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Sensitivity of Spatially Explicit Land-use Logistic Regression Models to the Errors Land-use Change Maps

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Abstract: Land-use change (LUC) is a common process around the world and LUC models help elucidate LUC. Models are commonly parameterized with LUC maps derived from satellite imagery. However, such LUC maps have errors, and it is unclear how sensitive spatially explicit LUC models are to such errors. We studied the effects of errors maps on spatially explicit LUC logistic regression models of agricultural land abandonment within one Landsat footprint in Eastern Europe that covered the part of Lithuania. The selected footprint had six matching image dates (Spring, Summer and Fall) that were important to separate land-use classes for pre- (circa 1989) and post-abandonment (circa 2000). We simulated errors maps classifying all possible 49 sub-optimal image dates combinations with non-parametric support vector machines (SVM) classifier. We assessed the sensitivity of the spatially explicit LUC logistic models that had socio-economic and environmental variables to the mapping errors for the produced 49 LUC maps. When fewer image-dates combinations were used, the spatially explicit logistic regression LUC models were prone to the mapping errors. Results suggest avoiding using the classifications lower than 80% of individual class accuracy for the spatially explicit logistic regression models of agricultural land abandonment in Eastern Europe.

***Keywords**:* land use; remote sensing; sensitivity; errors; logistic regressions; abandonment.

1. INTRODUCTION

1.1. Background

Human actions and land use are at the heart of global land-cover change and primarily the cause of the declines of biodiversity and ecosystem services. Among the key land-use changes (LUC) agricultural expansion goes in parallel with widespread agricultural land abandonment, particularly in post-industrial countries of the world [Hatna and Bakker 2011, Prishchepov et al. 2012]. LUC models should facilitate in finding the solutions, for instance, between agricultural expansion and abandonment. LUC maps with aid of remote sensing became the core components of LUC models. However, the origin and quality of the input datasets to produce LUC maps, the selection of the minimum mapping unit and the aggregation of the thematic LUC classes may alter substantially LUC model outcomes [Van Dessel et al. 2011]. This may cause wrong inferences about the actual determinants and drivers of LUC [Hatna and Bakker 2011, Van Dessel et al. 2011]. Studies have explored the sensitivity of LUC models to the error induced datasets, for instance prototyping error inclusion into the LUC maps and predictor variables [Van Dessel et al. 2011]. However, little research has been conducted so far to estimate the error effects on LUC model from misclassified LUC maps due-to limited use of the satellite images that are commonly utilized to produce such maps.

1.2 State of the Art

Mapping with the aid satellite images plays the crucial role to produce land-cover products that are important components of LUC models. For instance, the use of the coarse-scale resolution satellite images (e.g., from MODIS 250m-1 km pixel resolution sensor), due to spatial and temporal coverage, allows to monitor the state of land cover almost at daily basis and at the global scale. However, the compromise to have global LU and LUC products comes in the sacrifice of the number of thematic LUC classes and the size of the minimum mapping units may not necessarily match with the actual land use pattern [Ozdogan and Woodcock 2006]. To meet the demands for the detailed thematic LUC products, with finer minimum mapping unit and larger spatial extent, currently more efforts are taking place to benefit on the free available multispectral 30 m resolution 185km*185 km Landsat Thematic Mapper (TM)/ Enhanced Thematic Mapper Plus (ETM+) satellite images [Potapov et al. 2011] that have long-term historical record. However, generated LUC products based on the mosaics of Landsat TM/ETM+ like satellite images at the regional and global level pose number of challenges for LUC modeling. For instance, infrequent repetitive coverage of the study area with medium resolution Landsat TM/ETM+ like sensors and cloud contamination of the satellite images, pose a challenge to map accurately thematic LUC classes when certain optimal multi-seasonal satellite image-date combinations are needed to separate accurately LUC classes [Prishchepov et al. 2012]. Thus, the generated mosaics of the sub-optimal satellite images combinations, contain errors that may vary dramatically across mosaiced LUC maps and may alter substantially LUC modeling results [Hatna and Bakker 2011, Van Dessel et al. 2011]. However, to which extent such induced error LUC maps due to the use of sub-optimal satellite images may alter LUC models are not well studied.

Among types of LUC models spatially explicit economic models became particularly popular among geographers, economists and natural scientists as an approach to study spatial association of the determinants of LUC at the disaggregated scales [Irwin and Geoghegan 2001]. Logistic regression approach became a common approach for spatially explicit LUC modeling due to the simplicity to present change and non-change LU classes as dichotomous variables- “0s” and “1s”. However, the question here is remaining: how these models are robust to the error induced LUC maps produced with the use of sub-optimal image-date combinations.

