Wars, protected areas, and land cover change in the Caucasus Mountains

By

Johanna Buchner

A dissertation completed in partial fulfillment of

the requirements for the degree of

Doctor of Philosophy

(Forestry)

at the

UNIVERSITY OF WISCONSIN – MADISON

2020

Date of final oral examination: 9/18/20

This dissertation is approved by the following committee:

Volker C. Radeloff, Professor, Department of Forest and Wildlife Ecology

Scott Gehlbach, Professor, Department of Political Science, University of Chicago

Tobias Kuemmerle, Professor, Department of Geography, Humboldt-Universität zu Berlin

Lisa Naughton, Professor, Department of Geography

Philip A. Townsend, Professor, Department of Forest and Wildlife Ecology

Acknowledgments

“A journey of a thousand miles begins with a single step.” (Chinese proverb). Pursuing a PhD is certainly a journey of a thousand miles, but I was fortunate to have wonderful people by my side who walked with me along the way. I want to express my deepest gratitude to my advisor Volker Radeloff, who made this journey possible, inspired me by sharing his passion for research with me, supported me throughout my PhD, and had always good advice for any situation in life. I am grateful for my committee members, Tobias Kuemmerle, who enriched my research with excellent ideas, Lisa Naughton, who taught me that conservation is about nature and people, Scott Gehlbach, who opened the door to the Soviet Union to me, and Phil Townsend, who provided great feedback for my remote sensing questions.

I am thankful to my collaborators in the Caucasus, who taught me so much about that beautiful region and shared data with me, and my co-authors for improving each of my chapters tremendously. I would like to thank Benjamin Bleyhl, Matthias Baumann, Bin Tan, Arash Ghoddousi, Afag Rizayeva, and Natalia Rogova, for sharing their knowledge about remote sensing and the Caucasus with me and for many fruitful conversations. I am extremely grateful to Nugzar Zazanashvili and Elshad Askerov for their hospitality when we visited the Caucasus. I learned so much from both of you. Tamar Bakuradze, Anna Komarova, Garegin Tepanosyar, Elshad Askerov, Nodar Elizbarashvili, and Hovik Sayadyan, thank you for your time and collaboration and for patiently answering all my emails.

This dissertation wouldn’t have been possible without He Yin, Katarzyna Lewińska, Van Butsic, and David Frantz, who never got tired of answering my endless amount of questions and providing valuable feedback. Thank you, He, for supporting and guiding me throughout the entire journey, sharing your garden harvest with me, and all the excitement fighting over board game wins. Kasia, thank you for your encouragement, your help, and simply being a great office mate with great discussions about research and everything else, and even fixing my bike. Van, thank you so much for inviting me to Berkeley, taking me to the one and only baseball game I have ever been, and dedicating a tremendous amount of time to explain econometrics to me. David, thank you so much for helping me troubleshooting from far away, and being so responsive despite the many hours between us.

I can’t think of a better lab to be part of, thank you, Silvis lab, for being an amazing group of people and a huge support system. Thank you, Diana, Anu, Catalina, Niwa, Laura, Genya, David, Konrad, and all other Silvinauts for great company and many great conversations during my time in the lab. Thank you, Dave, for all the help when it came to computers, and sharing your precious beer with us on lab trips. Martina and Michi, I am very grateful that our time in Madison overlapped and that you fed me with so many delicious dinners. Spending time with you two felt like home.

I am extremely thankful to Achim Roeder and Joerg Mueller. Achim, thank you for getting the ball rolling by sending me to Madison to work with Volker. Joerg, thank you for encouraging me to take the step into the unknown.

I would like to thank my nearby and far away dear friends. Julia, thank you for being my magic mate. Clare, thanks for making my transition to the US such a smooth experience, I enjoyed every minute of our patio-time, and competing with me in my ever first trail run. Heather, Sam, and Katie, thank you so much for sharing all the excitement, sweat, fear, frustration, and final success in climbing with me. Zu, thanks for becoming a great friend in such a short amount of time and for believing in me that I can climb 8a.

The only reason why I was able to do the first step of my journey was because of my amazing family back home. I feel so fortunate to have the endless amount of support from my parents Anne and Richard, and my sisters Amelie and Hedi and their families. Thank you for being by my side the whole time, and reminding me to do one step at a time until the end.

John, I can’t express how much it means to me that you went through this journey with me. You listened to me when I felt overwhelmed by the miles ahead of me, you went on runs with me to clear my mind, we climbed at night when the day didn’t have enough hours, and you still make coffee for me every morning. Thank you!

Table of Contents

List of Tables

List of Figures

List of Appendices

List of Table A

List of Figure A

Introductory Chapter

Humans have transformed large proportions of the Earth's land surface, and with increasing globalization and a higher consumption demand, the modification of the land surface has accelerated (Foley et al., 2011; Lambin and Meyfroidt, 2011). Indeed, 83% of the Earth's land surface is directly or indirectly affected by humans (Sanderson et al., 2002). Land-use changes such as agricultural expansion and deforestation cause water pollution, greenhouse gas emissions, and biodiversity loss (Foley et al., 2011). Humans are facing the challenge of mitigating the loss of ecosystems that provide goods and services society relies on (Foley et al., 2005).

The land surface is changed by agriculture, forestry, and urbanization, due to the growing demand for resources (DeFries et al., 2004; Vitousek et al., 1997). Cropland and pasture cover approximately 33% of the land surface and have become some of the most widespread land surface type on the Earth (DeFries et al., 2004). Between 1980 and 2000, 55% of newly developed agricultural land in the Tropics occurred in formerly intact forests and an additional 28% was converted from disturbed forest (Gibbs et al., 2010). However, forests are not only logged for the expansion of intensive agriculture, but also for timber supply (Matthews et al., 2000). Globally forest loss is almost 2.8 times higher than forest gain from 2000 to 2012 (Hansen et al., 2013). For example, in boreal Eurasia, not only fires but also the increase in logging activity, such as clear cuts and high intensity selective logging, has resulted in rapid forest-cover changes (Achard et al., 2006).

Land-cover changes can stem from socio-economic changes such as shifts in a political regime (Lambin and Meyfroidt, 2010). The collapse of the Soviet Union, for example, strongly affected land-use management after 1991. In many Eastern European countries and European Russia, widespread agricultural abandonment was a result of the break-up of collective farms, a change from a planned to a market economy, and institutional changes (Gutman and Radeloff, 2016; Prishchepov et al., 2012). However, in some countries there was re-cultivation or agriculture intensification (Kuemmerle et al., 2016), but in others, there was permanent abandonment with forests re-growing on former abandoned fields (Prishchepov et al., 2017). A similar decline in land-use intensity occurred in the forest sector, with a general decline in logging rates, but an increase in illegal logging in countries where restitution of forest to former owners took place (Potapov et al., 2015). However, since the 2000s the logging rates started to increase in many parts of Eastern Europe, for example, in Romania and the Baltic countries (Gutman and Radeloff, 2016; Kuemmerle et al., 2016).

Among the causes that lead to land-use change, wars and armed conflicts can have detrimental effects on land use. Wars have strong direct effects where conflicts occur, and even areas farther away may still be affected, often for a long time (Baumann and Kuemmerle, 2016). The land-use type that is primarily affected by war is agriculture (Baumann and Kuemmerle, 2016). The adverse effects of wars result in agricultural abandonment either directly, for example, due to the contamination of landmines and destruction by bombs (The Halo Trust, 2014), or indirectly, for example, due to the weakening of the economy or shortages of agricultural supplies (ICRC, 2007). In general, the closer the conflict event is to the agricultural fields, the more likely it is that field will be abandoned (Yin et al., 2019). Furthermore, wars can also affect agriculture indirectly due to a lack of workforce when people are displaced and seek refuge elsewhere (Alix-Garcia et al., 2013). However, the displacement of people can result in an agricultural expansion in the destination area, including the vicinity of refugee camps (Alix-Garcia et al., 2013; Kranz et al., 2015). Wars can also result in agricultural expansions to create revenue (Eklund et al., 2017).

The varied outcomes of war on agriculture may be partly due to the inherently different backgrounds and characteristics of the wars, such as their intensity or their duration. However, differences in reported effects may also be due to the different methods employed in studies, which do not allow for direct comparisons of the effects of different wars on agricultural abandonment.

Forests are also affected during political upheavals. When people have to flee from the war, lower human pressure may lead to forest recovery (Sanchez-Cuervo and Aide, 2013). However, when people seek refuge in forests during the time of war, forests are illegally logged which results in forest degradation (Draulans and Krunkelsven, 2002; Nackoney et al., 2014). A strong dependency on forest resources during armed conflicts occurred, for example, in Rwanda (Ordway, 2015), and wildlife harbored by forests is especially at risk to poaching as protected species are sold as bushmeat in urban markets (Merode and Cowlishaw, 2006).

To preserve biodiversity, protected areas are the cornerstone of conservation. As of 2018, 14.9% of the Earth's land surface was under protection, but how much area was protected differed among countries (UNEP-WCMC, IUCN and NGS, 2018). Protected areas reduce deforestation in tropical Africa (Bowker et al., 2017), prevent overexploitation of plant species (Souza and Prevedello, 2020), and protect avian species richness (Evans et al., 2006). Moreover, protected areas supply many cultural services, thus supporting human wellbeing and local livelihoods (Naidoo et al., 2019). However, protected areas are not always effective. For example, large mammal populations are declining in western African protected areas (Craigie et al., 2010), and protected areas can exhibit forest loss, for example, in the Carpathians (Butsic et al., 2016), or Guatemala (Bullock et al., 2019). To assess the effectiveness of protected areas, deforestation is typically used as a proxy (Andam et al., 2008; Bowker et al., 2017; Pfaff et al., 2015). However, deforestation as a sole measure may bias protected area effectiveness, especially when deforestation pressure is low, and forest degradation plus the loss of specific forest types may be better indicators.

To map changes in cropland and forests, remote sensing is essential, especially when mapping large areas. The freely available Landsat archive provides 30-m resolution satellite imagery going back to 1983, which allows to map land cover and it's changes over more than 30 years (Wulder et al., 2012). Image composting allows to map large-areas without gaps due to clouds or limited data availability (Frantz et al., 2016; Griffiths et al., 2013). However, challenges occur in mountainous regions where illumination differences due to topography introduce classification errors (Vanonckelen et al., 2014). Topographic correction methods can remove differences in illumination in topographically complex terrain prior to classifications by estimating the reflectance of a pixel without topography (Liang, 2005). Topographic correction can improve land-cover classification accuracy and forest change detection (Tan et al., 2013; Vanonckelen et al., 2014). However, topographic correction has typically only been tested for small areas. Fortunately, recent advances in software development allow to apply topographic correction methods over large areas (Frantz et al., 2016).

However, the removal of single tress can lead to forest degradation and is more challenging to detect than forest loss, because the spectral response is subtle and does not result in land-cover conversion (Bullock et al., 2019; Souza et al., 2003). Analyzing intra-class variability, for example, via spectral mixture analysis, allows to detect forest degradation. Spectral mixture analysis quantifies the abundance of pre-selected spectrally-pure land surfaces within a pixel and allows to estimate fraction of, e.g., green vegetation, soil or shade. Combining spectral mixture analysis with time series analysis captures shifts among the fractions over time. Spectral mixture analysis of long satellite data record detected vegetation loss and degradation in grasslands in the Caucasus (Lewińska et al., 2020) and in forests in the Amazon (Bullock et al., 2020).

Overarching goal

The overarching goal of my dissertation was to understand large-scale land-cover change, to assess what causes the observed land-cover change, and consequently to evaluate whether conservation tools are sufficient in preventing land-cover change.

My specific objectives were:

1) Does topographic correction improve large-area land-cover classification accuracy? To what extent did cropland and forest change in the Caucasus from 1987 to 2015, what was the timing of these changes, and how did the countries in the Caucasus differ among each other?

2) What is the overall effect of war on cropland abandonment, and how does the effect differ among wars in the Caucasus?

3) Are strictly protected areas effective in preventing forest loss and forest degradation, and forest degradation in different forest types, in the Caucasus?

To address my dissertation goal, I mapped land-cover changes in the Caucasus Mountains based on almost 30 years of Landsat data which I corrected for topographic effects. I employed large-area imagery compositing, land-cover probabilities, and a post-classification approach to assess changes in cropland and forest. The Caucasus Mountains presented an ideal study area for this research question because of the complex topography and a long history of land use, and because there was no prior comprehensive land-cover change assessment.

The Caucasus also allowed me to assess the effect of wars on cropland abandonment. After the collapse of the Soviet Union, tensions among countries and within countries flared up and resulted in four major wars in the Caucasus. Agriculture is a leading economic sector with many people relying on farming for their livelihoods in the Caucasus. I assessed the effect of war on cropland abandonment for each war and compared the outcomes among the wars that differed greatly in their level of violence. To do so, I employed econometrics such as matching statistics and panel regression to compare conflict areas affected by wars with valid non-conflict areas, as well as the interaction between distances to conflict locations and intensity of these conflict locations.

Last but not least, the Caucasus is a biodiversity hotspot, but forest loss and forest degradation are threats to the endemic biodiversity of the region. Protected areas are a conservation tool to prevent forest loss and forest degradation, and consequently, protect biodiversity, however the commonly used effectiveness measure is forest loss. I analyzed forest loss, overall forest degradation, and forest degradation in different forest types, to assess the effectiveness of strictly protected areas. In terms of statistical methods, I analyzed protected area effectiveness using matching statistics and panel regressions.

Chapter summaries

Chapter I. Land-cover change in the Caucasus Mountains since 1987 based on the topographic correction of multi-temporal Landsat composites

Mountainous regions are important for ecosystem services and biodiversity, but the resources they harbor are under threat due to land-use change and climate change. Satellite data, such as Landsat imagery, provide a great resource to map land-cover changes because the data are freely available for more than 30 years. However, the use of remotely sensed imagery for land-cover classification in the mountains is challenging because of the so-called ‘topographic effect’, i.e., differences in illumination in topographically complex terrain. Despite the general understanding how topography affects classification accuracy, an assessment of topographic correction on the accuracy of land-cover classifications for large areas has not been done. In my first chapter, I 1) examined the effect of topographic correction on land-cover classification for a mountainous region, and 2) assessed land-cover changes, specifically cropland and forest changes, since 1987 across the Caucasus. The Caucasus represents an ideal study area for these objectives due to the complex topography and the long history of land-cover change, especially after the breakdown of the Soviet Union in 1991.

In a first step, I compared two land-cover classifications for 2015, one based on topographically corrected and one on non-topographically corrected data, to assess the effect of topographic correction on the accuracy of large-area land-cover classifications. I applied the open-source software FORCE with an integrated enhanced C-correction to derive a non-topographically corrected and a topographically-corrected classification for 2015. Once it was clear that the topographic correction improved classification results, I calculated best-available pixel composites based on Landsat imagery for six time steps (1987, 1995, 2000, 2005, 2010, and 2015) using FORCE. Gap-free imagery composites allow to overcome limited data availability in one year by including observations from the previous or the following year. I derived topographically-corrected land-cover classifications based on class probabilities derived with a C5.0 algorithm and a post-classification approach to assess cropland and forest changes.

Topographic correction improved the overall accuracy of the 2015 land-cover classification by 2% from 79% to 81%, and the F1-score of the topographically-corrected map outperformed the non-topographically corrected map for all but two classes. The greatest improvement among land-cover classes was for coniferous forest (0.15 points), deciduous forest (0.05 points), and mixed forest (0.04 points). Disagreement rates between the non-topographically corrected and the topographically corrected classification were as high as 100% in rugged terrain, where illumination conditions were most extreme. In these areas, rangeland pixels were often misclassified as deciduous forest, and deciduous forest as mixed forest, when the satellite data were not corrected for topographic effects. This misclassification was especially widespread in very-low illuminated areas. Cropland loss was the most dominant land-cover change in the Caucasus since 1987, and cropland decreased in all four countries, albeit with different rates. Cropland loss was especially widespread in the South Caucasus countries, i.e., Georgia, Armenia, and Azerbaijan, with a ~30% decrease in cropland in Georgia in 2015, and Azerbaijan in 2005, compared to 1987. In the North Caucasus, i.e., the Russian Federation, active cropland had the largest extent and was relatively stable over time. Forest-cover changes were minor across the Caucasus, with forest loss and forest gain almost equal in area. I found that Azerbaijan had the largest extent of forest loss, where forest cover decreased by 4% in 2005 relative to 1987.

My first chapter represents the first large-area land-cover change assessment for the Caucasus Mountains spanning almost 30 years. I found that the overall extent of cropland loss was much smaller than in e.g., temperate European Russia or the Baltics. I assume that the different land reforms of the different countries after the collapse of the Soviet Union may have affected cropland loss rates in the Caucasus. In Russia, the structure of the former collective farms was often maintained, making the cultivation of large areas easier. In the South Caucasus countries, the distribution of land resulted in fragmented land ownership, potentially leading to more agricultural abandonment. Limited access to the international market for the South Caucasus just after 1991 may also have caused higher cropland loss rates in Georgia, Armenia, and Azerbaijan. The very fertile soils, the flat landscape, and the mild climate in the North Caucasus may further explain the lower rates of cropland loss there. The low rates of forest change may be related to the high protection status of forests under the Soviet Union, small scale illegal logging, and fuelwood extraction rather than large-scale clear cuts, and a decrease in grazing pressure since the collapse of the Soviet Union.

The results of my first chapter highlight the feasibility and the importance of topographic correction in steep terrain, especially when distinguishing among forest types. Accurate land-cover mapping is crucial for land-cover change assessments which helps to improve our understanding of how socio-economic changes such as the collapse of the Soviet Union affect land use.

Resulting paper: Buchner, J., Yin, H., Frantz, D., Kuemmerle, T., Askerov, E., Bakuradze, T., Bleyhl, B., Elizbarashvili, N., Komarova, A., Lewińska, K.E., Rizayeva, A., Sayadyan, H., Tan, B., Tepanosyan, G., Zazanashvili, N., Radeloff, V.C., 2020. Land-cover change in the Caucasus Mountains since 1987 based on the topographic correction of multi-temporal Landsat composites. Remote Sensing of Environment 248, 111967.

Chapter II. Different effects of wars on cropland abandonment in the Caucasus

Wars are unfortunately frequent and can have strong effects on land use, especially agriculture. However, wars vary greatly in their overall intensity and may affect land-use differently. In my second chapter, I assessed the effect of wars on cropland abandonment in the Caucasus. The Caucasus presented a ‘natural’ experiment, as the region went through several wars after the collapse of the Soviet Union in 1991, namely the Chechen wars (Russia), the wars in Abkhazia and South Ossetia (Georgia), and the war over Nagorno-Karabakh (between Armenia and Azerbaijan). The Chechen wars were the most brutal ones with an estimated 72,000 casualties and the war in Nagorno-Karabakh forced an estimated 1,000,000 people to leave their homes. Both regions saw fighting with heavy military operations. The wars in Abkhazia and South Ossetia had fewer casualties, but travel restrictions and a crash of the economy still keep these regions struggling. The wars have different historic backgrounds and vary in their intensity in terms of number of events, the number of people killed, the number of refugees or internally displaced people, or the duration of the war, which may affect land use differently. I assumed that wars that were extremely brutal and violent have a stronger and broader effect on agriculture than wars with a low intensity level of violence. However, to assess the effect of war, a valid control group and observations before and after conflict events are needed and land-use decisions may depend on complex interaction of near and far away conflict events. Multiple conflict events may put more pressure on agriculture and may lead to higher abandonment. In general, the assessment of the effect of war includes a single war at a time and the lack of a consistent methodology makes direct comparison among wars difficult. To better understand the differences among wars, and the effect of the wars on permanent cropland abandonment, I was interested in 1) the intensity of each war in terms of the number of conflict events, the number of fatalities, and which land-cover classes were affected most, 2) the effect of all wars and of each war in its entirety on permanent cropland abandonment, and 3) whether permanent cropland abandonment was more likely when conflict locations occurred nearby with additional conflict locations farther away, and accounting for their intensity.

To address my questions I analyzed the Uppsala Conflict Data Program dataset from 1989 to 2015, cropland abandonment derived from Landsat imagery for five time periods from 1995 to

2015 from my first chapter, plus several physical and socio-economic variables that may affect agricultural land use. To better understand the differences among wars, I summarized the number of conflict events and the total number of fatalities in each war, as well as the number of conflict events in different land-cover classes. I applied matching statistics to account for differences in observable covariates, and a difference-in-differences model to isolate the overall effect of wars and the individual effect of wars on cropland abandonment by using both a conflict area and a valid non-conflict area. To assess the interaction between distance and intensity on cropland abandonment I parameterized logistic regression with panel data.

The results showed that the wars in Chechnya resulted in seven times more conflict events and four times more fatalities than the wars in Abkhazia, South Ossetia, and Nagorno-Karabakh combined. Across the Caucasus, I found that the majority of conflict locations occurred in cropland, rangeland, and urban areas. When I isolated the effect of wars on cropland abandonment, I found that 47% and 45% of cropland abandonment in the conflict area was attributed to the wars in Chechnya and Abkhazia, respectively, a result that was surprising, because the overall intensity in Chechnya was much higher than in Abkhazia. However, the effect of the wars differed greatly in spatial extent. Permanent cropland abandonment was wide-ranging in Abkhazia and affected almost the entire region, but was localized in Chechnya, where the effect was strongest near conflict locations. In Nagorno-Karabakh, the war did not result in higher abandonment, despite intense combat. I found that across the Caucasus, nearby conflict events had a stronger effect on land use than conflict events father away. For Chechnya and Nagorno-Karabakh the probability of cropland abandonment was significantly higher when conflict events occurred <10 km away. However, the war in Abkhazia resulted in the highest probability of abandonment when conflict events were within 10-20 km, indicating a broader effect on cropland abandonment there.

By applying consistent methodology and harmonized data I was able to directly compare the effects of wars on cropland abandonment among different wars. Both in Chechnya and Abkhazia, almost half of the abandonment in the conflict area can be attributed to the wars, despite the different character and levels of violence of the wars. However, in Chechnya the effect was rather localized maybe because attacks targeted the military, police, and government, and less the rural population. The wide-ranging effect in Abkhazia is most likely related to the patterns of displacement and refugee movement, and the post-war travel restriction. Across the Caucasus, the probability of abandonment was the highest when conflict events occurred nearby, especially in Chechnya and Nagorno-Karabakh. However, in Abkhazia, conflict events farther away resulted in higher probability of abandonment, which shows that considering only the closest conflict events would lead to imprecise estimations. Although there was a clear effect of the wars, my results and overall low abandonment rates in the Caucasus suggest that the people in the Caucasus continued cultivating their fields despite life-threatening challenges and they showed exceptional resilience during the time of war.

My second chapter shows the importance of applying consistent methods to compare the effect of wars on cropland abandonment directly. More broadly, the results of my second chapter highlight that the effect of wars is far from uniform, and wars that vary greatly in their intensity, can have similar detrimental effects on permanent land-use change.

Related manuscript: Buchner, J., Butsic, V., Yin, H., Kuemmerle, T., Baumann, M., Zazanashvili, N., Stapp, J., Radeloff, V.C. (in preparation). Different effects of wars on cropland abandonment in the Caucasus. To be submitted to *Global Environmental Change.*

Chapter III. The effectiveness of protected areas in the Caucasus in preventing forest loss and forest degradation of different forest types

Protected areas are a cornerstone of conservation designed to preserve biodiversity and ecosystems. However, not all protected areas are effective. When assessing effectiveness, the proxy measure is typically forest loss. While forest loss, when present, is a clear indicator for protected area effectiveness, selective logging and the removal of single valuable trees is also detrimental to forests causing forest degradation. However, forest degradation does not indicate a land-cover conversion and often remains undetected. It is essential to check for both forest loss and forest degradation and also if effectiveness differs by forest type because forest types may vary in their conservation value. The Caucasus has an extensive network of protected areas and forests in the Caucasus harbor many endemic species. However, forests are under threat due to illegal selective logging, especially in coniferous forests where species like the Nordmann fir are of high economic value. My goal was to assess if strictly protected areas across the Caucasus were effective in reducing 1) forest loss, 2) forest degradation, and 3) forest degradation in different forest types, namely in coniferous, mixed, and deciduous forests.

I analyzed both forest loss and forest degradation maps derived from Landsat imagery. Land-cover change maps from 1987 to 2015 derived from my first chapter captured forest loss, and annual spectral mixture analyses of all 1988 to 2018 Landsat data captured forest degradation, a new dataset produced for this study. To assess protected area effectiveness, I applied propensity score matching, including a set of control variables to account for non-random placement of protected areas, and panel regression techniques.

In terms of forest loss, protected areas appeared to be ineffective for the whole Caucasus in that probability of forest loss was significantly higher with protection than without protection from 1995 to 2015 (0.1 p.p.). Results were different among countries, but consistent within, e.g., in Azerbaijan protected areas were effective in reducing forest loss, but in Russia they were not. In Georgia, the result was insignificant and varied over time. In contrast, forest degradation was significantly lower inside protected areas for the entire Caucasus (-1.1 p. p.) from 1988 to 2018. However, that effectiveness was limited to deciduous forests and coniferous forest, and forest degradation in mixed forests was insignificant.

The effect of protected areas was overall low in the Caucasus, because in general forest loss and forest degradation is low across the Caucasus. However, larger clear-cuts in preparation for the Olympic Games in Sochinksy National Park and ski resorts in Kavkazsky most likely resulted in the in-effectiveness of protected areas in reducing forest loss in Russia. Protected areas were effective in reducing forest degradation, which is promising despite the small effect. Both deciduous forests and coniferous forests harbor endemic species in the Caucasus. Especially in the western Caucasus, the endemic Nordmann fir is at higher risk for logging due to its high commercial value.

Despite the overall low effect of protected areas in the Caucasus, the results from my third chapter highlight two important points. First, including forest degradation in protected area analysis provides important additional information and should be considered when forest loss is overall rare. Second, it is necessary to differentiate among forest types when assessing protected area effectiveness because effectiveness measures will depend largely on the most common forest types. Even when forests overall are secure, rare forest types may still be lost, and they may have higher conservation value than the dominant forest type.

Related manuscript: Buchner, J., Butsic, V., Lewinska, K. E., Burivalova, Z., Kuemmerle, T., Rogova, N., Bragina, E., Zazanashvili, N., Ghoddousi, A., Radeloff, V.C. (in preparation). The effectiveness of protected areas in the Caucasus in preventing forest loss and forest degradation of different forest types. To be submitted to *Conservation Biology*.

Significance and implications

Humans have transformed large proportions of the Earth’s land surface, but to manage resources sustainably, it is necessary to better understand where land-cover changes occur, and what causes the changes in land cover. My dissertation advances the knowledge in land-use science and conservation by providing the timing and the extent of cropland and forest-cover changes during the time of a political regime shift and wars, subsequently addressing the effect of war on cropland changes, and assessing the role of protected areas to prevent forest changes.

Scientifically my dissertation provides insight in long-term land-cover changes in the Caucasus. In my first chapter my findings highlight the variability of land-cover changes among countries, at a time of political upheaval, the breakdown of the Soviet Union. I showed that cropland abandonment was the major land-cover change in the South Caucasus, but cropland was surprisingly stable in the North Caucasus. Forest loss and forest gain were almost equal for the whole Caucasus. After the collapse of the Soviet Union four major wars broke out in the Caucasus. Wars can cause major disruption in land management and can have substantial effects on a farmer's decision whether to farm their fields or not. I advance the understanding of how wars in their entirety affect land abandonment, by comparing wars of different intensity and duration in my second chapter. I showed that the effect of individual wars on cropland abandonment can be similarly strong, despite their difference in violence intensity. An important scientific contribution because usually the effect of war is assessed for one war at a time, which makes the direct comparison with other wars difficult.

The methodological contribution of my research includes the application of large-area compositing with implemented topographic correction of Landsat imagery to provide accurate and gap-free land-cover classification. The methods I used are available through the open-source software FORCE, which makes the approach and topographic correction available for any mountain region. I further provide consistent methodology when I assessed the effect of wars on land-use change to allow direct comparison among regions. Different effects of wars on cropland in other studies partially result from inconsistent methods that do not allow for direct comparisons. By applying difference-in-differences models, I took into account valid non-conflict controls, to estimate the effect of wars consistently. This method is not region-specific and can be applied in other war-torn areas worldwide. It can also be used to assess the effect of other drivers that can be of socio-economic nature, e.g., political interventions or ecological nature, e.g., fire events. In my third chapter, I tested new measures to assess the effectiveness of protected areas by focusing on forest degradation, and applying it to different forest types. Forest loss is a standard measure to evaluate whether protected areas are effective or not. However, in many regions of the world, selective logging poses a great risk to forests, which is not detected when using data on forest-cover loss only.

My dissertation makes major contributions to conservation by 1) providing new insight into the effectiveness of protected areas using forest loss and forest degradation in different forest types as effectiveness measures, and 2) providing land-cover change maps for the Caucasus. Firstly, the results for my third chapter have strong implications for conservation because using either forest loss or forest degradation can lead to an incomplete picture and can bias conservation management. Assessing protected area effectiveness for both forest loss and forest degradation is not only useful in the Caucasus but should become common practice when evaluating protected area effectiveness in forest biomes. Further, I showed that it is essential to assess differences in forest types because forest types often differ in their conservation value. In the forests of the western Caucasus, coniferous forests originally occupied larger areas and are nowadays reduced to a small extent of their original extent. My study emphasizes the assessment of forest types separately because the effectiveness of protected areas is dominated by the most common forest type and rare forest types may be lost in the assessment. Thus, conservation efforts should include and prioritize rare forest types. Second, the developed land-cover change maps from my first chapter are directly available for conservation applications in the Caucasus. Land-cover change information is especially important for conservation in a biodiversity hotspot such as the Caucasus. To protect endemic species such as the snow leopard, land-cover information is needed for species distribution modelling, connectivity analysis, or future range maps. My land-cover maps can be used to prioritize regions for future protection, and to develop plans to integrate protected areas into the broader landscape.

References

Achard, F., Mollicone, D., Stibig, H.-J., Aksenov, D., Laestadius, L., Li, Z., Popatov, P., Yaroshenko, A., 2006. Areas of rapid forest-cover change in boreal Eurasia. For. Ecol. Manag. 237, 322–334. https://doi.org/10.1016/j.foreco.2006.09.080

Alix-Garcia, J., Bartlett, A., Saah, D., 2013. The landscape of conflict: IDPs, aid and land-use change in Darfur. J. Econ. Geogr. 13, 589–617. https://doi.org/10.1093/jeg/lbs044

Andam, K.S., Ferraro, P.J., Pfaff, A., Sanchez-Azofeifa, G.A., Robalino, J.A., 2008. Measuring the effectiveness of protected area networks in reducing deforestation. Proc. Natl. Acad. Sci. 105, 16089–16094. https://doi.org/10.1073/pnas.0800437105

Baumann, M., Kuemmerle, T., 2016. The impacts of warfare and armed conflict on land systems. J. Land Use Sci. 11, 672–688. https://doi.org/10.1080/1747423X.2016.1241317

Bowker, J.N., De Vos, A., Ament, J.M., Cumming, G.S., 2017. Effectiveness of Africa's tropical protected areas for maintaining forest cover. Conserv. Biol. 31, 559–569. https://doi.org/10.1111/cobi.12851

Bullock, E.L., Nolte, C., Segovia, A.R., Woodcock, C.E., 2019. Ongoing forest disturbance in Guatemala's protected areas. Remote Sens. Ecol. Conserv. 6, 141–152. https://doi.org/10.1002/rse2.130

Bullock, E.L., Woodcock, C.E., Souza, C., Olofsson, P., 2020. Satellite-based estimates reveal widespread forest degradation in the Amazon. Glob. Change Biol. 26, 2956–2969. https://doi.org/10.1111/gcb.15029

Butsic, V., Munteanu, C., Griffiths, P., Knorn, J., Radeloff, V.C., Lieskovský, J., Mueller, D., Kuemmerle, T., 2016. The effect of protected areas on forest disturbance in the Carpathian Mountains 1985-2010. Conserv. Biol. J. Soc. Conserv. Biol. 31, 570–580. https://doi.org/10.1111/cobi.12835

Craigie, I.D., Baillie, J.E.M., Balmford, A., Carbone, C., Collen, B., Green, R.E., Hutton, J.M., 2010. Large mammal population declines in Africa's protected areas. Biol. Conserv. 143, 2221–2228. https://doi.org/10.1016/j.biocon.2010.06.007

DeFries, R.S., Foley, J.A., Asner, G.P., 2004. Land-use choices: balancing human needs and ecosystem function. Front. Ecol. Environ. 2, 249–257. https://doi.org/10.1890/1540-9295(2004)002[0249:LCBHNA]2.0.CO;2

Draulans, D., Krunkelsven, E.V., 2002. The impact of war on forest areas in the Democratic Republic of Congo. Oryx 36, 35–40. https://doi.org/10.1017/S0030605302000066

Eklund, L., Degerald, M., Brandt, M., Prishchepov, A.V., Pilesjö, P., 2017. How conflict affects land use: agricultural activity in areas seized by the Islamic State. Environ. Res. Lett. 12, 054004. https://doi.org/10.1088/1748-9326/aa673a

Evans, K.L., Rodrigues, A.S.L., Chown, S.L., Gaston, K.J., 2006. Protected areas and regional avian species richness in South Africa. Biol. Lett. 2, 184–188. https://doi.org/10.1098/rsbl.2005.0435

Foley, J.A., DeFries, R., Asner, G.P., Barford, C., Bonan, G., Carpenter, S.R., Chapin, F.S., Coe, M.T., Daily, G.C., Gibbs, H.K., Helkowski, J.H., Holloway, T., Howard, E.A., Kucharik, C.J., Monfreda, C., Patz, J.A., Prentice, I.C., Ramankutty, N., Snyder, P.K., 2005. Global Consequences of Land Use. Science 309, 570–574. https://doi.org/10.1126/science.1111772

Foley, J.A., Ramankutty, N., Brauman, K.A., Cassidy, E.S., Gerber, J.S., Johnston, M., Mueller, N.D., O'Connell, C., Ray, D.K., West, P.C., Balzer, C., Bennett, E.M., Carpenter, S.R., Hill, J., Monfreda, C., Polasky, S., Rockström, J., Sheehan, J., Siebert, S., Tilman, D., Zaks, D.P.M., 2011. Solutions for a cultivated planet. Nature 478, 337–342. https://doi.org/10.1038/nature10452

Frantz, D., Röder, A., Stellmes, M., Hill, J., 2016. An Operational Radiometric Landsat Preprocessing Framework for Large-Area Time Series Applications. IEEE Trans. Geosci. Remote Sens. 54, 3928–3943. https://doi.org/10.1109/TGRS.2016.2530856

Gibbs, H.K., Ruesch, A.S., Achard, F., Clayton, M.K., Holmgren, P., Ramankutty, N., Foley, J.A., 2010. Tropical forests were the primary sources of new agricultural land in the 1980s and 1990s. Proc. Natl. Acad. Sci. 107, 16732–16737. https://doi.org/10.1073/pnas.0910275107

Griffiths, P., Linden, S. van der, Kuemmerle, T., Hostert, P., 2013. A Pixel-Based Landsat Compositing Algorithm for Large Area Land Cover Mapping. IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 6, 2088–2101. https://doi.org/10.1109/JSTARS.2012.2228167

Gutman, G., Radeloff, V., 2016. Land-Cover and Land-Use Changes in Eastern Europe after the Collapse of the Soviet Union in 1991. Springer, Switzerland.

Hansen, M.C., Potapov, P.V., Moore, R., Hancher, M., Turubanova, S.A., Tyukavina, A., Thau, D., Stehman, S.V., Goetz, S.J., Loveland, T.R., Kommareddy, A., Egorov, A., Chini, L., Justice, C.O., Townshend, J.R.G., 2013. High-Resolution Global Maps of 21st-Century Forest Cover Change. Science 342, 850–853. https://doi.org/10.1126/science.1244693

ICRC, 2007. Farming through conflict (No. T2007 93/ 002 10/ 2007 2000). ICRC Economic Security Unit.

Kranz, O., Sachs, A., Lang, S., 2015. Assessment of environmental changes induced by internally displaced person (IDP) camps in the Darfur region, Sudan, based on multitemporal MODIS data. Int. J. Remote Sens. 36, 190–210. https://doi.org/10.1080/01431161.2014.999386

Kuemmerle, T., Levers, C., Erb, K., Estel, S., Jepsen, M.R., Daniel Müller, Plutzar, C., Stürck, J., Verkerk, P.J., Verburg, P.H., Reenberg, A., 2016. Hotspots of land use change in Europe. Environ. Res. Lett. 11, 064020. https://doi.org/10.1088/1748-9326/11/6/064020

Lambin, E.F., Meyfroidt, P., 2011. Global land use change, economic globalization, and the looming land scarcity. Proc. Natl. Acad. Sci. 108, 3465–3472. https://doi.org/10.1073/pnas.1100480108

Lambin, E.F., Meyfroidt, P., 2010. Land use transitions: Socio-ecological feedback versus socio-economic change. Land Use Policy, Forest transitions, Wind power planning, landscapes and publics 27, 108–118. https://doi.org/10.1016/j.landusepol.2009.09.003

Lewińska, K.E., Hostert, P., Buchner, J., Bleyhl, B., Radeloff, V.C., 2020. Short-term vegetation loss versus decadal degradation of grasslands in the Caucasus based on Cumulative Endmember Fractions. Remote Sens. Environ. 248, 111969. https://doi.org/10.1016/j.rse.2020.111969

Liang, S., 2005. Topographic Correction Methods, in: Kong, J.A. (Ed.), Quantitative Remote Sensing of Land Surfaces. John Wiley & Sons, Ltd, pp. 231–245. https://doi.org/10.1002/047172372X.ch7

Matthews, E., Payne, R., Rohweder, M., Murray, S., 2000. Pilot analysis of global ecosystems: forest ecosystems. Pilot Anal. Glob. Ecosyst. For. Ecosyst.

Merode, E.D., Cowlishaw, G., 2006. Species Protection, the Changing Informal Economy, and the Politics of Access to the Bushmeat Trade in the Democratic Republic of Congo. Conserv. Biol. 20, 1262–1271. https://doi.org/10.1111/j.1523-1739.2006.00425.x

Nackoney, J., Molinario, G., Potapov, P., Turubanova, S., Hansen, M.C., Furuichi, T., 2014. Impacts of civil conflict on primary forest habitat in northern Democratic Republic of the

Congo, 1990–2010. Biol. Conserv. 170, 321–328. https://doi.org/10.1016/j.biocon.2013.12.033

Naidoo, R., Gerkey, D., Hole, D., Pfaff, A., Ellis, A.M., Golden, C.D., Herrera, D., Johnson, K., Mulligan, M., Ricketts, T.H., Fisher, B., 2019. Evaluating the impacts of protected areas on human well-being across the developing world. Sci. Adv. 5, eaav3006. https://doi.org/10.1126/sciadv.aav3006

Ordway, E.M., 2015. Political shifts and changing forests: Effects of armed conflict on forest conservation in Rwanda. Glob. Ecol. Conserv. 3, 448–460. https://doi.org/10.1016/j.gecco.2015.01.013

Pfaff, A., Robalino, J., Herrera, D., Sandoval, C., 2015. Protected Areas' Impacts on Brazilian Amazon Deforestation: Examining Conservation – Development Interactions to Inform Planning. PLOS ONE 10, e0129460. https://doi.org/10.1371/journal.pone.0129460

Potapov, P.V., Turubanova, S.A., Tyukavina, A., Krylov, A.M., McCarty, J.L., Radeloff, V.C., Hansen, M.C., 2015. Eastern Europe's forest cover dynamics from 1985 to 2012 quantified from the full Landsat archive. Remote Sens. Environ. 159, 28–43. https://doi.org/10.1016/j.rse.2014.11.027

Prishchepov, A.V., Müller, D., Baumann, M., Kuemmerle, T., Alcantara, C., Radeloff, V.C., 2017. Underlying Drivers and Spatial Determinants of post-Soviet Agricultural Land Abandonment in Temperate Eastern Europe, in: Gutman, G., Radeloff, V. (Eds.), Land-Cover and Land-Use Changes in Eastern Europe after the Collapse of the Soviet Union in 1991. Springer International Publishing, Cham, pp. 91–117. https://doi.org/10.1007/978-3-319-42638-9_5

Prishchepov, A.V., Radeloff, V.C., Baumann, M., Kuemmerle, T., Mueller, D., 2012. Effects of institutional changes on land use: agricultural land abandonment during the transition from state-command to market-driven economies in post-Soviet Eastern Europe. Environ. Res. Lett. 7, 024021. https://doi.org/10.1088/1748-9326/7/2/024021

Sanchez-Cuervo, A.M., Aide, T.M., 2013. Identifying hotspots of deforestation and reforestation in Colombia (2001–2010): implications for protected areas. Ecosphere 4, 1–21. https://doi.org/10.1890/ES13-00207.1

Sanderson, E.W., Jaiteh, M., Levy, M.A., Redford, K.H., Wannebo, A.V., Woolmer, G., 2002. The Human Footprint and the Last of the Wild: The human footprint is a global map of human influence on the land surface, which suggests that human beings are stewards of nature, whether we like it or not. BioScience 52, 891–904. https://doi.org/10.1641/0006-3568(2002)052[0891:THFATL]2.0.CO;2

Souza, C., Firestone, L., Silva, L.M., Roberts, D., 2003. Mapping forest degradation in the Eastern Amazon from SPOT 4 through spectral mixture models. Remote Sens. Environ., Large Scale Biosphere Atmosphere Experiment in Amazonia 87, 494–506. https://doi.org/10.1016/j.rse.2002.08.002

Souza, A.C. de, Prevedello, J.A., 2020. The importance of protected areas for overexploited plants: Evidence from a biodiversity hotspot. Biol. Conserv. 243, 108482. https://doi.org/10.1016/j.biocon.2020.108482

Tan, B., Masek, J.G., Wolfe, R., Gao, F., Huang, C., Vermote, E.F., Sexton, J.O., Ederer, G., 2013. Improved forest change detection with terrain illumination corrected Landsat images. Remote Sens. Environ. 136, 469–483. https://doi.org/10.1016/j.rse.2013.05.013

The Halo Trust, 2014. 25 years of getting mines out of the ground, for good. (Donor Report 2014). The Halo Trust, Dumfries, United Kingdom.

UNEP-WCMC, IUCN and NGS, 2018. Protected Planet Report 2018 - UNEP-WCMC. UNEP-WCMC, IUCN, NGS, Cambridge UK; Gland, Switzerland; Washington, D.C., USA.

Vanonckelen, S., Lhermitte, S., Balthazar, V., Rompaey, A.V., 2014. Performance of atmospheric and topographic correction methods on Landsat imagery in mountain areas. Int. J. Remote Sens. 35, 4952–4972. https://doi.org/10.1080/01431161.2014.933280

Vitousek, P.M., Mooney, H.A., Lubchenco, J., Melillo, J.M., 1997. Human Domination of Earth’s Ecosystems. Science 277, 494–499. https://doi.org/10.1126/science.277.5325.494

Wulder, M.A., Masek, J.G., Cohen, W.B., Loveland, T.R., Woodcock, C.E., 2012. Opening the archive: How free data has enabled the science and monitoring promise of Landsat. Remote Sens. Environ., Landsat Legacy Special Issue 122, 2–10. https://doi.org/10.1016/j.rse.2012.01.010

Yin, H., Butsic, V., Buchner, J., Kuemmerle, T., Prishchepov, A.V., Baumann, M., Bragina, E.V., Sayadyan, H., Radeloff, V.C., 2019. Agricultural abandonment and re-cultivation during and after the Chechen Wars in the northern Caucasus. Glob. Environ. Change 55, 149–159. https://doi.org/10.1016/j.gloenvcha.2019.01.005

Chapter I. Land-cover change in the Caucasus Mountains since 1987 based on the topographic correction of multi-temporal Landsat composites

Contributors: Buchner, J., Yin, H., Frantz, D., Kuemmerle, T., Askerov, E., Bakuradze, T., Bleyhl, B., Elizbarashvili, N., Komarova, A., Lewińska, K.E., Rizayeva, A., Sayadyan, H., Tan, B., Tepanosyan, G., Zazanashvili, N., Radeloff, V.C.

Abstract

Mountainous regions are changing rapidly across the world due to both land-use change and climate change. Given the importance of mountainous regions for ecosystem services and endemic biodiversity, monitoring these changes is essential. Satellite data provide a great resource to map land-cover change in mountainous regions, however mapping is especially challenging there because topographic complexity affects reflectance. The so-called 'topographic effect' has been successfully corrected for in case studies of small areas, but a comparison of large-area classifications and land-cover change analyses with and without topographic correction is missing. Here, we performed a long-term land-cover change assessment for a large mountainous region, i.e., the Caucasus Mountains with topographic correction. Our two goals were 1) to examine the effect of topographic correction on land-cover classification for a large mountainous region, and 2) to assess land-cover changes since 1987 across the Caucasus based on the full Landsat archive. Both the complex topography and the history of land-use changes, especially after the collapse of the Soviet Union in 1991, make the Caucasus Mountains an ideal study area to understand topographic effects on large-area land-cover mapping for the last three decades. First, we compared a non-topographically-corrected Landsat classification for 2015 with a classification that was topographically-corrected with an enhanced C-correction for the same year and assessed the accuracy of both. Second, we derived topographically-corrected

Landsat classifications for six dates to assess changes in cropland and forest from 1987 to 2015, based on class probabilities and post-classification comparisons. In regard to our first goal, topographic correction improved the overall accuracy of the classification only by 2% (from 79 to 81%), but disagreement rates were as high as 100% in mountainous regions, especially among forest types. In regard to our second goal, we found that cropland loss was the most prevalent change process since 1987. Cropland loss was particularly widespread in Georgia and Armenia until 2000, and in Azerbaijan until 2005. The North Caucasus (the Russian Federation) had more stable cropland over time, most likely due to different land reforms after the collapse of the Soviet Union, and the prevalence of flat landscapes and very fertile soils, which make cultivation easier than in the South Caucasus. Rates of forest change throughout the Caucasus Mountains were surprisingly low, with forest loss and forest gain being roughly equal. Forest loss was most likely related to both illegal logging and natural disturbance, whereas forest gain was most likely due to cropland abandonment and less grazing pressure. Our results highlight both the importance and the feasibility of topographic correction for accurate large-area land-cover classifications in steep terrain.

Introduction

Mountainous regions have a unique environment, harbor rich biodiversity, are high in endemism, and provide important ecosystem services such as water supply and recreation (EEA, 2010). However, mountainous regions are often subjected to land-use changes and climate changes, both of which impact mountain environments substantially. For example, forests in mountainous regions are often under threat due to illegal logging and livestock grazing (Bhatta et al., 2018; García-Ruiz et al., 1996). Mountainous areas are also often hotspots of agricultural abandonment resulting in forest expansion, particularly on steep slopes where cultivation is labor-intensive, for example, in the European Alps (Gellrich and Zimmermann, 2007; MacDonald et al., 2000). Changes in climate have contributed to increased tree mortality in some areas, but also increased growth and tree line shifts in other areas (Kulakowski et al., 2011). Further, extreme weather events such as drought can have detrimental effects on agricultural production, especially in regions where water is scarce (Lipper et al., 2014). Last but not least, land-use change and climate change often interact (Oliver and Morecroft, 2014), and to identify the causes of changes in land cover in mountainous regions, and ultimately ensure their sustainable management, it is necessary to map their spatial and temporal patterns accurately.

Land-cover changes in mountains require long-term observation with high-spatial resolution to ensure accurate mapping. With the opening of the Landsat archive (Woodcock et al., 2008; Wulder et al., 2012) the spatial and temporal coverage of satellite imagery has increased substantially, opening new opportunities for land-cover mapping such as gap-free imagery composites for large areas that overcome the challenges of limited, cloud-free data availability for large-areas (Griffiths et al., 2013; White et al., 2014). Such composites ensure that satellite image analyses are no longer restricted to scenes that are cloud-free in their entirety, and include all pixels that are not affected by clouds (Griffiths et al., 2013). Similarly, multi-seasonal imagery composites derived from Landsat imagery can capture phenological patterns among different parts of a study area. Phenology-adapted compositing algorithms dynamically adjust for spatial and temporal variations in land surface phenology due to, e.g., climate or altitude, and choose observations that matches the phenological phase of interest best (Frantz et al., 2017). Additionally, image metrics (e.g., average, standard deviation or percentiles) created during the compositing process based on all available cloud-free observations can provide valuable information for land-cover classifications (Bleyhl et al., 2017; Frantz et al., 2017; Gómez et al., 2016).

However, in mountainous regions land-cover mapping is challenging because of topographic effects (Tan et al., 2013; Vanonckelen et al., 2013). Topographic illumination effects due to shadows and steep slopes alter reflectance and thereby introduce classification errors (Vanonckelen et al., 2014). Topographic correction methods aim to remove these effects by calculating the radiance a pixel would have received and reflected without topography (Liang, 2005). Multiple topographic correction algorithms have been proposed to eliminate topographic effects. These algorithms can be categorized into three different types. First, empirical approaches only considering image-based statistical relationships that transform pixel reflectance so that the correlation between reflectance and illumination condition derived from a Digital Elevation Model (DEM) is eliminated (Tan et al., 2013). Second, physically based models model the transfer of radiance through the atmosphere to the target pixel and back (Balthazar et al., 2012). Third, semi-empirical models combine empirical and physical terms, via the inclusion of both image-based statistics and physical formula. The C-correction is one such semi-empirical model and compares favorably to other correction methods (Riano et al., 2003; Richter et al., 2009; Sola et al., 2016). The original C-correction has been improved to a modified C-correction, which includes an additional empirically derived parameter C (Frantz, 2019; Frantz et al., 2016; Kobayashi and Sanga-Ngoie, 2008). In prior studies, topographic correction of Landsat imagery improved land-cover classification accuracy in general (Moreira and Valeriano, 2014) and of forest mapping in particular to distinguish between forest types (i.e., coniferous forest and mixed forest) (Vanonckelen et al., 2013; Yin et al., in review). Topographic correction also increased overall accuracy of forest change maps up to 34% (Tan et al., 2013). However, most studies testing topographic correction have been limited to one or two Landsat footprints (e.g., Balthazar et al., 2012; Dorren et al., 2003; Hantson and Chuvieco, 2011; Li et al., 2015; Moreira and Valeriano, 2014), and very few have analyzed large areas (Flood et al., 2013; Frantz et al., 2016; Rufin et al., 2019). A topographically corrected Sentinel-2 product is made available by ESA since May of 2019, but the USGS does not offer operational correction for the Landsat data, and there is little information how topographic correction can affect broad-scale land-cover classification accuracy. In the era of Analysis Ready Data (ARD), an automatic approach for atmospheric and topographic correction of satellite imagery covering large areas is of growing importance though. Our aim was thus to test the feasibility and effectiveness of topographic correction for large-area mapping, and we selected the Caucasus Mountains as our study area. The Caucasus Mountains with their high elevation range and complex land-cover patterns are an ideal study area to assess the value of topographic correction for land-cover mapping of large areas.

The Caucasus underwent major institutional and political changes after the collapse of the Soviet Union in 1991 when the transition from a planned economy to a market-oriented economy altered institutions and triggered land reforms (Hartvigsen, 2014). The countries of the Caucasus implemented different land reforms regarding land ownership, affecting primarily agriculture and forests (Hartvigsen, 2013). The Russian Federation mostly distributed agricultural land through land shares to individuals, who often leased their acquired land shares back to large corporate farms, ultimately limiting the fragmentation of the land ownership. In Georgia, Armenia, and Azerbaijan, collective farms were privatized, and parcels were distributed to new owners resulting in a high fragmentation of both ownership and land use with an average parcel size of < 2.8 ha (Giovarelli and Bledsoe, 2001; Hartvigsen, 2014, 2013; Spoor, 2004; Terra

Institute, 2005). Forest was also state-owned during Soviet times and highly protected under the Soviet forest code since the 1950s (FAO, 2019). Public ownership and management of forests remained in the Caucasus region after the collapse (FAO, 2019). However, enforcement of environmental regulations varies, and there have been several armed conflicts in the Caucasus region raising the question of how land cover, particularly cropland and forest, has changed since the collapse.

Our overall goals were thus 1) to compare large-area Landsat classification accuracy for non-topographically-corrected versus imagery that was topographically-corrected with an enhanced C-correction, and 2) to map gains and losses of croplands and forests, the timing of these changes, and differences in these change trajectories among countries, across the Caucasus Mountains from 1987 to 2015. These two goals were mutually dependent. Our first, technical goal required to evaluate a land-cover classification in a large mountainous region, and our second goal, mapping land-cover changes in a mountainous region with steep terrain required topographic correction to obtain accurate results.

Methods

Study area

Our study area encompassed Georgia, Armenia and Azerbaijan in the south (South Caucasus) and parts of the Russian Federation in the north (North Caucasus), with a total area of 455,000 km^2 and included two major mountain ranges: the Greater Caucasus Mountain Range and the Lesser Caucasus Mountain Chain (Figure 1) (Zazanashvili et al., 2012). The mountains in the Greater Caucasus range from 500 - 3,000 m a.s.l. in the west but are lower eastwards towards the Caspian Sea (Volodicheva, 2002). The so called Side or Parallel range contains the tallest mountains peaking at 5,642 m a.s.l. at Mount Elbrus in the western part. Precipitation exceeds 2,000 mm per year in the coastal area close to the Black Sea (Zazanashvili et al., 1999). The majority of the mountains in the Lesser Caucasus range from 2,000 - 2,800 m a.s.l. in the west and 2,500 - 3,300 m a.s.l. in the south-east with the highest point of 4,090 m a.s.l. at Mount Aragats in Armenia (Volodicheva, 2002). Similar to the Greater Caucasus, the Lesser Caucasus has wet climate in its western part, but is more continental and dry in the eastern and south-eastern parts (Zazanashvili et al., 1999).

The Caucasus region contains seven major vegetation zones: deserts and semi-deserts, steppes, sparse arid woodlands, forests, subalpine woodlands, subalpine meadows, and alpine meadows (Gulisashvili, 1964; Volodicheva, 2002). Semi-deserts occur in southern Armenia and Nikhichevan, Azerbaijan, and along the coast of the Caspian Sea. Steppes occur in both the North Caucasus and South Caucasus, but have been heavily modified by humans and are largely replaced by agriculture. In the Russian part, secondary steppe occurs on the highlands of Stavropol and on lower elevation slopes of the Greater Caucasus. In the south, steppes occur on plains and upper mountain ranges of Armenia. The transitional zone between semi-desert and forests is typically covered by sparse arid woodland. Natural formations of this vegetation type remain in eastern Georgia, Azerbaijan, and Karabakh. Forests span across the entire Caucasus and occur from sea level up to 2,700 m a.s.l. Forests are often dominated by one or two species and species'-rich forests are fairly rare. Mixed and coniferous forests, including spruce (*Picea orientalis*), fir (*Abies nordmanniana*), and pine (*Pinus* spp.), are typical for the western part of the Caucasus at higher altitudes, whereas deciduous forests, including monodominant beech (*Fagus orientalis*), oak (*Quercus* spp.), oak and hornbeam (*Qercus-Carpinus caucasica*), and chestnut and hornbeam (*Castanea sativa-Carpinus caucasica*), are typical at lower elevations and towards the east. Forests transition into subalpine woodlands in higher altitude, but both being threatened by wood cutting and grazing. Subalpine woodlands are succeeded by subalpine meadows and alpine meadows between 2300 and 3700m (Gulisashvili, 1964; Volodicheva, 2002).

The countries of the South Caucasus, i.e., Georgia, Armenia, and Azerbaijan are relatively small with a population of 3.7 million, 2.9 million, and 9.6 million in 2015, respectively (World Bank Data, 2019a), especially when compared to their northern neighbor, the Russian Federation. Russia's North Caucasian Federal District, which covers parts of our study area, had a population of 9.4 million in 2010 (Rosstat, 2010). Both the North Caucasus and the countries of the South Caucasus are highly agrarian and have a high rural population (Holland, 2016; Lerman, 2009; O'Loughlin et al., 2007). The agricultural sector is important for employment, economic growth, poverty reduction, and food security (Welton et al., 2013). Agricultural employment rates in Georgia, Armenia, and Azerbaijan were 44%, 35%, and 36% in 2015 and agriculture provided 7%, 18%, and 6% of the country's GDP respectively in 2010 (World Bank Data, 2019b). Agriculture is predominantly carried out by individual households and is often a mix of crop and fruit production and small-scale animal husbandry, with specific products such as wine, nuts, cognac, or sugar concentrated in individual countries (Ahouissoussi et al., 2014; Welton et al., 2013). The republics of the North Caucasus were famous for their potato production during Soviet times, but the economy of the region was weaker compared to other republics in Russia after the collapse. Although increasing social polarization occurred in the North Caucasus, agriculture remains important for rural livelihoods and some republics experienced rising consumer demands, which created an increase of agricultural products such as wheat, corn, sunflower, and fruits (O'Loughlin et al., 2007; Rada et al., 2017).

Image pre-processing and topographic correction

We processed 12,651 L1T Landsat TM/ETM+/OLI images from the USGS archive acquired between 1985 and 2016, i.e., all available images with < 70% cloud cover for 35 WRS-2 footprints covering the Caucasus Mountains (Figure 1). We processed the imagery with the Framework for Operational Radiometric Correction for Environmental monitoring (FORCE) software (version 1.1 beta, available at http://force.feut.de) (Frantz, 2019; Frantz et al., 2016). FORCE is based on the radiative transfer theory and includes both atmospheric and topographic correction, as well as a correction for adjacency effects to estimate Bottom-of-Atmosphere (BOA) reflectance. Topographic correction is included in the form of an enhanced C-correction in FORCE (Frantz et al., 2016). Please refer to Appendix A at the end of the paper for a detailed description of FORCE and the implemented topographic correction. All images were projected to Lambert Azimuthal Equal Area (Datum: WGS 1984, latitude of origin: 42.5, central meridian: 43.5) with a spatial resolution of 30 m and were organized as data cubes with a tile size of 30 x 30 km.

To generate a gap-free dataset of clear-sky observations, we used FORCE to calculate pixel-based composites for six target years (1987, 1995, 2000, 2005, 2010, 2015, including +/- 1 year for 1995, because we expected most changes during the transition period, and +/- 2 years for the others ones). We analyzed multi-year time steps, because image availability from 1987 to 1995 was too limited for annual analyses (Figure A1).

We embedded land surface phenology in the compositing process to account for phenological differences related to both climatic variability and topographic complexity (Frantz et al., 2017). We calculated land surface phenology by pooling all available observations across all years to one annual set, because the number of cloud-free Landsat pixels was too limited to derive annual phenology, especially from 1985 to 1995. We used the Spline analysis of Time Series (SpliTS) algorithm to calculate land surface phenology (Mader, 2012). SpliTS derives phenological parameters (e.g., beginning and end of the growing season) by fitting polynomial splines to a time series of enhanced vegetation index (EVI) values and extracts parameters thereof. The pixel-based land surface phenology dynamically adjusts the target date for each pixel in an image composite (Frantz et al., 2017). We choose the following key vegetation stages such as start of season (SOS), which is the timing of year when vegetation growth begins, peak of season (POS), which is timing of maximum vegetation growth, and end of season (EOS), which is the timing when senescence occurs, for our analysis. We defined the extracted phenological parameters, i.e., SOS, POS, and EOS as the anchor sequence for the three image composites (Figure A2). We calculated land surface phenology only for one set of imagery, the uncorrected images, because our motivation for calculating this phenology was to account for the strong climatic gradient from east to west, and the elevation gradient. Furthermore, we needed to ensure that the target dates for our composites were the same for both the topographically-corrected and non-topographically corrected datasets. We determined the suitability of each observation for each seasonal composite based on several scores, i.e., acquisition day, acquisition year, distance to clouds or cloud shadows, potential contamination with haze, spectral correlation, and off-nadir view angle. A detailed description of the derivation of these scores is provided in Frantz et al. (2017). The total score S_T was computed as the weighted linear combination of the scores following Frantz et al. (2017):

$$S_T = \frac{\Sigma WS}{\Sigma W} \qquad (1)$$

where S denotes the phenology-adapted suitability of the acquisition day (S_D) and year (S_Y), the probability of cloudiness (S_C), the potential contamination with haze (S_H), the spectral correlation (S_R) and the view zenith angle (S_V), and W denotes the weight for each score. The highest total score defined the best observation which in turn was used for the seasonal composite (Frantz et al., 2017). In addition we calculated spectral-temporal metrics for each season to take advantage of all clear observations and to represent the variability of the land surface during the compositing period (target year +/- 2 years) (Frantz et al., 2017; Griffiths et al., 2013) (Table A1, Table A2, Figure A3). We calculated average, 25% quantile, 50% quantile, 75% quantile, range, standard deviation, and the number of observations for each spectral band for each of the three seasons.

To quantify the effect of topographic correction on land-cover classification, we calculated one set of Landsat imagery and seasonal composites for 2015 that were topographically-corrected and a second set of Landsat imagery and composites that were not topographically-corrected (detailed workflow Figure A4).

Land-cover classification with and without topographic correction

In our land-cover classifications we separated 10 land-cover classes namely coniferous forest, mixed forest, deciduous forest, barren, rangeland, cropland, built-up, wetlands, water, and snow and ice. To obtain training samples for all classes, we digitized polygons in areas that were both homogenous and stable over time according to high-resolution imagery in Google Earth, field visits, and the Climate Engine web app (Huntington et al., 2017) and assured that training samples were located across the study area to capture the heterogeneity of the landscape. Forest types were identified based on their phenology in fall and winter imagery and mixed forest was defined as woody vegetation with neither coniferous nor deciduous tree species covering > 70%

of the canopy. Cropland was identified based on the shape of the cultivated fields, evidence of plowing, and the homogenous green-up cover during one year. Areas with sparse vegetation, shrubs, and grassland were defined as rangeland. Barren was defined as high altitude areas in rocky terrain and areas with no vegetation cover (Figure A5). We randomly collected 2000 training pixels within the polygons of each class with a minimum distance of 30 m, and combined these with training samples that were available for two footprints in our study area from previous studies that followed the same land-cover classification scheme and mapped land-cover classes such as stable cropland, as well as different forest types and grassland (Yin et al., in review, 2018b). Our final set of training samples consisted of 9.7% coniferous forest, 9.1% mixed forest, 10.8% deciduous forest, 10% barren, 10.1% rangeland, 11.7% cropland, 9.5% built-up, 9.5% wetlands, 10% water, and 9.7% snow and ice. As input for our 2015 non-topographically and topographically-corrected classifications, we used the three seasonal Landsat composites plus the following spectral-temporal metrics, i.e., average, 25% quantile, 50% quantile, 75% quantile, range, standard deviation, and number of observations, calculated for each season (Bleyhl et al., 2017; Griffiths et al., 2013; Yin et al., 2017). As our classifier, we used the R package ‘C5.0‘ (Kuhn and Quinlan, 2018) for all classifications. ‘C5.0’ is a decision tree classifier that consists of a collection of tree-structured classifiers and can accommodate missing values (Friedl et al., 2002; Quinlan, 1986). By using C5.0 we were able to keep pixels with missing values in the seasonal composites by using values from the spectral-temporal metrics layers for the classification instead. We applied adaptive boosting with 100 trials. Ultimately, we calculated the per-pixel class probability based on the percentage of tree votes for each given class.

