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Research article

Spatial prediction of armed conflicts from the perspective of political geography using bivariate frequency ratio method (FR) in East African States

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ABSTRACT

Armed conflicts, as significant human phenomena, profoundly impact populations and reflect a state's capacity to fulfill its responsibilities. These conflicts arise from various causes, necessitating robust predictive models to understand their spatial distribution. This study employs the Bivariate Frequency Ratio (FR) method to spatially predict the occurrence of armed conflicts across the East African States, drawing on 42 political geography-related criteria. The development of the predictive model involved classifying the region into five conflict-prone categories influenced by critical political geography factors. Geospatial datasets, curated in a GIS environment, were sourced from approved online portals. The findings indicate that Burundi exhibits the highest vulnerability to armed conflict, followed closely by Rwanda, Uganda, and Somalia. Ethiopia and South Sudan show a moderate risk, while predictions for Zimbabwe, Zambia, and Mozambique suggest lower likelihoods of conflict. The model's accuracy was validated using the Receiver Operating Characteristic (ROC) curve, demonstrating its effectiveness. Furthermore, the model's applicability extends to other regions, offering a valuable tool for global conflict prediction.

1. Introduction

Armed conflict poses a significant and recurring threat to states and their functions, affecting regions worldwide. To mitigate its devastating impacts, we require predictive models that leverage detailed spatial and temporal data to anticipate conflict zones, enabling swift risk assessment for political decision-makers. Conflict, rooted in the Latin term "conflictus," meaning "collision or clash," is characterized by rivalries for status, power, and resources [1]. Armed conflicts, an extreme manifestation of international relations, jeopardize national security, lives, and political geography structures, particularly in regions like East Africa. This region,

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marked by ethnic diversity and a legacy of colonialism, remains vulnerable to conflict due to evolving climate patterns and global politics [2] Efforts in conflict prediction date back to the 1960s, evolving with technological advancements. Geographic Information Systems (GIS) have revolutionized the spatial and temporal analysis of conflicts, making it a mainstream endeavor [3]. These predictive models play a vital role in averting political instability, as witnessed by the support provided by the US government to programs like the Political Instability Task Force [4]. Geographic Information Systems (GIS) serve as a powerful tool for analyzing spatial data and conducting multi-criteria decision analysis (MCDA) [5]. MCDA techniques integrate spatial data with decision-maker preferences, offering a comprehensive approach to evaluating conflict risks [5].

The Frequency Ratio (FR) statistical analysis method employs natural and human factors to predict armed conflicts. The FR method has been widely used in the general literature for various applications, including landslides and groundwater mapping. These studies increased significantly in the nineties as a result of the expansion of the use of computers, including studies by Davis & Weddle on using algorithms to classify political events and the innovation of the early warning system for conflict [6]. The Special Literature encompasses studies specifically focused on the spatial prediction of armed conflicts. These studies utilize various methods, from regression models to machine learning algorithms.

Various approaches exist for spatial prediction, each with its advantages and disadvantages. The Analytic Hierarchy Process (AHP) is famous for its flexibility and hierarchical structure, making decision-making systematic [7]. While the Best-Worst Method (BWM) uses fewer comparisons, it is challenged in solving nonlinear models. The Simple Additive Weighting with Ranks (SWARA) method is straightforward but lacks validation capabilities. The Decision-Making Trial and Evaluation Laboratory (DEMATEL) method also faces validation issues. The Entropy method determines criteria weights based on data, ignoring decision-maker preferences [7].

Machine learning algorithms such as CatBoost, GBDT, LightGBM [8], LR, SVM, KNN, and RF (Ganesh et al., 2023) have been applied to conflict prediction, enhancing accuracy and timeliness. In summary, this study aims to create a conflict prediction map using the Frequency Ratio (FR) method and GIS technology for East Africa, potentially applicable to other regions. This methodology simplifies complex criteria into quantifiable forms, providing decision-makers valuable insights into mitigating violent conflicts.

The objective of the present study is first to establish a spatial predictability database for armed conflicts and to identify variables specific to the regional study context that directly impact the occurrence of armed conflicts. The second objective is to develop a spatial predictability map of armed conflicts for the first time in the East African region. Thus, future prevention measures can be proactive and effective. To achieve this, one of the most influential and widely used operational methods in future predictability mapping (FR) was chosen as it provides a better understanding of the impact of the selected variables, "natural or human," on the occurrence of armed conflicts over many other methods in spatial prediction.

2. Materials and methods

2.1. Literature review of the previous work

Conflict is a social condition that occurs when two or more actors pursue mutually exclusive or incompatible purposes. In fact, "conflict is the pursuit of incompatible goals by different groups/organizations." [9]. The existence of an armed conflict triggers IHL. Yet there is no settled definition of the term "armed conflict,"—which is used freely in both the Geneva Conventions and the Additional Protocols but is not defined in either [10]. An armed conflict refers to a state of disputed disagreement between two parties - at least one of which is a government of a state - concerning the government, territory, or both, where the use of armed force by the parties results in the deaths of at least 25 people in conflict-related combat in a single year, while a conflict that results in the deaths of 1000 or more people in a single year is classified as a war [11].

The importance of classifying armed conflicts is that if there is no armed conflict, international humanitarian law does not apply; instead, local criminal law, such as the law of terrorism, and international human rights law also applies.

Uppsala classified armed conflicts into two categories: the first is low-intensity armed conflict, in which the number of deaths ranges from 25 to 999, and the second is high-intensity armed conflict, called a major armed conflict, in which the number of deaths ranges from 1000 to 9999 [12].

International humanitarian law distinguishes two types of armed conflicts: international armed conflicts, opposing two or more States, and · non-international armed conflicts, between governmental forces and nongovernmental armed groups or between such groups only.

IHL treaty law also distinguishes non-international armed conflicts in the meaning of standard Article 3 of the Geneva Conventions of 1949 and non-international armed conflicts falling within the definition provided in Art. 1 of Additional Protocol II. Legally speaking, no other type of armed conflict exists. It is nevertheless essential to underline that a situation can evolve from one kind of armed conflict to another, depending on the facts prevailing at a particular moment [13–15].

The International Criminal Tribunal for the Former Yugoslavia (ICTY) proposed a general definition of international armed conflict. In the Tadic case, the Tribunal stated that "an armed conflict exists whenever there is a resort to armed force between States." 5 This definition has been adopted by other international bodies since then [15].

International law has set two criteria for the existence of a state of armed conflict. The first is the existence of a degree of organization among the armed groups participating as parties to the conflict. The second is the intensity of the conflict, which is determined by the duration of the armed clashes, the number of forces participating in the conflict, the intensity of the violence, and the amount of damage resulting from the conflict.

The category of IAC encompasses a broad range of international hostilities, including, but not limited to: "All cases of partial or total occupation of the territory of a High Contracting Party, even if the said occupation meets with no armed resistance." "An unconsented invasion or deployment of a State's armed forces on the territory of another State – even if it does not meet with armed resistance." [16]. "Armed conflicts in which peoples are fighting against colonial domination, alien occupation or racist regimes" [17].

"Minor skirmishes between the armed forces, be they land, air or naval forces" [16,18].

Armed forces and non-military agencies acting on behalf of the State may be involved in the means and methods of IAC, and the use of armed force may be directed against a State's armed forces, territory, population, or military or civilian infrastructure [16].

Non-international armed conflict is protracted armed confrontations between governmental armed forces and the forces of one or more-armed groups or between such groups arising on the territory of a State. The armed confrontation must reach a minimum level of intensity, and the parties involved in the conflict must show a minimum organization [15].

Domestic armed conflicts do not include " internal disturbances and tensions, such as riots, isolated and sporadic acts of violence or other acts of a similar nature." They include "armed conflicts that take place in the territory of a State when there is protracted armed conflict between governmental authorities and organized armed groups or between such groups."

armed conflicts are distinguished from "internal disturbances and tensions [or] isolated and sporadic acts of violence." One of the factors relevant to such a factual determination is the nature, intensity, and duration of the violence. Additionally, the protections applicable in non-international armed conflicts bind all parties to the conflict, including non-state actors. As a result, for a non-state actor to be deemed a party to a non-international armed conflict, it must have attained a certain level of organization and command structure such that it is capable of being identified as a party in the first place [10] It should be noted that ACLED classifies armed conflicts into:

- Battles: include armed clashes and government seizure of land.
- Protests: include peaceful protests, protests with intervention, and excessive force against demonstrators.
- Violence against civilians: includes arrests, change to an activity/group, use of weapons, the establishment of headquarters, looting, and destruction of property.
- Riots: include mob violence and violent demonstrations.
- Explosions/remote violence: include grenades/remote explosives, landmines, suicide bombs, drone strikes, and chemical weapons. For more: (ACLED:2023, p. 8).

The main factors and roots of the conflict need to be systematized. At the level of the individual, the causes can be seen in human nature and characteristics, biological instincts, aggressive behavior (aroused by frustration), misperception, and failure to satisfy primary basic needs. At the state and society level, they are found in the state regime's nature (e.g., autocratic regimes, early-stage democracies). Relative to stable democratic states, authoritarian states are more aggressive in their efforts to start wars because they do not have the mechanisms regulating social and political relations within their administrative structures, which limits the intentions for war of democratic governments. Regarding the nature of society, conflict is generated by ethnic diversity. A heterogeneous society is more susceptible to trigger mechanisms of a security dilemma and mass manipulation than a homogeneous society. War is also triggered by differences in economic development, a particular appearance of a contradiction between diversity rates of economic increment and the ability to provide a livelihood for a rapidly growing population. At the level of the international system, generally, its unruly nature generates armed conflicts. More precisely, war arises due to the state's security dilemma caused by the imbalance of power between significant states (and their allies) and other state members of the system. The source of the conflict is the phenomenon of power transition that has arisen due to a rising power challenging the position of the dominant state (the so-called challenger) due to dissatisfaction with its position in the system, established world order, or the existing status quo. This action is mainly motivated by the challenger's economic growth. Moreover, armed conflicts are also caused by the state's aspiration to assume the position of the leader-hegemon in the international system, which leads to direct contests between the dominant power(s) and a rising challenger, so-called hegemonic wars [19].

Moreover, it must be noted that there is a fundamental difference between armed conflict and terrorism; armed conflict is a situation in which certain acts of violence are considered lawful, and others are unlawful, while any act of violence designated as "terrorist" is always unlawful. The ultimate aim of an armed conflict is to prevail over the enemy's armed forces. For this reason, the parties to a conflict are permitted, or at least are not prohibited from, attacking each other's military objectives or individuals not entitled to protection against direct attacks. Violence directed at those targets is not forbidden as a matter of IHL, regardless of whether a State or a non-state party inflicts it. Acts of violence directed against civilians and civilian objects are, by contrast, unlawful, as one of the primary purposes of IHL is to spare them from the effects of hostilities. IHL thus regulates both lawful and illegal acts of violence [20].

There are many prediction methods, such as qualitative, deterministic, statistical, machine learning, and other methods; however, after comparing various statistical methods, the FR model's performance was generally better than others. For example, Wang [21] Comparing the FR model and the index of entropy model, finding that, in terms of the success rate curve, the area under the curve (AUC) of FR and the index of entropy models were 0.8191 and 0.8109 for accuracy, respectively. Similarly, the prediction accuracy was 81.75 % for the FR model and 81.44 % for the index of entropy model. Bourenane et al. (Bourenane, eds; 2016) compared five methods (FR, weighting factor, logistic regression, weights-of-evidence, and the analytical hierarchy process), concluding that the FR method can provide a more accurate prediction (86.59 %), while the logistic regression model had the lowest accuracy (70.45 %). Furthermore, it is easy to implement as a bivariate statistical method and has accurate results. As a traditional method, the FR model may gradually fade with the rapid development of machine learning. What is more, the input, output, and calculation process of the FR model are easy to understand, and even massive data can be processed quickly and easily in the GIS environment [21].

However, the limitations or weaknesses of the selected method: Certain irrationality in the distribution of weights, Generally less predictive accuracy than multivariate methods, and Difficult to include a large number of factors [22].

A crucial tool for geospatial evaluation, frequency ratio is a bivariate statistical approach to ascertain the probability link between dependent and independent variables or multi-classified thematic layers [23]. Frequency ratio calculations are based on values representing the probability of present versus absent armed conflict occurrences for each armed conflict conditioning factor class. A higher FR value denotes a more vital observed spatial link between the occurrence of armed conflict and the conditioning factor for armed conflict [24].

The region where armed conflict occurred in the entire study area is known as the frequency ratio, and the probability of armed conflict occurrence about non-armed conflict occurrence for a particular attribute is known as the probability ratio. This method's fundamental tenet is based on evaluating the geographical relationship between previously recorded Armed Conflicts and several Armed Conflict conditioning factors [25].

