

Ecological consequences of armed conflict: vegetation change in Ukraine from remote sensing
and conflict intensity modeling

by

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Abstract

Armed conflict generates extensive and long-lasting environmental consequences, yet large-scale quantitative assessments of these impacts remain limited. This thesis examines the ecological effects of the Russia–Ukraine War by integrating remote sensing time-series analysis with spatial Bayesian modeling to quantify vegetation change and link it to patterns of military activity. Using 22 years (2001–2023) of MODIS Enhanced Vegetation Index (EVI) data, the Breaks for Additive Season and Trend (BFAST) methodology was applied to detect long-term vegetation trends and structural disturbances across Ukraine. The BFAST analysis revealed that approximately two-thirds of the country exhibited positive vegetation trends while localized but substantial negative trends were concentrated in eastern and southern regions experiencing the most intense military activity. Additional analyses show that cropland and urban areas significantly influence national patterns and may mask conflict-related ecological signals. Explosion events recorded in the ACLED database (2018–2023) were modeled as a spatial statistical process using Bayesian Integrated Nested Laplace Approximation (INLA) with a stochastic partial differential equation (SPDE) framework, demonstrating that explosion intensity was strongly clustered near infrastructure, population centers, and front-line regions, with spatial dependence extending approximately 10 km. Predicted explosion intensity surfaces were incorporated into a generalized additive modeling framework to evaluate relationships between conflict intensity, climatic variables, and vegetation trends, indicating that higher modeled explosion intensity is associated with more negative vegetation trends. Together, these findings represent the first national-scale application of BFAST to assess vegetation dynamics across Ukraine and the first spatial modeling of explosion intensity counts using Bayesian methods, advancing methodological approaches for studying environmental impacts in active war zones

and providing a replicable framework to support post-conflict environmental assessment, ecological risk analysis, and long-term recovery planning.

Table of Contents

List of Figures	vi
List of Tables	vii
Acknowledgements	viii
Dedication	ix
Chapter 1 - Introduction.....	1
Chapter 2 - Literature Review.....	10
Chapter 3 - Detecting Vegetation Change in Ukraine using Satellite Imagery and BFAST Analysis	42
Chapter 4 - Spatial Bayesian Modeling of Explosion Intensity and Vegetation Change during the Russia-Ukraine War.....	81
Chapter 5 - Overall Synthesis	107
References.....	112
Appendix A - Publication of R Code	125

List of Figures

Figure 2-1- Russia-Ukraine War Timeline	11
Figure 2-2: Geographic Scope of the Russia-Ukraine War	13
Figure 2-3: Example of Bombturbation -.....	16
Figure 2-4: Example of Tank Deposition.	18
Figure 2-5: Environmental Consequences from Military Operations.....	21
Figure 2-6: Before and after satellite images of Nova Kakhovka dam.....	28
Figure 2-7: BFAST Components Graph	33
Figure 2-8: SPDE Triangulation Mesh.	37
Figure 3-1: Ecoregions in Ukraine.....	51
Figure 3-2: Land Cover Classification of Ukraine	52
Figure 3-3: BFAST Trend Map of Ukraine.	58
Figure 3-4: BFAST Trend Map of Ukraine without Cropland and Urban Areas.	61
Figure 3-5: Number of Structural Breaks Detected by BFAST in Ukraine.....	64
Figure 3-6: Number of Structural Breaks Detected by BFAST in Ukraine Excluding Cropland and Urban Areas.	65
Figure 3-7: Frequency Distribution of Vegetation Structural Breaks in Ukraine (2001–2023) ...	67
Figure 3-8: Frequency Distribution of Vegetation Structural Breaks Across Ukrainian Ecoregions (2001–2023).....	68
Figure 3-9: BFAST Vegetation Trends Within Ukrainian Counteroffensive Areas	69
Figure 3-10: Number of BFAST Structural Breaks Within Ukrainian Counteroffensive Areas .	70
Figure 3-11: BFAST Vegetation Trends Within Russian-Occupied Areas.....	71
Figure 3-12: Number of BFAST Structural Breaks Within Russian-Occupied Areas.	72
Figure 4-1: Spatial Covariate Raster Layers Used in the Explosion Model.	87
Figure 4-2: Predicted Explosion Intensity Count from INLA Poisson Model	90
Figure 4-3: Marginal Effects of Covariates on Predicted Explosion Intensity.....	92
Figure 4-4: Marginal Posterior Distribution of Spatial Range Parameter.	94
Figure 4-5: Predicted Spatial Spline Surface ($k = 1$).	95
Figure 4-6: Predicted Spatial Spline Surface ($k = 75$) applicable).	97

List of Tables

Table 3-1: Percentage of BFAST Trend from Ukrainian Ecoregions	59
Table 3-2: Percentage of BFAST Trend from Ukrainian Ecoregions without Cropland and Urban Areas	62
Table 4-1: Covariate Model Results	91
Table 4-2: Explosion Model Hyperparameters	93
Table 4-3: Model Coefficients for the Vegetation Change Model	98

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Dedication

I dedicate this thesis to my family; Chris, Kathy, and Lizzie; for their unwavering love and encouragement throughout this journey. I am especially grateful to my girlfriend, Jaylee, for her constant support, patience, and belief in me. I also extend my sincere thanks to everyone who offered guidance, encouragement, and enthusiasm for this research along the way.

Chapter 1 - Introduction

The aim of this introductory chapter is to lay the necessary foundations for this thesis. It introduces the key concepts of Breaks for Additive Seasons and Trend (BFAST), explosion intensity modeling, and generalize additive models. The focus of this thesis is to describe the ecological consequences of the Russian-Ukraine war on the environment. It also outlines the structure of this thesis, providing a brief overview of each of the chapters that follow.

Armed conflict has long been recognized as a significant driver of environmental degradation, with modern warfare producing widespread and ecological consequences. The Russia–Ukraine War has intensified concerns regarding the environmental costs of military activity, particularly in heavily contested regions of Eastern and Southern Ukraine. Explosive munitions, artillery bombardment, and drone strikes have resulted in direct physical disturbances to landscapes, including crater formation, soil compaction, and vegetation loss. The process of “Bombturbation,” defined as soil disturbance caused by explosive impacts, alters surface topography and mixes soil horizons, fundamentally changing ecosystem structure (Hupy et al., 2006; Broomandi et al., 2020). In addition to these immediate impacts, military operations introduce chemical contaminants such as heavy metals, explosive residues, and petroleum products into soil and water systems, further degrading soil quality and ecosystem function (Lawrence et al., 2015; Mystrioti & Papassiopi, 2024).

Beyond direct battlefield impacts, indirect consequences of warfare further contribute to landscape transformation. Disruption of agricultural activities, abandonment of farmland, and damage to critical infrastructure have altered land-use patterns across Ukraine. Armed conflicts are known to reduce agricultural productivity and lead to long-term land abandonment due to population displacement, infrastructure destruction, and contamination (Baumann & Kuemmerle,

2016; Yin et al., 2019). The presence of unexploded ordnance and landmines has rendered large areas unsafe for cultivation, accelerating processes of land degradation and ecological change. Military vehicle movement and trench construction exacerbate erosion and soil compaction, while increased wildfire risk associated with combat operations threatens forests and grasslands (Hutchinson et al., 2015; Hryhorczuk et al., 2024). These indirect effects demonstrate that the environmental footprint of war extends far beyond immediate combat zones and can persist long after war has been ceased.

Remote sensing has emerged as a crucial tool for monitoring environmental change in conflict-affected regions where field access is limited or dangerous. Time-series satellite data provides an effective means of detecting vegetation disturbances and assessing landscape recovery over large spatial extents. Methods such as Breaks for Additive Season and Trend (BFAST) allow researchers to separate long-term trends from seasonal variability and to identify abrupt changes in vegetation condition (Verbesselt et al., 2010). BFAST has been widely applied to investigate ecosystem dynamics, forest disturbances, and land degradation using remotely sensed vegetation indices (De Jong et al., 2013; Geng et al., 2019). In the context of Ukraine, remotely sensed indices such as the Enhanced Vegetation Index (EVI) and Normalized Difference Vegetation Index (NDVI) provide measures for quantifying ecological impacts associated with explosions and other military activities over time.

Statistical modeling frameworks are also essential for understanding the spatial patterns and drivers of conflict-related environmental change. Bayesian approaches such as Integrated Nested Laplace Approximation (INLA) offer efficient tools for modeling complex spatial processes and accounting for spatial dependence in environmental data (Rue et al., 2009; Illian et al., 2013). Flexible regression techniques like Generalized Additive Models (GAMs) further allow

researchers to model nonlinear relationships between environmental covariates and observed impacts (Wood, 2017). These methods enable the analysis of explosion intensity patterns, the assessment of environmental risk factors, and the generation of predictive maps that link military activity to landscape change. By integrating geospatial data with advanced statistical models, researchers can better evaluate how proximity to infrastructure, population centers, and front lines influences the distribution of environmental impacts. Collectively, this body of literature shows the importance of combining remote sensing and spatial modeling to understand and mitigate the environmental consequences of the Russia–Ukraine War.

Despite the growing body of research examining the environmental consequences of armed conflict, significant methodological and geographic gaps remain in understanding the large-scale ecological impacts of the Russia–Ukraine War. To date, most studies investigating war-related environmental change have relied on localized field assessments or small regional case studies, largely due to limitations in data availability and analytical approaches. No known research has applied the Breaks for Additive Season and Trend (BFAST) methodology to assess vegetation disturbance across the entirety of Ukraine. Existing applications of BFAST in conflict or disturbance contexts have typically focused on limited spatial extents such as protected areas (Lambert et al., 2013), training grounds (Hutchinson et al., 2015), or individual ecosystems (Geng et al., 2019). A countrywide analysis is therefore necessary to capture the full spatial extent of environmental impacts and to provide a comprehensive national scale assessment of vegetation change associated with ongoing military activities.

In addition to this gap in large-scale remote sensing applications, there is currently no published research that models explosion intensity counts as a spatial statistical process. Previous studies examining conflict events have primarily focused on documenting occurrences or mapping event

locations, without attempting to quantitatively model the spatial distribution and drivers of explosion activity. The integration of Bayesian spatial modeling approaches, such as INLA, to predict explosion intensity and evaluate covariate influences represents a novel methodological contribution. By treating explosions as a point process influenced by environmental and infrastructural factors, this research moves beyond descriptive mapping and provides a predictive framework capable of identifying high-risk areas and key determinants of military activity.

The proposed study, methodologically, represents the first effort to combine national-scale BFAST time-series analysis with spatial modeling of explosion intensity, linking remotely sensed vegetation change directly to patterns of military activity. From an applied perspective, the research provides information for environmental monitoring, post-conflict recovery planning, and ecological risk assessment in Ukraine. Understanding where and how explosions are concentrated, and how they influence vegetation dynamics over time, is essential for remediation efforts and guiding long-term environmental management. Given the unprecedented scale of the Russia–Ukraine War and the absence of comprehensive national analyses, this study fills an important gap in both conflict-environment research and applied geospatial modeling.

The aim of this thesis is to examine the ecological consequences of war-related activities in Ukraine by quantifying how vegetation conditions have changed over time and identifying the primary drivers of those changes. Specifically, this research seeks to determine the spatial and temporal patterns of vegetation trends across Ukraine from 2001–2023 and to evaluate the extent to which these trends are associated with military actions, particularly explosive events. To achieve this aim, the study is guided by three key research questions: (1) How have vegetation trends across Ukraine changed, as detected throughout a BFAST time-series analysis? (2) What is the spatial distribution and intensity of explosion events, and which environmental and

infrastructural factors best explain their occurrence? and (3) To what extent are negative vegetation trends statistically related to modeled explosion intensity and other landscape covariates? By addressing these questions, this research will provide a comprehensive assessment of the environmental impacts of the Russia–Ukraine War and contribute new methodological approaches for linking remotely sensed vegetation change with spatial patterns of armed conflict.

This research makes several important and novel contributions to the study of conflict-related environmental change. First, it represents the first known application of BFAST time-series analysis at a full national scale to assess vegetation dynamics across all of Ukraine, providing a countrywide evaluation of how time has influenced ecological conditions. Previous studies have been limited to localized case studies or short temporal windows, whereas this research offers a comprehensive, multi-year assessment that captures spatial heterogeneity in vegetation responses across diverse landscapes and conflict intensities. Second, this study introduces an entirely new methodological approach by modeling explosion intensity counts as a spatial statistical process using Bayesian INLA techniques, an analysis that has not previously been attempted in the literature. By integrating remotely sensed vegetation trends with predictive modeling of explosion activity and environmental covariates, this research establishes a quantitative link between military actions and ecological outcomes. Together, these contributions fill gaps in both remote sensing and conflict-environment research, providing a replicable framework for monitoring environmental impacts in active war zones and offering valuable insights for post-conflict environmental assessment.

This thesis is organized into 5 chapters. The first chapter introduces what the research is about and how the research is going to be approached. This thesis investigates the ecological

consequences of the Russia–Ukraine War by integrating remote sensing and spatial statistical modeling to quantify how military activities have affected vegetation across Ukraine. It builds on existing literature demonstrating that modern warfare causes extensive environmental degradation through direct impacts such as explosions, soil disturbance, and contamination, as well as indirect effects including land abandonment, infrastructure damage, and increased wildfire risk. To overcome limitations of field-based studies in active conflict zones, the research applies national-scale remote sensing methods, Breaks for Additive Season and Trend (BFAST), to detect long-term vegetation changes from 2001–2023. In parallel, the study develops a Bayesian spatial modeling framework using Integrated Nested Laplace Approximation (INLA) and Generalized Additive Models to predict explosion intensity and examine how environmental and infrastructural factors influence the distribution of military activity. This research is justified in the current literature, as no previous work has been conducted for a countrywide BFAST assessment for Ukraine or modeled explosion events as a spatial statistical process. Guided by questions on vegetation trends, the drivers of explosion patterns, and the relationship between modeled explosions and ecological change, this study provides the first comprehensive linkage between remotely sensed vegetation dynamics and conflict intensity. Its contributions include a replicable methodological framework for analyzing environmental impacts in war zones and critical insights to support environmental monitoring, risk assessment, and post-conflict recovery planning in Ukraine.

Chapter Two reviews the current literature related to this research and is organized into five sections. The first section provides background on the Russia–Ukraine war, including an overview of how the conflict began and a timeline of major territorial events. This section also discusses the geographic scope of the war, the international response, and existing environmental

monitoring efforts. The second section examines how military actions have disturbed vegetation in Ukraine, focusing on both the direct and indirect environmental consequences of ongoing military operations. The third section explores specific environmental impacts, including changes to soil physical and chemical properties, biological soil health, water contamination, damage to Ukraine's water infrastructure, fire-related land degradation, and biodiversity loss resulting from military activities. The fourth section presents the theoretical foundation of the Breaks for Additive Season and Trend (BFAST) analysis, its applications in environmental modeling, and its advantages and limitations. This section also discusses Integrated Nested Laplace Approximation (INLA) models and Generalized Additive Models (GAM) from a theoretical perspective.

Chapter Three represents the first paper that describes the BFAST model. It is called “*Detecting Vegetation Change in Ukraine using Satellite Imagery and BFAST Analysis*”. Using 22 years of MODIS Enhanced Vegetation Index (EVI) data from 2001–2023, the study evaluates spatial and temporal trends in vegetation conditions across Ukraine and examines whether observed changes may be linked to military conflict and other disturbances. The research reviews major landscape impacts of warfare including cratering, soil compaction, fires, chemical contamination, and land abandonment. It discusses how these processes can alter vegetation and ecosystem health.

BFAST analysis was applied to classify vegetation trends as positive, negative, or stable and to detect the number of structural breaks in the time series. Results show that approximately 67% of Ukraine experienced positive vegetation trends, while 18% showed negative trends, with the strongest declines concentrated in ecoregions most affected by active conflict in eastern and southern Ukraine. Additional analyses revealed that cropland and urban areas contribute substantially to observed changes, often masking natural vegetation patterns. The study

concludes that while BFAST effectively identifies where and when vegetation change occurs, determining the specific causes of these changes whether from military activity, agricultural cycles, or natural variability requires further investigation and integration with additional ground-based data.

Chapter Four shows the second paper that uses INLA to model explosion intensity counts and uses a GAM model to show how the variables are interacting with the BFAST slope. Using conflict event records from the ACLED database (2018–2023), the study develops a Bayesian spatial model implemented with Integrated Nested Laplace Approximation (INLA) to estimate explosion intensity as a function of proximity to infrastructure, population centers, and the front line, while accounting for spatial autocorrelation through a stochastic partial differential equation (SPDE) approach. Predicted explosion intensity surfaces are then incorporated into a second analysis examining vegetation trends derived from the BFAST time-series method. A generalized additive model with spatial splines is used to assess whether vegetation changes are associated with explosion intensity alongside climatic variables such as temperature, precipitation, and soil characteristics. Results show that explosions are strongly clustered near roads, railways, hospitals, power plants, and populated areas, with spatial correlation extending roughly 10 km. The vegetation model indicates that explosions, climatic conditions, and disturbance breaks all contribute to observed vegetation trends. The study concludes that while the current models provide a useful framework for mapping conflict intensity and linking it to ecological impacts, further refinement and additional covariates are needed to fully understand long-term environmental consequences of warfare in Ukraine.

Chapter Five synthesizes the findings of the thesis by integrating national-scale vegetation change analysis with spatial modeling of conflict activity to assess the environmental impacts of

the Russia–Ukraine War. The research addresses three core questions concerning long-term vegetation trends, the spatial distribution and drivers of explosion intensity, and the relationship between conflict activity and ecological change. Results from Chapter 3 demonstrate that MODIS EVI time-series analysis using the BFAST method effectively captures broad patterns of vegetation dynamics across Ukraine, revealing generally stable to positive national trends alongside localized negative trends in heavily affected conflict regions. Chapter 4 builds on this foundation by applying Bayesian spatial modeling to show that explosion intensity is strongly clustered near strategic infrastructure and population centers, and that higher modeled explosion intensity is significantly associated with more negative vegetation trends when combined with climatic and landscape factors. Together, these studies provide a comprehensive, multi-method assessment of how warfare influences environmental conditions, while advancing methodological approaches for linking remotely sensed vegetation change with spatial conflict data to better understand and monitor ecological impacts in conflict-affected landscapes.

Chapter 2 - Literature Review

I. Background of the Russia-Ukraine War

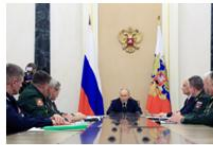
The origins of the current conflict in Ukraine can be traced to March 2014, when Russian special forces seized control of the Crimean Peninsula. At the time, Ukrainian President Viktor Yanukovich, who maintained pro-Russian policies, rejected a proposed economic agreement with the European Union, triggering widespread domestic protests known as the Revolution of Dignity in late 2013. Following these events, Russian President Vladimir Putin moved to annex Crimea, justifying the action as necessary to “protect the rights of Russian citizens and Russian speakers in Crimea and southeast Ukraine.” Russia formally annexed the region after conducting a local referendum; however, the vote was widely criticized for irregularities, falsifications, and violations of international law, and the results were not recognized by the international community.

In the months leading up to the 2022 invasion, U.S. intelligence agencies reported significant Russian military buildups along Ukraine’s borders. Satellite imagery from late 2021 documented the movement of armored vehicles, missile systems, and other heavy military equipment toward the region, indicating preparations for a large-scale offensive. In February 2022, President Putin ordered Russian troops into the separatist-controlled regions of Luhansk and Donetsk, prompting the United States and its allies to impose sanctions on those areas as well as on the Nord Stream 2 pipeline linking Russia and Germany. On February 24, 2022, Putin announced the beginning of a full-scale invasion of Ukraine, involving coordinated land, sea, and air assaults targeting Ukrainian military infrastructure and major cities. The Russian government framed the invasion

as an effort to “demilitarize and denazify” Ukraine and to halt alleged persecution of ethnic Russians, claims that have been widely rejected by the international community.

Main Territorial Events of the Russia-Ukraine War Timeline

February 24, 2022 – Russian President Vladimir Putin launches full-scale invasion in Ukraine



April 2, 2022 – Ukraine forces defeat Russian forces in Kyiv



November 2022 – Ukrainian forces reclaim parts of the Kharkiv, Mykolaiv, and Kherson regions

February 18, 2024 – Russian forces take control of the city of Avdiivka



May 10, 2024 – Russian forces launch a new offensive in the Northeastern region of Kharkiv

April 26, 2025 – Ukrainian troops have been forced out of Russia's Kursk region

June 30, 2025 — Russia says it has taken full control of Ukraine's Luhansk, one of four regions that Moscow illegally annexed in September 2022.



March 5, 2022 – Russia advances towards Kyiv and Kherson and the port city of Mariupol



September 30, 2022 – Russia claims control of Donetsk, Luhansk, Kherson and Zaporizhzhia regions in Ukraine



June 6, 2023 – Russian-controlled Kakhovka Dam explodes, sending water into Southern Ukraine



April 19, 2024 – The U.S. House of Representatives approves \$61 billion package for Ukraine



August 6, 2024 – Ukraine launches a lighting incursion into Russia's Kursk region

June 1, 2025 – Operation Spider Web takes effect deep inside Russia, where Ukraine launched drones from the back of trucks



Aug. 15, 2025 — Putin meets Trump in Alaska for the first Russia-U.S. summit in four years to discuss ending the war in Ukraine.



Figure 2-1- Russia-Ukraine War Timeline - a chronological timeline of major events in the Russia–Ukraine War based on reporting from PBS NewsHour (Press, 2025) between 2022 and 2025. It highlights key military and political developments, illustrating the sequence and progression of the conflict over time.

Geographic Scope of the War

The primary areas of active combat in the Russia–Ukraine war have been concentrated in eastern and southern Ukraine, particularly within the Luhansk, Donetsk, Zaporizhzhia, and Kherson oblasts. Hostilities initially extended into northern Ukraine, including the areas surrounding Chernobyl and the capital city of Kyiv. However, by April 2022, Ukrainian counteroffensives had successfully recaptured much of northern Ukraine, forcing Russian forces to withdraw from the Kyiv region. Following this setback, Russian military strategy shifted toward consolidating control over eastern Ukraine, specifically the Donbas region.

The Donbas holds significant strategic and economic importance. Historically, it served as a major industrial center of the former Soviet Union and remains rich in coal reserves and other natural resources that contribute substantially to Ukraine’s economy. Russian leadership has long viewed the Donbas as culturally and politically aligned with Russia, and its capture has been framed as a central objective of the war. Control of this region would also provide Russia with greater influence over key trade routes, particularly access to the Sea of Azov and the Black Sea. The seizure of the port city of Mariupol has been especially critical in this regard, as it facilitates the establishment of a land corridor connecting mainland Russia to the annexed Crimean Peninsula. Such a corridor would grant Russia effective control over much of Ukraine’s southern coastline and maritime trade.

More broadly, Russian objectives in the Donbas reflect a wider geopolitical goal of preventing Ukraine’s integration with Western political, economic, and military institutions. By securing eastern and southern Ukraine, Russia seeks to limit Ukraine’s sovereignty and its ability to align more closely with the European Union and NATO.



Figure 2-2: Geographic Scope of the Russia-Ukraine War - The spatial extent of Russian military presence across eastern and southern Ukraine includes areas of full control, limited control, and claimed control, particularly in Luhansk, Donetsk, Zaporizhzhia, Kherson, and Crimea. These data are derived from the Institute for the Study of War and the Critical Threats Project, as reported by BBC (*Ukraine in Maps*, 2026).

International Response/Environmental Monitoring of Ukraine

The most significant international response to the war has come from the North Atlantic Treaty Organization (NATO), a defensive alliance composed of 32 member states from Europe and North America. Although Ukraine is not a NATO member, the alliance has played a central role in providing military, financial, and humanitarian assistance. Support to Ukraine is coordinated through several key initiatives, including the Comprehensive Assistance Package for Ukraine (CAP), the NATO Security Assistance and Training for Ukraine (NSATU), and the NATO-Ukraine Joint Analysis, Training and Education Centre (JATEC). These programs facilitate the delivery of equipment, training, and long-term capacity building, demonstrating NATO's

commitment to supporting Ukraine both during the conflict and in post-war reconstruction efforts.

