Determinants of Agricultural Land Abandonment in Post-Soviet European Russia

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DETERMINANTS OF AGRICULTURAL LAND ABANDONMENT IN POST-SOVIET EUROPEAN RUSSIA

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Abstract

Socio-economic and institutional changes may accelerate the rates and determinants 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 transition from-state command to market driven economy from 1990 to 2000. Based on economic assumptions of the profit maximization we selected and analyzed the determinants of agricultural land abandonment for one large agro-climatic and economic region of European Russia that covered 150,500 km^2 and 67 districts in Kaluga, Rjazan, Smolensk, Tula and Vladimir provinces. We integrated maps of abandoned agricultural land (five Landsat TM/ETM+ footprints 185*185 km each with 30-m resolution), environmental and geographic determinants, and socioeconomic statistics and estimated logistic regressions at the pixel-level.

Our results showed that agricultural land abandonment was significantly associated with lower average grain yields in the late 1980s, distances to villages, municipalities and settlements > 500 citizens, isolated agricultural areas within the forest matrix and distances from forest edges. Hierarchical partitioning showed that average grain yields in the late 1980s contributed the most in explaining the variability of abandonment (42%, of the explained variability), followed by location characteristics of the land. The results suggest that the underling driving forces such as massive decline of state subsidies for agriculture was a key contributor for the amount of abandonment and those areas socially, economically and environmentally marginal agriculture areas were the first to be left uncultivated.

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) or shift the land-use in the new mode. A major recent rapid socio-economic change was the collapse of socialism and the transition from state-command to market-driven economies (further transition) 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). For instance, during the first decade of the transition from state command to market driven economies from 1990 to

2000 (subsequently labeled “transition”), overall Russian life expectancy declined from 69 to 65 years and male life expectancy in rural area even slumped from 61 to 53 years in central European Russia (Rosstat, 2002). Profound changes were particularly common in rural regions of Russia where state-support of agriculture ceased, and rural development almost stopped (Rosstat, 2002).

These drastic socio-economic changes affected land use, but rates and patterns of LULCC varied dramatically both in Russia and among the post-communist countries in Eastern Europe (Prishcheopv, et al., *in review*). During the transition period institutional changes heavily affected the agricultural sector in post-communist countries in Eastern Europe and agricultural land abandonment was widespread (Kuemmerle, et al., 2008, Baumann, et al., 2011, Prishchepov, et al., *in review*). Agricultural land abandonment rates were higher in the post-Soviet countries in Eastern Europe, which had weak institutions during the transition (Prishchepov, et al., *in review*). However, our knowledge about the drivers of LULCC in Eastern Europe and Russia, and of agricultural abandonment in particular, is limited.

The knowledge on the determinants of agricultural land abandonment were largely gained from the studies which took place in the European Union (EU) countries, where abandonment of agricultural land was long-term process over the 20th century and especially after Second World War (Baldock, et al., 1996). In European Union countries the abandoned agricultural lands were generally found in the unfavorable environmental conditions (e.g., higher elevation, steeper slopes, poorer soils, and poorly meliorated agricultural fields), in physical remoteness, and isolated agricultural areas (Baldock, et al., 1996, MacDonald, et al. 2000). Agricultural land abandonment was also strongly associated with landowner characteristics (Grinfelde & Mathijs, 2004, Kristensen, et al., 2004). Part-time farmers and older landowners were more likely to reforest agricultural land than any other types of landowners in EU (Kristensen, et al., 2004). Last but not least, smaller farms throughout Europe were more likely to abandon farmland than larger enterprises (Baldock, et al., 1996, Kristensen, et al., 2004).

.Yet to date, only few quantitative studies have examined the determinants of post-socialist agricultural abandonment in Eastern Europe in general (Müller, et al., 2008, Baumann, et al., 2011) and for such vast agricultural lands as in Russia in particular. However, it is not clear if the same set of factors which determined agricultural land abandonment in European Union were important in the former Soviet Bloc countries, including Russia where agricultural production was dominated by large-scale farming.

