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**THE UNIVERSITY OF EDINBURGH**

**SCHOOL OF GEOSCIENCES**

**THE VISIBILITY OF SOCIO-POLITICO-ECONOMIC EVENTS ACROSS A LATVIAN LANDSCAPE**

*BY*

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in partial fulfilment of the requirement for the

Degree of BSc with Honours in

Ecological and Environmental Sciences

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**Abstract**

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Abstract

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**List of abbreviations**

EU – European Union

EUA – European Union Accession

GEE – Google Earth Engine

LUC – Land use change

LUCAS – Land Use and Coverage Area frame Survey

SAP – Single Area Payment

SPE – Socio-politico-economic

SUC – Soviet Union collapse

**1. Introduction**

Land-use, as defined by human use of land (Meyer and Turner, 1992), is undoubtedly an

important part of all civilisations, owing to the provision of natural resources (Foley *et al.*, 2005; Turner *et al.*, 2007). Human-driven land use change (LUC) through urbanisation, deforestation and agricultural expansion has placed pressure on the functioning of several ecological processes such as carbon cycling, as well as ecosystems themselves (Foley *et al.*, 2005; Turner *et al.*, 2007). Natural habitat destruction through land conversion is one of the largest threats to terrestrial biodiversity, causing extinctions and range reductions (Jetz *et al.*, 2007). However, habitat fragmentation and loss have both proven to have potential positive effects, including increased population size (Fahrig, 2017; Daskalova *et al.*, 2018). Overwhelmingly still, land use is linked to deforestation and the climate warming that accompanies it (Lawrence and Vandecar, 2015).

Habitat fragmentation and destruction has primarily occurred through changes in agricultural

practices (Foley and Ramankutty, 1999), with croplands and pastures covering over 40% of

Earth’s land surface (Foley *et al.*, 2005). Expansion is made possible through technologies

produced during the ‘Green Revolution,’ an agricultural revolution during the mid-twentieth

century that increased global food production (Foley *et al.*, 2005). Modern practices

may be compromising long-term ecosystem services (e.g. air quality and nutrient cycling) for

short-term yield increases (Foley *et al.*, 2005). Scientists are therefore concerned with

mitigating against the negative effects of LUC (Foley and Ramankutty, 1999).

Countries appear to follow similar trajectories of changing land use regimes, moving from

subsistence to intensive agriculture at differing rates depending on their socio-politico-economic (SPE) context (Lambin *et al.*, 2001; Foley *et al.*, 2005). However, a study in Ethiopia indicates that not all countries follow this pattern, as Ethiopia experienced deintensification within a changing SPE environment (Reid *et al.*, 2000). Rapid SPE changes are said to accelerate LUC, with agricultural land abandonment rates high with regulation change and the establishment of new institutions (Prishchepov *et al.*, 2013). Agricultural abandonment, defined as the cessation of agricultural activities, is linked with a shift towards more intensive agriculture, with smaller, extensive farms more likely to be abandoned (Prishchepov *et al.*, 2013). With rapid SPE shifts, Latvia proves as an ample study site to examine the effects of changing SPE conditions on a country’s land use trajectory.

In the last half-century, Latvia has undergone substantial SPE shifts. Latvia was occupied by the Soviet Union from 1944 until Soviet Union collapse (SUC) in August, 1991 (Plakans, 1994). Land use during Soviet occupation was characterised by large areas of homogenously farmed land, known as collective farms (Vanwambeke *et al.*, 2012). Collective farms were in stark contrast to pre-Soviet times, where an agricultural mosaic of small, extensively farmed areas was key to Latvia’s culture. Following SUC, Soviet collective farmland was restituted to previous landowners. In May 2004, Latvia joined the European Union (EU) (Mikkel and Pridham, 2004). European Union accession (EUA) brought the support of EU payments, which aimed to both support restoring Latvia’s traditional, cultural landscape, as well as promote increased agricultural production (Vanwambeke *et al.*, 2012). Latvia’s changing SPE environment has caused significant land use fluctuations, but it remains unclear if such effects can be seen and quantified on a broad scale.

Satellite imagery has often been used in studies aiming to quantify SPE influence

on LUC (Alexander V Prishchepov *et al.*, 2012; Fonji and Taff, 2014). However,

satellite imagery cannot show land use specifically, instead depicting land cover, which

indicates solely the type of land (e.g. water, forest etc.). Algorithms, such as classifications, must therefore be developed to effectively categorise land use types. Previous studies focusing on Latvia only consider the impacts of one SPE event (Alexander V Prishchepov *et al.*, 2012; Fonji and Taff, 2014) or one region (Vanwambeke *et al.*, 2012), rather than several over time across Latvia’s landscape. Analysing if the signature of multiple SPE events can be detected

through land cover change may shed light into the importance of SPE events as drivers of agricultural transitions across Latvia, allowing broad-scale effects to be determined. This type of analysis could be replicated for other countries to outline the impacts of shifting SPE status on land use and thus, have implications for wider aspects such as ecosystem services, the economy and urbanisation across Europe and wider society.

* 1. **Objectives and rationale**

This study aims to investigate the importance of SPE events as drivers of agricultural LUC in Latvia through the use of satellite imagery. Although the importance of SPE events on LUC is acknowledged (Alexander V Prishchepov *et al.*, 2012; Vanwambeke *et al.*, 2012), it remains unclear whether a signature of agricultural LUC is left across a country. By using satellite imagery to determine the strength and direction of agricultural LUC and transitions, patterns of a changing landscape can be unraveled to unveil when the effect of SPE events is most visible. My findings will give insight into the homogeneity, or lack thereof, of the effects of SPE events across a Latvian landscape. Results will reveal the transition patterns between each agricultural land use type, including extensive, intensive and abandoned land, providing insight into the relationship between land uses. Ultimately, my study will uncover the importance of SPE events as drivers of LUC in Latvia, permitting predictions about land use under changing SPE conditions to be made.

* 1. **Research questions and hypotheses**

I have not included alternative hypotheses for the sake of brevity and the wide range of possible alternatives.

**RQ1: Across Latvia, is intensive, extensive and abandoned land use change visible within the three years following socio-politico-economic events?**

**H1**: Directly following SUC, intensive agriculture will decrease (H1a) and abandoned land will increase across Latvia (H1b). Extensive cover change will be weakly positive (H1c). After EUA, intensive agriculture will increase (H1d) and abandoned land will decrease across Latvia (H1e). Extensive cover change will be weakly negative (H1f).

**H10**: There is no visible relationship between intensive, extensive and abandoned land use change and SPE events. Intensive, extensive and abandoned land use will not visibly increase or decrease in Latvia directly following SUC and EUA.

**RQ2**: **Do the strength and direction of land use transitions change within the three years following socio-politico-economic events?**

**H2**: Following SUC, intensive land will transition to abandoned (H2a) and extensive land (H2b), with the transition to abandoned land being stronger. After EUA, abandoned (H2c) and extensive (H2d) land will transition to intensive land.

**H20**: There is no visible relationship between land use transitions and SPE events. Land use transitions between intensive, extensive and abandoned land will not significantly increase or decrease in Latvia following SUC and EUA.

**RQ3: Is there a time lag between socio-politico-economic events and the visibility of LUC and transitions?**

**H3**: Following SUC, a weak lag relationship will be present for intensive cover decrease (H3a) and abandoned land increase (H3b). There will be a strong relationship between the new time window and extensive land cover increase (H3c). There will be a strong lag for the transition from intensive to extensive land (H3d) and a weak lag for the transition to abandoned land (H3e). After EUA, a strong lag will be present for the decrease of extensive agriculture (H3f). A weak lag relationship will be visible for abandoned land cover decrease (H3g), intensive land increase (H3h) and the transition from abandoned land to intensive land (H3i). A strong lag will be observed for the transition from extensive to intensive land (H3j).