In addition to military and humanitarian responses, international organizations have focused on monitoring the environmental consequences of the war. The Conflict and Environment Observatory (CEOBS) has been actively documenting environmental damage in Ukraine since the beginning of the invasion in 2022. The CEOBS tracks incidents of environmental harm using a combination of satellite imagery, social and traditional media reports, and data from academic and governmental sources. This monitoring effort has been critical in identifying pollution events, ecosystem destruction, and other forms of environmental degradation resulting from military activity.

The European Union (EU) has also assessed the environmental and climate-related impacts of the conflict. The escalation of military activities, including the widespread use of explosives, has further increased the risk and frequency of large-scale fires in recent years. In addition to forest damage, Ukrainian soils are experiencing significant degradation due to both climate change and wartime disturbances. The EU identifies erosion as the primary driver of soil degradation, although other factors such as nutrient depletion, acidification, compaction, salinization, and contamination also play important roles (Efthimiou, 2025). Soil health is particularly critical for Ukraine's economy, as the country is a major global producer of wheat, corn, barley, and sunflower seeds.

The Black Sea region has also emerged as an area of growing environmental concern. Even prior to the war, the sea faced challenges related to pollution, invasive species, and increasing maritime traffic. Military operations have intensified these pressures by contributing to chemical contamination, physical destruction of marine habitats, and disruptions to ecological systems.

Together, these impacts illustrate the wide-ranging and long-term environmental consequences of the conflict, extending beyond immediate human and infrastructural losses.

II. Military Actions Disturbing Vegetation in Ukraine

Direct military activities, like artillery bombardment, drone strikes, fiber optic drones, and Improvised Explosive devices (IEDs) are disturbing vegetation in Ukraine. Explosives are not the only activities that disrupt the vegetation, but vehicles movements and trench construction can impact the vegetation and the landscape of the land. Destruction of landscapes or infrastructures from military activities can directly affect ecosystems that are in or around the area of destruction.

Artillery Bombardment and Explosive Damage

Cratering is a widespread consequence of warfare and military activities, resulting from the detonation of various explosive munitions. Common sources of these disturbances include artillery strikes, aerial bombs, drone-delivered explosives, and improvised explosive devices (IEDs). In the context of the Russian–Ukrainian War, propelled explosives represent the primary mechanism driving soil disruption and landscape alteration. The physical impact of craters is influenced by several factors, including the amount of energy released during detonation, local soil characteristics, and the angle of impact (Celebi et al., 2025). (Hupy et al., 2006) introduced the term “Bombturbation” to describe the cratering and mixing of soils caused by explosive munitions in both warfare and military training environments. Soils affected by Bombturbation are typically compacted, destabilized, and often contaminated with metal fragments, ash, and other residues (Broomandi et al., 2020). This process disrupts natural soil horizons, leading to alterations in surface topography and ecological conditions. As a result, cratering serves as a

clear example of how armed conflict can reshape landscapes and could contribute changes in vegetation structure and environmental quality.



Figure 2-3: Example of Bombturbation - This figure shows an example of Bombturbation, illustrating soil and surface disturbance caused by explosive detonations (image credit: Jerry Redfern, 1998 (Coates, 2016)). It is analytically important because it demonstrates the physical mechanism by which explosions disrupt soil structure and alter vegetation patterns.

One increasingly prominent tactic in the Russian–Ukrainian War is the use of fiber optic guided drones. Unlike conventional unmanned aerial vehicles, fiber-optic drones are resistant to electronic warfare interference and cannot be jammed or electronically detected, as the connection between the operator and the drone is maintained through a physical cable rather than radio signals (Sabbagh, 2025). These systems are tethered to long, thin fiber-optic lines that remain on the landscape after the drone crashes or detonates on its target. The widespread deployment of these systems has resulted in extensive networks of discarded plastic cabling across frontline regions. Estimates suggest that thousands of kilometers of fiber-optic wire are

now scattered throughout conflict zones, introducing a novel form of battlefield debris (Larson, 2025). This technology has only recently been adopted in modern warfare; the ecological implications remain unclear. The persistence of plastic materials in natural environments has potential risks to wildlife, and broader landscape impacts represent issues that require further investigation.

In addition to explosive cratering, military conflicts generate substantial environmental impacts through the process of deposition. Deposition refers to the introduction of manufactured solid materials into the natural environment because of military activities (Radunzel, 2024). This includes landmines, improvised explosive devices (IEDs), unexploded devices, and a wide range of other military hardware deliberately or unintentionally left in the soil. Such materials contribute to soil contamination through the accumulation of metallic fragments, destabilization of soil structure, and the long-term abandonment of land due to safety risks. Projectiles from small arms as well as larger munitions frequently remain embedded in the ground, where their chemical components can leach into surrounding soils and groundwater (Thestorff et al., 2022). Although expended ammunition is typically non-explosive, it is often composed of reactive metals that can produce long-term chemical disturbances and ecological degradation (Broomandi et al., 2020; Williams et al., 2022). Deposition also occurs through damaged or abandoned military vehicles, which introduce additional contaminants such as fuel, lubricants, and heavy metals. These materials gradually corrode, releasing chemical residues into the surrounding soil. While contamination from vehicles tends to be more localized than that from munitions, it can still contribute to measurable changes in soil quality and vegetation conditions at smaller spatial scales.



Figure 2-4: Example of Tank Deposition - This figure shows an example of tank deposition, illustrating the physical disturbance and soil compaction caused by heavy military vehicle movement (*Ukraine's Winter War: Scenes from the Frozen Frontlines - February 15, 2024 | Reuters, n.d.*). It demonstrates how mechanized warfare contributes to land degradation and alters vegetation patterns.

Vehicle Movement and Trench Construction

The movement of military vehicles across Ukraine has produced environmental degradation in both rural and urban landscapes. Heavy equipment traveling through agricultural fields, natural areas, and along road networks contributes to a range of ecological disturbances. These activities generate large quantities of dust and exhaust emissions from fossil fuels, which can negatively affect air quality and human health (Hryhorczuk et al., 2024). In addition to operational impacts, many military vehicles in Ukraine are abandoned, damaged, or destroyed, creating long-term sources of environmental contamination (Broomandi et al., 2020). Such vehicles disrupt both terrestrial and aquatic ecosystems through physical destruction and the release of hazardous materials (Hryhorczuk et al., 2024).

Vehicle movements is a driver of land degradation, primarily through soil compaction and the removal of vegetative cover (Hutchinson et al., 2015; Milchunas et al., 1999). Compacted soils experience reduced infiltration and aeration, which limits plant growth and increases its chances to erode. Among the various impacts associated with military traffic, accelerated soil erosion is considered one of the most persistent problems. The extent of environmental damage caused by vehicle activity depends on multiple factors, including vehicle weight and speed, frequency of movement, turning behavior, and preexisting soil and moisture conditions (Hutchinson et al., 2015; Liu et al., 2009). Under unfavorable conditions, repeated vehicle passages can rapidly transform stable landscapes into disturbed and degraded terrain.

The environmental effects of vehicle movements are comparable to those produced by explosions and other direct combat activities. Abandoned or destroyed vehicles frequently leak fuel, oil, and other chemical substances into surrounding soils and waterways, introducing localized but long-lasting contamination. Over time, corroding metal components and residual fluids further degrade soil quality and disrupt ecological processes. Collectively, these impacts illustrate that military vehicle activity represents a source of environmental damage within conflict zones.

Indirect Environmental Consequences

Disrupted Agricultural Practices

As we know, warfare and armed conflicts have the most drastic shocks that impact societies and land systems (Baumann et al., 2016). Land systems, like agricultural fields, have outcomes that are temporary and reverse when peace gets established (Baumann et al, 2016). Armed conflicts in agricultural land-use cause the destruction of agricultural fields and contaminate the

environment (Yin et al., 2019). For the war in Ukraine; it may take years if not longer to remediate the soil and other land systems around the crop fields. Farming could be on hold for farmers because of landmine contamination in their fields, which landmines are being used in Ukraine. This has been shown in studies in Croatia and in the Southern Caucasus (Vidosavljević et al., 2013; Yin et al., 2019).

Abandoned Farmland and Rewilding Processes

Armed conflicts can affect agricultural land use both directly and indirectly through the destruction of cropland and environmental contamination (Yin et al., 2019). Agricultural abandonment is driven by a diminished agricultural workforce, population displacement, and farmers' participation in armed fighting (Baumann et al., 2016). As conflicts intensify, farmland is abandoned because agricultural fields are destroyed by military actions, infrastructure is damaged, and farmers are forced to flee or join the fighting. In addition, farmland becomes unsafe or unusable due to landmine placement, bombardment, and chemical contamination associated with warfare.

Armed conflict also undermines the agricultural economy by discouraging investment and disrupting regular maintenance of irrigation and farming infrastructure (Alix-Garcia et al., 2013; Baumann et al., 2016). This insecurity reduces irrigation-based agriculture, as systems cannot be properly maintained or repaired during prolonged periods of violence. (Yin et al., 2019) found that areas experiencing higher conflict intensity also exhibited higher rates of agricultural abandonment, highlighting a strong link between violence and land-use change. This relationship is unsurprising, as highly conflicted landscapes are often characterized by soil degradation, chemical contamination, unexploded devices, and physical damage such as craters from airstrikes. These conditions make it extremely difficult for farmers to safely resume production

or rehabilitate soil horizons for crop cultivation without the risk of contamination. Consequently, agricultural abandonment has profound implications not only for farmers' livelihoods but also for national food security, rural economies, and long-term land degradation in conflict-affected regions.

III. Specific Environmental Impacts

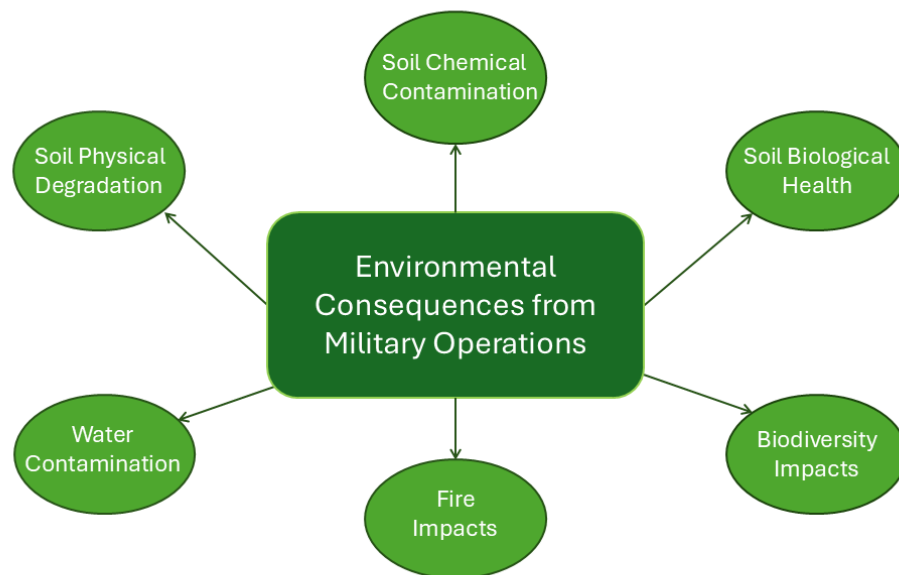


Figure 2-5: Environmental Consequences from Military Operations - outlining the primary environmental impacts associated with military operations. The diagram is author-generated for this study to synthesize pathways of environmental disturbance from military operations.

A. Soil Properties

Soil Physical Degradation

The extent of physical soil degradation in wartime environments is quite substantial. Soil destruction is caused by a range of military activities, including tunneling, bomb and artillery shell explosions, heavy machinery traffic, abandoned equipment and mines, and an increased risk

of fires in croplands and forests (Broomandi et al., 2020). *Bombturbation* refers to the cratering and disturbance of the landscape resulting from explosive munitions. Soils within these craters are often compacted, highly disturbed, and contaminated with metallic fragments (Broomandi et al., 2020). Bombturbation also leads to the mixing of soil horizons, altering soil structure and creating heterogeneous topography across the landscape.

Several studies (Solokha et al., 2024; Vidosavljević et al., 2013) have demonstrated that military vehicles, such as tanks and other armored equipment, can cause soil contamination at the locations where they operate or are destroyed. This contamination is typically localized and tends to remain confined to the immediate area. While evidence indicates that soil contamination occurs in fields where tanks have been destroyed or abandoned, current research samples are too limited to conclusively determine whether warfare results in widespread heavy metal contamination at larger spatial scales. Additional research with larger sample sizes is needed to assess the broader extent of this impact.

Soil compaction plays a role in physical soil degradation during warfare. Compaction occurs when soil particles are compressed, reducing pore space and limiting air and water movement within the soil profile (*Soil Compaction | UMN Extension*, n.d.). This process is commonly caused by the movement of large military vehicles, both tracked and wheeled, across the landscape. Reduced pore space alters soil hydraulic properties, increasing susceptibility to runoff and erosion (Broomandi et al., 2020). In Ukraine, the primary contributors to physical soil degradation include compaction from military traffic, crater formation from air strikes, and the presence of metallic debris such as tanks and weaponry. Collectively, these processes contribute to soil degradation and extensive landscape damage. While physical disturbance represents the most immediate and visible form of soil degradation in wartime landscapes, these processes also

create pathways for chemical contamination. Explosive residues, metallic debris, and fuel leaks introduced during military activity can persist in disturbed soils, altering soil chemistry and can cause long-term environmental risks.

Soil Chemical Contamination

Soil contamination resulting from chemical exposure during warfare, including explosive residues, metallic debris, and fuel leaks can disrupt soil chemical properties and soil biological health. Among explosive munitions, 2,4,6-trinitrotoluene (TNT) and 1,3,5-trinitroperhydro-1,3,5-triazine (RDX) are the most used compounds (Mystrioti & Papassiopi, 2024). TNT is a high-energy explosive that, when detonated or exposed to heat, generates intense shockwaves and thermal energy responsible for extensive physical destruction. TNT exhibits relatively high affinity for soil particles compared to its mobility in water, leading to persistent soil contamination. Such contamination poses significant risks to terrestrial ecosystems and human health in affected areas (Mystrioti & Papassiopi, 2024).

RDX is another widely used explosive in both military and mining applications. Unlike TNT, RDX is highly resistant to decomposition and can persist in soils for extended periods. Previous studies (Bordeleau et al., 2008; Pichtel., 2012; Mystrioti & Papassiopi, 2024; Pennington et al., 2002) have shown that RDX negatively impacts soil quality, plant growth, and microbial communities. Additionally, RDX can leach into groundwater, thereby posing risks to aquatic ecosystems and local drinking water supplies (Mystrioti & Papassiopi, 2024).

Beyond explosive residues, military activities introduce potentially toxic elements (PTEs) into soils. Common PTEs associated with munitions and military debris include lead (Pb), antimony (Sb), chromium (Cr), arsenic (As), mercury (Hg), nickel (Ni), zinc (Zn), and cadmium (Cd)

(Broomandi et al., 2020). Bullets, shell casings, and other metallic components are primary sources of these contaminants. Lead is particularly prevalent and represents one of contributors to soil contamination in conflict zones (Lawrence et al., 2015). Although lead contamination may not cause immediate environmental damage, prolonged exposure increases its mobility and bioavailability, substantially elevating ecological and human health risks over time (Broomandi et al., 2020).

Evidence of long-term PTE accumulation has been documented in post-conflict regions. In Croatia, soil samples collected from sites bombed during the Yugoslav War (1991–1999) revealed elevated concentrations of several PTEs (Vidosavljević et al., 2013). While antimony was the only element directly attributable to military activity 14 years after the conflict, increased concentrations of other PTEs suggested delayed environmental impacts, highlighting the long-term nature of chemical contamination in war-affected soils.

Overall, chemical contamination from explosive compounds such as TNT and RDX has enduring effects on soil structure, function, and biological health. When combined with the accumulation of potentially toxic elements, the severity and persistence of soil degradation could increase substantially. Ongoing and recent military activities, such as those occurring in Ukraine, are therefore likely to result in long-term soil contamination with potentially lasting ecological and human health consequences. While chemical contamination alters soil chemical properties, it also triggers effects on biological soil health. Soil microorganisms and fauna are particularly sensitive to toxic residues, which can lead to disruptions in nutrient cycling and overall ecosystem functioning.

Soil Biological Health

Biological soil health is closely linked to the composition and functioning of soil microbial communities. Soil microorganisms play a critical role in regulating ecosystem processes and are widely used as indicators of soil ecosystem status (Rodríguez-Seijo et al., 2024). Energetic compounds such as TNT and RDX, along with other potentially toxic elements (PTEs), disrupt these microbial communities by altering microbial abundance and diversity. Elevated concentrations of TNT and RDX have been shown to degrade soil ecosystem balance and reduce overall microbial diversity (Rodríguez-Seijo et al., 2024).

Among affected microbial groups, *Proteobacteria* consistently emerge as a dominant bacterial phylum in highly TNT-contaminated soils, with relative abundance increasing alongside contamination levels (Rodríguez-Seijo et al., 2024). This dominance is attributed to their tolerance of pollutants and adaptive capacity, allowing them to outcompete more sensitive bacterial taxa. *Proteobacteria* play key roles in nutrient cycling and pollutant degradation, suggesting a potential capacity to metabolize or transform explosive compounds (Rodríguez-Seijo et al., 2024; Serrano-González et al., 2018).

Soil contamination also affects soil fauna across multiple trophic levels, including microfauna, mesofauna, and macrofauna. Nematodes, the most abundant soil microfauna, are commonly used as indicators of soil quality due to their sensitivity to environmental stressors. Microfauna communities are particularly vulnerable to disturbance from heavy machinery, vehicular traffic, and organic contaminants (Zhu et al., 2025). Macrofauna, especially earthworms, function as ecosystem engineers by improving soil bulk density, porosity, and aggregate stability (Zhu et al., 2025). Under suitable soil and climatic conditions, the introduction of earthworms into soils

contaminated with TNT, RDX, and other PTEs may offer a potential remediation strategy by enhancing contaminant processing and soil recovery (Zhu et al., 2025).

Overall, the introduction of energetic compounds into soils could result in substantial alterations to soil ecosystem structure, including reduced microbial health and biodiversity (Rodríguez-Seijo et al., 2024). However, much of the existing research is derived from studies conducted at ammunition ranges, leaving the impacts of large-scale bombing events on soil ecosystems poorly understood. Given the vast complexity of soil microbial systems, the ecological effects of TNT and RDX contamination remain under-researched, highlighting the need for further investigation at broader spatial and temporal scales.

B. Waterways Impact

Water Contamination

Water is a critical natural resource that supports human populations and ecological systems worldwide. During armed conflicts, water resources and associated infrastructure are particularly vulnerable to damage and disruption, often in proportion to the intensity and duration of hostilities (Shumilova et al., 2023). According to the Water Conflict Chronology, the role of water in conflict can be classified into three categories: (1) water as a *trigger*, where competition or control over water resources leads to violence; (2) water as a *weapon*, in which water is deliberately manipulated or withheld during conflict; and (3) water as a *casualty*, where water systems are directly targeted or damaged (Shumilova et al., 2023).

In many cases, water contamination occurs indirectly through collateral damage rather than intentional targeting. For example, oil leaks from military vehicles, damaged fuel storage, and debris from military operations can introduce pollutants into surface and groundwater systems.

Chemical contamination from explosive compounds such as 2,4,6-trinitrotoluene (TNT) and hexahydro-1,3,5-trinitro-1,3,5-triazine (RDX) has also been documented in conflict-affected water systems (Meaza et al., 2024). Additionally, metallic debris from artillery shells, drone strikes, and bullet casings can further degrade water quality through the release of potentially toxic elements (Meaza et al., 2024).

Armed conflicts also contribute to the accumulation of solid waste in water bodies, exacerbating physical and chemical contamination. Previous studies have documented water pollution resulting from military activities in diverse contexts, including military training and operations in Canada (Bordeleau et al., 2008) and during and after World War II (Maser et al., 2020; Meaza et al., 2024; Pennington et al., 2002). Collectively, these findings demonstrate that armed conflicts have profound and lasting impacts on water resources and the infrastructure required to sustain their availability and quality.

Ukraine's Water Infrastructure

The Russia–Ukraine War has had a profound impact on Ukraine's water infrastructure. Critical water systems include large multi-purpose reservoirs, hydropower dams, cooling facilities for nuclear power plants, and extensive networks of water distribution canals and pipelines have been impacted (Shumilova et al., 2023). A substantial portion of this infrastructure is concentrated in the eastern and southern regions of Ukraine, areas located closest to the Russian border and most exposed to military activity (Shumilova et al., 2023).

Military operations affecting the Kyiv Reservoir dam resulted in the flooding of approximately 2,500 hectares of the Irpin floodplain (Meaza et al., 2024). On June 6, 2023, the Kakhovka Dam on the Dnieper River was destroyed during military operations, leading to catastrophic

downstream impacts, including the loss of extensive agricultural land. In addition, pumping stations, pipelines, wastewater treatment plants, and water filtration facilities across Ukraine were damaged, in many cases resulting in complete system failures (Shumilova et al., 2023).



Figure 2-6: Before and after satellite images of Nova Kakhovka dam - This figure shows pre- and post-event satellite imagery of the Nova Kakhovka Dam, highlighting structural damage and downstream flooding following its destruction (*Satellite Images Show Ukraine's Kakhovka Dam after Destruction | Russia-Ukraine War News | Al Jazeera*, n.d.). It is analytically important because it illustrates the large-scale environmental and hydrological disruption caused by conflict-related infrastructure damage.

Infrastructure associated with oil extraction and reservoirs used for storing mineral fertilizers were also reportedly targeted, contributing to the release of oil and other hazardous substances into water systems (Shumilova et al., 2023). These releases caused widespread fish mortality and led to restrictions on fishing and river navigation. Overall, evidence suggests that during the early stages of the conflict, Russia systematically targeted Ukraine's water infrastructure by destroying dams, reservoirs, underground mining operations, urban water supply networks, and wastewater treatment systems (Shumilova et al., 2023).

C. Fire-related environmental effects

Direct Fire Impacts

Widespread military activities, including shelling and bombing, can severely damage surrounding environments and, in some cases, directly ignite fires or wildfires. Since the onset of military operations in Ukraine, the frequency and spatial extent of wildfires have increased, facilitating rapid fire spread across affected landscapes. It is estimated that more than 183,000 hectares of forests and plantations in Ukraine have burned as a result of wildfires linked to the conflict (Hryhorczuk et al., 2024). Wildfires exert substantial impacts on soil systems by altering their biological, chemical, and physical properties (Agbeshie et al., 2022). The severity of these impacts is largely dependent on wildfire intensity and frequency. Chemically, wildfires can modify soil organic carbon (SOC) content, soil pH, nitrogen levels, and overall nutrient availability (Agbeshie et al., 2022). Physical soil properties are also affected, with changes observed in soil texture, bulk density, aggregate stability, and soil water repellency (SWR) following fire exposure (Agbeshie et al., 2022).

Biological soil properties are particularly vulnerable to high temperatures generated during wildfires. Exposure to temperatures ranging from approximately 50–150 °C can destroy or denature soil microorganisms, including bacteria, fungi, seeds, and fine roots (Agbeshie et al., 2022). As a result, wildfires can significantly alter soil microbial community composition and disrupt enzymatic activity, leading to broader impacts on soil ecosystem functioning. Although these effects vary with fire intensity and recurrence, wildfires consistently exert direct and long-lasting influences on soil ecosystems. In addition to soil degradation, wildfires contribute to air pollution through the release of smoke composed of carbon monoxide, methane, nitrogen oxides, and volatile organic compounds (Hryhorczuk et al., 2024). The widespread occurrence of

wildfires in Ukraine has therefore increased exposure to atmospheric pollutants while simultaneously intensifying degradation of soil systems across affected regions.

