MSc Thesis

BEST PRACTICES FOR CREATING HIGH-RESOLUTION 3D PRE-PEAT LANDSCAPES

SUPERVISORS:
C (Cindy) Quik MSc[1]
dr. R (Roy) van Beek[1,2]

EXAMINORS:
dr. R (Roy) van Beek[1,2]
dr. ir. GBM (Gerard) Heuvelink[1,3]

1: Soil Geography and Landscapes Group (WUR)
2: Cultural Geography Group (WUR)
3: ISRIC – World Soil Information

Dillen Bruil
930527-1377020
Chairgroup: SGL

MEE – Specialization D
Course: SGL-80436
Wageningen University
13 May 2018

ABSTRACT

As part of the NWO-Vidi project "Home Turf. An integrated approach to the long-term development, cultural connections and heritage management of Dutch raised bogs", this MSc thesis aims to find the best practice for creating a high-resolution 3D pre-peat landscape. The pre-peat landscape, the landscape that could be found just before the peat started developing, is reconstructed using legacy data and new collected data with Ground Penetrating Radar (GPR). Different geostatistical approaches are used and assessed on quality. A case study within the Bargerveen (South-East Drenthe, The Netherlands), which has only bog remnants and no reclaimed peat, is chosen to test ordinary-, co- and regression kriging with both transformed and untransformed legacy data, new collected GPR data and a combination of both data. Either the peat height above sea level or peat depth below surface level is used as input for the kriging, depending on the best variogram function. The quality assessment is done calculating the standard deviation, the mean error and the root mean square error. The data preparation, processing and assessing is all done with R. 2D maps of the peat height above sea level predictions and the corresponding standard deviations are created. The best scenario for reconstructing on a 2 x 2 meter grid is in any case using untransformed data. Co-kriging untransformed GPR data with legacy data as covariable is assessed to be the best reconstruction, followed by regression and ordinary kriging of the GPR and legacy datasets combined. For regression kriging the AHN is used as regression data. For the best reconstruction a (rotating) 3D map is created. From an applicability analysis it is concluded that this method should be applicable to all bogs in the world, as long as there are bog remnants and an accurate digital elevation model available.

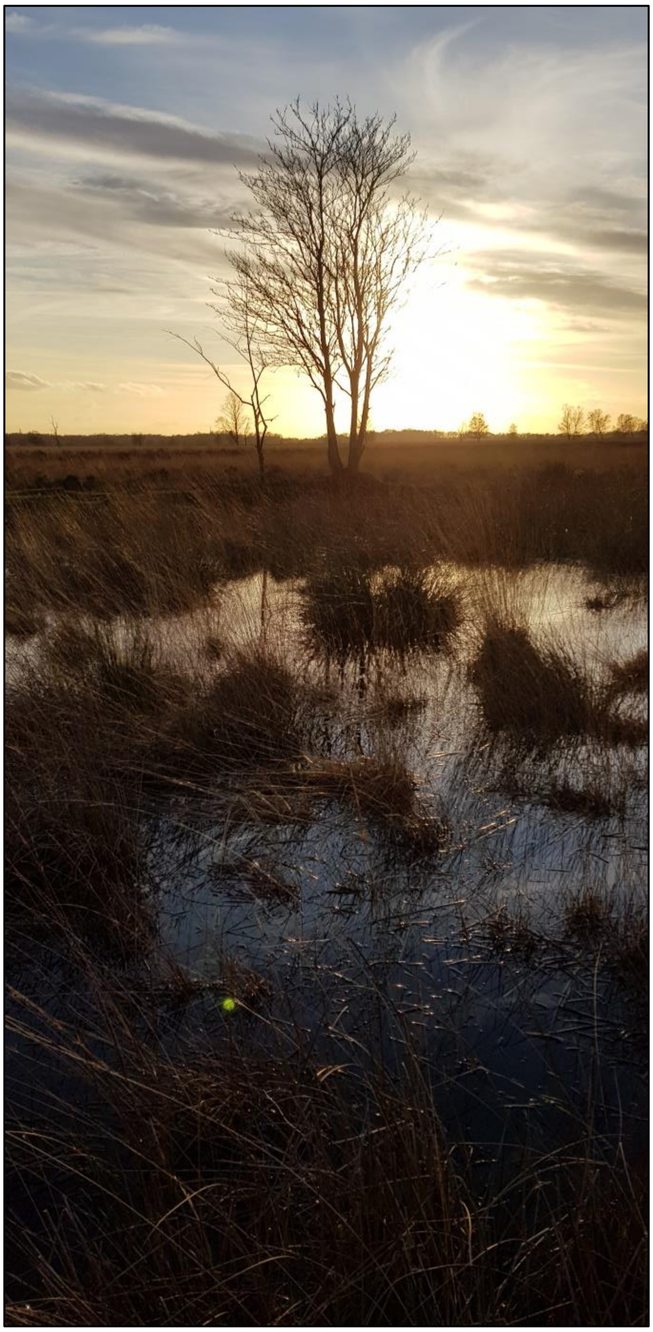

FIGURE I: PHOTO TAKEN IN THE BARGERVEEN, JUST BEFORE SUNSET.

INDEX

LIST OF FIGURES

LIST OF TABLES

1. INTRODUCTION

1.1. PROBLEM DESCRIPTION

Research has shown that raised bogs can date back 3000 to 5300 years BP in The Netherlands (Casparie et al., 2008; Van Geel et al., 1996) and Poland (Lamentowicz et al., 2015) and to almost 6000 BP in Sweden (Foster et al., 1988; Svensson, 1988). Nevertheless, research on the long term spatial development of these raised mires deficits (Van Beek et al., 2015). Due to peat exploitation the mires have declined in size over the past centuries (De Zeeuw, 1978; Gerding, 1995; Leenders, 2014; Montanarella et al., 2006). The present shape of the mires in the landscape is therefore not the shape of the mire centuries ago. Modelling the pre-peat landscape is a way to gain more knowledge on peat and landscape development (Chapman and Gearey, 2013). The purpose of this thesis was to find the best practice for creating a 3D pre-peat landscape. In this thesis the use of legacy data, collecting new data with a geophysical technique and augering is tested, to reconstruct a high resolution pre-peat landscape of a raised bog remnant in the Netherlands. When a digital elevation model (DEM) is created for the pre-peat landscape, this DEM can be used for landscape evolution models. A DEM is the main input to this (Temme et al., 2017). If the DEM or its resolution changes, the model output can be completely different (Perron and Fagherazzi, 2012; Schoorl et al., 2000). A case study was selected to test and compare multiple created DEMs. The DEMs are subjected to multiple quality assessments. The data for this geostatistics was collected from online databases and in the field with ground penetrating radar (GPR) and augering. With more information about creating pre-peat landscapes, gaining more insight in peat development in the Holocene should become a step closer.

In this research a pre-peat landscape is defined as the landscape that could be found just before peat began to grow. From Medieval times onwards peat has been cut and reclaimed (De Zeeuw, 1978; Deforce et al., 2007; Segal, 1966). Due to this human activity there are two different peat landscapes nowadays: a former, reclaimed peatland and a landscape with bog remnants. When reconstructing the pre-peat landscape both landscapes require a different approach. When there are still remnants left then the reconstructed landscape is the landscape directly underneath the bog. When all peat is reclaimed, the landscape that could be found before the peat began to grow could have been higher,

FIGURE 1.1: PHOTO OF THE BARGERVEEN AREA.

lower or at the same level as the landscape is nowadays. That depends on e.g. how much erosion, deposition or equalisation there has been since all peat was reclaimed. A way to reconstruct this pre-peat landscape can be for example with historical maps or reports that show the elevation of the landscape just after reclamation or that tell how much peat has been reclaimed. In this research only the landscape that is found underneath bog remnants will be reconstructed and thus this is also the kind of landscape that is referred to with pre-peat landscape.

The thesis is part of the NWO (Netherlands Organization for Scientific Research/*Nederlandse Organisatie voor Wetenschappelijk Onderzoek*) - Vidi project "Home Turf. An integrated approach to the long-term development, cultural connections and heritage management of Dutch raised bogs." (NWO, 2017; Van Beek et al., 2017). The results will contribute to future landscape evolution studies on spatio-temporal bog development in which a DEM of the reconstructed pre-peat landscape is an input.

1.2. THEORETIC BACKGROUND

This is not the first research about GPR measurements in peatlands. Different researchers have successfully used GPR for recording the thickness of peat layers (Candel et al., 2017; Chapman and Gearey, 2013; Lowry et al., 2009; Pîrnău et al., 2014; Proulx-McInnis et al., 2013; Warner et al., 1990). These successes show that GPR is a good geophysical technique to gather new data with depths of the peat base.

Also reconstructing a pre-peat landscape has been done before (Chapman and Gearey, 2013), but renewing about this thesis research is the testing and assessing of different geostatistical methodologies, e.g. Chapman and Gearey (2013) have only tried one interpolation method in Hatfield and Thorne Moors, eastern England and created a reconstruction with a grid size of 20 meters. This research aims to get a high-resolution DEM reconstruction, with a much smaller grid size and eventually the best geostatistical methodology, resulting from the research, will used to reconstruct this DEM.

1.3. RESEARCH QUESTIONS

A research was defined. To achieve this goal the main question was answered, making use of the sub questions addressing different aspects like quality assessment and applicability of the method in a broader context. By means of an objective a case study area was chosen as pilot study to test different methodologies.

RESEARCH GOAL

To develop a spatial reconstruction of the mineral surface underlying bog remnants.

MAIN RESEARCH QUESTION

Which geostatistical methodology is most suitable to reach the goal above, given the need to co-analyse legacy, auxiliary and newly collected data (which may have different degrees of uncertainty)?

SUB QUESTIONS

- *Do additional data significantly improve the quality of the resulting DEM compared to a reconstruction based on legacy data alone?*
- *What is the best possible accuracy that can be reached for the reconstruction?*
- *What is the best possible resolution and support that can be reached for the reconstruction?*
- *To which spatial scale and to which types of bog landscapes can the method successfully be applied?*

OBJECTIVE

Select a case study as tool to test different geostatistical approaches, which meets a range of pre-defined suitability criteria regarding data availability, size, and accessibility.

2. TECHNICAL BACKGROUND

For the reconstruction of the pre-peat landscape, the peat height and peat depth were reconstructed as intermediate steps. The peat height is defined as *the height of the peat base in meters above sea level* and the peat depth is defined as *the depth of the peat base in meters below surface level*. To clarify, Figure 2.1 is a schematic drawing of the peat height and the peat depth relative to the peat base, surface level and sea level.

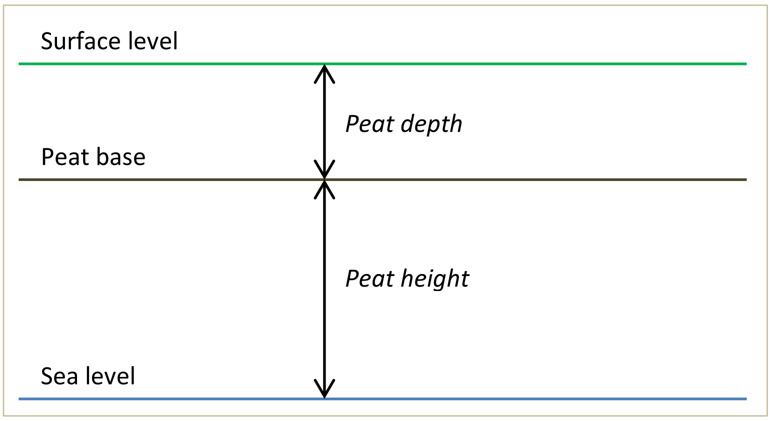

FIGURE 2.1: SCHEMATIC DRAWING OF THE PEAT DEPTH AND PEAT HEIGHT RELATIVE TO THE PEAT BASE, SURFACE LEVEL AND SEA LEVEL.

2.1. GROUND PENETRATING RADAR

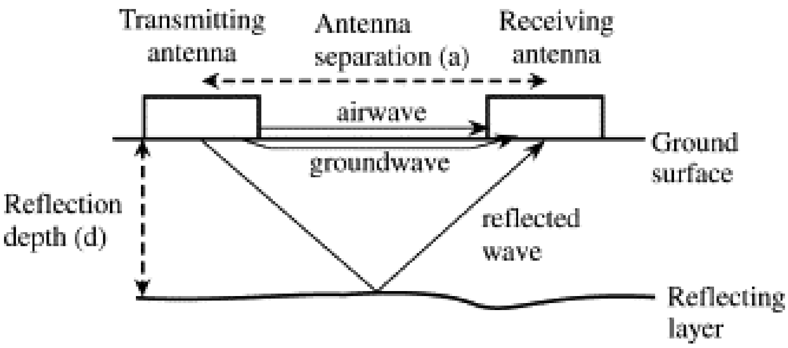

FIGURE 2.2: SCHEMATIC VIEW OF GROUND PENETRATING RADAR (LUNT ET AL., 2005).

Ground Penetrating Radar (GPR) is a geophysical technique for finding different sedimentary layers in the soil. As stated in Paragraph 1.2, different researchers have used GPR for recording the thickness of peat layers. Due to these successes and accurate measurements, GPR is chosen as geophysical technique to measure the depth of the peat base. GPR transmits energy at a certain frequency into the ground, and will be reflected when the energy propagates deeper into the soil (see also Figure 2.2). In the best conditions GPR will propagate up to tens of meters deep. The soil absorbs the energy and at some point the energy is too low to be transmitted back to the receiver (Griffin and Pippett, 2002). Different sedimentary layers will show a different transmittance, making calculations to find the depth possible (Lowry et al., 2009). The results can be visualized in a radargram. An example (processed) radargram can be found in Figure 2.3, the yellow lines showing peat/sand transitions (Candel et al., 2017)

GPR radargrams of peat covering Late Pleistocene to Early Holocene slope deposits have shown a variety of reflection patterns, indicating the peat base clearly (Bristow and Jol, 2003; Leopold and Völkel, 2003). This is another reason why GPR is chosen to assess the peat base depth for this research. Also, an advantage of GPR is that it is a non-destructive method (Daniels, 2005). This implies that the soil does not get disturbed when the layer thickness is measure, easing obtaining permission from the land owner because nothing gets damaged. This is important because it is very likely that the case study is (part of) a protected natural area.