2.2. Study area

The term "East Africa" refers to the nations in the east of the continent and the seven nations south of the Sahara Desert, which are "Somalia, Djibouti, Ethiopia, Eritrea, Kenya, Tanzania, and Uganda." East Africa is one of the five major geographical regions on the

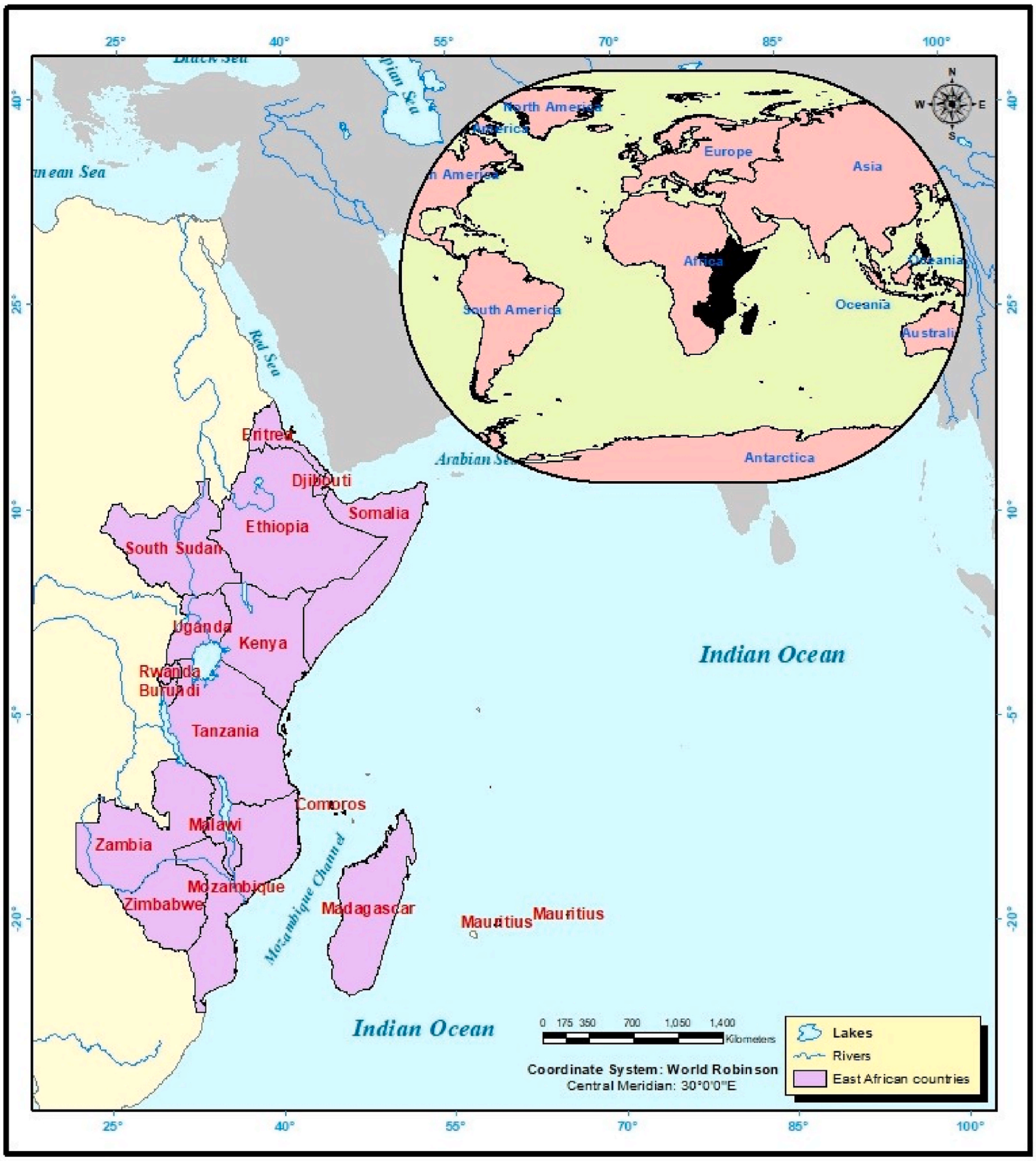

Figure. (1). Location map of the study area.

continent. Zimbabwe, Zambia, Mozambique, Uganda, Tanzania, Somalia, Seychelles, Rwanda, Mauritius, Malawi, Madagascar, Kenya, Ethiopia, Eritrea, Djibouti, Comoros, Burundi, and South Sudan are among the 18 African nations that were used in the current study.

The study region is situated between longitudes 38° 0 22′ and 42° 45′ 63′ east and latitudes 24° 50° 17′ north and 35° 57′ 26′ south. Consequently, it has a 5,816,405 km^2 area and following nations. It is an island region in the Indian Ocean that includes “Mauritius, Seychelles, and Madagascar.” Eritrea, Djibouti, Somalia, Kenya, Tanzania, and Mozambique are the six nations that gaze out over the Red Sea and the Indian Ocean, respectively. The remaining nations are landlocked—figure (1).

The population of its countries reached about 470,510,574 in 2023. Thus, it is the most densely populated region in Africa, with Ethiopia occupying approximately 26.89 % of the total population. Seychelles is the least populated among the region’s countries by about 0.02 %, and about 70 % live in rural areas. The Swahili language is widely used to communicate in many countries of the region. The region’s population largely embraces either Christianity or Islam. The region’s countries are considered an anthropological museum as they transcend races, cultures, languages, and religions, which is a significant driver of conflict in the region.

Some countries in the region have the fastest-growing economies in the world. Like Kenya, the largest economy in East Africa, the same is true in Ethiopia, Tanzania, and Rwanda [26].

Due to its location overlooking the southern entrance to the Red Maritime, the Gulf of Aden, and Bab al-Mandab, the area is a significant maritime port for international oil transportation. Along with being a security corridor for major powers traveling to the Middle East and the Arabian Gulf, the region is known for its abundant natural riches. However, the area is hampered by the fragility of some of its states, including South Sudan, Eritrea, Djibouti, Somalia, Mozambique, and Zambia, where poverty, violence, and bad governance exist. These nations lack access to external borrowing, have uneven economic growth, high inflation rates, armed conflicts, insecurity, and infrastructure destruction. The population of its countries will reach approximately 470,510,574 in 2023 [27].

2.3. Study methodology

2.3.1. Data preparation and model validation

In the first phase of the methodology, the study area was precisely defined, focusing on the East African countries’ region. Subsequently, the selection and verification of study variables representing key conflict catalysts were meticulously conducted. Data collection was thorough, encompassing a variety of formats, including digital and raster data. These preliminary stages laid the foundation for the following comprehensive analysis. Data processing and analysis were executed using specialized software tools, primarily ArcGIS Pro 3.0.2 and Microsoft Excel. This digital environment provided a robust data manipulation and transformation

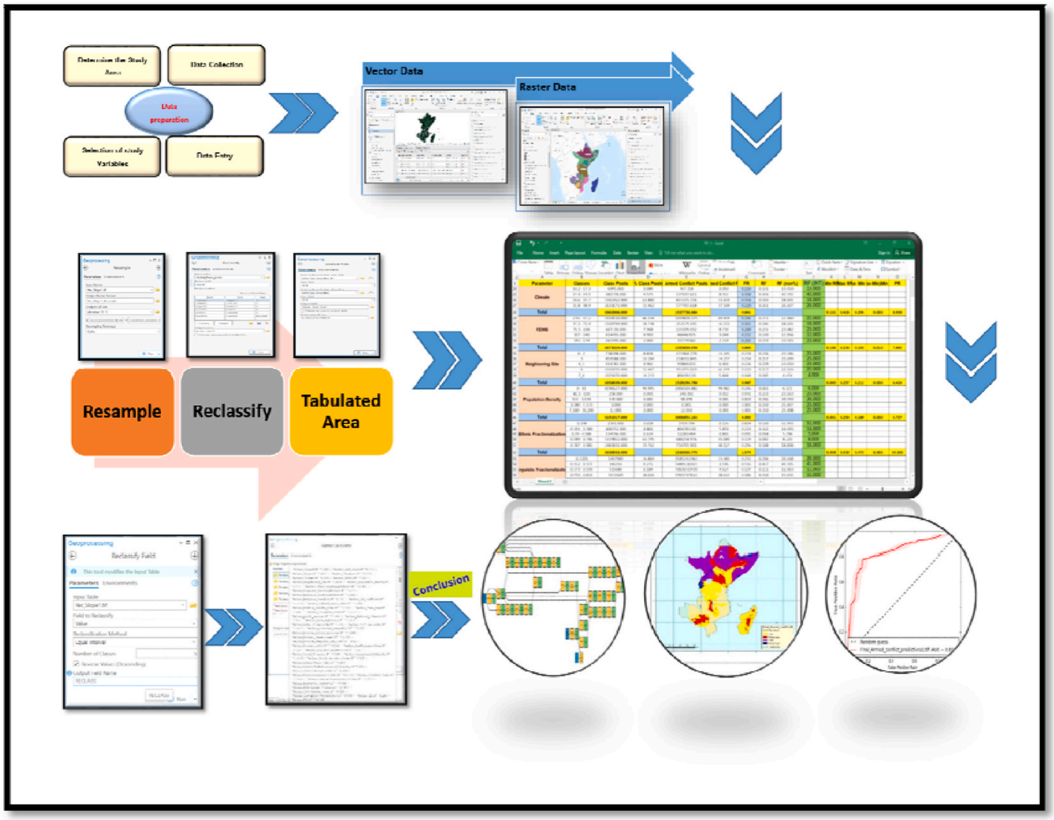

Figure. (2). Flowchart for the Study’s methodology.

platform, setting the stage for subsequent data preparation and transformation. The complete methodology encompassed a series of distinct phases, including data standardization, reclassification, and the critical process of variable weighting. Variable weights were calculated by applying various methods such as Frequency Ratio (FR), Relative Frequency (RF), and PR, ensuring their suitability in the conflict prediction model. The ultimate aim of the study was to produce a predictive map, based on the weighted criteria, outlining potential locations of armed conflicts in the East African countries' region. This predictive model, constructed through Model Builder, also demonstrated adaptability for application in other global areas with similar criteria and weight parameters. Model validation was crucial in confirming the model's reliability and accuracy, a task undertaken using the ArcSDM tool and the Area Under the Curve (AUC) method. Fig. 2 shows the Schematic Representation of Methodology Steps. The comprehensive methodology, rooted in meticulous data preparation, transformation, and rigorous analysis, developed a predictive map for potential armed conflict locations in the East African region. Moreover, this model can extend its predictive capabilities to diverse global regions with analogous criteria and weight settings, aiding conflict prevention and resolution strategies.