Initial results showed strong confusion between built-up, rangeland, and barren land, with built-up having a high commission error. To better separate the built-up class from other classes, we used class probability and a calibration approach (Yin et al., 2018a). Specifically, we sampled 200 validation points with < 50% probability and 200 validation points with > 50% probability of the built-up class for each time step, and labeled them based on high-resolution imagery in Google Earth. Based on these 400 validation points we calculated user's and producer's accuracy for different probability thresholds for the build-up class (i.e., probability > 50%, > 60%, > 70%, > 80%, and > 90%). The threshold that yielded the most balanced user's and producer's accuracy was selected for mapping the built-up class (Figure A6) (Yin et al., 2018a). Every built-up pixel that was below the probability threshold was assigned to the second-highest ranked class. Furthermore, based on visual interpretation, we label pixels above 2,000 m a.s.l that were classified as 'built-up' as 'rangeland'. In a final step, we applied a minimum mapping unit of 8 connected pixels and assigned smaller areas to the nearest neighboring class. We applied the same post-classification rules to both the non-topographically and the topographically-corrected classification.

To understand in which parts of our study area the topographic correction made the biggest difference, we summarized the disagreement between the non-topographically-corrected and the topographically-corrected classifications in a 300-m grid. Furthermore, we summarized the disagreement results based on the cosine correction term A_{CC} for the annual classification as follows:

$$A_{CC} = \left(\frac{\cos \Theta_{S\ SOS}}{\cos i_{\ SOS}} + \frac{\cos \Theta_{S\ POS}}{\cos i_{\ POS}} + \frac{\cos \Theta_{S\ EOS}}{\cos i_{\ EOS}}\right)/3 \qquad (2)$$

where Θ_S denotes the solar zenith angle and i denotes the solar incidence angle, both for the different seasons. Values above 1 indicate shaded areas, and values below 1 indicate brightened areas. Cos i is defined as in eq. (6) in Appendix A.

Land-cover change assessment for 1987, 1995, 2000, 2005, 2010, and 2015

Based on our results for 2015 (see section 3.1) we analyzed cropland and forest changes after 1987 using only topographically-corrected composites because they yielded higher classification accuracy. Data processing for all the remaining target years (1987, 1995, 2000, 2005, and 2010) followed the steps outlined for year 2015 in section 2.3. For our cropland change assessment, we retained two classes, ‘cropland’ and ‘non-cropland’. For the forest change assessment, we aggregated coniferous, mixed, and deciduous forest to ‘forest’ and the remaining classes to ‘non-forest’. We applied a post-classification comparison based on the classification maps for the six time steps. We did not classify change classes directly, because changes were generally rare making it infeasible to collect sufficient training samples for each of the 20 changes classes among the six time steps for both cropland and forest. In a final step, we applied a 3 x 3 window majority filter for both the cropland change map and the forest change map to reduce noise.

To compare cropland loss and gain, and forest loss and gain among different countries, regions and time steps, we calculated relative net changes (RNC) following Kuemmerle et al. (2009) as:

$$\mathrm{RNC} = \left(\frac{\mathrm{L_{i+1}}}{\mathrm{L_i}} - 1\right)100 \qquad i = \{1987, 1995, 2000, 2005, 2010\} \tag{3}$$

where L denotes the land class (either cropland or forest in km^2), and i denotes the time step.

Accuracy assessment

We validated both the non-topographically-corrected and the topographically-corrected classification map for 2015 by calculating overall accuracy, user's and producer's accuracy (Congalton, 1991), and the F1-score. The F1-score was calculated following Powers (2011) as:

$$\mathrm{F1} = \frac{2\ \mathrm{UA}\ \mathrm{PA}}{\mathrm{UA}+\mathrm{PA}} \tag{4}$$

where UA denotes user's accuracy, and PA producer's accuracy. The F1-score ranges from 0 to 1, being 1 when both UA and PA are 1, and being 0 if either UA or PA is 0. Greater differences between UA and PA result in a lower F1-score (Powers, 2011).

We selected a disproportionate stratified sampling approach for our validation samples to account for small classes (Olofsson et al., 2014; Stehman et al., 2003). We generated a total of 1,553 validation samples (Table A3), randomly sampled within each class of the topographically-corrected map and corrected the resulting confusion matrix by the area proportions of each class (Griffiths et al., 2014; Olofsson et al., 2014). For the accuracy assessment of the non-topographically-corrected map we used the same validation samples. Because the strata of the topographically-corrected map differed spatially from the non-topographically-corrected map, we took the inclusion probability of the validation samples into account to derive unbiased estimators (Stehman, 2014; Yin et al., 2018b). All samples for the accuracy assessment of the topographically-corrected classification were visually interpreted and labeled by two independent interpreters using high-resolution images in Google Earth and time series of the normalized difference vegetation index (NDVI), the bare soil index (BSI), and tasseled cap wetness calculated from the original Landsat imagery for 2015 in Google Earth Engine (Gorelick et al., 2017; Yin et al., 2020).

For the validation of our change detection maps, we selected new samples, and calculated overall, user's and producer's accuracies (Congalton, 1991). For both the cropland and the forest change map we aggregated some of the change classes, and kept single classes only when one consistent change and no deviations in any year occurred (example 1: 1987-'95: cropland and 2000-'15: non-cropland; example 2: 1987-'00: non-cropland and 2005-'15: cropland). Classes with a deviation in any year were aggregated to a 'transitional' class (e.g., 1987-'95: cropland, 1995-'00: non-cropland, and 2005-'15: cropland). We applied disproportional random sampling for both the cropland and the forest change map. We randomly selected 50 validation samples for each cropland and each forest change class. Because the transitional cropland class was much larger than the transitional forest class, we selected 150 validation samples for the former and 50 validation samples for the latter. Furthermore, we selected 150 validation samples each for the stable non-cropland class, stable non-forest class, stable cropland class, and stable forest class. In total, we generated 950 validation samples for the cropland change map and 850 validation samples for the forest change map (Olofsson et al., 2014). Samples for the change detection assessment were visually interpreted and labeled by only one interpreter, who was very familiar with the study region and the prevailing land-cover changes, using high-resolution images in Google Earth, and plotting NDVI, BSI, and tasseled cap wetness times series based on 1985 - 2016 Landsat imagery in Google Earth Engine to detect changes (Gorelick et al., 2017; Yin et al., 2020). Lastly, we calculated the error matrix with estimated proportions of area for both the cropland change map and the forest change map.

Results

Effects of topographic correction on land-cover mapping

Applying topographic correction improved the overall accuracy of the 2015 classifications from 79.4 ±0.9% to 81.2 ±1.8% (Table A4, Table A5). The error adjusted area estimates for our topographically-corrected classes were the largest for rangeland (175,787 km^2 ±14,904 km^2), followed by cropland (142,669 km^2 ±11,522 km^2), deciduous forest (72,669 km^2 ±9,593 km^2), water (21,066 km^2 ±5,210 km^2), barren (11,408 km^2 ±3,069 km^2), wetlands (11,062 km^2 ±2,308 km^2), mixed forest (10,455 km^2 ±3,662 km^2), coniferous forest 7,685 km^2 ±1,670 km^2), built-up (1,466 km^2 ±2,552 km^2), and ice and snow (564 km^2 ±135 km^2) (Figure 2, Figure A7).

User's accuracy for the non-topographically-corrected map was highest for deciduous forest (87%) and lowest for mixed forest (23%) (Figure 3). User's accuracy for the topographically-corrected map was generally higher and highest for rangeland (89%) and lowest for mixed forest (36%). The topographically-corrected classification had higher user's accuracies for all three forest types (coniferous forest (65%), mixed forest (36%), deciduous forest (88%)) compared to the non-topographically-corrected classification (coniferous forest (48%), mixed forest (23%), deciduous forest (87%)). Producers' accuracy was always higher for the topographically-corrected classification map, except for two classes (mixed forest and rangeland). Confidence intervals for producer's accuracy were always smaller for the topographically-corrected classification, except mixed forest (Figure 3).

The F1-score of the topographically-corrected map outperformed the non-topographically-corrected map for all but two classes (barren and snow and ice) (Figure 3). Topographic correction improved the F1-score of the coniferous forest class by 0.15 change points, deciduous forest by 0.05, mixed forest by 0.04, and rangeland, and cropland by 0.01 change points.

We found that barren, coniferous forest, mixed forest, and deciduous forest occurred on steeper slopes (on average 26.57°, 25.97°, 23.15°, and 17.15° respectively). Rangeland occurred on slopes with an average of 10.35° and cropland, built-up, wetlands, and water occurred in flat terrain with an average slope smaller than 3° (Table A6). We found the highest disagreement in class assignments between the non-topographically-corrected and the topographically-corrected maps along the crests of both the Greater and the Lesser Caucasus Mountain ranges (Figure 2). We observed the lowest agreement for the mixed forest class (Figure A8). When summarizing the disagreement by A_{CC}, disagreement was generally highest in extreme conditions, i.e., with very high A_{CC} (Figure 4). In areas that were moderately shaded or moderately brightend the disagreement rates were slightly higher for shaded areas than for bright areas. Disagreement rates were very low for highly brightend areas, however the percentage of cells, where that was the case, was less than 0.05% of the study region. In almost flat areas where the solar zenith angle Θ_S and the incidence angle i were roughly the same, disagreement rates were lowest (7%) (Figure 4). A good expample for this are the flat lands of the Northern Caucasus.

Cropland change

The overall cropland area decreased in all four countries when using 1987 as the baseline (Figure 5, Figure 6). The North Caucasus had the least amount of cropland loss, i.e., only 6% in 2000 compared to 1987. Georgia had biggest cropland loss in 2005 (-28%) and 2015 (-31%). Armenia had its highest cropland loss in 2000 (-17%), followed by an immediate increase in 2005. Armenia was the only country where cropland increased by 2% in 2010 compared to 1987. Azerbaijan went through the greatest cropland loss from 1987 to 2005 (-30%), with an increase in 2010 before again decreasing in 2015 (Figure 6). Throughout the study region cropland loss was mainly due to the conversion of cropland to rangeland and only occasionally due to the conversion to forest. Cropland gain was mostly due to the conversion of rangeland to cropland (Figure A9).

The North Caucasus had the largest extent of stable cropland (Figure 7), 39% of the total land area was continuously in cultivation from 1987 to 2015 there, and only 8% of what was cropland in 1987 was abandoned in a later year. In contrast, in Georgia, Armenia, and Azerbaijan, only 7%, 9%, and 10% of the total land area was continuously cultivated until 2015, and 10%, 10% and 15% of cropland in 1987 was abandoned in each country, respectively (Figure 7).

Aggregating cropland changes by administrative units (see Figure A10 for names of administrative units) revealed the substantial spatial variation in land-cover change trends (Figure 8). From 1987 to 1995 cropland decreased in all countries but Armenia, where a 6% increase was observed in its southern regions. Until 2000, Samtskeh-Javakheti and Shida Kartli in Georgia, as well as Shirak in Armenia showed a decrease in cropland. At the same time, parts of the North Caucasus, Kakheti in Georgia, and several regions in Azerbaijan had a slight increase in cropland. Between 2000 and 2005 cropland decreased in the eastern regions of the North Caucasus, Georgia and in two regions of Azerbaijan, namely Aran and Lankaran with a decrease of 14.9% and 7.4%, respectively. In Armenia, we found hardly any decrease in cropland between 2000 and 2005. In Azerbaijan, Aran and Lankaran had the highest increases of 13.3% and 6.6%, respectively, from 2005 to 2010, the time period during which most areas showed cropland gains. From 2010 to 2015 we observed a slight decrease in all regions in the North Caucasus and Georgia, as well as a decrease of 7.2% in Lori, Armenia. In Azerbaijan we found an increase in most regions, except Lankaran with a decrease of 7.4% (Figure 8).

Forest change

We found far less forest changes than cropland changes (Figure 9). Overall, forests increased during our study period (Figure 10). Most forest gains occurred along forest edges and on abandoned cropland and were due to the conversion of barren, rangeland, and cropland to forest (Figure 9, Figure A9). Forest loss was scattered throughout the study region and mostly due to the conversion of forest to rangeland or cropland (Figure A9).

Forest area increased in the North Caucasus (6%), Armenia (8%), and Georgia (6%) from 1987 to 2015, and only Azerbaijan experienced a decrease of forest compared to 1987 (-4%) (Figure 10). The highest forest loss rates of 6% occurred in Azerbaijan between 2000 and 2005 (Figure 10).

We found the highest forest loss rates in earlier years and less forest loss in later years. The highest forest loss rates from 1987 to 1995 were in mountain regions in the North Caucasus, in two regions in Georgia and in the northern part of Azerbaijan (Figure 11). During that time, Kalbajar-Lachin in Azerbaijan and Racha-Lechkhumi-Kvemo Svaneti in Georgia had the highest forest gain of 4.7% and 4.2%, respectively. From 1995 to 2000 more regions experienced forest loss than forest gain, with the highest forest loss rates occurring in two regions in Georgia, concomitant to the highest forest gain in Georgia. Between 2000 and 2005, forest loss was again more widespread than forest gain, although forest losses in the northern part of the Caucasus were minor, whereas the southern part of the Caucasus showed higher forest losses, especially in Azerbaijan. The highest forest gain occurred in Georgia (Imereti, 2.6%) and Armenia. From 2005 to 2010 forests mostly increased in Georgia, with a forest gain up to 6% in Guria. Lankaran in Azerbaijan had the highest forest loss (2.7%) for this time period. From 2010 to 2015, only one region in Georgia showed a decrease in forest higher than 2%, all other areas were more or less stable (< 1.9% change) or experienced forest gain (Figure 11).

Change accuracy assessment

Our cropland change map had an overall accuracy of 75.7 ±2.6%, but with high variation among classes (Table 1). We observed highest user's and producer's accuracies of 97% and 78%, respectively, for non-cropland, and 71% and 88%, respectively, for stable cropland. Cropland change classes obtained much lower accuracies ranging from 8% to 43% for user's accuracy, and from 9% to 68% for producer's accuracy. Confusion occurred mainly between the non-cropland and stable cropland classes, and change classes often showed confusion with the previous or following time step, i.e., the change was mapped correctly but its timing was not (Table 1).

The overall accuracy for the forest change map was 90.2 ±2.7%, and similar to the cropland change map with high variation among classes (Table 2). We found highest user's and producer's accuracies of 95% and 97%, respectively, for non-forest, and 95% and 83%, respectively, for stable forest. Our forest gain classes had lower producer's accuracies from 5% to 30%, and higher user's accuracies from 22% to 36%. The forest loss classes had higher producer's accuracies from 14% to 78%, but lower user's accuracies from 4% to 24%. Forest change classes, similar to cropland, often showed confusion with the previous or the following time step (Table 2).

Discussion

Effects of topographic correction on land-cover mapping

Land cover in mountainous regions is notoriously difficult to map with satellite images, because high variation in illumination conditions introduces errors in land-cover classifications. Here we show that topographic correction for large-area and long-term analyses is feasible and can improve classifications considerably. Our results are in line with previous studies for small study areas that showed that topographic correction improves the separation of forest types (Pimple et al., 2017; Vanonckelen et al., 2013), and these results make sense given that forests are often found in steep terrain where topographic correction has the largest effect. Topographic correction also enhanced the separation of forests from other land-cover classes, such as rangeland. By applying topographic correction, we were able to improve our large-area land-cover classifications, and hence our broad-scale land-cover change assessment.

The overall accuracy of the topographically-corrected classification map improved by only 2% compared to uncorrected imagery. The reason why that number was relatively low was that the large northern part of our study area has little topography and that is where mostly cropland and rangeland occur. Topographically-corrected imagery improved the classification especially in areas with extreme illumination conditions. In areas with steep topography, differences between the classification of topographically-corrected and uncorrected imagery were substantial, similar to what has been found previously (Vanonckelen et al., 2013; Yin et al., in review) and especially the accuracies for forest classes were higher when topographic correction was applied (Huang et al., 2008). Only two of our land-cover classes, barren and snow and ice, had a slightly higher F1-score for the non-topographically corrected classification. In a previous study of topographic correction methods for different land-cover classes (Sola et al., 2016), the intraclass interquartile range (IQR) reduction was best for the rock class, suggesting that this class is very homogenous and therefore its reflective behavior more controlled. In our case, barren and snow and ice were not homogenous, but rather often a mix of rock and ice that occurred in heavily jointed terrain with cast-shadows and very low illumination conditions. It is likely that a low availability of same-class pixels in the local pixel neighborhood resulted in an unreliable estimate of the regression parameters for the C-factor. Thus, the topographic correction potentially produced less accurate corrections. Indications for this can be derived from Figure A11, where a lower number of same-class pixels is apparent for snow-covered areas – although a lower number of available pixels does not result in lower R^2 for all land-cover classes. A second potential reason for the slightly higher F1-scores for barren, and snow and ice are errors in the SRTM, both in terms of geolocation relative to Landsat and the SRTM height estimates. In high relief areas with steep slopes and high elevation, SRTM tends to underestimate both slope and elevation (Guth, 2006; Mukul et al., 2017), and that may have adversely affected our topographic corrections. The highest disagreement rate between the two classification maps occurred in areas with extreme illumination conditions. In these areas, rangeland pixels were misclassified as deciduous forest, and deciduous forest was misclassified as mixed forest, when using uncorrected imagery. This is in line with a previous study that found that land-cover mapping accuracies for uncorrected images were lowest in very low and high illuminated areas (Moreira and Valeriano, 2014). Results from Vanonckelen et al. (2013) show similar results that the largest accuracy improvements were obtained in low illuminated areas. The disagreement between our two maps was lowest in areas where $\cos \Theta_S$ and $\cos i$ were similar, which is the case in areas where the topographic effect is minimum, such as in flat terrain, which was in our study area especially the case in the Northern Caucasus. We further found that within the total area where the land-cover classification differed, shaded pixels were more common than brightened pixels. For brightened pixels topographic correction mainly has to correct for geometric terms, whereas in shaded areas, direct illumination is reduced, resulting in larger correction factor areas, and consequently higher disagreement rates, too. This result is in line with Dorren et al. (2003), who found that classification errors for uncorrected images are more common for pixels with high incidence angles. Another reason for the lower disagreement rates in brightened areas may be the favored distribution of training samples in sunlit areas and therefore an optimized classification result (Meyer et al., 1993).

We found that in mountainous regions topographic correction is particularly valuable for distinguishing forest types, especially in a study region such as the Caucasus, where most forest occurs in rugged terrain. The mixed forest class had the highest disagreement between the non-topographically-corrected and topographically-corrected maps, which is similar to previous studies (Hill et al., 1995; Meyer et al., 1993). When illumination conditions are high, mixed forest is misclassified as deciduous forest, and when illumination conditions are low, mixed forest is misclassified as coniferous forest. By using topographically-corrected imagery, we greatly reduced the classification error among forest types, thereby improving the F1-score for all three forest types.

Cropland and forest change assessment

Our study presents the first broad-scale land-cover change assessment for the Caucasus Mountains that spans the entire 30-m resolution Landsat record. We successfully mapped cropland and forest changes over a large spatial extent with high-temporal frequency. By mapping the Caucasus Mountains frequently and identifying the timing of cropland and forest change, we provide important information to understand determinants for land-change processes.

We found a general decline in cropland from 1987 to 2000 (North Caucasus, Georgia, Armenia) and 2005 (Azerbaijan), similar to what occurred elsewhere in Eastern Europe and former Soviet Union countries (Estel et al., 2015; Kraemer et al., 2015; Kuemmerle et al., 2006; Schierhorn et al., 2013). However, we were surprised to find though that the North Caucasus had much less cropland loss than temperate European Russia, the Baltics, and Ukraine (Alcantara et al., 2013; Prishchepov et al., 2013). Our rates of cropland loss were also considerably lower than what had been previously estimated based on the mapping of early-successional woody vegetation as a proxy of abandonment, but those maps were based on 250-m MODIS data (Alcantara et al., 2013), which may be too coarse for the finely grained cropland cover in the Caucasus Mountains (Yin et al., 2019, 2018b).

Interestingly, we detected much more stable cropland in the North Caucasus compared to Georgia, Armenia, and Azerbaijan, although the agricultural sector of all four countries underwent major land reforms after the collapse of the Soviet Union (Lerman, 2006). A possible explanation for observed differences may be the differences in land distribution (Spoor, 2012). In Georgia, Armenia, and Azerbaijan, land of collective farms was distributed among community members and villagers (Hartvigsen, 2014). Communities with higher population density received smaller parcels resulting in highly fragmented land ownership, which may have hampered cultivation if parcels were far apart from each other. In contrast, in the Russian Federation, land distribution was carried out through land shares and the structure of the collective farms was often maintained resulting in less ownership fragmentation (Hartvigsen, 2014; Spoor, 2012). Another possible reason for higher rates of stable agriculture in the North Caucasus could be market demand, market accessibility and cost of cultivation (Rada et al., 2017). In the North Caucasus, the internal demand and access to the main market (the Russian Federation) did not change considerably shortly after the collapse of the Soviet Union. In the South Caucasus however, crop production that was oriented towards the Russian market (e.g. tea) became problematic, due to, among others factors, increased transportation costs and rising competition with other countries (Kochlamazashvili and Kakulia, 2013; O’Loughlin et al., 2007). Further, the plains of the North Caucasus with fertile chernozem soils and good climatic conditions make cultivation much easier than the hilly terrain of the South Caucasus (Afonin et al., 2008; de Beurs et al., 2017). The South Caucasus, especially the eastern part, is also prone to climate change. Droughts, heat events and water stress, as well as insufficiently managed irrigation and drainage systems, make cropland cultivation challenging (Ahouissoussi et al., 2014; Elizbarashvili et al., 2018).

We found that forest change rates in the Caucasus between 1987 and 2015 were smaller than forest changes in Central and Eastern Europe, and the former Soviet Union during the same time (Baumann et al., 2012; Griffiths et al., 2014; Potapov et al., 2015), which also surprised us. In general, we found a slight increase in forest cover for the North Caucasus, Georgia and Armenia since 1987, but a decrease until 2005 for Azerbaijan. Forest gain was often due to the conversion of cropland or rangeland to forest. Forest recovery on abandoned agricultural fields is common across former Soviet countries (Griffiths et al., 2014). Our results generally matched those from prior case studies of parts of our study area. For the war-torn regions Chechnya and Nagorno-Karabakh, located in Kalbajar-Lachin and Yukhari-Karabakh, we found very low rates of both forest loss and forest gain, and cropland change dominated, similar to previous results (Baumann et al., 2015; Yin et al., 2018b). For Georgia, a previous study found 0.8% forest loss from 1990 to 2000 and forest gain was miniscule (0.09%, (Olofsson et al., 2010)). We found an overall slight increase of 1.17% in forest cover between 1987 and 2000 across Georgia and some forest gains along forests edges and on abandoned fields in Abkhazia, which may be related to the armed conflict there in the early 1990s. In the North Caucasus, our results are in line with a previous study that detected large areas of forest loss related to the Olympic Games in Sochi in 2014 (Bragina et al., 2015).

In general, the reasons for forest change in the Caucasus Mountains are multifold, but are most likely primarily a result of the political situation, illegal logging, and sheep and cattle grazing (FAO, 2019). The increase in forest in Georgia and Armenia is likely related to the reduction of sheep grazing. After the collapse of the Soviet Union not only did the demand for sheep decrease, but the herds from Georgia also lost access to winter pastures in Dagestan (North Caucasus) (Radvanyi and Muduyev, 2007). As a result, forests started to regrow on former pastures in the mountains. A similar decline in sheep herds was observed in Armenia, when the Azerbaijani population moved to Azerbaijan after the start of the Nagorno-Karabakh conflict and forests started to regrow in some areas of former rangelands located within forested zones. Yet, in Azerbaijan pressure from sheep grazing on mountain grasslands increased since the collapse of the Soviet Union and may have resulted in forest loss (de Leeuw et al., 2019) and cattle grazing inside forests is causing forest degradation (UNECE and FAO, 2019). Another reason for forest loss in all four countries between 1987 and 2000/2005 was the unstable political situation. The forest sectors suffered from weak law enforcement and illegal logging both for fuelwood by the local population and for wood export by companies (FAO, 2015; Ozdogan et al., 2017). Illegal forest cutting has been identified as one of the main threats to biodiversity in the Caucasus (Zazanashvili et al., 2012). However, most forests occur in high elevation making transportation costly. Further, the establishment of many protected areas with relatively high protection status in the last 20 years likely protected forest from large clear cuts and broad-scale exploitation.

Limitations

To our knowledge, this is the first broad-scale land-cover change assessment for the Caucasus Mountains back to the 1980s. However, we acknowledge that our maps have some limitations.

To account for the climatic variability in our study region we integrated phenology for each pixel. Unfortunately, the number of cloud-free Landsat pixels was very limited in some years and consequently we had to average phenology across all years. Moreover, to generate gap-free composites we had to use satellite observations acquired within 1 or 2 years of the target year. Both steps reduced the temporal accuracy of our maps. This is why we restricted our land-cover change assessment to only two trajectories (gain and loss) and aggregated more complex changes to one transitional class, which improved change classification accuracies but prohibited an analysis of re-cultivation. Further, because of the lack of ground truth, most of our training samples were gathered using visual image interpretation. Labeling errors may have biased our accuracy assessment, but collecting a sufficient amount of error-free reference to validate land-use change maps over a large area is challenging (Stehman and Foody, 2019), and was not feasible for our study.

Our change detection maps had overall high accuracy, but user's and producer's accuracies for change classes were low. Validating a large number of change classes is challenging, especially for small change classes (Stehman and Foody, 2019). In our case, 19 out of the 20 change classes covered less than 1% of the study area, making it difficult to achieve high area adjusted user's and producer's accuracies. However, change classes often showed confusion with the previous or following time step, indicating that the changes are mapped correctly, but the exact timing may be shifted by one time step. Cropland change mapping is especially difficult in areas where the climate is highly variable, and where a variety of cropland cultivation methods are applied. Furthermore, non-intensively managed fields in arid regions are spectrally very similar to rangelands. For forest change maps, forest gain is typically more difficult to map than forest loss, because it occurs gradually and its timing is difficult to determine (Hansen et al., 2010; Li et al., 2017). Spectral similarities between orchards, vineyards, and forests also resulted in some classification errors. Lastly, we were not able to detect sub-pixel-level changes, which is unfortunate because overgrazing and selective logging are the dominant threats to forests, not large clear cuts (FAO, 2019).

Conclusion

We applied an integrated atmospheric and topographic correction approach and mapped land-cover changes in the Caucasus Mountains from 1987 to 2015 based on the full Landsat archive. In deriving our topographically-corrected land-cover classification, we demonstrated that it is feasible to correct for topographic effects when mapping large areas. The resulting maps were considerably more accurate, especially where the terrain is steep. It follows that we recommend making an integrated atmospheric and topographic correction of Landsat satellite imagery a matter of routine in mountainous regions to ensure accurate land-cover classifications. We found that the majority of the land-cover changes in the Caucasus were related to cropland changes that occurred between 1987 and 2005. Cropland was much more stable in the northern part of the Caucasus (the Russian Federation) compared to the southern countries, Georgia, Armenia, and Azerbaijan. In the South Caucasus, cropland was much more variable and the amount of cultivated cropland dropped especially from 2000 to 2005. Few changes occurred in forests, and forest loss and forest gain had similar magnitude. The observed changes are most likely connected to the collapse of the Soviet Union in 1991, and the subsequent land reforms and armed conflicts during the 1990s.

Data availability

All land-cover maps can be downloaded at http://silvis.forest.wisc.edu/maps-data/caucasus.

Acknowledgments

We gratefully acknowledge support for this research by the Land-cover and Land-Use Change (LCLUC) Program of the National Aeronautic Space Administration (NASA) through Grants 570NNX15AD93G and 80NSSC18K0316. We want to thank Dave Helmers for technical support. The authors also want to thank three anonymous reviewers whose comments improved the quality of the paper tremendously.

Appendix A: Methods - FORCE and implemented topographic correction

The framework for operational radiometric correction for environmental monitoring (FORCE) is a software to enable mass-processing of medium-resolution satellite imagery for large area applications. The FORCE Level 2 Processing system (L2PS) masks clouds, cloud shadows and snow pixels with an extended Fmask algorithm, which drops the termination criterion to increase cloud classification producer's accuracy, and includes a darkness filter to counteract false positives in dryland areas (modifications are described in Frantz et al., 2015; Zhu et al., 2015; Zhu and Woodcock, 2012). The cloud masking was evaluated in the Cloud Masking Inter-comparison Exercise (Earth ESA, 2016).

The atmospheric correction in FORCE L2PS is based on radiative transfer theory (Tanre et al., 1979) and includes integrated atmospheric and topographic correction, as well as a correction for adjacency effects to estimate Bottom-of-Atmosphere (BOA) reflectance (Frantz et al., 2016). Aerosol optical depth is estimated for each image over dark water and dense dark vegetation objects using multiple scattering. A precompiled water vapor database (Frantz et al., 2019; Frantz and Stellmes, 2018) was derived from MODIS (Gao and Kaufman, 2003) to correct for gaseous absorption (Frantz et al., 2016). The performance of the atmospheric correction implemented in FORCE was compared to other approaches (including ATCOR, LaSRC, and

Sen2Cor) in the Atmospheric Correction Intercomparison eXercise (ACIX) (Doxani et al., 2018). In those comparisons, FORCE produced high quality estimates of aerosol optical thickness and surface reflectance that were similar to those from LaSRC. The second edition of ACIX will include more in the depth comparison using a much larger reference dataset (Earth ESA, 2016)

The topographic correction algorithm in FORCE L2PS is an enhanced C-correction based on the theoretical principles outlined in Kobayashi and Sanga-Ngoie (2008) and on the predecessor algorithm described in Frantz et al. (2016). The topographic correction is closely integrated with atmospheric correction featuring both empirical and physical terms.

The traditional C-correction complements the cosine correction with a factor C (Teillet et al., 1982):

$$A_{\lambda} = \frac{\cos\Theta_S + C_{\lambda}}{\cos i + C_{\lambda}} \qquad (5)$$

where cos i represents the illumination angle and is defined as:

$$\cos i = \cos\Theta_S \cos\Theta_n + \sin\Theta_S \sin\Theta_n \cos(\Phi_S - \Phi_n) \qquad (6)$$

with Θ_S being the solar zenith angle, Θ_n the topographic slope angle, Φ_S is the solar azimuth angle, and Φ_n is the aspect angle of the topographic surface (Civco, 1989). Cos i ranges from -1 (minimum illumination) to 1 (maximum illumination). Values below 0 do not receive direct radiance. The subscript λ indicates terms that are dependent on wavelength.

The C-factor is assumed to model the contribution of the diffuse illumination (Teillet et al., 1982) and thus the C-correction is less affected by overcorrection in poorly illuminated areas because C_{λ} has a moderating influence on the cosine correction (Teillet et al., 1982). Commonly,

C_λ is empirically derived from a linear regression between the at-satellite radiance or reflectance and the illumination angle:

$$C_\lambda = \frac{b_\lambda}{m_\lambda} \quad (7)$$

with b_λ and m_λ being the intercept and slope of the regression line, respectively. The empirical estimation of C_λ accounts for non-Lambertian scattering of the surface target (Teillet et al., 1982). However, due to different Lambertian characteristics of different land surfaces, it is generally advised to estimate C_λ for at least vegetated and non-vegetated surfaces separately, e.g., by applying an NDVI threshold and to exclude relatively flat pixels (e.g. Hantson and Chuvieco, 2011). Frantz et al. (2016) analyzed the performance of approx. 40,000 C-corrected Landsat images, and results indicated that the correction was generally successful for the near and shortwave infrared bands, whereas topographic correction results for the visible bands were not a substantial improvement over non-corrected imagery for a considerable share of images. Frantz et al. (2016) concluded that this was likely due to the lack of a relationship between radiance and illumination angle in the visible bands when aerosol optical depth was high, i.e., when a strong and spatially homogeneous diffuse illumination component affected both sunlit and shaded areas.

Kobayashi and Sanga-Ngoie (2008) proposed that the topographic correction factor A_λ can be expressed with consideration of diffuse and direct illumination components as:

$$A_\lambda = \frac{\cos\Theta_S + f_\lambda \cos\Theta_S}{\cos i + h\, f_\lambda \cos\Theta_S} \quad (8)$$

where h is the portion of the sky dome diffusing on to the tilted surface:

$$h = \frac{1 - \Theta_n}{\pi} \quad (\Theta_n \text{ in radians}) \tag{9}$$

and f_λ is the proportionality factor between the direct $E_{b,\lambda}$ and the diffuse $E_{d,\lambda}$ irradiance reaching the horizontal surface:

$$f_\lambda = \frac{E_{d,\lambda}}{E_{b,\lambda}} \tag{10}$$

Kobayashi and Sanga-Ngoie (2008) derived that C_λ can be expressed as:

$$C_\lambda = h_0 \, f_\lambda \cos \Theta_S \tag{11}$$

with h_0 being the h-factor at cos i = 0, and can be expressed as:

$$h_0 = \frac{\pi + 2\Theta_S}{2\pi} \quad (\Theta_S \text{ in radians}) \tag{12}$$

When combining eq. 8 and 11, the A-factor becomes

$$A_\lambda = \frac{\cos \Theta_S + C_\lambda \, h_0^{-1}}{\cos i + C_\lambda \, h_0^{-1} \, h} \tag{13}$$

Thus, if direct and diffuse illumination terms are known, and that is the case when the topographic correction is integrated with atmospheric correction, the topographic correction factor can be computed. However, the reader may notice that this formulation of C_λ only takes into account the diffuse illumination, but not land surface characteristics such as non-Lambertian behavior. Therefore, an image-based estimation of C_λ might still be more practical. Nevertheless, as 1) C_λ can be modelled when direct and diffuse components are available, and 2) the empirical estimation of C is most successful for the SWIR2 band, but 3) might fail for the visual bands, it is feasible to empirically estimate C in the SWIR2 band only (C_{SW2}) and then propagate through the spectrum to any other wavelength. From eq. 11, it follows that the wavelength-dependency of C_λ is only due to f_λ. Thus, C_λ can be computed from C_{SW2} as:

$$C_\lambda = C_{SW2}\, f_{SW2}^{-1}\, f_\lambda \tag{14}$$

As shown in literature, it is most desirable to estimate C_{SW2} for each land-cover class individually to capture different land surface characteristics. Our approach thus estimated C_{SW2} for each pixel individually. However, this is computationally expensive, thus, we only estimated C_{SW2} for lower illumination areas ($\cos i < \cos \Theta_S$), whereas C_{SW2} was computed with eq. 11 for sunlit areas where overcorrections were less problematic. No topographic correction was attempted for deep shadow areas ($\cos i < 0$), and we assumed that topographic correction became less reliable for $i > 80°$ (Flood et al., 2013). For relatively flat pixels (slope < 2°), the traditional cosine correction was used. Please see an example map of C_{SW2} in Figure A11 for one Landsat image.

To calculate C_{SW2} for each pixel, it is necessary to include pixels from its neighborhood to parameterize the linear regression. Tan et al. (2013) suggested to use 3 x 3 km kernels for their empirical correction, which we basically adopted. Nevertheless, for performance considerations we only used sparse sampling, wherein the area closer to the central pixel was more densely sampled. Flat pixels (slope < 2°) were excluded from the linear regression. Pixels that were in a different land-cover class were excluded, too. Commonly, this is achieved using a fixed NDVI threshold of e.g., 0.4. However, this was disadvantageous in two respects: 1) this arbitrary division is ill-suited for pixels that are close to this threshold and 2) NDVI only separates vegetated a non-vegetated areas, thus e.g., forest and grassland are in the same class although they have substantially different Lambertian characteristics. Therefore, we used a (SWIR1 -

SWIR2) / (SWIR1 + SWIR2) threshold, which we found more meaningful when estimating C for the SWIR band. In addition, we did not use a fixed threshold but accepted a pixel if it differs less than + / - 0.025 from the central pixel. If C could not be estimated (e.g., because there were not enough samples or negative retrieval), the computed C (eq. 11) was used instead.

Reference

Afonin, A.N., Greene, S.L., Dzyubenko, N.I., Frolow, A.N., 2008. Interactive Agricultural Ecological Atlas of Russia and Neighboring Countries. Economic Plants and their Diseases, Pests and Weeds [Online] [WWW Document]. URL http://www.agroatlas.ru.

Ahouissoussi, N., Neumann, J.E., Srivastava, J.P., 2014. Building resilience to climate change in South Caucasus agriculture (No. 87601). The World Bank.

Alcantara, C., Kuemmerle, T., Baumann, M., Bragina, E.V., Griffiths, P., Patrick Hostert, Knorn, J., Müller, D., Prishchepov, A.V., Schierhorn, F., Sieber, A., Radeloff, V.C., 2013. Mapping the extent of abandoned farmland in Central and Eastern Europe using MODIS time series satellite data. Environ. Res. Lett. 8, 035035. https://doi.org/10.1088/1748-9326/8/3/035035

Balthazar, V., Vanacker, V., Lambin, E.F., 2012. Evaluation and parameterization of ATCOR3 topographic correction method for forest cover mapping in mountain areas. Int. J. Appl. Earth Obs. Geoinformation 18, 436–450. https://doi.org/10.1016/j.jag.2012.03.010

Baumann, M., Ozdogan, M., Kuemmerle, T., Wendland, K.J., Esipova, E., Radeloff, V.C., 2012. Using the Landsat record to detect forest-cover changes during and after the collapse of the Soviet Union in the temperate zone of European Russia. Remote Sens. Environ. 124, 174–184. https://doi.org/10.1016/j.rse.2012.05.001

Baumann, M., Radeloff, V.C., Avedian, V., Kuemmerle, T., 2015. Land-use change in the Caucasus during and after the Nagorno-Karabakh conflict. Reg. Environ. Change 15, 1703–1716. https://doi.org/10.1007/s10113-014-0728-3

Bhatta, K.P., Grytnes, J.-A., Vetaas, O.R., 2018. Downhill shift of alpine plant assemblages under contemporary climate and land-use changes. Ecosphere 9, e02084. https://doi.org/10.1002/ecs2.2084

Bleyhl, B., Baumann, M., Griffiths, P., Heidelberg, A., Manvelyan, K., Radeloff, V.C., Zazanashvili, N., Kuemmerle, T., 2017. Assessing landscape connectivity for large mammals in the Caucasus using Landsat 8 seasonal image composites. Remote Sens. Environ. 193, 193–203. https://doi.org/10.1016/j.rse.2017.03.001

Bragina, E.V., Radeloff, V.C., Baumann, M., Wendland, K., Kuemmerle, T., Pidgeon, A.M., 2015. Effectiveness of protected areas in the Western Caucasus before and after the transition to post-socialism. Biol. Conserv. 184, 456–464. https://doi.org/10.1016/j.biocon.2015.02.013

Civco, D.L., 1989. Topographic Normalization of Landsat Thematic Mapper Digital Imagery. Photogramm. Eng. Remote Sens. 55, 1303–1309.

Congalton, R.G., 1991. A review of assessing the accuracy of classifications of remotely sensed data. Remote Sens. Environ. 37, 35–46. https://doi.org/10.1016/0034-4257(91)90048-B

de Beurs, K., Ioffe, G., Nefedova, T., Henebry, G., 2017. Land Change in European Russia: 1982–2011, in: Gutman, G., Radeloff, V. (Eds.), Land-Cover and Land-Use Changes in Eastern Europe after the Collapse of the Soviet Union in 1991. Springer International Publishing, Cham, pp. 223–241. https://doi.org/10.1007/978-3-319-42638-9_10 de Leeuw, J., Rizayeva, A., Namazov, E., Bayramov, E., Marshall, M.T., Etzold, J., Neudert, R., 2019. Application of the MODIS MOD 17 Net Primary Production product in grassland carrying capacity assessment. Int. J. Appl. Earth Obs. Geoinformation 78, 66–76. https://doi.org/10.1016/j.jag.2018.09.014

Dorren, L.K.A., Maier, B., Seijmonsbergen, A.C., 2003. Improved Landsat-based forest mapping in steep mountainous terrain using object-based classification. For. Ecol. Manag. 183, 31–46. https://doi.org/10.1016/S0378-1127(03)00113-0

Doxani, G., Vermote, E., Roger, J.-C., Gascon, F., Adriaensen, S., Frantz, D., Hagolle, O., Hollstein, A., Kirches, G., Li, F., Louis, J., Mangin, A., Pahlevan, N., Pflug, B., Vanhellemont, Q., 2018. Atmospheric Correction Inter-Comparison Exercise. Remote Sens. 10, 352. https://doi.org/10.3390/rs10020352

Earth ESA, 2016. ACIX II - CMIX 1st WS [WWW Document]. URL https://earth.esa.int/web/sppa/meetings-workshops/hosted-and-co-sponsored-meetings/acix-ii-cmix (accessed 6.2.20).

EEA, 2010. Europe’s ecological backbone: recognising the true value of our mountains. European Environment Agency EEA, Copenhagen.

Elizbarashvili, N., Meessen, H., Khoetsyan, A., Meladze, G., Kohler, T., 2018. Sustainable development of mountain regions and resource management. Publish House “DANI,” Tbilisi.

Estel, S., Kuemmerle, T., Alcántara, C., Levers, C., Prishchepov, A., Hostert, P., 2015. Mapping farmland abandonment and recultivation across Europe using MODIS NDVI time series. Remote Sens. Environ. 163, 312–325. https://doi.org/10.1016/j.rse.2015.03.028

FAO, 2019. State of Forests of the Caucasus and Central Asia. Food and Agriculture Organization of the United Nations, New York and Geneva.

FAO, 2015. Global Forest Resources Assessment 2015. How are the world's forests changing? Food and Agriculture Organization of the United Nations, Rome, Italy.

Flood, N., Danaher, T., Gill, T., Gillingham, S., 2013. An Operational Scheme for Deriving Standardised Surface Reflectance from Landsat TM/ETM+ and SPOT HRG Imagery for Eastern Australia. Remote Sens. 5, 83–109. https://doi.org/10.3390/rs5010083

Frantz, D., 2019. FORCE—Landsat + Sentinel-2 Analysis Ready Data and Beyond. Remote Sens. 11, 1124. https://doi.org/10.3390/rs11091124

Frantz, D., Röder, A., Stellmes, M., Hill, J., 2017. Phenology-adaptive pixel-based compositing using optical earth observation imagery. Remote Sens. Environ. 190, 331–347. https://doi.org/10.1016/j.rse.2017.01.002

Frantz, D., Röder, A., Stellmes, M., Hill, J., 2016. An Operational Radiometric Landsat Preprocessing Framework for Large-Area Time Series Applications. IEEE Trans. Geosci. Remote Sens. 54, 4153–4164. https://doi.org/10.1109/TGRS.2016.2530856

Frantz, D., Röder, A., Udelhoven, T., Schmidt, M., 2015. Enhancing the Detectability of Clouds and Their Shadows in Multitemporal Dryland Landsat Imagery: Extending Fmask. IEEE Geosci. Remote Sens. Lett. 12, 1242–1246. https://doi.org/10.1109/LGRS.2015.2390673

Frantz, D., Stellmes, M., 2018. Water vapor database for atmospheric correction of Landsat imagery. Suppl. Frantz David Röder Achim Stellmes Marion Hill Joachim 2016 Oper. Radiom. Landsat Preprocessing Framew. Large-Area Time Ser. Appl. IEEE Trans. Geosci. Remote Sens. 547 3928-3943. https://doi.org/10.1594/PANGAEA.893109

Frantz, D., Stellmes, M., Hostert, P., 2019. A Global MODIS Water Vapor Database for the Operational Atmospheric Correction of Historic and Recent Landsat Imagery. Remote Sens. 11, 257. https://doi.org/10.3390/rs11030257

Friedl, M.A., McIver, D.K., Hodges, J.C.F., Zhang, X.Y., Muchoney, D., Strahler, A.H., Woodcock, C.E., Gopal, S., Schneider, A., Cooper, A., Baccini, A., Gao, F., Schaaf, C., 2002. Global land cover mapping from MODIS: algorithms and early results. Remote Sens. Environ., The Moderate Resolution Imaging Spectroradiometer (MODIS): a new generation of Land Surface Monitoring 83, 287–302. https://doi.org/10.1016/S0034-4257(02)00078-0

Gao, B.-C., Kaufman, Y.J., 2003. Water vapor retrievals using Moderate Resolution Imaging Spectroradiometer (MODIS) near-infrared channels. J. Geophys. Res. Atmospheres 108, 4389. https://doi.org/10.1029/2002JD003023

García-Ruiz, J.M., Lasanta, T., Ruiz-Flano, P., Ortigosa, L., White, S., González, C., Martí, C., 1996. Land-use changes and sustainable development in mountain areas: a case study in the Spanish Pyrenees. Landsc. Ecol. 11, 267–277. https://doi.org/10.1007/BF02059854

Gellrich, M., Zimmermann, N.E., 2007. Investigating the regional-scale pattern of agricultural land abandonment in the Swiss mountains: A spatial statistical modelling approach. Landsc. Urban Plan. 79, 65–76. https://doi.org/10.1016/j.landurbplan.2006.03.004

Giovarelli, R., Bledsoe, D., 2001. Land reform in Eastern Europe, Western CIS, Transcaucasus, Balkans, and EU Accession Countries. Seattle, Washington.

Gómez, C., White, J.C., Wulder, M.A., 2016. Optical remotely sensed time series data for land cover classification: A review. ISPRS J. Photogramm. Remote Sens. 116, 55–72. https://doi.org/10.1016/j.isprsjprs.2016.03.008

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., Moore, R., 2017. Google Earth Engine: Planetary-scale geospatial analysis for everyone. Remote Sens. Environ., Big Remotely Sensed Data: tools, applications and experiences 202, 18–27. https://doi.org/10.1016/j.rse.2017.06.031

Griffiths, P., Kuemmerle, T., Baumann, M., Radeloff, V.C., Abrudan, I.V., Lieskovsky, J., Munteanu, C., Ostapowicz, K., Hostert, P., 2014. Forest disturbances, forest recovery, and changes in forest types across the Carpathian ecoregion from 1985 to 2010 based on Landsat image composites. Remote Sens. Environ., Special Issue on 2012 ForestSAT 151, 72–88. https://doi.org/10.1016/j.rse.2013.04.022

Griffiths, P., Linden, S. van der, Kuemmerle, T., Hostert, P., 2013. A Pixel-Based Landsat Compositing Algorithm for Large Area Land Cover Mapping. IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 6, 2088–2101. https://doi.org/10.1109/JSTARS.2012.2228167

Gulisashvili, V.Z., 1964. Prirodnye zony i estestvenno-istoricheskie oblasti Kavkaza (Natural Zones and Historical Environmental Regions in the Caucasus). Nauka Publ. Mosc. 327 pp.

Guth, P.L., 2006. Geomorphometry from SRTM: Comparison to NED. Photogramm. Eng. Remote Sens. 72, 269–277.

Hansen, M.C., Stehman, S.V., Potapov, P.V., 2010. Quantification of global gross forest cover loss. Proc. Natl. Acad. Sci. U. S. A. 107, 8650–8655. https://doi.org/10.1073/pnas.0912668107

Hantson, S., Chuvieco, E., 2011. Evaluation of different topographic correction methods for Landsat imagery. Int. J. Appl. Earth Obs. Geoinformation 13, 691–700. https://doi.org/10.1016/j.jag.2011.05.001

Hartvigsen, M., 2014. Land reform and land fragmentation in Central and Eastern Europe. Land Use Policy 36, 330–341. https://doi.org/10.1016/j.landusepol.2013.08.016

Hartvigsen, M.B., 2013. Land Reform in Central and Eastern Europe after 1989 and its outcome in form of farm structures and land fragmentation (FAO Land Tenure Working No. 24).

Hill, J., Mehl, W., Radeloff, V., 1995. Improved forest mapping by combining corrections of atmospheric and topographic effects in Landsat TM imagery., in: Askne, J. Ed. Sensors and Environmental Applications of Remote Sensing. Balkena, Rotterdam, pp. 143–151.

Holland, E.C., 2016. Economic Development and Subsidies in the North Caucasus. Probl. Post-Communism 63, 50–61. https://doi.org/10.1080/10758216.2015.1067750

Huang, H., Gong, P., Clinton, N., Hui, F., 2008. Reduction of atmospheric and topographic effect on Landsat TM data for forest classification. Int. J. Remote Sens. 29, 5623–5642. https://doi.org/10.1080/01431160802082148

Huntington, J.L., Hegewisch, K.C., Daudert, B., Morton, C.G., Abatzoglou, J.T., McEvoy, D.J., Erickson, T., 2017. Climate Engine: Cloud Computing and Visualization of Climate and Remote Sensing Data for Advanced Natural Resource Monitoring and Process Understanding. Bull. Am. Meteorol. Soc. 98, 2397–2410. https://doi.org/10.1175/BAMS-D-15-00324.1

Kobayashi, S., Sanga-Ngoie, K., 2008. The integrated radiometric correction of optical remote sensing imageries. Int. J. Remote Sens. 29, 5957–5985. https://doi.org/10.1080/01431160701881889

Kochlamazashvili, I., Kakulia, N., 2013. The Georgian Tea Sector: A Value Chain Study. ENPARD - European Neighbourhood Programme for Agriculture and Rural Development, Tbilisi, Georgia.

Kraemer, R., Prishchepov, A.V., Müller, D., Kuemmerle, T., Radeloff, V.C., Dara, A., Terekhov, A., Frühauf, M., 2015. Long-term agricultural land-cover change and potential for cropland expansion in the former Virgin Lands area of Kazakhstan. Environ. Res. Lett. 10, 054012. https://doi.org/10.1088/1748-9326/10/5/054012

Kuemmerle, T., Chaskovskyy, O., Knorn, J., Radeloff, V.C., Kruhlov, I., Keeton, W.S., Hostert, P., 2009. Forest cover change and illegal logging in the Ukrainian Carpathians in the transition period from 1988 to 2007. Remote Sens. Environ. 113, 1194–1207. https://doi.org/10.1016/j.rse.2009.02.006

Kuemmerle, T., Radeloff, V.C., Perzanowski, K., Hostert, P., 2006. Cross-border comparison of land cover and landscape pattern in Eastern Europe using a hybrid classification technique. Remote Sens. Environ. 103, 449–464. https://doi.org/10.1016/j.rse.2006.04.015

Kuhn, M., Quinlan, R., 2018. C50: C5.0 Decision Trees and Rule-Based Models. R package version 0.1.2.

Kulakowski, D., Bebi, P., Rixen, C., 2011. The interacting effects of land use change, climate change and suppression of natural disturbances on landscape forest structure in the Swiss Alps. Oikos 120, 216–225. https://doi.org/10.1111/j.1600-0706.2010.18726.x

Lerman, Z., 2009. Land reform, farm structure, and agricultural performance in CIS countries. China Econ. Rev., Special Issue: Agriculture in TransitionAgriculture in Transition 20, 316–326. https://doi.org/10.1016/j.chieco.2008.10.007

Lerman, Z., 2006. The Impact of Land Reform on Rural Household Incomes in Transcaucasia. Eurasian Geogr. Econ. 47, 112–123. https://doi.org/10.2747/1538-7216.47.1.112

Li, A., Wang, Q., Bian, J., Lei, G., Li, A., Wang, Q., Bian, J., Lei, G., 2015. An Improved Physics-Based Model for Topographic Correction of Landsat TM Images. Remote Sens. 7, 6296–6319. https://doi.org/10.3390/rs70506296

Li, Y., Sulla-Menashe, D., Motesharrei, S., Song, X.-P., Kalnay, E., Ying, Q., Li, S., Ma, Z., 2017. Inconsistent estimates of forest cover change in China between 2000 and 2013 from multiple datasets: differences in parameters, spatial resolution, and definitions. Sci. Rep. 7, 8748. https://doi.org/10.1038/s41598-017-07732-5

Liang, S., 2005. Topographic Correction Methods, in: Kong, J.A. (Ed.), Quantitative Remote Sensing of Land Surfaces. John Wiley & Sons, Ltd, pp. 231–245. https://doi.org/10.1002/047172372X.ch7

Lipper, L., Thornton, P., Campbell, B.M., Baedeker, T., Braimoh, A., Bwalya, M., Caron, P., Cattaneo, A., Garrity, D., Henry, K., Hottle, R., Jackson, L., Jarvis, A., Kossam, F., Mann, W., McCarthy, N., Meybeck, A., Neufeldt, H., Remington, T., Sen, P.T., Sessa, R., Shula, R., Tibu, A., Torquebiau, E.F., 2014. Climate-smart agriculture for food security. Nat. Clim. Change 4, 1068–1072. https://doi.org/10.1038/nclimate2437

MacDonald, D., Crabtree, J.R., Wiesinger, G., Dax, T., Stamou, N., Fleury, P., Gutierrez Lazpita, J., Gibon, A., 2000. Agricultural abandonment in mountain areas of Europe: Environmental consequences and policy response. J. Environ. Manage. 59, 47–69. https://doi.org/10.1006/jema.1999.0335

Mader, S., 2012. A Framework for the Phenological Analysis of Hypertemporal Remote Sensing Data Based on Polynomial Spline Models [WWW Document]. URL http://ubt.opus.hbz-nrw.de/volltexte/2012/783/ (accessed 9.13.16).

Meyer, P., Itten, K.I., Kellenberger, T., Sandmeier, S., Sandmeier, R., 1993. Radiometric corrections of topographically induced effects on Landsat TM data in an alpine environment. ISPRS J. Photogramm. Remote Sens. 48, 17–28. https://doi.org/10.1016/0924-2716(93)90028-L

Moreira, E.P., Valeriano, M.M., 2014. Application and evaluation of topographic correction methods to improve land cover mapping using object-based classification. Int. J. Appl. Earth Obs. Geoinformation 32, 208–217. https://doi.org/10.1016/j.jag.2014.04.006

Mukul, Manas, Srivastava, V., Jade, S., Mukul, Malay, 2017. Uncertainties in the Shuttle Radar Topography Mission (SRTM) Heights: Insights from the Indian Himalaya and Peninsula. Sci. Rep. 7. https://doi.org/10.1038/srep41672

Oliver, T.H., Morecroft, M.D., 2014. Interactions between climate change and land use change on biodiversity: attribution problems, risks, and opportunities. Wiley Interdiscip. Rev. Clim. Change 5, 317–335. https://doi.org/10.1002/wcc.271

Olofsson, P., Foody, G.M., Herold, M., Stehman, S.V., Woodcock, C.E., Wulder, M.A., 2014. Good practices for estimating area and assessing accuracy of land change. Remote Sens. Environ. 148, 42–57. https://doi.org/10.1016/j.rse.2014.02.015

Olofsson, P., Torchinava, P., Woodcock, C.E., Baccini, A., Houghton, R.A., Ozdogan, M., Zhao, F., Yang, X., 2010. Implications of land use change on the national terrestrial carbon budget of Georgia. Carbon Balance Manag. 5, 4. https://doi.org/10.1186/1750-0680-5-4

O'Loughlin, J., Kolossov, V., Radvanyi, J., 2007. The Caucasus in a Time of Conflict, Demographic Transition, and Economic Change. Eurasian Geogr. Econ. 48, 135–156. https://doi.org/10.2747/1538-7216.48.2.135

Ozdogan, M., Olofsson, P., Woodcock, C.E., Baccini, A., 2017. Forest Changes and Carbon Budgets in the Black Sea Region, in: Gutman, G., Radeloff, V. (Eds.), Land-Cover and Land-Use Changes in Eastern Europe after the Collapse of the Soviet Union in 1991. Springer International Publishing, Cham, pp. 149–171. https://doi.org/10.1007/978-3-319-42638-9_7

Pimple, U., Sitthi, A., Simonetti, D., Pungkul, S., Leadprathom, K., Chidthaisong, A., 2017. Topographic Correction of Landsat TM-5 and Landsat OLI-8 Imagery to Improve the Performance of Forest Classification in the Mountainous Terrain of Northeast Thailand. Sustainability 9, 258. https://doi.org/10.3390/su9020258

Potapov, P.V., Turubanova, S.A., Tyukavina, A., Krylov, A.M., McCarty, J.L., Radeloff, V.C., Hansen, M.C., 2015. Eastern Europe's forest cover dynamics from 1985 to 2012 quantified from the full Landsat archive. Remote Sens. Environ. 159, 28–43. https://doi.org/10.1016/j.rse.2014.11.027

Powers, D.M., 2011. Evaluation: from Precision, Recall and F-measure to ROC, Informedness, Markedness and Correlation. J. Mach. Learn. Technol. 2, 37–63.

Prishchepov, A.V., Mueller, D., Dubinin, M., Baumann, M., Radeloff, V.C., 2013. Determinants of agricultural land abandonment in post-Soviet European Russia. Land Use Policy 30, 873–884. https://doi.org/10.1016/j.landusepol.2012.06.011

Quinlan, J.R., 1986. Induction of decision trees. Mach. Learn. 1, 81–106. https://doi.org/10.1007/BF00116251

Rada, N., Liefert, W., Liefert, O., 2017. Productivity Growth and the Revival of Russian Agriculture (Economic Research Service No. ERR-228). U.S. Department of Agriculture.

Radvanyi, J., Muduyev, S.S., 2007. Challenges Facing the Mountain Peoples of the Caucasus. Eurasian Geogr. Econ. 48, 157–177. https://doi.org/10.2747/1538-7216.48.2.157

Riano, D., Chuvieco, E., Salas, J., Aguado, I., 2003. Assessment of different topographic corrections in Landsat-TM data for mapping vegetation types (2003). IEEE Trans. Geosci. Remote Sens. 41, 1056–1061. https://doi.org/10.1109/TGRS.2003.811693

Richter, R., Kellenberger, T., Kaufmann, H., 2009. Comparison of Topographic Correction Methods. Remote Sens. 1, 184–196. https://doi.org/10.3390/rs1030184

Rosstat, 2010. Federal State Statistic Service, Rosstat [WWW Document]. URL https://www.gks.ru/ (accessed 12.20.19).

Rufin, P., Frantz, D., Ernst, S., Rabe, A., Griffiths, P., Özdoğan, M., Hostert, P., 2019. Mapping Cropping Practices on a National Scale Using Intra-Annual Landsat Time Series Binning. Remote Sens. 11, 232. https://doi.org/10.3390/rs11030232

Schierhorn, F., Müller, D., Beringer, T., Prishchepov, A.V., Kuemmerle, T., Balmann, A., 2013. Post-Soviet cropland abandonment and carbon sequestration in European Russia, Ukraine, and Belarus. Glob. Biogeochem. Cycles 27, 1175–1185. https://doi.org/10.1002/2013GB004654

Sola, I., González-Audícana, M., Álvarez-Mozos, J., 2016. Multi-criteria evaluation of topographic correction methods. Remote Sens. Environ. 184, 247–262. https://doi.org/10.1016/j.rse.2016.07.002

Spoor, M., 2012. Agrarian reform and transition: what can we learn from ‘the east’? J. Peasant Stud. 39, 175–194. https://doi.org/10.1080/03066150.2011.652949

Spoor, M., 2004. Land reform, rural poverty and inequality: a pro-poor approach to land policies (UNDP Armenia White Paper). The Hague/Yerevan.

Stehman, S.V., 2014. Estimating area and map accuracy for stratified random sampling when the strata are different from the map classes. Int. J. Remote Sens. 35, 4923–4939. https://doi.org/10.1080/01431161.2014.930207

Stehman, S.V., Foody, G.M., 2019. Key issues in rigorous accuracy assessment of land cover products. Remote Sens. Environ. 231, 111199. https://doi.org/10.1016/j.rse.2019.05.018

Stehman, S.V., Wickham, J.D., Smith, J.H., Yang, L., 2003. Thematic accuracy of the 1992 National Land-Cover Data for the eastern United States: Statistical methodology and regional results. Remote Sens. Environ. 86, 500–516. https://doi.org/10.1016/S0034-4257(03)00128-7

Tan, B., Masek, J.G., Wolfe, R., Gao, F., Huang, C., Vermote, E.F., Sexton, J.O., Ederer, G., 2013. Improved forest change detection with terrain illumination corrected Landsat images. Remote Sens. Environ. 136, 469–483. https://doi.org/10.1016/j.rse.2013.05.013

Tanre, D., Herman, M., Deschamps, P.Y., de Leffe, A., 1979. Atmospheric modeling for space measurements of ground reflectances, including bidirectional properties. Appl. Opt. 18, 3587. https://doi.org/10.1364/AO.18.003587

Teillet, P.M., Guindon, B., Goodenough, D.G., 1982. On the Slope-Aspect Correction of Multispectral Scanner Data. Can. J. Remote Sens. 8, 84–106. https://doi.org/10.1080/07038992.1982.10855028

Terra Institute, 2005. Final Report - Georgia Land Market Development Project. Terra Institute LTD for USAID.

UNECE, FAO, 2019. Forest Landscape Restoration in the Caucasus and Central Asia (GENEVA TIMBER AND FOREST DISCUSSION PAPER 72 No. ECE/TIM/DP/72). Geneva, Switzerland.

Vanonckelen, S., Lhermitte, S., Balthazar, V., Rompaey, A.V., 2014. Performance of atmospheric and topographic correction methods on Landsat imagery in mountain areas. Int. J. Remote Sens. 35, 4952–4972. https://doi.org/10.1080/01431161.2014.933280

Vanonckelen, S., Lhermitte, S., Van Rompaey, A., 2013. The effect of atmospheric and topographic correction methods on land cover classification accuracy. Int. J. Appl. Earth Obs. Geoinformation 24, 9–21. https://doi.org/10.1016/j.jag.2013.02.003

Volodicheva, N., 2002. The Caucasus, in: Shahgedanova, M. (Ed.), The Physical Geography of Northern Eurasia. Oxford University Press, Oxford, New York, pp. 350–376.

Welton, G., Asatryan, A.A., Jijelava, D., 2013. Comparative analysis of agriculture in the South Caucasus. UNDP Georgia, Tbilisi, Georgia.

