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Utilizing remote sensing and big data to quantify conflict intensity: The Arab Spring as a case study

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ABSTRACT

Tracking global and regional conflict zones requires spatially explicit information in near real-time. Here, we examined the potential of remote sensing time-series data (night lights) and big data (data mining of news events and Flickr photos) for monitoring and understanding crisis development and refugee flows. We used the recent Arab Spring as a case study, and examined temporal trends in monthly time series of variables which we hypothesized to indicate conflict intensity, covering all Arab countries. Both Flickr photos and night-time lights proved as sensitive indicators for loss of economic and human capital, and news items from the Global Data on Events, Location and Tone (GDELT) project on fight events were positively correlated with actual deaths from conflicts. We propose that big data and remote sensing datasets have potential to provide disaggregated and timely data on conflicts where official statistics are lacking, offering an effective approach for monitoring geopolitical and environmental changes on Earth.

1. Introduction

In recent years, the world has experienced a dramatic increase in the number of migrants, refugees, and asylum seekers as a result of instability, however reliable real-time and large-scale data on human movement and migration and their drivers is lacking (Dijstelbloem, 2017). The increasing availability of high quality global monitoring of the Earth from space and "big data" from online sources (Sui & Goodchild, 2011) offers new possibilities for quantifying and identifying conflict and other areas from which people might emigrate, where traditional data sources are often scarce. Examples include new methods to mapping poverty using night light intensity (Jean et al., 2016) and mobile phone usage (Steele et al., 2017), evaluating the Syrian crisis and war effects in Iraq, Yemen, and elsewhere using changes in night time lights (Li, Zhang, Huang, & Li, 2015, 2017, 2013; Jiang, He, Long, & Liu, 2017; Li & Li, 2014), and quantifying the impacts of warfare through changes in agricultural land use as mapped by satellites (Gibson, Taylor, Lamo, & Lackey, 2017; Müller, Yoon, Gorelick, Avisse, & Tilmant, 2016). Geographically explicit social media data such as Flickr photos has been shown to quantify visitation to protected areas globally (Levin, Kark, & Crandall, 2015), as well as to quantify landscape values (van Zanten, Van Berkel, Meentemeyer, & Smith, 2016) and the perceived importance of protected areas (Levin, Lechner, & Brown, 2017). Collaborative mapping using web interfaces allows the generation of live crisis maps, based on crowdsourced information both from official sources and from individuals and volunteers (Meier, 2012).

As reviewed by Gleditsch, Metternich, and Ruggeri (2014), data development has helped to advance research on peace and conflict. Following the call of Blattman and Miguel (2010) to collect new types of disaggregated data to facilitate research in economics and political science, and to better understand the impacts of civil war on economic and human capital, we here propose and demonstrate the use of a variety of remote sensing and big data metrics for quantifying conflicts and their intensity. Whereas previous studies have examined such indicators individually and mostly for single countries, we are not aware of studies which have aimed to combine both remote sensing indictors and big data to examine the impacts of conflicts at the regional scale, e.g., for the entire Arab World.

1.1. Aims

Given the lack of quantitative knowledge on the spatial relationships between conflicts and economic impacts and between conflicts

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and human migration (Bank, Fröhlich, & Schneiker, 2017), in this paper we examine the use of remote sensing data (night lights) in conjunction with social media (Flickr photos) and big data (conflict related events mentioned in broadcast, print, and web news items, collated by the Global Data on Events, Location and Tone (GDELT) project; Leetaru & Schrodt, 2013), for identifying times and areas of conflict, based on spatially explicit time series datasets. We aim to examine how to integrate remote sensing data on night lights, social media data from photos uploaded to Flickr, big data from online news items, and traditional statistics on conflicts, refugees, tourism, and economic indicators to inform us on developing crisis areas. We examine which variables are most useful for quantifying conflict intensity, and the response times of those metrics to the development of a conflict. Using remote sensing and big data is especially important for monitoring conflict areas, where official data is usually scarce but urgently required for handling and mitigating human disasters. We focus on the Arab countries in the Middle East, almost seven years after what was first described as the Arab Spring but has since been also known as the Arab Winter (Roy, 2012).

1.2. Hypothesis

We predict that conflict areas can be identified by a combination of remotely sensed and big data metrics, and, based on the literature, hypothesize that areas with high intensity conflicts would:

1. Show a rapid decline in night lights due to damage to infrastructure;
2. Show a rapid decrease in the number of Flickr photos due to avoidance by tourists; and
3. Show an increased coverage by world news.

Because many human activities are seasonal in their nature, the temporal resolution of our analysis is monthly, so that seasonal patterns can be identified. Fig. 1 provides a schematic presentation of the main variables analyzed by class and their hypothesized relationships.

2. Methods

2.1. Datasets

The datasets used in this study included remote sensing sources, big data sources, and traditional statistics collected by governments and other organizations. Remote sensing derived data included VIIRS monthly night lights (Elvidge, Baugh, Zhizhin, Hsu, & Ghosh, 2017; Miller et al., 2012), while Big Data sources included Flickr photos (Crandall, Backstrom, Huttenlocher, & Kleinberg, 2009) and news items related to conflicts. We chose Flickr in order to highlight peace-time activities such as recreational photographic exchange and tourism activity, since that site is used more for recreational photographic sharing (Yang, Wu, Liu, & Kang, 2017) than other social media platforms such as Facebook or Twitter (which may represent live news on events as they take place in the field as well as the interest that people elsewhere have in those events; Crampton et al., 2013). For news items, we used the Global Data on Events, Location and Tone (GDELT) dataset, a Conflict and Mediation Event Observations (CAMEO) coded data set containing hundreds of millions of geolocated events with global coverage from 1979 onwards (Gerner, Schrodt, & Yilmaz, 2009; Leetaru & Schrodt, 2013). Within the GDELT dataset, events are hierarchically coded based on event classes. We counted frequency of events per administrative region and per country on a monthly basis: protests (code 14), coerce (code 17), assault (code 18), and fight (code 19) (Schrodt, 2012). In addition, we downloaded (from http://gdeltproject.org/data.html#documentation) events in the GDELT 1.0 Event Database across all event types broken down by time and country, which is needed for normalization (to compensate for the exponential increase in the availability of global news material over time and for the differential reporting of different countries in world news).

We used real-world datasets of geopolitical events on conflicts (from the Uppsala Conflict Data Program Georeferenced Event Dataset; Sundberg & Melander, 2013; Croicu & Sundberg, 2016), terrorist acts from the global terrorism database (GTD; START, 2017), asylum seeker numbers at the country level based on United Nations High Commissioner for Refugees (UNHCR) statistics, monthly import and export statistics from the World Bank, and tourism and airports statistics (see sources in Table 1).

Most datasets were spatially explicit, either as points with longitude and latitude, or as raster layers (in the case of the remotely sensed night lights). Correspondingly, some of the analyses were done at the scale of countries, and some were aggregated and analyzed at the level of administrative regions, depending on the input variables. Some of the datasets were only available at the country level, such as statistics on asylum seekers and time series of import and export.

2.2. Spatial and temporal analyses

All variables were aggregated and analyzed as monthly time series at the country level (n = 18), covering all Arab countries (as well as the Palestinian Authority) from Morocco to the west, Sudan to the south, Syria to the north, Iraq to the east, and the entire Arab Peninsula. The spatially explicit datasets were also analyzed as monthly time series at

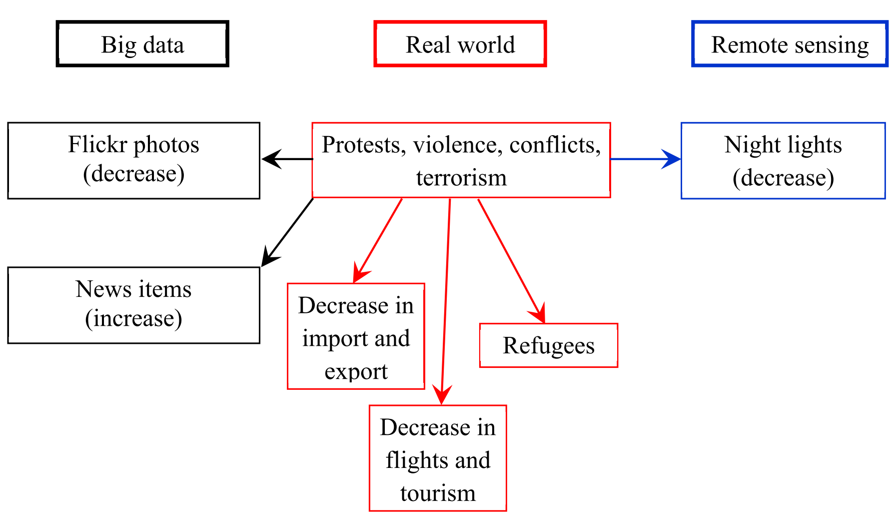

Fig. 1. Schematic representation of the main variables analyzed by class and their hypothesized relationships.

Table 1
Data sets used in the study.

Variable	Source	Time frame	Spatial resolution	Comments
VIIRS monthly night lights	https://ngdc.noaa.gov/eog/viirs/download_monthly.html	Apr 2012–Jan 2017	0.00416°	
Flickr photos	David Crandall	Jan 2007–Dec 2015	0.01°	Crandall et al., 2009
News items related to conflicts: Percent of news items relating to a country, out of all global news items (GDELT % global); News items about the following four classes of events: protests, coerce, assaults and fights.	The Global Database of Events, Language, and Tone (GDELT) Project, http://gdeltproject.org/	Jan 2000–Jan 2017	Spatially explicit coordinates	Leetaru & Schrodt, 2013
Military conflicts: number of conflicts and number of deaths	http://ucdp.uu.se/downloads/ UCDP Georeferenced Event Dataset (GED) Global version 5.0 (2015) - disaggregated dataset, covering individual events of organized violence	Jan 2000–Dec 2015	Spatially explicit coordinates	Data for Syria were not available from this source, and were thus obtained from http://syrianshuhada.com/default.asp?lang=en&a=st&st=8 (at the country level)
National Consortium for the Study of Terrorism and Responses to Terrorism (START) (2017). Global Terrorism Database	http://www.start.umd.edu/gtd	Jan 2000–Dec 2016	Spatially explicit coordinates	
Refugee data: numbers of asylum seekers	http://popstats.unhcr.org/en/overview UNHCR Population Statistics Reference Database	Jan 2000–Oct 2016	Country level	
Monthly import/export	http://databank.worldbank.org/data/reports.aspx?source=global-economic-monitor-(gem)#	Varies between countries	Country level (data not available for certain countries)	
Airport activity in Egypt	http://www.ehcaan.com/statistics.aspx	Monthly data from 2005 onwards	Egyptian airports	
Tourism arrivals in Egypt	https://ieconomics.com/	Jan 2000–Mar 2017	Egypt	

the finer spatial resolution of first level administrative regions (n = 280, with a median of 13.5 regions per country, ranging between 2 for the Palestinian Authority, and 48 in Algeria). We used Version 2.8 of the GADM database of Global Administrative Areas http://www.gadm.org/.

All variables (except VIIRS night lights) were available from 2007 onwards, and most were available from 2000 onwards. To examine the possible impact of events following the "Arab Spring" (which began with the Tunisian Revolution which sparked in 17 December 2010) and its aftermath, we compared two periods: Jan 2007–Nov 2010, and Dec 2010 – present. We calculated Spearman's rank correlations for each variable to examine its changes during these two time periods, as well as over the entire time frame. To examine the differences in the values of each variable between the two time periods, we calculated the percent change between the monthly averages of each variable between the time periods, and we conducted a two way *t*-test to examine whether there were statistically significant differences between the average values of each. In addition to the statistical tests, to ease comparison between countries and across variables, we normalized each time series to be between 0 and 1, based on its minimum and maximum values.

3. Results

We start by presenting the temporal trends for the countries most affected by the Arab Spring. We note that only for Tunisia did the hopes fulfill themselves with democracy being the outcome of the events.

3.1. Temporal trends across countries

Following the civil protests that began in Tunisia, a peak in protests was identified across most Arab countries during the end of 2010 (Fig. 2). However, protests did not evolve to disorder and violent actions with casualties in all countries. Events classified as fighting and assault (Figs. S1 and 3), terrorism (Fig. S2) and deadly casualties from conflicts (Fig. S3) following the protests of late 2010 were most noted in Bahrain, Egypt, Libya, Syria and Yemen, whereas in Algeria conflict-related deaths and terrorism declined after the Arab Spring (Figs. S2 and S3). The deterioration of public security within those countries is easier to identify when the values are normalized by the maximum across all countries (bottom panels in Fig. 3, Figs. S1-S3). Note that the instability and conflicts in Iraq started long before 2010. Peak numbers of asylum seekers corresponding in time with the protests in late 2010 were identified in Bahrain, Libya, and Tunisia (Fig. 4). However, the significant rise in asylum seeker numbers started in 2014, most notably from Syria and Iraq, and had a trickling effect on migration from many other Arab countries, even for those with few violent events (Kuwait, Lebanon and Morocco, for example; Fig. 4).

3.2. Temporal trends within case-study countries

The events of the Arab Spring started in Tunisia, where the Tunisian Revolution led to the resignation of its president and the democratization of the country. This line of events is reflected in the peak of GDELT events and asylum seekers in early 2011 (with a corresponding drop in Flickr photos) (Fig. 5). Following the elections, violent events decreased (other than two deadly terrorist attacks in 2015), Flickr photo numbers resumed previous values (indicating the return of tourists), and night-time brightness increased with time (indicating growth in the economy) (Fig. 5). Unfortunately, the Arab Spring had such positive outcomes only in Tunisia.

In Egypt, the revolution began in January 2011, leading to the resignation of President Mubarak in February 2011. Following elections, the Muslim Brotherhood took power in June 2012, but their attempts to pass an Islamist constitution led to mass protests in summer 2013 and to a military coup d'etat. These events are reflected in the peak in asylum seekers' numbers in late 2013, the decrease in Flickr

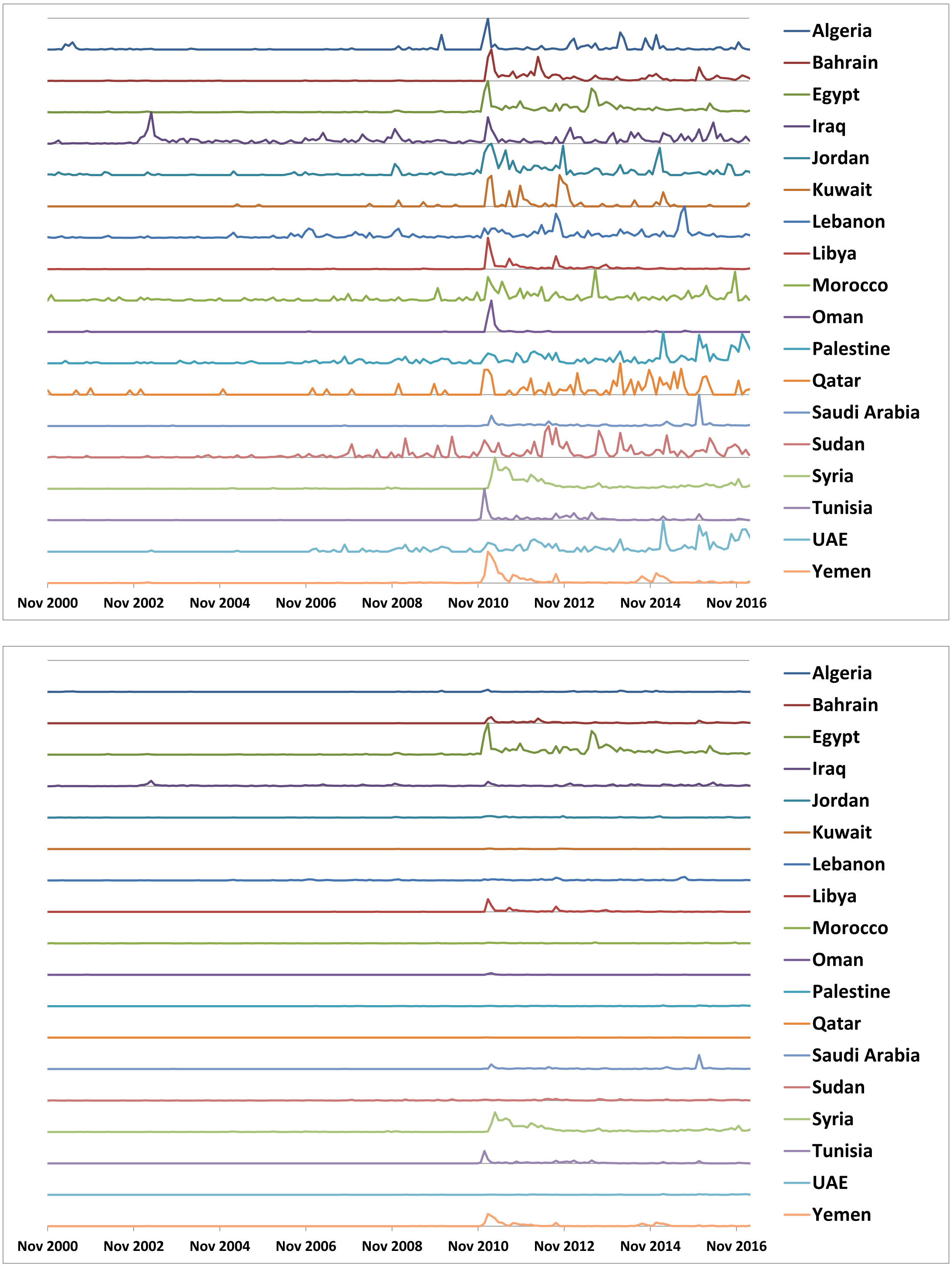

Fig. 2. Monthly time series of GDELT protest events. In the upper panel events are normalized between 0 and 1 based on the minimum and maximum values of each country, whereas in the bottom panel events are normalized between 0 and 1 based on the minimum and maximum values across all countries.

photos since 2011 and again since 2013, and a decrease in night-time brightness (Fig. 6). The tourism industry is one of Egypt's most important economic sectors, and both Flickr photos, tourists arrivals and flight passenger numbers are highly sensitive to conflict times; while tourism succeeded in recovering after each one of the above mentioned events, tourist numbers fell dramatically following the Sinai plane crash in September 2015 (Fig. 6; Tomazos, 2017). However, not all regions in Egypt experienced similar levels of civil instability and terrorism, and consequently, the impacts on tourism and on economic activity varied spatially (Fig. S4; Tomazos, 2017). Both the Alexandria and Luxor regions experienced significant decreases in tourism activity following the onset of the Arab Spring, whereas in the Sinai Peninsula, one of Egypt's tourism strongholds, tourism was only impacted negatively later on (Fig. S4).

