Unlocking the secrets of Corona spy satellite imagery to capture historical land use change and wildlife habitat for large areas

Introduction

The legacy of past human activities strongly affects current landscapes[1], and current activities will likely have similar legacies in the future. However, predicting future legacies requires understanding past ones, and hence spatially detailed long-term data for large areas[2]. Unfortunately, most land and habitat change studies only start in the 1980s, when 30-m Landsat TM data became available, or in the 2000s when high-resolution satellites were launched. However, there is an exciting opportunity to look at half-a-century of changes at high spatial resolution thanks to 1960s and 1970s US spy satellites from the Corona, Gambit, and Hexagon satellite series. Capitalizing on these data requires new analysis methods though. Following NASA's vision statement: "to discover and expand knowledge for the benefit of humanity", I propose here to unlock the secrets of the spy satellite image archives to understand the effects of land use legacies and long-term changes in land use and large mammal habitat.

The main goal of my proposed investigation is **to advance remote sensing, long-term land change science and species habitat modelling.** Specifically, I will:

Objective 1. Apply Convolutional Neural Networks to classify land cover types from the historical Corona imagery;

Objective 2. Test the value of pansharpening early MSS data with high-resolution panchromatic Corona imagery for land cover classifications;

Objective 3. Evaluate the legacy effects of dam construction on row crop agriculture;

Objective 4. Assess long-term changes in habitat availability for large mammals.

Understanding the past helps reveal the long-term *changes in the global Earth system*, identify the *causes that result in these changes*, and predict *the future of the Earth system,* so my proposed research will address three out of four key NASA science questions of the Earth science program. My research pertains to the Carbon Cycle and Ecosystems Focus Area, by helping to "*detect and predict changes in Earth's ecological and chemical cycles, including land cover, biodiversity, and the global carbon cycle*". To assess land use and habitat change, I will analyze NASA satellite data for historical (MSS) and recent land cover maps (TM/ETM+/OLI).

Study area

I will study the Caucasus region (756,000 km^2, Fig. 1), which is highly diverse in elevation (-27 to 5,633 m a.s.l.), precipitation (annual average 240-2704 mm[3]), and ecosystems. The Caucasus is one of the 36 global biodiversity hotspots, with many rare ecosystems and endemic species of conservation concern. The diversity in ecosystems means that my new methods should also be applicable in many other parts of the globe. Furthermore, there have been major shifts in government and in land use, e.g. after the collapse of the Soviet Union, that make it an ideal location to study land use change and its effect on wildlife habitat.

Fig. 1. The Caucasus ecoregion including Russia, Armenia, Azerbaijan, Georgia

Currently, I am working as a research assistant making an initial set of land cover maps from Corona imagery as a part of NASA LCLUC project "Long-term land degradation in the Caucasus" (PI Radeloff). That project will end in 12/2021, and the work proposed for my FINESST grant does not overlap with what is covered in the current project. In my current work, I am developing land use maps from Corona imagery for the Caucasus using pixel-based classifications, and image segmentation (Fig. 2). That work will be completed prior to this grant, and I will have a manuscript describing that work submitted and geo-rectified Corona images in hand. However, during my current work I developed novel ideas how to extract land cover information from Corona imagery by using convolutional neural network algorithms for Corona image classifications, and by pansharpening MSS 70-m multispectral data with Corona imagery. Furthermore, I propose here to ask scientific questions about the causes of land use change, and historical wildlife habitat. None of these methods and questions are part of the current LCLUC project.

