# THESIS

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## Hungarian University of Agriculture and Life Science Szent István Campus Agricultural Water Management Engineering

## **Modeling and Analysis of Soil Erosion in Hungary**

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### Abbreviations

FAO	UN Food and Agriculture Organization.
PESERA	Pan European Soil Erosion Risk Assessment
USLE	Universal Soil Loss Equation
USDA	United States Department of Agriculture
GIS	Geographic Information Systems
MS	Master of Science
RF	Random Forest
LULC	Land Use Land Cover

#### Introduction

Soil erosion by water remains to be a major concern on a global scale, and is associated with a range of environmental, ecological, and economic problems. This is particularly worrisome when it occurs on land used for agriculture, as it can seriously impact productivity. While soil erosion is a natural part of landscape formation, human activities have greatly accelerated the rate at which it occurs. Factors such as deforestation, overgrazing, forest fires, construction activities, and unsustainable farming practices all contribute to this acceleration.

Soil erosion is not simply a farming problem, but is a significant issue at both the local and global levels. At a global level, soil erosion has been identified as one of the most severe forms of soil degradation. For example, according to the Global Soil Partnership led by the UN Food and Agriculture Organization (FAO) in 2017, around 75 billion tonnes of soil are eroded annually from arable lands worldwide, resulting in an estimated financial loss of US \$400 billion per year. The average rate of soil erosion is estimated at 2.8 Mg/ha/y (Borrelli et al. 2017).

Erosion has negative impacts on both land and water resources. It results in the loss of the most productive topsoil, a decrease in soil fertility leading to lower productivity, reduced water availability for plants, and depletion of nutrients and organic matter. Moreover, erosion causes sedimentation that affects the morphology of irrigation canals and rivers, as well as the quality of water and aquatic life. Therefore, in order to reduce these negative effects, there is an urgent requirement for reliable and accurate information to identify the amount and clarify the sources zones of erosion where soil conservation strategies and technologies have to focus on.

Several models can accomplish the quantification of the erosion. The literature contains more than 80 erosion models have been established in half a century for various purposes, such models provide valuable information on the spatial distribution of soil erosion and sediment yield, and how land use and/or climate change can affect it (Karydas et al., 2014).

The research focuses on the regression analysis of soil erosion rates in the Hungary, using random forest model in R Studio. This study utilizes data on soil erosion obtained from the latest soil erosion risk maps of Hungary (Waltner et al. 2020). The data was collected based on the combined results of the PESERA and USLE models.

The overall objective of this MS thesis is to identify the outlier values (extreme values) that are far away from the central mass of observations, which are considered extreme and not typical under Hungarian conditions. To achieve this, a random forest model has been developed to effectively eliminate these outliers from the observations at a reasonable value and an appropriate threshold. It must be noted that this work will complement recent soil loss assessment of Hungary, conducted and published by (Waltner et al. 2018).

This research has the following specific objectives:

- Identification of the optimum threshold value of soil erosion rates at national scale.
- Identification of the critical threshold value over lowland areas.
- Identification of the critical threshold value over mountain areas.

• Recommendations for land users and decision makers on erosion control measures, especially with regard to prevent erosion impacts.

This thesis consists of five parts interconnected that encompass conducted research and its result as presented below.

Introduction, this part gives a brief background on the topic, present the research problem, provide the objectives. In addition, the structure of the thesis is defined.

Chapter 1 reviews the theories and general concepts of erosion as reported in literature. The erosion modeling was discussed including the various models that are available. The chapter also examines the role of Geographic Information Systems (GIS) and Remote Sensing in erosion modeling. The last section of this chapter dealt with erosion and sediment management, and mitigation measures.

Chapter 2 provides an overview of the study area and describes the dataset needed for the work, including its information source. A detailed explanation of the Methodology and procedure of the regression analysis using random forest model in R Studio used was given.

Chapter 3 presents the results of the regression analysis modeling in Hungary with a general discussion on all the findings of the study.

The last part is the conclusion, shows the significance of the results, draws conclusions and making recommendations

#### **Chapter 1. Literature review**

#### 1.1 Soil erosion

Erosion is defined as the process of detachment, movement, and deposition of solid particles by the forces of erosive agents such as water and wind. It is a naturally landscape-forming mechanism where the main source of soil particles is the mechanical and chemical cracking of rocks through rainfall, living organisms, temperature change, freezing, hydration, and oxidation. Accelerated soil erosion is the most concern about erosion, where human activities significantly increase the natural rate (Verheijen *et al.* 2009). The accelerated soil erosion processes are caused by deforestation, overgrazing, forest fires, construction activities, and unsustainable farming practices.

Soil erosion is one form of soil degradation and recognized as one of the most crucial and serious environmental issues worldwide, especially when it occurs on productive lands. The effects of soil loss in agriculture lead to removing the most fertile topsoil, reducing soil productivity by declining soil fertility, decreasing water availability for plants as well as nutrient and organic matter depletion. In some areas, the productivity of eroded soils cannot be restored, even with a heavy application of fertilizers and other inputs (Lal 2003), or, in extreme cases, to the abandonment of the land (Gomiero 2016). In addition, soil erosion decreases the valuable diversity of plants, animals, and soil microorganisms (Pimentel and Burgess 2013).

Soil erosion is not simply a farming problem, but is a significant issue at both the local and global levels. At a global level, soil erosion has been identified as one of the most severe forms of soil degradation. For example, according to the Global Soil Partnership led by the UN Food and Agriculture Organization (FAO) in 2017, around 75 billion tonnes of soil are eroded annually from arable lands worldwide, resulting in an estimated financial loss of US \$400 billion per year. The average rate of soil erosion is estimated at 2.8 Mg ha<sup>-1</sup> yr<sup>-1</sup> (Borrelli *et al.* 2017).

Soil erosion is another environmental concern. According to the Food and Agriculture Organization (FAO), the world's cultivated soils have lost between 25 and 75 percent of their original carbon stock, which has been released into the atmosphere in the form of carbon dioxide. This is mostly due to land degradation, which is unable to conserve and store carbon, contributing to climate change (Montanarella *et al.* 2015).

Hergarten and Kenkmann (2019) confirmed that topography accounts for the majority of the huge variation in erosion on Earth, but also identified a significant systematic dependence on climate, in contrast to several previous studies, and discovered that very high erosion rates above 1000 m M yr-1 occur over significant areas only when tropical climate and high relief are combined. In addition, as shown in, New Guinea has the biggest domain with predicted erosion rates above 1000 m M yr<sup>-1</sup> (Figure 1).

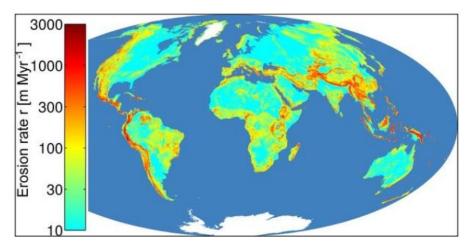


Figure 1. World map of the erosion rates (Source: Hergarten and Kenkmann 2019)

In Europe, an estimated 115 million hectares (12% of land area) are subject to water erosion (EEA-JRC-WHO 2008). The extent of soil degradation in Europe is provided in Table 1. According to Panagos *et al.* (2015), the mean soil loss rate in the European Union's erosion-prone lands (agricultural, forests and semi-natural areas) was found to be 2.46 t ha<sup>-1</sup> yr<sup>-1</sup>, resulting in a total soil loss of 970 Mt per year. The area of erosion in northern Europe is much more restricted than in southern Europe because, unlike other parts of the world, the Mediterranean region is susceptible to long dry periods, followed by heavy rainfall, falling on steep slopes with fragile soils.(Grimm, Jones and Montanarella 2001).

Water Erosion	Light	Moderate	Strong	Extreme	Total
Loss of topsoil	18.9	64.7	9.2	-	92.8
Terrain deformation	2.5	16.3	0.6	2.4	21.8
Total	21.4	81.0	9.8	2.4	114.6

Table 1: Human-induced Soil Degradation in Europe (M ha).

#### Source: Grimm et al. 2001

#### 1.2 Water erosion process

The type of erosion is generally classified by the erosive agent inducing the process; wind or water (Toy, Foster and Renard 2002). Globally, water erosion is the most severe type of soil erosion. Soil erosion by water is defined by (Schwab *et al.* 1981) as the removal of soil from

any kind of land by runoff generated by melting ice and snow, rain or any type of running water.

Soil erosion by water manifests in a two-phase process, consisting of the detachment of individual particles from the soil mass and their transport by erosive agents (Figure 2), and the third stage of soil erosion which is the deposition when the transport energy of the agent is no longer available to transport the particles (Morgan 2009).

The detachability of the soil aggregate from the parent soil is a result of rainfall impact and overland flow. According to Kinnell (2005), The soil particles are detached from soil surface when the energy of falling raindrops and/or overland flow exceeds a critical threshold, soil's structure is broken down.

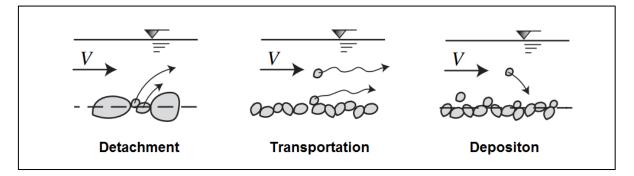


Figure 2: Process of water erosion by overland flow impact (Source: Julien 2010).