D. Broader Ecological Disturbances

Biodiversity Impacts

Armed conflicts and military operations can have profound impacts on biodiversity and the environments in which they occur. In modern warfare, ground-based military activities significantly alter natural landscapes and disrupt wildlife populations (Lawrence et al., 2015). As discussed previously, the weapons and strategies employed in warfare pose substantial threats to terrestrial ecosystems and land systems (Lawrence et al., 2015; Zheng et al., 2023). Landscapes are often scarred by large craters, shrapnel, and chemical contamination, exposing soils, water resources, the atmosphere, and wildlife to hazardous conditions. Wildlife is particularly affected, with many animals experiencing injury or mortality as a direct or indirect result of military activity (Serhii et al., 2022). In addition, animals may be hunted or poached for food by military forces to support survival during prolonged conflicts. The ecological consequences of armed conflict are extensive, and may require large-scale remediation and rehabilitation efforts, particularly in Ukraine. Restoring biodiversity to pre-war conditions will likely take many years and require diverse and coordinated restoration strategies. The Russian invasion of Ukraine has therefore resulted in severe and lasting impacts on land systems and biodiversity across the affected landscapes (Lawrence et al., 2015; Serhii et al., 2022; Zheng et al., 2023).

IV. Remote Sensing and Statistical Analysis Methods

A. BFAST (Breaks for Additive Season and Trend) Analysis

Theoretical Foundation

The Breaks for Additive Season and Trend (BFAST) analysis is a parametric time-series method that uses an additive decomposition model to separate each pixel's time series into three components: trend, seasonal, and remainder (noise or residuals) (Hutchinson et al., 2015; Verbesselt et al., 2010). BFAST integrates an iterative decomposition process that allows for the detection of structural changes in both trend and seasonal components without requiring the selection of a reference period or predefined thresholds (Verbesselt et al., 2010).

The BFAST model analyzing a single pixel is expressed as:

$$Y_t = T_t + S_t + e_t,$$

where Y_t represents the observed value for that pixel at time t , T_t is the trend component, S_t is the seasonal component and is a function of time, and e_t is the remainder or noise component. The noise component captures the variability in the data not explained by either the trend or seasonal components (Geng et al., 2019; Hutchinson et al., 2015; Verbesselt et al., 2010).

The primary objectives of BFAST are (1) to detect multiple abrupt changes in the trend and seasonal components of a time series and (2) to characterize both gradual and abrupt ecosystem changes by estimating the timing, magnitude, and direction of change within the trend component (Verbesselt et al., 2010). Abrupt negative changes are commonly associated with disturbances such as wildfires, prescribed burns, timber harvesting, or disease outbreaks, whereas abrupt positive changes may result from increased precipitation or reduced snow cover (De Jong et al., 2013). Gradual changes occur over longer temporal scales and are often linked to long-term trends in mean annual rainfall, land management practices, or land degradation processes (Verbesselt et al., 2010).

To assess the statistical significance of detected trends, a student's t -test was employed to evaluate whether the estimated slope differs significantly from a null slope of zero (Hutchinson et al., 2015). Based on the sign and significance of the slope, the trend component is classified into three vegetation change categories: positive, negative, or stable. A positive trend indicates vegetation greening, a negative trend reflects vegetation browning, and a stable trend suggests no significant long-term change in vegetation condition.

The seasonal component in BFAST is assumed to remain constant between detected breakpoints but may vary across different segments of the time series (Verbesselt et al., 2010). Seasonal breakpoints are not required to coincide temporally with trend breakpoints, allowing independent detection of changes in seasonal behavior (Verbesselt et al., 2010). The seasonal term is modeled using indicator variables, where $d_{t,i} = 1$ if time t falls within season i . This formulation enables flexible representation of seasonal dynamics across the time series (Verbesselt et al., 2010).

Together, this framework establishes the theoretical foundation of BFAST by linking statistical decomposition with ecological interpretation, enabling robust detection and characterization of temporal changes in vegetation and land-surface processes.

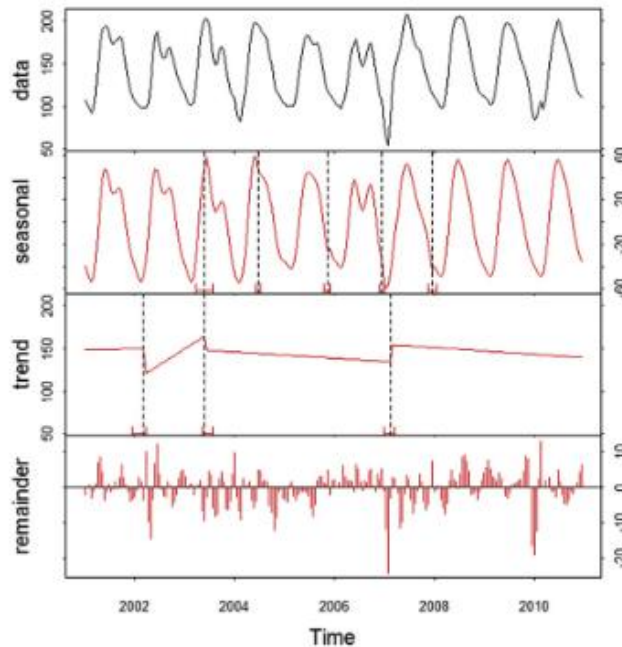


Figure 2-7: BFAST Components Graph - This figure shows the decomposition of a remotely sensed vegetation time series into observed data, seasonal variation, long-term trend, and residual components using the BFAST (Breaks For Additive Season and Trend) methodology (adapted from Hutchinson et al., 2015). It is analytically important because it illustrates how structural breaks and trend changes are detected in vegetation time-series data used to assess environmental disturbance.

Application for Environmental Modeling

Breaks For Additive Season and Trend (BFAST) is a widely used method in environmental modeling for detecting and characterizing structural changes in long-term remotely sensed time series. The approach decomposes observations into trend, seasonal, and residual components, enabling the identification of both abrupt disturbances (breakpoints) and gradual environmental changes (Verbesselt et al., 2010). This decomposition makes BFAST particularly well suited for monitoring ecosystem dynamics in systems where strong seasonal variability coexists with long-term trends.

BFAST has been extensively applied to the analysis of vegetation dynamics using the Normalized Difference Vegetation Index (NDVI) and other spectral indices derived from satellite imagery. Previous studies have employed BFAST to investigate forest responses to climatic drivers (Lambert et al., 2013; Geng et al., 2019), large-scale vegetation changes (De Jong et al.,

2012), vegetation dynamics in arid grassland ecosystems (Browning et al., 2017; Watts et al., 2014), and vegetation change on U.S. Army training lands (Hutchinson et al., 2015). Across these applications, BFAST has been used to improve understanding of the timing, magnitude, and potential drivers of observed vegetation change. Its pixel-based implementation allows for spatially explicit analyses across large geographic extents, supporting regional- to national-scale environmental assessments.

Beyond vegetation monitoring, BFAST has also been applied in hydrological and climatic studies, including analyses of changes in surface water extent (Watts et al., 2014) and climate-driven ecosystem shifts. By explicitly separating seasonal signals from long-term trends, BFAST improves interpretability when analyzing complex environmental systems influenced by both natural variability and anthropogenic disturbances. Consequently, BFAST has become a valuable tool in environmental modeling for early warning systems, impact assessment, and long-term monitoring of ecosystem resilience and change.

Advantages and Limitations

BFAST has several advantages that make it well suited for time series decomposition compared to other methods. First, BFAST decomposes a time series into trend, seasonal, and remainder components, enabling researchers to distinguish long-term changes from seasonal variability and short-term disturbances (Verbesselt et al., 2010). Second, BFAST can detect both abrupt and gradual structural breaks, which is particularly valuable for environmental monitoring applications. Third, BFAST operates at the pixel level, allowing spatially explicit analyses across large remote sensing datasets and facilitating the mapping of trends, seasonality, and disturbance events. Fourth, BFAST is a fully data-driven approach and does not require prior disturbance

information, as breakpoints are identified directly from the time series. Fifth, BFAST relies on the OLS-MOSUM statistical framework, providing a rigorous statistical basis for detecting trends and structural breaks without the need for predefined thresholds (Ben Abbes et al., 2018; Hutchinson et al., 2015). Finally, BFAST has been widely validated in literature (Ben Abbes et al., 2018; Browning et al., 2017; De Jong et al., 2012; Geng et al., 2019; Hutchinson et al., 2015; Rodriguez et al., 2024; Verbesselt et al., 2010; Watts et al., 2014) and is implemented in open-source tools, such as the *bfast* package in R, which enhances reproducibility and comparability across studies.

Despite these strengths, BFAST also has several limitations. First, it requires long and regularly sampled time series often exceeding 10 years of imagery to reliably estimate seasonal and trend components. Its performance may be reduced when applied to shorter time series or datasets with substantial temporal gaps. Second, BFAST can be computationally intensive, as pixel-level decomposition across long time series demands significant processing time and computational resources. Finally, while BFAST is effective at identifying the timing of changes, it does not explain the underlying causes of those changes. Additional analyses and contextual data are required to attribute detected disturbances to specific environmental or anthropogenic drivers.

Overall, BFAST is a powerful and statistically robust method for detecting structural changes in remotely sensed time series, particularly in environments with strong seasonal dynamics.

However, its effectiveness depends on data quality, appropriate parameter selection, and careful interpretation, and it is best applied in conjunction with complementary methods and ancillary information.

B. INLA (Integrated Nested Laplace Approximation) Models

Bayesian Statistical Framework

Integrated Nested Laplace Approximation (INLA) is a Bayesian inference framework developed for fast and accurate approximation of posterior distributions in latent Gaussian models (Rue et al., 2009). In INLA-based models, an underlying stochastic structure—referred to as the latent field—is used to account for spatial and/or temporal autocorrelation in the data (Illian et al., 2013). Compared to simulation-based approaches such as Markov Chain Monte Carlo (MCMC), INLA is computationally more efficient because it relies on deterministic approximations based on Laplace methods rather than repeated sampling (Illian et al., 2013). The latent field in spatial Gaussian models is commonly represented as a Gaussian Markov random field (GMRF), which captures spatial autocorrelation through structured random effects (Rue et al., 2009; Illian et al., 2013). GMRFs are particularly advantageous computationally because spatial dependence is restricted to a limited set of neighboring locations, resulting in sparse precision matrices and reduced computational burden (Illian et al., 2013).

The R-INLA implementation has further expanded the applicability of INLA by enabling efficient modeling of complex spatial and spatiotemporal processes. R-INLA commonly employs the stochastic partial differential equation (SPDE) approach to approximate continuous Gaussian random fields (GRFs) using GMRFs while preserving the underlying spatial structure (Bakka et al., 2018). Through the SPDE framework, a continuous spatial process is defined over the entire study region, most often using a Matérn covariance function to characterize spatial dependence (Bakka et al., 2018; Carson et al., 2014).

The SPDE approach relies on triangulation to discretize the spatial domain into a mesh, which plays a critical role in model construction and inference. Proper mesh design is essential, as the

triangulation must extend beyond the study boundary to mitigate edge effects, which can otherwise lead to inflated uncertainty near the borders of the spatial domain (Carson et al., 2014; Lindgren et al., 2011). The resulting mesh consists of nodes distributed across the study area, often informed by the spatial distribution of observation points, such as explosion locations. Within the model, the SPDE component is used to capture unmeasured spatial variation that is not explained by observed covariates.

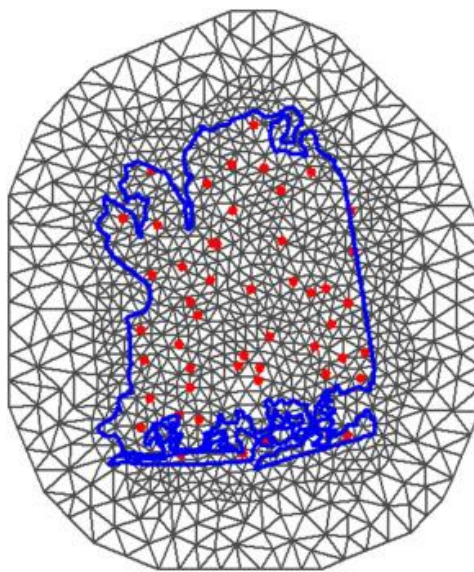


Figure 2-8: SPDE Triangulation Mesh - This figure shows an example of a triangulated mesh used in the Stochastic Partial Differential Equation (SPDE) approach for spatial modeling (adapted from Myer et al., 2019). It is analytically important because the mesh structure underpins the spatial random field used to model explosion intensity and spatial dependence.

INLA has been widely applied across numerous research domains, including disease risk mapping (Adegboye et al., 2021; Asmarian et al., 2019; Sahoo et al., 2024), ecological and environmental change modeling (Carson et al., 2014; Koh et al., 2023; Law et al., 2009; Martínez-Minaya et al., 2018; Valente et al., 2020), and spatial point process modeling (Illian et al., 2013). Its broad adoption across disciplines and acceptance in the scientific literature highlight its robustness and flexibility. The ability of INLA to integrate covariates, spatial random effects, and uncertainty within a coherent Bayesian framework makes it particularly well

suited for modeling military activities, such as explosions, and for analyzing their spatial distribution across complex landscapes.

C. Generalized Additive Models (GAM) and Big Additive Models (BAM)

Generalized Additive Models (GAMs) extend generalized linear models by allowing the linear predictor to be expressed as a sum of smooth functions of covariates, where the functional forms are estimated from the data (Wood, 2025). This formulation provides a flexible framework for modeling nonlinear covariate effects within exponential family models and other likelihood-based regression settings (Hastie et al., 1986). Rather than assuming strictly linear relationships, GAMs model the mean of the response as an additive combination of smooth terms, enabling the data to determine the shape of each effect.

A general representation of a GAM is given by:

$$y \sim P(\mu, \psi),$$

$$g(\mu) = \beta_0 + f_1(x_1) + f_1(x_2) + \cdots + f_p(x_p),$$

where y is the response, P is a probability distribution from the exponential family, μ is the expected value, ψ is the dispersion, $g(\mu)$ is the link function, β_0 is the intercept, and $f_p(x_p)$ are smooth functions of the covariates estimated from the data. These smooth functions are typically constructed using basis functions, such as splines, together with smoothing penalties that control model complexity and help prevent overfitting (Wood, 2017). In statistics, splines are flexible tools that are well suited for representing complex, nonlinear relationships between continuous data. In a spatial context, splines can be used to characterize gradual spatial variability and to identify regions of relatively high or low response values. In this research, spline-based smooths play an integral role in determining model outcomes and capturing underlying nonlinear

structure. GAMs are estimated within a penalized regression framework, which allows for flexible, nonlinear patterns while maintaining computational efficiency. The penalty term constrains the wiggleness of each smooth function, thereby balancing goodness-of-fit against model parsimony (Wood, 2017). In practice, GAMs are mostly implemented using the *mgcv* package in R (Wood, 2025), which provides efficient estimation of smoothing parameters using generalized cross-validation (GCV) or restricted maximum likelihood (REML).

GAMs are particularly well suited for environmental and spatial modeling, where covariate effects are rarely linear and often vary smoothly over space or time. Environmental processes frequently exhibit seasonal behavior, threshold effects, and nonlinear responses to drivers such as temperature, precipitation, elevation, land cover, and distance to landscape features. GAMs allow these covariate effects to be modeled using smooth functions rather than restrictive linear terms. Consequently, GAMs have been widely applied in species distribution modeling, habitat suitability analysis, and biodiversity assessment (Elith et al., 2006). Spatial smooths defined over geographic coordinates further enable GAMs to capture broad-scale spatial structure and residual spatial autocorrelation not explained by observed covariates (Augustin et al., 1998; Wood, 2003). Overall, GAMs offer a powerful and flexible framework for representing smooth nonlinear effects, spatial and temporal structure, and multiple environmental drivers within a likelihood-based modeling approach, making them a standard tool in modern environmental and ecological modeling.

V. Data Selection

A. MODIS EVI 250m Resolution Imagery

Advantages and limitations

The MODIS 250-m Enhanced Vegetation Index (EVI) product provides significant advantages for monitoring broad-scale environmental change, particularly in conflict-affected regions where frequent observations are required. MODIS offers near-daily global coverage and a continuous data record extending from 2000 to the present, making it well suited for long-term time-series analysis of vegetation dynamics. The high temporal resolution allows researchers to track seasonal patterns, detect abrupt disturbances, and assess recovery trends over large geographic areas. In addition, the EVI algorithm is designed to minimize atmospheric noise and soil background effects, providing improved sensitivity in high-biomass regions compared to NDVI (Didan et al., 2015). MODIS data are also freely available, consistently processed, and widely validated, which facilitates reproducibility and comparison across studies (Didan et al., 2015).

Despite these strengths, the 250m spatial resolution of MODIS imagery presents important limitations for analyzing localized environmental impacts of warfare. Many conflict-related disturbances in Ukraine such as individual explosions, vehicle tracks, trench networks, and small burn scars occur at spatial scales far smaller than a single MODIS pixel. As a result, such features are often within mixed pixels that contain a combination of vegetation, bare soil, and built surfaces. This mixed-pixel problem makes it difficult to attribute observed vegetation changes to specific military activities and reduces the ability to detect fine-scale damage. Cloud contamination and compositing artifacts can further obscure short-term disturbances, while geolocation uncertainty may introduce additional spatial error.

Consequently, MODIS 250m imagery is most appropriate for identifying regional trends and large-scale patterns of vegetation change, rather than precise mapping of individual disturbance events. It is particularly valuable for assessing cumulative or widespread impacts over time, such as generalized vegetation decline near active front lines or broad recovery following periods of

reduced hostilities. However, for detailed analysis of highly localized damage, higher-resolution sensors such as Landsat or Sentinel-2 are necessary. Many studies therefore adopt a multi-sensor approach in which MODIS provides the temporal context for change detection, while finer-resolution imagery is used to validate and interpret site-specific impacts. Recognizing these advantages and limitations is essential when applying MODIS EVI data to assess the ecological consequences of war-related activities.

Armed Conflict Location and Event Data

A key methodological consideration in conflict-related environmental research is the quality and reliability of event datasets such as the Armed Conflict Location and Event Data Project (ACLED) (*Conflict Data* | ACLED, n.d.). While ACLED provides one of the most comprehensive publicly available records of violent events, it is subject to inherent spatial uncertainty and potential reporting bias. Event locations are often approximated to the nearest town or administrative unit, and coverage can vary depending on media access, security conditions, and reporting capacity. These factors may result in underreporting in remote areas or overrepresentation in highly monitored regions (*Conflict Data* | ACLED, n.d.), potentially influencing spatial analyses and model outcomes. Consequently, studies utilizing ACLED data must acknowledge these limitations and interpret findings with appropriate caution.

Chapter 3 - Detecting Vegetation Change in Ukraine using Satellite

Imagery and BFAST Analysis

Introduction

Armed conflicts can cause extensive destruction from a humanitarian, economic, and environmental perspectives. Although the human costs of war typically receive the greatest attention, the environmental consequences are often severe and long-lasting, yet comparatively under-appreciated (Leal Filho et al., 2024). Among the most affected components of the environment are soil systems, wildlife, and water resources. Wartime activities produce significant physical impacts on soils through multiple pathways, including crater formation from explosive munitions, compaction caused by heavy military vehicles, and the effects of wildfires triggered by destroyed equipment and detonations. These disturbances degrade soil structure and function, and in many cases ecological recovery may take decades. The scale of landscape damage associated with modern conflict is so extensive that large portions of Ukraine are unlikely to return to their pre-war environmental conditions (Baumann et al., 2016; Broomandi et al., 2020; Hryhorczuk et al., 2024; Lawrence et al., 2015). The objective of this research is to examine vegetation change across Ukraine at a broad spatial scale in order to determine whether landscape disturbances resulting from armed conflict are producing measurable impacts on regional vegetation patterns.

Landscape impacts due to conflict

Cratering

Cratering is one of the most common and visible forms of landscape disturbance associated with warfare and military activities. Explosive munitions such as artillery shells, aerial bombs, drone strikes, and improvised explosive devices (IEDs) routinely generate craters that

directly disrupt soil and surface conditions. In the Russian-Ukrainian War, propelled explosives represent the primary mechanism driving widespread soil disturbance. The characteristics and severity of individual craters depend on several factors, including the amount of energy released during detonation, local soil properties, and the angle of impact (Celebi et al., 2025). (Hupy et al., 2006) introduced the term *Bombturbation* to describe the physical disruption and reworking of soils caused by explosive munitions during military conflicts. Soils affected by Bombturbation are typically compacted, destabilized, and contaminated with metal fragments, chemical residues, and ash (Broomandi et al., 2020). These disturbances mix previously distinct soil horizons, fundamentally altering both soil structure and surface topography. As a result, cratering serves as a clear example of how armed conflict transforms landscapes, with direct consequences for ecosystem function and vegetation conditions.

Compaction of the Soil

In addition to Bombturbation, military vehicle traffic represents another major source of soil disturbance during armed conflict. Heavy-wheeled and tracked vehicles exert substantial pressure on the ground surface, leading to significant soil compaction. This compaction alters soil hydraulic properties, reduces structural stability, and increases susceptibility to erosion and surface runoff (Cambi et al., 2015). Soil compaction can occur at multiple depths and is generally categorized as either surface or subsurface compaction (Understanding and Managing Soil Compaction, n.d.). During compaction, soil porosity is reduced as larger pore spaces are compressed into smaller ones, limiting the soil's capacity to absorb and transmit water. As a result, compacted soils experience lower infiltration rates and increased runoff,

which can transport fertilizers, herbicides, and other contaminants into adjacent water bodies and surrounding landscapes.

The impacts of military-induced soil compaction can persist long after active conflict has ended, particularly in agricultural regions. Research has shown that compacted soils restrict root penetration, inhibit plant establishment, and reduce the movement and availability of water within the soil profile (Understanding and Managing Soil Compaction, n.d.). These long-term effects pose significant challenges for post-conflict land recovery and agricultural productivity, demonstrating that the environmental legacy of warfare extends well beyond the immediate period of hostilities.

Fires

Fires associated with wartime activities, whether occurring in forests or agricultural lands, can have substantial impacts on the physical, chemical, and biological properties of soils (Agbeshie et al., 2022). High-intensity fires are particularly damaging, as they can significantly reduce soil organic matter and deplete essential nutrients such as nitrogen (Ibáñez et al., 2022). The effects of fire on soil chemistry, however, are highly variable. Low-intensity fires may result in minimal changes or even temporary increases in the availability of certain nutrients, including K^+ , Ca^{2+} , Mg^{2+} , PO_4^{3-} , and NH_4^+ , due to the deposition of nutrient-rich ash (Agbeshie et al., 2022).

Wildfires also strongly influence soil biological properties. Soil microbial communities and other biota can be directly harmed or eliminated by extreme heat during combustion, while indirect effects may arise from altered vegetation cover and post-fire recovery processes (Ibáñez et al., 2022). These changes to soil biology can disrupt key ecosystem functions such as nutrient cycling and organic matter decomposition. Together, the physical disturbance of

fire and its chemical and biological effects highlight another important pathway through which armed conflict can degrade environmental conditions and alter landscape resilience.

Deposition

Deposition refers to the introduction of manufactured solid foreign materials into the natural environment as a result of military activities (Radunzel, 2024). In conflict zones, these materials commonly include landmines, improvised explosive devices (IEDs), unexploded devices, and other military debris that are intentionally or unintentionally left in the ground. The environmental consequences of such deposition are wide-ranging and include soil contamination from metallic fragments, physical destabilization of soil structure, and the long-term abandonment of land due to safety hazards.

While mines and IEDs represent highly visible forms of deposition, spent ammunition from small arms and heavy weaponry constitutes one of the sources of foreign material in conflict-affected landscapes. Once embedded in the soil, components of this ammunition can either remain bound within the soil matrix or be transported through soil water (Thestorff et al, 2022).

