Land Use Change analysis of wildfires in Portugal

Relation between land-use change processes and occurrence of wildfires in Portugal between 2012 and 2018

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Abstract

Across the globe, the occurrence of wildfires is becoming a more and more urgent problem. Recently we've seen a number of major scale wildfires greatly affecting both human and non-human habitats and ecosystems. As quality, availability and variety of remote sensing data products increases, studies into analysing natural disasters and land-use change processes are becoming more reliable when studying these processes in greater detail. This study aims to analyse relationships between these phenomena in Portugal.

Portugal is one of Europe's heaviest hit countries regarding wildfires. One of the most recent major wildfire series in Portugal erupted in a central region of the country near Pedrógão Grande in the middle of June, 2017. With 112 casualties it is the most lethal series of wildfires in the history of Portugal.
In this thesis, a case study is performed based on data from the summer of 2017 when these wildfires took place. Also, Corine Land Cover data is used to determine land use change processes in order to be able to conduct a statistical analysis comparing land cover processes from the period 2012 to 2018 and the occurrence of wildfires in June, 2017 and analysing the relationships between them.

The study aims to use Geographic Information Systems and statistical analysis to correlate spatial variables to occurrence of wildfires and in doing so define and explain the parameters and spatial influence of the phenomenon wildfire in Portugal.
It is found that the distance to roads correlates positively to the occurrence of wildfires and the distance to water correlates negatively. These spatial parameters however mostly indicate spatial relevance regarding regional variables being relevant to the occurrence of wildfires. The nature of these regional variables would have to be researched with more scrutiny in future research, to be able to make relevant statements regarding prevention methods and governmental policies.

A lot of the LUC-processes correlate negatively with occurrence of wildfires. However, the "grassland to agriculture" and "grassland to shrub" variables did not show a significant correlation.
Two other dominant LUC-processes, "Shrub to forest" and "forest to shrub", both had negative correlations.
It is possible these land cover types need to be subdivided into more accurate classifications to distinguish these effects accurately. Also, local vegetative types and soil conditions might play important roles in these processes. This would have to be researched further in the future on a regional to local scale.

Content

1 Keywords & abbreviations

CIESIN	Center for International Earth Science Information Network
CGIAR	Consultative Group for International Agricultural Research
CGLS	Copernicus Global Land Service
DEM	Digital Elevation Model
EFFIS	European Forest Fire Information System
FIRMS	Fire Information for Resource Management System
GIS	Geographic Information Systems/Science
LUC	Land Use Change
MODIS	Moderate Resolution Imaging Spectroradiometer
NASA	National Aeronautics and Space Administration
SRTM	Shuttle Radar Topography Mission (NASA DEM project)
VIRS	Visible Infrared Imaging Radiometer Suite

2 Introduction

2.1 Problem definition

The past few decades, major wildfires have been ever so relevant in shaping land-use change processes around the world. As we have seen over the past time with examples such as the fires in the Outback in Australia, the Western coast of the United States of America and the Amazon in Brazil, wildfires can have huge and devastating impacts.
However, it can very realistically be argued that these wildfire occurrences are in fact not unnatural and unhealthy to existing ecosystems, which have been in many cases been thriving on similar conditions for a long time. Richard L. Hutto says the following about wildfire seasons in Western America regarding this subject in his 2008 research for ESA (Ecological Society of America): “severely burned forest conditions have probably occurred naturally across a broad range of forest types for millennia” (Hutto, 2008, p. 1833).
In many ecosystems, wildfires can play a very important role which functions as a collection of managerial impact and driver processes. The occurrence of wildfires can be an important factor across a broad spectrum of influences on adjacent ecosystems and even animal species farther away from the fire source, specially avian species, who can profit from a lot of these factors. Examples of this phenomenon can be found found in West-America within several species of woodpeckers, such as stated in the results of Hutto’s research: “the Black-backed Woodpecker is 16 times more likely to be detected in burned forest than in the next most commonly occupied vegetation type”, (Hutto, 2008).
Additionally, occurrence of wildfires can be a very important driver for nutritional values in ecosystems. Nutritional elements needed by a plethora of organisms such as N, Na, K, Ca and Mg can be provided by occurrence of wildfires better than through other natural means, for example precipitation. Redistribution of such nutrients through smoke can be an important factor in the nutrition cycle for different ecosystems, stimulating depositional processes (Clayton, 1976).
On the other hand, in addition to the discussion about the possible positive effects of wildfires, both on the short and long run, it is becoming increasingly clear that under present global circumstances and climatological conditions combined with current anthropogenic climate change processes (Abatzoglou & Williams, 2016), there are many regions in the world where increase of wildfire burned areas is a very likely scenario, if not a given for the decades to come (Westerling et al., 2011).
Furthermore, certain climates can be specially vulnerable to increasing aridity and increasing drought in the fire seasons. This is also the case in most countries in Southern-Europe, specially Mediterranean climates such as is the case in Portugal. (Sarris et al., 2013).
Also, soil erosion processes can play a big part in occurrence of wildfires and hence create a positive feedback loop, constantly supporting the instigation of larger wildfires during the fire season, also being reinforced by increasing aridity and soil erosion due to intensive agricultural processes (Nunes, Coelho, de Almeida, & Figueiredo, 2010).

Because of these fundamental processes, it should be researched whether this poses newly increased threats to societies and ecosystems around the world and whether governmental policies should be adapted to these issues accordingly. To make a first step in this process, this study aims to find locations which are more prone to fire than others in Portugal and explain this feat using land-use change analysis and spatial variables.

Different methods of prevention measures have been discussed over time and are still a point of debate to this date.
Some argue that we must keep nature and ecosystems in balance by allowing the fire to roam free as much as possible while limiting hazards, sometimes even by controlling biomass levels through instigating small-scale wildfires as a regulating policy (Hoofdredactie, 2020).

However, before jumping to conclusions about prevention and mitigation measures, one should gain a significant understanding of driving factors when it comes to occurrence of wildfires.
It could be a great benefit for decision-making policies and landscape-planning if we gain better insight in the causes and effects between Land-Use Change (LUC) on one hand and occurrence of wildfires on the other (Carmo, Moreira, Casimiro, & Vaz, 2011).
Through this research we want to gain insight in the relation between LUC and occurrence of wildfires. This means we will ask ourselves the question whether there's a relation between land use change between timestamps X and Y and occurrence of wildfires in a specific case. The specific case which is used in this research is the series of wildfires during June 2017 in central Portugal.
This can be an interesting factor in the development of wildfire analysis and policy and decision-making processes which follow. This way, we can research the ways we can influence future LUC constituted by wildfires positively for societies, local communities, ecosystems and animal habitats.
Thus, this leads us to our main research question:
'Is there a relationship between land-use change and occurrence of wildfires in Portugal?'