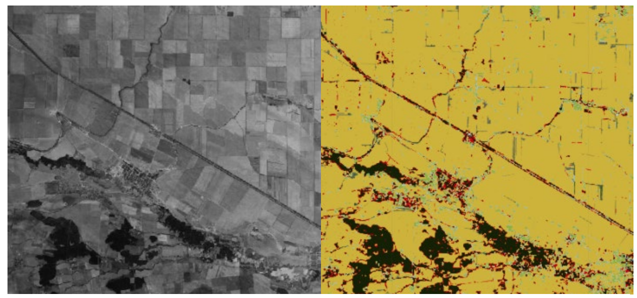

Fig. 2. Corona spy satellite imagery (left) and its land cover classification (right; crop in yellow, urban in red, forest in dark green and grass in light green)

Approach

Objective 1: Convolutional neural network classifications of Corona imagery

When classifying very high-resolution (VHR) satellite images, such as Corona imagery, there is rich spatial information, thanks to its 2.5-m resolution, but little spectral information. Object-based image analysis (OBIA)[4] is one approach to classify such imagery, and I am employing it in my current work. However, while OBIA techniques can be powerful[5,6], they also have some limitations: the image objects smaller than the "minimum size" parameter defined are excluded and classification accuracy depends greatly on the segmentation[7]. Convolutional neural networks (CNN) present exciting new opportunities to extract land cover information from VHR satellite data[8] because they extract deep image features[9–11]. Indeed, CNNs have worked well for analyses of historical aerial photos[12]. However, I am not aware of any prior study classifying Corona imagery with CNNs.

My main goal here is to apply and evaluate various architectures of both CNN[13] and fully convolutional networks (FCN[14]) and test their value for broad-scale analyses of historical panchromatic VHR satellite imagery. CNN algorithms learn spatial-contextual features from simple features in the lower layers to differentiate complex features in the deeper layers. Patch-based CNNs, have a label assigned to the central pixel of an input patch[15], while FCNs employ fully labelled image patches for training[14]. This avoids redundant operations on neighboring patches, making FCN computationally more efficient than CNN when training and testing tiles[16,17]. To check and compare the reliability of the resulting maps that each of the architectures applied exhibit, I will perform accuracy assessments using independent validation samples[18].

The expected outcomes of objective 1 will be the land cover maps produced by each neural network architecture and I will openly share those and my software code immediately after completion of my work. The results of this objective will help advance the science of remote sensing and expand the use of CNNs in large-scale fine-resolution land cover mapping. I am planning to submit the results for publication to *Remote Sensing of Environment*.

Objective 2: Integration of MSS and Corona data: pansharpening using panchromatic historical imagery for further land cover analyses

Multispectral images have valuable reflectance information but often lack in spatial resolution. Conversely, panchromatic images have only one wide spectral band but often high spatial resolution. Hence, pansharpening combines the two to generate a single high-resolution color image. I propose to use 2.5-m resolution Corona imagery to pansharpen 70-m Multispectral Scanning System (MSS) data in order to improve 1960s/70s land cover classifications. I will apply Intensity-Hue-Saturation[19], Brovey[20], Gram-Schmidt[21] and Principal Component Analysis[22] algorithms for pansharpening to enhance the spectra of Corona imagery and provide additional data for further analyses. The results of preliminary analyses (Fig. 3) implemented in ENVI 5.2 with application of Gram-Schmidt algorithm suggest great potential for land cover analyses. However, given that pansharpening affects the pixel values[23], it is not clear, whether pansharpening will improve the classification results. However, I am optimistic that both temporal and spectral information from MSS can especially improve the separation of grasslands and cropland, which are frequently confused in my current classifications based on Corona data alone. My main purpose for this objective is to apply and to test the value of pansharpening MSS imagery with Corona Spy satellite images to improve land cover classifications. To evaluate reliability of the resulting map, I will conduct a thorough accuracy assessment[18].

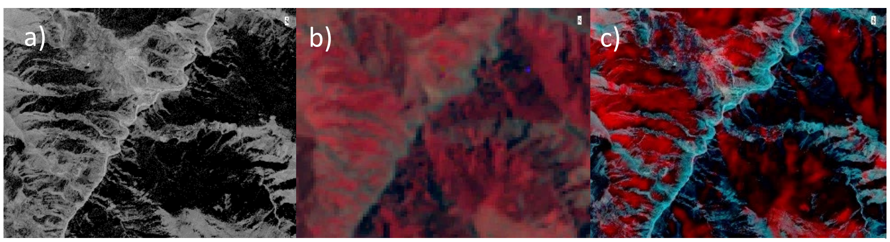

Fig. 3. A small-scale pansharpening test of a) panchromatic Corona satellite image (August 23, 1965), b) false color composite (NIR, red, green) MSS image (July 6, 1976), and c) false color composite (NIR, red, green) pansharpening result of the synergy of (a) and (b), for the central Caucasus

