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ARTICLE

Conflict susceptibility mapping methodology and data experiments

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This research presents an innovative approach and methodology to conflict susceptibility mapping by integrating machine learning technologies with geospatial data analysis. Utilizing public datasets from Somalia, the study experiments with applying machine learning models such as random forest classifier, support vector machine classifier, and gradient boosting classifier models to predict areas susceptible to conflict. The methodology includes data preprocessing, model training, execution, and validation, employing various software and machine learning techniques. The random forest classifier emerged as the most accurate model through experiments with the machine learning models, demonstrating the potential of using machine learning to enhance our understanding of conflict dynamics. The study highlights the critical role of selecting appropriate conditioning factors and the need to continuously refine methodologies to improve prediction accuracy. By providing a practical method for conflict susceptibility mapping, this research contributes to the broader field of peace and security research, which directly contributes to Sustainable Development Goal 16 and explores the potential of using machine learning to support peace, justice, and strong institutions, and contribute to global peace and security.

Keywords – Conditioning factors, conflict analysis, conflict susceptibility mapping, machine learning, SDG 16

1. INTRODUCTION

In 2015, the United Nations General Assembly set a global agenda by adopting the 17 Sustainable Development Goals (SDGs) to ensure prosperity, environmental sustainability, and social equity by 2030. These goals address today's most pressing challenges, including poverty, inequality, climate change, environmental issues, peace, and justice. The SDGs build upon the success and lessons learned from the Millennium Development Goals (MDGs), aiming to address the root causes of these challenges and foster an inclusive approach involving all stakeholders: governments, the private sector, civil society, and individuals worldwide [1, 2]. The SDGs envision a future where no one is left behind, highlighting the interdependencies of social, economic, and environmental sustainability and the collective effort required to achieve these ambitious objectives.

Sustainable Development Goal 16 (SDG 16) focuses on promoting peaceful and inclusive societies for sustainable development, providing access to justice for all, and building effective, accountable, and inclusive institutions at all levels. This goal underscores the importance of peace, security, justice, and strong institutions for sustainable development. It acknowledges that without a peaceful environment and a justice system that serves all members of society equally, achieving the other SDGs would be challenging. The SDG 16 targets are to significantly reduce all forms of violence, protect children from abuse, exploitation, trafficking, and violence, promote the rule of law and ensure equal access to justice, develop effective, accountable, and transparent institutions, provide responsive, inclusive, and representative decision-making, and strengthen the participation of developing countries in the institutions of global governance. The realization of SDG 16 is crucial for creating and maintaining the social and political stability necessary to implement initiatives across all other SDGs [3, 4].

Applying machine learning technology to SDG 16 offers innovative pathways to enhance peace, security, and justice. Machine learning models can analyze vast datasets to recognize patterns, predict the onset of conflicts, monitor elections for fairness, and identify patterns of corruption and human rights abuses, thus providing actionable insights for policymakers and law enforcement [5, 6]. However, based on comprehensive research on the identification of conflict susceptibility, the application of machine learning technologies to predict the likelihood of conflict onset [7] and, in general, SDG 16 is limited. The research has revealed that machine learning technology is promising in predicting conflicts; machine learning models can process vast datasets, recognize complex patterns, and generate reliable predictions, making them instrumental in conflict analysis and prevention [7].

Machine learning technologies offer nuanced insights into conflict dynamics by integrating socio-economic, governance, environmental, and political factors into predictive models. This approach not only enhances the understanding of conflict triggers but also aids in developing targeted strategies for conflict mitigation and prevention. As the accuracy of these predictive models relies on the quality of data and the selection of conditioning factors, the study advocates for continuing improvement of methodologies to improve prediction accuracy. In essence, leveraging machine learning in the context of conflict analysis represents a forward-thinking method to identify conflict-prone areas and contribute to global peace and security. This research identified a set of conflict susceptibility factors that can be instrumental in accurately predicting conflict locations. However, there are no universal condition factors that can apply to conflicts. Given the diverse factors influencing conflict susceptibility, the study argues for a tailored approach to developing machine learning models. The unique aspects and drivers of conflicts in various regions should be considered for more precise and relevant predictions [7].

The research "Identifying Conditioning Factors and Predictors of Conflict Likelihood for Machine Learning Models: A Literature Review" [7] served as a foundational reference for this study. We further explored the methodology of developing machine learning models to create a susceptibility map of Somalia to identify areas susceptible to conflict.

2. PUBLIC SOMALIA DATASETS

This research uses a case study methodology, focusing on public Somalia datasets. Somalia was selected due to its geopolitical significance and the complexity of its ongoing conflict. The case study provides insights into various conflict dynamics, the involvement of numerous parties and actors, the significant humanitarian needs, and the security implications for the Somali people.

We conducted in-depth research on primary historical conflict datasets, which are also used to train and validate the models in this document. These datasets include the Armed Conflict Location & Event Data Project (ACLED) [42] and the Uppsala Conflict Data Program (UCDP) [43]. Both datasets provide detailed information on conflict events, actors, and their interactions across various geographical regions and timelines.

The ACLED data is a widely used dataset that tracks and reports conflict events and provides data on each event's location, timing, type, and severity. The ACLED also includes information on the actors involved and their affiliations and interactions. This dataset covers state and non-state actors, allowing for a thorough examination of the complexities of conflicts. Various scholars and academic institutions, international organizations such as the United Nations and its Agencies, Funds and Programmes (UNAFP), International Committee of the Red Cross (ICRC), European Union agencies, and other government and inter-government institutions, think tanks, as well as media news agencies use the ACLED database [8] for their research and analysis of historic and ongoing events in different parts of the world.

The UCDP is another prominent dataset that systematically collects and categorizes data on violence, armed conflicts, and related events worldwide. The UCDP includes information on conflict events, actors, fatalities, and conflict dynamics. The UCDP data is combined with the ACLED data to provide a more comprehensive understanding of global conflict patterns.

These two data sources are used for training and validating machine learning models to understand, predict, and map conflict susceptibility in different areas in Somalia. The data provided by the ACLED is event-based, and the UCDP provides data that focuses on significant wars or conflicts and the number of victims associated with a conflict. Both the ACLED and UCDP datasets are used for conflict analysis. While they share the same aim of documenting violent conflicts, they use different methodologies and levels of granularity. The ACLED covers political violence and protest events and the UCDP covers individual incidents of violence, both fatal and non-fatal. In terms of timeline and update aspects, the ACLED is near-real time, and the UCDP datasets are updated yearly. Overall, the ACLED and UCDP provide invaluable insight into conflict dynamics, and they are used complementarily to gain a comprehensive understanding of violent conflicts [7].

Leveraging the information provided by the ACLED and UCDP, researchers develop models that take into account a wide range of conflict-related factors from the local to the global level. These datasets enable the development of training and evaluation of our machine learning models.

Furthermore, we explored a set of conditioning factors that play a crucial role in providing context for conflict events. Different factors may lead to armed conflicts in different countries. Some conditions that increase the likelihood of conflicts include the inability of governments to provide essential governance and the protection of their populations [9]. Various publications refer to such factors that could potentially lead to conflicts. Armed conflicts are still among the biggest threats to human societies, and identifying the underlying pro-cases and potential drivers is an area of intense scientific research [10]. The possible factors that enhance the conflict have been identified in the scientific research literature, including poverty [11], income inequality [12], economic struggle [13], weak governance [14], or pre-existing history of conflicts [15], financial assets from natural resource exploitation [25], ethnic fractionalization [16, 17], vulnerability to natural disasters [18] and climate change [19]. However, after years of research, there has been no agreement among scholars regarding whether and how climate change influences the risk of conflict [19]. By incorporating these datasets into our analysis, we want to identify the factors that influence conflict dynamics and enhance the interpretability of our machine learning models.

The idea of conceptualizing conflict conditioning factors was derived from applying conditioning factors in determining landslide susceptibility mapping [21]. This approach uses conditioning factors, such as topographical, geological, and environmental variables, to identify areas prone to landslides. Similarly, in the context of conflict susceptibility, conditioning factors such as socio-political dynamics, economic disparities, and environmental factors can be applied to locate areas susceptible to conflicts. Many complex factors contribute to the occurrence of armed conflicts. Conditions that enhance the probability of conflicts include governments' inability to provide effective governance and safeguard their populations [9]. This study used available public datasets from various public sources, including several international organizations, UNAFPs, and government agencies.

