Estimating ground surface motion from historical maps

A case study in the Zuid-Limburg mining area from 1914 till 1974

Tijs J. Lips
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by

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This thesis is confidential and cannot be made public until June 13, 2016.

An electronic version of this thesis is available at http://repository.tudelft.nl/.

TU Delft
Preface

This document is the final report of a study on ground surface motion in the Zuid-Limburg mining area, which is commissioned by the Geoscience and Remote Sensing department of the TU Delft and supervised by dr.ir. Hans van der Marel. This thesis and research is performed to obtain the degree of Master of Science at the Delft University of Technology as a part of the Geoscience and Remote Sensing program. To get insight on the environmental effects of coal mining activities in Zuid-Limburg, a study is initiated and coordinated by The Dutch State Supervision of Mines (SodM) and managed by IHS. This study focussed on the ground surface heave after closing of the mines due to rising mine water. During this study it became apparent that the full extent of surface subsidence during the mining activities was not fully known. This lack of knowledge became the main driver for this study: can we determine ground surface motion from historical analogue maps?

Quality of some figures in this document could not be improved. For this reason a CD is included, which contains higher resolution images of some figures used throughout the thesis.

Tijs J. Lips and Hans van der Marel
June 15, 2016
Summary

This study shows how historical topographic maps of the Zuid-Limburg mining area can be used to estimate the effects of mining activities on vertical ground surface motion. Coal has been the most important energy supplier for the Netherlands from the 19th century until the discovery of the large Slochteren gas field. After 1960, mining of coal was rapidly reduced until the last mine finally shut down in 1974. In the study Na-ijlende gevolgen steenkolenwinning Zuid-Limburg it became clear that the full extent of vertical ground surface subsidence, which happened during the active mining period, was not fully known. Since the available data on ground motion only covers a part of the mining area or is handwritten of which digitizing would be a gigantic undertaking, the question arose: "is it possible to infer vertical ground motion from historical maps?"

The available historical maps, historical measurement techniques, georeferencing, data extraction methods, spatio-temporal modelling, integration of multiple datasets, and the accuracy (uncertainty) of all processing steps were all investigated. The study shows that sampling contourlines from maps is best practiced by sampling along specifically chosen transects. 2D profiles and 3D maps are created from the datasets showing the estimated ground surface motion over the period 1918-1955 and 1955-1977. Overall, subsidence occurred mainly between 1918 – 1955, and much less between 1955 – 1977, which is also what we expected. The final results showed that subsidence in the area around Heerlen occurred within the [0, -10] metre range, with values closest to zero stretching from south-west of Heerlen to east of Heerlen. However, at some locations large variations in estimated height changes occurred as a result of errors made in field measurements and interpolation, as well as changes in the landscape. The profile method showed to have great potential and worked well, but results should be interpreted with great care for these reasons.
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Introduction

The goal of this introduction chapter is to give insight on the background of this study, which includes a brief description of the main objectives of this study, a history review on coal mining in the Netherlands, an introduction on geophysical effects of mining activities before and after mine closure, the relevance of the conducted study, and a geographical overview of the area of interest. This Chapter is closed off by the research questions. The structure of this chapter follows this outline.

Figure 1.1: Mineworker at work in the Domaniale Mijn near Kerkrade - W. Jongma, Collectie de Staatsmijnen. Wooden struts prevented the tunnels to collapse, but made it sometimes difficult to work efficiently. Thicker coal layers made it possible to work in almost upright position, whereas a mine worker was forced to kneeling position in thin layers.

1.1. Main objectives

This study aims to show how historical maps of the Zuid-Limburg mining area can be used to estimate the effects of mining activities on vertical ground surface motion. The main motivation for this study was the study Na-ijlende gevolgen steenkolenwinning Zuid-Limburg, which looked into the effects of coal mining after mine closure in 1974, including geological and hydrogeological effects [13]. In this study it became clear that the full extent of vertical ground surface subsidence, which happened during the active mining period, was not fully known. Although a lot of levelling data was collected during this period, this data is only available in analogue form and handwritten. The best known source of surface deformation during the active mining period is from a publication by Bekenkamp and Pöttgens [5]. Furthermore, this publication only covers part of the area where mining took place. Since it is not known if the
available analogue levelling data cover the missing areas, and also because digitizing all hand-written data would be a gigantic undertaking, the question arose "is it possible to infer vertical ground motion from historic maps?". In order for us to estimate vertical ground surface motion from historic maps, research was done on available data (Chapter 2), georeferencing (Chapter 3), data extraction methods (Chapter 4), spatio-temporal modelling (Chapter 5), integration of multiple datasets (Chapter 7), and the accuracy (uncertainty) of all processing steps. It was chosen to present results throughout the Chapters. Some additional figures or equations are presented in the separate Appendices.

1.2. Coal mining history of the Netherlands

Coal has been the most important energy supplier for the Netherlands from the 19th century until the discovery of the large Slochteren gasfield in 1957 and started to produce in 1960 [6]. After 1960, mining of coal was rapidly reduced until the last mine finally shut down in 1974.

Romans where the first to start mining for rocks in the Zuid-Limburg surface. Silesian limestones and sandstones (with embedded coal) where used as a building stone which had reached the surface due to tectonic uplift [30] [39]. Wood was the only energy supply for the Netherlands until the 12th century when the first coal layers were discovered in Kalkulen, which name is a predecessor of the Dutch word kolenkuil [11]. Coal initially only used by the poor. As soon as the woods in the area became more scarce from logging, a long transition from wood to coal as main energy supply started. From the 13th century the first larger scale coal mining activities started around Kerkrade in the Wormdal. Only the coal layers that had reached the surface were mined (simple pit-mining), but soon these upper coal layers were all depleted [11].

Later from the 14th century, the more technical challenging subsurface mining started to be established [38]. From then on, until halfway the 19th century, the industry grew to approximately 500 up to 700 mine workers [11] [20]. New technological developments in the 19th century, such as a renovated railway network to Zuid-Limburg (1853) [11], made it possible to expand production and fulfil the increasing need for coal as a result of industrialisation. Despite the harsh conditions in the mines, over one-third of the Limburg working population became directly or indirectly dependant on the mines, with up to 60,000 underground mine workers at its peak [20]. The Oranje-Nassau concession was the largest private concession which started production in 1899 [38] [39]. Later in the first decade of the 20th century the state started to incorporate in mining by collectivisation of new concessions, which resulted in an increase of annual production from 4 [Mt] to 13 [Mt] between 1920 and 1930, and a more or less stable production between 13 and 14 [Mt] until 1965 [4][6] [39]. The coal production per year between intensification of coal production around 1914 till last mine closure (1974) is plotted in Figure 1.2. The peak production value is 14.5 [Mt] around 1937, and the local minimum around 1945 is due to World War II.

Discovery of the large gasfield in Slochteren in 1960 together with cheap imported coal form the United States diminished the importance of coal production in the Netherlands [6] [11]. Under provision of Minister of Economic Affairs J. den Uyl the state put coal production in state owned mines on hold between 1963 and 1973, and also the private Oranje-Nassau mine shut down at last in 1974 [38].

1.3. Local effects of mining activities before mine closure

Previous studies have shown effects of coal extraction in the Zuid-Limburg area on ground surface motion [5] [32]. The most interesting and important effect is vertical motion of the surface. Mining activities and with that pumping of mine water caused subsidence (downward movement) of the land surface of several meters in the mining district. Bekendam and Pöttgens studied these effects which resulted in a 2.5-D deformation map as shown in figure 1.3.

The map in figure 1.3 shows subsidence with a maximum of 10 meters on a 2.5 meter interval scale. Deformation of the area was measured by levelling, following transects through the area. Due to the large interval scale of the deformation, the 'holes' of data in the map, and simple deformation contours, this map only gives a very rough picture of effects of mining in the area. A better insight in the 'historic' movements of the surface helps better understand
1.4. Local effects of mining activities after mine closure

After 1974 pumping of mine water continued to prevent operating German mines to flood. As from 1994 also the German mines nearby Zuid-Limburg shut down and then also mine water control was eventually suspended [25]. Suspension of pumping leads to underground water level rise and the effects on ground surface motion are estimated around several decimetres.
uplift [13]. Surface uplift is one of the multiple effects that have been studied by the study Na-ijlende gevolgen steenkolenwinning Zuid-Limburg [13]. The studied effects are:

1. Surface uplift
2. Water pollution
3. Water level rise
4. Local subsidence, sinkholes
5. Earthquakes
6. (Mine gas release)

Safety of local civilians is the main reason that research on ground surface motion is necessary. In Heerlen a shopping mall had almost collapsed due to local subsidence in 2013\(^1\). Similar effects are shown near gas extraction locations in Groningen, were houses are at risk of collapsing due subsidence and earthquakes\(^2\). Since many concessions of the Zuid-Limburg mining industry were owned by the Dutch state, politics are also involved as the state is responsible for damages incurred by mining activities. Consequently, SodM initiated a pre-study in 2015 [25] to summarize all expected and known recent effects on land surface and hydrology. The enumerated effects are investigated by IHS and TU Delft among others. Focus of TU Delft is on surface uplift of which some results will be integrated in the historical ground motion results from this study.

The focus of this study is on geophysical effects linked to the mining activities, but also the economic and sociological effects are worth to mention briefly. As noted in the coal mining history (section 1.2), one-third of the Limburg population was directly or indirectly financially dependant on the mines which equals approximately 300.000 people. Economic growth in the region was also strictly linked to mining [11], and closure resulted in highest unemployment percentage in the Netherlands in 1978 [7]. Furthermore, health problems were a result of the bad underground working conditions. The phenomenon of pneumoconiosis (e.g. silicosis) is a well know lung disease mineworkers faced [19].

1.5. Study relevance

Firstly, the effects of mining in Zuid-Limburg are still measurable and have effect on the landscape, infrastructure, and people’s health. This makes the full study (this and the study on Na-ijlende gevolgen [13]) highly important for decision makers and inhabitants of the affected area. The relation between the Zuid-Limburg mining area and the Groningen gas field has been mentioned before, as both regions suffer or have suffered from natural effects of compaction in a large scale area. The question in both cases is who is responsible for damage, and to what level is damage caused by mining resources? A study on all effects correlated to mining activities will help better answer these questions.

Secondly, a little is yet known about the ground surface motion in the mining area, especially around Heerlen. The coarse map from Pöttgens and the white area invite for further research in this subject. Its fundamental value to the study on effects after mine closure should be noted here. The relation of rising mine water and uplift of the ground is not enough to prove causality, but the historic nature of this study can show that ground surface motion changed over time from the beginning of mining, to mine closure and after mine closure.

Finally, the subject of mining in Zuid-Limburg is still vivid in the ‘mining’ generation in the region. Speaking with people from the area easily leads to this subject and stories about the mines are plentiful.

\(^1\)www.11.nl/nieuws/209194-meest-waarschijnlijke-oorzaak-verzakking-t-loon-mijnbouw
\(^2\)www.rtvnoord.nl/artikel/artikel.asp?p=146070
1.6. Area of interest

It is fundamental to understand the geographical characteristics of the area to obtain reliable results, put context to the study and to give directions in processing. This section is divided into subsections related to geographical aspects of Zuid-Limburg including: Geology and Topography. Texts of the subsections are intermittently based on literature from Berendsen (2008) [6] and De Bosatlas van Nederland (2007) [4].

1.6.1. Geology

Special attention will be paid to the geological settings from the Carboniferous period and sediments from the Cenozoic era. The layers of coal in Zuid-Limburg date from the Late Carboniferous, which is the most recent second epoch of the carboniferous (approximately 318 till 299 Ma). In this epoch the global sea-level was subject to a decrease (regression) resulting in a deltaic setting with lagoons around the current position of Zuid-Limburg. Peat was able to form due to the warm climate where plants were able to grow and conserved in the fresh water lagoons. After the period of regression, marine influence increased and the formation of peat was terminated. 300 million years of pressure and heat, peat has transformed into minerals that we use as a resource for human energy supply, such as lignite (brown coal) and coal.

In the periods after the Carboniferous, most of the geological settings present in the upper layers are from the Cenozoic era. Eolic sediments such loess are found in the upper layers of Zuid-Limburg, which is result of the periglacial conditions in the Pleistocene. The loess sand covers the Carboniferous settings and also the less thick Cretaceous limestone layers. The sequence of layers is schematically drawn by the NAM as shown in Figure 1.4. Nevertheless, some carbon layers in the Zuid-Limburg area exposed the surface (see section 1.2) and were still near surface and resourceful during the intensified mining activities. The exposure and near-surface appearance of carbon layers is a result of the Variscan orogeny in the Devonian epoch, which started around 380 Ma and continued till the Early Carboniferous. This event occurred due to collision of Gondwana and Laurasia and had its effect on the geological structure of the Zuid-Limburg area: mountainous areas such as the Ardennes and Eiffel were formed and faulting occurred in the Zuid-Limburg underground. Nowadays, these faults are still visible and active and are the basis for so called horst and graben structures. The relative movements of both subsidence (graben) and uplift (horst) created a discontinuity of geologic settings and erosion on the top layers of the horst. This explains how carbon is found near the surface in Zuid-Limburg. In Figure 1.5 the position of the Feldbiss fault is shown, which is the main fault zone that separates the Roerdalslenk (graben) on the north-side and the Kempenblok (horst) on the south-side. The main mine shafts (green dots on the map) are almost all located on the south-side of the Feldbiss fault, as the coal layers are here closest to the surface.

1.6.2. Topography

Figure 1.6 is based on Figure 1.3, but now with the location of mine shafts and concession borders with respect to the pre-estimated subsidence in Zuid-Limburg.
The relation between the appearance of subsidence and position of mine shafts is seen quickly by first inspection of the map. For example, in the Emma concession most of the subsidence has occurred between the mine shafts. The white area around Heerlen has no data, but from the hypothesis of the relation between subsidence and position of mine shafts it is logical to research ground surface motion in this area too. In the example map only the largest cities in the area are shown, but many smaller towns are located throughout the area. The importance of this research is therefore not only for the people living in Heerlen, but also for villagers around Heerlen.
1.7. Research questions

The research questions in this section will be used as a guideline for the rest of this study. In the Conclusions Chapter in section 9 the questions are noted again with summarized answers that are found throughout the study. The main research question is reformulated from the graduation proposal [24]:

"How can the historic 4D ground surface motion in the mining region of Zuid-Limburg be modelled from analogue topography maps and integrated with data from modern techniques?"

The main research question was reformulated to emphasize the modelling and data integration part of the study for it will contain the largest part of the study. Sub-questions are formulated in the graduation proposal [24] as:

1. For each of the data sources/techniques:
   - What is the availability in time and space of the data?
   - What is the reference frame of the data?
   - What is the accuracy of the data?

2. How can the data of the different techniques be integrated?

3. Which spatio-temporal modelling technique is appropriate to integrate the results from different measurement techniques and describe 4D ground surface motion?

4. How to separate between outliers in the measurements and anomalous, and therefore by definition interesting, surface motion?

5. How can the results be optimally visualized in a 4D model?
Historical and modern data

The fundamental ingredients for this study are the historical topographic maps of Zuid-Limburg which are produced during active mining in the 20th century. These maps are further referred briefly as historical maps. Other important data ingredients are modern data sources that provide information about elevation or ground surface motion over a recent period. The historical information on elevation will be derived from historical maps, due to the absence of original survey data. This chapter will focus on the availability of data and their characteristics in uniqueness, elevation measurement techniques and position in time.

2.1. Historical elevation data

Elevation is presented on historical maps by contourlines and sometimes single point-measurements. An example of an historical map is shown in the snippet of the 1925 map in Figure 2.1. Contourlines are the reddish isolines that connect equal heights by a line. The historical maps used in this study have contourlines every 2.5 meter interval, and corresponding height is indicated along the lines. Point-measurements are mostly taken and represented at local summits and local lowest points [3], and are visualized on maps by a decimal number and an arrow or point at the measurement location. The individual value of these two data types in estimating ground surface motion will be further studied throughout this thesis.

2.2. Available data

Available maps and some details on their specifications will be listed here. The overview in Table 2.1 will be referred to throughout the document and also serves as a guideline in the nomenclature of maps and other data that is used in this thesis. The first column in Table 2.1 shows the name that is given to data derived from the release date of the map. Instead of choosing a name for each map that is derived from the year of survey, the release date was chosen due to uncertainty in the exact year of some surveys. The latter can be directly seen.
in column two, where the year of measurement is given. The measurement column refers to year of field survey, when elevation measurements where taken according to the corresponding map information. For 1925 and 1979 it is unknown when the measurements of elevation were exactly taken, as it has not been indicated on the maps.

Table 2.1: Historical map availability of the Zuid-Limburg mining area. The columns represent respectively the map code by the Kadaster with release year, the years of survey when height measurements were taken, measurement technique or tools, and the uniqueness of the elevation data where No means not unique and Yes means unique elevation data.

<table>
<thead>
<tr>
<th>Map code (year)</th>
<th>Measurement [YR]</th>
<th>Measurement technique</th>
<th>Uniqueness</th>
</tr>
</thead>
<tbody>
<tr>
<td>b759 + b763 (1925)</td>
<td>Unknown</td>
<td>Theodolites and Tachymetres</td>
<td>Yes</td>
</tr>
<tr>
<td>b763 (1937)</td>
<td>1918-1919</td>
<td>Theodolites and Tachymetres</td>
<td>No</td>
</tr>
<tr>
<td>62B (1955)</td>
<td>1918-1923</td>
<td>Theodolites and Tachymetres</td>
<td>No</td>
</tr>
<tr>
<td>60D + 62B (1960)</td>
<td>1955</td>
<td>Photogrammetry</td>
<td>Yes</td>
</tr>
<tr>
<td>62B (1968)</td>
<td>1955</td>
<td>Photogrammetry</td>
<td>No</td>
</tr>
<tr>
<td>62B (1979)</td>
<td>Unknown</td>
<td>Photogrammetry</td>
<td>Yes</td>
</tr>
<tr>
<td>62B (1989)</td>
<td>1986</td>
<td>Photogrammetry</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Each map in table 2.1 was downloaded as a digital non-georeferenced raster file from the Kadaster. The map codes correspond to the ones used by the Kadaster, but in this study the year of release date is chosen to refer to a certain map.

A small background study was done to determine the years of field survey for the 1925 and 1979 map. Since they are not mentioned on the map and not available by the Kadaster, the elevation data on the maps are compared. From visual interpretation, elevation data on the 1925, 1937, and 1955 maps show to be equal. This was done by stacking the three map on top of eachother in GIS-software, and then by changing transparency of the maps. Elevation on the 1955 map seems to be a direct generalised derivative of the 1925 and 1937 contourlines, as it shows less details. The same method was performed for the 1979 map, but no significant similarities were found with the other maps. Although information on the 1925, 1937, and 1955 maps do not comply (see Figure 2.2), years of measurement from these three maps are assumed to be 1918/1919 throughout the rest of this study. Uniqueness in column 4 of Table 2.1 is based on the elevation data comparisons.

Although the main focus of this study is on ground surface motion in the period of historical data, modern data can be used for validation and comparison purposes. In the following table (2.2) the used modern elevation data is listed, which shows over when measurements were taken, which measurement technique was used, and from which source the data was gathered.
2.3. Time frame

Table 2.2: Modern elevation data availability of the Zuid-Limburg mining area. The columns represent respectively the name of the dataset, the years of measurements, measurement technique, and the source of the data.

