



THE UNIVERSITY OF EDINBURGH

SCHOOL OF GEO SCIENCES

**THE VISIBILITY OF SOVIET UNION
COLLAPSE AND EUROPEAN UNION
ACCESSION ON AGRICULTURAL
LAND USE IN LATVIA**

BY

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Abstract

Land use change has commonly been associated with negative environmental impacts, including population decreases and reduced ecosystem functioning. One of the key drivers of land use change is agricultural expansion and intensification. It is acknowledged that a socio-politico-economic change has the potential to influence agricultural land use on a regional scale. However, country level implications of multiple socio-politico-economic fluctuations over time have yet to be determined. Using Latvia as a case study, this investigation aims to quantify the changes in intensive, extensive and abandoned agricultural land to determine if land use conversions can be linked to the collapse of the Soviet Union (1991) and Latvia's accession to the European Union (2004). A classification was constructed using satellite imagery to determine specific land use cover across Latvia between 1989 and 2011. Intensive agricultural cover change was found to decrease following Soviet Union collapse and increase after European Union accession. Extensive and abandoned agricultural cover change were not found to be clearly linked to either event. While classification error may have influenced results, the methods used and results obtained are still relevant due to the rise of socio-politico-economic change around the world. By exploring the direction, size and drivers of agricultural land use change, countries can create evidence-based policies to lessen negative environmental impacts of socio-politico-economic fluctuations.

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List of abbreviations

AAL – Abandoned Agricultural Land

EAL – Extensive Agricultural Land

EU – European Union

EUA – European Union Accession

GEE – Google Earth Engine

IAL – Intensive Agricultural Land

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 & Turner, 1992), is an important part of all civilisations, owing to natural resource provision (Foley *et al.*, 2005; Turner *et al.*, 2007).

Human-driven land use change (LUC) through urbanisation, deforestation and agricultural expansion has placed pressure on ecological processes such as carbon cycling, as well as ecosystems themselves (Foley *et al.*, 2005; Turner *et al.*, 2007). Habitat change through land conversion is one of the largest threats to terrestrial biodiversity, causing extinctions and range reductions (Jetz *et al.*, 2007). While habitat fragmentation and loss have the potential to cause increased terrestrial plant and animal population size (Fahrig, 2017; Daskalova *et al.*, 2018), LUC is still overwhelmingly linked to deforestation and the climate change that accompanies it (Lawrence & Vandecar, 2015).

Habitat conversion has primarily occurred through agricultural practice changes (Dallimer *et al.*, 2009). Expansion is made possible by 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 negative LUC impacts (Dallimer *et al.*, 2009). Identifying the drivers of LUC is an important component in designing effective mitigation and preventative policy.

Several countries appear to follow similar trajectories of changing land use regimes, moving from subsistence to intensive agricultural land (IAL) 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 not all countries follow a transition to intensive land uses, 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 alongside regulation and institutional changes (Prishchepov *et al.*, 2013). My study proposes to closely examine LUC in a country that has experienced rapid SPE shifts – Latvia.

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 homogeneously farmed land, known as collective farms (Vanwambeke *et al.*, 2012). Collective farms are 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, causing large scale abandonment when individuals did not return to their farms (Prishchepov *et al.*, 2012a). Another largescale SPE change occurred in May 2004, when Latvia joined the European Union (EU) (Mikkil & Pridham, 2004). European Union accession (EUA) brought the support of EU payments, which aimed to both restore Latvia's traditional landscape and 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 visible and quantified on a broad scale.

Satellite imagery has often been used in studies aiming to quantify SPE influence on LUC across large areas, as it is impossible to physically sample land use across a country (Prishchepov *et al.*, 2012a; Fonji & Taff, 2014). Satellite imagery cannot show land use specifically, instead depicting land cover, which indicates solely the observable natural or anthropogenic features (Fonji & Taff, 2014). Inferring land use requires more regional knowledge. To assess LUC, it is therefore necessary to relate land use to land cover using spectral information (Fonji & Taff, 2014). Algorithms, such as classifications, which can categorise areas based on defining properties, can be developed to effectively assess LUC across a large area.

1.1 Objectives and rationale

This study aims to investigate the importance of two SPE events, SUC and EUA, as drivers of agricultural LUC in Latvia by using satellite imagery. An SPE event can be defined as a drastic change in a country's SPE environment. Previous studies which focused on Latvia considered the impacts of only one SPE event (SUC study: Prishchepov *et al.*, 2012a; EUA study: Fonji & Taff, 2014) or one region (Vanwambeke *et al.*, 2012), rather than several over time across Latvia's landscape. It therefore remains unclear whether a signature of agricultural LUC is visible in Latvia on a broad-scale. Using satellite imagery to determine the strength and direction of agricultural LUC and transitions, the timing and visibility of SPE effects on LUC can be determined. 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 agricultural land (EAL), intensive agricultural land (IAL) and abandoned agricultural land (AAL), providing insight into the relationship between land uses. My study closely examines two time frames: (a) directly following the SPE event (within three years) and (b) a time lag (within six years), in accordance with Fonji & Taff (2014). Ultimately, my study will uncover the importance of SPE events as drivers of LUC in Latvia, permitting the formation of predictions about land use under changing SPE conditions.

1.2 Research questions and hypotheses

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

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

H₁: Directly following SUC, IAL cover will decrease (H_{1a}) and AAL cover will increase across Latvia (H_{1b}). EAL cover change will be weakly positive (H_{1c}). After EUA, IAL will increase (H_{1d}) and AAL will decrease across Latvia (H_{1e}). EAL cover change will be weakly negative (H_{1f}).

H₁₀: There is no visible relationship between IAL, EAL and AAL use change and SPE events. IAL, EAL and AAL 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, IAL will transition to AAL (H_{2a}) and EAL (H_{2b}), with the transition to AAL being stronger. After EUA, AAL (H_{2c}) and EAL (H_{2d}) land will transition to IAL.

H₂₀: There is no visible relationship between land use transitions and SPE events. Land use transitions between IAL, EAL and AAL 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: Within six years following SUC, a weak lag relationship will be present for IAL cover decrease (H_{3a}) and AAL increase (H_{3b}). There will be a strong relationship between the new time window and EAL cover increase (H_{3c}). There will be a strong lag for the transition from IAL to EAL (H_{3d}) and a weak lag for the transition to AAL (H_{3e}). Within six years after EUA, a strong lag will be present for the decrease of EAL (H_{3f}). A weak lag relationship will be visible for AAL cover decrease (H_{3g}), IAL increase (H_{3h}) and the transition from AAL to IAL (H_{3i}). A strong lag will be observed for the transition from EAL to IAL (H_{3j}).

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

1.3 Predictions

1.3.1 Soviet Union Collapse

I predict that AAL will increase visibly following SUC due to the sharp decline of the agricultural sector (Prishchepov *et al.*, 2012a). I predict that IAL will be replaced by EAL 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 EAL increase, resulting in a large rise in AAL within three years following SUC. I predict IAL 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 (Prishchepov *et al.*, 2012a).

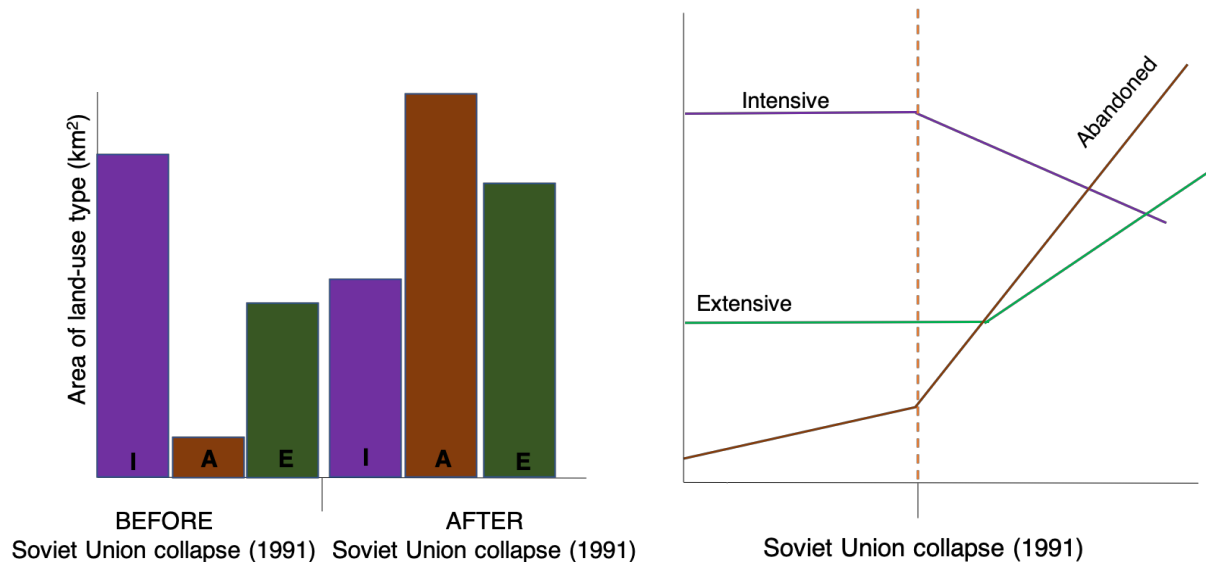


Figure 1.1 – Prediction figures showing abandoned (A) and extensive (E) agricultural land increase and intensive (I) agricultural land decrease directly following SUC, with a lag on extensive LUC. Created using invented data. Specific transitions not depicted. Not drawn to scale.

1.3.2 European Union Accession

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

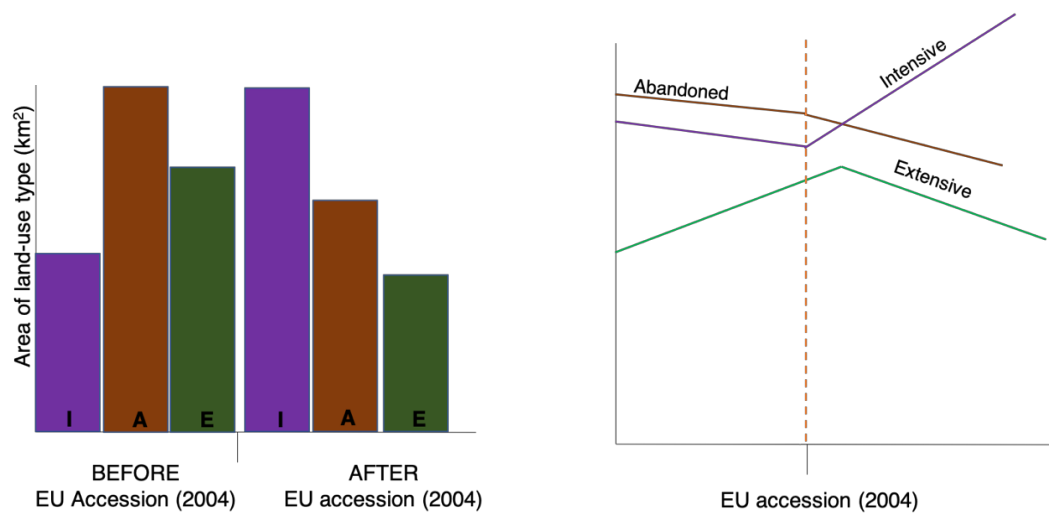


Figure 1.2 – Prediction figures showing abandoned (A) and extensive (E) agricultural land decrease and intensive (I) agricultural land increase directly following EUA, with a lag on extensive LUC. Created using invented data. Specific transitions not depicted. Not drawn to scale.

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. Heterogeneous effects would signify that the SPE event was not the main driver of LUC or that it was coupled with other drivers, such as urbanisation or climate change. My study is particularly relevant due to the rise of SPE change around the world, with notable recent examples including Brexit in the United Kingdom and the election of Donald Trump in the United States of America (Inglehart & Norris, 2016; O'Reilly *et al.*, 2016). By showing the direction, size and drivers of LUC, countries can create evidence-based policies to dampen negative environmental impacts of SPE change.

2. Methods

To quantify the effects of SUC and EUA on agricultural LUC in Latvia, I constructed a classification of LUC. Classifications aim to identify sub-categories that data can be grouped by based on certain characteristics. Here, I aim to determine if agriculture land use can be classed by spectral properties found in satellite data. I will further explain classifications in section 2.3. Instead of using a pre-existing classification, I constructed a new classification for the purpose of this study, with the two benefits being the ability to (a) use field data and (b) classify LUC over each year. Common pre-existing land use classifiers, like CORINE, use photointerpretation to determine land use, potentially limiting accuracy (European Environment Agency, 2019). Furthermore, CORINE does not have records for each year, preventing smaller timesteps from being analysed. I determined that the creation of a new classification would provide more specific insight into the effect of SPE events on LUC.