2.1 Challenges of using Somalia datasets

The exploration of publicly available data for this research presented its challenges. First, there is limited availability of reliable data [20]. This is a common challenge in conflict zones like Somalia, where data collection can be dangerous. Moreover, available data often contains inconsistencies, particularly in the completeness of geographical coordinates for data points, such as in datasets for health facilities and school locations. Further, the data collection projects or processes are not collected in Somalia due to a lack of statistical capacity and financial or security constraints [20]. These challenges collectively complicated the process of data collection and validation. Despite these challenges, the data gathered from public sources for Somalia provided valuable insights into the conflict dynamics in the country, and it is necessary to keep these limitations in mind when interpreting the findings.

The temporal period selected for the Somalia data in this research is from 2000 to 2023. This time frame was chosen to ensure temporal data consistency across all datasets used in our study. Aligning the temporal boundaries of the different datasets can minimize potential discrepancies in the entire collection of datasets. This selection balances capturing an adequate amount of data and ensuring that the data is as recent and relevant as possible. Thus, the chosen period significantly enhances the integrity and robustness of our analysis and findings.

If this methodology and process can be developed and successfully applied in an exceptionally data-challenging situation like Somalia, these processes could be even more efficient in other regions, where data is more available, reliable, and consistent. Applying these processes and methods would provide more precise and accurate results. Therefore, this research contributes to our understanding of conflict dynamics in Somalia and provides a methodological framework that can be adapted to other geographical areas. This adaptability contributes to the broader field of conflict analysis and geospatial data science.

3. CONFLICT SUSCEPTIBILITY METHODOLOGY

Conflict susceptibility mapping is a methodology that leverages machine learning technology to predict areas at risk of conflict by analyzing diverse conditioning factors, including socio-economic, political, environmental, and other relevant variables. The conflict susceptibility mapping methodology concept is presented in Fig. 1; the concept includes four main components: data preprocessing, deployment and execution of machine learning models, development of conflict susceptibility maps, and validation of machine learning models.

Data preprocessing is one of the important steps for machine learning applications [22] to conflict susceptibility mapping. Conflict susceptibility mapping relies on a broad spectrum of public unstructured data sources, providing data in various data models and formats, using different spatial and temporal resolutions and scales, often containing inconsistencies, missing values, and noise. Data preprocessing aims to transform this raw data into a clean, standardized format that machine learning models can easily process and provide accurate prediction results. By transforming the datasets to a consistent data format structure such as GeoTIFF and bringing the data grids to a uniform resolution and WGS84 coordinate reference system, we ensure the compatibility of data from different data sources across various spatial and temporal data resolutions. Furthermore, preprocessing also involves dealing with missing data, a critical aspect of improving the quality of the input data [23]. Without such preprocessing steps, the machine learning algorithms may produce misleading results, leading to unreliable conflict susceptibility mapping results.

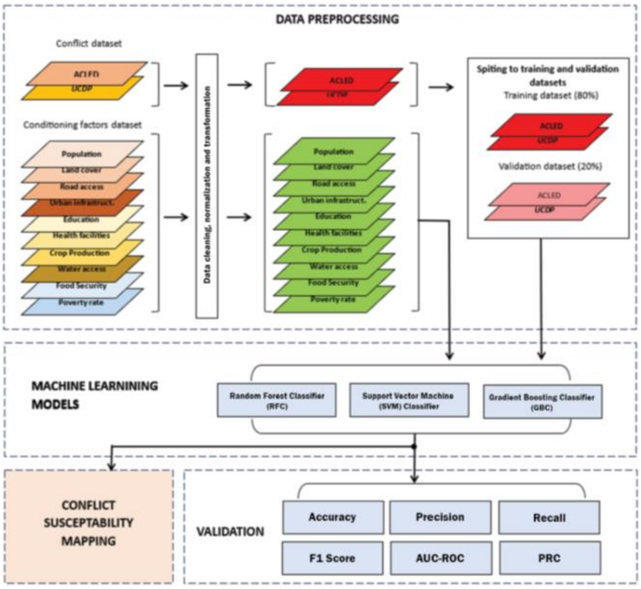

Figure 1 – Concept of conflict susceptibility mapping methodology.

To split conflict data between training and validation, we selected the standard principle 80/20 [24, 25]. Data division into 80% for training and 20% for validation. This concept is used for model development and is called the 80/20 rule. 80% of the data is allocated for the training dataset, allowing the model to learn from a larger portion of the historical dataset. That provides enough information to understand the data patterns and relationships between data points. The training portion is necessary for the model to develop predictive capabilities. The 20% of the data is allocated for model validation for the model performance testbed. Using the 80/20 rule, we can validate machine learning models and ensure they are trained and tested for accuracy, reliability, and effectiveness.

Regarding the application of data splitting processes, we considered two options: splitting data during the preprocessing stage, as provided in Fig. 1. This approach is typically conducted before the execution of the machine learning model and involves segmentation of the dataset using QGIS software. The second option, which we have used in our case, consists of splitting the data dynamically while executing the machine learning model using Python code. This method offers flexibility and integration with the modeling process. This splitting process during model execution ensures that our models are trained and tested on current conflict historical data.

We selected a Random Forest Classifier (RFC), a Support Vector Machine (SVM) classifier, and a Gradient Boosting Classifier (GBC) for the development of our conflict susceptibility mapping models. Because each machine learning technique has its specific strengths and weaknesses, we also aim to identify which algorithm is better suited to the particular requirements of conflict susceptibility mapping. Throughout the research process, it was noted that the selection of machine learning algorithms applied to the conflict susceptibility mapping machine learning model depends on the data quality, their resolution, the complexity of the system, and the required degree of accuracy from the outcome of the predictions and, also, to the available computing power.

Model validation is essential in our methodology to ensure that the conflict susceptibility mapping models have the required accuracy and reliability. We used several metrics and validation techniques, each designed to assess different aspects of model performance. Among these, the Area Under the Receiver Operating Characteristic Curve (AUC-ROC) and Precision Recall Curve (PRC) are crucial metrics used in binary classification tasks [26]. In addition to AUC-ROC, we also employed metrics like accuracy, Precision, Recall, and F1 score. Accuracy represents the proportion of total predictions the model got correct, while precision (also known as the positive predictive value) measures the proportion of correct identifications among all predicted positives. Recall is the proportion of actual positives that were correctly identified. The F1 score, which is the harmonic mean of precision *(P)* and recall *(R)*, balances these two metrics, making it particularly useful in cases of class imbalance. Equation (1) represents the mathematical formula of the F1 score:

$$F1 = 2 \times \frac{P \times R}{P + R} \tag{1}$$

The conflict susceptibility mapping methodology provides flexibility and adaptability, independent of specific algorithms, models, or datasets. This approach allows for the customization of the methodology based on conflicts' unique context and geographical location. The conflict susceptibility mapping concept provides the ability to select from various machine learning models. We used RFC, SVM classifier, and GBC for our case study. These algorithms can be replaced with other algorithms depending on the technical requirements and historical conflict and conditioning factors data. Each model brings specific strengths and can be selected based on factors like data complexity, required prediction accuracy, and available computing power.

4. SOFTWARE AND MACHINE LEARNING TECHNIQUES

In this research, we employed different tools and software to execute different tasks for data preprocessing, data research, development, execution, and validation of machine learning models.

For data exploration and cleansing tasks, we employed both R [28] and RStudio [31] for their statistical computation capabilities. R programming language provides statistical techniques such as linear and nonlinear modeling, classical statistical tests, time-series analysis, classification, clustering, graphs, and chart plotting. RStudio is an Integrated Development Environment (IDE) for R. It provides a user-friendly interface for using R and developing R scripts. These tools are used to verify public data quality and assist in identifying the patterns otherwise invisible during the data review. R is free and open-source software for statistical computing and the development of graphs. R software is provided under the GNU General Public License (GPL) [32].

In conjunction, the RStudio integrated development environment (IDE) operates under the GNU Affero General Public License version 3 (AGPL v3) [33]. AGPL v3 is an open-source license that promotes the sharing of code.

For geographic data preprocessing and visualization, we used QGIS [27], an open-source geographic information system software. It is used for managing geospatial data and geostatistical analyses. The synergy of QGIS and Python allowed the conversion of various data formats to GeoTIFF format and the normalization of data grids to uniform mapping units.

We used an open-source programming language, Python, to prove the methodological concept for machine learning models' development for conflict susceptibility mapping. We selected Google Colab's free cloud service to deploy and execute machine learning code. Google Colab is based on the Jupiter Notebook environment, which allows you to write and execute Python code and deploy machine learning models. Using libraries, frameworks, and a variety of machine learning techniques, we employed various machine learning algorithms and models to train, execute, and validate conflict susceptibility mapping models. These models include, but are not limited to, the random forest classifier [34, 35], the support vector machine classifier, and the gradient boosting classifier [36].