There are two types of errors that may alter modeling of LUC: a) input error, that may associate with the input datasets, including LUC maps; b) model errors that are coming from the parameterization of the model by itself [Van Dessel et al. 2011]. A number of measures were developed to estimate the accuracy of the error induced maps [Congalton and Green 2008]. The common method is the comparison of the produced map with the independently of the map production training datasets reference data (e.g., reference map or/and field-based validation observations) [Congalton and Green 2008]. Commonly, based on the cross-tabulation matrix accuracy assessment statistical measures can be computed (e.g., number of commonly classified minimum mapping unites, overall accuracy, producers and users accuracies, conditional Kappa) [Congalton and Green 2008]. Such measures may assist in the estimation if one map is statistically more accurate than another one based on the thematic classes comparison. Additional statistical measures such as fuzzy Kappa can be computed in order the estimate spatial propagation of the error across the map [Pontius 2000, Hagen-Zanker et al. 2005]. However, it is unclear how these measures reflect the usefulness of the produced LUC product, for instance for LUC modeling purposes. As a rule of thumb LUC maps are generally produced with self-defined target accuracy thresholds without any prior test of the impact of the error induced LUC maps on end-user applications.

1.3 Aim and Scope

The major question we are addressing here how the use error-induced LUC maps due to the classification of sub-optimal satellite images affect LUC model performance. As an example of LUC model we will test the performance of spatially explicit logistic regressions and as LUC phenomenon we will use the case of agricultural land abandonment in Eastern Europe.

2. METHODS

We benefited on the LUC maps that were already produced in our previous work [Prishchepov et al. In Review]. We estimated first important multi-seasonal images dates for different type of crops and land uses based on literature and calculated vegetation indices (e.g., Normalized Difference Vegetation Index). For instance, to map accurately actively managed agricultural fields and agricultural land abandonment it was required to have three satellite image-dates for pre- and post-abandonment. The fist image represented spring from agricultural LU perspective (April 20th to May 20th) i.e., when mean daily temperatures rise above 5° C, 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), i.e., 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 is not yet dormant, 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 queried all major Landsat TM/ETM+ satellite image archives. For our study we selected Landsat footprint World Reference System 2 (WRS) path 186 row 22 (cf. figure 1) that covered post-Soviet Belarus and Lithuania, because it had the best image availability and abundant agricultural land abandonment that often represents non-managed grasslands with succession of shrubs in the study area.

2.1 Study Area

For the scope of this work the Lithuanian part, which represented 45% of the selected Landsat TM/ETM+ footprint (cf. figure 1), was considered as our study area. The region is well suited for agriculture. In 1989 and 2000, summer crops were sown on approximately 60% of the total crop land. Summer crops 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 and Ladyga 1995].The study region experienced drastic changes in agriculture after collapse of the USSR and widespread agricultural land abandonment from 1989 to 2000.

2.2 LUC Mapping

For the selected footprint Landsat TM and ETM+ images were acquired for pre-abandonment –time I (May 3rd 1989, July 6th 1989, September 24th 1989) and post-abandonment –time II (July 10th 1999, September 20th 1999, May 5th 2000). Satellite images were coregistered and clouds that represented < 5% of the study area were masked out [Prishchepov et al. In Review]. For each satellite image we used 30 m resolution Landsat TM/ ETM+ bands 1-5 and 7 bands. In order to estimate the effects of image dates selection on classification accuracy, we grouped multi-date images into all possible 49 image dates composites (cf. figure 1). Our initial classification catalog consisted of 12 thematic classes. For given work we used only following classes: a) non-changing (e.g., "arable land in time I and time II", "managed grassland in time I and time II"); b) transition classes (e.g., "change from arable land in time I to abandoned in time II", "change from managed grassland in time I to abandoned in time II"). For our initial 12 thematic classes classification training datasets were collected during the field campaigns and from ancillary sources (1.28 meter resolution QuickBird and IKONOS images, topographic maps, multitemporal dense layers of Landsat TM/ETM+ images) [Prishchepov et al. In Review].

Each of 49 image date composite was classified simultaneously with non-parametric machine learning Support Vector Machines classification algorithm [Prishchepov et al. 2012]. Once classification was performed for the produced LUC maps accuracy assessment was performed with the independent of training datasets field collected datasets. Cross-tabulation matrices were constructed between classification and validation data. Overall Kappa, producer's users, user's accuracies, individual class conditional Kappa measurers were calculated (cf. figure 1). Complementary to these measures, we calculated the spatial agreement of the produced maps. Using Geonamica's Map Comparison Kit [http://www.riks.nl/mck/], we calculated number of correctly classified pixels in both compared maps, Kappa, fuzzy Kappa [Hagen-Zanker et al. 2005] (cf. figure 1).