The recent fine-scale detailed mapping of agricultural land abandonment with remote sensing data in European Russia allowed receiving spatially explicit results on agricultural land abandonment rates and patterns for the first decade of transition (1989-1991 to 1991-2001) for the large territory (Prishchepov et al., *in review*). Using produced agricultural land abandonment maps, socio-economic and biophysical statistics our major goal was to explore determinants of agricultural land abandonment during the first decade of transition (1990-2000) in one large agro-climatic and economic region of post-Soviet Russia. We do this with spatially explicit-logistic regression analysis of the determinants of land-use change at the pixel level. To identify the relative contribution of the covariates to agricultural abandonment we used hierarchical partitioning.

2 Methods

2.1 Study area

Available to us maps of abandoned agricultural represent temperate zone of European Russia. The area covered by five 184x184 km 30 meter resolution Landsat TM/ETM+ satellite footprints comprised 150,541 km^2 and allowed covering statistically meaningful number of districts in Smolensk, Kaluga, Tula, Rjazan and Vladimir provinces of Russia (Figure 1).

Climate in the outlined study region is temperate-continental. Days with temperatures >10 °C are from 125 to 142 days and annual precipitation is from 428 mm to 713 mm (Afonin, et al., 2010). The topography ranges only between 0 and 300 m. On average, 30% of the region is forested, with higher proportions of forest in the northern part of the study area. 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.

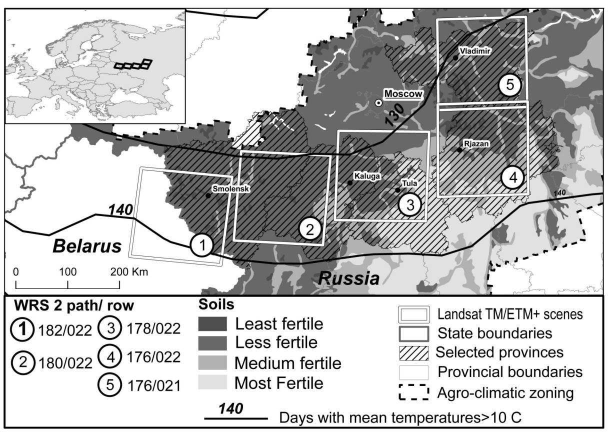

Figure 1: Study area

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 the failed attempts of the Soviet government to expand wheat growing in Kazakhstan (Ioffe, et al., 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 (Afonin, et al., 2010). Cattle breeding, dairy farming, and poultry production is also common. State and collective farms were controlling for more than 98% of agricultural land and produced more than 90% of agricultural output during the Soviet time.

The study area experienced rural depopulation, especially during the last three decades before the collapse of the USSR (Ioffe, et al., 2004). Prior the dissolution of the Soviet Union rural population was as low as 5 people/ km^2 in some districts of the studied region (e.g., in Smolensk province).

Russia transitioned from a state-controlled to a market-driven economy after the dissolution of the Soviet Union in 1990 (Lerman & Shagaida, 2007). 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 the form 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). National official statistics mirror the accompanying decline of agricultural production during the first decade of postsocialism with a decrease in sown area of up to 44% in Smolensk province since 1990 and of livestock numbers by up to 68%, again in Smolensk (Rosstat, 2002).

2.2 Maps of abandoned agricultural land

Detailed data on agricultural land abandonment derived from remote sensing classifications and covered Kaluga, Vladimir, Rjazan province, Smolensk province, and Tula provinces (Prishchepov, et al., *in review*) (Figure 1). The authors used multi-date images and support vector machines classifier to derive land cover maps. The classifications yielded "Stable agriculture" and "Abandoned agricultural land". "Stable agriculture" consisted of tilled agricultural land and grasslands intensively used for grazing and hay-cutting. Authors defined abandoned agricultural land from a remote-sensing perspective as agricultural land used before 1990 for grains, hay cutting, and livestock grazing, but no longer used in 1999-2001, and thus covered by non-managed grasslands often with succession shrubs at different stages. Conditional Kappa for "Stable agriculture" equaled to 0.89 and "Abandoned agricultural land" equaled to 0.84. The classifications indicated that from 1989-1991 to 1999-2001 31% of the agricultural land in 1989 was abandoned in the study area, comprising 1.7 million hectares. 46% of total 1989 agricultural land was abandoned in Smolensk province, 30% in Kaluga, 26% in Tula, 28% in Rjazan, and 27% in Vladimir province and abandonment rates were much higher at the district level (Prishchepov, et al., *in review*) (Figure 2).

