Estimating countries' peace index through the lens of the world news as monitored by GDELT

Vasiliki Voukelatou
Scuola Normale Superiore and ISTI-CNR, Pisa, Italy
vasiliki.voukelatou@sns.it

Luca Pappalardo
ISTI-CNR, Pisa, Italy
luca.pappalardo@isti.cnr.it

Ioanna Miliou
University of Pisa and ISTI-CNR, Pisa, Italy
ioanna.miliou@for.unipi.it

Lorenzo Gabrielli
ISTI-CNR, Pisa, Italy
lorenzo.gabrielli@isti.cnr.it

Fosca Giannotti
ISTI-CNR, Pisa, Italy
fosca.giannotti@isti.cnr.it

***Abstract*—Peacefulness is a principal dimension of well-being, and its measurement has lately drawn the attention of researchers and policy-makers. During the last years, novel digital data streams have drastically changed research in this field. In the current study, we exploit information extracted from Global Data on Events, Location, and Tone (GDELT) digital news database, to capture peacefulness through the Global Peace Index (GPI). Applying machine learning techniques, we demonstrate that news media attention, sentiment, and social stability from GDELT can be used as proxies for measuring GPI at a monthly level. Additionally, through the variable importance analysis, we show that each country's socio-economic, political, and military profile emerges. This could bring added value to researchers interested in "Data Science for Social Good", to policy-makers, and peacekeeping organizations since they could monitor peacefulness almost real-time, and therefore facilitate timely and more efficient policy-making.**

***Index Terms*—well-being, peacefulness, Global Peace Index, GDELT, news, Data Science for Social Good**

I. Introduction

Well-being is essential for people's lives, and it could be considered as an index of societal progress [1]. Due to its multi-dimensionality, well-being encompasses a set of health, socio-economic, safety, environmental, and political dimensions [2], [3]. These dimensions are embodied by the United Nations Development Programme (UNDP) into 17 Sustainable Development Goals, labeled as SDGs [4], such as "No Poverty", "Zero Hunger", "Peace, Justice, and Strong Institutions".

Gross Domestic Product (GDP) has been traditionally considered a good indicator of societal well-being. However, it has received criticisms for being a weak indicator of well-being and, therefore, a misleading tool for public policies [1], [5]. Thus, researchers have created various indexes, for the measurement of well-being, for many purposes and for capturing a variety of its dimensions [1]. Some prominent examples are the Human Development Index (HDI), created by the UNDP [6], the Better Life Index (BLI), created by the Organisation for Economic Co-operation and Development (OECD) [2], and the Sustainable Well-Being Index (Benessere Equo Sostenibile-BES), created by the Italian National Statistics Institute (ISTAT) [7].

In the current study, we explore well-being in terms of peace through the estimation of **Global Peace Index (GPI)** [8]. GPI captures the peacefulness around the world, one of the main goals (SDG) of the UNDP. A GPI score is assigned to each country, and a higher GPI score shows less peacefulness. Historical GPI data are available at a yearly level since 2008.

Well-being indexes, such as the GPI, are traditionally measured by institutional surveys and governmental data, which are usually expensive and time-consuming. Additionally, these indexes are generally determined with a lag, and final estimates are produced only after a series of revisions, few weeks, or even months later. In this context, novel digital data streams and machine learning techniques make the measurement of well-being cost and time-efficient, and in real-time. This is also highlighted by the UN, in 2014, that recognized the importance of harnessing the data revolution [9] to put the best available tools and methods to work in achieving the SDGs.

Therefore, the focus of this research is the estimation of the GPI score around the world through a new data source. In particular, we use news media attention, sentiment, and social stability, from **Global Data on Events, Location, and Tone (GDELT)** digital news database [10], as proxies for estimating GPI, to complement traditional data sources, and overcome their limitations. Considering that GDELT is updated every 15 minutes, and it is a free access database, it can contribute to the estimation of GPI at a higher frequency, i.e., monthly frequency, at a low cost, and in a time-efficient way.

To tackle this task, we apply machine learning techniques, exploiting information extracted from GDELT, to provide valid estimates of the GPI monthly values. Our results demonstrate that GDELT variables can indeed be used as proxies for capturing GPI at a monthly level. We categorize the presented countries into war-torn, peaceful, or powerful. For each country, we conduct variable importance analysis, to discover the most important variables for capturing peacefulness. We observe that the socio-economic, political, and military profile of each country emerges through this analysis, confirming our countries categorization. Moreover, we inspect the most important variables to identify and explain the events that drive the errors in the predictions.

978-1-7281-8206-3/20/$31.00 ©2020 IEEE
DOI 10.1109/DSAA49011.2020.00034

Frequent estimation updates of the GPI score through the GDELT database could be beneficial for researchers, policymakers, and peacekeeping organizations, such as the United Nations and Red Cross. In particular, almost real-time GPI estimations can reveal month-to-month peacefulness fluctuations and significant events, to facilitate the timely reaction on applying the right policies, prevent detrimental societal effects and contribute effectively to societal progress.

The remainder of the paper is structured as follows. Section II presents an overview of the literature in peacefulness indicators and research conducted with the use of the GDELT data. Section III describes the data sets used for the study and the prediction models, and Section IV presents and analyzes the results. Finally, Section V discusses the conclusions derived from the research, limitations, and future work.

II. Related Works

Peacefulness is traditionally captured with official data, such as surveys, and socio-economic data [11]–[13]. In assessing peacefulness, the GPI explores the ongoing domestic and international conflicts, and militarisation, at a country and yearly level. It also seeks to determine the level of harmony or disagreement in a nation, through indicators that evaluate safety and security in society (see, e.g., [52] for a detailed list of the GPI indicators). For example, a low level of violent crime, a low number of homicides, low presence of police forces, and harmonious relations with neighboring countries can be suggestive of peacefulness [14].

With the growth of technology, researchers are inclined to use new data sources to measure the aforementioned GPI indicators, as an alternative or complement to traditional data. To begin with, social media, such as Twitter, have been primarily used to assess public safety, external conflicts, foreign policy, and migration phenomena, as they render individuals' online activities accessible for analysis. Given this enormous potential, social media data are used by researchers to predict crime rates [15]–[17] or detect the fear of crime [18] and by local governments to track civil unrest and violent crimes [19]–[21]. Similarly, terrorist propaganda in the Islamic State of Iraq and al-Sham (ISIS) [22], military conflicts in Gaza Strip [23], [24], as well as foreign policy discussions between Israel and Iran [25], are studied through Twitter data. Finally, social media data are rather useful in estimating turning points in migration trends [26] and stocks of migrants [27].

Besides social media data, many researchers use mobility data, such as CDRs and GPS traces, usually in combination with traditional data, to prevent crime [28]–[31]. Additionally, the volume and momentum of web search queries, such as Google Trends, provide useful indicators of periods of civil unrest over several countries [32], [33]. Moreover, crowdsourced data are used to map violence against women [34], for police-involved killings [35], and for analyzing the international crisis between India and Pakistan for the dispute over Kashmir [36]. Finally, researchers combine data from a conflict-related news database (ACLED) [37] and other traditional data to capture peace indicators and measure conflict risks [38], [39].

GDELT is another major news data source, yet barely explored. It describes the worldwide socio-economic and political situation through the eyes of the news media, making it an ideal data source for measuring well-being indexes and indicators related to peacefulness.