I classified imagery between 1989 and 2011 to effectively cover the before and after time period of both SPE events. I used the programme Google Earth Engine (GEE) to create my classification (Gorelick *et al.*, 2017). My workflow diagram, depicting the key steps to my analysis, is shown in Figure 2.2. Excerpts from my GEE and R code are available in Appendices 7 and 8. Complete scripts of all code are available on GitHub (<https://github.com/izzyrich/dissertation>).

2.1 Study site

Latvia (55°40'–58°05'N and 20°58'–28°14'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 (Figure 2.1). Latvia spans 64.6 thousand km² and is largely flat, with the majority of terrain between 40–200 metres above sea level (Prieditis, 1993). The growing season is 180–200 days annually (Prieditis, 1993). Latvia is a particularly interesting case study, owing to the rapid SPE transitions within the past half-century.



Figure 2.1 – Situational map of Latvia (shaded), screenshotted in GEE. Scale of 100 kilometres.

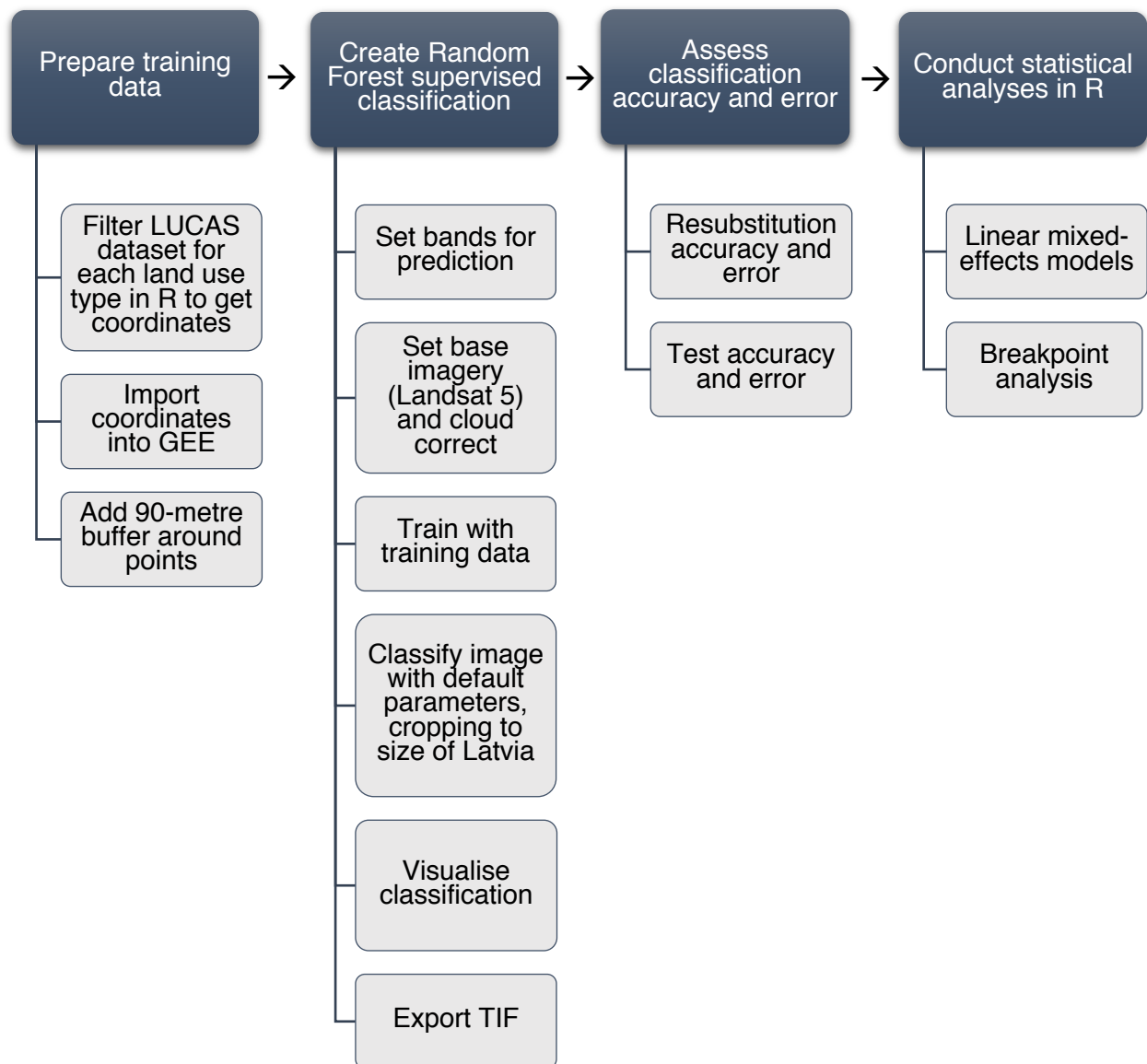


Figure 2.1 – Workflow diagram, created on Microsoft PowerPoint.

2.2 Image processing

Landsat 5 Thematic Mapper satellite imagery covers my study period well and is used in similar investigations (Prishchepov *et al.*, 2012a; Fonji & Taff, 2014; Sidhu *et al.*, 2018). I selected the partially pre-processed, Landsat 5 Surface Reflectance imagery (30 metre resolution), which is atmospherically corrected, preventing clouds and shadows from interfering with 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 needed. I chose summer images, depicting the growing season, to best characterise the spectral signatures of my different classes (Fonji & Taff, 2014). I selected the median image in 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. I selected blue, green, red, near-infrared and shortwave infrared bands, each with corresponding wavelengths (Appendix 1), as the bands for my classification, as supported by Pimple *et al.* (2018) and Prishchepov *et al.* (2012a). My chosen bands acted as predictor variables for my classification.

2.3 Classification background

This section aims to provide background to those who are unfamiliar with classifications. My specific methods will continue in section 2.4. 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 by examining specific characteristics, such as spectral bandwidth (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 classes, also called training points (Albalade & Minker, 2013). Unlike unsupervised classifications, where the software determines the classes, supervised classifications allow the creator to choose classes of interest. A supervised classification is suitable for my study, as it enables me to choose what classes to analyse, using field data as training points. Training points train the classifier to infer prediction rules that form a decision tree (Albalade & Minker, 2013). Decision trees are composed of binary questions which group data by specific characteristics, such as specific wavelengths or bandwidths (Strobl *et al.*, 2009). With each step of the tree, the classifier asks whether a criterion 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 (Figure 2.3; 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).

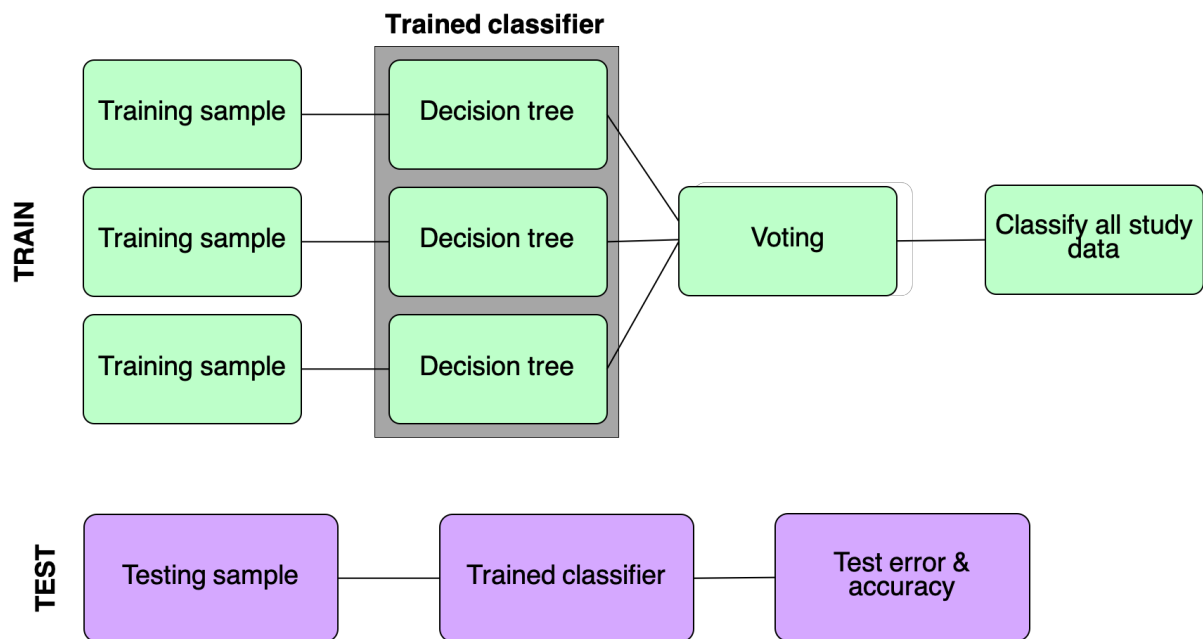


Figure 2.3 – Random forest conceptual diagram, created with Microsoft PowerPoint.

2.4 Training data

My training data represent the known locations of each land use type in 2012. The use of field data results in high certainty in the training set (Millard & 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 AAL. It is important to differentiate between these types, as fallow land is likely to be returned to for future agricultural use. Transitions would most likely happen at a faster rate if fallow land was included. Within R statistical software, version 3.5.3 (R Core Team, 2019), I filtered data to represent each of my land use classes: AAL, EAL and IAL. These three classes were chosen due to the clear connection with changing land use practices and SPE events (Reidsma *et al.*, 2006). I also included four additional classes (artificial land, wetlands, water and forestry), as a larger training dataset improves classification stability and accuracy (Millard & 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 2.

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

Land use	Criteria
Abandoned	<ol style="list-style-type: none"> 1. Abandoned agricultural land. 2. AAL, 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.
Intensive	Industrial agriculture, filtered to include cropland, woodland, grassland and bare land.

Following filtering, I obtained the coordinates of 4013 data points, 1434 of which are from my three key classes (Table 2.2; Appendix 3). I transformed these coordinates into a spatial file by setting the projection to that of GEE: Pseudo-Mercator WGS 84 (EPSG: 3857).

Once imported into GEE, I created a 90-metre buffer around each point, turning point data into circular polygons (Figure 2.4). 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, which created a circular polygon with an area of 25,446.9 square metres. A 90-metre 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 & Pilvere, 2015).

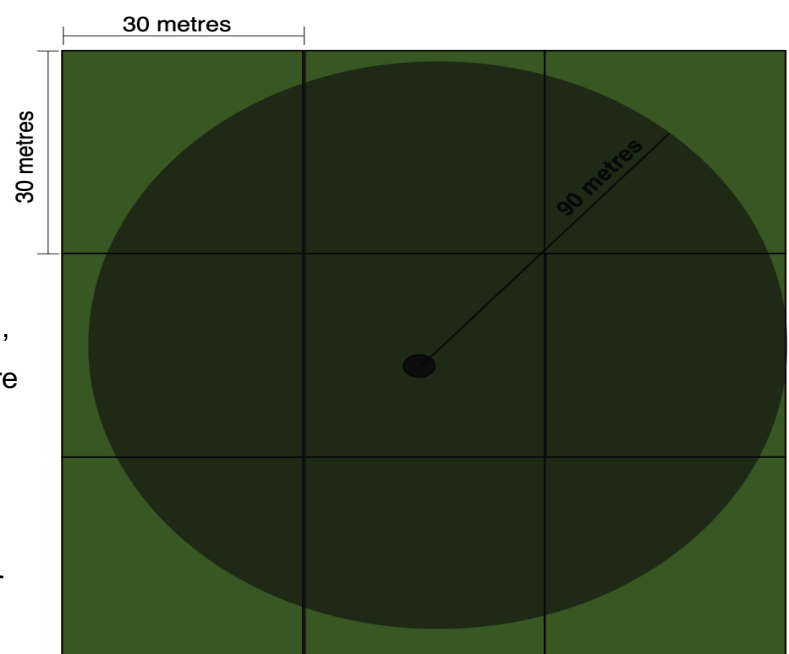


Figure 2.4 – Circular buffer with 90-metre radius around data point, created with Microsoft PowerPoint. Square boxes represent pixels with 30-metre resolution.

To set up the training data for my classification, I divided my data randomly by class into two groups: training (80%) and testing (20%) (Table 2.2; Appendix 2), 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 (Appendix 4). 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 LUC 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 & Jekabsone, 2013; Arika & 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 & 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 & Thapa, 2011) and is an indication of the classifier's performance (Dougherty, 2013). Appendix 5.2 depicts a conceptual example of a confusion matrix, where the number of points that were classified correctly and incorrectly are reported.

