Land-use and land cover change in times of massive socio-economic changes: detecting agricultural land abandonment and understanding its drivers in post-Soviet Eastern Europe

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Alexander V. Prishchepov

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Alexander V. Prishchepov

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The dissertation is approved by the following members of the Final Oral Committee:
Volker C. Radeloff, associate professor,Forest & Wildlife Ecology
Amy C. Burnicky, assistant professor, Geography
David, C. Lewis, assistant professor, Agricultural and Applied Economics
Philip Townsend, professor, Forest & Wildlife Ecology
Mutlu Ozdogan, assistant professor, Forest & Wildlife Ecology

LAND-USE AND LAND COVER CHANGE IN TIMES OF MASSIVE SOCIO-ECONOMIC CHANGES: DETECTING AGRICULTURAL LAND ABANDONMENT AND UNDERSTANDING ITS DRIVERS IN POST-SOVIET EASTERN EUROPE

Alexander V. Prishchepov

Under supervision of Professor Volker C. Radeloff

At the University of Wisconsin-Madison

Abstract

People and the way they use land are the leading drivers of global environmental change. Ultimately, all decisions are made by local actors, but their actions are constrained by broad scale factors such as national policies and institutions. However, the effect of the institutional changes on land use is not well understood. The collapse of the Soviet Bloc in Eastern Europe provides a great natural experiment to test different hypotheses about the effects of socio-economic change on land use. The overreaching goal of the dissertation was to study determinants of agricultural land abandonment at broad-scale (across countries) and fine-scale (within a given country at the hierarchical level) in post-Soviet Eastern Europe. I selected one uniform agro-climatic area stretching across four former Soviet Union republics – Belarus, Latvia, Lithuania, Russia - and former socialist Poland. Satellite data (30 m Landsat TM/ETM+ images) were used to quantify agricultural land abandonment in each country. The effects of image dates and classification algorithm on classification accuracy was examined in the cross-border area of Belarus-Lithuania, for on Landsat footprint with ideal image dates. Results revealed strong relationship between classification accuracy and certain image dates and better suitability of non-parametric support vector machine classifier. The classifications of agricultural land abandonment showed widespread abandonment reaching very high rates at province level and district level (up to 46% and 62% in Smolensk province of Russia respectively). Agricultural land abandonment rates were highest in countries with weak institutions during the transition period (Latvia, Lithuania and Russia). District–level statistical socio-economic analysis of agricultural land abandonment in Russia showed that abandonment was associated with lower agricultural yields during socialism and with low rural population density. Additional spatially explicit analysis revealed that at pixel level abandonment was also associated with greater distances from markets. The study provides the clear evidence of the negative effects of weak institutions during the transition on agricultural land-use.

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INTRODUCTION

People and their land use are among leading drivers of global environmental change, and a major cause of biodiversity declines and the loss of ecosystems services (Foley et al. 2005). The extent of human dominated landscapes now is higher than ever before. The world population is projected to reach over 9 billion people by 2050 (UN Millennium Project 2005). Furthermore, the rapid increase of the world's population may lead to even more intensive land use, with likely negative side effects on the environment. We are living in the "anthropocene" epoch (Zalasiewicz et al. 2010), and croplands are one of the world dominant land-cover types (Ramankutty & Foley 1999).

The human domination of most of the worlds ecosystems make it necessary to understand coupled human-environmental interactions (UN Millennium Project 2005). However, our understanding of global land-use change and its drivers is still incomplete. For instance, one of the current land use theories predicts unidirectional land use intensification over time (Foley et al. 2005). However, this theory does not account for large socio-economic disturbances which may either accelerate land-use change or completely change its direction. Another theory is forest transition theory (Rudel et al. 2005), which describes a general shift from forest loss to forest gains as nations become more developed. However, forest transition theory was developed in the context of post-industrial societies and does not predicts the pace of land use changes, nor the relationship of land use change to socio-economic changes (Eickhout et al. 2007, Erb et al. 2009).

One reason why our understanding of land use change is limited is that ultimately all land-use decisions are made by local actors, but data on local actors is rarely available for large areas and cumbersome to collect. In many cases, the agent (e.g., the agricultural producer) makes his/her decision based on exogenous factors, local environmental and socio-economic conditions, and serves as a mediator between institutions and land use (Irwin & Geoghegan 2001, Lambin & Geist 2006). The underlying drivers of LULCC (national policies, laws on land tenure, etc.) often underpin the proximate factors of LULCC (Lambin et al. 2001), but it can be difficult to measure policies effects. The result is that there is a limited understanding of these interactions, and it is challenging to measure exogenous factors affecting LULCC such as governmental policies and LULCC. ***The collapse of socialism in Eastern Europe provided a unique natural experiment that I used in my dissertation to examine how LULCC is affected by major socioeconomic shifts.***

After the collapse of socialism, Eastern European countries transformed politically, economically and socially. Regulated markets were substituted by the open markets (Bradshaw & Stenning 2004). However, different countries embraced different transition approach from state-command to market driven economy, ranging from “shock therapy”, where governmental deregulation of the economy was very rapid (e.g., in Poland and Russia) to a very slow pace of transitioning, with strong governmental control of the economy still remaining (e.g., in Belarus) (Bradshaw & Stenning 2004).

One result of the economic changes was widespread agricultural abandonment. According to official estimates, for example, in Estonia almost 60% of the arable land in 1989 arable had been abandoned by 2000 (FAO 2005). Similarly, 10-20% of the arable land was abandoned in Czech Republic during the first decade of transition (Doucha 1998), and 19% of the arable land was abandoned in Latvia (Bushmanis 2001). In Russia, more than 20 million hectares of arable land were abandoned during the first decade of transition (Sivkova 2003). The rates of abandonment in Russia were as high as 35% of the arable land in 1989 even in the agriculturally most productive regions of Russia (Sivkova 2003, GOSKOMSTAT 2000, Kharitonov 2002, Ioffe 2005). However, statistical data can be fraught with error, and comparisons among countries are difficult because of different definitions of abandonment and different assessment methods.

The major goal of my dissertation was thus to understand patterns and process of agricultural abandonment in Eastern Europe. Specifically, I examined three research questions in the three main chapters of my dissertations that were closely connected. In the first chapter, I developed and tested remote sensing methods to monitor agricultural abandonment accurately. In the second chapter, I applied these methods to assess post-socialist abandonment for seven Landsat footprints within one agro-climatic zone ranging from the Baltics, to Belarus and ultimately European Russia. In the third chapter, I related the observed patterns of abandonment in Russia to socio-economic and environmental variables that might be associated with higher rates of abandonment. In the following, I will briefly present the key findings of each of these three chapters.

Research Question I: "How can we accurately monitor agricultural land abandonment and what is effect of image-dates acquisition on agricultural land abandonment classification accuracy?"

In **Chapter I,** I examined the effect of image dates acquisition on agricultural land abandonment classification accuracy within one Landsat footprint (World Reference System path 186, row 22). My results showed that the highest classification accuracy was obtained with near-anniversary image dates for spring, summer and fall for both pre- and post abandonment. If a full set of images is not available, then my results showed that specific image dates had particularly strong influence on the accuracy of satellite classifications of land abandonment. However, the importance of different image dates differed for the two types of agricultural land abandonment: “abandoned arable land” and “abandoned managed grassland”. Last but not least, my results showed that a non-parametric classifier (support vector machines) was better suited to accurately map agricultural land abandonment, than a parametric classifier (maximum likelihood). The results from this methodological chapter were very useful to identify the best method and the optimal Landsat TM/ ETM+ images dates to map agricultural land abandonment across study area (Chapter II).

Research Question II: “How much agricultural land was abandoned in temperate Eastern Europe; what was the pattern of LULCC and if agricultural abandonment was the highest LULCC class?”

In **Chapter II,** I mapped post-socialist agricultural land abandonment in Belarus, Latvia, Lithuania, Poland and Russia using multi-date Landsat TM/ ETM+. My results showed widespread agricultural land abandonment. During the first decade of the transition (1989-1999), agricultural land abandonment occurred on over 30% of the agricultural land in 1989 in the study area. The pattern of agricultural land abandonment differed among countries. Abandonment rates were generally higher in those countries that had weaker institutions during the transition (e.g., Latvia, Lithuania and Russia). Compared to other studies on post-socialist agricultural land abandonment (Kuemmerle et al. 2008, Kuemmerle et al. 2009), as well as post-socialist logging (Kuemmerle et al. 2009, Eikeland,et al. 2004, Urbel-Piirsalu & Backlund 2009, Achard et al. 2006), and urban sprawl (Boentje & Blinnikov 2007), agricultural land abandonment rates in my study areas were higher than elsewhere in Eastern Europe, and agricultural land abandonment was the highest land-use change class.

Research Question III: "What are the determinants of agricultural abandonment at coarse and fine scales within a given country?"

In **Chapter III,** I studied determinants of agricultural land abandonment in Russia using the satellite classifications of agricultural land abandonment maps from Chapter II and comparing them to various socio-economic and biophysical data. At the district level, agricultural land abandonment was negatively correlated with crop yields in the pre-abandonment period. Complementary fine-scale modeling of agricultural land abandonment for one province (Rjazan) highlighted local correlates of agricultural land abandonment, such as markets proximities and biophysical constraints for agricultural production.

In general, the following conclusions emerged from my research. Among countries, the rates of agricultural land abandonment were likely determined by institutional changes and abandonment was more common where institutions were weaker. In Russia, higher agricultural land abandonment rates at broad-scale were associated with lower crop yields prior the abandonment, which were likely also the area where the withdrawal of agricultural subsidies had the greatest consequences. At the fine scale, agricultural land abandonment was driven by decision making based on local socio-economic and environmental constraints. From remote sensing perspective, to monitor agricultural abandonment is not trivial, especially when key image dates are missing, as this might lead to very low classification accuracies.

References

Achard,F., Mollicone,D., S.,H. -J, Aksenov,D., Laestadius,L., Li,Z., Popatov,P. & Yaroshenko,A. (2006). Areas of rapid forest-cover change in boreal Eurasia. *Forest Ecology and Management, 237*(1-3), 322-334.

Boentje,J. P. & Blinnikov,M. S. (2007). Post-Soviet forest fragmentation and loss in the Green Belt around Moscow, Russia (1991-2001): a remote sensing perspective. *Landscape and Urban Planning, 82*(4), 208-221.

Bradshaw,M. & Stenning,A. (2004). *East Central Europe and the former Soviet Union: the post-socialist state.* Prentice Hall. 266 p.

Eickhout,B., van Meijl,H., Tabeau,A. & van Rheenen,T. (2007). Economic and ecological consequences of four European land use scenarios. *Land Use Policy, 24*(3), 562-575.

Eikeland,S., Eythorsson,E. & Ivanova,L. (2004). From management to mediation: Local forestry management and the forestry crisis in post-socialist Russia. *Environmental management, 33*(3), 285-293.

Erb,K.-H., Krausmann,F., Lucht,W. & Haberl,H.. (2009). Embodied HANPP: Mapping the spatial disconnect between global biomass production and consumption. *Ecological Economics, 69*(2), 328-334.

Foley,J. A., DeFries,R., Asner,G. P., Barford,C., Bonan,G., Carpenter,S. R., Chapin,F. S., Coe,M. T., Daily,G. C., Gibbs,H. K., Helkowski,J. H., Holloway,T., Howard,E. A., Kucharik,C. J., Monfreda,C., Patz,J. A., Prentice,I. C., Ramankutty,N. & Snyder,P. K. (2005). Global consequences of land use. *Science, 309*(5734), 570-574.

GOSKOMSTAT. (2000). *Agricultural sector in Russia (Selskoje khozjaistvo v Rossii). Statistical Compendium.* Goskomstat Rossii, Moscow, Russia, 414 p.

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

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), 913-943.

Irwin,E. G. & Geoghegan,J. (2001). Theory, data, methods: developing spatially explicit economic models of land use change. *Agriculture Ecosystems & Environment, 85*(1-3), 7-23.

Kharitonov,N. (2002). online conference through Izvestiya. Izvesitya,

Kuemmerle,T., Hostert,P., Radeloff,V. C., van der Linden,S., Perzanowski,K. & Kruhlov,I. (2008). Cross-border comparison of post-socialist farmland abandonment in the Carpathians. Ecosystems, 11(4), 614-628.

Kuemmerle,T., Kozak,J., Radeloff,V. C. & 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., Mueller,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,E. F. & Geist,H. J. (2006). *Land Use and Land Cover Change. Local Processes and Global Impacts(Global Change - The IGBP Series).* Springer Verlag, Berlin, Heidelberg, New York, 222 p.

Lambin,E. F., Turner,B. L., Geist,H. J., Agbola,S. B., Angelsen,A., Bruce,J. W., Coomes,O. T., Dirzo,R., Fischer,G., Folke,C., George,P. S., Homewood,K., Imbernon,J., Leemans,R., Li,X. B., Moran,E. F., Mortimore,M., Ramakrishnan,P. S., Richards,J. F., Skanes,H., Steffen,W., Stone,G. D., Svedin,U., Veldkamp,T. A., Vogel,C. & Xu,J. C. (2001). The causes of land-use and land-cover change: moving beyond the myths. *Global Environmental Change-Human and Policy Dimensions, 11*(4), 261-269.

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

Rudel,T. K., Coomes,O. T., Moran,E., Achard,F., Angelsen,A., Xu,J. C. & Lambin,E. (2005). Forest transitions: towards a global understanding of land use change. *Global Environmental Change-Human and Policy Dimensions, 15*(1), 23-31.

Sivkova,V. (2003). “Chto strana budet est’ (What the Country is going to eat: Interview with Alexey Gordeyev),”. *Argumenty i Fakty, (3)*, 29.

UN Millennium Project. (2005). *Halving Hunger: It Can be Done*. Report of the Task Force on Hunger. Earthscan. London, UK and Sterling, USA (last accessed August 30, 2010, http://www.unmillenniumproject.org/documents/HTF-SumVers_FINAL.pdf)

Urbel-Piirsalu,E. & Backlund,A.-K. (2009). Exploring the Sustainability of Estonian Forestry: The Socioeconomic Drivers. *Ambio, 38*(2), 101-108.

Zalasiewicz,J., Williams,M., Steffen,W. & Crutzen,P. (2010). The New World of the Anthropocene. *Environmental science & technology, 44*(7), 2228-2231.

THE EFFECT OF IMAGE ACQUISITION DATES ON THE DETECTION OF AGRICULTURAL LAND ABANDONMENT IN EASTERN EUROPE

Co-authors: Volker C. Radeloff, Maxim Dubinin and Camilo Alcantara

In review: Remote Sensing of Environment

Abstract

Many terrestrial biomes are experiencing intensifying human land use. However, declines in the intensity of agricultural land-use are also common and can result in agricultural land abandonment. Agricultural land abandonment has strong environmental and socio-economic consequences, but fine-scale spatially explicit data on agricultural land abandonment is sparse, particularly for countries that have experienced recent institutional changes, such as Eastern Europe. Remote sensing can potentially fill this gap, but satellite-based detection of fallow fields and shrub encroachment is difficult and requires multiple images during the growing season. However, multi-date cloud-free imagery is often lacking. Our question was how much 'missing' images at key times of the growing season affect classification accuracy when mapping agricultural land abandonment. We selected a study area in temperate Eastern Europe, where post-socialist agricultural land abandonment was widespread. We analyzed six near-anniversary cloud-free Landsat images for Spring, Summer and Fall for pre-abandonment (1989) and post-abandonment (1999/2000). In a factorial experiment, we tested how accuracy changed for all possible 49 image date combinations mapping “abandoned arable land” and “abandoned managed grassland” separately. We also tested whether Support Vector Machines (SVM) performed better than maximum likelihood classifier. Conditional Kappa was 90% for “abandoned arable land” and 72% for “abandoned managed grassland” when all six images we used for classification. Results with fewer images showed a substantial decrease in the conditional Kappa to just 62% for “abandoned arable land” and 52% for “abandoned managed grassland”. Accuracy of different abandonment classes was sensitive to different seasons. For “abandoned arable land” it was important to use a Spring image for pre-abandonment and as many images as possible for post-abandonment, with a Spring image again being most important. “Abandoned managed grassland” required more images for pre-abandonment (preferably Spring plus either Summer or Fall), and at least a Spring image for post-abandonment. To obtain a conditional Kappa of at least 70% for both abandonment classes a Spring and a Fall image for both pre- and post-abandonment were necessary. SVM outperformed maximum likelihood classifier only for “abandoned arable land”. Our results highlight that limited image date availability in the Landsat record places substantial limits on the accuracy of classifications of agricultural abandonment. However, the abundance of agricultural abandonment in many parts of the world, and its strong ecological and socio-economic consequences, suggests that better monitoring of abandonment is necessary, and our results show which image dates are most important to do so.

Keywords: abandonment, accuracy assessment, change detection, Eastern Europe, land use, land cover change, Landsat, LULCC, multi-date, multi-seasonal, maximum likelihood classifier, support vector machines, SVM.

Introduction

Many terrestrial biomes are experiencing intensifying human land use (Vitousek, et al., 1997), but the extensification of agriculture is also common and can result in agricultural land abandonment (Baldock et al., 1996). Agricultural land abandonment has occurred throughout history (Hart, 1968; Yeloff & van Geel, 2007) and in many parts of the world (de Beurs & Henebry, 2004; Meyfroidt & Lambin, 2008; Petz & Skole, 2003). In some regions, for instance in Eastern Europe, agricultural land abandonment may represent the highest land-use change class partly in response to rapid socio-economic changes after the breakdown of the Soviet Union (Kuemmerle et al., 2008).

Agricultural land abandonment has strong environmental and socio-economic consequences. Reforestation on abandoned agricultural land can reconnect previously separated forests fragments, sequester carbon (Smith, et al., 2007), and improve hydrological regimes and water quality (Lofgren et al., 1999; Sileika et al., 2006). Early succession on abandoned farmfields can increase biodiversity, but biodiversity may decline in late successional stages (Baur et al. 2006 ; DLG 2004). Abandoned agricultural fields can also be a source for pests (Smelanksy 2003), and provide fuel for wildfires (Dubinin et al., 2010; Lloret et al., 2002). Averting agricultural land abandonment and its socio-economic implications is an impetus of many agricultural and land-use policies (IEEP, 2006). Agricultural land abandonment threatens traditional land use practices (Angelstam et al. 2003) and in some parts of the world abandonment can be negatively perceived by native villagers (Benjamin et al. 2007).

Despite the environmental and socio-economic importance of agricultural land abandonment, information on abandonment rates and the geographic distribution of abandonment is sparse, particularly in countries that have experienced institutional changes, such as Eastern Europe.

Agricultural statistical surveys in Eastern Europe measure mainly agricultural land-use dynamics (e.g., how much of agricultural land was used for sowing the crops), but they are often out of date and sampling techniques are questionable (Ioffe et al., 2004). Moreover, statistical reports are spatially coarse and usually aggregated by administrative districts (Ioffe et al., 2004). Remote sensing can be a reliable source of information on agricultural land abandonment (de Beurs & Henebry, 2004; Kuemmerle et al., 2008; Peterson & Aunap, 1998). However, abandoned agricultural land (which we defined here as both formerly plowed fields and managed grasslands that are now non-managed grasslands with early-successional shrubs and forest regrowth) are not easily distinguishable from managed grasslands and arable fields (Kuemmerle et al., 2006; Oetter et al., 2001; Peterson & Aunap, 1998).

The best classification accuracies in any land cover classification are usually obtained with multidate imagery that captures different parts of the growing season (Civco, 1989; Oetter et al., 2001; Wagner, 1993; Wolter et al., 1995). Multidate imagery is particularly important when classifying agricultural land use, because of different timing of crops sowing and harvesting (Guerschman et al., 2003; Kalensky, 1974; Pax-Lenney & Woodcock, 1997). Coarse-resolution (250 – 1000 m) AQUA/ TERRA MODIS multidate remote sensing products (e.g., reflectance bands, calculated indices –NDVI, EVI) can be used to monitor agricultural land-use dynamics, especially where the agricultural sector is dominated by large-scale farming. However, where agricultural land is highly fragmented coarse-resolution products may result in false estimates of the actual agricultural land use (Ozdogan & Woodcock, 2007). Moreover, the relatively short data record MODIS imagery precludes land-use change analysis starting, for instance, during the socialist period in Eastern Europe. In such instance, Landsat TM/ ETM+ data is the only reliable source of information to monitor land-use change at fine-scale.

Unfortunately, fine-scale images (e.g., Landsat TM/ ETM+ images) that capture different phenological and land-use stages (i.e., the beginning, middle, and end of the growing season) are not always available. For example, when we conducted a thorough check of all major Landsat data archives we found that out of 995 Landsat TM/ ETM+ footprints in Eastern Europe and neighboring countries, there was not a single footprint for which spring, mid-summer and fall cloud free images were available for both a single year prior to the breakdown of the Soviet Union (1988 to 1990) and a single year a decade after the transition to a market economy (1998 to 2000) (Figure 1-1 A,B). This raises the question how image dates affect classification accuracies for maps of agricultural abandonment, and which images dates are best.

In addition to the effects of image dates, there is the question of which classification algorithm results in the highest accuracy when classifying agricultural land abandonment. Non-parametric machine learning classification algorithms (e.g., support vector machines, further SVM) often outperform parametric classifiers (e.g., maximum likelihood classifier) (Foody & Mathur, 2004; Huang et al., 2002). In the case of agricultural land abandonment, training data are often not normally distributed because different crops and grasslands have different reflectance values during the year, and these classes often exhibit multi-modal reflectance distributions. However, normal distribution is a requirement for statistical classifiers such as maximum likelihood. Thus, we expected that non-parametric classifiers would better classify agricultural land abandonment (e.g., SVM).

Our overarching goal was to identify an approach to map post-socialist agricultural land abandonment in Eastern Europe accurately at a fine scale using Landsat TM/ ETM+ images. To accomplish this goal, our first objective was to assess the effects of image dates on the classification accuracy for abandoned agricultural land. Our second objective was to test if SVM would result in higher classification accuracy than using maximum likelihood classifier, thus potentially overcoming image date dependences.

Materials and methods

Image selection

In order to examine the effect of image dates we selected one Landsat footprint in temperate Eastern Europe with ideal image date availability and widespread farmland abandonment. Based on crop management cycles and vegetation phenologies, we assumed that three image dates would be crucial. The first image represented spring from an agricultural land use perspective (April 20th to May 20th), i.e., the period when mean daily temperatures rise above 5° C. At this point, soils for summer crops are still bare, but both winter crops and managed grassland are vegetatively active. The second image represented summer (June 20th to July 20th), the end of the first phase of hay harvesting, and the maturing of winter crops. The third image captured fall (August 20th to October 10th), when vegetation not yet dormant. Both winter crops and major summer crops are already harvested and tilling of soil begins, but some summer crops (e.g., corn, rape, beets, and potatoes) remain unharvested. We limited cloud contamination to less than 5%, and searched for near-anniversary images for 1989 and 1999 to capture land use at the end of socialism and the first decade after the transition to a market economy. Querying major Landsat archives (University of Maryland Global Land Cover Facility [www.landcover.org], USGS [glovis.usgs.gov], Eurimage Inc. [www.eurimage.com], and R&D Scanex [www.scanex.com]) not a single Landsat footprint met all requirements. We thus relaxed our requirement for single-year imagery, used a spring image from 2000 instead of 1999, and selected Landsat footprint, World Reference System 2 (WRS 2) path 186 row 22. The selected Landsat footprint includes two former Soviet Union republics (Belarus and Lithuania) plus former socialist Poland (33.5%, 65.1% and 1.4% of the area of the Landsat footprint respectively) (Fig. 1-2 A, B,C). For this footprint we acquired nearly anniversary TM and ETM+ images for pre-abandonment (May 3rd 1989, July 6th 1989, September 24th 1989) and post-abandonment (May 5th 2000, July 10th 1999, September 20th 1999). Agricultural statistics surveys showed declines in both in the number of livestock (e.g., for cattle in Belarus from 7,271 thousand heads in 1989 to just 4,685 thousand heads in 1999 and in Lithuania from 2,435 thousand heads to just 923 thousand heads) and crop production (e.g., for grain in Belarus from 7,384 thousand tons in 1989 to 3,645 thousand tons in 1999 and in Lithuania and from 3,272 to just 2,112 thousand tons), suggesting that agricultural abandonment was widespread in that period (Belstat, 2002; Grodnostat, 2001; Lithstat, 2001).

Study area

The climate in the region is transitional from maritime to continental. Annual precipitation ranges between 585 and 664 mm. The mean daily temperature in July is +16.9°C, and -6.1°C in January. The growing period (temperatures above 5°C) ranges from 120 days in the north of the scene to 179 days in the south (IIASA, 2000; Stuikys & Ladyga, 1995). Topography is relatively flat (0 to 298 m).

Soil types are predominantly acid soddy podzolic sandy loams as well as sands and drained soddy podzolic gleys. Different soils have resulted in different agricultural practices. The most productive soils are soddy calcerous soils, predominantly loams in Central Lithuania (western part of the study site), where both row crops and cattle breeding are important (Stuikys & Ladyga 1995). In Eastern Lithuania (central part of the study area), where acid podzolic soils are common, cattle breeding and dairy farming are playing an important role. In Western Belarus, Grodno region (eastern part of the study area), where podzolic soils dominate, large-scale livestock industry and row crops are common.

Both in 1989 and 2000, summer crops were sown on approximately 66% of the total crop land (Belstat 2002; Lithstat 2001). Summer crops mainly consisted of barley, rye, oats, sugar beets, fodder maize, potatoes, peas, summer rapeseed, and flax. Winter crops consisted of winter wheat, winter barley and winter rapeseed (Stuikys & Ladyga, 1995). Crop planting, harvesting and hay cutting follows a distinct schedule, which we used together with vegetation phenologies to identify the optimal image dates (Figure 1-3).

After agricultural lands, forest is the second most important land cover type, and represented 40% of the study area. The dominant tree species were northern spruce (*Picea abies*), scots pine (*Pinus sylvestris*), silver birch (*Betula pendula*), and pedunculate oak (*Quercus robur*) (Folch, 2000; Kashtanov A.N., 1983).

Image preprocessing

Images were co-registered using automatic tie points (Leica Geosystems 2006). No atmospheric correction was performed as it does not improve classification accuracy significantly when multi-dates composites are classified simultaneously (Song et al., 2001). We used Landsat TM/ ETM+ bands 1-5 and 7. Clouds and cloud shadows were masked out using iterative automatic clustering (ISODATA) (Leica Geosystems 2006) and manual digitizing. Total cloud contamination was < 5% of the study area, primarily covering forests.

Classifications training and reference data collection

The classification scheme focused on agricultural transition classes (Table 1-1), but also included forest clearcuts and forest regeneration, because they can potentially be confused with agricultural land abandonment.

Training and validation data were selected via a three-step stratified random sampling approach modified from Edwards et al. (1998). First, we selected cloud-free 1.28-m resolution QuickBird and IKONOS images (Table 1-2) available via GoogleEarth™ mapping service which covered 33% of the Landsat footprint, including all major soil and land use types (Fig. 1-2B). Since different soils correspond to different agricultural practices or land cover types (e.g., forests dominate arenosols), we cross-checked the percentage of major type of soils within and outside of high-resolution footprints used for stratification of reference data sampling (Table 1-3), and found no major differences.

Second, we derived a forest versus non-forest mask for the QuickBird and IKONOS images. For Lithuania, we used an expert-based manual land cover classification of Landsat TM/ ETM+ and SPOT data at 100-m resolution for the year 2000 conducted by the Coordination of Information on the Environment-CORINE project (EEA, 2006). Forests were classified in the CORINE project with accuracies over 86%. For Belarus we used a 1:500,000 GIS product based on circa 1989 digitized Soviet topographic maps. Stratification forest/ non-forest was used to concentrate field-based reference data collection for agricultural and agricultural land abandonment classes. Finally, we randomly placed reference points within the non-forested areas that were within 300 m off roads, which we had digitized from the QuickBird and IKONOS images to facilitate field visits (Fig. 1-2C). To avoid spatial autocorrelation, we separated reference points by at least 500 m, after we estimated the range of spatial autocorrelation with variograms using GS+ geostatistical package (Gammadesign, 2010).