GDELT is mostly used to explore social unrest, protests, civil wars and coups, crime, migration, and refugee patterns. Many researchers try to explain and predict social unrest events in several geographic areas around the world, such as in Egypt [40], in Southeast Asia [41], in the United States [42], in Saudi Arabia [43], or recognize social unrest patterns in the countries of India, Pakistan, and Bangladesh [44]. Similarly, GDELT is a valuable source of data for the detection of protest events [45], as well as for detecting and forecasting domestic political crises [46]. GDELT is also used for the exploration of severe internal and external conflicts, such as the Sri Lankan civil war, the 2006 Fijian coup [47], and the Afganistan violence events [48]. Last, news data from GDELT are combined with other data sources, such as migration data and socio-economic indicators [49], refugee data (D4R) [50], D4R and housing market data [51], to analyze and produce short and medium-term forecasts of migration patterns.

The main contribution of this study is the use of GDELT to capture the monthly peacefulness as a whole, through the estimation of the GPI. The wide variety of GDELT event categories can cover most GPI indicators, and the daily updates of its data allow the GPI estimation at a higher frequency.

III. Methodology

In this section, we describe the data used in our study, highlighting their main characteristics, and explaining how they are used in our analysis. Additionally, we describe the three models that we use to produce the GPI estimates: Elastic Net, Decision Tree, and Random Forest, and the process of their dynamic training. We provide the data and the code of our study for reproducibility in https://github.com/VickyVouk/GDELT_GPI_project.

A. Data description

GPI data: GPI [8] measures the relative position of nations' and regions' peacefulness. The index ranks 163 independent states and territories according to their level of peacefulness, and it is created by the Institute for Economics & Peace (IEP). GPI score data are available from 2008 until 2019 at a yearly level (see, e.g., the most recent GPI report (2019) [52]). The score for each country is continuous, normalized on a scale of 1 to 5. It should be underlined that the higher the score, the less peaceful a country is. For example, in 2019, Iceland has been the most peaceful country with GPI 1.072, whereas Somalia has been the least peaceful country with GPI 3.574. The index is constructed from 23 indicators related to Ongoing Domestic and International Conflict, Societal Safety and Security, and Militarisation domains (see, e.g., [52] for a detailed list of the indicators). These indicators are weighted and combined into one overall score. For GPI construction, data are derived from official sources, such as governmental data, institutional surveys, and military data.

For the purposes of this study, the frequency of the GPI increases from yearly to monthly data. In particular, the GPI data are upsampled linearly. Every yearly GPI value is assigned to January of the corresponding year. The upsampling is definitively an assumption, since the monthly data generated do not correspond to the real monthly GPI. However, considering that monthly data are not available, linear upsampling is the simplest assumption. After upsampling, from 11 yearly values (2008 - 2019), we obtain 133 monthly values in total (January 2008 - January 2019).

GDELT data: GDELT [10] is a publicly available digital news database related to socio-political events, and it is supported by Google. In particular, it is a collection of international English-language news sources, such as Associated Press, The New York Times, etc. GDELT data are based on news reports coded with the Tabari system [53], which extracts the events from the media and assigns the corresponding code to each event. Events are coded based on an expanded version of the dyadic CAMEO format, a conflict, and mediation event taxonomy [54]. GDELT compiles a list of 200 categories of events, from riots and protests to peace appeals and diplomatic exchanges, from public statements and consulting to fights and mass violence. Examples of identified events are "Express intent to cooperate", "Conduct strike or boycott", "Use conventional military force", and "Reduce or break diplomatic relations" (see [54] for a detailed list of the topics covered in GDELT).

The database offers various information for each event, such as the date, location, **Tone**, **Goldstein**, and the URL of the news article the event is found in. The **Tone** dimension represents the emotional impact of each event, calculated by the tonal algorithm from Shook et al. [55], with a score range from -100 (extremely negative) to +100 (extremely positive). The **Goldstein** [56] dimension captures the potential impact a type of event might have on the stability of a country, with a score range from -10 (negative) to +10 (positive). Data from the GDELT database are updated every 15 minutes, and therefore data are available at a 15-minute, daily, monthly, and yearly frequency. Historical data are also available since 1979 (see [57] for more details).

In Fig. 1 we present an example of the daily total number of events derived from the GDELT news on Libya, from the middle of March to the middle of April 2019. We also provide two examples of news articles of two events that occurred in this period. We notice a rise in the total events at the beginning of April 2019, exactly when a new conflict, the "Western Libya offensive", took place. Therefore, it is evident that GDELT news can depict the worldwide socio-economic, political, and military reality.

For the prediction of GPI, we derive three different types of GDELT variables (features) at country and monthly level: i) **No. events - News Media Attention**, the total number of news per event category, ii) **Tone - Sentiment**, total aggregated positive or negative emotional impact of the news per event category, and iii) **Goldstein - Social Stability**, total aggregated positive or negative potential impact of the news per event category on the stability of the country. The aggregated Tone and Goldstein values are created by the sum of **Tone - Sentiment** and **Goldstein - Social Stability** respectively, for the corresponding country and month. For simplicity, in the rest of the paper, we use the terms Tone and Goldstein to refer to the aggregated monthly values of each country. On average, the total number of variables per country is 274, varying from 80 to 419. This indicates that some event categories may not be present in the news of a country. We use the BigQuery data manipulation language (DML) in the Google Cloud Platform to extract the GDELT variables (see Listing 1).

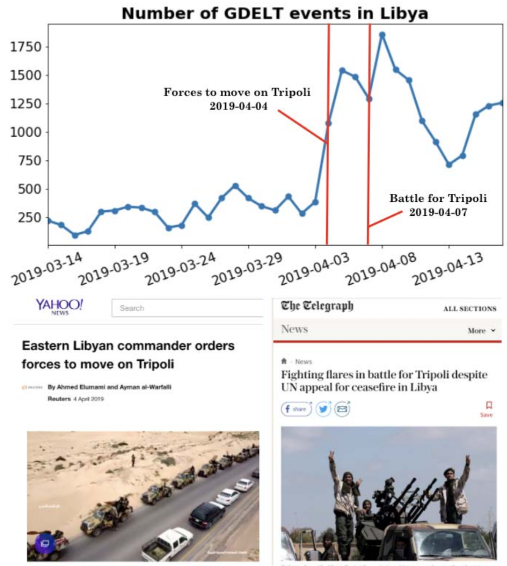


Fig. 1. Daily total number of events derived from the GDELT news on Libya, from the middle of March to the middle of April 2019 and two examples of news articles of two events that occurred in this period. GDELT depicts a noticeable rise of the total events at the beginning of April 2019, exactly when the "Western Libya offensive" took place.

Listing 1. Query for the extraction of GDELT variables.

```
SELECT ActionGeo_CountryCode, MonthYear, EventBaseCode,
COUNT(EventBaseCode) AS No_events,
SUM(AvgTone) AS Tone, SUM(GoldsteinScale) AS Goldstein
FROM 'gdelt-bq.full.events'
WHERE (MonthYear>200712 AND MonthYear<201902)
AND (ActionGeo_CountryCode<>'null')
GROUP BY ActionGeo_CountryCode, MonthYear, EventBaseCode
ORDER BY ActionGeo_CountryCode, EventBaseCode, MonthYear
```

Table I shows some random examples of the United States variables in March 2018. For example, for the event category "Engage in mass killings" the *No. events* is 574. The corresponding values of *Tone* (-1733.21) and *Goldstein* (-5740) are negative since this event has a negative emotional impact and a negative impact on the social stability of the country. Another negative event category is "Reject, request or demand for material aid", with negative *Tone* (-1112.18) and *Goldstein* (-2136) values. It is notable that the event category "Engage in mass killings" is more negative than the "Reject, request or demand for material aid", which is reflected in its values. The amount of negativity is proportional to the gravity of the event. Accordingly, for a positive event, such as "Express intent to provide material aid", the amount of positiveness is proportional to the event's importance.

