PROJECT I

LITERATURE SURVEY

Halkia, M., Ferri, S., Papazoglou, M., Van Damme, M., & Thomakos, D. (2020). Conflict Event Modelling: Research Experiment and Event Data Limitations. *Language Resources and Evaluation Conference (LREC 2020), Marseille,* 42–48. https://www.aclweb.org/anthology/2020.aespen-1.8/

Research on conflict event modeling has become increasingly important due to the need for accurate predictions of conflict escalation, which are critical for informing global policies. Traditional quantitative models often rely on historical data, like casualty numbers, to measure conflict severity. However, this method can miss early conflict indicators and the complexity of events such as protests or election violence. To improve upon this, Halkia, Matina and Ferri(2020) introduces the use of Long Short-Term Memory (LSTM) Cell Recurrent Neural Networks (RNN) for tracking conflict triggers like strikes, demonstrations, and verbal disputes. This neural network architecture excels at analyzing temporal data sequences, making it suitable for detecting patterns of conflict from actor-based datasets. The research explores how a rise in conflict-related events tends to align with a decline in cooperative actions, suggesting a link between different conflict stages and cooperation, utilizing large-scale datasets such as the Global Database of Events, Language, and Tone (GDELT) and the Integrated Crisis Early Warning System (ICEWS) to analyze conflict events. These datasets are coded using the Conflict and Mediation Event Observations (CAMEO) framework, which classifies events into categories like verbal or material conflict. Despite the value of these datasets, the paper notes challenges, including the presence of noise in GDELT data and difficulties in validating ICEWS entries. Nevertheless, the research offers valuable insights into conflict escalation predictions, highlighting the importance of early warning systems in preventing conflict and shaping policy decisions.

Large event datasets such as GDELT and ICEWS aligns with the growing use of big data for conflict prediction. Leetaru & Schrodt (2013) and Raleigh et al. (2010) have extensively documented the advantages and challenges of using such datasets, especially in terms of scale, noise, and bias. This paper addresses these challenges by applying filters, similar to Leetaru’s approach of pre-processing event data to reduce information noise, thereby improving model accuracy.

The ethical and methodological challenges of event-based conflict prediction, a theme explored in works like those of Hanson & Richards (2019) and Fujii (2015), who discuss the limitations and biases inherent in conflict datasets. The paper's emphasis on dataset validation and the refinement of automated classification methods highlights a key challenge in conflict modeling, as false positives and dataset biases can significantly distort predictions. This aligns with concerns raised by Bagozzi et al. (2019) on the need for more reliable validation techniques in conflict data collection and prediction.

In terms of early warning systems, such as those discussed by Goldstein (1992) and Heldt & Gurr (2012), by applying machine learning to detect abnormal increases in conflict-related events. The model’s ability to trigger alarms during periods of social unrest, such as the Arab Spring, demonstrates the potential for integrating deep learning with early warning systems, a concept also explored by Chadefaux (2014) in his study of conflict prediction models. Incorporating new classifiers like the Political Language Ontology for Verifiable Event Records (PLOVER), reflect ongoing discussions in the literature about the need for more accurate and context-aware classification systems, a topic discussed by Risse et al. (2013) in the context of political event coding.

Bush, K., & Duggan, C. (2013). Evaluation in Conflict Zones: Methodological and Ethical Challenges. Journal of Peacebuilding & Development, 8(2), 5-25. <https://doi.org/10.1080/15423166.2013.812891>

Evaluating interventions in conflict zones involves navigating numerous challenges due to the inherently unpredictable and complex nature of these environments. While systems thinking and complexity theory provide useful perspectives for understanding the dynamic and non-linear aspects of such contexts, their practical implementation is still evolving. A central problem is the ethical quandaries evaluators encounter, including issues like political interference and the misuse of data, which are exacerbated by the absence of robust institutional oversight typically found in more stable settings. Current ethical guidelines from organizations like the OECD and European Commission do not adequately address the specific needs of these high-risk environments, leaving evaluators with limited guidance on managing ethical dilemmas effectively.

Bush, K., & Duggan, C. (2013) has stated that core ethical principles such as integrity and accountability are crucial, they need to be adapted to the specific challenges of conflict zones. There is an urgent need for more nuanced, context-sensitive ethical frameworks that can assist evaluators in dealing with the unique complexities of these settings. Although scenario-based training and peer support may offer some assistance, they are not enough on their own. The conclusion underscores the importance of developing comprehensive ethical guidelines and embedding them throughout the evaluation process to enhance the effectiveness and ethical integrity of interventions in conflict-affected areas.

Krause, J. (2021). The ethics of ethnographic methods in conflict zones. Journal of Peace Research, 58(3), 329-341. https://doi.org/10.1177/0022343320971021

Krause 2021 pdf file

In the field of ethnographic research within conflict zones, the ethical implications of uneven immersion have garnered increasing attention. Fujii (2015) and Malejacq & Mukhopadhyay (2016) highlight that traditional ethnographic practices often face significant challenges when applied to violent contexts. These scholars argue that researchers' access and immersion are intricately linked to their personal characteristics, including gender and ethnicity, which in turn affect their ability to navigate and gather data in such environments. Schatz (2009) and Wood (2006) further explore how the logistics of fieldwork and the performance of gendered behaviour impact researchers’ engagement and access to sensitive populations. Contemporary discussions, such as those by Theidon (2014). The necessity of acknowledging these limitations openly, advocating for a balance between the pursuit of comprehensive data and ethical considerations that safeguard both researchers and respondents has been emphasized by Hanson & Richards (2019).