The main outcome of objective 2 will be high spectral and high spatial resolution pansharpened historical satellites images and a land cover map produced with application of these data. I will assess the accuracy of the resulting map to examine the value of pansharpening. I will submit the results to *Remote Sensing of Environment*.

Objective 3: Row crop agricultural expansion as a result of dam construction – what are the effects of historical decisions on present-day land use?

Land use legacies of human activities over half-a-century ago still shape current landscape patterns[24–28], highlighting the importance of land use history in explaining contemporary patterns[1]. The global population explosion in the 1960s developed a need in dam construction for agricultural purposes to meet the planet's food supply. Availability of reliable satellite data from that period presents exciting opportunities to assess the impact of important past land use on today's.

My main goal for this objective is to quantify dam-induced land use legacies on contemporary agricultural land use. I define the dam-induced land use legacies as the effects of historical land use driven by dam construction on today's agricultural land use. I will investigate dam-induced legacies (Fig. 4) in the Kura-Araz lowland (22,000 km^2). There, a cascade of dams were built in the mid-20th century on the longest (1515 km) river in the Caucasus[29] for energy supply, water level control and to improve row crop agriculture. I hypothesize that those fields started after irrigation became available are more likely to be abandoned, because they were less suitable for agriculture, which is why they were not used before. My alternative hypothesis is that fields that existed before the dam construction are more likely to be abandoned because they had already been used for decades or centuries, and thus been degraded longer. I will identify whether fields abandoned since 1987 existed before or appeared after the dam construction while controlling for other factors that can explain land abandonment. For example, I also hypothesize that more accessible fields nearer larger cities are less likely to be abandoned.

Fig. 4. Corona satellite image, August 23, 1965 (left) and the Google Earth view, May 8, 2019 (right) depicting the Kura River. Development of row crop agriculture and settlements can be observed

I will analyze land cover maps from the Corona satellite images (1965) to identify pre-dam fields and previously derived Landsat-based land cover maps (1987, 1995, 2000, 2005, 2010, 2015[30]) for post-dam fields. I will use the Global Surface Water occurrence layer[31] for nearest water sources and will obtain data on distances from market locations, and rural population numbers from local agencies. Using a systematic sampling grid, I will model the current land use (agriculture vs. non-agriculture) as a function of past land use and other factors. I will assess the marginal effect of each predictor variable and quantify the effects of pre-dam and post-dam land use legacies through odds ratios[32,33]. While I realize that there are other drivers of abandonment, such as emigration or health problems of a farmer, for which I do not have data, I assume these factors are random and thus will not bias my assessment of the legacy effects.

The main outcomes from this objective will be the assessment of land use legacies' in combination with other factors on present-day land abandonment. I will generate a half-a-century change map showing the effect of the dams built in rivers on agriculture through the development of irrigation systems. The importance of my study lays in quantifying the effect of past land use on land abandonment patterns today and in understanding how the dam construction and irrigation systems development affected the land use in the past and may thus affect it in the future. I will focus on the dams on Kura River, but my approach can be applied to other regions with legacy effects. I will submit the paper to *Global Environmental Change*.

Objective 4: Long-term changes in habitats of large mammal species

Habitat loss due to human activities and global climate change is a major threat to biodiversity especially in hotspots[34–39]. To identify the causes and try to prevent further loss, it is necessary to quantify how much habitat has already been lost. Most time series of habitat loss start after the launch of freely available 30-m resolution satellite data (i.e., 1983[40]), but by then much habitat had already been lost. This is a great example of a shifting baseline syndrome: limited or missing information on past conditions resulting in a gradual change in the understanding of natural environment[41]. The Corona Spy satellite images will allow me to extend understanding of past conditions to the 1960s and thus reduce the shifting baseline syndrome. Long-term data from my 1960s land cover maps can extend the baseline of species' habitat availability, which is especially important because it takes decades to correctly assess habitat changes of large mammals with their relatively long lifespans and low reproduction rates causing extinction debts[42].

