University of Tartu

Faculty of Science and Technology

Institute of Ecology and Earth Sciences

Department of Geography

Master Thesis in Geoinformatics

Investigating Relationships Between Environmental Variables and Sold Land Prices in Hiiu County, Estonia

Alex Jarvis

Supervisors: PhD Age Poom,

PhD Evelyn Uuemaa

Approved for defence:

Supervisor:

Head of Department:

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Abstract

This thesis, titled 'Investigating Relationships Between Environmental Variables and Sold Land Prices in Hiiu County, Estonia', looked at profit-yielding and residential land plots in Hiiu County, Estonia. With official sold land data from the Estonian Land Board, the county's environmental variables were measured and used in multiple linear regression models to see how much they could predict the sold prices (€/m^2) of land parcels designated as profit-yielding or residential. The results show that the price (€/m^2) of Hiiu County's profit-yielding land parcels cannot be predicted to an adequate level with only the use of physical environmental variables, whereas the price (€/m^2) of Hiiu County's residential land parcels can be predicted to a moderate level, with only the use of physical environmental variables. The results suggest that were the findings combined with economic data, then they could increase the accuracy of a model to determine land prices.

Keywords: Estonia, Hiiumaa, residential land, profit-yielding land, environmental factors, land price.

CERCS code: P510

Annotatsioon

Käesolevas magistritöös hinnatakse seoseid tulundusmaa ja elamumaa müügihindade vahel Eestis, Hiiu maakonnas. Kasutades Eesti Maa-ameti ametlikke andmeid maade müügi kohta ja sama organisatsiooni geoportaali ruumiandmeid erinevate keskkonnategurite kohta, koostati suur andmekogu, kus igale müüdud maatulundusmaa ja elamumaa krundile omistati vastavate keskkonnategurite väärtused. Korrelatsiooni- ja lineaarse regressioonanalüüsi abil hinnati maa müügihinna ja keskkonnategurite vahelisi seoseid ning kas koostatud mudelit saab kasutada müümata maatükkide hinna ennustamiseks.

Märksõnad: Eesti, Hiiumaa, hinnaennustus, lineaarregressioon, maa hinna kujunemine, maatulundusmaa, elamumaa, keskkonnategurid.

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Introduction

Physically, land embraces all the stable or predictable attributes of the biosphere above and below the earth's surface, including those of the atmosphere; the soil and underlying geology; hydrology; plant and animal populations; and the results of past and present human activity. The extent of these attributes and processes are reflected in the physical state of the land's surface cover and determine its present and future use by man (Malczewski, 2004; Verheye, 2009).

The three main drivers of land value can be described as productive value, consumption value and speculative value. Productive value refers to the obtainable financial return of the land, either from rents (Střeleček et al., 2010), profit or subsidies (Quiroga et al., 2019). Consumption value refers to amenity factors and ideological, intangible quality-of-life factors (Cellmer et al., 2012). Speculative value refers to the potential financial return of the land (Journeaux, 2016). The three drivers of land value are informed by a number of factors including its productivity, internal quality, location (Choumert & Phélinas, 2015) and use (Maddison, 2000).

Typically, land price modelling focuses on a particular land use or set of variables to research their impact on the dependent variables. This study chose two different land use designations to assess which variables were able to determine their official sold prices. As opposed to limiting the number of input variables, the aim was to test a range of variables that were relevant and could be physically measured within the study site. The applied methodology was based on the measurement of spatial data using geostatistical techniques and applied statistical modelling.

The thesis looked for relationships between selected variables and official sold land prices (€/m^2) for profit-yielding and residential land parcels in Hiiu County, Estonia, sold between 01.01.2013 and 31.12.2017. The study benefitted from the author being provided with the official notary sales information during his internship at the Estonian Land Board (in Estonian: Maa-amet). The state organisation is in the process of conducting a new mass evaluation of the country's land for taxation purposes and potentially, sales valuation (A. Juss, personal communication, 2019), and therefore, the thesis was designed to have practical value for them. The task afforded the author flexibility in his approach and the decision was made to consider Hiiu County as the study site due to it being a closed physical space that had a variety of different measurable factors.

The research questions were as follows:

1. What physical environmental factors have an association with the price (€/m^2) of sold land parcels for profit-yielding purposes and for residential purposes in Hiiu County, Estonia?
2. Can the price (€/m^2) of sold land parcels for profit-yielding purposes and for residential purposes be predicted using physical environmental variables in Hiiu County, Estonia?

1. Theoretical Background

1.1. Estonia's Land Management

The Estonian Land Board are responsible for the management of state-owned land that is under the administration of the Ministry of the Environment. This includes responsibility for the authorization of the use of land. They administer the national land cadastre, which is the register of land parcels. This contains data including the plot measurements, location, land type and designated land purpose. The cadastral information is available as a shapefile, which represents every land parcel nationwide as a polygon. They also provide the Estonian Topographic Database (ETAK), which contains surveyed layers of the various physical and zonal features of the nation.

The Land Board generate revenue through the sale of state-owned land. The privatisation of land is a European-wide approach (Quiroga et al., 2019) that requires purchasers to abide with the land plot's legal regulations, which are determined by designated land use and by the specific plot. The main category of land in Estonia is listed as profit-yielding. Land designated as profit-yielding includes cultivated land, forested land, natural grassland, yard land and other lands (Riigi Teataja, 2012). The last mass Estonian land evaluation was carried out in 2001 by the Estonian Land Board and this is the valuation which is still in use today for taxation purposes and land reform. However, due to the time gap and limited methodology involved (which used 40 evaluators and was performed manually), it is not accurate enough to value land for sale (A. Juss, personal communication, 2019). Despite some alterations and updates to the 2001 re-evaluation, the need to create a new model is a priority of the Land Board (A. Juss, personal communication, 2018). This will need to be relevant to the social, economic and physical environmental changes that have occurred since in Estonia.

The variables used in the previous re-evaluation were real estate transactions, immovable estate transactions (e.g. houses), rent, the local economy, and soil productivity (UNECE, 2001). Since the 2001 re-evaluation, there has been the introduction of several special value zones in Estonia that recognise the key property value influencer of location. These subdivided zones for taxation are generally located on coastal strips and in urban areas. Between 2001 and 2007, there was a housing price index rise, before an economic recession and property price crash. The overall index score reached its highest ever level in January 2018, after increasing every quarter between the start of 2013 and the end of 2017. The indices increased by approximately

40% for 'unimproved' land and 45% for residential land between 2013 and 2017 (Maa-amet, 2019).

1.2. Factors Affecting the Price of Land

In economics, value is the esteem in which something is held or can be exchanged under current market conditions (Verheye, 2009). Land belongs to the type of object of value that can be subject to a deal and thus an exchange or sales value (ibid). With commodities; the greater the exchange value, the greater the demand for the desired object. This also means that for some land, it might be considered of no worth. There is a fundamental difference between price and value. Market price designates what a property might be sold for at a specific period in time, whereas value designates a property's actual worth in relation to other similar properties (Ewert, 1979; as cited in Verheye, 2009).

There are two main approaches to the valuation of land. The first approach is focused on the production potential of the land, with some minor adjustments for socio-economic considerations. This is currently applied in rural areas where there is either no functional market and/or where there are very few land sales (Verheye, 2009). The second approach, which is commonly used in developed countries, is inspired by the economic value of the land in comparison to recent sales of similar plots under similar conditions. This is the sales comparison approach, which, therefore involves a strong temporal aspect (Střeleček et al., 2010). This is the methodology that the Estonian Land Board currently use when selling off state land and determining the auction starting price (A. Juss, personal communication, 2019). The price of other land parcels, sold in Estonia between private buyers and sellers, can be set at the discretion of the two parties, provided that a mortgage is unrequired (ibid). The Land Board, through its taxation department, has access to the nationwide notary information of land sales.

Land has the condition of being difficult to obtain (Verheye, 2009). In many countries, due to population pressure and the finite amount of the resource available, this is increasingly the case. Demand drives cost in free-market economics and the price of a land parcel is subject to change, for reasons of internal physical changes that may occur to it, or external changes that affect it. These may be physical, or they may be non-physical, such a political change, administrative change or social change (ibid). Market value is explained by TEGOVA (1997) as the estimated amount for which an asset should exchange on the date of valuation between a willing buyer and a willing seller.

There is a growing interest in land as an investment. In the US, land has traditionally been considered a good investment with above-inflation returns (Scott, 1983). Land can provide earnings, in the form of agricultural rent, government subsidies (Põllumäe et al., 2014) or capital gains. In the UK, land ownership brings certain tax-planning benefits and is seen as a 'safe haven' investment (Jadevicius et al., 2015). To avoid conflict as land value increased, land property rights were installed. This initially led to the establishment of national land cadastre services and then systems of land taxation (Verheye, 2009). Land values dictate property market price changes. Land use policy, including the changes in land designation, purpose, developments, and taxation is dictated by land price (Albouy & Ehrlich, 2015).

Land planning decisions are made by assessing the results of the analysis of quantitative and qualitative evaluations and classifications of land surveys, combined with economic and social analyses. As well as analysing the past and contemporary land usages, the land use potential for change is assessed. Change is considered an essential property of landscape and in turn, landscape reflects the natural and socio-economic processes (Antrop, 2000). It has been, and still is, a core focus of attention for geographers, with von Humdoldt implying that regional diversification is expressed by landscape, which should be considered as a holistic phenomenon that is perceived by humans (Antrop, 2000). Changes brought about by the move in the former Soviet Bloc towards privatisation and policies that can see it divided further upon the sharing of inheritance, have led to the increasingly fragmented ownership of land (Sklenicka et al., 2014). Mixed ownership creates patches of mixed land types, and varying levels of management and sustainability (ibid). Patterns of open arable land or grasslands and closed, forested land that reduce the visual homogeneity of landscape, affect, among other things, light and microclimate, biodiversity and vista. Settlements lead to intensification of this process, acting as a 'control' centre for the territory of the social group living there, who organises space around it according to ecological, economic, social, cultural and psychological rules (Antrop, 2000). A clear example of this is the marking of territories by fences and enclosures. Such territories are usually located close to services and utilities, either in linear or cluster patterns. In a free market economy, these amenities affect marketed goods such as land or real estate (Pyykkönen, 2006).

Agricultural land

Traditionally, land value primarily came about through agricultural market competition for the most productive lands that produced the best crop yields. Agricultural land with high soil quality and high yields can command higher rent for the owners, and demand for a particular crop can increase prices (Scott, 1983). Land is surveyed to evaluate its attributes, and its potential affects price. Soil quality is therefore a central determinate in the price of agricultural land (Drescher et al., 2001; Maddison, 2000). Increasingly, soil quality is seen as an indicator of sustainable land management practices (Herrick, 2000). Soil quality can be defined as the capacity of soils to function, both within its ecosystem boundaries and within the environment external to that system. Soils function as a medium for plant growth; a partition and regulator of the flow of water in the environment, and an environmental buffer (Verheye, 2009). Basic soil quality indicators include physical characteristics, such as clay, sand, silt and rock content, and biological characteristics. Along with air and water, soil quality affects the health and productivity of a given ecosystem and therefore the environment within and surrounding it (Doran & Zeiss, 2000). However, soil is not the only determinate of agricultural land price. Studies assessing the price of farmland often seek to analyse the causal relationships between the fluctuation in the price and land price determinants. More recent studies have assumed that price does have internal causes of origin and have sought to quantify what these are. The commonly used explanatory variables can be grouped into the categories related to measures of government programs, measures of net return to agriculture, measures of land quantity and measures of financial and macroeconomic activity (Awokuse & Duke, 2006). All these categories are underpinned by location, with environmental location determining yield and market access determining logistical costs (Dirgasova et al., 2017). As knowledge of land has increased and assessment methods have improved, other factors have been taken consideration when valuing it (Maddison, 2000; Rubinfeld & Harrison Jr, 1978; Xiao et al., 2017). These, which are discussed in the following paragraphs, include other physical environmental variables and socio-economic factors which determine other potential forms of land utilisation (Verheye, 2009).

Wood-covered land

There are certain environmental factors and land types that can be considered important for different land use designations. Forested land can hold great economic value, with positive relationships found between the price of Swedish forest land and the proportion of productive forest land, the mean standing volume and the mean site productivity (Roos, 1996). As has been shown in other studies (Huber et al., 2017; Toppinen et al., 2005; Vedeld et al., 2007), forests can generate income, self-sufficiency or subsidies (Quiroga et al., 2019). The financial incentives of forest ownership make owning privatised land a good short-term investment, along with a potential long term one, should the country's population change and demand for land raise the price.

Forests across Central and Eastern Europe are still going through a process of privatisation, for which EU subsidies are often available, to encourage good management (Quiroga et al., 2019). The acquisition of private forest and agricultural land has little restriction in Estonia (Teder et al., 2015) since the 2012 'Restrictions on Acquisition of Immovables Act', which states that EU and EEA citizens have the right to acquire immovables that contain agricultural or forested land without restrictions (Teder et al., 2015). Additionally, this land type is not subjected to inheritance laws, which in the UK, add value, due to the tax breaks provided (Profeta et al., 2014). Fast growing pine and spruce plantation forests, if well managed, can bring great productive value to land owners. In the Baltic states, there have been large private investments in the sawmilling industry, due to increased demand for saw log or pulpwood products (Toppinen et al., 2005) from the coniferous trees, which thrive in low quality, acidic soils. This has led to concerns about the sale of forest logging rights leading to increasing clear-cutting. Wood-covered land parcels are also purchased for different reasons, including self-sufficiency for firewood, ideological and sustainable reasons, and as long-term investments. Large numbers of forest owners provide challenges about the land types' coordinated management, such as ensuring road access, drainage, the prevention of disease and bark beetle (Põllumäe et al., 2014).

The effect of access

Road access is an important consideration for the majority of land buyers. A surfaced road means year-round access for most vehicles, and rapid transit from rural areas to urban areas and the services located there. A non-surfaced road is likely to have an inferior surface which is unsuited to most vehicles and potentially impassable during certain weather situations. However, they are a key means of rural infrastructure and market access (Jacoby, 2000). The planning of roads is not merely an economic task, but increasingly involves considering ecological and scenic aspects (Antrop, 2004). Despite this, roads tend to be detrimental to landscape and life quality. In terms of noise pollution, there are various sub-variables within the noise variable that will affect noise from a road on a land parcel, including elevation, tunnels, trees, surface type and vehicle type. However, in terms of correlations, in cities such as Seoul, noise has sometimes been found to have a positive correlation with property price (Kim et al., 2007). Noise and pollution from roads depend on the number and type of vehicles using it.