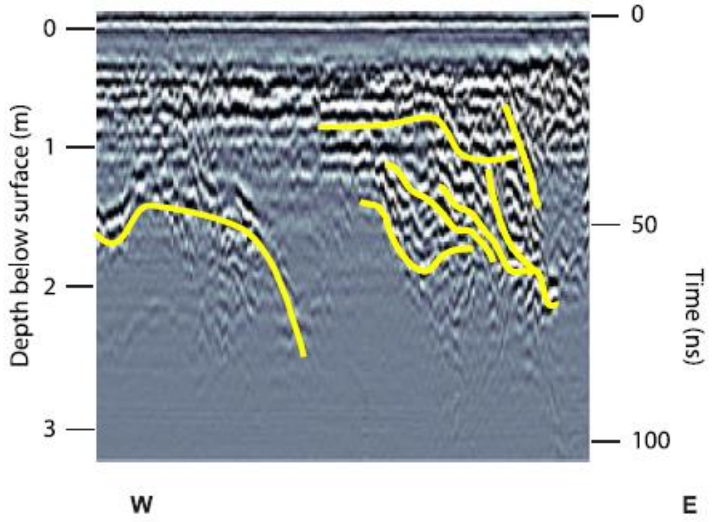

FIGURE 2.3: PROCESSED RADARGRAM OF A VALLEY IN THE DRENTSE AA, YELLOW LINES INDICATING PEAT/SAND TRANSITIONS IN THE VALLEY-FILL (CANDEL ET AL., 2017). HORIZONTAL AXIS: DISTANCE FROM WEST TO EAST, VERTICAL AXIS: TIME AND DEPTH (CONVERTED SCALE).

Different materials (sediments) have different properties. These control the behaviour of the energy of the GPR. These properties are dielectric permittivity, electrical conductivity and magnetic permeability (Neal, 2004). Common travel velocities can be found in Appendix A. The GPR records traveling time of the (reflected) waves and distance travelled. With the corresponding software a radargram can be created and from this radargram the recorded travel times can be read. The first clear solid black line in the radargram indicates the peat base most likely. The GPR needs to be calibrated to find out at what velocity the electromagnetic waves travel through the peat. When knowing the depth of the peat layer at calibration points a traveling velocity can be calculating. This is used to transform all travel times in depths (Finlay et al., 2008). More about the calibration can be read in Paragraphs 3.4.1 and 3.4.2. With the travel velocity and the recorded peat base depth it can be verified whether the peat base is indicated correctly or that another clear solid black line should be the peat base.

2.1.1. RESEARCH SPECIFIC GPR INFORMATION

Underneath the peat blankets the main sediment is sand (Beets and van der Spek, 2000). GPR measurements in peat landscapes with underlying sand deposits have shown that at 250 MHz the border between both sediments is well visible (Candel et al., 2017), Figure 2.3.
For the GPR measurements a pulseEKKO PRO 250 Hz with a SmartTow configuration is used. See also Figure 2.4 An external GPS is carried in the backpack. The odometer, transmitter, receiver and GPS

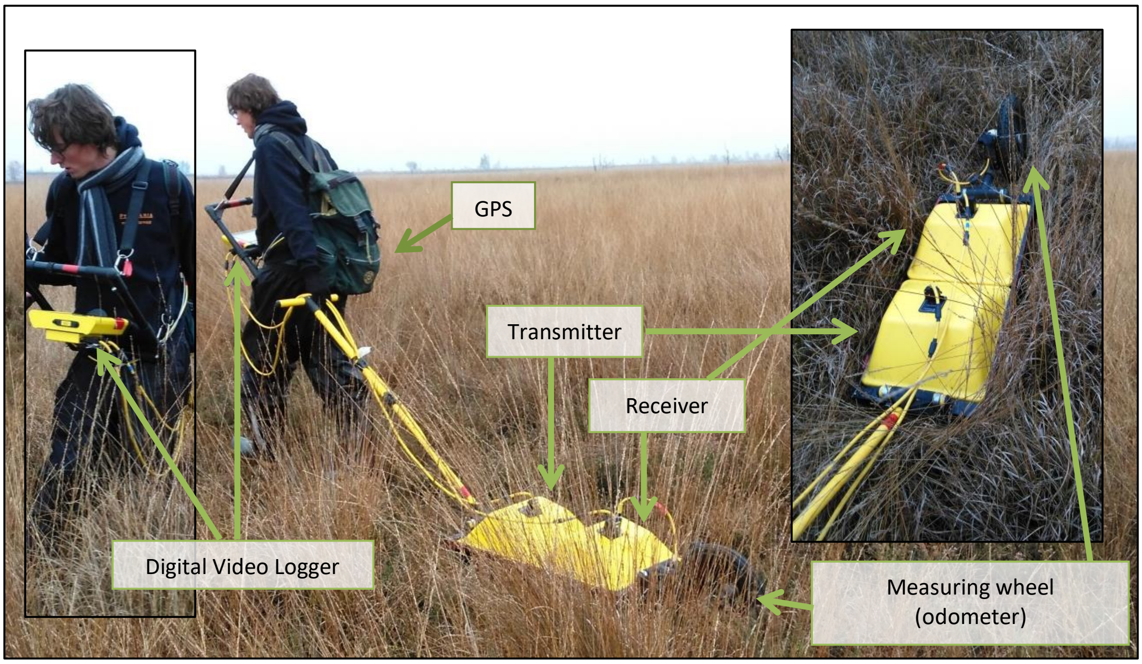

FIGURE 2.4: PHOTO OF DILLEN BRUIL WALKING WITH THE PULSEEKKO PRO 250 HZ GROUND PENETRATING RADAR WITH SMARTTOW. PHOTO CREDITS: ROY VAN BEEK.

are all connected to the Digital Video Logger: a computer to change settings, displaying a live radargram and storing data.

2.2. GEOSTATISTICS

Kriging is an optimal form of spatial linear prediction at known locations. Field observations are used to find out covariance structures within the field to predict the unknown locations (Cressie, 1990; Stein, 2012). It is also called spatial correlation modelling (Kleijnen, 2009). Three different methods for kriging are tested in this thesis: ordinary kriging (OK), co-kriging (CK) and regression kriging (RK). The differences will be explained below.

The transition border between the peat base and the underlying mineral layer is based on different data sources, possibly having a different measurement error. Suppose that $Z(x)$ is the prediction at location x. Each data source can have a different measurement error (ε). As already stated, Z is calculated using different sources of data: legacy (DINO- and BIS-) data and new collected data by GPR, leading to the following set of Equations (1):

$$\begin{aligned} Z(x)_{DINO} &= Z(x) + \varepsilon_{DINO} \\ Z(x)_{BIS} &= Z(x) + \varepsilon_{BIS} \\ Z(x)_{GPR} &= Z(x) + \varepsilon_{GPR} \end{aligned} \tag{1}$$

For the legacy data it is assumed that both databases have the same measurement error since both databases contain the same methods of gathering the data. This assumption implies that the set of Equations 1 can be combined into the set of Equations 2:

$$\begin{aligned} Z(x)_{GPR} &= Z(x) + \varepsilon_{GPR} \\ Z(x)_{LEGACY} &= Z(x) + \varepsilon_{LEGACY} \end{aligned} \tag{2}$$

2.2.1. ORDINARY KRIGING

With ordinary kriging it is assumed that both measurement errors are equal:

$$\varepsilon_{LEGACY} = \varepsilon_{GPR} \tag{3}$$

Due to this assumption, the differences in measurement errors of the databases cannot lead to bigger errors in the final reconstruction and therefore the measurement errors are not of interest anymore. For this reason the measurement error is neglected and:

$$Z(x) = Z(x) + \varepsilon \tag{4}$$

2.2.2. CO-KRIGING

The assumption of Equation 4 may not lead to the best reconstruction. This is why co-kriging is also tested. Co-kriging is used when there is a covariable besides the target variable, used to help predict the target variable at unknown locations (Rossiter, 2012). It is mostly used to reduce the estimation variance of the prediction (Myers, 1982). For co-kriging it is not assumed that the measurement errors are equal. Leading, in contrast to ordinary kriging, to equation 5:

$$\varepsilon_{LEGACY} \neq \varepsilon_{GPR} \qquad [5]$$

Consequently this reverts to Equation 2. Following up on Equation 4, the measurement error of the target variable is neglected to enhance the comparison between ordinary- and co-kriging, because the input data is equal. Hence, the other dataset does have a measurement error and is therefore used as covariable.

Both the GPR and the legacy data are assessed as both target- and covariable. So when the GPR data is the target variable and the legacy data is the covariable, the following set of Equations (6) are used:

$$\begin{aligned} Z(x)_{target\ variable} &= Z(x)_{GPR} &&= Z(x) \\ Z(x)_{covariable} &= Z(x)_{LEGACY} &&= Z(x) + \varepsilon_{LEGACY} \end{aligned} \qquad [6]$$

If it is the other way around, with the legacy data as target variable and GPR data as covariable, the set of Equations 7 is used when co-kriging.

$$\begin{aligned} Z(x)_{covariable} &= Z(x)_{GPR} &&= Z(x) + \varepsilon_{GPR} \\ Z(x)_{target\ variable} &= Z(x)_{LEGACY} &&= Z(x) \end{aligned} \qquad [7]$$

Both cases of co-kriging will be assessed, for both transformed and untransformed data. Because the measurement errors are assumed to be different, the combined legacy + GPR data is not used with co-kriging, instead co-kriging is done to compensate for the measurement error.

2.2.3. REGRESSION KRIGING

For regression kriging, just like ordinary kriging, it is assumed that that the measurement errors are equal (Equation 3). Furthermore, it is assumed that $Z(x)$ is linear dependant on $X(x)$, in which X is the surface level elevation at location x. A linear relation between $Z(x)$ and $X(x)$ is therefore required.

2.3. RECONSTRUCTION DATABASES

The basis of the reconstruction was a database with the data points. This database needed to be designed according to Table 2.1 in order to let the written function to optimize databases (Appendix G1) work properly. The database should contain the following items:

- Name: Name of the data point,
- X.Coord: X coordinate of the data point,

- Y.Coord: Y coordinate of the data point,
- SurfaceLevel: Elevation of the surface level. If the surface level is not known the database should be completed with: "Unknown",
- Layer1 Depth: Depth of the first layer relative to the surface level,
- Layer1 Deposit: Deposit of the first layer, e.g.: Peat/Sand/Clay,
- Layer1 Details: If Sand is the layer to be constructed, a distinction can be made on for example sand median, this can be completed in this column, e.g.: Fine/Coarse.

The database continues with Layer2 Depth, Deposit and Details, Layer3 Depth, Deposit and Details, etc. until the last layer. The database should be saved as a .csv file.

TABLE 2.1: DATABASE DESIGN, REQUIRED FOR THE RECONSTRUCTION.

Name	X.Coord	Y.Coord	SurfaceLevel	Layer1 Depth	Layer1 Deposit	Layer1 Details	Layer2 Depth	Layer2 Deposit	Layer2 Details	…	…	…
…												
↓										…	→	…
…												

Important is that the names of column 2, 3 and 4 were not changed. Furthermore when the depth of the last examined layer was recorded, something should be filled in at the next Layer Deposit in the database (or Layer Details in case the reconstruction is based on the Layer Details). If this is not done the last examined layer is not taken into account when reconstructing because exclusion whether the corresponding depth is the depth of the layer base or the end of the recording is not possible.

2.4. TRANSFORMATIONS

Normally distributed data lead to lower residuals when cross validating the interpolated data (Hengl et al., 2004). If the data substantially deviate from normality, a mathematical transformation is required. For elevation data a natural logarithm transformation is proven to be working, but also square root or normal logarithm transformations can work (Gobin et al., 2001). Some of these transformations (and more) are also covered by a family of transformations proposed by Box and Cox (Box and Cox, 1964; Osborne, 2010). Box-Cox transformations therefore are also checked to improve normality, using lambda parameters relevant in the Box-Cox regression: -5 to 5 (Komunjer, 2009; Statistics How To, 2018).

The family of Box-Cox transformations is given by Equation 8, given the lambda parameter (λ), the to be transformed positive variable x and its transformation(Box and Cox, 1964):

$$x_{transformed} = \begin{cases} \dfrac{x^{\lambda} - 1}{\lambda} & \lambda \neq 0\,,\ x > 0 \\ \log x & \lambda = 0,\ x > 0 \end{cases} \qquad [8]$$

For the transformed data the calculated kriging predictions and kriging variances should be back transformed. With the back transforming it is ensured that there is a bias adjustment. This bias is generated due to fact that when back transforming not the mean of a distribution is obtained but the median is (Miller, 1984), see also Figure 2.5. For the inverse Box-Cox transformation Equation 8 can be rewritten to Equation 9:

[9]

$$x = \begin{cases} (\lambda \cdot x_{transformed} + 1)^{\frac{1}{\lambda}} & \lambda \neq 0,\ x > 0 \\ 10^{x_{transformed}} & \lambda = 0,\ x > 0 \end{cases}$$

The bias correction for this Box-Cox transformation is given by Equation10:

$$x_{adjusted} = x \cdot \frac{1 + \frac{1}{2}\sigma^2 \cdot (1 - \lambda)}{x^{2\lambda}} \qquad [10]$$

With x as the back transformed variable (Equation 9), λ the used lambda parameter and σ^2 the variance.

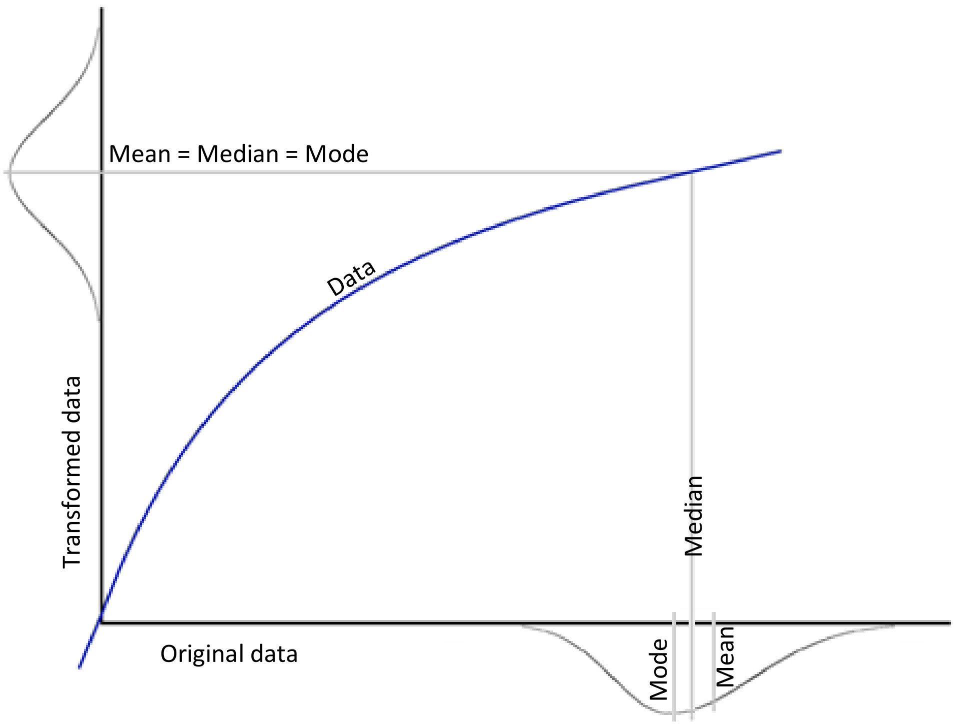

FIGURE 2.5: DATA TRANSFORMATION: WHEN BACK TRANSFORMING MEAN (AND THUS MEDIAN) VALUE OF A DATASET TO ORIGINAL VALUES, THE MEDIAN VALUE IS OBTAINED AND NOT THE DESIRED MEAN.

