Analysing the relation between land use and subsidence in the Randstad in the Netherlands

MSc. Thesis

Author
Stijn Mars
5983290
s.s.w.mars@uu.nl

Supervisors
Dr. Lixia Chu & Dainius Masiliunas MSc

Professor
Prof.dr.ir. Peter van Oosterom

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I hope you will enjoy reading this thesis.

Stijn Mars

Abstract

Subsidence has been an issue in the Netherlands for many years. It causes damage to buildings and infrastructure and associated costs are expected to keep increasing in the future. Subsidence can be caused by a number of different factors, but human activity is heavily associated with an increase in subsidence rates. In the Randstad area in the Netherlands the main causes for subsidence are identified as oxidation and compaction due to loading. Recent research has identified these causes to be linked to different types of land use. Quantitative research on this topic is however still limited. This thesis tries to identify which factors cause subsidence and how they are linked to land use in the Randstad area in the Netherlands. This is done using methods developed by Minderhoud et al. (2018). Using a combination of an analysis of variance and a linear regression using predicted subsidence rates based on land use classes, a very small but significant link was identified between land use and subsidence in the research area. Further research is, however, required in order to identify the exact relation of individual land use classes and subsidence. The confirmation of this relation is a first step towards identifying the structures that cause subsidence and informing policy decisions about how to prevent subsidence in the Randstad area.

List of figures and tables

List of abbreviations

CSV	Comma-Separated Value
InSAR	Interferometric Synthetic Aperture Radar
LGN	Landelijk Grondgebruik Nederland
OBIA	Object-Based Image Analysis
SAR	Synthetic Aperture Radar

Contents

1. Introduction

In the past years more and more calls have been made in the Netherlands for a national program to reduce subsidence and its consequences (Platform Slappe Bodem, 2021). Subsidence, or the vertical displacement of points on the earth's surface (Whittaker & Reddish, 1989, p. 1), has been an ongoing problem in the Netherlands for many years (Kwakernaak et al., 1998). It is caused by different factors such as the drainage of peatlands and polders, the expansion of built-up areas and infrastructure, and salt mining and gas extraction operations (Stouthamer et al., 2020). See Figure 1 for an illustration of the impact of some these factors.

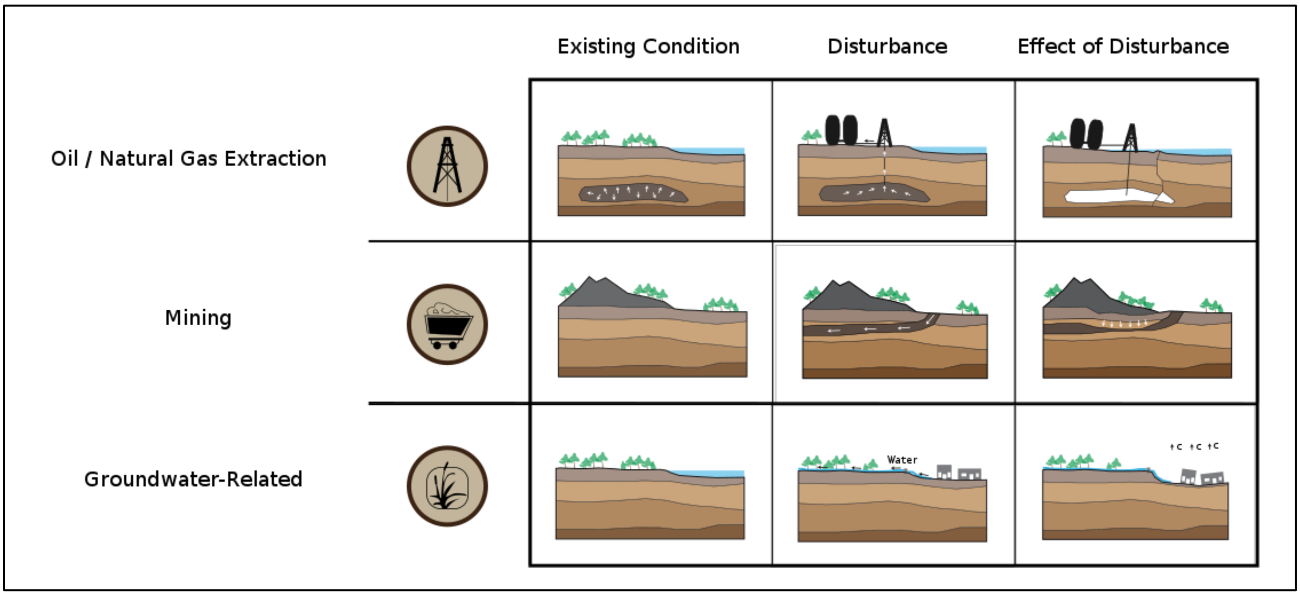

Figure 1: Examples of types of subsidence and their causes (source: (Petty, 2011)*)*

Subsidence in the Netherlands has a number of negative consequences, which are affecting an increasing number of people. For example, costs caused by damage to infrastructure are rising quickly, and are expected to increase to over five billion euros in 2050 (Van den Born et al., 2016). This doesn't take into account the costs from damage to buildings, which is expected to be at least four times as high (Velsink et al., 2020). Additionally, subsidence is making water management in the Netherlands more complex and is likely to increase flood risk both inland and along the coast significantly (Oude Essink et al., 2010; Velsink et al., 2020).

Despite these negative effects, it has proven difficult to effectively reduce subsidence in the Netherlands (Erkens et al., 2015; Seijger & Verheijen, 2016; van Hardeveld et al., 2014). Due to the limited awareness of the problem, the difficulty in identifying effective measures and the fragmentation of both costs and responsibilities, there has only been a limited effort to counter the problem. Because of these factors, Velsink et al. (2020) identify subsidence in the Netherlands as a “wicked problem”. They write:

> A problem is wicked, if (1) it is intertwined with various related problems and knowledge fields, if (2) many different stakeholders with their own interests are involved, with different – often conflicting – perceptions and insights, and if (3) the problem has major consequences. This means that a detailed elaboration and application of measures is not sufficient. (Velsink et al., 2020, p. 852)

Because of this, land subsidence can only be dealt with using an unconventional, interactive approach in which all affected parties work together (Levin et al., 2012).

An important part of dealing with a wicked problem such as subsidence is expanding the knowledge about the topic that can be used to make informed decisions (Levin et al., 2012). The impact of subsidence on specific land uses in the Netherlands is often discussed (Velsink et al., 2020). However, information on the impact of land use on subsidence is much rarer, despite land use being identified as an important driver of subsidence (Van den Born et al., 2016).

1.1 Research objectives

The goal of this research is to discover the links between land use and subsidence in the Netherlands. This was be done by analysing the relation between land use and subsidence rates in the Randstad area in the Netherlands using a prediction method proposed by Minderhoud et al. (2018). This method was extended upon by adjusting the scale of the used data and by adjusting the used methods.
With this in mind, this thesis aims to answer the following research questions:

1. *What are known causes of subsidence and to what extent are these causes linked to different land use types?*
2. *How was subsidence between 2015 and 2020 spatially distributed in the Randstad in the Netherlands?*
3. *What is the relation between subsidence rates and land use (change) in the Randstad in the Netherlands?*

Due to the nature of land use, it is not possible to analyse causality between it and subsidence. Land use itself does not directly cause subsidence but certain land use types may have characteristics that do. For example, certain types of agriculture demand lower water levels which, in peat areas, causes compaction of the soil (Stouthamer et al., 2020; Velsink et al., 2020). Land use may therefore be used as an effective identifier of subsidence. By trying to predict subsidence rates using land use, it can be analysed to what extent land use can actually be used as a good predictor of subsidence in the Randstad area in the Netherlands. Due to availability of data, the research will look at subsidence rates between 2015 and 2020 and land use in the Netherlands between 2012 and 2018.

Many studies have already looked at specific drivers of land use in the Netherlands, focusing either on mining and gas extraction, or on oxidation. Recent studies, however, indicate that these approaches are too limited, and that they underestimate the impact of surface loading on subsidence in the west of the Netherlands (van Asselen et al., 2018). Other articles also mention land use as an important role of subsidence in the Netherlands (Van den Born et al., 2016). Research looking into this relation however remains very limited for the Netherlands. This research takes a broader look at subsidence and it's causes in the Randstad area in the Netherlands and tries to more broadly identify how land use is linked to subsidence and which types of land use have the largest impacts on subsidence. These insights can help inform long term policy decisions and can assist local spatial planners in preventing the negative effects of subsidence.

2. Literature review

In this literature review, the theoretical basis will be given for this research project. In the first half of the chapter the main terminology related to the research questions will be discussed in detail. They will be discussed both in a broader sense and more specifically related to the research area. The second half of the chapter will look at similar research that has tried to identify the relationship between land use and subsidence.

2.1 Subsidence

Subsidence, as applied to the earth's surface, is the sinking of a surface point to a lower level (Bagheri-Gavkosh et al., 2021; Whittaker & Reddish, 1989). Subsidence can take the form of structures settling into the ground, the ground itself lowering and carrying any structure with it or even the collapse of the surface into a cavity. There are many different types of subsidence, which are generally differentiated by their causes, and sometimes by their consequences. These types of subsidence can be categorized into two groups. On the one hand Whittaker and Reddish (1989) describe *en masse* subsidence, which refers to subsidence caused by local geological factors such as volcanic and tectonic activity, mining and tunnelling operations and natural localised causes, such as underground chalk and limestone cavities collapsing (Goodings & Abdulla, 2002), causing sinkholes. On the other hand subsidence can refer to localized compaction of soil, which is subsidence caused by settlement (loading and shrinkage due to moisture loss) or oxidation due to drainage (Whittaker & Reddish, 1989). Compaction subsidence only takes place in soft soil areas (Erkens et al., 2015; Yang et al., 2022). Soft soil is characterized by six factors: high moisture content, high sensitivity, high compressibility, low permeability, low strength and low density (Zhang et al., 2020; Y. Zhou, 2006). Soft soils are generally peat and soft clay soils, and can mostly be found in low lying areas including swamps and deltas (Omar & Jaafar, 2020; Vermeer & Neher, 1999).

An alternative categorization distinguishes between anthropogenic subsidence on the one hand and natural subsidence on the other (Carminati & Martinelli, 2002; Gambolati et al., 2005; Ingebritsen & Galloway, 2014; Tosi et al., 2013). Anthropogenic subsidence, or subsidence directly or indirectly caused by human activities, has a significantly different timescale than natural subsidence. While natural subsidence is identified over periods of millions to thousands of years, anthropogenic subsidence has a relevant timescale closer to hundreds to tens of years (Carminati & Martinelli, 2002). The types of subsidence that Whittaker and Reddish identify as *en masse* subsidence mostly overlap with what would be classified as natural subsidence, with the exception of mining and tunnelling operations. Subsidence caused by extraction of deeply located natural resources such as natural gas and water from aquifers is typically included as both *en masse* subsidence and anthropogenic subsidence (Candela & Koster, 2022).

The main way that different types of compaction are distinguished, is by looking at its causes. As mentioned, the two main causes for compaction are settlement or oxidation. Settlement and subsidence are sometimes distinguished as two different processes, however settlement itself is a form of subsidence (Whittaker & Reddish, 1989, p. 1). Settlement happens when soft soil compresses due to a change in the composition of the soil or an increase in the load on top of the soil, or both (Li et al., 2021). When the groundwater level is lowered in an area, the moisture content of the soil reduces which causes the soil to compact (shrinkage). Similarly, when weight is added to a soil layer containing fluids, this causes the fluids to be squeezed out of the soil layer and the soil layer therefore to be compacted. This takes place naturally in areas where sediment is deposited, but human activity can also cause it (Doornhof et al., 2006; Higgins et al., 2014). Building infrastructure and buildings on top of soft soils, puts pressure on the soft soils which causes it to compact (Stouthamer et al., 2020). In peat rich areas such as the Netherlands subsidence can also be caused by the drainage of groundwater from peat areas, which causes oxidation (Stouthamer et al., 2020; Wösten et al., 1997). Wösten et al. define oxidation as "volume reduction of peat above the groundwater level resulting from loss of organic matter due to decomposition by biochemical processes" (Wösten et al., 1997, p. 26). When groundwater is drained it exposes peat to oxygen which sets in motion certain biochemical processes, which cause some of the organic matter to be transformed into carbon dioxide, which causes a volume reduction of the peat. This in turn causes the ground to lower. All the above mentioned causes of subsidence usually do not take place independently. For example, subsidence in peat areas is often caused by some combination of shrinkage, loading and oxidation (Wösten et al., 1997), and subsidence in urban areas can be caused by both an increase in the load due to buildings and infrastructure, but also due to shrinkage when the use of groundwater lowers the phreatic groundwater level (Li et al., 2021).

Subsidence has a number of documented consequences. One of the main effects of subsidence that is often discussed is the socio-economic impact. Subsidence can significantly damage buildings and infrastructure, which comes at a high economic cost. There are no global and only few local damage reports available on this topic, but Deltares estimates that subsidence currently causes damage with costs in the billions of dollars annually around the globe (Waltham, 2015). Another major consequence of subsidence is an increase in flood risk in coastal areas and around rivers. Coastal areas in which subsidence takes place are significantly more susceptible to flooding due to the combination of this subsidence and the sea level rise that is taking place and is expected to increase in the coming years (Bird, 1996; Clabby, 2010; Corbau et al., 2019; Moe et al., 2017). Additionally, subsidence in deltas can increase the likelihood of river flooding and can even impact river flow patterns, which can in the long term increase coastal erosion (Stanley, 1988). A last, indirect consequence of subsidence is the emission of greenhouse gasses in peat areas. When oxidation takes place, it releases a large amount of carbon dioxide into the atmosphere (Koster, Stafleu, Cohen, et al., 2018; van Asselen et al., 2018; Wösten et al., 1997). This carbon dioxide is a by-product of the decomposition of the peat when it comes into contact with oxygen. In 2008, the emissions of this process in the Netherlands were calculated to be as much as 2.5% of total carbon emissions, being equivalent to 25% of all car emissions in the country (Van der Akker et al., 2008).

2.2 Subsidence research in the Netherlands

Subsidence in the Netherlands is mainly identified as anthropogenic subsidence. It is caused by salt mining and gas extraction on the one hand (Ketelaar, 2009; Mehranpour et al., 2021; Van Thienen-Visser et al., 2015; Van Thienen-Visser & Fokker, 2017) and subsidence caused by oxidation and compaction on the other (Cuenca & Hanssen, 2008; Koster, Stafleu, Cohen, et al., 2018; Nieuwenhuis & Schokking, 1997; Schothorst, 1977; van Asselen et al., 2018). Subsidence caused by salt mining and gas extraction predominantly takes place in the north-east of the Netherlands, and is identified to be caused by the extraction of gas from the Groningen gas and oil field (Van Thienen-Visser et al., 2015; Van Thienen-Visser & Fokker, 2017). Subsidence caused by oxidation takes place in peat areas, which are mostly located in the west of the Netherlands, although some peat areas are also located in the east (Koster, Stafleu, Cohen, et al., 2018; Nieuwenhuis & Schokking, 1997). On a regional scale however, the largest threat is identified to be shallow subsidence, which is subsidence that takes place close to the surface and does not include salt mining and gas extraction (Candela et al., 2020).

