A picture containing clipart

Description automatically generated

**THE UNIVERSITY OF EDINBURGH**

**SCHOOL OF GEOSCIENCES**

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

*BY*

**Isabelle Rich**

in partial fulfilment of the requirement for the

Degree of BSc with Honours in

Ecological and Environmental Sciences

April 2019

**Abstract**

**Table of contents**

Abstract

Table of contents

Acknowledgements

List of abbreviations

1. Introduction……………………………………………………………… 1
   1. Objectives and rationale…………………………………... 2
   2. Research questions, hypotheses and predictions…….... 2
2. Methods
3. Results
   1. Q1
   2. Q2
   3. Q3
4. Discussion
   1. Key findings
   2. Q1
   3. Q2
   4. Q3
   5. Limitations
   6. Future research
5. Conclusion
6. Reference list
7. Appendices

**Acknowledgements**

I firstly would like to thank Dr Isla Myers-Smith, not only for her continuous support, wisdom and advice that kept me grounded during dissertation work, but for all the opportunities working with her has given me: I can safely say that assisting with her 2017 field season changed my life for the better. I am grateful for PhD student Gergana Daskalova for sharing code and resources, and her dedication, knowledge and encouragement throughout this process and always. Without her, I would have never found my love for data science. I would like to also thank the rest of the Team Shrub research group at the University of Edinburgh: my coursemate Cameron Cosgrove, Dr Sandra Algers-Blondin and Mariana Garcia Criadio for helping me plan and achieve the goals of my dissertation.

I would like to thank all the additional academics I reached out to that graciously provided advice: Sam Harrison (University of Edinburgh, PhD candidate), Keiko Nomura (University of Edinburgh, PhD candidate) and Dr Alemayehu Midekisa (Geospatial research specialist, University of California, San Francisco), thank you for solving some seemingly unsolvable problems. I am also grateful for the vast amount of resources on the internet for assisting me within seconds.

I must acknowledge my large and wonderful support network. Thank you to my coursemates for sharing their wisdom, time and company during our long days at the library. I am beyond grateful for my flatmates. Without these ladies, I would not have the confidence, strength and passion to complete this dissertation. A final thanks goes to my family: thank you for supporting my decision to travel across the pond for university. I can confidently say it was the best decision I’ve ever made.

**List of abbreviations**

EU – European Union

EUA – European Union Accession

GEE – Google Earth Engine

LUC – Land use change

LUCAS – Land Use and Coverage Area frame Survey

SPE – Socio-politico-economic

SUC – Soviet Union collapse

1. **Introduction** 
   1. **Objectives and rationale**

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

* 1. **Research questions and hypotheses**

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

**H1**: Directly following SUC, intensive agriculture will decrease, and abandoned land will increase across Latvia. Extensive cover change will be weakly positive. After EUA, intensive agriculture will increase, and abandoned land will decrease across Latvia. Extensive cover change will be weakly negative.

**H10**: Intensive, extensive and abandoned land use will not visibly increase or decrease in Latvia directly following SUC and EUA.

**RQ2**: **Do the strength and direction of land use transitions change within the three years following SPE events?**

**H2**: Following SUC, intensive land will transition to abandoned and extensive land, with the transition to abandoned land being stronger. After EUA, extensive and abandoned land will transition to intensive land.

**H20**: Land use transitions between intensive, extensive and abandoned land will not significantly increase or decrease in Latvia following SUC and EUA.

**RQ3: Is there a time lag between SPE events and the visibility of LUC and transitions?**

**H3**: Following SUC, there will be a lag in extensive land cover increase, but not in intensive cover decrease or abandoned land increase. A lag will be present in the transition from intensive to extensive land, but not in the transition to abandoned land. After EUA, a lag will be present for the decrease of extensive agriculture. There will not be a lag for abandoned land cover decrease, and intensive land increase. A lag will not be apparent for the transition from abandoned land to intensive land, but a lag will be observed for the transition from extensive to intensive land.