Commonly, water erosion is identified by five main types. As Figure 3 shows, water erosion comprises splash, sheet, rill, gully, and stream bank erosion. Splash erosion is also known as raindrop erosion.

#### 1.2.1 Splash erosion

The first stage of erosion is splash. Splash erosion starts when raindrops impinging directly unprotected land surface, causing detachment and movement of soil particles. Rainfall detachment is caused by the locally intense shear stresses at the ground surface by raindrop impact (Loch and Silburn 1996), which break down the interstitial forces holding soil particles together (Catari Yujra 2010). The capacity of detachment is a function of intensity, size, and velocity of rain droplets and the soil susceptibility of being detached.

#### 1.2.2 Sheet erosion

Sheet erosion is the most common type of soil erosion by water. Sheet and splash erosion occurs simultaneously with the splash erosion dominating during the initial process (Bashir *et al.* 2018). Detached particles are laterally delivered downslope to the rills by thin overland flow and this process is called sheet erosion (Foster and Meyer 1977). Sheet erosion takes place primarily in ploughed fields or areas with sparse vegetation and still unnoticed until the fertile

topsoil will be lost. When sheet erosion occurs mainly between irregularly spaced rills, it is referred to as interrill erosion (Weil and Brady 2017).

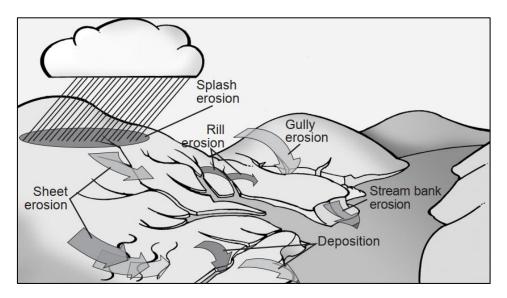


Figure 3: Types of soil erosion by water (Source: Broz et al. 2003).

#### 1.2.3 Rill erosion

Rill erosion is the detachment and transport of soil by a concentrated flow of water (Ward and Trimble 2003). It is the second most prevalent form of water erosion and it is the dominant type in the hilly areas. Rills are small intermittent channels. The ordinary tillage practices can easily smooth these rills and they will not reform at the same location.

Rill erosion relies on the runoff amount, which is influenced by rainfall intensity, soil infiltration rates, and length of the slope contributing to overland flow (Ward and Trimble 2003).

#### 1.2.4 Gully erosion

Gully erosion occurs when the erosive energy of runoff increases during rainstorms and more than one rill join together to form a larger channel, termed gully. Their length may vary from a few meters to hundreds of meters and their width and depths from several decimeters to tens of meters (Poesen and Valentin 2003). Unlike rills, Gullies on cultivated land present obstacles for farm equipment as tractors and cannot be obliterated by the conventional tillage.

The rate of gully erosion depends primarily on the runoff-producing characteristics of the watershed, the drainage area, soil characteristics, the alignment, size, and shape of the gully, and the slope in the channel (Bradford, Farrell and Larson 1973)

#### 1.2.5 Stream bank erosion

In this form of erosion by water, the removal of soil from stream banks or movements of soil materiel in the channel occurs due to the erosive power of runoff from uplands areas after rainstorms. The increased volume of water in the drainage channel raises the water level and increases the speed of flow. This can quickly undercut banks and cause the river or stream to change its course (Jones *et al.* 2003).

Overgrazing, tilling too near to the banks, the removal of vegetation, and the presence of bare land accelerate stream bank erosion. This type of erosion can be controlled by planting grasses and trees, establishing engineering structures, mulching stream borders with rocks and woody materials, geo-textile fencing, and diverting runoff (Blanco and Lal 2008).

#### 1.3 Factors affecting water erosion

The amount of erosion by water is influenced by significant variables which are: climate, topography, soil properties, and vegetation. Of these, climatic conditions are outside the human ability to control. In contrast, vegetation and in some degree soil and topography could be managed (Ward and Trimble 2003).

#### 1.3.1 Climate

Soil erosion is primarily connected to climate and its factors such as temperature, precipitation, humidity, and wind. The magnitude of erosion is determined by critical factors which are: amount, intensity, and frequency of rainfall. The runoff rate is related to the amount of rainfall and the permeability of the soil. The more intensity of rain, the greater transporting capacity of surface flow and soil loss are (Blanco and Lal 2008).

According to Mullan *et al.* (2012), climate change will affect the hydrological cycle through changes in precipitation. Besides, climate change causes an increase in global temperatures and carbon dioxide concentrations in the atmosphere. It will end in changes in the rate, erosive power, temporal pattern of rainstorm events. It is reported by Mullan *et al.* (2012) that these changes will undoubtedly be accompanied by changes in vegetative cover and crop management to accommodate this new climatic regime as the implementation of new cultivars and shifting the growing season.

#### 1.3.2 Vegetative cover

The vegetation is an important factor to protect soil from the abrasive raindrops impacts and control soil erosion rates. The loss of vegetative cover caused by fires, ploughing, and overgrazing leads to an increase in the susceptibility and the ability of soil to be eroded, as well as the detachment rate of soil particles increases with the reduction in the vegetative cover (Blanco and Lal 2008).

Surface vegetative enhances the resistance of the soil against erosion mainly by intercepting and reducing the erosive energy of rain droplets (Blanco and Lal 2008), reducing the velocity of runoff, holding soil in place, and stabilizing soil structure (Ward and Trimble 2003). Dense and short canopies are the best soil protector against water erosion due to intercept a large proportion of rainfall such as the grass (Bashir *et al.* 2018).

Natural or agricultural vegetation has a positive impact on soil protection from soil erosion not only when the vegetative cover is present but also linked with its management, particularly regarding farm practices (Karydas and Panagos 2018).

#### 1.3.3 Soil properties

The interaction process between different soil characteristics defines soil erodibility. Soil texture is the most important physical property and it is mainly related to soil susceptibility to erosion. Also, soil structure, organic matter content, macroporosity, and water infiltration affect the erodibility and contribute to soil erosion (Blanco and Lal 2008).

Clay soils have low soil erodibility because the particles are difficult to detach despite, they can be easily transported. In return, sandy soils have also low erodibility because the transport of particles is difficult even though they are easy to be detached. Generally, soils with a medium texture are the most susceptible to erosion especially silty and fine sandy soils.

Bashir *et al.* (2018) reported that soils with poor organic matter and poor structure are readily compacted. This compaction reduces water infiltration and causes high runoff rates.

#### 1.3.4 Topography

Erosion is a gravity-triggered mechanism. It is influenced by topographic features which are: the degree, the length, and the site-specific shape (Karydas and Panagos 2018). Soil erosion increases with increase in slope steepness and as the length of terrain slope increases the eroded effect of surface runoff increases similarly (Bashir *et al.* 2018). In addition, The slope gradient has a significant change in the strength and the volatility in the processes of running water formation and sediment yield (Ma *et al.* 2019). As it relates to site-specific shape, soils on convex area are more easily eroded than concave slopes because of interaction with surface creeping of soil by gravity (Blanco and Lal 2008).

#### 1.4 Soil erosion assessment

Within the last decades, several attempts have been made to comprehend the soil erosion phenomena either using field measurements or modelling approaches. The literature of water erosion modelling contains diverse models to predict spatial patterns and trends in soil erosion and sediment yield as physically based, empirical, and conceptual models.

The most popular used soil erosion model is the Universal Soil Loss Equation (USLE), which is an empirical equation developed by the United States Department of Agriculture (USDA) with data collected from more than 10,000 plot years in the United States (Wischmeier and Smith 1978). This method computes long-term average annual soil loss at field scale based on the interaction of rainfall pattern, soil type, topography features, crop system, and management practices.

The USLE was designed for use in specific cropping and management systems, but it is also applicable to non-agricultural conditions such as construction sites. This erosion model accounts only for sheet and rill soil loss and does not take into account additional soil loss that may result from gully, wind, and tillage erosion (Stone and Hilborn 2001). It was applied in many places worldwide including Italy (Van der Knijff, Jones and Montanarella 1999).

The soil loss equation is expressed as following:

$$\mathbf{E} = \mathbf{R} \times \mathbf{K} \times \mathbf{L} \times \mathbf{S} \times \mathbf{C} \times \mathbf{P} \tag{1}$$

Where: E: main annual soil loss (t ha-1 y<sup>-1</sup>), R: rainfall erosivity factor (MJ mm ha<sup>-1</sup> h<sup>-1</sup> y<sup>-1</sup>), K: soil erodibility factor (t ha<sup>-1</sup> MJ<sup>-1</sup> mm<sup>-1</sup>), L: slope length factor (dimensionless), S: slope factor (dimensionless), C: cover management factor (dimensionless), P: support practice factor (dimensionless).

Diverse modifications and updates of USLE resulted in new models, as an example, RUSLE, MUSLE, EPIC, USPED which meet the different requirements of end users. The empirical nature of USLE family models requires calibration to local conditions prior to use, a condition that is not at all time met in the erosion literature (Panagos *et al.* 2012). Besides, soil scientists have been developed several models based on the USLE (or later RUSLE) to be applicable at a variety of spatial and temporal scales, such as PESERA (Kirkby *et al.* 2004) and G2 (Karydas and Panagos 2016)

According to (Karydas, Panagos and Gitas 2014), three geospatial properties are most important when modeling water erosion: spatial scale, temporal scale, and spatial methodology. Using these geospatial properties as classification criteria and a library classification system (where each model can only be placed in one class), an 8-class nomenclature of models was developed from the combination of two options per criterion represented in (Table 2).