The main cause for subsidence in the west of the Netherlands is identified by Cuenca and Hanssen (2008) as being oxidation. In their research they find a strong correlation between subsidence and peat areas. Asselen et al. (2018) however indicate that the conclusion that oxidation must be the main cause is too limited. They argue that peat compaction and oxidation studies in the Netherlands have largely avoided built-up areas and therefore underestimate the impact of compaction due to loading and drainage. In their study they found that oxidation is the main cause for subsidence in peat areas with limited loading, but that subsidence in areas with long-term loading is mainly caused by compaction (van Asselen et al., 2018).

2.3 Land use

When discussing the causes of anthropogenic subsidence, one of the factors that plays an important role is the way that the surface is used by humans, also known as land use. The term land use cannot be accurately described without discussing land cover. Land cover can be defined as “biophysical attributes of the earth’s surface” (Lambin et al., 2001, p. 262) whereas land use is “human purpose or intent applied to these attributes”(Lambin et al., 2001, p. 262). Although both land use and land cover can be linked to human actions, the human actions are what give land use its meaning. Another way to distinguish between land use and land cover is the method of classification. Land cover is determined by direct observation, while land use needs to be interpreted from the activities that take place on that surface. (Batty et al., 2005, p. 86; Somantri & Nandi, 2018). In practice, large scale data about land use can however most easily be derived from land cover data or object detection, based on assumptions about the economic use of the different land cover types and objects (Liu et al., 2017). Because of this, and because land cover is inextricably linked to land use and human actions, the two terms are most often used interchangeably in research (Yadav et al., 2012).

2.4 Land use and subsidence

Land use and subsidence are not directly linked. Land use is linked to subsidence through what Minderhoud et al. (2018) describe as drivers and processes. Drivers are characteristics of specific types of land use, like water use or the physical characteristics of built up areas, which set in motion certain processes, such as compaction, which result in subsidence. The majority of research that looks into the relation between land use and subsidence focusses solely on the driver water extraction, both from groundwater and from underground aquifers (Andaryani et al., 2019; Corbau et al., 2019; Du et al., 2018; Nayyeri et al., 2021; C. Zhou et al., 2016, 2017, 2020). Multiple of these papers have found a direct relationship between water use of certain land use types and subsidence (Andaryani et al., 2019; Du et al., 2018; C. Zhou et al., 2017). In earlier publications, looking at subsidence in Indonesia, the focus is mainly put on industrial water use and its impacts on subsidence (Abidin et al., 2006). Du et al. (2018) however identify that other types of land use have a larger impact than expected in this area, which later publications have taken up in their research (Corbau et al., 2019; C. Zhou et al., 2017, 2020). Other than industrial water use, the main land use types that are identified to have a large impact on local water use are on the one hand different forms of agriculture (C. Zhou et al., 2016) and on the other hand growing urban areas (C. Zhou et al., 2020), which in turn cause significant subsidence.

Another driver that is often discussed in relation to land use is mining (Lamich et al., 2016; Machowski et al., 2016). Mining is however more difficult to link to land use when using some variation of InSAR derived subsidence data, which is the preferred data source in most recent subsidence research. Research on this topic however shows that land use does not only influence subsidence, but that subsidence can also cause land use change (Corbau et al., 2019). Changes in the landscape or damage to infrastructure due to subsidence caused by mining can influence changes to land use (Corbau et al., 2019; Lamich et al., 2016). For example, damage to infrastructure and buildings caused by subsidence can have the consequence that built up areas are abandoned or relocated (Lamich et al., 2016). Additionally, areas that are prone to subsidence due to certain characteristics may also attract certain types of land use due to those characteristics (Minderhoud et al., 2018). Minderhoud et al. (2018) show that mining and water usage are however not the only ways in which land use can cause subsidence. They discuss another driver that is linked to land use and can cause subsidence. According to their article, loading is also an important potential driver of subsidence and it should be taken into account when looking at the link between land use and subsidence. Similarly, Oh and Lee (2010) identify a strong link between the locations of railroads and roads, as well as agricultural fields, and subsidence. Using groundwater levels and land use to model subsidence rates, they reach a model accuracy of 90%.

Minderhoud et al. (2018) analyse the relation between land use and subsidence in the Mehkong Delta in Vietnam by predicting subsidence rates based on land use change. Using this method, they arrive at a 65% to 92% prediction accuracy, indicating that subsidence in this area is strongly connected to changes in land use during the observed period. Minderhoud et al. (2018) show that changes in land use are a much stronger predictor for changes in subsidence rates than just land use types. This is supported by the research from Wösten et al. (1997), which indicates that large changes in land use such as reclamation and drainage in order to increase the surface area which can be used for agriculture, have caused large scale subsidence in Malaysia.

It should be noted that a majority of research on this topic looks at areas in south-east Asia, mainly in Indonesia, Thailand and China. Koster et al. (2018) indicate that the Dutch delta differs from other deltas in the world in that agricultural areas are much more prone to subsidence compared to built-up areas. Where subsidence in other deltas is mainly caused by water extraction from aquifers, subsidence in the Dutch delta is mainly caused by the lowering of the phreatic groundwater level. The research by Koster et al. (2018) is among the few publications that link subsidence in The Netherlands to specific land use types. Van den Born et al. (2016) also identify different types of land use in the Netherlands as the causes of subsidence, based on observations by local governments and research into the broader causes of subsidence. They differentiate between two causes of subsidence connected to different types of land uses: In agricultural areas water boards use dehydration to make the ground suitable for agricultural practices, which causes oxidation in peat-areas. In built-up areas subsidence is caused by loading due to infrastructure and buildings. Other than these publications there is limited research about the links between land use and subsidence in the Netherlands. Individual drivers have been thoroughly researched, as discussed, but the link between these drivers and different land use types is often overlooked.

2.5 Measuring subsidence

Interferometric Synthetic Aperture Radar (InSAR) has become a common way to measure subsidence in recent years. This method uses multiple Synthetic Aperture Radar (SAR) measurements in order to determine the relative height of a target (Burgmann et al., 2000). SAR systems send out electromagnetic waves and measure the return energy of these waves. If a radar emits radiation in the microwave portion of the spectrum, the emitted radiation has a sinusoidal pattern, of which the amplitude and phase are known. This means that the amplitude and phase of the reflected wave can then be measured. InSAR makes use of this by combining two different SAR measurements with different angles and measuring the phase change in order to accurately calculate the distance that the waves have travelled and the point at which the two waves intersect (Ferretti et al., 2007; Osmanoglu et al., 2016).

The different SAR measurements can be acquired using two different methods: either a single satellite with two radar antennas or two different passes from the same satellite (known as repeat-pass-interferometry) with a different look angle can be used (Ferretti et al., 2007).

The resulting interferograms can then be used to derive subsidence using one of methods as described by Hanssen (2001) as well as newer methods (Ferretti et al., 2007; Osmanoglu et al., 2016). In order to use the interferograms to derive subsidence, a number of factors have to be taken into account. In the case of repeat-pass interferograms, changes in the atmospheric refractivity needs to be accounted for (Hanssen, 2001). Additionally, the interferograms need to be adjusted for a number of factors that cause systematic surface deformation, such as hydrological loading, ocean loading and atmospheric loading (Nederlands Centrum voor Geodesie en Geo-informatica & SkyGeo, 2020a). Lastly, orbital drift of the satellites that make the SAR measurements causes a constant random phase offset. Because of this, measurements cannot be used as absolute values, but must be calibrated using a point of zero deformation or other measurements such as GPS or gravity measurements (Higgins et al., 2014). Derived subsidence rates are however not calculated for pixels with low InSAR correlation, which means that subsidence rate estimates based on InSAR do not have continuous spatial coverage (Minderhoud et al., 2018).

3. Methodology

In this chapter, the methods used to identify the spatial distribution of subsidence and relation between land use and subsidence in the Randstad area in the Netherlands will be discussed. First, the choice of and characteristics of the research area will be considered. Next, the input data used for the analysis will be looked at. Both datasets required a significant amount of pre-processing, which will be discussed in the next paragraphs. Lastly, the method adapted from Minderhoud et al (2018) will be discussed.

3.1 Research area

The Dutch Randstad is commonly identified as the western part of the Netherlands, encompassing the four largest cities in the country, namely Amsterdam, Rotterdam, The Hague and Utrecht, and their agglomerations. The Randstad is characterized by a number of factors that lend themselves to research into subsidence and land use. The area has been suffering from significant subsidence for the past decades (Caro Cuenca et al., 2020; Cuenca & Hanssen, 2008; Koster, Stafleu, & Stouthamer, 2018; Schothorst, 1977). This is linked to the fact that the area mainly consists of soft top soils such as peat and clay. As discussed in the previous chapter, soft soils are most prone to subsidence caused by drainage and compression (Erkens et al., 2015; Stouthamer et al., 2020; Yang et al., 2022), which are the main types of subsidence that are linked to land use in the literature. The research area also contains a large variety of land uses, including a number of large cities, many agricultural areas and protected nature (see Figure 2). This variety makes the likelihood of better prediction rates for all the different land use types higher.

Areas that contain large scale salt mining and active gas fields were intentionally left out of the research area. The choice was made to exclude the analysis of subsidence caused by salt mining and gas extraction operations, because it is expected that these will have a different spatial relation with subsidence. Subsidence caused by mining can be found in all areas above the gas- or other reservoir that is being mined (Mehranpour et al., 2021). This reservoir can however encompass many different land uses on the surface. Because of this it is expected that including mining in the research would have a confounding impact on the prediction level of the used methods.

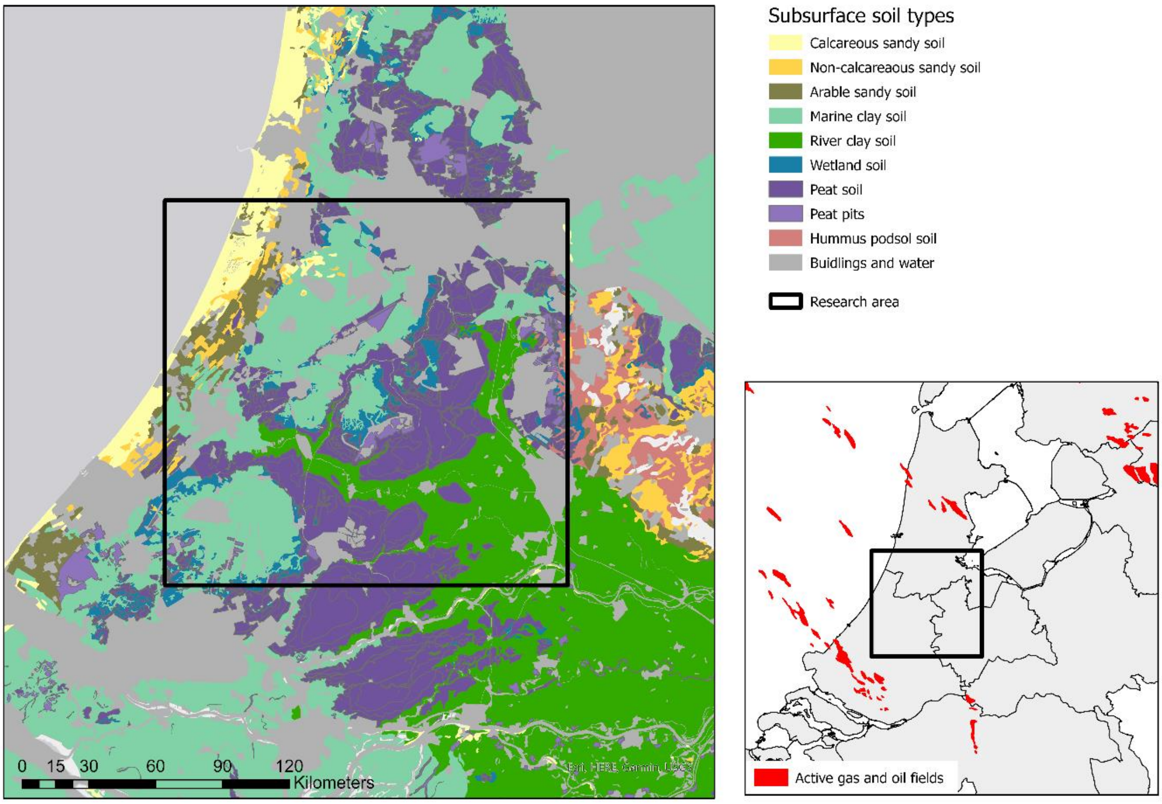

Figure 2: Overview of the research area including subsurface soil types and locations of active oil and gas fields (Data source: (Kadaster, 2021; Ministry of the Interior and Kingdom Relations, 2023)*).*

3.2 Input data

In order to determine the relationship between land use and subsidence in the Netherlands, an existing dataset was used to identify land use, and InSAR-derived measurements were used to measure subsidence. For land use the dataset Landelijk Grondgebruik Nederland (LGN) was used. This is a land use dataset that was created by Wageningen University & Research using land use information and address data from Dutch municipalities and remote sensing imagery. There are a number of iterations of the LGN which represent land use in the Netherlands in different periods. For this research four different iterations were used in order to compare different time periods. The LGN consists of approximately 50 different land use classes with a focus on different agricultural crops and natural land use types (respectively encompassing 10 and 23 of the 50 classes). The LGN dataset was chosen over other available land use datasets for its higher temporal accuracy. The LGN data that was used has four iterations, which encompass land use around 2004, 2008, 2012 and 2018. Initially it was planned to compare the different versions of the LGN in order to identify land use changes before and during the period in which the subsidence measurements were made. This however turned out to be impossible due to the large difference in classification methods between the different versions of the LGN (Hazeu et al., 2011). The LGN has a spatial resolution of 25 m by 25 m. For the 2018 version of the LGN a spatial resolution of 5 m by 5 m was also available, however this resolution was not available for earlier versions of the LGN, which did not fit with the time period of the InSAR data.

InSAR-derived subsidence data for the Netherlands were retrieved from a project headed by the Dutch Centre for Geodesy and Geo-information (GNC) and SkyGeo (Nederlands Centrum voor Geodesie en Geo-informatica & SkyGeo, n.d.-b). This project has the goal of making subsidence information in the Netherlands available to the public. The dataset from this project consists of millions of measurement points spread over the entirety of the Netherlands, which are retrieved from multiple paths of Sentinel-1a and Sentinel-1b. Each of these measurement points contains between 240 and 260 measurements (depending on the satellite), measured approximately every 8 days spanning 5 years between 2015 and 2020. Each of these measurements reflects a relative height change (compared to the first measurement).