White, J.C., Wulder, M.A., Hobart, G.W., Luther, J.E., Hermosilla, T., Griffiths, P., Coops, N.C., Hall, R.J., Hostert, P., Dyk, A., Guindon, L., 2014. Pixel-Based Image Compositing for Large-Area Dense Time Series Applications and Science. Can. J. Remote Sens. 40, 192–212. https://doi.org/10.1080/07038992.2014.945827

Woodcock, C.E., Allen, R., Anderson, M., Belward, A., Bindschadler, R., Cohen, W., Gao, F., Goward, S.N., Helder, D., Helmer, E., Nemani, R., Oreopoulos, L., Schott, J., Thenkabail, P.S., Vermote, E.F., Vogelmann, J., Wulder, M.A., Wynne, R., 2008. Free Access to Landsat Imagery. Science 320, 1011–1011. https://doi.org/10.1126/science.320.5879.1011a

World Bank Data, 2019a. Country Data [WWW Document]. World Bank Data. URL https://data.worldbank.org/ (accessed 11.27.19).

World Bank Data, 2019b. Employment in agriculture (% of total employment) (modeled ILO estimate) | Data [WWW Document]. World Bank Data. URL https://data.worldbank.org/indicator/sl.agr.empl.zs?end=2018&start=2018&view=map (accessed 5.24.19).

Wulder, M.A., Masek, J.G., Cohen, W.B., Loveland, T.R., Woodcock, C.E., 2012. Opening the archive: How free data has enabled the science and monitoring promise of Landsat. Remote Sens. Environ., Landsat Legacy Special Issue 122, 2–10. https://doi.org/10.1016/j.rse.2012.01.010

Yin, H., Brandão, A., Buchner, J., Helmers, D., Iuliano, B.G., Kimambo, N.E., Lewińska, K.E., Razenkova, E., Rizayeva, A., Rogova, N., Spawn, S.A., Xie, Y., Radeloff, V.C., 2020. Monitoring cropland abandonment with Landsat time series. Remote Sens. Environ. 246, 111873. https://doi.org/10.1016/j.rse.2020.111873

Yin, H., Butsic, V., Buchner, J., Kuemmerle, T., Prishchepov, A.V., Baumann, M., Bragina, E.V., Sayadyan, H., Radeloff, V.C., 2019. Agricultural abandonment and re-cultivation during and after the Chechen Wars in the northern Caucasus. Glob. Environ. Change 55, 149–159. https://doi.org/10.1016/j.gloenvcha.2019.01.005

Yin, H., Khamzina, A., Pflugmacher, D., Martius, C., 2017. Forest cover mapping in post-Soviet Central Asia using multi-resolution remote sensing imagery. Sci. Rep. 7, 1375. https://doi.org/10.1038/s41598-017-01582-x

Yin, H., Pflugmacher, D., Li, A., Li, Z., Hostert, P., 2018a. Land use and land cover change in Inner Mongolia - understanding the effects of China’s re-vegetation programs. Remote Sens. Environ. 204, 918–930. https://doi.org/10.1016/j.rse.2017.08.030

Yin, H., Prishchepov, A.V., Kuemmerle, T., Bleyhl, B., Buchner, J., Radeloff, V.C., 2018b. Mapping agricultural land abandonment from spatial and temporal segmentation of

Landsat time series. Remote Sens. Environ. 210, 12–24. https://doi.org/10.1016/j.rse.2018.02.050

Yin, H., Tan, B., Frantz, D., Radeloff, V., in review. The value of topographic correction for forest classification using Landsat Imagery. Remote Sens. Environ.

Zazanashvili, N., Gagnidze, R., Nakhutsrishvili, G., 1999. Main types of vegetation zonation on the mountains of the Caucasus. Acta Phytogeogr. Suec. 85, 7–16.

Zazanashvili, N., Garforth, M., Jungius, H., Gamkrelidze, T., 2012. Ecoregion Conservation Plan for the Caucasus. 2012 revised and updated edition. Ga. Tbilisi WWF KfW BMZ.

Zhu, Z., Wang, S., Woodcock, C.E., 2015. Improvement and expansion of the Fmask algorithm: cloud, cloud shadow, and snow detection for Landsats 4–7, 8, and Sentinel 2 images. Remote Sens. Environ. 159, 269–277. https://doi.org/10.1016/j.rse.2014.12.014

Zhu, Z., Woodcock, C.E., 2012. Object-based cloud and cloud shadow detection in Landsat imagery. Remote Sens. Environ. 118, 83–94. https://doi.org/10.1016/j.rse.2011.10.028

Tables and figures

Table 1: Error matrix (area proportion in percent) for user's accuracy (UA) and producer's accuracy (PA) for cropland change map (NC = non-cropland, TC = transitional cropland, SC = stable cropland, CG = cropland gain, CL = cropland loss) for topographically-corrected images for the five time intervals.

Reference (columns); **Classification** (rows)

Class	NC	TC	SC	CG15	CG10	CG05	CG00	CG95	CL95	CL00	CL05	CL10	CL15	UA
NC	**52.05**	0.00	0.72	0.36	0.00	0.00	0.00	0.00	0.36	0.00	0.36	0.00	0.00	**96.67**
TC	8.55	**7.39**	0.92	0.00	0.00	0.00	0.00	0.00	0.23	0.23	0.00	0.00	0.00	**42.67**
SC	1.54	3.51	**15.01**	0.00	0.00	0.00	0.14	0.14	0.00	0.00	0.14	0.42	0.14	**71.33**
CG15	0.61	0.08	0.00	**0.07**	0.05	0.00	0.00	0.00	0.02	0.00	0.02	0.00	0.00	**8.00**
CG10	0.25	0.04	0.01	0.01	**0.07**	0.01	0.02	0.00	0.00	0.00	0.00	0.00	0.00	**18.00**
CG05	0.17	0.05	0.01	0.00	0.01	**0.05**	0.00	0.00	0.00	0.01	0.00	0.00	0.00	**16.00**
CG00	0.21	0.04	0.03	0.00	0.01	0.01	**0.03**	0.00	0.00	0.00	0.00	0.00	0.00	**10.00**
CG95	0.30	0.21	0.19	0.00	0.06	0.00	0.06	**0.11**	0.02	0.00	0.00	0.00	0.00	**12.00**
CL95	1.60	0.13	0.00	0.00	0.00	0.00	0.00	0.00	**0.43**	0.00	0.00	0.00	0.00	**20.00**
CL00	0.40	0.08	0.00	0.00	0.00	0.00	0.00	0.00	0.11	**0.14**	0.06	0.00	0.00	**18.00**
CL05	0.23	0.04	0.03	0.00	0.00	0.00	0.00	0.00	0.04	0.02	**0.12**	0.00	0.00	**26.00**
CL10	0.12	0.05	0.02	0.00	0.00	0.00	0.00	0.00	0.04	0.07	0.08	**0.05**	0.00	**12.00**
CL15	0.39	0.22	0.11	0.00	0.00	0.00	0.00	0.00	0.02	0.09	0.02	0.09	**0.15**	**14.00**
PA	**78.36**	**62.43**	**88.07**	**15.52**	**36.33**	**67.60**	**13.99**	**44.59**	**33.91**	**25.98**	**15.48**	**9.31**	**52.16**	**75.7±2.6**

Table 2: Error matrix (area proportion in percent) for user's accuracy (UA) and producer's accuracy (PA) for forest change map (NF = non-forest, TF = transitional forest, SF = stable forest, FG = forest gain, FL = forest loss) for topographically-corrected images for the five time intervals.

Reference

Classification

Class	NF	TF	SF	FG15	FG10	FG05	FG00	FG95	FL95	FL00	FL05	FL10	FL15	UA
NF	**73.46**	0.00	0.51	1.54	1.03	0.51	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**95.33**
TF	1.33	**0.63**	1.72	0.00	0.08	0.00	0.08	0.00	0.00	0.00	0.00	0.00	0.08	**16.00**
SF	0.00	0.00	**15.50**	0.00	0.33	0.00	0.00	0.33	0.00	0.00	0.00	0.00	0.11	**95.33**
FG15	0.14	0.00	0.08	**0.16**	0.04	0.01	0.02	0.00	0.00	0.00	0.00	0.00	0.00	**36.00**
FG10	0.04	0.00	0.05	0.03	**0.07**	0.02	0.01	0.02	0.00	0.00	0.00	0.00	0.00	**30.00**
FG05	0.04	0.00	0.04	0.00	0.01	**0.06**	0.01	0.00	0.00	0.00	0.00	0.00	0.00	**34.00**
FG00	0.04	0.02	0.12	0.00	0.01	0.01	**0.06**	0.01	0.00	0.00	0.00	0.00	0.00	**22.00**
FG95	0.06	0.04	0.31	0.01	0.00	0.02	0.00	**0.15**	0.00	0.00	0.00	0.00	0.00	**26.00**
FL95	0.37	0.01	0.07	0.00	0.00	0.00	0.00	0.00	**0.02**	0.02	0.00	0.00	0.00	**4.00**
FL00	0.09	0.00	0.04	0.00	0.00	0.00	0.00	0.00	0.01	**0.02**	0.01	0.00	0.00	**12.00**
FL05	0.03	0.01	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.01	**0.03**	0.01	0.00	**24.00**
FL10	0.03	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**0.02**	0.01	**20.00**
FL15	0.04	0.00	0.09	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**0.03**	**20.00**
PA	**97.07**	**87.71**	**83.43**	**9.24**	**4.73**	**9.18**	**34.28**	**29.84**	**63.66**	**40.58**	**77.93**	**53.50**	**14.06**	**90.2±2.7**

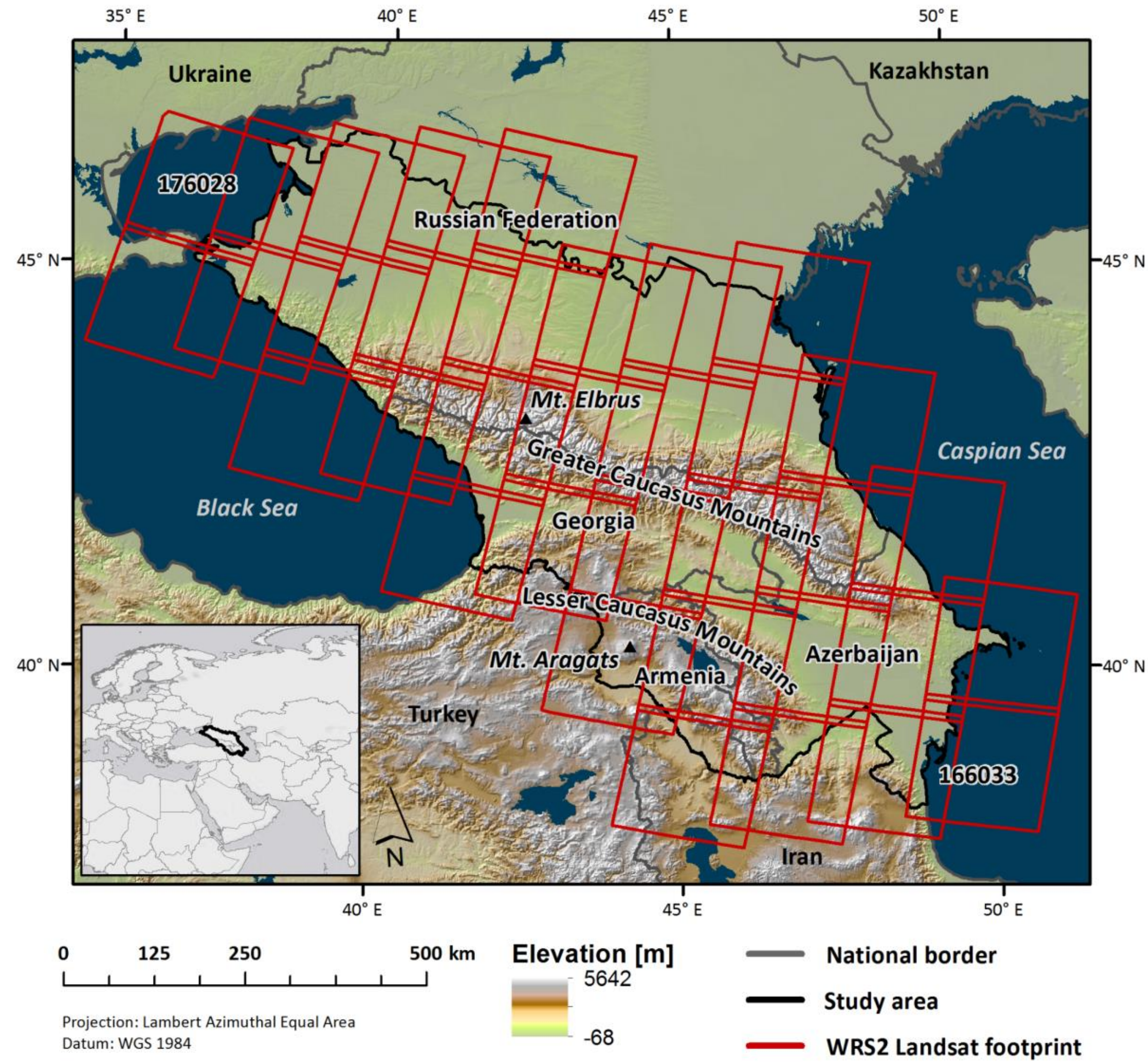


Figure 1: Overview of the 35 WRS2 Landsat footprints covering the Caucasus study area between the Black Sea and the Caspian Sea, including parts of the Russian Federation in the north, and Georgia, Armenia and Azerbaijan in the south.

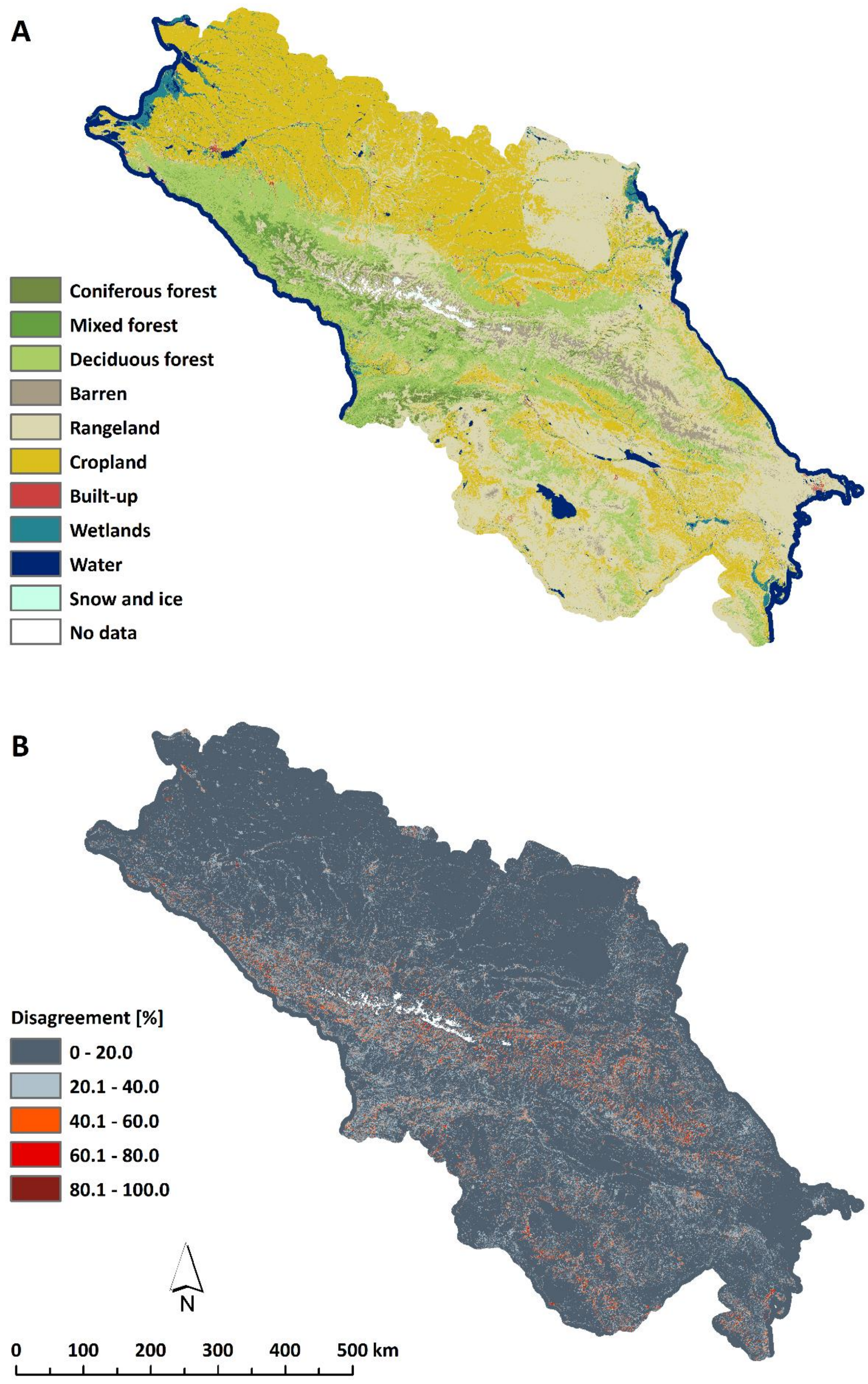


Figure 2: (A) Topographically-corrected land-cover classification for 2015 and (B) disagreement in percent between non-topographically-corrected and topographically-corrected classification maps summarized in a 300-m grid for visualization and analysis purposes.

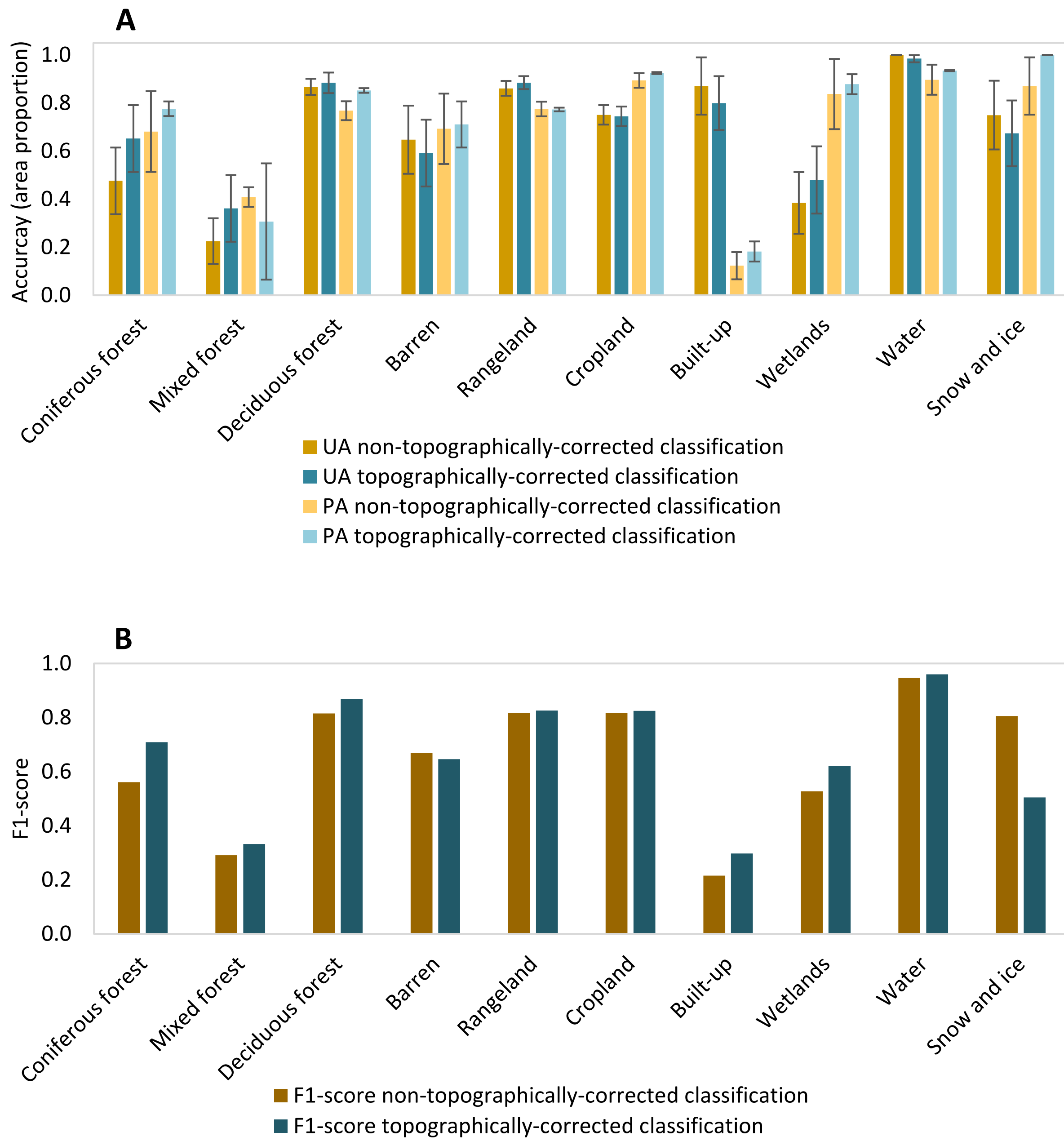


Figure 3: (A) Area adjusted user's accuracies (UA) and producer's accuracies (PA) of non-topographically-corrected and topographically-corrected classification. Error bars indicate the 95% confidence intervals. (B) F1-score based on user's and producer's accuracy of non-topographically-corrected and topographically-corrected classification.

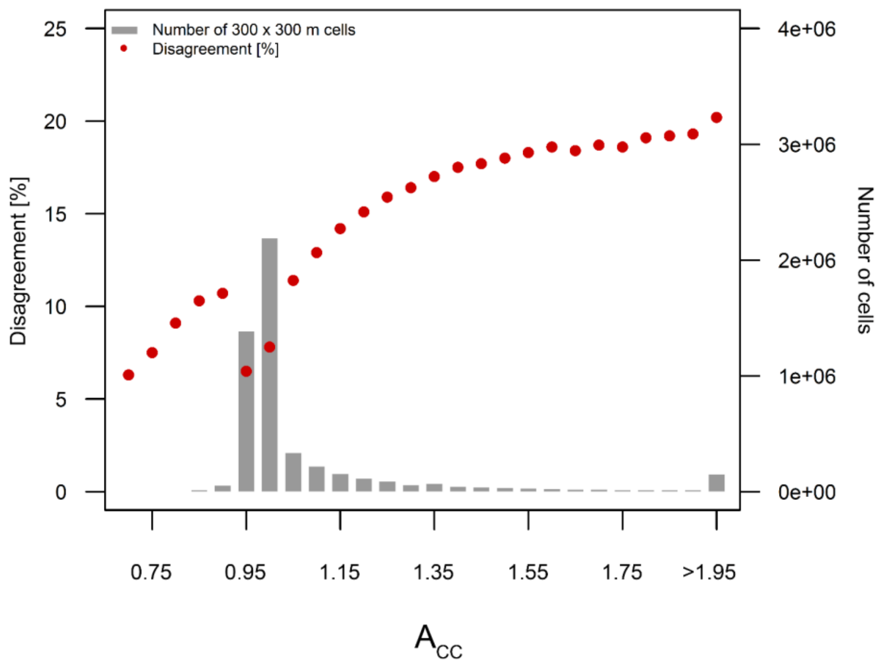


Figure 4: Mean disagreement in percent between the non-topographically-corrected and the topographically-corrected classification in a 300-m grid based on the mean annual values of A_{CC} for 2015. Please note that bin sizes on the extreme ends differ ($0.75<A_{CC}<=0.80$, $A_{CC}>1.95$).

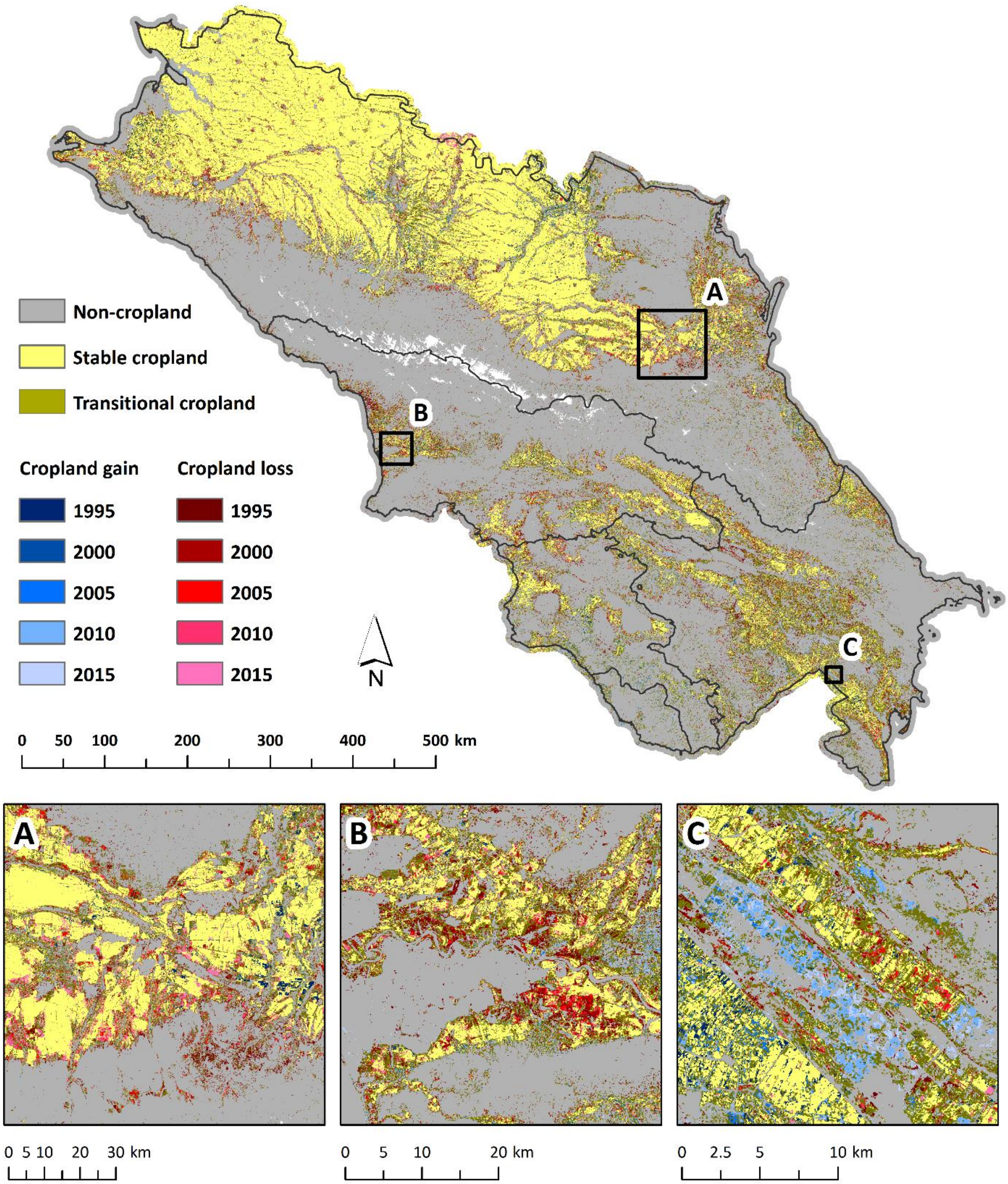


Figure 5: Cropland gain and loss in the Caucasus region from 1987 to 2015. The transitional cropland class contains pixels that alternated between cropland gain and loss. Zoom-ins show (A) cropland loss in Chechnya (Russian Federation), (B) cropland loss in parts of Guria and Samegrelo-Zemo Svaneti (Georgia), and (C) cropland gain in Aran (Azerbaijan).

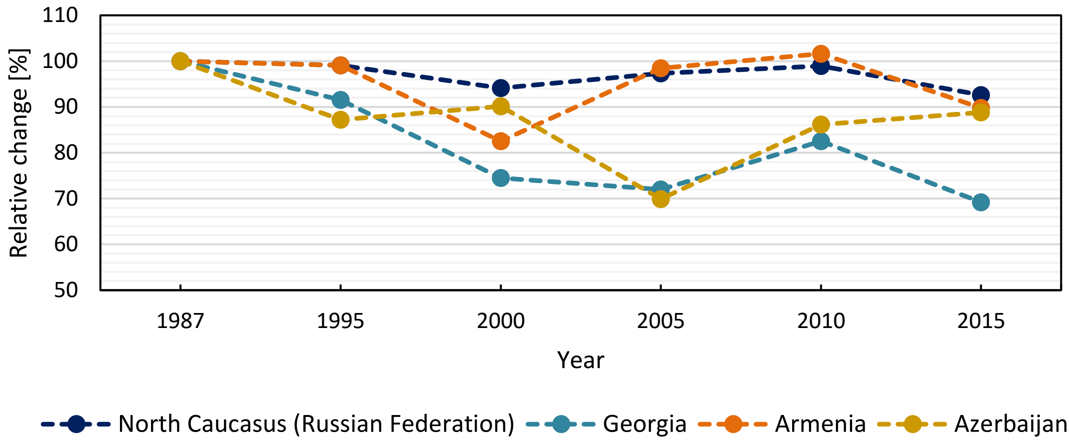


Figure 6: Relative cropland change for six time steps with 1987 as baseline for the North Caucasus (Russian Federation), Georgia, Armenia and Azerbaijan. Note that the y-axis starts at 50%.

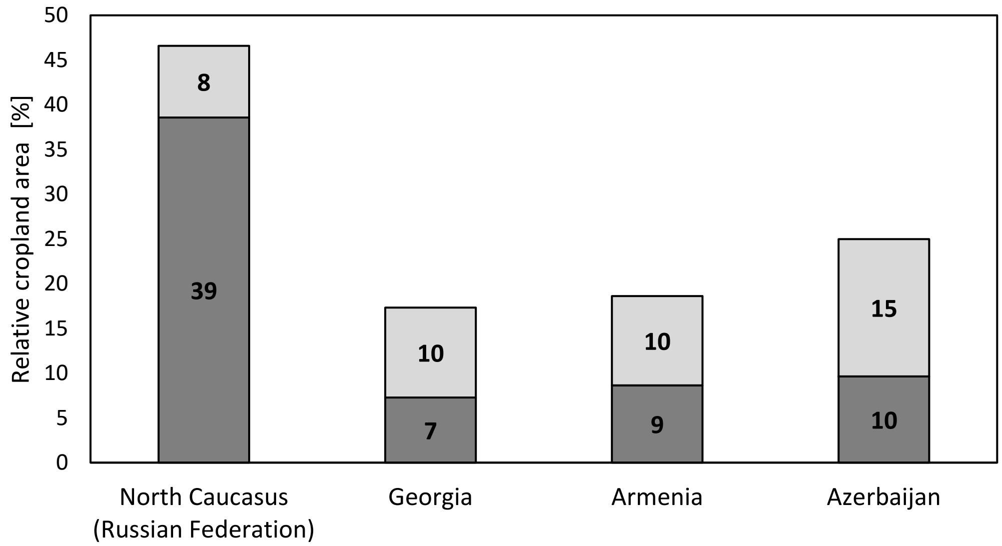


Figure 7: Percentage of stable active cropland from 1987 to 2015 (dark grey) and of cropland in 1987 that was subsequently abandoned (light grey).

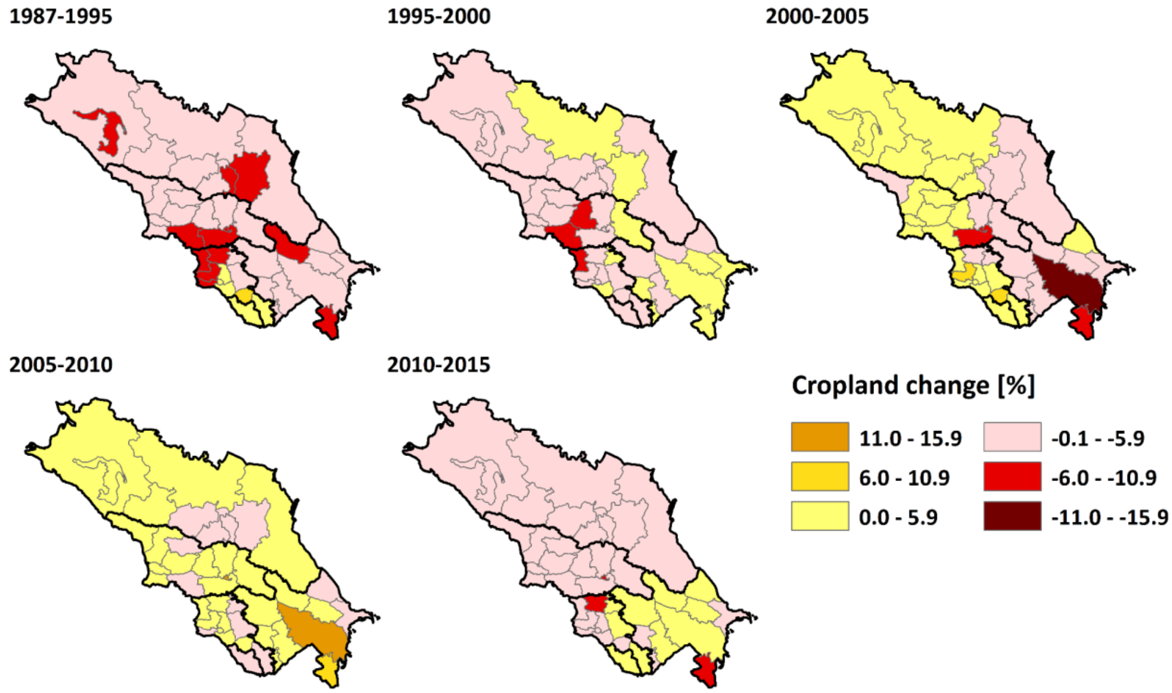


Figure 8: Cropland change aggregated for administrative units of the North Caucasus (Russian Federation), Georgia, Armenia and Azerbaijan. Please refer to supplemental information Figure A10 for names of administrative units.

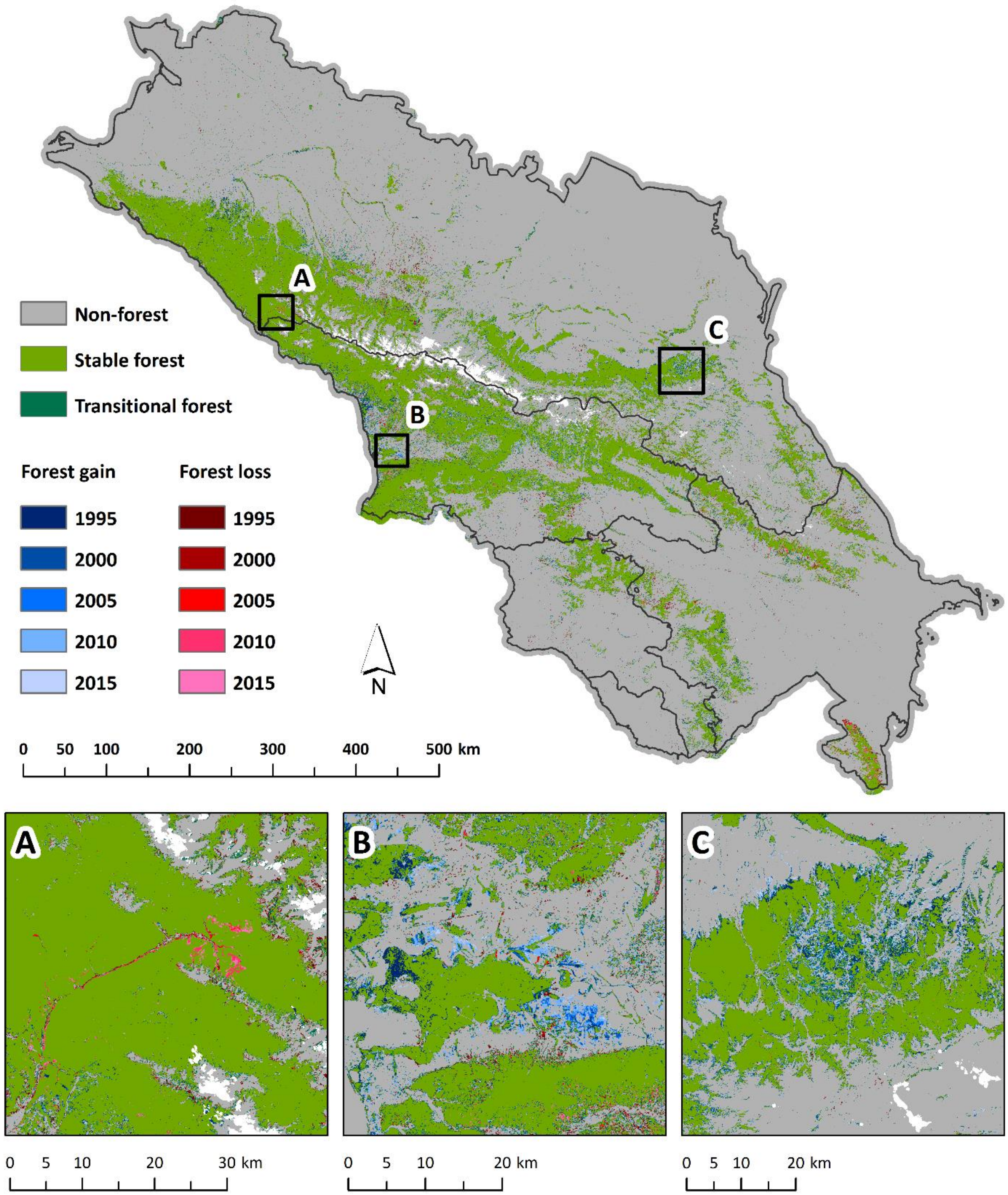


Figure 9: Forest gain and loss in the Caucasus region from 1987 to 2015. The transitional forest class contains pixels that alternated between forest gain and loss. Zoom-ins show (A) forest loss in Sochi (Russian Federation), (B) forest gain in Guria and Samegrelo-Zemo Svaneti (Georgia), and (C) forest gain in Chechnya (Russian Federation).

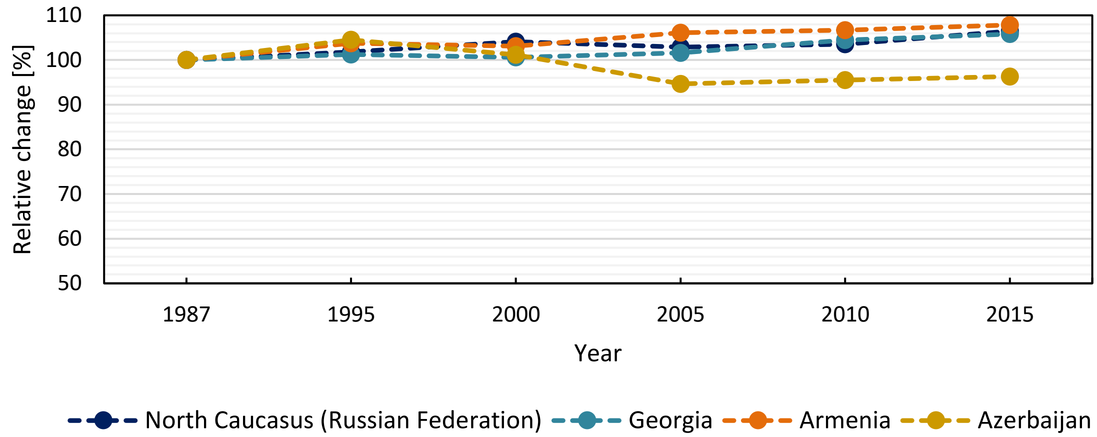


Figure 10: Relative forest change for six time steps with 1987 as baseline for the North Caucasus (Russian Federation), Georgia, Armenia and Azerbaijan. Note that the y-axis starts at 50%.

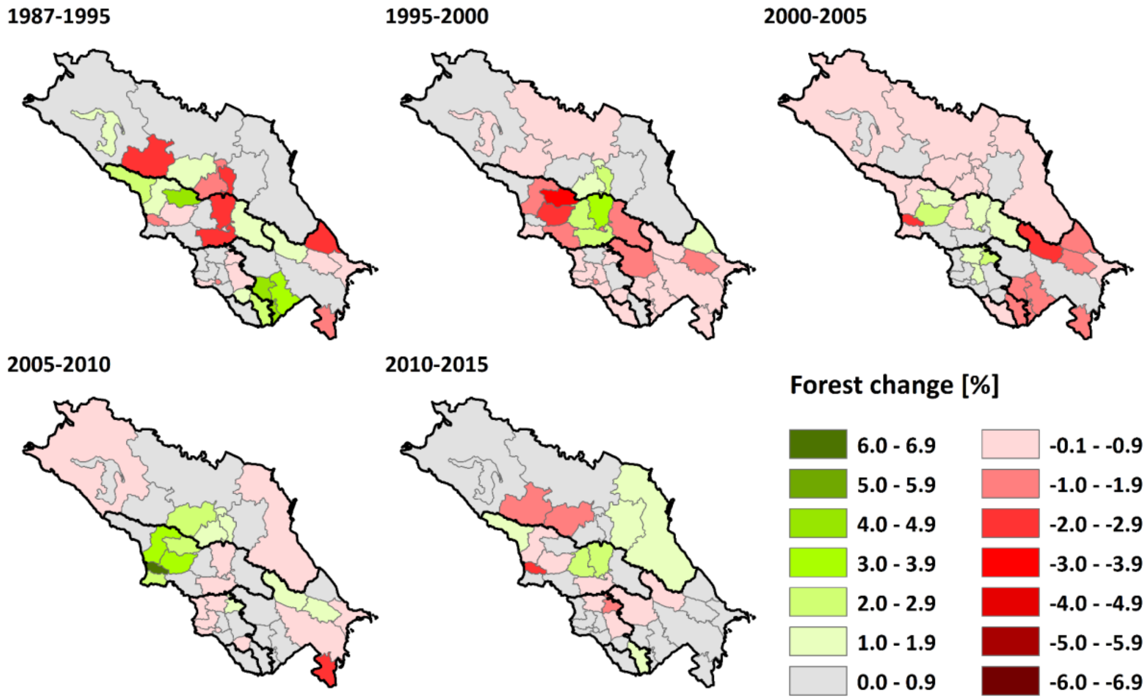


Figure 11: Forest change aggregated for administrative units of the North Caucasus (Russian Federation), Georgia, Armenia and Azerbaijan. Please refer to supplemental information Figure A10 for names of administrative units.

Appendix B: Supplementary information

Table A1: Mapping accuracies for topographically-corrected classification for 2015 based on bottom 20th percentile of validation data (1: Coniferous forest, 2: Mixed forest, 3: Deciduous forest, 4: Barren, 5: Rangeland, 6: Cropland, 7: Built-up, 8: Wetlands, 9: Water, 10: Snow and ice).

		Reference										
	Class	1	2	3	4	5	6	7	8	9	10	UA
Classification	1	19	4	4	0	0	0	0	0	0	0	0.7
	2	0	3	5	0	1	0	0	0	0	0	0.3
	3	1	1	25	0	4	2	0	0	0	0	0.8
	4	1	0	2	29	18	0	0	0	0	0	0.6
	5	0	0	4	0	92	3	1	0	1	0	0.9
	6	0	0	0	0	8	11	6	0	0	1	0.4
	7	0	0	1	4	3	0	5	0	0	1	0.4
	8	0	0	0	2	1	0	0	7	5	3	0.4
	9	0	0	0	4	0	0	0	0	6	1	0.5
	10	0	0	0	3	0	0	0	0	0	24	0.9
	PA	0.9	0.4	0.6	0.7	0.7	0.7	0.4	1.0	0.5	0.8	0.7

Table A2: Mapping accuracies for topographically-corrected classification for 2015 based on top 20th percentile of validation data (1: Coniferous forest, 2: Mixed forest, 3: Deciduous forest, 4: Barren, 5: Rangeland, 6: Cropland, 7: Built-up, 8: Wetlands, 9: Water, 10: Snow and ice).

		Reference										
	Class	1	2	3	4	5	6	7	8	9	10	UA
Classification	1											
	2											
	3			51	0	1	0	0	0	0		1.0
	4			3	0	2	0	0	0	0		0.0
	5			4	3	95	7	2	0	0		0.9
	6			2	0	27	82	4	1	0		0.7
	7			0	0	0	1	6	1	0		0.8
	8			0	0	1	0	0	2	0		0.7
	9			0	0	0	0	0	0	20		1.0
	10											
	PA			0.9	0.0	0.8	0.9	0.5	0.5	1.0		0.8

Table A3: Number of validation samples for all land-cover classes for the topographically-corrected map for 2015 after Olofsson et al. (2014) (Wi=mapped area proportion, Ui=conjectured values of user's accuracy, Si=standard deviation). Columns 5 and 6 are two different allocations with Alloc2(cleaned) as final allocation.

Stratum	Wi	Ui	Si	Alloc1	Alloc2(cleaned)
1 Conif. forest	0.017	0.7	0.46	50	46
2 Mixed forest	0.023	0.7	0.46	50	47
3 Decid. forest	0.160	0.8	0.40	228	216
4 Barren	0.025	0.7	0.46	50	49
5 Rangeland	0.386	0.8	0.40	552	540
6 Cropland	0.314	0.8	0.40	448	443
7 Built-up	0.003	0.8	0.40	50	50
8 Wetlands	0.024	0.8	0.40	50	50
9 Water	0.046	0.9	0.30	66	66
10 Snow and ice	0.001	0.7	0.46	50	46

Table A4: Area adjusted mapping accuracies for non-topographically-corrected classification for 2015 (1: Coniferous forest, 2: Mixed forest, 3: Deciduous forest, 4: Barren, 5: Rangeland, 6: Cropland, 7: Built-up, 8: Wetlands, 9: Water, 10: Snow and ice).

		Reference										
	Class	1	2	3	4	5	6	7	8	9	10	adj UA
Classification	1	0.97	0.34	0.41	0.00	0.24	0.00	0.04	0.04	0.00	0.00	0.48±0.14
	2	0.27	0.55	1.62	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.23±0.09
	3	0.11	0.45	13.78	0.00	1.32	0.22	0.00	0.00	0.00	0.00	0.87±0.03
	4	0.00	0.00	0.00	1.45	0.72	0.00	0.01	0.00	0.05	0.01	0.65±0.14
	5	0.07	0.00	1.36	0.62	34.30	2.40	0.99	0.00	0.07	0.00	0.86±0.03
	6	0.00	0.00	0.41	0.00	6.72	22.59	0.20	0.17	0.00	0.00	0.75±0.04
	7	0.00	0.00	0.00	0.00	0.03	0.00	0.17	0.00	0.00	0.00	0.87±0.12
	8	0.00	0.00	0.36	0.00	0.92	0.05	0.00	1.07	0.38	0.00	0.38±0.13
	9	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	4.42	0.00	1.00±0.03
	10	0.00	0.00	0.00	0.02	0.01	0.00	0.00	0.00	0.00	0.07	0.75±0.14
	adj PA	0.68±0.03	0.41±0.24	0.77±0.01	0.69±0.10	0.78±0.01	0.89±0.00	0.12±0.04	0.84±0.04	0.90±0.00	0.87±0.00	0.79±0.02

Table A5: Area adjusted mapping accuracies for topographically-corrected classification for 2015 (1: Coniferous forest, 2: Mixed forest, 3: Deciduous forest, 4: Barren, 5: Rangeland, 6: Cropland, 7: Built-up, 8: Wetlands, 9: Water, 10: Snow and ice).

		Reference										
	Class	1	2	3	4	5	6	7	8	9	10	adj UA
Classification	1	1.10	0.22	0.29	0.00	0.00	0.00	0.04	0.04	0.00	0.00	0.65±0.14
	2	0.10	0.83	1.27	0.00	0.10	0.00	0.00	0.00	0.00	0.00	0.36±0.14
	3	0.15	0.30	14.13	0.00	1.18	0.22	0.00	0.00	0.00	0.00	0.88±0.04
	4	0.00	0.00	0.00	1.48	0.92	0.05	0.00	0.05	0.00	0.00	0.59±0.14
	5	0.07	1.36	0.00	0.50	34.21	1.57	0.86	0.00	0.07	0.00	0.89±0.03
	6	0.00	0.00	0.64	0.00	7.08	23.37	0.21	0.07	0.00	0.00	0.74±0.04
	7	0.00	0.00	0.00	0.00	0.06	0.00	0.26	0.00	0.00	0.00	0.80±0.11
	8	0.00	0.00	0.24	0.00	0.68	0.05	0.05	1.17	0.24	0.00	0.48±0.14
	9	0.00	0.00	0.00	0.07	0.00	0.00	0.00	0.00	4.56	0.00	0.98±0.03
	10	0.00	0.00	0.00	0.03	0.01	0.00	0.00	0.00	0.00	0.08	0.67±0.14
	adj PA	0.78±0.17	0.31±0.04	0.85±0.04	0.71±0.15	0.77±0.03	0.92±0.03	0.18±0.06	0.88±0.15	0.94±0.06	1.00±0.12	0.81±0.01

Table A6: Average slope in degree for each land-cover class across the entire study region.

Land-cover class	Average slope in [°]
Coniferous forest	25.97
Mixed forest	23.15
Deciduous forest	17.15
Barren	26.57
Rangeland	10.35
Cropland	2.64
Built-up	2.65
Wetlands	1.71
Water	0.14
Snow and ice	29.03

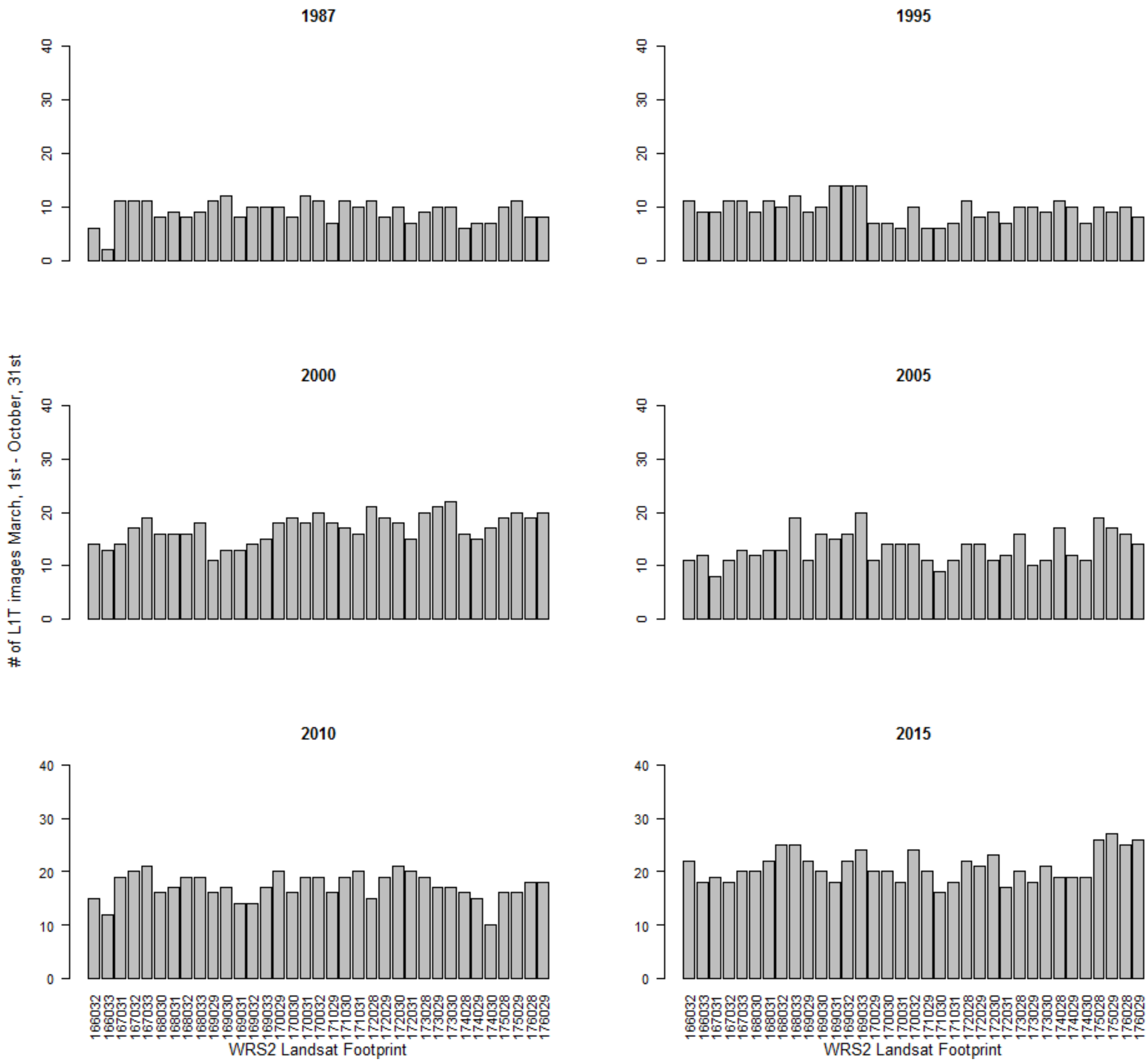


Figure A1: Number of L1T images (Landsat 4/5 TM, Landsat 7 ETM+, Landsat 8 OLI + TIRS) for 35 Landsat footprint from March, 1st to October, 31st for each target year 1987, 1995, 2000, 2005, 2010, 2015 with cloud cover <70%.

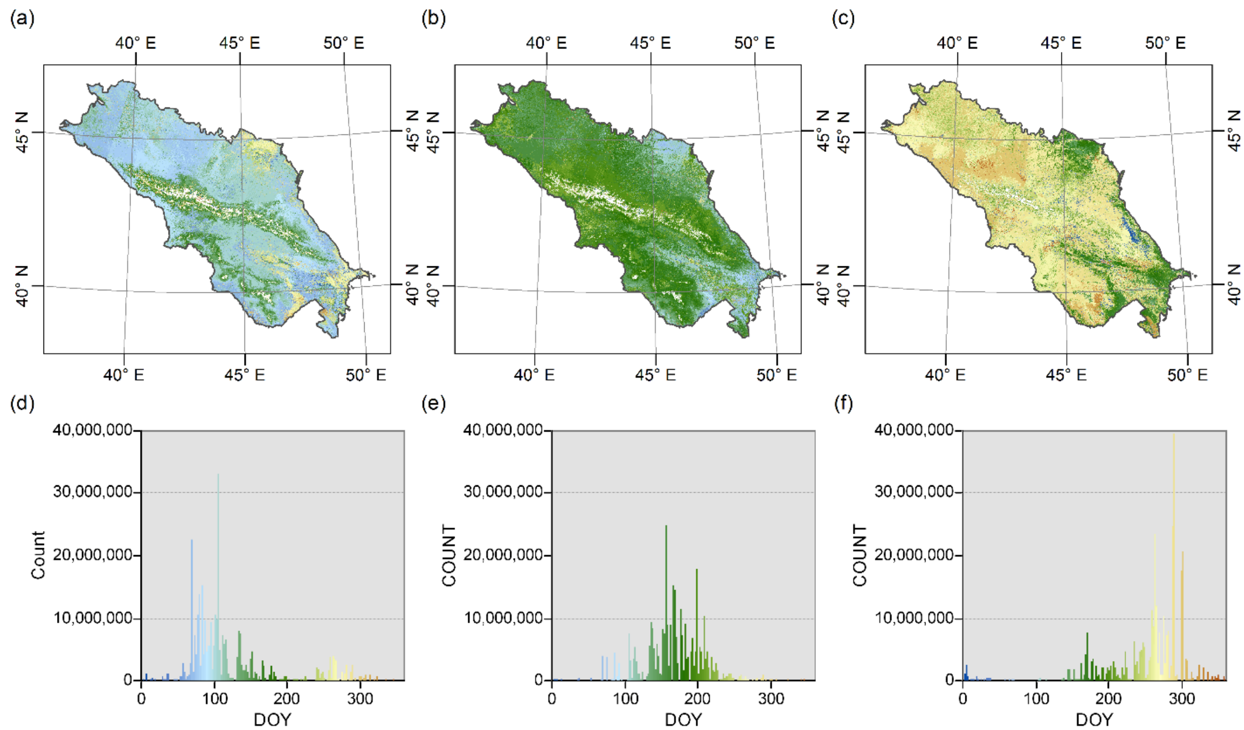


Figure A2: Land Surface Phenology for (a) start of season (SOS), (b) peak of season (POS), (c) end of season (EOS) for the 2015 composites. (d-f) number of counts per DOY for SOS, POS and EOS. Same color ramp applies for a-f.

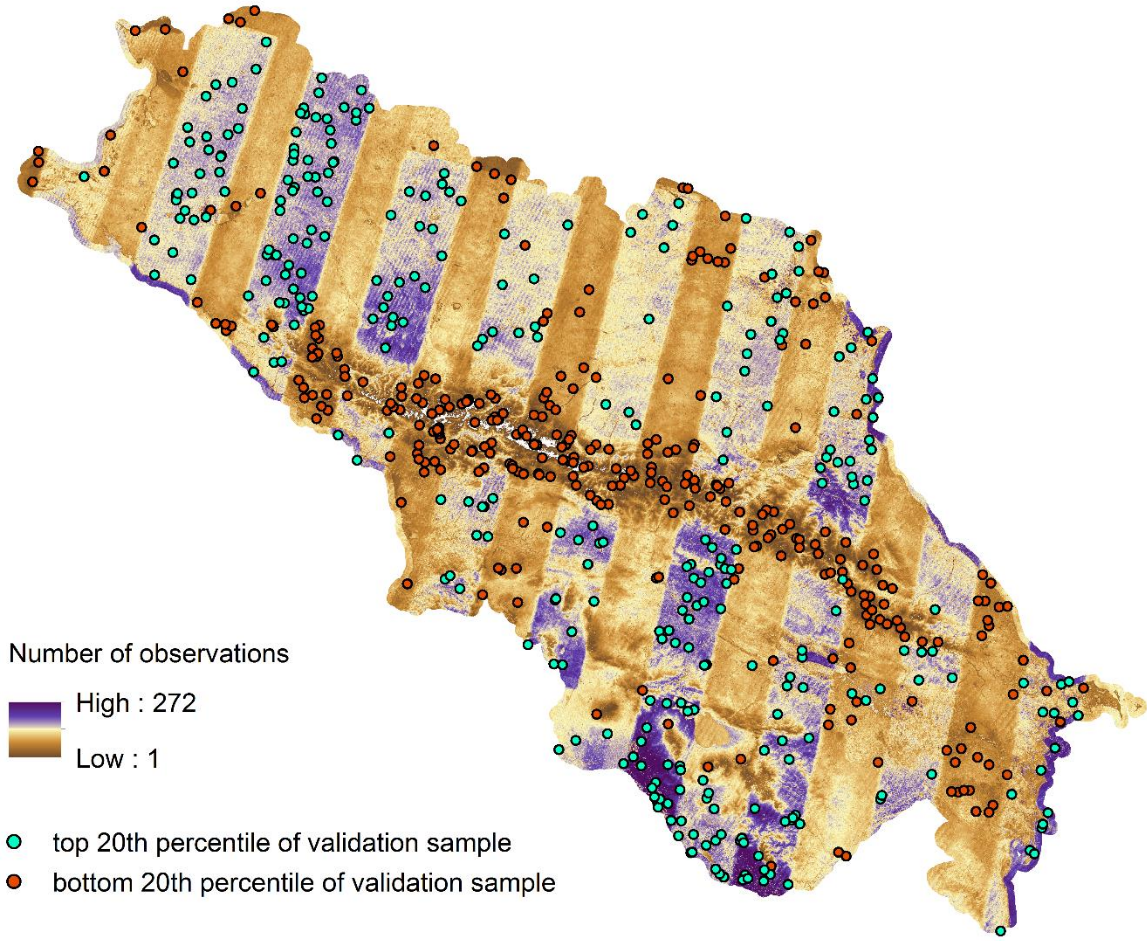


Figure A3: Number of observations available for the three seasonal composites for the 2015 land-cover classification.

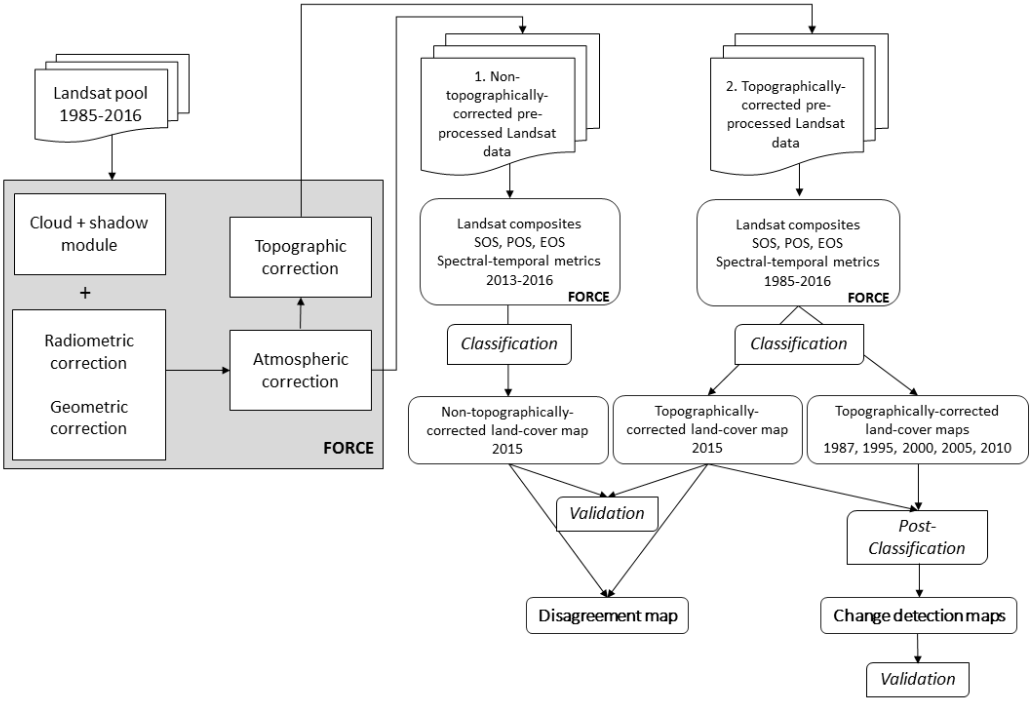


Figure A4: Processing workflow for Landsat compositing and classification.

