Nature of War

The Political Ecology of the 2020 Nagorno-Karabakh Conflict

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Abstract

The Nagorno-Karabakh conflict has had profound consequences for both the political and physical geography of the South Caucasus region. Since the fighting of the 1990s there has been a relative status quo, with a militarised line of contact separating the two sides; the Armenia-backed Nagorno-Karabakh Republic (Artsakh) and Azerbaijan. This changed on September 27 2020, when intense fighting erupted along the whole of the front, and especially in the south-east. After a month and a half, fighting concluded on 10 November 2020 which saw the implementation of a ceasefire which ceded large portions of the Nagorno-Karabakh (Artsakh) Republic to Azerbaijan. There has yet to be an investigation on the kinds of changes to human and natural systems that the most recent conflict (2020) engendered.

In response to this research lacuna, this paper asked whether the effects of the 2020 armed conflict had a significant effect on the region's agricultural systems. This paper approached the question by examining per-pixel NDVI metrics - derived from Landsat 8 composites from April through June - before and after the conflict. These per-pixel metrics were correlated with conflict data from ACLED. This approach aims to test the hypothesis that areas which witnessed the most intense fighting saw significant drops in NDVI, indicating land fallowness and abandonment. The results from this study indicate that conflict intensity has a significant effect on vegetation health (p-value $< 2.2e-16$), and supports the hypothesis that conflict leads to a decrease in NDVI, however conflict intensity on its own does not have strong explanatory power for estimating changes in NDVI (R^2 0.09667) and future work ought to segment the study area in order to obtain a non-obfuscated regression coefficient (coefficient - 0.0057322).

Keywords

Landsat, Karabakh, Conflict, Landcover and Land Use Change, NDVI, Social Ecological Systems

Introduction

Overt and silent forms of violence form a fundamental component of social ecological systems (SES) (Biggs, 2021). Armed conflict is a form of intense overt violence, which has the potential to cause devastation to more than just combatants engaging each other on the battlefield. Recent research has examined the complex relationship between warfare and the environment by investigating the various effects of conflict on the environment (Machlis et al., 2011). Despite the recent turn to focusing on armed conflict in ecological research, there are many historical and temporal contexts where conflict-ecology analysis is still lacking.

One such context is the 1991-1994 war between Azerbaijan, the Nagorno-Karabakh Republic, and Armenia. The war has had profound consequences for both the political and physical geography of the South Caucasus region. In their 2015 article, Baumann et al. examined these changes by studying the war's effects on local land-use during the conflict period between 1987–2000 (Baumann et al., 2015). Their results uncovered that these changes consisted primarily of destroyed cities or settlements and the abandonment of agricultural lands in the vicinity of the conflict zone. Baumann et al. found a total of 140 destroyed cities or settlements, and 29% rate of agricultural abandonment. Moreover, after the cessation of the conflict, only 17% of the abandoned agricultural areas were re-cultivated indicating that "the land use system may have transformed profoundly."

Since the fighting of the 1990s. there has been a relative status quo, with a militarised line of contact separating the two sides (de Waal, 2003). This changed on September 27 2020, when intense fighting erupted along the whole of the front, and especially in the south-east. After a month and a half, fighting concluded on 10 November 2020 which saw the implementation of a ceasefire which ceded large portions of the Nagorno-Karabakh (Artsakh) Republic to Azerbaijan. This ceasefire represents the most momentous shift in both the de-facto and de-jure political boundaries of the region since the fighting of the 1990s (Darbyshire, 2021). While there is substantial literature on armed conflict and changes to human and natural systems, including Baumann et al.'s article on Karabakh, there has yet to be an investigation on the kinds of changes that the most recent conflict (2020) engendered. In response to this research lacuna, this project presents a proof of concept for a remote sensing methodology which examines whether conflict is a significant driver of changes across the natural landscape. In particular, this project looks at whether conflict intensity has a significant impact on vegetation health, as measured by the normalised difference vegetation index (NDVI). Assessing the significance of changes to NDVI provides the foundation for future research into how human and natural systems have changed as a result of the 2020 armed conflict.