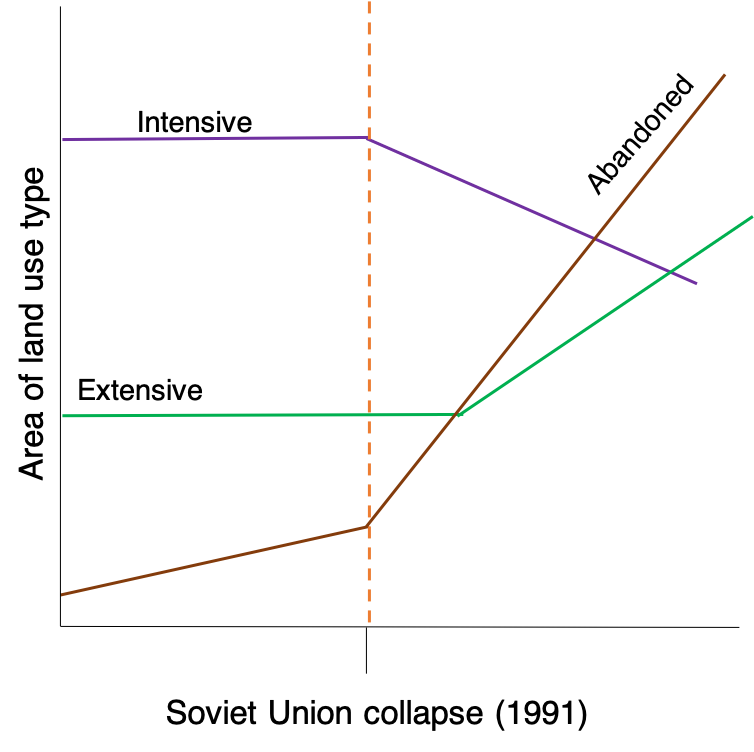
**H30**: Time following SPE events will not have an effect on strength of LUC and land use transitions.

* 1. **Predictions**

**1.3.1 SUC**

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

**A screen shot of a computer

Description automatically generated**

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

**1.3.2 EUA**

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

**A screen shot of a computer

Description automatically generatedA close up of a light

Description automatically generated**

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

**1.3.3 Implications of results**

If areas of a land use increase or decrease 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 seen, it is likely that different regions experienced LUC with differing strengths and directions. Such heterogeneous effects would also signify that the SPE event was not the main driver of LUC or that it was coupled with other key drivers.

**2. Methods**

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

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

**2.1 Study site**

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

**2.2 Image processing**

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

**2.3 Classification background**

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

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

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

A close up of a sign

Description automatically generated

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

**2.4 Training data**

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

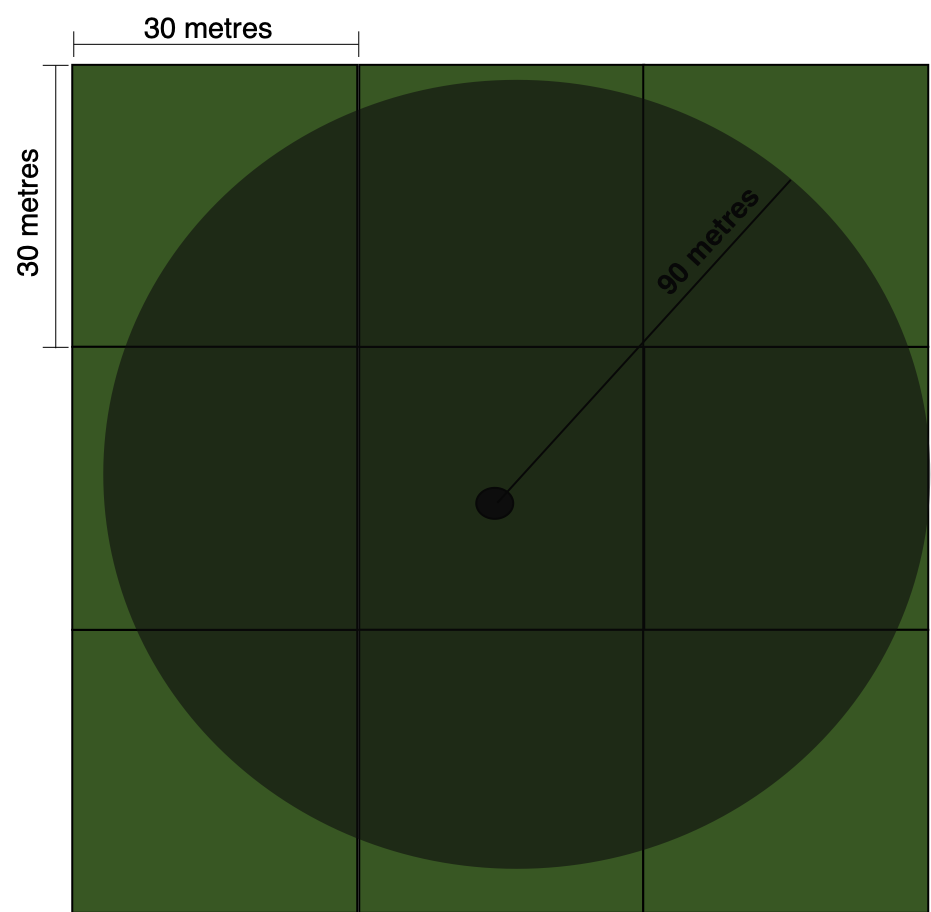
I used the LUCAS dataset (Eurostat, 2013), which contains GPS coordinates of both land use, as defined by the socioeconomic activities and land cover for European countries, for every three years since 2009. I chose to use 2012 data, as it is the earliest dataset that clearly separates fallow and abandoned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

