University of Tartu
Faculty of Science and Technology
Institute of Ecology and Earth Sciences
Department of Geography

Master's thesis in Geoinformatics for Urbanised Society (30 ECTS)

Risk Assessment of Landscape Fires in Estonia

Kingsley Adu Koranteng

Supervisor: Prof. Tõnu Oja

Approved for defence:

Supervisor:

Head of Department:

Tartu 2020

Eesti maastikutulekahjude riskianalüüs

Abstrakt

Tulekahjuriskide kaardistamiseks on maailma eri piirkondades läbi viidud ulatuslikke uuringuid, eriti metsade osas. Siiski on vaid vähesel määral uuritud tulekahjuriskide ulatust teistel maastikel. Käesoleva uurimistöö eesmärgiks oli analüüsida tulekahjude esinemist erinevatel maastikel ning tuvastada seonduvad tulekahjude puhkemise riskifaktorid vastavatel maastikel Eestis. Riskifaktoreid sisaldavaid andmeid on analüüsitud seonduvalt ajalooliste tulekahjudega. Metodoloogiliselt on rakendatud geoinformaatika (GIS) tehnikaid ning kohandatult lineaarset regressiooni, et selgitada välja riskifaktorite mõju tulekahjusündmustele.

Uuringu tulemused osutavad sellele, et tulekahjude esinemisele avaldavad olulist mõju inimtekkelised põhjused. Maakate – turbarabad ja sisemaised märgalad – ei oma tulekahjusündmuste sagedusele mingisugust mõju. Veelgi enam: vaadeldud ajaperioodi toimunud tulekahjude kõige olulisema parameetri identifitseerimiseks kumulatiivse aastakeskmise alusel hinnatud erinevad ilmastikunäitajad osutasid sellele, et ei tulekahjude tekkele ega levikule polnud ühelgi ilmastikulisel muutujal olulist mõju. Siiski on turvasmuld tulekahjudele väga vastuvõtlik ning kujutab endast ühtlasi kõige olulisemat üksikut tulekahjude esinemise riskifaktorit Eestis.

Võtmesõnad: tulekahjurisk, ruumiline jaotus, maakate, turvasmuld, regressioon

CERCS-i kood: T181 kaugseire

Risk Assessment of Landscape Fires in Estonia

Abstract

Extensive studies have been done in fire risk mapping from different regions across the globe, specifically in forests. However, little investigation has been undertaken in terms of the degree of fire risk in other landscapes. The study sought to analyze fire incidence in different landscapes and identify associated risk factors for fire occurrence in these landscapes in Estonia. Data involving risk factors were analyzed in relation to historical fires. Methodology involved the use of GIS techniques and adoption of linear regression to find the impact of risk factors on fire events.

The outcome of research indicates that anthropogenic causes have a significant impact on fire occurrence. Spatial coverage of landscapes – peat bogs and inland marshes – does not have any effect on the rate of fire events. Furthermore, diverse weather parameters based on cumulative annual mean assessed to identify the most significant parameter on fire happenings over a period indicates that no weather variable has a significant impact on fire ignition and spread. Nevertheless, peat soil is highly susceptible to fires and also the single most significant risk factor on fire incidence in Estonia.

Keywords: Fire Risk, Spatial Distribution, Land Cover, Peat Soil, Regression

CERCS Code: T181 Remote Sensing

Table of Contents

Introduction

Fires have been very important in the survival of mankind since the stone-age and still continues to provide help to humans in their evolution. Fires are also the most important and recurrent enemies of forests and other landscapes besides diseases and insects, overgrazing, unlawful change of use, and logging (Tampakis et al., 2010).

Fires in general cause devastating havoc to ecosystems, human health by way of inhalation of smoke and in worse cases loss of lives, and economies of nations dependent on natural resources from forests and other landscapes. However, the release of seeds for certain tree species, control of disease and insects, and exposure of mineral soils which support regeneration of the trees are some benefits that fires bring in diverse landscapes (Akther & Hassan, 2011). The incidence of fires in different landscapes generally have more negative consequences than positive impact.

The ignition of fires in forests and other landscapes and the frequency of fires occurring in these areas are reasons for degradation of forests/landscapes in Estonia and worldwide. Globally, there has been an alarming pace of destruction of forests and other landscapes by fire. As a result of global climate change and the impact of human activity, the landscape/forest area reduces rapidly, while fires lead to most of the reduction (Gai et al., 2011). In the year 2017, landscape fires destruction was 51 percent higher than the preceding year with a loss of 73.4 million acres (29.7 million hectares) in specifically forests, and this could partially be attributed to climate change that has increased the risks and intensity of fires by triggering temperature rise and drought in some places (France-Presse, 2017).

Comparatively, in 2017, Estonia recorded about 13 percent increase in landscape fire events compared to the previous year even though overall fire events reduced (Estonian Rescue Board, 2018). This shows the severity of yearly landscape fire risk on a global scale and also in the local context of Estonia.

Undoubtedly, there must be the presence of certain conditions in order to ignite and propel fires in the first place. Adinugroho et al., 2005 (as cited in Amalina et al., 2016) posited that the combustion process depends on the presence of heat source (fire) as an igniter, available fuel, and oxygen in a simultaneous manner which they termed as “the fire triangle”. These factors stimulate fires and as such landscape fires are actually triggered by anthropogenic and natural factors. The anthropogenic factors are human-related activities and idiosyncrasies such as smoking, hiking and camping, burning of bushes, etc. There is a high tendency of landscape fire frequency where these human activities mostly occur. The human aspect as a major cause of landscape fires can either be intentional (arson) or accidental.

Alternatively, lightning is commonly the natural factor which is the ignition source of many landscape fires besides anthropogenic causes. Nonetheless, information on lightning characteristics and impact points is missing or controversial, due to the difficulty of lightning stroke localization and the relation to single fire events (Müller & Vacik, 2017). According to Gai et al. (2011), natural factors like lightning cause landscape fires when population density of a region is low and when the population density is high, human activity becomes the dominant causative factor of landscape fires. The assessment of landscape fire risk especially is therefore linked to comprehension and analysis of these ignition sources.

It becomes highly prudent to investigate landscape fires in order to develop the best methods and technologies in assessment of susceptibility of diverse landscapes to fires that are useful for monitoring fire events in risk prone areas in Estonia. This ensures the improvement in fire and landscape management by way of understanding fire behaviour and detecting early warning systems. However, there are limited studies in fire risk mapping in varied Estonian landscapes. It is as a consequence of this, that the research seeks to concentrate on fire events in different landscapes in order to fill this gap and contribute to research knowledge in the scope of fire risk assessment in Estonia.

Therefore, the general focus of this research is to assess some risk factors relating to landscape fires in Estonia. The aim of the thesis is to analyze fire incidence in different landscapes and identify associated risk factors for fire occurrence in these landscapes in Estonia. The outcome of research will provide a basis for understanding the dynamics of fire events in several landscapes in Estonia while improving general knowledge in fire risk mapping. The purpose is to introduce some novelty so the following research questions have been developed;

1. What is the relationship between population, accessibility and the incidence of landscape fires?
2. To what extent does the spatial distribution of peatlands and reed beds contribute to frequency of fires?
3. What is the degree of vulnerability of fire in areas with peat soil?

4. What is the most significant climatic parameter on fire occurrence?
5. What is the most influential factor on fire occurrence?

The thesis is structured into four chapters. The first chapter introduces the topic and theoretical overview. Data and methodology is then explained in the second chapter. Third chapter consists of analysis and results derived from analysis and the last chapter entails discussions and conclusions of the research.

1. Theoretical Overview

1.1 Definition of Terms and Types of Landscape Fires

Landscape is defined as an area that is based on the perception of people, having a character as a result of the action and interaction of natural and/or human factors (Council of Europe, 2000). However, there are many meanings of landscape depending on the origin, objectives, cultural perspective and can be said to be common to anyone who has some kind of interaction with the environment (Antrop, 2015). Thus, landscape is any scenery of natural phenomenon as can also be altered by human design.

On the other hand, forest is land spanning more than 0.5 hectares with trees higher than 5 meters and a canopy cover of more than 10 percent, or trees able to reach these thresholds in situ. It does not include land that is predominantly under agricultural or urban land use (FAO, 2012).

Forests and other landscapes are typically threatened by wildfires. Hence, wildfire is any unexpected and unmanageable fire in vegetation, which may require a swift suppression response irrespective of the ignition source (Lampin-Maillet, et al., 2010). Fire is the result of a chemical reaction of combustion where the presence of fuel, oxygen and heat is required in the right proportions to facilitate combustion (Stacey & Gibson, 2012). Fires, as a more general terminology is adopted for use in this study since the behaviour of historical fire data used is unknown to the researcher.

Furthermore, fire risk means the likelihood of the event occurring; fire hazard refers to the potential for loss in case of a fire event; and vulnerability is the potential effect of a threat and considers capacity of the affected entity to adapt over time (Miller & Ager, 2013). The forecast of fire risks in many landscapes can be achieved with the use of fire risk zone maps. Fire risk zones are locations where a fire is likely to start, and from where it can easily spread to other areas (Jaiswal et al., 2002).

There are two types of landscape fires: (i) surface fires, which spread with a flaming front and burn senescent leaves, twigs, dry grass, leaf litter, fallen branches and other fuels located at ground level and (ii) crown fires, in which burning occurs in the top layer of tree foliage and shrubs, often sustained by a surface fire. The latter is the most intense type of fire, often the most difficult to contain, needing strong winds, steep slopes and a heavy fuel load to continue burning (Herrera, 2016).

1.2 Factors Responsible for Landscape Fires

There are several factors that contribute to the susceptibility of landscapes to fires. A region can be predisposed to fires based on the existing conditions in that region. These conditions can be categorized into human-induced factors and natural factors. Some of the factors are but not limited to: climate, vegetation type, topography, distance from roads and proximity to settlement. These factors can be termed as either vulnerability factors that ignite fire or propagation factors that cause the intensity and spread of fires in several landscapes.

1.2.1 Anthropogenic Factors

The two main sources of ignition are human and natural considered in fire risk mapping (Chuvieco, et al., 2010). The human related causes are undoubtedly the most significant worldwide (FAO, 2007). The source of ignition related to humans are mainly categorized into intentional and unintentional factors. The intentional causes in Europe especially in Mediterranean areas are mainly arson (Ganteaume, et al., 2012); and backed by criminal intent of people. Humans have a broad influence on fires through intentional or accidental ignitions, exclusion (e.g., suppression and fuel alteration from grazing), and indirectly through climate change (Marlon, et al., 2012). The involvement of humans as the catalyst in landscape fires globally cannot be overemphasized. As a general rule, humans are responsible for 96% of global fires be it consciously or negligence (Hirschberger, 2016).

Also, activities due to movement of people and vehicles on roads serve as catalyst for landscape fires which are usually unintentional. For example, the occurrence of a motor accident on a road could transmit fire to a nearby landscape depending on the nature of the accident and conditions of the nearby landscape. Fires are preferentially ignited because of proximity to roads in all landscapes and the impact is much stronger in places where availability of human-induced ignition is dependent on accessibility networks (Ricotta et al., 2018).

Thus, the closer people are to particular landscapes, the more likely these areas are prone to fires as a result of their routine activities. According to Suryabhagavan et al. (2016), landscapes closer to settlements are more prone to fires because the habitation/cultural practices of the residents can lead to accidental fires. There are countless ways by which people as a result of their proximity from settlement can result in landscape fires like fireworks, discarded cigarette, someone lighting matches playfully, campfires, etc.

1.2.2 Natural Factors

Lightning strikes are also an important factor to consider in fire risk estimation as they tend to burn larger areas than human-caused fires, because they occur in more isolated and steeper areas and frequently have various simultaneous ignited spots, and therefore are more difficult to control (Wotton & Martell, 2005). Lightning fires are frequent in temperate zones with large forested areas and also those that occur at night can result in large burned area because the timing restricts firefighting (Müller & Vacik, 2017). Hall & Brown (2006) cited three factors of lightning strikes that influence the probability of wildfire ignition: i) polarity of the stroke; ii) multiplicity of the lightning; iii) the existence of along continuing current (LCC). Lightning as the natural source of ignition in forest and other landscape fires are spontaneous and nothing can be done to prevent them from striking when the weather conditions demand it. However, the same cannot be said for the human factors because of the fallible nature of people, their living conditions and environment where they live. Thus, human factors can be altered to diminish the risk of landscape fires but lightning strikes are uncontrollable.

Climatic conditions of a region determines the vegetation in that region and hence, plays a dominant role in creating fire prone areas. The drier the climate is in a particular region, the more fire prone the site will be and vice versa (Jaiswal et al., 2002). A number of climate researchers have been interested in investigating not just the impact of climate change on the occurrence of fires in many landscapes but also the effect of these fires on the climate (Konca-Kędzierska & Pianko-Kluczyńska, 2018). Climate is made up of weather variables that influence the spatio-temporal risk of landscape fires. Some of these dynamic weather variables are: wind force, temperature, relative humidity, etc. The potential changes in fire danger conditions associated to climate warming may be easily estimated using these meteorological danger indices, based on the different climate scenarios currently available (Gillett et al., 2004).

This is an indication that weather or meteorological conditions are fundamental risk factors in determining the ignition and spread propensity of fires. According to Konca-Kędzierska & Pianko-Kluczyńska (2018), relative air humidity is one possible factor on fires and ultimately, the occurrence and spread of landscape fires is greatly impacted by this meteorological factor. Wind, based on its speed and direction determines the intensity and spread of fires which makes it a major factor on fire behaviour in diverse landscapes (Hamadeh et al., 2017). Bedia et al. (2018) found out that there is a positive relationship between increased fire danger conditions and temperature. There is a strong correlation in areas with low precipitation regimes and high frequency of landscape fires. Therefore, drought is a major influence on risk of occurrence of landscape fires since drought can dry up and reduce moisture content in fuel in a given landscape making it more susceptible and thereby increasing the risk of fuel ignition (Chen, et al., 2014).

All these are natural factors influencing the fire risk in many landscapes. Many empirical studies have developed models based on meteorological parameters like wind speed, relative humidity, atmospheric pressure, precipitation, etc. to determine and predict the risk of fires occurring in a particular area beforehand (Giuseppe et al. 2016; Hamadeh et al. 2017; Bedia et al., 2018).

Furthermore, the type of vegetation in an area defines fire risk since the vulnerability to fires differ across various vegetation in a particular region. Therefore, landscape fire risk is greatly influenced by fuel type. The presence of fuel (i.e., vegetation composition) and its status are important in describing fire danger conditions (Mallinis et al., 2008).

One important variable that influences fire in terms of vegetation characteristics is the fuel moisture content. According to the National Oceanic and Atmospheric Administration (NOAA, 2019), "fuel moisture is a measure of the amount of water in a fuel (vegetation) available to a fire, and is expressed as a percent of the dry weight of that specific fuel". Fuel moisture content (FMC) is an important fuel property for assessing wildfire hazard, since it influences fuel flammability and fire behavior. The relationship between FMC and fire activity differs among land covers and seems to be a property of each ecosystem (Argañaraz et al., 2018).

FMC is categorized into dead and live components and contributes to landscape fires differently. Fuel moisture content, be it live or dead is influenced by the phenological phase in the life cycle of plants, the seasonal variations in weather conditions (rainfall, humidity, solar radiation) by way of environmental conditions, and the diurnal fluctuations of air temperature and air relative humidity (AUTH, 2007). This determines the flammability or combustion characteristics of a given land cover or landscape.