In Iraq, the United States-organized coalition invaded in March 2003, but fighting continued incessantly (Fig. 7). In 2011 US troops withdrew from Iraq, but the Arab Spring protests took their place and levels of violence increased through the influence of the Syrian Civil War. In 2014 insurgents belonging to the Islamic State of Iraq and Syria (ISIS) took control of several major cities in northern Iraq. The impact

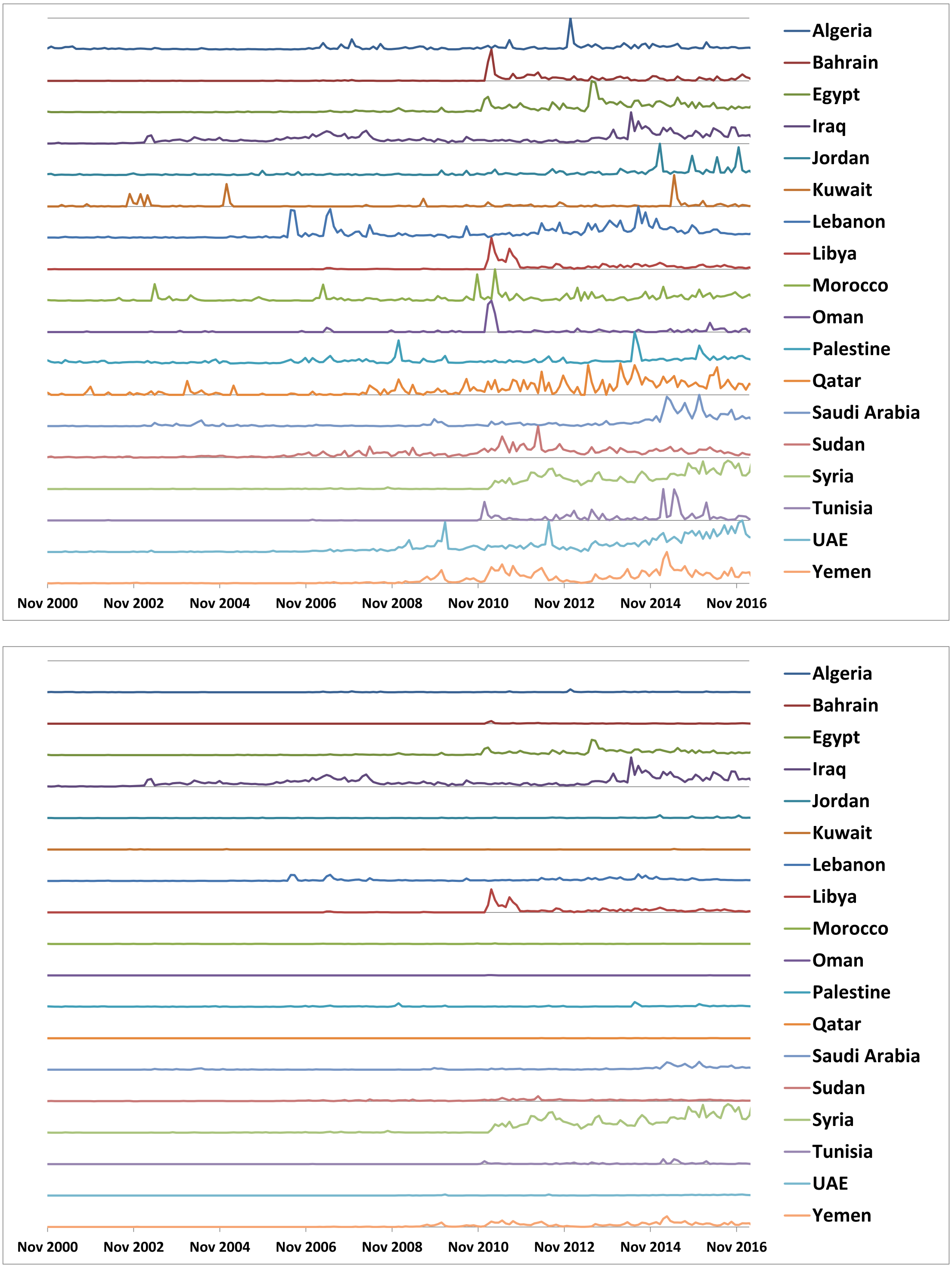

Fig. 3. Monthly time series of GDELT fight events. In the upper panel events are normalized between 0 and 1 based on the minimum and maximum values of each country, whereas in the bottom panel events are normalized between 0 and 1 based on the minimum and maximum values across all countries.

of the 2014 fighting is clearly observed in the GDELT statistics, the rise in asylum seekers, and the fall in Flickr photos, but not in VIIRS night lights. However, the spatial differences are clear when examined by province, with decreases or stability in Flickr photos and in VIIRS night lights in provinces with more fighting related to ISIS, such as Al-Anbar, Ninawa and Sala ad-Din (Fig. S5). The intensification of fighting in northern and western Iraq in recent years is clearly seen via the reduction of night-time lights brightness (Fig. 8) and increase in GDELT fight events and terrorism (Figs. S5 and S6) in those regions.

In Libya, a full-scale revolt began in February 2011, supported by NATO forces following a UN Security Council resolution in March 2011. The revolt ended with the killing of Gaddafi and the defeat of the loyalist forces in October 2011. However, the overthrow of Gaddafi's regime left a vacuum, and a second civil war started in Libya in May 2014. The violent conflicts in Libya are well observed in the GDELT datasets, and caused a sudden decrease in the number of Flickr photos after early 2011, an overall decrease in night-time brightness, and decreases in both imports and exports (Fig. 9).

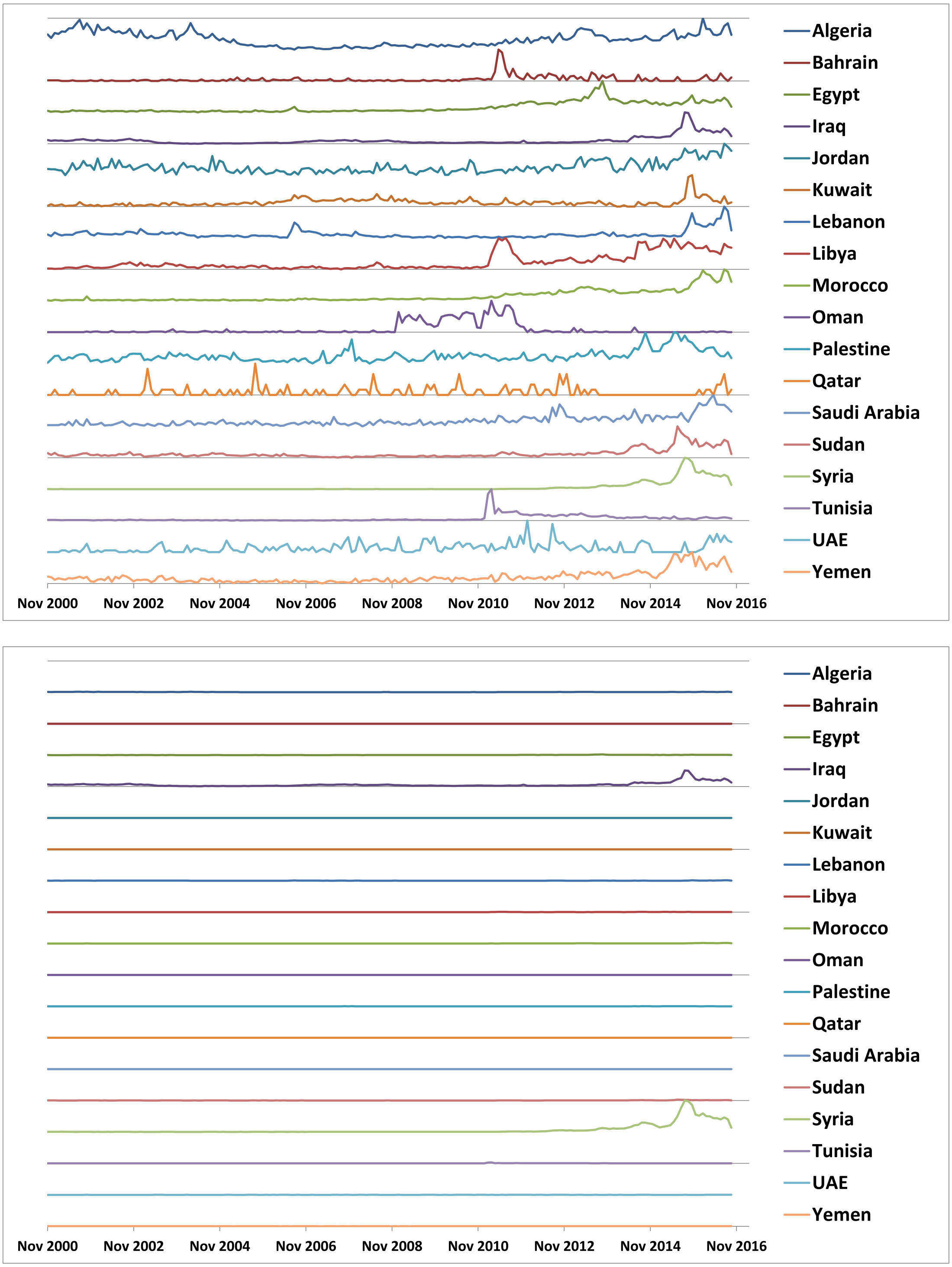

Fig. 4. Monthly time series of asylum seekers. In the upper panel numbers are normalized between 0 and 1 based on the minimum and maximum values of each country, whereas in the bottom panel numbers are normalized between 0 and 1 based on the minimum and maximum values across all countries.

The civil uprising in Syria began in March 2011 and developed into a full scale civil war with multiple state and non-state actors, involving citizens from many countries flowing in to support various sides (such as ISIS) as well as the direct involvement of neighboring countries, Russia, and the United States. People affected by the Syrian Civil War included more than 150,000 casualties, one million asylum seekers, and more than five million registered refugees (Fig. 10). The civil war was associated with an immediate dramatic decrease in the number of Flickr photos and a gradual decrease in night-time brightness (Fig. 10). The dimming of Syria's night lights is especially noted along its northern border with Turkey (Fig. 8), although heavy fighting took place almost everywhere in Syria (Fig. S6). Internally displaced refugee numbers began rising already in 2012, but the mass movement of asylum seekers to western countries mainly began in 2015 (Fig. 10).

The Yemeni revolution started in January 2011, and led to the overthrow of the Saleh government and to presidential elections in February 2012. The Houti takeover of Yemen began with protests in August 2014 and culminated with the actual takeover in January/February 2015. A civil war started in March 2015, involving ISIS, Al-Qaeda and foreign countries led by Saudi Arabia, and still continues as

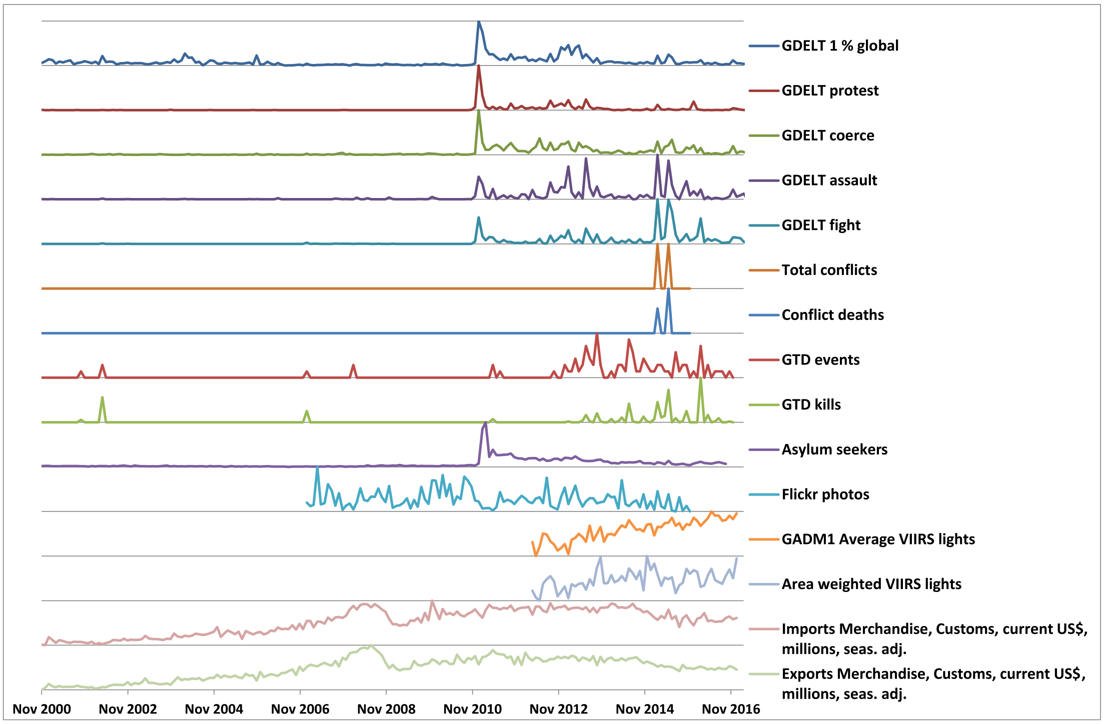

Fig. 5. Monthly time series of all variables for Tunisia. All variables are normalized between 0 and 1 based on the minimum and maximum values of each variable, to ease comparison of temporal trends across variables.

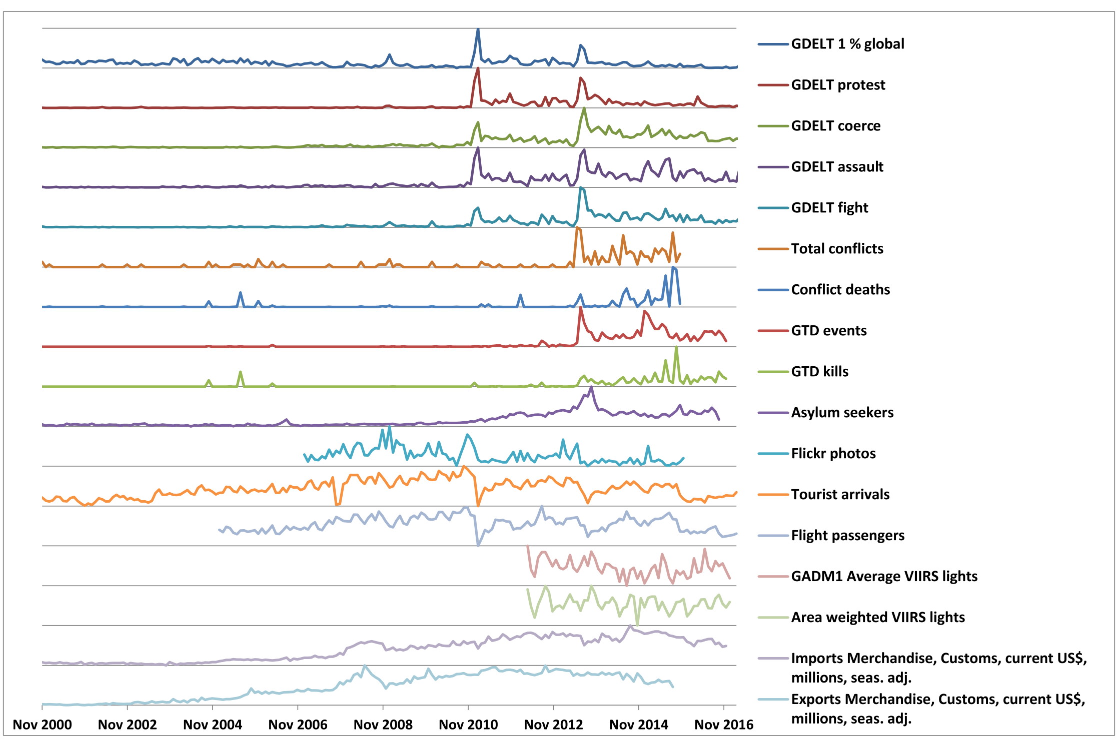

Fig. 6. Monthly time series of all variables for Egypt. All variables are normalized between 0 and 1 based on the minimum and maximum values of each variable, to ease comparison of temporal trends across variables.

of February 2018. The violent acts which began in 2014 resulted in a sharp decrease in night time brightness of Yemeni cities, and a dramatic decrease in imports and exports (Figs. S5 and S6, Fig. 11).