Study Area and Data Description

The research covers the areas of the Nagorno-Karabakh region which witnessed armed conflict from September 27 to November 10 2020. To demarcate the study area, Soviet military topographic maps at a 1:100,000 scale, from between 1972-1990, were sourced from a free and open source database, and georeferenced in the Pulkovo 1942 coordinate system to establish the exact location of the border between the Armenian and Azerbaijan Soviet Socialist Republics (SSRs). This was a necessary step, because the current border is contested and existing shapefiles do not account for the intricacies of the boundary line. The north of the study area was traced to the ridgeline of the Murovdağ (Mrav) mountain range, while the south of the study area was traced to the Aras (Arax) river. The eastern boundary was more difficult to trace, as there is no de-jure boundary between the Nagorno-Karabakh Republic and Azerbaijan, but rather a de-facto militarised line of contact. This line has been frozen since the Bishkek Protocol was implemented in 1994, with some minor changes as a result of clashes in the past decade. To respond to the challenge of tracing an unmarked and shifting line of contact, the boundary in the east was traced to the districts that make up the Yukhari-Karabakh and Kalbajar-Lachin regions of Azerbaijan. Including the 12 districts within these regions ensured that the study area would overestimate the spatial extent of the conflict. These areas were dissolved together in ArcGIS Pro to create a single-part feature class (see Figure 1). Moreover, to ensure that the study area boundary overestimated areas with conflict, a 5 km buffer was also calculated using the Buffer Analysis tool in ArcGIS Pro. This study area was used as the input feature for the creation of a grid consisting of 1 km2 plots, which was generated using the Grid Index Features tool in ArcGIS Pro. The resulting grid accounted for the entire study area, including areas outside the study area that were part of a 1 km2 plot that fell partially within the study area. As such, the resulting gridded study area included three safeguards for ensuring that all parts of the Nagorno-Karabakh region which witnessed armed conflict were accounted for.

The data used for this analysis can be divided into two broad categories: social and ecological. The social data is concerned with the spatiality of the conflict, and was acquired from the The Armed Conflict Location & Event Data Project (ACLED). ACLED datasets are compiled by researchers who synthesise disparate sources to generate exhaustive lists of violent events. These violent events are subsequently georeferenced, and other contextual data is appended to the entries. To acquire this data, I downloaded the ACLED dataset for Armenia and Azerbaijan from between September 1st and December 1st 2020, filtering event types to include "Battles" and "Explosions/Remote violence" exclusively. This dataset was subsequently filtered using the Intersect Analysis tool in ArcGIS Pro to include only points which intersected the gridded study area. I used the Kernel Density analysis tool in ArcGIS Pro to generate values for conflict intensity. The conflict kernel was snapped to the grid of 1 km2 plots to ensure that each plot had a single conflict density value assigned to it. The values for conflict intensity were vectorised using the Zonal Statistics as Table tool in ArcGIS Pro, and then joined to the study area grid. The ecological data is concerned with vegetation health on a landscape scale, and consequently Landsat 8 spectral reflectance (Level 2, Collection 2, Tier 1) imagery, with a 30 m resolution, was ideal. This imagery was acquired using Google Earth Engine, using the QA_PIXEL band to set bit 3 (cloud) and bit 4 (cloud shadow) to 0, indicating clear conditions (Gorelick et al., 2017). This cloud and shadow mask was applied to composite imagery collected from between April 1 and July 1 2013-2021, indicating the full temporal range of Landsat imagery as of the completion of this analysis in March 2022.

