Near-Real Time Analysis of War and Economic Activity during Russia's Invasion of Ukraine*

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Abstract

This paper introduces new near-real time data on Russia's full-scale invasion of Ukraine, and uses these data to investigate the short-term impact of occupation and violence on local economic activity. The data project — VIINA (Violent Incident Information from News Articles) — scrapes and parses news reports from Ukrainian and Russian media, georeferences them, and classifies them into standard event categories (e.g. air raid alert, artillery shelling) through machine learning. We show that VIINA has more comprehensive geographic coverage and more thorough documentation than any other open-source time event tracking system on Ukraine, and is the only such effort that includes information on territorial control. To illustrate potential applications of these data for research on political economy, we utilize remote sensing data on luminosity and vegetation as proxies for urban economic activity and agricultural land use. We find that economic activity declined most in urban areas that neither side fully controlled, and in places where artillery shelling was more intense. Contested territories also experienced a significant short-term decline in vegetation. Areas under Russian occupation, however, remained largely insulated from these negative shocks.

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To understand how war affects everyday economic life, policymakers, NGOs, and social scientists need comprehensive, up-to-date information about who did what to whom, when and where. These are the "hard facts" on which empirical knowledge about war is based. Knowing which side controlled which village on what day, and where shelling and airstrikes were most intense, can help prosecutors build a case for a war crimes trial, help humanitarian relief workers find a safe corridor to deliver aid, help analysts understand the scope of future recovery and reconstruction efforts — and estimate the potential cost of reparations to be paid by the aggressor state. This information is not always easy to acquire, and it can be surprisingly perishable. Websites can be taken offline, social media posts can be deleted, witnesses can be silenced. If information is not preserved in a timely and systematic way, reconstructing a sequence of events becomes very challenging.

This article introduces VIINA (Violent Incident Information from News Articles), a near-real time territorial control and violent event tracking system for Russia's 2022 invasion of Ukraine. VIINA scrapes and parses news reports from Ukrainian and Russian media, georeferences them, and classifies them into standard event categories (e.g. firefight, tank battle, artillery shelling) through machine learning. It also tracks reported changes in territorial control for every populated place in Ukraine. Launched publicly on March 7, 2022, this resource is updated daily, and is freely available at github.com/zhukovyuri/VIINA. This article provides an overview of the project, compares it to other near-real time data efforts on this war, and illustrates potential applications for research on political economy.

Event data on armed conflict and violence have a long tradition in social science, ranging in scale from large, cross-national collection projects (e.g. Azar 1980; Schrodt, Davis and Weddle 1994; Sundberg and Melander 2013) to specialized studies of individual countries (e.g. Berman, Shapiro and Felter 2011; Zhukov 2016; Dell and Querubin 2018). Such efforts typically revolve around the extraction of georeferenced information on political events from press reports, social media, or government records, either manually or with automated text-as-data techniques. Some of these projects — like Global Database of Events, Language, and Tone (GDELT) (Leetaru and Schrodt, 2013), the Integrated Conflict Early Warning System (ICEWS) (Shilliday, Lautenschlager et al., 2012) and the Armed Conflict Location and Event Data (ACLED) project (Raleigh et al., 2010) — have sought to generate event data in near-real time, with daily or semi-weekly updates.

These data have facilitated novel research designs at granular levels of analysis, but they have important shortcomings that are consequential for applied research. First, automated cross-national event datasets often rely on English-language (or machine-translated) sources and standard event typologies, like the World Interaction/Event Survey (WEIS) (McClelland, 1978), Conflict and Mediation Event Observations (CAMEO) (Gerner et al., 2002), or Integrated Data for Events Analysis (IDEA) coding systems (Bond et al., 2003). Such an approach enables consistency and scalability across countries, but at the cost of noisier data that are not optimized to reflect the particularities of any one conflict.

While more bespoke single-country datasets avoid some of these problems by relying on custom event typologies, human coders, and local sources of reporting, such projects have a second limitation: they are less scalable, less comprehensive, and usually less consistent in their event classifications. Hand-coded event data collection is labor-intensive, requiring many hours of tedious and painstaking work by large teams (King and Lowe, 2003, 618). Humans have limited working memories and tend to rely on heuristics, resulting in subjective and ad hoc decisions, and broader risks associated with fatigue and inattention.

A third limitation is that no open-source event data project, to our knowledge, tracks changes in territorial control. Gains in territory are standard measures of battlefield success in the literature on military effectiveness (Dupuy, 1979; Biddle, 2004). On a more fundamental level, territorial control is a central prerequisite of sovereignty (Tilly, 1978). Without it, states cannot effectively collect revenues, enforce laws, provide public goods, or perform basic administrative tasks. Territorial control is also a key (hypothesized) predictor of behavior by armed groups, particularly as regards their ability to extract resources and information from the population, and selectively punish their political opponents (Kalyvas, 2006). Yet time-variant data on territorial control are notoriously hard to collect, and are unavailable for all but a handful of armed conflicts.

VIINA avoids many of these limitations. As a project dedicated to tracking the Russian invasion of Ukraine, it relies exclusively on local sources of reporting and employs a custom geocoding dictionary and event typology that reflect the conventional, artillery-centric nature of this war. It is a fully automated, scalable system, which employs a deep learning model — Long Short-Term Memory (LSTM) (Hochreiter and Schmidhuber, 1997; Sherstinsky, 2020) — to classify events with high out-of-sample predictive accuracy. We show that VIINA captures events at a volume comparable to other automated near-real time projects (GDELT, ICEWS), but with a geographic distribution that more closely resembles that of curated, manually-collected data (ACLED). It is also the first data project of its type to feature daily, municipality-level indicators of territorial control, by combining crowd-sourced geospatial data with LSTM predictions of territories changing hands.

We use these data to examine the short-term economic consequences of Russian occupation and artillery shelling, in a pair of illustrative analyses. First, we investigate the impact of the war on economic activity in urban areas, by using VIIRS satellite data on nighttime luminosity. Second, we investigate the war's impact on the agricultural sector, with remote sensing data on the normalized difference vegetation index (NDVI) in areas with irrigated cropland. Using a simple linear regression model with an offset for prewar levels of luminosity, and fixed effects at the level of municipality and month of the war, we estimate that populated places that spent a month under contestation (i.e. where neither Ukraine nor Russia had full control) saw a decrease in luminosity of 50 percentage points. A month of Russian occupation, meanwhile, is associated with a 62 percentage point increase in luminosity relative to Ukrainian-controlled areas. We further estimate that a doubling of artillery shelling in a given month is associated with a 6 percentage point decrease in municipality's luminosity the following month. Using an analogous estimation strategy for changes in vegetation, we find that NDVI decreased by an average of 5 percentage points following a month of contestation, and increased by 3 percentage points following a month of Russian occupation. These patterns suggest that war brings not only economic devastation, but also vast inequalities that are observable even in the short-term.

These tentative findings — and the data used to produce them — should be of interest to researchers studying the economic costs of conflict (Abadie and Gardeazabal, 2003; Collier et al., 2003; Glick and Taylor, 2010; Miguel and Roland, 2011; Korovkin and Makarin, 2023), and the broader social, economic and political legacies of violence (Grosjean, 2014; Bauer et al., 2016; Dell and Querubin, 2018; Rozenas and Zhukov, 2019).

This article also contributes more generally to the empirical literature on armed conflict, by introducing a new public good, and by providing a "walk-through" of how researchers can build a near-real time data project from scratch, and at relatively low cost. VIINA is a modular public good, which users can expand and adapt for their needs. One could easily use the original text, URLs, and other raw materials included in VIINA to develop new classification models, add new event categories, or filter these data by source, location, or date for specialized research purposes beyond the ones illustrated here. There is nothing in the design of VIINA that cannot be generalized to other ongoing and future conflicts in other countries. All software and data sources employed in VIINA's creation are open-source, with no licensing requirements or data hosting fees.

The article proceeds as follows. Section 1 summarizes the sources and methods used to construct VIINA, along with out-of-sample accuracy statistics and other validation metrics. Section 2 compares the scope, features, and spatio-temporal distribution of VIINA to those of three other near-real time data projects actively monitoring events in Ukraine, including two large-scale automated datasets (GDELT and ICEWS) and one manually curated event dataset (ACLED). Section 3 provides two illustrative applications of VIINA, investigating the short-term economic consequences of the war in urban and rural areas. Section 4 offers a discussion of the broader significance of this project, and some concluding remarks.

1 System Overview

VIINA is an effort to preserve publicly-reported information about Russia's full-scale invasion of Ukraine, both in raw form and as data on political violence and territorial control. It scrapes and parses news reports from Ukrainian and Russian media, assigns geographic coordinates to all reports that mention specific locations, and classify them into standard conflict event categories, by actor, tactic and target.

1.1 Sources

Data sources for VIINA include Ukrainian and Russian news agencies, broadcast, print and social media.[1] Rather than use an international news wire service — a standard approach

[1] News agencies include `interfax.com.ua`, `kbrria.ru`, `ria.ru`, `unian.ua`, `ukrinform.ua`. Broadcast media include `24tv.ua`, `ntv.ru`, `nv.ua`. Print media include `epravda.com.ua`, `eurointegration.com.ua`, `forbes.ua`, `kp.ru`, `ng.ru`, `pravda.com.ua`. Other online media include `church.ua`, `liga.net`, `mil.in.ua`, `zaxid.net`, `zona.media`. Social media sources (via liveuamap) include `facebook.com`, `instagram.com`, `twitter.com`, `youtube.com`.

in the field — source selection for VIINA prioritizes high-impact local news sources, in the Ukrainian or Russian languages, which most closely reflect what media consumers in the two warring countries are likely to read or see on a daily basis.