The ethical complexities of fieldwork in conflict zones extend beyond mere logistical challenges to include profound considerations of researcher identity and emotional impact. Studies by Baird (2018) reveal how researchers’ backgrounds and personal experiences shape their interactions and access to various social groups within conflict settings. These findings underscore the need for greater transparency and reflexivity in ethnographic research, as advocated by MacLean et al. (2018) and Lake, Majic & Maxwell (2019). The emphasis on openly discussing the researcher’s positionality and the inherent biases affecting data collection processes reflects a broader call for a more nuanced understanding of how ethnographic methods can be adapted to ethical constraints without compromising the integrity of the research.

Raleigh, C., Linke, rew, Hegre, H., & Karlsen, J. (2010). Introducing ACLED: An Armed Conflict Location and Event Dataset. Journal of Peace Research, 47(5), 651-660. <https://doi.org/10.1177/0022343310378914>

Raleigh2010 pdf file

The ACLED (Armed Conflict Location and Event Dataset) dataset has emerged as a crucial tool for analyzing patterns of conflict and political instability, offering a highly granular view of conflict events over time and space. The dataset provides researchers with disaggregated data on violent and nonviolent events in conflict zones, capturing interactions between rebel groups, militias, and governments at specific locations and times. This fine-resolution data allows for the exploration of how battles, territorial control, and one-sided violence shape conflict dynamics, making it a significant advancement over national and zonal datasets that aggregate conflict data. Studies such as those by Earl et al. (2004) and Restrepo, Spagat, & Vargas (2006) have validated ACLED's reliability, emphasizing its accuracy and flexibility in analyzing both temporal and spatial aspects of civil wars.

However, as with all event-based data, ACLED’s use of secondary sources, including media reports, raises concerns about the potential biases inherent in conflict reporting. Scholars like Bocquier & Maupeu (2005) have pointed out how fatalities, a key metric in conflict studies, can be underreported or misreported due to biases in coverage. To address these concerns, ACLED incorporates data triangulation and verification techniques, offering a level of credibility not always present in similar datasets. By including both violent and nonviolent events, and allowing for multi-level aggregation, ACLED provides a comprehensive lens through which to analyze conflict intensity and its escalation, thus facilitating advanced geostatistical and crisis-mapping research.

Chojnacki, S., Ickler, C., Spies, M., & Wiesel, J. (2012). Event Data on Armed Conflict and Security: New Perspectives, Old Challenges, and Some Solutions. *International Interactions*, *38*(4), 382–401. <https://doi.org/10.1080/03050629.2012.696981>

chojnacki2012 pdf file

Fujii (2015) and Malejacq & Mukhopadhyay (2016) underscore the difficulties ethnographers face in violent settings, emphasizing how personal characteristics, such as gender and ethnicity, influence access and data collection. This discussion is complemented by Schatz (2009) and Wood (2006), who explore the impact of gendered behaviours and logistical issues on fieldwork engagement. The ethical dimension of these challenges is further highlighted by Hanson & Richards (2019), who advocate for balancing thorough data collection with ethical safeguards. In addition, Baird (2018) and MacLean et al. (2018) stress the importance of researcher reflexivity and the influence of personal backgrounds on field interactions. Lake, Majic & Maxwell (2019) extend this discourse by emphasizing the need for transparency regarding researcher positionality and biases. The paper integrates these perspectives by addressing the complexities of transforming unstructured conflict data into reliable event datasets, emphasizing the importance of methodological rigor and ethical considerations to improve data quality and contextual accuracy.

Akande, Dapo, Classification of Armed Conflicts: Relevant Legal Concepts (August 20, 2012). In E Wilmshurst (ed), International Law and the Classification of Conflicts (OUP 2012) chapter 3, Oxford Legal Studies Research Paper No 50/2012, Available at SSRN: <https://ssrn.com/abstract=2132573> or [http://dx.doi.org/10.2139/ssrn.2132573](https://dx.doi.org/10.2139/ssrn.2132573)  
  
ssrn pdf fileOgira, Carol & Kamau, Roselynn & Kamau, Shallom & Bwoma, Bridgette & Komora, Bonaya & Athiany, Henry. (2024). Predicting Conflict Zones in Kenya Using a Point Process Model. International Journal of Data Science and Analysis. 10.11648/ijdsa.20241001.11.

**ijdsa.20241001.11a.pdf**

Spatial point process modeling has been widely utilized in various fields such as ecology, epidemiology, and criminology to analyze spatial data. The application of this method to conflict analysis is relatively recent. The current study draws upon the work of Bartolucci et al. (2018) and Weidmann and Ward (2010), who demonstrated the value of spatial models in understanding the geographic distribution of conflict events. Weidmann and Ward explored how social and political interactions could be analyzed spatially to predict conflict, emphasizing the importance of spatial proximity in conflict dissemination. Berman and Turner (1992) provided the statistical foundation for the PPM approach employed in this study. Their algorithm, which the authors used to estimate model parameters for conflict prediction, is a cornerstone of spatial statistics. The Berman-Turner algorithm facilitates the estimation of maximum likelihoods for point process models, and its application in the Kenyan context proves the method's flexibility across domains.

The relationship between population density and conflict has been examined in depth by Fearon and Laitin (2003), who argued that areas with higher population densities are more likely to experience civil unrest due to increased competition for resources. This concept is a central point of the current study, where population density emerges as the most significant predictor of conflict in Kenya. Additionally, Buhaug and Rød (2006) expanded on this concept by highlighting the role of urbanization and demographic pressures in exacerbating violence, especially during periods of political instability. This study reaffirms their findings, showing that densely populated urban areas like Nairobi, Nakuru, and Mandera counties are hotspots for electoral violence. Collier and Vicente (2014) investigated the rise of election-related violence in Sub-Saharan Africa, attributing it to the intense political competition and lack of robust democratic institutions. The Kenyan case, particularly the elections of 2007-2008 and 2017-2018, mirrors the trends observed by Collier and Vicente, where contested elections lead to violent clashes.