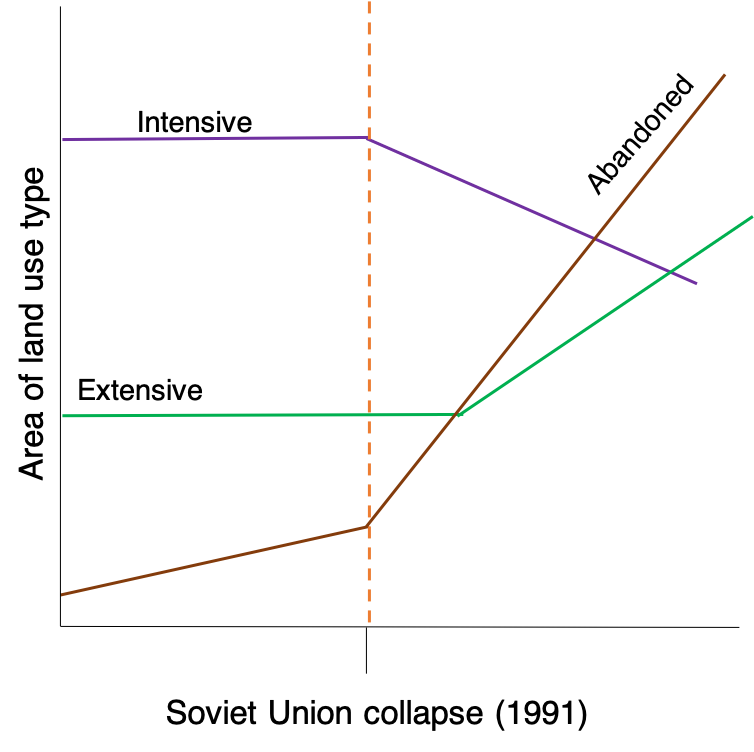
**H30**: Time following SPE events will not have an effect on strength of LUC and land use transitions, with no visible relationship observed.

* 1. **Predictions**

**1.3.1 Soviet Union Collapse**

I predict that abandoned land will increase visibly following SUC due to the sharp decline of the agricultural sector (Alexander V Prishchepov *et al.*, 2012). I predict that intensive agriculture will be replaced by extensively farmed land due to a large scale shift from Soviet collective farms to small-scale subsistence farms (Vanwambeke *et al.*, 2012). However, I predict that uncertainty around land access during the post-Soviet transition period will cause a lag in the increase of the transition to extensive land, resulting in a large increase in abandoned land within three years following SUC. I predict intensive agriculture decrease will be observed directly following SUC, representing the rapid decrease in government investment in agriculture (Vanwambeke *et al.*, 2012) contributing to the high levels of abandonment (Alexander V Prishchepov *et al.*, 2012).

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**Figure 1.1** – Prediction figures illustrating my hypotheses regarding LUC following SUC, created in Microsoft PowerPoint. Specific transitions not depicted. Not drawn to scale.

**1.3.2 European Union Accession**

I predict an increase in intensive land will be visible directly following EUA, as public support facilitated the increase of agricultural production and income (Veveris and Kalis, 2016). In turn, I predict that abandoned land decreases within three years of EUA to facilitate forming large, intensive farms. I predict that, although extensive land will decrease due to difficulty adapting to working within a single EU market, it will not happen directly following EUA. I predict instead that there will be a time lag on this decrease and transition, representing a desire to maintain traditional farming practices (Nikodemus *et al.*, 2010)

**A screen shot of a computer

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**Figure 1.2** – Prediction figures illustrating my hypotheses regarding LUC following EUA, created in Microsoft PowerPoint. Specific transitions not depicted. Not drawn to scale.

**1.3.3 Implications of results**

If the area of a land use type increases or decreases significantly directly following an SPE event, the SPE event can be seen as the main driver of LUC. Significant LUC also would indicate a homogeneous shift across the Latvian landscape. If no significant LUC is observed, it is likely that different regions experienced LUC with differing strengths and directions. Such heterogeneous effects would also signify that the SPE event was not the main driver of LUC or that it was coupled with other key drivers.

**2. Methods**

To answer my three main research questions, I constructed a classification of land use change in Latvia between 1989 to 2011 using the Google Earth Engine (GEE) (Gorelick *et al.*, 2017). My workflow diagram, depicting the key steps to this process, is shown in Figure 1.

**Figure 2.1** – Workflow diagram, created on Microsoft PowerPoint.

**2.1 Study site**

Latvia (55º40’-58 º05’N and 20º58’-28º14’E) is on the Baltic coast, in North Eastern Europe (Prieditis, 1993). Latvia borders Estonia to the north, Lithuania to the south and both Russia and Belarus to the east. Latvia spans 64.6 thousand km2 and is largely flat, with the majority of terrain between 40-200 metres above sea level (Prieditis, 1993). Land is vegetated for 180-200 days annually (Prieditis, 1993). Latvia was a Soviet state during 1945-1990, where there were predominantly large, homogenously cultivated farms on favourable areas, with the rest of the land largely forested (Vanwambeke *et al.*, 2012). Following SUC in 1991, land reform aimed to restore pre-Soviet farming culture where extensive, small farms were key to Latvia’s culture. Leading up to EUA, agricultural support schemes played a large role in promoting such extensive farming practices (Vanwambeke *et al.*, 2012).

**2.2 Image processing**

Landsat 5 Thematic Mapper satellite imagery (1985-2011) covers my study period well and is commonly used in similar classification studies (Alexander V Prishchepov *et al.*, 2012; Fonji and Taff, 2014; Sidhu *et al.*, 2018). I selected Landsat 5 Surface Reflectance imagery (30 metre resolution), which is atmospherically corrected, preventing the occurrence of clouds and shadows in the imagery (Zanter, 2018). For each study year (1989-2011), I employed an additional cloud mask to remove any remaining pixels containing clouds or shadows, as well as any edge pixels that did not contain all bands of interest. I chose summer images, depicting the growing season, to best characterise the spectral signatures of my different classes (Fonji and Taff, 2014). I took the median of each year’s image collection to obtain an annual composite for each study year (Pimple *et al.*, 2018). I cropped each year’s image to the border of Latvia to increase the speed of my classification, preventing the classification from being applied across the world. Lastly, I selected blue, green, red, near-infrared and shortwave infrared bands, each with corresponding wavelengths, as the bands for my classification (Pimple *et al.*, 2018). My chosen bands will act as predictor variables for my classification.

**2.3 Classification background**

Classification approaches create categorical datasets, such as land use (Horning, 2010). Classifications aim to investigate the relationships within a group of objects to determine if the data can be summarised into classes (Gordon, 1999). There are three key steps to a classification: train, validate and test (Suthaharan, 2016).

In a supervised classification, relationships are discovered using data of known values, also called training points (Albalate and Minker, 2013). Training points train the classifier to infer prediction rules that form a decision tree (Albalate and Minker, 2013). Decision trees are composed of binary questions which group data by specific characteristics, such as bandwidth (Strobl *et al.*, 2009). With each step of the tree, the classifier asks whether a criterium of a specific class is met. After the classifier is trained, it can be applied across data of unknown classes. Test data of known values, normally obtained in the training phase, are then passed through the classifier to determine classifier accuracy and error (Suthaharan, 2016).