3.3. *Relationships between time series*

The previous section demonstrated the correspondence between the studied variables in a qualitative and visual way for a number of case studies. We now quantitatively demonstrate the value of remote sensing and Big Data time series for explaining real world events following the Arab Spring.

A linear correlation was found between monthly GDELT fight events and monthly deaths from conflicts ($R^2 = 0.47$, $p < 0.01$) (Fig. 12a). The correspondence improved significantly when we normalized the

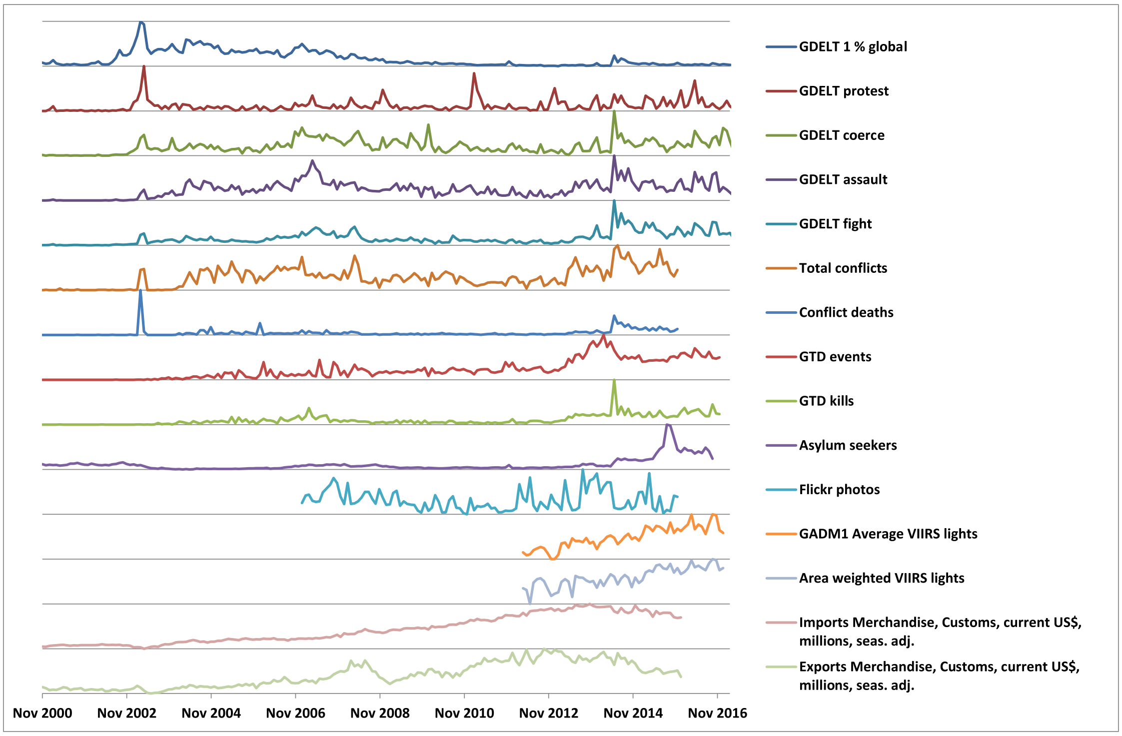

Fig. 7. Monthly time series of all variables for Iraq. All variables are normalized between 0 and 1 based on the minimum and maximum values of each variable, to ease comparison of temporal trends across variables.

monthly GDELT fight events by the share of a country from all GDELT events globally, reaching an R^2 value 0.61 (Fig. 12b). A positive correlation was also found between monthly GDELT fight events and monthly numbers of asylum seekers ($R^2 = 0.43$, $p < 0.01$; Fig. S7), and between monthly deaths from conflicts and monthly Flickr photo counts ($R^2 = 0.20$, $p < 0.01$; Fig. S8).

In the previous section we noted that a phase shift often takes place in response variables such as Flickr photos, night time lights etc. following violent conflict of high intensity. We therefore examined the correspondence between metrics representing trends in these variables. At the country level, countries where more protests took place experienced a decrease in the number of Flickr photos (Fig. S9). Flickr photos were also positively correlated with temporal trends in VIIRS night-time brightness values ($R^2 = 0.59$, $p < 0.01$; Fig. 13a) and negatively correlated with changes in numbers of asylum seekers following the onset of the Arab Spring ($R^2 = 0.52$, $p < 0.01$; Fig. 13b). Average VIIRS night-time brightness values were lower in countries where there was an increase in the numbers of asylum seekers ($R^2 = 0.46$, $p < 0.01$; Fig. 14a). In addition, countries with higher numbers of deaths from conflicts experienced a decrease in their night time brightness ($R^2 = 0.27$, $p = 0.02$; Fig. 14b).

Examining the overall patterns, six variables experienced statistically significant changes following the Arab Spring for more than 60% of all Arab countries: the four GDELT event types, GTD events, and the number of asylum seekers (Table 2). The four countries where the Arab Spring had the most negative outcomes were Syria (83%), Egypt (79%), Libya (71%), and Yemen (71%) (Table 2). Iraq (29%) did not appear to be negatively affected by the Arab Spring in our analysis, because it had already experienced continuous unrest since the 2003 US invasion.

3.4. Spatial patterns

Because most variables are spatially explicit, they can be analyzed at finer spatial aggregations than the country level, and here we focus on the first level of administrative regions. The monthly number of GDELT fight events increased following the onset of the Arab Spring in 177 (63%) of the first level administrative regions, and a statistically significant relationship (*t*-test $p < 0.05$) was found in 147 (53%) of those regions (Fig. S10). When examined by the actual number of GDELT fight events after the Arab Spring, the leading countries were Syria, Iraq and the Palestinian Authority, followed by other countries such as Egypt, Libya, and Yemen (Fig. S11). The number of Flickr photos and night-time brightness variables exhibited sharp decreases following heavy fighting. The number of Flickr photos dropped to less than 25% following the Arab Spring in 34 (12%) of first level administrative regions, most notably in Syria, Iraq, Yemen, Libya, Algeria, and Sudan (Fig. 15). Negative trends in night-time brightness values were found in 41 (15%) of first level administrative regions, especially in Syria, Yemen, and Libya (Fig. S12). Some of the relationships which were described above at the country level also hold at the level of administrative regions; for example, a negative correlation was found between the average monthly number of GDELT fight events following the Arab Spring and temporal trends in Flickr photos ($R_s = -0.33$, $p < 0.01$) (Fig. S13).

4. Discussion

4.1. Value of different variables

We observed different temporal behavior for our different variables with respect to the dynamics of violent conflicts. In each country in which it was manifested, the Arab Spring began with protests which in some countries evolved into violent acts with many casualties. GDELT events reflected those protests, assaults, and fights immediately, without lag time, thus providing high correspondence with actual conflicts and death events. The number of photos uploaded to Flickr (representing tourism in many cases; Levin et al., 2015) also responded quickly to violent conflicts: following protests and violent events there was a sharp decrease in Flickr photo numbers, and recovery was not immediate, presumably because people were hesitant to visit unstable regions. Night time brightness (as measured by VIIRS) also dropped quickly and dramatically after high intensity conflicts where mass

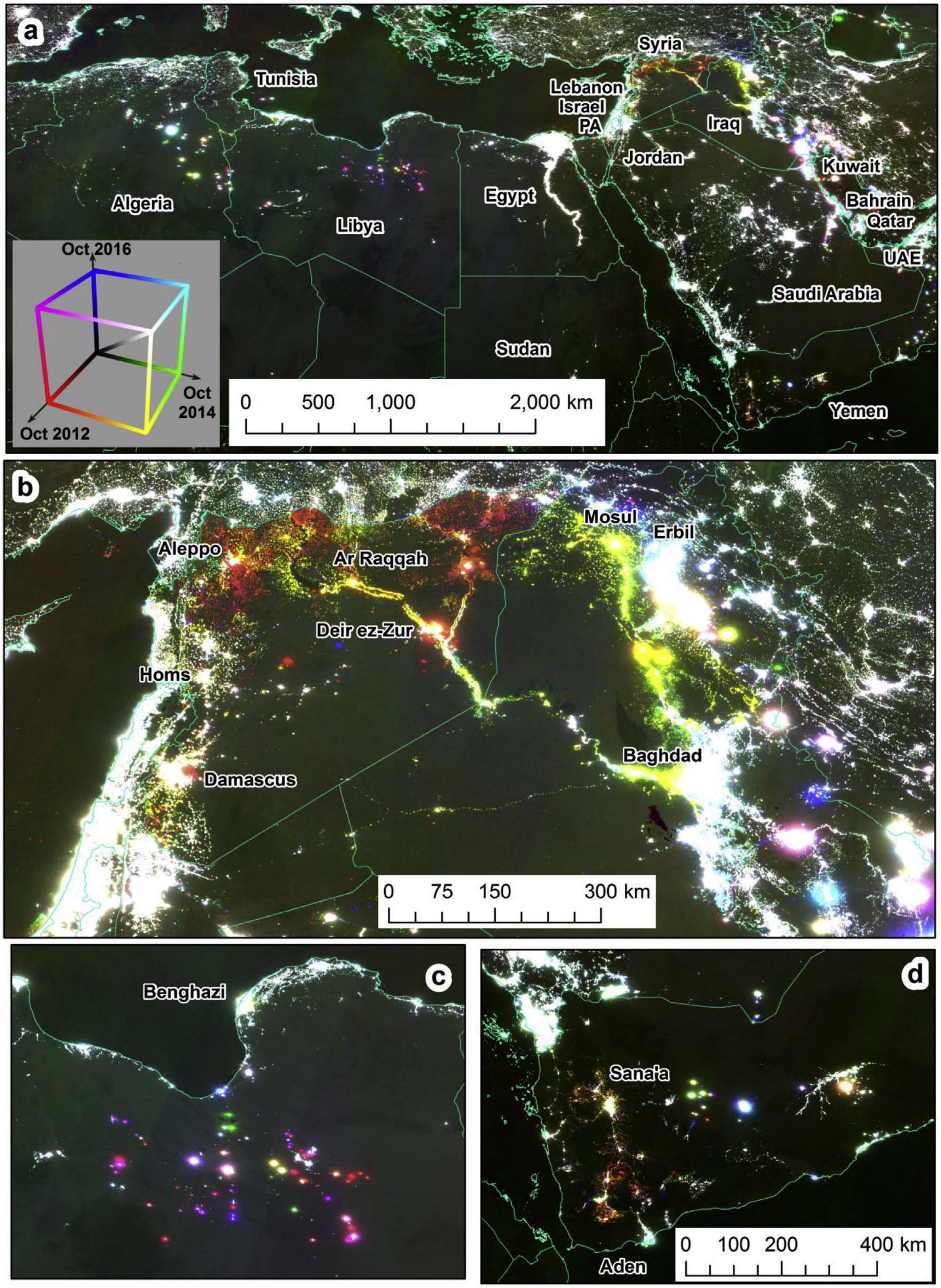

Fig. 8. A false color composite of VIIRS night time brightness in October 2012 (in red), October 2014 (in green), and October 2016 (in blue). Areas which experienced a decrease in night-time lights brightness already after late 2012 appear in red, and regions which experienced a decrease in night-time lights brightness since late 2014 appear in yellow. Areas with high night time lights brightness in all three dates appear in white. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

destruction occurred; this variable also took time to recover once a conflict is over, as infrastructure must be rebuilt gradually. Following fighting, many people in the affected countries were internally displaced, forced to flee their homes while remaining in their own countries or becoming refugees in neighboring countries (Hanafi, 2014). Some of those refugees later became asylum seekers, mostly to European countries (Fargues & Fandrich, 2012). Asylum seekers depend on both push factors (conflicts) and on pull factors including the very possibility to get to the destination (Schoorl et al., 2000). People do not migrate immediately as a conflict begins, and once mass migration starts from several countries, people from other countries notice this option and follow the lead (Crawley, Duvell, Sigona, McMahon, &

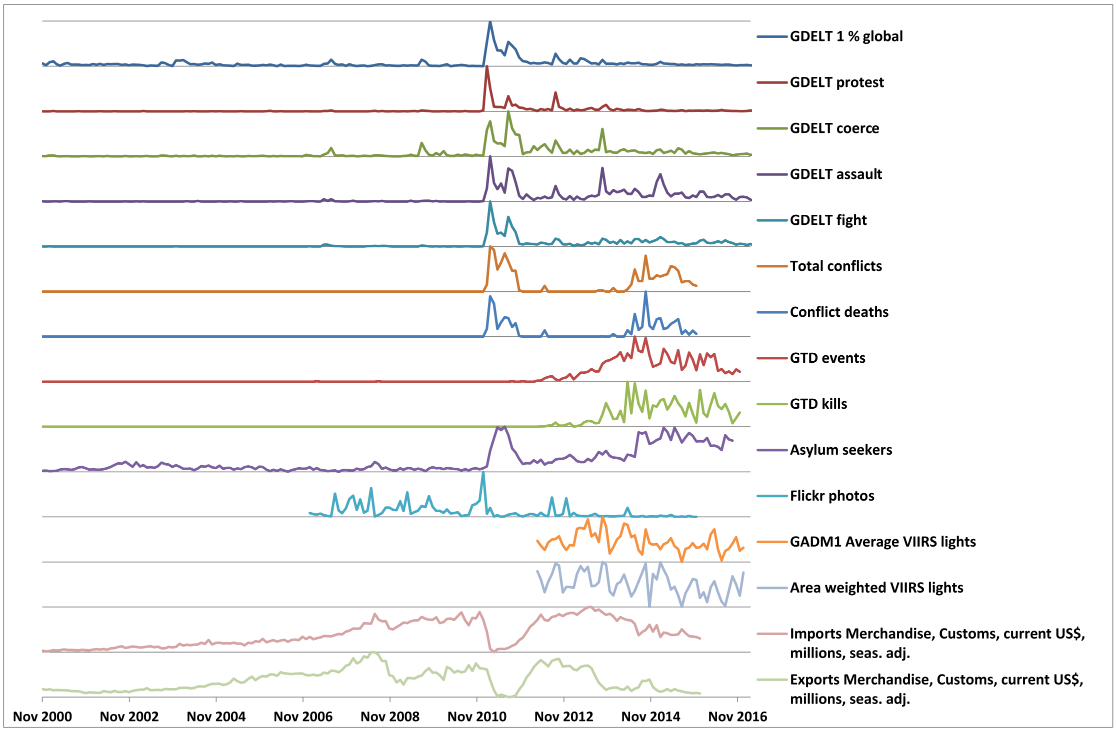

Fig. 9. Monthly time series of all variables for Libya. All variables are normalized between 0 and 1 based on the minimum and maximum values of each variable, to ease comparison of temporal trends across variables.

