Student thesis series INES nr 264

Uncertainty and Sensitivity Analysis in Soil Strata Model Generation for Ground Settlement Risk Evaluation

Minyi Pan

2012
Department of
Physical Geography and Ecosystem Science
Lund University
Sölvegatan 12
S-223 62 Lund
Sweden

Minyi Pan. Uncertainty and sensitivity analysis in soil strata model generation for ground settlement risk evaluation.

Master degree thesis, 30 credits in Geomatics

Department of Physical Geography and Ecosystem Science, Lund University

Uncertainty and Sensitivity Analysis in Soil Strata Model Generation for Ground Settlement Risk Evaluation

Minyi Pan

Master thesis, 30 credits, in *Geomatics*

Supervisors:

Jonas Sundell

Section of Built Environment Engineering

Cowi AB, Gothenborg

Andreas Persson

Department of Physical Geography and Ecosystem Science

Lund University

Acknowledgements

Thanks to Jonas Sundell from Cowi and Anders Bergström from NCC for your endless help. Thanks to Victoria Tiesell and Elyas Hashemi and you were both great co-workers. Thanks to Andreas Persson from Lund University who gave me a lot of help in report writing. Last, thanks to my best friend in Lund Mohamed Mabrouk who always gives suggestion and inspiration and my dearest boyfriend Robert, who is always there, gives love and support.

Table of Contents

Abstract

Ground settlement due to groundwater drainage during construction is important to be considered since ground settlement may cause severe building damages. The calculation of ground settlement contained several parameters with different magnitude of uncertainties. Thus a risk evaluation of ground settlement is necessary. The aim of this thesis was first to build a soil strata model for ground settlement risk evaluation purpose. Second was to carry out the uncertainty and sensitivity analysis of the soil strata model. Third was to carry out the ground settlement risk evaluation by integrating soil strata model and two other models, with defined uncertainties of each model. The case study site was located in Motala, Sweden with area about 0.39 km^2.

The soil strata model was generated by utilizing kriging interpolation. The continuous elevations of each soil layer in the soil strata were interpolated from boreholes and then all the soil layers were combined to create a “layer-cake model”. The uncertainty in kriging was quantified by prediction standard error. By utilizing Monte Carlo simulation, the stochastic representation of the soil strata was created and the uncertainty and sensitivity analysis of the soil strata model was carried out. The risk evaluation of ground settlement was conducted by carrying out Monte Carlo simulation for the integrated model of soil strata, groundwater and ground settlement.

The uncertainties of the soil strata model were mapped in the form of median, standard deviation, skewnesss, etc. from different soil layers. From sensitivity analysis, it could be inferred that the most influential parameters on the thickness a soil layer would be the upper and lower boundary elevations of that layer. The risk areas of building damage have been mapped where the 50^{th} and 95^{th} percentile of the calculated ground settlement exceeded critical values. The most influential parameters on ground settlement were found varied in different places. More efforts and resources could be spent on these parameters to decrease the unacceptable risks.

It was conclude that kriging interpolation was an effective way for generating soil strata model from boreholes.

Keywords: Kriging, Monte Carlo simulation, Soil strata, Uncertainty analysis, Sensitivity analysis, Risk analysis

1. Introduction

Groundwater drainage is a common consequence when dealing with tunnel construction and deep excavation. When water drainage happens in the soil, the loss of water content in the soils can make soils compress in volume and may present the ground settlement (Terzaghi 1943). The ground settlement may cause significant building damage. Besides, this kind of ground settlement would maybe influence a wider area than the construction itself since the groundwater level is also lowered in neighboring areas. Thus it is important for constructor to estimate the ground settlement before the actual construction stage.

In ground settlement estimation there are a number of parameters of different magnitude of uncertainties such as permeability, compression and consolidation properties of different soil layers and the soil strata generated from boreholes. All the uncertainties in the parameters make it necessary to give a stochastic representation of ground settlement rather than a deterministic one. If the uncertainties in the parameters are defined, the uncertainties in ground settlement could be estimated by stochastic modeling such as Monte Carlo simulation. Through sensitivity analysis in Monte Carlo simulation, it is also possible to address the most influential parameters on the ground settlement in a certain area. Ground settlement may cause building damage. One of the purposes of ground settlement risk evaluation is to tell that whether the risk of building damage is too high in a certain place according to the calculated ground settlement. Based on the risk evaluation results, corresponding prevention measures or further investigations can be addressed.

Modeling soil strata is of great importance for ground settlement modeling since ground settlement is calculated according to the thickness and relative position of every soil layer. The continuous soil strata is usually interpolated and extrapolated from boreholes. In this thesis, a soil strata model was generated by utilizing kriging. The elevations of each soil layer in the soil strata were interpolated and then all the layers were put together to create a "layer-cake model".

The uncertainties exist in kriging interpolation could be quantified by prediction standard error. Kriging not only creates a predicted value at each interpolation location but also a prediction standard error which measures the uncertainty of the prediction (Kumar and Remadevi 2006). This means in this thesis kriging interpolated not an exact value but a probability distribution of the elevation. A stochastic representation of the soil strata model was given in this thesis by introducing prediction standard error in Monte Carlo simulation. The uncertainties and sensitivity analysis were carried out for the soil strata model.

This thesis was a part of a development project where the aim was to evaluate risks of ground settlement in an integrated model of soil strata, groundwater and ground settlement. Except for soil strata modeling which was presented in this thesis, the project also included groundwater and ground settlement modeling which were presented in two other separate theses. The groundwater modeling part employed results from soil strata modeling part and the ground settlement modeling part used results both from groundwater modeling and soil strata modeling part. If the readers are interested on these two theses, please refer to Tisell (2012) and Hashemi (2012). The uncertainties in each model were defined/calculated first and then the three models were integrated to give a stochastic representation of ground settlement. Besides, the most influential parameters on the ground settlement were found out by sensitivity analysis.

The case study area was located in Motala, Sweden where a pedestrian tunnel was considered to be built. The ground settlement caused by groundwater drainage during the tunnel construction was necessary to be calculated to prevent building damage in surrounding sites.

1.1 Objectives

The objectives of this thesis are:

1. Utilize kriging interpolation to generate a soil strata model from borehole data.

2. Introducing prediction standard error as a source of uncertainty in soil strata model. Create a stochastic representation of the soil strata model by utilizing Monte Carlo simulation. Carry out uncertainty and sensitivity analysis of the soil strata model.

3. Create an integrated model of soil strata, groundwater and ground settlement model to evaluate risks of the ground settlement. Carry out sensitivity analysis to find out the most influential parameters on ground settlement.

2. Background

2.1 Soil strata model generation

Soil strata models are useful tools for geologists and engineers (Lemon and Jones 2003). Soil strata models are representations of the stratigraphy for the site being modeled. Boreholes are the main sources for engineers to know the distribution of soil strata. Boreholes here are holes drilled into the ground for soil strata investigation. The boreholes investigation could be corresponded with different geotechnical tests, such as various sampling tests and sounding tests. In sampling test, the soil sample along the borehole is taken out and soil type identification along the borehole is done in the laboratory. In sounding tests, the penetration resistance is registered as the sounding rod of the drilling equipment is pushed into the soil. Different soil types have different penetration resistance thus the soil types along the borehole could be interpreted.

To create a soil strata model, the boreholes should be spatially interpolated and extrapolated. Traditionally, this is done manually on the paper. It is a tedious method and is difficult in editing, copying and saving (Zhu and Wu 2005). Utilizing computer aided software like CAD to create continuous strata is an improvement compared with manual plotting, but the automation degree of the interpolation process is still low. Recently GIS has been used in soil strata modeling due to its excellent ability in data management, data analysis and graphical visualization. Using GIS for modeling soil strata also makes easier to automate the interpolation process (Zhu and Wu 2005).

Any spatial interpolation methods could be used in creating continuous strata model from boreholes. Some of them are *Nearest neighbor methods, Trend surface methods, Inverse-distance weighting methods (IDW)* and *kriging* (Lemon and Jones 2003). Kriging is usually regarded as the optimal one among all the other interpolation methods since kriging considers the spatial structure of the variable. Besides, a prediction standard error is created in kriging at each interpolation location which measures the interpolation uncertainty. However, kriging technique requires user to build a semivariogram for each soil layer and this can be difficult for sites having insufficient boreholes in order to build a meaningful semivariogram (Lemon and Jones 2003).

2.2 Kriging

2.2.1 Overview of kriging

Kriging, as other spatial interpolation methods, predicts the behaviors at unknown location based upon known locations. All the spatial interpolation methods are based on the Tobler's Law – "All places are related but nearby places are more related than distant places". In other words, to estimate the value of a variable at some point, it is more likely that the value is similar to the nearby place than the distant place.

The basic idea of kriging is to discover some general properties of the field from the measured values, and then apply those properties in estimating the un-measured locations (Longley et al. 2005: 336).

Kriging not only creates a prediction value at each place but also a prediction standard error which measures the uncertainty of the prediction (Kumar and Remadevi 2006). The prediction standard error is an important concept in kriging. Kriging predicts not an exact value but the probability distribution of the likely values at each place. The prediction value could be regarded as the mean value and the prediction standard error could be regarded as the standard deviation. As a common rule, the prediction standard error would be bigger further away from sample points. The prediction standard error could be used together with the prediction value for decision making, e.g., mapping the probability of ozone exceeding a critical threshold (ArcGIS geostatistical analyst tutorial).

2.2.2 Normal procedure of implementing kriging

Building semivariogram is central of implementing kriging. Semivariogram is a representation of the spatial structure of the field, indicates the degree of correlation between values of the variable as a function of distance (Virdee 1984). The first step for constructing semivariogram is to build an experimental semivariogram by plotting the semi-variance between each two samples as a function of the distance. Semi-variance value here is calculated by squaring the value difference between two samples and then divided by two. To give a summary form of the semivariogram, usually the distance axis is divided into a few bins (lags) and the averaged semivariance within each bin is calculated.

After building the experimental semivariogram, a theoretical model is used to fit it. And this theoretical model is intended to represent the whole population of all possible pairs of values over the area. The most common theoretical models include linear model, spherical model, exponential model and Gaussian model. A typical semivariogram (Figure 1) would start from low value (equal to the semivariance for very close points) and rises up with increasing distances between points and finally levels off at certain distance. This pattern is observed for most of the geographical field (Longley et al. 2005: 336).

Different information could be interpreted from the semivariogram: "Range" is the distance at which the curve levels off. It defines the maximum distance at which there is any spatial dependence; "Sill" is the value of the semivariogram at the distance of range; "Nugget" is the point where the curve intercepts the y-axis; Nuggets come from measurement error or small scale variations which could not be captured by current scale.

Often fitting a semivariogram is tricky, and the fitted model depends on the geostatistian's knowledge and experience on the data (Chilès and Delfiner: 104).

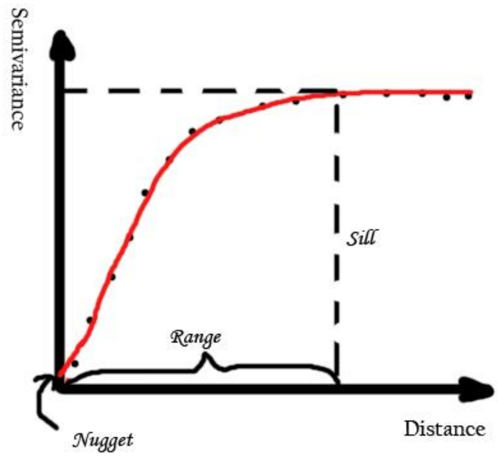


Figure 1 An example of semivariogram. The red line is the model used to fit the experimental semivariance

The prediction of likely values at location which has not been sampled is based on the fitted semivariogram and the surrounding sample points:

$$z^* = \sum_{i=1}^{m} w_i z_i = w_1 z_1 + w_2 z_2 + w_3 z_3 + \cdots + w_m z_m$$

Eq.1

where, z^* is the prediction value at un-measured location; z_i and w_i are the value and weight of the sample point, respectively; and m is the number of samples included in the estimation. Eq.1 could be actually used as a general estimator for all the other interpolation methods that decide the sample weights by the closeness. However in kriging, the weights are chosen in a way that the prediction standard error is minimized. Refer to Clark and Harper (2000: 239) for the calculation of weight and prediction standard error in kriging.

The quality of kriging could be checked by validation process. There is one kind of validation called cross validation which is used especially when a limited number of samples are available. In cross validation, the data set omits one sample and uses the remaining samples to interpolate the value in that point. The difference between the predicted value and the measured value of the omitted sample point is called residual. This process is repeated for all the sample points in the dataset in turn (Clark and Harper 2000: 271). The averaged difference between the predicted and measured value could be represented by Mean Error:

Mean Error: (ME) = $\frac{1}{n}\sum_{i=1}^{n}(z_i^* - z_i)$

And how close the predicted value is to the measured value could be represented by Root Mean Square Error:

Root Mean Square Error (RMSE) = $\sqrt{\frac{1}{n}\sum_{i=1}^{n}(z_i^* - z_i)^2}$

where, n is the number of samples used for cross validation. z_i^*, z_i are the predicted value, measured value, respectively at the same point. As a practical rule, RMSE should be less than the standard deviation of the sample values (Kumar and Remadevi 2006) for considering that a specific kriging schema is adequate.

2.3 Monte Carlo Simulation

When there are several inputs with uncertainties in the system being modeled, stochastic analysis can be used to analyze uncertainty propagation, i.e., how the uncertainties in the inputs affects the performance, reliability and sensitivity of the model (Wittwer 2004).

In stochastic modeling, the probability distributions of the outputs are described by allowing random variation of one or more inputs. Monte Carlo simulation is one kind of stochastic modeling where the probability distribution of the output is derived from repeated random sampling over the inputs. Usually a large number of simulations were ensured to reflect the random variation in the inputs.

In the soil strata model, the parameters containing uncertainties are elevations of different soil layers that calculated from kriging. The uncertainties come from the interpolation process and could be measured by prediction standard error. By Monte Carlo simulation, it is possible to evaluate how the uncertainties of different soil layers affect each other and the soil strata.