Out of a total of 1,178 randomly placed points, 250 points on agricultural land were visited in the field in 2007 and 2008. Points were geolocated using a non-differential GPS. To avoid potential error due to the time difference between our fieldwork (2007 and 2008), the high-resolution imagery (2000 to 2005), and the Landsat images used for the classification (2000 and earlier), we used a Landsat 5 image for May 20, 2007 to verify that no land use change took place between 2000 and 2007.

Using semi-structured questionnaires, where it was possible, we reconstructed the land management in 1989 and in 1999/2000 by interviewing local farmers and agronomists. Where possible, we also measured the height and age (by counting the tree rings) of shrubs and trees on sites that appeared to be agricultural land to ensure that these were in use in 1989, and abandoned by 1999/2000. For non-agricultural classes, reference data were collected from the same sources used for the stratification and by visual interpretation of the Landsat images.

Classification methods

For the classification we used both a non-parametric Support Vector Machines (SVM) and a parametric maximum likelihood classifier as our classification algorithms. The training data for the maximum likelihood classifier consisted of polygons, which we obtained by selecting representative areas during field campaigns and using the 1.28-m resolution QuickBird and IKONOS images available via GoogleEarth™ mapping service (Table 1-2). We compared classifications where all the training polygons for one land cover class were merged into one training signature, with classifications where the training polygons were clustered (Ward Euclidian distance hierarchical clustering) into 124 different spectral types. Tests showed no substantial difference in classification accuracies among training approaches for the maximum likelihood classifier, and we used only one averaged signature for each land cover class in the classifications to save processing time.

SVM is a non-parametric machine-learning classifier, that often outperforms other classifiers (Foody & Mathur, 2004; Huang, et al., 2002). SVM achieves optimal class separation by fitting a hyperplane based on training data. SVM is well suited to separate multimodal classes, which parametric-based classifiers (e.g., maximum likelihood classifier) have difficultly to classify accurately. SVM captures agricultural land abandonment well especially when optimal dates are available (Kuemmerle et al., 2008), but have not been tested in regards to their ability to handle suboptimal image dates nor compared to parametric classifiers in their use for abandonment mapping. We used the SVM implemented in ImageSVM (Rabe et al., 2009) based on LIBSVM (Chang & Lin, 2001), which can be run as stand-alone application via IDL Virtual Machine™ or as an add-on to ENVI™. To select support vectors, ImageSVM automatically selects the optimum Gaussian radial basis function parameter (γ) and Regularization Parameter (C) within a range from 0.1 to 1000. We used a "one-against-one" approach for multi-class SVM classifications to avoid unbalanced classifications that have been reported for the "one-against-all" approach (Melgani & Bruzzone, 2004).

SVM is computationally demanding, and that precluded using exactly the same training data that we had selected for the maximum likelihood classification (Huang et al., 2002). Based on several sampling experiments and assessing accuracies, we randomly sampled 300 to 1000 training pixels per class from the training polygons (Table 1-1). We tested several sets with different number of sampled training pixels and performed the classifications using SVM with full load of image dates into image dates composite to ensure that selected final training sample lead to the stability of classification in terms of the accuracy. To ensure that differences between SVM and maximum likelihood classifications were not caused by the different training data sets, we also trained selected SVM with the training set used for the maximum likelihood classifier, and we trained the maximum likelihood classification with the subset of the training data used for the SVM.

Accuracy assessment

Classification accuracy was estimated with contingency matrices. We calculated the Kappa coefficient for the overall classification, conditional Kappa coefficients for each class, and user's and producer's accuracies. We used the non-parametric McNemar's test with continuity correction to see if the SVM classifications were statistically more accurate than the corresponding maximum likelihood classifications (Foody, 2004). For this test, both "abandoned arable land" and "abandoned managed grassland" were recoded as "one" and all other classes as "zero". Statistical tests we also adjusted for false discovery rate (FDR) in order to avoid incorrectly rejected null hypotheses (Benjamini, & Yekutieli, 2001). Classification results were grouped according to the number of Landsat images used in the pre- and post-abandonment period (i.e., "one and one", "one and two" and "two and one", "one and three" and "three and one", "two and two", "two and three" and "three and two", and "three and three" image date combinations). In total, there were 49 possible combinations for each agricultural land abandonment class, and all of them were tested.

Results

The best classifications for agricultural land abandonment were acquired using the SVM classifier. Using SVM, among the 49 image date combinations, overall Kappa using a 12 class catalog varied between 73 and 88% and for 22 image date combinations overall Kappa was higher 80% (Figure 1-4).

Generally, we observed higher user's accuracies and lower producer's accuracies mapping for both agricultural land abandonment classes (Figure 1-5, 1-6).

A check of the land cover distribution inside and outside the areas covered by the Quickbird imagery showed similar proportions for each class according to our best overall classification with “three and three” Landsat TM/ETM+ footprints for both pre- and post- abandonment (Table 1-4), suggesting that the limited availability of Quickbird images did not bias our accuracy assessments.

Classification accuracy was consistently lower for "abandoned managed grassland" compared to "abandoned arable land" (Figure 1-4). For “abandoned arable land” conditional Kappa ranged between 54 and 93% and for “abandoned managed grassland” between 50 and 75%. Seventeen image date combinations yielded conditional Kappa of at least 70% for “abandoned arable land” and sixteen image date combinations yielded a conditional Kappa of at least 80%. For "abandoned managed grassland", eleven image date combinations yielded conditional Kappa of at least 70 %. Only ten image date combinations yielded conditional Kappa of at least 70 % for both classes simultaneously. Overall Kappa was highest when classifying maximum number of images (three) for pre-abandonment and post-abandonment. However, for “abandoned arable land” a “two and three” image combination was the best (Spring and Summer 1989 versus Spring, Summer, and Fall 1999/2000), and for “abandoned managed grassland” a “three and two” combination (Spring, Summer, and Fall 1989 versus Spring, and Summer 1999/2000) resulted in the highest classification accuracy.

All six “two and three” and “three and two” image date combinations yielded conditional Kappa of at least 80% for “abandoned arable land” and at least 70% for “abandoned managed grassland” respectively. For “abandoned arable land”, it was best to include either Spring and Summer, or Spring and Fall images for pre-abandonment and all three images for post-abandonment. To detect “abandoned managed grassland” it was best to include Spring and Summer images for post-abandonment and all three images for pre-abandonment.

When only two images were analyzed for each year (“two and two” image date combinations with 9 possible image dates combinations) conditional Kappa ranged between 70 and 84 % for “abandoned arable land”. For “abandoned managed grassland” conditional Kappa ranged between 62 and 70 %. Only two “two and two” image date combinations yielded conditional Kappa values of at least 70% for both abandonment classes. For “abandoned arable land” it was best to have Spring and Summer or Spring and Fall images for both pre- and post-abandonment periods, or Summer and Fall images for pre-abandonment and any combination with a Spring image for post-abandonment. For “abandoned managed grassland” it was best to use Spring and Summer for pre-abandonment and Spring and Summer or Spring and Fall for post-abandonment.

In the case of “one and three” and “three and one” image dates (6 possible combinations), conditional Kappa ranged between 54 and 90% for “abandoned arable land”. For “abandoned managed grassland” the range of conditional Kappa was between 50 and 75%. No single image date combination yielded conditional Kappa values of greater than 70% for both abandonment classes. In the case of “abandoned arable land” it was best to have three images for post-abandonment and a single Spring or Fall image for pre-abandonment. In the case of “abandoned managed grassland” the accuracy was highest with three image dates for pre-abandonment period and any single image for post-abandonment.

In the case of “one and two” and “two and one” image dates (18 possible combinations) conditional Kappa ranged between 54 and 86% for "abandoned arable land". For "abandoned managed grassland" conditional Kappa ranged between 50 and 75%. Three image date combinations yielded conditional Kappa values between 70 and 75% for both abandonment classes simultaneously. Similarly to “one and three” image date combinations, “abandoned arable land” was best classified when two post-abandonment images were included, and when the single image was from either Spring or Summer for pre-abandonment. If only one image was available for post-abandonment then Spring was best. For “abandoned managed grassland” it was best to use Spring and Fall for pre-abandonment and either Spring or Fall image dates for post-abandonment. If only one image date was available for pre-abandonment, Spring was best.

When only one image was available for both pre-abandonment and post- abandonment (“one and one” image date combinations with 9 possible image date combinations), conditional Kappa for "abandoned arable land" varied between 62 and 73% and for "abandoned managed grassland" between 52 and 70%. No image date combination yielded conditional Kappa values greater than 70% for both abandonment classes. Generally, for "abandoned arable land" conditional Kappa was at least 70% when any pre-abandonment image was combined with Spring for post-abandonment. For “abandoned managed grassland” Spring was best for pre-abandonment and either Spring or Fall for post-abandonment.

Out of the 49 possible image date combinations, only 13 were statistically significantly different when comparing maximum likelihood and SVM in their ability to map “abandoned arable land” and none were different when mapping “abandoned managed grassland” (Figure 1-4). Due to a higher share of arable land in the study region (84% of total agricultural land in 2000) it was more important to detect accurately “abandoned arable land” and thus we suggest that SVM should be considered a better classifier than maximum likelihood to map agricultural land abandonment.

Altogether, our results indicated widespread agricultural land abandonment in the study area. The best classification (SVM based classification for 6 image dates composites) revealed that by

2000 22% of the agricultural land in 1989 was abandoned (273,500 ha within the area of our Landsat footprint) (27% abandoned in Lithuania (222,000 ha), and 13% in Belarus (51,500 Ha)). In Lithuania 18% of the 1989 arable land (153,000 ha) and 8% of the 1989 managed grassland (69,000 ha) was abandoned by 2000; in Belarus the rates were 8% (33,500 ha) and 5% (18,000 ha) respectively.

Discussion

Our methodological analysis showed that abandoned agriculture could be mapped from Landsat satellite imagery with accuracies exceeding 80%. However, such high classification accuracies required multi-date imagery, ideally three images (Spring, Summer, and Fall) each for a single year in both the pre- and the post-abandonment period. When fewer images were analyzed, thus reflecting the conditions for most of Landsat footprints for which optimally timed images do not exist (Figure 1-1, Figure 1-6), then classification accuracy dropped markedly, and was as low as 54% of conditional Kappa for “abandoned arable land” and 50% for “abandoned managed grassland”. However, some suboptimal image date combinations can map abandoned agricultural lands accurately (Figure 1-4).

In addition to the number of images, we found that the specific image dates mattered greatly, but the best dates differed for the two abandonment classes. Generally, “abandoned arable land” was more accurately mapped than “abandoned managed grassland”. For “abandoned arable land” it was crucial to have at least one image date from any season for pre-abandonment and at least a Spring image for post-abandonment, allowing to reach conditional Kappa of 70%. In general, there was no difference among the dates of the pre-abandonment image; all pre-abandonment images captured agriculture pretty well. The Spring image enabled distinguishing new vegetative growth of winter crops and managed grasses, senescent vegetation on fallow fields, and exposed soil after tilling for summer crops, which represented 66% of the total crop area in 2000. The Summer image allowed to separate agricultural land associated with rigorous crops, matured crops, exposed tilled soil, grasslands after the first campaign of hay cutting, actively used managed grasslands for livestock grazing and non-managed grassland encroached by shrubs. The Fall image captured exposed soil after harvesting summer crops, or tilled soil before sowing winter crops from actively managed grasslands and from abandoned agricultural lands with abundant senescent herbaceous vegetation and shrubs. However, if more images were available, then allocation of more post-abandonment images was most beneficial in order to reach higher accuracies of “abandoned arable land” with inclusion Spring or/ and Summer images as post-abandonment image dates.

The accurate classification of “abandoned managed grassland” required allocation of as many images as possible for pre-abandonment, with a preferable inclusion of a Spring image for pre-abandonment. The inclusion of as many pre-abandonment images as possible was particularly important for accurate mapping of “abandoned managed grassland. We were surprised that the Summer image was of relatively minor importance, especially for the detection of “abandoned managed grassland”. This might be due to similar reflectance of managed and non managed grasslands in the summer, especially if hay cutting did not occur before image acquisition. Fall and Spring images captured unmanaged grasses with accumulated non-photosynthetic vegetation at the end of the growing season in Fall, or the delay of green-up for the same reasons in Spring. Thus, it was better to allocate either a Spring and Fall combination or Spring or Fall image in combination with a Summer image for pre-abandonment.

To have roughly equal accuracies for both abandonment classes (e.g., conditional Kappa for both abandonment classes equaling to at least 70%), it was better to have Spring and Fall images for pre-abandonment and Spring or Fall images for post-abandonment. When only one image was available for pre-abandonment, it was best to have a Fall for pre-abandonment and both Spring and Fall images for post-abandonment.

"Abandoned managed grassland" was more difficult to map accurately than "abandoned arable land" for several reasons. Managed grasslands typically occur in this region where the soils are marginal (e.g., highly acidic soils, dried peatlands, and fens and mires converted for managed grasslands). Succession is slower on these marginal sites, and that means that there will be less shrub encroachment than on previously fertilized and meliorated arable land that became abandoned. Succession may also be slower on former grasslands compared to arable land, because a dense sod and senescent vegetative material may inhibit the establishment of woody vegetation.

From a remote sensing perspective, the change in the reflectance that occurs when arable land is abandoned is very marked, and that makes it easier to classify than the more gradual change from managed to abandoned grasslands. Our accuracy assessment showed that the classes "managed grassland", "abandoned managed grassland" and "shrubs" were commonly misclassified even with optimal image dates (Table 1-5A), and errors increased when key dates were missed (Table 1-5B, C). Since hay cutting occurs in our study area only once or twice a year, it was crucial to capture areas right after they were cut. If no satellite image was available for that time, then it became very difficult to assess if grassland management actually took place in a given year.

Comparing the performance of SVM and maximum likelihood classifiers, the SVM performed particularly well when the change in the reflectance was drastic ("abandoned arable land"). SVM also was better at classifying image dates combinations containing summer images, and SVM performed better than maximum likelihood at classifying "abandoned arable land" in few cases when image dates did not match (e.g., Spring image for pre-abandonment and Summer image for post-abandonment or Spring and Fall instead of Spring and Spring). Moreover, SVM performed better than maximum likelihood at classifying image-date combinations when more image dates were available (e.g., "two and two", "two and three", "three and three" and "three and three" image dates combinations). However, SVM did not perform as well as maximum likelihood classifier to detect "abandoned managed grassland". Parametric approaches may be more suited to map "abandoned managed grassland" especially when the number of distinctive support vectors is limited and complex support vectors collection is required for the successful training of the SVM (Foody & Mathur, 2006). When we examined the support vectors for the 49 combinations in detail, we found that the number of support vectors increased by a factor of two to three when we mapped less separable classes such as "abandoned managed grassland" or when image dates were suboptimal. Thus, while we considered SVM a preferable classification method for agricultural land abandonment, the overall classification performance of SVM, specific classes mapping (e.g., mapping "abandoned managed grassland"), and longer computation time (classification time ranged up to several days for all six images), still leaves room for parametric based classifiers and other non-parametric classifiers (e.g., decision trees). In our study, maximum likelihood classifier was a reasonably accurate, and comparatively fast classifier.

In our study we tested the effects of image dates acquisition on classification accuracy for one available footprint in temperate Eastern Europe. While ideally it might be interesting to compare the stability of the acquired results elsewhere , we were limited to conduct such rigorous analysis for another Landsat TM/ETM+ footprint in Eastern Europe. However, as this study was designed to facilitate mapping agricultural land abandonment for wider area, acquired results significantly helped us to allocate important image dates and classify accurately agricultural land abandonment for 8 Landsat TM/ETM+ footprints in temperate Eastern Europe (Prishchepov et al., *in preparation*).

Finally, our results indicated that classification algorithms could not overcome limitations imposed by limited image availability. This is unfortunate, because there is not a single footprint among the 995 Landsat footprints in Eastern Europe for which there are three cloud-free images in a single year available for both pre-abandonment (1988-1990) and post-abandonment (1998-2000) (Figure 1-7A). Furthermore, only two footprints have “two and three” and “three and two” images, five tiles “two and two” images, three tiles “one and three” and “three and one” images available. Our results highlight the importance of multi-seasonal imagery for accurate classifications of agricultural land abandonment, but the necessary multi-seasonal imagery is rarely available.

Image availability improved when we included images with up to 5% cloud contamination and relaxed image date constraints to allow image dates from different years (e.g., Spring from 1988, Summer from 1989 and Fall from 2000) (Figure 1-7B). In this case, 35 Landsat tiles had all three image dates for both pre- and post-abandonment, and 75 tiles provided “two and three” and “three and two” image dates combinations. However, imagery from multiple years will result in reduced classification accuracy since land cover change may occur among years.

In other words, even after relaxing the temporal and cloud constraints, results showed that few Landsat footprints have all three images for pre- and post- abandonment available in the Landsat archives. Even with the freeing of the USGS Landsat archives, the actual available image dates suited for change detection are limited. Thus a better understanding of the effects of sub-optimal image dates on change detection accuracies, as provided in our study, is important to provide realistic expectations of the quality of land abandonment maps that can be obtained from satellite imagery for large areas.

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Literature

Angelstam, P., Boresjo-Bronge, L., Mikusinski, G., Sporrong, U., & Wastfelt, A. (2003). Assessing village authenticity with satellite images: A method to identify intact cultural landscapes in Europe. *Ambio, 32*(8), 594-604.

Baldock D, Beaufoy G, Brouwer F., & Godeschalk F. (1996). *Farming at the margins: abandonment or redeployment of agricultural land in Europe*. Institute for European Environmental Policy (IEEP) and Agricultural Economics Research Institute (LEI-DLO). London, the Hague.

Belstat. (2002). *Regions of Belarus republic: Statistical compendium. (Regioni Respubliki Belarus. Statisticheskii Sbornik)*. Minsk, Belarus: Ministry of statistics and analysis of Belarus republic.

Benjamin, K., Bouchard, A., & Domon, G. (2007). Abandoned farmlands as components of rural landscapes: An analysis of perceptions and representations. *Landscape and Urban Planning, 83*(4), 228-244.

Benjamini, Y. & Yekutieli, D. (2001). The control of the false discovery rate in multiple testing under dependency. *Annals of Statistics 29* (4), 1165–1188.

Bujauskas, A., & Paršeliūnas, E. (2006). Analysis of the most suitable period for the mapping of the land-tenures from the satellite multispectral images (Laikotarpio tinkamumo kartografuoti zemes naudmenas pagal palydovines daugiaspektres nuotraukas analize). *Geodezija ir kartografija, Vilnius, Technica 32*(2), 46-50.

Chang, C. C., & Lin., C.-J. (2001). LIBSVM: a library for support vector machines.

Civco, D. (1989). Knowledge-based land use and land cover mapping. *1989 ASPRS/ACSM Annual Convention, Baltimore, MD; United States; 2-7 Apr. 1989,* 276-291.

Congalton, R. G. (1988). A Comparison of Sampling Schemes used in Generating Error Matrices for Assessing the Accuracy of Maps Generated from Remotely Sensed Data. *Photogrammetric Engineering and Remote Sensing, 54*(5), 593-600.

Coppin, P., Jonckheere, I., Nackaerts, K., Muys, B., & Lambin, E. (2004). Digital change detection methods in ecosystem monitoring: a review. *International Journal of Remote Sensing, 25*(9), 1565-1596.

Crist, E. P., & Kauth, R. J. (1986). The Tasseled Cap de-mystified. *Photogrammetric Engineering and Remote Sensing, 52*(1), 81-86.

Crist, E. P., Laurin, R., & Cicone, R. C. (1986). Vegetation and soils information contained in transformed Thematic Mapper data. 1465-70.

de Beurs,K. M., & Henebry,G. M. (2004). Land surface phenology, climatic variation, and institutional change: Analyzing agricultural land cover change in Kazakhstan. *Remote Sensing of Environment, 89*(4), 497-509.

DLG. (2004). *Land Abandonment and Biodiversity in Relation to the 1st and 2nd Pillars of the EU's Common Agricultural Policy, Outcome of an International Seminar in Sigulda, Latvia, 7-8 October, 2004.* DLG, Utrecht.

Dubinin, M., P. Potapov, A. Luschekina, & V. C. Radeloff. (2009). Reconstructing long time series of burned areas in arid grasslands of Southern Russia. *Remote Sensing of Environment* (in review).

Edwards, T. C., Moisen, G. G., & Cutler, D. R. (1998). Assessing map accuracy in a remotely sensed, ecoregion-scale cover map. *Remote Sensing of Environment, 63*(1), 73-83.

EEA. (2006). The thematic accuracy of Corine land cover 2000 - Assessment using LUCAS. *7*1-90.

Folch, R. (2000). Encyclopedia of the Biosphere: Deciduous forests. *7*438.

Foody, G. M. (2004). Thematic map comparison: Evaluating the statistical significance of differences in classification accuracy. *Photogrammetric Engineering and Remote Sensing, 70*(5), 627-633.

Foody, G. M., & Mathur, A. (2004). A relative evaluation of multiclass image classification by support vector machines. *IEEE Transactions on Geoscience and Remote Sensing, 42*(6), 1335-1343.

Foody, G. M., & Mathur, A. (2006). The use of small training sets containing mixed pixels for accurate hard image classification: Training on mixed spectral responses for classification by a SVM. *Remote Sensing of Environment. 103*(2), 179-183

Gammadesign (2010), GS+ GeoStatistics for the Environmental Sciences. GS+ User's Guide Version 9. (last accessed August 8th, 2010, http://www.gammadesign.com/files/GS+%20User's%20Guide.pdf).

Grodnostat. (2001). *Grodno region in numbers: Statistical compendium. (Grodnenskaja oblast v cifrah. Statisticheskii sbornik).* Minsk, Belarus: Ministry of statistics and analysis of Belarus republic.

Guerschman, J. P., Paruelo, J. M., Di Bella, C., Giallorenzi, M. C., & Pacin, F. (2003). Land cover classification in the Argentine Pampas using multi-temporal Landsat TM data. *International Journal of Remote Sensing, 24*(17), 3381-3402.

Hart,J. F. (1968). Loss and abandonment of cleared farm land in the Eastern United States. *Annals of the Association of American Geographers, 58*(3), 417-440.

Huang, C., Davis, L. S., & Townshend, J. R. G. (2002). An assessment of support vector machines for land cover classification. *International Journal of Remote Sensing, 23*(4), 725-749.

Huang, C., Wylie, B., Yang, L., Homer, C., & Zylstra, G. (2002). Derivation of a tasseled cap transformation based on Landsat 7 at-satellite reflectance. *International Journal of Remote Sensing, 23*(8), 1741-1748.

IEEP. (2006). An evaluation of the less favoured area measure in the 25 member states of the European Union.

IIASA. (2000). *Global Agro-Ecological Zones (Global-AEZ) CD-ROM.* FAO/IIASA (last accessed December 7th, 2009, http://www.iiasa.ac.at/Research/LUC/GAEZ/index.htm).

Kalensky, Z. (1974). ERTS thematic map from multidate digital images. *Proceedings of the 1974 Symposium on Remote Sensing of 1974 Symposium on Remote Sensing and Photo Interpretation,* Canadian Institute of Surveying, 7-11 October (Banff, Alberta), (7),767-785

Kashtanov A. N. (1983). *Natural-agriculture zoning and utilizing of land resources of USSR (Prirodno-Selskohozjaistvennoe raionirovanie i ispolzovanije zemelnogo resursa SSSR).* Moscow: Kolos.

Kuemmerle, T., Radeloff, V. C., Perzanowski, K., & Hostert, P. (2006). Cross-border comparison of land cover and landscape pattern in Eastern Europe using a hybrid classification technique. *Remote Sensing of Environment, 103*(4), 449-464.

Kuemmerle, T., Hostert, P., Radeloff, V. C., van der Linden, S., Perzanowski, K., & Kruhlov, I. (2008). Cross-border comparison of post-socialist farmland abandonment in the Carpathians. *Ecosystems, 11*(4), 614-628.

Leica Geosystems (2006). *Imagine AutoSync™ White Paper.* Norcross, USA: Leica geosystems geospatial imaging.

Lerman, Z., Csaki, C., & Feder, G. (2004). *Agriculture in transition: land policies and evolving farm structures in post-Soviet countries.* Lanham, Boulder, New York, Toronto, Oxford: Lexington Books.

Lithstat. (2001). *Lithuanian Counties in 2000 (Lietuvos apskritys 2000).* Vilnius: Department of Statistics to the Government of the Republic of Lithuania

Lloret, F., Calvo, E., Pons, X., & Diaz-Delgado, R. (2002). Wildfires and landscape patterns in the Eastern Iberian peninsula. *Landscape Ecology, 17*(8), 745-759.

Lofgren, S., Gustafson, A., Steineck, S., & Stahlnacke, P. (1999). Agricultural development and nutrient flows in the Baltic states and Sweden after 1988. *Ambio, 28*(4), 320-327.

Melgani,F., & Bruzzone,L. (2004). Classification of hyperspectral remote sensing images with support vector machines. *IEEE Transactions on Geoscience and Remote Sensing, 42*(8), 1778-1790.

Meyfroidt, P. & Lambin, E. F. (2008). The causes of the reforestation in Vietnam. *Land Use Policy*, *25*(2), 182-197.

Oetter, D. R., Cohen, W. B., Berterretche, M., Maiersperger, T. K., & Kennedy, R. E. (2001). Land cover mapping in an agricultural setting using multiseasonal Thematic Mapper data. *Remote Sensing of Environment*, *76*(2), 139-155.

Pax-Lenney, M., & Woodcock, C. E. (1997). Monitoring agricultural lands in Egypt with multitemporal Landsat TM imagery: How many images are needed? *Remote Sensing of Environment, 59*(3), 522-529.

Perz, S. G., & Skole, D. L. (2003). Social determinants of secondary forests in the Brazilian Amazon. *Social science research, 32*(1), 25-60.

Peterson, U., & 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.

Rabe, A., van der Linden, S., Hostert, P. (2009). *ImageSVM, Version 2.0.* Software available at www.hu-geomatics.de

Ratanova, M. P. (2004). *Economic and social geography of the near abroad (Ekonomicheskaja i sotsialnaja geograhija stran blizhnego zarubezhja: Posobije dlja vuzov)*. Moscow: Drofa.

Sakovich, V. S. (2008). *Agriculture in Belarus between 1980-2007: tendency of the development (Selskoe Hozjaistvo v Respublike Belarus v 1980-2007 g.: tendencii razvitija)*. Minsk: Belorusskaja nauka.

Sileika, A. S., Stalnacke, P., Kutra, S., Gaigalis, K., & Berankiene, L. (2006). Temporal and spatial variation of nutrient levels in the Nemunas River (Lithuania and Belarus). *Environmental monitoring and assessment, 122*(1-3), 335-354.

Smelanksy, I. (2003). *Biodiversity of agricultural lands in Russia: current state and trends.* IUCN - The World Conservation Union Report. Moscow: IUCN - The World Conservation Union.

Smith, J., Smith, P., Wattenbach, M., Gottschalk, P., Romanenkov, V. A., Shevtsova, L. K., Sirotenko, O. D., Rukhovich,D. I., Koroleva,P. V., Romanenko,I. A., & Lisovoi,N. V. (2007). Projected changes in the organic carbon stocks of cropland mineral soils of European Russia and the Ukraine, 1990-2070. *Global Change Biology, 13*(2), 342-356.

Song, C., Woodcock, C. E., Seto, K. C., Pax-Lenney,, & Macomber, S. A. (2001). Classification and change detection using Landsat TM data: When and how to correct atmospheric effects? *Remote Sensing of Environment, 75*(2), 230-244.

Stuikys, V., & Ladyga, A. (1995). *Agriculture of Lithuania. (Lietuvos zemes ukis).* (in English and in Lithuanian) Valstybinis leidybos centras, Vilnius 176 p.

Van Sickle, J., Baker, J., Herlihy, A., Bayley, P., Gregory, S., Haggerty, P., Ashkenas, L., & Li, J. (2004). Projecting the biological condition of streams under alternative scenarios of human land use. *Ecological Applications, 14*(2), 368-380.

Vitousek, P. M., Mooney, H. A., Lubchenco, J., & Melillo, J. M. (1997). Human domination of Earth's ecosystems. *Science, 277*(5325), 494-499.