Ukrainian news sources include one of the country's main news wire services (UNIAN), the country's most widely-read newspaper (Ukrayins'ka Pravda), one of its largest radio stations (NV), and a major social media and OSINT aggregator (liveuamap), among other sources. Russian sources include the country's leading news wire — and the most widely cited news source on Russian social media — (RIA Novosti), the country's third highest-rated television channel (NTV), one of Russia's last remaining independent online news outlets (Mediazona), and one of the country's most influential — and allegedly Putin's personal favorite — newspapers (Komsomol'skaya Pravda), among others.

Every six hours, VIINA crawls through the website of each source, downloads the headlines and descriptions in the "latest news" or "war chronology" sections — so as to avoid stories about arts, culture, sports and other unrelated topics — along with timestamps and links to the full text. Due to frequent server-side disruptions (e.g. DDoS attacks, power outages, blocking of URLs and domain names), the system is designed to be redundant, with the same queries being sent repeatedly from multiple locations, using different VPNs, so as to minimize interruptions and gaps in coverage. The system then removes unambiguously duplicate entries (i.e. same source, date, headline, text) from the resulting corpus. At the time of writing (February 26, 2023), the corpus included 699,309 individual news items, although this number is by now almost certainly out of date.

1.2 Geocoding

Approximately 17% of the news items in the corpus mention at least one geographic location within Ukraine. VIINA assigns geographic coordinates to these locations using a custom geocoding dictionary, assembled by (a) extracting all words in title case from each entry, (b) running these words through geocoding APIs from Yandex and OpenStreetMap, (c) manually inspecting the list to remove likely false positives. The dictionary is periodically updated, as the war shifts to new locations, and new place names enter the corpus.

While the scale of the project precludes manual verification of each geocoded address, this approach yields superior performance to a purely-automated geocoding system — using either an API or a list of known locations from a gazetteer. Notably, our method avoids some of the most common types of false positives (e.g. misclassifying popular surnames as locations), while also reducing false negatives by preserving Ukrainian- and Russian-language suffixes and locative case endings that exact string matching might overlook.

The dictionary tracks the precision of cited location names, so as to separate events geocoded to the street, municipal, district (rayon), and provincial (oblast) levels. If an event report mentions more than one location, VIINA splits the report into multiple observations. In cases where the source material already contains georeferenced metadata at the municipal level or better (e.g. liveuamap), VIINA keeps the original set of coordinates.

1.3 Classification of Armed Conflict Events

To classify reported events by actor, tactic, and other key details, VIINA relies on a recurrent neural network with long short-term memory (LSTM) (Hochreiter and Schmidhuber, 1997; Sherstinsky, 2020). LSTMs are well-suited for learning problems related to sequential data, where sequences of words are of differential length, where the vocabulary is potentially large, where the long-term context and dependencies are informative, and where word order matters. The training sets include 3500 randomly-selected hand-coded reports, updated periodically as new types of events enter the corpus. Intercoder reliability statistics, reported in Appendix A1, indicate high levels of agreement for the subset of training documents that were held constant across multiple coders.

Rather than build separate classifiers for Russian and Ukrainian-language texts, VIINA pools both languages together into a single corpus. As we report in Appendix A2, this bilingual approach yielded superior predictive accuracy than models trained on either monolingual training set alone. Standard preprocessing steps included removing punctuation and special characters, converting to lower case, removing Russian and Ukrainian stopwords, and cleaning the text (e.g. standardizing acronyms and abbreviations). Because Slavic languages have highly informative systems of declension and conjugation — where words are appended with prefixes and suffixes to indicate grammatical tense, number, case and gender — we did not use a stemmer. By preserving these inflections, among other benefits, we can better distinguish subjects (initiators) from objects (targets) of events.

We use the Keras (Chollet, 2015) and TensorFlow deep learning libraries (Abadi et al., 2016) in Python 3 to implement the LSTMs. The fitting procedure sets aside one fifth of the training data as a validation set, and tunes the model with out-of-sample accuracy and loss metrics from this validation set, before generating predictions on the unlabeled test set. We set the model to run for 1200 epochs (i.e. 1200 full passes of the training data forward and backward through the neural network), with an early stopping rule to prevent overfitting if too many epochs pass without an improvement in validation accuracy.

Variable	Description	In-Sample	Out-Sample
t_mil	Event is about war/military operations	0.999	0.817
t_loc	Report includes reference to specific location	0.999	0.857
t_san	Report mentions economic sanctions imposed on Russia	0.999	0.947
a_rus	Event initiated by Russian/Russian-aligned forces	1.000	0.857
a_ukr	Event initiated by Ukrainian/Ukrainian-aligned forces	0.999	0.940
a_civ	Event initiated by civilians	1.000	0.993
a_other	Event initiated by a third party (e.g. U.S., EU, Red Cross)	1.000	0.960
t_aad	Anti-air defense, including shoulder-fired missiles	1.000	0.989
t_airstrike	Air strike, strategic bombing, helicopter strike	1.000	0.978
t_airalert	Air raid siren/alert	1.000	0.993
t_armor	Tank battle or assault	1.000	0.991
t_arrest	Arrest by security services or detention of prisoners of war	1.000	0.971
t_artillery	Shelling by field artillery, mortar, missiles or rockets	1.000	0.958
t_control	Establishment/claim of control over population center	0.999	0.989
t_firefight	Any exchange of small arms fire	1.000	0.987
t_killing	Assassination or targeted killing	1.000	0.985
t_ied	Improvised explosive device, landmine, car bomb, blast	1.000	0.980
t_raid	Ground assault, usually followed by a retreat	0.989	0.998
t_occupy	Occupation of territory or building	1.000	0.978
t_property	Destruction of property or infrastructure	1.000	0.949
t_cyber	Cyber attacks, including DDOS, website defacement	1.000	0.962
t_hospital	Attacks on hospitals and humanitarian convoys	1.000	0.978
t_milcas	Event report mentions military casualties	1.000	0.960
t_civcas	Event report mentions civilian casualties	1.000	0.954

Table 1: **In and Out-of-Sample Accuracy Statistics, by Variable**

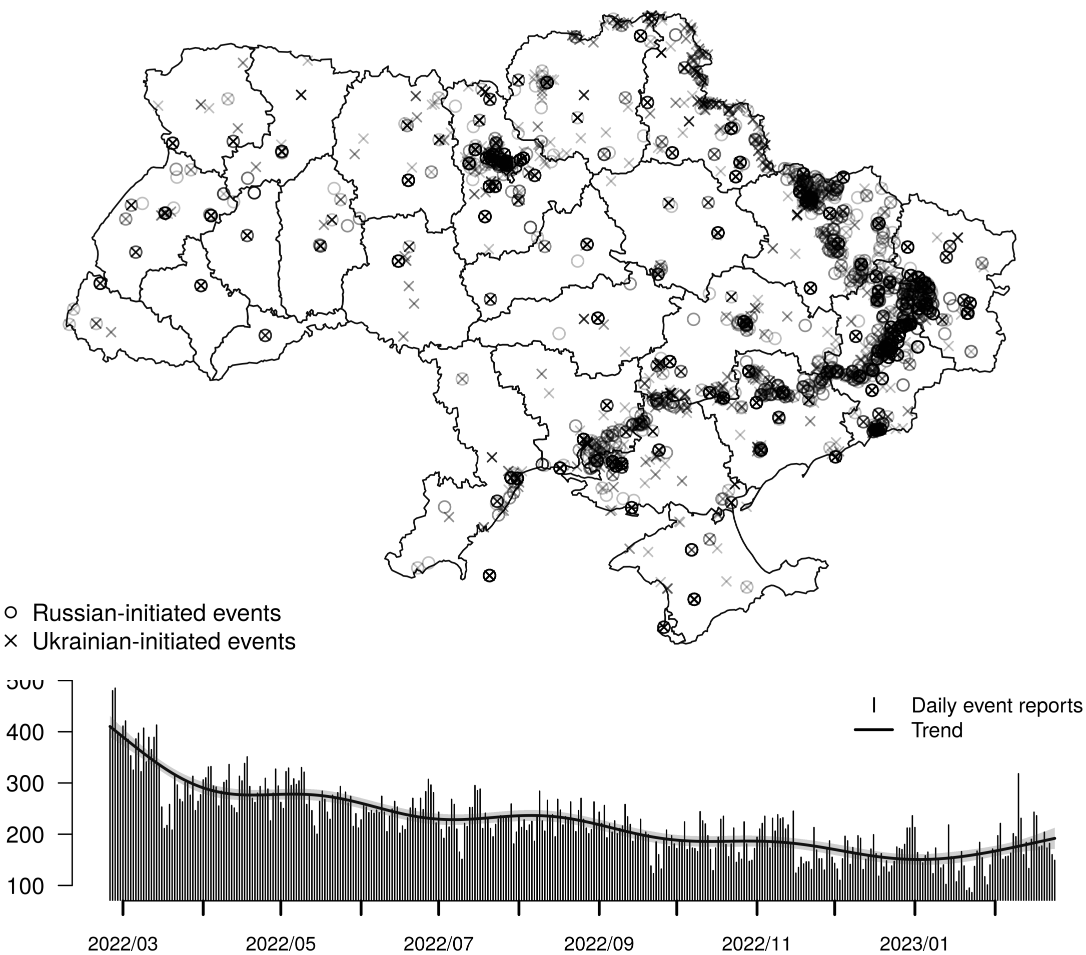
Table 1 describes the VIINA event categories, and reports the in- and out-of-sample predictive accuracy of LSTM-classified labels.[2] Each VIINA data release include two versions of each variable: (a) the predicted probability that a reported event belongs to each category, from the LSTM model, and (b) a binary indicator, coded 1 or 0. We dichotomize the predicted probabilities by minimizing Type I and Type II errors against the training set. For each variable, the algorithm considers 50,000 potential cutoffs from 0 to 1, compares the resulting binary values to training set labels, calculates false positive and negative rates, and selects the cutoff that minimizes the sum of these rates. Wordclouds (Appendix A2) indicate that predicted labels align with the conceptual definitions in Table 1.