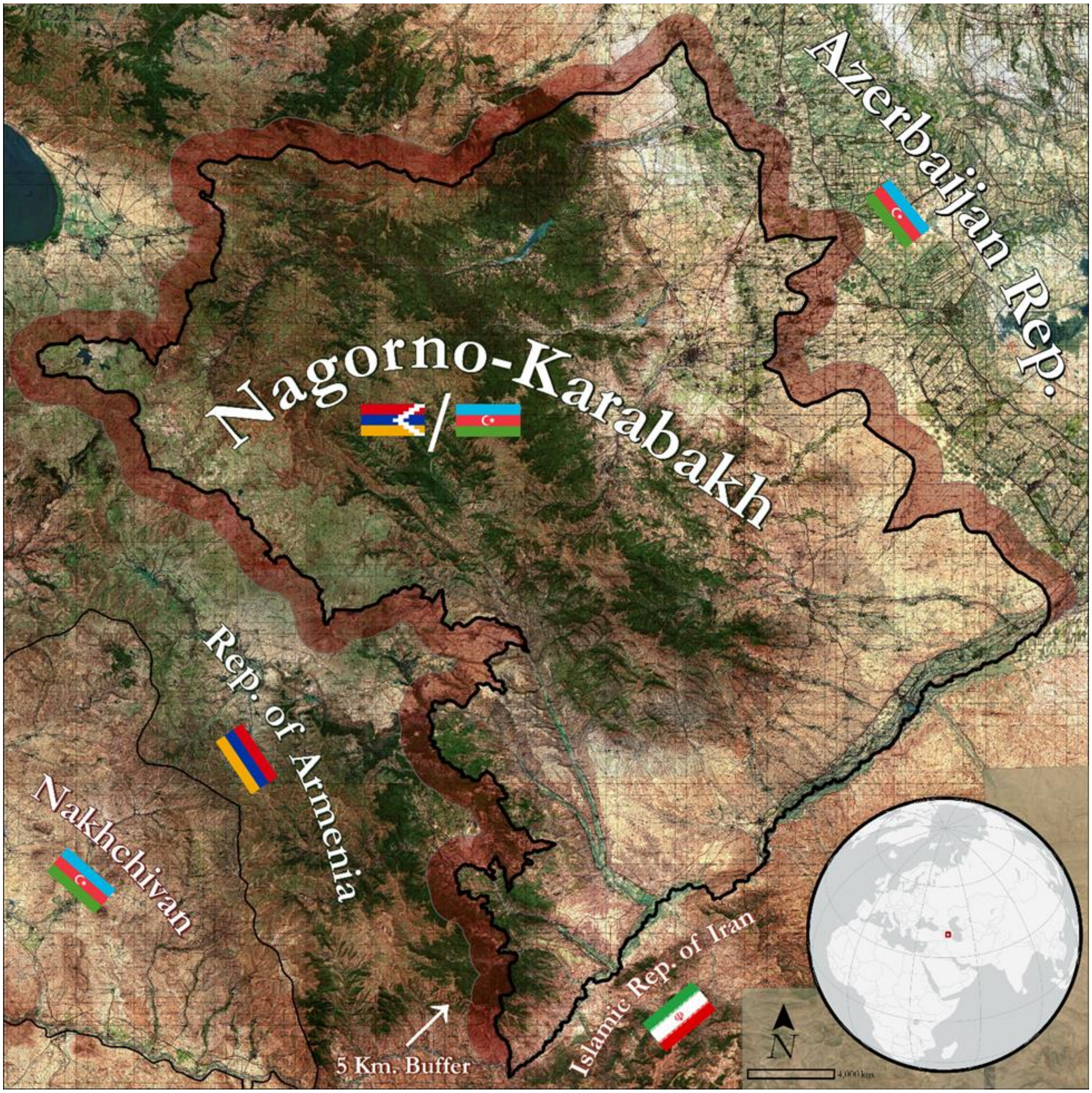

Figure 1. The Nagorno-Karabakh study area, including the 5 km denoted in red.

Methods

To understand how the Nagorno-Karabakh war of 2020 has affected agriculture in the conflict area, I examined the normalised difference vegetation index (NDVI) for 100 sample 1 km2 plots (n = 100). NDVI is calculated according to the formula:

$$NDVI = \frac{(NIR - RED)}{(NIR + RED)}$$

whereby NIR is spectral reflectance of the near-infrared portion of the electromagnetic spectrum (0.851-0.879 μm, Landsat 8), and RED is the spectral reflectance in the red portion of the electromagnetic spectrum (0.636-0.673 μm, Landsat 8) (Rouse et al., 1974). The entire study was made up of 16,551 1 km2 plots. The per-pixel NDVI was obtained from the April 1st to July 1st Landsat composites, which were processed in Google Earth Engine as outlined in the above section. The composite for 2016 was not included due to problems with atmospheric cloud cover. The NDVI value for each pixel was calculated using a script written in the R programming language (R Core Team, 2022). The script sampled 100 random plots from within the study site grid, and masked the seven Landsat spectral reflectance mosaics to each of the 100 plots. The per-pixel NDVI values were subsequently calculated using the Terra package for each Landsat mosaic in each plot (Hijmans, 2021). Each plot-masked raster was then converted to a data frame, to allow for per-pixel analysis, and the average pre-conflict (2013-2020) per-pixel NDVI value was subtracted from the post-conflict (2021) per-pixel NDVI. This process was automated using nested for-loops to calculate the change in per-pixel NDVI for all 100 plots.

To understand the relationship between changes in NDVI and conflict intensity, the R script extracted the conflict intensity value, obtained from the Kernel Density analysis, for all 100 plots. It then merged per-plot conflict intensity values with per-pixel NDVI change for each plot. The result was a two-column data frame, consisting of NDVI difference values and corresponding conflict intensity values (see Figure 2). To test for statistical significance, NDVI difference and conflict intensity were fitted to the following simple linear model:

$$y_i = \alpha + \beta x_i + \varepsilon_i$$

where y_i is the dependent variable (change in NDVI), α is the y intercept, βx_i is the independent variable (conflict intensity), and ε_i is the error. A t-test was performed on the model, providing a statistical summary of the NDVI-conflict intensity data frame.