Random forest classifications are a supervised learning technique that is composed of numerous decision trees, creating a forest of trees (Horning, 2010). As multiple trees decide the class of each object, a voting process begins, where the final class assigned is the one that is predicted most (Horning, 2010). Using multiple trees increases classification accuracy (Suthaharan, 2016), as there is decreased overfitting, where noise is used to predict classes (Horning, 2010). A separate validation set, where overfitting is accounted for and parameters are pruned, is therefore not required (Suthaharan, 2016).

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**Figure 2.2** – Random forest conceptual diagram, created with Microsoft PowerPoint.

**2.4 Training data**

My training data represent the known locations of each land use type in 2012. Field data results in high certainty in the training set (Millard and Richardson, 2015).

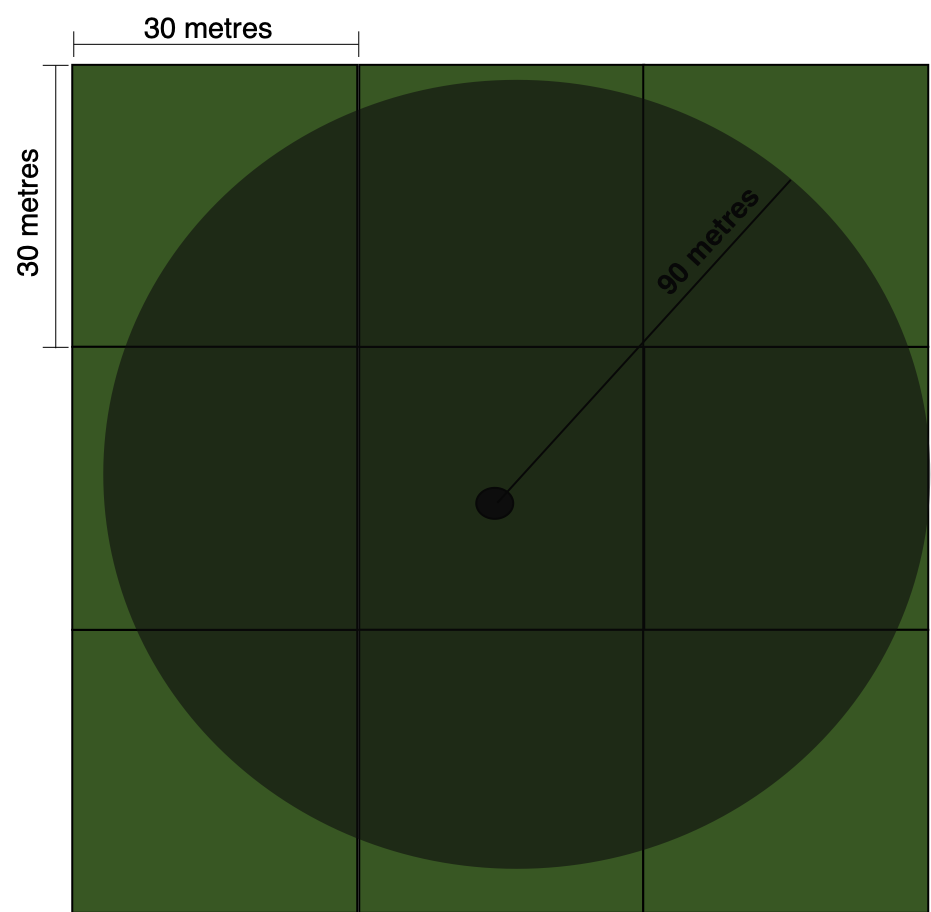
I used the Land Use and Coverage Area frame Survey (LUCAS) dataset (Eurostat, 2013), which contains GPS coordinates of both land use, as defined by the socioeconomic activities, and land cover for European countries, for every three years since 2009. I chose to use 2012 data, as it is the earliest dataset that clearly separates fallow and abandoned agricultural land. Within R statistical software, version 3.5.3 (R Core Team, 2019), I filtered data to represent each of my land use classes: abandoned land and extensive and intensive agriculture. I also included four additional classes (artificial land, wetlands, water and forestry), as a larger training dataset improves classification stability and accuracy (Millard and Richardson, 2015). This collection of classes is supported by a similar study conducted by Fonji and Taff (2014).

To select which data would form each of my classes, I used the LUCAS 2012 Technical Reference Document (Eurostat, 2013), which contains descriptions of each land use and land cover category. Table 2.1 displays the criteria that define each of my key classes. The criteria to determine additional class can be found in Appendix X.

**Table 2.1 –** Criteria chosen to represent each key land use class.

|  |  |
| --- | --- |
| **Land use** | **Criteria** |
| **Abandoned** | 1. Abandoned agricultural land. 2. Abandoned land, filtered to include cropland, woodland, grassland and bare land. 3. Semi-natural and natural areas not in use. 4. Unused, spontaneously revegetated land. |
| **Extensive** | Heterogeneous crops planted mainly for own consumption produced in kitchen gardens or allotments, filtered to include cropland, woodland, grassland and bare land (natural areas). |
| **Intensive** | Industrial agriculture, filtered to include cropland, woodland, grassland and bare land. |

Following filtering, I had the coordinates of 4013 data points, 1434 of which are from my three key classes (Table 2.2; Appendix X). I transformed these coordinates into a spatial file by setting the projection to that of GEE: Pseudo-Mercator WGS 84 (EPSG: 3857).



**Figure 2.3** – Circular buffer with 90 metre radius around data point, created with Microsoft PowerPoint. Square boxes represent pixels with 30 metre resolution.

Once imported into GEE, I created a 90-metre buffer around each point, turning point data into circular polygons (Figure 2.3). As each point represents an area or polygon of land, a buffer was necessary to compensate for GPS precision (Wulder *et al.*, 2005) and ensure the surrounding pixels were included. I chose a 90-metre buffer, creating a circular polygon with an area of 25446.9 square metres. This buffer size was used by Sader *et al.* (1995) for their land use classification. It is further supported by the average farm size in Latvia, with more than 91% of farms being this size or larger in 2003 (Zdanovskis and Pilvere, 2015).

To set up the training data for my classification, I divided my data randomly by class into two groups: training (80%) and testing (20%), also known as a hold-out approach (Suthaharan, 2016). The hold-out approach permits assessment of how the trained classifier works with unseen data (testing group).

**Table 2.2** – Total number of points obtained from LUCAS and the number used for training (80%) and testing (20%) for key classes. Total includes four additional classes.

|  |  |  |  |
| --- | --- | --- | --- |
| **Land type** | **Number of LUCAS points** | **Number of points in training sample** | **Number of points in testing sample** |
| **Abandoned** | 112 | 90 | 22 |
| **Extensive** | 27 | 18 | 9 |
| **Intensive** | 1295 | 1038 | 257 |
| **Total** | 4013 | 3223 | 817 |

I then sampled the imagery to collect the bandwidths across the locations of my training set. The bandwidths correspond to the unique spectral signature of each land type. As the training set refers to 2012 data, it would be most suitable to sample 2012 imagery. However, Landsat 5 only contains imagery until the beginning of 2012 and does not cover the summer months that my data corresponds with. Landsat 7 could have been used, however, 22% of images are missing due to instrument failure (Alexandridis *et al.*, 2013). When examining error, it was clear that this failure had an effect on images covering Latvia. I therefore chose to substitute 2012 images with 2011 images. Consequently, my training points do not precisely match up with the imagery. However, large-scale land use change is not expected to occur between 2011 and 2012, as this period was a stable time for Latvia’s economy and therefore, land use was likely kept relatively constant (Skribane and Jekabsone, 2013). For instance, abandoned area coverage changed less than 0.1% between 2011 and 2012 (Arika and Mazure, 2017). Upon retrieving the unique bands, the classifier was ready to be constructed and trained.