My main goal for objective 4 is to produce habitat maps of large mammals for the 1960s and for 2015, compare them to each other and delineate habitat losses. Specifically, I will map habitats of three cloven-hoofed ungulates: red deer (*Cervus elaphus*), East Caucasian tur (*Capra cylindricornis*) and chamois (*Rupicapra rupicapra*); one carnivore: Eurasian lynx (*Lynx lynx)*, and one omnivore: brown bear (*Ursus arctos)*. I will build the models with presence-only data and ensemble models in the BIOMOD2 package in R[43]. To model current habitat, I will use data from monitoring by local rangers and NGOs and the Landsat land cover maps. For the 1960s, I will use the land cover map produced using Corona satellite imagery and analyze occurrence data archived for protected areas that existed in the 1960s and were monitored in detail. The Soviet Division on Nature Conservation employed regularly updated plans and instructions[44] how to monitor large mammals. This resulted in 27 reliable reports and studies produced in the 1960s (e.g., Annual report of Zagatala State Reserve on scientific research - 1960, Chamois ecology on Southern slopes of the Greater Caucasus - 1961, etc.) that consist of occurrence data for my species of interest. I have analyzed these reports while working at a local NGO and have all the data in hand. In my study, I will incorporate the climate data for the 1960s along with a number of natural (e.g. topography, land cover types) and anthropogenic (e.g. road and settlement density) factors that are important for the distributions of my focal species[45–50].

The results from objective 4 will be the models and maps for each of my five species representing their current habitats, historical habitats and changes that occurred over the last half century. I will investigate the species' earlier habitat availability, thus helping to limit the shifting baseline syndrome and to establish more appropriate baselines for nature conservation. I will submit the results for publication to *Conservation Biology*.

Expected outcomes

I propose here to perform interdisciplinary research that contributes to remote sensing, land use change science, and conservation biology. A NASA ROSES-20 FINESST grant would be an important step in building a strong scientific foundation for my future career at the intersection of these fields. I will publish at least four peer-reviewed journal articles, one for each Objective:

1. Convolutional neural network classifications of Corona imagery – *Remote Sensing of Environment*;
2. Integration of MSS and Corona data: pansharpening using panchromatic historical imagery for further land cover analyses – *Remote Sensing of Environment*;
3. Row crop agricultural expansion as a result of dam construction – what are the effects of historical decisions on present-day land use? – *Global Environmental Change*;
4. Long-term changes in habitats of large mammal species – *Conservation Biology*.

I will use data from several NASA assets including Landsat MSS/TM/ETM+/OLI, and SRTM elevation data and use such tools as Google Earth Engine, R, ENVI, ArcGIS. I will work closely with partners from the region and the U.S., to strengthen international network. Immediately after the completion of my work, I will freely share the following deliverables:

1. An improved large-scale very high-resolution land cover map of the Caucasus region for the 1960s and half-a-century change maps;
2. Results of pansharpening test of MSS images with Corona data;
3. Large mammal species' habitat maps and the change map revealing the disturbance areas;
4. Java Script and R codes that I scripted for each objective.

My methods will be generally applicable by remote sensing specialists and conservationists interested to map long-term changes in land cover and mammal habitat availability. I am also planning to present the results of my research at conferences and to distribute the findings among collaborators and conservation groups in the study area to help continue this work in future.