Industrial land

Industrial sites and their heavy goods vehicles require access. Industry can have a negative effect on land prices (Bloodworth et al., 2009). For some industries, such as a quarry, a mine or a landfill, the effects are clear and long-lasting. Despite the economic and employment benefits, they reduce the local land price and have negative public perceptions, due to various types of pollutants produced whilst in operation. After closure, if well restored, former pits can be turned into biodiversity hotspots, assets in flood management or sites of carbon sequestration (Fourie & Brent, 2006; Rhoades et al., 2001). In this way, their local environmental effects can be positive. However, if poorly restored, large pit lakes can be left, which are unsuitable for leisure activities and can lead to the evaporative loss of groundwater (ibid). Similarly, depending on the standards involved, landfills can be environmentally hazardous. However, the real issue in developed countries, where landfills are properly sealed, is the ideological one. Unless viewed by the public as essentially benign, they have been shown to negatively influence prices (Nelson et al., 1992). Land price has been shown to be affected by risk aversion (Thomas, 1999), and distance to nuclear energy sites provide another example, which, for part-ideological and part-founded reasons, has been shown to reduce average land prices, compared to other comparable areas further away (Folland & Hough, 1991). However, it should be noted that the choice of locations for such industries will typically have been selected for the already cheap land prices and lesser esteemed value.

Water

Freshwater from rivers, drainage channels, lakes or ground sources is a necessary resource for most land uses. Groundwater contamination can seriously impact land price (Page & Rabinowitz, 1993). Surface water is considered one of the most important factors for residential property prices. Water bodies are considered key determinates of scenic environmental value (Cellmer et al., 2012). In urban zones, it is said that green spaces, water bodies and healthy environments provide amenities and services that raise the quality of life. Quality of life, sentiment, ideology and scenic quality, although very influential on the property price, are not tangible and are therefore difficult to assess and quantify (Jim & Chen, 2006). There is a lack of academic literature that considers these subjective values, although some studies have attempted to look for such relationships (Cellmer et al., 2012). There is, however, a lot of research that goes into the negative effects of water as a risk on land and property prices. In the event of a flood or drought, or even the increased probability of one, land prices can fall (Daniel et al., 2009). For coastal zones, a direct sea view is one of the most desirable attributes of a residential property (Shi Ming & Chee Hian, 2005), and a desirable sandy beach in a warm climate provides a unique pull-factor for leisure and tourism. However, many of the property owners in low-lying coastal zones have to contend with the risk of flooding. Wetlands, which also benefit eco-tourism, have recently been the focus of numerous economic studies and conservation drives. Scientists have attempted to quantify their value as carbon and nitrogen sinks, natural sites of wastewater treatment and flood defences (Mitsch & Gosselink, 2005). Their proximity to properties has also been measured, with open wetlands in Portland, US, shown to have a positive relationship with price, whilst other types of wetlands either had a negative or non-significant relationship (Bin, 2005).

Opportunity cost

For many investors in profit-yielding designated land, the land's potential future use will likely have been factored into the rationale behind the purchase. This is the 'opportunity cost': the cost of the most appropriate alternative use (Verheye, 2009) and the growth potential of the money invested, compared to if it had been invested elsewhere. One way of maximising the land's price without any major alterations would be by the sound maintenance of it (Põllumäe et al., 2014). A change in the land's designation, from rural to urban, will encourage new suburban developments and will be implemented with the aim of increasing the real estate value of the area (Roka & Palmquist, 1997). Private construction companies will be encouraged to physically alter the land, as the land-use designation changes from profit yielding to residential. Likewise, brownfield sites, such as industrial zones, can become zones of redevelopment, which can improve the livability of an area (Ruelle et al., 2013). In some greenfield developments, pre-planned networks of planned surfaced roads and utilities, such as electricity lines, are laid out in advance of the construction of homes. Owners can also add value to the land themselves, but structural improvements may affect the land's taxation rate (Verheye, 2009).

Recent research concludes that homebuyers are willing to pay for a better environment (Montero et al., 2018). Land is, in Western countries, considered a prerequisite of achieving individual freedom (Verheye, 2009). The selection of location and environment is not neutral, because humans aspire to live in areas where they can enjoy a high quality of life (Cellmer et al., 2012). Across Europe, there is a growing demand for green areas for living, due to population growth, increased leisure time and increasing knowledge and awareness of the environment (Tyrväinen & Miettinen, 2000). Counter urbanisation, including to distant rural areas has been an academic focus in some former Soviet Bloc countries (Šimon, 2014). There is a desire to meet one of man's basic needs by returning to live in a landscape where there is the presence of greenery, forests and water (Cellmer et al., 2012), and remote working has made this a possibility for those of working age.

When studying the price of residential land, the assumption is that residential land is purchased in order to construct a dwelling, live in or renovate a property that is already in place. Therefore, hedonic theory can be applied (Orford, 2017; Xiao et al., 2017). This means not only predicting the value of the property based on the known variables related to the building or land in which the property is or will be located, but also a set of variables related to the neighbourhood, economy (census tract data and income), local politics, as yet-unmapped information, or variables that have not been studied but which affect the demand for a property (such as noise levels) (Kim et al., 2007). Some of these features may or may not affect the property in question. However, the assumption can be made that residential land is selected for its proximity to working location or for pleasant environmental factors (Cellmer et al., 2012). Therefore, residential land is usually located close to services, such as schools and leisure facilities, either in a linear or cluster pattern. Land use patterns are therefore not random. They are organised based on the factors that add value. Differently from agricultural land, the areas surrounding residential land plots are often improved or purchased because of their quality. This is particularly true of those associated with pleasant natural or managed environments (such as beaches, parks, golf courses), and reduced distance to these leisure locations has been seen to increase property prices (Bolitzer & Netusil, 2000). Human improvement and change are considered essential properties of landscape (Antrop, 2004). Land ownership creates patterns and patches of mixed land types. Patterns of open and closed, or arable, grassland or forested land affect the homogeneity of landscape and affect, among other things, light and microclimate, biodiversity and vista. Each human settlement has been described as a 'control' centre for the territory of the social group living there. It organises space around it according to ecological, economic, social, cultural and psychological rules (Antrop, 2000). A clear example of this is the marking of territories by fences and enclosures. Residential land change has been measured by regression analyses, with researchers looking at factors such as the number of bedrooms, through to the spatial density and size of properties in order to assess the movement of boundaries between urban and rural zones. Administrative methods such as the implementation of split taxation zones can be used to control these changes (Banzhaf & Lavery, 2010).

2. Data and Methods

2.1. Study Area

Hiiu County was chosen as the investigation site for this thesis. It is a geographically closed space, which has the aforementioned environmental qualities and mix of land types, urban spaces, industrial zones, forest and protected zones. It can be considered an ideal starting point for further research across Estonia. The county is a group of nearly 200 islands to the west of the mainland, which is made up almost entirely by the 989 km² island of Hiiumaa. Hiiu County is by far the least populated county in Estonia, with 9387 (as of 2018) inhabitants and a population density of 9.1 inhabitants per km². The county centre is the town of Kärdla, on the northern shore of Hiiumaa.

Hiiumaa is accessible year-round, either by ferry port, harbours, airport or temporary ice-road. Internally, the island has well-maintained main roads, and numerous secondary roads, including unsurfaced tracks. With its proximity to the capital, Tallinn, its well-regarded nature reserves, sandy beaches and milder climate, it is a popular summer destination and location for second homeowners, of whom there has been a relative increase in recent years (Hiiu County Government, 2015).

Hiiu County can be considered as the wildest county in Estonia, with nearly 70% of the main island covered with different types of woody vegetation, from scrub to ancient coniferous and deciduous forests. These land types have increased as the reprivatisation of land at the beginning of the 1990s saw the demise of collective agriculture and the natural rewilding of large parts of the county. The 'saving grace' of the natural landscapes was the young and mostly thin and stony limestone soils, which have only limited intensive agriculture (Kaasik et al., 2011). In the modern day, there are still various open spaces, from arable land and agricultural fields to natural grasslands. 24% of the territory is environmentally protected, including the alvars and the still-significant wetland environments (although twentieth century land reclamation reduced the number significantly (ibid)). Nowadays, saturated land accounts for 7% of the island's surface area and varies from bogs, quaking bogs and fens to shoreline reeds (Hiiu County Government, 2015). There are various short and small streams, with most merging with the rows of drainage ditches that cover the southern half of Hiiumaa. Extensive land improvement work has significantly improved the flow and seasonal levels of the rivers and streams (ibid).

Most of Hiiu County's soils are poor quality for arable purposes (Reintam et al., 2005). In terms of industry and production land, the forestry industry that is set around the extensive biomass resource is central to the local economy. The industry provides energy sources for the country, and for export. Other zones of economic resource include quarries. Other major economic sectors are tourism and manufacturing, which is located within production sites (Hiiu County Government, 2015).

In the years 2013 to 2017, there were 2945 real estate transactions in Hiiu County, representing 1% of the total nationwide sales, 2.2% of the total nationwide territory sold, and 0.48% of the total value of nationwide sales. There were 1964 transactions of immovables without buildings over the 5-year period. 80% of these transactions were purchase and sale transactions (Maa-amet, 2019). The average price per square metre over the 5-year period was €0.16 (figure 1) and remained steady.

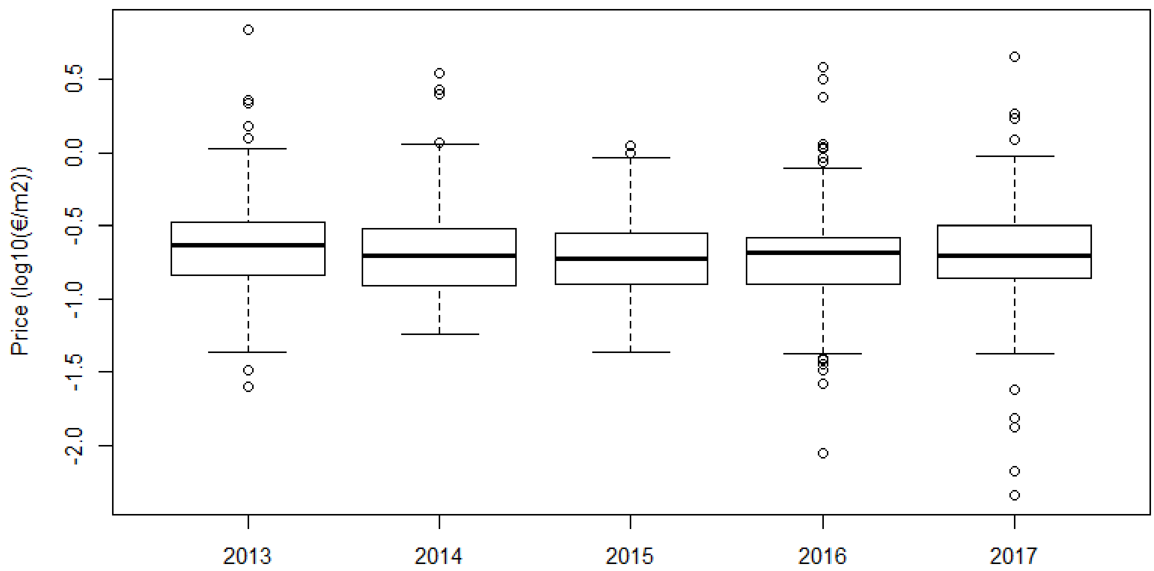

Figure 1. Yearly median, quartiles and range of Sold Profit-Yielding Land Price (log10(€/m^2)) for Hiiu County (2013-2017)).

The price of sold residential land (€/m^2) in Hiiumaa, where one land parcel was sold per transaction, decreased slightly between 2013 and 2014, before increasing considerably in 2015. The average price dropped again in 2016, before recovering in 2017 (figure 2). The average price per square metre over the 5-year period was €0.54.

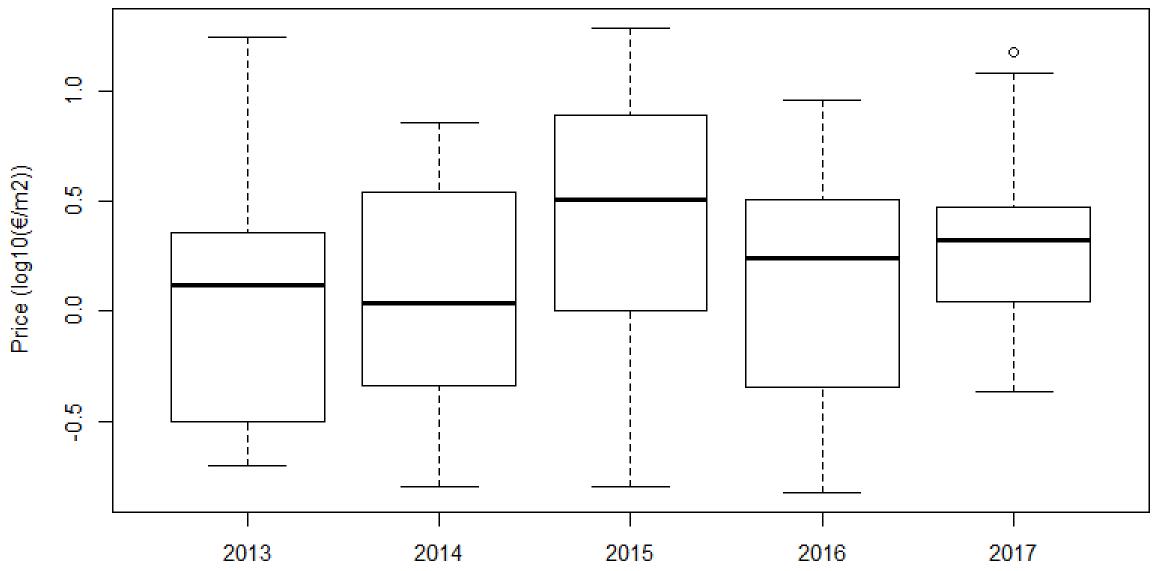

Figure 2. Yearly median, quartiles and range of Sold Residential Land Price (log10(€/m^2)) for Hiiu County (2013-2017).

2.2. Data

There were two datasets used for the dependent variable throughout the statistical analysis of land parcel prices for 1) designated profit-yielding (in Estonian: maatulundusmaa) land parcels and 2) designated residential land (in Estonian: elamumaa) parcels. The dependent variable was provided by the Estonian Land Board. The provided dataset contained the sales of all land parcels without buildings in Hiiu County, both by private sellers and the Land Board themselves, for the 5-year period between 01.01.2013 and 31.01.2017. The sold land prices had already been index-linked for 31.12.2017 by the Land Board and divided by the size of the land parcel to give their indexed price per square metre (€/m^2) ('indexed sold land price' is the term which is used throughout this document to refer to this). The independent variables were selected for their relevance to the study site. The independent variables can be grouped into three:

1) the proximity of each land parcel to selected environmental factors: distance in metres from the outer boundary of the land parcel to the environmental factor 2) the internal land type of the land parcels: the weighted percentage of each land type per land parcel 3) the weighted soil percentage parameters per land parcel.

The information of the first two groups were obtained from the Estonian National Topographic database (ETAK) (1:10 000), and the third group from Estonian Soil Map (1:10 000). Each of the ETAK layers were checked to see if they were present within the study site, and if so, which of the subcategories could be extracted, using the layers' attribute tables. The two main land types of agricultural land and wood-covered land were subdivided using the attribute tables into the respective categories of arable land; fields; and horticultural land, and forest; woody vegetation; and woodland.