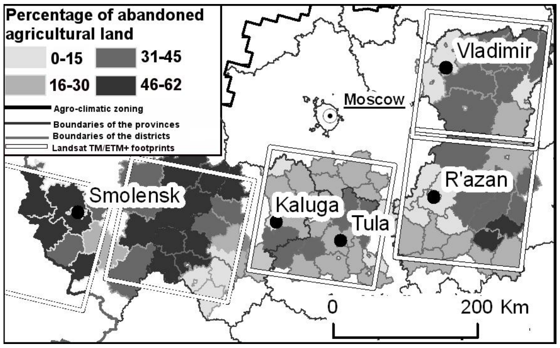

Figure 2: Rates of agricultural abandonment from 1989-1991 to 1999-2001 at the district level.

2.3 Explanatory variables for logistic regression model

From 1990 to 2000, the most detailed agricultural statistics for Russia were available at the district (rayon) level, which is roughly equivalent to counties in the United States or NUTS 3 level in the European Union. The average size of rural districts is 1,520 km^2 and our remote sensing classifications covered 67 districts.

We assumed that agricultural land abandonment was mainly driven by economic decisions (Irwin & Geoghegan, 2001). Based on these assumptions we selected variables that impact on the productivity of agricultural production, that capture the proximity of locations to roads and markets centers, demographic changes, the availability of infrastructural facilities, and variables that capture agricultural productivity. We also assumed that the natural suitability of a plot of land crucially affects the profits that can be derived from agricultural production and included spatially explicit biophysical variables (Table 1). Since time variant socio-economic variables can be partially representing endogeneity to LULCC (Chomitz & Gray, 1996, Müller, et al., 2009) we used only time-invariant variables (e.g., elevation, slope) and variables which represent socio-economic conditions prior the dissolution of the Soviet Union (e.g., average grain yields and population densities, road densities in the late 1980s) (Table 1).

<<Table 1>>

Average annual reference evapotranspiration, the number of days with temperature larger than 10 degrees Celsius, and the soil pH were derived climatic variables using GIS Agroatlas for Russia at 10-km resolution (Afonin, et al., 2010).

Elevation and slope were derived from the 90 meter digital elevation model (USGS, 2004). We also assumed that higher forest percentage in the districts indicate that land surfaces in the respective area are of minor quality and less suited for agricultural production. Forest percentage was derived from 30-m resolution forest-cover maps for pre-abandonment (circa 1989) from the same classifications that yielded agricultural land abandonment (Prishchepov, et al, *in review*). We also assumed that abandoned agricultural fields would be closer to the forest edges and we included the Euclidean distances to forest edges in the regression. We also observed that many abandoned agricultural areas were individual patches surrounded by a forest matrix. We thus digitized isolated agricultural areas within the forest matrix and created a binary variable that captures these areas.

To measure the effects of agricultural productivity we obtained agricultural statistics about average grain and milk yields in the late 1980s from official sources at the district level (Ioffe, et al., 2004).

To calculate continuous population densities from the settlements we used 1:100,000 Soviet topographic maps from the end of the 1980s (VTU Gsh, 1989b). We digitized provincial, district, municipality centers and villages and we assigned the population for each settlement as printed in these maps. We calculated a continuous measure for population density from digitized settlements by interpolating the population using second-order inverse distance weights (Müller, et al., 2008). By late 1980s, 38% of 11,972 digitized settlements for our study area represented settlements with a population of less than 20 people.

To estimate the proximities effects we calculated the Euclidean distances to provincial, district and municipal centers indicating travel costs to the potential markets and distances to villages. Based on the field observations and summary of the digitized settlements by population, we assumed many villages were not playing the forming stable population and services provision network in the Central Russia. Additionally we calculated the proximities to the settlements with over 500 people as we assumed that such large settlements were important in provision of the goods and socio-economic services in the countryside.