Fuel is said to be totally dry when the fuel moisture content is zero percent and when it is less than 30 percent then the fuel is deemed as being dead. The higher the fuel moisture content, the lower the risk of ignition because heat energy needs to evaporate the moisture in the fuel before it can burn and the lower the fuel moisture content, the higher the risk of fire starting and spreading quickly as heat energy goes directly into the burning flame (NOAA, 2019).

The moisture values of dead fuels is usually properly estimated by taking cognizance of changes in atmospheric conditions since they form an underlining factor in accurate estimation. Alternatively, live fuels depend on their own physiology, their own water regulation mechanism as well as their resistance to summer drought. Consistent atmospheric conditions may lead to a wide variety of moisture values depending on the vegetation species under consideration (Aguado et al., 2003). Classically, the assessment of FMC has included approaches such as field sampling, mathematical models, calculation of meteorological indices and application of remote sensing techniques (NOAA, 2019).

The topography of a region affects its susceptibility to fire which is also another risk factor in landscape fires assessment. Some topographic variables that are known to influence severity of fires are: slope, aspect and elevation; and fires travel faster and are more severe in steeper slopes than downslopes (Lecina-Diaz et al., 2014). The terrain makes slope a significant contributor in the spread of landscape fires because wind velocity propels fires upslope of a terrain and reduces flow enhancement downslope (Eftekharian, et al., 2019). Morandini et al. (2018) investigated to have a better understanding of why wildfires spread upslope and attributed reasons to major change in fluid dynamics surrounding the flame.

1.3 Estimating the Amount of Fuel (Fuel load)

Fuel load is a significant component in assessing risk of fires in many landscapes. Fuel is defined as any material that is likely to provide support to combustion within a wildfire environment and usually estimated in tonnes per hectare (Stacey & Gibson, 2012). Some aspects of fuel that are considered in fire risk analysis include loading (weight per unit area), size (particle diameter), and bulk density which is weight per unit volume (Arroyo et al., 2008). The type and condition of vegetation determine fuel load which directly impacts on the spread and intensity of fires especially when the vegetation in a specific landscape is predominantly made up of fine fuels like grasses and bushes (Franke, et al., 2018).

Traditionally, fuel mapping has been done by way of field work, use of aerial photography and ecological modelling. However, these approaches are limited because they are time-consuming and expensive. Contemporary methods applied involve remote sensing whereby depending on the purpose of the study, a wide variety of systems based on new improved sensors such as LiDAR, radar, hyperspectral, etc. and also new techniques of handling heterogeneous data. Remote sensing techniques are more accurate, cost-effective and provide a wider spatial and temporal coverage but are limited in observation of horizontal fuel distribution (Arroyo et al., 2008). Therefore, it is appropriate to combine both traditional and contemporary methodologies in mapping landscape fuels in order to arrive at a more accurate result for all fuel types.

Notwithstanding the aforementioned, the type of fire to be anticipated depend distinctively on the vertical distribution of the fuel load (Fernandes, 2009). Landscape fuel like forest fuel load estimation relies on some forest canopy characteristics such as bulk density, canopy height, canopy fuel weight, and canopy base height to accurately and efficiently assess the quantity and distribution of canopy biomass and fuels. This is done based on reliable airborne LiDAR data for efficient estimation of canopy fuel characteristics over extensive areas of forests and other landscapes (Andersen et al., 2005).

The estimation of fuel load when mapping fires has been done in different regions using different approaches. A more generic approach involves using vegetation indices by way of classification whereby a "stratify and assign" technique is employed to categorize vegetation into classes and assign fire risk values to each category in order to determine fuel type and consequently the load (Maselli et al., 2000; Van Wagtendonk & Root, 2003; Arroyo et al., 2006). The "classify and assign" approach was criticized as not being reliable in fuel load mapping since it does not resolve spatio-temporal dynamics of fuel loads within different vegetation classes which is a vital factor in fire incidence and propagation (Franke, et al., 2018); since fuel condition and loads do not solely rely of vegetation types/classes (Keane, 2013).

Correspondingly, the spatial distribution is taken into consideration as a component of fuel assessment. Information on surface fuel spatial distribution is one of the necessary prerequisites in modelling fire behaviour (Majlingová et al., 2018). The quantity of live and dead fuel per unit area is the main factor determining fuel load and has been estimated from satellite data using a partial unmixing method for the Brazilian open savannah ecosystem which is the most species-rich savannah region in the world (Franke, et al., 2018). Spatial distribution, combustibility, horizontal or vertical continuity, etc. are some multiple vegetation characteristics that influence the fire spread (Vallejo-Villalta et al., 2019)

Andersen et al. (2005) used LiDAR data in assessing canopy fuel parameters in coniferous forests in Washington State, USA by calculating field-based canopy values from sample data whereby trees included had diameter at breast height above 14.5 cm and also, canopy fuel characteristics were estimated with LiDAR point cloud metrics using regression modelling. Price & Gordon (2016) analyzed the prospects of LiDAR technology to map forest fire fuel hazard in Australia. The LiDAR point cloud density was about 1 point per m^2 which is comparable to the measurements made by the Estonian Land Board. Price & Gordon (2016) differentiated three tree strata by height (0.5-4 m, 4-15 m, > 15 m) and 20 by 20 m horizontal spatial resolution giving a precise quantification of fuel load in vegetation strata which is significant for crown fire propagation. They discovered that the accuracy of LiDAR based estimates were higher than the exclusively time based models since the last fire.

In comparison with Estonia, many studies have sought to determine the fuel load and their contribution to fires. In Aegviidu and Laeva test sites, there has been the assessment of forest stand inventory variables using airborne LiDAR metrics (Lang et al., 2012, Lang et al., 2014). Moreover, airborne LiDAR data was analyzed and presented a simple model to evaluate canopy base height of forests (Arumäe & Lang, 2013). LiDAR based canopy fuel models have a comparatively higher accuracy with aerial photography but it is rarely available and mode of collection is expensive (Filippelli et al., 2019). Lang et al. (2018) used random forest machine learning technique to develop a variety of tree species map for the whole of Estonia from Landsat-8 OLI and Sentinel-2 MSI multispectral satellite images.

Furthermore, the proper management of fuels would ultimately reduce the risk of fires in landscapes. Many empirical studies on fuel management have suggested reducing the amount of fuel load per unit area which has proven to be an effective mode to decrease fire risk by up to 50% especially in urban boundaries (Stephens & Moghaddas, 2005; Schmidt et al., 2008; Safford et al., 2009). According to Franke et al. (2018), decisions on the management of fuel load in landscapes can be aided to be more effective and reliable by consistent creation of fuel load maps at appropriate temporal scales.

1.4 Remote Sensing in Fire Risk Mapping

Satellite imaging is a technology growing steadily in its application for mapping forests/landscape fires and associated risks. It provides a high-resolution and consistent information that covers a wide area irrespective of the remoteness of location and also shows vegetation characteristics as integrated response to different factors influencing its status as a fuel for burning (Abbot et al., 2007). Satellite data with higher resolution and accuracy can be relied upon by forest and landscape managers to reduce the risk of tragic fires in forests and other landscapes (Filippelli et al., 2019).

Moreover, it is theoretically feasible to surmount the problem associated with interpolation techniques which use data at a source to generalize in order to obtain a spatial coverage over an entire area by using remote sensing data when generating wildfire hazard maps (Chowdhury & Hassan, 2015). Spatial interpolation of danger indices is not the most appropriate technique in comparison with satellite images, since satellite images cover a much wider territory (Aguado et al., 2003).

Land cover, land surface temperature, Normalized Difference Vegetation Index (NDVI), and Normalized Difference Moisture Index (NDMI) are some remote sensing derived variables that influence prompting of forest and other landscape fires which provide a substantial basis for determining the level of fire vulnerability in several regions (Amalina et al., 2016). The assessment of these variables, coupled with analysis of human activity factors provide the basis for fire risk mapping.

1.5 Fire Occurrences in Different Landscapes

Fires interact in a complicated manner with land-use and land-cover (LULC) change and impacts widely in various ways on different landscapes. The effect of fires on vegetation is primarily controlled by land use and timing associated with evolution of land-cover. There is a significant link between the rate of fires and type of ecosystem but it cannot be concluded that fires always cause LULC changes (Eva & Lambin, 2000). Additionally, fire exhibits various levels of selectivity towards different land cover types. Small fires have a tendency to be selective through either avoidance or preference towards a specific land cover whereas large fires continue to burn regardless of land cover type (Barros & Pereira, 2014).

Spatial distribution of land cover depending on the type and density of vegetation present can increase the risk of fires. Thus, the wider the spatial context of a landscape, the more likelihood of fire occurrence. Alternatively, fires greatly impact on landscapes by causing a more heterogeneous landscapes and allows for more insight into finding connection between fire severity and landscape composition and structure (Hayes & Robeson, 2009).

According to Suryatmojo et al. (2019), peat is a type of soil formed from half-decaying plant remains; containing high acidic content as well as organic matter but low in nutrient, usually brown or blackish in colour and the texture is unstructured and clay dust in nature. It is referred to by names like mire, bogs, moor, etc. depending on the region but most commonly known as peat. Fire occurrence in peat is associated with many problems ranging from environmental, economic, health and mortality (Suryatmojo et al., 2019).

Furthermore, wetland ecosystems like peat bogs and inland marshes undergo restructuring due to the incidence of fires in these areas. There are effects of fire on peat bogs and their vegetation through microclimatic patterns, peat stratigraphy and changes in vegetation. It can be concluded that historical fires have significance for maintaining diversity in some deteriorating plant species in peat bogs (Norton & De Lange, 2003).

A significant proportion of the world's carbon emission are from peatlands which consist of layers of organic materials (Razali et al., 2010). Peatlands are sensitive ecosystems that are susceptible to local and regional climatic fluctuations, human activities and disruptive fire events leading to release of carbon emissions into the atmosphere while causing environmental degradation (Razali et al., 2010).

Many peat fires occur as a result of deliberate clearing of land for agriculture necessitated by mainly drought consequently leading to deteriorating effect on air quality and has now become a global crisis (Laurance & Laurance, 2015; Wijedasa et al., 2015). Peatlands suffer extreme damages as a result of fires and land processing for mainly agricultural purposes.

It is therefore imperative to study fires in peat and other landscapes due to its negative effect on the local as well as global society in order to highlight the problem in Estonia for land management experts to provide solutions to curb this menace. Conservation and protection of peatlands and other landscapes against fires from further degradation is necessary to mitigate climate change (FAO, 2012).

2. Data and Methods

2.1 Dataset

The data for the research is varied from different reliable sources. The data includes fire events, population, road network, land cover, soil and meteorological data for the whole of Estonia. A description of data, source as well as format is summarized in Table 1 below and further details provided subsequently.

Table 1: Data Information Summary

Data Description	Source	Format
Fire Events	Estonian Rescue Board	Vector/Point
Population	Statistics Estonia	Vector/Polygon
Land Cover	Copernicus	Raster/Remote Sensing
Soil	Estonia Land Board	Vector/Polygon
Estonia Contour	Estonian Land Board	Vector/Polygon
Estonia Topographic Data (Road Network)	Estonia Land Board	Vector/Line
Meteorological Parameters	Estonian Weather Service	Figures

Data related to actual fires in Estonia is obtained from Estonian Rescue Board and has a temporal range covering a five-year period from the year 2014 to 2018. The data consists of fire events with attributes such as date and time, ignition location (X and Y coordinates), level of severity, type of fire event, total area burnt, and reason that resulted in the fire. The data provides details of exactly 7588 fire events over the five-year period for the entire Estonia. The Figure 1 below depicts the annual distribution of fires. It portrays that fires have a fluctuating pattern rather than a consistent upsurge or decline pattern over the years.

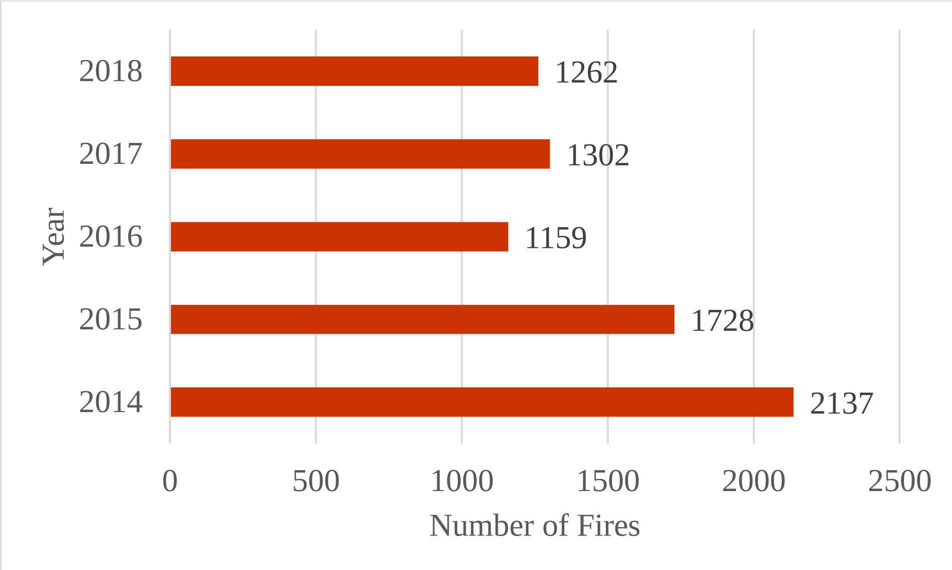

Figure 1: Fire Data in Estonia

Data relating to population is derived from Statistics Estonia in a form of shapefile covering all Estonia for 2018. The population data is in local government (administrative) unit and includes data on total population figures. The population is provided for both gender and covers a five-year age groups total. Some population attributes include local government unit name, code, and total population for each local government unit, etc. Additionally, population figures based on county level in 2017 are used for further statistical analysis.

The CORINE land cover (CLC) 2018 as derived from Copernicus is used in this study. The CORINE land cover deals with satellite imagery of high spatial resolution (100-meter) captured by Sentinel-2 under the Copernicus programme. The data consists of pixel count of each land cover classification, diverse land cover classifications such as forests, natural grasslands, pastures, peat bogs, water bodies, etc. and other attributes.

Soil data is retrieved from the Estonian Land Board for the purpose of this study. The soil data entails varied soil types like humus, silt, clay, peat, gravels, etc. The type of soil of interest in the study is peat soil.

The contour map of Estonia is used in this study. This is in a form of a shapefile obtained from the Estonia Land Board consisting of all 15 counties that are analyzed in relation to fires.

Road network data is acquired from the Estonia Land Board and covers the whole of Estonia. The road data has different classes of roads that are taken into consideration. All roads, regardless of class are used for the analysis for a better overview.

Meteorological data is obtained from the Estonian Weather Service. It includes details of climatic variables such as temperature, relative humidity, wind speed and precipitation. The data provided is based on monthly distribution and spans a five-year period from 2014 to 2018. It has information on location of weather stations for all counties in Estonia. The weather data is given based on spatial distribution recordings from these weather stations.