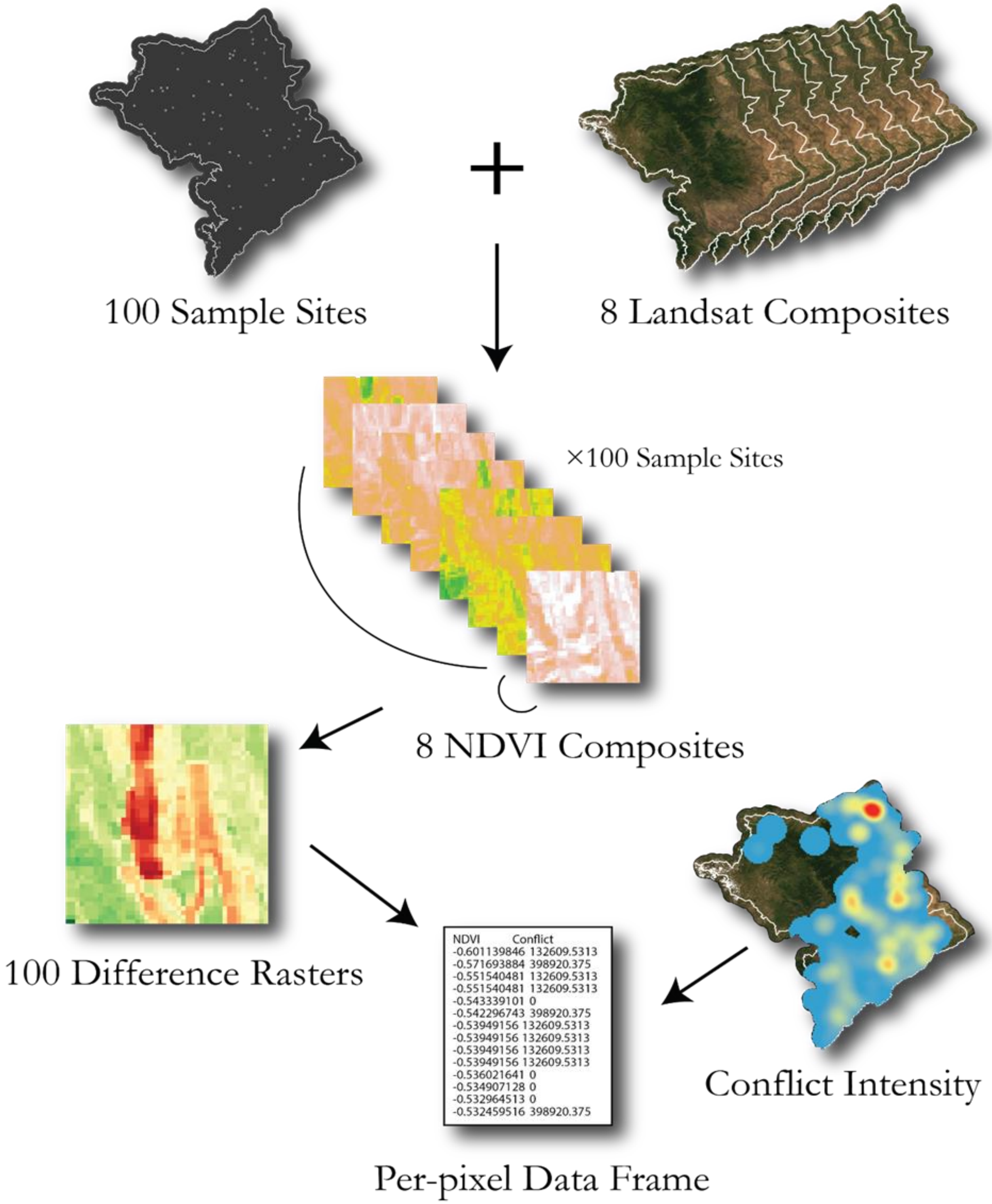

Figure 2. The analysis workflow, showing the processing of Landsat and ACLED to generate a per-pixel data frame showing the relationship between NDVI change and conflict intensity.

Results

The result of performing the t-test on the fitted linear model was a p-value of < 2.2e-16. The null hypothesis was that there is no relationship between the intensity of conflict and the changes in NDVI. The alternative hypothesis was that there is a relationship between the intensity of conflict and the changes in NDVI. The null (H0) and alternative (H1) hypotheses can be stated as the following parameters:

$$H_0: \beta = 0$$

$$H_1: \beta \neq 0$$

where a slope of 0 in the null hypothesis indicates that, as per the model, that the independent variable βx_i (conflict intensity) has no effect on the dependent variable y_i (change in NDVI) (Seltman, 2012). The alternative hypothesis is that changes to the independent variable βx_i (conflict intensity) are associated with changes to the dependent variable y_i. The resulting p-value of < 2.2e-16 is lower than the confidence level of 95% (p-value 0.05), and allows us to reject the null hypothesis and affirm the alternative hypothesis. This result indicates that the probability that the relationship between NDVI difference and conflict intensity is random is very low. It is likely that conflict intensity has an effect on changes to NDVI.