As a measure of the infrastructure we also calculated settlements densities on district level. We thus incorporated the importance of larger population settlements for the provision of social infrastructures (e.g., stores, schools and hospitals), because we anticipated the availability of public service as an important factor for curbing outmigration and thus agricultural land abandonment. To calculate road densities and distances to roads we used a GIS dataset for Russia that was derived from 1:500,000 declassified Soviet topographic maps from the late 1980s (VTU Gsh, 1989a).

2.4 Logistic regression and hierarchical partitioning

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 defined “1” to represent abandoned agricultural land and “0” for stable agricultural land.

For our global model we randomly sampled 132,015 pixels from the available 52 million pixels for agricultural areas, which represent 0.25% of the total population of the total number of pixels. In the sampling process we ensured a gap of at least 500-m distance between sampled observations to reduce the spatial autocorrelation which was measured previously for our study area (Prishchepov, et al., *in review*). For each of 67 districts we had on average 2,000 sampled pixels. The final sample is fairly balanced with 30% of the sampled pixels labeled as abandoned.

For the statistical analysis we used R statistical package (R Team, 2009). We checked for collinearity (Maddala & Lahiri, 2009). When R >0.5 for two explanatory variable, we retained 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.

Since the observations within districts may not be completely independent from each other we introduced a group structure and conducted a statistical adjustment of the clustered data structure in our logistic model (Gellrich, et al., 2007, Müller, et al., 2008). Wi fitted logistic models using the “lrm” function and for cluster adjustment we used “robcov” function based on the Huber-White method (Huber, 1967) in the R Design package (R Team, 2009). To assess the goodness-of-fit of the regression we calculated the log-likelihood for the logistic model, the Akaike Information Criterion (AIC), the deviance for the residuals of the null and fitted models and the area under the receiver operating characteristics curve (AUC) (Pontius & Schneider 2001, R Team, 2009). We used hierarchical partitioning to assess the contribution of the independent variables for explaining the variability of the dependent variable individually or in the conjunction with other variables/ models (Baumann, et al., 2011). To construct hierarchical partitioning we used “hier.part” package (Walsh & Mac Nally, 2009) in the R (R Team, 2009).

3. Results

3.1 Selection of the variables for the logistic regression

We found that grain yields in the late 1980s were positively correlated with average milk yields in 1990 (R=0.54). We hence retained only grain yields in late 1980s for the multivariate logistic regression modeling. Forest percentage and distances to forest edges variables represented medium correlation (R=0.51) above the self-imposed threshold of R=0.5 and negatively correlates with the density of municipal centers (R=-0.57). For the model we retained only distances to forest villages as it had higher correlation with abandoned and non-abandoned agricultural land (R=0.16) comparable to forest percentage (R=0.1) and density of municipal centers (R=-0.1).

Average annual reference evapotranspiration was also positively correlated with settlements densities in the late 1980s (R=0.59) and elevation (R=0.67). We retained average annual reference evapotranspiration as it had higher correlation with agricultural land abandonment comparable to settlements densities in the late 1980s and elevation. We also decided to exclude number of days with temperature >10 °C as it had medium negative correlation with the retained variable (R=-0.52).

For our modeling out of initial 27 explanatory variables we selected only 17 of which only one was at the district level (Table 2).

3.2 Logistic regression modeling

The explanatory power of the models for the studied area was relatively low (adjusted R^2 = 0.151) (Table 2). However it is the common case to have low adjusted R^2 for spatially-explicit pixel-based logistic regression models and this measure has to be interpreted with caution (Gellrich, et al., 2007, Müller, et al., 2008). The model goodness-of-fit (area under the curve, AUC) for our logistic regression model was 0.708 (Table 2). This means that with a probability of 71% model can distinguish correctly between two classes (stable agriculture and agricultural land abandonment) which is substantially better than separability by chance (AUC=0.5) (Gellrich, et al., 2007).

<<Table 2>>

Most of the significant independent variables ($p<0.05$) showed the expected sign. However, the direction of the relationship between the response and predictor in some cases was opposite to what it was expected. For instance, abandonment was higher in the districts with higher roads density. However, this variable which had signs opposite of the expected ones was statistically insignificant.