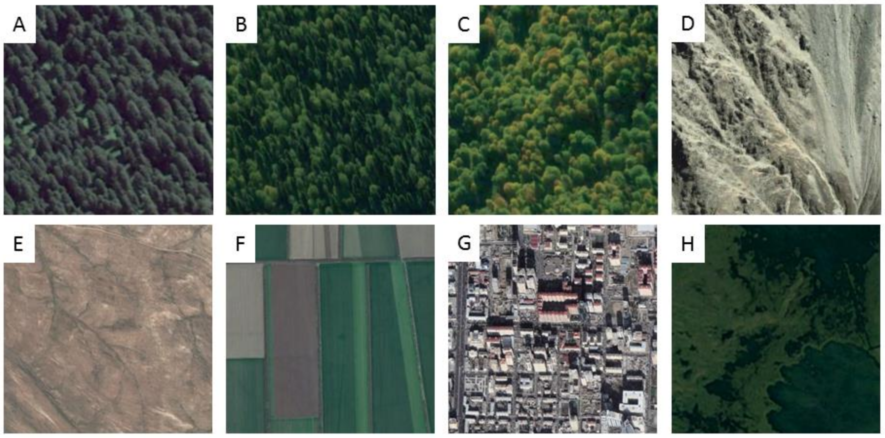
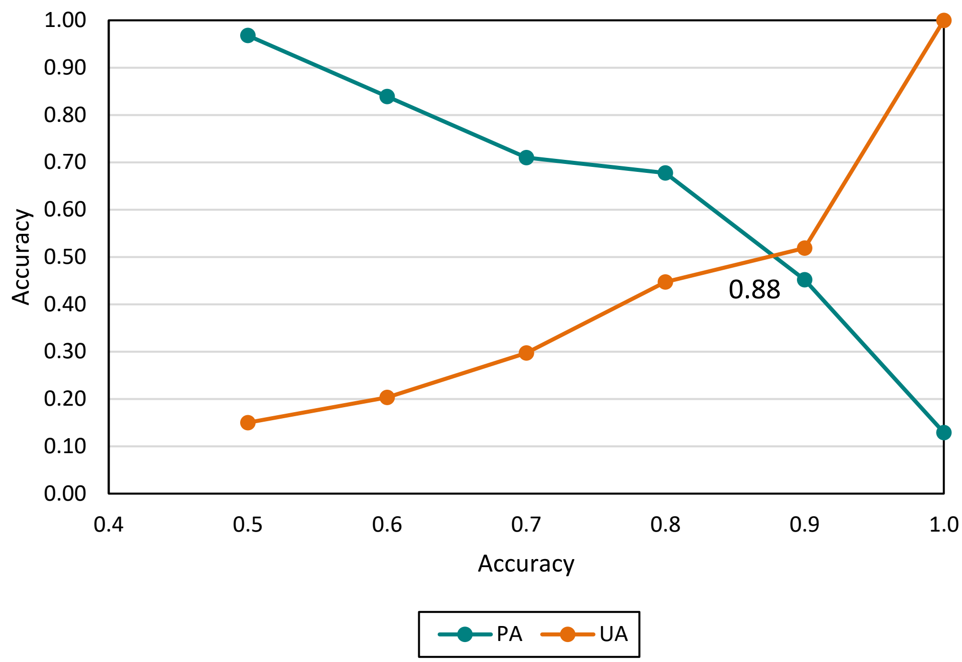


Figure A5: Examples of homogenous areas on high-resolution images in Google Earth that were used for classification training samples: (A) coniferous forest, (B) mixed forest, (C) deciduous forest, (D) barren, (E) rangeland, (F) cropland, (G) built-up, (H) wetlands. Water and snow and ice not shown.



50-100%	reference			
		urban	non-urban	sum
class	urban	30	170	200
	non-urban	1	199	200
	sum	31	369	400
PA	**0.97**			
UA	**0.15**			

90-100%	reference			
		urban	non-urban	sum
class	urban	14	13	27
	non-urban	17	356	373
	sum	31	369	400
PA	**0.45**			
UA	**0.52**			

Figure A6: Threshold for ’built-up‘ class probability based on user’s accuracy (UA) and producer’s accuracy (PA) (200 validation samples < 0.5 probability, 200 validation samples > 0.5 probability). Examples for 50-100% probability error matrix and 90-100% probability error matrix to receive intersection ~ threshold between PA and UA.

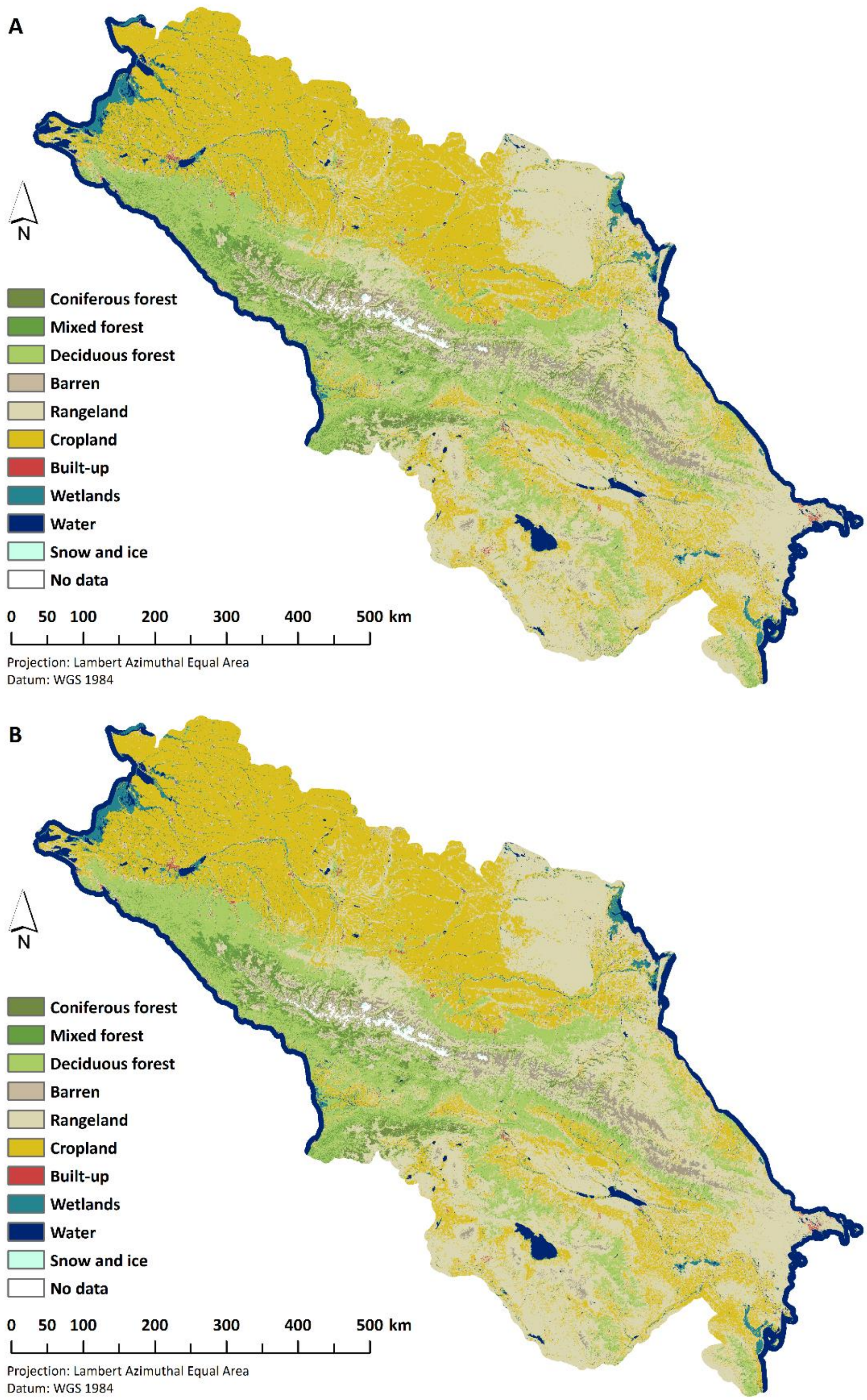


Figure A7: Land-cover classification map for 2015 derived from (A) non-topographically-corrected Landsat image composites and spectral-temporal metrics and (B) topographically-corrected Landsat image composites and spectral-temporal metrics.

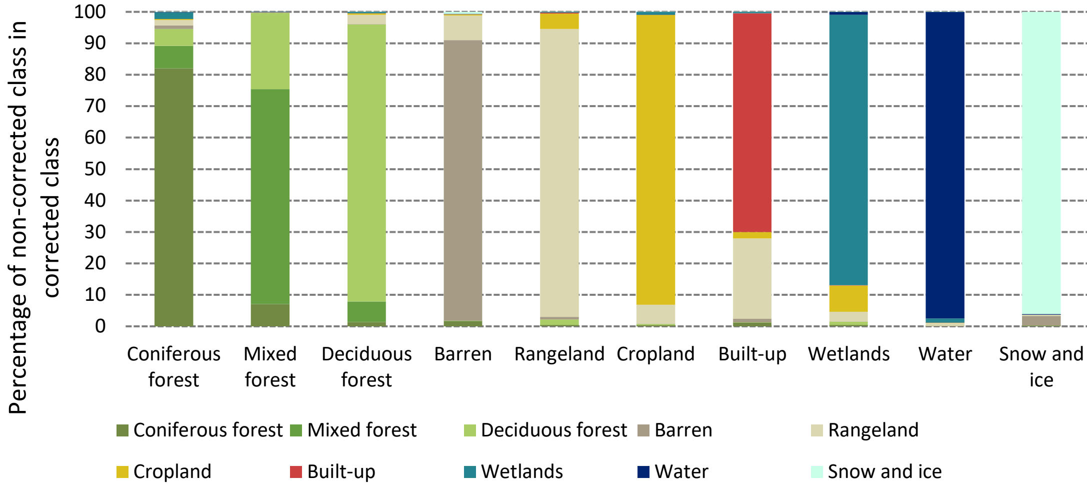


Figure A8: Percentage of non-topographically-corrected classes within topographically-corrected class for 2015, with mixed forest having lowest agreement of 68% and water having the highest agreement of 97%.

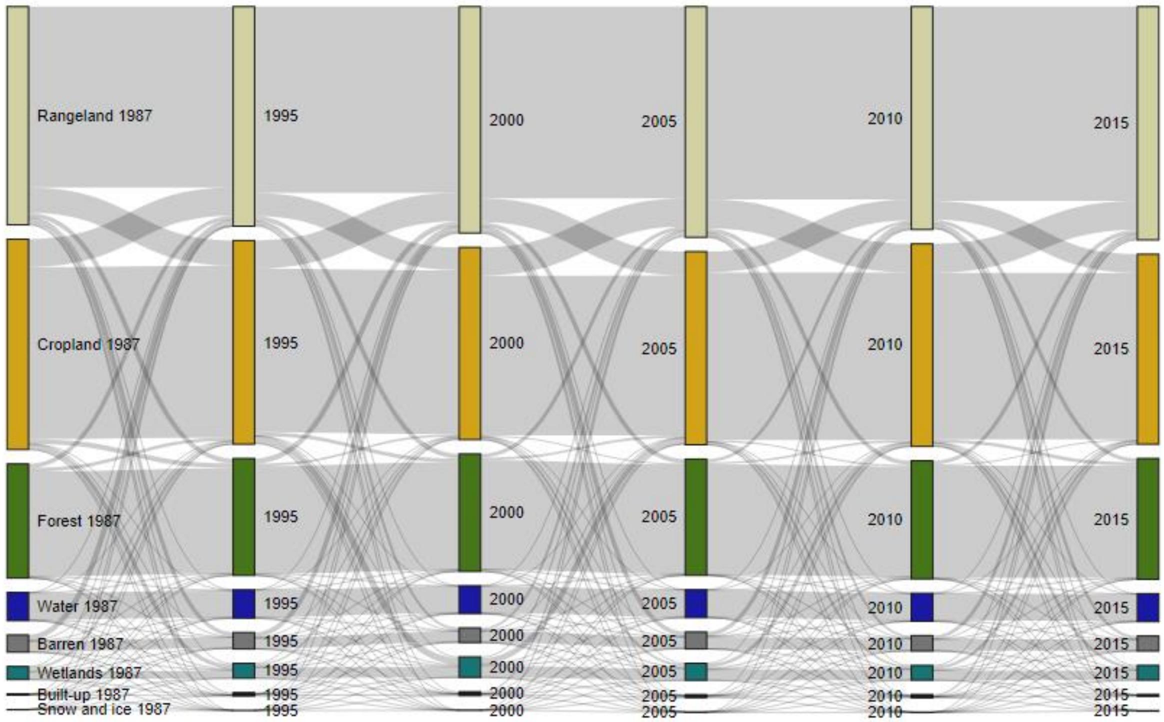


Figure A9: Land-cover flow diagram (Sankey diagram) between consecutive time steps from 1987 to 2015.

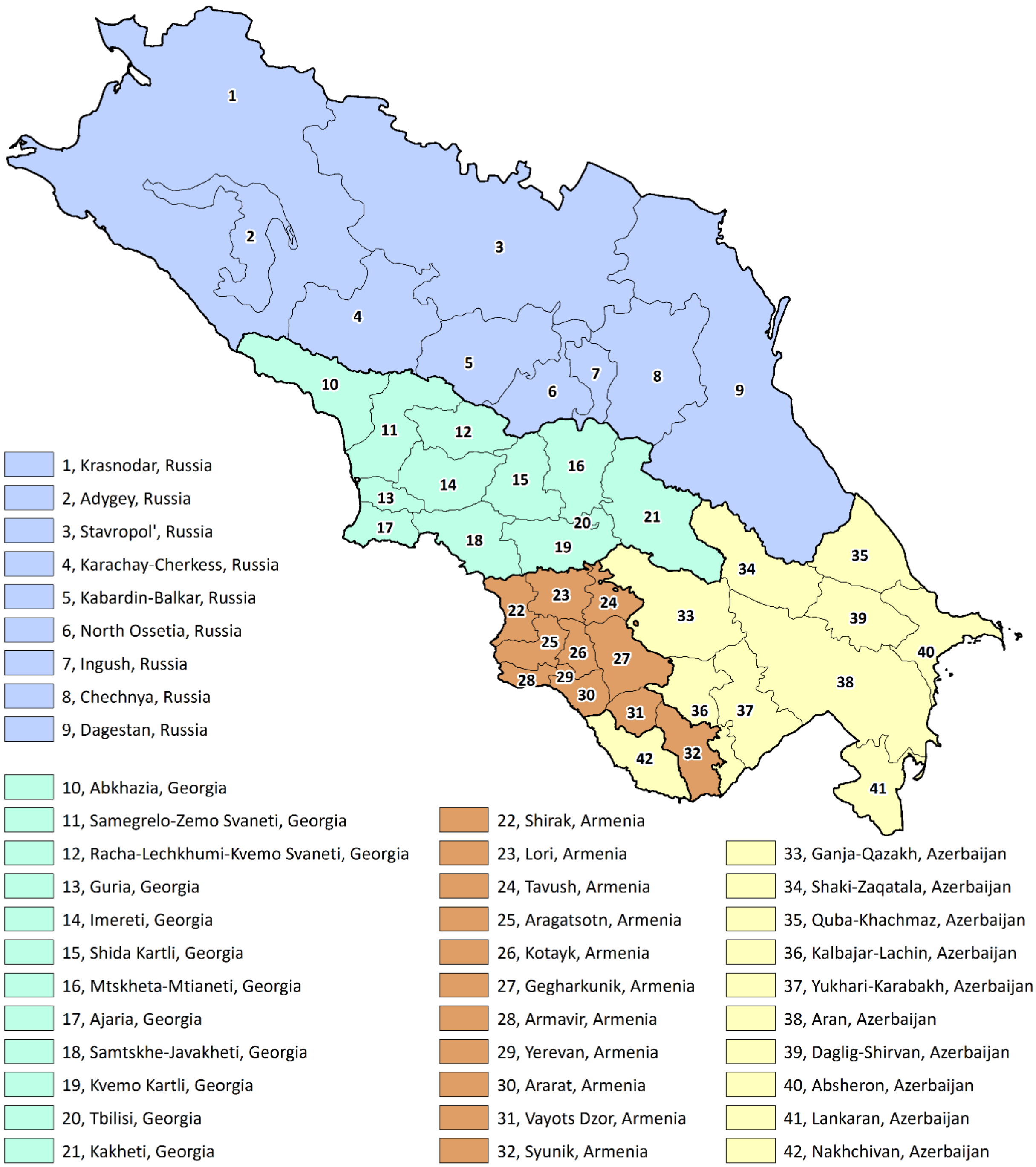


Figure A10: Administrative unites in the North Caucasus (Russian Federation), Georgia, Armenia, and Azerbaijan.

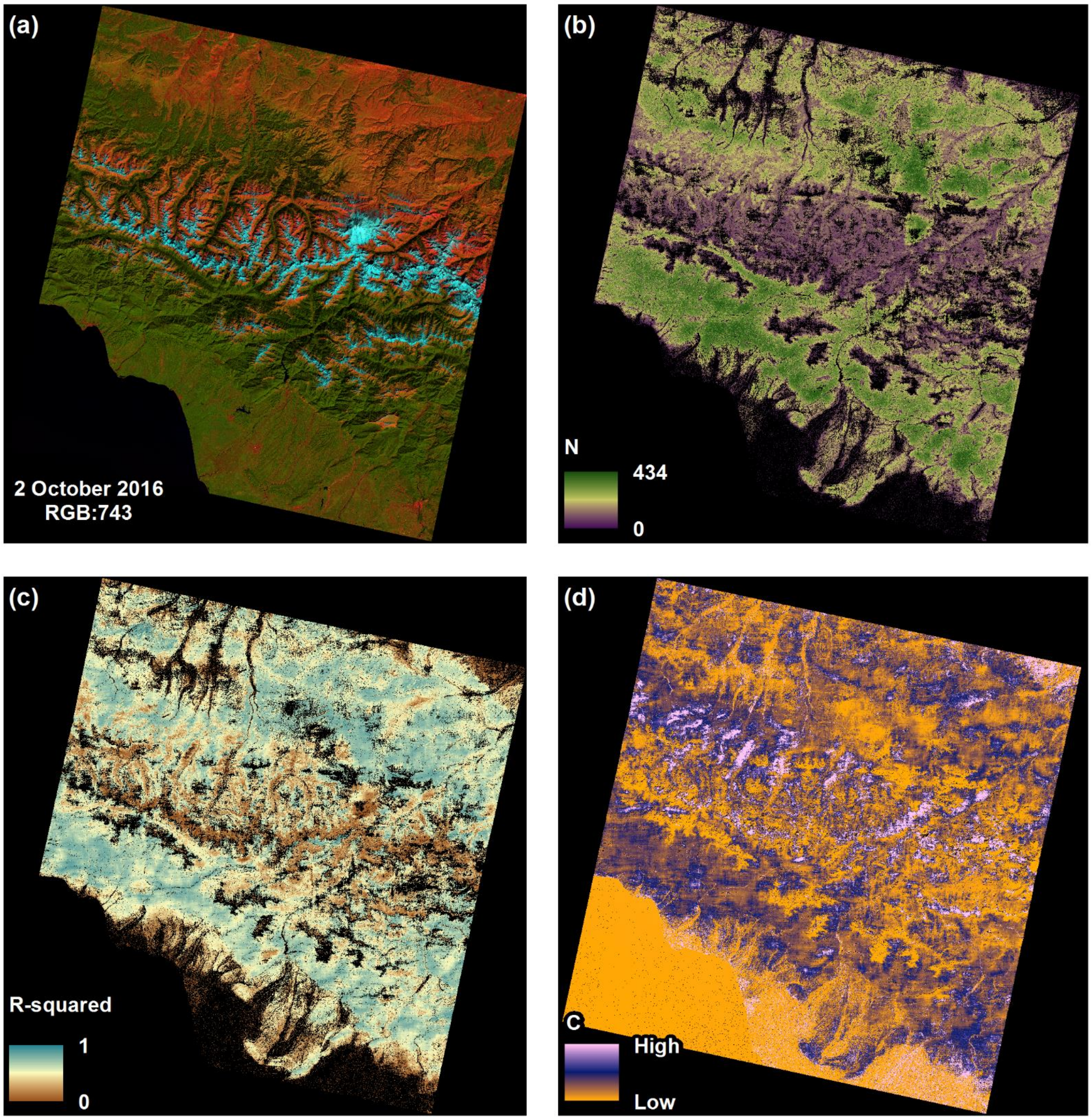


Figure A11: (a) Landsat fall image (RGB: 743) for footprint 172/030, (b) number of pixels N, (c) R^2 value of linear regression, and (d) C-factor (for visualization the color stretch is bounded between 0 and 0.5, values for C range from 0 to 10).

Chapter II. Different effects of wars on cropland abandonment in the Caucasus

Contributors: Buchner, J., Butsic, V., Yin, H., Kuemmerle, T., Baumann, M., Zazanashvili, N., Stapp, J., Radeloff, V.C.

Abstract

Wars are unfortunately frequent and can have strong and long-lasting consequences for agriculture. However, wars vary greatly in their overall intensity, which may affect permanent land-use outcomes differently, but this is not well understood. The challenge of assessing the effect of wars on land use is that valid control observations are needed before and after the conflict events, and that land-use decisions may depend on complex interaction of near and far away conflict locations. Our goal here was to isolate and compare the effect of four very different wars on permanent cropland abandonment in the Caucasus region since the breakdown of the Soviet Union. Specifically, we (1) assessed the intensity of each war in terms of conflict events and fatalities, and affected land-cover types, (2) tested the hypothesis that a war with an overall higher intensity leads to higher cropland abandonment than a war with overall lower intensity, and (3) tested the hypothesis that the probability of cropland abandonment increases when not only the closest but additional conflict locations farther away were considered, while accounting for the intensity at the conflict location. To do so we analyzed the Uppsala Conflict Data Program Dataset from 1989 to 2015 and Landsat-derived land-cover maps from 1987 to 2015, and used matching statistics and difference-in-differences estimators as well as logistic regressions with panel data. We found that among the four wars, Chechnya had the highest overall intensity with seven times more conflict events and four times more fatalities from 1989 to 2015 than Abkhazia, South Ossetia, and Nagorno-Karabakh combined. Surprisingly though, the war in Abkhazia had a similar strong effect on abandonment than the wars in Chechnya

despite their differences in overall intensity. In other words, 45% and 47% of permanent cropland abandonment can be attribute to the war in Abkhazia and Chechnya, respectively. However, the effect of the wars differed greatly in spatial extent. Permanent cropland abandonment was wide-ranging in Abkhazia and affected almost the entire region, but was localized in Chechnya, where the effect was strongest near conflict locations. We suggest that the wide-ranging effect in Abkhazia was both related to the conflict events and the indirect mechanisms such as migration patterns, travel restrictions, and economic hardship in the post-war period. The war over Nagorno-Karabakh did not result in higher permanent abandonment, despite very intense fighting. Neither did the war in South Ossetia, where the overall intensity of the war was lowest in the Caucasus region. Interestingly, conflict locations father away did not have an additional effect, and abandonment depended mostly on the distance to the nearest conflict location. We suggest that farmers continued farming amidst war unless threat was nearby. Overall, we applied consistent methods which allowed us to compare wars among each other. By doing so we showed that almost half of the cropland abandonment can be attributed to war even when the overall war intensity is low, affecting land-use outcomes noticeably.

Introduction

Wars can have strong and potentially long-lasting consequences on land use (Baumann and Kuemmerle, 2016). The effects of war on agricultural land use are particularly important, because conflict events are often concentrated in agricultural areas (Baumann and Kuemmerle, 2016). Furthermore, in many developing countries, subsistence farming is crucial for food security (Adelaja and George, 2019a), but wars can be highly detrimental for farmers (Baumann and Kuemmerle, 2016). One effect of wars is thus land abandonment. Land abandonment can result from the destruction of irrigation infrastructure (Özerdem and Roberts, 2012), or directly through the contamination of farm land with land mines or combat (The Halo Trust, 2014). Additionally, wars can have indirect effects when agricultural input such as seeds and tools are short (ICRC, 2007), when agricultural labor is lacking during wars due to military service and people fleeing the region, or - in the worst case - death, which causes abandoned agricultural fields (Eklund et al., 2016; Sanchez-Cuervo and Aide, 2013; Temudo and Silva, 2012). However, the effect of wars on land use and the spatial extent of land abandonment varies greatly among different wars, as do the wars themselves. The differences of the effects of wars on land use are partially due to the history and the heterogeneous characteristics of wars. Wars can vary greatly in their overall intensity, with some of them entailing fairly little violence and few displaced people, while others are extremely brutal and cause mass-displacement (Cook and Lounsbery, 2017). However the effect of wars on permanent land-use change is not well understood, and the overall intensity of the war in terms of conflict events and fatalities, may affect land-use outcomes differently. Our assumption was that wars with an overall higher intensity of violence would have stronger and wide-ranging effects on permanent land-use change than wars with an overall lower intensity.

For the remainder of this article, we use the term ‘war’ for the overall hostile situation between two countries, i.e., inter-state war (e.g., Armenia vs Azerbaijan, or within a country, i.e., intra-state war (e.g., Chechnya within Russia). Each war is a combination of many ‘conflict locations’, and at each conflict location the number of ‘conflict events’ and the number of ‘fatalities’ are a measure of ‘conflict intensity’. We define the ‘overall intensity’ of a war as the sum of all conflict events and all fatalities during the study period. We define the ‘conflict area’ of each war as the area surrounding all conflict locations of this war at a certain distance.

We suggest that the differences in the reported effects of wars not only depend on unique characteristics of the wars, but may also arise from two analytical challenges. First, assessing the effect of a given war on land use has to account for changes in land use that would have happened even without the war, and that means that both a valid non-conflict area for control is needed and land-use information before and after conflict events. Assessments that lack such a control area cannot provide reliable estimates (Schutte and Donnay, 2014). The problem with just summarizing the changes in land use before and after the war in the conflict area itself (Jaafar et al., 2015; Witmer and O'Loughlin, 2009) is that land abandonment can be caused by many factors such as environmental conditions, e.g., draughts, or changes in markets. In studies that do not consider environmental conditions that confound the effect of wars (Eklund et al., 2016; Jaafar et al., 2015), the results may be biased. Here, we propose an approach that includes both matching statistics and a difference-in-differences model, also known as before-after-control-impact (BACI), to consistently estimate the effect of wars. By comparing cropland abandonment before and after the conflict events and with valid non-conflict area controls for different areas around conflict locations, we can assess the spatial extent, such as localized or wide-ranging, of land abandonment due to the war (Figure 12).

The second analytical challenge is that typically the effect of war is either based on a pre-defined unit of analysis such as a region or a municipality (Schutte and Donnay, 2014) which does not take into account the distance to conflict locations, or the effect is assessed based only on the nearest conflict location (Landholm et al., 2019; Yin et al., 2019). The expectation is that cropland closer to a conflict location is more likely to be affected, and that the effect is larger when the number of conflict events or the number of fatalities is high, which was the case in Chechnya (Yin et al., 2019). However, if there are multiple conflict locations, farmers may be more likely to abandon their fields than if there is only a single conflict location, and land-use decisions may also vary based on the intensity of the near and far conflict locations (Linke and O'Loughlin, 2015). For example, we would predict that farmer A, who experienced a conflict event in 1 km distance and a second conflict event in 2 km distance, is more likely to abandon his field than farmer B, who only experienced one conflict event in 1 km distance.

Last but not least, because wars are different in their characteristics, it is challenging to derive conclusions about the effect of war on land use in general from a single war. The comparison of the effect of different wars requires consistency in methods and the way conflict intensity is measured. To compare the effect of individual wars among each other, we analyzed four wars with the same datasets and with consistent methods.

Our goal was to assess the effect of four wars on land use. In particular, we wanted to know how the effect of wars on permanent cropland abandonment differed among the four wars in the Caucasus that varied greatly in their overall intensity and how the interactions between distance-to and intensity-of conflict locations influenced permanent cropland abandonment. The Caucasus, with its unfortunately high number of wars, provided a unique site to evaluate the effect of wars on land use and during the era detailed satellite imagery was available to provide land-cover data. Regarding cropland abandonment outcomes, we hypothesized that the effect of a war with overall higher intensity resulted in more cropland abandonment with a wide-ranging spatial extent, compared to a war with overall low intensity. We further hypothesized that conflict locations that were farther away added further pressure on cropland abandonment in addition to the conflict locations nearby, especially if those far-away conflict locations were of high intensity.

Specifically, we asked the following questions:

1. How different were the four wars in the Caucasus, i.e., Chechnya, Abkhazia, South Ossetia, and Nagorno-Karabakh, in the number of conflict events, the number of fatalities, and the affected land-cover types?
2. How much permanent cropland abandonment did all wars cause, how did their effects differ, and how broad was the effect on the spatial extent?
3. What was the effect of the number of conflict events and fatalities of both near and far conflict locations on permanent cropland abandonment for the whole Caucasus and for each war individually?

Methods

Study area and the four wars in the Caucasus

Our study area encompassed parts of the Russian Federation (North Caucasus), Georgia, Armenia, and Azerbaijan (South Caucasus), with a total area of approximately 455,000 km^2 (Figure 13). The study area included two major mountain ranges: the Greater Caucasus Mountain Range and the Lesser Caucasus Mountain Chain (Zazanashvili et al., 2012). In the Greater Caucasus the average elevation ranges from 500-3,000 m a.s.l. in the west and declines towards the Caspian Sea in the east (Volodicheva, 2002), peaking at 5,642 m a.s.l. at Mount Elbrus. Precipitation is highest in the coastal area close to the Black Sea, exceeding 2,000 mm per year (Zazanashvili et al., 1999). Elevation in the Lesser Caucasus ranges from 2,000-2,800 m a.s.l. in the west and 2,500-3,300 m a.s.l. in the south-east with the highest point being Mount Aragats (4,090 m a.s.l.) in Armenia (Volodicheva, 2002). The climate in the Lesser Caucasus is wet in its western part, but continental in the east and south-east (Zazanashvili et al., 1999).

In all four countries agriculture is important for employment, economic growth, poverty alleviation, and food security (Holland, 2016; Welton et al., 2013). In the North Caucasus agriculture accounts for 22% of the gross regional product (Holland, 2016). In Georgia, Armenia, and Azerbaijan, in 2015 agricultural employment was as high as 44%, 35%, and 36%, respectively (World Bank Data, 2019). In the South Caucasus, small family farms practice agriculture as a combination of crop and fruit production as well as animal husbandry. Agriculture focuses on vegetables and crops such as wheat and potatoes, but also specialty products such as grapes and nuts (Ahouissoussi et al., 2014; Welton et al., 2013).

During Stalin's regime and hard-ruling policy, tensions were generally suppressed, but started to rise with the dissolution of the Soviet Union. After the collapse of the Soviet Union in 1991, the tensions turned into full-scale wars in Chechnya (Russia), Abkhazia and South Ossetia (Georgia), and Nagorno-Karabakh (between Armenia and Azerbaijan) (Zürcher, 2007). The collapse of the federal system of the Soviet Union and its planned economy forced the countries to rebuild nations (Cornell, 2000; Freni, 2013; Lerman, 2001; Witmer and O'Loughlin, 2011). The Caucasus is a region of high ethnic diversity and strong national differences, as well as unequal living standards and economic disadvantages, which fueled four major wars in Chechnya, Abkhazia, South Ossetia, and Nagorno-Karabakh (Freni, 2013; Kolossov and O'Loughlin, 2011; Nussberger, 2008). As a successor of the Soviet Union, Russia's continued interest further contributed to the wars in the Caucasus (Wiberg and Scherrer, 1999).

The Chechen wars were the most intense with an estimated 72,000 casualties (Zürcher, 2007). The first Chechen war (1994 – 1996) started three years after Chechnya declared independence from Russia and caused an immediate wave of Chechens fleeing into neighboring Ingushetia and into the mountains. Although the capital Grozny was largely destroyed, the majority of villages and cities in the region remained intact. Nevertheless, the war killed 25,000 civilians (Zürcher, 2007). The first war ended with a withdrawal of the Russian Army. Between the first and the second war, crime increased dramatically in Chechnya, state institutions were dismantled, and an Islamic governing body was established. The invasion of Dagestan and several bombings in Moscow by Islamic rebels from Chechnya triggered the Second Chechen War in 1999. Better prepared than the First Chechen War, the Russian military relied this time on heavy artillery and aerial bombing. The bombing destroyed many settlements and cities, and the number of civilian deaths was even higher. Attacks from rebels mostly targeted Russian offices, military, and police. Major operations ended in 2001, and in 2003 Chechnya presidential elections were held, overseen by Russia. The second war displaced more than 700,000 people, many more than the first war (Zürcher, 2007).

In Abkhazia, the fighting started in 1992 after Abkhazia declared itself independent from Georgia. In August 1992, roughly 5,000 soldiers form others parts of Georgia entered Abkhazia (Zürcher, 2007). Nevertheless, by September 1993, Abkhazian forces gained control over Abkhazia, with weapons and tanks provided by Russia (De Waal, 2010). Roughly 240,000 Georgians fled the region, 8000 - 10,000 people died, more than half of whom were civilians (De Waal, 2010; Zürcher, 2007). Russian peacekeepers were stationed in Abkhazia in July 1994, but further clashes occurred in 1997 and 2001 (Zürcher, 2007). Clashes occurred again in 2008 during the Five-Day War between Georgia and Russia (Pallin and Westerlund, 2009). Traveling between Georgia and Abkhazia has been even more restricted since then (De Waal, 2010).

The war in South Ossetia started right after South Ossetia proclaimed itself independent from Georgia in 1991. In 1992, the Dagomys agreement on South Ossetia was implemented, but did not solve the underlying issues (De Waal, 2010). The Five-Day War in 2008 primarily affected

South Ossetia (Pallin and Westerlund, 2009). However, compared to the other wars in the Caucasus the South Ossetia war was not as intense with 600 - 1,000 people died and 42,000 Georgian refugees (De Waal, 2010; Zürcher, 2007). Over time ordinary civilians who lived within the conflict zone were allowed to cross the border between South Ossetia and Georgia.

In Nagorno-Karabakh the tensions started to rise in 1988 and intensified by 1991 when Armenia and Azerbaijan both declared independence and started the war over Nagorno-Karabakh, after Karabakh declaring independence from Azerbaijan (De Waal, 2010; Zürcher, 2007). By 1992, both sides were fighting with heavy weapons including rockets and tanks, causing widespread damage and destroying entire villages (De Waal, 2010). After 1992, both, Armenia and Azerbaijan, operated state-run armies (Zürcher, 2007). Once Armenia gained control over Lachin, it was able to provide arms and supplies to Karabkah and occupied additional territory outside Nagorno-Karabakh, which triggered a large wave of refugees to Azerbaijan in 1993. In 1994 the numbers of casualties increased steeply during a failed offensive in the Kelbajar region, and Armenia gained full or partial control over seven Azerbaijani regions. In total , the war in Nagorno-Karabakh killed about 16,000 people, and displaced 604,000 Azerbaijani citizens and 72,000 Armenians, by the time a ceasefire was signed in May 1994 (Zürcher, 2007). Since then, ceasefire violations have occurred repeatedly (Bekiarova and Ilina, 2019). The latest military events in 2020 changed the situation over Nagorno-Karabakh, but to discuss the latest political events is out of scope of the article.

For the remainder of this paper we named conflict locations after the region in which the war originated in. For example, we referred to conflict location in the North Caucasus as ‘Chechnya’, even though some conflict locations were outside Chechnya. We further analyzed wars related to one region as one, for example, we analyzed the first and the second Chechen war jointly.

Data

Remotely sensed land-cover change

To estimate cropland abandonment from 1987 to 2015, we analyzed six land-cover maps (1987, 1995, 2000, 2005, 2010, and 2015) that captured active cropland for each time step from Landsat imagery covering the Caucasus region with 35 Landsat footprints, which we had classified previously (Buchner et al., 2020). We compiled the 30-m resolution Landsat imagery into large-area imagery composites and classified them with the C5.0 decision tree classifier. The stable cropland class had a user's accuracy of 71.3% and a producer's accuracy of 88.1%. We defined permanent cropland abandonment when a pixel was classified as cropland in 1987, but non-cropland in the following time steps, and mapped cropland abandonment in 1995, 2000, 2005, 2010, and 2015. We did not include pixels that were re-cultivated after abandonment.

Conflict data and control variables

We analyzed conflict data provided by the Uppsala Conflict Data Program Georeferenced Event Dataset (UCDP GED, Version 19.1) (Högbladh, 2019; Sundberg and Melander, 2013). This dataset defines a conflict event as 'an instance of organized violence with at least one fatality'. The UCDP dataset provides detailed information about the location and time, the number of events per location and the best estimate of number of total fatalities, which we used as proxies for 'conflict intensity'. We chose the UCDP dataset because it dates back to 1989 and covers all four wars in their entirety. Although the actual duration of the wars did not last for the length of the study period, frequent ceasefire violations occurred for all four wars and therefore we included all conflict events and fatalities that occurred for the duration of the study period. We summarized the number of conflict events and the number of total fatalities for each location for five time periods based on the land-cover maps (1989-1995, 1996-2000, 2001-2005, 2006-2010, and 2011-2015). In total, there were 543 conflict locations with a total of 2633 conflict events from 1989 to 2015 (Figure 13).

When estimating the effect of wars on cropland abandonment, other factors that affect agricultural land use needed to be accounted for (Adelaja and George, 2019a; Yin et al., 2019). To do so, we included a suite of environmental, accessibility, and political-economic variables in our analyses (Table 3). We selected the ALOS Global Digital Surface Model (DSM) dataset to calculate elevation, slope, and aspect (Tadono et al., 2014; Takaku et al., 2014) and the TerraClimate database to extract maximum temperature and precipitation accumulation (Abatzoglou et al., 2018). We extracted soil carbon content from the FAO Harmonized World Soil Database (Wieder et al., 2014). Other variables captured accessibility to market and infrastructure, such as the distance to highways, and settlements, which we based on OpenStreetMap (OpenStreetMap contributors, 2017). All of the datasets were available and processed in Google Earth Engine (GGE, Gorelick et al., 2017). We further included information about the percentage of rangeland and forests within 100 m window, because cropland is more likely to be abandoned on marginal lands (Prishchepov et al., 2013). Finally, we added the country name as a categorical dummy variable to account for political and economic differences. We natural log-transformed the control variables and the conflict intensity measures to decrease the effects of scaling on the model.

Models

Sampling design and summary statistics

We generated a 2-km point grid covering the entire study area, as a tradeoff between the need of a sufficient amount of samples and the computational costs for our statistical models, and minimizing spatial autocorrelation between observations. We further ensured that observations were cropland in 1987 and removed observations that were not cropland in 1987. This resulted in 40,220 grid points with a total of 241,320 observations over six time steps. For each observation we calculated the distance to each conflict location within 35 km, for which we had summarized the number of events and the number of total fatalities for the five time periods (1989-1995, 1996-2000, 2001-2005, 2006-2010, and 2011-2015). We selected the 35-km threshold based on the size of our study region, and because two prior studies in the Caucasus region found a negligible influence of conflict events on cropland abandonment beyond that distance (Baumann et al., 2015; Yin et al., 2019). We binned the number of events and the number of total fatalities within distances of 0-5, 5-10, 10-20, and 20-30 km for each observation. In a final step, we extracted and added the value of the response variable (i.e., cropland abandonment or not), and the control variables to the observations.

We calculated summary statistics for each of the four wars. First, we summarized the number of events and the number of fatalities from the UCDP dataset for each of the four wars -- Chechnya, Abkhazia, South Ossetia, and Nagorno-Karabakh -- for each of our five time periods. Second, we summed the number of conflict events for each land-cover class for each war and time period.

Effects of war in its entirety on cropland abandonment

Our second objective was to identify the effect of all wars together and of each war in its entirety on permanent cropland abandonment. To do so, we first controlled for differences in observables between conflict area and non-conflict area by creating valid treatment and control datasets via propensity score matching. We estimated the propensity score using a probit model (Guo and Fraser, 2014; Jones and Lewis, 2015), where the propensity score is the probability of an observation experiencing treatment, e.g., conflict event. Similar techniques have been successfully used to build valid counterfactuals for analyzing the effects of protected areas (Andam et al., 2008; Bragina et al., 2015, Jones and Lewis, 2015) and payments for environmental services (Arriagada et al., 2012).

Second, we controlled for unobservable or omitted-variable bias. To do this, we parameterized difference-in-differences models. These are regression models that compare observations in areas with and without treatment before and after the treatment event (Butsic et al., 2017). In this study, we compared permanent cropland abandonment in conflict area and non-conflict area before and after conflict events. The estimated difference in abandonment from observations in the conflict area and the non-conflict area is based solely on changes that took place between the two time periods. Therefore, time-invariant unobservable covariates, such as land-use history, do not bias the estimated effect (Wooldridge, 2002). We used the same observations as described in section 2.3.1. We defined the conflict area as the area within a distance of 5, 10, 20, or 30 km of all the conflict locations with conflict events for each war (Figure 14). We excluded observations within a distance of 30-35 km to clearly separate the conflict area from the non-conflict area. We then matched conflict area observations and non-conflict area observations (i.e. observations >35 km away from conflict events) based on our natural log-transformed control variables (Table 3) for 1995, 2000, 2005, and 2010 for each distance. In total we had 16 matched datasets, i.e., matched conflict area observations (5 km distance of all conflict events) with non-conflict area for 1995, 2000, 2005, 2010, matched conflict area observation (10 km distance of all conflict events) with non-conflict area for 1995, 2000, 2005, 2010, and the same for 20 km and 30 km distance and all years. We removed observations labeled as conflict area in the subsequent time step to avoid double labeling with non-conflict area observations. We merged the years for each conflict area definition, resulting in four datasets with conflict area defined as 5, 10, 20, and 30 km distance of all conflict events.

We analyzed the four datasets to estimate the effect of war on cropland abandonment using the following difference-in-differences model for the entire Caucasus, i.e., the four wars together (Wooldridge, 2002):

$$Y_{it} = \beta_1 * Co_{it} + \beta_2 * A_{it} + \beta_3 * Co_{it} * A_{it} + \beta_4 * Time_{it} + \beta_5 * C_i + \beta_{6-9} * X_{it} + e_{it} \quad (1)$$

In this model, Y_{it} is cropland abandonment (1), or not (0), for observation *i* in period *t*, Co_{it} is whether observation *i* in a time period *t* was in conflict area (1) or not (0), i.e., treated or not, A_{it} stands for after and indicates before (0), or after (1), conflict event, $Co_{it} * A_{it}$ is the interaction between treatment and A_{it} and indicates the effect of war, $Time_{it}$ is a categorical variable indicating time period, C_i indicates the country, X_{it} is the vector of control variables (i.e., maximum temperature, precipitation accumulation, percent rangeland, and percent forest), β_1- β_9 are the coefficients to be estimated, and e_{it} is the error term (equation for individual wars in the appendix). In the fixed effects model time-invariant covariates (e.g., elevation) were not considered. The fixed effect model eliminates the assumption that unobserved variables are uncorrelated with the error term but relies on linear regression to fit a binary dependent variable. In total, we ran 4 regressions incorporating the four conflict areas at a distance of 5, 10, 20, or 30 km from all the conflict locations. We used the 'margins' command in StataSE 16 to calculate the marginal effects of war on permanent cropland abandonment. Marginal effects represent the percentage point change in the probability an observation is abandoned due to war. In addition to the model for the entire Caucasus, we also modeled the effect of each individual war (equation (1) in the appendix).

Effects of distance to and intensity of conflict locations

To understand how the nearest conflict location and additional ones farther away, plus their intensities, affected permanent cropland abandonment, we parameterized a logistic panel regression with random effects. In this model, we included a large number of interactions, and these interactions can be best interpreted through predicted probabilities, which is why we chose a random-effects model. Our goal was to estimate the effect of multiple conflict locations. Therefore, we considered the nearest conflict location and its intensity, as well as additional conflict locations and their intensities that took place at farther distances, which is a novel contribution of our study (Figure 14). We again used the point grid described in section 2.3.1. We identified the nearest conflict location by distance bins (i.e., 0-5, 5-10, 10-20, and 20-30 km), and included the number of conflict events or fatalities at each location as measures of intensity. The inclusion of the additional variables allowed us to understand how conflict events or fatalities farther way from the observation affected cropland abandonment. Again, we included the natural log-transformed control variables (Table 3) to account for factors related to agricultural land use. We estimated the following regression for the entire Caucasus.

$$Y_{it} = \beta_1 * nearest_{0-5km\,it} + \beta_2 * I_{0-5km\,it} + \beta_3 * nearest_{0-5km\,it} * I_{0-5km\,it} + \beta_4 * nearest_{5-10km\,it} + \beta_5 * I_{5-10km\,it} + \beta_6 * nearest_{5-10km\,it} * I_{5-10km\,it} + \beta_7 * nearest_{10-20km\,it} + \beta_8 * I_{10-20km\,it} + \beta_9 * nearest_{10-20km\,it} * I_{10-20km\,it} + \beta_{10} * nearest_{20-30km\,it} + \beta_{11} * I_{20-30km\,it} + \beta_{12} * nearest_{20-30km\,it} * I_{20-30km\,it} + \beta_{13} * C_i + \beta_{14-23} * X_{it} + \beta_{24} * C_i X_{it} + \beta_{25} * Year_{it} + e_{it} \quad (2)$$

In this model, Y_{it} is cropland abandonment (1), or not (0), for observation *i* in time period *t*, $nearest_{it}$ is a dummy variable indicating if conflict location within defined distances (0-5, 5-10, 10-20, and 20-30 km) is nearest (1), or not (0), I_{it} is the intensity measure, i.e., the number of conflict events or number of total fatalities, of observation i in time period t, $nearest_{it} * I_{it}$ is the interaction term between $nearest_{it}$ and I_{it}, C_i is a categorical variable indicating the country, X_{it} is the vector of control variables (e.g., elevation, maximum temperature, distance to settlements), $C_i * X_{it}$ is the interaction term between country and the control variables, $Year_{it}$ is a categorical variable indicating the time step, β_1-β_{25} are the coefficients to be estimated, and e_{it} is the error term. We ran one model with number of conflict events as intensity measure and a second one with fatalities as intensity measure. In addition to the model for the entire Caucasus, we also modeled the effect of each individual war (equation (2) in the appendix).

The model resulted in coefficients indicating the relationship between conflict intensity at different distances and cropland abandonment, and we calculated the predictive margins of conflict intensity and distance on cropland abandonment for better interpretability. In addition, we used the regression results to predict the probability of abandonment over a range of distance scenarios and conflict intensities to understand how abandonment changed due to both near and far conflict events and fatalities.

Results

Summary statistics of the four wars

The overall intensity of the wars, e.g., the sum of all events and fatalities, differed greatly among the four wars. Chechnya had by far the overall highest number of conflict events and the highest number of fatalities (Figure 15), with seven times more conflict events and four times more fatalities than the three other wars combined from 1989 to 2015. In Abkhazia, South Ossetia, and Nagorno-Karabakh the overall number of events were much lower, but most of the events occurred before 1995. The war in South Ossetia had the overall lowest number of conflict events and the lowest number of total fatalities (Figure 15).

Across the four wars, the majority of conflict events occurred in rangeland, cropland, and built-up areas (Figure A12). We found differences among wars in land cover and over time. In Chechnya, most conflict events occurred in urban, cropland areas or rangeland, but the number of events started to increase in urban areas from 1996 until 2000. In Abkhazia and South Ossetia, most conflict events occurred in cropland and urban areas, and in Nagorno-Karabakh in rangeland and cropland.

Overall effect and effect of each of the four wars on cropland abandonment

The results of our difference-in-differences model showed that across the whole Caucasus, conflict areas had higher permanent cropland abandonment probability after a war than non-conflict areas (Table 4, Figure 16). Across the Caucasus that result was consistent and abandonment was significantly higher if the conflict area included all conflict events within 10 km and 20 km, but highest within 30 km. Our global model for all four wars together showed that overall 27% of cropland abandonment in the conflict area was due to the wars. However, we found clear differences among individual wars. First, while abandonment was significantly higher in the conflict area in Chechnya and in Abkhazia, this was not the case in Nagorno-Karabakh and in South Ossetia. Second, in Chechnya, abandonment was highest in the conflict area within 10 km of all conflict events. In contrast, in Abkhazia abandonment was only significantly higher within 20, or 30 km of all conflict events (Table 4). Please refer to the appendix for matching results (Table A7 - Table A38), and full regression results (Table A39, Table A40).

Effects of distance and intensity of conflict locations

In regards to the effects of conflict locations, the results of the panel logit regression with random effects showed that conflict events nearby were more important than conflict events farther away for the whole Caucasus (Figure 17). However, we found again clear differences among the four wars. In Chechnya and Nagorno-Karabakh, the probability of abandonment was highest, and significant, when the nearest conflict event occurred within 5 km, e.g., in the immediate surrounding of an observation with cropland abandonment. The probability of abandonment was four times higher in Nagorno-Karabakh (28%) than in Chechnya (6.7%). In contrast, in Abkhazia, conflict events within a 10-20 km distance resulted in the highest probability of abandonment (45%), and that was also the highest probability of abandonment among all four wars. In South Ossetia, there were no significance differences in the effects of conflict events among different distances (Figure 17).

When taking into account the distance and the intensity of the conflict locations, we found that the probability of abandonment was higher across the Caucasus when the conflict event intensity was higher, especially when the nearest conflict event was within 5 km (Figure 18). However, neither the number of conflict events nor the number of fatalities resulted in significant differences within a given distance. The pattern that we found for the whole Caucasus held true for Chechnya, but the probability of abandonment was generally lower there. In contrast, in Abkhazia a low number of fatalities within a distance of 10-20 km resulted in a higher probability of abandonment than a higher number of fatalities closer or farther away. In Nagorno-Karabakh, the probability of abandonment was highest for the nearest distance (<5 km) and differed significantly from the 10-20 and 20-30 km distance when using fatalities, but neither the number of conflict events nor the number of fatalities resulted in significant differences within a given distance. In South Ossetia none of the distances and intensities differed significantly from each other (Figure 18).

When we combined the nearest conflict location with the ones father away as well as the intensity measures, we found that adding conflict locations farther away to the ones nearby, did not significantly increase the probability of abandonment for any of the wars (Figure 19). In Abkhazia, adding fatalities in 5-10 km distance to the nearest fatalities in 5 km distance, resulted in higher probability of abandonment, but was insignificant due to the large confidence intervals. Our panel logistic regression results also allowed us to assess the importance of other control variables for cropland abandonment. For the most part, they had only a small marginal effect on cropland abandonment. The exception was the percent rangeland and percent forest within 100 m. When their values were highest, e.g. 100%, the probability of abandonment reached 50% and 26%, respectively (Figure A13). Please refer to the appendix for full regression results (Table A41 - Table A44).

Discussion

Comparing the effect of wars on land use is challenging due to the unique characteristics of individual wars and the implementation of different methods that lack consistency. We investigated the effects of wars that differed greatly in their overall intensity and the effect of distance to conflict locations on permanent land-use change using consistent data and methodology. We hypothesized that wars with overall higher intensity have a stronger effect on permanent cropland abandonment than low intensity wars, but we found that wars that varied greatly in their overall intensity affected permanent cropland abandonment similarly. However, the spatial extent of abandonment affected by the wars varied and was localized in Chechnya and wide-ranging in Abkhazia. The effect of distance-to and the intensity-of conflict locations also differed among wars. In Chechnya and Nagorno-Karabakh conflict events within 5 km had the largest effects on the probability of cropland abandonment, whereas in Abkhazia conflict events that were 10-20 km away had the highest abandonment probability. For each war individually, a higher number of events, or a higher number of fatalities at conflict location was associated with higher abandonment probability, but those differences were not significant, and only the distance to the nearest conflict location was important. Furthermore, when there were conflict locations nearby, additional conflict locations farther away did not have an additional effect on cropland abandonment, a finding that surprised us.

The wars in the Caucasus entailed large numbers of conflict events and fatalities, but the Chechen wars differed the most in their overall intensity compared to Nagorno-Karabakh, Abkhazia, or South Ossetia. The war in Chechnya resulted in the overall highest number of fatalities and conflict events over the study period from 1989 to 2015, largely due to heavy artillery and bombing from the air by the Russian military, and Grozny, the largest city in Chechnya with the highest population density was fully destroyed (Zürcher, 2007). In Nagorno-Karabakh rockets and tanks caused widespread damages of houses and settlements (De Waal, 2010), but the duration of heavy fighting was shorter and concentrated before 1995. In Abkhazia and South Ossetia the overall numbers were lower, most likely due to the shorter duration of active combat and sporadic airstrikes (Pallin and Westerlund, 2009). Most of the conflict events occurred in croplands, rangelands, and urban areas, which is similar to most wars globally: cities are disproportionally targeted, and fighting often occurs in agricultural land and grassland (Baumann and Kuemmerle, 2016; Landholm et al., 2019).

We found a clear effect of wars on cropland abandonment using a difference-in-differences model and thereby comparing the conflict area with a valid non-conflict area before and after conflict events. Our global model that combined all four wars showed that 27% of permanent cropland abandonment in the conflict areas was due to the wars. Among the four wars, we hypothesized that the wars in Chechnya would result in the most abandonment and at broader spatial extent, because of the prolonged intensity of the wars. However, we found that the war over Abkhazia affected a similar amount of abandonment in the conflict area than in Chechnya. Almost half of the abandonment could be attributed to the war in each conflict area, despite the overall higher level and duration of violence in Chechnya. But we also found that the effect of the wars in Chechnya and Abkhazia occurred at different spatial extents, where in Chechnya the effect of war was localized, but wide-ranging in Abkhazia, opposite to what we had expected. We hypothesized that overall higher intensity would lead to a broader spatial extent of permanent cropland abandonment. However, the indirect underlying mechanism of internally displaced persons movements, subsequent travel restrictions hindering people returning to their homes, and economic hardship, is important to understand the spatial extent of abandonment, in combination with the overall number of conflict events. In other war-torn areas, such as Colombia, a higher level of violence results in farmers shifting to subsistence farming and cultivating their fields amidst conflict rather than abandoning their land. Further, farmers maintain and cultivate their neighbors' fields as well (Arias et al., 2018). Similar, in Nigeria, an increase intensity of attacks by the Boko Haram, significantly reduce the output and productivity in agriculture, but do not decrease the total amount of land that is cultivated (Adelaja and George, 2019b). This shows that when people can retain their land, the spatial extent of permanent land-use change may differ greatly compared to areas with limited access in the post-war period. Agriculture is remarkably resilient, but extremely difficult to rebuilt once the agricultural system is lost (FAO, 2018).

Surprisingly, the war in Nagorno-Karabakh did not result in widespread permanent cropland abandonment, despite intense combat and large numbers of refugees and internally displaces persons. Previously, abandonment near the battle field had been estimated to be up to 60%, based on matching statistics (Baumann et al., 2015). We found that permanent cropland abandonment was higher in non-conflict areas than in conflict areas. The differences between our study and the one by Baumann et al. 2015, are related to multiple aspects. First Baumann et al. 2015 analyzed major battle sites collected from literature, a more narrow definition of the conflict area than the one we employed here. Second, our abandonment was lower in the conflict area because we included a much longer time period for our abandonment definition (1987 to 2000 in Baumann et al. 2015, versus 1987 to 2015 in our study). Third, we excluded re-cultivated observations because we were interested in the effects of wars on permanent land-use change. Lastly, we included the entire non-conflict area of Armenia and Azerbaijan as control and found more abandonment in our non-conflict areas.

Assessing the interaction of distance to conflict locations and intensity of conflict locations showed that the highest probability of permanent cropland abandonment depended largely on the nearest conflict location, and additional locations were less important than we expected. Our findings are in line with a previous study in Chechnya that found higher probability of abandonment nearest to the conflict event, but the mapped probability was higher than in our study (Yin et al., 2019). We believe that the differences in abandonment probability was most likely due to the much larger size of our study region. Nevertheless, these results show that using the nearest conflict location for assessing the effect on permanent cropland abandonment was valid for Chechnya and Nagorno-Karabakh war. The same pattern occurred in Dafur, where a higher number of violent events result in less cropland, with a stronger effect when conflict events were close (Alix-Garcia et al., 2013). However, the pattern was different in Abkhazia, where conflict locations farther away had a larger effect than conflict locations nearby.

When the nearest conflict locations was accounted for, additional conflict locations farther away did not result in higher abandonment. We had hypothesized that farmers would base their decision whether to cultivate or to abandonment a field not only on the nearest conflict location but also on conflict locations that were father away, especially when those conflict locations had high intensity. Our results, however, did not support this hypothesis. One explanation for this could be that a farmer may only heard or read about the additional violence farther away and this may not affect the land-use decision as much as it does when the conflict location occurs in the immediate vicinity (Linke and O'Loughlin, 2015). Further, farmers may rather adjust their management and diversify their crop than abandoning their fields (Adelaja and George, 2019a), especially when off-farm alternatives for income are rare (Bozzoli and Brück, 2009).

In the following we want to discuss the land use effects of the four wars for each war individually, starting with Chechnya. In Chechnya, one reason for the localized effect of the wars may be that the majority of rural residents are farmers and household based agriculture is their main source of income (ICG, 2015). Further, during the early years attacks were targeted towards the military, police, and governmental officials (O'Loughlin et al., 2011), and may have had less influence on farmers and hence on permanent cropland abandonment. In later years, the war spread into neighboring republics, which were initially involved in the fight for Chechnya's independence (O'Loughlin et al., 2011; O'Loughlin and Witmer, 2011). After the war, many people that were displaced, were relocated within Chechnya and to neighboring Ingushetia and Dagestan (UNHCR, 1996) and may have maintained agricultural activity. Furthermore, a majority of the land is still under state control in the Russian Caucasus, which may have eased the process to re-cultivate the land (Yin et al., 2019). Last but not least, most active fighting occurred in urban areas (O'Loughlin et al., 2011), especially in the later years of the war, and that may also explain the localized nature of the wars and may have prevented farmers in the countryside abandoning their fields.

In Abkhazia, the effects of the war were wide-ranging and rather regional. This may be mostly due to the patterns of displacement and refugee movements. 230.000 people that were registered in Georgia in 2010 had fled Abkhazia and South Ossetia due to the wars there (IDMC, 2011). After the war, people displaced from Abkhazia were not allowed to return to their homes (NRC/IDMC, 2015; UNHCR, 1996), except in one district in Abkhazia, i.e., Gali (IDMC, 2011). This limited access may explain the wide-ranging effect of the war on permanent cropland abandonment. The effect of the war is also visible in a reduction of tourism, even in regions that are remote from military activates (Radvanyi and Muduyev, 2007). Travelling from and to Abkhazia is still very restricted and the border between Abkhazia and Georgia is controlled by Russian troops (ICG, 2006). The limited access, the dispute over land, and the impeded return of internally displaced persons to their homes most likely hampered the cultivation of the agricultural fields (NRC/IDMC, 2015).

The effect of the war in South Ossetia on cropland abandonment was insignificant. One reason could be the lower numbers of conflict events and fatalities compared to Chechnya, Abkhazia, and Nagorno-Karabakh, leading to fewer observations in our models and therefore insignificant results. Another reason may be that agriculture is less common there. Furthermore, most of South Ossetia's agriculture is in the form of small-scale subsistence farming (Gerrits and Bader, 2016).

The war in Nagorno-Karabakh resulted in the largest number of internally displaced persons and refugees, but did not result in widespread permanent cropland abandonment. Roughly 205,000 Azerbaijani fled Armenia and 247,000 Armenians fled Azerbaijan (Zürcher, 2007). The agricultural sector suffered heavy losses because of remaining mines and damaged irrigation systems (NRC/IDMC, 2005). However, Armenia provided economic support to the Karabakh region and subsidized wheat exports to Armenia (ICG, 2016, 2005), fostering agriculture in the region. Since 2006, the de facto government of Nagorno-Karabakh established programs to support agriculture (ICG, 2017), and arranged long-term land rental agreements (ICG, 2017). This activities were valid for the duration of our study period, but may change due to the political changes in 2020.

In general, cropland abandonment in the Caucasus was low compared to post-soviet abandonment rates in other parts of Russia and Eastern Europe. We expected that the four wars on top of the collapse of the Soviet Union would have resulted in very high cropland abandonment rates. However, while cropland abandonment varied across our study region (6-30%) (Buchner et al., 2020), rates in all countries were low compared to European Russia, where up to 56% of pre-collapse agricultural land is no longer farmed (Alcantara et al., 2012; Baumann et al., 2011; Prishchepov et al., 2013). This means that although we found a clear effect of the four wars on cropland abandonment, and even though these wars were intense and resulted in large numbers of refugees, people in the Caucasus largely continued to cultivate their fields amidst the wars, despite the many challenges, and were exceptionally resilient during difficult times (Radvanyi and Muduyev, 2007). Similar patterns occurred in Colombia and Niger, where farmer’s continued cultivating their fields amidst conflict (Adelaja and George, 2019a; Arias et al., 2018). However, this also highlights the importance of humanitarian help for farmers in these war-torn regions to support their livelihood during the challenging times of war.

When interpreting our results, it is important keep some limitations of our models in mind. Although we included many variables, we were not able to include information on numbers of internally displaced persons and refugees, land ownership, or economic welfare of farmers. Similarly, we only included permanent abandonment in our analysis, because we were interested in long-term effects, but this means we may have missed fields that were abandoned due to the wars, but re-cultivated later. Another limitation is that our difference-in-differences approach may have missed abandonment before some of the conflict events occurred, because we mapped abandonment the first time in 1995. Furthermore, our land-cover maps included some mapping errors, but we assume that errors were randomly distributed across space. Spatial autocorrelation is another source of uncertainty and can lead to biased standard errors. To address this, we spaced the points in our sampling grid afar from each other to minimize autocorrelation, and included a country dummy variable to account for potential unobserved variation.

In summary, political instability after the collapse of the Soviet Union resulted in four major wars in the Caucasus since 1991. However, the characteristics of each war in terms of overall number of conflict events, differed greatly and even wars with a lower overall intensity can have detrimental effects on permanent land-use change. It is important to assess the effect of wars in their entirety as they may vary in their spatial extent. Additional conflict locations farther away were not as important as hypothesized. We highlight the importance of applying a consistent methodology when making comparison among wars to better understand their effects on permanent cropland abandonment in particular, and on land use in general. More broadly, our results highlight that the effects of wars on land use are far from uniform, and that it is important to consider the differences among wars.

Acknowledgments

We gratefully acknowledge support for this research by the Land-cover and Land-Use Change (LCLUC) Program of the National Aeronautic Space Administration (NASA) through Grants 570NNX15AD93G and 80NSSC18K0316. The study contributes to the Global Land Programme (GLP). We would like to thank Afag Rizayeva for valuable comments on the history and the current situation in the Caucasus.