<table>
<thead>
<tr>
<th>Name</th>
<th>Measurement [YR]</th>
<th>Measurement technique</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>TOPhoogteMD</td>
<td>1977</td>
<td>Historical maps</td>
<td>Rijksoverheid¹</td>
</tr>
<tr>
<td>AHN-1</td>
<td>1997 till 2003</td>
<td>Laser altimetry</td>
<td>Actueel</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Hoogtebestand Nederland²</td>
</tr>
<tr>
<td>AHN-2</td>
<td>2007 till 2012</td>
<td>Laser altimetry</td>
<td>Actueel</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Hoogtebestand Nederland</td>
</tr>
<tr>
<td>AHN-3</td>
<td>2015</td>
<td>Laser altimetry</td>
<td>Actueel</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Hoogtebestand Nederland</td>
</tr>
</tbody>
</table>

Besides elevation data, also data on ground surface motion is available. These datasets are the previously discussed Pöttgens map, and one of the datasets used in the study *Na-ijlende gevolgen* [13]. Table 2.3 presents information about these two datasets.

Table 2.3: Ground surface motion data availability of the Zuid-Limburg mining area. The columns represent respectively the name of the dataset, the years of measurements, measurement technique, and the source of the data.

<table>
<thead>
<tr>
<th>Name</th>
<th>Measurement period [YR]</th>
<th>Measurement technique</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Levelling + InSAR</td>
<td>1974-2015</td>
<td>Levelling and InSAR</td>
<td>Projectgroup GS-ZL [13]</td>
</tr>
</tbody>
</table>

Modern elevation data used in this study is not presented on paper maps, but in digital geo-tagged formats. The difference in data formats between historical and modern data come from the fast improvement of measurement techniques during the 20th century, which also brings along differences in accuracy, projections, size etc. It is therefore expected that results after modelling and simulations will not be equally accurate for the period before and after the modern measurement techniques were available. In Chapter 7 integration of all results from different datasets is explained, including additional information on data format specifications. Chapter 8 pays special attention to the uncertainty involved with the different types of measurement techniques.

2.3. Time frame

A list of data is already given in Tables 2.1, 2.2, and 2.2, but an image representation of a timeline may help getting a better overview of the data in time. Figure 2.3 provides the time frame image with selected datasets.

¹www.data.overheid.nl/data/dataset/tophoogtemd
²www.ahn.nl
Figure 2.3: A schematic overview with selection of available data and their position in time.
Georeferencing

Georeferencing is an important step in processing because errors in georeferencing will affect the computation of height differences from two maps. This Chapter discusses georeferencing principles, processing steps, and the accuracy of the used georeferencing process. The processing steps that will be explained are listed below:

1. Determination of the CRS and coordinates (3.2)
2. Mosaicking (3.3)
3. Choosing ground control points (3.4)
4. Transformation (3.5)
5. Resampling (3.6)
6. Accuracy assessment (3.7)

3.1. Georeferencing principles

About georeferencing a lot literature can be found and consulted, but the general idea of this process is always the same: an object is positioned in a coordinate reference system (CRS) related to a geodetic datum that "describes the relationship between a spherical model of the Earth and the real Earth" [17]. The CRS determines the space that span the coordinates we use for positioning objects. A scanned image of a map is positioned by the image space with pixels as 'coordinates'. The objects that need a geodetic reference are the pixels of an image, which requires a transformation from the pixel coordinates to geodetic coordinates. Visualization of the geodetic space on a computer screen requires projection of the geo-tagged objects on a two-dimensional map, called map projection. The transformation process of pixel coordinates to geodetic coordinates will be discussed in the consecutive sections. This process will be of influence on the accuracy of results, whereas the map projection process only has influence on visualization of results.

Map projection is also performed in the mapping process of historical maps. Maps are printed with multiple attributes to inform the user about the projection and the CRS that is used. These objects are grid lines, grid coordinates, CRS name, and sometimes a north arrow. The terms grid lines and grid coordinates will be used throughout this chapter and can be recognized by a black lined grid on the maps with corresponding coordinate values outside the map border.

3.2. Determination of the CRS and coordinates

Knowing the map CRS will result in a transformation of the image to the right position in geographical space. When the CRS of the historical map is unknown and a wrong CRS was chosen, comparing the data from this map with data from another CRS will lead to large positioning
errors. Also, when one is only interested in the height, accurate georeferencing to the correct CRS is very important. In this case study it means that if one of the maps is georeferenced to the wrong CRS, a hill might be misplaced by a few meters, which will give large discrepancies in the estimation of ground surface motion. This effect is not desired and therefore the reference system and geodetic coordinates on each map should be determined with care. An estimation of the effects from errors made during georeferencing on ground surface motion will be discussed in Chapter 8.

Since all historical maps cover Dutch territory it is likely to assume that the CRS of all maps is the Rijksdriehoekstelsel (RD) [8]. On all historical maps used in this study the CRS name is printed, except for the maps dating 1925 and 1937. Nevertheless, according to de Bruijne et al. [8], all landsurveys in the period 1898 till 1928 were performed using the so called secondary RD-system, which is a precursor of the modern RD-systems. This secondary RD-system is a network of markers with precise coordinates used to determine one’s position in the field when surveying the area. This network is renewed and densified over the 20th century to establish higher positioning accuracy. An important difference between the secondary system and the more recent RD system from 1960 is the shift of origin from the Onze Lieve Vrouwe church at Amersfoort to a point outside the Netherlands. It is therefore important to know if a map CRS is in the old or new RD system. The reference systems are printed on the maps later then 1937, including the coordinates of grid lines. The black lines forming a grid on each map represent coordinates and where the lines intersect a x and y (respectively longitude and latitude) as two integers can be found. However, for the maps of 1925 and 1937 the CRS and grid coordinates are not clearly mentioned on the maps. Although the categorical name of these two maps (i.e. bonnebladen) is presuming a bonne projection1, the four corner coordinates that are printed on the 1937 map are recognizable as old RD coordinates. This is illustrated in Figure 3.1. For this reason a workaround was designed to get the highest georeferencing accuracy for the 1925 map (the 1937 map was left out for its non-uniqueness 2.2. The workaround is explained in section 3.4.

Figure 3.1: Detail of the 1937 historic maps providing information on the coordinates of the corners of the map

### 3.3. Mosaicking

Molnar (2010) proposed to perform georeferencing of multiple historical map series after mosaicking the maps, based on common edges of each map [12]. This method could also apply for this study since there are adjacent maps in the study area. Mosaicking is a method to create one coherent rasterimage of multiple rastersets by stitching and relative georeferencing [34]. This is convenient for image processing and analysis because edges or roads can be aligned by mosaicking and will stay aligned after georeferencing the mosaicked image as well. This will result in a seamless topological georeferenced map. For this reason Molnar chose to perform mosaicking before georeferencing. The downside of this method is the reduction of accuracy of the final image compared to georeferencing each image separately and then mosaicking [12]. Therefore, it was chosen not to mosaic the historical maps but to choose accuracy above adjacency.

1 [http://www.kadaster.nl/web/artikel/producten/Bonnebladen.htm](http://www.kadaster.nl/web/artikel/producten/Bonnebladen.htm)
3.4. Choosing ground control points

Transformation of pixel coordinates to geodetic coordinates in RD requires that for some pixels the geodetic coordinates are known. These 'known' coordinates can be the intersections of gridlines on a map, or e.g. a mapped field markers from the RD network. The location on the map of these points are called ground control points or GCP's. In GIS software it is possible to perform georeferencing by adding GCP's in the original raster image and use these to transform the image. This section describes three methods to find GCP's, and which method was chosen for further processing of the 1925 and 1960 map. The three methods are:

1. Single transformation.
2. Double transformation.
3. Relative georeferencing.

In section 3.5 the actual transformation is explained.

3.4.1. Single transformation

The simplest and fastest method is to find GCP’s on the raster image and transform these to the geographical coordinate space. The basic idea is to use gridline intersections with corresponding coordinates in RD as GCP’s, which are plentiful on all maps. This is the regular method in georeferencing, but for the 1925 it was already known that coordinates of gridlines are not printed. Only the four corners of the 1925 maps can be used as GCP’s, which is rather minimal. Therefore, this method is not a reliable method for the 1925 map but only for the 1960 map.

The example intersection point in figure 3.2 shows that gridline intersection points share approximately 12 pixels in total size (red bounding box). There is not 1 pixel in the centre, which makes manual sampling of the correct position of the intersection difficult. The green bounding box shows an approximation of the centre of intersection. In this green square the GCP should be picked. Instead of manually choosing the centre, there are semi-automatic ways to choose the right GCP location. Titova (2009) proposed to use a cross-correlation method to automatically search for coordinate intersection lines [28]. According to their study the semi-automatic method saves 10 to 20 minutes of time per map, but no evaluation on accuracy was described. In this study GCP’s where chosen manually while staying within the accuracy of half a pixel (sampling inside the green box).

Figure 3.2: Georeferencing historical maps. Where to sample?
3.4.2. Double transformation

To find GPC’s for the 1925 map, this method was designed. This method is called ‘double transformation’ for twice the ‘single transformation’ method will be performed. The first transformation of the 1925 map will use the four corner GCP’s, with expected inaccurate results. However, the georeferenced map of 1925 might be just accurate enough to determine gridline coordinates in GIS. In case it is possible to trace back the grid intersection coordinates from the inaccurate georeferenced map, a second transformation can be performed using the found intersection coordinates as GCP’s. A higher accuracy may be expected due to an increased number of GCP’s resulting in a higher redundancy in the transformation process [35].

3.4.3. Relative georeferencing

Again this method was designed to find GCP’s for the 1925 map. It does not make use of coordinates shown on the map, but GCP’s are chosen at locations that correspond with maps that are already georeferenced. An example may be the location of a church or country border, that has not changed over time and is visible in both the 1925 map and a georeferenced map. Enough of such points can be found on the maps, which makes higher order polynomial transformations possible (see section 3.5). An example of a ground control point used for relative georeferencing is given in Figure 3.3. The position of the red dots on the example are picked by hand, before transforming the whole 1925 map. Since the representation of churches on maps has changed in style over the years, the centre of the church was tried to be sampled as GCP. This has a larger uncertainty involved then by sampling grid intersections.

![Figure 3.3: Example of relative georeferencing. The left map is the 1989 map centred around a church in Heerlen. Churches are stable points relative to e.g. forests which change over time more often. On the right the map of 1925 is centred around the same church.](image)

3.4.4. Choosing a method using GPC’s

The fastest and simplest method for choosing GCP’s is single transformation, which was chosen to use for the 1960 map. It was concluded that the accuracy of the georeferenced map from single transformation was very low for the 1925 map \((\text{RMSE}^2 = 258.63 \text{ pixels})\) with a linear transformation). After testing method 2, the georeferencing accuracy output of the first transformation was too low to determine the gridline coordinates from it. Method 3 was chosen for further process, using the georeferenced 1989 map as reference. Specifications and estimation of georeferencing accuracy for this method are found in section 3.7.

\(^2\text{Root Mean Square Error, see for explanation section 3.7}\)
3.5. Coordinate transformation

A transformation method should be chosen to reproject the map (image space) into the right reference projection (geographical coordinate space). This can be represented in matrix form as a linear system of equations as illustrated in equation 3.1

\[
\begin{bmatrix}
x \\
y \\
\end{bmatrix} + \begin{bmatrix}
e_x \\
e_y \\
\end{bmatrix} = T \begin{bmatrix}
u \\
v \\
\end{bmatrix}
\] (3.1)

where \(u\) and \(v\) are the image space coordinates, \(x\) and \(y\) are the corresponding coordinates of the GCP's (latitude/longitude or map projection coordinates) and \(T\) is the transformation matrix of a chosen method. A least-squares approximation of the above equation minimizes the differences, \(e_x\) and \(e_y\), between the true coordinates of the ground control points and the transformed georeferenced image coordinates of the GCPs. As was shown in Figure 3.2 sampling of ground control points cannot be done without inevitably making human errors, and incorporating other errors from scanning and paper conservation. The transformation matrix \(T\) contains unknown coefficients for the transformation. These coefficients are estimated by least squares, while minimizing the \(e_x\) and \(e_y\) in least squares sense. A common choice for \(T\) is a polynomial transformation. A low order polynomial transformation tends to have a lower accuracy after least-squares estimation of the coefficients, as it has less coefficients to fit the polynomial to the dataset. Higher order polynomial transformations are more accurate but will then also 'follow' errors of GCPs. For this reason only a 2\(^{nd}\)-order polynomial and 3\(^{rd}\)-order polynomial transformation are compared in this study.

Equations 3.2 and 3.3 show respectively the transformation methods for 2\(^{nd}\)-order and 3\(^{rd}\)-order polynomial functions:

\[
\begin{align*}
x_i &= a_1 + a_2 u_i + a_3 v_i + a_4 u_i^2 + a_5 u_i v_i + a_6 v_i^2 \\
y_i &= b_1 + b_2 u_i + b_3 v_i + b_4 u_i^2 + b_5 u_i v_i + b_6 v_i^2
\end{align*}
\] (3.2)

\[
\begin{align*}
x_i &= a_1 + a_2 u_i + a_3 v_i + a_4 u_i^2 + a_5 u_i v_i + a_6 v_i^2 + a_7 u_i^3 + a_8 u_i^2 v_i + a_9 u_i v_i^2 + a_{10} v_i^3 \\
y_i &= b_1 + b_2 u_i + b_3 v_i + b_4 u_i^2 + b_5 u_i v_i + b_6 v_i^2 + b_7 u_i^3 + b_8 u_i^2 v_i + b_9 u_i v_i^2 + b_{10} v_i^3
\end{align*}
\] (3.3)

Where \(a\) and \(b\) are the coefficients to be estimated and \(i\) indicates the index number of a point in the set of GCPs. Coefficients \(a\) and \(b\) are estimated through least-squares. Before finding the least-squares solutions, equations 3.2 and 3.3 are written in matrix form (only example of 2\(^{nd}\)-order polynomial for \(x\) is given here. For 3\(^{rd}\)-order polynomial find Appendix B Equations).

\[
y = A\hat{x} + \hat{e} \quad \begin{bmatrix}x_1 \\ x_2 \\ \vdots \\ x_n\end{bmatrix} = \begin{bmatrix}1 & u_1 & v_1 & u_1^2 & u_1 v_1 & v_1^2 \\ 1 & u_2 & v_2 & u_2^2 & u_2 v_2 & v_2^2 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & u_n & v_n & u_n^2 & u_n v_n & v_n^2\end{bmatrix} \begin{bmatrix}a_1 \\ a_2 \\ \vdots \\ a_n\end{bmatrix} + \begin{bmatrix}\hat{e}_1 \\ \hat{e}_2 \\ \vdots \\ \hat{e}_n\end{bmatrix}
\] (3.4)

In this equation \(y\) is the observation vector of all \(x\)-coordinates, \(A\) is the design matrix which describes the transformation method and contains all raster coordinates \(u_n\) and \(v_n\). \(\hat{x}\) is the solution for each coefficient \(a_n\) (for \(x\)) and \(b_n\) (for \(y\)), and \(\hat{e}\) is the residual vector. \(\hat{e}\) can also be described by the difference between the observed (true) \(x\)-coordinates in \(y\) and estimated \(x\)-coordinates in \(\hat{y}\). The squared norm of the residual vector, \(||\hat{e}||^2\), is desired to be as small as possible (hence the name least-squares). The least-squares solution assuming equal weights (no weight matrix \(W\)) to each measurement is given by:

\[
\hat{x} = [A^T \cdot A]^{-1} \cdot A^T \cdot y
\] (3.5)

By choosing equal weights for each GCP it is implied that the accuracy of each GCP is equal. In order to apply weighted least-squares transformation the quality of each individual field measurement should be known. Weights are dependant on e.g. quality of equipment, surveyors and field conditions. This is, however, not known.
3.6. Resampling

For mapping purposes, it is convenient to transform all image pixels to the geographical reference. Georeferenced maps can then be used in GIS software for visualizing results. Due to high order transformation, pixels of the original raster image may become reoriented when transformed following the transformation method. Creating a georeferenced image coinciding with a regular grid of pixels (output raster) on the screen requires resampling of the georeferenced image. Resampling is an interpolation of pixel values from fit the input raster into the output raster [23]. Multiple interpolation methods can be chosen, but to obtain the best appealing image a cubic convolution interpolation was chosen, which is a weighted average of the surrounding 16 values of each output raster pixel.

3.7. Accuracy assessment

The residual vector $\hat{e}$ gives an indication of positioning accuracy of the georeferenced map. Residuals are in the case of this study the euclidean distance in map units [pixels] between observed $x, y$-coordinates and estimated $x, y$-coordinates of the GCPs. The euclidean distance ($d$) for each GCP is computed via the Pythagorean theorem:

$$d = \sqrt{\hat{e}_x^2 + \hat{e}_y^2} \quad (3.6)$$

From the vector of euclidean distances the empirical standard deviation (RMSE) can be found for each georeferenced map. The RMSE is computed the same way as the standard deviation equation in Appendix B, equation B.4. Table 3.1 gives an overview of the RMSE values of each map used throughout the study, after georeferencing using a 2nd−order polynomial and 3rd−order polynomial transformation.

<table>
<thead>
<tr>
<th>Map code (year)</th>
<th>RMSE$^2$ [pixels]</th>
<th>RMSE$^3$ [pixels]</th>
<th>number of used GCPs</th>
</tr>
</thead>
<tbody>
<tr>
<td>b759 (1925)</td>
<td>8.86</td>
<td>8.78</td>
<td>142</td>
</tr>
<tr>
<td>b763 (1925)</td>
<td>6.80</td>
<td>6.79</td>
<td>142</td>
</tr>
<tr>
<td>60D (1959)</td>
<td>1.39</td>
<td>1.17</td>
<td>142</td>
</tr>
<tr>
<td>62B (1960)</td>
<td>0.97</td>
<td>0.77</td>
<td>142</td>
</tr>
<tr>
<td>69E (1989)</td>
<td>0.82</td>
<td>0.79</td>
<td>221</td>
</tr>
<tr>
<td>68G (1989)</td>
<td>0.94</td>
<td>0.90</td>
<td>178</td>
</tr>
</tbody>
</table>

From the table it can be concluded that the 3rd−order polynomial gives better results, which makes choosing this transformation method more logical. However, a balance should be found between the lower transformation accuracy of low order polynomials and the tendency of following errors in GCP’s by higher order polynomials. It was therefore chosen to remove GCP’s with large errors in the euclidean distance vector after 2nd−order polynomial transformation. Remaining GCP’s are then used to transform the coordinates, which improves the outcome of the RMSE of the georeferenced points. Table 3.2 shows the new RMSE values after removal of the largest biased GCP’s. The new number of GCP’s can be found in the third column of the Table.
Table 3.2: Accuracy evaluation for the used historical maps. RMSE is computed for each year from different numbers of ground control points after removal of largely biased GCP’s. Superscript 2 refers to the 2\textsuperscript{nd}−order polynomial transformation method.

<table>
<thead>
<tr>
<th>Map code (year)</th>
<th>RMSE\textsuperscript{2} [pixels]</th>
<th>number of used GCPs</th>
</tr>
</thead>
<tbody>
<tr>
<td>b759 (1925)</td>
<td>4.09</td>
<td>107</td>
</tr>
<tr>
<td>b763 (1925)</td>
<td>4.00</td>
<td>107</td>
</tr>
<tr>
<td>60D (1959)</td>
<td>0.61</td>
<td>112</td>
</tr>
<tr>
<td>62B (1960)</td>
<td>0.50</td>
<td>94</td>
</tr>
<tr>
<td>69E (1989)</td>
<td>0.45</td>
<td>185</td>
</tr>
<tr>
<td>68G (1989)</td>
<td>0.80</td>
<td>157</td>
</tr>
</tbody>
</table>

The large RMSE values for the 1925 maps are a result of the relative georeferencing method, due to the uncertainties as shown by the example in Figure 3.3. How RMSE values have influence on the estimation of ground surface motion will be discussed in Chapter 8, in Section 8.3.3. The meaning of the RMSE values can be interpreted as an object on the particular map that has an expected coordinate discrepancy within a radius of the RMSE.