Table 1: Overview of the input data

Data	Datatype	Spatial resolution	Temporal resolution	Attribute accuracy	Source
InSAR-derived subsidence rates	Vector (point)	~10 m horizontal error	Measurements each 8 days between 19-01-15 and 30-06-20	Individual height change measurements accurate to 1 mm (Nederlands Centrum voor Geodesie en Geo-informatica & SkyGeo, 2020a)	(Nederlands Centrum voor Geodesie en Geo-informatica & SkyGeo, 2020b)
LGN5	Raster	25x25 m	2003/2004	General accuracy of more than 90% (Hazeu, 2005)	(Wageningen Environmental Research, 2006)
LGN6	Raster	25x25 m	2007/2008	Land use change and crop accuracies of respectively 94.5% and 84.5% (Hazeu et al., 2012)	(Wageningen Environmental Research, 2012)
LGN7	Raster	25x25 m	2012	Crop accuracy between 85.7% and 96.3% (Hazeu et al., 2014)	(Wageningen Environmental Research, 2014)
LGN2018	Raster	5x5 m	2018	General accuracy of 95% (Hazeu et al., 2020)	(Wageningen Environmental Research, 2020)

3.3 Data pre-processing

In order to use the land use and InSAR-derived subsidence data for this research a significant amount of pre-processing was necessary. The next paragraphs will discuss the pre-processing steps for both datasets. See Figure 3 for an overview of these steps.

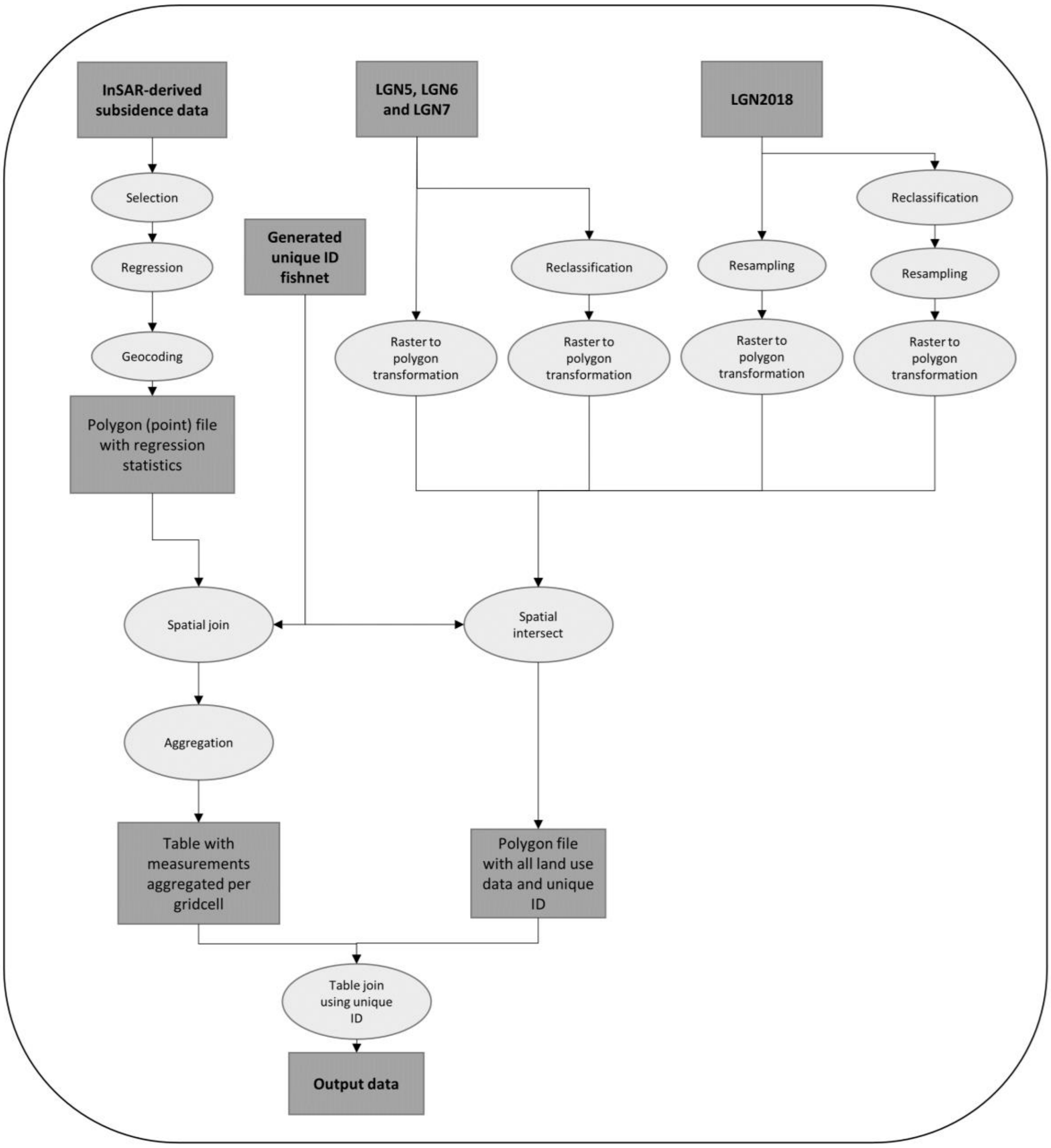

Figure 3: Overview of pre-processing steps

3.3.1 Land use reclassification

The choice was made to reclassify the LGN datasets from the approximately 50 land use classes to 10 classes. The reclassification was partially based on the monitoring classes of the LGN, which are overarching land use classes that are used to identify large scale trends (Hazeu et al., 2020). More classes were however distinguished based on the land use classes used by Minderhoud et al. (2018) in order to better represent the land use classes that may have an impact on subsidence and to allow for comparison. An overview of the reclassified land use classes can be found in Appendix I. Figure 4 shows the distribution of the reclassified land use classes of the LGN7 dataset in the research area (for an overview of the non-reclassified land use, see Appendix II).

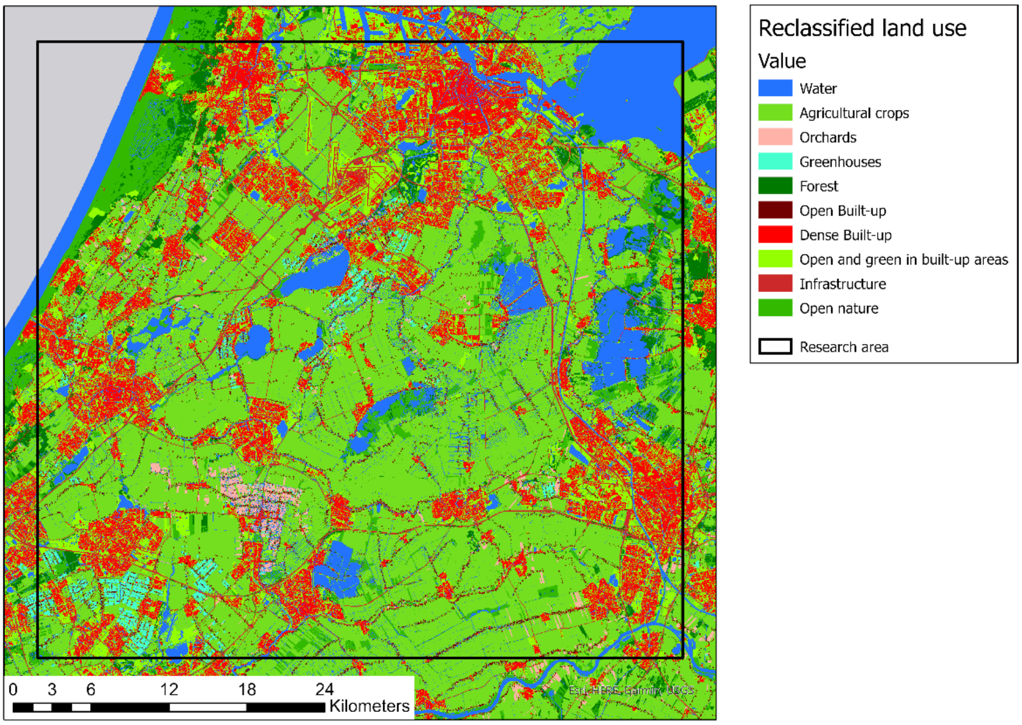

Figure 4: Overview of the distribution of the reclassified land use classes of the LGN7, showing land use in the research area in 2012 (Data source: Wageningen Environmental Research (2014))

Because of the finer spatial resolution of the LGN2018 dataset, it had to be resampled to 25 by 25 meters. This was done in ArcGIS Pro using the resampling tool. Using this tool, the most common land use type within each 25 by 25 meter area was selected as the land use type of the raster cell. In order to keep the highest possible accuracy, the resampling was done separately for the reclassified and non-reclassified versions of the dataset. For all versions of the LGN both the reclassified and non-reclassified datasets were then transformed into vector datasets. These datasets were then all merged with a generated fishnet (a vector dataset with a net of rectangular polygons the exact spatial dimensions of the LGN raster cells) using the intersect tool in ArcGIS Pro. This resulted in a single vector file with rectangular polygons representing the cells of the LGN raster and with a connected table containing the LGN class values of all the non-reclassified and reclassified versions of the LGN. The choice was made to use this vectorization method instead of layering multiple rasters or connecting a table to a single raster file with unique ID values because this seemed to speed up later steps in the process. Additionally, the non-reclassified LGN data was kept in the dataset so it could also be used in the analysis.

3.3.2 InSAR data pre-processing

The InSAR dataset consisted of five comma separated value (csv) files which were together combined approximately 370GB worth of data for the entirety of the Netherlands. Due to the large size of the dataset, the first step that was taken was shrinking the dataset size by selecting only those measurement points within the research area. This was done by selecting all measurement points within a certain range of latitude and longitude (see Table 2). The coordinate system of the measurement points is WGS84 Web Mercator (Auxiliary Sphere) EPSG:3857.

Table 2: Latitude and Longitude values used as border of the research area (in WGS84 EPSG:3857)

	Minimum	**Maximum**
Latitude	51.890901	52.405770
Longitude	4.207764	5.136108

The resulting dataset contained approximately 17 million measurement points, spread out over the research area. As mentioned, each measurement point in the selection contained multiple relative measurements from between 2015 and 2020, which each have a certain amount of variation and error. In order to derive an approximate subsidence rate in mm/year a model was created using Ordinary Least Squares (linear regression), implemented using the skicit-learn library in Python. This model was created for the entire period and for individual years. The model estimates the rate of subsidence assuming a linear development. In order to run the analysis in a feasible timeframe, DASK was used to speed up the analysis. This resulted in estimations of the subsidence rate in mm/year between 2015 and 2020 (see Figure 5).

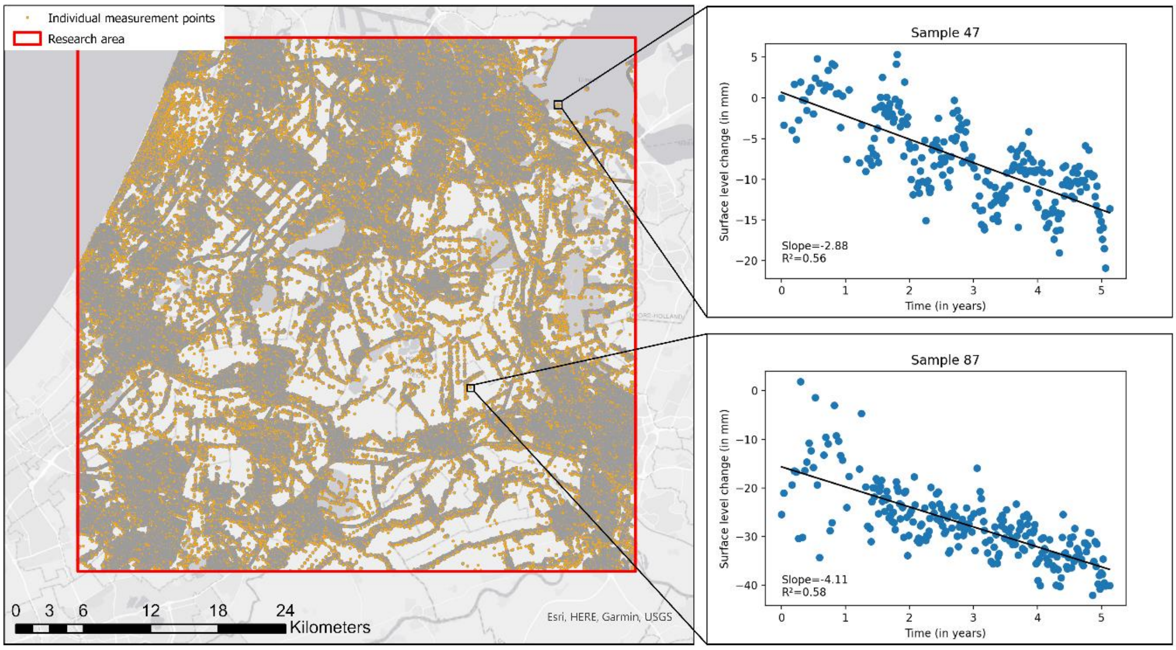

Figure 5: Distribution of measurement points in the research area with examples of the associated data (Data source: Nederlands Centrum voor Geodesie en Geo-informatica & SkyGeo (2020b)*)*

These measurements where then geocoded and joined with the generated fishnet file using ArcGIS Pro. The measurements were aggregated to the scale of the LGN dataset (cells of 25 m by 25 m), using the unique ID, in order to reduce the measure of spatial autocorrelation within the dataset and to reduce the size of the dataset to improve computing speeds. The measurements where aggregated by calculating a weighted mean and median of the individual subsidence measurements contained in each 25 m by 25 m gridcell. The weight of each measurement was determined using the root-mean-square error as an indication of the reliability of the individual measurement points. Lastly, the aggregated measurements were joined with the land use data using the unique ID value. This resulted in a final vector dataset consisting of rectangular polygons equivalent to the raster cells of the LGN, which contained both the LGN classifications from each LGN version and the weighted aggregated subsidence rate values from the InSAR-derived dataset.

3.4 Analysing land use and subsidence

This study makes use of and tries to improve on the methodology used by Minderhoud et al. (2018) in order to determine the relationship between land use and subsidence in the Randstad in The Netherlands. In their study, Minderhoud et al. (2018) make use of land use data which they create themselves using object-based image analysis (OBIA) and a random forest algorithm. They first identify different land use objects using OBIA, which are then classified as different types of land use using a random forest algorithm. This is done for a number of different years, after which the land use maps for these years are combined into land use-sequence maps. The InSAR-derived subsidence data is combined with the land use-sequence maps by assigning the median subsidence value of all measurements within each land use object to the object.