A dataset of the dependent variables and independent variables was created. Only land parcels designated as 100% profit-yielding or 100% residential purpose and where there was only one cadastre registered per sale were considered. Table 1 lists all the 48 variables in each of the two investigation datasets and the abbreviations used in the figures in Annexes 1-2.

Table 1. The measured independent variables and the dependent variable.

Full Variable Name	**Unit**
The Size of The Land Parcel	m^2
Distance to Airport	m
Distance to Arable Land	m
Distance to Building*	m
Distance to Bog	m
Distance to Coast	m
Distance to Drainage Feature (Ditches and Dykes)	m
Distance to Electrical Line	m
Distance to Zone of Environmental Protection	m
Distance to Fen	m
Distance to Forest (Excluding Woody-Vegetation)	m
Distance to Grassland	m
Distance to Graveyard	m
Distance to Harbour (Including Ferry Port)	m
Distance to Landfill	m
Distance to Building for Living (Living and Communal Buildings)	m
Distance to Non-Main Roads	m
Distance to Pathways	m
Distance to Production Land	m
Distance to Quarry	m
Distance to Quaking Bog	m
Distance to Rivers	m
Distance to Main Roads	m
Distance to Sandy Beach (Sandy Land within 100m of The Coast)	m
Distance to School	m
Distance to Shoreline Reeds (Reeds within 100m of The Coast)	m
Distance to Sporting Venues	m
…Continued	

Distance to Spring (Water Source)	m
Distance to Waterbodies (Lakes and Ponds)	m
Distance to Wetlands**	m
Distance to Waterlogged Land	m
Distance to Woody Vegetation (Excluding Forest)	m
Percentage of Arable Land in Land Parcel	%
Percentage of Buildings* In Land Parcel	%
Percentage of Fields in Land Parcel	%
Percentage of Grassland in Land Parcel	%
Percentage of Horticultural Land in Land Parcel	%
Percentage of Private Land in Land Parcel	%
Percentage of Production Land in Land Parcel	%
Percentage of Water Bodies in Land Parcel (Lakes and Ponds)	%
Percentage of Wetlands** in Land Parcel	%
Percentage of Woodlands in Land Parcel (Forest & Woody Vegetation)	%
Average Soil Clay Content Percentage in Land Parcel	%
Average Soil Rock Content Percentage in Land Parcel	%
Average Soil Sand Content in Percentage in Land Parcel	%
Average Soil Silt Content Percentage in Land Parcel	%
Average Soil Fertility Level Percentage in Land Parcel	%
Sold Land Parcel Price (Dependent Variable)	€/m^2

*Buildings refer to any type (buildings, foundations, ruins, outside buildings).

**Wetlands refer to a combination of bog, fen, quaking bog and waterlogged land.

There were 15930 registered land parcels (cadastral units) in Hiiu County at the end of 2017 (covering 98.6% of the territory (Maa-amet, 2017)). The dependent variable was joined to the land cadastral shapefile, which already contained information for land use designation and land type. After non-100% profit-yielding and non-100% residential land parcels were removed, along with land parcels without soil survey data, a joined shapefile and data table containing 10254 100% profit-yielding purpose land parcels and 2693 100% residential purpose land parcels remained. From the 100% profit-yielding purpose land parcels, 913 had at least one sale registered. These counted for 64% of the total registered land parcels in the county. From the 100% residential purpose land parcels, 131 had at least one sale registered. These counted for 17% of the total registered land parcels in the county. Figure 3 shows the location of each land parcel type in the study site.

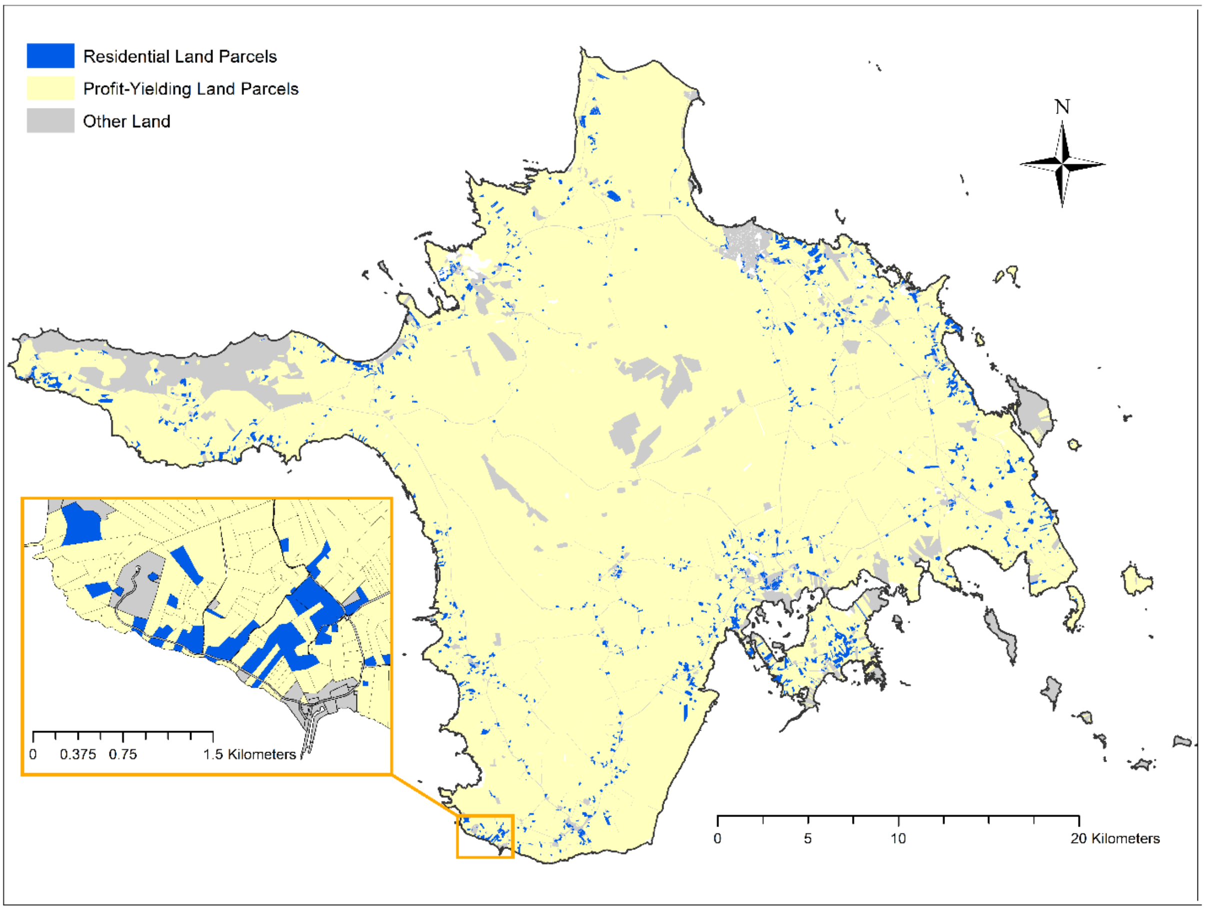

Figure 3. Profit-yielding & residential land parcels in Hiiumaa. (Source: Estonian Land Board).

2.3. Data analysis and preparation

Correlation analyses are used to gain an overview of the variables' relationships (Bolitzer & Netusil, 2000). They help to focus the research, as sometimes a bivariate correlation can bring unexpected results (Kim et al., 2007). However, environmental researchers have to be aware of contradictory findings, which are possibly because of spatial autocorrelation (ibid). In datasets where the variables are non-parametrically distributed, the alternative procedure of Spearman's rank can be used to measure the correlation coefficient. Because environmental data is often non-normally distributed, Spearman's rank is typically preferred to study land values, with an example being the further investigation into the effects of land use regulation restrictiveness on house and vacant land prices (Ihlanfeldt, 2007).

In this research project, for profit-yielding land, although still weak, the strongest overall correlation with sold indexed land price (€/m^2) was distance to arable land (Table 2), with a positive correlation coefficient of 0.27. The relationship indicated that indexed sold land price (€/m^2) increased with increasing distance from arable land. The second strongest correlation with indexed sold land price (€/m^2) was percentage of fields. The relationship indicated that indexed sold land price (€/m^2) increased with a reduced internal percentage of fields. The other variables with statistically significant correlations were only very weakly correlated with indexed sold land price (€/m^2).

Table 2. Statistically significant ($p<0.05$) Spearman correlations with indexed sold land price (€/m^2) for profit-yielding land.

Positive Correlation Coefficients (r)	**Independent Variable**	**Negative Correlation Coefficients (r)**	**Independent Variable**
0.27	Distance to Arable Land	-0.26	% Fields
0.18	% Woodland	-0.15	Average Soil Fertility %
0.14	Distance to Drainage Feature	-0.13	Distance to Coast
0.14	Distance to Landfill	-0.13	Size of Plot
0.13	Distance to Airport	-0.1	Distance to Harbour
0.1	Distance to Production Land	-0.09	Average Soil Silt Content %
0.1	Distance to Quaking bog	-0.08	Average Soil Clay Content %
0.1	Distance to River	-0.08	Distance to Shoreline Reeds
0.07	Distance to Electric Line	-0.07	Distance to Forest
0.07	Distance to Waterbody		

For residential land, the strongest overall correlation with indexed sold land price (€/m^2) was size of plot, with a negative correlation coefficient of -0.55 (Table 3). This can be considered a moderate relationship which indicated that indexed sold land price (€/m^2) increased with decreasing sold land plot size. The distance variables with weak to moderate positive correlations were distance to drainage feature, distance to arable land and distance to grassland. The direction of these relationships, although weak, indicated that indexed sold land price (€/m^2) increased with increasing distance from them. The distance variables with weak positive correlations were distance to waterbody, distance to landfill, distance to schools and distance to spring. The direction of these relationships, although very weak, indicated that indexed sold land price (€/m^2) increased with increasing distance from them. The distance variables with weak to moderate negative correlations were distance to sandy beach and distance to coast. The direction of these relationships, although weak, indicated that indexed sold land price (€/m^2) increased with reduced distance from them. The variables with weak negative correlations were distance to living or communal building and distance to building. The direction of these relationships, although very weak, indicated that indexed sold land price (€/m^2) increased with reduced distance from them. The other variables with statistically significant correlations were only very weakly correlated with indexed sold land price (€/m^2).

The percentage variable with a weak positive correlation was percentage of woodland. The direction of this relationship, although very weak, indicated that indexed sold land price (€/m^2) increased with a larger internal percentage of woodland. The percentage variables with weak negative correlations were percentage of fields and percentage of grasslands. The direction of this relationship, although weak, indicated that indexed sold land price (€/m^2) increased with a smaller internal percentage of these land types.

The average soil percentage variables with weak negative correlations were average percentage of soil fertility, average percentage of clay soils and average percentage of silty soils. The direction of these relationships, although very weak, indicated that indexed sold land price (€/m^2) increased with a reduced internal average percentage of these soil properties.

Full correlation matrices can be found in Annex A. These show the variables with statistically significant ($p<0.05$) and non-significant correlation coefficients.

Table 3. Statistically significant ($p<0.05$) Spearman correlations with indexed sold land price (€/m^2) for residential land.

Positive Correlation Coefficients (r)	**Independent Variable**	**Negative Correlation Coefficients (r)**	**Independent Variable**
0.44	Distance to Drainage Feature	-0.55	Size of plot
0.32	Distance to Arable Land	-0.41	Distance to Sandy Beach
0.3	Distance to Grassland	-0.33	Distance to Coast
0.28	Distance to Waterbody	-0.3	Average Soil Silt Content %
0.25	% Woodland	-0.27	Distance to Living/Communal Building
0.24	Distance to Landfill	-0.26	Average Soil Clay Content %
0.22	Average Soil Sand Content %	-0.25	Average Soil Fertility %
0.21	Distance to Schools	-0.23	% Fields
0.21	Distance to Spring	-0.22	% Grassland
		-0.21	Distance to Building
		-0.19	Distance to Non-Main Roads
		-0.18	Distance to Harbour

Multicollinearity causes issues within linear regression, which requires the careful selection of the geographic domain from which observations are drawn (Heikkila, 1988). Choumert & Phélina's (2015) study on Argentinian farmlands explained that the heterogeneity of farmlands can cause heteroscedasticity in the residuals of the hedonic price estimation. They used variance influence factors (VIF) to check for and find multicollinearity, noting that their model's high number of characteristics was one of the main reasons for this issue. Kim et al. (2007), as well as using correlation analysis, checked for VIF in each of the four models (linear, semi-log, inverse semi-log and double log) that they used as the functional forms in their overall hedonic price model.

The results of the correlation analysis between independent variables (Annex A) were used for preparing the linear regression model. Independent variables with correlation coefficients over 0.7 (collinearity) with other independent variables were detected by the correlation analysis. Of the two variables, the variable with the lower individual correlation coefficient value was generally dropped. Where the variables had the same correlation coefficient, if one was statically non-significant, then it was dropped. However, as the models were repeat-tested, the VIF test within the model showed that some variables, such as distance to school, scored very high for multicollinearity. Therefore, the variable with the lower correlation score with the dependent variable was selected instead.

To fix the non-parametric distributions of many of the independent variables, including the dependent variable, skewness was calculated. Variables with an absolute skew greater than 0.8 were log-transformed using log10+1 (+1 to avoid division by zero issues). This was a quick technique, which was satisfactorily effective for all but a few of the percentage independent variables, which had spreads of observations from 0-100, but were zero-heavy. In these cases, the transformation improved the skewness, but did not reduce it to within the optimum range of -1 to 1. The dependent variable's distribution was normalised, and its skewness score reduced from 9.06 to 0.19 after a log10 transformation. Boxplots displaying the remaining independent and dependent variables after removal for high collinearity, which were then transformed, can be found in Annex B for both datasets. Finally, to ensure a stable convergence of weight and biases, all variables except the dependent variable were normalised and placed into the same range.

2.4. Multiple Linear Regression

Price prediction academic literature is explanatory and at best advisory, rather than instructional. This can be explained by the different study locations and methodical and data constraints (Mulley, 2014). A price investigation typically involves a regression analysis. There are various forms of regression analyses, which vary in complexity and user input. Regression can be described as "the study of how the conditional distribution of y|x changes with the value of x" (Cook & Weisberg, 2009, p. 37). Linear regression is a preferred starting and comparison point for other regression techniques and is associated with the hedonic model. The hedonic model refers to a range of techniques to identify and estimate price factors by measuring the economic values of goods based on the concept that their value comes from peoples' valuation of their characteristics, or the services they produce (Pyykkönen, 2006), rather than the simple physical object or space. One of the most common ways to assess hedonic pricing is with a regression model. This is a revealed-preference method to determine the relative importance of the variable affecting goods or service prices. A typical linear regression model is shown in equation 1.

$$y = a.x1 + b.x2 + \ldots + n.xI$$

(1)

where y is the predicted price, x^1, x^2 and x^i are the property attributes and a, b and n indicate the correlation coefficients of each variable in determining property price (Nur et al., 2017).