TABLE I
EXAMPLES OF THE UNITED STATES VARIABLES IN MARCH 2018. THE EVENT CODE AND CATEGORY THAT DESCRIBE THE EVENT ARE REPORTED. THE NO. EVENTS THAT OCCURRED ARE ALSO PRESENTED, ALONG WITH THEIR TONE, AND GOLDSTEIN. NEGATIVE VALUES INDICATE A NEGATIVE IMPACT, AND VICE VERSA.

Event Code	Event Category	No.events	Tone	Goldstein
011	Decline comment	7064	-22151.28	-706.40
022	Appeal for diplomatic cooperation	2561	-2410.50	8195.20
033	Express intent to provide material aid	6775	1123.99	35312.40
091	Investigate crime	799	-3120.12	-1598.00
104	Demand political reform	950	-1939.37	-4750.00
122	Reject, request or demand for material aid	534	-1112.18	-2136.00
138	Threaten with military force	5860	-25135.12	-41020.00
181	Abduct, hijack, take hostage	2115	-9343.68	-19035.00
202	Engage in mass killings	574	-1733.21	-5740.00
203	Engage in ethnic cleansing	166	-597.23	-1660.00
⋮	⋮	⋮	⋮	⋮

B. Prediction models

Models handling time series are used in order to predict future values of indices by extracting relevant information from historical data. Traditional time series models are based on various mathematical approaches, such as autoregression. Autoregressive models specify that the output variable depends linearly on its previous values and a stochastic term. Considering that our data are upsampled linearly, it is not feasible to apply autoregressive models, because of the linear relationship between the dependent variable (GPI) and its past values.

In the current study, we use machine learning models to estimate the GPI values. We choose Elastic Net, Decision Tree, and Random Forest models, to describe the relationship between the GPI score and the GDELT variables at a country level. Specifically, the aim is to develop GPI estimates one month in advance of the latest ground truth GPI value.

Elastic Net: Elastic Net is a regularized and variable selection regression method. One of the essential advantages of Elastic Net is that it combines penalization techniques from the Lasso and Ridge regression methods into a single algorithm [58]. Lasso regression penalizes the sum of absolute values of the coefficients (L1 penalty), Ridge regression penalizes the sum of squared coefficients (L2 penalty), while Elastic Net imposes both L1 and L2 penalties. This means that Elastic Net can completely remove weak variables, as Lasso does, or reduce them by bringing them closer to zero, as Ridge does. Therefore, it does not lose valuable information, but still imposes penalties to lessen the impact of certain variables.

Decision Tree: Decision Tree is a machine learning algorithm that is used to visually and explicitly represent decisions, in the form of a tree structure. A Decision Tree is called regression tree when the dependent variable takes continuous values [58]. The goal of using a Regression Decision Tree is to create a training model that can predict the value of the dependent variable by learning simple decision rules inferred from the training data. In particular, Decision Tree divides the data set into smaller data groups, while simultaneously, an associated decision tree is incrementally developed. The final tree consists of decision nodes and leaf nodes. A decision node has two or more branches, each representing values for the variable tested. A leaf node represents a decision on the value of the dependent variable. The topmost decision node, called the root node, corresponds to the most important variable.

Random Forest: Random Forest limits the risk of a Decision Tree to overfit the training data. [58]. As the names "Tree" and "Forest" imply, a Random Forest Regression is essentially a collection of individual Regression Decision Trees that operate as a whole. A Decision Tree is built on the entire data set, using all the variables of interest. On the contrary, Random Forest builds multiple Decision Trees from randomly selecting observations and specific variables and then combines the predictions into a single model. Individually, predictions made by Decision Trees may not be accurate, but combined, are, on average, closer to the true value.

C. Dynamic training

Traditionally, before modeling, researchers start by dividing the data into training data and test data. Training data are used to estimate and generate the models' parameters, and the test data are used to calculate the accuracy of the models. Because the test data are not taken into account to estimate the model, they should be a reliable indicator of the models' predictive power on new data [59], [60].

We borrow the idea of the rolling forecast to perform a dynamic training of the models [64]. Considering that the socio-economic and political situation around the world is not stable and extreme events might occur, it is necessary to retrain the model with the latest information available.

We initially use the first half of our data as training set for all models and we dynamically increase it to include all valuable information to a given month. First, we train the model to predict one month ahead, and then we update the training data by adding the real value of GPI of that month and the corresponding GDELT values. Next, we remove these values from the test data, and we perform the training again to predict the next monthly value. We continue this process for all subsequent months until we predict the last GPI monthly value.

Specifically, we use the data from January 2008 to June 2013 (66 values) to train the model and predict the GPI value of July 2013, the data up to July 2013 (67 values) for August 2013. We repeat this procedure until we use data up to December 2018 (132 values) to predict the GPI value of January 2019.

At every step, we obtain a new predicted value for GPI. By the end of the dynamic training process described above, we have 67 predictions according to the initial test set's length.

Then, we evaluate the accuracy of the predictions with respect to the initial test set, that contains the real GPI values.

For each of the models mentioned in section III-B, the best hyperparameters are estimated in each training phase through 10-fold Cross-validation. The hyperparameters we tune for Elastic Net are α, which is the relative importance of the L1 (LASSO) and L2 (Ridge) penalties, and λ, which is the amount of regularization used in the model. For Decision Tree, we tune the complexity parameter, cp, which imposes a penalty to the tree for having too many splits. Finally, for Random Forest, we tune $mtry$, which accounts for the number of variables available for splitting at each tree node.

IV. Results

The three prediction models, Elastic Net, Decision Tree, and Random Forest (see section III-B), are constructed for every country to generate the GPI estimates. In these models, each country's GPI values are the ground truth data (dependent variable), and the GDELT variables are the exogenous (independent) variables. We consider standard performance indicators to evaluate the performance of the prediction models: the Pearson Correlation, the R^2, the Root Mean Square Error (RMSE), and the Mean Absolute Percentage Error (MAPE) [61]–[63].

The analysis is conducted for 162 of the 163 countries that have a GPI score. Palestine is excluded since its GPI values start only from 2016, instead of 2008, and are not sufficient for the training of the model. Fig. 2 presents the Pearson correlation between the real and the predicted GPI values at a country level for all the models. It is evident that Random Forest, with a median Pearson correlation 0.67, outperforms Decision Tree and Elastic Net, with a median 0.47 and 0.43, respectively. For example, we find out that for Portugal, Lesotho, the United Kingdom, the United Arab Emirates, and Peru, all models have a very strong correlation higher than 0.85. On the contrary, there are countries, such as Latvia, Canada, Estonia, and Romania, that show a negative correlation, indicating a very low performance of the models. Although the reasons for such low performance are rather complicated, we deduce that not all countries are represented sufficiently in the GDELT news database.

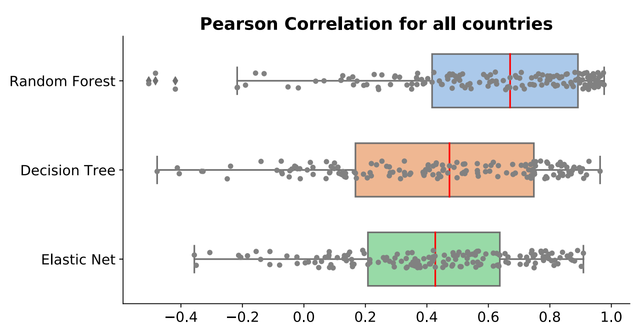


Fig. 2. Pearson correlation between the real and the predicted GPI values at a country level, for Random Forest, Decision Tree, and Elastic Net models. It is evident that Random Forest outperforms Decision Tree and Elastic Net.

TABLE II
Performance indicators with respect to GPI ground truth of the prediction models, for five war-torn countries.

