Integrated Spatial and Social Network Analysis of Conflict Impacts on Food Production in Eastern Ukraine; A Geospatial Perspective

by

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Abstract

Ukraine-Russian geopolitical relations over the years have experienced periods of tranquility and violence with conflicts since 1917, including the events of the 2014 annexation of Crimea and the 2022 Russian invasion of the entirety of Ukraine. These conflicts remain developmental threats as their ramifications extend beyond battleground casualties and their assessment requires multi-perspective analysis. Understanding the spatial dimensions of such conflicts and their consequences on physical and social spaces at varying scales could provide credible scientific impetuses on which targeted post-conflict remediations could be built. This study therefore takes advantage of the capabilities of satellite remote sensing, to provide quick and effective spatiotemporal analysis of agricultural landcover change in eastern Ukraine from 2021 to 2023 while exploring patterns of civilian casualty, and dynamics of information flow on social media by examining Twitter #tags to uncover the network of social groups and interrelationships that emerged amidst the Russian-Ukrainian war.

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Contents

List of Tables

List of Figures

Chapter 1: Introduction

1.1.Background

Ukraine-Russian geopolitical relations over the years have alternatively experienced periods of tranquility and swift chaos with violent conflicts dating as far back as the Ukraine-Soviet insurgency of 1917 to the most recent conflicts of the 2014 Russian annexation of Crimea and the 2022 Russian invasion of the entirety of Ukraine. Current major attacks have been reported across Ukraine, including the capital, Kyiv, and multiple other urban spaces while the pre-existing hostilities in the Donetsk and Luhansk oblasts (states) have significantly intensified (UNHCR 2022), settling into largely recognizable patterns as other past conflicts of the region. These conflicts have remained multidimensional with complex causative factors which interact in multifarious fashions, the analysis of which is further complicated by the intensive informational wars that accompany them (Mandel 2016; Khaldarova and Pantti 2016).

Many of these recurrent conflicts in the contemporary era (Aalto 2006; Haukkala 2015) have been in part due to an attempt to lock Russia into an institutionalized post-sovereign arrangement with the view of creating an essentially unipolar Europe based on the European Union's liberal norms and values. This, however, has been contradictorily met by Russia's evolving radically unfavorable responses to that project, which alternatively aimed at restoring dissolved Soviet Union legacies (Haukkala 2015) and reasserting Russian power and influence abroad, particularly in the post-Soviet space (Larrabee 2022), since accustomed to being a superpower, the Russian Federation found it herculean to imbibe the new normal which seeks to suggest that both its importance and influence in global affairs had fallen and that its voice in foreign policy no longer conveys much impact (Larrabee 2022).

Within these dynamics, Ukraine emerges pivotal in the sociopolitical stability of Europe and is of sacrosanct geopolitical interest to both Russia and the West (D'Anieri, Kravchuk, and Kuzio 1999). To Russia, Ukraine remains a buffer against a possible invasion by the North Atlantic Treaty Organization (NATO) (Talabi et al. 2022) owing to its considerable expansion into the post-Soviet space, while to the West, an independent Ukraine creates a strong, sovereign state through which Russia would have to penetrate before it could renew its threat to regions west (of Ukraine) (D'Anieri, Kravchuk, and Kuzio 1999). As symbolized in Figure 1 below, historical Soviet Republics such as Estonia, Latvia and Lithuania have become members of NATO, sanctioning membership after the collapse of the Soviet Union (NATO 2022). Similarly, such countries as Albania, Bulgaria, Romania, Czechloslovakia (Czech and Slovakia), Hungry and Poland which were member states of the Warsaw Pact, a historical 'Russian version' of NATO, are currently members of NATO, with Finland joining in April, 2023 as the thirty-first ally of the NATO defense alliance. This eastward expansion is visualized by Russia as a threat to its national security, that, which ought to be either curtailed or erased even by radical violence to prevent the remaining 'safe-zone' post-soviet space, Ukraine, Moldova, Georgia and Belarus, from joining NATO.

Figure 1: NATO within Ukraine-Russian relations and Eastern European Geopolitics||Source: Deutsche_Welle, 2023 https://www.dw.com/en/how-russias-invasion-of-ukraine-threatens-geopolitical-order/a-60904451."

The conduct of a political agenda in Ukraine therefore would be for tipping this political equilibrium usurping favor for any of these blocks which initiates it. It is therefore unimaginative if Russian hostility in Ukraine is regarded as fighting for a version of Ukraine that is subservient to Russia's idea of what Ukraine should be: a buffer under a Russian hegemony, where Ukraine's national identity, nationhood, ideals, and interpretation of history can be vetted, sanctioned and vetoed by the Russian State (Knott 2022). It is essential to clarify that, NATO being a collective security clique, a case in which an attack on any member state is regarded as an attack on all and warrants a collective military action (NATO 2022), Ukraine's membership and attachment denies the Russian Federation its de facto control and military influences in Ukraine (Kuzio 2018).

The current conflict has been characterized by the functional utility of explosive weaponry with varying effects in populated and other areas, including heavy artillery and multiple-launch rocket systems (UNHR 2022), with reports of Ukrainian armed force's equally responsive shelling of populated areas in territories controlled by Russian affiliated armed groups in the Donetsk and Luhansk oblasts (UNHR 2022). This chaos has drawn a global spectacle and the world has been watching its multivariate impacts with concern, as several thousands of civilians were reportedly killed and schools among other social facilities so far destroyed (Júnior et al. 2022).

These violent conflicts remain a developmental issue as their resultant ramifications usually are complexly deleterious and extend beyond recorded direct battleground casualties (Gates et al. 2012). Military and other forms of armed operations usually target and transpire within the physical environment, and thus entail adverse environmental outcomes such as vegetation defoliation, structural deterioration, environmental damage, water contamination, land use/land cover (LU/LC) modifications (Yin et al. 2019), habitat destruction and fragmentation (George et al. 2021) and other impacts. As indicated in Figure 2 below, the ensuing conflict is pragmatically associated with destruction of industrial, airport and military facilities, incidents at facilities with radioactive materials, attacks on strategic resource control locations, deterioration of port facilities, damages to natural and protected areas, among others. As these dissensions may significantly fragment economic space (Bar-Nahum et al. 2020), truncate local and macro food supply chains and influence both society and the environment (Yin et al. 2019; Baumann and Kuemmerle 2016), they also ignite agricultural land abandonment (Yin et al. 2019) and labor switch, inducing food insecurity (Brück and d'Errico 2019) and other unexpected outcomes.

Other significant imprints of the current conflict have been assessed in relation to energy costs, household consumption expenditures, global remittance flow, healthcare, food security, vaccine diplomacy, stock market returns and internet universality. The continuous ascendance of energy prices, dwindling confidence in the economy including financial markets plagued with bold international sanctions were for instance opined by (Liadze et al. 2022) as the main impacts of the conflict on the world economy. The works of Boubaker et al. (2022) pointed negative cumulative returns for global stock market indices as an impact of the escalating conflict, while Roborgh et al. (2022) maintains the position that the conflict has created another 21st-century humanitarian disaster. Similarly, Bluszcz and Valente (2022) cited both civilian casualties and 15.1 percent per capita of GDP foregone as imprints of the conflict just as Kismödi and Pitchforth (2022) espoused forced migration, sexual and reproductive health as well as human right crisis as issues in the context of the Russian-Ukraine war for Ukraine, on which international attention must focus.

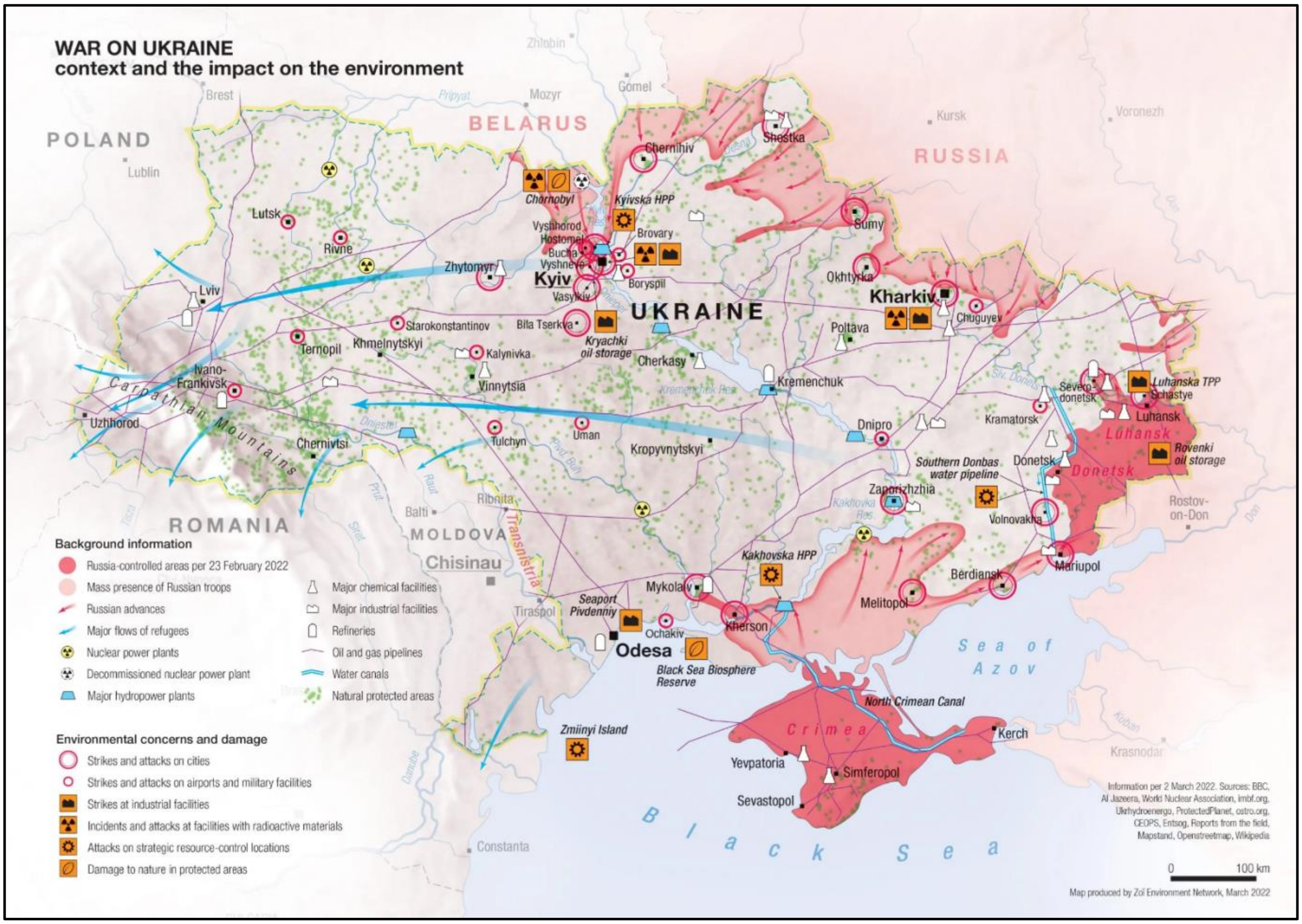

Figure 2: Map of environmental issues stemming from Russia's invasion of Ukraine. This map was produced by Zoï Environment Network www.zoinet.org and published on March 2nd, 2022.

Despite growing studies on the multifaceted impacts of this conflict, there is yet a study to be conducted specifically on its impacts on agricultural landcover in Eastern Ukraine, limiting insights into the susceptibility of agricultural space in this region to evolution amidst geopolitical chaos. This study therefore employed a socio-geospatial methodology, integrating remote sensing spatiotemporal landcover analysis with Sentinel-2 constellation datasets, and Social Network Analysis (SNA) with Twitter data to explore the impacts of the 2022 Russian-Ukrainian war on landcover and crop fields in Eastern Ukraine while assessing online colloquial social structures and patterns of information flow that emanated during the period. Specifically, the study investigated what LC underwent the most drastic change in the Kharkiv and Luhansk Oblasts during June 2021, June 2022 and June 2023, examined the spatial extent and rate of decline of agricultural vegetation in Luhansk and Kharkiv, explored spatial patterns of civilian casualty, and conducted a social network analysis to uncover social clusters and relations on the communication of war information from February 2022 to October 2023.

1.2.Study Area

The Kharkiv and Luhansk oblasts in Eastern Ukraine as shown in Figure 3 are two of the country's five proximal oblasts sharing boundaries with the Russian Federation. Located at 49°59′ 33″, 36°13′52″ at the confluence of the Uda, Lopan, and Kharkiv rivers (Britannica 2022a), the Kharkiv oblast extends to a total surface area of 31,400km² covering about 5.23 percent of the county's land surface of 600,000 km² (GeoHack 2022b) while Luhansk encompasses a surface area of 26, 684 km² (4.45% of Ukraine) and is located at the confluence of the Vilkhivka and Luhanka rivers (Internet Encyclopedia of Ukraine, 2022) at 48˚ 55′ 12″, 39˚ 1′ 12″ (GeoHack 2022a). Both oblasts together cover the longest segment of Ukraine's eastern national land boundary with Russia, with Donetsk to the southwest, and Russia to the southeast, east, and north, rendering them two of the five most spatially proximate oblasts to Russia. These oblasts together with Donestk territorially comprise Ukraine's Eastern sub-region, a section of which is colloquially known as the Donbas, an enclave plagued with repeated violent chaos and Russian infiltration. As a prominent fraction of the region remains under separatists' control since 2014 (ICJ 2018), state structures had also become benumbed initiating the region into a quasi-state (Aljukov 2019).

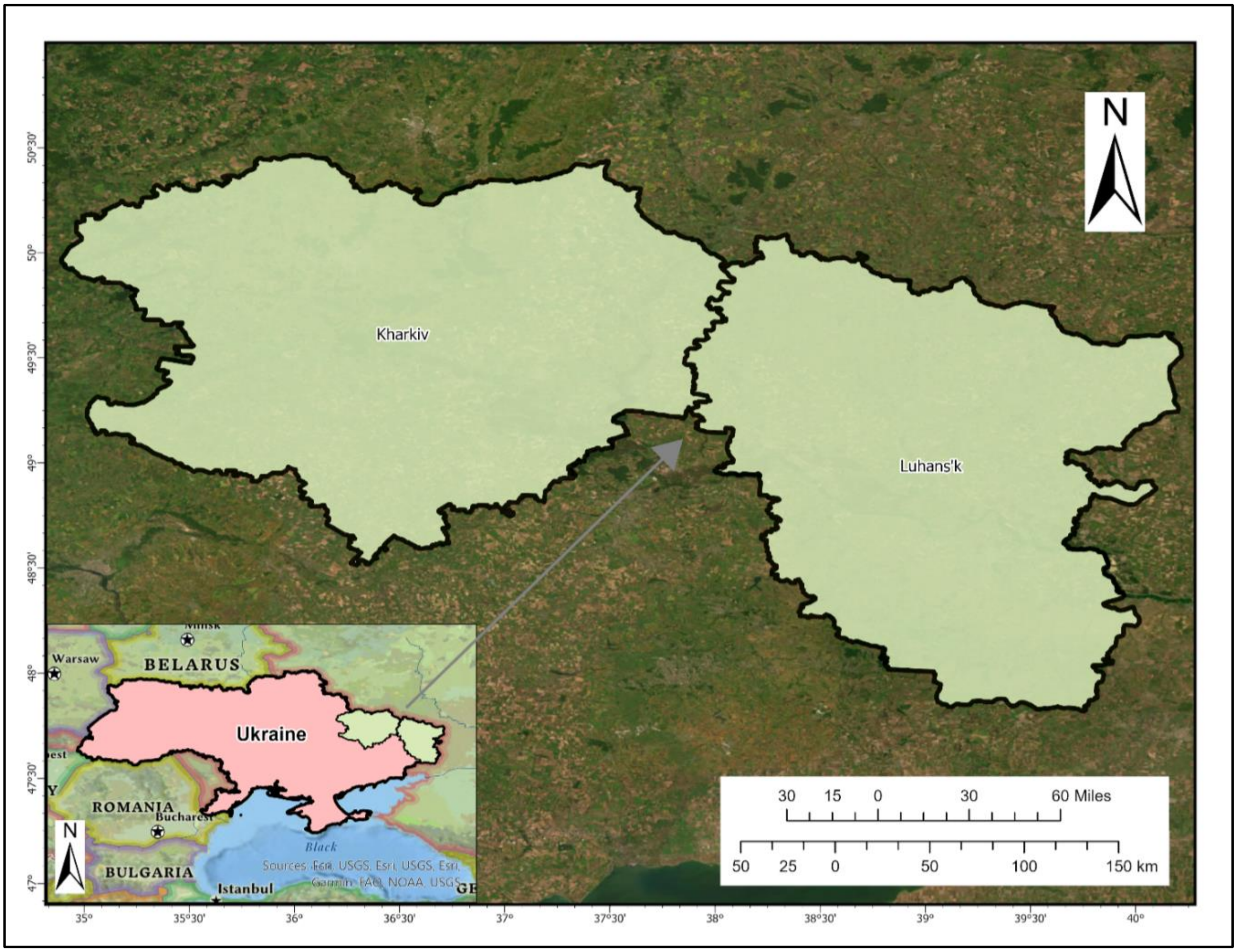

Figure 3: Study Area; Map of Ukraine, with the Kharkiv and Luhansk Oblasts in Perspective.

With its capital, Kharkiv, the Kharkiv Oblast hosts a 2022 population of 2.6 million inhabitants (City Population 2022) and has a humid continental climate with long, cold, snowy winters, warm to hot summers, and average rainfall totals of 519mm (20in) per year, with the most rainfalls recorded in June and July. The oblast has a topographic range of 93m to 218m with an average of 148m above sea level. Its capital, Kharkiv, was founded around 1655 as a military stronghold for protecting Russia's southern borderlands (Britannica, 2022) and grew to become a major center of industry, trade, and Ukrainian culture. The Luhansk Oblast on the other hand has a total population of about 2.1 million people and a 2022 population density of 78.81 per kilometer square (City

Population 2022) 87% of which is urban (Internet Encyclopedia of Ukraine 2022). Having a temperate-continental climate with dry and hot summers and cold winters, the oblast experiences an annual precipitation range of about 500 to 550 mm (19.69 to 21.65 in) with moisture deficits notably in the south, where dry winds and dust storms commonly present themselves in the spring (Internet Encyclopedia of Ukraine 2022). Cropland areas account for approximately half of the region's spatial extent and was a leading producer in gross regional product until 2014 when it experienced a 59% decrease in total regional output compared to 2015 figures (Britannica, 2022).

1.3.Study Objectives

The aim of this study is to assess the impacts of the 2022 Russian-Ukrainian war on landcover and agricultural fields in Eastern Ukraine while assessing social structures that emanated from online communication and war information dissemination during the period. The specific objectives of the study are as follows:

- Investigate the spatial evolution of landcover, and rate of decline in agricultural vegetation in the Kharkiv and Luhansk Oblasts between 2001 and 2023. This objective stems from the hypothesis that, there has been a rampant deterioration of crop fields and unharvested crops in Ukraine and this forms one of the most pronounced effects of the conflict for Ukraine, severing global food supply chain and spiking food crisis.
- Examine the flow of social media information, social structures and networks that emerged on Twitter during the conflict period. It is hypothesized that the current conflict is characterized by intense communications framing and selective reportage, with social media users' engagement with and acceptance of information dependent on which political block they are affiliated to.

- Assess the spatial pattern of civilian casualty in Kharkiv and Luhansk during the conflict period. This objective emerged from the hypothesis that the closer a location is to an urban space, the severe its recorded casualties.

1.4.Research Questions

- How did conflict modify the geospatial character of landcover and agricultural fields in Eastern Ukraine between June 2021 and June 2023?
- What social networks and structures emerged from online communication and war information dissemination during the 2022 Russian-Ukrainian war?
- What is the spatial pattern of civilian casualty in Kharkiv and Luhansk during the 2022 Russian-Ukrainian war?

1.5.Outline of the Study

This study is sectioned into five chapters, incorporating remote sensing, spatial analysis and social network analysis to explore the conflict and its impacts on landcover and agricultural fields while examining the spatial patterns of civilian casualty and social media information flow.

Chapter One provides a comprehensive background on Eastern European geopolitics and political dynamics for Ukraine amidst its relations with NATO and the Russian Federation. This chapter also sets out the objectives of the study, hypotheses, questions, the study area, thesis outline and significance.

Chapter Two provides a detailed review of related literature on Ukrainian agriculture, remote sensing applications and technologies in LU/LC change and conflict assessment, social media in Ukraine and social network analysis.

Chapter Three details a section of the thesis accepted for publication in the Special Issue; *Earth from Above: AmericaView, Remote Sensing, and Geospatial Technology* in ***The Geographical Bulletin.*** This chapter includes the aspect of the thesis that focused on remote sensing spatiotemporal environmental change and detection of agricultural land declination and abandonment. The chapter consisted of an introduction on post-Soviet geopolitics in Ukraine, remote sensing of conflict, agriculture in Ukraine and breadbasket in Europe, an overview of the study area, study methodology, results and discussions, and conclusion.

Chapter Four consists of the social network analysis of Twitter information flow during the 2022 Russian invasion of Ukraine. The chapter recapitulates the role of social media in the visual framing of conflict, dissemination of information and propaganda, contribution of both spatial and sociological data for research, and social network analysis. This chapter also provides comprehensive information on the varying datasets used for this section of the study, processing methods, results and discussions as well as conclusion.

Chapter Five provides a comprehensive summary of the study and elucidates conclusions specific to each study objective while drawing out the importance of the research and its contributions to academic literature on the explored topics.

1.6.Significance of the Study

Armed conflicts remain an active driver of geo-environmental change, imposing varying socioeconomic and physical implications, the understanding of which mostly remains partial. This research provides practical evidence on the immediate impacts of conflict on landcover in general and agricultural fields in specifics. By focusing on Eastern Ukraine, the study accentuates the importance of remote sensing as a valuable tool for monitoring and analyzing environmental evolution in conflict zones while adding to the broader discourse on the environmental consequences of armed conflicts, enriching the field of environmental security and conflict studies. The statistical explorations quantifying rates and extents of change in landcover classes, especially the decline in agricultural vegetation and land abandonment shed light on the vulnerability of agricultural spaces to warfare. While confirming some findings of pre-existing literature, discoveries from the spatial analysis and social network analysis can inform policymakers and international organizations on the immediate environmental repercussions of Russia's invasion of Ukraine, emphasizing the need for targeted interventions and aid in post-conflict reconstruction efforts. Understanding these impacts could facilitate the development of effective strategies for mitigating environmental degradation and promote sustainable recovery.

While highlighting the gaps in the understanding of conflict-induced landcover trajectories, this study also sets the stage for future investigations into the 2022 Russian-Ukrainian war that could delve deeper into the temporal continuum of post-conflict landcover changes, integrating socio-environmental impacts such as population displacement, water contamination, and agricultural disruptions. This paves the way for comprehensive studies addressing the full spectrum of conflict-induced environmental ramifications even in other regions. In essence, this study offers valuable insights into the immediate effects of conflict on agricultural landcover through remote sensing techniques, laying the groundwork for further research and informing policies aimed at mitigating the environmental impact of conflicts on land systems and livelihoods.

Chapter 2: Literature Review

2.1. Agriculture in Ukraine and Breadbasket in Europe

Following the collapse of the Union of Soviet Socialist Republics (USSR) in December 1991 (Strayer 1998) and the subsequent independence of Ukraine, the country's agriculture has been uniquely evolutionary (Sheldon 2022). State and collective farm systems were dismantled, farm properties and land shares were divided among farm workers and these shareholders subleased their newly acquired parcels of land to newly formed private agricultural associations (WDC-Ukraine 2020). About 71 percent of the country's land surface area was subjected to intensive agriculture with a primary focus on food crops such as barley, wheat, corn, rice, sugar beets, soybeans, and potatoes, as about eighty percent of these lands were chiefly arable (Advameg 2023) and have agriculturally conducive climate (Khalatur 2017). Crop production was actively complemented by husbandry in the first seven years of Ukraine's independence and the production of beef, veal, lamb, pork, chicken, horse, and rabbit generated $1.898 billion in gross national income and a total of $899 million in balance of payments for 1998 alone (Advameg 2023). Within this period, leading consumer crops such as potatoes, sugar beets and wheat recorded macroeconomic aggregates of 15.4 million metric tons, 13.89 million metric tons and 13.47 million metric tons respectively. Pork production totaled 668,000 tons, chicken with 194,500 tons while beef and veal collectively generated 786,000 metric tons (Advameg 2023) drifting Ukraine towards a regional export economy.

The subsequent introduction of intensive technologies of precision agriculture, irrigation, mechanization, increased scientific breeding including the creation of genetically modified varieties of crops facilitated a new level of agricultural development (Demydenko et al. 2018;

Orekhivskyi 2019) operated both by enterprises and individual households (Fileccia et al. 2014). Ukraine remains a leading exporter of agricultural products and plays a critical role in the global market supply of grains and oilseeds (USDA 2022) to about 146 countries globally in 2020 alone (WITS 2020) while controlling a significant global market share of 50 percent in sunflower oil (Lee 2022), 15 percent in corn, 13 percent in barley, 10 percent in wheat (Sheldon 2022) and is still regarded as the *breadbasket of Europe* (Osborne and Trueblood 2002; Lee 2022). Jointly with Russia, Ukraine between 1988 and 1990 contributed more than 70 percent of the total USSR agricultural outputs including meats and grains, a pattern that still holds for the post-soviet space and Eastern Europe today (Osborne and Trueblood 2002). Prior to the current conflict, Ukraine (together with Russia) provided 30 percent of the world's wheat and one-fifth of maize exports, with at least 50 other nations relying on both for about 33 percent of their wheat imports (FAO, 2022a; Yazbeck et al. 2022), while accounting for 19 and 4 percent of global output of barley and maize respectively between the 2016/17 and 2020/21 fiscal years (FAO 2022b).

The current state of agriculture in Ukraine is however characterized by deep crisis resulting from the combined effects of the general economic character, inadequacies in agricultural policy (Khalatur 2017), and war (Berkhout, Bergevoet, and van Berkum 2022). Despite promising prospects for recently produced crops in Ukraine, the ensuing conflict has truncated farmers' access to crop fields for harvesting (Yazbeck, et al. 2022), disturbing shipping and export, supply and pricing (Hassen and Bilali 2022). About 20 to 30 percent of crops remain unharvested during the 2022/23 season while yields are expected to decline as well (FAO 2022b). Military actions on critical transport infrastructure particularly on port facilities and railroads dwindled Ukraine's ability to transport agricultural products both for exports and domestic market distribution. About 95 percent of grain exports in Ukraine are transported through the ports of Odessa, Mariupol, and

Kherson (Hassen and Bilali 2022), all of which have experienced significant levels of deterioration while all Black Sea ports have also been blocked (Hassen and Bilali 2022). As the conflict continues to ensue between these major agricultural powers, it evidently imposes significant negative implications on the general socio-economy and food security of not only the region but the global economy (Hassen and Bilali 2022). Global prices for food, fertilizer and fuel have surged significantly in recent months in response to market fallouts from the conflict in Ukraine and sanctions on Russia (Abay et al. 2022) while long-term market disruptions are still expected for grains, especially wheat, maize and soybeans (Wall Street Journal 2022; Benton et al. 2022).