The R^2 is 0.09667, which indicates conflict intensity on its own does not explain changes in NDVI well. The estimated regression coefficient is -0.0057322, indicating that as conflict intensity increases, there is an overall decrease in post-conflict NDVI values. The relationship between higher conflict intensity and lower post-conflict NDVI values can be seen in Figure 3. Figure 3 shows how as conflict intensity increases, the NDVI differences are lower. As seen in Figure 4, looking at the sampled plot with the second highest conflict intensity (CA139) reveals how the plot's proximity to the line of contact has adversely affected the NDVI values of pixels. This is especially true for values in portions of the plot that appear to be cultivated agricultural areas. This mean decline in NDVI values is also reflected in Figure 5, which shows how this negative trend in 2021 is shared by almost every single pixel in the plot.

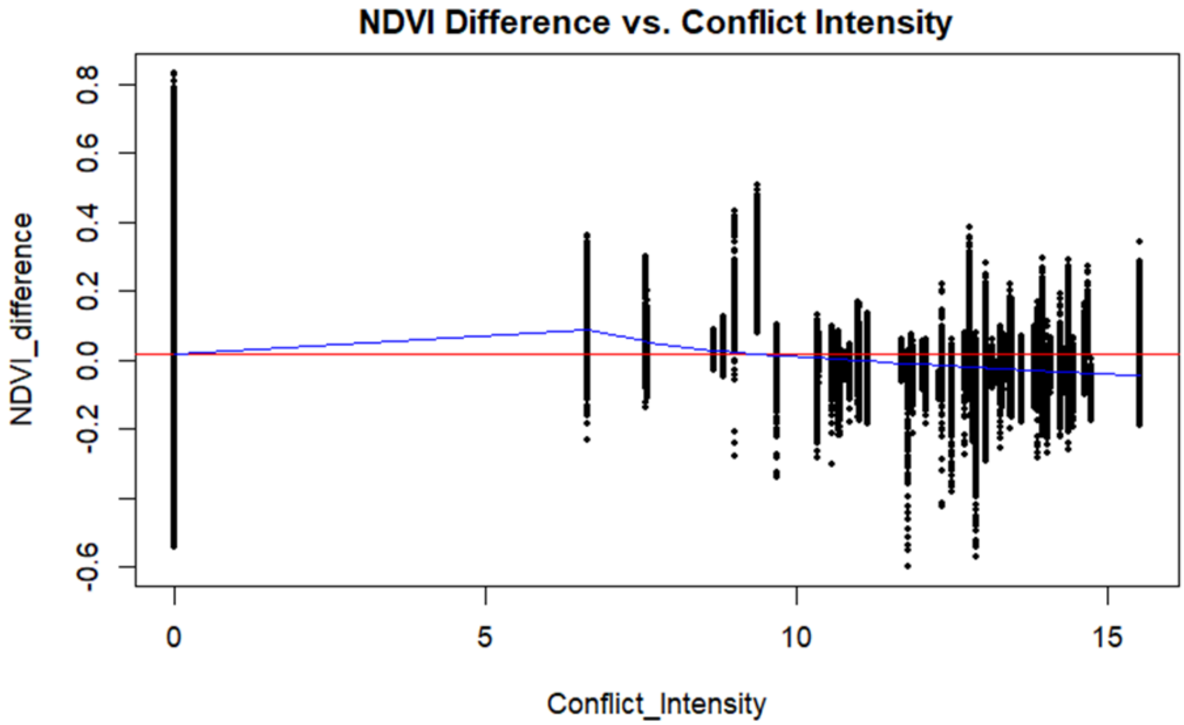

Figure 3. The analysis workflow, showing the processing of Landsat and ACLED to generate a per-pixel data frame showing the relationship between NDVI change and conflict intensity.