♦ Spatial scale: Two types of models were introduced based on their spatial scale:

• Field to hillslope-scale models, which included models developed for "hillslopes up to small homogeneous catchments."

• The watershed to landscape-scale models; in erosion modeling, "landscape" should be defined as an area far bigger than a hillslope and not necessarily fitting within a watershed (Karydas, Panagos and Gitas 2014).

• Temporal scale of application: Can be divided into two categories:

• The first category is event-based models, which evaluate one or multiple events. In some literature, these are also referred to as "continuous models" for multiple events (Merritt, Letcher and Jakeman 2003).

• The second category is averaged-based models, which assess erosion over a specific period of time such as hourly, daily, monthly, or yearly. These periods are predetermined based on long-term rainfall statistics, as discussed by Karydas, Panagos and Gitas (2014).

• Spatial methodology type adopted by the model structure:

• Spatial coexistence method, which only takes into account the position as the only spatial property of erosion parameters considered by the model.

• Pathway method, which establishes a clear process for the transportation of soil sediment between sources and receptors (Karydas, Panagos and Gitas 2014).

	5	.,	, ,
		Temporal scale	
Spatial	Spatial	Avorago	l (Daily / monthly / ann

#### Table 2. Classification of water erosion models according to their geospatial characteristics (Source: Karydas et al., 2014).

scale	method	Event-based (Single event / multi event)	Averaged (Daily / monthly / annual / long term)
Field to hillslope	Coexisance	MULTSED (1990) [M], MUSLE (1975) [E] Rose (1988) [M], OPUS (1992) [M], MEDALUS (1993) [M], PEPP (1994) [M], GUEST (1996) [M], RHEM (2007) [M], PRT (1967) [M], ACTMO (1975) [M], CREAMS (1980) [M]	SLEMSA (1982) [E], WATEM (SEDEM) (2000) [M], USLE (1965) [E], MMF (1984) [E], RUSLE (RUSLE1) (1991) [M], USPED (1996) [E], RUSLE2 (2003)[M]
Watershed to landscape	Pathway type Coexisance type	PRT (1967) [M], ACTMO (1975) [M], CREAMS (1980) [M], EPIC (1984) [E], EGEM (1986) [M], GLEAMS (1987) [M], SMODERP (1988) [M], WEPP (1989) [M], EUROSEM (1993) [M], RillGrow (1996à [M], RillGrow2 (1998) [M], PALMS (2008) [M], ARM (1977) [M], SWRRB (1987) [M], IHACRES-WQ (1999) [M], LEAP (1976) [M], TOPMODEL (1977) [M], SHE (1977) [M], ANSWERS (1980)[M], MIKE/SHE (1982) [M], PRMS (1983) [M], SHE-SED (1986) [M], AGNPS (1987)[M], SEM (SEM/SHE) (1987) [M], WESP (1987) [M], LISEM (1989) [M], RUNOFF (1989) [M], TOPOG (1990) [M], KINEROS (1990) [M], CASC2D-SED (1990) [M], RDI (1991) [M], KINEROS2 (1995) [M], EROSION 2D/3D (1995) [M], IQQM (1995) [M], ACRU (1995) [E], TREX (1995) [M], HSPF (1996) [M], MEDRUSH (1997) [M], USLE-M (1998) [E], ANNAGNPS (1998) [M], LASCAM (1999) [E], BTOPMC (1999) [M], SEDD (2000) [E], EUROWISE (2001) [M], STREAM (2002) [E], DWSM (2002), MEFIDIS (2004) [M], WEHY (2004) [M].	USPED (1996) [E], RUSLE2 (2003)[M], Gavrilovic (EPM) (1972) [E], FKSM ((1982) [E], PSIAC (1986) [E], EHU (1988) [E], CSEP (1991) [E], CORINE (1992) [E], FSM (1997) [E], VSD (2004) [E], WSM (2004) [E], SCALES (2008) [E], CSSM (1986) [E], SWAT (1993) [M], SEMMED (1994) [E], SHETRAN (1995) [M], SWIM (1997) [M], SIMWE (1998) [M], SedNet (2001) [E], PESERA (MESALES) (2003) [M], G2 (2011) [E].

# 1.5 Geographic Information System, remote sensing and soil erosion modeling1.5.1 Geographic Information System (GIS)

The Geographic Information System is a computerized system utilized for collecting, storing, transforming, analyzing, managing and displaying spatial data in order to solve geospatial problems (Longley *et al.* 2005). GIS incorporates geostatistical analysis, database and mapping functions that enable users to identify geographic information, relationships, patterns and trends (Omar 2010).

Geographic Information System has a wide application in the field of the environment such as hydraulic and hydrological modeling, catchment management, ground water modeling, and flood mapping. According to Renschler and Harbor (2002), GIS has become an effective tool for managing spatial information and interacting with erosion models in order to provide extensive problem solving capabilities that are helpful for effective decision-making processes.

The development of computers and GIS programs has led to an increase in the use of GIS in many recent erosion studies, mainly to simulate the processes of watersheds, including runoff, soil erosion and sediment yield. The GIS has shown to be useful for mapping and modeling soil erosion at different spatial and temporal scales in complicated basins (Huang *et al.* 2003). The GIS models operate on different time scales ranging from a few months to decades, as well as modeling the yield of sediments on different spatial scales that cannot be achieved by plot measurements (EEA-JRC-WHO 2008). Most erosion models that run in GIS environment use geographical data as inputs such as climate data, soil properties, land use, and digital elevation models (DEM). These inputs represented as a set of layers where each layer may contain a unique set of spatial information.

The drawback of GIS models includes requirements for large data, over-simplification of catchment processes, lack of clear statements of their limitations (Devia, Ganasri and Dwarakish 2015), and increased complexity in data- method relations (Karydas, Panagos and Gitas 2014).

#### 1.5.2 Remote sensing

Remote sensing refers to the technique of reconnaissance and detecting information about object, feature, or phenomenon at a distance using an observation devices (Dwivedi 2017). Traditionally, remote sensing has been linked to satellites or manned aircraft with a set of airborne sensors. Over the last decade, the growing developments and improvements of unmanned platforms, as well as the development of detection technologies installed on board these platforms, have provided excellent opportunities for remote sensing applications.

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Certainly, they can offer a great deal of versatility and flexibility, as compared to airborne or satellite systems, and can run quickly without planned programming. In addition, they can fly at low altitude and slowly, with the ability to acquire high resolution spatial and temporal data (Pajares 2015).

The advancement of the remote sensing technique explores the opportunity to make hydrological forecasts for ungauged regions as well as on a large scale, or even on a global scale, using the remote sensing data for the implementation of models, parametrization, forcing, etc. In addition, remote sensing data provide information on hydrological forcing (precipitation) and observation (flow and reservoir) that can be integrated to the hydrological system to expand prediction capabilities (Hong, Zhang and Khan 2016).

Satellite data can be used to detect erosion directly or to identify the consequences of erosion. Direct detection has been achieved by identifying individual significant erosion characteristics, the discrimination of eroding areas and the assessment of erosion intensity based on empirical relationships. Detectable effects include damage caused by major erosion events and reservoirs sedimentation. Besides, the most recent erosion studies focus on the assessment of erosion control factors by remote sensing. In particular, land use and soil properties have often been determined by satellite data, and to a lesser extent, by topography and management (Vrieling 2006). Much research on erosion and sediment yield have been done using high resolution satellite imagery (such as ASTER imagery) to generate land use classification (Yuksel, Gundogan and Akay 2008).

De Vente and Poesen (2005) pointed out that the wide availability of Geographic Information Systems (GIS) and the use of remotely sensed data have significantly accelerated the development of the erosion model, allowing data input from multiple sources, easy modification of the model structure and unconditioned model rescaling. Besides, the integration remote sensing and GIS into erosion models not only for soil erosion prediction, but also for producing and providing spatial distribution of soil erosion at different scales.

Landsat satellite remain among the most widely utilized satellites for predicting and mapping soil erosion, partly because its long-time data set (it has been used since the 1970's) of currently available satellites (Vrieling 2006).

## 1.6 Impacts and damages of soil erosion

#### **1.6.1** On site effects of erosion

Erosion has detrimental effects on both managed and natural ecosystems. It can cause significant damage to crops, pastures, and forests, as well as reduce the water-holding capacity of soil due to water runoff. Moreover, erosion can decrease the amount of soil organic matter, which results in the transport of important nutrients and soil biota. Additionally, erosion leads to a decrease in the diversity of plant, animal, and microbial species (Zuazo and Pleguezuelo 2009).

Soil erosion causes the degradation of the physical, chemical, and biological characteristics of soil. This degradation leads to a depletion of nutrients and lower agricultural yields (Lal 2003). This, in turn, results in the decline in agricultural productivity, and in severe cases, the loss of cropland (Pimentel 2006).

#### 1.6.1 Off-site effects of erosion

Boardman *et al.* (2009) have pointed out that the consequences of soil erosion and runoff are not limited to the site of origin. They can have far-reaching effects, including eutrophication of water bodies, sedimentation of gravel-bedded rivers, loss of reservoir capacity, and muddy flooding of roads and communities. These impacts are being increasingly recognized and accounted for. In addition, Mullan (2013) has noted that soil erosion can cause fluvial sediment deposition, reservoir sedimentation, and channel silting.