**2.5 Random forest classification**

There are two main inputs when constructing a random forest classifier: the number of decision trees and number of predictor variables per node of each decision tree. I set the number of decision trees to 30 with consideration of the computational burden on GEE (Nomura and Mitchard, 2018). The default number of predictor variables used at each node to form the binary rules within the classifier is commonly set to the square root of the number of input variables (Gislason *et al.*, 2006). Here, the number of input variables is the number of bands (6) used to classify the image. Limiting the number of predictor variables reduces the computational complexity, as well as the correlation between decision trees (Gislason *et al.*, 2006).

I trained the classifier using the bandwidths gathered from sampling the input imagery and applied this classification across Latvia. For each year, I applied the trained classifier to the new imagery. Each classified image was exported as both an image and a GEE asset at 30 metre resolution. Exporting as an asset allows for data to be used in other scripts by the same user, which was important for preventing GEE exceeding memory capacity during data collection.

**2.6 Classification accuracy and error**

I tested classification accuracy and error in two ways: (1) the resubstitution method and (2) the hold-out method. Accuracy was obtained as the percent of pixels classified correctly and error was given in the form of a confusion matrix. A confusion matrix compares the field data to the classification output on a class by class basis (Murayama and Thapa, 2011) and is an indication of the classifier’s performance (Dougherty, 2013). Table 2.3 represents a conceptual example of a confusion matrix, where the number of points that were classified correctly and incorrectly are reported.

**Table 2.3** – Conceptual output of confusion matrix.

|  |  |  |  |
| --- | --- | --- | --- |
|  | **Predicted Class A** | **Predicted Class B** | **Predicted Class C** |
| **Known Class A** | True A | False B | False C |
| **Known Class B** | False A | True B | False C |
| **Known Class C** | False A | False B | True C |

**2.6.1 Resubstitution accuracy and error**

The resubstitution method tests the classifier’s ability to resample bandwidths that were used to train the classifier originally (Verbyla and Litvaitis, 1989). Resubstitution is known to produce optimistically biased results on the overall accuracy of the classifier (Verbyla and Litvaitis, 1989), therefore, the results of the leave-out method should be considered more representative.

**2.6.2 Hold-out accuracy and error**

The hold-out method makes use of the test set left aside when forming the training sample. This process depicts the efficiency with which the trained model classifies unseen data (Suthaharan, 2016). I resampled the input imagery using my test set to reclassify the image. From this, a test accuracy and error matrix can be obtained.

**2.7 Data collection and processing**

As my classification is computationally intensive, memory constraints prevented both the classification and the calculations to be completed in the same script. I imported each year’s classified image and applied a grid composed of 124 equally sized cells (689.5 km2) onto Latvia. Collecting data by cell prevented exceeding the memory capacity of GEE and improved the replication within my study. A larger grid of five blocks was also imposed manually using R statistical software to allow for regional variation to be accounted for.

**2.7.1 Area**

For each year, I collected the number of pixels per cell of each of my three key land use classes. I saved each file as a CSV and aggregated them using R statistical software, version 3.5.3 (R Core Team, 2019). I calculated area in square kilometres using the following formula:

**2.7.2 Transition**

To calculate the number of pixels undergoing land use transitions, I first outlined the transitions I needed to gather data for, shown in Table 2.4.

**Table 2.4** – Transitions to examine for each time step.

|  |  |
| --- | --- |
| **Start land use** | **End land use** |
| Abandoned | Intensive |
| Intensive | Abandoned |
| Extensive | Intensive |
| Intensive | Extensive |

The process will be explained using the abandoned to intensive transition as an example. First, taking the first year’s imagery, solely land that is abandoned is selected. Using the next year’s imagery, only intensive land is selected. I then overlaid the intensive land imagery atop the abandoned imagery. With the *and* command in GEE, I was able to select pixels that were both abandoned land in the first year *and* intensive land in the next year. This process was completed for all transitions for a yearly time step, meaning from one year to the following year, for each of my study years (1989-2011). I saved each file as a CSV and aggregated them using R statistical software, version 3.5.3 (R Core Team, 2019). I calculated area in square kilometres using the same formula in section 2.7.1.

**2.8 Statistical analyses**

All data analysis was performed using R statistical software, version 3.5.3 (R Core Team, 2019). Examples of key code chunks used are available in Appendix X. Complete scripts of all code written is available on GitHub (https://github.com/izzyrich/dissertation).

**2.8.1 Data setup**

To test my three questions, I aggregated yearly data into groups, representing the before and after period of each SPE event (Table 2.5). As SUC happened in December 1991, 1991 is grouped in the before category. EUA happened in May 2004, thus 2004 is in the after category, as land cover was examined over summer months. Area was averaged for each cell in each time period to obtain one value for each cell. Although this lowers sample size, aggregation was necessary to meet linear mixed-model (LMM) assumptions.

**Table 2.5** – Time periods representing before and after each event.

|  |  |  |
| --- | --- | --- |
| **Event** | **Before period** | **After period** |
| **SUC** | 1989-1991 | 1992-1994 |
| **SUC lag** | 1989-1991 | 1995-1997 |
| **EUA** | 2001-2003 | 2004-2006 |
| **EUA lag** | 2001-2003 | 2007-2009 |

**2.8.2 Linear mixed models**

LMMs were used due to the hierarchical nature of the data, with values grouped by location. LMMs help account for the lack of independence of each data point and consider what values are true replicates. In my data, smaller cells would be true replicates, but as all assumptions of a LMM were violated without data aggregation, cell was not used as a random effect. Deviations from normality and homoscedasticity were tested using visual assessment with Q-Q plots and histograms (Arnau *et al.*, 2013). No apparent violations were observed when data was averaged across cells. I used the R package *lme4* to run all LMMs (Bates *et al.*, 2015). All LMMs followed the same structure, with time period as the fixed effect and the larger grid as the random effect:

Separate models for each time period combination were run for each land use type and transition.

To determine model fit, pseudo-R2 values were calculated to examine the amount of variation explained by the fixed effects, as well as the whole model (Nakagawa and Schielzeth, 2013). Using R2 values allows for between-model comparison, helping to assess the relative importance of time period as a predictor for each land use type and transition. Variables were considered significant when the error around the slope was low and when the *p*-value was under 0.05 (Zhu, 2012). Pseudo *P*-values were calculated using the *lmerTest* package (Kuznetsova *et al.*, 2017). Significance was further examined looking at the effect size, which can be defined as the average group difference (Zhu, 2012).

**2.8.3 Breakpoint analysis**

Breakpoint analysis examines the location of tipping points, where properties in a dataset change dramatically (Toms and Villard, 2015). Breakpoints are determined by a change in the relationship between the response and explanatory variable, visible through a sharp change in the slope. Breakpoints were determined using the *segmented* R package (Muggeo, 2017). Breakpoint analysis does not allow for a LMM design, so linear models were used. Data was thus summed by year to obtain a total yearly sum of area for each land use type and transition. A separate model was run for each land use type and transition using the following structure:

Breakpoints were examined visually to determine if they align with the SPE events.

