



Geographical spread analysis of terrorist attacks in Pakistan

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Abstract Pakistan has been facing terrorism for the last two decades, especially after 9/11 and the start of the war on terrorism in Afghanistan. The core objectives of this study are to analyse terrorism spread geographically, and variation in attack intensity values over time using existing and modified attack intensity equations and the impact of different weapons in collateral damage assessment. Moreover, this research proposes a modified equation for attack intensity or collateral damage assessment using Exploratory Regression Analysis. The geographical spread of attack intensity values over time was measured for the 2004–2016, period and their respective

levels of violence. Spatial autocorrelation using Global Moran’s I statistic and cluster and outlier analysis using Anselin Local Moran’s I statistic were performed to locate high and low attack intensity clusters in the study area. Results reveal that from 2004 to 2016, terrorism peaked in Pakistan, especially in the Northern, North–West, and Southern regions. Cities like Karachi, Peshawar, Lahore, Quetta, and Khyber Agencies witnessed maximum attacks and fatalities. During 2004–16 districts having the highest attack intensity values were randomly distributed across the study area. Using Exploratory Regression Analysis, the modified attack intensity equation resulted in a smooth pattern with fewer outlier effects and abrupt changes. Data analysis of 2004–16 reveals that maximum collateral damage occurred due to suicide attacks in one-by-one relationships. In one-by-two relationships, suicide attacks plus firearms had maximum collateral damage.

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Introduction

The term “terrorism” does not have a discrete definition. It has been defined, in different ways, by different organisations and professionals. United Nations (UN) members could not develop a consensus

to define terrorism (Saul, 2005). Hence, in this study, the definition used by Global Terrorism Database (GTD) is used, which defines terrorism as “The threatened or actual use of illegal force and violence by a non-state actor to attain a political, economic, religious, or social goal through fear, coercion, or intimidation” (National Consortium for the Study of Terrorism & Responses to Terrorism START, 2020).

Since 2000, terrorism has had a severe impact on the world and caused more than \$700 billion loss to the global economy. It has also caused 350,000 fatalities worldwide (Global Terrorism Index, 2017). Likewise, forty thousand deaths of Pakistani citizens have been witnessed due to terrorism and more than \$124 billion loss to the national economy. During this period, terrorists challenged the state’s writ and destabilised the country’s social infrastructure and resources. Furthermore, the causes of terrorism in Pakistan can be associated with poorly managed economic and democratic systems frameworks. The weak democratic framework created room for terrorism to flourish. Other causes, which paved the way for expanded militancy in Pakistan, are the madrassah system, poor educational infrastructure, dictatorship, poor socio-economic index, Afghan factor, and anti-Americanism (Azam, 2014).

Planning countermeasures to tackle terrorism is still an unanswered question because terrorists make choices of attack type, location, and weapons used. These are based on environmental properties, constraints, and personal knowledge often learned from friends, acquaintances, and their so-called role models who have acted before them (Arce & Sandler, 2003). In recent years, different techniques and methods have been developed to study and analyse the causes of terrorism. Geospatial technologies are playing a vital role in this regard. According to Raleigh et al. (2010) approaching a socio-political problem, such as terrorism, through the geospatial lens leads to a greater understanding of the locations of terrorists and their activities. This approach also helps to understand spatial processes, social network connections, systemic social operations, and changes in space and time. Social, political, and other systems and their agents operate in specific geographical contexts, whereby they are researched in socio-spatial or geopolitical realms. For instance, traditional statistical analysis can identify the cause-effect relationship, but this proves suitable for

space and time. The reality is that geographic and temporal factors make such interactions dynamic. A variable may have a major effect on another variable from one side, but this impact might not exist long. According to Medina et al. (2011), the characteristics of spatial location are key elements of terrorist training, planning, and activities. Spatial locations are considered to be the main parts of terrorist networks due to the increased development in the field of information technology and easy access to information. Terrorists work in those geographic areas where consideration must be given to exact spots of activity; these are the spots where planning, training, other social collaborations, and assaults take place. Each target has a specific strategic and geospatial significance. Generally, target selection is made considering the recreational importance of the target places, symbolic value, and other civilian use, for example, the Bali Bombing in 2002 and 2005, the World Trade Centre attack in 2001, and the Islamabad Marriot Hotel attack in 2008, etc.

Above cited studies provide a good base for understanding terrorism locally. These studies mostly performed simple statistical analyses, e.g., Descriptive Statistics, Univariate Time Series Analyses, Auto regression, Bivariate Analyses, etc. Few of them have used elementary-level GIS-based techniques. The present study deals with multiple and advanced geospatial analysis, i.e. spatial and temporal spread analysis, proximity, Exploratory Regression Analysis, spatial autocorrelation (Global Moran’s I statistics), clustering and outlier analysis (Anselin and Local Moran’s I statistics), etc. Furthermore, a new attack intensity equation has been devised in this study to assess collateral damage, which is purely based on statistical models and analyses data more realistically. This study also analyses the impact of different weapons on collateral damage. Moreover, this study used an updated dataset since 2016, which has yet to be used in previous studies. The main innovation point of this study is that it deals with the data not only statistically but also spatially using advanced geospatial and geo-statistical analysis so that terrorist attacks can be understood in a better way. This study also helps to understand and analyse trends and patterns based on multiple parameters as well as collateral damage assessment, using an attack intensity equation, a modified equation, and a comparative analysis in the post-9/11 scenario.

The main goals of this research are to analyse terrorism spread geographically after the 9/11 incident using geospatial techniques and to assess the collateral damage in the study area as a result of terrorist attacks using existing as well as modified attack intensity equations. Moreover, this paper starts with the introduction section, which deals with the background of terrorism and some basic concepts related to terrorism, and the use of geospatial techniques in terrorism studies. The second part of the paper is a brief but comprehensive review of the literature to support the theoretical aspect of the study. The next part deals with the methods used for this study which includes the development of a modified attack intensity equation by using the already developed equations, and this is the uniqueness of this study as this is the first equation that has been used for the study area. This section also deals with the impact of different weapons on attack intensity or collateral damage. The final section comprises the results achieved by using geospatial techniques and a modified attack intensity equation. A conclusion and recommendations for further research follow the results and discussion section.

Literature review

The devastating global terrorism incident occurred on September 11, 2001, in a set of integrated attacks on the United States. After this United States declared the “War on Terrorism” the integral part of its international strategy since the attacks. The “war on terror” greatly impacted Pakistan’s pacification and protection. Pakistan has attested to different trends of militancy, from the inability to bear extremism, radicalisation and infringement. The interaction of al Qaeda with the Taliban and the collation of sectarian extremist groups into this fatal mix has given a complex character to the militancy problems (Azam, 2014). Researchers have inferred that the studies on geography and terrorism and their contribution to elaborate terrorism in a better way is an empirical phenomenon. Three important contributions have been recommended by researchers about the geographical approach. 1) The geography of terrorism is associated with particular areas and situations worldwide where government failure causes protests and provides an opportunity for such elements. 2)

The activities of terrorists happen in a specific cycle; usually, the places to be attacked can be recognised, and they are likely to be regulated. 3) Most terrorist attacks lead to negative consequences; however, they are not spatially widespread and relatively lower in intensity as compared to the literature. Furthermore, these traits differ for territorial and non-territorial terrorist organisations (Bahgat & Medina, 2013).