Figure 1 illustrates the spatial and temporal distribution of all geocoded events in VIINA. The front line is clearly visible on the map, with a long, continuous cluster of event locations stretching from the northeast to the south. There is a secondary cluster around Kyiv, the location of heavy fighting early in the war, and a persistent target for Russian missile strikes. The remainder of events are scattered across the territory of Ukraine; these include a mix of rocket strikes and drone attacks behind enemy lines, arrests of suspected spies and collaborators, and other isolated incidents. Some of these are inevitably false positives, mostly resulting from geocoding errors (e.g. a similarly-named municipality in the wrong oblast). The time plot shows that event reporting peaked during the first month of the war, after which it settled into a plateau of 200-300 reported events per day.

In raw form, VIINA data include a high number of duplicate events. Duplicates occur whenever two or more media sources publish reports on the same incident, or when the same source publishes a follow-up story or update. These duplicates can be informative for certain research purposes, such as assessing the perceived "newsworthiness" of specific events, weighting events by media attention, or comparing coverage patterns across sources. For other research purposes, particularly those involving the analysis of local point pattern intensities and event counts, it is important to remove duplicates. Methods for doing so include one-a-day filters, where multiple reports of an event of the same type (e.g. Russian-initiated tank battle resulting in military casualties) in the same location on the same day are collapsed into a single unique event (e.g. Donnay et al., 2018), capture-recapture techniques, multiple systems estimation, and probabilistic record linkage.

[2] Validation accuracy calculated on February 3, 2023, the latest training set update at time of writing.

Figure 1: **Spatial and Temporal Distribution of VIINA Events**



1.4 Measurement of Territorial Control

In addition to event reports, VIINA tracks changes in territorial control. For every populated place in Ukraine on each day, VIINA classifies its control status into one of three categories: Russian control, Ukrainian control, and contested.[3] The third of these categories denotes that a populated place is either under divided control (e.g. Russian and Ukrainian forces each hold part of it), is under siege (e.g. Ukrainian forces hold an area surrounded by Russian forces, or vice versa), or is not controlled by either side (e.g. the "no man's land" between Russian and Ukrainian front line positions). These classifications are based on three sources: VIINA event reports on territorial control, polygon map layers from the Ukraine-based DeepStateMap project, and crowdsourced maps from Wikipedia.

The classification proceeds in four steps. First, on each day, the algorithm scans LSTM-classified event reports for indicators of changes in control within 10 kilometers of the front line, as it appeared in the VIINA territorial dataset on the previous day.[4] If there are no reported changes, we keep the previous day's control designation.[5] Second, we check whether each populated place falls within the territories designated by DeepStateMap as being under the control of Ukrainian forces, Russian forces, or being actively contested. Third, we use a similar spatial join procedure to extract the control status from Wikipedia's crowdsourced maps. Fourth, the algorithm takes a "vote", and assigns to each populated place the control status that a majority of these sources (two out of three) report.

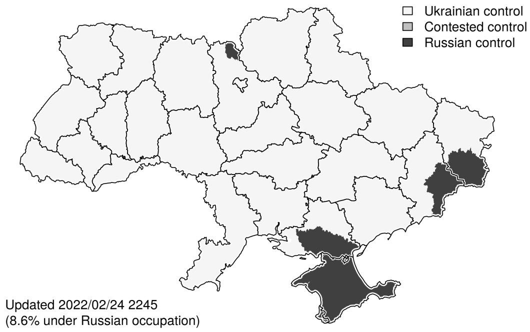
Figure 2 illustrates snapshots of territorial control from different periods in the war, using VIINA data. Figure 2a, from the evening of February 24, 2022, shows initial Russian gains over the first day of the full-scale invasion. Figure 2b, from March 15, 2022, shows Russian forces near the maximum extent of their territorial reach, with parts of the northern Kyiv, Chernihiv and Sumy oblasts under their control. Figure 2c, from July 15, 2022, shows Russia's modest gains in the Donbas, three months after Russia withdrew from the north and redeployed its forces for a more concentrated operation in the Donbas, eventually driving Ukrainian forces out of Sieverodonets'k and Lysychans'k in Luhans'k oblast. Figure

[3] We use all Ukrainian populated places listed in the GeoNames gazetteer (N = 33,156).

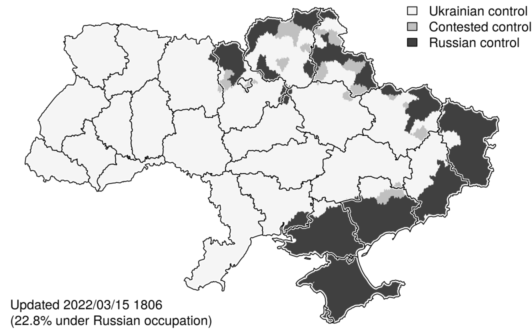
[4] We define "front line" locations as ones where the median distance between Ukrainian-controlled and Russian-controlled populated places is less than 10 kilometers.

[5] For the first day with available territorial control data (February 24, 2022), we use Wikipedia maps to establish the approximate location of the front line.

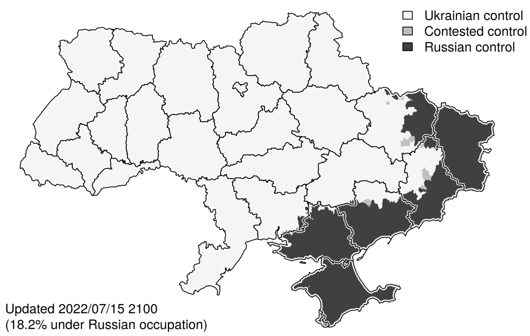
Figure 2: **Territorial Control Across All Populated Places in Ukraine**.



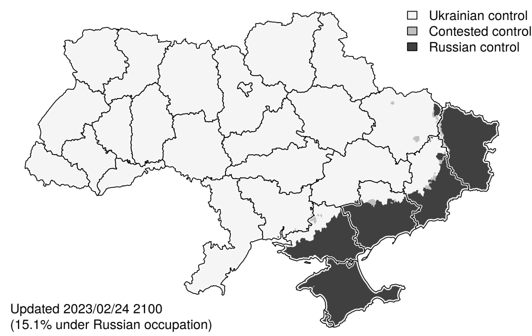
(a) **February 24, 2022**



(b) **March 15, 2022**



(c) **July 15, 2022**



(d) **February 24, 2023**

Note: white: Ukrainian control; gray: Contested control; black: Russian control.

2d, from February 24, 2023, shows Ukrainian and Russian positions one year into the war, several months after Ukraine's late-summer counteroffensive in Kharkiv and Kherson, and several weeks into Russia's 2023 winter offensive in Donets'k oblast.

2 Comparison of VIINA to Other Near-Real Time Datasets

Although VIINA went "live" less than two weeks into the war (March 7, 2022), it is not the only near-real time data project with coverage of Ukraine. On May 26, 2022, ACLED (Raleigh et al., 2010) launched a "Ukraine Crisis Hub," with manually-curated event data and interactive maps, updated weekly. In addition, VIINA was preceded by two global automated event datasets, both of which employ the CAMEO event coding typology:

GDELT (Leetaru and Schrodt, 2013) and ICEWS (Shilliday, Lautenschlager et al., 2012). We now compare the scope, features and spatio-temporal distributions of these datasets.

Table 2 summarizes the four projects. To facilitate direct comparisons, we subset each dataset by date (February 24, 2022 – February 24, 2023), location (Ukraine), and event type (conflict-related and/or violent events only).[6] Several patterns are worth noting. First, VIINA is the only near-real time resource to feature data on territorial control. Second, VIINA data updates are more frequent than ICEWS or ACLED — as of February 24, 2023, the latest available data for those projects were from January 3 and February 17, respectively, while GDELT and VIINA both had same-day data available. Third, VIINA has the most comprehensive event-level documentation, as the only resource with both text descriptions and source URLs for each report. Fourth, VIINA has the second-highest number of reported conflict events, behind only GDELT. Fifth, VIINA has the most comprehensive geocoding dictionary, with by far the largest number of unique event locations. Sixth, VIINA is the only resource based exclusively on local (Ukrainian, Russian) sources.