#### 1.7 Control methods of soil erosion

Gobin *et al.* (2004) state that controlling erosion is crucial for maintaining or restoring the health of ecosystems because erosion has negative effects on waterways and the organisms that live in them. The principles of erosion control include using land based on its capability and protecting the soil surface with some form of cover, as well as controlling runoff before it turns into an erosive force.

Effective soil erosion prevention requires the selection of appropriate soil conservation strategies. From a technical standpoint, the best approaches involve adopting conservation tillage systems, constructing terraces, practicing strip cultivation, appropriately applying fertilizers, using crop rotations, and developing appropriate administrative policies (Liu *et al.* 2011).

Balasubramanian and Balasubramanian (2017) suggests that soil erosion can be effectively managed by adopting appropriate land management practices and modifying certain human activities that accelerate soil erosion.

Some techniques that can be employed to control soil erosion include:

• Contour tillage, conservation tillage, and the construction of terraces. Contour tillage, which involves cultivation perpendicular to the slope, is a simple and effective method of reducing runoff and increasing water infiltration on sloping land (Liu *et al.* 2010).

• Conservation tillage, on the other hand, comprises two main approaches for local farmers to control soil erosion and enhance crop yield: reduced tillage with straw removal, which maintains ridges and crop stubble year-round and utilizes deep-tillage in the summer between ridges to improve water infiltration and storage; and no tillage, which involves cross-slope planting and keeping crop residues on the surface throughout winter (Zhang *et al.* 2011).

• Terraces, which are embankments constructed across the slope, intercept surface runoff and convey it to a stable outlet at a non-erosive velocity, thus reducing slope length and preventing erosion (Morgan 2009).

#### **Chapter 2. Materials and Methods**

#### 2.1 Study area

The study will be conducted in Hungary. The country is located in the Carpathian Basin in central Europe, with coordinates of  $45.480^{\circ}$  to  $48.350^{\circ}$  N and  $16.050^{\circ}$  to  $22.580^{\circ}$  E. The entire region of the country is within the basin of the Danube River. The morphology of the study area is characterized by an altitude range between 78 and 1014 meters, above sea level (Kocsis 2018). The relief is quite uniform (Figure 4). The majority of the area is comprised of lowlands, with 82.4% of the land being below 200 meters in elevation. Only a small portion of the terrain (0.5%) is above 500 meters. Medium-height mountains, ranging from 200 to 500 meters in elevation, make up 2.1% of the land, while hills and foothills comprise 15.5% (Gábris *et al.* 2018).

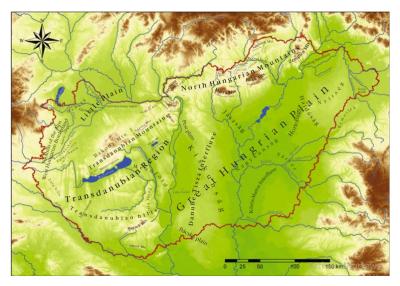


Figure 4: Landscapes of Hungary (Source: Mezősi 2016).

#### 2.1.1 Climate

The climate in Hungary is very erratic. It is a blend of neighboring regions due to its location between different climatic zones. It primarily exhibits characteristics of a humid oceanic climate with slight temperature variations and a less humid continental climate with more extreme temperatures. The annual mean temperature is higher than expected for its latitude by approximately 2.5°C, likely due to the positive temperature anomaly resulting from the influences of the Atlantic Ocean and the Mediterranean Sea, such as currents, in the Carpathian Basin (Mezősi 2016). The climate in the country can vary significantly despite its lower altitudes and relatively small size, which can be attributed to these factors.

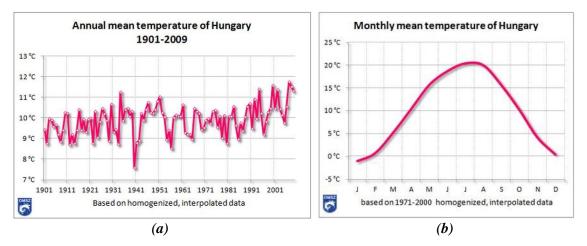


Figure 5. Annual mean temperature of Hungary, 1901–2009 (a) Monthly mean temperature of Hungary 1971–2000 (b) (Source: OMSZ 2023).

The annual mean temperature falls within the range of 10 to 11 °C in most parts of Hungary (Figure 5.a). During the 1971-2000 period, the winter months were identified as the coldest period of the year in Hungary (Figure 5.b). The average temperature in January and generally throughout the winter months had a greater range of fluctuation compared to the summer months. The period from the end of July to the beginning of August was recorded as the warmest time of the year, although any month during summer had the potential to be the warmest month of the year (OMSZ 2023).

Hungary receives an annual precipitation of 500-850 mm (as shown in Figure 6), however, there are significant variations in different regions. The southwestern areas of the country and the mountainous regions receive the highest amount of rainfall, which can exceed 800 mm. On the other hand, the low-altitude valley of the river Tisza receives the least amount of precipitation with a value below 500 mm. In general, there is a decrease in precipitation from west to east due to an increase in continental characteristics, while an increase in height above sea level leads to an increase in precipitation (OMSZ 2023).

The quantity of precipitation typically surpasses evaporation (which ranges between 400-600 mm) throughout the entire country (Weidinger and Mészáros 2000). During the summer months in Hungary, the potential evaporation rate is significantly higher than the precipitation rate. This leads to a water shortage of up to 250-300 mm in the central region of the Great Hungarian Plain. In times of reduced precipitation, decreased air humidity, or higher temperatures, droughts can occur, especially in the central parts of the Great Hungarian Plain (Mezősi 2016).

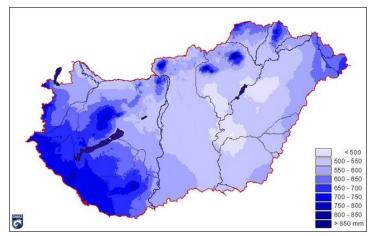


Figure 6. Average annual precipitation in Hungary based on the 1971–2000 period (Source: OMSZ 2023).

#### 2.1.2 Soil

The soils within Hungary are almost heterogeneous, due to the different textures and compositions of soil and generally exhibit textures varying from Luvisols and Cambisols in mountainous or hilly areas, Chernozems, Vertisols, Solonchaks and Solonetz soils situated in the Great Plain area, Luvisols are commonly found in alluvial plains, whereas Arenosols are the predominant soil type in specific regions with sand deposits (Pásztor *et al.* 2018). Additional soil types can be identified based on the particular characteristics of the pedogenic processes. The following Figure 7 shows the distributions of each soil type over the country.

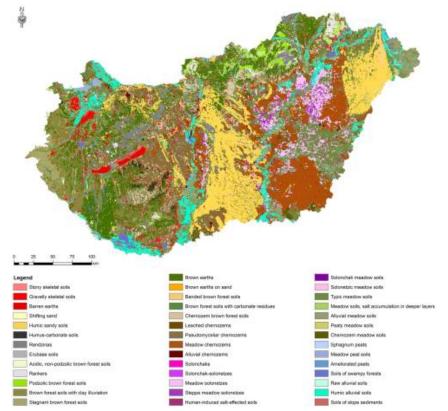


Figure 7. National soil type map (Source: Pásztor et al. 2018).

In Hungary, soil degradation primarily happens through physical degradation, like compaction and erosion, and chemical degradation, which is caused by acidification, salt accumulation, and salinization. Soil erosion is currently the most widespread form of soil degradation, affecting around 2 million hectares of arable land in the country.

#### 2.1.3 Land cover and land use

The Great plains are the main part of the Hungary from an economic and productive perspective (Figure 8). It is known for their fertile soils, are primarily covered by arable lands, while hilly and mountainous areas are mostly characterized by forests (Pásztor *et al.* 2018).

The types of plants that grow in Hungary are influenced by various factors including the climate, terrain, soil type, and water conditions. There are two main types of vegetation that are found in Hungary: deciduous forests, which are mainly composed of oak and beech trees in hilly and mountainous regions, with the most common forest type being the turkey oak-oak forest; and forest steppe vegetation in lowland areas, which consists of various types of sand and loess forest steppes as well as herbaceous groups such as lossy and sandy steppe grasslands. (Mezősi 2016).

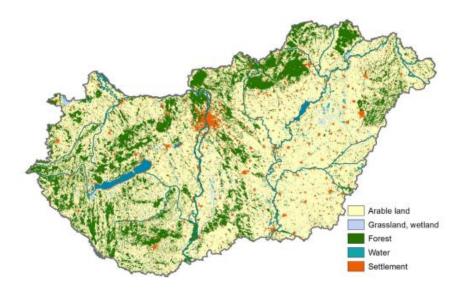


Figure 8. National land cover map (Source: Pásztor et al. 2018).

#### 2.1.4 Hydrography

The distribution of water in Hungary is mainly reliant on the amount of rainfall it receives from the nearby and surrounding regions, particularly the Carpathian Basin. Direct rainfall accounts for roughly 56 km<sup>3</sup> in the basin, and an extra 114 km<sup>3</sup> of water enters the region through rivers. As the basin is predominantly made up of permeable sediments, there is a notable subsurface inflow and outflow as well (Mezősi 2016).