Geographical analysis can be helpful in identifying the activity spaces and provide important information about the spatial patterns of terrorist operations and their relative locations. Geospatial techniques can also be used to identify and analyse terrorist networks in real and social spaces. In real space, terrorists must consider geographies of recruitment, safe havens, training, the transfer of information, and so on. While social and geospatial topologies help terrorist organisations to continue and prosper (Medina & Hepner, 2008). Some fields of conflict studies use GIS-based methods and approaches, but their use is restricted and needs to be expanded. The use of geography and geospatial technologies for terrorism studies has increased since 2001, after the 9/11 incident. However, the use of the geospatial approach is lacking in the literature on terrorism, and its true potential has not been explored yet. Geospatial analysis also includes map-making, and it is considered an efficient way because it helps to visualise the information rather than putting data in tabular form (Siebeneck et al., 2009). According to (Medina et al., 2011), the analysis of terrorist attack patterns helps researchers to understand the causes of terrorism. Recent studies on terrorism have shown that patterns in space and time exist for such attacks. It has also been observed that meaningful information can be extracted from the results of spatiotemporal pattern analysis. A study on terrorism risk in Israel (Berrebi & Lakdawalla, 2007) used GIS and a rational choice framework. In this study, terrorist behaviour was modelled based on resource, target value, and probability of success estimations. LaFree et al. (2012) described terrorism as a form of crime in all essential respects and further inferred that terrorist attacks will cluster in time and space like ordinary crimes do. He further added that terrorist attacks are often rational. He also explored the possibility that the spatial and longitudinal patterns of attacks may provide important insights into the strategies employed by terrorists. Sumathipala and Wijesekera

(2008) used a geospatial overlay model for roadside attacks. This model can be successfully used to plan and deputise security to ensure the safety of road users.

Different studies on terrorism also have been conducted in Pakistan after the 9/11, 2001 incident (Kazim et al., 2008; Lanche, 2009; Hussain, 2010; Burnham, 2011; Bhatti et al., 2011; Afsar et al., 2012; Afridi et al., 2014; Rasheed & Khalid, 2016). But all these studies need more information or data in analysing attack intensity or collateral damage assessment and advanced geospatial and geo-statistical analysis. These studies deal mostly with simple GIS or statistical analyses. Afsar et al. (2012) analysed terrorism geospatially in Pakistan; as per their finding to eradicate terrorism and launch counter-terrorism operations, there is a need for a thorough examination of the factors leading to its rise over the years. There is a shortage of research that aims at understanding whether certain geographic areas possess such features that reduce their probability of experiencing terrorist attacks in the future. This lack of comprehensive geospatial analysis limits our ability to do operational planning properly, formulate and test hypotheses, and develop a counter-terrorism policy. Similarly, (Hussain, 2010) conducted research to study temporal and spatial patterns of terrorism incidents in Pakistan from 1974 to 2007. This research covers the personal, socio-economic, and demographic characteristics of arrested terrorists in Pakistan from 1990 to 2009. This study describes the patterns in target types, weapon types, and terrorist types.

Moreover, it explains the patterns before and after the U.S.-involvement in the Afghan and Iraq wars in a simple empirical way, hence, leaving a gap for geospatial modelling and analysis. (Smith et al., 2008) stated that these assertions have essential significance not only for the spatial distribution of subservient and propaedeutic terrorist crimes but also for the temporal features of the terrorist design. Different researchers proposed different models as (Hao et al., 2019) also analysed attacks by developing a model using the machine learning Random Forest (RF) technique combined with GIS for Indo-China Peninsula. This model can analyse terrorist attack data for any geographical area without considering the impact of

the timescale. If the time scale is considered, the study may only be applied nationally. Henkin et al. (2020) used a method of mapping spatial arrangements of radicalisation in Malaysia. The study concluded that a geospatial analysis is better than other methods. It bridges spatial statistical analytics and qualitative socio-spatial investigation. An epidemiological method that is called two-component spatiotemporal intensity modelling was used by (Youngblood, 2020) for 416 far-right extremist groups in the US between 2005 and 2017. This model also has limitations for assessing all types of terrorism data. (O'Sullivan & Unwin, 2002) used point pattern analysis to analyse the patterns of locations of point events, i.e., (terrorist attacks) and test whether there is a significant occurrence of clustering of points in a particular area, which was time-consuming. While (Webb & Cutter, 2009) analysed the geographic spread of terrorist attacks and the behaviour of terrorist organisations in the USA using point distribution maps.

Materials and methods

Terrorist attacks data from 2004 to 2016 from the Global Terrorism Database (GTD) of START USA was used. GTD database is one of the most comprehensive databases regarding terrorism, which different researchers across the world are using. (Hussain, 2010) also used GTD data for Pakistan for empirical analysis of temporal and spatial patterns of terrorism. GTD data from 2004 has been used in this study. The main reason to use this period is that the temporal trend started to rise from 2004 onward. Furthermore, this period also covers the post-9/11 scenario, the US involvement in the Afghan war, and the impact of this war on Pakistan. The GTD dataset was further refined, corrected and standardised as per analysis and modelling requirements. The location of each incident was cross-matched and corrected using village, town, city, and district-level point data as a reference.

In Pakistan, the district is the core unit of local administration, so the district-level boundary was considered useful as a study unit to analyse the data. The district, provincial, and national boundaries data

were acquired from the UNOCHA website, and the information database regarding important events was created by review of the literature (newspapers, magazines, research papers, and online links). Furthermore, all data were standardized as per the study requirement.

Methods

ArcGIS 10.5 software was used along with Python Language and Structured Query Language (SQL) to conduct this study. A combination of well-defined tools to analyse data geographically and statistically was used. The detailed methodology is given in Fig. 1.

Geographical spread analysis of terrorist attacks

The Standard Deviation Ellipse (SDE) was used to analyse the trend of data as (Wang et al., 2015) state that SDE is a versatile GIS tool for delineating the geographic distribution of concerned features. As a GIS tool for delineating spatial point data, SDE is mainly determined by three measures: average location, dispersion (or concentration), and orientation. It is generally used for sketching the geographical distribution trend of the features by summarising their dispersion and orientation. The variances are scaled by an adjustment factor to produce an ellipse containing the desired percentage of the data points. This analysis mainly measures average location, orientation, dispersion, or concentration. It is generally employed to