The interactivity between violent conflicts and agriculture manifests in several dimensions (Zurayk, Woertz, and Bahn 2018). Violent conflicts impact agricultural lands either directly through the destruction and burning of crop fields or indirectly through water contamination, soil acidification, and declination of farm inputs (Yin et al. 2019), and may induce changes in vegetation similar to the effects of drought (Beurs and Henebry 2008). These similarly influence micro-agricultural and labor markets, transaction costs, agricultural networks (Justino 2011), and in the presence of non-state actors could consequently dictate consumption patterns, especially to households (George, Adelaja, and Awokuse 2021).

Land systems, social, economic, and agricultural systems remain susceptible to pronounced evolutions, particularly in conflict-afflicted spaces (Baumann and Kuemmerle 2016) with conflict engineering biophysical transformations both via the displacement of human populations and agricultural land desertions which in some cases cause the reduction of farmlands and increased forest cover (Eklund, Persson, and Pilesjö 2016). As changes in agricultural land use represent the largest impact of some wars on the landscape, the detection of trends in the intensity and agglomeration of vegetative biomes via the utility of satellite imagery and other photogrammetric data play functional roles in identifying and quantifying the impact of such wars both on the spatial extent and output of agricultural lands (Witmer 2008).

2.2. Remote Sensing of conflict

The emergence of robust imaging technologies, classifier algorithms, computational devices, and simulations in contemporary geospatial science inquiry has advanced the remote observation of geographic phenomena in space in temporal fashions, facilitating not only the monitoring of their evolutionary patterns through time but also the assessment of both their instantaneous and incessant domino effects over time. The evaluation of the spatial signature of violent conflicts is by no means an exception, even in geo-urban enclaves. The utility of remotely sensed imagery to detect the effects of violent conflicts has experienced a dramatic increase in recent years (Witmer 2015) with specific concerns on the urban dimensions of such conflicts (Höglund et al. 2016). Understanding the spatial dimensions of these conflicts (and for that matter, wars) involves the task of digging into the complexity of space, which requires multidimensional methodologies of analysis to which urban mapping as a primary method of spatial analysis is essentially relevant (Ristic 2018). As geographic technologies have made significant contributions to military effectiveness, the preparation for war and the valuation of the geographic extent of the physical impacts of war provided the impetus for the rapid redevelopment of geographic technologies (Corson and Palka 2004; Witmer 2015). To this effect, remote sensing technology has been driven by these military applications, with the use of satellite imagery and aerial reconnaissance tied to improving the effectiveness of military operations (Witmer 2008).

The relevance of the comprehension of the spatial dimensions and consequences of violent conflicts has been highlighted in a growing body of scholarship from the fields of geography, urban design, architecture, history, politics, and sociology, with a series of concepts emerging to theorize the relationship between geo-urban space and warfare (Ristic 2018). The continuous improvements in the spectral, spatial, and temporal resolution of satellite imagery, aerial photos, and other digital photogrammetric products in recent times have made it possible to apply very high-resolution geospatial data for the assessment of the aftermaths of war, (Witmer 2008) including LU/LC change, structural damage, (Witmer 2015) vegetation dynamics, (Mao et al. 2012), and a variety of global land processes, (Tucker et al. 2005). As existing geospatial science literature dug into the complexity of these aftermaths of armed conflicts, further research assessed which change detection and classifier algorithms are best suited for specific aftermaths under study. Witmer (2008) proposed that the literature which seeks to consider the footprints of war using satellite imagery can be grouped into two categories; of those focusing on direct impacts resulting from bomb detonations, military movements, and minefields, and of those considering indirect impacts that result from displaced persons and their environmental imprints (both internally displaced populations and refugees). There seems, however, an emerging additional (third) category that aims at testing and enhancing the remote sensing technologies and science used in studying Witmer's two categories. This category of the geospatial science literature focuses its attention on what kind of sensor product best presents a suitable resolution(s) for the better study of the specific aftermath, as well as what analytic algorithm (machine learning, cellular automata, neural networks, etc.) best presents high accuracy results for a specific issue. These visual interpretations of pre and post-crisis fine-resolution satellite imagery have become the most straightforward method for discriminating the spatial footprints of violent conflicts (Al-Khudhairy, Caravaggi, and Giada 2005a) and remote sensing and aerial photogrammetry play significant leading roles in providing necessary data for spatiotemporal analysis (Kaplan et al. 2022), as well as LU/LC products for large areas at regular intervals (Zeng et al. 2010; Nyamekye et al. 2020; Friedl, Brodley, and Strahler 1999) for such purposes.

Civil war and other forms of violent conflicts that displace human populations are influential underlying drivers of LU/LC change (Geist and Lambin 2002; Gbanie, Griffin, and Thornton 2018) as are such other causal mechanisms as urban expansion and agrarian extensification (Nyamekye, et al. 2020). Land cover in its most definitive conceptualization is described as the observed (bio) physical cover of the earth's surface (Gregorio 2005) which is a "critical descriptor of the earth's terrestrial surface" (Wulder et al. 2018). In geo-urban spaces, anthropogenic engagements subject LC to rapid evolution (Phiri et al. 2020; Kursah et al. 2023) and is therefore a chief functional consequence of general man-land interrelationships. These interrelationships are characteristically reflexive of the human employment of the land (Meyer and Turner 1996), that is, the function to which a land parcel within the defined space is put. As such, land use (LU) determines both the type and character of land cover (LC) within space while the LU permitted within this space is also dependent in part on the pre-existing LC within the space and the environmental possibilism technology and capital sanction in the space, within time. There is therefore a repeated, ongoing cyclical relationship between LC and LU, moderated by man with the aid of technology and liquid capital, over time. Post this period, the effigy(ies) of the LU becomes the LC and/or determines and shapes the LC while this resultant LC in return bears influences on what other future LU occurs within the space.

Drivers of land cover change are distinguished into proximate and underlying causes (Lambin et al. 2001; Wilson and Wilson 2013). As proximate causes directly modify land cover, underlying causes operate at scales encompassing national, regional, and global levels, exhibiting complex interactions and may include social, political, economic, demographic, technological, cultural, and biophysical factors (Wilson and Wilson 2013). Changes to LU and LC typically take months to years to manifest, following a period of violent conflict. While violent conflict is the underlying causal factor, typically one or multiple proximate causes such as displacement/relocation, livestock decline, economic recession, security restrictions or landmine placement may also be responsible, (Witmer 2015). While qualitative sampling may aid in uncovering the proximate factor(s) at play, remote sensing and GIS help detect the geospatial extent of the underlying causal mechanism—violent conflict.

2.3. Pixel-based Classification

Image classification is a commonly utilized method for extracting LU/LC information from satellite data and many classification algorithms have been experimented in such investigations (Gao and Mas 2008). The classification and extraction of LU/LC information from remotely sensed data can be categorized into the two general approaches of pixel-based classification and object-based classification (Duro, Franklin, and Dubé 2012) otherwise referenced as Geographic Object-based Image Analysis (GeoBIA). As machine and deep learning algorithms could be applied in both methods and verified with confusion matrices and/or kappa statistics to quantify the quality and accuracy of results (McIver and Friedl 2001), both approaches have been proven to achieve varying levels of exactitude and precision (Whiteside, Boggs, and Maier 2011; Weih and Riggan 2010; Estoque, Murayama, and Akiyama 2015; G. Chen et al. 2018; Thomas Blaschke et al. 2014; Al-Khudhairy, Caravaggi, and Giada 2005; Jones et al. 2019). Earth observation information usually useful for such inquiries are captured by panchromatic sensors, synthetic aperture radar, and lidar, hyperspectral and multispectral scanners with a minimum of two sensors operating at red and near-infrared wavelengths (Belward and Skøien 2015) at varying spatial, temporal and radiometric resolutions. Since these imagery data consist of rows and columns of pixels, typical LC analysis has been based on single pixels (Gao and Mas 2008) using spectral reflectance stored as digital numbers in the satellite data (Gao and Mas 2008).

Conventional classification algorithms are pixel-based (Jixian and Zhengjun 2005), analyzing the spectral properties of each pixel, creating pixel-level clusters and such classification methods as k-means, neural networks, support vector machines, random forest, etc., which are widely applicable for 10-30 meter spatial resolution images (Guo et al. 2018). The overall objective of these classifiers therefore is to automatically categorize each pixel in an image into specific land cover classes (Jixian and Zhengjun 2005) using a typical workflow that includes a decision on the sensor product and algorithm, developing a classification scheme, training samples, feature extraction, image pre-processing, classification, precision validation and change detection (Varma et al. 2016).

2.4. Geographic Object-based Image Analysis

Remote sensing technologies have not only made possible the study of physical changes and patterns but also made available a great deal of LU/LC information as well as the necessary tools for studying and understanding these changes within space and over time, (Babalola and Akinsanola 2016). This has facilitated the temporal comparison of phenomena in space over varying durations of time and across space within a specific duration of time. Analyzing the trajectories of LU/LC can occur at fine temporal scales of less than a year, to broader scales of half a decade or more, and can be conducted within urban, rural, local, regional and global scales, (Wilson and Wilson 2013), presenting an uncommon perspective of the spatial and temporal dynamics of LU/LC processes (Gregorio 2005; Kafi, Shafri, and Shariff 2014). In such contexts, pixel-based classifiers received appropriate acceptability and were widely applied in many remote-sensing investigations (Emran et al. 2020) but the proliferation of high-resolution imagery with their associated high-frequency intra-class heterogeneity and horizontal layovers introduced further sophistications in image processing (Im et al. 2008) which pixel-based classifiers cannot handle without the introduction of considerable errors (Blaschke et al. 2014a). This initiated a shift from this category of classifiers toward a new paradigm that incorporates not only pixels but also the contextual attributes of the associated neighborhood.

Geographic Object-Based Image Analysis (GeOBIA) entails a set of digital image analysis approaches in remote sensing that study spatial phenomena by extracting and analyzing visually perceptible objects in space (Castilla and Hay 2008; Blaschke 2010; Chen et al. 2018), replicating human interpretation of remotely sensed data in automated/semi-automated approaches that facilitate, iteration, repeatability and re-production, while reducing subjectivity, labor and time costs (Hay and Castilla 2006). GeoBIA builds on older segmentation, edge-detection, feature extraction, and classification concepts that have been historically used in remote sensing image analysis for decades (Blaschke et al. 2014b), but has nevertheless provided a new, critical bridge between the spatial concepts applied in multiscale landscape analysis (Wu 1999). GeOBIA is essentially useful for remote sensing land cover analysis (Lizarazo and Elsner 2009) and has created a novel and robust paradigm for analyzing high spatial resolution imagery with advanced object-based models in a wide variety of real-world applications (G. Chen et al. 2018). As assumed that groups of raster pixels contained in imagery are in tune with geographic objects of the corresponding physical space, GeOBIA delineates clusters of these similar neighboring pixels that share a common landcover attribute into image objects and holds these image objects as the basic unit of the analysis (G. Chen et al. 2018). The use of GeOBIA, however, is not limited to images with small-resolution cells (Blaschke et al. 2014a) and its evolutionary algorithms lay out the relationship between the spatial resolution and the object under consideration, thereby overcoming challenges associated with pixel-based classifiers (Blaschke 2010; Ma et al. 2017).

GeoBIA incorporates both the spectral information of color and tone as well as spatial attributes of size, shape, texture, and neighborhood associations (Laliberte et al. 2004) and therefore accounts for homogeneity, pattern, shape, position, and other conditions of a complex and high-resolution satellite data (Emran, Marzen, and King 2020), getting closer to human visual image interpretation (Laliberte et al. 2004). In considering the information contained in satellite data as spatial, it is more appropriate to analyze objects georeferenced to space; a region of interest, as opposed to pixel reflectance, because landscapes consist of patches and objects that are spatially detectible (Laliberte et al. 2004).

2.4.1. Image Segmentation

Image segmentation is the fragmentation of a raster dataset into image primitives (Jones et al. 2019) and acts as the fundamental step on which a GeOBIA workflow is dependent (G. Chen et al. 2018). The process of segmentation partitions an image into non-overlapping spatially continuous regions termed segments (Blaschke et al. 2014b) which are designated as categorical land cover classes (Lizarazo and Elsner 2009) on the basis of homogeneity (Blaschke 2010) spectral property, shape, texture, size and associated topological objects (Im et al. 2008). Computer vision algorithms in image classification are less able for instance to distinguish between rivers and canals as a human eye would, since both have the same spectral signature as contained in pixels but segmentation in GeOBIA groups these pixels together as digitized vector objects and replicates how a human eye would visualize them; as objects (GISGeography 2014). As these image objects are merged with other image primitives, they produce hierarchies that though spatially continuous, retain statistically discrete properties which can be used for advanced analysis

(Lang 2008; Jones et al. 2019). These consequent analyses result in image objects that could be attributed with class labels that correspond to such spatial phenomena as land cover classes or categories of vegetative biomes (Jones et al. 2019). This shift from pixel spectral signatures to meaningful objects in space permits rule-based image analysis (Hay and Castilla 2006; Jones et al. 2019) and caters for the high-accuracy limitations associated with pixel-based classifiers.

As explicated by Benz et al. (2004), these image objects, otherwise referred to as segments, become the basic processing units of GeOBIA and within each of these segments, pixels are homogenic and correspond to actual-ground objects (Weng 2010). Several segmentation techniques are applicable in GeOBIA and may include the multi-resolution segmentation (MRS), spectral differenced segmentation (SDS), multi-threshold, contrast filter, contrast split, chessboard and quadtree based segmentation, among others. As such, the appropriate segmentation technique needs to be selected and executed with caution as under-segmentation results in a mixture of different features, while over-segmentation creates divided features (Weng 2010).

Multi-resolution segmentation is a region-based algorithm (Y. Chen, Chen, and Jing 2021) that locally minimizes the average heterogeneity of segments for a given resolution. It segments images with a homogeneity threshold which usually is a provided scale parameter while exporting the segmented polygons. It usually is used as an initial step in LU/LC and change detection workflows as it generates segments with optimum geographical significance and strong adaptability (Hay et al. 2003; Y. Chen et al. 2021) and therefore remains one of the most successful image segmentation algorithms in the GeOBIA framework (Aguilar et al. 2016). With the multi-resolution segmentation, however, scale, shape, and compactness become fundamental parameters available to the analyst, which may affect the performance of the algorithm (Aguilar et al. 2016) as large scales could result in small segments being covered by larger segments—under-segmentation—whereas small scales could create fragmentary segments—over-segmentation as depicted in Figure 4. It is therefore essential to utilize optimal scales for this algorithm as this will enhance the accuracy of the classification and change detection (Y. Chen et al., 2021).

These three primary constants of scale, compactness and shape basically influence MRS (Liu et al. 2012; Emran et al. 2020) and despite its suitability for generating meaningful segments

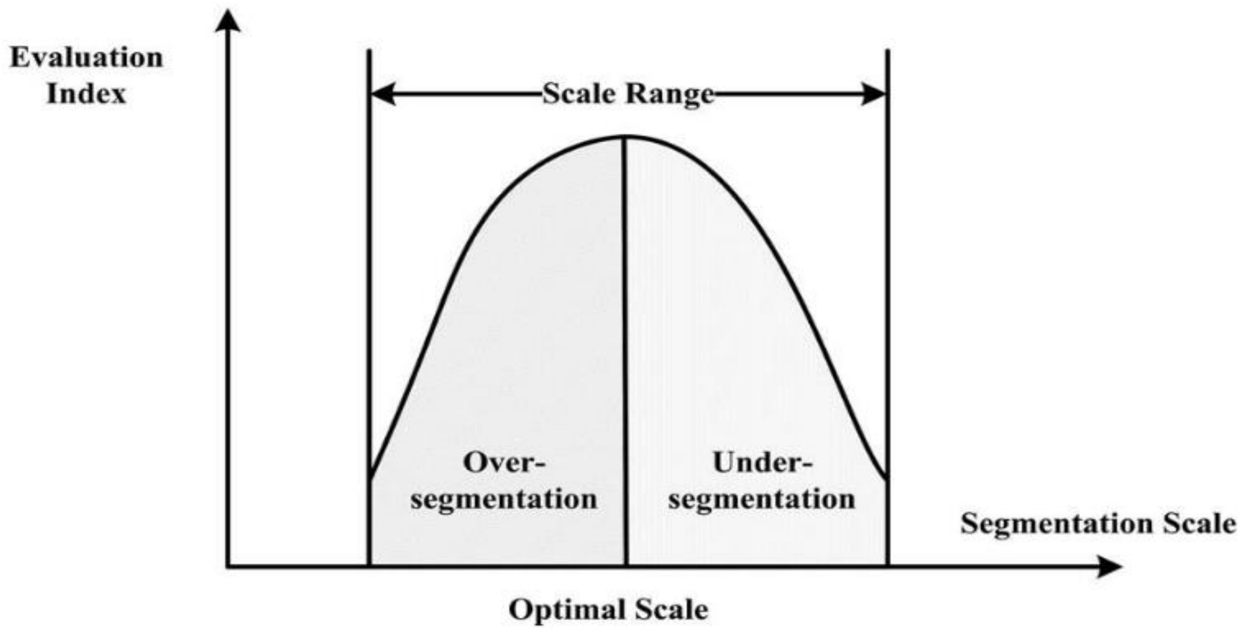

Figure 4: Relationship between segmentation scale and evaluation index. Source: Y. Chen et al., (2021).

adaptable to the spatial pattern of land cover distribution (Mugiraneza et al., 2019), it uses user-defined constants (Emran et al. 2020). Adjusting these parameters produces varying results. The determination of optimal parameters for segment delineation therefore is dependent upon repeated trials and pretests by the researcher to decide which provides the most suitable contextual information for the study area (Jones et al. 2019). Figure 5 below for instance indicates six consecutive MRS scale parameters tested with the default shape and compactness values of 0.1 and 0.5 respectively with each multispectral band weight of 1 except NIR which was given the weight of 2 due to its depiction of vegetative information (Elvidge and Chen 1995).

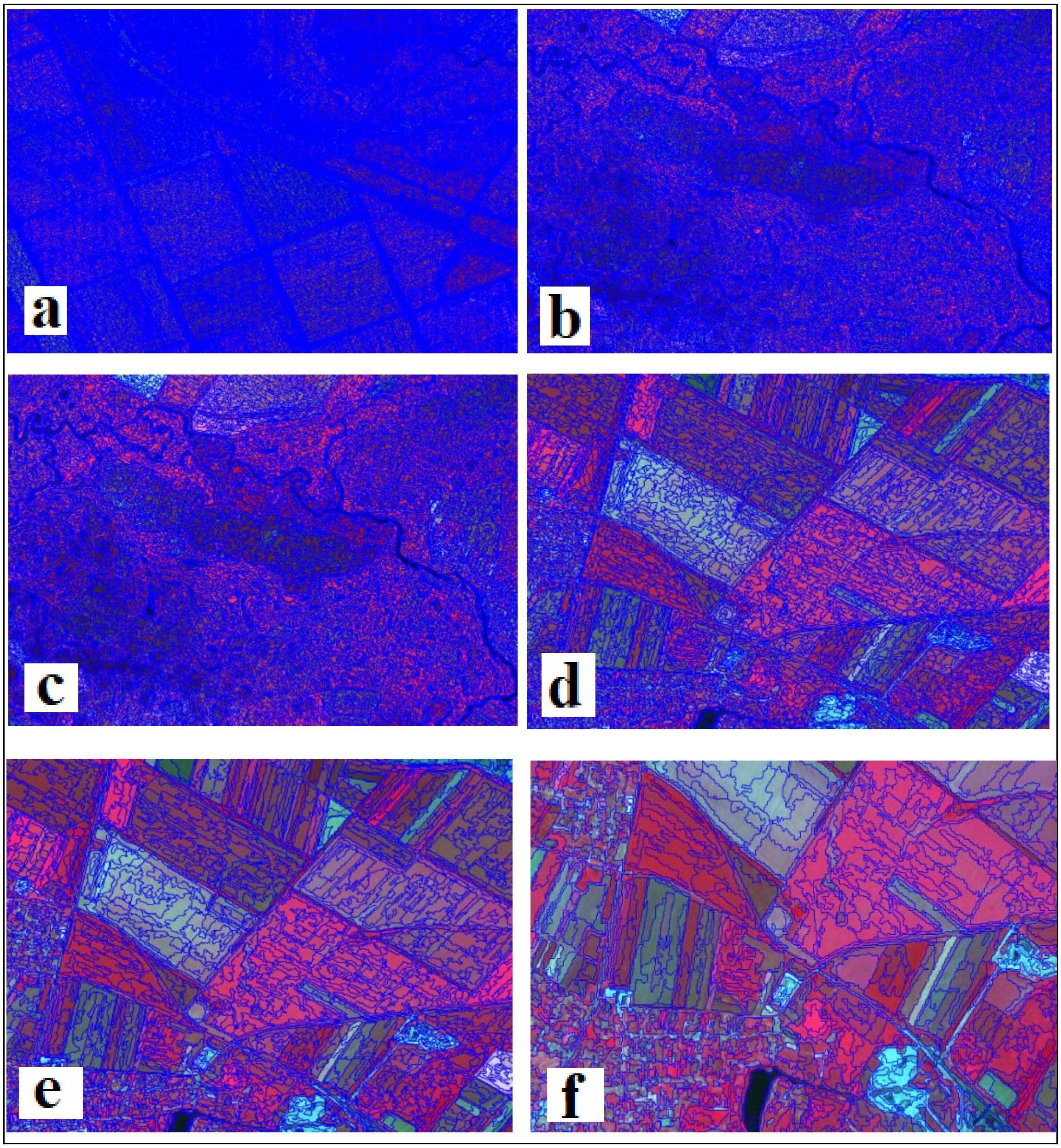

Figure 5: Determination of scale parameter, shape, and compactness.

Scale parameters below 20 (b:10, c:15) well segmented the south-east swift flowing river, while a:5 created over-segmented objects with hardly discernible boundaries. However, they all hindered the visual inspection of segments depictive of crop fields. Parameters above 20 (e:35, f:60) both performed better at segmenting crop fields but grouped pixels of different LCs into the same segments in regions southwest. The scale parameter of 20 (d) resolved this error but based on its handling of crop fields would need to be combined with other segmentation algorithms in a hierarchical multi-level bottom-up segmentation ruleset as suggested by (Liu et al. 2012; Benz et al. 2004) for a subset of the region as experimented in (Jones et al. 2019) and reapplied on the entire region of interest. These rulesets allow for the hierarchical link within image objects, as previously created segments are linked with other objects and attributes created from them (Mugiraneza, Nascetti, and Ban 2019). This algorithm will be utilized in a future study to further explore insights uncovered in this study by the pixel-based classifiers.

2.5. Social Media in Ukraine

Social media has created a conversational territory for the visual framing of conflict and conflict narratives and has become an integral part of contemporary warfare, affecting not only the public perception of conflict but also policy decisions about these conflicts and how their history is captured by historians (Makhortykh and Sydorova 2017). It has by far reshaped the dynamics of war reportage both in Ukraine and around the world (Suciu 2022). In Ukraine, much of the conflict period communication was more about identity and media (Dyczok 2014) with social media becoming important information sources which were often picked up and disseminated by mainstream and global media outlets (Dyczok 2014). Government institutions, civilians and the armed forces engaged social media platforms in communicating both their successes and the losses of opposing forces (Suciu 2022). These include both authentic and completely imaginative storylines, notable of which was "the computer versions of a combat flight simulator—The Ghost of Kyiv" (Mallick 2022; Galey 2022).

Social media discourse and public opinion are inextricable parallel systems of constructing meaning, creating and presenting interpretive packages for relevant issues and events (Gamson and Modigliani 1989). The use of social media has contemporarily become increasingly prevalent, and its influences have been felt in many facets of human life, including war, and in the context of the Russian-Ukrainian conflict, has been used to inform, recruit fighters, disseminate propaganda and shape public opinion (Hoskins 2022; Mallick 2022; Alberti and Serio 2020). With the onset of the Crimean crisis and its subsequent annexation, the sole official structure for the resolution and management of conflict in Ukraine has been the Minsk Agreements clinched between Ukraine and Russian-backed separatists, with Russia, Germany and France as guarantors (Rojansky 2016) which have nonetheless been unable to remedy the reality of Russia's de facto control over Crimea and the recurrent violent conflicts in Ukraine's Donbas (Rojansky 2016). Evident within these insurgencies were the important roles played by social media in mobilizing civil society (Pospieszna and Galus 2019), constructing visual frames by both pro-Ukrainian and pro-Russian online communities (Makhortykh and Sydorova 2017), instigating regime changes (Brantly 2019), active disinformation campaigns (Mallick 2022; Mejias and Vokuev 2017), diffusion of information, compounding and facilitation of pre-existing social network ties (Onuch 2015) as well as the facilitation of the exchange of psychological contents in support of and opposition to protest activities (Jost et al. 2018).

Nonetheless, social media has equally provided a universal communication infrastructure for seeking help by war-affected populations during the Ukrainian conflict (Talabi et al. 2022), created a rostrum for in-person first-hand self-expression by affected persons about the impact of the war on their lives (Zasiekin et al. 2022), alleviated social isolation during active warfare (Singer and Brooking 2018), cataloged digital evidence of potential war crimes (Goujard 2022) while providing a means of social media-based music, art and drama therapies to aid the active remediation of war-induced post-traumatic stress disorder symptoms (Gever et al. 2023) and depression among affected populations (Ahmad et al. 2022). This has proffered useful alternatives for delivering interventions and eliminating barriers that must have otherwise truncated them (Gever et al. 2023).

About 30 million Ukrainians are subscribed to active social media (Dzyubenko 2022; Kemp 2022; Alberti and Serio 2020) notably including Yandex, VKontakte, Facebook, Pinterest, Instagram, YouTube, Twitter, Reddit, LinkedIn, TikTok, among others (GlobalStats 2023), generating open source social information even for research purposes. Social media data including videos and photographs provide both big-picture details and micro-details, revealing spatial and other attributes in aid of geolocation and spatial attributions (Toler 2022). Geolocation techniques facilitate the conclusive confirmation of where these images and videos were taken. Big-picture details such as the angular perspective of buildings both from streets and aerial photos inform what locations to look at in the preliminary phase of geolocation. Additionally, micro details such as floor cracks, paint patterns, building columns, adjacent road signs, door, window and stairway structures as well as general architecture as contained in the captured video/photograph facilitate positive identification of the actual locations where these social media information were first generated to which x,y coordinates could be attributed to provide ground references (Toler 2022). Consequently, such spatial data could be integrated into spatial and other forms of analysis, especially in remote sensing and GIS applications.

