PATTERNS OF LAND USE AND LAND COVER CHANGE

AND IT'S CONSEQUENCES FOR WILDLIFE:

AGRICULTURAL ABANDONMENT

AND BROWN BEARS (URSUS ARCTOS)

IN EASTERN EUROPE

by

Pedro Camilo Alcántara Concepción

A dissertation submitted in partial fulfillment of

the requirements for the degree of

Doctor of Philosophy

(Forestry)

at the

UNIVERSITY OF WISCONSIN-MADISON

2010

Acknowledgment

I gratefully acknowledge support by all the people of México that allowed me to pursue each of my educational achievements. In particular since 2005 I received support from all Mexicans through the Consejo Nacional de Ciencia y Tecnología (CONACyT, México). Now it is my obligation to return to México all the years of hard work that implies to educate me. I owe as well my deepest gratitude to all my family, in particular my mother Guillermina Concepción, my brothers Tamara, Víctor and Ernesto Alcántara, my wife Lizbeth Ochoa Peña and my daughter Malinalli that cheered me up in any moment and help me in a wide variety of ways, from a simple smile to insightful comments. Thank you all.

I am heartily thankful to my supervisor, Volker Radeloff, whose encouragement, support and continuous advice allowed me to develop and finish this dissertation. I want to thank as well to NASA Land Cover and Land Use Change Program, and the University of Wisconsin-Madison, and the collaboration by M. Bauman, Daniel Müller, P. Hostert, Leonid Baskin, Nick Labonte institutions and people that support the research and without whom I would not be able to finish. My warmest regards and thanks to all the Silvis Lab folks from whom I learnt many things, from discipline to better ways to spend an evening. Especially to Gregorio Gavier-Pizarro, T. Kuemmerle, M. Dubinin, A. Prischepov, Eric Wood, Jodi Brandt and many others that share thoughts and nice moments. From my standpoint a big lab is not measured in number of integrants but in the willingness to share experiences, work and knowledge, and I truly believe the Silvis Lab is a very big lab from whom any conversation always thought me something.

I want to thank as well to all the people that I met on this five years in Madison that allowed me to know different cultures and have new experiences. Studying abroad allowed me to put in perspective my own culture, my country and the education I received prior to come. Especial thanks to Jordan, Allison, Josephine and Austin Muss, Julia Dubinina and Katya, A. Brokestrand and Egon.

And last but not least I want to acknowledge as well to the members of my committee: Murray Clayton, David Mladenoff, Tim Van Deelen, and Mutlu Ozdogan who supported me and gave me very insightful comments, being always willing to collaborate and teach me.

Index

Index of tables

Index of figures

1 Introduction

The overarching goal of my dissertation was to contribute to a better understanding of the consequences of land use change for wildlife. My dissertation consists of three chapters based on coarse-resolution satellite images, remote sensing (RS), and geographic information systems (GIS). In my first chapter, I tested a novel Land Use Land Cover Change (LULCC) classification method to map agricultural land abandonment using broad-scale imagery, exemplifying the method in the northwestern part of Eastern Europe with MODIS imagery. In my second chapter, I applied this method to map abandoned agricultural land and examined agro-ecological constraints across Eastern Europe. In the third chapter I analyzed the relationship between land abandonment, and resulting changes in landscape patterns, with brown bear (*Ursus arctos arctos*) populations in European Russia.

The Earth is a dynamic and complex system, nature and humans are completely interdependent. The actions we take to modify the environment in order to obtain goods and services have often unintended consequences in nature and feedbacks are affecting human well-being (Reid et al. 2006). In the last century it has become clear that human activities increasingly affect the Earth's natural systems (Vitousek and others 1997) to the point that ecosystems ability to support human needs in the future may be compromised (Reid et al 2006).

Both the impacts of human activities on the Earth's system and the consequences of these changes for human well-being justify the need to improve our knowledge of the transformations in human and natural systems (Sanderson,et al 2002). Our understanding of the complexity of impacts that human activities pose over each natural system are still in its infancy (Brashares 2010). Furthermore, there is increasing awareness that changes in biodiversity will affect ultimately human well being (Faith et al 2010).

More than a half of the world's surface area has been converted to human dominated ecosystems (Ellis and Ramankutty 2008; Foley and others 2005; Vitousek and others 1997). Agriculture has been the dominant land cover change of the Earth's history (Ramankutty and Foley 1999). As of 2007, up to 38% of the Earth's land cover has been dedicated to agriculture (Food and Agriculture Organization of the United Nations 2010). The pace of LULCC has been particularly rapid in the last 30 years (Lambin and Geist 2006; Leff, Ramankutty, Foley 2004; Lepers and others 2005), and it is the main cause of habitat loss (Matson and others 1997), and subsequent loss of biodiversity (Butchart and others 2010, Harding and others 1998; Reidsma and others 2006; Zebisch, Wechsung, Kenneweg 2004) through extinctions and population declines (Kruess and Tscharntke 1994; Pimm and Raven 2000).

However, agricultural land use has also decreased in extension, primarily in areas that are only marginally suited for modern agriculture (Beddow and others 2010; Lambin and Geist 2006; Rudel and others 2005), with concomitant increases in forested area (Kauppi and others 2006). It is well documented that expansion and intensification of land use resulted in major biodiversity changes, especially in the last decades (Hansen, DeFries, Turner 2004). Less understood are the effects of other land cover changes on biodiversity such as agricultural land abandonment (Ramankutty and others 2007).

Understanding the relation between land cover changes and biodiversity requires developing tools to assess promptly and accurately the extent of agricultural changes in both directions: expansion and intensification on one hand, and abandonment and de-intensification on the other. Mapping land cover changes on land abandonment is at least equally important as assessing agricultural land expansion, given the strong implications on biodiversity, soil stability (Tasser, Tappeiner, Cernusca 2005), carbon sequestration (Ramankutty and others 2007; Vuichard and others 2008), water quality (Scanlon and others 2007), and nutrient cycles (Stoate and others 2001). Unfortunately, current data on agricultural abandonment is poor and methods to inventory abandonment accurately for large areas are lacking.

Agricultural land abandonment is a process, and abandoned agricultural land a land cover type, that can vary in appearance in space and time making it difficult to define it. An accurate and consistent definition to map agricultural land abandonment is necessary as well as a method that allow us to assess that process. The use of remote sensing and new mapping methods can help to find an operative definition that quickly allow mapping agricultural abandonment across large areas. Furthermore, developing a method to map agricultural land abandonment over large areas will allow us to better focus conservation and management efforts and improve actions to revert the negative effects of land abandonment. The first goal of this dissertation was to develop and test a method to map abandoned agricultural land.

Eastern Europe represents a prime example of rapid land cover change where several studies reported widespread agricultural land abandonment since 1990 (Baumann in press, Brooks and Bruce 2004; Gobulev and Dronin 2004; Hostert in preparation, Ioffe, Nefedova, Ilya 2006; Lerman and Csaki 2004; Kuemmerle 2008, Müller 2006, Prischepov in preparation, Unwin 1997), including, in some cases, reforestation (Taff and others 2010). Both a trend towards less intensive farming systems and land abandonment after the collapse of the Soviet Union occurred, the latter particularly on marginal land (Dutch National Reference Center for Agriculture and others 2005; Swinnen, Van Herck, Vranken 2010). However, to date a comprehensive assessment of abandoned agricultural land across Eastern Europe is lacking

(Lepers and others 2005) and only a small set of case studies have mapped and analyzed its pattern.

Agricultural land abandonment is a complex process that may be driven by both socioeconomic factors and biophysical conditions (Lambin and others 2001). A particularly important role is played by institutions and governmental policies that have control over inputs for agriculture, which in turn have direct effects on land use change. On the other side, biophysical conditions define the natural capacity of the land, and changing biophysical conditions may predispose areas for land use change (Turner and others 2007). The challenge is to disentangle which of these factors matter most in a given place, because agricultural land use change in general, and land abandonment in particular, is typically gradual, and not amenable to scientific experiments. In the second chapter of this dissertation I conducted a classification of MODIS images across Eastern Europe to map agricultural abandonment. The goal was to examine agricultural abandonment patterns and agro-ecological constraints across Eastern Europe to assess if biophysical factors or national policies played the main role on the agricultural abandonment pattern.

The extent and degree of biodiversity changes that resulted from set aside lands is not well known yet. Currently there are only a handful of efforts that assess the consequences of agricultural land abandonment to biodiversity; efforts are especially focused on birds (Sirami and others 2008). Large predators are key elements in many ecosystems (Morrison and others 2007). They play a critical role on trophic cascades as top-down force to regulate terrestrial ecosystems (Terborgh and others 2001). Large predators usually have wide home ranges, often requiring large areas (Maehr, Noos, Larkin 2001). They are also particularly vulnerable, at species and population levels, and indeed less than 21 % of the earth‘s terrestrial surface still contain all of the large mammals (>20 kg) it once held (Morrison and others 2007). Given the ecological importance of large mammals and in particular of top predators, it is necessary to analyze the relationship between land abandonment and top predators (Carroll, Noss, Paquet 2001; Niemi and McDonald 2004; Simberloff 1998; Simberloff 1999). One of the main large carnivore population recoveries in recent decades probably occurred in Eastern Europe. Brown bears (*Ursus arctos arctos*) registered a large expansion of their geographical range in the European part of Russia from 1960 to 1989 (Chestin and others 1992). My third chapter explored how land cover change, human disturbance and environmental conditions influenced brown bear range expansion and habitat use in European Russia after 1990.

The remainder of my thesis is structured in three main sections (Chapters I-III) that build upon each other, and address the specific goals outlined above. All three chapters were written as standalone manuscripts to be published in international peer-reviewed journals. Each chapter was structured accordingly, with background, study area, methods, results, and discussion.

1. Chapter I. Mapping abandoned agriculture using coarse-resolution multi-temporal MODIS satellite imagery.
2. Chapter II. Patterns of abandoned agriculture across Central and Eastern Europe after the breakdown of the USSR derived from multi-temporal MODIS NDVI, and phenology data.
3. Chapter III. Effects of land-use and land cover changes and fragmentation on brown bear (*Ursus arctos arctos*) populations in Russia.

In my first chapter I conducted and compared twenty one alternative classifications to map abandoned land for one MODIS tile in Eastern Europe (~1,236,000 Km^2) were abandoned agriculture was widespread. Input data was NDVI and reflectance bands (~250-m pixel /size), as well as phenology parameters calculated with TIMESAT. The data were classified with a support vector machine. Training data were derived from several Landsat classifications of abandonment in the study area and validation was conducted using independently collected data. My goal for the first chapter was to test methods to map abandoned agriculture at broad scales with coarse-resolution (MODIS) satellite imagery. Specifically, my questions were if abandoned agriculture was more accurately detected with:

a) Near-Infrared (NIR) and Red reflectance data, or with Normalized Difference Vegetation Indices (NDVI) data;
b) A specific best year of data, or if any year results in an equally accurate classification;
c) The entire year of data or just data for the growing season;
d) Data for one year, or for multiple years;
e) NDVI time series, phenology measures (e.g., start, end, length, amplitude, and maximum of the season) or the combination of them?

My results demonstrated that it is feasible to map agricultural land abandonment consistently using coarse resolution imagery. Support vector machines applied to growing season NDVI data for multiple years, plus phenology information captured in six parameters provided the highest classification accuracy when mapping abandoned land from MODIS data.

In my second chapter, I assessed for the first time, abandoned agricultural land across Eastern Europe including European Russia. The main goal of second chapter was thus to assess agricultural land abandonment across Central and Eastern Europe including the European part of Russia. My objectives were:

a) To map abandonment from satellite data wall-to-wall across the region; and

b) To compare abandonment rates among countries and among agro-ecological zones as a first exploration into potential drivers of abandonment.

I demonstrated in this chapter that the method developed on the first chapter is extensible to other areas and allows to compare abandonment across countries. I conducted a supervised classification using a Support Vector Machine as our classifier, 250-m resolution 2004 – '06 MODIS NDVI data, and TIMESAT phenology indices. Training and validation data were derived from Landsat classifications from the late 1980s and the mid 2000s. The main finding was that abandoned agricultural land was widespread across Central and Eastern Europe. Countries differed strongly in terms of their abandonment rates, but differences among agro-climatic regions were less pronounced. This suggests that agricultural abandonment after the collapse of the USSR was more closely associated with socioeconomic factors than with biophysical conditions.

In the third chapter I analyzed the relationship between the documented land abandonment in the second chapter, and resulting changes in landscape configuration with brown bear populations in European Russia. My goal was to explore how land-cover change, human disturbance and environmental conditions influenced brown bear range expansion and habitat use in European Russia after 1990. Specifically, I conducted an analysis at two scales:

1) I analyzed general population trends from 1991 to 2007 throughout European Russia; and

2) I analyzed habitat use in the areas where brown bear's geographical range expanded recently.

In my analysis of habitat use, I examined in particular:

a) environmental factors,

b) human presence,

c) land cover, landscape changes, and land cover fragmentation, and last but not least

d) the effects of dispersal distances.

The third chapter showed that brown bears have expanded their distribution southwards, that habitat use was strongly affected by human disturbance, and that bears selected against agricultural land abandonment. Additionally, I evaluated two relatively new methodologies each to measure a) dispersal and b) fragmentation. To measure brown bear dispersal I tested the use of Euclidean distances versus Cost-path analysis and included both measures alternatively in multivariate linear regression models. Surprisingly, Cost-path analysis did not show the expected strength to justify its use instead of the use of Euclidean distances. In the case of the measurement of fragmentation I implemented a modified version to map morphological features on the landscape such as patch, edge, interior, gap and exterior of suitable habitat. Again I was surprised to see that image morphology did not show differences when included in the multiple linear regression compared to forest abundance, but it provided interesting insights regarding the different habitat uses by the brown bears.

My dissertation does make contributions in three main areas: a) basic science, b) methodologies and c) conservation and management. In my first chapter I developed a new approach to map agricultural land abandonment; the main contribution here was thus the development and refinement of remote sensing methods, by complementing the toolbox on mapping land cover changes that currently focus especially on agricultural intensification and extensification. To map the opposite trend of land abandonment, and less intensive agricultural use can elucidate the impacts and feedbacks between land cover change and other ecosystem's components such as biodiversity; soil stability, carbon sequestration, water quality, and nutrient cycles.

In my second chapter I made contributions in two dimensions: basic science and methodologies. My contribution on basic science here was to establish that institutions and policies can be the main driver of LULCC and that socioeconomic disturbances (such as the collapse of the Soviet Union) can occur rapidly and have large effects on LULCC. My methodological contribution was to provide a new dataset on agricultural land abandonment across Eastern Europe, a region that has not been studied well before, and that experienced widespread land abandonment. By providing this map across a large region I open the possibility to focus on specific regions where land abandonment happened at large allowing a systematic comparison to determine drivers *sensu* Lambin and Geist (2006), to model trajectories of land use change *sensu* Verburg et al. (2009), and to refine forest transition theory (MacDonald and others 2000; Rudel and others 2005) and land use transition theory (DeFries, Foley, Asner 2004; Foley and others 2005).

In my third chapter I made contributions to all three dimensions: basic science, methodologies, and conservation and management. My basic science contribution was to provide a better understanding of bear habitat use at the range-scale. My methodological contribution was to analyze a Brown bear population not yet well known in the current peer review literature and to test new methodologies to measure dispersal and fragmentation. My contribution for conservation and management was to show potential areas of human-wildlife conflicts and the inclusion of a model to identify areas of opportunity for bear population recovery.

Humans are changing the Earth very rapidly, and it will take concerted efforts to protect wildlife species, and to ensure their long-term population viability in the face of these changes. The overarching goal of my dissertation was to contribute to a better understanding of the consequences of land use change for wildlife. As such, I think that it is critical to do both, *monitor* the changes that are occurring better, and *quantify* the effects of these changes on wildlife populations. Hopefully, the research presented here will provide others with the tools to do so in other areas, and the joint insights provided by my dissertations and other projects will contribute to the conservation of biodiversity upon which we all depend.

1.1 References

Baumann M, Kuemmerle T, Elbakidze M, Ozdogan M, Radeloff VC, Keuler NS, Prischepov A, Kruhlov I, Hostert P. in press. Patterns and drivers of post-socialist farmland abandonment in Western Ukraine. Land use Policy.

Beddow JM, Pardey PG, Koo J, Wood SJ. 2010. The changing landscape of global agriculture. Alston JM, Babcock BA,Pardey PG, editors. In: The shifting patterns of agricultural production and productivity worldwide. . p8.

Brashares JS. 2010. Filtering Wildlife. Science 329(5990):402-3.

Brooks K and Bruce G. 2004. Russian agriculture in the transition to market economy. Economic Development and Cultural Change 52:571-86.

Butchart SHM, Walpole M, Collen B, Van Strien A, Scharlemann JPW, Almond REA, Baillie JEM, Bomhard B, Brown C, Bruno J. 2010. Global biodiversity: indicators of recent declines. Science 328(5982):1164.

Carroll C, Noss RF, Paquet PC. 2001. Carnivores as focal species for conservation planning in the Rocky Mountain region. Ecological Applications 11(4):961-80.

Chestin IE, Gubar YP, Sokolov VE, Lovachev VS. 1992. The Brown bear (Ursus arctos L.) in the USSR: numbers, hunting and systematics. Annales Zoologici Fennici 29(2):57-68.

DeFries RS, Foley JA, Asner GP. 2004. Land-use choices: balancing human needs and ecosystem function. Frontiers in Ecology and the Environment 2(5):249-57.

Dirzo R and Raven PH. 2003. Global state of biodiversity and loss. Annual Review of Environment and Resources 28:137-67.

Dutch National Reference Center for Agriculture, Nature and Food Quality, Latvian Ministry of Agriculture, Latvian State. 2005. Land abandonment and biodiversity, in relation to the 1st and 2nd pillars of the European Union's Common Agricultural Policy; outcome of an international seminar in Sigulda, Latvia, 7-8 October, 2004. :1-64.

Faith DP, Magallón S, Hendry AP, Conti E, Yahara T, Donoghue MJ. 2010. Evosystem services: an evolutionary perspective on the links between biodiversity and human well-being. Current Opinion in Environmental Sustainability. 2:1-9

Foley JA, DeFries RS, Asner GP, Barford C, Bonan G, Carpenter SR, Chapin FS, Coe MT, Daily GC, Gibbs HK, Helkowski JH, Holloway T, Howard EA, Kucharik CJ, Monfreda C, Patz JA, Prentice IC, Ramankutty N, Snyder PK. 2005. Global consequences of land use. Science 309(5734):570-4.

Food and Agriculture Organization of the United Nations. 2010. FAOSTAT data web page. 2010(07/27) http://faostat.fao.org/.

Gobulev G and Dronin N. 2004. Geography of drougths and food problems in Russia (1900-2000). A 0401:1-28.

Hansen AJ, DeFries RS, Turner W. 2004. Land use change and biodiversity: a synthesis of rates and consequences during the period of satellite imagery. Land Change Science 6(III):277-99.

Harding JS, Benfield EF, Bolstad PV, Helfman GS, Jones EBD. 1998. Stream Biodiversity: The Ghost of Land Use Past. Proceedings of the National Academy of Sciences of the United States of America 95(25):14843-7.

Hostert P, Kuemmerle T, Prischepov A, Sieber A, Lambin E, Radeloff VC. in preparation. Rapid land use changes after socioeconomic disturbances: Chernobyl and the collapse of the Soviet Union. Science.

Ioffe G, Nefedova T, Ilya Z. 2006. The end of peasantry? disintegration of rural Russia. First ed. Pittsburgh, PA: University of Pittsburgh Press. 258p.

Kauppi PE, Ausubel JH, Fang J, Mather AS, Sedjo RA, Waggoner PE. 2006. Returning forests analyzed with the forest identity. Proceedings of the National Academy of Sciences 103(46):17574-9.

Kruess A and Tscharntke T. 1994. Habitat fragmentation, species loss, and biological control. Science 264(5165):1581-4.

Kuemmerle T, Hostert P, Radeloff VC, van derLinden S, Perzanowski K, Kruhlov I. 2008. Cross-border comparison of post-socialist farmland abandonment in the Carpathians. Ecosystems 11(4):614-28.

Kuemmerle T, Müller D, Griffiths P, Rusu M. 2009. Land use change in Southern Romania after the collapse of socialism. Regional Environmental Change 9(1):1-12.

Lambin EF and Geist HJ, editors. 2006. Land-use and land-cover change: Local processes and global impacts. First ed. Berlin Heidelberg New York: Springer. p222.

Lambin EF, Turner BL, Geist HJ, Agbola SB, Angelsen A, Bruce JW, Coomes OT, Dirzo R, Fischer G, Folke C, George PS, Homewood K, Imbernon J, Leemans R, Li XB, Moran EF, Mortimore M, Ramakrishnan PS, Richards JF, Skanes H, Steffen W, Stone GD, Svedin U, Veldkamp TA, Vogel C, Xu JC. 2001. The causes of land-use and land-cover change: moving beyond the myths. Global Environmental Change-Human and Policy Dimensions 11(4):261-9.

Leff B, Ramankutty N, Foley JA. 2004. Geographic distribution of major crops across the world. Global Biogeochemical Cycles 18(1):1-27.

Lepers E, Lambin EF, Janetos AC, DeFries RS, Achard F, Ramankutty N, Scholes RJ. 2005. A synthesis of information on rapid land-cover change for the period 1981–2000. BioScience 55(2):115-24.

Lerman Z and Csaki C. 2004. Evolving farm structures and land use patterns in former socialist countries. Quarterly Journal of International Agriculture 43(4):309-35.

MacDonald D, Crabtree JR, 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. Journal of Environmental Management, 59(1):47-69.

Maehr DS, Noos RF, Larkin JL, editors. 2001. Large mammal restoration: Ecological and sociological considerations in the 21st century. First ed. Washington DC: Island Press. p336.

Matson PA, Parton WJ, Power AG, Swift MJ. 1997. Agricultural intensification and ecosystem properties. Science 277(5325):504-9.

Morrison JC, Sechrest W, Dinerstein E, Wilcove DS, Lamoreux JF. 2007. Persistence of large mammal faunas as indicators of global human impacts. Journal of Mammalogy :1363-80.

Müller D and Sikor T. 2006. Effects of postsocialist reforms on land cover and land use in South-Eastern Albania. Applied Geography 26(3-4):175-91.

Niemi GJ and McDonald ME. 2004. Applicattion of Ecological Indicators. Annual Review of Ecology, Evolution, and Systematics 35:89-111.

Pimm SL and Raven P. 2000. Biodiversity: Extinction by numbers. Nature 403(6772):843-5.

Prischepov A, Radeloff VC, Baumann M, Kuemmerle T. in preparation. Impact of massive socio-economic changes on land use change: agricultural abandonment during socio-economic transition in post-Soviet Eastern Europe.

Ramankutty N and Foley JA. 1999. Estimating historical changes in global land cover: Croplands from 1700 to 1992. Global Biogeochemical Cycles 13(4):997-1027.

Ramankutty N, Gibbs HK, Achard F, DeFries RS, Foley JA, Houghton RA. 2007. Challenges to estimating carbon emissions from tropical deforestation. Global Change Biology 13(1):51-66.

Reid W, Mooney H, Cropper A, Capistrano D, Carpenter S, Chopra K, Dasgupta P, Dietz T, Duraiappah A, Hassan R. 2006. Millennium Ecosystem Assessment. Survey of initial impacts 28.

Reidsma P, Tekelenburg T, van den Berg M, Alkemade R. 2006. Impacts of land-use change on biodiversity: An assessment of agricultural biodiversity in the European Union. Agriculture, Ecosystems & Environment 114(1):86-102.

Rudel TK, Coomes OT, Moran E, Achard F, Angelsen A, Xu J, Lambin EF. 2005. Forest transitions: Towards a global understanding of land use change. Global Environmental Change Part A, 15(1):23-31.

Sanderson EW, Jaitheh M, Levy MA, Redford KH, Wannebo AV, Woolmer G. 2002. The human footprint and the last of the wild. BioScience 52(10):891-904.

Scanlon BR, Jolly I, Sophocleous M, Zhang L. 2007. Global impacts of conversions from natural to agricultural ecosystems on water resources: Quantity versus quality. Water Resources Research 43:1-18.

Simberloff D. 1998. Flagships, umbrellas, and keystones: Is single-species management passé in the landscape era? Biological Conservation 83(3):247-57.

Simberloff D. 1999. Biodiversity and Bears: A conservation paradigm shift. Ursus 11(, A selection of papers from the eleventh international conference on bear research and management, Graz, Austria, September 1997, and Gatlinburg, Tennessee, April 1998):21-7.

Sirami C, Brotons L, Burfield I, Fonderflick J, Martin J. 2008. Is land abandonment having an impact on biodiversity? A meta-analytical approach to bird distribution changes in the north-western Mediterranean. Biological Conservation 141(2):450-9.

Stoate C, Boatman ND, Borralho RJ, Carvalho CR, Snoo GRd, Eden P. 2001. Ecological impacts of arable intensification in Europe. Journal of Environmental Management, 63(4):337-65.

Swinnen J, Van Herck K, Vranken L. 2010. Shifting patterns of agricultural production and productivity in the former Soviet Union and Central and Eastern Europe. Alston JM, Babcock BA,Pardey PG, editors. In: The shifting patterns of agricultural production and productivity worldwide. p279.

Taff GN, Müller D, Kuemmerle T, Ozdeneral E, Walsh SJ. 2010. Reforestation in Central and Eastern Europe after the breakdown of socialism. Nagendra H and Southworth J, editors. In: Reforesting landscapes: Linking pattern and process. Springer. p121.

Tasser E, Tappeiner U, Cernusca A. 2005. Ecological effects of land-use changes in the European Alps. 23:409-20.

Terborgh J, Lopez L, Nunez P, Rao M, Shahabuddin G, Orihuela G, Riveros M, Ascanio R, Adler GH, Lambert TD, Balbas L. 2001. Ecological meltdown in predator-free forest fragments. Science 294(5548):1923-6.

Turner BL, Lambin EF, Reenberg A. 2007. The emergence of land change science for global environmental change and sustainability. Proceedings of the National Academy of Sciences 104(52):20666-71.

Unwin T. 1997. Agricultural restructuring and integrated rural development in Estonia. Journal of Rural Studies 13(1):93-112.

Verburg PH, van de Steeg J, Veldkamp A, Willemen L. 2009. From land cover change to land function dynamics: A major challenge to improve land characterization. Journal of Environmental Management 90(3):1327-35.

Zebisch M, Wechsung F, Kenneweg H. 2004. Landscape response functions for biodiversity-assessing the impact of land-use changes at the county level. Landscape and Urban Planning, 67(1-4):157-72.

2 Chapter I. Mapping abandoned agriculture using coarse-resolution multi-temporal MODIS satellite imagery

Authors

Camilo Alcantara[1*], Volker C. Radeloff[1], Alexander V. Prishchepov[1], and Tobias Kuemmerle[1]

[1]Department of Forest and Wildlife Ecology, University of Wisconsin-Madison,

1630 Linden Drive, Madison, WI, 53706-1598, USA

[*]Corresponding author.

Phone +1 608 265-9219; fax: +1 608 262-9922

E-mail: **alcantara@wisc.edu**

2.1 Abstract

Agriculture is generally expanding and intensifying, but agricultural abandonment is also becoming more common, especially in temperate regions. Unfortunately, data on agricultural abandonment is poor and methods to inventory abandonment accurately for large areas are lacking. Remote sensing may be able to fill this gap, but past efforts to map abandonment relied mainly on Landsat data, making it hard to map large regions, and limiting opportunities to use phenology to identify abandoned land. Our objective here was to test methods to map abandoned agriculture at broad scales from coarse-resolution (MODIS) satellite imagery. We classified abandoned land for one MODIS tile in Eastern Europe (~1,236,000 Km^2) were abandoned agriculture was widespread. Input data were NDVI and reflectance bands (NASA Global MODIS Terra and Aqua 16-Day vegetation indices for the years 2003 through 2008, ~250 m. pixel /size), as well as phenology parameters calculated with TIMESAT. The data were classified with a support vector machine. Training data were derived from several Landsat classifications of abandonment in the study area and validation was conducted using independently collected data. Our results showed that it is possible to map abandoned agriculture for large areas from MODIS 250-m resolution data with overall accuracies of around 65%. Abandoned agriculture was widespread in our study area (15.1% compared to 29.6% agriculture). We found strong differences in the MODIS data quality for different years, with data from 2005 resulting in the highest classification accuracy (42.8% producer's accuracy). MODIS NDVI data performed almost as well as a combination of red and near-infrared reflectance data. MODIS NDVI data from the growing season alone performed as well as data for the full year. Using multiple years of MODIS data did not increase classification accuracy. Last but not least, six phenological parameters derived with TIMESAT from the

MODIS NDVI time series (2003-2008) were by themselves insufficient to detect abandoned land, but improved classification accuracies when used in conjunction with NDVI time series by more than 8%.We identified approaches here to map land abandonment and proposed methods that facilitate the mapping of abandoned agriculture at broad scales. Our results are promising and suggest that mapping of abandoned agriculture at broad scales is possible.

Keywords: abandonment, agricultural abandonment, accuracy assessment, change detection, Eastern Europe, Soviet Union, farmland, land use, land cover change, MODIS, Landsat, multi-date, multi-seasonal, old fields, support vector machines, SVM

2.2 Introduction

More than half of the earth has been transformed by humans through land-use and land-cover change (LULCC) (Ellis and Ramankutty 2008; Foley and others 2005; Vitousek and others 1997). Assessing rates and spatial patterns of LULCC is important for both policy making and the scientific understanding of the earth system (Lambin and others 2001). Remote sensing can monitor LULCC and thereby improve land management and decision making (Boyd and Danson 2005; Cohen and Goward 2004; Laurance, Albenaz, Da Costa 2001; Nepstad and others 1999), but different aspects of LULCC need different remote sensing approaches. Agricultural change is a key component of LULCC (Foley and others 2005; Goldewijk and Ramankutty 2004; Haberl and others 2007; Leff, Ramankutty, Foley 2004; Tilman and others 2001). More than 38% of the earth's land surface was either covered by crops or grazed in 2005 (Food and Agriculture Organization of the United Nations 2010). Cropland alone has increased exponentially during the last centuries, occupying 3 - 4 million km^2 in 1700 and 15 – 18 million km^2 in 1990 (corresponding to about 12% of the land surface of the globe) (Lambin and Geist

2006; Leff, Ramankutty, Foley 2004). However, in the last 50 years agricultural area has stabilized or even decreased in several regions of the world, especially in the temperate zone (Lambin and Geist 2006), resulting in agricultural land abandonment, and sometimes concomitant increases in forest area (Kauppi and others 2006; Millennium Ecosystem Assessment 2005; Rudel and others 2005).

Agricultural expansion, and concomitant deforestation have been widely monitored and well documented (Lambin and Geist 2006), raising concerns about long-term sustainability and environmental consequences (Stoate and others 2001; Tilman 1999). Less attention has been paid to the monitoring and environmental consequences of agricultural abandonment both in temperate and tropical forest (Aide and Grau 2004; Cramer, Hobbs, Standish 2008; Vandermeer and Perfecto 2007; Wright 2005). Agricultural abandonment is not a new phenomenon though. Expansion and contraction of the agricultural land area has been common throughout history (Ellis and others 2010, Ramankutty and Foley 1999). However, recently land cover has suffered dramatic changes at the global scale, and there has been a substantial increase of agricultural land abandonment (Kauppi and others 2006), for instance, in parts of the United States (Hart 1968), Europe (Dutch National Reference Center for Agriculture and others 2005; Ministerial Conference on the Protection of Forests in Europe - Liason Unit Warsaw, United Nations Economic Commission for Europe, Food and Agriculture Organization of the United Nations 2007) and South America (Aide and others 1995; Farley 2007). Most land abandonment has occurred in temperate ecosystems, though abandonment has also been reported in tropical countries such as Puerto Rico (Grau and others 2003), Mexico (Klooster 2003), Ecuador (Farley 2007), Honduras (Redo, Joby Bass, Millington 2009), Panama (Sloan 2008), and Vietnam (Meyfroydt and Lambin 2008). However, although abandonment is not uncommon, reliable data on abandonment are missing for most countries. This lack of data on abandonment is unfortunate because abandonment has strong implications for soil stability, carbon sequestration, water quality and nutrient cycling (MacDonald and others 2000; Moreira and Russo 2007; Ramankutty and others 2007; Stoate and others 2001). Environmental benefits of abandonment includes less pollution by agricultural chemicals (Lesschen and others 2008), and the creation of new wildlife habitat (Chauchard, Carcaillet, Guibal 2007; Russo 2007). However, abandonment can also increase the risk of natural hazards (Romero-Calcerrada and Perry 2004) and alter water resources (Poyatos, Latron, Llorens 2003). In economic terms, land abandonment decreases food production, and threaten traditional landscapes, their cultures and the biodiversity connected to these landscapes (Dutch National Reference Center for Agriculture and others 2005).