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 & Litvaitis, 1989). Resubstitution is known to produce optimistically biased results on the overall accuracy of the classifier (Verbyla & Litvaitis, 1989), therefore, the results of the hold-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 (Appendix 5.1) and error matrix were obtained (Appendix 5.3).

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 (Figure 2.5). Collecting data by cell prevented exceeding GEE's memory capacity and improved the replication within my study. A larger grid of five blocks was also imposed manually using R to account for regional variation (Figure 2.5).

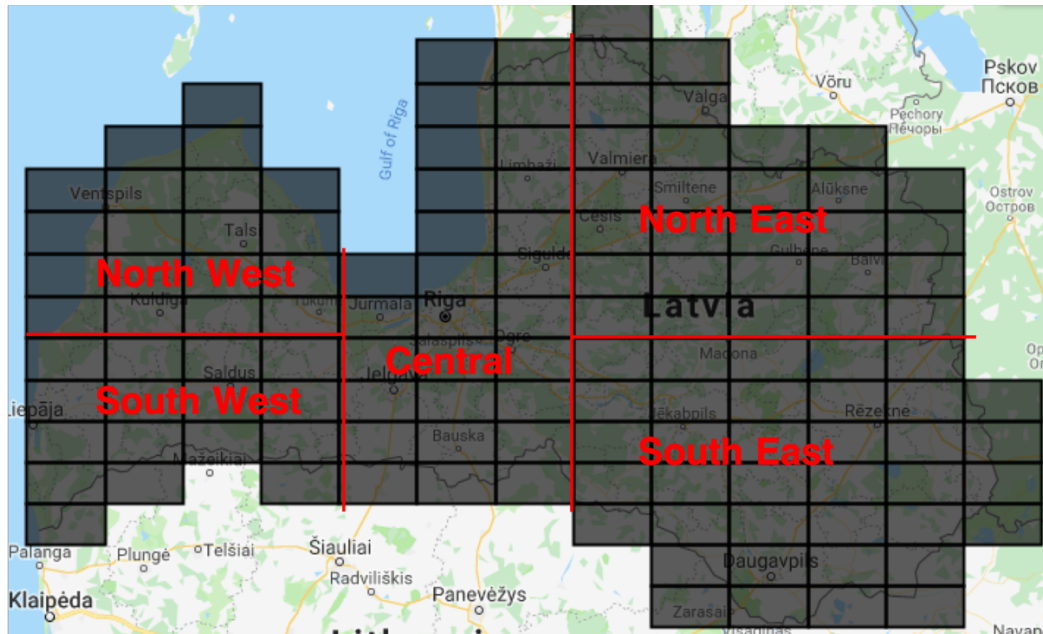


Figure 2.5 – Cells and larger grid imposed, screenshots in GEE. Scale of 50 kilometres. Cells crossing Latvian border were cropped before analysis.

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 (R Core Team, 2019). I calculated area in square kilometres using the following formula:

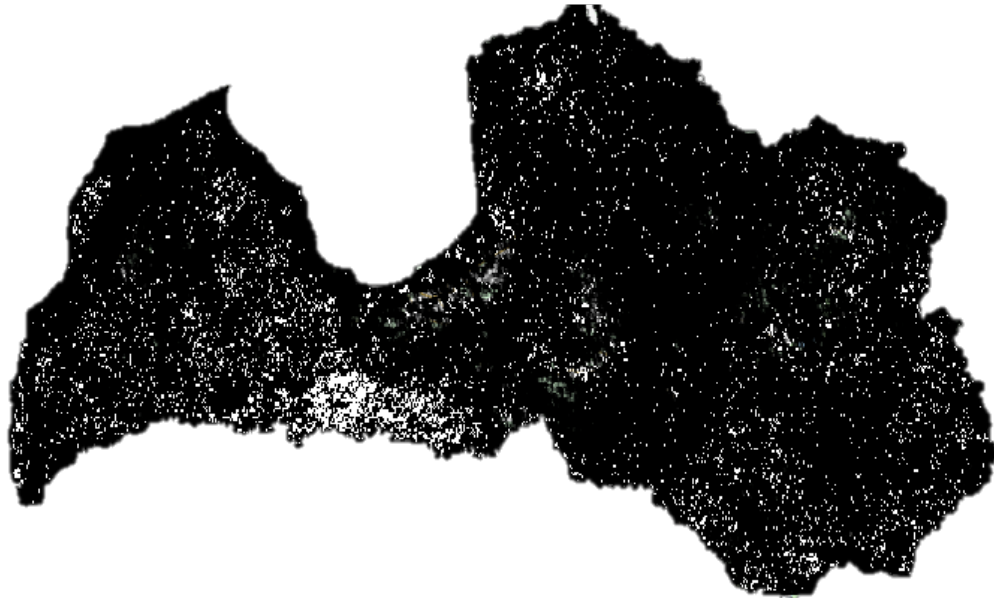
$$\text{Area} = \text{number of pixels} * \text{resolution} / 1000$$

2.7.2 Transition

To explain how I calculated the number of pixels undergoing any of four transitions (Table 2.3), I will use the AAL to IAL transition as an example (Figure 2.6). First, taking the first year's imagery, solely land that is AAL is selected. Using the next year's imagery, only IAL is selected. I then overlaid the IAL imagery atop the AAL imagery. With the *and* command in GEE, I was able to select pixels that were both AAL in the first year *and* IAL in the next year. Transition calculations were 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 (R Core Team, 2019). I calculated area in square kilometres using the same formula in section 2.7.1.

Table 2.3 – Transitions to examine for each time step.

Start land use	End land use
Abandoned	Intensive
Intensive	Abandoned
Extensive	Intensive
Intensive	Extensive

**Figure 2.6 – Example transition image.** White areas indicate a transition from forestry to IAL between 2010 and 2011. Black areas indicate no transition. Scale of 50 kilometres.

2.8 Statistical analyses

All data analysis was performed using R (R Core Team, 2019).

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 2.4). Since SUC happened in December 1991, 1991 is grouped in the before category, as land cover was examined over summer months. EUA happened in May 2004, thus 2004 is in the after category. 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 2.4 – 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, with separate models run for each time period and land use type/transition combination (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:

$$\text{area} \sim \text{time_period} + (1|\text{grid})$$

To determine model fit, pseudo- R^2 values were calculated to examine the amount of variation explained by the fixed effects, as well as the whole model (Nakagawa & Schielzeth, 2013). Using R^2 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 & Villard, 2015). Breakpoints are determined by a change in the relationship between the response and explanatory variable, visible through a sharp change in the relationship's 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 area value for each land use type and transition. A separate model was run for each land use type and transition using the following structure:

$$\text{year_area} \sim \text{year}$$

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

3. Results

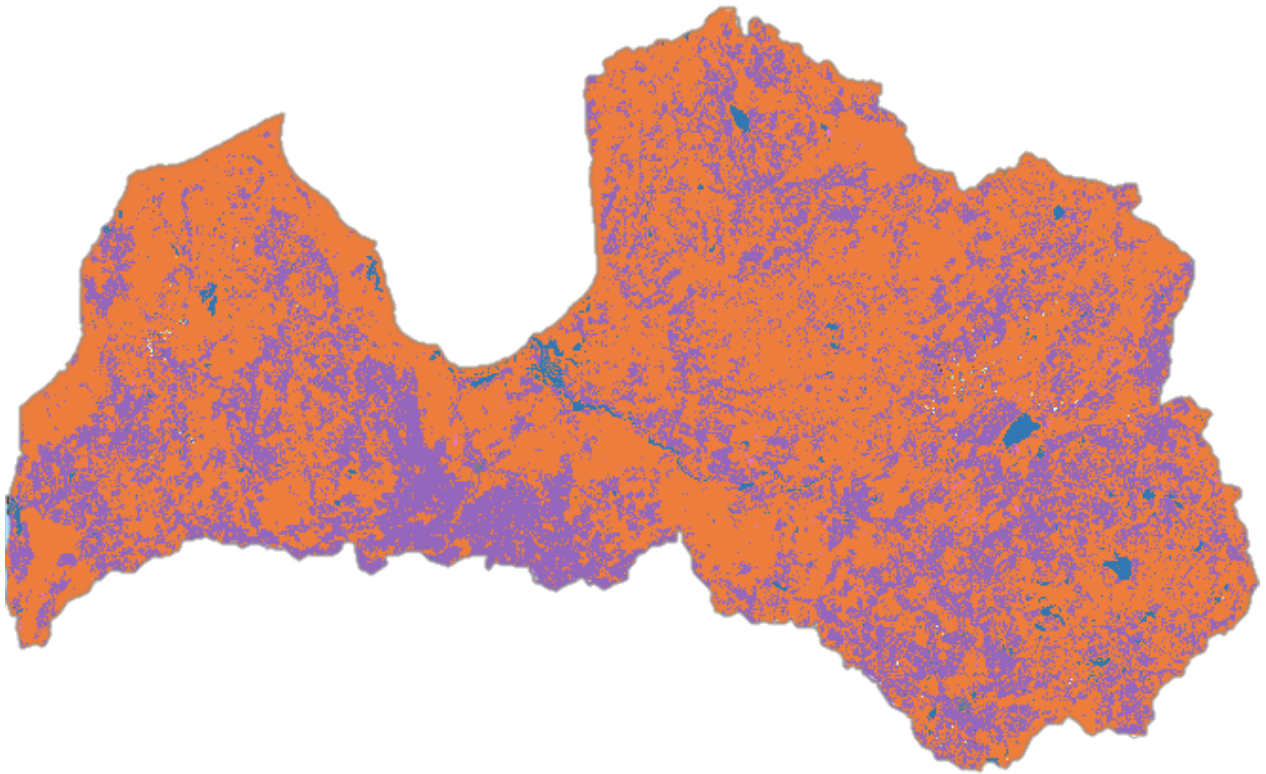


Figure 3.1 – Example classification image (2011), with orange representing forest, blue representing water and purple representing IAL. EAL (green) and AAL (brown) cannot be seen on a large scale. Scale of 50 kilometres.

3.1 Land use change visibility within three years following socio-politico-economic events

3.1.1 Is land use change visible directly following Soviet Union Collapse?

Within three years following SUC, AAL cover decreased by 31% (Figure 3.2; Appendix 6.1), implying a rejection of H_{1b} , where AAL cover is predicted to visibly increase. Time period explained a very low proportion of the variation observed ($R^2M = 6\%$). By adding grid as a random effect, a greater proportion of variation was explained ($R^2C = 30\%$).

I found no clear difference between time period and both IAL and EAL, owing to the high standard error around each slope and the lack of variation explained by the model (Appendix 6.1). The absence of a clear relationship implies an acceptance of the null hypothesis (H_{10}) for each land use type.

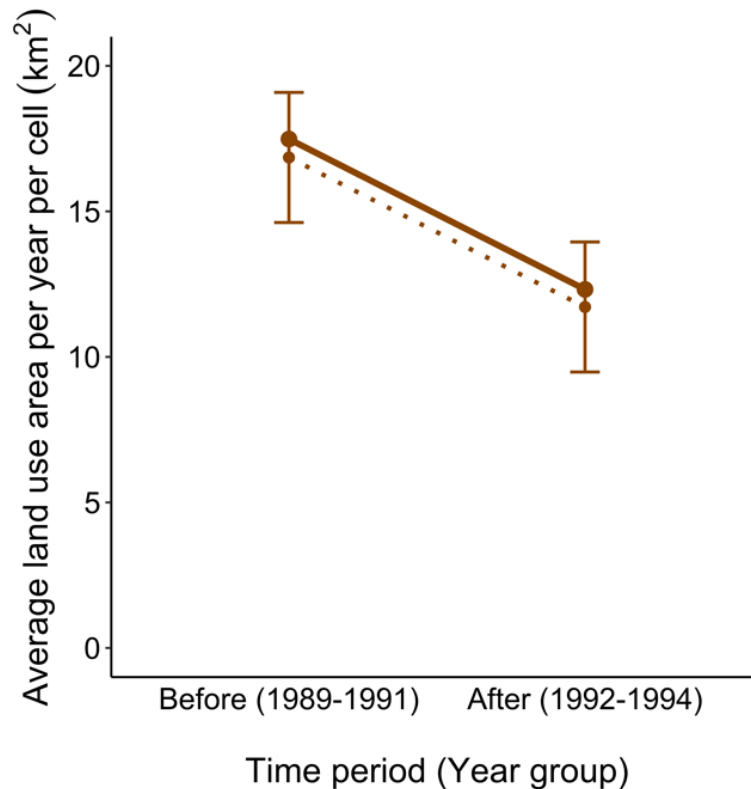


Figure 3.2 – Effect size graph showing AAL cover decrease directly following SUC. Dashed line represents effect size and error bar shows error around effect size, as determined by the model (estimate: -5.14, \pm SE of estimate: 1.13, t -value: -4.56, p -value: <0.0001, R^2M : 0.06, R^2C : 0.30). Solid line represents actual data (N = 255).