Höglund (2009) further explored how political rivalries in fragile democracies often lead to post-election violence, arguing that the root causes of conflict lie in systemic political failures and elite manipulation. This perspective is supported by the findings of the current paper, which notes that election violence in Kenya spikes during contested elections, but post-election resolutions, such as the 2018 handshake between political rivals, can reduce the intensity of violence. Socioeconomic and political variables as drivers of conflict have been thoroughly explored by Stewart (2002) and Murshed and Gates (2005), who emphasized the role of resource scarcity, poverty, and political exclusion in conflict-prone regions. Their work is crucial for understanding why certain regions in Kenya, such as the Western and South-Central parts, are more susceptible to violence

Buhaug, H., & Rød, J. K. (2006). Local determinants of African civil wars, 1970–2001. Political Geography, 25(3), 315–335. https://doi.org/10.1016/j.polgeo.2006.02.005

**Buhaug2006.pdf**

The role of geography in shaping civil conflicts has been an important focus in conflict studies. Scholars like Buhaug and Gates (2002) emphasized that terrain, borders, and natural resources can either promote or inhibit armed conflict. In the context of African civil wars, Fearon and Laitin (2003) showed that countries with rough terrain are more likely to experience civil war, as it provides insurgent groups with natural hideouts and strategic advantages. The current study builds on this by analyzing how rough terrain in African countries contributes to prolonged civil unrest. Similarly, Buhaug and Rød (2006) explored the spatial dispersion of conflict across territories, identifying border regions as hotspots for violence. This work directly influences the current study, which looks at localized factors in African countries, such as border regions and physical landscapes, contributing to the onset and sustainability of conflict. The geographical factors help identify how civil wars in Africa tend to break out in remote and rugged regions that are often far from political power centers. Their research further builds on the methodology of localized data collection and emphasizes that understanding local conflict determinants such as proximity to borders, terrain, and population clusters provides a more accurate prediction of where violence may erupt.

Several scholars have noted the correlation between population density and conflict, particularly in Africa. Urdal (2005) and others highlighted how high population density, combined with low economic development, can lead to intense resource competition and, consequently, violent conflict. The current study draws on Fearon and Laitin’s (2003) seminal work on the relationship between population density and civil wars, finding that higher population densities in regions of low government presence or poor economic development can trigger unrest. Moreover, Collier and Hoeffler (2004) emphasized the role of economic inequality in fostering conflict. This is particularly relevant in Africa, where high urbanization rates and uneven economic distribution create fertile ground for violence. This study aligns with their findings by analyzing how local economic conditions and population pressures exacerbate civil conflicts.

Political instability has long been recognized as a driving force behind civil wars, particularly in Africa. Scholars such as Gurr (1970) introduced the concept of political marginalization, where excluded groups are more likely to engage in rebellion. The current study finds that regions in Africa with weak political institutions and a history of exclusion are more prone to violence. Herbst (2000) argued that the failure of African governments to penetrate rural areas creates a power vacuum, making these areas vulnerable to insurgency.

In line with this, Collier and Sambanis (2002) focused on how poor governance and lack of political representation lead to armed rebellion. This study contributes to the literature by analyzing how localized failures in governance, coupled with ethnic marginalization, contribute to civil war outbreaks in African regions.

Research on African civil wars often focuses on country-level analyses, but recent scholarship emphasizes the importance of subnational data. Raleigh and Hegre (2009) were pioneers in applying localized data to understand the diffusion of violence across geographic regions. Their work informs the current study’s approach, which takes into account the importance of disaggregated data to explore how conflict manifests in different areas within a country. Murshed and Tadjoeddin (2007) argued that the combination of poverty and political exclusion often leads to civil unrest, particularly in African countries with low economic development. This perspective is crucial for the current study, as it analyzes how economic deprivation in certain African regions plays a significant role in fostering violence further focuses on the socioeconomic factors that contribute to civil wars. Moreover, Stewart (2002) highlighted the interaction between horizontal inequalities (inequality between groups) and violent conflict, particularly in Africa. The current study corroborates these findings by showing how unequal access to resources and political power among ethnic groups in African countries can fuel civil wars.

**Spatial–Horizontal Inequality and the Maoist Insurgency in Nepal (DOUBTED)**

Horizontal inequalities, referring to inequalities among culturally defined groups, have been linked to violent conflict in multiple regions. Stewart (2008) laid the foundation for this framework, arguing that disparities in socioeconomic and political access among ethnic or regional groups are key drivers of conflict. Her work is central to understanding the Maoist insurgency in Nepal, where regional and caste-based inequalities contributed to the insurgency’s development. Stewart's (2010) further research into conflict areas, including Sierra Leone and Indonesia, highlights how entrenched horizontal inequalities can destabilize governance structures, mirroring the conditions in Nepal during the insurgency. The insurgency in Nepal can also be analyzed using the framework proposed by Østby (2008), who explored the spatial dimensions of horizontal inequality in triggering violence. Østby’s findings, that regions with higher inequality experience more frequent conflict, are corroborated by the Maoist insurgency in Nepal, where geographic disparities in development and political exclusion of rural populations fueled unrest.

Nepal's rugged geography exacerbates spatial inequalities, with the hill and mountain regions historically suffering from underdevelopment compared to the more accessible Terai plains. This spatial disparity is a significant factor in the Maoist insurgency, which found strong support in the remote areas where economic opportunities were limited, and state presence was minimal. Bohara et al. (2006) examined the relationship between economic underdevelopment and the insurgency in Nepal, finding that regions with higher poverty levels were more likely to support the Maoist cause. The authors highlight that these spatial disparities were not only economic but also political, as marginalized regions were often excluded from meaningful participation in national governance. Similarly, Deraniyagala (2005) discusses the role of spatial inequality in fueling insurgencies, focusing on Nepal as a case study. Deraniyagala suggests that the Maoist insurgency was not only a reaction to economic deprivation but also to the perceived lack of political inclusion, especially in regions with a majority of marginalized ethnic groups such as the Magar and Tamang.

