22	P23	P24	P25	P26
Total Deaths	1	-0,036	-0,014	0,073	0,016	0,013	0,032	0,041	-0,001	0,008	0,006	0,001	-0,005	0,058	-0,048	0,019	0,002	-0,025	0,037	-0,043	-0,028	-0,016	0,012	0,021	-0,013	-0,009	0,003
P1	-0,036	1	0,167	-0,254	-0,274	-0,016	-0,025	-0,133	0,139	-0,013	-0,052	-0,013	0,033	-0,104	0,071	-0,092	0,005	0,117	-0,077	0,253	0,445	0,154	0,174	0,097	-0,017	0,109	-0,071
P2	-0,014	0,167	1	-0,062	-0,111	-0,009	0,011	0,034	0,033	-0,047	-0,019	0,026	0,03	0,052	-0,058	0,017	-0,024	0,025	0,06	0,114	0,195	0,074	0,061	0,07	-0,013	0,005	-0,025
P3	0,073	-0,254	-0,062	1	-0,004	-0,007	0,154	0,3	0,154	-0,004	-0,006	0,049	-0,008	0,161	-0,075	0,163	0,004	-0,184	0,448	-0,21	-0,219	0,085	0,13	0,329	0,026	-0,109	-0,019
P4	0,016	-0,274	-0,111	-0,004	1	-0,033	-0,038	0,036	-0,091	0,009	0,069	-0,018	-0,045	-0,016	0,016	0,021	0,011	-0,043	-0,085	-0,123	-0,28	-0,103	-0,089	-0,155	0,016	-0,054	0,024
P5	0,013	-0,016	-0,009	-0,007	-0,033	1	0,227	0,049	0,01	-0,056	0,013	0,028	-0,006	0,152	-0,133	0,1	-0,025	-0,055	0,104	0	-0,008	-0,077	0,013	0,037	-0,001	-0,089	-0,003
P6	0,032	-0,025	0,011	0,154	-0,038	0,227	1	0,073	0,039	-0,102	0,003	0,033	0,015	0,053	-0,03	0,075	-0,012	-0,099	0,141	0	-0,027	-0,014	0,06	0,104	-0,007	-0,083	-0,049
P7	0,041	-0,133	0,034	0,3	0,036	0,049	0,073	1	0,088	-0,041	-0,01	0,02	0,013	0,218	-0,144	0,1	0	-0,101	0,186	-0,074	-0,112	0,112	0,192	0,12	0,004	-0,02	-0,056
P8	-0,001	0,139	0,033	0,154	-0,091	0,01	0,039	0,088	1	0,129	0,003	0,005	0	-0,004	0,038	0,011	0,002	-0,027	0,148	0,061	0,105	0,24	0,245	0,115	0,009	-0,016	-0,034
P9	0,008	-0,013	-0,047	-0,004	0,009	-0,056	-0,102	-0,041	0,129	1	-0,007	-0,047	-0,016	-0,009	0,01	-0,016	0,023	0,108	-0,035	-0,054	-0,006	-0,009	0,011	-0,018	0,005	0,026	0,034
P10	0,006	-0,052	-0,019	-0,006	0,069	0,013	0,003	-0,01	0,003	-0,007	1	0,063	-0,016	0,019	-0,01	0,051	-0,008	-0,01	-0,004	-0,008	-0,043	-0,014	-0,042	-0,136	0,016	-0,1	-0,03
P11	0,001	-0,013	0,026	0,049	-0,018	0,028	0,033	0,02	0,005	-0,047	0,063	1	0,042	0,031	-0,015	0,039	-0,066	-0,049	0,031	0,002	-0,004	0,005	0,011	0,024	0,013	-0,055	-0,016
P12	-0,005	0,033	0,03	-0,008	-0,045	-0,006	0,015	0,013	0	-0,016	-0,016	0,042	1	0,042	-0,047	0,013	0,003	-0,001	-0,006	0,029	0,039	0,013	0,007	0,02	-0,028	0,012	0,005