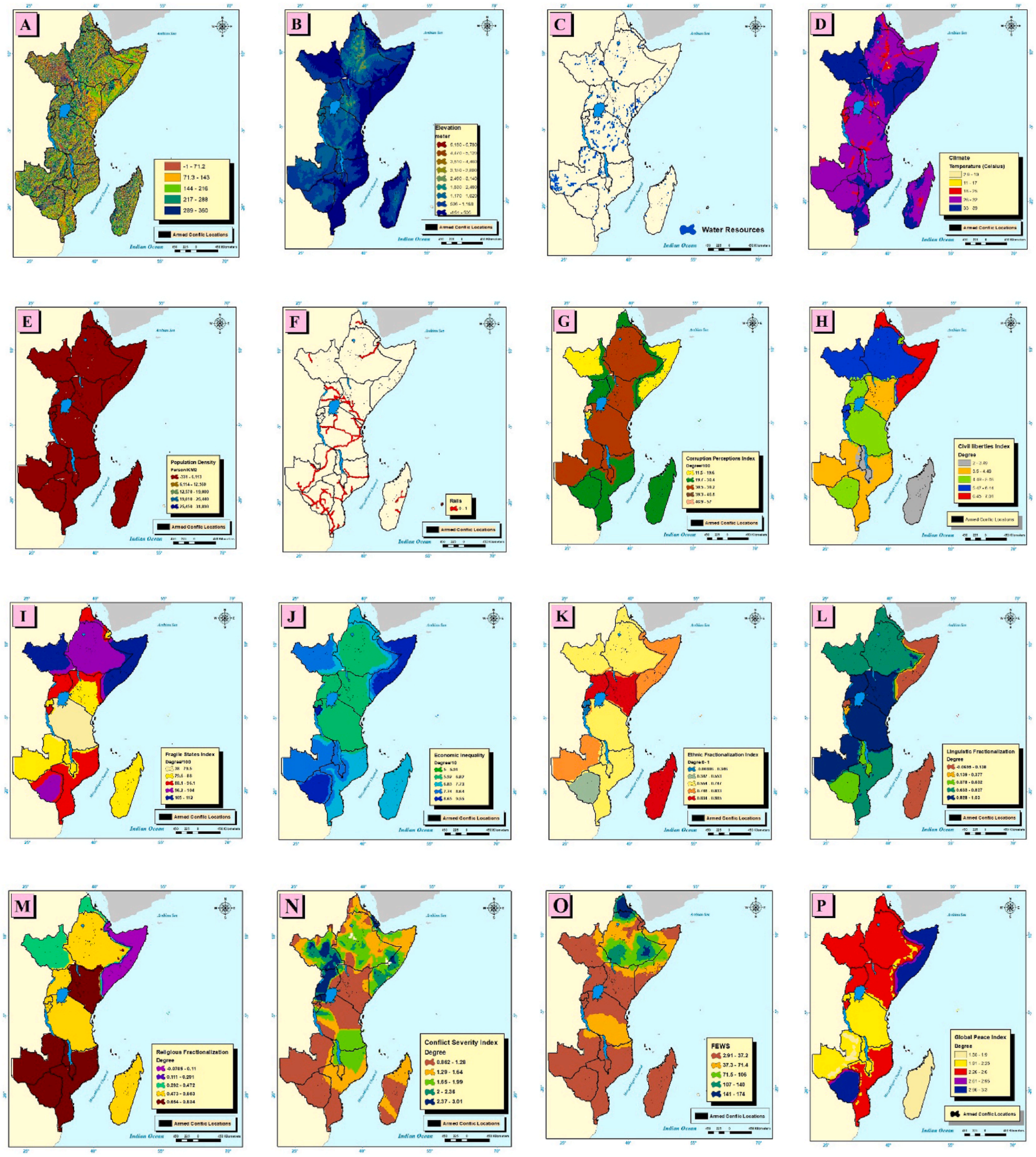

Figure. (3). Thematic spatial maps of study area: (a) Aspect, (B) Elevation, (C) Water Resources, (D) Climate, (E) Population Density, (F) Rails, (G) Corruption Perceptions, (H) Civil liberties Index, (I)Fragile States Index, (J) Economic Inequality, (K) Ethnic Fractionalization, (L) Linguistic Fractionalization, (M) Religious Fractionalization, (N)Conflict Severity Index, (O) FEWS, (P) Global Peace Index, (Q) Global Hunger Index, (R) Global Terrorism Index, (S) GX Coefficient, (T) Neighboring Site, (U) Health Expenditure, (V) Education Expenditure, (W) Demography Pressures, (X) Political Stability Index, (Y) Political Rights Index, (Z) External Interventions Index.

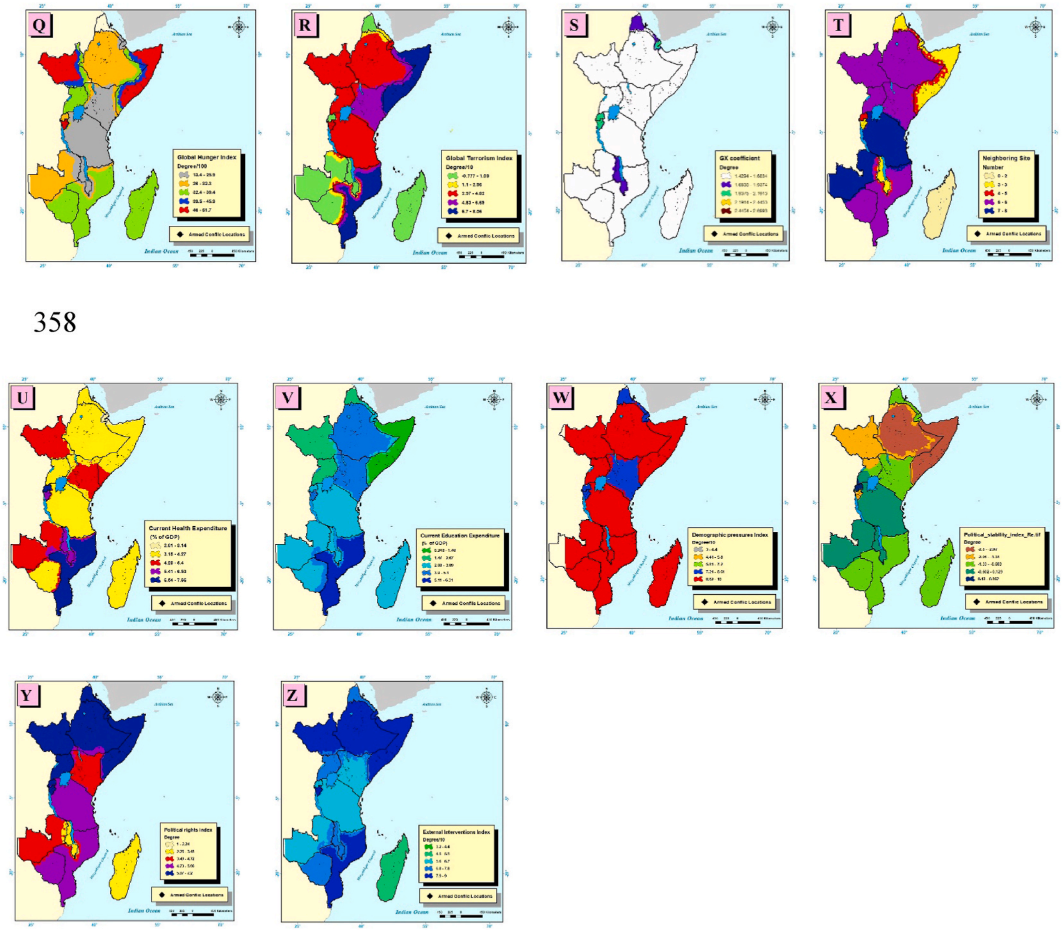

Figure. (3). (*continued*).

2.3.2. Study variables and theoretical background

The occurrence and prediction of armed conflicts reflect the combination of several specific natural and human factors, internal and external. To carry out the prediction process seriously from the perspective of political geography, as it is the science that seeks to analyze the characteristics of the state and its distinctive personality and shed light on its most essential negatives, it is necessary to examine the geographical characteristics morphologically from the perspective of political geography. In addition, the region's countries are a cultural mosaic that includes dozens of diverse ethnic groups. Ethnic tensions, power dynamics, and historical legacy are essential to understanding all aspects of the region's political, economic, and social affairs. The diversity of flawed democratic structures, the decline of legitimacy, and the fragile social contract are significant reasons that push the region's countries towards armed conflicts at present and in the future and are evident in security and living conditions, making them the primary drivers of armed conflicts. In addition to this, there is flawed democracy and increasing internal displacement, which is of pivotal importance in the weakness of the countries of the region, as well as the state's inability to address ethnic inequality and external dependency. Notably, natural and human factors, ethnic composition, and colonial heritage do not lead to armed conflicts. Still, the political manipulation of these factors can affect the region's stability, and this manipulation is more likely in countries with weak institutions.

Many complex factors lead to armed conflicts within States. Some conditions that increase the likelihood of war include the inability of governments to provide good, essential governance and the protection of their populations. In many cases, weak governments have little means to stop the eruption and spread of violence. These better-organized and more legitimate governments could have prevented or stopped. Armed conflict can also be seen as the struggle for power by a part of the elite that has been excluded from exercising power in authoritarian systems of single-party government [28].

Ethnic composition, including linguistic, ethnic, and religious data, as well as human rights violations, minorities, and ethnic cleansing, are all factors that exacerbate armed conflicts.

Economic decline and mismanagement are also associated with violent conflicts, in part because the policies of a shrinking economy are inherently subject to disputes over those of economic growth. In some cases, the impact of radical market-oriented economic reforms, the structural adjustment imposed without compensatory social policies, is seen as an obstacle to political stability. Poor economic conditions are the most critical long-term causes of intra-state armed conflicts. Repressive political systems are also susceptible to war, particularly during transition periods. The degradation of renewable resources (in particular soil erosion, deforestation, and water scarcity) can also contribute significantly to the likelihood of a violent conflict but are generally not as important as political and economic factors. Ethnic diversity is not a cause of armed conflict, but ethnicity often defines parties to a conflict [28].

To carry out the process of predicting armed conflict, the triggers of conflict, and its geographical, human, and natural factors affecting the occurrence of armed conflicts, different criteria have been chosen to draw a map for predicting armed conflicts. Although some studies have determined some criteria affecting the occurrence of armed conflicts, the current study relied on 42 standards. Some standards even include 25 indicators in their calculation, contributing to the results' accuracy and distinction. The data for these criteria were obtained from their sources, converted into event files, and then into vector raster format, and a Resample was created from the layers and reclassified using Reclassify from the Spatial Analysis Toolbox in the Arc GIS Pro 3.0.2. The data was obtained from Layers using Tabulate Area and exported to Microsoft Excel, and equations were prepared to derive the Frequency Ratio for them.

Aspect: The effect of this variable is represented by its general impact on temperature, and thus its effect on the local climate and, therefore, its impact on the distribution of plants and agriculture. Its effect also appears on the difference in soil patterns and then its impact on economic activity, the extent of the country's financial wealth, and the cohesion or discord of the population; its data type is in the form of Grid 30 Seconds *(CGIAR-SRTM),* (Fig. 3A).

Elevation: This criterion directly measures its impact on the state's degree of union or disintegration and the type of government system. It is the plainness of the surface that melts the population. At the same time, the complex terrain hinders mixing and prevents the unification of the state, which may increase the chances of armed conflicts within the state; its data type is in the form of Grid 30 Seconds *(Ibid)*, (Fig. 3B).

Water Resources: include Lakes, rivers, and canals *(Diva-gis)*; its data type is Vector. (Fig. 3C).

Climate: It consists of Data on monthly temperatures *(WorldClim)*; its data type is in the form of Grid 30 Seconds; climatic conditions have a significant role in directing the economy, human activity, population stability, and the distribution of centers of gravity, and thus its impact on the rest of the criteria leading to the occurrence of armed conflicts, as the more the country enjoys similar climatic conditions, the more that leads to the homogeneity of its population and vice versa. (Fig. 3D).

Population density is obtained by dividing the country's total population by its total area (Ciesin). Its data type is Grid 30 Seconds. The more the population is spread equally across all parts of the state, the better, and it is a reason for population homogeneity if there are disarrayed areas that pose a danger to the state (Fig. 3E).

Railroads: Roads aid in communication and integration between the populace and the authorities, strengthening a sense of national and national belonging. It includes railways in the countries of the study area, and its data type is in the form of a Vector. (Fig. 3F).

Corruption Perceptions Index: The Corruption Perceptions Index (CPI) is a ranking system for nations based on opinions and expert assessments of perceived levels of public sector corruption. According to the CPI, corruption is commonly defined as misusing authority for personal benefit—perceptions of corruption in the public sector [29] (Fig. 3G).

The Civil Liberties Index is a metric for assessing religious and free speech rights. It involves several elements, such as the ability to form organizations and associations, the application of the law, and civil freedoms. Its values run from 0, which denotes substantial liberties, to 7, which means complete freedom [30] (Fig. 3H).

Fragile States Index: The measure is based on 12 factors, such as "the inability to collect taxes, internal displacement, severe economic downturn, uneven development, brain drain, state legitimacy, services, public domain, human rights, the rule of law, and external interference." The scale runs in either direction from 0 (the most stable) to 120 (the least durable). [31], (Fig. 3I).

Economic Inequality: The index is based on equality in race, religion, language, and education, which are the worlds responsible for the economic inequality within the country [32]. Its score ranges from (0 for the most stable and 10 for the least stable), *(Ibid),* (Fig. 3J).

Ethnic Fractionalization Index: The ethnic fragmentation index covers 162 countries, and its data covers the period 1945 to 2013. The index scores range between (0, meaning harmony, and 10, representing diversity and division), [33]*; it* is a crucial indicator of the degree to which the various components of the state are interdependent or weak, the degree to which the population is homogeneous and cohesive, and the degree to which they feel a feeling of integration and loyalty to the state, and consequently, its stability. (Fig. 3K).

Linguistic Fractionalization: It measures the degree of linguistic diversity within countries, and the higher scores of countries reflect the state of linguistic diversity [34]. *(Ibid),* The best and most efficient way to engender population homogeneity in a country is through language. (Fig. 3L).

Religious Fractionalization: The variable, which measures religious diversity within the states, depends on higher scores to indicate nations with religious plurality and lower values to indicate countries with religious homogeneity *(Ibid)* [35] (Fig. 3M).