The Maoist insurgency in Nepal is part of a broader trend in which political exclusion and unaddressed grievances lead to violent uprisings. Murshed and Gates (2005) explore the economic and political grievances that motivate insurgencies, arguing that regions excluded from political power are more likely to resort to violence as a means of achieving their aims. Their model, which integrates both economic and political inequality, can be applied to Nepal, where historically marginalized communities in the hills and mountain regions supported the insurgency as a way to challenge Kathmandu’s centralized power. In the context of Nepal, Upreti (2006) argues that the insurgency was largely driven by the exclusionary policies of the central government, which failed to adequately represent the interests of the rural and ethnic populations. Upreti emphasizes that the conflict was not merely about economic inequality but was deeply rooted in political marginalization, particularly of the indigenous and lower-caste populations.

Nepal’s Maoist insurgency can also be understood within the broader context of conflict and inequality in South Asia.

Bohara, Mitchell, and Nepal (2006) suggest that inequality and political exclusion have been recurrent themes in many South Asian conflicts, from Sri Lanka to India’s Naxalite movement. Their comparative analysis shows that insurgencies often emerge in areas where the state has failed to provide equitable economic opportunities and political representation. In the case of Nepal, the insurgency was fueled by both economic deprivation and political exclusion, particularly in the hill and mountain regions. Gellner (2007) provides an ethnographic perspective on the Maoist insurgency, highlighting how caste and ethnic inequalities contributed to the conflict. He argues that the Maoist movement was able to mobilize support by appealing to these entrenched grievances, particularly among lower-caste groups such as the Dalits and marginalized ethnic groups like the Magar.

Spatial inequality has been a central theme in conflict studies, particularly in understanding how uneven distribution of resources and opportunities can lead to insurgency and unrest. The work of Kanbur and Venables (2005) is foundational in this area, highlighting how spatial disparities in economic development contribute to regional tensions and conflict. Their analysis of spatial inequality in developing countries underscores the critical role of uneven economic opportunities in fueling social unrest.

In the context of Nepal, the research by Østby (2008) provides valuable insights into how spatial inequalities and horizontal inequalities—inequalities between different ethnic or social groups—can exacerbate conflict. Østby’s study, focusing on the link between regional disparities and violent conflict, supports the argument that areas with pronounced horizontal inequalities are more prone to insurgency. This perspective is crucial for understanding the spatial dimensions of the Maoist insurgency in Nepal.

The Maoist insurgency in Nepal, as analyzed by Lawoti (2007), illustrates how horizontal inequalities—particularly those related to ethnicity, caste, and region—can contribute to the emergence and persistence of insurgent movements. Lawoti’s research details how the marginalization of specific groups, such as the indigenous and lower-caste communities, played a critical role in the insurgency's appeal and support base. This aligns with the current study’s focus on how spatially distributed inequalities in Nepal have influenced the Maoist conflict.

The examination of regional disparities in relation to insurgent activity has been explored extensively in conflict studies. The work of Collier and Hoeffler (2004) provides an economic perspective, arguing that regions with significant economic disadvantages are more likely to experience conflict. Their model, which links economic and spatial inequalities to the likelihood of civil war, is instrumental in understanding the Maoist insurgency’s regional dimensions.

In Nepal, the research by Murshed and Gates (2005) further elaborates on how regional disparities, combined with historical grievances and socio-economic deprivation, have fueled the insurgency. Their study highlights the interplay between geographic and socio-economic factors, showing how areas with limited development and historical neglect are more susceptible to insurgent activities.

Political institutions and their role in addressing or exacerbating spatial and horizontal inequalities have been widely studied. The work of North, Wallis, and Weingast (2009) on institutional development provides a framework for understanding how weak or exclusionary political institutions can contribute to conflict. Their analysis is relevant for understanding the political backdrop of the Maoist insurgency in Nepal, where institutional failures and political exclusion have been significant factors.

Nepal’s experience, as described by Hachhethu (2004), illustrates how the inadequacies of political institutions in addressing regional and ethnic grievances contributed to the Maoist insurgency. Hachhethu’s study emphasizes the role of ineffective governance and the lack of inclusive political processes in perpetuating horizontal inequalities and insurgent support.

The relationship between socioeconomic conditions and conflict drivers is well-documented in the literature. The research by de Soysa (2002) explores how poverty and socioeconomic deprivation are linked to conflict, providing a broader understanding of how economic conditions can influence insurgent activities. This perspective is essential for analyzing the socioeconomic conditions in Nepal and their role in the Maoist insurgency.

Additionally, the study by Thapa and Saigal (2014) provides a detailed account of how socioeconomic factors, including poverty and inequality, have influenced the insurgency dynamics in Nepal. Their findings support the notion that regions with higher levels of deprivation and economic inequality are more prone to insurgent movements, reinforcing the study’s focus on spatial and horizontal inequalities.

<https://www.taylorfrancis.com/chapters/edit/10.4324/9781003139850-41/conflict-event-data-clionadh-raleigh-roudabeh-kishi>

<https://journals.sagepub.com/doi/abs/10.1177/00220027221119085>

Schutte, S. (2016). Regions at risk: Predicting conflict zones in African insurgencies. Political Science Research and Methods, 5(3), 447–465. https://doi.org/10.1017/psrm.2015.84

Regions at Risk Predicting Conflict Zones in African Insurgencies

Spatial point process models have become an essential tool in analyzing the geographic distribution of violence in civil conflicts, as shown by Buhaug and Rød (2006) and Fearon and Laitin (2003). Schutte’s (2014) study expands on this by applying geographic covariates such as population density, distance to capital cities, and accessibility to predict the location of conflict zones in African insurgencies. The study demonstrates the predictive power of spatial data through cross-validation techniques, contributing to the body of literature on civil war prediction models. This method, which builds on previous works, emphasizes the importance of spatial determinants in understanding where insurgencies are likely to erupt. These findings align with earlier research on the role of geographic conditions in civil war, further reinforcing the argument that insurgent violence tends to concentrate in regions where terrain, population, and proximity to borders provide strategic advantages to non-state actors.