The environmental and socioeconomic implications of land abandonment make it necessary to improve our ability to monitor abandonment as a process, and abandoned agriculture as a land cover type. Satellite imagery can provide independent and consistent data to map LULCC such as abandoned agriculture (Lu and others 2004, Fassnacht, Cohen, Spies 2006). In the United States of America remote sensing has been used to map abandoned farmland resulting from the Conservation Reserve Program (Egbert and others 1998; Egbert and others 2002; Park and Egbert 2008). In Europe, abandoned farmland was successfully mapped from satellite imagery in Italy (Falcucci, Maiorano, Boitani 2007), Denmark(Kristensen, Thenail, Kristensen 2004), Estonia (Peterson and Aunap 1998), Belarus and Lithuania (Prischepov and others 2010), and the Carpathians (Kuemmerle and others 2008; Kuemmerle and others 2009). In Asia a study mapped abandoned agriculture in the Siberian part of Russia (Bergen and others 2008). All these studies used Landsat imagery from multiple dates, separated at least by three years, an employed some form of change detection to identify areas that were initially in agricultural use, and later in various stages of succession.

While these Landsat-based studies highlight that agricultural abandonment can be accurately mapped with satellite imagery, they also point to some shortcomings of current approaches. First, past efforts to map agricultural abandoned were spatially limited to a single Landsat scene, and cannot be easily compared because of different change detection algorithms, class catalogs, abandonment definitions, and images dates (Prishchepov and others in preparation). Second, past efforts used typically one or two Landsat images for a given year. This is unfortunate, because differences in phenology can help separate abandoned agriculture from agricultural areas still in use. Test show that three images per year both pre- and post-abandonment are necessary to achieve classification accuracies up to 80%, but sufficient cloud free images are simply not available for most locales (Prishchepov and others in preparation). Landsat imagery may thus not be the best data source to map abandoned agriculture for large areas. In contrast coarse-resolution satellite imagery may offer advantages in terms of both spatial and temporal coverage with their ability to capture phenology, but their ability to map abandoned agriculture has not been tested.

The most common satellite sensors used to map LULCC at broad scale have been AVHRR, SPOT-VGT, and MODIS (Friedl and others 2002, Fensholt and Sandholt 2005). Phenological parameters, such as start, end, middle and length of the season over broad scale images have been used to map land cover with good results (Jacquin, Sheeren, Lacombe 2010; White and others 2008; Xiao and others 2006; Zhang and others 2003). Land cover classifications from coarse-resolution imagery are most accurate when using non-parametric, machine-learning algorithms such as neural networks (Justice and others 2002), or decision trees (Friedl and Brodley 1997). Among the machine learning algorithms, support vector machines have shown particular promise when applied to Landsat data (Hermes and others 1999) (Kuemmerle and others 2009) including for mapping agricultural abandonment (Kuemmerle and others 2008, Prischepov and others, 2010). For broad scale mapping SVM has been used successfully to predict Gross Primary Production (GPP) for the conterminous U.S. (Yang and others 2007). However, land cover classification with Support Vector Machines are rare, although a case study classifying land cover from MODIS in Portugal shows promises (Goncalves and others 2005).

Our goal here was to test methods to map abandoned agriculture at broad scales with coarse-resolution (MODIS) satellite imagery. Specifically, we asked if abandoned agriculture was more accurately detected with:

f) Near-Infrared (NIR) and Red reflectance data, or with Normalized Difference Vegetation Indices (NDVI) data;
g) A specific best year of data, or if any year results in an equally accurate classification;
h) The entire year of data or just data for the growing season;
i) Data for one year, or for multiple years;
j) NDVI time series, phenology measures (e.g., start, end, length, amplitude, and maximum of the season) or the combination of them

2.3 Methods

2.3.1 Eastern Europe study area

We classified different MODIS datasets from 2003 to 2008 with Support Vector Machines to detect abandoned agricultural land in the Baltic countries, Belarus and Poland (Figure 1). The study area encompassed 12,364,340 km^2, the extent of one MODIS scene (Tile h19-v03) covering the entire area of Lithuania, Latvia, Estonia and Belarus, 77.4% of Poland, 18.4% of Ukraine, 8.4% of Czech Republic and only 2.1% of Russia (However, this included the entire Kaliningrad region and the equivalent of more than 110% the land area of Poland). This part of Eastern Europe provides an ideal study because abandoned agriculture became widespread after the breakdown of the USSR ((Kuemmerle and others 2008, Prishchepov and others 2010, Charles 2010; Dutch National Reference Center for Agriculture and others 2005; Nikodemus and others 2005; Peterson and Aunap 1998).

FIGURE 1. APPROXIMATELY HERE

The entire study area was glaciated several times and the Last Glacial Maximum was approximately 20,000 years ago. As a result, topographic variation is low (0 – 292 m) (Zeeberg 1998). The dominant soils in the study area are arenosols, phaeozems, fluvisols, cambisols and luvisols. Podzols, which are poorly suited for agriculture, are common throughout the study area, especially in the north. The climate in the study area is characterized by moist, cloudy, and cool summers and relatively mild winters. Frost free periods range from 150-179 days in the northeast to 210-240 days in the south. Average temperatures in July are 20 to 25 °C and average temperature in January is-3 to -5 °C. Annual precipitation ranges from 500 mm in the central Poland to 900 mm in the mountains between Poland and Czech Republic. Forests are boreal in the north (dominant tree species include *Pinus sylvestris, Picea abies, and Betula spp.*) and temperate in the south (dominant tree species include *Quercus spp, Pinus sylvestris,* and *Picea abies*).

The majority of the agricultural abandonment in the study area occurred during the 1990s, right after the breakdown of the USSR (Prischepov and others 2010). MODIS data is only available after 2001, and can thus not be used for actual change detection (i.e., the mapping of areas that were farmed during socialist times and covered by secondary succession later). Instead, we used the MODIS data to map abandoned agriculture, i.e., areas covered by secondary succession such as grasses that were neither mowed nor grazed, shrubs, and in some cases young trees. Whether or not these areas were indeed farmed during socialism (pre-1991) was verified with Landsat imagery which was analyzed to provide validation data (see below). The operative definition of abandoned agriculture that we used for this paper is thus all former agricultural land (including both plowed fields and managed grasslands) that is no longer used for agriculture. Thus our goal was to map abandoned agriculture as a land cover class, rather than the process of agricultural abandonment.

2.3.2 Input data for the classifications

We based all of our classifications on the two NASA Global MODIS Vegetation Indices datasets Terra and Aqua (MODIS VI) 16-Day L3 Global Collection 5.0 (MOD13Q1 and MYD13Q1) from January 1, 2003 to December 31, 2008 (231.65 m pixel size or 5.36 hectares). Data was retrieved from the Land Processes Distributed Active Archive Center (LP DAAC) on August 31, 2009 (http://lpdaac.usgs.gov). The combined MODIS VI dataset includes weekly reflectance, NDVI, and quality data. We analyzed 250-m 16-day red reflectance data, 250-m 16-day near infrared reflectance data, and 250-m, 16-day NDVI data, each of which is available for 46 dates per year, including both Terra and Aqua datasets.

To identify the best year or years for our analysis, we examined the amount of MODIS NBAR data available in different quality classes in each year for the red and infrared bands (Science Data Sets for MODIS Terra+Aqua BRDF/Albedo Quality 16-Day L3 Global 500m SIN Grid V005, MCD43A2). Results showed that high-quality data prior to 2003 was very sparse (Figure 2). For example, in 2005, there were 19 MODIS images with more than 90% usable data in each image (Categories 1 -3 of MCD43A2: "best quality, full inversion", "good quality, full inversion" and "Magnitude inversion, number of observations >=7"), versus only four of such images in 2001. Because of limited availability of usable data, we used only data from 2003 to 2008 in our analysis. Initial results also showed that 2006 provided the highest single-year classification accuracies (see below), and since 2006 was also among the years with the most reflectance data in the 'best' quality category, we focused in some of our tests on 2005 and 2006.

FIGURE 2. APPROXIMATELY HERE

Phenology information can improve land cover classifications from coarse-resolution satellite imagery (Jacquin, Sheeren, Lacombe 2010; White and others 2008; Xiao and others 2006; Zhang and others 2003). We calculated eleven phenological indices for each year (Start of the growing season, end of the growing season, length of the growing season, base level, middle of the growing season, largest data value for the fitted function during the growing season, growing seasonal amplitude, rate of increase at the beginning of the growing season, rate of decrease at the end of the growing season, large growing seasonal integral, and small growing seasonal integral) from the 2003 – 2008 NDVI time series. We used the Savitsky-Golay algorithm included in the program TIMESAT (Jonsson and Eklundh 2004). We defined the growing season as starting on day 129 (May 9^{th}, or May 8^{th} on leap years) and ending on day 297 (October 24^{th}, or October 23th in leap years) based on initial TIMESAT results.

2.3.3 Training data for the classifications

Training data was extracted from land cover maps that had been previously derived for three Landsat scenes. Two of the Landsat land-cover maps captured land abandonment between 1989 and 1999 in parts of Lithuania and Russia (Prishchepov and others in preparation). The third Landsat scene mapped abandonment between 1986 and 2000 around Chernobyl, Ukraine (Hostert and others 2010). The classification scheme included 8 classes (Abandonment, Cropland, Grassland, Deciduous Forest, Needle-leaved Forest, Regrowth, Water, and Other Classes). We summarized the percentage of each land cover class in grid cells within 500 m resolution. The 500-m cells fully encompassed one 250-m pixel, leaving 125 m around the edges to account for location uncertainty in the MODIS data (Tan and others 2006). For training purposes, we used 1,459 cells with at least 90% dominance in one land cover class. Training data was grouped into four classes: abandoned (157 cells), agriculture (444, both plowed fields and managed grasslands), forest (307, including deciduous, coniferous and mixed), and other (551, including water, urban areas, and wetlands).

2.3.4 Classification algorithm, and classification tests

All land cover classes exhibited multi-modal or non-normal distributions in our training data. In the case of abandoned agricultural land, for instance, multi-modal distributions represented areas covered by grasses versus young trees. We thus applied a non-parametric classifier: Support Vector Machines (SVM) (Huang, Davis, Townshend 2002) to classify the MODIS data. The software package that we used was ImageSVM, programmed in IDL (Janz and others 2007). SVMs are highly accurate classifiers, but computationally demanding. We therefore evaluated five questions to assess what input dataset results in the most accurate maps of abandoned agriculture:

a) Our first question was if near-infrared and red reflectance data was better suited than NDVI data to map abandoned land. This test was conducted with single-year data for the growing season only for both 2005 and 2006. We derived two classifications for each year (one with red and near infrared data as input, one with NDVI) and compared their classification accuracies (see below).

b) Our second question was which year of MODIS data provided the best classification results, and we classified growing-season-only NDVI data for each single year from 2003 to 2008.

c) Our third question was if data for a whole year is necessary or if it suffices to classify data for the growing season. We conducted four classifications: two of red and near-infrared reflectance data and two with NDVI data for 2006, two using all 46 images, and two with 22 images for the growing season only.

d) Our fourth question was if with data for one year sufficed, or if data from multiple years resulted in higher accuracies. We conducted six classifications with growing season NDVI data. The first three were with data for 2004, 2005 and 2006 only, the fourth with data for both 2005 and 2006, the fifth with data for 2004 and 2006 and the sixth with data for 2004, 2005 and 2006.

e) Our fifth and last question was if phenology metrics by themselves, or used in conjunction with time series data would result in higher classification accuracies. We conducted eight classifications that include different datasets of phenology metrics. The first classification was based on six years of the eleven phenology metrics parameterized with 2003-2008 MODIS-NDVI data: Classifications two and three included the six years of eleven phenology metrics parameterized with 2003-2008 MODIS NDVI data, combined with 2005 and 2006 growing season NDVI data, respectively. Classifications four and five included the eleven phenology metrics for one year each (2005 and 2006), parameterized with 2003-2008 MODIS NDVI data. Classification six and seven included three years of eleven phenology metrics parameterized with 2004-2006 MODIS NDVI data, combined with 2005 and 2006 growing season NDVI data, respectively. Classification eight include only three years of five phenology metrics parameterized with 2004-2006 MODIS NDVI data, combined with 2005 growing season NDVI data.

2.3.5 Validation data

Independent validation data was collected for a stratified random sample over five Landsat footprints within the study area (Figure 1). Two Landsat images for each footprint were obtained from United States Geological Survey (http://glovis.usgs.gov), the first for the late 1980s and the second for either 2005 or 2006. To select pixels for validation, we used a grid of MODIS pixels with 2,500 m distance between pixels to minimize spatial autocorrelation. Using the 2005 MODIS land cover classification for stratification we selected 99 MODIS pixels for each of the four land cover classes. The resultant MODIS pixels were interpreted visually using the two Landsat images and, where available, high-resolution QuickBird images in GoogleEarth™. We recorded for each pixel the dominant land cover class in 2005/06, and in the case of abandoned agriculture also if the pixel was actively farmed in the late 1980s.

We generated an area adjusted confusion matrix (Card 1982; Stehman 1996) for each classification and calculated the overall accuracy expressed by the kappa coefficient of agreement, the proportion of pixels correctly allocated, and the user's and producer's accuracy for each class. The statistical significance of the observed differences in the mean classification accuracies was evaluated with McNemar tests (De Leeuw and others 2006; Foody 2004; Foody 2009). Based on the statistical significance of the differences among classifications, we derived a hierarchical clustering distance dendrogram.

2.4 Results

The best classification resulted from the growing season data for 2005 plus all phenological parameters from 2003 to 2008; with an overall accuracy (69.0%), the lowest omission and commission errors (57.2% and 59.1 % respectively), and the best producer's (42.7%) and user's (40.9%) accuracy for agricultural abandonment. Based on this classification the land cover class distribution was 29.6% agriculture, 33.8% forest, 15.1% abandoned agriculture, and 21.5% in other land covers (Figure 3, Table 1).

TABLE 1. APPROXIMATELY HERE

FIGURE 3. APPROXIMATELY HERE

FIGURE 4. APPROXIMATELY HERE

2.4.1 Classification tests

In terms of the twenty one tested input datasets, the differences in the resulting classifications were small in many cases. When we compared red and near-infrared reflectance data versus NDVI data to the two years compared, (2005 and 2006), both comparisons had opposite but inconclusive results. For the year 2005 the use of NDVI performed better than using red and near-infrared reflectance data (Figure 5 A). For the 2006, the inclusion of NDVI had slightly lower kappa values than the use of red and near-infrared reflectance data (Table 2 and Figure 6), but there was not enough evidence to state a difference on the use of NDVI and red and near-infrared reflectance data (Figure 5 **Error! Reference source not found.**).

TABLE 2. APPROXIMATELY HERE

FIGURE 5. APPROXIMATELY HERE

TABLE 3. APPROXIMATELY HERE

Classification of either red and near-infrared reflectance data or NDVI time series for the entire year (2006) of data versus data from the growing season showed also minor differences. Kappa values for the growing season were slightly higher for either red and near-infrared reflectance data or NDVI data (Table 2, Figure 5 B), but there were not significantly different from each other (Table 2). Classifications for 2005 were part of the same McNemar cluster (Figure 6, cluster 4) whereas classifications for 2006 were part of a different McNemar cluster (Figure 6, cluster 2).

FIGURE 6. APPROXIMATELY HERE

When we compared classification accuracies for different years based on the growing season NDVI data, all yearly classifications had kappa values over 61% but 2004. In the case of years 2003, 2005 and 2007 classification accuracy was good (around 60% overall accuracy, 27% producer's, and 33% user's accuracy), but the best years were 2005 and 2008 (Table 2, Figure 5 C). Comparing individual McNemar differences we found that these two classifications were not significantly different from each other, but there were weak differences between 2004 and 2006 and between 2004 and 2008 (Table 2).

When we added 2005 growing season NDVI data to the NDVI data for 2004, classification accuracy was similar, but the use of 2004 plus 2006 data improved the classification. Adding three years, from 2004 to 2006, the classification did improve classification accuracy compared to the use of only two years of data (Table 2, Figure 5 D) but they were not significant differences (Table 2). All classifications involving multiple NDVI years were part of the same McNemar cluster (Figure 5, cluster 4).

Our experiments with phenological information showed that the worst classification performance obtained was based on phenological information alone. However, combining phenological information with NDVI bands for the growing season did improve the classifications substantially. Classifications that included NDVI and phenology yielded five out of the six best classifications. Indeed the best performing out of all the 21 classifications conducted included all the phenology parameters from 2003 to 2008 plus the NDVI series for 2005. However, classifications that included phenology for only one year based on a time series from 2003 to 2008 did not improve the performance of the classifier significantly. The inclusion of phenological parameters based on data from 2004 to 2006 did show a minor improvement. Last but not least, the inclusion of all eleven phenological parameters versus the use of only five parameters did result on almost identical maps (Table 2, Figure 5 E).

2.4.2 Mapping agricultural abandonment

In terms of the spatial patterns of the land cover classes all eight countries fully or partially covered by this study, exhibited agricultural abandonment (0). Four countries had around 50% of the land covered by forest (Estonia (52.6%), Latvia (52%), and the portions mapped of Russia (51.4%) and Czech Republic (49.4%)). Three countries had around 30% of the land covered by forest (Belarus (36.3%), Lithuania (31.5%), and Ukraine (29%)). In contrast, Poland had only 21.3% of the land covered by forest.

Regarding the area mapped covered by agriculture we found that Poland stands out with 66.8% , Lithuania 48.3%, Ukraine 45.5%, Czech Republic 38.6% and Belarus had 32.1%. Finally, Latvia and Estonia were the countries with the least agriculture (24.4% and 18.0% respectively).

In the case of abandoned agriculture, Russia and Belarus had the largest shares of abandoned agriculture with 27.6% and 20.8% respectively. Three countries had around 14% of abandoned agriculture (Ukraine (16.9%), Latvia (12.4%), and Estonia (11.7%)). And three countries had less than 10% of the surface covered by abandoned agriculture (Lithuania (9.5%), Czech Republic (4.6%), and Poland (4.0%)) (0).

2.4.3 Validation

Based on the validation data, 51 out of 67 sampling points labeled as abandoned agriculture (76.12%) were indeed farmed in the late 1980s and in a successional stage by 2005/2006. Only 16 data points out of the 67 (23.88%) were not agriculture but covered by shrubs already in the late 1980s.

All conducted classifications had kappa values above 51% (Table 2, Figure 4). Using the McNemar test as distance metric for a hierarchical clustering, we found four significantly different clusters of classifications (Figure 6,Table 3). The best performing classification was in cluster one, which included only one classification (2005 NDVI growing season data plus phenology information from 2003 to 2008). Cluster two included ten classifications with intermediate results, subdivided into two subgroups: one with four classifications based on data from 2006 and one with data from 2008 and the second subgroup had five classifications, all of them including phenology data (Figure 5, Figure 6). The classification with best performance for group two included red and near infrared 2006 data for the whole year (Kappa value equal to 66%)

Cluster three, with one map, had the worst accuracies. This classification included only phenological parameters from 2003 to 2008 (Figure 5, Figure 6). Cluster four was composed by nine classifications with kappa values from 59.8 to 63.1% (Figure 5, Figure 6). Within cluster four, were included four classifications based on growing season of NDVI data for one year (years 2003, 2004, 2005, and 2007) plus all three classifications that included NDVI data for two and three years (2004, 2005, 2006 and the combinations among them). In comparison with the eight classifications included on cluster four, the classification conducted using year 2005 of NDVI growing season had slightly better results, followed by the growing season NDVI data for year 2003 and the growing season NDVI data for years 2004-2006. The last two classifications for cluster four utilized first, red and near-infrared reflectance data for the 2005 growing season and second, NDVI data for 2006 plus phenological based on data from 2004 to2006 (Figure 5, Figure 6).

2.5 Discussion

Our results showed that it is possible to map agricultural abandonment for large areas from MODIS 250 m data with overall accuracies around 65%. This result is similar to the accuracy reported of other MODIS-based land cover classifications (Tan and others 2006). Abandoned agriculture was widespread in our study area, covering approximately 15% of the land. Compared this number to the remaining 30% of land in agriculture, we deduct that about 45%

of the area was farmed in the 1980s and a third of those areas were abandoned. Our validation data showed that a clear majority (> 75%) of the areas mapped as abandoned were indeed actively farmed during the 1980s, highlighting how rapid the abandonment process was in the first two decades after the breakdown of the USSR.

Our results are in close agreement with more localized studies that have used Landsat images or other data sources to map abandoned agriculture. In Russia, the reported declines of arable land reached 20% due to the transition to the market economy (Ioffe and Nefedova 2004). Of the 127 million hectares of farmland in the early 1980s, 20 to 30 million were no longer used by 2000s (Franks and Davydova 2005; Ioffe, Nefedova, Zaslavsky 2004; Ioffe 2005). Similarly, the Landsat based classifications of abandonment covering 5% of our study area had 37.5 % agriculture, 33.4% forest, and 18% abandonment respectively (compared to 30% agriculture, 34% forest, 15% abandoned agriculture, and 21% other land covers that we found for the entire MODIS tile).

We conducted numerous tests to identify the optimal input data for mapping abandoned lands and these tests provided interesting results. The use of near-infrared and red reflectance data instead of NDVI data did not make a significant difference for the final classification accuracy. Reflectance bands were slightly better than NDVI, but this finding was not statistically significant according to the McNemar tests. In other words NDVI captured the information necessary to classify abandoned farmland as well as the near-infrared and red reflectance data. Since there was no significant difference on the maps obtained from NDVI and near-infrared and red reflectance data, we recommend the use of NDVI bands to conduct classifications on land abandonment, reducing the data volume by 50%.

We also did not find a clear best specific year to map agricultural abandonment, nor a clear pattern across the six individual years from 2003 to 2008. The early years (2003-2004) had lower accuracies, but that may be due to the sources used for training and validation. The fact that there was not clear best year to map agricultural abandonment was encouraging. Ultimately we recommend the use of the year with the best data that corresponds more closely to the dates of the training and validation datasets. In our case the best year was 2005.

The use of data for all year instead of only data from the growing season did not make a significant difference in our results. All-year data had better overall accuracies than only growing season, but this finding was not statistically significant according to the McNemar test. We recommend the use of growing season bands to conduct classifications on land abandonment reducing the data volume to 22 bands for a growing season instead of the 46 of the whole year.

The inclusion of a second year of MODIS data did improve classification accuracies, and it did matter if the two years were contiguous. We recommend the inclusion of at least two years of NDVI data around the validation and training data to conduct classifications on land abandonment. If only two years are included, we recommend to have a separation of a year around the validation and training data (in our case 2004, and 2006)

The use of phenology parameters alone did not provided a good basis for a classification (our worst classification resulted from using only phenology) but coupled with NDVI growing season data, the phenology metrics resulted in our best classification (the best map produced includes growing season for 2005 and phenology metrics). We thus recommend the inclusion of phenology when mapping agricultural land abandonment. Only five phenological parameters captured the information necessary to classify abandoned farmland as well as the eleven phenology parameter data. Classifications resulting from both phenology datasets were identical. Since there was no significant difference on the maps obtained from eleven and five parameter datasets, we recommend the use of only six parameters (End of the season, start of the season, base level, maximum level, length of the season and middle of the season) coupled with NDVI data to conduct classifications on land abandonment, reducing the data volume by 40%.

The limited number of statistically significant different classifications highlights the importance of including McNemar test when comparing multiple maps. Hierarchical cluster dendrograms offer an easy way to visualize multiple McNemar comparisons, which facilitate the analysis and selection of classifications to be used for other purposes.

In terms of the patterns of abandoned agriculture, our mapped area covered eight countries situated in Eastern Europe. Lithuania, Latvia, Estonia and Belarus were completely mapped and more than 75% of Poland was mapped, making possible to compare them. In the case of Poland, it was clear that abandonment was rare after the breakdown of the USSR. Current abandoned agriculture areas correspond mainly with Natural Protected Areas in the north of the country and a shifting in the economical activities from agriculture to industry in the south of the country. In the case of Latvia and Estonia abandonment agriculture was widespread, covering in 2005 about 39% of what was agriculture in the 1980s. Given similar historical processes for all three Baltic countries, it was somewhat surprising that Lithuania had less abandoned agriculture than Latvia and Estonia (only 16% of what was formerly agriculture was abandoned agriculture in 2005). However, both Latvia and Estonia had more forest than Lithuania. The economic growth is different among the three countries; Lithuania had one of the fastest growing economies of the European Union, compared with Latvia which is one of the poorest economies of the European Union. Both Latvia and Estonia have been hit particularly by recent economic crises that started in 2008-2009. Those economical differences apparently were reflected on land cover and resulted in less abandoned agriculture in Lithuania compared to Latvia and Estonia. In the case of Belarus, abandoned areas reached also more than 39% of the areas that were agriculture back in the 1980s. However Belarus' economy is still state controlled, industrial production plunged in early 1980s because of decreases in imported inputs, in investment, and in demand for exports from traditional trading partners. On the other side, the mapped area of Russia showed widespread agricultural abandonment. More than 75% of the areas who were used for agriculture are now abandoned.

Our findings confirmed that land abandonment in Eastern Europe is widespread and current work will extend the classification to map all of Eastern Europe, but abandonment is not unique to Eastern Europe. It is necessary to make worldwide studies regarding land abandonment spatial configuration and its environmental, social and food production implications. Land abandonment can be a consequence of the socio-economic situation at different levels as well as the exposure to hazards, technology and the loss of nutrients in the soil. The reasons for land abandonment can range from changes in land tenure to the simple "recovery" that a landowner decides to give to a field. At the individual scale land abandonment can be due to the introduction of new technologies, changes in agricultural practices, new land tenure policies, and/or economic change. The process of land abandonment can be abrupt, in which case the land is no longer used, or gradual, when grazing replaces the production of crops. After abandonment, different successional pathways can occur depending on prior land uses, and the environmental conditions of the land.

Reductions in agricultural production can be viewed in a negative sense, mainly because of the large number of people who leave the land abandoned and moved to the cities, but it also can be viewed as an opportunity for conservation and environmental protection(Young and others 2005). Given the strong ramifications of agricultural abandonment on the environment, economy and societies mapping and monitoring should be a top research priority. Current efforts are promising, but unfortunately it still hard to conduct accurate mapping on land abandonment using coarse resolution.

We identified approaches here to map land abandonment and proposed methods that facilitate the mapping of abandoned agriculture at broad scales.

2.6 Acknowledgements

We gratefully acknowledge support by Consejo Nacional de Ciencia y Tecnologia (CONACyT, Mexico), the NASA Land Cover and Land Use Change Program, and the University of Wisconsin-Madison School of International Studies. P. Hostert and A. Sieber from the Humboldt University in Berlin generously provided their classification of abandonment near Chernobyl. We also express our gratitude to SILVIS lab fellows, especially to M. Dubinin for their technical assistance and fruitful discussions.

2.7 References

Aide TM and Grau HR. 2004. Globalization, migration, and Latin American ecosystems. Science 305(5692):1915-6.

Aide TM, Zimmerman JK, Herrera L, Rosario M, Serrano M. 1995. Forest recovery in abandoned tropical pastures in Puerto Rico. Forest Ecology and Management 77(1-3):77-86.

Bergen KM, Zhao T, Kharuk V, Blam Y, Brown DG, Peterson LK, Miller N. 2008. Changing regimes: Forested land cover dynamics in central Siberia 1974-2001. Photogrammetric Engineering and Remote Sensing 74(6):787-98.

Boyd DS and Danson FM. 2005. Satellite remote sensing of forest resources: Three decades of research development. Progress in Physical Geography 29(1):1-26.

Card DH. 1982. Using known map category marginal frequencies to improve estimates of thematic map accuracy. Photogrammetric Engineering and Remote Sensing 48:431-9.

Charles D. 2010. Renewing the post-soviet steppe. Science 328(5983):1225.

Chauchard S, Carcaillet C, Guibal F. 2007. Patterns of land-use abandonment control tree-recruitment and forest dynamics in Mediterranean mountains. Ecosystems 10(6):936-48.

Cohen WB and Goward SN. 2004. Landsat's role in ecological applications of remote sensing. Bioscience 54(6):535-45.

Cramer VA, Hobbs RJ, Standish RJ. 2008. What's new about old fields? Land abandonment and ecosystem assembly. Trends in Ecology & Evolution 23(2):104-12.

De Leeuw J, Jia H, Yang L, Liu X, Schmidt K, Skidmore A. 2006. Comparing accuracy assessments to infer superiority of image classification methods. International Journal of Remote Sensing 27(1):223-32.

Dutch National Reference Center for Agriculture, Nature and Food Quality, Latvian Ministry of Agriculture, Latvian State. 2005. Land abandonment and biodiversity, in relation to the 1st and 2nd pillars of the European Union's Common Agricultural Policy; outcome of an international seminar in Sigulda, Latvia, 7-8 October, 2004. :1-64.

Egbert SL, Lee RY, Price KP, Boyce R. 1998. Mapping Conservation Reserve Program grasslands using multi-seasonal thematic mapper imagery. Geocarto International 13(4):17-24.

Egbert SL, Park S, Price KP, Lee R, Wu J, Duane Nellis M. 2002. Using Conservation Reserve Program maps derived from satellite imagery to characterize landscape structure. Computers and Electronics in Agriculture 37(1-3):141-56.

Ellis EC, Goldewijk KK, Siebert S, Lightman D, Ramankutty N. 2010. Anthropogenic transformation of the biomes, 1700 to 2000geb_540.

Ellis EC and Ramankutty N. 2008. Putting people in the map: anthropogenic biomes of the world. Frontiers in Ecology and the Environment 6:439-47.

Falcucci A, Maiorano L, Boitani L. 2007. Changes in land-use/land-cover patterns in Italy and their implications for biodiversity conservation. Landscape Ecology 22(4):617-31.

Farley KA. 2007. Grasslands to tree plantations: Forest transition in the Andes of Ecuador. Annals of the Association of American Geographers 97(4):755-71.

Fassnacht KS, Cohen WB, Spies TA. 2006. Key issues in making and using satellite-based maps in ecology: A primer. Forest Ecology and Management 222(1):167-81.

Fensholt R and Sandholt I. 2005. Evaluation of MODIS and NOAA AVHRR vegetation indices with in situ measurements in a semi-arid environment. International Journal of Remote Sensing 26(12):2561-94.

Foley JA, DeFries RS, Asner GP, Barford C, Bonan G, Carpenter SR, Chapin FS, Coe MT, Daily GC, Gibbs HK, Helkowski JH, Holloway T, Howard EA, Kucharik CJ, Monfreda C, Patz JA, Prentice IC, Ramankutty N, Snyder PK. 2005. Global consequences of land use. Science 309(5734):570-4.

Food and Agriculture Organization of the United Nations. 2010. FAOSTAT data web page. 2010(07/27)http://faostat.fao.org/.

Foody GM. 2009. Sample size determination for image classification accuracy assessment and comparison. International Journal of Remote Sensing 30(20):5273-91.

Foody GM. 2004. Thematic map comparison: Evaluating the statistical significance of differences in classification accuracy. Photogrammetric Engineering and Remote Sensing 70(5):627-34.

Franks JR and Davydova I. 2005. Reforming the farming sector in Russia, new options for old problems. Outlook on Agriculture 34(2):97-103.

Friedl MA and Brodley CE. 1997. Decision tree classification of land cover from remotely sensed data. Remote Sensing of Environment 61(3):399-409.

Friedl MA, McIver DK, Hodges JCF, Zhang XY, Muchoney D, Strahler AH, Woodcock CE, Gopal S, Schneider A, Cooper A, Baccini A, Gao F, Schaaf C. 2002. Global land cover mapping from MODIS: algorithms and early results. Remote Sensing of Environment 83(1-2):287-302.

Goldewijk KK and Ramankutty N. 2004. Land cover change over the last three centuries due to human activities: The availability of new global data sets. GeoJournal 61(4):335-44.

Goncalves P, Carrão H, Pinheiro A, Caetano M. 2005. Land cover classification with a support vector machine applied to MODIS imagery. Proceedings of the 25th Annual Symposium of the

European Association of Remote Sensing Laboratories, Porto, Portugal, June 6-11, 2005 :517-25.

Grau HR, Aide TM, Zimmerman JK, Thomlinson JR, Helmer E, Zou X. 2003. The ecological consequences of socioeconomic and land-use changes in postagriculture Puerto Rico. BioScience 53(12):1159-68.

Haberl H, Erb KH, Krausmann F, Gaube V, Bondeau A, Plutzar C, Gingrich S, Lucht W, Fischer-Kowalski M. 2007. Quantifying and mapping the human appropriation of net primary production in earth's terrestrial ecosystems. Proceedings of the National Academy of Sciences 104(31):12942-7.

Hart JF. 1968. Loss and abandonment of cleared farm land in the eastern United States. Annals of the Association of American Geographers 58(3):417-40.