The Monte Carlo simulations generally follow these steps (Wittwer 2004):

1. Define the probability distributions of possible inputs.

2. Generate inputs randomly from the probability distribution over the domain

3. Define a formula to calculate the results (outputs) from the randomly generated inputs.

4. Repeat Step 1 – 3 for a large number of times

5. Aggregates the results

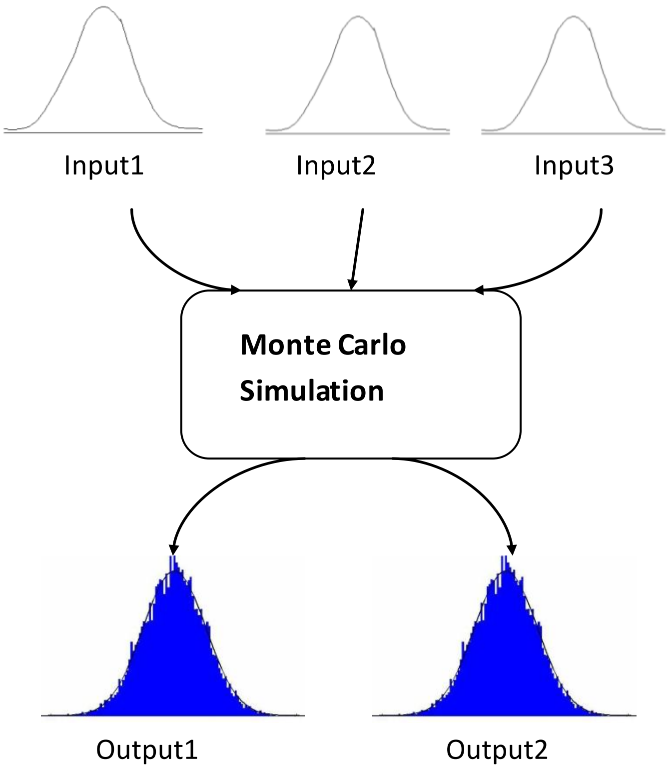


Figure 2 The schematic prodedure of Monte Carlo simulation

The schematic illustration of the Monte Carlo simulation process was showed in Figure 2.

One of the analyses used to quantify the outputs of the model is called uncertainty analysis. The word ‘uncertainty’ means that a quantity has a number of different values. The uncertainties of the outputs could be described by different ways such as histogram, cumulative frequency chart and different descriptive statistics, etc (Roger 1999).

Sensitivity analysis is also used quite often as a complementary to the uncertainty analysis. Sensitivity analysis helps to understand how the uncertainty in the output can be apportioned to different sources of uncertainties in the model input (Saltelli et al. 2008). The significances of the risks relating to different inputs are identified and ranked. More time and research can be spent on the significant risks, at the expense of the less significant risks (Roger 1999).

Risk is an overall assessment of probability (or uncertainty) and consequence of a hazardous event. The risk can be expressed as a formula:

$$\text{Risk} = \text{probability} * \text{consequence}$$

The probability could be obtained from uncertainty analysis. In this thesis, the consequence was building damages caused by ground settlement. Thus the risk was the probability of building damage.

2.4 Case study

The case study site was located in Motala, Sweden. A pedestrian tunnel was considered to be built in the study area. The tunnel involved with excavation below groundwater level, making it necessary to drain water both during construction and operating stage. There were a lot of residential and industrial buildings around the tunnel, which may be influence by the ground settlement caused by groundwater draingae. According to Swedish law (Environmental Code 1998:808 chp.16), the constructor is responsible for the cost and consequence of the ground subsidence damage if an unacceptable risk level is reached. Thus it is important for the construction project to know the amount of ground settlement and its uncertainty. If the risks are not acceptable, further investigation and preventions measures are maybe necessary.

There were a number of parameters containing uncertainties in the prediction of ground settlement, such as permeability, compression and consolidation properties of different soils and also soil strata generated from borehole. By quantifying the uncertainties of those parameters through Monte Carlo methods, it was possible to evaluate the reliability of the model and which parameters were significant to the ground settlement in certain area.

To calculate the ground settlement and evaluate the risks, the work was divided into three parts: soil strata modeling (presented in this thesis), groundwater modeling and ground settlement modeling. The groundwater modeling and ground settlement modeling were presented in two other separate theses. If the readers are interested on these two theses, please refer to Tisell (2012) and Hashemi (2012). The groundwater modeling part employed results from soil strata modeling part and the ground settlement modeling part used results both from groundwater modeling and soil strata modeling part. The uncertainties in each model were defined/calculated first and then the three models were integrated to give a stochastic representation of ground settlement. A brief description of the three models was given below.

Soil strata model:

In this part the soil strata was generated by interpolation from borehole data. The interpolation technique used was kriging. The elevations of each soil layer were interpolated first and then all the layers were put together to create a “layer-cake model”. The uncertainty in the model came from the interpolation error and was measured by prediction standard error derived from kriging.

Groundwater model:

The model reflected the groundwater decrease around a drainage well with respect to estimated groundwater recharge, the soil strata and the hydraulic conductivity of different soils. The parameters with uncertainties in the model were hydraulic conductivity of different soil types and annual precipitation.

Ground settlement model:

This model calculated the ground settlement based on the soil strata and groundwater drawdown. The parameters with uncertainties in the model were soil modulus, over-consolidation ratio (OCR) and unit weight of different soil types. The outcome of the model included the buildings which were in the risk zone of building damage. By having the sensitivity analysis, the type of investigation which was needed for reducing the risks was clarified.

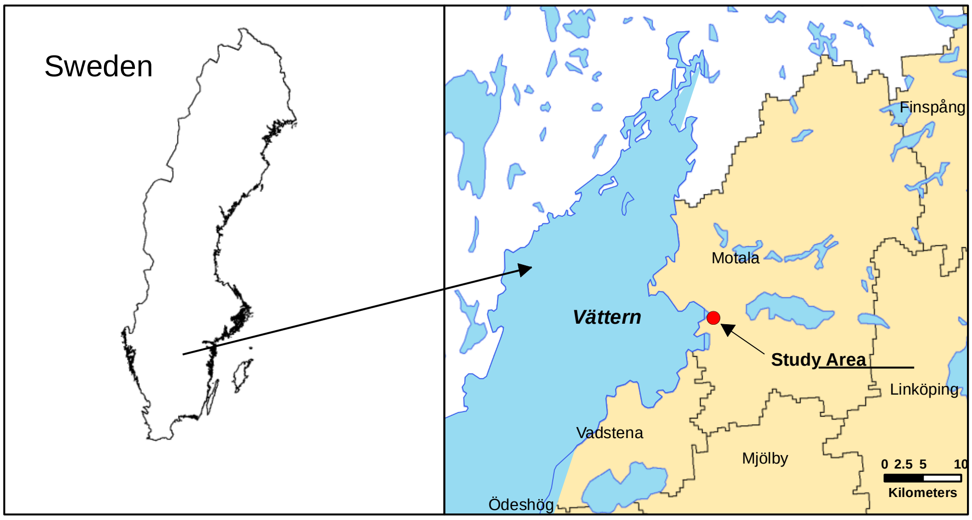
3. Methods

3.1 Data and study area

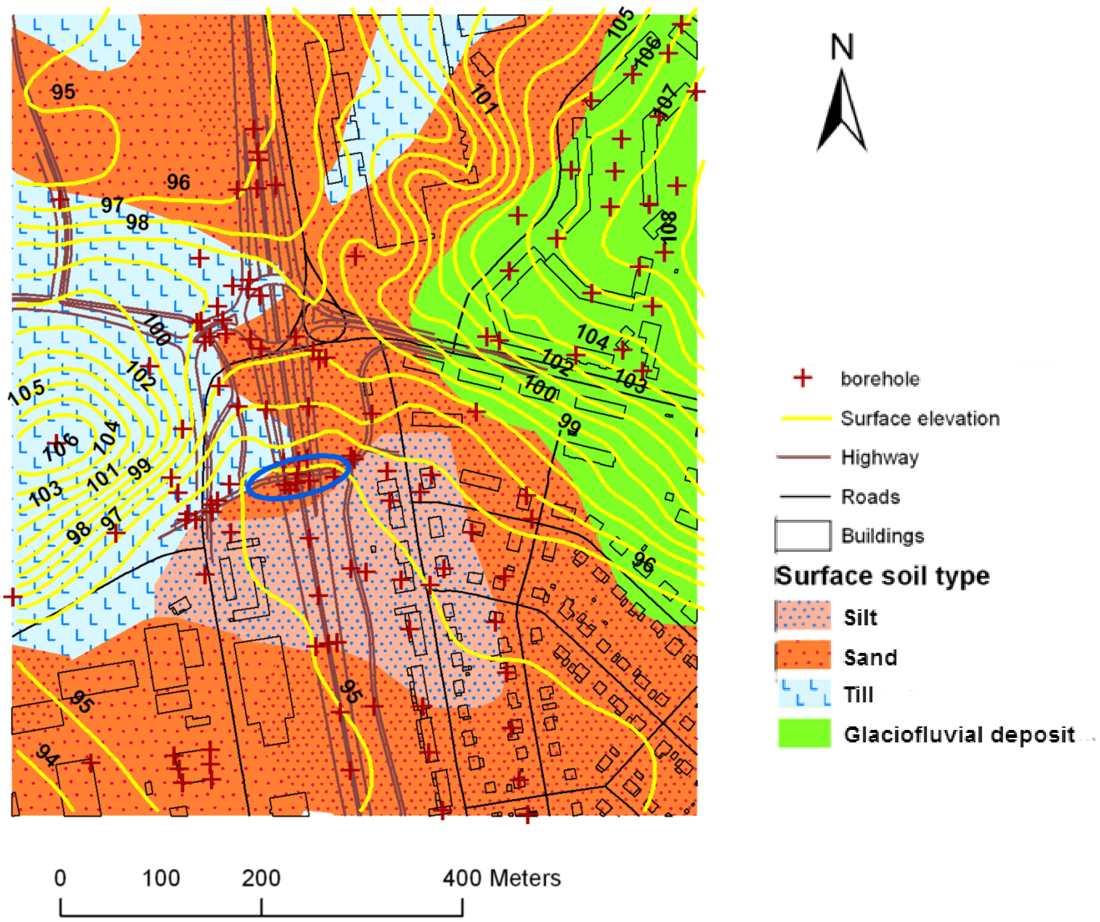
The study area was located in Motala, Östergötland province, Sweden (Figure 3a). Motala is situated at the east shore of Lake Vättern. The study area was with dimension of about 580m (W-E) and 680m (N-W) (Figure 3b). The surface soil type included clay, sand, till and glaciofluvial deposit. The topography was lower in the center and higher at the two sides. The tunnel position was indicated in Figure 3b. The soil strata in the study area can be one or two layers of clay and friction materials interbedded structure underlain by till (Figure 4). Friction material here was defined as coarser material like sand and gravel.

120 samples were used for interpolation of soil strata and they were mainly concentrated around the highway (Figure 3b). Among them, 7 points were read directly from the surface soil type map since it was known that the only soil type existing in these samples was till. The rest of the sample points were boreholes investigated by different geotechnical methods like soil sampling and sounding tests. Some boreholes were drilled recently and some were old investigations.

Ground surface elevation was provided in a 20*20m regular spaced squared grid, provided by Lantmäteriet (National Land Survey of Sweden). The map projection used in this study was SWEREF 99_15_00.



(a)



(b)

Figure 3 (a) Location map of study area. (b) Map of the sample points location, surface elevation, surface soil type and buildings and roads. The tunnel area was marked by blue circle.

3.2 Interpretation of the boreholes

In order to implement kriging interpolation, the boreholes should be interpreted first to extract information about soil types and elevations of different soil layers. The boreholes were investigated by different geotechnical methods and they could be classified as either sampling test or sounding test. In sampling test, the soil sample was taken out from the borehole and the soil types and thickness of different soil layers were identified in the laboratory. In sounding test, the soil types along the borehole were interpreted by observing the soil penetration resistances (firmness of the soil).

For the convenience of ground settlement calculation where only the clay layers settlement was included, the soil types were divided into clay, friction material (sand, gravel, etc.) and till. Maximum two layers of clay and friction material interbedded structure were found along the boreholes in the study area and till layer was always regarded as the most bottom layer in the study. Thus the maximum number of soil layers to be presented was 5 layers (See figure 4 illustrating the possible soil stratification). The soil layers were called clay1, friction1, clay2, friction2 and till. And the corresponding upper boundary elevations of these layers were called Elev_clay1, Elev_fr1, Elev_clay2, Elev_fr2 and Elev_till. The elevation of the ground was called Elev_ground.

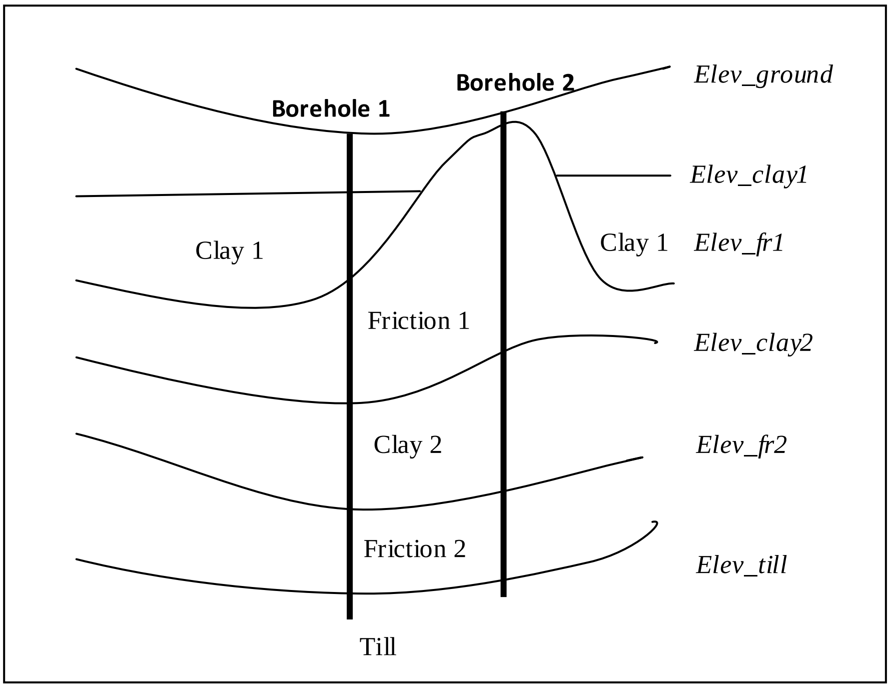


Figure 4 A schematic illustration of the possible soil strata in the study area

The boundary elevations of the five soil layers along the boreholes were interpreted in due order for each borehole. Not in every borehole we found all the soil layers. This was contributed by two factors: Firstly, specific soil layers may never exist in a borehole, e.g., borehole 2 in Figure 4 missed clay1 layer; secondly, a borehole may not be investigated deep enough to reach all the possible soil layers. Any layer did not found in a borehole was given a zero thickness.