It should be noted that the above table only shows the RMSE values for the euclidean distance between the input coordinates and estimated coordinates, instead of computing the RMSE for the residuals in $x$ and $y$ separately. The reason for this choice was the result of a covariance test that showed positive linear relation between $\hat{e}_x$ and $\hat{e}_y$. The sample covariance between $\hat{e}_x$ and $\hat{e}_y$ was computed following equation B.6 in Appendix B. Below the covariance matrix for the b763 (1925) map is given.

$$
C = \begin{pmatrix}
cov(\hat{e}_x, \hat{e}_x) & cov(\hat{e}_y, \hat{e}_x) \\
cov(\hat{e}_x, \hat{e}_y) & cov(\hat{e}_y, \hat{e}_y)
\end{pmatrix}
= \begin{pmatrix}
7.4977 & 4.0781 \\
4.0781 & 18.7447
\end{pmatrix}
$$

Where $\hat{e}_x$ and $\hat{e}_y$ are respectively the residual vectors in $x$-direction and $y$-direction after transformation. The value 4.0781 shows that there is a linear relation between the residuals of $x$ and $y$. The difference in variance along the diagonal of matrix $C$ shows that there are, however, differences in accuracy for GCP’s over $x$ and $y$. Covariance matrices for all other maps were not computed due to the time consuming and complex transitions of generated RMSE tables between multiple software packages. It is therefore assumed that there is a linear relation between $\hat{e}_x$ and $\hat{e}_y$ for all maps.
Data extraction from historical maps

This chapter describes how historical maps can be used to provide quantitative information about topography. Modern digital GIS-maps can contain a lot of information at the same time by stacking layers of data in one map. To create these digital maps multiple datasets are combined and analysed through multiple functions such as overlay functions, neighbourhood functions, connectivity functions or classification [16]. Historical hand-drawn paper maps without any modern digital layered database make it difficult to perform spatial analysis in GIS-software. It is therefore not surprising that estimating ground surface motion from historical maps requires some additional work in processing. Original databases of the elevation measurements are no longer available and therefore, a series of methods had to be designed to obtain elevation data from the historical maps. In the end it is desired to find the best method to describe the relief and ground surface motion of the area without losing important information. The six methods that will be described in this chapter are designed after a literature study and after interviews were held at the Geoscience and Remote Sensing department of the TU Delft, as well as with F. v.d. Heuvel, Engineer at Skygeo in Delft. A list of the six methods is given below:

- Automated detection
  1. PCA
  2. Supervised classification
- Manual sampling
  3. Contourline sampling
  4. Pseudo-random contourline sampling
  5. Profile sampling
  6. Point measurement digitization

The word ‘extraction’ throughout this chapter implies that elevation data should be detached from its map, which is in some way the goal of these methods: the important map elements are only the contourlines and point measurements, all other information on the maps is irrelevant for further ground motion analysis and can be ignored. To make sure only the relevant data is extracted without additional irrelevant information, their unique properties should be detected and sampled. The first method shows how this could be done using automated (semi-automatic) detection, described in section 4.1. Methods 3 to 6 requires manual sampling and digitization, which is discussed in section 4.2. The chapter will be disclosed with a qualitative and quantitative comparison between the methods.
4. Automated detection

The process of automatic detection involves sophisticated programming to distinguish the relevant elevation data from the other map elements. A close look to the snipped of the map in figure 2.1 shows that colours of contourlines and towns or infrastructure mingle. An automatic detection process will require many criteria to distinguish contourlines from buildings or roads. The only extractable quantitative value from the maps is the RGB value. RGB stands for the three primary colours red, green and blue (ranging from 0 till 255) which will be used to perform automatic detection. A testing environment was built in Matlab to identify contourlines of a snipped part of the 1925 historical map. Two analysing methods are considered in the test: PCA and Supervised classification. Expectations of automated detection are lower than for manual sampling, as exploring all possibilities in automated detection is impossible to accomplish in the time constraints of this study. Improvements of the automated method that have not been tested will be mentioned accordingly.

4.1.1. PCA

PCA stands for Principal Component Analysis and creates \( m \)-components in the \( m \)-dimensional dataset by determining the maximum variance (desired information) in the first one or two components and suppressing redundant information in the other components [21]. An ideal result will separate the contourlines in one of the created components from the other topographical information on the map. The three available inputs from a map (red, green, and blue) can also be combined as ratios to add information to the analysis. This creates three additional input variables: \( R/G \), \( R/B \), and \( G/B \). Introducing more combinations and machine learning operations will give likely better results, but finding an optimal result for each map would initiate a full research on this topic. In this study the 6-dimensional dataset \( (m = 6) \) was used as input for the automatic PCA. A brief background on the process of PCA will be given here. First, in order for us to use the variances of each component, the variables are standardized to suppress influence by scaling (ratios of the last three components are scaled). Standardization is shown in equation 4.1.

\[
\hat{x}_i = \frac{x_i - \mu_x}{\sigma_x} \tag{4.1}
\]

Where \( \hat{x}_i \) is the \( \text{i}^{th} \) \([n \times 1]\) standardized observation vector in the \([n \times m]\) \( \mathbf{x} \) matrix, \( x \) is an observation vector for a component in the dataset (e.g. Red), \( \mu_x \) is the component mean (B.3), and \( \sigma_x \) is the component standard deviation (B.4). At this moment each image pixel of the example image has 6 standardized values. In the second step the covariance matrix of the standardized observation matrix is computed by:

\[
S = \frac{1}{n-1} \hat{x}\hat{x}^T \tag{4.2}
\]

This matrix \( S \) will be used to find the eigenvectors and eigenvalues, because the goal of this method is to find the maximum variance in the dataset. No further attention will be paid to finding the eigenspace, as it is beyond the scope of this study. After the eigenvectors and eigenvalues, the vectors are sorted in descending order of the eigenvalues. Then, the standardized values will be multiplied by the eigenvector of each component. In other words, the \( m \)-number of \([1 \times m]\) eigenvectors that describe the loadings of each component per variable will form the new basis of the data space, and thus each entry in the eigenvector is a weight applied to the standardized values per variable. The final step is to sum all weighted values so that every pixel has a weighted sum over all components. In matrix form this process can be summarized as follows:

\[
\hat{x} = Py \quad \rightarrow \quad y = P^T\hat{x} \tag{4.3}
\]

With \( P \) as the \([6 \times 6]\) matrix of eigenvectors per new component, \( \mathbf{\hat{x}} \) is the standardized values matrix, and \( y \) is the \([n \times 6]\) matrix of all PCA scores. The scores are the new values of each observation per new axis.
Figure 4.1 shows the results of the first three components of the 1925 historical map snippet. From the results of PCA the following conclusions can be drawn:

1. The first component is mainly determined from the variance in dark and light colours on the map. The result looks somewhat like a simple black-and-white version of the original map. Dark colors are separated from the light colors which does not lead to a distinction between contourlines and other dark map elements.

2. Component 2 shows contourlines more clearly and some infrastructure in white. Compared to the original map, it can be seen that in this component the red is the dominant colour in this component's variance. The dominance of the red colour in component 2 can also be seen in the loadings inside the eigenvector $e_2$:

$$e_2 = \begin{pmatrix} 0.7915 \\ -0.2058 \\ -0.5752 \\ 0.0112 \\ 0.0148 \\ -0.0025 \end{pmatrix}$$ (4.4)
Where the loadings are from top to bottom the weights applied to red, green, blue, R/G, R/B, and G/B.

3. The third component does not show large differences in colours any more, which should be the case by definition after PCA. Components 4, 5, and 6 are shown in Appendix C, Figure C.1.

The second component seems to be the best component to extract the contourlines. Extraction was performed by sampling contourlines from the second component and defining the component’s pixel intensity interval within a 0 to 1 scale. The approximate interval was then found as $0.4 < I < 0.7$, where $I$ is the scaled image value. Pixels with values within this interval were assigned 1 and pixels outside this interval were assigned 0. The resulting image is shown in Figure 4.2. The resulting image shows clearly the disadvantage of PCA as the roads are still visible and contourlines are freckled. Playing with the interval does not give a perfect outcome, but only an approximation of where the contourlines are.

4.1.2. Supervised classification

Supervised classification is user controlled classification of map elements. The number of classes can be determined by the user itself based on user defined criteria. In some way it is similar to PCA as characteristics of contourline colours are separated from other map elements. However, where PCA uses the variance to distinguish, supervised classification uses training sites of manually chosen contourline-pixels. This method requires sampling of contourlines in order to define the training sites. Characteristics of the training sites are based on the RGB values and ratios between them. Table 4.1 shows examples of training sites (pixels) of manually selected contourlines. The samples correspond to the numbers in Figure 4.3.

Table 4.1: Training sites characteristics of 5 sampled contourlines.

<table>
<thead>
<tr>
<th>Training site</th>
<th>Red</th>
<th>Green</th>
<th>Blue</th>
<th>Red / Blue</th>
<th>Red / Green</th>
<th>Green / Blue</th>
</tr>
</thead>
<tbody>
<tr>
<td>no. 1</td>
<td>69</td>
<td>31</td>
<td>10</td>
<td>6.90</td>
<td>2.23</td>
<td>3.10</td>
</tr>
<tr>
<td>no. 2</td>
<td>219</td>
<td>213</td>
<td>191</td>
<td>1.15</td>
<td>1.03</td>
<td>1.12</td>
</tr>
<tr>
<td>no. 3</td>
<td>205</td>
<td>187</td>
<td>165</td>
<td>1.24</td>
<td>1.10</td>
<td>1.13</td>
</tr>
<tr>
<td>no. 4</td>
<td>201</td>
<td>175</td>
<td>148</td>
<td>1.36</td>
<td>1.15</td>
<td>1.18</td>
</tr>
<tr>
<td>no. 5</td>
<td>209</td>
<td>199</td>
<td>172</td>
<td>1.22</td>
<td>1.05</td>
<td>1.16</td>
</tr>
</tbody>
</table>

In the example of Table 4.1 the first site is very different from the others. This site was derived from the decadal (multiplications of ten) contourline which is thicker and darker on the historical maps, hence the lower RGB values. Due to this difference the sampling of training sites should include both the decadal contourlines and the intermediate contourlines. The eventual classification uses the distribution of 10 decadal contourlines and 30 intermediate contourlines separately. The ratio 10:30 equals the ratio of amount of decadal versus intermediate contourlines on a map. Two classifiers are thus created from a total of 40 samples, which
4.2. Manual sampling

For manual sampling of elevation data the user should use GIS software with georeferenced data. The georeferenced historical maps are the base layers from which the elevation data will be digitized in a new vector layer. Depending in the chosen data extraction method, for each map and each area, all necessary elevation data should be sampled by hand. In this section (pseudo-random) sampling of contourlines, profiles, and point measurements will be discussed. Throughout this section the strong relation to interpolation will be noted, but full details on interpolation will be discussed in the separate spatio-temporal modelling section (Chapter 5). The area for which the first two sampling methods will be discussed covers a part of the deformation map from Pöttgens [32] for later validation purposes. This area is indicated in Figure 4.5.
4. Data extraction from historical maps

4.2.1. Contourline sampling

The dominant elevation data on the historical maps are the contourlines. Sampling all the contourlines requires eye for detail; colours mingle when contourlines interfere with infrastructure or houses and the corresponding height is not always explicit. Furthermore, the large amount of contourlines on the maps requires a lot of time and concentration to prevent biased data. Despite focus of this study is put on the ‘white’ gap in Pöttgens map, sampling of contourlines was tested for a smaller area from Figure 4.5 to be able to validate this method first before performing the time consuming sampling of the larger ‘white’ gap area.

Digitization of contourlines was done by first creating a vector layer of line types. Each sampled line in the layer should follow the contourlines on the historical map. This is shown in step B of Figure 4.6. Attribution of corresponding height to the line vectors is only needed once per line, when one line is finished. This is the advantage of choosing line type vectors instead of point type; when a point type is chosen, for every point the height should be attributed which is both less time efficient and more error sensitive. Drawn lines that follow the contourlines on the map should always be exactly on a contourline. Contourlines are on average 5 pixels wide, within which the vector line should be drawn. In the analysis of sampling uncertainty in Chapter 8 this condition is assumed.

The last step in digitization of contourlines is the conversion of lines to points (step C in Figure 4.6). This step makes data processing in Matlab easier and increases the amount of data by adding points on the created lines. The sampling interval between points should be small enough to prevent aliasing, but also large enough to reduce the amount of redundant information (and therefore also computation time). Aliasing is a frequency ambiguity which is hard to detect in the results, but can be prevented by simply choosing a sufficiently small interpolation distance between two points of a contourline. This distance can be determined by estimating the Nyquist distance. The Nyquist distance is equal to 2 times the minimal shortest euclidean distance between two contourlines ($\Delta D$) in the whole dataset [31]. Aliasing occurs when the interpolation distance is too large ($> 2\Delta D$), which may lead to unwanted ridges or valleys resulting in the model. This is illustrated in figure 4.7. The methods of interpolation will be discussed in Chapter 5.
Figure 4.6: Contourline extraction in GIS software. A: Original georeferenced historical map of 1960, B: Contourlines sampled by creating line vectors of each contourline, C: Converting lines to points by interpolating over equal distance (here: 5 meter).

Figure 4.7: Example of aliasing: Left: plot that shows the result of a DEM when contourlines are sampled at 49 [m] distance and the distance between two contourlines is 25 [m]. The interpolation distance is then less than twice the contourline distance ($\Delta D > 0.5\Delta X$), a valley appears. Right: plot that shows the result of a DEM when contourlines are sampled at 50 [m] distance and the distance between two contourlines is 25 [m]. The interpolation distance is then twice the contourline distance ($\Delta D = 0.5\Delta X$) an unwanted ridge appears due to aliasing.

The used sampling distance to create points from the sampled vector lines is 5 meter. This implies that it is assumed that the minimum shortest euclidean distance between two contourlines is larger than 2.5 meter. Or in other words, the maximum slope (plane tangent) of the area should not be larger than 45° or 1 $[m \cdot m^{-1}]$ (see equation 4.5).

$$\text{Interval} = \Delta X = 2.5 [m] \quad \Delta D = 2.5 [m] \quad \frac{\Delta X}{\Delta D} = 1 [m \cdot m^{-1}]$$ (4.5)

The 2.5 meter interpolation distance ($\Delta X$) was derived from literature [15] as slopes tend to adopt the angle of repose of approximately 35° without erosion processes. The chosen 45° is larger than the angle of repose and should therefore be sufficiently large. Since the tectonic activity in the area is relatively low, it can be assumed that the hills are in the latest phases of development (from debris controlled to wash controlled [15]). Corresponding hillslopes are in the range from 5° to 35°.
4.2.2. Pseudo-random contourline sampling

The second method of manual data extraction is pseudo-random sampling of contourlines. This method uses the contourlines of the historical map as elevation data source, but does not follow each contourline as discussed in the previous section. Here the contourlines are sampled pseudo-randomly with larger spacing to reduce the sampling time significantly. Instead of creating line vectors, contourlines are sampled by single points immediately. The number of sample points is determined using equation 4.6, which describes how the number of samples, desired DEM pixel size and the study area are related [14]:

\[ p = 0.25 \cdot \sqrt{\frac{A}{N}} \]  (4.6)

Where \( p \) is the size of a pixel in a DEM \([m]\), \( A \) is the surface of the study area in \([m^2]\) and \( N \) is the number of samples. For the study area it was chosen to divide the area in subsets of 50x50 \([m]\). This is illustrated in figure 4.8 with random example sample points. The chosen subset size gives for \( p \) a value of 50, and \( A \) equals 1 \([km^2]\) (size of one gridcell on the historical maps). Substitution of these values in equation 4.6 results in \( N = 25 \) sample points. The chosen method for pseudo-random sampling of contourlines with 25 points still requires to determine the position of the samples. In the example of Figure 4.8 the samples are generated randomly which saves time, but contourlines are not everywhere on the map. Consequently, the user should choose the samples manually. Due to interpolation accuracy, regular spacing of samples is the desired alternative. Again, since contourlines are not everywhere on the map, a balance must be found between regular spatial distribution and random distribution of the samples. Hence, Pseudo-random sampling. The result of the example area is shown in Figure 4.9.

4.2.3. Profile sampling

A third method was designed to retrieve results with a large spatial and temporal coverage but with even less data than the first two methods. Instead of sampling every contourline by its whole or by pseudo-random points, only the contourlines are sampled at the intersections with chosen transects. The goal of this method is to create profiles along the transect, showing...
vertical ground surface motion over multiple years. The example area is extended to the whole area of interest (see section 1.6) to better test the capabilities for this method. Since sampling of the contourlines is only done at the intersections with the chosen transects, selection of the transects is the most important part of this method.

To get a comprehensive insight in ground surface motion with much less data, many transects should be taken through the study area. A regular grid of transects will not work for some parts of the area as in some parts of the historical data, contourlines are not visible (see section 4.1) or a chosen transect misses a contourline by just a few meters. The latter will cause an invalid representation of elevation in a profile, as the transect will only be sampled at intersection points. This issue could be solved in two ways: either sample nearby the contourline on the transect and attribute a value to the sample of approximately the contourline elevation value (i.e. linear interpolation) or otherwise by reshaping transects that this occurs as less as possible. The last solution was chosen to prevent errors due to human mistakes. The downside of this method is that it requires additional processing later, due to the non-linear shape of the transects. In Figure 4.10 the developed grid of transects for the area of interest is presented. As can be seen on the transect map the orientation of each transect is either slightly South-West to North-East or North-West to South-East. This effect is due to the the preference of choosing transects perpendicular to the contourlines (if possible) and the overall orientation of the hills in the area. Transects perpendicular to the contourlines will lead to a better profile representation of the relief than along contourline profiles. Another reason for the current shape of transects is the presence of mines in the area and the urban boundaries of Heerlen.

### 4.2.4. Point sampling

The last method for data extraction uses single point measurements. This data is less spatially dense than the contourlines, as the measurements appear approximately once per square kilometre grid. The height of these points are printed on the maps and they could therefore be used for the study on ground surface motion as well. Instead of sampling contourlines, the points can be digitized and their corresponding height need to be attributed to the object. Since the point measurements have a relatively sparse spatial coverage compared to contourlines, digitizing these points is far less time consuming but results may be subject to higher uncertainty when data is interpolated.

From Chapter 2 it was already concluded that the point measurement data on the 1925, 1937, and 1955 maps are equal, making only the 1925, 1960 and 1989 map valuable. However, spatial consistency is also very important; multiple years point measurements should be taken on the same location throughout the maps. If this is not the case, it can be expected that such dataset will lead to the same type of results as derived from the pseudo-random sampling method. Evaluation of all points on the 1925, 1960 and 1989 maps of the Heerlen area lead to the follow-
4. Data extraction from historical maps

Figure 4.10: Chosen transects in the area of interest. Transect shape and position are determined based on contourlines of 1925 and 1960, mine shaft positions and spatial distribution.

Concluding conclusions:

1. Most points on the 1925 and 1960 maps correspond to the same location
2. Points on the 1989 map are almost always at a different location

The conclusions are illustrated in figure 4.11. On the left map of the figure, four points were sampled all at approximately the same location for each year as shown in the labelled objects. Due to georeferencing errors and mapping inaccuracy the points are not on the exact same location. The base layer in figure 4.11 is the map from 1989 and one point measurement value can be seen printed with an arrow pointing from the location where a measurement was taken. The corresponding height is +93.8 above NAP which is also indicated by the lilac star and its corresponding label. On the right hand side of figure 4.11 no printed value is shown on the underlying map and thus no point was sampled at this location for 1989. Only three stars are shown corresponding to a point measurement in 1925, 1937 and 1960.

Figure 4.11: Point measurements near Weustenrade
Complications in digitizing arise from the resolution of the raster maps. As previously shown in Figure 3.2, the lines on the map cover multiple pixels and therefore sampling the beginning of the arrow involves the same type of uncertainty as discussed in section 3.4, Figure 3.2. The effect of this error is negligibly small after averaging the location of both the 1925 and 1960 measurement, as the difference in location is about a factor ten larger than the error from sampling inaccuracy. For further processing all locations of corresponding point measurements from 1925 and 1960 are averaged in order to compare data from the two epochs. This method resulted in the descriptive statistics of central tendency and dispersion of the positioning error as shown in table 4.3.