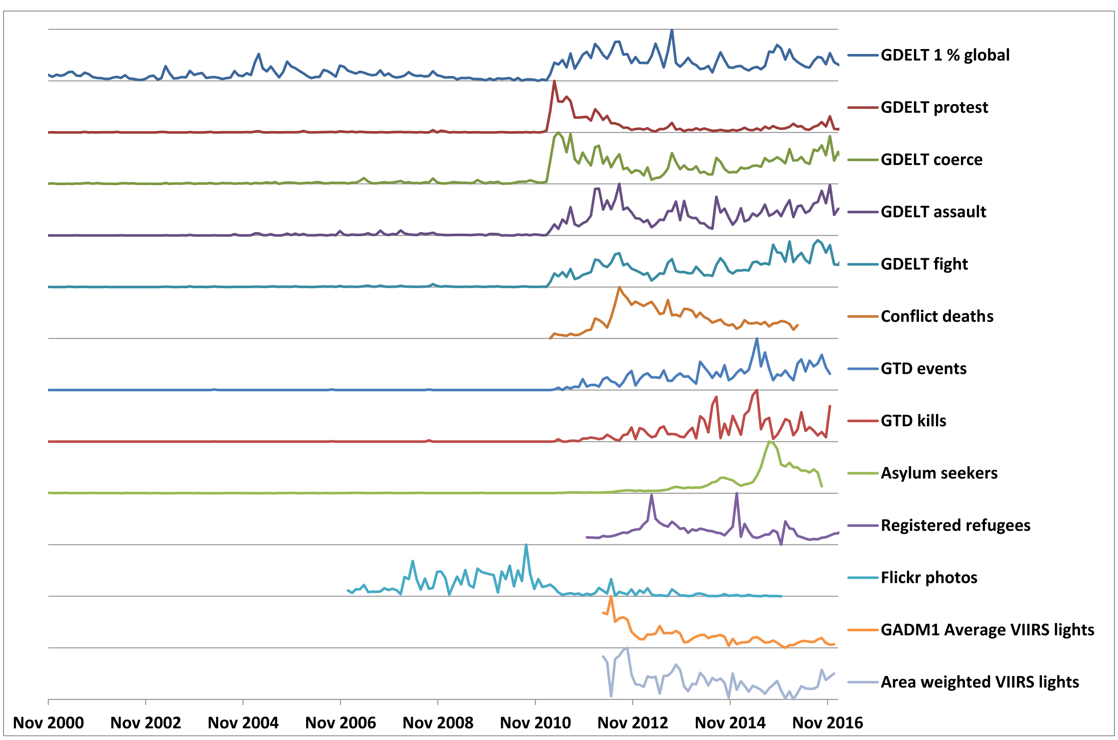

Fig. 10. Monthly time series of all variables for Syria. All variables are normalized between 0 and 1 based on the minimum and maximum values of each variable, to ease comparison of temporal trends across variables.

Jones, 2016). We did not examine here whether there were changes in agricultural areas due to military conflicts, as done by Müller et al. (2016) and Gibson et al. (2017). However, the relationship between violent regime changes and agriculture may not necessarily be negative. For example, agricultural production has been sustained within ISIS controlled areas (Jaafar & Woertz, 2016), with some areas even experiencing cropland expansion (Eklund, Degerald, Brandt, Prishchepov, & Pilesjö, 2017) due to the importance of agriculture as a funding source for ISIS.

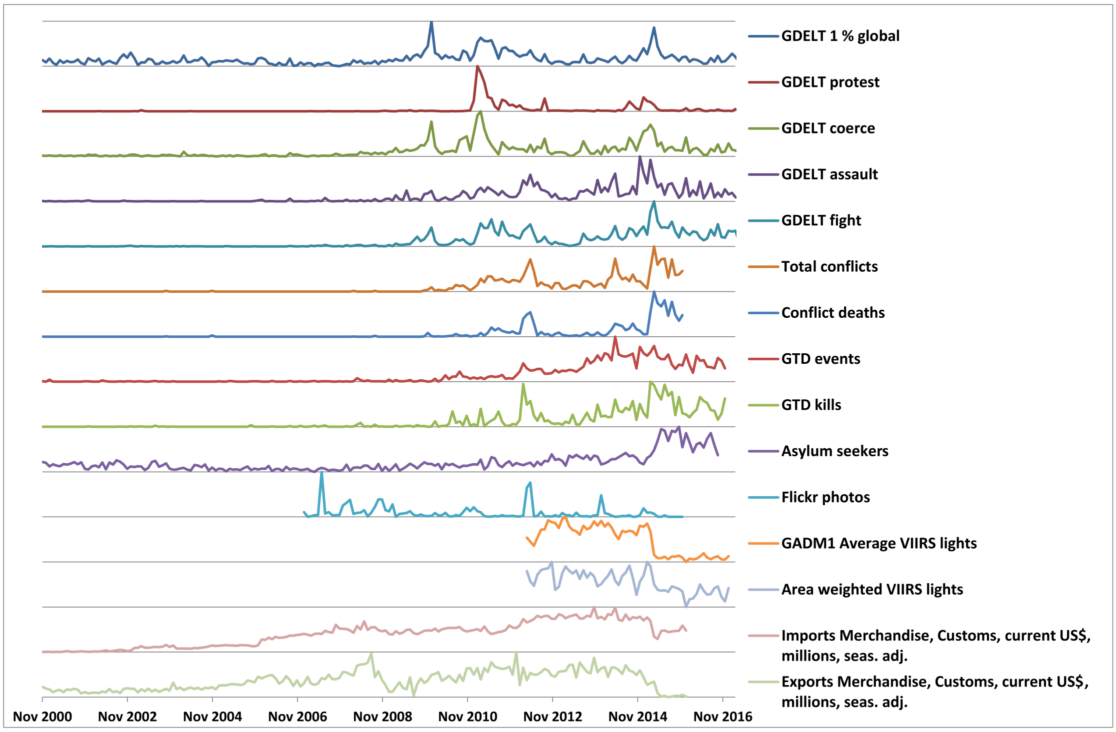

Fig. 11. Monthly time series of all variables for Yemen. All variables are normalized between 0 and 1 based on the minimum and maximum values of each variable, to ease comparison of temporal trends across variables.

4.2. Incorporating remote sensing and big data in geopolitics

With the growing importance of incorporating computational tools and geographic information in the human and social sciences, a new field known as Digital Humanities (Berry, 2011) has emerged. The importance of geographic distance and spatial context has long been recognized in the field of International Relations (O'loughlin & Anselin, 1991), and spatial dimensions, concepts, and methods developed in Geography can have much to contribute to International Relations (Starr, 1991). While spatial analysis in the past may have been underused in the international relations literature due to lack of access to necessary Geographic Information Systems (GIS) software, this is no longer the case, with the emergence and proliferation of open source GIS tools such as GRASS and QGIS (Neteler, Bowman, Landa, & Metz, 2012; Steiniger & Hunter, 2013). Analyzing spatially explicit information is imperative in order to escape "territorial trap" analyses constrained (both theoretically and technically) by the territorial limits of sovereign states (Agnew, 1994), in order to disaggregate and to analyze data at various spatial resolutions, units, and, agglomerations. This has become common practice in the field of conflict studies (Raleigh, Linke, Hegre, & Karlsen, 2010), and the importance of data disaggregation in space and time for conflict research has been highlighted by Gleditsch et al. (2014). The technological revolutions of recent years will continue to transform not only our access to information and our ability to analyze data, but also some basic organizational concepts to which we are accustomed; nation states and cities may be losing some of their power to global corporations of the internet age (such as Google; Shaw & Graham, 2017).

Whereas the use of remote sensing is well established in the natural sciences, it also has great value for quantifying land use and urban areas, identifying and assessing conflicts (Witmer, 2015) and their negative (Hanson et al., 2009) or positive outcomes (as in the case of the demilitarized zone in Korea; Kim, 1997), and creating proxies for a variety of human indicators, such as poverty. In addition, remote sensing offers the ability to analyze spatial data at various spatial and temporal resolutions, thus allowing disaggregation of data. For example, night time light remote sensing has proved its value in social science research, helping to bridge the gap between social sciences (interested in explaining social processes) and remote sensing (offering the means to map spatial patterns and processes) (Rindfuss & Stern, 1998). Night-time brightness observations of the Earth have proven to be a good proxy for population density, economic activity, military conflicts and poverty, among other variables (Bharti, Lu, Bengtsson, Wetter, & Tatem, 2015; Coscieme, Sutton, Anderson, Liu, & Elvidge, 2017; Elvidge et al., 1997; Jean et al., 2016; Li & Li, 2014; Zhang, Levin, Chalkias, & Letu, 2015). Such applications are especially important in data-poor areas, such as third world countries and conflict areas. Whereas the spatial resolution of the sensors we used here (VIIRS) is relatively coarse (around 700 m), the ongoing and planned launch of constellations of dozens of micro Earth-observing, high spatial resolution (between 2.5 and 5 m) satellites by companies such as PlanetLabs and AstroDigital (Anderson, 2016; Butler, 2014; Hand, 2015; Strauss, 2017) will collect global daily time series at fine spatial resolutions, and enable monitoring ongoing conflicts in a way never before possible.

The advent and combination of technologies including the Global Positioning System (GPS), the internet, Google Maps, smartphones, and social media have transformed the ways we generate, consume, and interact with geographic information (Goodchild, 2007; Haklay, 2010). The world of Web 2.0, in which citizens can be seen as "social sensors" (Goodchild, 2007) who voluntarily contribute geographic data either knowingly or unknowingly, has opened new avenues for spatial research (e.g., Crandall et al., 2009). This "Big Data" is characterized by the three Vs: Volume (large datasets), Velocity (close to real time data collection), and Variety (gathered from many sources without much quality assurance) (Goodchild, 2013). Examples of big data utilized for international relations include the automatic analysis and identification of data about conflicts (and other types of events) using algorithms that scan text and determine the actions and actors involved (Ward et al., 2013). Recently, the value of crowd-seeded data (using real time reports on events via short message services) has been demonstrated for understanding dynamics of conflict at micro levels, although upscaling

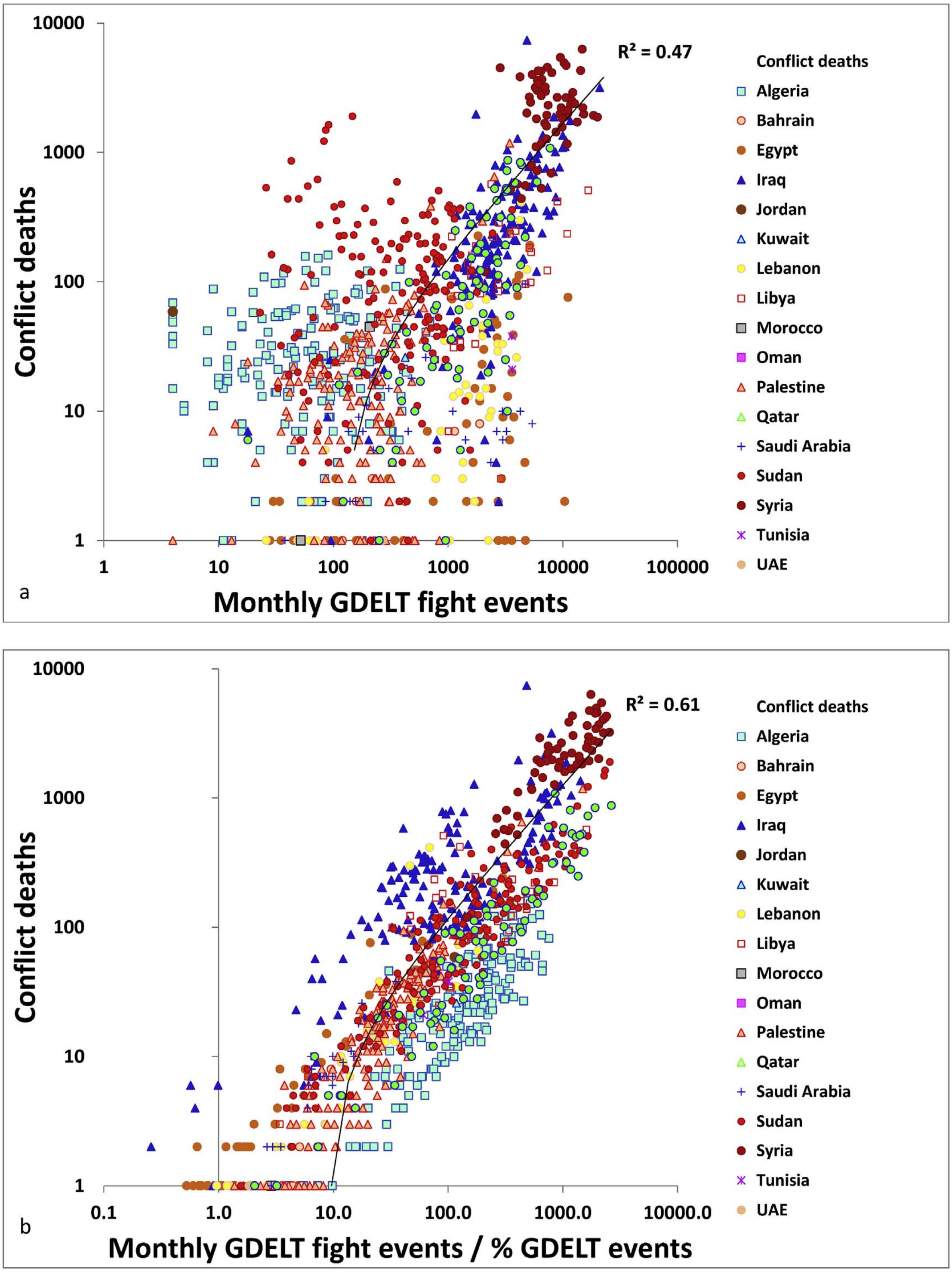

Fig. 12. Correspondence between monthly GDELT fight events and deaths from conflicts, at the country level. Each point represents a different month between November 2000 and December 2015.

this approach might create risks for the reporters from armed groups (Van der Windt & Humphreys, 2016).

Other applications include using social media for inferences about foreign policy issues and real-time conflict data (Lotan, Graeff, Ananny, Gaffney, & Pearce, 2011; Zeitzoff, Kelly, & Lotan, 2015). It has also been demonstrated that the frequency of edits to Wikipedia articles can identify controversial topics and real-world conflicts (Yasseri, Spoerri, Graham, & Kertész, 2014). While access to the internet has given some the illusion that geographic distance may not matter in the future (as in the flat world of Friedman, 2005), spatial inequalities persist in the internet, not only in accessibility to web services, but also in the information available and presented (Graham, Hogan, Straumann, & Medhat, 2014). As visibility and invisibility of people in the "real world" are affected by their prominence and presence on the Internet (Graham & Zook, 2011), mapping of cyberspace can have important implications for International Relations.

We note that it was not our aim to investigate whether these conflicts and the resulting migrations were caused by global environmental

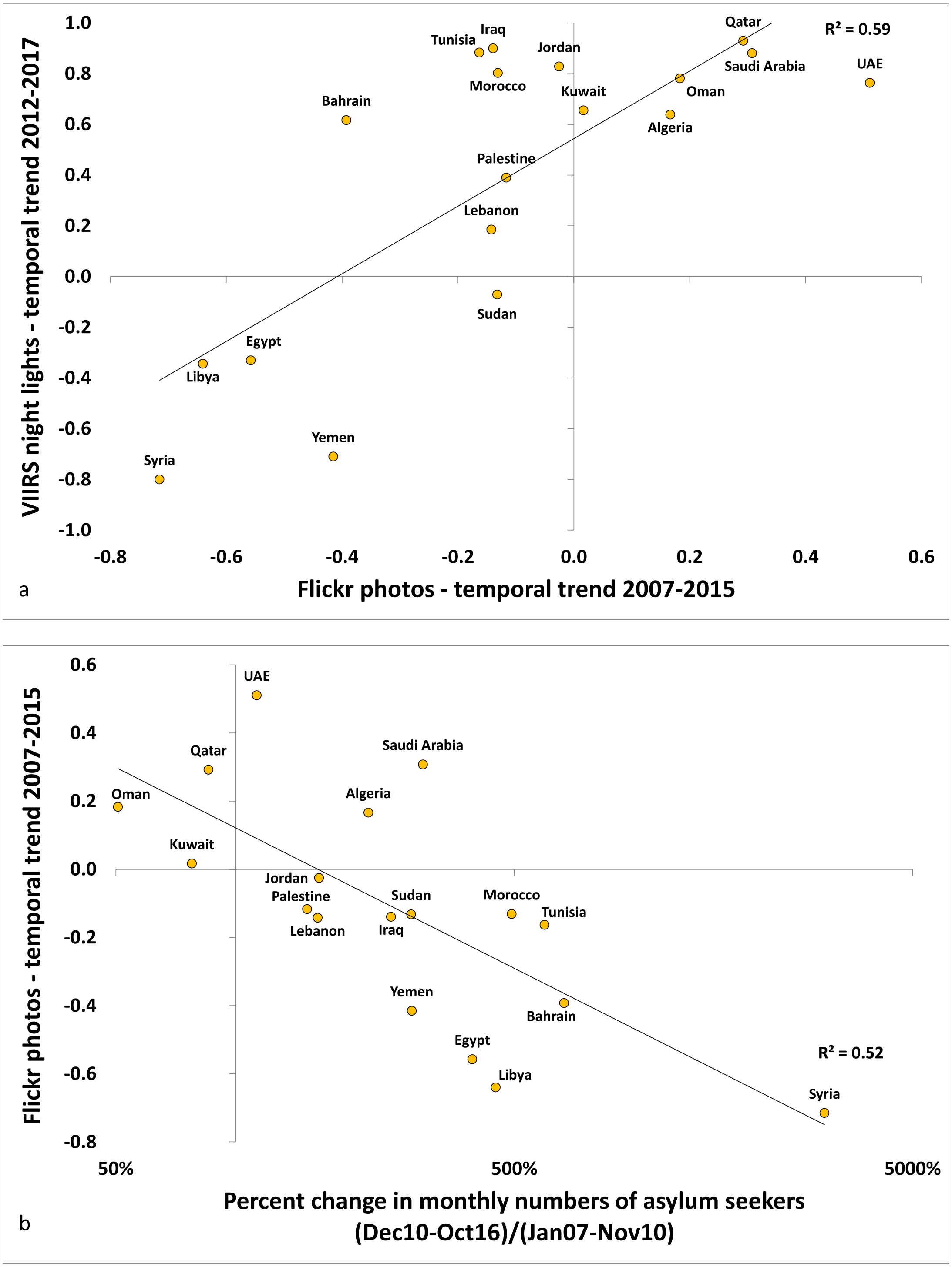

Fig. 13. Correspondence between temporal trends in monthly numbers of Flickr photos (2007–2015) with the temporal trends in night-time brightness (top), and with the change in the numbers of asylum seekers (bottom), following the onset of the Arab Spring.

change (see Burke, Hsiang, & Miguel, 2015) or by more complex socio, economic and political factors (Feitelson & Tubi, 2017; Fröhlich, 2016). However, our approach may contribute to efforts aimed at better monitoring ongoing conflicts and crises, and potentially even forecasting civil uprising or revolutions (as attempted by Asongu & Nwachukwu, 2016). In addition, datasets such as the ones we used to estimate conflict intensity could be used to feed models which aim to predict migration pathways of refugees (see Hébert, Perez, & Harati, 2018).