2.2 Research questions

Our main research question: 'Is there a relationship between land-use change and occurrence of wildfires in Portugal?'
This research question will be sub-divided into multiple sub-questions which we will answer throughout the research.
The following sub-questions are composed:

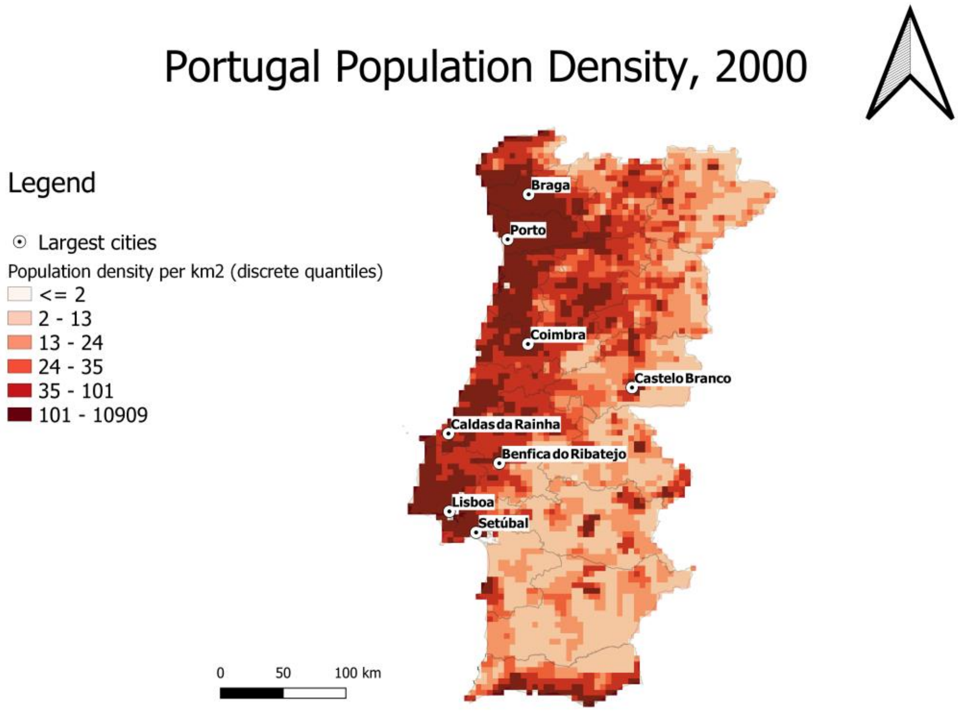
- What is the scale of the wildfires supposedly constituted by Land-Use Change?
- What are the affected regions of the wildfire in Portugal of June 2017?
- Are there land-cover activities which influence Land-Use Change?
- What are the most heavily affected land-cover classes?
- What are the most important spatial variables regarding occurrence of wildfires?
- How can those spatial variables be interpreted?

3 Study area

Portugal is a Mediterranean European country and largely has a Mesomediterranean climate, which includes moderate temperatures, plains combined with hills and mountainous areas and different types of forest (Mariotti Lippi, Mercuri, & Foggi, 2018). There are around 10,2 million inhabitants in the study area ('Portugal Population (2020) - Worldometer', 2020). Lots of this population is clustered around the coastal cities as can be seen in map 1.

Portugal has a reasonable amount of arable land and about 40% of the Portuguese land is classified as Utilised Agricultural Area ('Archive:Agricultural census in Portugal - Statistics Explained', 2010).

From 2000 to 2010, this percentage decreased with 5%. Abandonment of agricultural land is not uncommon.



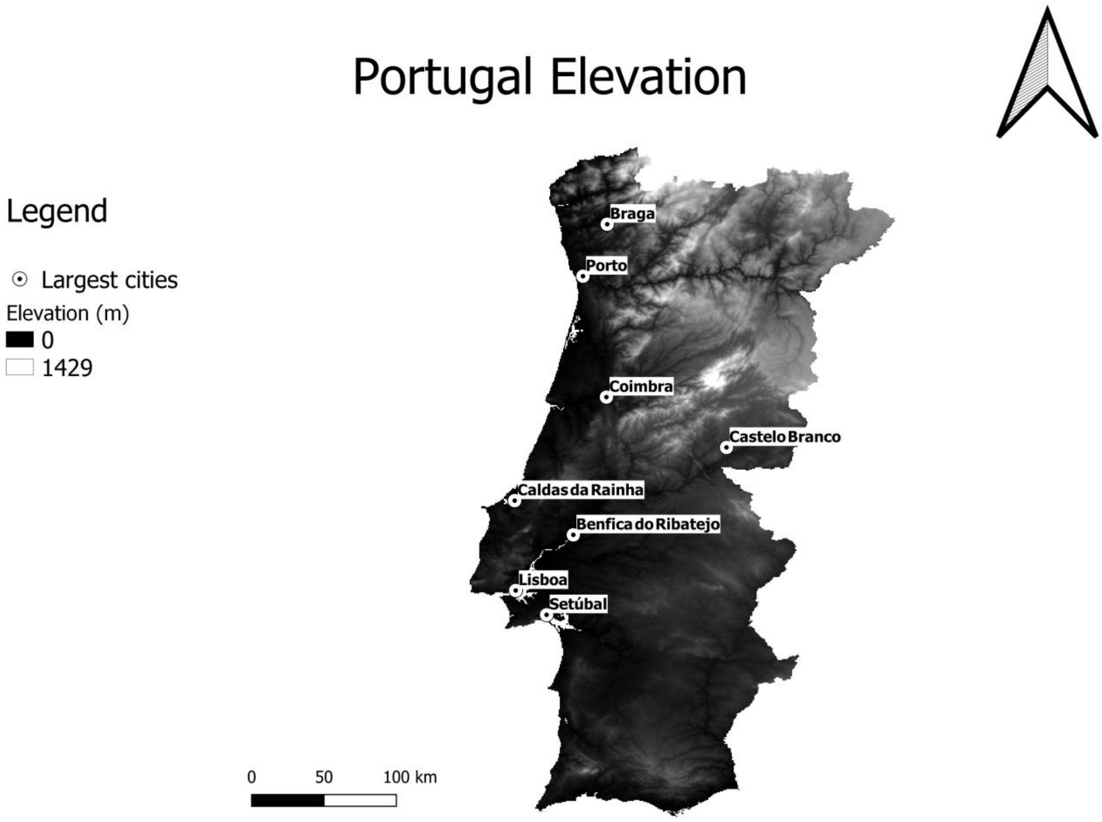
Map 1: Portugal population density 2020

Due to Portugal being a coastal country, the average climate is fairly temperate. However, local differences exist. Generally, the summers are quite hot and dry and during the winters Portugal enjoys a somewhat wetter climate due to the maritime conditions (Portugal live, 'Climate', 2020). The mountainous areas, especially in the north, are cooler on average.

Geographically speaking, there are some noticeable features about the Portuguese landscape. There are not many rivers and deltas, but some major rivers do cross the landscape, providing the inlands with humidity and providing moisture for soil conditions required by vegetative land covers.

On Portugal's mainland, the altitude of the different peaks are not very high for a mountainous area. Most of the mountains are situated in the central and Northern parts of Portugal, as can be seen on map 2. The highest peak is the Torre in the Serra da Estrela mountain range, with an altitude of roughly 1900 meters above sea-level (Portugal live, 'Physical Geography', 2020).