Table 4.3: Central tendency and dispersion of digitized point measurements after averaging position of corresponding point measurements for 1925 and 1960. Equations of computed statistics are found in Appendix B. Values are in meters and rounded to two decimals.

<table>
<thead>
<tr>
<th>Coordinate</th>
<th>Mean $\mu$</th>
<th>Median $M$</th>
<th>Standard deviation $\sigma$</th>
<th>Skewness $S$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$x$</td>
<td>8.69</td>
<td>5.59</td>
<td>9.99</td>
<td>2.42</td>
</tr>
<tr>
<td>$y$</td>
<td>10.07</td>
<td>7.46</td>
<td>9.60</td>
<td>2.16</td>
</tr>
</tbody>
</table>

From the values in Table 4.3 it can be seen that there is a large variability ($\sigma$) in positions of corresponding point measurements between 1925 and 1960. However, the large mean values are not a good representation of the error when looking at the skewness of both distributions. A normally distributed population will result in $S$ equals zero, whereas a positive $S$ indicates that there are more values of observations below the mean (skewed distribution to the left) and vice versa. Therefore, in this case, the median is a better representation of the point measurement positioning digitization error.

4.3. Comparing data extraction methods

From the two main types of data extraction methods, each subtype has its own advantages and disadvantages. Table 4.4 shows an empirical evaluation of all these (dis-)advantages, which will be elaborated consequently.

Table 4.4: Evaluation and comparison of the six chosen data extraction methods. Values are empirical and derived from the corresponding example areas.

<table>
<thead>
<tr>
<th>Method</th>
<th>Time [min·km$^{-2}$]</th>
<th>Size [$n·km^{-2}$]</th>
<th>Accuracy</th>
<th>Data type</th>
</tr>
</thead>
<tbody>
<tr>
<td>PCA</td>
<td>1</td>
<td>18717</td>
<td>-</td>
<td>Raster</td>
</tr>
<tr>
<td>Supervised classification</td>
<td>5</td>
<td>9763</td>
<td>0</td>
<td>Raster</td>
</tr>
<tr>
<td>Contourline sampling</td>
<td>60</td>
<td>4085</td>
<td>+</td>
<td>Vector</td>
</tr>
<tr>
<td>Pseudo-random sampling</td>
<td>20</td>
<td>25</td>
<td>+</td>
<td>Vector</td>
</tr>
<tr>
<td>Profile sampling</td>
<td>15 [min·km$^{-1}$]</td>
<td>6.5 [$n·km^{-1}$]</td>
<td>+</td>
<td>Vector</td>
</tr>
<tr>
<td>Point-measurement digitization</td>
<td>10</td>
<td>1</td>
<td>+</td>
<td>Vector</td>
</tr>
</tbody>
</table>

The first column in Table 4.4 shows for each method the time spent on either sampling or computer processing. As can be seen PCA is the fastest method for data extraction and also provides the largest dataset (size, column two). However, the accuracy of the retrieved dataset is the lowest, which is a large disadvantage. The minus sign, naught, and plus sign indicate the relative accuracy of the methods mutually. The actual accuracy will be further discussed in the separate Chapter ‘Uncertainty analysis’. The manual sampling methods all have a positive relative accuracy, as the user determines the sampling position which can be done in maximum accuracy (left out accidental gross errors and biases). Supervised classification is also less time consuming than manual sampling methods, due to automatic processing of the input (training sites). The data size of this method (number of classified pixels as ‘contourline’) is much smaller than PCA, and approximately double the size of contourline sampling. This difference is caused by higher accuracy than PCA, and higher density of pixels than contourline samples. Less time consuming and smaller datasets are derived from the last three methods.
Point-measurements have a significantly low spatial distribution, which may cause later issues in data processing (see Chapter 5). Pseudo-random sampling and Profile sampling both are also less time consuming than Contourline sampling, and the data size is more feasible for larger areas.

PCA and Supervised classification share the same data type after extraction, which is a raster format. The downside of this format at this stage of processing is that elevation should still be attributed to each contourline pixel. In order to attribute elevation to each pixel a user should find pixels of common contourlines in the dataset, which requires additional computation time. Implications may arise from non-adjacent pixels due to e.g. dashed contourlines and inaccurate classification. In the scope of this study it was therefore chosen to continue with vector data, which are sampled manually in GIS-software.

The four remaining methods are Contourline sampling, Pseudo-random sampling, Profile sampling, and Point-measurement digitization. All these methods are used in the next chapters for further processing, but only profile sampled data was used to create final results of the whole 'white' area in the Pöttgens map. This is due to the best balance between work and amount of data of this method, and time constraints of this study.
In this chapter it is described how different spatial models are computed from the datasets that represent the historical elevation of the area. After all elevation data from the sample area and transects are extracted, the database contains six different datasets from the six methods. Since the manual sampling methods are preferred over the automated methods the four manual methods will be further processed to estimate ground surface motion. In section 5.1 an introduction to spatial modelling of sampled elevation data is given. Sections 5.2 and 5.3 discuss different modelling techniques with respect to the four datasets. Section 5.4 gives a brief explanation of used interpolation techniques. This chapter will be closed off with a summary including conclusions drawn from spatial modelling.

5.1. Introduction to spatial modelling of sampled elevation data

The data extraction methods of the previous chapter resulted in either sampled contour lines, sampled profiles or point data. The contour lines and profiles have been sampled at discrete height values with a regular interval (i.e. 2.5 metre). The data is not sampled at the same geographic location in different epochs. Therefore, in order to compute the height difference between two epochs, the data must be resampled to common geographic locations. For the sampled profiles this involves a 1D resampling with the distance along the profile as independent variable, and the discrete height samples as input. For the sampled contour lines and point data the resampling is of 2D nature\(^1\). Resampling can be done either to a common 1D or 2D grid, or to a set of discrete points not associated to a grid; the so called common query points. To compute the height at the new points 1D or 2D interpolation of the height values is needed.

Interpolation or fitting over 1D or 2D data, depending on the dataset, is the main process in creating a spatial model. The amount of interpolation and fitting techniques is numerous, but to reduce this number for this study, specific objectives and interpolation characteristics are determined in advance. There is not simply one method that always gives the best results, which also depends on the question 'what is best?'. According to Desmet (1997) [9] and Hengl (2006) [14] finding the best method is dependant on three main aspects:

1. Precision [9]
2. Shape reliability [9]
3. Gridsize [14]

**Precision** of an elevation model is defined by the accuracy of height prediction at unsampled areas [9]. In order to evaluate the precision, a similar area (e.g. similar relief) can be used as

\(^1\)For the point data in some cases resampling can be replaced by identifying common points between epochs, at for example hill tops.
a testing environment under the condition that the area has not been subject to ground surface motion. A follow up on this study would be necessary to do such a precision test. Here the guidelines derived from Desmet and Hengl will be followed as a directory for choosing the most precise interpolation method instead. Shape reliability is the 'degree of fidelity' with which the shape of the true topography is reproduced in the DEM. Shape can be described with many different criteria such as slope gradient, slope orientation and profile curvature (second order derivative of the slope along the steepest slope). The gridsize is the length of the space between two adjacent points. In 1D this is the distance between two query points, in 2D it corresponds with the pixel size of the resulting model. Hengl's method for finding the right gridsize is a compromise between efficiency of computation and reliability of the relief (spatial variability) and will be used to define the gridsize.

Depending on the data extraction method, spatial modelling is done over 1 dimensional or 2 dimensional data. To explain how this works in our case study, first the example of 1D spatial modelling is given in section 5.2, followed by a more concise description of 2D spatial modelling 5.3. For profiles it will only require interpolation in one direction to obtain height change information which can then be interpolated to a 2D grid. Using profiles is therefore a more direct way to obtain ground motion information than when contourline data is used. Height difference from interpolated contourline data is then the difference between two DEMs. The profile methods seem to have fewer uncertainties especially along the profiles themselves.

5.2. Spatial modelling of 1D data

The profile sampling method (4.2.3) obtained samples of the contourlines at intersections with the chosen transects. The position of samples is attributed to the point vectors as $x$ and $y$ in RD, together with the corresponding height $z$. Theoretically, if the samples are interpolated over $x$ and $y$ to get the height over the full profile, it concerns modelling of 2D data. However, it is computationally more efficient, and visually better interpretable to transform $x$ and $y$ to a distance $d$ from the origin of the transect, and interpolate over the 1 dimensional 'distance'. Hence, spatial modelling of profiles is considered as 1D interpolation.

Transformation of $x$ and $y$ to $d$ was done by first sorting all samples ascendantly by shortest euclidean distance (as the crow flies) to origin. This is necessary in case samples were not taken in this order directly, as often it is more convenient to sample decadal contourlines first and sample intermediate contourlines afterwards. If sorting by distance from origin is skipped, the order of the sample points cannot be determined and profiles will not give the correct shape. Second, from the sorted data the euclidean distance between each sample is computed and cumulatively summed. Distance vector $d$ then contains for each sample point the distance to the origin of the transect.

After preparation of distance vectors, a spatial consistent dataset must be created from the 1925 and 1960 datasets since they are not the same for both epochs. Therefore, common query points must be defined over which profiles of the two epochs should be interpolated (resampling). There are multiple options to do this (subscript $i$ symbolizes the profile number):

1. Interpolate one epoch to $d_i$ of other epoch, and vice versa
2. Interpolate both epochs to new $d_i$ somewhere in the 'middle'
3. Interpolate to a regular grid $d_i$, i.e. equal distances
4. Interpolate to a selected grid $d_i$ (i.e. equal distance), with 'far' points removed.

The fourth option of a selected regular grid with 'far' points removed is preferred, combined with sampled data positions. In other words, each distance vector will contain all distances with respect to the origin of all sample points on the transect and common query points at chosen distances. Creating these new 'common' distance vectors for each profile is described in the next section, followed up by an evaluation of 1D interpolation techniques.
5.2. Defining common distance vectors

Definition of distance vectors for each profile involves three computational steps. The three steps are:

1. Combining distance vectors of both epochs
2. Inserting common query points to $d_i$ of one epoch
3. Masking non-overlapping points

The first step is the most simple step, combining the distance vectors of the two epochs (1925 and 1960) into one distance vector $d_c$. This is illustrated in the following example with arbitrary values (values are in [km]):

$$d_{1925} = \begin{bmatrix} 0.22 \\ 0.28 \\ 0.31 \\ 0.33 \end{bmatrix}, \quad d_{1960} = \begin{bmatrix} 0.23 \\ 0.29 \\ 0.30 \\ 0.34 \end{bmatrix} \rightarrow d_c = \begin{bmatrix} 0.22 \\ 0.23 \\ 0.28 \\ 0.29 \\ 0.30 \\ 0.31 \\ 0.33 \\ 0.34 \end{bmatrix} \quad (5.1)$$

Where $d_{1925}$ and $d_{1960}$ are the distance vectors of one transect for two map years, $d_c$ is the combined distance vector (5.1).

The second step, insertion of common query points into $d_c$, is preceded by investigation of Hengl’s [14] method to determine the gridsize. The number of query points and their distance to the origin in each vector $d_i$ are found by this method. The term gridsize is normally only used in 2D models with regular grids, but to avoid mixing of terms, here gridsize is also used in 1D context as being the space between two query points. Gridsize forms the basis of the precision and shape reliability of our model, which is also dependant on the interpolation technique as described in section 5.2.2. Choosing the gridsize over 1D data Hengl uses ‘inflection points’. The inflection points are derived from taking the second order derivative of a profile and finding the intersections with the x-axis. Computing a second order derivative of a yet unknown profile requires an example profile with highly dense query points and an interpolation method that has a continuous second order derivative; a piecewise cubic spline. In practice this was solved by computing the second difference of elevation values and then by finding the change in signs. The number of sign changes are the number of inflection points of the profile. Figure 5.1 shows the example profile with computed inflection points in orange.

Now the gridsize will be determined according to equation 5.2 [14]:

$$p \leq \frac{l}{2 \cdot n(\delta z)} \quad (5.2)$$

where $p$ is the gridsize in meters, $l$ is the length of the transect in meters, and $n(\delta z)$ is the number of observed inflection points. From the example profile the number of inflection points was 23 and the profile length is approximately 5000 [m]. Filling in the numbers in equation 5.2 gives:

$$p \leq \frac{5000}{2 \cdot 23} \rightarrow p \leq 108 \quad (5.3)$$

The query distance should thus not be larger than 108 [m]. This value does not count for every transect and may be too coarse to preserve shape reliability for some interpolation methods. Also, the problem with this one profile analysis is that any change in length of this exact profile (by e.g. only using half of it) will give different results. Other values than 108 [m] will be found, thus this gridsize is more of stochastic nature. For this study it was chosen to reduce the gridsize from 198 [m] to 50 [m], which corresponds to the chosen gridsize $p$ for pseudorandom contourline sampling and is expected to give appropriate visualization results (not too detailed).
Now that the gridsize is set to 50 [m] or 0.05 [km], the query points can be added to $d_c$ to get pre-final distance vector $d_f$. It was chosen to add a query point every 50 metre starting from the first value in $d_c$. In the example case it means that $d_f(1)$ is equal to $d_c(1) + 0.05$, $d_f(2)$ is equal to $d_c(1) + (0.05 \times 2)$, and so forth. This is done until the largest distance value in $d_c$ has been reached. The result of the example is illustrated in (5.4).

$$d_c = \begin{bmatrix} 0.22 \\ 0.23 \\ 0.28 \\ 0.29 \\ 0.30 \\ 0.31 \\ 0.33 \\ 0.34 \end{bmatrix}, \quad d_q = \begin{bmatrix} 0.27 \\ 0.32 \end{bmatrix} \quad \rightarrow \quad d_f = \begin{bmatrix} 0.22 \\ 0.23 \\ 0.27 \\ 0.28 \\ 0.29 \\ 0.30 \\ 0.31 \\ 0.32 \\ 0.33 \\ 0.34 \end{bmatrix}$$

(5.4)

Where $d_q$ is the distance vector of query points, and $d_f$ is the pre-final distance vector for both 1925 and 1960 for one transect.

The third step in defining common distance vectors is masking non-overlapping points. One should notice that when the example final distance vector $d_f$ is used for interpolation it involves extrapolation between 0.33 and 0.34 for 1925 and 0.22 and 0.23 for 1960. This is caused by contourlines intersecting the transect not at the exact end points of a transect. Extrapolation can give very unreliable results and these query points are therefore masked out over each year per transect. In Figure 5.2 an example illustration is given of masking query points.
The final distance vector \( d_f \) that can be used to interpolate both 1925 and 1960 of the arbitrary example transect will look as follows:

\[
d_f = \begin{bmatrix}
0.23 \\
0.27 \\
0.28 \\
0.29 \\
0.30 \\
0.31 \\
0.32 \\
0.33 
\end{bmatrix}
\]  

(5.5)

5.2.2. 1D interpolation

Having a (masked) distance vector for all transects, spatial modelling of the 1D dataset can be continued by interpolation. The gridsize will have influence on the precision and shape reliability of the model, however this depends on the interpolation method. 1D linear interpolation method will not be influenced by this by definition. Desmet [9] proposed to use a piecewise cubic spline interpolation (further referred as spline), for its highest precision and shape reliability. For this study also the exact linear interpolation and ordinary kriging are considered. Instead of interpolation, the data can also be fitted. Fitting a profile by a mathematical model through the data points (by e.g. a least squares approximation) is not necessarily exact, as it does not always respects the observations. Fitting the data through least-squares also gives an indication of the extent of possible errors and is therefore a stochastic approach. It was found to be more complex than performing an exact interpolation. The least-squares method was therefore not further investigated. Uncertainty in the sample data is invoked by a Monte Carlo simulation which is further described in Chapter 8, section 8.3.5.

The difference between the exact methods with one hand spline and linear interpolation, and on the other hand ordinary kriging is that the former are deterministic methods and the latter is stochastic. For spline interpolation and linear interpolation it is assumed that the only relevant information to interpolate between two points, is the height of two (linear) or three points (spline). In the stochastic model of ordinary kriging, it is assumed that there is a correlation (and variance) between each point in the dataset, depending on the distance. This idea is derived from Tobler [36], who designed the first law in geography: "Everything is related to everything else, but near things are more related than distant things". To describe this relationship between points in a stochastic model, variograms need to be created for each transect (assuming profiles are mutually uncorrelated) and/or for each year (assuming uncorrelated profiles over time), or one variogram for all profiles (assuming spatial and temporal correlation). This is a tricky set of assumptions and choices, but most logical seems to create variograms for each profile and each year (i.e. 20 variograms for 10 profiles and 2 years) as it is expected that ground has been subject to vertical displacement (no temporal correlation), varying over the area (no spatial correlation). The advantage of this distance-weighted method is that it gives an indi-
cation of uncertainty of interpolated values. Based on the arguments above, it was chosen not to perform ordinary kriging interpolation. In the following steps only the deterministic spline and linear methods are further discussed.

From this point the two proposed methods (spline and linear) should be compared for precision, shape reliability, and efficiency. Computation of the interpolated values are performed in Matlab software, using inbuilt functions. Subsections 5.4.1 and 5.4.2 give insight in the theoretical background of the two interpolation methods. Figure 5.3 shows an example of a spline interpolation and linear interpolation of transect 1 for 1925.

![Figure 5.3: Example of two interpolation methods over the distance vector of transect 1 with height data from 1925 at black dotted data points.](image)

**5.2.3. Evaluation of two 1D interpolation methods**

Precision and shape reliability are the two evaluation points that determines whether the piecewise cubic spline interpolant or linear interpolant should be chosen as ‘best’ method. In Figure 5.3 the blue line represents the cubic spline interpolated profile and the red line is the linearly interpolated profile. The black striped boundary around the data points indicate the maximum offset of interpolated values with respect to the data points: if an interpolated profile crosses this +/- 2.5 [m] boundary, a contourline should have intersected the transect on the historical maps. For the example transect this means that the spline method is biased, as it overshoots the maximum offset boundary between ~2 and ~2.5 [km] on the x-axis. Due to the chosen gridsize of 50 [m] many data points will be biased. Logically, the linearly interpolated profile will never overshoot this boundary (as it is a weighted average). Contrarily, the smooth profile of the spline method has a better shape reliability (tested for drainage patterns, erosion models, and profile curvature by Desmet). However, linear slopes (by approximation) in the Zuid-Limburg area, are best represented by a linear method.

The 1D linear interpolation method is chosen for further analysis for the following reasons: overshooting the +/- 2.5 [m] boundary is unacceptable, the linear method is fast and unbiased, and adding query points is no longer necessary. In later results query points are still added, only for visualization purposes of the diagrams (see Appendix C).
5.2.4. Masking biased areas

The last computational step concerns masking out parts of a profile that are biased caused by the position of transects. When choosing profiles (see section 4.2.3) it can happen that a transect crosses areas that contains contourlines in one year, but due to changes by natural or human activities that are not related to the processes we are interested in (e.g. urbanization, open pit mining, natural geomorphological changes). An example of an area that should be masked out profile 6 is shown in Figure 5.4.

![Figure 5.4: Masking polygon overlaying an open pit mine that is crossed by transect 6. The light blue transect 6 crosses a mine that did not yet exist on the 1925 map. Black dots indicate contourline intersections (data points).](image)

The intersections of contourlines with transect 6 within the mask polygon should be removed from the interpolated profile of 1925 and 1960. The profiles of 1925 and 1960 before and after masking are shown in Figure 5.5. In the left plot of the figure the red box indicates where an open pit mine is located. The red interpolated profile of 1960 has an non-logically looking shape inside the red box, compared to the blue 1925 profile. The flat line is caused by absence of contourlines in the area and will give biased results in estimating ground surface motion. The right plot shows the result after masking the data. Black dots inside the empty space are still shown, which is a result from the repeated method in step 2, shown in Figure 5.2.