Figure 5 gave an example of how the borehole was interpreted based on the geotechnical test. The borehole has been investigated by two ways, soil sampling (skr) and cone penetration test (CPT) (a kind of sounding test). Interpretation of the sampling test was straight forward. In figure 5, the soil types along the borehole were presented at the horizontal marks in the sampling column and different soil layers elevations could be read directly. The interpretation of sounding test was based on penetration resistance (in this case the point resistance) graph in the right side of Figure 5. Smaller point resistance value indicated softer material encountered like clay and bigger point resistance value indicated harder material encountered like sand or gravel.

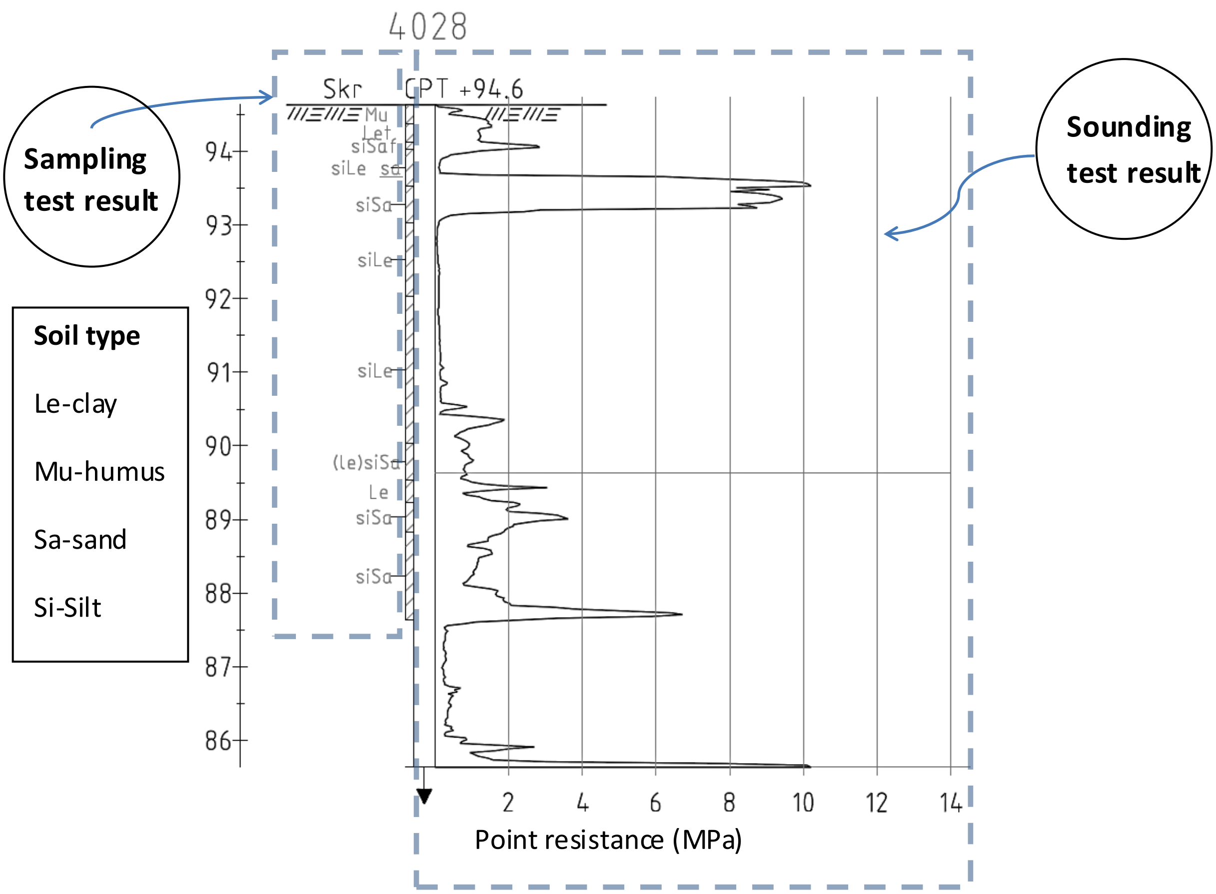


Figure 5 Interpretation of borehole data

Table 1 is an example of the interpreted sample points with information of the x and y coordinates, name, and elevations at each soil layer. The information in the table could be directly used for interpolation. For example, if a continuous Elev_clay1 is going to be created from the 4 samples in table 1, the column "Elev_clay1" together with the columns of x, y coordination would be used for spatial interpolation.

All the elevation data was registered in meter and the height system used was RH2000. RH2000 has been the official Swedish height system since 2005. The zero level in RH2000 is defined by Normaal Amsterdams Peil (NAP). It is a vertical datum in use in large parts of Western Europe.

Table 1 An example of interpreted sample points

x coordinate	y coordinate	name	Elev_clay1 (m)	Elev_fr1 (m)	Elev_clay2 (m)	Elev_fr2 (m)	Elev_till (m)
150961.1	6491609	4020	93	91.5	91	88.8	88.7
150953	6491658	4021	93.4	92.2	90.8	88	87.9
150876.9	6491975	4033	93	93	93	93	93
150856.1	6491979	4034	98.5	98.5	98.5	98.5	98.5

3.3 Soil strata model generation by kriging

The basic idea of soil strata generation was to interpolation each soil layer from borehole first and then put all the layers together to create a "layer-cake model". Here it was the upper boundary elevation of each soil layer was interpolated. We will call the upper boundary elevation of the soil layer "elevation of the soil layer" or "soil layer's elevation" for simplification. The software used for interpolation was Surfer 8 from Golden Software.

The experimental semivariogram for every soil layer's elevation was built first. The sample points used for building semivariogram of a soil layer were the points having this specific layer (not the points missing the specific layer). The outliers would change the appearance of semivariogram in a great extent so suspected outliers were removed. After that, a theoretical model was fit to the each experimental semivariogram. The range, sill and nugget were chosen.

The interpolation of a soil layer's elevation was based on the semivariogram. The soil layer's elevations were interpolated in a 10*10m regular spaced square grid. Besides, the prediction standard error maps were also created for each soil layer in the 10*10m resolution. The prediction values together with prediction standard errors would be used later as inputs in the Monte Carlo simulation. The thickness of the soil layer was calculated by the difference between upper and lower boundary elevation of that soil layer.

Cross validation was carried out for each layer to check how well the model predicted the measured values. The sample points used for cross validation of a soil layer were the points having this specific layer. Mean Error (ME) and Root Mean Squared error (RMSE) were calculated for each soil layer. The RMSE from cross validation was compared with the standard deviation of sample values to evaluate if the semivariogram model could be considered adequate.

The interpolated soil layer elevations (prediction values) needed to be adjusted due to a problem found after interpolation. The problem could be described as follows: For the same location in the soil strata model, there were 6 elevation values corresponding to 6 different layers' elevation (among them 5 values were obtained from interpolation except for Elev_ground). These 6 elevations may overlap each other in vertical direction, i.e., the interpolated lower soil layers may have higher elevations than the upper layers. The interpolated soil layer elevations were rearranged in the vertical direction so that they did not overlap each other. This was done by using the following algorithm in Matlab:

1. We call the top soil layer "first layer" and the layer beneath it "second layer" and so on. For each cell, start from the first layer and compare if it is high than the second layer. If yes, nothing happens. If no (which is contradictory to the reality), give the elevation of first layer to the second layer.

2. Now check the second layer with the third layer, the third layer with the fourth layer as step 1 till all the layers are checked. Make sure that the upper layer always has higher elevations than the lower layer.

3. Go through every cell and do step 1 and 2.

To check the overlapping area and magnitude, the areas where Elev_ground and Elev_clay1 overlapped were mapped. This was done by subtracting Elev_clay1 from Elev_ground. The areas where Elev_clay1 and Elev_fr1 overlapped were mapped by using the same method.

After adjusting overlapping, the soil layers' elevations were put together and presented in a "layer-cake model". The soil strata cross section along the highway was mapped.

3.4 A stochastic representation of the soil strata

3.4.1 Monte Carlo simulation

The uncertainties existed in kriging interpolation was measured by prediction standard error. The probability distribution of the soil layer's elevation was represented by the prediction value and prediction standard error obtained from kriging. To build a stochastic representation of the soil strata, we just need to check whether different soil layers' probability distribution overlap each other, similar to the way we did in previous section. The software used for Monte Carlo simulation was Oracle Crystal Ball.

The stochastic representation of the soil strata was created by using Monte Carlo (MC) simulation. The stochastic representation of the soil strata was based on a 30*30m regular spaced square grid. The cell resolution was changed from 10m*10m in kriging to 30m*30m since a 10*10 m grid would result a lot more cells and huge amount of computation that the PC used in this study couldn't manage. Although the MC simulation was based on 30*30 m resolution, the results obtained from MC simulation were mapped in 10*10 m resolution again. Bilinear interpolation was the resampling method used for changing the cell resolution.

Figure 6 showed the MC simulation process considering one single cell. This process was carried out for all the 480 cells in the study area simultaneously. The probability distribution between the cells would not influence each other. The process of the MC simulation could be described as following:

1. The inputs were different soil layers' elevations with the uncertainties. The probability distribution of the input was defined as a normal distribution with the prediction value from kriging as mean and prediction standard error from kriging as standard deviation. Elev_ground was fixed value but also functioned in the model which regulated the elevations of lower layers.

2. In each run of MC simulation, 5 random inputs were generated from the 5 probability distributions corresponding to different soil layers' elevation.

3. The non-overlapping formula worked as to ensure the lower layers' elevations would never be high than the upper layers' elevations. For example, the formula compared the value generated for Elev_caly1 and Elev_ground. If Elev-clay1 was even bigger than Elev_ground which was contradictory to the reality, elev_clay1 was given the same value as Elev_ground. And then the value generated for Elev_fr1 was compared with Elev_clay1. If Elev_fr1 was even bigger than elev_clay1, elev_fr1 was given the same value as Elev_clay1. Similar procedure went through the entire soil strata till all the layers were checked.

4. Step 2 and 3 were repeated for 1000 runs. Then the results were aggregated.

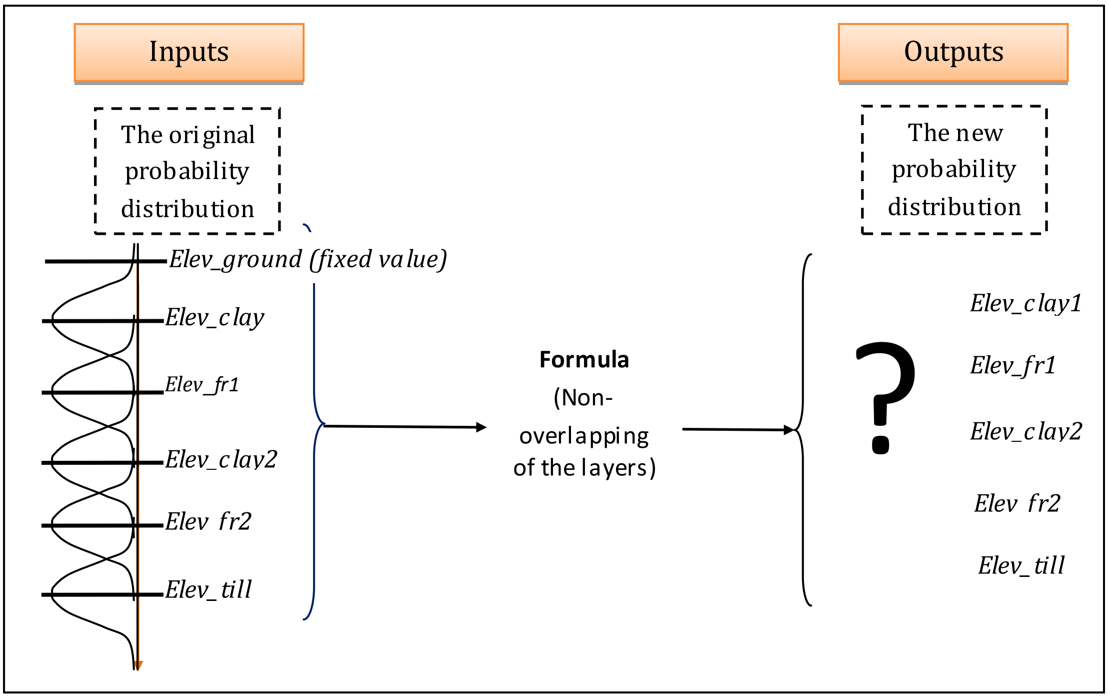


Figure 6 The Monte Carlo simulation process considering one single cell

The model was tested to run for both 1000 and 10000 times and the results were extracted for two of the soil layers. It was showed that when comparing the results from model running 1000 with model running 10000 times, the results differed in a very minor way. So finally 1000 runs were chosen for the simulation since 10000 runs were much more time consuming in both running and data extraction stages.

3.4.2 Uncertainty and sensitivity analysis of the soil strata

After 1000 run, the new probability distribution of each soil layer's elevation was created as output (Figure 5). To present the uncertainties of the outputs, firstly 50^{th} percentile and standard deviation of the outputs were extracted for all the cells and mapped. A percentile is the value achieved below a particular threshold and 50^{th} percentile is the value below which half of the observations found. The 50^{th} percentile which measured the central tendency of the output was compared with the prediction values from kriging results; the standard deviation which measured the dispersion of the output was compared with the prediction standard error which also measured the dispersion of the kriging results. The skewness of the outputs was mapped to explore the asymmetry of the output probability distribution.

Except for the elevations of different soil layers, the thicknesses of the two clay layers were also interesting for this thesis since the ground settlement was calculated for the two clay layers. Thus the thickness of clay1 and clay2 were also extracted as outputs of MC simulation.

Firstly, the two clay layers' thicknesses were mapped in 50^{th} percentile and compared with the relevant kriging results. Then the thickness of clay1 was mapped in both 5th and 95th percentile. The combination of 5^{th}, 50^{th} and 95^{th} percentile was a good presentation of the range of the variable.