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

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

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

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



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

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

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

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

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

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

**2.5 Random forest classification**

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

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

**2.6 Classification accuracy and error**

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

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

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

**2.6.1 Resubstitution accuracy and error**

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

**2.6.2 Hold-out accuracy and error**

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

**2.7 Data collection and processing**

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

**2.7.1 Area**

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

**2.7.2 Transition**

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

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

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

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

**2.8 Statistical analyses**

All data analysis was performed using R statistical software, version 3.5.3 (R Core Team, 2019). All code used is available in Appendix X.

**3. Results**

EXAMPLE MAP

**3.1 LUC visibility within three years following SPE events**

BAR GRAPH NOT DEPICTING MODEL

**3.1.1 SUC**

Within three years following SUC, abandoned land cover significantly decreased (Table 3.1 and Graph), implying a rejection of H1 where abandoned land cover is predicted to visibly increase. Time period explained a very low proportion of the variation within the abandoned land cover data (R2M = 6%). By adding grid as a random effect, a greater proportion of variation observed was explained (R2C = 30%).

EFFECT SIZE GRAPH

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

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

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

**3.1.2 EUA**

Within three years following EUA, abandoned land cover significantly decreased (Table 3.2 and graph), causing an acceptance of H2. Intensive land cover significantly increased within three years following EUA (Table 3.2), allowing acceptance of H2. The time period predictor explained little variation in both land use models, with a slight increase when grid was introduced as a random effect (Table 3.2).

2 X EFFECT SIZE GRAPHS

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

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

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

**3.1.3 Other potential predictors of LUC: location**

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

GRID figure – area of each grid bar graph – other ones in appendix

CELL FIGURE OF WHAT GOING TO WHAT for one land type – other ones in appendix

**3.2 Land use transition visibility within three years following SPE events**

BAR GRAPH NOT DEPICTING MODEL

**3.2.1 SUC**

Within three years following SUC, the amount of intensive land transitioning to abandoned land significantly decreased (Table 3.3 and graph). A negative relationship for this transition rejects H2. Again, the fixed effect explains a very small proportion of variation in the data, with model fit considerably improved when considering grid as a random effect (Table 3.3).

EFFECT SIZE GRAPH

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

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

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

**3.2.2 EUA**

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

**3.3 Time lag on LUC visibility following SPE events**

LINE GRAPH OVER TIME WITH DASHED LINES FOR EACH LAND USE

**3.3.1 SUC**

If the time periods are shifted to allow for a time lag following SUC, all LUCs and transitions are significant (Table 3.4). WRITE WORDS HERE

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

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

**3.3.2 EUA**

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

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

**3.3.3 Breakpoints**

**References**

Albalate, A. & Minker, W. (2013) *Semi-Supervised and Unsupervised Machine Learning: Novel Strategies*, Hoboken, NJ, USA: John Wiley & Sons, Inc.

Alexandridis, T.K., Cherif, I., Kalogeropoulos, C., Monachou, S., Eskridge, K. & Silleos, N. (2013) ‘Rapid error assessment for quantitative estimations from Landsat 7 gap-filled images’, *Remote Sensing Letters*, 4, 920–928.

Arika, E. & Mazure, G. (2017) ‘PROBLEMS AND SOLUTIONS FOR ABANDONMENT OF UTILISED AGRICULTURAL AREAS IN LATVIA’, *Economic Science for Rural Development*, 307–314.

Dougherty, G. (2013) *Pattern recognition and classification: an introduction*, New York: Springer.

Eurostat, E.C. (2013) ‘LUCAS 2012 (Land Use / Cover Area Frame Survey)Technical Reference Document: C-3 Land use and Land Cover Classification (revised)’.

Fonji, S. & Taff, G.N. (2014) ‘Using satellite data to monitor land-use land-cover change in North-eastern Latvia’, *SpringerPlus*, 3, 61.

Gislason, P.O., Benediktsson, J.A. & Sveinsson, J.R. (2006) ‘Random Forests for land cover classification’, *Pattern Recognition Letters*, 27, 294–300.

Gordon, A.D. (1999) *Classification*. 2nd ed., Chapman & Hall/CRC (Monographs on statistics and applied probability, 82).