Country	Model	Pearson	R^2	RMSE	MAPE(%)
Somalia	Elastic Net	0.75	0.57	0.085	1.97
	Decision Tree	0.89	0.80	0.078	1.79
	Random Forest	**0.96**	**0.91**	**0.059**	**1.51**
Yemen	Elastic Net	0.66	0.43	0.247	5.74
	Decision Tree	0.92	0.85	0.128	**2.67**
	Random Forest	**0.95**	**0.91**	**0.122**	3.05
Libya	Elastic Net	0.74	0.55	0.369	10.62
	Decision Tree	0.75	0.56	0.237	5.18
	Random Forest	**0.89**	**0.80**	**0.174**	**4.75**
Pakistan	Elastic Net	0.48	0.23	0.034	0.69
	Decision Tree	0.56	0.31	0.023	0.59
	Random Forest	**0.81**	**0.66**	**0.021**	**0.55**
DR Congo	Elastic Net	0.57	0.32	**0.076**	1.98
	Decision Tree	0.68	0.47	0.081	2.05
	Random Forest	**0.75**	**0.56**	**0.076**	**1.90**
Average	Elastic Net	0.64	0.42	0.162	4.20
	Decision Tree	0.76	0.60	0.109	2.46
	Random Forest	**0.87**	**0.77**	**0.090**	**2.35**

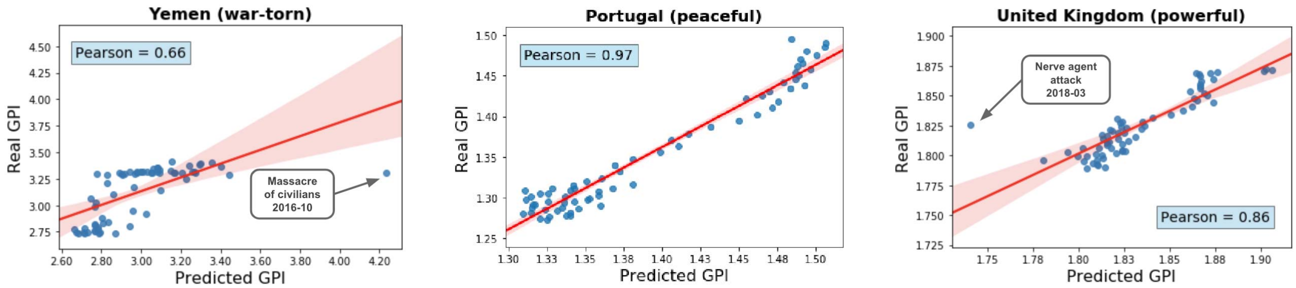
Considering the complexity of each country's analysis, we choose to present fifteen representative countries considering the current worldwide socio-economic and political situation. These countries are grouped based on war, peace, and power criteria. We use various sources, such as the official GPI ranking [52], to choose five of the most war-torn (with the highest GPI) and five of the most peaceful countries (with the lowest GPI). We also consider it valuable to analyze five of the most powerful countries since they shape global economic patterns and preoccupy policy-makers (see, e.g., [65]).

The first group includes the war-torn countries, i.e., Somalia, Yemen, Libya, Pakistan, and the Democratic Republic of the Congo (DR Congo). Despite the ongoing war in Syria, it is not selected as a war-torn country, since its GPI values start only from 2011, instead of 2008. Consequently, data are not sufficient for the training of the model. The second group consists of the peaceful countries, i.e., Portugal, New Zealand, Slovenia, Iceland, and Singapore. Last, the third group includes the powerful countries, i.e., the United Kingdom, Japan, United States, Saudi Arabia, and China.

Table II presents the performance indicators for the war-torn countries. Overall, the Random Forest models' estimates are more accurate compared to the other prediction models. We also present in Fig. 3a the scatter plot of the real and predicted GPI values of Elastic Net for Yemen, where a major outlier is also highlighted (for further analysis, see section IV-B). Finally, comparing the accuracy of Elastic Net and Decision Tree, for example for Yemen Decision Tree shows superior performance, while for Libya they show similar performance.

Table III presents the performance indicators for the peaceful countries. All prediction models perform rather well. Similar to the war-torn countries, the results demonstrate, on average, superior performance of the Random Forest. Also, Fig. 3b shows the scatter plot of the real and predicted GPI values of Portugal Random Forest, which indicates a very strong linear relationship between the two.

Table IV presents the performance indicators for the powerful countries. Similar to the results presented in the tables above, Random forest seems to outperform Elastic Net and



(a) Elastic Net results for Yemen. (b) Random Forest results for Portugal. (c) Elastic Net results for the United Kingdom.

Fig. 3. Scatter plots of the real and predicted GPI values of Yemen, Portugal, and the United Kingdom. In all the cases, the scatter plots indicate a strong correlation between the real and predicted values. The Random Forest results for Portugal are outstanding, and there are no outliers. The Elastic Net results for Yemen and the United Kingdom show a strong correlation between real and predicted values, but present a significant outlier.

TABLE III
PERFORMANCE INDICATORS WITH RESPECT TO GPI GROUND TRUTH OF THE PREDICTION MODELS, FOR FIVE PEACEFUL COUNTRIES.

Country	Model	Pearson	R^2	RMSE	MAPE(%)
Portugal	Elastic Net	0.91	0.83	0.048	3.10
	Decision Tree	0.88	0.79	0.058	3.43
	Random Forest	**0.97**	**0.95**	**0.041**	**2.85**
New Zealand	Elastic Net	0.87	0.75	0.023	1.56
	Decision Tree	0.81	0.66	0.023	1.50
	Random Forest	**0.93**	**0.87**	**0.019**	**1.32**
Slovenia	Elastic Net	0.74	0.55	0.021	1.20
	Decision Tree	0.74	0.55	0.018	1.07
	Random Forest	**0.90**	**0.80**	**0.015**	**0.91**
Iceland	Elastic Net	0.83	0.69	0.027	1.95
	Decision Tree	0.76	0.57	0.024	1.66
	Random Forest	**0.88**	**0.78**	**0.021**	**1.50**
Singapore	Elastic Net	0.41	0.17	0.033	1.75
	Decision Tree	0.76	0.58	0.024	1.35
	Random Forest	**0.81**	**0.66**	**0.016**	**0.93**
Average	Elastic Net	0.75	0.60	0.030	1.91
	Decision Tree	0.79	0.63	0.029	1.80
	Random Forest	**0.90**	**0.81**	**0.022**	**1.50**

TABLE IV
PERFORMANCE INDICATORS WITH RESPECT TO GPI GROUND TRUTH OF THE PREDICTION MODELS, FOR FIVE POWERFUL COUNTRIES.

Country	Model	Pearson	R^2	RMSE	MAPE(%)
United Kingdom	Elastic Net	0.86	0.75	0.017	0.69
	Decision Tree	0.90	0.80	0.015	0.67
	Random Forest	**0.94**	**0.89**	**0.011**	**0.54**
Japan	Elastic Net	0.84	0.71	0.018	1.03
	Decision Tree	0.76	0.57	0.019	0.94
	Random Forest	**0.92**	**0.85**	**0.015**	**0.87**
United States	**Elastic Net**	**0.86**	**0.73**	**0.034**	**1.14**
	Decision Tree	0.65	0.43	0.043	1.45
	Random Forest	0.80	0.64	0.038	1.34
Saudi Arabia	Elastic Net	0.59	0.35	0.138	4.23
	Decision Tree	0.68	0.46	0.084	**2.79**
	Random Forest	**0.77**	**0.59**	**0.076**	2.89
China	Elastic Net	0.53	0.28	0.020	0.71
	Decision Tree	0.51	0.26	0.018	0.63
	Random Forest	**0.63**	**0.39**	**0.016**	**0.58**
Average	Elastic Net	0.74	0.56	0.045	1.56
	Decision Tree	0.70	0.50	0.036	1.30
	Random Forest	**0.81**	**0.67**	**0.031**	**1.24**

Decision Tree, except the case of the United States that Elastic Net seems to be the best model. Additionally, Fig. 3c shows the scatter plot of the real and predicted GPI values of Elastic Net for the United Kingdom and highlights a major outlier (see further analysis in section IV-B). We notice that the accuracy of the models for the United Kingdom and Japan is very high, for the United States and Saudi Arabia slightly decreases, while for China, the accuracy is quite lower.