Although fired munitions are typically no longer explosive, they are composed of reactive metals and chemical compounds that can lead to persistent contamination and chemical disruption of soil systems (Broomandi et al., 2020; Williams et al., 2022).

Deposition also occurs through the destruction or abandonment of military vehicles and equipment. Damaged vehicles often release fuels, oils, lubricants, and other hazardous substances that gradually seep into surrounding soils. Over time, corrosion and leakage further contribute to localized contamination. While these forms of deposition tend to be spatially limited, they can still produce concentrated areas of soil degradation and negatively affect vegetation at a local scale.

Chemical Impact of the Soil

In addition to the physical degradation of soils, the chemical impacts of armed conflict are equally significant yet often less visible. One of the most persistent legacies of warfare is metallic debris from bullets, shrapnel, and other weapon fragments, which can remain in the environment for decades (Broomandi et al., 2020). A recent study conducted in Ukraine found that soils surrounding abandoned military tanks were heavily contaminated with lead (Pb), zinc (Zn), and cadmium (Cd), and that explosions and pyrolysis of armored vehicles negatively affected soil biological properties, including increased toxicity to soil organisms and plants (Solokha et al., 2024). Similar research in Croatia has demonstrated that elevated concentrations of heavy metals in soils can be directly linked to historical military activities (Vidosavljević et al., 2013). Although it is often difficult to attribute specific contamination levels to individual munitions or events, the cumulative evidence indicates that the chemical consequences of warfare represent a serious long-term environmental threat. These contaminants can persist in soil for decades, posing ongoing risks to ecosystem health, agricultural productivity, and human well-being long after active conflict has ended.

Habitat Loss/Degradation

Ecological disturbance plays a major role in shaping plant diversity and species composition (Pickett, 1985). Such disturbances can reduce existing vegetation, promote regeneration, or create entirely new ecological conditions (Krawczyk et al., 2019). While Bombturbation is known to produce long-term changes in the physical, chemical, and biological properties of soils, explosion craters caused by military munitions can also function as a form of ecological disturbance comparable to natural small-scale events (Krawczyk et al., 2019). Research conducted in Poland found that explosion craters generate lasting impacts on local habitats by

eliminating dominant competitors and effectively resetting ecological succession (Krawczyk et al., 2019). Although these disturbances often result in the destruction of wildlife habitats, they can also lead to increased plant species diversity and altered community composition. Overall, warfare-related disturbances can severely disrupt ecosystem functioning and degrade the biosphere, yet they also illustrate the complex and sometimes unexpected ecological responses that can emerge following large-scale environmental disruption.

Land Abandonment

Military conflict often leads to widespread cropland abandonment and long-term alterations to land systems. A review conducted by researchers in Germany (Thestorff et al., 2022) suggests that some land-system impacts of armed conflict are temporary and may gradually reverse once peace is restored. However, prolonged wars frequently produce changes that persist for many years or even decades, as landscapes struggle to recover from extensive damage. Agricultural abandonment represents one of the most common and visible outcomes of conflict. For example, a study in Mali documented how violence resulted in the abandonment of farmland and examined patterns of subsequent recultivation once conditions stabilized (Boudinaud et al., 2021). Similarly, research on the Chechen Wars in the northern Caucasus found that areas experiencing higher conflict intensity showed little evidence of agricultural recovery, indicating that the effects of military operations on land use can be long-lasting (Yin et al., 2019).

Collectively, the literature demonstrates that armed conflicts significantly transform land systems by destroying habitats, contaminating soils physically and chemically, and disrupting agricultural production. At the same time, these disturbances can trigger ecological responses that alter vegetation dynamics, including shifts in plant community composition and diversity.

Environmental Status from the Russo-Ukrainian War

On February 24, 2022, Russia launched a full-scale invasion of Ukraine, triggering a global crisis with profound humanitarian and economic consequences. In the context of armed conflict, environmental impacts are often overlooked as immediate human suffering takes precedence (Leal Filho et al., 2024). This is particularly concerning in Ukraine, a country that, together with Russia, is often referred to as part of the “breadbasket of Europe” due to its major role in global production of wheat, barley, corn, sunflower seed, and soybeans (Pereira et al., 2022). Prolonged military operations have significantly disrupted agricultural production and have placed immense pressure on environmental systems, including soil, water, air quality, and wildlife (Hutchinson et al., 2015). Environmental degradation in wartime can occur both directly through military actions and indirectly through the breakdown of infrastructure and land management systems (Lawrence et al., 2015).

In Ukraine, extensive artillery bombardments and drone strikes have contributed to widespread wildfires and large-scale Bombturbation, which has led to altering landscapes. The destruction of the Nova Kakhovka Dam on June 6, 2023, further intensified environmental damage in southern Ukraine by disrupting irrigation networks, flooding agricultural land, and leaving large areas without sufficient water for crop production. As reservoirs and canals dried up, agricultural output and exports declined due to the loss of arable land. These combined impacts have resulted in increased greenhouse gas emissions, deteriorating air and water quality, widespread physical and chemical soil contamination, and extensive habitat destruction (Hryhorczuk et al., 2024). Southern and eastern Ukraine have been particularly affected, experiencing repeated disturbances from major military operations, including Ukrainian counteroffensives and the breaching of heavily fortified defensive positions such as the Surovikin Line. This defensive system consisted of approximately 2,000 kilometers of Russian fortifications stretching from the

Belarusian border to the Dnipro River Delta and included dense networks of trenches and minefields. Although the 2022 invasion marked a dramatic escalation, environmental pressures in Ukraine have been accumulating since Russia's annexation of Crimea in 2014. As a result of years of conflict combined with ongoing natural environmental processes, the overall ecological condition of Ukraine can be characterized as severely degraded and increasingly vulnerable.

Material and Methods

Material

Study Area

Ukraine is a country in Eastern Europe (49.0° N, 32.0° E) that borders Belarus, Russia, Moldova, Romania, Hungary, Slovakia, Poland, the Black Sea and the Sea of Azov. Ukraine is 603,500 sq km, which makes it the largest country by area in Europe.

“Ukraine is characterized by parallel, non-continuous belts of mountains, depressions, uplands, and lowlands that extend from east to west” (*Geography of Ukraine*, n.d.). Ukraine is made of upland and lowland plains as you travel east, with the Carpathian Mountains found in the west. The Crimean Peninsula, occupied by Russia, is home to the Crimean Mountains and several other upland plains. Major rivers that flow through Ukraine are the Dunay, Dnipro, Dniester, and Vistula rivers (*Geography of Ukraine*, n.d.). Ukraine has a mean elevation of 175 m above sea level with the highest point being at Hora Hoverla in the Carpathian Mountains, 2,061 m, and the lowest point being the Black Sea, 0 m (*Geography of Ukraine*, n.d.).

Ukraine's climate is mostly a temperate climate, except for the southern coast of Crimea which has a subtropical Mediterranean climate. Typical weather conditions in Ukraine include moderate to hot, wet summers, and cold, wet winters, with rainfall is highly varied depending upon the area of the country and seasonal patterns (*World Bank Climate Change Knowledge*

Portal, n.d.). Mean summer temperature (May to August) ranges from 18°C to 22°C. The mean winter temperature (December to March) ranges from -4.8°C to 2°C (*World Bank Climate Change Knowledge Portal*, n.d.).

Most of Ukraine's soils are chernozems, which are the most fertile soils in the world.

Chernozems have a thick, rich, black surface horizon that is high in organic matter or humus.

The water-holding capacity of chernozems exceeds 150mm (Kögel-Knabner et al., 2014). High fertility and water-holding capacity make chernozems great for farming. In Ukraine, these soils allow for the growth of many crops. The main five crops grown in Ukraine are maize, wheat, barley, sunflower, and soybean. Ukraine before the invasion of Russia was the fifth-largest exporter of wheat, the third-largest exporter of maize and barley, and the largest exporter of sunflower in the world (Welsh et al., 2024). Russia has taken advantage of Ukraine's agricultural sector and damaged global food security at the same time (Welsh et al., 2024).

Ukraine is broken into 6 different ecoregions according to Worldwide Fund for Nature (WWF).

The 6 ecoregions are the Carpathian montane forests, the Central European mixed forests, Crimean Submediterranean forest complex, the East European Forest steppe, the Pannonian mixed forests, and the Pontic steppe. Figure 3-1 shows the location boundaries of these ecoregions. For more information about all these ecoregions, please visit

<https://www.oneearth.org/navigator/> for more details.

Landcover Data (Figure 3-2) used in this research is from the ESA Worldcover Version 2. Worldcover version 2 was developed in 2021 using Sentinel 1 and 2 data to create a 10 m resolution global land cover product (Zanaga et al., 2022).

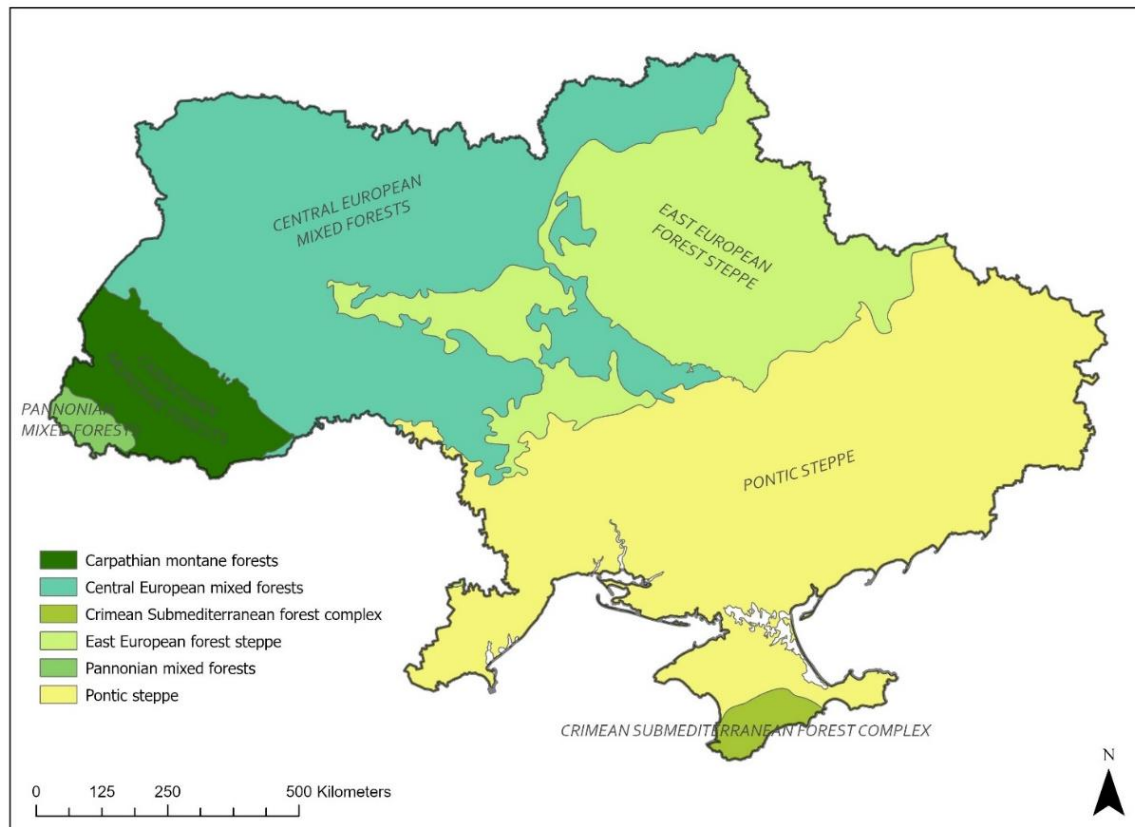


Figure 3-1: Ecoregions in Ukraine - This figure shows the major terrestrial ecoregions of Ukraine, including the Carpathian montane forests, Central European mixed forests, East European forest steppe, Pontic steppe, Pannonian mixed forests, and the Crimean Submediterranean forest complex (data from World Wildlife Fund biome delineations). It is analytically important because it provides the ecological context needed to interpret spatial variation in vegetation trends and conflict-related environmental impacts.

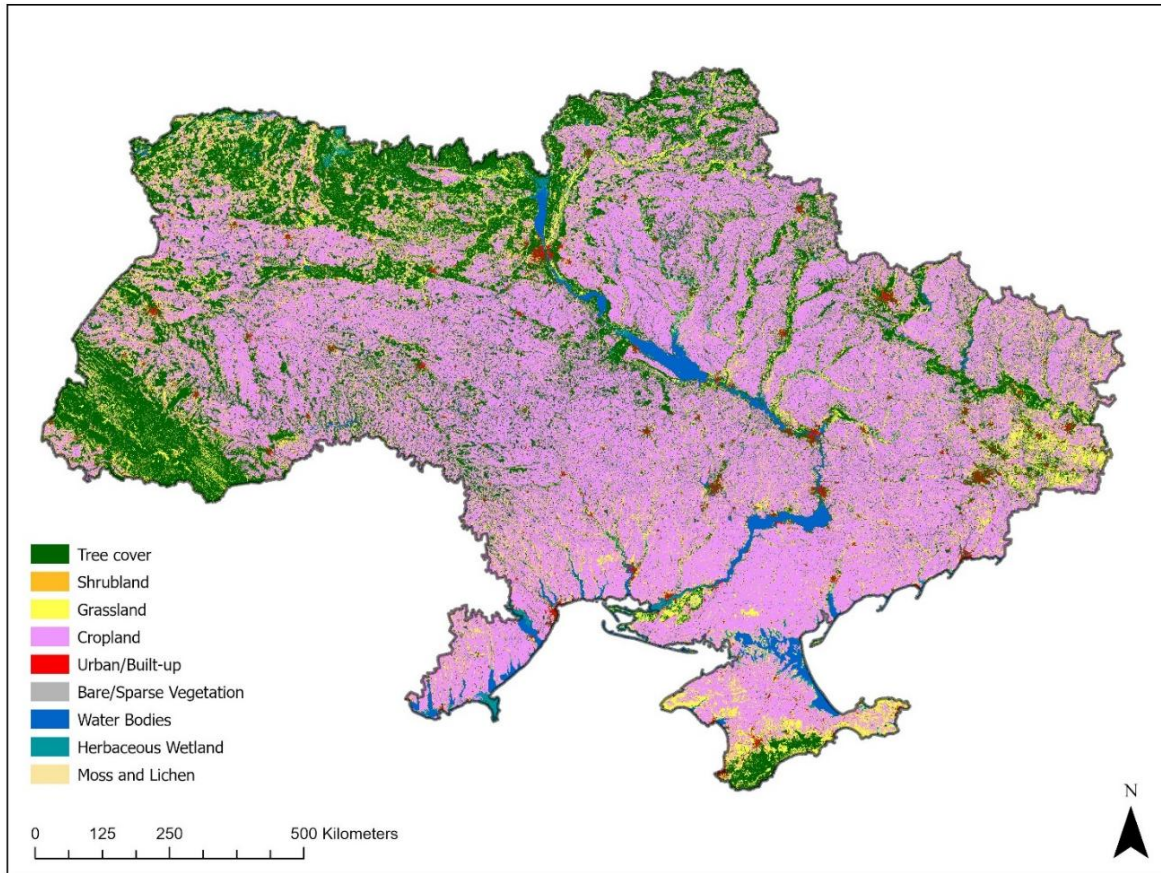


Figure 3-2: Land Cover Classification of Ukraine - This figure shows the spatial distribution of major land cover classes across Ukraine, including tree cover, shrubland, grassland, cropland, urban/built-up areas, bare or sparse vegetation, water bodies, herbaceous wetlands, and moss and lichen (data from the European Space Agency Land Cover dataset). It is analytically important because land cover type serves as a key covariate for explaining spatial variation in explosion intensity and vegetation trends.

Image Data

The imagery selected for the time series analysis was the 16-day Moderate Resolution Imaging Spectroradiometer (MODIS) using the vegetation layer, Enhanced Vegetation Index (EVI). The MODIS EVI imagery comes from NASA's Terra satellite and provides users with consistent, spatial, and temporal time series comparisons of vegetation conditions (Didan et al., 2015). The (MOD13Q1 Collection 6) composites reduce the saturation of dense biomass and decrease the influence of bare soil (Didan et al., 2019). The images were collected from NASA Appear (Application for Extracting and Exploring Analysis Ready Samples). The MOD13Q1 composites have a spatial resolution of 250 meters and are created using the CV-MVC algorithm to create a

composite value for the pixel that represents the full 16-day time period (Didan & Munoz, 2019). Five hundred and forty (540) total images were acquired from the time period of January 1, 2001, to December 31, 2023, to produce 22 years' worth of EVI imagery for Ukraine. This is especially important because BFAST requires a continuous dataset with no gaps. If gaps are present, the EVI values are averaged so that a value is still incorporated. Composites are in the geographic coordinate system, WGS 1984.

Methods

Breaks for Additive Season and Trend (BFAST)

Breaks for Additive Season and Trend (BFAST) is a parametric method that uses an additive model to decompose each pixel of the time series into three components, Seasonal, Trend, and Reminder (Noise or Residuals) (Verbesselt et al., 2010, Hutchinson et al., 2015). The equation for BFAST is:

$$Y_t = T_t + S_t + e_t,$$

where Y_t is the observed data at time(t), T_t is the trend component, S_t is the seasonal component, and e_t is the noise component. The noise component is the remaining variation in the data that was not picked up by either the trend or seasonal component (Hutchinson et al., 2015).

The trend component of BFAST represents the long-term direction of the data and is independent of the seasonal component. BFAST models the trend component as a piecewise linear function, which allows for breakpoints to occur where the slope of the trend occurs (Verbesselt et al., 2010). Since T_t is a piecewise linear function with breakpoints $t_1^*, \dots, t_m^*$ and defined $t_0^* = 0$; the equation for T_t is Geng et al., 2019; Verbesselt et al., 2010):

$$T_t = \alpha_j + \beta_j t,$$

where $j = 1, \dots, m$ and $t_{j-1}^* < t \leq t_j^*$. The intercept and slope of consecutive linear models, α_j and β_j , are used to derive the magnitude and direction of the abrupt change and slope of the gradual change between breakpoints (Verbesselt et al., 2010). Magnitude of an abrupt change at a breakpoint can be derived by the difference between T_t at t_{j-1}^* and t_j^* :

$$\text{Magnitude} = (\alpha_{j-1} - \alpha_j) + (\beta_{j-1} - \beta_j)t$$

The slopes of the gradual change before and after breakpoints are β_{j-1} and β_j (Verbesselt et al., 2010).

The seasonal component of BFAST captures the regular and repeating patterns within each year of the time-series. BFAST models seasonality using harmonic terms or the use of sine and cosine functions. The seasonal component is a piecewise linear model that is transformed into a multiple linear harmonic regression model (Verbesselt et al., 2010):

$$S_t = \sum_{k=1}^K [y_{j,k} \sin\left(\frac{2\pi ikt}{f}\right) + \theta_{j,k} \cos\left(\frac{2\pi ikt}{f}\right)]$$

The harmonic model offers three main advantages compared to the seasonal dummy model also created by (Verbesselt et al., 2010). (1) The model is less sensitive to short-term data variations and noise at lower frequency harmonic terms, (2) fewer observations are required since fewer parameters are needed to be estimates which increases speed in the algorithm, and (3) the fitted parameters can be more easily be used to characterize phenological change (Verbesselt et al., 2010).

The main objectives of BFAST are (1) the detection of multiple abrupt changes in seasonal and trend components and (2) the characterization of gradual and abrupt change by deriving time, magnitude, and the direction of change within the trend component of the time series (Verbesselt et al., 2010). Abrupt negative changes may be processes like wildfires, prescribed burning,

harvesting, or diseases (De Jong et al., 2013). Abrupt positive changes are processes that include increased precipitation and reduced snow cover (De Jong et al., 2013). Gradual changes occur over longer periods of time and can be classified as trends in mean annual rainfall, or gradual changes in land management or land degradation (Verbesselt et al., 2010). BFAST can detect vegetation change in drought-related conditions and flood-related conditions (Browning et al., 2017; Huang et al., 2014; Watts et al., 2014). For each of the MODIS pixels analyzed in Ukraine, the BFAST method was applied to the twenty-two-year MODIS EVI time series. In the statistical software, R, the BFAST package can be used to accomplish this (Verbesselt et al., 2024). The seasonal component follows the “harmonic” model because it is the most adapted to detect natural vegetation phenological change (Geng et al., 2019; Hutchinson et al., 2015; Verbesselt et al., 2010). The “harmonic” model requires fewer observations, more robust against noise, and the parameters can be more easily used to characterize phenological change (Verbesselt et al., 2010). The h value used in the BFAST function is set at 0.1, meaning that one break point per year could be detected for a possible maximum of 22 breakpoints in the time series (Hutchinson et al., 2015). BFAST uses a statistical analysis, a student t -test, to see if the BFAST slope is significant against a null slope (0) (Hutchinson et al., 2015).

Validation

In the research paper, a validation strategy was not developed to confirm whether that the detected BFAST changes were real or caused by the data. The use of high-resolution satellite imagery in the given study area was hard to come by. A validation method created by (Hutchinson et al., 2015) could be used to show if BFAST is giving accurate results or not.

Results/Discussions

The trend component derived from the BFAST decomposition was classified into three vegetation categories: positive, negative, and stable based on the statistical significance and direction of the slope. A positive trend (positive slope) represents a green signal in vegetation condition, while a negative trend (negative slope) indicates browning or declining vegetation condition. Stable trends correspond to areas where no statistically significant change in vegetation was detected.

Across Ukraine as a whole (Figure 3-3), 67% of the land area exhibited a positive vegetation trend over the 2001–2023 period, while 18% experienced a negative trend (Table 3-1). Positive trends were distributed throughout much of the country but were most prominent in the western ecoregions, particularly the Pannonian Mixed Forests, Carpathian Montane Forests, and Central European Mixed Forests. These regions contain a large proportion of Ukraine’s forest cover and have been less directly affected by large-scale military activity, which may help explain the predominance of greening trends.

Negative vegetation trends were more spatially concentrated in eastern and southern Ukraine. The highest proportions of declining vegetation conditions were observed in the East European Forest Steppe (24%), the Crimean Submediterranean Forest Complex (32%), and the Pontic Steppe (17%). These ecoregions largely overlap with areas experiencing the most intense military conflict, suggesting a potential relationship between armed conflict and vegetation decline. In addition to conflict-related disturbances, these regions contain extensive areas of agricultural land, including approximately 16.3 million hectares in the Pontic Steppe, 7.4 million hectares in the East European Forest Steppe, 8.2 million hectares in the Central European Mixed

Forests, 660,802 hectares in the Carpathian Montane Forests, 134,338 hectares in the Pannonian Mixed Forests, and 110,558 hectares in the Crimean Submediterranean Forest Complex.

Vegetation dynamics in cropland areas are inherently cyclical and strongly influenced by seasonal agricultural practices. During the growing season, croplands generally exhibit increased greenness, which may contribute to positive trends, while harvest periods often produce browning signals that can be interpreted as negative trends. As a result, it is difficult to attribute observed vegetation changes solely to conflict-related impacts without further analysis. These findings highlight the complexity of interpreting large-scale vegetation trends in Ukraine and indicate that additional research is needed to better disentangle the relative contributions of agricultural cycles, environmental variability, and wartime disturbances.