Voichard, N., Ciais, P. & Wolf,A. (2009). Soil Carbon sequestration or biofuel production: New land-use opportunities for mitigating climate over abandoned soviet farmlands. *Environmental Science & Technology*, *43*(22), 8678-8683

Wagner, D. G. (1993). Comparison of multitemporal and unitemporal classification accuracy using Lansat TM imagery. *1993 ACSM/ASPRS Annual Convention & Exposition: technical papers, New Orleans /LA,* 416-425.

Wickham, J. D., Stehman, S. V., Smith, J. H., & Yang, L. (2004). Thematic accuracy of the 1992 National Land-Cover Data for the western United States. *Remote Sensing of Environment, 91*(3-4), 452-468.

Wolter, P. T., Mladenoff, D. J., Host, G. E., & Crow,T. R. (1995). Improved forest classification in the northern lake-states using multitemporal LANDSAT imagery. *Photogrammetric Engineering and Remote Sensing, 61*(9), 1129-1143.

Yeloff, D., & van Geel, B. (2007). Abandonment of farmland and vegetation succession following the Eurasian plague pandemic of AD 1347-52. *Journal of Biogeography*, *34*(4), 575-582.

Tables

Table 1-1: Class catalog, training data for the SVM and maximum likelihood classifiers, and validation pixels.

Class Name	Acronym	Number of validation pixels	Number of training pixels used for maximum likelihood classifier	Number of training pixels used for SVM
Forest	F	380	7311	731
Clearcut	Cl	92	1527	229
Regrowth	Rg	42	660	198
Arable land in pre- and post-abandonment	Ar	154	10494	840
Transition from arable land to managed grassland	ArMGr	70	1637	327
Abandoned arable land	ArAb	102	1241	434
Managed grassland in pre- and post-abandonment	MGr	133	893	402
Abandoned managed grassland	MGrAb	42	1051	399
Transition from managed grassland to arable land	MGrAr	44	1656	331
Non-managed grassland and shrubs in pre-	NGrShr	32	1145	401

and post-abandonment				
Wetland	Wt	33	3969	397
Impervious surface, bare soil, open peat quarries, water	Other	54	15289	438

Table 1-2: High resolution satellite images used to support ground based training and reference data collection.

ID	Year	Month	Day	Digital Globe Image ID	Cloud Cover (%)
1	2002	9	25	101001000147BF01	0
2	2002	7	28	1010010000E18301	1
3	2002	7	10	1010010000C2DE02	3
4	2002	7	10	1010010000C2DE03	9
5	2003	5	25	1010010001ED8B01	4
6	2003	6	4	1010010001F4A302	0
7	2003	9	23	10100100024FCB01	0
8	2004	8	4	1010010003251301	4
9	2004	7	30	1010010003232C02	4
10	2004	7	30	1010010003232C03	1
11	2004	7	30	1010010003232C03	1
12	2004	7	30	1010010003232C20	0
13	2004	9	7	10100100033BA501	8
14	2005	7	10	10100100045C8B01	2
15	2005	7	10	10100100045C8B02	7
16	2005	7	15	10100100045F6701	7
17	2006	6	30	10100100050E3D0E	0
18	2007	4	27	1010010005986700	8

19	2007	10	14	101010010007434E	0
20	2007	4	17	1010010005942903	1
21	2007	4	17	1010010005942904	0
22	2007	4	17	1010010005942905	0

Table 1-3: Soil types distribution inside and outside Quickbird and IKONOS footprints.

Class	Inside high resolution footprints (%)	Outside high-resolution footprints (%)
Histosols	6	10
Podzoluvisols	10	7
Luvisols	28	44
Arenosols	56	38

Table 1-4: LULCC classes within and outside Quickbird and IKONOS images according to the best land cover classification (6 images, SVM classifier)

	Histosols		Podzoluvisols		Luvisols		Arenosols	
Class	*Inside high resolution images (%)*	*Outside high-resolution images (%)*	*Inside high resolution images (%)*	*Outside high-resolution images (%)*	*Inside high resolution images (%)*	*Outside high-resolution images (%)*	*Inside high resolution images (%)*	*Outside high-resolution images (%)*
F	28	24	31	37	26	24	49	47
Cl	3	3	3	3	4	5	5	6
Rg	5	8	5	5	5	3	6	5
Ar	20	23	16	16	15	15	8	8
ArMGr	6	5	7	6	10	12	4	4
ArAb	6	6	7	5	9	7	6	6
MGr	6	4	6	4	9	10	4	3
MGrAb	3	1	3	2	4	3	2	2
MGrAr	4	5	4	4	6	7	2	2
NGrShr	12	13	12	13	7	6	6	5
Wt	3	3	3	4	5	7	4	7
Other	4	3	2	2	1	1	5	4

Table 1-5: Confusion matrixes of A) the best overall classification, B) the worst case for “Abandoned arable land”, and C) the worst case for “Abandoned managed grassland” using SVM

1-5A: Best overall classification using SVM and Spring, Summer and Fall images for both pre- and post-abandonment.

	Reference													User’s Accuracy
Classification	F	Cl	Rg	Ar	ArMGr	ArAb	MGr	MGrAb	MGrAr	NGrShr	Other	Wt	Total	(%)
F	371	10	2					1			1	1	386	96.1
Cl		78									1		79	98.7
Rg	5	3	39							2	2	2	53	73.6
Ar	2			136	1	3			3				145	93.8
ArMGr		1		3	63	2	1			1			71	88.7
ArAb				6	2	93							101	92.1
MGr					1		110	2	2				115	95.7
MGrAb		0				2	10	31	1	4			48	64.6
MGrAr				7			2		37				46	80.4

NGrShr	1			1	3	2	10	8		25			50	50.0
Other				1					1		50		52	96.2
Wt	1		1									30	32	93.8
Total	380	92	42	154	70	102	133	42	44	32	54	33	1178	
Producer's Accuracy (%)	97.6	84.8	92.9	88.3	90.0	91.2	82.7	73.8	84.1	78.1	92.6	90.9		90.2

1-5B: Worst case for “Abandoned arable land” using SVM, pre-abandonment Spring and Fall images and one Summer post-abandonment image.

	Reference													A User’s Accuracy
Classification	F	Cl	Rg	Ar	ArMGr	ArAb	MGr	MGrAb	MGrAr	NGrShr	Other	Wt	Total	(%)
F	338	7	2					1				1	349	96.8
Cl	29	83	1									1	114	72.8
Rg	7	1	37	1						1		3	50	74.0
Ar	2			125	14	30	1	1	1		2	1	177	70.6
ArMGr		1		12	40	12	6			2	1		74	54.1
ArAb				6	8	58		2					74	78.4
MGr				1	2		75	4	3				85	88.2
MGrAb					1		30	26	3	4			64	40.6
MGrAr				8			13	4	31				56	55.4
NGrShr	1		1		3	2	8	4	3	25			47	53.2

Other	1			1	2				3		50		57	87.7
Wt	2		1								1	27	31	87.1
Total	380	92	42	154	70	102	133	42	44	32	54	33	1178	
Producer's Accuracy (%)	88.9	90.2	88.1	81.2	57.1	56.9	56.4	61.9	70.5	78.1	92.6	81.8		77.7

1-5C: Worst case for “Abandoned managed grassland” using SVM, Spring and Summer pre-abandonment images and Summer post-abandonment image.

	Reference													User’s Accuracy
Classification	F	Cl	Rg	Ar	ArMGr	ArAb	MGr	MGrAb	MGrAr	NGrShr	Other	Wt	Total	(%)
F	357	6	1					1				1	366	97.5
Cl	12	85	2									2	101	84.2
Rg	4	1	33								2	1	41	80.5
Ar	2			131	14	18	14	2	5	2	2	1	191	68.6
ArMGr				5	39	9	3	3		4	1		64	60.9
ArAb				11	10	72	1						94	76.6
MGr					2		76	6	1				85	89.4
MGrAb					1	1	20	22	5	3			52	42.3
MGrAr				2		1	8		30	1			42	71.4
NGrShr	2		6	1	2	1	10	8		22		1	53	41.5

Other	1			4	2		1		3		48		59	81.4
Wt	2										1	27	30	90.0
Total	380	92	42	154	70	102	133	42	44	32	54	33	1178	
Producer's Accuracy (%)	93.9	92.4	78.6	85.1	55.7	70.6	57.1	52.4	68.2	68.8	88.9	81.8		80.0

Figure Captions

Figure 1-1. Cloud free image dates availability for spring, summer and fall across Eastern Europe. A: Landsat footprints for which three images are available in one of three pre-abandonment years (1988-1990). B: Landsat footprints for which three images are available in one of three post-abandonment years (1998-2000).

Figure 1-2: A: Location of the study area in Eastern Europe. B: Footprints of high-resolution satellite images available in Google Earth. C: Reference points sample using the three step-stratification approach.

Figure 1-3: Crop planting and harvesting schedule in the study area and corresponding Landsat image date selection. Adopted from Bujauskas & Paršeliūnas (2006).

Figure 1-4: Accuracy of “Abandoned arable land” and “Abandoned managed grassland” detection for all 49 possible image combinations using SVM as the classification algorithm.

Figure 1-5: User’s accuracy of “Abandoned arable land” and “Abandoned managed grassland” detection for all 49 possible image combinations using SVM as the classification algorithm.

Figure 1-6: Producer’s accuracy of “Abandoned arable land” and “Abandoned managed grassland” detection for all 49 possible image combinations using SVM as the classification algorithm.

Figure 1-7: A: Image date combinations available with a 0% cloud constraints when selecting a spring, summer and fall image during three pre-abandonment years (1988-1990) and during three post-abandonment years (1998-2000). B: Image date combinations available with a 5% cloud constraints when selecting a spring, summer and fall image during three pre-abandonment years (1988-1990) and during three post-abandonment years (1998-2000).

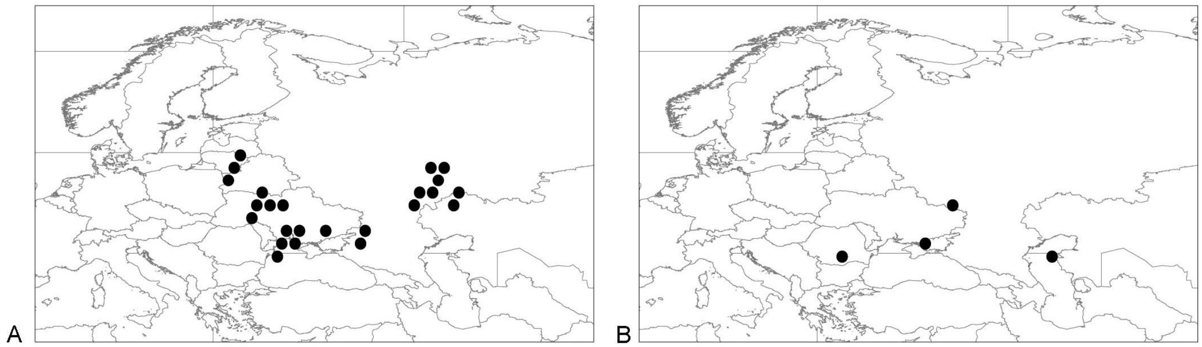


Figure 1-1.

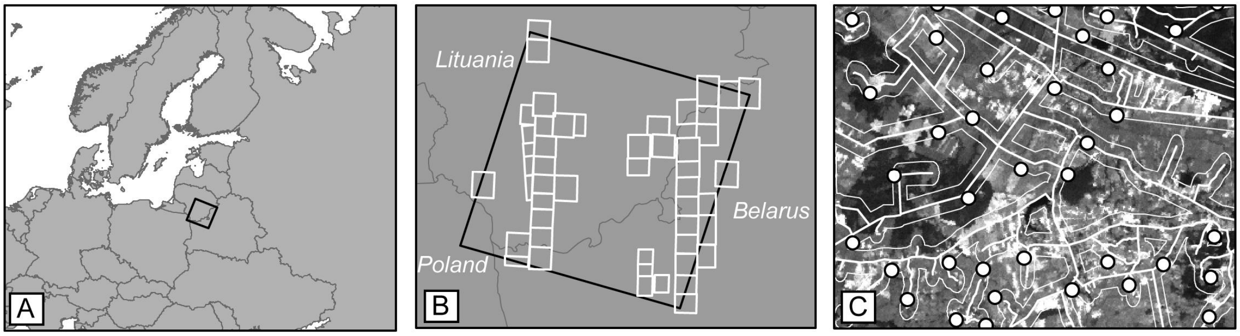


Figure 1-2.

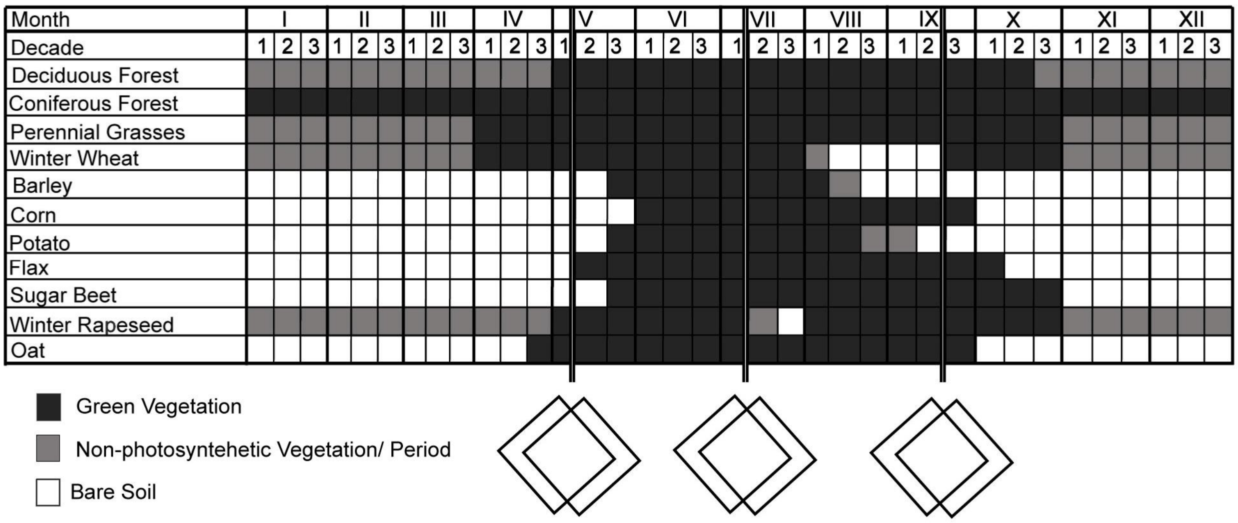
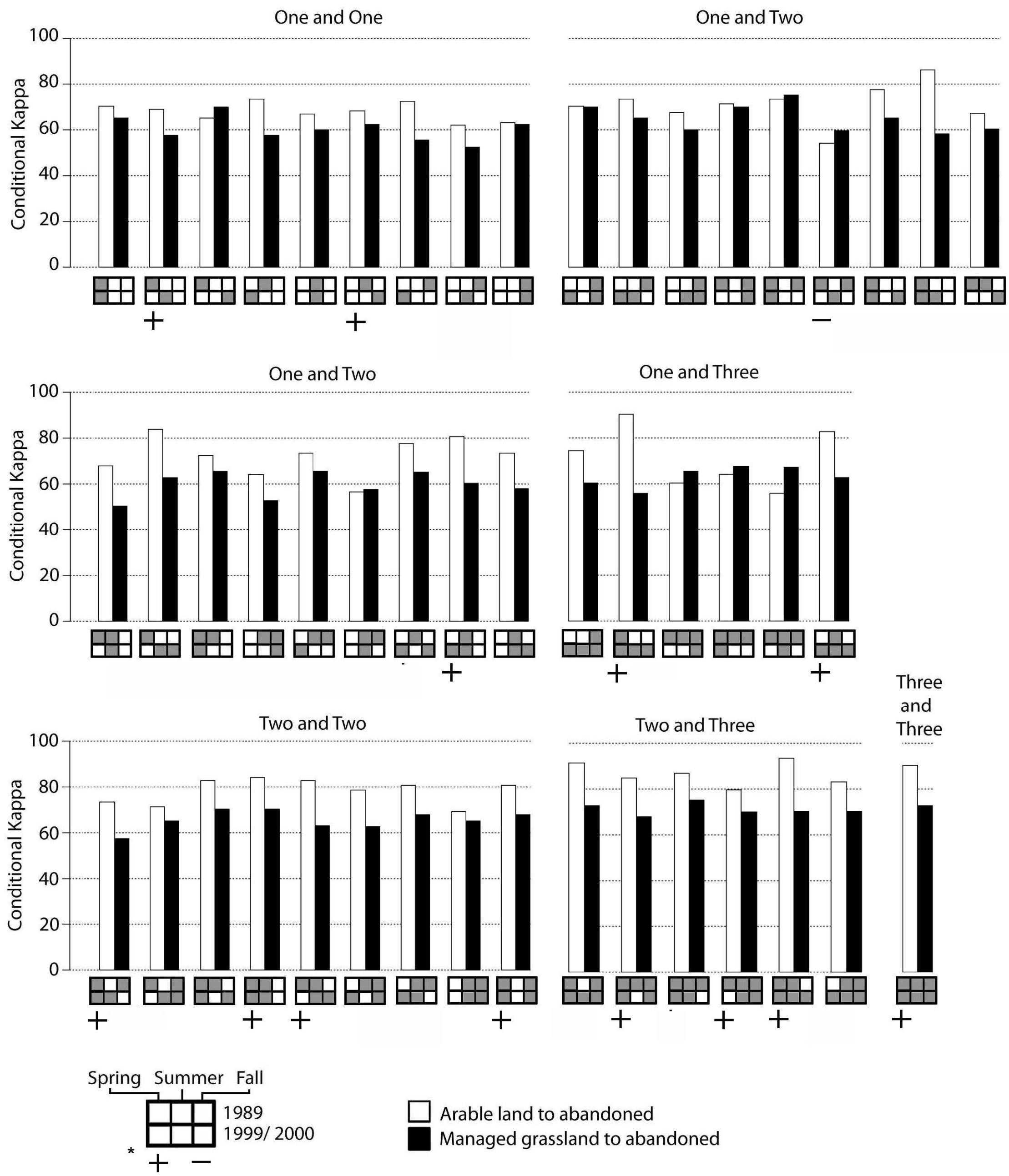

Month
I
II
III
IV
V
VI
VII
VIII
IX
X
XI
XII
Decade
1 2 3 1 2 3 1 2 3 1 2 3 1 2 3 1 2 3 1 2 3 1 2 3 1 2 3 1 2 3 1 2 3 1 2 3
Deciduous Forest
Coniferous Forest
Perennial Grasses
Winter Wheat
Barley
Corn
Potato
Flax
Sugar Beet
Winter Rapeseed
Oat
Green Vegetation
Non-photosyntehetic Vegetation/ Period
Bare Soil

Figure 1-3.



* Statistical test for abandoned arable land (left side),for abandoned managed grassland (right side).
"+"-indicates positive statistical difference between SVMs and maximum likelihood classifier.
"-" -indicates negative statistical difference between SVMs and maximum likelihood classifier.
Empty space indicates no statistical difference between SVMs and maximum likelihood classifier.

Figure 1-4.

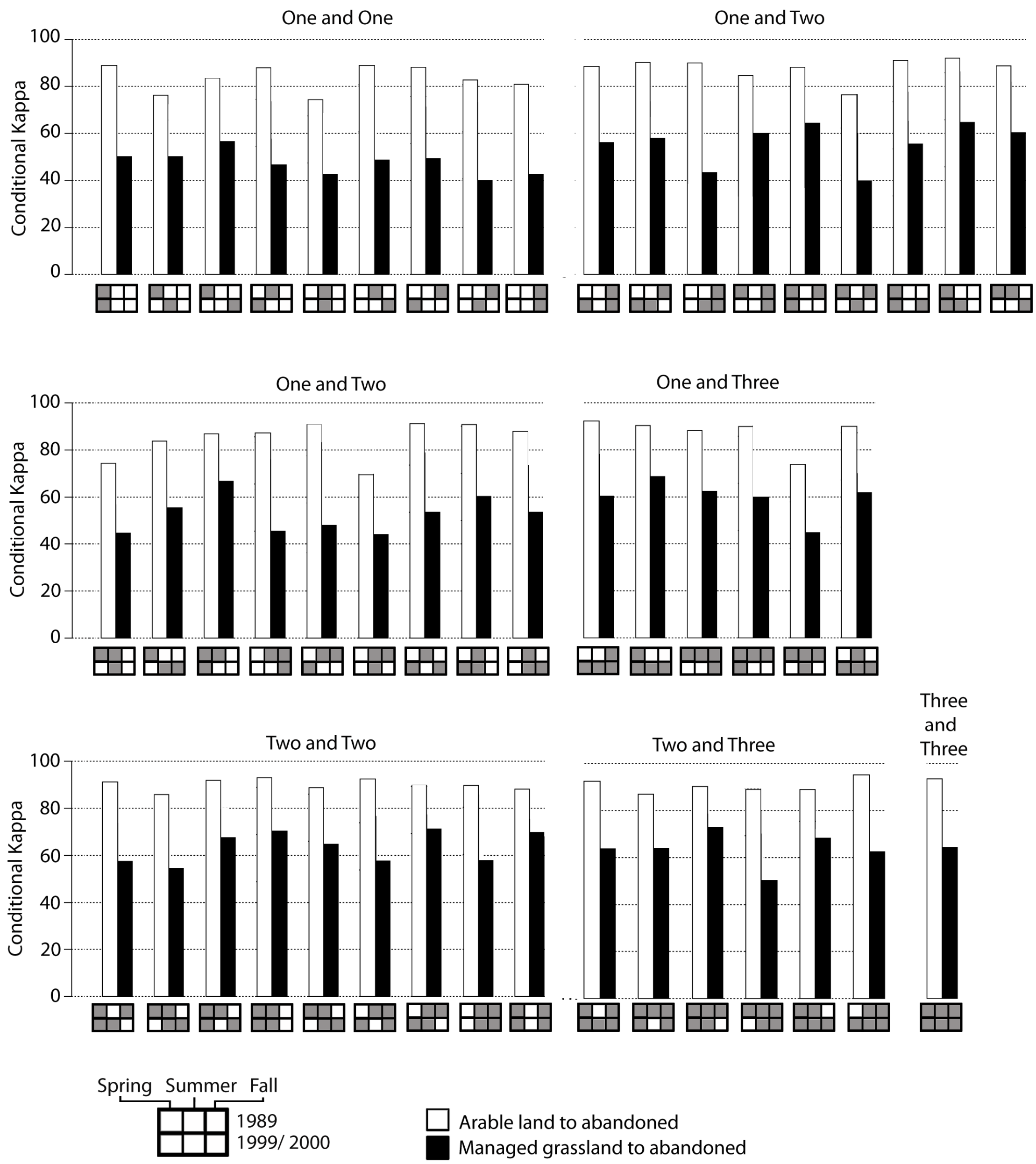
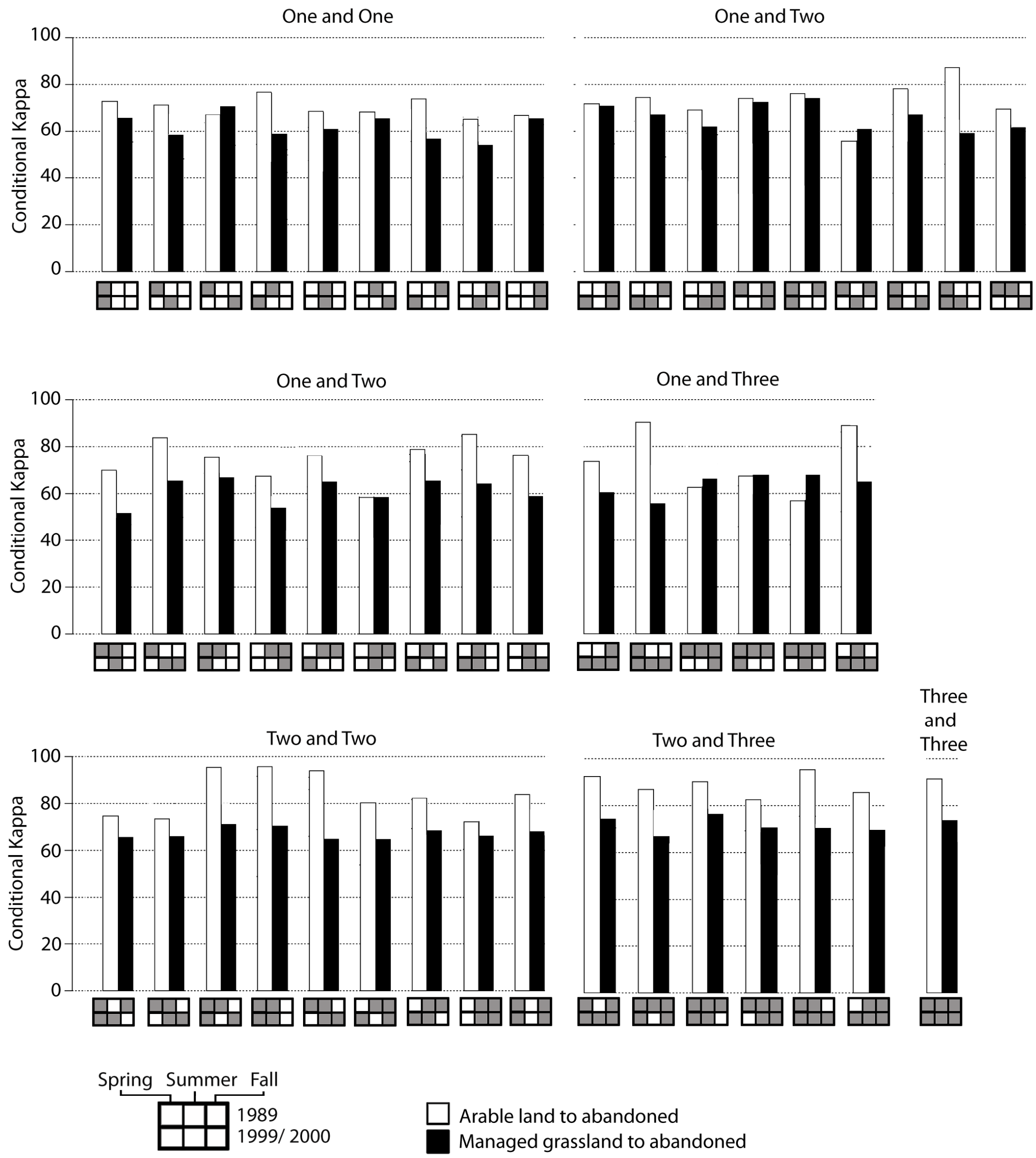

One and One
One and Two
One and Two
One and Three
Two and Two
Two and Three
Three and Three
Conditional Kappa
100
80
60
40
20
0
Spring
Summer
Fall
1989
1999/ 2000
Arable land to abandoned
Managed grassland to abandoned

Figure 1-5.


One and One
One and Two
Conditional Kappa
100
80
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40
20
0
One and Two
One and Three
Two and Two
Two and Three
Three and Three
Spring
Summer
Fall
1989
1999/ 2000
Arable land to abandoned
Managed grassland to abandoned

Figure 1-6.

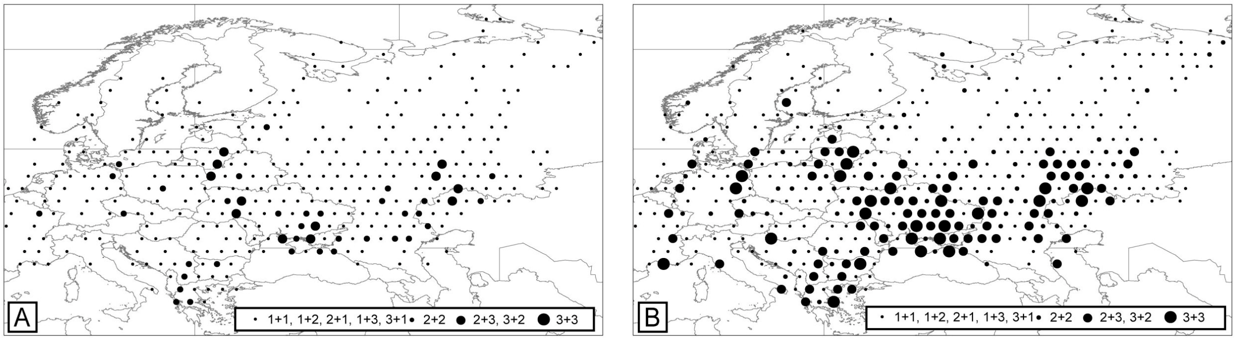

Figure 1-7.