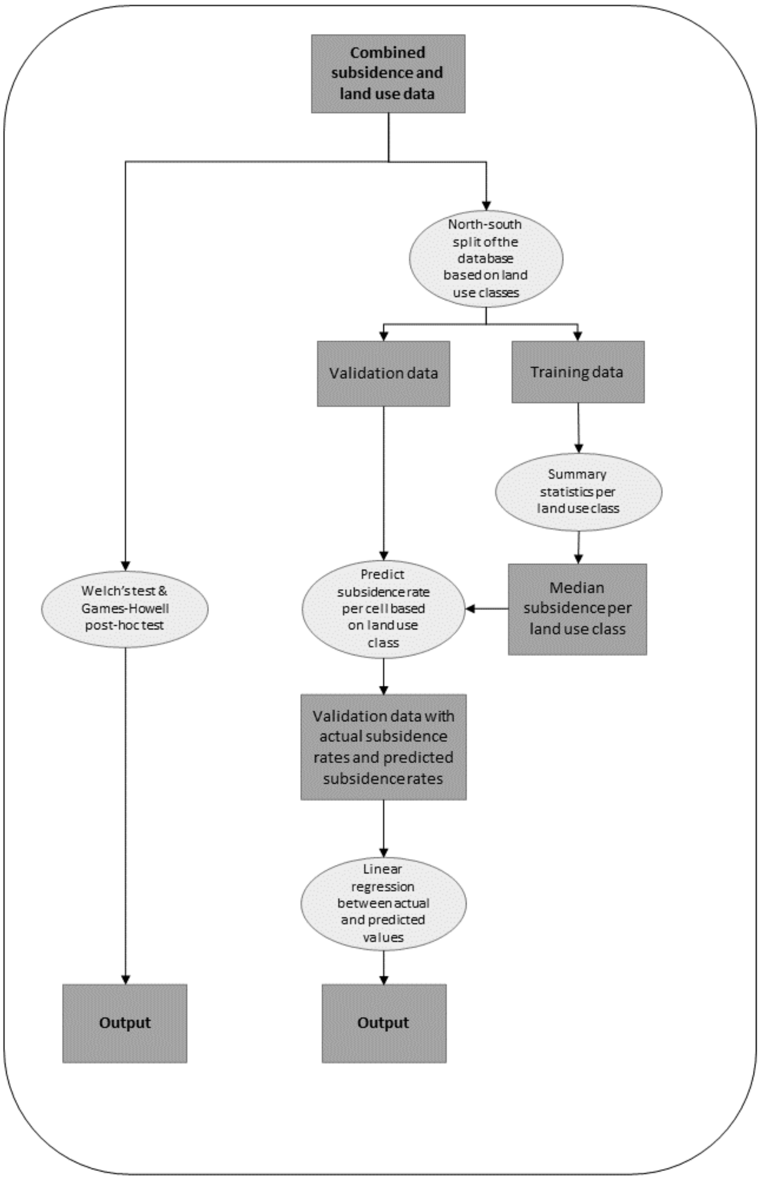

Figure 6: Overview of the analysis steps.

As a first step to identify the relationship between subsidence and land use in their research area Minderhoud et al. (2018) perform an ANOVA with the post-hoc Tukey HSD test. In this research, a Welch test was used instead of a standard ANOVA and a Games-Howell test was done instead of the Tukey HSD. This was done because the data did not meet all assumptions for an ANOVA (see Chapter 5). Minderhoud et al. (2018) additionally perform a regression analysis, for which they use a generated prediction variable as a surrogate for land use. Prediction rates are calculated for each land use class by taking the median of all the subsidence values of the different land use objects within one class. These prediction rates, which are based on a random training sample consisting of two thirds of the land use objects, are then compared to the subsidence rates of the remaining third of land use objects, which are used as a validation set, using linear regression in order to determine the prediction accuracy of the predicted rates.

In this study a similar but adjusted approach was used. First of all, the land use data that is used by Minderhoud et al. differs from the LGN dataset used in this research. The important difference between the land use data used by Minderhoud et al. and the LGN is that the LGN does not contain land use objects, but consists of a raster dataset with land use classes. Subsidence measurements in this study were therefore not linked to land use objects but to individual cells. Because of this, the training and validation datasets could not be generated randomly, since neighbouring cells might be part of the same land use object but be split between the training and validation datasets. This would likely result in a significant overestimation of the regression due to spatial autocorrelation. In order to prevent this, the training and validation datasets were split from north to south, making sure to keep the distribution of cells equal for each land use class (see Figure 7). Another change made to the described method is that instead of land use sequences, the land use at a single point in time was used in order to create a predictor value based on the training dataset. This choice was made because, as described, the different versions of the land use dataset have very different classification methods which made comparison between years to identify land use change impossible.

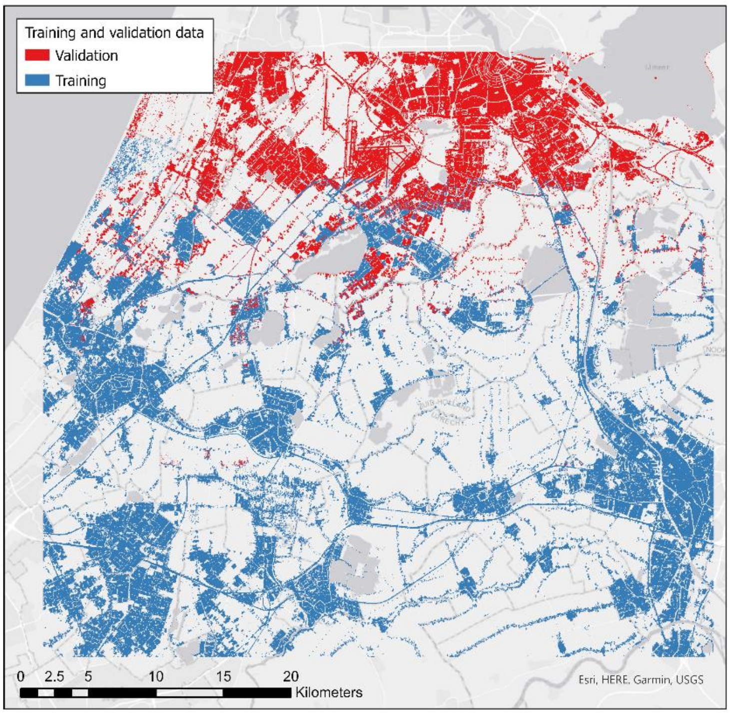

Figure 7: Overview of the training and validation parts of the dataset.

Using the validation dataset, a median subsidence rate for each land use class was calculated as a predictor value. These median subsidence rates based on the land use classes where then used in a linear regression model to identify to what extent they can be used to predict actual subsidence rates. The results of this regression model indicate if a relation between land use and subsidence exists and how strong this relation is.

4. Results

This chapter discusses the results of the different analyses. First, the general trends in the data and results of the pre-processing steps will be discussed. These results are important to understand the strengths and weaknesses of the input data and the impact of the used pre-processing methods. Secondly, the results of the Welch and post-hoc tests will be discussed. These indicate to what extent there is a significant difference between the measured subsidence per land use class and therefore if there might be a correlation between land use classes and subsidence in the areas. Lastly, the results of the method copied from Minderhoud et al. (2018) will be looked at to indicate the strength of the relationship between subsidence and land use in the research area.

4.1 Subsidence data exploration

As discussed, an OLS regression was used on the raw data to estimate the surface level change rate in mm/year. Figure 8 shows the raw data and calculated OLS regression of four measurement points in the research area, which were chosen from a hundred randomly selected points. The consistency of the individual measurements varies significantly, with a large number of measurements showing changes of up to 20mm in a short time period. This variation can at least partially be explained by interference and measurement error. It should be noted that some of the randomly selected measurement points show signs of seasonality, as can be seen in sample 6 and sample 47.

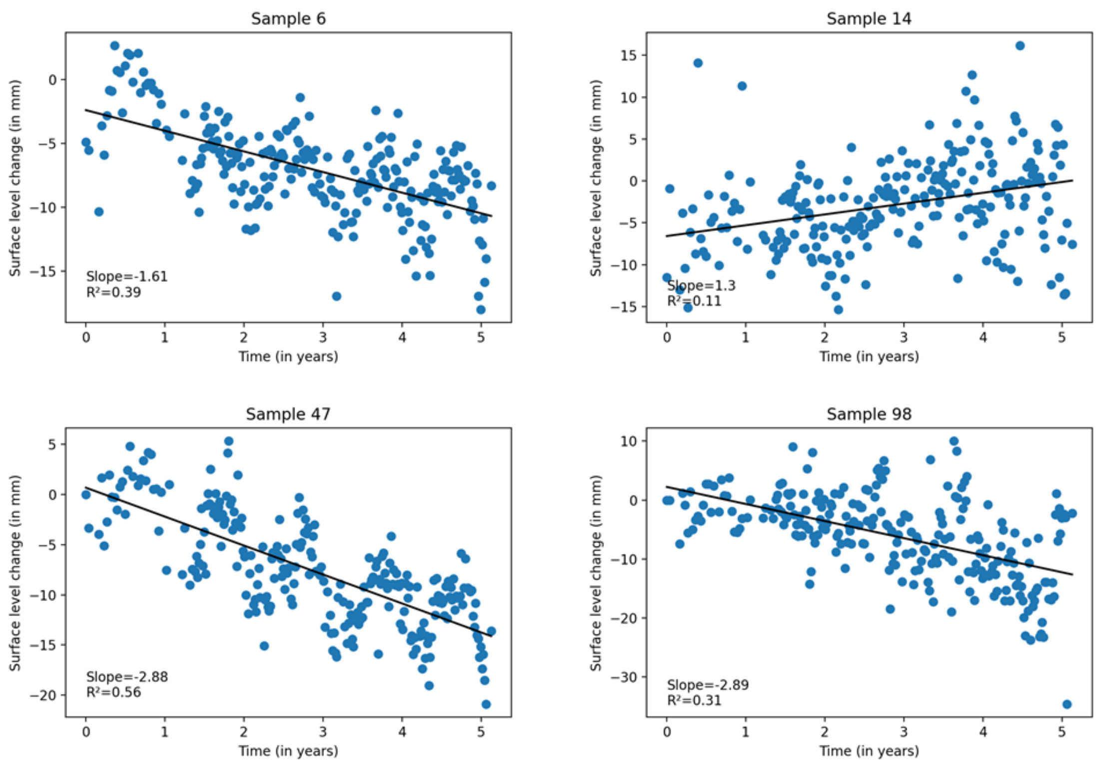

Figure 8: Scatterplots with OLS regression of four randomly selected measurement points in the research area.

The research area contains approximately 14.4 million measurement points. The measurement points are not distributed equally over space due to poor backscatter and inconsistency of certain surfaces. The 14.4 million individual measurement points were aggregated to a 25 m by 25 m grid. Figure 9 shows the number of measurements that were aggregated to each gridcell. The figure clearly shows that measurements are clustered around impervious surfaces, such as buildings and roads, due to their more consistent backscatter.

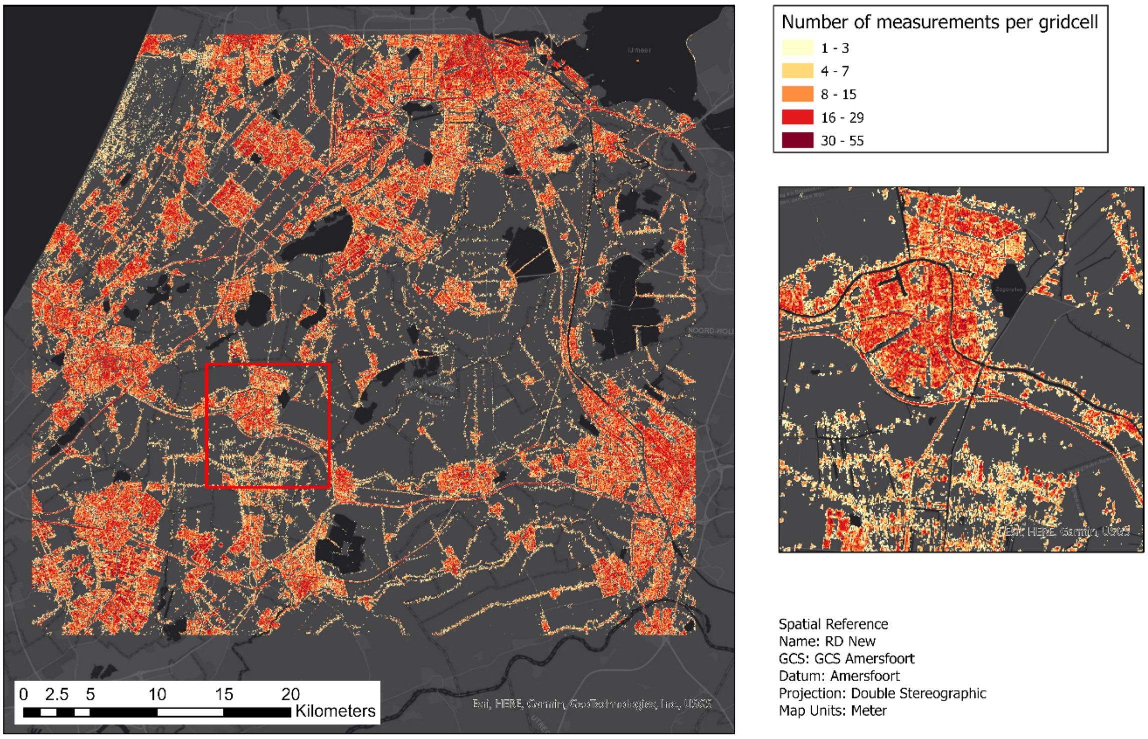

Figure 9: Weighted mean subsidence in the research area between 2015 and 2020 in mm/year

The number of measurements per cell varies significantly. Figure 10 shows the distribution of the number of measurements per gridcell for the entire research area. The distribution indicates that the majority of cells contain a low number of measurements. A low number of measurements in a cell may negatively affect the accuracy of the aggregated data. The figure therefore indicates that further results that include cells with low numbers of measurements should be treated with some caution.

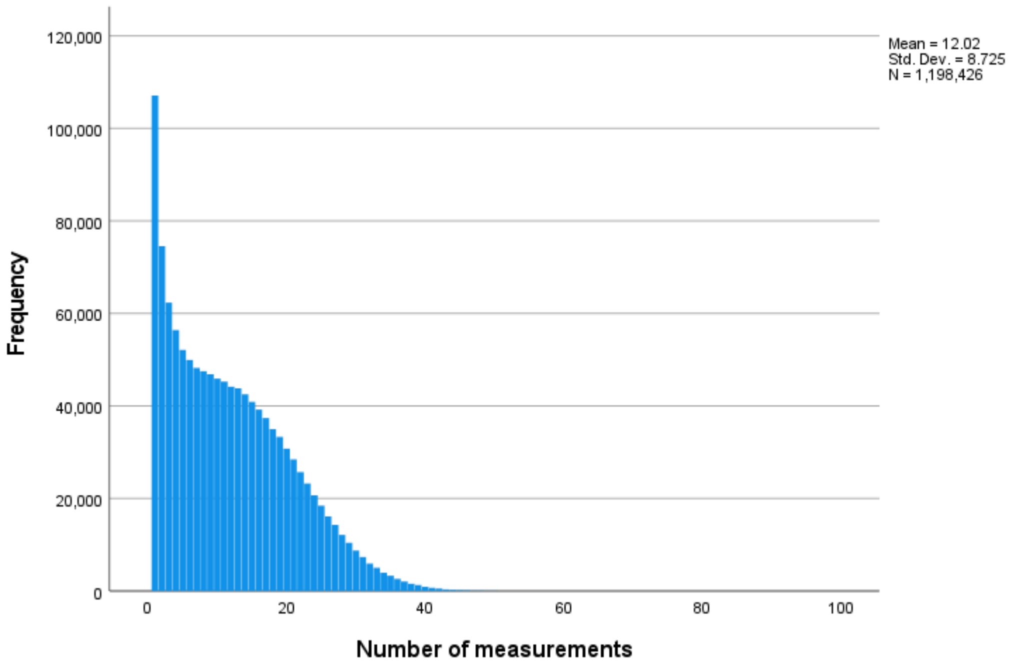

Figure 10: Distribution of the number of measurements per gridcell in the research area.