Conflict Severity Index: The variable uses four indicators: the level of devastation, spread, danger, and fragmentation to gauge the conflict's seriousness. The conflict's intensity is reflected in higher ratings, whereas lower values indicate stability [36] (Fig. 3N).

Famine Early Warning Systems Network: The variable, created in 1985, quantifies food insecurity. It covers nations from both eastern and western Africa. The index considers variables like the weather, agricultural output, prices, nutrition, etc. [37] (Fig. 3O).

Global Peace Index: The variable depends on 23 indicators, such as "the number of internal and external wars, the number of deaths resulting from wars, relations with neighboring countries, political instability, political terrorism, terrorist events, the level of violent crimes, the number of prisoners, military spending, etc." 163 countries are represented in the indicator [38], (Fig. 3P).

Global Hunger Index: The variable was first established in 2006. The four indicators that comprise the variable are chronic undernutrition, child stunting, general undernutrition, and child mortality. Higher scores indicate a higher level of hunger [39]. The impact of hunger in armed conflicts is that it is a direct cause of political revolutions and the establishment of fascist political regimes, as the provision of food is one of the primary factors that preserve the state's sovereignty and the freedom to make crucial decisions. (Fig. 3Q).

Global Terrorism Index: The organization IEP publishes the variable covering 163 nations. The four indicators that form the basis of the variable are "the total number of terrorist incidents, the total number of deaths resulting from terrorism, the total number of injuries resulting from terrorism, and the total property damage." The variables' degrees vary from zero for the ten least terroristic states to one for the least (Charles and Emrouznejad, 2022) (Fig. 3R).

GX coefficient: A variable used to measure the importance of the country's area; some people have created a scale called (G) to calculate the importance of the country's area [40] through equation (1):

$$\mathrm{GX} = \log \frac{GA}{RX} \tag{1}$$

Where:

Ga = logarithm of the area of the world, RX = logarithm of the country's area, and the smallness of the result means the large area and vice versa. (Fig. 3S).

Neighboring Site: One of the spatial characteristics that is associated with the study of the state's relations with the countries located along its borders is the relations that are known as Vicinal Relations [41], as the proximity of states leads to a lot of friction and provoking problems, and accordingly; The best countries are those that have no neighbors to share, (Fig. 3T).

Current health spending as a percentage of GDP: The variable, which measures health spending as a percentage of a state's national income and covers health care and medical supplies, group services, and required health insurance, was developed in 2000 [42], (Fig. 3U).

Current Education Expenditure (%of GDP): It measures how much of the country's GDP is spent on education [43] (Fig. 3V).

Demographic Pressures Index: The index measures population pressures related to food supply, access to potable water, and other resources that sustain life or health, such as spreading diseases and epidemics. The higher the value of the index, the greater the demographic pressures in the country [44] (Fig. 3W).

Political stability index: The variable measures political stability indicators, the lack of violence, variables affecting government instability, and indicators of politically motivated violence and terrorism. Its scores range from (−2.5 weak; 2.5 strong), *(Ibid),* [45] (Fig. 3X).

Political rights index: Three categories -electoral process, political plurality and involvement, and government efficiency-are evaluated in the Freedom House Political Rights ratings. The scale goes from 1 for solid rights to 7 for weak rights [46] (Fig. 3Y).

External interventions index: The External Intervention Indicator examines how external actors, notably its economic and security systems, affect a state's ability to run its affairs. An indicator with a higher value indicates more excellent external interventions in the nation. [47], (Fig. 3Z).

GDP per capita (current US$): A brief definition. GDP per capita is calculated as the total gross value created by all producers who are residents of the economy, plus any product taxes (less subsidies), divided by the mid-year population. *(The World Bank: 2023),* (Fig. 4Aa).

Global Multidimensional Poverty Index: The variable covers several indicators, including: (Nutrition, Child Mortality, Years of Schooling, Attendance at School, Cooking Fuel, Sanitation, Drinking Water, Electricity, and Housing resources) [48], (Fig. 4Bb).

Economic Freedom Index: The ability to trade with anyone of one's choosing is called economic freedom. Their independence is diminished if the government imposes tariffs or otherwise forbids them from dealing with citizens of other nations. Ten factors that make up the overall index of economic freedom are divided into four major categories: rule of law, limited government, regulatory efficiency, and open markets. The general economic freedom is assessed on a scale of 0–100, with 100 denoting the most significant degree of freedom [49] *(The Heritage Foundation),* (Fig. 4Cc).

Food production index: The food production variable measures food commodities suitable for human consumption that contain nutrients, and stimulants are excluded [50] (Figure.4Dd).

Income from natural resources, (% of GDP): The variable measures the proportion of the country's natural resources income out of total national income, which includes oil, natural gas, coal, minerals, and forests *(Ibid)* [51] (Figure.4Ee).

Human Development Index: a measurement that combines the nation's three fundamental qualities of health, education, and standard of living. The variable's value is determined by considering four indicators: per capita gross national income, average years spent in school, middle years spent in school, and average life expectancy at birth [52] (Fig. 4Ff).

State legitimacy index: The state legitimacy variable tracks instances of public protests, civil disobedience, and armed revolt movements, as well as the degree of the state's interaction with its citizens, its openness, and citizens' confidence in state institutions. The state's legitimacy decreases as the variable's value increases [53] (Fig. 4Gg).

Index of Human Rights and the Rule of Law: The variable depends on the control of fundamental human rights, respect for liberties, and the rule of law in the country. The values of the variable range from 0, which means high protection of human rights, while 10 indicates low protection of human rights and the rule of law in the country [54] (Figure.4Hh).

Social Progress Index: The measure of how much society has advanced. The standard is based on 54 indicators dispersed over three primary sectors representative of basic human requirements, such as health services, access to energy, drinkable water, and personal security. The expansion of rights and freedoms for individuals [55] (Figure.4Ii).

Public services index: The variable considers both the state's capacity to enforce security for its citizens and infrastructural services with diverse characteristics. More of the state's public services are in good shape, and vice versa, the lower the index's score [56] (Fig. 4Jj).

Freedom Index: Through indicators of a measure of the state's legitimacy, the degree of security and safety, civil society, the population's ability to express themselves, the flow of information, and property rights, the standard is used to assess the level of public freedom in the state. The greater the state's availability of freedom, the higher its score [57] (Fig. 4Kk).

National Cohesion Index: A standard for measuring the extent of cohesion and integration of the country's population through indicators of ethnic composition, including its "linguistic, religious, and ethnic" data, and the national income of individuals. The higher the value of the standard within the country, the more evidence it has of the extent of social cohesion [58] (Figure.4Ll).

Press Freedom Index: The variable evaluates what level in terms of political independence journalists have from the government, the legal penalties meted out to media professionals, the free flow of information, the existence of economic restraints, and the potential dangers to which they may be exposed [59] (Figure.4Mm).

Prosperity Index: The variable depends on twelve indicators to measure the degree of prosperity, including the security index, which measures the degree of conflict and terrorism, personal rights and freedoms, the government and the extent to which it performs its functions, the degree of corruption, social relations, access to markets, the quality of the country's economy, social conditions,

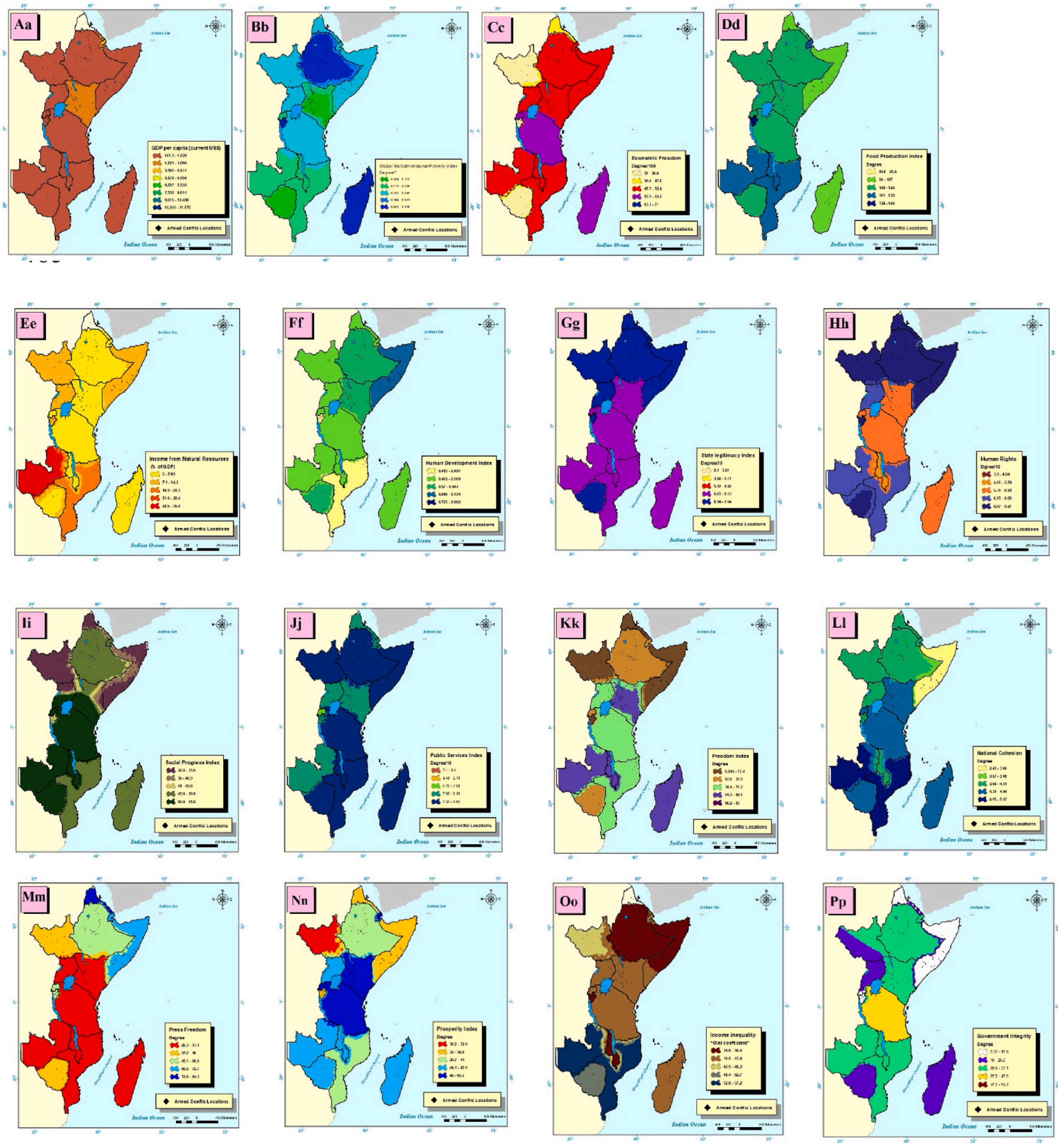

Figure. (4). Thematic spatial maps of study area: (Aa) GDP Per Capita, (Bb) Global Multidimensional Poverty, (*Cc*) Economic Freedom, (Dd) Food Production Index, (Ee) Income Natural Resources of GDP, (Ff) Human Development, (Gg) State legitimacy, (Hh) Human Rights, (Ii) Social Progress Index, (Jj) Public Services, (Kk)Freedom Index, (Ll) National Cohesion, (Mm) Press Free, (Nn) Prosperity Index, (Oo) Income Inequality Gini Coefficient, (Pp) Government Integrity.

education, environment, and health. The lower the indicator's value, the more this indicates the social prosperity enjoyed by the state [60] (Fig. 4Nn).

Income inequality "Gini coefficient": It is used to measure income inequality, and its values range from 0 for complete equality to 100 for total inequality among the population of the country [61] (Figure.4Oo).

Government Integrity Index: The standard is based on assessing the integrity of the state in the face of corruption risks in its institutions. and its data is derived from the Corruption Perceptions Index, and its scores range from zero for corrupt governments to ten for governments with high integrity [62] (Fig.4Pp).

2.3.3. Prediction of armed conflicts mapping and validation

Any region's Prediction of Armed Conflicts can be calculated using the contribution of causative variables and the connection behind them. These days, both human and natural occurrences examinations include a lot of machine learning techniques. To improve accuracy, these approaches require vast amounts of data for training. We employed probabilistic models based on the frequency and ratio of Armed Conflicts in various parameters because of the insufficient data.