Hermes L, Frieauff D, Puzicha J, Buhmann JM. 1999. Support vector machines for land usage classification in Landsat TM imagery. Geoscience and Remote Sensing Symposium, 1999 IGARSS '99 Proceedings IEEE 1999 International 1:348-50.

Huang C, Davis LS, Townshend JRG. 2002. An assessment of support vector machines for land cover classification. International Journal of Remote Sensing 23:725-49.

Ioffe G. 2005. The downsizing of Russian agriculture. Europe-Asia Studies 57(2):179-208.

Ioffe G and Nefedova T. 2004. Marginal farmland in european Russia. Eurasian Geography and Economics 45(1):45-59.

Ioffe G, Nefedova T, Zaslavsky I. 2004. From spatial continuity to fragmentation: The case of Russian farming. Annals of the Association of American Geographers 94(4):913-43.

Jacquin A, Sheeren D, Lacombe J. 2010. Vegetation cover degradation assessment in Madagascar savanna based on trend analysis of MODIS NDVI time series. International Journal of Applied Earth Observation and Geoinformation 12(Supplement 1):S3-S10.

Janz A, van der Linden S, Waske B, Hostert P. 2007. ImageSVM-A user-oriented tool for advanced classification of hyperspectral data using support vector machines. Proceedings 5th EARSeL Workshop on Imaging Spectroscopy 1:1-5.

Jonsson P and Eklundh L. 2004. TIMESAT - A program for analyzing time-series of satellite sensor data. Computers & Geosciences 30(8):833-45.

Justice CO, Townshend JRG, Fermote V, Masuoka E, Wolfe RE, Saleous N, Roy DP, Morisette JT. 2002. An overview of MODIS Land data, processing and product status. Remote Sensing of Environment 83:3-15.

Kauppi PE, Ausubel JH, Fang J, Mather AS, Sedjo RA, Waggoner PE. 2006. Returning forests analyzed with the forest identity. Proceedings of the National Academy of Sciences 103(46):17574-9.

Klooster D. 2003. Forest transitions in Mexico: Institutions and forests in a globalized countryside. The Professional Geographer 55(2):227.

Kristensen LS, Thenail C, Kristensen SP. 2004. Landscape changes in agrarian landscapes in the 1990s: The interaction between farmers and the farmed landscape. A case study from Jutland, Denmark. Journal of Environmental Management 71(3):231-44.

Kuemmerle T, Kozak J, Radeloff VC, Hostert P. 2009. Differences in forest disturbance among land ownership types in Poland during and after socialism. Journal of Land use Science 4(1 & 2):73-83.

Kuemmerle T, Hostert P, Radeloff VC, van derLinden S, Perzanowski K, Kruhlov I. 2008. Cross-border comparison of post-socialist farmland abandonment in the Carpathians. Ecosystems 11(4):614-28.

Lambin EF and Geist HJ, editors. 2006. Land-use and land-cover change: Local processes and global impacts. First ed. Berlin Heidelberg New York: Springer. p222.

Lambin EF, Turner BL, Geist HJ, Agbola SB, Angelsen A, Bruce JW, Coomes OT, Dirzo R, Fischer G, Folke C, George PS, Homewood K, Imbernon J, Leemans R, Li XB, Moran EF, Mortimore M, Ramakrishnan PS, Richards JF, Skanes H, Steffen W, Stone GD, Svedin U, Veldkamp TA, Vogel C, Xu JC. 2001. The causes of land-use and land-cover change: moving beyond the myths. Global Environmental Change-Human and Policy Dimensions 11(4):261-9.

Laurance WF, Albenaz AK, Da Costa C. 2001. Is deforestation accelerating in the Brazilian Amazon? Environmental Conservation 28(4):305-11.

Leff B, Ramankutty N, Foley JA. 2004. Geographic distribution of major crops across the world. Global Biogeochemical Cycles 18(1):1-27.

Lesschen J, Cammeraat L, Kooijman A, Van Wesemael B. 2008. Development of spatial heterogeneity in vegetation and soil properties after land abandonment in a semi-arid ecosystem. Journal of Arid Environments 72(11):2082-92.

Lu D, Mausel E, Brondizios E, Moran E. 2004. Change detection techniques. International Journal of Remote Sensing 25(12):2365-407.

MacDonald D, Crabtree JR, 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. Journal of Environmental Management, 59(1):47-69.

Meyfroydt P and Lambin EF. 2008. Forest transition in Vietnam and its environmental impacts. Global Change Biology 14(6):1319-36.

Millennium Ecosystem Assessment. 2005. Ecosystems and human well-being : current state and trends : findings of the Condition and Trends Working Group. 1:1-917.

Ministerial Conference on the Protection of Forests in Europe - Liason Unit Warsaw, United Nations Economic Commission for Europe, Food and Agriculture Organization of the United Nations. 2007. State Of Europe's Forests 2007, The MCPFE Report on sustainable forest management in Europe. 1:1-153.

Moreira F and Russo D. 2007. Modeling the impact of agricultural abandonment and wildfires on vertebrate diversity in Mediterranean Europe. Landscape Ecology 22(10):1461-76.

Nepstad DC, Verssimo A, Alencar A, Nobre C, Lima E, Lefebvre P, Schlesinger P, Potter C, Moutinho P, Mendoza E, Cochrane M, Brooks V. 1999. Large-scale impoverishment of Amazonian forests by logging and fire. Nature 398(6727):505-8.

Nikodemus O, Bell S, Grine I, Liepins I. 2005. The impact of economic, social and political factors on the landscape structure of the Vidzeme uplands in Latvia. Landscape and Urban Planning 70(1-2):57-67.

Park S and Egbert S. 2008. Remote sensing-measured impacts of the Conservation Reserve Program on landscape structure in southwestern Kansas. GIScience & Remote Sensing 45(1):83-108.

Peterson U and Aunap R. 1998. Changes in agricultural land use in Estonia in the 1990s detected with multitemporal Landsat MSS imagery. Landscape and Urban Planning, 41(3-4):193-201.

Prischepov A, Radeloff VC, Dubinin M, Alcantara C. 2010. The effect of image acquisition dates on detection of agricultural land abandonment in Eastern Europe. Remote Sensing of Environment. in Review .

Poyatos R, Latron J, Llorens P. 2003. Land use and land cover change after agricultural abandonment: The case of a Mediterranean mountain area (Catalan Pre-Pyrenees). Mountain Research and Development 23(4):362-8.

Ramankutty N, Gibbs HK, Achard F, DeFries RS, Foley JA, Houghton RA. 2007. Challenges to estimating carbon emissions from tropical deforestation. Global Change Biology 13(1):51-66.

Ramankutty N and Foley JA. 1999. Estimating historical changes in global land cover: Croplands from 1700 to 1992. Global Biogeochemical Cycles 13(4):997-1027.

Redo D, Joby Bass JO, Millington AC. 2009. Forest dynamics and the importance of place in western Honduras. Applied Geography 29(1):91-110.

Romero-Calcerrada R and Perry GLW. 2004. The role of land abandonment in landscape dynamics in the SPA 'Encinares del río Alberche y Cofio, Central Spain, 1984-1999. Landscape and Urban Planning 66(4):217-32.

Rudel TK, Coomes OT, Moran E, Achard F, Angelsen A, Xu J, Lambin EF. 2005. Forest transitions: Towards a global understanding of land use change. Global Environmental Change Part A, 15(1):23-31.

Russo D. 2007. The effects of land abandonment on animal species in Europe: Conservation and management implications. Integrated Assessment of Vulnerable Ecosystems Under Global Change in the European Union.Directorate-General for Research Environment, European Commission, Brussels :1-51.

Sloan S. 2008. Reforestation amidst deforestation: Simultaneity and succession. Global Environmental Change 18(3):425-41.

Stehman S. 1996. Estimating the kappa coefficient and its variance under stratified random sampling. Photogrammetric Engineering and Remote Sensing 62(4):401-7.

Stoate C, Boatman ND, Borralho RJ, Carvalho CR, Snoo GRd, Eden P. 2001. Ecological impacts of arable intensification in Europe. Journal of Environmental Management, 63(4):337-65.

Tan B, Woodcock CE, Hu J, Zhang P, Ozdogan M, Huang D, Yang W, Knyazikhin Y, Myneni RB. 2006. The impact of gridding artifacts on the local spatial properties of MODIS data: Implications for validation, compositing, and band-to-band registration across resolutions. Remote Sensing of Environment 105(2):98-114.

Tilman D. 1999. Global environmental impacts of agricultural expansion: The need for sustainable and efficient practices. Proceedings of the National Academy of Sciences of the United States of America 96(11):5995-6000.

Tilman D, Fargione J, Wolff B, D'Antonio C, Dobson A, Howarth R, Schindler D, Schlesinger WH, Simberloff D, Swackhamer D. 2001. Forecasting agriculturally driven global environmental change. Science 292(5515):281-4.

Vandermeer J and Perfecto I. 2007. The agricultural matrix and a future paradigm for conservation. Conservation Biology 21(1):274-7.

Vitousek PM, Mooney HA, Lubchenco J, Melillo JM. 1997. Human domination of earth's ecosystems. Science 277(5325):494-9.

White MA, de Beurs KM, Didan K, Inouye DW, Richardson AD, Jensen OP, O’Keefe J, Zhang G, Nemani RR, van Leewen WJD. 2008. Intercomparison, interpretation, and assessment of spring phenology in North America estimated from remote sensing for 1982 to 2006. Remote Sensing of Environment 112:4333-43.

Wright SJ. 2005. Tropical forests in a changing environment. Trends in Ecology & Evolution 20(10):553-60.

Xiao X, Hagen S, Zhang Q, Keller M, Moore B. 2006. Detecting leaf phenology of seasonally moist tropical forests in South America with multi-temporal MODIS images. Remote Sensing of Environment 103(4):465-73.

Yang F, Ichii K, White MA, Hashimoto H, Michaelis AR, Votava P, Zhu A, Huete A, Running SW, Nemani RR. 2007. Developing a continental-scale measure of gross primary production by combining MODIS and AmeriFlux data through support vector machine approach. Remote Sensing of Environment 110(1):109-22.

Young J, Watt A, Nowicki P, Alard D, Clitherow J, Henle K, Johnson R, Laczko E, McCracken D, Matouch S, Niemela J, Richards C. 2005. Towards sustainable land use: identifying and managing the conflicts between human activities and biodiversity conservation in Europe. Biodiversity and Conservation 14(7):1641-61.

Zeeberg J. 1998. The European sand belt in Eastern Europe-and comparison of Late Glacial dune orientation with GCM simulation results. Boreas-International Journal of Quaternary Research 27(2):127-39.

Zhang X, Friedl MA, Schaaf CB, Strahler AH, Hodges JCF, Gao F, Reed BC, Huete A. 2003. Monitoring vegetation phenology using MODIS. Remote Sensing of Environment 84(3):471-5.

2.8 Tables

Table 1. Accuracies of the classification with the best kappa errors (NDVI for 2005, plus phenology data for 2003-2008). *TAP:True Area Proportion, PA: Producer's accuracy, UA: User's accuracy, O: Error of omission, C: Error of commission.

Standard error matrix

		Reference				
		Agriculture	Forest	Abandoned Ag.	Other Classes	**Sum**
Classification	Agriculture	103	7	8	4	122
	Forest	12	81	18	2	113
	Abandoned Agriculture	32	18	38	5	93
	Other Classes	14	8	3	43	68
Sum		161	114	67	54	396

Area-adjusted calculation

	PA	**UA**	**C**	**O**
Agriculture	65.4%	84.4%	34.6%	15.6%
Forest	77.2%	71.7%	22.8%	28.3%
Abandoned Agriculture	42.7%	40.9%	57.3%	59.1%
Other Classes	85.1%	63.2%	14.9%	36.8%

Overall accuracy = 69.0%
Khat = 69.0%

Table 2. Accuracy assessment for the 21 MODIS classifications. Results are organized by McNemar significance test. There is no significant difference within each hierarchical cluster (McNemar).

	McNemar Cluster Group	1	2										3	4								
McNemar Cluster Group		NDVI2005ph0308	REDNIR2006all	NDVI2006all	NDVI2006	REDNIR2006	NDVI2008	NDVI2006ph0308	NDVI2005ph0308_05	NDVI2006ph0308_06	NDVI2005ph0406sel	NDVI2005ph0406	Ph0308	NDVI2004	NDVI20042005	NDVI20042006	NDVI2006ph0406	REDNIR2005	NDVI2007	NDVI2003	NDVI200420052006	NDVI2005
1	NDVI2005ph0308			**	**	**	**	*	**	*	**	**	****	****	****	****	**	***	***	***	****	****
2	REDNIR2006all												****	***	***	**					**	**
	NDVI2006all	**											***	**	*							
	NDVI2006	**											***	*								
	REDNIR2006	**											***	*								
	NDVI2008	**											***	*								
	NDVI2006ph0308	*											****	**	**	**					*	
	NDVI2005ph0308_05	**											****	**	**	*					*	*
	NDVI2006ph0308_06	*											***	**	*	*						
	NDVI2005ph0406sel	**											***	**	**	*					*	**
	NDVI2005ph0406	**											***	**	**	*					*	**
3	Ph0308	****	****	***	***	***	***	****	****	***	***	***				*	**	**	**	**	*	*
4	NDVI2004	****	***	**	*	*	*	**	**	**	**	**										
	NDVI20042005	****	***	*				**	**	*	**	**										
	NDVI20042006	****	**					**	*	*	*	*	*									
	NDVI2006ph0406	**											**									
	REDNIR2005	***											**									
	NDVI2007	***											**									
	NDVI2003	***											**									
	NDVI200420052006	****	**					*	*		*	*	*									
	NDVI2005	****	**						*		**	**	*									

McNemar Significance test of difference among maps. Empty cell: No evidence (<0.10); * Weak evidence (0.05 > 0.10); **Moderate evidence (0.01>0.05); *** Strong evidence (0.001>0.01): **** Very strong evidence (<0.001).

2.9 Figures

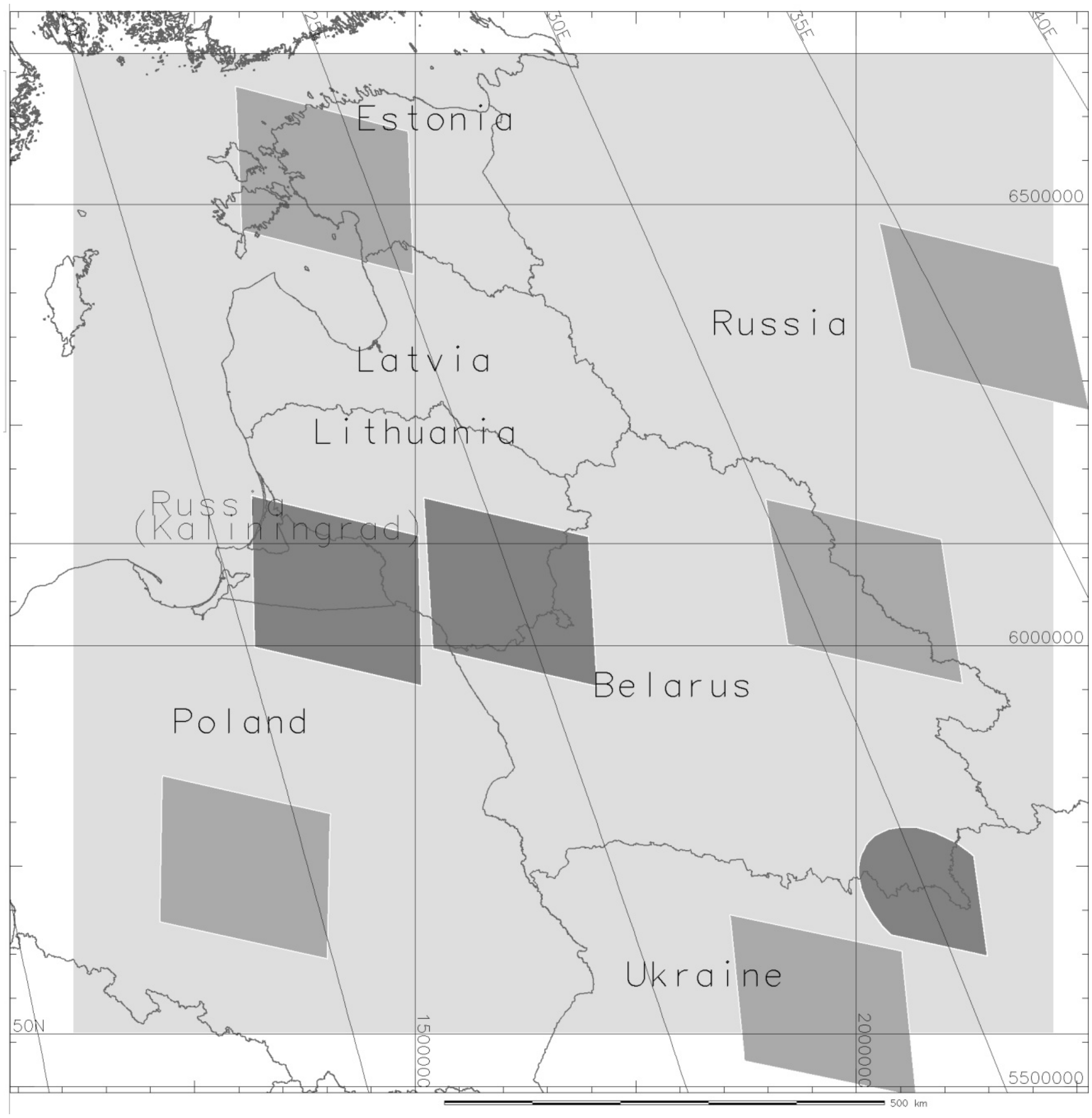


Figure 1. Study area, light gray box represents the classified area, dark gray areas represent the training Landsat-based classifications and the intermediate gray areas represent the validation Landsat scenes. The map is displayed in Sinusoidal projection

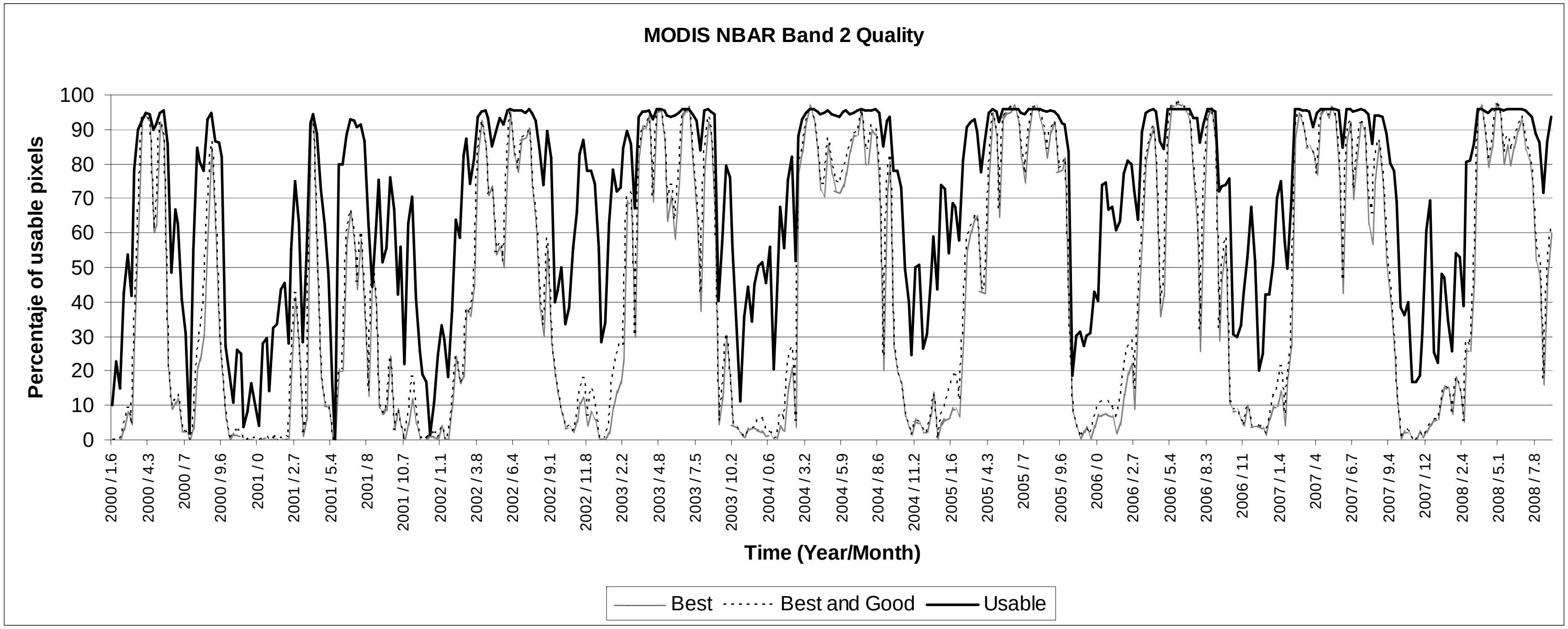


Figure 2. MODIS NBAR Band 2 Quality data tile h19-v03.

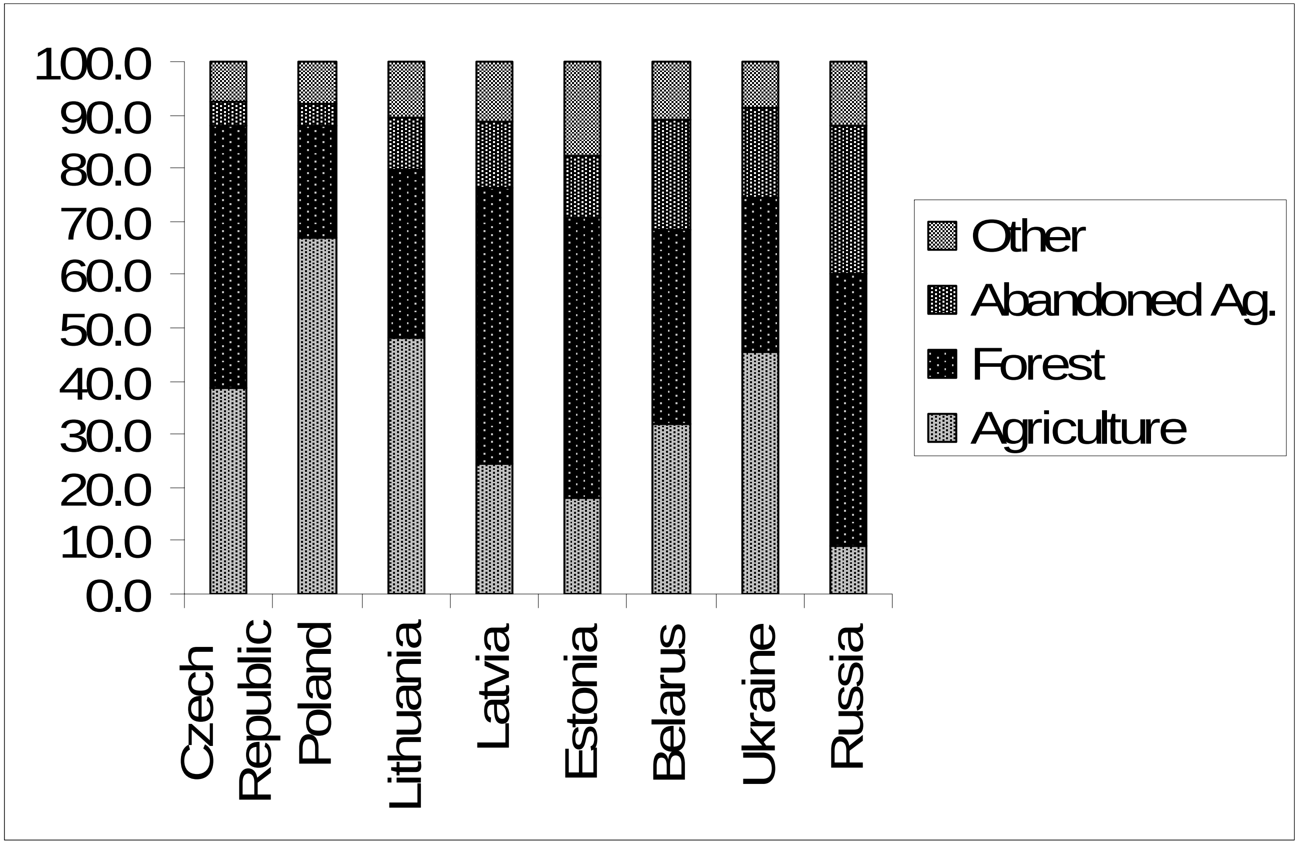


Figure 3. Land cover class distribution of the best classification resulted from the growing season NDVI data for 2005 plus all the phenological parameters from 2003 to 2008.

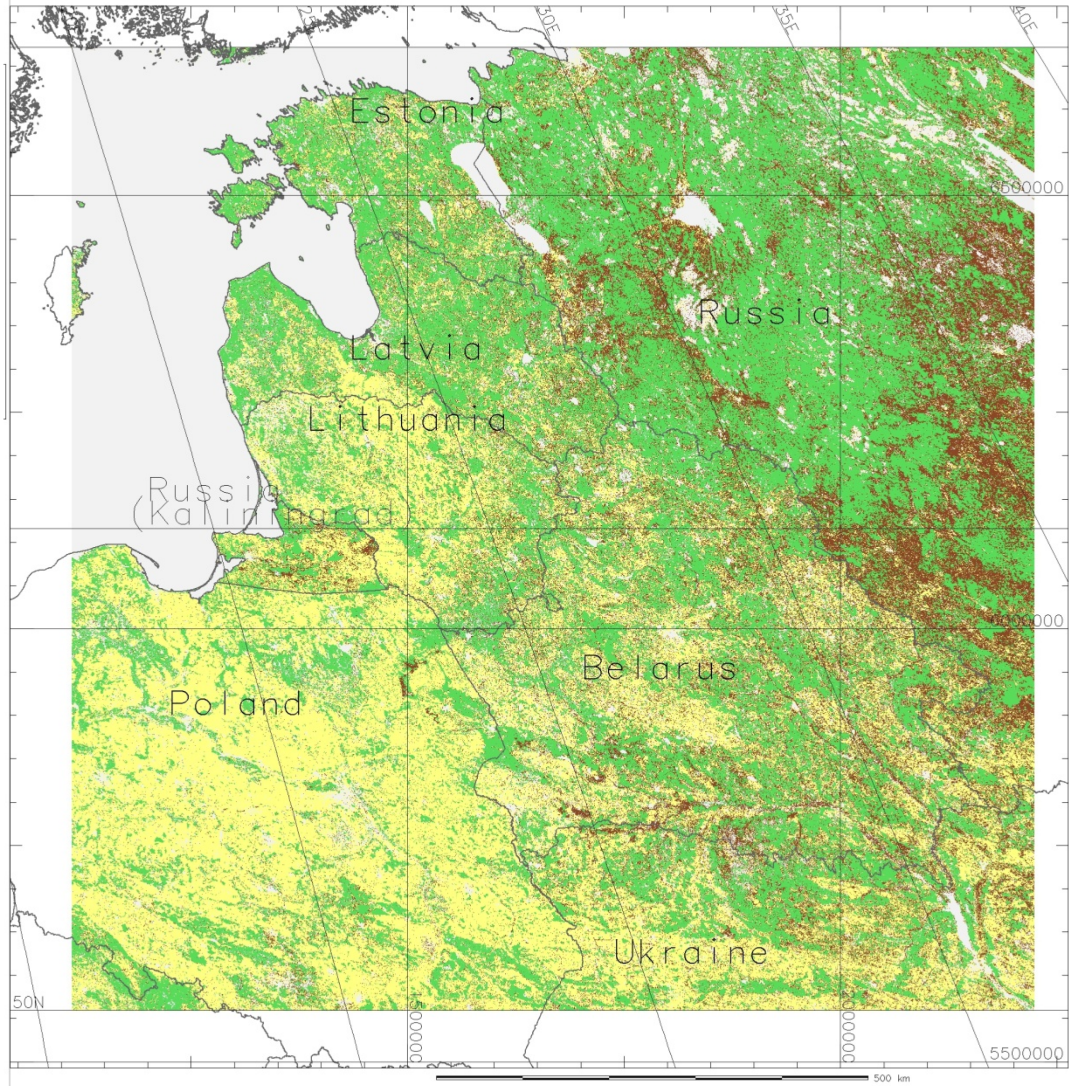


Figure 4. Best classification based on growing season data for 2005 and all phenological parameters from 2003 to 2008. Yellow areas represent agriculture, green areas represent forest, brown areas represent abandoned agriculture and grey areas represent other classes

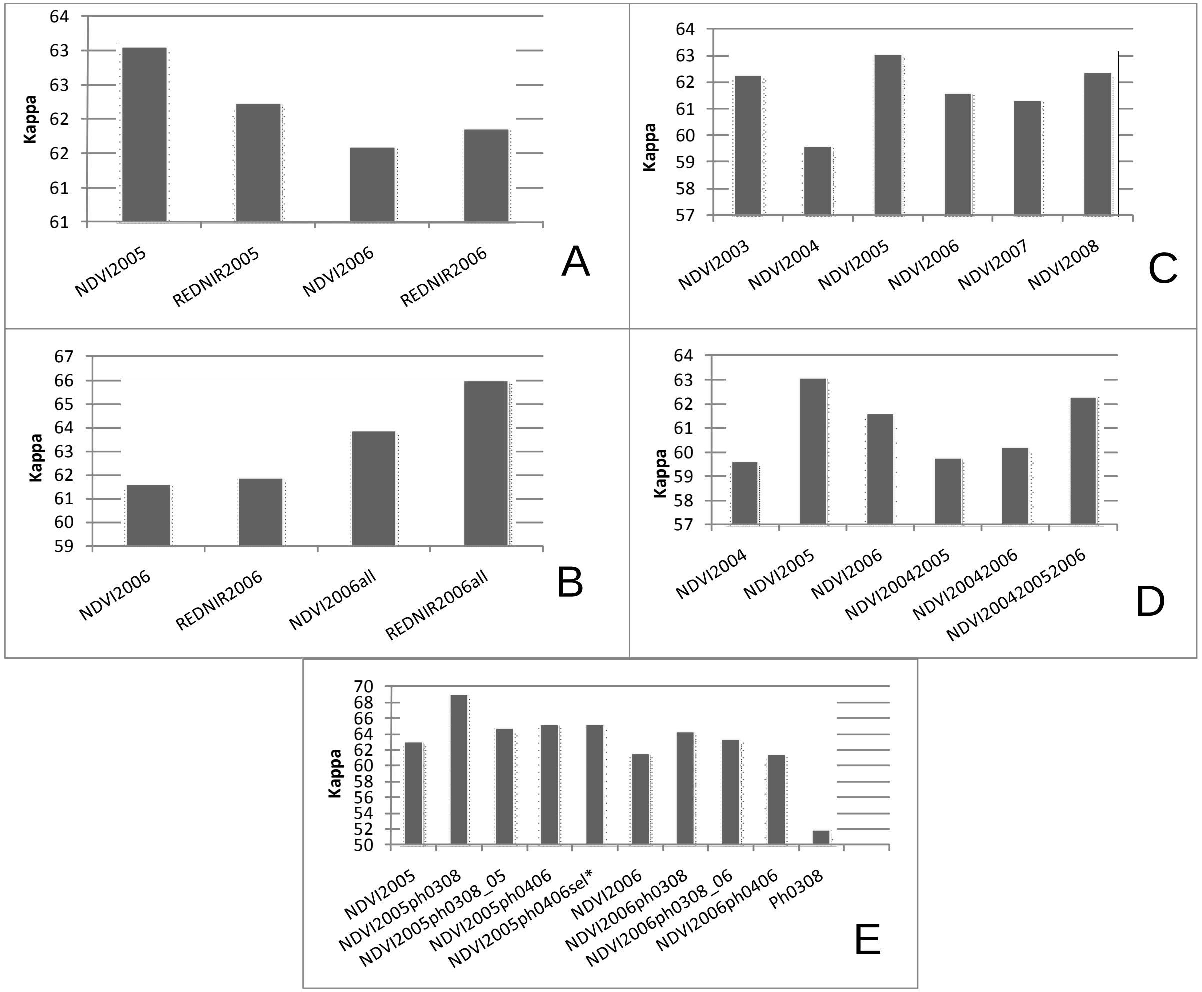


Figure 5. Classification accuracies (Kappa values) for the classifications stemming from different datasets. A. NDVI vs. Red Near-infrared. B. Growing season vs. all year. C. Individual years. D. Multiple years, E. Including phenological data.