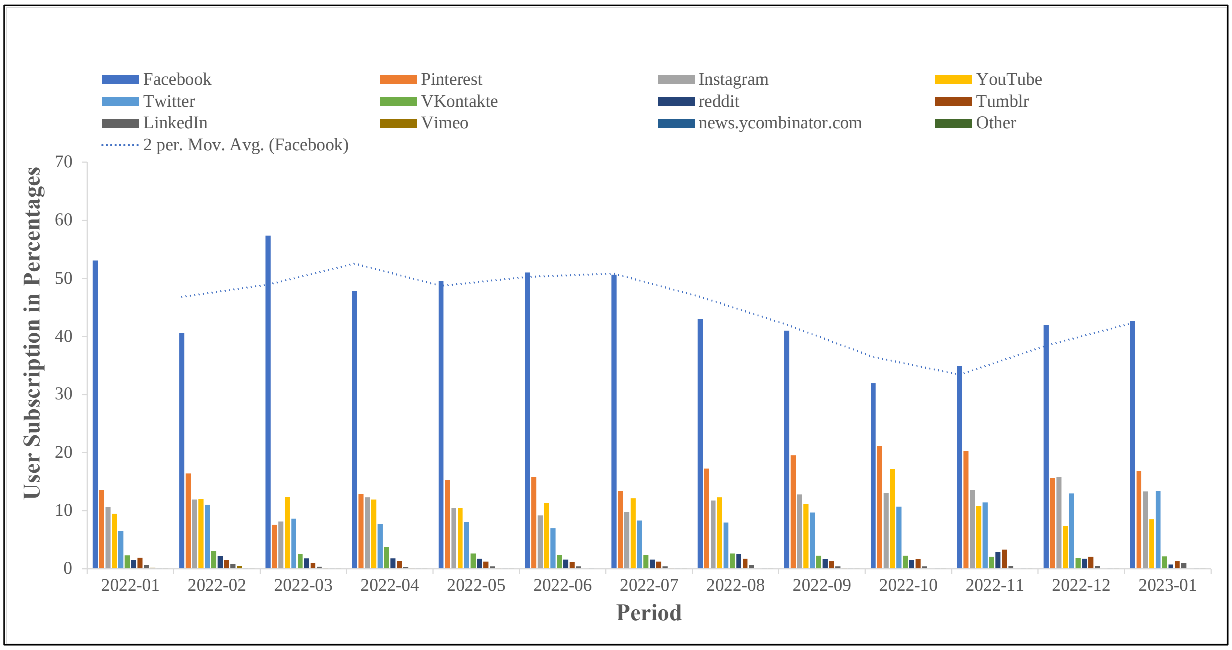

Figure 6: Social Media Subscriber Statistics in Ukraine. Data source: GlobalStats 2023 file:///Users/air/Zotero/storage/EVWKI6J3/ukraine.html

2.6. Social Network Analysis

Social Network Analysis (SNA) has attracted considerable interest from social and behavioral research with a critical focus on the interrelationships among social actors as well as the patterns and implications of these interrelationships (Wasserman and Faust 1994). It is the study of structure within and among social groups based on theoretical constructs of sociological and mathematical foundations of graph theory (Columbia Mailman School of Public Health 2016). The network consists of a set of people and other social entities connected by a set of social attributes that could be patterned, visualized, and interpreted with the aid of computational modeling (Jamali and Abolhassani 2006). The patterning of these relationships is undertaken based on the assumption, among other things that, network structure and the properties of that structure have significant implications on the outcome of interests investigated (Columbia Mailman School of Public Health 2016). Social network analysis attributes networked structures as vertices (points or nodes) and links (or edges). As individuals or groups within the network structure are conceptualized as nodes, the observed relations evident between and among them are characterized as edges (Scott 2012), complementarily engineering patterns of points and lines that can be explored mathematically or visually, in order to assess their effects on the entities that constitute the formed network.

The origins of the approaches to social structure with explicit attention on social network stemmed from sociological traditions, with emphasis on the formal properties of social interaction in which investigators could configure social relations through the interweaving of social encounters (Scott 2011). Nevertheless, SNA evolved into an interdisciplinary endeavor, developing from social theory, statics and computational methodologies while its central concepts of relation, network and structure emerged from the social and behavioral sciences (Wasserman and Faust 1994) with wide applications in the biological sciences and information systems (Crnovrsanin, Correa, and Ma 2009). Considering these focuses, its application especially in open-source and social media investigation requires ethical and methodological imperatives as prerequisites for guaranteeing the accuracy, quality and higher confidence of both the networked datasets, procedures and overall investigation outcomes (UN Human Rights Center 2022).

Social media were invented to enable individual members of the public connect with one another and interact with ease, and have therefore also become platforms for interaction during disasters, war and emergencies (Daga 2017). As such, they have generated substantial amounts of information on social interaction on a range of social issues and topics (Ahmed and Lugovic 2018a), the nature and dynamics of which could be better comprehended using SNA (Daga 2017). The challenge however in incorporating social media into geolocation and spatial investigation is dealing with the discovery and verification of relevant material within an increasing volume of online information, especially photographs and videos captured on smartphones and other mobile devices, some of which could be characteristically subjected to compromise and misattribution (UN Human Rights Center 2022). As large-scale vulnerability, war crimes and displacements however intensify in times of armed conflicts, there is a heightened need for common standards in investigative mechanisms for spatial research, particularly for the acquisition, preservation, and analysis of open-source information (UN Human Rights Center 2022). With the aid of SNA, the resultant patterns of these social interactions and networks emanating from such conflicts could be investigated to provide specific social insights alongside the stated spatial analyses.

2.6.1. Visualization of Social Networks in NodeXL

Network Overview for Discovery and Exploration in Excel (NodeXL) is an open-source SNA plug-in for Microsoft (Bonsignore et al. 2009) that simplifies basic network analysis tasks and supports the analysis of social media networks (Smith 2013) similar to other network visualization tools such as Pajek, UCINet, and Gephi (Ramachandran et al. 2013). By design, NodeXL facilitates the import of network data from multiple media including Twitter, Facebook, YouTube, Flickr, email, blogs, wikis, and the world wide web (Smith 2013), enhancing cleaning, analysis and visualization in Excel while extending existing spreadsheet graph features with added network charts to alleviate historical bottlenecks associated with computer-based visualization of social networks (Smith et al. 2009). Recognized as an efficient substitute for other network analysis software that demand complex computer programing skills, NodeXL offers a flexible, interactive and effective exploratory interface for network analysis (Jagals and Van der Walt 2016). Farmed network datasets could be directly imported into NodeXL and graphically displayed, and as such positioned to support network analysts without stepping through complex programming interfaces (Bonsignore et al. 2009).

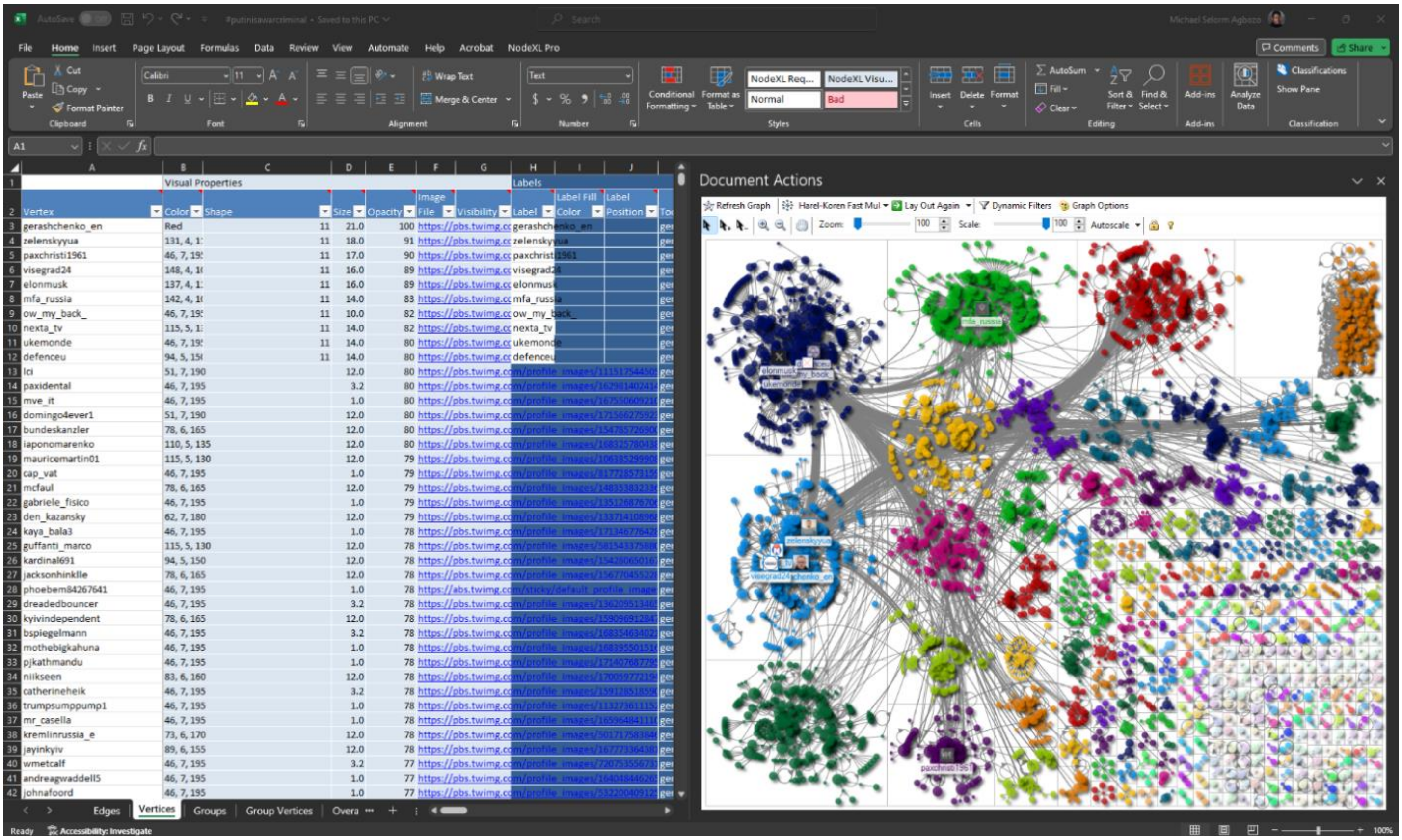

Figure 7: NodeXL interface.

Chapter 3: A Remote Sensing Investigation of the 2022 Invasion of Eastern Ukraine on Agricultural Landcover

3.1. Introduction

Ukraine-Russian geopolitical relations over the years have seen alternate periods of tranquility and swift chaos with violent conflicts dating as far back as the Ukraine-Soviet insurgency of 1917 to the most recent conflicts of the 2014 Russian annexation of Crimea and the 2022 Russian invasion of the entirety of Ukraine. Current major attacks have been reported across Ukraine, including the capital, Kyiv, and multiple other urban spaces while the pre-existing hostilities in the Donetsk and Luhansk oblasts (states) have significantly intensified (UNHCR 2022), settling into largely recognizable patterns as other past conflicts of the region. These conflicts have remained multidimensional with complex causative factors that interact in multifarious fashions, the analysis of which is further complicated by the intensive informational wars that accompany them (Mandel 2016; Khaldarova and Pantti 2016).

Many of these recurrent conflicts in the contemporary era (Aalto 2006; Haukkala 2015) have been in part due to an attempt to lock Russia into an institutionalized post-sovereign arrangement with the view of creating an essentially unipolar Europe based on the European Union's liberal norms and values. This, however, has been contradictorily met by Russia's evolving radically unfavorable responses to that project, which alternatively aimed at restoring dissolved Soviet Union legacies (Haukkala 2015) and reasserting Russian power and influence abroad, particularly in the post-Soviet space (Larrabee 2022), since accustomed to being a superpower, the Russian Federation found it herculean to imbibe the new normal which seeks to suggest that both its importance and influence in global affairs had fallen and that its voice in foreign policy no longer conveys much impact (Larrabee 2022).

Within these dynamics, Ukraine emerges pivotal in the sociopolitical stability of Europe and is of sacrosanct geopolitical interests to both Russia and the West (D'Anieri, Kravchuk, and Kuzio 1999). To Russia, Ukraine remains a buffer against a possible invasion by the North Atlantic Treaty Organization (NATO) (Talabi et al. 2022) owing to its considerable expansion into the post-Soviet space, while to the West, an independent Ukraine creates a strong, sovereign state through which Russia would have to penetrate before it could renew its threat to regions west (of Ukraine) (D'Anieri, Kravchuk, and Kuzio 1999). As symbolized in Figure 1, historical Soviet Republics such as Estonia, Latvia and Lithuania have become members of NATO, sanctioning membership after the collapse of the Soviet Union (NATO 2022). Similarly, such countries as Albania, Bulgaria, Romania, Czechloslovakia (Czech and Slovakia), Hungry and Poland which were member states of the Warsaw Pact, a historical 'Russian version' of NATO, are currently members of NATO, with Finland joining in April 2023 as the thirty-first ally of the NATO defense alliance. This eastward expansion is visualized by Russia as a threat to its national security, that, which ought to be either curtailed or erased even by radical violence to prevent the remaining 'safe zone' post-soviet space, Ukraine, Moldova, Georgia and Belarus, from joining NATO.

The conduct of a political agenda in Ukraine therefore would be for tipping this political equilibrium to usurp favor for any of these blocks which initiates it. It is therefore unimaginative if Russian hostility in Ukraine is regarded as fighting for a version of Ukraine that is subservient to Russia's idea of what Ukraine should be: a buffer under a Russian hegemony, where Ukraine's national identity, nationhood, ideals, and interpretation of history can be vetted, sanctioned and vetoed by the Russian state (Knott 2022). It is essential to clarify that, NATO being a collective security clique, a case in which an attack on any member state is regarded as an attack on all and warrants a collective military action (NATO 2022), Ukraine's membership and attachment denies the Russian Federation its de facto control and military influences in Ukraine (Kuzio 2018).

The current conflict has been characterized by the functional utility of explosive weaponry with varying effects in populated and other areas, including heavy artillery and multiple-launch rocket systems (UNHR 2022), with reports of Ukrainian armed force's equally responsive shelling of populated areas in territories controlled by Russian affiliated armed groups in the Donetsk and Luhansk oblasts (UNHR 2022). This chaos has drawn a global spectacle and the world has been watching its multivariate impacts with concern, as several thousands of civilians were reportedly killed and schools among other social facilities so far destroyed (Júnior et al. 2022).

These violent conflicts remain a developmental issue as their resultant ramifications usually are complexly deleterious and extend beyond recorded direct battleground casualties (Gates et al. 2012). Military and other forms of armed operations usually target and transpire within the physical environment, and thus entail adverse environmental outcomes such as vegetation defoliation, structural deterioration, environmental damage, water contamination, land use/land cover (LU/LC) modifications (Yin et al. 2019), habitat destruction and fragmentation (George et al. 2021) and other impacts. As these dissensions may significantly fragment economic space (Bar-Nahum et al. 2020), truncate local and macro food supply chains and influence both society and the environment (Yin et al. 2019; Baumann and Kuemmerle 2016), they also ignite agricultural land abandonment (Yin et al. 2019) and labor switch, inducing food insecurity (Brück and d'Errico 2019) and other unexpected outcomes.

Other significant imprints of the current conflict have been assessed in relation to energy costs, household consumption expenditures, global remittance flow, healthcare, food security, vaccine diplomacy, stock market returns and internet universality. The continuous ascendance of energy prices, dwindling confidence in the economy including financial markets plagued with bold international sanctions were for instance opined by (Liadze, et al. 2022) as the main impacts of the conflict on the world economy. The works of (Boubaker, et al. 2022) pointed negative cumulative returns for global stock market indices as an impact of the escalating conflict, while (Roborgh, et al. 2022) maintains the position that the conflict has created another 21st-century humanitarian disaster. Similarly, (Bluszcz and Valente 2022) cited both civilian casualties and 15.1 percent per capita of GDP foregone as imprints of the conflict just as (Kismödi and Pitchforth 2022) espoused forced migration, sexual and reproductive health as well as human right crisis as issues in the context of the Russian-Ukraine war for Ukraine, on which international attention must focus.

Despite growing studies on the multifaceted impacts of this conflict, there is currently very limited study conducted specifically on its impacts on agricultural landcover in Eastern Ukraine. This study, therefore, employs remote sensing and spatiotemporal landcover analysis with Sentinel-2 constellation datasets in both supervised maximum likelihood classification and unsupervised ISODATA algorithm to explore the impact of the 2022 Russian-Ukrainian war on land cover and crop fields in Eastern Ukraine between June 2021 and June 2023. Specifically, the study investigated what LC underwent the most drastic change in the Kharkiv Oblast between 2021 and 2023, and examined the spatial extent and rates of decline in agricultural vegetation in both Kharkiv and Luhansk Oblasts between 2001 and 2023.

3.2. Agriculture in Ukraine and Breadbasket in Europe

Following the collapse of the Union of Soviet Socialist Republics (USSR) in December 1991 (Strayer 1998) and the subsequent independence of Ukraine, the country's agriculture has been uniquely evolutionary (Sheldon 2022). State and collective farm systems were dismantled, farm properties and land shares were divided among farm workers and these shareholders subleased their newly acquired parcels of land to newly formed private agricultural associations (WDC-Ukraine 2020). About 71 percent of the country's land surface area was subjected to intensive agriculture with a primary focus on food crops such as barley, wheat, corn, rice, sugar beets, soybeans, and potatoes, as about eighty percent of these lands were chiefly arable (Advameg 2023) and have agriculturally conducive climate (Khalatur 2017). Crop production was actively complemented by husbandry in the first seven years of Ukraine’s independence and the production of beef, veal, lamb, pork, chicken, horse, and rabbit generated $1.898 billion in gross national income and a total of $899 million in balance of payments for 1998 alone (Advameg 2023). Within this period, leading consumer crops such as potatoes, sugar beets and wheat recorded macroeconomic aggregates of 15.4 million metric tons, 13.89 million metric tons and 13.47 million metric tons respectively. Pork production totaled 668,000 tons, chicken with 194,500 tons while beef and veal collectively generated 786,000 metric tons (Advameg 2023) drifting Ukraine towards a regional export economy.

The subsequent introduction of intensive technologies of precision agriculture, irrigation, mechanization, increased scientific breeding including the creation of genetically modified varieties of crops facilitated a new level of agricultural development (Demydenko et al. 2018; Orekhivskyi 2019) operated both by enterprises and individual households (Fileccia et al. 2014). Ukraine remains a leading exporter of agricultural products and plays a critical role in the global market supply of grains and oilseeds (USDA 2022) to about 146 countries globally in 2020 alone (WITS 2020) while controlling a significant global market share of 50 percent in sunflower oil (Lee 2022), 15 percent in corn, 13 percent in barley, 10 percent in wheat (Sheldon 2022) and is still regarded as the *breadbasket of Europe* (Osborne and Trueblood 2002; Lee 2022). Jointly with Russia, Ukraine between 1988 and 1990 contributed more than 70 percent of the total USSR agricultural outputs including meats and grains, a pattern that still holds for the post-soviet space and Eastern Europe today (Osborne and Trueblood 2002). Prior to the current conflict, Ukraine (together with Russia) provided 30 percent of the world's wheat and one-fifth of maize exports, with at least 50 other nations relying on both for about 33 percent of their wheat imports (FAO, 2022a; Yazbeck et al. 2022), while accounting for 19 and 4 percent of global output of barley and maize respectively between the 2016/17 and 2020/21 fiscal years (FAO 2022b).

The current state of agriculture in Ukraine is however characterized by deep crisis resulting from the combined effects of the general economic character, inadequacies in agricultural policy (Khalatur 2017), and war (Berkhout, Bergevoet, and van Berkum 2022). Despite promising prospects for recently produced crops in Ukraine, the ensuing conflict has truncated farmers' access to crop fields for harvesting (Yazbeck, et al. 2022), disturbing shipping and export, supply and pricing (Hassen and Bilali 2022). About 20 to 30 percent of crops remain unharvested during the 2022/23 season while yields are expected to decline as well (FAO 2022b). Military actions on critical transport infrastructure particularly on port facilities and railroads dwindled Ukraine's ability to transport agricultural products both for exports and domestic market distribution. About 95 percent of grain exports in Ukraine are transported through the ports of Odessa, Mariupol, and Kherson (Hassen and Bilali 2022), all of which have experienced significant levels of deterioration while all Black Sea ports have also been blocked (Hassen and Bilali 2022). As the conflict continues to ensue between these major agricultural powers, it evidently imposes significant negative implications on the general socio-economy and food security of not only the region but the global economy (Hassen and Bilali 2022). Global prices for food, fertilizer and fuel have surged significantly in recent months in response to market fallouts from the conflict in Ukraine and sanctions on Russia (Abay et al. 2022) while long-term market disruptions are still expected for grains, especially wheat, maize and soybeans (Wall Street Journal 2022; Benton et al. 2022).

The interactivity between violent conflicts and agriculture manifests in several dimensions (Zurayk, Woertz, and Bahn 2018). Violent conflicts impact agricultural lands either directly through the destruction and burning of crop fields or indirectly through water contamination, soil acidification, and declination of farm inputs (Yin et al. 2019), and may induce changes in vegetation similar to the effects of drought (Beurs and Henebry 2008). These similarly influence micro-agricultural and labor markets, transaction costs, agricultural networks (Justino 2011), and in the presence of non-state actors could consequently dictate consumption patterns, especially to households (George, Adelaja, and Awokuse 2021).

Land systems, social, economic, and agricultural systems remain susceptible to pronounced evolutions, particularly in conflict-afflicted spaces (Baumann and Kuemmerle 2016) with conflict engineering biophysical transformations both via the displacement of human populations and agricultural land desertions which in some cases cause the reduction of farmlands and increased forest cover (Eklund, Persson, and Pilesjö 2016). As changes in agricultural land use represent the largest impact of some wars on the landscape, the detection of trends in the intensity and agglomeration of vegetative biomes via the utility of satellite imagery and other photogrammetric data play functional roles in identifying and quantifying the impact of such wars both on the spatial extent and output of agricultural lands (Witmer 2008).

3.3. Remote Sensing of conflict

The emergence of robust imaging technologies, classifier algorithms, computational devices, and simulations in contemporary geospatial science inquiry has advanced the remote observation of geographic phenomena in space in temporal fashions, facilitating not only the monitoring of their evolutionary patterns through time but also the assessment of both their instantaneous and incessant domino effects over time. The evaluation of the spatial signature of violent conflicts is by no means an exception, even in geo-urban enclaves. The utility of remotely sensed imagery to detect the effects of violent conflicts has experienced a dramatic increase in recent years (Witmer 2015) with specific concerns on the urban dimensions of such conflicts (Höglund et al. 2016). Understanding the spatial dimensions of these conflicts (and for that matter, wars) involves the task of digging into the complexity of space, which requires multidimensional methodologies of analysis to which urban mapping as a primary method of spatial analysis is essentially relevant (Ristic 2018). As geographic technologies have made significant contributions to military effectiveness, the preparation for war and the valuation of the geographic extent of the physical impacts of war provided the impetus for the rapid redevelopment of geographic technologies (Corson and Palka 2004; Witmer 2015). To this effect, remote sensing technology has been driven by these military applications, with the use of satellite imagery and aerial reconnaissance tied to improving the effectiveness of military operations (Witmer 2008).

The relevance of the comprehension of the spatial dimensions and consequences of violent conflicts has been highlighted in a growing body of scholarship from the fields of geography, urban design, architecture, history, politics, and sociology, with a series of concepts emerging to theorize the relationship between geo-urban space and warfare (Ristic 2018). The continuous improvements in the spectral, spatial, and temporal resolution of satellite imagery, aerial photos, and other digital photogrammetric products in recent times have made it possible to apply very high-resolution geospatial data for the assessment of the aftermaths of war, (Witmer 2008) including LU/LC change, structural damage, (Witmer 2015) vegetation dynamics, (Mao et al.

2012), and a variety of global land processes, (Tucker et al. 2005). As existing geospatial science literature dug into the complexity of these aftermaths of armed conflicts, further research assessed which change detection and classifier algorithms are best suited for specific aftermaths under study. Witmer (2008) proposed that the literature which seeks to consider the footprints of war using satellite imagery can be grouped into two categories; of those focusing on direct impacts resulting from bomb detonations, military movements, and minefields, and of those considering indirect impacts that result from displaced persons and their environmental imprints (both internally displaced populations and refugees). There seems, however, an emerging additional (third) category that aims at testing and enhancing the remote sensing technologies and science used in studying Witmer's two categories. This category of the geospatial science literature focuses its attention on what kind of sensor product best presents a suitable resolution(s) for the better study of the specific aftermath, as well as what analytic algorithm (machine learning, cellular automata, neural networks, etc.) best presents high accuracy results for a specific issue. These visual interpretations of pre and post-crisis fine-resolution satellite imagery have become the most straightforward method for discriminating the spatial footprints of violent conflicts (Al-Khudhairy, Caravaggi, and Giada 2005a) and remote sensing and aerial photogrammetry play significant leading roles in providing necessary data for spatiotemporal analysis (Kaplan et al. 2022), as well as LU/LC products for large areas at regular intervals (Zeng et al. 2010; Nyamekye et al. 2020; Friedl, Brodley, and Strahler 1999) for such purposes.

Civil war and other forms of violent conflicts that displace human populations are influential underlying drivers of LU/LC change (Geist and Lambin 2002; Gbanie, Griffin, and Thornton 2018) as are such other causal mechanisms as urban expansion and agrarian extensification (Nyamekye, et al. 2020). Land cover in its most definitive conceptualization is described as the observed (bio) physical cover of the earth's surface (Gregorio 2005) which is a "critical descriptor of the earth's terrestrial surface" (Wulder et al. 2018). In geo-urban spaces, anthropogenic engagements subject LC to rapid evolution (Phiri et al. 2020; Kursah et al. 2023) and is therefore a chief functional consequence of general man-land interrelationships. These interrelationships are characteristically reflexive of the human employment of the land (Meyer and Turner 1996), that is, the function to which a land parcel within the defined space is put. As such, land use (LU) determines both the type and character of land cover (LC) within space while the LU permitted within this space is also dependent in part on the pre-existing LC within the space and the environmental possibilism technology and capital sanction in the space, within time. There is therefore a repeated, ongoing cyclical relationship between LC and LU, moderated by man with the aid of technology and liquid capital, over time. Post this period, the effigy(ies) of the LU becomes the LC and/or determines and shapes the LC while this resultant LC in return bears influences on what other future LU occurs within the space.

Drivers of land cover change are distinguished into proximate and underlying causes (Lambin et al. 2001; Wilson and Wilson 2013). As proximate causes directly modify land cover, underlying causes operate at scales encompassing national, regional, and global levels, exhibiting complex interactions and may include social, political, economic, demographic, technological, cultural, and biophysical factors (Wilson and Wilson 2013). Changes to LU and LC typically take months to years to manifest, following a period of violent conflict. While violent conflict is the underlying causal factor, typically one or multiple proximate causes such as displacement/relocation, livestock decline, economic recession, security restrictions or landmine placement may also be responsible, (Witmer 2015). While qualitative sampling may aid in uncovering the proximate factor(s) at play, remote sensing and GIS help detect the geospatial extent of the underlying causal mechanism—violent conflict.

3.4. Study Area

The Kharkiv and Luhansk oblasts in Eastern Ukraine as shown in Figure 3.0., are two of the country's five proximal oblasts sharing boundaries with the Russian Federation. Located at 49°59′ 33″, 36°13′52″ at the confluence of the Uda, Lopan, and Kharkiv rivers (Britannica 2022a), the Kharkiv oblast extends to a total surface area of 31,400km² covering about 5.23 percent of the county's land surface of 600,000 km² (GeoHack 2022b) while Luhansk encompasses a surface area of 26, 684 km² (4.45% of Ukraine) and is located at the confluence of the Vilkhivka and Luhanka rivers (Internet Encyclopedia of Ukraine, 2022) at 48° 55′ 12″, 39° 1′ 12″ (GeoHack 2022a). Both oblasts together cover the longest segment of Ukraine's eastern national land boundary with Russia, with Donetsk to the southwest, and Russia to the southeast, east, and north, rendering them two of the five most spatially proximate oblasts to Russia. These oblasts together with Donestk territorially comprise Ukraine's Eastern sub-region, a section of which is colloquially known as the Donbas, an enclave plagued with repeated violent chaos and Russian infiltration. As a prominent fraction of the region remains under separatists' control since 2014 (ICJ 2018), state structures had also become benumbed initiating the region into a quasi-state (Aljukov 2019).