![Figure 5.5: Result of masking out areas using a masking polygon. Left: Profiles of transect 6 before masking. Red box indicates where profiles will be masked out. Right: Result of profiles after masking. Inside the red box data points are removed from the transect and leaves a gap. Black dots indicate contourline intersections (data points).](image)
5.2.5. 1D interpolation profile results

The method for 1D spatial modelling as described in the sections is performed for all 10 transects. These results are shown in Figure 5.6. A masked area in transect 4 can be detected as well, which was due to a lack of contourlines around the Heerlen train station and the Emma mines.

These results already show that the elevation derived from 1960 is almost always laying under the 1925 profile, cautiously implying a change in height of the surface between these two years. Before change in height is further analysed, this Chapter continues with a description of 2D spatial modelling.

5.3. Spatial modelling of 2D data

Defining the best spatial model to describe the surface elevation in 2.5D is again a matter of precision, shape reliability, and gridsize. According to Desnet interpolation of 2D data to a 2.5D surface model, a smooth hilly landscape is best represented using a piecewise cubic spline interpolant. But as we have seen for 1D profile models, a linear method was preferred. From this conclusion an evaluation on 2D interpolation methods would be valuable. This section will pay attention to the interpolation effects for contour data, pseudo-random data, and also pro-
file data. It was chosen not to use the point-measurement data for 2D interpolation, due to the sparse amount of data. How ground motion from point-measurements is estimated without 2D interpolation will be discussed in the next chapter.

First an evaluation of interpolating 2D contourline- and pseudo-random data is given in section 5.3.1, followed by an evaluation of interpolating 2D profile data.

### 5.3.1. 2D interpolation of contourline- and pseudo-random data

Desmet proposed a piecewise cubic spline method for 2D interpolation for DEMs, which would have a preference in this study for its higher shape reliability. It is expected that overshooting will not occur because the interpolant is constrained to more surrounding data samples in 2D than in 1D. After the gridsize of the surface model is defined, we will see that the results of the example DEMs are unbiased by overshooting.

For pseudo-random sampling we have already chosen a 50 [m] gridsize in section 4.2.2, in order to determine the number of samples to be taken in each map gridcell. This 50 [m] gridsize will also be used for the surface model based on contourline data for comparison reasons, although a higher resolution is feasible for its larger number of samples per square kilometer. With the RD coordinates of the example area boundary the regular spaced grid for the surface models can be generated. The boundary corner coordinates are given below:

\[
\begin{align*}
 p_1 &: (191000, 328000) \\
 p_2 &: (191000, 329000) \\
 p_3 &: (192000, 329000) \\
 p_4 &: (192000, 328000)
\end{align*}
\]

Data from both sampling methods are resampled to the grid and height values are interpolated by a piecewise cubic spline interpolant. This was done for data from both 1925 and 1960. Results for 1925 are shown in Figure 5.7 and 5.8, for contourline sampling data and pseudo-random sampling data respectively.

![Figure 5.7: Left: DEM derived from a piecewise cubic spline interpolation of data from the contourline sampling method. Middle: Contourlines derived from the DEM on the left at 2.5 [m] interval. Right: Raw samples from the contourline sampling method. Colours indicate elevation.](image1)

![Figure 5.8: Left: DEM derived from a piecewise cubic spline interpolation of data from the pseudo-random sampling method. Middle: Contourlines derived from the DEM on the left at 2.5 [m] interval. Right: Raw samples from the contourline sampling method. Colours indicate elevation.](image2)
The middle figures in 5.7 and 5.8 show contourlines that are derived from 50 [m] resolution DEM for each sampling method. By comparing these middle figures with the right raw contourline sampled data, it can be seen that this interpolation method is unbiased for both methods except at the edges. The advantage of higher shape reliability and unbiased results makes linear interpolation superfluous.

One of the goals of this research is to fill the white gap around Heerlen in Pöttgens deformation map (Figure 1.3), which requires interpolation of 2D data. For further analysis of the contour- and pseudo-random methods, much more time would be necessary to generate enough data to fill the ‘white’ area on Pöttgens deformation map. As mentioned in the conclusions of the sampling methodologies, profile samples are the preferred data for among others, its time efficiency. The next section continues with 2D interpolation over the ‘white’ area by using profile data.

### 5.3.2. 2D interpolation of profile data

The profiles that are inside the ‘white’ gap will be used to interpolate over the area and will be mapped on Pöttgens deformation map to visualize the estimated height difference from the profile sampling methods. The ‘white’ area is indicated by the red outline in Figure 5.9. Since the profile data is highly clustered, interpolation and extrapolation would give very unreliable results. To diminish errors it was chosen to add samples from Pöttgens deformation map to the dataset of profiles. This implicitly means that elevation data should be transformed into deformation data before Pöttgens samples can be implemented in the profile data. Chapter 6 is dedicated to temporal modelling of data, but for this section simple subtraction of the 1D linear interpolated profile of 1925 from 1960 was performed.

Pöttgens deformation map is categorized by intervals of 2.5 [m] which resulted in a course and simple looking map. Samples are taken at these interval transitions, along the border of the ‘white’ area. Choice of interpolation method and how it treats data from profiles and Pöttgens is very important to fill the area in a seamless and similar looking manner. A suitable method that is both deterministic (making it seamless) and can apply weights to data points is Inverse Distance Weighting (IDW). Weights are useful in the sense that the value of an interpolated raster cell is more dependant on close data points. As we want to get most information from profile data in the centre of the area, and most influence of Pöttgens samples along the border, this technique is the preferred interpolation method to use. The basic equation for IDW is given in the separate section 5.4.3.

The weight applied to the sample data is determined from the distance (as the name of the method implies). The number of surrounding sample points used for interpolation is defined by either a fixed number of nearest neighbours ($n$) or the number of samples within a radius. The latter may lead to gaps when the radius is too small or may lead to a too high degree of smoothness when the chosen radius is too large. The first method was preferred to be able to choose $n$ sufficiently small to achieve a smooth surface and reduce computation time. In Figure 5.9 the result of IDW with $n$ set to 20, weighting factor set to $-2$, and the gridsize set to 100 [m] is shown. These three values are a result of tweaking these parameters to optimize visualization.
5.4. Interpolation methods

A brief summary of interpolation techniques that are used in this study is given in this section. Section 5.4.1 is about 1D linear interpolation, section 5.4.2 is about 1D piecewise cubic spline interpolation, and section 5.4.3 is about IDW interpolation.

5.4.1. Linear interpolation

Linear interpolation is one of the simplest interpolation methods, and can be recognized as straight lines between data points. The value of an interpolated point is equal to the weighted average of the two (in 1D) surrounding data points (observations). The weight that is applied is the ratio of the distances between the observations. Mathematically this is denoted as follows:

\[ \hat{y}(x) = y_0 + (y_1 - y_0) \cdot \frac{x - x_0}{x_1 - x_0} \]  

(5.6)

Where \( \hat{y}(x) \) is the estimated value at \( x \), \( y_0 \) equals the the observation value on the left of \( x \) at \( x_0 \), and \( y_1 \) equals the the observation value on the right of \( x \) at \( x_1 \). In 2D, linear interpolation is called bilinear interpolation and uses the same mathematical approach of weighted averaging, only using 4 surrounding points.

5.4.2. Piecewise cubic spline interpolation

The idea of a piecewise cubic spline interpolation is to fit a third order polynomial through data for each segment of the data. This means that if a dataset consists of 8 points as in the example of distance vector \( d_f \) (5.5), the number of segments (pieces) is 7. Mathematically this can be expressed as \( n \) equals the number of data points and \( n - 1 \) equals the number of segments. The 1D third order polynomial for each \( i^{th} \) segment looks as follows:

\[ \hat{y}_i(x) = y_i + ax + bx^2 + cx^3 \]  

(5.7)

Where \( \hat{y}_i(x) \) is the estimated value at \( x \) that is inside the \( i^{th} \) segment, \( y_i \) is the \( i^{th} \) known value in observation vector \( y \), and \( a, b, \) and \( c \) are parameters to be found. Solving this alge-
braically is beyond the scope of this study, but the essence is that both the first and second order derivatives of the result are continuous.

5.4.3. Inverse Distance Weighting
The deterministic Inverse Distance Weighting method or IDW is a form of weighted averaging, that uses $n$ number of nearest data points to determine the value of a query point (or all data points within a radius). The weighting is based on the euclidean distance between query point $p(j)$ and each surrounding data point. Equation 5.8 shows how the IDW process works mathematically.

$$p(j) = \frac{\sum_{i=1}^{n} z(i) \cdot d(i)^w}{\sum_{i=1}^{n} d(i)^w}$$

(5.8)

Where $z$ is the vector of $n$ nearest known values, $d$ is the vector of $n$ corresponding distances, and $w$ is the weighting factor applied as a power to the distance. Thus the weighting of a surrounding data point decreases quadratically by every distance unit if $w$ is equal to $-2$. 
Temporal modelling

This Chapter aims to provide full background on the temporal modelling techniques that are used to estimate ground surface motion, which involves again interpolation or fitting of the data. Previously, map release years were used to indicate which data was being discussed. Since this section focuses on the actual moments in time, the years of measurements will be used from here instead. The table below provides a brief summary of the years of maps and measurements that are used in this section:

Table 6.1: Summary of the elevation data that is used for temporal modelling, with corresponding years that measurements were taken.

<table>
<thead>
<tr>
<th>Map name</th>
<th>Measurement year</th>
</tr>
</thead>
<tbody>
<tr>
<td>Historical map 1925</td>
<td>1918/1919</td>
</tr>
<tr>
<td>Historical map 1960</td>
<td>1955</td>
</tr>
<tr>
<td>Pöttgens map</td>
<td>1914 - 1975</td>
</tr>
<tr>
<td>TOPhoogteMD</td>
<td>1977</td>
</tr>
</tbody>
</table>

In section 5.3.2 of Chapter 5 we have seen that subtraction is one way to find height changes, and this will be applied to point-measurements, contour samples, and pseudo-random samples as well. Since main focus is put on the profile method more modelling methods than simple subtraction will be discussed for profile data. First, in section 6.1 temporal modelling of point-measurements is discussed. Second, in section 6.2 temporal modelling of contour and pseudo-random data is discussed. The final section 6.3 will discuss temporal modelling of profile data.

6.1. Height changes in point-measurements

The dataset to be discussed consists of 44 point-measurements. Recall that the data points are halfway between the actual samples of 1918/1919 and 1960, as we have seen in Chapter 4, section 4.2.4. Difference in height for each point is computed by subtracting 1955 heights from 1918/1919 heights. The results are mapped and visualized with same colours as the Pöttgens deformation map. This way the colours can be compared with the existing deformation map and their correlation can be estimated. Figure 6.1 shows the map of point-measurements and Pöttgens deformation map.
Figure 6.1: Map of the 1918/1919 - 1955 epoch differences from point-measurements with Pöttgens deformation map on the background. Legend indicates the intervals of subsidence according to Pöttgens deformation map.

From visual interpretation there seems to be a spatial correlation between the computed differences and the deformation map, but there is also some nonconformity. In Figure 6.2 the values of estimated differences from point-measurements ($x$-axis) and approximated values from the deformation map ($y$-axis), sampled at same position, are scattered to get a better insight on the correlation.

Figure 6.2: Scatter plot of estimated differences between point-measurements of 1918/1919 and 1955 ($x$-axis, and approximated deformation values from Pöttgens deformation map. Correlation coefficient $r^2$ equals 0.84 and the linear regression line in red was found by ordinary least-squares estimation.

This result shows that a strong linear correlation exists between estimated ground motion and Pöttgens map, by $r^2$ equals 0.84. This correlation is estimated through Pearson's formula, dividing the covariance by the product of the two standard deviations. Point-measurements are rather sparsely distributed over the area and will therefore not give a detailed insight on ground surface motion by itself. The results would have additional value in validation of other methods, but time constraints did not allow to digitize enough point-measurements in the 'white' area.
6.2. Height changes in contour- and pseudo-random data

Contour- and pseudo-random derived surface models created in Chapter 5, section 5.3.1, are used as input for computing the height change in the example area. This area was chosen in such a way that it also covers a part of Pöttgens map. A same type of visualization is used to map both a 3.5D pseudo-random model and 3.5D contourline model. In advance the 1955 2.5D models are subtracted from the 1918/1919 models, then the same 2.5 [m] deformation interval was chosen for visualization of height differences. Finally, the results are plotted over the Pöttgens deformation map. These results are shown in Figure 6.3 for the contourline model (A) and pseudo-random model (B).

Figure 6.3: Left (A): Estimated height difference per gridcell of the example area, derived from 2.5D contourline based DEMs. Right (B): Estimated height difference per gridcell of the example area, derived from 2.5D pseudo-random based DEMs. Colours of the mapped height differences and Pöttgens map correspond to the same interval values. The red line on the background stretching from left to right represents a geological faulting zone.

We can see from the two results that there are clear differences between the two methods and also between Pöttgens map and the estimations. The edges of the models are not very reliable due to extrapolation in these parts, and we will therefore focus on the centres. Both maps do show largest downward movement in the south-western parts (red), and smallest in the northern part (green and yellow). However, the colours are much more scattered than the underlaying Pöttgens map, which may lead to the conclusion that both methods do not give reliable results, or that the two methods give better accuracy and precision of height change estimations. The conclusions could be provided with a scientific backing if the correlation between each method and Pöttgens map is computed, or more temporal interpolation/fitting methods are applied to the data, but time constraints did not allow to perform this. However, in general we see that the stretching of contourlines on Pöttgens map do show a similar orientation to the two methods.
6.3. Temporal modelling of profile data

As we have seen in the previous methods, subtraction will only give us an estimation of the height difference between two years, but cannot provide information on what happened e.g. halfway the period or before and after these two years. In an ideal case, for every year between 1914 and 1974 an elevation model should be available and vertical motion could then be estimated for each epoch between all years. Due to the lack of elevation data for all years, three methods were developed to estimate the ground surface motion over multiple years. These methods involve interpolation and/or extrapolation of the height changes, which will be further referred as scaling. The three methods are listed below and are further investigated in the consecutive subsections.

1. **Linear scaling**
   - Height difference per epoch
   - Scaling to 1914-1974

2. **Empirical scaling**

3. **Matching coal production**

Methods discussed in this section are applied to validation transect 4, in order to test the validity of each method.

6.3.1. Linear scaling

With the linear scaling method vertical motion will be estimated according to a linear trend. This is performed in two different ways: the first is by scaling (extrapolating) to the time interval of active coal production (1914 till 1974) and the second is creating two height differences, for the epochs 1918/1919 - 1955 and 1955 - 1977. The main difference between the two methods is that the first performs a linear extrapolation, whereas the second performs two linear interpolations.

**Height difference per epoch** This method is the most simple and the same as performed for the other sampling methods. The defined common distance vectors allow us to subtract the 1955 elevation profiles from the 1918/1919 elevation profiles. Results of subtraction is presented in two different ways for clarity reasons of the figures. The first shows the result of subtraction and the interpolated elevation profiles for validation transect 4 in Figure 6.4. The second only shows the results of subtraction for all transects in Figure 6.5. The interpolated elevation profiles of all transects can be found in Figure 5.6.

![Figure 6.4: Left: Linearly interpolated elevation profiles of 1918/1919 and 1955 from transect 4. Right: Height differences per epoch: subtracted 1955 elevation model from 1918/1919 elevation.](image)
In general we see that the height differences are below zero, implying that subsidence has occurred over all profiles with the exception of a few peaks above the zero line. They also show a large variation along the profiles, which raises the question "do the results make sense?". The answer to this question requires validation of these results, and a more in depth research on the uncertainty in the data. Attention to validation of this method is paid in section 6.3.4 of this chapter together with the other temporal modelling methods, in Chapter 7, and in the uncertainty analysis of Chapter 8.

Scaling to 1914 - 1974. If we want to get insight on ground motion over the period of active coal production, or compare it to Pöttgens deformation map, it seems logical to scale height differences from the previous method to 1914 - 1974. Scaling the height differences for each point to the time interval 1914 - 1974 requires relatively simple computations. The time scale of the maps covers 1955–1918 = 37 years and active coal production covers 1974–1914 = 60 years. Extrapolating a linear trend is here the same as multiplying all height anomalies by the ratio $\frac{60}{37} = 1.62$. Due to the large variation in the profiles, it is for visual purposes chosen to scale transect data from Pöttgens map from 1914-1974 to 1918-1955. The results of linear scaled subsidence for transect 4 is plotted in Figure 6.7. Conclusions on this method follow in section 6.3.4.
6.3.2. Empirical scaling

This method is based on validation data extracted from Pöttgens deformation map along transect 4. Since this is the only other data available about ground surface motion in the area, it will be used to scale profile height difference by an empirical factor. The reason to do this, is to do a simple fit of found data to validation data, improving the reliability of the height difference profiles. The idea is to compute the average and median height difference of both the historical maps and Pöttgens map along validation transect 4, and then scale them proportionally. Using the median is preferred because height differences are not expected to be normally distributed over a transect (spatially uncorrelated). The empirical ratio between the medians of the two datasets was found to be 0.83 (height data:Pöttgens data). All other transects can be multiplied with the same ratio to get anomalies for the 1914 - 1974 time interval. Results of validation transect 4 are plotted in Figure 6.7. Conclusions on this method follow in section 6.3.4.

6.3.3. Matching coal production

The final method was designed to get insight on ground surface motion per year inside the interval based on the expected geophysical relation between surface motion and coal production in the area. In the previous two methods the yearly ground motion rate were both linear, although with a different extrapolation scale factor. With this method interpolation and extrapolation was performed by yearly rates that are derived from the yearly coal production. Since coal production changed over the years (see Figure 1.2, ground surface motion may have changed accordingly.

First, relative cumulative production of coal production between 1914 and 1974 was computed, giving a function of 0 (no production) to 1 (end of production) over time. This is illustrated in the left plot of Figure 6.6. Secondly, the linear yearly height difference from method 1 (scaled to 1914-1974) was retrieved and also its relative cumulative rate was computed, which is a straight line from 0 to 1 between 1914 and 1974. The third step is to compute the ratio of both relative cumulative functions.

These ratios are computed for every year. For each data point its linear yearly height change rate is computed and multiplied by the yearly ratios of the corresponding data point. The result of one example data point on transect 4 is given in the right plot of Figure 6.6.

Looking at Figure 6.6, the beginning and end points of the two methods are equal. At the full 1914-1974 time interval the results of the linear scaling method and matching coal production method are thus the same. But if we want to scale our data to e.g. 1918-1955, there will be a difference in outcome between the two methods. Mutual difference in height change at 1918
6.3. Temporal modelling of profile data

will be called $\Delta Y_a$ and difference in height change at 1955 will be called $\Delta Y_b$. Letters $a$ and $b$ in the figure correspond to subscripts $a$ and $b$. The sum of differences between $\Delta Y_a$ and $\Delta Y_b$ will give the absolute difference in estimated height change: $\Delta Y_a + \Delta Y_b = 0.1652 \text{[m]}$. In Figure 6.7 we can see that the green line of Pöttgens data scaled to 1918-1955 lies just a little above the yellow line of linear scaled data. The next section discusses conclusions of the temporal modelling methods.

6.3.4. Conclusions on validation of temporal modelling methods

First the results of scaling methods (linear, empirical, and coal matching) and without scaling (height difference per epoch) are plotted in Figure 6.7.

The first thing to remark from the plot results of the validation transect is that there is a large visual difference in variance of height change between historical and Pöttgens derived data. Still some little agreements can be found, for example, in the far end between 4 and 5 [km] distance from origin Pöttgens lines approach the blue historical line. Imagining a straight line between the masked gap will also give the impression that from about 1.5 [km] to 5 [km] the trend of all lines coincide. The error with the purple line of empirical scaled data is in this area about +/- 1 [m]. However, when looking at the first kilometre of the transect, the absolute difference between blue and yellow/green is the smallest (still very large).