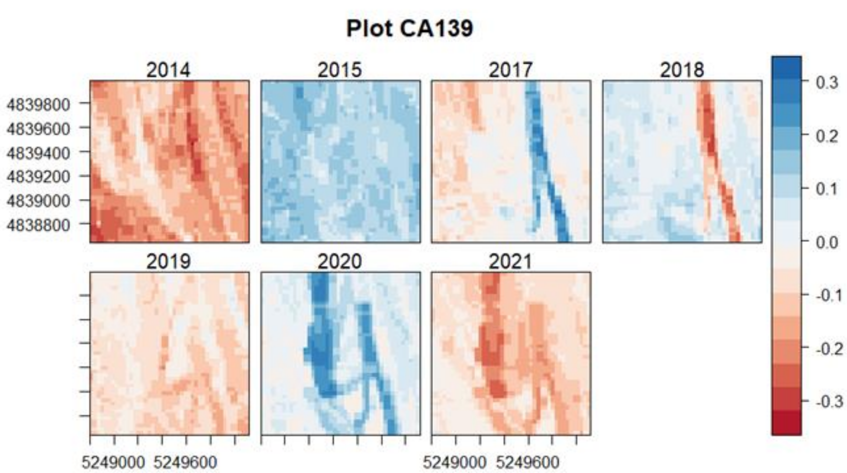

Figure 4. The left figure shows the change in NDVI value per-pixel for plot CA139 from between 2014 and 2021.

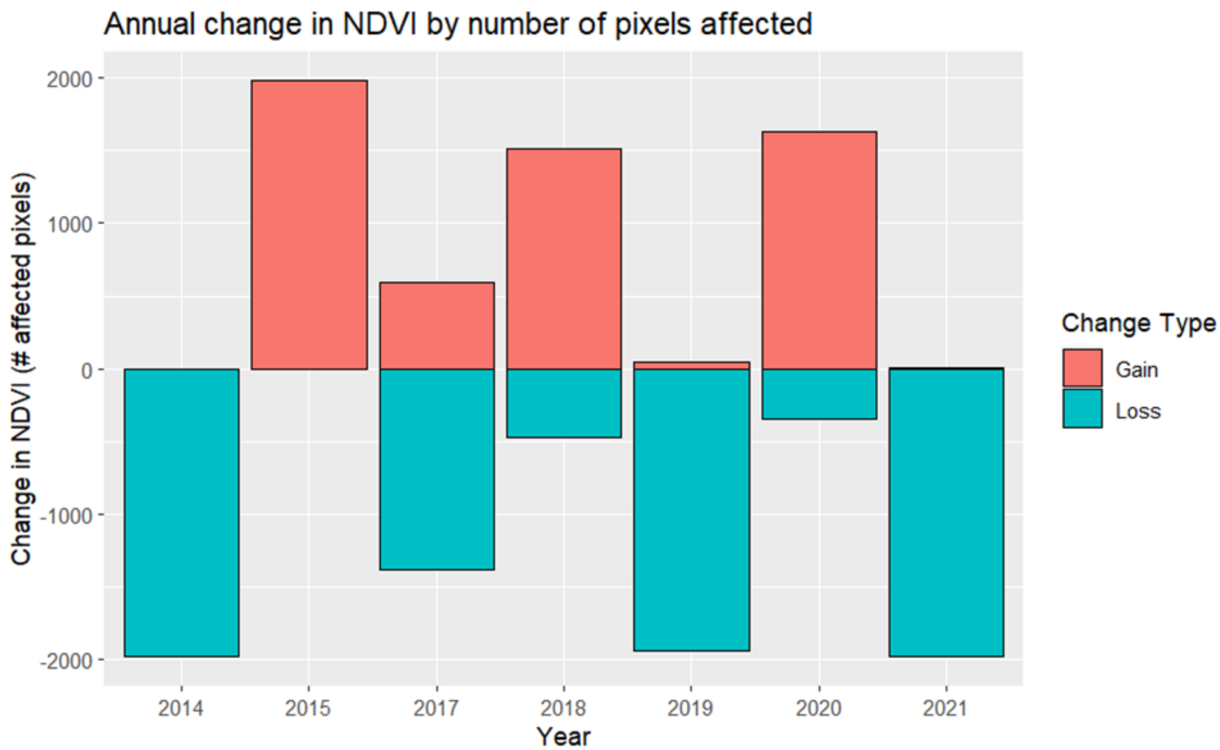

Figure 5. The total number of pixels that have seen their NDVI increase or decrease in plot CA139.

Discussion

Armed conflict is an intense form of violence which has the potential to significantly disrupt social ecological systems (SES) in a given context. This paper picks up from the work of Baumann et al. 2015, and addresses the question as to how the Nagorno-Karabakh war of 2020 impacted the natural environment. As a first step to understanding how the conflict has affected the natural environment, I examined pre- and post-conflict changes to NDVI across the study area. This analysis found that the 2020 conflict significantly affected vegetation health, as measured by NDVI.

To answer this question, I generated a data frame which summarised NDVI difference values with corresponding conflict intensity values across 100 randomly selected sites. The result from conducting a t-test on a simple linear model was a p-value of $< 2.2e-16$ with a coefficient of -0.0057322, and an R^2 0.09667. This result suggests that areas of the landscape which have witnessed more conflict during the 2020 war are likely to have also witnessed decreases in their NDVI.