Out of 17 only 7 variables were statistically significant ($p<0.05$). They represented agricultural productivity, population and proximities, namely, average grain yield in the late 1980s, forest villages dummy variable, distance to forest edges, interpolated population densities, distance to villages, distance to municipality and distance to populated places >500 inhabitants.

3.3 Hierarchical partitioning

In our model according to hierarchical partitioning analysis for seven statistically significant variables average grain yields in the late 1980s contributed the most in the explaining agricultural land abandonment (42.1%, of the explained variability. This was followed by distances to forest edges (19.5%), distances to the settlements > 500 people (11.5%), isolated agricultural areas in the forest matrix (11.9%), distances to municipalities (6.9%) and interpolated population densities (6.4%). Distances to villages contributed the least (1.6%) in explained variability.

4. Discussion

While the explanatory power of the models for the studied area was relatively low (adjusted R^2 = 0.151), similarly to Gellrich et al. (2007) and to Müller & Munroe (2008) we also considered accuracy of the models predictions was satisfactory as the large territories were analyzed to generalize the determinants of agricultural land abandonment. We didn't use structural characteristics of agriculture (e.g., types of farms) or characteristics of agricultural producers (e.g., education), which would potentially increase accuracies of the models predictions. Hence, our models were limited to an exploration of the determinants of agricultural land abandonment rather than the modeling of causal factors at the level of individual decision making. Our global model for all five provinces combined was also developed for very large agro-environmental and economic region of European Russia and models for each province alone indicated some variation in the factors which determined agricultural land abandonment. However, here again, we achieved the goal to find generalized determinants explaining agricultural land abandonment across large agro-climatically and economically uniform region.

The degree of the relationship for many independent variables, except for average annual reference evapotranspiration, slope and roads densities, was found with the expected sign. In the case of average annual reference evapotranspiration, we would assume, as this variable was resampled from 10*10km dataset to 30 meter, it may not represent sufficient variability to properly distinguish between abandoned and non-abandoned agricultural land. Another reason that agricultural land abandonment had different sign of the relationship from the expected is that areas with higher annual reference evapotranspiration are generally found in areas unsuited for agriculture, such as marshlands. In the case of slope, similarly to annual evapotranspiration we would assume that elevation and calculated slope we derived from resampled 90 meter product and variation of the elevation over almost 150,500 km^2 was just between 0 and 344 meters, thus the variation of this variable was minimal. In the case of the roads distances, it could be a situation that the accessibility to the different sets of the roads (not federal highways and roads with improved pavement, but commonly used local motorways) had the statistically significant relationship with agricultural land abandonment and also the expected sign of the relationship.

As we expected, the distances from the nearest forest edge were statistically significant variables for the global model (p<0.05). As we would assume, farmers tended to abandon less suitable agricultural fields found in near the forests and in less accessible agricultural areas. Another explanation can be that abandonment usually starts with forest succession from the forest edges, where seedling material exists. The dummy variable representing isolated agricultural areas surrounded by forest matrix was statistically significant, possibly because of adverse access from the farm and from markets (cf. MacDonald, et al. 2000). Commonly, such territories have marginal quality of the roads in the Russian countryside, which make difficult to access with farm machinery and from the district centers. Villages in isolated agricultural areas also had lower population densities. Abandonment in forested areas and nearby forest edges provide a promising opportunity to defragment the forests, because forest regrowth may increase the habitat for umbrella species. The unimportance of other environmental factors (e.g., soil pH, average annual evapotranspiration) for the global model was likely due to the fact, that we outlined large agro-climatic region in order to emphasize more socio-economic variables, thus the effects of environmental variables was masked out.

The statistical significance of the grain yields in the late 1980s variable additionally proved that agricultural land abandonment took place in socio-economically and environmentally unfavorable regions, which we subsidized during the Soviet period. Moreover, additional analysis showed that grain yields in the late 1980s was a function of both environmental and socio-economic factors, similarly to Ioffe, et al. (2004). Both rural population densities, distances to administrative centers, temperature and moisture conditions determined the grain yields at the district level in European Russia Ioffe & Nefedova (2004).