In this paper we demonstrated that remote sensing and big data can be combined to gain new, quantitative understanding of geopolitical events which have wide ranging implications. Such new types of data are promoted by some as promises for an emerging digital humanitarianism (with more accurate, timely and empowering data). However, it should be remembered that data is not information (Read, Taithe, & Mac Ginty, 2016), that there is still a long way to go, and that more research is needed in order to enable us to transform the stream of information from space-borne imagery, social media, and big data into insights and meaningful understanding.

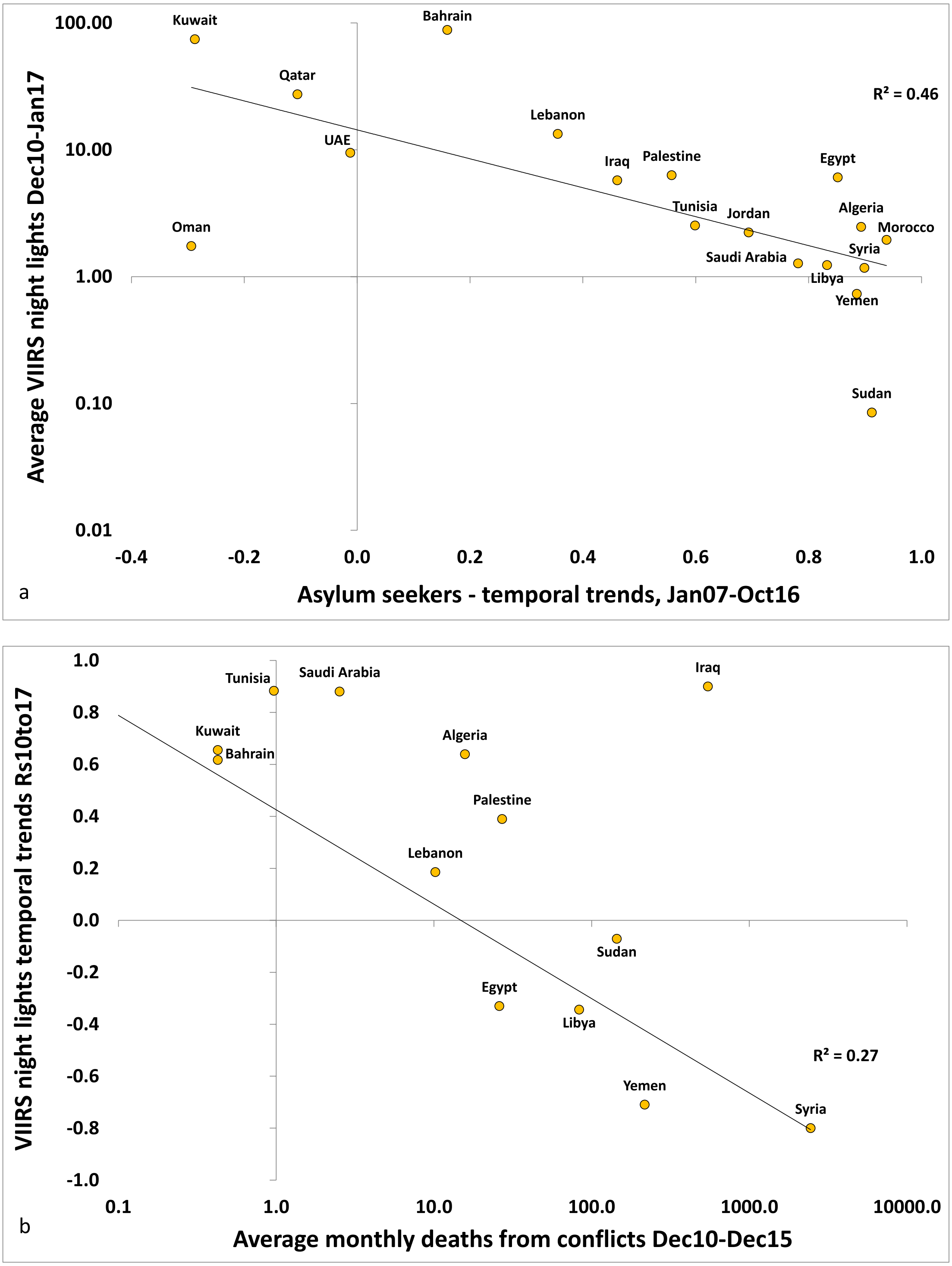

Fig. 14. Correspondence between temporal trends of VIIRS night-time brightness (2012–2017) with the temporal trends in numbers of asylum seekers (top), and with the monthly average of deaths from conflicts (bottom) since the onset of the Arab Spring.

5. Conclusions

Official statistics on various socio-economic indices are easily available within OECD (Organization for Economic Co-operation and Development) and other western countries, but are more difficult to access in the developing world, especially in times of conflict and warfare. This paper demonstrated the use of remote sensing (such as night lights) and big data sources (such as news events and Flickr photos) for supplying near real-time metrics on human activity within one of the world's most important recent geopolitical crises – the Arab Spring. By examining the correspondence between those metrics and real-world events, we showed that whereas some of the metrics quickly respond to fighting events (depending on their intensity, e.g., news reports, Flickr photos, night lights), others show lag times (e.g., numbers of asylum seekers). The combination of remote sensing and big data thus offers a powerful way to monitor large-scale socio-economic, geopolitical, and environmental changes on Earth, potentially improving our understanding of conflicts.

In order to further enable the use of such data in more effective response to conflicts, the speed of data availability needs to be better

Table 2
Statistically significant changes at the country level in the variables analyzed, before (2007–Nov 2010) and after (Dec 2010 - present) the onset of the Arab Spring. In all cells, if the *t*-test was found statistically significant comparing monthly averages before and after the Arab Spring, a value of 1 represents an increase, and a value of −1 represents a decrease. VIIRS night-time brightness data was only available since Apr 2012, so for this variable, values of 1 and -1 represent statistically significant results of trends (Spearman's correlation coefficient). Cells coloured in light red represent values where the change indicates negative outcomes of the Arab Spring. Variables and countries are ordered in decreasing order of the number of coloured cells. "NA" indicates that a variable was not available for a certain country.

	Syria	Egypt	Libya	Yemen	Tunisia	Bahrain	Saudi Arabia	Lebanon	Jordan	Sudan	Palestinian Authority	Iraq	Qatar	UAE	Algeria	Morocco	Oman	Kuwait
GDELT coerce	1	1	1	1	1	1	1	1	1	0	1	-1	1	1	1	1	1	1
GDELT protest	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	0	1
Asylum seekers	1	1	1	1	1	1	1	1	1	1	1	1	0	0	1	1	0	0
GDELT fight	1	1	1	1	1	1	1	1	1	1	0	0	1	1	0	0	1	0
GTD events	1	1	1	1	1	1	1	1	1	1	1	1	0	0	-1	0	0	0
GDELT assault	1	1	1	1	1	1	1	1	1	0	0	0	1	1	0	0	0	0
GTD kills	1	1	0	1	1	1	1	0	0	0	0	1	0	0	-1	0	0	0
GDELT 1 % global	1	1	1	0	1	1	0	-1	0	-1	-1	-1	0	-1	0	0	1	0
Flickr photos	-1	-1	-1	0	-1	0	0	0	0	0	0	0	1	1	0	0	0	0
Total conflicts	0	1	0	1	0	0	0	1	0	1	0	0	0	0	-1	0	0	0
Conflict deaths	0	1	0	1	0	0	0	1	0	0	0	1	0	0	-1	0	0	0
Average VIIRS lights	-1	0	-1	-1	1	1	1	0	1	0	1	1	1	1	1	1	1	1
Exports Merchandise, Customs, current US$, millions, seas. adj.	NA	1	-1	0	0	1	-1	0	1	-1	NA	1	1	1	0	1	1	1
Imports Merchandise, Customs, current US$, millions, seas. adj.	NA	1	0	1	1	0	1	1	1	0	NA	1	1	1	1	1	1	1

managed by the international community. Furthermore, international organizations which could potentially use resultant data, such as the United Nations Security Council, need to be able to operationalize these tools in their decision-making. Although such data availability might not prevent the advent of conflict, it could certainly lead to more effective responses from the international security establishment. There may be concerns raised about how such data could also be misused by authoritarian forces to quash civil protest. However, in most cases, oppressive regimes already have on-the-ground access to sites, and it is the external mediation forces which lack requisite real-time information. Just as social networking technologies were instrumental in the rapid spread of dissent during the Arab Spring, so too can big data

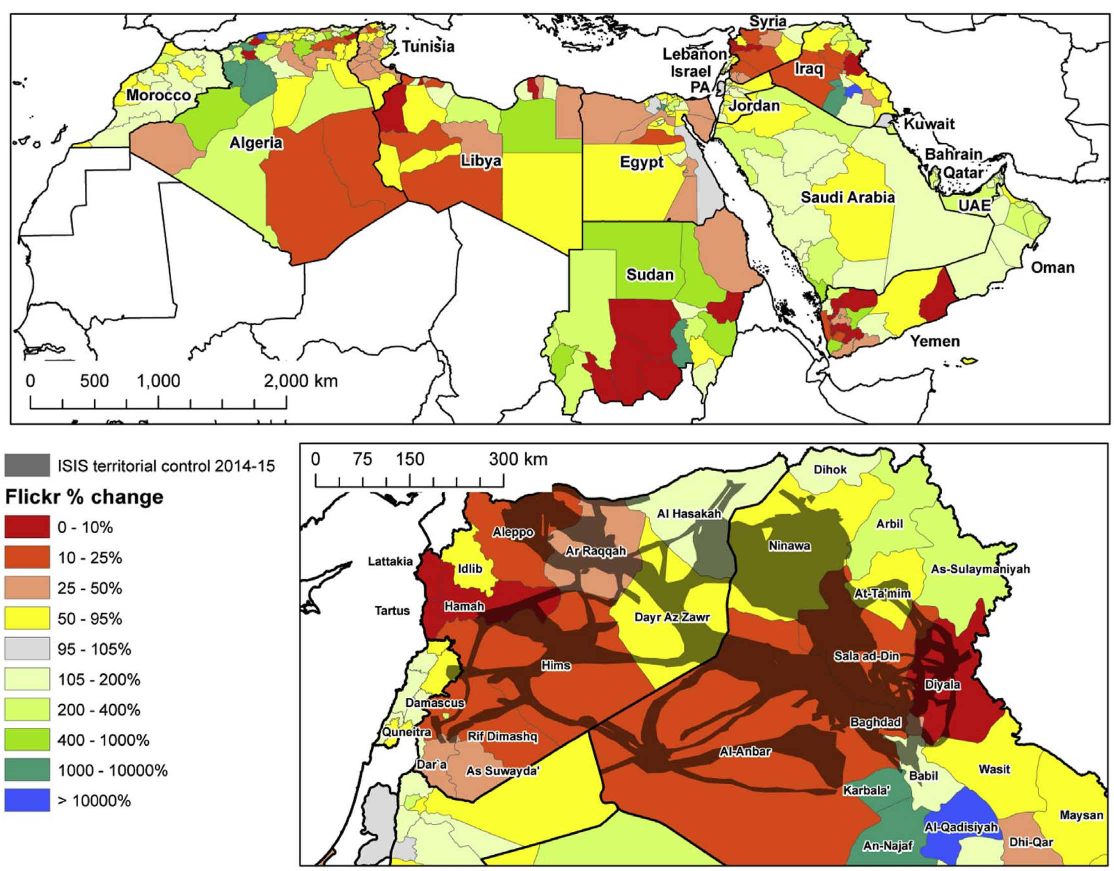

Fig. 15. The percent change in average monthly number of Flickr photos, between January 2007–November 2010, and December 2010–December 2015.

geospatial technologies be useful in a more effective strategy to respond to those in need of humanitarian assistance. Ultimately, spatial data concerning conflict intensity is empowering to decision-makers at multiple levels, and this paper has shown how it can practically be obtained and utilized for monitoring and responding to the impact of violent conflicts.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.apgeog.2018.03.001.

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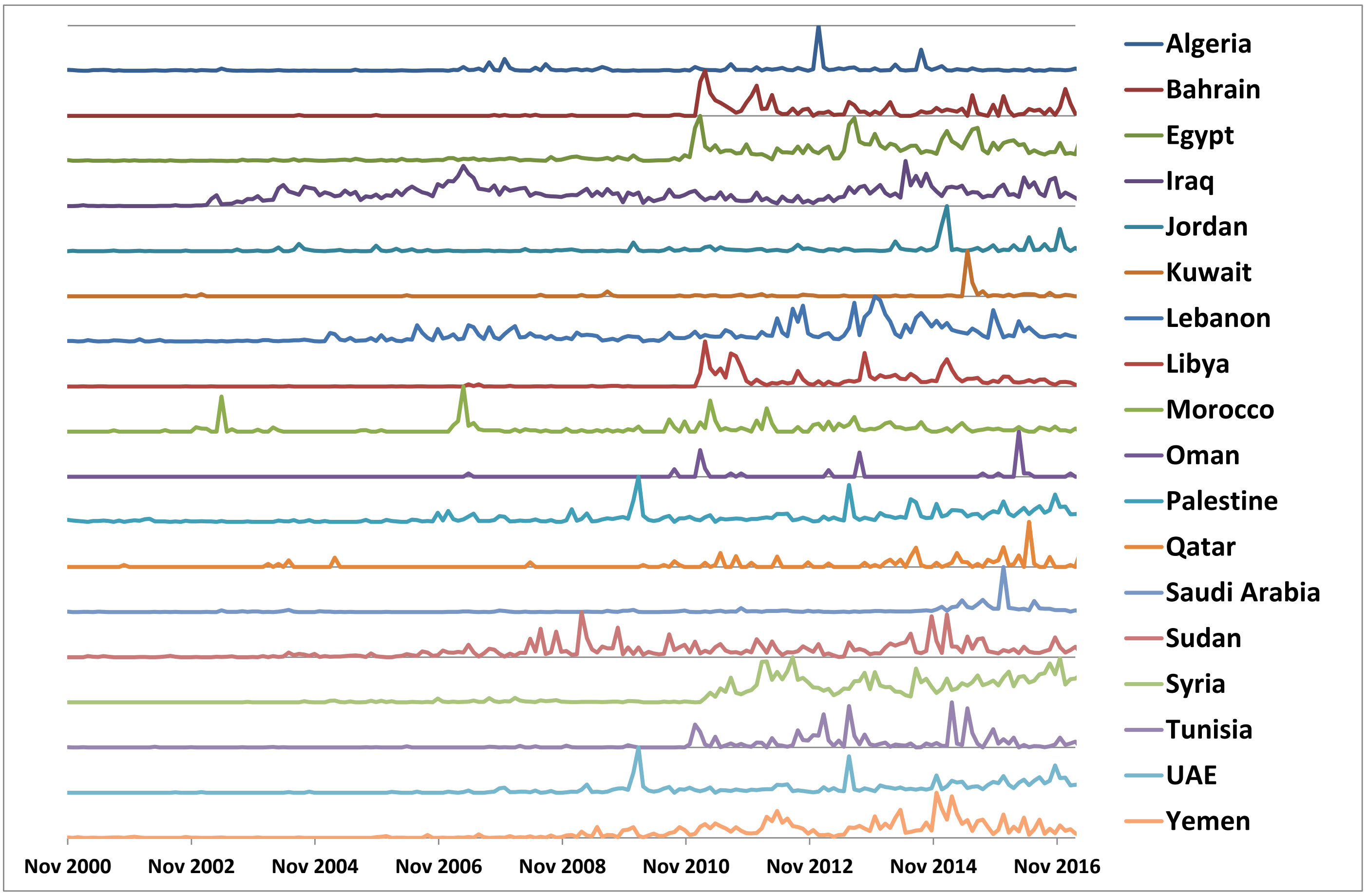
Figure S1: Monthly time series of GDELT assault events. In the upper panel events are normalized between 0 and 1 based on the minimum and maximum values of each country, whereas in the bottom panel events are normalized between 0 and 1 based on the minimum and maximum values across all countries.