Figure 3 reveals key differences between the geographic and temporal distributions of events in the four datasets. Whereas ACLED events are concentrated in the south and east of the country, the largest clusters of GDELT and ICEWS events are in major cities, like Kyiv, Kharkiv and Kherson. VIINA resembles a hybrid of these distributions, with a large mass of events in the south-east (like ACLED), but also sizeable clusters in large cities (although less extreme than in GDELT or ICEWS). A closer look at nearest neighbor distances across these datasets confirms that the spatial distribution of VIINA events is closer to that of the manually-curated ACLED events.[7]

The temporal distributions in Figure 3 reveal additional differences between these datasets. GDELT, ICEWS and VIINA all feature a peak toward the beginning the invasion in February and March, followed by a gradual leveling-off. By contrast, ACLED shows a relatively flat trajectory until July 2022, followed by a gradual ratcheting-up of violence. Reports of shelling and missile strikes account for most of this mid-summer increase

[6] In the case of GDELT, we include only events under Quad Class 4 (Material Conflict). For ICEWS, we include only events with negative intensity (hostile). For SUNGEO, we include only events with `t_mil_b`= 1 (war/military operations). ACLED events did not require filtering by type.

[7] The average distance between each VIINA event and its geographically closest ACLED counterpart is 3.7 kilometers, compared to 4 km for GDELT and 5.8 km for ICEWS.

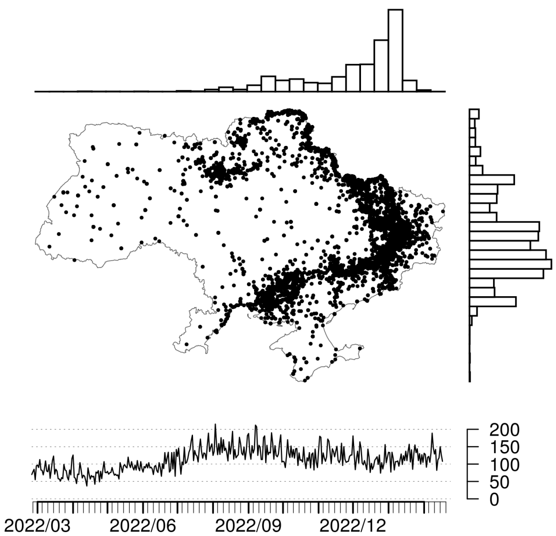
Dataset	ACLED	GDELT	ICEWS	**VIINA**
Includes Data on Violent Events?	✓	✓	✓	✓
Includes Data on Territorial Control?				✓
Fully Automated Event Classification?		✓	✓	✓
Includes Text Descriptions?	✓			✓
Includes URLs of Source Documents?		✓		✓
Number of Conflict Events in First Year	40,448	778,350	27,858	113,052
Number of Unique Event Locations	2,430	1,762	581	9,891
Most Recent Event (as of 2023/02/24)	2023/02/17	2023/02/24	2023/01/03	2023/02/24
Number of Event Types	24	50	105	21
Number of Sources	97	8,887	126	30
English-Only Corpus and Training Data?	No	Yes	Yes	No
Events from Ukrainian Sources (%)	74.2	10.1	4.2	92.6
Events from Russian Sources (%)	14	11.8	12	7.4
Events from Unknown Sources (%)	0	0	47.3	0

Table 2: **Comparison of VIINA to Other Near-Real Time Data on Ukraine**

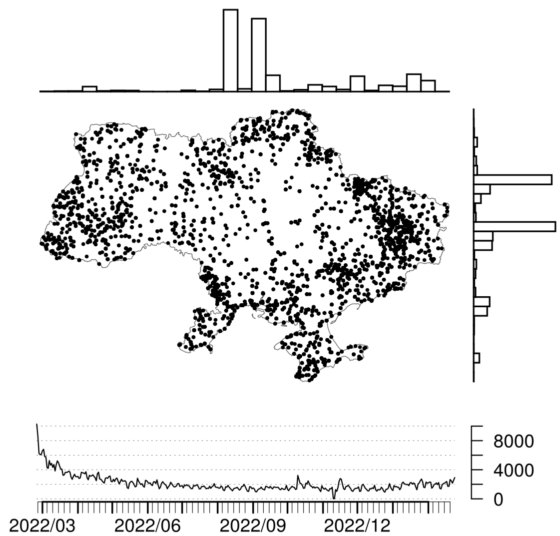
in ACLED's case; however, these event types are also present in the other three datasets, and their temporal distributions look nothing like ACLED's. A structural decomposition of these time series into their trend, seasonal and residual components (Appendix A3) further confirms ACLED's outlier status. ACLED's trend component — like its raw time series — is negatively correlated with the other three, while its residuals show almost no correlation with the others. Meanwhile, the VIINA, GDELT and ICEWS time series are all positively correlated with each other, both in raw form and decomposed.

Because there is no "ground truth" data source that we can use as a benchmark, we cannot definitely say which of these four datasets most faithfully captures the reality on the ground. However, our analysis shows that VIINA has some notable comparative advantages, especially as regards the availability of territorial control data and frequency of updates. Furthermore, its spatio-temporal distribution occupies a middle ground between existing alternatives. The geographic distribution of VIINA events more closely resembles the manually-curated ACLED, while their temporal distribution more closely resembles those of the CAMEO-based automated GDELT and ICEWS datasets.

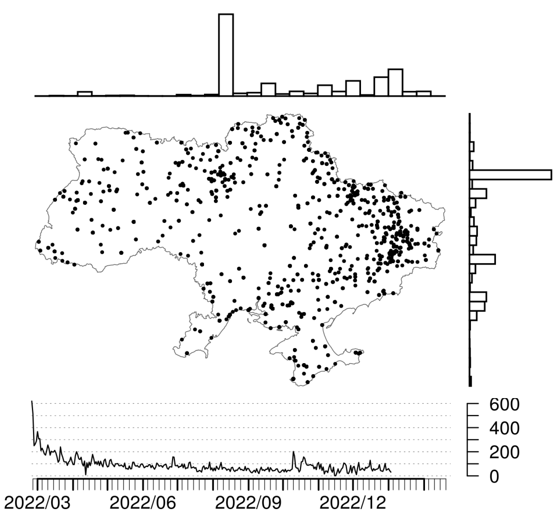
Figure 3: **Summary of Near-Real Time Event Datasets on Ukraine**



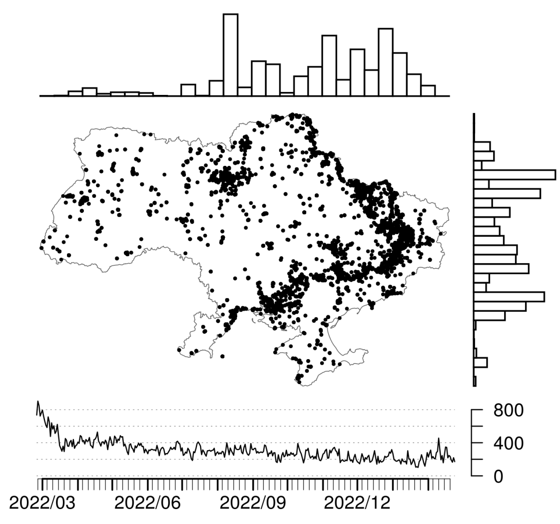
(a) ACLED



(b) GDELT



(c) ICEWS



(d) VIINA

3 Applications: War and Economic Activity

To demonstrate how students of political economy might use VIINA in their own research, we offer two illustrative examples. In the first, we will consider the empirical relationship between battlefield dynamics (territorial control, artillery shelling) and urban economic activity, using satellite-observed nighttime light emissions as a proxy for the latter. In the second, we consider the consequences of war for Ukraine's agricultural sector, using a satellite-observed vegetation index as a proxy for crop cultivation.

Both of these analyses explore the short-term economic consequences of armed conflict. A significant body of social science research has considered the role of wartime physical damage and occupation as drivers (or inhibitors) of economic productivity and growth. Despite general agreement that the physical destruction of assets, capital, and human life can generate a negative economic shock (Collier et al., 2003), there is debate over the magnitude and durability of these shocks (Davis and Weinstein, 2002; Miguel and Roland, 2011). The economic costs of war can also be quite difficult to assess in the near term, due to war-related disruptions in national accounting systems, survey research, and other data limitations. For example, information on key explanatory variables, like changes of territorial control, is often unavailable, unreliable or imprecise, precluding inquiry into the short-term effects of occupation and divided control.[8] The following illustrative analyses are therefore ones that would be difficult, if not impossible, to implement with datasets other than VIINA, including those we explored in the previous section.

3.1 Nighttime Economic Activity in Urban Areas

Nearly all production processes and consumption activities in the evening require light. Light emissions capture a wide range of human activity, from the use of household appliances and office equipment to transportation, sporting events, street markets, restaurants, nighttime factory operations, roadworks and construction. War can affect these activities through several channels, including power grid damage, population displacement, curfews,

[8] For example, Arias, Ibáñez and Zambrano (2019) — a rare study that considers territorial control as an explanatory variable (in Colombia) — uses information on the presence of armed groups at the rural district level in the preceding 10 years, rather than time-variant information on changes in control.

and intentional dimming to avoid detection. Such disruptions constrain economic development (Andersen and Dalgaard, 2013), and have many negative downstream consequences for public health (Klinger, Landeg and Murray, 2014).