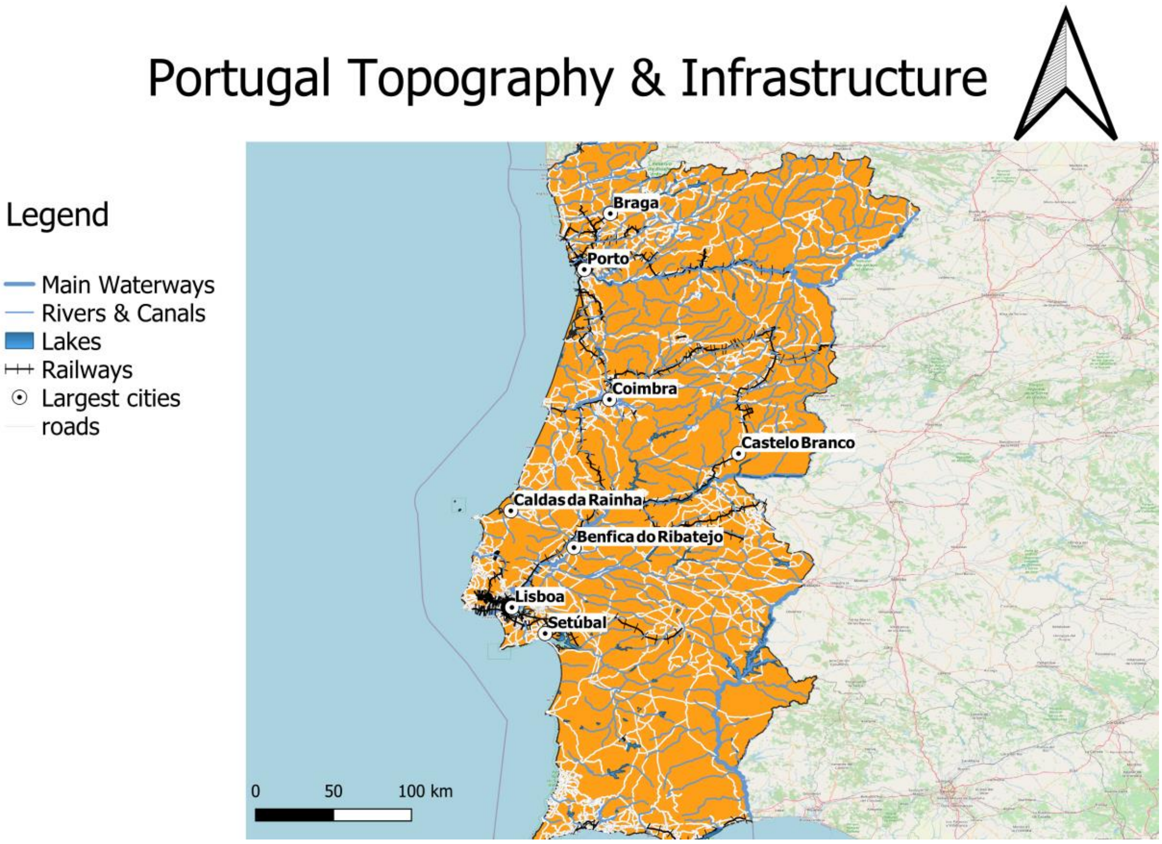
These mountainous inland areas are also filled with a reasonably dense river network. Most of these rivers originate in Spain and flow towards the Atlantic ocean, as can also be seen on map 3.



Map 2: Elevation levels Portugal

The southern parts of the country are more characterised by plains and intensive agriculture such as vineyards, olive trees and figs (Portugal live, ‘Physical Geography’, 2020).

Since the slope is not as high in the southern regions, most of the rivers in central and Northern Portugal have a bit of more ‘chaotic’ structure and often form a more dense river-network than in the south where large rivers have the space to meander.



Map 3: Portugal topography 2020

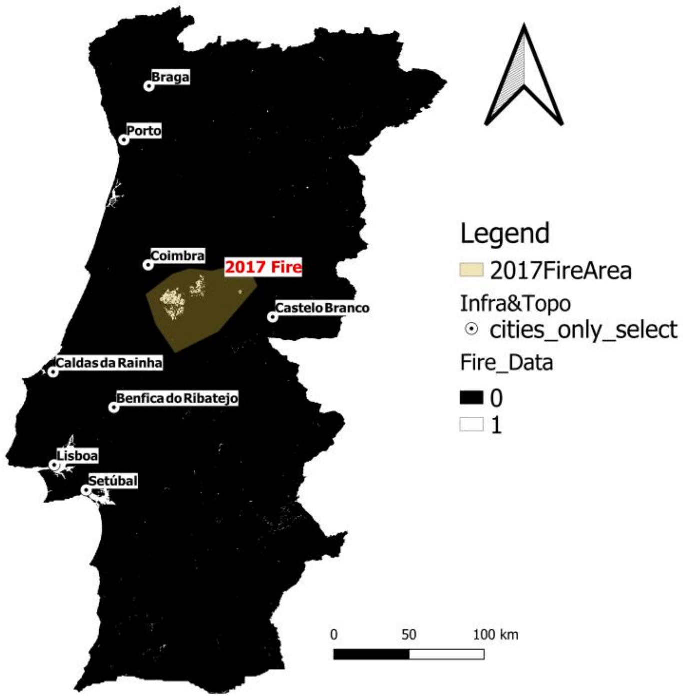
3.1 Case study

In this study where we research the relationship between land-use change processes and wildfire occurrence, a specific case study is chosen to base our LUC-analysis and statistical analysis on.
This specific case is the series of wildfires that took place in the central regions of Portugal in the summer of June, 2017, near Pedrógão Grande (see map 4).
During these fires, a number of at least 112 people died either as direct result of the fires or due to health implications caused by indirect consequences of the wildfires, making it the most lethal wildfire in Portugal's recorded history (Viegas, 2018, p. 1).

Graphic 1: 2017 fires in Portugal

During these wildfires, an estimated 500,000 hectares of land was burned. As comparison: this is about equally as much burned area as the average land burned in entire Southern Europe during the yearly fire season (Turco et al., 2019).
The wildfires erupted during rather exceptional local weather conditions; Portugal was in the middle of a lengthy heat wave, with temperature surpassing 40 degrees Celsius and a relative air humidity under 20% (Viegas, 2018, p. 1). Research has later shown that these high temperatures and dry conditions have indeed been important factors during the outbreak of these wildfires (Turco et al., 2019, p. 3)

There were also factors which supported the rapid spreading of the fire besides the unusually dry conditions, namely a strong and dry southern wind, a tempest named Ophelia (Viegas, 2018), which stirred up the flames and carried sparks over long distances, creating new ignition hotspots. The report by Viegas for the University of Coimbra, ascribed the dramatic proportions of the series of wildfires to "socio economic changes in land use", and other factors such as human management of the region, failing policies and climate change. These factors are all very relevant to this study. According to this report, over 90% of wildfire occurrences can be traced back to human activity.



Map 4: 2017 wildfires Portugal

4 Data description

To conduct this research and perform our different analyses, different data products must be inquired. The needed data is then extracted and imported into a GIS (QGIS, ArcMap), to be able to visualise and the data work with the data.
The data was then integrated into the GIS and from there on the necessary modifications and analyses were conducted as will be explained further on in the methodology section.

The data used for this study can be roughly divided into three categories:

1. Land Cover data, to determine and analyse land use change processes.
2. Fire data to, to correlate with LUC processes and to perform spatial analysis with.
3. Spatial variable data, used for the spatial variable analysis and correlation with occurrence of wildfires.

The different data products and their properties are given in the table below.

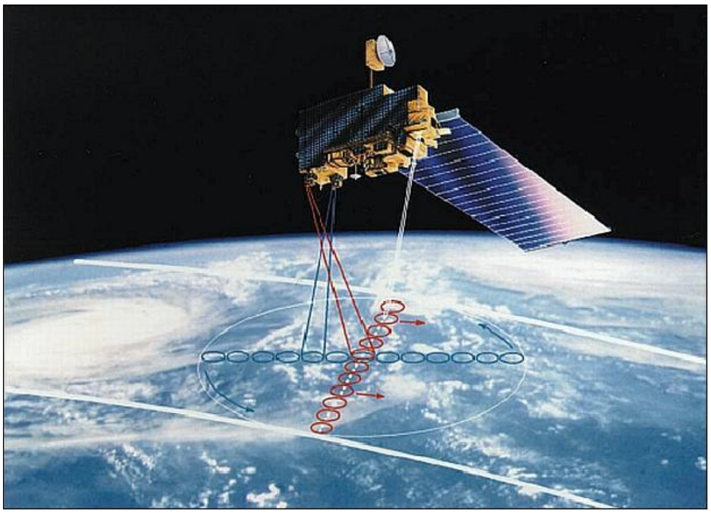
Category	**Data**	**Type**	**Source**	**Resolution**
1	Corine Land Cover 2018	Raster	CGLS	100m
1	Corine Land Cover 2012	Raster	CGLS	100m
2	Active Fire Data	Raster	MODIS	1km
3	Roadways	Vector (line)	Digital Chart of the World	-
3	Railroads	Vector (line)	Digital Chart of the World	-
3	Elevation	Raster	CGIAR SRTM	30 seconds (~1km2)
3	Population density 2000	Raster	CIESIN	30 seconds (~1km2)
3	Avg. Temperature C 1970-2000	Raster	WorldClim	2.5min (~21km2)
3	Places/settlements	Vector (points)	Openstreetmap.org	-