P13	0,058	-0,104	0,052	0,161	-0,016	0,152	0,053	0,218	-0,004	-0,009	0,019	0,031	0,042	1	-0,796	0,277	-0,04	-0,045	0,144	-0,096	-0,044	0,017	0,106	0,097	-0,017	-0,138	-0,026
P14	-0,048	0,071	-0,058	-0,075	0,016	-0,133	-0,03	-0,144	0,038	0,01	-0,01	-0,015	-0,047	-0,796	1	-0,212	0,029	0,034	-0,093	0,061	0,026	0,025	-0,081	-0,08	0,023	0,135	0,03
P15	0,019	-0,092	0,017	0,163	0,021	0,1	0,075	0,1	0,011	-0,016	0,051	0,039	0,013	0,277	-0,212	1	-0,034	-0,063	0,135	-0,122	-0,074	-0,01	0,051	0,073	0,02	-0,199	-0,004
P16	0,002	0,005	-0,024	0,004	0,011	-0,025	-0,012	0	0,002	0,023	-0,008	-0,066	0,003	-0,04	0,029	-0,034	1	0,014	-0,033	0,01	-0,008	0,013	-0,005	-0,032	0,013	0,007	0,06
P17	-0,025	0,117	0,025	-0,184	-0,043	-0,055	-0,099	-0,101	-0,027	0,108	-0,01	-0,049	-0,001	-0,045	0,034	-0,063	0,014	1	-0,118	0,051	0,133	0,021	-0,032	-0,024	-0,011	0,114	-0,009
P18	0,037	-0,077	0,06	0,448	-0,085	0,104	0,141	0,186	0,148	-0,035	-0,004	0,031	-0,006	0,144	-0,093	0,135	-0,033	-0,118	1	-0,036	-0,025	0,063	0,07	0,304	0,025	-0,083	-0,096
P19	-0,043	0,253	0,114	-0,21	-0,123	0	0	-0,074	0,061	-0,054	-0,008	0,002	0,029	-0,096	0,061	-0,122	0,01	0,051	-0,036	1	0,434	0,138	-0,001	-0,024	-0,014	0,037	-0,012
P20	-0,028	0,445	0,195	-0,219	-0,28	-0,008	-0,027	-0,112	0,105	-0,006	-0,043	-0,004	0,039	-0,044	0,026	-0,074	-0,008	0,133	-0,025	0,434	1	0,208	0,069	0,078	-0,023	0,079	-0,009
P21	-0,016	0,154	0,074	0,085	-0,103	-0,077	-0,014	0,112	0,24	-0,009	-0,014	0,005	0,013	0,017	0,025	-0,01	0,013	0,021	0,063	0,138	0,208	1	0,14	0,089	0,004	0,091	0,049
P22	0,012	0,174	0,061	0,13	-0,089	0,013	0,06	0,192	0,245	0,011	-0,042	0,011	0,007	0,106	-0,081	0,051	-0,005	-0,032	0,07	-0,001	0,069	0,14	1	0,187	-0,002	0,019	-0,036
P23	0,021	0,097	0,07	0,329	-0,155	0,037	0,104	0,12	0,115	-0,018	-0,136	0,024	0,02	0,097	-0,08	0,073	-0,032	-0,024	0,304	-0,024	0,078	0,089	0,187	1	0,012	-0,007	-0,087
P24	-0,013	-0,017	-0,013	0,026	0,016	-0,001	-0,007	0,004	0,009	0,005	0,016	0,013	-0,028	-0,017	0,023	0,02	0,013	-0,011	0,025	-0,014	-0,023	0,004	-0,002	0,012	1	-0,013	0,02
P25	-0,009	0,109	0,005	-0,109	-0,054	-0,089	-0,083	-0,02	-0,016	0,026	-0,1	-0,055	0,012	-0,138	0,135	-0,199	0,007	0,114	-0,083	0,037	0,079	0,091	0,019	-0,007	-0,013	1	0,03
P26	0,003	-0,071	-0,025	-0,019	0,024	-0,003	-0,049	-0,056	-0,034	0,034	-0,03	-0,016	0,005	-0,026	0,03	-0,004	0,06	-0,009	-0,096	-0,012	-0,009	0,049	-0,036	-0,087	0,02	0,03	1