The frequency ratio method was used to find the correlation between Natural and human study variables and each factor that affects Forecasting armed conflicts in countries of the East African region. In general, factor classes with a frequency ratio value of >1 will have higher probability armed Conflict. The number of pixels of each class of causal factors were automatically counted by using the reclassify tool in ArcGIS software and the number pixels of armed conflict in each class of causal factors was found on overlaying them. By using Eq. (1), the ratio of each class was calculated by dividing the number of pixels in each factor's class by the total number of pixels in the entire study area. Then the frequency ratio values of each factor classes were computed by dividing the armed conflict percentage by the area of percentage as Table 1.

The Frequency Ratio (FR) is applied by comparing the distribution of observed armed conflict occurrences with the characteristics influencing the potential for conflict. It represents the likelihood of a specific factor contributing to the occurrence of armed conflict. In this study, the FR can be calculated using the following equation (Eq 2):

$$\mathrm{FR} = \text{available} \begin{bmatrix} \left(\dfrac{PAM}{T\,Am}\right) \\ \div \\ \left(\dfrac{Pf}{T\,f}\right) \end{bmatrix} = \frac{\%\,Armed\ Conflict}{\%\,Pixels} \tag{2}$$

Where FR refers to the frequency ratio, P_AM stands for the number of pixels representing armed conflict for each subclass of a variable, T_AM stands for the overall number of armed conflicts, P_f stands for the number of pixels within each subclass of a factor, and T_f stands for the total number of pixels of a factor. Using ACLED data, it was possible to calculate the number and locations of armed confrontations [23]. The resulting findings are displayed in Table (2):

Table 1 shows the use of Microsoft Excel to calculate the weights of all criteria, then relying on the Raster Calculator tool in the Arc GIS pro 3.0.2 to produce the final map. The following figure shows the equation used within the tool to produce a map for predicting armed conflicts in the countries of the study area, Figure 1s.

The next stage was normalizing (FRs) in the probability value range [0,1] as (RF), which was established for each class using the following Eq. (3):

$$\mathrm{RF} = \mathrm{FRi} \;/\; \mathrm{Sum}\ (\mathrm{FRi}) \tag{3}$$

The RF frequency still has the disadvantage of giving all conditioning elements the same weight even after equalization. In order to address the shortcoming and take into account the interdependencies between the independent variables, the (PR) was computed using the training dataset for each conditioning factor rating as mentioned in equation (4):

$$\mathrm{PR} = (\mathrm{RF}_{max} - \mathrm{RF}_{min}) \;/\; (\mathrm{RF}_{max} - \mathrm{RF}_{min})_{min} \tag{4}$$

Lastly, as indicated in equation (5) below, the predicting armed conflicts in East African countries (PACEAC) was determined by multiplying the PR and RF of each element by the class:

$$\mathrm{PACEAC} = \mathrm{Sum}\ (\mathrm{PR} * \mathrm{RF}) \tag{5}$$

A map of PACEAC was created using these PACEAC values. The developed map's accuracy and dependability are crucial. Note that only the training dataset was used by the PACEAC; the remaining 30 % was used for validation.

This work has employed the widely utilized Receiver Operating Characteristic *(ROC)* curve approach to evaluate the efficacy and precision of a both human and natural occurrences modeling. The dynamic variations in categorization results are shown in a sensitivity or specificity curve. The area between the horizontal line and the ROC curve, or Area Under the Curve *(AUC)*, is used to evaluate the ROC curve.

AUC values vary from 0.5 to 1, with a value greater than 0.5 indicating that the model is deemed satisfactory [63]. The forecast is better the higher the percentage of the region below the curve, or the steeper the slope of the curve. An excellent model would have an AUC of 0.9, meaning that 90 % of PACEAC occur in the 10 % most susceptible area [64].

Table 1
Spatial Relationships between study criteria "variables" and armed conflicts with an assigned FR for each sub-class.

Variables	Classes	Class Pixels	%	Armed Conflict Pixels	%	FR	RF [a]	PR [b]
Aspect	N57°17′45″W - S60°46′59″E	1826588	21.92	328199.34	21.43	0.18	0.1946	1.000
	S60°46′58″E – N64°16′14″W	1897394	22.77	345089.14	22.54	0.18	0.1970	
	N64°16′13″W - S67°45′29″E	1656470	19.88	279065.41	18.23	0.16	0.1825	
	S67°45′28″E – N71°14′44″W	1507028	18.09	290965.03	19.00	0.19	0.2091	
	N71°14′43″W - S74°43′58″E	1443691	17.33	287894.16	18.80	0.19	0.2160	
Total		8331171	100.00	1531213.08	100.0	0.92	0.9994	
slop	0–6.563	8003944	96.07	1449834.999	94.69	0.18	0.1655	5.455
	6.564–13.126	283604	3.40	68326.8811	4.46	0.24	0.2202	
	13.127–19.689	40441	0.49	11899.62536	0.78	0.29	0.2689	
	19.69–26.252	3047	0.04	1151.576648	0.08	0.37	0.3454	
Total		8331036	100	1531213.083	100	1.09	1.0002	
Elevation	−150–1300	5233387	167.22	842186.3883	54.77	0.16	0.2312	16.57
	1400–2800	2940978	93.97	616477.3654	40.09	0.21	0.3011	
	2900–4300	181513	5.80	78691.07093	5.12	0.43	0.6228	
	4400–5800	7233	0.23	383.858883	0.02	0.05	0.0762	
Total		3129724	267.2	1537738.684	100	0.69	1.2315	
Temperature	10.2–17.3	6995	0.08	767.717765	0.05	0.11	0.1305	8.939
	17.4–24.5	382578	4.57	137037.6211	8.91	0.35	0.4259	
	24.6–31.7	5342262	63.88	822225.7264	53.47	0.15	0.1830	
	31.8–38.9	2631171	31.46	577707.6183	37.57	0.22	0.2610	
Total		8363006	100.0	1537738.684	100.0	0.84	1.0005	
Famine Early Warning Systems Network (FEWS)	2.91–37.2	5554150	66.33	1059834.375	69.46	0.19	0.2206	7.692
	37.3–71.4	1569794	18.75	252579.1447	16.55	0.16	0.1860	
	71.5–106	667130	7.97	133199.0322	8.73	0.20	0.2308	
	107–140	414455	4.95	46446.92479	3.04	0.11	0.1295	
	141–174	167495	2.00	33779.58167	2.21	0.20	0.2331	
Total		8373024	100.0	1525839.058	100.0	0.86	1.0001	
Neighboring Site	0–2	738398	8.83	171968.7794	11.24	0.23	0.2359	6.424
	3	859588	10.28	218031.8453	14.26	0.25	0.2569	
	4–5	414782	4.96	97884.01505	6.40	0.23	0.2391	
	6	4320201	51.69	951970.0287	62.25	0.22	0.2232	
	7–8	2025470	24.23	89439.11964	5.85	0.04	0.0447	
Total		8358439	100.00	1529293.788	100.0	0.98	1.0	
Population Density	0–81	8190627	100.00	2006503.882	99.98	0.24	0.0612	5.727
	81.1–320	258	0.00	240.192115	0.01	0.93	0.2326	
	321 - 1570	119	0.00	98.078447	0.00	0.82	0.2059	
	1580–7170	1	0.00	1.0008	0.00	1.00	0.2500	
	7180–30,200	12	0.00	12.009606	0.00	1.00	0.2500	
Total		8191017	100.0	2006855.163	100.0	4.00	0.9999	
Ethnic Fractionalization	−0.198	2301	0.03	1919.294413	0.13	0.83	0.5299	14.30
	0.191–0.389	400352	4.80	89439.11964	5.86	0.22	0.1419	
	0.39–0.588	134596	1.61	12283.48424	0.80	0.09	0.0579	
	0.589–0.786	5319852	63.80	688258.9764	45.08	0.12	0.0822	
	0.787–0.985	2481832	29.76	734705.9012	48.13	0.29	0.1880	
Total		8338933	100.0	1526606.776	100.0	1.57	1.0001	
Linguistic Fractionalization	−0.2205	1407983	16.88	358524.1963	23.49	0.25	0.2056	9.273
	0.152–0.372	106316	1.27	54891.82021	3.60	0.51	0.4170	
	0.373–0.593	515680	6.18	70630.03439	4.63	0.13	0.1106	
	0.594–0.814	3172609	38.05	590374.9614	38.67	0.18	0.1503	
	0.815–1.03	3136345	37.61	452185.7637	29.62	0.14	0.1164	
Total		8338933	100.0	1526606.776	100.0	1.23	1.0001	
Religious Fractionalization	−0.1805	674789	8.09	178110.5215	11.67	0.26	0.2315	4.848
	0.111–0.291	79753	0.96	24566.96848	1.61	0.30	0.2702	
	0.292–0.472	868961	10.42	208819.2321	13.68	0.24	0.2108	
	0.473–0.653	3544258	42.50	717048.3926	46.97	0.20	0.1774	
	0.654–0.834	3171172	38.03	398061.6612	26.07	0.12	0.1101	
Total		8338933	100.0	1526606.776	100.0	1.14	1.0001	
Religious Freedom	−0.2205	656484	7.97	181949.1103	11.92	0.27	0.2634	6.727
	5.03–5.97	94315	1.15	30324.85172	1.99	0.32	0.3056	
	5.98–6.92	4262194	51.75	905906.9628	59.37	0.21	0.2020	
	6.93–7.88	1313210	15.94	115541.5237	7.57	0.08	0.0836	
	7.89–8.83	1910646	23.20	292116.6096	19.14	0.15	0.1453	
Total		8236849	100.0	1525839.058	100.0	1.05	1.0001	
GX Coefficient	1.43–1.75	7966308	95.31	1426419.608	93.27	0.17	0.0948	12.2
	1.76–2.06	307871	3.68	48366.2192	3.16	0.15	0.0832	
	2.07–2.38	79258	0.95	49901.65473	3.26	0.63	0.3336	
	2.39–2.7	5002	0.06	4606.306591	0.30	0.92	0.4880	
Total		8358439	100.0	1529293.788	100.0	1.88	0.9998	

(continued on next page)

Table 1 (*continued*)