2.5. ACCURACY AND PRECISION

Accuracy is the correctness of the reconstruction. So when something is accurate the average deviation is small. This is estimated by the Mean Error (ME). The closer the ME is to zero, the higher the estimation of accuracy, or lower the bias is. Precision is the degree to which repetitions result in the same value. If something is precise than all measurements are very close to each other, but not necessarily close to the real value (if it is, it is accurate as well). By calculating the Root Mean Square Error (RMSE), an indication of both the accuracy and precision is given. The lower the RMSE the higher the accuracy and precision together.

3. METHODOLOGY

3.1. OVERVIEW

A smaller area within the Bargerveen is chosen as case study area. More information on this area and why this area is selected can be read in Chapter 4. A schematic overview with all steps taken during this research, can be found in Figure 3.1.

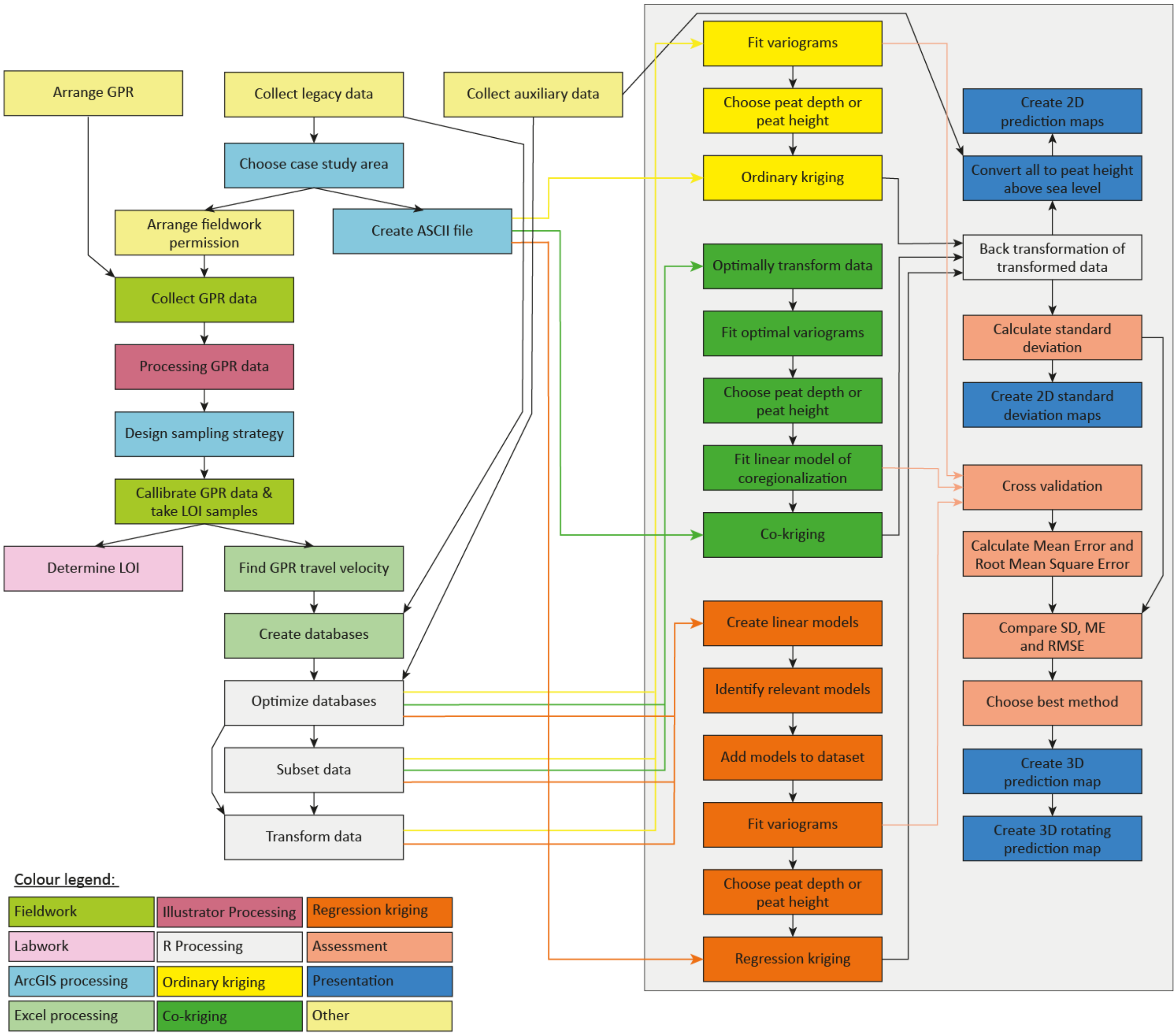

FIGURE 3.1: SCHEMATIC OVERVIEW WITH ALL STEPS TAKEN DURING THIS RESEARCH IN CHRONOLOGICAL ORDER (FOLLOWING THE ARROWS) OF THE (PRE)PROCESSING, THE COLLECTING AND ANALYSING THE DATA AND THE RECONSTRUCTIONS. DIFFERENT COLOURS INDICATE DIFFERENT ENVIRONMENTS. ALL STEPS WITHIN THE LARGE GREY BOX ARE DONE WITH R.

3.2. SAMPLING STRATEGY

The sampling strategy was based on the available legacy data. For every location in the area the Euclidean distance to the nearest data point was calculated. At the points of the largest Euclidean distance, transects were drawn to walk along. A sampling route was created based on the transects. Sampling was done walking along the route, using the Avenza PDF Maps application (Avenza, 2018) on a tablet in the field.

FIGURE 3.2: PHOTO OF DILLEN BRUIL AND ROY VAN BEEK PREPARING GPR MEASUREMENTS. PHOTO CREDITS: CINDY QUIK.

All predefined transects were sampled (unless field conditions made it impossible), as well as some parts in between the transects. While measuring the walking speed had to be kept low, because a higher walking speed caused that measurements were skipped. This balance between speed and no skips determined the walking speed. In the field it was decided when and where to do extra measurements along the route, depending on field conditions e.g. surface water, relief, vegetation and daylight time.

The sampling design was created with ArcGIS. The Toolbox model used can be found in Appendix B1. First the roads (heartline of the roads, extracted from the TOP10NL file), the DINO points, BIS points and Bargerveen area with and without water were clipped on the new, smaller case study area. A raster was created from the area without water (so the water parts could not influence any calculations at this point). The DINO and BIS points were merged and the Euclidean distance was calculated from the merged legacy data. At the largest Euclidean distance transects for GPR measurements were drawn. All outputs were clipped on the case study raster and projected to WGS_1984 (coordinate system for the PDF Maps application) and maps were created to design a sampling route.

The designed sampling strategy can be found in Figure 3.3. Due road work in the north, the case study are was only accessible via the road east of number 1. Transects were sampled from 1 to 5, walking mainly over the white areas of the Euclidean distance. The sampling route deviated a little due to field conditions; the GPR must stay dry so crossing large water areas were avoided.

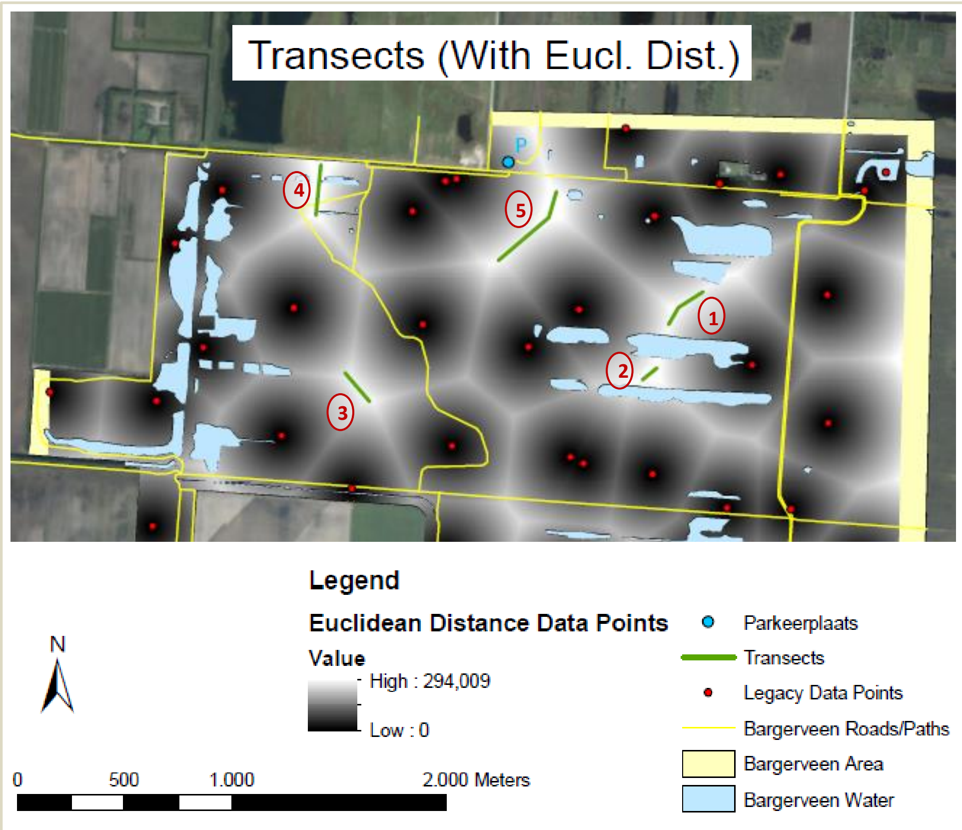

FIGURE 3.3: CASE STUDY AREA WITH THE LEGACY POINTS (RED) AND CORRESPONDING EUCLIDEAN DISTANCE. IN GREEN THE TRANSECTS NUMBERED IN ORDER OF SAMPLING

3.3. REUSE OF DATA

3.3.1. LEGACY DATA

DINOLOKET

The legacy data had two origins. The first was from the DINOloket, the other was the BIS. DINO (Data and Information of the Dutch Subsurface/*Data en Informatie van de Nederlandse Ondergrond*) is a database of the Geological Survey of the Netherlands (GDN, *Geologische Dienst Nederland*), part of TNO (an organization for applied physical research in the Netherlands), and it is a database with millions of subsurface data. This data is accessed via the portal at the DINOloket. Before this data was included in the database all data was checked on DINOloket terms, format and duplicates (DINOloket, 2017) and therefore they can be assumed to be reliable. All data points available within the area of the case study were downloaded from the DINOloket via the portal. With the downloaded DINO data come files containing the point data (one file per data point) and a KML (Keyhole Markup Language - a file format used to display geographic data in an Earth browser such as Google Earth (Google Developers, 2017)) file with the locations of the data points. The latter was opened in ArcGIS (Appendix B2). The KML data was projected to RDNew (the coordinate reference system of the Netherlands) and by using the shapefiles of the potential case study areas, the data points within the areas were selected (Appendix B3).

FIGURE 3.4: PHOTO OF THE TREE NEXT TO CP26A.

BIS

The second origin of the legacy data was from the BIS (*Bodemkundig informatie systeem*/Soil information system), a soil data base provided by Wageningen Environmental Research (former known as Alterra) (Wageningen Environmental Research, 2017a). The BIS data consists of two data types: BPK (standard auger descriptions) and the PFB (with somewhat more extensive descriptions/auger method). The BIS data is only available for all case study areas in the Netherlands, as a geodatabase through Geodesk. This geodatabase contains two files with locations (BPK and PFB locations) and two files with belonging layer information). The BPK and PFB location data was merged, identical features were deleted, the data points were clipped on the shapefiles of the potential case study areas and the name of that area was added as extra column (Appendix B4). To select the layer information per case study area, the area names of the just created location data of the BPK and PFB were joined to the layer information data. As a result, the layer information table had four new joined fields. A new field was created in which the area names of the four joined fields were put together and the four joined fields were deleted and the table is exported to Excel (Appendix B5). Peat depths were assessed per potential area in Excel.

3.3.2. AUXILIARY DATA

AHN

The Actual Height file of the Netherlands (AHN, *Actueel Hoogtebestand Nederland*) is a digital elevation map. It contains detailed and precise height data with on average eight elevation measures per square meter, collected by laser altimetry (AHN, 2018). The AHN will be used to convert the peat depth into peat height above sea level in order to get a reconstruction with heights relative to sea level. To work with the AHN in R, .TIF tiles are downloaded from the ArcGIS website (ArcGIS, 2017). The tiles needed to cover the complete case study area are downloaded. For the reconstruction the 0,5 m resolution AHN2 filled maps are used. The AHN of the Bargerveen can be found in Figure 4.5.

Using R, the AHN .TIF tiles were merged. A spatial grid data frame was created with the ASCII location data and AHN values. The ASCII location data is created with ArcGIS. A polygon with the area that was desired as case study area was clipped on the Bargerveen shapefile. From this new file unnecessary fields were deleted and a new field was created for calculating the new area. Thereafter the polygon was transformed to a raster with a grid cell size of two meters and an ASCII file was created from this, see also Appendix B6. The ASCII file contains the area (with correct boundaries) of the reconstructions, over which the reconstruction points were predicted.

3.4. DATA COLLECTION AND PROCESSING

3.4.1. GPR DATA COLLECTION

FIELDWORK

With the permission of the ranger of Staatsbosbeheer, the Bargerveen was entered. The GPR was installed (see also Paragraph 2.1) and the route was walked according to the sampling strategy (Paragraph 3.2).