#### 2.2 Data description

This study utilizes data on soil erosion obtained from the latest soil erosion risk maps of Hungary (Waltner *et al.* 2020). The data was collected based on the combined results of the PESERA and USLE soil erosion models (For each grid cell, the mean value of the two output maps was computed), which were used to estimate sheet and rill erosion under the effects of land cover change from 1990 to 2018 (for the years 1990, 2000, 2006, 2012, and 2018) and on the basis of the extremely wet year of 2010. Three specific input variables have been identified representing the potential effects of precipitation (total annual rainfall in 2010), slope and land cover (CORINE Land Cover). The figure 9 represente estimated soil loss for 2018 LULC by the combination of the PESERA and USLE models.

In the present study, we will use 5 samples for each year. The size of each single sample is 3000 observations. The samples are randomly selected from the data frame.

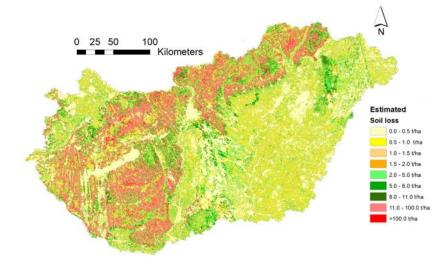


Figure 9. Estimated soil loss for 2018 LULC by the combination of the PESERA and USLE models. (Source: Waltner et al. 2020).

The input datasets used for the soil erosion risk maps of Hungary and its geospatial properties are illustrated in the Table 3:

Input Data	Source	Original Grid Resolution				
Land use and land cover	CORINE Land cover	$100 \times 100 \text{ m}$				
Climate data	CARPATCLIM database	$0.1^{\circ}  imes 0.1^{\circ}$				
Climate data	Agri4Cast MARS	$25 \times 25 \text{ km}$				
Topographic information	EU-DEM	$30 \times 30 \text{ m}$				
Soil data	DOSoReMI.hu	$100 \times 100 \text{ m}$				

Table 3: The input datasets used for the soil erosion risk maps of Hungary.

Source: Waltner et al. 2020

#### 2.3 Methodology overview

#### 2.3.1 Rationale

The current MS thesis will be focused on the regression analysis of soil erosion rates in the Hungary, using random forest model in R Studio. It must be noted that the proposed work will complement recent soil loss assessment of Hungary, using the USLE and PESERA models, conducted and published by (Pásztor *et al.* 2016) and (Waltner *et al.* 2018). The regression analysis will address the issue of outlier values (extreme values) that are far away from the central mass of observations and that are not at all typical under Hungarian conditions. As a result, a random forest model is written to deal with the outliers by removing them from the datasets at a reasonable value and an appropriate threshold.

The key reasons for choosing the random forest regression in this MS thesis are:

• Good performance: Random forest regression is known to perform well on a wide range of datasets, including those with a large number of variables and complicated inter-variable connections. As a result, it is a popular solution for a wide range of machine learning applications.

• Handles missing data: Without requiring imputation or data pretreatment, random forest regression may manage missing data. This saves time and effort while cleaning and preparing data.

• Feature significance: Random forest regression provides a measure of feature importance, allowing for the identification of the most important variables in a dataset. This information can then be used to perform feature selection and gain insight into the underlying connections between variables.

• Non-linear relationships: Unlike linear regression models, Random forest regression can capture non-linear relationships between variables. This increases its flexibility and applicability to a wider range of datasets.

• Robustness: Random forest regression is a robust algorithm that can deal with outliers and noisy data. It does not assume any specific distribution of the data and is unaffected by slight changes in the dataset.

Overall, random forest regression is a powerful and versatile machine learning algorithm that can be straightforwardly executed in R Studio via the "randomForest" package.

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#### 2.3.2 Description of random forest regression

Random forest regression is a machine learning algorithm that uses an ensemble of decision trees to make predictions. It is a variant of the random forest algorithm, which is used for both classification and regression problems.

The algorithm works by building a large number of decision trees, each trained on a random subset of the training data and a random subset of the features. Each tree is trained to predict the target variable based on the input features, and the final prediction is obtained by averaging the predictions of all the trees in the forest.

During the training process, the algorithm randomly selects a subset of the input features at each node of each decision tree. This helps to reduce overfitting by creating diverse trees that are less correlated with each other. To make a prediction for a new input, the algorithm passes the input through each of the decision trees in the forest, and averages the output of all the trees to obtain the final prediction.

Random forest regression is also less prone to overfitting compared to a single decision tree. However, the primary goal of random forest regression is to minimize the prediction error (i.e., the difference between the predicted and actual values of the target variable) on new, unseen data. This is typically accomplished by tuning the hyperparameters of the model, such as the number of trees in the forest, the maximum depth of each tree, the size of the subset of predictors used at each split and features used to construct each tree.

#### 2.4 Implementation of random forest regression

A number of operations are executed to perform random forest regression in R Studio:

1- Import the data: Start by importing the data for the regression analysis into R Studio. Depending on the format of the data, data conversion is needed from raster to vector first, then from vector to data frame.

2- Prepare the data: Clean and preprocess the data as necessary to ensure that it is in the appropriate format for random forest regression. This include removing missing values and converting the type of variables.

3- Train the model: Use the randomForest() function from the randomForest package to train the random forest regression model on the training data. Set the appropriate hyperparameters, such as the number of trees, and the number of variables to sample at each split (500 regression trees have been grown, with one variable tried at each node).

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4- Selecting outliers: Remove the extreme values that are due to a malfunctioning process from the samples and compare RF model predictions to the one without outliers to evaluate thier performance using the variance explained.

5- Visualize the results: Use plots and other visualization techniques to communicate the results of the analysis and any insights gained from the model.

#### **Chapter 3. Results and Discussion**

#### 3.1 Random forest regression analysis at the country level

In this study, we implemented a random forest model in R studio environment to deal with the problem of outlier values for soil erosion rates in Hungary that was obtiened from USLE and PESERA models. In order to identify the optimum threshold at the country level, a 25 Random Forest regression models have been calculated. The R script used in this thesis and an example of a random forest model for 2018 is presented in Appendix 1. Detailed accuracy assessment results of these 25 RF models are presented in Appendix 2 and Figure 10.

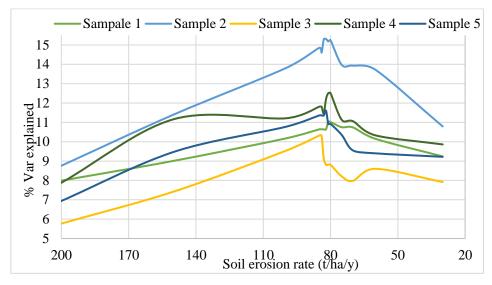


Figure 10a. Accuracy assessment of RF regression at the country level (soil erosion rate of 1990).

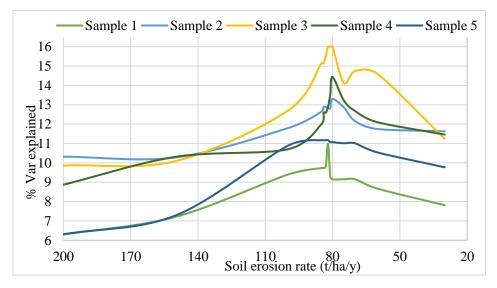


Figure 10b. Accuracy assessment of RF regression at the country level (soil erosion rate of 2000).

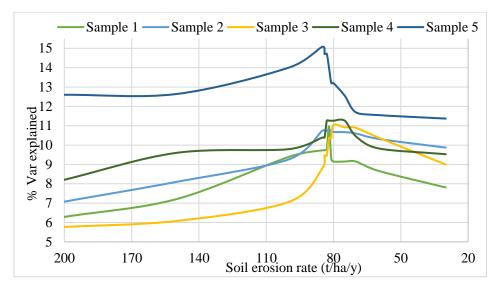


Figure 10c. Accuracy assessment of RF regression at the country level (soil erosion rate of 2006).

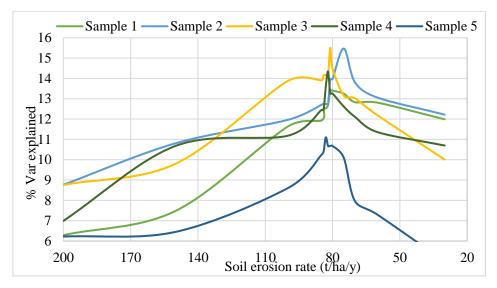


Figure 10d. Accuracy assessment of RF regression at the country level (soil erosion rate of 2012).

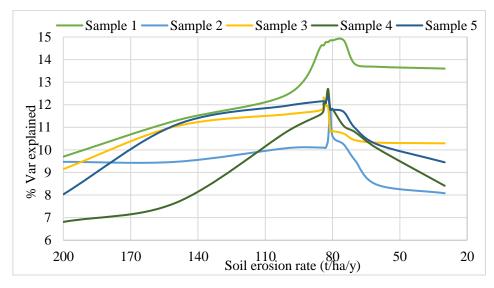


Figure 10e. Accuracy assessment of RF regression at the country level (soil erosion rate of 2018).

The overall optimum threshold value of soil erosion rates in Hungary from 1990 to 2018 derived from the 25 RF models was found to be 82 t/ha/y (Table 4). The maximum optimum threshold value was 82 t/ha/y in 2000 and 2006, whereas the minimum value was 75 t/ha/y in 2012. 84 % of the optimum threshold values ranged from 80 t/ha/y to 84 t/ha/y, while the remaining 16% show predicted values outside the range of  $82 \pm 2$  t/ha/y (Figure 11).