Variables	Classes	Class Pixels	%	Armed Conflict Pixels	%	FR	RF [(a)]	PR [(b)]
Political Rights Index	1–2.24	2701	0.03	2303.153295	0.15	0.85	0.5427	15
	2.25–3.48	945314	11.31	209203.091	13.68	0.22	0.1408	
	3.49–4.72	1576763	18.86	224173.5874	14.66	0.14	0.0905	
	4.73–5.96	2633245	31.50	199606.6189	13.05	0.07	0.0482	
	5.97–7.2	3200416	38.29	894007.3375	58.46	0.27	0.1778	
Total		8358439	100.0	1529293.788	100.0	1.57	1.0002	
Political Stability Index	−0.73	1832115	22.18	434912.1139	28.44	0.23	0.1629	12.3
	−0.72	1169729	14.16	347392.2887	22.72	0.29	0.2038	
	−0.727	3055204	36.99	556211.5208	36.37	0.18	0.1249	
	−0.602–0.129	2268557	27.47	168897.9083	11.04	0.07	0.0511	
	0.13–0.862	32834	0.40	21879.95631	1.43	0.66	0.4573	
Total		8358439	101.2	1529293.788	100.0	1.45	1.0001	
Press Free	25.3–37.1	4841239	57.92	738928.3489	48.32	0.15	0.1732	7.50
	37.2–49	1266528	15.15	271388.23	17.75	0.21	0.2432	
	49.1–60.8	1446964	17.31	350463.1598	22.92	0.24	0.2749	
	60.9–72.7	673958	8.06	165059.3195	10.79	0.24	0.2779	
	72.8–84.5	129750	1.55	3454.729943	0.23	0.02	0.0302	
Total		8358439	100.0	1529293.788	100.0	0.88	0.9996	
Prosperity Index	30.2–37.3	1474394	17.64	377333.2816	24.67	0.25	0.1459	12.2
	37.4–44.4	2417241	28.92	416870.7465	27.26	0.17	0.0983	
	44.5–51.5	3949227	47.25	563504.8396	36.85	0.14	0.0814	
	51.6–58.6	514876	6.16	169281.7672	11.07	0.32	0.1875	
	58.7–65.7	2701	0.03	2303.153295	0.15	0.85	0.4864	
Total		8358439	100.0	1529293.788	100.0	1.75	0.9997	
Public Services	3.1–4.73	2701	0.03	2303.153295	0.15	0.85	0.4718	11.4
	4.74–6.36	19766	0.24	11131.90759	0.73	0.56	0.3116	
	6.37–7.99	1927839	23.06	425699.5008	27.84	0.22	0.1222	
	8–9.62	6408133	76.67	1090159.226	71.29	0.17	0.0941	
Total		8358439	100.0	1529293.788	100.0	1.80	0.9999	
National Cohesion	2.43–3.06	711051	8.51	192697.159	12.62	0.27	0.3210	7.36
	3.07–3.68	165391	1.98	13051.20201	0.85	0.07	0.0935	
	3.69–4.31	2637746	31.57	724341.7114	47.44	0.27	0.3253	
	4.32–4.94	3250564	38.90	486349.2042	31.85	0.15	0.1772	
	4.95–5.57	1590986	19.04	110551.3582	7.24	0.06	0.0823	
Total		8355738	100.0	1526990.635	100.0	0.84	0.9995	
State legitimacy	2.1–4.61	2701	0.03	2303.153295	0.15	0.85	0.6921	17.8
	4.62–7.12	4629458	55.39	587304.0903	38.40	0.12	0.1029	
	7.13–9.64	3726280	44.58	939686.5445	61.45	0.25	0.2046	
Total		8358439	100.0	1529293.788	100.0	1.23	0.9997	
GDP Per Capita	141 - 4080	8202398	99.58	1518545.739	99.52	0.18	0.1549	17.6
	4090–8030	31750	0.39	4990.165473	0.33	0.15	0.1315	
	8040–12,000	2701	0.03	2303.153295	0.15	0.85	0.7135	
Total		8236849	100.00	1525839.058	100.00	1.19	1.0	
Economic Inequality	5–5.9	2301	0.03	1919.294413	0.13	0.83	0.5299	13.3
	6–6.8	3133044	37.57	656782.5481	43.02	0.210	0.13318	
	6.9–7.7	2124353	25.48	345089.1354	22.60	0.162	0.10320	
	7.8–8.6	2074852	24.88	297106.7751	19.46	0.143	0.09097	
	8.7–9.5	1004383	12.04	225709.0229	14.79	0.225	0.14277	
Total		8338933	100.00	1526606.776	100.00	1.574	1.00007	
Income Natural Resources of GDP	0–7.1	4400005	53.42	773091.7895	50.67	0.176	0.26784	11.69
	7.2–14	2180008	26.47	646802.2171	42.39	0.297	0.45228	
	15–21	831731	10.10	69094.59886	4.53	0.083	0.12664	
	22–28	67116	0.81	3838.588826	0.25	0.057	0.08718	
	29–35	757989	9.20	33011.8639	2.16	0.044	0.06639	
Total		8236849	100.00	1525839.058	100.00	0.656	1.00033	
Human Development	0.41–0.49	962754	11.52	112470.6526	7.35	0.117	0.07229	13.79
	0.5–0.57	4298058	51.42	720119.2637	47.09	0.168	0.10368	
	0.58–0.65	2351755	28.14	494410.2407	32.33	0.210	0.13009	
	0.66–0.72	743171	8.89	199990.4778	13.08	0.269	0.16652	
	0.73–0.8	2701	0.03	2303.153295	0.15	0.853	0.52766	
Total		8358439	100.00	1529293.788	100.00	1.616	1.00025	
Income Inequality Gini Coefficient	35–39	2217538	26.92	515138.6204	33.76	0.232	0.26610	6.857
	40–44	3248905	39.44	694400.7185	45.51	0.214	0.24483	
	45–48	599339	7.28	156614.4241	10.26	0.261	0.29933	
	49–53	563657	6.84	57194.9735	3.75	0.101	0.11623	
	54–57	1607410	19.51	102490.3216	6.72	0.064	0.07304	
Total		8236849	100.00	1525839.058	100.00	0.873	0.99952	
Human Rights	3.5–4.6	5002	0.06	4606.306591	0.30	0.921	0.56015	14.26
	4.7–5.8	207266	2.48	39537.4649	2.59	0.191	0.11603	

(*continued on next page*)

Table 1 (*continued*)

Variables	Classes	Class Pixels	%	Armed Conflict Pixels	%	FR	RF [(a)]	PR [(b)]
	5.9–6.9	2718159	32.52	426851.0774	27.91	0.157	0.09552	
	7–8.1	2224511	26.61	326663.9091	21.36	0.147	0.08932	
	8.2–9.2	3203501	38.33	731635.0302	47.84	0.228	0.13892	
Total		8358439	100.00	1529293.788	100.00	1.644	0.99995	
Health Expenditure	2–3.1	76142	0.91	8061.036534	0.53	0.106	0.12573	5.129
	3.2–4.3	4898941	58.61	923564.4714	60.39	0.189	0.22390	
	4.4–5.4	2150445	25.73	424547.9241	27.76	0.197	0.23447	
	5.5–6.5	314445	3.76	77539.49428	5.07	0.247	0.29286	
	6.6–7.7	918466	10.99	95580.86176	6.25	0.104	0.12359	
Total		8358439	100.00	1529293.788	100.00	0.842	1.00056	
Education Expenditure	0.25–1.5	681934	8.16	181565.2515	11.87	0.266	0.25750	7.501
	1.6–2.7	1130750	13.53	385778.177	25.23	0.341	0.32995	
	2.8–3.9	3496584	41.83	390000.6247	25.50	0.112	0.10787	
	4–5.1	2157423	25.81	495945.6763	32.43	0.230	0.22232	
	5.2–6.3	891748	10.67	76004.05875	4.97	0.085	0.08243	
Total		8358439	100.00	1529293.788	100.00	1.034	1.00007	
Social Progress	31–36	1340591	16.06	381555.7293	24.99	0.285	0.25435	4.180
	37–41	456647	5.47	114006.0881	7.47	0.250	0.22311	
	42–46	260279	3.12	72933.18769	4.78	0.280	0.25041	
	47–51	3115548	37.31	544311.8955	35.66	0.175	0.15613	
	52–56	3176490	38.04	413799.8754	27.11	0.130	0.11642	
Total		8349555	100.00	1526606.776	100.00	1.119	1.00042	
Government Integrity	5.4–16	865396	10.35	234921.6361	15.36	0.271	0.17127	15.65
	17–26	2069820	24.76	544311.8955	35.59	0.263	0.16592	
	27–37	4334895	51.86	710906.6505	46.49	0.164	0.10347	
	38–48	1085627	12.99	36850.45273	2.41	0.034	0.02142	
	49–58	2701	0.03	2303.153295	0.15	0.853	0.53798	
Total		8358439	100.00	1529293.788	100.00	1.585	1.00005	
Global Terrorism Index	−1.88	2135725	25.61	295955.1985	19.39	0.139	0.15855	4.020
	1.2–3	281182	3.37	33395.72278	2.19	0.119	0.13589	
	3.1–4.8	3594056	43.10	725109.4292	47.50	0.202	0.23084	
	4.9–6.7	953512	11.43	223789.7285	14.66	0.235	0.26854	
	6.8–8.6	1374458	16.48	248356.697	16.27	0.181	0.20674	
Total		8338933	100.00	1526606.776	100.00	0.874	1.00056	
Global Peace Index	1.5–1.9	907423	10.88	180413.6748	11.82	0.199	0.21084	5.264
	2–2.2	2292321	27.49	165827.0373	10.86	0.072	0.07671	
	2.3–2.6	3927352	47.10	927403.0603	60.75	0.236	0.25041	
	2.7–3	169832	2.04	39153.60602	2.56	0.231	0.24448	
	3.1–3.3	1042005	12.50	213809.3976	14.01	0.205	0.21759	
Total		8338933	100.00	1526606.776	100.00	0.943	1.00004	
Global Multidimensional Poverty	0.109–0.172	817887	9.79	175807.3682	11.50	0.215	0.24454	4.892
	0.173–0.235	2212635	26.47	226476.7407	14.81	0.102	0.11645	
	0.236–0.298	3150020	37.69	641428.1928	41.94	0.204	0.23166	
	0.299–0.361	354985	4.25	40305.18267	2.64	0.114	0.12917	
	0.362–0.425	1822912	21.81	445276.3038	29.12	0.244	0.27789	
Total		8358439	100.00	1529293.788	100.00	0.879	0.99971	
Global Hunger Index	13.4–21.1	149356	1.82	38769.74714	2.55	0.260	0.23177	6.390
	21.2–28.7	3208189	39.05	506693.725	33.28	0.158	0.14102	
	28.8–36.4	2374826	28.91	209586.9499	13.77	0.088	0.07880	
	36.5–44.1	1363056	16.59	442205.4327	29.05	0.324	0.28966	
	44.2–51.7	1120000	13.63	325128.4735	21.36	0.290	0.25919	
Total		8215427	100.00	1522384.328	100.00	1.120	1.00043	
Food Production Index	81–94	2701	0.03	2303.153295	0.15	0.853	0.37764	10.77
	95–110	1590776	19.03	377333.2816	24.67	0.237	0.10505	
	110–120	4708711	56.33	951586.1699	62.22	0.202	0.08950	
	120–130	2018045	24.14	164291.6017	10.74	0.081	0.03605	
	130–140	38206	0.46	33779.58167	2.21	0.884	0.39156	
Total		8358439	100.00	1529293.788	100.00	2.258	0.99980	
Freedom Index	0.55–17	1621142	19.40	423780.2063	0.28	0.261	0.16338	13.34
	18–34	1839034	22.00	357756.4785	0.23	0.195	0.12158	
	35–51	2691184	32.20	349311.5831	0.23	0.130	0.08112	
	52–68	2204319	26.37	396142.3668	0.26	0.180	0.11232	
	69–85	2760	0.03	2303.153295	0.00	0.00	0.00000	
Total		8358439	100.00	1529293.788	1.00	1.600	0.99996	
External Interventions Index	3.2–4.4	2701	0.03	2303.153295	0.15	0.853	0.52604	13.97
	4.5–5.5	736097	8.81	169665.6261	11.09	0.230	0.14219	
	5.6–6.7	2465410	29.50	259488.6046	16.97	0.105	0.06493	
	6.8–7.8	1530313	18.31	343553.6999	22.46	0.224	0.13849	
	7.9–9	3623918	43.36	754282.7042	49.32	0.208	0.12840	

(*continued on next page*)

Table 1 (*continued*)

Variables	Classes	Class Pixels	%	Armed Conflict Pixels	%	FR	RF [a]	PR [b]
Total		8358439	100.00	1529293.788	100.00	1.621	1.00005	
Economic Freedom	32–40	1110319	13.28	260640.1813	17.04	0.235	0.15293	14.46
	41–48	309417	3.70	39921.32379	2.61	0.129	0.08405	
	49–55	4987356	59.67	993042.9292	64.93	0.199	0.12971	
	56–63	1948646	23.31	233386.2006	15.26	0.120	0.07803	
	64–71	2701	0.03	2303.153295	0.15	0.853	0.55551	
Total		8358439	100.00	1529293.788	100.00	1.535	1.00023	
Demography Pressures	3–5.3	2301	0.03	1919.294413	0.13	0.834	0.21481	21.01
	5.4–7.7	79688	1.08	228779.894	14.96	2.871	0.73936	
	7.8–10	7283527	98.89	1298210.741	84.91	0.178	0.04590	
Total		7365516	100.00	1528909.929	100.00	3.883	1.00008	
Civil liberties Index	2–3.00	872490	10.44	208051.5143	13.60	0.238	0.24685	4.459
	3.1–4	1846083	22.09	222254.293	14.53	0.120	0.12463	
	4.1–5	2539369	30.38	341634.4055	22.34	0.135	0.13927	
	5.1–6	2022038	24.19	530876.8346	34.71	0.263	0.27179	
	6.1–7	1078459	12.90	226476.7407	14.81	0.210	0.21739	
Total		8358439	100.00	1529293.788	100.00	0.966	0.99993	
Corruption Perceptions	11.54–20.63	1205035	14.45	351998.5953	23.06	0.292	0.18054	9.798
	20.64–29.73	2921419	35.03	583849.3604	38.24	0.200	0.12352	
	29.74–38.82	4176986	50.09	571182.0172	37.42	0.137	0.08451	
	38.83–47.91	11644	0.14	3838.588826	0.25	0.330	0.20375	
	47.92–57	23849	0.29	15738.21419	1.03	0.660	0.40786	
Total		8338933	100.00	1526606.776	100.00	1.618	1.00017	
Conflict Severity Index (CSI)	0.86–1.3	3585153	43.06	515906.3382	34.36	0.144	0.10257	8.263
	1.4–1.7	2441755	29.33	366969.0917	24.44	0.150	0.10712	
	1.8–2.1	1637581	19.67	346240.7121	23.06	0.211	0.15070	
	2.2–2.6	486347	5.84	180413.6748	12.01	0.371	0.26440	
	2.7–3	174995	2.10	92126.13181	6.13	0.526	0.37523	
Total		8325831	100.00	1501655.949	100.00	1.403	1.00002	
Fragile States Index (FSI)	38–57	2301	0.03	1919.294413	0.13	0.834	0.60575	16.16
	58–75	2595401	31.12	258720.8868	16.95	0.100	0.07239	
	76–94	3007085	36.06	599203.7157	39.25	0.199	0.14471	
	95–110	2734146	32.79	666762.879	43.68	0.244	0.17710	
Total		8338933	100.00	1526606.776	100.00	1.377	0.99995	

[a] $RF = \frac{\textbf{Factor Class FR}}{\sum \textbf{Factor Classes FR}}$.