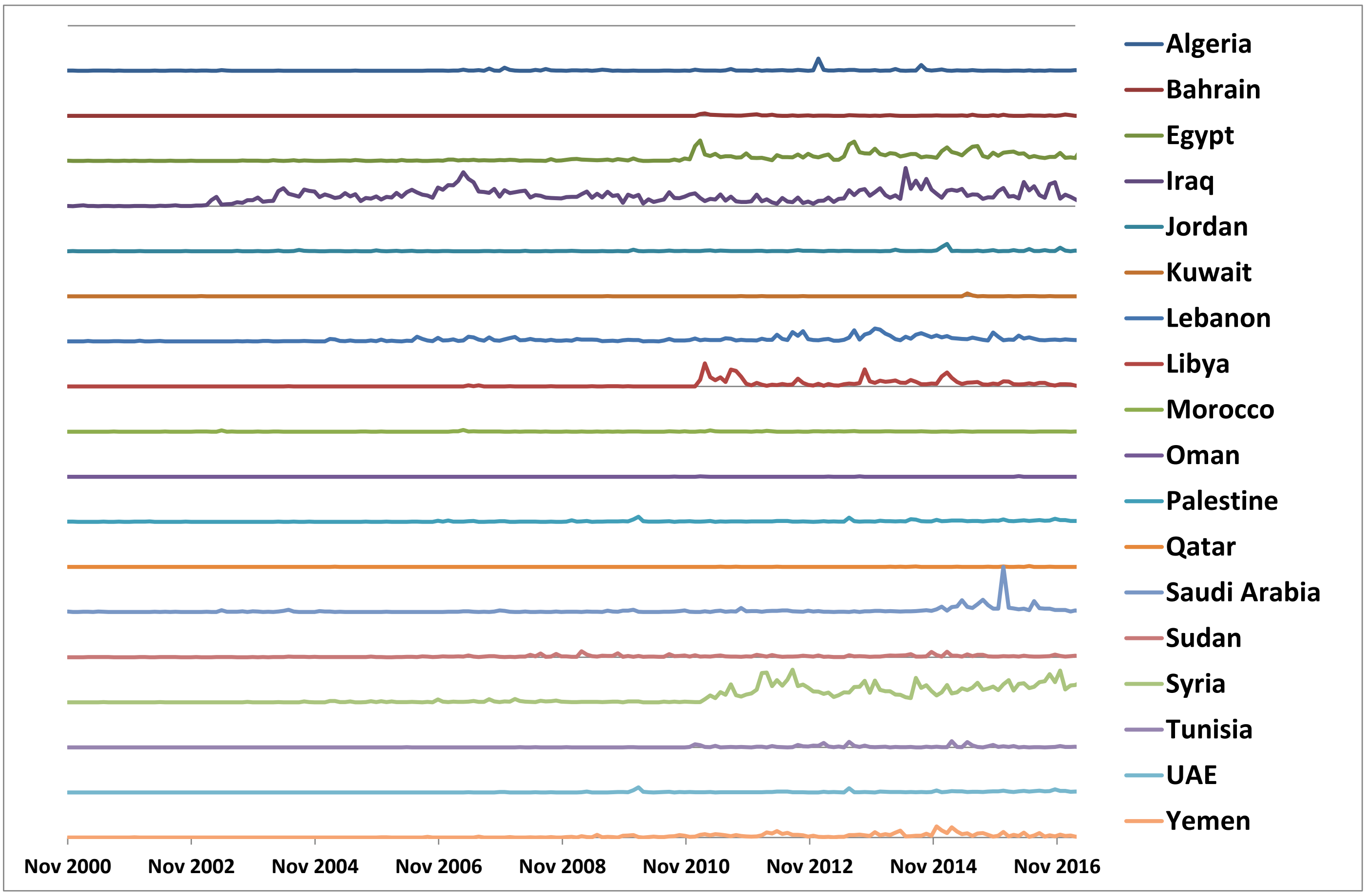
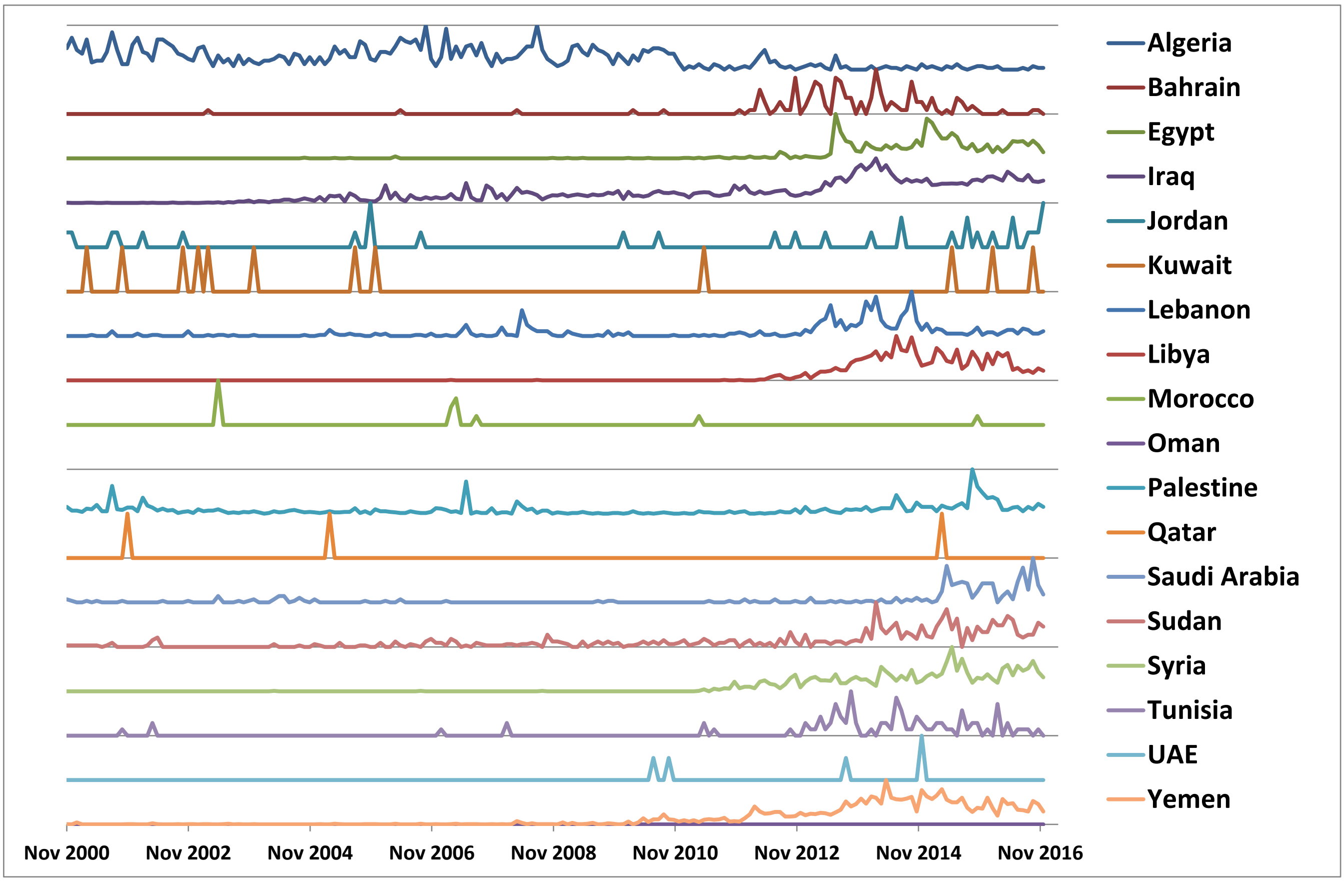


Figure S2: Monthly time series of terrorism events, from the Global Terrorism Database (START, 2017). In the upper panel numbers are normalized between 0 and 1 based on the minimum and maximum values of each country, whereas in the bottom panel numbers are normalized between 0 and 1 based on the minimum and maximum values across all countries.



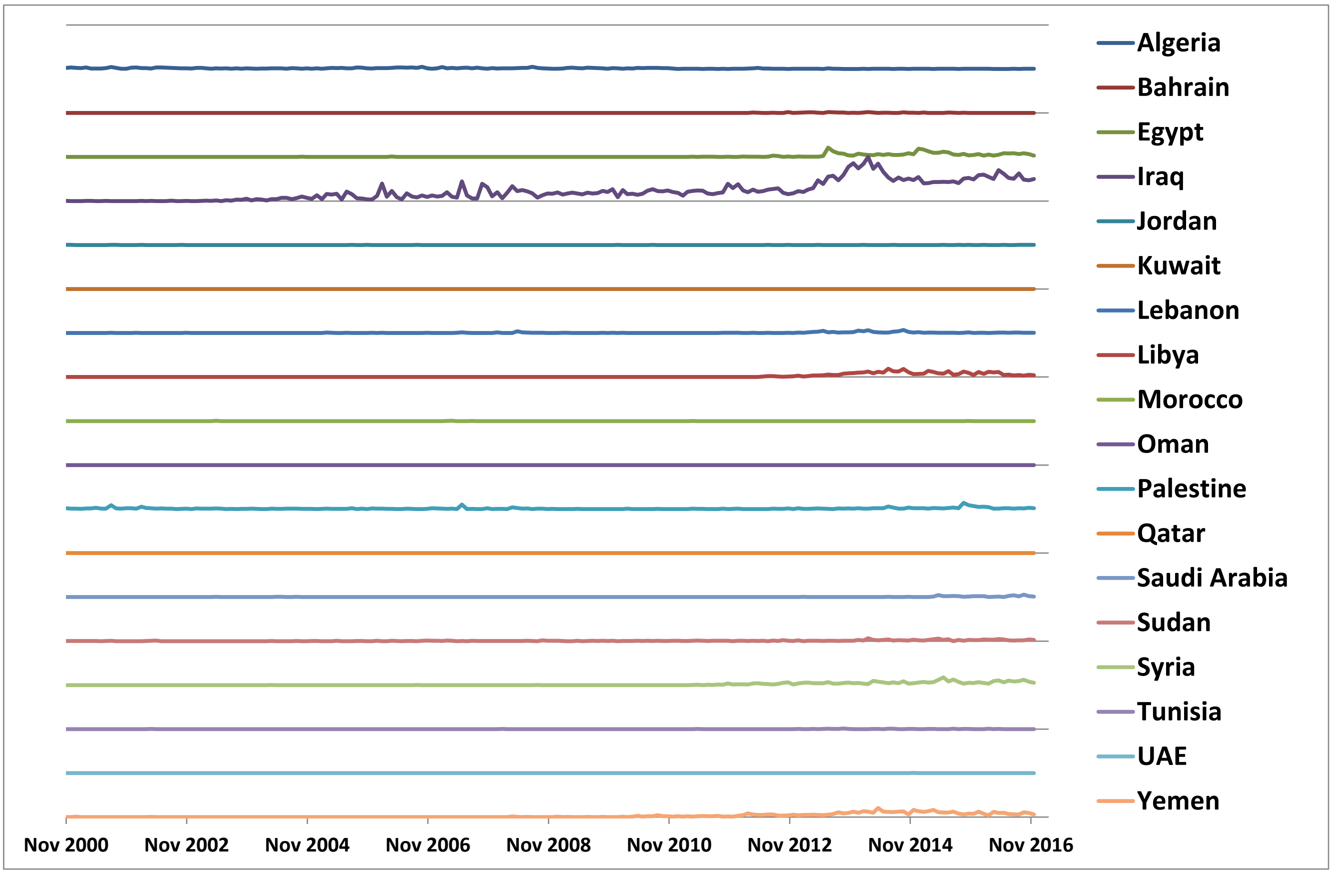


Figure S3: Monthly time series of conflict related deaths. In the upper panel numbers are normalized between 0 and 1 based on the minimum and maximum values of each country, whereas in the bottom panel numbers are normalized between 0 and 1 based on the minimum and maximum values across all countries.

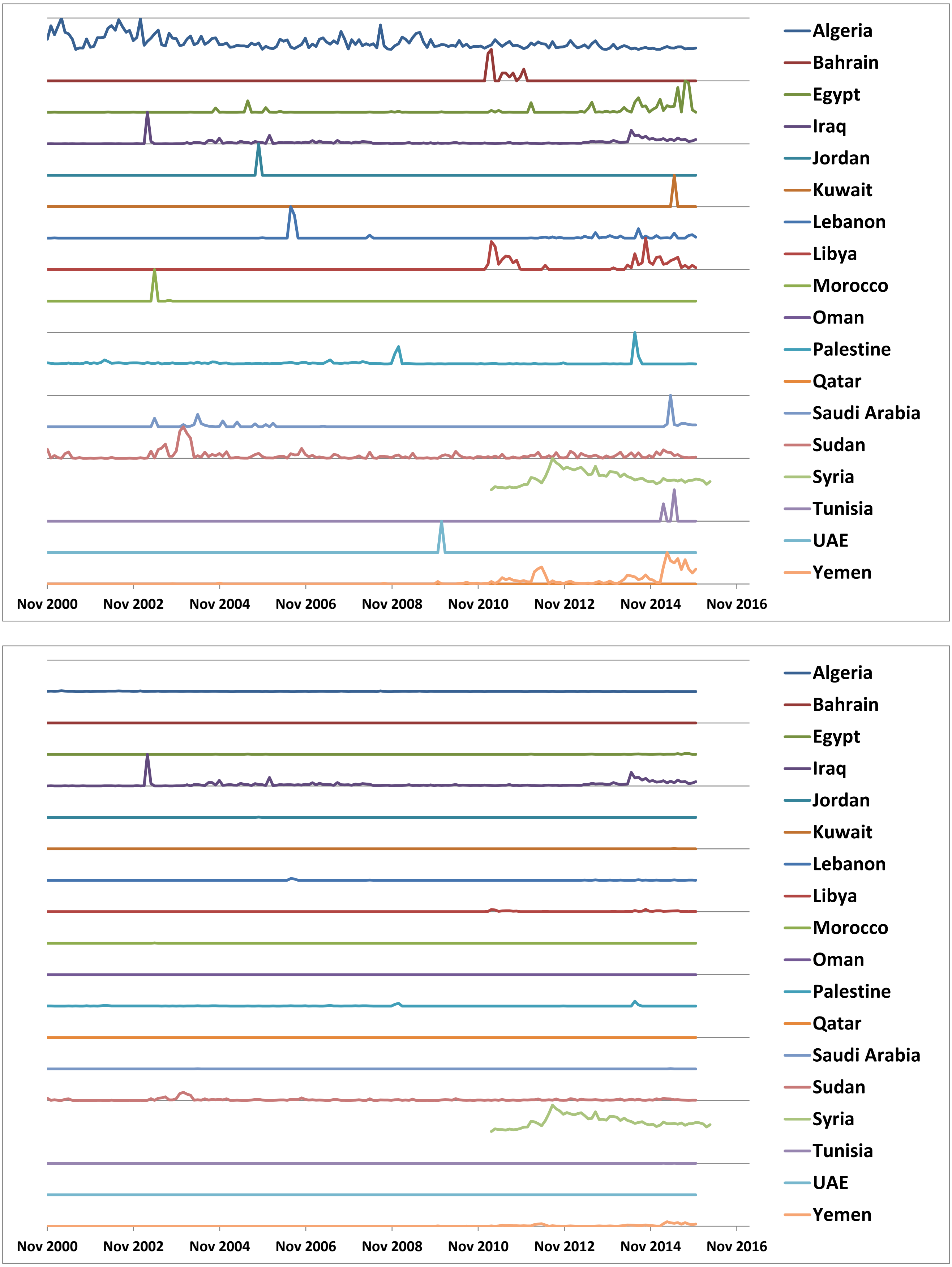


Figure S4: Monthly time series of conflict related deaths, Global Terrorism Database (GTD) events, GDELT fight events, flight passengers, Flickr photos, and VIIRS night lights, in five provinces in Egypt: Alexandria, Cairo, Luxor, Southern Sinai and Northern Sinai. The x-axis in each of the rectangles is between November 2000 and April 2017. All variables are normalized between 0 and 1 based on the minimum and maximum values of each variable, to ease comparison of temporal trends across variables.