A common use of a hedonic regression model is to attempt to quantify the effect of one or several similar environmental factors on the price of land. Many counties, such as Estonia and Lithuania, implemented at least one hedonic regression model in their overall methodology of state mass land evaluation (Bagdonavičius & Deveikis, 2011). Hedonic regression models can require a lot of data preparation and can incorporate many variables. Stepwise linear regression, where the variables are either added (forwards) or removed (backwards) is used to reduce a model with many independent input variables down to the few that contributed most to it. It was employed as part of a hedonic study into the Ankara housing market, where, according to the root mean squared error (RMSE) scores, it was shown to perform best out of the applied regression models and was able to explain 78% of the variance in the residential sales prices (Hayrullahoğlu et al., 2018).

The spatial limitations of linear models are undoubtedly their weakness in this field. Therefore, in recent years, more advanced methodologies, which include spatial variables that account for the issues of autocorrelation, heterogeneity and nonlinearity have been designed, to absorb the unwanted spatial effect of environmental variables on prediction. A successful example of this was with the reduced environmental effect on the housing dataset of Madrid (Montero et al., 2018). When investigations become more complex, other regression techniques are implemented. A quantile regression approach allowed the researchers looking at determinants of the agricultural land prices in Sweden with a focus on location-specific factors to examine the relative importance of explanatory variables at different points of the distribution of the dependent variable. This enabled a more complete picture of price determinants. (Nilsson & Johansson, 2013).

Geographically weighted regression (GWR) is a complimentary approach (Sá et al., 2011) to global spatial analysis methods, which has been used to study the effects of geographically non-stationary phenomenon such as sub-Saharan wildfires (Sá et al., 2011). The GWR method was compared to standard ordinary least squares (OLS) linear regression and was found to be able to replicate the data by 87% (R^2), due to dealing far better with spatial autocorrelation and discovering local patterns in parameter estimates. Such findings provide improved understandings of multiple variable relationships. Alongside the well-documented and statistically analysed effect of a property's internal features and neighbourhood effects, accessibility has been investigated using GWR. There are certain techniques that can be used to account for spatial dependency on price estimation values. GWR was used to add the geographical component to the regression model to discover that transportation accessibility did improve land prices, albeit moderately, and that within closer proximity, the transportation's negative externalities of noise and pollution were detrimental to land price (Mulley, 2014). In addition, it was concluded that flat rate land taxation to fund such a network would cause cost/benefit imbalances.

Other alternatives to regression can be more manually iterative and participatory, such as the mixed method qualitative and quantitative approach of MCA that successfully provided an insight into the opportunities from non-wood forest products in Austria and Finland (Huber et al., 2017). Alternative mapping techniques such as kriging and semivariograms can be used to provide price zones, as demonstrated with the investigation into desirable environmental living spaces in Poland (Cellmer et al., 2012). Finally, there are a range of sophisticated modelling alternatives that have kept interest high in attempting to accurately predict land price. An example is the artificial neural network (ANN) method, which, compared to the typical hedonic multiple regression technique, was found to be a better alternative for predicting the house prices in Turkey (Selim, 2009). The other alternative is to combine the benefits of multiple models. ANN, regression and GWR were combined to study house prices in the riverside city of Wuhan, China. A stepwise linear regression hedonic model was found to be inferior to the other two models, which were combined to produce the results. The advantage that linear regression has over ANN is its clear interpretability and ability to analyse the importance of each factor (Wu et al., 2018), which is the primary reason for its use in this thesis.

In this thesis, before modelling, both the sold profit-yielding land dataset and sold residential land dataset were split into training and verification datasets, at a ratio of 7:3. Multiple linear regressions were performed using each land use designation's training datasets. The process (the same for each land use designation dataset) was as follows:

Diagnostic steps were performed with the backward elimination of independent variables one at a time. After every elimination and refit, the model's F-statistic score improved. Variance influence factors (VIF) were checked and variables were removed for having high scores above 5. Distance to quaking bog was removed from both the profit-yielding and residential multiple linear regression models for this reason. For residential land, distance to quarry, distance to fen and distance to bog were also removed for VIF. Next, variables with non-statistically significant p-values (>0.05) were removed from the multiple linear regression model. Outliers with leverage were detected using Cook's distance plots. 9 extreme observations were removed from the profit-yielding regression model and 6 extreme observations were removed from the residential regression model before leverage was satisfied. The models were used to predict the prices on the training datasets, before they were verified by predicting the prices on the unseen verification datasets. The predicted and real prices were reverse transformed so that the predictions and errors were in the original values of €/m^2. From these, the correlations between the predicted and real prices (R2) were calculated. Also calculated were the root mean squared error (RMSE) score (the square root of the average squared residual distance) and the mean absolute error (MAE) (the average of all the absolute residual errors).

3. Results

The results chapter displays the results of the multiple linear regression models for the profit-yielding and residential datasets.

The trained multiple linear regression model for profit-yielding land was able to describe 15% of the variance in the dependent variable. When tested on the validation dataset, and the real and predicted prices reverse transformed, the correlation between the real and predicted sold prices (€/m^2) was 8% (R^2).

The trained multiple linear regression linear model for residential land was able to describe 77% of the variance in the dependent variables. When tested on the validation dataset, and the real and predicted prices reverse transformed, the correlation between the real and predicted sold prices (€/m^2) was 44% (R^2).

3.1. Profit-Yielding Land

The best fitting regression model for profit-yielding land explained 15% (adjusted R^2) of the variation in the training data. The model was statistically significant ($p<0.001$). Residual plots can be found in Annex C. The residuals were reasonably balanced around the line of best fit and all within Cook's distance. The residual's minimum value was -3.63, the maximum 2.34 and the median 0.021. The first quartile was 0.36 and the third quartile was 2.34.

The variables contributing to the model with positive correlations in descending order of significance of contribution (Table 4) were distance to arable land (0.18), size of plot (0.12) and percentage of grassland (0.10). The variables contributing to the model with negative correlations in descending order of significance of contribution were percentage of waterbody (-0.20), average soil fertility percentage (-0.12), distance to harbour (-0.09) and distance to spring (-0.08).

Table 4. Independent variable coefficients of the multiple linear regression model for profit-yielding land (adj. R2 of 0.15).

Coefficient Name	**Coefficient Estimate**	**Coefficient Standard Error**	**Coefficient t-Value**	**Sig.**
Intercept)	-1.51233	0.02942	-51.407	***
Size of Plot	0.12073	0.03018	-4.5100	***
Dist. Arable Land	0.17528	0.02661	6.5870	***
Dist. Harbour	-0.08667	0.02898	-2.9900	**
Dist. Spring	-0.07616	0.02665	-2.8580	**
% Grassland	0.09605	0.03359	2.8600	**
% Waterbody	-0.20144	0.07112	-2.8320	**
Average Soil Fertility %	-0.11665	0.03590	-3.2500	**

Significance: *** 0.001, ** 0.01, * 0.05

Table 5 shows the results of the implimentation of the model on the training and verification datasets. The results were taken after both the predicted and real prices had been reverse transformed back to the original measure of €/m^2. The correlation between the real and predicted indexed sold land prices (€/m^2) when the model was used on the training dataset was 15%. The correlation between the real and predicted indexed sold land price (€/m^2) when the model used on the verification dataset to verify the model's ability to predict unseen data was only 8%, which is very low predictive ability. The root mean squared error (RMSE) score, which is the square root of the average squared residual distance from the line of best fit was 1.52 for the training dataset and 0.50 for the verification dataset. The mean absolute error (MAE), the average of all the absolute residual errors, was 0.18 for the training dataset and 0.09 for the verification dataset. The RMSE and MAE scores were lower for the verification dataset.

Table 5. Indexed profit-yielding sold land price (€/m^2) prediction results using the multiple linear regression model.

Real Price (€/m^2) Vs Predicted Price (€/m^2)	**Training Dataset**	**Verification Dataset**
Correlation (R^2)	0.15	0.08
RMSE	1.52	0.50
MAE	0.18	0.09

3.2. Residential Land

The best fitting regression model for residential land explained 77% (adjusted R^2) of the variation in the training data. The model was statistically significant ($p<0.001$). Residual plots can be found in Annex C. The residuals were reasonably balanced around the line of best fit and all within Cook's distance. The residual's minimum value was -0.54, the maximum 0.45 and the median 0.025. The first quartile was 0.15 and the third quartile was 0.45.

The variables contributing to the model with positive correlations in descending order of significance of contribution (Table 6) were distance to spring (0.2), distance to main road (0.16), distance to shoreline reeds (0.15), distance to arable land (0.12), average soil rock content (0.09), distance to waterbody (0.8), distance to woody vegetation (0.7) and distance to grassland (0.7). The variables contributing to the model with negative correlations in descending order of significance of contribution were distance to coast (-0.3), distance to harbour (-0.27), distance to graveyard (-0.17), distance to sporting venue (-0.16), distance to electric line (-0.14), distance to sandy beach (-0.12), distance to zone of environmental protection (-0.9) and average soil fertility percentage (-0.8).

Table 6. Independent variable coefficients of the multiple linear regression model for residential land (adj. R2 of 0.77).

Coefficient Name	Coefficient Estimate	Coefficient Standard Error	Coefficient t-value	Sig.
(Intercept)	-0.20163	0.04262	-4.731	***
Dist. Arable Land	0.120730	0.0437	2.762	**
Dist. Coast	-0.303990	0.05239	-5.802	***
Dist. Electric Line	-0.142450	0.04071	-3.499	***
Dist. Zone of Environmental Protection	-0.089380	0.03545	-2.522	*
Dist. Grassland	0.071180	0.03138	2.268	*
Dist. Graveyard	-0.166310	0.04403	-3.777	***
Dist. Harbour	-0.268550	0.03561	-7.54	***
Dist. Main Road	0.160400	0.04143	3.872	***
Dist. Sandy Beach	-0.122080	0.04819	-2.533	*
Dist. Shoreline Reeds	0.152990	0.04898	3.124	**
Dist. Sporting Venue	-0.164850	0.05259	-3.135	**
Dist. Spring	0.204000	0.04323	4.719	***
Dist. Waterbody	0.08484	0.03121	2.719	**
Dist. Woody Vegetation	0.07189	0.03241	2.218	*
…Continued				

Average Soil Rock Content %	0.09165	0.03052	3.003	**
Average Soil Fertility %	-0.07769	0.02104	-3.693	***

Significance: *** 0.001, ** 0.01, * 0.05

Table 7 shows the results of the implimentation of the model on the training and verification datasets. The results were taken after both the predicted and real prices had been reverse transformed back to the original measure of €/m^2. The correlation between the real and predicted indexed sold land prices (€/m^2) after the model had been used to predict the dependent variable of the training dataset was 81%. The correlation between the real and predicted indexed sold land price (€/m^2) when the model was used on the verification dataset to verify the model's ability to predict unseen data was 44%, which is still good predictive ability. The root mean squared error (RMSE) score was 1.37 for the training dataset and 2.2 for the verification dataset. The mean absolute error (MAE) was 0.71 for the training dataset and 1.22 for the verification dataset.

Table 7. Indexed residential sold land price (€/m^2) prediction results using the multiple linear regression model.

Real Price (€/m^2) Vs Predicted Price (€/m^2)	**Training Dataset**	**Verification Dataset**
Correlation (R^2)	0.81	0.44
RMSE	1.37	2.2
MAE	0.71	1.22

4. Discussion

4.1. Predicting the indexed transaction price (€/m^2)

The multiple linear regression for the two land designations produced very different results. For profit-yielding land, the model's 7 statistically-significant independent input variables that were shown to have an association with the dependent variable were only able to explain 15% of the variance in the sold indexed land prices (€/m^2). When the model was verified, the R^2 score for the correlation between the real sold prices and the predicted prices was only 8%. Therefore, this model was inadequate to predict indexed sold land price (€/m^2) for profit-yielding land and it was shown to have no potential use for this purpose in Hiiu County.

For residential land, the model's 16 statistically-significant independent input variables that were shown to have an association with the dependent variable were able to explain 77% of the variance in the sold indexed land prices (€/m^2). When the model was verified, the R^2 score for the correlation between the real sold prices and the predicted prices was 44%, which was a lot lower than the testing dataset, but still a good score. Therefore, at this point, the model is merely suggestive, but it has potential for improvement. Overall, it can be said that the indexed sold price (€/m^2) of residential land can be partially predicted by using physical environmental variables in Hiiu County.

Despite the disappointing performance of the profit-yielding multiple linear regression model, the model achieved better than the 7% score produced by the first multiple linear regression in Dirgasova et al's (2017) analysis to predict the price of agricultural land in Slovakia. In their study, the variables used also included size of plot, and the distance variables (distance from district city and distance from regional seat). However, when other region-specific factors were added, the model improved significantly (R^2=21%).

The results of the residential multiple linear regression model were better than the 33% R^2 score produced by the multiple linear regression in Cellmer et al's (2012) analysis to predict the price of land zoned for residential or residential development in Poland. However, they only used three independent input variables to gauge scenic value, which were waterbody, forests and elevation.

4.2. Variables' association with indexed sold land price (€/m^2)

Coastal

For residential land, correlations were expected between the pleasant environmental variables, such as those considered scenic for residential land. The strongest correlation of all input independent variables was distance to coast. The results suggest that indexed land price increased as the distance to Hiiu County's famous coastline decreased. This is no surprise, as the coasts are the locations of most of the main island's residences, services and seasonal tourism industry hotspots, and the variable showed one of the strongest relationships with indexed sold land price (€/m2) for residential land, both in the bivariate Spearman correlations and the linear model. Interestingly (and worth further investigation despite the weak relationship), reduced distance to coast also showed a statistically significant bivariate correlation with increasing indexed sold land price (€/m2) for profit-yielding land. The purpose of such purchases might a financial investment, with coastal land being traditionally one of the most valuable locations (Conroy & Milosch, 2011). With poor soils and heavy woodland, land use is restricted, although as seen in the peripheral coastal zones of urban areas, many permanent and summer residences have been constructed since independence (Rivis et al., 2009), and if the land use changes from profit-yielding to residential, the value of the land should increase substantially (Roka & Palmquist, 1997).