A growing literature in economics (Chen and Nordhaus, 2011; Henderson, Storeygard and Weil, 2012) and political science (Agnew et al., 2008; Weidmann and Schutte, 2017) has used luminosity as a proxy for economic output. The motivating assumption behind this approach is that measurement error in nighttime lights is uncorrelated with measurement error in national accounts and survey means, because luminosity is the product of a wholly independent data generating process, captured by satellites homogeneously across and within national borders (Pinkovskiy and Sala-i Martin, 2016). This measurement strategy has particular appeal in places where reliable statistics and income accounts are unavailable, and in difficult-to-reach areas, like zones of ongoing armed conflict. Past studies have used luminosity data to investigate the economic impact of war in Iraq (Lyall, 2022), Syria (Li and Li, 2014), Yemen (Jiang et al., 2017), and Ukraine's Donbas region (Kochnev, 2019).

In the following analysis, we use luminosity data from the Visible Infrared Imaging Radiometer Suite (VIIRS) program's day/night band (DNB) (Elvidge et al., 2017), which have a resolution of 15 arc seconds, or roughly 322 meters at Ukraine's latitude. Following the approach taken by past studies, we pre-process the VIIRS data by excluding pixels potentially contaminated by cloud cover, and use an urban mask to limit the sample to built-up areas, where contamination from transient lights (i.e. fires and other events unrelated to economic activity) is less likely.[9] We aggregate these data to the municipality-month level, using the subset of Ukrainian populated places listed in the GeoNames gazetteer that overlap with the urban mask.[10] This yields a panel dataset of 880 populated places observed over 10 months, ending in February 2023.[11] For each municipality-month observation, we calculated average nightly luminosity from the VIIRS data, along with the proportion of days spent under Ukrainian, Russian or contested control, and the total number of artillery or rocket strikes — both from VIINA. To prevent double-counts of shelling incidents, we

[9] We use the VIIRS DNB Cloud Mask to exclude pixels marked as "Probably" or "Confident Cloudy," and a 2020 built-up extent layer from (Zhao et al., 2022) as the urban mask.

[10] The approximate boundaries of these populated places are represented by tessellated polygons, available through the VIINA GitHub page in `geojson` format.

[11] The time period excludes July and August due to missing luminosity data.

used a one-a-day filter prior to this aggregation, collapsing multiple reports of shelling on the same day at the same location into a single unique event.

Our interest is in how the luminosity of a populated place changed relative to its pre-invasion benchmark in the same month of the previous year. Following Kronmal (1993)'s specification correction for ratio dependent variables, we express the log of this year-on-year ratio as a difference of two logged variables, and include the log of its denominator as an offset variable on the right hand side. Our estimating equation is the following:

$$\begin{aligned}\log(Y_{it}^{\text{wartime}}) = &\log(Y_{it}^{\text{peacetime}}) + \beta_1 \text{Contested}_{it-1} + \beta_2 \text{Russian-occupied}_{it-1} \\ &+ \beta_3 \log(\text{Shelling}_{it-1}) + \alpha_i + \omega_t + \epsilon_{it} \end{aligned} \tag{1}$$

where i indexes the populated place and t indexes the month. Y_{it}^{wartime} represents average nightly luminosity in location i and month t following Russia's invasion, $Y_{it}^{\text{peacetime}}$ is average luminosity for the same location and month of the most recent year before the invasion.[12] In addition to this offset, the right-hand side includes fixed effects for municipality and month of the war (α_i, ω_t), the proportion of days in the past month that i was under contested or Russian control (with Ukrainian control as the omitted, baseline category), and the number of unique artillery shelling incidents reported during the previous month, logged to reduce skewness in this variable. Robust standard errors are clustered by populated place.

Column (1) in Table 3 reports coefficient estimates from this regression. The results suggest that populated places under contested control tend to experience a significant decline in economic activity. A full month of contestation is associated with a 52 percentage point decrease in luminosity the following month (i.e. $(e^{-0.7}-1)\times 100 = -50.2$). Luminosity in municipalities fully under Russian occupation, meanwhile, is significantly *higher* than in Ukrainian-controlled areas. All else equal, locations that spend a month under Russian occupation experience a 62 percentage point rise in luminosity (i.e. $(e^{0.48}-1)\times 100 = 61.5$).

Table 3 further suggests that luminosity is lower in areas exposed to artillery shelling and rocket strikes. Doubling the number of shelling incidents per month is associated with a 6 percent decline in a municipality's luminosity the following month (i.e. $(2^{-0.08}-1)\times 100 =$

[12] While the specification in equation (1) constrains the coefficient estimate on the offset variable $\log(Y_{it}^{\text{peacetime}})$ to be equal to 1, we also estimated an analogous model, which lifts this restriction. Numerical estimates for $\hat{\beta}_1, \hat{\beta}_2$ and $\hat{\beta}_3$ align with to those reported here.

−5.5). This latter result is not surprising, considering that the period of observation includes Russia's campaign of massive missile strikes against Ukraine's critical infrastructure in the fall of 2022. While the model's results do not reveal the mechanism behind this empirical relationship — whether, for instance, the decline in luminosity reflects physical damage to the electrical grid or planned power shutoffs to ease the strain on the generating system — they are consistent with anecdotal accounts that these strikes have been quite disruptive to economic life in Ukraine's cities.

Taken together with the positive coefficient estimate on Russian territorial control, these results illuminate some of the regional inequalities induced by Russia's invasion: much of the country has gone dark, while Russian-occupied territories have mostly avoided this fate. This pattern may reflect Russia's efforts to insulate occupied territories from its own strike campaign (e.g. by integrating them into Russia's electrical grid), Ukraine's hesitancy to attack energy infrastructure in these areas, or some combination of the two.

We note that our estimation strategy is not designed to identify a causal effect, and it is quite possible that some unobserved variable is driving variation in both luminosity and contestation. For example, more economically vibrant places may be more attractive targets for Russian attack, or they may be higher priority areas for Ukraine's defense. Other threats to inference include spillover effects: war-induced power outages in one location might trigger outages elsewhere due to the tight coupling of power systems across municipalities. In most such cases, we would expect the direction of bias to be in the opposite direction from what we find, attenuating rather than inflating the negative estimates for contestation and artillery shelling.[13] While space constraints limit the scope of our brief inquiry here, a more rigorous analysis with VIINA might consider additional sources of variation and bias, including interdependence, spatial autocorrelation, and the endogeneity of violence and territorial control to pre-existing local economic realities.

[13] If more luminous cities are more likely to be contested or shelled, we should expect a positive correlation between these variables. If locations not exposed to violence or contestation experience blackouts due to disruptions elsewhere in the system, we should expect a noisier relationship between these variables.

Table 3: Violence, Occupation, and Economic Activity.

	Luminosity (1)	NDVI (2)
Contested control	-0.7^{**}	-0.05^{**}
	(0.14)	(0.01)
Russian control	0.48^{**}	0.03^{**}
	(0.13)	(0.01)
log(Shelling Incidents)	-0.08^{*}	-0.004
	(0.03)	(0.01)
Number of observations	8,140	190,264
RMSE	0.742	0.247
AIC	20,030	42,524
BIC	26,285	220,531
Adjusted R^2	0.648	0.627
FE: populated places (α_i)	✓	✓
FE: months (ω_t)	✓	✓
Number of pop. places × months	880 × 10	17,513 × 11

Outcomes are (1) logged average nightly luminosity and (2) logged normalized difference vegetation index in populated place i and month t. Fixed effect OLS coefficient estimates, standard errors clustered by pop. place in parentheses. All models include offset for (1) logged luminosity and (2) logged NDVI in the same month of past year. Sample restricted to (1) built-up areas and (2) irrigated cropland and pasture. Significance levels: $^{*}p < 0.05$, $^{**}p < 0.01$

3.2 Vegetation in Cropland Areas

Our second illustrative example considers the costs of war for Ukraine's agricultural sector. Armed conflict can have profound consequences for agricultural land use, short term and long term. Active combat can restrict farmers' access to their fields, destroy irrigation infrastructure, tractors and other farming equipment, and contaminate fields with landmines and unexploded munitions. More indirectly, war can create supply disruptions to agricultural inputs, like seeds and fertilizers, limit access to markets, and create agricultural labor shortages due to death, displacement and conscription. There is some debate over how severe and persistent these disruptions are. Research on the long-term agricultural legacy of war has found conflicting evidence on whether the bombing of fertile land generates a durable pattern of underdevelopment and poverty (Miguel and Roland, 2011; Lin, 2022). There is also disagreement across studies of short-term disruptions. Some researchers have found that war exposure inhibits the cultivation of land, leading to a decrease in agricultural activity and, ultimately, the abandonment of cropland (Witmer and O'Loughlin, 2009; Baumann and Kuemmerle, 2016). Others have found that agricultural production can be surprisingly resilient even during periods of active conflict, as households adapt their farming practices to these new realities (Arias, Ibáñez and Zambrano, 2019).

