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**Abstract**

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**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.

**2. Methods**

To answer my three research questions, I constructed a classification of land use change in Latvia 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.

**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).

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

**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 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 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 classes.

**Table 2.1 –** Criteria chosen to 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. |

Following filtering, coordinates of known locations of each class were obtained. 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 (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). I chose 90-metres, synonymous to three pixels at a 30-metre scale, to ensure that the surrounding pixels of the same type were grouped.

**Image processing**

Landsat 5 Thematic Mapper satellite imagery 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, 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. The additional mask increased average classification accuracy by 4%. I chose summer images, depicting the growing season, to best characterise the spectral signatures of my different classes (Fonji and Taff, 2014). I cropped images to the borders of Latvia and placed a grid over the area in which to extract data from. Lastly, I selected blue, green, red, near-infrared and shortwave infrared band, each having corresponding wavelengths, for my classification (Pimple *et al.*, 2018).

**Random Forest classification**

**Data collection**

**Classification accuracy and error**

**Statistical analyses**

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