IMPACT OF MASSIVE SOCIO-ECONOMIC CHANGES ON LAND-USE: AGRICULTURAL LAND ABANDONMENT DURING THE SOCIO-ECONOMIC TRANSITION IN POST-SOVIET EASTERN EUROPE.

Co-authors: Volker C. Radeloff, Matthias Baumann, and Tobias Kuemmerle

Intended for: Global Environmental Change

Abstract

Rapid socio-economic and institutional changes may accelerate rates of land use and land cover change (LULCC). The collapse of socialism and the transition from state-command to market-driven economies in Eastern Europe represented such a rapid socio-economic change, but the transition's impact on LULCC is not well understood. Previous studies suggest that agricultural land abandonment has been widespread in Eastern Europe, but abandonment rates can not be compared among countries because of different assessment methods, and varying environmental conditions. Our goal was compare agricultural land abandonment rates among former Soviet republics in Eastern Europe that had common starting point, but chose different transition approaches towards a market economy. We studied one agro-climatic zone stretching across four former USSR republics (Belarus, Latvia, Lithuania, and European Russia) and formerly socialist Poland. Using eight Landsat TM/ETM+ tiles with multi-date scenes centered on 1989 (the end of socialism) and 1999 (the first decade after the collapse of socialism) we classified land cover change using a support vector machine. Classifications showed marked differences in the rates of post-socialist agricultural land abandonment among countries and rates coincided with different “transition” approaches from state command to open market economies. Within classified Landsat TM/ETM+ footprints the highest statistically error adjusted abandonment rates were observed for Latvia (39% +/- 2.6% of all agriculture in 1989) followed by Russia (31%+/- 1.4%), Lithuania (28% +/- 1.4%), Poland (14% +/- 2%) and Belarus (12% +/- 1.2%). Cross-border areas exhibited striking differences among countries, likely connected to different transition approaches, such as in the Belarus-Russia cross-border area (10% +/- 1.2% and 47% +/- 2.2% abandonment respectively). Belarus, which largely retained governmental control of the agricultural sector, had the least agricultural abandonment, while some of the highest agricultural land abandonment rates were observed in neighboring Russia, which adapted a more liberal transition approach to a market economy. In addition to variation in agricultural land abandonment rates among countries, we observed large variation in abandonment rates within countries. For example in Russia, abandonment reached up to 46% +/- 2.2% at the provincial level (Smolensk province) and 60% at the district level (Ugranskij district, Smolensk province). In general, our results highlight that rapid socioeconomic changes had strong effects on LULCC, but abandonment rates and patterns were mediated by institutional settings and policies.

Keywords: farmland abandonment, institutional change, land use and land cover change, socio-economic transition, post-socialist, USSR.

Introduction

People, and the way they use land, are the most important drivers of global land cover change, affecting biodiversity, ecosystem services, and ultimately human well-being (Foley, et al., 2005, Millennium Ecosystem Assessment, 2005). Ultimately, all land use decisions are made by local actors (e.g., land owners), but their actions are constrained by broad-scale factors such as national policies and global markets (Geist, et al., 2006). Increasingly, evidence suggests that these broad-scale factors are at the heart of land-use and land-cover change trends (further, LULCC), and globalization is rapidly changing the way countries interact and impact one another (Eickhout, et al., 2007, Erb, et al., 2009). For example, drastic declines in the Russian domestic meat production since 1990 has resulted in a steep increase in meat imports from Brazil (Novozhenina, et al., 2009), contributing to the factors driving deforestation in Amazonia (Kaimowitz, et al., 2004). However, the effects of broad-scale factors on local decision-making, and thereby LULCC, are not well-understood, partly because high-level causes of land use change such as socio-economic and institutional transformation often occur gradually which makes it difficult to assess their relative importance.

When societies and institutions change rapidly, opportunities arise for better understanding drivers and processes of land use change. Possibly the most drastic socio-economic and political changes in the late 20th century was the dissolution of the Soviet Bloc and the region's shift from state-command to marked-driven economies (further, transition). Dismantling of the state-command system, introduction of free-market principles, and the withdrawal of governmental regulation and support caused fundamental changes in all sectors of economy, including agriculture (Lerman, et al., 2004). Official statistics and case study evidence suggest that the most common land use changes resulting from the transition were urban sprawl (Boentje & Blinnikov, 2007), increased logging (Achard, et al., 2006, Brukas, et al., 2009, Kuemmerle, et al., 2009, Urbel-Piirsalu & Backlund,

2009) and decreased logging (Pallot & Moran, 2000, Eikeland, et al., 2004, Bergen, et al., 2008), and agricultural land abandonment (Ioffe & Nefedova, 2004, Bergen, et al., 2008, Kuemmerle, et al., 2008, Kuemmerle, et al., 2009, Baumann, et al. 2010, Prishchepov, et al. 2010). Among these, the agricultural land abandonment was probably the most drastic and widespread land use changes, globally possibly one of the most extensive land-use changes between 1990 and 2000 (Ioffe, et al., 2004, Henebry, 2009). The exact rates and patterns of post-Soviet land abandonment, however, remain uncertain. The problem is that the official statistics are of varying quality and difficult to compare over time and among countries in Eastern Europe (Ioffe & Nefedova, 2004). Moreover, existing studies using remote sensing focused on fairly small regions with varying environmental conditions, and relied on different approaches and abandonment definitions.

While direct comparisons among different case studies are thus difficult, existing studies emphasize the diversity of rates and patterns o f abandonment, and suggest that different transition approaches to land-use change may explain these differences. For example, agricultural land abandonment rates differed between Poland, Slovakia and Ukraine (14%, 13% and 21% of abandoned agricultural land, respectively, Kuemmerle, et al., 2008) in the cross-border region of Eastern Carpathians, where each of these countries adopted different types of agricultural sector restructuring and land reforms. Further to the north, post-socialist agricultural abandonment rates differed in the cross-border region of Belarus and Lithuania (13% +- 1.2% and 27% +-1.4% of abandoned agricultural land, respectively, Prishchepov, et al., *in review*). Similarly, between 1990 and 2005, abandonment rates differed between Albania (28% of total agricultural land, Mueller & Munroe, 2008) and Romania (21% of total agricultural land, Muller, et al., 2008, Kuemmerle, et al., 2009), also two countries that selected different strategies of post-socialist land reform. Unfortunately, no comprehensive and consistent database of land-use change data exists for the post-socialist period, that would allow assessing the relative importance of different transition strategies and land reforms on agricultural land abandonment.

The lack of consistent land-use change data is unfortunate because Eastern Europe represents an ideal "natural experiment" (Diamond, 2001) to examine the effects of rapid socio-economic changes on LULCC, and to examine how different transition approaches from state-command to market driven economies may have modulated those effects. Eastern European countries chose very different transition approaches (Lerman, et al., 2004), yet environmental conditions are fairly similar across large areas. Ideally, an open-market system would be characterized by secured land ownership, accessibility of credits, existence and competitiveness of different forms of landownership (e.g., privatization, restitution, and access to land for both national and international land owners), and functioning land market as a mediator between successful and unsuccessful farmers (Deininger, 2003, Lerman, et al., 2004). These criteria would enable true competitiveness for agricultural land use (Capozza & Helsley, 1989, Irwin & Geoghegan, 2001), thus minimizing agricultural land abandonment due to redistribution of agricultural lands from less competitive to more competitive farmers. However, no country in Eastern Europe satisfied all these conditions (Lerman, et al., 2004). Thus, we expected minimal agricultural land abandonment where at least secured land markets or secured land titling was established prior or during the transition (e.g., in Poland, where the majority of the agricultural land was in private properties during the socialism) (Turnock, 1998), and where land owners retained a stronger connection to their former properties during socialism (e.g., in Czech Republic, Latvia, Lithuania, Romania, and Slovakia where collectivization of agricultural land was shorter than in other Soviet Bloc countries) (Macey, et al., 2004, Lerman, et al., 2004, Sakovich, 2008, Stuikys & Ladyga, 1995, Turnock, 1998,). Conversely, we expected higher rates of agricultural land abandonment, where land markets were lacking, where land tenure was unsecure (e.g., Albania, Belarus, Russia and Ukraine) (Lerman, et al., 2004, Macey, et al., 2004, Turnock, 1998, Sakovich, 2008) and where people were more disconnected from their former properties (e.g., Belarus, Russia, and Ukraine) (Macey, et al., 2004, Lerman, et al., 2004, Sakovich, 2008).

Utilizing the natural experiment that the collapse of socialism in Eastern Europe presents, our major goal was to assess differences in rates and patterns of land-use change among and within Eastern European countries with similar environmental conditions (e.g., precipitation, days with temperatures >10°C, soil types). Focusing on agricultural land abandonment we aimed at elucidating the modulating effects of different transition approaches on land use change patterns. Our specific objectives were to:

1) identify a uniform agro-climatic region stretching across several countries in Eastern Europe, which had a common starting point (e.g., similar agro-climatic and socio-economic conditions before the collapse of socialism), but chose different transition approaches;

2) map agricultural land abandonment from 1989 to 1999 via classifying multi-temporal Landsat TM/ ETM+ satellite images;

3) summarize the rates and spatial patterns of agricultural land abandonment among and within the countries;

4) relate agricultural land abandonment rates to different transition approaches.

Methods

Study area

To stratify Eastern European countries by agro-environmental conditions, we used climate data including average annual mean temperature for January and July, days with temperatures >10°C, and annual precipitation (Afonin, 2010). We also constrained our study region based on climatic limits to wheat growth (IIASA, 2000), agro-natural zoning, and geobotanical maps for USSR (Alexandrova & Yurkovskaja, 1989, Kashtanov, 1983). Based on these stratifications, we selected the largest region with homogeneous environmental conditions that allowed for broad-scale, cross-country comparisons (Figure 2-1). An additional benefit of this region was that all countries except

Poland were part of the Soviet Union before 1990, and thus had a similar starting point (e.g., similar land-tenure policies, similar socio-economic and agricultural production conditions), but chose different transition approaches (Table 2-1).

Climate in the study region is temperate-continental, with mean temperatures in the warmest month (July) ranging from 17°C to 21°C. Mean temperatures in the coldest month (January) ranges from -14.0°C to -6.1°C (Afonin, 2010). Accumulated temperatures above 10°C range from 1,980°C to 2,660°C. Annual precipitation ranges from 506 mm to 807 mm.

Topography is essentially flat, and ranges from 0 to 300 m (Folch, 2000, Kashtanov, 1983). The region is a part of the temperate mixed forest zone and the Sarmatic mixed forests formed after the last glaciations (Olson, et al., 2001). The northernmost part of the study area represents the southern taiga-mixed forest boundary and the south of the study region borders the mixed forest-steppe zone (Tula and Rjazan provinces - *oblasti* - of Russia). On average, 30% of the region is forest-covered, with higher proportions of forest in Russia. Dominant tree species include Northern spruce (*Picea abies*), Scots pine (*Pinus sylvestris*), Silver birch (*Betula pendula*) and English oak (*Quercus robur*) (Folch, 2000, Kashtanov, 1983). Soils in the study region mainly consist of podzols, luvisols and gleysols and fluvisols along rivers (together covering 78% of the study area) (Batijes, 2001). In the south-eastern corner of the region phaozems and chernozems are dominant (14% of the study area, Figure 2-1).

The study region is well-suited for agriculture, especially after melioration, liming and fertilization of podzolic soils (Folch, 2000). During the last decades of the socialist era, the region became one of the primary agricultural areas of the USSR, especially after the failure of the Soviet government to expand wheat cultivation in Kazakhstan (Ioffe, 2004, Ioffe & Nefedova, 2006). Primary summer crops are barley, rye, oats, sugar beets, fodder maize, potatoes, peas, summer rapeseed, and flax, and main winter crops are winter wheat, winter barley and winter rapeseed (Gataulina, 1992). Cattle breeding, dairy farming, and poultry production are also common.

The agricultural sector was highly subsidized and markets were guaranteed during the Soviet Era. While similar land-tenure and types of agricultural management were similar in the selected countries, except of Poland, differences existed in agricultural sector and rural development (Lerman, et al., 2004, Nefedova & Treivish, 1994). For instance, paved road density in the study region was four times higher in Lithuania than in the central European Russian provinces, representing west-east gradient (Table 2-2). Belarusian, Latvian and Lithuanian agricultural enterprises were also better equipped than those in Russia and more tractors were available for Polish farmers. After the collapse of the Soviet Bloc, national official statistics highlighted substantial decline in sown crops across the study area (up to 39% in Russia and 38% in Latvia, Figure 2-2). Similarly, livestock numbers declined by up to 62% in Lithuania and 34% in Russia (Goskomstat, 2002, CSB, 2010, Lithstat, 2010).

After the collapse of the USSR, each country in the study region followed a unique transition approach regarding land reforms and the restructuring of the agricultural sector (Lerman, et al., 2004, Macey, et al., 2004) (Table 2-1). In Russia, agricultural lands and former state and collective farms' assets were privatized and shares in the form of certificates were distributed among former farm employees. Farms often continued operating in the form of corporate farms (e.g., joint-stock enterprises and cooperatives) (Lerman, et al., 2004). However, a moratorium on private agricultural land purchases and sales was enacted, lasting until 2003 (Lerman & Shagaida, 2007) and the restructuring of the agricultural sector did not facilitate the emergence of substantial private commercial farming. By 1998, Russia's agricultural sector was dominated by corporate farms with an average size of 6,000 hectares, 88% of which were essentially bankrupt (Goskomstat, 2002, Ioffe & Nefedova, 2004, Lerman, et al., 2004). By 2000, more than 60% of agricultural land was still owned by the government (Shagaida, 2002).

In the case of the Baltic countries, Lithuania and Latvia restituted previously nationalized agricultural lands to previous owners and their heirs (nationalization has been accomplished by forcibly abolishing of the private ownership with lands transfer for the government and creation of state and collective farms to manage nationalize agricultural lands) (Stuikys & Ladyga, 1995, Knappe, 2002). For instance, by 2003, in Lithuania 89% of all agricultural land was utilized by farmers' and family farms, 78% of which was in private farms of less than 5 hectares (Stuikys & Ladyga, 1995, Lithstat, 2010). The Belarusian government adapted privatization and private ownership of agricultural lands early in the transition period, but after 1994, the government reversed the course and agricultural land ownership moved back to the state (Drager, 2002, Ioffe, 2004, Sakovich, 2008). By 2000, the state controlled 98% of Belarus' agricultural lands, and state and collective farms managed these lands, similar to the Soviet period (Drager, 2002, Sakovich, 2008). Poland was the only country in our study region that allowed private land ownership during socialism, albeit with strong governmental regulations (Turnock, 1998). However, some agricultural lands were nationalized after forced migrations (especially in the north, and south-eastern corners of Poland) (Turnock, 1998, Kuemmerle, et al., 2008) and the state owned 24% of all Polish agricultural land, which was managed by state farms (GUS, 1992, Csaki & Lerman, 2002). After the system change, the state and collective farms were dismantled, but state-owned agricultural lands had only declined from 24% to 20% by 1997 (Csaki & Lerman, 2002).

Based on our assumptions that unconstrained, open-market conditions with different stakeholders facilitate the competition for agricultural land, we expected that abandonment rates would be lowest in Poland, following up the Baltic states (Latvia, Lithuania), and finally, by Belarus, and Russia.

Satellite image processing

To detect abandoned agricultural lands and highlight differences among the countries in our study region, we selected eight Landsat TM/ETM+ footprints that covered cross-border regions and were within the same agro-climatic zone (Figure 2-1). We placed more footprints in Russia to investigate differences at the provincial level. We omitted Moscow province, due to the disproportional allocation of welfare, foreign direct investment and the speculative value of lands in the vicinity of

Moscow (Bater, 1994, Ioffe & Nefedova, 2004, Rosstat, 2002) (Figure 2-1). Overall, we selected footprints covered 19% of Latvia, 61% of Lithuania, and 41% of the Warminsko-Mazurskie region of Poland (former Olsztyn and Suwałki provinces - *wojewodztwa*). In Belarus, our footprints covered 39% of Grodno province, 32% of Mogilev province, and 22% of Vitebsk province. In the Russia, our footprints covered 80% of Kaliningrad province, 77% of Kaluga province, 72% of Vladimir province, 72% of Rjazan province, 55% of Smolensk province and 51% of Tula province. Altogether, we classified 46 Landsat TM/ ETM+ images for the eight Landsat footprints to map agricultural abandonment between 1989 and 1999. Images were selected to capture key image dates for accurate agricultural land abandonment detection (Prishchepov, et al., *in review*) (Table 2-3).

Images were coregistered using automatic tie point search (Leica Geosystems, 2006) and ortho-corrected images from the USGS archive as base maps. Positional accuracy for co-registered images was higher than 15 m. Clouds and cloud shadows were eliminated using image segmentation (Definiens Imaging, 2004). To classify agricultural land abandonment, we used a Support Vector Machines classifier (further SVM). SVM are well suited to monitor agricultural land abandonment (Kuemmerle, et al., 2008, Prishchepov, et al., *in review*). We used the IDL tool ImageSVM (Chang & Lin, 2001, Rabe, et al., 2009), that automatically selects an optimal SVM parameterization. More information on SVM can be found in Burges (1998), Mather & Tso (2001), and Pal & Mather (2005).

Our classification resulted in four classes: “Forest and wetland”, “Riparian vegetation and permanent shrubs”, “Stable agriculture”, “Abandoned agricultural land”, and “Other”. “Stable agriculture” consisted of tilled agricultural land and grasslands intensively used for grazing and hay-cutting. Whether agricultural land is truly abandoned or simply fallow on a year-to-year basis is often difficult to judge in the field. We therefore defined abandoned agricultural land from a remote-sensing perspective as agricultural land used before 1990 for crops, hay cutting, and livestock grazing, but no longer used 1998-2000, and thus covered by non-managed grasslands often with early successional shrubs. Shrub encroachment in the study area usually takes place for about five years after abandonment with faster shrubs advancement on well-drained and formerly plowed fields (Gul'be & Ermolova, 2005, Karlsson, et al., 1998,). Fields encroached by shrubs tend to remain abandoned leading to subsequent forest succession, due to the loss of its economic value for agricultural production and high costs of converting such fields back to agriculture (Larsson & Nilsson, 2005). Training data was collected during field visits and from high-resolution satellite images (IKONOS and Quickbird scenes available via GoogleEarth™ mapping service) (Prishchepov et al. *in review*).

For the accuracy assessment, we used a three-step, stratified-random sampling approach modified from Edwards, et al. (1998): a) to have a representative sample for the agricultural and transition classes; b) to optimize field data collection. Our reference data were collected independent of training samples. First, we selected cloud-free, 1.28 meter resolution QuickBird and IKONOS images available from GoogleEarth™. For Landsat scenes with limited coverage by high-resolution images (WRS 2 path/row 182/22 and 180/22), we randomly generated 20 x 20 km blocks, similar in size to a QuickBird image. Second, to concentrate field data collection on agricultural lands we derived a forest / non-forest mask for the QuickBird and IKONOS images and for the generated blocks. For Latvia, Lithuania, and Poland, we used the 100-m-resolution land cover product of the Coordination of Information on the Environment program (CORINE) for the year 2000 (EEA, 2006). For the forest / non-forest mask in Belarus and Russia, we used 1:500,000 digital Soviet topographic maps from circa 1989. Third, we randomly placed reference points within the non-forested areas that were within 300 m of roads, which we had digitized from the QuickBird, IKONOS snapshots and topographic maps, to facilitate field visits. To avoid spatial autocorrelation, we separated reference points by at least 500 m (Prishchepov et al, *in review*).

During field work in 2007 and 2008, we visited five out of eight Landsat footprints (Table 2-3). Reference points were geolocated using a non-differential GPS. Using semi-structured questionnaires, we reconstructed land management in 1989 and in 1999 wherever possible interviewing local farmers and agronomists. Additionally, where it was possible, we measured the height and age (by counting tree rings) of shrubs and trees on sites that had been in agricultural use in 1989, and abandoned by 1999-2002. Within the forest mask we assessed forest accuracy using only high-resolution scenes and expert interpretation of the reflectances of multemporal Landsat TM/ ETM+ scenes. The classification accuracy was estimated using contingency matrices. We calculated area-weighted overall accuracy, the Kappa coefficient (KHAT), and producer's and user's accuracies and conditional kappa coefficients for each class (Congalton & Green, 2008). We also adjusted the calculated the areas and the rates of abandoned agricultural land based on our accuracy assessments using an inverse calibration estimator with a Monte Carlo simulation technique (Czaplewski & Catts, 1992). Based on Monte Carlo simulation results with 10,000 iterations for our area weighted contingency matrices results for each classified Landsat footprint, we constructed a normal curve of the error distribution with its mean and confidence intervals and alpha< 0.05.

Results

In general, we achieved very accurate classifications using multi-date imagery and our SVM change detection approach. Conditional Kappa coefficients for "Abandoned agriculture" were above 76% (Table 2-4). The accuracies of agricultural land abandonment varied for the selected scenes with user's accuracies between 80.6% (Figure 2-1, footprint 6) path and 92.7% (Figure 2-1, footprint 2) and conditional Kappa values between 76% and 91.7% for the same Landsat TM/ETM+ footprints respectively. The highest classification overall accuracies for agricultural land abandonment were achieved for WRS2 path 186, row 21 (Figure 2-1, footprint 3), path 176, row 21

(Figure 2-1, footprint 2), path 186, row 22 (Figure 2-1, footprint 8) (overall accuracies were equal to 95.2%, 92.8% and 92.6% and respectively) (Table 2-4).

Our results indicated widespread agricultural land abandonment across our study region. Within the eight classified Landsat TM/ETM footprints, statistically adjusted estimates of agricultural land abandonment showed that 9 million hectares (+/- 99,600 hectares) were in agricultural use in 1989, of which 27%+/- 1% (2.5 million hectares +/- 82,300 hectares) were abandoned by 1999-2002. Contrary to our expectations, the highest agricultural land abandonment rates at the national level were observed for the studied part of Latvia, comprising 42% +/- 2.6%, (176,700 hectares, +/ 4,700 hectares) of the agricultural land managed in 1989 (Figure 2-3A). Six of our eight Landsat TM/ ETM+ footprints covered Russian regions, where we also observed high agricultural land abandonment comprising 31.3% +/- 1.4% (1.7 million hectares +/- 23,300 hectares), of agricultural land managed in 1989. Abandonment rates in Lithuania were lower than in Latvia's and in Russia's parts of the study area, comprising 28.4% +/- 1.4% (543,900 hectares +/- 7,600 hectares) of the agricultural land managed in 1989. The case of Belarus really surprised us. Contrary to our expectations, abandonment rates were low, comprising 13.5% +/- 1.2% (133,000 hectares +/- 1,600 hectares) of agricultural land managed in 1989, the lowest abandonment rates among the countries we studied. As expected agricultural abandonment rates in the studied part of Poland during the ten-year transition period were also small (but higher than in Belarus), comprising 14% (101,000 hectares) of all agricultural land managed in 1989.

Our results showed marked differences among countries in such cross-border regions. For example, in the cross-border area of Belarus–Russia (Figure 2-4C), abandonment rates were 10% +/- 1.2% and 47% +/- respectively, and this was the strongest cross-border difference in land use change in our study area. In the cross-border region of Russia, Lithuania and Poland (WRS2 path 188, row 22, Figure 2-4A) the rates of agricultural land abandonment were 43%+/- 2.0%, 19% +/-2.0%, and

14% +/- 2.0% , respectively. For the cross-border region of Lithuania and Belarus (WRS2 path 188, row 22) abandonment rates were 29% +/- 1.0% and 15% +/- 1.2% (Figure 2-4B).

While we observed the highest rates of agricultural land abandonment for Latvia, we also found consistently high rates of abandonment at the regional level in Russia, especially in Kaliningrad and Smolensk provinces (Figure 2-3B). The largest rates of abandonment were observed for the studied part of Smolensk province (46% +/- 1.4% of agricultural land abandoned). The rates of abandoned agricultural land in Kaliningrad province, a Russian exclave in the Baltic region, were comparable to the rates of abandoned agricultural land in other Russian provinces (Figure 2-3B). In the case of Belarus, abandonment rates were similar among Belarusian provinces and consistently lower compared to other countries in our study area (Figure 2-3B).

Finally, abandonment rates varied greatly at the district level (“rayons” in Belarus, Latvia and Russia; “apskritys” in Lithuania, and “gminy” in Poland) (Figure 2-5). Again, the highest rates of abandoned agricultural land were found in Russia (Figure 2-5). During the first decade of the transition period, abandonment rates at the district level were as high as 60% of all agricultural lands used in 1989 in some Russian districts (e.g., Ugranskij and Temkinskij districts of Smolensk province;61% and 60% respectively; Putjiatinskij district of Rjazan province; 60%). These districts had a smaller share of agricultural lands, were distant from provincial capitals (Smolensk and Kaluga), and were socio-economically marginal (e.g., strong rural population decline between 1989 and 1999, low road density, and isolated villages) (Figure 2-4D). Conversely, districts with lowest abandonment rates were often found near provincial capitals (Figure 2-5), similar to what has been suggested for post-Soviet Western Ukraine (Baumann, et al., *in review*).

Discussion

Our analyses showed that the fundamental political, institutional and socio-economic changes in Eastern Europe after the collapse of the Soviet Union resulted in widespread agricultural land abandonment. Because we minimized agro-climatic differences among countries, the differences of agricultural land abandonment rates reflected most likely the effects of different institutional changes ranging from 12% +-1.2% (Belarus) to 42% +- 2.6% (Latvia).

One of our results was that agricultural land abandonment rates in the studied part of Latvia and Lithuania were much higher than expected (Figure 2-3), despite their fast transition to market economies that should have fostered more efficient agricultural land use patterns. In Latvia we observed the highest abandonment rates among all countries (Figure 2-3). Reasons for this may include the restitution of agricultural land to the previous owners who and their heirs, to city and town dwellers, retired people, all who were not interested in agriculture as a profession, and unskilled former state and collective farm workers (e.g., milkers, herdsmen) (Bušmanis, et al., 2001, Knappe, 2002, Nefedova & Treivish, 1994). The disappearance of guaranteed markets for agricultural production within the USSR and of subsidized fuel, machinery and fertilizers, as well as a lack of competitiveness with imported agricultural products also contributed to the decline in agricultural production both in Latvia and Lithuania (Knappe, 2002, Nefedova & Treivish, 1994, Stuikys & Ladyga, 1995). Lower abandonment rates in the studied part of Lithuania compared to Latvia might be explained by the higher share in GDP of agriculture remaining (7.8% in Lithuania and 4.6% in Latvia in 2000), higher employment rates in the agricultural sector, and better socioeconomic and rural infrastructure (e.g., higher road density) in Lithuania (Knappe, 2002) (Table 2-2). Statistics also showed a decrease of the number of tractors by 6 % in Latvia, but an increase by 40% in Lithuania (Goskomstat 1991).

In the Russian part of the study area, rates of agricultural land abandonment were the second highest after Latvia (Figure 2-3). Abandonment rates were consistently high in all regions, including Kaliningrad province, the westernmost Russian exclave. This may indicate that the underlying driving forces of abandonment (e.g., institutional changes and policies) operating at the national scale largely masked regional determinants of abandonment. The withdrawal of the government support for agriculture, the slow establishment of a functioning land market, and limited availability of credits potentially caused the decline in agricultural production in Russia (Lerman & Shagaida, 2007) and may explain the high rates of agricultural land abandonment we found.

We observed relatively uniform and high abandonment rates at the provincial level, but the variation of abandonment rates at the district level was substantial. In Russia we observed very high rates of agricultural land abandonment (up to 75%) in some districts, especially those that afar from provincial capitals (Figure 2-4 D, H).We observed less abandonment near provincial capitals, indicating likely centripetal Thuenen-ring like gradients, which also characterize patterns of agriculture productivity and population density in central European Russia (Ioffe & Nefedova, 2004, Ioffe, et al., 2004). Similarly, we witnessed that fields around many Russian villages only remained managed in close vicinity to the village, and were most likely used for subsistence farming (Dannenberg & Kuemmerle, 2010, Elbakidze & Angelstam, 2007).