A sensitivity analysis was made to investigate which inputs had significant impacts on the variations of clay1 and clay2 thickness, respectively. The sensitivity was determined by rank order correlation coefficient (RCC) between every input and the output when the MC simulation was running. RCC ranges from -1 to 1. Positive coefficients indicated that an increase in the input was associated with an increase in the output. Negative coefficients implied the opposite situation. And the larger the absolute value of RCC, the stronger relation between input and output.

3.5 Ground settlement risk evaluation

For ground settlement risk evaluation, the soil strata model, groundwater model and ground settlement model were integrated with the uncertainties defined in each model. Monte Carlo simulation was employed for the stochastic simulation of the integrated model. The software used for MC simulation was again Oracle Crystal Ball. The integrated model contained parameters from all the three models, e.g., soil layer elevations from soil strata model, annual precipitation and hydraulic conductivity of different soils from groundwater model and over consolidation rate (OCR), soil modulus of different soils from ground settlement model.

The uncertainties in the ground settlement were quantified. Risky areas where the ground settlement exceeded a critical value were identified. Then a sensitivity analysis was carried out to see which parameters contributed to the biggest uncertainties in the ground settlement.

4. Results

4.1 Soil strata model generated by kriging

The descriptive statistics of the sample data elevations were shown in Table 2. Not every sample point was observed having all the 5 soil layers as explained before. Among 120 sample points, 72 points were observed having layer clay1, 54 points having layer friction1, etc (see Table 2). Elev_till had the biggest range and variance among all the soil layers. Elev_clay1 had the smallest range and variance and Elev_fr2 had the second largest ones.

For building semivariograms, suspected outliers were removed for each layer so the number of sample points used for constructing semivariogram was less than the original number of sample points in Table 2, see Table 3. The experimental semivariograms of all the soil layers were found to be best fitted by spherical model (Figure 7). The spherical model has form like:

$$y(h) = c_0 + c(\frac{3}{2}\frac{h}{a} - \frac{1}{2}\frac{h^3}{a^3})$$

where, c_0 is the nugget effect, c is the sill and a is the range. The ranges and sills for different layers were showed in Table 3. There was no nugget effect found for all the soil layers. Elev_till had the largest sill, Elev_clay1 had the smallest one and Elev_fr2 had the second largest one. The ranges were the same of 120 m for the three most top layers and decreased to 70 m for Elev_fr2 and increased to 170 m for Elev_till.

Table 2 Descriptive statistics of the sample data for each soil layer

	Elev_clay1	Elev_fr1	Elev_clay2	Elev_fr2	Elev_till
No.of points	72	54	41	30	109
Mean(m)	93.64	91.61	89.64	87.25	93.39
Standard Deviation(m)	1.23	1.47	1.35	1.80	7.13
Variance(m^2)	1.51	2.16	1.82	3.24	50.84
Range(m)	6.70	8.20	6.35	9.75	25.50
Minimum(m)	91.30	88.00	87.00	83.00	82.50
Maximum(m)	98.00	96.20	93.35	92.75	108.00

Table 3 Semivariogram parameters of each soil layer's elevation

	Elev_clay1	Elev_fr1	Elev_clay2	Elev_fr2	Elev_till
No.of points	71	54	40	29	104
Sill(m^2)	1.15	2.8	2.1	3	15
Range(m)	120	120	120	70	170

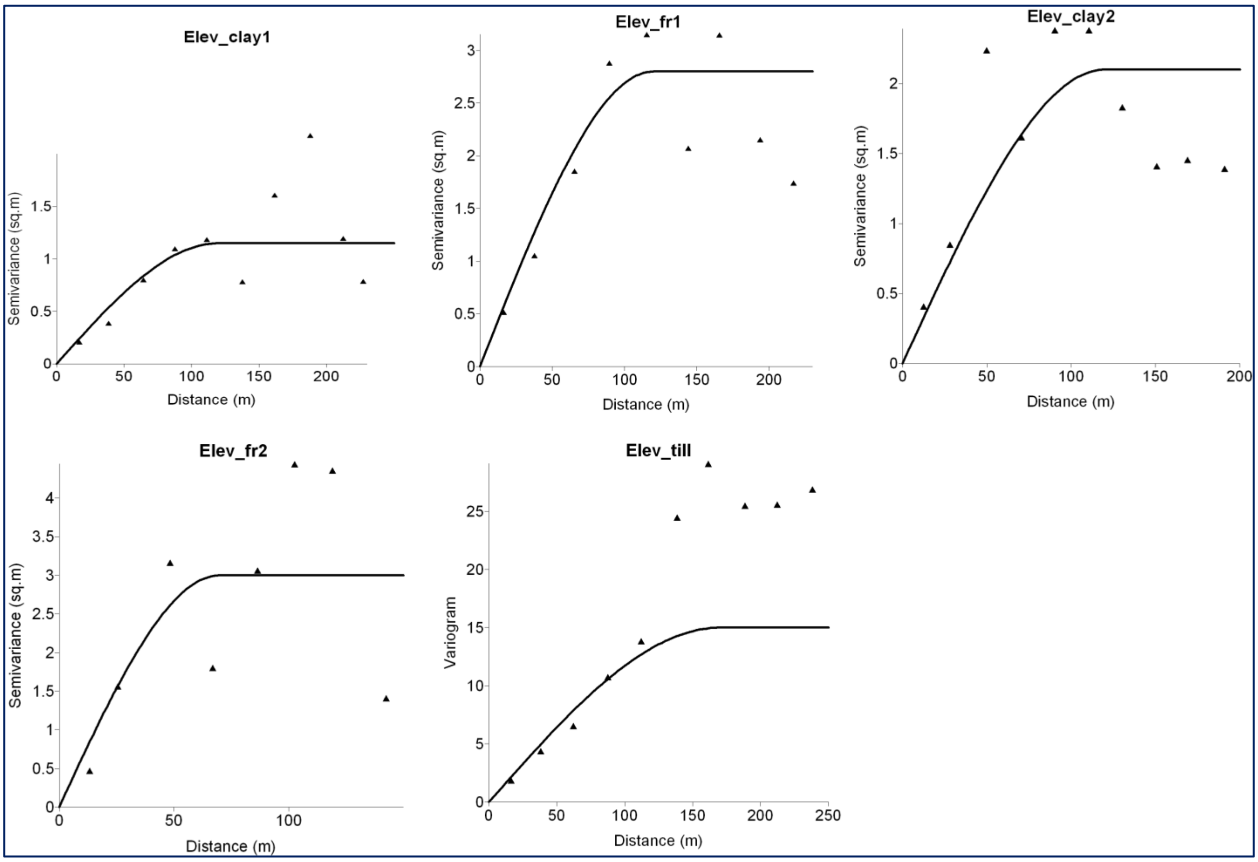


Figure 7 Experimental (small triangle dots) and fitted (curve) semivariogram of each soil layer's elevation.

Tables 4 listed the averaged prediction standard error for the 5 interpolated soil layers elevations. Among all the soil layer elevations, Elev_clay1 had the smallest averaged standard error of 0.79m. The standard errors increased when the soil layers were further lower except for Elev_clay2.

Table 5 was the cross validation statistics for the interpolated soil layers. The Mean Error (ME) was the lowest for Elev_clay1 of 0.1m. The largest ME was found for Elev_fr2 of 1.77m. All the layers were over-estimated with observed positive ME except for Elev_till was under-estimated.

The Root Mean Square Error (RMSE) was found for Elev_clay1 of 1.2m and it was a bit lower than 1.23m (Table 2), the standard deviation of Elev_clay1 of the sample data. The highest RMSE was found for Elev_fr2 of 2.86m and it was higher than 1.80m (Table 2), the standard deviation of Elev_fr2 of the sample data. By comparing the cross validation RMSE and the sample data standard deviation of different soil layers, the prediction of Elev_clay1, Elev_fr1 and Elev_till could be considered adequate but not Elev_clay2 and Elev_fr2.

Table 4 The averaged prediction standard error of each soil layer

	Elev_clay1	Elev_fr1	Elev_clay2	Elev_fr2	Elev_till
Mean(m)	0.79	1.24	1.12	1.49	2.52

Table 5 The ME and RMSE from cross validation results

	Elev_clay1	Elev_fr1	Elev_clay2	Elev_fr2	Elev_till
ME(m)	0.1	0.27	0.75	1.77	-0.22
RMSE(m)	1.2	1.33	1.4	2.86	2.8

Figure 8 (left) showed areas where Elev_ground and the prediction value of Elev_clay1 overlapped each other. Severe overlapping happened mostly at places far away from the sample points. Figure 8 (right) showed areas where the prediction value of Elev_clay1 and Elev_fr1 overlapped. The areas and magnitude of overlapping were much smaller.

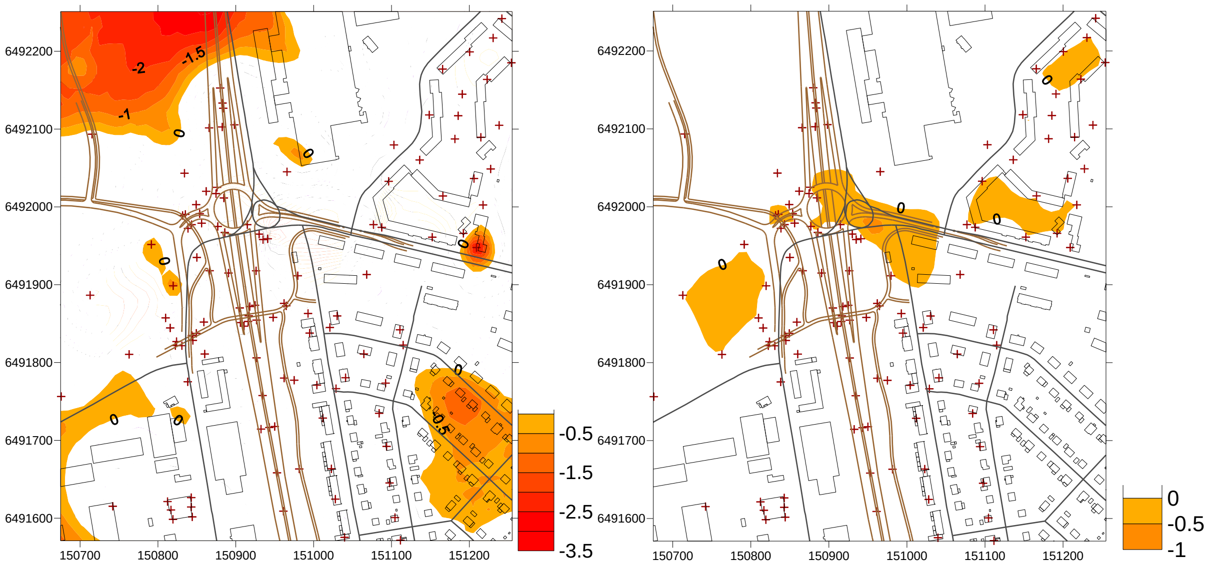


Figure 8 Overlapping area and magnitude of Elev_ground and Elev_clay1 prediction values (left), Elev_clay1 and Elev_fr1 prediction values (right).

The soil strata cross section along the highway was mapped in Figure 9.

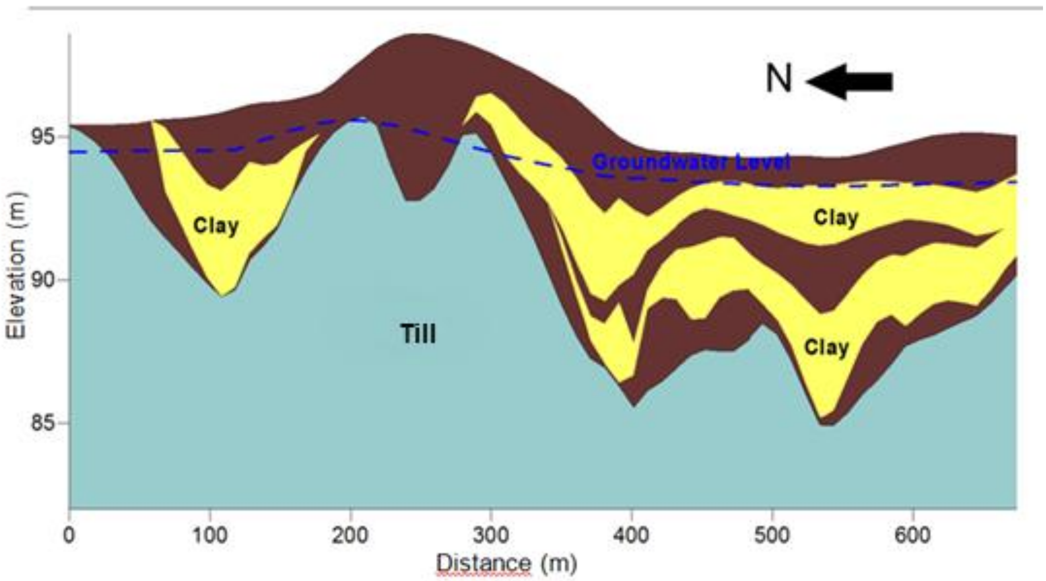


Figure 9 The cross section map of soil strata along the highway.