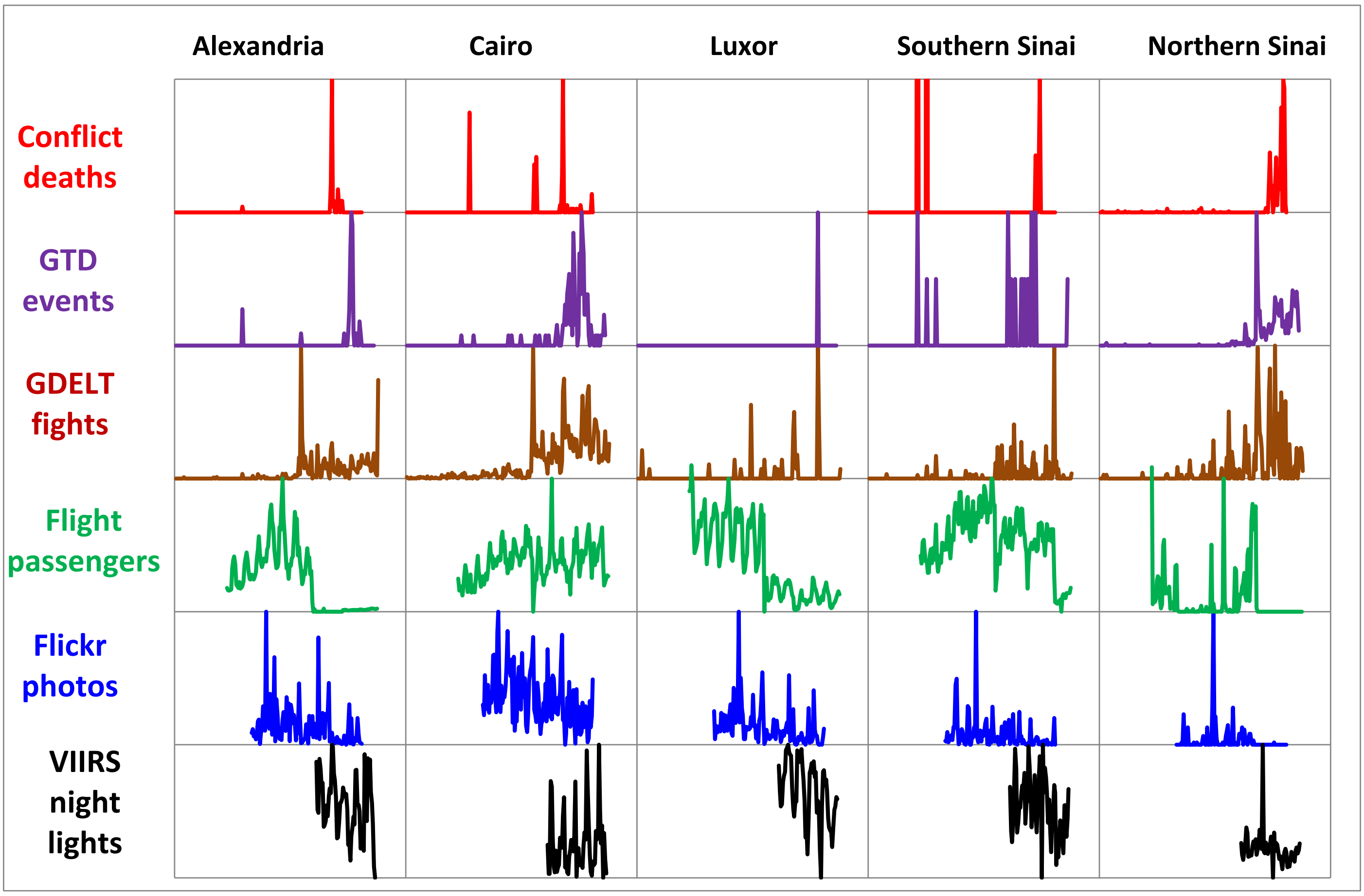


Figure S5: Monthly time series of conflict related deaths, Global Terrorism Database (GTD) events, GDELT fight events, Flickr photos, and VIIRS night lights, in five provinces in Iraq: Baghdad, Arbil (where the capital of Kurdish Iraq is located), and provinces which experienced some of the heaviest fighting with ISIS in Iraq (Al-Anbar, Ninawa and Sala ad-Din). The x-axis in each of the rectangles is between November 2000 and April 2017. All variables are normalized between 0 and 1 based on the minimum and maximum values of each variable, to ease comparison of temporal trends across variables.

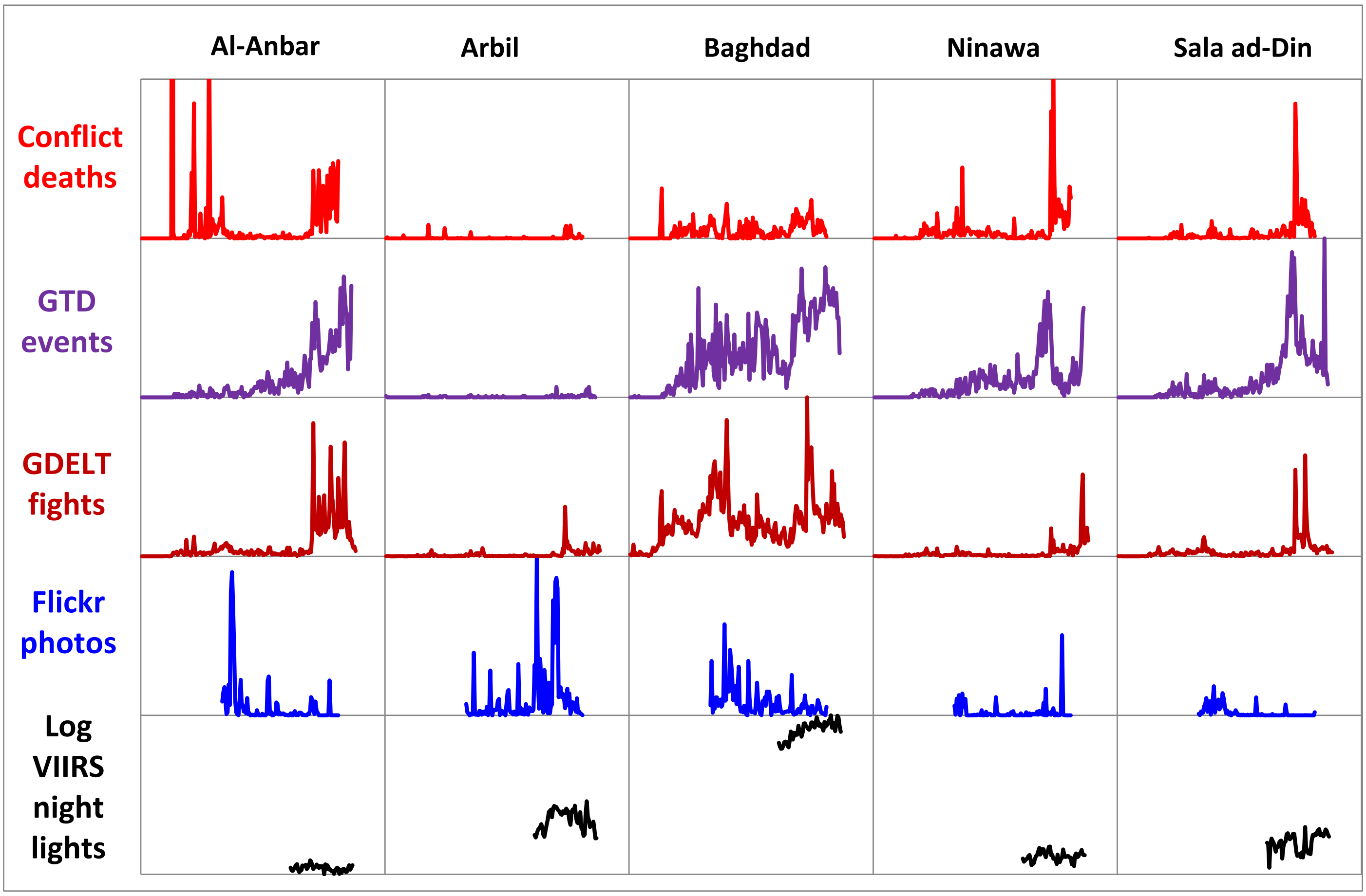


Figure S6: A false color composite of GDELT fight events gridded within 10×10 km grid cells. GDELT fight events are colored based on the time using the following three periods: 2007 – Nov 2010 (in blue), Dec 2010 - Oct 2014 (in green), and Nov 2014 – Apr 2017 (in red). Areas which experienced an increase in GDELT fight events since late 2010 appear in yellow, whereas regions where GDELT fight events increased since later 2014 appear in red.

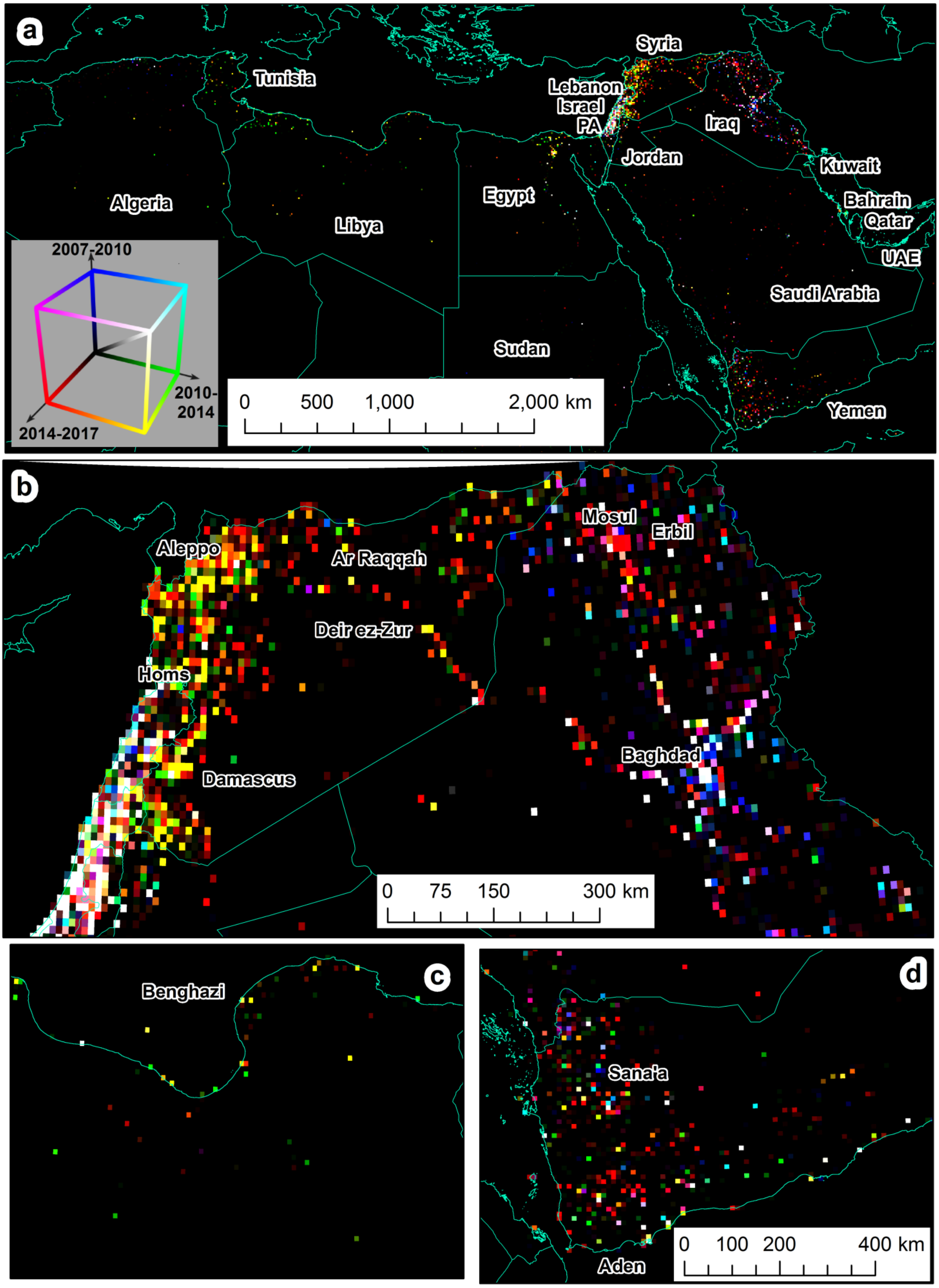


Figure S7: Correspondence between monthly GDELT fight events and asylum seekers, at the country level. Each point represents a different month between November 2000 and October 2016.

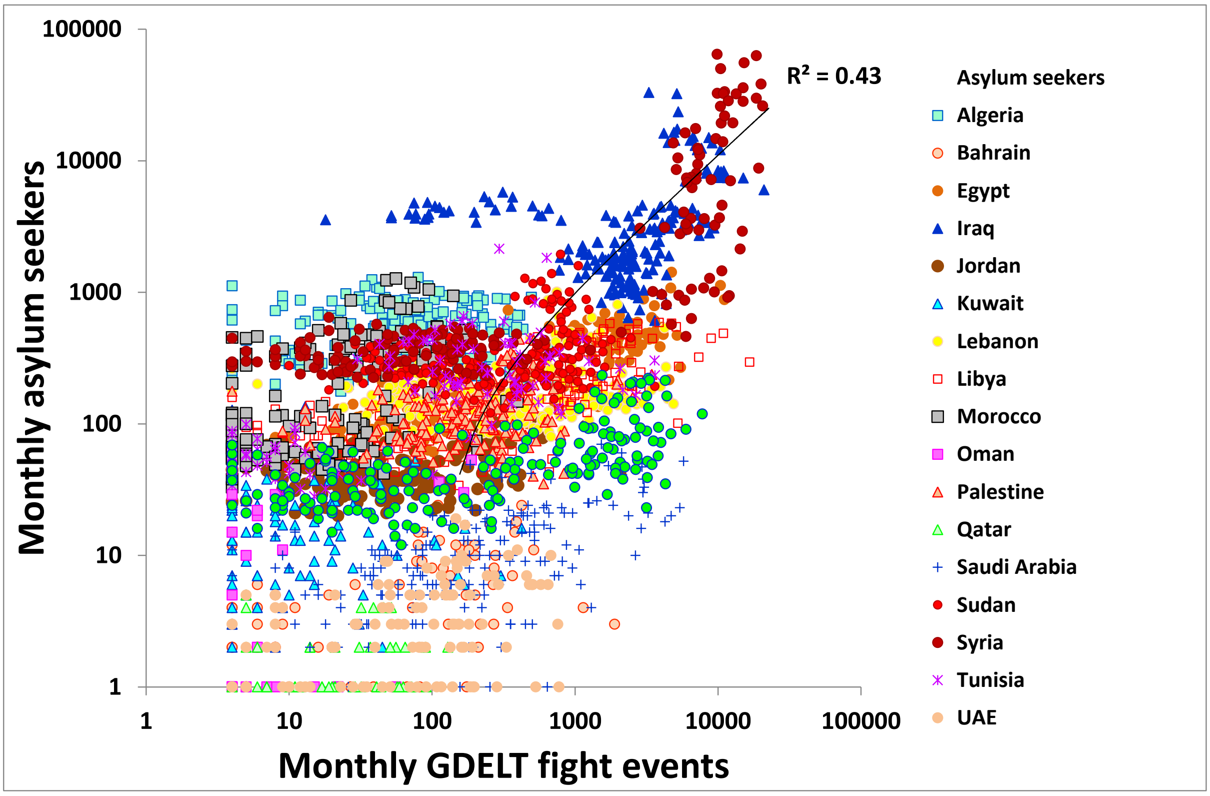


Figure S8: Correspondence between monthly of deaths from conflicts and Flickr photos, at the country level. Each point represents a different month between January 2007 and December 2015.