Last, the tables II,III, IV also demonstrate the average score of the performance indicators for each group of countries, which is computed with respect to the five countries shown in each of the aforementioned tables. We observe that Random Forest outperforms Decision Tree and Elastic Net for all groups of countries. In addition, the results of all groups show a high accuracy, with peaceful countries performing slightly better than war-torn and powerful countries.

A. Variable importance

The results of the training of the models could reveal the most significant factors to explain peacefulness. Since the Random Forests show superior performance for the GPI estimation, we choose to explore the most important variables, as identified from these models. In particular, Random Forests perform implicit variable selection and provide variable importance through the Mean Decrease Accuracy (MDA) [66], which is an indicator of the average decrease of model accuracy in predicting the outcome of the out-of-bag samples, when a specific variable is excluded from the model. At every training phase, an MDA value is assigned to each variable, capturing its contribution to the accuracy of the prediction.

Considering that we apply a dynamic approach for the training of the models (see section III-C), we obtain 67 different MDA values for each variable in each of the 67 training phases. Therefore, we define the *Importance* of each variable as the arithmetic mean of its MDA values. Based on the *Importance*, we identify the most important variables per country. We apply the same process to estimate the *Importance* of each variable for Elastic Net and Decision Tree models as well.

For each of the three groups of countries presented before, i.e., war-torn, peaceful, and powerful countries, we choose a representative country to analyze its most important variables. Therefore, Fig. 4, 5, 6 present the 10 most important variables for Somalia, Iceland, and United States, respectively.

We notice that for Somalia, the content of the variables indicates a country involved in conflicts or war. This is evident since the variables are related to military engagement, improvised explosives, international involvement, arrests, and endorsement of people and actions. In particular, the most important event categories are "De-escalate military engagement", "Conduct suicide, car, or other non-military bombing", "Allow international involvement", "Appeal to others to settle dispute", "Arrest, detain, or charge with legal action", and "Praise or endorse" (see Fig. 4). For clarification, the "Praise or endorse" variables are related to the expression of support and approval of policy, action, or international actors.

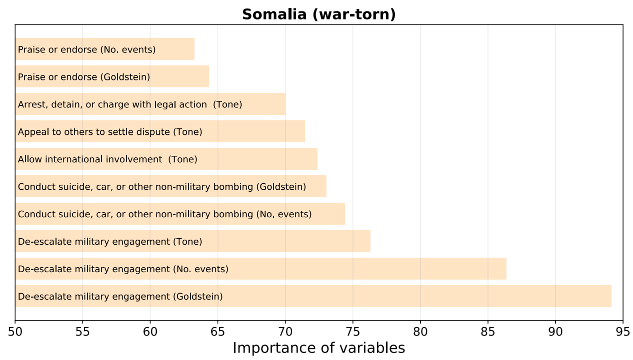


Fig. 4. Important variables for Somalia, a war-torn country. In the parenthesis, we mention the type of variable. The variables are related to military engagement, improvised explosives, international involvement, arrests, and endorsement of people and actions.

On the other hand, the variables for Iceland indicate a more peaceful country since they are related to releases of people and property, negotiations, public statements, endorsement of people and actions, and political reforms. In particular, the most important event categories are "Return, release", "Appeal to others to meet or negotiate", "Make statement", " Praise or endorse", "Accede to requests or demands for political reform", "Make pessimistic comment", and "Reject" (see Fig. 5). For clarification, the "Return, release" variables are related to releases of people and returns or releases of confiscated property. Additionally, the "Make statement" variable refers to all public statements expressed verbally or in action, while the "Make pessimistic comment" variable refers to verbal expression of pessimism. Moreover, the "Reject" variable refers to rejection or refusal to cooperate or yield.

The variables for the United States show a profile of a strong player in the economic and political foreground. This is evident since the variables are related to economic and material cooperation, formal agreements and meetings, disapprovals, political reforms, and strikes or boycotts. In particular, the most important event categories are "Cooperate economically", "Sign formal agreement", "Disapprove", "Demand meeting, negotiation", "Demand political reform", and "Conduct strike or boycott" (see Fig. 6).

We notice that several event categories appear more than once per country. For example, for Somalia, the event category "De-escalate military engagement" appears three times, with a different annotation in the parenthesis, i.e., *Tone*, *No. events*, and *Goldstein*. However, the type of variable differs, as it captures different aspects of the event category. In other words,

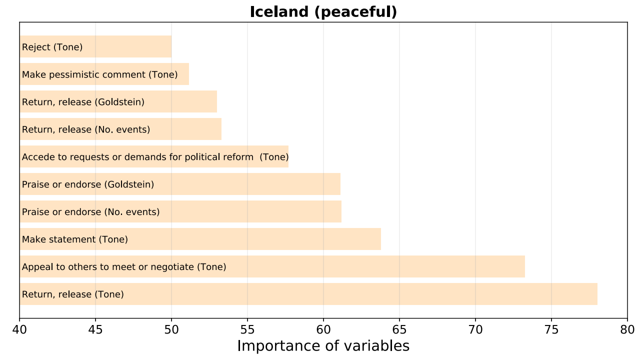


Fig. 5. Important variables for Iceland, a peaceful country. In the parenthesis, we mention the type of variable. The variables are related to releases of people and property, negotiations, public statements, endorsement of people and actions, and political reforms.

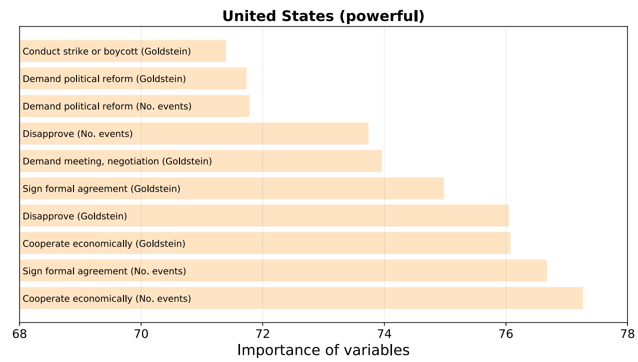


Fig. 6. Important variables for the United States, a powerful country. In the parenthesis, we mention the type of variable. The variables are related to economic and material cooperation, formal agreements and meetings, disapprovals, political reforms, and strikes or boycotts.

although all these variables refer to the same news on "De-escalate military engagement" events, they capture different dimensions (see section III-A).

B. Interpretation of errors in the predictions

The analysis of the variable importance allows us to explain why a model performs worse in certain countries and in certain cases. In other words, some important variables can work as a key to understanding errors in the predictions.