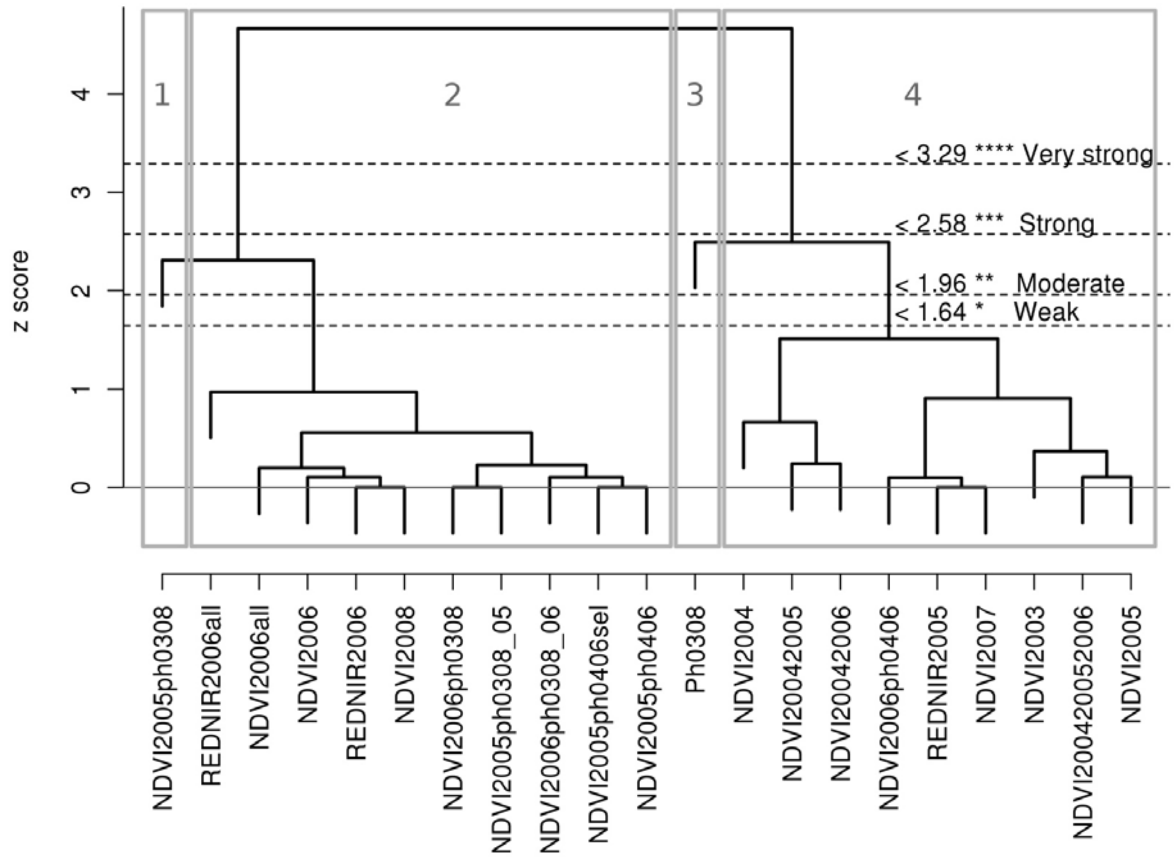


Figure 6. Hierarchical clustering using McNemar test as distance metric. Gray lines divide McNemar Cluster Group

3 Chapter II. Patterns of abandoned agriculture across Central and Eastern Europe after the breakdown of the USSR derived from multi-temporal MODIS NDVI, and phenology data

Authors

Camilo Alcantara[1*], Volker C. Radeloff[1], and Tobias Kuemmerle[1]

[1]Department of Forest and Wildlife Ecology, University of Wisconsin-Madison,

1630 Linden Drive, Madison, WI, 53706-1598, USA

[*]Corresponding author.

Phone +1 608 265-9219; fax: +1 608 262-9922

E-mail: **alcantara@wisc.edu**

3.1 Abstract

Land use and land cover changed rapidly in Central and Eastern Europe after the collapse of the USSR in the early 1990s. Prior case studies reported widespread land abandonment, but abandonment rates differed widely among studies. A comprehensive and consistent assessment of abandoned agricultural land across Eastern Europe is lacking. Our goal here was to map abandoned agricultural land across Central and Eastern Europe; including European Russia, and to compare abandonment rates among countries and among agro-ecological zones because both national policies and environmental constraints can affect abandonment. We conducted a supervised classification using a Support Vector Machine as our classifier, 250-m resolution 2004 – '06 MODIS NDVI data, and TIMESAT phenology indices. Training and validation data were derived from Landsat classifications from the late 1980s and the mid 2000s. Abandoned agricultural land was widespread across Central and Eastern Europe, representing 24.4% of our study area, compared to 21.8% agricultural land. Assuming that all areas mapped as either agricultural land or abandoned agriculture in the mid-2000s, were farmed in Soviet times, this translates into an abandonment rate of 52.9%. Countries differed strongly in terms of their abandonment rates, but differences among agro-climatic regions were less pronounced. This suggests that agricultural abandonment after the collapse of the USSR was more closely associated with socioeconomic factors than with biophysical conditions. Our results also suggest that agricultural abandonment can be very rapid, which may provide opportunities to improve water quality; nutrient cycles, biodiversity, and carbon sequestration, but also threatens livelihoods, socioeconomic conditions, and rural cultures.

Keywords: abandonment, agricultural abandonment, Land-cover change, Europe, Central Europe, Eastern Europe, Soviet Union, farmland, land use, MODIS, multi-date, multi-seasonal, old fields, support vector machines, SVM

3.2 Introduction

Land Use and Land Cover Change (LULCC) accelerated greatly in both extent and magnitude over the last century, and especially so in recent decades (Ellis and others 2010; Foley and others 2005). The results have been declines in ecosystem services and biodiversity, degraded soils, water and air pollution, and LULCC is also partially responsible for climate change (DeFries, Foley, Asner 2004). At this point, land use and the utilization of ecosystem services in general may have reached a point where the resulting environmental changes are compromising ecosystems' ability to support human needs in the future (Millennium Ecosystem Assessment 2005).

Among the different land uses, agriculture has transformed the largest portion of the Earth's terrestrial area. As of 2007, up to 38% of the Earth's land cover has been dedicated to agricultural use (Food and Agriculture Organization of the United Nations 2010). Agriculture intensified greatly during the 20th century, and expanded into new areas as well (Foley and others 2005). However, agricultural also contracted, primarily on marginal lands that are not suitable for modern agriculture (Beddow and others 2010; Lambin and Geist 2006; Rudel and others 2005), with concomitant increases in forested area (Kauppi and others 2006).

The problem is that in-depth studies of LULCC patterns and processes have typically focused on land use intensification, such as tropical deforestation, dryland degradation, agricultural intensification, and urbanization (Lambin and Geist 2006). The opposite process of agricultural abandonment and subsequent forest regrowth has been studied much less (Ramankutty and others 2007). This is unfortunate, because agricultural land abandonment has strong effects on soil stability (Tasser, Tappeiner, Cernusca 2005), carbon sequestration (Ramankutty and others 2007; Vuichard and others 2008), water quality (Scanlon and others 2007), nutrient cycles

(Stoate and others 2001), and biodiversity (MacDonald and others 2000; Sirami and others 2008).

Agricultural abandonment is caused and mediated by both, socioeconomic factors, and biophysical conditions (Lambin and others 2001). Among the socioeconomic factors, institutions play a particularly critical role, and so do government policies that affect access to land, labor, capital, technology, and access to information, which all have direct effects on land use change. On the other side, biophysical conditions define the natural capacity of the land, and changing biophysical conditions may predispose areas for land use change (Turner and others 2007). Agricultural land use is thus related to the productive capacity of the land, which is set by climate, soil, landforms, by technology, markets, and land management (Fischer and others 2002). The challenge is to disentangle which of these factors matter most in a given place, because agricultural land use change in general, and land abandonment in particular, is typically gradual, and not amenable to scientific experiments.

A particular case was the collapse of the USSR, which caused rapid land use change in Eastern Europe, and especially widespread land abandonment (Beddow and others 2010; Brooks and Bruce 2004; Gobulev and Dronin 2004; Unwin 1997, Ioffe, Nefedova, Ilya 2006; Lerman and Csaki 2004) (Table 3), including, in some cases, reforestation (Taff and others 2010). Both a trend towards less intensive farming systems and land abandonment, have been reported, the latter particularly on marginal lands (Dutch National Reference Center for Agriculture and others 2005; Swinnen, Van Herck, Vranken 2010). However, the patterns, rate and extent of that agricultural decline have not yet been comprehensively studied (Lepers and others 2005).

TABLE 3 APPROXIMATELY HERE

After the collapse of the USSR, the region went through radical economic and political reforms. In the early 1990s, the dissolution of the Soviet Union allowed countries to gain independence, and to transform centralized state-economies into market economies, often accompanied by land de-collectivization (Dekker 2006; Lerman 2001). The result was that most Eastern European countries reduced the land used for agriculture between 1990 and 2005 (Food and Agriculture Organization of the United Nations 2010). There was also a sudden decline in agricultural output, particularly in the livestock sector, in most countries in the early 1990s (Liefert and Swinnen 2002).

Declines in agricultural production after the breakdown of the USSR were not uniform across Eastern Europe though. Different policies, cultures, and land use traditions in each country affected rates of abandonment. Unfortunately though, previously reported abandonment rates cannot be easily compared due to differences in the temporal and spatial scale among studies, as well as the method utilized to assess agricultural abandonment (Table 3, Prishchepov et al. 2010b). Similarly, agricultural statistics in Russia and other Eastern European countries differ widely in their spatial and temporal characteristics, limiting their relevance for regional comparisons (Filer and Hanousek 2002; Goldewijk and Ramankutty 2004). This means that to date a comprehensive assessment of abandoned agricultural land across Eastern Europe is lacking, and only a small set of case studies have mapped and analyzes its pattern (Table 3).

The main goal of this paper was thus to assess agricultural land abandonment across Central and Eastern Europe including the European part of Russia. Our objectives were first, to map abandonment from satellite data wall-to-wall across the region; and second, to compare abandonment rates among countries and among agro-ecological zones as a first exploration into potential drivers of abandonment.

3.3 Study Area

Our study area encompassed thirty countries in Central and Eastern Europe and the Balkan Peninsula (6.4 million km^2, Figure 7). Sixteen countries were entirely mapped; two countries were almost entirely mapped (more than 95% of their surface), for four more countries more than 50% of their surface was mapped, and for seven additional countries we mapped less than 50% of their surface. This last group included Russia, for which we mapped only 18.4%, but this area alone corresponded to approximately half of our study area, encompassed most of European Russia, and eleven of its twenty largest cities, including the capital, Moscow, and Saint Petersburg.

TABLE 4 APPROXIMATELY HERE

FIGURE 7 APPROXIMATELY HERE

The study area exhibits strong climate gradients from north to south (Figure 8). The north is characterized by low temperatures (a mean temperature around 6 °C) and yearly precipitations around 600 mm. The south has mean temperatures around 16 °C and low precipitation (around 100 mm per year). However, the study area also included areas with high precipitation (for instance Slovenia with more than 1,300 mm) and dry areas (The three countries with the lowest annual precipitation are Turkmenistan, Uzbekistan and Kazakhstan with less than 130 mm) (Figure 8).

FIGURE 8 APPROXIMATELY HERE

The study area does not have many topographical features, containing only four mountainous chains: the Ural Mountains in the northeast, the Carpathians in the west, the Dinaric Alps in the southwest, and the Caucasus in the southeast. Ecologically, the study area is diverse, and contains more than 40 biomes. The north is covered by boreal forest (mainly Spruce and Fir, but pine and larch can occur as well). Mixed forest dominate the northwest and southwest (Dominated by birch, aspen and gray alder), but the Dinaric Alps are covered by deciduous forest (mainly oak, lime, ash, maple, and elm). The interface between boreal and mixed forest has some large patches of pine forest (Scotch pine dominated, usually mixed with spruce, birch, and aspen). Montane forest is present in the Urals, and mixed forest in the Carpathians and the Caucasus. The southeast of the study area is arid, and the Caspian depression is covered mainly by grasslands and xeric scrublands.

Agriculture is most common in the western and southwestern portions of our study area. In terms of the land's suitability for agriculture, as assessed by the UN Food and Agriculture Organization (FAO) (Fischer and others 2002), the majority of the study area has constraints for agriculture (62.3%), only 23.3% of the area has very few or no constraints, and 13.8% is undefined.

3.4 Materials and methods

3.4.1 Input data

Satellite image classifications were based on two Terra and Aqua NASA Global MODIS Vegetation Indices data products: MODIS VI 16-Day L3 Global Collection 5.0 (MOD13Q1 and MYD13Q1) from January 1st, 2003 to December 31st, 2009 (231.65 m pixel size, 5.36 hectares), tiles h19/v3, h19/v4, h20/v3, h20/v4, h21/v3, and h21/v4. Data was retrieved from the Land Processes Distributed Active Archive Center (LP DAAC) on August 7th, 2010 (http://lpdaac.usgs.gov). The combined MODIS VI dataset included weekly reflectance, NDVI, and quality data.

To summarize abandonment rates by country and by administrative regions, we downloaded the international administrative boundaries and the first level of administrative subdivisions from Natural Earth (Free vector and raster map data @ naturalearthdata.com) on September 19th, 2010, and complemented the data with ESRI maps (Environmental Research Systems Institute (ESRI) 2008).

To characterize the suitability of the land for agriculture, we used the Global Agro-ecological Assessment for Agriculture for the year 2000 (GAEZ) (Fischer and others 2002). The variables included in the assessment were climate, soil, and terrain slope constraints. The GAEZ provided a ranked measure of the severity of the constraints that agriculture faces in a given location, and we used this measure to examine if environmental constraints affected abandonment rates.

3.4.2 Training data

Training data for the MODIS image classification was derived via an automated selection of representative polygons of each land cover class from Landsat image classifications, obtained from six different land abandonment studies (Figure 7). The automated selection method was developed in chapter I. Landsat classifications were located in Poland, Latvia, Lithuania, Belarus and Russia (Prishchepov and others in preparation), Romania (Müller and others 2009), Ukraine (Baumann and others in press), Chernobyl region (Hostert and others in preparation), and the border region of Poland, Slovakia and Ukraine (Kuemmerle and others 2007; Kuemmerle and others 2008).

We recoded all the classifications to one of four classes: Agriculture (including pastures), Forest (coniferous, mixed and deciduous forest), Abandoned agricultural land, and Other classes (including water, urban areas, sand, and wetlands).

To obtain training pixels, we used a stratified sampling design and applied it to a grid of MODIS pixels with 2500 m distance between pixels of the same class to minimize spatial autocorrelation. Using the Landsat classifications we randomly selected 1000 MODIS pixels within the grid for each of the four land cover classes with the constraint that at least 90% of the MODIS pixel had to be within the same Landsat land cover class (Figure 7).

3.4.3 Classification algorithm

In chapter I, we showed that Support Vector Machines (SVM) applied to growing season NDVI data for multiple years plus phenology information captured in six parameters provided the highest classification accuracy when mapping abandoned land from MODIS data. We used the results from chapter I and classified the MODIS data for our larger study area here accordingly. Our classification used the MODIS NDVI data from 2004, 2005, and 2006, plus phenology data; parameterized with 2003-2009 MODIS NDVI data. The entire satellite dataset was classified with imageSVM v2.0.1 (Janz and others 2007), an IDL tool for SVM classification for remote sensing based on LIBSVM (Chang and Lin 2001).

To obtain phenology data, we analyzed the MODIS NDVI time-series from 2003-2009 using the Savitsky-Golay algorithm included in the program TIMESAT 2.3 (Jönsson and Eklundh 2004). Within TIMESAT, we chose the following options: a) spikes were defined as values in the time-series that were larger than two standard deviations; b) small changes were interpreted as a change in the phenological cycle (this resulted in the expected six yearly cycles for the entire time-series); c) curves were fitted with three fitting steps with window sizes of 5, 6, and 7; and d) normal strength of adaptation. The phenology indices that we calculated were: End of the season, start of the season, base level, maximum level, length of the season, and middle of the season (resulting in 42 metrics total, six for each year). The six phenology metrics for the seven years were calculated independently for each of the six MODIS tiles and mosaicked for the classification.

We conducted the classification for 108 bands, including the growing season NDVI data for the years 2004, 2005, and 2006 (66 bands in total, 22 for each year), and the six phenology metrics for seven years. We defined the growing season for MODIS NDVI data as starting on day 129 (May 9th, or May 8th on leap years) and ending on day 297 (October 24th, or October 23th in leap years) based on initial TIMESAT results. We rescaled each band to values from 0 to 1 prior to the SVM classification.

Following the general recommendations for training SVM for remote sensing (Foody 2009a), the total number of training points was 4,000. To parameterize the SVM, we used a Maximum probability approach with an automatic parameterization. Our resultant Gaussian kernel (g) value was equal to 0.1 and a regularization parameter (C) value equal to 25.6. The performance measure was the Kappa value estimated via a three-fold cross validation. We used a "one-against-one" approach for the multi-class SVM to avoid unbalanced classifications reported for the "one-against-all" approach (Melgani and Bruzzone 2004).

3.4.4 Validation

The classification was evaluated with independently collected validation data obtained from 77 Landsat images recorded for eighteen random Landsat footprints within the study area (Figure

7). Four Landsat images for each footprint were obtained from GLOVIS (http://glovis.usgs.gov): two for summer and fall images, each centered on the years of 1990 and 2005 (we used only cloud-free imagery; and images within one year of either 1990 or 2005 were included when necessary. Five Landsat 7 SLC-off within two months of these target dates were included because Landsat 5 data was unavailable for the selected date). Five Landsat footprints overlapped one of the agricultural abandonment Landsat classifications (Prishchepov and others in preparation).

The validation dataset was collected using a stratified random sample. To select pixels for validation, a new grid of MODIS pixels with 2500 m distance between pixels was built, to minimize problems with spatial autocorrelation. Using a preliminary MODIS map, classified with SVM for the NDVI bands for the growing season of 2005 season (22 dates) for stratification, 120 MODIS pixels for each of the four land cover classes were selected. A second layer of stratification was added to assure that 20 sampling points for each class were selected per MODIS tile. The resultant MODIS pixels were interpreted visually using the two Landsat images, and, where available, high-resolution QuickBird images in GoogleEarth™. The dominant land cover class in 2005 was recorded for each MODIS pixel. Additionally, we evaluated the accuracy of each of the six MODIS tiles separately.

A second accuracy assessment was performed using 396 validation pixels from the assessment conducted in Chapter 1 for the only tile analyzed in that chapter (h19v03). This independent analysis had the goal to determine the performance of our classification for all six MODIS tiles relatively to the classification of one tile in Chapter 1. We calculated confusion matrices for the entire study area and for each MODIS tile, and adjusted the area estimates based on the user's and producer's accuracy for each class (Card 1982; Foody 2009b; Stehman 1996). However, these area adjustments could only be conducted for the study area as a whole, and not for each country and agroecological zone, because we lacked country-specific accuracy assessments.

3.4.5 Patterns of abandoned agricultural land

To summarize the amount of land abandoned in Central and Eastern Europe, we calculated a) the percentage of abandoned agricultural land compared to all land, b) the percentage of abandoned agricultural land compared to the sum of agriculture and abandoned agricultural land in 2005. Assuming that all areas classified as abandoned had been previously farmed, this second measure provides an estimate of the rate of abandonment. The two measures were calculated for each of the countries in our study area and for each agro-climatic constraint class (Fischer and others 2002).

Country-level summaries are valuable, but can obscure regional variability, especially in large countries such as Russia. This is why we also summarized land abandonment by administrative units (provinces). The challenge was that administrative units at the first level below the nation can vary greatly in size, and such scale differences can distort the results. We took account of the large differences in the size of the first level of administrative division by considering some small countries as a province. The criterion for “small countries” was that they did not have province-level administrative units (‘oblasts’) during Soviet times. These countries were: Albania, Armenia, Azerbaijan, Bosnia, Croatia, Estonia, Georgia, Kosovo, Latvia, Lithuania, Macedonia, Moldova, Montenegro, Serbia, Slovenia, Czech Republic, and Slovakia.

3.5 Results

3.5.1 Patterns of abandoned agriculture

For our entire study area, 21.77% ±3.35% was estimated as agriculture and pastures, 30.28% ± 3.44% as forest, 24.41% ± 4.17% as abandonment, and 23.54% ± 3.98% as other classes according to our adjusted area estimates based on the observed user's and producer's accuracies. The northern and north-eastern parts of our study area had large amounts of abandoned agricultural land, often at the interface between forest and agriculture (Figure 9). The west side of the Ural Mountains, Kaliningrad region, and the northern foothills of the Caucasus also had abundant abandoned agricultural land. In the north and in mountainous areas the dominant land cover was forest. Agriculture prevailed in the plains with the exception of northern Ukraine and the west side of the Volga basin where forests were common. 'Other' land cover classes, which were mainly inland water, wetlands, and urban areas, were scattered throughout the area, and only dominating in the southeast where xeric shrubs and deserts were classified as well as 'other'.

FIGURE 9. APPROXIMATELY HERE

The area mapped as abandoned was larger than the area in active, and this is an important comparison, because it suggests that the abandonment rate was 52.9% in 2005, if we assume that all land mapped as agriculture and abandoned was farmed previously. However, there were some interesting regional variations.

Nine countries, comprising 67.6% of the study area, contained 92.3% of the mapped agricultural abandonment, and all had abandonment rates above 20% (unadjusted area estimates, Table 5), assuming that all land mapped as agriculture and abandoned was farmed previously. Six out of those nine countries (Belarus, Russia, Lithuania, Ukraine, Moldova and Latvia) had abandonment rates of 30% of more (Table 5). Countries with a particularly large share of abandoned agricultural land were Belarus (23%) and Ukraine (23%) (Table 5). Agricultural abandonment also was common in two other countries: The portion of Russia in our study area, and Lithuania with 21 and 20% of the land area respectively. In Russia, agricultural abandonment rate reached 43%. Two Baltic countries, Latvia and Lithuania also had high proportions of abandoned land 15% in Latvia and 20% in Lithuania, representing abandonment rates of 43% and 34% respectively. Moldova and Latvia had also large shares of areas classified as abandoned agricultural land with 17% and 15% respectively, and abandonment rates of 30% and 43% respectively. Three other countries showed shares of abandoned agricultural land above 10% (Czech Republic, Poland, and Kosovo). In contrast, however, twenty one countries, occupying 32.4% of the study area, presented only 8% of less of their area classified as abandoned agriculture had and abandonment rates equal to or lower than 20% (Table 5).

TABLE 5 APPROXIMATELY HERE

FIGURE 10. APPROXIMATELY HERE

Summarizing our classifications by administrative regions showed that agricultural abandonment was widespread but some regions showed particularly high agricultural abandonment rates; especially in the western part of European Russia, the northern Ukraine, eastern Belarus, central Romania, northern Bulgaria, and the countries of Lithuania, Latvia, and Moldova (Figure 11).

Within Russia, abandonment was concentrated in the provinces of Tula, Oryol, Kaluga, Bryansk, and Smolensk, located along the border with Ukraine and Belarus and south-

southwest from Moscow. Three additional regions within Russia presented large shares of abandonment: The first was Kaliningrad province, a Russian enclave between Poland and Lithuania. The second was in the east side of the Ural Mountains (Sverdlovsk province) and the third was the province of Karachi, in the Caucasus. In Ukraine the provinces with largest amount of abandonment were in the northern areas of the country (especially Ternopil and Khmelnytskyi provinces). The six central provinces of Romania had also high abandonment rates with more than 15% of each region classified as abandoned agricultural land (Alba, Brasov, Covasna, Harghita, Mures, and Sibiu).

FIGURE 11 APPROXIMATELY HERE

When we summarized agricultural abandonment rates by agro ecological constraints in each country, we found three different patterns (Table 6). First, twenty countries had similar abandonment rates along the agro-ecological gradient within each country, which means no trend towards or against abandonment in areas more suitable for agriculture. Second, Lithuania, Moldova, Romania, Kazakhstan and Armenia showed surprisingly a trend towards higher agricultural abandonment rates in areas that were more suitable for agriculture. And third, Georgia, Serbia and Macedonia showed higher abandonment rates in not-suitable areas, and Kosovo that abandoned agricultural land only in not-suitable areas.

TABLE 6 APPROXIMATELY HERE

3.5.2 Accuracy

The accuracy assessment of our MODIS classification found an overall area-adjusted Kappa accuracy of 46% ±4.3%, derived from a contingency table with 480 sampling points (Table 7 and Table 8). Forested areas had high user’s accuracies (80.9% ±7.3%) and producer’s accuracies (62%±6%), whereas abandoned agriculture class had user's accuracies of 41% ± 10% and producer's accuracies of 25%±6%. The map proportions and the estimated proportions for all classes showed differences ranging between 7% and 9% (Table 8).

TABLE 7 APPROXIMATELY HERE

TABLE 8 APPROXIMATELY HERE

For MODIS tile h19v03, located in the northwest side of the study area, we found an overall accuracy of 60.2% ±4.7%, with user's accuracies for agricultural abandonment equal to 28.87%±9%, agriculture 78.7% ±7.3%, forest 66.4% ±8.9%, and other 33.9% ± 11.6% and producer's accuracies for agricultural abandonment of 30.4%±9%, agriculture 54.8%±5.9%, forest 69.7%±6.7% and other classes 83.5% ± 7.6% when we estimated the classification accuracy with the independent validation dataset collected for Chapter 1. This means that our classification for all six tiles had slightly lower accuracies for this northwestern tile than the previous classification of this tile alone. Regarding the other tiles, we found that the best performance to map agricultural abandonment was in tile h20v03 in the north of the study area, followed by h19v04, h19v03, h20v04, h21v03 and h21v04, which means the northwest side of the study area had higher accuracies than the southeast. Visual assessments of 1990s Landsat images showed that up to 62% of the validation points labeled as agricultural abandonment were areas that had agriculture in the late 1990s and were abandoned in the mid 2000s; the remaining 38% had some successional stage in late 1990s and remained as scrublands by the mid 2000s.

3.6 Discussion

The key findings from our study are that abandoned agricultural land covered about 24% of our study area in 2005, seven countries contained the majority of the abandoned agricultural land in the region (Estonia, Latvia, Belarus, Russia, Lithuania, Montenegro and Ukraine), and there was no a clear relationship between agro-climatic conditions and agricultural abandonment rates in twenty out of the thirty countries that we studied. This suggested that agricultural abandonment was driven mainly by socioeconomic factors rather than by biophysical conditions.

When comparing the countries, we found five distinctive groups. The first was represented by Russia, which had a large amount of abandoned agricultural land, and moderated shares of agriculture, forest and 'other 'classes. Second, Belarus and Lithuania, were dominated by agriculture and forest, had low proportion of 'other' classes and a large proportion of abandoned agricultural land. Third, Ukraine and Moldova had large proportions of agriculture, low proportion of forest and 'other' classes, and a large proportion of abandoned agricultural land. Fourth, Latvia was dominated by forest and had a large proportion of abandonment. And fifth, Poland, Czech Republic, Kosovo and Armenia, were dominated by agriculture and had only moderate amounts of abandonment. Extreme cases when a country had large proportion of forest or large proportion of other classes showed almost no abandonment.

The accuracy assessment results were consistent with Chapter I and the nature of the data source, mainly due to mixed pixels confusion (active croplands and 'other' classes were confused with agricultural abandonment). Despite the fact that we found relatively low user's and producer's accuracies, we suggest that the general pattern of abandonment and analysis provided here are acceptable, especially when summarizing our results by countries or administrative units. Our proportion estimate for agricultural abandonment, was about 24.4%±4.2, but our map showed only 15.1% mapped agricultural abandonment (the difference was due to the area adjustment). This suggests that our map represented a conservative estimate of the amount of abandoned agricultural land in the region. Our results by country were in close agreement with more localized studies that use Landsat imagery to map abandoned agriculture (Table 3). For instance, in Estonia our map reported an abandonment rate of 29% and Peterson and Aunap (1998) found an abandonment rate of 32%. In southern Romania abandonment rates were 21% (Kuemmerle and others 2009) and our map predicts an abandonment rate of 18%. In Albania, our map reports an abandonment rate of 13% and Müller and Sikor (2006) report a rate of 27% for the southeast of the country; for the mapped portion of Russia our results showed abandonment rate of 43% while and Prischepov and others (in preparation) reported an abandonment rate of 37%. In Poland abandonment rates were 13.9% (Kuemmerle and others 2008) in the Carpathians and about 15% in the northeast of the country (Prischepov and others in preparation) while our map reports an agricultural abandonment rate of 17%. The remaining differences between these Landsat classifications and our classification are well within the confidence interval of our mapping, and could also be caused by the fact that the Landsat classifications only cover portions of the countries being compared. Additionally, the classification for the area mapped with the tile h19v03 (Northwest of the study area) yield an accuracy equivalent to the classifications conducted in the chapter 1 (accuracies around 60%). This is encouraging because it means that we were successful in mapping a very complex land cover class (i.e., abandoned agricultural land) over a large and diverse area.

Another factor to consider when interpreting our accuracy assessment results is that coarse spatial resolution data are limited by the spatial configuration and spectral features of the class to be mapped. Gridding artifacts and resolution discrepancies limit accurate mapping, especially at coarse resolutions (Tan and others 2006). The relation between the object to be mapped and the pixel size as well as the thematic resolution also determined the accuracy (Latifovic and Olthof 2004). The achieved accuracies may be due also to the wide variety of class-patch sizes (Woodcock and Strahler 1987). If the average size of parcels varies widely, there can be biases underestimating or overestimating areas (Ozdogan and Woodcock 2006). Another source of error might have been that we trained the classifier with data from six different case studies across Eastern Europe, all with high but different accuracies, and not all of them have the same definition of agricultural abandonment. Additionally, our class of interest (abandoned agricultural land) is often a mixture of fallow land, shrub, and early-successional forest lands. However, the method developed here demonstrated that it is possible to map agricultural land abandonment using MODIS data using Landsat thematic maps given the nature of the classifier employed.

Irrespective of the accuracy of our classification, it is clear that abandoned agricultural land was very widespread throughout our study area. Market disruption and limited access to capital resulted from a lack of governance on the first years after the breakdown of the Soviet Union (Estrin and Wright 1999). Competing on global markets required the use of new technologies to improve yields but the scarcity of equipment and technical support made yield increases challenging (Liefert and Swinnen 2002), especially for small farmers without formal education (Dutch National Reference Center for Agriculture and others 2005).

By 2005 the different countries in our study area had diverged considerably along the path of market reforms from a common institutional and organizational heritage and the so-called Soviet model of agriculture. Land ownership in particular differed greatly among countries, and land ownership has strong effects on farming efficiency and productivity (Lerman and Csaki 2004), and hence be an underlying cause for the observed pattern of abandoned agricultural land in the study area.

The two most relevant aspects of land ownership were the privatization of land in the law and disposition of the socialized land after the collapse of the Soviet Union (Dijk 2003; Lerman 2001). Once the laws had changed, there were two main procedures to dispose the socialized land: restitution to former owners and distribution to workers. However some also followed a mixed strategy: land was restituted to former owners and also distributed without payment to agricultural workers in the interest of social equity (Csaki and others 2003; Lerman 2001).

The changes in land ownership were accompanied by a near elimination of agricultural subsidies in the former Soviet Union, price liberalization, sudden competition on the global markets in the newly independent countries, change of governments, and change of institutions (Liefert and Swinnen 2002). Furthermore, several countries (e.g., Poland, Lithuania, Latvia, and Estonia) were integrated to the European Union after 2000 and gained access to EU agricultural subsidies (Dutch National Reference Center for Agriculture and others 2005).

Both, land use transition theory (DeFries, Foley, Asner 2004; Foley and others 2005) and forest transition theory (MacDonald and others 2000; Rudel and others 2005) aim to explain forest regrowth after initial deforestation, which is a fairly common pattern as countries develop. Three alternative explanations for this so-called ‘forest transition’ have been proposed. First, expansion in the forest extent is attributed to shifts in market forces due to the urbanization of societies and the globalization of forest products markets (Market-based explanation) (Rudel and others 2005). Second, political decisions to retain or regain ecosystem services that the forest provides may lead countries to promote forest regrowth (Ecosystem service explanation)

(Rudel 2008; Satake and Rudel 2007). And third, arid conditions or deforestation may cause forest product scarcity, leading to a response of planting trees (Forest scarcity explanation) (Rudel 2008; Satake and Rudel 2007). Forests are indeed regrowing on many if not all of the abandoned agricultural lands that we mapped. However, there were no political decisions based on ecosystem services to promoted forest, and neither did forest scarcity cause planting of forests. The southeastern part of the study area was dominated by arid conditions but abandonment rates were lower than in the northern more humid areas. The reason for the increase in forest cover was instead a shift in market forces, but this shift was not due to urbanization but rather due to globalization and triggered by social change rather than national decisions promoting reforestation. Forest transition theory thus needs to be refined to apply to post-Soviet Eastern European.