In the studied part of Poland, rates of agricultural land abandonment were higher than expected (Figure 2-3). This may be due to the higher share of previously nationalized farmland in the studied province compared to other parts of Poland (GUS, 1992, GUS, 1999, Kuemmerle, et al., 2008, Turnock, 1998). The region in Poland we studied was part of Germany before WWII After the war, the German population was forcefully relocated, agricultural lands were nationalized, and state farms were established (Turnock, 1998). Nevertheless, agricultural land abandonment rates in Poland were substantially lower than in the other countries in our study area. This suggests that the largely unchanged and secure private agriculture during the transition period (Lerman, et al., 2004) allowed the Polish agricultural sector to adjust relatively easily to the new economic conditions. Poland also represents an interesting case, since the country served as a prime example of a successful implementation of the “shock therapy”, the most liberal transition approach suggested by the World Bank (Bradshaw & Stenning, 2004). It was also likely that prior the accession to the EU, which took place in 2004, Polish economy including agricultural sector were attractive for initial development funds by the EU and foreign direct investment.

In the studied part of Belarus, the rates of agricultural land abandonment were lowest, and comparable to the rates in the Polish part of our study region. This was interesting since these two countries chose opposite transition approaches of towards an open-market economy. In Belarus, the government abolished privatization of agricultural land and capital assets of state and collective farms in 1994, thus limiting key principles of open-market economies as suggested by the Word Bank (Bradshaw & Stenning, 2004). Similarly to the Soviet period, subsidies and a complex system of offsets among Belarusian state enterprises ensured that state and collective farms continued to receive cheap fertilizers, fuel, and equipment, and that farms could sell agricultural products at fixed prices (Ioffe, 2004, Sakovich, 2008). State and collective farms also retained their key social role in the countryside, providing workplaces, housing, and social infrastructure (e.g., kindergartens, cultural clubs) (Drager, 2002, Sakovich, 2008).

The differences in government support between Belarus and Russia may also explain substantial differences in abandonment rates in the border region between these countries. For example, in 2000 in the Mogilev province of Belarus the share of unprofitable agricultural enterprises was very similar to in the neighboring Smolensk province of Russia (65% versus 75%, Belstat, 2002, Rosstat, 2002) (Figure 2-6). However, the rates of agricultural land abandonment detected in the cross-border area of Belarus and Russia were much lower in the studied part of Mogilev province of Belarus (10%) than in the studied part of Smolensk province of Russia (46%), likely as a result of higher state-support for agriculture in Belarus.

During our field campaigns in 2007 and 2008, we also observed that succession on abandoned farmfields had progressed further in the Russia compared to Belarus, the Baltic States, and Poland. This may indicate that abandonment in the Russian part of the study area took place early in the transition period. This may result from the illiquidity state and collective farms due to nonfunctioning land market in first years of transition (e.g., the moratorium on land sales was officially withdrawn in 2003) and the immediate collapse of the subsidized system. Interviews with farmers and stakeholders in Russia suggest that this resulted in a considerable depreciation of how former state and collective farm workers and their heirs valued land rights, thereby diminishing the willingness and ability to maintain agricultural land.

Comparable to other studies that monitored agricultural land abandonment with Landsat satellite imagery in Eastern Europe (Baumann et al., *in review,* Bergen et al. 2008, Kuemmerle et al. 2008, Kuemmerle et al. 2009, Vaclavik & Rogan, 2009), we found, by far, the highest rates of agricultural land abandonment after the first decade of transition. Abandonment rates were particularly high in light of our conservative definition for agricultural land abandonment. We did not include fallow land (unused agricultural land that had not clear signs of abandonment, such as shrub encroachment) in our assessment, although it is likely that at least a portion of these areas are abandoned.

Agro-climatic differences, dissimilar mapping approaches, abandonment definitions, and different study periods do not allow direct comparison of abandonment rates of our study with those of other studies in Eastern Europe. However, it is still possible to observe some common patterns, especially among the studies conducted by the same research groups. For example, similar to our study, abandonment rates between 1990 and 2005 were higher in Albania than in Romania (Mueller & Munroe, 2008), which chose a transition approach similar to Russia, than in Romania, which had a unique land reform approach, and employed both restitution and redistribution of agricultural assets to former collective and state farm workers. Likewise, among three countries studied in the cross-border triangle in the Eastern Carpathians, higher rates of agricultural land abandonment were observed for Slovakia, compared to Poland and Ukraine (Kuemmerle, et al., 2008). Slovakia had a similar transition approach as Latvia and Lithuania, where we observed highest abandonment rates.

And in both, the Eastern Carpathians (Kuemmerle, et al., 2008) and in our study, the rates of agricultural land abandonment in Poland were low compared to the neighboring countries.

Abandonment rates in the Ukrainian Carpathians were relatively low compared to our study (Kuemmerle, et al., 2008). This was surprising at first, because Russia and Ukraine adopted similar transition approaches. However, the portion of Ukraine that was studied was small, and differed substantially from the rest of Ukraine in terms of their socio-economic, and biophysical settings (Kuemmerle, et al., 2008). Subsistence farming in the Ukrainian Carpathians became very important during the first decade of transition (Elbakidze & Angelstam, 2007) and in the early transition years the Ukrainian government continued subsidizing agriculture substantially (Nefedova & Treivish, 1994). This may explain the lower abandonment rates reported by Kuemmerle et al. (2008). In a recent study, we have extended our analysis of agricultural land abandonment to a larger region in Western Ukraine (Baumann et al., *in review*) and found much high abandonment rates (up to 56% at the district level by the year 2007). Subsidies diminished quickly in Ukraine during the second decade of transition, Ukraine experienced an economic crisis, and a functioning land market is still missing, thereby explaining why delayed abandonment in Western Ukraine compared to Russia (Baumann et al., *in review*). Overall, these findings suggest that Russia and Ukraine had indeed similar abandonment rates, supporting our main conclusion of the importance of transition strategies and national-level policies on abandonment patterns in the post-Soviet period.

In summary, our results showed that post-Soviet socio-economic changes in Eastern Europe significantly affected land use and triggered widespread agricultural abandonment. In the transition period from 1990 to 2000, 32% of agricultural land in our study region (3 million hectares) was abandoned. Our study area was designed by minimizing environmental variation, yet we found strong differences in abandonment rates among countries, and also strong variation in abandonment rates at the district level. This suggests that differences among countries, stemming from different transition approaches, affected land use. Generally we observed higher agricultural abandonment rates for those countries that privatized land and agricultural enterprises, where governments withdrew support for the agricultural sector (e.g., Russia), and where secure land ownership or well-functioning land markets were lacking.

Ultimately, institutional settings and their changes are playing the key role in the modification of land cover and land-use, and countries that changed their institutions related to land use had the highest abandonment rates. Knowing the effect of reforms on land-use is important, because land reforms and institutional changes are not rare and being able to predict the potential impact of the possible transition approach is essential for an effective land use policy.

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Literature

Achard,F., Mollicone,D., Stibig,H.-J., Aksenov,D., Laestadius,L., Li,Z., Popatov,P. & Yaroshenko,A.. (2006). Areas of rapid forest-cover change in boreal Eurasia. *Forest Ecology and Management, 237*(1-3), 322-334.

Alexandrova,V. D. & Yurkovskaja,T. K. (1989). Geobotanical zoning of Nonchernozem european part of RSFSR (Geobotanicheskoe rayonirovanie Nechernozemjia evropeiskoi chasti RSFSR).

Barbier,E. B., Burgess,J. C. & Grainger,A. (2010). The forest transition: Towards a more comprehensive theoretical framework. *Land Use Policy, 27*(2), 98-107.

Bater,J. H. (1994). Housing Developments in Moscow in the 1990s. *Post-Soviet Geography, 35*(6), 309-328.

Batijes,N. H. (2001). Soil data for land suitability assessment and environmental protection in Central Eastern Europe -the 1:2500000 scale SOVEUR project. *The Land, (5), 151-68.*

Baumann,M., Kuemmerle,T., Elbakidze,M., Ozdogan,M., Radeloff,V. C., Keuler,N. S., Prishchepov,A. V., Kruhlov,I. & Hostert,P. Patterns and drivers of post-socialist farmland abandonment in Western Ukraine. *In review*

Belstat. (2002). *Regions of Belarus republic. Statistical compendium. (Regioni Respubliki Belarus. Statisticheskii Sbornik).* Minsk, Belarus: Ministry of statistics and analysis of Belarus republic. 707 p.

Bergen,K. M., Zhao,T., Kharuk,V., Blam,Y., Brown,D. G., Peterson,L. K. & Miller,N. (2008). Changing regimes: Forested land cover dynamics in Central Siberia 1974 to 2001. *Photogrammetric Engineering and Remote Sensing, 74*(6), 787-798.

Boentje,J. P. & Blinnikov,M. S. (2007). Post-Soviet forest fragmentation and loss in the Green Belt around Moscow, Russia (1991-2001): a remote sensing perspective. *Landscape and Urban Planning, 82*(4), 208-221.

Bradshaw,M. & Stenning,A. (2004). *East Central Europe and the former Soviet Union: the post-socialist state.* Prentice Hall. 266 p.

Brukas,V., Linkevicius,E. & Cinga,G. (2009). Policy Drivers Behind Forest Utilisation in Lithuania in 1986-2007. *Baltic Forestry, 15*(1), 86-96.

Burges,C. J. C. (1998). A tutorial on Support Vector Machines for pattern recognition. *Data Mining and Knowledge Discovery, 2*(2), 121-167.

Bušmanis,P., Zobena,A., Dzalbe,I. & Grīnfelde,I. (2001). Privatisation and soil in Latvia: Land Abandonment. *Proceedings of ACE Phare Seminar on Sustainable Agriculture in Central and Eastern European Countries in Transition: The Environmental Effects of Transition and Needs for Change*. 10-16 September,2001, Nitra, Slovakia

Capozza,D. R. & Helsley,R. W. (1989). The Fundamentals of Land Prices and Urban-Growth. *Journal of Urban Economics, 26*(3), 295-306.

Chang,C. C. & Lin,C. J. (2001). LIBSVM : a library for support vector machines. *Computer program*. (last accessed August 29, 2010, http://www.csie.ntu.edu.tw/~cjlin/libsvm).

Congalton,R. G. & Green,K. (2008). *Assessing the accuracy of remotely sensed data, principles and practices*. CRC Press, Boca Raton, London, New York, Second Edition, 200 p.

Csaki,C. & Lerman,Z. (2002). Land and farm structure in transition: The case of Poland. *Eurasian Geography and Economics, 43*(4), 305-322.

CSB. (2010). *Online statistical database of the Central Statistical Bureau o f Latvia.* (last accessed August 29, 2010, http://www.csb.gov.lv/).

Czaplewski,R. L. & Catts,G. P. (1992). Calibration of Remotely Sensed Proportion Or Area Estimates for Misclassification Error. *Remote Sensing of Environment, 39*(1), 29-43.

Dannenberg,P. & Kuemmerle,T. (2010). Farm Size and Land Use Pattern Changes in Postsocialist Poland. *Professional Geographer, 62*(2), 197-210.

Definiens Imaging. (2004). *ECognition^{TM} User's guide.* Computer program. (last accessed August 29, 2010, http://www.definiens-imaging.com).

Deininger,K., Sarris,A. & Savastano,S. (2004). Rural land markets in transition: evidence from six European Countries. *Quarterly Journal of International Agriculture, 43*(4), 361-389.

Deninger,K. (2003). *Land Policies for Growth and Poverty Reduction.* World Bank and Oxford University Press, Washington, DC, USA, 239 p.

Diamond,J. (2001). Ecology - Dammed experiments! *Science*, *294*(5548), 1847-1848.

Drager,D. (2002). Belarus. *In: Agricultural Transformation and Land Use in Central and Eastern Europe*, Ashgate Publishing, Aldershot, England, 107-340 (364 p.)

Edwards,T. C., Moisen,G. G. & Cutler,D. R. (1998). Assessing map accuracy in a remotely sensed, ecoregion-scale cover map. *Remote Sensing of Environment*, *63*(1), 73-83.

EEA. (2006). *The thematic accuracy of Corine land cover 2000 - Assessment using LUCAS.* European Environmental Agency. (last accessed August 29, 2010, http://www.eea.europa.eu/publications/technical_report_2006_7).

Eickhout,B., van Meijl,H., Tabeau,A. & van Rheenen,T. (2007). Economic and ecological consequences of four European land use scenarios. *Land Use Policy*, *24*(3), 562-575.

Eikeland,S., Eythorsson,E. & Ivanova,L. (2004). From management to mediation: Local forestry management and the forestry crisis in post-socialist Russia. *Environmental management, 33*(3), 285-293.

Elbakidze,M. & Angelstam,P. (2007). Implementing sustainable forest management in Ukraine's Carpathian Mountains: The role of traditional village systems. *Forest Ecology and Management, 249*(1-2), 28-38.

Erb,K.-H., Krausmann,F., Lucht,W. & Haberl,H. (2009). Embodied HANPP: Mapping the spatial disconnect between global biomass production and consumption. *Ecological Economics, 69*(2), 328-334.

Folch,R. (2000). *Encyclopedia of the Biosphere: Deciduous forests*. Gale Group, Detroit, Mi, USA, 438 p.

Foley,J. A., DeFries,R., Asner,G. P., Barford,C., Bonan,G., Carpenter,S. R., Chapin,F. S., Coe,M. T., Daily,G. C., Gibbs,H. K., Helkowski,J. H., Holloway,T., Howard,E. A., Kucharik,C. J., Monfreda,C., Patz,J. A., Prentice,I. C., Ramankutty,N. & Snyder,P. K. (2005). Global consequences of land use. *Science, 309*(5734), 570-574.

Fox,J., Rindfuss,R. R., Walsh,S. J. & Mishra,V. (2003). People and the Environment. Approaches for Linking Household and Community Surveys to Remote Sensing and GIS. Springer, 344 p.

Gataulina,G. G. (1992). Small-grain cereal systems in the Soviet. Union. *In: Pearson, C.J. (Ed.) Ecosystems of the world. Field crop ecosystems, Elsevier Science Publishing Company, Amsterdam, Netherlands, New York, USA 18*(17), 385-400 (560 p.).

Geist,H. J., McConnell,W. J., Lambin,E. F., Moran,E., Alves,D. & Rudel,T. (2006). Causes and trajectories of land use/cover change. *In: Lambin,E. F. & Geist,H. J. (Eds.) Land Use and Land Cover Change. Local Processes and Global Impacts.* Springer Verlag, Berlin, Heidelberg, New York 41-70.

Goskomstat. (2002). *Agriculture in Russia (Selskoje khozjaistvo v Rossii)*. Goskomstat Rossii, Moscow, Russia, 397 p.

GOSKOMSTAT. (2000). *Agricultural sector in Russia (Selskoje khozjaistvo v Rossii). Statistical Compendium.* Goskomstat Rossii, Moscow, Russia, 414 p.

Goskomstat. (1991). *National economy of USSR in 1990. (Narodnoe hozyaistvo in 1990).* Finansy i Statistika, Moscow, 752 p.

Goskomstat LitSSR. (1989). *Statistical yearbook of Lithuanian SSR, 1988. (Statisticheskii ezhegodnik Litovskoi SSR, 1988).* Vilnius, Lithuanian SSR.

Gul'be,A. Y. & Ermolova,L. S. (2005). Birch and grey alder forests is ecotone between coniferous forest ecosystems and agricultural lands in the Central Region of the Russian Plain. Lesovedenie, (4), 49-66.

GUS. (1999). *Statistical Yearbook of agriculture in 1998 (Rocznik statystyczny rolnictwa, 1998).* In Polish. Glowny urzad statystyczny, Warszawa, Poland, 482 p.

GUS. (1992). *Agriculture and livestock sector in 1986-1990. (Rolnictwo i gospodarka zywnociowa 1986-1990).* In Polish. Glowny urzad statystyczny, Warszawa, Poland, 399 p.

GUS. (1987). *Statistical yearbook for transport in 1986 (Rocznik statystyczny transportu 1986).* In Polish. Glowny urzad statystyczny, Warszawa, Poland, 339 p.

Henebry,G. M. (2009). GLOBAL CHANGE Carbon in idle croplands. *Nature, 457*(7233), 1089-1090.

Huang,C., Davis,L. S. & Townshend,J. R. G. (2002). An assessment of support vector machines for land cover classification. *International Journal of Remote Sensing, 23*(4), 725-749.

IIASA. (2000). *Global Agro-Ecological Zones (Global-AEZ).* CD-ROM FAO/IIASA. (last accessed August 29, 2010, http://www.fao.org.ezproxy.library.wisc.edu/WAICENT/FAOINFO/AGRICULT/AGL/agll/gaez/index.htm)

Ioffe,G. (2004). Understanding Belarus: Economy and political landscape. *Europe-Asia Studies, 56*(1), 85-118.

Ioffe,G. & Nefedova,T. (2004). Marginal farmland in European Russia. *Eurasian Geography and Economics, 45*(1), 45-59.

Ioffe,G. & Nefedova,T.,Zaslavsky I. (2006). *The End of Peasantry? Disintegration of Rural Russia.* University of Pittsburgh Press, 256 p.

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), 913-943.

Irwin,E. G. & Geoghegan,J. (2001). Theory, data, methods: developing spatially explicit economic models of land use change. *Agriculture Ecosystems & Environment, 85*(1-3), 7-23.

Kaimowitz,D., Mertens,B., Wunder,S. & Pacheco,P. (2004). Hamburger Connection Fuels Amazon Destruction: Cattle ranching and deforestation in Brazil's Amazon. Centre for International Forestry Research (CIFOR), (last accessed August 29, 2010, http://www.cifor.cgiar.org/publications/pdf_files/media/Amazon.pdf).

Karlsson,A., Albrektson,A., Forsgren,A. & Svensson,L.. (1998). An analysis of successful natural regeneration of downy and silver birch on abandoned farmland in Sweden. *Silva Fennica, 32*(3), 229-240.

Kashtanov,A. N. (1983). *Natural-agriculture zoning and utilizing of land resources of USSR (Prirodno-Selskohozjaistvennoe raionirovanie i ispolzovanije zemelnogo resursa SSSR).* VASHNIL, Kolos, Moscow, 336 p.

Knappe,E. (2002). Lithuania. *In: Agricultural Transformation and Land Use in Central and Eastern Europe*, Ashgate Publishing, Aldershot, England, 95-340 (364 p.)

Knappe,E. (2002). Latvia. *In: Agricultural Transformation and Land Use in Central and Eastern Europe*, Ashgate Publishing, Aldershot, England, 83-340 (364 p.)

Kuemmerle,T., Hostert,P., Radeloff,V. C., van der Linden,S., Perzanowski,K. & Kruhlov,I. (2008). Cross-border comparison of post-socialist farmland abandonment in the Carpathians. Ecosystems, 11(4), 614-628.

Kuemmerle,T., Kozak,J., Radeloff,V. C. & 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., Mueller,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,E. F. & Meyfroidt,P. (2010). Land use transitions: Socio-ecological feedback versus socio-economic change. *Land Use Policy, 27*(2), 108-118.

Larsson,S. & Nilsson,C. (2005). A remote sensing methodology to assess the costs of preparing abandoned farmland for energy crop cultivation in northern Sweden. *Biomass & Bioenergy, 28*(1), 1-6.

LatvStat. (1990). *National economy of Latvia in 1989. Statistical Yearbook. (Narodnoe hozjaistvo Latvii. Statisticheskii ezhegodnik 1989).* Avots, Riga, 330 p.

Leica Geosystems. (2006). Imagine AutosyncTM White Paper. *Computer Program.* Leica geosystems geospatial imaging., Norcross, USA (last accessed August 19, 2010, http://gi.leica-geosystems.com/documents/pdf/IMAGINEAutoSyncWhitePapeFeb06.pdf)

Lerman,Z., Csaki,C. & Feder,G. (2004). *Agriculture in transition: land policies and evolving farm structures in post-Soviet countries.* Lexington Books, Lanham, Boulder, New York, Toronto, Oxford 254. p

Lerman,Z. & Shagaida,N. (2007). Land policies and agricultural land markets in Russia. *Land Use Policy, 24*(1), 14-23.

Lithstat. (2010). Online statistical database of the Department of Statistics to the Government of the Republic of Lithuania. (last accessed August 30, 2010, http://www.stat.gov.lt/en/)

Lithstat. (2001). *Lithuanian Counties in 2000 (Lietuvos apskritys 2000).* In English and Lithuanian.

Department of Statistics to the Government of the Republic of Lithuania. Vilnius 393 p.

Macey,D. J., Pyle,W. & Wegren,S. K. (2004). *Building Market Institutions in Post-Communist Agriculture: Land, Credit, and Assistance.* Lexington Books, Lanham, Boulder, New-York, Toronto, Oxford, 256 p.

Mather,A. S. & Needle,C. L. (1998). The forest transition: a theoretical basis. *Area, 30*(2), 117-124.

Mather,P. & Tso,B. (2001). *Classification Methods for Remotely Sensed Data.* CRC Press. 352 p.

Mertens,H. (2002). Poland. *In: Agricultural Transformation and Land Use in Central and Eastern Europe*, Ashgate Publishing, Aldershot, England, 223-269 (364 p.).

Mueller,D. & Munroe,D. K. (2008). Changing Rural Landscapes in Albania: Cropland Abandonment and Forest Clearing in the Postsocialist Transition. *Annals of the Association of American Geographers, 98*(4), 855-876.

Muller,D., Kuemmerle,T., Rusu,M. & Griffiths,P. (2008). Lost in transition: determinants of post-socialist cropland abandonment in Romania. *Journal of Land Use Science*, 4109-129.

Nefedova,T. & Treivish,A. (1994). Regions of Russia and other European countries in transition in the early 90s (Rayony Rossii i drugih Evropeiskih stran s perekhodnoi ekonomikoi). *Russia of the 90s: Problems of Regional Development (Rossija 90s: problemy regionalnogo razvitija)* In Russian. Institute of Geography, Russian Academy of Science, Moscow.70 p.

New,M., Lister,D., Hulme,M. & Makin,I. (2002). A high-resolution data set of surface climate over global land areas. *Climate Research*, *21*(1), 1-25.

Novozhenina,O., Baharev,I. & Mollicone,D. (2009). "Hard-Okorok"("Hard-hock"). Gazeta.ru, (last accessed August 30, 2010, http://www.gazeta.ru/business/2009/01/23/2928922.shtml).

NRC. (1998). *People and Pixels: Linking Remote Sensing and Social Science.* National Research Council. National Academic Press, Washington, D.C., USA, 258 p.

Olson,D. M., Dinerstein,E., Wikramanayake,E. D., Burgess,N. D., Powell,G. V. N., Underwood,E. C., D'Amico,J. A., Itoua,I., Strand,H. E., Morrison,J. C., Loucks,C. J., Allnutt,T. F., Ricketts,T. H., Kura,Y., Lamoreux,J. F., Wettengel,W. W., Hedao,P. & Kassem,K. R. (2001). Terrestrial ecoregions of the worlds: A new map of life on Earth. *Bioscience, 51*(11), 933-938.

Pal,M. & Mather,P. M. (2005). Support vector machines for classification in remote sensing. *International Journal of Remote Sensing, 26*(5), 1007-1011.

Pallot,J. & Moran,D. (2000). Surviving the margins in post-Soviet Russia: Forestry villages in northern Perm' Oblast. *Post-Soviet Geography and Economics, 41*(5), 341-364.

Prishchepov,A. V., Radeloff,V. C., Dubinin,M. & Alcantara,C. The effect of satellite image dates selection on land cover change detection and the mapping of agricultural land abandonment in Eastern Europe. *Remote Sensing of Environment. In review.*

Rabe,A., van der Linden,S. & Hostert,P. (2009). ImageSVM. 2.0. *Computer Program.* Humboldt-Universitat zu Berlin, Geomatics Lab. (last accessed August 30, 2010, www.hu-geomatics.de).

Riasanovsky,N. V. (2000). *A History of Russia*. Oxford press, New-York,Oxford, 776 p.

Rosstat. (2002). *Regions of Russia. Socio-economic indicators. (Regiony Rossii. Sotsial'no-ekonomicheskie pokazateli).* In Russian. Federal service for state statistics, Moscow. Online statistical database via EastView Publishing. (last accessed August 30, 2010, http://udbstat.eastview.com.ezproxy.library.wisc.edu/catalog/edition.jsp?id=2200).

Rudel,T. K., Coomes,O. T., Moran,E., Achard,F., Angelsen,A., Xu,J. C. & Lambin,E. (2005). Forest transitions: towards a global understanding of land use change. *Global Environmental Change-Human and Policy Dimensions, 15*(1), 23-31.

Sakovich,V. S. (2008). Agriculture in Belarus between 1980-2007: tendency of the development (Selskoe Hozjaistvo v Respublike Belarus v 1980-2007 g.: tendencii razvitija). In Russian. Belorusskaja nauka, Minsk. 497 p.

Shagaida,N. I. (2002). Land market. *Proceedings of the Conference entitled "Markets of production factors in agriculture of Russia: analysis of perspectives"*, 6-7th of July, 2001, Golitsino, Moscow oblast, Russia. Published by Moscow institute of economics of transition period. Analytical center of agroproduction economics, 82-219.

Song,C., Woodcock,C. E., Seto,K. C., Lenney,M. P. & Macomber,S. A. (2001). Classification and change detection using Landsat TM data: When and how to correct atmospheric effects? *Remote Sensing of Environment, 75*(2), 230-244.

Stuikys,V. & Ladyga,A. (1995). *Agriculture of Lithuania.* In English and Lithuanian. Valystybinis Leidybos Centras, Vilnius, 176 p.

Tsvetkov,M. A. (1957). *Forestness change in European Russia since the end of 18th century till 1914.* In Russian. USSR Academy of Science of USSR, Institute of Forest, 213 p.

Turnock,T. (1998). Privatization in rural Eastern Europe : the process of restitution and restructuring. In: Hill,R.J. (Ed.), Studies of communism in transition. Edward Elgar Publishing Limited, Northampton, MA, USA, 427 p.

Urbel-Piirsalu,E. & Backlund,A.-K. (2009). Exploring the Sustainability of Estonian Forestry: The Socioeconomic Drivers. *Ambio, 38*(2), 101-108.

Vaclavik,T. & Rogan,J. (2009). Identifying Trends in Land Use/Land Cover Changes in the Context of Post-Socialist Transformation in Central Europe: A Case Study of the Greater Olomouc Region, Czech Republic. *Giscience & Remote Sensing, 46*(1), 54-76.

Vranken,L., Noev,N. & Swinnen,J. F. M. (2004). Fragmentation, abandonment, and co-ownership: transition problems of the Bulgarian land market. *Quarterly Journal of International Agriculture, 43*(4), 391-408.

Vuichard,N., Ciais,P. & Wolf,A. (2009). Soil Carbon Sequestration or Biofuel Production: New Land-Use Opportunities for Mitigating Climate over Abandoned Soviet Farmlands. *Environmental science & technology, 43*(22), 8678-8683.

Yeloff,D. & van Geel,B. (2007). Abandonment of farmland and vegetation succession following the Eurasian plague pandemic of AD 1347-52. *Journal of Biogeography, 34*(4), 575-582.

Dimensions, 20(3), 378-385.

Table 2-1: Summary of the transition approaches. Adopted from Lerman, et al., 2004.

Country	Potential private ownership after 1990	Privatization strategy	Allocation strategy	Legal attitude to transferability after 1990	Relevant legislation
Belarus	Household plots only	None	None	Use rights non-transferable; buy-and-sell of private plots dubious	Law and Land ownership, June 1993
Latvia	All land	Restitution	Plots	Buy-and-sell, leasing	Land Reform in Rural Areas Act, November 1990
Lithuania	All land	Restitution	Plots	Buy-and-sell, leasing	Law on Land Reform , June 1991
Poland	-	Sell state land	Plots	Buy-and-sell, leasing	-
Russia	All land	Distribution	Shares	Leasing, buy-and-sell dubious	Law on Land Reform , November 1990; Constitution , December 1993; Land Code, January 2002

Table 2-2: Socio-economic and environmental conditions of selected regions in 1989, i.e., the pre-transition time from state-state command to market driven economies.