3.1.2 Is land use change visible directly following European Union Accession?

Within three years following EUA, AAL cover decreased by 17% of original cover (Figure 3.3a; Appendix 6.2), suggesting an acceptance of H_{1e} . IAL cover increased by 28% within three years following EUA (Figure 3.3b; Appendix 6.2), allowing an acceptance of H_{1d} . The time period predictor explained little variation in both land use models, with a slight increase when grid was introduced as a random effect (Appendix 6.2).

There was no evident difference between time period and EAL cover change, with a relatively flat slope and high standard error (Appendix 6.2). A flat slope implies an acceptance of H_{10} for EAL, indicating that extensive LUC is not visible directly following EUA.

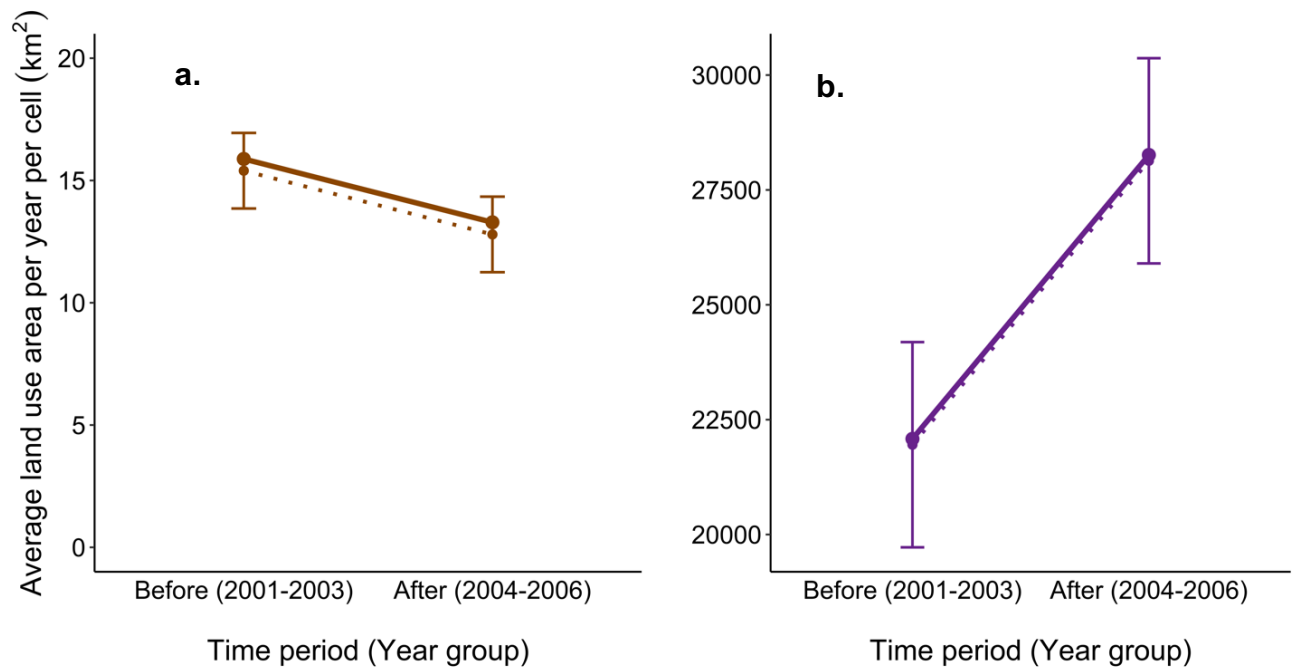


Figure 3.3 – Effect size graph showing (a) AAL cover decrease and (b) IAL cover increase directly following EUA. Dashed line represents effect size and error bar shows error around effect size, as determined by the model (abandoned – estimate: -2.61, \pm SE of estimate: 1.20, t-value: -2.12, p-value: 0.03 R^2M : 0.01, R^2C : 0.10; intensive – estimate: 6179.11, \pm SE of estimate: 1942.18, t-value: 3.18, p-value: <0.01, R^2M : 0.04, R^2C : 0.09). Solid line represents actual data (abandoned $N = 255$; intensive $N = 258$). Scale of y-axis different for effective visualisation – two graphs should not be compared directly.

3.1.3 Could location be a predictor of land use change?

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, including cell as a random effect increased total model fit (R^2C) and decreased standard error as compared to models solely including the larger grid as a random effect (Appendix 6.3). However, the variation explained by the fixed effect (R^2M) was only increased for the EAL change LMM for the EUA time period (Appendix 6.3). 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 (Appendix 6.3.1 & Appendix 6.3.2).

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

3.2.1 Are land use transitions visible directly following Soviet Union Collapse?

Within three years following SUC, the amount of IAL transitioning to AAL decreased by 29% (Figure 3.4; Appendix 6.4). A negative relationship for this transition suggests a rejection of H_{2a} . 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 (Appendix 6.4).

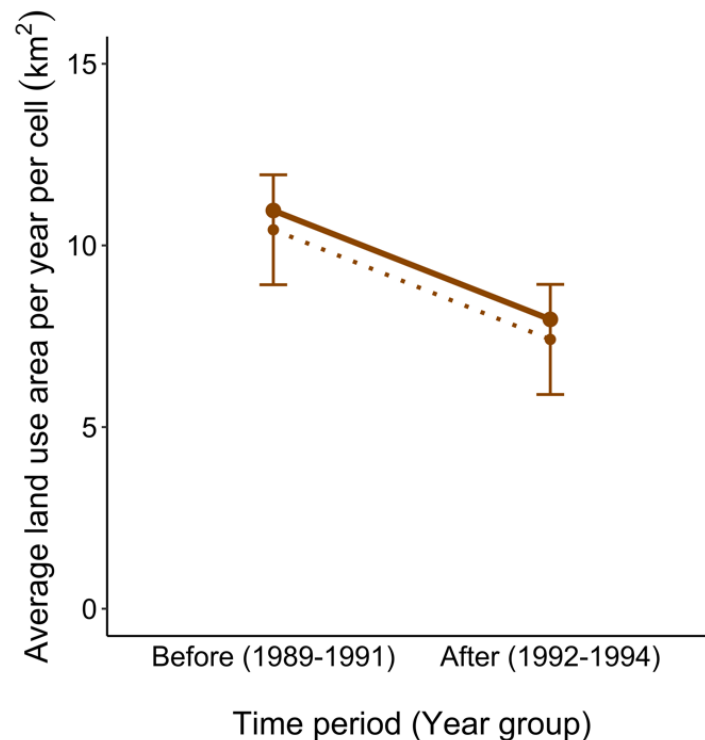


Figure 3.4 – Effect size graph showing decrease in land transitioning from intensive to AAL following SUC. Dashed line represents effect size and error bar shows error around effect size, as determined by the mode (estimate: -3.02, \pm SE of estimate: 0.70, t-value: -3.76, p-value: <0.001 R^2M : 0.04, R^2C : 0.24). Solid line represents actual data (N = 258).

I found no evident difference between SUC time periods and the transition from intensive to EAL, owing to a nearly flat slope (Appendix 6.4), suggesting null hypothesis acceptance (H_{20}).

3.2.2 Are land use transitions visible directly following European Union Accession?

For both transitions to IAL from extensive and AAL, no clear relationship was found (Appendix 6.5). Both transitions exhibited weak slopes with large standard errors (Appendix 6.5). By accepting the null hypothesis (H_{20}), 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 What is the effect of a time lag on land use change following Soviet Union Collapse?

When examining the influence of a time lag following SUC on LUC and transitions, clear differences were seen within each land use and transition (Table 3.1).

For AAL, land cover decreased by 44% since Soviet times, with a steeper slope than that seen directly following SUC (Table 3.1 & Appendix 6.1), suggesting a rejection of H_{3b} . For the time lag model, a greater proportion of the data's variation is explained by the fixed effect ($R^2M = 14\%$). By moving the time window, EAL use has a weakly negative change following SUC, with the fixed effect being the sole explainer of variation in the model (Table 3.1), thus H_{3c} is rejected.

The strength and direction of IAL cover change also becomes evident, with a strong negative relationship indicating a loss of IAL (Table 3.1). H_{3a} is thus rejected due to the strength of the relationship. A slightly weaker relationship is seen for the transition from IAL to AAL as compared to the change observed directly following SUC (Table 3.1; Appendix 6.4), causing H_{3e} to be accepted. There appears to be an effect of time period on the transition to EAL from IAL, with less error around the slope and more variation explained by the model than directly following SUC (Table 3.1; Appendix 6.4). A very weak relationship is seen for the transition to EAL from IAL, with slightly less transitioning to EAL six years following SUC. H_{3j} is thus rejected due to the strength of the relationship.

Table 3.1 – LUC observed six years following SUC, with AAL, EAL, IAL and transitions to AAL and EAL exhibiting a decrease in cover (AAL – N = 255; EAL – N = 249; IAL – N = 258; IAL → AAL – N = 258, IAL → EAL – N = 258).

Land use/transition	Estimate	± SE of estimate	t-value	p-value	R ² M	R ² C
AAL	-7.41	1.08	-6.90	<0.0001	0.14	0.27
EAL	-0.60	0.11	-5.75	<0.0001	0.11	0.11
IAL	-4910.30	2416.93	-2.03	0.04	0.01	0.09
IAL → AAL	-2.09	0.84	-2.50	0.01	0.04	0.24
IAL → EAL	-0.13	0.03	-3.70	<0.001	0.06	0.10

3.3.2 What is the effect of a time lag on land use change following European Union Accession?

When examining LUC and transitions six years following EUA, only IAL had an evident relationship with EUA. A positive relationship indicates a move towards IAL use following EUA, with a 21% increase in IAL cover (Table 3.2). The slope of this relationship is weaker than that seen directly following EUA (Figure 3.3), suggesting H_{3h} acceptance. No other relationship was evident six years following EUA (Appendix 6.6).

Table 3.2 – Positive IAL cover change observed six years following EUA (N = 258).

Land use	Estimate	± SE of estimate	t-value	p-value	R ² M	R ² C
IAL	4522.85	1904.92	2.37	0.02	0.02	0.10

3.3.3 Do breakpoints align with Soviet Union Collapse and European Union Accession?

For all LUCs and transitions, breakpoints did not line up evenly with the two SPE events. IAL was the only land use type to have one breakpoint point precisely match an SPE event: EUA (Figure 3.5a). AAL experienced two breakpoints directly following SUC: one signifying a sharp

decrease in land cover, trailed by a sharp increase (Figure 3.5b). EAL experienced a breakpoint four years following SUC and three years following EUA (Figure 3.5c).

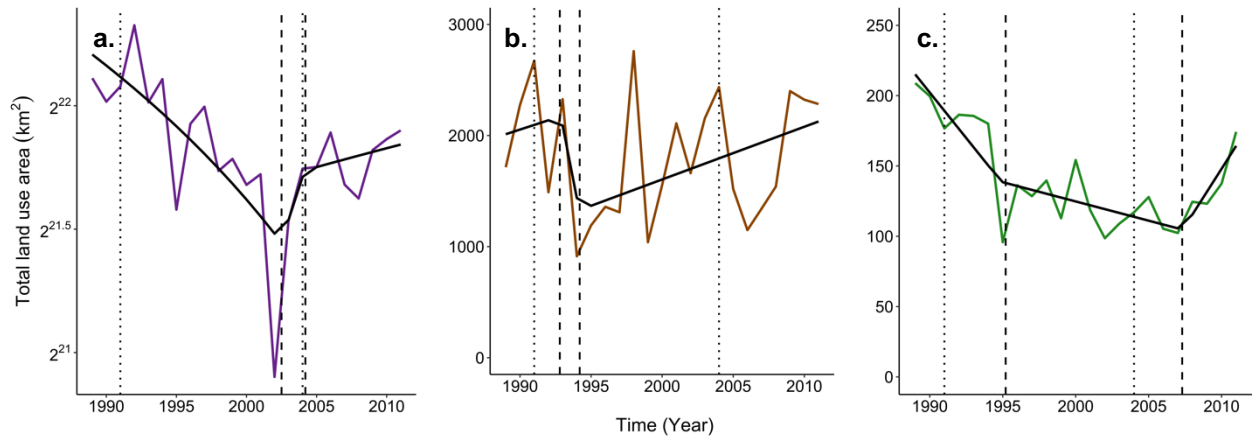


Figure 3.5 – Breakpoint figures for (a) IAL, (b) AAL and (c) EAL. Coloured line shows total land use area (km^2) per year. Dotted line represents the two SPE events (SUC and EUA). Dashed line indicates where model fit two breakpoints. Solid black line represents segmented regression, as fit by the model.