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Supplementary S3. Total number of injured and killed people in traffic accidents by ITA



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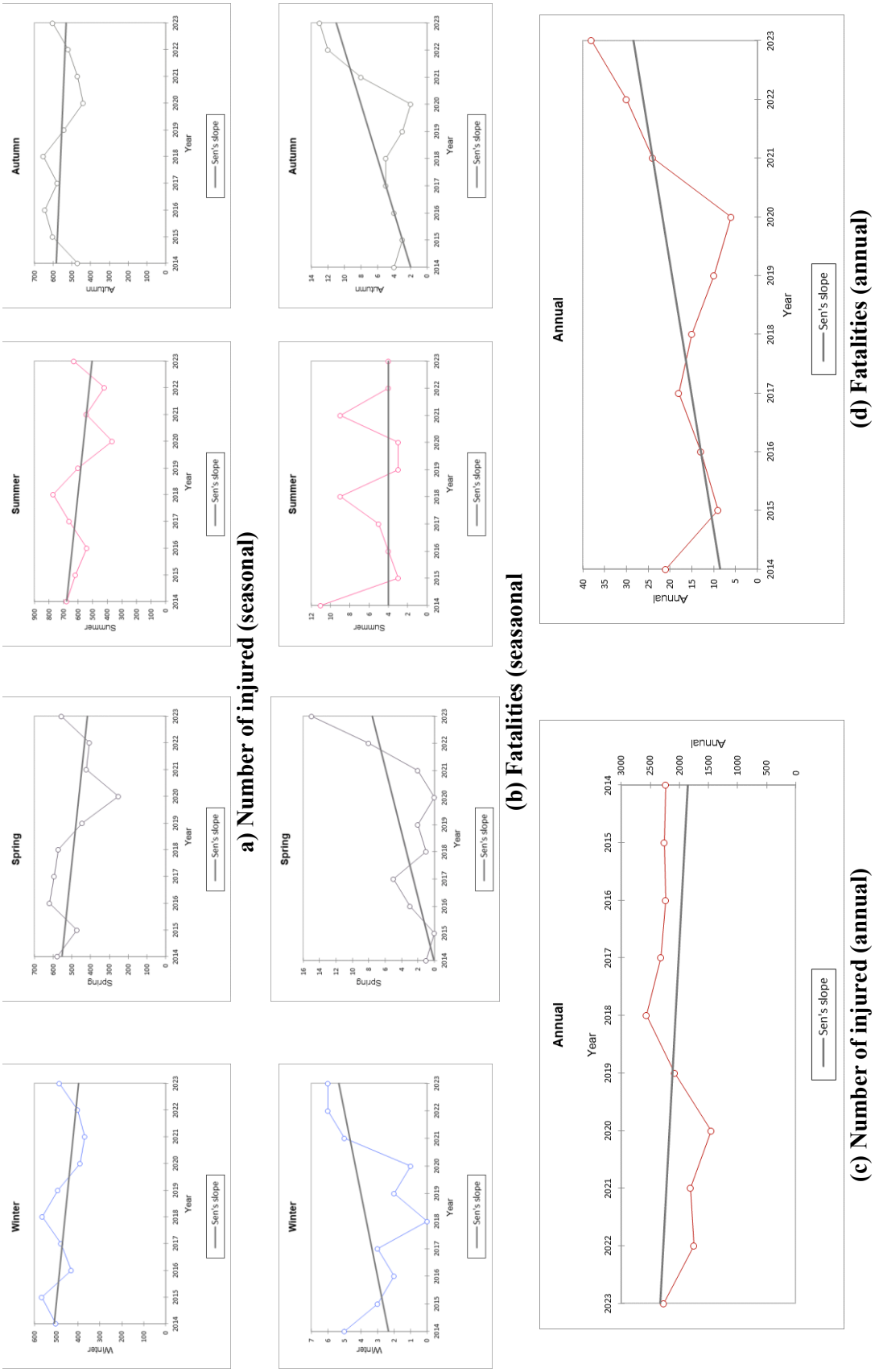


(a) Number of injured (monthly)

(b) Fatalities (monthly)

Supplementary S4. Total number of injured and killed people in traffic accidents by SSTM - monthly based

GU J Sci, Part A | 13(3) 1328-1354 (2026) | 10.54287/gujsa.1968177



Supplementary S5. Total number of injured and killed people in traffic accidents by SSTM - seasonal and annual based