References

Abatzoglou, J.T., Dobrowski, S.Z., Parks, S.A., Hegewisch, K.C., 2018. TerraClimate, a high-resolution global dataset of monthly climate and climatic water balance from 1958–2015. Sci. Data 5, 170191. https://doi.org/10.1038/sdata.2017.191

Adelaja, A., George, J., 2019a. Terrorism and land use in agriculture: The case of Boko Haram in Nigeria. Land Use Policy 88, UNSP 104116. https://doi.org/10.1016/j.landusepol.2019.104116

Adelaja, A., George, J., 2019b. Effects of conflict on agriculture: Evidence from the Boko Haram insurgency. World Dev. 117, 184–195. https://doi.org/10.1016/j.worlddev.2019.01.010

Ahouissoussi, N., Neumann, J.E., Srivastava, J.P., 2014. Building resilience to climate change in South Caucasus agriculture (No. 87601). The World Bank.

Alcantara, C., Kuemmerle, T., Prishchepov, A.V., Radeloff, V.C., 2012. Mapping abandoned agriculture with multi-temporal MODIS satellite data. Remote Sens. Environ. 124, 334–347. https://doi.org/10.1016/j.rse.2012.05.019

Alix-Garcia, J., Bartlett, A., Saah, D., 2013. The landscape of conflict: IDPs, aid and land-use change in Darfur. J. Econ. Geogr. 13, 589–617. https://doi.org/10.1093/jeg/lbs044

Andam, K.S., Ferraro, P.J., Pfaff, A., Sanchez-Azofeifa, G.A., Robalino, J.A., 2008. Measuring the effectiveness of protected area networks in reducing deforestation. Proc. Natl. Acad. Sci. 105, 16089–16094. https://doi.org/10.1073/pnas.0800437105

Arias, M.A., Ibáñez, A.M., Zambrano, A., 2018. Agricultural production amid conflict: Separating the effects of conflict into shocks and uncertainty. World Dev. https://doi.org/10.1016/j.worlddev.2017.11.011

Arriagada, R.A., Ferraro, P.J., Sills, E.O., Pattanayak, S.K., Cordero-Sancho, S., 2012. Do Payments for Environmental Services Affect Forest Cover? A Farm-Level Evaluation from Costa Rica. Land Econ. 88, 382–399. https://doi.org/10.3368/le.88.2.382

Baumann, M., Kuemmerle, T., 2016. The impacts of warfare and armed conflict on land systems. J. Land Use Sci. 11, 672–688. https://doi.org/10.1080/1747423X.2016.1241317

Baumann, M., Kuemmerle, T., Elbakidze, M., Ozdogan, M., Radeloff, V.C., Keuler, N.S., Prishchepov, A.V., Kruhlov, I., Hostert, P., 2011. Patterns and drivers of post-socialist farmland abandonment in Western Ukraine. Land Use Policy 28, 552–562. https://doi.org/10.1016/j.landusepol.2010.11.003

Baumann, M., Radeloff, V.C., Avedian, V., Kuemmerle, T., 2015. Land-use change in the Caucasus during and after the Nagorno-Karabakh conflict. Reg. Environ. Change 15, 1703–1716. https://doi.org/10.1007/s10113-014-0728-3

Bekiarova, N., Ilina, A., 2019. Is the Peaceful Regulation of the Nagorno-Karabakh Conflict – Mission Possible? (SSRN Scholarly Paper No. ID 3332351). Social Science Research Network, Rochester, NY.

Bozzoli, C., Brück, T., 2009. Agriculture, Poverty, and Postwar Reconstruction: Micro-Level Evidence from Northern Mozambique. J. Peace Res. 46, 377–397.

Bragina, E.V., Radeloff, V.C., Baumann, M., Wendland, K., Kuemmerle, T., Pidgeon, A.M., 2015. Effectiveness of protected areas in the Western Caucasus before and after the transition to post-socialism. Biol. Conserv. 184, 456–464. https://doi.org/10.1016/j.biocon.2015.02.013

Buchner, J., Yin, H., Frantz, D., Kuemmerle, T., Askerov, E., Bakuradze, T., Bleyhl, B., Elizbarashvili, N., Komarova, A., Lewińska, K.E., Rizayeva, A., Sayadyan, H., Tan, B., Tepanosyan, G., Zazanashvili, N., Radeloff, V.C., 2020. Land-cover change in the Caucasus Mountains since 1987 based on the topographic correction of multi-temporal Landsat composites. Remote Sens. Environ. 248, 111967. https://doi.org/10.1016/j.rse.2020.111967

Butsic, V., Lewis, D.J., Radeloff, V.C., Baumann, M., Kuemmerle, T., 2017. Quasi-experimental methods enable stronger inferences from observational data in ecology. Basic Appl. Ecol. 19, 1–10. https://doi.org/10.1016/j.baae.2017.01.005

Cook, A.H., Lounsbery, M.O., 2017. Conflict Dynamics: A Comparative Framework, in: Conflict Dynamics, Civil Wars, Armed Actors, and Their Tactics. University of Georgia Press, pp. 11–28.

Cornell, S.E., 2000. Small Nations and Great Powers: A Study of Ethnopolitical Conflict in the Caucasus. RoutledgeCurzon, Richmond, Surrey, England.

De Waal, T., 2010. The Caucasus : An Introduction. Oxford University Press, Oxford.

Eklund, L., Persson, A., Pilesjö, P., 2016. Cropland changes in times of conflict, reconstruction, and economic development in Iraqi Kurdistan. Ambio 45, 78–88. https://doi.org/10.1007/s13280-015-0686-0

FAO, 2018. FAO - News Article: Helping farmers helps peace [WWW Document]. Help. Farmers Helps Peace. URL http://www.fao.org/news/story/en/item/1146356/icode/ (accessed 11.24.20).

Freni, S.J., 2013. Causes of Violent Conflict in the Caucasus since the Collapse of Communism. Inq. J. 5.

Gerrits, A.W.M., Bader, M., 2016. Russian patronage over Abkhazia and South Ossetia: implications for conflict resolution. East Eur. Polit. 32, 297–313. https://doi.org/10.1080/21599165.2016.1166104

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., Moore, R., 2017. Google Earth Engine: Planetary-scale geospatial analysis for everyone. Remote Sens. Environ., Big Remotely Sensed Data: tools, applications and experiences 202, 18–27. https://doi.org/10.1016/j.rse.2017.06.031

Guo, S., Fraser, M.W., 2014. Propensity Score Analysis, Second. ed, Advanced Quantitative Techniques in the Social Sciences. SAGE Publications, Inc.

Högbladh, S., 2019. UCDP GED Codebook version 19.1. Department of Peace and Conflict Research, Uppsala University.

Holland, E.C., 2016. Economic Development and Subsidies in the North Caucasus. Probl. Post-Communism 63, 50–61. https://doi.org/10.1080/10758216.2015.1067750

ICG, I.C.G., 2017. Nagorno-Karabakh’s Gathering War Clouds (Europe Report No. No 244). Brussels.

ICG, I.C.G., 2016. Isolation of Post-Soviet Conflict Regions Narrows the Road to Peace [WWW Document]. Refworld. URL https://www.refworld.org/docid/5836e9143.html (accessed 4.2.20).

ICG, I.C.G., 2015. North Caucasus: The Challenges of Integration (IV): Economic and Social Imperatives (Europe Report No. No 237).

ICG, I.C.G., 2006. Abkhazia Today (Europe Report No. 176).

ICG, I.C.G., 2005. Nagorno-Karabakh: Viewing the Conflict from the Ground (Europe Report No. 166).

ICRC, 2007. Farming through conflict (No. T2007 93/ 002 10/ 2007 2000). ICRC Economic Security Unit.

IDMC, 2011. Internal Displacement - Global Overview of Trends and Developments in 2010. Internal Displacement Monitoring Centre, Norwegian Refugee Council, Geneva, Switzerland.

Jaafar, H.H., Zurayk, R., King, C., Ahmad, F., Al-Outa, R., 2015. Impact of the Syrian conflict on irrigated agriculture in the Orontes Basin. Int. J. Water Resour. Dev. 31, 436–449. https://doi.org/10.1080/07900627.2015.1023892

Jones, K.W., Lewis, D.J., 2015. Estimating the Counterfactual Impact of Conservation Programs on Land Cover Outcomes: The Role of Matching and Panel Regression Techniques. PLOS ONE 10, e0141380. https://doi.org/10.1371/journal.pone.0141380

Kolossov, V., O’Loughlin, J., 2011. After the Wars in the South Caucasus State of Georgia: Economic Insecurities and Migration in the “De Facto” States of Abkhazia and South Ossetia. Eurasian Geogr. Econ. 52, 631–654. https://doi.org/10.2747/1539-7216.52.5.631

Landholm, D.M., Pradhan, P., Kropp, J.P., 2019. Diverging forest land use dynamics induced by armed conflict across the tropics. Glob. Environ. Change 56, 86–94. https://doi.org/10.1016/j.gloenvcha.2019.03.006

Lerman, Z., 2001. Agriculture in transition economies: from common heritage to divergence. Agric. Econ. 26, 95–114. https://doi.org/10.1111/j.1574-0862.2001.tb00057.x

Linke, A.M., O'Loughlin, J., 2015. Reconceptualizing, Measuring, and Evaluating Distance and Context in the Study of Conflicts: Using Survey Data from the North Caucasus of Russia. Int. Stud. Rev. 17, 107–125. https://doi.org/10.1111/misr.12207

NRC/IDMC, N.R.C.D.M.C., 2005. Profile of Internal Displacement: Azerbaijan [WWW Document]. Refworld. URL https://www.refworld.org/docid/3ae6a6250.html (accessed 4.2.20).

NRC/IDMC, N.R.C.D.M.C. (NRC/IDMC), 2015. Global Overview 2015: People internally displaced by conflict and violence - Europe, The Caucasus and central Asia [WWW Document]. Refworld. URL https://www.refworld.org/docid/55a617634.html (accessed 4.2.20).

Nussberger, A., 2008. The "Five-Day War" in Court Russia, Georgia, and International Law. Osteuropa 58, 19–39.

O'Loughlin, J., Holland, E.C., Witmer, F.D.W., 2011. The Changing Geography of Violence in Russia's North Caucasus, 1999-2011: Regional Trends and Local Dynamics in Dagestan, Ingushetia, and Kabardino-Balkaria. Eurasian Geogr. Econ. 52, 596–630. https://doi.org/10.2747/1539-7216.52.5.596

O’Loughlin, J., Witmer, F.D.W., 2011. The Localized Geographies of Violence in the North Caucasus of Russia, 1999-2007. Ann. Assoc. Am. Geogr. 101, 178–201. https://doi.org/10.1080/00045608.2010.534713

OpenStreetMap contributors, 2017. OpenStreetMap [WWW Document]. URL www.openstreetmap.org

Özerdem, A., Roberts, R., 2012. The Impact of Conflict on Agriculture and Post-conflict Reconstruction Challenges, in: Özerdem, A., Roberts, R. (Eds.), Challenging Post-Conflict Environments: Sustainable Agriculture. Taylor & Francis Group, London, UNITED KINGDOM.

Pallin, C.V., Westerlund, F., 2009. Russia’s war in Georgia: lessons and consequences. Small Wars Insur. 20, 400–424. https://doi.org/10.1080/09592310902975539

Prishchepov, A.V., Müller, D., Dubinin, M., Baumann, M., Radeloff, V.C., 2013. Determinants of agricultural land abandonment in post-Soviet European Russia. Land Use Policy 30, 873–884. https://doi.org/10.1016/j.landusepol.2012.06.011

Radvanyi, J., Muduyev, S.S., 2007. Challenges Facing the Mountain Peoples of the Caucasus. Eurasian Geogr. Econ. 48, 157–177. https://doi.org/10.2747/1538-7216.48.2.157

Sanchez-Cuervo, A.M., Aide, T.M., 2013. Identifying hotspots of deforestation and reforestation in Colombia (2001–2010): implications for protected areas. Ecosphere 4, 1–21. https://doi.org/10.1890/ES13-00207.1

Schutte, S., Donnay, K., 2014. Matched wake analysis: Finding causal relationships in spatiotemporal event data. Polit. Geogr. 41, 1–10. https://doi.org/10.1016/j.polgeo.2014.03.001

Sundberg, R., Melander, E., 2013. Introducing the UCDP Georeferenced Event Dataset. J. Peace Res. 50, 523–532. https://doi.org/10.1177/0022343313484347

Tadono, T., Ishida, H., Oda, F., Naito, S., Minakawa, K., Iwamoto, H., 2014. Precise Global DEM Generation by ALOS PRISM. ISPRS Ann. Photogramm. Remote Sens. Spat. Inf. Sci. 4, 71–76. https://doi.org/10.5194/isprsannals-II-4-71-2014

Takaku, J., Tadono, T., Tsutsui, K., 2014. Generation of High Resolution Global DSM from ALOS PRISM. ISPRS - Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci. 4, 243–248. https://doi.org/10.5194/isprsarchives-XL-4-243-2014

Temudo, M.P., Silva, J.M.N., 2012. Agriculture and forest cover changes in post-war Mozambique. J. Land Use Sci. 7, 425–442. https://doi.org/10.1080/1747423X.2011.595834

The Halo Trust, 2014. 25 years of getting mines out of the ground, for good. (Donor Report 2014). The Halo Trust, Dumfries, United Kingdom.

UNHCR, T.U.R.A.U., 1996. UNHCR publication for CIS Conference (Displacement in the CIS) - Conflicts in the Caucasus. Presented at the CIS Conference.

Volodicheva, N., 2002. The Caucasus, in: Shahgedanova, M. (Ed.), The Physical Geography of Northern Eurasia. Oxford University Press, Oxford, New York, pp. 350–376.

Welton, G., Asatryan, A.A., Jijelava, D., 2013. Comparative analysis of agriculture in the South Caucasus. UNDP Georgia, Tbilisi, Georgia.

Wiberg, H., Scherrer, C. (Eds.), 1999. Ethnicity and intra-state conflict. Aldershot, Hants, England: Ashgate.

Wieder, W.R., Boehnert, J., Bonan, G.B., Langseth, M., 2014. Regridded Harmonized World Soil Database v1.2. ORNL DAAC.

Witmer, F.D.W., O'Loughlin, J., 2011. Detecting the Effects of Wars in the Caucasus Regions of Russia and Georgia Using Radiometrically Normalized DMSP-OLS Nighttime Lights Imagery. GIScience Remote Sens. 48, 478–500. https://doi.org/10.2747/1548-1603.48.4.478

Witmer, F.D.W., O'Loughlin, J., 2009. Satellite Data Methods and Application in the Evaluation of War Outcomes: Abandoned Agricultural Land in Bosnia-Herzegovina After the 1992–1995 Conflict. Ann. Assoc. Am. Geogr. 99, 1033–1044. https://doi.org/10.1080/00045600903260697

Wooldridge, J.M., 2002. Econometric Analysis of Cross Section and Panel Data, second. ed. MIT Press, Cambridge, Massachusetts.

World Bank Data, 2019. Employment in agriculture (% of total employment) (modeled ILO estimate) | Data [WWW Document]. World Bank Data. URL https://data.worldbank.org/indicator/sl.agr.empl.zs?end=2018&start=2018&view=map (accessed 5.24.19).

Yamskov, Anatoly.N., 1991. Ethnic conflict in the Transcausasus. Theory Soc. 20, 631–660. https://doi.org/10.1007/BF00232663

Yin, H., Butsic, V., Buchner, J., Kuemmerle, T., Prishchepov, A.V., Baumann, M., Bragina, E.V., Sayadyan, H., Radeloff, V.C., 2019. Agricultural abandonment and re-cultivation during and after the Chechen Wars in the northern Caucasus. Glob. Environ. Change 55, 149–159. https://doi.org/10.1016/j.gloenvcha.2019.01.005

Zazanashvili, N., Gagnidze, R., Nakhutsrishvili, G., 1999. Main types of vegetation zonation on the mountains of the Caucasus. Acta Phytogeogr. Suec. 85, 7–16.

Zazanashvili, N., Garforth, M., Jungius, H., Gamkrelidze, T., 2012. Ecoregion Conservation Plan for the Caucasus. 2012 revised and updated edition. Ga. Tbilisi WWF KfW BMZ.

Zürcher, C., 2007. The Post-Soviet Wars: Rebellion, Ethnic Conflict, and Nationhood in the Caucasus. NYU Press.

Tables and figures

Table 3: Variables included in the models to assess the effect of wars on cropland abandonment.

	Variable	Unit	Period	Resolution	Source
Response variable	Cropland change	1: cropland abandonment 0: no abandonment	1987, 1995, 2000, 2005, 2010, 2015	30 m	Buchner et al. 2020
Conflict intensity variables	Number of conflict events	Count	annual numbers summarized for following time periods: 1987-1995, 1996-2000, 2001-2005, 2006-2010, 2011-2015	Point location	Sundberg and Melander, 2013
	Number of total fatalities				
Control variables	Elevation	m	Time-invariant	1 arc second	Tadono et al., 2014, Takaku et al., 2014
	Slope	degree			
	Aspect	degree			
	Maximum temperature	℃	1990, 1995, 2000, 2005, 2010, 2015	2.5 arc minutes	Abatzoglou et al., 2018
	Precipitation accumulation	mm			
	Topsoil carbon content	%	Time-invariant	0.05 degree	Wieder et al. 2014
	Euclidean distance to highways	m	Time-invariant	-	OpenStreetMap contributors, 2017
	Euclidean distance to settlements				
	Percent rangeland within 100m	%	1987, 1995, 2000, 2005, 2010, 2015	30 m	Buchner et al. 2020
	Percent forest within 100m				
	Administrative boundaries of countries	dummy	Time-invariant	vector	Database of Global Administrative Areas (GADM version 3.6) (www.gadm.org)

Table 4: Marginal effects of conflict events on cropland abandonment expressed as both percentage point change and percent change (based on cropland abandonment in conflict area) depending on the distance from conflict events that delineated the conflict area affected by a given war (5, 10, 20, and 30 km). A positive percentage point change indicates an increase from non-conflict to conflict area. Standard error in parentheses, *** p-value < 0.01, ** p-value < 0.05, * p-value < 0.1. Bold formatting indicates significant results.

War	Marginal effect (Percentage point change)				Marginal effect (Percent change in abandonment)			
	5km	10km	20km	30km	5km	10km	20km	30km
Whole Caucasus	0.3 (0.8)	**0.9 (0.4)****	**1.0 (0.3)*****	**1.2 (0.2)*****	4.4	**15.8**	**20.4**	**27.3**
Chechnya	1.2 (0.8)	**2.0 (0.5)*****	**1.7 (0.3)*****	**1.2 (0.2)*****	20.7	**46.5**	**47.2**	**38.7**
Abkhazia	2.0 (14.7)	11.7 (11.2)	**22.0 (5.8)*****	**18.4 (3.3)*****	3.14	19.0	**40.9**	**45.1**
South Ossetia	4.4 (5.6)	4.8 (3.5)	-1.5 (2.2	-0.9 (1.7)	48.9	50.0	-9.1	-7.1
Nagorno-Karabakh	-9.1 (3.8)	**-12.5 (2.0)*****	**-7.6 (1.1)*****	**-5.4 (0.8)*****	-66.0	**-64.4**	**-53.1**	**-39.7**

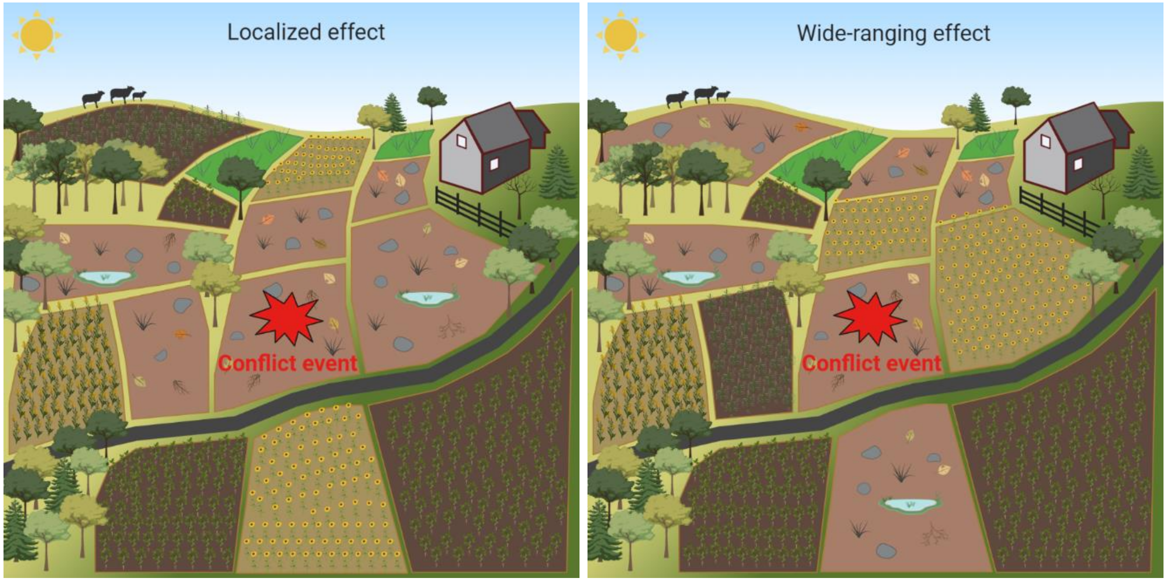


Figure 12: Conceptual figure of the effect of war on the spatial extent of cropland abandonment. Localized effect when the abandonment is closest to conflict events vs. wide-ranging when abandonment also occurs farther away (created with BioRender.com).

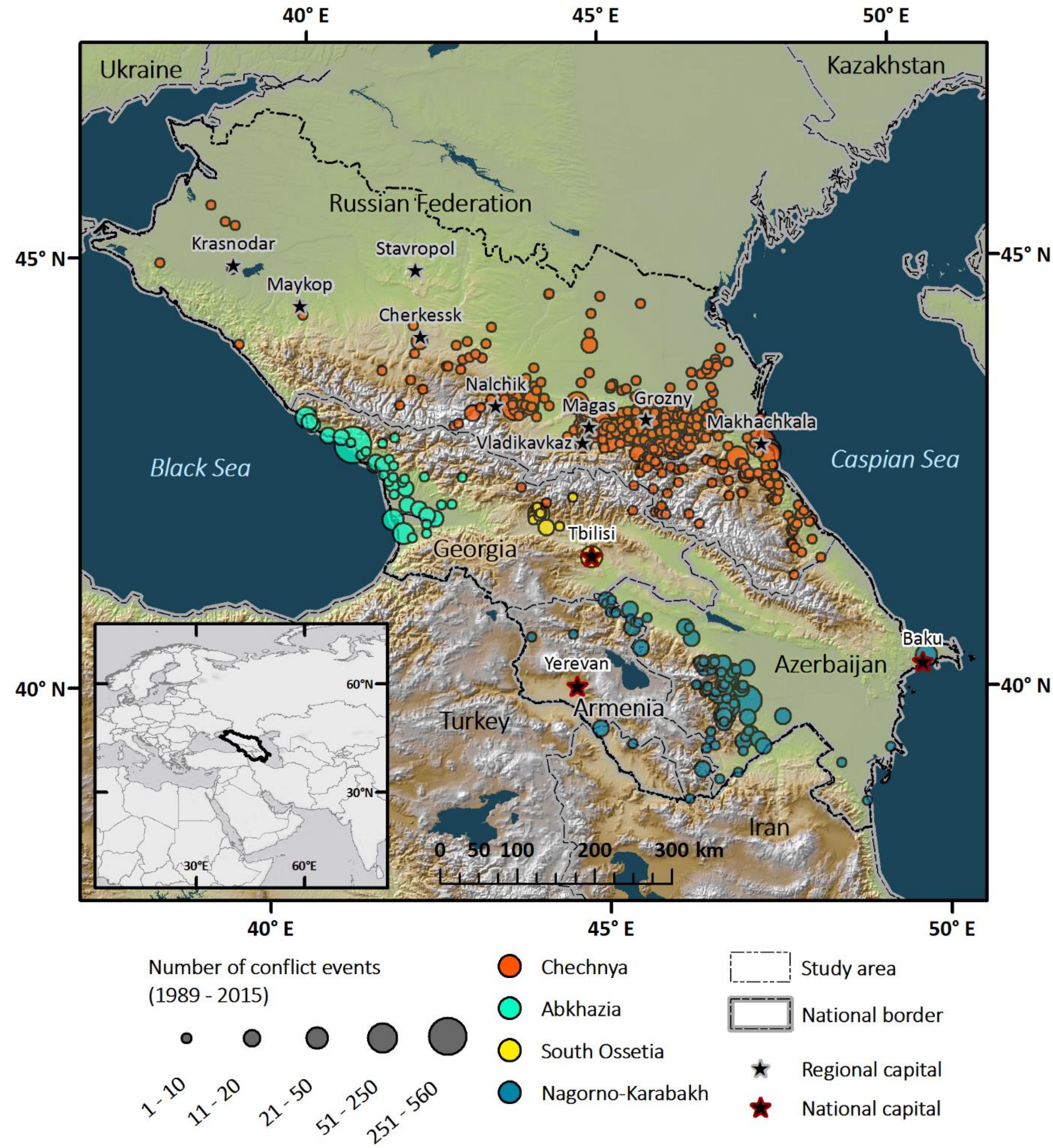


Figure 13: Study area in the Caucasus, and the four major wars in Chechnya, Abkhazia, South Ossetia, and Nagorno-Karabakh with the number of conflict events from 1989 to 2015 in each conflict location (source: UCDP).

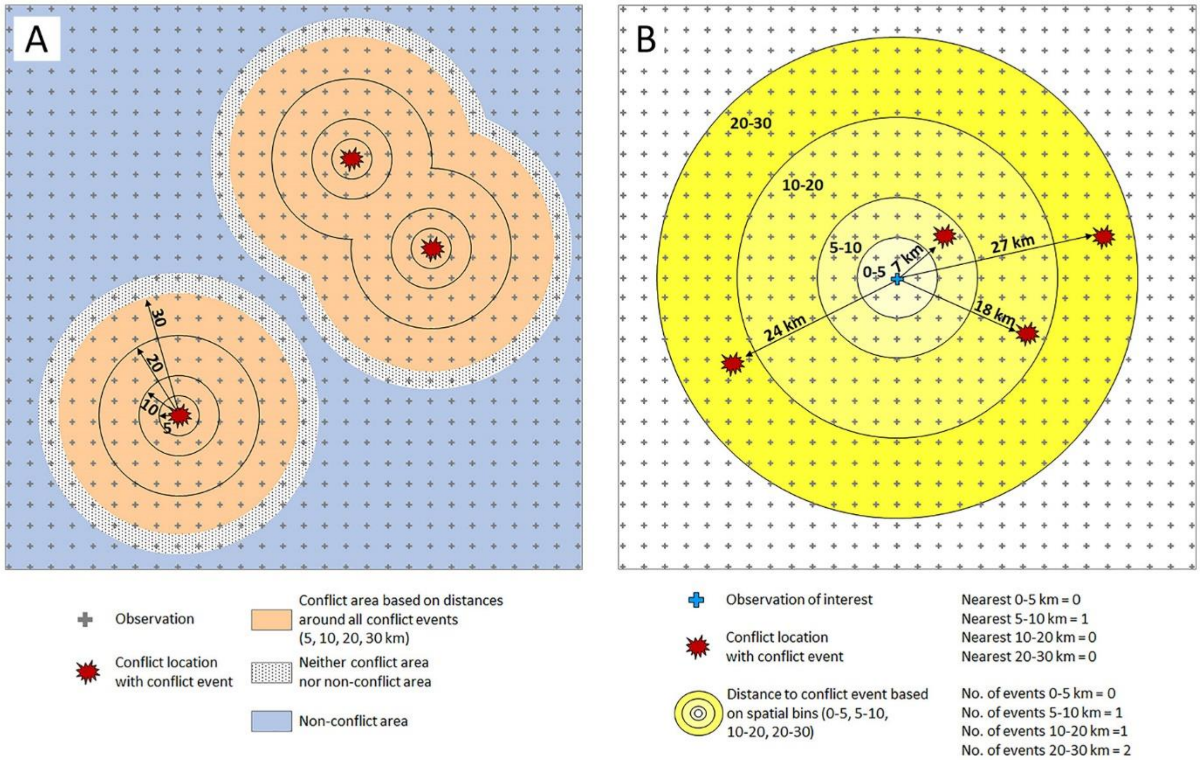


Figure 14: Conceptual figure for (A) matching procedure to assess the effects of wars in their entirety on cropland abandonment and (B) to assess the effects of conflict locations with events, including the interaction between distance to conflict locations and intensity thereof, on abandonment. For the observation of interest, the nearest conflict location occurred within a distance of 5-10 km, with a conflict intensity of one conflict event, and additional conflict locations with one conflict event each occurred within a distance of 10-20 and 20-30 km that were also considered in the model.

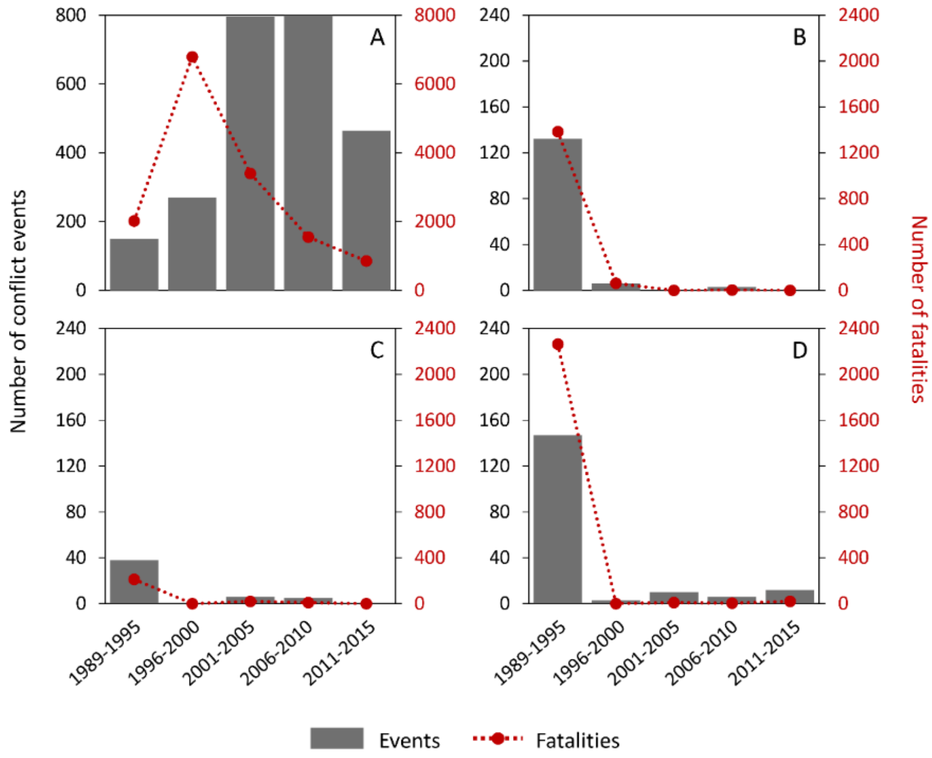


Figure 15: Number of conflict events and number of total fatalities in the five time periods for (A) Chechnya, (B) Abkhazia, (C) South Ossetia, and (D) Nagorno-Karabakh. Note: y-axis ranges differ among wars.

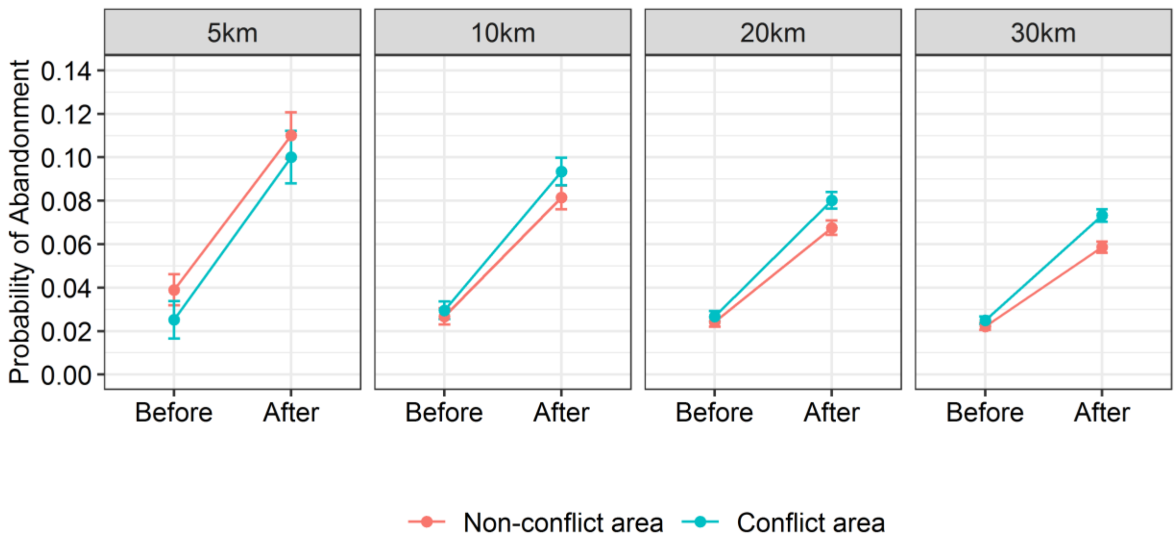


Figure 16: Predictive margins with 95% confidence intervals (CI) across the Caucasus before and after conflict events based on the area around all conflict events (5, 10, 20, and 30 km) that are considered conflict area of the four wars.

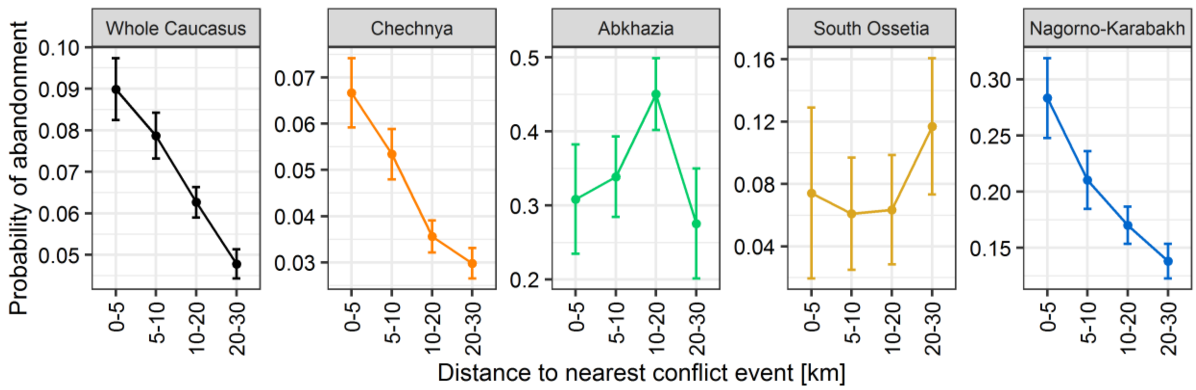


Figure 17: Predictive margins of conflict events on cropland abandonment when nearest conflict events occurred at different distances (0-5, 5-10, 10-20, and 20-30 km) with 95% confidence intervals. Note that y-axes differ among panels. For the whole Caucasus, and for Chechnya, and Nagorno-Karabakh the probability was highest when the conflict event was nearby, but the opposite was true for Abkhazia, and there were no differences among distances for South Ossetia.

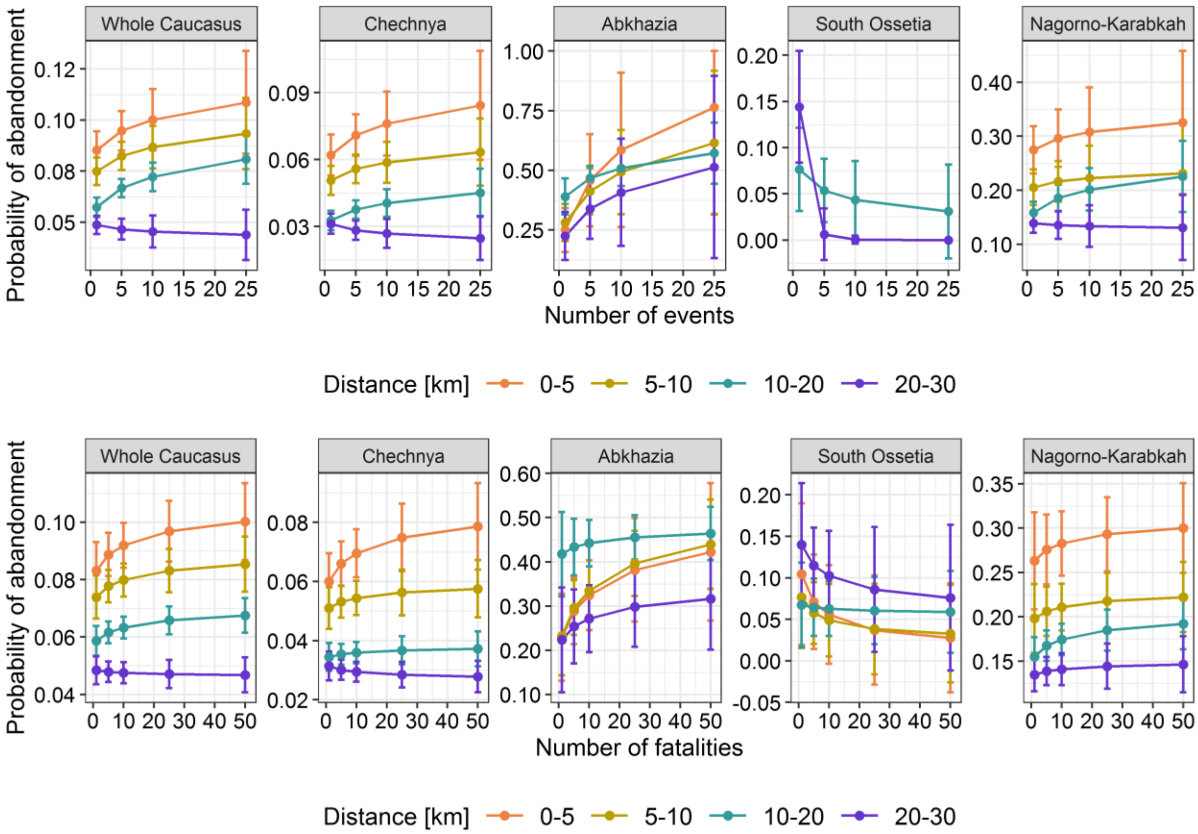
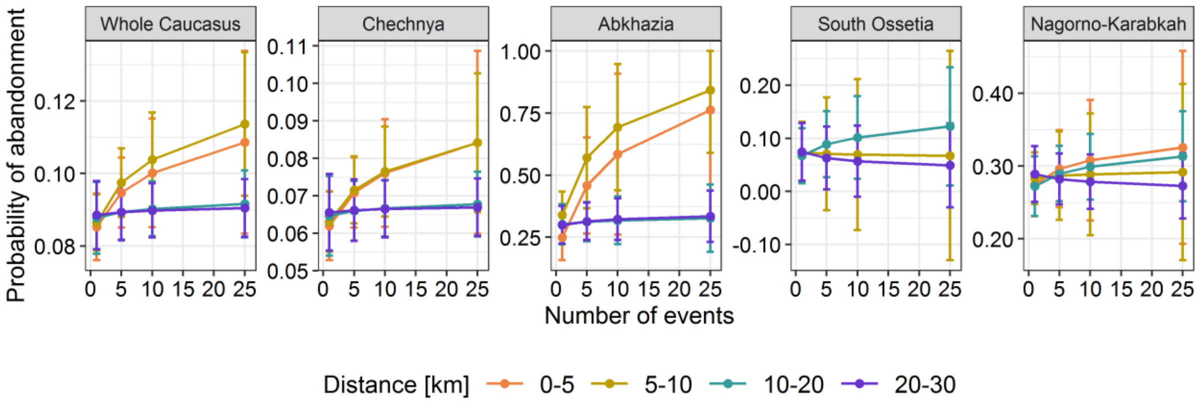


Figure 18: Predicted margins of cropland abandonment with increasing intensity of conflict location (i.e., increasing events or fatalities) for different distances with 95% confidence intervals. Note that y-axes differ among panels. For the whole Caucasus, the line representing effects of conflicts within 5 km (orange line) is on top, indicating that nearest conflict event or fatalities resulted in a higher probability for abandonment. With an increasing number of conflict events (top row) or number of fatalities (bottom row), probability of abandonment increased.



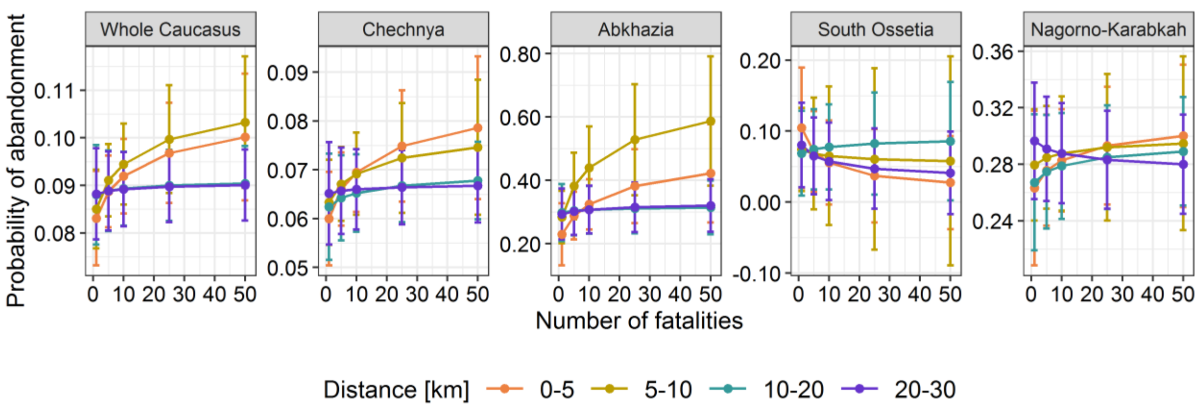


Figure 19: Predicted margins of cropland abandonment when the nearest conflict event or fatalities is within 5 km and the number of conflict events or fatalities increases at distances > 5 km (95% confidence intervals). Note that y-axes differ among panels. For the whole Caucasus, the line representing effects of conflict events or fatalities within 5-10 km (yellow line) is overlapping with 0-5 km distance (orange line), indicating that additional conflict events or fatalities in a 5-10 km distance do not result in a higher probability for abandonment, with conflict events as intensity measure (top row) or number of fatalities as intensity measure (bottom row).

Appendix: Supplementary information

Difference-in-Difference model with individual wars taken into account.

$$Y_{it} = \beta_1 * Co_{it} + \beta_2 * A_{it} + \beta_3 * CoID_i + \beta_4 * Co_{it} * A_{it} + \beta_5 * Co_{it} * CoID_i + \beta_6 * A_{it} * CoID_i + \beta_7 * Co_{it} * A_{it} * CoID_i + \beta_8 * Time_{it} + \beta_{9-12} * X_{it} + e_{it} \quad (1)$$

Y_{it} is cropland abandonment (1) or not (0) for observation *i* in time period *t*, Co_{it} is whether observation *i* in a time period *t* was in conflict area (1) or not (0), i.e., treated or not, A_{it} stands for after and indicates before (0) or after (1) a conflict event, $CoID_i$ is a war specific dummy variable, Co_{it} *A_{it} *$CoID_i$ is the interaction between treatment and A_{it} and war specific dummy variable indicating the effect of each war, $Time_{it}$ is a categorical variable indicating time periods, X_{it} is the vector of covariates, β_1- β_{12} are the coefficients to be estimated, and e_{it} is the error term. In the fixed effects model time-invariant covariates are not considered.

Panel logistic regression with random effects for individual wars:

$$Y_{itCoID} = \beta_1 * closest_{0-5km\,it} + \beta_2 * I_{0-5km\,it} + \beta_3 * closest_{0-5km\,it} * \; I_{0-5km\,it} + \beta_4 * closest_{5-10km\,it} + \beta_5 * I_{5-10km\,it} + \beta_6 * closest_{5-10km\,it} * \; I_{5-10km\,it} + \beta_7 * closest_{10-20km\,it} + \beta_8 * I_{10-20km\,it} + \beta_9 * closest_{10-20km\,it} * \; I_{10-20km\,it} + \beta_{10} * closest_{20-30km\,it} + \beta_{12} * I_{20-30km\,it} + \beta_{13} * closest_{20-30km\,it} * \; I_{20-30km\,it} + \beta_{14-23} * X_{it} + \beta_{24} * Year_{it} + \beta_{25} * CI_{it} + e_{it} \quad (2)$$

In this model, Y_{itCoID} is cropland abandonment (1) or not (0) for observation *i* in time period *t* for individual conflict with conflict id *CoID* (Chechnya, Abkhazia, South Ossetia, Nagorno-Karabakh), $closest_{it}$ is a dummy variable indicating if conflict within defined spatial interval is nearest (1) otherwise (0), I_{it} is the intensity measure, i.e., number of conflict events or number of total fatalities, of observation *i* in time period *t*, $closest_{it} * I_{it}$ is the interaction term between closest-interval variable and the intensity measure, X_{it} is the vector of covariates, $Year_{it}$ is a categorical variable indicating each time step, β_1-β_{25} are the coefficients to be estimated, and e_{it} is the error term.

.

Table A7: Probit regression results from propensity score matching model in 1995 for conflict area vs non-conflict area with conflict area defined as 5 km.

Variables	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
ln_elevation	0.198792	0.016507	12.04	0	0.166439	0.231146
ln_slope	-0.01319	0.041415	-0.32	0.75	0.0943662	0.067979
ln_aspect	-0.0265	0.011901	-2.23	0.026	0.0498235	-0.00317
ln_distance_to_highways	0.009619	0.01491	0.65	0.519	0.0196035	0.038842
ln_distance_to_settlements	-0.07033	0.030293	-2.32	0.02	0.1297066	-0.01096
ln_maximum_temperature	3.778519	0.289093	13.07	0	3.211907	4.34513
ln_precipitation_accumul.	-0.91443	0.111167	-8.23	0	-1.132309	-0.69654
ln_topsoil_organic_content	0.301325	0.096464	3.12	0.002	0.1122594	0.490391
ln_percent_rangeland_100m	-0.08647	0.014388	-6.01	0	0.1146678	-0.05827
ln_percent_forest_100m	0.076453	0.03605	2.12	0.034	0.0057962	0.14711
_cons	-18.274	1.757762	-10.4	0	-21.71918	-14.8289

Table A8: Balance between conflict area (treated) and non-conflict area (untreated), matched (M) and unmatched (U) observations in 1995. Conflict area defined as 5 km.

Variables		Treated	Control	% bias	% bias reduction
ln_elevation	U	5.05	4.6612	26.4	
	M	5.05	4.7349	21.4	18.7
ln_slope	U	1.15	1.1583	-0.5	
	M	1.15	1.0971	9	-1599.3
ln_aspect	U	3.64	3.8323	-8.7	
	M	3.64	3.5058	6	30.6
ln_distance_to_highways	U	6.4	6.3945	0.6	
	M	6.4	6.4508	-3	-383.5
ln_distance_to_settlements	U	9.89	9.9904	-13.4	
	M	9.89	9.7865	13	3.3
ln_maximum_temperature	U	5.1	5.0109	91.2	
	M	5.1	5.1189	-18	80.3
ln_precipitation_accumul.	U	3.64	3.8623	-82.8	
	M	3.64	3.6178	9.7	88.3
ln_topsoil_organic_content	U	0.91	0.9543	-19.3	
	M	0.91	0.895	7.1	63.2
ln_percent_rangeland_100m	U	0.99	1.0309	-2.6	
	M	0.99	1.3709	-22.8	-794
ln_percent_forest_100m	U	0.16	0.0973	10.5	
	M	0.16	0.1496	2	80.9

Table A9: Probit regression results from propensity score matching model in 2000 for conflict area vs non-conflict area with conflict area defined as 5 km (country id: 1 - Azerbaijan, 2 – Georgia, 3 – Russia, 4 – Armenia).

Variables	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
country_id						
2	1.124436	0.159631	7.04	0	0.8115657	1.437307
3	1.400112	0.087752	15.96	0	1.228121	1.572104
4	-0.3219	0.213305	-1.51	0.131	0.7399696	0.096172
ln_elevation	0.215317	0.013772	15.63	0	0.188325	0.24231
ln_slope	-0.00523	0.03426	-0.15	0.879	0.0723794	0.061919
ln_aspect	-0.01499	0.009879	-1.52	0.129	0.0343518	0.004373
ln_distance_to_highways	0.005447	0.012072	0.45	0.652	0.0182129	0.029107
ln_distance_to_settlements	-0.02293	0.025172	-0.91	0.362	0.0722618	0.02641
ln_maximum_temperature	2.364774	0.38758	6.1	0	1.605132	3.124416
ln_precipitation_accumul.	-2.68728	0.124486	-21.59	0	-2.93127	-2.44329
ln_topsoil_organic_content	0.490888	0.09371	5.24	0	0.3072203	0.674556
ln_percent_rangeland_100m	0.025085	0.011322	2.22	0.027	0.0028947	0.047276
ln_percent_forest_100m	0.030688	0.03986	0.77	0.441	0.0474364	0.108812
_cons	-6.37273	2.297277	-2.77	0.006	-10.87531	-1.87015

Table A10: Balance between conflict area (treated) and non-conflict area (untreated), matched (M) and unmatched (U) observations in 2000. Conflict area defined as 5 km (country id: 1 - Azerbaijan, 2 – Georgia, 3 – Russia, 4 – Armenia).

Variables		Treated	Control	% bias	% bias reduction
2.country_id	U	0.00635	0.0689	-33.3	
	M	0.00635	0.0127	-3.4	89.8
3.country_id	U	0.92122	0.7402	49.7	
	M	0.92122	0.8869	9.4	81.1
4.country_id	U	0.00381	0.0486	-28.3	
	M	0.00381	0.0178	-8.8	68.8
ln_elevation	U	4.8842	4.5539	18.7	
	M	4.8842	4.4408	25.2	-34.3
ln_slope	U	1.1405	1.1452	-0.7	
	M	1.1405	1.1641	-3.6	-406
ln_aspect	U	3.6892	3.8033	-5.1	
	M	3.6892	3.7789	-4	21.4
ln_distance_to_highways	U	6.3832	6.3867	-0.2	
	M	6.3832	6.4019	-1.2	-434.1
ln_distance_to_settlements	U	9.9402	9.9872	-6.2	
	M	9.9402	9.9639	-3.1	49.6
ln_maximum_temperature	U	5.1317	5.0901	45.4	
	M	5.1317	5.1068	27.2	40.1
ln_precipitation_accumul.	U	3.6084	3.8645	-100.9	
	M	3.6084	3.5252	32.8	67.5
ln_topsoil_organic_content	U	0.95512	0.9606	-2.5	
	M	0.95512	0.8968	26.6	-964.4
ln_percent_rangeland_100m	U	1.1111	1.101	0.6	
	M	1.1111	1.8029	-39.9	-6760.7
ln_percent_forest_100m	U	0.07745	0.0989	-4.3	
	M	0.07745	0.0584	3.8	11.3

Table A11: Probit regression results from propensity score matching model in 2005 for conflict area vs non-conflict area with conflict area defined as 5 km (country id: 1 - Azerbaijan, 2 – Georgia, 3 – Russia, 4 – Armenia).

Variables	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
country_id						
2	1.100864	0.120466	9.14	0	0.8647549	1.336973
3	1.804212	0.092641	19.48	0	1.622639	1.985785
4	0.090927	0.199703	0.46	0.649	0.3004841	0.482339
ln_elevation	0.173613	0.014233	12.2	0	0.1457166	0.201509
ln_slope	0.060573	0.030506	1.99	0.047	0.0007817	0.120364
ln_aspect	-0.00433	0.009162	-0.47	0.636	0.0222905	0.013625
ln_distance_to_highways	0.004266	0.011024	0.39	0.699	0.0173405	0.025872
ln_distance_to_settlements	-0.03775	0.022825	-1.65	0.098	0.0824844	0.006987
ln_maximum_temperature	1.935691	0.270921	7.14	0	1.404695	2.466686
ln_precipitation_accumul.	-0.85652	0.094525	-9.06	0	-1.041786	-0.67126
ln_topsoil_organic_content	-0.3199	0.084301	-3.79	0	-0.48513	-0.15467
ln_percent_rangeland_100m	0.178081	0.010565	16.86	0	0.1573735	0.198788
ln_percent_forest_100m	0.101665	0.038803	2.62	0.009	0.0256125	0.177718
_cons	-10.2537	1.633812	-6.28	0	-13.45587	-7.05144

Table A12: Balance between conflict area (treated) and non-conflict area (untreated), matched (M) and unmatched (U) observations in 2005. Conflict area defined as 5 km (country id: 1 - Azerbaijan, 2 – Georgia, 3 – Russia, 4 – Armenia).

Variables		Treated	Control	% bias	% bias reduction
2.country_id	U	0.0342	0.0728	-17.2	
	M	0.0342	0.0425	-3.7	78.5
3.country_id	U	0.93161	0.701	62.4	
	M	0.93161	0.8808	13.7	78
4.country_id	U	0.00415	0.0539	-30	
	M	0.00415	0.0145	-6.2	79.2
ln_elevation	U	5.0331	4.6525	22.7	
	M	5.0331	5.0551	-1.3	94.2
ln_slope	U	1.2261	1.1459	12	
	M	1.2261	1.2583	-4.8	59.9
ln_aspect	U	3.8947	3.7899	4.8	
	M	3.8947	4.0163	-5.6	-16
ln_distance_to_highways	U	6.3892	6.3912	-0.1	
	M	6.3892	6.4179	-1.8	-1358.7
ln_distance_to_settlements	U	9.9429	9.9864	-5.7	
	M	9.9429	9.926	2.2	61.1
ln_maximum_temperature	U	5.0878	5.0704	15.2	
	M	5.0878	5.0756	10.7	29.8
ln_precipitation_accumul.	U	3.7741	3.8919	-43.6	
	M	3.7741	3.7536	7.6	82.6
ln_topsoil_organic_content	U	0.94037	0.9617	-9.5	
	M	0.94037	0.8957	19.8	-109
ln_percent_rangeland_100m	U	1.4994	1.1821	17.2	
	M	1.4994	1.8612	-19.6	-14
ln_percent_forest_100m	U	0.08091	0.0494	7.2	
	M	0.08091	0.1023	-4.9	32.1

Table A13: Probit regression results from propensity score matching model in 2010 for conflict area vs non-conflict area with conflict area defined as 5 km (country id: 1 - Azerbaijan, 2 – Georgia, 3 – Russia, 4 – Armenia).

Variables	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
country_id						
2	0	(empty)				
3	1.976858	0.111034	17.8	0	1.759236	2.194479
4	1.266542	0.155044	8.17	0	0.9626612	1.570423
ln_elevation	0.120912	0.013234	9.14	0	0.0949735	0.146851
ln_slope	0.087163	0.032647	2.67	0.008	0.0231749	0.15115
ln_aspect	-0.01746	0.009736	-1.79	0.073	-0.036545	0.001621
ln_distance_to_highways	0.011028	0.011862	0.93	0.353	0.0122212	0.034277
ln_distance_to_settlements	-0.0414	0.024412	-1.7	0.09	0.0892491	0.006443
ln_maximum_temperature	1.252147	0.32214	3.89	0	0.620764	1.88353
ln_precipitation_accumul.	-1.16448	0.105125	-11.08	0	-1.370524	-0.95844
ln_topsoil_organic_content	-0.28694	0.085461	-3.36	0.001	0.4544451	-0.11944
ln_percent_rangeland_100m	0.178926	0.011246	15.91	0	0.1568837	0.200968
ln_percent_forest_100m	0.174911	0.040547	4.31	0	0.0954407	0.254382
_cons	-5.71113	1.902467	-3	0.003	-9.439891	-1.98235

Table A14: Balance between conflict area (treated) and non-conflict area (untreated), matched (M) and unmatched (U) observations in 2010. Conflict area defined as 5 km (country id: 1 - Azerbaijan, 2 – Georgia, 3 – Russia, 4 – Armenia).

Variables		Treated	Control	% bias	% bias reduction
2.country_id	U	0	0.0723	-39.5	
	M	0	0	0	100
3.country_id	U	0.94574	0.719	63.7	
	M	0.94574	0.9225	6.5	89.7
4.country_id	U	0.0323	0.0366	-2.4	
	M	0.0323	0.0491	-9.2	-289.2
ln_elevation	U	4.8218	4.5057	16.3	
	M	4.8218	4.9348	-5.8	64.3
ln_slope	U	1.2331	1.1439	13.5	
	M	1.2331	1.299	-9.9	26.1
ln_aspect	U	3.8411	3.8045	1.7	
	M	3.8411	3.9772	-6.3	-271.7
ln_distance_to_highways	U	6.4278	6.3972	1.9	
	M	6.4278	6.3697	3.7	-90.1
ln_distance_to_settlements	U	9.9522	9.9909	-5.1	
	M	9.9522	9.9442	1.1	79.2
ln_maximum_temperature	U	5.0931	5.093	0.1	
	M	5.0931	5.0834	8.8	-11600.1
ln_precipitation_accumul.	U	3.7489	3.8659	-44.7	
	M	3.7489	3.7479	0.4	99.2
ln_topsoil_organic_content	U	0.96037	0.9627	-1.1	
	M	0.96037	0.9475	5.9	-449.5
ln_percent_rangeland_100m	U	1.515	1.0158	27.6	
	M	1.515	1.6025	-4.8	82.5
ln_percent_forest_100m	U	0.10255	0.0498	11.1	
	M	0.10255	0.092	2.2	80

Table A15: Probit regression results from propensity score matching model in 1995 for conflict area vs non-conflict area with conflict area defined as 10 km.

Variables	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
ln_elevation	0.138869	0.010496	13.23	0	0.118297	0.15944
ln_slope	0.0716	0.02906	2.46	0.014	0.014644	0.128556
ln_aspect	-0.0213	0.008604	-2.48	0.013	-0.03816	-0.00444
ln_distance_to_highways	-0.00874	0.010389	-0.84	0.4	-0.0291	0.011621
ln_distance_to_settlements	-0.02631	0.021702	-1.21	0.225	-0.06885	0.01622
ln_maximum_temperature	-1.08031	0.077108	-14.01	0	-1.23144	-0.92918
ln_precipitation_accumul.	2.908565	0.194591	14.95	0	2.527175	3.289956
ln_topsoil_organic_content	0.176689	0.06823	2.59	0.01	0.042961	0.310416
ln_percent_rangeland_100m	-0.06587	0.009849	-6.69	0	-0.08517	-0.04657
ln_percent_forest_100m	0.12458	0.024656	5.05	0	0.076255	0.172906
_cons	-12.9023	1.181171	-10.92	0	-15.2174	-10.5873

Table A16: Balance between conflict area (treated) and non-conflict area (untreated), matched (M) and unmatched (U) observations in 1995. Conflict area defined as 10 km.

Variables		Treated	Control	% bias	% bias reduction
ln_elevation	U	4.8687	4.653	13.2	
	M	4.8687	4.4781	24	-81.1
ln_slope	U	1.2202	1.1544	9.9	
	M	1.2202	1.2282	-1.2	87.8
ln_aspect	U	3.8379	3.8268	0.5	
	M	3.8379	3.6261	9.8	-1806.9
ln_distance_to_highways	U	6.35	6.3951	-2.8	
	M	6.35	6.3403	0.6	78.6
ln_distance_to_settlements	U	9.9335	9.9912	-7.4	
	M	9.9335	9.8724	7.9	-5.8
ln_maximum_temperature	U	5.0896	5.0114	74	
	M	5.0896	5.0975	-7.4	89.9
ln_precipitation_accumul.	U	3.6518	3.8604	-79.1	
	M	3.6518	3.608	16.6	79
ln_topsoil_organic_content	U	0.91649	0.95805	-18.3	
	M	0.91649	0.88488	13.9	24
ln_percent_rangeland_100m	U	1.0469	1.0162	1.8	
	M	1.0469	1.3238	-16.4	-799.7
ln_percent_forest_100m	U	0.18247	0.09509	13.6	
	M	0.18247	0.19327	-1.7	87.6

Table A17: Probit regression results from propensity score matching model in 2000 for conflict area vs non-conflict area with conflict area defined as 10 km (country id: 1 - Azerbaijan, 2 – Georgia, 3 – Russia, 4 – Armenia).

Variables	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
country_id						
2	0.852911	0.099817	8.54	0	0.657274	1.048547
3	0.959889	0.051968	18.47	0	0.858034	1.061744
4	-1.05341	0.143426	-7.34	0	-1.33452	-0.7723
ln_elevation	0.173603	0.009528	18.22	0	0.154929	0.192278
ln_slope	0.024493	0.02467	0.99	0.321	-0.02386	0.072845
ln_aspect	-0.00562	0.007334	-0.77	0.444	-0.01999	0.008758
ln_distance_to_highways	0.002394	0.008856	0.27	0.787	-0.01496	0.019751
ln_distance_to_settlements	-0.01683	0.018607	-0.9	0.366	-0.0533	0.019637
ln_maximum_temperature	-0.49609	0.202623	-2.45	0.014	-0.89323	-0.09896
ln_precipitation_accumul.	-2.75273	0.086804	-31.71	0	-2.92287	-2.5826
ln_topsoil_organic_content	0.245717	0.067737	3.63	0	0.112956	0.378479
ln_percent_rangeland_100m	0.011893	0.008545	1.39	0.164	-0.00485	0.02864
ln_percent_forest_100m	0.036771	0.027085	1.36	0.175	-0.01632	0.089857
_cons	9.655396	1.253233	7.7	0	7.199103	12.11169

Table A18: Balance between conflict area (treated) and non-conflict area (untreated), matched (M) and unmatched (U) observations in 2000. Conflict area defined as 10 km (country id: 1 - Azerbaijan, 2 – Georgia, 3 – Russia, 4 – Armenia).

Variables		Treated	Control	% bias	% bias reduction
2.country_id	U	0.01165	0.0687	-29.4	
	M	0.01165	0.00388	4	86.4
3.country_id	U	0.90571	0.74021	44.4	
	M	0.90571	0.86356	11.3	74.5
4.country_id	U	0.00333	0.04861	-28.8	
	M	0.00333	0.01387	-6.7	76.7
ln_elevation	U	4.8222	4.5536	14.8	
	M	4.8222	4.9509	-7.1	52.1
ln_slope	U	1.1988	1.1451	8	
	M	1.1988	1.2392	-6	24.8
ln_aspect	U	3.8474	3.8028	2	
	M	3.8474	3.9607	-5.2	-154.3
ln_distance_to_highways	U	6.3858	6.3869	-0.1	
	M	6.3858	6.4457	-3.8	-5184.3
ln_distance_to_settlements	U	9.9603	9.9872	-3.6	
	M	9.9603	9.9349	3.4	5.8
ln_maximum_temperature	U	5.1171	5.09	26.6	
	M	5.1171	5.1022	14.7	44.9
ln_precipitation_accumul.	U	3.642	3.8642	-84.2	
	M	3.642	3.6287	5	94
ln_topsoil_organic_content	U	0.94826	0.96067	-5.5	
	M	0.94826	0.90048	21.2	-284.9
ln_percent_rangeland_100m	U	1.0845	1.1002	-0.9	
	M	1.0845	1.4145	-19.1	-2005.2
ln_percent_forest_100m	U	0.08647	0.09865	-2.4	
	M	0.08647	0.08274	0.7	69.4

Table A19: Probit regression results from propensity score matching model in 2005 for conflict area vs non-conflict area with conflict area defined as 10 km (country id: 1 - Azerbaijan, 2 – Georgia, 3 – Russia, 4 – Armenia).