For example, we notice that for the United Kingdom, Elastic Net performs in general well, but there is a large error for March 2018 (see Fig. 7a). We, therefore, inspect the most important Elastic Net variables to find the explanation of this behavior. We observe that the variable "Attempt to assassinate" (Tone) has a similar trend with the trend of the predictions for March 2018 (see Fig. 7b). In March 2018, in the United Kingdom, a nerve agent attack occurred. In particular, a lot of news reported on the poisoning of a former Russian military officer in the United Kingdom. Consequently, the news on this event had a very negative emotional impact (Tone) this specific month. We observe an abrupt decrease in the predicted GPI value, which is also very different from the real GPI value. It seems that this decrease in the prediction of the GPI value is driven by the accordingly abrupt decrease of the variable “Attempt to assassinate” (Tone) this month. However, the GPI decrease would mean a more peaceful month, which is not correct, considering an assassination attempt took place. It would be expected that the GPI value rises, indicating a less peaceful month. Therefore, Elastic Net fails to capture this, and as so, produces a wrong prediction.

Similarly, we notice that for Yemen, Elastic Net performs in general well, but there is a large error for October 2016 (see Fig. 8a). We observe that the variable “Engage in mass killings” (No. events) has a similar trend with the trend of the predictions for October 2016 (see Fig. 8b). In October 2016, in Yemen, a massacre of civilians took place. In particular, a lot of news reported on a coalition airstrike on a crowded funeral ceremony in Yemen’s capital. The event attracted considerable media attention, and as a result, we notice a spike in the No. events for this specific month. We observe an abrupt increase in the predicted GPI value, which is also very different from the real GPI value. It seems that this increase in the prediction of the GPI value is driven by the accordingly abrupt increase of the variable “Engage in mass killings” (No. events) this month. Elastic Net manages to detect that a negative event took place by predicting a GPI monthly value indicating a less peaceful month. Unlike the case of the United Kingdom above, in this case, the model successfully detects this disturbance in the peacefulness of the country. This demonstrates the power of GDELT in capturing monthly variations of the GPI, which might be useful from a social scientists’ point of view.

On the other hand, from a model’s accuracy point of view, the predicted GPI value does not capture the real GPI value and produces a large error. Thus, in the next training phases, the model learns from its mistakes and is not highly driven anymore from this variable. As a result, we do not notice an additional increase in the predicted GPI value of August 2018 even though there is a second abrupt increase in the trend of “Engage in mass killings” (No. events).

V. Conclusion

Digital data streams are starting to find a place in well-being research, offering many opportunities in the measurement of socio-economic indexes. Traditionally, to capture well-being, researchers and policy-makers collect data through surveys and official governmental sources, which is expensive and time-consuming. Supplementing traditional data, digital data streams, explored by machine learning, are making the estimation of well-being cost-efficient and almost real-time.

In the current study, we exploit information extracted from GDELT, a digital news database, to estimate the monthly peacefulness values through GPI. GDELT news is related to socio-political events and, as a consequence, can be used as proxies for measuring GPI around the world. Estimating the GPI score at a monthly level can indicate trends at a much finer scale than it is possible with yearly measurements, capturing month-to-month fluctuations and significant events, otherwise neglected. In particular, using machine learning techniques, we estimate the GPI values for countries with different socio-economic, political, and military profile, i.e., war-torn, peaceful, and powerful. We produce GPI estimates for each country through the Elastic Net, Decision Tree, and Random Forest models. Comparing the models’ performance, it is evident that Random Forest outperforms Elastic Net and Decision Tree.

In addition, we conduct variable importance analysis to understand the most important GDELT variables that contribute to the estimation of the GPI values. As expected, the most important variables verify the profile of each country. For example, the most important Somalia variables are related to military engagement, improvised explosives, international involvement, arrests, and endorsement of people and actions. Thus, they confirm the war-torn profile of the country. Moreover, we inspect the most important variables to explain the errors in the predictions and identify the events that drive the errors.

There are two aspects of our study that we should take into consideration. Firstly, traditional media sometimes miss-represent reality. For example, they give a distorted version of the crimes within a city with a significant bias towards violence [67]. Therefore, the prediction of GPI through the news might be affected by media biases. Secondly, since the GPI is a yearly index, we upsampled its yearly values linearly to monthly values. The linear upsampling is definitively an assumption since the monthly data generated do not correspond to the real monthly GPI. However, considering that monthly data are not available, linear upsampling is the simplest assumption. Future studies could deepen more the analysis by trying different upsampling methodologies. Alternatively, a monthly index could be used instead of GPI to avoid the need for upsampling.

Another line of future research lies in the analysis of the results per country. As discussed in section IV, for certain countries, the models show low performance in predicting the GPI value. The reasons for this could be explored in depth through analysis of the representativeness of GDELT news, as not all countries are equally covered.

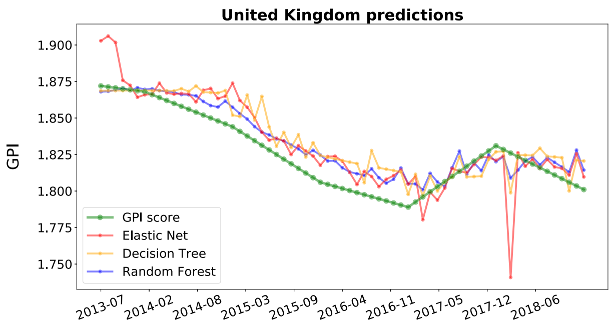
The analysis of our results shows great promise for the estimation of GPI through GDELT, yet an unexplored data source. We believe that this study is valuable to policy-makers and the scientific community, especially to researchers interested in “Data Science for Social Good”. In other words, GDELT could be used not only for peacefulness but for any other well-being dimension and socio-economic index related to the societal progress.

Acknowledgments

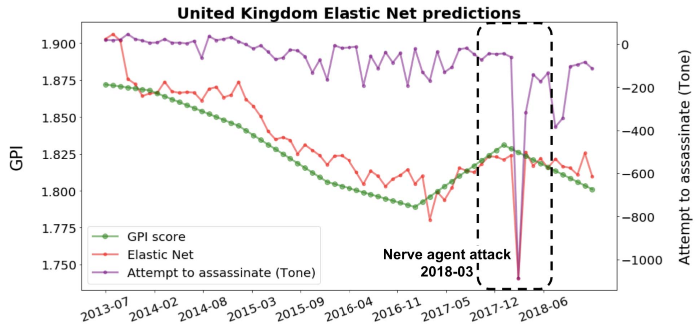
This work is supported by H2020 SoBigData++ #871042. We thank Prof. S. Matwin and S. M. Iacus for their valuable feedback.

References

[1] M. Fleurbaey, “Beyond GDP: The quest for a measure of social welfare,” *Journal of Economic literature*, vol. 47, no. 4, pp. 1029–75, 2009.

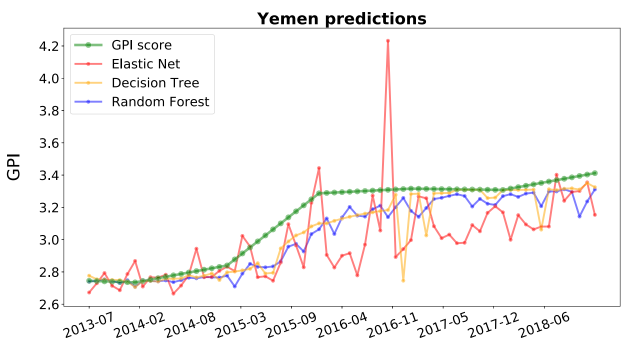


(a) GPI predictions of all models, i.e., Elastic Net, Decision Tree, and Random Forest, for the United Kingdom, with respect to the real GPI score.