Provinces	**Landsat TM/ETM+ footprint (path/row)**	**Country after 1990**	**Rural population density (people/km²)[1]**	**Road density (km/km²)[1]**	**Milk production (kg/cow)[1]**	**Grain yield (centners/hectare)[1]**	**Tractors (Tractors/hectare of arable lands)[1]**	**Average annual precipitation[2]**	**Temperature growing periods > 5 °C[2]**	**Percentage of podzolic soils[3]**	**Percentage of agricultural land before 1990[4]**
Kaliningrad	188/022 188/022, 186/021,	Russia	14	35	3152		12	720	2803	74	55
-	186/022	Lithuania		51	3733	28.5	47	629	2744	60	48
-	186/021	Latvia		28	2880	23.5	44	630	2598	34	36
Mogilev	182/022	Belarus	15	22	3219	25.8	55	594	2705	83	57
Vitebsk	182/022	Belarus	12	20	3031	21.8	50	640	2658	98	43
Grodno	186/022	Belarus	20	25	3486	30.8	48	631	2780	87	37
Smolensk	182/022	Russia	7.4	11	2478	11.3	82	649	2649	89	31

Kaluga	180/022	Russia	11.0	14	2527	13.8	54	680	2663	86	35
Tula	178/022	Russia	13.5	18	2645	19.2	*	638	2735	39	55
Rjazan	176/022	Russia	11.8	12	2881	16.8	70	566	2791	36	49
Vladimir	176/021	Russia	11.8	15	2880	16.2	74	605	2684	79	23
Olstyn	188/022	Poland	24.0	41	2914	34.8	23	713	2818	100	67
Suwałki	188/022	Poland	20.0	34	2958	28.5	20	642	2808	69	51

[1]-Statistical data from (Belstat 2002, Goskomstat 1991, Goskomstat LitSSR 1989; GUS 1987, GUS 1992); [2]–climatic data from (IIASA 2000); [3]-soil data are taken from (Batijes, 2001);[4] -percentage of agricultural land are calculated from classified multi-date Landsat TM/ ETM+ images; *- not available.

Table 2-3: Images used and cloud contamination for each Landsat TM/ETM+ footprint.

WRS2 Path/Row	**176/021***	**176/022***	**178/022**	**180/022***	**182/022***	**186/022***	**186/021**	**188/022**
Image dates (yyyy/mm/dd)	1987/06|01	1988/07/21	1985/06/01	1986/05/01	1988/05/28	1989/05/03	1985/06/25	1985/05/22
	1988/07/21	1988/08/22	1986/06/20	1986/07/04	1999/09/08	1989/07/06	1989/09/08	1988/05/14
	1988/08/22	1999/09/06	1989/09/05	1986/10/05	2000/04/27	1989/09/24	1999/07/10	1986/10/16
	1999/09/06	2000/05/11	2000/09/22	1999/07/08	1999/09/08	2000/05/05	2000/04/23	2002/05/21
	2002/05/09	2000/07/14	2001/07/31	1999/09/10	2000/06/06	1999/07/10	2000/06/10	2002/06/06
	2002/07/28		2002/05/23			1999/09/20	2000/09/30	2002/07/16
								2002/11/05
Clouds (%)	7	9	3	10		4	6	8

Path/Row* - Landsat footprints visited during 2007-2008 field campaign

Table 2-4: Accuracy of the land cover classifications in each Landsat footprint (UA = User's accuracy (%), PA = Producer's accuracy (%), CK = Conditional Kappa (%))

WRS 2 path/row	Forest and Wetland			Stable Agriculture			Abandoned Agricultural Land			Riparian Vegetation and Permanent Shrubs			Other			OA	KHAT
	UA	PA	CK	UA	PA	CK	UA	PA	CK	UA	PA	CK	UA	PA	CK		
176/021	96.4	97.5	94.8	96.3	89.6	93.4	92.7	76.2	91.7	63.9	86.5	59.2	100.0	81.2	100.0	92.8	87.5
176/022	100.0	99.2	100.0	86.8	94.3	83.6	85.8	83.7	81.8	82.6	81.8	76.4	100.0	35.2	100.0	90.7	87.1
178/022	95.3	92.9	94.4	89.6	91.5	79.6	80.6	51.7	76.0	46.9	80.3	41.3	88.9	79.5	88.2	83.7	77.3
180/022	97.4	83.0	95.5	89.0	88.2	86.4	89.1	92.7	85.5	60.0	88.2	54.4	100.0	100.0	100.0	86.7	81.0
182/022	95.1	76.8	92.9	95.1	91.2	91.9	92.3	85.7	91.2	63.7	94.2	57.0	100.0	70.6	100.0	86.1	81.0
186/021	98.2	98.0	97.2	96.4	93.8	94.7	90.7	98.6	88.7	83.8	87.6	82.4	96.3	82.5	96.0	95.2	93.2
186/022	99.3	98.7	98.6	97.4	89.0	96.0	84.0	76.8	81.7	50.0	89.9	48.6	97.9	98.0	97.8	92.6	89.0
188/022	97.5	92.8	94.4	90.1	88.2	89.3	82.5	79.2	80.0	62.2	77.8	56.3	96.4	97.0	96.2	84.1	81.5

Figure Captions

Figure 2-1. Study area and Landsat footprints

Figure 2-2. Agricultural change in the study region (livestock and crops decline)

Figure 2-3. Abandonment rates (A: By countries; B: Separately for Belarus and Russia by provinces)

Figure 2-4. A: Abandonment pattern in the cross-border the cross-border Poland and Kaliningrad province of Russia . B: Abandonment pattern in the cross-border Grodno province of Belarus and Lithuania. C: Abandonment pattern in the cross-border Mogilev province of Belarus and Smolensk province of Russia. D: Abandonment pattern in Iznokovskij district, Kaluga province of Russia. E: Abandonment pattern between Moscow and Tula province of Russia. F,G: Abandoned pattern in Rjazan province of Russia. H: Abandonment pattern in Vladimir province of Russia.

Figure 2-5. Abandonment rates by districts

Figure 2-6. Share of unprofitable agricultural enterprises and abandoned agricultural land in cross-border region between Belarus and Russia in the year 2000.

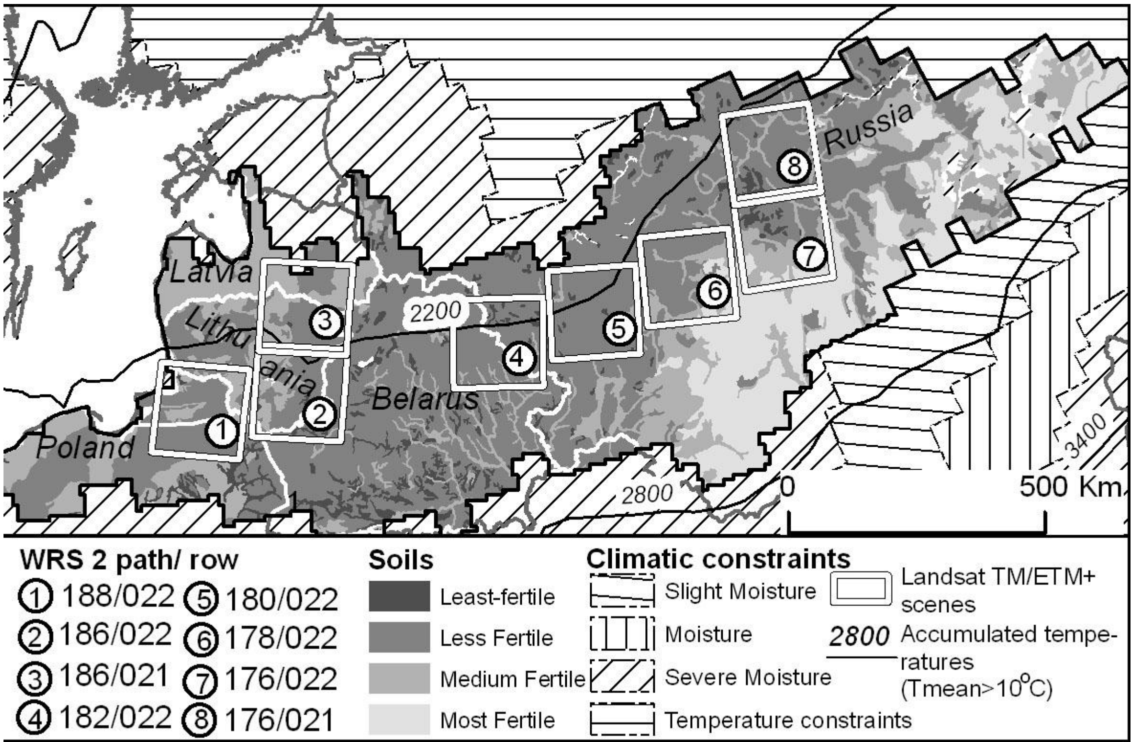
Russia
Latvia
Lithuania
Belarus
Poland
2200
2800
3400
0
500 Km
WRS 2 path/ row
1 188/022
2 186/022
3 186/021
4 182/022
5 180/022
6 178/022
7 176/022
8 176/021
Soils
Least-fertile
Less Fertile
Medium Fertile
Most Fertile
Climatic constraints
Slight Moisture
Moisture
Severe Moisture
Temperature constraints
Landsat TM/ETM+ scenes
2800 Accumulated temperatures (Tmean>10°C)

Figure 2-1

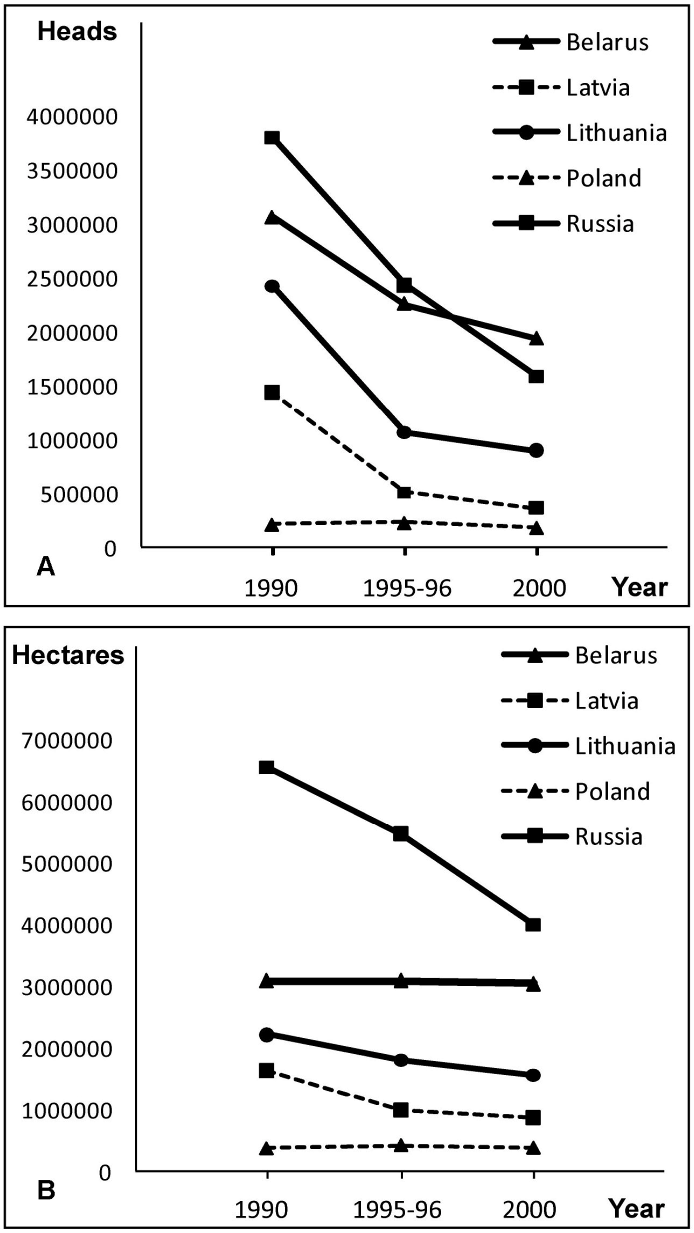
Heads
Belarus
Latvia
Lithuania
Poland
Russia
4000000
3500000
3000000
2500000
2000000
1500000
1000000
500000
0
A
1990
1995-96
2000
Year
Hectares
Belarus
Latvia
Lithuania
Poland
Russia
7000000
6000000
5000000
4000000
3000000
2000000
1000000
0
B
1990
1995-96
2000
Year

Figure 2-2

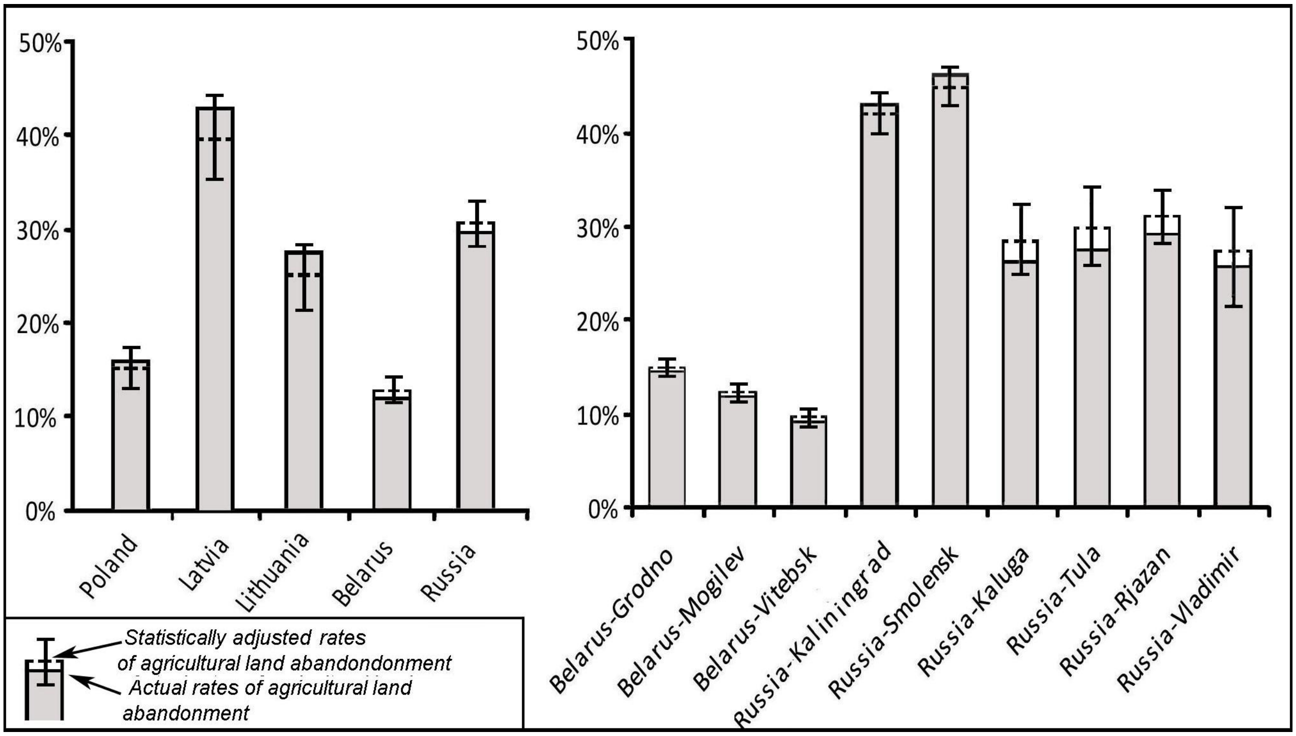
50%
40%
30%
20%
10%
0%
Poland
Latvia
Lithuania
Belarus
Russia
Statistically adjusted rates of agricultural land abandondonment
Actual rates of agricultural land abandonment
Belarus-Grodno
Belarus-Mogilev
Belarus-Vitebsk
Russia-Kaliningrad
Russia-Smolensk
Russia-Kaluga
Russia-Tula
Russia-Rjazan
Russia-Vladimir

Figure 2-3

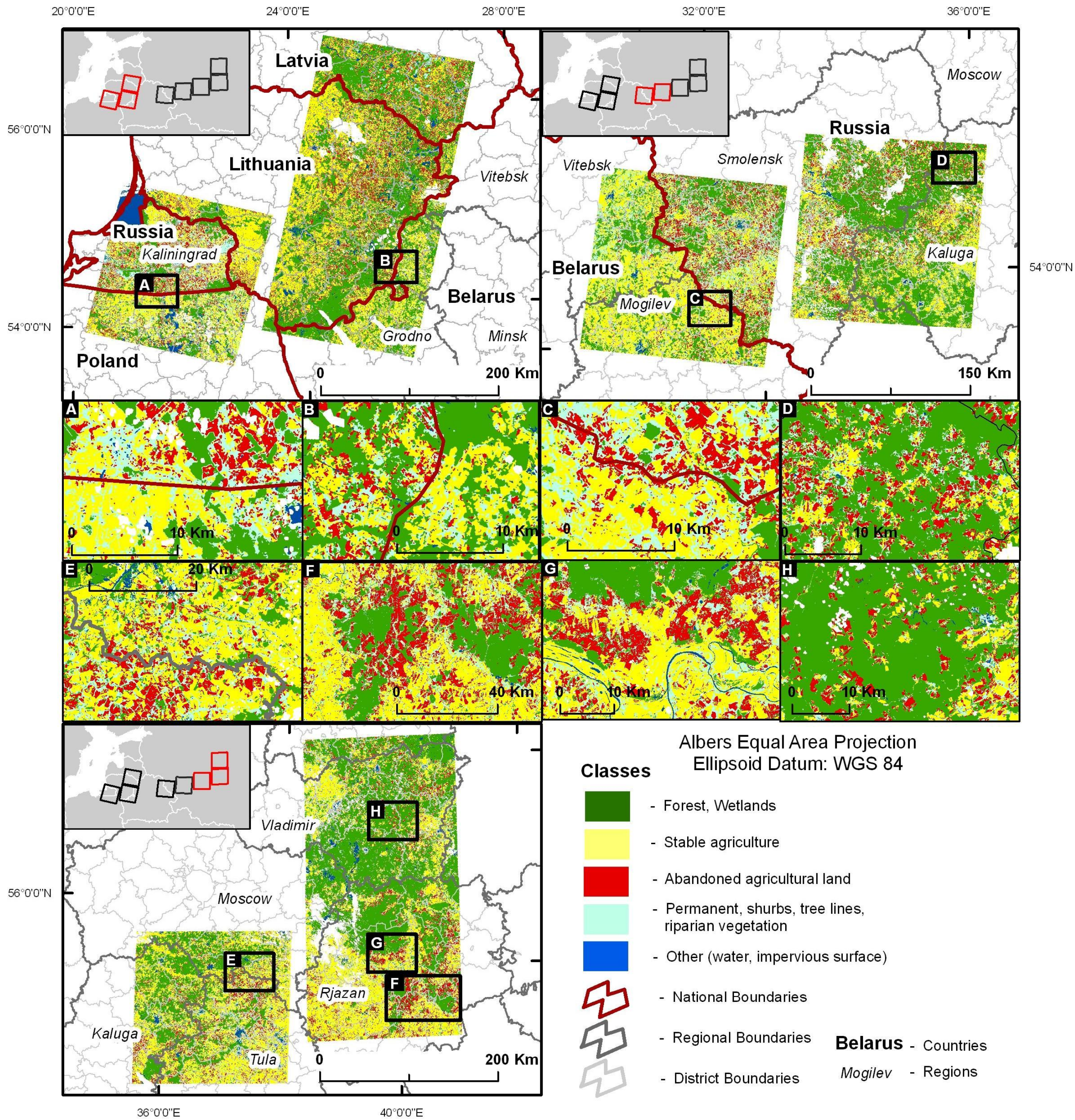
20°0'0"E
24°0'0"E
28°0'0"E
32°0'0"E
36°0'0"E
56°0'0"N
54°0'0"N
Latvia
Lithuania
Russia
Kaliningrad
Poland
Belarus
Vitebsk
Grodno
Minsk
Smolensk
Mogilev
Moscow
Kaluga
200 Km
150 Km
10 Km
20 Km
40 Km
Vladimir
Rjazan
Tula
Albers Equal Area Projection
Ellipsoid Datum: WGS 84
Classes
- Forest, Wetlands
- Stable agriculture
- Abandoned agricultural land
- Permanent, shurbs, tree lines, riparian vegetation
- Other (water, impervious surface)
- National Boundaries
- Regional Boundaries
- District Boundaries
Belarus - Countries
Mogilev - Regions
36°0'0"E
40°0'0"E

Figure 2-4

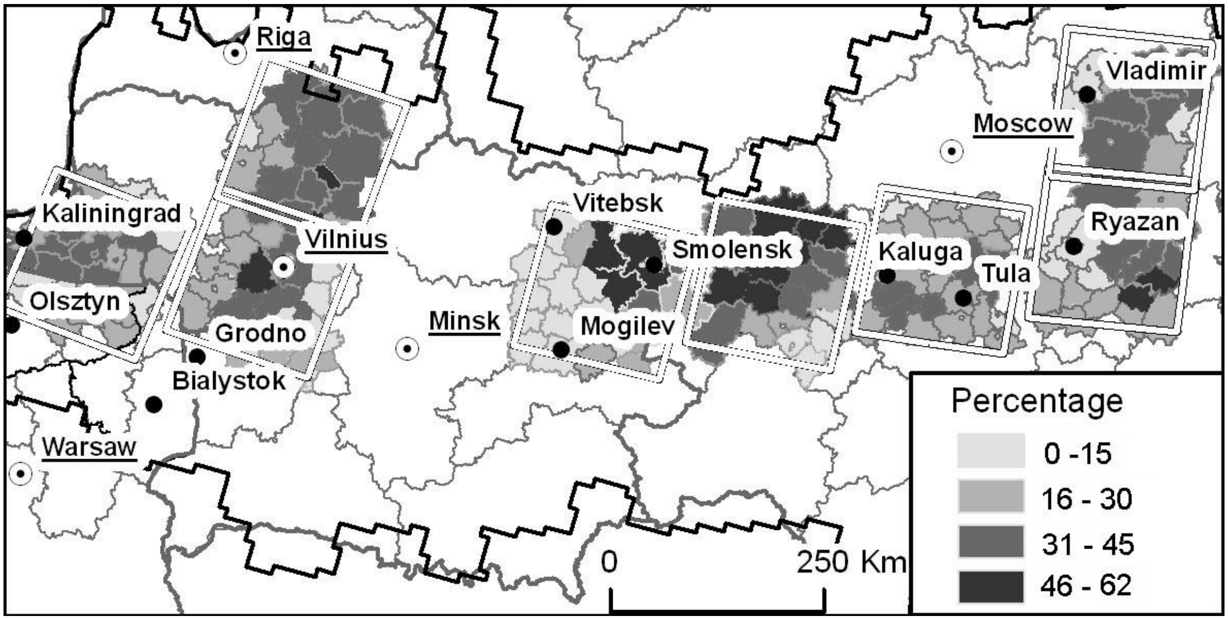
Riga
Vladimir
Moscow
Kaliningrad
Vilnius
Vitebsk
Smolensk
Kaluga
Tula
Ryazan
Olsztyn
Grodno
Minsk
Mogilev
Bialystok
Warsaw
0
250 Km
Percentage
0 -15
16 - 30
31 - 45
46 - 62

Figure 2-5

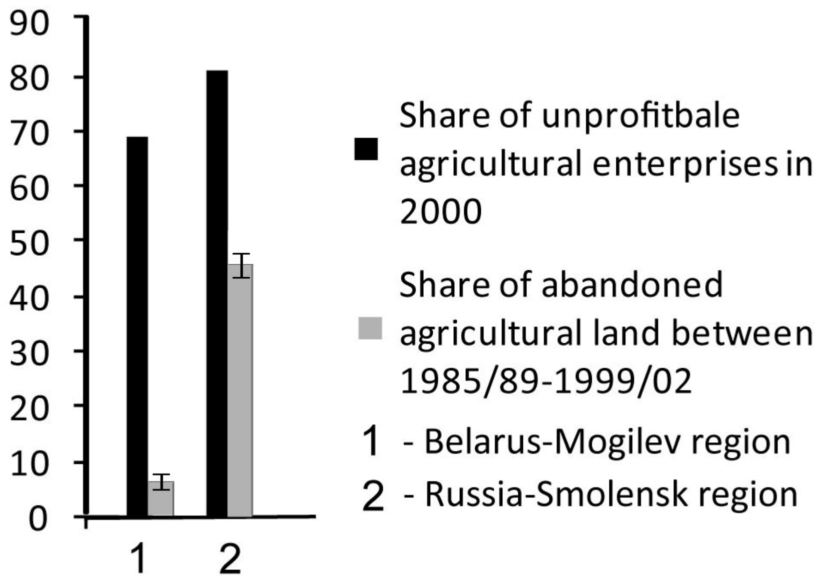
90
80
70
60
50
40
30
20
10
0
1
2
Share of unprofitbale agricultural enterprises in 2000
Share of abandoned agricultural land between 1985/89-1999/02
1 - Belarus-Mogilev region
2 - Russia-Smolensk region

Figure 2-6

DETERMINANTS OF AGRICULTURAL LAND ABANDONMENT IN POST-SOVIET EUROPEAN RUSSIA

Co-authors; Volker C. Radeloff, Daniel Muller, Maxim Dubinin, Matthias Baumann, and Kelly Wendland

Intended for: Agricultural Economics

Abstract

Socio-economic and institutional changes may affect the rates of land-use and land-cover change (LULCC). Our goal was to explore the determinants of agricultural land abandonment in post-Soviet Russia during the first decade of the transition from state-command to market-driven economy (1989-2000). We analyzed determinants of agricultural land abandonment at two scales (coarse and fine) in one agro-climatic and economic region of European Russia using satellite maps of agricultural land abandonment (5 Landsat TM/ETM+ footprints with 30-m resolution) and socioeconomic statistics. At the coarser scale (districts, or 'rayons'), we regressed land abandonment rates against socio-economic and environmental statistics (75 districts in Kaluga, Rjazan, Smolensk, Tula and Vladimir provinces) using ordinary least square (OLS) regression. At the finer scale (pixel level), we analyzed spatially explicit determinants of agricultural land abandonment for one representative province (Rjazan). At the district-scale, agricultural land abandonment was statistically significantly associated with lower agricultural average crop and milk yields in the late 1980s. As agricultural productivity (crop and milk yields) was a function of environmental conditions (soil, climate), social factors (rural population density), and economic conditions (distances to administrative centers). We also observed that agricultural land abandonment was highly correlated with nighttime light intensity change between 1992 and 2000, a variable which may serve as an indicator of GDP change. Our fine-scale (pixel-level) model for one representative province (Rjazan) showed that distance to markets and environmental constraints were the major factors associated with abandonment. At coarse- scale, we suggest that 90% declines of governmental subsidies for agriculture after 1990 caused the abandonment of previously subsidized low-productivity agricultural lands. At the fine scale, we suggest that transportation costs were important since classic micro-economic theories, such as von Thünen's and Ricardo's land-rent theories matched our observed agricultural land abandonment patterns but played at finer level that districts.

Keywords: Land-use change, land-use transitions, institutional changes, cropland abandonment, Russia, remote sensing, Support Vector Machines, land use models, logistic regression, spatially explicit-econometric models, change detection.

1. Introduction

Land use is a major cause of biodiversity declines, and diminishing ecosystem functioning and services (Vitousek, et al., 1997). Rapid socio-economic and institutional changes may accelerate land-use and land cover change (LULCC). A major recent rapid socio-economic change was the collapse of socialism and the transition from state-command to market-driven economies in Eastern Europe in the early 1990s. However, the impacts of this transition on LULCC are not well understood. The dismantling of state-governed economies, withdrawal of governmental support, and implementation of open markets changed the economy, human welfare, and health drastically (Kontorovich, 2001, Shkolnikov, et al., 2001). For instance, during the first of decade of the transition from state command to market driven economies (further "transition"), Russian life expectancy declined from 69 to 65 years and GDP declined by 67% (Rosstat, 2002, World Bank, 2008). Profound changes were particularly common in rural regions of Russia where state-support of agriculture ceased, and rural development stopped (Rosstat, 2002). Between 1990 and 1999 investments in the Russian agricultural sector declined from $39 Billion to $2 Billion (Goskomstat, 2000). Male life expectancy in rural area declined from 61 to 53 years in central European Russia (Rosstat, 2002).