[b] PR= $(RF_{max}$- $RF_{min})/(RF_{Max}$-$RF_{Min})$.

3. Results and discussion

3.1. Frequency-ratio and predicted-risk models

Upon analyzing the dataset to pinpoint the factors affecting armed conflict analysis is complete; we computed Frequency Ratio (FR) and Predicted Risk (PR). These values were determined for every factor. Are outlined in Table 1 for reference purposes. Table 2 gives a summary of how armed conflicts relate to different variable classes spatially and showcases the associated FR values, alongside Relative Frequency (RF) and PR values. This method assists in identifying the factors that play a major role in triggering conflicts in the East African region. The FR values have been adjusted to a scale of 0–1 to make it simpler to compare variables based on techniques employed in previous spatial forecasting research studies. Subsequently the PR values offer an understanding of the significance of each factor in influencing the risk of conflict occurrence.

In cases some directions like from North to West and South to East display a greater occurrence rate in the aspect factor which is crucial due to how the geographical and environmental conditions of the area impact settlement trends leading to a rise in potential conflicts within these orientations. Lines with slopes surpassing 13° are rated higher compared to others. Those exceeding 19° stand out significantly demonstrating that steep and rough terrain could offer tactical benefits, for insurgent activities. This is why regions

Table 2
Results of applying the FR method in predicting armed conflicts in East African countries.

Classes	Classes	Class Pixels	area km^2	%	% Armed Conflict
Very Low	4680–5730	1901329	1711196.1	25.14	7.98
Low	5740–6770	2826433	2543789.7	37.37	23.85
Moderate	6780–7820	2646190	2381571	34.98	61.36
High	7830–8860	173860	156474	2.30	5.70
Very High	8870–9900	16126	14513.4	0.21	1.11
Total		7563938	6807544.2	100.00	100.00

located at elevations typically more remote and challenging to reach tend to encounter a higher frequency of disputes. The spatial relationship between temperature and conflict shows that regions with moderate temperatures (17.4°C-24.5 °C) exhibit the highest Frequency Ratio (RF = 0.4259), indicating a greater likelihood of conflict in these areas. The stability and predictability of the climate in these regions likely make them favorable for agriculture and human settlement, which in turn increases competition over resources, land, and political power. Similarly, regions with more extreme temperatures, too hot, show the highest RF values, indicating a greater likelihood of conflict, likely due to harsher living conditions.

The RF model reveals that areas with Famine Early Warning Systems Network (FEWS) values between 2.91 and 37.2, covering 66.33 % of the study area, are responsible for 69.46 % of conflict pixels, with an RF of 0.2206, demonstrating a strong link between food insecurity and conflict. Conversely, regions with FEWS values from 107 to 140, which cover only 4.95 % of the area and 3.04 % of conflict pixels, have a much lower RF of 0.1295, indicating that better food security diminishes the risk of conflict.

Regarding wealth, the RF model shows that regions with a GDP per capita between $141 and $4080, covering 99.58 % of the area, account for 99.52 % of conflict pixels, with an RF of 0.1549, suggesting that greater economic prosperity reduces the likelihood of conflict. Similarly, areas with higher income inequality (Gini values between 45 and 48), covering 10.26 % of conflict pixels, have a higher RF of 0.2993, indicating a higher risk of conflict. In contrast, more equitable regions with Gini values between 35 and 39 (33.76 % of conflict pixels) exhibit a lower RF of 0.2661, suggesting a reduced likelihood of conflict.

Regions with higher poverty levels, as reflected by higher MPI scores and global hunger index values, show increased RF values, which are closely associated with a higher likelihood of conflict. Similarly, areas where natural resources contribute 7.2–14 % of GDP account for 42.39 % of conflict pixels, with an RF of 0.4523, highlighting the potential for resource-driven tensions. Regions with a lower reliance on natural resources (0–7.1 % of GDP) represent 50.67 % of conflict pixels, but with a much lower RF of 0.2678, signaling a reduced risk of conflict.

Areas with lower food production (index values 81–94) account for only 0.15 % of conflict pixels but have a higher RF of 0.3776, indicating a greater likelihood of conflict in these regions. Conversely, areas with higher food production (index values 120–130) cover 10.74 % of conflict pixels and have a much lower RF of 0.0361, reflecting a reduced risk of conflict. Furthermore, regions with limited economic freedom (index values 32–40) account for 17.04 % of conflict pixels with an RF of 0.1529, suggesting a higher risk of conflict. In contrast, areas with greater economic freedom (index values 49–55) cover 64.93 % of conflict pixels and have a lower RF of 0.1297, indicating a decreased likelihood of conflict in these regions.

The study suggests that regions sharing borders with two to six neighboring countries exhibit a RF value which implies a heightened possibility of conflicts arising from intricate cross border dynamics and tensions with multiple nations involved in the area's affairs. Notably areas with population density (ranging from 0 to 81 individuals per square kilometer) encompass 99.98 % Of conflict prone locations and boast a lower RF value of 0.0612 Pointing towards a reduced risk of potential conflicts occurring in these regions. Conversely regions, with population densities showcase increased RF values highlighting an augmented probability of conflicts stemming from uneven distribution of inhabitants throughout the area.

For ethnic fractionalization, the class with the highest ethnic diversity (0.787–0.985) contains 48.13 % of the armed conflict pixels, with an RF of 0.188, indicating a strong association between higher ethnic diversity and conflict occurrence. Linguistic fractionalization significantly affects conflict likelihood, with regions of diversity Linguistic (RF = 0.417 for the 0.152–0.372 class) being more prone to conflict due to social fragmentation. Religious fractionalization also influences conflict risk, with regions of religious diversity (RF = 0.2702 for the 0.111–0.291 class) being more prone to conflict. In contrast, areas with higher religious plurality (RF = 0.1101 for the 0.654–0.834 class) experience fewer conflicts, likely due to established mechanisms for coexistence and tolerance. While you bear witness regions with lower religious freedom (−0.2205) account for 11.92 % of conflict pixels, with an RF of 0.2634, indicating higher conflict risk. Conversely, areas with greater religious freedom (7.89–8.83) account for only 19.14 % of conflicts, with a lower RF of 0.1453. The GX Coefficient analysis shows that countries in the lower range (1.43–1.75), form 93.27 % of conflict pixels, have a lower RF of 0.0948, implying that larger countries have a reduced likelihood of experiencing conflict, likely due to factors such more available resources. Conversely, countries with higher GX values (2.39–2.7), covering just 0.30 % of conflict pixels, have a higher RF of 0.488, indicating that areas with limited resources face a greater risk of conflict.

Countries with weaker political rights (index values from 5.97 to 7.2) cover 38.29 % of the total area and account for 58.46 % of conflict pixels, with an RF of 0.1778, indicating a higher likelihood of conflict in these regions. This suggests that restricted political rights, such as limited electoral fairness and political plurality, contribute to conditions where grievances are more likely to lead to conflict. On the other hand, countries with lower political stability, represented by negative index values, tend to have higher (RF). This suggests a strong association between low political stability and a higher likelihood of conflict. The RF model reveals that regions with lower levels of press freedom, where journalists are more constrained by government control, legal repercussions, or economic pressures, tend to exhibit higher RF values, indicating a stronger likelihood of conflict. According to the RF model, regions with lower Prosperity Index values (indicating higher prosperity) tend to have lower RF values, suggesting a reduced likelihood of conflict. For example, areas with Prosperity Index values between 30.2 and 37.3 cover 24.67 % of conflict pixels, with an RF of 0.1459. Conversely, regions with higher Prosperity Index values (51.6–58.6) have an RF of 0.1875, showing a stronger correlation between lower prosperity and conflict. Also, On the other hand, countries with lower Public Services Index values, tend to have higher (RF). According to the RF model, regions with higher National Cohesion Index values, reflecting stronger social integration, show lower RF values, indicating a reduced likelihood of conflict. According to the RF model, regions with lower state legitimacy, indicated by higher index values, tend to show a stronger likelihood of conflict. The Human Development Index (HDI), the RF values show that lower development correlates with a reduced probability of conflict. Regions with lower HDI values (0.41–0.49) account for 7.35 % of conflict pixels with an RF of 0.0723, indicating a lower likelihood of conflict. Conversely, regions with higher HDI values (0.66–0.72) account for 13.08 % of conflict pixels with a higher RF of 0.1665, suggesting that while development contributes to stability, it does not eliminate conflict risks.

The RF model for the Index of Human Rights and the Rule of Law shows a clear relationship between human rights protections and conflict risk. Regions with weaker human rights protections (index values between 8.2 and 9.2) account for 47.84 % of conflict pixels with an RF of 0.1389, indicating a higher likelihood of conflict. The RF values indicate a clear relationship between health spending and conflict probability. Regions with lower health expenditure (2–3.1 %) account for 0.53 % of conflict pixels with an RF of 0.1257, indicating a reduced likelihood of conflict. Conversely, regions with higher health expenditure (5.5–6.5 %) account for 5.07 % of conflict pixels with an RF of 0.2929, suggesting that even with higher health spending, other factors may still contribute to conflict risk. Regions with lower education expenditure (0.25–1.5 %) account for 11.87 % of conflict pixels with an RF of 0.2575, indicating a higher probability of conflict in areas with insufficient educational investment. In contrast, regions with higher education spending (5.2–6.3 %) account for 4.97 % of conflict pixels with a lower RF of 0.0824, suggesting that increased education expenditure promotes stability by reducing social tensions and improving economic opportunities. Regions with lower social progress, indicated by Social Progress Index values between 31 and 36, with an RF of 0.2544, highlighting a greater probability of conflict due to weaker social conditions. Conversely, areas with higher social progress (52–56) with a lower RF of 0.1164, reflecting reduced conflict risk in regions with stronger and more inclusive social systems. Also, regions with lower government integrity, indicated by values between 5.4 and 16, account for 15.36 % of conflict pixels with an RF of 0.1713, highlighting a greater probability of conflict in areas where corruption and lack of transparency prevail. In contrast, regions with higher government integrity (38–48) account for just 2.41 % of conflict pixels with a lower RF of 0.0214, reflecting reduced conflict risk in areas where institutions are more transparent and accountable. Likewise, regions with higher Global Terrorism Index (GTI), Global Peace Index values, indicating more frequent and severe terrorism, tend to have higher (RF), signifying a greater probability of conflict, On the other hand, regions with lower freedom (index values 52–68) have an RF of 0.1123, indicating a higher conflict likelihood. Conversely, areas with greater freedom (index values 0.55–17) have an RF of 0.1634, showing that conflict can still occur despite higher freedom levels.