Transitions between both extensive and AAL to IAL and the reverse, followed roughly the same trajectory observed by the land use type transitioning into (Appendix 6.7.1 & Appendix 6.7.2). Appendix 6.8 has a complete list of each LUC type's breakpoints and their associated error.

4. Discussion

4.1 Key findings

Directly following SUC, AAL was found to decrease by 31%, causing a rejection of H_{1b} and all relevant literature (Figure 3.2; Prishchepov *et al.*, 2012a; 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 AAL. Within six years after SUC, all three key land uses and both transitions decreased (Table 3.1), suggesting an acceptance of H_{3a} and a rejection of H_{3b-e} . Directly after EUA, AAL cover decreased and intensive cover increased, causing an acceptance of H_{1e-d} (Figure 3.3). Six years following EUA, IAL still significantly increased (Table 3.5; H_{3h} acceptance). However, the importance of this increase may be conflated with time passing, and therefore, may not indicate a clear signature of EUA on the landscape. Regional specific examination helps explain variation in the data, but does not help develop country-level land use policies (Prishchepov *et al.*, 2012a). Only IAL change exhibited a breakpoint that matched with EUA, while all other breakpoints either lagged behind SPE events or were seemingly unrelated.

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

4.2.1 Soviet Union Collapse

Abandoned agricultural land cover decrease

My results demonstrate that, out of IAL, EAL and AAL cover change, only AAL change is visible within three years of SUC. I predicted AAL to visibly increase directly following SUC, a change that is well documented in literature, with many citing dramatic levels of agricultural abandonment directly following SUC (Bell *et al.*, 2009; Prishchepov *et al.*, 2012a; Vanwambeke *et al.*, 2012). An increase in AAL is not supported by my results, where it was suggested that AAL coverage decreased in the three years following SUC, as compared to the three years prior. Findings by Prishchepov *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 within three years of SUC.

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; Prishchepov *et al.*, 2012a; Fonji & Taff, 2014). 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, 2013). However, previous owners often had limited interest in adopting farming practices on this

newfound land. Land reform was not fully complete until roughly 2002, preventing the transfer of land to individuals more suited to farming (Prishchepov *et al.*, 2012a). 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.

My classification may not have been sensitive to agricultural land abandonment within the three year window. Prishchepov *et al.* (2012b) uncovered the importance of imagery when determining areas of AAL, with the number of images used cited as the largest accuracy determiner. Specifically, the Landsat record was noted for limited image-date availability, restricting the detection accuracy of agricultural land abandonment and potentially limiting my classifier's sensitivity. 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 & Helmer, 2004; Ruskule *et al.*, 2012), potentially causing an underestimation of AAL following SUC. It is likely that my classifier's accuracy influenced the amount of AAL observed directly after SUC.

No clear change in intensive and extensive agricultural area

IAL and EAL cover change were not found to be visible within three years of SUC. I predicted IAL to decrease following SUC, in line with the large scale abandonment noted and the collapse of the collective farming system (Nikodemus *et al.*, 2005; Prishchepov *et al.*, 2012a). I expected EAL to weakly increase directly following SUC due to land restitution. It is predicted that, upon completion of land reform, EAL coverage would be significantly larger Latvia-wide as subsistence farming acts to replace Soviet collective farms (Vanwambeke *et al.*, 2012). Owing to the lack of relationship seen, it is likely three years is not enough time for intensive and extensive agricultural LUC to be visible, an idea which will be explored in section 4.3.1.

4.2.2 European Union Accession

Abandoned agricultural land cover decrease

My results suggest that within the three years following EUA, AAL decreased. AAL decrease aligns with my predictions and can be supported by the potential for rapid colonisation of woody species and transition to young forests on abandoned land (Nikodemus *et al.*, 2010; Ruskule *et al.*, 2012; Vanwambeke *et al.*, 2012). Additionally, EU payment schemes have been successful in decreasing the level of agricultural abandonment seen (Abolina & Luzadis, 2015), owing to the attractiveness of land uptake as a source of income (Griffiths *et al.*, 2013). Following EUA, land salvation rates surpassed land abandonment, similarly explaining the decrease in land

abandonment (Vanwambeke *et al.*, 2012). AAL decrease directly following EUA is suggested by my results and is further maintained by rapid transitions to woody species and EUA payment schemes.

Intensive agricultural land cover increase

My data indicate IAL cover increased directly following EUA. IAL increase is well cited, as EU support schemes promote 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 and tend to encourage traditional landscape restoration, as well as intensive agriculture to increase production, potentially causing the increase seen (Nikodemus *et al.*, 2010; Fonji & Taff, 2014). The IAL increase directly following EUA is understood through my results and EU SAPs.

No clear change in extensive agricultural area

I did not find a clear change in EAL directly following EUA. The weak, negative relationship I predicted is likely not to be seen, owing to the EU's promotion of traditional landscape restoration (Vanwambeke *et al.*, 2012). EU payment schemes still promote intensive agriculture increase; IAL increase may annul the effects of traditional landscape promotion, thus causing no clear increase or decrease in EAL cover.

4.2.3 Other potential predictors of land use change: location

It is anticipated that specific location characteristics can partially determine LUC and its variation. Case studies examining north-eastern (Fonji & 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 dissimilarities, 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 (Prishchepov *et al.*, 2012a). 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

Decrease in land transitioning from intensive to abandoned agricultural land

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

No clear change in the transition from intensive to extensive agricultural land

My results demonstrate the lack of a clear relationship between the transition from intensive to EAL. On account of slow land reform, it is plausible that a clear relationship is not evident within three years of SUC.

4.3.2 European Union Accession

No clear change in the transition from abandoned to intensive agricultural land

My data did not exhibit a clear change in the transition from AAL to IAL directly following EUA, contradicting my positive prediction. The lack of an increase in this transition may be attributed to the previously discussed rapid succession of woody species on AAL (Nikodemus *et al.*, 2010; Vanwambeke *et al.*, 2012). 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, becoming a large industry competitor to agriculture (Vanwambeke *et al.*, 2012). The importance of forestry to the Latvian economy may be an indicator as to why AAL did not always transition to IAL.

AAL not transitioning to forestry may also not be used for IAL, ascribed to the ability to gain EU SAPs for managing previously AAL (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 promoting traditional landscapes. However, there is a higher uptake of SAPs on abandoned areas with better soils, most likely suggesting that the use of AAL for SAPs often occurs with the aim of reinstating agricultural practices (Nikodemus *et al.*, 2010). It is therefore likely that AAL

was transitioning to IAL, but not at a rate considerably different to before EUA. It is probable that the transition between AAL and forested areas has a steeper increase following EUA.

No clear change in the transition from extensive to intensive agricultural land

My results did not indicate a clear change in the transition to IAL from EAL directly following EUA. The lack of difference 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. However, without institutional assistance, many farmers do not have substantial income and thus, land abandonment may increase owing to subsistence farm failure. The interplay between IAL and EAL here may not be as strong as I originally predicted. Instead, it is feasible that EAL has a stronger connection to AAL following EUA. I did not examine the transition from EAL to AAL, as it did not align with my hypotheses. As I did not find EAL cover to change following EUA (section 4.2.2), it is not unlikely that no transition is exhibited from EAL.

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

Stronger decrease of abandoned land six years following SUC

I found AAL cover decrease to be stronger six years following SUC, as compared to three years after SUC. A sharp decrease in AAL over this period is not well cited in literature, as previously mentioned. With the peak of AAL cover likely to be around the year 2000 (Prishchepov *et al.*, 2012a; Vanwambeke *et al.*, 2012), it is probable that my classification did not pick up the steady increase that many studies discuss. It is more likely, however, that my classification underestimated AAL cover due to unrepresentative training points (Prishchepov *et al.*, 2012b). The AAL cover decrease found is unlikely to depict a new pattern and can be better attributed to error in my classification.

Stronger increase of intensive agricultural land six years following SUC

My results indicate that there is a potential time lag on the visibility of IAL cover change, with a steeper change and shift in direction observed. A shift to a negative relationship most likely signifies a lack of visibility of IAL cover decrease directly following SUC. My results are supported by the aforementioned slow land reformation process. It is probable that a move away from IAL would not have been visible until completion of land restitution, thus explaining the necessity of time lag inspection for IAL.

Weak decrease of extensive agricultural land six years following SUC

A weak, negative relationship was observed for EAL six years following SUC. Despite the seeming significance of this relationship, the direction is likely to be arbitrary due to the large amount of error relative to the rate of change. 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 IAL (Vanwambeke *et al.*, 2012). It is plausible that EAL did not change due to SUC at any timescale.

Weak transitions from intensive agricultural land to abandoned and extensive agricultural land six years following SUC

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

4.3.2 European Union Accession

Weaker increase of intensive agricultural land six years following EUA

The strength of IAL cover change is less than directly following EUA, indicating that perhaps, instead of there being a lag on EUA effects, the main impact happened directly following EUA. Thus, the relationship has weakened and the move to IAL has lessened. Logically, farmers willing to accept and adopt the potential benefits of EU payments would have done so directly following EUA to aid 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). All other LUC relationships and transitions did not have an observable relationship. It is likely that the other land use types either (a) reached a turning point directly following EUA or (b) reached a breakpoint after this six-year lag or (c) do exhibit EUA-related change. From my data, it is evident that IAL cover change is more directly associated with the time period directly following EUA, rather than six years later.

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.

Abandoned agricultural land cover change exhibited trends not previously found

For AAL change, a sharp decrease is noted at the end of 1992, which is not a breakpoint noted by literature. It is probable that AAL increased in the lead up to SUC, as noted by Vanwambeke *et al.* (2012). However, it is unclear why AAL coverage would decrease slightly following SUC. One potential explanation could be the decrease of IAL, turning quickly to AAL to then be up taken immediately by farmers interested in forestry to gain quick income from clear-cutting (Gutman & Radeloff, 2017). An alternative to that would be the maintenance of IAL on previously AAL, owing to the opinion that continuing large-scale agriculture increases productivity (Osborne & 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. However, classification accuracy and comparison would need to be completed before a new pattern is confirmed. Following 1994, a steady increase in AAL was seen, which is well supported by literature (Ioffe *et al.*, 2004; Prishchepov *et al.*, 2012a; Gutman & Radeloff, 2017). No clear breakpoint was observed around the time of EUA, implying that it had little effect on AAL cover within my study period. The trend of AAL change seen is not well supported by literature, owing most likely to classification error, with a slight potential for a new pattern to be discovered.

Intensive agricultural land cover change exhibited trends found in previous studies

For IAL change, 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 (Prishchepov *et al.*, 2012a; 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 & Jambor, 2009; Skribane & Jekabsone, 2013). The fluctuations in IAL cover observed are documented and likely show a relationship between both SPE events.

Extensive agricultural land cover change not likely to be significant

The breakpoints for EAL 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 & 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 & Taff, 2014). Although changes in EAL cover coincide with SPE events, change is not seen on a large scale, preventing a specific signature to be left on the landscape.

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. Furthermore, the inequality in the quantities of training data for each class may have limited accuracy; IAL showed the most informative relationship and had the most training points. The smaller quantities of training points for AAL and EAL may have reduced my classifier's capacity to accurately categorise both land use types. My study could be improved through introducing more training data, as well as refining the existing points.

The use of a 90-metre buffer may have introduced error, especially when quantifying EAL. With subsistence farming, farm size can be as low as two hectares (Davis, 1997), which is the equivalent of 20,000 square metres. With the polygon created by the buffer being 25,446.9 square metres, it is likely that other land uses would have been captured within the same polygon. The inclusion of multiple classes may lower the classifier's accuracy by linking land use to the incorrect spectral bandwidths. A reduction in buffer size would likely increase the amount of EAL observed.

An assessment of classification accuracy would have improved reliability. However, there is no standard method of accuracy assessment 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, CORINE 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 Latvian land use classification applied to every study year. Nonetheless, my classification would benefit from a more thorough accuracy assessment.

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 6.3.1), 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 could have caused a false rejection of the null hypothesis (Royston, 1982). Psuedo- R^2 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). Models examining time lag ignore other events that may have happened during the six-year period, attributing all change to the SPE event prior. Before accepting results, statistical refinement, including revisiting model assumptions and the strength of results, should be completed.

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 relative importance. Additional 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 & 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 AAL, the exact rate of conversion can be determined. The importance of forestry in Latvia is well established (Vanwambeke *et al.*, 2012), but the quantitative relationship between forestry and agricultural land use in Latvia is not well understood. Examining other events, such as the Chernobyl nuclear disaster in 1986 (Rahu *et al.*, 2006) and the Latvian economic crisis in 2008-2010 (Skribane & Jekabsone, 2013), may also provide insight into the agricultural LUC observed. By creating a more holistic image of LUC in Latvia, results can be more readily applied to country-level land use policy (Prishchepov *et al.*, 2012a).