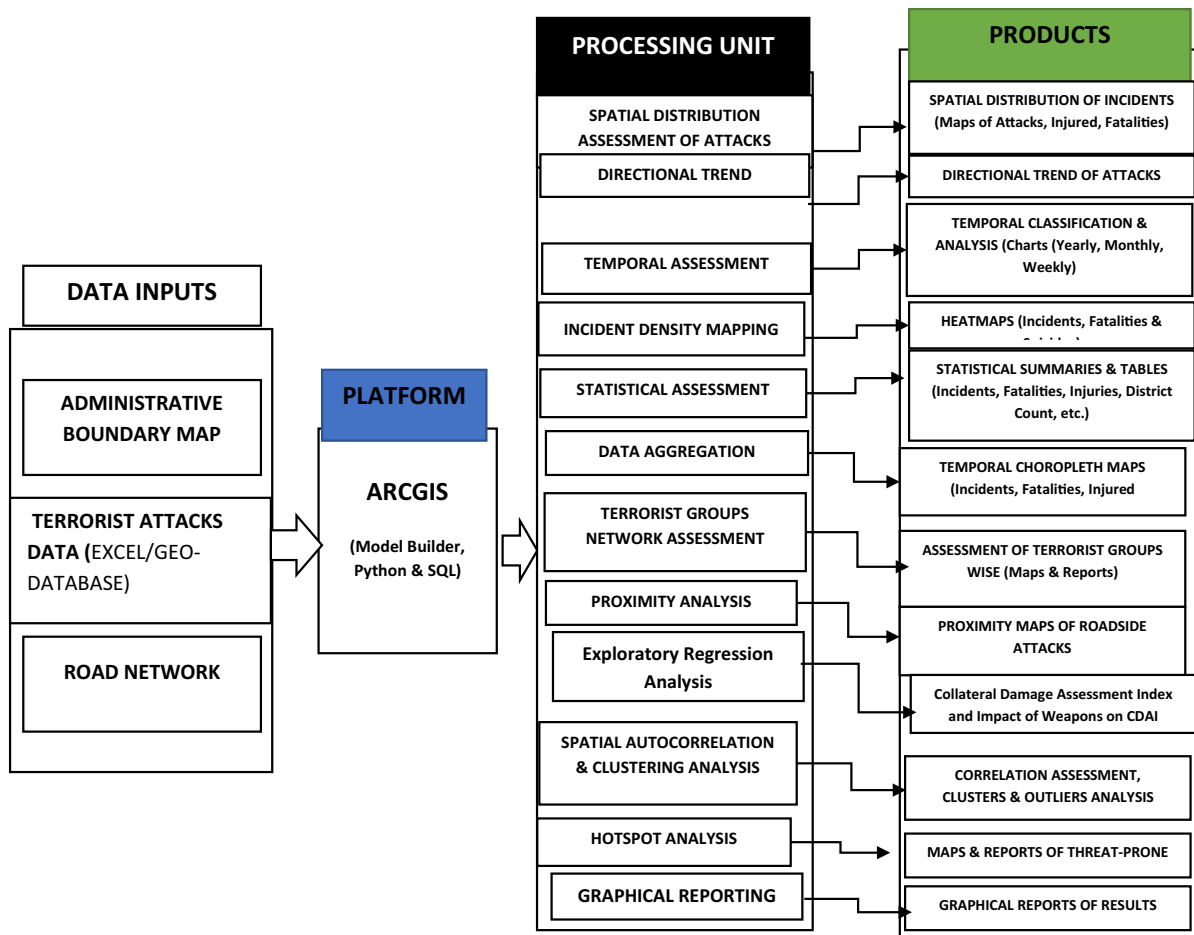


Fig. 1 Conceptual diagram of research

understand spatial distribution trends. The working of SDE is given below.

$$C = \begin{pmatrix} \text{var}(x) & \text{cov}(x, y) \\ \text{cov}(y, x) & \text{var}(y) \end{pmatrix} = \frac{1}{n} \begin{pmatrix} \sum_{i=1}^n \tilde{x}_i^2 & \sum_{i=1}^n \tilde{x}_i \tilde{y}_i \\ \sum_{i=1}^n \tilde{x}_i \tilde{y}_i & \sum_{i=1}^n \tilde{y}_i^2 \end{pmatrix} \text{ where}$$

$$\text{var}(x) = \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2 = \frac{1}{n} \sum_{i=1}^n \tilde{x}_i^2$$

$$\text{cov}(x, y) = \frac{1}{n} \sum_{i=1}^n (\tilde{x}_i - \bar{x})(\tilde{y}_i - \bar{y}) = \frac{1}{n} \sum_{i=1}^n \tilde{x}_i \tilde{y}_i$$

$$\text{var}(y) = \frac{1}{n} \sum_{i=1}^n (y_i - \bar{y})^2 = \frac{1}{n} \sum_{i=1}^n \tilde{y}_i^2 \quad (1)$$

Equation (1): Equations of SDE [Wang et al., 2015].

Where x and y are the coordinates for feature i , $\{\bar{x}, \bar{y}\}$ represent the Mean Center for the features, and n equals the total number of features.

The sample covariate matrix is factored into a standard form which results in the matrix being represented by its eigenvalues and eigenvectors. The standard deviations for the x - and y -axis are then:

$$\sigma_{1,2} = \left(\frac{(\sum_{i=1}^n \tilde{x}_i^2 + \sum_{i=1}^n \tilde{y}_i^2) + \sqrt{(\sum_{i=1}^n \tilde{x}_i^2 - \sum_{i=1}^n \tilde{y}_i^2)^2 + 4(\sum_{i=1}^n \tilde{x}_i \tilde{y}_i)^2}}{2n} \right) \quad (2)$$

Equation (2): Equation of standard deviation (Wang et al., 2015).

The variances are scaled by an adjustment factor to produce an ellipse containing the desired percentage of the data points. The geographic distribution of terrorist attacks was analysed using the point distribution map technique and Directional Trend, which used 1st-order SDE. SDE used the number of attacks at each district level to find out the directional trend.

Spatiotemporal assessment of terrorist attacks and fatality at the district level using data aggregation technique

According to Eck (1997), vector data can represent irregular object boundaries (at the district level) more precisely than raster data. Therefore, choropleth

maps were prepared to show the spatial distribution of terrorist attacks and the number of fatalities at the district level. The choropleth maps at the district level explain the number of attacks and fatalities in a well-defined and discrete way, which can easily differentiate each district from the other and help to understand the terrorism pattern at a more localised level. Each district boundary was considered a separate entity, and a defined colour scheme was assigned to each category which discriminates each district based on the number of attacks and fatalities.

Geographical analysis of attack intensity, modified attack intensity, and impact of weapons on attacks

Medina et al. (2011) state that analyses can be performed strictly based on the number of or standardised incidents; however, this ignores the intensity of attacks. So, to analyse terrorist attacks in a detailed way, attack intensity analysis is required. They analysed terrorism data in Iraq using the Attack Intensity Formula. Intensity means the number of victims per attack or incident per day at a specific location. This explores victims by the sum

of fatalities, injured, and hostages. For this equation, injured and a hostage is taken as potential fatalities. The total human loss for a specific time is divided by the total number of attacks for the same period. The attack intensity is defined as:

$$A = (F + I + H)/T \quad (3)$$

Equation (3): Equations of Attack Intensity.

Where “F” is for fatalities, “I” is for injured, “H” is for hostages, and “T” is for the total number of incidents. Table 1.

Development of modified attack intensity equation

It has been observed during this study that Eq. 3 creates an outlier effect when incidents are fewer or have more hostages because this equation does not assign any weightage to fatalities, injuries, and hostages.

Table 1 Exploratory regression analysis results for modified attack intensity equation

| Sr.No | Exploratory variables | Dependent variable | AdjR ² |
|-------|---|--|-------------------|
| 1 | To the number of fatalities in each study unit (district) at a specified period (F) | To the number of incidents in each study unit (district) at the specified period | 0.924 = f |
| 2 | To the number of injuries in each study unit (district) at a specified period (I) | To the number of incidents in each study unit (district) at the specified time | 0.789 = i |
| 3 | To the number of hostages in each study unit (district) at a specified time (H) | To the number of incidents in each study unit (district) at the specified time | 0.4645 = h |

Keeping in view the limitations of the equation as mentioned earlier 3, it has been revised. To develop a new equation, Exploratory Regression Analysis (ERA) was used; the main reason to use ERA is to identify such factors which have the maximum impact on collateral damage. In the devised equation, the total number of incidents was used as a dependent variable, while the total number of fatalities, injuries, and hostages was used as an exploratory variable. Adj R² was calculated among all variables concerning the total number of attacks. These Adj R² values are named the coefficient of fatalities (f), coefficient of injured (i), and coefficient of hostages (t). The coefficient values may vary in each data set. The modified equation is given as follows:

$$\text{Modified Attack Intensity (MAI)} = (F * f + I * i + H * h) / T \tag{4}$$

Equation (4): Modified attack intensity equation. The values for the coefficients of this dataset are given below. $f = 0.924$, $i = 0.789$, $h = 0.455$.
 Modified attack intensity = $(F * 0.924 + I * 0.789 + H * 0.455)$.

$$\text{Modified attack intensity per incident} = (F * 0.924 + I * 0.789 + H * 0.455) / T.$$

During this study, all point data were converted into aggregated form at the district level and then calculated attack intensity at the district level considering the number of injured, fatalities, and hostages by incorporating regression analysis. It took input from a statistical summary of Exploratory Regression Analysis and joined it with an administrative boundary map. The class intervals for mapping attack intensity data were defined by ArcGIS 10.5 based on the distribution of the data using the technique of natural breaks (Khan et al., 2015) for mapping purposes.