PROCESSING

Once the GPR data was processed, the transition layer between the peat base and the underlying mineral layer was interpreted. With Adobe Illustrator a line was drawn on the processed radargrams, at the transition, which is the first most solid black line. Hereafter every 10 meters the depth of the transition was determined.

Next the calibration points were determined. At each transect two calibration points were chosen to get at least one calibration point per transect sampled. The calibration points were chosen with use of the drawn transition border. At a location where the transition border is horizontal, meaning no increase or decrease in depth, the calibration point was placed. This way it was secured that if due to GPS accuracy the calibration point was sampled along the transect but next to the location where it was placed, the recorded depth was still the depth of the placed calibration point (Figure 3.5).

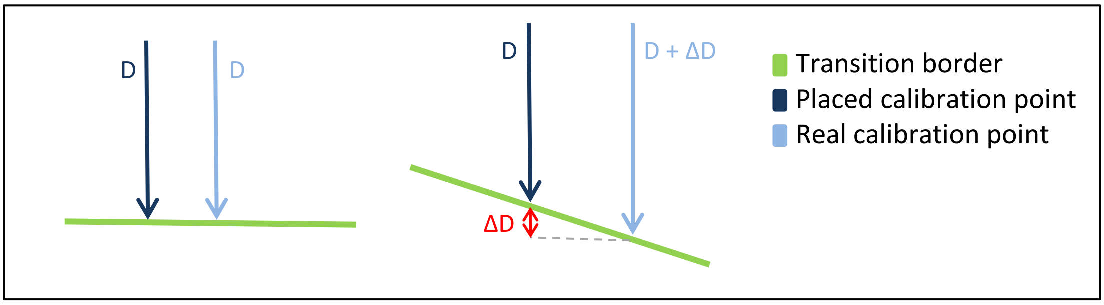

FIGURE 3.5: ILLUSTRATION OF THE EFFECT ON PEATDEPTH (D) WITH A HORIZONTAL TRANSITION BORDER VERSUS AN INCREASING/DECREASING TRANSITION BORDER WHEN, DUE TO GPS ACCURACY, THE REAL CALIBRATION POINT IS SAMPLED NEXT TO THE PLACED CALIBRATION POINT.

The transects were loaded into ArcGIS. With the GPR results come .gps files with coordinates of all traces for each walked transect. With a GPXconverter (GPSVisualizer, 2018) the .gps files were converted to .gpx files and imported in ArcGIS. The imported points were projected to RDNew and lines were created from the points, see also Appendix B7.

In order to display the calibration points in ArcGIS, a new point feature class was created. At the distance of the calibration points from the start of the transect, a point is added to this class, until all calibration points were visualized as points in this class.

For the coordinates of the 10 meter intervals used for the transition border depth determination, also new feature point classes were created. Now, for every transect every 10 meter a point is added to the class. All feature classes are merged to calculate the X and Y coordinates at once. All points, including coordinate data, were exported to Microsoft Excel. A Toolbox model, including a more detailed, technical description can be found in Appendix B8.

All calibration points are displayed with ArcGIS and new maps (in WGS_1984) are created for sampling the calibration points during the second fieldwork.

FIGURE 3.6: PHOTO TAKEN DURING THE CALIBRATION FIELDWORK, NEAR CP27A.

3.4.2. GPR CALIBRATION

FIELDWORK

Again with permission of the ranger of Staatsbosbeheer the Bargerveen was entered. The calibration points were located with the Avenza PDF Map application on the tablet. At each calibration point the depth of the transition border between the peat and the underlying mineral layer was determined using an Edelmanboor or a gouge, depending on the wetness and compactness of the soil. Gouging is a much less time consuming method than augering and therefore gouging was preferred. Elongation sticks were brought in case the transition border is deeper than the length of the Edelmanboor or gouge.

PROCESSING

With the calibrated point data it was possible to calculate the travel velocity per calibration point. The highest and lowest velocities were neglected and the remaining velocities were averaged. This average was used to transform the travel times measured with the GPR into depths. For the calibration points the calculated depth was used instead of the measured depth in order to keep the error per location the same, instead of having one real but outlying depth in a line of more or less equal estimated depths. When the difference between the calculated and measured depth was really large it was checked whether the transition border was drawn correctly, and if necessary it was drawn again.

3.4.3. LOSS ON IGNITION

At least two locations were needed for a loss on ignition experiment. If samples for this test for one auger hole turned out to be corrupt than there is still the second auger hole that can be used, otherwise the samples were averaged. The samples were taken during the GPR calibration fieldwork. Per location two samples were taken. One sample was taken just above the transition border and one sample just below this. With these samples the organic matter content was investigated. This was done to proof that the determined transition border is really the transition border between the peat and the underlying mineral layer, because the organic matter content in peat is much higher than the organic matter content in the expected cover sand deposit below (more about these layers can be read in Paragraph 4.4). The loss on ignition is an indication of the organic matter content, although iron oxide also influences the loss on ignition (Lechler and Desilets, 1987). In cover sand just outside the Bargerveen area traces of iron oxide are found (Van Hoof, 2014), so this was taken into account.

The loss on ignition (LOI) experiment was done the following way: the empty crucibles were weighed and the soil samples homogenized. A part of the sample was put in the crucibles and the crucibles with the samples were dried 48 hours in the oven at 105°C and weighed again. Afterwards they were put in the oven for ignition, this time 4 hours at 550°C and weighed again. The loss on ignition was calculated with Equation 11 (Heiri et al., 2001).

$$LOI = \frac{DW_{105} - DW_{550}}{DW_{105}} * 100 \qquad [11]$$

With DW_{105} the dry soil weight (weight of the crucible and dry soil weight minus the empty crucible weight) and DW_{550} the ignited soil weight (weight of the crucible and ignited soil weight minus the empty crucible weight). The LOI is used to support which organic matter content is regarded as peat and which organic matter content is not, to give a detailed characterisation of the peat-sand interface.

3.4.4. DATA ANALYSIS

DATABASE PREPARATION

The DINO database was created going through all single files downloaded from the DINOLoket manually and filling out the database template (Table 2.1). The BIS database was created using a pivot table in Excel. For the layer information, the lower limit of all peat layers were displayed per ID. This table was copied next to the BIS location information, containing the coordinates and was used to complete the database template (Table 2.1) for both the BPK and PFB data. Because only peat layers were displayed, there were layers that do not have a Layer Deposit but do have a lower limit (depth of another mineral base). For these layers the deposit as completed as "unknown" as this layer was important to note down but the mineral deposit itself was not importance for this thesis.

Unless mentioned otherwise every processing described in this chapter was done with R from here onward. All steps taken are presented in R Markdown (R Studio, 2016), to enhance readability and reproducibility. The created databases were transformed to three new databases: GPR data, legacy data, and combined GPR + legacy data. These databases were optimized to correctly work with them. In order to have all same input values for the surface level, all known surface level elevations were replaced by the elevations extracted from the AHN. Data frames were created from these new databases and the depths of the transition border between the peat base and the underlying mineral layer was selected. It was made sure that the deepest peat layer was selected as reference peat layer in case there were more layers with peat, unless it is plausible that this peat layer was deposited before the to be reconstructed pre-peat landscape. The selected column contained the depth of the peat layer in the current landscape. It was desired that the final reconstruction indicates the height in meters above sea level. For this a column was created with peat height above sea level; the depth of the peat layer was subtracted from the height of the surface level, which was extracted from the AHN. One way to reconstruct the peat height above sea level was to krige with the peat height data. Another way was to use the peat depth for kriging, and subtracting this reconstructed peat depth from the surface level elevation.

FIGURE 3.7: PHOTO OF DILLEN BRUIL. LOCATION DETERMINATION FOR GPR MEASURMENTS IN THE BARGERVEEN. PHOTO CREDITS: CINDY QUIK.

Because every ten meters a depth was recorded with the GPR data, there was a lot of local coherence of the depths on the different lines. This local influence had a large effect on the distribution of peat depths and consequently on the transformation of the data in order to get it less skewed. Besides, the fitted variogram functions were also influenced by this coherence. To account for this, a subset of 5 random records per line was taken. The subsets replaced the GPR data and the GPR data points in the combined data and the subsets were used for transforming data and subsequently for variogram fitting. More about transformations and variogram fitting can be read in the following paragraphs and in Paragraph 2.4.

DISTRIBUTION

Both the peat depth and peat height were checked on distribution. If transformation of the data leaded to a more normal distribution (Paragraph 2.4), the data was transformed. The transformation that leaded to the distribution with the lowest absolute skewness was used.

VARIOGRAM FUNCTIONS

For both the peat depths and the peat heights a variogram were made, using both transformed and untransformed data. A variogram is a plot with variances of all observations at a given spatial separation (lag) (Bachmaier and Backes, 2011). Through these variances a model was fitted. This was done with the `fit.variogram()` function of the *gstat* package (Pebesma, 2017b). It was researched which variogram type fitted best, e.g. Linear, Exponential, Gaussian, or Spherical. Kriging predictions were based on a variogram function, the variogram with the lowest weighted sum of squared errors gives the best prediction values and thus the best variogram type was determined. Whether the peat depth or peat height was used for kriging depended on the variogram function. The variogram function with the lowest nugget and sill was used for kriging, and so whether the peat depth or peat height data was used as observation data.

RECONSTRUCTIONS

Ordinary kriging was done with the *gstat* package `krige()` function (Pebesma, 2017c). In order to do so, a gstat object was created for the peat depth and peat height of the transformed and untransformed subsetted GPR data, the combined subsetted GPR and legacy data (all data) and the legacy data. The best fitted variogram functions were used for the kriging. For the kriging the complete datasets are used, so not the subsetted data. For the kriging, not the subsetted data, but the complete dataset was used. Transforming the complete dataset required using the same transformation as applied on the subsetted data. Predictions were done for the locations in the ASCII file of the case study area.

For transforming co-krige data, both the legacy and the GPR subset should have the same transformation. Therefore it was checked what on average gave the best transformation when transforming legacy data with the most optimal transformation of the GPR subset and vice versa. These transformations were used for determining the best, optimal, variogram model, which should also be the same for both datasets. The combined best fitted variogram function with the optimal variogram model was used for co-kriging and meanwhile it was determined whether peat height or peat depth was more suitable. This fitted variogram function was used for creating a gstat object. First for the (subsetted) target variable and secondly for the (subsetted) covariable, using the first gstat object as input for the second gstat object. A third gstat object was created for the combined target- and covariable, using the second gstat object as input for the third gstat object. Contradicting the first two gstat objects, the variogram function for the latter was estimated manually, with the same model as the former variogram functions. This function must lead to a linear model of coregionalization when kriging with the complete dataset, which means that all predicted values have a representation (Goulard and Voltz, 1992; Lark and Papritz, 2003; Myers, 1982). Three new gstat objects with the complete dataset instead of the subsetted datasets were created, using respectively the automatically fitted variogram functions of the target variable and the covariable and the manual fitted variogram function just described. This gstat object was used to create a linear model of coregionalization with the `fit.lmc()` function (Pebesma, 2017a). The kriging was done with the `predict()` function (Pebesma, 2017e) over the ASCII file of the case study area.

For regression kriging first it was tested whether there is a linear relation between the peat depth or height and the surface level elevation. If there was, the variogram function was based on the residuals of the linear model of the relation. The same steps as for the ordinary kriging were followed. Only now the kriging was done over the spatial grid data frame of the cases study ASCII file with AHN values.

The kriging gave two outputs, a kriging prediction and a kriging variance. All transformed kriging predictions and variances were back transformed to 'normal' values, see also Paragraph 2.4.

The predicted peat depths were subtracted from the surface level elevation. The predicted peat heights were multiplied with the case study ASCII file, to have the same area boundaries for all reconstructions. From these new created peat height prediction values new spatial grid data frames were created with the ASCII case study coordinates. Maps were plotted with the `spplot()` function of the *sp* package (Pebesma, 2017f). The plot is a map with the heights of the pre-peat landscape. Different colours were used to indicate the different heights of the pre-peat landscape predictions above sea level, in m. For all maps the same colours were used for the different heights, easing comparison.

The final reconstructions that were assessed can be distinguished by their name. All names have a fixed design of different abbreviations to characterize them. The used design is: `Prepeat. ...` (or `Peatdepth./Peatheight.` before correcting the reconstructions for peat height above sea level), With on the dots the abbreviations that were used, separated by an underscore. The used abbreviations are:

- `OK:` Ordinary kriging
- `CK:` Co-kriging
- `RK:` Regression kriging
- `A:` All data, GPR and Legacy data combined, used
- `G:` Only GPR data used
- `L:` Only legacy data used
- `GC:` GPR data as covariable
- `LC:` Legacy data as covariable
- `T:` Transformed data
- `UT:` Universal Transformed data

ASSESSMENT

KRIGING STANDARD DEVIATION

Kriging standard deviation maps were used to compare kriged maps mutually. A lower standard deviation gives a more reliable map and thus the map with the lowest standard deviation is the best reconstruction based on standard deviation. The kriging standard deviation is the square root of the kriging variance, an output of the kriging. The standard deviation was plotted the same way as the prediction was plotted (see also the previous paragraph). The legend was scaled such way that all kriging standard deviation maps have the same colour scale indicating the standard deviation, easing comparison between the maps. For calculating the standard deviation, the back transformed data was used. Expected is a mean standard deviation of 1 since normality is reached again (mean = 0, standard deviation = 1). Besides the maps, the minimum, mean and

FIGURE 3.8: PHOTO OF AN ELONGATED GOUGE AT CP23A.

maximum standard deviations of all reconstructions were calculated and used to assess the reconstructions.

ACCURACY

The Mean Error (ME) and Root Mean Square Error (RMSE) were calculated using a leave-one-out cross validation. This is a cross validation in which the number of cross validated points equals the size of the dataset (Refaeilzadeh et al., 2009). So for all observed values a new value was predicted by leaving one observation out when kriging and this way of kriging was repeated until all observations have been left out once. The leave-one-out cross validation is strongly influenced by the local coherence on the GPR lines. So for the predictions that have GPR observations, all clustered data (walked lines) were taken out and cross validated with the remaining data. To do so a hold-out cross validation is done for every cluster (Refaeilzadeh et al., 2009) and both the leave-one-out and hold-out cross validated data was combined.