Years	Threshold (t/ha /y)						
Tears	75	80	81	82	83	84	85
1990			2	2	1		
2000		2		2			1
2006		2			1		2
2012	1		2	1	1		
2018			2	2		1	
<b>Overall Threshold</b>	82						

Table 4: Statistical results of random forest models at different years.

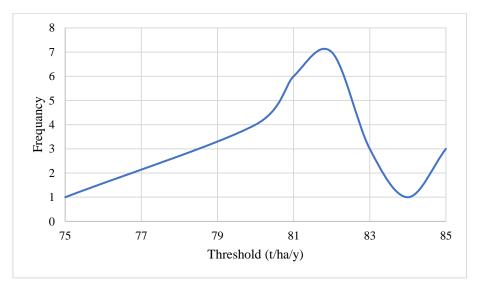


Figure 11. Variation of the threshold at the country level over the years.

# 3.2 Random forest regression analysis at regional level (lowland and mountain areas):

Moreover, the application of random forest model allowed detection of changes in threshold values between lowland and mountain areas (regional level), thus enabling the effect of topography to be highlighted. The detailed accuracy assessment findings and the identification of critical threshold values of 5 RF models over lowland areas for the year 2006 are provided in Table 5 and figures 11.

Threshold		% Var explained					
t/ha /y	1	2	3	4	5		
No	6.29	5.39	8.32	9.09	4.89		
50	8.29	5.93	8.41	9.09	5.57		
25	9.13	8.58	9.93	9.36	8.17		
15	10.75	8.65	10.13	9.63	9.04		
14	11.35	9.25	10.15	9.57	9.11		
13	11.40	9.84	10.15	9.73	9.33		
12	11.72	10.59	10.45	9.73	9.33		
11	12.26	11.02	10.45	9.75	9.42		
10	11.29	11.62	11.41	10.05	9.57		
9	10.24	11.58	10.53	9.42	9.13		
8	9.00	10.74	10.50	8.69	6.84		
7	8.77	9.99	10.28	8.11	6.75		
6	7.22	9.56	10.28	8.11	6.75		
5	6.80	8.70	10.28	8.11	6.75		

 Table 5: Accuracy assessment findings of 5 RF models over lowland areas (year 2006).

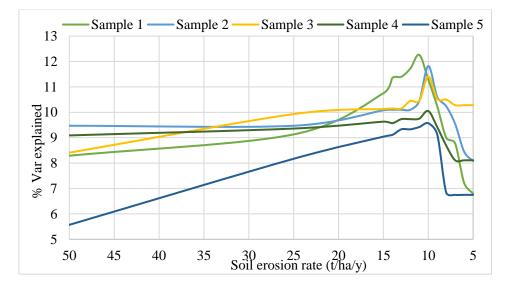


Figure 12. Accuracy assessment of RF regression over lowland areas (soil erosion rate of 2006).

Table 6 and Figure 12 present a detailed accuracy assessment results and identification of critical threshold values of 5 RF models over mountain areas for the year 2006.

Threshold	% Var explained					
t/ha /y	1	2	3	4	5	
No	6.61	5.76	1.36	7.17	5.45	
500	7.39	6.31	3.03	8.01	6.06	
300	8.51	6.56	3.47	8.75	6.10	
200	10.39	6.86	3.62	10.78	7.77	
150	10.73	7.28	3.64	11.11	7.76	
140	10.94	7.78	3.79	11.20	8.40	
130	11.04	8.42	4.12	11.54	9.12	
125	11.15	8.69	4.12	12.19	9.30	
120	11.79	8.93	5.49	12.37	7.93	
115	11.31	8.84	5.34	11.92	7.92	
110	11.05	8.17	5.34	11.77	6.98	
105	10.69	8.14	5.34	11.07	5.90	
90	10.69	8.14	5.34	11.07	5.90	
80	9.51	8.14	5.03	11.07	5.90	

 Table 6: Accuracy assessment findings of 5 RF models over mountain areas (year 2006).

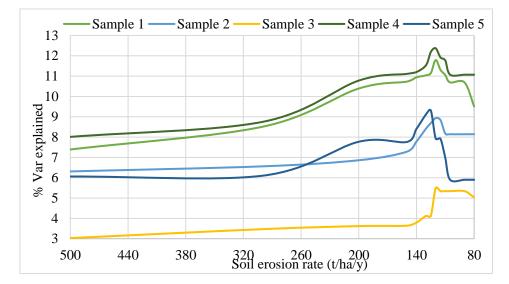


Figure 13. Accuracy assessment of RF regression over mountain areas (soil erosion rate of 2006).

According to the accuracy assessment of RF regression results showing in (Tables 5 and 6) and (Figures 12 and 13), a significant spacial variability of the optimum threshold value of soil erosion rates is observed. The overall optimum threshold value over lowland areas for the year 2006 was found to be 10 t/ha/y, whereas, the overall optimum threshold value over mountain areas was found to be 120 t/ha/y. This is attributed to the slope gradient which cause a high runoff rates over unprotected soils and stream channels of the mountain areas.

The research provides a clear picture of areas where the maximum threshold values of soil erosion rates is most likely in the study area. Based on the findings of this study, the variability in the geomorphology of the country and its hydrological features are the key factors for the variability of the optimum threshold values. Besides, the identification of the most hawardous zones assists decisionmakers to select the appropriate water and soil conservation practices in order to reduce the detrimental impacts of soil erosion.

# **Conclusion and recommendations**

In this research, a regression analysis of soil erosion rates were modeled in Hungary using random forest model in R Studio. The study provides detailed prediction of the outliers and their removal from the datasets. This information is important as the national erosion monitoring network does not exist and it helps in the feasibility studies, planning and management of water resources with regard to control and management of soil erosion.

Model results showed that the country was characterized by an overall optimum threshold value of 82 t/ha/y, 84 % of the optimum threshold values ranged from 80 t/ha/y to 84 t/ha/y, while the remaining 16% show predicted values outside the range of 82  $\pm$ 2 t/ha/y. The maximum optimum threshold value was 82 t/ha/y in 2000 and 2006, whereas the minimum value was 75 t/ha/y in 2012. A significant spacial variability of the optimum threshold value of soil erosion rates is observed. The overall optimum threshold value over lowland areas for the year 2006 was found to be 10 t/ha/y, whereas, the overall optimum threshold value over mountain areas was found to be 120 t/ha/y.

The USLE and PESERA models takes into account only sheet and rill erosion. Therefore, the modeling of gully-derived erosion in future research would be beneficial for a more accurate assessment of the soil eroosion in the country.

The model was used to predict optimum threshold values. This helps to identify where water and soil conservation activities have to focus on. However, these areas of high erosion rates require careful monitoring and sustainable land management, especially in areas characterized by steep slopes that may dramatically exacerbate the production of erosion and sediment under future effects of land use and climate changes.

In this regard, the results of this research could be useful for the stakeholders in Hungary to maintain a permanent soil cover consisting of fast growing and/or perennial vegetation which provides temporary and/or permanent stability in exposed areas. The adaptation of land management practices and the change in pattern of certain human activities that speed up soil erosion can also control erosion. For the hilly area, the hillside terracing is one effective solution to reduce runoff rates and by consequence reducing erosion rates. Finally, sustainable farming practices such as conservation of agriculture, minimum tillage and cultivation of cover crops should be implemented across all agriculture areas.

## **Summary**

Soil erosion by water remains to be a major concern on a global scale, and is associated with a range of environmental, ecological, and economic problems. This is particularly worrisome when it occurs on land used for agriculture, as it can seriously impact productivity. While soil erosion is a natural part of landscape formation, human activities have greatly accelerated the rate at which it occurs. Factors such as deforestation, overgrazing, forest fires, construction activities, and unsustainable farming practices all contribute to this acceleration.

Soil erosion is not simply a farming problem, but is a significant issue at both the local and global levels. At a global level, soil erosion has been identified as one of the most severe forms of soil degradation. For example, according to the Global Soil Partnership led by the UN Food and Agriculture Organization (FAO) in 2017, around 75 billion tonnes of soil are eroded annually from arable lands worldwide, resulting in an estimated financial loss of US \$400 billion per year. The average rate of soil erosion is estimated at 2.8 Mg/ha/y (Borrelli et al. 2017).

The research focuses on the regression analysis of soil erosion rates in the Hungary, using random forest model in R Studio. This study utilizes data on soil erosion obtained from the latest soil erosion risk maps of Hungary (Waltner et al. 2020). The data was collected based on the combined results of the PESERA and USLE models.

The overall objective of this MS thesis is to identify the outlier values (extreme values) that are far away from the central mass of observations, which are considered extreme and not typical under Hungarian conditions. To achieve this, a random forest model has been developed to effectively eliminate these outliers from the observations at a reasonable value and an appropriate threshold. It must be noted that this work will complement recent soil loss assessment of Hungary, conducted and published by (Waltner et al. 2018).

This research has the following specific objectives:

- Identification of the optimum threshold value of soil erosion rates at national scale.
- Identification of the critical threshold value over lowland areas.
- Identification of the critical threshold value over mountain areas.

• Recommendations for land users and decision makers on erosion control measures, especially with regard to prevent erosion impacts.

Model results showed that the country was characterized by an overall optimum threshold value of 82 t/ha/y, 84 % of the optimum threshold values ranged from 80 t/ha/y to 84 t/ha/y, while the remaining 16% show predicted values outside the range of 82  $\pm$ 2 t/ha/y. The maximum optimum threshold value was 82 t/ha/y in 2000 and 2006, whereas the minimum value was 75 t/ha/y in 2012. A significant spacial variability of the optimum threshold value of soil erosion rates is observed. The overall optimum threshold value over lowland areas for the year 2006 was found to be 10 t/ha/y, whereas, the overall optimum threshold value over mountain areas was found to be 120 t/ha/y.