The calculated values for AdjR² using exploratory and dependent variables for each coefficient are given in Table 2.

Spatial autocorrelation, clustering, and outlier analysis of attack intensity

Spatial Autocorrelation, Clustering, and Outlier Analysis were performed for 2004–16 data for existing and modified attack intensity. Moran’s I statistic and Anselin Local Moran’s I statistic were used and

Table 2 Results of exploratory regression analysis lethality of weapon types vs attack intensity

| Sr.No | AdjR ² | AICc | JB | K_BP | Max VIF | SA | Num Vars | Variables |
|-------|-------------------|----------|----|-------|---------|--------|----------|--------------------------------------|
| 1 | 0.8740 | 2053.397 | 0 | 0 | 1 | 0.038 | 1 | Suicide |
| 2 | 0.764 | 2144.717 | 0 | 0 | 1 | 0.014 | 1 | Explosives_Bombs_Dynamite |
| 3 | 0.647 | 2202.691 | 0 | 0 | 1 | 0 | 1 | Firearms |
| 4 | 0.904 | 2014.714 | 0 | 0 | 3.232 | 0.045 | 2 | Suicide + Explosives_Bombs_Dynamite |
| 5 | 0.942 | 1942.64 | 0 | 0 | 1.734 | 0.07 | 2 | Suicide + Firearms |
| 6 | 0.836 | 2092.945 | 0 | 0.011 | 1.969 | <Null> | 2 | Explosives_Bombs_Dynamite + Firearms |

Exploratory Regression Global Summary: Min Adjusted R-Squared > 0.50, Max Coefficient p-value < 0.05, Max VIF Value < 7.50, Min Jarque–Bera p-value > 0.10, Min Spatial Autocorrelation p-value > 0.10, AdjR² Adjusted R-Squared, AICc Akaike’s Information Criterion, JB Jarque–Bera p-value, K(BP) Koenker (BP) Statistic p-value, VIF Max Variance Inflation Factor, SA Global Moran’s I p-value. Model Variable sign (+/–), Model Variable significance (* = 0.10, ** = 0.05, *** = 0.01)

identified clusters and outliers among aggregated as well as point data at the district level.

Results and discussion

Geographical spread analysis of terrorist attacks

Siebeneck et al. (2009) state that the world community is involved in the fight against terrorism. They further describe that one of the most important assets in today's age is knowledge. In particular, the war on terrorism must begin when one has a deep understanding of terrorists and terrorist groups, as well as an expanded knowledge of dynamic terrorist networks and the inner workings of terrorist systems. In addition, the analysis of the spatial and temporal patterns of terrorist activities should provide information about geographical activities and the underlying behaviour of the terrorist activity.

In this study, descriptive statistics for the period of 2004 to 2016 revealed that 11,607 terrorist attacks occurred during this period. As a result of these attacks, there were 18,936 fatalities and 32,136 injured during the period, the maximum of 2205 attacks was recorded in 2013 and a minimum of 66 attacks from 2004 to 2016 (Fig. 2). While during the period from 2004 to 2016, the average attack rate per year remained at 893 with 705 standard deviations, respectively. Results are quite similar to studies conducted by (Hussain, 2010) and (Afsar et al., 2012).

The geographical spread of terrorist attacks during the period 2004 to 2016 shows (Fig. 3) that terrorist attacks spread all across Pakistan. More

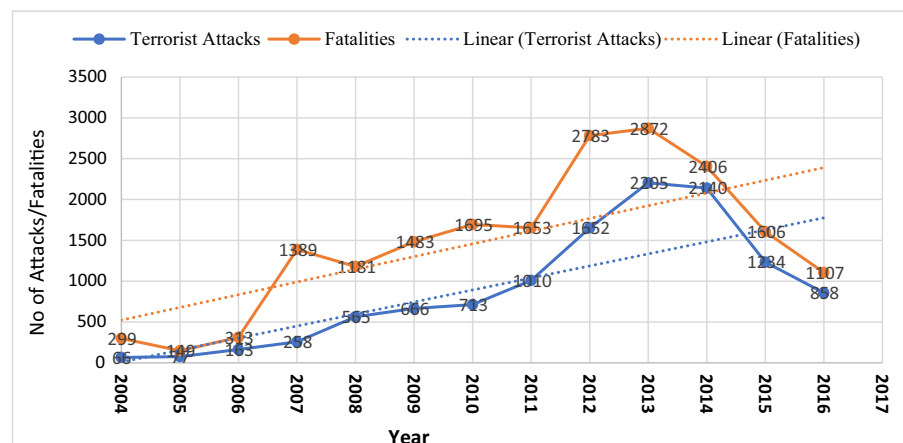
terrorist attacks were observed on the North-Western side, Khyber Pakhtunkhwa (KPK) and Federally Administrated Tribal Areas (FATA), and then towards Balochistan province. The directional trend was also elongated more towards the North-west from the South. The areas mentioned earlier witnessed a tremendous rise in attacks after the 9/11 incident and the war in Afghanistan. During this period, the maximum number of attacks occurred in KPK province (3690), 32% of total attacks. The spread of attacks also shows that insurgency in Afghanistan resulted in the evolution of different terrorist groups in the areas along with the Pak-Afghan border, which included Tehrike-e-Taleban Pakistan (TTP) and Lushkr-e-Islam Pakistan (LeIP) etc. Nemeth et al. (2014) illustrate that local population, difficult terrain patterns, and closeness to the international border significantly reduce the ability to counter terrorist activity.

While attacks in Balochistan were mainly due to Baloch Nationalists who are operating in different parts of the province, especially in border areas, Hussain (2010), in a study, also observed that Baloch nationalists were operating in Balochistan and TTP across Pakistan, especially in KPK and FATA. A map of the geographic distribution of terrorist attacks and directional trends is given in Fig. 3.

Spatiotemporal assessment of terrorist attacks and fatality at the district level

To analyse attack intensities, first of all, the terrorist attacks and fatalities at the district level were analysed

Fig. 2 Yearly temporal trend of terrorist attacks along with fatalities since 2004–16