With its capital, Kharkiv, the Kharkiv Oblast hosts a 2022 population of 2.6 million inhabitants (City Population 2022) and has a humid continental climate with long, cold, snowy winters, warm to hot summers, and average rainfall totals of 519mm (20in) per year, with the most rainfalls recorded in June and July. The oblast has a topographic range of 93m to 218m with an average of 148m above sea level. Its capital, Kharkiv, was founded around 1655 as a military stronghold for protecting Russia's southern borderlands (Britannica 2022) and grew to become a major center of industry, trade, and Ukrainian culture. The Luhansk Oblast on the other hand has a total population of about 2.1 million people and a 2022 population density of 78.81 per kilometer square (City Population 2022) 87% of which is urban (Internet Encyclopedia of Ukraine 2022). Having a temperate-continental climate with dry and hot summers and cold winters, the oblast experiences an annual precipitation range of about 500 to 550 mm (19.69 to 21.65 in) with moisture deficits notably in the south, where dry winds and dust storms commonly present themselves in the spring (Internet Encyclopedia of Ukraine 2022). Cropland areas account for approximately half of the region's spatial extent and was a leading producer in gross regional product until 2014 when it experienced a 59% decrease in total regional output compared to 2015 figures (Britannica 2022).

3.5. Datasets

A commonly employed technique for the temporal transition and sequential change analysis of LU/LC classes is the bi-temporal change detection technique (Gbanie, Griffin, and Thornton 2018) using information from multiple remote-sensing images of the same area at different times, comparing and analyzing them through mathematical statistics or artificial intelligence methods to obtain ground change information in the area (Wang, et al. 2022). For the purposes of temporal juxtaposition, this study utilized bitemporal satellite imagery of the Kharkiv and Luhansk Oblasts from the European Space Agency's (ESA) Sentinel 2 Copernicus Open Access Hub for June 2021 and June 2023 in the targeted geo-investigation. These are images obtained by the Multi-Spectral Instrument (MSI) aboard the Sentinel-2A/B constellation (ESA 2023b). This constellation captures earth observation products in 13 spectral bands at varying spatial resolutions of 10, 20 and 60 meters (ESA 2023c; GISGeography 2019). Spectral bands with the finest spatial resolution (10 meters); red (R) band (B4) with the central wavelength of 665 nm, green (G) band (B3) with the central wavelength of 560 nm, blue (B) band (B2) with the central wavelength of (493 nm) and the visible/near-infrared (VNIR) band (B8) with the central wavelength of 833 nm (ESA 2023a; GISGeography 2019) were focused on (Table 1).

MSI Band Designation	Spatial Resolution in meters	MSI Band Description	Central Wavelength in nm (Sentinel 2A)	Central Wavelength in nm (Sentinel 2B)
Band 1	60	Coastal Aerosol	442.7	442.3
Band 2	10	Blue	492.7	492.3
Band 3	10	Green	559.8	558.9
Band 4	10	Red	664.6	664.9
Band 5	20	Vegetative Red edge	704.1	703.8
Band 6	20	Vegetative Red edge	740.5	739.1
Band 7	20	Vegetative Red edge	782.8	779.7
Band 8	10	Visible Near Infrared	832.8	832.9
Band 8a	20	Narrow Near Infrared	864.7	864.0
Band 9	20	Water Vapor	945.1	943.2
Band 10	60	Shortwave Infrared Cirrus	1373.5	1376.9
Band 11	60	Shortwave Infrared	1613.7	1610.4
Band 12	20	Shortwave Infrared	2202.4	2185.7

Table 1: Spectral bands and wavelengths of the Sentinel-2A/B MSI. Sources: (ESA 2023a, 2023c; Montoya 2017; GISGeography 2019).

Anniversary June images of the targeted years were obtained for analysis as June marks the end of a growing season after which July initiates the onset of a harvest period within this region (FAO 2022a); a period after which the elimination of vegetation on a crop field could be attributed to harvesting, not deterioration via a violent conflict, burning, bomb detonation or abandonment. Winter crops are often grown in September and October of the preceding year and bloom in early spring after a brief period of dormancy in winter, and are typically harvested in July (Skakun et al. 2019). Summer crops are usually planted in April and May and harvested in August–September (Skakun et al. 2019). June, therefore, marks an agricultural midpoint when both winter and summer crops could be observed from remote sensors. Since these oblasts of interest transcend the boundaries of a single Sentinel scene, multiple images were obtained for the period under study and mosaicked for continuous spatial coverage. As June 2021 datasets were targeted as pre-war data, June 2022 and 2023 datasets were treated as war period data with transitionary insights from 2022. The obtained datasets were already (prior to download) corrected for geometric and radiometric errors along with orthorectification to generate highly accurate geolocated products and had less than 10% cloud infestation. They are therefore suitable for the purpose of this study.

3.6. Data Processing

The visible R, G, B and VNIR corresponding to bands 4, 3, 2 and 8 respectively for each scene were extricated, stacked in nearest neighbor, and mosaicked to generate June 2021, June 2022 and June 2023 subsets for Kharkiv and Luhansk as separate regions of interest (ROI). This process was intended to obtain high-resolution optical landcover images at 10-meter spatial resolution for each region as R, G, B and VNIR possess the high optical abilities for revealing landcover information both in natural color (4, 3, 2) and false color (8, 4, 3) (Addabbo et al. 2016) at 10 meters. Similar to (Tzepkenlis, Marthoglou, and Grammalidis 2023) and (Garnot et al. 2020), the other spectral bands were exempted from this combination since they either contain coastal aerosol or cirrus cloud with the potential of introducing atmospheric noise (band 1; ultra blue) or possess spatial resolutions (20 meters and 60 meters) that are incapable of providing useful landcover information at 10 meters (bands 5 to 7, 8a, 9 to 12) (Addabbo et al. 2016). Each ROI was visually inspected at natural color and composed into false color composites to enhance near-infrared surface reflectance signatures to facilitate the spectral discrimination of vegetation from other land cover categories. Preliminary exploratory analysis was conducted in the Kharkiv oblast using unsupervised ISODATA classification of 50 classes with a maximum of 15 iterations and recoded into targeted classes for further statistical and spatial analysis. Heavy spectral conflict was noted in areas south-west of the Kharkiv region (region **a′**) and were further "subset" and resubjected to further classification and cluster blustering to enhance spectral differentiation of the seemingly identical but different spectral signatures. This pretest was intended to uncover the evolutionary rate of various landcover classes during the study period. As vegetation was revealed as the most impacted landcover, the study further explored what exact vegetation type underwent this change in order to ascertain impacts on agricultural vegetation during this period. Also, based on the accuracy results of the ISODATA pretest, the study adopted supervised maximum likelihood classification (MLC) in the further analysis similar to (Patil, Desai, and Umrikar 2012; Sisodia, Tiwari, and Kumar 2014a) as MLC has been proven as a robust algorithm for pixel-based landcover classification with very little chances of misclassification (Sisodia, Tiwari, and Kumar 2014a), produces better accuracy results than unsupervised classifiers (Domadia, Department, and Zaveri 2011) and compared to parallelepiped, minimum distance, mahalanobis and fisher (linear discrimination) classifiers (Akgün, Eronat, and Türk 2004; Sisodia, Tiwari, and Kumar 2014b), is found to be more reliable for satellite image classification purposes.

Targeted land cover classes for the preliminary unsupervised classification included the technosphere—"*the mass of all human-made objects, including the mass of buildings, transportation networks, and communication infrastructure*" (Turner 2023), bare ground, vegetation and waterbody. At this stage of the study, it was hypothesized that the deterioration of built spaces was the most rampant effect of the war in Ukraine. This was, however, proven untrue as vegetation was revealed as the most impacted landcover. At the second stage of analysis, therefore, the vegetation class was broken into agricultural vegetation and non-agricultural vegetation to ascertain which vegetation type changed the most—if crop fields were in jeopardy during the period under study or other vegetation types were the biomes at risk. While the technosphere class consisted of urban centrosomes, dispersed sprawling areas, roads and other built isolated structures, the waterbody class included rivers, streams, ponds, and other observed hydrological enclaves. The vegetation class comprised crop fields, dense and heavy course-textured foliage as well as fine-textured low-lying green covers while bare ground consisted of surfaces devoid of vegetative biome, exposing the soil.

After the conduct of the preliminary exploratory tests and associated spatial statistics, supervised MLC was conducted on the two oblasts to examine impacts on agricultural vegetation from June 2021 to June 2023. It is of interest to note that this study explored different methods across the region in examining the impacts of conflict on LC in general and specifically on agricultural vegetation.

The preprocessed dataset of the Kharkiv and Luhansk Oblasts were subjected to supervised classification with the maximum likelihood parametric rule. Training data were created from the false color infrared datasets and re-examined in Google Earth Pro with sampled coordinates from the Imagine inquire tools, for agricultural vegetation and non-agricultural vegetation while all other non-vegetative LCs were trained as *other*. It was hypothesized at this stage of the study that of all vegetative covers in the study area, agricultural vegetation was the most impacted. This vegetation class was therefore separated from all other forms of vegetation for closer observation. As agricultural vegetation consisted of crop fields, non-agricultural vegetation comprised of dense and heavy course-textured foliage and forests, as well as isolated patches of green cover evidenced by shape, site, and texture as non-agricultural vegetation. The *other* class consisted of water bodies, built spaces and bare ground surfaces. The rate of landcover change/evolution described in this study as percentage change (X) over the two periods was computed as follows:

$\mathrm{X} = \frac{\boldsymbol{M-I}}{\boldsymbol{I}} \times \mathbf{100}\%$,

Where, M = Reference years (2022 and 2023)

I = Base year (2021)

X = Percentage change,

$$\mathrm{X} = \frac{2022 - 2021}{2021} \times \mathbf{100}\%$$

3.6.1. Accuracy Assessment and Post-classification Change Detection

The process of investigating the accuracy of classified datasets usually follows the standard method of comparing a set of sampled pixels from a classified image with a referenced dataset (Estoque, Murayama, and Akiyama 2015). This assessment was conducted for 2021, 2022 and 2023 both in Kharkiv and Luhansk. Twenty stratified random points were generated in a confusion matrix from each classified dataset for pixel-to-pixel comparison, class verification, and ground-truthing. Original false color infrared datasets and UTM WGS coordinates in Google Earth Pro were used as reference data, while accuracy was reported both in kappa statistics and overall accuracy. This was intended to evaluate how representative the classifications are of the real-life geospatial character of the study area and to verify the confidence level of each result. For the purposes of change detection and quantification, post-classification comparison was conducted with the aid of a change detection matrix applied to the classified bi-temporal datasets. This was intended to produce a from-to differenced-raster-image to ascertain the scope and magnitude of changes within the respective classes over the said duration.

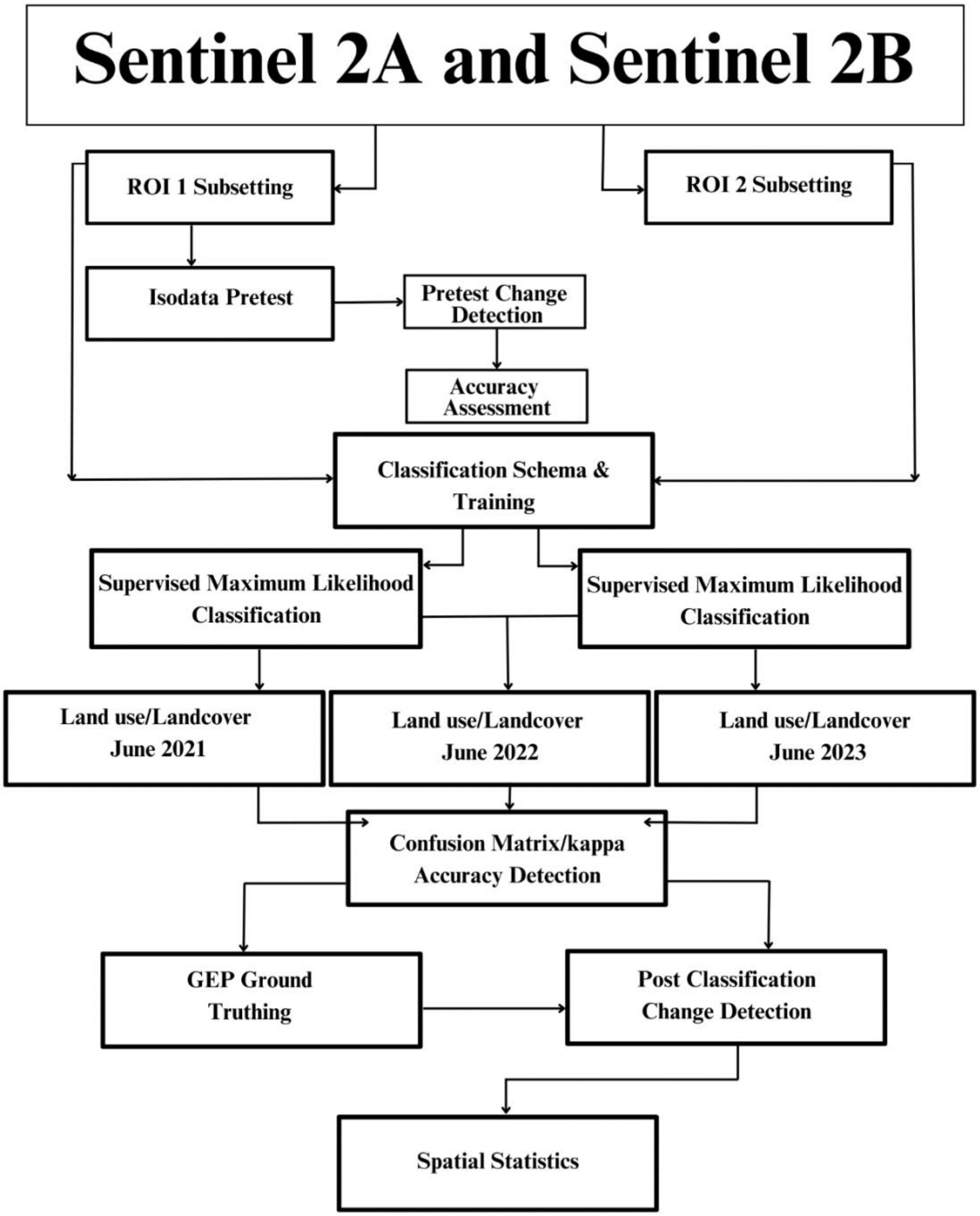

Figure 8: Summary of Methods.

3.7. Results and Discussion

3.7.1. Preliminary Exploratory Test

Figure 8 indicates proportions of the Kharkiv Oblast occupied by each landcover class between 2021 and 2022 while Figure 9 **a** and **b** show their spatial distribution. Over the said period, bare grounds increased remarkably from 732.8 square miles to about 4,438.6 square miles while all other landcover classes experienced spatial decline including built space which reduced from 388.7 square miles to 380.6 square miles. Vegetative cover dominated the study area over the period of consideration, while bare ground and technosphere followed closely as second and third dominant landcovers respectively. Waterbody was the least prominent landcover in Kharkiv. As technosphere concentrated around areas of the city of Kharkiv, Krasnohrad КрасНограЛ, Izyum, and Bohodukhiv, vegetation concentrated in remote spaces of the Oblast while bare ground and water traversed both built and remote spaces. Within Kharkiv, all landcover classes, with the exception of bare ground, experienced a spatial decline with built space declining from 388.7 square miles to 380.6 square miles between 2021 and 2022, (Table 2). The total built space lost during the period of study was 8.108 miles square, representing -2.09% of the spatial decline in one year.

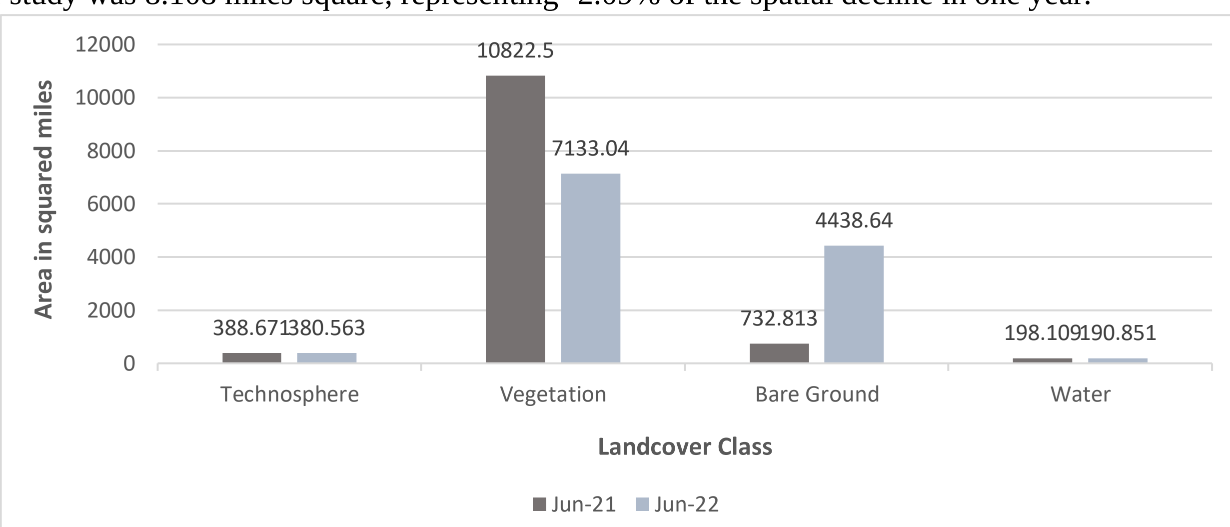

Figure 9: Proportions of landcover classes in 2021 and 2022.

Over the said period, built space experienced -2.09% growth rate, together with vegetation and water which both declined by 34.1% and 3.7% respectively. This disproved the presumed hypothesis that the most impacted landcover in Kharkiv was built space. Bare ground as the only positively growing space expanded by 505.7% (Table 2). Each landcover class under study had experienced some form of growth over time, registering either an increase or a decline. Technosphere which consists of such built spaces as urban centrosomes, dispersed sprawling spaces, isolated structures as well as paved surfaces such as car lots and tiled roads decreased by 2.09% from 388.671 square miles in 2021 to 380.563 square miles in 2022. This spatial loss was quantified as 8.108 miles square presumed as built space either blasted into remnant debris reclassified as bare space, or built space blasted, deserted, and taken over by vegetative cover. This presumption however requires field observation to ascertain whether they were actually due to detonations or other locally contingent causal factors were at play.

Class Name	**Area** (miles^2)		**Coverage gained/lost** (miles^2)		**Percentage change**
	2021	**2022**			
Technosphere	388.671	380.563	-8.108	(lost)	-2.0861
Vegetation	1,0822.5	7,133.04	-3689.46	(lost)	-34.0906
Bare Ground	732.813	4,438.64	3,705.827	(gained)	505.6989
Water	198.109	190.851	-7.258	(lost)	-3.6636

Table 2: Surface area of landcover gained or lost.

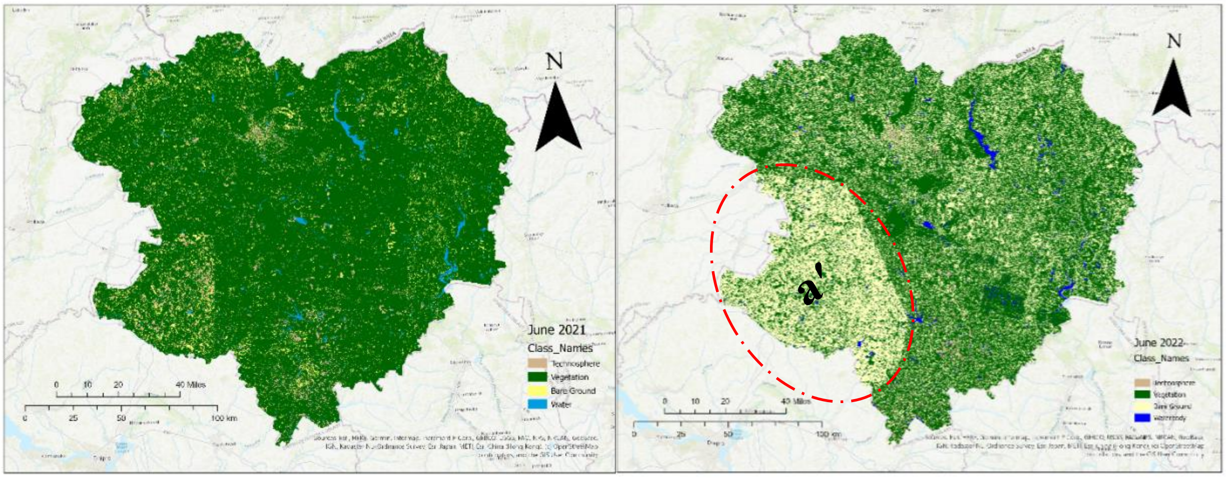

Figure 10 a and b: Spatial distribution of landcover classes in 2021 and 2022.

As 4,158,019 pixels of 2021 classified as built space changed to bare ground in 2022, 4,805,681 changed into vegetative cover over the same period (Fig. 5). As the spatial magnitude of these changes were outlined in the results of this study, no direct causal mechanisms was evidenced by remotely sensed data as responsible for such changes. Inferences drawn at this stage were based entirely on the current geopolitics of the study area and needs to be authenticated by qualitative sampling in a further study. The landcover class registering the highest spatial loss, however, was vegetative cover. Vegetation in the Kharkiv Oblast declined from the spatial extent of 10,822.5 miles square in 2021 to 7,133.04 miles square in 2022. Constituents of this landcover included forested lands, grass, and crop fields. It was observed that many cultivated and freshly harvested 2021 crop fields were bare in 2022 while a couple of others remained unchanged based on their respective spectral signatures. Total spatial loss of vegetative landcover was quantified as 3, 689.46 miles square which was 32.01% higher than spatial loss experienced by built space. It is therefore thought by this study that between 2021 and 2022, vegetative ecology was more massively impacted than built space and any other LC in Kharkiv. This finding was retested across the entire study area using supervised MLC with focus on vegetation to check what exact vegetation type suffered this change and to explore specific impacts on crop fields, i.e., agricultural vegetation in eastern Ukraine (Kharkiv and Luhansk oblasts).

3.7.2. Temporal Character of Agricultural Land Cover in Kharkiv and Luhansk between 2021 and 2022

Agricultural landcover change in Kharkiv as investigated by supervised MLC followed similar trajectories declining from an overall spatial extent of 9,758.16 miles square in 2021 to 3,828.52 miles square in 2022. Spatial decline for this LC class was quantified as -5,929.64 miles square representing 60.77% of loss from June 2021 to June 2022 alone (Table 3). As shown in Figure 12 a and b, agricultural vegetation being the principal landcover in 2021 transitioned into the second least class in 2022. It is interesting to note that this being a June dataset, a month of

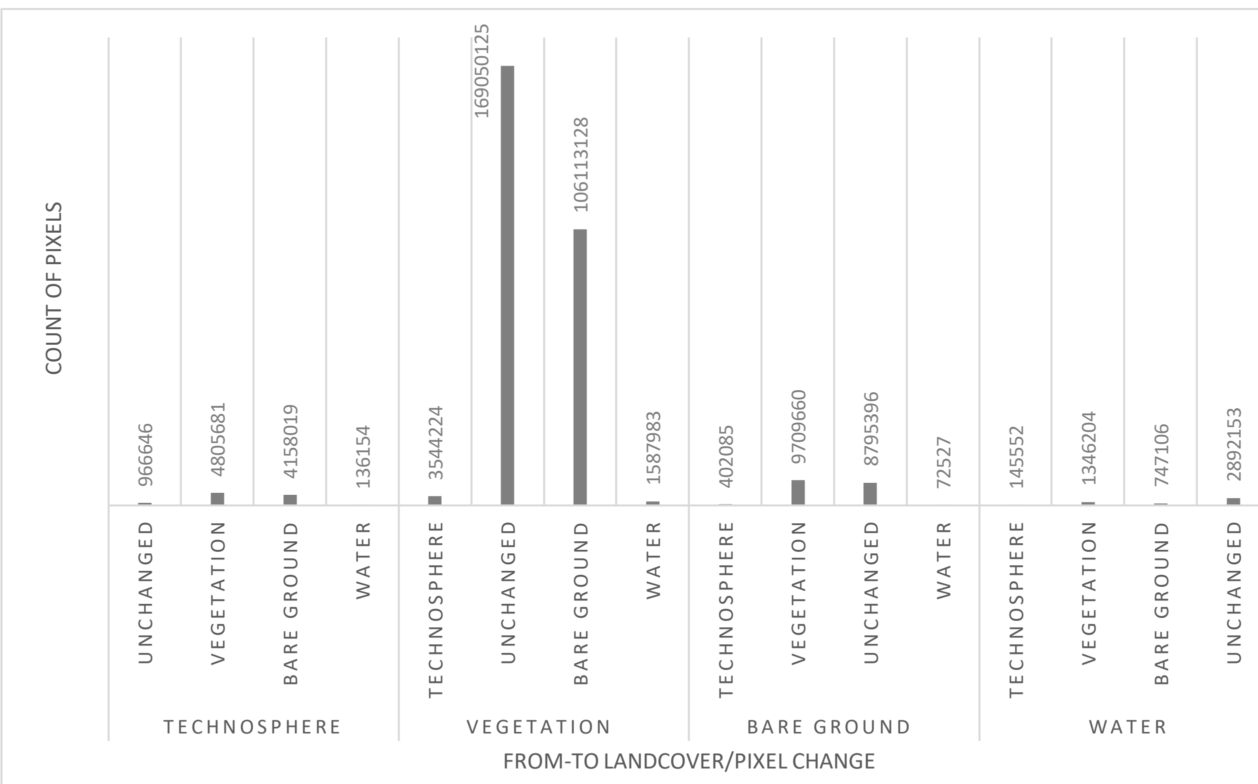

Figure 11: Count of changed pixels from base landcover to new landcover.

agricultural midpoint in the study area where both winter and summer crops should have been blossoming (Skakun et al. 2019) and easily detectable to remote sensors, this dynamics is rather alarming as this depicts 60.77% decline of crops/agricultural vegetation on crop fields. Similarly, the confusion matrix kappa coefficient and overall accuracy indicated 0.76 and 90% respectively for 2021 MLC and 0.70 and 83% respectively for 2022 MLC, increasing the confidence levels of these statistics over the unsupervised ISODATA pretest results.

Class Name	**Area** (miles^2)		**Coverage gained/lost** (miles^2)	**Percentage change**
	2021	**2022**		
Agricultural Vegetation	9,758.16	3,828.52	-5,929.64	-60.77
Non-Agricultural Vegetation	1,204.62	6,333.65	5,129.03	425.78
Other	1,181.51	1,982.12	800.61	67.76

Table 3: Percentage change of landcover classes between 2021 and 2022 (Kharkiv).