Gorelick, N., Hancher, M., Ilyushchenko, S., Thau, D. & Moore, R. (2017) ‘Google Earth Engine: Planetary-scale geospatial analysis for everyone’, *Remote Sensing of Environment*, 202, 18–27.

Horning, N. (2010) ‘Random Forests : An algorithm for image classification and generation of continuous fields data sets’, *International Conference on Geoinformatics for Spatial Infrastructure Development in Earth and Allied Sciences*.

Millard, K. & Richardson, M. (2015) ‘On the Importance of Training Data Sample Selection in Random Forest Image Classification: A Case Study in Peatland Ecosystem Mapping’, *Remote Sensing*, 8489–8515.

Murayama, Y. & Thapa, R.B. (eds) (2011) *Spatial Analysis and Modeling in Geographical Transformation Process*, Dordrecht: Springer Netherlands (GeoJournal Library).

Nikodemus, O., Bell, S., Penēze, Z. & Imants Krūze (2010) ‘The Influence of European Union Single Area Payments and Less Favoured Area Payments on the Latvian Landscape’, *European Countryside*, 1, 25–41.

Nomura, K. & Mitchard, E. (2018) ‘More Than Meets the Eye: Using Sentinel-2 to Map Small Plantations in Complex Forest Landscapes’, *Remote Sensing*, 10, 1693.

Pimple, U., Simonetti, D., Sitthi, A., Pungkul, S., Leadprathom, K., Skupek, H., Som-ard, J., Gond, V. & Towprayoon, S. (2018) ‘Google Earth Engine Based Three Decadal Landsat Imagery Analysis for Mapping of Mangrove Forests and Its Surroundings in the Trat Province of Thailand’, *Journal of Computer and Communications*, 06, 247–264.

Prieditis, N. (1993) ‘Black alder swamps on forested peatlands in Latvia’, *Folia Geobotanica et Phytotaxonomica*, 28, 261–277.

Prishchepov, A.V., Radeloff, V.C., Baumann, M., Kuemmerle, T. & Müller, D. (2012) ‘Effects of institutional changes on land use: agricultural land abandonment during the transition from state-command to market-driven economies in post-Soviet Eastern Europe’, *Environmental Research Letters*, 7, 024021.

R Core Team (2019) *R: A language and environment for statistical computing*, Vienna (R Foundation for Statistical Computing).

Sader, S.A., Ahl, D. & Liou, W.-S. (1995) ‘Accuracy of Landsat-TM and GIS Rule-Based Methods for Forest Wetland Classification in Maine’, *Remote Sensing of Environment*, 53, 133–144.

Sidhu, N., Pebesma, E. & Câmara, G. (2018) ‘Using Google Earth Engine to detect land cover change: Singapore as a use case’, *European Journal of Remote Sensing*, 51, 486–500.

Skribane, I. & Jekabsone, S. (2013) ‘Structural Changes in the Economy of Latvia after it Joined the European Union’, *Intellectual Economics*, 7, 29–41.

Strobl, C., Malley, J. & Tutz, G. (2009) ‘An Introduction to Recursive Partitioning: Rationale, Application and Characteristics of Classification and Regression Trees, Bagging and Random Forests’, *Psychological methods*, 14, 323–348.

Suthaharan, S. (2016) *Machine Learning Models and Algorithms for Big Data Classification: Thinking with Examples for Effective Learning*, (Integrated Series in Information Systems).

Vanwambeke, S.O., Meyfroidt, P. & Nikodemus, O. (2012) ‘From USSR to EU: 20 years of rural landscape changes in Vidzeme, Latvia’, *Landscape and Urban Planning*, 105, 241–249.

Verbyla, D.L. & Litvaitis, J.A. (1989) ‘Resampling methods for evaluating classification accuracy of wildlife habitat models’, *Environmental Management*, 13, 783–787.

Veveris, A. & Kalis, I. (2016) ‘The Impact of EU Agricultural Policy on the Competitiveness of the Farms in Latvia’, *Economics and Mangement*, 16, 452–458.

Wulder, M.A., Skakun, R.S., Dymond, C.C., Kurz, W.A. & White, J.C. (2005) ‘Characterization of the diminishing accuracy in detecting forest insect damage over time’, *Canadian Journal of Remote Sensing*, 31, 421–431.

Zanter, K. (2018) ‘Landsat 4-7 Surface Reflectance (LEDAPS) Product Guide’, US Geological Survey.

Zdanovskis, K. & Pilvere, I. (2015) ‘AGRICULTURAL DEVELOPMENT IN LATVIA AFTER JOINING’, *V OLUME*, 8.