Regions with higher levels of external interventions (index values between 7.9 and 9) have an RF of 0.12840, indicating a higher likelihood of conflict due to external involvement potentially undermining state autonomy or provoking resistance. In contrast, areas with lower levels of external interventions (index values between 3.2 and 4.4) exhibit a much higher RF of 0.52604, suggesting that

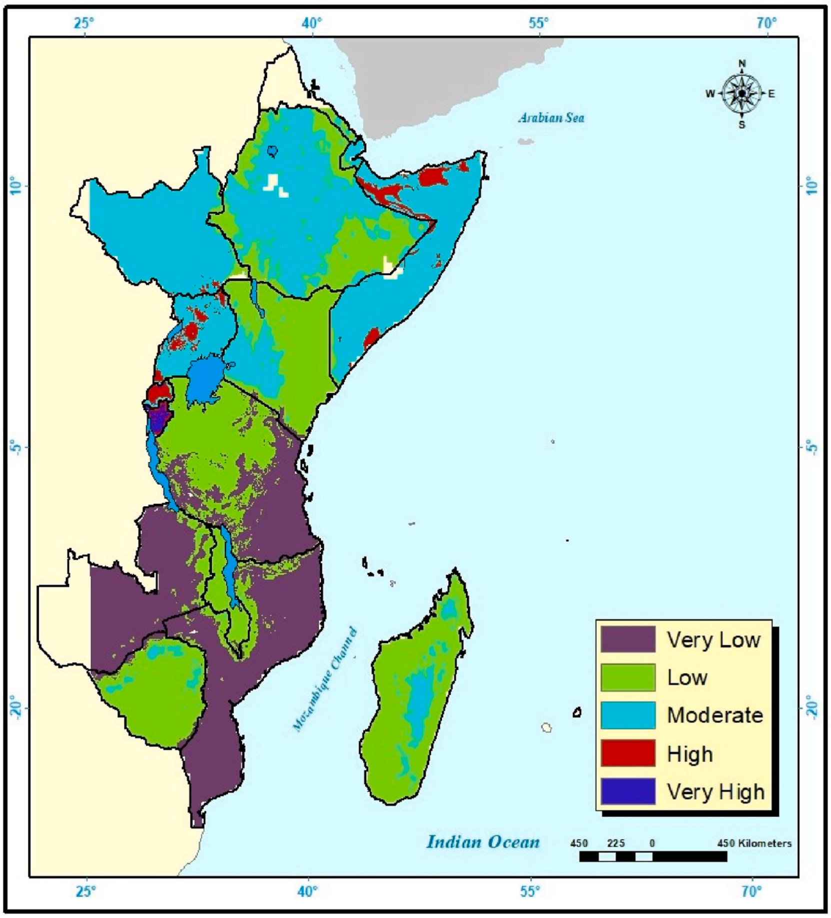

Fig. 5. Spatial prediction of armed conflicts in East African states.

even with minimal external involvement, internal governance weaknesses can still lead to significant conflict risks. Regions with moderate demographic pressures (index range 5.4–7.7) exhibit an RF value of 0.73936, which indicates a higher likelihood of conflict. In contrast, areas with high demographic pressures (index range 7.8–10) show a lower RF of 0.04590, suggesting that while significant pressures exist, they are less likely to contribute to conflict compared to regions experiencing moderate demographic pressures. Regions with higher civil liberties (index values between 5.1 and 6) exhibit an RF of 0.27179, indicating a higher probability of conflict. In contrast, regions with lower civil liberties (index values between 2 and 3) show an RF of 0.24685, suggesting that even with more restrictive environments, the conflict risk remains slightly lower compared to areas with greater freedoms. Regions with Corruption Perceptions Index (CPI) values between 11.54 and 20.63 have an RF of 0.18054, suggesting moderate conflict risk. However, as CPI values increase to the 47.92–57 range, the RF rises to 0.40786, indicating a stronger likelihood of conflict in areas with higher corruption.

The conflict Severity Index (CSI) values between 2.7 and 3 have an RF of 0.37523, indicating a significantly elevated likelihood of conflict in areas with the highest conflict severity. In contrast, regions with CSI values between 0.86 and 1.3 exhibit a lower RF of 0.10257, reflecting greater stability in less severe conflict zones. This highlights the importance of addressing conflict intensity in mitigation efforts. However, Regions with high state fragility (FSI (values 95–110 have an RF of 0.17710, indicating a higher conflict risk, while moderately fragile areas (FSI (values 58–75 show a lower RF of 0.07239. Interestingly, stable regions (FSI(values 38–57 exhibit a significant RF of 0.60575, suggesting conflict can still arise despite overall stability. Table 1 and Fig. 5 show that Demography Pressures has the highest PR value, closely followed by GDP Per Capita, Fragile States Index (FSI), Government Integrity, Political Rights Index, Ethnic Fractionalization, Human Rights, External Interventions Index, Human Development, Freedom Index, and Economic Inequality, and GX Coefficient, Political Stability Index, Income Natural Resources of GDP, Public Services, Food Production Index, Corruption Perceptions, Linguistic Fractionalization, Conflict Severity Index (CSI), Press Free, Education Expenditure, Famine Early Warning Systems Network (FEWS), National Cohesion, Religious Freedom, Global Hunger Index, Health Expenditure, Global Multidimensional Poverty, Social Progress, Civil Liberties Index, Global Terrorism Index all have a moderate impact in anticipating the occurrence of Armed Conflicts. Elevation, Temperature, Slope, Aspect, Neighboring Site, Population Density, Prosperity Index, State Legitimacy, Press Free (Lower Value), Food Production Index (Lower Value), Global Hunger Index (Lower Value), and Income Inequality Gini Coefficient are the least significant conditioning factors in the study were examined.

The PACEAC (predicting armed conflicts in East African countries) value, calculated from the PR and RF of the thirteen conditioning factors, ranged from 4.60 to 9.90 (as shown in Table 2). Based on this range of PACEAC values, the total area was divided into five discrete susceptibility classes: (very low to very high), according to the natural break (Jenks) method, as illustrated in Fig. 5. This method helps to identify natural groupings in the data and categorize areas based on their exposedness to armed conflicts.

In regions where armed conflicts are anticipated to have a "very high" likelihood, the cumulative area encompasses 14,513.4 square kilometers, equivalent to a mere 0.21 % of the entire regional expanse. Notably, this heightened risk is predominantly concentrated within the boundaries of Burundi, specifically its constituent states such as Ruyigi, Karuzi, and Rutana, among others. Conversely, areas categorized with a "high" potential for armed conflicts encompass 2.30 % of the total land area in East African countries. Noteworthy concentrations of this elevated risk are observed in significant portions of Somalia, particularly within Woqooyi Galbeed and Sanaag states, as well as extensive regions within Rwanda and Uganda. Regions where the anticipation of armed conflicts is deemed "moderate" constitute a substantial 34.98 % of the total regional land area. This moderate risk is predominantly associated with the state of South Sudan, extensive territories in Ethiopia, Somalia, Uganda, the western regions of Kenya, and the central zones of Madagascar. Moreover, regions characterized by "low" potential for armed conflicts span across 37.37 % of the entire regional land area. These more stable areas are observed in countries such as Zimbabwe, Madagascar, significant portions of Tanzania and Malawi, and the eastern segments of Kenya. In areas deemed to have a "very low" risk of armed conflicts, which encompass 25.14 % of the total regional land area, the predominant representation occurs within the states of Zambia and Mozambique, along with the eastern territories of Tanzania. The findings illustrated underline a crucial revelation that a causal relationship exists between key variables,

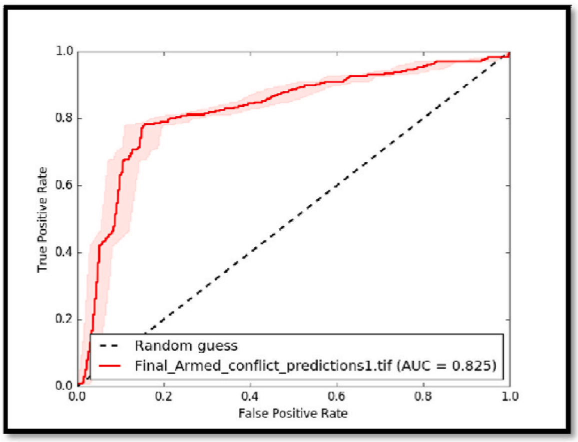

Fig. 6. AUC for the RF model for Predicting Armed Conflict.

including climatic fluctuations, topographical variations, declining economic metrics, ethnically heterogeneous compositions, and the propensity for armed conflicts. Remarkably, our research highlights the novel insight that this relationship is predominantly inverse, underscoring the potential for conflict mitigation through targeted interventions.

Validation of the results by Area Under Curve (AUC) requires reliance on two criteria, the first of which is the valid positive rate, represented by the model of actual armed conflicts obtained through ACLEAD data. In contrast, the other is represented by the false positive rate, represented by the final map resulting from the prediction of armed conflicts. In the region using FR, this was done by running the ArcSDM tool from the ArcToolbox toolbox, and the model quality ranges between the following results: 0.9–1.0 Excellent, 0.8–0.9 Very Good, 0.7–0.8 Good, 0.6–0.7 Satisfactory, 0.5–0.6 Unsatisfactory, it is clear from applying to the subject of the study that the final result reached … which indicates that the accuracy of the results has got a very good level, which is evident from Fig. 6.

One of the notable aspects of this research lies in applying a Visual Programming approach to model armed conflict spatially. The interconnected and sequential execution of various stages offers a systematic and replicable method for predicting armed conflict risk in different regions worldwide. The research's reliance on the Frequency Ratio (FR) application, along with its validation using AUC, showcases the robustness of the model in predicting the likelihood of armed conflict. The attainment of "Very Good" quality in validation underscores the model's efficacy and reliability. The implications of this research are significant, as it provides a valuable tool for policymakers, researchers, and organizations to assess and mitigate the risk of armed conflicts. The systematic approach, combined with the model's quality, ensures the applicability of the findings in diverse geopolitical contexts.

3.2. Recommendations based on the current findings

The study recommends structural prevention to reduce armed conflicts in the countries of the region, which was explained by Bellamy [65] as follow:

3.2.1. Economic measures

- Reducing deprivation and poverty.
- Reducing inequalities, especially horizontal.
- Promoting economic growth.
- Supporting structural reform.
- Providing technical assistance.
- Improving the terms of trade and trade openness.
- Supporting community development and local ownership

3.2.2. Governance measures

- Building institutional capacity and ensuring delivery of social services.
- Strengthening and supporting democracy.
- Supporting the diffusion or sharing of power.
- Strengthening the independence of judiciaries.
- Eradicating corruption.
- Strengthening local conflict resolution capacity

3.2.2.1. Security measures.

- Strengthening rule of law.
- Ending/preventing impunity.
- Reforming the security sector.
- Encouraging disarmament and effective arms control/management with particular reference to small arms

3.2.2.2. Human rights measures.

- Protecting fundamental human rights and building national capacity, with specific protection of minority, women, and children's rights.
- Supporting the work of the International Criminal Court.

3.2.2.3. Social measures.

- Intergroup confidence building, including interfaith dialogue.
- Strengthening and supporting civil society.
- Establishing freedom of the press.
- Preventing and punishing incitement and hate speech.
- Educating on diversity and tolerance.

4. Conclusion

Armed conflicts have far-reaching consequences, profoundly affecting people's lives and reflecting a nation's capacity to govern. This study employed the Frequency Ratio method and political geography criteria to predict the spatial distribution of armed conflicts in East African states, offering valuable insights for policymakers and researchers. We identified five risk categories associated with political geography factors: "very high," "high," "moderate," "low," and "very low." The current analysis highlighted the heightened vulnerability of Burundi to "very high" likelihoods of armed conflicts, with significant risk also observed in Rwanda, Uganda, and Somalia. Ethiopia and South Sudan exhibited a "moderate" likelihood, while Zimbabwe, Zambia, and Mozambique experienced "low" risk. Areas of "very low" conflict likelihood were primarily found in Zambia, Mozambique, and the eastern parts of Tanzania. We uncovered an inverse relationship between key variables, including climatic fluctuations, topographical variations, declining economic metrics, ethnically diverse populations, and the propensity for armed conflicts. This novel insight suggests that targeted interventions addressing these variables can mitigate conflict risk. The following actions are recommended to reduce the risk of armed conflicts in East African regions.

(i) Early Warning Systems: Implement robust early warning systems to monitor and respond to climatic changes and potential conflict impacts, preventing resource-driven conflicts and displacement.
(ii) Economic Development Initiatives: Prioritize economic development efforts to reduce inequalities in high-risk conflict areas, focusing on education, job creation, and poverty reduction.
(iii) Peacebuilding Efforts: Concentrate on peacebuilding and conflict resolution initiatives, engaging with local communities and stakeholders to address ethnic tensions and grievances.
(iv) Environmental Sustainability: Implement sustainable environmental practices to manage climate change effects, especially in conflict-prone regions, including resource management and disaster preparedness.
(v) Cross-Border Cooperation: Encourage diplomatic cooperation among neighboring countries to address conflicts that transcend borders, fostering lasting peace and stability.
(vi) Conflict-Sensitive Development: Ensure development projects and policies consider potential conflict risks, incorporating conflict-sensitive approaches.

This research enhances our understanding of armed conflicts in East Africa and provides a systematic model for predicting and managing conflict risk. Using the Frequency Ratio method and validation through the Area Under Curve underscores the model's robustness and reliability. These findings offer crucial insights for policymakers and researchers working towards conflict prevention and resolution, fostering regional stability and peace. In conclusion, this study contributes to conflict management and prevention efforts in East Africa, offering a valuable tool to guide future interventions.

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Data availability

The datasets utilized and/or analyzed during the current study are available upon request from the corresponding author.

CRediT authorship contribution statement

Mohamed Hamdy Eid: Writing – original draft, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Mohamed Sayed Kamel:** Writing – original draft, Software, Formal analysis, Data curation, Conceptualization. **Anwar Sayed kamel Amer:** Writing – original draft, Visualization, Validation, Methodology, Investigation. **Péter Szűcs:** Writing – review & editing, Supervision, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2024.e38684.

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