Oscillation of the blue line may be caused by inaccuracy of elevation data, which will be further evaluated in Chapter 8. In general it should be concluded that the validation of the methods did not result in a confident solution to the temporal modelling problem. In the next Chapter it is tried to perform further validation by integration of Levelling + InSAR data, and TOPhoogteMD from 1977 is integrated to elevation profiles to add the epoch of 1955 - 1977 in estimating ground surface motion.
Historic and modern data integration

Main purpose of this Chapter is to estimate ground motion after 1955 and to validate results of 1918/1919-1955 ground motion estimations by integrating ‘modern’ data and historical data. The terms compare and integrate are used in this chapter by means of creating a dataset with the same spatial distribution in the x, y-field; having values for historic data and modern data at the same position. How this is done will be explained in this chapter by first denoting the data types of the used datasets in section 7.1, then by evaluating the processing steps in integration in section 7.2, and finally by providing results of the integrated models and conclusions in section 7.3.

7.1. Data type evaluation

The modern data consist of TOPhoogteMD, AHN-3, and Levelling + InSAR datasets. They all have a different spatial distribution mutually as well as they differ from the historical data. Table 7.1 gives an overview of the datasets with important information that should be known if thou want to integrate the datasets.

Table 7.1: Summary of available elevation models datasets from sampled historical data and modern data with some specifications.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Data dimensions</th>
<th>Measurement type</th>
<th>Spatial distribution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Contourline</td>
<td>2.5D + 3.5D</td>
<td>Height + Anomaly [m]</td>
<td>Gridded [50m]</td>
</tr>
<tr>
<td>Pseudo-random</td>
<td>2.5D + 3.5D</td>
<td>Height + Anomaly [m]</td>
<td>Gridded [50m]</td>
</tr>
<tr>
<td>Profile</td>
<td>2D1 + 2.5D2</td>
<td>Height + Anomaly [m]</td>
<td>Scattered [~50m]</td>
</tr>
<tr>
<td>Point-measurement</td>
<td>2D + 2.5D + 3.5D</td>
<td>Height + Anomaly [m]</td>
<td>Scattered</td>
</tr>
<tr>
<td>TOPhoogteMD 1977</td>
<td>2.5D</td>
<td>Height [m]</td>
<td>Scattered [~75m]</td>
</tr>
<tr>
<td>AHN-3 2015</td>
<td>2.5D</td>
<td>Height [m]</td>
<td>Gridded [5m]</td>
</tr>
<tr>
<td>Levelling + InSAR 1974-2015</td>
<td>2.5D</td>
<td>Anomaly [mm]</td>
<td>Gridded [100m]</td>
</tr>
</tbody>
</table>

The spacing values in Table 7.1 are based on the gridsize or approximated average distance between scattered data. From this table it can be seen that integration of datasets requires conversions of spatial dimensions, units, and spatial distribution. Since our main focus is put on profile data, only the integration with profile models will be further discussed.

1See section 5.2.5
2See section 5.3.2
7.2. Data integration process

Integration of the different data types involves several steps:

1. Choosing preferred data type

2. Resampling and interpolation

3. Adjust units

1. Choosing preferred data type. In the previous chapter already same spatial interpolation choices were made, e.g. the 50 [m] spacing between query points. The resampling of TOPhoogteMD, AHN-3, and Levelling + InSAR data in the next step has consequences for the resolution of all three datasets. The high resolution of the AHN will be lowered from [5m] to approximately [50m]. This seems to be a huge loss of information, but the height variability will still be much larger than the linear interpolated profiles. For the TOPhoogteMD and Levelling + InSAR data the spatial resolution will be increased. Hence the profile sample data has height intervals of 2.5 metre, both TOPhoogteMD and Levelling + InSAR data will still have a larger elevation variability after this spatial resolution reduction. These datasets are not limited to the 2.5 metre interval but have more continuous heights. The next step is to perform resampling and interpolation, bearing the above mentioned consequences in mind.

2. Resampling and interpolation. As seen before in spatial modelling of profiles, resampling and interpolation is necessary to subtract height \( A \) from height \( B \) at the exact same position. For this reason, integration of the modern data requires adjustments in spatial distribution of the modern data as well. Resampling of the scattered and gridded modern data to the profile samples and query points requires 2D interpolation of all three modern datasets. The same piecewise cubic spline interpolation method was used as for the contourline sampling data and pseudo-random sampling data in section 5.3.

3. Adjust units. The last step is to adjust the measurement units of the datasets to be equal for each model. Table 7.1 shows that only Levelling + InSAR data has different units. This data was therefore divided by 1000 to change the units into metres as well.

7.3. Results of integrated profiles

Results of the integration into the 2D profile models are presented here. First the result after integration of all modern data with elevation profiles are presented. Second, the integration results of Levelling + InSAR data with ground motion profiles for validation purposes are shown. Finally, the results of ground motion estimation between the epochs 1918/1919, 1955, and 1977 are shown.

7.3.1. Integrated elevation profiles

For Figures 7.1 and 7.2 it was chosen to subtract the Levelling + InSAR profile from the AHN-3 2015 profile to get an idea of the profile that could be reconstructed for the year 1974. Figure 7.2 shows a detail of Figure 7.1 to get a better visualization of the differences between the integrated profiles.
7.3. Results of integrated profiles

Figure 7.1: Integrated elevation profile of transect 4 for 1925, 1960, TOPhoogteMD 1977, AHN-3 2015, and AHN-3 2015 with subtracted Levelling + InSAR.

We see in the above figures that the largest changes in height is between 1918/1919 (blue) and 1955 (red). The differences between 1955 and the modern data are mostly within +/- 1 [m], which is relatively small compared to 1918/1919 differences. The variation of the differences between 1955 and later is likely due to the lower resolution in z of historical data, errors in both historical data and modern data (also from resampling and interpolating modern data). Overall, we see a strong agreement in shape of the profile, which gives hope for the reliability of the historical elevation profiles. To get more insight in the reliability of ground motion estimations, the height difference profiles of the 1918/1919 - 1955 epoch will be compared with Levelling + InSAR data in the next section.

Figure 7.2: Detail of the integrated elevation profile of transect 4 for 1925, 1960, TOPhoogteMD 1977, AHN-3 2015, and AHN-3 2015 with subtracted Levelling + InSAR.
7.3.2. Validation of profile height change with Levelling + InSAR data

Due to the difference in vertical resolution between the historical elevation data and the Levelling + InSAR data, a perfect validation is not possible. We would expect that the estimated height differences along the profiles show an opposite effect to the Levelling + InSAR profiles; uplift due to increase of groundwater levels after 1974 is expected to be largest in areas with largest subsidence before 1974 [32]. Plotting both profiles over each other should show this effect, which is done in Figure 7.3.

![Figure 7.3: Plots of transect 1 to 10 showing the estimated ground motion from historical data in blue and Levelling + InSAR data in orange. Mean ratios between the two profiles for each transect are indicated in the plot titles.](image)

In the above figure the mean ratios between Levelling + InSAR profiles and historical profiles are given as an indicator of the difference in magnitude of subsidence and uplift. The expected opposite effect of subsidence and uplift is rather difficult to interpret from these results. Along transect 3, 4, 5 and 8 we may see some mirrored symmetry between the two lines, but looking at for example transect 9, the two lines seem to follow each others trend. Whereas our conclusions from Figure 7.2 gave good hope on valid results, the validation of height changes from Levelling + InSAR do not truly validate our expectations.

7.3.3. Comparing 2.5D height change with Levelling + InSAR data

In this section the 2.5D profile map from section 5.3.2 is out next to the Levelling + InSAR map. As we have seen in the 2D profile, an obvious opposite effect between the two models was not spotted. In Figure 7.4 the same opposite effect is tried to be found. On the left (A) of the figure the 2.5D IDW interpolated profile model is shown, on the right (B) the Levelling + InSAR model is shown.
7.3. Results of integrated profiles

Figure 7.4: Two maps of the ‘white’ area with in A the IDW interpolated profile model and in B the Levelling + InSAR model. Colours are attributed to values within the quantile ranges as indicated.

Colours are attributed to values within the quantile ranges as indicated and provide insight in where the quantiles of data values are located. For example, the lowest 25% of the range of data values are visualized in green. In this way we can see the distribution pattern of values over the area for both maps, which makes it easy to compare the maps. It should be noted that high values (blue, red) on the left map indicate large subsidence, and on the right map they indicate large uplift. It should therefore be expected that the coloured areas in both maps correspond. The area north-west of Heerlen to south of Heerlen do show similar colours in both maps, a green and yellow mixture which supports the expectations. In the south-eastern part of the area we find the highest 25% of values in A, but for B these are found in the for north of the area. However, a blue colour in the south-east of B indicates that also here a large uplift has occurred. The western corner of the area in A is predominantly blue, corresponding to the dominant blue colour in B, although the pattern of the colours do differ in shape. A final comparison to be made is around the northern edge of Heerlen, where a blue band can be spotted which is also present in B.

In general we do not see evidence that the results spatially correlate, but still some similarities are present. The 2D correlation coefficient that is computed from the two models is $r = 0.4198$.

7.3.4. Results of height changes per epoch

The goal of this section is not to validate results, but only to show the estimated height differences between the epochs 1918/1919, 1955, and 1977. TOPhoogteMD 1977 is integrated and is used as reference for visualization purposes. It was chosen to plot the results over the distance vectors in 2D, and to map profiles over the historical maps using GIS. Mapping in a GIS required transformation of $d$ back to RD $x, y$ coordinates and a different visualization of values by bars instead of a line plot. Figure 7.5 shows the 2D plots of both elevation profiles and height differences, and Figures 7.6, 7.7, 7.8, and 7.9 show a few examples of the mapped height change profiles (all other transects can be found in Appendix C to save space). The height change information for both visualizations is the same, but it was chosen to plot the height change of 1955 with respect to 1918/1919 as well in a separate map. Position of transects in the mining area can be found in Figure 4.10, and are also plotted in the left overview map in the mapped results.
Historic and modern data integration

Figure 7.5: 2D plots of the 1918/1919, 1955, and 1977 elevation and corresponding height differences. Column 1 and three show the integrated elevation profiles, and column 2 and 4 show the height differences with respect to 1977. Positive values of the 1918/1919 (blue) line and 1955 (red) line thus imply a subsidence of the ground surface.
7.3. Results of integrated profiles

Mapped profile results transect 3:

![Figure 7.6](image1)

Figure 7.6: A: Profile vertical displacement of transect 3 for 1918/1919 - 1977 (blue) and 1955 - 1977 (red). Displacements are computed with respect to 1977. B: Profile vertical displacement of transect 3 between 1918/1919 and 1955.

Mapped profile results transect 4:

![Figure 7.7](image2)

Figure 7.7: A: Profile vertical displacement of transect 4 for 1918/1919 - 1977 (blue) and 1955 - 1977 (red). Displacements are computed with respect to 1977. B: Profile vertical displacement of transect 4 between 1918/1919 and 1955.
From the two visualizations a few conclusions can be drawn. The 1D plots do not show the relation to the position of transects in the area, and large peaks in e.g. transect 3, 6, and 10 are therefore difficult to understand. These peaks are also visible in the mapped plots above. They show that the peaks in profile 3 and 10 are due to the presence of a river. Contourlines near a river are drawn closely next to each other (steep slopes) and small inaccuracies in field measurements, mapping, georeferencing, or interpolation will give large discrepancies in the estimations. For transect 6 this is not the case. The historical maps do not give a clue on what happened to cause this large peak. However, the peak is very near the masked area due to
open pit mining, which gives us a hint on what might happened: between 1955 and 1977 the existing pit mine has likely expanded. A quick look in Google Earth shows that this thought is probably correct, as shown in the snapshot presented in Figure 7.10.

Figure 7.10: Printscreen taken from Google Earth near the Oranje Nassau IV-I mine. The red circle indicates the area of the large peak in transect 6.

Within the red circle we see a small lake and a terraced landscape which indicates that mining activities take or have taken place here. Now that large peaks are explained by rivers and mining activities the smaller variations have not been explained yet. Are they due to ground motion or errors in the estimations? In the uncertainty analysis in Chapter 8 it was tried to get a grip on all the uncertainties that have influence on the estimations on ground surface motion.

In general we see that, according to these results, most of the height change has occurred between 1918/1919 and 1955, as the red line and bars are closer to the reference of 1977 than the blue lines and bars. The best example is seen in validation transect 4. To support this interpretation the percentage of negative values from the total data points is computed for the two epochs (1918/1919-1955 and 1955-1977), which gave 90% and 50% respectively. This change in number of occurrences of subsidence between the epochs show that the area was dominated by subsidence between 1918/1919 and 1955, and in a transition to a period of more between 1955 and 1977. This is also a logical conclusion by keeping in mind that after 1974 uplift was measured due to mine water level rise.
Uncertainty analysis

In this chapter it is tried to get a fundamental understanding of the uncertainties that are related to the estimation of ground surface motion from historical maps using the profile method. Three approaches are discussed consequently. Section 8.1 describes the literature based approach, section 8.2 describes a more empirical approach, and finally, section 8.3 describes a process based approach. This will result in three conclusions on the total uncertainty which will be depicted in the final section 8.4.

For all three approaches it should be noted that no validation/ground truth data is available. One hypothetical method to perform a validation process when ground truth data is available will be described in section 8.2.1. The total uncertainty is defined as the combination of systematic and random errors of the estimated ground surface motion. In some cases the errors are not well know due to the historical nature of this study and therefore some assumptions are made throughout this chapter. These assumptions will be mentioned accordingly.

8.1. Uncertainty analysis from literature

Some literature studies tell us how the uncertainty of a surface model can be explained by shape modelling and by descriptive statistics, such as the Root Mean Square Error and Mean Error [9] [33]. These methods are designed for uncertainty analysis of interpolated DEMs with validation data, and not for profiles derived from elevation data. It should therefore be kept in mind that uncertainty estimations from these articles will not be truly valid for the profile method. However, the information from literature might be very useful to get a first insight on uncertainty magnitude to be expected.

The main driving factor of uncertainty in historical elevation modelling is spatial interpolation [33] and therefore it is important to choose the best interpolation method. In our case study a linear interpolation of elevation profiles was preferred which is according to Desmet [9] a good second option for reliable 2.5D surface models. The study area used by Desmet is similar to the hilly landscape of Zuid-Limburg, and for this reason the estimates from their study will be incorporated in our analysis. Inaccuracy of multiple interpolation methods, including linear interpolation, for DEMs were in the order of centimetres. For 2D linear interpolation the accuracy (RMSE) of the interpolated values compared to ground truth data was found to be 5.5 [cm] by approximation. The accuracy is however morphology dependant [29], and linear interpolated profiles are likely to be more accurate on slopes than on smooth hill tops and valleys. Consequently, it is likely to assume that the uncertainty of a linear interpolated DEM is not a very reliable estimator of elevation profiles, and therefore, ground surface motion. With the empirical approach in the next section, the uncertainty of hill tops and valleys for the profile methods will have the main interest.
8.2. Empirical uncertainty analysis

The empirical analysis of the uncertainty involved in profile based ground surface motion estimations, has been developed during a brainstorming session at the faculty of Geoscience and Remote Sensing at the Delft UT. Two potential methods were the result of this session and are discussed accordingly in sections 8.2.1 and 8.2.2.

8.2.1. Validation by similar area

Possibilities of this first method is only evaluated theoretically, and has not been performed due to time constraints of this study. The idea is to build a testing environment in a similar landscape area, which can be sampled by the profile method. The similar area should be chosen under the condition that in the same epoch (1918/1919 till 1955) no or a well known ground motion took place. Results of ground motion estimations in this area should be equal to 0 or the known value along the transect, and any abnormality to that value can be counted as 'error'. Analysis on these errors will give insight in the total expected ground motion uncertainty derived from the profile method. Nevertheless, this method has not been performed yet as a research should be done on finding such an area with similar landscape, historical data availability, and well known ground surface motion.

8.2.2. Local contourline sampling

The second method that has been discussed is called 'local contourline sampling'. As briefly mentioned in the literature approach, the elevation error is expected to be highest at local maxima and minima, for linearly interpolated elevation profiles. It has therefore the main focus in this method. In order for us to estimate this error, pseudo-randomly picked samples are added around profiles at local maxima and minima. A local elevation model can then be created at these hilltops and valleys by resampling the added data to the $x, y$ position of profile data points and interpolate height to these points. The local elevation models can be used as a validation model for the 'simple' 1D profiles. The difference in height would give an insight on the local uncertainty of the profile method. The assumption is made that the precision of the local models is much better than that of the profiles. It should be noted that if a higher precision is expected, replacement of the profile hill tops by the newly modelled hill tops would give better final results. However, this will also cost a large amount of time and for now the goal is to get insight in the profile uncertainty.

For this study only one example area was used to demonstrate this method. A hill top along transect 10 was chosen arbitrarily. For 1925 and 1960 contourlines are sampled inside a bounding box around a hill top, by picking samples pseudo-randomly. Ideally, full sampling of all contourlines would be give even better results, but considering time pseudo-random sampling is preferred. In Figure 8.1 the example area is indicated in the black dotted box, in which samples around the hill top of profile 10 are added for both the 1925 and 1960 map. The additional samples of the two epochs are resampled to the profile data positions in $x, y$ and elevation values are interpolated by a piecewise cubic spline technique. From the resampled elevation data a 1D representation ($x, y$ to $d$) is created to compare the newly modelled heights with the profile heights. Figure 8.2 shows the results of the example area along transect 10. In the left plot the elevation models from both added samples and profiles are combined, and in the right plot the subtracted difference between the two methods are plotted with the profile eleva.
Figure 8.1: Map showing the added samples to a local summit of profile 10. The upper map shows the added samples to the 1925 dataset, and the lower map shows the added samples to the 1960 dataset.

Figure 8.2: Left: Red and blue dots indicate the linear interpolated profiles for 1925 and 1960 respectively. The solid lines are created from the added samples of contour lines after 2D piecewise cubic spline interpolation and resampled to the profile data points. The black rectangle symbolizes the area of the hill top. Right: Height differences of the linear interpolated profile and spline interpolated profile are plotted over the distance vector. Red indicates the 1925 'linear profile' minus the 'spline profile' (black dotted line is the reference linear profile), and blue represents the same for 1960.

The results in Figure 8.2 show that there is a significant difference between the two epochs. According to this result elevation from the 1960 profile method is underestimated by approximately 1.7 [m], whereas this is only 0.3 [m] in 1925 at this particular hill top. This difference will have a large effect on the estimation of ground surface motion between the two epochs. In this
example it implies that using the profile method, the estimated subsidence is overestimated by −1.4 [m] at its maximum.

Using this example only, not much can be concluded on the exact errors made in estimating ground surface motion for all profiles. However, the uncertainty involved with this method is very large by order of magnitude (metres).

8.3. Process based uncertainty analysis

The final approach to estimate the uncertainty of ground motion estimations from profiles will follow through all processing steps from field to estimations. This is a far more complex approach to determine uncertainty, due to the large number of sub-processes taken in the full process. To tackle this problem this section is divided into four main processing steps that capture the full palette of main processes:

1. Topographic measurements (8.3.1)
2. Mapping (8.3.2)
3. Georeferencing (8.3.3)
4. Sampling (8.3.4)

In the previous approaches it was assumed that sampled data points are true, which is a rather bad assumption acknowledging the fact that before interpolation the above processes have taken place. With this approach the individual processing errors can be used as input for Monte Carlo simulations to get insight in the effect of processing errors on the uncertainty in ground surface motion estimation.

Besides the issue of the large number of sub-processes, most of the errors made during field measurements are unknown or difficult to estimate. To find the best estimation of errors in the measurement process, assumptions are made, interviews were held, and literature is consulted. In some cases the available information is too sparse, that an educated guess of the error magnitude is chosen. It is assumed that blunders made in field measurements are eliminated before the moment of mapping, and are therefore not taken into account in this description. The next sections of the process based uncertainty analysis approach will follow the order of the listed processing steps.