2.2 Methods

The methodology applied in this study takes into consideration natural and human factors affecting landscape fire risk. The occurrence of fire is analyzed based on historical data of fire incidence in Estonia. Primarily, the relationship between fire events and human related factors like population and road network etc. as well as other factors. Population is based on census figures of people living within an administrative area and road network analysis is based on the creation of 500-metre buffer as walkability indicator on either side of road network. The walkability range of a given environment can objectively be analyzed using road network buffer (Luijkx & Helbich, 2019). A calculation of area of road network buffer per county is used as an indicator of road network for the empirical study. Based on the research questions, different methods are applied and each method is subsequently elaborated.

In order to get a general overview, better visualization and understanding of the spatial variability of fire incidents, a point density method is applied. A point density method generally defines the number of cases within a unit area of each location covering an area of interest (Carlos et al., 2010). Several density methods have been applied in many landscape fire risk mapping studies (Amatulli et al., 2006; Caceres, 2011; Oliveira et al., 2012). The resultant value of fire density is important to comprehend the intensity of fires within a specific area. A point density map is created for the whole of Estonia based on historical fire data before going further to research questions.

A further analysis is done to ascertain the fire variability in each county based on historical data to understand the dynamics of fire in different counties. A visual representation of bar graph is displayed to determine the quantity of fires that occurred in each county in Estonia in relation to the data available – road network buffer, peat bogs, inland marshes and areas with peat soil – to have an insight into the dynamics of fire events and consequently the risk levels for each county based on the distribution. Overall share of fire events by counties is compared with normalized quantity of fires per county to get a better relationship between them. The frequency of the number of fires per square kilometer is also represented with a graph.

Furthermore, a logarithmic transformation in statistical analysis is applied on the fire dataset as a dependent variable in order not to violate the assumptions of inferential statistics and improve the interpretation of patterns in the dataset respectively.

2.2.1 Human-Related Factors on Fire Events

The point density analysis is then compared with population map of Estonia. This gives an additional overview of the relationship between fire occurrence and population as to be seen in the results. Moreover, in order to determine the relationship between population and the frequency of fires, a statistical measure of Pearson's correlation analysis is used. Correlation is interpreted by 'r' values depicted as $-1 \leq r \leq 1$. The resultant values of correlation is explained in three ways. So, the closer the value is to 1, then there a positive relationship, if it is negative 1, then there is a negative relationship and if it is 0 then there is no relationship (Mukaka, 2012). This is a used statistical measure to gain some basic understanding of the relationship between two variables, in this case, fire incidents and population as well as road buffers and fire incidents within road buffers.

However, a higher correlation of variables does not guarantee that one factor causes the other, thus correlation analysis imply association but not causation (Akoglu, 2018). Accordingly, a regression analysis is applied to determine the causal relationship between fires and population. Furthermore, road network is also added to the regression model to get a more reliable results as to human related factors in fire occurrence.

$$log(Y_{fire}) = \beta_0 + \beta_1 X_{population} + \epsilon \quad (1)$$

$$log(Y_{fire}) = \beta_0 + \beta_1 X_{road\ network} + \epsilon \quad (2)$$

where;

Y_{fire} means the fire incidents (total quantity of fires – equation 1; fire events within road buffer – equation 2), β_0 means constant, $X_{population}$ is the number of population in an area, $X_{road\ network}$ is the total area of road network buffers in a region and ϵ is error.

After regression analysis, whether or not a factor has statistical significance is checked based on P-value. If P-value of explanatory variable is less than 5 percent, then it has a statistically significant effect on response variable, in this case being the incidents of fire.

2.2.2 Spatial Distribution of Peat Bogs/Inland Marshes and Frequency of Fires

In order to be more specific, there is the need to find out how many of these fires occurred, based on the historical data in different land cover types – in peatlands and reed beds. Peatlands is same as peat bogs as in the CLC data and reed beds is also synonymous to inland marshes since it is a subclass as can be derived from the CLC data nomenclature. To this end, these terms are used interchangeably to mean the same thing and should be duly noted.

A comprehension of the amount of fires that have occurred in these land covers can lead to a conclusion of the risk assessment level of fires in different areas. It is recognized that fire behaves differently depending on unit area of coverage and fuel type in a particular land cover and its devastating impact is also different. Based on the CLC and fire data, spatial analysis is used to determine the quantity of landscape fires in these land cover classes for better understanding of fire behaviour.

The area of peatlands and reed beds per county is deduced from land cover classification to determine the extent to which spatial distribution of these landscapes affect fire occurrence. A collect events method is applied to visualize the quantity of fires in these land cover classes. Furthermore, a correlation analysis is used to discover the relationship between different types of land cover (i.e., peat bogs and inland marshes) and fire in these areas. Also, regression analysis is done to check the causal relationship between variables; peat bogs and fire as well as inland marshes and fires that fall within these areas. The formula below is applied;

$$log(Y_{fire}) = \beta_0 + \beta_1 X_{peat\ bogs} + \epsilon \tag{3}$$

$$log(Y_{fire}) = \beta_0 + \beta_1 X_{reed\ beds} + \epsilon \tag{4}$$

Where Y_{fire} explains the fire frequency in the area whereas $X_{peat\ bogs}$ indicates the area of peatland and $X_{reed\ beds}$ means area of reed beds in land cover.

2.2.3 Susceptibility of Fires in Areas with Peat Soil

In determining the vulnerability of peat soil to fires, spatial analysis is done using the soil data. The application of different geographic information systems (GIS) techniques are applied to extract only areas with peat soil class from the entire soil data. The peat soil class is then compared with fire incidents to determine the frequency of fires in areas with peat soil, by inference raised bogs to ascertain their level of risk. This is also done using further techniques. Some spatial analysis applied include selection by attributes, location, and selections within certain spatial settings.

Also, a correlation analysis is done to determine the link between areas with peat soil and fires in these areas. A regression analysis is further executed to determine true relationship between areas with peat soil class (raised bogs) and fire incidents and explore the impact of different data sources in understanding fire mapping. This is denoted by the formula below;

$$log(Y_{fire}) = \beta_0 + \beta_1 X_{peat\ soil} + \epsilon \tag{5}$$

Where Y_{fire} represents the number of fires in the area whereas $X_{peat\ soil}$ indicates the areas with peat soil and by inference raised bogs.

2.2.4 Determining the Most Influential Meteorological Parameter

Based on the temporal range of the meteorological data, mean cumulative values for climatic factors covering the period of the data are deduced for analysis. The outcome of each meteorological parameter – temperature, relative humidity, wind speed and precipitation – is used to discover the level of relationship with fire occurrences within counties using a correlation analysis. The seasonality of fires is also assessed since these climatic variables tend to fluctuate over seasons and can have a consequent impact on fire occurrences.

Additionally, a multiple linear regression is devised to ensure a better comprehension of the true impact of each of those climatic variables on the incidence of fires. Hence, the most significant factor that influences the ignition and behaviour of fire events is established. Statistical regression and different correlation analyses can be used to identify most important weather factors on the ignition of fires and also as a basis for developing a fire danger index (Hamadeh et al., 2017). In order to find out the most influential weather parameter, it is denoted by the formula below;

$$log(Y_{fire}) = \beta_0 + \beta_1 X_{temp} + \beta_2 X_{RH} + \beta_3 X_{WS} + \beta_4 X_R + \epsilon \tag{6}$$

Where;

Y_{fire} = the number of fires in each county

X_{temp} = temperature

X_{RH} = relative humidity

X_{WS} = wind speed

X_R = precipitation

The significance level adopted as a basis for identifying the most influential weather variable on fire events is 5 percent.

2.2.5 Most Influential Factor on Fire Occurrence

A regression analysis as a statistical method of analyzing data enables the identification and representation of connection among multiple factors and often illustrates a relationship between two variables or among many variables. These are often single or multiple evaluation based on the variables involved. Many times, a multivariable or multiple linear regression is necessary to know the impact of multiple variables on a dependent variable since the application of only a single independent variable does not always provide enough evidence to understand the purpose of a study (Schneider et al, 2010).

Therefore, in order to figure out the most influential factor on landscape fires, a multiple regression model is constructed;

$$\log(Y_{fire}) = \beta_0 + \beta_1 X_{population} + \beta_2 X_{road\ network} + \beta_3 X_{peatbogs} + \beta_4 X_{reed\ beds} + \beta_5 X_{soil} + \epsilon \tag{7}$$

where;

Y_{fire} = the total number of fires

$X_{population}$ = population figures

$X_{road\ network}$ = road network buffer area

$X_{peat\ bogs}$ = area of peat bogs

$X_{reed\ beds}$ = area of reed beds

X_{soil} = area of peat soil class

Also, a 5 percent significance level is used to determine the impact of each factor on the occurrence of fires. The results provide the most influential factor and have a clear comprehension of the general impact of all these factors on fire occurrences.

3. Results

3.1 The nexus between human-related factors and fire incidence

The study results show the connection between anthropogenic factors – population and accessibility – on the rate of fires. It can be derived from Table 2 that, there is a positive relationship between population and fire events.

Table 2: Correlation between fire events and different variables

Factor	Correlation Co-efficient
Population	0.891
Road accessibility (buffer zone)	0.421
Peat soil	0.671
Peat bogs	0.531
Inland marshes (reed beds)	0.325

The Figure 2 is derived on the basis of spatial analysis. This is indicative of a map that combines population data and fire events data. The used method is point density of fires per square kilometre. It is vividly displayed on the map based on fire density that, fires occur more frequently in regions that are highly populated. Thus, population relates to the rate of fire incidents in a certain administrative unit or county.

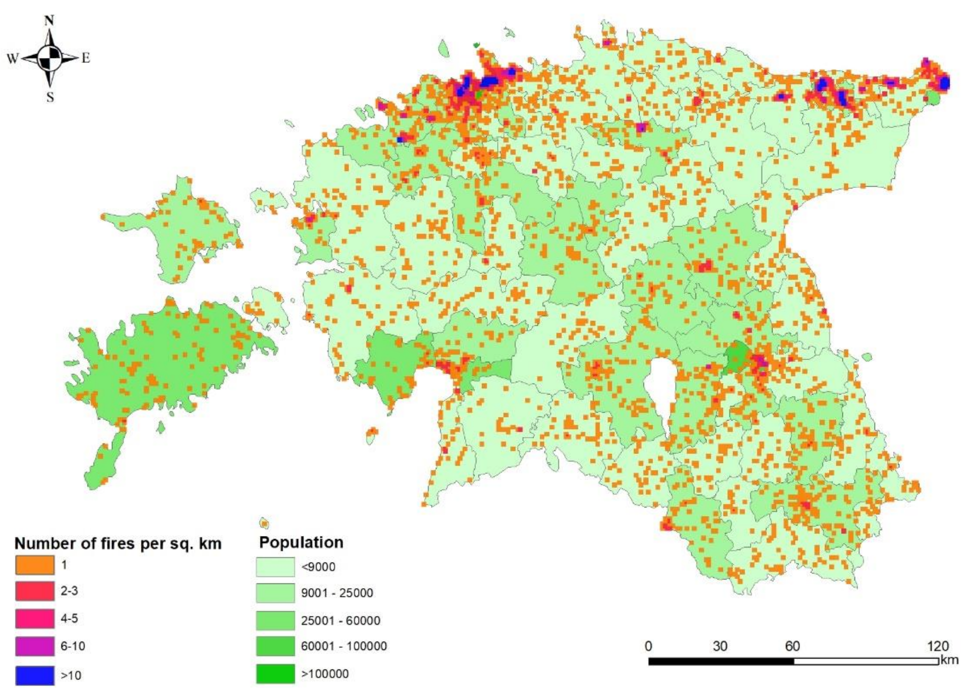

Figure 2: Population (2018) and fire density map (2014-2018)

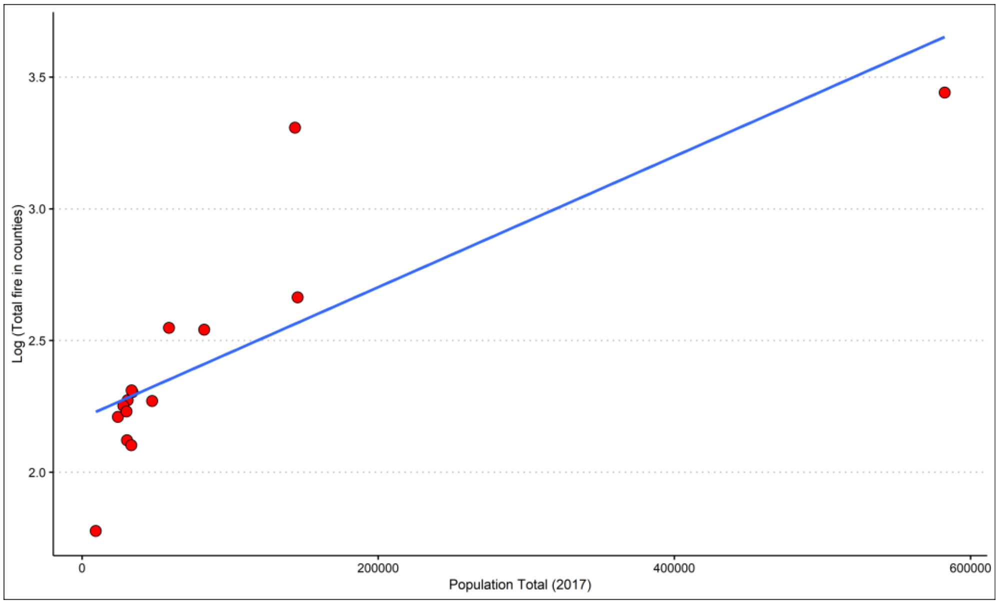

Figure 3: Correlation between population and total fires

The Figure 3 above is explanatory of the positive correlation between population and fire events because it provides a visual representation. It can be observed that there are some outliers due to the wide disparity in population figures based on counties in Estonia.

