A picture containing clipart

Description automatically generated

**THE UNIVERSITY OF EDINBURGH**

**SCHOOL OF GEOSCIENCES**

**TITLE IN CAPITALS GOES HERE**

*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

GEE Google Earth Engine

LUC Land use change

LUCAS Land Use and Coverage Area frame Survey

SPE Socio-politico-economic

SUC Soviet Union collapse

**Introduction**

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

important part of all civilisations due to the provision of natural resources (Foley et al., 2005;

Turner et al., 2007). Human-driven land use change through urbanisation, deforestation and

agricultural expansion has placed pressure on the functioning of several ecological processes

such as carbon cycling, as well as ecosystems themselves (Foley et al., 2005; Turner et al.,

2007). Since 1850, roughly 35% of anthropogenic carbon dioxide (CO2) emissions have

resulted directly from human land use, altering the global carbon cycle (Foley et al., 2005;

Turner et al., 2007). Natural habitat destruction through land conversion is also one of the

largest threats to terrestrial biodiversity, causing extinctions and range reductions (Foley et

al., 2005; Jetz et al., 2007). However, habitat loss such as forest loss and habitat

fragmentation have both proven to also have possible positive effects, including increased

population size (Fahrig, 2017; Daskalova et al., 2018).

Habitat fragmentation and destruction has primarily occurred through changes in agricultural

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

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

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

century that increased global food production (Foley et al., 2005). However, modern practices

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

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

mitigating against the negative effects of land use change (Foley and Ramankutty, 1999).

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

subsistence to intensive agriculture at differing rates, depending on their socio-economic

contexts (Lambin et al., 2001; Foley et al., 2005). However, a study in Ethiopia indicates that

not all countries follow this pattern, as Ethiopia experienced deintensification within a changing

socio-economic environment (Reid et al., 2000). Rapid socio-economic changes are said to

accelerate land use change, with land abandonment rates high with regulation change and

the establishment of new institutions (Prishchepov et al., 2013). Agricultural abandonment,

defined as the cessation of agricultural activities, is linked with a shift towards more intensive

agriculture, with smaller farms more likely to be abandoned (Prishchepov et al., 2013). With

rapid shifts in the socio-economic environment, Latvia proves as an ample study site to

examine the common land use trajectory.

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

events on land use change (Reid et al., 2000; Prishchepov et al., 2012). However,

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

indicates solely the type of land (e.g. water, forest etc.). Algorithms must therefore be

developed to effectively categorise land use types. Such studies (Reid et al., 2000;

Prishchepov et al., 2012) only consider the impacts of one socio-economic event, rather than

several over time. Analysing if the signature of multiple socio-economic shifts can be detected

through land cover change could shed light into the importance of socio-economic events as

drivers of agricultural transitions on a country-scale.

In this study, I will focus on Latvia due to its quick-changing socio-economic status, making it

an appropriate case study to examine if land use change can be linked to socio-economic

events. The two events I will examine are (1) the Soviet Union collapse in 1991 and (2) the

addition of Latvia to the European Union (EU) in 2004. After the Soviet Union, there was an

increase in abandoned land, tree cutting and percent coverage of protected areas

(Prishchepov et al., 2013). After joining the EU, the share of large farms (intensive) increased,

while the share in small farms (extensive) decreased (Csaki and Jambor, 2009). Ultimately,

this type of analysis could be replicated for other countries to outline the impacts of shifting

economic status on land use and thus, have implications for wider aspects such as ecosystem

services, the economy and human movement and urbanisation across Europe and globally.

**Objectives**

This study aims to investigate the importance of SPE events as drivers of land use

change in Latvia through the use of satellite imagery. Although the importance of SPE

events on land use change is acknowledged (Prishchepov *et al.*, 2012), it remains

unclear whether a recognisable, country-scale signature is left on the landscape. Using

satellite imagery, pixel-scale analysis can be completed to determine specific land cover

transitions over time, potentially unveiling a link between socio-economic events and land use

change. My findings will give insight into the homogeneity, or lack thereof, of the effects of

socio-economic events on a country-scale. Results will reveal the transition patterns between

each land use type, including extensive, intensive and abandoned land. Ultimately, my study

will uncover the importance of socio-economic events as a driver of land use change in Latvia,

permitting predictions about land use under changing socio-economic conditions to be made.

**Methods**

To answer my three research questions, I constructed a classification of land use change in Latvia in GEE (SOURCE). My workflow diagram, depicting the key steps to this process, can be seen in Figure 1. All code can be found in Appendix X.

**Figure 1** – Workflow diagram, created on Microsoft PowerPoint.

**Classification background**

A classification is a simple, nonparametric approach to create categorical datasets, such as land cover (Horning, 2010). Classifications group data by specific characteristics through asking binary questions, which compose decision trees (Strobl *et al.*, 2009). With each step of the tree, the classifier asks whether a criterium is met. Random forest classifications are composed of numerous decision trees, creating a forest of trees (Horning, 2010). Each object, such as a pixel, is passed down each of the decision trees to determine which category it falls into. The category, or class, that is predicted most is the class assigned to that pixel (Horning, 2010).

*How do random forests create decision trees?*

Known points of each class are used to develop the decision tree model

There are three key steps to classifications: train, test and validate.

**Training data**

Training data represent the known occurrences of each land use type. Ground-truthed areas train the classifier to help it decide which class to assign areas it has not seen before.

I used the LUCAS dataset (Eurostat, 2012), which contains field data on 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 clearly separates fallow and abandoned agricultural land, whereas previous data combined these two categories. Within R 3.5.3 (R Core Team, 2013), I filtered data to represent each of my land use classes: abandoned land and extensive and intensive agriculture. I also included four other classes (artificial land, wetlands, water and forestry) to improve classification accuracy by causing the classifier to create more precise decision trees (SOURCE). To select which data would form each of my classes, I used the LUCAS 2012 Technical Reference Document, which contains descriptions of each land use and land cover category, as defined by Eurostat. Table X displays the criteria that define each of my classes.

**Table 1 –** Criteria to determine which points from LUCAS (2012) represent each 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. |
| **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. |

Using each point’s latitude and longitude, I transformed each set of points into a spatial file by setting the coordinate reference system, which matched that of GEE for improved accuracy. Points were loading to GEE as assets, meaning that these datasets were saved to my account at all time.

**Random Forest classification**

**Classification accuracy and error**

**Statistical analyses**