Schutte (2014) reaffirms the connection between population density and the likelihood of violent conflict, building on Raleigh and Hegre’s (2009) identification of “population-centric warfare.” In this framework, areas with high civilian concentrations serve as both hiding grounds for insurgents and recruitment zones. This concept mirrors findings from studies like Buhaug and Gates (2002), which observed that densely populated areas in Africa are hotspots for insurgencies. In Schutte’s model, population density serves as a critical predictor, especially when coupled with factors like proximity to capitals and national borders, adding to the growing body of evidence that population centers often attract conflict due to their strategic and symbolic value.

The role of geography in insurgent warfare has long been studied, with Schutte (2014) drawing on Fearon and Laitin’s (2003) analysis of how remote, inaccessible regions provide safe havens for rebel forces. Schutte uses a global friction map created by Nelson (2008) to calculate the travel times to and from cities, showing how accessibility correlates with violence. The study supports previous findings that less accessible areas, such as forests and mountainous regions, offer strategic advantages for insurgents, as demonstrated in earlier work by McColl (1969) and Kalyvas (2006). Schutte’s use of accessibility as a covariate in predicting conflict intensity adds a new layer to the existing literature on terrain’s role in civil conflict, particularly in African insurgencies.

Schutte (2014) incorporates wealth distribution into the predictive model by utilizing data on regional GDP, following the work of Hegre et al. (2009), which showed that wealthier regions often experience higher levels of violence. This contrasts with the common assumption that poorer regions are more susceptible to conflict due to deprivation. Instead, Schutte’s findings suggest that wealthier areas become targets for insurgents seeking to gain resources and control key economic centers. This insight aligns with earlier research by Buhaug et al. (2011), which found that geographically wealthy regions in Sub-Saharan Africa saw intense conflict outbreaks, further supporting the idea that socioeconomic factors significantly influence the geographic spread of violence.

The integration of spatial point process models in conflict prediction represents an advancement in the quantitative study of civil wars. Schutte (2014) builds on earlier work by Weidmann and Ward (2010), employing point process models to predict the spatial distribution of insurgent violence. The use of spatial covariates like accessibility, wealth, and distance to borders, combined with advanced modeling techniques, provides robust predictions of conflict zones across ten African insurgencies. Schutte’s contribution to the literature is significant, as it demonstrates the external validity of these spatial models, enhancing their applicability to real-world conflict prediction and humanitarian planning efforts. The study's predictive power, especially in out-of-sample testing, highlights the importance of spatial determinants in understanding the dynamics of insurgent warfare.

Final draft

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The Inception module has been a pivotal architecture in the evolution of convolutional neural networks (CNNs), particularly for image classification tasks. Szegedy et al. (2014) introduced the Inception architecture, designed to efficiently capture spatial and cross-channel correlations in an input. Building on this foundation, Chollet (2017) proposes that depthwise separable convolutions are an extension of the Inception module, where the number of towers is maximized. This conceptual leap aligns with earlier findings, where depthwise separable convolutions were shown to significantly improve model efficiency without increasing parameter counts. In Xception, these convolutions replace Inception modules, simplifying the architecture while improving performance on large-scale datasets such as ImageNet.

Convolutional neural networks (CNNs) have undergone considerable development since the introduction of LeNet (LeCun et al., 1995) and the AlexNet architecture (Krizhevsky et al., 2012). The focus of early CNNs, including VGG (Simonyan & Zisserman, 2014), was on progressively deeper stacks of convolutional and max-pooling layers to extract hierarchical features from images. However, as noted by Szegedy et al. (2015), the Inception module introduced a new paradigm by factoring convolutions into multiple branches, thereby improving computational efficiency. The Xception architecture builds upon this idea by decoupling spatial and cross-channel correlations, treating these two dimensions independently. The use of depthwise separable convolutions in Xception enables the model to perform this decoupling more effectively than previous Inception-based architectures.

Depthwise separable convolutions were first introduced by Sifre and Mallat (2014) as a means of reducing the computational cost of convolutional operations. By separating the spatial convolution from the pointwise (1x1) convolution, this technique drastically reduces the number of parameters and operations required to process an input. In the Xception architecture, depthwise separable convolutions serve as the core building blocks, replacing Inception modules. This change results in a more streamlined model that retains the same parameter count as Inception V3 but achieves better performance due to a more efficient use of these parameters. The authors demonstrate that Xception not only outperforms Inception V3 on the ImageNet dataset but also excels on a much larger dataset comprising 350 million images across 17,000 classes.

The need for efficient CNN architectures has grown with the increasing scale of image classification tasks. Early networks like AlexNet and VGG were computationally expensive, requiring significant hardware resources to train. The introduction of the Inception module in GoogLeNet (Szegedy et al., 2014) marked a shift towards more efficient models that could perform as well or better than deeper networks without the same computational burden. In a similar vein, the Xception architecture reduces the complexity of convolutional operations by decoupling cross-channel and spatial feature extraction, making it more efficient than Inception V3. The success of Xception in large-scale datasets suggests that the model's efficiency does not come at the expense of accuracy, making it a practical solution for real-world applications where computational resources may be limited.

Residual connections, introduced by He et al. (2016), have been instrumental in improving the training of deep neural networks. These connections allow the gradient to flow more easily through the network, mitigating the vanishing gradient problem commonly encountered in very deep architectures. Xception leverages residual connections extensively, incorporating them into all but the first and last modules of the network. This design choice not only improves the network's convergence speed but also enhances its performance on large-scale classification tasks. The use of residual connections in combination with depthwise separable convolutions allows Xception to achieve state-of-the-art results while maintaining a relatively low parameter count.