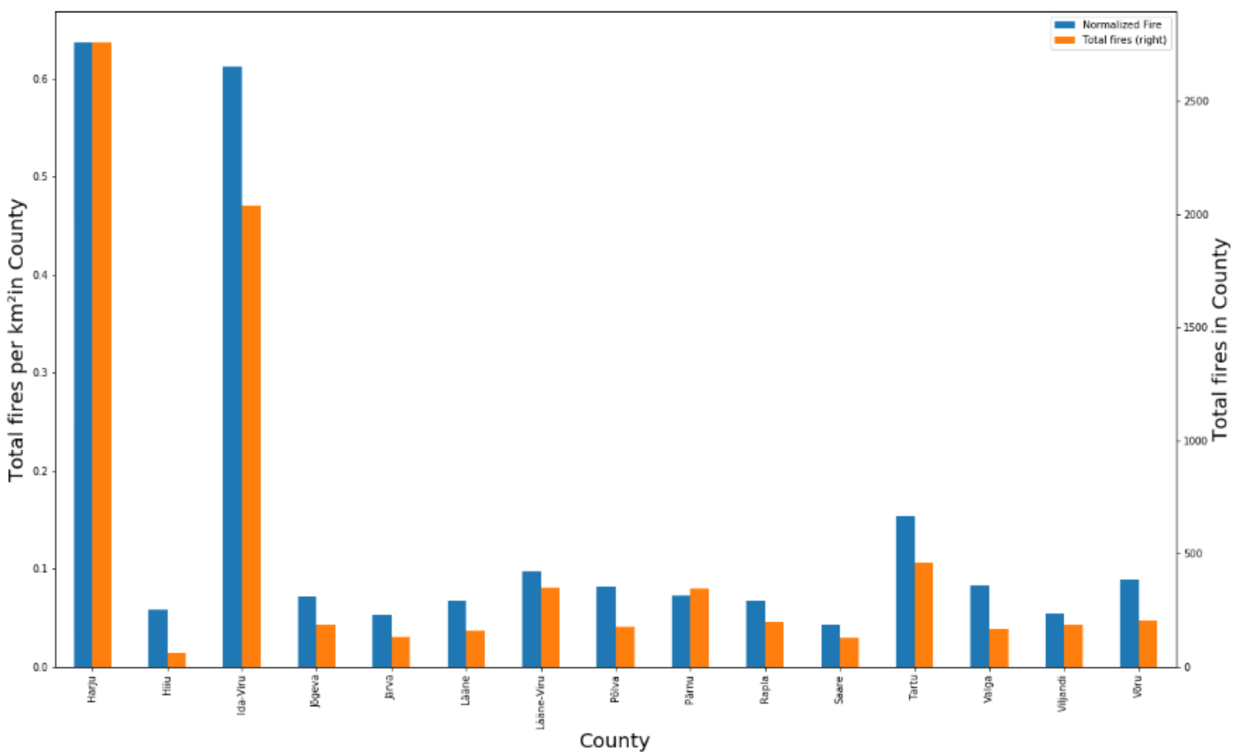

Figure 4: Comparison of absolute and normalized fires per county

Figure 4 shows a comparison of fire in terms of absolute figures and normalized fire events per county which highlights the significance of fire prone areas in Estonia by county. The normalized fires are estimated by using absolute fires in each county divided by the unit area of that county and results range between 0 and 1. It can be seen that normalized fires have a much higher frequency than absolute fires except in Pärnu County, due to it being the biggest county by area. Due to the similarities in distribution, absolute figures were subsequently used for the analysis.

Additionally, the Figure 5 below is indicative of the number of fires per square kilometer. The x-axis shows the number of fires per square kilometer and the y-axis represents the frequency of fire events in different square kilometer range across Estonia.

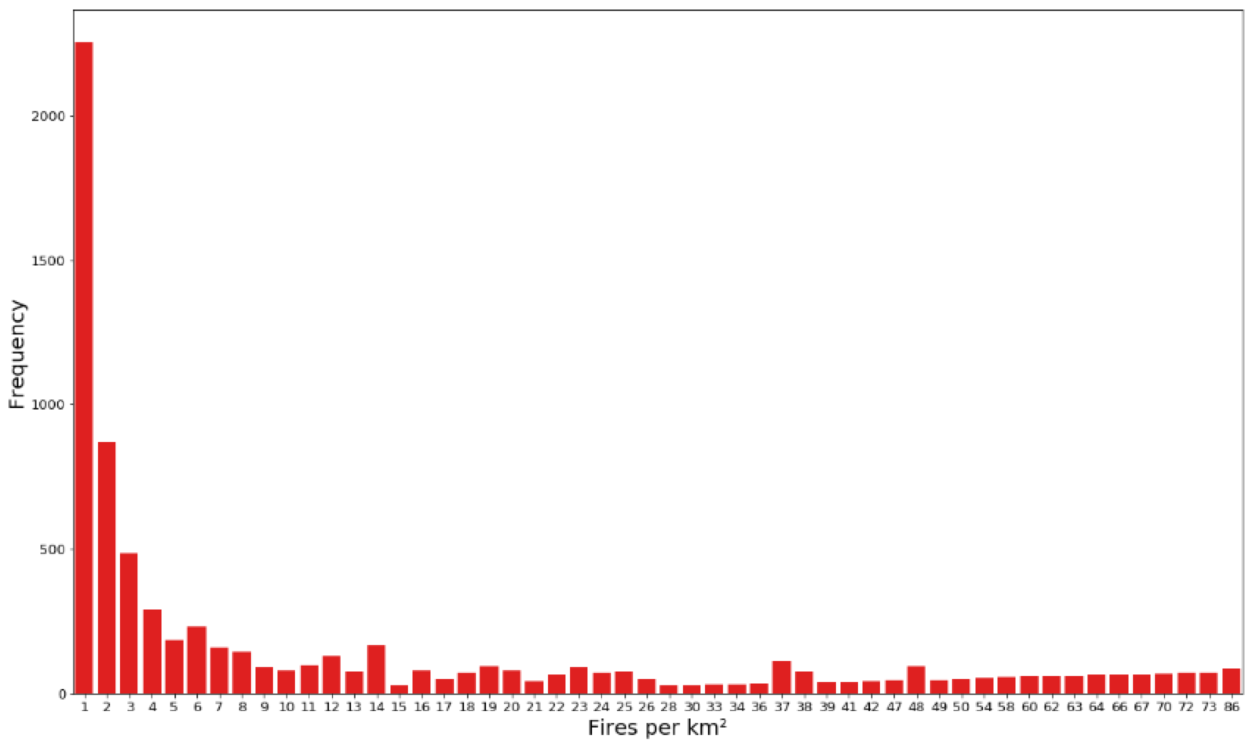

Figure 5: Number of fires per square kilometer

Since the result of regression analysis shows p-values lower than 0.05, it can be deduced that there is a causal relationship between population and fire (Table 3). One unit increase of population has a significantly positive effect on the number of fire occurrences.

Table 3: Fire and population linear regression

Dependent variable: log_total_fire	
Model	Co-efficient
Constant	0.000*
	(0.189)
Population	0.000*
	(0.000)

* indicates 5 percent significance level and standard error inside the parenthesis

The Figure 6 below is a map of the all roads in Estonia with one kilometer buffer zone. The researcher deems this to be the most suitable accessibility range for people within the territory and indicates the risk of fire occurring within this buffer zone due to continuous human activity.

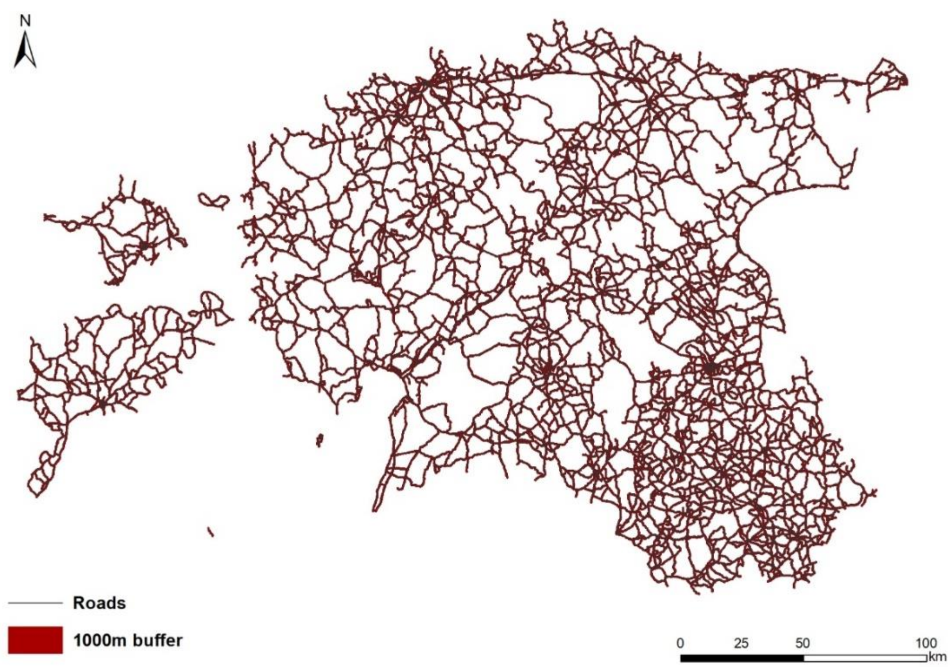

Figure 6: Road network and buffer zone

Results from analysis of accessibility as human-related factor show that about 80% of all fire events occur within a buffer zone of one kilometer along road network as depicted in Figure 7.

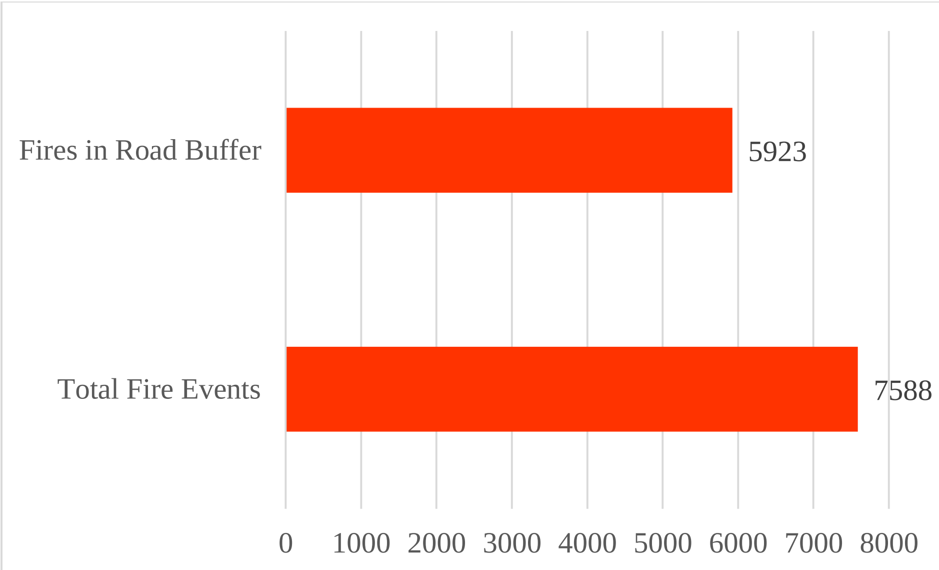

Figure 7: Total fires vis-à-vis fires in road buffer

The correlation analysis shows there is a moderate positive relationship between road network buffer zone and fire incidence within this scope. It is depicted by a correlation co-efficient of 0.421 as in Table 2 and same is seen from Figure 8 whereby the positive relationship is visually represented.

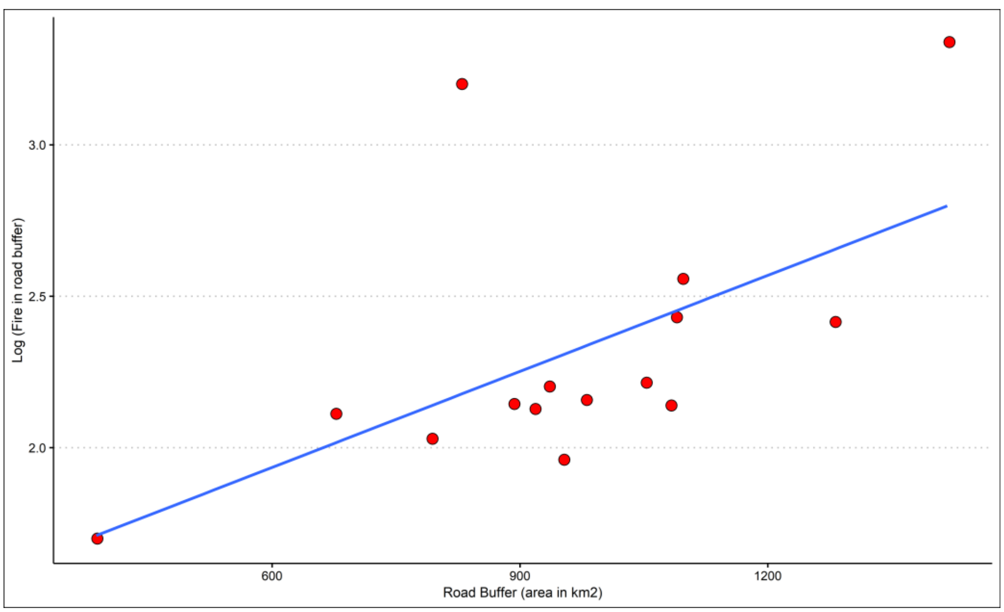

Figure 8: Correlation between road network buffer and fires within buffer

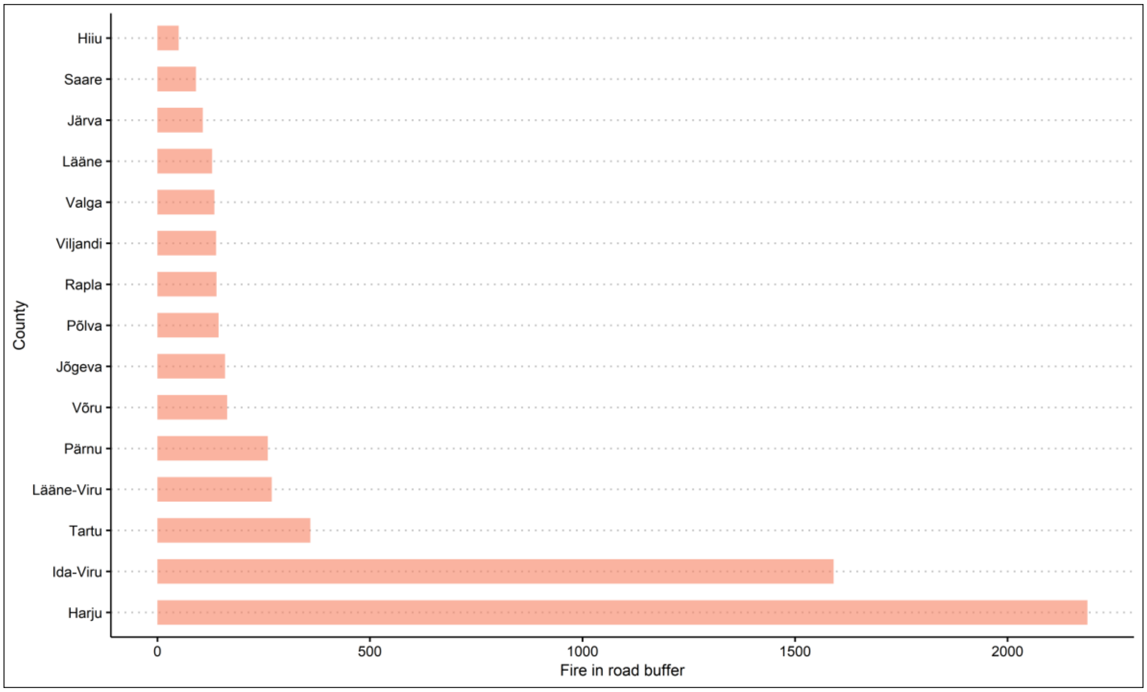

Figure 9: Number of fires in road network buffer per county

Figure 9 depicts a graphical representation of the number of fires that occurred within one kilometer buffer zone based on the historical fire data. Harju County, followed by Ida-Viru County have the highest fire rates within the road network buffer whereas the other counties have a comparatively close number of fires with Hiiu County having the least. This can be linked to the area of the road network buffer zone, thus the higher the area, the more the fire frequency (see Appendix).

The impact of road network accessibility is seen in the linear regression analysis. Table 4 establishes the true relationship between accessibility and fire because significance value of 0.021 is given and this means road network buffer area significantly impacts on the incidence of fire.