3	Waterways	Vector (lines + polygons)	Digital Chart of the World + Openstreetmap.org	-

Table 1: used data products and properties

4.1 Fire data

For the data on fire detection, we can choose from different datasets.
The data product which was chosen for this study is the active fire detection dataset (MOD14).
This dataset is derived from the MODIS product, which stands for Moderate Resolution Imaging Spectrometer ('Active Fire Data | Earthdata', 2020).
This instrument was issued by NASA (National Aeronautics and Space Administration) and operates from the Terra and Aqua spacecrafts ('MODIS Web', 2020).
Its spectral range lies between 0.405 and 14.385 µm. Different resolution of the MODIS data are available, up until 250m, but for this study the 1km resolution dataset is used.
This data product is chosen because it is one of the most consistent datasets that is available and also because its detection methods are deemed the most appropriate and accurate for this type of research.



Graphic 2: NASA's Terra sattelite

Rather than with other data products, the Active Fire Data set classifies a cell as being an active fire or not based on remote sensing imagery processed by the imaging spectrometer. The burned area data set for example, classifies cells differently, based on whether more than 50% of the cell is sensed as 'burned' ('MODIS Web', 2020). However, we are more interested in the occurrence of wildfires themselves and not land classified as burned areas (which are already classified within the Corine Land Cover data product as well) and therefore it is believed the Active Fire Data product is the most suitable for this study.
This dataset is a binomial dataset, which means that if a cell is classified as active fire, the value 1 is assigned and otherwise the value 0 is assigned to the particular cell.

4.2 Land-use data

To be able to distinguish different types of land cover within our study area and thus be able to execute the land-use change analysis, a dataset with different land use classifications is needed. For this purpose, the Corine Land Cover data products of 2012 and 2018 are used.

The Corine Land Cover dataset is a product which also consists out of data acquired from remote sensing sensors. Therefore, the availability and consistency is relatively good as data is constantly available through the Copernicus portal (‘CORINE Land Cover | Copernicus’, 2020).

Source sensors have changed over time since the launch of the Corine Land Cover project. The dataset for 2012 was created using captured data from the ‘IRS P6 LISS III’ and ‘RapidEye dual date’ satellites.

The dataset for 2018 was created using captured data from the Sentinel-2 and Landsat-8 satellites. While these are different sensors and thus different methods of creating these data products where applied, both datasets have a geometric accuracy that’s better than 100m, a thematic accuracy over 85% (generally perceived as ‘good’ data quality) and have a resolution of 100m (‘CORINE Land Cover | Copernicus’, 2020). As these aspects of the datasets are congruent it is believed that it can be justified to use these datasets as reference for a land-use change analysis.

5 Methodology

The main components of the research for the analyses are the GIS based land-use change analysis and a statistical analysis (with SPSS) to perform logistic regression to gain insight in the spatial variables and the correlations of those variables with the binomial value, which represents the occurrence of wildfires in Portugal during June, 2017.

To analyse and determine the change in land cover and its most notable properties, a GIS-based analysis was constituted using QGIS and ArcMap. The advantages of GIS (Geographical Information Systems) are that data sets are allowed to be compared in a structured manner. This means we can aggregate and transform data in ways that are suitable to the study at hand.

The results derived from the first part of the GIS analysis will play a significant role in approaching the answer to our research question. Through mapping and visualising the land use change over a longer period of time we are enabled to investigate the relationship between occurrence of wildfires and land-use change.

To look into what factors decide whether a location is more correlated with active fires, we will be testing the correlations between land-use change processes and occurrence of wildfire.
After all the required data is processed and collected in our GIS, the different analysis-steps can start being executed.

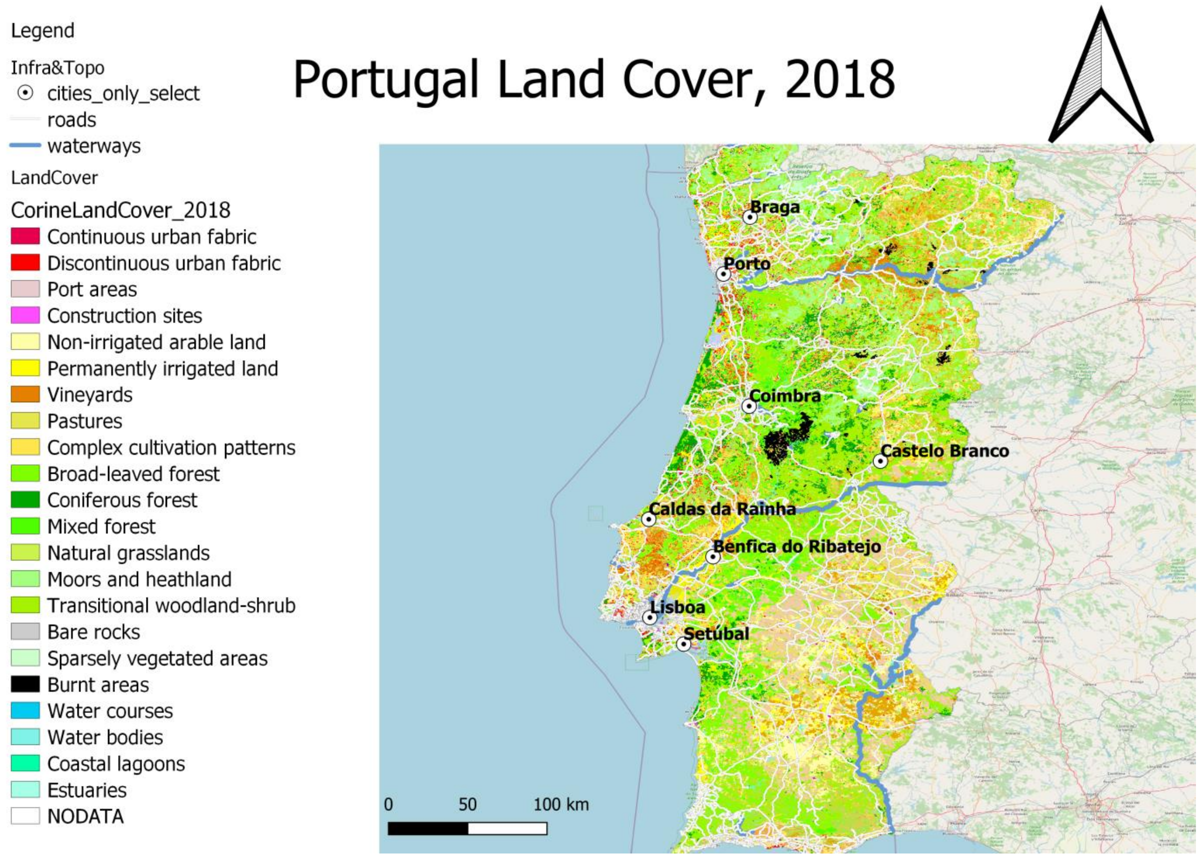
5.1 Land-Use Change analysis

Firstly, a land-use change analysis will be conducted using the Corine Land Cover data (2018). This is done because we need to gain insight in which processes are the most prevalent and the most dominant within our study area.