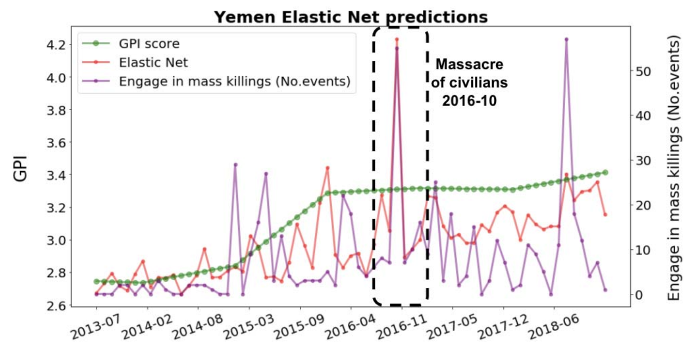


(b) GPI predictions of Elastic Net and "Attempt to assassinate" (Tone) GDELT variable, for the United Kingdom.

Fig. 7. Analysis of the GPI predictions of all models for the United Kingdom. The left plot presents Elastic Net, Decision Tree, and Random Forest predictions with respect to the real GPI score. In the right plot, the error in the prediction of Elastic Net for March 2018 is explained through the GDELT variable "Attempt to assassinate" (Tone). The reason for that error is the nerve agent attack in the United Kingdom this specific month.



(a) GPI predictions of all models, i.e., Elastic Net, Decision Tree, and Random Forest, for Yemen, with respect to the real GPI score.



(b) GPI predictions of Elastic Net and "Engage in mass killings" (No. events) GDELT variable, for Yemen.

Fig. 8. Analysis of the GPI predictions of all models for Yemen. The left plot presents Elastic Net, Decision Tree, and Random Forest predictions with respect to the real GPI score. In the right plot, the error in Elastic Net predictions for October 2016 is explained through the GDELT variable "Engage in mass killings" (No. events). The reason for that error is the massacre of civilians in Yemen this specific month.

[2] Organisation for Economic Co-operation and Development, *How's life?: measuring well-being*. OECD Paris, 2011.

[3] V. Voukelatou, L. Gabrielli, I. Miliou, S. Cresci, R. Sharma, M. Tesconi, and L. Pappalardo, "Measuring objective and subjective well-being: dimensions and data sources," *International Journal of Data Science and Analytics*, pp. 1–31, 2020.

[4] UNDP, "Sustainable Development Goals." https://sustainabledevelopment.un.org/sdgs, 2015.

[5] J. E. Stiglitz, A. Sen, and J.-P. Fitoussi, *Mismeasuring our lives: Why GDP doesn't add up*. The New Press, 2010.

[6] S. Anand and A. Sen, "Human Development Index: Methodology and Measurement.," 1994.

[7] Rapporto, BES, "Il benessere equo e sostenibile in Italia," 2015. ISTAT.

[8] The Institute for Economics and Peace, "VISION of HUMANITY." http://visionofhumanity.org//, 2017.

[9] C. Melamed, L. Morales, Y. Hsu, J. Poole, B. Rae, I. Rutherford, and A. Jahic, "A World That Counts-Mobilising the Data Revolution for Sustainable Development," *United Nations. Accessed March*, vol. 12, p. 2018, 2014.

[10] K. Leetaru, "The GDELT Project." https://www.gdeltproject.org/, 2013.

[11] M. Brückner and A. Ciccone, "International commodity prices, growth and the outbreak of civil war in Sub-Saharan Africa," *The Economic Journal*, vol. 120, no. 544, pp. 519–534, 2010.

[12] P. Gries, A. Fox, Y. Jing, M. Mader, T. J. Scotto, and J. Reifler, "A new measure of the 'democratic peace': what country feeling thermometer data can teach us about the drivers of American and Western European foreign policy," *Political Research Exchange*, vol. 2, no. 1, p. 1716630, 2020.

[13] The Institute for Economics & Peace, "Structures of peace: identifying what leads to peaceful societies," 2011.

[14] The Institute for Economics & Peace, "Global Peace Index 2015," 2015.

[15] X. Chen, Y. Cho, and S. Y. Jang, "Crime prediction using Twitter sentiment and weather," in *2015 Systems and Information Engineering Design Symposium*, pp. 63–68, IEEE, 2015.

[16] M. Al Boni and M. S. Gerber, "Predicting crime with routine activity patterns inferred from social media," in *2016 IEEE International Conf. on Systems, Man, and Cybernetics (SMC)*, pp. 001233–001238, IEEE, 2016.

[17] C. Kadar, R. R. Brüngger, and I. Pletikosa, "Measuring ambient population from location-based social networks to describe urban crime," in *International conf. on social informatics*, pp. 521–535, Springer, 2017.

[18] R. P. Curiel, S. Cresci, C. I. Muntean, and S. R. Bishop, "Crime and its fear in social media," *Palgrave Communications*, vol. 6, no. 1, pp. 1–12, 2020.

[19] F. Chen and D. B. Neill, "Non-parametric scan statistics for event detection and forecasting in heterogeneous social media graphs," in *Proc. of the 20th ACM SIGKDD intenational conf. on Knowledge discovery and data mining*, pp. 1166–1175, ACM, 2014.

[20] M. Nobles, D. B. Neill, and S. Flaxman, "Predicting and Preventing Emerging Outbreaks of Crime," 2014.

[21] D. B. Neill and W. L. Gorr, "Detecting and preventing emerging epidemics of crime," *Advances in Disease Surveillance*, vol. 4, no. 13, 2007.

[22] L. Nizzoli, M. Avvenuti, S. Cresci, and M. Tesconi, "Extremist Propaganda Tweet Classification with Deep Learning in Realistic Scenarios," in *Proc. of the 10th ACM Conf. on Web Science*, pp. 203–204, 2019.

[23] T. Zeitzoff, "Using social media to measure conflict dynamics: An application to the 2008-2009 Gaza conflict," *Journal of Conflict Resolution*, vol. 55, no. 6, pp. 938–969, 2011.

[24] E. Siapera, G. Hunt, and T. Lynn, "# GazaUnderAttack: Twitter, Palestine and diffused war," *Information, Communication & Society*, vol. 18, no. 11, pp. 1297–1319, 2015.

[25] T. Zeitzoff, J. Kelly, and G. Lotan, "Using social media to measure foreign policy dynamics: An empirical analysis of the Iranian-Israeli confrontation (2012-13)," *Journal of Peace Research*, vol. 52, no. 3, pp. 368–383, 2015.

[26] E. Zagheni, V. R. K. Garimella, I. Weber, and B. State, "Inferring international and internal migration patterns from twitter data," in *Proc. of the 23rd International Conf. on World Wide Web*, pp. 439–444, 2014.

[27] E. Zagheni, I. Weber, and K. Gummadi, "Leveraging facebook's advertising platform to monitor stocks of migrants," *Population and Development Review*, pp. 721–734, 2017.

[28] A. Bogomolov, B. Lepri, J. Staiano, N. Oliver, F. Pianesi, and A. Pentland, "Once upon a crime: towards crime prediction from demographics and mobile data," in *Proc. of the 16th international conf. on multimodal interaction*, pp. 427–434, ACM, 2014.

[29] B. Ariel and H. Partridge, "Predictable policing: Measuring the crime control benefits of hotspots policing at bus stops," *Journal of Quantitative Criminology*, vol. 33, no. 4, pp. 809–833, 2017.

[30] E. Ferrara, P. De Meo, S. Catanese, and G. Fiumara, "Detecting criminal organizations in mobile phone networks," *Expert Systems with Applications*, vol. 41, no. 13, pp. 5733–5750, 2014.

[31] A. I. Robinson, F. Carnes, and N. M. Oreskovic, "Spatial analysis of crime incidence and adolescent physical activity," *Preventive medicine*, vol. 85, pp. 74–77, 2016.

[32] H. Qi, P. Manrique, D. Johnson, E. Restrepo, and N. F. Johnson, "Open source data reveals connection between online and on-street protest activity," *EPJ data science*, vol. 5, no. 1, p. 18, 2016.