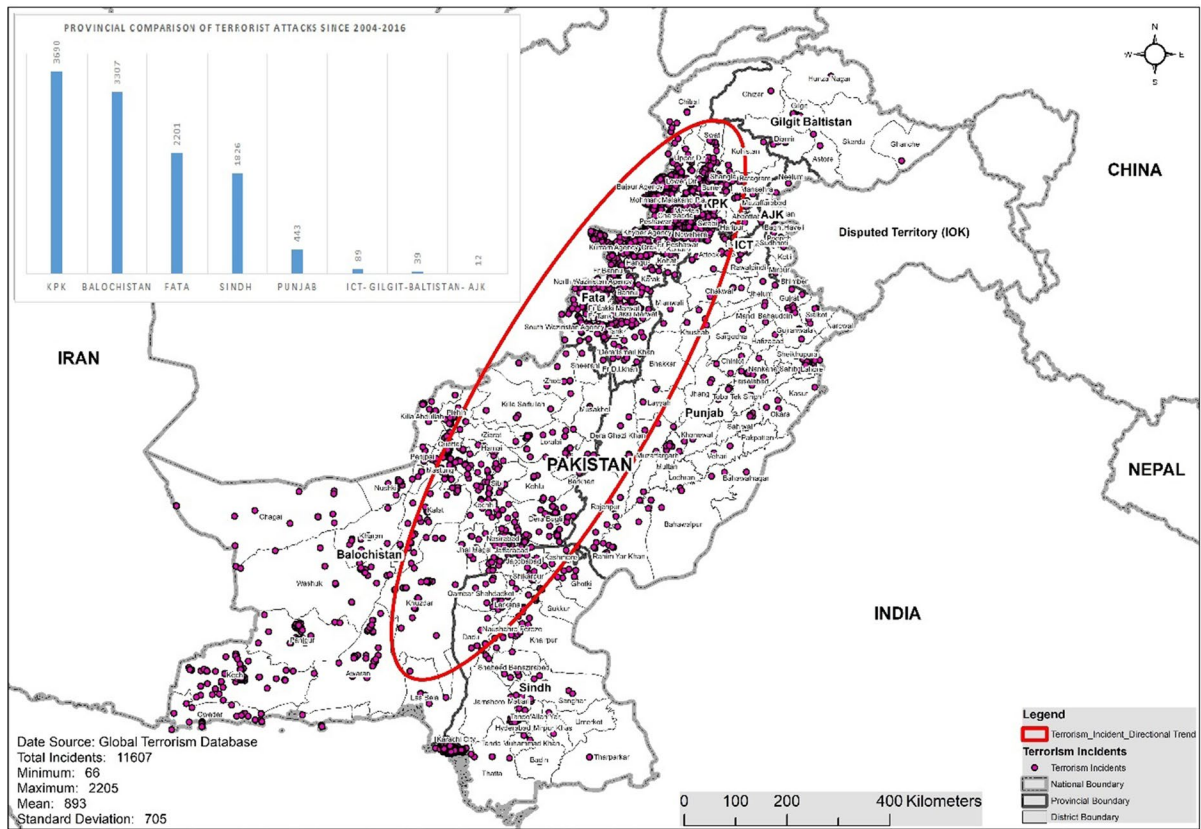


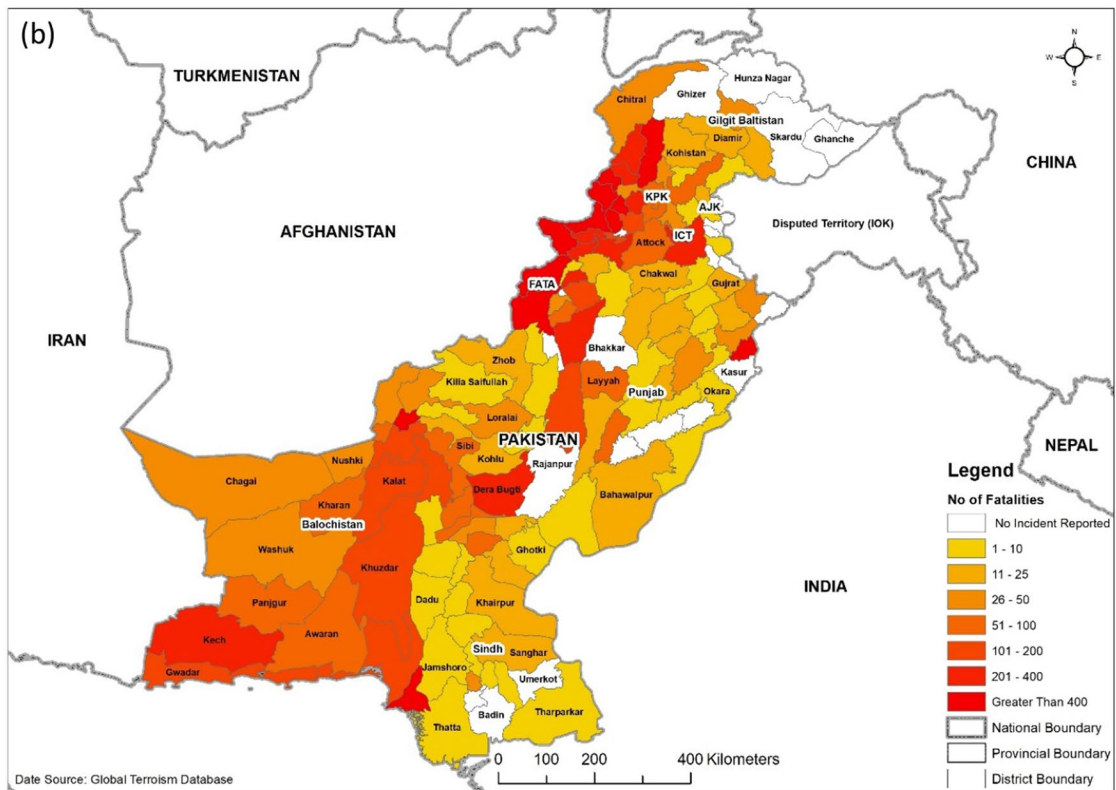
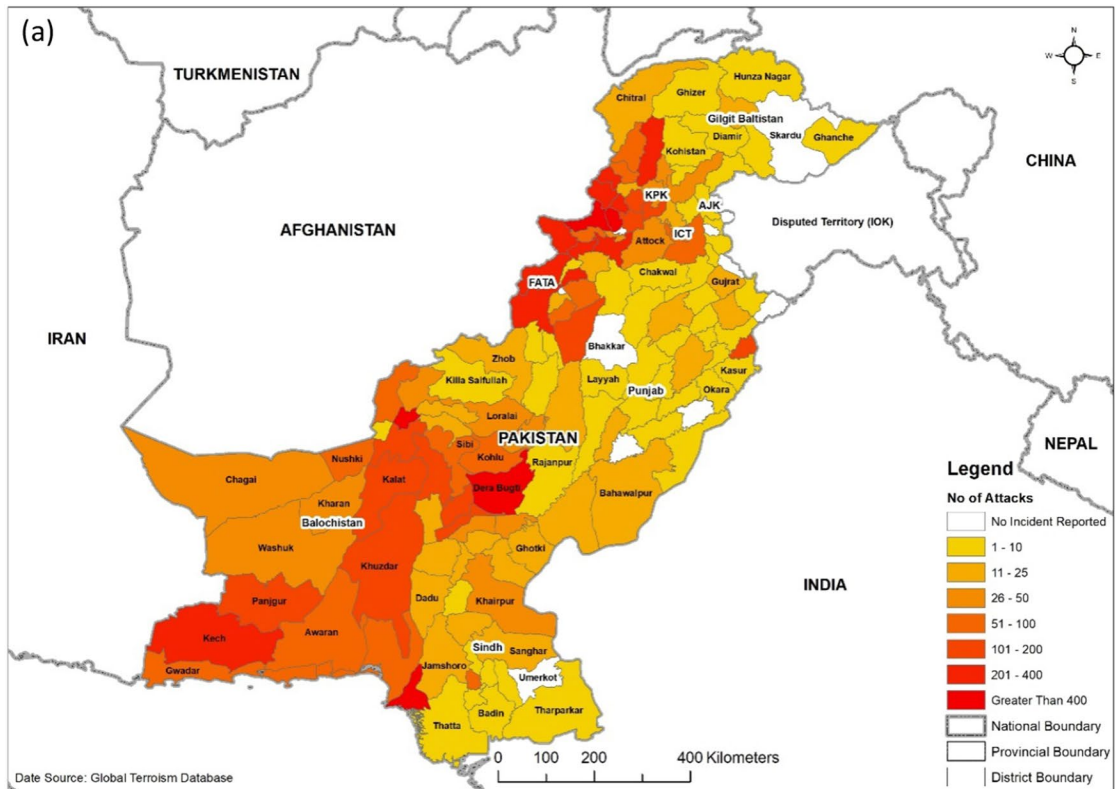
Fig. 3 Spatial distribution of terrorist attacks along with directional trend 2004–16

using aggregated data techniques separately so that differences may be measured, as done by (Medina et al., 2011). As a result, they found that the attacks and intensities have different correlations within the districts.