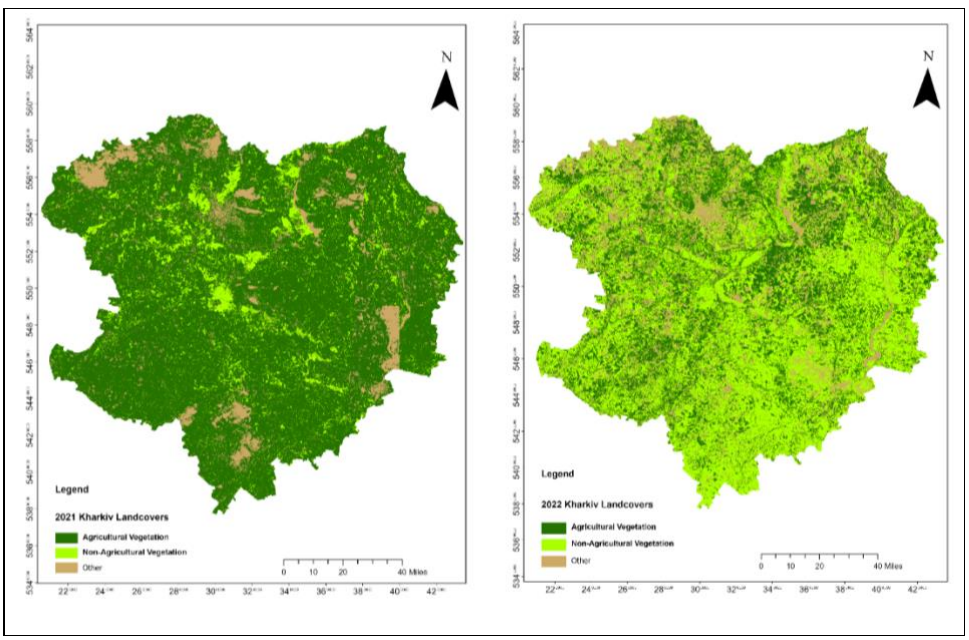

Figure 12 a and b: MLC spatial distribution of Kharkiv landcover classes in 2021 and 2022.

Similarly in Luhansk, agricultural vegetation diminished remarkably from a total surface coverage of about 5,529.81 square miles to 1,760.97 square miles while all other landcover classes experienced spatial increase over the said period. Agricultural vegetation which was established as the dominant landcover in 2021 transitioned into the least landcover in 2022 (Fig. 8), declining by 3,768 square miles, representing a negative growth of 68.15% (Table 4). Non-agricultural vegetation which comprised of dense and heavy course-textured foliage and forests, as well as isolated patches of low-lying green cover dominated the study area in 2022 both in Kharkiv and Luhansk, growing by 425.78% in Kharkiv from a total surface area of 1,204.62 square miles to 6,333.65 square miles in 2022 and by 270.17% in Luhansk from a surface coverage of 1,363.56 square miles in 2021 to 5,047.53 square miles in 2022.

Class Name	**Area** (miles^2)		**Coverage gained/lost** (miles^2)	**Percentage change**
	2021	**2022**		
Agricultural vegetation	5,529.81	1,760.97	-3,768.84 (lost)	-68.15
Non-agricultural vegetation	1,363.56	5,047.53	3,683.97 (gained)	270.17
Other	3,551.52	3,636.39	84.87 (gained)	2.39

Table 4: Percentage change of landcover classes between 2021 and 2022 (Luhansk).

It is intriguing to note that the apparent spatial decline of agricultural vegetation spread across the entirety of the two oblasts with notable concentrations at regions north and southwest of Luhansk (Fig. 13 **b**) and everywhere else in Kharkiv (Fig. 12 **b**). The spatial differentials identified in Tables 3 and 4 were rendered valid by the post-classification change matrix in Figure 14 **a** and **b** and Table 5. The totals of unchanged and lost agricultural vegetation in Table 5 equates to the spatial extent of 2021 agricultural vegetation in Tables 3 and 4. Here, agricultural vegetation classes that remained unchanged throughout the period were recoded as unchanged agriculture while those that changed into other classes were recoded as lost agriculture. Non-agricultural classes that transitioned into agricultural classes were recoded as agricultural gain while the *other* class was recoded as non-agricultural.

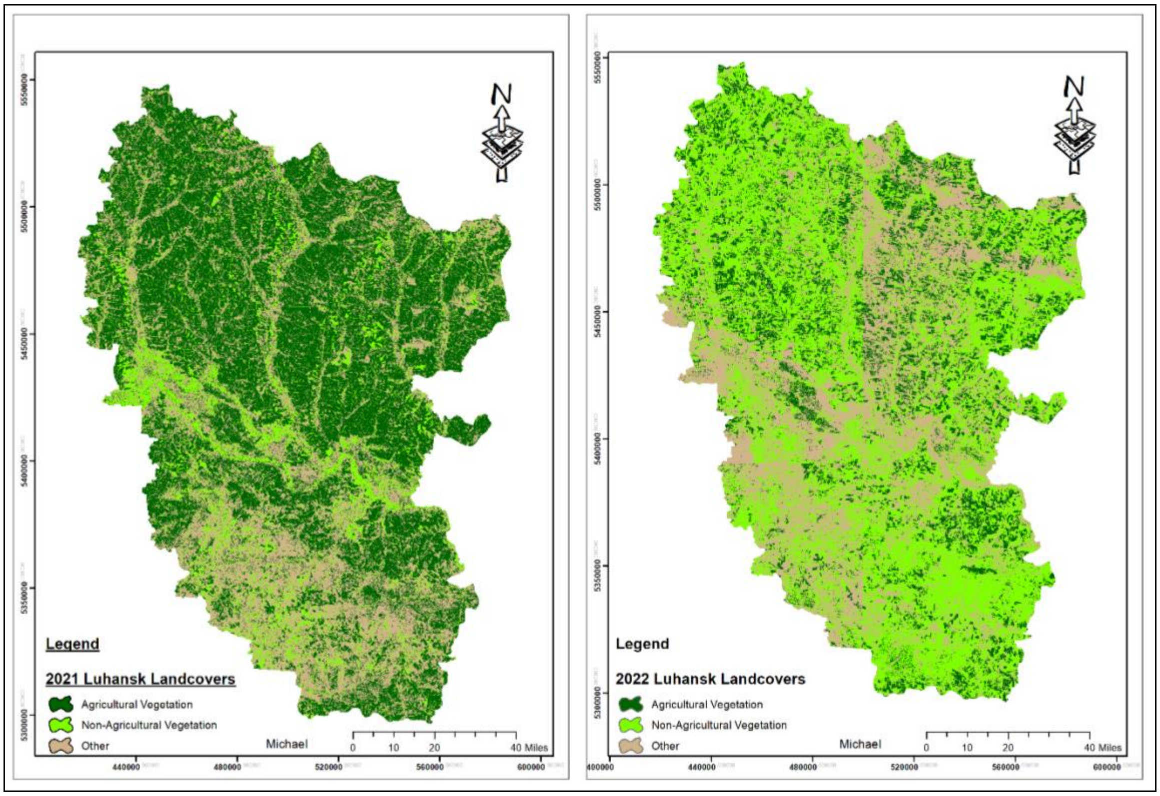

Figure 13a and b: MLC spatial distribution of Luhansk landcover classes in 2021 and 2022

In Luhansk, agricultural vegetation diminished remarkably by -68.16% from a total surface coverage of about 5,529.81 square miles to 1,760.97 square miles, while non-agricultural vegetation and *other* land cover classes increased in area at rates of 270.17% and 2.39% respectively as shown in Table 4. Similar trends were seen in Kharkiv as illustrated in Table 3. The spatial loss of agricultural landcover was quantified as 60.77% in Kharkiv and 68.15% in Luhansk which represents croplands uncultivated and (or) abandoned in 2022. This non-cultivation is attributed either to desertion and flee to safety by farm labor or the occupational mobility of agricultural labor to civilian army, joining the fight to defend the territory. It is intriguing to note that the spatial loss of agricultural vegetation was pronounced throughout the two oblasts. As this occurred during a conflict period, there is specifically no evidence from satellite imagery that these changes were absolutely caused by the ongoing conflict, but this inference is a huge possibility considering the geopolitics of the region. A quantitative field survey is therefore required as a complementary methodology to ascertain the contribution of conflict amidst other sociopolitical and economic factors at play in the region. This will equally verify the perceived mechanisms through which some pieces of landcovers changed into agricultural vegetation in Table 5.

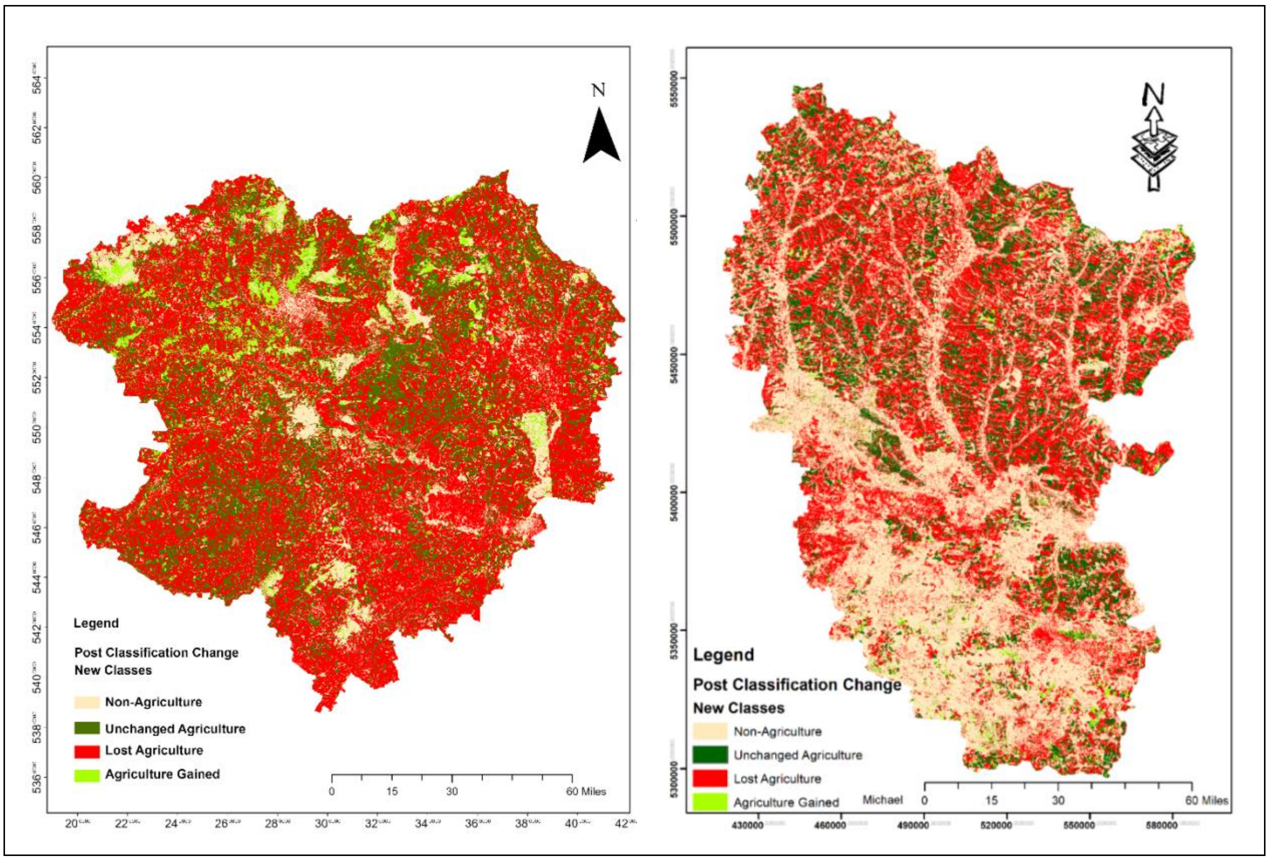

Figure 14 a and b: 2022 post classification landcover change a. Kharkiv, b. Luhansk.

Landcover	Kharkiv spatial extent (miles^2)	Luhansk spatial extent (miles^2)
Unchanged Agriculture	3,063.01	1,532.13
Gained Agricultural space	768.31	228.84
Lost Agriculture	6,693.32	3,997.68
Non-agricultural space	1,617.47	4,686.24

Table 5: Spatial change in Kharkiv and Luhansk 2022.

3.7.3. 2023 Land Cover Character in Kharkiv and Luhansk

Agricultural space in 2023 was severely invaded by vegetative biomes indicative of non-agricultural green and newly sprouting surface regrowth both in Kharkiv and Luhansk while herbaceous life near water bodies thickened and increased in spectral reflectance throughout the study area. Within Kharkiv, agricultural vegetation which used to occupy the surface area of about 9,758.16 miles square in 2021 shrunk to 265.44 miles square while Luhansk's 2021 agricultural

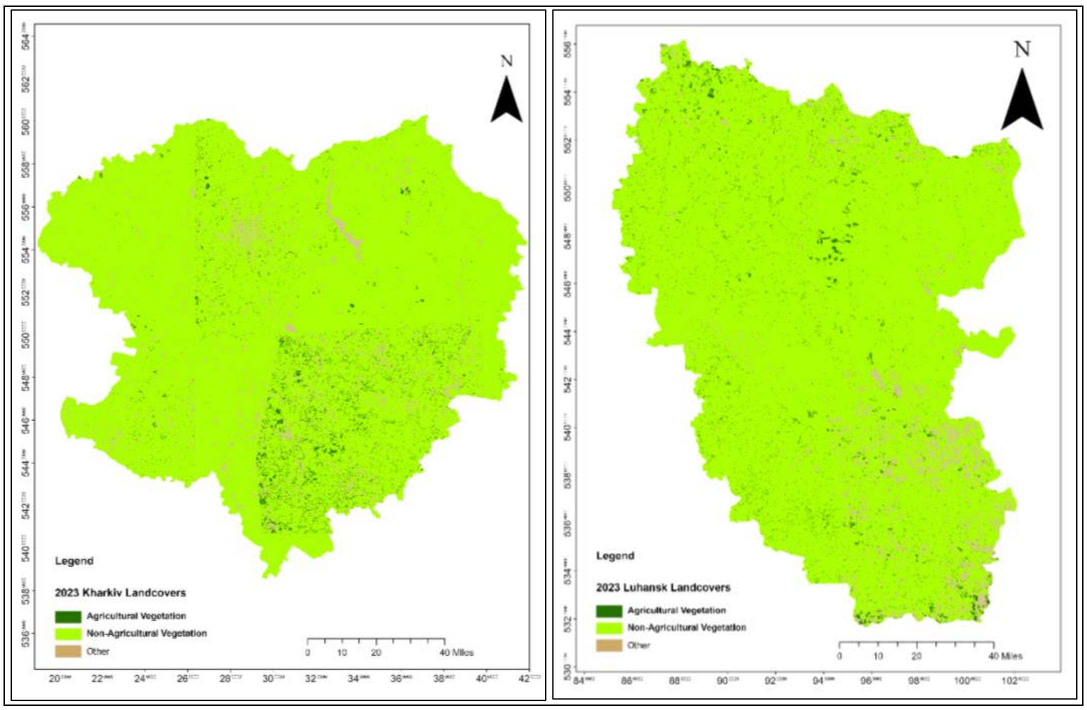

Figure 15: 2023 landcover distribution

space of 5,529.81 miles square shrunk to 235.05 miles square as shown in Figure 15. Non-agricultural vegetation in both oblasts grew significantly, occupying spaces previously characteristic of farming activity and bare ground. In Kharkiv, the spatial extent of non-agricultural vegetation grew to 11, 308.25 miles square in 2023 while increasing to 9792.05 miles square in Luhansk. Landover classes classified as *Other* similarly shrank significantly in 2023 as many 2022 bare grounds were captured by newly sprouting non-agricultural vegetation. The post-classification change quantification as shown in Table 6 and Figure 16 a and b indicated that between 2021 and 2023, 9,568.66 miles square and 5,425.42 miles square of agricultural space were lost in Kharkiv and Luhansk respectively.

Landcover	Kharkiv spatial extent (miles^2)	Luhansk spatial extent (miles^2)
Unchanged Agriculture	189.17	103.94
Gained Agricultural space	76.27	129.98
Lost Agriculture	9,568.66	5,425.42
Non-agricultural space	2,309.8	4,784.71

Table 6: Spatial change in Kharkiv and Luhansk 2023

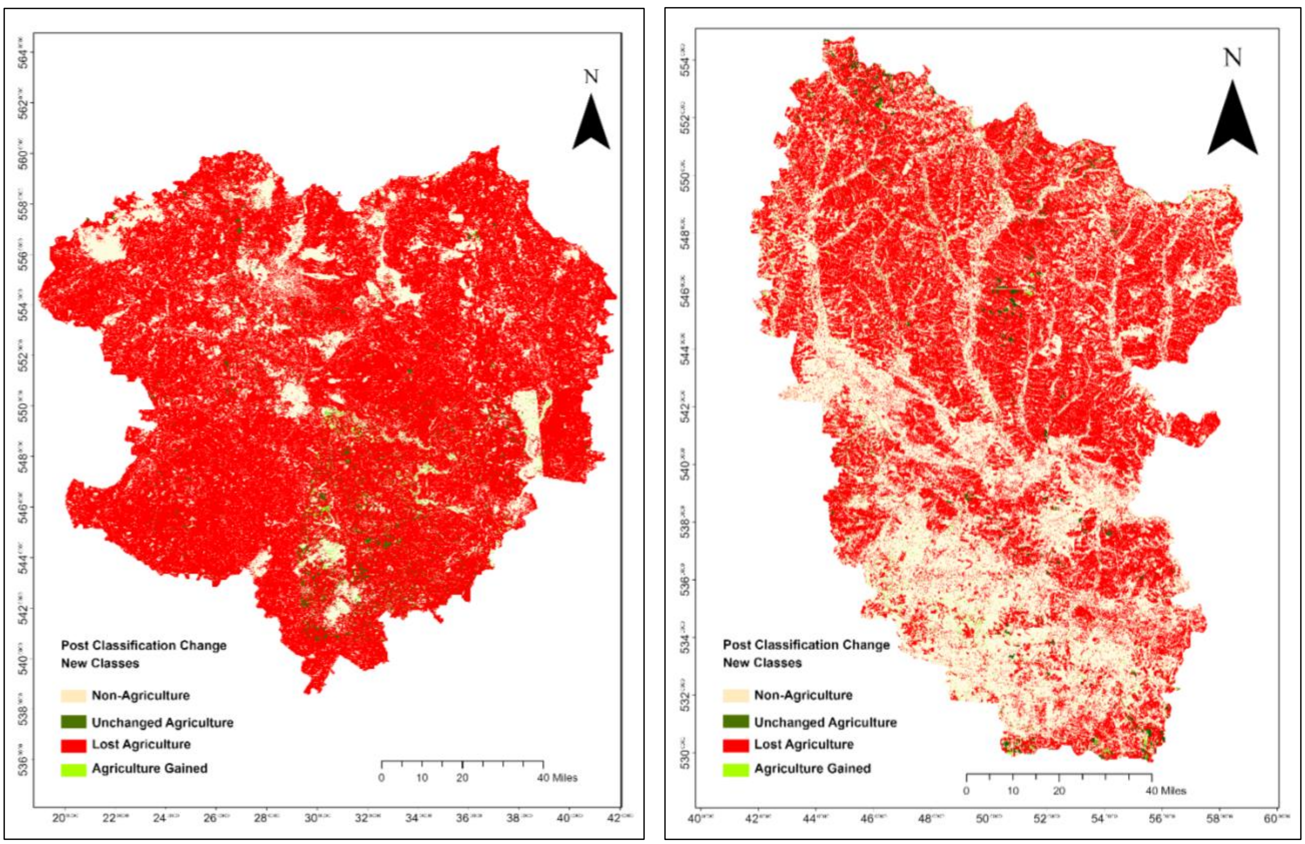

Figure 16 a and b: 2021 to 2023 post classification landcover change a. Kharkiv, b. Luhansk.

3.7.4. Accuracy Assessment

The resultant confusion matrix and kappa accuracy coefficients indicated that the unsupervised pretest ISODATA image classification of both the 2021 and 2022 Kharkiv datasets recorded overall accuracy levels of 85% each with the average kappa of 0.515. With supervised MLC however, the overall accuracy of 2021 Kharkiv result stood at 90% with kappa statistic of 0.76 while 2022 results recorded the overall accuracy of 83% with the kappa of 0.70. Overall accuracy in Luhansk was 80% and 75% for 2021 and 2022 respectively with the average kappa of 0.62. Overall accuracy for the 2023 Kharkiv MLC classification stood at 100% with a kappa statistic of 1.00 while Luhansk recorded an overall accuracy of 96.67% with the kappa of 0.79. Based on the kappa coefficients in this study therefore, supervised maximum likelihood classification exhibited higher accuracy and produced results with higher levels of confidence than unsupervised ISODATA classification. This solidifies the propositions of (Li, Liu, and Huang 2020) that the maximum likelihood method in supervised classification is relatively high in accuracy than both ISODATA and K-means. Similarly, (Shanmugam, Ahn, and Sanjeevi 2006) discovered that maximum likelihood classification produced maps with higher accuracy than ISODATA classification in their comparison of the classification of wetland characteristics by linear spectral mixture modelling and traditional hard classifiers on multispectral remotely sensed imagery in southern India.

3.8. Conclusion

This study explored the impacts of the 2022 Russian-Ukrainian war on landcover and crop fields in Eastern Ukraine via remote sensing and spatiotemporal landcover analysis with Sentinel-2 constellation data in both supervised and unsupervised classification. Landcover classes that underwent the most drastic changes in the Kharkiv and Luhansk oblasts between June 2021 and June 2023 were examined. Spatial extents and rates of change were computed. The Kharkiv Oblast recorded a geospatial loss both in its built space and agricultural vegetation. Massive decline in agricultural vegetation was detected, making vegetative ecology and agricultural vegetation for that matter the most impacted LC in Kharkiv during the period under study. As indicated by (Baumann and Kuemmerle 2016), warfare and armed conflicts are among the most drastic and globally frequent shocks. Yet, the understanding of where armed conflict affects land systems, how land-use patterns are impacted, and how far-reaching and persistent these changes are, is partial. This study used a spatially detailed dataset on armed conflict to explore these questions. A number of key insights emerged from this study: (1, armed conflicts affect landcover and land systems regardless of the dominating land use (Baumann and Kuemmerle 2016). (2, Both agricultural and forested non-agricultural vegetative biomes are susceptible to some sort of change during armed conflicts. However, as the former experiences massive rates of declination, the latter captures the space cleared off of the former. War therefore is an active driver of land use/ landcover (LU/LC) change, and agricultural regions are the most susceptible to those types of changes (Gibson, Campbell, and Wynne 2012) and (3, warfare and armed conflicts are among the most drastic drivers of geo-environmental evolution and globally frequent shocks.

Similar changes were seen in Luhansk in terms of decline in agricultural vegetation. The Luhansk region of Ukraine recorded a geospatial declination of 68.15% in its agricultural landcover in 2022 alone, representing the most impacted LC as well in this region, which however worsened in 2023. Uncultivated crop fields sprang across the region while non-agricultural vegetation grew over many areas across the oblast. Agricultural land abandonment was therefore seen in Luhansk reiterating (Eklund et al. 2017) and (Yin et al. 2019) that violent conflicts entail adverse environmental outcomes such as vegetative defoliation, LU/LC modifications and agricultural land abandonments. This similarly corresponds to the findings of (Wilson and Wilson 2013) maintaining that non-agricultural vegetation and forest cover during periods of war exhibit growth while going through reduction during periods of peace. The study, however, assessed these impacts only within a two-year temporal duration and treated 2023 data as war period data. Landcover trajectories after the war are therefore unseen in this study. This is in part attributed to the still unfolding continuity of the conflict as post-war data is yet unavailable for the study area. A future study is therefore recommended to assess landcover transformations for the entire lifespan of the conflict (pre, during and post) with an expanded focus to integrate such other socio-environmental impacts as water contamination, air pollution, population displacements, agricultural exports, food supply relative to conflict regimes (pre, during and post), visual framing of conflict, among others. As seen in these findings, remote sensing has facilitated the assessment of the impacts of war. Although data from this technology are incapable of comprehensive environmental assessment of conflict impacts, they provide valuable information on changes in vegetation which when integrated with social and environmental impacts could provide a better understanding of how these complex systems interrelate (Witmer 2008).

Chapter 4: Social Network Analysis of Twitter Information Flow During The 2022 Russian Invasion of Ukraine

4.1. Introduction

Social media has created a conversational territory for the visual framing of conflict and conflict narratives and has become an integral part of contemporary warfare, affecting not only the public perception of conflict but also policy decisions about these conflicts and how their history is captured by historians (Makhortykh and Sydorova 2017). It has by far reshaped the dynamics of war reportage both in Ukraine and around the world (Suciu 2022). In Ukraine, much of the conflict period communication was more about identity and media (Dyczok 2014) with social media becoming important information sources which were often picked up and disseminated by mainstream and global media outlets (Dyczok 2014). Government institutions, civilians and the armed forces engaged social media platforms in communicating both their successes and the losses of opposing forces (Suciu 2022). These include both authentic and completely imaginative storylines, notable of which was "the computer versions of a combat flight simulator—The Ghost of Kyiv" (Mallick 2022; Galey 2022).

Social media discourse and public opinion are inextricable parallel systems of constructing meaning, creating and presenting interpretive packages for relevant issues and events (Gamson and Modigliani 1989). The use of social media has contemporarily become increasingly prevalent, and its influences have been felt in many facets of human life, including war, and in the context of the Russian-Ukrainian conflict, has been used to inform, recruit fighters, disseminate propaganda and shape public opinion (Hoskins 2022; Mallick 2022; Alberti and Serio 2020). With the onset of the Crimean crisis and its subsequent annexation, the sole official structure for the resolution and management of conflict in Ukraine has been the Minsk Agreements clinched between Ukraine and Russian-backed separatists, with Russia, Germany and France as guarantors (Rojansky 2016) which have nonetheless been unable to remedy the reality of Russia's de facto control over Crimea and the recurrent violent conflicts in Ukraine's Donbas (Rojansky 2016). Evident within these insurgencies were the important roles played by social media in mobilizing civil society (Pospieszna and Galus 2019), constructing visual frames by both pro-Ukrainian and pro-Russian online communities (Makhortykh and Sydorova 2017), instigating regime changes (Brantly 2019), active disinformation campaigns (Mallick 2022; Mejias and Vokuev 2017), diffusion of information, compounding and facilitation of pre-existing social network ties (Onuch 2015) as well as the facilitation of the exchange of psychological contents in support of and opposition to protest activities (Jost et al. 2018).

Nonetheless, social media has equally provided a universal communication infrastructure for seeking help by war-affected populations during the Ukrainian conflict (Talabi et al. 2022), created a rostrum for in-person first-hand self-expression by affected persons about the impact of the war on their lives (Zasiekin et al. 2022), alleviated social isolation during active warfare (Singer and Brooking 2018), cataloged digital evidence of potential war crimes (Goujard 2022) while providing a means of social media-based music, art and drama therapies to aid the active remediation of war-induced post-traumatic stress disorder symptoms (Gever et al. 2023) and depression among affected populations (Ahmad et al. 2022). This has proffered useful alternatives for delivering interventions and eliminating barriers that must have otherwise truncated them (Gever et al. 2023).