The cross validation is done using the functions `krige.cv()` (ordinary and regression kriged predictions) and `gstat.cv()` (co-kriged predictions) from the *gstat* package (Pebesma, 2017d). From the residuals, the difference between the observed (*obs*) and predicted (*pred*) values, the Mean Error (Equation 12) and Root Mean Square Error (Equation 13) were calculated, with *n* the number of data points used for the kriging.

$$ME = \frac{\sum_{i=1}^{n} obs_i - pred_i}{n} = \frac{1}{n} \cdot \sum_{i=1}^{n} residuals_i \qquad [12]$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(obs_i - pred_i)^2}{n}} = \sqrt{\frac{1}{n} \cdot \sum_{i=1}^{n} residuals_i{}^2} \qquad [13]$$

As with the standard deviation calculations, for the RMSE and ME untransformed data was used as well. The residuals that are calculated by the cross validation are of a different range than the prediction and observation values, because observation and prediction are supposed (when correctly kriged) to be more or less the same, leaving a very low residual. So the residuals had to be recalculated with back transformed observation data and back transformed prediction data in order to correctly calculate the RMSE and ME.

RESOLUTION/SUPPORT

The resolution is the number of grid cells that are used for the reconstruction and consequently the area that one grid cell represents. The support is number of observations that have been used and consequently this is the area that one observation represents. The resolution and support were derived from the kriging statistics.

BEST METHOD

The best method was determined based on the standard deviation and accuracy/precision. The reconstructions were ordered from low to high error for both the ME and RMSE. The standard deviation was ordered from low to high mean standard deviation. For each criterion points were divided, 1 point for the best reconstruction, counting on to 15 points for the worst reconstruction. Since the RMSE indicates both accuracy and precision and ME only accuracy, the ME points were halved, making it more important to be accurate and precise than only accurate. For each criterion the points were added up. The reconstruction with the least total points was assessed as best reconstruction. In case of equal or very close scores, different rankings were assigned based on mutual differences between the assessed parts. Whenever the assessment results were evidentially different than the assessment tables indicate, reconstructions were declassified. For the best method a 3D plot and a 3D rotating plot were made.

3D PLOT

A 3D surface plot was made with the *lattice* package and the `wireframe()` function (Sarkar, 2018). From this 3D plot also a rotating .GIF file was made, to get a 360° view of the pre-peat landscape. This was done with a programme called ImageMagick and the `saveGIF()` function from the *animation* package (Xie, 2018; Xie and Yu, 2017). The rotating image enables the 3D view from different angles.

3.5. APPLICABILITY

To answer the last sub question the methodology was re-examined and assessed on applicability in other regions. It was researched whether the tested methodology can also be applied on other bogs in the Netherlands, Europe or the World and thereby, whether the obtained results would be derived for these other bogs as well.

Furthermore it was investigated whether the methodology is also applicable on a smaller and larger spatial scale. What happens if the area increases or decreases and the amount of data points remain the same? Which means that the sample density changes. This was reasoned based on the reconstruction assessment. Moreover, the variance will be influenced by a different spatial scale. This makes the reconstruction very case specific and its influence was therefore also discussed.

The above asked questions were a way to find information and argue about the applicability of the tested methods in a broader context.

4. CASE STUDY SELECTION

Picking a case study is a crucial step in the research. The case study will be used as tool to test the different methods. All collected data and all calculations are done for the case study and the conclusions will be drawn on basis of this. Also for the case study the pre-peat landscape will be reconstructed which can directly be an input for the landscape evolution model designed within the NWO-Vidi project Home Turf.

4.1. SELECTION CRITERIA

One case study area was chosen based on certain criteria, to apply the methodology on. These criteria meet standards that were required and/or desired to test the methodology for collecting new data and reconstructing the DEMs of the pre-peat landscape. The following criteria have been used:

- The topsoil of the area should be peat, either peat remnants or natural peat that has not been reworked.
- Legacy data points with registered peat depth should be available.
- The thickness of the peat layer may not exceed 4 meters, that is the maximum depth the 250 MHz GPR can detect (Candel et al., 2017). Legacy data can provide information about the peat layer thickness.
- The case study should be one of the areas presented in Figure 4.1: Bourtangerveen, Bollenveen, Drents Plateau/Drentse Aa, Vriezenveen, Zwillbrocker Venn, De Peel or Reuselse Moeren, these are seven areas selected for the Home Turf project.
- The case study may also be a smaller area within a larger peat landscape.
- It should be possible to obtain permission from the owner to go into the area and to auger/gouge and to do GPR measurements.

The following steps need to be taken for selecting a proper case study and have all, unless mentioned differently, been done using ArcMap.

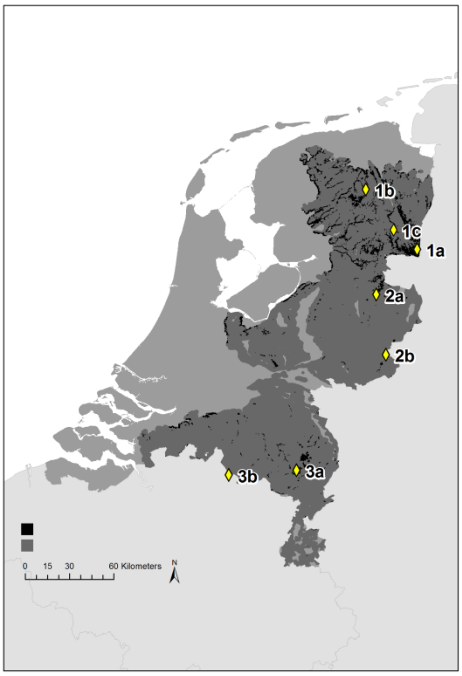

FIGURE 4.1: SEVEN PEAT AREAS THAT ARE PART OF THE HOME TURF PROJECT: 1A: BOURTANGERVEEN, 1B: BOLLENVEEN, 1C: DRENTS PLATEAU/DRENTSE AA, 2A: VRIEZENVEEN, 2B: ZWILLBROCKER VENN, 3A: DE PEEL AND 3B: REUSELSE MOEREN.

4.2. ASSESSED STUDY AREAS

For the different potential areas some crucial information was needed to check on the criteria. First of all it was necessary to know who owns the area and whether there are still bogs (or remnants) present or whether there is also reclaimed peat in the area. This information is found on webpages about the specific areas. Since in the Netherlands almost all peat has been reclaimed (Verhoeven, 2013), there are not many contiguous areas with no reclaimed peat. Therefore, for the larger peatlands, smaller areas are used as case study.

The second step was to create shapefiles of the different potential study areas. The shapefiles were created by selecting the correct areas from the Natura2000 shapefile (European Environment Agency, 2017). From these resulting shapefiles the surface water parts were subtracted. These were extracted from the TOP10NL provided by GeoDesk. GeoDesk is a facility within Wageningen University and Research Centre. They make geodata available and refer to documents of others (Wageningen Environmental Research, 2017b) The amount of surface water in a bog is a moment recording; it will vary over time during the year. The used water area is from November 2016. Both the Natura2000 shapefiles and the water parts contain size information of which the total area can be calculated for both the shapefiles with and without water parts (Appendix B9).

Only for the Bollenveen and the Reuselse Moeren there was no shapefile available because these areas are not part of the Natura2000 (LNV, 2018), so this area was assessed using Google Maps (see also Appendix CB9). The total area, with and without surface water, of all potential case study areas are found in the attribute tables.

4.3. AREA SELECTION

Based on the criteria described in paragraph 4.1, Table 4.1 is completed. Due to time limits (DINO data needed to be assessed all one by one, while BIS data could be assessed all in one) only BIS data was used for selecting the case study area to find the maximum depth of the peat layer in the potential case study areas, assuming that the BIS data alone represents the area enough to give an estimation of the maximum peat depth. A decision was made which potential case study area was the most suitable area. Permission was requested to the owner to do GPR measurements in the case study area. After the permission was obtained, that area was selected as case study area, when no permission could be obtained another area should was selected where it was possible to auger and to do GPR measurements. All potential case study areas, based on the Natura2000, and the available legacy data points are presented in Figure 4.2.

The Bollenveen is a too small area, mainly consisting of surface water (see Figure 10.16, B9). This makes the area not suitable as case study area because with only 80m^2 of surface area, collecting GPR data every 10m of a transect, would lead to minimal data points. When testing different datasets, more data is desirable. The Reuselse Moeren is also not very large (see Figure 10.17, B9) but a major disadvantage here is that there are only a few remnants left, leaving a very small case study. Therefore these potential case study areas were not further researched (indicated with NR in Table 4.1). The Zwillbrocker Venn is just over the Dutch border in Germany, the used legacy data is only available for The Netherlands, so this area was not suitable as well due to absence of DINO and BIS data.

Both Bourtangerveen and Vriezenveen are large areas that are not only remnants, but for these area's there are bogs that only have remnants: The Bargerveen and the Engbertdijksvenen respectively (Staatsbosbeheer, 2017f, h). These bogs were further researched instead of researching the whole area. The same counted for De Peel, of which the Groote Peel, Deurnse Peel and Mariapeel were combined, but contrasting these areas do have reclaimed peat. Based on the presence of reclaimed peat the Drents Plauteau/Drentse Aa region and De Peel were not considered suitable as potential case study.

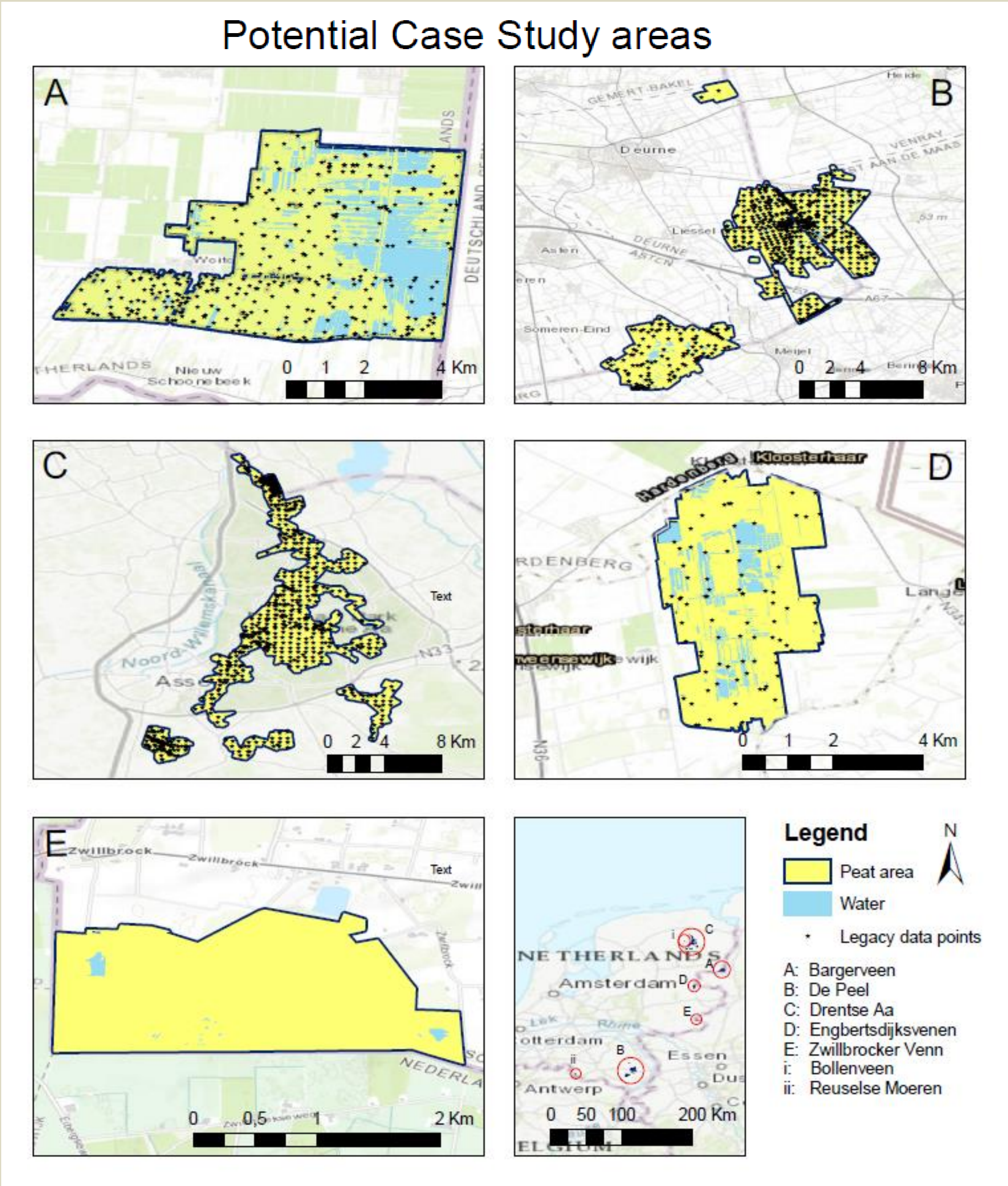

FIGURE 4.2: POTENTIAL CASE STUDY AREAS BASED ON THE NATURA2000 AND THE AVAILABLE LEGACY DATA POINTS. A: BARGERVEEN, B: DE PEEL, C: C: DRENTSE AA, D: ENGBERTSDIJKSVENEN AND E: ZWILLBROCKER VENN. RIGHT BOTTOM: THE NETHERLANDS WITH INDICATION OF THE POTENTIAL CASE STUDY AREAS.