Figure 6, which depicts the annual changes to the NDVI of plot CA139 from the previous year, tells a fascinating story. In 2014 and 2015, there does not appear to be any anthropogenic activity in the plot area. There are annual fluctuations that affect the entirety of the plot, likely caused by changes to annual precipitation. This changed in 2017, when a lambda shaped portion of the plot underwent a surge in NDVI, suggesting that it has been cultivated. This same portion of the plot underwent a decline in NDVI the following year (2018), and remained unchanged the year after (2019), indicating that the land has been left fallow. There was a surge of NDVI in an expanded portion of the cultivated land in 2020, indicating that the plot was being cultivated again. The following year (2021), in the aftermath of the war, the NDVI declined again, especially in areas proximate to the front line which is visible in Figure 6. This trajectory indicates that the conflict acted as a breakpoint for NDVI values in the cultivated portion of the plot. This phenomenon could be more strongly supported by expanding the temporal range of the Landsat composites in order to understand how much the pre- and post-2020 plot NDVI dynamics differ from the larger trends.

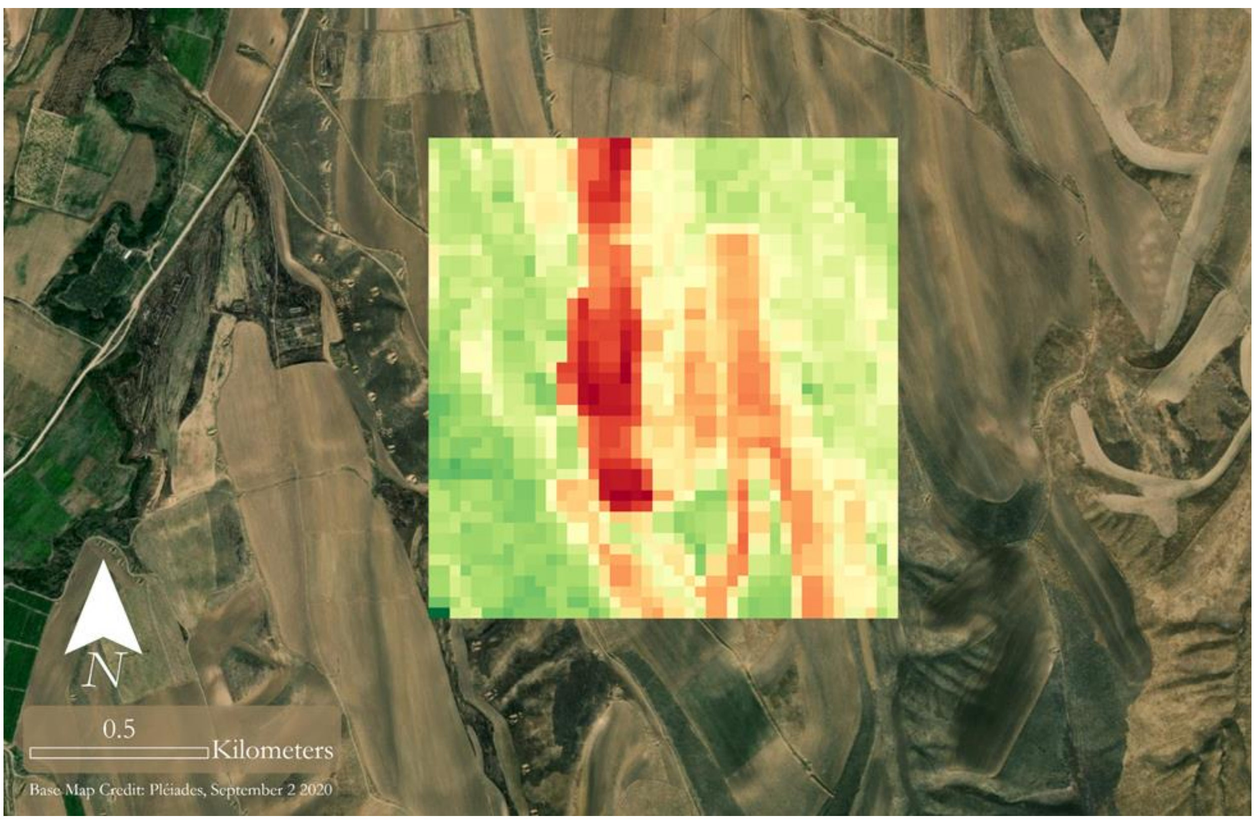

Figure 6. Plot CA139 symbolised to show changes in NDVI value pre- and post- conflict with Airbus/CNES imagery from the Pléiades satellite (0.5 m resolution) on September 2nd 2020 as a basemap.