About 30 million Ukrainians are subscribed to active social media (Dzyubenko 2022; Kemp 2022; Alberti and Serio 2020) notably including Yandex, VKontakte, Facebook, Pinterest, Instagram, YouTube, Twitter, Reddit, LinkedIn, TikTok, among others (GlobalStats 2023), generating open source social information even for research purposes. Social media data including videos and photographs provide both big-picture details and micro-details, revealing spatial and other attributes in aid of geolocation and spatial attributions (Toler 2022). Geolocation techniques facilitate the conclusive confirmation of where these images and videos were taken. Big-picture details such as the angular perspective of buildings both from streets and aerial photos inform what locations to look at in the preliminary phase of geolocation. Additionally, micro details such as floor cracks, paint patterns, building columns, adjacent road signs, door, window and stairway structures as well as general architecture as contained in the captured video/photograph facilitate positive identification of the actual locations where these social media information were first generated to which x,y coordinates could be attributed to provide ground references (Toler 2022). Consequently, such spatial data could be integrated into spatial and other forms of analysis, especially in remote sensing and GIS applications.

4.2. Social Network Analysis

Social Network Analysis (SNA) has attracted considerable interest from social and behavioral research with a critical focus on the interrelationships among social actors as well as the patterns and implications of these interrelationships (Wasserman and Faust 1994). It is the study of structure within and among social groups based on theoretical constructs of sociological and mathematical foundations of graph theory (Columbia Mailman School of Public Health 2016). The network consists of a set of people and other social entities connected by a set of social attributes that could be patterned, visualized, and interpreted with the aid of computational modeling (Jamali and Abolhassani 2006). The patterning of these relationships is undertaken based on the assumption, among other things that, network structure and the properties of that structure have significant implications on the outcome of interests investigated (Columbia Mailman School of Public Health 2016). Social network analysis attributes networked structures as vertices (points or nodes) and links (or edges). Individuals within the network structure are conceptualized as nodes. In a Twitter network, therefore, nodes seen within the structure are indicative of individual Twitter accounts (Twitter users). The social groups formed by these nodes based on interactivity are characterized as clusters while the observed relations evident between and among them are characterized as edges (Scott 2012), complementarily engineering patterns of points and lines that can be explored mathematically or visually, in order to assess their effects on the entities that constitute the formed network.

The origins of the approaches to social structure with explicit attention on social network stemmed from sociological traditions, with emphasis on the formal properties of social interaction in which investigators could configure social relations through the interweaving of social encounters (Scott 2011). Nevertheless, SNA evolved into an interdisciplinary endeavor, developing from social theory, statistics and computational methodologies while its central concepts of relation, network and structure emerged from the social and behavioral sciences (Wasserman and Faust 1994) with wide applications in the biological sciences and information systems (Crnovrsanin, Correa, and Ma 2009). Considering these focuses, its application especially in open-source and social media investigation requires ethical and methodological imperatives as prerequisites for guaranteeing the accuracy, quality and higher confidence of both the networked datasets, procedures and overall investigation outcomes (UN Human Rights Center 2022).

Social media were invented to enable individual members of the public connect with one another and interact with ease, and have therefore also become platforms for interaction during disasters, war and emergencies (Daga 2017). As such, they have generated substantial amounts of information on social interaction on a range of social issues and topics (Ahmed and Lugovic

2018a), the nature and dynamics of which could be better comprehended using SNA (Daga 2017). The challenge however in incorporating social media into geolocation and spatial investigation is dealing with the discovery and verification of relevant material within an increasing volume of online information, especially photographs and videos captured on smartphones and other mobile devices, some of which could be characteristically subjected to compromise and misattribution (UN Human Rights Center 2022). As large-scale vulnerability, war crimes and displacements however intensify in times of armed conflicts, there is a heightened need for common standards in investigative mechanisms for spatial research, particularly for the acquisition, preservation, and analysis of open-source information (UN Human Rights Center 2022). With the aid of SNA, the resultant patterns of these social interactions and networks emanating from such conflicts could be investigated to provide specific social insights alongside the stated spatial analyses.

4.2.1. Visualization of Social Networks in NodeXL

Network Overview for Discovery and Exploration in Excel (NodeXL) is an open-source SNA plug-in for Microsoft (Bonsignore et al. 2009) that simplifies basic network analysis tasks and supports the analysis of social media networks (Smith 2013) similar to other network visualization tools such as Pajek, UCINet, and Gephi (Ramachandran et al. 2013). By design, NodeXL facilitates the import of network data from multiple media including Twitter, Facebook, YouTube, Flickr, email, blogs, wikis, and the world wide web (Smith 2013), enhancing cleaning, analysis and visualization in Excel while extending existing spreadsheet graph features with added network charts to alleviate historical bottlenecks associated with computer-based visualization of social networks (Smith et al. 2009). Recognized as an efficient substitute for other network analysis software that demand complex computer programing skills, NodeXL offers a flexible, interactive and effective exploratory interface for network analysis (Jagals and Van der Walt 2016). Farmed network datasets could be directly imported into NodeXL and graphically displayed, and as such positioned to support network analysts without stepping through complex programming interfaces (Bonsignore et al. 2009).

4.3. Datasets

4.3.1. Twitter #tags

Social media data used in this study consist of tweets, replies and retweets of the Russian-Ukrainian war-related hashtags (#tags) farmed from the Twitter (X) microblogging space from the official onset of the conflict on February 24, 2022, to October 15, 2023. The choice of October 15, 2023, was dependent on the timeline of this study. Hashtags are topical keywords preceded by '#' to brand conversations on social media handles (Small 2011), functioning as tools for sorting and aggregating social media information according to topics (Laucuka 2018). They have therefore become an increasingly popular means for sharing and organizing web resources, leading to a huge amount of user-generated metadata (Bischoff et al. 2008). Prior to #tag farming, twenty randomly sampled popular #tags captioned on the conflict were collected from Twitter. Each #tag was pulled and tested to verify their relevance and connectedness to the current conflict, frequency of usage and accessorial contents carried within their conversation threads. The verification included direct reading and checking of contents tweeted, topical keywords reflected in the tweet and whether such tweets were made on or after February 24, 2022. Tested #tags that generated valid content were input into the Twitter search network in NodeXL Pro, while those not meeting the said criteria were considered invalid and rejected. Such #tags as #deathinukraine2022, #putin2022, #russiainvadesukraine2022, #zilenskiukraine2022, #zelenskyy2022, #bombblastukraine2022, #natovsrussia2022, #natorussia2022, #volodymyrzelenskyy2022, #russiafightsukraine2022,

#ukraineweeps2022, #ukraineweeps and #vladimir2022 were considered invalid and rejected after this preliminary verification. These #tags generated no search results and within the Twitter search network in NodeXL Pro, they had neither vertices nor edges. #vladimir2022 yielded three tweets that were largely unrelated to the conflict. As the first was a reply to a musical tweet by @atlztico, the second was a sports commentary by @kakog94 while the last was a reply to a currently deleted May 2019 post. #putin2022 generated non-war diplomacy content while #ukraineweeps had only two vertices.

Some other #tags which were originally not included in the sampled list were later discovered (#putinisawarcriminal, #russianwarcrimes and #putinisaloser). #putinisaloser and #russianwarcrimes were rejected. The contents of #putinisaloser were chiefly comic and unrelated to the topic under study while #russianwarcrimes generated less than 130 vertices. #putinisawarcriminal was included as a valid and accepted #tag based on its 4161 farmed vertices and resultant contents. Such other #tags as #ukrainewar2022, #warinukraine2022, #putinswar and #standwithukraine were valid, accepted and captured for farming. Limited to 5,000 tweets, each valid #tag was farmed from 6:00 a.m. on the onset day of the conflict, February 24, 2022, to 6:00 p.m. of October 15, 2023, with specific attributes as shown in Table 7. below. #vladimirputin2022, #russiainvassion2022 and #russiaukraine2022 were also rejected. Even though preliminary test results indicate they were valid #tags for the purpose of this study, #russiainvassion2022 had neither vertices nor edges, #vladimirputin2022 generated only three vertices while #russiaukraine2022 had only five vertices within its network presenting a statistically insignificant sample for analysis.

#tag	**Nature of Content**	**Accepted/Rejected**	**Number of Vertices**

#russiainvassion2022	Valid	Rejected	0
#ukrainewar2022	Valid	Accepted	235
#warinukraine2022	Valid	Accepted	3279
#vladimirputin2022	Valid	Rejected	3
#russiaukraine2022	Valid	Rejected	5
#putinswar	Valid	Accepted	1889
#standwithukraine	Valid	Accepted	4005
#ukraineweeps	Valid	Rejected	2
#deathinukraine2022	No result	Rejected	
#putin2022	Invalid	Rejected	
#russiainvadesukraine2022	No result	Rejected	
#zilenskiukraine2022	No result	Rejected	
#zelenskyy2022	No result	Rejected	
#bombblastukraine2022	No result	Rejected	
#natovsrussia2022	No result	Rejected	
#natorussia2022	No result	Rejected	
#volodymyrzelenskyy2022	No result	Rejected	
#russiafightsukraine2022	No result	Rejected	
#ukraineweeps2022	No result	Rejected	
#vladimir2022	Invalid	Rejected	
#putinisawarcriminal	Valid	Accepted	4161

#putinisaloser	Invalid	Rejected	
#russianwarcrimes	Valid	Rejected	123

Table 7: Twitter Search Network 3.0 SNA Data.

4.3.2. Bellingcat Civilian Harm Data

Twitter data was complemented by Bellingcat geotagged spatial data obtained from the civilian casualty Timemap. These data highlight incidents of civilian injury and casualty during the onset of the conflict to date, posted on social media handles as videos and photos. Bellingcat is an independent social investigative journalism network consisting of "researchers, investigators, and citizen journalists who employ open source and social media investigative methodologies to probe a variety of subjects including the tracking of the use of chemical weapons, military violence against civilian populations and conflicts worldwide" (Bellingcat 2022). Datasets from this source are videos and pictures extracted from social media handles as reported by civilians who have had first-hand encounters with such occurrences during the Russian-Ukrainian war, including instances in Figure 17, where civilian areas and infrastructure have been damaged, instances of visible civilian injuries and the presence of immobile civilian bodies (Bellingcat 2022).

Figure 17: Rescue of a wounded person in central Kharkiv, northeastern Ukraine, on March 1, 2022. (Photo by Vyacheslav Madiyevskyy/Ukrinform/NurPhoto). Source: Bellingcat 2022.

The collection of these incidences commenced on February 24, 2022, and subjected to geolocation techniques to extract conclusive spatial and temporal attributes with mapped spatial coordinates. These datasets were extracted, preprocessed (by Bellingcat) and composed on the Forensic Architecture's Timemap platform according to the legal frameworks, professional, ethical, and methodological principles of the Office of the United Nations High Commissioner for Human Rights (OHCHR) as espoused in the Berkeley Protocol (United Nations 2022), for the purposes of reporting and prosecuting human right infractions, and intended to be a living infrastructure that will continue to be updated as long as the conflict persists (Bellingcat 2022). Such contents whose originality and conclusive spatial location could not be authenticated were omitted from the database and is therefore a collection of confirmable incidents only, rather than a comprehensive catalog.

4.4. Data Processing

4.4.1. Twitter #tags

The investigation of social networks and clusters in this study focused on centrality and edge analysis of tweets, replies, retweets and mentions of the pretested, valid and accepted #tags with the Clauset-Newman-Moore (CNM) cluster algorithm and the Harel-Koren Fast Multiscale (HKFM) graph layout similar to (Ahmed et al. 2020). Overall network metrics, clusters and relationships were first explored in each #tag with specific graph metrics such as nodes, vertices, network density and diameter as well as in-degrees, out-degrees, betweenness centrality, and eigenvector centrality. As a vertex's in-degree measures the number of times it is referred/connected to, out-degree indicates its reference to others while eigenvector measures its importance within the network. The measure of betweenness centrality was used to detect unique Twitter users serving as potential '*bridge-nodes*' within each network. This metric (betweenness centrality) measures how much an identified vertex is the only means of connection from one part of the network to another and is a sociometric proxy for influence and reputation within the network (Social Media Research Foundation 2023). It is a measure of others' dependence on the given node for information (Brandes, Borgatti, and Freeman 2016) and quantifies the frequency of the node's occurrence along the shortest path between two other nodes, while potentially bridging those nodes that may essentially belong to different clusters within the network. These vertices lie on fractions of the relatively shortest paths connecting others and as such, information flowing to and from those other nodes would have to pass through them (Brandes 2001). As indicated by (Newman 2005; Freeman 1977; Brandes 2001), such vertices control the flow of information between and among other actors within the network. A user/vertex/node with high betweenness centrality is therefore said to be highly connected to other users and has much influence within the network, and if associatively records high in-degree centrality, their tweets are highly retweeted and highly circulated within the network. Therefore, a vertex with both high (above average) betweenness centrality and high in-degree is regarded as a principal figure in this study. The size and connectivity of each network was explored in relation to density and modularity as proposed by (Himelboim et al. 2017) while principal figures identified by betweenness centrality and in-degree in each network were further observed.

The exploration of density was to ascertain the degree of information fluidity by distinguishing seemingly cohesive from obviously sparse networks. Density in NodeXL is automatically calculated in overall metrics as the ratio of the number of actual links to the number of potential links of the network and ranges between 0 and 1 (Bhattacharya et al. 2023). This compares the counts of edges in the network graph with the maximum count of edges it would have had if all vertices were linked, excluding duplicates and self-loops (Social Media Research Foundation 2023). As actual links are present within the network as edges, potential links are connections that could possibly exists between two nodes within the network (Bhattacharya et al. 2023). According to (Himelboim et al. 2017; Henneman and Riddle 2005), the extent to which a network is densely interconnected affects the rate of information flow within it. However, a dense network may as well, based on its modularity, be either unified or divided. Highly modular networks are highly divided and have many groups separated from each other with limited connections among them (Himelboim et al. 2017). Similar to density, modularity ranges between 0 and 1, with high values indicating high modularity and distinctiveness or division while low modularity indicates high interconnection (Himelboim et al. 2017). Highly dense networks with low modularity scores are therefore highly interconnected networks with very little divisions within them while less dense networks with high modular values are less interconnected and heavily separated. Information flow within this type of network is heavily fragmented with clusters of ‘pro’ and ‘anti’ opinions existing within the same network with little flow of information across clusters. In the exploration of density therefore, network modularity ought to be associatively explored as both metrics can provide relevant insights into the levels of connectivity within a cluster and relations of those cluster nodes to other groups (Himelboim et al. 2017).

Each network was graphed in the HKFM layout for preliminary visualization and the overall graph metrics, in-degree, out-degree, eigenvector, closeness and betweenness centralities were computed in the NodeXL Pro Graph Metrics box. Though clustering was graphically evidenced for each network, modularity coefficients were inapplicable, indicating that in the explored contexts, modularity was not meaningful. Clusterization was therefore investigated for each network using the CNM cluster function as an agglomerative algorithm, as CNM is an effective cluster methodology for big data analysis (Yum 2020) and practically proves better in cluster detection (Makris, Pispirigos, and Simos 2020). This generated identifiable groups within each network which were re-diagramed as directed graphs in HKFM, with each group laid out in its separate box. The optimized graph metrics were regenerated together with modularity coefficients as shown in Table 8 below.

4.4.2. Analysis of Principal Figures

The determination of principal figures was achieved on the basis of betweenness centrality and in-degree, similar to (Cha et al. 2012; Milani, Weitkamp, and Webb 2020; Chatfield and Brajawidagda 2012; Ahmed and Lugovic 2018). These metrics respectively indicate nodes who control information flow the most within each network by virtue of their influential bridge-node centrality and those who have the greatest number of followers who actually engaged with the posted Twitter content. Thresholds were determined for betweenness centrality and in-degree, and vertices/nodes with such coefficients above their network mean were classified as principal figures. Qualified betweenness centrality nodes within this threshold have the highest connections to other nodes both within and outside their cluster. Information flowing into the cluster passes through them (Brandes 2001) while information flowing within the cluster most potentially is taken from them (Newman 2005; Freeman 1977; Brandes 2001). The in-degree principal figure nodes potentially have the highest visibility within the network as their Twitter posts/tweets are referred to, the most, and therefore generated the most engagements either by comment, like, mention or repost/retweet. Thirty principal figures were sampled from each network and subjected to further observation to ascertain whether they are pro-war or anti-war as proposed in (Milani, Weitkamp, and Webb 2020), in other words, whether their propagation of news and Twitter engagements are in justification of the ensuing violence or in condemnation of the war. Focusing on words used in their tweets and which side of the warring factions they support, the 150 principal figures were grouped into anti and pro categories. Such tweets/posts as

"*there will be no impunity for Russian war crimes in Ukraine. The EU supports the International Criminal Court with €7.25 million to increase its investigation capacity into war crimes committed under Russian occupation. #StandWithUkraine*",

"*The illegal annexation proclaimed by Putin won't change anything. All territories illegally occupied by Russian invaders are Ukrainian land"* and

"*#PutinsWar and the deaths of tens of thousands of innocents have consequences!"*

were codified as anti-war. The inclination of these nodes against the conflict was directly extracted from sentiments demonstrated in their tweets/posts. Similarly, such tweets/posts as

"*We stand in solidarity with African nations' demands for the complete liberation of Africa from the last vestiges of colonial legacy. ?? Russia has played a leading role in decolonisation and in consolidating decolonisation processes."* and

"#Ukraine? #WarInUkraine2022 #Iran #Syrie #Russians @EmmanuelMacron @vonderleyen @CharlesMichel @cavousf5 @Cdanslair ALL these people who HATE OUR western countries, culture and way of life but come to Europe and USA when they face problems in their countries, should be refused"

appeared pro-Russian and in opposition to aid for Ukrainian refugees. Such posts and their likes were coded as pro-war. Many other tweets were non-English and hardened the classification process. Categorizing them was however achieved using the auto-detect features of google translator, to first and foremost translate these tweets/posts into English language for easy comprehension, then categorization. A couple of other tweets do not directly reflect either a pro or anti orientation. At first sight, they seem neutral but a further exploration of their Twitter profiles and images included in these posts as shown in Figure 18 generated secondary information to determine where these belong. Additionally, nodes such as *Potus, nato, un, zelenskyyua, emmanuelmacron* and *joebiden* were notably anti while *kremlinrussia_e, mfa_russia* and *russianembassy* were notably pro.

The principal figures by betweenness centrality was computed as;

$$\boldsymbol{P_{BC} = R_{15} * \frac{\sum bC}{n}},$$

(source: Author's construct),

where P_{BC} is principal figure by betweenness centrality, R_{15} is first 15 nodes in descending order above the network mean, bC is betweenness centrality coefficient of each node within the network and n is the number of nodes in the network. Principal figure by in-degree centrality was computed as;

$\boldsymbol{P_{id}} = \boldsymbol{R_{15}} * \frac{\sum \boldsymbol{idC}}{\boldsymbol{n}}$, (source: Author’s construct), where P_{id} is principal figure by in-degree and idC is the in-degree coefficient of each node within the network.

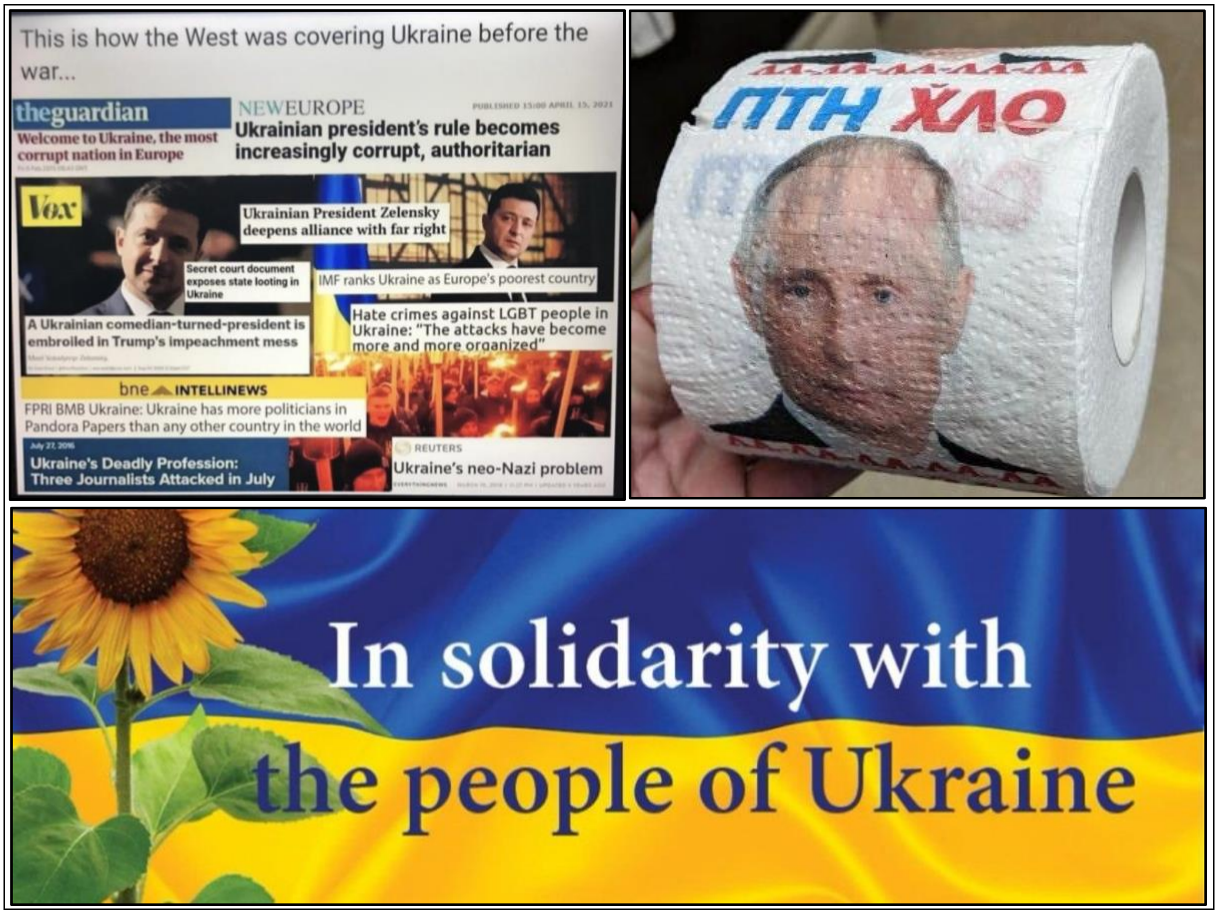

Figure 18: Secondary information for the classification of anti and pro principal figures

4.4.3. Civilian Harm and Spatial Patterns

The spatial patterns of civilian harm incidents were explored via the combination of spatial autocorrelation (SA) and the Gertis-Ord Gi* spatial statistic. Spatial autocorrelation is the measure of the relationship among values of a variable in relation to their respective locational positions on a two-dimensional surface (Griffith 2005; Legendre 1993; Anselin 1995; ESRI 2023; Monzur 2015). Based on Tobler’s first law of geography (Miller 2004), that, “*everything is related to* *everything else, but near things are more related than distant things*" (Waters 2017), SA as a geographic variant of conventional correlation (Griffith 2005) measures the relationship with neighboring spatial observations based on both the location of these observations and associated attributes (ESRI 2023) while returning a ***global*** indicator of spatial association, a correlation coefficient, as a Global Moran's I index value with both a z-score and p-value that aid the evaluation of the significance of the spatial autocorrelation index (Anselin 1995; Rey and Anselin 2007).

Given a set of features and associated attributes, SA evaluates whether there is an observable geographic pattern within them and whether the observed pattern expressed is clustered, dispersed, or random (ESRI 2023). SA is usually indicative of a form of spatial relationship (positive vs negative) in the mapped data (Haining 2015) as well as the degree of the said relationship (Fischer and Getis 2010). Positive SA is evident where adjacent observations have similar data values whereas adjacent contrasting values denote negative SA (Haining 2015). In the event of closely proximate dissimilar values, the spatial process(es) responsible for the observed pattern of values is random chance (Gimond 2023). The presence of SA in a geographically referenced data is worthy of exploration as it may reveal unique spatial characteristics of interest in the distribution of the observed variable (Haining 2015), which may warrant further investigation to unveil insights into probable spatial and other causations. The targeted SA exploration in this study was to ascertain the spatial pattern of civilian harm in the Kharkiv and Luhansk Oblasts and implications of such patterns for Eastern Ukraine. As SA could detect the said spatial relationships, it is incapable of determining the location of detected spatial clusters, if any. With the detection of spatial randomness, Gertis-Ord Gi was explored to detect outliers that may be potential hot spots and cold spots of civilian harm.

Geotagged social media point data from the Bellingcat civilian harm Timemap were obtained, cleaned to correspond to the spatial extent of the study area and subjected to spatial join with level 3 administrative regions otherwise known as hromadas (Dudley and Wissenschaft 2019). This was intended to create a valid count of reported casualties in each hromada for geovisualization, SA and potential hotspot exploration by aid of the Gertis-Ord Gi* spatial statistic. The Gertis-Ord Gi* spatial statistic identifies ***local*** patterns of spatial association by determining statistically significant spatial clusters of hot spots and cold spots (Anselin 1995; ESRI 2023) while calculating GiZScore, GiPValue and confidence level bin (GiBin) values for each feature within the input feature class to ascertain significance and statistical levels of confidence (ESRI 2023). For statistically significant positive z-scores, the larger the z-score, the more intense the clustering of high values (hot spot) while for statistically significant negative z-scores, the smaller the z-score, the more intense the clustering of low values (cold spot) (ESRI 2023).

The Gertis-Ord Gi* is computed as

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j} x_j - \bar{X} \sum_{j=1}^{n} w_{i,j}}{s\sqrt{\frac{\left[n \sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j}\right)^2\right]}{n-1}}}$$

where x_j is the attribute value for feature *j*, $w_{i,j}$ is the spatial weight between feature *i* and *j*, *n* is equal to the total number of features, $\bar{X}$ is the mean of the corresponding attribute and:

$$\bar{X} = \frac{\sum_{j=1}^{n} x_j}{n}$$

while

$$S = \sqrt{\frac{\sum_{j=1}^{n} x_j}{n} - (\bar{X})^2}$$

(source: ESRI 2023)

4.5. Results and Discussion

4.5.1. Overall Network Metrics

The propagation and flow of information among Twitter users create structures and interconnectivities, the nature and scope of which could be comprehensively explored to map and measure social relationships (Johnson et al. 2013; South et al. 2022), detect social information hubs (Ahmed et al. 2020), identify patterns of disinformation (South et al. 2022) and social opportunity (Cha et al. 2012). Thirteen thousand, five hundred and fifty-nine (13,559) tweets, replies, retweets and mentions from valid topical #tags on the 2022 Russian-Ukrainian war were collected from 6:00 AM of February 24, 2022, to 6:00 PM of October 15, 2023, cleaned and visualized in network graphs with CNM and HKFM as described above. These included 233 unique searches on #ukrainewar2022, 3277 on #warinukraine2022, 1887 on #putinswar, 4003 on #standwithukraine and 4159 on #putinisawarcriminal. As indicated in Figure 19 to 23, each network community demonstrated varying levels of clustering of users with a loosely dense inter-cluster connectivity in highly modular structures.