However, such coastal investments are not without risk. Despite the isostatic uplift of Estonia, (which has been modelled to show that Hiiumaa is in the fastest-rising land zone (Kall et al., 2014)), Hiiu County's coastal zones are still predicted to suffer ecological damage, including the shrinkage or disappearance of many of the valuable recreational beaches (Kont et al., 2003). Of course, sand beaches were also positively correlated with indexed sold land price (€/m2) for the residential model, as well as the bivariate correlations, for which it had a stronger correlation than distance to coast. Thus, unsurprisingly, the benefit of proximity to a sandy beach was not shown to be affected by risk thinking (Thomas, 1999). By contrast, the other major type of coastal frontier, the shoreline reed beds, were shown to negatively affect indexed sold land price (€/m^2) (or the variable does not increase it as much as the easily accessible coastal alternatives). As opposed to the benefits of leisure space (Bolitzer & Netusil, 2000; Cellmer et al., 2012), the coastal reed beds provide a key habitat for breeding fish. Like sandy beaches, they are also threatened and will either retreat inland or disappear along with the complete disappearance of the northern coast's lagoons and orchid-rich calcareous meadows (Kont et al., 2003). Another potential risk for the Northern and Western coastal regions of Hiiumaa is the drifting oil pollutants and other harmful substances from the busy shipping channels to the island's north into the Baltic Sea (Lehmann et al., 2014). This could prove an interesting further area of research, with beach quality considered an important determinate of coastal property values, alongside beach width, which had the highest coefficient in Pompe & Rinehart's (1995) regression model. However, in comparison to heavily populated beach resort islands, Hiiumaa's coastal villages tend to be located a few kilometres inland from the coast (Kont et al., 2003), with the land parcels connecting with beaches mostly profit-yielding woodlands. Therefore, competition can currently be assumed to be high for the intermittent residential land plots with open views of the sea.

Another coastal factor, distance to harbour, was the second strongest correlated of the residential model's variables. The variable was also included in the profit-yielding model. Hiiumaa's harbours were variables included in both land use designation's final regression models, with the negative values suggesting that closer distance to this variable increased land price. Spread around the island, this variable had a moderate to weak bivariate correlation coefficient with coast. A preparatory thesis investigation into the land prices in Kärdla had showed clear indications of higher land prices close to the town's harbour.

Saturated land

In terms of negative factors, water-related variables were the strongest correlated model variables that were seen to reduce indexed sold land price (€/m^2) for both land use designations. However, the other water variables had different results. For profit-yielding land, percentage to waterbody was the strongest correlated of all the variables, despite having only shown a very weak but statistically significant positive bivariate relationship with indexed sold land price (€/m^2). Profit-yielding land also had a correlation with distance to springs, which showed that reduced distance meant a higher indexed sold land price (€/m^2).

The residential land model also showed that reduced distance to waterbody (the same factor) had an adverse effect on price. These findings contrasted with Snyder et al's (2007) hedonic model of forest land, where waterbody (and river) were found to be positively correlated with price. It also goes against the idea that scenic value or recreational potential adds value to land (Cellmer et al., 2012). However, in a local context, most of Hiiu County's waterbodies are small and are located within the forested heartland, which is a closed land type and therefore removed from view. Additionally, some of the waterbodies are within zones of environmental protection, for which imposed building restrictions could drive down value (Spalatro & Provencher, 2001). In terms of profit-yielding land, a percentage of waterbody might reduce the forest capacity considerably, for which there is usage potential and financial incentive (Põllumäe et al., 2014; Quiroga et al., 2019).

Distance to spring, which was shown to have an adverse effect on residential indexed sold land price (€/m^2) showed the opposite for the profit-yielding land model. This suggests that fresh water might add value to profit-yielding land, although further investigation would be required to determine the correlation for agricultural land vs forest land.

Wood-covered vs agricultural

For the profit yielding land model, none of the two main land cover types of wood-covered land (woodland/woody vegetation/forest land) and agricultural land (arable land/fields/horticultural) were statistically significant in the model and therefore were dropped. This was surprising, given that distance to arable land and percentage of woodland were two of the three highest correlated variables with price. Percentage of fields had the second highest correlation, but this was dropped for high collinearity with both of the other variables. These results are unfortunate and do not allow for any further comparison to be made regarding the value of Hiiu County's agricultural land types verses its wood-covered land types, and therefore cannot be contextualised within the theory relating to the economic value of wood-covered land. It has been demonstrated across academic literature that price for agricultural or wood-covered land can be modelled with far greater accuracy. Studies that focused on one of the land types and therefore went into greater depth were able to produce far superior results. An example is Maddison's (2000) study into the price of farmland. In this instance, typical hedonic variables, such as those related to the size of farmhouse were included and the model was able to account for 60% of the variance in price. Likewise, for wood-covered land, Snyder et al's (2007) study into the determinants of forest land prices was able to determine 53% of the variability in per hectare sale price. In this instance, a range of variables were used that looked at the details of financing methods, road access, river frontage and timber growing volume. Thus, it might be the case that the methodology used in this study was too broad and lacking in detail. There was, however, a positive correlation between profit-yielding indexed sold land price (€/m^2) and percentage of grassland in the model. It was noted that this might be due to the economic benefit that this land type also brings with taxation incentives (EMTA, 2016). For residential land, the opposite was true, and one can suggest that the restrictions on much of the protected grassland lessen demand and price.

Soils

The relationship between average soil fertility percentage is particularly interesting. One might assume, given the history of land price, that higher soil fertility levels would mean higher land prices, due to the higher potential output of the land and therefore return from it (Verheye, 2009). Additionally, the Estonian Land Board used soil quality as one of the input variables in their hedonic regression model and one would assume that as one of the few variables chosen, there would have been stronger correlations with indexed sold land price (€/m^2) for profit-yielding lands. However, this might have been the case were the soils productive, but where there are examples of poor soil characteristics, including erodibility, wetlands or excessive water permeability (of which Hiiu County has all three), there are agricultural limitations and this therefore exerts a negative influence on land price (Roka & Palmquist, 1997). The trend in Hiiu County, as indicated by the results, is that the more expensive plots had lower average soil fertility levels. Certainly, more local analyses would be required, to investigate whether this is a relationship pattern across the county, or whether it varies by land type, location or other variables. With most of the investigation area's land type being wood-covered, and the higher the percentage of woodland variable having a positive impact on sold land prices, one might assume that the 'poorer' quality soils benefit the wood vegetation, such as the fast-growing coniferous forests that thrive in these conditions, and which makes the land more valuable for the logging and biomass industries. However, the relationship between increased percentage of woodland and decreasing soil fertility only shows weak significance. The island's profit-yielding and residential soils, which tend to be around 80% sand, are protected by the trees, including those on the delicate coastal sand dunes (Rivis et al., 2009). The soils may also be affected by privatisation and fragmentation of the land, which is recognised as an issue in Estonia (Jürgenson, 2016) and the Czech Republic, where fragmentation has made smaller plots commercially unviable for owners, who lease them out. There are concerns over neglect and abandonment for soil sustainability from the tenants (Jürgenson, 2016; Sklenicka et al., 2014). In terms of size of plot, Roka & Palmquist (1997) explain that the direction of the trend with price depends on the type of land being analysed. For farmland, one would expect the price per acre to decrease as the land parcel reaches towards a commercially viable size (ibid). However, for this study, size of land plot, which was included in the profit-yielding model showed a positive correlation. This went against the bivariate correlation using Spearman's rank. If the model correlation is more accurate, then the positive relationship could be linked to the potential for profit-yielding land to be converted into another land use designation which commands a better price (€/m^2), such as residential. The other soil variable in the residential model was average percentage of rocks. It may be the case that residential land has greater value when firmer soils with higher percentages of rocks are present, since they may be more suitable for construction. This would require further investigation.

Services

The elimination of the capital Kärdla, and other urban zones from the dataset, to focus on the areas that had been soil surveyed likely affected the results for the mostly urban-specific variables: distance to schools, distance to sporting venue, distance to living or communal building, distance to any building, and even distance to main roads. These were expected to show stronger relationships with sold price. However, for residential land, there was still a weak bivariate correlation coefficient with distance to sporting venue. Distance to sporting venue, whilst not showing a statistically significant correlational relationship with indexed sold land price (€/m^2), did provided a significant but weak correlation coefficient in the linear model, showing that it needed to interact with other independent variables to produce a significant relationship. Distance to graveyard, unlike when measured against house prices in Portland (Bolitzer & Netusil, 2000), was statistically significant in the residential land linear model. Finally, given the theory that people wish to live in the countryside, but be able to telecommute and enjoy modern amenities, reduced distance to electric lines unsurprisingly showed a positive relationship with increasing indexed sold land price (€/m^2) for residential land.

Access

In terms of access, the model showed that increased distance from main roads increased price. This goes with the general theory regarding traffic noise (Kim et al., 2007), although there are exceptions, and Hiiumaa does not have a lot of traffic compared to the mainland. In the bivariate relationships, indexed sold residential land price (€/m^2) had a negative relationship with distance to non-main roads. However, this did not appear in the model and so it cannot be said that accessibility appears to affect price, which goes against the notion that it is the primary criterion of suburban access and rural settlement merge in Estonia (Roose et al., 2013), and crucial for profit-yielding land access.

Industrial

The industrial factors of distance to landfill, distance to airport and distance to production land all showed bivariate correlations with profit yielding indexed sold land price (€/m^2). These, unsurprisingly, suggested that ideological and environmentally detrimental factors reduce value (Folland & Hough, 1991; Nelson et al., 1992). However, none of these variables made it to the final linear model. This can be assumed to be due to them mostly being monocentric variables (Heikkila et al., 1989); located inland or within relatively close proximity. Distance to landfill and distance to airport produced instances of multicollinearity. The high correlation between distance to airport and distance to landfill was very clear in the correlation matrices, whereas VIF highlighted distance to quaking bog for removal in the linear model. For residential land, distance to schools had high multicollinearity. This is despite there being 6 schools which were measured from land parcels and which were spread around the island. Spatially, the residential land plots were less spread around the island. They were mostly located around (but not in, due the lack of soil survey map) Kärdla, Käina, Meelste and other coastal areas. This explains why more distance residential variables were removed for multicollinearity than profit-yielding variables (Heikkila, 1988), as they followed similar directional paths between the residential land clusters to the variables.

4.3. Limitations

The study into profit-yielding land was clearly flawed in terms of its approach. The division of land types, as per the subcategories within the ETAK shapefile was insufficient to remove the issue of collinearity/multicollinearity between the variants of the two main land types; agricultural land and wood-covered land. If one wishes to be able to confidently explain the variance in indexed sold land price (€/m^2), then as demonstrated in other studies (Maddison, 2000), the focus should go deeper into one land type and focus on smaller study sites to begin with. For purchase motivations, a multipart model with a participatory approach to find out the profit yielding buyers' motivations, such as MCA, might prove helpful at focusing the dataset, as per the successful study into the opportunities provided by non-wood forest products in Austria and Finland (Huber et al., 2017). One starting place for further research might be with forestry committees, as discussed in Põllumäe et al., (2014). To focus a study into Hiiu County's agricultural land, focus could change from the physical farmland soil values to yields, livestock inventories and a larger range of hedonic variables related to buildings and amenities.

The study into residential indexed sold land price (€/m^2) was limited due a small dataset, in part due to the quiet economic activity of Hiiumaa. However, whilst it specifically did not consider the typical key drivers of price: housing quality; neighbourhood; societal status; economic status; pollution; and political and further legal restrictions, it still obtained positive results. The predictive power without these variables shows that there is a clear correlation between the physical environmental factors and indexed sold residential land price (€/m^2) in Hiiu County.

This study could have better informed by considering different types of variables, such as social, political, economic, legal, building type and quality, and further environmental factors. As is the nature of land price modelling, a model cannot simply be borrowed from another spatial location; it needs to be constructed and tuned to the local factors. As discussed, multiple linear modelling is often either a first step in regression modelling or used to compare the results of more powerful models (Wu et al., 2018), all of which come under the process of determining a methodology to provide accurate results for land price prediction. Non-linear models or robust regression models that can better manage non-parametrically distributed variables and zero-heavy independent variables are recommended. Likewise, the linear model assumes autocorrelation and doesn't account for the natural variations within the study site. The other major issue was the dataset. Hiiumaa's low population and relative number of sales, compared to the other counties, restricted the residential land dataset to 131 sold observations. These were not randomly located around the study site. Most were in coastal clusters on the main island of Hiiumaa. The results would likely have been different, and correlations with some of the service variables stronger, had Kärdla and other urban zones not been removed from the model due their ommission from the soil survey. The removal of variables for multicollinearity to improve modelling results could have been avoided with alternative, more spatially-aware selections (Heikkila, 1988). Indeed, the models might be improved with a smaller selection of independent variables, since environmental characteristics can lead to residual heteroscedasticity (Choumert & Phélinas, 2015).

Alternative regression methods that do not assume autoregression might work better for the selected environmental variables; many of which were heavily skewed and some of which were zero-heavy. The linear model's functional form has been shown to be lacking in determining land prices compared to other model forms. Non-linear perspectives, which don't assume that all influencing factors have a constant influence and ignore spatial location, are often proven to provide better fitting models that can deal more adeptly with the dynamic nature of price and can account for the non-linearity of environmental factors (Maddison, 2000; Mulley, 2014; Sklenicka et al., 2014; Wu et al., 2018).

5. Summary

The thesis' findings should be able to inform the Estonian Land Board about the associations between the indexed price (€/m^2) of sold residential land parcels and physical environmental variables. If some of the measured variables from this study were included alongside additional variables related to society, local economy, administrative zones, planning restrictions and taxation price, then there is the potential for this study's dataset to have utilitarian value and increase the accuracy of the new valuation zones for residential land. In terms of specific variables, the clear correlation between the indexed sold land price (€/m^2) and the variables distance to the coast and distance to sandy beaches (as opposed to shoreline reeds) could be used to better understand the spatial structure of the demand on land in these regions and mitigate the environmental damage caused by private residential constructions in fragile environments (Rivis et al., 2009), possibly with the use of administrative and economic measures (Banzhaf & Lavery, 2010). Overall, the study showed that 16 of the environmental variables, when combined, were able to account for a moderate amount of the variance in the indexed sold residential land prices (€/m^2).

Keskkonnategurite ja maa müügihinna seoste hindamine Hiiumaa näitel

Alex Jarvis

Kokkuvõte

Magistritöö käsitleb keskkonnategurite mõju maa müügihinnale Hiiu maakonnas, EestisVaatluse all olid maaüksused, mille riiklikult registreeritud sihtotstarve on tulundusmaa või elamumaa.

Magistritöö esimene peatükk annab teoreetilise ülevaate keskkonnategurite mõjust maa hinnale. Keskkonnategureid käsitletakse üldises kontekstis, kuid sellises, millel on tähendus neile, kes asuvad uuringu alas st Hiiu maakonnas.

Töö teises peatükis antakse ülevaade uuritavast alast, andmetest ja metoodikast. Uuringus kasutatakse sõltuvate muutujatenas maatulundumaa ja elamumaa müügihinnad ajavahemikus 01.01.2013 kuni 31.12.2017 (€/m^2). Sõltumatud keskkonnategurid arvutati ruumianalüüsi meetodeid kasutades Eesti Topograafilise Andmekogu (ETAK) põhjal kasutades ArcGIS tarkvara. Selle tulemusena loodi andmekogu, mis sisaldab rida iga maatüki kohta ja veergu iga 47 keskkonnamuutuja ning maahinna kohta. Statistilise analüüsi meetodina kasutati korrelatsiooni ja lineaarset regressiooni analüüsi leidmaks seoseid maa hinna ja keskkonnategurite vahel. Statistiline analüüs viidi läbi R-Studios.