Convolutional Neural Networks (CNNs) have become the dominant method for various computer vision tasks, including scene classification. Krizhevsky et al. (2012) pioneered CNN architecture with the introduction of AlexNet, which significantly improved the performance of visual object recognition, specifically in the ImageNet Large Scale Visual Recognition Competition. The success of AlexNet prompted widespread adoption of CNNs for a variety of image-based tasks, including remote sensing (LeCun et al., 2015). CNNs excel at extracting high-level features from images by automatically learning complex patterns through stacked convolutional layers, which has proven beneficial in remote-sensing scene classification, where the data can often be heterogeneous and difficult to process through traditional methods (Cheng et al., 2017).

Transfer learning has emerged as a crucial technique in overcoming the challenges posed by limited datasets in remote sensing. Unlike tasks with abundant data, such as natural image classification, remote-sensing datasets are often smaller and domain-specific. Transfer learning allows models pre-trained on large-scale natural image datasets to be fine-tuned for remote-sensing tasks (Yosinski et al., 2014). The layers of CNN models trained on general datasets, such as ImageNet, learn hierarchical feature representations that are applicable to other domains. By transferring these learned features to remote-sensing applications, researchers can accelerate training, improve performance, and reduce the need for large labeled datasets (Hu et al., 2015). Pires de Lima and Marfurt (2020) demonstrated that transfer learning outperforms training from scratch, even when applied to smaller remote-sensing datasets.

The size of the dataset and the depth of the model play critical roles in the success of transfer learning. Larger datasets allow models to learn more generalizable features, which can then be fine-tuned for domain-specific tasks such as remote-sensing scene classification. However, as reported by Yosinski et al. (2014), the effectiveness of transfer learning diminishes as the primary and secondary tasks become more distinct. Pires de Lima and Marfurt (2020) investigated how the depth of CNN models, such as VGG-19 and Inception V3, influenced performance on remote-sensing datasets of different sizes. Their results showed that deeper models performed better on larger datasets due to their ability to capture more complex features. However, on smaller datasets, simpler models with fewer layers tended to perform better, indicating that model complexity should align with the size and complexity of the dataset used.

The optimization method used to train CNNs can significantly affect model performance. Stochastic Gradient Descent (SGD) remains a foundational optimization method for large-scale machine learning problems due to its computational efficiency (Bottou, 2012). Adam, an adaptive optimization method, has gained popularity for its faster convergence in training (Kingma & Ba, 2015). However, Wilson et al. (2017) reported that adaptive methods like Adam may lead to worse generalization compared to SGD. Pires de Lima and Marfurt (2020) compared various optimization methods, including SGD, Adam, and Adamax, for training CNNs on the UCMerced dataset, concluding that while adaptive methods improved training performance, SGD provided better generalization, particularly for remote-sensing datasets.

One of the key advantages of CNNs in transfer learning is the transition from general to specific features across the network layers. Initial layers in CNNs typically capture low-level features such as edges, textures, and colors, which are useful across a variety of tasks (Yosinski et al., 2014). As layers deepen, the learned features become more specific to the task at hand, allowing CNNs to excel in domain-specific tasks like remote-sensing scene classification. Pires de Lima and Marfurt (2020) explored this transition by freezing different layers of pre-trained VGG-19 and Inception V3 models and evaluating their performance on remote-sensing datasets. Their findings indicated that using feature extraction from shallower layers produced suboptimal results, whereas fine-tuning deeper layers enhanced performance by allowing the model to learn features specific to remote-sensing tasks.

Transfer learning has been widely applied in remote-sensing applications, ranging from land-use and land-cover classification to detecting natural disasters. Hu et al. (2015) demonstrated that transfer learning significantly improved classification accuracy for high-resolution satellite imagery. Similarly, Rostami et al. (2019) used transfer learning for synthetic aperture radar (SAR) image classification, while Weinstein et al. (2019) applied transfer learning to identify individual tree crowns from RGB images captured by Light Detection and Ranging (LiDAR). The ability of CNNs to generalize across tasks highlights the versatility of transfer learning in remote-sensing, making it an indispensable tool for scene classification.

Object detection has been significantly advanced by convolutional neural networks (CNNs), which allow for the automated extraction of features from images and the identification of objects within them. Earlier models, such as Faster R-CNN (Ren et al., 2015), utilized region proposal networks to generate object proposals, followed by classification and localization. However, these methods were computationally expensive and often slow in real-time applications. The YOLO (You Only Look Once) family of models was introduced to address this speed limitation by re-framing object detection as a single regression problem. Redmon et al. (2016) proposed the first YOLO version, which allowed object detection in real-time by dividing the image into a grid and predicting bounding boxes and class probabilities directly. With YOLOv2, Redmon and Farhadi (2017) further improved detection speed and accuracy by introducing anchor boxes and using a new backbone network, Darknet-19. These early advancements laid the foundation for YOLOv3, which improved upon its predecessors in terms of both performance and architectural changes.

YOLOv3 introduces multiple updates over YOLOv2, most notably in bounding box predictions. Redmon and Farhadi (2018) retain the use of anchor boxes but employ a more sophisticated bounding box prediction technique based on dimension clusters, similar to Faster R-CNN (Ren et al., 2015). YOLOv3 predicts four coordinates (tx, ty, tw, th) for each bounding box, using a combination of width, height, and center offset to generate more accurate box placements (Redmon & Farhadi, 2018). This approach minimizes the problem of predicting absolute positions, making YOLOv3 more robust to varying object sizes and locations within the image. As a result, YOLOv3 is able to maintain a high accuracy on small objects, a weakness observed in previous versions.

One of the significant improvements introduced in YOLOv3 is the use of predictions across multiple scales. Inspired by Feature Pyramid Networks (FPN) (Lin et al., 2017), YOLOv3 predicts bounding boxes at three different scales, extracting features from different layers of the network. This method improves the network’s ability to detect objects of varying sizes by utilizing information from both coarse and fine feature maps. This multiscale approach helps in enhancing the detection of small objects, addressing a key limitation in earlier versions of YOLO (Redmon & Farhadi, 2018).