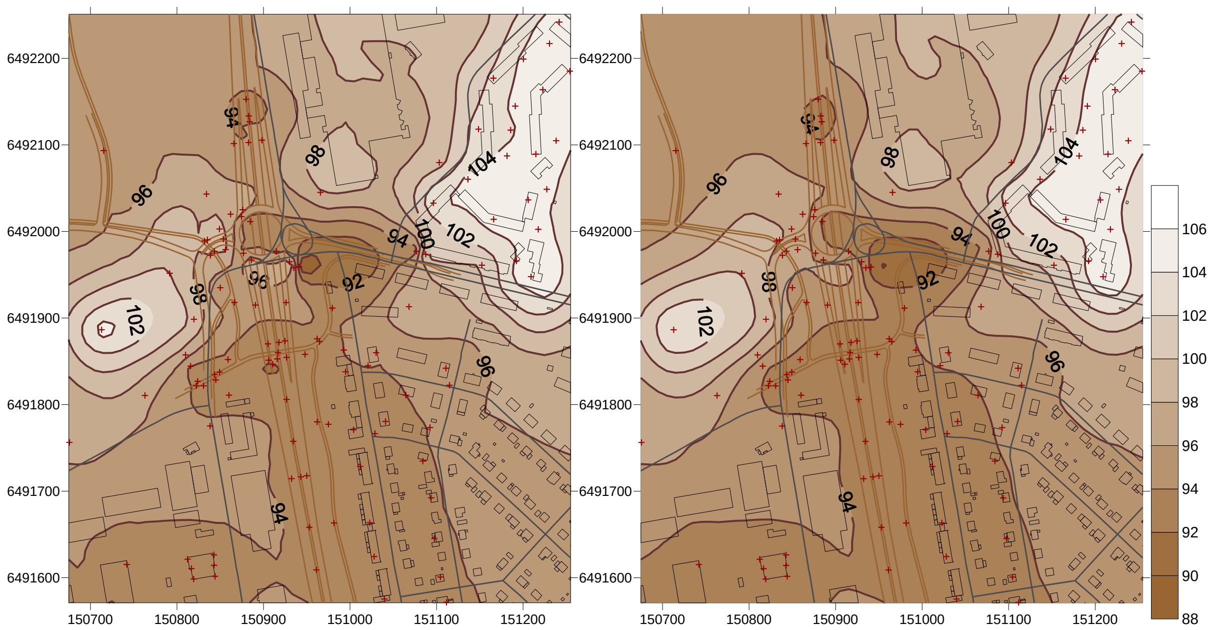
4.2 Uncertainty and sensitivity analysis of the soil strata model

4.2.1 Uncertainty analysis

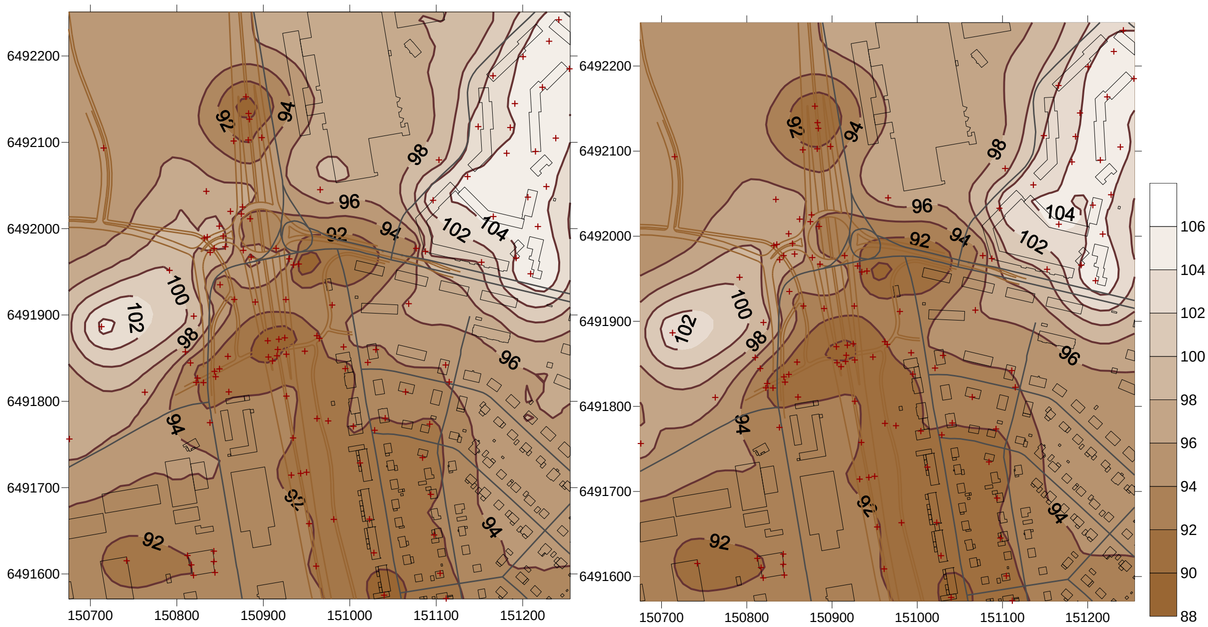
In Figure 10, soil layer's elevations were mapped in 50th percentile from Monte Carlo (MC) simulation results (right side) and compared with the kriging results (left side). For Elev_clay1, the two contour maps were similar, so as for Elev_fr1. But for Elev_clay2, Elev_fr2 and Elev_till, the two contour maps were more different and the MC results tended to show lower values, especially at places far from the sample points.

Elev_clay1

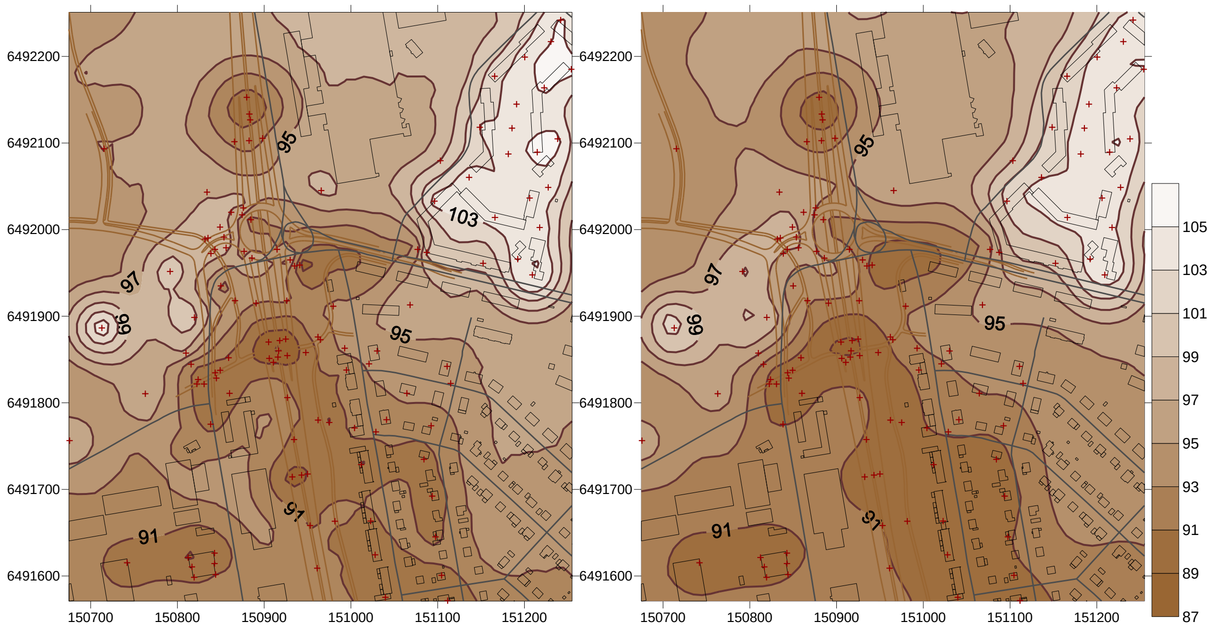
Kriging results MC results



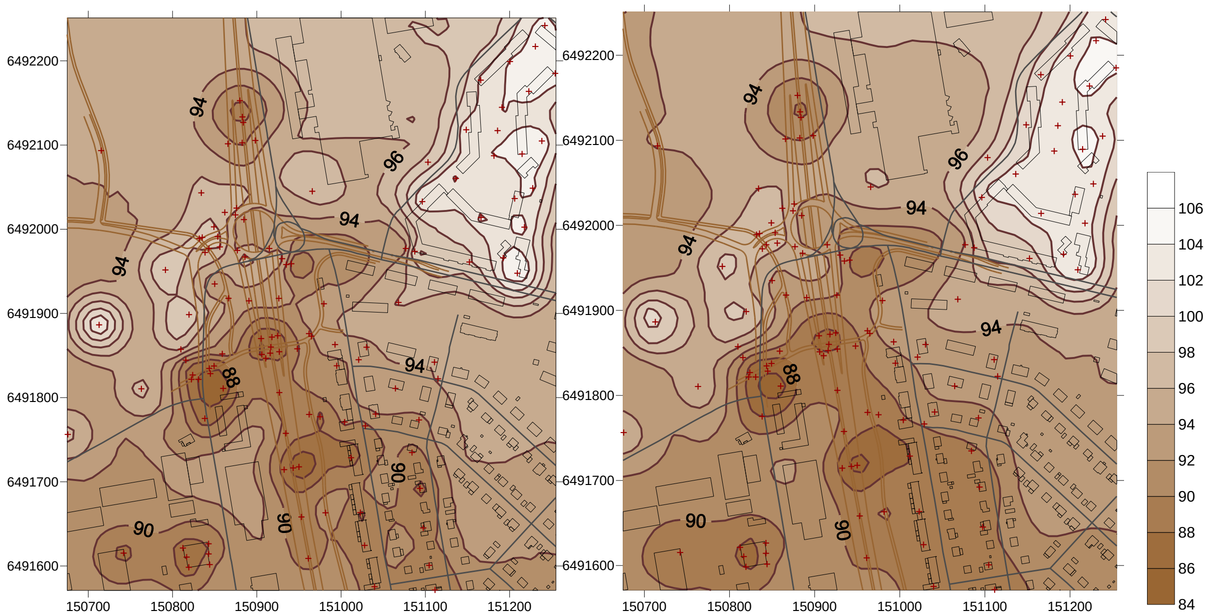
Elev_fr1



Elev_clay2



Elev_fr2



Elev_till

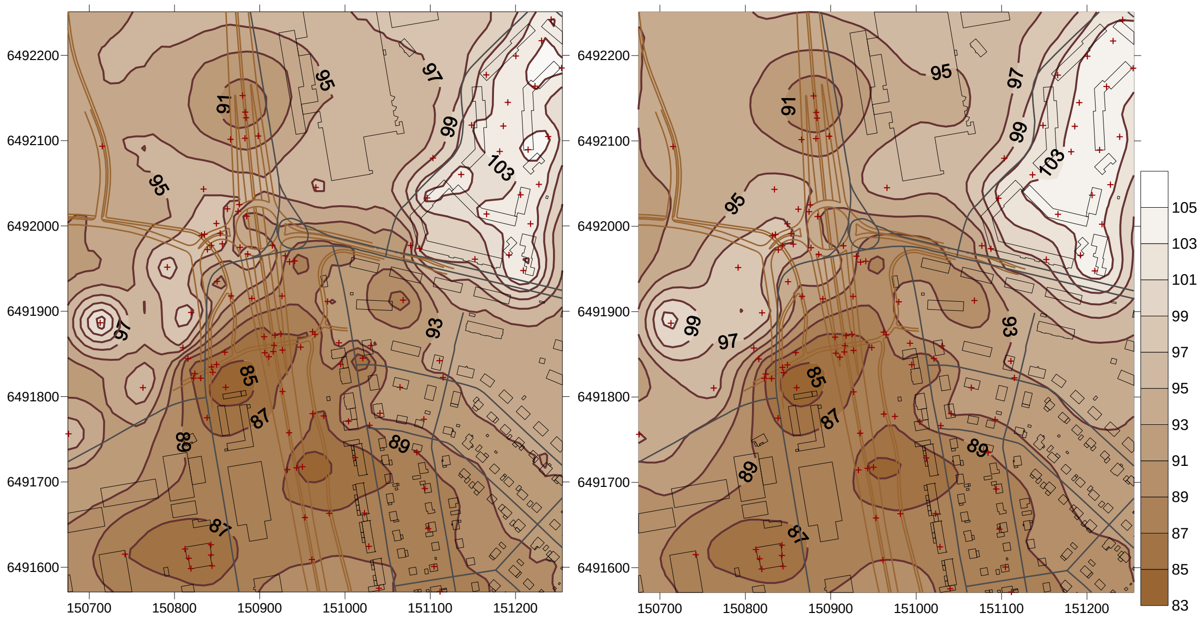
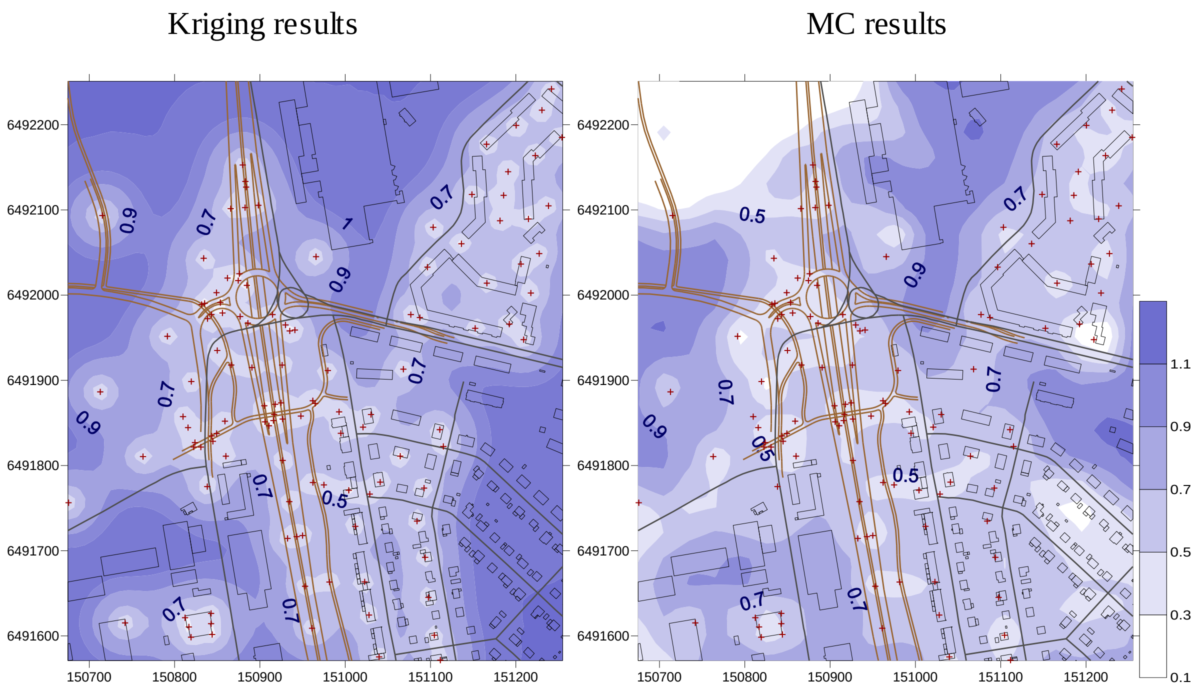


Figure 10 The contour maps of different soil layers's elevations from kriging results (left) and 50th percentile of MC results (right).