Variables	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
country_id						
2	0.52864	0.078974	6.69	0	0.373854	0.683426
3	1.454602	0.053183	27.35	0	1.350365	1.558839
4	-0.28165	0.109641	-2.57	0.01	-0.49654	-0.06676
ln_elevation	0.111561	0.008826	12.64	0	0.094262	0.128859
ln_slope	0.076156	0.021386	3.56	0	0.034241	0.118072
ln_aspect	0.002609	0.006485	0.4	0.687	-0.0101	0.01532
ln_distance_to_highways	-0.00311	0.007737	-0.4	0.688	-0.01827	0.012059
ln_distance_to_settlements	-0.0283	0.016197	-1.75	0.081	-0.06005	0.003444
ln_maximum_temperature	0.235218	0.149351	1.57	0.115	-0.0575	0.52794
ln_precipitation_accumul.	-0.66344	0.061149	-10.85	0	-0.78328	-0.54359
ln_topsoil_organic_content	-0.48895	0.057393	-8.52	0	-0.60144	-0.37647
ln_percent_rangeland_100m	0.160745	0.007807	20.59	0	0.145443	0.176046
ln_percent_forest_100m	0.113846	0.026855	4.24	0	0.061211	0.166482
_cons	-1.10519	0.926451	-1.19	0.233	-2.921	0.710618

Table A20: Balance between conflict area (treated) and non-conflict area (untreated), matched (M) and unmatched (U) observations in 2005. Conflict area defined as 10 km (country id: 1 - Azerbaijan, 2 – Georgia, 3 – Russia, 4 – Armenia).

Variables		Treated	Control	% bias	% bias reduction
2.country_id	U	0.02807	0.07294	-20.6	
	M	0.02808	0.02808	0	100
3.country_id	U	0.91882	0.70126	57.7	
	M	0.91879	0.90398	3.9	93.2
4.country_id	U	0.00683	0.05394	-27.7	
	M	0.00683	0.01366	-4	85.5
ln_elevation	U	4.9139	4.6501	14.9	
	M	4.9129	5.0128	-5.7	62.1
ln_slope	U	1.2411	1.1455	14	
	M	1.2403	1.2469	-1	93.1
ln_aspect	U	3.9321	3.789	6.6	
	M	3.9314	3.9599	-1.3	80.1
ln_distance_to_highways	U	6.3665	6.3911	-1.6	
	M	6.3661	6.3423	1.5	3.5
ln_distance_to_settlements	U	9.955	9.9862	-4.2	
	M	9.9552	9.9522	0.4	90.4
ln_maximum_temperature	U	5.0704	5.0706	-0.1	
	M	5.0704	5.0649	4.4	-3316.9
ln_precipitation_accumul.	U	3.8132	3.8919	-28.6	
	M	3.8132	3.8058	2.7	90.6
ln_topsoil_organic_content	U	0.94424	0.9618	-7.5	
	M	0.94426	0.92737	7.3	3.9
ln_percent_rangeland_100m	U	1.3923	1.1818	11.4	
	M	1.3912	1.3998	-0.5	95.9
ln_percent_forest_100m	U	0.08902	0.04953	8.8	
	M	0.08792	0.07689	2.4	72.1

Table A21: Probit regression results from propensity score matching model in 2010 for conflict area vs non-conflict area with conflict area defined as 10 km (country id: 1 - Azerbaijan, 2 – Georgia, 3 – Russia, 4 – Armenia).

Variables	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
country_id						
2	-0.55807	0.304364	-1.83	0.067	-1.15461	0.038477
3	1.785331	0.06266	28.49	0	1.662519	1.908142
4	0.894928	0.088944	10.06	0	0.7206	1.069255
ln_elevation	0.147347	0.008983	16.4	0	0.12974	0.164953
ln_slope	0.042728	0.022707	1.88	0.06	-0.00178	0.087234
ln_aspect	-0.0044	0.006791	-0.65	0.517	-0.01771	0.008913
ln_distance_to_highways	-0.00358	0.008187	-0.44	0.662	-0.01962	0.012466
ln_distance_to_settlements	-0.02742	0.017177	-1.6	0.11	-0.06108	0.00625
ln_maximum_temperature	-0.00522	0.180519	-0.03	0.977	-0.35903	0.348594
ln_precipitation_accumul.	-1.26656	0.071839	-17.63	0	-1.40736	-1.12576
ln_topsoil_organic_content	-0.43166	0.059709	-7.23	0	-0.54869	-0.31463
ln_percent_rangeland_100m	0.180171	0.008155	22.09	0	0.164187	0.196154
ln_percent_forest_100m	0.149701	0.030362	4.93	0	0.090193	0.20921
_cons	1.774395	1.099479	1.61	0.107	-0.38054	3.929334

Table A22: Balance between conflict area (treated) and non-conflict area (untreated), matched (M) and unmatched (U) observations in 2010. Conflict area defined as 10 km (country id: 1 - Azerbaijan, 2 – Georgia, 3 – Russia, 4 – Armenia).

Variables		Treated	Control	% bias	% bias reduction
2.country_id	U	0.00044	0.07147	-38.9	
	M	0.00044	0.00221	-1	97.5
3.country_id	U	0.93251	0.71878	58.7	
	M	0.93251	0.90428	7.8	86.8
4.country_id	U	0.03661	0.03704	-0.2	
	M	0.03661	0.04543	-4.7	-1976.9
ln_elevation	U	4.9181	4.5116	21	
	M	4.9181	5.0405	-6.3	69.9
ln_slope	U	1.2332	1.1431	13.3	
	M	1.2332	1.2159	2.6	80.8
ln_aspect	U	3.8868	3.8017	3.9	
	M	3.8868	3.8987	-0.5	86
ln_distance_to_highways	U	6.3679	6.3968	-1.8	
	M	6.3679	6.4456	-4.9	-168.8
ln_distance_to_settlements	U	9.9652	9.9912	-3.5	
	M	9.9652	9.9965	-4.2	-20.3
ln_maximum_temperature	U	5.0824	5.0933	-9.6	
	M	5.0824	5.0797	2.3	76
ln_precipitation_accumul.	U	3.7691	3.8646	-36.5	
	M	3.7691	3.7544	5.6	84.6
ln_topsoil_organic_content	U	0.95752	0.96304	-2.5	
	M	0.95752	0.95828	-0.3	86.3
ln_percent_rangeland_100m	U	1.4345	1.0151	23.3	
	M	1.4345	1.5126	-4.3	81.4
ln_percent_forest_100m	U	0.08964	0.04869	9.1	
	M	0.08964	0.05717	7.2	20.7

Table A23: Probit regression results from propensity score matching model in 1995 for conflict area vs non-conflict area with conflict area defined as 20 km (country id: 1 - Azerbaijan, 2 – Georgia, 3 – Russia, 4 – Armenia).

Variables	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
country_id						
2	0.521619	0.075653	6.89	0	0.373342	0.669896
3	0.802233	0.048108	16.68	0	0.707943	0.896523
4	-0.12037	0.105266	-1.14	0.253	-0.32669	0.085945
ln_elevation	0.132162	0.007965	16.59	0	0.116551	0.147772
ln_slope	0.087515	0.022039	3.97	0	0.04432	0.13071
ln_aspect	-0.01563	0.006572	-2.38	0.017	-0.02851	-0.00274
ln_distance_to_highways	-0.01944	0.007844	-2.48	0.013	-0.03482	-0.00407
ln_distance_to_settlements	0.018405	0.016636	1.11	0.269	-0.0142	0.051011
ln_maximum_temperature	2.908098	0.174037	16.71	0	2.566991	3.249205
ln_precipitation_accumul.	-1.10445	0.06334	-17.44	0	-1.22859	-0.9803
ln_topsoil_organic_content	-0.2148	0.058057	-3.7	0	-0.32859	-0.10101
ln_percent_rangeland_100m	0.048274	0.007571	6.38	0	0.033435	0.063113
ln_percent_forest_100m	0.10225	0.020458	5	0	0.062152	0.142347
_cons	-13.1463	1.03946	-12.65	0	-15.1836	-11.109

Table A24: Balance between conflict area (treated) and non-conflict area (untreated), matched (M) and unmatched (U) observations in 1995. Conflict area defined as 20 km (country id: 1 - Azerbaijan, 2 – Georgia, 3 – Russia, 4 – Armenia).

Variables		Treated	Control	% bias	% bias reduction
2.country_id	U	0.02982	0.0576	-13.6	
	M	0.02982	0.04473	-7.3	46.3
3.country_id	U	0.82386	0.77674	11.8	
	M	0.82386	0.75116	18.2	-54.3
4.country_id	U	0.01072	0.04455	-20.7	
	M	0.01072	0.01445	-2.3	89
ln_elevation	U	4.816	4.6424	9.7	
	M	4.816	4.921	-5.9	39.5
ln_slope	U	1.2224	1.1487	10.8	
	M	1.2224	1.2757	-7.9	27.6
ln_aspect	U	3.8669	3.8171	2.3	
	M	3.8669	3.9484	-3.8	-63.9
ln_distance_to_highways	U	6.3293	6.3975	-4.3	
	M	6.3293	6.2691	3.8	11.7
ln_distance_to_settlements	U	9.9872	9.9931	-0.8	
	M	9.9872	10.011	-3.1	-303
ln_maximum_temperature	U	5.0708	5.0101	50.5	
	M	5.0708	5.0602	8.8	82.5
ln_precipitation_accumul.	U	3.6861	3.8636	-65.2	
	M	3.6861	3.6676	6.8	89.6
ln_topsoil_organic_content	U	0.91335	0.96372	-21.7	
	M	0.91335	0.83989	31.6	-45.8
ln_percent_rangeland_100m	U	1.2635	0.97513	16.7	
	M	1.2635	1.7926	-30.6	-83.5
ln_percent_forest_100m	U	0.14002	0.09314	8	
	M	0.14002	0.15488	-2.5	68.3

Table A25: Probit regression results from propensity score matching model in 2000 for conflict area vs non-conflict area with conflict area defined as 20 km (country id: 1 - Azerbaijan, 2 – Georgia, 3 – Russia, 4 – Armenia).

Variables	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
country_id						
2	0.258854	0.068186	3.8	0	0.125211	0.392497
3	0.599647	0.034442	17.41	0	0.532141	0.667153
4	-1.57606	0.095347	-16.53	0	-1.76294	-1.38918
ln_elevation	0.176484	0.00701	25.17	0	0.162744	0.190224
ln_slope	-0.00372	0.018719	-0.2	0.842	-0.04041	0.032968
ln_aspect	0.005155	0.005599	0.92	0.357	-0.00582	0.01613
ln_distance_to_highways	-0.00727	0.006682	-1.09	0.276	-0.02037	0.005824
ln_distance_to_settlements	0.016513	0.014232	1.16	0.246	-0.01138	0.044407
ln_maximum_temperature	-1.63542	0.128115	-12.77	0	-1.88653	-1.38432
ln_precipitation_accumul.	-2.40825	0.062209	-38.71	0	-2.53017	-2.28632
ln_topsoil_organic_content	-0.11576	0.049175	-2.35	0.019	-0.21214	-0.01938
ln_percent_rangeland_100m	0.022296	0.006513	3.42	0.001	0.009532	0.035061
ln_percent_forest_100m	-0.03194	0.021551	-1.48	0.138	-0.07418	0.010298
_cons	15.01331	0.817814	18.36	0	13.41043	16.6162

Table A26: Balance between conflict area (treated) and non-conflict area (untreated), matched (M) and unmatched (U) observations in 2000. Conflict area defined as 20 km (country id: 1 - Azerbaijan, 2 – Georgia, 3 – Russia, 4 – Armenia).

Variables		Treated	Control	% bias	% bias reduction
2.country_id	U	0.01662	0.06833	-25.9	
	M	0.01662	0.00471	6	77
3.country_id	U	0.85612	0.73959	29.3	
	M	0.85612	0.84322	3.2	88.9
4.country_id	U	0.00422	0.04889	-28.1	
	M	0.00422	0.00521	-0.6	97.8
ln_elevation	U	4.8824	4.5468	18.4	
	M	4.8824	5.0465	-9	51.1
ln_slope	U	1.2103	1.1453	9.7	
	M	1.2103	1.2036	1	89.7
ln_aspect	U	3.9092	3.804	4.9	
	M	3.9092	3.9306	-1	79.7
ln_distance_to_highways	U	6.3644	6.3876	-1.5	
	M	6.3644	6.3975	-2.1	-42.5
ln_distance_to_settlements	U	9.9831	9.9872	-0.6	
	M	9.9831	9.9802	0.4	30
ln_maximum_temperature	U	5.1023	5.0901	10.9	
	M	5.1023	5.0917	9.4	13.8
ln_precipitation_accumul.	U	3.6849	3.8635	-65.3	
	M	3.6849	3.6968	-4.4	93.3
ln_topsoil_organic_content	U	0.92575	0.96032	-14.7	
	M	0.92575	0.91968	2.6	82.4
ln_percent_rangeland_100m	U	1.1987	1.0975	5.7	
	M	1.1987	1.2451	-2.6	54.2
ln_percent_forest_100m	U	0.07239	0.09849	-5.2	
	M	0.07239	0.07323	-0.2	96.8

Table A27: Probit regression results from propensity score matching model in 2005 for conflict area vs non-conflict area with conflict area defined as 20 km (country id: 1 - Azerbaijan, 2 – Georgia, 3 – Russia, 4 – Armenia).

Variables	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
country_id						
2	0.081094	0.055964	1.45	0.147	-0.02859	0.190781
3	1.19621	0.03657	32.71	0	1.124535	1.267885
4	-0.49955	0.075556	-6.61	0	-0.64764	-0.35146
ln_elevation	0.070612	0.006211	11.37	0	0.058439	0.082785
ln_slope	0.055154	0.016668	3.31	0.001	0.022486	0.087822
ln_aspect	0.006088	0.004991	1.22	0.223	-0.00369	0.015869
ln_distance_to_highways	-0.00673	0.005933	-1.13	0.257	-0.01835	0.004902
ln_distance_to_settlements	0.010579	0.012609	0.84	0.401	-0.01413	0.035293
ln_maximum_temperature	-0.07664	0.103944	-0.74	0.461	-0.28037	0.127087
ln_precipitation_accumul.	-0.19401	0.042896	-4.52	0	-0.27808	-0.10993
ln_topsoil_organic_content	-0.6694	0.044004	-15.21	0	-0.75564	-0.58315
ln_percent_rangeland_100m	0.149338	0.006096	24.5	0	0.13739	0.161287
ln_percent_forest_100m	0.074579	0.021524	3.46	0.001	0.032393	0.116764
_cons	-0.57787	0.644382	-0.9	0.37	-1.84084	0.685093

Table A28: Balance between conflict area (treated) and non-conflict area (untreated), matched (M) and unmatched (U) observations in 2005. Conflict area defined as 20 km (country id: 1 - Azerbaijan, 2 – Georgia, 3 – Russia, 4 – Armenia).

Variables		Treated	Control	% bias	% bias reduction
2.country_id	U	0.03195	0.07356	-18.7	
	M	0.03276	0.03531	-1.1	93.9
3.country_id	U	0.88675	0.70159	47	
	M	0.88389	0.8586	6.4	86.3
4.country_id	U	0.00828	0.05439	-26.7	
	M	0.00849	0.01664	-4.7	82.3
ln_elevation	U	4.7918	4.6413	8.1	
	M	4.7604	4.8722	-6.1	25.7
ln_slope	U	1.2153	1.1455	10.2	
	M	1.1941	1.2075	-2	80.9
ln_aspect	U	3.901	3.7886	5.2	
	M	3.8818	3.8539	1.3	75.2
ln_distance_to_highways	U	6.3753	6.3905	-1	
	M	6.3852	6.3952	-0.6	34.5
ln_distance_to_settlements	U	9.9952	9.9859	1.2	
	M	9.996	9.9929	0.4	65.8
ln_maximum_temperature	U	5.0621	5.0712	-7.1	
	M	5.066	5.0631	2.3	68.2
ln_precipitation_accumul.	U	3.8565	3.8921	-12.5	
	M	3.8558	3.843	4.5	64
ln_topsoil_organic_content	U	0.93982	0.96207	-9.4	
	M	0.94795	0.91595	13.6	-43.8
ln_percent_rangeland_100m	U	1.3836	1.1827	10.9	
	M	1.3092	1.3404	-1.7	84.5
ln_percent_forest_100m	U	0.07933	0.04965	6.9	
	M	0.06407	0.085	-4.8	29.5

Table A29: Probit regression results from propensity score matching model in 2010 for conflict area vs non-conflict area with conflict area defined as 20 km (country id: 1 - Azerbaijan, 2 – Georgia, 3 – Russia, 4 – Armenia).

Variables	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
country_id						
2	-0.18811	0.093058	-2.02	0.043	-0.3705	-0.00572
3	1.534835	0.042418	36.18	0	1.451698	1.617973
4	0.558799	0.064203	8.7	0	0.432964	0.684634
ln_elevation	0.194164	0.007155	27.14	0	0.180141	0.208187
ln_slope	-0.00518	0.017813	-0.29	0.771	-0.04009	0.029734
ln_aspect	0.010002	0.005363	1.87	0.062	-0.00051	0.020513
ln_distance_to_highways	-0.0114	0.006378	-1.79	0.074	-0.0239	0.001095
ln_distance_to_settlements	0.013751	0.013511	1.02	0.309	-0.01273	0.040232
ln_maximum_temperature	-0.04039	0.129722	-0.31	0.756	-0.29464	0.213859
ln_precipitation_accumul.	-1.18454	0.054583	-21.7	0	-1.29152	-1.07756
ln_topsoil_organic_content	-0.56903	0.047301	-12.03	0	-0.66174	-0.47632
ln_percent_rangeland_100m	0.165618	0.006601	25.09	0	0.152681	0.178556
ln_percent_forest_100m	0.119723	0.024147	4.96	0	0.072396	0.16705
_cons	1.908338	0.799733	2.39	0.017	0.340891	3.475786

Table A30: Balance between conflict area (treated) and non-conflict area (untreated), matched (M) and unmatched (U) observations in 2010. Conflict area defined as 20 km (country id: 1 - Azerbaijan, 2 – Georgia, 3 – Russia, 4 – Armenia).

Variables		Treated	Control	% bias	% bias reduction
2.country_id	U	0.00497	0.07003	-34.8	
	M	0.0051	0.00755	-1.3	96.2
3.country_id	U	0.90541	0.717	49.6	
	M	0.9029	0.86475	10	79.8
4.country_id	U	0.03835	0.03802	0.2	
	M	0.03937	0.05182	-6.5	-3577.5
ln_elevation	U	5.0319	4.5336	26.9	
	M	5.0067	5.1776	-9.2	65.7
ln_slope	U	1.2298	1.1436	12.7	
	M	1.2154	1.2256	-1.5	88.2
ln_aspect	U	3.9317	3.7972	6.2	
	M	3.919	3.9046	0.7	89.4
ln_distance_to_highways	U	6.3675	6.3974	-1.9	
	M	6.3732	6.3826	-0.6	68.7
ln_distance_to_settlements	U	9.9948	9.989	0.8	
	M	9.9964	9.9905	0.8	-0.4
ln_maximum_temperature	U	5.0814	5.0942	-11.1	
	M	5.0819	5.0804	1.3	88.2
ln_precipitation_accumul.	U	3.7841	3.8596	-28.8	
	M	3.7869	3.7677	7.3	74.6
ln_topsoil_organic_content	U	0.95174	0.96314	-5	
	M	0.95723	0.9492	3.5	29.6
ln_percent_rangeland_100m	U	1.3158	1.0153	16.9	
	M	1.2383	1.2252	0.7	95.6
ln_percent_forest_100m	U	0.07765	0.04887	6.7	
	M	0.06221	0.06034	0.4	93.5

Table A31: Probit regression results from propensity score matching model in 1995 for conflict area vs non-conflict area with conflict area defined as 30 km (country id: 1 - Azerbaijan, 2 – Georgia, 3 – Russia, 4 – Armenia).

Variables	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
country_id						
2	0.396095	0.058673	6.75	0	0.281098	0.511092
3	0.368605	0.037368	9.86	0	0.295365	0.441845
4	-0.78371	0.090297	-8.68	0	-0.96069	-0.60673
ln_elevation	0.122582	0.006503	18.85	0	0.109837	0.135327
ln_slope	0.069626	0.01883	3.7	0	0.032721	0.106531
ln_aspect	-0.00912	0.005611	-1.63	0.104	-0.02012	0.001876
ln_distance_to_highways	-0.01841	0.006672	-2.76	0.006	-0.03148	-0.00533
ln_distance_to_settlements	0.012899	0.014141	0.91	0.362	-0.01482	0.040615
ln_maximum_temperature	1.614117	0.123283	13.09	0	1.372487	1.855748
ln_precipitation_accumul.	-1.18999	0.052031	-22.87	0	-1.29197	-1.08801
ln_topsoil_organic_content	-0.1851	0.049388	-3.75	0	-0.2819	-0.0883
ln_percent_rangeland_100m	0.055997	0.006482	8.64	0	0.043293	0.0687
ln_percent_forest_100m	0.095553	0.017248	5.54	0	0.061747	0.129359
_cons	-5.566	0.754404	-7.38	0	-7.0446	-4.08739

Table A32: Balance between conflict area (treated) and non-conflict area (untreated), matched (M) and unmatched (U) observations in 1995. Conflict area defined as 30 km (country id: 1 - Azerbaijan, 2 – Georgia, 3 – Russia, 4 – Armenia).

Variables		Treated	Control	% bias	% bias reduction
2.country_id	U	0.04268	0.05402	-5.3	
	M	0.04268	0.07077	-13.1	-147.8
3.country_id	U	0.78349	0.79865	-3.7	
	M	0.78349	0.75793	6.3	-68.5
4.country_id	U	0.00814	0.04249	-22	
	M	0.00814	0.01545	-4.7	78.7
ln_elevation	U	4.7915	4.636	8.3	
	M	4.7915	4.8543	-3.4	59.6
ln_slope	U	1.2174	1.144	10.8	
	M	1.2174	1.2477	-4.5	58.6
ln_aspect	U	3.8983	3.8044	4.4	
	M	3.8983	4.0312	-6.2	-41.4
ln_distance_to_highways	U	6.3317	6.3979	-4.1	
	M	6.3317	6.2938	2.4	42.7
ln_distance_to_settlements	U	9.9812	9.9933	-1.6	
	M	9.9812	9.9699	1.5	6
ln_maximum_temperature	U	5.0603	5.0082	42.1	
	M	5.0603	5.0476	10.2	75.8
ln_precipitation_accumul.	U	3.7084	3.8715	-59.4	
	M	3.7084	3.7082	0.1	99.8
ln_topsoil_organic_content	U	0.91588	0.97238	-24.3	
	M	0.91588	0.88372	13.8	43.1
ln_percent_rangeland_100m	U	1.3243	0.91734	23.6	
	M	1.3243	1.5086	-10.7	54.7
ln_percent_forest_100m	U	0.13809	0.09342	7.7	
	M	0.13809	0.12567	2.1	72.2

Table A33: Probit regression results from propensity score matching model in 2000 for conflict area vs non-conflict area with conflict area defined as 30 km (country id: 1 - Azerbaijan, 2 – Georgia, 3 – Russia, 4 – Armenia).

Variables	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
country_id						
2	0.153092	0.05472	2.8	0.005	0.045843	0.260341
3	0.417227	0.029518	14.13	0	0.359372	0.475082
4	-1.79554	0.073439	-24.45	0	-1.93947	-1.6516
ln_elevation	0.205904	0.006261	32.89	0	0.193633	0.218175
ln_slope	-0.02935	0.01651	-1.78	0.075	-0.06171	0.003011
ln_aspect	0.009114	0.00495	1.84	0.066	-0.00059	0.018816
ln_distance_to_highways	-0.0057	0.005894	-0.97	0.333	-0.01726	0.005847
ln_distance_to_settlements	0.017341	0.012511	1.39	0.166	-0.00718	0.041862
ln_maximum_temperature	-2.13867	0.103799	-20.6	0	-2.34212	-1.93523
ln_precipitation_accumul.	-2.35838	0.052469	-44.95	0	-2.46122	-2.25555
ln_topsoil_organic_content	-0.12026	0.042674	-2.82	0.005	-0.2039	-0.03662
ln_percent_rangeland_100m	0.032662	0.005657	5.77	0	0.021576	0.043749
ln_percent_forest_100m	-0.02786	0.018195	-1.53	0.126	-0.06352	0.007806
_cons	17.65687	0.666344	26.5	0	16.35086	18.96288

Table A34: Balance between conflict area (treated) and non-conflict area (untreated), matched (M) and unmatched (U) observations in 2000. Conflict area defined as 30 km (country id: 1 - Azerbaijan, 2 – Georgia, 3 – Russia, 4 – Armenia).

Variables		Treated	Control	% bias	% bias reduction
2.country_id	U	0.02722	0.06653	-18.7	
	M	0.02722	0.02738	-0.1	99.6
3.country_id	U	0.81978	0.73946	19.5	
	M	0.81978	0.78902	7.5	61.7
4.country_id	U	0.00628	0.04974	-26.6	
	M	0.00628	0.00564	0.4	98.5
ln_elevation	U	4.9818	4.5236	25.1	
	M	4.9818	5.1294	-8.1	67.8
ln_slope	U	1.2171	1.1438	10.9	
	M	1.2171	1.2012	2.4	78.4
ln_aspect	U	3.9302	3.8021	5.9	
	M	3.9302	3.9216	0.4	93.3
ln_distance_to_highways	U	6.3786	6.3897	-0.7	
	M	6.3786	6.3815	-0.2	74.3
ln_distance_to_settlements	U	9.9879	9.9881	0	
	M	9.9879	9.9741	1.8	-8154.5
ln_maximum_temperature	U	5.0896	5.0904	-0.6	
	M	5.0896	5.0921	-2	-215.6
ln_precipitation_accumul.	U	3.7085	3.8631	-54.2	
	M	3.7085	3.7137	-1.8	96.7
ln_topsoil_organic_content	U	0.92423	0.96028	-15	
	M	0.92423	0.91849	2.4	84.1
ln_percent_rangeland_100m	U	1.3074	1.0939	11.9	
	M	1.3074	1.3142	-0.4	96.8
ln_percent_forest_100m	U	0.0825	0.09765	-3	
	M	0.0825	0.08488	-0.5	84.2

Table A35: Probit regression results from propensity score matching model in 2005 for conflict area vs non-conflict area with conflict area defined as 30 km (country id: 1 - Azerbaijan, 2 – Georgia, 3 – Russia, 4 – Armenia).

Variables	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
country_id						
2	-0.17786	0.047957	-3.71	0	-0.27185	-0.08386
3	0.975134	0.030768	31.69	0	0.914829	1.035439
4	-0.57803	0.062282	-9.28	0	-0.7001	-0.45596
ln_elevation	0.048721	0.005265	9.25	0	0.038401	0.059041
ln_slope	0.028423	0.014929	1.9	0.057	-0.00084	0.057683
ln_aspect	0.013491	0.004408	3.06	0.002	0.004853	0.02213
ln_distance_to_highways	-0.00516	0.005227	-0.99	0.324	-0.0154	0.005087
ln_distance_to_settlements	0.004981	0.011072	0.45	0.653	-0.01672	0.026681
ln_maximum_temperature	-0.08209	0.092739	-0.89	0.376	-0.26385	0.09968
ln_precipitation_accumul.	0.040404	0.036194	1.12	0.264	-0.03054	0.111343
ln_topsoil_organic_content	-0.72945	0.038329	-19.03	0	-0.80458	-0.65433
ln_percent_rangeland_100m	0.130451	0.005375	24.27	0	0.119915	0.140986
ln_percent_forest_100m	0.063145	0.019095	3.31	0.001	0.02572	0.10057
_cons	-0.74437	0.567916	-1.31	0.19	-1.85747	0.368722

Table A36: Balance between conflict area (treated) and non-conflict area (untreated), matched (M) and unmatched (U) observations in 2005. Conflict area defined as 30 km (country id: 1 - Azerbaijan, 2 – Georgia, 3 – Russia, 4 – Armenia).

Variables		Treated	Control	% bias	% bias reduction
2.country_id	U	0.0336	0.07314	-17.7	
	M	0.03516	0.04015	-2.2	87.4
3.country_id	U	0.86275	0.70471	39.1	
	M	0.85637	0.83152	6.1	84.3
4.country_id	U	0.01007	0.05521	-25.6	
	M	0.01054	0.01686	-3.6	86
ln_elevation	U	4.6853	4.6223	3.4	
	M	4.6398	4.7918	-8.1	-141
ln_slope	U	1.1902	1.1439	6.8	
	M	1.1658	1.1887	-3.4	50.3
ln_aspect	U	3.9121	3.792	5.5	
	M	3.8816	3.9161	-1.6	71.3
ln_distance_to_highways	U	6.3762	6.3892	-0.8	
	M	6.3813	6.395	-0.9	-5
ln_distance_to_settlements	U	9.9893	9.986	0.4	
	M	9.9873	9.9851	0.3	33.8
ln_maximum_temperature	U	5.0655	5.0732	-6.3	
	M	5.0711	5.0647	5.2	17.4
ln_precipitation_accumul.	U	3.8733	3.8918	-6.4	
	M	3.8714	3.8748	-1.2	81.6
ln_topsoil_organic_content	U	0.93492	0.96273	-11.7	
	M	0.94631	0.9067	16.6	-42.5
ln_percent_rangeland_100m	U	1.3429	1.1732	9.3	
	M	1.2104	1.2122	-0.1	98.9
ln_percent_forest_100m	U	0.07526	0.05017	5.9	
	M	0.05832	0.07623	-4.2	28.6

Table A37: Probit regression results from propensity score matching model in 2010 for conflict area vs non-conflict area with conflict area defined as 30 km (country id: 1 - Azerbaijan, 2 – Georgia, 3 – Russia, 4 – Armenia).

Variables	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
country_id						
2	-0.06065	0.062811	-0.97	0.334	-0.18375	0.062462
3	1.347993	0.035385	38.1	0	1.278639	1.417346
4	0.466079	0.055136	8.45	0	0.358014	0.574144
ln_elevation	0.207059	0.006545	31.64	0	0.194231	0.219887
ln_slope	-0.05245	0.016131	-3.25	0.001	-0.08406	-0.02083
ln_aspect	0.01535	0.004833	3.18	0.001	0.005878	0.024823
ln_distance_to_highways	-0.0077	0.005733	-1.34	0.179	-0.01893	0.003537
ln_distance_to_settlements	0.002937	0.012133	0.24	0.809	-0.02084	0.026718
ln_maximum_temperature	-0.15659	0.111381	-1.41	0.16	-0.37489	0.061715
ln_precipitation_accumul.	-1.09002	0.048223	-22.6	0	-1.18453	-0.9955
ln_topsoil_organic_content	-0.81416	0.042783	-19.03	0	-0.89801	-0.7303
ln_percent_rangeland_100m	0.147461	0.005961	24.74	0	0.135779	0.159144
ln_percent_forest_100m	0.104405	0.022258	4.69	0	0.06078	0.14803
_cons	2.87909	0.690154	4.17	0	1.526413	4.231767

Table A38: Balance between conflict area (treated) and non-conflict area (untreated), matched (M) and unmatched (U) observations in 2010. Conflict area defined as 30 km (country id: 1 - Azerbaijan, 2 – Georgia, 3 – Russia, 4 – Armenia).

Variables		Treated	Control	% bias	% bias reduction
2.country_id	U	0.01269	0.07132	-29.5	
	M	0.01303	0.01538	-1.2	96
3.country_id	U	0.87368	0.71136	40.9	
	M	0.87029	0.82816	10.6	74
4.country_id	U	0.04453	0.03873	2.9	
	M	0.04573	0.06444	-9.4	-222.1
ln_elevation	U	5.0713	4.5607	28.2	
	M	5.0503	5.2253	-9.7	65.7
ln_slope	U	1.2047	1.1429	9	
	M	1.1913	1.2092	-2.6	71
ln_aspect	U	3.9096	3.7893	5.5	
	M	3.8974	3.9577	-2.8	49.9
ln_distance_to_highways	U	6.3716	6.3951	-1.5	
	M	6.3779	6.3839	-0.4	74.3
ln_distance_to_settlements	U	9.9864	9.988	-0.2	
	M	9.9891	9.9846	0.6	-181
ln_maximum_temperature	U	5.0806	5.0949	-12.4	
	M	5.0819	5.0815	0.3	97.2
ln_precipitation_accumul.	U	3.7884	3.8517	-23.8	
	M	3.7904	3.7701	7.7	67.9
ln_topsoil_organic_content	U	0.93395	0.96254	-12.2	
	M	0.94237	0.93859	1.6	86.7
ln_percent_rangeland_100m	U	1.2813	1.0229	14.5	
	M	1.201	1.1431	3.2	77.6
ln_percent_forest_100m	U	0.06962	0.04626	5.6	
	M	0.05978	0.04594	3.3	40.7

Table A39: Overall difference-in-difference model, linear regression with fixed effects results on cropland abandonment, with the conflict area defined as a 5, 10, 20 and 30 km (Country id: 1 - Azerbaijan, 2 – Georgia, 3 – Russia, 4 – Armenia).

Variables	5km_all_FE	10km_all_FE	20km_all_FE	30km_all_FE
1.conflict				
1.after	0.0710***	0.0548***	0.0433***	0.0365***
	(0.00685)	(0.00361)	(0.00215)	(0.00167)
1.conflict#1.after	0.00381	0.00909**	0.0101***	0.0118***
	(0.00781)	(0.00435)	(0.00268)	(0.00207)
2.time	0.0683**	0.0131	0.0391***	0.0439***
	(0.0324)	(0.0176)	(0.0104)	(0.00797)
3.time	0.0253	-0.00708	0.0159*	0.0271***
	(0.0260)	(0.0139)	(0.00828)	(0.00637)
4.time	0.0445	-0.0171	0.0112	0.0251***
	(0.0330)	(0.0179)	(0.0107)	(0.00827)
5.time	0.0724	-0.0107	0.0292**	0.0448***
	(0.0444)	(0.0238)	(0.0137)	(0.0104)
ln_maximum_temperature	-1.295**	0.0857	-0.237	-0.457***
	(0.525)	(0.279)	(0.159)	(0.119)
ln_precipitation_accumul.	0.00645	0.109**	0.0771**	-0.0184
	(0.0955)	(0.0523)	(0.0323)	(0.0238)
ln_percent_rangeland_100m	0.0591***	0.0615***	0.0527***	0.0521***
	(0.00257)	(0.00154)	(0.000983)	(0.000762)
ln_percent_forest_100m	0.00484	0.0268***	0.0265***	0.0272***
	(0.00734)	(0.00433)	(0.00286)	(0.00220)
Constant	6.527**	-0.853	0.884	2.356***
	(2.819)	(1.500)	(0.863)	(0.647)
Observations	7,907	20,297	43,326	64,361
R-squared	0.163	0.174	0.146	0.144
Number of grid_pt_id	3,511	8,424	16,429	22,542

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A40: Conflict specific difference-in-difference model, linear regression with fixed effects results on cropland abandonment, with the conflict area defined as a 5, 10, 20, 30 km (Conflict id: 1 – Chechnya, 2 – Abkhazia, 3 – South Ossetia, 4 – Nagorno-Karabakh).

Variables	5km_conflict FE	10km_conflict FE	20km_conflict FE	30km_conflict FE
1.after	0.0622***	0.0408***	0.0316***	0.0248***
	(0.00724)	(0.00376)	(0.00224)	(0.00175)
1.conflict#1.after	0.0116	0.0199***	0.0165***	0.0179***
	(0.00818)	(0.00450)	(0.00278)	(0.00216)
1.after#2.conflict_id	0.276***	0.247**	0.112**	0.0955***
	(0.0933)	(0.102)	(0.0527)	(0.0281)
1.after#3.conflict_id	0.0430*	0.0259*	0.0797***	0.0560***
	(0.0234)	(0.0150)	(0.0116)	(0.00773)
1.after#4.conflict_id	0.0587***	0.152***	0.110***	0.0979***
	(0.0187)	(0.0110)	(0.00697)	(0.00526)
1.conflict#1.after#2.conflict_id	0.00893	0.0967	0.203***	0.166***
	(0.147)	(0.112)	(0.0582)	(0.0332)
1.conflict#1.after#3.conflict_id	0.0328	0.0276	-0.0317	-0.0273
	(0.0569)	(0.0352)	(0.0222)	(0.0167)
1.conflict#1.after#4.conflict_id	-0.103***	-0.145***	-0.0921***	-0.0716***
	(0.0387)	(0.0201)	(0.0111)	(0.00792)
2.time	0.0506	-0.0332*	0.00530	0.00544
	(0.0330)	(0.0178)	(0.0105)	(0.00815)
3.time	0.0131	-0.0416***	-0.00796	-0.000837
	(0.0264)	(0.0141)	(0.00837)	(0.00649)
4.time	0.0310	-0.0564***	-0.0191*	-0.0123
	(0.0334)	(0.0181)	(0.0108)	(0.00843)
5.time	0.0596	-0.0582**	-0.00841	-0.00222
	(0.0448)	(0.0240)	(0.0139)	(0.0106)
ln_maximum_temperature	-1.194**	0.559**	0.179	0.0904
	(0.529)	(0.282)	(0.161)	(0.121)
ln_precipitation_accumul.	0.00666	0.146***	0.0865***	0.0159
	(0.0961)	(0.0526)	(0.0321)	(0.0237)
ln_percent_rangeland_100m	0.0587***	0.0613***	0.0523***	0.0518***
	(0.00257)	(0.00153)	(0.000975)	(0.000757)
ln_percent_forest_100m	0.00573	0.0247***	0.0254***	0.0255***
	(0.00733)	(0.00430)	(0.00284)	(0.00219)
Constant	6.026**	-3.368**	-1.235	-0.522
	(2.839)	(1.516)	(0.872)	(0.660)
Observations	7,907	20,297	43,326	64,361
Number of grid_pt_id	3,511	8,424	16,429	22,542
R-squared	0.168	0.191	0.160	0.156

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A41: Overall results of logistic regression with random effects on cropland abandonment, with interaction term between distances and number of events (Country id: 1 - Azerbaijan, 2 – Georgia, 3 – Russia, 4 – Armenia).

Variables	All_events	Standard error
2000.year	-0.789***	-0.0835
2005.year	-1.343***	-0.0964
2010.year	-0.939***	-0.1
2015.year	-0.0354	-0.0873
1.closest0_5	-0.0766	-0.2
ln_no._events0_5km	0.173	-0.124
1.closest5_10	0.0259	-0.162
ln_no._events5_10km	0.203**	-0.084
1.closest5_10#c.ln_no._events5_10km	-0.0365	-0.125
1.closest10_20	-0.240*	-0.139
ln_no._events10_20km	0.0515	-0.056
1.closest10_20#c.ln_no._events10_20km	0.219**	-0.0977
1.closest20_30	-0.0576	-0.167
ln_no._events20_30km	0.0199	-0.0402
1.closest20_30#c.ln_no._events20_30km	-0.108	-0.132
ln_elevation	-0.0828	-0.0749
2.country_id	4.936	-4.609
3.country_id	3.856	-4.123
4.country_id	-0.742	-9.264
2.country_id#c.ln_elevation	-0.179*	-0.101
3.country_id#c.ln_elevation	-0.0587	-0.0802
4.country_id#c.ln_elevation	0.652	-0.449
ln_slope	0.0177	-0.116
2.country_id#c.ln_slope	0.412**	-0.169
3.country_id#c.ln_slope	0.0694	-0.13
4.country_id#c.ln_slope	0.0265	-0.221
ln_aspect	0.0212	-0.0386
2.country_id#c.ln_aspect	-0.061	-0.0578
3.country_id#c.ln_aspect	-0.0282	-0.0434
4.country_id#c.ln_aspect	-0.0494	-0.0943
ln_distance_to_highways	0.0383	-0.0439
2.country_id#c.ln_distance_to_highways	-0.00921	-0.0618
3.country_id#c.ln_distance_to_highways	-0.0297	-0.0501
4.country_id#c.ln_distance_to_highways	0.0387	-0.103
ln_distance_to_settlements	-0.0557	-0.0948
2.country_id#c.ln_distance_to_settlements	0.194	-0.139
3.country_id#c.ln_distance_to_settlements	-0.0292	-0.108
4.country_id#c.ln_distance_to_settlements	-0.0198	-0.23
ln_maximum_temperature	0.0347	-0.489
2.country_id#c.ln_maximum_temperature	0.307	-0.695

continued		
3.country_id#c.ln_maximum_temperature	-0.128	-0.562
4.country_id#c.ln_maximum_temperature	0.041	-1.261
ln_precipitation_accumul.	0.731*	-0.394
2.country_id#c.ln_precipitation_accumul.	-0.665	-0.54
3.country_id#c.ln_precipitation_accumul.	0.282	-0.416
4.country_id#c.ln_precipitation_accumul.	-1.316*	-0.736
ln_topsoil_organic_content	-0.128	-0.256
2.country_id#c.ln_topsoil_organic_content	0.2	-0.494
3.country_id#c.ln_topsoil_organic_content	-0.416	-0.306
4.country_id#c.ln_topsoil_organic_content	-0.628	-0.827
ln_percent_rangeland_100m	2.188***	-0.114
2.country_id#c.ln_percent_rangeland_100m	-1.411***	-0.12
3.country_id#c.ln_percent_rangeland_100m	-0.826***	-0.114
4.country_id#c.ln_percent_rangeland_100m	0.358	-0.272
ln_percent_forest_100m	1.410***	-0.116
2.country_id#c.ln_percent_forest_100m	-0.717***	-0.123
3.country_id#c.ln_percent_forest_100m	-0.523***	-0.118
4.country_id#c.ln_percent_forest_100m	0.392	-0.279
lnsig2u	-1.931**	-0.775
Constant	-11.12***	-3.707
Observations	49,740	
Number of grid_pt_id	11,257	

*** p<0.01, ** p<0.05, * p<0.1

Table A42: Conflict specific results of logistic regression with random effects on cropland abandonment, with interaction term between distances and number of events (CH: Chechnya, AK: Abkhazia, SO: South Ossetia, NK: Nagorno-Karabakh).

Variables	CH_events	AK_events	SO_events	NK_events
2000.year	-0.931***	-0.388	0.0260	-0.427**
	(0.112)	(0.370)	(0.674)	(0.205)
2005.year	-1.314***	-0.808	0.0150	-1.331***
	(0.130)	(0.526)	(0.738)	(0.227)
2010.year	-0.708***	-1.418***	-0.227	-0.963***
	(0.138)	(0.474)	(0.860)	(0.249)
2015.year	0.163	-0.441	1.463**	-0.268
	(0.117)	(0.504)	(0.648)	(0.219)
1.closest0_5	-0.120	-2.275**	30.10	0.0308
	(0.248)	(1.095)	(4,919)	(0.581)
ln_no._events0_5km	0.218	1.297	-40.43	0.174
	(0.142)	(0.867)	(7,097)	(0.398)
1.closest5_10	0.0176	-0.864	27.66	-0.0844
	(0.206)	(0.733)	(5,208)	(0.414)
ln_no._events5_10km	0.173*	1.372***	-0.0618	0.0159
	(0.0980)	(0.454)	(0.875)	(0.311)
1.closest5_10#c.ln_no._events5_10km	-0.0215	-0.483	-37.97	0.0412
	(0.144)	(0.639)	(7,514)	(0.409)
1.closest10_20	-0.288	-0.0234	1.670*	-0.405
	(0.191)	(0.505)	(0.989)	(0.273)
ln_no._events10_20km	0.0522	0.0932	0.488	0.224
	(0.0670)	(0.241)	(0.436)	(0.175)
1.closest10_20#c.ln_no._events10_20km	0.165	0.310	-1.053	0.0915
	(0.127)	(0.335)	(0.701)	(0.240)
1.closest20_30	-0.0694	-0.956	4.853*	-0.0999
	(0.236)	(0.882)	(2.480)	(0.266)
ln_no._events20_30km	-0.00198	0.127	-0.271	-0.0334
	(0.0501)	(0.149)	(0.431)	(0.119)
1.closest20_30#c.ln_no._events20_30km	-0.144	0.659	-4.956	-0.0177
	(0.177)	(0.652)	(3.262)	(0.237)
ln_elevation	-0.145***	-0.191**	1.064	-0.0630
	(0.0312)	(0.0849)	(0.666)	(0.0579)
ln_slope	0.104*	0.307*	0.476**	0.0109
	(0.0629)	(0.166)	(0.240)	(0.0916)
ln_aspect	-0.00923	-0.0335	-0.104	0.00278
	(0.0208)	(0.0503)	(0.111)	(0.0337)
ln_distance_to_highways	0.00579	0.0232	0.0289	0.0448
	(0.0253)	(0.0513)	(0.0993)	(0.0380)
ln_distance_to_settlements	-0.0844	0.195	-0.0385	-0.0739
	(0.0533)	(0.124)	(0.218)	(0.0827)
ln_maximum_temperature	-0.235	0.367	-3.864*	-0.145
	(0.323)	(1.044)	(2.135)	(0.456)

continued				
ln_precipitation_accumul.	0.990***	-0.822	-3.575**	0.317
	(0.163)	(2.015)	(1.663)	(0.338)
ln_topsoil_organic_content	-0.591***	0.105	0.808	-0.168
	(0.180)	(0.464)	(1.895)	(0.227)
ln_percent_rangeland_100m	1.394***	0.709***	1.319***	2.185***
	(0.0363)	(0.0730)	(0.192)	(0.0988)
ln_percent_forest_100m	0.934***	0.641***	0.988***	1.423***
	(0.0453)	(0.0777)	(0.168)	(0.101)
lnsig2u	-0.992**	-1.748	-2.199	-12.91
	(0.447)	(2.091)	(4.959)	(21.45)
Constant	-6.554***	-2.575	19.37	-8.513**
	(2.082)	(6.601)	(17.29)	(3.356)
Observations	41,805	1,368	916	5,651
Number of grid_pt_id	9,000	490	222	1,545

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A43: Overall results of logistic regression with random effects on cropland abandonment, with interaction term between distances and number of total fatalities (Country id: 1 - Azerbaijan, 2 – Georgia, 3 – Russia, 4 – Armenia).

Variables	All_fatal	Standard error
2000.year	-0.780***	-0.084
2005.year	-1.298***	-0.0961
2010.year	-0.864***	-0.102
2015.year	0.0198	-0.0893
1.closest0_5	-0.0338	-0.191
ln_no._fatalities0_5km	0.106	-0.065
1.closest5_10	0.043	-0.158
ln_no._fatalities5_10km	0.129**	-0.0542
1.closest5_10#c.ln_no._fatalities5_10km	-0.0276	-0.0747
1.closest10_20	-0.0748	-0.127
ln_no._fatalities10_20km	0.0238	-0.037
1.closest10_20#c.ln_no._fatalities10_20km	0.065	-0.055
1.closest20_30	-0.115	-0.139
ln_no._fatalities20_30km	0.0108	-0.0266
1.closest20_30#c.ln_no._fatalities20_30km	-0.0353	-0.0607
ln_elevation	-0.0823	-0.0749
2.country_id	5.197	-4.634
3.country_id	3.903	-4.149
4.country_id	-0.529	-9.297
2.country_id#c.ln_elevation	-0.182*	-0.101
3.country_id#c.ln_elevation	-0.0559	-0.0802
4.country_id#c.ln_elevation	0.675	-0.451
ln_slope	0.012	-0.117
2.country_id#c.ln_slope	0.429**	-0.169
3.country_id#c.ln_slope	0.0789	-0.131
4.country_id#c.ln_slope	0.0316	-0.222
ln_aspect	0.0221	-0.0387
2.country_id#c.ln_aspect	-0.0634	-0.0578
3.country_id#c.ln_aspect	-0.0314	-0.0435
4.country_id#c.ln_aspect	-0.0477	-0.0944
ln_distance_to_highways	0.0377	-0.044
2.country_id#c.ln_distance_to_highways	-0.00596	-0.0619
3.country_id#c.ln_distance_to_highways	-0.028	-0.0501
4.country_id#c.ln_distance_to_highways	0.0403	-0.104
ln_distance_to_settlements	-0.0544	-0.0951
2.country_id#c.ln_distance_to_settlements	0.192	-0.139
3.country_id#c.ln_distance_to_settlements	-0.032	-0.108
4.country_id#c.ln_distance_to_settlements	-0.0201	-0.23
ln_maximum_temperature	0.0656	-0.493
2.country_id#c.ln_maximum_temperature	0.288	-0.698

continued		
3.country_id#c.ln_maximum_temperature	-0.136	-0.565
4.country_id#c.ln_maximum_temperature	-0.0178	-1.266
ln_precipitation_accumul.	0.720*	-0.398
2.country_id#c.ln_precipitation_accumul.	-0.683	-0.543
3.country_id#c.ln_precipitation_accumul.	0.287	-0.419
4.country_id#c.ln_precipitation_accumul.	-1.339*	-0.74
ln_topsoil_organic_content	-0.125	-0.257
2.country_id#c.ln_topsoil_organic_content	0.2	-0.495
3.country_id#c.ln_topsoil_organic_content	-0.364	-0.307
4.country_id#c.ln_topsoil_organic_content	-0.619	-0.828
ln_percent_rangeland_100m	2.200***	-0.114
2.country_id#c.ln_percent_rangeland_100m	-1.427***	-0.12
3.country_id#c.ln_percent_rangeland_100m	-0.836***	-0.114
4.country_id#c.ln_percent_rangeland_100m	0.354	-0.272
ln_percent_forest_100m	1.401***	-0.115
2.country_id#c.ln_percent_forest_100m	-0.704***	-0.122
3.country_id#c.ln_percent_forest_100m	-0.516***	-0.118
4.country_id#c.ln_percent_forest_100m	0.414	-0.28
lnsig2u	-1.909**	-0.756
Constant	-11.34***	-3.739
Observations	49,740	
Number of grid_pt_id	11,257	

*** p<0.01, ** p<0.05, * p<0.1

Table A44: Conflict specific results of logistic regression with random effects on cropland abandonment, with interaction term between distances and number of total fatalities (CH: Chechnya, AK: Abkhazia, SO: South Ossetia, NK: Nagorno-Karabakh).

Variables	CH_fatal	AK_fatal	SO_fatal	NK_fatal
2000.year	-0.940***	-0.488	-0.213	-0.372*
	(0.112)	(0.352)	(0.669)	(0.212)
2005.year	-1.282***	-0.949*	-0.268	-1.282***
	(0.129)	(0.515)	(0.738)	(0.232)
2010.year	-0.640***	-1.466***	-1.002	-0.914***
	(0.140)	(0.478)	(0.882)	(0.254)
2015.year	0.214*	-0.500	1.179*	-0.228
	(0.120)	(0.493)	(0.646)	(0.221)
1.closest0_5	-0.136	-1.934**	3.096**	-0.0594
	(0.238)	(0.909)	(1.475)	(0.490)
ln_no._fatalities0_5km	0.145*	0.461*	-0.631	0.131
	(0.0804)	(0.264)	(0.604)	(0.159)
1.closest5_10	-0.0253	-1.046	2.409*	-0.0283
	(0.206)	(0.711)	(1.349)	(0.345)
ln_no._fatalities5_10km	0.0891	0.624***	-0.119	0.0603
	(0.0684)	(0.203)	(0.548)	(0.144)
1.closest5_10#c.ln_no._fatalities5_10km	0.00392	-0.166	-0.351	-0.0143
	(0.0939)	(0.272)	(0.820)	(0.176)
1.closest10_20	-0.0943	0.297	1.282	-0.252
	(0.182)	(0.509)	(1.000)	(0.225)
ln_no._fatalities10_20km	0.0574	0.0554	0.117	0.107
	(0.0481)	(0.115)	(0.285)	(0.0902)
1.closest10_20#c.ln_no._fatalities10_20km	-0.0200	0.00758	-0.193	0.0331
	(0.0782)	(0.170)	(0.404)	(0.111)
1.closest20_30	-0.128	-0.521	1.322	-0.204
	(0.206)	(0.689)	(0.928)	(0.215)
ln_no._fatalities20_30km	-0.00558	0.0769	-0.323	-0.0420
	(0.0359)	(0.0823)	(0.267)	(0.0628)
1.closest20_30#c.ln_no._fatalities20_30km	-0.0620	0.108	-0.0493	0.0879
	(0.0871)	(0.241)	(0.504)	(0.109)
ln_elevation	-0.142***	-0.206**	0.991	-0.0602
	(0.0312)	(0.0832)	(0.655)	(0.0577)
ln_slope	0.106*	0.347**	0.413*	0.0158
	(0.0629)	(0.167)	(0.238)	(0.0916)
ln_aspect	-0.0106	-0.0374	-0.105	0.00351
	(0.0208)	(0.0502)	(0.109)	(0.0337)
ln_distance_to_highways	0.00694	0.0348	0.0185	0.0446
	(0.0253)	(0.0512)	(0.0978)	(0.0380)
ln_distance_to_settlements	-0.0863	0.179	-0.0408	-0.0717
	(0.0533)	(0.122)	(0.216)	(0.0827)
ln_maximum_temperature	-0.238	0.325	-3.843*	-0.0838
	(0.322)	(1.046)	(2.095)	(0.456)

continued				
ln_precipitation_accumul.	0.985***	-0.184	-3.425**	0.343
	(0.163)	(2.031)	(1.635)	(0.338)
ln_topsoil_organic_content	-0.547***	0.0751	0.476	-0.178
	(0.179)	(0.456)	(1.869)	(0.229)
ln_percent_rangeland_100m	1.396***	0.693***	1.313***	2.189***
	(0.0363)	(0.0718)	(0.193)	(0.0990)
ln_percent_forest_100m	0.930***	0.647***	0.955***	1.422***
	(0.0452)	(0.0781)	(0.168)	(0.101)
lnsig2u	-1.006**	-1.903	-2.469	-12.90
	(0.450)	(2.404)	(6.732)	(21.54)
Constant	-6.577***	-5.266	19.84	-9.020***
	(2.078)	(6.668)	(17.01)	(3.368)
Observations	41,805	1,368	916	5,651
Number of grid_pt_id	9,000	490	222	1,545

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

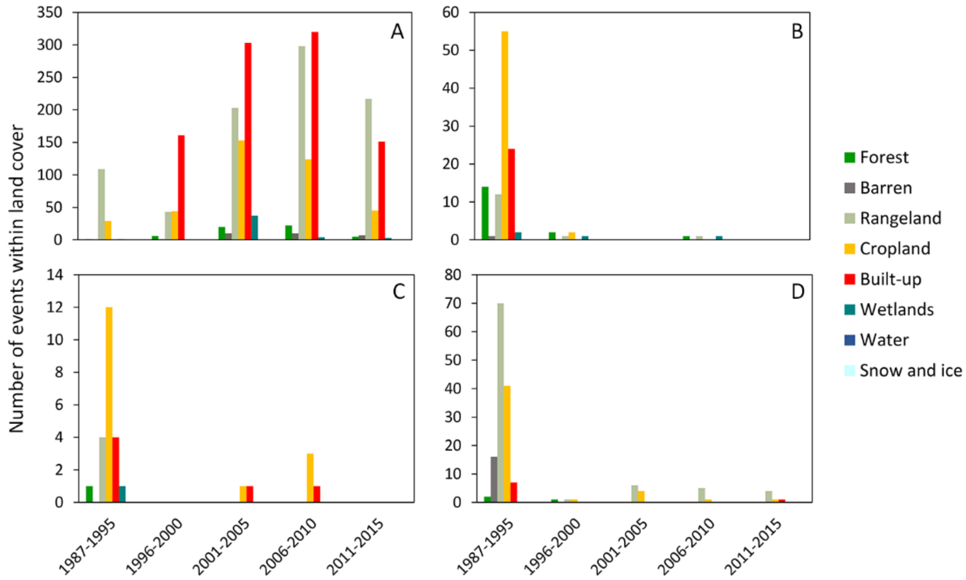


Figure A12: Land cover and number of conflict events for (A) Chechnya, (B) Abkhazia, (C) South Ossetia, and (D) Nagorno-Karabakh, for five time periods. Note: y-axis ranges differ among wars.

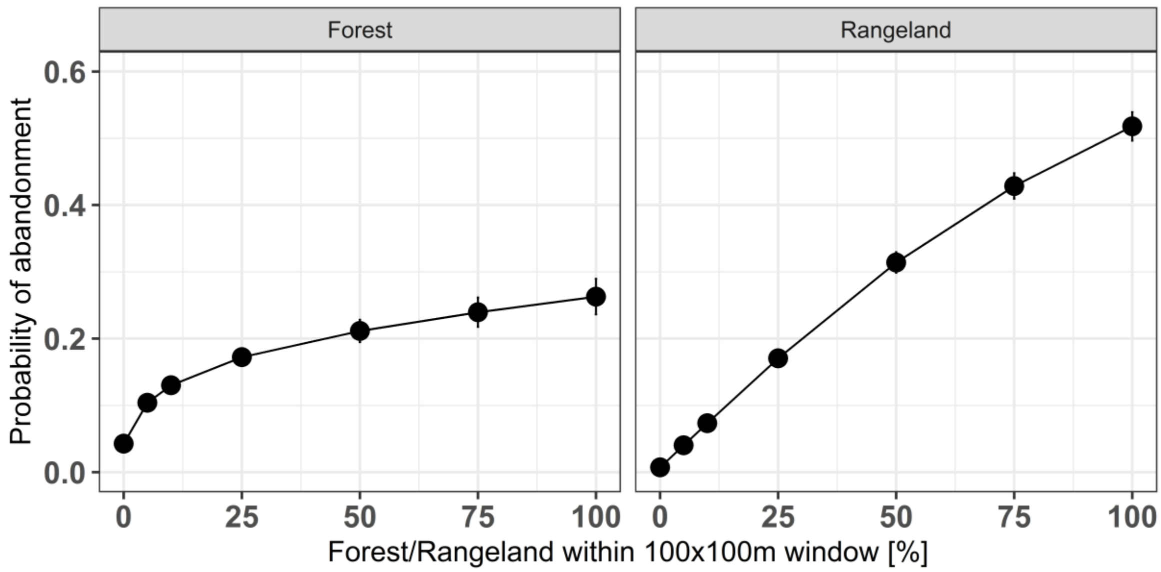


Figure A13: Predictive margins on cropland abandonment at different levels of percent forest/rangeland within 100x100 m window with 95% confidence intervals (based on logistic regression with interaction term between distances and number of events).

Chapter 3. The effectiveness of protected areas in the Caucasus in preventing forest loss and forest degradation of different forest types

Contributors: Buchner, J., Butsic, V., Lewinska, K. E., Burivalova, Z., Kuemmerle, T., Rogova, N., Bragina, E. V., Zazanashvili, N., Ghoddousi, A., Radeloff, V.C.

Abstract

Protected areas are a cornerstone of conservation designed to preserve biodiversity and ecosystems. However, not all protected areas are effective at stopping forest loss or forest degradation. When assessing the effectiveness of protection, it is thus important to check for both, forest loss and forest degradation, and if effectiveness differs by forest type. Our goal here was to assess if strictly protected areas were effective in preventing forest loss and forest degradation, in coniferous, mixed, and deciduous forests across the Caucasus, a biodiversity hotspot where forests are important habitat for endemic flora and fauna. We mapped forest loss with 1987-2015 land-cover change maps, and forest degradation with annual spectral mixture analyses of all 1988 to 2018 Landsat data. We assessed effectiveness for forest overall, and for coniferous, mixed, and deciduous forests separately, because conifers are rare and have a high commercial value in the Caucasus. We applied propensity score matching and panel regression techniques to assess effectiveness. We found that in terms of forest loss, protected areas appeared to be in-effective in that the probability of forest loss was significantly higher in protected areas than outside from 1995 to 2015. In contrast, forest degradation was significantly lower in protected areas than outside across the entire Caucasus (-1.1 percentage points) from 1988 to 2018. However, that effectiveness was limited to deciduous forests and coniferous forest, whereas protected areas were insignificant for mixed forests. Our results highlight that a) including forest degradation in protected area analysis can improve their usefulness, especially in

regions where forest loss is overall rare, and b) that it is necessary to differentiate among forest types when assessing protected area effectiveness, because effectiveness measures will be dominated by the most common forest types, yet rare forest types may still be lost.

Introduction

Protected areas are the cornerstone of conservation and play an important role in preserving biodiversity, habitat, ecosystem functions, as well as for education and recreation (EEA, 2012). As of 2020, protected areas covered 15.2% of the terrestrial area of the globe (UNEP-WCMC et al., 2020). However, protected area effectiveness varies and depends on, for example, protected area location (Joppa and Pfaff, 2009), and governance (Ferraro et al., 2013; Sims and Alix-Garcia, 2017). Furthermore, protected areas are missing in some important biomes (Brooks et al., 2004; Mancheno et al., 2017), do not cover species diversity adequately (Rodrigues et al., 2004), and are sometimes downgraded, downsized, or eliminated (Kroner et al., 2019; Mascia and Pailler, 2011). Understanding where protected areas are effective is crucial to improve protected area management and ultimately their success (Armsworth et al., 2011).

Protected areas that are forested are particularly important for endemic flora and fauna, carbon sequestration, drinking water, and other ecosystem services (EEA, 2010; FAO and UNEP, 2020). A total of 18% of the world's forest is protected (FAO and UNEP, 2020). However, the effectiveness of the protected areas in terms of stopping forest loss also varies greatly across the globe. Protected areas have been generally effective in curtailing deforestation in the tropics (Naughton-Treves et al., 2005), Africa (Bowker et al., 2017), and Brazil (Nolte et al., 2013), but not as successful in the Carpathians (Butsic et al., 2016), or Russia (Sieber et al., 2013; Wendland et al., 2015). While forest loss is a clear indicator of a lack of protected area effectiveness and is mapped annually across the globe (Hansen et al., 2013), selective logging, which includes the removal of highly valuable tree species, is also highly detrimental, but remains largely undetected (Burivalova et al., 2015). Unfortunately though, forest loss, e.g., the conversion from forest to another land-cover class such as grassland, is typically the only measure that is used to estimate the effectiveness of protected areas (Andam et al., 2008; Bowker et al., 2017; Ferraro et al., 2013; Nolte et al., 2013; Pfaff et al., 2015), which can bias the evaluation of the effectiveness of protected areas (Geldmann et al., 2019).