Available Python libraries, such as Scikit-learn [37], NumPy [38], SciPy [39], Pandas, and Geopandas, along with validation metrics including accuracy, precision, recall, F1 score, and Area Under the Curve—Receiver Operating Characteristic (AUC-ROC) and Precision-Recall Curve (PRC), were used in the model deployment process.

For our tasks, Python is utilized in data preprocessing, normalizations, training, and validation of machine learning models and generating conflict susceptibility mapping. Python is an open-source programming language licensed under the Python Software Foundation License [40]. This license allows for free distribution, modification, and use of the software, even in commercial applications, without the requirement to disclose the source code of the proprietary part.

Two processes were researched for using conflict historical data in conflict susceptibility mapping models. One is to transform the vector dataset into a raster format. We employed the Inverse Distance Weighting (IDW) interpolation process in QGIS for this process. This technique allowed us to interpolate the density of conflict locations, using the number of fatalities per event as the observed value. In our research, we considered the number of deaths per event as an indicator of the severity of each conflict event in ACLED and UCDP GED datasets. The second process included conflict historical data in the original CSV format, which was directly used in the machine learning models. Python code was used to process geospatial vector data using available libraries.

The relevance of IDW interpolation lies in its ability to convert raw conflict event data into spatially continuous patterns by interpolating the density of conflict locations using the number of fatalities per event as the observed value. This transformation enables machine learning models to analyze conflict severity and conflict distribution effectively.

IDW interpolation generates a continuous surface that reflects the severity of conflicts by assigning values based on neighboring data points. This method transforms discrete conflict events into a spatially smooth distribution of conflict data. In this process, each conflict event contributes proportionally to the interpolated values based on its severity (number of fatalities) and its distance from other points, with closer events having a more significant impact.

The IDW is a deterministic method for multivariate interpolation with a known scattered set of points [41]. The IDW algorithm is used in QGIS, among other software, for spatial interpolation. The interpolated surface is a weighted average of the data points, and the weight assigned to each point diminishes as the distance from the interpolation point to the data point increases.

Mathematically, the IDW interpolation function (2) can be represented as:

$$f(u) = \begin{cases} \frac{\sum_{i=1}^{N} w_i(u) z_i}{\sum_{i=1}^{N} w_i(u)}, if\ d(u,u_i) \neq 0 for\ all\ i, \\ u_i, \qquad if\ \ d(u,u_i) = 0 for\ some\ i, \end{cases} \tag{2}$$

$f(u)$ is the interpolated value at location u,

z_i are the observed values at location i,

$w_i(u)$ is the weight based on the distance between the interpolated location u and the data point i, and

N is the total number of points.

The weight $w_i(u)$ is typically defined as:

$$w_i(u) = \frac{1}{d(u,u_i)^p} \tag{3}$$

where:

$d(u,u_i)$ is the distance between the interpolated location *u* and the data point *i*, and

p is a power parameter that controls the significance of known points on the interpolated values based on their distance to *u*. A larger *p* decreases the influence of distant points.

It is important to note that the selection of the power parameter p can influence the results of the IDW interpolation, and it should be chosen carefully based on the specifics of the dataset and the intended use of the interpolated surface. To convert the ACLED and UCDP GED vector point data into a raster format, we employed the IDW interpolation method in QGIS. The weighting factor in this process was determined by both the number of fatalities and the density of conflict incidents, allowing us to capture the severity and the spatial concentration of conflicts in our study area.

5. EXPERIMENTS WITH RANDOM FOREST CLASSIFIER MODEL

The choice of the Random Forest Classifier (RFC) for developing the conflict susceptibility mapping model was based on the algorithm's capability to handle complex datasets, which is crucial when working with public conflict and socio-economic conditioning factor datasets. These datasets often exist in various formats and with differing levels of accuracy. The RFC-based model is particularly useful at capturing the complex and non-linear relationships between socio-economic, political, and geographical factors that contribute to conflict.

A key aspect of RFC is its ability to aggregate decisions from multiple decision trees, using an ensemble learning method known as bootstrapping. This process ensures that predictions are more accurate than those of individual models by averaging outputs from trees trained on different subsets of the data. By exposing each tree to only a portion of the dataset, the RFC minimizes the risk of overfitting while maintaining robustness. This is important in conflict datasets, which often contain irregular patterns, noise, and other anomalies. Averaging decisions helps the RFC focus on broader trends, ensuring the model remains reliable even when faced with data inconsistencies. Additionally, the RFC's ability to handle missing data is a significant advantage in scenarios where field data collection processes may lack reliability or completeness, as is common in conflict zones.

Tree height is a significant hyperparameter in the RFC that impacts both performance and interpretability. In the context of conflict susceptibility mapping, higher trees enable the model to capture interactions between variables such as population density, road networks, and conflict events. However, overly high trees can lead to overfitting, where the model learns noise or anomalies rather than meaningful patterns. Conversely, shallow trees may underfit the data, oversimplifying the relationships and missing critical patterns.

Despite the obvious RFC advantage, developing models for conflict susceptibility mapping using the RFC presents numerous challenges. The RFC models lack straightforward interpretability, which can be critical for understanding the influence of specific conditioning factors on conflicts. The computation requirements for the models with numerous trees or large datasets lead to extended training and processing times. The model's performance can present a challenge with the imbalanced datasets often observed in conflict-related public datasets. Additionally, the performance of an RFC heavily relies on the correct tuning of hyperparameters, like the number of trees and their depth, adding complexity to model development. Lastly, the "black box" nature of an RFC limits the understanding of the internal decision-making processes for peacemaking and mediation-related activities.

However, despite the challenges presented by using an RFC, the model provides the required accuracy, interpretability, and robustness, which makes it a good choice for developing models for predicting conflict susceptibility and mapping. The model's technical capabilities help predict conflicts and understand key conditioning factors, supporting the formulation of more effective preventive strategies and policies.

5.1 Training and executing the random forest classifier model

The Python code was deployed in Google Colab to train and execute the model based on the RFC. In this paragraph, we describe the process of developing the RFC-based conflict susceptibility mapping model using a combination of RFC machine learning techniques and geospatial data analysis.

After mounting Google Drive and providing access to the datasets, we set up the Python environment by installing essential packages. The loading phase involves importing conflict data from a CSV file using panda. This dataset contains geospatial coordinates and other conflict-related attributes and undergoes a process of marking for "presence" (indicative of conflict) and "pseudo-absence" (indicative of non-conflict scenarios). The geospatial features are extracted from various conditioning factors raster files, such as population densities and road networks. This step is crucial to understanding the geographic nuances of conflict areas and conditioning factors potentially influencing the conflict. The data is then subjected to preprocessing, where non-numeric and missing values are addressed, and the dataset is split into training and testing sets. This ensures the model is evaluated on any missing values presented in the datasets, a key aspect of the model assessment.

The fundamental aspect of this process is model training and hyperparameter tuning. The model is fine-tuned with the grid search cross-validation process, determining optimal configurations of parameters such as tree numbers and depth.

The accuracy test has returned high accuracy values for the predictions for the RFC of the conflict susceptibility mapping model. Below, the "0" value indicates "non-conflict" predictions, and "1" means "conflict" predictions.

```
Accuracy on Test Set (RF): 0.9352992957746479
Classification Report (RF):
          Precision recall  f1-score   support

       0       0.93      0.94      0.94      1136
       1       0.94      0.93      0.93      1136

    accuracy                       0.94      2272
   macro avg   0.94      0.94      0.94      2272
weighted avg   0.94      0.94      0.94      2272
```

The model's effectiveness is assessed using key performance metrics like accuracy, precision, recall, and F1-score, calculated against the validation dataset. This evaluation phase is crucial in understanding the model's predictive capabilities in real-world scenarios.

The final stage of the model conducts the visualization of the model's predictions on a map. A geodata frame is created and plotted over a map with a base map from OpenStreetMap by merging these predictions with the validation set of geospatial data. The geodata frame defines the geographical locations and boundaries of the data points.

Through this process, combining machine learning with geospatial analysis, we provide a tool capable of predicting and visualizing areas susceptible to conflict. The RFC delivers a robust, reliable model, while geographic visualization represents the results.

5.2 Visualization of random forest classifier model predictions

Fig. 2 presents a map of predicted conflict and non-conflict locations derived from the RFC machine learning model. This visual representation provides a spatial understanding of potential hotspots and areas requiring further investigation. The symbology is designed to display the locations of “conflict” and “non-conflict” areas by a point. The prediction dataset's latitude and longitude indicate each point's position on the map.

The color coding of the points is presented in two colors used to differentiate between “conflict” and “non-conflict” predictions. “Conflict” areas (positive prediction) points are given in red color, and “non-conflict” (negative prediction) points are colored in green color. In the resulting dataset of RFC model conflict predictions, the value of predicted conflicts is “1,” and the value of non-conflict is “0”. This symbology allows researchers and stakeholders to visually identify the areas that might require attention or prevention for potential conflicts. It also helps to understand the geographical distribution of conflict risk across the mapped region and identify visual patterns in relation to various geographical objects such as roads, rivers, international or administrative borders, etc.