Korrelatsioonanalüüsi tulemused näitasid, et kokku 32-l 48-st keskkonnategurist leiti olevat mingi seos müüdud elamumaa hinnaga (€t/m^2). Teisest küljest, kokku ainult 12-l 47-st keskkonnategurist leiti olevat mingi seos müüdud tulundusmaa hinnaga (€t/m^2).

Lineaarse regressiooni tulemused näitaseid, et elamumaa maatükkide puhul moodustas kombinatsioon 16 sõltumatust keskkonnamuutujast statistiliselt olulise mudeli, kus sõltumatute andmetega testides oli R^2 0,44. See tähendab, et mudel kirjeldab ära 44% müüdud elamumaa hinnast (€t/m^2).Maatulundumaa maatükkide puhul moodustas kombinatsioon seitsmest sõltumatust keskkonnamuutujast statistiliselt olulise mudeli, kus sõltumatute andmetega testides oli R^2 0,08 ja seega kirjeldab mudel ära väga väikese osa hinna varieeruvusest.

Lõppkokkuvõttes näitas magistritöö, et Hiiu maakonnas müüdud elamumaa maatükkide hinnal oli palju tugevam seos valitud keskkonnateguritega kui müüdud tulundusmaamaatükkide hinnal.

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Annex A

Table 1. Sold profit-yielding land variables Spearman's rank correlation matrix.

	AREA	D_AIR	D_ARA	D_BUI	D_BOG	D_COA	D_DRA	D_ELE	D_ENV	D_FEN	D_FOR	D_GRA	D_GVE	D_HAR	D_LDF	D_LCB	D_ORD	D_PAT	D_PRO	D_QUA	D_QKM	D_RIV	D_RDS	D_SAN	D_SCH	D_SHO	D_SPO	D_SPR	D_WAT	D_WET	D_WLL	D_WDV	P_ARA	P_BUI	P_FIE	P_GRA	P_HOR	P_PRI	P_PRO	P_WAT	P_WET	P_WOO	S_CLA	S_ROC	S_SAN	S_SIL	S_FER
AREA																																															
D_AIR	-0.06																																														
D_ARA	0.04	0.2																																													
D_BUI	0.04	0.07	0.31																																												
D_BOG	-0.16	0.43	-0.07	-0.17																																											
D_COA	0.13	-0.25	-0.12	0.35	-0.45																																										
D_DRA	-0.24	0.17	0.29	0.06	0.14	-0.23																																									
D_ELE	0	0.1	0.35	0.53	-0.01	0.18	0.04																																								
D_ENV	-0.02	-0.09	-0.03	0.28	-0.2	0.35	-0.16	0.13																																							
D_FEN	-0.14	0.04	-0.1	-0.15	0.36	-0.23	0	-0.15	0.11																																						
D_FOR	-0.16	-0.08	-0.32	-0.07	0	0.02	0	-0.1	0.02	0.12																																					
D_GRA	-0.02	0.1	0.29	0.69	-0.13	0.33	0.09	0.36	0.22	-0.11	-0.03																																				
D_GVE	0.04	0.09	0.22	0.35	-0.16	0.33	-0.04	0.3	0.19	0.03	-0.09	0.26																																			
D_HAR	0.13	-0.07	0.15	0.15	-0.28	0.34	-0.1	0.11	-0.06	-0.27	-0.1	0.12	0.21																																		
D_LDF	-0.1	0.83	0.23	-0.12	0.62	-0.61	0.27	0.02	-0.31	0.04	-0.11	-0.06	-0.17	-0.17																																	
D_LCB	0.07	-0.01	0.34	0.89	-0.22	0.41	0.04	0.56	0.28	-0.17	-0.08	0.61	0.41	0.21	-0.21																																
D_ORD	-0.11	0.05	0.31	0.39	0	0.15	0.21	0.29	0.11	0	-0.06	0.33	0.15	0.15	0	0.36																															
D_PAT	-0.15	0.16	-0.02	0.31	0.04	0.2	-0.01	0.21	0.23	0.16	0.16	0.3	0.12	-0.02	-0.01	0.28	0.11																														
D_PRO	0.07	0.15	0.48	0.45	-0.38	0.09	0.1	0.36	0.06	-0.4	-0.18	0.32	0.26	0.25	0.1	0.45	0.18	0.02																													
D_QUA	-0.12	0.56	-0.11	0.1	0.56	-0.01	0.04	0.09	0.12	0.37	0.07	0.08	0.16	-0.46	0.4	0.03	0.03	0.28	-0.22																												
D_QKM	-0.19	0.43	-0.07	-0.12	0.62	-0.5	0.19	-0.03	-0.2	0.18	0.08	-0.14	-0.12	-0.33	0.53	-0.17	0.07	-0.02	-0.22	0.42																											
D_RIV	-0.2	0.1	0.17	-0.13	0.25	-0.41	0.18	-0.03	-0.24	0.1	-0.02	-0.02	-0.09	-0.2	0.29	-0.15	0.08	-0.04	0.03	-0.03	0.36																										
D_RDS	0.06	0.06	0.3	0.53	-0.15	0.18	0.04	0.49	0.15	-0.08	-0.13	0.41	0.28	0.16	-0.03	0.55	0.23	0.2	0.34	0.05	-0.12	-0.11																									
D_SAN	-0.05	-0.33	-0.3	0.16	-0.25	0.47	-0.17	0.01	0.32	0.18	0.17	0.1	0.2	-0.18	-0.63	0.19	-0.02	0.22	-0.22	0.25	-0.03	-0.2	0.01																								
D_SCH	0.03	0.33	0.16	0.24	-0.02	0.2	-0.06	0.21	0.13	-0.05	-0.09	0.26	0.35	0.1	0.12	0.22	-0.02	0.24	0.24	0.2	-0.34	-0.11	0.15	0.13																							
D_SHO	0.11	-0.19	-0.01	0.32	-0.45	0.89	-0.17	0.17	0.25	-0.23	-0.01	0.29	0.38	0.41	-0.51	0.39	0.16	0.14	0.17	-0.09	-0.47	-0.36	0.19	0.3	0.14																						
D_SPO	0.04	0.04	0.22	0.1	0.14	-0.13	0.01	0.15	0	-0.12	-0.1	0.03	0.28	-0.05	0.19	0.11	0.06	-0.06	0.26	0	0.18	0.2	0.07	-0.03	0.34	-0.16																					
D_SPR	-0.07	0.28	0.12	0.06	0.21	-0.2	0.04	0.22	0.03	0.08	-0.07	-0.07	0.18	-0.1	0.23	0.08	0.03	0.09	0.14	0.23	0.14	0.05	0.04	-0.13	0.12	-0.2	0.12																				
D_WAT	-0.09	-0.01	0.17	0.54	-0.05	0.18	0.15	0.32	0.19	-0.04	0.01	0.41	0.2	-0.03	-0.07	0.51	0.38	0.16	0.27	0.08	0.07	0.01	0.31	0.16	0.06	0.12	0.1	0.03																			
D_WET	-0.21	0.07	-0.25	0.04	0.18	0.12	-0.07	-0.06	0.27	0.48	0.18	0.08	-0.04	-0.28	-0.03	-0.01	0.05	0.31	-0.24	0.39	0.11	-0.05	-0.04	0.25	-0.01	0.02	-0.18	0.06	0.15																		
D_WLL	-0.16	0.05	-0.18	0.11	-0.01	0.24	-0.08	0.03	0.24	0.16	0.16	0.13	0	-0.22	-0.09	0.09	0.07	0.34	-0.06	0.32	0.05	-0.09	0.03	0.26	0.01	0.13	-0.09	0.11	0.19	0.8																	
D_WDV	0.02	0.16	0.28	0.44	-0.23	0.25	-0.06	0.3	0.11	-0.27	-0.09	0.46	0.25	0.31	0	0.43	0.17	0.12	0.42	-0.11	-0.22	-0.11	0.29	-0.09	0.3	0.26	0.05	0.14	0.28	0.01	0.14																
P_ARA	-0.04	-0.01	-0.07	-0.09	0.02	0	-0.01	-0.03	-0.05	0.05	0.03	-0.03	-0.07	-0.01	0	-0.04	-0.01	0.02	-0.07	0.03	0.02	0.04	-0.04	0.04	-0.03	0	-0.01	-0.01	-0.05	0	0	-0.05															
P_BUI	0.02	-0.03	-0.05	-0.33	0.04	0	-0.04	-0.07	-0.06	0.03	-0.04	-0.2	0.01	0.02	-0.02	-0.18	-0.12	-0.1	-0.08	0.01	0	-0.03	-0.06	-0.02	-0.06	0	-0.03	0.02	-0.12	-0.01	0	-0.08	0.07														
P_FIE	-0.05	-0.18	-0.82	-0.15	0	0.15	-0.26	-0.23	0.03	0.06	0.5	-0.13	-0.18	-0.12	-0.23	-0.19	-0.25	0.12	-0.33	0.08	0.03	-0.14	-0.2	0.28	-0.12	0.06	-0.2	-0.1	-0.08	0.23	0.18	-0.14	0.04	-0.03													
P_GRA	0.01	-0.06	-0.14	-0.48	0.13	-0.28	-0.06	-0.22	-0.21	0.1	-0.05	-0.78	-0.16	-0.08	0.08	-0.41	-0.28	-0.26	-0.2	-0.05	0.09	0.05	-0.26	-0.1	-0.15	-0.24	0.01	0.07	-0.3	-0.1	-0.12	-0.3	0.02	0.28	0												
P_HOR	-0.04	-0.01	-0.07	-0.09	0.02	0	-0.01	-0.03	-0.05	0.05	0.03	-0.03	-0.07	-0.01	0	-0.04	-0.01	0.02	-0.07	0.03	0.02	0.04	-0.04	0.04	-0.03	0	-0.01	-0.01	-0.05	0	0	-0.05	1	0.07	0.04	0.02											
P_PRI	-0.09	0.01	-0.04	-0.25	0.07	-0.05	-0.09	-0.07	-0.07	0.02	-0.03	-0.13	-0.04	-0.02	0.04	-0.25	-0.14	-0.03	-0.1	0	0.01	0.03	-0.07	-0.03	0	-0.07	-0.02	-0.04	-0.15	-0.03	-0.03	-0.08	0.1	0.3	-0.02	0.15	0.1										
P_PRO	0.02	-0.06	-0.07	-0.12	-0.01	0.02	-0.02	-0.1	-0.04	0.02	0.05	-0.05	-0.06	0.06	-0.06	-0.08	-0.05	-0.03	-0.16	-0.04	-0.04	0.02	-0.07	0.01	-0.08	0.05	-0.1	-0.05	-0.13	-0.03	-0.05	-0.05	-0.01	-0.02	0.08	0.01	-0.01	-0.02									
P_WAT	0.05	0.03	0.06	-0.08	-0.03	-0.03	-0.07	0.01	-0.09	-0.04	-0.06	-0.04	-0.05	0.07	0.07	-0.04	-0.06	-0.06	0.02	-0.03	-0.07	-0.01	-0.02	-0.12	0.01	-0.01	-0.01	-0.01	-0.29	-0.06	-0.04	-0.04	-0.01	0.07	-0.07	0.07	-0.01	0.05	0.12								
P_WET	0.19	0.11	0.21	0.02	-0.06	-0.09	0.11	0.05	-0.15	-0.22	-0.08	0.03	0.01	0.12	0.13	0.03	0.01	-0.16	0.15	-0.1	0.02	-0.05	0	-0.16	0	-0.05	0.04	-0.02	-0.03	-0.43	-0.27	0.08	0.05	-0.01	-0.17	-0.01	0.05	-0.01	-0.02	0							
P_WOO	0.09	0.16	0.68	0.32	-0.07	0.06	0.18	0.32	0.11	-0.13	-0.5	0.37	0.2	0.14	0.13	0.33	0.33	0.01	0.36	-0.04	-0.09	0.11	0.3	-0.19	0.15	0.11	0.14	0.05	0.21	-0.09	-0.05	0.23	-0.06	-0.07	-0.81	-0.32	-0.06	-0.05	-0.11	-0.01	-0.02						
S_CLA	0.09	-0.1	-0.11	-0.14	-0.07	-0.04	-0.04	-0.08	-0.18	-0.04	0.09	-0.1	-0.19	0.14	-0.05	-0.13	-0.05	0	-0.07	-0.21	-0.03	0.06	-0.11	-0.06	-0.15	-0.04	-0.14	-0.09	-0.09	-0.07	0.03	-0.04	0.07	0.02	0.14	0.05	0.07	0.03	0.07	-0.05	0.14	-0.17					
S_ROC	0	-0.15	-0.05	0.13	-0.05	0.18	-0.04	0.05	0.13	-0.01	-0.04	0.13	0.06	-0.03	-0.2	0.09	0.04	-0.05	0	0.06	-0.03	-0.2	0.02	0.23	-0.03	0.19	-0.03	-0.11	0.08	0.06	0	0.05	-0.06	0.01	0.02	-0.08	-0.06	-0.03	-0.04	-0.04	-0.1	0.06	-0.42				
S_SAN	-0.06	0.08	0.11	0.18	0.01	0.1	0.02	0.1	0.23	-0.05	-0.09	0.15	0.22	-0.07	0.02	0.18	0.07	0.02	0.12	0.15	-0.01	-0.06	0.14	0.04	0.16	0.1	0.14	0.07	0.12	0.05	-0.02	0.1	-0.07	-0.02	-0.14	-0.13	-0.07	-0.03	-0.08	-0.01	-0.12	0.22	-0.91	0.45			
S_SIL	0.06	-0.13	-0.16	-0.19	-0.02	-0.06	-0.04	-0.13	-0.16	0.07	0.12	-0.15	-0.21	0.08	-0.07	-0.18	-0.06	0.01	-0.16	-0.17	-0.01	0.08	-0.15	-0.02	-0.19	-0.06	-0.16	-0.1	-0.1	-0.02	0.02	-0.13	0.08	0.03	0.19	0.1	0.08	0.05	0.09	-0.06	0.1	-0.22	0.96	-0.41	-0.9		
S_FER	-0.03	-0.09	-0.22	0.12	-0.01	0.18	-0.1	0.02	0.2	0.16	0.13	0.1	0	-0.08	-0.17	0.07	0.1	0.24	-0.16	0.1	0.05	-0.07	0.04	0.19	-0.13	0.08	-0.12	-0.01	0.12	0.29	0.27	-0.06	0.07	-0.06	0.25	-0.16	0.07	-0.02	0	-0.1	-0.18	-0.12	0.27	-0.01	-0.24	0.3	
AV_PR_	-0.13	0.13	0.27	0.03	0.05	-0.13	0.14	0.07	0.03	0.06	-0.07	0.01	0.04	-0.1	0.14	0.04	0.04	0.03	0.1	0.06	0.1	0.1	0.04	-0.06	0.03	-0.08	0.06	-0.03	0.07	-0.02	0	0	0.03	-0.01	-0.26	0.04	0.03	0.01	-0.06	-0.02	-0.01	0.18	-0.08	0.02	0.04	-0.09	-0.15

Significance: Green cells = $p<0.05$

Table 2. Sold residential land variables Spearman's rank correlation matrix.