Overall significance

The Caucasus region is very diverse in terms of elevation, and unique biomes, which means that my new approaches should also be applicable in many other parts of the Earth. In addition, major shifts in government and in land use, e.g. after the collapse of the Soviet Union, make it an ideal location to study land use change and its effect on wildlife habitat. **Methodologically**, I will advance remote sensing by applying pansharpening and employing Convolutional Neural Networks to very high-resolution Corona Spy satellite images. The technique can later be used for the analyses of other available historical images, such as aerial photographs. My investigation will help understand **scientifically**, the effect of dam construction and irrigation development on land use and the role of pre-dam and post-dam land use legacies on land abandonment today. This may allow future long-term projections to possible changes in a region after the dam construction and will have a strong **management** value. Another **management** and **conservation** value of my study is that it will extend the baseline of species' habitat availability, thus help limit reduce the shifting baseline syndrome and prevent species' extinction.

My proposed work directly addresses NASA's Earth Science Division's strategic objective to "Advance knowledge of Earth as a system to meet the challenges of environmental change, and to improve life on our planet" and the Carbon Cycle and Ecosystems Focus Area, because my research is tailored to "detect and predict changes in Earth's ecological and chemical cycles, including land cover, biodiversity, and the global carbon cycle".

My interdisciplinary research will address three of four NASA's key science questions of the Earth science program because understanding the past will help reveal the trajectory of long-term *changes in the global Earth system*, to identify the *causes that result in these changes*, and to predict *the future of the Earth system*. Along with testing new methods to analyze historical satellite imagery, I will analyze NASA satellite data to produce land cover maps and apply them for land use and habitat change assessments. My investigation represents a big step towards understanding and predicting the global ecosystem changes and their effects on biodiversity. Last but not least, my research will support species conservation efforts in a biodiversity hotspot.

Project timeline

Year	**2021**		**2022**				**2023**				**2024**		
Quarter	III	IV	I	II	III	IV	I	II	III	IV	I	II	III
Objective 1	DA/A	A/MP	P										
Objective 2			DA	A	A/MP	P							
Objective 3						DA	A/MP	A/MP	P				
Objective 4									DA	DA/A	A/MP	P	
Dissertation													P

DA - Data Acquisition, A - Analysis, MP - Manuscript Preparation, P - Publication/Submission

The milestones of my degree program:

Start Date: September 1, 2018
Dissertator Status: June 1, 2020
Finish Coursework: May 7, 2020
Expected PhD Completion: August, 2024

References

1. Munteanu C, Kuemmerle T, Boltiziar M, et al. 2017. Nineteenth-century land-use legacies affect contemporary land abandonment in the Carpathians. *Reg Environ Chang*. 17(8):2209-2222.
2. Foster D, Swanson F, Aber J, et al. 2003. The importance of land-use legacies to ecology and conservation. *Bioscience*. 53(1):77-88.
3. Coene F. 2009. The Caucasus-an Introduction. Routledge, London.
4. Blaschke T, Lang S, Lorup E, Strobl J, Zeil P. 2000. Object-oriented image processing in an integrated GIS/remote sensing environment and perspectives for environmental applications. *Environmental information for planning, politics and the public*. 2:555-570.
5. Kressler FP, Kim YS, Steinnocher KT. 2003. Object-oriented land cover classification of panchromatic KOMPSAT-1 and SPOT-5 data. In: *International Geoscience and Remote Sensing Symposium (IGARSS)*. IEEE Inc. 6:3471-3473.
6. Ye S, Pontius RG, Rakshit R. 2018. A review of accuracy assessment for object-based image analysis: From per-pixel to per-polygon approaches. *ISPRS J Photogramm Remote Sens*. 141:137-147.
7. Kavzoglu T, Tonbul H. 2018. An experimental comparison of multi-resolution segmentation, slic and k-means clustering for object-based classification of vhr imagery. *Int J Remote Sens*. 39(18):6020-6036.
8. Hoeser T, Kuenzer C. 2020. Object detection and image segmentation with deep learning on earth observation data: a review-part i: evolution and recent trends. *Remote Sens*. 12(10):1667.
9. Bischke B, Helber P, Folz J, Borth D, Dengel A. 2019. Multi-task learning for segmentation of building footprints with deep neural networks. In: 2019 *Proceedings of International Conference on Image Processing (ICIP)*. IEEE Computer Society. 1480-1484.
10. Liu P, Liu X, Liu M, et al. 2019. Building footprint extraction from high-resolution images via spatial residual inception convolutional neural network. *Remote Sens*. 11(7):830.
11. Shao Z, Tang P, Wang Z, Saleem N, Yam S, Sommai C. 2020. BRRNet: a fully convolutional neural network for automatic building extraction from high-resolution remote sensing images. *Remote Sens*. 12(6):1050.
12. Mboga N, Grippa T, Georganos S, et al. 2020. Fully convolutional networks for land cover classification from historical panchromatic aerial photographs. *ISPRS J Photogramm Remote Sens*. 167:385-395.
13. LeCun Y, Bottou L, Bengio Y, Haffner P. 1998. Gradient-based learning applied to document recognition. *Proc IEEE*. 86(11):2278-2323.
14. Long J, Shelhamer E, Darrell T. 2015. Fully Convolutional Networks for Semantic Segmentation. In *Proceedings of the IEEE conference on computer vision and pattern recognition.* 3431-3440.