We will do this by reclassifying the needed classifications and creating a transition table. The original Corine Land Cover data product contains 44 different classes (see map 5), which is not very suitable for our analysis. Therefore, this reclassification is needed.

To perform the reclassification, firstly a table is created which contains the old values with their corresponding land cover types and the new groups of land cover types into which the old classes are converted, also with their corresponding new values (see table 2).

To execute the reclassification, the *reclassify by table* QGIS tool is used. Then, the reclassification table we made is used in this tool. Once executed, the result will be a map with only 10 land cover types, as seen in map 6.



Map 5: Portugal, Land cover CLC 2018

After reclassification we want to be able to determine how much land cover types transitioned from the initial CLC 2012 data set compared to the most recent CLC 2018 data set.

To do this we use the Raster calculator tool and apply the following expression:

$$Equation\ 1 \qquad Raster\ value = \text{land cover 2012} * 10 + \text{land cover 2018}$$

From this we will get a classified values ranging from 11 to 111, defining which land use type from 2012 transitioned to which land use type in 2018.

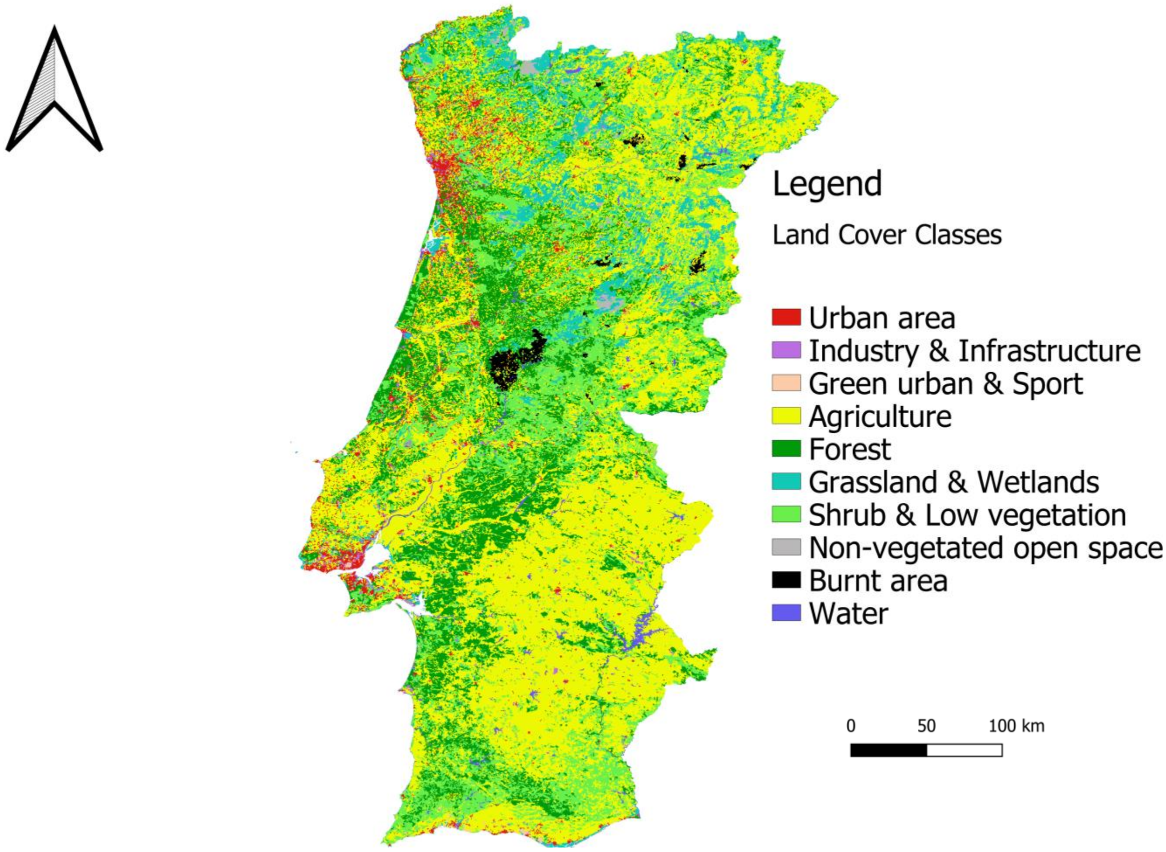
Once we have this transition map, we can define different land-use change processes between 2012 and 2018 and quantify them. To do so, a transition table and matrix will be made. These transitions represent the changes in land-use that are classified by the Corine Land Cover data products between 2012 and 2018.

These results can be found further on in the results section.

Reclassification table			
Old Values*	Old Land Use Classes	Reclassified Land-Use Classes	New values
1 / 111	Continuous urban fabric	Urban area	1
2 / 112	Discontinuous urban fabric		
3 / 121	Industrial or commercial units	Industry & Infrastructure	2
4 / 122	Roads and rail networks		
5 / 123	Port areas		
6 / 124	Airports		
7 / 131	Mineral extraction sites		
8 / 132	Dump sites		
9 / 133	Construction sites		
10 / 141	Green urban areas	Green urban & sport	3
11 / 142	Sport and leisure facilities		
12 / 211	Non-irrigated arable land	Agriculture	4
13 / 212	Permanently irrigated land		
14 / 213	Rice fields		
15 / 221	Vineyards		
16 / 222	Fruit trees and berry plantations		
17 / 223	Olive groves		
18 / 231	Pastures		
19 / 241	Annual crops		
20 / 242	Complex cultivation patterns		
21 / 243	Land principally occupied by agriculture		
22 / 244	Agro foresty areas		
23 / 311	Broad leaved forest	Forest	5
24 / 312	Coniferous foest		
25 / 313	Mixed forest		
26 / 321	Natural grassland	Grassland & Wetland	6
27 / 322	Moors and heathland		
28 / 323	Sclerophyllous vegetation	Shrub & low vegetation	7
29 / 324	Transitional woodland shrub		
30 / 331	Beaches, dunes and plains	Non-vegetated open space	8
31 / 332	Bare rock		
32 / 333	Sparsely vegetated areas		
33 / 334	Burnt areas	Burnt area	9
34 / 335	Glaciers & Perpetual snow		8
35 / 411	Inland marshes	Grassland & Wetland	6
36 / 412	Peat bogs		
37 / 421	Salt marches		
38 / 422	Salines		
39 / 423	Intertidal flats		
40 / 511	Water courses	Water	10
41 / 512	Water bodies		
42 /521	Coastal lagoons		
43 / 522	Estuaries		

44 / 523	Sea and acean		

Table 2: Land cover reclassification table



Map 6: Portugal, CLC 2018 reclassified

5.2 Spatial variable analysis

A binary logistic regression analysis will be performed to estimate the correlations with several spatial variables we have selected for further investigation.

Before we can move on to the statistical analysis, we have to combine the spatial distribution of wildfire occurrence in Portugal during June 2017 with the data of spatial variables.

Researching geographically related phenomena by relating in this case land-use change processes to explicit spatial variables can be very effective way to perform such a GIS-based analysis which makes use of remote sensing data. This is for example also done in a 2002 research regarding the Zhujiang delta in China (Weng, 2002). This is a relevant comparison to this study because similar processes are studied and similar data processing strategies are applied here.