Karachi city was ranked at the top from 2004 to 2016 with 1487 attacks causing 2119 fatalities, while many districts from Gilgit Baltistan and AJK did not witness terrorist attacks. Peshawar in KPK province remained the highest with 1266 attacks and 2029 fatalities, Quetta from Balochistan province with 803 attacks and 1631 fatalities, Khyber Agency from FATA with 578 attacks and 933 fatalities, and Lahore district from Punjab province with 128 attacks and 695 fatalities remained at the top at the provincial level. This trend shows that densely populated urban areas were the soft targets for terrorist activities, as all these cities are provincial capitals. The same pattern was observed by Webb and Cutter (2009) and Medina

et al., (2011). As per their studies, terrorist attacks occurred in and around relatively large urban areas having high populations. During this period, the average number of attacks per district remained at 87, with 122 average fatalities per district. While standard deviation for the number of attacks for districts is 198.6, and for fatalities, it is 326. As Webb and Cutter, (2009) claimed, the fatalities rate because of terrorist attacks increased, and the same is observed in the present study. Toll (2017) also analysed variation in attack intensity values over time and identified changes in the spatial clustering of high attack intensity values in Colombia but used Eq. (3).

Further detail on all districts is in Fig. 4.



◀**Fig. 4** District profile map **a** Terrorist attacks **b** fatalities

Geographical analysis of attack intensity, modified attack intensity, and impact of weapons on attack intensity

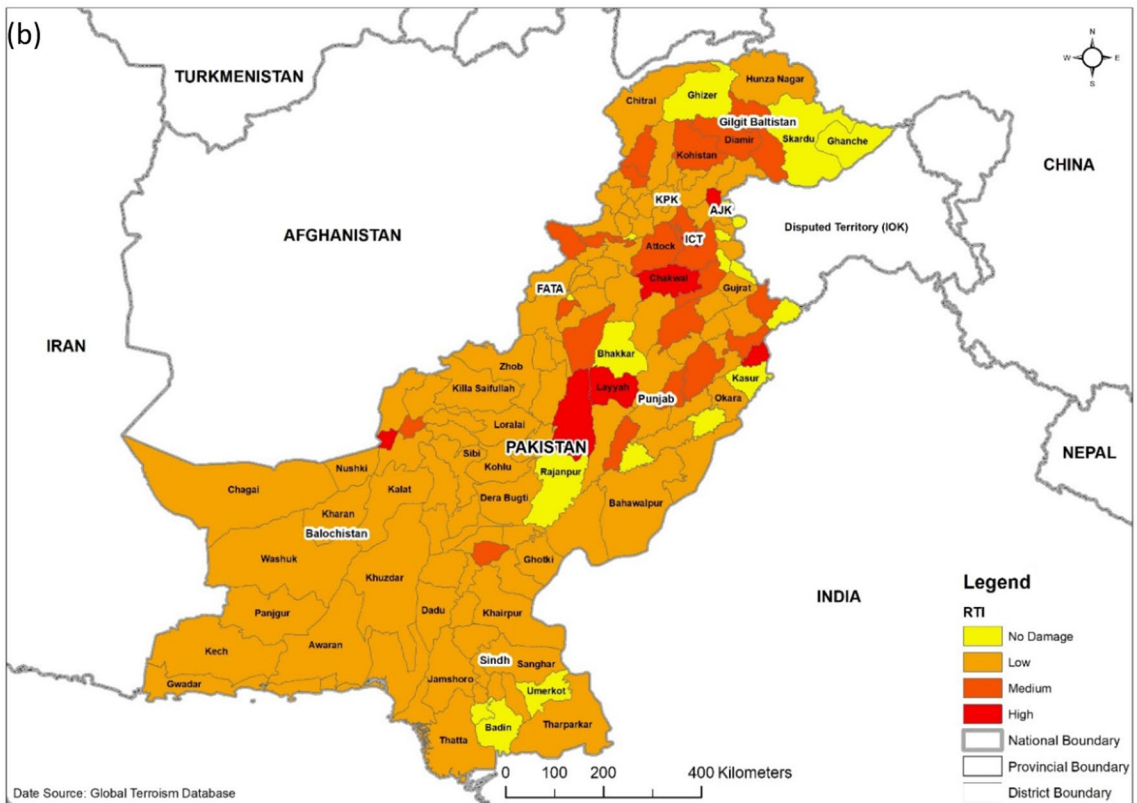
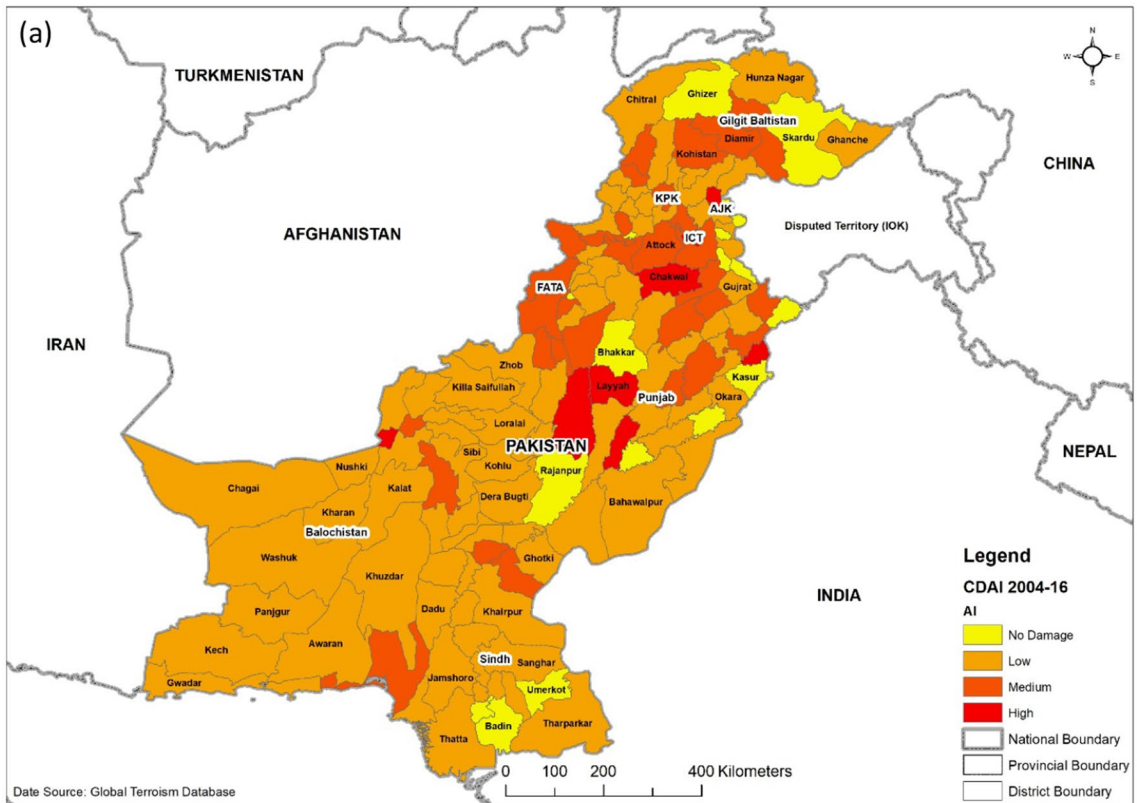
Attack intensity analysis of 2004–2016 terrorism data reveals that the minimum value was 0 and the maximum value 31.085 with a 4.56 mean district attack intensity value of 5.49 Std. During 2004–2016, Lahore from Punjab province remained at the top with the highest attack intensity value, 31.085. In other words, Lahore witnessed maximum damage per attack; similarly, Upper Dir from KPK remained at the highest with 9.947, Panjpai from Balochistan with 20, and Kurram Agency from FATA with 9.975 attack intensity value remained at the top from their respective provinces. Attack intensity analysis further revealed that collateral damage due to terrorism incidents makes a proper corridor that starts from FATA with high values and passes through KPK (DI Khan), South Punjab (DG Khan and Layyah). In comparison, Balochistan had scattered high to medium-damaged areas due to attacks (Panjpai and Quetta). These areas suffered maximum collateral damage from 2004 to 2016. The high value of attack intensity was due to suicide attacks and the use of bombs and armed firearms. Attack intensity analysis further revealed that 49 out of 145 districts have more value than the mean value. This further shows that the highest attack intensity did not exist in such areas where most of the attacks occurred because areas having more attacks have less use of lethal weapons like suicide attacks etc. (Fig. 5).