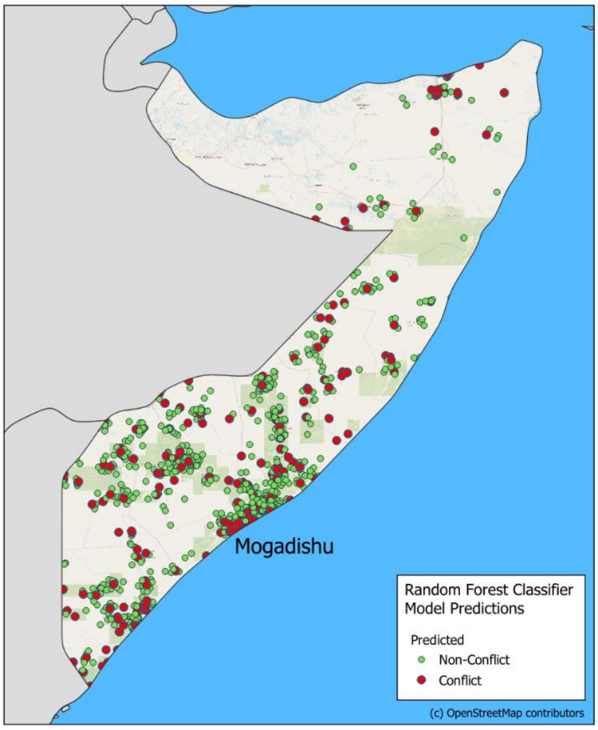

Figure 2 – RFC Conflict Susceptibility Map

OpenStreetMap layers are selected as the baseline data for this map. These layers provide the geographical context necessary to understand the locations of predictions. They include geographical features like roads, water bodies, and urban areas, allowing for a better understanding of the terrain and landscape where these predictions are located.

This visual representation is crucial for stakeholders, such as policymakers, researchers, and humanitarian organizations, as it helps them identify areas that might require attention, intervention, or further study.

5.3 Random forest classifier model validation

Fig. 3 presents a graph of the Area Under Curve—Receiver Operating Characteristic (AUC-ROC) of a binary classifier's performance as its discrimination threshold varies. The curve is generated by plotting the True Positive Rate (TPR) against the False Positive Rate (FPR) at various threshold settings. The true Positive Rate (Sensitivity) presented in Equation 4 is the percentage of positive instances (actual "1"s) that are correctly identified by the classifier.

$$TRP\ (Sensitivity) = \frac{TruePositive}{TruePositive+FalseNegative} \qquad (4)$$

False Positive Rate (1-Specificity) presented in Equation 5 is the percentage of negative instances (actual "0"s) that are incorrectly identified as positive by the classifier.

$$TRP\ (Specificity) = \frac{FalseNegative}{TruePositive+FalseNegative} \qquad (5)$$

The Python code evaluates the AUC-ROC and PRC scores for the RFC model and plots the graphs for both performance indicators. Initially, the code imports necessary libraries for plotting and calculating evaluation metrics. It then computes the False Positive Rate and True Positive Rate at various threshold settings to create a ROC curve. The AUC-ROC is calculated to provide a single measure of the model's performance. In parallel, the code computes the precision and recall for different probability thresholds to construct a Precision-Recall Curve (PRC). It also calculates the Average Precision (AP), which summarizes the precision-recall curve.

Visualization is plotted for understanding the model’s capacity to accurately distinguish between “conflict” and “non-conflict” areas. The ROC curve shows the model’s effectiveness across different thresholds, while the PRC is particularly informative in the context of imbalanced datasets typical of conflict susceptibility scenarios. Using both the ROC curve and PRC, this evaluation provides insights into the model’s predictive power and the reliability of conflict susceptibility mapping.

The AUC-ROC score of RFC conflict susceptibility mapping models is high, 0.98. It indicates the model is good at distinguishing between areas that are prone to “conflict” (labeled as "1" or positive) and areas identified as “non-conflicts” (labeled as "0" or negative). A score of 0.98 means there's a 98% chance that the model will rate a randomly chosen susceptible area as more likely to have “conflict” than a randomly selected “non-conflict” area.

An AUC of 1 indicates perfect conflict prediction, though this suggests overfitting, while an AUC of 0.5 implies random guessing, highlighting a lack of meaningful insights into conflict.

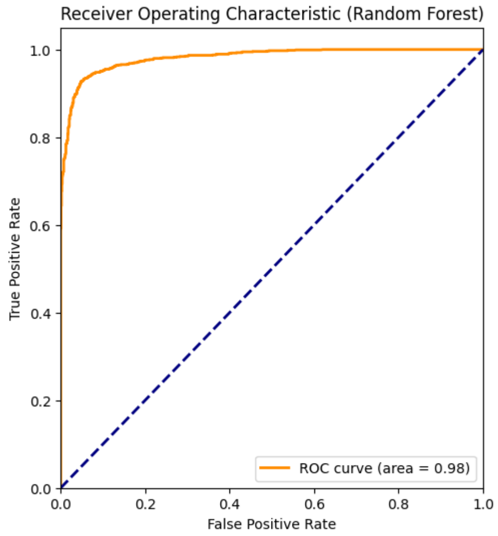

Figure 3 – AUC-ROC graph validating the accuracy of the RFC model

Another assessment indicator that was applied in this research was AUC-PRC. The PRC is a graphical representation that plots precision against recall for different thresholds. The area under this curve quantifies the classifier's overall performance across all possible decision thresholds. In other words, using different probability thresholds, AUC-PRC summarizes the balance between the true positive rate and the positive predictive value.

Fig. 4 is the graph representing the PRC for conflict susceptibility mapping trained and executed based on RFC models. The PRC score for our model is 0.98.

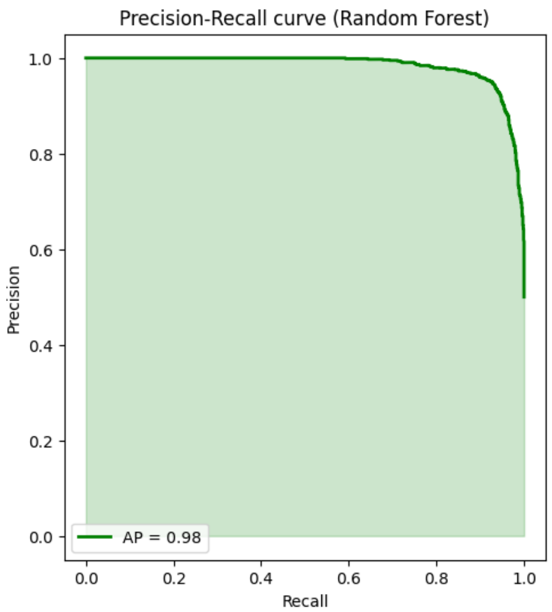

Figure 4 – PRC graph validating the accuracy of the RFC Model

The AUC-PRC score of 0.98 is very good, indicating that the RFC model can distinguish between areas that are susceptible to "conflict" and those that are "non-conflicts." Similar to AUC-ROC, if 0.5 PRC, this is no better than a random guess. On the other hand, 1.0 PRC is a perfect classifier but can also indicate an overfitting.

A PRC of 0.98 suggests that the model has a good balance of precision and recall. It means that for most thresholds, the model can identify a high percentage of actual susceptible areas (high recall) while maintaining a low rate of false positives (high precision).

Both validation models, AUC-ROC and PRC, returned a score of 0.98. Such a high score can provide relative confidence in using the model's predictions to give actionable information to the decision-making processes for conflict prevention. It suggests that the random forest classifier model can correctly identify areas of high conflict susceptibility based on the provided data and features.

6. EXPERIMENTS WITH SUPPORT VECTOR MACHINE CLASSIFIER MODEL

The Support Vector Machine (SVM) classifier is a powerful and versatile machine learning model experimented with in developing conflict susceptibility mapping models. The SVM demonstrates its effectiveness in managing complex and high-dimensional data, typically present in conflict and socio-economic datasets. The SVM is particularly good at finding a hyperplane that best separates data into different classes, which is essential for distinguishing between "conflict" and "non-conflict" areas based on various socio-economic, political, and geographical indicators and other conflict conditioning factors. One of the key strengths of SVM in conflict susceptibility mapping is its ability to model non-linear relationships using kernel functions. These capabilities are important for capturing the interactions between multiple factors that can contribute to conflict. Unlike simpler linear models, SVM can handle the complexity and nuances present in conflict data, making it generally well-suited for conflict analysis.