For Elev_clay1 and Elev_fr1, the standard deviation from MC results were mapped (Figure 11 right) and compared with the prediction standard error obtained from kriging (Figure 11 left). The standard deviation and standard error of Elev_fr1 were generally bigger than those of Elev_clay1. For both Elev_clay1 and Elev_fr1, the standard deviation maps from MC results generally showed lower value than the same places in the standard error maps. Similar results were found for the other layers.

Elev_clay1



Elev_fr1

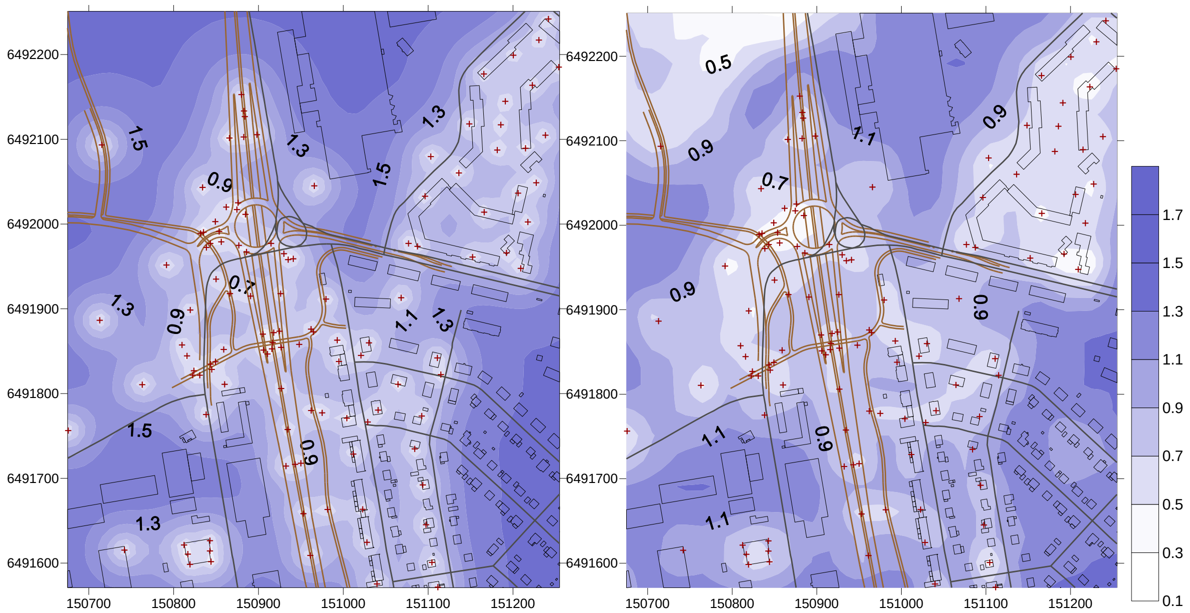


Figure 11 The contour maps of standard error from kriging (left) and standard deviation from MC results (Right) for Elev_clay1 and Elev_fr1.

Figure 12 mapped the skewness of Elev_clay1 from MC results. The data tended to show negative skewness and the skewness values were very big in the upper left and lower right corner.

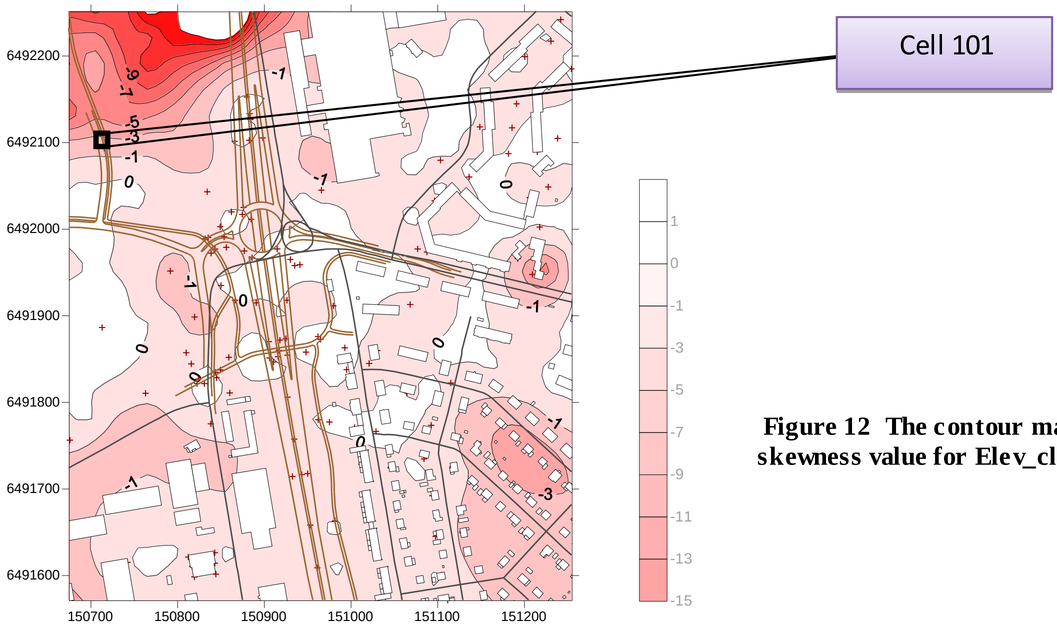


Figure 12 The contour map of skewness value for Elev_clay1

To better illustrate the skewness observed for Elev_clay1 in Figure 12, cell 101 (see Figure 12 for its position) was extracted and the probability distributions of Elev_clay1 at that cell were examined both before and after MC simulation. The descriptive statistics of Elev_clay1 at that cell showed the mean, median and standard deviation after MC simulation were lower than before MC simulation (Table 6). The data was obviously skewness after MC simuation. The probability distribution of Elev_clay1 at that cell was plotted in Figure 13. A very obvious peak was observed around 95.03 m and almost 80% of the data was at that value. According to the formula defined in MC simulation process, all the generated Elev_clay1 values from the original distribution were given the same value as Elev_ground if they were bigger than the value of Elev_ground (95.03m). This explained the change of probability distribution of Elev_clay1at that cell.

Table 6 The descriptive statistics for Elev_ground and Elev_clay1 before and after MC simulation

Cell 101	Elev_ground	Elev_clay1 (origin)	Elev_clay1 (after Monte Carlo simulation)
Mean	95.03	95.62	94.90
Median	-	95.62	95.03
Standard deviation	-	0.94	0.33
Skewness	-	0	-3.06

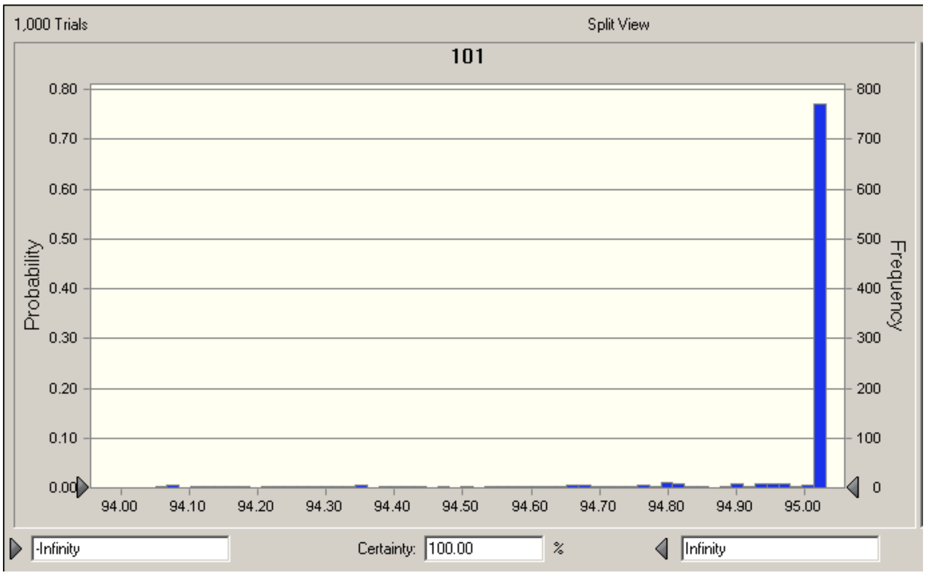
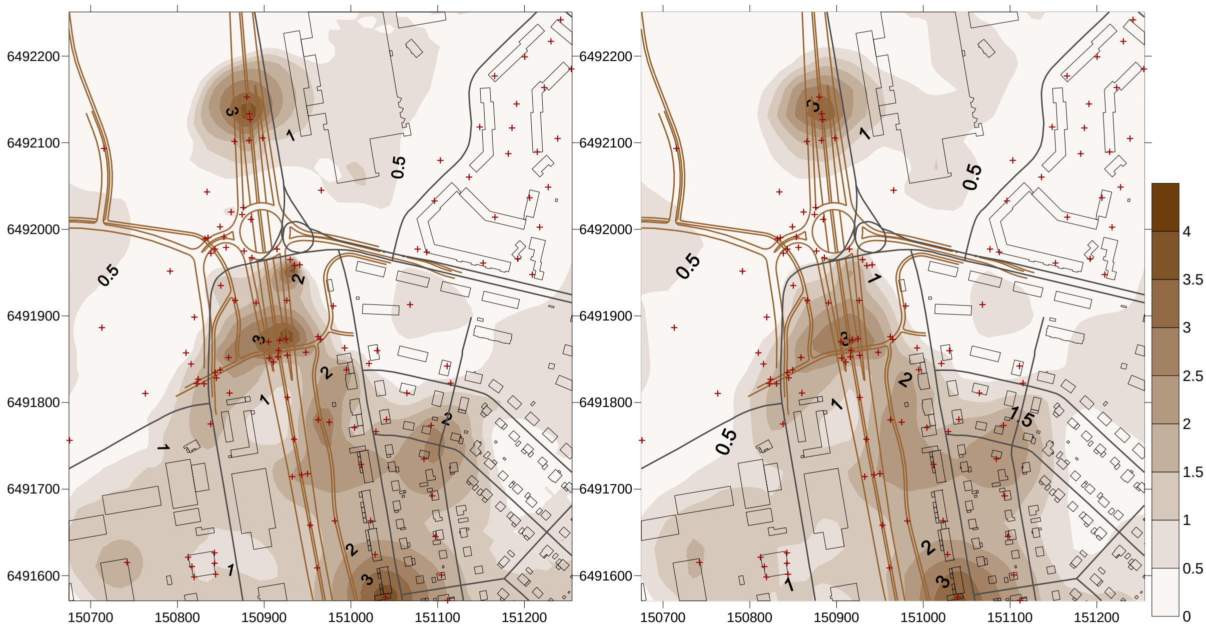


Figure 13 The probability distribution for Elev_clay1 at cell 101 after MC simulation

Figure 14 mapped the thickness of clay1 and clay2 in 50th percentile from MC results and compared with the kriging results. A thinner clay1 layer and clay2 layer were found from MC results than kriging results. The maps looked more different at the places far away from the samples.

Clay1 layer thickness

Kriging results MC results



Clay2 layer thickness

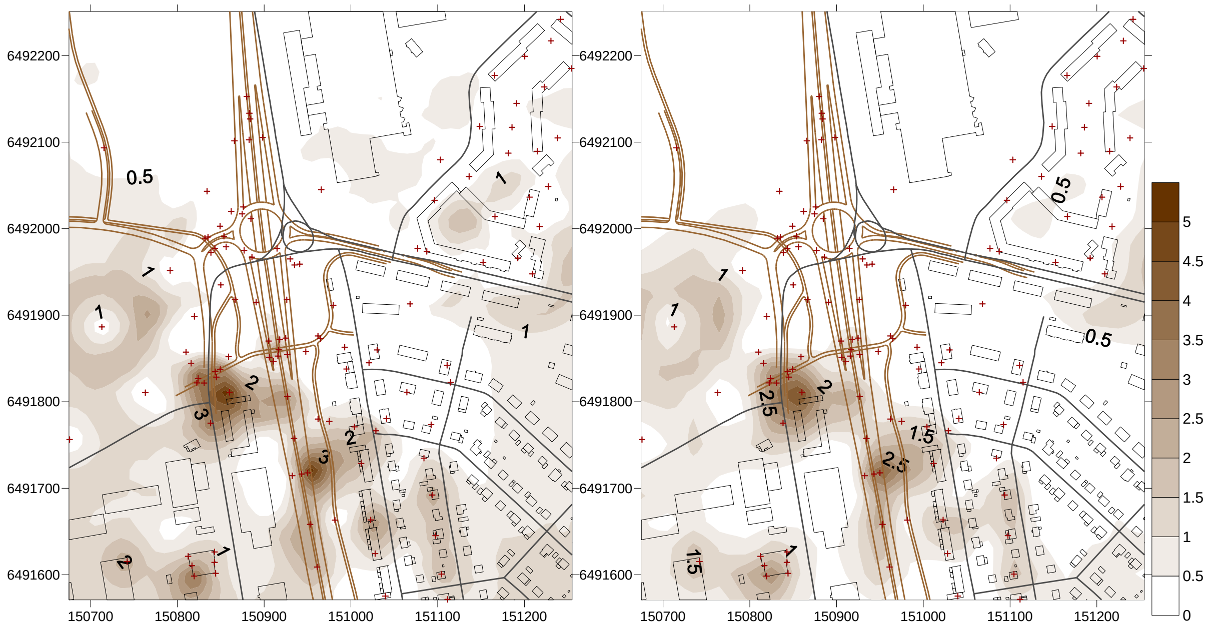
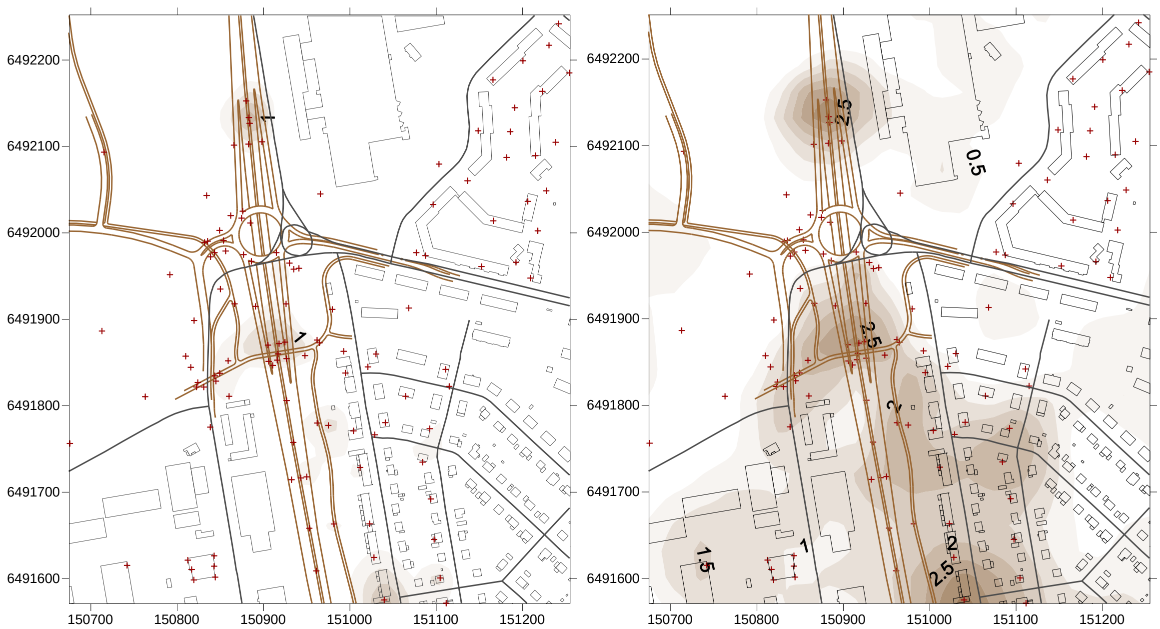


Figure 14 The thickness for clay1 and clay2. Left ones were kriging results. Right ones were mapped fin 50th percentile from MC results.