Per the modified Attack Intensity Equation 2004–2016, terrorism data revealed that the minimum value was 0 and the maximum value 24.766, with a mean value of 3.615 per district attack intensity value and 4.458 Std. The modified equation reduced maximum, mean, and Std values and decreased the abrupt changes. The reason is the inclusion of the coefficients of fatalities, Injured, and hostages. As per the modified equation, Muzaffarabad from AJK witnessed maximum damage with a value of 24.766 as contrary to Lahore, while on a provincial basis, Lahore (22.89) from Punjab, Upper Dir (8.466) from KPK, Panjpai (17.072) from Balochistan, Islamabad Federal Capital (16.139) and Kurram Agency

(7.921) from FATA witnessed maximum attack intensity or collateral damage. The results of the modified equation show a smooth pattern with fewer fluctuations (Fig. 6). The high rate of attack intensity was observed in locations where suicide attacks occurred. This caused brutal collateral damage with the highest Adj R^2 value.

Furthermore, districts having higher attack intensities are scattered, as discussed by Medina et al., (2011) in Iraq. Districts with high intensities were scattered throughout the study area seemingly randomly. Interestingly, terrorists who operate in a specific district cannot maintain high intensity for attacks. The terrorists may constantly be moving to evade capture or being forced out by counterterrorist forces. Counterterrorist efforts were found to be effective in routing out terrorists from districts of high terrorist activity.

While (Medina et al., 2011) conducted research and could not find the answer to “why districts have varying levels of attack intensities over time”? It may have to do with the scarcity and dynamics of effective terrorists or the populations they are attacking. Hence in this study, an attempt was made to find out the answer to the above-mentioned question. Exploratory Regression Analysis was used to analyse the impact of weapons on collateral damage; it means which weapon has done more collateral damage in any attack. For this analysis, modified attack intensity value was considered as a dependent variable, while weapon types such as Firearms, Explosives_Bomb_Dynamite, and Incendiary were kept as exploratory variables. Possible combinations regarding the impact of weapons on Modified attack intensity values were analysed. The main advantage of ERA is that it attempts all possible combinations of exploratory variables to see which model passes all of the necessary Ordinary Least Square (OLS) diagnostics. After evaluating all possible relations of the candidate exploratory variables, it enhances the chances of finding the best model to solve the issue. In other words, ERA is similar to Stepwise Regression; rather than only looking for models with high Adjusted R^2 values, Exploratory Regression searches for models that meet all of the requirements and assumptions of the OLS method as AICs, JB, K_BP, Max VIF, and SA. (ArcGIS help 10.5, 2016). The impact of weapons used during attacks was analysed using one-by-one and one-by-many relationships. Analysis



◀**Fig. 5** District level attack intensity maps for Pakistan 2004–16 **a** Attack Intensity **b** Modified Attack Intensity

of the impact of weapons on attack intensity using Exploratory Regression Analysis reveals that from 2004 through 2016, maximum collateral damage occurred due to suicide attacks having $AdjR^2$ 0.874 on one-by-one relationship, while on one by two relation suicide attacks and firearms did maximum collateral damage with $AdjR^2$ 0.94174 (Table 2).

Spatial autocorrelation, clustering, and outlier analysis

As simple linear regression shows a relationship between two objects without including spatial locations of attacks and related fatalities, spatial autocorrelation analysis was used to analyse terrorism spread at any place using Moran’s I statistic. This statistic estimates whether the pattern is dispersed, clustered, or random based on a user-provided set of features along with attached values. After that, it computes Moran’s I Index value and both a z-score and *p*-value to analyse the significance of that index. The *p*-values are arithmetic approximations of the area under the curve for a given distribution, limited by the test

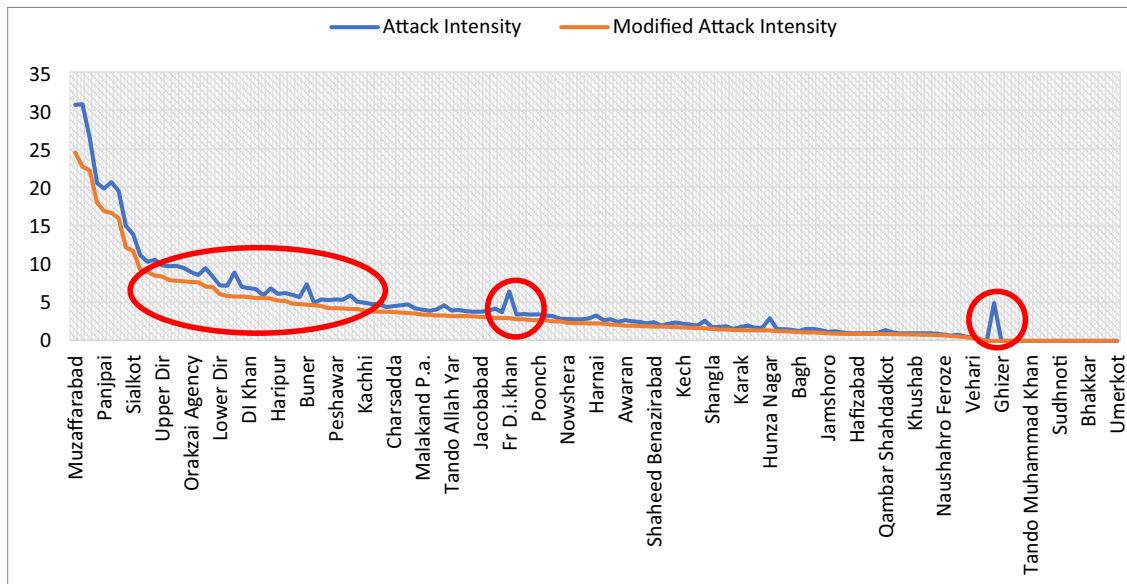


Fig. 6 Graphical comparison of results of Attack Intensity and Modified Attack Intensity Equation

Table 3 Summary statistic of global Moran’s I for attack intensity & modified attack intensity 2004–16

| Sr.No | Global Moran’s I statistics | Attack intensity value | Modified attack intensity value |
|-------|-----------------------------|------------------------|---------------------------------|
| 1 | Moran’ index | 0.002537 | 0.009194 |
| 2 | Expected index | −0.006944 | −0.006944 |
| 3 | Variance | 0.000854 | 0.000859 |
| 4 | z-score | 0.324398 | 0.550504 |
| 5 | <i>p</i> -value | 0.745636 | 0.5819740 |
| | Spatial pattern | Random | Random |

statistic. A positive Moran's *I* show data in clusters, and a negative Moran's *I* indicate data as dispersed (ESRI, 2016). Moreover, (Mitchell, 2005) states that there are two very significant statistical parameters in spatial autocorrelation: the *z*-score and the *p*-value.

Spatial autocorrelation of attack intensity data of 2004–2016 indicates a random pattern in attack intensity across the country with Moran's Index value of 0.002537, *z*-score 0.324398, and *p*-value 0.745636. Results show terrorism data were randomly distributed across the study area, and no clustering was found (Table 3). A similar pattern was observed by (Toll, 2017), showing that areas with high attack intensity values were not more clustered in space throughout time.