Forest degradation is caused by many factors, but one of the major causes is selective logging, e.g., the removal of single trees or a small portion of trees (Hosonuma et al., 2012; Mon et al., 2012). Forest degradation is also caused by the collection of fuelwood and non-timber products (Burivalova et al., 2015), livestock grazing (Krever et al., 2001), and can result in lower carbon storage (Asner et al., 2005; Putz et al., 2012) and biodiversity decline (Burivalova et al., 2014; Putz et al., 2012). In the tropics, forest degradation has been wide spread, for example, in the Amazon (Bullock et al., 2020), especially in the Brazil Amazon (Asner et al., 2005), and exceeded deforestation inside a protected area in Myanmar (Mon et al., 2010). In Western Siberia, selective logging and stripcuts account for 96.3% of all forest disturbances (Shchur et al., 2017). For our study, we define forest degradation as a change in green vegetation in forests, which we assumed occurred most likely due to the removal of single trees, i.e., selective logging.

Another limitation of both forest loss and forest degradation as measures of protected area effectiveness is that not all forest types are affected the same due to differences in their economic value. Often some forest types harbor tree species that have higher economic value but may also have a high conservation value if they provide important habitat, and effectiveness assessment may need to focus on those. For example, protected areas in southwest China are effective in protecting old-growth forests, but not pine forests (Brandt et al., 2015). In mountain forests in the

Himalayas, the number of IUCN listed tree species is equally low inside and outside protected areas, but woody species richness is higher inside protected areas (Måren and Sharma, 2018), and in Sudan tree species richness in dry forest is not significantly higher inside protected than outside, indicating that conservation efforts are not sufficient (Paré et al., 2010).

Advances in remote sensing allow mapping forest loss, forest degradation, and forest types for large areas. However, detecting forest degradation from satellite imagery is more challenging than detecting forest loss because the spectral changes caused by degradation are more subtle (Bullock et al., 2019; Souza et al., 2003). Spectral mixture analysis allows to decomposes the spectral signature of a pixel into different land-cover fractions, such as green vegetation, soil, or shade (Adams et al., 1995; Shi and Wang, 2014). Time series of these fractions capture even subtle shifts in land-cover composition (Bullock et al., 2020; Lewińska, submitted; Souza et al., 2003). By comparing fractions over time it is possible to identify changes, e.g. a decrease in the green vegetation fraction concomitant with an increase of either the soil or the shade fraction. The magnitude of the change in the green vegetation fraction can be quantified and is a proxy for forest degradation.

The Caucasus region is one of the world's 35 biodiversity hotspots, and has a well-developed protected area network, but is also a place of political unrest and experienced several wars since the collapse of the Soviet Union in 1991. During Soviet times protected areas and forests were centrally managed by the government through Moscow (Wells and Williams, 1998). The highest level of protection are the strictly protected areas ('zapovedniks'), which were solely established for conservation and scientific monitoring, and access was limited to wardens and scientists only (Wells and Williams, 1998). However, after the collapse of the Soviet Union in 1991 a time of political upheaval followed, when countries became independent and law enforcement was weak

(Freni, 2013). Shortage of energy supply increased the amount of fuelwood collected (Ozdogan et al., 2017) and the weak economy resulted in the extraction of valuable timber for sale (FAO, 2019). Even after the transition period and in recent years, forest degradation due to selective logging is a prevalent threat in the Caucasus, decreasing the ecological capacity of the forest ecosystem (Zazanashvili et al., 2012). The question arises whether protected areas are effective in preventing forest loss and forest degradation in a region with political unrest and weak institutions after the collapse of the Soviet Union.

Our goal was to assess the effectiveness of protected areas in the Caucasus in preventing forest loss and forest degradation in different forest types. Our specific questions were:

1) Did strictly protected areas have less forest loss compared to non-protected areas?
2) Did strictly protected areas have less forest degradation compared to non-protected areas?
3) How did the effectiveness of protected areas differ for forest degradation among forest types?

Methods

Study area

Our study area, the Caucasus region, encompassed Georgia, Armenia, and Azerbaijan in the south (South Caucasus) and parts of the Russian Federation in the north (North Caucasus), with a total area of 455,000 km^2 (Figure 20). The mountains in the Greater Caucasus range from 500 to 3,000 m a.s.l. in the west, peaking at 5,642 m a.s.l. at Mount Elbrus, and decrease in height towards the Caspian Sea (Volodicheva, 2002). Precipitation exceeds 2,000 mm a year close to the Black Sea but drops to 150 mm a year near the Caspian Sea (Zazanashvili et al., 1999). The majority of the mountains in the Lesser Caucasus range from 2,000 to 3,300 m a.s.l. (Volodicheva, 2002). Similar to the Greater Caucasus, the Lesser Caucasus has a wet climate in the west, but is more continental and dry in the east and south-east (Zazanashvili et al., 1999).

The Caucasus has many different forest types, and forest is one of four priority biomes for conservation in the Caucasus (Zazanashvili et al., 2012). The majority of forests is deciduous (~80%), followed by mixed (~12%) and coniferous forest (~8%) (Buchner et al., 2020) (Figure 20). Forests are often dominated by one or two species. Coniferous forests, often dominated by spruce (*Picea orientalis*), fir (*Abies nordmanniana*), and pine (*Pinus* spp.), are typical for higher altitudes in the western part of the Caucasus. Deciduous forests, including beech (*Fagus orientalis*), oak (*Quercus* spp.), oak and hornbeam (*Qercus-Carpinus caucasica*), and chestnut and hornbeam forests (*Castanea sativa-Carpinus caucasica*), are typical at lower elevations and towards the east. Forests transition into subalpine woodlands in higher altitude, and the upper tree line is affected by both logging and grazing (Gulisashvili, 1964; Volodicheva, 2002). Two forests of special conservation concern are the Colchic forests in the East along the Black Sea and the Hyrcanian forests in the West close to the Caspian Sea. Both harbor relict and endemic species (Nakhutsrishvili et al., 2015).

The Caucasus has a long history of human activities, and this resulted in an extensive land conversion, with only 12% of the vegetation remaining pristine (Krever et al., 2001; Zazanashvili et al., 2012). Forests have been under threat from unsustainable logging for timber and fuelwood, agriculture, and grazing (Krever et al., 2001). Beech forests have been logged due to their importance for the timber industry, and oak forests have been replaced with agriculture because they were most common on soils that are favorable for grapes and crops. Chestnut forest were lost due to their valuable wood, and coniferous forests such as spruce, spruce-fir, and beech-fir were logged for pulpwood (Krever et al., 2001). Especially in the Western Caucasus the Nordmann fir is an endemic tree species, but its timer has a high commercial value (Bragina et al., 2015). However, compared to other regions of the world the rates of forest loss and forest degradation are generally low in the Caucasus (Buchner et al., 2020; Krever et al., 2001).

The Caucasus has a very extensive network of protected areas. The oldest protected area in the Caucasus is the Lagodekhi strict nature reserve in Georgia (est. 1912). Before 1991, i.e., during Soviet times, many protected areas were established in the Caucasus, but some were also downgraded or eliminated (Krever et al., 2001). After 1991, the rate at which new protected areas were established increased even further (Krever et al., 2001; Zazanashvili et al., 2012). Among the four countries, 54 protected areas are strict nature reserves and national parks, which do not allow for human actives other than for scientific, educational or recreational purposes (IUCN I and II, IUCN and UNEP, 2014). Of these, 43 protected areas were established before 1991 (IUCN and UNEP, 2014). 23 out of these 43 protected areas had ≥ 5% forest cover in 1987 (Figure 20, Table A45) (Buchner et al., 2020), and those were the protected areas that we analyzed.

Data: forest loss and forest degradation

We analyzed two datasets, one for forest loss and one for forest degradation, to analyze protected area effectiveness, respectively (Figure 21, Table A45, Figure A14). The forest loss dataset captures the conversion from forest to a different land-cover class, and we developed that dataset in a prior study (Buchner et al., 2020). Our classification was based on Landsat imagery using large-area best-pixel compositing to ensure gap-free coverage and a C5.0 classifier, followed by post-classification comparisons to derive forest loss for five time steps (i.e., 1987-‘95, 1995-2000, 2000-‘05, 2005-‘10, and 2010-‘15). User’s accuracy and producer’s accuracy was 65%

and 78 % for coniferous forests, 36% and 30% for mixed forests, and 88% and 85% for deciduous forests for the 2015 land-cover classification, and 95% and 83% for stable forest for the forest change classification. For a detailed description of the land-cover and forest change dataset, see Buchner et al. (2020).

In the forest degradation dataset, which we developed newly for this study, we defined forest degradation as a decrease in green vegetation fraction. For this, we analyzed 43.800 Landsat Collection 1 Tier 1 surface reflectance images that were available in Google Earth Engine (Gorelick et al., 2017) for the Caucasus from 1987 to 2019 as of December 2019. All Landsat data were atmospherically corrected (LEDAPS (TM, ETM+ (Masek et al., 2006), LaSRC (OLI, (Vermote et al., 2016)) and clouds, cloud shadows, and snow was removed by USGS.

We mapped forest degradation based on time series of fractions for green vegetation, non-photosynthetic vegetation, soil, and shade, which we derived from spectral mixture analysis of the complete Landsat record (Lewińska et al. 2020). Spectral mixture analysis quantifies the fractions of different surface types (Bullock et al., 2020; Souza et al., 2003). We calculated these fractions for each Landsat scene using the same input parameters as in Lewińska et al. (2020, submitted). Next, we created monthly composites for each of our four surface fractions and applied a weighted Whittaker filter to fill in missing values due to cloud cover, in our time series (Atkinson et al., 2012; Eilers, 2003; Whittaker, 1922). We combined the original monthly fraction time series with the predicted time series preserving the original data, and using the predicted values to fill–in missing observations.

Based on the final monthly surface fraction time series, we summed up all monthly fractions for one year. We used the summed up green vegetation to run LandTrendr, and masked the forest area based on our land-cover maps (Buchner et al., 2020). LandTrendr breaks up a time series into trend segments based on statistically significant changes in the data (Kennedy et al., 2018, 2010), that indicates a change in e.g., forest over time. We defined a forested pixel as degraded when the green vegetation fraction was ≤ 20% of the per-pixel maximum across the entire time series. For each change-segment representing a decline in green vegetation we calculated the corresponding change in the non-photosynthetic vegetation, soil and shade fractions. We excluded all declines in green vegetation with a corresponding increase in non-photosynthetic vegetation, because we assumed that such changes were not caused by humans, but rather by e.g., droughts, insects, or pathogens. Overall, we defined degradation as a decrease in green vegetation with a corresponding increase in the soil or the shade fraction. For each change degradation segment we derived its timing, absolute change and annual change rate, i.e., the absolute change divided by the duration of the segment.

Data: protected areas and control variables

We analyzed protected area boundaries from the World Database on Protected Areas (WDPA, IUCN and UNEP, 2014), and included all terrestrial IUCN category I and II protected areas that were established prior to 1988, i.e., the first year of our degradation datasets. We further limited our analysis to protected areas with ≥ 5% and ≥ 300 ha of forest cover in 1987 according to Buchner et al. (2020). For our robustness check, we analyzed three additional protected area datasets. One dataset delineated protected area boundaries of protected areas in Georgia, Armenia, and Azerbaijan in 1991 that were subsequently downgraded, downsized, and degazetted according to the World Wide Fund for Nature (WWF Caucasus). For the North Caucasus we obtained two datasets with the protected areas boundaries in 2014 and 2020 (http://oopt.aari.ru/oopt/) to compare forest loss and forest degradation in Sochinsky National Park boundaries before and after boundary change made for the Winter Olympic Games in 2014.

To control for factors other than protected area status that can affect forest loss and forest degradation, we included environmental variables as well as variables related to access to markets, and the percent of forest within a certain area to define core and edge forest in our models (Table 5) (Butsic et al., 2016; Jones and Lewis, 2015). We calculated elevation, slope, and aspect from the ALOS Global Digital Surface Model (DSM) (Tadono et al., 2014; Takaku et al., 2014), and distance to highways, settlements, and waterways based on OpenStreetMap (OpenStreetMap contributors, 2017). All datasets were processed in Google Earth Engine. We further calculated the percentage of the nearest 4 (120 m) and 34 pixels (~1 km) that were forested as a proxy whether a pixel was surrounded by dense forest or not. Lastly, we added a country dummy variable to account for political and economic differences (GADM, 2020).

Statistical analysis

We applied matching statistics and panel regression to determine the effectiveness of protected areas. We accounted for non-random placement of protected areas (Joppa and Pfaff, 2009), and selected observations that were similar in their underlying characteristics, but differed in their protection status (treated versus control). Specifically, we applied nearest-neighbor propensity score matching without replacement and a caliper size of 0.2 (Guo and Fraser, 2014). The propensity score is the probability of a unit of interest receiving a treatment (i.e., protection) (Guo and Fraser, 2014; Jones and Lewis, 2015) and is estimated in Stata with a probit model based on a set of observable control variables. We did not analyze every pixel to limit the potential effects of spatial autocorrelation. Instead we implemented a systematic sample in form of a 500 -m grid covering our study area, and extracted values for all variables for each grid point. Furthermore, we did not include any control points if there were within 5 km of a protected areas ICUN category I&II to exclude areas that were potentially affected by leakage (Fuller et al., 2019). We further removed observations from protected areas with a lower protection status (IUCN III-V) and from protected areas that were established after 1988. We matched observations forested in 1987, based on our natural log transformed variables (Table 5) (Brandt et al., 2015). We used the same matched points to assess (1) forest loss and (2) forest degradation. Furthermore, we created three matched datasets for coniferous, mixed, and deciduous forest in 1987. Lastly, we analyzed each matched datasets with random-effects panel regressions. The lack of temporal variation in the location of protected areas prevented the use of a fixed-effects model (Wendland et al., 2015).

Specifically, we determined effectiveness based on forest loss for five time periods using the following logistic regression model:

$$Y_{it} = \beta_1 * P_i + \beta_2 * Year_{it} + \ \beta_3 * C_i + \beta_4 * P_i Year_{it} + \beta_5 * P_i C_i + \beta_6 * Year_i C_i + \beta_7 * P_i Year_{it} C_i + \ \beta_{8-15} * X_i + e_{it}$$

where Y_{it} is forest loss (1) or not (0) for pixel i in time period t, P_i indicates if an observation is protected (1) or not (0), $Year_{it}$ is the time dummy variable indicating the five time period, C_i is a categorical variable indicating the country of observation i, P_i*Year_{it}, P_i*C_i, $Year_{it}*C_i$, and $P_i*Year_{it}*C_i$ are the respective interaction terms, with $P_i*Year_{it}*C_i$ indicating the effect, X_i is the vector of control variables, β_1-β_{15} are the coefficients to be estimated, and e_{it} is the error term.

Similarly, we determined effectiveness based on forest degradation using a linear panel regression applying the same equation as for forest loss, but where Y_{it} is the forest degradation change rate for observation i in time period t and $Year_{it}$ is the time dummy variable indicating the annual time steps from 1988 to 2018. In addition, we ran three separate forest type models, where Y_{it} indicated the forest degradation in 1) coniferous, 2) mixed, and 3) deciduous forest.

We performed all statistical analyses in StataSE 16 and calculated the marginal effects using the 'margins' command (full model results in the appendix Table A46 - Table A50). Marginal effects represent the percentage point change in the probability of forest loss if an observation switches from unprotected to protected.

Robustness check

We were concerned that changes in protected area boundaries during our analysis period may have affected our results. Therefore, we compared forest loss and forest degradation rates based on the 2020 protected area boundaries from the WDPA dataset and on the 1991 boundaries provided by the WWF. To do so, we applied the same statistical analyses outlined above for forest loss but added three indicators of protection: 1) pixels that were only designated as protected in 2020, 2) pixels only designated as protected in 1991, and 3) pixels that were protected in both 2020 and 1991. Observations in (1) are areas that may have been unprotected in 1991 but are protected now. Observations in (2) are areas that may have been protected in 1991 but are no longer protected in 2020 and observation in (3) were protected in 1991 and 2020. By including these time points of protection, we could statistically test if forest loss differed systematically between categories. We excluded Russia for this analysis because the dataset from 1991 only covered the South Caucasus. However, for the North Caucasus we compared forest loss and forest degradation within Sochinsky National Park before 2014, before the Olympic Games, and 2020, after the Olympic Games.

Results

Protected area effectiveness

We found that across the Caucasus, strictly protected areas increased forest loss by 0.1 percentage point (p.p.), a small but statistically significant effect (Table 6), suggesting that protected areas were ineffective in preventing forest loss. In Russia protection increased forest loss by 0.4 p.p. (Table 6) and this was true for each time step (Figure 22). However, protected areas reduced the probability of forest loss significantly in Azerbaijan (-1.1 p.p.) and Georgia (-0.2 p.p.) (Table 6). For Azerbaijan this pattern was consistent over time (Figure 22). In Georgia the effect of protected areas varied over time and probability of forest loss in protected areas was sometimes lower and sometimes insignificant over time (Figure 22). Armenia had too few forest loss observations to credibly estimate the effectiveness of protected areas based on forest loss.

The percentage of surrounding forest had a strong effect, in that the probability of forest loss decreased with more forest in the surrounding area, indicating that forest along forest edges was most likely to be lost. Slope decreased the probability of forest loss, i.e., on steeper slopes forest loss was less likely, and elevation had a positive effect, i.e., forest at higher elevations was more likely to be lost than forest at lower elevation.

In contrast to forest loss, protected areas were overall effective in preventing forest degradation in the Caucasus, and decreased degradation by (-1.1 p.p.) (Table 7). This was especially the case in Russia (-1.4 p.p.), whereas estimates for Georgia, and Azerbaijan, were negative but not significantly different from zero. For Armenia estimates were positive but insignificant (Table 7).

The effectiveness of protected areas for different forest types for the whole Caucasus was significant for coniferous (-0.2 p.p.) and deciduous forest (-1.3 p.p.), but not for mixed forest (Table 7, Figure 23). However, among countries the effectiveness among forest types differed (Table 7, Figure 23). First, for coniferous forest, protected areas were ineffective in Azerbaijan (1.1 p.p.), effective in Russia (-0.04 p.p.), and had no significant effect in Georgia (-0.1 p.p.). Second, for mixed forest the percentage point changes were insignificant in each countries. Third, for deciduous forest protected areas had a lower probability of loss in all countries, but was only statistically significant in Russia. Armenia had again too few forest degradation observations in coniferous and mixed forest to estimate the effectiveness of protected areas on forest degradation in these forest types.

Results of the robustness check

We compared the overall area of forest loss and forest degradation for protected areas in Sochinsky National Park (North Caucasus) based on protected area boundaries before and after the Olympic Games in 2014, and in the South Caucasus based on protected area boundaries in both 1991 and 2020, to account for downgrading, downsizing, and degazettment. Our summary statistics for Sochinsky National Park showed that the area of forest loss was overall higher when we used the protected area boundaries before 2014 compared to 2020, but forest degradation was almost the same (Figure A15). This means that by using protected area boundaries of 2020, we may have underestimated the ineffectiveness of protected areas in the North Caucasus. However, the overall picture of the ineffectiveness of protected areas would not have changed. .

For the South Caucasus, our summary statistics showed that the area of forest loss and forest degradation was overall higher when we used the protected area boundaries in 2020 (WDPA) compared to the protected area boundaries in 1991 (WWF) (Figure A16). This indicates that by using the protected area boundaries from 2020 we mapped more forest loss and forest degradation inside protected areas and we did not underestimate the overall amount of forest loss or forest degradation by using the protected area delineation in 2020.

Our modeling approach for the South Caucasus with different indictors for protection, i.e., 1) only protected in 2020, 2) only protected in 1991, and 3) protected in 2020 and 1991, showed that there was no significant difference between the estimated effects of the three categories (Table A51). This also indicates that using only the 2020 boundaries is appropriate.

Discussion

Our results showed that effectiveness of protected areas in terms of stemming forest loss differed considerably from their effectiveness to stem degradation. Protected areas that were not effective in preventing forest loss none-the-less prevented forest degradation in the Caucasus. The results for the different forest types, and the different countries were heterogeneous. While protected areas in Russia were ineffective in preventing forest loss, they were effective in preventing forest degradation overall, and in coniferous and deciduous forests. Protected areas in Georgia and Azerbaijan were effective in preventing forest loss, but the effect was insignificant for forest degradation.

Overall the magnitude of the effect of protected areas was low in the Caucasus, which is similar to what has been found in Russia (Wendland et al., 2015) and in the Western part of the Russian Caucasus (Bragina et al., 2015). The forest loss rates are generally low in the Caucasus, and forest loss and forest gain are almost equal (Buchner et al., 2020). However, the effect of protected areas on forest loss differed among countries in the Caucasus, which is in line with a study in the Carpathian where effectiveness of protected areas varied greatly among countries and years (Butsic et al., 2016). For the Russian part of the Caucasus, we found that the probability of forest loss was significantly higher inside protected areas (0.4 p.p.). However in other parts of Russia, protected areas were effective in preventing forest loss, i.e., reducing forest disturbance in comparison to their surrounding area (Sieber et al., 2013). For both the whole Caucasus and Russia, it is important to point out the effect size was small, where protection was not effective. For Russia, where protected areas where ineffective, we found 17,030 ha forest loss inside protected areas, and an effect of (0.4 p.p.) translates into an additional 3.4 ha/year. The largest effect size (-1.1 p.p. in Azerbaijan) means that with a total forest loss of 2,180 ha inside protected areas, protection prevented the loss of 23.9 ha of forest over 20 years, or approximately 1.2 ha/year.

We found that protected areas that were not effective in reducing forest loss, often significantly reduced forest degradation. This surprised us because forest degradation is known to occur across the Caucasus. However, the overall amount of forest degradation in the Caucasus is even smaller than the amount of forest loss, which explains the rather small effect of protected areas on forest degradation, similar to what we found for forest loss. Although the marginal effect was overall significant for the whole Caucasus, of all the countries it was only significant for Russia. To put the effect size into perspective, the largest effect size (-1.4 p.p. in Russia) indicates that with a forest degradation of 6,650 ha inside protected areas, protection prevented 93.1 ha of forest degradation over 30 years (1988-2018), or approximately 3.1 ha a year. For the whole Caucasus, forest degradation of 9,165 ha inside protected areas and an effect size of -1.1 p.p. translates to 3.4 ha/year. Nevertheless, we suggest that it is important to examine both forest loss and forest degradation when estimating protected area effectiveness, especially when there is little forest loss. In Myanmar mapped deforestation is lower inside the protected area, but forest degradation rates are higher than outside (Htun et al., 2013, 2009). Similarly, in Guatemala, forest degradation is wide-spread inside protected areas (Bullock et al., 2019). In other words, forest loss alone cannot confirm that protected areas are effective (Bullock et al., 2019; Htun et al., 2013, 2009).

Analyzing forest degradation in different forest types is a further step, and necessary if some forest types are more likely to be lost. We found that protected areas were effective in preventing the degradation of coniferous forests, which is encouraging given Nordmann fir's high commercial value (Bragina et al., 2015). Similarly, we found that protected areas were effective for deciduous forests, which is encouraging in the case of Colchic forests, which harbor many endemic species in the Caucasus (Nakhutsrishvili et al., 2015; Zazanashvili et al., 1999). The effect of protected areas on mixed forest was small and insignificant. This was surprising to us because mixed forests cover a slightly larger area than coniferous forests. In general, separating forest types when assessing effectiveness is important because assessment based on forests overall may mask the ineffectiveness of protected areas of forest types that are rare. This is especially important for countries such as Georgia and Russia that harbor the last remaining Colchic forests along the Black Sea providing habitat for many endemic tree species such as the Nordmann fir and several oak species (Nakhutsrishvili et al., 2015). However, we found that for these two countries, the effect of protection on forest degradation in mixed forest was not significant, and lowest among countries. Most studies use forests overall to assess protected area effectiveness and may draw incomplete conclusion on the conservation success. However, in southwest China protected areas were not effective in preventing forest loss of forest overall nor in pine forests, but did protect old-growth forests effectively (Brandt et al., 2015). Although this finding is opposite to what we found, the conservation implications are the same: a simple binary analysis of forest versus non-forest can obscure the effectiveness of protected areas (Brandt et al., 2015).

In general protected area effectiveness can be less clear when there is an overall low rate of forest loss or forest degradation. Low rates of forest loss or forest degradation usually result in a low effect of protected areas or in insignificant results (Bragina et al., 2015; Wendland et al., 2015). When forest loss or forest degradation is overall low and similar inside and outside protected areas the effect may not be statistical significant. We want to caution that this does not mean that protected areas have no ecological relevance or that they are not effective, it rather shows that forest loss or forest degradation was not a good proxy to measure the effectiveness of protected areas there. However, if forest loss or forest degradation is overall widespread and is not lower inside protected areas, then a statistical significance allows to conclude that protected areas are ineffective.

We suggest that several factors are related to the observed differences in protected area effectiveness in the Caucasus. The collapse of the Soviet Union in 1991, which resulted in weak institutions and low law enforcement, as well as wars in all four countries, certainly affected protected areas effectiveness (Krever et al., 2001). Wars in the region, may have contributed to increased logging rates, as happened in Rwanda where widespread forest loss occurred inside protected areas during the conflict (Ordway, 2015). A shortage of energy in Georgia and Armenia caused increased fuelwood collection by 200-300 % compared to the 1980s (Krever et al., 2001). In Armenia, during the 1990s, 30% of the deforestation during that time was due to illegal exports and an increasing black market for forest products (Sayadyan and Moreno-Sanchez, 2006). A decrease in funding for protected areas hampered the management of protected areas as ranger patrols declined and scientific research was cutback in Russia (Wells and Williams, 1998), and may explain the higher forest loss inside protected areas in 1995. In Russia, we assume that a decline in enforcement after the collapse of the Soviet Union, may also explain higher forest loss inside protected areas. During Soviet Union times, zapovedniks were strictly controlled and regulated, and had a high acceptance in the public (Müller, 2014; Wells and Williams, 1998). However, similar to the other countries, a lack of personnel resulted in increasing numbers of violations inside protected areas, and some reserves had to create revenue through logging (Müller, 2014). In the 2000s economic development and fostering economic growth was more important in Russia than conserving biodiversity, and conservation was nog a high priority for policy makers (Müller, 2014). Examples for this are the deforestation in Sochinsky National Park in preparation for the Olympic Games in 2014 (Bragina et al., 2015), and the ski resorts and recreation facilities that were built in Kavkazsky (Müller, 2014).

Management implications

Extending these findings, our research suggests that the assessment of the effectiveness of protected areas should be based on multiple indicators and conservation priorities. This allows to specifically address conservation efforts towards areas that are under threat and thereby minimizing management costs. Differentiating the effectiveness of strictly protected areas among forest types helps to monitor smaller areas for illegal activities and to promote specific changes in management if needed, and to reassess the area at a later point in time. Further, the integration of the livelihood of local communities is becoming an increasing goal of protected area management (Adams et al., 2004) which needs to ensure a sustainable use of resources. We suggest that a refined assessment of protected area assessment can further benefit a community based protected area management plan in the long term.

Methodological considerations

Advances in remote sensing allowed us to analyze forest degradation as an additional proxy to assess protected area effectiveness, in a region where forest degradation is a known threat. Our study highlights the benefits of spectral mixture analysis, the depth of the full Landsat archive, and temporal segmentation for change detection (Lewińska, submitted). Forest degradation was also successfully mapped using spectral mixture analysis and Landsat time series in Guatemala's protected areas (Bullock et al., 2019). Using the complete Landsat archive and the Whittaker filter to address missing values allowed us to extend our analysis back to 1988. Our approach provides spatial and temporal information of forest degradation on an annual basis. Our change assessment is based on green vegetation fraction, which is advantageous in complex topography and intra-annual changes in illumination conditions, such as the Caucasus, and in different forest types such as deciduous and conifers forests, compared to approaches that are developed for the tropics (Bullock et al., 2019, 2020). Furthermore, comparison among surface fraction abundance allows to identify different degradation trajectories (i.e., changes from green vegetation to soil, shade, or non-photosynthetic vegetation) (Lewińska, submitted), which makes it possible to distinguish, for example, clear cuts from defoliation caused by drought.

Our study has some limitations in terms of our input datasets. Our protected area boundaries do not include detailed information on protected areas downgrading, downsizing, and degazettment over time. In general protected areas in the South Caucasus are mostly affected by downgrading (Mancheno et al., 2017), upsizing exceeded the area of downsizing (Mancheno et al., 2017). To account for downsizing and degazettment, we conducted a robustness check using the WWF dataset outlining protected area boundaries in 1991 and compared the results with results derived using the WDPA protected area boundaries from 2020. There was no evidence that downsizing and degazettment affected our region-wide analysis significantly. We emphasize though that the differences may be more important locally. A further limitation is that our forest loss data includes both loss due to human activities, such as clear cutting, but also due to natural disturbance such as windthrow or fire, which may lead to an underestimation of the effectiveness of protected areas. In addition both user's and producer's classification accuracies were low for mixed forest, and mixed pixels may have been misclassified as coniferous or deciduous forest in the original classification. This may have reduced the significance level of our estimates of the effect of protected areas for the different forest types, however this was not the case for the assessment of forest degradation of all forest types. Our forest degradation was further not validated against ground truth data.

Conclusion

Protected areas are an important conservation tool to preserve biodiversity and pristine landscapes. The Caucasus is a biodiversity hotspot harboring a large number of endemic species and forests of high conservation value. Although forest loss is generally low compared to other regions of the world, protection of the forests needs to be ensured to decrease any further detrimental impact. We argue that using canopy removal as a proxy is not enough in regions where a) degradation is a threat to forests, and b) different forest types are affected differently. Here, we provide additional insight in protected areas effectiveness by providing forest loss and forest degradation among forest types. A combination of both, forest loss and forest degradation, allowed us to show that protected areas were overall not effective in preventing forest loss in the Caucasus, and that protected areas affected forest degradation differently in coniferous, mixed, and deciduous forests. Our results show that conservation efforts need to be targeted towards specific goals, such as protecting different forest types, to fulfil their purpose.

Acknowledgments

We gratefully acknowledge support for this research by the Land-cover and Land-Use Change (LCLUC) Program of the National Aeronautic Space Administration (NASA) through Grants 570NNX15AD93G and 80NSSC18K0316. We would like to thank the WWF Caucasus for providing us with the dataset on protected areas subject to PADDD events in the South Caucasus.

References

Adams, J.B., Sabol, D.E., Kapos, V., Filho, R.A., Roberts, D.A., Smith, M.O., Gillespie, A.R., 1995. Classification of multispectral images based on fractions of endmembers: Application to land-cover change in the Brazilian Amazon. Remote Sens. Environ. 52, 137–154. https://doi.org/10.1016/0034-4257(94)00098-8

Adams, W.M., Aveling, R., Brockington, D., Dickson, B., Elliott, J., Hutton, J., Roe, D., Vira, B., Wolmer, W., 2004. Biodiversity Conservation and the Eradication of Poverty. Science 306, 1146–1149. https://doi.org/10.1126/science.1097920

Andam, K.S., Ferraro, P.J., Pfaff, A., Sanchez-Azofeifa, G.A., Robalino, J.A., 2008. Measuring the effectiveness of protected area networks in reducing deforestation. Proc. Natl. Acad. Sci. 105, 16089–16094. https://doi.org/10.1073/pnas.0800437105

Armsworth, P.R., Cantú-Salazar, L., Parnell, M., Davies, Z.G., Stoneman, R., 2011. Management costs for small protected areas and economies of scale in habitat conservation. Biol. Conserv. 144, 423–429. https://doi.org/10.1016/j.biocon.2010.09.026

Asner, G.P., Knapp, D.E., Broadbent, E.N., Oliveira, P.J.C., Keller, M., Silva, J.N., 2005. Selective Logging in the Brazilian Amazon. Science 310, 480–482. https://doi.org/10.1126/science.1118051

Atkinson, P.M., Jeganathan, C., Dash, J., Atzberger, C., 2012. Inter-comparison of four models for smoothing satellite sensor time-series data to estimate vegetation phenology. Remote Sens. Environ. 123, 400–417. https://doi.org/10.1016/j.rse.2012.04.001

Bowker, J.N., De Vos, A., Ament, J.M., Cumming, G.S., 2017. Effectiveness of Africa's tropical protected areas for maintaining forest cover. Conserv. Biol. 31, 559–569. https://doi.org/10.1111/cobi.12851

Bragina, E.V., Radeloff, V.C., Baumann, M., Wendland, K., Kuemmerle, T., Pidgeon, A.M., 2015. Effectiveness of protected areas in the Western Caucasus before and after the transition to post-socialism. Biol. Conserv. 184, 456–464. https://doi.org/10.1016/j.biocon.2015.02.013

Brandt, J.S., Butsic, V., Schwab, B., Kuemmerle, T., Radeloff, V.C., 2015. The relative effectiveness of protected areas, a logging ban, and sacred areas for old-growth forest protection in southwest China. Biol. Conserv. 181, 1–8. https://doi.org/10.1016/j.biocon.2014.09.043

Brooks, T.M., Bakarr, M.I., Boucher, T., Da Fonseca, G.A.B., Hilton-Taylor, C., Hoekstra, J.M., Moritz, T., Olivieri, S., Parrish, J., Pressey, R.L., Rodrigues, A.S.L., Sechrest, W., Stattersfield, A., Strahm, W., Stuart, S.N., 2004. Coverage Provided by the Global Protected-Area System: Is It Enough? BioScience 54, 1081–1091. https://doi.org/10.1641/0006-3568(2004)054[1081:CPBTGP]2.0.CO;2

Buchner, J., Yin, H., Frantz, D., Kuemmerle, T., Askerov, E., Bakuradze, T., Bleyhl, B., Elizbarashvili, N., Komarova, A., Lewińska, K.E., Rizayeva, A., Sayadyan, H., Tan, B., Tepanosyan, G., Zazanashvili, N., Radeloff, V.C., 2020. Land-cover change in the Caucasus Mountains since 1987 based on the topographic correction of multi-temporal

Landsat composites. Remote Sens. Environ. 248, 111967. https://doi.org/10.1016/j.rse.2020.111967

Bullock, E.L., Nolte, C., Segovia, A.R., Woodcock, C.E., 2019. Ongoing forest disturbance in Guatemala’s protected areas. Remote Sens. Ecol. Conserv. 6, 141–152. https://doi.org/10.1002/rse2.130

Bullock, E.L., Woodcock, C.E., Souza, C., Olofsson, P., 2020. Satellite-based estimates reveal widespread forest degradation in the Amazon. Glob. Change Biol. 26, 2956–2969. https://doi.org/10.1111/gcb.15029

Burivalova, Z., Bauert, M.R., Hassold, S., Fatroandrianjafinonjasolomiovazo, N.T., Koh, L.P., 2015. Relevance of Global Forest Change Data Set to Local Conservation: Case Study of Forest Degradation in Masoala National Park, Madagascar. Biotropica 47, 267–274. https://doi.org/10.1111/btp.12194

Burivalova, Z., Şekercioğlu, Ç.H., Koh, L.P., 2014. Thresholds of Logging Intensity to Maintain Tropical Forest Biodiversity. Curr. Biol. 24, 1893–1898. https://doi.org/10.1016/j.cub.2014.06.065

Butsic, V., Munteanu, C., Griffiths, P., Knorn, J., Radeloff, V.C., Lieskovský, J., Mueller, D., Kuemmerle, T., 2016. The effect of protected areas on forest disturbance in the Carpathian Mountains 1985-2010. Conserv. Biol. J. Soc. Conserv. Biol. 31, 570–580. https://doi.org/10.1111/cobi.12835

EEA, 2012. Protected areas in Europe - an overview (Publication No. 5). European Environment Agency, Luxembourg.

EEA, 2010. Europe’s ecological backbone: recognising the true value of our mountains. European Environment Agency EEA, Copenhagen.

Eilers, P.H.C., 2003. A perfect smoother. Anal. Chem. 75, 3631–3636. https://doi.org/10.1021/ac034173t

FAO, 2019. State of Forests of the Caucasus and Central Asia. Food and Agriculture Organization of the United Nations, New York and Geneva.

FAO and UNEP, 2020. The State of the World's Forests 2020: Forests, biodiversity and people. FAO and UNEP, Rome, Italy. https://doi.org/10.4060/ca8642enAlso Available in:Chinese Spanish Arabic French Russian

Ferraro, P.J., Hanauer, M.M., Miteva, D.A., Canavire-Bacarreza, G.J., Pattanayak, S.K., Sims, K.R.E., 2013. More strictly protected areas are not necessarily more protective: evidence from Bolivia, Costa Rica, Indonesia, and Thailand. Environ. Res. Lett. 8, 025011. https://doi.org/10.1088/1748-9326/8/2/025011

Freni, S.J., 2013. Causes of Violent Conflict in the Caucasus since the Collapse of Communism. Inq. J. 5.

Fuller, C., Ondei, S., Brook, B.W., Buettel, J.C., 2019. First, do no harm: A systematic review of deforestation spillovers from protected areas. Glob. Ecol. Conserv. 18, e00591. https://doi.org/10.1016/j.gecco.2019.e00591

GADM, 2020. GADM maps and data version 3.6 [WWW Document]. GADM. URL https://gadm.org/

Geldmann, J., Manica, A., Burgess, N.D., Coad, L., Balmford, A., 2019. A global-level assessment of the effectiveness of protected areas at resisting anthropogenic pressures. Proc. Natl. Acad. Sci. 116, 23209–23215. https://doi.org/10.1073/pnas.1908221116

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., Moore, R., 2017. Google Earth Engine: Planetary-scale geospatial analysis for everyone. Remote Sens. Environ., Big Remotely Sensed Data: tools, applications and experiences 202, 18–27. https://doi.org/10.1016/j.rse.2017.06.031

Gulisashvili, V.Z., 1964. Prirodnye zony i estestvenno-istoricheskie oblasti Kavkaza (Natural Zones and Historical Environmental Regions in the Caucasus). Nauka Publ. Mosc. 327 pp.

Guo, S., Fraser, M.W., 2014. Propensity Score Analysis, Second. ed, Advanced Quantitative Techniques in the Social Sciences. SAGE Publications, Inc.

Hosonuma, N., Herold, M., Sy, V.D., Fries, R.S.D., Brockhaus, M., Verchot, L., Angelsen, A., Romijn, E., 2012. An assessment of deforestation and forest degradation drivers in developing countries. Environ. Res. Lett. 7, 044009. https://doi.org/10.1088/1748-9326/7/4/044009

Htun, N.Z., Mizoue, N., Kajisa, T., Yoshida, S., 2009. Deforestation and forest degradation as measures of Popa Mountain Park (Myanmar) effectiveness. Environ. Conserv. 36, 218–224. https://doi.org/10.1017/S0376892909990415

Htun, N.Z., Mizoue, N., Yoshida, S., 2013. Changes in Determinants of Deforestation and Forest Degradation in Popa Mountain Park, Central Myanmar. Environ. Manage. 51, 423–434. https://doi.org/10.1007/s00267-012-9968-5

IUCN and UNEP, 2014. World Database on Protected Areas (WDPA) [WWW Document]. URL https://protectedplanet.net/

Jones, K.W., Lewis, D.J., 2015. Estimating the Counterfactual Impact of Conservation Programs on Land Cover Outcomes: The Role of Matching and Panel Regression Techniques. PLOS ONE 10, e0141380. https://doi.org/10.1371/journal.pone.0141380

Joppa, L.N., Pfaff, A., 2009. High and Far: Biases in the Location of Protected Areas. PLOS ONE 4, e8273. https://doi.org/10.1371/journal.pone.0008273

Kennedy, R.E., Yang, Z., Cohen, W.B., 2010. Detecting trends in forest disturbance and recovery using yearly Landsat time series: 1. LandTrendr — Temporal segmentation algorithms. Remote Sens. Environ. 114, 2897–2910. https://doi.org/10.1016/j.rse.2010.07.008

Kennedy, R.E., Yang, Z., Gorelick, N., Braaten, J., Cavalcante, L., Cohen, W.B., Healey, S., 2018. Implementation of the LandTrendr Algorithm on Google Earth Engine. Remote Sens. 10, 691. https://doi.org/10.3390/rs10050691

Krever, V., Zazanashvili, N., Jungius, H., Williams, L., Petelin, D., 2001. Biodiversity of the Caucasus ecoregion : an analysis of biodiversity and current threats and initial investment portfolio. Moscow.

Kroner, R.E.G., Qin, S., Cook, C.N., Krithivasan, R., Pack, S.M., Bonilla, O.D., Cort-Kansinally, K.A., Coutinho, B., Feng, M., Garcia, M.I.M., He, Y., Kennedy, C.J., Lebreton, C., Ledezma, J.C., Lovejoy, T.E., Luther, D.A., Parmanand, Y., Ruíz-Agudelo, C.A., Yerena, E., Zambrano, V.M., Mascia, M.B., 2019. The uncertain future of protected lands and waters. Science 364, 881–886. https://doi.org/10.1126/science.aau5525

Lewińska, K.E., submitted. Vegetation loss in grasslands in the Caucasus based on Cumulative Endmember Fractions form the full Landsat record. Remote Sens. Environ.

Lewińska, K.E., Hostert, P., Buchner, J., Bleyhl, B., Radeloff, V.C., 2020. Short-term vegetation loss versus decadal degradation of grasslands in the Caucasus based on Cumulative Endmember Fractions. Remote Sens. Environ. 248, 111969. https://doi.org/10.1016/j.rse.2020.111969

Mancheno, C.S.M., Zazanashvili, N., Beruchashvili, G., 2017. Effectiveness of the network of protected areas of the South Caucasus at representing terrestrial ecosystems after the dissolution of the Soviet Union. Environ. Conserv. 44, 158–165. https://doi.org/10.1017/S0376892916000424

Måren, I.E., Sharma, L.N., 2018. Managing Biodiversity: Impacts of Legal Protection in Mountain Forests of the Himalayas. Forests 9, 476. https://doi.org/10.3390/f9080476

Mascia, M.B., Pailler, S., 2011. Protected area downgrading, downsizing, and degazettement (PADDD) and its conservation implications. Conserv. Lett. 4, 9–20. https://doi.org/10.1111/j.1755-263X.2010.00147.x

Masek, J.G., Vermote, E.F., Saleous, N.E., Wolfe, R., Hall, F.G., Huemmrich, K.F., Gao, F., Kutler, J., Lim, T.-K., 2006. A Landsat surface reflectance dataset for North America, 1990-2000. IEEE Geosci. Remote Sens. Lett. 3, 68–72. https://doi.org/10.1109/LGRS.2005.857030

Mon, M.S., Kajisa, T., Mizoue, N., Yoshida, S., 2010. Monitoring Deforestation and Forest Degradation in the Bago Mountain Area, Myanmar using FCD Mapper. J. For. Plan. 15, 63–72. https://doi.org/10.20659/jfp.15.2_63

Mon, M.S., Mizoue, N., Htun, N.Z., Kajisa, T., Yoshida, S., 2012. Factors affecting deforestation and forest degradation in selectively logged production forest: A case study in Myanmar. For. Ecol. Manag. 267, 190–198. https://doi.org/10.1016/j.foreco.2011.11.036

Müller, M., 2014. From sacred cow to cash cow: The shifting political ecologies of protected areas in Russia. Z. Für Wirtsch. 58, 127–143. https://doi.org/10.5167/uzh-100273

Nakhutsrishvili, G., Zazanashvili, N., Batsatsashvili, K., Mancheno, C.S.M., 2015. Colchic and Hyrcanian forests of the Caucasus: similarities, differences and conservation status. https://doi.org/10.7320/flmedit25si.185

Naughton-Treves, L., Holland, M.B., Brandon, K., 2005. The Role of Protected Areas in Conserving Biodiversity and Sustaining Local Livelihoods. Annu. Rev. Environ. Resour. 30, 219–252. https://doi.org/10.1146/annurev.energy.30.050504.164507

Nolte, C., Agrawal, A., Barreto, P., 2013. Setting priorities to avoid deforestation in Amazon protected areas: are we choosing the right indicators? Environ. Res. Lett. 8, 015039. https://doi.org/10.1088/1748-9326/8/1/015039

OpenStreetMap contributors, 2017. OpenStreetMap [WWW Document]. URL www.openstreetmap.org

Ordway, E.M., 2015. Political shifts and changing forests: Effects of armed conflict on forest conservation in Rwanda. Glob. Ecol. Conserv. 3, 448–460. https://doi.org/10.1016/j.gecco.2015.01.013

Ozdogan, M., Olofsson, P., Woodcock, C.E., Baccini, A., 2017. Forest Changes and Carbon Budgets in the Black Sea Region, in: Gutman, G., Radeloff, V. (Eds.), Land-Cover and Land-Use Changes in Eastern Europe after the Collapse of the Soviet Union in 1991. Springer International Publishing, Cham, pp. 149–171. https://doi.org/10.1007/978-3-319-42638-9_7

Paré, S., Tigabu, M., Savadogo, P., Odén, P.C., Ouadba, J.M., 2010. Does designation of protected areas ensure conservation of tree diversity in the Sudanian dry forest of Burkina Faso? Afr. J. Ecol. 48, 347–360. https://doi.org/10.1111/j.1365-2028.2009.01113.x

Pfaff, A., Robalino, J., Herrera, D., Sandoval, C., 2015. Protected Areas' Impacts on Brazilian Amazon Deforestation: Examining Conservation – Development Interactions to Inform Planning. PLOS ONE 10, e0129460. https://doi.org/10.1371/journal.pone.0129460

Putz, F.E., Zuidema, P.A., Synnott, T., Peña-Claros, M., Pinard, M.A., Sheil, D., Vanclay, J.K., Sist, P., Gourlet-Fleury, S., Griscom, B., Palmer, J., Zagt, R., 2012. Sustaining conservation values in selectively logged tropical forests: the attained and the attainable. Conserv. Lett. 5, 296–303. https://doi.org/10.1111/j.1755-263X.2012.00242.x

Rodrigues, A.S.L., Andelman, S.J., Bakarr, M.I., Boitani, L., Brooks, T.M., Cowling, R.M., Fishpool, L.D.C., Da Fonseca, G.A.B., Gaston, K.J., Hoffmann, M., Long, J.S., Marquet, P.A., Pilgrim, J.D., Pressey, R.L., Schipper, J., Sechrest, W., Stuart, S.N., Underhill, L.G., Waller, R.W., Watts, M.E.J., Yan, X., 2004. Effectiveness of the global protected area network in representing species diversity. Nature 428, 640–643. https://doi.org/10.1038/nature02422

Sayadyan, H.Y., Moreno-Sanchez, R., 2006. Forest policies, management and conservation in Soviet (1920–1991) and post-Soviet (1991–2005) Armenia. Environ. Conserv. 33, 60–72. https://doi.org/10.1017/S0376892906002852

Shchur, A., Bragina, E., Sieber, A., Pidgeon, A.M., Radeloff, V.C., 2017. Monitoring selective logging with Landsat satellite imagery reveals that protected forests in Western Siberia experience greater harvest than non-protected forests. Environ. Conserv. 44, 191–199. https://doi.org/10.1017/S0376892916000576

Shi, C., Wang, L., 2014. Incorporating spatial information in spectral unmixing: A review. Remote Sens. Environ. 149, 70–87. https://doi.org/10.1016/j.rse.2014.03.034

Sieber, A., Kuemmerle, T., Prishchepov, A.V., Wendland, K.J., Baumann, M., Radeloff, V.C., Baskin, L.M., Hostert, P., 2013. Landsat-based mapping of post-Soviet land-use change to assess the effectiveness of the Oksky and Mordovsky protected areas in European Russia. Remote Sens. Environ. 133, 38–51. https://doi.org/10.1016/j.rse.2013.01.021

Sims, K.R.E., Alix-Garcia, J.M., 2017. Parks versus PES: Evaluating direct and incentive-based land conservation in Mexico. J. Environ. Econ. Manag., Special issue on environmental economics in developing countries 86, 8–28. https://doi.org/10.1016/j.jeem.2016.11.010

Souza, C., Firestone, L., Silva, L.M., Roberts, D., 2003. Mapping forest degradation in the Eastern Amazon from SPOT 4 through spectral mixture models. Remote Sens. Environ., Large Scale Biosphere Atmosphere Experiment in Amazonia 87, 494–506. https://doi.org/10.1016/j.rse.2002.08.002

Tadono, T., Ishida, H., Oda, F., Naito, S., Minakawa, K., Iwamoto, H., 2014. Precise Global DEM Generation by ALOS PRISM. ISPRS Ann. Photogramm. Remote Sens. Spat. Inf. Sci. 4, 71–76. https://doi.org/10.5194/isprsannals-II-4-71-2014

Takaku, J., Tadono, T., Tsutsui, K., 2014. Generation of High Resolution Global DSM from ALOS PRISM. ISPRS - Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci. 4, 243–248. https://doi.org/10.5194/isprsarchives-XL-4-243-2014

UNEP-WCMC, ICUN, NGS, 2020. Protected Planet Live Repoert 2020. Cambridge, UK; Gland, Switzerland; Washington, D.C., USA.

Vermote, E., Justice, C., Claverie, M., Franch, B., 2016. Preliminary analysis of the performance of the Landsat 8/OLI land surface reflectance product. Remote Sens. Environ., Landsat 8 Science Results 185, 46–56. https://doi.org/10.1016/j.rse.2016.04.008

Volodicheva, N., 2002. The Caucasus, in: Shahgedanova, M. (Ed.), The Physical Geography of Northern Eurasia. Oxford University Press, Oxford, New York, pp. 350–376.

Wells, M.P., Williams, M.D., 1998. Russia's Protected Areas in Transition: The Impacts of Perestroika, Economic Reform and the Move Towards Democracy. Ambio 27, 198–206.

Wendland, K.J., Baumann, M., Lewis, D.J., Sieber, A., Radeloff, V.C., 2015. Protected Area Effectiveness in European Russia: A Postmatching Panel Data Analysis. Land Econ. 91, 149–168. https://doi.org/10.3368/le.91.1.149

Whittaker, E.T., 1922. On a New Method of Graduation. Proc. Edinb. Math. Soc. 41, 63–75. https://doi.org/10.1017/S0013091500077853

Zazanashvili, N., Gagnidze, R., Nakhutsrishvili, G., 1999. Main types of vegetation zonation on the mountains of the Caucasus. Acta Phytogeogr. Suec. 85, 7–16.

Zazanashvili, N., Garforth, M., Jungius, H., Gamkrelidze, T., 2012. Ecoregion Conservation Plan for the Caucasus. 2012 revised and updated edition. Ga. Tbilisi WWF KfW BMZ.

Tables and figures

Table 5: Variables used to assess protected area effectiveness.

	Variable	Unit	Period	Resolution	Source
Response variable	Forest-cover loss	1: forest loss 0: no forest loss	1987, 1995, 2000, 2005, 2010, 2015	30 m	Buchner et al., 2020
	Forest degradation	>0-1: magnitude change rate 0: no change rate	1988-2018	30 m	Newly calculated for this study
Treatment variable	Protected area	1: protection 0: no protection	2020	vector	World Database on Protected Areas (www.protectedplanet.com, April 2020)
	Protected area (South Caucasus)	1: protection 0: no protection	1991	vector	World Wide Fund For Nature (WWF) Caucasus
	Protected area (Sochinsky National Park)	1: protection 0: no protection	2014, 2020	vector	http://oopt.aari.ru/oopt
Control variables	Elevation Slope Aspect	m degree degree	Time-invariant	1 arcsecond	Tadono et al., 2014, Takaku et al., 2014
	Euclidean distance to highways, settlements, waterways	m	Time invariant	-	OpenStreetMap contributors, 2017
	Percentage of forest within 120 m Percentage of forest within 1 km window	%	Time-invariant based on forest in 1987	30 m	Buchner et al., 2020
	Administrative boundaries of countries	dummy	Time invariant	vector	Database of Global Administrative Areas (GADM version 3.6) (www.gadm.org)

Table 6: Marginal effect (percentage point change) of strict protection on the probability that a forest pixel will be lost (1995-2015), for the whole Caucasus and for each country (logistic regression with random effects, standard error in parentheses, *** p-value < 0.01, ** p-value < 0.05, * p-value < 0.1). Negative values indicate that protected areas reduce forest loss.

	Marginal effect Percentage point change
Whole Caucasus	0.1 (0.1)*
Azerbaijan	-1.1 (0.2)***
Georgia	-0.2 (0.1)*
Russia	0.4 (0.1)***

Table 7: Marginal effect (percentage point change) of strict protection on the probability that a forest pixel will be degraded (1988-2015), for total, coniferous, mixed, and deciduous forest, for the whole Caucasus and by country (standard error in parentheses, *** p-value < 0.01, ** p-value < 0.05, * p-value < 0.1). Negative values indicate that protected areas reduce forest degradation.

	Perc. point change Total forest	Perc. point change Conif. forest	Perc. point change Mixed forest	Perc. point change Decid. forest
Whole Caucasus	-1.1 (0.1)***	-0.2 (0.1)*	-0.1 (0.2)	-1.3 (0.2)***
Azerbaijan	-0.2 (0.4)	1.1 (0.5)*	-0.8 (0.8)	-0.1 (0.4)
Georgia	-0.4 (0.3)	-0.1 (0.3)	0.001 (0.4)	-0.7 (0.4)
Russia	-1.4 (0.1)***	-0.04 (0.1)**	-0.003 (0.2)	-1.7 (0.2)***
Armenia	0.7 (0.8)	-	-	-1.1 (0.8)

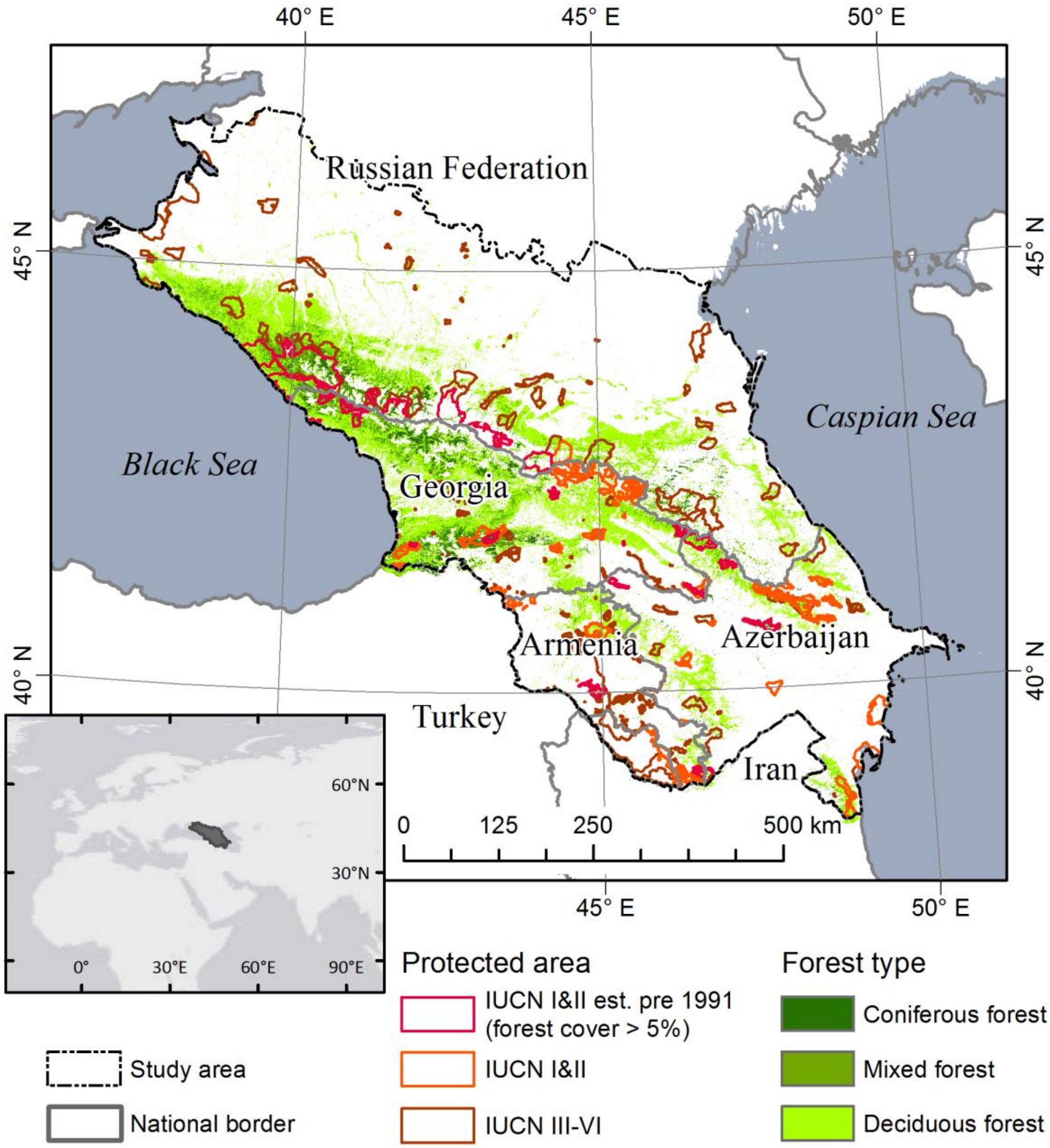


Figure 20: Forest types and terrestrial protected areas (World Database on Protected Areas) in the study area (IUCN I&II: strict nature reserves and national parks, IUCN III-VI: multiple-use protected areas).

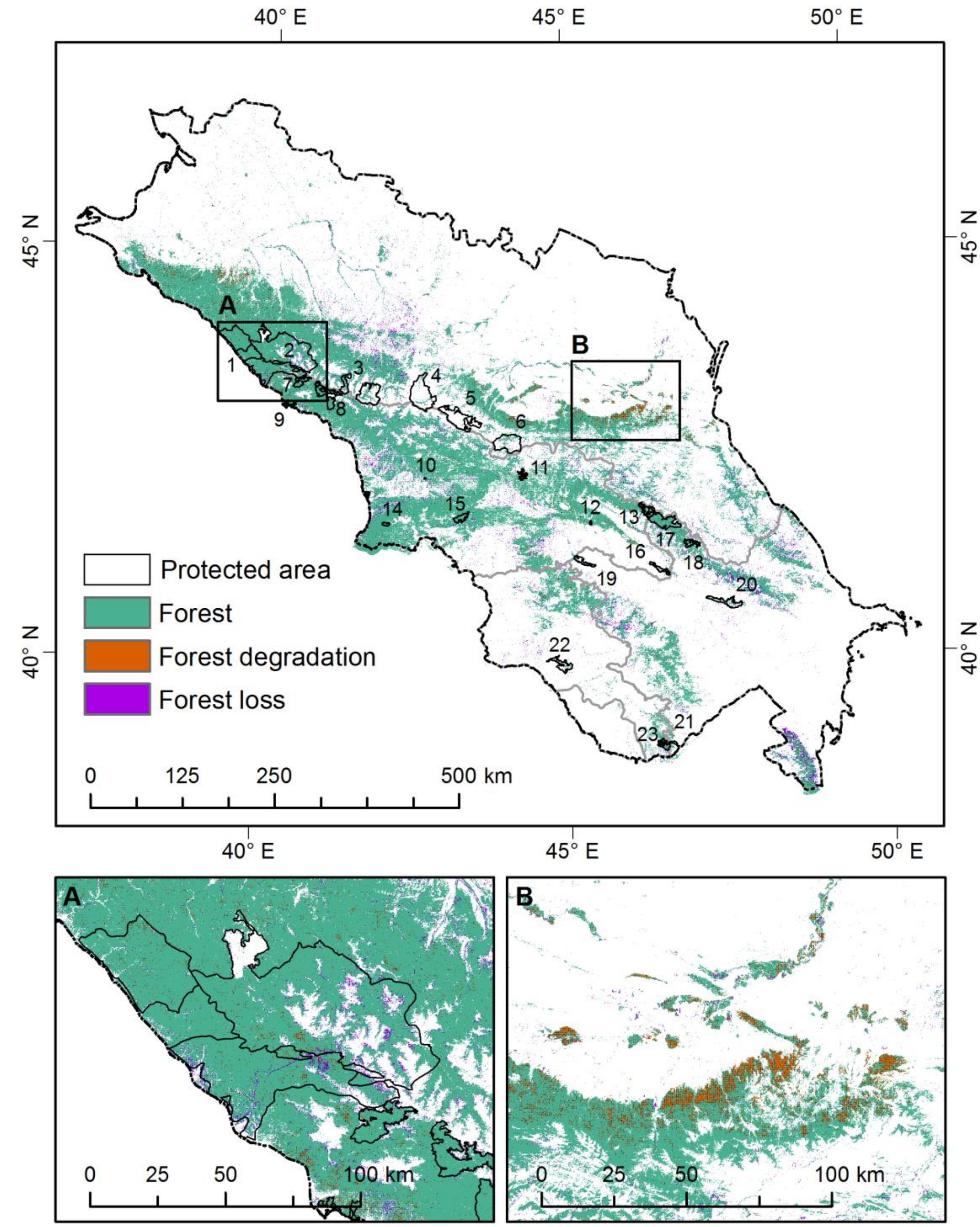


Figure 21: Forest loss (1995-2015) and forest degradation (1988-2018) in the Caucasus with forest depicted in 1987 and protected areas used in this study (numbering of protected areas corresponds with Table A45). Zoom-in to areas with (A) high forest loss in Sochinsky National Park, Russia, and (B) high forest degradation in the south of Chechnya, Russia.