In figure 15 the thickness of the clay1 was mapped in different percentiles (5th, 50th and 95th). The three maps showed quite different results, indicating the ranges of clay1 thickness were quite big in some places.



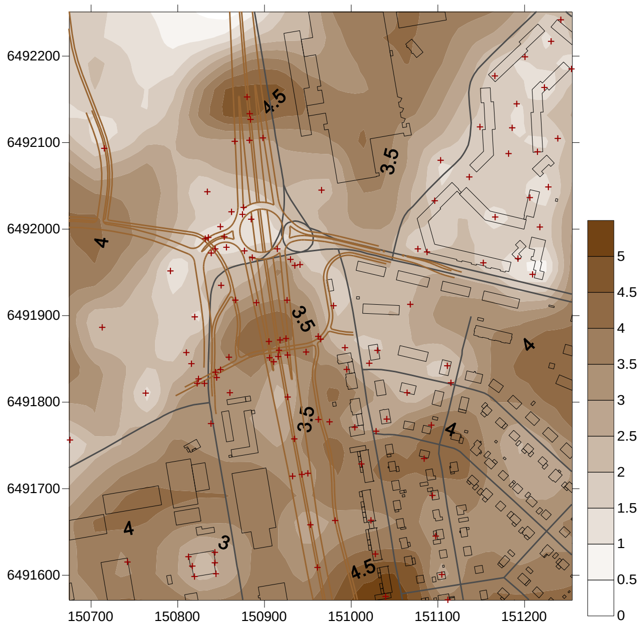
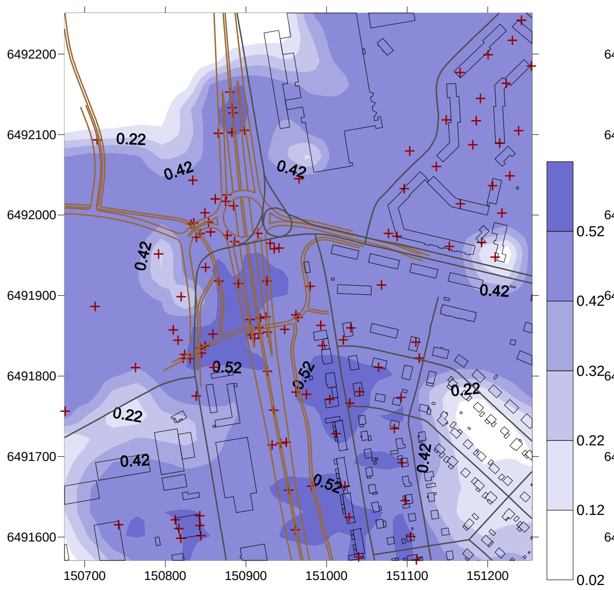


Figure 15 The thickness of clay1 mapped in 5th, 50th, 95th percentile from MC results

4.2.2 Sensitivity analysis

The sensitivity analysis showed in every place, input Elev_fr1 and Elev_clay1 had the biggest and second biggest rank correlation coefficient (RCC) with the thickness of clay1, respectively. The RCCs between the thickness of clay1 and Elev_clay1 were mapped in Figure 15 (left) and the RCCs between the thickness of clay1 and Elev_fr1 were mapped in Figure 15 (right). Elev_clay1 always had positive RCCs and Elev_fr1 always had negative values. Elev_fr1 and Elev_clay1 were the most and second most influential inputs on the variations in the clay1 layer thickness, respectively.



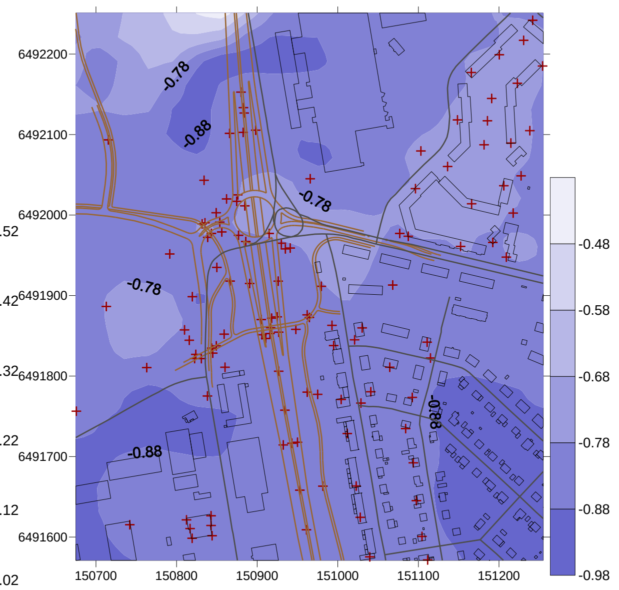


Figure 16 Left: the RCC between the thickness of clay1 layer and Elev_clay1. Right: the RCC between the thickness of clay1 layer and Elev_fr1.

Sensitivity analysis also showed that in every place, Elev_fr2 had the largest RCC with the thickness of clay2. At most of the places, Elev_clay2 had the second largest RCC with the thickness of clay2. Some other inputs had the second largest RCCs with the thickness of clay2 could be Elev_le1, Elev_fr1 and those values were usually smaller (between -0.25 to 0.25). The RCCs between the thickness of clay2 layer and Elev_clay2 were mapped in Figure 17 (left) and the RCCs between the thickness of clay2 layer and Elev_fr2 were mapped in Figure 17 (right). Elev_clay2 always had positive RCCs and Elev_fr2 always had negative values. Elev_fr2 and Elev_clay2 (at most of the places) were the most and second most influential inputs on the variations in the clay2 layer thickness.

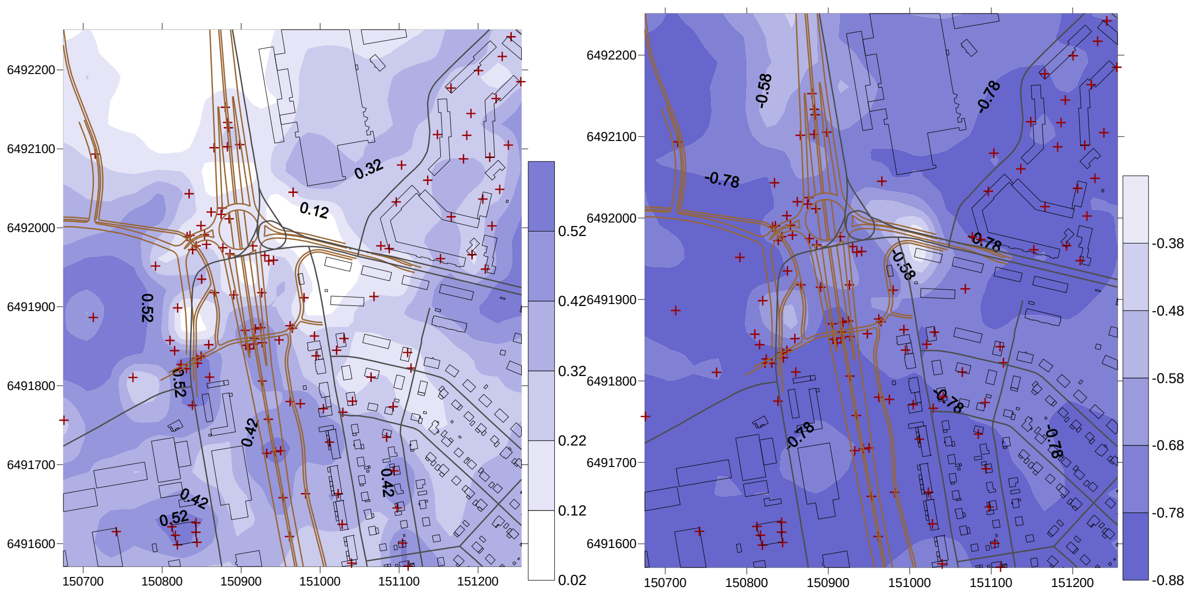


Figure 17 Left: the RCC between the thickness of clay2 layer and Elev_clay2. Right: the RCC between the thickness of clay2 layer and Elev_fr2.

4.3 Ground settlement risk evaluation

In Figure 18, the areas inside the marked contour lines were risky area where the standard deviation and 95th percentile of the calculated ground settlement exceeding a critical value. The critical value is 0.02m for standard deviation of ground settlement and 0.05m for 95th percentile of ground settlement. The buildings within the risk area were masked with blue color. Figure 18 also mapped the parameters that contributed to the biggest uncertainties in the final ground settlement model. Elev_fr1, Elev_fr2, Elev_clay1 were parameters in the soil strata model. Further studies and investigation could be made according to this map to decrease the risks in ground settlement. For example, if Elev_clay1 was found in this sensitivity map in a risky area, then more time could be spent on Elev_clay1 in the hopes of reducing its uncertainty, therefore, its effect on the ground settlement.

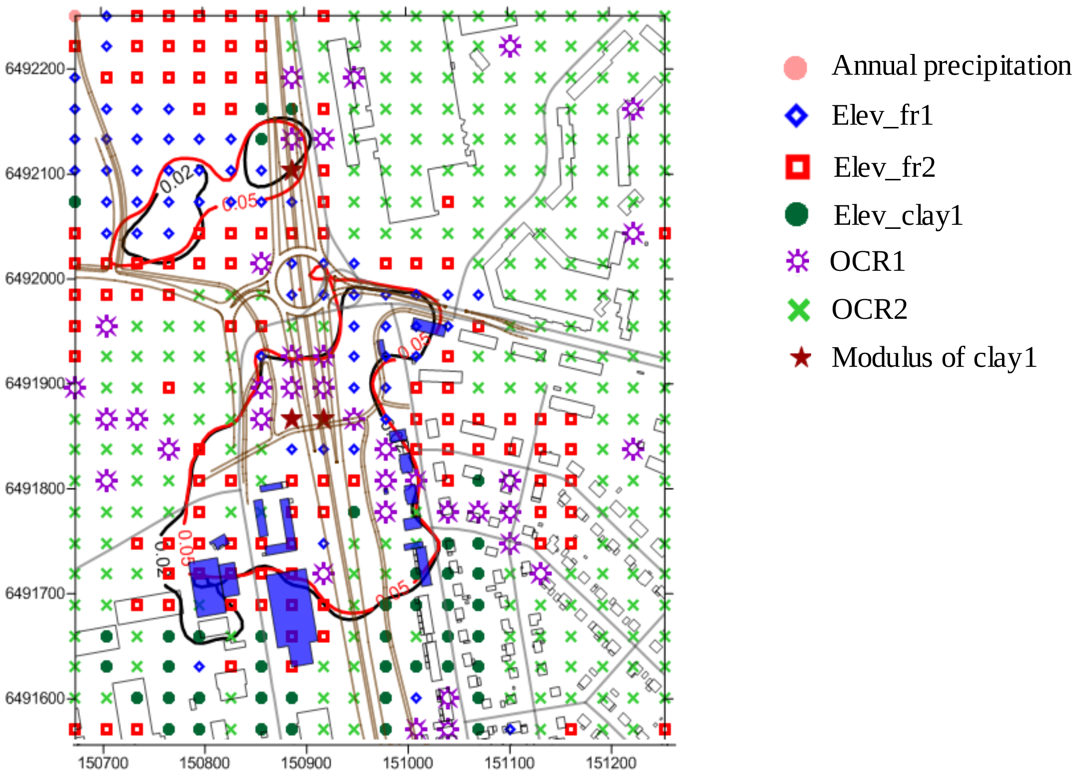


Figure 18 The sensitivity map for final ground settlement model. Risky areas where the ground settlement exceeded a critical value were showed.

5. Discussion

Fitting the semivariogram

The most common semivariogram models that can fit most of the data sets are the *linear*, *exponential*, and *spherical* models (Barnes). If a semivariogram never level off, then a linear model should be chosen. If a semivariogram levels off but still curves up a bit, then an exponential model should be used. In our case, the spherical models were chosen since all the semivariogram leveled off in a certain distance and did not go all the way up.

The different ranges and sills observed for the soil layers' elevations indicated that their spatial variability were different. The semivariogram in real life would not look the same as the theoretical one showed in Figure 1. The experimental semivariogram in Figure 7 showed more fluctuation in the high distances than the low distances. The fluctuation of semivariogram in higher distances implied the weak spatial dependency between far away locations.

Soil layers overlapping in kriging

The overlapping between different soil layers could be explained by the interpolation error (uncertainty), i.e., the incorrectly predicted elevation values caused the overlapping problem. From figure 8, we could see that in two kinds of situation, overlapping was prone: First, since the place further away from sample points would have more un-reliable results, the uncertainties in those places were also bigger. Thus overlapping would happen more in the places far away from sample points (Figure 8 left). Second, overlapping happens more in the places where the upper layer elevation and lower layer elevation were very similar (Figure 8 right). And in this case, the degree of overlapping was smaller.

It can be inferred that the overlapping problem in modeling soil strata from kriging is common, since kriging (or any other spatial interpolation method) is an intelligent guesswork and erroneous prediction is inevitable. However, Overlapping problems may indicate an inadequate kriging model (semivariogram model) so special cautions need to be paid.