These drastic socio-economic changes affected land use, but patterns of LULCC varied. During the transition period, logging increased in Western Ukraine and the Baltics (Brukas, et al., 2009, Kuemmerle, et al., 2007, Urbel-Piirsalu & Backlund, 2009), some of which was illegal (Kuemmerle, et al., 2007). But logging also decreased in remote provinces of European Russia (Pallot & Moran, 2000), urban areas sprawled (Boentje & Blinnikov, 2007), and agricultural land abandonment was widespread in Eastern Europe (Baumann et al., in review, Henebry, 2009, Kuemmerle, et al., 2007, Prishchepov, et al., *in review*). Agricultural land abandonment rates were especially high in countries which experienced institutional changes and which had weak institutions during the transition (Prishchepov, et al., *in review*). However, little is known about the drivers of LULCC in Eastern Europe in general, and those of agricultural abandonment in particular.

Previous studies of agricultural abandonment in Western Europe identified factors such as unfavorable environmental conditions (e.g., higher elevation, steeper slopes, poor soils, and poorly meliorated farmfields), remoteness, high part-time agricultural employment, and rural population migration as the key determinants of agricultural land abandonment. However, there were also exceptions to this common set of drivers. In Southern France (Van Eetvelde & Antrop, 2004) and Switzerland (Gellrich, et al., 2007), there was more agricultural land abandonment close to administrative centers and in areas with rapid population growth. Agricultural land abandonment can also be strongly associated with landowner characteristics (Kristensen, et al., 2004, Van Doorn & Bakker, 2007). “Mixed” activity landowners (i.e., agricultural producers who also engage in alternative businesses) were more likely to reforest agricultural land than any other types of landowners (Van Doorn & Bakker, 2007). Similarly, older landowners in Portugal, Denmark, and Finland were more likely to reforest agricultural land (Kristensen, et al., 2004, Selby, 1997, Van Doorn & Bakker, 2007). Grasslands were more likely abandoned where the dairy industry has been replaced by the less labor-intensive practice of breeding calves, and also in areas with low income and high rents for grassland (Baldock D, et al., 1996). Last but not least, smaller farms throughout Europe were more likely to abandon farmland than larger enterprises (Baldock D, et al., 1996, Kristensen, et al., 2004).

However, it is not clear if the same set of factors is associated with agricultural land abandonment in the transition economies of former Soviet Bloc countries. So far, only few quantitative studies have examined the spatial determinants of post-socialist agricultural abandonment (Baumann et al., *in review*, Ioffe, et al., 2004, Lowicki, 2008, Muller & Sikor, 2006, Muller, et al., 2008). Results from these studies have varied. For instance, in Albania and Romania, agricultural land abandonment is more common at larger distances from roads and administrative centers (Muller & Sikor, 2006, Muller, et al., 2008), but distance does not matter in Western Ukraine, where high agricultural land abandonment rates occur near populated centers and on favorable soils (Baumann, et al., *in review*). Surprisingly, abandonment is also higher in districts with higher investments in agriculture (i.e., in municipalities with higher number of livestock units in Romania (Muller et al., 2008), and in districts with higher number of tractors in Ukraine (Baumann et al., *in review*)). Additionally, agricultural land abandonment is more common where agricultural landownership is more fragmented (Muller, et al., 2008).

All prior studies on post-socialist determinants of agricultural land abandonment have focused on environmentally marginal regions, just as prior studies in EU countries had. However, agricultural land abandonment was widespread throughout Eastern Europe and affected also productive areas. Our knowledge of the drivers of post-socialist land use change is thus still incomplete, especially since no studies to date took place in the country with the most agricultural area, i.e., Russia. This is also unfortunate, because the large size of the Russian territory offers "natural experiments" (Diamond, 2001). When controlling for environmental variation (i.e., by studying a single, large agro-climatic region), studying Russia allows to emphasize socio-economic factors associated with agricultural land abandonment (Prishchepov, et al., *in review*). Our prior mapping of agricultural land abandonment in Russia indicated that agricultural land abandonment in the first decade of transition (1989-1999) reached very high rates (up to 44% in Smolensk province) even in areas that were environmentally favorable for agriculture (Prishchepov, et al., *in review*).

Thus, our goal here was to explore socio-economic and environmental factors associated with agricultural land abandonment in one agro-climatic region of post-Soviet Russia. Our first objective was to use ordinary least squares linear regression to explore determinants of agricultural land abandonment at the district level ('rayons') within one uniform agro-climatic region in European Russia. Our second objective was to explore local socio-economic and environmental determinants of agricultural land abandonment at a finer scale (pixel-level in one representative province for the outlined Russian region (Rjazan province).

At the district level, our major hypotheses were that agricultural land abandonment was more common in areas that were marginal for agriculture, as indicated by lower (and declining) crop yields , lower (and declining) rural population densities, and farther distances to provincial centers. At the pixel scale, we hypothesized that agricultural lands futher away from local markets, and in areas with lower road densities would be more likely to be abandoned.

2 Methods

2.1 Study area

We used climate maps for a coarse stratification of agricultural suitability, specifically average annual mean temperature for January and July, days with temperatures >10 °C, and annual precipitation (Afonin, et al., 2010). We also constrained our study region based on climatic limits to wheat growth, agro-natural zoning, and geobotanical maps (Alexandrova & Yurkovskaja, 1989, Kashtanov, 1983,). Based on these coarse stratifications, we selected the largest region with homogeneous environmental conditions that allowed for broad-scale-analysis by covering a statistically meaningful number of districts (Figure 3-1).

Climate in the study region is temperate-continental, with average maximum temperatures in the warmest month (July) ranging from 30°C to 34°C. Average minimum temperatures in the coldest month (January) range from -37 °C to -28°C (Afonin, et al., 2010). Days with temperatures >10 °C are in the range from 125 to 142 days. Annual precipitation ranges from 428 mm to 713 mm (Afonin, et al., 2010). Topography is flat, and ranges from 0 to 300 m. Geobotanically, the region is a part of the temperate mixed forest zone and the Sarmatic mixed forests (Olson, et al., 2001). The northernmost part of the study area represents the southern taiga-mixed forest boundary and the south of the study region borders the forest-steppe zone (Tula and Rjazan provinces of Russia) (Alexandrova & Yurkovskaja, 1989). On average, 30% of the region is forested, with higher proportions of forest in northern part of the study area. Dominant tree species include northern spruce (*Picea abies*), scots pine (*Pinus sylvestris*), silver birch (*Betula pendula*), and pedunculate oak (*Quercus robur*) (Folch, 2000). Soils mainly consist of podzols, luvisols and gleysols and fluvisols along rivers (Batijes, 2001). In the south-eastern corner of the region phaeozem and chernozem soils occur (Figure 3-1). In total though, the outlined study region is a part of the non-chernozem economic zone of Russia.

The study region is well-suited for agriculture, especially after melioration, liming and fertilization of podzolic soils. During the last decades of the Soviet era, the region became one of primary agricultural areas, especially after failed attempts to expand wheat growing in Kazakhstan (Ioffe & Nefedova, 2004). Main summer crops are barley, rye, oats, sugar beets, fodder maize, potatoes, peas, summer rapeseed, and flax, and main winter crops are winter wheat, winter barley, and winter rapeseed. Crop yields per hectare are lower than in neighboring countries (e.g., Belarus, Lithuania, Poland, Ioffe & Nefedova, 2006). Cattle breeding, dairy farming, and poultry production is also common.

After the dissolution of the Soviet Union in 1990, Russia transitioned from a state-controlled to a market-driven economy (Lerman, et al., 2004). Governmental regulation of agriculture and subsidies were largely withdrawn. The land and assets of collective and state farms were redistributed among former farms workers in forms of paper shares. However, a moratorium on agricultural land transactions was imposed to prevent potential land speculation and kept in place until 2002 (Lerman & Shagaida, 2007). As a result, after the collapse of the Soviet Union, national official statistics show substantial declines in sown crops (by up to 44% in Smolensk province) (Rosstat, 2002) and livestock numbers (by up to 68% again in Smolensk province) (Figure 3-2).

2.2 Land-cover maps

Land-cover maps were available from our previous work (Prishchepov, et al., 2010) and provided detailed agricultural land abandonment data for five 184x184 km Landsat TM/ETM+ footprints. These footprints covered 77% of Kaluga province, 72% of Vladimir province, 72% of Rjazan province, 55% of Smolensk province, and 51% of Tula province (Figure 3-1). We used multi-date images and support vector machines classifier to derive land cover maps. Initial classification catalog consisted of “Forest”, “Stable agriculture”, “Abandoned agricultural land”, “Riparian Vegetation and Permanent Shrubs” and “Other” classes. Average Kappa for all five classifications was 0.84, ranging from 0.77 to 0.93. Conditional Kappa for “Stable agriculture” equaled to 0.89 (0.79 to 0.93). Conditional Kappa for “Abandoned agricultural land” equaled to 0.84 (0.76 to 0.91). Lowest overall and conditional Kappa estimates were observed for the footprint covering Tula province. For our modeling purposes we recoded the previous classifications to “Stable agriculture”, “Abandoned agricultural land”, and “Other” classes.

Our classifications indicated that from 1989 to 1999 31% of the agricultural land in 1989 was abandoned (1.7 million hectares, 44% of agricultural land was abandoned in Smolensk province (446,500 hectares), 29.8% in Kaluga province (382,100 hectares), 25.7% in Tula province (223,000 hectares), 27.8% in Rjazan province (377,300 hectares) and 27.4% in Vladimir province (189,530 hectares)) (Prishchepov, et al., *in review*). Abandonment rates were even higher in some districts, reaching 62% in parts of Smolensk province (Figure 3-3).

2.3 Explanatory variables for district-based OLS models and their hypothesized influences

For the study period from 1989 to 2000, the most detailed agricultural and population statistics for Russia were available at the district (’rayon’) level, which is roughly equivalent to counties in the United States. The average size of rural districts is 1,525 km^2 and our remote sensing classifications covered 76 districts (14 in Smolensk province, 18 in Kaluga province, 14 in Tula province, 18 in Riazan province and 11 in Vladimir province, Figure 3-3).

Economic theory generally assumes that actors choose the land use that maximizes the net stream of income (Gellrich, et al., 2007, Maddala & Lahiri, 2009). We assumed that agricultural land abandonment was mainly driven by economic decisions evolving from human behavior (Irwin & Geoghegan, 2001). An actor stops farming when rent expenditure and production costs were no longer balanced by the profit from agricultural output or when land becomes marginalized due to other socio-economic aspects such as rural population decline or rural population aging. Based on these assumptions we selected following groups of variables for the district level OLS model: population, infrastructure, proximate, economic activity, agricultural productivity, and biophysical variables (Table 3-1). Unfortunately, no statistical data was available to explore structural characteristics of agriculture (e.g., types of farms) or characteristics of agricultural producers (e.g., education). Hence, our models were limited to an exploration of broad-scale determinants of agricultural land abandonment rather than the modeling of causal factors at the level of individual decision making. Population and agricultural statistics at the district level had previously been compiled from official sources (Ioffe, et al., 2004). To calculate road densities and distances we used a GIS dataset for Russia derived from 1:500,000 declassified Soviet topographic maps from the late 1980s. Environmental variables were derived from 10-km pixel resolution GIS Agroatlas for Russia (Afonin, et al., 2010) and from 60-m resolution forest-cover maps for 2000 (Potapov, et al., 2010).

Our hypotheses were that agricultural abandonment would be higher where rural population density was lower in 1991, where population was lower in district centers in 2000, where a higher rural population decline was observed from 1991 to 2001, and where the share of retirees in 2000 was higher. We also assumed a positive correlation between abandonment and distances to provincial capitals from the district centroids due to higher travel costs, and higher abandonment rates where road density was lower. We also hypothesized that abandonment rates would be higher where agricultural productivity (crop yields and milk production) was low during the Soviet period. We also assumed that agricultural land abandonment would be higher where gross regional product declined more. Unfortunately, we did not have gross regional products available to us. Instead, we used satellite detected night-time lights intensity change from 1992 to 2000, which are strongly correlated with GDP change (Doll, et al., 2000, Henderson, et al., 2009). Lastly, we hypothesized that abandonment would be higher where forest percentage was higher, indicating marginality of agricultural land use. For our OLS regression model at the district level, we calculated the rate of abandoned agricultural land relative to the total pre-abandonment agricultural land as the response variable.

For the statistical analysis we used R statistical package (R Team, 2009). We checked for collinearity. When R >0.6 for two explanatory variable, we retained only the variable that was more strongly related to abandonment in our regression models. However, we did explore the predictive power of correlated explanatory variables using descriptive statistics and univariate models. For instance, average crop yield in the late 1980s and night-time lights intensity change from 1992 to 2000 were negatively correlated (R=0.66). We retained only crop yields in late 1980s for the multivariate regression modeling. High levels of collinearity were observed, especially for soil, climate variables and percentage of forest in 2000 for each district. Crop yields from different years and rural population variables were also highly correlated among themselves. Altogether, out of 64 variables we retained 11 variables for the initial assessment.

The models were evaluated based on the significance values (*p-value*) of the response variables and R^2 as a measure of model fit. Multivariate model residuals were checked for spatial autocorrelation.

2.4 Explanatory variables for hierarchical pixel-based logistic regression model and their hypothesized influences

For the detailed case study, we selected one province, Rjazan, which experienced 27.8% agricultural land abandonment .Based on the assumptions that the cumulative distribution function for the residual error of the explanatory variables follows the logistic distribution it is possible to construct spatially explicit logistic regression model. For the logistic regressions we changed our satellite classifications so that “1”- represented abandoned agricultural land and “0”-represented stable agricultural land. In addition to the district-level socio-economic variables we selected complementary socio-economic and environmental variables which varied within districts at either the municipality level or the pixel level.

Based on 1:100,000 Soviet topomaps from the end of the 1980s we digitized settlement centroids and assigned population for each settlement as stated in these maps. We identified municipality administrative centers prior to the 2006 administrative reform in Russia.

For the logistic regressions at the pixel level, we selected several continuous variables, including distance to provincial capital, and distance to municipality centers (Table 3-2). We also calculated continuous interpolated population density using second-order inverse distance weights (Muller, et al., 2008), which were digitized from the settlements on 1;100,000 Soviet topographic maps.

We sampled 3,716 pixels randomly from the available 16 million pixels, and ensured at least 500-m distance between samples to minimize spatial autocorrelation. Since in the studied part of Rjazan province abandonment was relatively high, and 30% of the sampled points (1,085) represented “presence” of abandonment we did not adjust our sampling design for an unbalanced sampling (Muller, et al., 2008).To remove collinear variables for the logistic regression we selected only one variable from each pair of variables with >0.60 Pearson correlation. For the final hierarchical pixel-based logistic regression model we retained 21 variables (Table 3-2)**.**
Multiple samples within the same administrative unit are not truly independent (Overmars & Verburg, 2006, Gellrich, et al., 2007, Muller, et al., 2008). To control for this, we introduced a group structure and conducted a cluster adjustment in our logistic model (Gellrich, et al., 2007, Muller, et al., 2008). Controlling thereby for the correlations of observations within administrative units also controls for spatial autocorrelation (Muller, et al., 2008). We assumed that cluster adjustment was necessary for variables belonging to the same district (rayon), since districts are the administrative unit where main land use decisions and governance are taking place.

To fit our logistic models we used the “lrm” function and for cluster adjustment we used “robcov” function based on Huber-White method (Huber, 1967, White, 1982) in the R Design package (R Team, 2009). We calculated log-likelihood for the logistic model, Akaike Information

Criterion (AIC), deviance for the residuals of the null and fitted models and goodness-of-fit measure area under the curve (AUC) (R Team, 2009).

3. Results

3.1 Multivariate OLS linear regression modeling for all provinces combined

Correlations among dependent and independent variables reprenseted different degree of the relationship (Figure 3-4). We observed high correlation of agricultural land abandonment rates with rural population density in 1991 (R=0.46), distance to provincial center (R=0.34), milk production per cow in 1990 (R=0.41), average crop yield in the late 1980s (R=0.76), average crop yiled change from the late 1980s to the late 1990s (R=0.36) and forest percentage in 2000 (R=0.37).

We included all of these variables into our multivariate OLS linear regression model. Results of multivariate model showed that variable average crop yield in the late 1980s was the only statistically significant variable at p<0.05. The multivariate OLS linear regression model expained 56% of variability. However, we also noticed moderate correlation of average crop yields in the late 1980s with rural population density in 1991 (R=0. 61), distance to provincial capital (R=0.51), milk production per cow in 1990 (R=0.54), average crop yield change from the late 1980s to the late 1990s (R=0.60). This suggested that agricultural productivity (e.g. crop yields) may have been a function of socio-economic and environmental factors.

3.2 Hierarchical pixel-based logistic regression modeling for Rjazan province

The model goodness-of-fit (area under the curve, AUC) for our logistic regression model was 0.76 (Table 3-3). The exploratory power of the model was low (adjusted R^2 = 0.19), but within the range of what has been reported for other logistic regression models of land use change (Gellrich, et al., 2007, Muller, et al., 2008).

All selected groups, namely, population, infrastructure, proximate, agricultural productivity and biophysical were represented in the model and had statistically significant relationship with agricultural land abandonment (Table 3-3). All variables, except the number of days with temperatures >10 °C appeared in the model with their expected signs of the relationship to the abandoned agricultural land.

Agricultural land abandonment was statistically significantly higher where villages densities in the late 1980s was lower, and where fields were further away from larger settlements (over 500 people) (Figure 3-5). Abandonment was also higher at higher elevations, on steeper slopes and on soils with lover pH (Figure 3-5) and in more forested districts. However, contrary to our expectations, abandonment was more common where number of accumulated days >10 °C was larger.

4. Discussion

4.1 Multivariate OLS linear regression modeling for all provinces combined

Average crop yields in the late 1980s had the highest explanatory power for agricultural land abandonment at the district level. Agricultural lands with low average crop yields in the late 1980s were generally found in more remote regions with lower rural population densities (Ioffe & Nefedova, 2004). It appears that abandoned agricultural lands were those that were already socially and environmentally marginal for agricultural production in 1989, but were subsidized during socialist time (Ioffe & Nefedova, 2004). The moderate negative correlation between agricultural land abandonment rates and rural population density in the late 1980s supported this idea.

We also observed a positive statistically significant relationship between night-time lights intensity decline from 1992 to 2000 and agricultural land abandonment. It is likely that processes of agricultural land abandonment were interconnected with Gross Regional Product decline (we used night-time lights change rates as a proxy for Gross Regional Product change) (Doll et al. 2006, Henderson et al. 2009). However, it was unclear if Gross Regional Product change affected agricultural land abandonment or, vice versa (Kaimovitz et al.2004), or if both simply occurred concomitantly.

The predictive power of the selected variables for our district based OLS linear regression models for all five provinces together was medium suggesting that we missed other drivers of agricultural abandonment, which is why we complemented the district-level model with a pixel-level model. Moreover, it is likely, that some socio-economic factors (e.g., rural population densities and proximities) have different effect on agricultural land abandonment between the provinces as well, reflecting different policies and socio-economic development of the selected provinces.

4.2 Hierarchical pixel-based logistic regression modeling for Rjazan province

Complementary to OLS linear regression model at district level. our pixel-based logistic regression analysis for Rjazan province contributed to the understanding of the determinants of agricultural land abandonment. It was especially useful approach since some district statistics (e.g., rural population density and distance to the regional centers) didn't appear statistically significant in the OLS model, likely due to the aggregated level. Another factor can be that, in the case of Rjazan proximities factors were important at the municipality level and finer level, rather than at the district scale (Table 3-3). In the logistic model for Rjazan province, proximities to settlements (i.e., district with population exceeding 500 people) and biophysical variables were additional statistically significant variables. Using pixel based modeling approach allowed us to disaggregate and use more socio-economic variables which were simply not available in the official district level statistics (e.g., population characteristics and proximities). The modeling output was consistent with the theory of rational economic decision making (e.g., abandonment was higher afar from settlements, in lower populated places, and on economically unfavorable agricultural lands). Generally, we identified variables that were significant in other studies as well and the relationship with abandonment mostly supported our hypotheses. However, we were surprised to see that abandonment was higher in places with more days with temperatures >10 °C.

This might indicate that social-economic changes in some cases overruled environmental gradients. While agricultural land abandonment was common where rural population density change (Selby, 1997, Baumann, et al, 2010), and share of retirees was higher (Selby, 1997, Kristensen, et al., 2004) we did not observe such statistically significant relationship in our case. Rural population density was fairly low prior the transition in the studied region, thus, it is likely, population decline didn't affect abandonment as much as other factors associated with structural economy changes and economic decision making (e.g., travel costs).

Conclusion

In general, we identified several factors that were associated with agricultural land abandonment in temperate European Russia. These factors were similar to those previously found in other studies on determinants of agricultural land abandonment and showed that rational decision making was behind of agricultural land abandonment process (i.e., areas that were abandoned were generally less productive and more distant to markets). Our sampling design largely controlled for agro-climatic differences, thus it was interesting to observe statistically significant relationship between agricultural land abandonment rates and socio-economic characteristics. It is likely that agricultural land abandonment was ultimately driven by macro-scale socio-economic drivers such as the withdrawal of agricultural subsidies supporting the agricultural production on marginal lands (Ioffe & Nefedova, 2004). At the fine scale we observed distance effects on agricultural land abandonment patterns, supporting micro-economic decision-making underlying the agricultural land abandonment process.

Acknowledgments

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Literature

Achard,F., Mollicone,D., S.,H. -J, Aksenov,D., Laestadius,L., Li,Z., Popatov,P. & Yaroshenko,A. (2006). Areas of rapid forest-cover change in boreal Eurasia. *Forest Ecology and Management, 237*(1-3), 322-334.

Afonin,A. N., Lipiyaynen,K. L. & Tsepelev,V. Y. (2010). Interactive Agricultural Ecological Atlas of Russia and Neighboring Countries, Economic Plants and theirs Diseases, Pests and Weeds. *Online GIS dataset*. (last accessed August 30, 2010, http://www.agroatlas.ru/en/).

Alexandrova,V. D. & Yurkovskaja,T. K. (1989). Geobotanical zoning of Nonchernozem european part of RSFSR (Geobotanicheskoe rayonirovanie Nechernozemjia evropeiskoi chasti RSFSR).

Baldock D, Beaufoy G, Brouwer F & Godeschalk F. (1996). *Farming at the margins: abandonment or redeployment of agricultural land in Europe.* Institute for European Environmental Policy (IEEP), London, and Agricultural Economics Research Institute (LEI-KLO), The Hague.

Batijes,N. H. (2001). Soil data for land suitability assessment and environmental protection in Central Eastern Europe -the 1:2500000 scale SOVEUR project. *The Land, 5.1*51-68.

Baumann,M., Kuemmerle,T., Elbakidze,M., Ozdogan,M., Radeloff,V. C., Keuler,N. S., Prishchepov,A. V., Kruhlov,I. & Hostert,P.. Patterns and drivers of post-socialist farmland abandonment in Western Ukraine. *Ecology and Society, in review*

Bergen,K. M., Zhao,T., Kharuk,V., Blam,Y., Brown,D. G., Peterson,L. K. & Miller,N. (2008). Changing regimes: Forested land cover dynamics in Central Siberia 1974 to 2001. *Photogrammetric Engineering and Remote Sensing, 74*(6), 787-798.

Boentje,J. P. & Blinnikov,Mi S. (2007). Post-Soviet forest fragmentation and loss in the Green Belt around Moscow, Russia (1991-2001): a remote sensing perspective. *Landscape and Urban Planning, 82*(4), 208-221.

Brukas,V., Linkevicius,E. & Cinga,G. (2009). Policy Drivers Behind Forest Utilisation in Lithuania in 1986-2007. *Baltic Forestry, 15*(1), 86-96.

Burges,C. J. C. (1998). A tutorial on Support Vector Machines for pattern recognition. *Data Mining and Knowledge Discovery, 2*(2), 121-167.

Capozza,D. R. & Helsley,R. W. (1989). The Fundamentals of Land Prices and Urban-Growth. *Journal of Urban Economics, 26*(3), 295-306.

Chang,C. C. & Lin,C. J. (2001). LIBSVM : a library for support vector machines. *Computer program*. (last accessed August 29, 2010, http://www.csie.ntu.edu.tw/~cjlin/libsvm).

Cooper,T., Baldock,D., Rayment,M., Kuhmonen,T., Terluin,I., Swales,V., Poux,X., Zakeossian,D. & Farmer,M. (2006). *An evaluation of the Less Favoured Area measure in the 25 member states of the European Union.* Institute for European Environmental Policy for DG Agriculture, London, UK, 262 p.

Definiens Imaging. (2004). *ECognition™ User's guide.* Computer program. (last accessed August 29, 2010, http://www.definiens-imaging.com).

Diamond,J. (2001). Ecology - Dammed experiments! *Science, 294*(5548), 1847-1848.

Doll,C. N. H., Muller,J. P. & Elvidge,C. D. (2000). Night-time imagery as a tool for global mapping of socioeconomic parameters and greenhouse gas emissions. *Ambio, 29*(3), 157-162.

Folch,R. (2000). *Encyclopedia of the Biosphere: Deciduous forests.* Gale Group, Detroit, Mi, USA, 438 p.

Gellrich,M., Baur,P., Koch,B. & Zimmermann,N. E. (2007). Agricultural land abandonment and natural forest re-growth in the Swiss mountains: A spatially explicit economic analysis. *Agriculture Ecosystems & Environment, 118*(1-4), 93-108.

GOSKOMSTAT. (2000). *Agricultural sector in Russia (Selskoje khozjaistvo v Rossii). Statistical Compendium.* Goskomstat Rossii, Moscow, Russia, 414 p.

Henderson,J. V., Storeygard,A. & Weil,D. N. (2009). Measuring Economic Growth from Outer Space. Working paper series, National Bureau of Economic Research (last accessed August 29, 2010, http://www.nber.org.ezproxy.library.wisc.edu/papers/w15199)

Henebry,G. M. (2009). Carbon in idle croplands. *Nature*, *457*(7233), 1089-1090.

Hijmans,R. J., Cameron,S. E., Parra,J. L., Jones,P. G. & Jarvis,A. (2005). Very high resolution interpolated climate surfaces for global land areas. *International Journal of Climatology, 25*(15), 1965-1978.

Huber,P. J. (1967). The Behavior of Maximum Likelihood Estimates Under NonstandardConditions. *Proceedings Fifth Berkeley Symposium Mathematical Statistics, 1*221-33.

Ioffe,G. & Nefedova,T. (2004). Marginal farmland in European Russia. *Eurasian Geography and Economics*, *45*(1), 45-59.

Ioffe,G. & Nefedova,T.,Zaslavsky I. (2006). *The End of Peasantry? Disintegration of Rural Russia.* University of Pittsburgh Press, 256 p.

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), 913-943.

Ioffe,G., Nefedova,T. & Zaslavsky,I. A Troubled Realm: Russian Agriculture's Spatial Constraints, Variance, and Prospects for Revival.*NSF report* (last accessed August 29, 2010, http://www.radford.edu/~agrorus/index.htm)

Irwin,E. G. & Geoghegan,J. (2001). Theory, data, methods: developing spatially explicit economic models of land use change. *Agriculture Ecosystems & Environment*, *85*(1-3), 7-23.

Kaimowitz,D., Mertens,B., Wunder,S. & Pacheco,P. (2004). Hamburger Connection Fuels Amazon Destruction: Cattle ranching and deforestation in Brazil's Amazon. Centre for International Forestry Research (CIFOR), (last accessed August 29, 2010, http://www.cifor.cgiar.org/publications/pdf_files/media/Amazon.pdf).

Kashtanov,A. N. (1983). *Natural-agriculture zoning and utilizing of land resources of USSR (Prirodno-Selskohozjaistvennoe raionirovanie i ispolzovanije zemelnogo resursa SSSR).* VASHNIL, Kolos, Moscow, 336 p.

Kontorovich,V. (2001). The Russian health crisis and the economy. *Communist and Post-Communist Studies, 34*(2), 221-240.

Kristensen,L. S., Thenail,C. & Kristensen,S. P. (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), 231-244.

Kuemmerle,T., Hostert,P., Radeloff,V. C., Perzanowski,K. & Kruhlov,I. (2007). Post-socialist forest disturbance in the Carpathian border region of Poland, Slovakia, and Ukraine. *Ecological Applications, 17*(5), 1279-1295.