However, the SVM models present several challenges in this context. SVM-based models can be computationally intensive, especially with large datasets and when using complex kernel functions. This requires consideration of computational resources and process optimization during model training. SVM-based models can present challenges in understanding how each feature influences the classification, which can present challenges in explaining the model's decisions in a policy-making context. Another challenge is the selection of an appropriate kernel and tuning of hyperparameters like the penalty parameter (C) and kernel parameters. The performance of SVM heavily relies on these choices. Additionally, SVM models can be challenging with very large datasets and may require techniques like data reduction or approximation methods for efficient processing.

Despite these challenges, the high accuracy and effectiveness of SVM-based models in complex classification tasks make it a valuable tool for conflict analysis and developing conflict susceptibility mapping models. By efficiently handling high-dimensional data and providing clear decision boundaries, SVM can contribute to predicting and understanding conflict dynamics.

6.1 Training and executing the support vector machine classifier model

The Python code in Google Colab for the training and execution of the model is based on the Support Vector Machine (SVM) classifier algorithm. This code develops a machine learning model to predict conflict susceptibility in Somalia and creates a map presenting the locations of "conflicts" and "non-conflicts" based on the SVM classifier. After mounting Google Drive and providing access to the datasets, we set up the Python environment by installing essential packages. To prepare historical Somali conflict data, we loaded it into a data frame. This data is then augmented by creating pseudo-absence data, which is critical to developing the model because it provides examples of locations where conflict is not present. This augmentation is conducted by randomly sampling data from the original dataset and then altering the "presence" flag to zero, simulating "non-conflict" areas. The following process involves extracting geographical features using raster data. The code processes various raster files, extracting features based on the latitude and longitude coordinates from the combined dataset. These extracted features are then added to the data frame, enriching the original data with spatially relevant information essential for understanding the geographical context of conflict.

After data preparation, the code handles non-numeric and missing data in the dataset using an imputer and standardizes using a scaler. This standardization is essential for an SVM's performance, as it is sensitive to the scale of input features. The data is then split into training and test sets, balancing the two classes using the Synthetic Minority Oversampling Technique (SMOTE). This is important for dealing with the imbalanced nature of conflict data, where data points of conflict might be significantly fewer than non-conflict instances. The SVM classifier tuned through a grid search to find the optimal parameters. This process involves experimenting with different values for the regularization parameter (C), kernel types, and gamma values to determine the best combination for the model. The SVM model is trained on the resampled training data when the best parameters are identified. The trained model is used to predict conflict susceptibility on the test dataset, and the model's performance is evaluated using standard metrics like accuracy and a detailed classification report. These metrics provide insights into the model's effectiveness in differentiating between "conflict" and "non-conflict" areas.

Finally, the predicted results are visualized on a map. Using the test set's latitude and longitude, along with the predicted values, a geodata frame is created. This geodata frame is then plotted on a base map sourced from OpenStreetMap, using different colors to represent predicted "conflict" and "non-conflict" areas. This visual representation is essential for understanding the geographical distribution of conflict susceptibility and helps in the practical application of the model's findings, such as conflict prevention and management.

The SVM-based model used in this analysis initially provided the lowest accuracy among the various models tested. In its first trial, the SVM model achieved an accuracy of approximately 0.752 on the test set. Following a detailed hyperparameter tuning process, there was a slight improvement in the model's performance, with the accuracy increasing to approximately 0.761. The training and execution time for the SVM model was significantly longer compared to other models.

```
Accuracy on Test Set (SVM): 0.761443661971831
Classification Report (SVM):
              precision    recall  f1-score   support
           0       0.74      0.82      0.77      1136
           1       0.79      0.71      0.75      1136

    accuracy                           0.76      2272
   macro avg       0.76      0.76      0.76      2272
weighted avg       0.76      0.76      0.76      2272
```

This extended processing time is a notable drawback of the SVM, particularly when handling large datasets such as raster image data and requiring extensive hyperparameter tuning. Such time-intensive computation can be a limiting factor in scenarios where quick model iteration or real-time analysis is needed.

6.2 Visualization of support vector machine classifier model predictions

Fig. 5 presents a map of predicted "conflict" and "non-conflicts" derived from the Support Vector Machine (SVM) classifier machine learning model. As in the RFC-based model, the map provides potential "conflict" and "non-conflict" locations. See Section 5.2 for details.

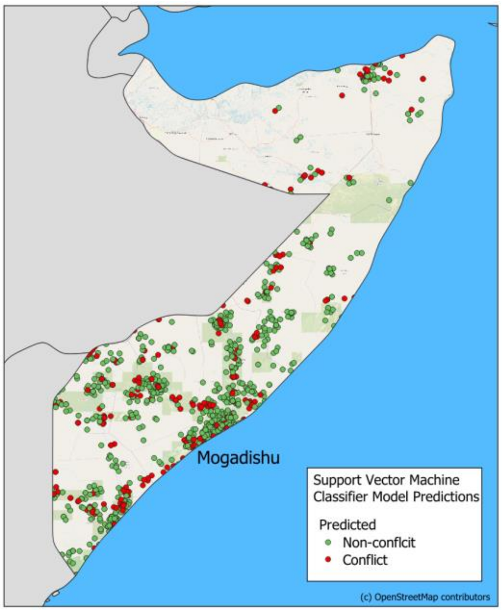

Figure 5 – SVM classifier conflict susceptibility map

6.3 Support vector machine classifier model validation

Fig. 6 presents a graph of AUC-ROC of the performance of a binary classifier for the validation of SVM classifier model performance.

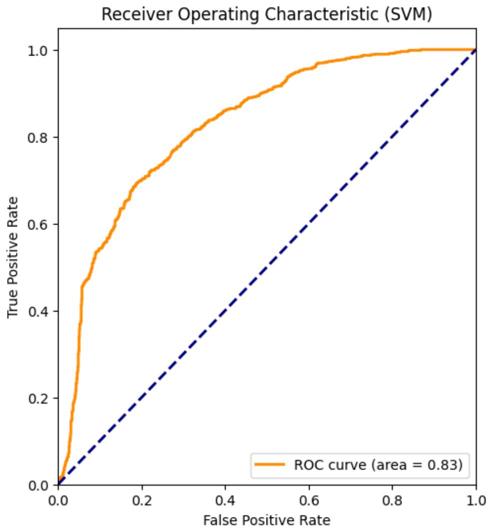

Figure 6 –AUC-ROC graph validating the accuracy of SVM.

As for the random fort classifier model validation, the curve is generated by plotting the True Positive Rate (TPR) against the False Positive Rate (FPR) at various threshold settings for SVM model validation. True Positive Rate (Sensitivity) presented in Equation 3 is the percentage of positive instances (actual "1"s) that are correctly identified by the classifier. False Positive Rate (1-Specificity) presented in Equation 5 is the percentage of negative instances (actual "0"s) that are incorrectly identified as positive by the classifier.

This Python code calculates the AUC-ROC and PRC scores for an SVM model and plots the graphs for both performance indicators. This code is set to evaluate and visualize the performance of an SVM model using two key metrics: the ROC curve and the PRC. It begins by importing the necessary functions for calculating these metrics and plotting data. The trained model provides the output probability estimates.

The script predicts the probabilities for the positive class of the test data using the trained conflict susceptibility SVM model. These predicted probabilities are crucial for calculating the ROC and PRC. Then, the code computes the false positive and true positive rates at various threshold levels and calculates the area under the ROC curve. This area represents a measure of the model's capability to differentiate between the positive and negative classes. Also, the PRC is computed. The area under the PRC provides an aggregated measure of the model's performance, especially when there is a class imbalance. The script then proceeds to the metrics and plots the graph. This visual representation is essential in many machine learning tasks, particularly for evaluating classification models.

The AUC-ROC score of 0.83 for the SVM-based conflict susceptibility mapping models signifies a strong predictive performance. The AUC-ROC provides a single measure of the model's overall performance. An AUC-ROC score of 0.83 indicates that the SVM model can correctly distinguish between the two classes, “conflict” and “non-conflict” areas. This score implies that in 83% of the cases, the model will correctly differentiate a randomly chosen positive instance (actual conflict area) from a negative one (non-conflict area). This level of accuracy is generally considered reasonable and suggests that the SVM model is effective for the task of conflict susceptibility mapping.

In Fig. 7, the PRC score of 0.78 for the SVM-based conflict susceptibility mapping models indicates a satisfactory level of performance, particularly in the context of class imbalance, which is often related to conflict databases and socio-economic conditioning factors.