Table 4: Fire and road network buffer linear regression

Dependent Variable: log_fire_road	
Model	Co-efficient
Constant	0.006* (0.917)
Road buffer (area in km^2)	0.021* (0.001)

* indicates 5 percent significance level and standard error inside the parenthesis

3.2 Impact of peatland and reed beds fuel on rate of fires

The Figure 10 is a representation of LULC map showing the quantity of fires that occurred in the two specific land cover classes – peat bogs and inland marshes. The number of fires are depicted as collected events. There are overlapping fire points and not all of them can be seen from the map because more fires occurred in a specific area and this nevertheless, map is easy to interpret and comprehend.

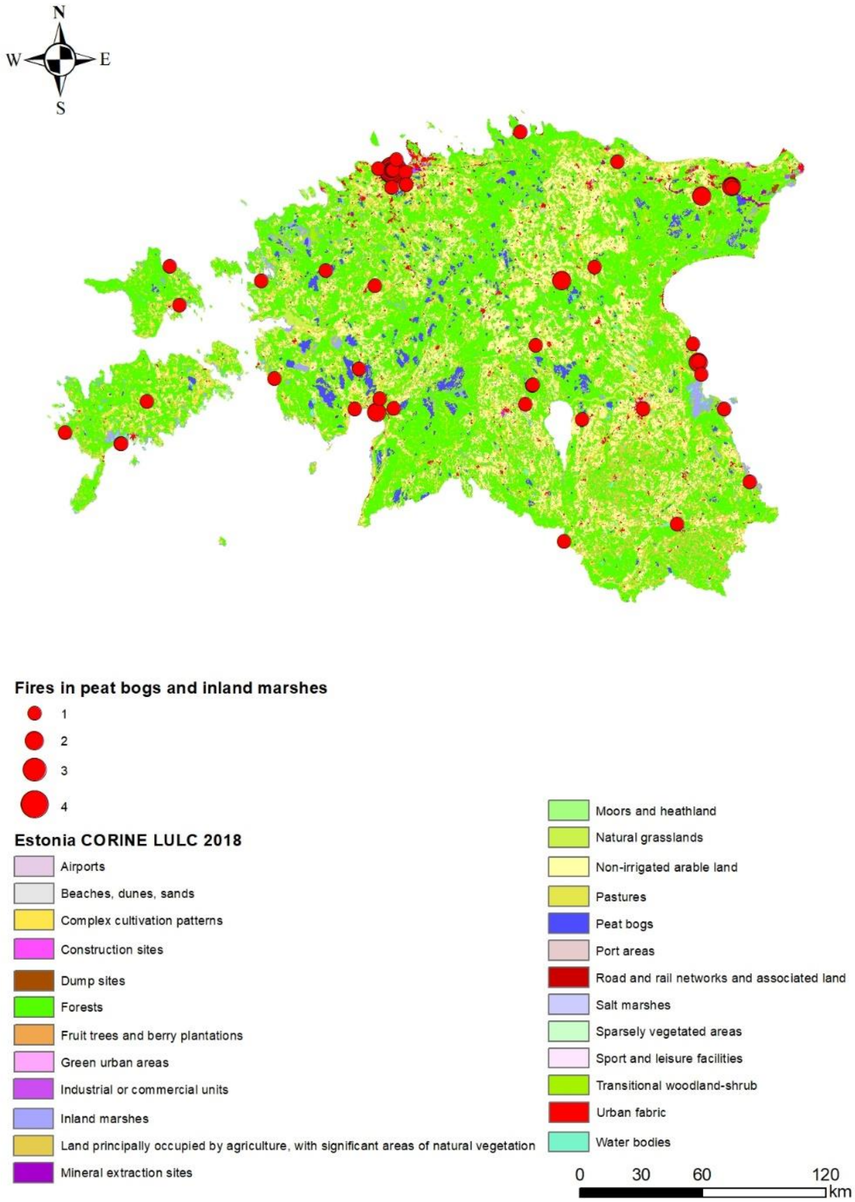

Figure 10: CORINE LULC map indicating fires in peat bogs and inland marshes

Further analysis is executed based on the unit area of coverage of each land cover, which is peat bogs and inland per county (see Appendix). In reference to Table 2, the results show that there is a moderate positive correlation between fire incidents and coverage of peat bogs as reflected in the correlation value of 0.531 and also there is a weak positive connection between the incidence of fires in reed beds and coverage area of reed beds with correlation value of 0.325.

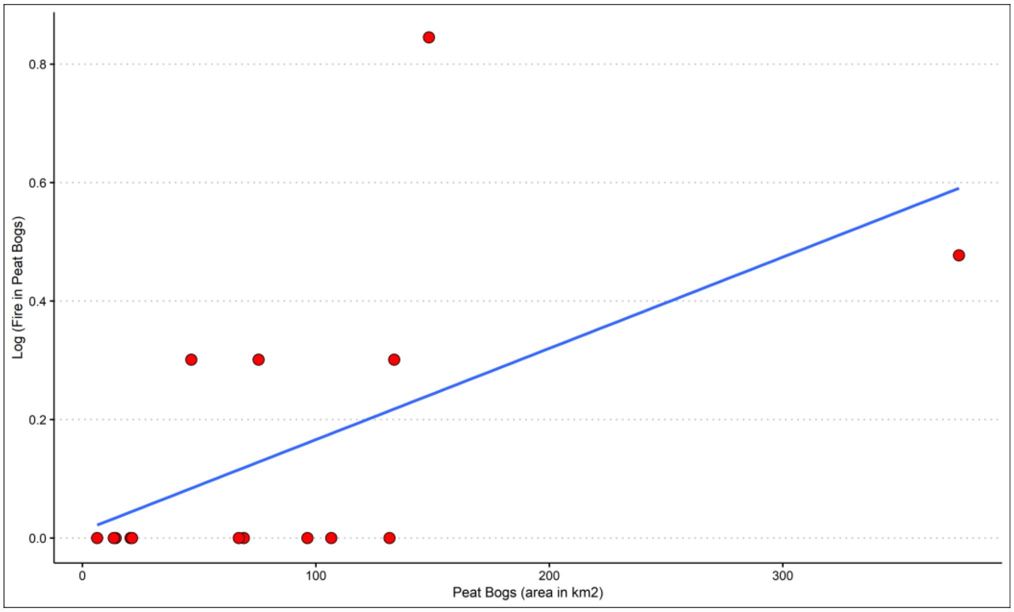

Figure 11: Correlation between fires and peat bogs

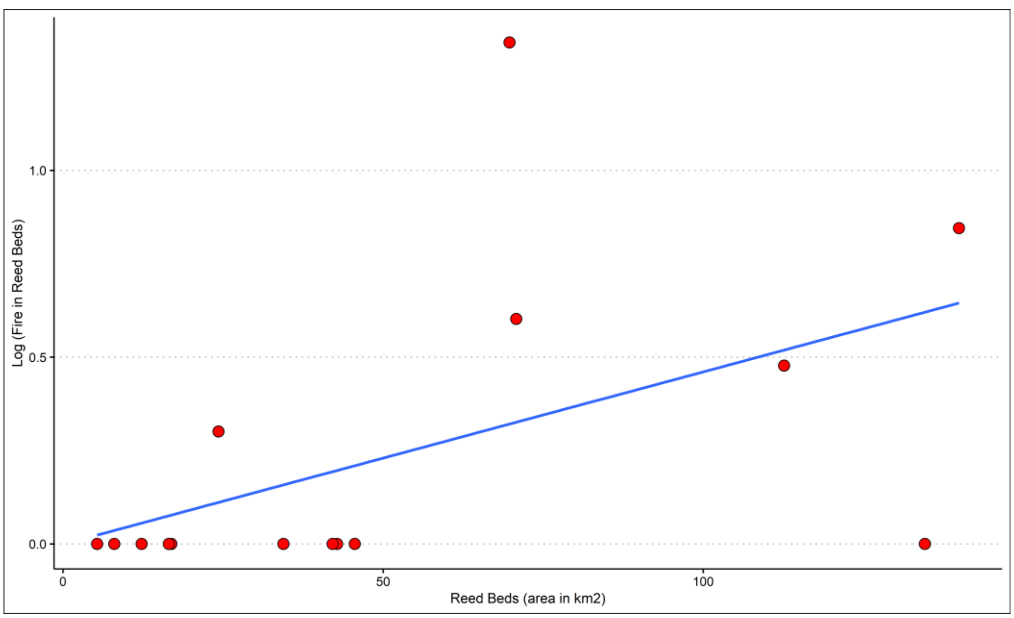

Figure 12: Correlation between fires and reed beds

Figure 11 is representative of the strength of relationship between fire events and coverage area of peat bogs being moderately positive whereas the relationship between fire incidents and coverage area of reed beds is visually presented from the scatterplot as having a weak positive connection (Figure 12).

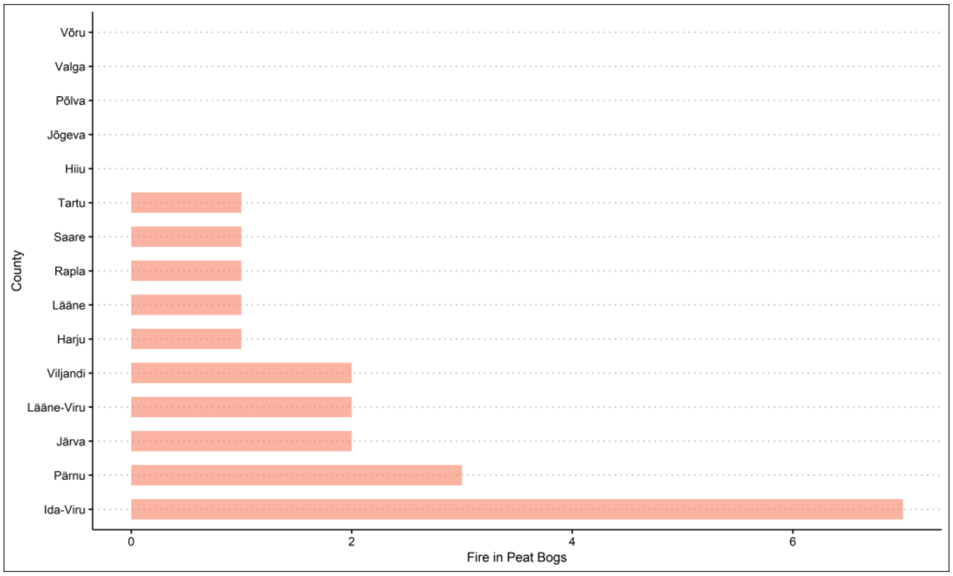

Figure 13: Number of fires in peat bogs per county

The spatial distribution of fire occurrences in land cover classes – peat bogs and reed beds – is graphically represented on the basis of counties. There are comparatively less fires occurring in peat bogs over the years. Specifically, majority of fires in peat bogs happened in Ida – Viru County and Pärnu County respectively but no fires were recorded in peat bogs when it comes to counties like Valga, Võru, Jõgeva, Põlva and Hiiu (Figure 13).

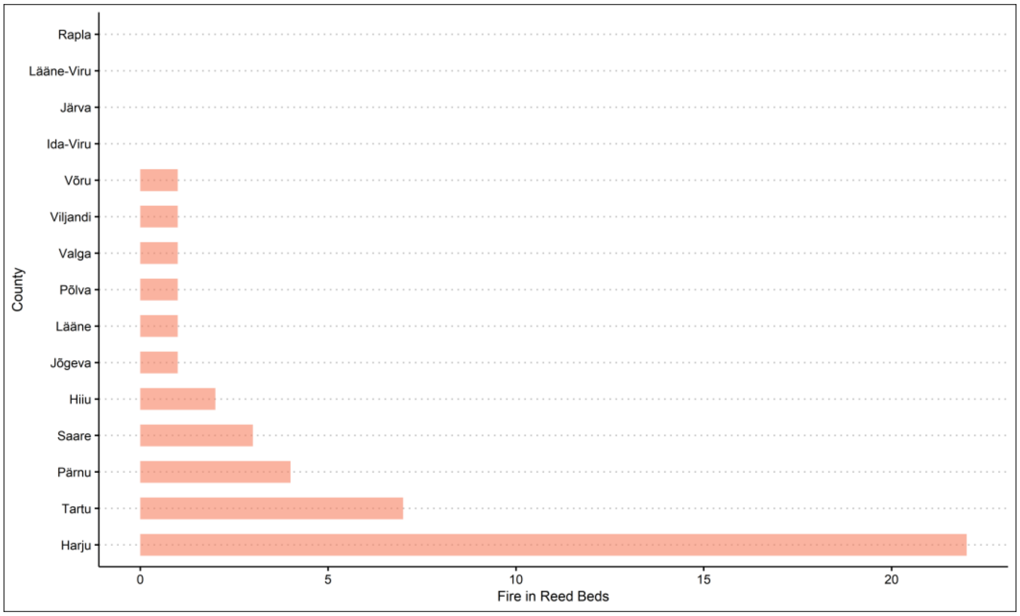

Figure 14: Number of fires in reed beds per county

Alternatively, it can be observed from Figure 14 that relatively more fire incidents occurred in reed beds. Harju County, followed by Tartu County had the highest number of fires taking place in reed beds but no fires happened in Rapla County, Järva County, Lääne-Viru County, and Ida-Viru County.

Table 5: Fire and peat bogs linear regression

Dependent Variable: log_fire_peat_bogs	
Model	Co-efficient
Constant	0.649 (0.317)
Peat bogs (area in km^2)	0.185 (0.002)

* indicates 5 percent significance level and standard error inside the parenthesis

The result from the linear regression analysis indicates that the causal relationship between spatial extent of peat bogs (unit area in a county) and rate of fires in this spatial context is statistically not significant (Table 5). Thus, spatial distribution of peat bogs have no significant effect on the incidence of fires in this landscape.

Table 6: Fire and reed beds linear regression

Dependent Variable: log_fire_reed_beds	
Model	**Co-efficient**
Constant	0.715 (0.475)
Reed beds (area in km^2)	0.161 (0.006)

* indicates 5 percent significance level and standard error inside the parenthesis

Table 6 depicts the result from linear regression analysis which indicates that the causal relationship between the spatial coverage area of reed beds (unit area per county) and the incidence of fires in this landscape is not statistically significant. A unit change of reed beds area does not result in the change of the occurrence of fire events at 5 percent significance level.

3.3 Vulnerability of fire in areas with peat soil (raised bogs)

The Figure 15 below is a representation of areas with peat soil in comparison with the number of fire events that occurred in these raised bogs. The spatial density of fire points is indicative of areas in Estonia that have fires happening predominantly. Counties such as Harju, Ida-Viru and Tartu have a high density of fire events relative to other areas and a distinctive spatial distribution of fires in peat soil is observed.