Unlike previous models that utilized a softmax layer for class prediction, YOLOv3 uses independent logistic classifiers for multilabel classification (Redmon & Farhadi, 2018). This change allows YOLOv3 to handle overlapping labels, a necessary feature when dealing with datasets such as the Open Images Dataset (Krasin et al., 2017), where objects may belong to multiple classes (e.g., a person can also be labeled as a woman). The shift from softmax to logistic regression improves the model’s ability to capture multiple labels per bounding box, making YOLOv3 better suited for complex detection tasks involving overlapping or co-occurring objects.

YOLOv3 also introduces a new feature extraction backbone, Darknet-53, which builds upon the success of Darknet-19 used in YOLOv2. Darknet-53 combines successive 3x3 and 1x1 convolutional layers with shortcut connections, akin to the residual connections in ResNet (He et al., 2016). This hybrid approach enhances the network’s ability to capture deep features while maintaining computational efficiency. According to Redmon and Farhadi (2018), Darknet-53 achieves performance on par with ResNet-101 but is significantly faster, making it a more optimal choice for real-time object detection tasks.

YOLOv3 maintains the use of common optimization techniques such as full-image training, batch normalization, and data augmentation, similar to earlier models. The model benefits from multi-scale training, allowing it to adapt to various input sizes during training, which enhances its generalization ability (Redmon & Farhadi, 2018). This approach allows YOLOv3 to outperform other models like SSD (Single Shot Multibox Detector) in terms of speed while maintaining comparable accuracy, particularly at lower Intersection over Union (IoU) thresholds.

YOLOv3's performance is evaluated using the COCO (Common Objects in Context) dataset (Lin et al., 2014), where it demonstrates competitive results. YOLOv3 achieves a mean Average Precision (mAP) of 57.9 at IOU = 0.5, which is comparable to RetinaNet’s 57.5 mAP, but with the added advantage of being significantly faster—3.8 times faster than RetinaNet (Redmon & Farhadi, 2018). However, as IoU thresholds increase, YOLOv3’s performance drops more significantly than RetinaNet, indicating that the model struggles with precise bounding box localization for certain objects.

Despite YOLOv3’s improvements, Redmon and Farhadi (2018) note several challenges that persist. For instance, YOLOv3 underperforms on larger objects and struggles with precise bounding box alignment at higher IoU thresholds. Some experimental modifications, such as using focal loss (Lin et al., 2017) and anchor box offset predictions, were explored but did not yield satisfactory improvements. Nonetheless, YOLOv3's balance between speed and accuracy makes it highly suitable for real-time applications where the trade-off between detection quality and performance must be carefully managed.

**Summary Detailing**

Summary of Research Papers on Event Extraction and Contextualization in Conflict Studies

Event Extraction Challenges

Event extraction refers to the process of converting unstructured information from news articles into structured event data. This transformation is fraught with various challenges that impact the accuracy, completeness, and consistency of the extracted data. Human coders often introduce subjective biases, which may lead to oversights and inconsistencies. Several studies, including those by Laver et al. (2003), Rothman (2007), and Ruggeri et al. (2009), have explored these challenges, and proposed solutions, such as using automated systems to supplement human coders. However, even automated systems have limitations, particularly with false positives, as reported by King and Lowe (2003), who found a high false positive rate of 77%. A combined approach using document classification and machine coding, as suggested by Nardulli et al. (2011), has shown promise in improving efficiency, though significant manual review remains necessary.

In response to these challenges, the EDACS (Event Data on Armed Conflict and Security) system employs various methods to improve the robustness of event extraction. It enforces constraints to ensure the quality of the data, including requiring every event to be attributed to a news source and a publication date. EDACS also uses a double-coding system, where two coders extract data independently, and a supervising coder reconciles discrepancies. This approach, while labor-intensive, improves the completeness and consistency of the data.

Automated Methods for Event Extraction

Automated event extraction methods have been evaluated in several studies, but results have been mixed. For example, King and Lowe (2003) found machine coding accuracy comparable to human coding, with a precision of 93%. However, the high false positive rate rendered the results less useful. Nardulli et al. (2011) addressed this issue by incorporating a more sophisticated document classification method, reducing the false positive rate to 35%, a significant improvement over earlier systems. Despite these advancements, manual intervention is still required for about 35% of irrelevant articles, highlighting the persistent burden on human coders.

EDACS incorporates a hybrid approach by using both supervised machine learning and natural language processing techniques to perform text classification and event extraction. This not only reduces the time required for manual coding but also allows for recoding using updated rules when necessary, further enhancing the system’s flexibility and robustness.

Event Contextualization and Geospatial Challenges

Event contextualization goes beyond extraction to include the geographical and temporal dimensions of conflict events. Inaccuracies in the location and time of events present further challenges. The EDACS system, alongside other conflict datasets like ACLED (Armed Conflict Location & Event Data) and UCDP-GED (Uppsala Conflict Data Program Georeferenced Event Dataset), addresses these issues using various geospatial methods. For instance, the GEOnet Names Server (GNS) is frequently used for location data, though it often lacks precision in conflict zones, particularly in urban or rural areas with rapidly changing environments.

To mitigate these issues, EDACS uses additional mapping tools like Google Earth and AfricaMap to estimate locations, especially when toponyms (place names) are ambiguous or when articles describe only approximate locations. A similar approach is taken with temporal inaccuracy, where ambiguous terms like “recently” are common in news reports. EDACS flags such cases with a Boolean variable indicating estimated dates, allowing researchers to handle these ambiguities consistently.