Total number of connected components in #putinisawarcriminal was 482 out of a total number (N) of 4159 vertices with a maximum geodesic distance (diameter) of 16 nodes and 3176 vertices in connected components. With a modularity index of 0.55, this network community registered a density of 0.0003 suggesting a highly disconnected network within which information is not easily flowing across the varying groups. Within each separate group however, there is also a very limited local cohesion as suggested by the mean clustering coefficient of 0.20. This network spanned across a very wide array of Twitter users who are not very much discussive on Twitter's #putinisawarcriminal on an individual level. Their connections are driven by a more centralized "bridge-node", gerashchenko_en, who has an in-degree of 152. The average in-degree for the 4059

Twitter users in this network was 1.43 with less than 7 users having in-degrees above 50. This very high in-degree of gerashchenko_en within a network of this character suggests its unmatched reference, relevance, influence and importance within the network. A very large number of users rely on gerashchenko_en for information on the Russian-Ukrainian war, while other users within this network who come across these pieces of information most likely obtain them from Twitter users who have either made a like, replied to, commented on or retweeted posts from gerashchenko_en.

Popular discourse by this node within the network include;

"BREAKING: Putin commented on the recently increased attacks of the Russian troops in Ukraine. According to him, Russia's current actions are "active defense". So, coming to a foreign country, occupying part of it, killing its civilians is "active defense. https://t.co/vYWjHBNPqW".

This post generated 292, 400 views, 4,448 likes, 1247 reposts, 92 quotes and 37 bookmarks. This is the official Twitter account of a Ukrainian member of Government whose account profile describes him as "*Ukrainian patriot. Advisor to the Minister of Internal Affairs of Ukraine. Founder of the Institute of the Future. Official enemy of Russian propaganda*", while having 528,700 followers and following 1005 other users. The top five referenced nodes in this network included visegrad24 who had the in-degree of 73, mfa_russia (in-degree, 70), elonmusk (in-degree, 68), zelenskyyua (in-degree, 63) and mauricemartin01 with an in-degree of 53.

Interestingly, the original post each of these users engaged with was gerashchenko_en's. This is similarly denoted by his eigenvector centrality of 0.4 which is more than 0.39 above the network's average of 0.0045. It is important to note that as eigenvector measures the importance/influence of a node within a network, gerashchenko_en's eigenvector (0.4) and betweenness centrality which was 226, 785,0.133 above the network average is worth noting. The second most referenced node, visegrad24, was the official Twitter handle of the Visegrád Group,

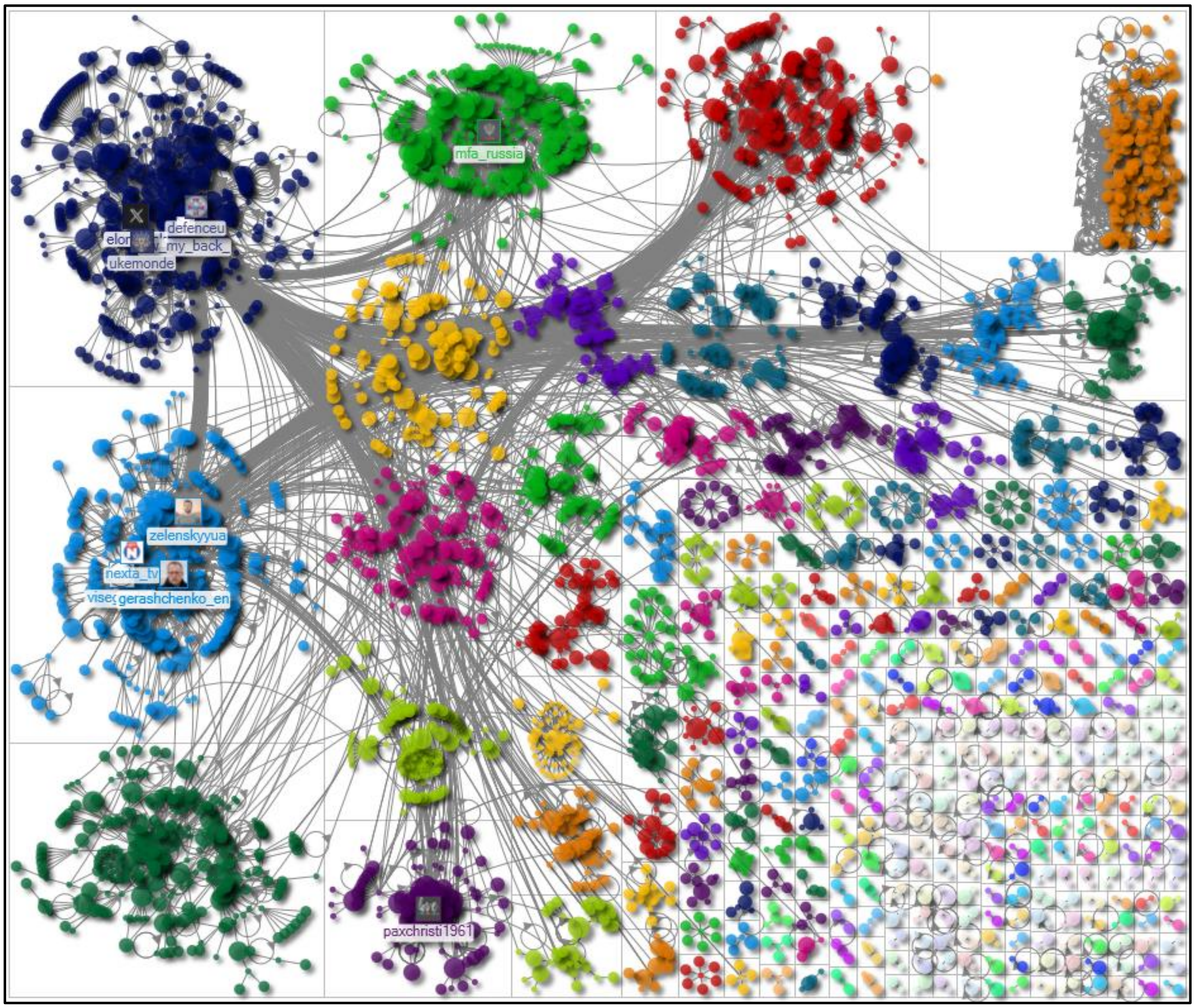

Figure 19: Network structure of #putinisawarcriminal, with each group laid in a separate box. Top 10 users with highest betweenness centrality shown in images and grey lines with arrowheads depict edges.

the official cultural and political alliance forum of the Czech Republic, Hungary, Poland and Slovakia for European integration (Braun 2020). Mfa_russia's account profile describes itself as

"*Ministry of Foreign Affairs of Russia, (Official account)| Country's account @Russia| По-русски @MID_FR| Espanňol@MAE_Rusia| Arabic* - *@russia_ar*", thus, the controllers of information flow within this network were government officials and government institutions. While the density of this network suggests a limited and slow flow of information within it, majority of the network's vertices/nodes who relate to any sort of conflict information on #putinisawarcriminal do so by connecting to these very small number of vertices for the majority of information, resulting in a concentration of power in the hands of these very few network actors.

Similar structures were visualized in all other #tags/networks in Figures 20 to 23, with #standwithukraine recording 162 connected components (N=4003) in a diameter of 12 nodes and the maximum of 3597 vertices in a connected component. #putinswar had 500 connected components (N=1887) and a diameter of 14 nodes, #warinukraine2022 had 1550 (N=3277) in a diameter of 16 nodes and #ukrainewar2022 had 157 connected components (N=233) in a diameter of 3 nodes. The maximum vertices in a connected component for #putinswar stood at 1116, #warinukraine had 931 while #ukrainewar2022 recorded 9 as its maximum vertices in a connected component.

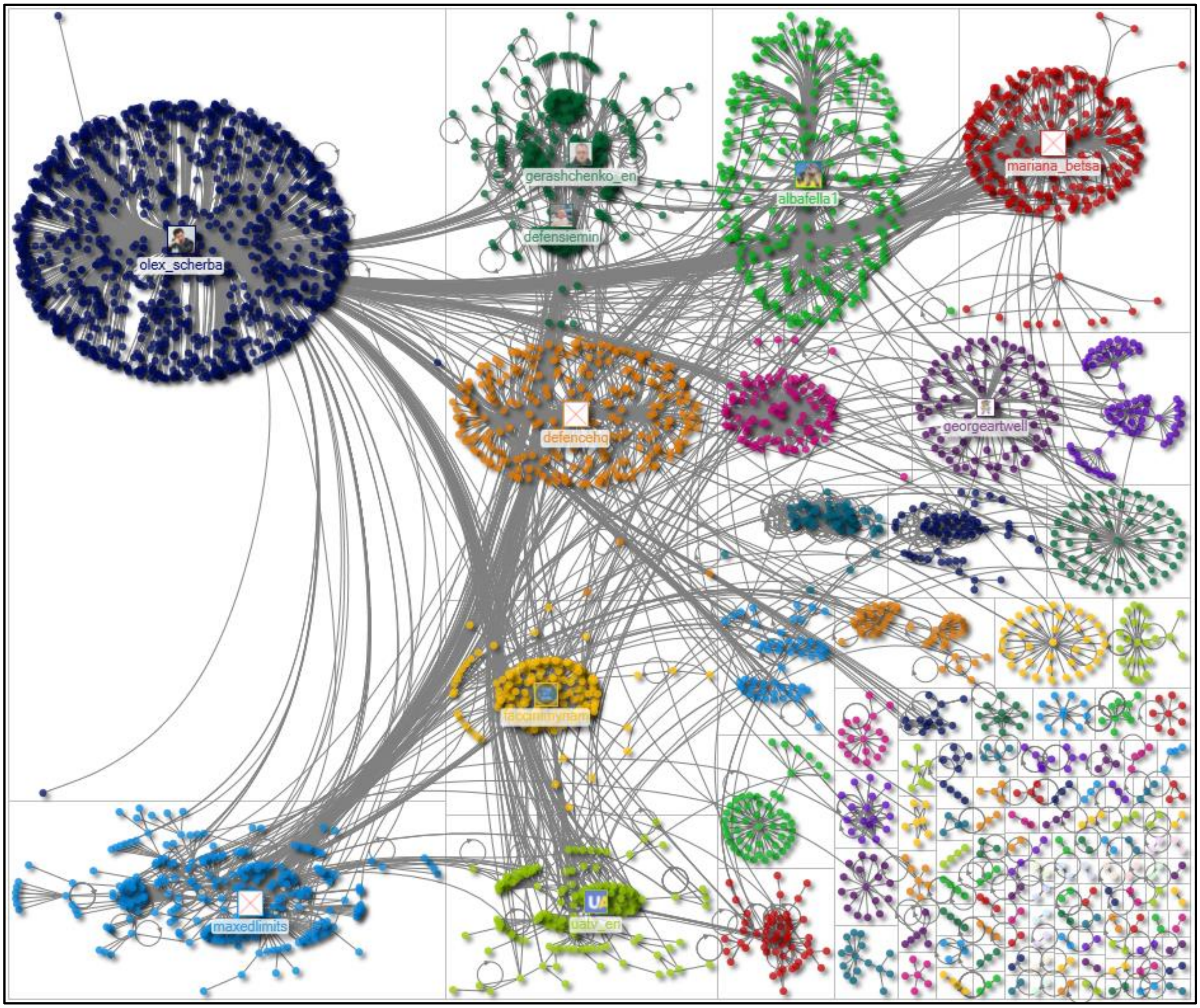

Figure 20: Network structure of #standwithukraine, with each group laid in a separate box. Top 10 users with highest betweenness centrality shown in images and grey lines with arrowheads depict directional edges.

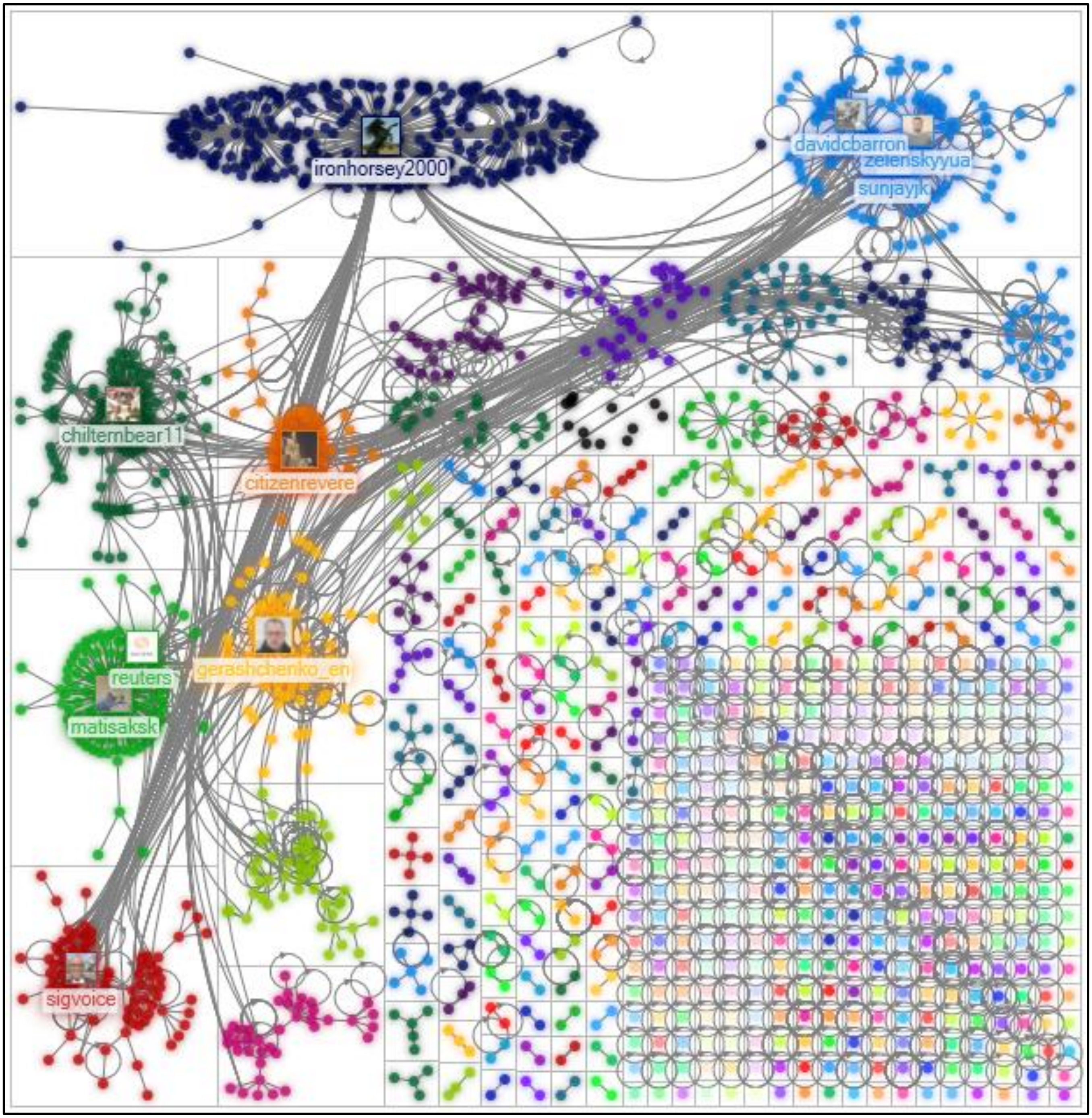

Figure 21: Network structure of #putinswar, with each group laid in a separate box. Top 10 users with highest betweenness centrality shown in images and grey lines with arrowheads depict directional edges.

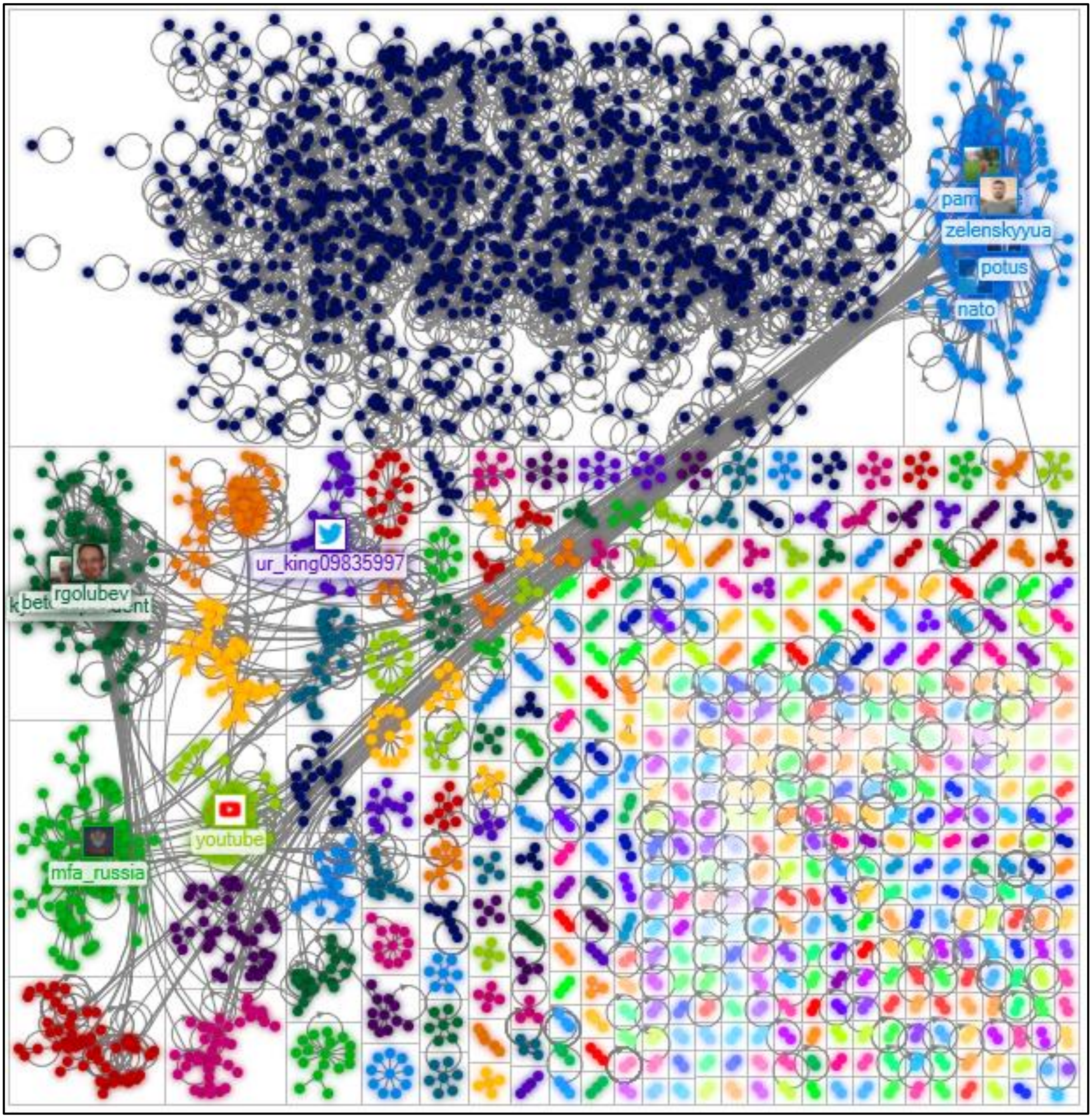

Figure 22: Network structure of #warinukraine2022, with each group laid in a separate box. Top 10 users with highest betweenness centrality shown in images and grey lines with arrowheads depict directional edges.

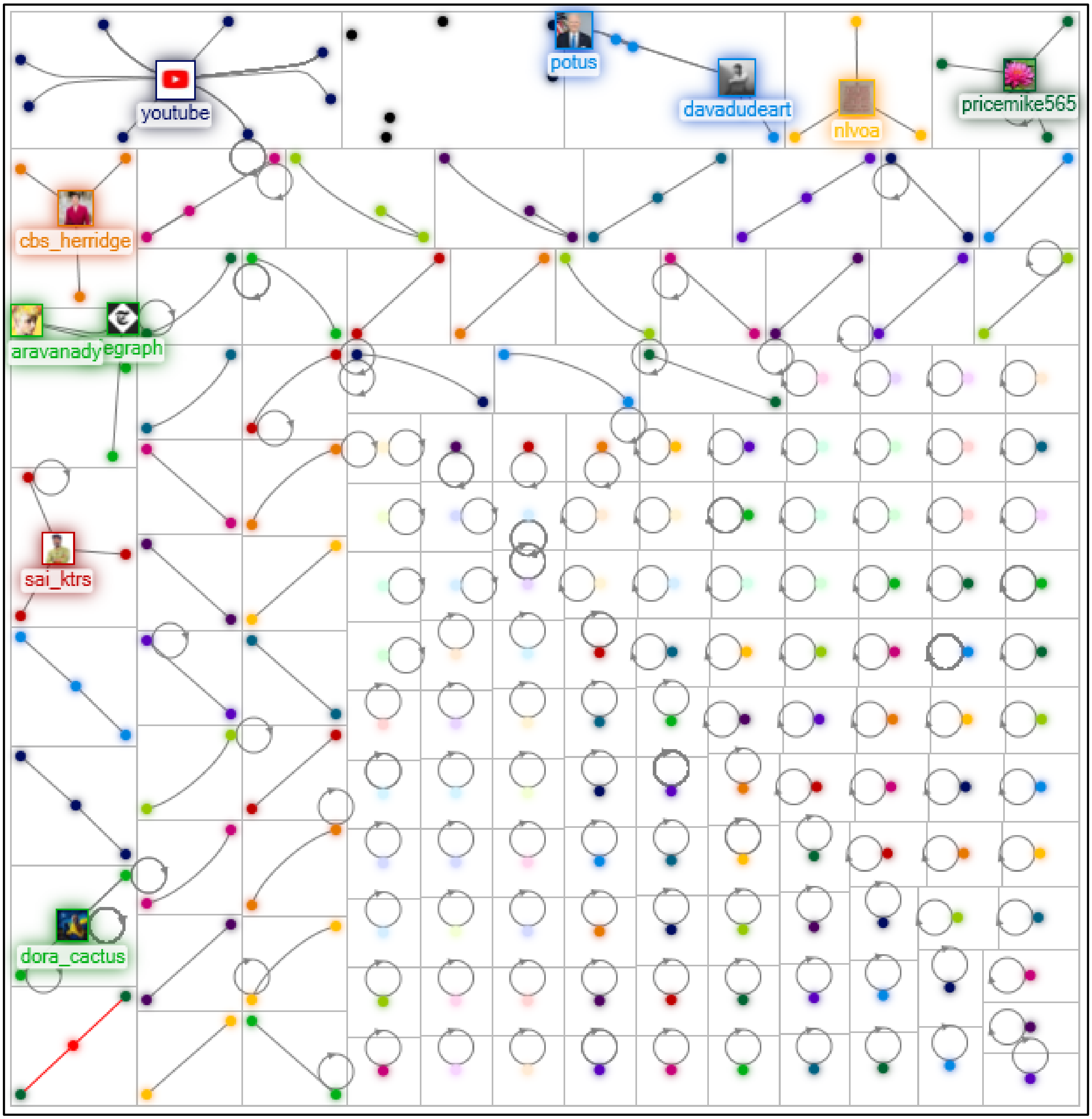

Figure 23: Network structure of #ukrainewar2022, with each group laid in a separate box. Top 10 users with highest betweenness centrality shown in images and grey lines with arrowheads depict directional edges.

4.5.2. Network Densities and Modularity

The recorded coefficients as shown in Table 8 suggest that networks sampled for this study had varying levels of modularity and density, however, with significantly low densities ranging between 0.0014 and 0.0005. #putinisawarcriminal recorded a density of 0.0003 in a network of 4159 vertices. This network is 0.03% full (connected) with only about one out of every thousand possible connections present. Maximum betweenness centrality within this network however ranged between 2,279,261.430 and 423,169.676 with in-degree connections of 152 to 28. A relatively small number of nodes in this network were connected to many other nodes with exceptionally high coefficients of importance and influence. This type of network is typically described by (Barabási 2012) as a 'scale free' network where power over information flow and importance within the network reside in a very few actors only, while users connect only with politically like-minded persons (Conover et al. 2021; Himelboim et al. 2017). These nodes have exceptionally high number of in-degree connections to other nodes, whereas the majority of those other nodes have very few connections (Hevey 2018). The clusters within this network are as well fairly disconnected as indicated by the modularity of 0.55, spreading across a maximum geodesic distance (diameter) of 16 nodes. #standwithukraine exhibited similar characteristics, recording a density of 0.0003 in a network of 4003 vertices while having a modularity of 0.67. The clusters are fairly *intra-connected* and less connected to other clusters (Himelboim et al. 2017). It is essential to reiterate that information circulated within a cluster in these networks emanated from very few highly influential nodes, while being highly modular, the nodes consuming these pieces of information do not connect with nodes in other clusters and therefore do not take information from them. #warinukraine2022 though having similar network features, also has a massive aggregation of isolate nodes and self-loops as shown in Figure 22. As isolates do not connect with other nodes within the network and have no influence on the flow of information, they reduce the density of the network by rendering it less interconnected. The self loops could be described as prolific broadcasters who only tweet and throw up information into the network but are not connected to anyone but themselves, iterating a repeated self-referential behavior. They liked, commented, mentioned and retweeted/reposted only their own original tweets/posts. The low modularity score of 0.27 for #putinswar seems to suggest a more unified network, but its density of 0.0005 indicated that it is rather a disconnected network which is 0.05% full and having only about one out of every thousand possible connections present, similar to #putinisawarcriminal, #standwithukraine, #warinukraine2022 and #ukrainewar2022, while the structure of #ukrainewar2022 suggests a rather random network with nodes having approximately the same number of connections (Hevey 2018) and no predominantly visible cluster.

#tag/network	Density	Modularity	Groups	# of connected components	Diameter	Vertices
#putinisawarcriminal	0.0003	0.55	318	482	16	4159
#standwithukraine	0.0003	0.67	121	162	12	4003
#putinswar	0.0005	0.27	175	500	14	1887
#warinukraine2022	0.0002	0.40	454	1550	16	3277
#ukrainewar2022	0.0014	0.32	47	157	3	233

Table 8: Network Density and Modularity

4.5.3. Principal Figures

Important influencers of information within the studied networks comprised of government officials, government institutions, international humanitarian and political organizations as well as individual actors whose Twitter engagements promoted campaign against violence, civilian casualty, geopolitical hegemony and pro-life sentiments. Majority (135 out of 150) of these principal figures were anti-war influencers. Eighty-three percent of #putinisawarcriminal's principal figures promoted contents that were either in solidarity with Ukraine or generated sympathy for Ukraine while seventeen percent supported the war. Out of the network's anti-war influencers, fifty-two percent were most visible within the network and had the most significant content followership as indicated by the network's $\boldsymbol{P_{id}}$ while forty-eight percent as shown by the network's $\boldsymbol{P_{BC}}$ had significant influence over the flow of information within the network. Within #putinisawarcriminal alone, gerashchenko_en, visegrad24, mfa_russia, elonmusk, zelenskyyua, nexta_tv and defenceu were principal both by reference and content engagement (P_{id}) and by power over information (P_{BC}) as shown in Table 9 below. While commanding huge audiences within the network, they barely refer to other vertices within the network, as indicated by their respective out-degrees.