15. Bergado JR, Persello C, Gevaert C. 2016. A deep learning approach to the classification of sub-decimetre resolution aerial images. In *2016 International Geoscience and Remote Sensing Symposium (IGARSS)*. IEEE Inc. 1516-1519.

16. Volpi M, Tuia D. 2017. Dense semantic labeling of subdecimeter resolution images with convolutional neural networks. *IEEE Trans Geosci Remote Sens*. 55(2):881-893.

17. Persello C, Stein A. 2017. Deep fully convolutional networks for the detection of informal settlements in VHR images. *IEEE Geosci Remote Sens Lett*. 14(12):2325-2329.

18. Olofsson P, Foody GM, Herold M, Stehman S V., Woodcock CE, Wulder MA. 2014. Good practices for estimating area and assessing accuracy of land change. *Remote Sens Environ*. 148:42-57.

19. Schetselaar EM. 1998. Fusion by the IHS transform: should we use cylindrical or spherical coordinates? *Int J Remote Sens*. 19(4):759-765.

20. Chavez P, Sides S, et al. 1991. Comparison of three different methods to merge multiresolution and multispectral data- Landsat TM and SPOT panchromatic. *Photogramm. Eng. Remote Sens*. *57*(3):295-303.

21. Laben CA, Brower BV. 2000. Process for enhancing the spatial resolution of multispectral imagery using pan-sharpening. *U.S. Patent No. 6,011,875*. Washington, DC: U.S. Patent and Trademark Office.

22. Chavez PS, Yaw Kwarteng A. Extracting spectral contrast in landsat thematic mapper image data using selective principal component analysis. *Photogramm. Eng. Remote Sens*. *55*(1):339-348.

23. Sarp G. 2014. Spectral and spatial quality analysis of pan-sharpening algorithms: A case study in Istanbul. *Eur J Remote Sens*. 47(1):19-28.

24. Thompson JR, Carpenter DN, Cogbill CV., Foster DR. 2013. Four centuries of change in northeastern united states forests. *PLoS One*. 8(9):e72540.

25. Bellemare J, Motzkin G, Foster DR. 2002. Legacies of the agricultural past in the forested present: An assessment of historical land-use effects on rich mesic forests. *J Biogeogr*. 29(10-11):1401-1420.

26. Krause A, Bayer A, Pugh TAM, Bayer AD, Arneth A. 2016. Impacts of land-use history on the recovery of ecosystems after agricultural abandonment. *Earth Syst Dynam*. 7:745-766.

27. Perring MP, De Frenne P, Baeten L, et al. 2016. Global environmental change effects on ecosystems: the importance of land-use legacies. *Glob Chang Biol*. 22(4):1361-1371.

28. Ziter C, Graves RA, Turner MG. 2017. How do land-use legacies affect ecosystem services in United States cultural landscapes? *Landsc Ecol*. 21(3):1129-1143.