For this study, the following spatial variables are composed:

#	Spatial variables	Type
1	Distance to roads (degrees)	Continuous
2	Distance to water (degrees)	Continuous
3	Average temperature (degrees Celsius)	Continuous
4	Elevation (km)	Continuous
5	Agriculture	Binomial
6	Population density (per km2)	Continuous
7	*Land-use change:* Forest to shrub (57)	Binomial
8	*Land-use change:* Shrub to forest (75)	Binomial
9	*Land-use change:* Grassland to agriculture (64)	Binomial
10	*Land-use change:* Grassland to shrub (67)	Binomial

Table 3: Spatial variables

Some explanation is needed for some of these variables. The distance to roads and waterways was calculated using Euclidean distance. However, since the units of the original datasets were in geographical degrees, the distance is measured in this unit.
The elevation data is originally in meters and is converted into kilometres for the sake of our statistical analysis, since this range is more appropriate for the regression analysis. To do this, the *raster calculator* tool is used, with the following expression:

$$Equation\ 2. \qquad Raster\ value = \frac{Elevation}{1000}$$

The agriculture variable represents whether a cell is occupied by the land cover type agriculture or not.
The land-use change variables each represent different land cover transitions in the period 2012-2018, with their transition values from the created transition map noted for each variable.

To assign the data of these variables to geographically referenced points, the raster dataset of the active fire data product is converted into a point dataset using the *Raster to points* tool. This renders 1078956 different data points.
A lot of the spatial data such as temperature and elevation is originally found in an CRS (Coordinate Reference System) unique to this area of Europe, and therefore has to be transformed before we can use this data and combine it into our point data file.
To do this, the *Warp (reproject)* tool was used, to convert these raster files from their original projected CRS to the standard CRS used in GIS, the WGS 84 Mercator projection. When all the spatial raster data is in the correct CRS, this data can be used in further steps. Following, the spatial variable data is aggregated into the point file we created (the roughly 1 million points) by using the *Add raster values to points* tool.

This way we have created a point file that contains each registered cell by the original active fire data product which now contains not only the 1 and 0 values, but also the respective spatial variable data (elevation, temperature, etc.)

5.3 Statistical analysis

In order to perform the statistical analysis, the data needed for this process is exported from our GIS. The aggregated point data file is exported in dBase format, to be imported into SPSS for the final statistical analysis.
Once the required dataset (the ca. 1 million points with assigned spatial variable data) is imported into SPSS, some measures have to be taken relating to the data quality.

To estimate the correlations between the spatial variables, the land-use change processes and the occurrence of wildfire in Portugal during the month of June, 2017, a binary logistic regression is made. This is done because we want our model to predict whether a cell will be assigned a 1 or a 0 value (active fire or no fire) depending on the data found in our spatial variables. Because the active fire data product is binomial in nature, a binary logistic regression is performed.

Before this regression is performed however, to get the best results, variables that correlate too strongly with each other should be excluded from the regression analysis. To perform this exclusion, a bivariate correlation analysis is run on our dataset (see Appendix 1).

After any unwanted variables are excluded, some of the outliers, missing data and other errors are to be removed from the dataset. To do this, we select outlying values based on the standard deviation and deselect those values. They will not be taken into account during the binary logistic regression analysis.

Finally, the binary logistic regression analysis is executed. Any insignificant variables can be removed. The final results are given in the following section.

6 Results

6.1 Land-Use Change results

Firstly, the results of our land-use change analysis are presented. After the reclassification (see table 2), the cell counts are given for each reclassified land cover type. Since the resolution of the Corine Land Cover dataset is 100m, 1 cell equals 1 Ha. Next to the count, the percentage of total land cover is given. As can be seen in table 4, agriculture is one of the most dominant land cover types, taking up roughly 47% of the Portuguese land.

In the final column, the transitional values are presented. These values are found with the following expression:

$$Equation\ 3. \qquad Transition\ value = 2018\ count - 2012\ count$$

Here, the percentages of total land cover are given as well.

Land-Use Change Transition table

	2012		2018		2018-2012	
Class	Hectare	%	Hectare	%	Hectare	%
1 – Urban area	262363	2.86%	263196	2.86%	833	0.01%
2 – Industry & Infra	82192	0.89%	83885	0.91%	1693	0.02%
3 – Green urban & Sport	17504	0.19%	18168	0.20%	664	0.01%
4 – Agriculture	4405374	47.95%	4404837	47.94%	-537	-0.01%
5 – Forest	1921318	20.91%	1713077	18.65%	-208241	-2.27%
6 – Grassland & Wetlands	606841	6.60%	601856	6.55%	-4985	-0.05%
7 – Shrub & Low vegetation	1717455	18.69%	1874066	20.40%	156611	1.70%
8 – Non-vegetated open space	61042	0.66%	61051	0.66%	9	0.00%
9 – Burnt area	20565	0.22%	69728	0.76%	49163	0.54%
10 – Water	93141	1.01%	97930	1.07%	4789	0.05%
total	9187795	100%	9187794*	100%	-	-

Table 4: Transition table

LUC Transition matrix Portugal 2012-2018											
		Land-use 2018									
		1- Urban area	2 - Industry & Infra	3 - Green urban & sport	4- Agri-culture	5 - Forest	6 - Grassland & Wetland	7 - Shrub & low vegetation	8 - Non-vegetated open space	9 – Burnt area	10 - Water
Land-use 2012	1 - Urban area	99.97%	0.01%	0.00%	0.01%	0.00%	0.00%	-	-	-	-
	2 - Industry & Infra	0.11%	98.46%	0.35%	0.15%	0.16%	0.24%	0.32%	-	-	0.21%
	3 - Green urban & sport	0.18%	-	99.57%	0.26%	-	-	-	-	-	-
	4 - Agriculture	0.01%	0.02%	0.00%	99.53%	0.06%	0.05%	0.24%	-	0.02%	0.06%
	5 - Forest	0.01%	0.05%	0.01%	0.31%	85.15%	0.12%	12.62%	0.00%	1.70%	0.03%
	6 - Grassland & Wetland	0.01%	0.03%	0.00%	0.73%	0.06%	96.74%	0.64%	0.00%	1.65%	0.13%
	7 - Shrub & low vegetation	0.01%	0.04%	0.00%	0.54%	4.25%	0.10%	93.48%	-	1.52%	0.05%
	8 - Non-vegetated open space	-	0.00%	-	0.01%	-	0.02%	0.04%	99.93%	-	-
	9 – Burnt area	-	0.03%	-	0.18%	3.73%	40.89%	55.01%	-	0.15%	-
	10 - Water	0.01%	-	-	0.07%	0.01%	-	-	-	-	99.91%

Table 5: Transition matrix

From the transition table (see table 4) this transition matrix can be created.
Equation 1 is used to calculate the different land cover type transitions during the period 2012-2018.
From this matrix, the most important/dominant land-use transitions can be derived. This matrix was used to determine the spatial variables in relation to land-use change processes used in our statistical analysis (see table 3).
Also, from this matrix can be seen how much of which land-use class is converted into ‘burned area’ between 2012 and 2018, most of which is the result of the wildfires from 2017.

6.2 Statistical results

After testing the inter-correlations of the different variables using bivariate correlation analysis, the spatial variable temperature was excluded from the model. However the correlation with elevation is not that high anymore after converting elevation from meters to kilometres, the temperature variable still does not perform well in the regression model and is thus excluded. Also, the elevation variable fulfils this role nicely, so the temperature variable is not really missed in the model.

Neither the 'Grassland to agriculture' or the 'Grassland to shrub' variables showed significant correlations in the regression analysis and were therefore also excluded from the final model. Other outliers or nonsense values (error values) in variables were deselected as to make the regression perform somewhat better.

In the month June of 2017, the MODIS Active Fire data product classified 3120 out of 1078956 points as active fires (see table 6). In this classification table can be seen that the model performs fairly well now.