Trend Map

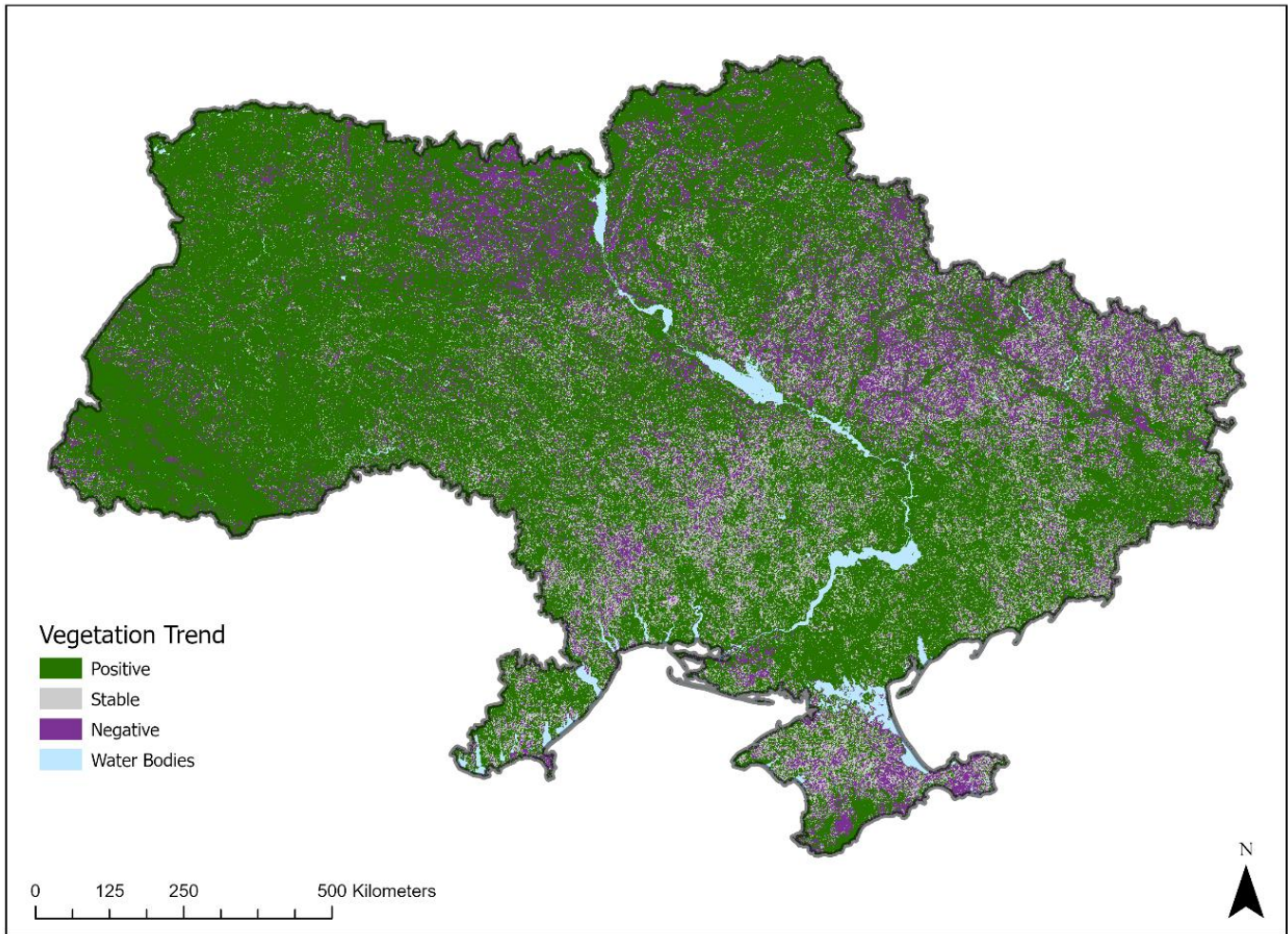


Figure 3-3: BFASST Trend Map of Ukraine - the spatial distribution of long-term vegetation trends classified as positive, stable, or negative based on the BFASST (Breaks For Additive Season and Trend) time-series analysis. Data are derived from MOD13Q1 NDVI imagery for the study period (2001–2023). This matters because it identifies areas of significant vegetation change used to assess environmental impacts of conflict.

Trend Table

Vegetation Change in the Pannonian Mixed Forests Region from 2001-2023		
	Number of Cells	Percentage of Cells (%)
Positive	43884	74.38
Stable	5520	9.36
Negative	9594	16.26
Vegetation Change in the Carpathian Montane Forest Region from 2001-2023		
	Number of Cells	Percentage of Cells
Positive	360629	87.66
Stable	9268	2.25
Negative	41510	10.09
Vegetation Change in the Central European Mixed Forests Region from 2001-2023		
	Number of Cells	Percentage of Cells
Positive	1924961	77.82
Stable	162898	6.59
Negative	385658	15.59
Vegetation Change in the East European Forest Steppe Region from 2001-2023		
	Number of Cells	Percentage of Cells
Positive	834411	60.38
Stable	216190	15.64
Negative	331328	23.98
Vegetation Change in the Pontic Steppe Region from 2001-2023		
	Number of Cells	Percentage of Cells
Positive	1629561	58.87
Stable	658609	23.79
Negative	479920	17.34
Vegetation Change in the Crimean Submediterranean Forest Complex Region from 2001-2023		
	Number of Cells	Percentage of Cells
Positive	40811	51.52
Stable	13086	16.52
Negative	25316	31.96

Table 3-1: Percentage of BFAST Trend from Ukrainian Ecoregions - the proportion of positive, stable, and negative BFAST vegetation trends within each major Ukrainian ecoregion. Data are derived from MOD13Q1 NDVI time-series imagery (2001–2023) and overlaid with World Wildlife Fund ecoregion boundaries. This matters because it quantifies how vegetation change varies across ecological zones in relation to conflict exposure.

A more detailed examination of natural vegetation trends in Ukraine (Figure 3-4) indicates that cropland and urban land cover contribute substantially to observed patterns of vegetation decline. When cropland and urban areas are excluded from the analysis, regional differences in trend distribution become more pronounced. As shown in Table 3-2, western regions of Ukraine exhibit notably higher proportions of positive trend cells when only natural vegetation is considered, suggesting that these areas are experiencing genuine greening trends independent of agricultural cycles.

In contrast, areas directly affected by the war show little change in the proportion of negative trends after cropland and urban areas are removed. However, the relative proportions of positive and stable trends shift, with positive values increasing and stable values decreasing. This indicates that a substantial portion of previously “stable” trends were associated with managed or built environments rather than natural ecosystems.

Overall, the removal of cropland and urban land cover results in a 9% increase in the proportion of positive vegetation trends at the national scale. This suggests that natural vegetation across Ukraine is generally exhibiting stronger greening signals than initially observed when agricultural and urban influences are included. Additionally, the proportion of stable trends decreases by approximately 7% in the non-cropland analysis, further indicating that cropland and urban areas are major contributors to areas classified as stable or unchanged. These findings demonstrate that land cover type plays a critical role in shaping national vegetation trend patterns and highlight the importance of isolating natural vegetation to better understand environmental change.

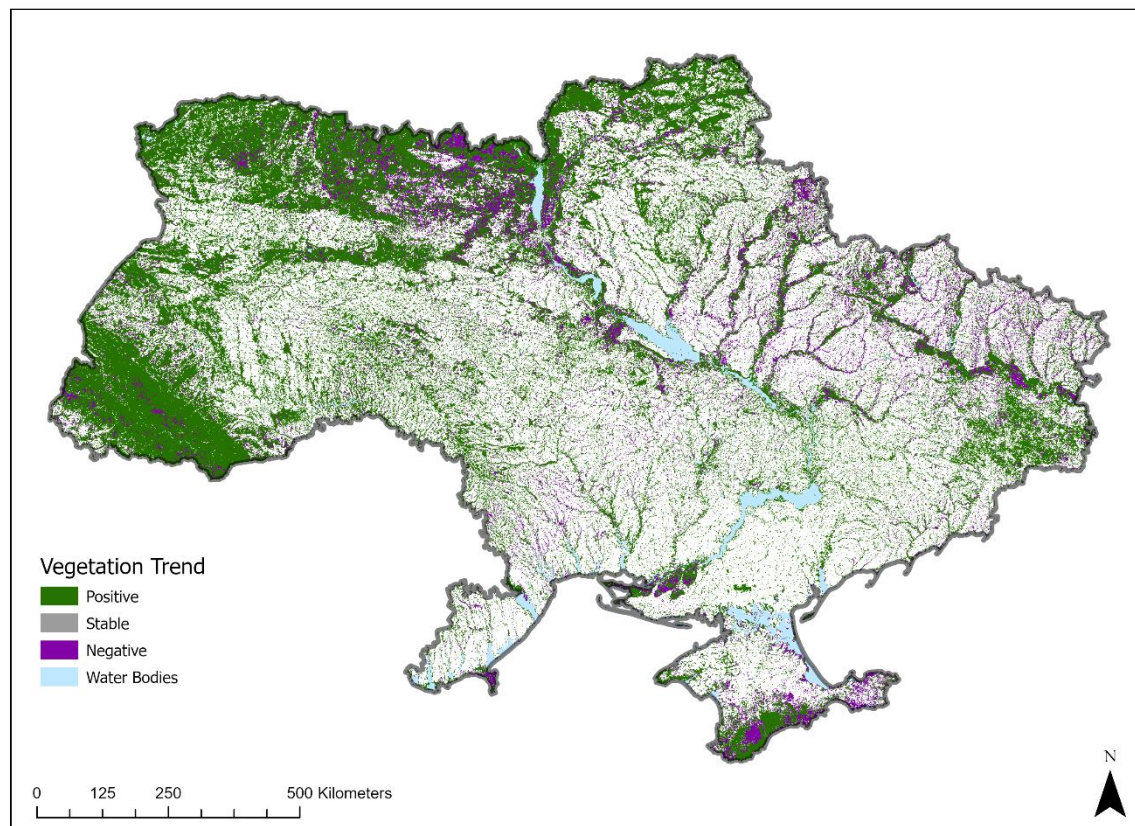


Figure 3-4: BFAST Trend Map of Ukraine without Cropland and Urban Areas - the spatial distribution of positive, stable, and negative vegetation trends identified using BFAST after removing cropland and urban land cover classes from the analysis. Data are derived from MOD13Q1 NDVI time-series imagery (2001–2023) and masked using ESA Land Cover classifications. This shows it isolates conflict-related vegetation change by minimizing agricultural and built-environment influences.

Trend Table without cropland

Vegetation Change in the Pannonian Mixed Forests Region without Non-Natural Vegetation (Cropland and Urban Areas)		
	Number of Cells	Percentage of Cells
Positive	33313	81.77
Stable	2249	5.52
Negative	5180	12.71
Vegetation Change in the Carpathian Montane Forest Region without Non-Natural Vegetation (Cropland and Urban Areas)		
	Number of Cells	Percentage of Cells
Positive	295649	91.37
Stable	3396	1.05
Negative	24529	7.58
Vegetation Change in the Central European Mixed Forests Region without Non-Natural Vegetation (Cropland and Urban Areas)		
	Number of Cells	Percentage of Cells
Positive	1137163	81.97
Stable	47373	3.41
Negative	202676	14.61
Vegetation Change in the East European Forest Steppe Region without Non-Natural Vegetation (Cropland and Urban Areas)		
	Number of Cells	Percentage of Cells
Positive	366967	68.96
Stable	39685	7.46
Negative	125478	23.58
Vegetation Change in the Pontic Steppe Region without Non-Natural Vegetation (Cropland and Urban Areas)		
	Number of Cells	Percentage of Cells
Positive	519134	65.08
Stable	128329	16.09
Negative	150210	18.83
Vegetation Change in the Crimean Submediterranean Forest Complex Region without Non-Natural Vegetation (Cropland and Urban Areas)		
	Number of Cells	Percentage of Cells
Positive	35647	55.71
Stable	9072	14.18
Negative	19270	30.11

Table 3-2: Percentage of BFAST Trend from Ukrainian Ecoregions without Cropland and Urban Areas - the proportion of positive, stable, and negative BFAST vegetation trends within each major Ukrainian ecoregion after removing cropland and urban land cover classes. Data are derived from MOD13Q1 NDVI time-series imagery (2001–2023) and masked using ESA Land Cover classifications, then summarized by World Wildlife Fund ecoregion boundaries. This matters analytically because it evaluates ecological vegetation change while reducing confounding effects from agriculture and built environments.

Number of Breaks

To better understand the temporal dynamics of vegetation change, the number of structural breaks identified through the BFAST decomposition was analyzed. The breaks component indicates how many times each pixel experienced a statistically significant shift in vegetation

condition over the 22-year time series. These breaks may represent either positive or negative changes, or transitions between periods of stability and change.

Across Ukraine, the majority of pixels exhibit zero detected breaks, particularly in mountainous and mixed forest regions where land cover tends to be more stable. In contrast, higher numbers of breaks are concentrated primarily in the steppe regions of the country. In these areas, pixels are commonly experienced between 2 and 15 breaks during the study period, indicating more frequent fluctuations in vegetation conditions. As shown in Figure 3-5, most of Ukraine is characterized by stable pixels with no breaks; however, this pattern is strongly influenced by large areas in the west and north that have experienced minimal direct conflict.

Southern and eastern Ukraine displays a different pattern. In these regions, where agricultural activity is intensive and military operations have been concentrated, pixels typically show an average of 2–10 breaks. A smaller proportion of cells exhibit more than 10 breaks, suggesting highly dynamic or unstable vegetation conditions over time. While the number of breaks provides valuable information about the magnitude and frequency of vegetation change, it does not indicate the specific drivers of those changes. Consequently, although this analysis reveals where vegetation dynamics are most pronounced, additional investigation is required to determine whether observed breaks are primarily related to conflict activity, agricultural cycles, climatic variability, or other environmental factors.

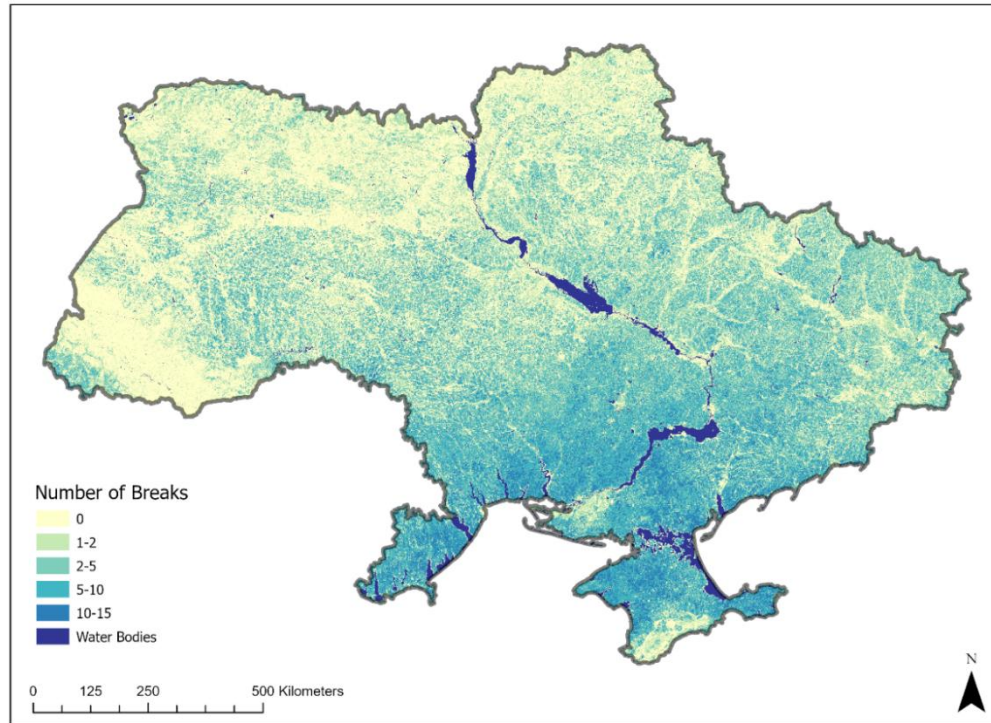


Figure 3-5: Number of Structural Breaks Detected by BFAST in Ukraine - the spatial distribution of the number of structural breaks identified in the vegetation time series using the BFAST (Breaks For Additive Season and Trend) method across Ukraine. Data are derived from MOD13Q1 NDVI time-series imagery for the study period (2001–2023). This matters because the frequency of breaks indicates areas experiencing repeated or abrupt vegetation disturbances potentially associated with conflict activity.

When cropland and urban areas are removed from the analysis of structural breaks, a clearer pattern of natural vegetation dynamics emerges. Mountainous regions and mixed forest zones continue to display predominantly zero breaks, indicating relatively stable vegetation conditions over time, while riparian corridors and other natural vegetation types remain visible as areas influenced mainly by seasonal cycles and environmental variability such as precipitation, temperature, and phenological change. As shown in Figure 3-6, excluding cropland and urban land cover results in a significant reduction in the overall number of detected breaks, demonstrating that natural vegetation across much of Ukraine experiences comparatively little abrupt change. In contrast, the majority of annual variability captured in the full dataset is associated with agricultural and urban landscapes, which undergo frequent shifts due to planting,

growth, and harvest cycles. Because cropland represents the dominant land-cover type in Ukraine, it strongly influences national vegetation trends, and its continual year-to-year change is therefore expected. These findings suggest that most of the temporal variability identified through the BFAST analysis reflects normal agricultural dynamics rather than changes in natural ecosystems or direct conflict-related impacts.

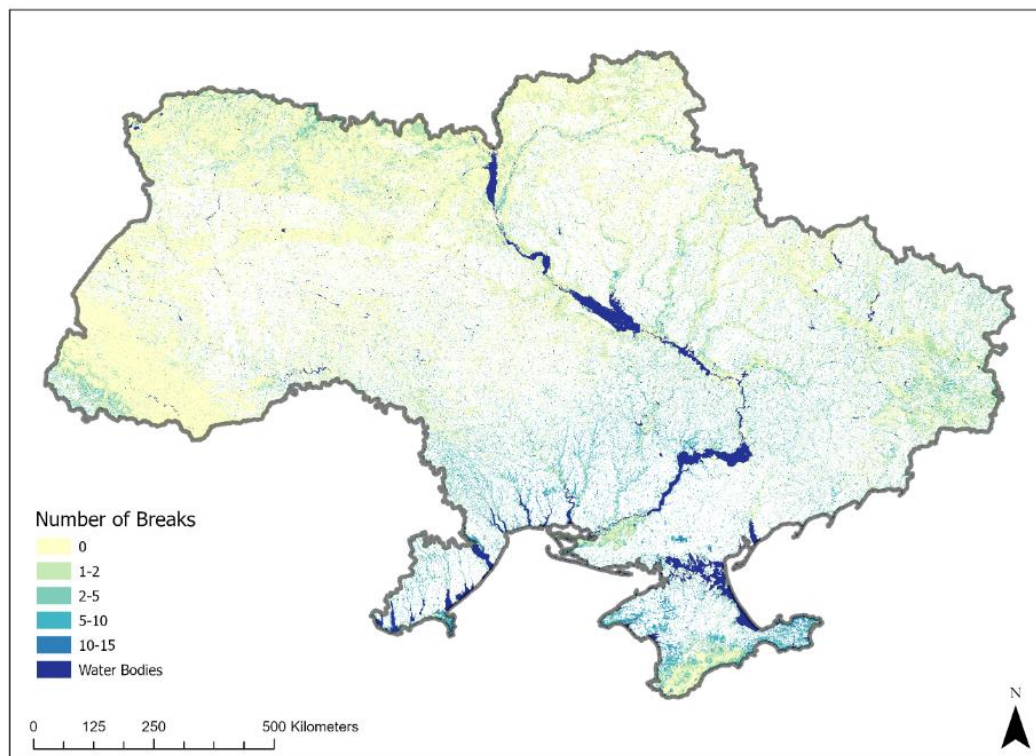


Figure 3-6: Number of Structural Breaks Detected by BFAST in Ukraine Excluding Cropland and Urban Areas - the spatial distribution of the number of structural breaks identified in the vegetation time series using the BFAST (Breaks For Additive Season and Trend) method after removing cropland and urban land cover classes. Data are derived from MOD13Q1 NDVI imagery (2001–2023) and masked using ESA Land Cover classifications. This matters because it highlights repeated vegetation disturbances in non-agricultural landscapes more likely attributable to conflict-related impacts.

Figure 3-7 illustrates the difference in the number of structural breaks between analyses that include cropland and urban areas and those that consider only natural vegetation. The map that includes cropland and urban land cover consistently exhibits a higher number of breaks, reflecting the dynamic and continually changing nature of these land-use types. Agricultural

fields undergo regular cycles of planting, growth, and harvest, while urban areas experience gradual expansion and modification, both of which contribute to frequent shifts in vegetation signals. In contrast, the analysis excluding cropland and urban areas shows that most natural vegetation remains stable over time, with the majority of pixels experiencing either no breaks or only one to two breaks across the 22-year period. This comparison demonstrates that cropland and urban land covers are the primary drivers of detected change in the national BFAST results, greatly influencing the overall number of breaks. Consequently, the strong influence of these managed landscapes makes it difficult to attribute observed changes directly to environmental factors or conflict-related disturbances without isolating natural vegetation from the analysis.

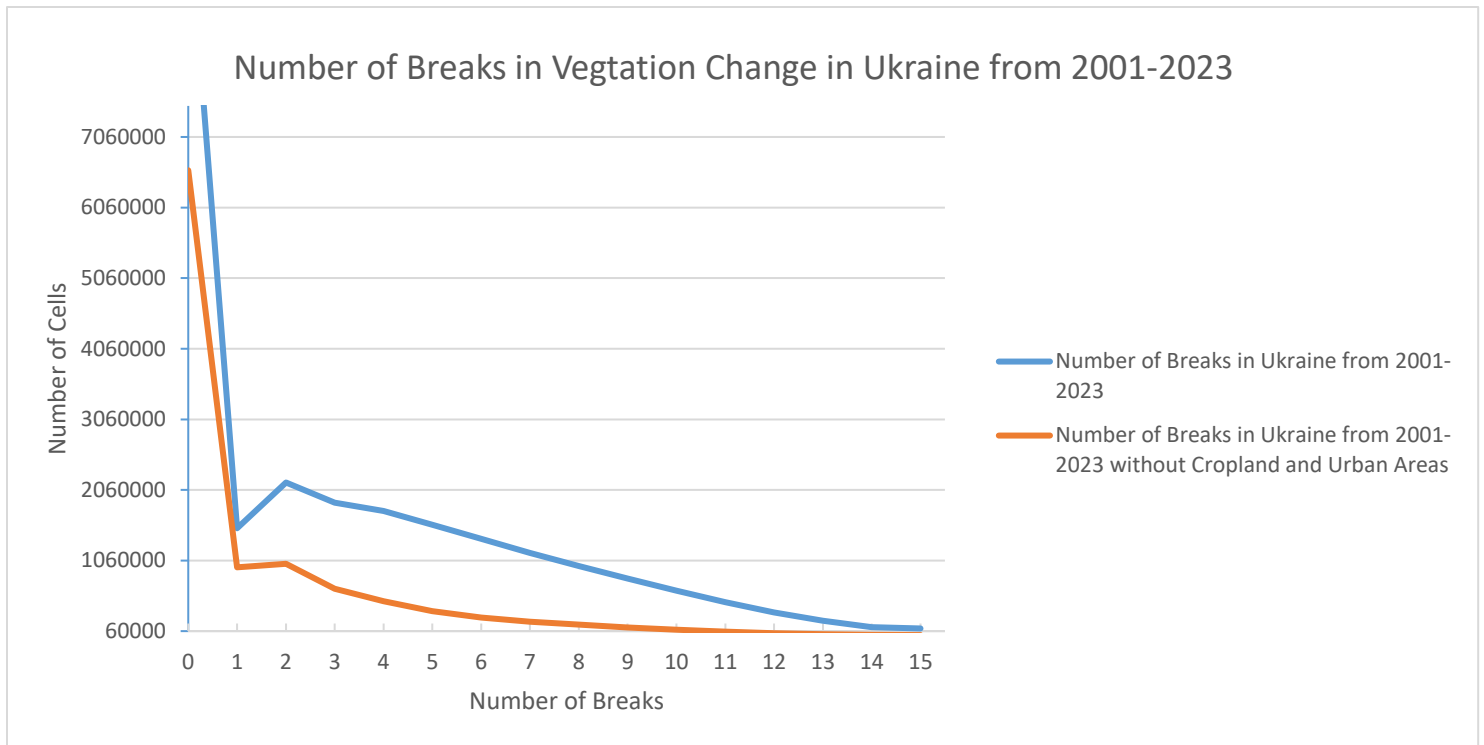


Figure 3-7: Frequency Distribution of Vegetation Structural Breaks in Ukraine (2001–2023) - the distribution of the number of BFAST-detected structural breaks per pixel across Ukraine from 2001–2023, comparing all land cover types with results excluding cropland and urban areas. Data are derived from MOD13Q1 NDVI time-series imagery analyzed using the BFAST method and masked using ESA Land Cover classifications. This matters analytically because it illustrates how repeated vegetation disturbances vary across landscapes and highlights the influence of agricultural and urban areas on detected break frequency.