Spatial autocorrelation of modified attack intensity of 2004–2016 also shows a random pattern at the national level with Moran's Index value of 0.009194, *z*-score 0.550504, and *p*-value of 0.5819740. Modified Attack Intensity also showed a random pattern but less probability value and a higher *z* value or Std value. Similarly, (Braithwaite & Johnson, 2012) used this analysis to assess spatiotemporal clusters of Improvised Explosive Device (IED) and non-IED attacks in Iraq from January to June 2005.

To further analyse the data, Anselin and Local Moran's *I* statistics were performed as used by (Toll, 2017). The Anselin and Local Moran's *I* statistics were used to identify clusters and outliers in terrorism data. The Anselin and Local Moran's *I* statistics segregate spatial clusters of features with high or low values. This analysis also identified spatial outliers by calculating a local Moran's *I* value, a *z*-score, a *p*-value, and a code representing the cluster type for each statistically significant object. The *z*-scores and pseudo-*p*-value reveal the statistical significance of the calculated index values (ESRI, 2016).

As a result of this analysis, most of the clusters were found in FATA and KPK regions which include (Kurram Agency, Khyber Agency, Mohmand Agency, Bajur Agency, Orakzai Agency, Fr Kohat, Fr Peshawar, Charsada, Nowshera, Hangu, Kohat and Malakund, (Lower Dir, Upper Dir for fatalities only) Districts. In contrast, one cluster was found in Lahore in Punjab province. These results infer that the areas mentioned earlier were more vulnerable concerning terrorist attacks and witnessed maximum collateral damage; further detail is given in Fig. 7.

Conclusion

The results show that most terrorist attacks occurred in urban areas, especially along with Pak-Afghan Border areas. Most of the terrorist attacks were observed on the North-Western side of Pakistan, which is KPK and FATA, the spread of attacks also shows that insurgency in Afghanistan resulted in the evolution of different terrorist groups in the areas along with the Pak-Afghan border, which included Tehrik-e-Taleban Pakistan (TTP) and Lushkr-e-Islam Pakistan (LeIP), etc. The main reason for these attacks was easy to access to populated areas and inability to counter terrorist activities, closeness to the Afghan border, less patrolling, and the roughness of the terrain. Nemeth et al. (2014) describe that local population, difficult terrain patterns, and closeness to the international border significantly affect the ability to counter terrorist activity. At the same time, attacks in Balochistan were mainly due to Baloch Nationalists operating in different parts of the province, especially in border areas, and getting advantage of the area's topography, poor law-and-order situation, and closeness with the international borders with Iran and Afghanistan.

Furthermore, the attack intensity values show that from 2004 to 2016, Karachi City from Sindh province remained at the top with the most significant collateral damage, while Peshawar from KPK, Lahore from Punjab, Khyber Agency from FATA, and Quetta from Balochistan witnessed maximum collateral damage. Results depict that areas with high-intensity values are placed randomly, and no cluster is found, meaning areas with more collateral damage are distributed unevenly across the country. While the modified attack intensity equation provides more realistic results, do not create an outlier effect and sharp peaks. The modified equation also found a random pattern with less probability and a higher *z* or Std value. The 2004–2016 data analysis reveals that maximum collateral damage occurred due to suicide attacks in one-by-one relationships. In one-by-two relationships, suicide attacks and firearms had maximum collateral damage.

Moreover, exploratory regression analysis can be used effectively to understand the behaviour of terrorism and factor correlated with terrorist activities. This study provides a robust method

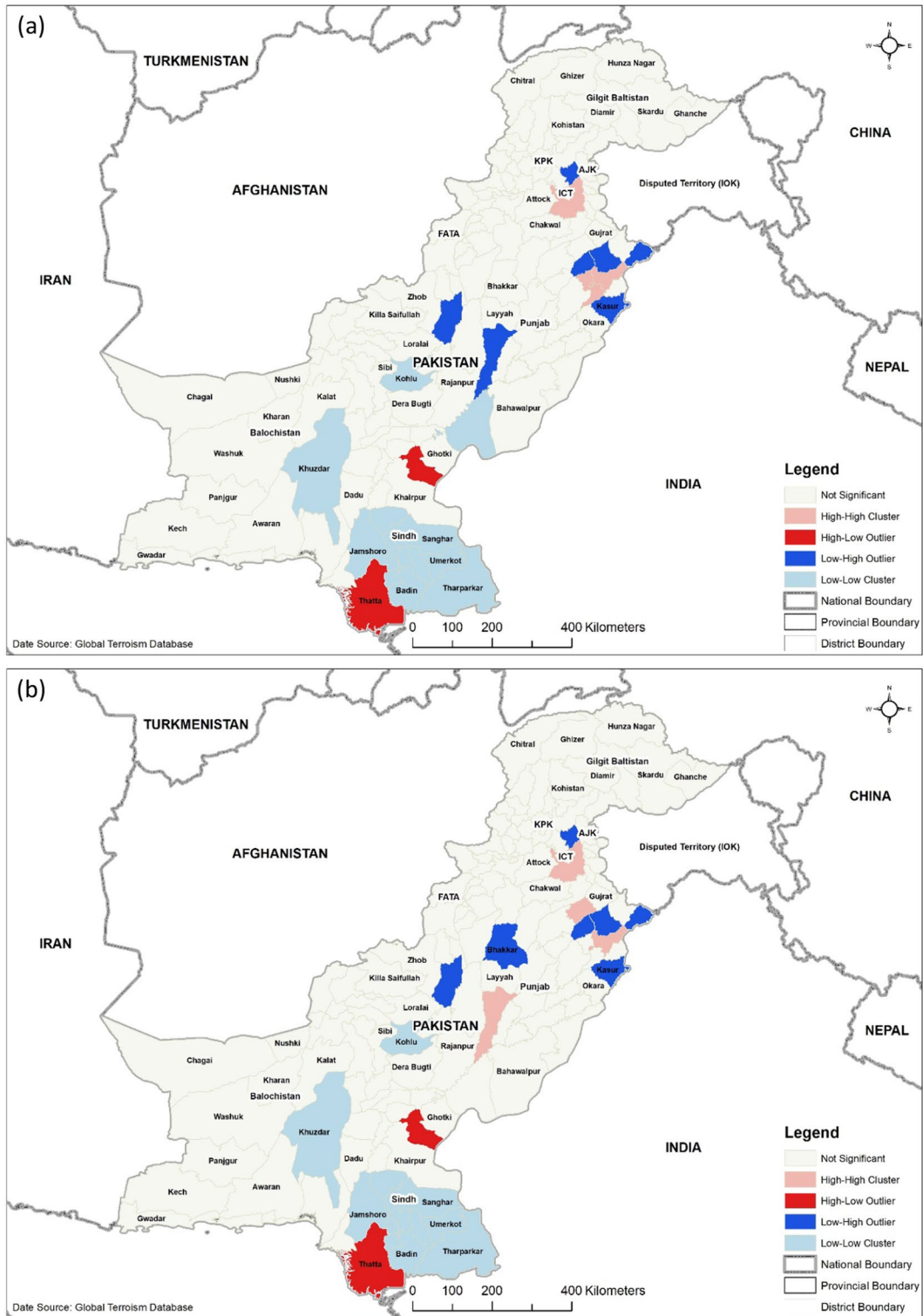


Fig. 7 Terrorist attacks Intensity cluster and outlier assessment in Pakistan **a** Attack intensity **b** Modified attack intensity

to analyse the role of weapons used in collateral damage assessment during terrorist attacks, which has not been analysed in such a detailed way earlier. The researchers may use and improve the modified attack intensity equation and work on new dimensions to analyse terrorism in any space and time environment.

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Declarations

Conflict of interest The authors declare that there is no conflict of interest among them regarding the publication of this work.

Ethical statement In this research, no human or animal was involved.

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