The solution of treating overlapping always gave the lower layer elevations to the higher layer elevations. This was due to that the higher layer elevations were more reliable, since more sample points were included for interpolation.

Stationarity

The type of kriging used for interpolation in this thesis was *Ordinary Kriging*. Data stationarity is one assumption behind *Ordinary Kriging* process. A stationary data must satisfy: (1) The mean of the data is the same of all the location, (2) The covariance (or semivariance) is the same between any two points that are at the same distance (Haas 1989). However in practice, this assumption is often violated. In fact, the data set used in this study has shown non-stationarity of mean and semivariance when assessing with Voronoi maps suggested by Krivoruchko (2002). An alternative way to perform kriging for non-stationary data is to use *Moving Window Kriging* (MWK) which builds local semivariogram at every location to be estimated. The local variogram is minimally affected by data non-stationarity and thus allows the accurate modeling of the spatial structure (Krivoruchko 2002; Haas 1989). MWK was complicated and difficult to understand. Due to the time limit, MWK was not utilized in this thesis.

Cross validation

The RMSE from cross validation indicated the prediction of Elev_clay1, Elev_fr1 and Elev_till could be considered adequate but not Elev_clay2 and Elev_fr2. This may be explained by that the number of samples used for constructing semivariogram of Elev_clay2 and Elev_fr2 was less than the other soil layers. Insufficient number of sample points may not be able to give a meaningful semivariogram (Lemon and Jones 2003).

Uncertainty analysis

Normal distribution was chosen as the probability distribution for the input due to the reason that many natural variables fall into a normal distribution. And the input (soil layer elevation) was thought to be symmetric and more likely to near the center than the extremes (Rodger 1999).

Figure 9 -13 mapped the central tendency, dispersion and skewness of the output probability distributions from Monte Carlo (MC) simulation and compared them with relevant kriging results. The central tendency of the output probability distribution showed the stochastic representation of the soil strata has been changed from the soil strata generated by kriging. Especially in the lower soil layers when the corresponded uncertainties were bigger. MC results tended to show lower values in elevations because the values bigger than the upper layer elevations were filtered by the non-overlapping formula.

The change of dispersion and skewness could be explained by the overlapping of probability distribution in the inputs. The overlapping values were filtered and caused a “narrower” distribution in the output. And since only the bigger values in the distribution were filtered so the distribution showed skewness.

Generally, the MC results and corresponding kriging results were more different at the places far away from the samples. In kriging the places further away from the sample points would have larger interpolation prediction error so the inputs uncertainties in MC simulation at those places were also lager. Larger uncertainties in the inputs would result more overlapping in the probability distributions between the soil layers and thus a more different output probability distribution would be found.

The different cell resolutions also made the extracted maps from kriging results and MC results looked different. The soil strata model developed by kriging was based on 10 m resolution and the MC results was based on a 30 m resolution simulation. Although the MC results were mapped in 10m resolution again later, some details have lost.

Sensitivity analysis

The thickness of the clay layer was calculated by upper boundary elevation subtracting lower boundary elevation. Thus the sensitivity results were consider to be reasonable in two ways: first, the two boundary elevations were the most relevant and thus most significant parameters for the thickness of the clay layer; secondly, the higher the upper boundary elevation, the thicker the clay layer thickness and thus positive correlation was observed between them; the higher the lower boundary elevation, the narrower the clay layer thickness and thus negative correlation was observed between them;

The sensitivity analysis showed that the lower boundary elevation always had bigger correlation than the upper boundary elevation. This can be explained by bigger uncertainties found in the lower boundary elevation than the upper boundary elevation (see table 4).

Since the thickness of the soil layer was always calculated by upper boundary elevation subtracting lower boundary elevation, it could be inferred that for the thicknesses of any soil layer, the most influential parameters would be the upper and lower boundary elevation of that layer. The upper boundary elevation would have positive correlation and the lower boundary elevation would have negative correlation. The degree of correlation depends on the uncertainties of the parameters.

It was argued by Rodger (1999) that RCC between -0.25 and 0.25 may be spurious so special cautions should be undertaken when interpreting RCC.

Ground settlement risk evaluation

At some places in Figure 18, parameters which came from the soil strata model contributed to the biggest uncertainties in the ground settlement, such as Elev_clay1, Elev_fr1 and Elev_fr2. More effort should be paid on these parameters in the hopes of reducing its uncertainties, thus, its effect on the ground settlement. To decrease the uncertainties in the parameters like Elev_clay1, one way is to increase the sampling density of soil strata investigation in order to decrease the prediction standard error in kriging.

In reality, the constructor would use the ground settlement risk evaluation results combined with economic factors. There are two ways to decrease the risk of building damage: first, further investigation (more samples perhaps) could be carried out to decrease the ground settlement uncertainties; second, prevention measures could be done to prevent the soils undergoing severe settlement. The constructor could compare the costs for further investigations and prevention measures and decide which methods to use.

Other errors/uncertainties existed in the soil strata model that have not been considered

The uncertainties in the soil strata model in this thesis only included the uncertainties in kriging interpolation. There are other kinds of uncertainties, for example the uncertainties exist in sample measurement and sample interpretation stage. The samples were measured in different times and by different investigation methods (see section 3.1). This corresponds to measurement error with different magnitudes. The interpretation of the boreholes contained subjectivity and the interpretation error could be minimized by professions with experiences in geotechnical engineering and geology.

6. Conclusion

In this thesis, the soil strata model was generated for ground settlement risk evaluation purpose. The kriging interpolation has been proved to be an effective way for generating soil strata in this thesis since it was a much more automatic way of generating soil strata comparing with manual plotting. Besides, the spatial structure of the variable was considered and the quality of interpolation could be checked by cross validation. Finally, the uncertainties in kriging could be quantified by prediction standard error.

It was a novel method to build an integrated model of soil strata, groundwater and ground settlement with defined uncertainties in each model. By dividing the ground settlement risk evaluation task into three parts, more time could be saved and each part could be accomplished by some professionals in that field. And the risk evaluation results could be referred back to a specific part for further analysis.

Improvement in soil strata modeling could be made at utilizing *Moving Window Kriging* in generating soil strata to improve the accuracy of interpolation. Besides, more sources of uncertainties in soil strata generation could be considered such as the uncertainties contained in sample measurement and sample interpretation.

References

Barnes, R. Variogram tutorial. Golden software, Inc.

Chiles, J. P. and Delfiner, P. (1999). *Geostatistics:modeling spatial uncertainty*. United States of America: John Wiley &Sons.

Clark, I. and Harper, W. V. (2000). *Practical Geostatistic 2000*. Scotland: Geostokos (Ecosse) Limited.

Haas, T. C. (1989). Kriging and automated variogram modeling within a moving window. *Atmospheric Environment*, Vol 24A, No7, pp 1759-1769, 1990.

Hashemi, E. (2012). *Ground settling due to groundwater drawdown*. Master's thesis, Chalmers University of Technology.

Krivoruchko. K and Gribov. A. (2002). Working on nonstationarity problems in geostatistics using detrending and transformation techniques: an agricultural case study. Joint Statistical Meetings, 2002, New York.

Kumar. V and Remadevi. (2006). Kriging of groundwater levels – a case study. *Journal of Spatial Hydrology*, Vol 6, No 1, Spring 2006.

Lemon, A.M. and Jones, N.L. (2002). Building solid models from boreholes and user-defined cross-section. *Computers & Geosciences*, 29 (2003) 547-555.

Longley, P. A., Goodchild, M. F., Maguire, D. J., Rhind, D. W. (2005). *Geographic information systems and science*. 2nd Ed. New York: John Wiley & Sons.

Roger, C. and Petch, J. (1999). *Uncertainty & risk analysis*. Business Dynamics, PricewaterhouseCoopers United Kingdom firm.

Saltelli, A., Ratto, M., Andres, T., Campolongo, F., Cariboni, J., Gatelli, D. Saisana, M., and Tarantola, S. (2008). *Global Sensitivity Analysis. The Primer*. John Wiley & Sons.

Terzaghi, K. (1943) *Theoretical Soil Mechanics*. New York: John Wiley and Sons

Tisell, V. (2012). *Risk management of groundwater drawdown in settlement sensitive areas*. Master's thesis, Royal Institute of Technology.

Virdee, T.S. and Kottegoda, N.T. (1984). A brief review of kriging and its application to optimal interpolation and observation well selection. *Hydrological Sciences*, 29, 4, 12/1984.

Wittwer, J. W., *Monte Carlo Simulation Basics*. From Vertex42.com, June 1, 2004, http://www.vertex42.com/ExcelArticles/mc/MonteCarloSimulation.html

Zhu, H. and Wu, J. (2005). 2D and 2.5D modeling of strata based on Delaunay triangulation. *Chinese Journal of Rock Mechanics and Engineering.* Vol 24, No 22, Nov 2005.

Institutionen för naturgeografi och ekosystemvetenskap, Lunds Universitet.

Student examensarbete (Seminarieuppsatser). Uppsatserna finns tillgängliga på institutionens geobibliotek, Sölvegatan 12, 223 62 LUND. Serien startade 1985. Hela listan och själva uppsatserna är även tillgängliga på LUP student papers (www.nateko.lu.se/masterthesis) och via Geobiblioteket (www.geobib.lu.se)

The student thesis reports are available at the Geo-Library, Department of Physical Geography and Ecosystem Science, University of Lund, Sölvegatan 12, S-223 62 Lund, Sweden. Report series started 1985. The complete list and electronic versions are also electronic available at the LUP student papers (www.nateko.lu.se/masterthesis) and through the Geo-library (www.geobib.lu.se)

225 Johanna Engström (2011) The effect of Northern Hemisphere teleconnections on the hydropower production in southern Sweden

226 Kosemani Bosede Adenike (2011) Deforestation and carbon stocks in Africa

227 Ouattara Adama (2011) Mauritania and Senegal coastal area urbanization, ground water flood risk in Nouakchott and land use/land cover change in Mbour area

228 Andrea Johansson (2011) Fire in Boreal forests

229 Arna Björk Þorsteinsdóttir (2011) Mapping *Lupinus nootkatensis* in Iceland using SPOT 5 images

230 Cléber Domingos Arruda (2011) Developing a Pedestrian Route Network Service (PRNS)

231 Nitin Chaudhary (2011) Evaluation of RCA & RCA GUESS and estimation of vegetation-climate feedbacks over India for present climate

232 Bjarne Munk Lyshede (2012) Diurnal variations in methane flux in a low-arctic fen in Southwest Greenland

233 Zhendong Wu (2012) Dissolved methane dynamics in a subarctic peatland

234 Lars Johansson (2012) Modelling near ground wind speed in urban environments using high-resolution digital surface models and statistical methods

235 Sanna Dufbäck (2012) Lokal dagvattenhantering med grönytefaktorn

236 Arash Amiri (2012)Automatic Geospatial Web Service Composition for

Developing a Routing System

237 Emma Li Johansson (2012) The Melting Himalayas: Examples of Water Harvesting Techniques

238 Adelina Osmani (2012) Forests as carbon sinks - A comparison between the boreal forest and the tropical forest

239 Uta Klönne (2012) Drought in the Sahel – global and local driving forces and their impact on vegetation in the 20th and 21st century

240 Max van Meeningen (2012) Metanutsläpp från det smältande Arktis

241 Joakim Lindberg (2012) Analys av tillväxt för enskilda träd efter gallring i ett blandbestånd av gran och tall, Sverige

242 Caroline Jonsson (2012) The relationship between climate change and grazing by herbivores; their impact on the carbon cycle in Arctic environments

243 Carolina Emanuelsson and Elna Rasmusson (2012) The effects of soil erosion on nutrient content in smallholding tea lands in Matara district, Sri Lanka

244 John Bengtsson and Eric Torkelsson (2012) The Potential Impact of Changing Vegetation on Thawing Permafrost: Effects of manipulated vegetation on summer ground temperatures and soil moisture in Abisko, Sweden

245 Linnea Jonsson (2012). Impacts of climate change on Pedunculate oak and Phytophthora activity in north and central Europe

246 Ulrika Belsing (2012) Arktis och Antarktis föränderliga havsistäcken

247 Anna Lindstein (2012) Riskområden för erosion och näringsläckage i Segeåns avrinningsområde

248 Bodil Englund (2012) Klimatanpassningsarbete kring stigande havsnivåer i Kalmar läns kustkommuner

249 Alexandra Dicander (2012) GIS-baserad översvämningskartering i Segeåns avrinningsområde

250 Johannes Jonsson (2012) Defining phenology events with digital repeat photography

251 Joel Lilljebjörn (2012) Flygbildsbaserad skyddszonsinventering vid Segeå

252 Camilla Persson (2012) Beräkning av glaciärers massbalans – En metodanalys med fjärranalys och jämviktslinjehöjd över Storglaciären

253 Rebecka Nilsson (2012) Torkan i Australien 2002-2010 Analys av möjliga orsaker och effekter

254 Ning Zhang (2012) Automated plane detection and extraction from airborne laser scanning data of dense urban areas

255 Bawar Tahir (2012) Comparison of the water balance of two forest stands using the BROOK90 model

256 Shubhangi Lamba (2012) Estimating contemporary methane emissions from tropical wetlands using multiple modelling approaches

257 Mohammed S. Alwesabi (2012) MODIS NDVI satellite data for assessing drought in Somalia during the period 2000-2011

258 Christine Walsh (2012) Aerosol light absorption measurement techniques:

A comparison of methods from field data and laboratory experimentation

259 Jole Forsmoo (2012) Desertification in China, causes and preventive actions in modern time

260 Min Wang (2012) Seasonal and inter-annual variability of soil respiration at Skyttorp, a Swedish boreal forest

261 Erica Perming (2012) Nitrogen Footprint vs. Life Cycle Impact Assessment methods – A comparison of the methods in a case study.

262 Sarah Loudin (2012) The response of European forests to the change in summer temperatures: a comparison between normal and warm years, from 1996 to 2006

263 Peng Wang (2012) Web-based public participation GIS application – a case study on flood emergency management

264 Minyi Pan (2012) Uncertainty and Sensitivity Analysis in Soil Strata Model Generation for Ground Settlement Risk Evaluation

265 Mohamed Ahmed (2012) Significance of soil moisture on vegetation greenness in the African Sahel from 1982 to 2008