Agricultural land abandonment has many negative consequences for many people but there were positive aspects too (Benayas and others 2007; Höchtl, Lehringer, Konold 2005). Some of the negative aspects of agricultural land abandonment were that land was not in production, abandonment results in a loss of agricultural landscapes, and potentially changes and declines in local biodiversity. Abandoned agricultural lands can be prone to fires because of fuel build up, and as rural populations loose work, they may cause problems in nearby cities that lack employments for the people.

Positive aspects of agricultural abandonment are though generally improved ecosystem services, including higher carbon sequestration, a significant reduction of erosion, as well as the preservation and restoration of the soils. Wildlife populations may recover since agricultural abandonment increases habitat connectivity (Sirami and others 2008), and lower fertilizer use can cause a reduction of eutrophication levels (Cramer, Hobbs, Standish 2008). And ultimately, when agricultural land is abandoned there is an opportunity to restore historical vegetation states (Bellemare, Motzkin, Foster 2002). Analysis like the one presented here can provide the information necessary to seize such opportunities.

3.7 Acknowledgements

We gratefully acknowledge support by Consejo Nacional de Ciencia y Tecnologia (CONACyT, Mexico), the NASA Land Cover and Land Use Change Program, and the University of Wisconsin-Madison School of International Studies. A. Prischepov, and M. Bauman, from the Silvis Lab at the University of Wisconsin-Madison; Daniel Müller from the Leibniz Institute of Agricultural Development in Central and Eastern Europe (IAMO), Germany; P. Hostert and A. Sieber from the Humboldt University in Berlin; all of them generously provided their classification maps of abandonment. We also express our gratitude to SILVIS lab fellows, especially to Nick Labonte for their technical assistance and fruitful discussions.

3.8 References

Baumann M, Kuemmerle T, Elbakidze M, Ozdogan M, Radeloff VC, Keuler NS, Prischepov A, Kruhlov I, Hostert P. in presss. Patterns and drivers of post-socialist farmland abandonment in Western Ukraine. Land use Policy.

Beddow JM, Pardey PG, Koo J, Wood SJ. 2010. The changing landscape of global agriculture. Alston JM, Babcock BA,Pardey PG, editors. In: The shifting patterns of agricultural production and productivity worldwide. . p8.

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. Journal of Biogeography 29(10-11):1401-20.

Benayas JMR, Martins A, Nicolau JM, Schulz JJ. 2007. Abandonment of agricultural land: an overview of drivers and consequences. CAB Reviews: Perspectives in Agriculture, Veterinary Science, Nutrition and Natural Resources 2(57):1-14.

Brooks K and Bruce G. 2004. Russian Agriculture in the Transition to Market Economy. Economic Development and Cultural Change 52:571-86.

Card DH. 1982. Using known map category marginal frequencies to improve estimates of thematic map accuracy. Photogrammetric Engineering and Remote Sensing 48:431-9.

Chang CC and Lin CJ. 2001. LIBSVM: a library for support vector machines. Software Available at: Http://www.Csie.Ntu.Edu.tw/~cjlin/libsvm [Accessed 20th March 2008]. 2010(9/19). http://www.csie.ntu.edu.tw/~cjlin/libsvm.

Cramer VA, Hobbs RJ, Standish RJ. 2008. What's new about old fields? Land abandonment and ecosystem assembly. Trends in Ecology & Evolution 23(2):104-12.

Csaki C, Lerman Z, Nucifora A, Blaas G. 2003. The Agricultural Sector of Slovakia on the Eve of EU Accession. Eurasian Geography and Economics 44(4):305-20.

DeFries RS, Foley JA, Asner GP. 2004. Land-use choices: balancing human needs and ecosystem function. Frontiers in Ecology and the Environment 2(5):249-57.

Dekker H. 2006. In pursuit of land tenure security. Amsterdam University Press. 640p.

Dijk Tv. 2003. Scenarios of Central European land fragmentation. Land use Policy 20(2):149-58.

Dutch National Reference Center for Agriculture, Nature and Food Quality, Latvian Ministry of Agriculture, Latvian State. 2005. Land abandonment and biodiversity, in relation to the 1st and 2nd pillars of the European Union's Common Agricultural Policy; outcome of an international seminar in Sigulda, Latvia, 7-8 October, 2004. :1-64.

Ellis EC, Goldewijk KK, Siebert S, Lightman D, Ramankutty N. 2010. Anthropogenic transformation of the biomes, 1700 to 2000geb_540. .

Enserink M and Vogel G. 2006. Wildlife conservation - The carnivore comeback. Science 314(5800):746-9.

Environmental Research Systems Institute (ESRI). 2008. Data & Maps, Version 9.3.

Estrin S and Wright M. 1999. Corporate Governance in the Former Soviet Union: An Overview. Journal of Comparative Economics 27(3):398-421.

Filer RK and Hanousek J. 2002. Data Watch: Research Data from Transition Economies. The Journal of Economic Perspectives 16(1):225-40.

Fischer G, van Velthuizen H, Shah M, Nachtergaele F. 2002. Global agro-ecological assessment for agriculture in the 21st century: methodology and results. Research report-International Institute for Applied Systems and Analysis IIASA RR.

Foley JA, DeFries RS, Asner GP, Barford C, Bonan G, Carpenter SR, Chapin FS, Coe MT, Daily GC, Gibbs HK, Helkowski JH, Holloway T, Howard EA, Kucharik CJ, Monfreda C, Patz JA, Prentice IC, Ramankutty N, Snyder PK. 2005. Global consequences of land use. Science 309(5734):570-4.

Food and Agriculture Organization of the United Nations. 2010. FAOSTAT data web page. 2010(07/27)http://faostat.fao.org/.

Foody GM. 2009a. On training and evaluation of SVM for remote sensing applications. Camps-Valls G and Bruzzone L, editors. In: Kernel methods for remote sensing data analysis. First ed. Singapore: John Wiley & Sons. p85.

Foody GM. 2009b. Sample size determination for image classification accuracy assessment and comparison. International Journal of Remote Sensing 30(20):5273-91.

Foster D, Swanson F, Aber J, Burke I, Brokaw N, Tilman D, Knapp A. 2003. The Importance of Land-Use Legacies to Ecology and Conservation. Bioscience 53(1):77-88.

Gobulev G and Dronin N. 2004. Geography of Drougths and Food Problems in Russia (1900-2000). A 0401:1-28.

Goldewijk KK and Ramankutty N. 2004. Land cover change over the last three centuries due to human activities: The availability of new global data sets. GeoJournal 61(4):335-44.

Höchtl F, Lehringer S, Konold W. 2005. “Wilderness”: what it means when it becomes a reality—a case study from the southwestern Alps. Landscape and Urban Planning 70(1-2):85-95.

Hostert P, Kuemmerle T, Prischepov A, Sieber A, Lambin E, Radeloff VC. in preparation. Rapid land use changes after socioeconomic disturbances: Chernobyl and the collapse of the Soviet Union. Science.

Ioffe G, Nefedova T, Ilya Z. 2006. The end of peasantry? disintegration of rural russia. First ed. Pittsburgh, PA: University of Pittsburgh Press. 258p.

Janz A, van der Linden S, Waske B, Hostert P. 2007. ImageSVM-A user-oriented tool for advanced classification of hyperspectral data using support vector machines. Proceedings 5th EARSeL Workshop on Imaging Spectroscopy 1:1-5.

Jönsson P and Eklundh L. 2004. TIMESAT - A program for analyzing time-series of satellite sensor data. Computers & Geosciences 30(8):833-45.

Kauppi PE, Ausubel JH, Fang J, Mather AS, Sedjo RA, Waggoner PE. 2006. Returning forests analyzed with the forest identity. Proceedings of the National Academy of Sciences 103(46):17574-9.

Kuemmerle T, Müller D, Griffiths P, Rusu M. 2009. Land use change in Southern Romania after the collapse of socialism. Regional Environmental Change 9(1):1-12.

Kuemmerle T, Hostert P, Radeloff VC, Perzanowski K, Kruhlov I. 2007. Post-Socialist Forest Disturbance in The Carpathian Border Region of Poland, Slovakia, and Uraine. Ecological Applications 17(5):1279-95.

Kuemmerle T, Hostert P, Radeloff VC, van derLinden S, Perzanowski K, Kruhlov I. 2008. Cross-border comparison of post-socialist farmland abandonment in the Carpathians. Ecosystems 11(4):614-28.

Lambin EF and Geist HJ, editors. 2006. Land-use and land-cover change: Local processes and global impacts. First ed. Berlin Heidelberg New York: Springer. p222.

Lambin EF, Turner BL, Geist HJ, Agbola SB, Angelsen A, Bruce JW, Coomes OT, Dirzo R, Fischer G, Folke C, George PS, Homewood K, Imbernon J, Leemans R, Li XB, Moran EF, Mortimore M, Ramakrishnan PS, Richards JF, Skanes H, Steffen W, Stone GD, Svedin U, Veldkamp TA, Vogel C, Xu JC. 2001. The causes of land-use and land-cover change: moving beyond the myths. Global Environmental Change-Human and Policy Dimensions 11(4):261-9.

Latifovic R and Olthof I. 2004. Accuracy assessment using sub-pixel fractional error matrices of global land cover products derived from satellite data. Remote Sensing of Environment 90(2):153-65.

Lepers E, Lambin EF, Janetos AC, DeFries RS, Achard F, Ramankutty N, Scholes RJ. 2005. A Synthesis of Information on Rapid Land-cover Change for the Period 1981–2000. BioScience 55(2):115-24.

Lerman Z. 2001. Agriculture in transition economies: from common heritage to divergence. Agricultural Economics 26(2):95-114.

Lerman Z and Csaki C. 2004. Evolving farm structures and land use patterns in former socialist countries. Quarterly Journal of International Agriculture 43(4):309-35.

Liefert W and Swinnen J. 2002. Changes in Agricultural Markets in Transition Economies. 806:1-32.

MacDonald D, Crabtree JR, 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. Journal of Environmental Management, 59(1):47-69.

Macours K and Swinnen JFM. 2002. Patterns of Agrarian Transition. Economic Development and Cultural Change 50(2):365-94.

Melgani F and Bruzzone L. 2004. Classification of hyperspectral remote sensing images with support vector machines. IEEE Transactions on Geoscience and Remote Sensing 42(8).

Millennium Ecosystem Assessment. 2005. Ecosystems and human well-being : current state and trends : findings of the Condition and Trends Working Group. 1:1-917.

Müller D, Kuemmerle T, Rusu M, Griffiths P. 2009. Lost in transition: determinants of post-socialist cropland abandonment in Romania. Journal of Land use Science 4(1):109-29.

Müller D and Sikor T. 2006. Effects of postsocialist reforms on land cover and land use in South-Eastern Albania. Applied Geography 26(3-4):175-91.

Ozdogan M and Woodcock CE. 2006. Resolution dependent errors in remote sensing of cultivated areas. Remote Sensing of Environment 103(2):203-17.

Perz SG. 2007. Grand Theory and Context-Specificity in the Study of Forest Dynamics: Forest Transition Theory and Other Directions. The Professional Geographer 59(1):105-14.

Peterson U and Aunap R. 1998. Changes in agricultural land use in Estonia in the 1990s detected with multitemporal Landsat MSS imagery. Landscape and Urban Planning, 41(3-4):193-201.

Prischepov A, Radeloff VC, Baumann M, Kuemmerle T. in preparation. Impact of massive socio-economic changes on land use change: agricultural abandonment during socio-economic transition in post-Soviet Eastern Europe.

Prishchepov A, Radeloff VC, Dubinin M, Alcantara C. in review. The effect of image acquisition dates on detection of agricultural land abandonment in Eastern Europe. Remote Sensing of Environment .

Ramankutty N, Gibbs HK, Achard F, DeFries RS, Foley JA, Houghton RA. 2007. Challenges to estimating carbon emissions from tropical deforestation. Global Change Biology 13(1):51-66.

Rudel TK. 2008. Tree farms: Driving forces and regional patterns in the global expansion of forest plantations. Land use Policy. In Press, Corrected Proof.

Rudel TK, Coomes OT, Moran E, Achard F, Angelsen A, Xu J, Lambin EF. 2005. Forest transitions: Towards a global understanding of land use change. Global Environmental Change Part A, 15(1):23-31.

Satake A and Rudel TK. 2007. Modeling The Forest Transition: Forest Scarcity and Ecosystem Service Hypotheses. Ecological Applications 17(7):2024-36.

Scanlon BR, Jolly I, Sophocleous M, Zhang L. 2007. Global impacts of conversions from natural to agricultural ecosystems on water resources: Quantity versus quality. Water Resources Research 43:1-18.

Sirami C, Brotons L, Burfield I, Fonderflick J, Martin J. 2008. Is land abandonment having an impact on biodiversity? A meta-analytical approach to bird distribution changes in the north-western Mediterranean. Biological Conservation 141(2):450-9.

Stehman S. 1996. Estimating the kappa coefficient and its variance under stratified random sampling. Photogrammetric Engineering and Remote Sensing 62(4):401-7.

Stoate C, Boatman ND, Borralho RJ, Carvalho CR, Snoo GRd, Eden P. 2001. Ecological impacts of arable intensification in Europe. Journal of Environmental Management, 63(4):337-65.

Swinnen J, Van Herck K, Vranken L. 2010. Shifting patterns of agricultural production and productivity in the former soviet union and central and eastern europe. Alston JM, Babcock BA,Pardey PG, editors. In: The shifting patterns of agricultural production and productivity worldwide. . p279.

Taff GN, Müller D, Kuemmerle T, Ozdeneral E, Walsh SJ. 2010. Reforestation in central and eastern europe after the breakdown of socialism. Nagendra H and Southworth J, editors. In: Reforesting landscapes: Linking pattern and process. Springer. p121.

Tan B, Woodcock CE, Hu J, Zhang P, Ozdogan M, Huang D, Yang W, Knyazikhin Y, Myneni RB. 2006. The impact of gridding artifacts on the local spatial properties of MODIS data: Implications for validation, compositing, and band-to-band registration across resolutions. Remote Sensing of Environment 105(2):98-114.

Tasser E, Tappeiner U, Cernusca A. 2005. Ecological Effects of Land-use Changes in the European Alps. 23:409-20.

Turner BL, Lambin EF, Reenberg A. 2007. The emergence of land change science for global environmental change and sustainability. Proceedings of the National Academy of Sciences 104(52):20666-71.

Unwin T. 1997. Agricultural restructuring and integrated rural development in Estonia. Journal of Rural Studies 13(1):93-112.

Vuichard N, Ciais P, Belelli L, Smith P, Valentini R. 2008. Carbon sequestration due to the abandonment of agriculture in the former USSR since 1990. Global Biogeochemical Cycles 44(4):1-8.

Woodcock CE and Strahler AH. 1987. The factor of scale in remote sensing. Remote Sensing of Environment 21(3):311-32.

3.9 Tables

Table 3. Prior studies on post-Soviet agricultural land abandonment in Central and Eastern Europe

	Abandonment Rate(%)	Classification Method	Data	Time span	Reference
Albania (Southeast)	27	Visual interpretation	Landsat TM and ASTER(30 m)	1988-2003	(Müller and Munroe 2008)
Czech Republic	12	Principal Component Analysis plus Maximum Likelihood	Landsat TM/ETM+ (30 m)	1991-2001	(Václavík and Rogan 2009)
Estonia	32	Principal Component Analysis	Landsat MSS (30 m)	1990-1993	(Peterson and Aunap 1998)
Kazakhstan	"widespread agriculture de-intensification"	3 statistical test for Growing degree days and NDVI	AVHRR (1 Km)	1985-1999	(de Beurs and Henebry 2004)
Latvia, Vidzeme Uplands	50	Visual interpretation	Ortho-photos, and official statistical surveys (<30cm)	1990-2000	(Nikodemus and others 2005)
Romania (Southern)	21	ISODATA plus Maximum Likelihood	Landsat TM/ETM+(30 m)	1990-2005	(Kuemmerle and others 2009)
Ukraine (Western)	56		Landsat TM/ETM+(30 m)	1987-2008	(Baumann and others in press)
Ukraine, Chernobyl	64.5 and 63	Support Vector Machines	Landsat TM/ETM+(30 m)	1986-1992 and 1992-1999	(Hostert and others in preparation)
Carpathian border region of: Poland Slovakia Ukraine	13.9 20.7 13.3	Support Vector Machines	Landsat TM/ETM+(30 m)	1988-2000	(Kuemmerle and others 2008)
NE and NW Belarus SE Latvia East Lithuania NE Poland Russia, 6 provinces	12 42 28 15 37	Support Vector Machines	Landsat TM/ETM+(30 m)	1989-2000	(Prischepov and others in preparation)

Table 4 Countries included

Name	% of the Country	% of the area mapped
Ukraine	100.0	9.3
Romania	100.0	3.7
Belarus	100.0	3.2
Bulgaria	100.0	1.7
Hungary	100.0	1.4
Serbia	100.0	1.2
Georgia	100.0	1.1
Lithuania	100.0	1.0
Latvia	100.0	1.0
Bosnia and Herzegovina	100.0	0.8
Slovakia	100.0	0.8
Estonia	100.0	0.7
Moldova	100.0	0.5
Macedonia	100.0	0.4
Montenegro	100.0	0.2
Kosovo	100.0	0.2
Albania	95.9	0.4
Croatia	95.0	0.8
Armenia	88.7	0.3
Poland	84.5	4.1
Slovenia	67.5	0.2
Azerbaijan	64.5	0.9
Czech Republic	44.3	0.5
Austria	39.6	0.5
Turkmenistan	36.3	0.1
Greece	32.7	0.7
Turkey	28.7	3.5
Kazakhstan	28.6	11.9
Italy	19.5	0.9
Russia	18.4	47.7

Table 5 Land-cover class distribution per country and agricultural abandonment rates

	Ag. Abandonment	Agriculture	Forest	Other Classes	Rate of abandonment (Ag. aband /(Ag+Ag. aband)
Belarus	23	25	38	14	47
Ukraine	23	46	14	18	33
Russia	21	28	25	25	43
Lithuania	20	39	31	11	34
Moldova	17	41	8	34	30
Latvia	15	20	52	12	43
Czech Republic	13	47	32	8	22
Poland	12	56	23	10	17
Kosovo	11	40	38	12	21
Bulgaria	8	44	32	16	16
Romania	8	35	36	21	18
Armenia	8	44	9	39	15
Estonia	7	19	58	16	29
Albania	7	43	15	35	13
Hungary	6	48	21	25	12
Slovakia	6	34	50	10	15
Macedonia	6	38	27	28	13
Serbia	5	31	39	26	14
Georgia	5	24	45	26	16
Austria	5	28	54	13	14
Turkey	4	30	19	47	11
Greece	3	38	19	40	8
Montenegro	3	30	54	14	10
Azerbaijan	2	25	9	63	9
Croatia	2	31	46	21	7
Bosnia and Herzegovina	2	22	67	9	9
Italy	2	36	13	49	5
Kazakhstan	1	8	0	91	9
Slovenia	1	13	76	10	5
Turkmenistan	0	0	0	100	
Total	**15.1**	**29.7**	**23.2**	**32**	**33.6**

Table 6 Agricultural abandonment rates by country and by agro-ecological constraints

	Country																												
	Russia	Belarus	Latvia	Lithuania	Estonia	Ukraine	Moldova	Czech Republic	Romania	Kosovo	Kazakhstan	Poland	Slovakia	Armenia	Bulgaria	Austria	Georgia	Hungary	Albania	Turkey	Serbia	Macedonia	Montenegro	Croatia	Bosnia and Herzegovina	Greece	Azerbaijan	Italy	Slovenia
No Constraints	20					14		17					26			14					0				0		2	0	
Very Few Constraints	44					36	33	18	17			19	19	26	14	15	11	13	12	17	7	7	11	17	7	8	9	0	1
Few Constraints	43	48	43	43	33	30	31	21	14		22	20	15	16	17	13	10	12	14	11	10	8	9	9	9	7	7	4	4
Partly with constraints	54	42	43	50	32	41	26	21	21	24	26	17	13	14	15	15	15	10	14	12	15	13	10	8	10	8	6	5	3
Frequently severe constr.	51	52	48	24	45	38	32	23	20	16	10	16	19	16	18	17	14	12	13	10	21	11	10	5	8	9	10	5	4
Very frequent severe constr.	45	49	11	33	54	56	26	19	12	20	18	17	12	20	14	12	18	13	15	17	14	16	12	8	5	7	9	6	9
Unsuitable for agriculture	32	48	39	25	26	11	26		30		6	17	12	3	12	11	22	12		3	11			13	4		5	5	

Table 7 Contingency table.

		Map				
		Agriculture	Forest	Ag. Aband	Other	Total
Reference	Agriculture	**52**	4	13	32	101
	Forest	18	**89**	24	16	147
	Ag. Aband.	46	7	**42**	28	123
	Other Classes	37	10	23	**39**	109
	Total	153	110	102	115	480

Table 8 Results of our accuracy assessment*

	Map proportions	Estimated proportions	Producer's accuracy	User's accuracy
Agriculture	29.75%	21.77% ± 3.35%	46.45% ± 8.29%	33.99% ± 7.51%
Forest	23.23%	30.28% ± 3.44%	62.05% ± 6.15%	80.91% ± 7.34%
Ag. Aband.	15.08%	24.41% ± 4.17%	25.44% ± 5.70%	41.18% ± 9.55%
Other	31.95%	23.54% ± 3.98%	46.02% ± 8.21%	33.91% ± 8.65%
Overall accuracy	**45.95% ± 4.26%**			

* Area adjusted calculations with 95% confidence intervals derived from maximum likelihood estimation suggested by Card (1982) for stratified random sampling.

3.10 Figures

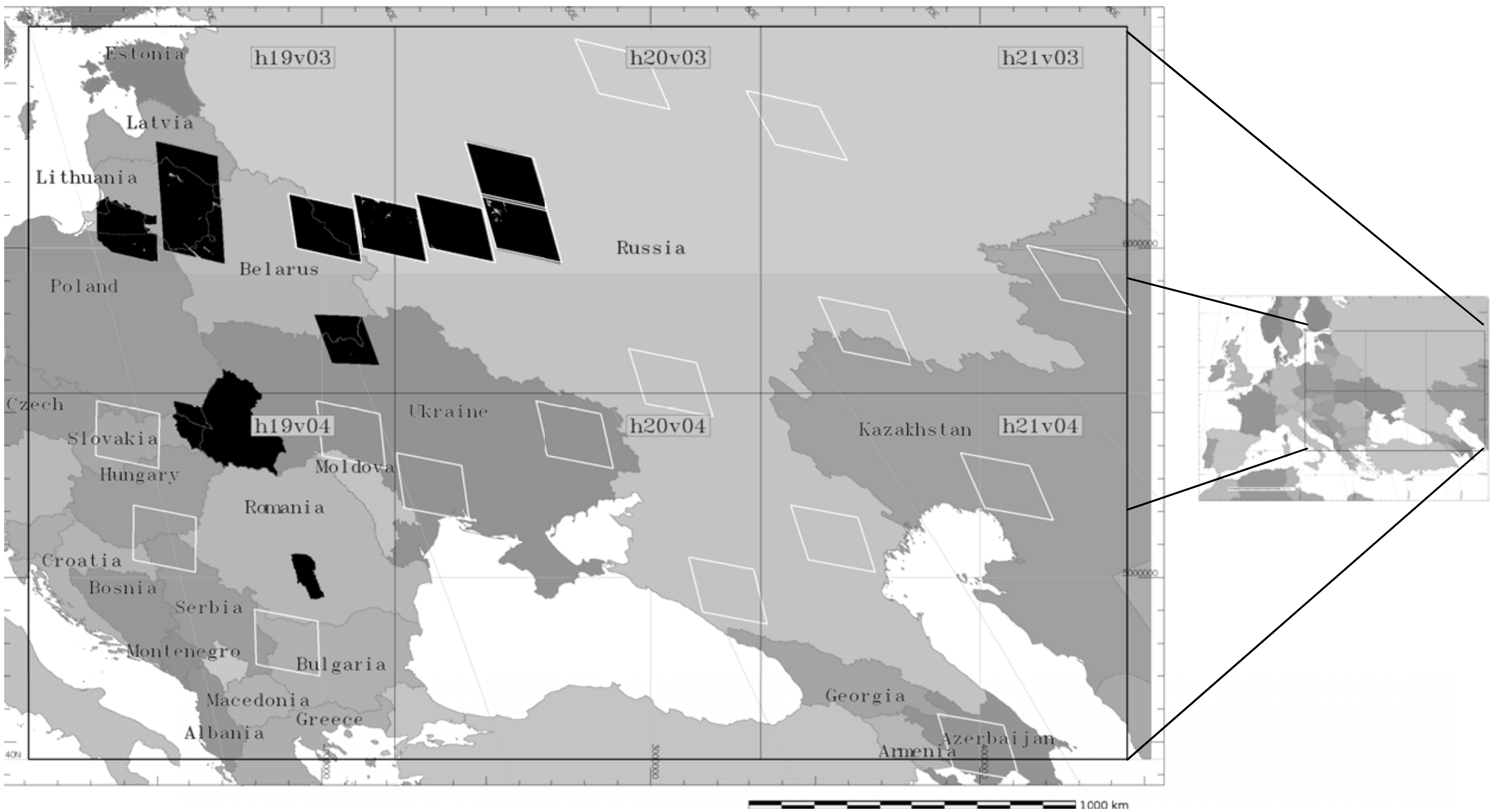
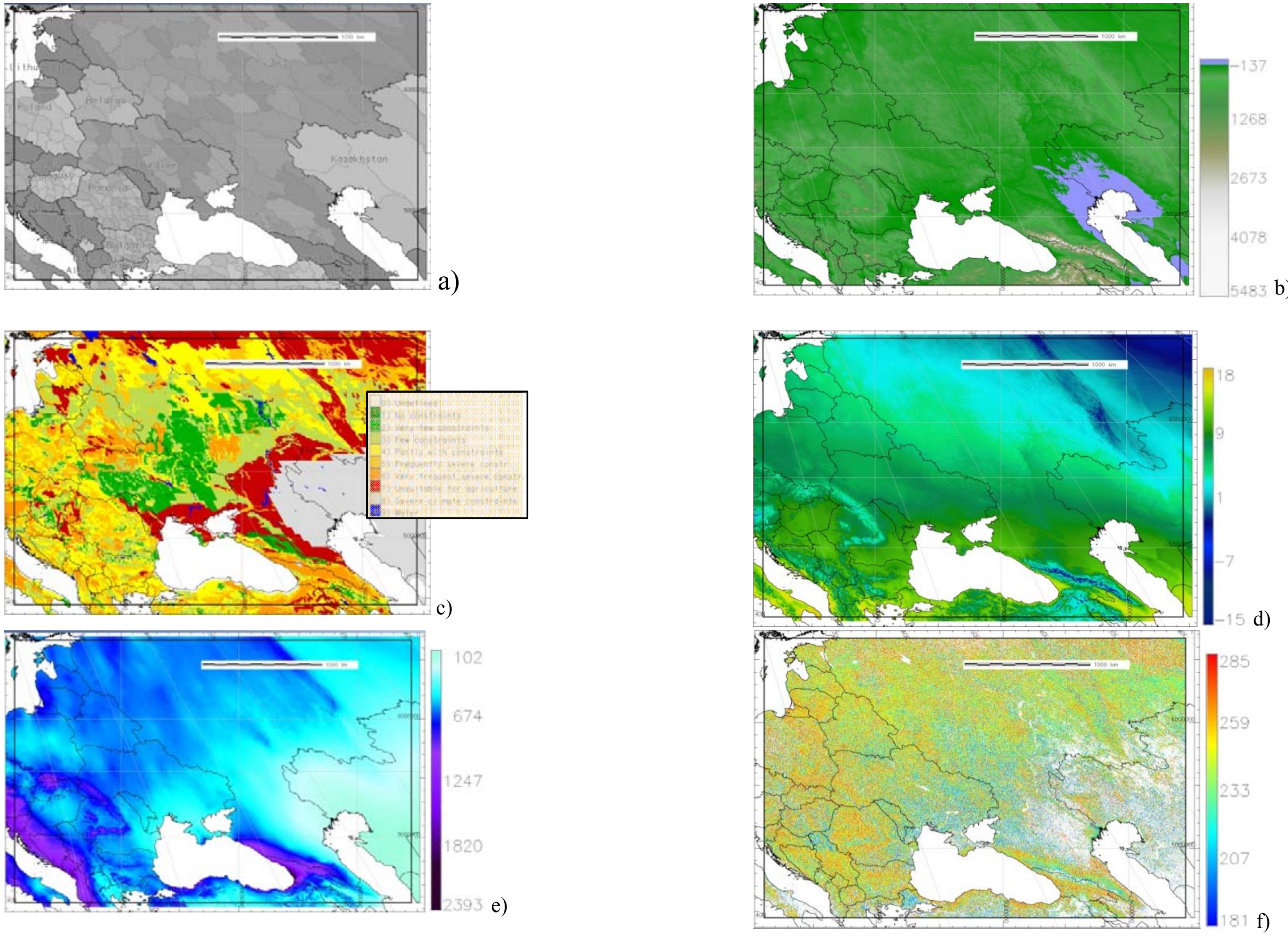


Figure 7 Study area. The six large labeled boxes represent the MODIS tiles classified in the study. Dark shapes are the Landsat classifications used to collect training samples. Validation dataset was collected from the Landsat scenes represented here by white outlines.



a))

Figure 8. Political and agroclimatic conditions of the study area. a) Political boundaries (Natural Earth 2010), b) Elevation (m) (USGS 1996), c)Agro-climatic constraints, plate 28 (Fischer, G. 2002), d) Annual temperature (°C) (Hijmans, R. J. 2005), e) Annual precipitation (mm) (Hijmans, R. J. 2005) and f) Mean length of growing season (days) (our MODIS TIMESAT analysis)

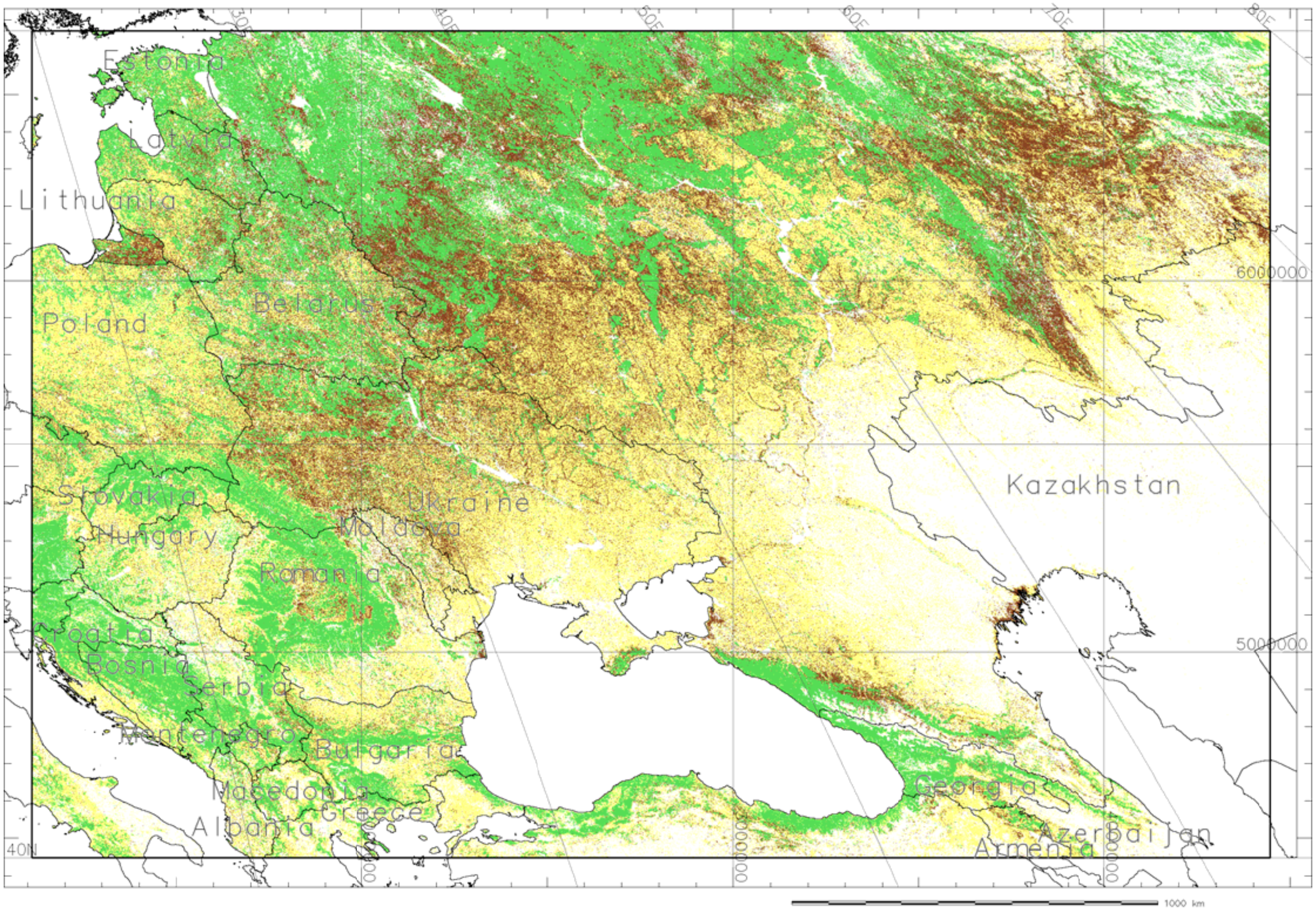


Figure 9 Land-cover classification for Central and Eastern Europe. Brown areas represent abandoned agricultural land, yellow areas agriculture, green forest and light gray other classes.