	AREA	D_AIR	D_ARA	D_BUI	D_BOG	D_COA	D_DRA	D_ELE	D_ENV	D_FEN	D_FOR	D_GRA	D_GVE	D_HAR	D_LDF	D_LCB	D_ORD	D_PAT	D_PRO	D_QUA	D_QKM	D_RIV	D_RDS	D_SAN	D_SCH	D_SHO	D_SPO	D_SPR	D_WAT	D_WET	D_WLL	D_WDV	P_ARA	P_BUI	P_FIE	P_GRA	P_HOR	P_PRI	P_PRO	P_WAT	P_WET	P_WOO	S_CLA	S_ROC	S_SAN	S_SIL	S_FER
AREA																																															
D_AIR	-0.05																																													
D_ARA	-0.41	0.11																																												
D_BUI	0.08	-0.1	0.17																																											
D_BOG	0.3	0.26	-0.45	-0.04																																										
D_COA	-0.09	-0.39	0.06	0.15	-0.62																																									
D_DRA	-0.18	0.03	0.06	-0.02	0.08	-0.24																																								
D_ELE	-0.13	0.19	0.46	0.22	-0.14	-0.03	-0.11																																							
D_ENV	-0.27	-0.15	0.35	0.09	-0.42	0.4	-0.34	0.16																																						
D_FEN	0.18	-0.04	-0.45	-0.08	0.6	-0.34	0.1	-0.26	-0.21																																					
D_FOR	-0.07	0.05	-0.19	-0.12	0	0.01	0.08	-0.25	-0.09	0.27																																				
D_GRA	-0.44	-0.22	0.62	0.17	-0.44	0.16	0.06	0.4	0.32	-0.39	-0.2																																			
D_GVE	-0.05	0.5	0.1	0.09	0.44	-0.4	0.1	0.17	-0.08	0	-0.06	0.03																																		
D_HAR	-0.02	-0.12	0.14	-0.08	-0.45	0.37	-0.27	0.16	0.11	-0.48	-0.19	0.15	-0.35																																	
D_LDF	-0.15	0.82	0.35	-0.04	0.18	-0.42	0.07	0.36	-0.1	-0.31	-0.22	0.08	0.54	-0.05																																
D_LCB	0.15	-0.11	0.07	0.81	-0.02	0.22	-0.09	0.04	0.02	-0.06	-0.09	0.03	-0.06	0.03	-0.07																															
D_ORD	-0.01	-0.08	0.21	0.15	-0.18	0.23	-0.29	0.09	0.29	-0.1	-0.01	0.29	-0.07	0.09	-0.01	0.13																														
D_PAT	-0.09	0.07	0.01	0.04	-0.07	0.04	-0.22	0.04	0.07	0.13	0.1	0.16	-0.09	0.14	-0.06	-0.02	0.24																													
D_PRO	-0.17	0.04	0.52	0.04	-0.63	0.24	-0.05	0.49	0.3	-0.59	-0.2	0.52	-0.11	0.46	0.28	-0.07	0.18	0.05																												
D_QUA	0.29	0.34	-0.44	-0.01	0.75	-0.42	0.06	-0.16	-0.18	0.74	0.26	-0.45	0.33	-0.61	0.03	-0.05	-0.09	0.1	-0.56																											
D_QKM	0.23	0.67	-0.36	-0.05	0.71	-0.53	0.18	-0.12	-0.44	0.33	0.1	-0.5	0.42	-0.46	0.47	-0.03	-0.11	-0.02	-0.44	0.67																										
D_RIV	-0.16	0.46	-0.09	0.03	0.39	-0.33	0.26	0.1	-0.26	0.24	-0.01	-0.2	0.27	-0.43	0.46	0.04	-0.04	-0.08	-0.22	0.29	0.6																									
D_RDS	-0.16	-0.02	0.31	0.3	-0.12	0.07	-0.08	0.6	0.13	-0.15	-0.24	0.37	0.08	0.1	0.22	0.29	0.04	0	0.34	-0.25	-0.26	0.16																								
D_SAN	0.33	-0.34	-0.54	0.14	0.25	0.18	0.04	-0.23	-0.14	0.63	0.33	-0.28	-0.28	-0.29	-0.64	0.11	0.03	0.14	-0.41	0.52	0.11	-0.05	-0.13																							
D_SCH	-0.36	0.27	0.51	-0.02	-0.14	-0.09	0.01	0.46	0.13	-0.27	-0.18	0.5	0.4	0.05	0.49	-0.14	0.01	0.02	0.43	-0.27	-0.22	0.14	0.42	-0.47																						
D_SHO	-0.38	0.15	0.4	-0.04	-0.35	0.39	0	0.14	0.27	-0.41	-0.15	0.31	0.26	0.04	0.24	-0.03	0.06	-0.06	0.24	-0.35	-0.12	0.09	0.1	-0.44	0.33																					
D_SPO	-0.11	0.21	0.32	0.14	0.08	-0.07	-0.01	0.42	0.06	-0.22	-0.26	0.36	0.4	-0.11	0.53	0.03	0.08	-0.1	0.36	-0.08	0.03	0.29	0.43	-0.32	0.73	0.21																				
D_SPR	-0.06	-0.04	0.21	0.05	-0.06	-0.16	0.13	0.22	-0.09	0.07	0.02	0.26	0.13	0.13	0.04	-0.07	-0.19	0.05	0.24	-0.04	-0.33	-0.26	0.22	-0.08	0.39	-0.25	0.11																			
D_WAT	-0.23	-0.11	-0.06	0.22	0.04	0.09	0.43	-0.07	-0.07	0.08	-0.01	0.05	0.02	-0.12	-0.02	0.1	-0.17	-0.1	-0.02	0.07	0.02	0.16	0.05	0.18	-0.01	-0.05	0.21	0.11																		
D_WET	-0.2	0.15	-0.07	-0.11	0.07	-0.01	0.06	0.02	0.05	0.27	0.33	-0.07	0.26	-0.39	0	-0.16	-0.02	0	-0.12	0.29	0.14	0.34	-0.03	0.13	0.17	0.26	0.08	-0.03	0.07																	
D_WLL	-0.33	0.14	0.08	-0.09	-0.17	0.17	0.08	0.05	0.13	0.01	0.24	0.09	0.14	-0.26	0.04	-0.11	0.12	0.05	0.03	0.02	0.01	0.39	0.03	0.01	0.25	0.41	0.11	-0.17	0.04	0.86																
D_WDV	-0.37	-0.01	0.63	0.01	-0.61	0.39	-0.11	0.37	0.33	-0.61	-0.1	0.55	0.06	0.33	0.18	-0.07	0.24	-0.02	0.61	-0.57	-0.49	-0.21	0.23	-0.44	0.54	0.49	0.32	0.21	-0.04	0.1	0.29															
P_ARA	-0.09	-0.13	-0.12	0.03	0.01	0.1	-0.1	0.04	-0.12	-0.14	-0.02	-0.01	-0.12	0.06	-0.12	0.04	-0.07	0.02	-0.01	-0.1	-0.02	-0.14	-0.03	0.08	-0.14	-0.02	-0.14	-0.11	0.06	-0.11	-0.05	-0.03														
P_BUI	0.09	-0.03	-0.19	-0.63	0.11	-0.07	-0.01	-0.22	-0.07	0.16	0.06	-0.2	-0.16	0.07	-0.07	-0.41	-0.04	0	-0.04	0.14	0.04	-0.06	-0.17	0.08	-0.16	-0.09	-0.2	-0.09	-0.13	-0.07	-0.14	-0.18	-0.04													
P_FIE	0.3	-0.22	-0.72	-0.01	0.26	0.12	0.05	-0.27	-0.24	0.34	0.2	-0.31	0	-0.13	-0.37	0.01	-0.11	0.03	-0.34	0.29	0.12	0.02	-0.11	0.51	-0.29	-0.16	-0.17	-0.02	0.21	0.28	0.16	-0.32	0.14	-0.01												
P_GRA	0.35	0.09	-0.47	-0.15	0.26	-0.03	-0.18	-0.24	-0.19	0.28	0.19	-0.83	-0.08	-0.04	-0.12	-0.03	-0.26	-0.12	-0.34	0.31	0.27	0.14	-0.27	0.21	-0.41	-0.25	-0.25	-0.13	-0.01	0.11	-0.04	-0.4	-0.07	0.2	0.21											
P_HOR	-0.09	-0.13	-0.12	0.03	0.01	0.1	-0.1	0.04	-0.12	-0.14	-0.02	-0.01	-0.12	0.06	-0.12	0.04	-0.07	0.02	-0.01	-0.1	-0.02	-0.14	-0.03	0.08	-0.14	-0.02	-0.14	-0.11	0.06	-0.11	-0.05	-0.03	1	-0.04	0.14	-0.07										
P_PRI	-0.07	0.13	-0.05	-0.43	0.03	0.03	-0.03	-0.07	-0.03	0.03	0.07	-0.16	0.03	-0.19	0.04	-0.44	-0.08	-0.01	-0.12	0.12	0.09	0.06	-0.06	0	0.05	0.14	-0.07	-0.07	-0.19	0.19	0.21	0.07	-0.04	0.28	-0.03	0.11	-0.04									
P_PRO	-0.15	-0.1	0.01	-0.07	-0.06	0.11	-0.02	-0.14	0.15	0.07	0.32	-0.01	-0.11	-0.09	-0.14	-0.01	0.13	0.04	-0.15	0.04	-0.07	-0.13	-0.08	0.01	-0.14	0	-0.14	-0.13	0.01	0.09	0.03	0.05	-0.01	-0.04	-0.05	-0.07	-0.01	0.2								
P_WAT	0.17	0.06	0	0.03	-0.1	0.04	-0.07	-0.02	0.08	-0.11	0.05	-0.03	0.03	-0.02	0.02	0.01	0.08	0.01	0.05	-0.04	0.1	-0.07	-0.08	-0.03	-0.06	0.18	-0.09	-0.17	-0.44	-0.05	0.01	-0.01	-0.02	-0.05	-0.01	-0.03	-0.02	-0.03	-0.02							
P_WET	0.14	0.11	0.13	0.18	-0.01	-0.05	0.07	0.05	-0.12	-0.23	-0.05	0	0.13	0.15	0.14	0.15	0.04	0.02	0.08	-0.02	0.1	-0.1	0.02	-0.12	-0.08	-0.02	-0.08	0.02	-0.08	-0.33	-0.26	0.15	-0.02	0	-0.11	-0.02	-0.02	0.03	-0.02	0.26						
P_WOO	-0.34	-0.05	0.66	0.18	-0.34	0.04	0.12	0.28	0.3	-0.35	-0.37	0.68	-0.01	0.13	0.21	0.11	0.15	0.02	0.46	-0.42	-0.37	-0.08	0.32	-0.39	0.45	0.24	0.35	0.17	0.09	-0.24	-0.07	0.39	-0.07	-0.12	-0.61	-0.64	-0.07	-0.27	-0.15	-0.14	-0.1					
S_CLA	0.33	-0.2	-0.47	0.19	0.24	-0.03	0.1	-0.31	-0.23	0.28	0.18	-0.31	-0.1	0.04	-0.32	0.21	-0.05	0.02	-0.2	0.24	0.13	-0.05	-0.08	0.43	-0.52	-0.34	-0.36	-0.02	0.13	-0.18	-0.26	-0.49	0.12	0.08	0.42	0.2	0.12	-0.18	-0.12	0.05	0.17	-0.31				
S_ROC	-0.01	-0.01	-0.16	-0.12	0.19	-0.1	0.18	-0.19	-0.13	0.24	0.09	-0.07	0.14	-0.3	-0.04	-0.11	-0.21	0.03	-0.22	0.2	0.18	0.07	-0.08	0.12	-0.04	0.17	0.11	-0.19	0.15	0.01	-0.03	-0.23	-0.05	0.08	0.09	0.09	-0.05	0.05	0.11	0.08	-0.09	-0.15	-0.03			
S_SAN	-0.37	0.26	0.4	-0.14	-0.22	0.01	-0.02	0.34	0.1	-0.32	-0.21	0.38	0.16	0	0.41	-0.16	-0.08	0.07	0.27	-0.27	-0.09	0.13	0.13	-0.44	0.61	0.39	0.44	0.08	-0.04	0.11	0.23	0.43	-0.13	-0.11	-0.36	-0.27	-0.13	0.05	-0.04	-0.07	-0.18	0.39	-0.84	0.1		
S_SIL	0.36	-0.22	-0.52	0.19	0.26	-0.02	0.08	-0.32	-0.2	0.31	0.17	-0.33	-0.12	0.01	-0.37	0.21	-0.07	0.03	-0.23	0.28	0.14	-0.07	-0.1	0.48	-0.54	-0.36	-0.35	-0.05	0.14	-0.14	-0.24	-0.56	0.15	0.06	0.46	0.23	0.15	-0.2	-0.12	0.06	0.08	-0.32	0.97	0	-0.83	
S_FER	0.06	-0.15	-0.33	0.04	0.16	0.04	-0.22	-0.27	-0.1	0.21	0.27	-0.22	-0.1	0	-0.26	0.1	0.06	0.11	-0.32	0.11	0.07	0.05	-0.12	0.2	-0.27	-0.08	-0.29	-0.06	-0.26	0.04	-0.02	-0.25	0.14	-0.01	0.27	0.17	0.14	-0.06	0.08	0.03	-0.05	-0.29	0.43	-0.06	-0.3	0.4
AV_PR_	-0.55	0.06	0.32	-0.21	-0.13	-0.33	0.44	0	0.03	-0.12	0.09	0.3	0.09	-0.18	0.24	-0.27	-0.19	-0.04	0.08	-0.16	-0.03	0.15	-0.03	-0.41	0.21	0.13	0.06	0.21	0.28	0.16	0.16	0.16	-0.1	-0.02	-0.23	-0.22	-0.1	0.04	0.11	-0.13	-0.07	0.25	-0.26	0.11	0.22	-0.3	-0.25