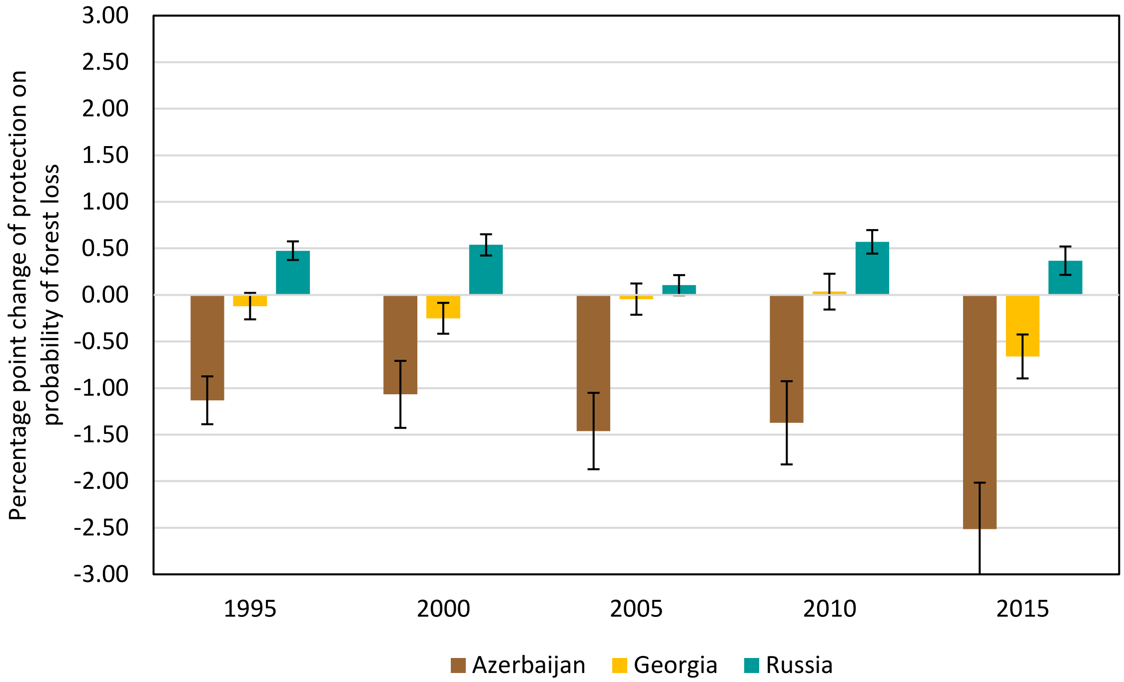


Figure 22: Marginal effects (percentage point change) of strict protection on the probability that a forest pixel will be lost, by country and year with standard errors. Armenia had too few forest loss observations to credibly estimate the effect and is therefore not shown. Negative values indicate that protected areas reduce forest loss.

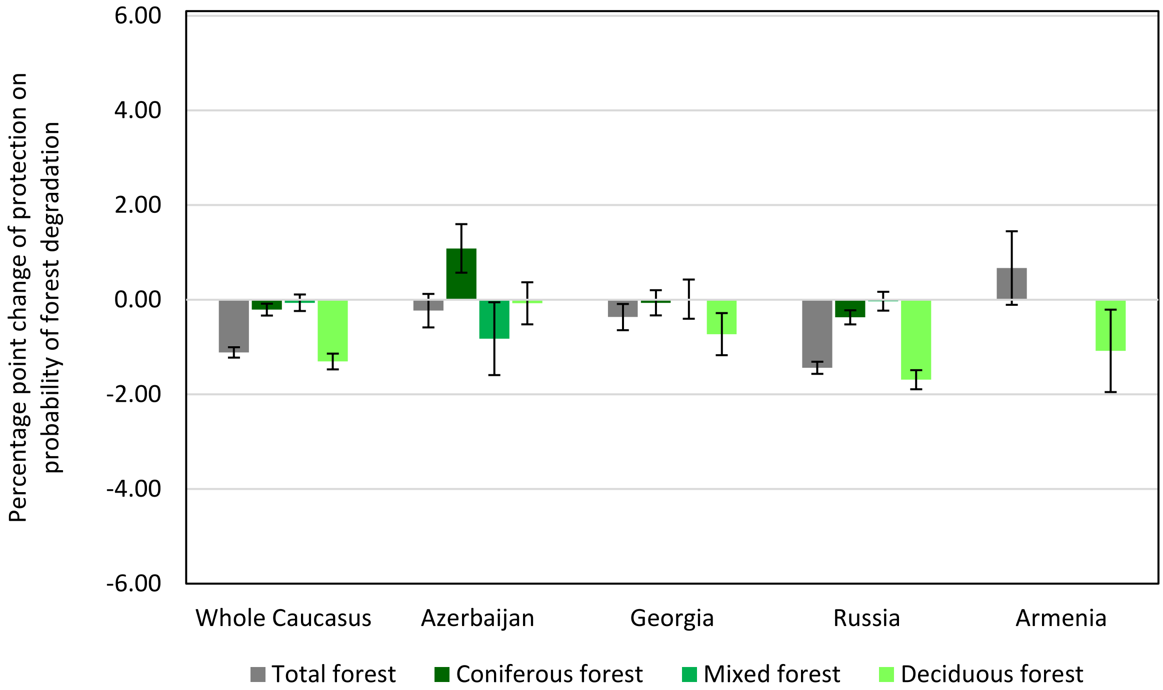


Figure 23: Marginal effects (Percentage point change) of strict protection on the probability of a forest pixel being degraded for total forest, coniferous forest, mixed forest, and deciduous forest, in the whole Caucasus and by country with standard errors. Armenia had too few forest degradation observations in coniferous and mixed forest to credibly estimate the effect and is therefore not shown. Negative values indicate that protected areas reduce forest degradation.

Appendix: Supplementary information

Table A45: List of protected areas (WDPA) included in the study with ICUN categories and year of establishment, forest cover in 1987, percent forest in 1987 based on the total area covered by the protected area, total forest loss in area and percent, and total forest degradation in area and percent.

No.	Name	IUCN Category	Year est.	Country	Forest in 1987 [ha]	Forest in 1987 [%]	Total forest loss [ha]	Total forest loss [%]	Total forest degradation [ha]	Total forest degradation [%]
1	Sochinsky	II	1983	RUS	184568.2	91.5	5475.2	3.0	3218.0	1.7
2	Kavkazsky	Ia	1924	RUS	191745.5	71.5	8204.9	4.3	2762.4	1.4
3	Teberdinsky	Ia	1936	RUS	25713.6	41.1	1613.3	6.3	492.2	1.9
4	Prielbrus'e	II	1986	RUS	9269.6	12.6	696.2	7.5	46.1	0.5
5	Kabardino-Balkarsky	Ia	1976	RUS	2701.4	9.1	138.7	5.1	5.0	0.2
6	Severo-Osetinsky	Ia	1967	RUS	14140.1	23.3	902.7	6.4	126.9	0.9
7	Ritsa	Ia	1930	GEO	15368.8	94.0	226.2	1.5	164.1	1.1
8	Pskhu-Gumista	Ia	1941	GEO	36672.8	94.7	451.5	1.2	274.1	0.7
9	Bichvinta-Miusera	Ia	1965	GEO	3649.2	91.2	20.7	0.6	305.6	8.4
10	Sataplia	Ia	1935	GEO	329.0	99.9	0.0	0.0	24.8	7.5
11	Liakhvi	Ia	1977	GEO	5731.6	87.4	20.2	0.4	59.6	1.0
12	Mariamjvari	Ia	1935	GEO	773.5	75.5	3.9	0.5	13.6	1.8
13	Lagodekhi	Ia	1912	GEO	13596.0	68.8	226.6	1.7	378.4	2.8
14	Kintrishi	Ia	1959	GEO	3061.4	98.5	9.3	0.3	13.0	0.4
15	Borjomi	Ia	1929	GEO	12703.6	96.4	22.4	0.2	188.9	1.5
16	Vashlovani	Ia	1957	GEO	1583.4	15.9	198.6	12.5	13.8	0.9
17	Zagatala State Nature Reserve	Ia	1929	AZE	42834.9	88.3	931.1	2.2	660.5	1.5
18	Ilisu State Nature Reserve	Ia	1987	AZE	9105.4	72.8	214.0	2.4	95.6	1.0
19	Garayazi State Nature Reserve	Ia	1978	AZE	2544.4	20.8	401.0	15.8	2.5	0.1
20	Turyanchay State Nature Reserve	Ia	1958	AZE	6214.1	23.2	606.5	9.8	171.3	2.8
21	Basitchay State Nature Reserve	Ia	1974	AZE	557.8	20.3	22.7	4.1	20.4	3.7
22	Khosrov Forest	Ia	1958	ARM	3007.5	13.2	153.6	5.1	32.1	1.1
23	Shikahogh	Ia	1958	ARM	10001.0	82.2	125.9	1.3	96.8	1.0

Table A46: Probit regression results from propensity score matching model for protected versus unprotected pixels (Country id: 1 - Azerbaijan, 2 – Georgia, 3 – Russia, 4 – Armenia).

Variables	Coef.	Std.Err.	z	P>|z|	[95% Conf. Interval]	
Country_id						
2	-0.67	0.01	-46.37	0.00	-0.70	-0.64
3	0.36	0.01	27.34	0.00	0.33	0.38
4	-0.37	0.03	-14.62	0.00	-0.42	-0.32
ln_elevation	0.22	0.01	35.74	0.00	0.21	0.23
ln_slope	0.62	0.01	75.36	0.00	0.60	0.63
ln_aspect	0.03	0.00	9.43	0.00	0.03	0.04
ln_distance_to_waterways	0.00	0.00	1.54	0.12	0.00	0.01
ln_distance_to_highways	0.00	0.00	0.95	0.34	0.00	0.01
ln_distance_to_settlements	0.00	0.01	0.35	0.73	-0.01	0.01
ln_percent_forest_120m	-0.30	0.03	-9.53	0.00	-0.36	-0.24
ln_percent_forest_1km	0.86	0.02	48.55	0.00	0.83	0.90
_cons	-7.44	0.14	-52.28	0.00	-7.72	-7.16

Table A47: Balance between treated (protected areas) and control for unmatched and matched observation (Country id: 1 - Azerbaijan, 2 – Georgia, 3 – Russia, 4 – Armenia).

Variables	Unmatched Matched	Mean Treated	Control	%bias	%bias reduction
2.country_id	U	0.16	0.42	-59.70	
	M	0.16	0.15	2.00	96.60
3.country_id	U	0.72	0.44	58.10	
	M	0.72	0.74	-4.60	92.10
4.country_id	U	0.02	0.04	-8.90	
	M	0.02	0.02	2.00	77.30
ln_elevation	U	6.91	6.56	40.20	
	M	6.91	6.92	-1.10	97.20
ln_slope	U	3.26	2.84	67.40	
	M	3.26	3.26	-0.30	99.60
ln_aspect	U	4.91	4.78	11.40	
	M	4.91	4.91	0.00	99.80
ln_distance_to_waterways	U	10.01	10.00	1.30	
	M	10.01	10.00	1.20	8.70
ln_distance_to_highways	U	6.38	6.37	0.70	
	M	6.38	6.36	1.30	-76.10
ln_distance_to_settlements	U	10.00	9.99	1.00	
	M	10.00	10.00	0.50	49.00
ln_percent_forest_120m	U	4.58	4.53	27.30	
	M	4.58	4.58	3.80	86.00
ln_percent_forest_1km	U	4.50	4.33	43.60	
	M	4.50	4.48	6.00	86.30

Table A48: Results of logistic regression with random effects on forest loss (Country id: 1 - Azerbaijan, 2 – Georgia, 3 – Russia, 4 – Armenia).

Variables	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
1.PA	-2.97262	0.686719	-4.33	0	-4.31856	-1.62667
year						
2000	1.034246	0.389644	2.65	0.008	0.270557	1.797935
2005	1.508034	0.405348	3.72	0	0.713567	2.302502
2010	1.597747	0.427574	3.74	0	0.759718	2.435776
2015	2.465806	0.406967	6.06	0	1.668165	3.263446
PA#year						
1 2000	1.490434	0.704257	2.12	0.034	0.110117	2.870752
1 2005	1.207158	0.761921	1.58	0.113	-0.28618	2.700496
1 2010	1.435555	0.781313	1.84	0.066	-0.09579	2.966901
1 2015	0.664906	0.782462	0.85	0.395	-0.86869	2.198503
country_id						
2	-0.8581	0.531195	-1.62	0.106	-1.89922	0.183028
3	-0.18371	0.389928	-0.47	0.638	-0.94796	0.580533
4	-0.78924	1.020918	-0.77	0.439	-2.7902	1.211724
PA#country_id						
1 2	2.452303	0.929352	2.64	0.008	0.630808	4.273798
1 3	3.91921	0.715984	5.47	0	2.515907	5.322513
1 4	0.948322	1.50066	0.63	0.527	-1.99292	3.889562
year#country_id						
2000 2	-0.52445	0.593597	-0.88	0.377	-1.68788	0.638975
2000 3	-0.85283	0.428998	-1.99	0.047	-1.69365	-0.01201
2000 4	0.016381	1.081562	0.02	0.988	-2.10344	2.136203
2005 2	-1.65577	0.697995	-2.37	0.018	-3.02382	-0.28773
2005 3	-1.58793	0.454401	-3.49	0	-2.47854	-0.69732
2005 4	0	(empty)				
2010 2	-1.36676	0.691824	-1.98	0.048	-2.72271	-0.01081
2010 3	-1.45988	0.473953	-3.08	0.002	-2.38881	-0.53095
2010 4	-1.87514	1.434465	-1.31	0.191	-4.68664	0.93636
2015 2	-0.74674	0.598954	-1.25	0.212	-1.92067	0.42719
2015 3	-0.98385	0.438996	-2.24	0.025	-1.84427	-0.12344
2015 4	-1.27047	1.153726	-1.1	0.271	-3.53173	0.990791
PA#year#country_id						
0 2005 4	0	(empty)				
1 2000 2	-1.90783	1.019963	-1.87	0.061	-3.90693	0.091257
1 2000 3	-1.46404	0.743286	-1.97	0.049	-2.92085	-0.00722
1 2000 4	-2.25371	1.602889	-1.41	0.16	-5.39531	0.887895
1 2005 2	-0.87912	1.137792	-0.77	0.44	-3.10915	1.350914
1 2005 3	-1.89508	0.818267	-2.32	0.021	-3.49885	-0.2913
1 2005 4	0	(empty)				

continued

1 2010 2	-0.79499	1.114493	-0.71	0.476	-2.97935	1.389378
1 2010 3	-1.34544	0.827058	-1.63	0.104	-2.96644	0.275564
1 2010 4	-1.66246	2.069651	-0.8	0.422	-5.7189	2.393986
1 2015 2	-1.69095	1.098499	-1.54	0.124	-3.84397	0.462071
1 2015 3	-1.19754	0.816883	-1.47	0.143	-2.7986	0.403524
1 2015 4	-2.27829	1.89422	-1.2	0.229	-5.99089	1.434311
ln_elevation	0.38832	0.078541	4.94	0	0.234383	0.542256
ln_slope	-0.84662	0.105391	-8.03	0	-1.05319	-0.64006
ln_aspect	0.261158	0.057266	4.56	0	0.148919	0.373397
ln_distance_to_waterways	-0.00627	0.039239	-0.16	0.873	-0.08318	0.070632
ln_distance_to_highways	-0.02195	0.035329	-0.62	0.534	-0.0912	0.047292
ln_distance_to_settlements	-0.02127	0.075702	-0.28	0.779	-0.16964	0.127104
ln_percent_forest_120m	-6.94631	0.256298	-27.1	0	-7.44864	-6.44397
ln_percent_forest_1km	-3.30486	0.160615	-20.58	0	-3.61966	-2.99006
_cons	34.52012	1.438331	24	0	31.70104	37.33919
/lnsig2u	2.795202	0.03328			2.729975	2.860429
sigma_u	4.045483	0.067316			3.915675	4.179595
rho	0.832626	0.004638			0.823338	0.84152

Table A49: Results of linear panel regression with random effects on forest degradation for total forest (Country id: 1 - Azerbaijan, 2 – Georgia, 3 – Russia, 4 – Armenia).

Variables	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
1.PA	-0.00123	0.005912	-0.21	0.835	-0.01282	0.010356
year						
1989	-0.00206	0.005883	-0.35	0.726	-0.01359	0.009471
1990	0.112249	0.005905	19.01	0	0.100676	0.123822
1991	0.031314	0.005903	5.3	0	0.019744	0.042884
1992	0.020758	0.00587	3.54	0	0.009253	0.032263
1993	0.004715	0.005905	0.8	0.425	-0.00686	0.016288
1994	0.011521	0.005916	1.95	0.051	-7.3E-05	0.023116
1995	0.017148	0.00587	2.92	0.003	0.005643	0.028652
1996	0.018288	0.005885	3.11	0.002	0.006754	0.029822
1997	0.020215	0.005862	3.45	0.001	0.008726	0.031704
1998	0.000999	0.005916	0.17	0.866	-0.0106	0.012594
1999	0.027936	0.005905	4.73	0	0.016364	0.039509
2000	0.001593	0.005944	0.27	0.789	-0.01006	0.013242
2001	0.002476	0.005895	0.42	0.674	-0.00908	0.014029
2002	0.007344	0.005862	1.25	0.21	-0.00415	0.018833
2003	0.058023	0.005874	9.88	0	0.04651	0.069537
2004	-0.00477	0.005865	-0.81	0.416	-0.01627	0.006722
2005	-0.0074	0.00587	-1.26	0.208	-0.0189	0.004106
2006	-0.00699	0.005868	-1.19	0.234	-0.01849	0.004512
2007	-0.00759	0.005876	-1.29	0.197	-0.0191	0.003931
2008	0.027269	0.005905	4.62	0	0.015696	0.038843
2009	-0.00028	0.005867	-0.05	0.961	-0.01178	0.011215
2010	-0.00276	0.005925	-0.47	0.642	-0.01437	0.008854
2011	0.004468	0.005861	0.76	0.446	-0.00702	0.015954
2012	0.007139	0.005941	1.2	0.23	-0.00451	0.018784
2013	0.024741	0.005886	4.2	0	0.013205	0.036277
2014	0.020206	0.005925	3.41	0.001	0.008593	0.031819
2015	0.008457	0.005901	1.43	0.152	-0.00311	0.020022
2016	-0.00365	0.005882	-0.62	0.534	-0.01518	0.007875
2017	-0.0109	0.006006	-1.82	0.069	-0.02267	0.000869
2018	-0.01092	0.005942	-1.84	0.066	-0.02256	0.000726
PA#year						
1 1989	-0.00165	0.008271	-0.2	0.842	-0.01786	0.014566
1 1990	-0.03838	0.008271	-4.64	0	-0.05459	-0.02217
1 1991	-0.03233	0.008271	-3.91	0	-0.04854	-0.01612
1 1992	-0.01826	0.008271	-2.21	0.027	-0.03447	-0.00205
1 1993	-0.00547	0.008271	-0.66	0.508	-0.02168	0.010738
1 1994	-0.01275	0.008271	-1.54	0.123	-0.02896	0.003466
1 1995	-0.01658	0.008271	-2	0.045	-0.03279	-0.00037
1 1996	-0.0091	0.008271	-1.1	0.271	-0.02532	0.007107
1 1997	-0.02173	0.008271	-2.63	0.009	-0.03794	-0.00552
1 1998	-0.00546	0.008271	-0.66	0.51	-0.02167	0.010756

continued						
1 1999	0.011226	0.008271	1.36	0.175	-0.00499	0.027437
1 2000	0.009523	0.008271	1.15	0.25	-0.00669	0.025734
1 2001	0.011889	0.008271	1.44	0.151	-0.00432	0.0281
1 2002	-0.00319	0.008271	-0.39	0.7	-0.0194	0.013019
1 2003	-0.04461	0.008271	-5.39	0	-0.06082	-0.0284
1 2004	0.014199	0.008271	1.72	0.086	-0.00201	0.03041
1 2005	0.002536	0.008271	0.31	0.759	-0.01368	0.018747
1 2006	0.000791	0.008271	0.1	0.924	-0.01542	0.017002
1 2007	-0.00017	0.008271	-0.02	0.984	-0.01638	0.016043
1 2008	-0.01775	0.008271	-2.15	0.032	-0.03397	-0.00154
1 2009	-0.00222	0.008271	-0.27	0.789	-0.01843	0.013996
1 2010	0.016179	0.008271	1.96	0.05	-3.3E-05	0.03239
1 2011	0.005228	0.008271	0.63	0.527	-0.01098	0.021439
1 2012	0.003627	0.008271	0.44	0.661	-0.01258	0.019838
1 2013	0.045238	0.008271	5.47	0	0.029026	0.061449
1 2014	0.003963	0.008271	0.48	0.632	-0.01225	0.020174
1 2015	-0.00034	0.008271	-0.04	0.967	-0.01655	0.015868
1 2016	-0.00055	0.008271	-0.07	0.947	-0.01676	0.015665
1 2017	-0.00066	0.008271	-0.08	0.936	-0.01687	0.015549
1 2018	-0.0003	0.008271	-0.04	0.971	-0.01651	0.015911
country_id						
2	-0.01169	0.002592	-4.51	0	-0.01677	-0.00661
3	-0.00382	0.002588	-1.47	0.14	-0.00889	0.001257
4	-0.00832	0.003663	-2.27	0.023	-0.0155	-0.00114
ln_elevation	0.000797	0.001525	0.52	0.601	-0.00219	0.003787
ln_slope	-0.00465	0.001477	-3.14	0.002	-0.00754	-0.00175
ln_aspect	-0.00354	0.000658	-5.38	0	-0.00483	-0.00225
ln_distance_to_waterways	0.000735	0.000482	1.53	0.127	-0.00021	0.001679
ln_distance_to_highways	-0.00104	0.000451	-2.31	0.021	-0.00193	-0.00016
ln_distance_to_settlements	-0.00124	0.000964	-1.29	0.197	-0.00313	0.000645
lnmax_temp	0.022315	0.003828	5.83	0	0.014813	0.029818
lnprecip_acc	-0.00998	0.002808	-3.55	0	-0.01549	-0.00448
ln_percent_forest_120m	0.013677	0.003954	3.46	0.001	0.005927	0.021428
ln_percent_forest_1km	0.007213	0.00248	2.91	0.004	0.002353	0.012073
_cons	-0.10012	0.033605	-2.98	0.003	-0.16598	-0.03425
Observations	724,686					
Number of grid_pt_id	23,377					

Table A50: Results of linear panel regression with random effects on forest degradation for forest types (Country id: 1 - Azerbaijan, 2 – Georgia, 3 – Russia, 4 – Armenia).

Variables	Coniferous forest	Mixed forest	Deciduous forest
1.PA	-0.00212	-0.00169	0.00942
	(0.0224)	(0.0342)	(0.0187)
1989.year	7.42e-11	-1.26e-10	0.00378
	(0.0209)	(0.0343)	(0.0186)
1990.year	7.42e-11	0.147***	0.347***
	(0.0209)	(0.0343)	(0.0186)
1991.year	7.42e-11	0.0154	0.0147
	(0.0209)	(0.0343)	(0.0186)
1992.year	7.42e-11	0.0154	0.0123
	(0.0209)	(0.0343)	(0.0186)
1993.year	7.42e-11	0.0154	0.0123
	(0.0209)	(0.0343)	(0.0186)
1994.year	7.42e-11	0.0154	0.00330
	(0.0209)	(0.0343)	(0.0186)
1995.year	7.42e-11	0.0172	0.00330
	(0.0209)	(0.0343)	(0.0186)
1996.year	0.0768***	0.157***	0.143***
	(0.0209)	(0.0343)	(0.0186)
1997.year	7.42e-11	0.0232	0.0382**
	(0.0209)	(0.0343)	(0.0186)
1998.year	7.42e-11	0.00770	0.0229
	(0.0209)	(0.0343)	(0.0186)
1999.year	7.42e-11	0.00770	0.0278
	(0.0209)	(0.0343)	(0.0186)
2000.year	7.42e-11	0.00598	0.0118
	(0.0209)	(0.0343)	(0.0186)
2001.year	7.42e-11	-1.26e-10	0.0169
	(0.0209)	(0.0343)	(0.0186)
2002.year	7.42e-11	0.0369	0.00152
	(0.0209)	(0.0343)	(0.0186)
2003.year	7.42e-11	0.0138	0.147***
	(0.0209)	(0.0343)	(0.0186)
2004.year	7.42e-11	0.0402	-0.00595
	(0.0209)	(0.0343)	(0.0186)
2005.year	0.00880	-0.00737	-0.00203
	(0.0209)	(0.0343)	(0.0186)
2006.year	0.00880	0.0253	0.00174
	(0.0209)	(0.0343)	(0.0186)
2007.year	0.00880	-0.00737	-0.000246
	(0.0209)	(0.0343)	(0.0186)
2008.year	7.42e-11	-0.00737	-0.00417
	(0.0209)	(0.0343)	(0.0186)

continued			
2009.year	7.42e-11	-0.00737	0.000830
	(0.0209)	(0.0343)	(0.0186)
2010.year	7.42e-11	-0.00737	0.000830
	(0.0209)	(0.0343)	(0.0186)
2011.year	7.42e-11	0.000692	0.00803
	(0.0209)	(0.0343)	(0.0186)
2012.year	7.42e-11	0.0300	0.00803
	(0.0209)	(0.0343)	(0.0186)
2013.year	7.42e-11	0.0681**	0.0882***
	(0.0209)	(0.0343)	(0.0186)
2014.year	7.42e-11	0.0152	0.0565***
	(0.0209)	(0.0343)	(0.0186)
2015.year	0.0186	0.0452	0.0511***
	(0.0209)	(0.0343)	(0.0186)
2016.year	0.0186	-0.00737	0.00843
	(0.0209)	(0.0343)	(0.0186)
2017.year	0.0186	-0.00737	-0.00191
	(0.0209)	(0.0343)	(0.0186)
2018.year	0.0186	-0.00737	-0.00368
	(0.0209)	(0.0343)	(0.0186)
1.PA#1989.year	-1.21e-10	1.56e-10	-0.00378
	(0.0313)	(0.0479)	(0.0260)
1.PA#1990.year	0.0667**	0.00658	0.000191
	(0.0313)	(0.0479)	(0.0260)
1.PA#1991.year	-1.21e-10	-0.000262	8.33e-05
	(0.0313)	(0.0479)	(0.0260)
1.PA#1992.year	-1.21e-10	-0.000262	0.0107
	(0.0313)	(0.0479)	(0.0260)
1.PA#1993.year	-1.21e-10	-0.0154	-0.00296
	(0.0313)	(0.0479)	(0.0260)
1.PA#1994.year	-1.21e-10	-0.0154	-0.00365
	(0.0313)	(0.0479)	(0.0260)
1.PA#1995.year	-1.21e-10	-0.0172	-0.00226
	(0.0313)	(0.0479)	(0.0260)
1.PA#1996.year	0.175***	-0.134***	-0.117***
	(0.0313)	(0.0479)	(0.0260)
1.PA#1997.year	0.0673**	-0.0188	-0.0356
	(0.0313)	(0.0479)	(0.0260)
1.PA#1998.year	0.0673**	-0.00336	-0.0218
	(0.0313)	(0.0479)	(0.0260)
1.PA#1999.year	0.0673**	0.0289	0.117***
	(0.0313)	(0.0479)	(0.0260)
1.PA#2000.year	0.0592*	0.00573	0.0420
	(0.0313)	(0.0479)	(0.0260)
1.PA#2001.year	-1.21e-10	0.0117	0.0369

continued			
	(0.0313)	(0.0479)	(0.0260)
1.PA#2002.year	-1.21e-10	-0.0326	0.00506
	(0.0313)	(0.0479)	(0.0260)
1.PA#2003.year	-1.21e-10	-0.00944	-0.0342
	(0.0313)	(0.0479)	(0.0260)
1.PA#2004.year	-1.21e-10	-0.0445	-0.00548
	(0.0313)	(0.0479)	(0.0260)
1.PA#2005.year	-0.00880	0.0131	-0.0109
	(0.0313)	(0.0479)	(0.0260)
1.PA#2006.year	-0.00880	-0.0196	-0.0172
	(0.0313)	(0.0479)	(0.0260)
1.PA#2007.year	-0.00880	0.0131	-0.0152
	(0.0313)	(0.0479)	(0.0260)
1.PA#2008.year	-1.21e-10	0.00311	-0.0128
	(0.0313)	(0.0479)	(0.0260)
1.PA#2009.year	-1.21e-10	0.00311	-0.0178
	(0.0313)	(0.0479)	(0.0260)
1.PA#2010.year	-1.21e-10	0.0261	-0.0158
	(0.0313)	(0.0479)	(0.0260)
1.PA#2011.year	-1.21e-10	0.0309	-0.0187
	(0.0313)	(0.0479)	(0.0260)
1.PA#2012.year	-1.21e-10	0.0293	-0.00722
	(0.0313)	(0.0479)	(0.0260)
1.PA#2013.year	-1.21e-10	-0.0365	-0.0207
	(0.0313)	(0.0479)	(0.0260)
1.PA#2014.year	-1.21e-10	-0.00139	-0.0610**
	(0.0313)	(0.0479)	(0.0260)
1.PA#2015.year	-0.0186	-0.0458	-0.0522**
	(0.0313)	(0.0479)	(0.0260)
1.PA#2016.year	-0.0186	0.00678	-0.0245
	(0.0313)	(0.0479)	(0.0260)
1.PA#2017.year	-0.0186	0.00678	-0.0141
	(0.0313)	(0.0479)	(0.0260)
1.PA#2018.year	-0.0186	0.00678	-0.0124
	(0.0313)	(0.0479)	(0.0260)
2.country_id	-0.000238	-0.00779	-0.00228
	(0.0171)	(0.0279)	(0.0189)
3.country_id	0.00352	-0.00313	0.000174
	(0.0157)	(0.0253)	(0.0146)
4.country_id	0.000856	5.40e-06	0.0200
	(0.130)	(0.213)	(0.0300)
1.PA#2.country_id	0.00195	0.00170	-0.0154
	(0.0253)	(0.0388)	(0.0264)
1.PA#3.country_id	-0.000544	-0.00613	-0.0183
	(0.0233)	(0.0353)	(0.0205)

continued			
1.PA#4.country_id	0.00191	0.0107	0.0450
	(0.160)	(0.368)	(0.0410)
1989.year#2.country_id	-7.56e-11	1.28e-10	-0.00111
	(0.0240)	(0.0391)	(0.0263)
1989.year#3.country_id	0.000313	0.00140	0.00488
	(0.0219)	(0.0354)	(0.0204)
1989.year#4.country_id	-7.42e-11	1.26e-10	-0.00378
	(0.182)	(0.299)	(0.0419)
1990.year#2.country_id	-7.56e-11	-0.147***	-0.338***
	(0.0240)	(0.0391)	(0.0263)
1990.year#3.country_id	0.0153	-0.123***	-0.237***
	(0.0219)	(0.0354)	(0.0204)
1990.year#4.country_id	-7.42e-11	-0.147	-0.347***
	(0.182)	(0.299)	(0.0419)
1991.year#2.country_id	-7.56e-11	-0.00464	-0.0162
	(0.0240)	(0.0391)	(0.0263)
1991.year#3.country_id	0.00195	0.0141	0.0519**
	(0.0219)	(0.0354)	(0.0204)
1991.year#4.country_id	-7.42e-11	-0.0154	0.0561
	(0.182)	(0.299)	(0.0419)
1992.year#2.country_id	-7.56e-11	-0.00345	-0.00763
	(0.0240)	(0.0391)	(0.0263)
1992.year#3.country_id	0.00195	-0.0144	0.0578***
	(0.0219)	(0.0354)	(0.0204)
1992.year#4.country_id	-7.42e-11	-0.0154	-0.0310
	(0.182)	(0.299)	(0.0419)
1993.year#2.country_id	-7.56e-11	0.0146	-0.0179
	(0.0240)	(0.0391)	(0.0263)
1993.year#3.country_id	0.0156	-0.0155	0.00385
	(0.0219)	(0.0354)	(0.0204)
1993.year#4.country_id	-7.42e-11	-0.0154	-0.0255
	(0.182)	(0.299)	(0.0419)
1994.year#2.country_id	0.00715	-0.0107	0.00952
	(0.0240)	(0.0391)	(0.0263)
1994.year#3.country_id	0.0300	-0.00138	0.0172
	(0.0219)	(0.0354)	(0.0204)
1994.year#4.country_id	-7.42e-11	-0.0154	0.00886
	(0.182)	(0.299)	(0.0419)
1995.year#2.country_id	-7.56e-11	-0.00203	-0.00285
	(0.0240)	(0.0391)	(0.0263)
1995.year#3.country_id	0.0152	0.0191	0.0249
	(0.0219)	(0.0354)	(0.0204)
1995.year#4.country_id	-7.42e-11	-0.0172	-0.0165
	(0.182)	(0.299)	(0.0419)
1996.year#2.country_id	-0.0768***	-0.157***	-0.111***

continued			
	(0.0240)	(0.0391)	(0.0263)
1996.year#3.country_id	-0.0685***	-0.160***	-0.0870***
	(0.0219)	(0.0354)	(0.0204)
1996.year#4.country_id	-0.0768	-0.157	-0.0839**
	(0.182)	(0.299)	(0.0419)
1997.year#2.country_id	-7.56e-11	-0.0165	-0.0336
	(0.0240)	(0.0391)	(0.0263)
1997.year#3.country_id	0.00600	-0.0157	0.00514
	(0.0219)	(0.0354)	(0.0204)
1997.year#4.country_id	-7.42e-11	-0.0232	0.0630
	(0.182)	(0.299)	(0.0419)
1998.year#2.country_id	-7.56e-11	-0.00770	0.00572
	(0.0240)	(0.0391)	(0.0263)
1998.year#3.country_id	0.00265	-0.00638	0.00499
	(0.0219)	(0.0354)	(0.0204)
1998.year#4.country_id	-7.42e-11	-0.00770	0.0693*
	(0.182)	(0.299)	(0.0419)
1999.year#2.country_id	0.0227	0.0425	0.0150
	(0.0240)	(0.0391)	(0.0263)
1999.year#3.country_id	0.0239	0.100***	0.119***
	(0.0219)	(0.0354)	(0.0204)
1999.year#4.country_id	-7.42e-11	-0.00770	0.0630
	(0.182)	(0.299)	(0.0419)
2000.year#2.country_id	-7.56e-11	-0.00310	-0.00417
	(0.0240)	(0.0391)	(0.0263)
2000.year#3.country_id	0.00599	-0.00400	0.0880***
	(0.0219)	(0.0354)	(0.0204)
2000.year#4.country_id	-7.42e-11	-0.00598	0.0540
	(0.182)	(0.299)	(0.0419)
2001.year#2.country_id	-7.56e-11	0.0167	-0.00626
	(0.0240)	(0.0391)	(0.0263)
2001.year#3.country_id	0.0139	0.00469	0.0776***
	(0.0219)	(0.0354)	(0.0204)
2001.year#4.country_id	-7.42e-11	1.26e-10	0.0269
	(0.182)	(0.299)	(0.0419)
2002.year#2.country_id	-7.56e-11	-0.0265	0.00463
	(0.0240)	(0.0391)	(0.0263)
2002.year#3.country_id	0.00689	-0.0295	0.0139
	(0.0219)	(0.0354)	(0.0204)
2002.year#4.country_id	-7.42e-11	-0.0369	0.0196
	(0.182)	(0.299)	(0.0419)
2003.year#2.country_id	0.0289	0.0406	0.0973***
	(0.0240)	(0.0391)	(0.0263)
2003.year#3.country_id	0.0195	-0.0171	-0.145***
	(0.0219)	(0.0354)	(0.0204)

continued			
2003.year#4.country_id	-7.42e-11	-0.0138	-0.0930**
	(0.182)	(0.299)	(0.0419)
2004.year#2.country_id	-7.56e-11	-0.0402	0.0172
	(0.0240)	(0.0391)	(0.0263)
2004.year#3.country_id	-0.00152	-0.0451	-0.00281
	(0.0219)	(0.0354)	(0.0204)
2004.year#4.country_id	-7.42e-11	-0.0402	-0.0194
	(0.182)	(0.299)	(0.0419)
2005.year#2.country_id	-0.00880	0.00737	0.000644
	(0.0240)	(0.0391)	(0.0263)
2005.year#3.country_id	-0.0101	0.00168	-0.00775
	(0.0219)	(0.0354)	(0.0204)
2005.year#4.country_id	-0.00880	0.00737	-0.0233
	(0.182)	(0.299)	(0.0419)
2006.year#2.country_id	-0.00880	-0.0195	0.00547
	(0.0240)	(0.0391)	(0.0263)
2006.year#3.country_id	-0.0111	-0.0264	-0.00878
	(0.0219)	(0.0354)	(0.0204)
2006.year#4.country_id	-0.00880	-0.0253	-0.0271
	(0.182)	(0.299)	(0.0419)
2007.year#2.country_id	-0.00880	0.0131	-0.00471
	(0.0240)	(0.0391)	(0.0263)
2007.year#3.country_id	-0.00983	0.00221	-0.00499
	(0.0219)	(0.0354)	(0.0204)
2007.year#4.country_id	-0.00880	0.00737	-0.0251
	(0.182)	(0.299)	(0.0419)
2008.year#2.country_id	0.0163	0.0225	0.0514*
	(0.0240)	(0.0391)	(0.0263)
2008.year#3.country_id	0.00226	0.144***	0.0721***
	(0.0219)	(0.0354)	(0.0204)
2008.year#4.country_id	-7.42e-11	0.00737	-0.0212
	(0.182)	(0.299)	(0.0419)
2009.year#2.country_id	-7.56e-11	0.00877	-0.00255
	(0.0240)	(0.0391)	(0.0263)
2009.year#3.country_id	-2.48e-06	0.0146	0.00508
	(0.0219)	(0.0354)	(0.0204)
2009.year#4.country_id	-7.42e-11	0.00737	-0.0262
	(0.182)	(0.299)	(0.0419)
2010.year#2.country_id	-7.56e-11	0.00877	-0.00152
	(0.0240)	(0.0391)	(0.0263)
2010.year#3.country_id	0.0135	0.0112	0.00333
	(0.0219)	(0.0354)	(0.0204)
2010.year#4.country_id	-7.42e-11	0.00737	-0.0262
	(0.182)	(0.299)	(0.0419)
2011.year#2.country_id	0.00328	0.00697	-0.00498

continued			
	(0.0240)	(0.0391)	(0.0263)
2011.year#3.country_id	0.00365	-0.00581	-0.00573
	(0.0219)	(0.0354)	(0.0204)
2011.year#4.country_id	-7.42e-11	-0.000692	-0.0334
	(0.182)	(0.299)	(0.0419)
2012.year#2.country_id	0.00550	0.00830	0.00626
	(0.0240)	(0.0391)	(0.0263)
2012.year#3.country_id	0.00553	-0.0357	0.00492
	(0.0219)	(0.0354)	(0.0204)
2012.year#4.country_id	-7.42e-11	-0.0300	-0.0179
	(0.182)	(0.299)	(0.0419)
2013.year#2.country_id	0.0152	-0.0403	-0.0353
	(0.0240)	(0.0391)	(0.0263)
2013.year#3.country_id	0.0142	-0.0546	-0.0653***
	(0.0219)	(0.0354)	(0.0204)
2013.year#4.country_id	-7.42e-11	-0.0681	-0.0724*
	(0.182)	(0.299)	(0.0419)
2014.year#2.country_id	0.00550	-0.000736	-0.0291
	(0.0240)	(0.0391)	(0.0263)
2014.year#3.country_id	0.00417	0.0223	-0.0282
	(0.0219)	(0.0354)	(0.0204)
2014.year#4.country_id	-7.42e-11	-0.0152	-0.0147
	(0.182)	(0.299)	(0.0419)
2015.year#2.country_id	0.000714	-0.0308	-0.0328
	(0.0240)	(0.0391)	(0.0263)
2015.year#3.country_id	-0.0197	-0.0328	-0.0494**
	(0.0219)	(0.0354)	(0.0204)
2015.year#4.country_id	-0.0186	-0.0452	-0.0476
	(0.182)	(0.299)	(0.0419)
2016.year#2.country_id	-0.0186	0.0147	-0.00105
	(0.0240)	(0.0391)	(0.0263)
2016.year#3.country_id	-0.0144	0.0103	-0.00973
	(0.0219)	(0.0354)	(0.0204)
2016.year#4.country_id	-0.0186	0.00737	-0.0305
	(0.182)	(0.299)	(0.0419)
2017.year#2.country_id	-0.0186	0.0147	0.000407
	(0.0240)	(0.0391)	(0.0263)
2017.year#3.country_id	-0.0144	0.00498	-0.00790
	(0.0219)	(0.0354)	(0.0204)
2017.year#4.country_id	-0.0186	0.00737	-0.0235
	(0.182)	(0.299)	(0.0419)
2018.year#2.country_id	-0.0186	0.0147	0.00217
	(0.0240)	(0.0391)	(0.0263)
2018.year#3.country_id	-0.0144	0.00447	-0.00658
	(0.0219)	(0.0354)	(0.0204)

continued			
2018.year#4.country_id	-0.0186	0.00737	-0.0217
	(0.182)	(0.299)	(0.0419)
1.PA#1989.year#2.country_id	1.23e-10	-1.57e-10	0.00239
	(0.0354)	(0.0544)	(0.0368)
1.PA#1989.year#3.country_id	-0.000313	-0.00140	-0.00440
	(0.0326)	(0.0494)	(0.0286)
1.PA#1989.year#4.country_id	1.21e-10	-1.56e-10	0.00378
	(0.224)	(0.516)	(0.0573)
1.PA#1990.year#2.country_id	-0.0667*	-0.00658	-0.00461
	(0.0354)	(0.0544)	(0.0368)
1.PA#1990.year#3.country_id	-0.0820**	-0.0160	-0.0586**
	(0.0326)	(0.0494)	(0.0286)
1.PA#1990.year#4.country_id	-0.0667	-0.00658	0.211***
	(0.224)	(0.516)	(0.0573)
1.PA#1991.year#2.country_id	1.23e-10	-0.0105	0.00269
	(0.0354)	(0.0544)	(0.0368)
1.PA#1991.year#3.country_id	-0.00195	-0.00834	-0.0324
	(0.0326)	(0.0494)	(0.0286)
1.PA#1991.year#4.country_id	1.21e-10	0.000262	-0.0874
	(0.224)	(0.516)	(0.0573)
1.PA#1992.year#2.country_id	1.23e-10	-0.0117	-0.0140
	(0.0354)	(0.0544)	(0.0368)
1.PA#1992.year#3.country_id	-0.00235	0.00470	-0.0651**
	(0.0326)	(0.0494)	(0.0286)
1.PA#1992.year#4.country_id	1.21e-10	0.000262	-0.0662
	(0.224)	(0.516)	(0.0573)
1.PA#1993.year#2.country_id	1.23e-10	-0.00920	0.00864
	(0.0354)	(0.0544)	(0.0368)
1.PA#1993.year#3.country_id	-0.00572	0.0195	-0.0123
	(0.0326)	(0.0494)	(0.0286)
1.PA#1993.year#4.country_id	1.21e-10	0.0154	-0.0580
	(0.224)	(0.516)	(0.0573)
1.PA#1994.year#2.country_id	-0.00715	0.0213	-0.00917
	(0.0354)	(0.0544)	(0.0368)
1.PA#1994.year#3.country_id	-0.00148	0.00657	-0.0142
	(0.0326)	(0.0494)	(0.0286)
1.PA#1994.year#4.country_id	1.21e-10	0.0154	-0.0859
	(0.224)	(0.516)	(0.0573)
1.PA#1995.year#2.country_id	1.23e-10	0.0260	0.00182
	(0.0354)	(0.0544)	(0.0368)
1.PA#1995.year#3.country_id	-0.00526	0.0578	0.00126
	(0.0326)	(0.0494)	(0.0286)
1.PA#1995.year#4.country_id	1.21e-10	0.0172	-0.0619
	(0.224)	(0.516)	(0.0573)
1.PA#1996.year#2.country_id	-0.132***	0.134**	0.100***

continued			
	(0.0354)	(0.0544)	(0.0368)
1.PA#1996.year#3.country_id	-0.183***	0.139***	0.0607**
	(0.0326)	(0.0494)	(0.0286)
1.PA#1996.year#4.country_id	-0.175	0.134	-0.0192
	(0.224)	(0.516)	(0.0573)
1.PA#1997.year#2.country_id	-0.0673*	0.0122	0.0310
	(0.0354)	(0.0544)	(0.0368)
1.PA#1997.year#3.country_id	-0.0737**	0.0158	-0.00230
	(0.0326)	(0.0494)	(0.0286)
1.PA#1997.year#4.country_id	-0.0673	0.0188	-0.131**
	(0.224)	(0.516)	(0.0573)
1.PA#1998.year#2.country_id	-0.0673*	0.00336	-0.00688
	(0.0354)	(0.0544)	(0.0368)
1.PA#1998.year#3.country_id	-0.0678**	0.00651	-0.000525
	(0.0326)	(0.0494)	(0.0286)
1.PA#1998.year#4.country_id	-0.0673	0.00336	-0.125**
	(0.224)	(0.516)	(0.0573)
1.PA#1999.year#2.country_id	-0.0899**	-0.0266	-0.0629*
	(0.0354)	(0.0544)	(0.0368)
1.PA#1999.year#3.country_id	-0.0618*	-0.0803	-0.237***
	(0.0326)	(0.0494)	(0.0286)
1.PA#1999.year#4.country_id	0.694***	-0.0289	-0.245***
	(0.224)	(0.516)	(0.0573)
1.PA#2000.year#2.country_id	-0.0592*	-0.00861	0.00683
	(0.0354)	(0.0544)	(0.0368)
1.PA#2000.year#3.country_id	-0.0523	-0.00785	-0.143***
	(0.0326)	(0.0494)	(0.0286)
1.PA#2000.year#4.country_id	-0.0592	-0.00573	-0.137**
	(0.224)	(0.516)	(0.0573)
1.PA#2001.year#2.country_id	1.23e-10	-0.0284	0.00988
	(0.0354)	(0.0544)	(0.0368)
1.PA#2001.year#3.country_id	-0.0106	-0.0110	-0.117***
	(0.0326)	(0.0494)	(0.0286)
1.PA#2001.year#4.country_id	1.21e-10	-0.0117	-0.148***
	(0.224)	(0.516)	(0.0573)
1.PA#2002.year#2.country_id	1.23e-10	0.0222	-0.0102
	(0.0354)	(0.0544)	(0.0368)
1.PA#2002.year#3.country_id	-0.00618	0.0306	-0.0149
	(0.0326)	(0.0494)	(0.0286)
1.PA#2002.year#4.country_id	1.21e-10	0.0326	-0.0711
	(0.224)	(0.516)	(0.0573)
1.PA#2003.year#2.country_id	-0.0289	-0.0446	-0.209***
	(0.0354)	(0.0544)	(0.0368)
1.PA#2003.year#3.country_id	-0.0155	0.0197	0.0413
	(0.0326)	(0.0494)	(0.0286)

continued			
1.PA#2003.year#4.country_id	1.21e-10	0.00944	-0.0865
	(0.224)	(0.516)	(0.0573)
1.PA#2004.year#2.country_id	1.23e-10	0.0740	0.0661*
	(0.0354)	(0.0544)	(0.0368)
1.PA#2004.year#3.country_id	0.000744	0.0684	0.0279
	(0.0326)	(0.0494)	(0.0286)
1.PA#2004.year#4.country_id	1.21e-10	0.0445	-0.0465
	(0.224)	(0.516)	(0.0573)
1.PA#2005.year#2.country_id	0.00880	-0.0127	0.0123
	(0.0354)	(0.0544)	(0.0368)
1.PA#2005.year#3.country_id	0.00928	-0.00593	0.0260
	(0.0326)	(0.0494)	(0.0286)
1.PA#2005.year#4.country_id	0.00880	-0.0131	-0.0411
	(0.224)	(0.516)	(0.0573)
1.PA#2006.year#2.country_id	0.00880	0.0141	0.00996
	(0.0354)	(0.0544)	(0.0368)
1.PA#2006.year#3.country_id	0.0103	0.0232	0.0253
	(0.0326)	(0.0494)	(0.0286)
1.PA#2006.year#4.country_id	0.00880	0.0196	-0.0348
	(0.224)	(0.516)	(0.0573)
1.PA#2007.year#2.country_id	0.00880	-0.0185	0.0278
	(0.0354)	(0.0544)	(0.0368)
1.PA#2007.year#3.country_id	0.00905	-0.00644	0.0189
	(0.0326)	(0.0494)	(0.0286)
1.PA#2007.year#4.country_id	0.00880	-0.0131	-0.0368
	(0.224)	(0.516)	(0.0573)
1.PA#2008.year#2.country_id	-0.0163	-0.0180	0.00240
	(0.0354)	(0.0544)	(0.0368)
1.PA#2008.year#3.country_id	-0.00304	-0.0689	-0.00803
	(0.0326)	(0.0494)	(0.0286)
1.PA#2008.year#4.country_id	1.21e-10	-0.00311	-0.0392
	(0.224)	(0.516)	(0.0573)
1.PA#2009.year#2.country_id	1.23e-10	-0.00421	0.0245
	(0.0354)	(0.0544)	(0.0368)
1.PA#2009.year#3.country_id	-0.000778	-0.00449	0.0293
	(0.0326)	(0.0494)	(0.0286)
1.PA#2009.year#4.country_id	1.21e-10	-0.00311	-0.0342
	(0.224)	(0.516)	(0.0573)
1.PA#2010.year#2.country_id	1.23e-10	-0.0251	0.0214
	(0.0354)	(0.0544)	(0.0368)
1.PA#2010.year#3.country_id	-0.00338	0.0409	0.0598**
	(0.0326)	(0.0494)	(0.0286)
1.PA#2010.year#4.country_id	1.21e-10	-0.0261	-0.0362
	(0.224)	(0.516)	(0.0573)
1.PA#2011.year#2.country_id	0.0104	-0.0233	0.0257

continued			
	(0.0354)	(0.0544)	(0.0368)
1.PA#2011.year#3.country_id	-0.000857	0.00708	0.0459
	(0.0326)	(0.0494)	(0.0286)
1.PA#2011.year#4.country_id	1.21e-10	-0.0309	-0.0333
	(0.224)	(0.516)	(0.0573)
1.PA#2012.year#2.country_id	-0.00253	-0.0389	0.00937
	(0.0354)	(0.0544)	(0.0368)
1.PA#2012.year#3.country_id	0.00233	0.0150	0.0251
	(0.0326)	(0.0494)	(0.0286)
1.PA#2012.year#4.country_id	1.21e-10	-0.0293	-0.0603
	(0.224)	(0.516)	(0.0573)
1.PA#2013.year#2.country_id	0.00495	0.0924*	0.0223
	(0.0354)	(0.0544)	(0.0368)
1.PA#2013.year#3.country_id	0.0227	0.130***	0.195***
	(0.0326)	(0.0494)	(0.0286)
1.PA#2013.year#4.country_id	1.21e-10	0.0365	-0.0419
	(0.224)	(0.516)	(0.0573)
1.PA#2014.year#2.country_id	0.00732	0.0101	0.0622*
	(0.0354)	(0.0544)	(0.0368)
1.PA#2014.year#3.country_id	0.00995	0.0334	0.0847***
	(0.0326)	(0.0494)	(0.0286)
1.PA#2014.year#4.country_id	1.21e-10	0.00139	-0.0582
	(0.224)	(0.516)	(0.0573)
1.PA#2015.year#2.country_id	0.00913	0.0818	0.0699*
	(0.0354)	(0.0544)	(0.0368)
1.PA#2015.year#3.country_id	0.0250	0.0400	0.0627**
	(0.0326)	(0.0494)	(0.0286)
1.PA#2015.year#4.country_id	0.0186	0.0458	-0.0286
	(0.224)	(0.516)	(0.0573)
1.PA#2016.year#2.country_id	0.0248	0.00403	0.0339
	(0.0354)	(0.0544)	(0.0368)
1.PA#2016.year#3.country_id	0.0181	-0.00639	0.0275
	(0.0326)	(0.0494)	(0.0286)
1.PA#2016.year#4.country_id	0.0186	-0.00678	-0.0308
	(0.224)	(0.516)	(0.0573)
1.PA#2017.year#2.country_id	0.0186	-0.00108	0.0217
	(0.0354)	(0.0544)	(0.0368)
1.PA#2017.year#3.country_id	0.0176	-0.00341	0.0222
	(0.0326)	(0.0494)	(0.0286)
1.PA#2017.year#4.country_id	0.0186	-0.00678	-0.0379
	(0.224)	(0.516)	(0.0573)
1.PA#2018.year#2.country_id	0.0186	-0.00108	0.0200
	(0.0354)	(0.0544)	(0.0368)
1.PA#2018.year#3.country_id	0.0176	-0.00290	0.0208
	(0.0326)	(0.0494)	(0.0286)

continued			
1.PA#2018.year#4.country_id	0.0186	-0.00678	-0.0396
	(0.224)	(0.516)	(0.0573)
ln_elevation	-0.00314***	-0.00713***	-0.00445***
	(0.00106)	(0.00232)	(0.00120)
ln_slope	-0.00136	-0.00514***	-0.0109***
	(0.00140)	(0.00192)	(0.00183)
ln_aspect	-0.00115**	-0.00301***	-0.00296***
	(0.000546)	(0.000753)	(0.000829)
ln_distance_to_waterways	0.000225	0.000663	0.000112
	(0.000470)	(0.000650)	(0.000605)
ln_distance_to_highways	-0.000190	-0.000233	-0.000185
	(0.000419)	(0.000580)	(0.000559)
ln_distance_to_settlements	0.000535	0.000624	-0.00182
	(0.000898)	(0.00125)	(0.00120)
ln_percent_forest_120m	0.0101**	0.00160	0.0154**
	(0.00468)	(0.0149)	(0.00640)
ln_percent_forest_1km	-0.00177	0.0212***	0.0180***
	(0.00240)	(0.00763)	(0.00371)
Constant	-0.0116	-0.0238	-0.0428
	(0.0252)	(0.0709)	(0.0323)
Observations	201,655	370,202	731,042
Number of grid_pt_id	6,505	11,942	23,582

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A51: Pairwise comparisons of predictive margins among different protected area boundary delineations. (PA = 0: no protection, PA = 1: only observations protected in 2020 (WDPA dataset), PA = 2: only observations protected in 1991 (WWF PADDD dataset), PA = 3: observations protected in both times).

	Margin	Std. Err. (Delta-method)	Unadjusted Groups
PA			
0	0.00738	0.000411	B
1	0.006478	0.001723	AB
2	0.006882	0.001575	AB
3	0.004031	0.000556	A

Note: Margins sharing a letter in the group label are not significantly different at the 5% level.

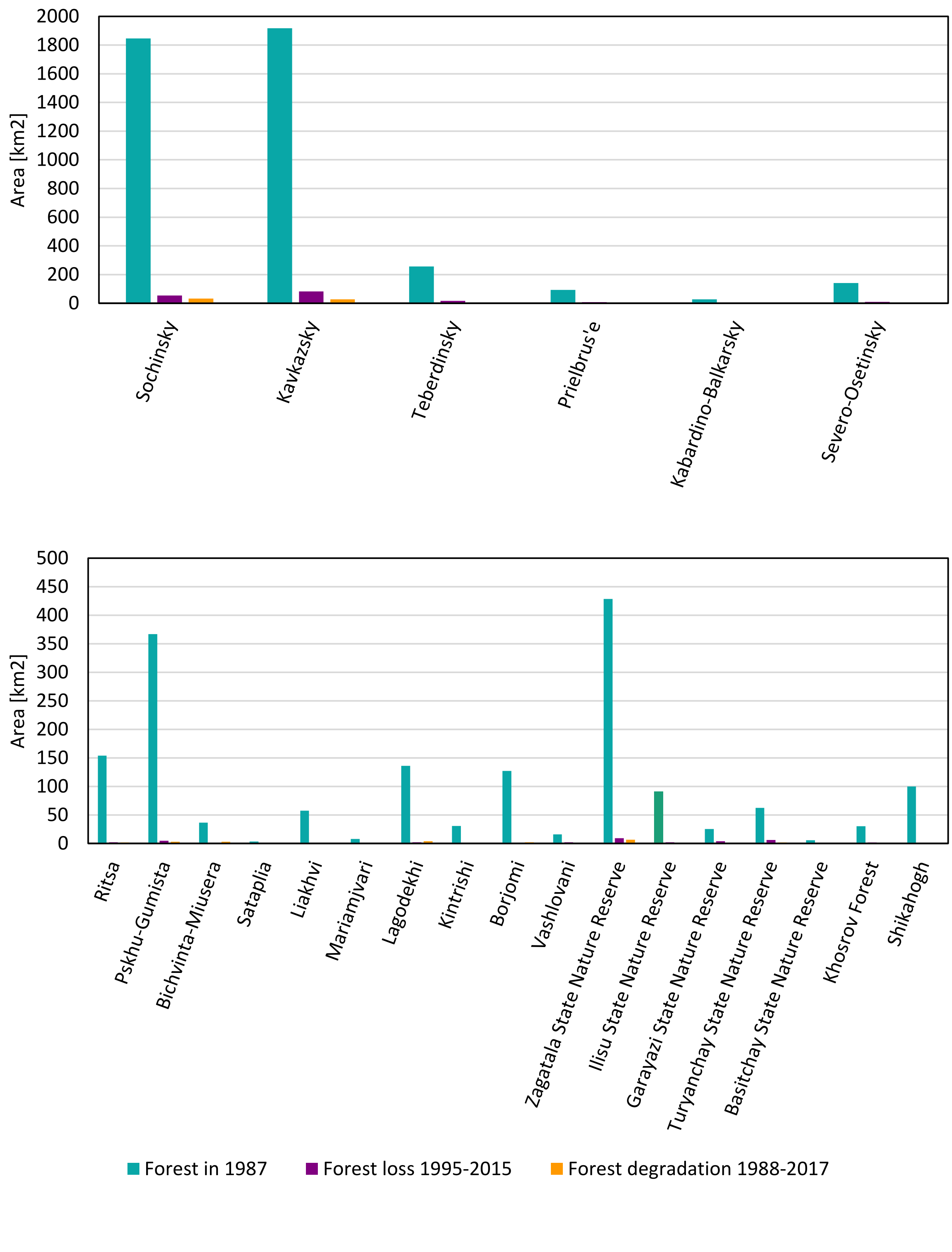


Figure A14: Area of forest in 1987, total area of forest loss from 1995 to 2015, and total area of forest degradation from 1988 to 2017 within strictly protected areas established before 1988 in Russia (upper panel), Georgia, Azerbaijan, and Armenia (lower panel) (the order of protected areas corresponds with the order in Table A45).

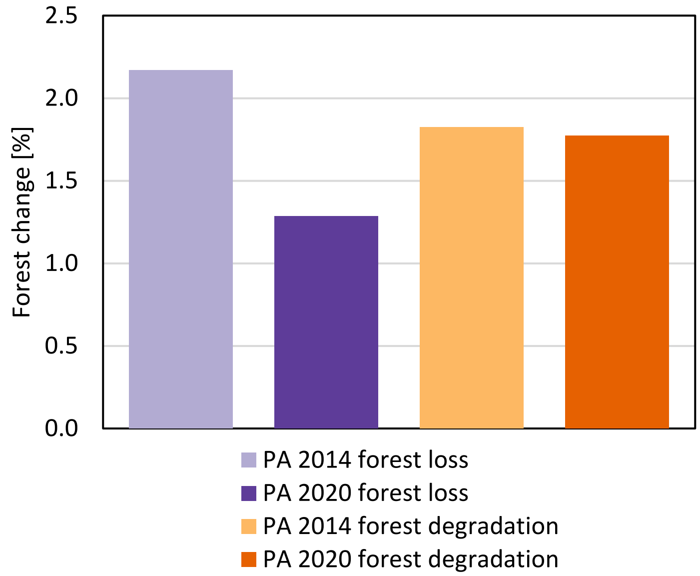


Figure A15: Forest loss and forest degradation presented as a percentage of the forest cover in 1987, presented within protected area boundaries in 2014 versus protected area boundaries in 2020 for Sochinsky National Park (Russian Federation).

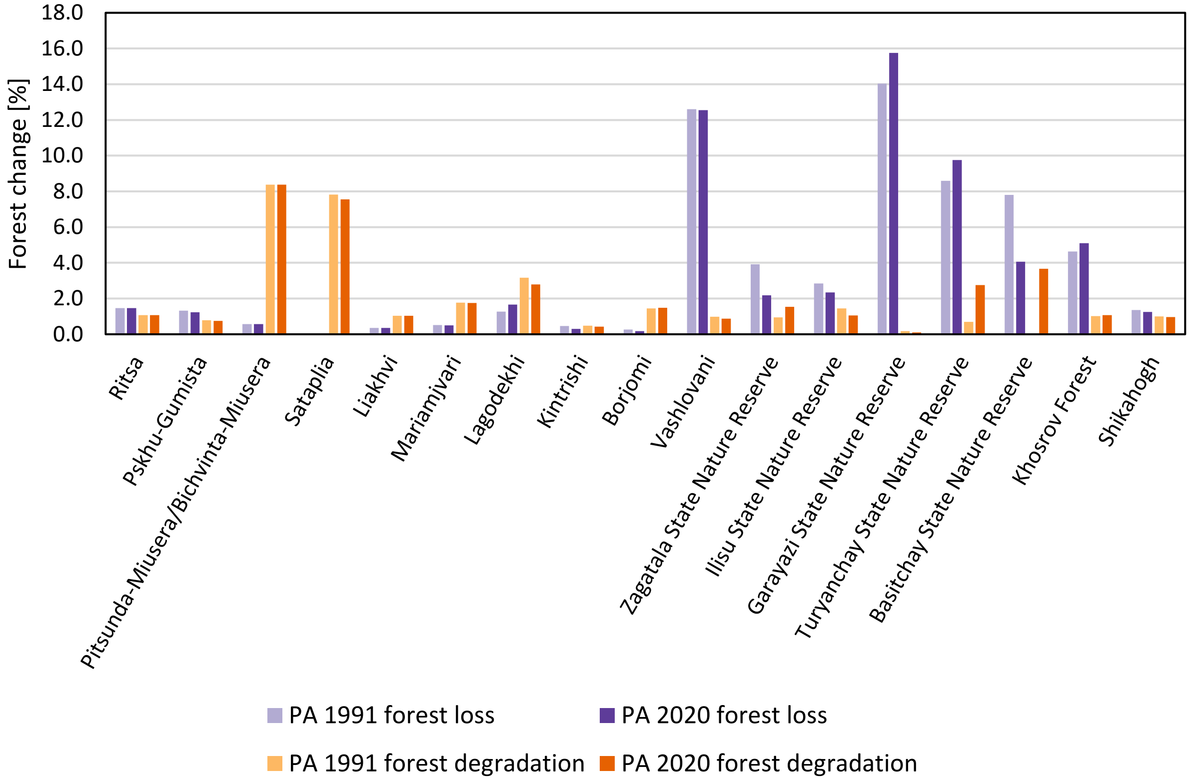


Figure A16: Forest loss and forest degradation presented as a percentage of the forest cover in 1987, presented within protected area boundaries in 2020 (WDPA) versus protected area boundaries in 1991 (PADDD, WWF) for the South Caucasus (Georgia, Azerbaijan, and Armenia; the order of protected areas corresponds with the order in Table A45).