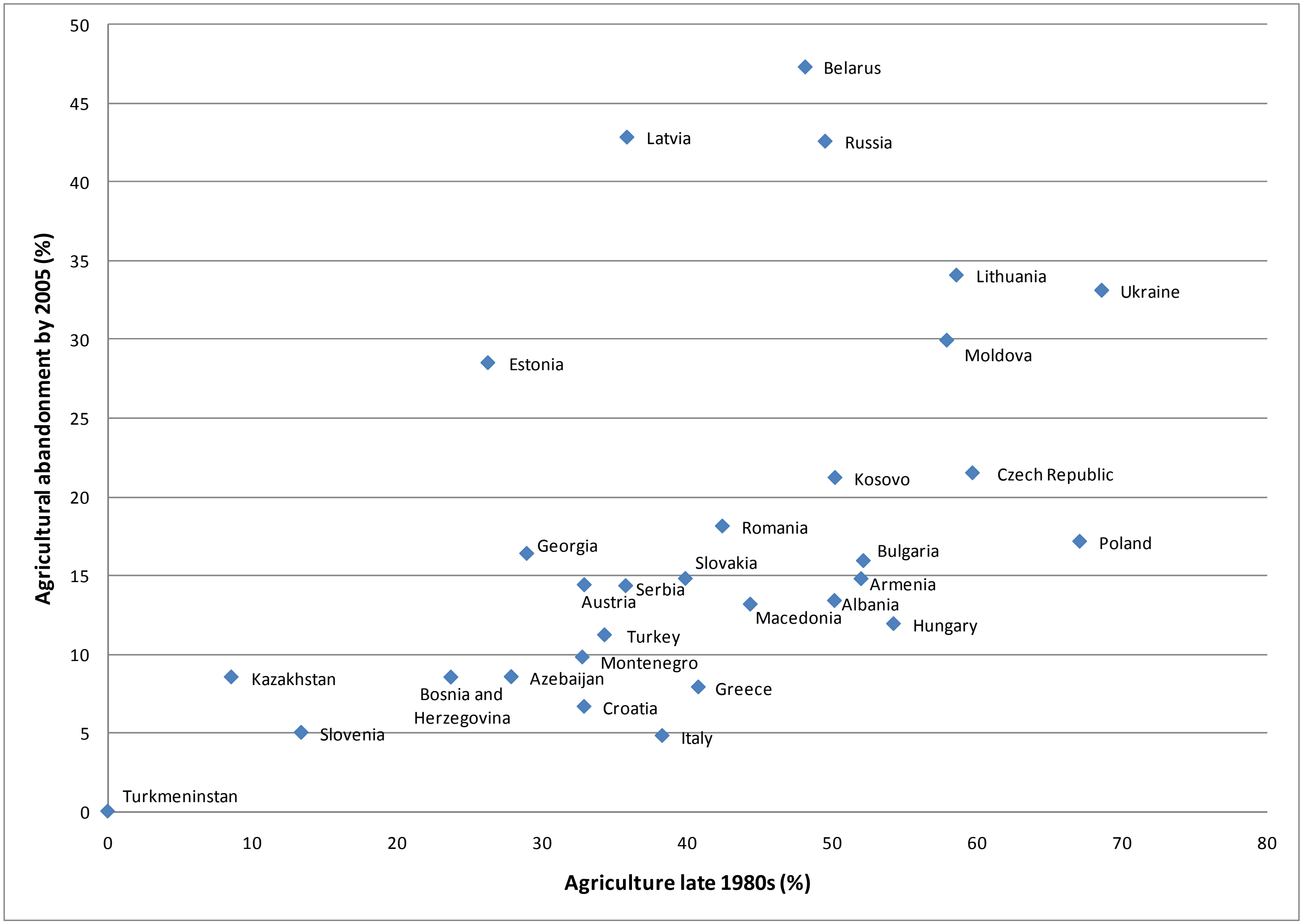


Figure 10. Agricultural abandonment rates per country compared to their share of agriculture in the late 1980s (i.e., the total area of agricultural land and abandoned agricultural land in 2005).

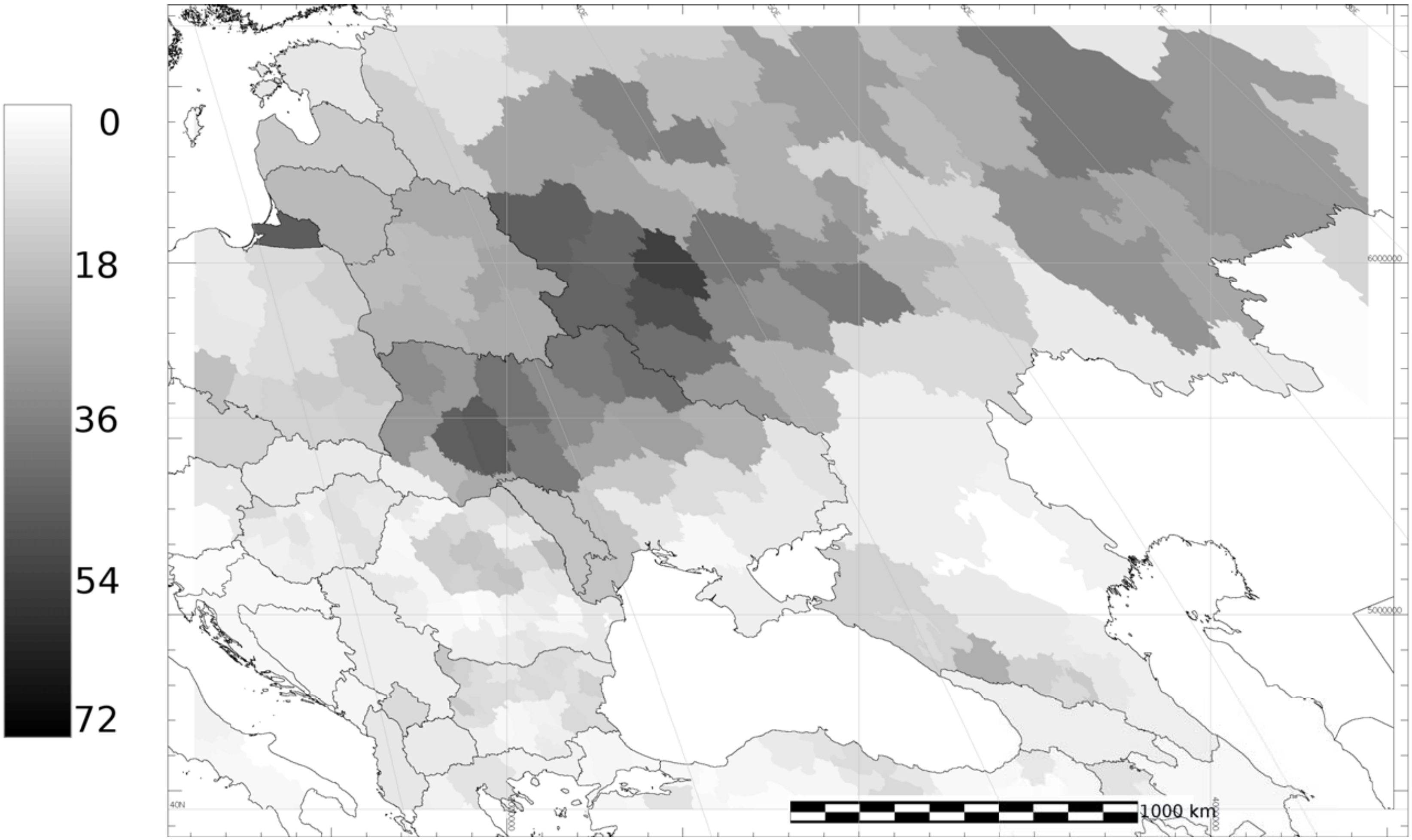


Figure 11 Agricultural abandonment rates by administrative unit at the first level below the nation (provinces).

4 Chapter III. Effects of land-use and land cover changes and fragmentation on brown bear (*Ursus arctos arctos*) populations in Russia

Authors

Camilo Alcantara[1*], Volker C. Radeloff[1], and Leonid Baskin[1]

[1]Department of Forest and Wildlife Ecology, University of Wisconsin-Madison,

1630 Linden Drive, Madison, WI, 53706-1598, USA

[*]Corresponding author.

Phone +1 608 265-9219; fax: +1 608 262-9922

E-mail: **alcantara@wisc.edu**

4.1 Abstract

Rapid land-cover and land-use change (LCLUC), mainly in the form of agricultural land abandonment, occurred since the early 1990s in European Russia. European Russia is also were one of the world's largest brown bear populations (*Ursus arctos arctos*) exhibited population changes and potentially range expansions recently. Our goal here was to examine the response of brown bear population to the recent LCLUC in European Russia in order to gain general insights about the management and the conservation of large mammals. We analyzed brown bear population trends from 1991 to 2007, and then focused on the area where brown bear's geographical range expanded with a more detailed analysis of bear habitat use. Single and multiple linear regressions quantified the relationship of environmental variables, human disturbance, land cover, fragmentation, and dispersal (explanatory variables) with brown bear densities in 2005 (response variable). Our results showed that brown bears in European Russia slightly increased in numbers and expanded their range southwards from 1991 to 2007 after a sharp population decline between 1991 and 1995. Our habitat use models performed well and indicated strong evidence that brown bear populations in the south were linked to northern source populations via dispersal. Multivariate models captured two thirds of the variation in bear abundance and showed that abundance was mainly driven by proxies of human disturbance and the presence of forest, but we found negative correlations with agricultural abandonment. Interestingly, bear abundances were not strongly associated with environmental conditions (topography and climate). Brown bear abundance patterns in the European part of Russia are probably the result of a long history of interactions with human populations.

Keywords: Brown bear, dispersal, disturbance, dynamics, fragmentation, habitat use, human influence, land cover, landscape, population density range, roads, Russia, Ursus arctos.

4.2 Introduction

One of the largest brown bear (*Ursus arctos arctos*) populations in the world is located in European Russia (Chestin 1999; Servheen, S., B. 1999). Rapid land-cover and land-use change (LCLUC), mainly resulting from agricultural land abandonment, occurred in the same region after the collapse of the USSR (Chapter 2). Agricultural land abandonment has strong impacts on biodiversity (Benayas and others 2007; Höchtl, Lehringer, Konold 2005; Moreira and Russo 2007; Russo 2007; Sirami and others 2008), but it is unknown how the Russian agricultural land abandonment affected brown bears at a broad scale. Here we examined the response of brown bear populations to the recent LCLUC in European Russia to gain general insights about the management and the conservation of large mammals.

Large mammals are particularly vulnerable to human presence at species and population levels (Cardillo and others 2005; Davidson and others 2009). Humans can cause large mammal extirpation directly, through hunting and extermination programs (Bennet and others 2002), but also indirectly, by modifying their habitat, mainly due to LCLUC (Foley and others 2005; Ojima, Galvin, Turner 1994; Sala and others 2000; Sanderson and others 2002). Additionally, other human induced factors can contribute to large mammal extinctions, such as climate change (Walther and others 2002), disease spread (Pedersen and others 2007), and the introduction of invasive species (Clout and Russell 2008). In modern times, large mammals have been extirpated from many areas, less than 21 % of the earth‘s terrestrial surface still contains all of the large mammals it once held (Morrison and others 2007), and up to 39% of large mammals living today are threatened by extinction as of 2008 (Vié, Hilton-Taylor, Stuart 2009).

Unfortunately, brown bears have endured the same fate as other large mammals and, especially, carnivores (Van Valkenburgh and Wayne 2010). Brown bears' range has been greatly reduced, and bears almost disappeared from large portions of the northern hemisphere by the beginning of the 20th century, including North America (Woodroffe 2000), and Western Europe (Breitenmoser 1998). However, recently there has been a change in public attitudes, a new awareness of the real possibility of the species' extinction, and the consequences of their disappearance (Linnell, Swenson, Anderson 2001). Several initiatives to protect endangered brown bear populations and to reintroduce them in area when they had been extirpated started, albeit with highly variable rates of success (Clark, Huber, Servheen 2002; Servheen, S., B. 1999; Swenson, Sandegren, Soderberg 1998). Nevertheless, one of the main large carnivore population recoveries in recent decades probably occurred in Eastern Europe in the case of brown bears, where Chestin reported a large expansion of the brown bear geographical range in the European part of Russia from 1960 to 1989 (Chestin and others 1992).

Since 1989, Russia has changed greatly, and the collapse of the USSR caused rapid and widespread land cover change, especially the abandonment of agricultural areas, which reverted to shrublands, and may ultimately become forests (Chapter 2). The question is how these changes may have affected bear populations. In general, brown bears use environments dominated by forest as their habitat, but they also occupy a wide variety of land covers at different times of the year (Apps and others 2004; McLellan and Shackleton 1988). In particular, bears include clearcuts and other early-successional areas in their habitat selection (Ciarniello and others 2007a; Martin and others 2010; Nielsen, Boyce, Stenhouse 2004; Nielsen and others 2010; Nielsen and others 2004). Land abandonment encourages the dispersal of large carnivores such as wolves, lynxs and bears by increasing the availability of forests, greater prey availability, and reduced human disturbance (Ciucci and Boitani 1998, Breitenmoser 1998). The large share of agricultural abandonment in European Russia by 2005 thus may have increased the amount of available habitat for the brown bears, and potentially have resulted in further range expansion and population increases, but the extent to which this is the case is unknown.

Habitat use and selection occurs at four spatial orders (Johnson 1980): first the physical-geographic range of a species; second the home range within a geographic range; third, feeding sites within a home range; and fourth, specific foraging decisions. Most studies of brown bear habitat use and selection focus on second and third order. Here, we studied brown bears habitat use at the geographic scale of the Eurasian brown bear subspecies (*Ursus arctos arctos*).

In general, brown bears habitat use depends mainly on food availability and human disturbance (Apps and others 2004; Ciarniello and others 2007a; Martin and others 2010), but bears' habitat use differs between bears in stable populations, and those that are dispersing (Nellemann and others 2007; Støen and others 2006). In this chapter we investigated brown bear population changes from 1991 to 2007, first at the population level, where we looked at changes in range, number, and density, and second at the sub-population level, where we focused on the area were brown bears recently increased their geographical range, to assess the effects of environmental factors, human disturbance, land cover change, fragmentation, and dispersal on bear densities.

Habitat loss, hunting, poaching, the removal of problematic bears, and defense for life and property by citizens account for as much as 90% of adult bears mortality (Schwartz et al. 2003). The European part of Russia has Russia's highest population densities and most developed transport network. Areas with high human density and dense infrastructures are avoided by brown bears at the landscape level (Nellemann and others 2007), although roadsides can be beneficial too, since they provide food and an easy means for travel and food (Ciarniello and others 2007a; Roever, Boyce, Stenhouse 2008a). Thus it is not clear how the dense road network in European Russia is affecting bears, and if effects differ among major and minor roads.

The large increase in agricultural land abandonment in the last 20 years changed both, the amount of habitat that is available, and its spatial pattern. Those changes in spatial patterns may have affected bear's habitat use. We used the map of agricultural abandonment developed in Chapter 2 to test if the brown bears used abandoned areas similarly to the way they use forest, by contrasting the landscape patterns of the forested area only with the patterns of the combined area of forest and agricultural abandonment. Currently, there are only a few studies that examined how different land cover types affect brown bears habitat use and selection and none of them analyzed landscape pattern effects on brown bears (Apps and others 2004; Ciarniello and others 2007a; Gibeau and others 2002; Singleton, Gaines, Lehmkuhl 2004). In terms of landscape patterns, features such as patches, edge, interior and gap may help to explain brown bear habitat use.

In summary, the geographic range of populations is influenced by their ecological traits plus environmental conditions, habitat availability, and human disturbance. Large and rapid LCLUC occurred in Russia since 1990 and brown bear populations may be expanding their range. Our goal here was to explore how land cover change, human disturbance and environmental conditions influenced brown bear range expansion and habitat use in European Russia after 1990. First, we analyzed general population trends from 1991 to 2007; and second, we focused on the change in brown bear's geographical range. We analyzed how the population responded to the changes in habitat in the area where bears expanded their range, and examined in particular: a) environmental factors, b) human presence, c) land cover, landscape changes, and land cover fragmentation, and last but not least d) the effects of dispersal distances.

4.3 Study Area

The area within which we analyzed general population trends encompassed 31 oblasts (provinces) in European Russia, covering about 2,835,000 km^2 or 16.6% of Russia (Figure 12). The area where we conducted the habitat selection analysis was a subset, and encompassed 569 rayons (or regions, corresponding to the second administrative level division, mean size 1900 ±400 km^2) in 19 Oblast (Figure 13 and Figure 14, covering about 969,250 km^2 or 5.7% of Russia).

FIGURE 12 APPROXIMATELY HERE

FIGURE 13 APPROXIMATELY HERE

FIGURE 14 APPROXIMATELY HERE

The study area exhibits a typical humid continental climate; classified as Dfc in the north and Dfb in the south according to the Köppen-Geiger climate classification, and is characterized by extreme variation in temperature with cold winters and hot summers (Peel, Finlayson, McMahon 2007). Both annual average temperatures and annual precipitation are low (Figure 15), with a temperature gradient from northeast (-5.5 °C) to southwest (6.2 °C), and an annual precipitation gradient from north (707 mm) to south (268 mm). Ecologically, the study area is dominated by 4 biomes (Olson and others 2001). The north is dominated by the Scandinavian and Russian Taiga (25% of the study area) with Sarmatic Mixed Forest (17%), East European Forest Steppe (12%) and the Pontic Steppe (4%). The region contains also Ural Montane Forest and Tundra (6%). The remainder of the study area represents the West Siberian Taiga and the Kazakh Forest Steppe in the east of the study area, the Kazakh steppe in the southeast, and the central European mixed forest in the southwest. The area where brown bear's expanded their range is dominated by the Sarmatic Mixed Forest and the East European Forest Steppe.

FIGURE 15 APPROXIMATELY HERE

The European part of Russia had 25% of the area covered by forest in 2005. The majority of the tree species are characteristic of boreal biomes: spruce, and fir, with less dominance of pine and larch). Mixed forest is located westward of the study area (dominated by birch, aspen and gray alder). The interface between boreal and mixed forest has also large patches of pine forest (Scotch pine dominated, usually mixed with spruce, birch, and aspen). The southeast of the study area is dry, with the Caspian depression covered mainly by grasslands and xeric scrublands. The area was dominated by abandoned agricultural land; covering about 43%, surpassing the forest cover by 18% (Chapter 2). Agriculture is most common in the southeastern portion of our study area and abandoned agricultural land is mainly located at the interface between agriculture and forest in the northwest and east of the Ural Mountains (Chapter 2).

4.4 Materials and methods

4.4.1 Brown bear's dataset

We analyzed two scales of bear data, both collected by the Russian Ministry of Agriculture - Governmental Service of Game Animals' Calculation (Gosokhotuchet RSFSR). The first dataset included bear population data for 31 European Russia oblasts and spanned from 1991 to 2007 (Figure 12). The second dataset encompassed bear population data at a finer resolution for the year 2005 only, for 565 rayons along the southern edge of brown bears' range in European Russia (Figure 13). Earlier Gosokhotuchet data at the oblast level had been analyzed by Sitsko (1983, reported by Chestin 1992, 1999) and Chestin (1999).

The brown bear data were systematically collected, but their accuracy varied widely. Regular counts by wildlife scientists were limited to only a few oblasts (Chestin et al. 1992). In others, the main method of evaluation was the expertise of local wildlife managers. Data for some oblasts were subjectively corrected by a bear specialist working in that region. Our population estimates of brown bears for Russia relied mainly on data from Gosokhotuchet RSFSR, and to a lesser degree on data collected by Y.P. Gubar, which he obtained in communication with local experts. Local hunting management authorities reported numbers that were often averaged over time. Furthermore, data for less than 10 bears in single rayons were not always reported, because such small populations were not hunted and bear reports thus did not affect quota requests (Y.P. Gubar, personal communication). Despite these shortcomings, this bear database was the only systematic data collected across Russia over long time by a long-standing group of experts in hunting management. The fact that populations of less than 10 bears were not always reported may have underestimated the population size and the full range, but also ensured that reported bears were real, and provides a conservative estimate. However, given the nature of the data we decided to be conservative, analyzing only those rayons where bears had been reported, and excluding rayons with zeroes from the analyses. This yielded a sample size of 290 rayons.

4.4.2 Population numbers and geographical range changes

To estimate the brown bear population dynamics in European Russia we summarized and plotted the total number of bears from 1991 to 2007. We reported hunting data per year and calculated bear density change relative to 1995. Additionally we fitted a logistic curve for the years between 1995 and 2007 to estimate their population growth rate.

Changes in bear density over time were summarized to identify three area patterns: first, oblasts with consistently high density of bears (more than 30 bears/1000 km^2) which we considered source areas for potential dispersal; second, oblasts that had variable or low brown bear densities, which we considered non source areas; and third, oblasts where bears occurred only recently to determine changes in the bears' range.

4.4.3 Data sources

A geographical information system was used to derive predictor variables from six data sources for the 290 rayons where we analyzed bear abundances and habitat use. The tabular and geographical data included: the land abandonment map for the year 2006 made in Chapter 2, based on MODIS VI data (~250-m resolution); the water class from ~500-km resolution MODIS 12 (Friedl and others 2010); the urban dataset from the Global Urban Areas dataset (Schneider, Friedl, Potere 2009) (~500-km resolution); main roads, unpaved roads, and railroads data obtained from CIRCA (Declassified Soviet Topographic Maps 1989; scale 1:500,000); digital elevation model (~1-km^2 resolution) (USGS and EROS 1996); mean annual temperature (°C), and annual precipitation (mm) from the WorldClim database (~1-km resolution) (Hijmans and others 2005); rural population density (1991 and 2000) derived from the Russian Federation Agriculture Census (tabular data). All land cover related datasets were integrated into a single 250-m resolution map in order to calculate predictor variables. The rest of the digital maps and the bear dataset were resampled at 250-m resolution. All maps were reprojected to the Mercator equal-area projection.

4.4.4 Predictor variables

To explore factors that influenced brown bears distribution by 2005 we calculated 14 variables derived from the six sources described above. All variables that we considered had been previously reported to affect brown bear habitat use and dispersal (Apps and others 2004; Ciarniello and others 2007a; Ciarniello and others 2007b; Dahle, Stoen, Swenson 2006; Graham and others 2010; Kaczensky and others 2006; McLoughlin and others 2002; Nams, Mowat, Panian 2006; Nellemann and others 2007; Nielsen, Boyce, Stenhouse 2004; Nielsen and others 2008; Nielsen and others 2010; Nielsen and others 2004; Roever, Boyce, Stenhouse 2008a; Roever, Boyce, Stenhouse 2008b; Singleton, Gaines, Lehmkuhl 2004; Støen and others 2006; Wielgus, Vernier, Schivatcheva 2002). We divided our explanatory variables into four categories. The first category included environmental variables, the second category focused on human disturbance; the third included land cover composition and fragmentation, and the fourth on evaluating dispersal-related metrics (Table 9).

TABLE 9 APPROXIMATELY HERE

4.4.5 Environmental

We evaluated environmental conditions by calculating the minimum, maximum, mean and variance of the elevation (m), slope (degrees), total annual precipitation (mm) and annual temperature (degrees Celsius), and distance to large water bodies (m) of each rayon.

4.4.6 Human presence and disturbance

We evaluated human disturbance by calculating the minimum, maximum, mean and variance of the distance to urban areas (m) and distance to highways (m). Additionally we included the length of highways, railroads, unpaved road lengths (km), and rural human densities for 1990 and 2005 (persons) of each rayon.

4.4.7 Land cover composition and fragmentation

We analyzed two main aspects regarding land cover and brown bear densities. The first was to test the habitat use of each land cover types by brown bears, especially forests and abandoned agricultural land. The second was to examine habitat's spatial patterns and its effects on brown bear distributions.

The importance of land cover composition for bears was evaluated by summarizing for each rayon the relative amount of each land cover type. To explore the importance of the spatial arrangement and landscape features for brown bears we conducted a modified version of the morphological characterization of the landscape (Vogt and others 2007; Vogt and others 2009) and calculated the area of seven habitat features that were used or avoided by bears, including: interior, null, exterior, patch, edge, gap and perforated in each rayon (Figure 16). Morphological features were calculated based on the land cover map recoded to three classes; first, suitable habitat (forest areas), second, unsuitable habitat (agriculture, urban, highways, and road areas), and third, null areas (neither considered suitable nor unsuitable habitat, including: water, wetlands, trails, and roads without pavement). Agricultural abandonment was considered in two different ways: we considered it both as unsuitable habitat and as suitable habitat, and ran the analyses twice. Image morphology features were calculated using a radius of 250 m; which meant that interior habitat included all areas of suitable habitat that were more than 250 m from the edge; while exterior habitat included only unsuitable areas. Edge habitat included areas within 250 m from the border of exterior habitat. Patches were areas of suitable habitat areas too small to include interior habitat. Gaps were areas of non-suitable habitat within a matrix of interior (suitable) habitat and small enough so that all pixels of non-suitable habitat bordered suitable habitat. Last but not least, perforated areas represented suitable habitat within 250 m of the edge of a gap (Figure 16).

FIGURE 16 APPROXIMATELY HERE

4.4.8 Dispersal

We used two approaches to measure potential dispersal limitations: the Euclidean distance from the source population and a cost-path analysis. Both approaches were based on the assumption that bears disperse from source areas. We identified population source areas by analyzing bear reports at rayon and oblast level from 1991 to 2007. Our first criterion was to select the contiguous administrative units (Rayons) with high bear densities (minimum density of 30 bears/1000 km^2) in 2005. Second, we selected additional oblasts north of the rayon-level data with consistently high bear densities. The oblasts selected as population source areas were Tver', Yaroslavl', Kostroma, Kirov and Udmurt, which included 53 rayons, plus Vologda, Komi and Perm' oblasts to the north (Figure 14).

Euclidean distances to the source were calculated in meters and averaged per rayon. Cost-path analysis was calculated via a travel cost-path algorithm. We defined travel cost-path as the movement from a population source area to the rayon were a bear numbers were recorded; it was related with the cumulative effects of landscape barriers that define routes and allow movement. The assumption was that distance, land cover characteristics, and the likelihood of human disturbance together determined travel cost, which was captured in a cost surface map. The travel cost-path was calculated by assigning each cell a cumulative cost c represented by:

$$c_i = c_{i-1} + d + L$$

where c_{i-1} was the cumulative travel cost value of the nearest cell towards the source area, d was the traveled distance in cells from the nearest cell towards the source area (our value was 1, since we calculate cost dispersal values for the entire region), and L represented the weighted-land cover of the current cell (i).

The weighted-land cover (L) was estimated by taking account of both land cover characteristics and the likelihood of human disturbance. We based our values on prior literature and expert's consultation. We assumed that the likelihood of human disturbance was related to the detectability of bears in a given land cover type, and this was measured in the field with two persons, one behaving as "the bear" and the other as "the human". "The human" moved across different land covers, randomly approaching "the bear", and we recorded the distance at which "the human" was first visible. The experiment was repeated 10 times in different forest stand ages and different land cover types. Land cover characteristics and human disturbance were integrated into a single L value (Table 10). Finally we summarized the cost-path value of each pixel by rayon to include it as a predictor variable.

TABLE 10 APPROXIMATELY HERE

4.4.9 Statistical analyses

Single and multiple linear regression analyses were conducted to analyze the relationship of environmental variables, human disturbance, land cover, fragmentation, and dispersal (explanatory variables) with brown bear densities in 2005 (response variable). Several of these variables were not normally distributed, and we tested three transformations for each variable (logarithmic, squared root, and quadratic terms) and selected the transformation that best ensured that a given variable entered the models linearly. The response variable (bear density in 2005) was log transformed and several explanatory variables required transformations as well. Variable selection for our multi-variate models occurred in two stages. First, we had different variants for many of our variables (such as maximum, minimum, mean, and variance of temperature) and among these variants we select the one with the strongest univariate relationship and the one that made the most biological sense. Second, we examined the correlation among explanatory variables and calculated a Pearson's correlation coefficient matrix. Most variables were correlated below 0.60. When two explanatory variables were correlated above 0.60, then we removed the explanatory variable which had the most collinearity problems with other variables, and the one with a less clear biological relationship with the response variable. Table 9 shows the variables that were included in the final models and the transformations that were conducted.

Some of our explanatory variables were highly correlated, but our research questions required a comparison of their relative explanatory power. Specifically, these were the forest abundance metric versus the suitable habitat morphology metrics, and the Euclidean distance versus the cost-path metric. We thus conducted four comparisons of the full model in a fully factorial design: 1) Cost-path metric and forest; 2) Euclidean distance and forest; 3) Cost-path analysis and selected morphological features (patch, interior and gap), 4) Euclidean distance and selected morphological features (patch, interior and gap), and selected one of these four models as our final multi-variate model.

For this final model, we conducted a best subset selection and hierarchical partitioning analysis to compare the importance of environmental variables, human presence, land cover composition and fragmentation, and dispersal for brown bear densities by 2005. Best subsets selection describes the frequency a variable enters in a set of models by conducting an exhaustive search for the models with highest goodness-of-fit measures (Miller 2002; Miller 1984), while hierarchical partitioning calculates goodness-of-fit measures for the entire hierarchy of models by applying the Chevan and Sutherland (1991) algorithm to calculate the percentage of the variance explained when a variable enters in a set of models (Mac Nally 2000; Mac Nally 2002). We used the adjusted R^2 as our measure of fit to rank our models, and limited the number of explanatory variables to five to avoid overfitting. We assessed the effects of spatial autocorrelation in the final model prior to the hierarchical partitioning analysis and best subsets selection by analyzing the residuals to test model assumptions. Since we did not find spatial autocorrelation, it was not necessary to account for it in our model.

4.5 Results

4.5.1 Population numbers and geographical range changes

There were about 49,300 brown bears in European Russia in 1991 (21.43 bears/1000 km^2), and 53,300 bears in 2007 (23.16 bears/1000 km^2). Official hunting quotas were equivalent to 3.5% ± 0.4% of the bear population per year in the period from 1998 to 2007. Brown bear population declined by 19% from 1991 to 1995 and steadily increased from 1995 to 2007. In 2005 the amount of bears surpassed the number reported by 1991 (about 51,880 bears). The estimated growth rate (λ) from 1995 to 2007 was 1.023 with a 95% confidence interval of 1.0199 < λ > 1.0266 (Figure 17).

FIGURE 17 APPROXIMATELY HERE

4.5.2 Expansion of the bear population in Russia

The highest densities of brown bears in 2005 were located in the central oblasts of European Russia. Four oblasts held about 60% of the total brown bear population in European Russia, all with ≥ 39 bears/1000 km^2 (these Oblasts were Arkangelsk (23%, 85.3 bears/1000km^2), Kirov (11%, 47.6 bears/1000km^2), Perm (12%, 39.0 bears/1000km^2) and Vologda (13%, 46.2 bears/1000km^2)). Five oblasts had no bears in 1991, but reported bears by 1997, and four more oblasts reported bears for the first time by 2000 (Figure 13). Based on these data we focused our statistical analysis and habitat selection regarding land cover, morphology and dispersal on the bear's expansion zone (highlighted by a blue border, Figure 13). The expansion zone had 569 rayons with 13,444 bears distributed within 290 rayons in 2005 (about 28% of the total number of bears in European Russia).

4.5.3 Environmental

The environmental variable that had the strongest univariate relationship with brown bear densities was the maximum distance to water (r=0.21) followed by mean annual precipitation (r=0.17) and mean elevation (r=0.10). Elevation and slope had strong correlations between them (r=0.73) as did slope and precipitation (r=-0.66). For the multivariate models we selected only maximum distance to water and mean slope (Table 11).

TABLE 11 APPROXIMATELY HERE

4.5.4 Human presence and disturbance

Rural population densities in 1991 and 2001 had relatively strong negative univariate relationships with brown bear densities (r=-0.51 and r=-0.50). Maximum distance to urban areas and maximum distance to highways had relatively strong positive relationships with brown bear densities (r=0.51 and r=0.47), as did length of unpaved roads (r=0.43), and maximum distance to railways (r=0.26). Both rural population density measures were highly correlated (r=0.95) and the length of unpaved roads was highly correlated with maximum distance to highways (r=0.70). For the multiple linear regression models we included only length of unpaved roads, maximum distances to railways, maximum distance to urban areas, and rural population density for 2001 (Table 12).