Figure 3-8 presents the distribution of structural breaks across the six major ecoregions of Ukraine. The ecoregions located in western and northern Ukraine, specifically the Carpathian Montane Forests, Pannonian Mixed Forests, and Central European Mixed Forests exhibit relatively low frequencies of high break counts, with comparatively few pixels experiencing between 7 and 15 breaks. These regions are dominated by forested and semi-natural landscapes and have been less directly affected by large-scale military activity.

In contrast, the Pontic Steppe, which is geographically closer to active conflict zones and contains the largest extent of cropland in Ukraine, shows substantially higher numbers of breaks within the 7–15 range. This indicates that vegetation in the Pontic Steppe has undergone more frequent changes throughout the 22-year time series than in other ecoregions. However, it is difficult to attribute these changes to a single cause. The observed variability is likely influenced by a combination of factors, including seasonal agricultural cycles, human land management practices, and potential impacts from military operations. As a result, while the Pontic Steppe clearly exhibits greater vegetation dynamics, further analysis is required to disentangle the relative contributions of these different drivers.

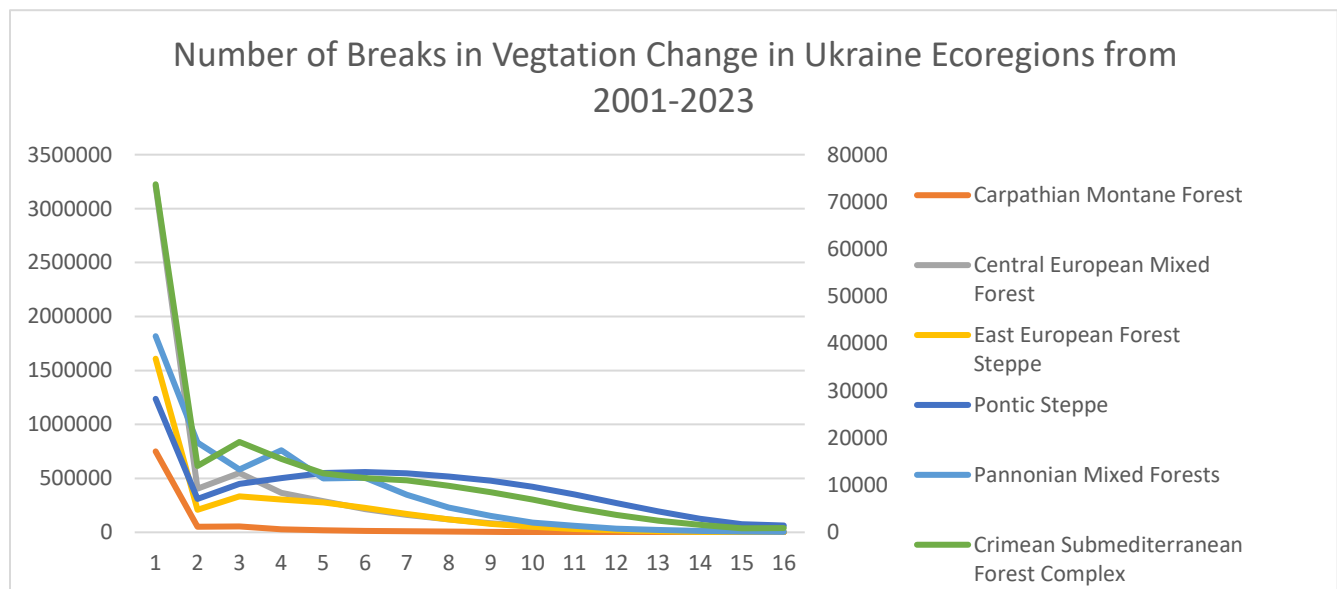


Figure 3-8: Frequency Distribution of Vegetation Structural Breaks Across Ukrainian Ecoregions (2001–2023) - the distribution of BFAST-detected structural breaks per pixel across major Ukrainian ecoregions from 2001–2023. Results are derived from MOD13Q1 NDVI time-series imagery processed using the BFAST algorithm and stratified by WWF terrestrial ecoregion boundaries. The figure demonstrates spatial heterogeneity in vegetation disturbance regimes, highlighting differences in disturbance frequency between forested, steppe, and Mediterranean-influenced landscapes.

Trend from Occupied Ukraine Counteroffensives

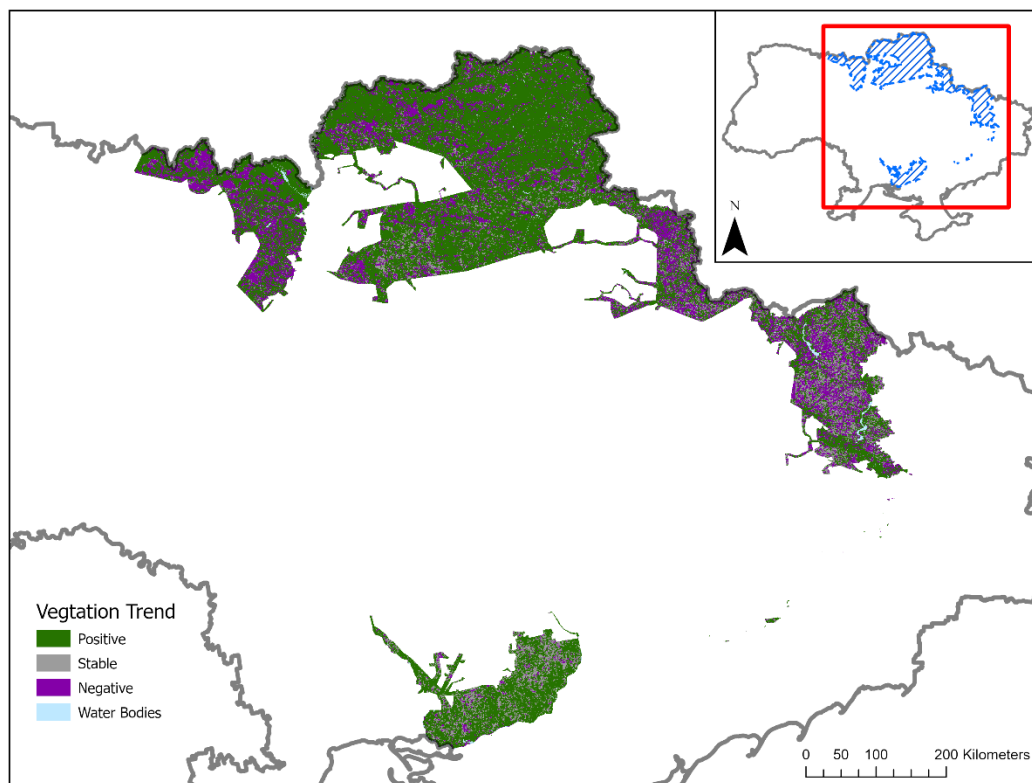


Figure 3-9: BFAST Vegetation Trends Within Ukrainian Counteroffensive Areas - the spatial distribution of positive, stable, and negative vegetation trends identified using the BFAST (Breaks For Additive Season and Trend) method within areas affected by Ukrainian counteroffensive operations. Data are derived from MOD13Q1 NDVI time-series imagery (2001–2023) and overlaid with delineated counteroffensive boundaries. This matters because it assesses whether reclaimed or contested territories exhibit distinct vegetation change patterns associated with conflict dynamics.

To examine spatial patterns of vegetation, change in relation to the conflict, the boundaries of Ukrainian counteroffensives and areas under Russian control were delineated and compared with BFAST trend results. Across the study area, 66% of cells exhibited positive trends, 12% remained stable, and 22% showed negative trends. Negative trend cells were primarily concentrated in the northwest near the active front line and closer to Russian-controlled territory, whereas many positive trend cells were located along Ukraine’s northern border and in parts of southern Ukraine. The spatial distribution of structural breaks (Figure 3-10) indicates a high frequency of breaks in southern Ukraine and relatively few in the north. Because much of

Ukraine is dominated by cropland, these patterns are likely influenced by seasonal agricultural dynamics, including planting and harvesting cycles, which naturally generate frequent vegetation change. Within the Ukrainian counteroffensive boundaries, approximately 3,572,533 hectares of cropland were identified, representing 49.8% of the total cropland in these areas, suggesting that a substantial portion of the observed vegetation change reflects agricultural processes and cyclical crop growth rather than conflict-related disturbance alone.

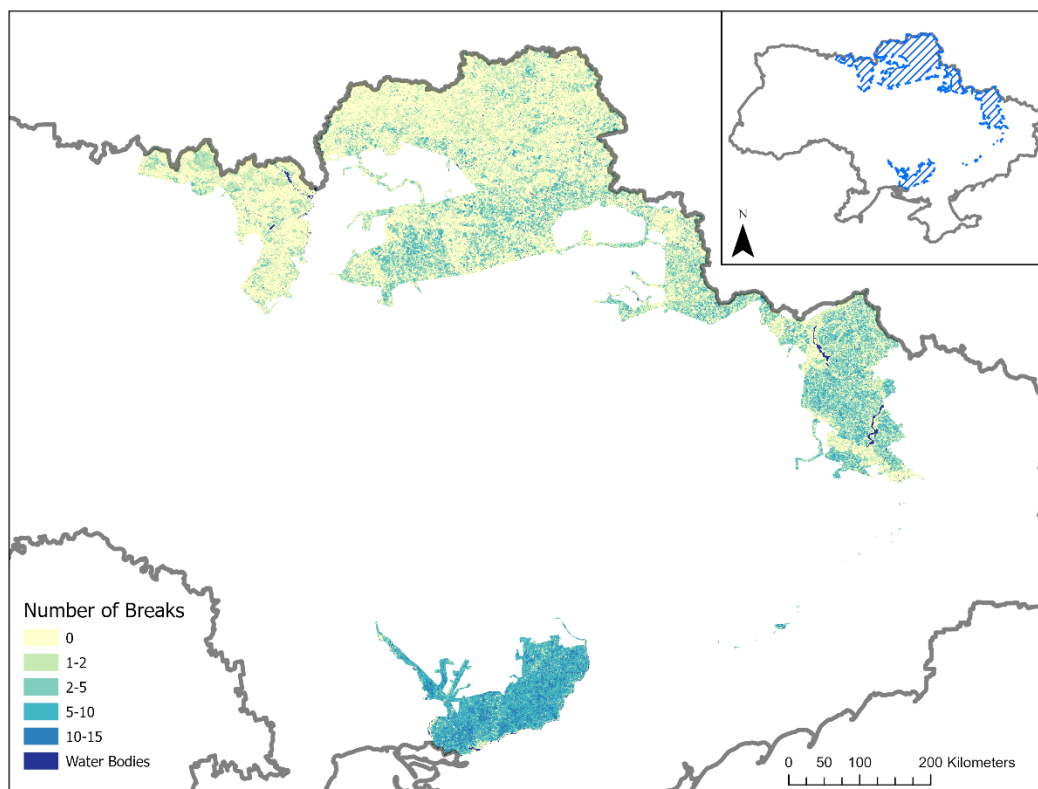


Figure 3-10: Number of BFAST Structural Breaks Within Ukrainian Counteroffensive Areas - the spatial distribution of the number of structural breaks detected in the vegetation time series using the BFAST (Breaks For Additive Season and Trend) method within areas affected by Ukrainian counteroffensive operations. Data are derived from MOD13Q1 NDVI imagery (2001–2023) and overlaid with delineated counteroffensive boundaries. This matters analytically because it identifies repeated or abrupt vegetation disturbances in territories experiencing shifts in military control.

Trend from Russia Occupied Areas

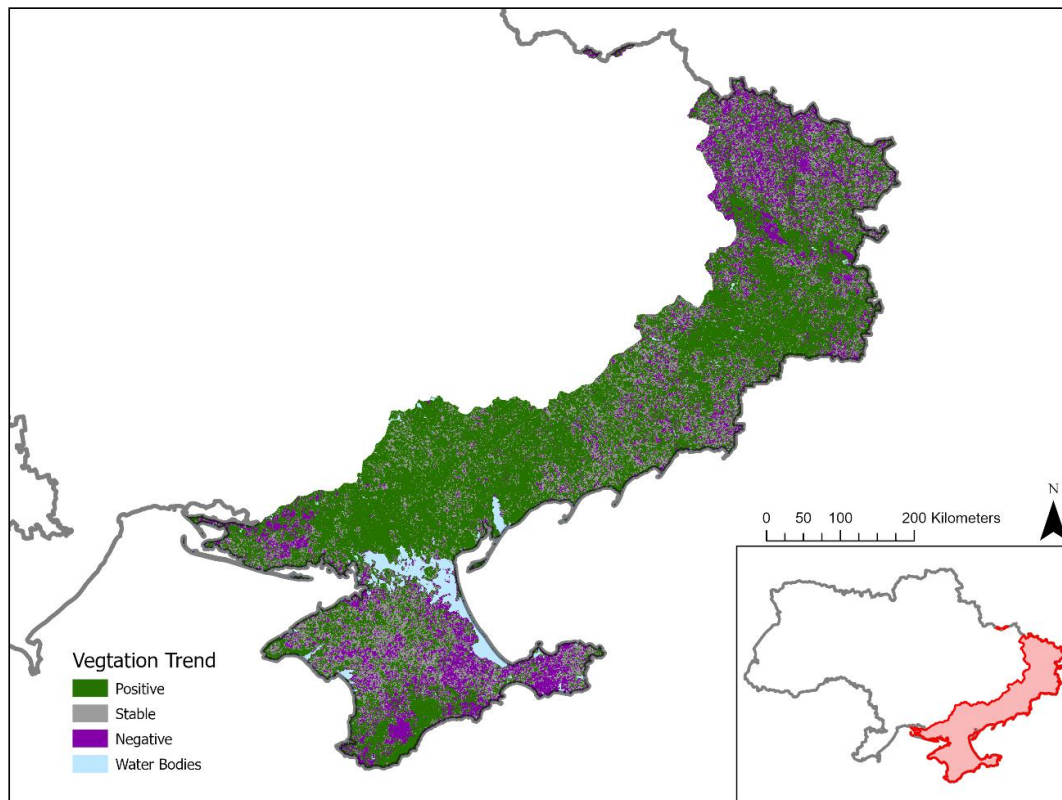


Figure 3-11: BFAST Vegetation Trends Within Russian-Occupied Areas - the spatial distribution of positive, stable, and negative vegetation trends identified using the BFAST (Breaks For Additive Season and Trend) method within Russian-occupied territories. Data are derived from MOD13Q1 NDVI time-series imagery (2001–2023) and overlaid with mapped Russian control boundaries. This matters because it evaluates whether sustained occupation is associated with distinct patterns of vegetation change.

Within the Russian-occupied areas, the spatial distribution of vegetation trend cells exhibits a bifurcated pattern. The northern and southern portions of the boundary contain a higher concentration of negative trend cells, while the central portion is dominated by positive trend cells. Overall, 59% of cells show positive trends, 22% remain stable, and 19% exhibit negative trends. The distribution of structural breaks (Figure 3-12) mirrors patterns observed in the Ukrainian counteroffensive areas, with a greater frequency of breaks occurring in the southern portion of the boundary and relatively fewer in the north. Although the underlying drivers of this north–south contrast are not entirely clear, land cover composition likely plays a significant role. Cropland accounts for approximately 6,663,241 hectares, representing 59.8% of land cover

within Russian-controlled areas. Given the dominance of agricultural land, the high number of breaks and prevalence of positive trends likely reflect seasonal crop dynamics and agricultural activity rather than solely conflict-related disturbance.

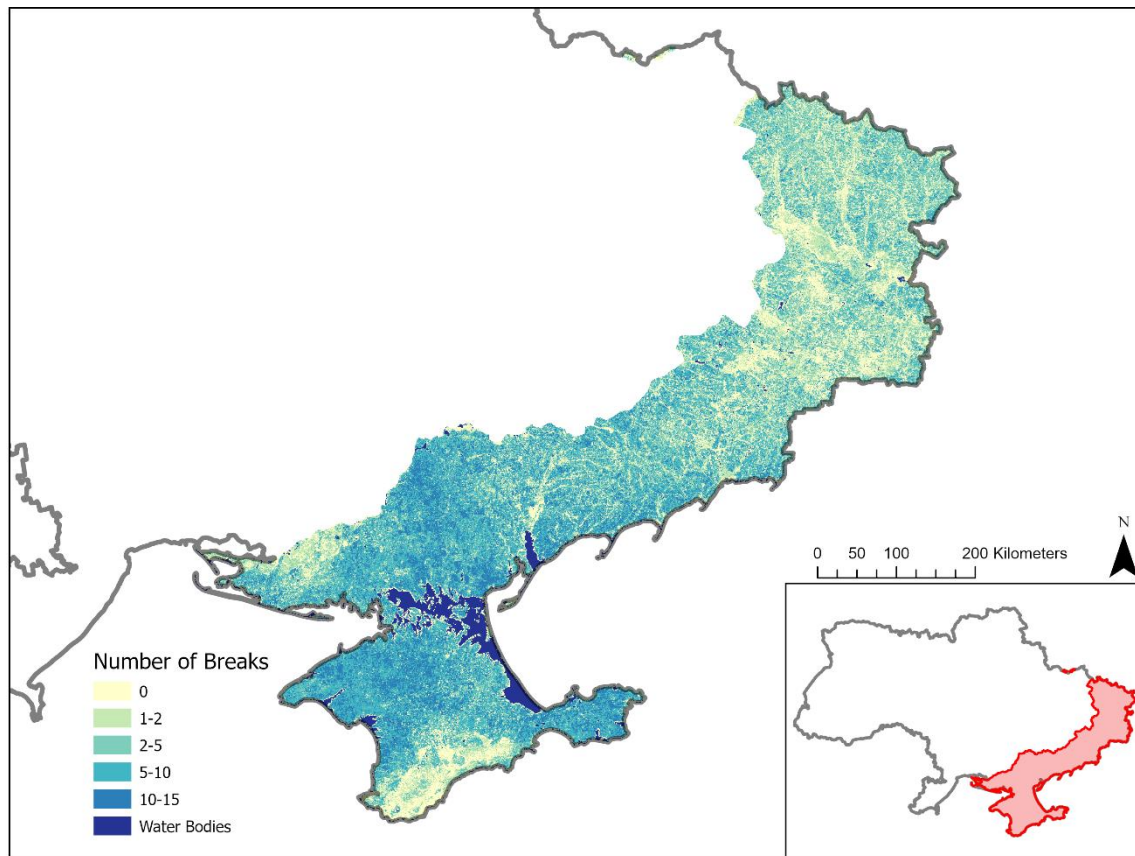


Figure 3-12: Number of BFAST Structural Breaks Within Russian-Occupied Areas - the spatial distribution of the number of structural breaks detected in the vegetation time series using the BFAST (Breaks For Additive Season and Trend) method within Russian-occupied territories. Data are derived from MOD13Q1 NDVI imagery (2001–2023) and overlaid with mapped Russian control boundaries. This matters analytically because it identifies repeated or abrupt vegetation disturbances associated with prolonged military occupation.

Conclusion

This study applied remotely sensed vegetation indices to conduct a long-term time-series analysis of vegetation dynamics in Ukraine using the BFAST methodology. The BFAST approach enabled classification of pixels into positive, stable, and negative trends, as well as quantification of structural breaks ranging from 0 to 15 per pixel. These outputs provide a systematic assessment of long-term vegetation trajectories and the frequency of abrupt changes across the country. However, a key limitation of the BFAST framework is its inability to directly attribute observed trends or breaks to specific causal mechanisms. While the method effectively detects where and when vegetation change occurs, it does not determine whether these changes are driven by conflict-related disturbances, agricultural practices, climatic variability, or other environmental processes.

Distinguishing among potential drivers—such as cratering, fire, soil compaction, deposition, or seasonal agricultural cycles—would substantially improve interpretation of the detected vegetation patterns. For example, the presence of numerous positive trend cells near active front lines raises important questions about the underlying processes responsible for these changes. Given the widespread distribution of both agricultural activity and military operations across Ukraine, separating anthropogenic land management effects from conflict-related impacts remains challenging without detailed ground validation or higher-resolution ancillary data.

Overall, this research provides a comprehensive examination of interannual EVI trends and structural breaks over a twenty-two-year period, highlighting the spatial and temporal complexity of vegetation change in Ukraine. The findings demonstrate that substantial variability in greenness and disturbance frequency has occurred throughout the study period. Future research should focus on integrating additional datasets—such as higher-resolution imagery, field

observations, or documented disturbance records—to better attribute detected changes to specific drivers and to evaluate whether these disturbances result in long-term degradation, recovery, or neutral ecological outcomes.

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Chapter 4 - Spatial Bayesian Modeling of Explosion Intensity and Vegetation Change during the Russia-Ukraine War

Introduction

On February 22, 2022, Russia declared war on Ukraine, triggering a large-scale invasion that has generated severe humanitarian, economic, and environmental consequences. While human suffering and infrastructure destruction have rightly drawn global attention, the environmental impacts of warfare are often under-appreciated (Leal Filho et al., 2024). Ukraine and Russia together form the “breadbasket of Europe,” serving as major producers of wheat, barley, corn, sunflower seed, and soybeans (Pereira et al., 2022). Prolonged military activity now threatens these agricultural systems and the broader environment through damage to soil, water, air quality, and wildlife (Hutchinson et al., 2015). Military operations in the Russo-Ukrainian War include artillery and drone strikes, improvised explosive devices (IEDs), vehicle-based maneuvers, indirect fire weapons, armed clashes, fires, flooding used as a weapon, and the construction of military infrastructure such as bunkers (Hutchinson et al., 2015; Pereira et al., 2022). Among these, artillery strikes, drone strikes, and IEDs are most strongly associated with soil contamination from heavy metals and explosive residues such as TNT and RDX, as well as with vegetation damage and habitat disruption. These explosions have also caused widespread destruction of roads, schools, hospitals, and power plants, further degrading Ukraine’s environmental economy and ecological stability.

To systematically examine these impacts, this study uses conflict event data from the Armed Conflict Location & Event Data (ACLED) project, which records the locations of artillery strikes, drone strikes, IEDs, armed clashes, and violence against civilians. The dataset spans January 1, 2018, to December 31, 2023. The primary objectives of this research are twofold: (1)

to model the spatial intensity of explosion events across Ukraine and (2) to assess whether these explosive events are statistically associated with changes in vegetation patterns and trends.

Explosion intensity is modeled using Integrated Nested Laplace Approximation (INLA), a Bayesian inference framework for latent Gaussian Markov random field (GMRF) models (Rue et al., 2009). INLA provides fast and accurate approximations to posterior distributions and offers substantial computational advantages over traditional simulation-based methods such as Markov Chain Monte Carlo (MCMC) (Illian et al., 2012). INLA has been widely applied in disease mapping (Adegboye et al., 2021; Asmarian et al., 2019; Sahoo et al., 2024), ecological modeling (Carson et al., 2014; Koh et al., 2023; Law et al., 2009; Martínez-Minaya et al., 2018; Valente et al., 2020), and spatial point process analysis (Illian et al., 2013). Implemented through the R-INLA package, the framework enables efficient Bayesian analysis without posterior sampling methods such as Metropolis-Hastings or Hamiltonian Monte Carlo (Carroll et al., 2015). By integrating ACLED explosion data with vegetation indicators and Bayesian spatial modeling, this study aims to support Ukraine in identifying vegetation-related environmental impacts of warfare and locating areas of elevated ecological risk. Such insights may contribute to post-conflict environmental assessment, land restoration planning, and long-term ecological monitoring.