Vertex (Twitter User)	**In-Degree** (P_{id})	**Out-Degree**	**Betweenness Centrality** (P_{BC})	**Type of Principal Figure**
gerashchenko_en	152	1	2,279,261	P_{id}
visegrad24	73	3	1,271,111	P_{id}
mfa_russia	70	1	711,272	P_{id}
elonmusk	68	1	1,237,197	P_{id}
zelenskyyua	63	1	1,449,075	P_{id}
mauricemartin01	53	4	402,968	P_{id}
nexta_tv	51	1	617,991	P_{id}
guffanti_marco	50	1	306,302	P_{id}
iaponomarenko	49	1	412,891	P_{id}
kardinal691	37	8	304,032	P_{id}
russianembassy	37	1	97,513	P_{id}
defenceu	36	5	428,265	P_{id}
jayinkyiv	31	2	230,066	P_{id}
marionmarechal	28	1	325	P_{id}
niikseen	27	23	256,409	P_{id}
gerashchenko_en	152	1	2,279,261	P_{BC}
zelenskyyua	63	1	1,449,074	P_{BC}
paxchristi1961	0	94	1,383,330	P_{BC}
visegrad24	73	3	1,271,111	P_{BC}
elonmusk	68	1	1,237,197	P_{BC}
mfa_russia	70	1	711,272	P_{BC}
ow_my_back_	2	37	667,637	P_{BC}

nexta_tv	51	1	617,991	P_{BC}
ukemonde	1	21	449,810	P_{BC}
defenceu	36	5	428,264	P_{BC}
lci	5	1	428,052	P_{BC}
paxidental	1	36	426,222	P_{BC}
mve_it	0	30	423,897	P_{BC}
domingo4ever1	5	32	423,169	P_{BC}
bundeskanzler	26	0	416,471	P_{BC}

Table 9:#putinisawarcriminal's principal figures

Vertex (Twitter User)	**In-Degree** (P_{id})	**Out-Degree**	**Betweenness Centrality** (P_{BC})	**Type of Principal Figure**
olex_scherba	1375	11	8,372,138	P_{id}
albafella1	322	2	2,415,350	P_{id}
mariana_betsa	280	1	1,840,965	P_{id}
defencehq	268	3	2,022,176	P_{id}
faccinimyriam	182	9	1,292,569	P_{id}
kyivpost	96	1	181,831	P_{id}
malcolmnance	90	5	127,635	P_{id}
chattjazz	89	6	129,714	P_{id}
georgeartwell	78	4	554,814	P_{id}
badbradrsr	73	0	53,964	P_{id}
fpwellman	68	0	49,211	P_{id}
uatv_en	66	7	425,186	P_{id}
defensiemin	65	1	419,854	P_{id}
defactohumanity	62	1	317,800	P_{id}
1annat	58	11	339,199	P_{id}
olex_scherba	1375	11	8,372,138	P_{BC}
albafella1	322	2	2,415,350	P_{BC}
defencehq	268	3	2,022,176	P_{BC}
mariana_betsa	280	1	1,840,965	P_{BC}
maxedlimits	0	35	1,532,809	P_{BC}
faccinimyriam	182	9	1,292,569	P_{BC}
georgeartwell	78	4	554,814	P_{BC}
gerashchenko_en	42	2	490,181	P_{BC}
uatv_en	66	7	425,186	P_{BC}
defensiemin	65	1	419,854	P_{BC}
suevisa	44	23	414,705	P_{BC}
sunnymica	45	17	405,597	P_{BC}
votejohnsond1sc	1	36	368,407	P_{BC}
1annat	58	11	339,199	P_{BC}

defactohumanity	62	1	317,800	P_{BC}

Table 10: #standwithukraine's principal figures

Within #standwithukraine, all principal figures both by P_{id} and P_{id} were actively anti-war with no presence of pro-war influence. As seen in Table 10 above, olex_scherba, albafella1, mariana_betsa, defencehq, faccinimyriam, georgeartwell, defensiemin, defactohumanity and 1annat appeared as principal, both by in-degree and betweenness centrality. These Twitter Users had heavy visibility and influence within the network and that was driven to promote peace and harness sympathy and support for Ukraine. As #standwithukraine had no pro-war principal figure, both #putinswar and #warinukraine2022 recorded ninety percent anti and 10 percent pro while #ukrainewar2022 had eighty-seven percent anti and thirteen percent pro-war principal figures. These majority of Twitter users within all the studied networks who had either in-degree or betweenness centrality well above the network mean directed much of their influence and engagements towards support for Ukraine as indicated in Figure 24.

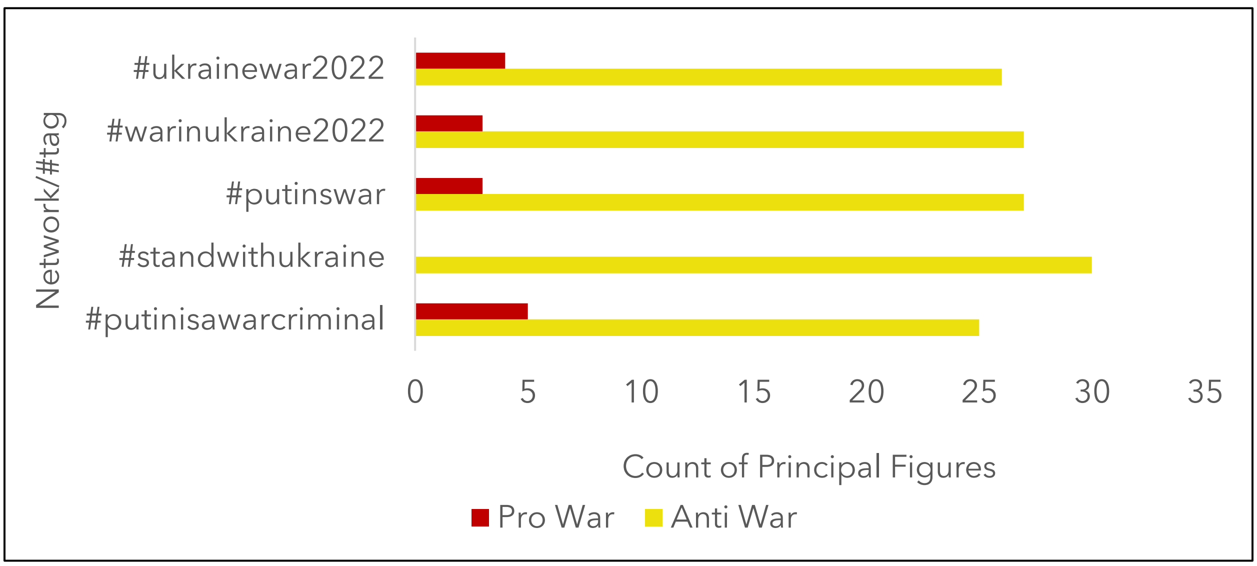

Figure 24: Anti and Pro Principal network Figures

Vertex (Twitter User)	In-Degree (P_{id})	Out-Degree	Betweenness Centrality (P_{BC})	Type of Principal Figure

gerashchenko_en	27	1	152,186	P_{id}
zelenskyyua	17	2	95,912	P_{id}
igorsushko	10	8	33,698	P_{id}
nato	10	0	33,300	P_{id}
kyivindependent	9	1	36,378	P_{id}
elonmusk	9	1	33,735	P_{id}
visegrad24	9	1	25,111	P_{id}
kremlinrussia_e	9	0	23,183	P_{id}
potus	8	0	68,644	P_{id}
wartranslated	8	1	35,740	P_{id}
mfa_russia	8	0	19,722	P_{id}
nexta_tv	8	1	16,786	P_{id}
repmtg	8	1	15,486	P_{id}
un	7	0	36,145	P_{id}
noelreports	7	1	28,411	P_{id}
ironhorsey2000	1	337	717,493	P_{BC}
matisaksk	2	95	227,329	P_{BC}
citizenrevere	0	69	154,314	P_{BC}
gerashchenko_en	27	1	152,186	P_{BC}
chilternbear11	1	55	145,042	P_{BC}
sunjayjk	1	46	123,762	P_{BC}
reuters	6	1	102,204	P_{BC}
zelenskyyua	17	2	95,912	P_{BC}
sigvoice	1	45	81,471	P_{BC}
davidcbarron	0	29	78,025	P_{BC}
hebawi	1	18	71,600	P_{BC}
potus	8	0	68,644	P_{BC}
jacksonhinklle	6	0	66,285	P_{BC}
bfs465	1	24	61,321	P_{BC}
alvisharding	1	28	60,924	P_{BC}

Table 11: #putinswar's principal figures

Vertex (Twitter User)	In-Degree (P_{id})	Out-Degree	Betweenness Centrality (P_{BC})	Type of Principal Figure
youtube	32	0	111,173	P_{id}
zelenskyyua	26	1	156,352	P_{id}
nato	23	0	119,163	P_{id}
kyivindependent	19	1	110,574	P_{id}
potus	18	0	83,419	P_{id}
nexta_tv	14	1	73,338	P_{id}
un	14	0	46,142	P_{id}

emmanuelmacron	14	0	43,444	P_{id}
mfa_russia	12	1	81,528	P_{id}
reuters	11	2	39,458	P_{id}
eu_commission	10	1	62,718	P_{id}
nytimes	10	1	44,506	P_{id}
iaponomarenko	10	1	43,176	P_{id}
defenceu	10	1	36,368	P_{id}
joebiden	10	0	24,317	P_{id}
zelenskyyua	26	1	156,352	P_{BC}
rgolubev	1	27	129,638	P_{BC}
pamartbe	1	55	128,717	P_{BC}
nato	23	0	119,163	P_{BC}
youtube	32	0	111,173	P_{BC}
kyivindependent	19	1	110,575	P_{BC}
betobarbo	0	16	98,664	P_{BC}
ur_king09835997	2	17	86,538	P_{BC}
potus	18	0	83,419	P_{BC}
mfa_russia	12	1	81,528	P_{BC}
_kyiv_sky_	1	30	79,336	P_{BC}
vonderleyen	9	1	77,714	P_{BC}
nexta_tv	14	1	73,338	P_{BC}
olgatokariuk	8	1	69,681	P_{BC}
dayanaaash	0	18	64,417	P_{BC}

Table 12: #warinukraine2022's principal figures

Vertex (Twitter User)	**In-Degree** (P_{id})	**Out-Degree**	**Betweenness Centrality** (P_{BC})	**Type of Principal Figure**
youtube	8	0	56.000	P_{id}
potus	2	0	8.000	P_{id}
telegraph	2	2	4.000	P_{id}
r1ght_now	2	1	0.000	P_{id}
smetanatborschu	2	1	0.000	P_{id}
basedpoland2	2	1	0.000	P_{id}
thenaveena	2	1	0.000	P_{id}
peng	2	1	0.000	P_{id}
jimsciutto	2	1	0.000	P_{id}
k_loukerenko	2	1	0.000	P_{id}
mattia_n	2	1	0.000	P_{id}
teachertwit2	2	1	0.000	P_{id}
npr	2	1	0.000	P_{id}
afp	2	1	0.000	P_{id}

middleeastmnt	2	1	0.000	P_{id}
youtube	8	0	56.000	P_{BC}
davadudeart	0	4	18.000	P_{BC}
potus	2	0	8.000	P_{BC}
cbs_herridge	1	2	6.000	P_{BC}
pricemike565	1	4	6.000	P_{BC}
nlvoa	0	3	6.000	P_{BC}
sai_ktrs	0	3	6.000	P_{BC}
telegraph	2	2	4.000	P_{BC}
aravanady	0	2	4.000	P_{BC}
dora_cactus	1	3	2.000	P_{BC}
deanccurry	0	2	2.000	P_{BC}
fireisborn3	0	2	2.000	P_{BC}
lucianaborsatti	0	2	2.000	P_{BC}
kcengel	0	2	2.000	P_{BC}
kevinbturner	0	2	2.000	P_{BC}

Table 13: #ukrainewar2022's principal figures

4.5.4. Pattern of Civilian Casualty

The spatial autocorrelation results as shown in Figure 25 indicate that the pattern observed for the reported incidents of civilian casualty between February 2022 and October 2023 does not appear to be significantly different than a random occurrence. This was evidenced by the low z-score of 0.3 for the Moran Index of -0.0059 and a p-value 0.76. Majority of the mapped incidents were distributed at the center of the bell curve inclining them towards a random distribution than one would expect for either a clustered or dispersed distribution. This result seemed affirmed by the Geritis-Ord Gi which indicated that there was no significant clustering within this dataset. However, it indicated Kharkivska within the Kharkiv oblast as a hotspot with 99% confidence. Except for Kharkivska therefore, civilian harm during this period of the conflict is more likely to have occurred all over the study area with little or no concentration in any particular hromada. A detailed further observation however indicated that, many locations recorded very little to no reported casualty while regions within and around central Kharkiv to the northern border with the Russian Federation, as well as regions west of Luhansk, to the border with Donetsk recorded the most reported casualties within the study area.

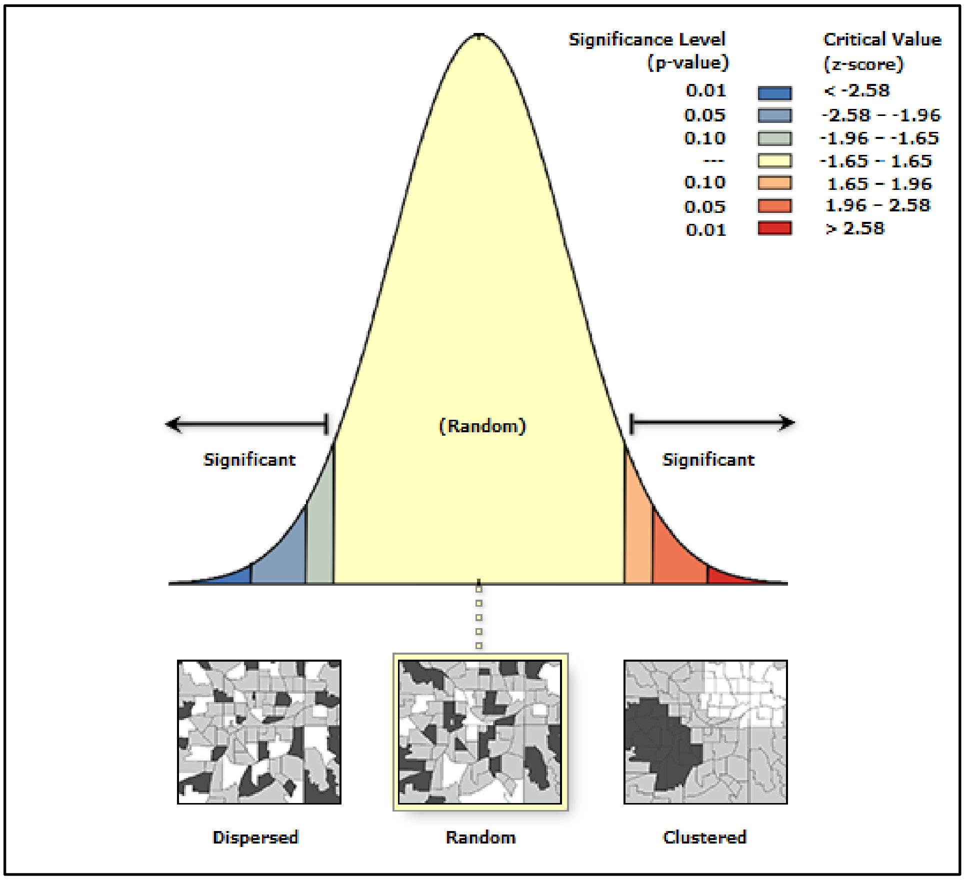

Figure 25: Spatial pattern of civilian harm in the study area.

As symbolized in four quartiles in Figure 26, these regions experienced not less than ten casualties, with highest frequencies occurring in Kharkivska at a total of 226 incidents of civilian harm. Some critical locations seemed to be of more interest and were attacked than others. Within the Kharkiv oblast, Kharkivska, Kupianska, Iziumska recorded the maximum casualties with 226, 21 and 14 incidents respectively while Vovchanska, Chuhuivska, Borivska, Derhachivska, Merefianska, Zolochivska, Vilkhivska, Malodanylivska and Pisochynska recorded about 9 to 4 casualties each.

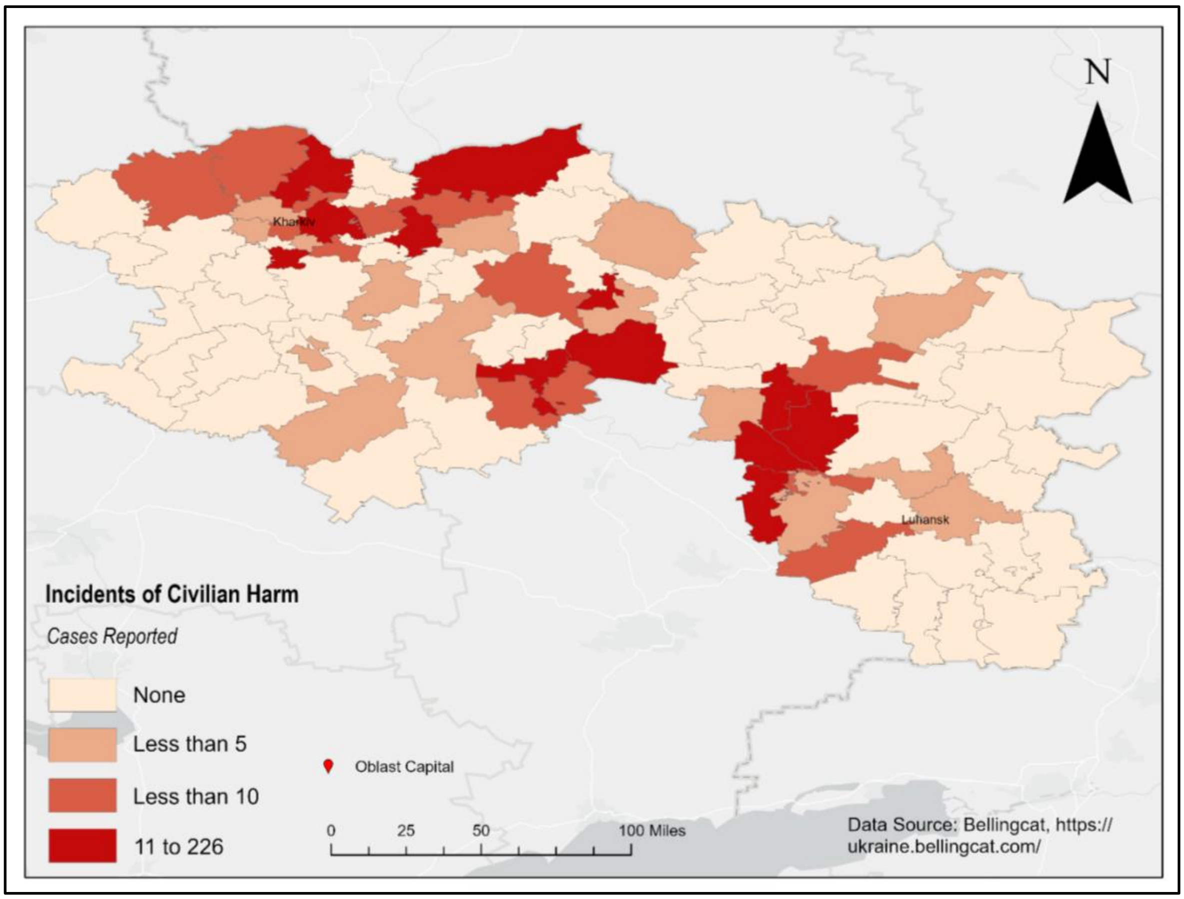

Figure 26: Incidents of civilian harm in the Kharkiv and Luhansk oblasts.

Within the Luhansk region, the maximum casualty occurred within Lysychanska (15 incidents), Sievierodonetska (14 incidents) and Rubizhanska (7 incidents). Popasnianska, Hirska, Alchevska, Starobilska, Kadiivska, Luhanska, Shchastynska about two to six incidents while both Kreminska and Novopskovska had only one incident each of reported civilian casualty. All other hromadas within the Luhansk region were incident-free, reporting no casualty. In the Kharkiv oblast, regions around Bohodukhivska, Oskilska, Shevchenkivska, Bezliudivska, Starosaltivska, Balakliiska, Dvorichanska, Kurylivska, Lozivska, Pervomaiska and Slobozhanska had minimal incidents of reported harm with incidents ranging between three (for the first five areas) and two for the rest, respectively. All other areas within the oblast were incident-free except for Vysochanska, Liubotynska, Solonytsivska and Pechenizka which recorded an incident each. Total count of incidents within the oblast stood at three hundred and forty-three with the average of 6.125 while all affected regions in the Kharkiv oblast collectively experienced less than fifty-two percent of casualties recorded for Kharkivska alone. Comparatively, the Luhansk oblast had fewer incidents totaling to sixty-one incidents, compared to Kharkiv's three hundred and forty-three. The average count of civilian harm in Luhansk stood at 1.65 incidents. While Lysychanska was the most impacted area in Luhansk, Kharkivska was the most affected region in Kharkiv.

4.6. Conclusion

This study explored, via social networks, the flow of social media information on Twitter from February 2022 to October 2023 using five pretested and valid popular Russian-Ukrainian war #tags and examined the patterns of reported civilian casualty in the Kharkiv and Luhansk oblasts in eastern Ukraine. Principal network figures in terms of Twitter users with the most visibility and content engagement as well as their pro and anti-war orientation, and degrees of power/influence over information flow were examined. Notable Twitter #tags that generated massive networks and conversation during this period included #putinisawarcriminal, #standwithukraine, #putinswar, #warinukraine2022 and #ukrainewar2022. Other #tags were actively present on Twitter but a good number of these generated less engagements, the exploration of which may have very little statistical significance. Such #tags include #russianwarcrimes, #ukraineweeps, #russiaukraine2022, #vladimirputin2022 and #russiainvassion2022. Within the valid and explored networks/#tags, Twitter users identified as most visible and having much influence over the flow of information consisted of government officials, government institutions, international humanitarian bodies, international political organizations and individual actors. A good majority (90%) of these people (135 out the sampled 150) vehemently objected the ensuing violence, declared and promoted solidarity with Ukraine while advocating aid, sympathy and support for Ukrainian people. Pro-war principal figures were chiefly eastern-bloc affiliated government institutions whose major Twitter content seemed to trivialize the impacts of the conflict and attempted diverting attention from the current geopolitical event to rather focus on the vestiges of colonialism in Africa while other pro-war individual actors advocated against the reception of internationally displaced war victims into western countries.

The occurrence of civilian casualty during the period under study was recorded all over the study area with little or no concentration in context of both the Kharkiv and Luhansk oblasts. There was no visible spatial relationship between closeness to urban areas and count of incidence, however, Kharkivska within the Kharkiv oblast suffered extreme damages with severe impacts nearing 65% of the reported total casualties in the oblast. Some regions and critical locations seemed of much interest for attack than other regions. The Luhansk oblast had fewer incidents of civilian casualty compared to Kharkiv while both oblasts had some identified safe zones, devoid of civilian harm.

Chapter 5: Summary and Conclusion

Following the conflicts in Crimea and its subsequent annexation in 2014, repeated chaos engulfed Ukraine's eastern territories and the Donbas for more than eight years (Dijkstra et al. 2022). Beyond the humanitarian and other crisis emanating from these conflicts, the current violence and war have present renewed challenges not only erasing solutions achieved for curtailing the impacts of historical conflicts, but actively presenting a plethora of new multifaceted developmental and social dilemmas the region would have to embrace for additional number of years. Similar conflicts in other regions were evidenced to have ignited significant structural disturbances and modifications to urban areas (Lisa et al. 2021; Pech and Lakes 2017), imposed detrimental psychological impacts on affected groups (Betancourt and Khan 2008; Bahgat et al. 2017), significant health consequences and living condition challenges for women (Jolof et al. 2022), state failure (Büscher 2012), food insecurity (Li et al. 2022; Yazbeck et al. 2022; Gibson, Campbell, and Wynne 2012) and protracted labor supply (Odozi and Oyelere 2021). In contexts of the environment, violent conflicts induce significant structural and environmental damage, LU/LC change (Witmer 2015), landscape fragmentation (Gbanie, Griffin, and Thornton 2018) and widespread environmental degradation (Bergius et al. 2020). The assessment of the impacts of violent conflicts on Ukraine indicated that, war has created heterogeneous impacts for equity markets (Boubaker et al. 2022), reproductive health and justice crisis (Kismödi and Pitchforth 2022) declination of food supply (Berkhout, Bergevoet, and van Berkum 2022) with associated consequences for food prices and global food security (Hassen and Bilali 2022; Benton et al. 2022) coupled with extreme environmental (Pereira et al. 2022), security, economic and health issues.

This study in contribution to these pre-existing assessments, explored the spatial evolution of landcover and rates of decline in agricultural vegetation specifically in the Kharkiv and Luhansk oblasts, while examining the flow of social media information via the social network analysis of Twitter communities and patterns of civilian casualty in Kharkiv and Luhansk to facilitate a rasp comprehension of the spatial dimensions of the conflicts for Ukraine's east and evolving social media powerplays. Several key insights emerged from this study; 1). Armed conflicts induce changes in landcover and land systems regardless of the dominating land use (Baumann and Kuemmerle 2016). 2). Both agricultural and forested non-agricultural vegetative biomes are susceptible to some sort of change during armed conflicts. However, as the former experience massive rates of declination, the latter captured the additional space cleared off of the former. This affirms the propositions of (Witmer 2015) and (Wilson and Wilson 2013) that non-agricultural vegetation and forest cover during periods of war exhibit growth while going through reduction during periods of peace. Similar to (Gibson, Campbell, and Wynne 2012), war was seen as an active driver of land use/ landcover (LU/LC) change and is among the most drastic drivers of geo-environmental evolution and globally frequent shocks. Ceteris paribus, agricultural regions are the most susceptible to those types of changes. 3). The ensuing conflict modified landcover in the study area by facilitating the abandonment of agricultural fields and aiding growth of non-farm vegetation as farm labor either flee farmwork for safety or quit farm work for a plethora of reasons qualitative survey would help to explore. As seen in these findings, remote sensing has facilitated the assessment of the impacts of war. Although data from this technology are incapable of comprehensive environmental assessment of conflict impacts, they provide valuable information on changes in vegetation which when integrated with social and environmental impacts could provide a better understanding of how these complex systems interrelate (Witmer 2008).

Further insights indicated that reported incidents of civilian casualty between February 2022 and October 2023 do not have any spatially significant pattern of clustering as of October 15

2023. Reported civilian casualty had a random occurrence, with no visible relationship between closeness to urban areas and count of incidence, however, out of 343 reported cases in the Kharkiv oblast, 66% (226) occurred in Kharkivska alone. Luhansk underwent less casualties than Kharkiv while many other regions within the two oblasts were safe, recording no casualty as of October 15, 2023. Furthermore, the dissemination of conflict information as themed in Twitter #tags, was significantly dominated by government officials, government institutions, international humanitarian bodies, international political organizations and individual actors, majority of whom were anti-war and pro Ukraine. Social clusters on Twitter for the explored networks were not very interconnected and information circulating within these social groups emanated from very few highly influential Twitter users within whom power over information flow and importance within the network heavily resided. Other users consuming these pieces of information from these users do not connect with nodes in other clusters and therefore do not take information from them, indicating exclusive connection only with politically like-minded persons.

5.1. Recommendation and Future Study

To provide a comprehensive insight into the overall nature and scope of the impact of war on eastern Ukraine, this study suggests a future study to assess landcover transformations for the entire lifespan of the conflict with an expanded focus to integrate such other socio-environmental impacts as water contamination, air pollution, population displacements, agricultural exports and food supply relative to conflict regimes (pre, during and post), among others. Other robust analytic algorithms such as GeoBIA and deep learning are recommended to be utilized in a future study to further explore insights uncovered in this study by the pixel-based classifiers. The study also recommends further studies into the Twitter clusters to investigate the roles and impacts of the dominating principal figures on the visual framing of the conflict.

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