8.3.1. Topographic measurement errors

Over the years from the oldest maps till the newest topographic maps, many different surveying techniques were used to measure topography. Field measurements were taken both in x,y-direction (point determination) and in z-direction (elevation measurements) [18]. Both of these errors have their influence on the estimation of elevations along transects. First, a rough distinction is made between types of topographic surveys dat are conducted by the Topografische Dienst (TD, now a division of the Kadaster) during period from 1900 till today:

1. Surveys with mainly theodolites and tachymetres (<1900 - 1970)
2. Surveys based on photogrammetry (1932 - >1970)

High-tech measurement techniques improved the precision and accuracy of the measurements rapidly and with that also the geodetic reference systems. Since 1987 the TD and many other organizations use satellite positioning systems (e.g., GPS) for their surveys [8]. The transition of measurement techniques involved a transformation of the reference system and corrections of the reference frame from RD to the later adopted ETRS89. This correction is known and applicable with a small error involved, but small enough to neglect when the results of historic ground surface motion are integrated with the modern data results.
The kadaster created a historic overview of instruments that were used by the TD, in which it is stated that in Zuid-Limburg a Wagner-Fennel Tachymetre-Theodolite (see Figure 8.3) has been used in the period of 1918-1940. This instrument is therefore likely to be used in the period that measurements for the 1925 map were taken and thus the 1925 map belongs to the first group of survey methods. On the 1960 map it is specifically noted that elevation of the area is derived from photogrammetric measurements and thus the 1960 map belongs to the second group of survey methods.

From this point we can discuss the errors that had influence on field measurements that are used for the 1925 and 1960 map, based on the survey types. On the one hand these errors could be estimated by listing all sub-processing steps, identify their influence on the observations, and check whether they have been corrected or not. On the other hand, many of the answers to these issues are unknown or simply too difficult to determine due to insufficient historic information. It was chosen to provide a concise review on error-sensitive sub-processes that have been performed in measuring topography for both survey types followed by conclusion on the expected magnitude of errors that could be used as input for the Monte Carlo simulations.

![Wagner-Fennel Tachymeter-Theodolite](image)

**Figure 8.3:** Wagner-Fennel Tachymeter-Theodolite used in Zuid-Limburg for topographic surveys by the Topografische Dienst from 1918 till 1940 [18].

**Errors from theodolites and tachymeters surveys.** It is not possible to say with 100% confidence that only the Wagner-Fennel Tachymetre-Theodolite in Figure 8.3 has been used for the 1925 map. Maybe other instruments have been used as well, but it is impossible to trace back this information. For this reason, a more general description will follow on systematic and random errors in field surveying. According to Muls [26] measurement errors that are most relevant for surveys from theodolites and tachymeters are:

1. Instrumental errors
2. Subjective errors
3. Environmental errors
The influence of these three error sources is typically present in the horizontal field, as the vertical errors are dominated only by the environmental errors due to refraction [26]. 

**Instrumental errors** are systematic and caused by the instrument’s construction. For example, turning axes of the theodolite may not be truly perpendicular causing distortions in the measured values. Most of the instrumental errors can be eliminated except for ‘graduation errors’, which is caused by decentralization of the inner circles of the theodolite [26]. Since the instrumental errors are systematic in time (same type of instruments and/or same graduation error minimization techniques were used) a relative error over the area and in time is excluded. The absolute errors are expected to be small enough to ignore due to high precision of assembling the instruments [2].

**Subjective errors** are caused by the surveyors in the field. The main errors derive from idealisation and moved borders and beacons due to e.g., maintenance of the terrain [1]. Idealisation is the process of positioning the instrument at the right point. The error type is random or gross and difficult to approximate as it is very terrain dependant. According to Baarda et al. the total horizontal error of idealisation ranges typically from 0.5 [cm] to 25 [cm] distortion due to for example waterbodies that make it hard to determine exact points (e.g., middle of a creek). On average a 5 [cm] standard deviation is a good prediction of the subjective errors [1] in the horizontal field.

According to Muls (2007) [26] the only significant vertical measurement distortions in optical measurements (e.g. Wagner Fennel Tachymetre-Theodolite) derives from refraction. There are two types of refraction which have influence on the measurements: **Astronomical refraction, and terrestrial refraction** [3]. The first is predictable and for this study it is assumed it has been eliminated from the measurements. Terrestrial refraction is less predictable due to variable heat transfer from soil to the lower atmospheric boundary layer. The effect of refraction can be approximated by a radius of curvature of the light ray seen through the instrument. This curvature can be estimated following equation 8.1:

$$ r = \frac{R}{k} $$

Where \( r \) is the curvature radius, \( R \) is the Earth’s radius and \( k \) is the refraction coefficient. With an average of \( k \approx 0.13 \) for field measurements [3] the curvature can be estimated. The total refraction effect can then be approximated as a function of the curvature radius and the distance between the measured point and the instrument. Figure 8.4 shows the relation between distance and the refraction with \( k = (0.1, 0.13, 0.2) \) and the Earth’s radius \( R \approx 6365.3 \) [km] at 51°N in WGS84 ellipsoid (computation is shown in B, equation B.2). In this example a steep slope was taken as a case study of approximately 11.3° over 100 meter distance to get insight of the effect of refraction in an extreme case. The three refraction coefficients symbolize respectively the best case, normal case and worst case scenarios.
The effect of refraction on actual height is negative, which implies that there will be a slight underestimation of height. Since the refraction coefficient varies over time, an accurate measure of the underestimation of field measurements from tachymetry cannot be taken into account. However, the error magnitude of the refraction is in sub millimetres which is negligibly small.

For the 1925 map the three types of errors show that only the subjective errors have a significant influence on the errors made in the measurement process of the 1925 map. This 5 [cm] error is of random nature and will be used as input as a standard deviation in \( x \) and \( y \) in the Monte Carlo simulations. This means that no random error is given as input in \( z \), which is not very realistic from an expert knowledge point of view. To improve reliability, a 10 [cm] error was introduced and used as input for \( z \) in the Monte Carlo simulations.

**Errors from photogrammetric surveys.** The method of aerial photogrammetry is based on optical pictures taken from an airplane, to produce a terrain model of \( x \), \( y \), and \( z \). Using two or more overlapping pictures and knowing the characteristics of the flight of the plane and of the camera, it is possible to derive 3D maps [3]. According to Ligterink (1972) [22] accuracy and precision of this method is not dependant on the processing instruments, but is mainly dependant on the quality of point determination. This is the method of determining the \( x \), \( y \), and \( z \) of a point in the map.

Since the upcoming availability of computers in the second half of the 20th century, processing of photogrammetric data became more precise [22]. For this reason the quality of \( x \) and \( y \) positioning is the main source of uncertainty in maps derived from photogrammetry. Precision of point determination is sensitive to many factors such as quality of the photograph, photo scale, and the number and quality of image coordinates (control points *orpaspunten*) [3]. This information is unknown for the 1960 map and therefore general descriptions of photogrammetric topography measurement precision are used for further study in this matter. A rule of thumb could be applied to determine the precision of point determination if only the photo scale is known. The exact photo scale of the 1960 map is unknown, but in calculation examples in literature [3] [27] [22] the used...
photo scale reciprocals (PSR) vary from 1:6000 to 1:10000. The rule of thumb is that a precision of 5 to 10 µm can be reached [3]. Applying the PSR to find the precision of \(x, y\) on the terrain will give about 5 to 10 [cm]. For vertical precision a different rule of thumb can be applied. The rule tells that the precision in \(z\) is related to the flying height of the air plane by a factor 500 to 1000 (or 0.2% and 0.1% respectively). The flying height can be computed using equation 8.2.

\[
PSR = \frac{H}{f}
\]  

(8.2)

Where \(PSR\) is the photo scale reciprocal, \(H\) the flying height above ground and \(f\) is the focal length. With a scale reciprocal of 10000 and a standard lens with a focal length of 152 millimetre [27] is assumed, which leads to a flying height of 1520 metre. The uncertainty of the measured height is then equal to \(\sim 1.5\) to \(\sim 3.0\) metre. This a rather coarse precision and a 3 metre error cannot be expected from a 2.5 metre interval contourline map. According to the Belgian National Geographic Institute (NGI), flying heights differ per occasion, and can be as low as 600 metre. This number will give an uncertainty of 0.6 metre, which is much more likely.

From photogrammetric measurements a \(x, y\) precision can be expected of 5 to 10 [cm] and in \(z\) 60 [cm]. These values will be used as a standard deviation input for the Monte Carlo simulations.

8.3.2. Mapping errors

The precision of the cartographic process is based on two main factors [3] [10], which will be discussed in this section respectively:

1. Generalisation

2. Digitization of maps

**Generalisation.** The process of generalisation is an inevitable step in mapping that occurs when measurement details are too precise to be drawn on a map. Details are left out (e.g. trees) or lines are simplified, which is called conceptual generalisation and graphical generalisation respectively. Graphical generalisation is both a software and hardware restriction, but also a matter of interpretability of a map [10]. An example of a restriction to drawing details is the line width of a pencil: a cartographer’s precision is limited to the width of a pencil stripe. The degree of generalisation of the historical maps can be approximated by \(0.15 \times \text{the map scale}\) [3], which results in a precision of map elements (including contourlines) of \(0.15 \times 25000 = 3750\) [mm]. The uncertainty that is a result of generalisation in \(x\) and \(y\) is thus 3.7 metre in the \(x, y\) field.

**Digitization of maps.** Historical maps in the period of field surveying (with theodolites and tachymetres) are hand noted in the field and mapped onto paper by the so called binndienst. Also the photogrammetric maps are drawn on paper by the binndienst. The transition of paper maps to digital raster maps requires digitization of the paper maps into a computer. For this study the used maps are raster files, which required scanning of the maps [10]. The precision of a scanner is dependant on the width of scanning strokes of e.g. 0.1 [mm]. This value is given as example by Ormeling [10], and is verified by dividing the length of 1 cm on a map by the number of pixels between it in the raster files (i.e. 100 for all maps). The value of 0.1 is within the generalisation range and this error type does not need to be taken further into account for Monte Carlo simulations.

From this analysis it can be concluded that a standard deviation of 3.7 [m] in \(x, y\) has to be used as input for the simulations.
8.3.3. Georeferencing errors

In Chapter 3 the accuracy of the georeferencing process was already discussed. The RMSE of the residuals were computed for all map elements in Section 3.7. The units of measure is in pixels, what will be transformed into metric units in order to comply with the other uncertainty measures of each processing step. First, the RMSE values of the 1925, 1960, and 1989 maps are obtained from Table 3.1 in Section 3.7. To convert pixels into a metric distance, the conversion values found in section 8.3.2 can be used: the size of one pixel is 0.1 [mm] on the map, and thus by multiplying this with the map scale reciprocal (which is 25000) the size of one pixel is known: 2500 [mm] or 250 [cm]. Multiplying the values from Table 3.1 with 250 results in the individual isotropic georeferencing errors of each map in metric units as given in Table 8.1.

Table 8.1: Total georeferencing uncertainty per map used in the study area. Direction of the errors are neglected due to the linear relationship between $\Delta X$ and $\Delta Y$ (see equation 3.7). An isotropic RMSE is used instead.

<table>
<thead>
<tr>
<th>Map (year)</th>
<th>RMSE [cm]</th>
</tr>
</thead>
<tbody>
<tr>
<td>b759 (1925)</td>
<td>1022.5</td>
</tr>
<tr>
<td>b763 (1925)</td>
<td>1000</td>
</tr>
<tr>
<td>60D (1959)</td>
<td>152.5</td>
</tr>
<tr>
<td>62B (1960)</td>
<td>125</td>
</tr>
<tr>
<td>69E (1989)</td>
<td>112.5</td>
</tr>
<tr>
<td>68G (1989)</td>
<td>200</td>
</tr>
</tbody>
</table>

The final uncertainty for the 1925 map involves the rule of independence of error propagation as illustrated in equation B.7 with the RMSE of 1925 and 1989 due to relative georeferencing. Because maps of 1925 and 1989 do not cover the exact same area and transects can also overlap multiple maps, an averaged value of the georeferencing uncertainties are used for the error propagation. The results is shown in Table 8.2, and the RMSE values will be used as standard deviation in the Monte Carlo simulations.

Table 8.2: Total georeferencing uncertainty after averaging and taking relative georeferencing into account.

<table>
<thead>
<tr>
<th>Map years)</th>
<th>Computation</th>
<th>RMSE [cm]</th>
</tr>
</thead>
<tbody>
<tr>
<td>maps 1925</td>
<td>$(1022.5 + 1000) \cdot 2^{-1}$</td>
<td>1011.25</td>
</tr>
<tr>
<td>maps 1960</td>
<td>$(125 + 152.5) \cdot 2^{-1}$</td>
<td>138.75</td>
</tr>
<tr>
<td>maps 1989</td>
<td>$(112.5 + 200) \cdot 2^{-1}$</td>
<td>156.25</td>
</tr>
<tr>
<td>total 1925</td>
<td>$\sqrt{1011.25^2 + 156.25^2}$</td>
<td>1023.25</td>
</tr>
</tbody>
</table>

8.3.4. Sampling errors

The last processing step before spatial modelling is sampling of data from the georeferenced maps. The error types that can be made in sampling are gross and random. Gross sampling errors occur when the wrong height is attributed to a sampled contourline. Prevention of this type of error is not always easy to do: corresponding heights of a contourline are harder to determine along steep slopes and in built-up areas. Accurate sampling is guaranteed by testing each profile for gaps of size $> 2.5$ and $< -2.5$ between consecutive samples. Consecutive heights should not differ more than 2.5 [m] in height due to contourline intervals of 2.5 [m]. Samples that are subject to such error are resampled accordingly. For this reason, gross errors are not taken into further account in the Monte Carlo simulations.

Random errors can happen when a sample is not exactly placed on a contourline. The manual process of contourline sampling is time consuming and require high concentration, and therefore it may cause misplacement of some samples. It is very hard to detect these errors but much easier to prevent by zooming in close enough to a contourline to make sure a sample will be placed within the linewidth of the contour. If all samples are sampled exactly on a contourline, which is always possible if sampled carefully, no random errors can be assumed from the sampling process. In the Monte Carlo simulations random errors are therefore not taken into account.
8.3.5. Monte Carlo simulations

Monte Carlo simulations can be used for a stochastic approach to create \( n \)-number of elevation profiles based on the found processing errors. Besides that it can be used to simulate elevation models, also the uncertainty of estimated ground motion can be derived through this method. First it is explained how the precision of a sample (in \( d \) and \( z \)) is determined, followed by a description of determining the precision in \( z \) for each point along a profile.

Errors of every processing step are used as noise input to the sample data. Each sampled height will have a mean (the attributed height) and a standard deviation as noise (the found precision of each processing step).

If we want to know the precision of a sample location in position and height, we try to answer the question “what is the probability that a measurement is taken at the right position with correct height?”. Of course, this probability is close to zero, but a confidence area can be estimated (maximum likelihood). To do so, the error propagation law is applied to the horizontal errors, and also for the vertical errors. The inputs are given in Table 8.3 as a result of the processing errors analysis.

Table 8.3: Precision estimates processing steps that are used as noise input for the Monte Carlo simulations.

<table>
<thead>
<tr>
<th>Error sources</th>
<th>Horizontal precision [cm]</th>
<th>Height precision [cm]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Measurements 1925</td>
<td>5</td>
<td>10</td>
</tr>
<tr>
<td>Measurements 1960</td>
<td>5-10</td>
<td>60</td>
</tr>
<tr>
<td>Mapping</td>
<td>370</td>
<td>-</td>
</tr>
<tr>
<td>Georeferencing 1925</td>
<td>1023.25</td>
<td>-</td>
</tr>
<tr>
<td>Georeferencing 1960</td>
<td>138.75</td>
<td>-</td>
</tr>
<tr>
<td>Sampling errors</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Total 1925</td>
<td>( \sqrt{5^2 + 370^2 + 1023.25^2} )</td>
<td>10</td>
</tr>
<tr>
<td>Total 1960</td>
<td>( \sqrt{10^2 + 370^2 + 138.75^2} )</td>
<td>60</td>
</tr>
</tbody>
</table>

Two probability functions can be created for each data point. This was done by simulating \( n \)-times a sample points with the sampled position as mean value and the error totals as the standard deviation, one for \( d \) and the other for \( z \). According to USGS standards [37] 90% of the elevation of test samples from control lines should be correct within half the contourline interval, for US maps only. In other words, if the same rule applies to the Zuid-Limburg case, 90% percent of the simulated sample positions should be within 1.25 [m] distance from the sampled points. Since we do not have ground truth data a quick test of 1000 simulations can give a little more insight if USGS standards can be met. The empirical probability of \( d \) at \( p = 0.05 \) and \( p = 0.95 \) are respectively -1.77 [m] and +1.74 [m] for the 1925 map. For 1960 these \( p \)-values are found at respectively -0.63 [m] and +0.67 [m]. These values indicate only that if the height of a measurement is correctly measured, there is a 90% chance that it is positioned on the 1925 map within -1.77 [m] and +1.74 [m] of the corresponding contourline.

We have to take the uncertainty of \( z \) into account to see what the exact uncertainty is of height at sampled locations and query points (determined \( d \)). Since the positions in \( d \) are fixed, we have to convert the simulated \( d \) values by simple Euclidean equations. Simulated distances can be converted to height by multiplying the simulated \( d \)-values and the slope. The average slope between the two adjacent points of a sample can be computed using equation 8.3:

\[
\hat{s}_b = \frac{1}{2} \left( \frac{\Delta Z_{ab}}{\Delta D_{ab}} + \frac{\Delta Z_{bc}}{\Delta D_{bc}} \right)
\]  

(8.3)

where \( \hat{s}_b \) is the estimated slope for sample point \( b \), \( \Delta Z \) is the sample height difference between two sample points (indicated with subscripts), and \( \Delta D \) is the sample distance along the profile between the sample points. The slope of each point is then multiplied by the simulated \( d \) values:

\[
\hat{e}_{z,b} = \hat{s}_b \cdot \hat{e}_d
\]  

(8.4)
With $\hat{e}_{z,b}$ equals the error in height at point $b$, $\hat{s}_b$ is the estimated slope for sample point $b$, and $\hat{e}_d$ is the simulated error in distance $d$. At this point the uncertainty in height can be included, by using again the error propagation law. For each sample point a probability density function is generated by $n$ simulations and using the inbuilt standardized normal function in Matlab. The 1000 simulated errors in $z$ are added to the sample heights finally, the simulated sample values are interpolated linearly to create $n$-times simulations of each profile and $n$-times simulations of the height difference. These results are shown in Figure 8.5. The $n$ number of interpolations also gives probability density functions for every query point.

![n=1000 simulations of profile 10](image1)

![Mean height difference with errorbars 1925-1960 (1925 = 0)](image2)

Figure 8.5: Top: Simulated profiles of transect 10, using Monte Carlo simulations for 1925 (red) and 1960 (blue). The black dotted line is the mean of the simulations per profile. Bottom: Mean anomaly of the simulated profiles. Errorbars indicate the standard deviation of the anomalies after 1000 profile simulations.