Significance: Green cells = $p<0.05$

Annex B

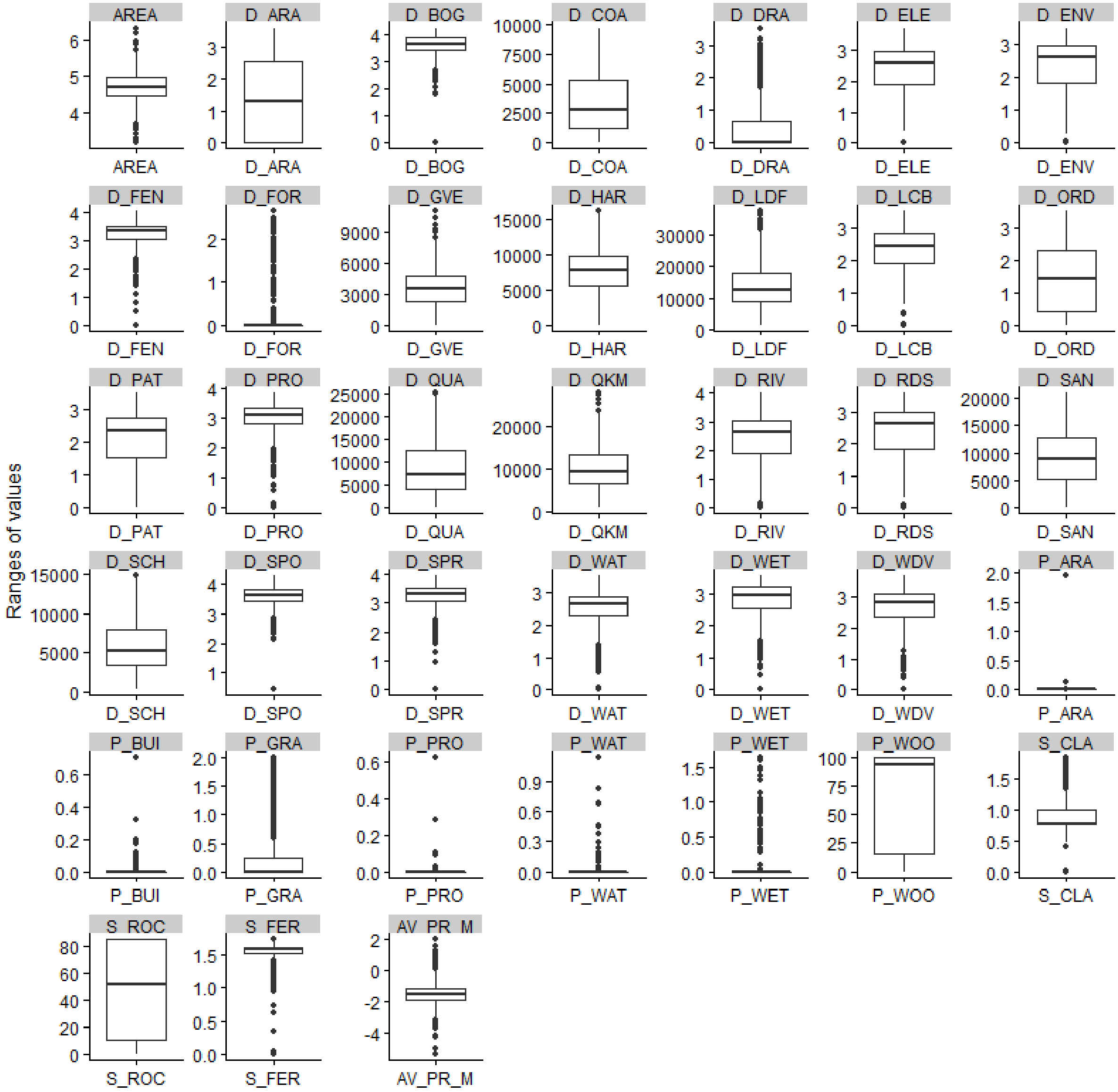

Figure 1. Median, quartiles and range of variables used in multiple linear regression model for profit-yielding land. Those with absolute skew >0.8 had been log10+1 transformed.

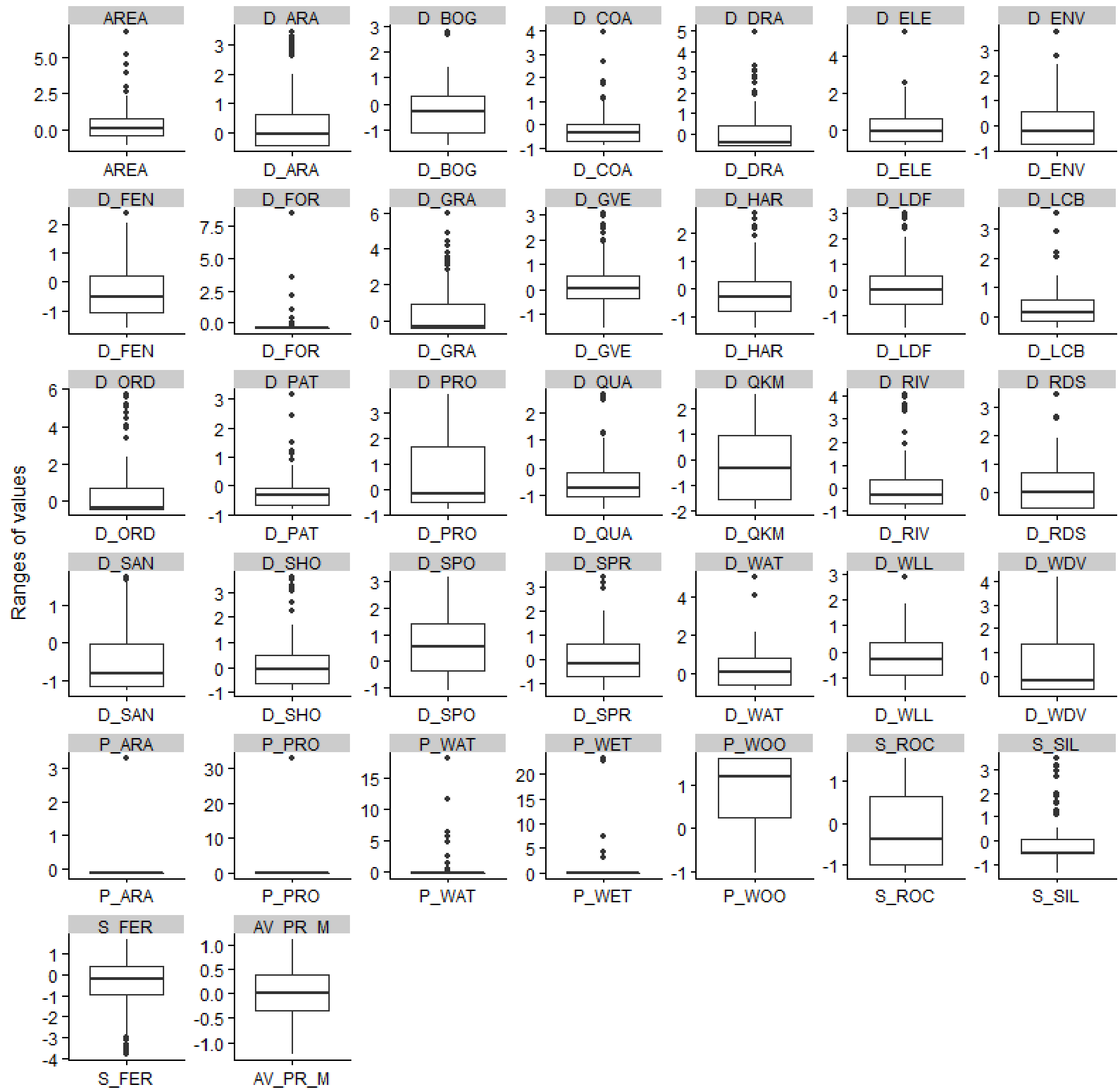

Figure 2. Median, quartiles and range of variables used in multiple linear regression model for residential land. Those with absolute skew >0.8 had been log10+1 transformed.

Annex C

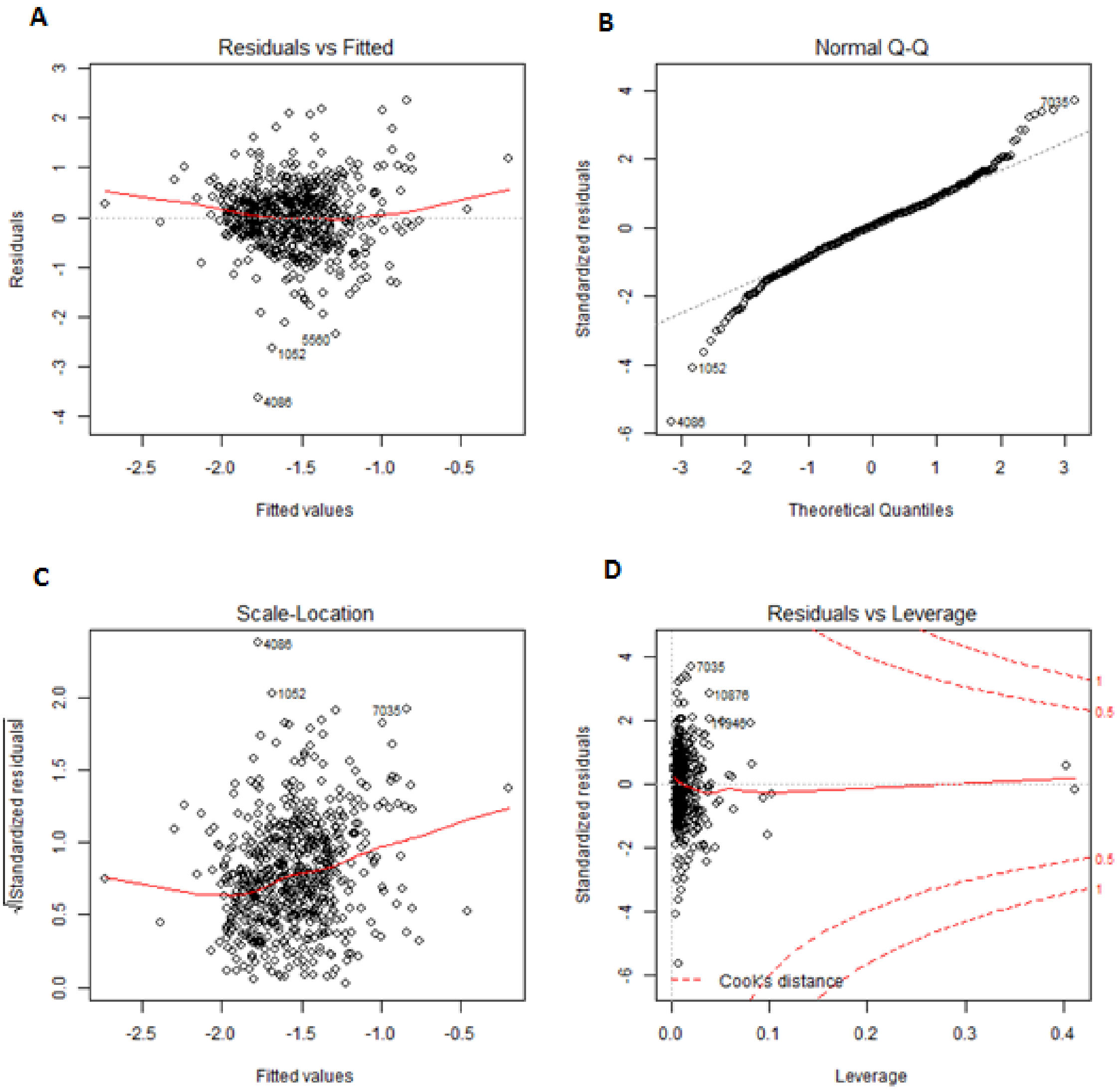

Figure 1. Residual plots for the profit-yielding land multiple regression model. A. the residuals vs the fitted values. B. The residual normal QQ plot. C. The plot of scale-location. D. The residuals within Cooks' distance plot.

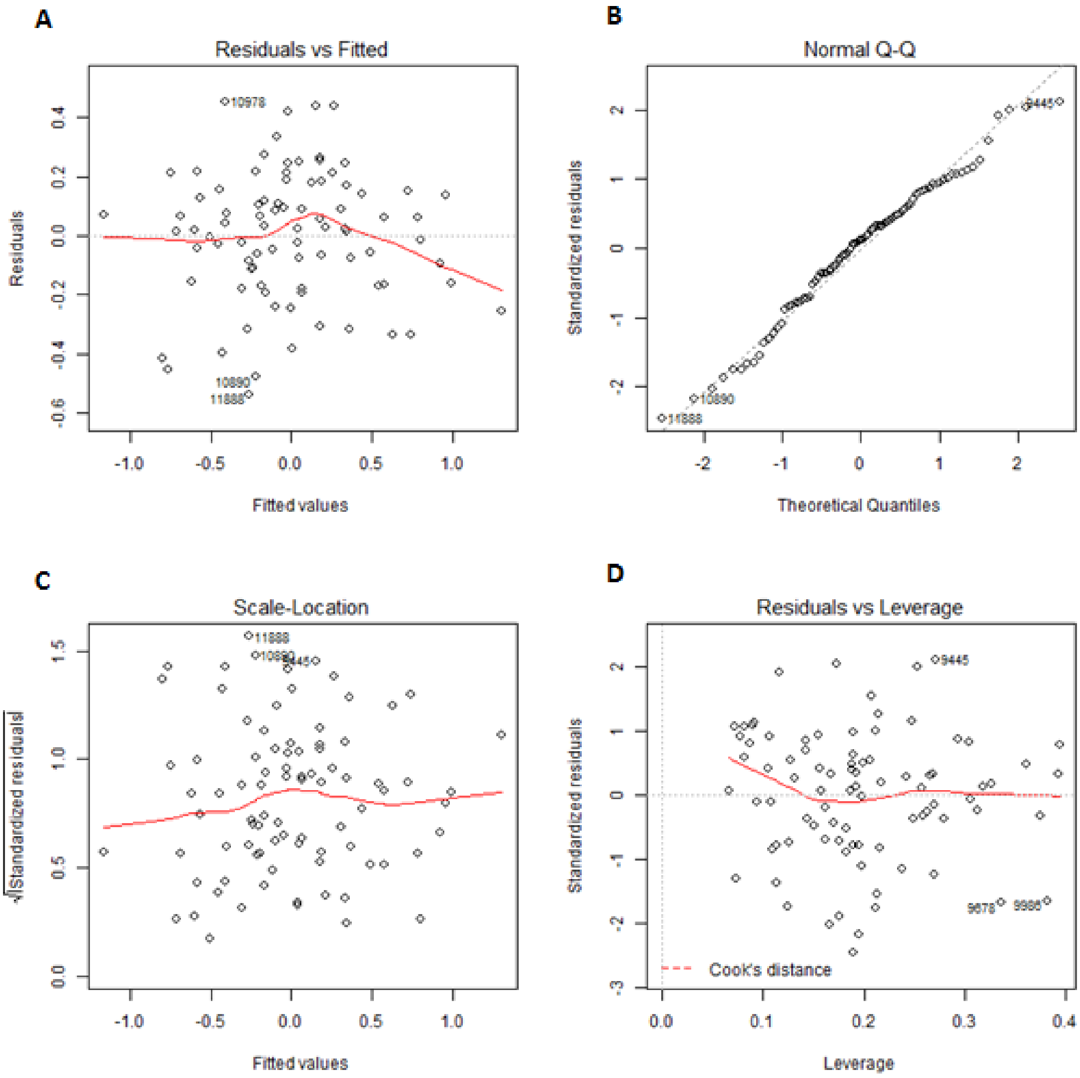

Figure 2. Residual plots for the residential land multiple regression model. A. the residuals vs the fitted values. B. The residual normal QQ plot. C. The plot of scale-location. D. The residuals within Cooks' distance plot.