A score of 0.78 in this case suggests that the SVM model is quite adept at identifying true “conflict” areas, however, with slightly less accuracy. However, the model is effective in correctly identifying areas of conflict susceptibility. While performing the model execution, we tried to improve the model's performance by tuning hyperparameters, which gave us an insignificant increase in PRC values. It improved from 0.77 to 0.78.

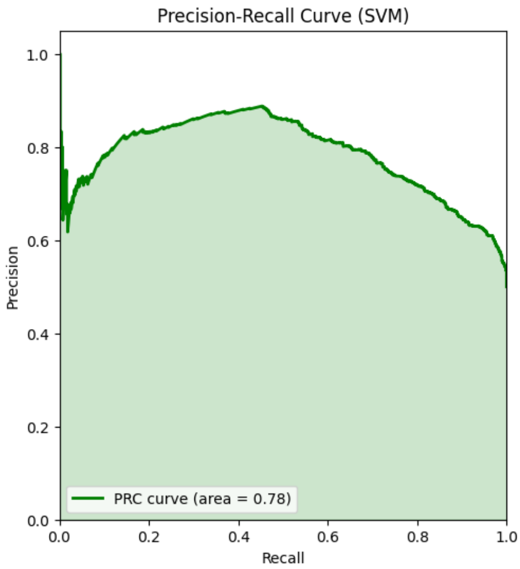

Figure 7 – PRC graph validating the accuracy of SVM.

For stakeholders, these scores mean the SVM-based model can distinguish between “conflict” and “non-conflict” with 83% accuracy and identify potential “conflict” areas with 78% accuracy. Overall, the SVM-based model can support early warning, although some misclassifications may be present. Thus, supplementing the model's results with expert validation and cross-referencing with other models is recommended to ensure the accuracy of the decision-making process.

7. EXPERIMENTS WITH GRADIENT BOOSTING CLASSIFIER MODEL

The Gradient Boosting Classifier (GBC) is selected for conflict susceptibility mapping models due to several factors aligned with conflict analysis and susceptibility mapping requirements [44]. GBC is recognized for high accuracy in complex classification tasks, which is essential for conflict analysis. One of the main reasons for selecting GBC is its capability to work with diverse and high-dimensional datasets, which are common in conflict, socio-economic, and conditioning factors datasets. These datasets often include various variables, such as socio-economic, political, and geographical indicators. GBC's approach of building successive decision trees, each correcting the errors of the previous, allows us to effectively interpret this complexity, providing insights into potential conflict drivers.

Another vital aspect is GBC's capability to model non-linear relationships [45]. The interactions between factors that contribute to conflicts are rarely linear or obvious. GBC's algorithms can uncover and model these complex interactions, providing an understanding of the underlying conflict dynamics. Moreover, the aspect of GBC, where each new model incrementally improves based on the previous, is particularly suited for the evolving nature of conflict data. As new data becomes available or the socio-political landscape changes, GBC models can be efficiently updated, ensuring that the conflict susceptibility mapping models remain relevant and accurate. While GBC requires careful tuning of hyperparameters and can be computationally intensive, its accuracy and ability to manage complex, high-dimensional data make it a good choice for conflict susceptibility mapping models. These strengths enable GBC to significantly contribute to predicting and understanding conflict dynamics, making it a valuable tool in conflict analysis.

Meanwhile, implementing GBC models in conflict susceptibility mapping presents some challenges. They are primarily related to the risk of overfitting [44], as GBC models might adapt too closely to the training data, leading to poor performance on unseen datasets. Another challenge is the intensive computational demand of GBC models [44], mainly when processing large datasets or during the extensive hyperparameter tuning process. This can strain resources and increase the time required for model development and deployment. The "black box" nature of GBC models [46] is another problem regarding interpretability and understanding how various conditioning factors influence predictions. The quality and availability of data significantly impact model performance. Data can often be incomplete, unbalanced, or inaccurate in conflict mapping, leading to skewed or unreliable predictions. These challenges require a careful approach to model development and continuous evaluation to ensure the reliability of conflict susceptibility mapping models.

7.1 Training and executing with the gradient boosting classifier model

The Python code in Google Colab for the training and execution of the model is based on the GBC model. The process involves data preparation, feature extraction, model training, hyperparameter tuning, and visualization of predictions. After mounting Google Drive and installing Python libraries, it imports relevant functions and classes for model selection, ensemble methods (specifically gradient boosting), metrics, preprocessing, imputation, and SMOTE for handling class imbalance. The historical conflict data is loaded from a CSV file, generating pseudo-absence data by sampling from the original data, adjusting the latitude and longitude, and generating "non-conflict" data points. These pseudo-absence data points are combined with the original data to form a complete dataset. The code then extracts raster features from a list of TIFF files related to conditioning factors of the conflicts, such as population density, roads, schools, etc.

The combined dataset is split into training and testing subsets, ensuring a balanced representation of presence and absence data. The script processes the data by selecting numeric columns, imputing missing values, and standardizing the features. It addresses class imbalance using the synthetic minority oversampling technique. The GBC is an ensemble learning method known for its effectiveness in classification tasks. The model is searched through a range of hyperparameters to find the most effective model configuration. The model is now trained on the resampled training data. The best model from the grid search is then used to make predictions on the test set. The accuracy and classification reports are printed to evaluate the model's performance.

The accuracy test result has returned quite a high percentage of accuracy of the predictions for the GBC of the conflict susceptibility mapping model, which is presented below. The GBC-based mode provided high accuracy, 0.91, closer to the results of the RFC-based models, which is 0.93. Such an accuracy test provides positive results and indicates that the GBC model was a good choice for the set of historical conflicts and conditioning factors datasets available for Somalia's use case.

```
Accuracy on Test Set (GB): 0.9141725352112676
Classification Report (GB):
              precision    recall  f1-score   support
           0       0.93      0.90      0.91      1136
           1       0.90      0.93      0.92      1136

    accuracy                           0.91      2272
   macro avg       0.91      0.91      0.91      2272
weighted avg       0.91      0.91      0.91      2272
```

7.2 Visualization of gradient boosting classifier model predictions

Fig. 8 presents a map of predicted "conflict" and "non-conflicts" derived from the GBC-based machine learning model. As in the RFC-based model, the map provides locations of potential "conflict" and "non-conflict" areas.

See Section 5.2 for details.

7.3 Gradient boosting classifier model validation

Fig. 9 presents a graph of the AUC-ROC of the performance of a binary classifier as its discrimination threshold is varied.

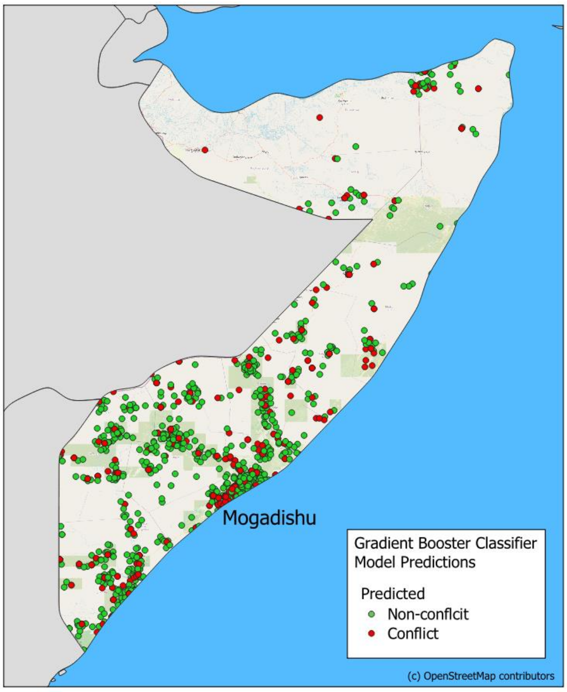

Figure 8 – GBC conflict susceptibility map

The Python code to calculate the AUC-ROC, PRC scores for GBC model evaluates a conflict susceptibility mapping model based on the GBC using AUC-ROC and PRC. It imports necessary libraries for plotting and calculating evaluation metrics. The code first predicts the probability of the positive class for the test set using the already trained GBC model. It then computes the false positive rate and true positive rate at various threshold settings to create a ROC curve. The AUC-ROC is calculated to provide a single measure of the model's performance.

In parallel, the code computes the precision and recall for different probability thresholds to construct a PRC. It also calculates the average precision that summarizes the precision-recall curve. Fig. 9 represents the AUC-ROC curve, plotting the tradeoff between true positive and false positive rates, and it is labeled with the AUC value. Fig. 10 presents PRC, highlighting the model's precision at different recall levels and labeling it with the average precision value.

Visualization helps understand the model’s capacity to accurately distinguish between “conflict” and “non-conflict” areas. The ROC curve shows the model’s effectiveness across different thresholds, while the precision-recall curve is particularly informative in the context of imbalanced datasets typical of conflict susceptibility scenarios. This comprehensive evaluation using both AUC-ROC and PRC provides a deep insight into the model’s predictive power and reliability in the domain of conflict mapping.