TABLE 12 APPROXIMATELY HERE

4.5.5 Bears and land cover

Single linear regressions for land cover composition showed consistently negative, low correlations with brown bears except for forest (r = 0.33). Agriculture and Forest were highly negative correlated with each other (r=-0.68). Abandoned agricultural land had a negative correlation coefficient (r=-0.18). For the multivariate analyses we decided to include only forest as an explanatory variable.

TABLE 13 APPROXIMATELY HERE

4.5.6 Habitat fragmentation

4.5.6.1 Morphology considering forest as suitable habitat

Gaps had the highest correlation with brown bear densities (r=0.42); followed by perforated (r=0.39), exterior (r=-0.33), interior (r=0.30), and patch (r=0.25). Edge and null areas had very weak correlations with brown bear densities (edge r=-0.017, and null r=0.004). Interior and exterior habitat were strongly correlated with each other (r=-0.88). Exterior habitat was also strongly correlated with perforated areas (r=-0.74). Perforated areas were strongly correlated with interior (r=0.73), exterior (r=-0.74), and gap (r=0.93). For the multivariate analyses we included only patch, interior, and gap because they had a more clear relationship with the response variable (Table 14).

TABLE 14 APPROXIMATELY HERE

4.5.6.2 Morphology considering both forest and agricultural abandonment as suitable habitat

Edge, interior, exterior and patch had the strongest correlations with brown bear densities (r=-0.33, r=0.24, r=-0.21, and r=-0.18 respectively). Gap, perforated and null had very weak correlations with brown bear densities (r=-0.08, r=-0.06, and r=0.00 respectively). Exterior and patch had strong correlations among them (r=0.93); exterior showed strong correlations as well with interior (r=-0.88). Interior and patch were highly negatively correlated (r=-0.87). Finally, we found strong correlations between Gap and perforated as well (r=0.93) (Table 15). Due to the lower correlations of the metrics when we considered both forest and agricultural abandonment as suitable habitat compared with the same metrics considering only forest as suitable habitat we did not include any of those variables in the multivariate analyses.

TABLE 15 APPROXIMATELY HERE

4.5.7 Dispersal

Our univariate correlations for the two dispersal-related metrics and bear densities showed relatively strong inverse relationships (r=-0.60 for Euclidean distance and r=-0.66 for the cost-path metric with bear densities. Both were also highly correlated (r=0.99). We thus compared two models where with only one of the two variables in each.

4.5.8 Multiple linear models

The four alternative multivariate models had between eight and twelve predictor variables (Table 16). In terms of the adjusted r-square, we found only minor differences among the four full models.

TABLE 16 APPROXIMATELY HERE

The simplest model using the six variables plus forest and Euclidean distance had an r-square = 0.6058, the model using forest and cost-path had an r-square = 0.6324, the model using morphology and Euclidean distance had an r-square = 0.6159, and the model with Cost-path and morphology had the highest r-square (0.6386). Given that the explanatory power of all four models was so similar, we selected the simplest model as our final model (forest and Euclidean distance plus maximum distance to railroads, maximum distance to urban, maximum distance to water, mean slope, human rural density by 2001 and unpaved roads length) and analyzed spatial autocorrelation, and conducted the hierarchical partitioning analysis and best subsets selection only for this model **(**Table 17**)**. We did not find spatial autocorrelation in our final model (Figure 18), thus, we proceeded to conduct hierarchical partitioning analysis and best subsets analyses.

TABLE 17 APPROXIMATELY HERE

FIGURE 18 APPROXIMATELY HERE

Brown bear densities in 2005 showed a strong association with dispersal and human presence and disturbance; these two predictor variables explained up to 72% of the variance that was explained in the model (Figure 19). Euclidean distance explained 48% of the variance and entered 20 of the 20 best subset models, and rural population density in 2001 explained 24% of the variation, and entered 16 out of 20 best models. Unpaved roads length and maximum distance to urban areas explained 17% and 15% of the variance respectively, and entered 9 and 14 of the 20 best models. Surprisingly, forest percentage, while significant, explained only 9.3 % of the variance and entered only 11 out of 20 best models. Environmental variables were weakly related to brown bear densities in 2005 (Slope explained only 2% of the variation and entered only 8 best subset models (Figure 19)).

FIGURE 19 APPROXIMATELY HERE

4.6 Discussion

Brown bears in European Russia slightly increased in numbers from 1991 to 2007 after a sharp decline between 1991 and 1995. Despite an only moderate overall population increase, brown bears considerably expanded their range southwards. Official hunting did not affect brown bear populations negatively since 1997, but the collapse of the USSR and its substantial socioeconomic impacts caused widespread agricultural land abandonment (Chapter II). Interestingly though, abandoned agricultural land was negatively related to bear densities, and the fragmentation analysis that included abandoned agricultural land as suitable habitat performed worse than the fragmentation analysis based on forest alone. The reasons for the range expansion are thus not clear. Brown bears exhibit an inversely density-dependent natal dispersal (Støen and others 2006), and the initial decline in brown bears suggest a possible relationship with their dispersal.

Our habitat model performed well and provided strong evidence that brown bear populations in the south were linked to northern source populations via dispersal. Multivariate models captured two thirds of the variation and human disturbance was the most limiting factor for brown bears in European Russia. Elevation, slope, avalanche chutes and other landscape features have been reportedly important for bear's habitat selection in other areas (Nams et al 2006). In fact, they select for different features on the landscape over the year and time of the day (Martin 2010, Nelleman et al 2007). Interestingly though, we found that bears in European Russia were not associated strongly with environmental conditions. The distribution was mainly driven by proxies of human disturbance and the presence of forest. These results are similar to other studies that demonstrated that bears avoid humans (Apps and others 2004; Martin and others 2010; Nellemann and others 2007).

Habitat selection is a hierarchical process that depends on scale, and this is true as well for bears (McLoughlin and others 2002). Bears select their habitat most strongly at the landscape scale (areas around 1,600 km^2) (Nams, Mowat, Panian 2006) suggesting that the rayon level that we used is an appropriate scale to analyze brown bear populations.

Surprisingly, the travel cost values did not yield a higher explanatory power compared to the simple Euclidean distance measurements. Cost-path analysis is biologically more meaningful, and in the univariate analysis the cost-path metric explained 46% of the variability of the bears, compared to 38% for Eucilidean distance. 8% more explanatory power is not a large difference, but does represent about a 5th of the explanatory power of the model, which is not trivial either.

However, in the multivariate models, the difference in the adjusted r-square of the two models with the two different distance metrics was negligible. One of the reasons for modeling species distributions is that it is hard to measure habitat use and habitat preferences directly and simple metrics can often explain a substantial part of the variation in habitat use. In cost-path analyses, one shortcoming is though that the metrics do not have unit, and are just a proxy for energy spent, disturbance, and avoidance. Other cost-path studies either assigned subjective values to land cover, or used resource selection functions (Chetkiewicz and Boyce 2009), weights of evidence (Kindall and Manen 2007) or expert opinion (Singleton, Gaines, Lehmkuhl 2004). Unfortunately, none of these studies compared cost-path metrics with plain Euclidean distance while accounting for other factors in a multivariate model. Our results here question the increased power of cost-path based metrics in multivariate models.

Ultimately one can define travel cost-path as the movement from a population source area along the landscape that serve a bear to find a place to live, and such movements depend on both, natal dispersal ability and the cumulative effects of landscape barriers that define routes and allow movement. Cost-path analysis makes biological sense but unfortunately includes subjective components that need to be refined. For instance both avoidance and disturbance are parameters that can be measured in the field and translated into energy expenditure for an individual. At the population level, a killed or accidentally died individual represents a cost that can be translated to the amount of energy spent to breed a new individual.

Regarding landscape composition, forest, particularly core forest, proved to be an important variable explaining bear densities. Morphology has been used to map functional connectivity and habitat use landscape (Vogt and others 2007; Vogt and others 2009) and our expectation was to find the strongest explanatory power for the multivariate models that included morphology metrics. Again though, the higher explanatory power of the morphological metrics in univariate models disappeared when morphological metrics replaced forest in alternative multivariate models. Possible explanations are that landscape composition is a function of the scale that it is mapped but also it is a function of the species under consideration.

Among the forest morphology metrics, we found that gaps (such as clearcuts) had the highest explanatory power. This supports other studies, which reported use of clearcuts by brown bears in Montana and British Columbia (Martin and others 2010; Nielsen, Boyce, Stenhouse 2004; Nielsen and others 2008; Roever, Boyce, Stenhouse 2008a; Wielgus, Vernier, Schivatcheva 2002). The second most important predictor among the morphology metrics was interior forest and that is also supported by other studies that demonstrate bears select interior forest at broader scale but young and logged forest at the finest scale (Apps and others 2004).

In terms of our human disturbance proxies, we were surprised to find that unpaved roads' length explained 17% of the variance, appeared in 9 out of 20 models, and was positively correlated with brown bear densities. This may be the result of the fact that bears use unpaved or low traffic roads to travel (Graham and others 2010; Mace and others 1996), or that the roads were placed in bears' preferred habitats and motivated by food availability nearby the roads (Roever, Boyce, Stenhouse 2008a). Another interesting finding was that bears responded differently to different types of road. While they did not avoid unpaved roads we found that they did select against highway length and in favor of maximum distance to highways and those findings coincide with other studies (Ciarniello and others 2007a; Mace and others 1996; McLellan and Shackleton 1988; Wielgus, Vernier, Schivatcheva 2002). The use and avoidance of roads varies widely among other vertebrate species, but large carnivores in general have negative response to roads (Fahrig and Rytwinski 2009). On the other hand, all our other human disturbance variables showed negative correlations, highlighting bears' avoidance of humans, and selection of areas, for example, far from urban centers, which is also supported by other studies (Nellemann and others 2007).

Dispersal, human avoidance, and forest cover explained the most variance in our models and we demonstrated that measuring brown bear habitat was both important, and computationally feasible, following the approach outlined here. Based on our bear density models, we can now at least speculate about the effects of potential further rural population declines, and forest succession on abandoned farm fields for future bear populations in European Russia. Increasing forest cover on abandoned farm fields may provide additional bear habitat reduce travel costs and increase dispersal in the future. Ultimately, socio-economic changes and resulting agricultural abandonment offers new opportunities for conservation.

The surprising population increases and range expansion of brown bear distribution in European Russia were not known previously and have important implications for the species. From a conservation standpoint, brown bears declined in the early 1990s but recovered surprisingly fast. From a management perspective, the range expansion creates new challenges because the presence of Brown bears in areas with people raises the likelihood for human-wildlife conflicts.

In general, large mammals are particularly vulnerable to human presence at species and population levels (Cardillo and others 2005; Davidson and others 2009). Our results confirm this pattern. Despite the fact that the bear population increased, their distribution was still heavily influenced by human disturbance proxies. Brown bears are highly adaptable animals that are capable of transmitting knowledge that is important for survival to their next generations. Brown bears' distribution in the European part of Russia is probably the result of a long history of interactions with human populations and the fact we found negative correlations with agricultural abandonment may reflect that long bear-human interactions.

4.7 Acknowledgements

We gratefully acknowledge support by Consejo Nacional de Ciencia y Tecnologia (CONACyT, Mexico), the NASA Land Cover and Land Use Change Program, and the University of Wisconsin-Madison School of International Studies. Natasha Novoselova and M. Vaisfeld from the Institute of Ecology and Evolution, Russian Academy of Sciences that collaborated on the initial stages of this research. We also express our gratitude to SILVIS lab fellows, especially to A. Prischepov, T. Kuemmerle, M. Dubinin and M. Baummann for technical assistance and fruitful discussions.

4.8 References

Apps C, D., McLellan BN, Woods JG, PROCTOR MF. 2004. Estimating Grizzly bear distribution and abundance relative to habitat and human influence. Journal of Wildlife Management 68(1):138-52.

Benayas JMR, Martins A, Nicolau JM, Schulz JJ. 2007. Abandonment of agricultural land: an overview of drivers and consequences. CAB Reviews: Perspectives in Agriculture, Veterinary Science, Nutrition and Natural Resources 2(57):1-14.

Bennet EL, Milner-Gulland EJ, Bakarr M, Eves HE, Robinson JG, Wilkie DS. 2002. Hunting the world's wildlife to extinction. Oryx 36:328-9.

Breitenmoser U. 1998. Large predators in the Alps: The fall and rise of man's competitors. Biological Conservation 83(3):279-89.

Cardillo M, Mace GM, Jones KE, Bielby J, Bininda-Emonds ORP, Sechrest W, Orme CDL, Purvis A. 2005. Multiple causes of high extinction risk in large mammal species. Science 309(5738):1239-41.

Chestin IE, Gubar YP, Sokolov VE, Lovachev VS. 1992. The Brown bear (Ursus arctos L.) in the USSR: numbers, hunting and systematics. Annales Zoologici Fennici 29(2):57-68.

Chestin IE. 1999. Status and management of the brown bear in russia. Servheen C, S. H,B. P, editors. In: Bears - status survey and conservation action plan. IUCN/SSC ed. Gland, Switzerland: IUCN/SSC bear and polar bear specialist groups. P. 136.

Chetkiewicz CLB and Boyce MS. 2009. Use of resource selection functions to identify conservation corridors. Journal of Applied Ecology 46(5):1036-47.

Chevan A and Sutherland M. 1991. Hierarchical Partitioning. The American Statistician 45(2):90-6.

Ciarniello LM, Boyce MS, Heard DC, Seip DR. 2007a. Components of Grizzly bear habitat selection: density, habitats, roads, and mortality risk. Journal of Wildlife Management 71(5):1446-57.

Ciarniello LM, Boyce MS, Seip DR, Heard DC. 2007b. Grizzly Bear habitat selection is scale dependent. Ecological Applications 17(5):1424-40.

Clark JD, Huber D, Servheen C. 2002. Bear reintroductions: Lessons and challenges: Invited Paper. Ursus 13:335-45.

Clout MN and Russell JC. 2008. The invasion ecology of mammals: a global perspective. Wildlife Research 35(3):180-4.

Dahle B, Stoen OG, Swenson JE. 2006. Factors influencing home-range size in subadult brown bears. Journal of Mammalogy 87(5):859-65.

Davidson AD, Hamilton MJ, Boyer AG, Brown JH, Ceballos G. 2009. Multiple ecological pathways to extinction in mammals. Proceedings of the National Academy of Sciences 106(26):10702-5.

Fahrig L and Rytwinski T. 2009. Effects of roads on animal abundance: an empirical review and synthesis. Ecology and Society 14(1):21.

Foley JA, DeFries RS, Asner GP, Barford C, Bonan G, Carpenter SR, Chapin FS, Coe MT, Daily GC, Gibbs HK, Helkowski JH, Holloway T, Howard EA, Kucharik CJ, Monfreda C, Patz JA, Prentice IC, Ramankutty N, Snyder PK. 2005. Global consequences of land use. Science 309(5734):570-4.

Friedl MA, Sulla-Menashe D, Tan B, Schneider A, Ramankutty N, Sibley A, Huang X. 2010. MODIS Collection 5 global land cover: algorithm refinements and characterization of new datasets. Remote Sensing of Environment 114(1):168-82.

Gibeau ML, Clevenger AP, Herrero S, Wierzchowski J. 2002. Grizzly bear response to human development and activities in the Bow River Watershed, Alberta, Canada. Biological Conservation 103(2):227-36.

Graham K, Boulanger J, Duval J, Stenhouse G. 2010. Spatial and temporal use of roads by grizzly bears in west-central Alberta. Ursus 21(1):43-56.

Hijmans RJ, Cameron SE, Parra JL, Jones PG, Jarvis A. 2005. Very high resolution interpolated climate surfaces for global land areas. http://www.worldclim.org/node/1. International Journal of Climatology (25):1965-78.

Höchtl F, Lehringer S, Konold W. 2005. "Wilderness": what it means when it becomes a reality—a case study from the southwestern Alps. Landscape and Urban Planning 70(1-2):85-95.

Johnson DH. 1980. The comparison of usage and availability measurements for evaluating resource preference. Ecology 61(1):65-71.

Kaczensky P, Huber D, Knauer F, Roth H, Wagner A, Kusak J. 2006. Activity patterns of brown bears (*Ursus arctos*) in Slovenia and Croatia. Journal of Zoology 269(4):474-85.

Kindall JL and Manen FTV. 2007. Identifying habitat linkages for American black bears in North Carolina, USA. Journal of Wildlife Management 71(2):487-95.

Linnell JDC, Swenson JE, Anderson R. 2001. Predators and people: conservation of large carnivores is possible at high human densities if management policy is favourable. Animal Conservation 4(4):345-9.

Mac Nally R. 2000. Regression and model-building in conservation biology, biogeography and ecology: The distinction between - and reconciliation of - predictive and explanatory models. Biodiversity and Conservation 9(5):655-71.

Mac Nally R. 2002. Multiple regression and inference in ecology and conservation biology: further comments on identifying important predictor variables. Biodiversity and Conservation 11(8):1397-401.

Mace RD, Waller JS, Manley TL, Lyon LJ, Zuuring H. 1996. Relationships among grizzly bears, roads and habitat in the Swan Mountains Montana. Journal of Applied Ecology 33(6):1395-404.

Martin J, Basille M, Van Moorter B, Kindberg J, Allaine D, Swenson JE. 2010. Coping with human disturbance: spatial and temporal tactics of the brown bear (*Ursus arctos*). Canadian Journal of Zoology 88(9):875-83.

McLellan BN and Shackleton DM. 1988. Grizzly bears and resource-extraction industries: effects of roads on behaviour, habitat use and demography. Journal of Applied Ecology 25(2):451-60.

McLoughlin P, Case R, Gau R, Cluff D, Mulders R, Messier F. 2002. Hierarchical habitat selection by barren-ground grizzly bears in the central Canadian Arctic. Oecologia 132(1):102-8.

Miller AJ. 1984. Selection of subsets of regression variables. Journal of the Royal Statistical Society.Series A (General) 147(3):pp. 389-425.

Miller A. J. 2002. Subset selection in regression. CRC Press.

Moreira F and Russo D. 2007. Modeling the impact of agricultural abandonment and wildfires on vertebrate diversity in Mediterranean Europe. Landscape Ecology 22(10):1461-76.

Morrison JC, Sechrest W, Dinerstein E, Wilcove DS, Lamoreux JF. 2007. Persistence of large mammal faunas as indicators of global human impacts. Journal of Mammalogy :1363-80.

Nams VO, Mowat G, Panian MA. 2006. Determining the spatial scale for conservation purposes-an example with grizzly bears. Biological Conservation 128(1):109-19.

Nellemann C, Støen OG, Kindberg J, Swenson JE, Vistnes I, Ericsson G, Katajisto J, Kaltenborn BP, Martin J, Ordiz A. 2007. Terrain use by an expanding brown bear population in relation to age, recreational resorts and human settlements. Biological Conservation 138(1-2):157-65.

Nielsen S, Munro R, Bainbridge E, Stenhouse G, Boyce M. 2004. Grizzly bears and forestry:: II. Distribution of grizzly bear foods in clearcuts of west-central Alberta, Canada. Forest Ecology and Management 199(1):67-82.

Nielsen SE, Boyce MS, Stenhouse GB. 2004. Grizzly bears and forestry: I. Selection of clearcuts by grizzly bears in west-central Alberta, Canada. Forest Ecology and Management 199(1):51-65.

Nielsen SE, McDermid G, Stenhouse GB, Boyce MS. 2010. Dynamic wildlife habitat models: Seasonal foods and mortality risk predict occupancy-abundance and habitat selection in grizzly bears. Biological Conservation. 143(7):1623-1634

Nielsen SE, Stenhouse GB, Beyer HL, Huettmann F, Boyce MS. 2008. Can natural disturbance-based forestry rescue a declining population of grizzly bears? Biological Conservation 141(9):2193-207.

Ojima DS, Galvin KA, Turner BL. 1994. The global impact of land-use change. Bioscience 44(5):300-4.

Olson DM, Dinerstein E, Wikramanayake ED, Burgess ND, Powell GVN, Underwood EC, D'Amico JA, Itoua I, Strand HE, Morrison JC, Loucks CJ, Allnutt TF, Ricketts TH, Kura Y, Lamoreux JF, Wettengel WW, Hedao P, Kassem KR. 2001. Terrestrial ecoregions of the world: A new map of life on Earth. Bioscience 51(11):933-8.

Pedersen AB, Jones KE, Nunn CL, Altizer S. 2007. Infectious diseases and extinction risk in wild mammals. Conservation Biology 21(5):1269-79.

Peel MC, Finlayson BL, McMahon TA. 2007. Updated world map of the Köppen-Geiger climate classification. Hydrology and Earth System Sciences Discussions 4(2):439-73.

Roever CL, Boyce MS, Stenhouse GB. 2008a. Grizzly bears and forestry: II: Grizzly bear habitat selection and conflicts with road placement. Forest Ecology and Management 256(6):1262-9.

Roever CL, Boyce MS, Stenhouse GB. 2008b. Grizzly bears and forestry: I: Road vegetation and placement as an attractant to grizzly bears. Forest Ecology and Management 256(6):1253-61.

Russo D. 2007. The effects of land abandonment on animal species in Europe: Conservation and management implications. Integrated Assessment of Vulnerable Ecosystems Under Global Change in the European Union. Directorate-General for Research Environment, European Commission, Brussels: 1-51.

Sala OE, Chapin FS,III, Armesto JJ, Berlow E, Bloomfield J, Dirzo R, Huber-Sanwald E, Huenneke LF, Jackson RB, Kinzig A, Leemans R, Lodge DM, Mooney HA, Oesterheld M, Poff NL, Sykes MT, Walker BH, Walker M, Wall DH. 2000. Global biodiversity scenarios for the year 2100. Science 287(5459):1770-4.

Sanderson EW, Jaitheh M, Levy MA, Redford KH, Wannebo AV, Woolmer G. 2002. The human footprint and the last of the wild. BioScience 52(10):891-904.

Schneider A, Friedl MA, Potere D. 2009. A new map of global urban extent from MODIS satellite data. Environmental Research Letters 4:044003.

Servheen C, S. H, B. P. 1999. Bears - status survey and conservation action plan. Servheen C, S. H,B. P, editors. IUCN/SSC ed. Cambridge UK: IUCN/SSC bear and polar bear specialist groups. 310p.

Singleton PH, Gaines WL, Lehmkuhl JF. 2004. Landscape permeability for grizzly bear movements in Washington and southwestern British Columbia. Ursus 15(1):90-103.

Sirami C, Brotons L, Burfield I, Fonderflick J, Martin J. 2008. Is land abandonment having an impact on biodiversity? A meta-analytical approach to bird distribution changes in the north-western Mediterranean. Biological Conservation 141(2):450-9.

Støen OG, Zedrosser A, Sæbø S, Swenson JE. 2006. Inversely density-dependent natal dispersal in brown bears Ursus arctos. Oecologia 148(2):356-64.

Swenson JE, Sandegren F, Soderberg A. 1998. Geographic expansion of an increasing brown bear population: evidence for presaturation dispersal. Journal of Animal Ecology 67(5):819-26.

USGS and EROS. 1996. GTOPO30 Digital elevation model. Grid 1 Km(World).

Van Valkenburgh B and Wayne RK. 2010. Carnivores. Current Biology 20(21):R915-9.

Vié J-, Hilton-Taylor C, Stuart SN, editors. 2009. Wildlife in a changing world – an analysis of the 2008 IUCN red list of threatened species. http://www.iucnredlist.org/ ed. Gland, Switzerland: International Union for Conservation of Nature and Natural Resources; p180.

Vogt P, Ferrari JR, Lookingbill TR, Gardner RH, Riitters KH, Ostapowicz K. 2009. Mapping functional connectivity. Ecological Indicators 9(1):64-71.

Vogt P, Riitters KH, Estreguil C, Kozak J, Wade TG, Wickham JD. 2007. Mapping spatial patterns with morphological image processing. Landscape Ecology 22(2):171-7.

Walther G, Post E, Convey P, Menzel A, Parmesan C, Beebee TJC, Fromentin J, Hoegh-Guldberg O, Bairlein F. 2002. Ecological responses to recent climate change. Nature 416(6879):389-95.

Wielgus RB, Vernier PR, Schivatcheva T. 2002. Grizzly bear use of open, closed, and restricted forestry roads. Canadian Journal of Forest Research 32(9):1597-606.

Woodroffe R. 2000. Predators and people: using human densities to interpret declines of large carnivores. Animal Conservation 3(02):165.

4.9 Tables

Table 9. Predictor variables considered for statistical analysis of brown bear densities in the European part of Russia, 2005. l Logarithmic transformation, s Square root transformation; q Quadratic transformation;* Variables include on the multiple regression models

I Environmental	**III Land cover and fragmentation**	**IV Dispersal**
*s Maximum distance to water	**a) Land cover composition**	s Mean dispersal cost
* Mean slope	*Forest	*s Mean Euclidean distance to source
II Human presence and disturbance	Agricultural abandonment	
*s Maximum distance to urban areas	Forest and agricultural abandonment	
*s Maximum distance to rail roads	Other classes	
s Highway's length	**b) Morphology of forest**	
s Rail road's length	Patch	
*s Unpaved road's length	Edge	
l Rural density 1991	Interior	
*l Rural density 2001	Exterior	
	Gap	
	Null	
	c) Morphology of forest and agricultural abandonment	
	Patch	
	Edge	
	Interior	
	Exterior	
	Gap	
	Null	

Table 10. Weighted-land cover values (*L*) assigned from land cover characteristics and human disturbance for the cost-path analysis. Land cover sources: * Chapter II, ** (Schneider, Friedl, Potere 2009),*MODIS12 (Friedl and others 2010),**** CIRCA 1989**

Land cover class	***L*** (cost distance)
Agriculture*	25
Forest*	5
Abandoned agriculture*	15
Water **	100
Urban ***	100
Railway ****	70
Embankments and dredges****	80
Trail****	40
Road****	100
Other classes*	30

Table 11. Pearson correlation coefficients for environmental factors and bear densities in 2005.

	Bear density	Mean slope	Mean Elevation	Mean total precipitation	Maximum Distance to Water
Bear density	1.00	0.12	0.10	0.17	0.21
Mean slope	0.12	1.00	0.73	-0.7	0.17
Mean Elevation	0.10	0.73	1.00	-0.4	0.09
Mean total precipitation	0.17	-0.7	-0.4	1.00	-0.1
Maximum Distance to Water	0.21	0.17	0.09	-0.1	1.00

Table 12. Pearson correlation coefficients for human disturbance factors and bear densities in 2005.

	Bear density	Maximum distance to higways	Length of highways	Maximum distance to railways	Length of railways	Length of unpaved roads	Maximum distance to urban	Rural human density 1991	Rural human density 2001
Bear density	1.00	0.47	-0.31	0.27	0.00	0.43	0.51	-0.51	-0.50
Maximum distance to highways	0.47	1.00	-0.52	0.33	0.16	0.70	0.61	-0.56	-0.54
Length of highways	-0.31	-0.52	1.00	-0.23	0.27	-0.09	-0.37	0.28	0.29
Maximum distance to railways	0.26	0.33	-0.23	1.00	-0.52	0.37	0.50	0.00	0.01
Length of railways	0.00	0.16	0.27	-0.52	1.00	0.26	-0.03	-0.24	-0.23
Length of unpaved roads	0.43	0.70	-0.09	0.37	0.26	1.00	0.47	-0.49	-0.50
Maximum distance to urban	0.51	0.61	-0.37	0.50	-0.03	0.47	1.00	-0.47	-0.46
Rural human density 1991	-0.51	-0.56	0.28	0.00	-0.24	-0.49	-0.47	1.00	0.95
Rural human density 2001	-0.50	-0.54	0.29	0.01	-0.23	-0.50	-0.46	0.95	1.00

Table 13 Pearson correlation coefficients for land cover classes and bear densities in 2005.

	Bears density	Agriculture	Forest	Abandoned agriculture	Other classes
Bears density	1.00	-0.18	0.33	-0.18	-0.17
Agriculture	-0.18	1.00	-0.68	-0.22	0.02
Forest	0.33	-0.68	1.00	-0.42	-0.33
Abandoned agriculture	-0.18	-0.22	-0.42	1.00	-0.07
Other classes	-0.17	0.02	-0.33	-0.07	1.00

Table 14. Pearson correlation coefficients for morphological features considering only forest as suitable habitat and bear densities in 2005.

	Bears density	Patch	Edge	Perforated	Interior	Exterior	Gap	Null
Bears density	1.00	0.25	-0.02	0.39	0.30	-0.33	0.42	0.00
Patch	0.25	1.00	0.28	0.05	-0.34	0.26	0.23	-0.08
Edge	-0.02	0.28	1.00	0.24	0.23	-0.22	0.30	-0.34
Perforated	0.39	0.05	0.24	1.00	0.73	-0.74	0.93	-0.18
Interior	0.30	-0.34	0.23	0.73	1.00	-0.88	0.58	-0.32
Exterior	-0.33	0.26	-0.22	-0.74	-0.88	1.00	-0.67	-0.14
Gap	0.42	0.23	0.30	0.93	0.58	-0.67	1.00	-0.07
Null	0.00	-0.08	-0.34	-0.18	-0.32	-0.14	-0.07	1.00

Table 15. Pearson correlation coefficients for morphological features considering both forest and agricultural abandonment as suitable habitat and bear densities in 2005.

	Bears density	Patch	Edge	Perforated	Interior	Exterior	Gap	Null
Bears density	1.00	-0.18	-0.33	-0.06	0.24	-0.21	-0.08	0.00
Patch	-0.18	1.00	0.59	-0.25	-0.87	0.93	0.02	-0.02
Edge	-0.33	0.59	1.00	0.28	-0.55	0.50	0.47	-0.17
Perforated	-0.06	-0.25	0.28	1.00	0.29	-0.36	0.93	-0.33
Interior	0.24	-0.87	-0.55	0.29	1.00	-0.88	0.03	-0.39
Exterior	-0.21	0.93	0.50	-0.36	-0.88	1.00	-0.14	-0.02
Gap	-0.08	0.02	0.47	0.93	0.03	-0.14	1.00	-0.25
Null	0.00	-0.02	-0.17	-0.33	-0.39	-0.02	-0.25	1.00

Table 16. Pearson correlation coefficients between predictor variables and bear densities in 2005 for the variables included in the multiple linear regression models. 1, 2, 3, and 4 highlight variables included in each of our four alternative models.