TABLE 4.1: COMPLETED TABLE WITH SELECTION CRITERIA FOR PICKING A CASE STUDY (NR: NOT RESEARCHED)

Potential case study area	Owner	Only peat (remnants), no reclaimed peat	Area (km^2) water incl.	Area (km^2) water excl.	Available legacy data points Total	Available legacy data points km^{-1}	Maximum thickness (cm) water incl.	Maximum thickness (cm) water excl.	Fieldwork permission available
Bourtangerveen ***Bargerveen***	Staatsbosbeheer *Staatsbosbeheer* (Staatsbosbeheer, 2017i)	No *Yes* (Staatsbosbeheer, 2017h)	*20.82*	*15.31*	*382*	*18.3*	*280*	*210*	*Yes*
Bollenveen	Staatsbosbeheer (Pingoruines, 2017)	No (Pingoruines, 2017)	0.011	0.008	NR		NR		NR
Drents Plateau/ Drentse Aa	Mostly Staatsbosbeheer (Staatsbosbeheer, 2017d)	No (Staatsbosbeheer, 2017c)	39.02	38.39	767	19.7	250	250	NR
Vriezenveen ***Engbertdijks-venen***	Staatsbosbeheer *Staatsbosbeheer* (Staatsbosbeheer, 2017g)	No *Yes* (Staatsbosbeheer, 2017f)	*9.32*	*7.81*	*83*	*8.9*	*300*	*300*	*No*
Zwillbrocker Venn	Zwillbrock Biologische Station (Zwillbrock Biologische Station, 2017)	No (LANUV NRW, 2013)	1.83	1.81	0		NR		NR
De Peel ***Groote Peel, Deurnse Peel and Mariapeel***	Staatsbosbeheer *Staatsbosbeheer* (Staatsbosbeheer, 2017b)	No *No* (Staatsbosbeheer, 2017a)	*40.83*	*37.01*	*734*	*17.9*	*210*	*205*	*NR*
Reuselse Moeren	Staatsbosbeheer (Staatsbosbeheer, 2017e)	No (de Brabantse Kempen, 2017)	1.81	1.81	NR		NR		NR

The two areas of interest which were left were the Bargerveen and the Engbertdijksvenen. The latter was prefered due to the fact that it is better coverable within the project limits (time, budget) due to the smaller area, but no permission was obtained by the ranger of Staatsbosbeheer. Therefore the Bargerveen was selected as case study area, but the Bargerveen was too large to completely cover with GPR. Therefore a smaller case study area within this pilot area was chosen based on available legacy data points and accessibility. Also it was taken into account that there was not too much surface water in the area, since that obstructs GPR measurements and surface water is a highly varying variable in bogs, depending on time of the year how much there is. The case study area was located in the west part of the Bargerveen, surrounded by roads around the area and a path in the middle. A map of the Bargerveen can be found in Figure 4.3.

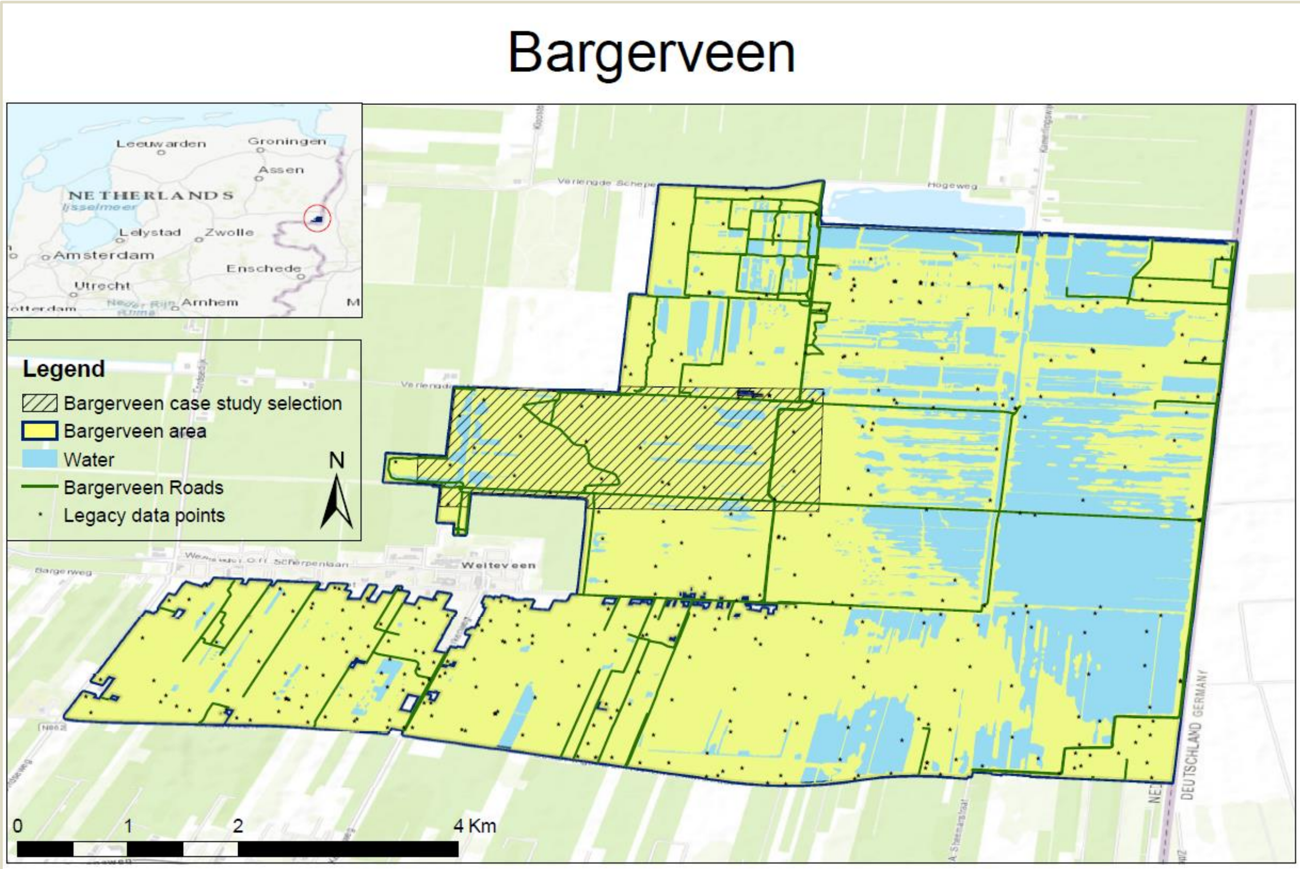

FIGURE 4.3: BARGERVEEN WITH CASE STUDY AREA INDICATED, LEFT TOP: INSET OF THE NORTHERN NETHERLANDS WITH BARGERVEEN LOCATION INDICATION.

4.4. AREA INTRODUCTION: BARGERVEEN

The Bargerveen is a nature reserve in the South East of the province Drenthe, The Netherlands. It is about the last remainder of the Bourtangerveen where peat is still growing due to water- and ecological management (Casparie et al., 2008).

During the second last glacial period, the Saale, the stream valley of the Hunze was eroded (50-60m deep). The Hondsrug was formed. This is a boulder clay ridge next to the Hunze valley where boulder clay is absent. During the same glacial period and the interglacial period, the Eemien, the valley has been filled with cover sands, fluviatile deposits and peat. During the last glacial period, the Weichselian, another layer of mostly cover sand is deposited. After the Weichselian the Hunze valley (still 10-15 meters deep) remained. The Hunze river emerged here. The first peat growth dates back to 5300 BC, where bogs developed in the banks of the Hunze. After a drier period, around 4950 BC the Bargerveen became wetter again. Due to these changes peat started developing again. Ombrogenic sphagnum peat

FIGURE 4.4: PHOTO OF SPHAGNUM IN THE BARGERVEEN. PHOTO CREDITS: CINDY QUIK.

moors developed. Different layers of different types of moors developed since then (Casparie et al., 2008). Old maps (dating from 1599) have indicated that the Southern part of the Bourtangerveen, including the Bargerveen, was unaffected by humans. It was abandoned and inaccessible due to the swampiness and large water richness (Casparie et al., 2008).

Still in the last glacial period cover sand ridges from the Hondsrug have ended up in the Hunze valley. At some of these locations cover sand ridges have more or less cut off the Hunze stream. In the Bargerveen one of these ridges can be found (Casparie et al., 2008). This is visible in the digital elevation model (AHN) of the Bargerveen, Figure 4.5. The white areas in the elevation model is unknown data, this can be either water or parts of Germany (which is not covered by the AHN). This digital elevation model was one of the inputs for the reconstruction (see also Paragraph 2.3).

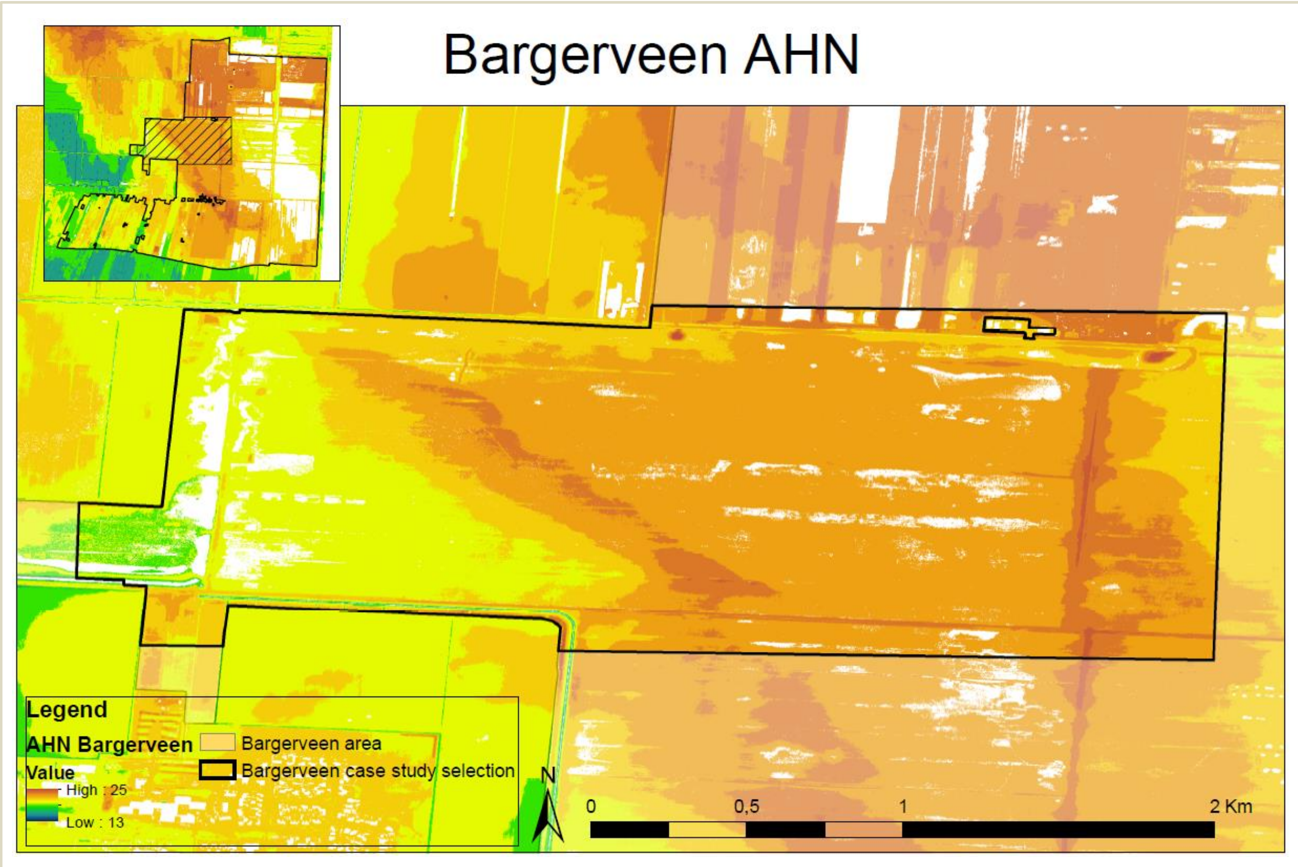

FIGURE 4.5: DIGITAL ELEVATION MAP (AHN) OF THE BARGERVEEN CASE STUDY AREA AND FULL BARGERVEEN AREA (INSET).

5. RESULTS

5.1. GPR MEASUREMENTS

5.1.1. RADARGRAMS

In total there were 12 transects sampled, named from Line21 to Line32. Figure 5.2 is a map with the recorded transects visualized. All radargrams of all walked lines can be found in Appendix D. On the horizontal axis of the radargrams, the walked distance is displayed and on the vertical axis the travel time. In Figure 5.1 an example of one of the radargrams can be found. The radargram shows the first 74 meters of Line27, with the interval points every 10 meters in yellow and at 70 meter the visited calibration point (blue). The transition border is drawn around 10-20 ns. At this travel time the black line is most solid and sharp.

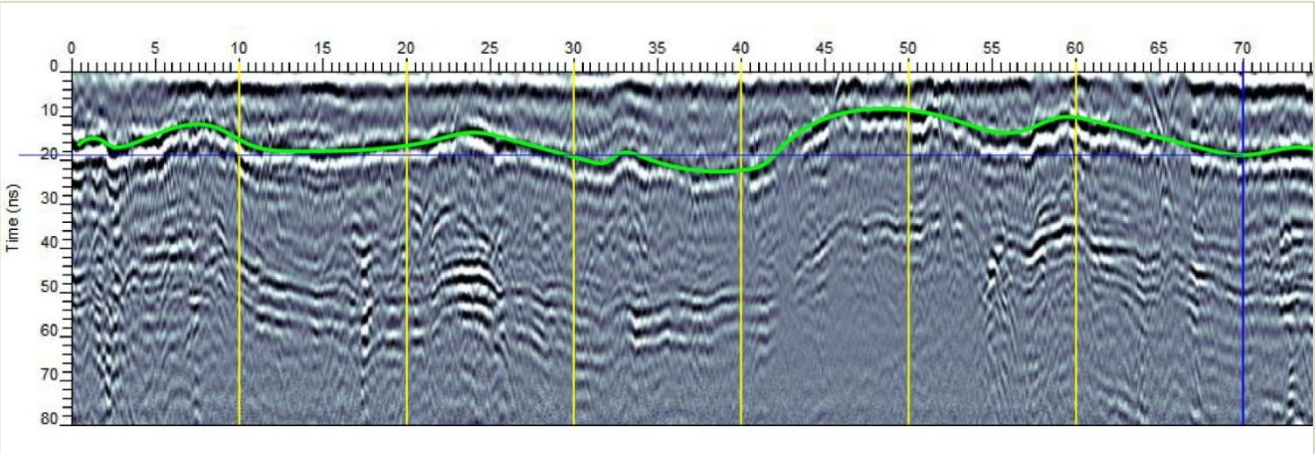

FIGURE 5.1: FIRST 74 METER OF THE RADARGRAM OF LINE27. GREEN: TRANSITION BORDER, BLUE: VISITED CALIBRATION POINT AND YELLOW: 10M INTERVAL POINTS.

5.1.2. GPR CALIBRATION

All walked lines have two calibration points (CP's), named A and B. These are found in Figure 5.2.