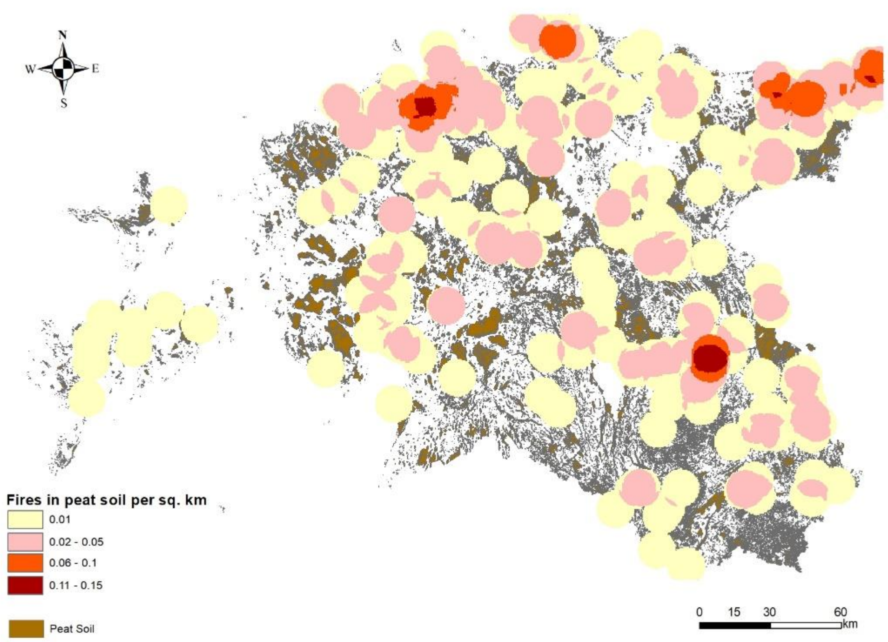

Figure 15: A map showing peat soil areas and quantity of fire events

The relationship between areas with peat soil (raised bogs) and fire incidents in raised bogs is moderate since correlation co-efficient is 0.671 (Table 2) and same can be interpreted from observation of scatterplot in Figure 16.

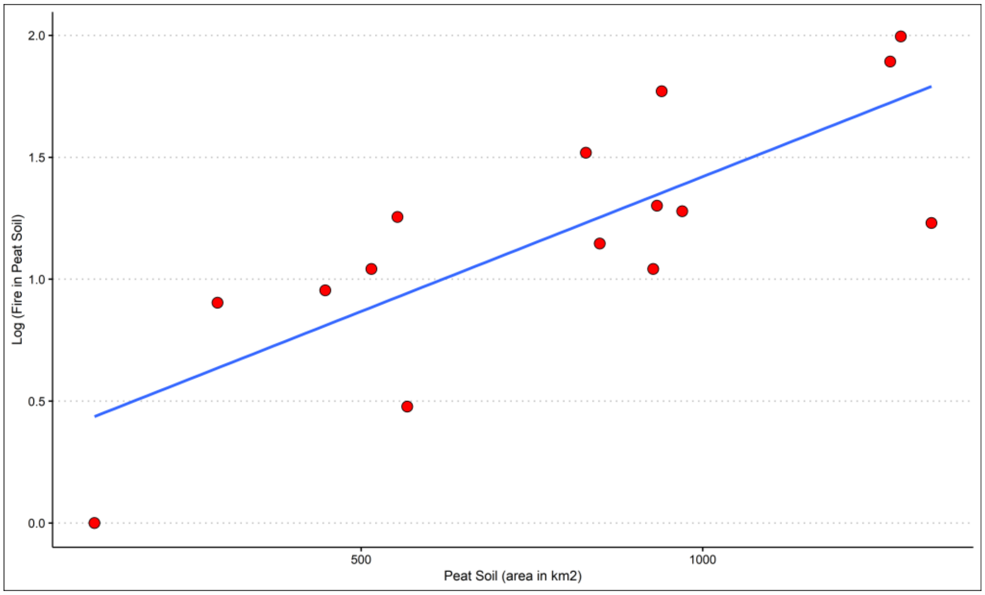

Figure 16: Correlation plot between peat soil areas and fires

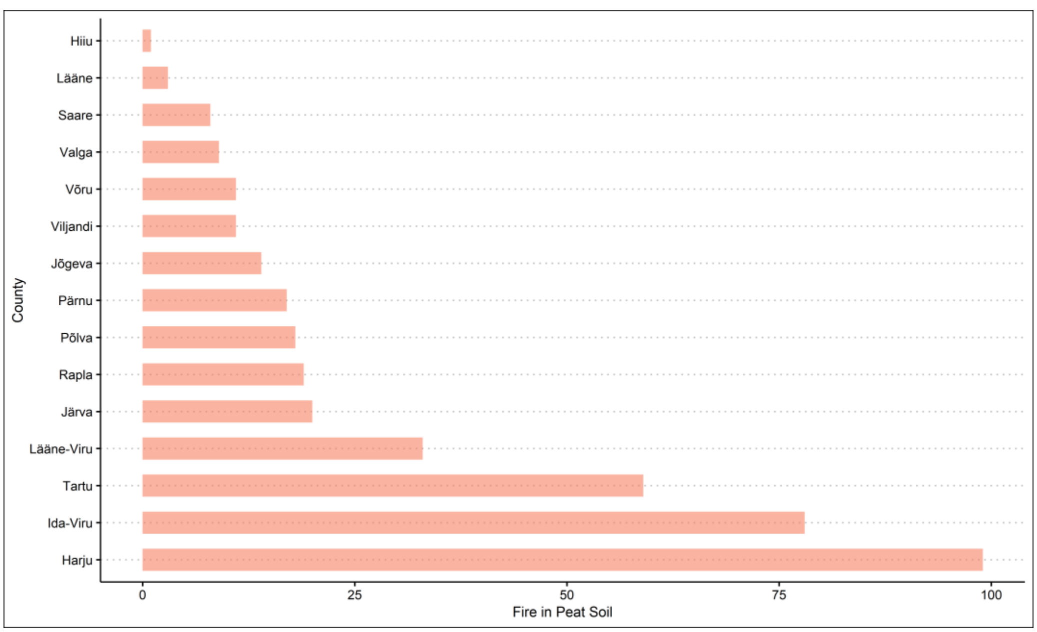

Figure 17: Number of fires in peat soil areas per county

The graphical representation of results in Figure 17 indicates the predominance of fires that happened in times past in every county and it is deduced that Harju County, Ida-Viru County and

Tartu County experienced most fires respectively in peat soil areas. Hiiu County had the least amount of fires occurring in raised bogs over the years.

Table 7: Fire and peat soil linear regression

Dependent Variable: log_fire_peat_soil	
Model	Co-efficient
Constant	0.152
	(0.477)
Peat soil (area in km^2)	0.000*
	(0.001)

* indicates 5 percent significance level and standard error inside the parenthesis

An analysis based on linear regression to ascertain the true relationship between peat soil areas and fires resulted in a statistically significant output. Hence, there is a positively significant effect of the area of peat soil on the number of fire occurrences in raised bogs (Table 7).

3.4 Most Influential Meteorological Parameter on Fire Events

This involves the analysis of different climatic variables using linear regression and correlation purported to find out the most significant climate factor on fire. The seasonality of fire was assessed based on the fire data and the results proved that fires mostly occur during spring (March – May) and summer (June – August), with autumn (September – November) and winter (December –February) indicating the lowest respectively as illustrated in Figure 18.

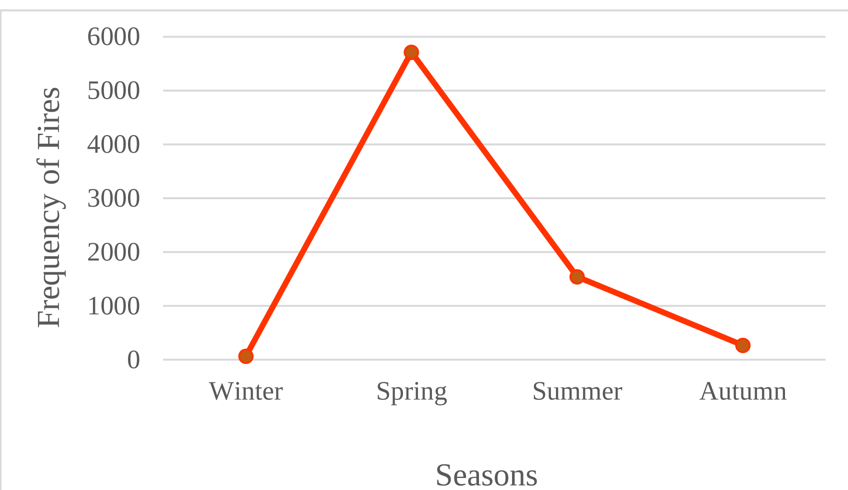

Figure 18: Seasonality of Fire in Estonia (2014 – 2018)

On the basis of availability and spatial distribution of meteorological data, an analysis was made in comparison with fire data. The Table 8 indicates that there is a weak positive relationship between fire incidence and relative humidity, wind speed as well as an inverse weak relationship with temperature and precipitation. The outcome of linear regression indicates that none of the climatic variables resulted in a statistically significant outcome since obtained P-values are higher than the chosen significance level of 5 percent (Table 8). This means that none of these meteorological indicators on average has any significant impact on the ignition and/or propagation of landscape fires.

Table 8: Linear Regression & Pearson correlation coefficients between fire occurrence and climate variables

Variables	Correlation Co-efficient	P-value
Temperature (^{o}C)	-0.18	0.095
Relative Humidity (%)	0.1	0.49
Wind Speed (m/s)	0.22	0.116
Precipitation(mm)	-0.08	0.875

3.5 Most Significant Factor on Fire Occurrence

The outcome of the multiple regression analysis indicates that, of all the independent variable factors, only peat soil has a statistically significant impact on fire events as a dependent variable at 5 percent significance level (Table 9). Thus, peat soil or areas with raised bogs have the most significance when it comes to fire susceptibility. However, all the other variables have no significance as far as fire incidence is concerned at the chosen significant level.

Table 9: Multiple regression analysis involving all appropriate data

Dependent Variable: log_total_fire	
Model	**Co-efficient**
Constant	0.000* (0.712)
Population	0.054 (0.000)
Reed beds	0.647 (0.003)
Peat soil	0.03* (0.001)
Road buffer	0.903 (0.001)
Peat bogs	0.3 (0.003)

* indicates 5 percent significance level and standard error inside the parenthesis

4. Discussion

4.1 Anthropogenic Causes of Fire

One of the areas of interest of this thesis was to discover anthropogenic causes of fires and their extent of relationship as a fire causative factor(s). There can be a myriad of anthropogenic fire causes as revealed from literature of fire risk mapping and highlighted in previous chapters. The focus of the thesis was therefore limited to only two aspects of human induced causes of fires which are population and accessibility based on the context of the research.

The research achieved the aim of using population data to determine its impact on fire occurrences by using density of fire and statistical analysis. It came out that high density of fires correspond to areas of high population figures and low density fire matches administrative regions with low population. A correlation and causal relationship between population and fire incidence became evident from the research to buttress the high degree of human impact as ignition source of fire. Similar outcome has been obtained by many researchers in their work (Guyette et al. 2002, Mercer & Prestemon, 2005, Bistinas et al. 2013) that basically discovered population as a human related function of fire ignition depending on the area of study. In general, fires occur more frequently in counties and cities like Harju (Tallinn), Ida-Viru (Narva, Jõhvi, Kohtla-Järve), and Tartu respectively.

Physical mobility of people within an appreciable walking distance alongside roads contribute to the risk of fire happenings. It was revealed that majority of fires, approximately 80% occur within 1km of a buffer of road networks. Similarly, Catry et al. (2009) in their study assessing the spatial distribution of fires, showed that 98% of ignitions occurred within a distance of 2km from the nearest road with 85% within a range of 500m. It is also noteworthy that the outcome of this research revealed a positive correlation of fires and the road network buffers. Furthermore, a level of significance was achieved to ascertain the true impact of human accessibility via road network buffer on fire events, thus human interaction through constant mobility close to roads has an impact on the risk of fire occurring. This is consistent with (Jaiswal et al. 2002, Amalina et al. 2016, Eugenio et al. 2016), whereby the accessibility factor was duly considered and weighted as a human disturbance variable towards developing fire hazard maps in different areas. Most of the fire events that occurred alongside road network were actually in counties with relatively large cities like Harju, Ida-Viru and Tartu in that order.

4.2 Fire Events in Varied Landscapes

The research sought to determine the level of fire risk occurring in different landscapes. This was achieved by adopting a unit coverage area of specific wetlands – inland marshes and peat bogs – using land cover classification data. The spatial coverage of these land cover classes was estimated for each county and then comparison made with fire events based on each county. Similarly, Arroyo et al. (2008) indicated that having knowledge of the spatial distribution of fuel types is an important step towards developing fire management systems.

The spatial coverage is consistent with the quantity of fires as shown from the study. This is shown as the area of coverage of inland marshes and peat bogs is positively correlated with fires in this zone. This demonstrates the connection between fuel types in these landscapes and their vulnerability to fires. However, it was proven that the spatial distribution of these land cover classes has no statistical significance on the incidence of fires since regression analysis results indicated as such. The fire risk is higher in reed beds than in peat bogs due to the quantity of fire events that happened in the former than latter land cover over the years. This finding shows fire regimes are greatly dependent on the land cover/land use type and fire activity is also influenced by natural conditions like the morphology of landscapes (Pereira et al., 2014).

Additionally, fires in other landscape was determined based on soil data. Peat soil was extracted to represent a wider scope that usually accommodate varied types of wetlands, raised bogs inclusive. It was realized that there is a positive relationship between peat soil and fire events. Thus, characteristics of vegetation in areas with peat soil actually pose a higher danger to fire occurring. This is in line with the regression analysis which gave a statistically significant outcome as regards the true relationship between peat soil areas and fire incidence. According to Firmansyah & Mokhtar, 2012 (as cited in Suryatmojo et al., 2019) in their research found that peat soil is a soil that is susceptible to fire especially during the dry season.

4.3 Natural Causes of Fire Events

The variability of fire regimes across different seasons is often determined as foundation to understand the influence of weather variables on the ignition and propagation of fires in many locations. This period was defined by Chen et al., (2014) as the fire season whereby their research discovered that majority of fires largely occur in the spring season. Similarly, the seasonality of fires also from this study showed that the fire regime is predominantly in spring.

It is factual that weather variables influence the seasonality in many regions. The seasons come along with varied levels of weather parameters which in turn have an impact on the incidence of fires in different landscapes. The risk associated with fires and their management requires an accurate knowledge of the probable repercussions of climate variables on fire risk (Bedia et al., 2018). The availability of meteorological data in the right format therefore becomes crucial in assessing the risk of fire based on such data. The researcher used four key climate variables - temperature, relative humidity, wind speed and precipitation – to determine their level of influence on landscape fires in Estonia. These meteorological indicators facilitate the development of fire danger, usually calculated as numerical indices and most fire management systems are developed based on these indices (Hamadeh et al., 2017).

Although there was expectation of at least one of the variables having an impact on fire incidence, the result indicated that none of the parameters observed had any impact on fire events. Therefore, it can be said that other factors other than weather influence fire ignition and propagation. The reason for this could be attributed to the spatial and temporal distribution limitation of the meteorological data retrieved for the study since Chen et al. (2014) succinctly stated that in order to understand the impact of weather variables on fire regimes, the frequency, distribution and duration should be considered but not only the total amount of weather variables over a period. Moreover, in line with this finding, Hamadeh et al. (2017) by using statistical regression methods identified relative humidity, wind speed and precipitation as having a weak relationship with fire occurrence which means these weather variables have no real impact on the quantity of fire incidences.