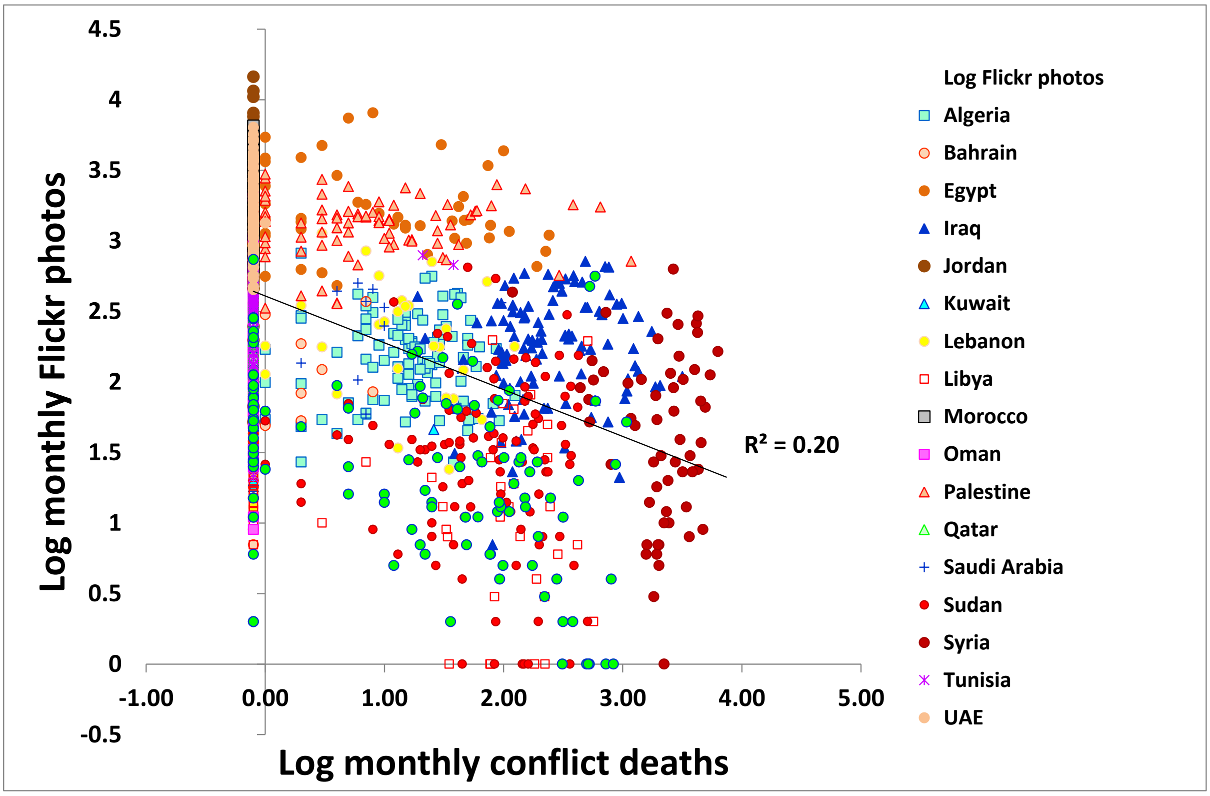


Figure S9: Correspondence between GDELT monthly protest events (average between 2007-2015) and changes in Flickr photo numbers. AvgPctChng represents the percent change of monthly Flickr photos before and after the Arab Spring. Rs07to17 represents countries' Spearman correlation coefficient between time and monthly numbers of Flickr photos.

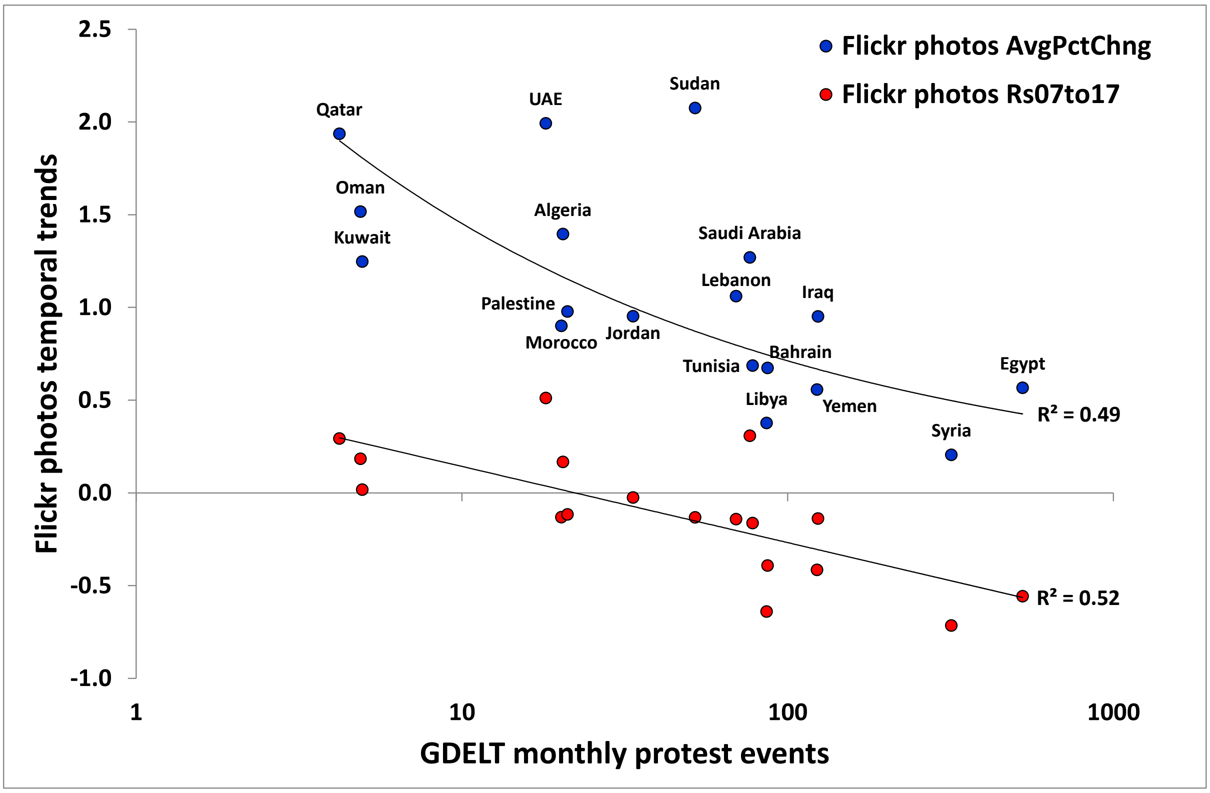


Figure S10: The percent change in average monthly number of GDELT fight events, between January 2007-November 2010, and December 2010-April 2017.

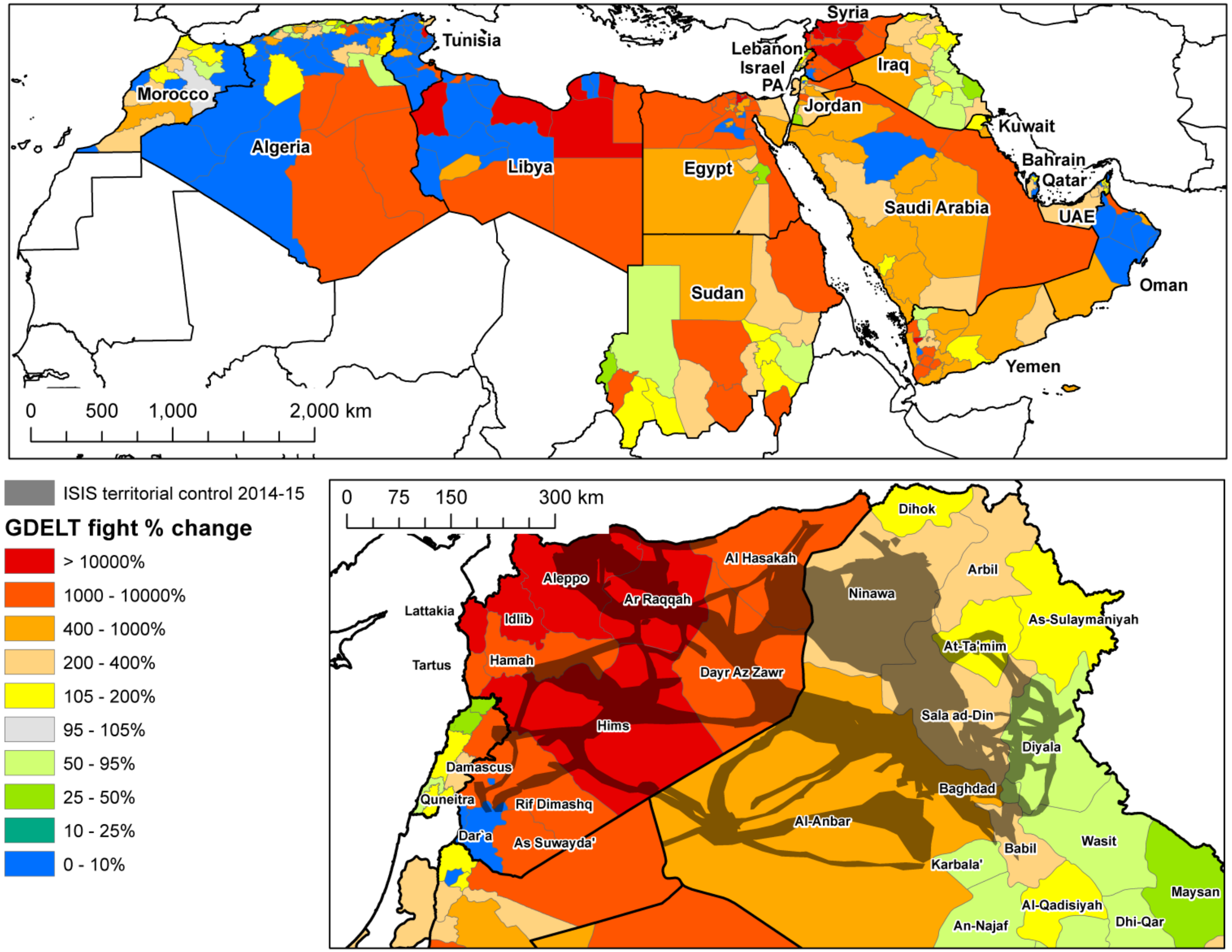


Figure S11: The average monthly number of GDELT fight events December 2010-April 2017.

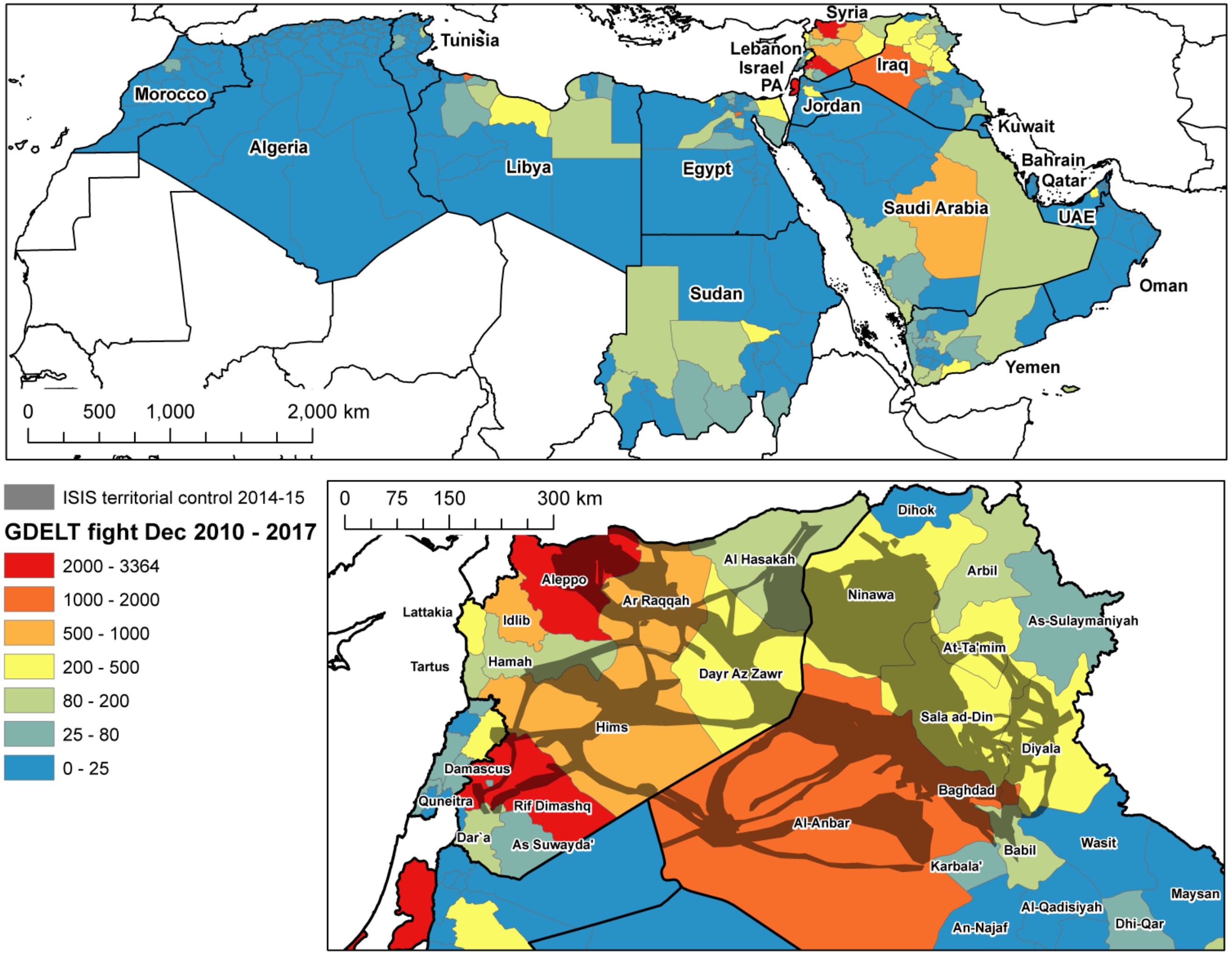


Figure S12: Spearman correlation coefficients of changes in monthly VIIRS night-time brightness as a function of time, between April 2012 – January 2017.

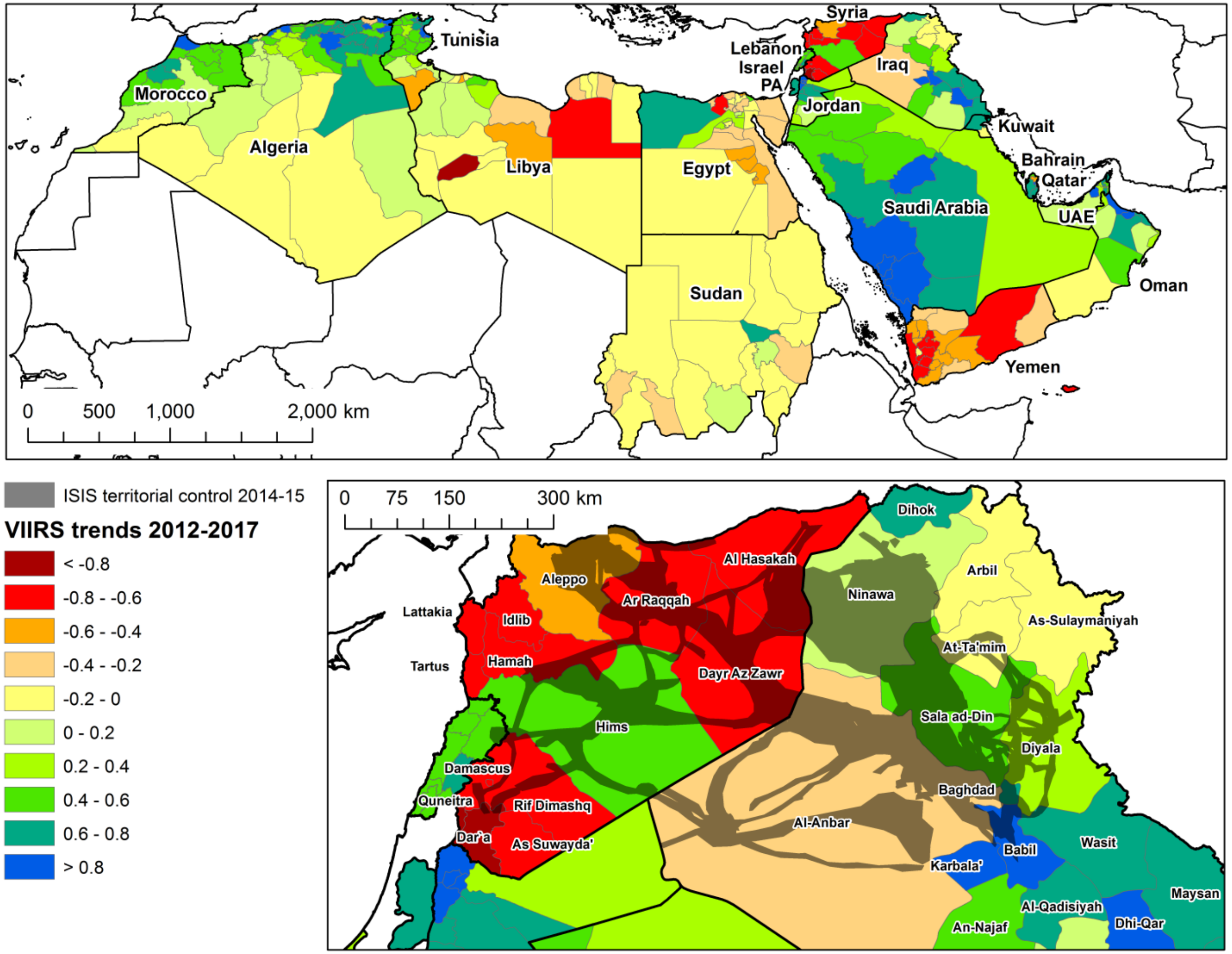


Figure S13: The correlation between GDELT fight events and temporal trends in Flickr photos. Each point represents an administrative region.