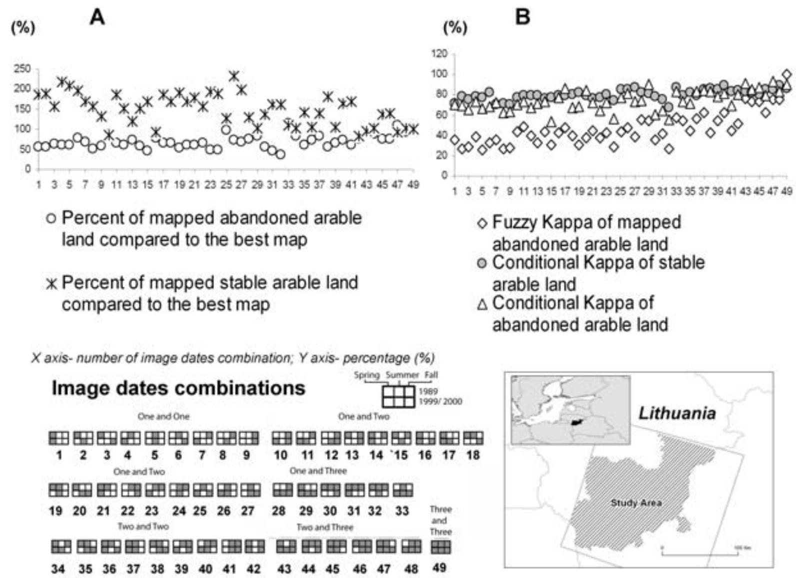

Figure 1. Selected study area, classified image dates combinations to produce error induced LUC maps and estimated accuracies and thematic class acreage as an example of mapped “abandoned arable land” and “stable arable land” LUC classes.

2.3 LUC Modeling

To prepare LUC maps for the sampling and further logistic regression modeling we applied a majority filter to remove the areas smaller than 3. To estimate the LUC maps error propagation effects we reclassified produced LUC maps and prepared two sets of LUC maps one showing “abandonment of arable land” and the other showing “abandonment of managed grassland”. The recoding was the following:

1) “arable land in time I and time II” as “0”, further “stable arable land”, “change from arable land in time I to abandoned in time II” as “1”, further “abandoned arable land”;
2) “managed grassland in time I and time II” as “0”, further “stable managed grassland”, “change from managed grassland in time I to abandoned in time II” as “1”, further “abandoned managed grassland”.

Based on the assumptions that agricultural land abandonment was largely driven by the economic decisions we calculated range of the explanatory variables that may affect decision about agricultural LUC. Time-variant variables can be endogenous to LUC, thus, we primarily calculated time-invariant explanatory variables.

Our best overall classification with SVM showed that roughly 18% of arable land and 8% of managed grassland was abandoned by 2000. We sampled “0s” and “1s” proportionally for each of 49 LUC maps, because disproportionate sampling in logistic regressions can affect predicted probabilities [Müller et al. 2009]. We maintained a gap of at least 500m between samples that reduced isotropic Moran’s I by 0.15, which was measured earlier with Gammadesign GS+ geostatistical package [www.gammadesign.com]. Since statistical significance of the certain variable in the model can be sensitive to the robustness sampling process and may appear in the model by chance [Hatna and Bakker 2011], we repeated sampling and further running the logistic regressions 10 times for each of 49 LUC maps using GRASS GIS software [www.grass.fbk.eu]. We considered variable to be statistically significant at $p<0.05$ if variable was statistically significant 9 out of 10 regressions [Hatna and Bakker 2011].

For our statistical analysis we used R statistical software [www.r-project.org], and checked all covariates for collinearity. When Pearson's correlation coefficient $R > 0.4$ for two variables, we retained only the variable that was more strongly related to abandonment in our regression models. Out of initially selected 23 variables only 12 were retained for further modeling (cf. table1). Multiple samples within the same administrative unit (i.e., the same district) are not truly independent [Müller et al. 2009] which we controlled with Huber-White sandwich estimator (R statistical software, Design package, robcov function) for variables belonging to the same district in Lithuania. To estimate model performances we calculated the area under the receiver operating characteristics curve (AUC), indentified statistically significant variables ($p<0.05$) and calculated odds ratios.

Table 1. Explanatory variables.