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 & Richardson, 2015). Precise transitions 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 impact of SPE events on Latvia's agricultural land use 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 for IAL. IAL, EAL and AAL cover were all observed to decrease after SUC and increase following EUA. The slight decrease in AAL cover following SUC may shed light into new land use patterns not yet determined, but more likely, point to classification error. 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 EAL over IAL. To best prevent biodiversity loss, fragmentation and the loss of cultural landscapes, policies may benefit from looking at the patterns explained in my, and similar, studies. With a changing SPE climate in both Latvia and wider society, my methods and results may help to mitigate against negative LUC impacts by providing evidence for new, country-wide, preventative land use policies.

6. References

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7. Appendices

Appendix 1: Table showing bands selected as classification predictors.

Band	Wavelength (µm)	Description
B1	0.45-0.52	Band 1 (blue) surface reflectance
B2	0.52-0.60	Band 2 (green) surface reflectance
B3	0.62-0.69	Band 3 (red) surface reflectance
B4	0.77-0.90	Band 4 (near infrared) surface reflectance
B5	1.55-1.75	Band 5 (shortwave infrared 1) surface reflectance
B7	2.08-2.35	Band 7 (shortwave infrared 2) surface reflectance

Appendix 2: Criteria chosen to represent each additional land use class.

Land use	Criteria
Forestry	Filtered to include all land used for forestry, including the production of timber, firewood and round wood.
Wetlands	Filtered to include all land classed as areas that fall between land and water, usually being inundated with water on a temporary or permanent basis.
Water	Filtered to include all land classed as water, including inland and coastal areas without vegetation that are covered by water.
Artificial	Filtered to include all land classed as artificial, including built-up areas and humanmade areas characterised by materials like concrete and gravel.

Appendix 3: Total number of points obtained from LUCAS and the number used for training (80%) and testing (20%) for additional classes. Total includes three key classes.

Land type	Number of LUCAS points	Number of points in training sample	Number of points in testing sample
Forestry	2272	1815	457
Wetlands	98	132	35
Water	167	1038	257
Artificial	69	54	15
Total	4013	3223	817



Appendix 4: Map indicating Landsat 7 error, as seen by the vertical lines in northwest Latvia. Image created in GEE. Scale of 50 kilometres.

Appendix 5: Classification accuracy and error

My classifier had a resubstitution accuracy of 96.9%, with the majority of pixels being redistributed to the correct class. The additional cloud mask increased average classification accuracy across all study years by 4%. My classifier had an average test accuracy of 70%.

Appendix 5.1: Test accuracy for each year and the average across all years.

Year	Test Accuracy	Year	Test Accuracy
1989	0.71	2001	0.70
1990	0.69	2002	0.70
1991	0.70	2003	0.67
1992	0.70	2004	0.67
1993	0.69	2005	0.69
1994	0.72	2006	0.70
1995	0.70	2007	0.71
1996	0.71	2008	0.68
1997	0.73	2009	0.70
1998	0.69	2010	0.69
1999	0.71	2011	0.72
2000	0.71	Average	0.70

Appendix 5.2: 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

Appendix 5.3: Example confusion matrix for 2011, which is the year with the highest test accuracy. Bolded numbers represent the number of points classed correctly. Other values are classed incorrectly.

	Forestry	Abandoned	Extensive	Intensive	Water	Wetlands	Artificial
Forestry	19688	8	1	3459	61	27	8
Abandoned	548	0	0	526	1	0	0
Extensive	141	0	0	312	1	0	0
Intensive	2997	12	1	9986	41	6	31
Water	1063	2	0	372	344	1	0
Wetlands	862	0	0	252	6	8	0
Artificial	280	0	0	489	33	0	10

From this, it is clear that my classifier overestimated forestry and IAL use cover. It incorrectly classed AAL and EAL cover 100% of the time.

Appendix 6: Results in tabular form and additional results

Appendix 6.1 – Abandoned and EAL cover decreased, and IAL cover increased directly following SUC. With a low standard error and the highest marginal R^2 , abandoned LUC shows the strongest relationship with SUC (abandoned – $N = 255$; extensive – $N = 247$; intensive – $N = 258$).

Land use	Estimate	\pm SE of estimate	t-value	p-value	R^2M	R^2C
Abandoned	-5.14	1.13	-4.56	<0.0001	0.06	0.30
Extensive	-0.08	0.13	-0.60	0.55	<0.01	0.01
Intensive	2089.51	2605.67	0.80	0.42	<0.01	0.11

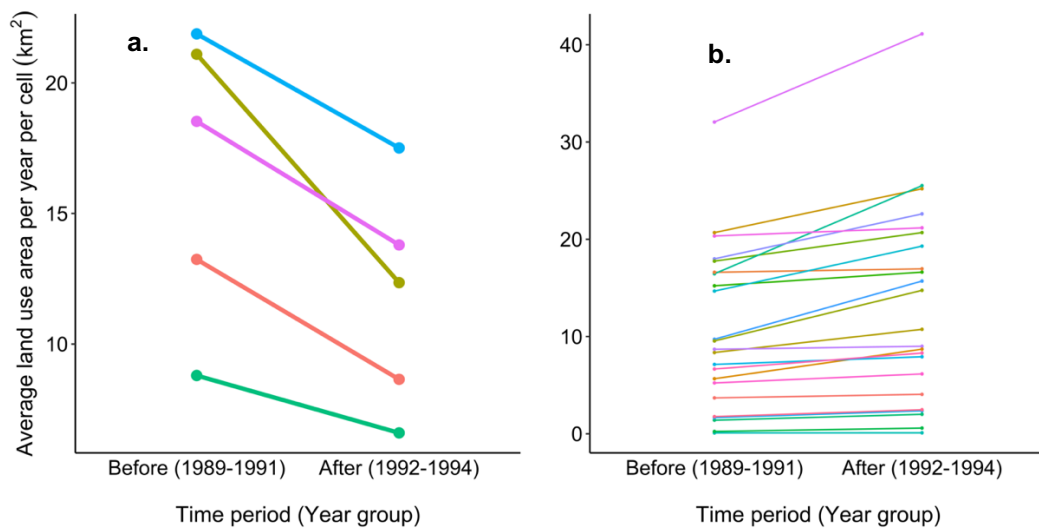
Appendix 6.2 – Abandoned and EAL cover decreased, and IAL cover increased directly following EUA. With a low standard error relative to the slope and the highest marginal R^2 , intensive LUC shows the strongest relationship with EUA (abandoned – $N = 255$; extensive – $N = 247$; intensive – $N = 258$).

Land use	Estimate	\pm SE of estimate	t-value	p-value	R^2M	R^2C
Abandoned	-2.61	1.20	-2.12	0.03	0.01	0.10
Extensive	-0.01	0.09	-0.13	0.90	<0.0001	0.05
Intensive	6179.11	1942.18	3.18	<0.01	0.04	0.09

Appendix 6.3 – Examining the impact of location as a predictor of LUC

Appendix 6.3.1 – Models including cell as a random effect show less error and increased model fit (R^2C).

Event	Land use	Estimate	\pm SE of estimate	t-value	p-value	R^2M	R^2C
SUC	Abandoned	-5.11	0.68	-7.47	<0.0001	0.04	0.48
	Extensive	-0.09	0.06	-1.39	0.16	<0.01	0.52
	Intensive	2089.51	331.90	6.30	<0.0001	<0.01	0.96
EUA	Abandoned	-2.59	0.85	-3.05	<0.01	<0.01	0.29
	Extensive	-0.02	0.04	-0.50	0.61	<0.01	0.54
	Intensive	6204.74	620.31	10.00	<0.0001	0.03	0.77



Appendix 6.3.2 – Figure depicting average AAL area per year per cell (a) aggregated by grid and (b) shown for all cells increasing in AAL cover. Scale of y-axis different for effective visualisation – two graphs should not be compared directly. Raw data used solely for visualisation purposes.

Appendix 6.4 – The amount of land transitioning to abandoned and EAL from IAL decreased following SUC. The direction for the transition to EAL is likely arbitrary due to the large error relative to the slope (N = 258).

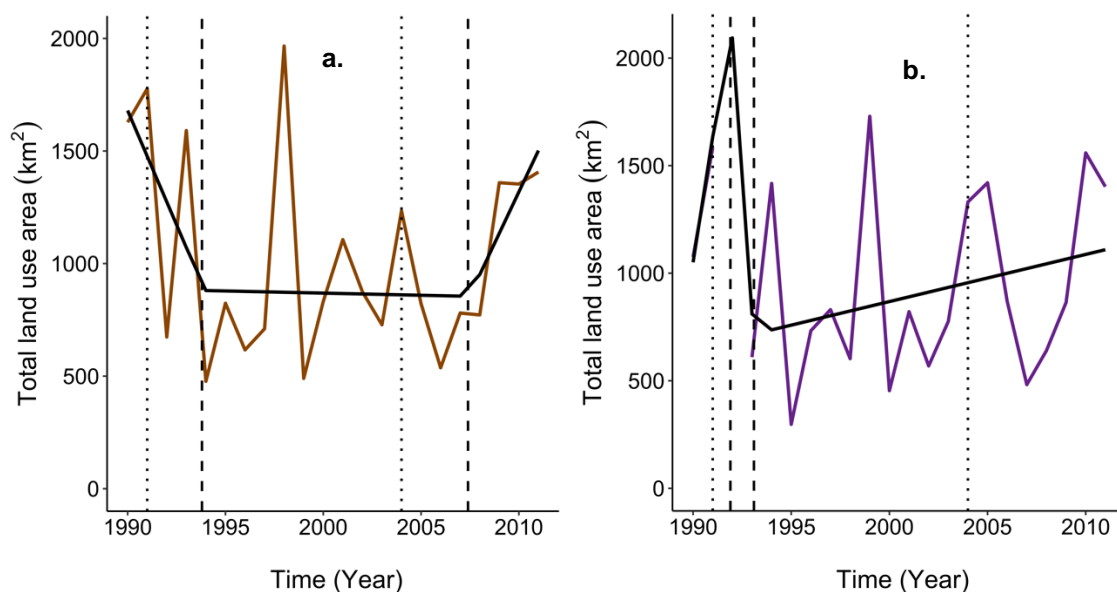
Land use transition	Estimate	\pm SE of estimate	t-value	p-value	R^2M	R^2C
Intensive to abandoned	-3.02	0.70	-3.76	<0.001	0.04	0.24
Intensive to extensive	-0.03	0.04	-0.67	0.50	<0.01	0.05

Appendix 6.5 – The amount of land transitioning from abandoned to intensive decreased following EUA, whereas land transitioning to intensive from extensive increased following SUC. Standard error is high relative to the slope and the model fit is low for both relationships, indicating a lack of a clear relationship (N = 258).

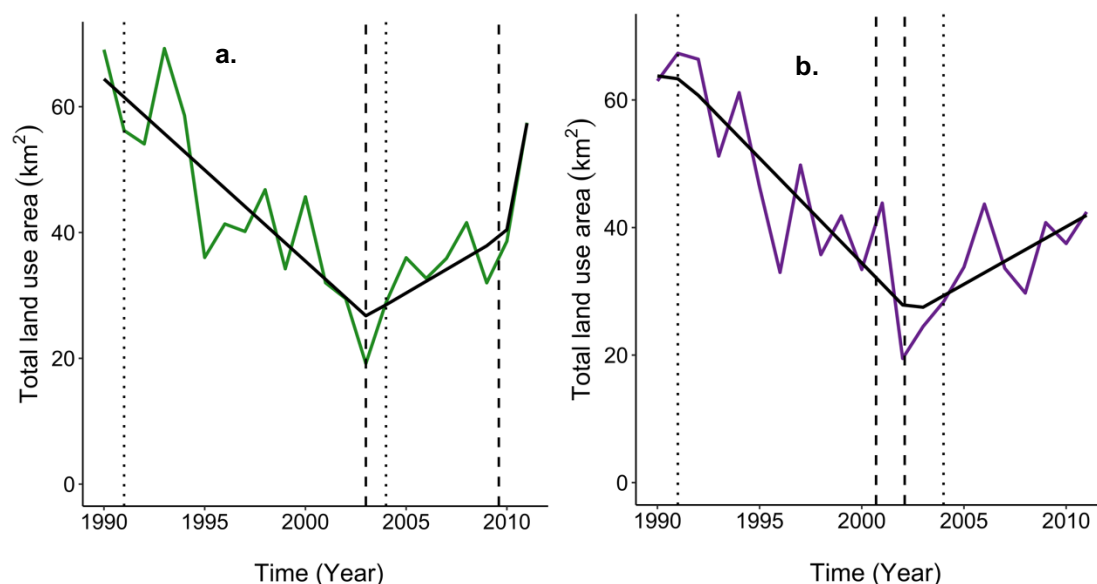
Land use transition	Estimate	± SE of estimate	t-value	p-value	R ² M	R ² C
Abandoned to intensive	-0.40	0.78	-0.51	0.61	<0.01	0.05
Extensive to intensive	0.04	0.04	1.12	0.27	<0.01	0.02

Appendix 6.6 – Unclear relationships tested on LUC six years following EUA. No clear relationship seen, owing to large error relative to the slope and low model fit (abandoned – N = 255; extensive – N = 249; A → I – N = 258, E → I – N = 258).