The aggregation of the measurements using a weight method resulted in an overview of the measured subsidence in mm/y between 2015 and 2020. This overview can be seen in Figure 11 (an enlarged version of this map can be found in Appendix III). A number of things stand out in the figure. Higher subsidence rates can be identified in and around some urban areas, but this is not consistent. For example, Amsterdam, at the top of the map, shows higher subsidence rates, while Utrecht, the cluster of pixels in the left bottom half of the map, seems to show low subsidence rates and even contains a significant number of cells with negative subsidence rates, indicating a raise in the surface level. This could potentially be explained by the subsurface soil types that each of these cities is built on (see Figure 2). Smaller urban areas however also contain a lot of variation in subsidence rates, both within the urban areas themselves and when comparing between different urban centres. Something else that stands out is the clear distinction of large-scale infrastructure, which is clearly visible in a number of areas due to its high subsidence rates. Large roads, such as the N11 located directly to the south of the built-up area of Alphen aan den Rijn, seen in the zoomed in image on the right, can clearly be distinguished by their subsidence rates of generally between 3mm and 15mm per year. In the same image the train tracks can also be distinguished as the orange line running through the centre of the built-up area. Lastly, an area that stands out clearly is the area to the south of Zoetermeer, in the bottom left of the map. When comparing the map with Figure 4, it can be seen that this area largely consists of greenhouses and some built-up areas. For more detailed images of the discussed areas, see Appendix IV.

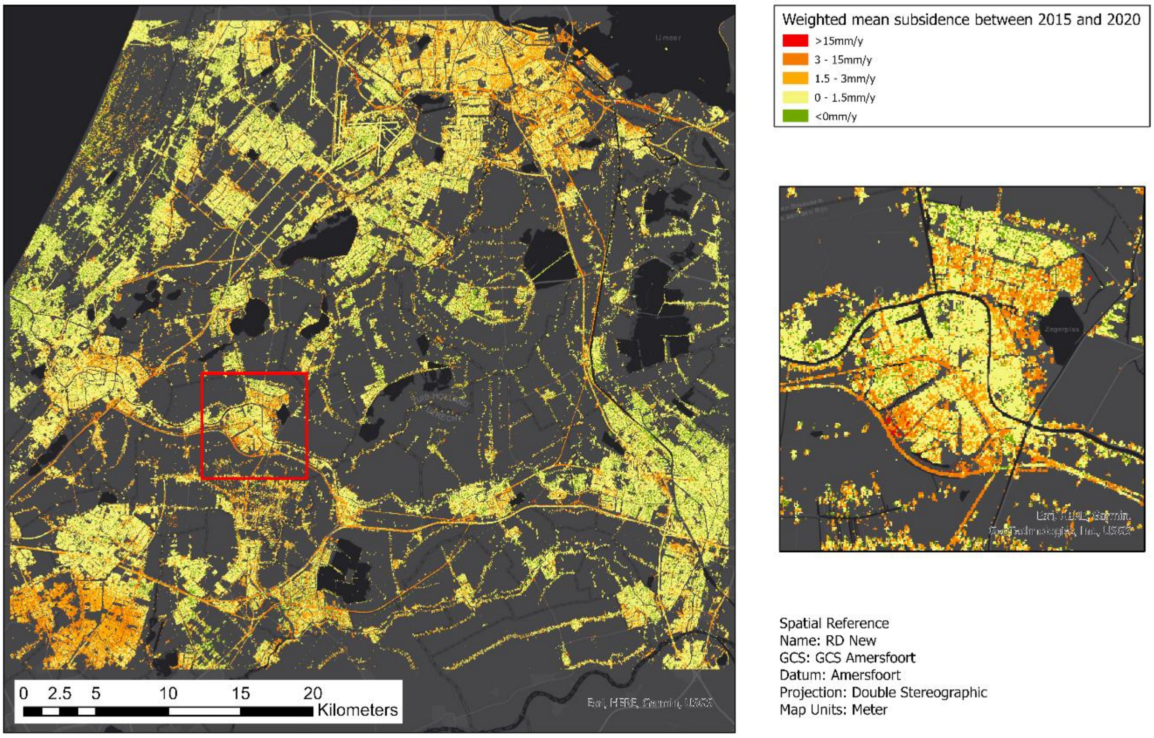

Figure 11: An overview of the spatial distribution of subsidence in the research

4.2 Comparing land use classes

The map with subsidence rates gives an indication wether and how land use and subsidence might be correlated. Table 3 shows descriptive statistics of the surface level change measurements for each reclassified LGN7 land use class. It should be noted that a negative value in this case represents a decrease in surface level, which means a positive subsidence rate. Overall 28.08% of the cells in the land use dataset contain one or more subsidence measurements (as seen under the % missing header). The coverage per class however differs significantly. This corresponds with the findings from Figure 12 as is to be expected. The land use classes with less consistent backscatter generally contain significantly fewer measurements per gridcell and therefore also have a larger number of cells that do not contain any measurements.

Table 3: Descriptive statistics of weighted mean surface level change per reclassified LGN7 land use class

LGN7	N	% Missing	Mean	Median	Std. Deviation	Lower Quartile	Upper Quartile
Agricultural crops	123,181	92.35%	-1.79	-1.14	2.65	-2.64	-0.32
Orchards	10,711	74.50%	-1.81	-1.26	2.42	-2.06	-0.39
Greenhouses	43,529	9.71%	-1.09	-0.78	1.40	-1.82	-0.23
Forest	6,013	94.32%	-1.84	-1.15	2.94	-2.43	-0.32
Open Built-up	71,118	18.24%	-1.24	-0.90	1.70	-1.84	-0.27
Dense Built-up	406,897	10.05%	-0.88	-0.68	1.07	-1.27	-0.26
Open and green in built-up areas	223,649	48.30%	-1.47	-1.00	2.03	-1.96	-0.38
Infrastructure	123,901	27.59%	-1.77	-1.27	2.01	-2.39	-0.57
Open nature	14,534	92.20%	-1.55	-1.14	2.92	-2.69	-0.03
Total	1,023,533	71.92%	-1.29	-0.87	1.83	-58.79	38.71

When comparing the mean surface level change per land use class an interesting pattern emerges. With the exception of infrastructure, higher mean subsidence rates (surface level change values further below zero) occur in land use classes with less backscatter consistency and therefore lower amounts of measurements per gridcell. The land use class with the highest mean subsidence rate is forests, followed by orchards and agriculture. The land use classes with the lowest mean subsidence rates on the other hand are dense urban, followed by greenhouses, open built-up and then open and green in built-up areas. This does not match with what would be expected based on the literature review. As one of the main identified contributors to subsidence is surface loading, it would be expected that higher density built-up areas have higher subsidence rates compared to some of the other land use classes.

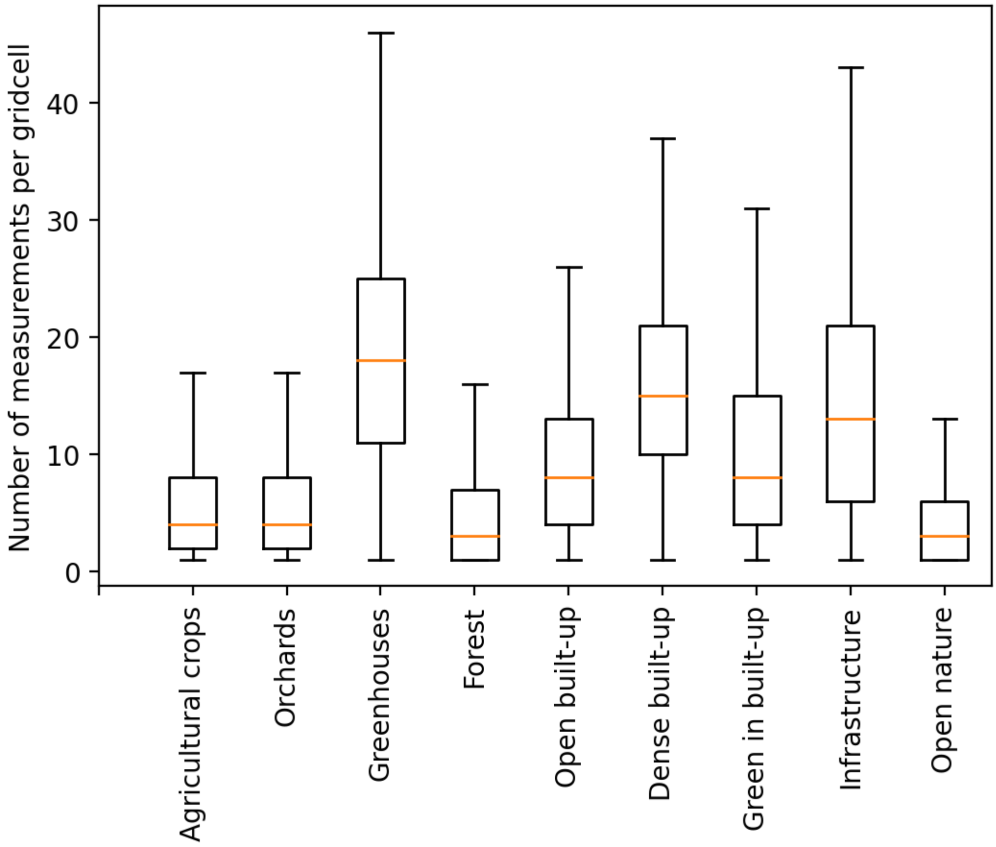

Figure 12: Boxplots of the number of measurements per gridcell per LGN7 land use class.

A number of tests were performed to check the assumptions associated with ANOVA. A Global Moran's I analysis was performed to check the assumption of independence. The weighted mean subsidence rate exhibited significant positive spatial autocorrelation (Moran's I = 0.430; p < 0.01), despite the aggregation of the data. This means that there is a possibility that calculated correlations are overestimated slightly. A Local Moran's I analysis did not reveal any large scale clustering, however due to the large size of the dataset this does not mean that clusters around objects do not exist. The assumption of normality was only partially met for the dataset. Plotting the weighted subsidence rate showed that the subsidence rate is skewed to the right and has a very large number of outliers (see Figure 13). A Kolmogorov-Smirnov test of normality showed that the distribution of measured subsidence is not normally distributed (see Table 4). ANOVA tests are however only affected to a limited extent by non-normality and especially skewedness (Khan & Rayner, 2003). Because of the large difference in the number of cases per LGN7 class, the assumption of homogeneity of variance was tested. A Levene test found that the assumption of homogeneity of variances was not met, $F(8, 1023524) = 9238$, $p < 0.01$.

Table 4: Results of a Kolmogorov-Smirnov test of normality for the measured subsidence rate per land use class.

Reclassified LGN7	**Kolmogorov-Smirnov test**		
	Statistic	df	Sig.
Agricultural crops	0.154	123,181	> 0.01
Orchards	0.129	10,711	> 0.01
Greenhouses	0.098	43,529	> 0.01
Forests	0.172	6,013	> 0.01
Open Built-up	0.120	71,118	> 0.01
Dense Builtup	0.111	406,897	> 0.01
Open and Green in builtup areas	0.157	223,649	> 0.01
Infrastructure	0.139	123,901	> 0.01
Open Nature	0.099	14,534	> 0.01

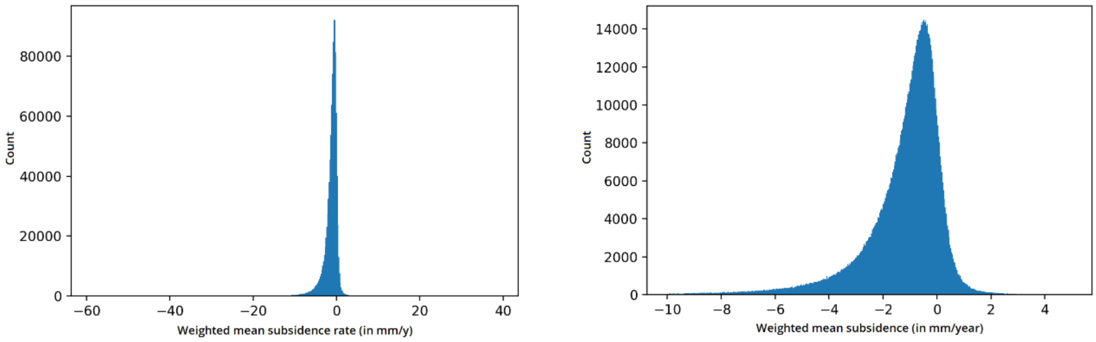

Figure 13: Histogram of the measured subsidence rate per gridcell (left) and the same histogram but with limited y-axis values (right).

Because multiple assumptions were not met, a Welch test was used instead of a normal ANOVA, since it is less sensitive to data with heterogeneous variances. The Welch test indicated a statistically significant difference between the mean subsidence rates of the LGN7 land use classes, *Welch's* $F(8, 70335.5) = 5997.5$, $p < 0.01$. This difference indicates a potential effect of the land use class on subsidence rates for at least some of the classes. A Games-Howell post-hoc test was performed to identify for which land use classes the subsidence rates significantly differ. The Games-Howell test results were additionally compared to Tamhane's T2 test and Dunnett's T3 test, since the Games-Howell test tends to overestimate in some cases (Shingala & Rajyaguru, 2015). All post-hoc tests gave approximately the same results.

The results of the Games-Howell test are shown in Table 5. The table should be read from left to right, where the value indicates the mean difference between the land use class on the y-axis, when compared to the land use class on the x-axis. The table for example indicates that the agriculture and greenhouse land use classes have significantly different surface level changes and that the surface level change in cells classified as agriculture is on average 0.7 mm/y lower than in cells classified as greenhouses. This therefore means that agricultural areas in the research area have a significantly higher subsidence rate than areas with greenhouses.

Table 5: Results of the Games-Howell test, showing significant difference in mean surface level change rates between land use classes and the mean difference between the classes.

	Orchards	Greenhouses	Forests	Open Built-up	Dense Built-up	Green in built-up areas	Infrastructure	Open nature
Agriculture		-0.7		-0.54	-0.91	-0.32		-0.24
Orchards		-0.72		-0.57	-0.93	-0.34		-0.26
Greenhouses			0.75	0.15	-0.21	0.38	0.68	0.46
Forests				-0.59	-0.96	-0.37		-0.29
Open Built-up					-0.36	0.22	0.53	0.3
Dense Built-up						0.59	0.89	0.67
Green in built-up areas							0.3	0.08
Infrastructure								-0.22

Significantly different mean

No significance

Interestingly, there are four land use classes that do not have significantly different surface level changes, namely agriculture, orchards, forest and infrastructure. These classes are the only classes with some non-significant differences and they only have non-significant differences compared to each other. They coincide with the highest mean subsidence rates of all land use classes, as can be seen when comparing the data with Table 3. Similarly to the mean surface level changes per land use class, this result does not match with expectations based on the literature review. Agricultural areas, orchards and infrastructure might be expected to have high subsidence rates due to compression caused by lower groundwater levels and oxidation on the one hand and surface loading on the other. It is however unexpected that forests have a mean surface level change that is not significantly different from these other land use classes. Additionally, because the causes of subsidence in agricultural areas are very different from those for infrastructure, it might be expected that these classes would also have high, but significantly different, mean surface level changes. This however does not seem to be the case.