The utilization of the model aided in predicting the most suitable threshold values, which in turn facilitated the identification of areas where water and soil conservation efforts should be concentrated. Nevertheless, these regions with elevated rates of erosion necessitate meticulous supervision and sustainable land management approaches, particularly in areas with steep slopes that may significantly worsen the generation of erosion and sediment due to the future impacts of land use and climate changes.

The outcomes of this study can be valuable for the stakeholders in Hungary who aim to preserve a lasting soil cover through the use of rapidly growing or perennial vegetation that provides temporary or permanent stability in open areas. Altering land management practices and modifying certain human activities that contribute to soil erosion can also help regulate erosion. In hilly regions, hillside terracing is a practical measure to diminish runoff rates and consequently lower erosion rates. Lastly, sustainable agricultural methods such as conservation of agriculture, minimal tillage, and cultivation of cover crops should be adopted in all farming regions.

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## Appendices

#### Appendix 1: The R script used with an example of a random forest model for 2018.

*## Combining to a dataframe* 

setwd("D:/MATE/Thesis/Soil Erosion Data \_ Hungary/RF regression/hgrid") library(sp) library(raster) library(randomForest)

ptest <- as.vector(as.matrix(read.asciigrid("p18.asc")))
slope <- as.vector(as.matrix(read.asciigrid("slope.asc")))
prec <- as.vector(as.matrix(read.asciigrid("prec2010.asc")))
clc18 <- as.vector(as.matrix(read.asciigrid("clc2018.asc")))</pre>

Erosion\_all <- data.frame(ptest, slope, prec, clc18) str(Erosion\_all)

summary(Erosion\_all)

##	ptest	slope	prec clc18
##	Min. : 0	Min. : 0	Min. : 674.7 Min. :111
##	1st Qu.: 0	1st Qu.: 0	1st Qu.: 873.8 1st Qu.:211
##	Median : 0	Median : 1	Median: 942.0 Median: 213
##	Mean : 5	Mean : 3	Mean : 956.5 Mean :243
##	3rd Qu.: 3	3rd Qu.: 3	3rd Qu.:1033.8 3rd Qu.:296
##	Max. :1764	Max. :80	Max. :1667.6 Max. :512
##	NA's :71594	480 NA's :70	005101 NA's :6985613

#### ## Removing records with NAs

Erosion\_noNA <- na.omit(Erosion\_all) summary(Erosion\_noNA)

## ptest slope prec clc18
## Min. : 0.0000 Min. : 0.0000 Min. : 677.8 Min. :111.0
## 1st Qu.: 0.0459 1st Qu.: 0.4844 1st Qu.: 907.6 1st Qu.:211.0
## Median : 0.3057 Median : 1.0381 Median : 959.8 Median :213.0
## Mean : 4.9285 Mean : 3.2355 Mean : 976.8 Mean :239.7
## 3rd Qu.: 2.6016 3rd Qu.: 3.3848 3rd Qu.:1046.2 3rd Qu.:289.0
## Max. :1763.6003 Max. :80.3568 Max. :1526.6 Max. :512.0

str(Erosion\_noNA)

## 'data.frame': 9145244 obs. of 4 variables: ## \$ ptest: num 0.025

```
## Subset
ErosionSub <- Erosion_noNA[sample(nrow(Erosion_noNA), 3000), ]</pre>
summary(ErosionSub)
##
                               prec
                                          clc18
      ptest
                  slope
## Min. : 0.0000 Min. : 0.0000 Min. : 679.2 Min. :111
## 1st Qu.: 0.0500 1st Qu.: 0.4849 1st Qu.: 907.4 1st Qu.:211
## Median : 0.2956 Median : 1.0606 Median : 958.7 Median :215
## Mean : 5.0968 Mean : 3.2618 Mean : 976.4 Mean : 242
## 3rd Qu.: 2.5830 3rd Qu.: 3.4585 3rd Qu.:1047.0 3rd Qu.:304
## Max. :527.0945 Max. :57.7332 Max. :1458.3 Max. :512
## Random Forest model
set.seed(123)
rf <- randomForest(ptest~., data=ErosionSub,
           ntree = 500,
           mtry = 1,
           importance = TRUE,
           proximity = TRUE)
print(rf)
## Call:
## randomForest(formula = ptest ~ ., data = ErosionSub, ntree = 500,
                                                                    mtry = 1, importance = TRU
E, proximity = TRUE)
##
           Type of random forest: regression
##
               Number of trees: 500
## No. of variables tried at each split: 1
##
##
        Mean of squared residuals: 447.8585
##
              % Var explained: 7.47
# Selecting observations/outliers
ErosionSub200 <- ErosionSub[which(ErosionSub$ptest <= 200),]
set.seed(123)
rf <- randomForest(ptest~., data=ErosionSub200,
           ntree = 500,
           mtry = 1,
           importance = TRUE,
           proximity = TRUE)
print(rf)
## Call:
## randomForest(formula = ptest \sim ., data = ErosionSub200, ntree = 500,
                                                                        mtry = 1, importance = T
RUE, proximity = TRUE)
           Type of random forest: regression
##
##
               Number of trees: 500
## No. of variables tried at each split: 1
##
        Mean of squared residuals: 158.5963
##
##
              % Var explained: 8.03
```

```
ErosionSub150 <- ErosionSub[which(ErosionSub$ptest <= 150),]
set.seed(123)
rf <- randomForest(ptest~., data=ErosionSub150,
           ntree = 500,
           mtry = 1,
           importance = TRUE,
           proximity = TRUE)
print(rf)
## Call:
## randomForest(formula = ptest \sim ., data = ErosionSub150, ntree = 500,
                                                                          mtry = 1, importance = T
RUE, proximity = TRUE)
            Type of random forest: regression
##
##
                Number of trees: 500
## No. of variables tried at each split: 1
##
##
         Mean of squared residuals: 118.3583
##
               % Var explained: 11.1
ErosionSub100 <- ErosionSub[which(ErosionSub$ptest <= 100), ]
set.seed(123)
rf <- randomForest(ptest~., data=ErosionSub100,
           ntree = 500,
           mtry = 1,
           importance = TRUE,
           proximity = TRUE)
print(rf)
## Call:
## randomForest(formula = ptest ~ ., data = ErosionSub100, ntree = 500,
                                                                          mtry = 1, importance = T
RUE, proximity = TRUE)
            Type of random forest: regression
##
##
                Number of trees: 500
## No. of variables tried at each split: 1
##
##
         Mean of squared residuals: 77.76482
               % Var explained: 11.96
##
ErosionSub85 <- ErosionSub[which(ErosionSub$ptest <= 85), ]</pre>
set.seed(123)
rf <- randomForest(ptest~., data=ErosionSub85,
           ntree = 500,
           mtry = 1,
           importance = TRUE,
           proximity = TRUE)
print(rf)
## Call:
## randomForest(formula = ptest \sim ., data = ErosionSub85, ntree = 500,
                                                                         mtry = 1, importance = T
RUE, proximity = TRUE)
            Type of random forest: regression
##
##
                Number of trees: 500
## No. of variables tried at each split: 1
##
##
         Mean of squared residuals: 69.62542
##
               % Var explained: 12.15
```

```
ErosionSub84 <- ErosionSub[which(ErosionSub$ptest <= 84), ]
set.seed(123)
rf <- randomForest(ptest~., data=ErosionSub84,
           ntree = 500,
           mtry = 1,
           importance = TRUE,
           proximity = TRUE)
print(rf)
## Call:
## randomForest(formula = ptest ~ ., data = ErosionSub84, ntree = 500,
                                                                         mtry = 1, importance = T
RUE, proximity = TRUE)
            Type of random forest: regression
##
##
                Number of trees: 500
## No. of variables tried at each split: 1
##
##
         Mean of squared residuals: 69.62542
##
               % Var explained: 12.15
ErosionSub83 <- ErosionSub[which(ErosionSub$ptest <= 83), ]
set.seed(123)
rf <- randomForest(ptest~., data=ErosionSub83,
           ntree = 500,
           mtry = 1,
           importance = TRUE,
           proximity = TRUE)
print(rf)
## Call:
## randomForest(formula = ptest ~ ., data = ErosionSub83, ntree = 500,
                                                                         mtry = 1, importance = T
RUE, proximity = TRUE)
            Type of random forest: regression
##
##
                Number of trees: 500
## No. of variables tried at each split: 1
##
##
         Mean of squared residuals: 69.62542
               % Var explained: 12.15
##
ErosionSub82 <- ErosionSub[which(ErosionSub$ptest <= 82), ]
set.seed(123)
rf <- randomForest(ptest~., data=ErosionSub82,
           ntree = 500,
           mtry = 1,
           importance = TRUE,
           proximity = TRUE)
print(rf)
## Call:
## randomForest(formula = ptest \sim ., data = ErosionSub82, ntree = 500,
                                                                         mtry = 1, importance = T
RUE, proximity = TRUE)
            Type of random forest: regression
##
##
                Number of trees: 500
## No. of variables tried at each split: 1
##
##
         Mean of squared residuals: 66.10975
##
               % Var explained: 12.35
```

```
ErosionSub81 <- ErosionSub[which(ErosionSub$ptest <= 81), ]</pre>
set.seed(123)
rf <- randomForest(ptest~., data=ErosionSub81,
           ntree = 500,
           mtry = 1,
           importance = TRUE,
           proximity = TRUE)
print(rf)
## Call:
## randomForest(formula = ptest ~ ., data = ErosionSub81, ntree = 500,
                                                                         mtry = 1, importance = T
RUE, proximity = TRUE)
            Type of random forest: regression
##
##
                Number of trees: 500
## No. of variables tried at each split: 1
##
##
         Mean of squared residuals: 64.75114
##
               % Var explained: 11.78
ErosionSub80 <- ErosionSub[which(ErosionSub$ptest <= 80), ]
set.seed(123)
rf <- randomForest(ptest~., data=ErosionSub80,
           ntree = 500,
           mtry = 1,
           importance = TRUE,
           proximity = TRUE)
print(rf)
## Call:
## randomForest(formula = ptest \sim ., data = ErosionSub80, ntree = 500,
                                                                         mtry = 1, importance = T
RUE, proximity = TRUE)
            Type of random forest: regression
##
##
                Number of trees: 500
## No. of variables tried at each split: 1
##
##
         Mean of squared residuals: 64.75114
               % Var explained: 11.78
##
ErosionSub75 <- ErosionSub[which(ErosionSub$ptest <= 75), ]
set.seed(123)
rf <- randomForest(ptest~., data=ErosionSub75,
           ntree = 500,
           mtry = 1,
           importance = TRUE,
           proximity = TRUE)
print(rf)
## Call:
## randomForest(formula = ptest \sim ., data = ErosionSub75, ntree = 500,
                                                                         mtry = 1, importance = T
RUE, proximity = TRUE)
##
            Type of random forest: regression
##
                Number of trees: 500
## No. of variables tried at each split: 1
##
##
         Mean of squared residuals: 59.78066
##
               % Var explained: 11.68
```

```
ErosionSub70 <- ErosionSub[which(ErosionSub$ptest <= 70), ]
set.seed(123)
rf <- randomForest(ptest~., data=ErosionSub70,
           ntree = 500,
           mtry = 1,
           importance = TRUE,
           proximity = TRUE)
print(rf)
## Call:
## randomForest(formula = ptest ~ ., data = ErosionSub70, ntree = 500,
                                                                         mtry = 1, importance = T
RUE, proximity = TRUE)
            Type of random forest: regression
##
##
                Number of trees: 500
## No. of variables tried at each split: 1
##
##
         Mean of squared residuals: 57.54086
##
               % Var explained: 10.97
ErosionSub60 <- ErosionSub[which(ErosionSub$ptest <= 60), ]
set.seed(123)
rf <- randomForest(ptest~., data=ErosionSub60,
           ntree = 500,
           mtry = 1,
           importance = TRUE,
           proximity = TRUE)
print(rf)
## Call:
## randomForest(formula = ptest \sim ., data = ErosionSub60, ntree = 500,
                                                                         mtry = 1, importance = T
RUE, proximity = TRUE)
            Type of random forest: regression
##
##
                Number of trees: 500
## No. of variables tried at each split: 1
##
##
         Mean of squared residuals: 47.77126
               % Var explained: 10.24
##
ErosionSub30 <- ErosionSub[which(ErosionSub$ptest <= 30), ]
set.seed(123)
rf <- randomForest(ptest~., data=ErosionSub30,
           ntree = 500,
           mtry = 1,
           importance = TRUE,
           proximity = TRUE)
print(rf)
## Call:
## randomForest(formula = ptest \sim ., data = ErosionSub30, ntree = 500,
                                                                         mtry = 1, importance = T
RUE, proximity = TRUE)
            Type of random forest: regression
##
##
                Number of trees: 500
## No. of variables tried at each split: 1
##
##
         Mean of squared residuals: 20.41901
##
               % Var explained: 9.45
```