Recent research in agricultural economics (Lobell et al., 2020) and remote sensing (Bai et al., 2008) has used the Normalized Difference Vegetation Index (NDVI) to assess changes in vegetation conditions and productivity. Positive changes in this index denote increases in vegetation, while a decline indicates degradation and desertification. How this index relates to agricultural land use depends on temporal scale. Long-term increases in NDVI — over years and decades — may indicate permanent crop abandonment, as shrubs and grassland encroach on fields that are not annually plowed or harvested (Witmer, 2008; Löw et al., 2018). In the short term — over weeks and months — NDVI can reliably approximate yield and track annual growth dynamics for a wide variety of crops, including rice (Tomar et al., 2014), corn (Johnson, 2014) and wheat (Becker-Reshef et al., 2010). A study of tomato farms in Ukraine's Kherson and Mykolayiv oblasts, for example, found the highest NDVI values during the fruit formation phase, and the lowest in the off-season and planting phase (Lykhovyd, Vozhehova and Lavrenko, 2022). More recently, researchers have used NDVI decreases to monitor war-induced wheat crop losses in Ukraine (Deininger et al., 2022).

To study changes in vegetation following Russia's invasion of Ukraine, we use NDVI estimates from Moderate Resolution Imaging Spectroradiometer (MODIS) MYD13C1 cloud-free spatial composites (Didan, 2021), which are available at twice-monthly, 16-day intervals at a resolution of 0.05 degrees, or 3,860 meters at Ukraine's latitude. To exclude forested areas, grassland and other non-agricultural land from the sample, we use a mask for areas designated by the USGS Land Use and Land Cover Classification system as irrigated cropland and pasture. As with luminosity data, we aggregate the NDVI values to the municipality-month level, using the subset of GeoNames populated places that overlap with this agricultural mask. The resulting panel dataset includes 17,513 populated places observed over 11 months. We adopt the same estimation strategy as in equation (1), with Y_{it}^{wartime} denoting average NDVI in location i and month t after the invasion, and $Y_{it}^{\text{peacetime}}$ representing NDVI for the same location and month in the last year before the invasion.

Coefficient estimates from this model appear in the second column of Table 3. According to these estimates, locations in contested areas saw a significant decline in vegetation relative to areas that remained under Ukrainian control: a month of contestation is associated with a 5 percentage point decrease in NDVI (i.e. $(e^{-0.05} - 1) \times 100 = -4.8$). Areas fully under Russian occupation, meanwhile, saw an *increase* in vegetation relative to Ukrainian-controlled areas: a month under Russian occupation is associated with a 3 percentage point rise in NDVI (i.e. $(e^{0.03} - 1) \times 100 = 3.1$).

What might be driving these divergent patterns of vegetation? Because abandoned cropland typically shows increases in natural vegetation only after fields are left fallow for several seasons, the observed short-term rise in vegetation vigor on Russian-occupied irrigated cropland likely suggests that farming on these territories has been less affected by the war than farming in areas under Ukrainian control.[14] Of course, this month-on-month increase in vegetation tells us little about how many of these crops ultimately reached the market, and even less about whether this apparent resilience reflects adaptation by local

[14] Agriculture disrupts natural conditions favorable to native plant growth. The leveling of land for irrigation and farming disrupts natural drainage patterns, concentrates salts, and displaces animals and microorganisms that disperse seeds and develop soils. Depending on rainfall levels and other local conditions, it can take several years for annual and perennial herbs to begin colonizing former farm lands, and more still for shrubs, trees and other longer-lived species to take root.

farmers (Arias, Ibáñez and Zambrano, 2019) or cultivation following the seizure of farm assets by occupying forces. Yet these estimates align with the view that the war has had disparate impacts on economic activity, depending on a location's proximity to the front line, and on which side of that line a location happened to be situated.

4 Conclusion

This article has introduced a new near-real time data project on violence and territorial control in a conventional interstate war (Russia's invasion of Ukraine), and illustrated two applications of these data to questions of political economy. Using remote sensing data on nighttime luminosity and remote sensing data on vegetation, we found significant decline in economic activity in locations most exposed to combat. We estimate that urban areas that spent a month under contestation — where neither combatant had full control — saw a 50 percentage point drop in nighttime luminosity the following month. We also find a decline in vegetation on agricultural land in actively contested areas. In areas fully under Russian occupation, however, we find an increase in both luminosity and vegetation.

These illustrative analyses are intended to spark ideas, rather than to offer a fully-realized set of empirical investigations. Yet these applications also ones that would be infeasible without VIINA data. No previous data projects, to our knowledge, have provided regularly-updated information on territorial control at the level of individual populated places — or at any other administrative level. No data project provides equally detailed documentation on each report, with text descriptions and URLs that could be used to replicate these analyses, construct new variables, and build entirely new models.

The main note of caution is that the results of any near-real time analyses are subject to change with the situation on the ground. As new events unfold, and as the geography of fighting changes, so will one's empirical results. If the purpose of one's analysis is prediction or forecasting, this may be less of an issue. If the purpose is hypothesis-testing or causal inference, any analysis should clearly articulate how its scope is bounded in space and time.

References

Abadi, Martín, Ashish Agarwal, Paul Barham, Eugene Brevdo, Zhifeng Chen, Craig Citro, Greg S Corrado, Andy Davis, Jeffrey Dean, Matthieu Devin et al. 2016. "Tensorflow: Large-scale machine learning on heterogeneous distributed systems." *arXiv preprint arXiv:1603.04467* .

Abadie, Alberto and Javier Gardeazabal. 2003. "The economic costs of conflict: A case study of the Basque Country." *American economic review* 93(1):113–132.

Agnew, John, Thomas W Gillespie, Jorge Gonzalez and Brian Min. 2008. "Baghdad nights: evaluating the US military 'surge'using nighttime light signatures." *Environment and Planning A* 40(10):2285–2295.

Andersen, Thomas Barnebeck and Carl-Johan Dalgaard. 2013. "Power outages and economic growth in Africa." *Energy Economics* 38:19–23.

Arias, María Alejandra, Ana María Ibáñez and Andrés Zambrano. 2019. "Agricultural production amid conflict: Separating the effects of conflict into shocks and uncertainty." *World Development* 119:165–184.

Azar, Edward E. 1980. "The conflict and peace data bank (COPDAB) project." *Journal of Conflict Resolution* 24(1):143–152.

Bai, Zhanguo G, David L Dent, Lennart Olsson and Michael E Schaepman. 2008. "Proxy global assessment of land degradation." *Soil use and management* 24(3):223–234.

Bauer, Michal, Christopher Blattman, Julie Chytilová, Joseph Henrich, Edward Miguel and Tamar Mitts. 2016. "Can War Foster Cooperation?" *Journal of Economic Perspectives* 30(3):249–74.

Baumann, Matthias and Tobias Kuemmerle. 2016. "The impacts of warfare and armed conflict on land systems." *Journal of land use science* 11(6):672–688.

Becker-Reshef, Inbal, Eric Vermote, Mark Lindeman and Christopher Justice. 2010. "A generalized regression-based model for forecasting winter wheat yields in Kansas and Ukraine using MODIS data." *Remote sensing of environment* 114(6):1312–1323.

Berman, Eli, Jacob N. Shapiro and Joseph H. Felter. 2011. "Can hearts and minds be bought? The economics of counterinsurgency in Iraq." *Journal of Political Economy* 119(4):766–819.

Biddle, Stephen. 2004. *Military power: Explaining victory and defeat in modern battle.* Princeton University Press.

Bond, Doug, Joe Bond, Churl Oh, J Craig Jenkins and Charles Lewis Taylor. 2003. "Integrated data for events analysis (IDEA): An event typology for automated events data development." *Journal of Peace Research* 40(6):733–745.

Chen, Xi and William D Nordhaus. 2011. "Using luminosity data as a proxy for economic statistics." *Proceedings of the National Academy of Sciences* 108(21):8589–8594.

Chollet, François. 2015. "keras.".
URL: *https://github.com/fchollet/keras*

Collier, Paul, Lani Elliott, Håvard Hegre, Anke Hoeffler, Marta Reynal-Querol and Nicholas Sambanis. 2003. *Breaking the conflict trap: Civil war and development policy.* Vol. 41181 World Bank Publications.

Davis, Donald R and David E Weinstein. 2002. "Bones, bombs, and break points: the geography of economic activity." *American Economic Review* 92(5):1269–1289.

Deininger, Klaus, Daniel Ayalew Ali, Nataliia Kussul, Andrii Shelestov, Guido Lemoine and Hanna Yailimova. 2022. "Quantifying war-induced crop losses in Ukraine in near real time to strengthen local and global food security." *World Bank Policy Research Working Paper* (10123).

Dell, Melissa and Pablo Querubin. 2018. "Nation building through foreign intervention: Evidence from discontinuities in military strategies." *The Quarterly Journal of Economics* 133(2):701–764.

Didan, K. 2021. *MODIS/Aqua Vegetation Indices 16-Day L3 Global 0.05Deg CMG V061*. NASA EOSDIS Land Processes DAAC.
URL: *https://doi.org/10.5067/MODIS/MYD13C1.061*

Donnay, Karsten, Eric Dunford, Erin C. McGrath, David Backer and David E. Cunningham. 2018. "Integrating Conflict Event Data." *Journal of Conflict Resolution* (forthcoming).