Lastly, all other land use classes do have significantly different mean surface level changes, although the differences are in some cases quite small. That these smaller differences are still significant can be explained by the fact that these same classes have relatively low standard deviations, which combined with a large number of cases means smaller differences can be found to be significant. The fact that all other land use classes have significantly different mean surface level changes indicates that there is a relation between land use and subsidence in the research area, although the strength of that relation is not fully clear.

4.3 Model results

In order to identify the strength of the relation between land use and subsidence in the research area, predictor values where calculated for each land use type, as discussed in the Methodology chapter. Figure 14 shows a density scatterplot of these predictor values compared to the actual surface level changes, with the associated linear regression line. Each vertical line indicates a land use class with it's associated predictor value on the x-axis. Each pixel within the lines consists of a number of measurements from the validation dataset, with the density of these measurements displayed in the bar on the right and with the actual surface level change of each measurement displayed on the y-axis.

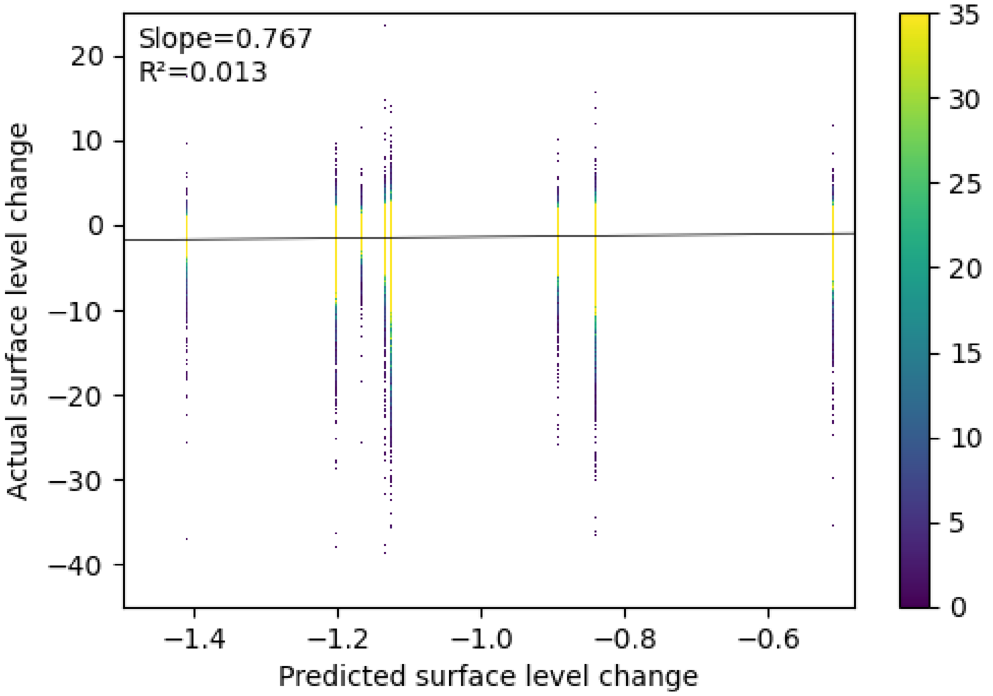

Figure 14: A density scatterplot of the predictor values and actual surface level change values, with the linear regression plotted as a line.

Using linear regression, the predictor values based on the eight reclassified land use classes of the LGN7 predicted the actual surface level changes to a very small but significant extent, R^2=0.013, $F(1, 337{,}760) = 4614$, $p < 0.01$. This indicates that land use has a very small but significant impact on subsidence. The regression values indicate that with every increase of 1 mm of the predictor value, the actual surface level increased by between 0.70 mm and 0.77 mm, depending on the statistic used to calculate the predictor value. Because of the way the predictor value is calculated, the expected increase would be one to one.

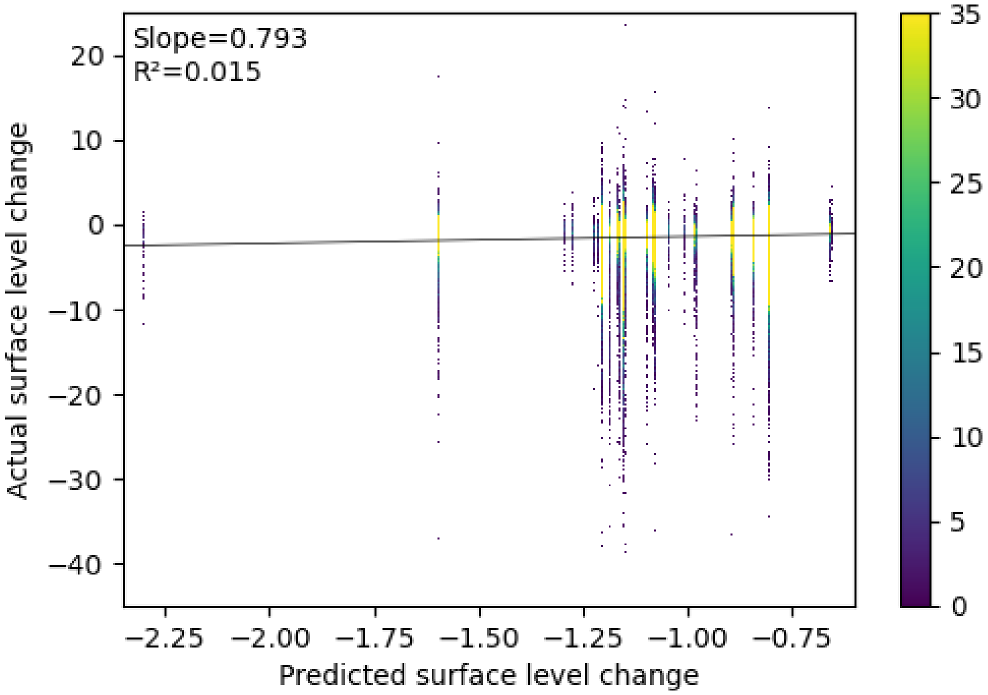

Figure 15: A density scatterplot of the predictor values based on non-reclassified LGN7 land use classes and actual surface level change values, with the linear regression plotted as a line.

Predictor values were also calculated using the original land use classes of the LGN. Using this alternative method to calculate the predictor values increased their prediction rate very slightly R^2=0.015, F(1, 337,750) = 5243, p < 0.01. This indicates that some of the land use classes that were aggregated into single classes have significantly different surface level changes and can therefore be used to predict actual surface level changes slightly better.

Figure 16 shows the spatial distribution of the predictor values compared to the measured surface level changes. As is seen in the density scatterplots, the measured values contain a lot of extremes that are ten to twenty times higher than the predictor values. This is of course to be expected due to the way the predictor values are calculated. The extremes clearly show why the prediction power of the predictor values is so low. The predictor values cannot accurately predict any of the more extreme actual surface level changes, which lowers the prediction power of the overall model. When looking closely at Figure 16, some small overlap can be seen between the predictor values and the actual surface level change values. For example some infrastructure has both higher predicted rates and measured rates when comparing it to the surrounding area. Where this can be distinguished, the measured rates are however significantly higher than the predicted rates.

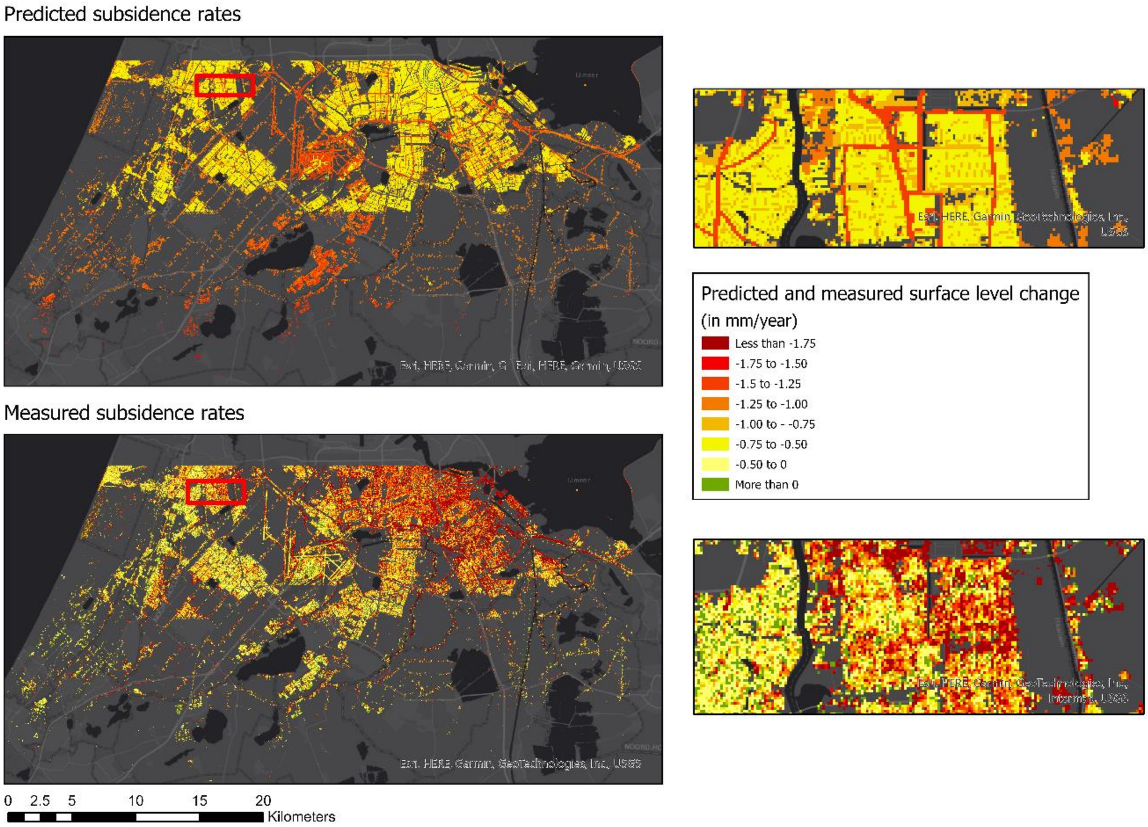

Figure 16: Comparison of predicted subsidence rates and actual subsidence rates.

5. Discussion

This chapter will discuss the interpretation of the results from the previous chapter, how these results relate to existing research and how the used methods for pre-processing and analysis may have influenced this.

5.1 Key findings

Based on the literature review a number of causes for subsidence were identified. These causes can be categorized as *en mass* subsidence on the one hand, and soil compaction on the other. *En mass* subsidence generally does not have a link with land use, with the exception of subsidence caused by mining and tunnelling operations. The most commonly identified causes for subsidence that are linked with land use are the lowering of groundwater levels and water extraction from aquifers. This can in turn cause shrinkage and oxidation, which causes subsidence. An additional driver linked to land use is compaction caused by loading of the surface, which happens when weight is put on top of the surface in the form of infrastructure and buildings.

A number of things stood out when looking at the spatial distribution of subsidence in the Randstad area. Firstly, subsidence rates seemed to differ significantly between urban areas. Some of these differences could potentially be explained by the subsurface soil types that these urban areas are built on, but even urban centres located in the same regions show some variation. Additionally the subsidence rates within urban centres varied wildly. Something else that stood out is that large infrastructure consistently shows high subsidence rates. Both train tracks and roads can be distinguished clearly by their more consistently high subsidence rates when compared to the surrounding areas. Lastly a cluster of high subsidence rates was identified in the area south of Zoetermeer, in the south-west of the research area. This area mainly contains greenhouses and some small urban areas. Interestingly this was contradicted by the results of the statistical analysis, which showed greenhouses and built-up areas to have some of the lowest overall subsidence rates in the research area. More interestingly even, when looking outside of the research area this cluster of high subsidence rates continues further south. Further research is required to identify the exact cause of increased subsidence in this area.

Both the analysis of variance and predictor value analysis indicated a link between land use and subsidence, although that link is very small. The land use classes with the highest mean subsidence rates were forests, orchards, agriculture and infrastructure. On the other hand the different built-up land use classes and greenhouses had the lowest mean subsidence rates, with subsidence rates slightly increasing for less dense built-up land use types. With the exception of infrastructure, these results seem to coincide with the expected backscatter consistencies and the coverage percentages of the different land use classes. Land use classes with lower backscatter consistencies and therefore lower coverage percentages, such as forests and agriculture, have higher mean subsidence rates, while land use classes with higher backscatter consistencies and therefore higher coverage percentage, such as built-up areas and greenhouses, have lower mean subsidence rates. This indicates that the differences in mean subsidence rates are likely to be caused by data quality issues rather than reflecting real differences between land use classes. As mentioned, infrastructure seems to be the exception, having both a relatively high coverage percentage and a high mean subsidence rate. Because of this, combined with the clear visual distinction of subsidence around infrastructure, it is unlikely that the high subsidence rates of infrastructure are due to data quality issues as well. This means that subsidence likely has a strong link with infrastructure in the research area.

A Welch test found a significant difference between the mean subsidence rates of the different land use classes and a Games-Howell post-hoc test indicated that the mean subsidence rates differed significantly between the majority of the land use classes. The only land use classes that did not have a significantly different mean were the classes with the highest mean subsidence rates discussed above. This seems to confirm further that differences in mean subsidence rates, at least for these classes, are at least partially caused by data quality issues. The predictor value analysis indicated that the predicted land subsidence values could be used to predict the actual subsidence values to a very small but significant extent, which confirms that there is a weak link between land use and subsidence. When the non-reclassified land use classes were used to calculate the predictor value, the prediction strength went up very slightly, indicating that some of the classes that were reclassified have significantly different subsidence levels and can therefore be used to predict subsidence slightly better.

5.2 Comparison with earlier research

These findings do not fully match with what would be expected based on previous research. The low subsidence rates of the different types of built-up areas are unexpected, since one of the identified causes of subsidence is compaction due to loading (Li et al., 2021; Stouthamer et al., 2020). An explanation for this might be the lower quantity and quality of measurements on non-hardened surfaces, but this would not explain why even dense built-up even has the lowest mean subsidence rate, when compared to the other built-up land use classes. Another explanation might be that subsidence in built-up areas varies greatly per city or even per neighbourhood. When looking at the spatial distribution of subsidence in built-up areas in the research area, both areas with high subsidence and with low subsidence or negative subsidence (an increase in surface level) were found. This may indicate that some other local factors are influencing to what extent loading causes subsidence in these areas.

Another unexpected result is that natural areas such as forests and open nature were identified as having a relatively high subsidence rate. The main identified cause for subsidence in the west of the Netherlands is oxidation caused by lowered groundwater levels (Candela et al., 2020; Cuenca & Hanssen, 2008), although long-term loading is identified to play a significant role as well (van Asselen et al., 2018). Natural areas are generally not connected to these drivers, since human activity in them is more limited. This might be explained by data quality issues. As discussed, the land use classes with higher mean subsidence rates overlap with the land use classes with worse backscatter consistency properties. Another explanation is potentially what Minderhoud et al. (2018) describe as "transboundary" subsidence, which is subsidence caused by activities in neighbouring areas with different land use types.