Kuemmerle,T., Hostert,P., Radeloff,V. C., van der Linden,S., Perzanowski,K. & Kruhlov,I. (2008). Cross-border comparison of post-socialist farmland abandonment in the Carpathians. *Ecosystems, 11*(4), 614-628.

Leica Geosystems. (2006). Imagine Autosync™ White Paper.

Lerman,Z., Csaki,C. & Feder,G. (2004). *Agriculture in transition: land policies and evolving farm structures in post-Soviet countries.* Lexington Books, Lanham, Boulder, New York, Toronto, Oxford 254. p

Lerman,Z. & Shagaida,N. (2007). Land policies and agricultural land markets in Russia. *Land Use Policy, 24*(1), 14-23.

Lowicki,D. (2008). Land use changes in Poland during transformation: case study of Wielkopolska region. *Landscape and Urban Planning, 87*(4), 279-288.

MacDonald,D., Crabtree,J. R., Wiesinger,G., Dax,T., Stamou,N., Fleury,P., Lazpita,J. G. & Gibon,A. (2000). Agricultural abandonment in mountain areas of Europe: Environmental consequences and policy response. *Journal of Environmental Management, 59*(1), 47-69.

Maddala,G. S. & Lahiri,K. (2009). *Introduction to Econometrics.* Wiley, New York, 654 p.

Mottet,Anne, Ladet,Sylvie, Coqué,Nathalie & Gibon,Annick. (2006). Agricultural land-use change and its drivers in mountain landscapes: A case study in the Pyrenees. *Agriculture, Ecosystems & Environment, 114*(2-4), 296-310.

Muller,D., Kuemmerle,T., Rusu,M. & Griffiths,P. (2008). Lost in transition: determinants of post-socialist cropland abandonment in Romania. *Journal of Land Use Science, 4*109-129.

Muller,D. & Sikor,T. (2006). Effects of postsocialist reforms on land cover and land use in South-Eastern Albania. *Applied Geography, 26*(3-4), 175-191.

New,M., Lister,D., Hulme,M. & Makin,I. (2002). A high-resolution data set of surface climate over global land areas. *Climate Research, 21*(1), 1-25.

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.

Novozhenina,O., Baharev,I. & Mollicone,D. (2009). "Hard-Okorok"("Hard-hock"). Gazeta.ru, (last accessed August 30, 2010, http://www.gazeta.ru/business/2009/01/23/2928922.shtml).

Olson,D. M., Dinerstein,E., Wikramanayake,E. D., Burgess,N. D., Powell,G. V. N., Underwood,E. C., D'Amico,J. A., Itoua,I., Strand,H. E., Morrison,J. C., Loucks,C. J., Allnutt,T. F., Ricketts,T. H., Kura,Y., Lamoreux,J. F., Wettengel,W. W., Hedao,P. & Kassem,K. R. (2001). Terrestrial ecoregions of the worlds: A new map of life on Earth. *Bioscience, 51*(11), 933-938.

Overmars,K. P. & Verburg,P. H. (2006). Multilevel modelling of land use from field to village level in the Philippines. *Agricultural Systems, 89*(2-3), 435-456.

Pallot,J. & Moran,D. (2000). Surviving the margins in post-Soviet Russia: Forestry villages in northern Perm' Oblast. *Post-Soviet Geography and Economics, 41*(5), 341-364.

Potapov,P., Turubanova,S. & Hansen,M. C. (2010). Regional-scale boreal forest monitoring using Landsat data composites: first results for European Russia. *Remote Sensing of Environment,in review.*

Prishchepov,A. V., Radeloff,V. C., Dubinin,M. & Alcantara,C. The effect of satellite image dates selection on land cover change detection and the mapping of agricultural land abandonment in Eastern Europe. *Remote Sensing of Environment, in review.*

Rabe,A., van der Linden,S. & Hostert,P. (2009). ImageSVM. *2.0*

Riasanovsky,N. V. (2000). *A History of Russia*. Oxford press, New-York,Oxford, 776 p.

Rosstat. (2002). *Regions of Russia. Socio-economic indicators. (Regiony Rossii. Sotsial'no-ekonomicheskie pokazateli).* In Russian. Federal service for state statistics, Moscow. Online statistical database via EastView Publishing. (last accessed August 30, 2010, http://udbstat.eastview.com.ezproxy.library.wisc.edu/catalog/edition.jsp?id=2200).

Rylski,I. (2000). *Development of animated maps of forest dynamics and agricultural lands in European Russia during last 300 years. In Russian.* Master thesis. Moscow State University, Department of geography.

Selby,J. A. (1997). The marginalization and afforestation of agricultural land in Finland. 3-42.

Shkolnikov,V., McKee,M. & Leon,D. A. (2001). Changes in life expectancy in Russia in the mid-1990s. *Lancet*, *357*(9260), 917-921.

Stata Corporation. (2003). Stata Statistical Software. *Release 8.0*

Strijker,D. (2005). Marginal lands in Europe - causes of decline. *Basic and Applied Ecology*, *6*(2), 99-106.

Team,R. Development Core. (2009). *R: A Language and Environment for Statistical Computing.* R Foundation for Statistical Computing, Vienna, Austria (last accessed August 30, 2010, http://www.R-project.org)

Tsvetkov,M. A. (1957). *Forestness change in European Russia since the end of 18th century till 1914*. In Russian. USSR Academy of Science of USSR, Institute of Forest, 213 p.

UN Millennium Project. (2005). *Halving Hunger: It Can be Done*. Report of the Task Force on Hunger. Earthscan. London, UK and Sterling, USA (last accessed August 30, 2010, http://www.unmillenniumproject.org/documents/HTF-SumVers_FINAL.pdf)

Urbel-Piirsalu,E. & Backlund,A.-K. (2009). Exploring the Sustainability of Estonian Forestry: The Socioeconomic Drivers. *Ambio, 38*(2), 101-108.

Van Doorn,A. M. & Bakker,M. M. (2007). The destination of arable land in a marginal agricultural landscape in South Portugal: an exploration of land use change determinants. *Landscape Ecology, 22*(7), 1073-1087.

Van Eetvelde,V. & Antrop,M. (2004). Analyzing structural and functional changes of traditional landscapes - two examples from Southern France. *Landscape and Urban Planning, 67*(1-4), 79-95.

Vitousek,P. M., Mooney,H. A., Lubchenco,J. & Melillo,J. M. (1997). Human domination of Earth's ecosystems. *Science, 277*(5325), 494-499.

Vuichard,N., Ciais,P. & Wolf,A. (2009). Soil Carbon Sequestration or Biofuel Production: New Land-Use Opportunities for Mitigating Climate over Abandoned Soviet Farmlands. *Environmental Science & Technology, 43*(22), 8678-8683.

White,H. (1982). Maximum Likelihood Estimation of Misspecified Models. *Econometrica,* 5*0*1-25.

World Bank. (2008). World Development Indicators Online. The World Bank,Development Data Group, Washington, DC ((last accessed August 30, 2010, http://go.worldbank.org/U0FSM7AQ40).

Table 3-1. Selected district-level variables for the ordinary least square regression models, and their hypothesized relationship with agricultural land abandonment.

Type	Source	Aggregated by districts	*A-Priori* Relationship to abandonment
Agro-Climatic and biophysical variables /			
Soil (soil texture, soil organic carbon content, soil drainage, soil types)	SOVEUR/ SOTER 1:2’0000’000 digital maps	Mean	None
Relief			
(Elevation, Slope, Aspect)	SRTM	Mean	None
Climatic			
(minimum temperature, maximum temperature, annual precipitation, excess of precipitation over potential evapotranspiration, number of days with temperature >10 °C, day of the first frost, day of the last frost)	AgroAtlas, 2010	Mean	None
Socio-economic determinants / Population			
Population of the district center in 2000	Rosstat, 2000	Value	-
Rural population density in 1991	Rosstat, 2000	Value	-
Rural population density in 1999	Rosstat, 2000	Value	-

Rural population density change 1989-1999	Rosstat, 2000	Value	-
Percentage of retirees in 2000	Rosstat, 2000	Value	+
Proximities			
Distance to the provincial capital from the district centroid	1:500,000 digital dataset	Value	+
Infrastructure			-
Roads (Road density)	1:500,000 digital dataset	Number	
Agricultural productivity			-
Average crop yield in the late 1980s	Rosstat, 2000	Value	
Average crop yield in the late 1990s	Rosstat, 2000	Value	-
Change of the average crop yield from the late 1980s to the late 1990s	Rosstat, 2000	Value	-
Milk production per cow in the late 1980s	Rosstat, 2000	Value	-
Milk production per cow in the late 1990s	Rosstat, 2000	Value	-
Change in the milk production per cow 1989-1999	Rosstat, 2000	Value	+

Table 3-2. Variables used in addition to those listed in Table 1 for the hierarchal spatially explicit logistic regression model.

Variable	Level	*A-priori* Relationship to abandonment
Dairy farm density in the late 1980s	district	-
Village density in the late 1980s	district	-
Dairy farms density in the late 1980s	municipality	-
Road density in 2000	municipality	-
Village density in the late 1980s	municipality	-
in 2000	municipality	+
Night-time lights intensity change 1992-2000	Pixel	-
Distance to the municipality center	Pixel	+
Distance to the nearest road	Pixel	+
Distance from the nearest municipality boundary	Pixel	-
Distance from the nearest district boundary	Pixel	-
Distance from the nearest forest	Pixel	-
Distance to the nearest settlement with over 500 people	Pixel	+
Interpolated population density from settlements within district boundaries	Pixel	+
Interpolated population density from settlements within municipality boundaries	Pixel	+
Accumulated daily mean temperatures >10 °C	Pixel	-
Elevation	Pixel	+
Slope	Pixel	+

Day of the first frost	Pixel	-
Aspect	Pixel	+
Excess of the precipitation over potential evapotranspiration	Pixel	+
soil pH	Pixel	+

Table 3-3. Hierarchical spatially explicit logistic regression results.

Variable	Level	Coefficient	OR	Standard Error	Wald z-Statistics	P
Constant		-8.692	0.0001	7.092	-1.23	0.2203
Road density	District	-0.0036	0.9964	0.00292	-1.22	0.2222
Villages density in the late 1980s	District	**-0.3139**	**0.7306**	**0.09214**	**-3.41**	**0.0007*** **
Forest percentage in 2000	District	**0.02379**	**1.0241**	**0.00254**	**9.384**	**0.000*** **
District to provincial capital	Pixel	0.000002		0.000003	0.07	0.9456
Distance to district centers	Pixel	-0.000006		0.0000096	-0.67	0.5041
Distance to municipality centers	Pixel	0.000066	1.0445	0.000036	1.84	0.0652’
Distance to settlements over 500 people	Pixel	**0.00008**	**0.9928**	**0.00001**	**7.4**	**0.000*** **
Distance to roads	Pixel	-0.00009		0.0001	-0.76	0.4460
Interpolated population density from settlements within district boundaries	Pixel	-0.0001	1.0153	0.00014	-1.97	0.3338
Number of days with temperatures	Pixel	**0.09**	**1.0000**	**0.038**	**2.38**	**0.0172***

>10 °C						
Elevation	Pixel	**0.0108**	**0.9997**	**0.00397**	**2.72**	**0.0065****
Slope	Pixel	**0.068**	**1.0003**	**0.03412**	**2.00**	**0.0458***
Aspect	Pixel	0.00012	0.9924	0.00019	0.63	0.5303
Excess of precipitation over potential evapotraspiration	Pixel	-0.0025	0.9998	0.0053	-0.42	0.6737
Soil pH	Pixel	**-0.0037**	**0.9985**	**0.0009**	**-4.14**	**0.0000*****
Number of observations	3716	*Adj. R2*		0.191		
AIC	3939.6	*AUC*		0.73		
Model log likelihood ratio	527.6	*Residual deviance*		3907.6		
Null Deviance	4435.2					

Significance is indicated with ***, **, * and ‘ for p<0.001, p<0.01, p<0.05 and p<0.01, respectively. Coefficients in boldface type indicate significance at p<0.05 or higher. Odds ratios are calculated as exp() where is the estimated coefficient.

Figure Captions

Figure 3-1. Study area and Landsat footprints

Figure 3-2. Crop and livestock production change between 1989 and 1999 at the provincial level.

Figure 3-3. Agricultural land abandonment at the district level between 1989 and 1999.

Figure 3-4. Scatterplots between agricultural land abandonment rates and selected explanatory variables for OLS linear regression.

Forest 3-5. Distribution of abandoned and non-abandoned pixels and statistically significant explanatory variables in the hierarchical spatially explicit logistic regression.

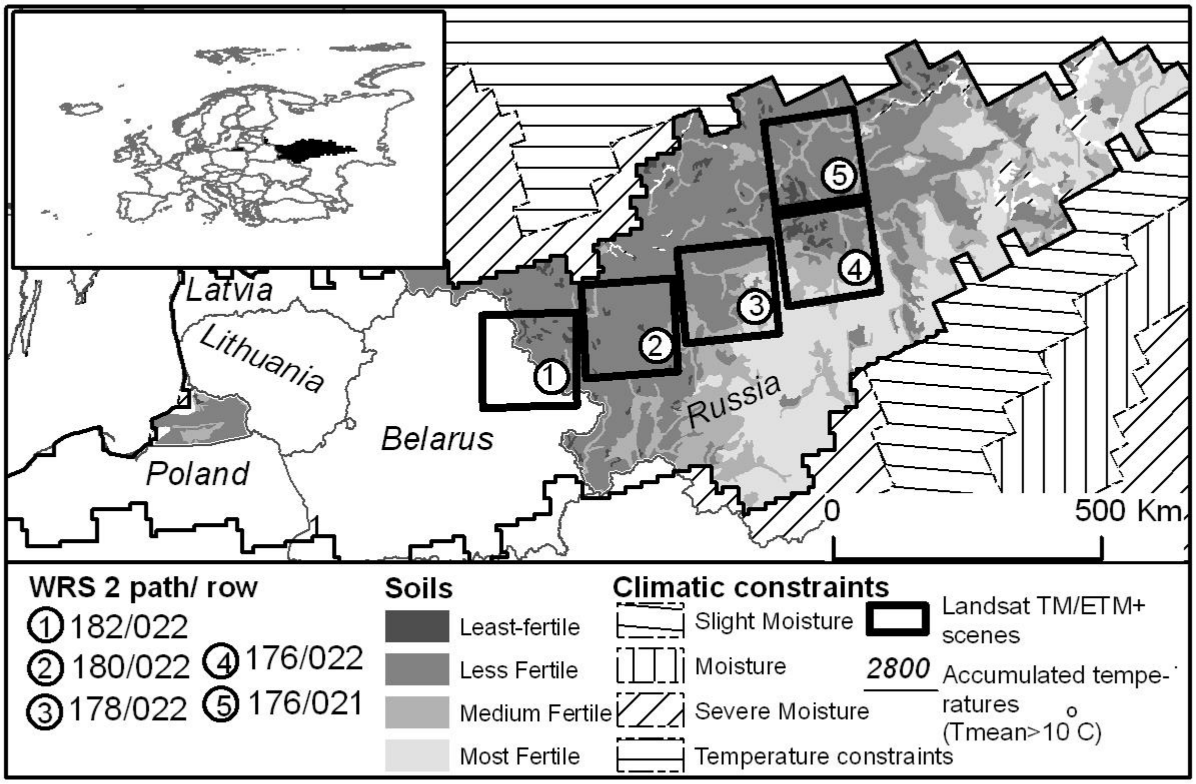

Latvia
Lithuania
Belarus
Poland
Russia
0
500 Km
WRS 2 path/ row
1 182/022
2 180/022
3 178/022
4 176/022
5 176/021
Soils
Least-fertile
Less Fertile
Medium Fertile
Most Fertile
Climatic constraints
Slight Moisture
Moisture
Severe Moisture
Temperature constraints
Landsat TM/ETM+ scenes
2800 Accumulated tempe-ratures (Tmean>10°C)

Figure 3-1

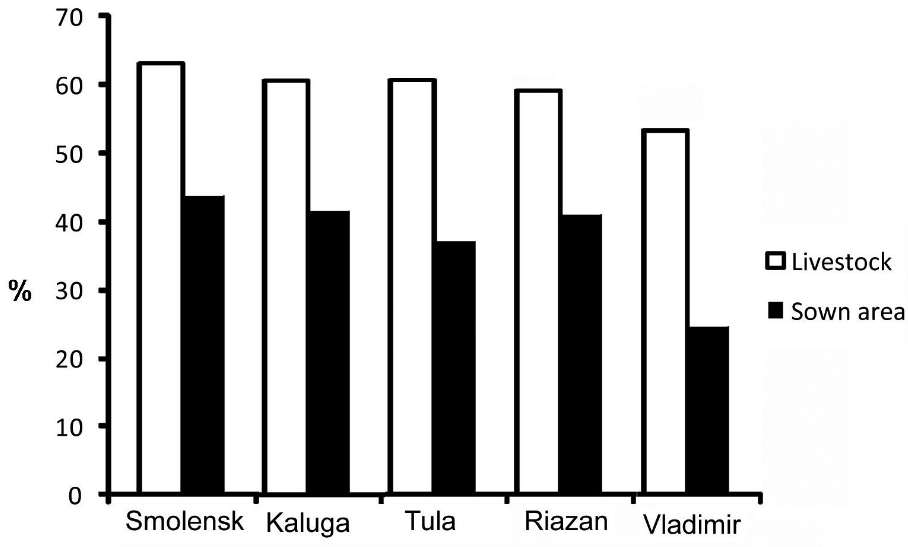

70
60
50
40
30
20
10
0
%
Smolensk
Kaluga
Tula
Riazan
Vladimir
Livestock
Sown area

Figure 3-2

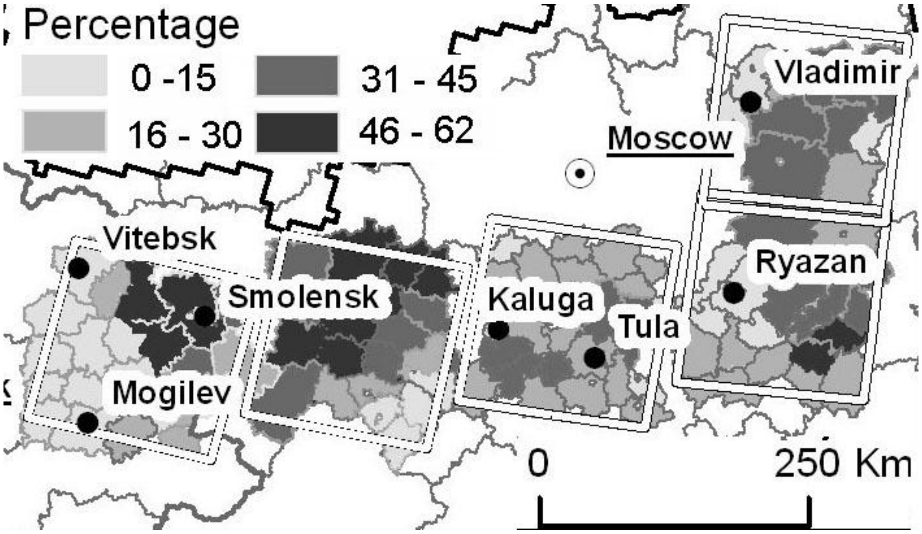
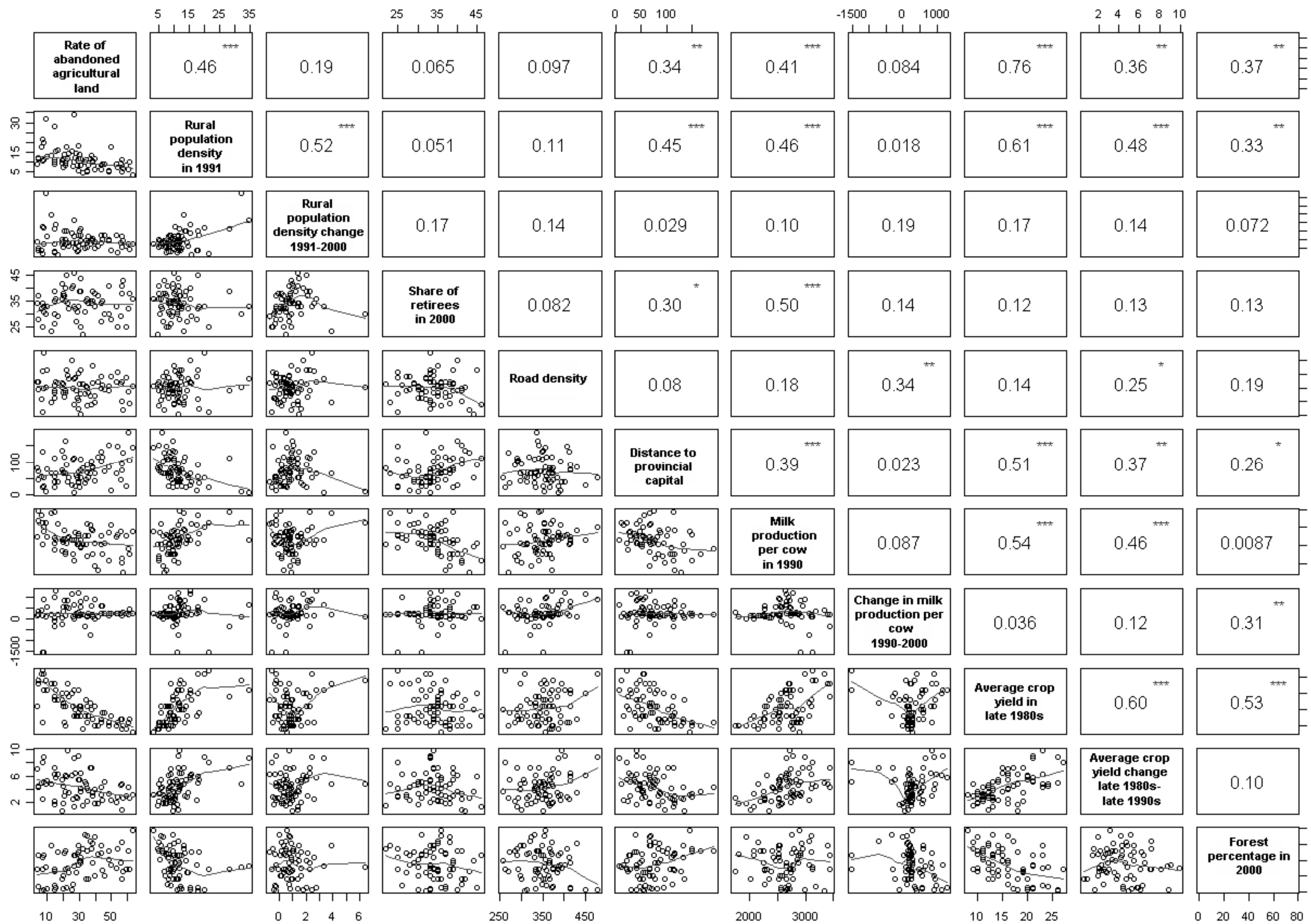

Percentage
0 -15
16 - 30
31 - 45
46 - 62
Vladimir
Moscow
Vitebsk
Smolensk
Kaluga
Tula
Ryazan
Mogilev
0
250 Km

Figure 3-3



Rate of abandoned agricultural land
0.46 ***
0.19
0.065
0.097
0.34 **
0.41 ***
0.084
0.76 ***
0.36 **
0.37 **
Rural population density in 1991
0.52 ***
0.051
0.11
0.45 ***
0.46 ***
0.018
0.61 ***
0.48 ***
0.33 **
Rural population density change 1991-2000
0.17
0.14
0.029
0.10
0.19
0.17
0.14
0.072
Share of retirees in 2000
0.082
0.30 *
0.50 ***
0.14
0.12
0.13
0.13
Road density
0.08
0.18
0.34 **
0.14
0.25 *
0.19
Distance to provincial capital
0.39 ***
0.023
0.51 ***
0.37 **
0.26 *
Milk production per cow in 1990
0.087
0.54 ***
0.46 ***
0.0087
Change in milk production per cow 1990-2000
0.036
0.12
0.31 **
Average crop yield in late 1980s
0.60 ***
0.53 ***
Average crop yield change late 1980s-late 1990s
0.10
Forest percentage in 2000

Figure 3-4.

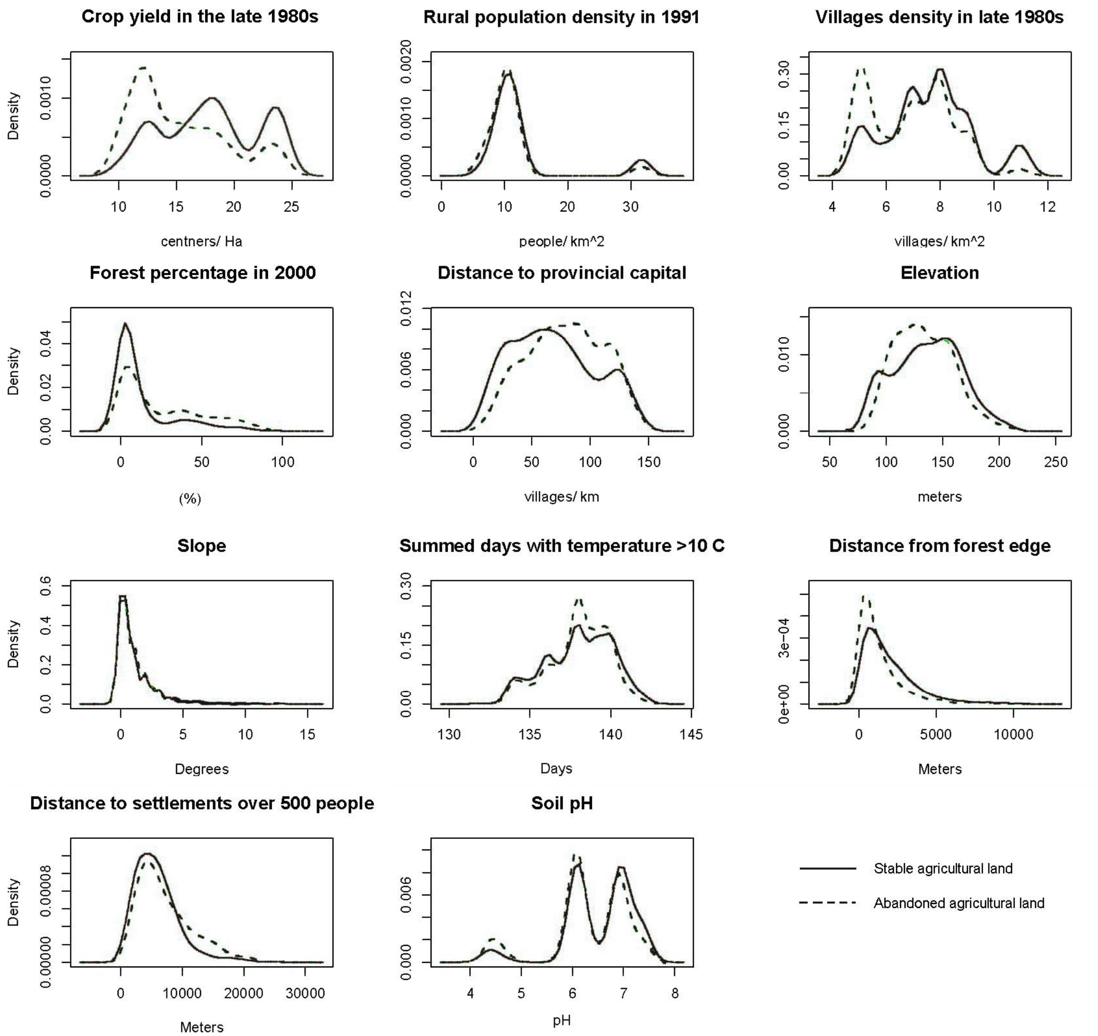

Crop yield in the late 1980s
centners/ Ha
Rural population density in 1991
people/ km^2
Villages density in late 1980s
villages/ km^2
Forest percentage in 2000
(%)
Distance to provincial capital
villages/ km
Elevation
meters
Slope
Degrees
Summed days with temperature >10 C
Days
Distance from forest edge
Meters
Distance to settlements over 500 people
Meters
Soil pH
pH
Density
Stable agricultural land
Abandoned agricultural land

Figure 3-5.