[33] H. Qi, P. Manrique, D. Johnson, E. Restrepo, and N. F. Johnson, "Association between volume and momentum of online searches and real-world collective unrest," *Results in physics*, vol. 6, pp. 414–419, 2016.

[34] S. G. Lea, E. D'Silva, and A. Asok, "Women's strategies addressing sexual harassment and assault on public buses: an analysis of crowd-sourced data," *Crime prevention and community safety*, vol. 19, no. 3-4, pp. 227–239, 2017.

[35] T. Ozkan, J. L. Worrall, and H. Zettler, "Validating media-driven and crowdsourced police shooting data: a research note," *Journal of crime and justice*, vol. 41, no. 3, pp. 334–345, 2018.

[36] S. Palakodety, A. R. KhudaBukhsh, and J. G. Carbonell, "Hope Speech Detection: A Computational Analysis of the Voice of Peace," 2019.

[37] R. Clionadh, A. Linke, H. Hegre, and J. Karlsen, "Introducing ACLED-Armed Conflict Location and Event Data.," *Journal of Peace Research*, vol. 47, no. 5, pp. 651–660, 2010.

[38] J. Brauer and C. H. Anderton, "Conflict and Peace Economics: Retrospective and Prospective Reflections on Concepts, Theories, and Data," *Defence and Peace Economics*, pp. 1–23, 2020.

[39] P. Firchow and R. M. Ginty, "Measuring peace: Comparability, commensurability, and complementarity using bottom-up indicators," *International Studies Review*, vol. 19, no. 1, pp. 6–27, 2017.

[40] C. Wu and M. S. Gerber, "Forecasting civil unrest using social media and protest participation theory," *IEEE Transactions on Computational Social Systems*, vol. 5, no. 1, pp. 82–94, 2017.

[41] F. Qiao, P. Li, X. Zhang, Z. Ding, J. Cheng, and H. Wang, "Predicting social unrest events with hidden Markov models using GDELT," *Discrete Dynamics in Nature and Society*, vol. 2017, 2017.

[42] D. Galla and J. Burke, "Predicting social unrest using GDELT," in *International Conf. on Machine Learning and Data Mining in Pattern Recognition*, pp. 103–116, Springer, 2018.

[43] A. Alsaqabi, F. Aldhubayi, and S. Albahli, "Using Machine Learning for Prediction of Factors Affecting Crimes in Saudi Arabia," in *Proc. of the 2019 International Conf. on Big Data Engineering*, pp. 57–62, 2019.

[44] D. Joshi, S. Basnet, H. Arunachalam, L.-K. Soh, A. Samal, S. Ratcliff, and R. Werum, "SURGE: Social Unrest Reconnaissance GazEteer," in *Proc. of the 25th ACM SIGSPATIAL International Conf. on Advances in Geographic Information Systems*, pp. 1–4, 2017.

[45] F. Qiao, P. Li, J. Deng, Z. Ding, and H. Wang, "Graph-based method for detecting occupy protest events using gdelt dataset," in *2015 International conf. on Cyber-Enabled Distributed Computing and Knowledge Discovery*, pp. 164–168, IEEE, 2015.

[46] Y. Keneshloo, J. Cadena, G. Korkmaz, and N. Ramakrishnan, "Detecting and forecasting domestic political crises: A graph-based approach," in *Proc. of the 2014 ACM conf. on Web science*, pp. 192–196, 2014.

[47] S. Keertipati, B. T. R. Savarimuthu, M. Purvis, and M. Purvis, "Multi-level analysis of peace and conflict data in GDELT," in *Proc. of the MLSDA 2014 2nd Workshop on Machine Learning for Sensory Data Analysis*, pp. 33–40, 2014.

[48] J. E. Yonamine, "Predicting future levels of violence in afghanistan districts using gdelt," *Unpublished manuscript*, 2013.

[49] M. N. Ahmed, G. Barlacchi, S. Braghin, F. Calabrese, M. Ferretti, V. Lonij, R. Nair, R. Novack, J. Paraszczak, and A. S. Toor, "A Multi-Scale Approach to Data-Driven Mass Migration Analysis.," in *SoGood@ ECML-PKDD*, 2016.

[50] M. Beine, L. Bertinelli, R. Cömertpay, A. Litina, J.-F. Maystadt, and B. Zou, "Refugee Mobility: Evidence from Phone Data in Turkey," in *Guide to Mobile Data Analytics in Refugee Scenarios*, pp. 433–449, Springer, 2019.

[51] S. Bertoli, P. Cintia, F. Giannotti, E. Madinier, C. Ozden, M. Packard, D. Pedreschi, H. Rapoport, A. Sîrbu, and B. Speciale, "Integration of Syrian refugees: insights from D4R, media events and housing market data," in *Guide to Mobile Data Analytics in Refugee Scenarios*, pp. 179–199, Springer, 2019.

[52] The Institute for Economics and Peace, "Global Peace Index 2019," 2019.

[53] R. H. Best, C. Carpino, and M. J. Crescenzi, "An analysis of the TABARI coding system," *Conflict Management and Peace Science*, vol. 30, no. 4, pp. 335–348, 2013.

[54] P. A. Schrodt, "Cameo: Conflict and mediation event observations event and actor codebook," *Pennsylvania State University*, 2012.

[55] E. Shook, K. Leetaru, G. Cao, A. Padmanabhan, and S. Wang, "Happy or not: Generating topic-based emotional heatmaps for Culturomics using CyberGIS," in *2012 IEEE 8th International Conf. on E-Science*, pp. 1–6, IEEE, 2012.

[56] J. S. Goldstein, "A conflict-cooperation scale for WEIS events data," *Journal of Conflict Resolution*, vol. 36, no. 2, pp. 369–385, 1992.

[57] K. Leetaru and P. A. Schrodt, "Gdelt: Global data on events, location, and tone, 1979-2012," in *ISA annual convention*, vol. 2, pp. 1–49, Citeseer, 2013.

[58] T. Hastie, R. Tibshirani, and J. Friedman, *The elements of statistical learning: data mining, inference, and prediction*. Springer Science & Business Media, 2009.

[59] R. Shanmugam, "Introduction to time series and forecasting," 1997.

[60] R. J. Hyndman and A. B. Koehler, "Another look at measures of forecast accuracy," *International journal of forecasting*, vol. 22, no. 4, pp. 679–688, 2006.

[61] G. James, D. Witten, T. Hastie, and R. Tibshirani, *An introduction to statistical learning*, vol. 112. Springer, 2013.

[62] A. De Myttenaere, B. Golden, B. Le Grand, and F. Rossi, "Mean absolute percentage error for regression models," *Neurocomputing*, vol. 192, pp. 38–48, 2016.

[63] A. Kassambara, *Machine Learning Essentials: Practical Guide in R*. sthda, 2018.

[64] K.-L. WEN, "Grey Systems: Modeling and Prediction, Yang's Scientific Research Institute, Yang's Scientific Press, Vol. 4," 2004.

[65] World Population Review organization, "Most Powerful Countries Population." https://worldpopulationreview.com/country-rankings/most-powerful-countries, 2020.

[66] B. Leo, C. Adele, L. Andy, and W. Matthew, "Breiman and Cutler's Random Forests for Classification and Regression." https://cran.r-project.org/web/packages/randomForest/randomForest.pdf, 2018.

[67] M. E. Hollis, S. Downey, A. del Carmen, and R. R. Dobbs, "The relationship between media portrayals and crime: perceptions of fear of crime among citizens," *Crime prevention and community safety*, vol. 19, no. 1, pp. 46–60, 2017.