Temporal Disaggregation and Actor Identification

Temporal disaggregation, or the process of breaking down events by specific time units, is another key challenge in event data extraction. EDACS addresses this by offering two versions of its dataset: one with aggregated events and another disaggregated by day, allowing researchers to analyze the temporal dynamics of conflict events more precisely.

Actor identification is also a complex issue. In some cases, news reports may not provide specific actor information, leading to potential selection bias. To ensure data completeness, EDACS codes events with generic actor categories (e.g., “rebels,” “clan militia”) when specific actors cannot be identified. The system relies on supplementary qualitative data and actor databases (e.g., UCDP, IISS) to refine actor identification while allowing flexibility for researchers to interpret actor involvement based on the context.

Data Quality and Credibility Issues

Despite advancements in event extraction and contextualization, significant challenges remain in ensuring data quality and credibility. The process of transforming unstructured news articles into structured event data is prone to errors, misinterpretation, and inconsistencies. The use of auxiliary data sources and cross-referencing multiple datasets can help mitigate some of these issues, but they are far from solved.

EDACS emphasizes the importance of transparency and a problem-oriented approach to data extraction. By allowing researchers to question the data and making coding decisions visible, the system aims to enhance the credibility of event datasets. However, the inherent limitations of conflict research data, such as temporal and spatial inaccuracies, mean that even the most sophisticated systems cannot fully capture the complexity of violent conflicts. Researchers must remain cautious of over-reliance on event data and the potential for cascading errors that can arise from inaccurate coding.

Conclusion

The research papers highlight the complexities of extracting and contextualizing conflict event data. While automated methods and hybrid approaches offer improvements in efficiency and accuracy, manual intervention remains necessary to ensure data quality. Challenges related to geospatial accuracy, temporal disaggregation, and actor identification continue to affect the completeness and consistency of event datasets. EDACS and similar systems strive to address these issues by implementing rigorous coding protocols, utilizing multiple data sources, and fostering transparency in the data extraction process. Ultimately, the goal is to provide researchers with more reliable tools for studying the dynamics of violent conflict, though limitations and uncertainties in the data remain inevitable.

### Summary of the Paper on ACLED (Armed Conflict Location and Event Data Project)

#### Problem Statement:

The paper addresses the challenge of collecting and organizing comprehensive, high-resolution data on conflict events, both violent and non-violent, that occur during civil wars and periods of political instability. The authors identify the limitations of existing conflict datasets, such as those that aggregate data at the national or zonal level, leading to gaps in understanding the dynamics of local conflicts. This research seeks to fill these gaps by providing a more detailed and disaggregated dataset, which includes information on the spatial and temporal aspects of conflicts, the types of events, actors involved, and the locations where they occur.

#### Method Proposed:

ACLED offers a method of coding conflict events with fine geographic and temporal resolution. The dataset includes nine types of events, categorized into violent (e.g., battles, one-sided violence) and nonviolent (e.g., protests, recruitment activities). These events involve interactions between various actors such as rebel groups, militias, and government forces. Events are coded with specific information regarding the location (with geographic coordinates) and the date of occurrence. Data collection is based on secondary sources such as local news outlets, humanitarian organizations, and press accounts.

The events are classified as follows:

1. Battles

2. One-sided violence

3. Riots

4. Nonviolent rebel activities (e.g., recruitment, speeches, protests).

5. Changes in territorial control without violence

Data Sources:

ACLED relies on secondary information sources including local and regional press accounts, humanitarian agencies, and other research reports. It does not require a minimum casualty count to include an event. Additionally, ACLED cross-verifies data with regional experts to ensure accuracy and aims to address the potential biases in media reporting, particularly urban bias.

Results:

The dataset created by ACLED offers a more detailed and flexible analysis of conflict dynamics at the local level. Key results and findings include:

- The data reveals how different countries experience varying proportions of territory covered by conflict. For example, Somalia in early 2009 experienced a significant expansion of conflict into the northern regions of the country, demonstrating the spatial variation of conflicts over time.

- ACLED data can represent both micro-level conflict events and large-scale conflict zones, offering a comprehensive view of how conflicts unfold on the ground.

- By focusing on local-level events, the data can be aggregated to any desired level for analysis, and different event types (e.g., battles vs. protests) can be studied separately or together.

Differences from Other Datasets:

ACLED differs from other conflict datasets (such as UCDP/PRIO) by including a broader range of events and actors. Unlike datasets that focus only on government-rebel dyads, ACLED records interactions between a variety of actors, including rebel-on-rebel violence. It also includes nonviolent events to capture the full range of activities during a conflict, such as the establishment of rebel headquarters and peaceful protests.

Conclusions:

The ACLED dataset addresses many of the shortcomings of existing conflict data by offering detailed, disaggregated data on conflict events. The paper concludes that this data can be used to improve conflict analysis by providing insights into local-level conflict dynamics, which are often overlooked in national-level datasets. The disaggregated nature of the data allows researchers and policymakers to analyze patterns of violence, territorial control, and the roles of different actors with greater precision. The ACLED dataset is also versatile, as it can be used to track conflict trajectories, predict crisis development, and inform next-generation research on civil wars and political violence.

Key Takeaways:

- \*\*Event-Level Data\*\*: ACLED focuses on recording individual events with fine geographic and temporal precision, making it more accurate and detailed than other conflict datasets.

- \*\*Types of Events\*\*: ACLED includes both violent and non-violent events to provide a comprehensive view of conflict dynamics.

- \*\*Actors Involved\*\*: Events are coded based on the specific actors involved, allowing for detailed analysis of their interactions.

- \*\*Data Sources\*\*: Secondary information sources, cross-verification, and collaboration with regional experts ensure the reliability of the data.

- \*\*Flexibility\*\*: The dataset is flexible enough to support both micro-level and macro-level conflict analyses, making it useful for various research applications.

The ACLED dataset serves as a valuable tool for studying civil wars, political instability, and violence, with the ability to support more accurate analyses and predictions of conflict patterns.