29. Frenken K. 2009. Irrigation in the Middle East Region in figures: AQUASTAT Survey - 2008. Food and Agriculture Organization of the United Nations. *Water Reports*. (34).

30. Buchner J, Yin H, Frantz D, et al. 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.

31. Pekel JF, Cottam A, Gorelick N, Belward AS. 2016. High-resolution mapping of global surface water and its long-term changes. *Nature*. 540(7633):418-422.

32. Hosmer DJ, Lemeshow S, Sturdivant R. 2013. Applied Logistic Regression. Vol. 398. John Wiley & Sons Inc.

33. Norton EC, Wang H, Ai C. 2004. Computing interaction effects and Standard errors in logit and probit models. *Stata Journal.* 4(2):154-167.

34. Bragina E V., Ives AR, Pidgeon AM, et al. 2015. Rapid declines of large mammal populations after the collapse of the Soviet Union. *Conserv Biol*. 29(3):844-853.

35. Tan CKW, Rocha DG, Clements GR, et al. 2017. Habitat use and predicted range for the mainland clouded leopard Neofelis nebulosa in Peninsular Malaysia. *Biol Conserv*. 206:65-74.

36. Macdonald DW. 2019. Mammal conservation: old problems, new perspectives, transdisciplinarity, and the coming of age of conservation geopolitics. *Annu Rev Environ Resour*. 44(1):61-88.

37. Di Marco M, Boitani L, Mallon D, et al. 2014. A retrospective evaluation of the Global decline of carnivores and ungulates. *Conserv Biol*. 28(4):1109-1118.

38. Hoffmann M, Belant JL, Chanson JS, et al. 2011. The changing fates of the world's mammals. *Philosophical Transactions of the Royal Society B: Biological Sciences.* 366(1578):2598-2610.

39. Schipper J, Chanson JS, Chiozza F, et al. 2008. The status of the world's land and marine mammals: diversity, threat, and knowledge. *Science*. 322(5899):225-230.

40. Congalton RG, Oderwald RG, Mead RA. 1983. Assessing Landsat classification accuracy using discrete multivariate analysis statistical techniques. *Photogramm. Eng. Remote Sens*. *49*(12):1671-1678.

41. Soga M, Gaston KJ. 2018. Shifting baseline syndrome: causes, consequences, and implications. *Front Ecol Environ*. 16(4):222-230.

42. Tilman D, May RM, Lehman CL, Nowak MA. 1994. Habitat destruction and the extinction debt. *Nature*. 371(6492):65-66.

43. Thuiller W. 2003. BIOMOD - optimizing predictions of species distributions and projecting potential future shifts under global change. *Glob Chang Biol*. 9(10):1353-1362.

44. Filonov KP, Nukhimovskaya D. 1985. Chronicles of Nature in Zapovedniks of the USSR. Nauka Press, Novosibirsk, Russia [in Russian].

45. Bleyhl B, Baumann M, Griffiths P, et al. 2017. Assessing landscape connectivity for large mammals in the Caucasus using Landsat 8 seasonal image composites. *Remote Sens Environ*. 193:193-203.

46. Gavashelishvili A. 2009. GIS-based habitat modeling of mountain ungulate species in the Caucasus hotspot. *Status and protection of globally threatened species in the Caucasus*, 74-82.

47. Heptner V, Nasimovich A, Bannikov A. 1961. Mammals of the Soviet Union. Vol. 1. Ungulates [in Russian].

48. Heptner VG, Sludskii AA. 1972. Mammals of the Soviet Union. Vol. 2, Part 2 Carnivora (Hyaenas and Cats) [in Russian].

49. Zazanashvili N, Mallon D. 2009. Status and protection of globally threatened species in the Caucasus. CEPF, WWF, Contour Ltd., Tbilisi

50. Ziółkowska E, Ostapowicz K, Radeloff VC, et al. 2016. Assessing differences in connectivity based on habitat versus movement models for brown bears in the Carpathians. *Landsc Ecol*. 31(8):1863-1882.