The calculation of the proximities to settlements showed that distances mattered at village, municipality and settlements > 500 people, but not at the higher administrative level (e.g., district centers and provincial capitals). We would assume that this set of the settlements (villages, municipalities and settlements>500 people) represent an important rural network where better accessibility was crucial in order to use agricultural fields for agricultural production. It is likely smaller market centers determine the access to input and output markets.

According to hierarchical partitioning analysis, for the global model for all 5 provinces combined average grain yields in the late 1980s had the highest explanatory power for agricultural land abandonment Agricultural lands with low average grain yields in the late 1980s were generally found in more remote regions with lower rural population densities (Ioffe, et al., 2004). It appears that abandoned agricultural lands were those that were already socially and environmentally marginal for the agricultural production in 1989, but were subsidized during the Soviet time (Ioffe, et al., 2004). Again it is more likely, that underlying causes, such as 90% of the subsidies withdrawal for the agricultural production from 1989-1991 to 1999-2001 fostered heavily agricultural land abandonment where agricultural productivity was low.

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Literature

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/).

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, 5.151-68.

Baumann, M.; Kuemmerle, T.; Elbakidze, M.; Ozdogan, M.; Radeloff, V.C.; Keuler, N.S.; Prishchepov, A.V.; Kruhlov, I.; Hostert, P. (2011): Patterns and drivers of post-socialist farmland abandonment in Western Ukraine. Land Use Policy 28, 552-562.

Chomitz,K.M & A. Gray. (1996). Roads, Land Use, and Deforestation: A Spatial Model Applied to Belize World Bank Econ Review10(3): 487-512

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.

Grinfelde, I., and Mathijs E. (2004). Agricultural land abandonment in Latvia: an econometric analysis of farmers’ choice. Paper presented at 2004 conference of Agricultural Economics Society, Newcastle upon Tyne, 2- 4 April 2004.

Huber,P. J. (1967). The Behavior of Maximum Likelihood Estimates Under Nonstandard Conditions. Proceedings Fifth Berkeley Symposium Mathematical Statistics, 1221-33.

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.

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., 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.
Lerman,Z. & Shagaida,N. (2007). Land policies and agricultural land markets in Russia. Land Use Policy, 24(1), 14-23.
Maddala,G. S. & Lahiri,K. (2009). Introduction to Econometrics. Wiley, New York, 654 p.
Müller,D., Kuemmerle,T., Rusu,M. & Griffiths,P. (2009). Lost in transition: determinants of post-socialist cropland abandonment in Romania. Journal of Land Use Science, 4109-129.
Müller,D. & D.K. Munroe (2008). Changing rural landscapes in Albania: Cropland abandonment and forestclearing in the postsocialist transition. Annals of the Association of American Geographers 98(4): 855-876.
Pontius, R.G.J., Schneider, L.C. (2001) Land-cover change model validation by an ROC method for the Ipswich watershed, Massachusetts, USA. Agriculture, Ecosystems & Environment 85, 239-248.
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*.
R Team. (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)
Rosstat. (2002). Regions of Russia. Socio-economic indicators. (Regiony Rossii. Sotsial'no-ekonomicheskie pokazateli). In Russian. Federal service for state statistics, Moscow.
USGS (2004), Shuttle Radar Topography Mission, 3 Arc Second SRTM_model, Unfilled Unfinished 2.0, Global Land Cover Facility, University of Maryland, College Park, Maryland, February 2000. Available from http://www.landcover.org/data/srtm/ (last accessed, January 2010).
Vitousek,P. M., Mooney,H. A., Lubchenco,J. & Melillo,J. M. (1997). Human domination of Earth's ecosystems. Science, 277(5325), 494-499.
VTU GSh. (1989a). Military 1:500,000 topographic maps. Military-topographic department of the General staff of the USSR. Voenno-topograficheskoe upravlenie General'nogo shtaba SSSR.
VTU GSh. (1989b). Military 1:100,000 topographic maps. Military-topographic department of the General staff of the USSR. Voenno-topograficheskoe upravlenie General'nogo shtaba SSSR.
Walsh, C. & Mac Nally, R.(2009). Package ‘hier. Part’. Version 1.0-3. (last accessed January 17, 2011, http://cran.r-project.org/web/packages/hier.part/hier.part.pdf).

Table 1. Selected explanatory variables for spatially explicit logistic regression.