When comparing the results with those of Minderhoud et al. (2018), the paper that this research was based on, some differences stand out. Minderhoud et al. (2018) identify the strongest subsidence rates in urban areas and some specific types of agriculture. They however do not distinguish infrastructure in their land use classification. The results of the ANOVA are mainly similar, although Minderhoud et al. do not identify the same cluster of non-significant land use classes. As described, this cluster may be caused by data quality issues. The results of the predictor value analysis differ significantly. Where Minderhoud et al. (2018) find that they are able to predict between 65 and 92% of the subsidence in their research area based on the land use sequences, this research found only a very small but significant prediction rate with an R^2 value of between 0.013 and 0.015. This difference is likely due to multiple factors. Firstly, the research areas differ quite significantly, which likely has a large impact on the final results. Previous research has shown a large impact of groundwater use and groundwater levels on subsidence rates in south-east Asia (Andaryani et al., 2019; Du et al., 2018; C. Zhou et al., 2017). The Dutch delta, however, differs significantly from other deltas in the world (Koster, Stafleu, & Stouthamer, 2018). Another explanation of the different results can be found in changes that had to be made to the methodology proposed by Minderhoud et al. (2018) due to data limitations. Instead of using land use objects, a dataset with individual land use cells was used. Additionally the subsidence dataset for this research had to be extensively pre-processed for use, whereas Minderhoud et al. made use of a premade subsidence dataset. Lastly, this research had to use single land use classes instead of land use sequences due to the large differences in classification methods between the versions of the LGN dataset. Minderhoud et al. (2018) specifically identify a certain time-lag effect between changes in land use and subsidence rates in their research area and indicate that their prediction model greatly improved when using the land use sequences.

5.3 Limitations

Due to the unique circumstances of subsidence in the Dutch delta (Koster, Stafleu, Cohen, et al., 2018), this research should only be applied to areas with similar conditions. The used methods will likely result in incorrect results in areas that do not mainly consist of soft soils or areas that contain underground mining or gas extraction

The choices made during pre-processing and the analysis, which were necessary due to restrictions of the available data, should however also be taken into account when looking at the results of this research. As described, the choice was made to aggregate the subsidence measurements. This reduced the spatial autocorrelation of the data slightly, and was necessary to speed up analysis due to the large size of the dataset. It did, however, mean that the land use classes with lower amounts of measurements due to worse backscatter consistencies ended up having disproportionately more extreme values. The impact of this could have been reduced by only selecting gridcells with a number of minimum measurements for the analysis. Some initial statistical analysis did however not show very significant differences and due to time constraints this alternative was dropped. An alternative approach could also have been to keep the data at measurement point level and identify for each measurement point in what type of land use class it was located. This would however have required significantly more computing time and power. The data would also have had to be corrected for the very high spatial autocorrelation levels of the data.

Even after aggregating the subsidence data, a high amount of spatial autocorrelation was still present. In the analysis the spatial autocorrelation was not controlled further due to time constraints. This, however, means that the ANOVA results may have been overestimated. The differences that were found however, were highly significant, which means that the results would likely be at least similar if spatial autocorrelation was further controlled for.

5.4 Recommendations

Future research could improve on the analysis in this research and additional research is required to confirm the more uncertain observations that were found. A first step to confirm the results of this thesis is to perform the analysis without aggregating the subsidence measurements to a raster. Using the individual measurements would reduce the unequal distribution of extreme values caused by low numbers of measurements per gridcell. This combined with an analysis taking into account spatial autocorrelation would be able to confirm or reject the more uncertain conclusions from this thesis. Alternatively, a land use dataset which includes land use objects and better land use change data could be used to more closely resemble the proposed analysis from the original paper that this analysis was based on.

Based on the results of this thesis, recommendations can also be made. The clear relation between infrastructure and high subsidence rates should be investigated on a more local level and local governments should take this into account when building new infrastructure. More research is required in order to identify how built-up areas relate to subsidence and what is the cause of the large differences between different cities and built-up areas. Furthermore, the clear seasonality of subsidence measurements in some areas should be investigated further and needs to be taken into account in further research on this topic.

Despite a number of limitations, this research has found a clear and significant, if very weak link between land use and subsidence in the Randstad area in the Netherlands. This link may help inform policy makers when planning future spatial development in order to reduce the large negative effects of subsidence. Further research will be needed on the exact relation of subsidence and land use in order to effectively prevent the negative effects of subsidence in the future.

6. Conclusion

The objective of this thesis has been to identify how subsidence is linked to land use, how subsidence is spatially distributed in the Randstad area in the Netherlands and to what extent a relation exists between subsidence and land use in this area. The main link between land use and subsidence as identified in previous research is threefold. Firstly, a large contributor to subsidence is identified as mining and gas extraction. This contributor, however, cannot easily be identified as a cause for subsidence when looking at surface-level land use, since underground mining operations can overlap with multiple surface land use types. The other identified links between land use and subsidence form an indirect relationship, with certain land use types having characteristics which cause subsidence. One of these is the link between land use and groundwater level control. When groundwater levels are lowered, often through anthropogenic causes, the processes of compaction and oxidation take place. The other is the link between land use and surface loading, caused by buildings and infrastructure. Both these processes take place individually or can combine to cause subsidence.

The spatial distribution of this subsidence in the Dutch Randstad area is mainly clustered around some built-up areas such as Amsterdam, although built-up areas do not consistently show higher subsidence rates. Consistently high subsidence can, however, be found around large scale infrastructure. Additionally, high subsidence rates were observed in of the research area, for which the causes are as of yet unknown.

Based on a combination of ANOVA and a method proposed by earlier research, which makes use of a training and validation separation in the dataset which are used to calculate predicted subsidence rates based on land use classes in order to perform a linear regression analysis, a weak but significant relation was found between land use and subsidence. The analyses indicated that a strong link likely exists between infrastructure and subsidence rates in the research area. A link between built-up areas and subsidence is likely to be influenced by unknown local factors, and the impact of built-up areas on subsidence seems to be lower than that of other land use classes. Based on existing research and on the results of this thesis, agriculture likely has a strong link with subsidence as well. This could, however, not be fully confirmed due to uncertainty in the available data. Further research is therefore needed to identify to what extent the differences in subsidence rates found for other land use classes reflect the real situation in the research area.

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Appendix I: LGN reclassification

LGN class values	LGN classes	Reclassified class values	Reclassified class names
16	Fresh water	-999	Water
17	Salt water	-999	Water
1	Agricultural grass	1	Agricultural crops
2	Corn	1	Agricultural crops
3	Potatoes	1	Agricultural crops
4	Beets	1	Agricultural crops
5	Grains	1	Agricultural crops
6	Other crops	1	Agricultural crops
10	Flower bulbs	1	Agricultural crops
9	Orchards	2	Orchards
61	Tree nurseries	2	Orchards
62	Fruit farms	2	Orchards
8	Greenhouses	3	Greenhouses
11	Deciduous forest	4	Forest
12	Coniferous forest	4	Forest
26	Built-up in the countryside	5	Open Built-up
18	Buildings in primary built-up areas	6	Dense Built-up
19	Buildings in secondary built-up areas	6	Dense Built-up
20	Forest in primary built-up areas	7	Open and green in built-up areas
22	Forest in secondary built-up areas	7	Open and green in built-up areas
23	Grass in primary built-up areas	7	Open and green in built-up areas
24	Bare ground in primary built-up areas	7	Open and green in built-up areas
27	Other land use in the countryside	7	Open and green in built-up areas
28	Grass in secondary built-up areas	7	Open and green in built-up areas
25	Main roads and railways	8	Infrastructure
30	Salt marches (kwelders)	9	Open nature
31	Open sand in coastal areas	9	Open nature
32	Dunes with low vegetation (<1m)	9	Open nature
33	Dunes with high vegetation (>1m)	9	Open nature
34	Dune heaths	9	Open nature
35	Open drift sand and/or river sand	9	Open nature
36	Heath	9	Open nature
37	Moderately grassy heath	9	Open nature
38	Strongly grassy heath	9	Open nature
39	Raised bog	9	Open nature
40	Forest in raised bog	9	Open nature

41	Other swamp vegetation	9	Open nature
42	Reed vegetation	9	Open nature
43	Forest in swamps	9	Open nature
45	Natural grasslands	9	Open nature
46	Grass in ccoastal areas	9	Open nature
47	Other grass	9	Open nature
321	Shrub vegetation in raised bog (low)	9	Open nature
322	Shrub vegetation in swamps (low)	9	Open nature
323	Other shrub vegetation (low)	9	Open nature
331	Shrub vegetation in raised bog (high)	9	Open nature
332	Shrub vegetation in swamps (high)	9	Open nature
333	Other shrub vegetation (high)	9	Open nature

Appendix II: Non-reclassified LGN7 land use map

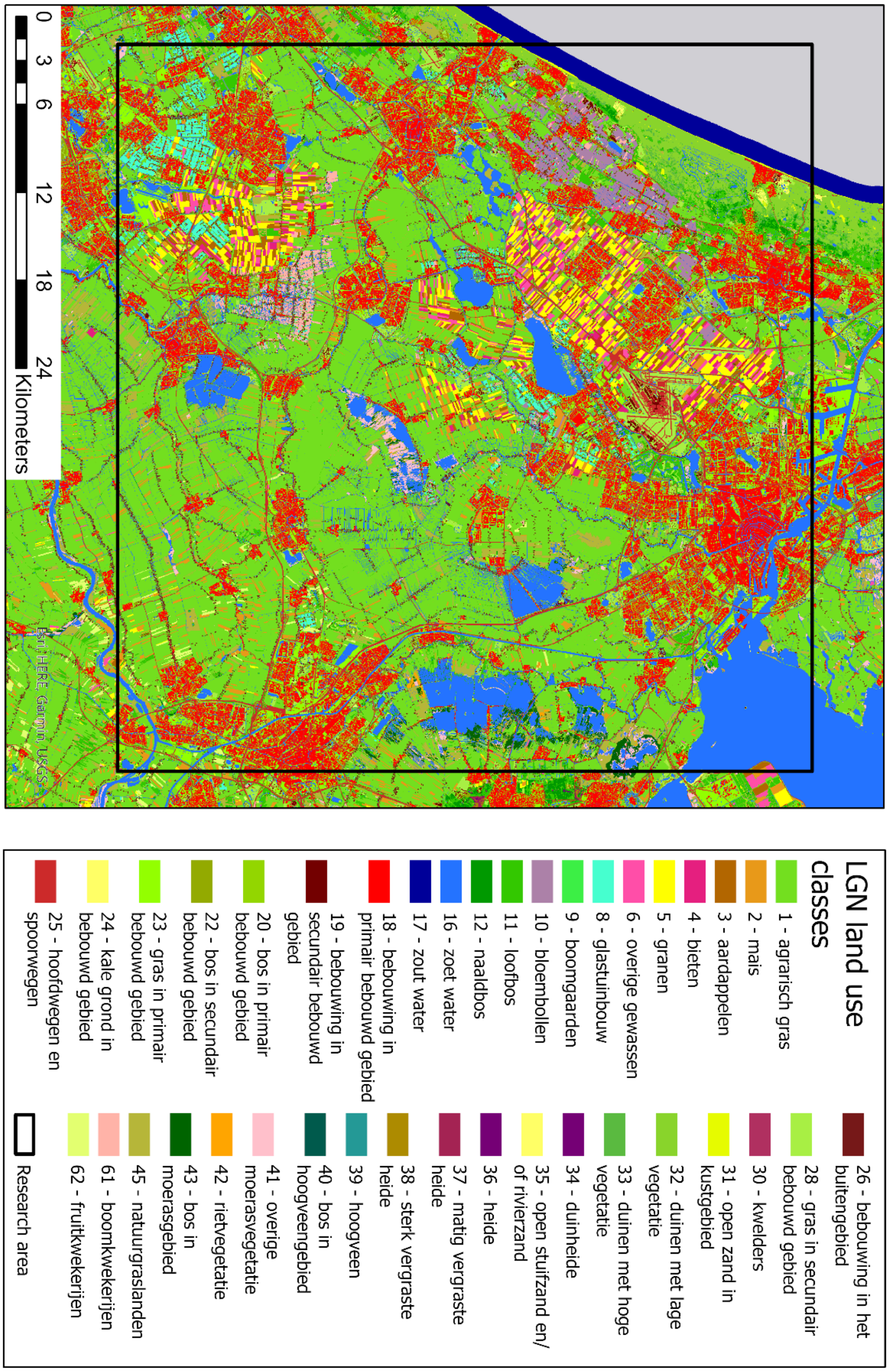

Figure 17: Non-reclassified LGN7 land use distribution in the research area

Appendix III: Enlarged map of the spatial distribution of subsidence

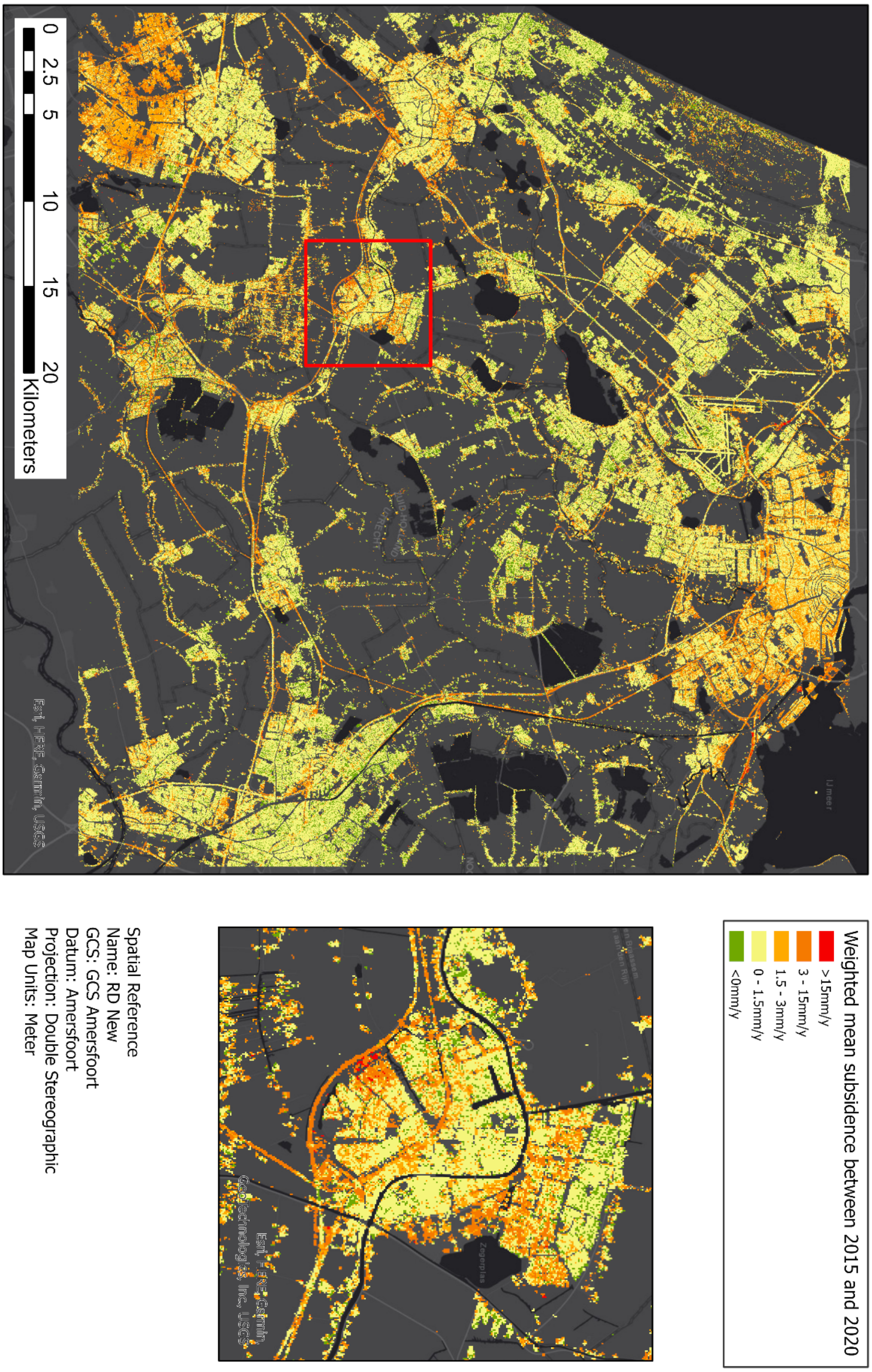

Figure 18: Enlarged overview of the spatial distribution of subsidence in the research