The low coefficient acquired from the model t-test can be explained by the fact that the random sampling was not geographically stratified, meaning that different landscape features were included together in the regression analysis. It was initially hypothesised that the conflict would lead to an increase in NDVI for urban areas, due to their abandonment, and a decrease in NDVI in non-urban areas due to fallowness and damage to vegetation from incendiary and explosive weaponry. The possible presence of abandoned settlements in the 100 random samples obfuscated the coefficient by introducing multiple phenomena - with oppositely hypothesised coefficients - into a single regression analysis.

The low R^2 indicates that there are more important variables for explaining the variability in NDVI values between pixels. This was expected from the outset, because other environmental variables such as temperature and precipitation are better explanatory variables for estimating NDVI (Hess et al., 1996). Building a model with better explained variability would require conducting sub-plot level analysis, a method which would be incompatible with current conflict intensity analysis method. The use of kernel density analysis with an output cell size of 1000.0 (1 km) and a search radius of 1000.0 (1 km) means that conflict intensity is overestimated in each plot. By having large cell sizes and search radii, pixels that possibly didn't witness any direct conflict have conflict intensity values associated with them.

Exploring the plots individually reveals how important conflict density cell size and search radii are for any analysis. Plot CA139, which is a randomly sampled plot with the second highest conflict intensity of all 100 random samples, witnessed a decrease to per-pixel NDVI in areas with proximity to the line of contact. Airbus / CNES imagery from the Pléiades satellite (0.5 m resolution) on September 2nd 2020 reveals what appears to be artillery and trench instalments. While the correlation between a high conflict intensity value is validated by the Pléiades imagery, it also reveals just how narrow the front line is. Given the reality of the conflict dynamics, a finer resolution conflict intensity map is necessary for accurately correlating conflict with changes to spectral indices.

Given the limitations discussed above, the current methodology could be deployed to conduct analysis in any study area in the world which has available ACLED data and clear Landsat 8 imagery. This study area would also have to be small enough to ensure there are not multiple landscape classes included. As discussed above, including multiple landscape classes, such as agricultural and urban areas, with opposite hypothesised regression coefficients would obfuscate the analysis results. With these conditions met, the methodology introduced in this paper could be used to establish whether conflict has had a significant effect on the natural environment of a given study area. This could prove particularly useful for laying the foundation for future research into political-ecology and social-ecological systems. It is critical for researchers to understand whether conflict has affected their study area before they begin investigating how conflict has affected it.

Future Directions

As outlined above, there are two key problems with the current methodology. The first problem relates to the low regression coefficient as a result of the plot selection and analysis not distinguishing between landscape types. This could be solved by using object based image analysis (OBIA) to segment the study area into classes of interest (Blaschke, 2010). This would allow for a much more nuanced breakdown of results, where the correlation between conflict and spectral trends for urban and non-urban areas could be analysed separately. The object-stratified analysis would provide models that are free from obfuscation, and also include coefficients that are likely to be more pronounced. The second problem relates to the resolution of the conflict data. While an easy solution is to change the cell size and search radius of the kernel density analysis, there is another more innovative option available. Using a collection of multiple spectral indices, the ACLED conflict dataset could be divided into two halves and used as training and validation data for a machine learning model which predicts conflict intensity. The output from this conflict intensity machine learning model could be used to understand the effect of conflict on the environment across the whole of the study area in much finer detail. This analysis would not be limited just to ACLED data, which was collected using qualitative methods and as such is inherently limited.

There are other potential avenues of analysis which go beyond testing for significance. An analysis which uses machine learning generated conflict data could be augmented by modelling individual indices using climatic and environmental variables such as precipitation, elevation, and temperature. For instance, research on modelling NDVI carried out by Hess et al. 1996 could form the basis of an analysis which looks at the difference between real and predicted values of indices. These results would be correlated with fine-scale conflict intensity, allowing for highly precise estimates of the impact of conflict on the environment. This analysis would have immense implications for conflict monitoring, as the destruction of the environment is recognised as a war crime by the International Criminal Court.

This analysis could also be augmented by expanding the datasets being used in the analysis. The chronological range of Landsat composites could be expanded into Landsat 7, in order to get a better sense of the variability of spectral patterns in the pre-conflict period. Repeating this analysis in future years to incorporate additional post-conflict Landsat composites could also provide a better sense of how spectral patterns have evolved since the conflict. This is especially relevant for analysing individual plots, such as CA139, as additional future composites could allow for a breakpoint analysis using BFAST in R (Verbesselt et al., 2010).

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