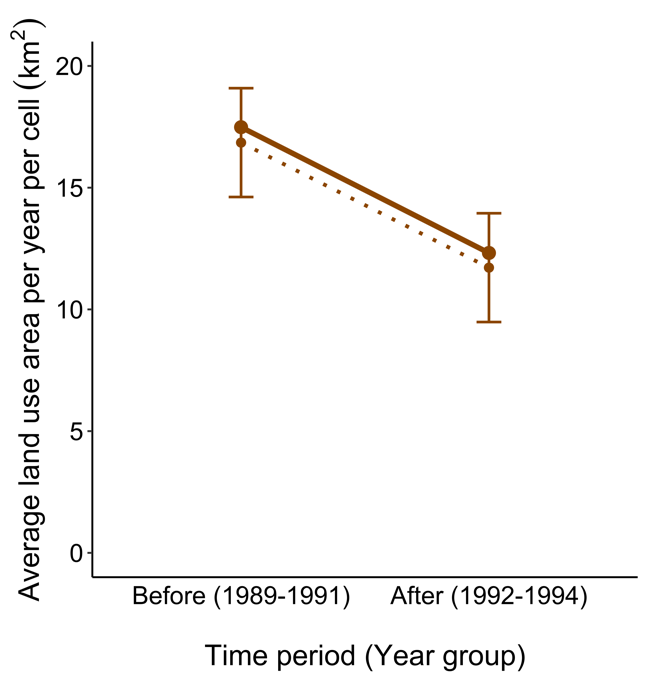
**3. Results**

EXAMPLE MAP

**3.1 LUC visibility within three years following socio-politico-economic events**

**3.1.1 Soviet Union Collapse**

|  |  |  |  |
| --- | --- | --- | --- |
| **Estimate** | | **± SE of estimate** |  |
| -5.14 | 1.13 | | |
| **t-value** | ***p*-value** | | |
| -4.56 | <0.0001 | | |
| **R2M** | **R2C** | | |
| 0.06 | 0.30 | | |



**Table 3.1** – Significant LMM ran between time period and abandoned land area.

**Figure 3.1 –** Effect size graph for abandoned land cover change following SUC. Dashed line represents effect size and error bar shows error around effect size, as determined by the model. Solid line represents actual data.

Within three years following SUC, abandoned land cover significantly decreased (Table 3.1; Figure 3.1), implying a rejection of H1b, where abandoned land cover is predicted to visibly increase. Time period explained a very low proportion of the variation within the abandoned land cover data (R2M = 6%). By adding grid as a random effect, a greater proportion of variation was explained (R2C = 30%).

I found no significant relationship between time period and both intensive and extensive land (Appendix), implying an acceptance of the null hypothesis (H10).

**3.1.2 European Union Accession**

Within three years following EUA, abandoned land cover significantly decreased (Table 3.2; Figure 3.1a), causing an acceptance of H1e. Intensive land cover significantly increased within three years following EUA (Table 3.2; Figure 3.2b), allowing acceptance of H1d. The time period predictor explained little variation in both land use models, with a slight increase when grid was introduced as a random effect (Table 3.2).

A close up of a map

Description automatically generated

**a.**

**b.**

**Figure 3.2 –** Effect size graph for (a) abandoned land cover change and (b) intensive land cover change following EUA. Dashed line represents effect size and error bar shows error around effect size, as determined by the model. Solid line represents actual data. Scale of y-axis different for effective visualisation – two graphs should not be compared directly.

**Table 3.2** – Two significant LMMs ran for the relationship between time period and two land use types.

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Land use** | **Estimate** | | **± SE of estimate** | **t-value** | | ***p*-value** | | **R2M** | **R2C** |
| **Abandoned** | -2.61 | 1.20 | | | -2.12 | | 0.03 | 0.01 | 0.10 |
| **Intensive** | 6179.11 | 1942.18 | | | 3.18 | | <0.01 | 0.04 | 0.09 |

There was no significant relationship between time period and extensive LUC (Appendix). This implies an acceptance of H10 for extensive land, indicating that extensive LUC is not visible directly following EUA.

**3.1.3 Other potential predictors of land use change: location**

When data is not aggregated, cell can be included as a nested random effect, which allows the use of finer scale data. In all cases, this increased total model fit (R2C) and significance (decreased *p*-value) as compared to the models solely including the larger grid as a random effect (Appendix). However, the variation explained by the fixed effect (R2M) was only increased for the extensive LUC LMM for the EUA time period (Appendix). Assumptions were not met for models including cell as a random effect, with no transformation able to mitigate against normality and homoscedasticity issues. Results still may indicate the importance of location in determining LUC and LUC visibility (Figure 3.3a & Figure 3.3b).

A close up of a map

Description automatically generated

**a.**

**b.**

**Figure 3.3 –** Figure depicting average abandoned land area per year per cell (a) aggregated by grid and (b) shown for all cells increasing in abandoned land cover. Scale of y-axis different for effective visualisation – two graphs should not be compared directly. Raw data used solely for visualisation purposes.

**3.2 Land use transition visibility within three years following socio-politico-economic events**

**3.2.1 Soviet Union Collapse**

Within three years following SUC, the amount of intensive land transitioning to abandoned land significantly decreased (Table 3.3; Figure 3.4). A negative relationship for this transition causes a rejection of H2a. Again, the fixed effect explains a very small proportion of variation in the data, with model fit considerably improved when considering grid as a random effect (Table 3.3).

|  |  |  |  |
| --- | --- | --- | --- |
| **Estimate** | | **± SE of estimate** |  |
| -3.02 | 0.70 | | |
| **t-value** | ***p*-value** | | |
| -3.76 | <0.001 | | |
| **R2M** | **R2C** | | |
| 0.04 | 0.24 | | |

A picture containing object, antenna

Description automatically generated

**Table 3.3** – Significant LMM ran between time period and transition to abandoned land.

**Figure 3.4** – Effect size graph for transition from intensive to abandoned land following SUC. Dashed line represents effect size and error bar shows error around effect size, as determined by the model. Solid line represents actual data.

I found no significant relationship between SUC and the transition from intensive to extensive land (Appendix), causing null hypothesis acceptance (H20).

**3.2.2 EUA**

For both transitions to intensive land from extensive and abandoned land, no significant relationship was found (Appendix). By accepting the null hypothesis (H20), it is implied that neither transition is visible directly following EUA.

**3.3 Time lag on land use change visibility following socio-politico-economic events**

**3.3.1 Soviet Union Collapse**

When examining the influence of a time lag following SUC on LUC and transitions, all LUC and transitions were significant (Table 3.4).

For abandoned land, land cover significantly decreased, with a steeper slope than that seen directly following SUC (Table 3.1 & 3.4), causing a rejection of H3b. For this model, a greater proportion of the data’s variation is explained by the fixed effect (R2M = 14%). By moving the time window, extensive land use has a weakly negative, significant relationship with time period, with the fixed effect being the sole explainer of variation in the model (Table 3.4), thus H3c is rejected. Intensive land use change also becomes significant, with a strong negative relationship indicating a loss of intensive land (Table 3.4). H3a is thus rejected due to the strength of the relationship. A slightly weaker relationship is seen for the transition from intensive to abandoned land, as compared to the change observed directly following SUC (Table 3.3 & 3.4), causing H3e to be accepted. The transition to extensive from intensive land becomes significant with this new time window as a predictor (Table 3.4). A very weak relationship is seen, with slightly less transitioning to extensive land following SUC. H3j is thus rejected due to the strength of the relationship.