Table 6: logistic regression classification table

Classification Table[a]

Observed			Predicted Value_Fire .0000000000	Predicted Value_Fire 1.000000000	Percentage Correct
Step 1	Value_Fire	.00000000000	1075833	0	100.0
		1.00000000000	3120	0	.0
	Overall Percentage				99.7

a. The cut value is .500

In the next figure (see table 7) the final estimated equation is given by the binary logistic regression model. The B column represents the Beta coefficients, which signify the correlation of the particular variable with the dependent variable, namely occurrence of wildfires.

The Sig. column represents the P-values. Essentially, if the P-value is lower than 0.05, the correlation can be considered significant. As can be seen from 7 all of the included variables have significant correlations.

Table 7: logistic regression variables

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Population	-.004	.000	114.055	1	.000	.996
	Roads_Dist	8.777	.296	881.724	1	.000	6483.865
	Water_Dist	-4.853	.764	40.385	1	.000	.008
	Agriculture	-2.450	.070	1210.607	1	.000	.086
	Forest_Shrub	-2.339	.268	76.151	1	.000	.096
	Shrub_Forest	-2.605	.578	20.325	1	.000	.074
	Elev_km	.274	.060	20.683	1	.000	1.315
	Constant	-5.421	.045	14314.847	1	.000	.004

a. Variable(s) entered on step 1: Population, Roads_Dist, Water_Dist, Agriculture, Forest_Shrub, Shrub_Forest, Elev_km.

7 Discussion

In this part we will discuss the findings of the results and how we got there, try to interpret them correctly and leave room for incentives for further research in the future. To do this we need to identify and clarify some limitations and implications our research has, for example regarding the data products that are used. Also it is discussed what would need to change or be enhanced in the future for those limitations to be diminished and for more conclusive results about local land-use types and their correlations to occurrence of wildfires to be found.

Also, some statements are made about possible follow-up governmental policies and land shaping decision-making concluded from the found results and the consulted literature.

7.1 Assumptions and limiting factors

As discussed before in the data section, most of the satellite imagery used for the analyses has a resolution that is quite good. Also the data quality of the Corine Land Cover and Active Fire data products is considered to be good. However, some of the raster data used to define topographical and spatial variables such as elevation, temperature and precipitation have been aggregated from their original satellite resolution into data products for the sake of usability (DIVA-GIS, 2020).
This could possibly reduce the original resolution of the data products and thus affect the quality of the data which could influence the outcomes of the analyses performed with it. Furthermore, within the general field of climatology and wildfire data, one of the main implications is the limited access to data records. Most of the researched processes play out over a very large time span, which makes it hard to derive significant conclusions from this data regarding longer-term processes. It is possible to analyse processes such as influence of wildfire occurrence on land use change on a shorter time span but within this scientific field it can be hard to relate the outcomes to processes which span a way larger time-scale than the availability of global satellite data can cover in a significant manner.

Also, some of the data is not perfectly up to date, such as the population data product which is from 2000. The climate data used from WorldClim, the average temperature and the average precipitation are also averaged over a longer period of time (1970-2000) and do not account for possible climate change in recent years, which could cause some inaccuracies as well.

Another limitation is that for some of the data sets that we used to define the spatial variables for the statistical analysis, the nature of those data sets is not optimal. For instance, the climatology data acquired from WorldClim (Fick, S.E. and R.J. Hijmans, 2017) contains the data product for average temperature that we used. This is however a historical monthly data set which contains monthly data over a wide temporal range, namely 1970-2000. Therefore the actual temperature data from the period in 2017 containing the examined wildfires is not available for this study. This could be a significant limitation, since the wildfires in Portugal of June 2017 were accompanied by unusual weather conditions (Turco et al., 2019, p. 3). This could be one of the reasons the spatial variable temperature had such a low coefficient outcome in our results.

7.2 Result interpretations

First of all, some choices had to be made regarding the statistical analysis used to estimate the correlation coefficients for the different spatial variables relating to the measure points as mentioned in the results section.
After looking into the results from the SPSS analysis, the following choices were made:

- The 'Grassland to agriculture' and 'Grassland to shrub' variables did not show a significant correlation with occurrence of wildfires. Their P-values were around 0.9, where a P-value of 0.05 or lower would be required for the correlations to be significant, assuming $\alpha = 0.95$. They were therefore excluded from the regression. It is to be questioned why these land-use change process variables did not return a significant correlation. Possibly still too few values were found for those variables across the entire dataset that was analysed. Another explanation is that those classifications are too broad and thus no significant effect could be found.
- The temperature and elevation variables showed a rather strong interdependent correlation after performing a bivariate correlation analysis. The correlation between temperature and elevation was way higher than correlations between other spatial variables. The rule of thumb is applied here that whenever correlation between variables is greater than 0.5, one has to be cautious of using this variable in a regression model. Since these correlations approached 0.7, the temperature was left out of the binary logistic regression model and only the elevation variable was used.

Next we will look at the correlation coefficients of the spatial variables:

- The strong positive correlation with distance to roads does make sense for this case study, since the area of the wildfires of 2017 was fairly secluded from the road network.

- Also, the strong negative correlation with distance to water could be explained due to the fact that streams and waterways form a more dense network within the central inland mountainous regions of Portugal, where the wildfires of 2017 took place. Thus, cells in this area are less likely to be far away from water.

- The negative correlation with population is probably due to the fact that mainly inland regions were affected by wildfires in 2017 and those regions are less densely populated

- The positive correlation with elevation also points out that mainly mountainous regions were affected by the wildfires in 2017

7.3 Governmental policies

In the course of this study, focus was set on LUC processes and the way they correlate with occurrence of wildfire. Therefore, little can be said in terms of conclusive results regarding political and socio-economical aspects of correct measures and policies to implement, when taking into account the researched relationships between LUC and wildfires.
However, based on the results of the analyses and consulted literature, some important notions can be stated about several different directions of governmental policies.

- Land abandonment might be a policy to consider, "… land abandonment followed by regeneration of the natural vegetation can result in exponential decreases in both runoff and sediment loss (Nunes, Coelho, de Almeida, & Figueiredo, 2010)

  "After abandonment, soil properties such as the organic matter content, soil structure and infiltration rate are improved, resulting in a more effective protection for the soil against erosion" (Nunes, Coelho, de Almeida, & Figueiredo, 2010., Kosmas, Danalatos, & Gerontidis, 2000).

  Unless future research offers a wider range of maintenance and control options making use of knowledge about vegetation types and local soil and climate conditions, land abandonment could be a viable short-term option to reduce fire-hazard.

- As mentioned in the Viegas report (Viegas, 2018, p. 1), there is no research programme regarding the monitoring of wildfires within the European Union. Such programmes are often organised nationally and focus on suppression instead of prevention and adaptation. The initiation of such a programme in the EU could be a possible scenario for the future.

- There are already some governmental policies which were initiated in Portugal after the 2017 fires, such as a Government Agency. The goal of this Agency is to monitor wildfire and fire seasons and to coordinate and manage certain issues relating to wildfires in Portugal (Viegas, 2018). However, these policies are not aimed towards taking measures which will tackle and solve problems on the long run, but rather suppressing and minimising damages.

Furthermore, it is mentioned that local governmental institutes should promote interaction with local population and communities, since most of wildfires in Portugal are derived from human interactions with their surroundings. To achieve this, a policy-shift is needed in regards to current decision-making processes within these organisation (Moreira, 2020)

7.4 Future research

To be able to gain better understanding of the influence of LUC prior to the occurrence of wildfire and the significance of these variables causal components, a more intensive analysis should be conducted which aims takes into account larger and more detailed collections of LUC classifications. Also data with more appropriate temporal ranges should be used for such a research.