Dupuy, Trevor Nevitt. 1979. *Numbers, Predictions and War: Using History to Evaluate Combat Factors and Predict the Outcome of Battles*. Bobbs-Merrill.

Elvidge, Christopher D, Kimberly Baugh, Mikhail Zhizhin, Feng Chi Hsu and Tilottama Ghosh. 2017. "VIIRS night-time lights." *International journal of remote sensing* 38(21):5860–5879.

Gerner, Deborah J, Philip A Schrodt, Omür Yilmaz and Rajaa Abu-Jabr. 2002. Conflict and mediation event observations (CAMEO): A new event data framework for a post cold war world. In *2002 Annual Meeting of the American Political Science Association*. Vol. 29.

Glick, Reuven and Alan M Taylor. 2010. "Collateral damage: Trade disruption and the economic impact of war." *The Review of Economics and Statistics* 92(1):102–127.

Grosjean, Pauline. 2014. "Conflict and social and political preferences: Evidence from World War II and civil conflict in 35 European countries." *Comparative Economic Studies* 56(3):424–451.

Henderson, J Vernon, Adam Storeygard and David N Weil. 2012. "Measuring economic growth from outer space." *American Economic Review* 102(2):994–1028.

Hochreiter, Sepp and Jürgen Schmidhuber. 1997. "Long short-term memory." *Neural computation* 9(8):1735–1780.

Jiang, Wei, Guojin He, Tengfei Long and Huichan Liu. 2017. "Ongoing conflict makes Yemen dark: From the perspective of nighttime light." *Remote Sensing* 9(8):798.

Johnson, David M. 2014. "An assessment of pre-and within-season remotely sensed variables for forecasting corn and soybean yields in the United States." *Remote Sensing of Environment* 141:116–128.

Kalyvas, Stathis N. 2006. *The Logic of Violence in Civil War.* Cambridge.

King, Gary and Will Lowe. 2003. "An Automated Information Extraction Tool for International Conflict Data with Performance as Good as Human Coders: A Rare Events Evaluation Design." *International Organization* 57:617–642.

Klinger, Chaamala, Owen Landeg and Virginia Murray. 2014. "Power outages, extreme events and health: a systematic review of the literature from 2011-2012." *PLoS currents* 6:ecurrents–dis.

Kochnev, Artem. 2019. "Dying light: War and trade of the separatist-controlled areas of Ukraine." *Available at SSRN 3579099* .

Korovkin, Vasily and Alexey Makarin. 2023. "Conflict and Intergroup Trade: Evidence from the 2014 Russia-Ukraine Crisis." *American Economic Review* 113(1):34–70.

Kronmal, Richard A. 1993. "Spurious correlation and the fallacy of the ratio standard revisited." *Journal of the Royal Statistical Society: Series A (Statistics in Society)* 156(3):379–392.

Leetaru, Kalev and Philip A. Schrodt. 2013. "GDELT: Global Data on Events, Location and Tone, 1979-2012.". International Studies Association Annual Meeting.

Li, Xi and Deren Li. 2014. "Can night-time light images play a role in evaluating the Syrian Crisis?" *International Journal of Remote Sensing* 35(18):6648–6661.

Lin, Erin. 2022. "How war changes land: Soil fertility, unexploded bombs, and the underdevelopment of Cambodia." *American journal of political science* 66(1):222–237.

Lobell, David B, George Azzari, Marshall Burke, Sydney Gourlay, Zhenong Jin, Talip Kilic and Siobhan Murray. 2020. "Eyes in the Sky, Boots on the Ground: Assessing Satellite- and Ground-Based Approaches to Crop Yield Measurement and Analysis."

American Journal of Agricultural Economics 102(1):202–219.
URL: *https://onlinelibrary-wiley-com.proxy.lib.umich.edu/doi/abs/10.1093/ajae/aaz051*

Löw, Fabian, Alexander V Prishchepov, François Waldner, Olena Dubovyk, Akmal Akramkhanov, Chandrashekhar Biradar and John PA Lamers. 2018. "Mapping cropland abandonment in the Aral Sea Basin with MODIS time series." *Remote Sensing* 10(2):159.

Lyall, Lloyd. 2022. "Diverse neighbors and post-conflict recovery at the village level: Evidence from Iraq after ISIL." *Journal of Peace Research* 59(4):543–561.

Lykhovyd, Pavlo, Raisa Vozhehova and Sergiy Lavrenko. 2022. "Annual NDVI dynamics observed in industrial tomato grown in the south of Ukraine." *Modern Phytomorphology* 16:160–164.

McClelland, Charles. 1978. *World Event/Interaction Survey:(WEIS), 1966-1978*. Inter-University Consortium for Political and Social Research.

Miguel, Edward and Gerard Roland. 2011. "The long-run impact of bombing Vietnam." *Journal of development Economics* 96(1):1–15.

Pinkovskiy, Maxim and Xavier Sala-i Martin. 2016. "Lights, camera... income! Illuminating the national accounts-household surveys debate." *The Quarterly Journal of Economics* 131(2):579–631.

Raleigh, Clionadh, Andrew Linke, Håvard Hegre and Joakim Karlsen. 2010. "Introducing ACLED: Armed Conflict Location and Event Data." *Journal of Peace Research* 47(5):651–660.

Rozenas, Arturas and Yuri Zhukov. 2019. "Mass Repression and Political Loyalty: Evidence from Stalin's 'Terror by Hunger'." *American Political Science Review* 113(2):569–583.

Schrodt, Philip A, Shannon G Davis and Judith L Weddle. 1994. "Political science: KEDS—a program for the machine coding of event data." *Social Science Computer Review* 12(4):561–587.

Sherstinsky, Alex. 2020. “Fundamentals of recurrent neural network (RNN) and long short-term memory (LSTM) network.” *Physica D: Nonlinear Phenomena* 404:132306.

Shilliday, Andrew, Jennifer Lautenschlager et al. 2012. “Data for a worldwide ICEWS and ongoing research.” *Advances in Design for Cross-Cultural Activities* 455.

Sundberg, Ralph and Erik Melander. 2013. “Introducing the UCDP georeferenced event dataset.” *Journal of Peace Research* 50(4):523–532.

Tilly, Charles. 1978. *From Mobilization to Revolution.* Addison-Wesley.

Tomar, Vandana, Vinay Prasad Mandal, Pragati Srivastava, Shashikanta Patairiya, Kartar Singh, Natesan Ravisankar, Natraj Subash and Pavan Kumar. 2014. “Rice equivalent crop yield assessment using MODIS sensors’ based MOD13A1-NDVI data.” *IEEE sensors journal* 14(10):3599–3605.

Weidmann, Nils B and Sebastian Schutte. 2017. “Using night light emissions for the prediction of local wealth.” *Journal of Peace Research* 54(2):125–140.

Witmer, Frank D. W. and John O’Loughlin. 2009. “Satellite Data Methods and Application in the Evaluation of War Outcomes: Abandoned Agricultural Land in Bosnia-Herzegovina After the 1992–1995 Conflict.” *Annals of the Association of American Geographers* 99(5):1033–1044.
URL: *https://doi.org/10.1080/00045600903260697*

Witmer, Frank DW. 2008. “Detecting war-induced abandoned agricultural land in northeast Bosnia using multispectral, multitemporal Landsat TM imagery.” *International Journal of Remote Sensing* 29(13):3805–3831.

Zhao, Min, Changxiu Cheng, Yuyu Zhou, Xuecao Li, Shi Shen and Changqing Song. 2022. “A global dataset of annual urban extents (1992–2020) from harmonized nighttime lights.” *Earth System Science Data* 14(2):517–534.

Zhukov, Yuri M. 2016. “Trading hard hats for combat helmets: The economics of rebellion is east Ukraine.” *Journal of Comparative Economics* 44(1):1–15.

Appendix

For Online Publication

A1 Intercoder Reliability Statistics

The current section reports intercoder reliability statistics for the subset of training set documents that were held constant across all coders. Two research assistants (coders 1 and 2) read 650 documents each, 300 of which overlapped. The author (coder 3) read all training set documents. Table A1.1 summarizes the intercoder reliability statistics, averaged across all variables. Table A1.2 reports full intercoder reliability statistics for each variable.

Coders	N Coders	Agreement	Holsti's CR	Krippendorff's α	Brennan Prediger's κ	Lotus
1,2,3 (N=300)	3	0.98	0.99	0.62	0.97	0.99
1,2 (N=300)	2	0.99	0.99	0.67	0.97	0.99
1,3 (N=650)	2	0.98	0.98	0.66	0.97	0.99
2,3 (N=650)	2	0.99	0.99	0.66	0.97	0.99

Table A1.1: **Intercoder Reliability Statistics, Averaged Over All Variables**

A2 Validation of Event Classifications

Table A2.3 reports validation accuracy statistics for LSTM models trained on the pooled, multilingual (Ukrainian and Russian) training set, compared to models trained on each monolingual training set alone. As the table reports, the pooled training set yields predictions with higher mean accuracy (i.e. averaged across variables) and lower variance (of accuracy statistics across variables) than either monolingual training set.