The AUC-ROC score of GBC conflict susceptibility mapping models is high: 0.98, which means there's a 98% chance that the model will rate a randomly chosen susceptible area as likely to have “conflict” than a randomly selected “non-conflict” area.

Another validation model that was applied in this research was PRC (Fig. 9). It is a graphical representation that plots precision against recall for different thresholds.

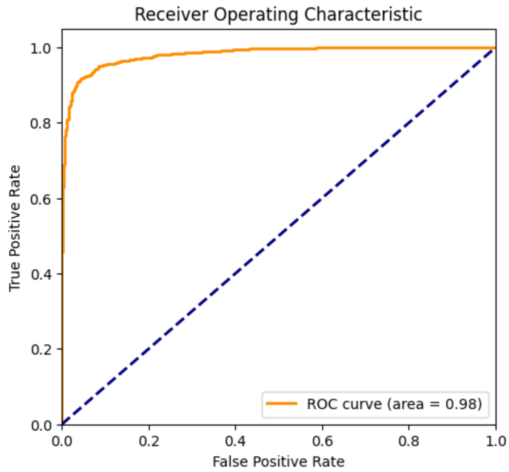

Figure 9 – AUC-ROC graph validating the accuracy of the GBC model

The area under this curve quantifies the classifier's overall performance across all possible decision thresholds. Using different probability thresholds, PRC summarizes the balance between the true positive rate and the positive predictive value. Conflict susceptibility mapping predicted areas that are considered vulnerable or prone to conflict. By training a model like the GBC on historical conflict data, we want to understand patterns and factors that lead to conflicts based on various conditioning factors. Our model is trained; it can be used to predict susceptibility for unobserved or future scenarios.

Fig. 10 represents the PRC for conflict susceptibility mapping trained and executed based on random forest classifier models. The PRC score for our model is 0.98. It is a very good score, indicating that the GBC model can distinguish between areas susceptible to conflict and those not. An AUC-PRC of 0.98 suggests that the model has a good balance of precision and recall. It means that for most thresholds, the model can identify a high percentage of actual susceptible areas (high recall) while maintaining a low rate of false positives (high precision).

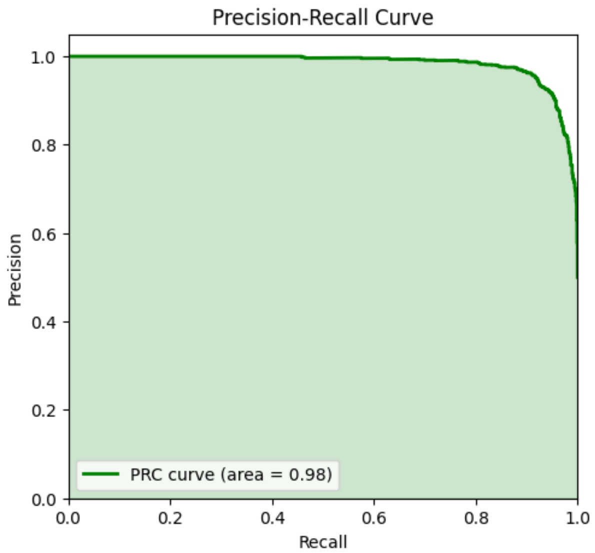

Figure 10 – AUC-PRC graph validating the accuracy of the GBC model.

Both validation models, AUC-ROC and AUC-PRC, returned a score of 0.98. Such a high score can provide relative confidence in using the model's predictions to guide interventions, allocate resources, or make strategic decisions related to conflict prevention. It suggests the GBC model can correctly identify areas of high conflict susceptibility based on the provided data and features.

8. COMPARISON OF MODELS' PERFORMANCE

Table 1 outlines the performance metrics for three machine learning models regarding conflict susceptibility mapping. The performance of three models, Random Forest Classifier (RFC), Support Vector Machine (SVM) classifier, and Gradient Boosting Classifier (GBC), was compared across various performance metrics. The RFC emerged as the most reliable, boasting the highest overall accuracy at 0.93, closely followed by the GBC at 0.91, while the SVMC lagged at 0.76. This trend of an RFC's superiority extended to precision in both "conflict" and "non-conflict" areas, scoring 0.94 and 0.93, respectively, indicating a lower false positive rate. The GBC was not far behind, especially in "non-conflict" areas, but the SVM model showed notably lower precision in both categories.

Regarding recall, which measures the ability to identify true positives, both the RFC and GBC demonstrated strong performance in identifying "conflict" and "non-conflict" areas, with scores around 0.93 and 0.94. However, the SVM was less effective, particularly in conflict zones, with a recall of only 0.71. The F1 scores, reflecting a balance between precision and recall, were consistently high for RFC and GBC across both zone types, underscoring their robustness. The SVM model's lower F1 score of 0.76 highlighted its weaker performance.

Table 1 – Comparison of performance of the models

Attribute	RFC	SVMC	GBC
Accuracy test	0.93	0.76	0.91
Precision			
Conflict zones (1)	0.94	0.79	0.90
Non-conflict zones (0)	0.93	0.74	0.93
Recall			
Conflict zones (1)	0.93	0.71	0.93
Non-conflict zones (0)	0.94	0.82	0.90
F1-score accuracy			
Conflict zones (1)	0.94	0.76	0.91
Non-conflict zones (0)	0.94	0.76	0.91
AUC-ROC	0.98	0.83	0.98
PRC	0.98	0.78	0.98

Another critical aspect is the AUC-ROC and PRC values, where both the RFC and GBC excelled with scores of 0.98, indicating excellent class separability and a strong relationship between precision and recall. SVM, on the other hand, had significantly lower scores in these areas, further confirming its comparatively weaker performance. Overall, the analysis suggests that the RFC and GBC are closely matched in effectiveness, making them more suitable for conflict susceptibility mapping than the SVM model. Table 2 presents the number of locations predicted as "conflict" areas by three machine learning models experimented with in this research: RFC, SVMC, and GBC-based models. According to the predictions made by the models, the RFC-based model identified 1 121 locations as potential conflict areas, the SVMC-based model predicted a lower number, 998 locations, as "conflict" areas, and the GBC-based model identified 1 123 locations as susceptible to conflict.

To identify geographical locations classified as "conflict" areas by all three machine learning models, RFC, SVMC, and GBC-based, we used QGIS software. We overlaid prediction layers generated by each of the three models in QGIS to conduct a spatial analysis of the specific locations where all three models predicted "conflict" areas. The number of the areas predicted as "conflict" by all three models is 908. This method helped to ensure a high level of confidence in the expected conflict areas, thereby reducing the likelihood of false positives and enhancing the reliability of the predictions.

Table 2 – Predicted "conflict" areas by individual models and locations that all three models predicted as "conflict" areas.

Attribute	RFC	SVMC	GBC
Predicted as "conflicts" areas	1 121	998	1 123
The exact locations predicted by all three models	908		

All three models predicted the overlap of 908 areas as "conflict" susceptible, suggesting the consensus among the models on data patterns that indicate a strong possibility of conflicts in overlapped areas. Such indicators include socio-economic, population, geographical, and environmental factors. In addition, the similarity in results among the machine learning models in identifying the "conflict" susceptible locations indicates the level of robustness in the models' predictions. Despite the methodological differences between the ensemble tree-based methods (RFC and GBC) and margin-based methods (SVM), the data patterns are strong enough to be identified as "conflict" susceptible across different models. The overlapping predictions also suggest that the training data was representative and comprehensive, enabling all three models to learn effectively and providing a balanced mix of "conflict" and "non-conflict" instances influencing the conflicts.

The locations of conflict-susceptible areas not overlapped by the predictions of one or more models resulted from several factors, including the methodological characteristics of each machine learning algorithm, hyperparameters tuning, model complexity, and elements of randomness in machine learning models' training. Considering the similarities between the RFC and GBC, we observe that the number of non-overlapping locations is considerably low, 82, which is approximately 7% of the number of RFC or GBC locations (overlapped locations between RFC (1 121 locations) and GBC (1 123 locations) 1 039). The geographical distribution of these 82 areas displays a predominantly non-urban trend, where the values of the conditioning datasets population distribution and availability services such as hospitals, schools, and others are at their lower margin. Other aspects, such as the methodology of machine learning algorithms, also contributed to predicting RFC and GBC models' "conflict" areas that geographically did not overlap. Although the RFC and GBC are ensemble tree-based models, they construct multiple decision trees during training and classify the individual trees for predicting "conflict" areas. However, these two methods have differences in their characteristics. GBC models focus on correcting previous errors and the RFC on random subsets of features. The GBC model's repeated correction can lead to increased sensitivity towards patterns of conflict in some areas and capture additional conflict indicators that the RFC might miss due to its random selection process, which results in a slightly higher number of predicted "conflict" areas identified by the GBC compared to RFC.