4.4 Most Significant Factor on Fire Ignition and/or Propagation

The combination of diverse factors like anthropogenic, natural and other biophysical factors as concerned with finding their relationship on fires was very crucial in this study. Each of these factors had some degree of impact on fire occurrences. It became prudent to determine which of them has a more significant impact on fires ignition and propagation through the adoption of a multivariable regression analysis. It can be observed that meteorological parameters were not included in finding the most significant factor on fires because earlier outcome from analysis of specific weather variables had no impact on fire occurrences and it would have been imprudent for the researcher to include same since they had no impact on fire ignition and propagation as seen from Table 8.

The degree of impact of all the factors was obtained and the outcome showed that peat soil significantly relates to fire activity. It was also found in a related research that peat soil, like most natural fuels are extremely susceptible to fires and logically, it is more likely to support smoldering fires but can also propel flaming fires (Lin et al., 2019). This therefore suggests and can be inferred that characteristics of different types of wetlands or overlying vegetation found in these areas with peat soil as well as peat soil properties have the most significant impact on fire behaviour in Estonia. Thus, susceptibility of fires is highest in these areas with peat soil and landscape management experts should consider focusing on these landscapes since peat soil is prone to fires.

4.5 Limitations of the Study

The use of meteorological indicators towards understanding its relationship with fire incidence causation and developing weather based models for fire prediction is very crucial in fire risk mapping. However, the format of weather variables received and the application of it can have an effect on fire or not as seen in this study. The methodology applied, which is adopting annual mean cumulative values averaged over the temporal range of the data may have resulted in the no significance output of weather on fire events but it cannot be conclusive. This is because the daily weather variables could not be obtained and compared with fire occurrences to determine whether or not they have any impact on fires so this should be pursued in further research. The daily recordings of weather indicators could be more reliable as a basis for determining the frequency and duration of observed data than using annual mean values.

The methodology used as far as statistical analysis is concerned limits validity of linear regression analysis since sample size derived for analysis is small as it was done based on counties due to the type of data retrieved. The validity could be improved by widening sample size in future research but the outcome of this study cannot be discounted or disregarded since the researcher found ways to capture all information in the study depending on data acquired.

Conclusion

In fire risk hazard mapping, a lot more focus has been on forests and devising a system to highlight fire risk zones putting into consideration different data sources (Jaiswal et al. 2002, Gai et al. 2011, Amalina et al. 2016). Spatial extent of landscape together with vegetation indices have been used for fuel load mapping in many regions using diverse methodological approaches (Franke, et al. 2018, Majlingová et al., 2018, Vallejo-Villalta et al., 2019). Many fire prediction models have been developed and are constantly being reviewed in many regions mostly based on meteorological indicators to report imminent fire danger in real time to ensure an early warning for the protection of lives and properties (Giuseppe et al. 2016, Hamadeh et al. 2017, Bedia et al. 2018). All these encapsulate the diversity of contribution towards fire risk modelling over the years from many geographical locations.

This study sought to make a contribution to this field by focusing on fire risk in diverse landscapes other than just forests where comparatively less research has been done. The aim was therefore to understand the variability of historical fires in nexus to some thematic areas: anthropogenic factors, land cover and peat soil areas susceptibility, meteorological impact as well as finding most influential factor on the ignition and spread of fires.

The researcher used population, land cover, peat soil, topographic (roads), and meteorological data for comparison with historical fires to determine risk levels in landscapes. Several analytical methods were employed including GIS techniques and statistical analysis. In terms of the GIS analysis, techniques like clipping, extract by mask, extract values to points, selection by attributes and location, buffer analysis and point density analysis were applied. Correlation and linear regression analysis were adopted for the statistical analysis. These techniques were adopted pursuant to finding solutions to research questions but the specific technique employed was due to the data format which helped towards achieving the aims of the study.

It can be concluded that anthropogenic factors are a major causative factor of landscape fires. Thus, population has a significant impact on fire events as realized from this study. One other human related factor which is accessibility proved to have significant relationship with fire incidence. Human mobility in terms of nearness to road networks is a high risk factor in fire occurrences. Fires are more frequent in counties and cities in Estonia with high population figures and high spatial coverage of road network buffers.

The identification and characterization of two land cover classes – peat bogs and inland marshes – in relation to the rate of fires proved that peat bogs are less prone to fires than inland marshes based on the historical fires. The spatial extent of these land cover classes per county has no significant impact on fire frequency in Estonian counties. In other landscape where there is presence of peat soil, it can be concluded that fire risk is significant in counties with high coverage of areas with peat soil. Thus, peat soil is deemed to be prone to fires.

Annual cumulative mean values of meteorological parameters like temperature, relative humidity, wind speed and precipitation averaged over the years from counties can conclusively be said to have no significant impact on the number of fires. The ignition and spread across counties are therefore not affected by weather conditions in Estonia.

Finally, many factors play a role in one way or the other towards ignition and propagation of landscape fires but a conclusion can be drawn from this study that, peat soil is the single most significant factor that influences fire occurrences in Estonia. The reason for this can be attributed to the properties of peat soil itself as well as characteristics, type of vegetation in areas with peat soil as these provide a highly flammable source by making them susceptible to fires.

Kokkuvõte

Eesti maastikutulekahjude riskianalüüs

Tulekahjud on kiviajast alates olnud inimkonna ellujäämise seisukohast väga tähtsad ning need on inimestele nende evolutsioonis jätkuvalt abiks. Ühtlasi on tulekahjud haiguste ja putukate, ülekarjatamise, ebaseadusliku kasutusala muutmise ja raie kõrval metsadele ja teistele maastikele kõige olulisemad ja korduvad vaenlased (Tampakis et al., 2010).

Üldiselt põhjustavad tulekahjud laastavat kahju ja kaost ökosüsteemidele ja inimeste tervisele suitsu sissehingamise ja halvimal juhul surmajuhtumite näol ning riikide majandustele, mis sõltuvad metsades ja teistel maastikel leiduvatest loodusvaradest. Siiski on erinevatel maastikel aset leidvatest tulekahjudest ka kasu, näiteks seemnete vabanemise näol teatud puuliikidest, haiguste ja putukate ohjamisel ning mineraalmuldade paljastumisel, mis soodustab puude uuenemist (Akther & Hassan, 2011).

Süttimise kaheks peamiseks põhjuseks on tulekahjuriskide kaardistamisel peetud inim- ja looduslikke allikaid (Chuvieco, et al., 2010). Lisaks põhjustavad maastikutulekahjusid looduslikud tegurid nagu pikselöögid, kui piirkonna rahvastikutihedus on hõre, ning kui rahvastikutihedus on kõrge, muutub peamiseks maastikutulekahjusid põhjustavaks teguriks inimtegevus (Gai et al., 2011).

Seetõttu on tulekahjuriski hindamine eriliselt seotud nimetatud süüteallikate mõistmise ja nende analüüsimisega. Maastikutulekahjude uurimine muutub ülimalt kasulikuks, kuna erinevate Eesti maastike tulekahjuriskide kaardistamise vallas on uuringuid läbi viidud vaid piiratud koguses. Uurimistöö eesmärgiks oli analüüsida tulekahjude esinemist erinevatel maastikel ning tuvastada seonduvad tulekahjude ilmnemise riskifaktorid nendel maastikel Eestis.

Uurimistöös kasutatud andmeteks on muuhulgas: ajaloolised tulekahjusündmused (2014–2018), rahvastikuandmed (2017–2018), teedevõrk (2018), maakate (2018), pinnase- ja meteoroloogilised andmed (2014–2018) kogu Eesti lõikes. Analüütiliste meetoditena olid muuhulgas kasutusel GIS tehnikad ja statistiline analüüs. GIS analüüsi raames rakendati tehnikaid nagu väljalõikamine (*clipping*), kihtidena ekstraheerimine (*extract by mask*), punktiväärtustena ekstraheerimine (*extract values to points*), valik omaduste ja asukoha järgi, puhveranalüüs ja punktitiheduse analüüs. Statistilises analüüsis kasutati korrelatsiooni ja lineaarset regressiooni, et tuvastada riskifaktorite mõju tulekahjude esinemisele.

Tulemus tõestas, et maastikutulekahjude üheks peamiseks põhjuslikuks faktoriks on inimtekkelised tegurid. Elanikkonnal on tulekahjusündmustele oluline mõju. Tulekahjude esinemisel on kõrgeks riskifaktoriks inimeste liikuvus läheduse mõistes teedevõrkudele. Tulekahjud on sagedasemad sellistes Eesti valdades ja linnades, kus elanikkond on tihe ning teevõrkude puhvrite (*road network buffers*, RNB) ruumiline kattuvus kõrge (1 km kasutatud).

Ajaloolistele andmete tuginedes saab järeldada, et turbarabad on tulekahjudele vähem aldid kui sisemaised märgalad. Nende maakatte klasside ruumiline ulatuvus valla kohta tulekahjude sagedusele olulist mõju ei avalda. Samuti järeldati, et turvasmullaga aladel on tulekahjude esinemise risk oluline.

Välja arvutati meteoroloogiliste parameetrite nagu temperatuuri, suhtelise õhuniiskuse, tuulte kiiruse ja sademete aastased kumulatiivsed keskmised, mille tulemusena võib öelda, et nende mõju tulekahjusündmuste arvule ei ole oluline.

Üldkokkuvõttes võib järeldada, et selles uurimistöös analüüsitud arvukate faktorite hulgas on turvasmuld olulisimaks eraldiseisvaks tulekahjude esinemist mõjutavaks faktoriks Eestis.

Acknowledgements

I would like to express my sincere gratitude to my supervisor, Prof. Tõnu Oja who meticulously provided the academic direction and guidance towards the completion of this research. My thankfulness is extended to all the related government agencies in Estonia for providing me with the necessary data used in my thesis. Special appreciation goes to my family who have truly supported me throughout my academic journey.

References

Abbott, K. N., Leblon , B., Staples, G. C., Maclean, D. A., & Alexander, M. E. (2007). Fire danger monitoring using RADARSAT-1 over northern boreal forests. *International Journal of Remote Sensing, 28:6*, 1317-1338.

Aguado, I., Chuvieco , E., Martín, P., & Salas, J. (2003). Assessment of forest fire danger conditions in southern Spain from NOAA images and meteorological indices. *International Journal of Remote Sensing, 24:8*, 1653-1668.

Akoglu, H. (2018). User's guide to correlation coefficients. *Turkish Journal of Emergency Medicine 18* , 91–93.

Akther, M. S., & Hassan, Q. K. (2011). Remote Sensing-Based Assessment of Fire Danger. *Ieee Journal Of Selected Topics In Applied Earth Observations And Remote Sensing, Vol. 4, No. 4*.

Amalina, P., Prasetyo, L. B., & Rushayati, S. B. (2016). Forest Fire Vulnerability Mapping in Way Kambas National Park. *Procedia Environmental Sciences 33* , 239 – 252.

Amatulli, G., Rodrigues, M. J., Trombetti, M., & Lovreglio, R. (2006). Assessing long-term fire risk at local scale by means of decision tree technique. *Journal of Geophysical Research Atmospheres*.

Andersen, H.-E., McGaughey, R. J., & Reutebuch, S. E. (2005). Estimating forest canopy fuel parameters using LIDAR data. *Remote Sensing of Environment 94* , 441–449.

Antrop, M. (2015). Interacting Cultural, Psychological and Geographical Factors of Landscape Preference. In D. Bruns , O. Kühne , A. Schönwald , & S. Theile, *Landscape Culture - Culturing Landscapes: The Differentiated Construction of Landscapes* (pp. 53-66). Wiesbaden: Springer.

Argañaraz, J. P., Landi, M. A., Scavuzzo, C. M., & Bellis, L. M. (2018). Determining fuel moisture thresholds to assess wildfire hazard: A contribution to an operational early warning system. *PLoS ONE13(10): e0204889.*

Arroyo, A. L., Pascual , C., & Manzanera, J. A. (2008). Fire models and methods to map fuel types: The role of remote sensing. *Forest Ecology and Management 256* , 1239–1252.

Arroyo, L. A., Healey, S. P., Cohen, W. P., Cocero, D., & Manzanera, J. A. (2006). Using object-oriented classification and high-resolution imagery to map fuel types in a Mediterranean region. *Journal of Geophysical Research 111*, G04S04.

Arumäe, T., & Lang, M. (2013). A simple model to estimate forest canopy base height from airborne lidar data. *Forestry Studies-Metsanduslikud Uurimused 58*, 46-56.

AUTH, X. (2007). Review of knowledge gaps and proposal for fuel data collection and test runs. *Fire Paradox*, 30.

Barros, A. M., & Pereira, J. M. (2014). Wildfire Selectivity for Land Cover Type: Does Size Matter? *PLoS ONE 9(1): e84760.* , doi:10.1371/journal.pone.0084760.

Bedia, J., Golding, N., Casanueva, A., Iturbide, M., Buontempo, C., & Gutiérrez, J. M. (2018). Seasonal predictions of Fire Weather Index: Paving the way for their operational applicability in Mediterranean Europe. *Climate Services*, 101-110.

Bistinas, I., Oom, D., Sá, A. C., Harrison, S. P., Prentice, I. C., & Pereira, J. M. (2013). Relationships between Human Population Density and Burned Area at Continental and Global Scales. *PLoS ONE 8 (12)*.

Cáceres, C. F. (2011). Using GIS in Hotspots Analysis and for Forest Fire Risk Zones Mapping in the Yeguare Region, Southeastern Honduras. *Available at https://www.researchgate.net/ DOI:10.13140/RG.2.2.18838.55369*.

Carlos, H. A., Shi, X., Sargent, J., Tanski, S., & Berke, E. M. (2010). Density estimation and adaptive bandwidths: A primer for public health practitioners. *International Journal of Health Geographics, 9(39)*, https://doi.org/10.1186/1476-072X-9-39.

Catry, F. X., Rego, F. C., Bação, F., & Moreira, F. (2009). Modeling and Mapping Wildfire Ignition Risk in Portugal. *International Journal ofWildland Fire 18,* , 921–931.

Chen, F., Niu, S., Tong, X., Zhao, J., Sun, Y., & He, T. (2014). The Impact of Precipitation Regimes on Forest Fires in Yunnan Province, Southwest China. *Hindawi*.

Chowdhury, E. H., & Hassan, Q. K. (2015). Operational Perspective of Remote Sensing-Based Forest Fire. *ISPRS Journal of Photogrammetry and Remote Sensing 104* , 224–236.

Chuvieco, E., Aguado, I., Yebra, M., Nieto, H., Salas, J., Martín, M. P., . . . Zamora, R. (2010). Development of a Framework for Fire Risk Assessment Using Remote Sensing and Geographic Information System Technologies. *Ecological Modelling 221* , 46–58.

Council of Europe. (2000). European Landscape Convention. *European Treaty Series-No. 176, Florence: Council of Europe*, https://rm.coe.int/1680080621. Retrieved from https://rm.coe.int/1680080621.

Eftekharian, E., Ghodrat, M., He, Y., Ong, R. H., Kwok, K. S., Zhao, M., & Samali , B. (2019). Investigation of terrain slope effects on wind enhancement by a line source fire. *Case Studies in Thermal Engineering, 14*.

Estonian Rescue Board. (2018, 10). *Estonian Rescue Board yearbook 2017*. Retrieved from Estonian Rescue Board: https://www.rescue.ee/files/2018-10/pa-aastaraamat-2017-eng.pdf. Accessed 17/04/2019

Eugenio, F. C., dos Santos, A. R., Fiedler, N. C., Ribeiro, G. A., da Silva, A. G., dos Santos, A. B., . . . Schettino, V. R. (2016). Applying GIS to develop a model for forest fire risk: A case study in Espírito Santo, Brazil. *Journal of Environmental Management 173* , 65-71.