Variables *(units)*
Soil pH *(units)*
Elevation *(meters),* slope *(degrees)*
Accumulated annual precipitation*(millimeters)*
Distance from nearest forest edge *(100 meters)*
Distance from nearest river *(100 meters)*
Interpolated population counts from settlements in the late 1980s (the proxy for population density) *(number of people)*
Distance from provincial capital *(km)*, distance from nearest district center *(km)*
Distance from nearest settlement with more than 500 people *(km)*
Distance from nearest village *(km)*
Distance from nearest road with hard surface *(100 meters)*
Night-time intensity for the year 1992- proxy for GDP *(units)*

3. RESULTS

Our best classified overall LUC map was when all satellite image-dates were used for the classification (cf. figure 1, image date combination # 49,"abandoned arable land"- 90% of conditional Kappa, abandoned managed grassland-72% of conditional Kappa) [Prishchepov et al. In Review]. Classifying fewer sub-optimal image-dates, the classification accuracy decreased drastically for our produced LUC maps (cf. figure 1). Classification accuracy became as low as 68% of conditional Kappa for "stable arable land" and 54% for "abandoned arable land" (cf. figure 1B). Decrease in the accuracies also reflected the use of less optimal image dates [Prishchepov et al. in Review]. Results also showed that the spatial agreement between the best (49^{th} image date combination) and other 48 maps (here we provide an example of the change in "abandoned arable land" pattern, see figure 1B, fuzzy Kappa) changed dramatically with the decrease of the number of sub-optimal image dates used for the classification. Misclassifications caused drastic overestimation and underestimation of the certain LU and LUC classes. For instance, in the case of mapped "stable arable land" overestimation comparable to the best map was as high as 234% and investigation of "abandoned arable land" LUC class almost two-fold when non-optimal images were used (cf. figure 1A). In the case of mapping "stable managed grassland" and "abandoned managed grassland" generally underestimation of "stable managed grassland" and overestimation of "mapped abandoned grassland" was observed with the decrease of the number of sub-optimal image dates used for the classification.

Overestimation and underestimation of certain thematic LU and LUC classes affected their proportions, which strongly emphasized the importance of the proportional sampling. For instance, we kept the same sample size equaling to 2000 sampled pixels in the case of "abandoned arable land" and sample size for "stable arable land" varied between 2,421 and 12,187 pixels depending on the used LUC maps.

Bringing the example of the modeling of "abandoned arable land" and "stable arable land" versus 12 selected predictors, in the case of the best overall classified map (cf. figure 1, combination # 49) only three predictors were statistically significant ($p<0.05$) more than 9 times out of 10, namely "distance from nearest forest edge" (measure for long-term marginality), "distance from nearest road with hard surface" and "distance from nearest village". With the decrease of the number of sub-optimal image dates used to produce LUC maps some of the predictor variables became statistically insignificant at $p<0.05$ and others appeared significant. For instance, in the case of one of the least accurate LUC maps (cf. figure 1, image date combination #2) only "distance from nearest road with hard surface" appeared statistically significant 9 times out of 10, other statistically significant were dropped off from the model, and new variable, namely "accumulated annual precipitation", entered the model. Bringing the case of the modeling of "abandoned arable land", what we observed though, results varied considerably across "one-and-one" image dates combinations used for LUC modeling (cf. figure 1).

Modeling LUC with the use of LUC maps produced with sub-optimal image dates combinations didn't alter substantially odds ratios for the "true" statistically significant variables estimated with the best overall classified map (Figure 1, combination # 49) and if these variables appeared statistically significant in one of any 49 LUC models. For instance, for the best classified LUC map in the case of "abandoned arable land", the likelihood to observe abandonment increased by 58%+/- 10% for each kilometer away from the road with hard surface. In the case of one of the least accurate classified LUC maps (cf. figure 1, combination # 2) the likelihood to observe abandonment increased by 55%+/- 9% for each kilometer away from the paved road. However, due to underestimated acreage of the mapped "abandoned arable land" with less accurate LUC maps, it caused substantial underprediction of agricultural land abandonment.

In our case, we found that receiver operating characteristics curve (AUC) goodness-of-fit measure was not sensitive to the use of the error-induced LUC maps. For instance, in the case of "abandoned arable land" LUC model AUC varied between 0.62 and 0.68 among 49 LUC models with error-induced LUC maps.

4. CONCLUSIONS AND RECOMMENDATIONS

Our general conclusion is that the use of the error-induced LUC maps due to suboptimal use of the satellite images, and which is common approach in remote sensing community, should be done with caution. When LUC maps produced with less optimal satellite images are used for the modelling, LUC model reflect the induced errors, and wrong predictor variables may become statistically significant that should belong to another LUC class (e.g., prediction of "abandoned arable land" versus "abandoned managed grassland"). The use of wrong predictors of LUC and underestimation or overestimation of LUC acreage may lead toward substantial overestimation or underestimation of LUC phenomena, and in the end to the wrong conclusions-"blaming the victims". Based on the actual acreage of LUC and robustness of LUC models to keep "true" predictor variables, we recommend to have classified LUC maps have to be at least 80% of conditional Kappa for stable agriculture and agricultural land abandonment classes.

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