This report is organized as follows. First, the data sources, Bayesian modeling framework, and generalized additive model are described. Next, the results and spatial prediction maps of explosion intensity and vegetation change variables are presented. Finally, the findings are discussed and evaluated.

Material & Methods

Study Area

Ukraine is located in Eastern Europe, centered approximately at 49.0° N latitude and 32.0° E longitude. It shares borders with Belarus, Russia, Moldova, Romania, Hungary, Slovakia, and Poland, with coastlines along the Black Sea and the Sea of Azov. Covering approximately 603,500 km², Ukraine is the largest country entirely within Europe. The study area encompasses Ukraine's diverse physical landscape, including both lowland and upland regions across the country.

Ukraine's topography consists primarily of plains, with alternating belts of uplands, depressions, and lowlands extending generally from east to west. The Carpathian Mountains dominate the western portion of the country, where the highest elevation, Mount Hoverla, reaches 2,061 m above sea level. In contrast, much of eastern and central Ukraine is characterized by broad lowland plains. To the south, the Crimean Peninsula contains the Crimean Mountains and additional upland areas. Major river systems, including the Danube River, Dnipro River, and Dniester River, traverse the country and play critical roles in hydrology, agriculture, and settlement patterns. Ukraine has a mean elevation of approximately 175 m, with its lowest point at sea level along the Black Sea coast.

Ukraine experiences a predominantly temperate continental climate, with the exception of the southern coast of Crimea, which exhibits subtropical Mediterranean characteristics. Summers (May–August) are typically warm and moderately wet, with mean temperatures ranging from 18°C to 22°C. Winters (December–March) are cold and wet, with mean temperatures ranging from −4.8°C to 2°C. Precipitation varies spatially and seasonally, influenced by topography and atmospheric circulation patterns.

Ukraine is widely recognized for its fertile chernozem soils, which are among the most productive agricultural soils in the world. These soils are characterized by a thick, dark surface horizon rich in organic matter and high water-holding capacity, often exceeding 150 mm. The presence of chernozems supports extensive agricultural production. Prior to the 2022 invasion by Russia, Ukraine was a major global agricultural exporter, ranking among the top producers and exporters of wheat, maize, barley, and sunflower. The ongoing conflict has significantly disrupted Ukraine's agricultural sector, with implications for both national production and global food security.

ACLED Data

The Armed Conflict Location & Event Data (ACLED) organization has curated data from the conflict in Ukraine starting on January 1st, 2018, to its most recent update. The ACLED data shows when the event took place, what type of event took place, who were the actors in the event, and the location of where the event occurred. This event data does not give exact locations of where events have happened. Instead, it gives the coordinates to be georeferenced to the largest populated city if it has a geoprecision of 1. A geoprecision of 2 means that the event took place in a small region of the country and a town is named, then it gives the coordinates to be georeferenced to that town. For research purposes, sub-events that include Air/drone strikes, Shelling/artillery/missile attacks, and Remote Explosive/landmine/IED with a geoprecision of 1 and 2 will be used.

Explosion Model

To predict explosion intensity, count the following Bayesian statistical model was proposed. The equation for the model is:

Data Model:

$$y(s) \sim \text{Pois}(\lambda(s)),$$

where $y(s)$ is the observed number of explosions at location “s” (tile number)

Process Model:

$$\lambda(s) = e^{z(s)},$$

$$z(s) = \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + f(\text{SPRE}),$$

$$f(\text{SPRE}) \sim \text{GRF} (0, \sigma^2 \text{Rv} (|s - s'|; p)),$$

where $\lambda(s)$ is the expected explosion intensity, X_1 is the distance to roads, X_2 is the distance to the Front Line of the war, X_3 is the distance to power plants, X_4 is the distance to hospitals, X_5 is the distance to railroads, X_6 is the population to the nearest town, $f(\text{SPRE})$ is the spatial random effect which uses a Gaussian Random field (GRF) and a Matern (Rv) correlation function that depends on the distance between explosions ($s - s'$) and a range parameter (p).

Priors:

$$[p] = (p < 5000) = 0.07$$

$$[\sigma] = (\sigma > 1) = 0.01$$

Where p is the range parameter that shows that there is a 7% chance that the range is less than 5000 meters or 5 kilometers, σ is the marginal standard deviation that shows that there is only 1% chance that σ exceeds 0.01.

The data is modeled in INLA. The spatial random effect is modeled using the Stochastic Partial Differential Equations (SPDE) method that allows us to create the Gaussian Random effect (Lindgren et al., 2011). The SPDE uses our priors $[p]$ and $[\sigma]$ to help construct the spatial random effect. For the SPDE to work, a mesh is required. The mesh is essentially a boundary with a lot of nodes that come from the explosion points. The SPDE is used in the model formula

to model unmeasured spatial variation, that was not spatially collected from the covariates. The data is modeled in R using the INLA package (Rue et al., 2009).

For INLA to computationally work properly, the observed covariate values are scaled. Covariate values, distance to roads, distance to front line, distance to power plants, distance to railroads, and distance to hospitals have been scaled by dividing the distance of the covariate value by its mean covariate value. Population data were obtained from WorldPop, which estimates population counts using satellite-derived nighttime light intensity and ancillary spatial covariates to predict the number of people residing in each location (www.worldpop.org).

The predicted covariate values are needed in our prediction stack. The prediction stack uses the centroid of every cell in our study area and puts a predicted value in it. The grid for the prediction stack looks like this. Raster images were created for each covariate besides population using the Euclidean Distance tool in ArcGIS Pro. Figure 4-1 shows the raster layers that were used in the prediction stack.

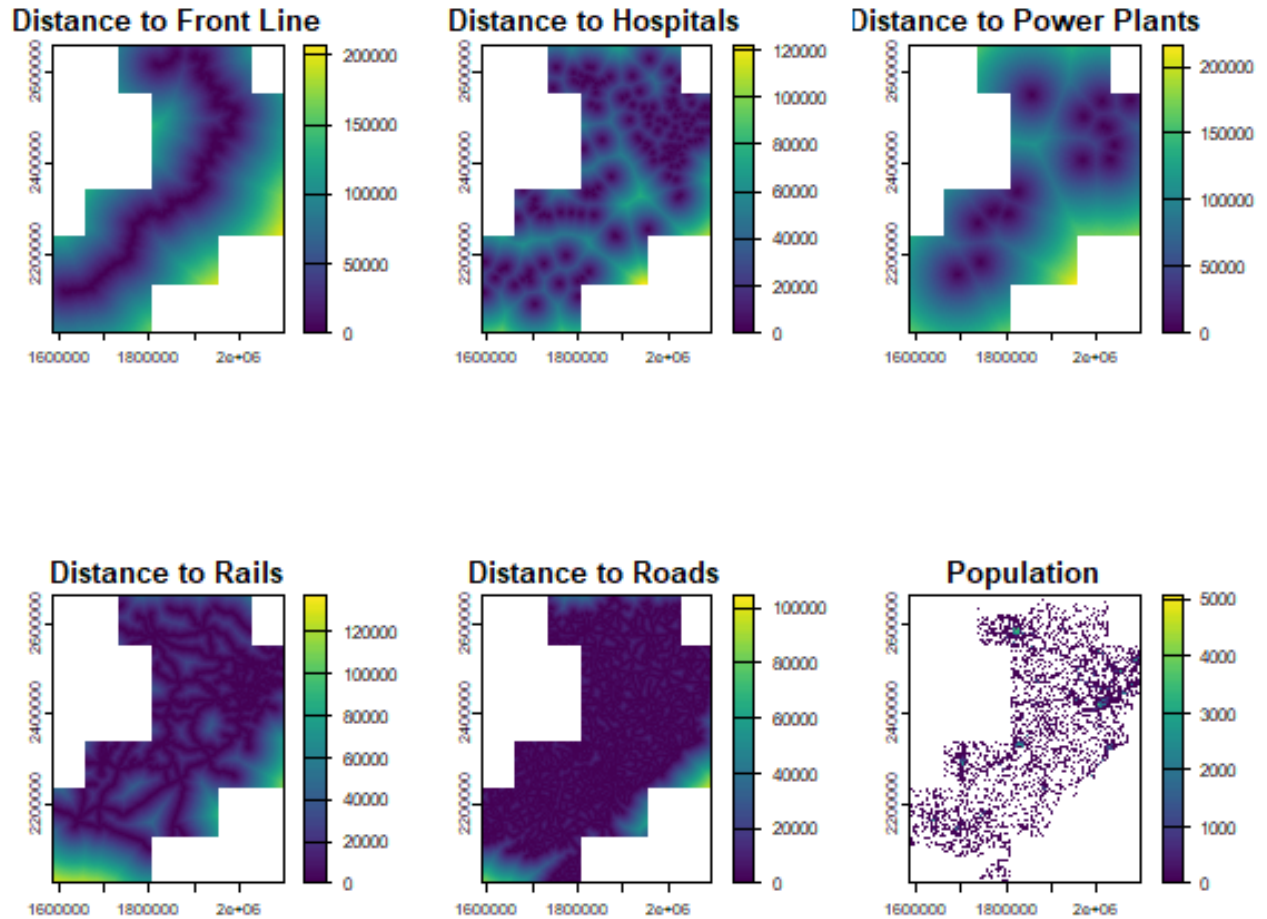


Figure 4-1: Spatial Covariate Raster Layers Used in the Explosion Model - Six raster layers covering the study area (coordinates in meters, projected CRS). Each cell value represents the relevant distance or counts for that grid location, enabling pixel-level covariate extraction for model training and prediction.

The INLA function in R reads in our $z(s)$ formula with the covariates and the spatial random field and applies the Poisson distribution to it. In the function, empirical bayes is used for the integration strategy. After running the INLA function, predictions are created using the mean from the posterior distribution. The mean from the posterior distribution is then exponentiation to get the predicted explosion intensity count. These values are used to create maps to help visualize and describe our results.

Vegetation Change Model

To see if the ACLED curated data is influencing the BFAST analysis slope a statistical model was proposed. The equation for the model is:

$$y_{ij} \sim N(\mu_{ij}, \sigma^2),$$
$$\mu_{ij} = f(s_i) + \beta_1 x_{1i} + \beta_2 x_{2i} + \beta_3 x_{3i} + H_j + \beta_4 x_{4i}$$

Where y_i is the BFAST slope for the i th tile, s_i are the coordinates of the i th tile and j th hydrologic soil group, $f(\cdot)$ is the spline (spatial effect), x_{1i} is the predicted explosion intensity shown in Figure 4-2, x_{2i} is the annual temperature (°C) for the time period (2018-2023), x_{3i} is the cumulative precipitation (mm) for the time period (2018-2023), H_j is the effect of the j th classification of hydrologic soil group for the study area, x_{4i} is the number of breaks happening from the BFAST analysis.

To show the spatial variability across Ukraine, a spline was used to show the change of high and low levels of space. A spline is a function where adjacent pieces are joined by knots, and smooth functional pieces to fit the data between the knots (A Review of Spline Function Procedures in R, 2019). The spline is calculated by using the X and Y coordinates for each point in the tile, uses

the thin plate spline method, and has a k value of 75. The “k” value was selected for the basis function dimension of 75 for the spatial thin-plate spline based on model diagnostics that indicated that was an adequate basis dimension, without unnecessary over-parameterization (see chapter 7 in Wood, 2017). The spline takes into account that every pixel has a different value whether it is in areas of high or low space. The higher the basis function dimension the more detailed the areas of high and low space will get. All the other variables in the model are seeing if they influence the calculated BFAST slope from the BFAST results. The data is modeled in R

using the bam function from the “mgcv” R package (Wood, 2023). The results table will have X and Y coordinates for each pixel, a density value per cell area for each type of explosion, and the results from the BFAST analysis. The basis function dimension (i.e., k) is checked using the gam.check function from the mgcv package. Gam.check uses the k-index to measure whether the k is large enough to recover the spatial patterns in the data. If the k-index is close to one, then the “k” value is appropriate and shows detailed areas of high and low space.

Results

Explosion Model

From the Explosion Model, the posterior distribution of the mean predicted values was generated. Since the model follows Poisson Distribution the values range from 0-1. 1 meaning that the intensity count of the explosion is very strong, while 0 means the intensity count of the explosions is very weak. Figure 4-2 shows the predicted posterior distribution map that was predicted from the Explosion Model.

From Figure 4-2, it is suggested that green areas of the study area have a low predicted intensity count, while areas in orange and white are areas where the predicted intensity count is high based on the observational explosion points and the predicted covariate raster layers.

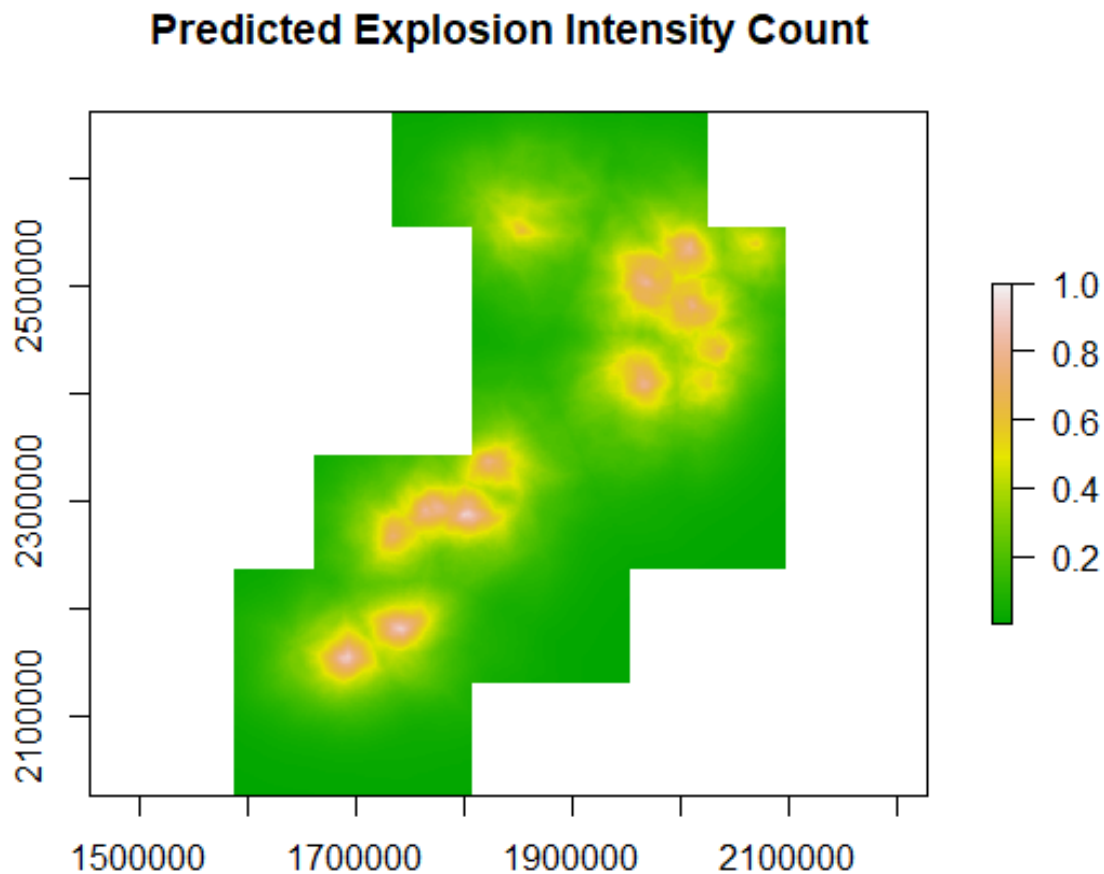


Figure 4-2: Predicted Explosion Intensity Count from INLA Poisson Model - the posterior mean predicted explosion intensity counts across the study area, with values ranging from low (green) to high (yellow–white) intensity. Data are derived from ACLED explosion event records and spatial covariates modeled using an INLA Poisson framework with an SPDE spatial random field (study period: 2018–2023). This matters analytically because it identifies spatial hotspots of conflict intensity used to evaluate relationships with vegetation change and environmental degradation.

Explosion Model Coefficients

The fixed variables (the covariates) indicate whether the variables are influencing the intensity of the predicted values. A 95% confidence interval is used to show where the values are likely to

been within that range of numbers. Table 1 shows the fixed variables coefficients as well as the 95% confidence interval for each variable.

Fixed Variables	Mean	Confidence Interval
Distance to Road	-9.27E-06	(-0.124, 0.0124)
Distance to Frontline	-6.48E-06	(-0.007, 0.007)
Distance to Railroads	-1.04E-05	(-0.006, 0.006)
Distance to Hospitals	-1.26E-06	(-0.0104, 0.0104)
Distance to Powerplants	-1.95E-05	(-0.0127, 0.0127)
Population	-7.25E-07	(-0.00328, 0.00328)

Table 4-1: Posterior Distribution of Mean Predicted Explosion Intensity Values - the summary statistics of the posterior distribution of mean predicted explosion intensity values derived from the Poisson-based Explosion Model. Data are based on ACLED explosion event records and associated spatial covariates for the study period (2018–2023). This matters because it quantifies the central tendency and uncertainty of modeled conflict intensity used in subsequent environmental analyses.

Table 4-1 summarizes the posterior distribution of mean predicted values from the Explosion Model, which is based on a Poisson modeling framework. Predicted values are scaled between 0 and 1 to represent relative explosion intensity, where values closer to 1 indicate areas of higher predicted explosion counts and values near 0 represent lower predicted intensity. The table presents the mean estimates and confidence intervals for each predictor variable included in the model. Although the confidence intervals for all variables cross zero—indicating that the effects are not statistically significant at conventional levels—the results still provide useful information about the direction and relative magnitude of potential relationships. The small coefficient values suggest that factors such as distance to roads, railroads, hospitals, powerplants, and local population density may have weak influences on explosion intensity within this dataset. These findings contribute to understanding overall model behavior and help identify which variables appear to have limited explanatory power, even if they do not reach formal statistical significance.

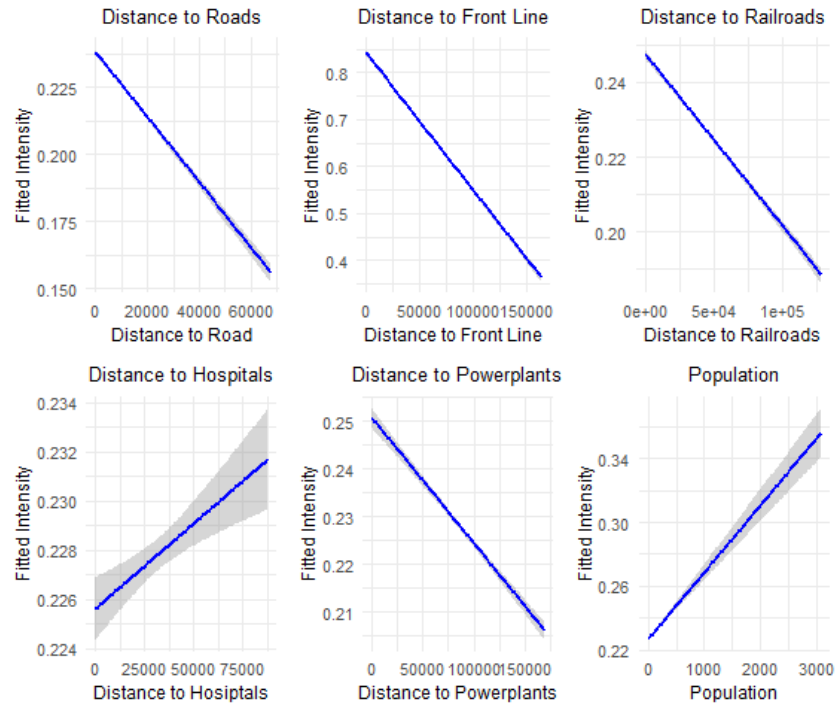


Figure 4-3: Marginal Effects of Covariates on Predicted Explosion Intensity - the fitted marginal effects of key covariates: distance to roads, distance to the front line, distance to railroads, distance to hospitals, distance to powerplants, and population on predicted explosion intensity from the Poisson INLA model. Data are derived from ACLED explosion event records and associated spatial covariates for the study period (2018–2023). This matters analytically because it illustrates how infrastructural proximity and population density influence modeled explosion intensity.

Figure 4-3 illustrates the modeled relationships between explosion intensity and several spatial covariates derived from the fitted statistical model. A consistent negative association is observed between fitted intensity and distance to key infrastructure features, including roads, the front line, railroads, and power plants, indicating that explosions are more likely to occur closer to these strategic or logistical targets. The steep decline in intensity with increasing distance to the front line suggests that conflict activity is strongly concentrated near active combat zones. In contrast, distance to hospitals shows a positive relationship, implying that explosions tend to occur farther away from medical facilities, potentially reflecting efforts to avoid critical civilian infrastructure. Population exhibits a clear positive relationship with fitted intensity, demonstrating that more densely populated areas experience higher modeled explosion intensity, likely due to their greater strategic importance and infrastructure density. Overall, these patterns align with

expectations that military activity is spatially structured around accessibility, tactical value, and human presence.

Explosion Model Hyperparameters

The spatial correlation between the explosion points is explained by the priors in the Explosion Model. The priors $[p]$ and $[\sigma]$ represent the range parameter and the marginal standard deviation.

The range parameter can tell us when the spatial correlation between explosions points has become negligible. Table 2 will show you when the spatial correlation becomes negligible and a 95% confidence interval of where spatial correlation could become negligible.

Hyperparameters	Mean	Confidence Interval
Range for Spatial Field	44572	(2171.67, 262271)
St.Dev for Spatial Field	0.0034	(0.00046, 0.0099)

Table 4-2: Explosion Model Hyperparameters - the posterior summaries of hyperparameters from the Poisson-based Explosion Model, including parameters associated with the spatial random field (SPDE) and precision terms. Data are derived from ACLED explosion event records and associated spatial covariates modeled using INLA for the study period (2018–2023). This matters because it characterizes spatial dependence and uncertainty underlying the modeled explosion intensity surface.

The range for the spatial effect has a meaning of 44,572 meaning that the spatial correlation becomes negligible beyond around 45,000 meters or 45 km. The confidence interval for the range parameter is very large showing that spatial correlation could become negligible at 2 km or 262 km. This wide confidence interval shows that there is wide uncertainty of the extent of spatial correlation. The standard deviation of the spatial field is telling us about the magnitude of the spatial variation happening in the Explosion Model. In other words, the standard deviation is telling us how much of the intensity of events varies across locations, after accounting for the covariates. The mean of the standard deviation is 0.003, which causes the spatial effect to either increase or decrease the intensity by 0.003. The 95% confidence interval shows that the spatial

effect can be increased or decreased from a range of 0.0004 to 0.0099. To visualize the range parameter, Figure 4-4 shows the marginal posterior distribution of the range parameter.