Land use transition	Estimate	± SE of estimate	t-value	p-value	R ² M	R ² C
Abandoned	-2.07	1.21	-1.73	0.09	0.01	0.13
Extensive	-0.01	0.08	-0.18	0/86	<0.001	0.10
Abandoned to intensive	0.04	0.04	1.12	0.27	<0.001	0.02
Extensive to intensive	0.04	0.03	1.11	0.27	<0.001	0.12



Appendix 6.7.1 – Breakpoint figures for (a) the transition from intensive to AAL and (b) the transition from abandoned to IAL. 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.



Appendix 6.7.2 – Breakpoint figures for (a) the transition from extensive to AAL and (b) the transition from extensive to IAL. 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.

Appendix 6.8: Complete list of breakpoints and their associated errors

Land use	Breakpoint 1	Error	Breakpoint 2	Error
Abandoned	1992.8	2.15	1994.2	2.29
Extensive	1995.2	1.93	2007.3	1.22
Intensive	2002.5	2.15	2004.2	1.91
Intensive to abandoned	1993.8	2.35	2007.4	2.72
Intensive to extensive	2003.0	1.42	2009.6	0.64
Extensive to intensive	2000.7	1.75	2002.1	2.65
Abandoned to intensive	1991.9	0.82	1993.1	1.34

Appendix 7: GEE code excerpts. For full code, for full code visit

<https://github.com/izzyrich/dissertation>. First box shows example code for classification and second box shows example code for calculations.

```
// classify land use in Latvia with LUCAS (2012) data

// SET UP DATA ----
// choose bands
var bands = ['B1', 'B2', 'B3', 'B4', 'B5', 'B7'];

// import all points of known land-use type from LUCAS
var fc_total = ee.FeatureCollection('users/izzyrich/full_2012');
var forestry = ee.FeatureCollection('users/izzyrich/forestry');
var abandoned = ee.FeatureCollection('users/izzyrich/abandoned');
```

```

var extensive = ee.FeatureCollection('users/izzyrich/extensive');
var intensive = ee.FeatureCollection('users/izzyrich/intensive');
var water = ee.FeatureCollection('users/izzyrich/water');
var wetlands = ee.FeatureCollection('users/izzyrich/wetlands');
var artificial = ee.FeatureCollection('users/izzyrich/artificial');

// function to cloud correct
var cloudMaskL457 = function(image) {
  var qa = image.select('pixel_qa');
  // If the cloud bit (5) is set and the cloud confidence (7) is high
  // or the cloud shadow bit is set (3), then it's a bad pixel.
  var cloud = qa.bitwiseAnd(1 << 5)
    .and(qa.bitwiseAnd(1 << 7))
    .or(qa.bitwiseAnd(1 << 3))
  // Remove edge pixels that don't occur in all bands
  var mask2 = image.mask().reduce(ee.Reducer.min());
  return image.updateMask(cloud.not()).updateMask(mask2);
};

// import shape of Latvia polygon to define ROI
var latvia_poly = ee.FeatureCollection('users/izzyrich/latvia_poly');

// add buffer of 90 metres to create polygons – do for each land use
var fc_total = fc_total.map(function(f) {
  return f.buffer(90);
});

// add satellite imagery for 2011 - surface reflectance
var landsatCollection = ee.ImageCollection('LANDSAT/LT05/C01/T1_SR')
  .filterDate('2011-06-01', '2011-08-30');

// get median of imagery to remove high and low reflectance (cloud and shadow)
var median = landsatCollection.map(cloudMaskL457).median();

// clip on size of latvia
var clipped = median.clip(latvia_poly);

// START CLASSIFICATION ----

// set random seed
var n = 0;

// get random columns for each land-use type
var randomForestry = forestry.randomColumn('random', n);
var randomAbandoned = abandoned.randomColumn('random', n);
var randomExtensive = extensive.randomColumn('random', n);
var randomIntensive = intensive.randomColumn('random', n);
var randomWater = water.randomColumn('random', n);
var randomWetlands = wetlands.randomColumn('random', n);
var randomArtificial = artificial.randomColumn('random', n);

// split up data for testing and training - 80% for training and 20% for testing
var split = 0.8;

// stratified training and testing samples
var trainingSample = randomForestry.filter(ee.Filter.lt('random', split))
  .merge(randomAbandoned.filter(ee.Filter.lt('random', split)))
  .merge(randomExtensive.filter(ee.Filter.lt('random', split)))
  .merge(randomIntensive.filter(ee.Filter.lt('random', split)))
  .merge(randomWater.filter(ee.Filter.lt('random', split)))
  .merge(randomWetlands.filter(ee.Filter.lt('random', split)))
  .merge(randomArtificial.filter(ee.Filter.lt('random', split)));

```

```

var testingSample = randomForestry.filter(ee.Filter.gte('random', split))
  .merge(randomAbandoned.filter(ee.Filter.gte('random', split)))
  .merge(randomExtensive.filter(ee.Filter.gte('random', split)))
  .merge(randomIntensive.filter(ee.Filter.gte('random', split)))
  .merge(randomWater.filter(ee.Filter.gte('random', split)))
  .merge(randomWetlands.filter(ee.Filter.gte('random', split)))
  .merge(randomArtificial.filter(ee.Filter.gte('random', split)));

// Sample the input imagery to get a FeatureCollection of training data.
var training = clipped.select(bands).sampleRegions({
  collection: trainingSample,
  properties: ['class'],
  scale: 30,
});

// trained with 80% of our data
var trainedClassifier = ee.Classifier.randomForest({
  numberOfTrees: 30
})
  .train(training, 'class');

// classify FeatureCollection
var classified = clipped.classify(trainedClassifier, 'classification');

// Get a confusion matrix representing resubstitution accuracy.
print('RF error matrix: ', trainedClassifier.confusionMatrix());
print('RF accuracy: ', trainedClassifier.confusionMatrix().accuracy());

// Sample input to get validation data
var validation = clipped.sampleRegions({
  collection: testingSample,
  properties: ['class'],
  scale: 30,
});

// Classify validation data
var validated = validation.classify(trainedClassifier);

// Get error of testing data + export to table to save time
var testError = validated.errorMatrix('class', 'classification');
var exportconfusionMatrix = ee.Feature(null, {matrix: testError.array()});
Export.table.toDrive({
  collection: ee.FeatureCollection(exportconfusionMatrix),
  description: 'exportconfusionMatrix_2011',
  fileFormat: 'CSV'
});

// Get accuracy of testing data + export to table to save time
var testAccuracy = testError.accuracy();
var exporttestAccuracy = ee.Feature(null, {matrix: testAccuracy});
Export.table.toDrive({
  collection: ee.FeatureCollection(exporttestAccuracy),
  description: 'testAccuracy_2011',
  fileFormat: 'CSV'
});

// Export the image to an Earth Engine asset.
Export.image.toAsset({
  image: classified.select(['classification']),
  description: 'classified',
  assetId: 'classified',
  scale: 30,
});

```

```
region: poly,  
maxPixels: 1e13  
});
```

```
// import all classification images - example  
var classified_1989 = ee.Image('users/izzyrich/classified_1989');  
var classified_1990 = ee.Image('users/izzyrich/classified_1990');  
  
// import shape of Latvia polygon to define ROI  
var latvia_poly = ee.FeatureCollection('users/izzyrich/latvia_poly');  
  
// MAKE GRID FOR Latvia  
  
// 1) Create bounding box  
var lon_start = 20.97139;  
var lon_end = 29.24051;  
var lat_start = 55.66372;  
var lat_end = 58.08577;  
  
// 2) Decide no. of (in this case: equally sized) cells  
var num_cells = 200;  
var lon_edge = (lon_end-lon_start)/Math.sqrt(num_cells);  
var lat_edge = (lat_end-lat_start)/Math.sqrt(num_cells);  
  
// 3) Create the grid  
var polys = [];  
var polys_line = [];  
var cell_id = 0;  
for (var lon = lon_start; lon < lon_end; lon += lon_edge) {  
  var x1 = lon;  
  var x2 = lon + lon_edge;  
  for (var lat = lat_start; lat < lat_end; lat += lat_edge) {  
    cell_id = cell_id + 1;  
    var y1 = lat;  
    var y2 = lat + lat_edge;  
  
    polys.push(ee.Feature(ee.Geometry.Rectangle(x1, y1, x2, y2), {label: cell_id}));  
  }  
}  
var grid = ee.FeatureCollection(polys);  
var filtered = grid.filterBounds(latvia_poly);  
  
// calculate transition area  
var transitionarea = function(image1, image2, class1, class2, name){  
  var first = image1.select('classification').eq(class1);  
  var second = image2.select('classification').eq(class2);  
  var change = first.and(second);  
  var reduce = change.addBands(change).reduceRegions({  
    collection: filtered,  
    reducer: ee.Reducer.sum().group({  
      groupField: 1,  
      groupName: 'classification',  
    }},  
    scale:30});  
  var feature = ee.Feature(reduce);  
  Export.table.toDrive({  
    collection: feature,  
    description: name,  
    fileFormat: 'CSV'  
  });  
};  
transitionarea(classified_1989, classified_1990, 1, 3, '89_90_1to3');
```



```

transitionarea(classified_1989, classified_1990, 1, 2, '89_90_1to2');
transitionarea(classified_1989, classified_1990, 2, 1, '89_90_2to1');
transitionarea(classified_1989, classified_1990, 2, 3, '89_90_2to3');
transitionarea(classified_1989, classified_1990, 3, 1, '89_90_3to1');
transitionarea(classified_1989, classified_1990, 3, 2, '89_90_3to2');

// calculate area of each class
var area = function(image, name){
  var areacount = image.addBands(image).reduceRegions({
    collection: filtered,
    reducer: ee.Reducer.sum().group({
      groupField: 1,
      groupName: 'classification',
    }),
    scale:30});
  var reduce = ee.FeatureCollection(ee.Feature(areacount));
  Export.table.toDrive({
    collection: areacount,
    description: name,
    fileFormat: 'CSV'
  });
};

area(classified_1989, 'classified_1989');

```

Appendix 8: R code excerpts. For full code, for full code visit <https://github.com/izzyrich/dissertation>.