**Table 3.4** – Significant LMMs ran for the new time period.

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Land use/transition** | **Estimate** | | **± SE of estimate** | **t-value** | | ***p*-value** | | **R2M** | **R2C** |
| **Abandoned** | -7.41 | 1.08 | | | -6.90 | | <0.0001 | 0.14 | 0.27 |
| **Extensive** | -0.60 | 0.11 | | | -5.75 | | <0.0001 | 0.11 | 0.11 |
| **Intensive** | -4910.30 | 2416.93 | | | -2.03 | | 0.04 | 0.01 | 0.09 |
| **I 🡪 A** | -2.09 | 0.84 | | | -2.50 | | 0.01 | 0.04 | 0.24 |
| **I 🡪 E** | -0.13 | 0.03 | | | -3.70 | | <0.001 | 0.06 | 0.10 |

**3.3.2 European Union Accession**

When testing the influence of a time lag following EUA on LUC and transitions, time lag was a significant predictor for intensive LUC only. A steep positive relationship indicates a strong move towards intensive land use following EUA (Table 3.5). The slope (estimate) of this relationship is weaker than that seen directly following EUA (Table 3.2), causing H3h to be accepted.

**Table 3.5** – Significant LMM ran for the new time period on intensive land.

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Land use** | **Estimate** | | **± SE of estimate** | **t-value** | | ***p*-value** | | **R2M** | **R2C** |
| **Intensive** | 4522.85 | 1904.92 | | | 2.37 | | 0.02 | 0.02 | 0.10 |

**3.4 Determining breakpoints**

For both the LUC and transitions, breakpoints did not line up with the two SPE events. Intensive land was the only land use type to have one breakpoint point precisely match an SPE event: EUA (Figure 3.5a). Abandoned land experienced two breakpoints directly following SUC: one signifying a sharp decrease in land cover, trailed by a sharp increase (Figure 3.5b). Extensive land experienced a breakpoint four years following SUC and three years following EUA (Figure 3.5c).

1. **b. c.**

**A close up of a map

Description automatically generated**

**Figure 3.5** – Breakpoint figures for (a) intensive land, (b) abandoned land and (c) extensive land. Coloured line shows total land use area (km2) per year. Dotted line represents the two SPE events (SUC and EUA). Dashed line indicates where model fit two breakpoints. Solid black line represents segmented regression, as fit by model.

Transitions between both extensive and abandoned land to intensive land and the reverse, followed roughly the same trajectory observed by the land use type transitioning into (Appendix).

**4. Discussion**

**4.1 Key findings**

Directly following SUC, abandoned land was found to significantly decrease, causing a rejection of H1b and all relevant literature (Figure 3.1; Alexander V Prishchepov *et al.*, 2012; Vanwambeke *et al.*, 2012). The disagreement with many previous studies may indicate either (1) a new trend not previously discovered or (2) error in my classifier’s ability to categorise abandoned land. Within six years after SUC, all three key land uses and both transitions decreased (Table 3.4), causing an acceptance of H3a and a rejection of H3b-e. Directly after EUA, abandoned land cover decreased and intensive cover increased, causing an acceptance of H1e-d (Figure 3.2). Six years following EUA, intensive land still significantly increased (Table 3.5; H3h acceptance). However, the importance of this increase may be conflated with time passing, and therefore, may not be a clear indicator of the effects of a time lag following EUA. Regional specific examination helps explain variation in the data, but does not help develop country-level land use policies (Alexander V Prishchepov *et al.*, 2012). Only intensive LUC exhibited a breakpoint that matched with EUA, while all other breakpoints either lagged behind SPE events or were seemingly unrelated.

**4.2 Is intensive, extensive and abandoned land use change visible within the three years following socio-politico-economic events?**

**4.2.1 Soviet Union Collapse**

My results demonstrate that, out of intensive, extensive and abandoned LUC, only abandoned LUC is visible within three years of SUC. Rapid abandoned LUC is well documented in literature, with many citing dramatic levels of agricultural abandonment (Alexander V Prishchepov *et al.*, 2012; Vanwambeke *et al.*, 2012) directly following SUC (Bell *et al.*, 2009). An increase in agricultural abandonment is not supported by my results, where it was shown that abandoned land coverage decreased in the three years following SUC, as compared to the three years prior. Findings by Prischepov *et al.* (2012) suggest that agricultural abandonment reached its peak around the year 2000, with a sharp increase from 1990-1996, while Vanwambeke *et al.* (2012) state that this shift occurred prior to SUC, between 1988-1992. The lack of agreement on the timing of a move to agricultural abandonment implies an absence of a clear signature on Latvia’s landscape.

Agricultural abandonment is said to increase following SUC due to the collapse of the collective farming system (Ruskule *et al.*, 2012; Gradinaru *et al.*, 2015) and the breakup of larger farmers into smaller areas to restitute land to previous owners (Nikodemus *et al.*, 2005; Alexander V Prishchepov *et al.*, 2012; Fonji and Taff, 2014). Previous owners had limited interest to uptake farming practices on this newfound land. As land reform was not complete until roughly 2002, the transfer of land to individuals more suited to farming was prevented (Alexander V Prishchepov *et al.*, 2012).The slow transfer of land may explain why agricultural abandonment was not seen directly following SUC in my classification, with the potential for increase following this three year study period. Although it is not completely improbable that my results introduce a new pattern, it is likely that agricultural abandonment decrease is observed due to another factor.

Prishchepov *et al.* (2012b) uncovered the importance of imagery when determining areas of abandoned land, with the number of images used cited as the largest accuracy determiner. Specifically, the Landsat record was noted for such limited image-date availability, restricting the detection accuracy of agricultural land abandonment. Thus, my classification may not have been sensitive to agricultural land abandonment in the years following this three-year window. Additionally, as my training points were from 2012, it is likely that these points represented areas that had been abandoned for a long period of time, as most land abandonment occurred before 2000 (Vanwambeke *et al.*, 2012). Newly abandoned points may have a different spectral signature than long standing abandoned points (Lugo and Helmer, 2004; Ruskule *et al.*, 2012), potentially causing an underestimation following SUC.

Intensive and extensive LUC were not found to be visible within three years of SUC. Intensive land was predicted to decrease following SUC, in line with the large scale abandonment noted and the collapse of the collective farming system (Nikodemus *et al.*, 2005; Alexander V Prishchepov *et al.*, 2012). It is not surprising that extensively farmed land did not statistically increase or decrease directly following SUC due to the slow returning of previously intensively used land. It is predicted that, upon completion of land reform, extensive land coverage would be significantly larger Latvia-wide as subsistence farming acts to replace Soviet collective farms (Vanwambeke *et al.*, 2012). It is likely that a time lag would better explain intensive and extensive LUC.

**4.2.2 European Union Accession**

My results suggest that within the three years following EUA, abandoned land decreased and intensive land cover increased. Intensive land use increase is well cited following EUA, as support schemes provided by the EU promoted agricultural restoration (Vanwambeke *et al.*, 2012). Directly following EUA, over 50% of agricultural land was cropped with the support of single area payments (SAPs) (Nikodemus *et al.*, 2010). SAPs are given at a fixed rate per hectare for maintained agricultural land. SAPs tend to encourage large, intensive fields, potentially causing the increase in intensive, homogeneous agriculture seen (Nikodemus *et al.*, 2010; Fonji and Taff, 2014). Csaki and Jambor (2010) found an 8% increase in large farms directly following EUA. Following EUA, land salvation rates surpassed land abandonment, explaining the decrease in land abandonment (Vanwambeke *et al.*, 2012).

After EUA, abandoned land is suggested to have decreased, owing to the rapid colonisation of woody species and transition into young forests (Nikodemus *et al.*, 2010; Ruskule *et al.*, 2012; Vanwambeke *et al.*, 2012). A transition to forest is not always even and can be delayed by herbaceous vegetation for up to twenty years (Ruskule *et al.*, 2012), giving rise to a variety of landscapes following abandonment. Additionally, support schemes have also been successful in decreasing the level of agricultural abandonment seen (Abolina and Luzadis, 2015), owing to the attractiveness of land uptake as a source of income from EU payment schemes (Griffiths *et al.*, 2013). It is not unlikely that, following this three year period, abandoned land will increase again, ascribed to outmigration from rural areas to cities (Fonji and Taff, 2014).