Appendix IV: Spatial distribution maps of subsidence in areas of interest

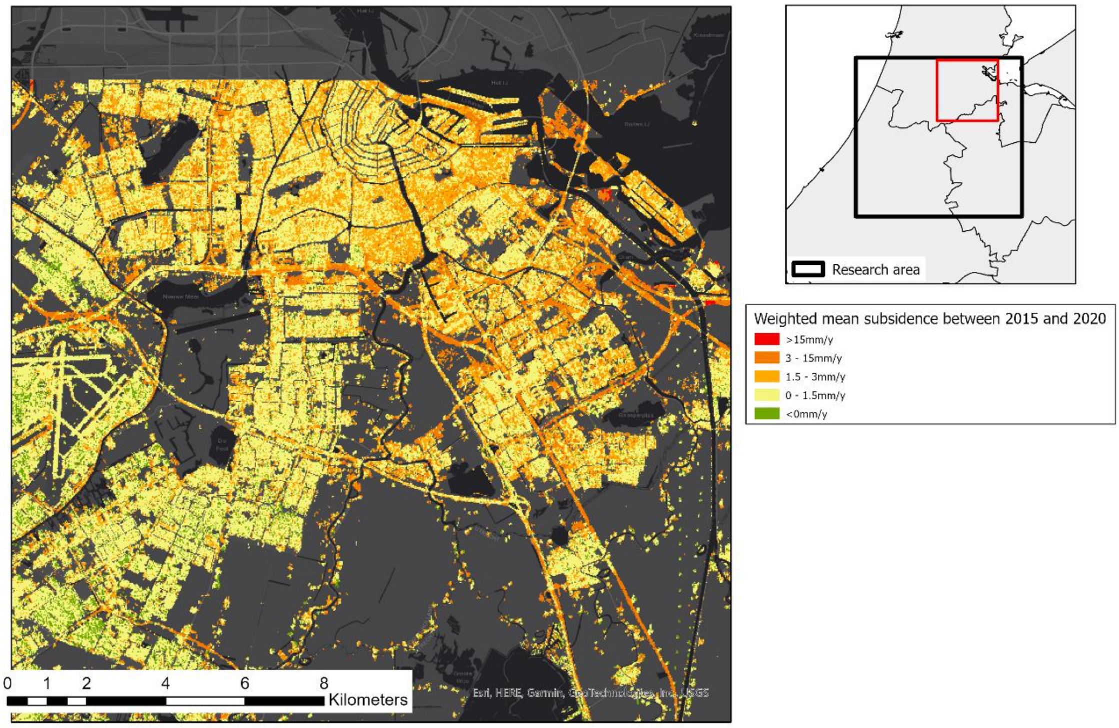

Figure 19: An overview of the spatial distribution of subsidence in the area of interest Amsterdam

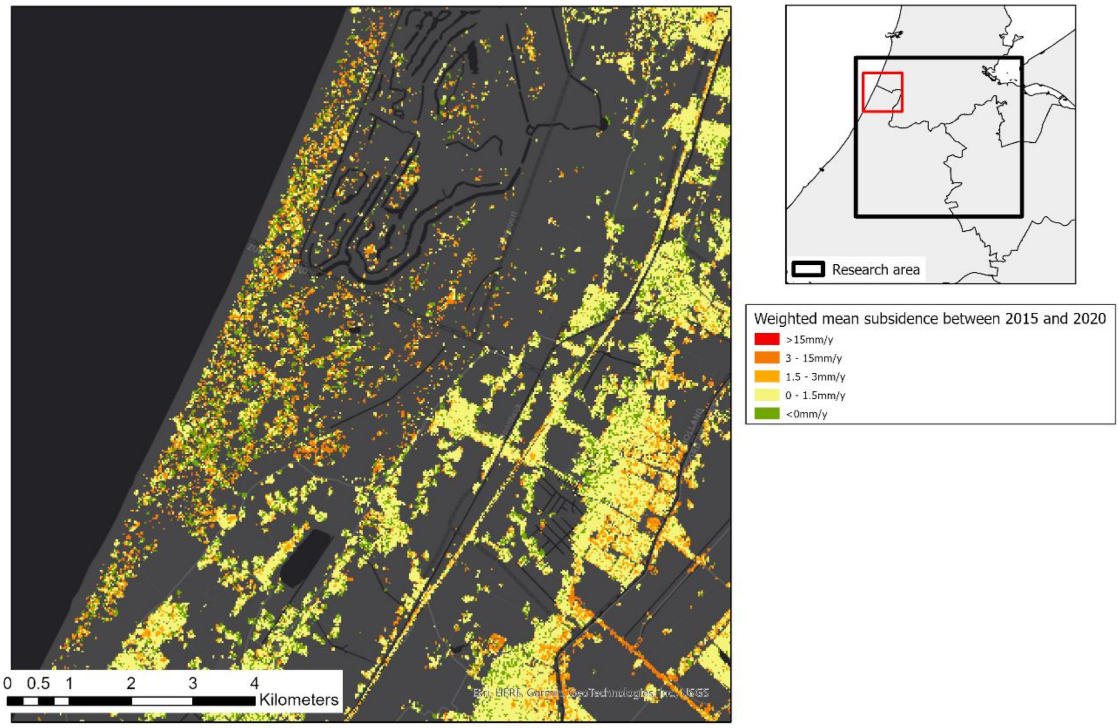

Figure 20: An overview of the spatial distribution of subsidence in the area of interest Zandvoort

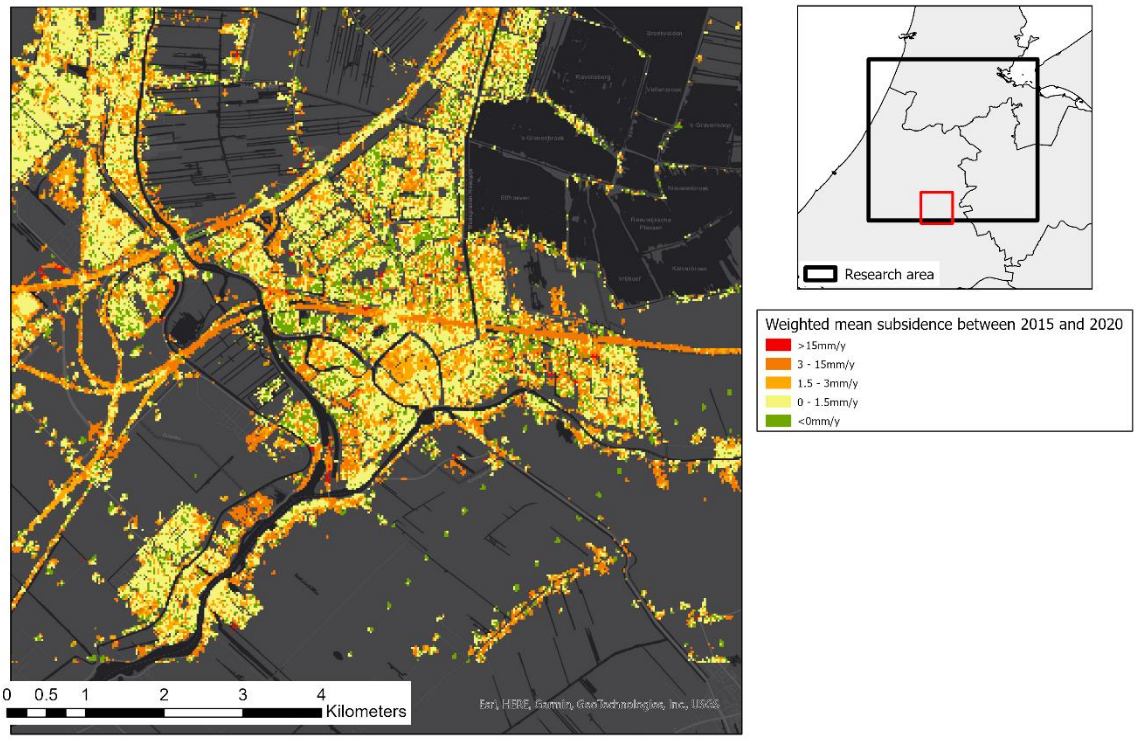

Figure 21: An overview of the spatial distribution of subsidence in the area of interest Gouda

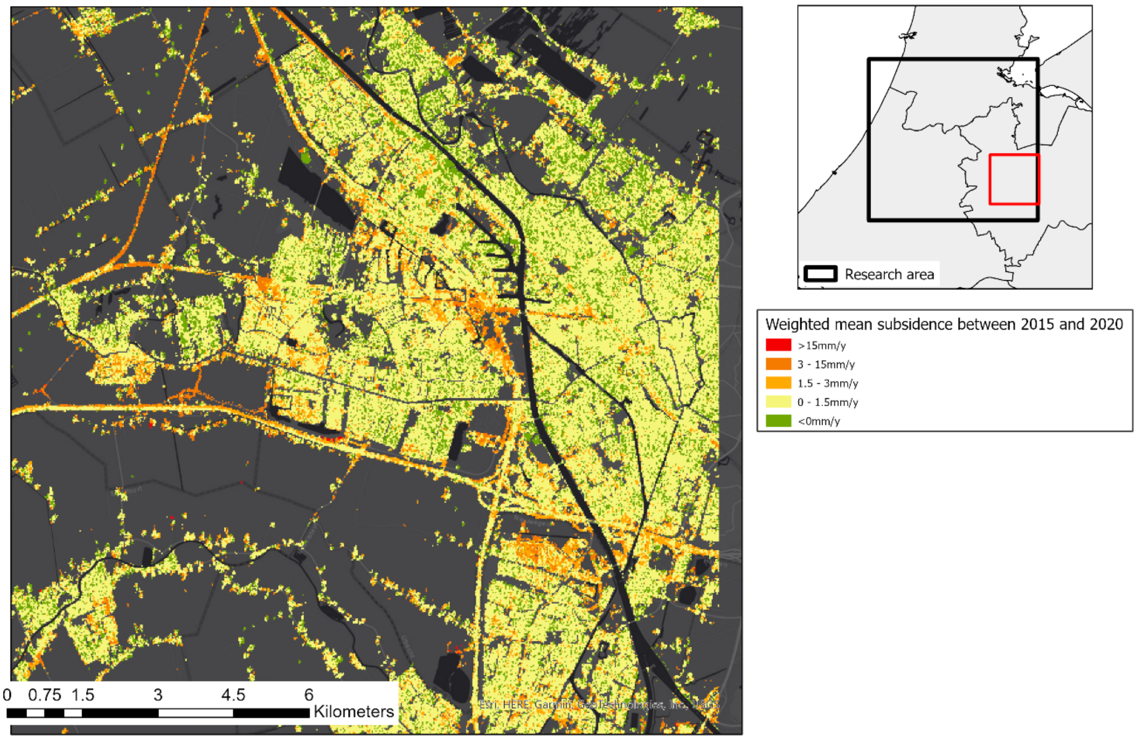

Figure 22: An overview of the spatial distribution of subsidence in the area of interest Utrecht

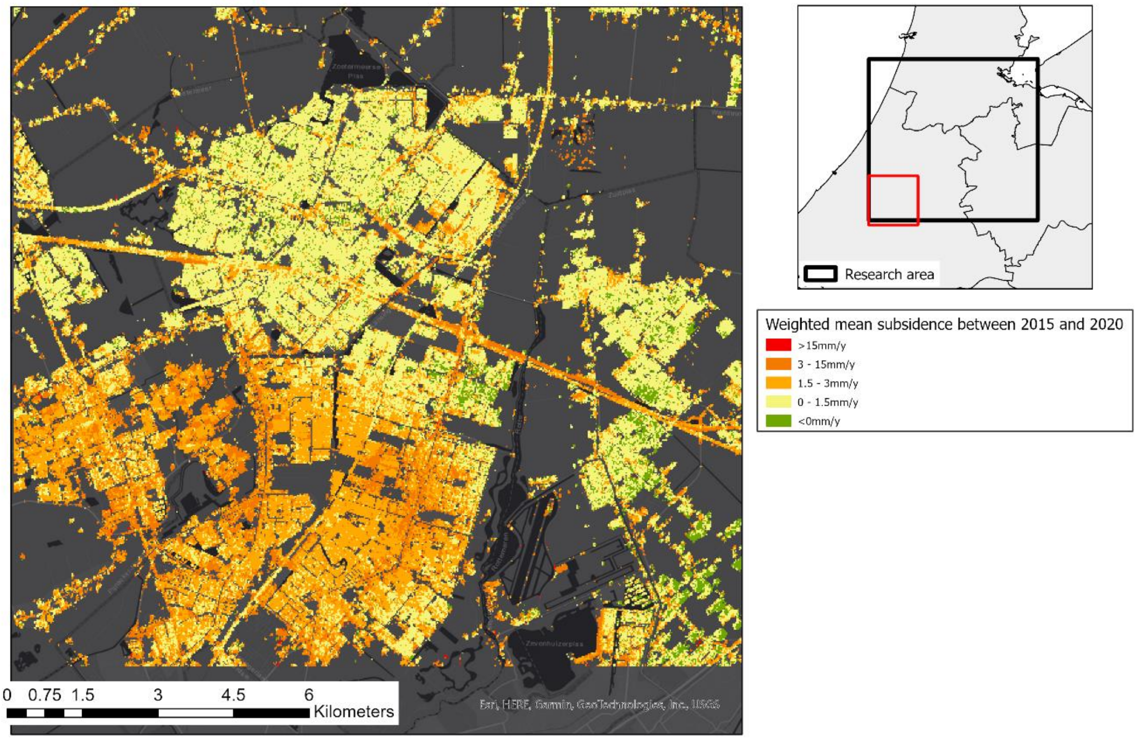

Figure 23: An overview of the spatial distribution of subsidence in the area of interest Zoetermeer