Eva, H., & Lambin, E. F. (2000). Fires and Land-Cover Change in the Tropics: A Remote Sensing Analysis at the Landscape Scale. *Journal of Biogeography, 27 (3),* 765-776.

FAO. (2007). *Fire Management-Global Assessment 2006. A Thematic Study Prepared in the Framework of the Global Forest Resources Assessment 2005.* Rome: FAO.

FAO. (2012). *Forest Resources Assessment Working Paper 180.* Rome, Italy: Food and Agriculture Organization of the United Nations.

FAO. (2012). *Peatlands - guidance for climate change mitigation through conservation, rehabilitation and sustainable use.* Rome, Italy: Food and Agriculture Organization of the United Nations and the Wetlands International, available at http://http://www.fao.org/3/a-an762e.pdf.

Feng, C., Wang, H., Lu, N., Chen, T., He, H., Lu, Y., & Tu, X. M. (2014). Log-transformation and its implications for data analysis. *Shanghai Archives of Psychiatry, 26(2),* 105-109.

Fernandes, P. M. (2009). Combining forest structure data and fuel modelling to classify fire hazard in Portugal. *Ann. For. Sci. 66*, 415.

Filippelli, S. K., Lefsky, M. A., & Rocca, M. E. (2019). Comparison and integration of lidar and photogrammetric point clouds for mapping pre-fire forest structure. *Remote Sensing of Environment 224* , 154–166.

France-Presse, A. (2017, October 24). *Environment*. Retrieved from The Jakarta Post: https://www.thejakartapost.com/life/2017/10/24/forest-fires-contributed-to-record-global-tree-cover-loss.html. Accessed on 17/04/2019

Franke, J., Barradas, A. C., Borges, M. A., Costa, M. M., Dias, P. A., Hoffmann, A. A., . . . Siegert, F. (2018). Fuel load mapping in the Brazilian Cerrado in support of integrated fire management. *Remote Sensing of Environment 217*, 221-232.

Gai, C., Weng, W., & Yuan, H. (2011). GIS-based Forest Fire Risk Assessment and Mapping. *Fourth International Joint Conference on Computational Sciences and Optimization, © 2011 IEEE*.

Ganteaume, A., Camia, A., Jappiot, M., San-Miguel-Ayanz, J., Long-Fournel, M., & Lampin, C. (2012). A Review of the Main Driving Factors of Forest Fire Ignition Over Europe. *Environmental Management 51(3)* , 10.1007/s00267-012-9961-z.

Gillett , N. P., Weaver , A. J., Zwiers , F. W., & Flanniga, M. D. (2004). Detecting the Effect of Climate Change on Canadian Forest Fires . *Geophysical Research Letters 31*.

Giuseppe, D. F., Pappenberger, F., Wetterhall, F., & Krzeminski, B. (2016). The Potential Predictability of Fire Danger Provided by Numerical Weather Prediction. *Journal of Applied Meteorology and Climatology*.

Guyette, R. P., Muzika, R. M., & Dey, D. C. (2002). Dynamics of an Anthropogenic Fire Regime. *Ecosystems,* 472–486.

Hall , B. L., & Brown , T. J. (2006). Climatology of Positive Polarity Lightnings and Multiplicity and their Relation to Natural Wildfire Ignitions. *19th International Lightning Detection Conference.* Tucson, Arizona, USA.

Hamadeh, N., Karouni, A., Daya, B., & Chauvet, P. (2017). Using correlative data analysis to develop weather index that estimates the risk of forest fires in Lebanon & Mediterranean: Assessment versus prevalent meteorological indices. *Case Studies in Fire Safety*, 8-22.

Hayes, J., & Robeson, S. (2009). Spatial Variability of Landscape Pattern Change Following a Ponderosa Pine Wildfire in Northeastern New Mexico, USA. *Physical Geography*, 410-429.

Herrera, G. V. (2016). Mexican Forest Fires and their Decadal Variations. *Advances in Space Research 58* , 2104–2115.

Hirschberger, P. (2016). *Forests Ablaze: causes and effects of global forest fires.* Berlin: WWF Deutschland.

Jaiswal, R. K., Mukherjee, S., Raju, K. D., & Saxena, R. (2002). Forest fire risk zone mapping from satellite imagery and GIS. *International Journal of Applied Earth Observation and Geoinformation*, 1-10.

Keane, R. E. (2013). Describing wildland surface fuel loading for fire management: a review of approaches, methods and systems. *International Journal of Wildland Fire 22 (1)*, 51-62.

Konca-Kędzierska, K., & Pianko-Kluczyńska, K. (2018). The influence of relative humidity on fires in forests of Central Poland. *Sciendo*, 269-276.

Lampin-Maillet, C., Mantzavelas, A., Galiana, L., Herrero, G., Karlsson, O., Iossifina, A., . . . Thanassis, P. (2010). Wildland urban interfaces, fire behaviour and vulnerability: characterization, mapping and assessment. *European Forest Institute 23*.

Lang , M., Kaha, M., Laarmann, D., & Sims, A. (2018). Construction of tree species composition map of Estonia using multispectral satellite images, soil map and a random forest algorithm. *Forestry Studies | Metsanduslikud Uurimused 68*, 5-24.

Lang, M., Arumäe, T., & Anniste, J. (2012). Estimation of main forest inventory variables from spectral and airbone lidar data in Aegviidu test sites, Estonia. *Forestry Studies - Metsanduslikud Uurimused 56*, 27-41.

Lang, M., Arumäe, T., Lukk, T., & Sims, A. (2014). Estimation of standing wood volume and species composition in managed nemoral multi-layer mixed forest by using nearest neighbour classifier, multispectral staelite images and airborne lidarr data. *Forestry Studies-Metsanduslikud Uurimused 61*, 47-68.

Laurance, S., & Laurance, W. (2015). Peat fires: emissions likely to worsen. *Nature 527*, https://doi.org/10.1038/527305a.

Lecina-Diaz, J., Alvarez, A., & Retana, J. (2014). Extreme Fire Severity Patterns in Topographic, Convective and Wind-Driven Historical Wildfires of Mediterranean Pine Forests. *PLoS ONE 9(1): e85127*, doi:10.1371/journal.pone.0085127.

Lin, S., Sun, P., & Huang, X. (2019). Can Peat Soil Support a Flaming Wildfire? *International Journal of Wildland Fire*, https://doi.org/10.1071/WF19018.

Luijkx , M., & Helbich, M. (2019). Neighborhood Walkability Is Not Associated with Adults' Sedentary Behavior in the Residential Setting: Evidence from Breda, The Netherlands. *International Journal of Environmental Research and Public Health*.

Majlingová, A., Sedliak, M., & Smreček, R. (2018). Spatial distribution of surface forest fuel in the Slovak Republic. *Journal of Maps, 14(2)*, 368-372.

Mallinis, G., Mitsopoulos, I. D., Dimitrakopou, A. P., Gitsas, I. Z., & Karteris, M. (2008). Local-Scale Fuel-Type Mapping and Fire Behavior Prediction by Employing High-Resolution Satellite Imagery. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 1(4)*, 230–239.

Marlon, J. R., Bartlein, P. J., Gavin, D. G., Long, C. J., Anderson, R. S., Briles, C. E., . . . Walsh, M. K. (2012). Long-term Perspective on Wildfires in the Western USA. *Environmental Science*.

Maselli, F., Rodolfi, A., Bottai, L., Romanelli, S., & Conese, C. (2000). Classification of Mediterranean vegetation by TM and ancillary data for the evaluation of fire risk. *International Journal of Remote Sensing 21*, 3303-3313.

Mercer, D. E., & Prestemon, J. P. (2005). Comparing production function models for wildfire risk analysis in the wildland–urban interface. *Forest Policy and Economics 7* , 782– 795.

Miller, C., & Ager, A. (2013). A review of recent advances in risk analysis for wildfire management. *International Journal of Wildland Fire 22(1)*, 10.1071/WF11114.

Morandini, F., Silvani, X., Dupuy, J.-L., & Susset, A. (2018). Fire Spread Across a Sloping Fuel Bed: Flame Dynamics and Heat. *Combustion and Flame 190* , 158–170.

Mukaka, M. M. (2012). Statistics Corner: A guide to appropriate use of Correlation coefficient in medical research. *Malawi Medical Journal; 24(3)* , 69-71.

Müller, M. M., & Vacik, H. (2017). Characteristics of Lightnings Igniting Forest Fires in Austria. *Agricultural and Forest Meteorology 240–241* , 26–34.

NOAA. (2019, July 23). *National Centers for Environmental Information*. Retrieved from National Oceanic and Atmospheric Administration: https://www.ncdc.noaa.gov/monitoring-references/dyk/deadfuelmoisture

Norton, D. A., & De Lange, P. J. (2003). Fire and Vegetation in a Temperate Peat Bog: Implications for the Management of Threatened Species. *Conservation Biology. 17(1)*, 138-148.

Oliveira, S., Oehler, F., San-Miguel-Ayanz, J., Camia, A., & Pereira, J. M. (2012). Modeling spatial patterns of fire occurrence in Mediterranean Europe using Multiple Regression and Random Forest. *Forest Ecology and Management*, 117-129.

Pereira, M. G., Aranha, J., & Amraoui, M. (2014). Land cover fire proneness in Europe. *Forest Systems 23(3)* , 598-610.

Price, O. F., & Gordon, C. E. (2016). The potential for LiDAR technology to map fire fuel hazard over large areas of Australian forest. *Journal of Environmental Management 181*, 663-673.

Razali, S. M., Nuruddin, A. A., Malek, I. A., & Patah, N. A. (2010). Forest fire hazard rating assessment in peat swamp forest using Landsat thematic mapper image. *Journal of Applied Remote Sensing, Vol. 4, 043531*.

Ricotta , C., Bajocco, S., Guglietta, D., & Conedera, M. (2018). Assessing the Influence of Roads on Fire Ignition: Does Land Cover Matter? *Fire*.

Safford, H. D., Schmidt, D. A., & Carlson, C. H. (2009). Effects of fuel treatments on fire severity in an area of wildland–urban interface, Angora Fire, Lake Tahoe Basin, California. *Forest Ecology and Management 258*, 773-787.

Schmidt, D. A., Taylor, A. H., & Skinner, C. N. (2008). The influence of fuels treatment and landscape arrangement on simulated fire behavior Southern Cascade range, California. *Forest Ecology and Management 255*, 3170-3184.

Schneider, A., Hommel, G., & Blettner, M. (2010). Linear regression analysis: part 14 of a series on evaluation of scientific publications. *Deutsches Arzteblatt International 107(44)*, 776–782 doi:10.3238/arztebl.2010.0776.

Stacey, R., & Gibson, S. (2012). *European Glossary for Wildfires and Forest Fires.* Northumberland: EUROFINET.

Stephens, S. L., & Moghaddas, J. J. (2005). Experimental fuel treatment impacts on forest structure potential fire behavior, and predicted tree mortality in a California mixed conifer forest. *Forest Ecology and Management 215*, 21-36.

Suryabhagavan, K. V., Alemu, M., & Balakrishnan, M. (2016). GIS-based multi-criteria decision analysis for forest fire susceptibility mapping: a case study in Harenna forest, southwestern Ethiopia. *Tropical Ecology, 57(1),* 33-43.

Suryatmojo , H., Imron, M. A., Gasa, M. S., Saputra, D. M., & Maryani. (2019). Groundwater level response of the primary forest, ex-peatland fire, and community mix plantation in the Kampar peninsula, Indonesia. *IOP Conf. Series: Earth and Environmental Science 361 012034*, doi:10.1088/1755-1315/361/1/012034.

Tampakis, S., Manolas , E., & Karanikola, P. (2010). Who are the enemies of the forest? The views of loggers and students. *Journal of environmental protection and ecology 11 (4)*, 1373-1381.

Vallejo-Villalta, I., Rodríguez-Navas, E., & Márquez-Pérez, J. (2019). Mapping Forest Fire Risk at a Local Scale—A Case Study in Andalusia (Spain). *Environments, 6(30).*

Van Wagtendonk, J. W., & Root, R. R. (2003). The use of multi-temporal Landsat Normalized Difference Vegetation Index (NDVI) data for mapping fuel models in Yosemite National Park, USA. *International Journal of Remote Sensing 24*, 1639–1651.

Wijedasa, L., Posa, M., & Clements, R. G. (2015). Peat fires: Consumers to help beat them out. *Nature 527*, 305.

Wotton , B. M., & Martell, D. L. (2005). A lightning fire occurrence model for Ontario. *Canadian Journal of Forest Research 35*, 1389–1401.

Appendix

Spatial Attributes of Various Data Used for Analysis

County	Population (2017)	Total County Fires	Peat Bogs (area in km^2)	Fire in Peat Bogs	Reed Beds (area in km^2)	Fire in Reed Beds	Peat Soil (area in km^2)	Fire in Peat Soil	Road Buffer (area in km^2)	Fire in Road Buffer
Harju	582556	2760	96.45	1	69.74	22	1290	99	1417	2188
Hiiu	9335	60	6.33	0	24.29	2	110	1	387	50
Ida-Viru	143880	2039	148.5	7	45.57	0	1275	78	827	1591
Jõgeva	30840	188	69.2	0	16.94	1	849	14	937	159
Järva	30378	132	75.5	2	16.55	0	933	20	793	107
Lääne	24301	162	106.67	1	134.63	1	568	3	679	129
Lääne-Viru	58856	352	46.69	2	12.3	0	829	33	1093	269
Põlva	27963	178	20.66	0	34.45	1	553	18	984	144
Pärnu	82535	348	375.51	3	70.8	4	1335	17	1281	260
Rapla	34085	202	131.59	1	42.84	0	970	19	893	139
Saare	33307	127	21.27	1	112.65	3	290	8	955	91
Tartu	145550	461	66.99	1	139.95	7	940	59	1100	360
Valga	30084	170	14.26	0	8.03	1	448	9	917	134
Viljandi	47288	186	133.59	2	42.13	1	928	11	1081	138
Võru	33505	205	13.46	0	5.34	1	515	11	1053	164

Non-exclusive licence to reproduce thesis and make thesis public

I, Kingsley Adu Koranteng,

1. herewith grant the University of Tartu a free permit (non-exclusive licence) to reproduce, for the purpose of preservation, including for adding to the DSpace digital archives until the expiry of the term of copyright,

"Risk Assessment of Landscape Fires in Estonia" supervised by Prof. Tõnu Oja

2. I grant the University of Tartu a permit to make the work specified in p. 1 available to the public via the web environment of the University of Tartu, including via the DSpace digital archives, under the Creative Commons licence CC BY NC ND 3.0, which allows, by giving appropriate credit to the author, to reproduce, distribute the work and communicate it to the public, and prohibits the creation of derivative works and any commercial use of the work until the expiry of the term of copyright.

3. I am aware of the fact that the author retains the rights specified in p. 1 and 2.

4. I certify that granting the non-exclusive licence does not infringe other persons' intellectual property rights or rights arising from the personal data protection legislation.

Kingsley Adu Koranteng

25.05.2020