Extensive land use was not found to be significantly related to EUA. I predicted a weakly negative relationship due to the increase of intensive land. However, it is likely that an increase is also possible. SAPs supported farmers regardless of their level of production (Nikodemus *et al.*, 2010), aiming to promote diverse and traditional mosaic landscapes (Vanwambeke *et al.*, 2012). However, the large difference between forests and agricultural area does not correspond to such mosaic landscapes, and instead, deters from small, extensive farms (Vanwambeke *et al.*, 2012). The strength of increasing agricultural production through intensive farms may annul the effects of traditional landscape promotion, thus causing no significant increase or decrease in extensive land cover.

**4.2.3 Other potential predictors of land use change: location**

It is not surprising that specific location characteristics can have a large stake in determining LUC and explaining LUC variation. Case studies examining north-eastern (Fonji and Taff, 2014) and central Latvia (Nikodemus *et al.*, 2005; Vanwambeke *et al.*, 2012) have shed light into the potential differences between regions. Most notably, the effect of varying environmental characteristics such as soil structure and altitude on the potential for agricultural success (Nikodemus *et al.*, 2010), as well as the varying cultural experiences of differing land use types (Bell *et al.*, 2009). Despite these clear differences, it is necessary to improve knowledge of the effects of large scale, continuous SPE change to discover patterns that can be applied across countries to help inform new land use policies (Alexander V Prishchepov *et al.*, 2012). As regional studies have been completed, I have focused my findings and discussion on a country level to help add to a discussion that is not yet refined.

**4.3 Do the strength and direction of land use transitions change within the three years following socio-politico-economic events?**

**4.3.1 Soviet Union Collapse**

My results indicate that there was a significant decrease in the amount of land transitioning from intensive agriculture to abandoned land directly following SUC. A decrease in this transition is emulated by the decline of abandoned land area explained in section 4.2.1. When coupled, it is evident that the interplay between abandoned and intensive land uses is significant: when abandoned land cover decreases, intensive land cover increases and vice versa. As described, I expected that the reverse would happen, with intensive land cover decreasing and abandoned land cover increasing. It is unlikely that intensive land cover would continue to increase, owing to the collapse of the intensive Soviet agricultural system (Fonji and Taff, 2014). It is probable that the transition between intensive to abandoned land will reverse in direction after this three-year period.

My results demonstrate the lack of a clear relationship between the transition from intensive to extensive land. On account of the slow reform where the once large, collective Soviet farms were divided and given to their previous land owners (Nikodemus *et al.*, 2005), it is plausible that a clear relationship is not evident within three years of SUC.

**4.3.2 European Union Accession**

The transition to intensive land from both abandoned and extensive land uses was not seen to significantly change directly following EUA. The lack of an increase of abandoned land transitioning to intensive agriculture may be attributed to the rapid succession of woody species on abandoned land (Nikodemus *et al.*, 2010; Vanwambeke *et al.*, 2012), rather than an uptake of abandoned land for new, intensive farms. Forests and tree cutting are an economic asset due to the speed at which income can be gained (Vanwambeke *et al.*, 2012). Following EUA, forestry gained size and professionalism and became a large industry competitor to agriculture (Vanwambeke *et al.*, 2012). The importance of forestry to the Latvian economy and culture may be an indicator as to why land use did not always transition to intensive agriculture.

Abandoned land undergoing slow transition may also not be used for intensive agriculture, ascribed to the ability to gain EU SAPs for managing previously abandoned land (Nikodemus *et al.*, 2010). SAPs do not require land to be used for agricultural production, thus transitioning land may remain untouched with the aim of maintaining open landscapes. However, there is a higher uptake of SAPs on abandoned areas with better soils, most likely suggesting that the use of abandoned land for SAPs often occurs with the aim of reinstating agricultural practices (Nikodemus *et al.*, 2010). It is therefore likely that abandoned land was transitioning to intensive agriculture, but that this was not the largest transition occurring. Instead, it is probable that the transition between abandoned land and forestry/forested areas is more significant.

The transition to intensive land from extensive land was not seen to be significantly different prior to EUA. The lack of a relationship may be attributed to the cultural significance of subsistence farming in Latvia. There is a strong divide between farmers that support EU payment schemes and those against them (Nikodemus *et al.*, 2010), which may shed light into the cultural importance of maintaining small-scale, subsistence farming without government aid. Without government assistance, many farmers do not have substantial income and thus, land abandonment may increase, owing to subsistence farm failure. The interplay between intensive and extensive land here may not be as strong as I originally predicted. Instead, it is likely that extensive land has a stronger connection to abandoned land following EUA.

**4.4: Is there a time lag between socio-politico-economic events and the visibility of land use change and transitions?**

**4.3.1 Soviet Union Collapse**

Within six years of SUC, all LUC and transitions were significantly different to pre-SUC conditions. The effect size of abandoned land cover decrease is stronger with time lag as a predictor of LUC, as compared to the years directly following SUC. A sharp decrease in abandoned land over this period is not well cited in literature, as previously mentioned. With the peak of abandoned land cover likely to be around 2000 (Alexander V Prishchepov *et al.*, 2012; Vanwambeke *et al.*, 2012), it is probable that my classification did not pick up the steady increase that many studies discuss. More likely, however, is that the spectral signature of abandoned land has changed within my time series. A change in spectral signature would indicate that the training points collected at the end of my time series (2012) do not accurately characterise abandoned land in the 1990s, thus, underestimating the amount of abandoned land observed following SUC (Alexander V. Prishchepov *et al.*, 2012).

The effect size of intensive LUC is significantly stronger when taking a potential time lag into account (Gutman and Radeloff, 2017). Furthermore, the direction of change shifts from positive to negative. A shift to a negative relationship most likely signifies a time lag on intensive land cover decrease. My results are supported by the slow land reformation process, where large, Soviet collective farms were redistributed to their previous owners. Land restitution began in 1990, but only in 1994 was the law adopted, with the deadline to submit restitution claims at the end of 1996 (Hartvigsen, n.d.). It is not unlikely that a move away from intensive land would not have been visible until completion of land restitution, thus explaining the time lag in this relationship.

A weak, negative relationship was observed for extensive LUC six years following SUC. Despite the significance of this relationship, the direction is likely to be arbitrary due to the large amount of error relative to the effect size. Consequently, according to my results, it is likely that extensive agricultural area did not significantly change following SUC. A neutral relationship is in accordance with land use history, in terms of the battle between maintaining a traditional landscape and shifting towards profitable, intensive agriculture (Vanwambeke *et al.*, 2012).

Both transitions from intensive agriculture to abandoned and extensive land showed a negative relationship, indicating that more land transitioned before SUC than after. The transition to extensive land, again, is significant but the direction is not likely to be precise, due to the relatively flat slope and large error. The transition to abandoned land is steeper, though still negative, going against my original prediction. The aspects at play when determining abandoned land cover in my classification, such as lack of precise training points, are likely having an impact on the strength and direction of this transition.