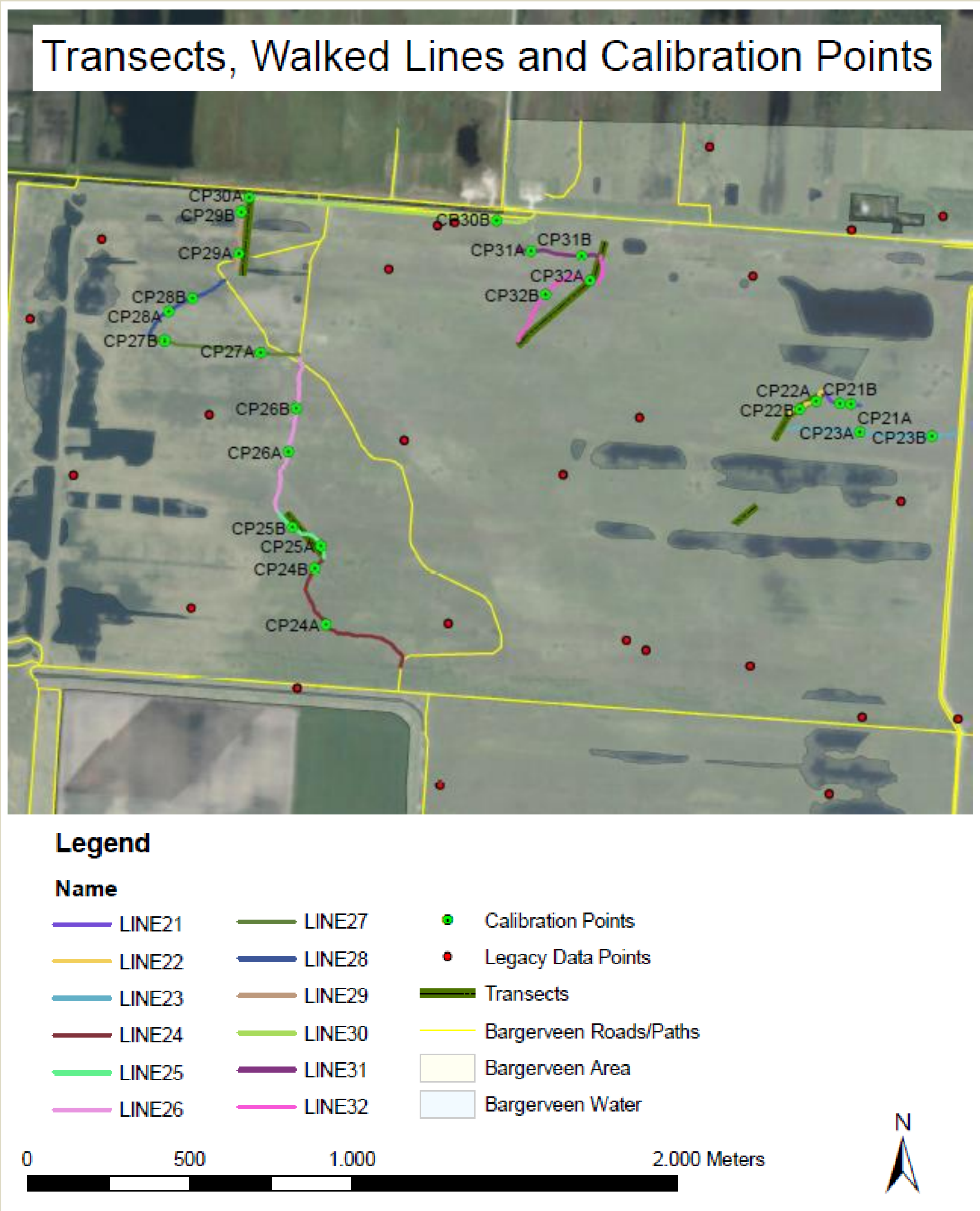

FIGURE 5.2: TRANSECTS, WALKED LINES AND CALIBRATION POINTS VISUALIZED IN THE CASE STUDY AREA.

During the second field work the locations of the records in the field were marked with the Avenza PDF Maps application. These locations did not correspond exactly with the planned calibration point locations. The differences can be seen in Figure 5.3. To correct for this, a new adjusted location was located at the closest position to the real calibration point location on the walked transects (so in a perpendicular line from the transect to the calibration point). The GPR travel time at the distance of this adjusted location was used as calibration time for calculating the GPR velocity. The exact as possible positioning is important due to the very high resolution DEM used and the high local spatial variability in surface elevation in the Bargerveen. To illustrate this: in the photo in Figure 6.4 there is quit some elevation difference visible close to CP24B.

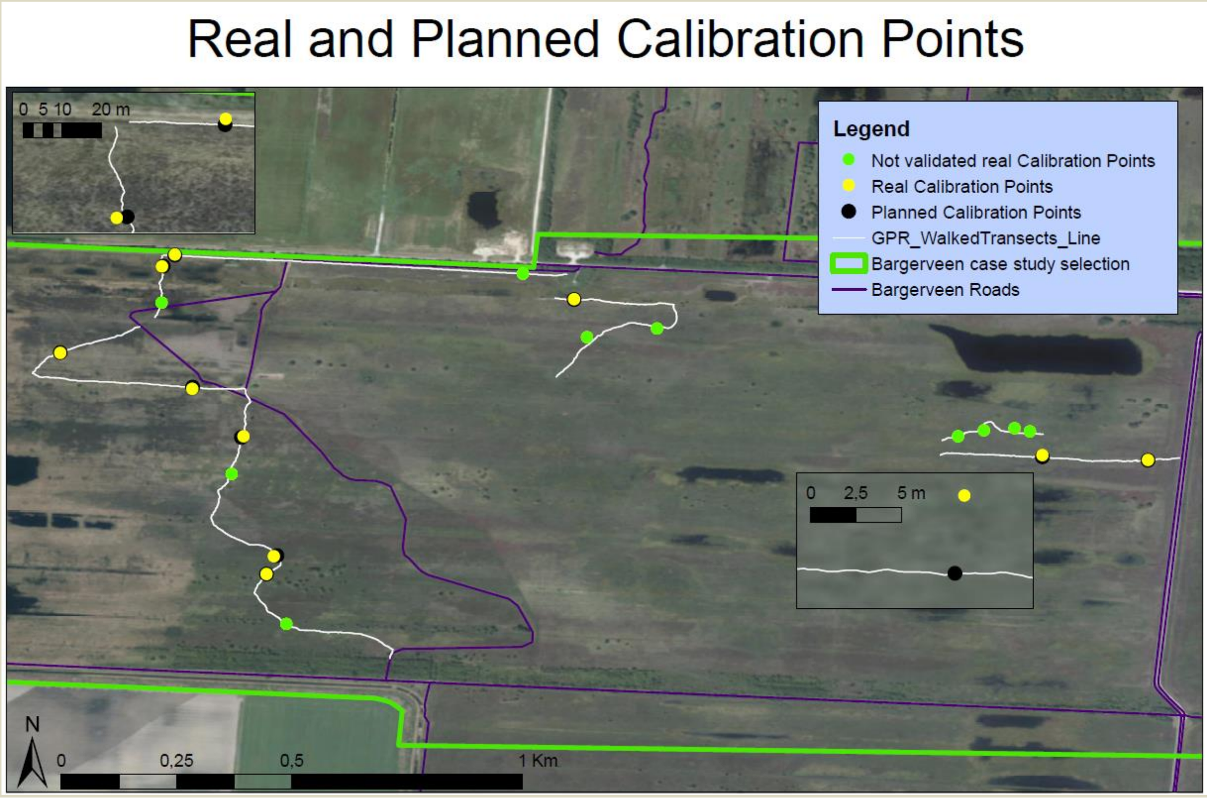

FIGURE 5.3: DIFFERENCES BETWEEN REAL (YELLOW) AND PLANNED CALIBRATION POINTS (BLACK), WITH INSETS OF ZOOMED SITUATIONS, LEFT TOP: CP29B/CP30A AND RIGHT CENTRE: CP23A. GREEN DOTS ARE THE REAL CALIBRATION POINTS THAT ARE NOT USED FOR VALIDATION.

From sampling the calibration points it turned out that the mineral layer underneath the peat is indeed cover sand. In Table 5.1 the calibration points that were not sampled can be found, in Table 5.2 the recorded depths can be found of the sampled calibration points. At all calibration points a gouge was used, except at CP26A, here an Edelmanboor was required.

TABLE 5.1: NOT VISITED CALIBRATION POINTS AND THE REASON WHY.

Name	Reason	Name	Reason
CP21A	Too wet	**CP28B**	Not visited, location CP28A satisfies
CP21B	Too wet	**CP29A**	Too wet
CP22A	Too wet	**CP30B**	Too wet
CP22B	Too wet	**CP31B**	Not visited
CP24A	Too wet	**CP32A**	Too wet
CP25B	Not visited, location CP25A satisfies	**CP32B**	Too wet
CP27B	Not visited, location CP26A satisfies		

TABLE 5.2: VISITED CALIBRATION POINTS WITH THE RECORDED TRANSITION DEPTH, THE ESTIMATED TRAVEL TIME AND THE CALCULATED TRAVEL VELOCITY.

Name	LOI Sample	Remarks	Transition depth [m]	GPR Travel Time [ns]	Travel Velocity [m/ns]
CP23A	Yes		0,95	53	0,0179
CP23B	No		0,60	26,5	0,0226
CP24B	Yes	Large local elevation differences (+/- 20 cm, see also Figure 6.4)	0,80	30	0,0267
CP25A	Yes	Heather	0,90	27	0,0333
CP26A	No	Barely any peat present, but very close peat is present. Lot of spatial variation Edelmanboor used (see also Figure 3.4)	0,05	6,5	~~0,0077~~
CP26B	No	Heather	0,60	28	0,0214
CP27A	No	Path, grassland. More loose peat on top (compared to other locations)	0,60	19,5	0,0308
CP28A	No	Half heather, half open field	0,65	29	0,0224
CP29B	No	Wet, very sharp transition peat/cover sand (Figure 5.4).	0,42	14,5	0,0290
CP30A	No	Path next to fence, road side, Very loose peat.	0,20	2	~~0,1000~~
CP31A	Yes	Seems very much like human interfered, very sharp transition border.	0,30	19,5	0,0154

Neglecting the highest and lowest travel velocities, respectively CP30A and CP26A, the average travel velocity is 0,0244 m/ns. Using this travel velocity, the depths of the transition border were calculated for all other estimated travel times. These results can be found in Appendix E, Table 10.2. The calculations of the peat depth lead to errors since the average travel velocity was used for this calculation. The errors can be found in Table 5.3. The average error of the difference between measured and calculated peat depths was -1.5cm.

FIGURE 5.4: PHOTO OF THE SHARP TRANSITION BETWEEN THE PEAT AND THE COVER SAND AT CP29B.

TABLE 5.3: MEASURED DEPTHS (CM) AND CALCULATED DEPTHS CM, WITH A GPR TRAVEL VELOCITY OF 0,0244 M/NS) AND THE DIFFERENCES BETWEEN THEM (* NOT TAKEN INTO ACCOUNT WHEN CALCULATING THE AVERAGE VELOCITY).

Calibration point	Measured depth (cm)	Calculated depth (cm)	Difference (cm)
CP23A	95	129,3	-34,3
CP23B	60	64,6	-4,6
CP24B	80	73,2	6,8
CP25A	90	65,9	24,1
CP26A *	5	15,9	-10,9
CP26B	60	68,3	-8,3
CP27A	60	47,6	12,4
CP28A	65	70,7	-5,7
CP29B	42	35,4	6,6
CP30A *	20	4,9	15,1
CP31A	30	47,6	-17,6

5.2. LOSS ON IGNITION

From the loss on ignition (LOI) experiment the results in Table 5.4 were obtained. From the LOI percentages and visual and textual observations in the field it is proven that the used transition border is definitely the transition border between the peat and the underlying mineral, cover sand, layer. Soils with an organic matter content of 50-90% are very organic and therefore very likely to be peat. The loss on ignition percentages of the underlying mineral layers are about 9 to 28 times as low as that of the peat, indicating that this is another layer. The iron oxides present in the area can have had a little influence on the ignition but this will not lead to different conclusions about the peat/cover sand boundary.

TABLE 5.4: LOSS ON IGNITION RESULTS FOR FOUR CALIBRATION POINTS

Name	Position	Crucible Number	Empty crucible weight (g)	Crucible + Dry soil weight (g)	Crucible + Soil weight after ignition (g)	Dry soil weight (g)	Soil weight after ignition (g)	LOI (%)
CP23A	**Top**	2	24,837	27,450	26,100	2,613	1,263	51,665
	Bottom	3	23,348	31,915	31,419	8,567	8,071	5,790
CP24B (Figure 5.5)	**Top**	4	25,881	27,942	26,089	2,061	0,208	89,908
	Bottom	5	22,653	33,553	33,080	10,900	10,427	4,339
CP25A	**Top**	17	26,420	28,268	27,276	1,848	0,856	53,680
	Bottom	25	22,655	31,901	31,727	9,246	9,072	1,882
CP30A	**Top**	30	23,684	26,062	24,112	2,378	0,428	82,002
	Bottom	35	23,714	27,008	26,689	3,294	2,975	9,684

5.3. SCRIPTING

The databases used for reconstructing the pre-peat landscape can be found in Appendix F. The full R Markdown script can be found in Appendix G and is divided into the used functions and the main reconstruction script, where the calculations can be found. While publishing some of the figure headings are cut, therefore captions are provided for all figures containing the header (or extending the header). Also the maps were deformed a little while publishing, leading to an unclear legend. In the HTML version of the Markdown script (provided with this thesis) the figures are all displayed correctly. The most important results are summarized below. All created maps and figures can be found in Appendix G2.

FIGURE 5.5: PHOTO OF LOI SAMPLES OF CP24B. LEFT: SAND (TOP), RIGHT: PEAT (BOTTOM).

5.3.1. ASSESSMENT

The minimum and maximum heights of the AHN are 14,96 and 24,61 respectively. The heights of the reconstruction should be lower than these values. In Table 5.5 this comparison is visible. The reconstructions are further assessed on and standard deviation (Table 5.6) and accuracy (Table 5.7). As expected the standard deviations of the reconstructions with transformed data are all close to 1, while reconstructions with non-transformed data have lower standard deviations.

What should be noticed is that the predicted heights when using GPR data are inconsistent with known observations. This is well visible when comparing the maps of a reconstruction with only GPR data and a map with legacy data. Where legacy data point observations are more or less 16-18m above sea level (e.g. in the south east), GPR data predicted locations have an elevation of about 18-20m above sea level (Figure 5.6). Cross validation (Table 5.7) is only done with the own dataset, consequently the ME and RMSE indicate that using only GPR data leads to good results, contradicting from comparing the maps it is known that the ME and RMSE should be worse.