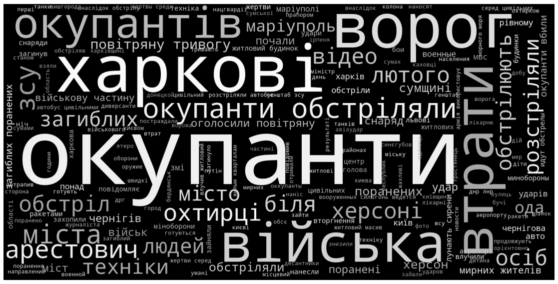
Figure A2.1 illustrates six of the event categories as wordclouds. These images represent the subset of reports in the test set, whose predicted probabilities of belonging to each category were in the 99th percentile. Font sizes are proportional to each word's frequency in the text. The wordclouds indicate that predicted labels generally align with the conceptual definitions in Table 1. For example, the `t_armor` category includes many documents mentioning tank battles, while `t_civcas` frequently mentions civilians in the accusative case, indicating that they are the direct object of an action. Figure A2.1 also reveals some idiosyncratic uses of language, which off-the-shelf dictionary classifiers — scanning the text for standard terms like "Russian forces" — might miss. For example, Ukrainian sources routinely refer to Russian troops as "occupiers" without mentioning their country of origin.

A3 Comparison of VIINA to Other Data Projects

Table A3.4 reports mean nearest neighbor distances between reported events in VIINA, GDELT, ICEWS and ACLED. The table shows that the average VIINA event is closest, on average, to events in ACLED (3.71 km), followed by GDELT (4.05 km) and ICEWS (5.77). Meanwhile, the average ACLED event is closest to events in VIINA (1.55 km), followed by GDELT (4.04 km) and ICEWS (6.31 km).

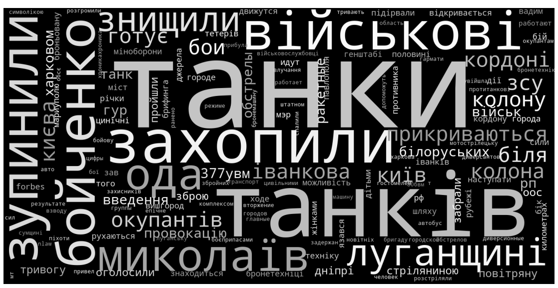
Table A3.5 reports Spearman's correlation coefficients for the time series of each dataset, both (a) in raw form, and decomposed into their (b) trend components, (c) seasonal components, and (d) residual components. The table shows that ACLED's time series is negatively correlated with the other three, both in raw form, and as a trend. The pairwise correlation coefficients are also substantially smaller for ACLED's seasonal and residual components than they are for any of the other datasets.

Figure A2.1: **Wordclouds of LSTM-Classified Events**.



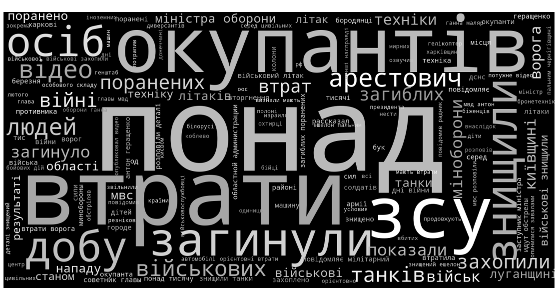
(a) **Russian-initiated events** [`a_rus`]
"окупанти" (okupanty) means "occupiers" (U)
"ворог" (voroh) means "enemy" (U)

(b) **Ukrainian-initiated events** [`a_ukr`]
"зсу" (zsu) is "Armed Forces of Ukraine" (U)
"всу" (vsu) is "Armed Forces of Ukraine" (R)

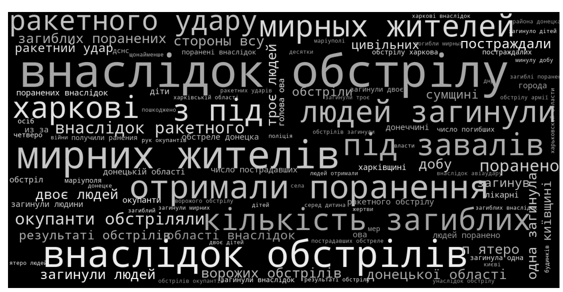


(c) **Armor / tank battles** [`t_armor`]
"танки" (tanki) means "tanks" (R)
"танків" (tankiv) means "tanks" (U, acc)

(d) **Arrests / detentions** [`t_arrest`]
"полон" (polon) means "captivity / POW camp" (U)
"захопили" (zahopyly) means "captured" (U)



(e) **Military casualties** [`t_milcas`]
"понад" (ponad) means "more than" (U)
"втрати" (vtraty) means "losses" (U)
"загинули" (zahynuly) means "died" (U)
"окупантів" (okupantiv) means "occupiers" (U, acc)



(d) **Civilian casualties** [`t_civcas`]
"внаслідок обстрілів" (vnasklidok obstriliv)
means "due to shelling" (U)
"мирних жителів" (myrnykh zhyteliv)
means "civilians" (U, acc)

Note: R: Russian language. U: Ukrainian language. acc: accusative case ending.

Variable	Agreement	Holsti's CR	Krippendorff's α	Brennan Prediger's κ	Lotus
t_mil	0.85	0.90	0.72	0.80	0.95
t_loc	0.89	0.93	0.78	0.85	0.96
t_san	0.97	0.98	0.67	0.96	0.99
a_rus	0.89	0.92	0.62	0.85	0.96
a_ukr	0.94	0.96	0.56	0.92	0.98
a_civ	0.97	0.98	0.10	0.96	0.99
a_other	0.95	0.96	0.51	0.93	0.98
t_aad	0.99	0.99	0.69	0.98	1
t_airstrike	0.98	0.99	0.73	0.97	0.99
t_armor	1	1	0.75	1	1
t_arrest	0.98	0.99	0.54	0.98	0.99
t_artillery	0.97	0.98	0.82	0.96	0.99
t_control	0.99	0.99	0.50	0.98	1
t_firefight	0.99	0.99	0.20	0.98	1
t_ied	0.98	0.98	0.62	0.97	0.99
t_raid	0.99	0.99	0.25	0.99	1
t_occupy	0.97	0.98	0.33	0.96	0.99
t_retreat	0.99	0.99	0.40	0.99	1
t_property	0.95	0.97	0.63	0.93	0.98
t_cyber	1	1	1	1	1
t_hospital	1	1	0	1	1
t_sexual	1	1	1		1
t_milcas	0.97	0.98	0.54	0.96	0.99
t_civcas	0.99	0.99	0.90	0.98	1

Table A1.2: **Intercoder Reliability Statistics, by Variable** (all three coders, N=300)

	Training Set		
Variable	Pooled	Russian	Ukrainian
t_mil	0.82	0.86	0.79
t_loc	0.86	0.92	0.80
t_san	0.95	0.67	0.95
a_rus	0.86	0.93	0.85
a_ukr	0.94	0.75	0.93
a_civ	0.99	0.99	1.00
a_other	0.96	0.75	0.95
t_aad	0.99	0.99	0.99
t_airstrike	0.98	0.99	0.99
t_airalert	0.99	1.00	0.98
t_armor	0.99	0.99	0.99
t_arrest	0.97	0.98	0.96
t_artillery	0.96	0.93	0.93
t_control	0.99	0.99	0.98
t_firefight	0.99	0.99	0.99
t_killing	0.98	0.99	0.98
t_ied	0.98	0.99	1.00
t_raid	1.00	1.00	1.00
t_occupy	0.98	1.00	0.97
t_property	0.95	0.97	0.95
t_cyber	0.96	0.99	0.97
t_hospital	0.98	1.00	0.98
t_milcas	0.96	0.99	0.97
t_civcas	0.95	0.98	0.96
Mean	0.96	0.94	0.95
Std.Dev.	0.05	0.09	0.06

Table A2.3: **Out-of-Sample Accuracy, Multilingual vs. Monolingual Training Sets**

	VIINA	GDELT	ICEWS	ACLED
VIINA	0.00	4.05	5.77	3.71
GDELT	9.60	0.00	1.61	9.89
ICEWS	1.49	2.21	0.00	2.04
ACLED	1.55	4.04	6.31	0.00

Table A3.4: **Mean Nearest Neighbor Distances Between Events in Each Dataset**. Each cell value d_{ij} represents the average distance, in kilometers, between each event in dataset i (in rows) and its geographically closest event in dataset j (in columns). Smaller values indicate greater similarity across point patterns.

	GDELT	ICEWS	ACLED
VIINA	0.56	0.61	-0.38
GDELT		0.75	-0.47
ICEWS			-0.50

(a) Raw Time Series

	GDELT	ICEWS	ACLED
VIINA	0.56	0.64	-0.44
GDELT		0.85	-0.72
ICEWS			-0.77

(b) Trend Component

	GDELT	ICEWS	ACLED
VIINA	0.81	0.93	-0.15
GDELT		0.88	0.25
ICEWS			0.11

(c) Seasonal Component

	GDELT	ICEWS	ACLED
VIINA	0.31	0.33	0.07
GDELT		0.37	0.13
ICEWS			0.07

(d) Residual Component

Table A3.5: **Pairwise Spearman's Correlation for Time Series of Event Data**