The SVM-based provided the lowest results in the accuracy test, 0.76. The number of "conflict" areas identified by the SVM-based model that did not overlap with ensemble-based models is considerably high, 212 or 19%. The geographical distribution of non-overlapped locations is more random, and no clear patterns were observed. Non-overlapped areas appear in both rural and urban locations, like Mogadishu city. From the methodological perspective, the SVM-based model's performance is sensitive to tuning the kernel or parameters (like C and gamma). If these parameters are not optimized, the SVM might not capture the complexity of the data or use tree-based methods, leading to lower accuracy.

The ensemble methods can also help generalize unseen data, averaging biases and reducing variance. The SVM's generalization is notably strong but relies heavily on tuning the parameters. Thus, in application to our use case and for the available datasets, we consider giving ensemble-based preferences for developing conflict susceptibility mapping models.

Fig. 11 presents the geographical locations predicted as susceptible to conflict by all three machine learning models: RFC, SVM, and GBC-based. This map provides the location represented in red points consistently identified across all models as potential conflict areas. This map provides a more reliable identification of areas that may require closer attention for conflict prevention. This alignment among diverse models provides the predictions' credibility and valuable insights for conflict analysis and resolution efforts.

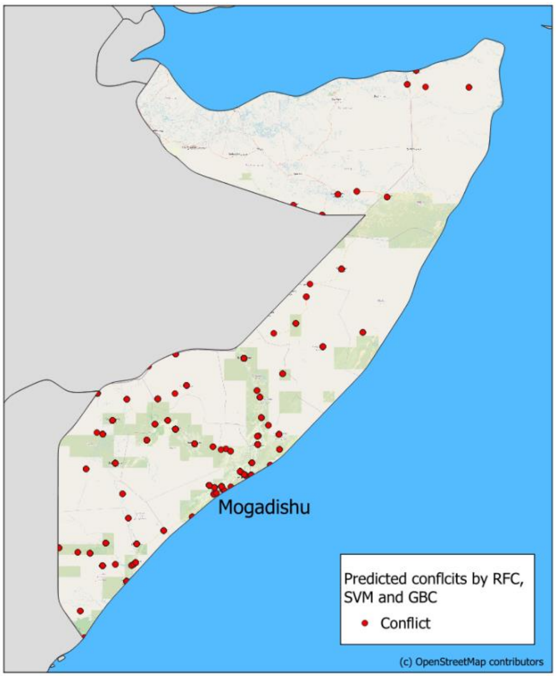

Figure 11 – Same locations of "Conflicts" predicted by all three models

In evaluating the suitability of the three conflict susceptibility mapping models, each has distinct advantages and limitations. The strong correlation between predictions of ensemble methods (RFC and GBC) and their high accuracy, precision, and recall indicates their effectiveness in correctly identifying conflict and non-conflict zones with minimal false positives and negatives. The Support Vector Machine (SVM) classifier is known for its efficacy in high-dimensional spaces. Despite these strengths, the SVM model falls behind the other models in almost all performance metrics. Such limitations are considered due to their sensitivity to the choice of kernel and the tuning of hyperparameters.

The large number of overlapping locations where all three models identify the typical conflict pattern confirms our hypothesis that thorough data cleansing and preprocessing of publicly available data provides good quality datasets for machine learning models to make accurate predictions of conflict-susceptible areas.

Moreover, selecting an appropriate machine learning model plays an important role in the accuracy of these predictions.

Choosing a suitable model, based on its strengths and the nature of the data, is crucial for capturing the patterns within the data, leading to more reliable predictions of conflict zones.

9. CONCLUSION

In this research, we provided the result of using Somalia data to develop the conflict susceptibility mapping models. The systematic development of this methodology provided the required integrity and reliability of the results. After thoroughly reviewing machine learning techniques and available data for Somalia, we developed three conflict susceptibility mapping models based on the RFC, SVM classifier, and GBC. Further, we provided a detailed explanation of the code of each machine learning model, along with the results of training, predictions, and maps of conflict-susceptible areas in Somalia. We also evaluated the performance metrics of these models, highlighting their strengths and potential areas for enhancement. Such metrics included the AUC-ROC, PRC, accuracy, precision, recall, and F1 score. The data preprocessing and experimentation phase relied on software tools for managing data-intensive operations, such as QGIS, R, Python, and the cloud-computing environment of Google Colab.

The developed conflict susceptibility mapping machine learning models based on the RFC, SVM classifier, and GBC provided promising results in predicting conflict-susceptible areas and the models' accuracy level. The RFC showed the highest accuracy on the accuracy test, 0.93, followed by GBC at 0.91 and SVM at 0.76. The AUC-ROC and PRC values for RFC and GBC were at 0.98, showing a precision-recall solid relationship. The SVM had significantly lower scores, confirming its lower performance. Regarding the number of locations predicted as “conflict” areas, the RFC identified 1121 locations, SVM 998 locations, and GBC 1123. An overlay analysis of the results of all three models using QGIS showed that 908 locations were predicted as “conflict” areas by all three models. This method enhanced the reliability of predictions by reducing false positives. Following the results of the experiments, the RFC provides the most suitable model for conflict susceptibility mapping using the experimental settings specific to Somalia.

The defined methodology of conflict susceptibility mapping satisfied our hypothesis that publicly available data related to socio-economic indicators, environmental variables, and others can be used as sources for relevant conditioning factors for conflict susceptibility mapping. The application of such conditioning factors is crucial for accurate predictions. However, it must be noted that no conditioning factors can be applied to any or all environments due to socio-cultural differences and conflict context. Each geographical location and each conflict should be studied through the prism of a unique set of conditioning factors. Thus, to use this framework to predict the likelihood of conflict escalation, we must identify a unique list of conditioning factors that can be applied to that specific geographic, political, or social scenario. It should be noted that conflict dynamics are constantly changing, and new types and elements may emerge in yet-to-be-studied situations. Additionally, certain conditioning factors may have been overlooked due to the limitations of available data during this research. Therefore, we perceive this research as a living process that is adaptable and open to future enhancements with additional conditioning factors as conflict prediction studies continue. As the application of machine learning to conflict prediction gains momentum, we anticipate an increase in the identification and understanding of conflict conditioning factors, further enhancing the accuracy of conflict prediction models. Machine learning can potentially become a crucial tool for conflict study and prevention. Understanding the elements that contribute to conflict escalation and their relations to society, politics, and geography enables the development of more effective conflict analysis techniques. The data quality and availability of data can provide challenges in using machine learning for conflict prediction. This research is believed to be a practical framework for using machine learning in conflict susceptibility research.

A literature review conducted in 2023 [7] by the authors revealed that research on machine learning susceptibility mapping and using conditioning factors remains limited. The application of machine learning technology to predict conflict likelihood has gained academic attention only in the past five years. Recognizing the importance of conditioning factors in conflict research and analysis, several initiatives have emerged. For instance, the Joint Research Centre (JRC) of the European Commission launched the Index for Risk Management (INFORM) project [47], a global open-source tool for assessing and predicting risks of humanitarian crises and disasters at the national level. This project represents a milestone in leveraging conditioning factors for risk assessment. Similarly, Uppsala University’s Violence Early Warning System (ViEWS) project provides predictions of armed conflict likelihood on a national scale [48].

While initiatives like INFORM and ViEWS focus on global or regional risk identification using conditioning factors and machine learning techniques, some scholars emphasize the importance of understanding local dynamics in conflict prediction and analysis [16, 49]. Local factors often play a pivotal role in the onset of conflicts, highlighting the need for tailored, case-by-case conflict studies focusing on the situation in the local communities. This study addresses this gap by focusing on conflict susceptibility analysis and mapping at a higher geographical resolution of 5 km, tailoring the analysis and mapping, considering local, cultural, socio-economic, and demographic nuances of the communities of interest.

In conclusion, this study represents an advancement in bridging fields such as data and geospatial science with political science, marking it an essential step in the interdisciplinary studies of conflict analysis. By integrating machine learning technologies with political analysis, this research provides a new understanding of conflict scenarios in various locations worldwide. The application of machine learning in this context is not only about technical achievements but also a tool that can provide deeper insights into the causes and possible resolutions of conflicts. The connection between data science technology and humanitarian studies highlights the importance of using data-driven approaches to understand political and social issues. As we leverage cutting-edge machine learning technologies to advance conflict studies, we must never forget the human implications of our predictions and ensure that our efforts serve the greater good.

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