Variables *(units)*	**Source**	**Spatial resolution**
Biophysical		
Soil pH *(units)*	SOVEUR/ SOTER 1:2,0000,000 digital maps	Rasterized vector dataset
Elevation *(meters)*, slope *(degrees)*	Shuttle Radar Terrain Mission (SRTM)	Resampled raster 90 m dataset
Average annual evapotranspiration *(millimeters)*, number of days with temperature >10 °C *(degrees)*	AgroAtlas, 2010	Resampled raster 10 km dataset
Distance from the nearest forest edge *(100 meters)*	30 m Landsat TM/ETM+ classifications	Pixel level calculations
Isolated agricultural areas within forest matrix in 1990	30 m Landsat TM/ETM+ classifications	Pixel level calculations
Agricultural productivity		
Average grain yields in the late 1980s *(centners/ hectare)*, milk production per cow in the late 1980s *(kilograms/ hectare)*	Rosstat, 2002	Rasterized district level statistics
Population		
Interpolated population densities for late 1980s *(people/ 30 meters^2)*	1:100,000 declassified Soviet topographic maps	Pixel level calculations
Proximate		
Distance to provincial capital *(kilometers)*, distance to district center *(kilometers)*, distance to the municipality center *(kilometers)*, distance to the nearest settlement with over 500 people *(kilometers)*, distance to village *(kilometers)*	1:100,000 declassified Soviet topographic maps	Pixel level calculations
Distance to the nearest road with hard coverage *(100 meters)*	1:500,000 declassified Soviet topographic maps	Pixel level calculations
Infrastructure		
Road density in the late 1980s *(kilometers/ kilometer^2)*	1:500,000 digital dataset	Rasterized district level statistics
Density of municipalities in the late 1980s *(settlements/100 kilometer^2)*, density of the settlements with over 500 people *(settlements/100 kilometer^2)*, density of villages in the late 1980s *(settlements/100 kilometer^2)*	1:100,000 digital dataset	Rasterized district level statistics

Table 2. Spatially explicit logistic regression results for the studied area of Russia.

Variable	Level	Coefficient	Odds ratio	Standard Error	Wald z-Statistics	P
Soil pH	Pixel	-4.11E-04	0.99	0.00085	-0.48	0.6288
Slope	Pixel	-7.54E-03	0.99	0.008328	-0.9	0.3656
Average annual reference evapotranspiration	Pixel	-2.38E-03	0.99	0.001231	-1.93	0.0531
Distance from the nearest forest edge	Pixel	-4.01E-02	0.96	0.005604	-7.15	**0.0001*** **
Isolated agricultural areas within forest matrix in 1990	Pixel	3.94E-01	1.48	0.125129	3.15	**0.0016** **
Average grain yields in the late 1980s	District	-1.17E-01	0.89	0.018938	-6.18	**0.0001*** **
Interpolated population density from settlements for late 1980s	Pixel	-3.48E-04	0.99	0.000146	-2.39	**0.017* **
Distance to provincial capitals	Pixel	-1.96E-03	0.99	0.001864	-1.05	0.2935
Distance to district centers	Pixel	6.06E-03	1.001	0.005517	1.1	0.2723
Distance to municipality centers	Pixel	6.08E-02	1.06	0.015025	4.04	**0.0001*** **
Distance to settlements over 500 people	Pixel	3.11E-02	1.03	0.008324	3.74	**0.0002*** **
Distance to villages	Pixel	8.27E-02	1.08	0.037934	2.18	**0.0293* **
Road density	Pixel	1.48E-03	1.00	0.001399	1.06	0.29
Distance to the nearest road with hard coverage	Pixel	3.58E-03	1.00	0.006313	0.57	0.5702
Number of observations= 132,015	*Number of "0s"= 93,289*			*Number of "1s"= 38,726*		
AIC= 145,704	*AUC= 70.3*			*Adj. R2= 0.144*		
Model log likelihood ratio= 14095.75	*Residual deviance= 145,674*			*Null Deviance= 159,770*		

Significance is indicated with ***, **, * and for p<0.001, p<0.01 and p<0.05, respectively. Coefficients in boldface indicate significance at p<0.05 or higher.