Threshold (t/ha /y)		% Var explained					
		1 2 3 4					
	no	5.32	7.68	2.91	7.14	5.63	
	200	7.99	8.76	5.77	7.88	6.94	
	150	9.01	11.40	7.42	11.16	9.47	
	100	10.17	13.80	9.53	11.21	10.77	
	85	10.64	14.85	10.32	11.81	11.36	
	84	10.64	14.60	10.32	11.81	11.36	
1990	83	10.64	15.29	9.11	11.46	11.36	
19	82	10.64	15.31	8.81	12.21	11.60	
	81	11.04	15.18	8.81	12.51	10.92	
	80	11.02	15.24	8.81	12.51	10.92	
	75	10.75	13.97	8.21	11.13	10.35	
	70	10.74	13.93	7.98	11.06	9.55	
	60	10.15	13.72	8.60	10.33	9.40	
	30	9.24	10.79	7.92	9.86	9.22	
	no	2.96	10.23	9.63	4.03	2.65	
	200	6.29	10.32	9.86	8.87	6.31	
	150	7.21	10.28	10.09	10.31	7.28	
	100	9.39	11.79	12.69	10.70	10.88	
	85	9.73	12.64	15.13	11.99	11.17	
	84	9.73	12.89	15.13	12.59	11.17	
2000	83	9.80	12.89	15.51	12.59	11.17	
20	82	10.97	12.83	16.00	12.90	11.17	
	81	9.28	12.83	16.00	13.54	11.07	
	80	9.15	13.30	16.00	14.44	11.07	
	75	9.15	12.87	14.13	13.23	11.01	
	70	9.15	12.16	14.74	12.68	11.01	
	60	8.67	11.75	14.60	12.10	10.54	
	30	7.81	11.63	11.24	11.46	9.77	
	no	6.32	6.82	2.51	7.16	9.90	
	200	8.85	7.08	5.77	8.21	12.60	
	150	10.23	8.10	6.08	9.60	12.64	
	100	10.56	9.26	7.06	9.79	14.00	
	85	10.68	10.75	8.79	10.39	15.08	
	84	10.68	10.75	9.47	10.39	14.71	
<b>0</b> 6	83	10.68	10.75	9.46	11.26	14.71	
2006	82	10.68	10.75	10.37	11.26	13.98	
	81	10.93	10.75	10.37	11.26	13.20	
	80	10.97	10.68	11.04	11.26	13.20	
	75	10.80	10.67	10.92	11.26	12.55	
	70	10.37	10.60	10.89	10.45	11.69	
	60	10.17	10.32	10.39	9.83	11.55	
	30	9.22	9.87	9.00	9.53	11.37	

Appendix 2: Detailed accuracy assessment results of 25 RF models over Hungary.

Appenaix 2: Continuation.								
Thresho	Threshold (t/ha /y)		% Var explained					
Theorem (what ty)		1	2	3	4	5		
	no	3.84	8.41	5.21	5.60	5.53		
	200	6.29	8.77	8.76	6.99	6.22		
	150	7.48	10.81	9.80	10.68	6.45		
	100	11.63	11.96	13.87	11.18	8.60		
	85	11.93	12.70	13.91	12.44	10.23		
	84	12.52	12.75	14.16	12.44	10.39		
12	83	12.52	12.75	14.16	13.60	11.10		
2012	82	12.70	12.75	14.16	14.34	10.68		
	81	13.40	13.97	15.50	13.26	10.68		
	80	13.40	13.97	14.49	13.26	10.68		
	75	13.25	15.47	13.16	12.62	10.10		
	70	12.83	13.81	13.02	12.11	7.96		
	60	12.81	13.06	12.19	11.36	7.30		
	30	11.99	12.22	10.01	10.70	5.00		
	no	6.73	5.45	5.09	5.76	7.47		
	200	9.70	9.47	9.15	6.81	8.03		
	150	11.29	9.47	11.04	7.65	11.10		
	100	12.46	10.08	11.58	10.83	11.96		
	85	14.62	10.10	11.77	11.59	12.15		
	84	14.62	10.10	12.32	12.06	12.15		
8	83	14.77	10.10	11.93	12.06	12.15		
2018	82	14.77	10.44	11.93	12.70	12.35		
	81	14.85	11.82	10.83	11.81	11.78		
	80	14.85	10.61	10.83	11.81	11.78		
	75	14.85	10.24	10.72	11.06	11.68		
	70	13.80	9.54	10.43	10.79	10.97		
	60	13.68	8.45	10.32	10.06	10.24		
	30	13.60	8.08	10.29	8.41	9.45		

Appendix 2: Continuation.

# STATEMENT ON CONSULTATION PRACTICES

As a supervisor of <u>HAROUN Houssem Eddine</u> (Student's name) ATAD6I (Student's NEPTUN ID), I here declare that the master's thesis has been reviewed by me, the student was informed about the requirements of literary sources management and its legal and ethical rules.

I <u>recommend</u>/don't recommend<sup>1</sup> the final essay/thesis/<u>master's thesis</u>/portfolio to be defended in a final exam.

The document contains state secrets or professional secrets: yes  $\underline{no}^{*2}$ 

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Internal supervisor

<sup>&</sup>lt;sup>1</sup> Please underline applicable.

<sup>&</sup>lt;sup>2</sup> Please underline applicable.

# DECLARATION

# on authenticity and public assess of final essay/thesis/mater's thesis/portfolio<sup>1</sup>

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Student's Neptun ID:	ATAD6I
Title of the document:	Master's thesis
Year of publication:	2013
Department:	Irrigation and Land Improvement

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<sup>&</sup>lt;sup>2</sup>Please select the one that applies, and delete the other types.