	Bears $density_{1234}$	Maximum distance to $water_{1234}$	Mean $slope_{1234}$	Length of unpaved $roads_{1234}$	Maximum distance to $railways_{1234}$	Maximum distance to $urban_{1234}$	Humans rural density by 2001_{1234}	Euclidean distance to $source_{13}$	Cost-$Path_{24}$	$Forest_{12}$	Patch/$Forest_{34}$	Inter/$Forest_{34}$	Gap/$Forest_{34}$
Bears $density_{1234}$	1.00	0.21	0.12	0.43	0.26	0.51	-0.50	-0.60	-0.66	0.33	0.25	0.30	0.42
Maximum distance to $water_{1234}$	0.21	1.00	0.17	0.27	0.13	0.37	-0.23	-0.13	-0.12	0.07	0.09	0.07	0.02
Mean $slope_{1234}$	0.12	0.17	1.00	0.30	0.45	0.15	0.26	0.04	0.06	-0.47	0.28	-0.46	-0.17
Length of unpaved $roads_{1234}$	0.43	0.27	0.30	1.00	0.37	0.47	-0.50	-0.03	-0.09	0.16	0.28	0.14	0.38
Maximum distance to $railways_{1234}$	0.26	0.13	0.45	0.37	1.00	0.50	0.01	-0.18	-0.17	-0.30	0.16	-0.27	-0.09
Maximum distance to $urban_{1234}$	0.51	0.37	0.15	0.47	0.50	1.00	-0.46	-0.35	-0.38	0.21	0.10	0.19	0.26
Humans rural density by 2001_{1234}	-0.50	-0.23	0.26	-0.50	0.01	-0.46	1.00	0.20	0.27	-0.56	-0.20	-0.50	-0.52
Euclidean distance to $source_{13}$	-0.60	-0.13	0.04	-0.03	-0.18	-0.35	0.20	1.00	0.99	-0.17	-0.11	-0.14	-0.25
Cost-$Path_{24}$	-0.66	-0.12	0.06	-0.09	-0.17	-0.38	0.27	0.99	1.00	-0.24	-0.15	-0.20	-0.33
$Forest_{12}$	0.33	0.07	-0.47	0.16	-0.30	0.21	-0.56	-0.17	-0.24	1.00	-0.26	0.96	0.62
Patch/$Forest_{34}$	0.25	0.09	0.28	0.28	0.16	0.10	-0.20	-0.11	-0.15	-0.26	1.00	-0.34	0.23
Inter/$Forest_{34}$	0.30	0.07	-0.46	0.14	-0.27	0.19	-0.50	-0.14	-0.20	0.96	-0.34	1.00	0.58
Gap/$Forest_{34}$	0.42	0.02	-0.17	0.38	-0.09	0.26	-0.52	-0.25	-0.33	0.62	0.23	0.58	1.00

Table 17. Coefficients for the full multiple linear regression for bear density in 2005. Residual standard error: 0.9413 on 280 degrees of freedom. Multiple R^2: 0.62, Adjusted R^2: 0.61. F-statistic: 56.31 on 8 and 280 DF, p-value: < 2.2e-16. Significance codes: 0 '*' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1**

	Estimate	Std. Error	t value	Pr (>|t|)	
Intercept	1.62E+00	5.85E-01	2.769	0.005997	**
Maximum distance to water	-1.00E-03	9.46E-04	-1.057	0.291255	
Mean slope	6.20E-01	1.39E-01	4.478	1.10E-05	***
Length of unpaved roads	3.48E-02	1.29E-02	2.688	0.007608	**
Maximum distance to railroads	1.83E-03	1.93E-03	0.95	0.343028	
Maximum distance to urban areas	4.18E-06	3.65E-06	1.146	0.252779	
Rural density by 2001	-6.05E-01	1.28E-01	-4.728	3.60E-06	***
Mean Euclidean distance to source	-3.35E-03	2.75E-04	-12.15	< 2.00E-16	***
Forest percentage	1.28E-02	3.62E-03	3.54	0.000469	***

4.10 Figures

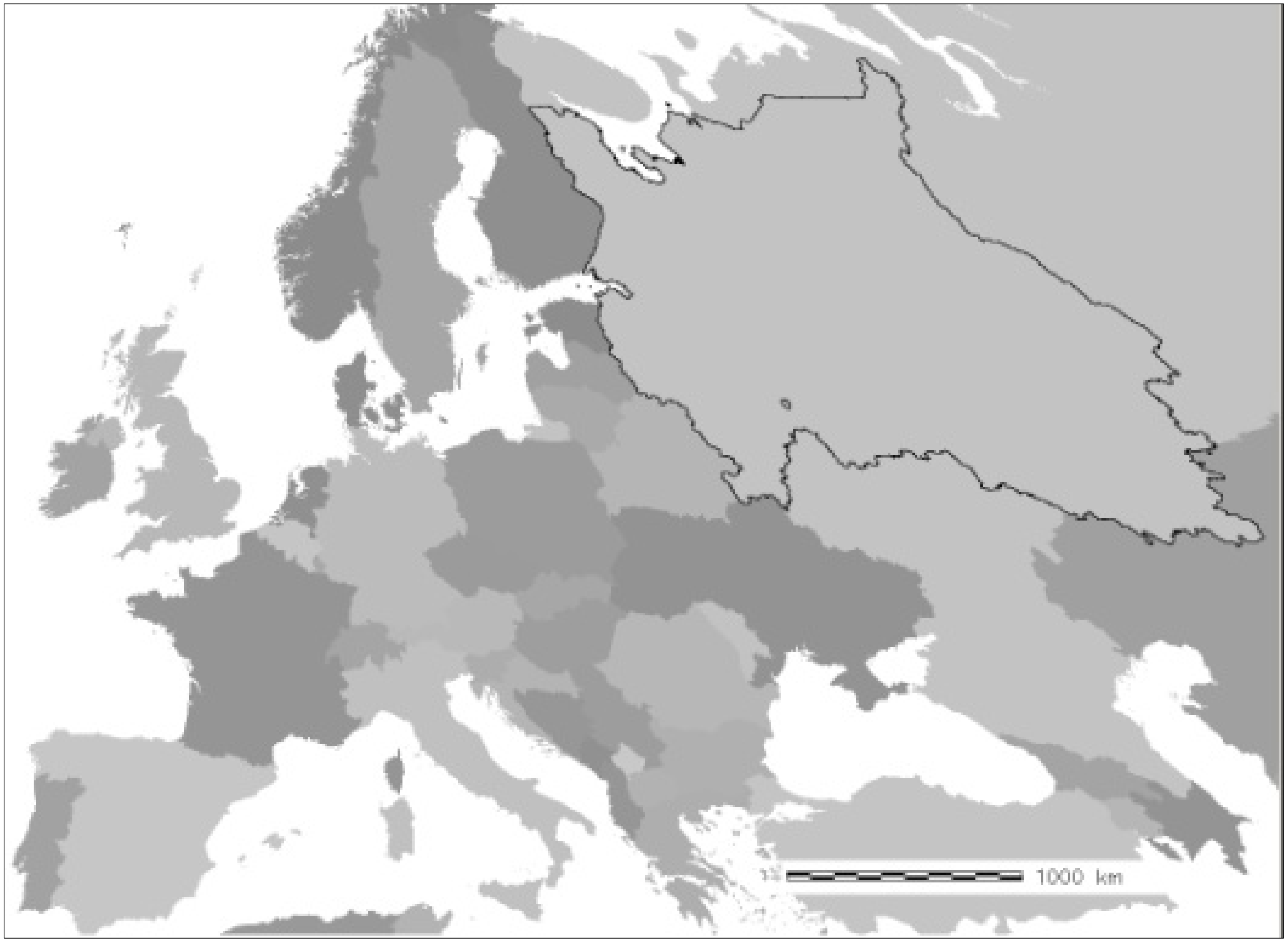


Figure 12. Our study area as defined by the oblast (provinces) in European Russia that reported Brown bears from 1991 to 2005.

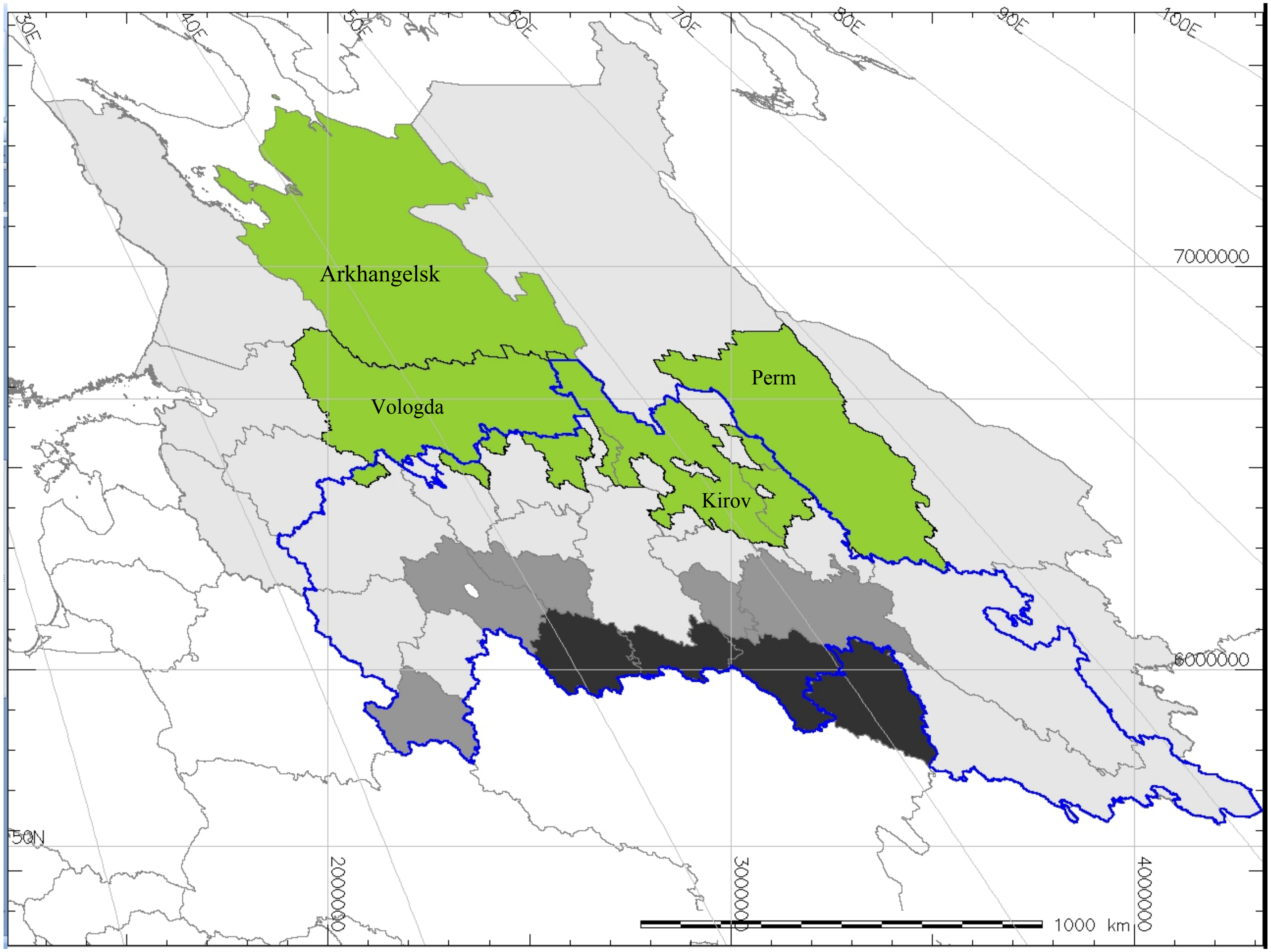


Figure 13. Brown bear expansion zone in blue. Light gray polygons represent regions with brown bear reports from 1991 to 2005. Dark gray polygons are regions with first time reports of bears by 1997 and black polygons are regions with first time reports of bears in 2000. Brown bears have still been reported in both the dark gray and the black areas until 2007. Green polygons are regions with large and increasing densities of bears since 1997.

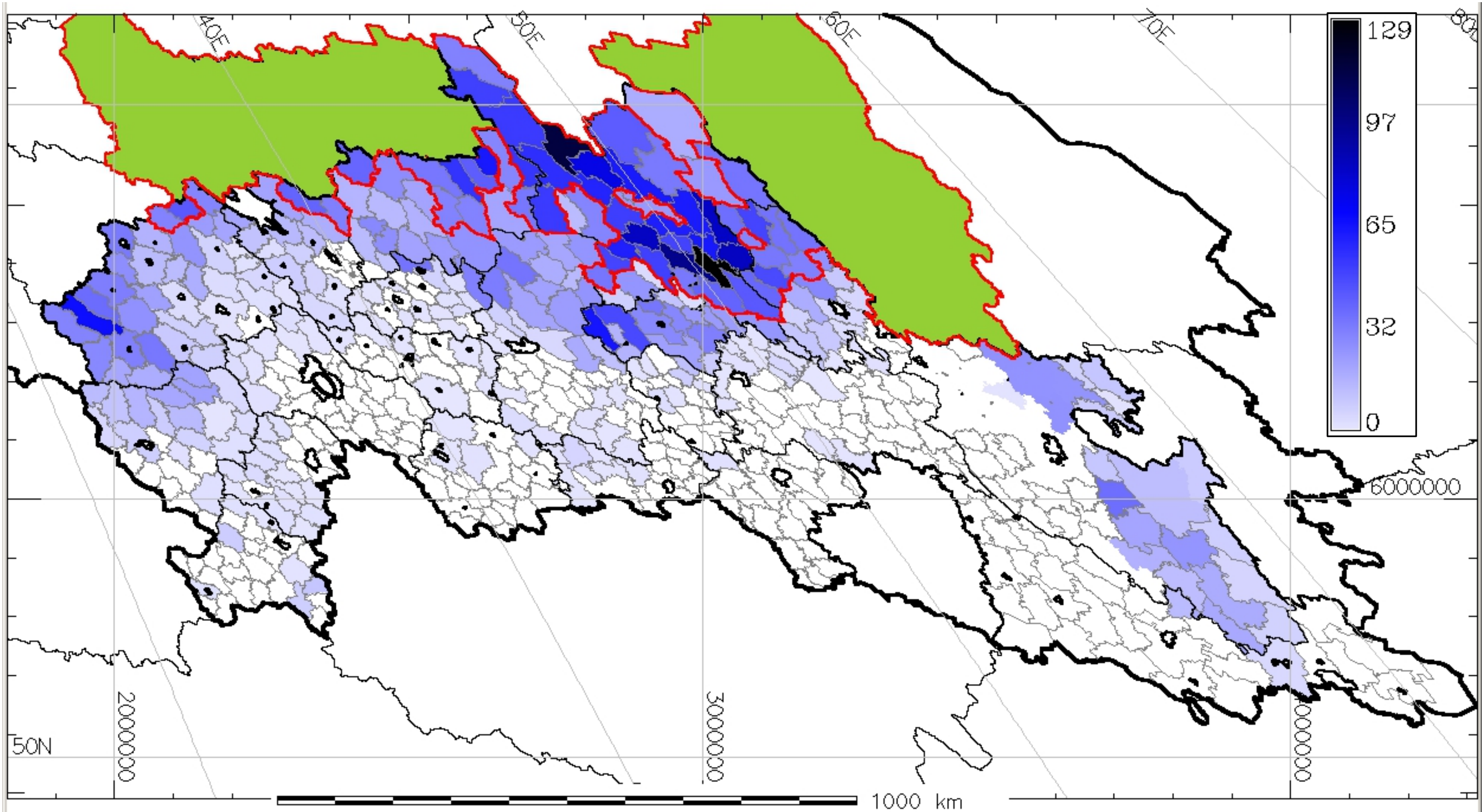


Figure 14. Brown Bear (*Ursus arctos arctos*) densities (Bears/1000 km^2) in the expansion zone of the European Russian (in blue). Red outlined, and green shaded areas were defined as our source area for the dispersal analysis. Data collected by Russian hunting authorities (Y.P. Gubar)

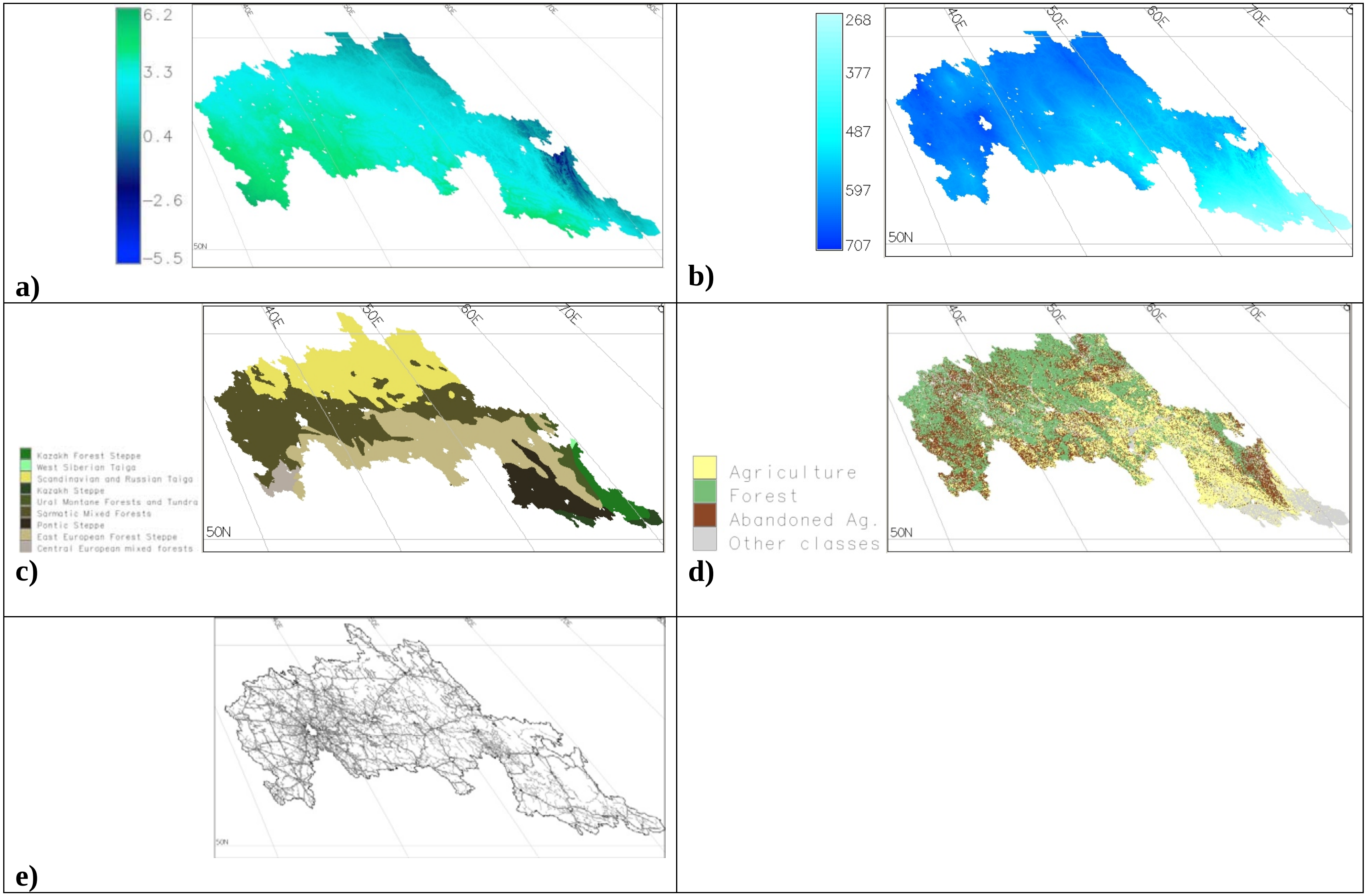


Figure 15. Environmental conditions in the study area: a) Annual average temperature (°C), b) Annual total precipitation (mm), c) Ecoregions, d) Land cover change, e) infrastructure.

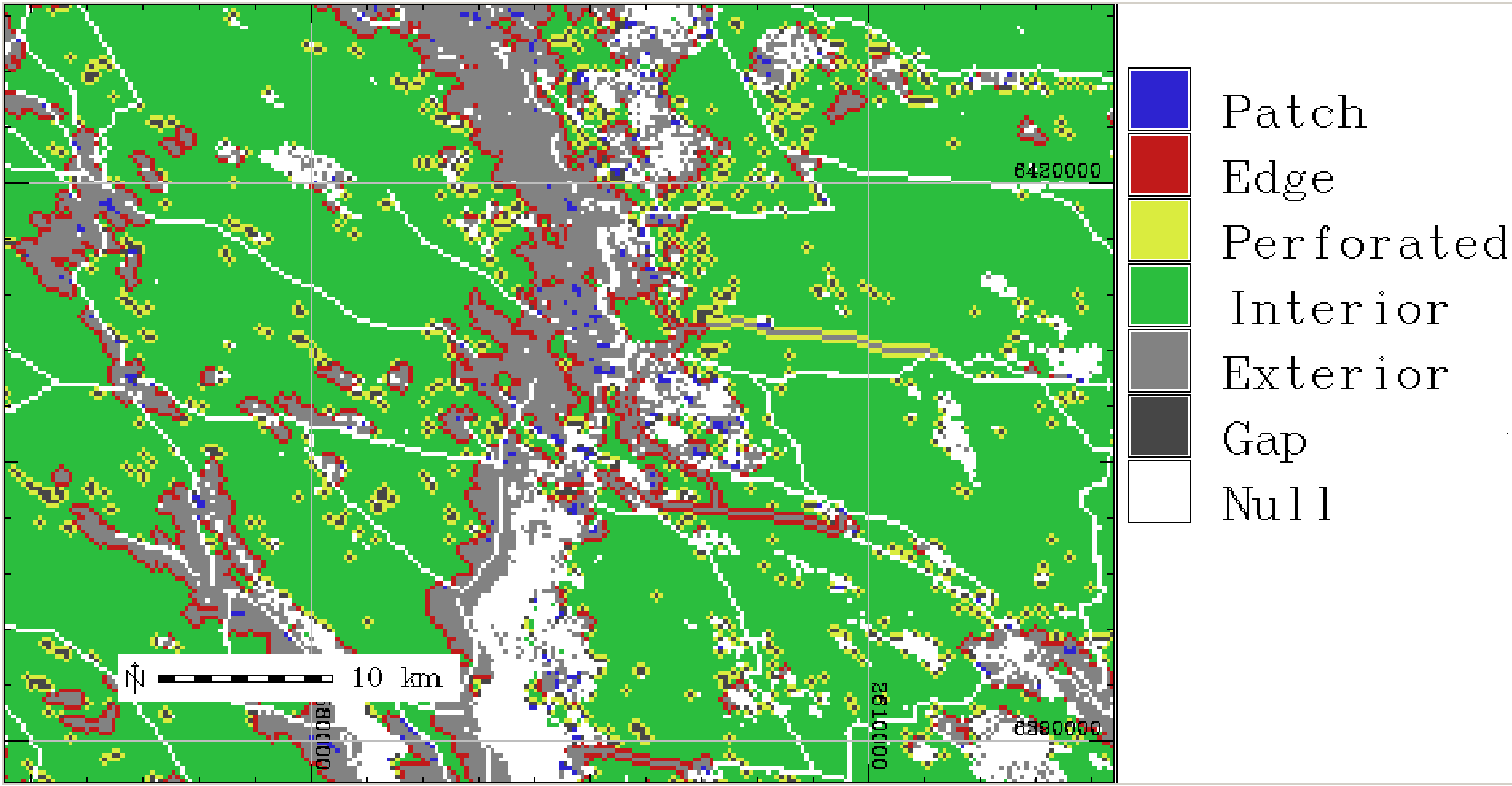


Figure 16. An example of the landscape morphological features included as habitat selection predictor variable.

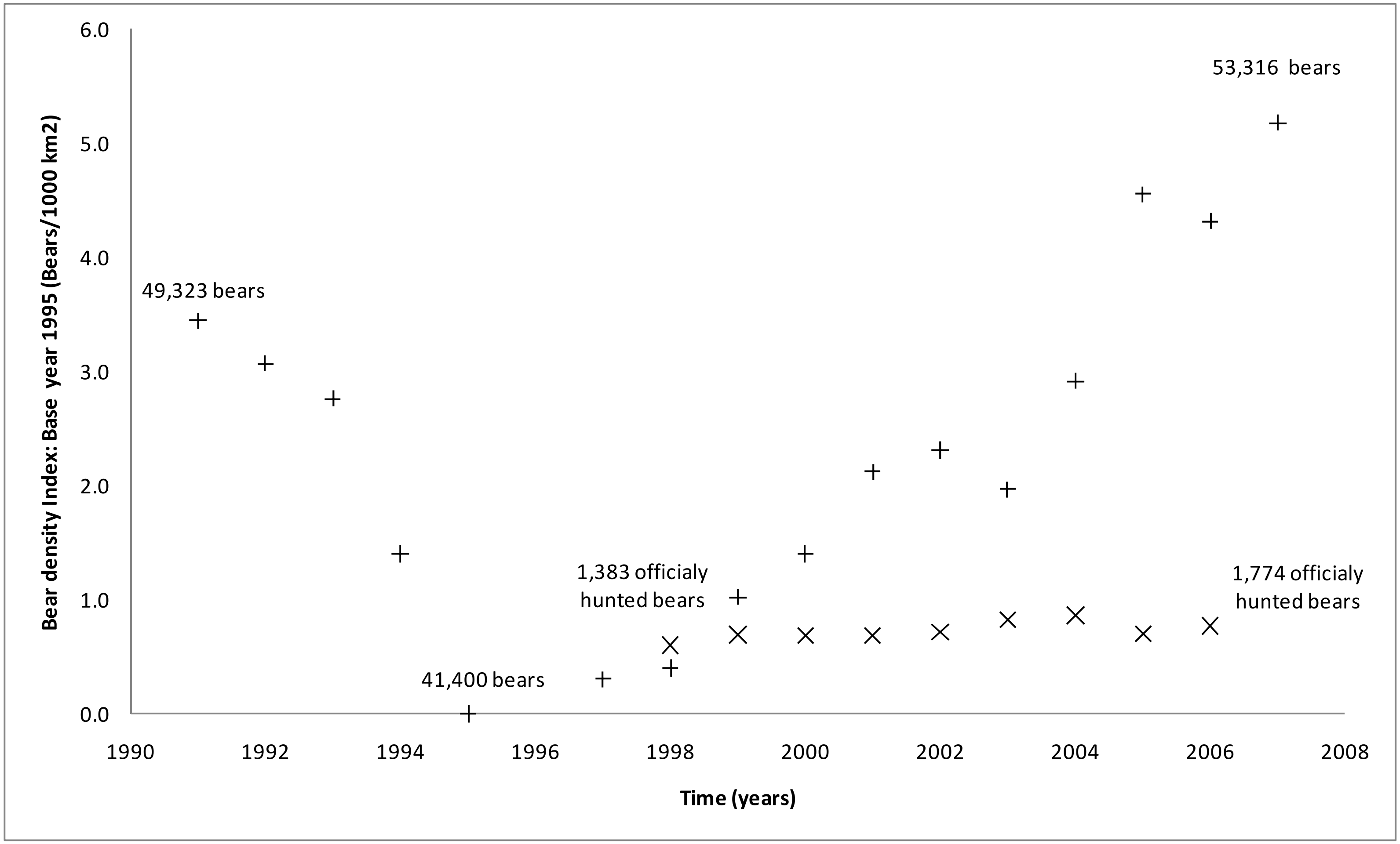


Figure 17. Brown bear density changes in European Russia based on bear reports for 31 Oblast (1 administrative level division) (Russian Ministry of Agriculture 2009).

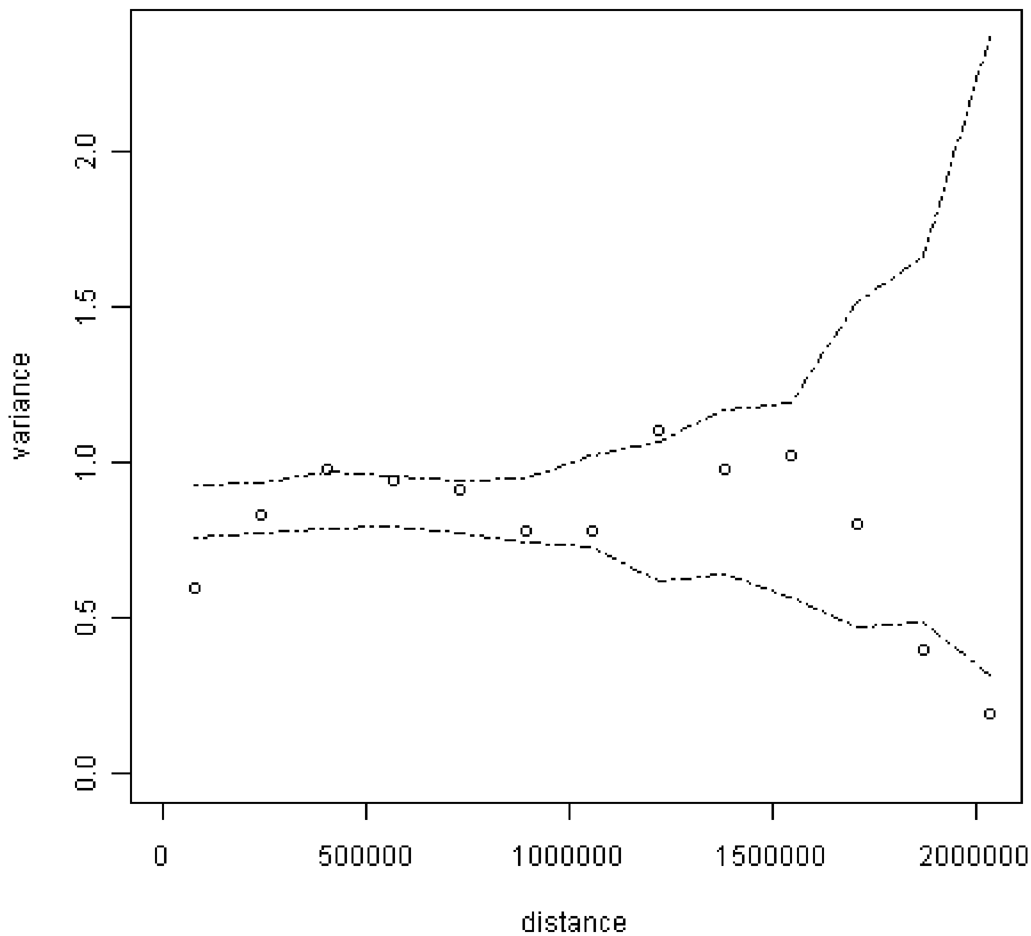


Figure 18. Semivariogram of the residuals of the final selected model.

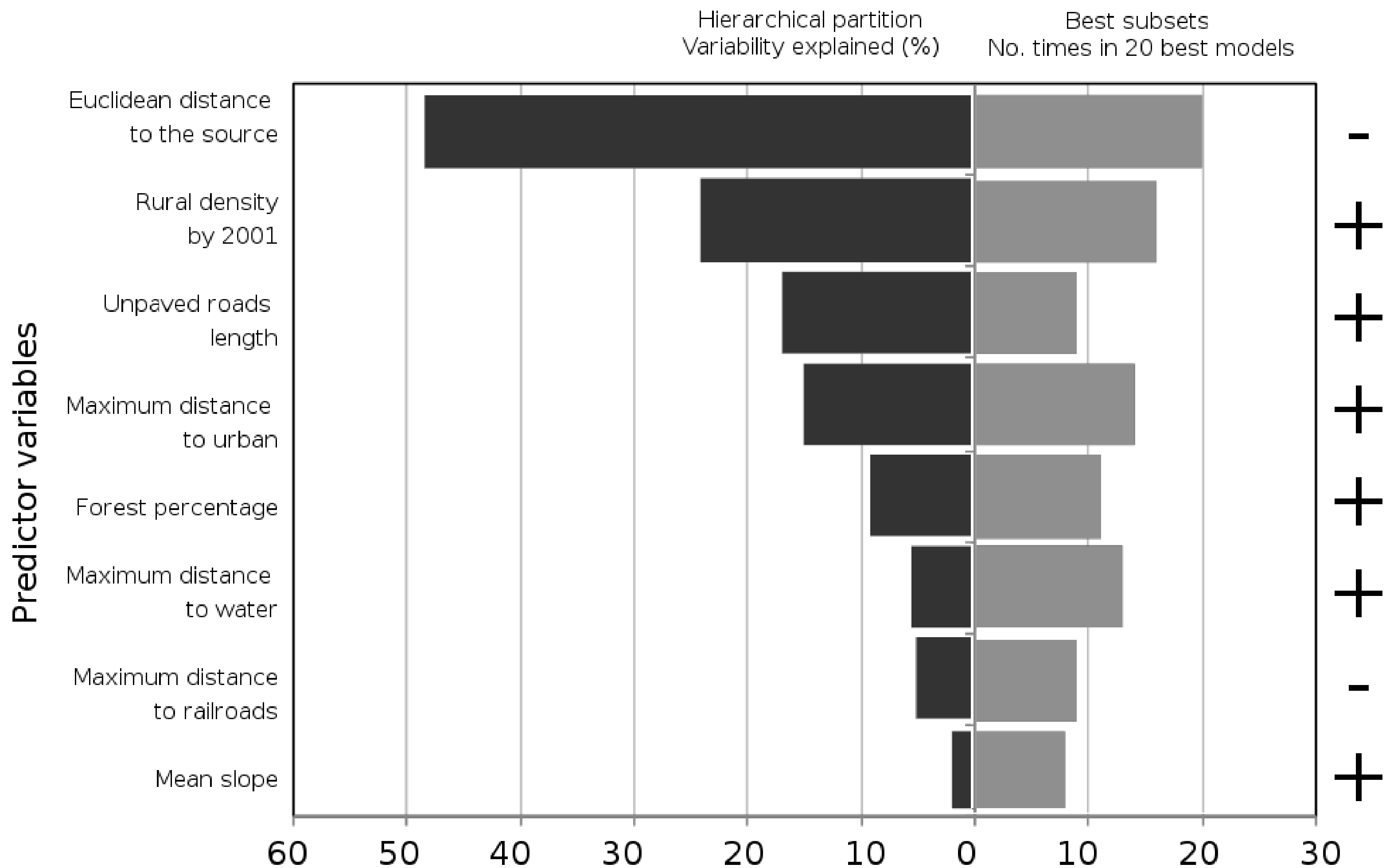


Figure 19. Summary of the regression analysis for brown bear densities in 2005. Right side bars (gray) represent results for the best subset analysis (i.e., the number that each variable was included in the best 20 models entered). The range of R^2 for the models fitted in the best subset analysis was 0.53 – 0.60. Bars on the left side (black) represent results of hierarchical partitioning analysis (i.e., the variance explained by each variable when all variables were included in the model). Plus and minus symbols represent the nature of the relationship between the explanatory variables and the density of brown bears (number of bears/1000 km^2).