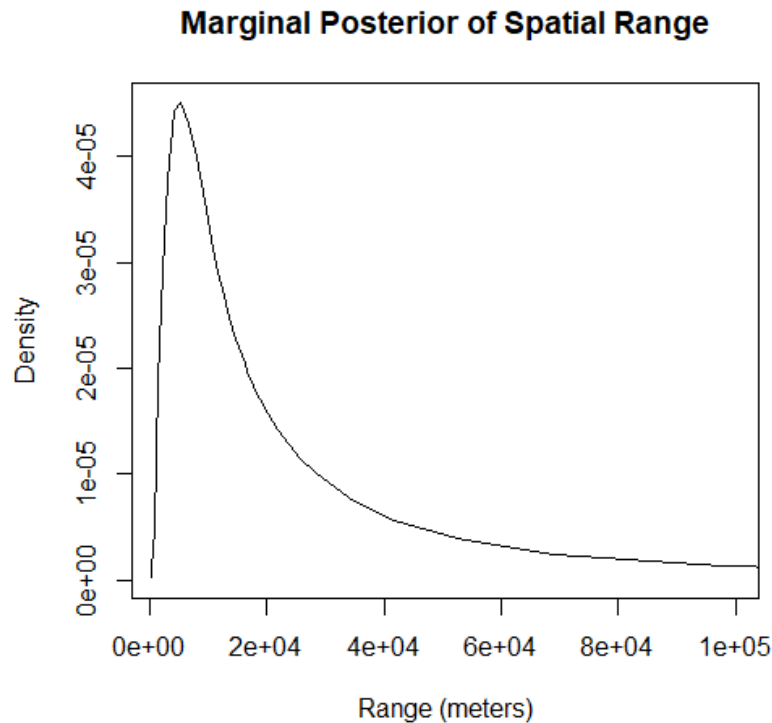


Figure 4-4: Marginal Posterior Distribution of Spatial Range Parameter - the marginal posterior distribution of the spatial range parameter from the SPDE component of the Poisson Explosion Model, expressed in meters. Data are derived from ACLED explosion event records and associated spatial covariates modeled using INLA for the study period (2018–2023). This matters analytically because the spatial range parameter quantifies the scale at which explosion events exhibit spatial dependence.

Figure 4 shows the extent of which spatial correlation is happening in the Explosion Model. The x-axis shows the spatial range of the spatial correlation, and the y-axis shows the posterior density of the values in the model. The peak of the curve is at 10,000 meters or 10 km. Showing that most of the values in the model are correlated with each other at distances of 10 km. The curve distribution is right-skewed and has a long tail, suggesting that the data is uncertain, and the model does not know what the exact spatial correlation distance is.

Vegetation Change Model

Difference between “K” values

In the spline function, knots or “k” are important pieces where data is being joined and smoothed together. In the model, the number of knots is important to how detailed the areas of high and low levels of space are going to be. The basis function dimension influences the estimated coefficients and the significance of the variable on the slope. Figure 4 and 5 shows the difference between “k” values for the study area.

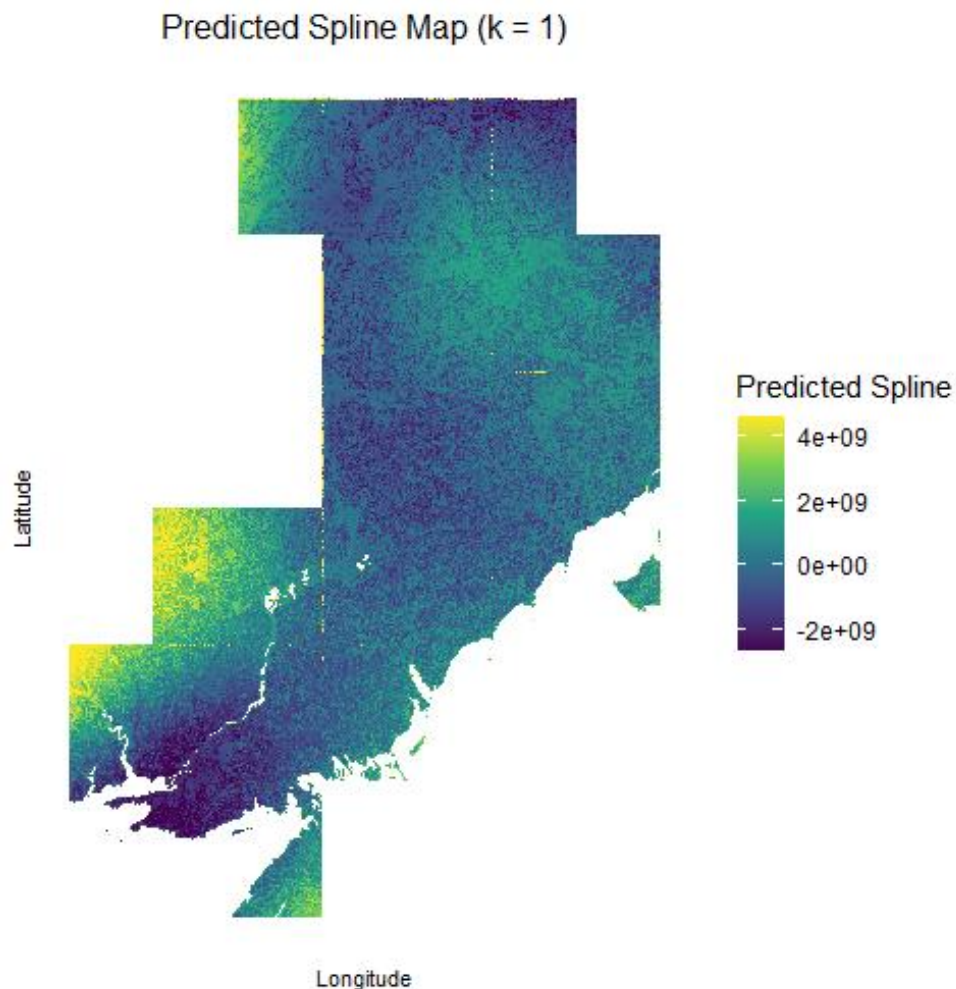


Figure 4-5: Predicted Spatial Spline Surface ($k = 1$) - the predicted spatial spline surface ($k = 1$) representing the smooth spatial effect estimated in the model across the study area. Data are derived from the fitted spatial model using explosion event records and associated covariates (study period: 2018–2023). This matters because it visualizes the underlying spatial structure not explained by observed covariates.

Figure 4-5 shows that when $k = 1$ the spline is smooth and pixels neighboring one other tend to follow their neighboring pixels. The spline is not incredibly detailed and lacks correct predictions in high and low areas of space. When $k = 75$ (Figure 4-6), the spline is more detailed and robust. The spline provides the model with correct predictions of spatial variability. A higher k value in the spline function allows for the model to capture more areas of high and low levels of space in every tile. A K-index is provided to show if the k -value accounts for all areas of space. The K-index for the vegetation change model (Table 4-3) was 0.91. This is an optimal k -index value because it is close to one.

Predicted Spline Map

Predicted Splines were calculated using the predict function in R. The predicted spline shows the spatial variability of high and low levels of space throughout each tile.

From Figure 4-5 and 4-6, the predicted splines are shown for eastern Ukraine. Areas of high levels of space are represented by yellow and green, and areas of low levels of space are represented by darker blue.

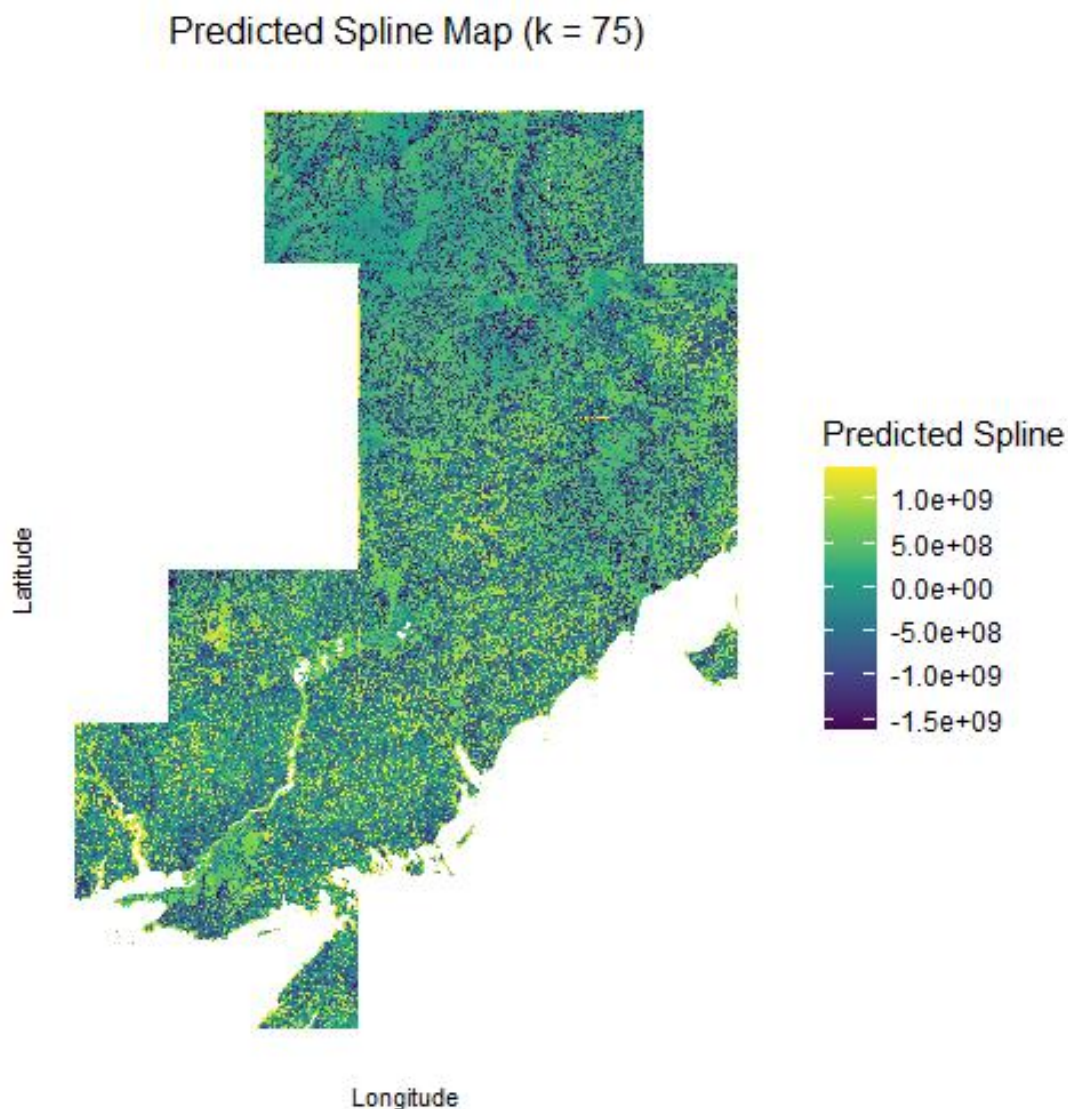


Figure 4-6: Predicted Spatial Spline Surface (k = 75) - the predicted spatial spline surface (k = 75), representing a higher-complexity smooth spatial effect estimated across the study area. Data are derived from the fitted spatial model using explosion event records and associated covariates (study period: 2022–2024, if applicable). This matters analytically because it illustrates how increasing spline flexibility captures finer-scale spatial variation in explosion intensity.

Model Coefficients & Confidence Intervals

The model estimate coefficient indicates whether the variables are affecting the response and whether they are significant or not. A 95% confidence interval is used to show where point estimates are likely to be located between a range of numbers. Table 2 shows the estimated coefficients, as well as the 95% confidence interval.

Variables	Point Estimate	Confidence Interval
Number of Breaks	-5.56E+11	(-5.556E11, -5.562E11)
Explosion Intensity	-3.12E+04	(-2.963E04, -3.275E04)
Temperature	-1.35E+10	(-1.347E10, -1.348E10)
Precipitation	-1.54E+06	(-1.306E06, -1.768E06)
Hydrologic Soil Group B	3.15E+08	(3.111E08, 3.185E08)
Hydrologic Soil Group D	3.28E+08	(3.244E08, 3.318E08)

Table 4-3: Model Coefficients for the Vegetation Change Model - the estimated regression coefficients, uncertainty measures (e.g., standard errors or credible intervals), and significance metrics for covariates included in the vegetation change model. Data are derived from BFAST-derived vegetation trend classifications combined with explosion intensity predictions and associated landscape covariates. This matters because it quantifies the statistical relationship between conflict intensity and observed vegetation change.

The sign in front of the point estimate shows whether the effect from the predictors was positive or negative in the response. From the model, the BFAST slope is affected negatively from the number of breaks occurring throughout the time series, the explosion intensity from the explosion model previous stated in this paper, annual average temperature, and cumulative precipitation. Hydrologic soil groups B and D were shown to be positively affecting the BFAST slope. All the variables in the model were statistically significant from their p-value from the model summary.

Discussion

The primary objective of this project was twofold: first, to develop a predicted explosion intensity count map for Ukraine to support a vegetation change model, and second, to assess whether explosive events are statistically influencing vegetation trends. Together, these components provide an integrated framework for understanding how armed conflict may affect environmental dynamics.

A point pattern analysis using a Poisson model was conducted to estimate explosion intensity counts for Ukraine from 2018–2023. The model incorporated covariates including distance to

roads, front lines, hospitals, railroads, and power plants, as well as the population of the nearest city. A spatial random effect was included using a stochastic partial differential equation (SPDE) with a Matérn covariance function to account for spatial autocorrelation. Model results indicate that explosion intensity increases as proximity to these covariates decreases and as nearby population increases. This aligns with expectations, as explosions are more likely to occur near infrastructure and densely populated areas. Coefficient estimates further confirm that intensity decreases with increasing distance from these features. Overall, the explosion model provides a realistic and spatially coherent representation of explosion intensity across Ukraine, supporting its use as an input to the vegetation change analysis.

Spatial dependence among explosion points played a critical role in model performance. Results suggest that explosions are spatially correlated within approximately 10 km, beyond which events are effectively independent. This spatial scale is plausible given the potential damage radius of explosive events and the tendency for clustered conflict activity. Explosions occurring closer together tend to exhibit higher intensities, reinforcing the importance of explicitly modeling spatial correlation when predicting conflict intensity surfaces.

The predicted explosion intensity map was subsequently used to support a vegetation change analysis based on the Breaks for Additive Season and Trend (BFAST). The BFAST method decomposed vegetation time series (2018–2023) into trend, seasonal, and remainder components, categorizing pixel-level trends as positive, stable, or negative. Tiles located closer to the front line exhibited higher counts of positive-trend pixels. While negative trends might be expected near conflict zones, the observed positive trends may reflect a prescribed burning or post-disturbance regrowth effect, in which vegetation rebounds following fire damage. Given that much of Ukraine consists of cropland, positive trends may also be influenced by favorable

precipitation conditions that enhance vegetation greenness. Conversely, negative trends may reflect direct vegetation destruction from explosions, reduced precipitation combined with rising temperatures, or agricultural harvesting cycles. These results highlight the difficulty of attributing vegetation change to a single causal factor, as vegetation dynamics operate across multiple interacting environmental and anthropogenic scales.

To statistically link explosive activity with vegetation trends, the vegetation change model was used to assess whether the selected variables influence BFAST slopes. The primary drivers of negative trends include the number of breaks, temperature, precipitation, and explosion intensity derived from the explosion model. Among these, the number of breaks is the strongest driver, as it has the largest magnitude of all model variables. This is followed by temperature and precipitation, both of which are associated with decreased trends. Explosion intensity also contributes to negative trends, although its effect is smaller due to its lower magnitude. In contrast, Hydrologic Soil Groups B and D exhibit a positive effect on vegetation trends, which may be attributed to their influence on soil moisture dynamics.

The spline term was included to capture spatial variability across regions with differing levels of conflict intensity and environmental change. It also accounts for temperature and precipitation, as those point estimates only change significantly when the value of “k” is adjusted.

Several limitations and avenues for refinement remain. The predicted explosion intensity map may need a change-of-support validation approach, such as Simpson’s rule, could be used to compare expected explosion counts from the predicted intensity surface with observed counts, providing a quantitative assessment of model accuracy.

In the spline-based vegetation model, a k-value of 75 was selected to reduce computational burden. However, the number of knots strongly influences point estimates and overall model

behavior. Finding the correct k-value in future work is a priority to bring the k-index closer to one and to produce a more detailed and robust spline representation of spatial variability. Future extensions could also incorporate Bayesian statistical principles more fully, allowing for coherent uncertainty propagation from explosion intensity estimation into vegetation trend modeling.

In summary, this project establishes a framework for integrating conflict intensity modeling with vegetation change analysis in Ukraine. The explosion model successfully captures spatial patterns of conflict intensity using infrastructure and population covariates, while the vegetation change model provides insight into complex vegetation responses during wartime. Although causal attribution remains challenging, the combined modeling approach offers a promising pathway for assessing how armed conflict may influence environmental change and sets the foundation for future refinement with additional environmental drivers and enhanced spatial modeling.

Conclusion

Presented in this research project were results from the Explosion Model and the vegetation change model, including an explanation of the model covariates, differences between “k” values, predicted splines, and the role of spatial hyperparameters in influencing the spatial correlation of explosions. Although the current analysis was limited to the eastern half of Ukraine, the long-term goal is to extend both the modeling framework and analyses to the entire country of Ukraine.

The vegetation change model remains a work in progress and requires further refinement to strengthen the spatial effect and incorporate additional environmental covariates, since vegetation change is driven by more than explosions and climatic variables. Despite these

limitations, this research represents a meaningful step forward in helping Ukraine analyze explosion intensity, vegetation change, and long-term trends. This research shows that the number of breaks, temperature, precipitation, and explosion intensity impact the BFAST slope, ultimately driving vegetation trends to decrease. This framework will be used to assess whether explosives are having a significant impact on vegetation dynamics across conflict-affected regions.

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Chapter 5 - Overall Synthesis

Previously stated, the aim of this research was to try an answer these questions: (1) How have vegetation trends across Ukraine changed, as detected throughout a BFAST time-series analysis? (2) What is the spatial distribution and intensity of explosion events, and which environmental and infrastructural factors best explain their occurrence? and (3) To what extent are negative vegetation trends statistically related to modeled explosion intensity and other landscape covariates? With the goal of providing a comprehensive assessment of the environmental impacts of the Russia–Ukraine War and contribute new methodological approaches for linking remotely sensed vegetation change with spatial patterns of armed conflict.

In Chapter 3 of this Thesis is “*Detecting Vegetation Change in Ukraine using Satellite Imagery and BFAST Analysis*” trying to answer the first question. This research demonstrates the long-term satellite time-series analysis using MODIS Enhanced Vegetation Index (EVI) and the BFAST (Breaks for Additive Season and Trend) method can effectively characterize broad patterns of vegetation change across Ukraine from 2001–2023. The results show that at the national scale, approximately 67% of Ukraine exhibited a positive vegetation trend over the study period, while 18% showed negative trends and the remainder remained stable. Positive trends were concentrated primarily in western and northern ecoregions such as the Carpathian Montane Forests and Central European Mixed Forests. These areas have experienced relatively limited direct military activity. In contrast, higher proportions of negative trends were observed in eastern and southern ecoregions, including the Pontic Steppe and Crimean Submediterranean Forests, which correspond to zones most affected by the Russia–Ukraine conflict. Analysis of BFAST breakpoints revealed that most pixels in natural forested regions experienced few or no structural changes, whereas agricultural and urban areas exhibited frequent breaks, reflecting

regular crop cycles and land-use dynamics. When cropland and urban classes were removed from the analysis, the overall proportion of positive trends increased, indicating that natural vegetation has generally remained resilient and stable despite wartime disturbances. However, the study also found that areas within active conflict zones displayed more frequent vegetation breaks and localized negative trends, suggesting that military activities may contribute to vegetation disruption, although these effects are difficult to separate from normal agricultural variability. Overall, the findings confirm that while Ukraine has experienced substantial environmental disturbance during the study period, national-scale satellite observations reveal predominantly stable to greening vegetation conditions, underscoring both the resilience of natural ecosystems and the complexity of attributing vegetation change solely to conflict-related impacts.

In Chapter 4 of this thesis is “*Spatial Bayesian Modeling of Explosion Intensity and Vegetation Change During the Russo-Ukrainian War*” which is trying to answer the second and third research question. The results of this study directly address the two central research questions regarding explosion patterns and their relationship to vegetation change in Ukraine. First, the spatial distribution of explosion events was found to be highly clustered and strongly structured around key infrastructural and strategic features. The Bayesian INLA model produced a detailed map of predicted explosion intensity, showing that higher intensities were concentrated near the front line, major roads, railways, power plants, and densely populated areas. Although individual covariates were not statistically significant at the 95% confidence level, their estimated effects consistently indicated that explosion intensity increases as distance to infrastructure decreases and as local population increases. Spatial hyperparameters further revealed that explosions exhibit strong spatial dependence within approximately 10 kilometers, confirming that conflict

activity is geographically concentrated rather than randomly distributed. Together, these results demonstrate that the occurrence and intensity of explosions are primarily explained by proximity to strategic infrastructure and areas of human activity.

Second, the vegetation change analysis indicates that negative vegetation trends are meaningfully and statistically related to modeled explosion intensity and additional landscape covariates.

Results from the vegetation change model show that higher predicted explosion intensity, greater numbers of BFAST structural breaks, higher temperatures, and increased cumulative precipitation were all significantly associated with more negative vegetation slopes. These relationships suggest that conflict-related explosions contribute to localized vegetation disturbance, while climatic and soil conditions mediate the magnitude and direction of observed trends. The inclusion of a spatial spline term further demonstrated the geographic variability in vegetation response, indicating that the environmental impacts of warfare are spatially heterogeneous across eastern Ukraine. Overall, the findings confirm that explosion intensity is a measurable driver of vegetation change, but that vegetation dynamics are influenced by a combination of conflict activity, climate, and underlying landscape characteristics.

Together, the results of Chapters 3 and 4 directly support the overarching goal of providing a comprehensive assessment of the environmental impacts of the Russia–Ukraine War while advancing methodological approaches for integrating remote sensing and conflict data. Chapter 3 establishes a national-scale baseline understanding of vegetation dynamics in Ukraine over more than two decades using MODIS EVI time-series and BFAST analysis. This chapter demonstrates how long-term satellite observations can identify spatial and temporal patterns of vegetation change, distinguish stable and resilient ecosystems from disturbed areas, and highlight regions where negative trends coincide with zones of military activity. Building on this foundation,

Chapter 4 moves beyond descriptive change detection to explicitly link vegetation outcomes with the spatial distribution of warfare. By applying Bayesian spatial modeling to explosion intensity and relating those predictions to vegetation trends, this chapter provides a quantitative framework for assessing how conflict-related disturbances interact with climatic and landscape factors to influence ecological conditions. Collectively, the two chapters illustrate a complementary methodological progression, from detecting where and when vegetation change occurs to explaining why it occurs, thereby contributing both empirical evidence of war-related environmental impacts and new analytical tools for monitoring conflict-affected landscapes. This research achieves its primary objective of providing a comprehensive assessment of the environmental impacts of the Russia–Ukraine War while contributing new methodological approaches for linking remotely sensed vegetation change with spatial patterns of armed conflict.

Future Work

Although the study offers important insights, several limitations and opportunities for future research remain. First, the use of finer spatial resolution imagery would improve the ability to capture small-scale vegetation change over time. MOD13Q1 products with a 250-meter resolution were selected due to the large geographic extent of the study area and the practical advantages of working with coarser resolution data. However, higher-resolution imagery would likely yield more detailed and accurate assessments of localized environmental impacts. Second, the analysis relied on ACLED conflict event data, which do not represent the exact locations of explosions in Ukraine. While the predicted explosion intensity map provides a valuable estimate of how conflict dynamics and critical infrastructure influence where explosions are most likely to occur, access to precise explosion location data would significantly enhance model accuracy. At present, such data is not publicly available, and it is uncertain whether they will become

accessible in the future. Finally, there is potential to expand the vegetation change model through the inclusion of additional explanatory variables. The current model is limited to covariates derived from open-source datasets; incorporating higher-quality environmental and climatic data could improve understanding of the factors influencing BFAST-derived vegetation trends. Despite these limitations, this research provides a robust and integrative analysis of war-related environmental impacts and demonstrates the value of combining remote sensing techniques with spatial conflict data to assess landscape change in conflict-affected regions.

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Appendix A - Publication of R Code

R Code used for BFAST Analysis can be found here:

[RPubs - Breaks for Additive Season and Trend \(BFAST\) Analysis](#)

R Code used for the Explosion Model can be found here:

[RPubs - Predicting Explosion Intensity - INLA](#)

R Code used for the Vegetation Change Model can be found here:

[RPubs - Vegetation Change Model Documentation](#)