Packages used for all code

```

# Load packages
library(readr)
library(tidyverse)
library(rgdal)
library(sp)
library(raster)
library(sf)
library(rworldmap)
library(grid)
library(rworldextra)
library(stringr)
library(maptools)
library(tiff)
library(dggridR)
library(modeest)
library(lme4)
library(MuMIn)
library(lmerTest)
library(segmented)
library(effects)
library(scales)
library(gridExtra)

```

Filter and format LUCAS data points and create polygon of Latvia

```
# Import base dataset
lucas <- read_csv("data/2012_lucas.csv")

# LATVIA BORDER and POLY ----

# get data
latvia <- raster::getData("GADM", country = "LVA", level = 0)

# change projection
latvia <- spTransform(latvia, "+proj=longlat +ellps=WGS84 +datum=WGS84 +init=epsg:3857")

# create polygon
data = data.frame(f=99.9)
spdf = SpatialPolygonsDataFrame(latvia, data)
shapefile(spdf, "data/latvia_poly", overwrite = TRUE)

# format data
map <- fortify(latvia)%>%
  dplyr::select(long, lat)
colnames(map)[colnames(map) == "lat"] <- "LAT"
colnames(map)[colnames(map) == "long"] <- "LONG"

# set CRS and transform
coordinates(map) <- c("LONG", "LAT")
proj4string(map) <- CRS("+proj=longlat +ellps=WGS84 +datum=WGS84 +init=epsg:3857")
border_points <- spTransform(map, "+proj=longlat +ellps=WGS84 +datum=WGS84 +init=epsg:3857")
r_border <- raster(border_points) # border as raster

## AAL ----

# filter for AAL
U112_options <- c("10", "20") # stated that these were abandoned agricultural areas
U410_options <- c("B", "C", "D", "E", "F") # classes that could be agriculture in U410 (natural terrestrial areas)

lucas_filtered <- lucas %>%
  separate(LC1, into = c('class', 'number'), sep = 1) %>%
  filter(LU1 == "U410" & class %in% U410_options |
         LU1 == "U112" & class == "D" & number %in% U112_options |
         LU1 == "U420" & class == "E" & number == "30") %>%
  dplyr::select(GPS_LAT, GPS_LONG) %>% # potentially need elevation here??
  mutate(class = "1") %>%
  mutate(name = "abandoned")

# write to csv
write.csv(lucas_filtered, file = "data/lucas_2012_filtered.csv")
```

Format and aggregate all data from classification

```
# TOTAL AREA ----

# import data 1989 ----
data <- read_csv("~/Documents/Edinburgh Year 4/dissertation/data/classified_1989.csv")

# format ----
new <- data %>%
  separate(groups, into = c('class0', 'number0',
                             'class1', 'number1',
                             'class2', 'number2',
                             'class3', 'number3',
                             'class4', 'number4',
                             'class5', 'number5',
                             'class6', 'number6'), sep = ",")

new$class1 <- gsub("[^0-9.-]", "", new$class1)
new$number1 <- gsub("[^0-9.-]", "", new$number1)
new$class2 <- gsub("[^0-9.-]", "", new$class2)
new$number2 <- gsub("[^0-9.-]", "", new$number2)
new$class3 <- gsub("[^0-9.-]", "", new$class3)
new$number3 <- gsub("[^0-9.-]", "", new$number3)

new$number1 <- as.numeric(new$number1)
new$number2 <- as.numeric(new$number2)
new$number3 <- as.numeric(new$number3)

delete89 <- new %>%
  dplyr::select(-c(.geo, `system:index`))

new_df89 <- bind_rows(
  delete89 %>% dplyr::select(label, class = class1, pixels = number1),
  delete89 %>% dplyr::select(label, class = class2, pixels = number2),
  delete89 %>% dplyr::select(label, class = class3, pixels = number3),
) %>%
  mutate(area = pixels*30) %>%
  mutate(year = 1989)

# TOTAL TRANSITION ----

# import data 89 to 90 1 to 3 ----
data <- read_csv("~/Documents/Edinburgh Year 4/dissertation/data/89_90_1to3.csv")

# format ----
new <- data %>%
  separate(groups, into = c('class0', 'number0',
                             'class1', 'number1'), sep = ",")

new$class0 <- gsub("[^0-9.-]", "", new$class0)
new$number0 <- gsub("[^0-9.-]", "", new$number0)
new$class1 <- gsub("[^0-9.-]", "", new$class1)
new$number1 <- gsub("[^0-9.-]", "", new$number1)
```

```

new$number0 <- as.numeric(new$number0)
new$number1 <- as.numeric(new$number1)

transition_8990_1 <- new %>%
  dplyr::select(-c(.geo, `system:index`, class0, class1, number0)) %>%
  mutate(area = number1*30) %>%
  mutate(year = "1990") %>%
  mutate(transition = "1") %>%
  mutate(previous_class = "1") %>%
  mutate(current_class = "3")

```

Create large grid and conduct statistical analyses

```

# load data ----
detailed_area <- read_csv("data/detailed_area.csv") %>%
  dplyr::select(-c("X1"))
colnames(detailed_area)[colnames(detailed_area) == "label"] <- "cell"
detailed_area$class <- factor(detailed_area$class)
detailed_area$cell <- factor(detailed_area$cell)

detailed_transition <- read_csv("data/detailed_transition.csv") %>%
  dplyr::select(-c("X1"))
colnames(detailed_transition)[colnames(detailed_transition) == "label"] <-
"cell"
detailed_transition$cell <- factor(detailed_transition$cell)
detailed_transition$transition <- factor(detailed_transition$transition)

# apply bigger grid
detailedA <- detailed_area %>%
  mutate(grid = if_else(cell == 8 | cell == 9 | cell == 10 | cell == 11 | c
ell == 23 |
                                cell == 24 | cell == 25 | cell == 26 | cell == 27
|
                                cell == 38 | cell == 39 | cell == 40 | cell == 41
|
                                cell == 42 | cell == 43 | cell == 53 | cell == 54
| cell == 55 | cell == 56, "NW",
                                if_else(cell == 3 | cell == 4 | cell == 5 | cell ==
6 | cell == 7 |
                                cell == 19 | cell == 20 | cell == 21 | ce
ll == 22 |
                                cell == 35 | cell == 36 | cell == 37 | ce
ll == 49 |
                                cell == 50 | cell == 51 | cell == 52, "SW
",
                                if_else(cell == 64 | cell == 65 | cell == 6
6 | cell == 67 | cell == 68 |
                                cell == 69 | cell == 79 | cell ==
80 | cell == 81 |
                                cell == 82 | cell == 83 | cell ==
84 | cell == 85 |
                                cell == 86 | cell == 87 | cell ==
88 | cell == 89 | cell == 94 |
                                cell == 95 | cell == 96 | cell ==
97 | cell == 98 | cell == 99 |

```

```

cell == 100 | cell == 101 | cell
== 102 | cell == 103 | cell == 104, "C",
if_else(cell == 113 | cell == 114 |
cell == 115 | cell == 116 | cell == 117 |
cell == 118 | cell == 119
| cell == 120 | cell == 128 |
cell == 129 | cell == 130
| cell == 131 | cell == 132 |
cell == 133 | cell == 134
| cell == 143 | cell == 144 | cell == 145 |
cell == 146 | cell == 147
| cell == 158 | cell == 159 | cell == 160 |
cell == 161 | cell == 162
| cell == 173 | cell == 174 | cell == 175 | cell == 176, "NE",
if_else(cell == 108 | cell
== 109 | cell == 110 | cell == 111 | cell == 112 |
cell == 121 | cel
l == 122 | cell == 123 | cell == 124 |
cell == 125 | cel
l == 126 | cell == 127 | cell == 136 |
cell == 137 | cel
l == 138 | cell == 139 | cell == 140 | cell == 141 |
cell == 142 | cel
l == 151 | cell == 152 | cell == 153 | cell == 154 |
cell == 155 | cel
l == 156 | cell == 157 | cell == 166 | cell == 167 | cell == 168 |
cell == 169 | cel
l == 170 | cell == 171 | cell == 172 | cell == 183 | cell == 184 | cell ==
185 |
cell == 186, "SE"
, "NA"))))))))

# apply bigger grid
detailedT <- detailed_transition %>%
  mutate(grid = if_else(cell == 8 | cell == 9 | cell == 10 | cell == 11 | c
ell == 23 |
cell == 24 | cell == 25 | cell == 26 | cell == 27
|
cell == 38 | cell == 39 | cell == 40 | cell == 41
|
cell == 42 | cell == 43 | cell == 53 | cell == 54
| cell == 55 | cell == 56, "NW",
if_else(cell == 3 | cell == 4 | cell == 5 | cell ==
6 | cell == 7 |
cell == 19 | cell == 20 | cell == 21 | ce
ll == 22 |
cell == 35 | cell == 36 | cell == 37 | ce
ll == 49 |
cell == 50 | cell == 51 | cell == 52, "SW
",
if_else(cell == 64 | cell == 65 | cell == 6
6 | cell == 67 | cell == 68 |
cell == 69 | cell == 79 | cell ==
80 | cell == 81 |
cell == 82 | cell == 83 | cell ==
84 | cell == 85 |

```

```

88 | cell == 89 | cell == 94 |
97 | cell == 98 | cell == 99 |
== 102 | cell == 103 | cell == 104, "C",
cell == 115 | cell == 116 | cell == 117 |
| cell == 120 | cell == 128 | |
| cell == 131 | cell == 132 |
| cell == 143 | cell == 144 | cell == 145 |
| cell == 158 | cell == 159 | cell == 160 |
| cell == 173 | cell == 174 | cell == 175 | cell == 176, "NE",
== 109 | cell == 110 | cell == 111 | cell == 112 |
1 == 122 | cell == 123 | cell == 124 |
1 == 126 | cell == 127 | cell == 136 |
1 == 138 | cell == 139 | cell == 140 | cell == 141 |
1 == 151 | cell == 152 | cell == 153 | cell == 154 |
1 == 156 | cell == 157 | cell == 166 | cell == 167 | cell == 168 |
1 == 170 | cell == 171 | cell == 172 | cell == 183 | cell == 184 | cell ==
185 |
, "NA")))))))

cell == 86 | cell == 87 | cell ==
cell == 95 | cell == 96 | cell ==
cell == 100 | cell == 101 | cell
if_else(cell == 113 | cell == 114 |
cell == 118 | cell == 119
cell == 129 | cell == 130
cell == 133 | cell == 134
cell == 146 | cell == 147
cell == 161 | cell == 162
if_else(cell == 108 | cell
cell == 121 | cel
cell == 125 | cel
cell == 137 | cel
cell == 142 | cel
cell == 155 | cel
cell == 169 | cel
cell == 186, "SE"

# DF for Q1
# before and after in km2 per cell
questiononeSUC <- detailedA %>%
  dplyr::filter(year == 1989 | year == 1990 | year == 1991 | year == 1992 |
year == 1993 | year == 1994) %>%
  dplyr::select(-c(pixels)) %>%
  mutate(before_after = ifelse(year == 1989 | year == 1990 | year == 1991,
"first", "second")) %>%
  dplyr::select(-c(year)) %>%
  group_by(before_after, grid, class, cell) %>%
  summarise(area = mean(area)/1000)

# DF for Q2
# before and after in km2
questiontwoSUC <- detailedT %>%
  dplyr::filter(year == 1990 | year == 1991 | year == 1992 | year == 1993 |
year == 1994 | year == 1995) %>%
  dplyr::select(-c(pixels)) %>%
  mutate(before_after = ifelse(year == 1990 | year == 1991 | year == 1992,
"first", "second")) %>%

```

```

dplyr::select(-c(year)) %>%
group_by(before_after, grid, transition, cell) %>%
summarise(area = mean(area)/1000)

# DF for Q3 ----
questionthreeASUC <- detailedA %>%
  dplyr::filter(year == 1989 | year == 1990 | year == 1991 | year == 1995 |
year == 1996 | year == 1997) %>%
  dplyr::select(-c(pixels)) %>%
  mutate(before_after = ifelse(year == 1989 | year == 1990 | year == 1991,
"first", "second")) %>%
  dplyr::select(-c(year)) %>%
  group_by(before_after, grid, class, cell) %>%
  summarise(area = mean(area)/1000)

# Abandoned SUC ----
questiononeSUC1 <- questiononeSUC %>%
  dplyr::filter(class == 1)

questiononeSUC1$grid <- factor(questiononeSUC1$grid)
questiononeSUC1$cell <- factor(questiononeSUC1$cell)
questiononeSUC1$before_after <- factor(questiononeSUC1$before_after)

# model
abandonedSUC <- lmer(area ~ before_after + (1|grid), data = questiononeSUC1
)
summary(abandonedSUC)

r.squaredGLMM(abandonedSUC)

# Q2 A--I: EUA ----
questiontwoEUA1 <- questiontwoEUA %>%
  dplyr::filter(transition == 1)

questiontwoEUA1$grid <- factor(questiontwoEUA1$grid)
questiontwoEUA1$cell <- factor(questiontwoEUA1$cell)
questiontwoEUA1$before_after <- factor(questiontwoEUA1$before_after)

atoiEUA <- lmer(area ~ before_after + (1|grid), data = questiontwoEUA1)
summary(atoiEUA)

r.squaredGLMM(atoiEUA)

# Q3 lag Abandoned SUC ----
questionthreeSUC1 <- questionthreeASUC %>%
  dplyr::filter(class == 1)

questionthreeSUC1$grid <- factor(questionthreeSUC1$grid)
questionthreeSUC1$cell <- factor(questionthreeSUC1$cell)
questionthreeSUC1$before_after <- factor(questionthreeSUC1$before_after)

# model
abandonedlagSUC <- lmer(area ~ before_after + (1|grid), data = questionthre
eSUC1)
summary(abandonedlagSUC)

```

```

r.squaredGLMM(abandonedlagSUC)

# Q3 part b ----
abandonedseglag <- detailedA %>%
  dplyr::select(-c(pixels)) %>%
  filter(class == "1") %>%
  group_by(year) %>%
  summarise(year_total = sum(area)/1000)

abandonedlm <- lm(year_total ~ year, data = abandonedseglag)
summary(abandonedlm)

abandonedmod <- segmented(abandonedlm, seg.Z = ~year, psi = list(year = c(1
996, 2004)))
summary(abandonedmod)

```