If research and monitor programmes could be launched in the future that do not limit themselves to nation boundaries or the needs of very specific regions, possibly more productive research could be conducted while preferably making use of interdisciplinary expert knowledge and highly consistent data flows.

8 Conclusion

From our study can be concluded that while significant land-use change is constituted through the occurrence of wildfires, there is also a relationship between land-use change prior to wildfire occurrence and active fires.

In this study the entire area of Portugal was transposed through the raster file of the active fire dataset into ca. 1 million points, which were tested for these correlations between first land-use change, second occurrence of wildfire. When researching the occurrence of wildfire, it is to be taken into account that land-use practices are regarded to be one of the main drivers of this phenomenon (Mateus & Fernandes, 2014).

However, causalities are hard to determine and there are numerous uncertainties and limitations when it comes to spatially analysing wildfire occurrence, especially in a (regional) case study. Also, when correlating these parameters it is hard to interpret direct relationships between occurrence of wildfire and spatial variables because local variety in different factors such as soil conditions and climate can play a big role.

These uncertainties and limitations are for example due to the fact that there are many local climate and weather variabilities that influence the occurrence of wildfire and they can thus affect the way a certain land-use type correlates with active fires. It is also hard to define and understand these climate variabilities as they can change under extreme conditions, as is often the case with unique natural disasters such as the wildfires of Portugal in June 2017, which was researched for this case study. A second reason these factors are hard to be modelled and taken into account during spatial variable analysis, is that availability of this type of data is often limited and sometimes not available in the needed temporal range or a sufficient resolution.

8.1 Relation between Land-Use change and occurrence of wildfires

It is evident that wildfires play a major role in forming landscape and thus affecting and altering land cover types and land-use practices. Between the years 2012 and 2018, roughly 3.19% from the land use classes of 2012 transitioned due to consequences of active fires and was thus converted to 'burned area', mainly due to the fires of 2017. Mainly vegetative land use types are transitioned in this process. However, this study does not explain the causality of this effect.

Furthermore, the relationships between occurrence of wildfires and land-use change processes that were found were all negative correlations. Thus can be concluded that, yes, there is a relationship between land-use change and wildfire occurrence in Portugal. However, it cannot be concluded that this correlation is always negative for all types of land-use, since more research is needed to explain the causal effects that act in these processes.

8.2 Important parameters/spatial variables

The most significant spatial variable explaining the prediction of active fires was distance to roads. With a beta coefficient of roughly 9.1, the regression analysis calculated this variable to be the most influential as to whether or not a fire would be active in any of the defined points. This means that according to the analysis, if a point is further from a road, it is more likely to be an active fire point. However, the spatial variable distance to water also showed an important relationship with occurrence of wildfires, albeit a negative one. With a beta coefficient of roughly -4.6, the analysis showed that if a point is further away from a cell classified as water, it's less likely to be an active fire classified cell.

This seems contradictory to most logical assumptions and literature reviews, but could very well, as mentioned before, have to do with geographical structure and local climate conditions during the fire season of 2017 in Portugal. Also, more spatial variables containing land cover information might be needed for suitable analysis.

This study did point out that the fires of 2017 in Portugal mainly correlated with spatial variables associated with inland, mountainous areas, relatively high altitude, low population density and close to river networks. These spatial correlations do give use information about geographical whereabouts of areas which are likely active fire spots, but need regional and/or local research for further investigation in the future.

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10 Appendix

Correlations

Correlations

		Value_Fire	Population	Roads_Dist	Water_Dist	Agriculture	Grass_Agri	Forest_Shrub	Grass_Shrub	Shrub_Forest	Elev_km	Temperature
Value_Fire	Pearson Correlation	1	-.010**	.041**	-.010**	-.043**	-.001	-.006**	.000	-.004**	.020**	.003**
	Sig. (2-tailed)		.000	.000	.000	.000	.213	.000	.775	.000	.000	.004
	N	1078956	1078956	1078956	1078956	1078956	1078956	1078956	1078956	1078956	1078956	1078956
Population	Pearson Correlation	-.010**	1	-.147**	.299**	-.063**	-.004**	-.003**	-.001	-.012**	-.142**	-.052**
	Sig. (2-tailed)	.000		.000	.000	.000	.000	.001	.347	.000	.000	.000
	N	1078956	1078956	1078956	1078956	1078956	1078956	1078956	1078956	1078956	1078956	1078956
Roads_Dist	Pearson Correlation	.041**	-.147**	1	-.050**	-.054**	.000	.021**	.000	.000	.188**	-.044**
	Sig. (2-tailed)	.000	.000		.000	.000	.693	.000	.974	.770	.000	.000
	N	1078956	1078956	1078956	1078956	1078956	1078956	1078956	1078956	1078956	1078956	1078956
Water_Dist	Pearson Correlation	-.010**	.299**	-.050**	1	.016**	.001	.001	-.001	.005**	-.121**	-.082**
	Sig. (2-tailed)	.000	.000	.000		.000	.342	.269	.130	.000	.000	.000
	N	1078956	1078956	1078956	1078956	1078956	1078956	1078956	1078956	1078956	1078956	1078956
Agriculture	Pearson Correlation	-.043**	-.063**	-.054**	.016**	1	-.017**	-.125**	-.005**	-.077**	-.108**	.049**
	Sig. (2-tailed)	.000	.000	.000	.000		.000	.000	.000	.000	.000	.000
	N	1078956	1078956	1078956	1078956	1078956	1078956	1078956	1078956	1078956	1078956	1078956
Grass_Agri	Pearson Correlation	-.001	-.004**	.000	.001	-.017**	1	-.003**	.001	-.002*	.018**	-.005**
	Sig. (2-tailed)	.213	.000	.693	.342	.000		.001	.166	.040	.000	.000
	N	1078956	1078956	1078956	1078956	1078956	1078956	1078956	1078956	1078956	1078956	1078956
Forest_Shrub	Pearson Correlation	-.006**	-.003**	.021**	.001	-.125**	-.003**	1	-.001	-.009**	-.011**	.008**
	Sig. (2-tailed)	.000	.001	.000	.269	.000	.001		.450	.000	.000	.000
	N	1078956	1078956	1078956	1078956	1078956	1078956	1078956	1078956	1078956	1078956	1078956
Grass_Shrub	Pearson Correlation	.000	-.001	.000	-.001	-.005**	.001	-.001	1	.000	.007**	.000
	Sig. (2-tailed)	.775	.347	.974	.130	.000	.166	.450		.638	.000	.721
	N	1078956	1078956	1078956	1078956	1078956	1078956	1078956	1078956	1078956	1078956	1078956
Shrub_Forest	Pearson Correlation	-.004**	-.012**	.000	.005**	-.077**	-.002*	-.009**	.000	1	-.019**	.007**
	Sig. (2-tailed)	.000	.000	.770	.000	.000	.040	.000	.638		.000	.000
Elev_km	Pearson Correlation	.020**	-.142**	.188**	-.121**	-.108**	.018**	-.011**	.007**	-.019**	1	.055**
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000	.000	.000		.000
	N	1078956	1078956	1078956	1078956	1078956	1078956	1078956	1078956	1078956	1078956	1078956
Temperature	Pearson Correlation	.003**	-.052**	-.044**	-.082**	.049**	-.005**	.008**	.000	.007**	.055**	1
	Sig. (2-tailed)	.004	.000	.000	.000	.000	.000	.000	.721	.000	.000	
	N	1078956	1078956	1078956	1078956	1078956	1078956	1078956	1078956	1078956	1078956	1078956

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Appendix fig. 1: Statistical bivariate correlations table