**4.3.2 European Union Accession**

My results indicate a significant time lag effect for solely intensive LUC. All other LUC and transitions did not have an observable relationship. The strength of intensive LUC is less than that directly following EUA, indicating that perhaps, instead of there being a lag on the effects of the SPE, the main impact happened directly following EUA. Thus, the relationship has weakened and the move to intensive agriculture is less strong. Logically, farmers willing to accept and adopt the potential benefits of EU payments would have done so directly following EUA to aid in their income: 67% of farms produced no output for sale previous to EUA (Nikodemus *et al.*, 2010). Those wishing to stick to traditional farming are unlikely to be swayed by potential economic benefits, owing to the importance of small-scale agriculture in the Latvian culture and landscape (Nikodemus *et al.*, 2005). It is likely that the other LUC and transitions either reached ta urning point directly following EUA (abandoned land), while others may hit a breakpoint after this six-year lag, an idea that will be explored in the next section.

**4.3.3 Breakpoints**

When conducting a segmentation analysis, the model fits a specified number of turning points to both uncover change patterns, as well as smooth fluctuations seen in the data. By creating a new, flattened model, the more general pattern of LUC can be determined. For intensive LUC, segmentation analysis indicated a steady decrease in coverage until 2002, where the lowest quantity was reached. A decreasing trend following SUC more closely matches results seen by similar studies (Alexander V Prishchepov *et al.*, 2012; Vanwambeke *et al.*, 2012). A sharp increase followed until the next break point at 2004 at which the rate of increase per year decreased. A steady increase as Latvia joins the EU and transitions to a market-based economy aligns with motives to increase economical and agricultural output (Csaki and Jambor, 2009; Skribane and Jekabsone, 2013).

For abandoned LUC, a sharp decrease is noted at the ended of 1992, which is not a breakpoint noted by literature. It is probable that abandoned land increased in the lead up to SUC, as noted by Vanwambeke *et al.* (2012). However, it is unclear why abandoned land coverage would decrease slightly following SUC. One potential explanation would be the decrease of intensive agriculture, turning quickly to abandoned land to then be up taken immediately by farmers interested in forestry to gain quick income for clear-cutting (Gutman and Radeloff, 2017). An alternative to that would be the maintenance of intensive agriculture in some areas on previously abandoned land, owing to the opinion that continuing large-scale agriculture increases productivity (Osborne and Trueblood, 2002). The intricacies of abandoned LUC on a yearly basis have yet to be effectively determined, so this slight decrease may avail a new pattern. Following 1994, a steady increase in abandoned land was seen, which is well supported by literature (Ioffe *et al.*, n.d.; Alexander V Prishchepov *et al.*, 2012; Gutman and Radeloff, 2017). No clear breakpoint was observed around the time of EUA, implying that it had little effect on abandoned land cover.

The breakpoints for extensive LUC were found to be at 1995 and 2007, indicating a four-year lag following SUC and a three-year lag following EUA. A slight decrease following SUC may be possible due to movement towards more profitable alternatives, such as forestry (Vanwambeke *et al.*, 2012; Gutman and Radeloff, 2017). Following EUA, an increase may indicate a move back towards cultural and traditional values, with an aim to restore a Latvian mosaic landscape (Nikodemus *et al.*, 2005). When examining the scale of this change, however, it is unlikely that these changes signify a specific signature left on Latvia. Instead, such gradual changes may be attributed to other, more gradual processes, including urban migration (Fonji and Taff, 2014).

**4.5 Limitations**

The main limitation in my study is the lack of training points for each year. Specific and precise field data is necessary for creating an accurate classifier (Foody, 2002). By training the classifier on only one set of training points at the end of my time series, I dismiss the fact that the spectral signature of each land cover time may change over time. It is probable that each land use type may look different in varying time periods, owing to advancing technology and practices and the succession of the land itself. Lu *et al.* (2004) state that when high-quality training data is not available, it is likely that change detection is not as precise. The use of a 90 metre radius buffer may have introduced error, especially when quantifying extensive land. With subsistence farming, farm size can be as low as 2 hectares (Davis, 1997), which is the equivalent of 20,000 square metres. With the polygon created by the buffer being roughly 25,500 square metres, it is not unlikely that other land uses would have been captured within the same plot. This may lower the classifier’s accuracy by linking land use to the incorrect spectral bandwidths. The addition of more classes also would have improved classification accuracy (Millard and Richardson, 2015).

An assessment of classification accuracy would have improved reliability. However, there is no accepted standard method of accuracy assessment or report for land cover classifications (Foody, 2002). Foody (2002) argues that solely using a confusion matrix is not sufficient for accuracy assessment, yet no alternative is provided. Comparing my classifier with other existing classifications such as CORINE land cover classification would help validate findings. However, it has lower resolution (100 metres), is not produced for every year and is not based on field data (European Environment Agency, 2019). My classification is the only publicly available classification applied to every study year, removing the need to solely compare time points, rather than year-by-year changes.

Data points needed to be aggregated to meet the assumptions of a LMM, disallowing the inclusion of cell as a nested random effect. If this was included, more variation in the data would have been explained (Appendix), improving the model and change detection. Furthermore, I did not check the assumptions of a LMM statistically. Instead, I only completed visual assessment using Q-Q plots and histograms. I considered my dataset to be too large to use statistical tests such as the Shapiro test for normality and the Bartlett test for homoscedasticity. Using these tests would have caused a false rejection of the null hypothesis (Royston, 1982). Psuedo-R2 and *p*-values were used, which may have provided unstable values and thus, their accuracy should be considered before using results for further research (Harrison *et al.*, 2018).

**4.6 Future research**

To add to the discussion surrounding the timing of agricultural LUC in Latvia, it would be beneficial to add other potential influencers of LUC to determine which was most the most important driver. Additional important indicators include environmental aspects, such as altitude and soil quality (Nikodemus *et al.*, 2010; Ruskule *et al.*, 2012) and demographic data regarding population and the migration of people to different regions (Fonji and Taff, 2014). Through investigating additional factors, ideas surrounding the causes of patterns seen can be confirmed or denied. For instance, by examining the transitions between forest and abandoned land, the exact rate of conversion can be determined. The importance of forestry in Latvia is well established (Vanwambeke *et al.*, 2012), but the relationship between forestry and agriculture land use is not well understood. By creating a more holistic image of LUC in Latvia, results can be more readily applied to country-level land use policy (Alexander V Prishchepov *et al.*, 2012).

It would be interesting to see how classification improvement could have an impact on results. As many transitions were not seen to be significant, it is likely that other land uses are contributing to the agricultural land changes seen. By creating more specific classes, transitions could be better understood (Millard and Richardson, 2015). Precise transition between land use type may vary between different agricultural types, such as cropland or orchard, and thus relationships should be examined more closely. The effect of classification accuracy should be explored through changing parameters and parameter pruning to create more specific decision trees (Suthaharan, 2016). Results could then be compared to examine the impact of different classifiers on the patterns observed.

**5. Conclusion**

My study provides important insight into the visibility of SPE events on Latvia’s agricultural land cover, as well as the capability of satellite imagery to determine LUC. Overwhelmingly, my results imply that country level patterns can be linked to SPE events. Intensive, extensive and abandoned land cover were all observed to decrease after SUC and increase following EUA. The slight decrease in abandoned land cover following SUC may shed light into new land use patterns not yet determined. My findings elucidate the intricacies of LUC visibility across varying time periods following SPE events, depicting how time lags may fluctuate between different land use types, with stronger lags observed for abandoned and extensive land over intensive land. To best prevent biodiversity loss, fragmentation and the scenic and cultural value of a landscape, policies should aim to look at the patterns confirmed and discovered in my study. With not only a changing SPE climate in Latvia, but globally, my results can help mitigate against negative LUC impacts by providing evidence for new, country-wide, preventative land use policies.

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