The interpolation uncertainty of the profiles in the upper plot of Figure 8.5 is very different for 1925 and 1960. Averaged standard deviations of profile 1925 and 1960 are respectively 25 [cm] and 100 [cm] by approximation. The difference between the 1925 and 1960 profiles is the effect of the large uncertainty in $Z$ from photogrammetric height measurements. Uncertainty of photogrammetric measurements from 8.3 is dominant in the interpolation uncertainty estimation. Effects of changes in this value are directly visible in the uncertainty outcome.
8.4. Overall conclusions on uncertainty

In order for us to answer the question "do the estimates on ground surface motion make sense?", we have used literature, a local additional sampling and Monte Carlo simulations to tell something about the uncertainty in processing and results. Especially the added samples and simulations show that errors in the order of magnitude of 1 to 1.5 [m] is common. However, estimates on ground surface motion do not variate much over the profile according to the simulations, but literature tells us that a lower error can be expected on slopes. By recalling the large peaks of height difference around rivers in section 7.3.4, the conclusions from literature seem to be doubtful. The large variance of height differences per epoch along the profiles seem to be a result of a combination of errors made in processing and the large errors in profile interpolation around local minima and maxima. A confident "yes" to the asked question can therefore not be given, but it can be best described as that the profile method provides a blurred picture on how ground motion changed over time, its spatial distribution, and to what order of magnitude.
Conclusions, Findings, and Recommendations

In this chapter findings and conclusions drawn from the study are reported and recommendations for continuation of the project are discussed. Research questions are answered in the first section of this chapter. Most research questions are already answered indirectly and more detailed throughout this report, leaving the opportunity for this chapter to reformulate and summarize these answers. The order of answering the research questions is the same as in section 1.7, only the main research question will be answered at last. Other conclusions and findings from methods and from results will be discussed in the Findings section (9.2). Finally, the Recommendations section will close of this chapter.

9.1. Answers to research questions

1. **What is the availability in time and space of the data?** In the period between rapid increase of coal production (1914) and last mine closure (1974) historical topographic maps with contourlines are available at Kadaster. Many of these maps showed equal elevation data (contourlines and point-measurements), which resulted in only two maps with unique elevation data. These two maps (1925 and 1960) were used for further analysis. Release date of the maps do not correspond to the moment of measurements, which is important to bear in mind in temporal modelling. Years of measurement were found to be 1918/1919 and 1955 respectively for the maps from 1925 and 1960. The area that is covered by the ordered maps is limited to the eastern part of the mining area. Maps of the whole mining area available but time constraints would not allow to use them in this study. Focus of this study was put on the ‘white’ gap in the map from Pöttgens, which was fully covered by the ordered maps mentioned in section 2.2. The deformation map from Bekendam and Pöttgens [5] covers the period between 1914 and 1974 and was used for validation of ground surface motion estimations.

   For the period after mine closure ‘modern’ datasets are available. These consisted of digital files with elevation data and vertical motion data. Three datasets were used in this study: TOPhoogteMD (1977), AHN-3 (2015), and Levelling + InSAR data (1974-2015).

2. **What is the reference frame of the data?** In most cases the reference frame of a map projection is printed on the map. Coordinate grids on the maps in combination with the reference frame will make it possible to transform maps from image space to a georeferenced map space. The reference frame and coordinate grid for the 1960 map is in RD and printed on the map. Indication of a reference frame was not printed on the 1925 map, which resulted in a workaround procedure to retrieve geotagged data from this map. This workaround was applied by georeferencing the map relative to the 1989 map. The dataset derived from both georeferenced maps consisted then of geotagged data in
RD. The other data, i.e. Pöttgens map and 'modern' data, was already georeferenced to the same RD reference frame.

3. **What is the accuracy of the data?** A research was done on the accuracy and precision of data by performance of an uncertainty analysis of ground surface motion estimations. Three approaches were developed to get insight on the uncertainty in our estimations: by a literature review, by sampling additional data locally and find differences in results with and without additional points, and by a process based approach. The process based approach forced us to quantify errors in all processing steps, including errors at the moment of field measurements. Since measurements were taken a long time ago, it showed to be very difficult to estimate measurement errors precisely. The measurement errors in $z$ were set to a [dm] magnitude, which also resulted in being the largest influencer in the final profile uncertainty. From the Monte Carlo simulations performed for transect 10 it is therefore concluded that the error magnitude of height measurements is the main driving factor of inaccuracies in the final results.

The added samples approach and simulations show that errors in ground surface motion estimations in the order of magnitude of about 1 to 1.5 [m] is common. Uncertainty in the estimates do not variate much over the profile according to the simulations, but literature tells us that a lower error can be expected on slopes.

The large variance of height differences per epoch along the profiles seem to be a result of a combination of errors made in processing and the large errors in profile interpolation around local minima and maxima.

4. **How can the data of the different techniques be integrated?** Working with different data types involves adjustments in many aspects of geo-data. The aspects that has been looked at are spatial distribution, spatial resolution, position in time, and type of measurement.

Interpolation of data to a defined grid or query points resolves the problem of inequality in spatial resolution and distribution. In this way data from contourline sampling, pseudo-random sampling, and profile sampling can be integrated with data from the TOPhoogteMD, AHN2015, and Levelling + InSAR datasets into one spatial consistent dataset.

Integration of multiple datasets by matter of position in time also requires interpolation. Another method is to keep datasets apart and compute elevation differences per epoch instead of integrating datasets into one model.

5. **Which spatio-temporal modelling technique is appropriate to integrate the results from different measurement techniques and describe 4D ground surface motion?** The answer to this question is related to the previous question, in the sense that for every mentioned integration step a choice must be made.

One of these steps is defining the gridsize. To determine the gridsize and spacing between query points the methods from Hengl [14] were used. Profiles of two years over the same transect have different data points if the area has been subject to ground surface motion, as contourlines are mapped on different positions. For spatio-temporal modelling resampling is necessary, and the gridsize or query point distance determines the amount of data and detail in visualizations. The chosen gridsize of 50 [m] formed the basis for integration with modern data. A linear 2D interpolation of modern data to the query points and grid centres was used to resolve differences in spatial distribution and resolution.

Integration over time of historical and modern data was only performed with elevation profiles. Interpolation over time for the two historical datasets (1918/1919 and 1955) was tested with three methods: 1) linear scaling, 2) empirical scaling, and 3) scaling to coal production. The empirical model fits best to the validation data of Pöttgens, but has no geophysical logic behind it. To get a feeling of what happened with the surface elevation between 1918/1919 and 1955 the third interpolation method is preferred. Although
it does not fit best to the validation data, the geophysical background of this method and the large uncertainty in Pöttgens validation data make this method reliable enough to get insight in the years between 1918/1919 and 1955. Linear scaling, and in particular differences per epoch, seemed to be give results that were easy to interpret and less complex to compute. The height differences between profiles of the two historical map years have been integrated with the TOPhoogteMD data from 1977 for 2D and Levelling + InSAR data from 1974-2015 for 2.5D.

6. How to separate between outliers in the measurements and anomalous, and therefore by definition interesting, surface motion? The results of subtraction from two profiles does not directly give the actual ground surface motion at each particular point. Uncertainty in the data propagates through the computations. This uncertainty has been estimated via Monte Carlo simulations. Besides the uncertainty found through going step-by-step through each process, biased samples and blunders should also be noticed and removed. These type of errors were filtered out of the data before simulations, by checking the data three times: 1) Checking for leaps in elevation larger than + or - 2.5 [m], 2) Checking for absence of contourlines on maps, and 3) Checking transect endpoints with contourline height. The constraint of the 2.5 [m] contourline interval makes detecting for blunders in profile sampled data not very complicated. Consecutive sample points should also follow the constraint of 0 [m] or +/−2.5 [m] height difference. If a leap is detected that exceeds this constraint, the sample should be checked and resampled if necessary. Other blunders that may appear are visible after interpolation of profiles. Built-up areas and mines that do not contain contourlines on a map will cause gross errors. These areas are masked out for all years of the affected profiles. With these checks it can be guaranteed that no blunders are made in the dataset.

Detection of systematic errors in samples is however, more difficult, since they cannot be detected by leaps in the elevation. These biased samples can be prevented by verifying the first and final sample of each transect with the corresponding contourline height. If a mistake was made in one or both endpoints the samples between will presumably be biased too. After this final check and biases are corrected, the dataset can be called unbiased.

7. How can the results be optimally visualized in a 4D model? From the multiple data extraction methods that were designed, also multiple data types were retrieved. On the one hand the dataset from profile sampling has 2 dimensions (height over distance) and 3 dimensions (height over coordinates), whereas on the other hand all other methods resulted in a dataset with 3 dimensions. In general the method of profiles was preferred over the other methods for sampling time, dataset size, and convenient data type reasons. Visualization of ground surface motion over transects are both performed in a 2D line plot, 3.5D bar plot on a map in GIS software, and a 3.5D surface model.

Only a little research was done on the modelling and visualization possibilities for the other manual data extraction datasets. A 3.5D representation of ground surface motion for pseudo-random and contourline data, with equal grids, was used to visualize results. For point-measurements it was chosen not to interpolate over a grid, but to keep the scattered representation with averaged locations of ‘same points’.

9.2. Findings
This section is dedicated to results of the research that were found beyond the research questions. Findings are summarized here for the data extraction methods and results of estimated ground surface motion.

9.2.1. Findings on data extraction methods
In the beginning of data extraction from historical maps, many options to retrieve information are considered, but only a few seemed useful. Useful in the sense that the method generates
enough data output, the data is convenient for further processing, the method is time efficient, and the dataset is reliable. Sampling all contourlines is the preferred data extraction method in literature if time and/or manpower is not an issue. Recommended improvements to the discussed methods can be found in Section 9.3. From the conclusions on data extraction methods, this study showed that creating transects and estimate elevation profiles is also a good method to estimate ground surface motion.

Choosing transect positions is a main concern, as it will have influence on the data availability and profile elevation results. A straight line transect will give unreliable shape representation in elevation profiles for a hilly landscape such as Zuid-Limburg. By definition the slope aspects from a contour map are in the direction of shortest distances between two contourlines. To get highest shape reliability in a profile representation from transects, transects should be drawn preferably along the slope aspects. This can be achieved by drawing transects perpendicular to contourlines. Due to change of contourlines over time, this is not always possible to achieve. In GIS-software a best practice approximation was performed by overlaying the 1925 and 1960 map with adjusted transparency.

9.2.2. Findings on estimated ground surface motion
In the results from the profile method, ground surface motion between 1918/1919 and 1955 varies between approximately -10 and 0 [m], with a maximum subsidence of -10.7 [m] found along validation transect 4. A few examples of uplift between 0 and 4 metres are found, which are present along transect 1, 7, 8, 9, and 10. In general the range of subsidence corresponds to the Pöttgens map deformation range and the expectation in advance of this study.

One of the reasons why a study on ground surface motion in this area was initiated, was the low resolution deformation and spatial variability on Pöttgens map. From the mapped ground surface motion estimations along the transect a large variability in displacements was found. Large variance of the height differences in Figure 7.5 was explained by three possible ways: 1) Uncertainty in height estimation from measurements and interpolation errors. 2) Presence of rivers causing large sample positioning errors. 3) Mining activities between 1955 and 1977. From the 2D plots in Figure 7.5 a clear connection between hilly areas and oscillating height differences can be seen. Inaccuracy of a sample position in x and y, either due to measurement inaccuracy or mapping generalisation, will lead to higher inaccuracy in z than on flat areas. Therefore, it is likely to assume oscillation is a combination of sample inaccuracy in x and y and spatial variability of ground surface motion.

Another finding from the results is that between 1955 and 1977 the empirical percentage of estimated subsidence from total estimated height change is significantly lower than for 1918/1919 and 1955. Computed percentages were found 90% for 1918/1919-1955 and 50% for 1955-1977. A conclusion from this significant difference could be that the area surface has been subject to a change from subsidence dominated to transition to uplift dominated.

Results from contourline sampling data and pseudo-random sampling data shows many differences mutually and compared with validation map of Pöttgens (see Figure 6.3). Especially the borders of the intervals do not match. However, the overall stretching of subsidence inside the example area is from north to south, with highest values in south-west for all three maps.

9.3. Recommendations
Recommendations for further research in this field will focus on improving estimation of the uncertainty of results from the profile models and improvements on data extraction methods. One method to improve estimation on the data uncertainty is by adding contourline samples method locally. This method was already performed for one hill along profile 10. A research could be done on how many additional points from surrounding contourlines are necessary to get an optimal balance between additional time (work) and added reliability of elevation profiles.
Insight of spatial variability of ground surface motion can be improved by adding transects, and therefore by adding data. Theoretically, transects can be created infinitely but this will be equal to sampling all contourlines. Addition of transects will therefore only make sense if the idea of time efficiency and spatial distribution is kept. One option would be to expand the study area from the ‘white’ area to the full mining area. The size of total mining district is approximately 250 [km$^2$] of which 35 [km$^2$] is covered by the ‘white’ area around Heerlen. A full study to ground surface motion in the whole mining district will therefore cost around 7 times more time.

To get a better feeling of the accuracy of the estimated ground surface motion an equal profile method could be applied to a similar area where the area has not been subject to change between 1918/1919 and 1955. This data can than be used for validation of the accuracy of the profile method. The validation area should have a similar landscape to validate findings of the differences in estimated ground surface motion between hills and flat areas. With this method the difference between estimated uncertainty from Monte Carlo simulations and from literature and local added points could be explained as well.

Improvement of ground surface motion uncertainty estimations could also be achieved by adding spatial variability of georeferencing errors. Each GCP has its own error in $x$ and $y$, but for Monte Carlo simulations in this study the average deviation of all GCP’s were used. Uncertainty in estimated ground surface motion will be lower around accurate GCP’s, and higher around inaccurate GCP’s.

The point-measurements method showed to give linearly correlated results to Pöttgens map, but the number of measurements is significantly lower then other methods. It is therefore recommended to use these point-measurements only for additional information and validation of models derived from the contourline sampling method and pseudo-random sampling method. Using point-measurements for validation purposes, more research should be done on their accuracy. The main objective would be to find the field measurement accuracy and where these measurements were taken. Yet an average position of point-measurements is the best approximation of the actual position that could be performed in this study.

Finally, due to time constraints and computational complexity an automatic detection method of contourlines was not fully developed. Improvements could be made in supervised classification by adding more samples and finding optimized ranges of RGB-values that describe the classifiers. Vectorization of the raster outputs of PCA and supervised classification will be necessary for further processing. Vectorization of contourline-pixels could simply be performed by existing GIS modules, which simplifies height attribution to the vectors. Accuracy of this method can be estimated by sampling the results after PCA and validate these with historical maps.
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Figure A.1: Schematic overview of the workflow with corresponding uncertainty subjects. The main processes in this study are performed based on this simplified workflow.
Equations

Transformations

Equation B.1, 3rd-order polynomial transformation of image space $u$ into coordinate space $x$:

\[
\begin{pmatrix}
  x_1 \\
nx_2 \\
\vdots \\
  x_n
\end{pmatrix} =
\begin{pmatrix}
  1 & u_1 & v_1^2 & u_1v_2 & v_1^3 & u_1v_2^2 & u_1v_2v_3 & \hat{e}_1 \\
  1 & u_2 & v_2^2 & u_2v_2 & v_2^3 & u_2v_2^2 & u_2v_2v_3 & \hat{e}_2 \\
  \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
  1 & u_n & v_n^2 & u_nv_2 & v_n^3 & u_nv_2^2 & u_nv_2v_3 & \hat{e}_n
\end{pmatrix}
\begin{pmatrix}
  a_1 \\
  a_2 \\
  \vdots \\
  a_n
\end{pmatrix}
\]  
\tag{B.1}

Earth radius

Equation B.2, computation of the Earth’s radius at 51° N, following the WGS84 reference ellipsoid.

\[
R = N \sqrt{1 + \sin(\phi)^2}
\]  
\tag{B.2}

Descriptive statistics

The following equation consider total population statistics only. If a population was sampled and used for descriptive statistics, population size $N$ will lose a degree of freedom: $N - 1$ is used instead.

**Population mean:** Equation B.3, computing the mean $\mu$ of population $X$ with $N$ the size of the population.

\[
\mu = \frac{\sum_{i=1}^{n} X_i}{N}
\]  
\tag{B.3}
Population standard deviation: Equation B.4, computing the standard deviation $\sigma$ of population $X$ with $N$ the size of the population, and $\mu$ the mean of the population.

$$\sigma = \sqrt{\frac{\sum_{i=1}^{N} (X_i - \mu)^2}{N}} \tag{B.4}$$

Population skewness: Equation B.5, computing the skewness $S$ of population $X$ with $N$ the size of the population, $\mu$ the mean of the population, and $\sigma$ the standard deviation of the population.

$$S = \sqrt{\frac{\sum_{i=1}^{N} (X_i - \mu)^3}{N\sigma^3}} \tag{B.5}$$

Population covariance: Equation B.6, computing the covariance $\text{cov}(X, Y)$ of the two populations $X$ and $Y$ with $N$ the size of the population, and $\bar{X}$ and $\bar{Y}$ the means of the two populations.

$$\text{cov}(X, Y) = \frac{\sum_{i=1}^{N} (X_i - \bar{X})(Y_i - \bar{Y})}{N} \tag{B.6}$$

Population median: The median of a population is equal to the value of the middle observation, ranked by in ascending order by value. The median therefore indicates the value at which 50% of the observations is below that value and the other 50% is above. It can be computed in three steps:

1. Ranking observations by ascending value
2. Compute the middle rank number by: $(N + 1)/2$
3. Find the value corresponding to the middle rank observation $(N + 1)/2$

Error propagation law of independent variables

The standard deviation (and also variance) of a variable that is based on two or more independent variables can be computed following equation B.7. In this study this propagation law was used for e.g. determining the combined RMSE for the relative georeferenced 1925 map.

$$\sigma_{a,b} = \sqrt{\sigma_a^2 + \sigma_b^2} \tag{B.7}$$
PCA results

Figure C.1: All 6 components after PCA. Example of the 1925 historical map around Wijnandsrade.
Profile 1 results

Figure C.2: A: Profile vertical displacement of transect 1 for 1918/1919 - 1977 (blue) and 1955 - 1977 (red). Displacements are computed with respect to 1977. B: Profile vertical displacement of transect 1 between 1918/1919 and 1955.

Profile 2 results

Figure C.3: A: Profile vertical displacement of transect 2 for 1918/1919 - 1977 (blue) and 1955 - 1977 (red). Displacements are computed with respect to 1977. B: Profile vertical displacement of transect 2 between 1918/1919 and 1955.
Profile 3 results

Figure C.4: A: Profile vertical displacement of transect 3 for 1918/1919 - 1977 (blue) and 1955 - 1977 (red). Displacements are computed with respect to 1977. B: Profile vertical displacement of transect 3 between 1918/1919 and 1955.

Profile 4 results

Figure C.5: A: Profile vertical displacement of transect 4 for 1918/1919 - 1977 (blue) and 1955 - 1977 (red). Displacements are computed with respect to 1977. B: Profile vertical displacement of transect 4 between 1918/1919 and 1955.
Profile 5 results

Figure C.6: A: Profile vertical displacement of transect 5 for 1918/1919 - 1977 (blue) and 1955 - 1977 (red). Displacements are computed with respect to 1977. B: Profile vertical displacement of transect 5 between 1918/1919 and 1955.

Profile 6 results

Figure C.7: A: Profile vertical displacement of transect 6 for 1918/1919 - 1977 (blue) and 1955 - 1977 (red). Displacements are computed with respect to 1977. B: Profile vertical displacement of transect 6 between 1918/1919 and 1955.
Profile 7 results

Figure C.8: A: Profile vertical displacement of transect 7 for 1918/1919 - 1977 (blue) and 1955 - 1977 (red). Displacements are computed with respect to 1977. B: Profile vertical displacement of transect 7 between 1918/1919 and 1955.

Profile 8 results

Figure C.9: A: Profile vertical displacement of transect 8 for 1918/1919 - 1977 (blue) and 1955 - 1977 (red). Displacements are computed with respect to 1977. B: Profile vertical displacement of transect 8 between 1918/1919 and 1955.
Profile 9 results


Profile 10 results

Figure C.11: A: Profile vertical displacement of transect 10 for 1918/1919 - 1977 (blue) and 1955 - 1977 (red). Displacements are computed with respect to 1977. B: Profile vertical displacement of transect 10 between 1918/1919 and 1955.