TABLE 5.5: MINIMUM AND MAXIMUM PREDICTED VALUES COMPARED TO AHN HEIGHTS. PREDICTED HEIGHTS HIGHER THAN THE AHN ARE MARKED BOLD AND ITALIC.

Reconstruction	Minimum prediction	Compare minimum to minimum AHN height	Maximum prediction	Compare maximum to maximum AHN height
Prepeat.OK_A	13,99061	Lower than AHN	24,29180	Lower than AHN
Prepeat.OK_A_T	***15,47256***	***Higher than AHN***	18,76183	Lower than AHN
Prepeat.OK_G	14,22666	Lower than AHN	24,33659	Lower than AHN
Prepeat.OK_G_T	14,22624	Lower than AHN	24,34136	Lower than AHN
Prepeat.OK_L	13,98010	Lower than AHN	23,74534	Lower than AHN
Prepeat.OK_L_T	***15,73332***	***Higher than AHN***	18,44945	Lower than AHN
Prepeat.CK_GC	13,91339	Lower than AHN	24,08770	Lower than AHN
Prepeat.CK_GC_UT	14,75795	Lower than AHN	19,98649	Lower than AHN
Prepeat.CK_LC	14,28441	Lower than AHN	24,26407	Lower than AHN
Prepeat.CK_LC_UT	***16,07515***	***Higher than AHN***	19,67128	Lower than AHN
Prepeat.RK_A	14,80655	Lower than AHN	21,48253	Lower than AHN
Prepeat.RK_A_T	14,86733	Lower than AHN	21,68824	Lower than AHN
Prepeat.RK_G	14,31440	Lower than AHN	24,12368	Lower than AHN
Prepeat.RK_L	***14,97576***	***Higher than AHN***	20,87845	Lower than AHN
Prepeat.RK_L_T	***15,27232***	***Higher than AHN***	22,34892	Lower than AHN

TABLE 5.6: MINIMUM, MEAN AND MAXIMUM STANDARD DEVIATIONS FOR ALL RECONSTRUCTIONS.

Reconstruction	Minimum standard deviation (m)	Mean standard deviation (m)	Maximum standard deviation (m)
Prepeat.OK_A	0,2899544	0,4123490	0,6393189
Prepeat.OK_A_T	1,0051098	1,0112982	1,0276680
Prepeat.OK_G	0,1270193	0,3234432	0,4075012
Prepeat.OK_G_T	1,0079381	1,0566233	1,0861299
Prepeat.OK_L	0,2585649	0,7690972	0,9590929
Prepeat.OK_L_T	1,0000000	1,0000000	1,0000000
Prepeat.CK_GC	0,5996035	0,9587153	1,1229258
Prepeat.CK_GC_UT	1,0000000	1,0000000	1,0000001
Prepeat.CK_LC	0,3598494	0,4560307	0,5296123
Prepeat.CK_LC_UT	1,0000000	1,0000000	1,0000000
Prepeat.RK_A	0,2926692	0,4003370	0,6070232
Prepeat.RK_A_T	1,0034438	1,0064923	1,0146510
Prepeat.RK_G	0,1269510	0,3306926	0,4900378
Prepeat.RK_L	0,4156591	0,6845412	0,8863981
Prepeat.RK_L_T	1,0000000	1,0000000	1,0000000

TABLE 5.7: MEAN ERROR AND ROOT MEAN SQUARE ERROR FOR ALL RECONSTRUCTIONS.

Reconstruction	ME (m)	RMSE (m)
Prepeat.OK_A	0,06478488	0,58160110
Prepeat.OK_A_T	0,05245758	0,59176650
Prepeat.OK_G	0,08396079	0,30890140
Prepeat.OK_G_T	1,09377850	1,13593050
Prepeat.OK_L	0,02784783	0,78223710
Prepeat.OK_L_T	0,05308218	0,77816940
Prepeat.CK_GC	0,02631493	0,78991060
Prepeat.CK_GC_UT	0,14036514	1,08620530
Prepeat.CK_LC	0,05843319	0,36721370
Prepeat.CK_LC_UT	0,09943318	0,44699580
Prepeat.RK_A	0,05629054	0,52756320
Prepeat.RK_A_T	0,52715985	4,39587180
Prepeat.RK_G	0,08048023	0,30666330
Prepeat.RK_L	0,01757814	0,70092230
Prepeat.RK_L_T	0,05341685	0,68731410

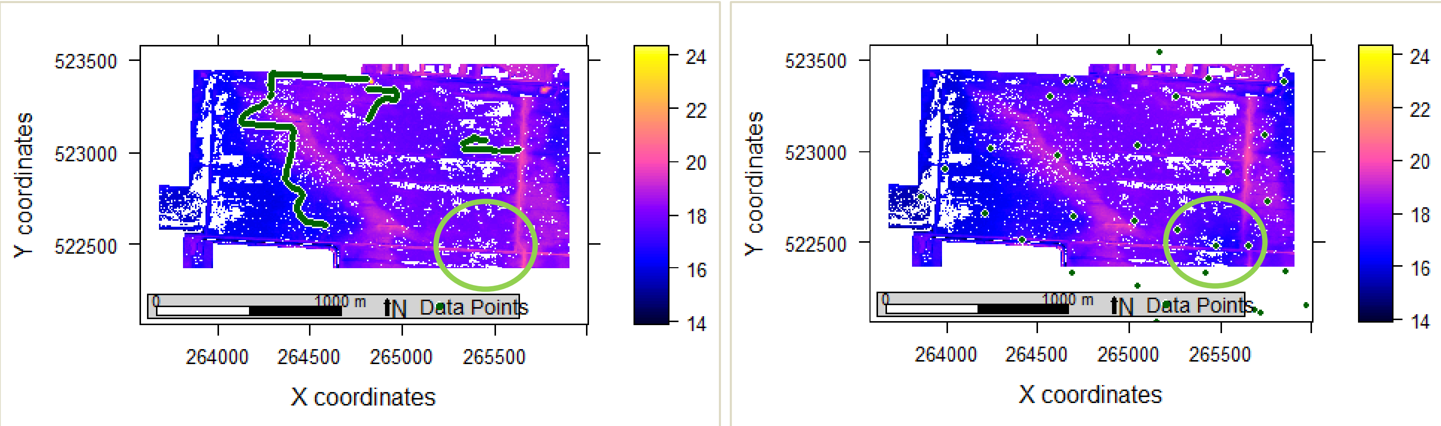

FIGURE 5.6: COMPARISON BETWEEN PREDICTION MAPS OF ORDINARY KRIGING WITH GPR DATA (LEFT) AND ORDINARY KRIGING WITH LEGACY DATA (RIGHT). WHERE LEGACY DATA POINT OBSERVATIONS ARE IN BLUE (GREEN CIRCLE), GPR DATA PREDICTIONS ARE PURPLE.

5.3.2. BEST RECONSTRUCTION

From the final assessment it becomes clear that the best method for reconstructing is using co-kriging with untransformed legacy data as covariable (Table 5.8). Although kriging with untransformed GPR data leads to a lower total score, these reconstructions are declassified for the reason explained above. The new lowest and second lowest total score only differ half a point, but because the mean standard deviations for these two reconstructions differ about 5 cm, which is the maximum measurement error of the legacy data (Paragraph 6.2), and the difference in RMSE of both reconstructions is almost factor 1.5. Therefore the RMSE is in this case predominate. For the assessment it is not taken into account that some predicted elevations of the pre-peat landscape are higher than the actual surface level, because the highest ranked reconstruction with this issue scores worse on standard deviation and RMSE. Although the ME is better than the top ranked reconstruction, the ME is regarded as less important than the RMSE.

TABLE 5.8: FINAL ASSESSMENT OF THE RECONSTRUCTIONS.

Reconstruction	ME	RMSE	SD	Total	Rank	Remarks
Prepeat.CK_LC	4,0	3,0	5,0	11,5	1	RK_A: much worse RMSE, SD almost equal
Prepeat.RK_A	3,5	5,0	3,0	12,0	2	CK_LC: much better RMSE, SD almost equal
Prepeat.OK_A	4,5	6,0	4,0	14,5	3	
Prepeat.RK_L	0,5	9,0	6,0	15,5	4	Prediction higher than AHN
Prepeat.OK_L	1,5	11,0	7,0	19,5	5	
Prepeat.CK_GC	1,0	12,0	8,0	21,0	6	
Prepeat.CK_LC_UT	6,0	4,0	12,0	22,0	7	Prediction higher than AHN
Prepeat.OK_A_T	2,0	7,0	14,0	23,0	8	RK_L_T: better RMSE, SD almost equal, Prediction higher than AHN,
Prepeat.RK_L_T	3,0	8,0	12,0	23,0	9	OK_A_T: worse RMSE, SD almost equal, Prediction higher than AHN
Prepeat.OK_L_T	2,5	10,0	12,0	24,5	10	
Prepeat.CK_GC_UT	6,5	13,0	12,0	31,5	11	
Prepeat.RK_A_T	7,0	15,0	13,0	35,0	12	
Prepeat.OK_G	5,5	2,0	1,0	8,5	-	No ranking, unreliable cross validation
Prepeat.RK_G	5,0	1,0	2,0	8,0	-	No ranking, unreliable cross validation
Prepeat.OK_G_T	7,5	14,0	15,0	36,0	-	No ranking, unreliable cross validation

For the best reconstruction, Prepeat.CK_LC, a 3D map has been created Figure 5.7. The influence of the AHN is very well visible in the reconstruction, with the high peak in the north (the viewpoint, Figure 6.2) and in the east and south roads are visible in blue, as well as the sand ridge present in the Bargerveen. A 3D rotating plot (.GIF file) of this reconstruction is provided with the thesis.

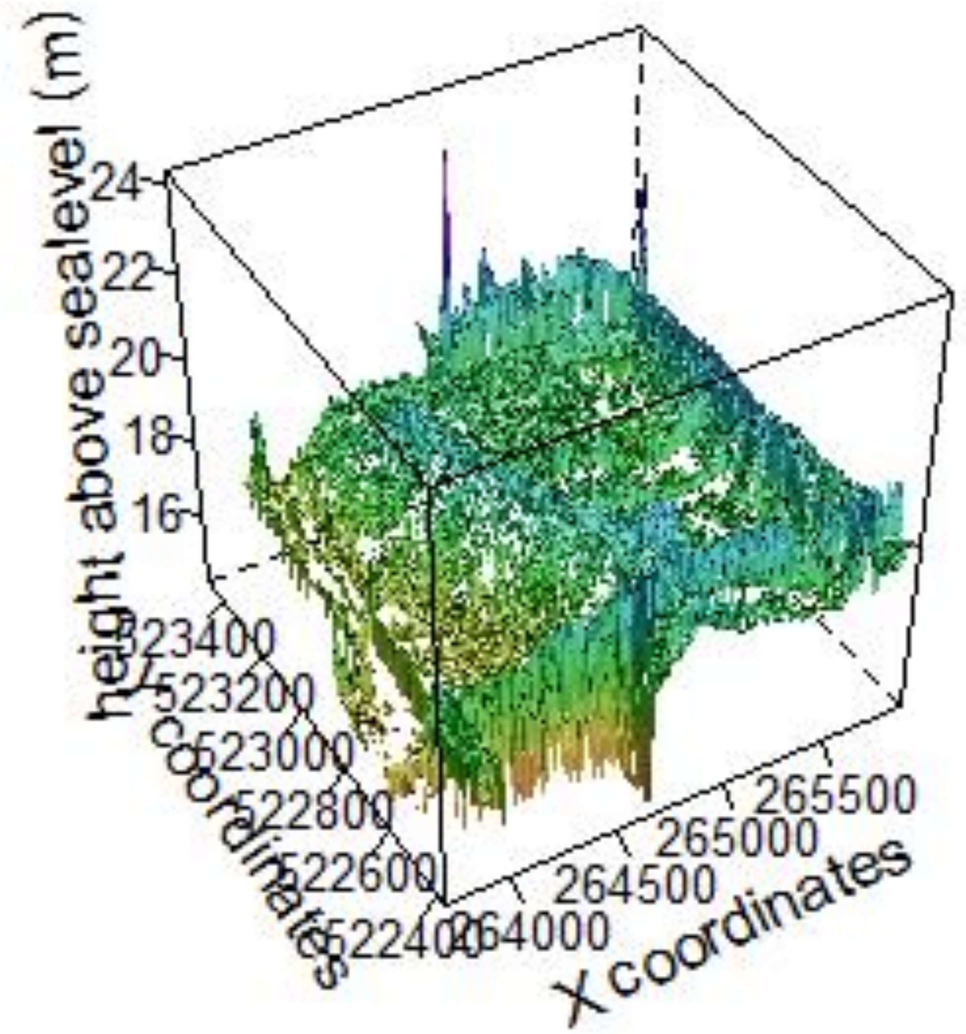

FIGURE 5.7: 3D MAP WITH ELEVATION PREDICTIONS, RECONSTRUCTED BY CO-KRIGING WITH UNTRANSFORMED LEGACY DATA AS COVARIABLE.

5.4. RESOLUTION/SUPPORT

From the kriging statistics Table 5.9 is derived with the resolution and support. A distinction has been made in support for the model fitting (with subsetted data) and support used for kriging (complete dataset). The best resolution and support that was reached within this research is a grid of 2 x 2 meter, kriging a grid of 482188 cells with 455 data points. This means that every observation should cover 4239 m^2.

TABLE 5.9: RESOLUTION AND SUPPORT FOR EACH RECONSTRUCTION.

Reconstruction	Number of grid cells	Area per grid cell (m^2)	Number of data points (model fitting)	Number of data points (kriging)	Area covered per kriging observation (m^2)
Prepeat.CK_LC	482188	2 x 2	238	455	4239,02
Prepeat.RK_A	482188	2 x 2	238	455	4239,02
Prepeat.OK_A	482188	2 x 2	238	455	4239,02
Prepeat.RK_L	482188	2 x 2	178	178	10835,68
Prepeat.OK_L	482188	2 x 2	178	178	10835,68
Prepeat.CK_GC	482188	2 x 2	238	455	4239,02
Prepeat.CK_LC_UT	482188	2 x 2	238	455	4239,02
Prepeat.OK_A_T	482188	2 x 2	238	455	4239,02
Prepeat.RK_L_T	482188	2 x 2	178	178	10835,68
Prepeat.OK_L_T	482188	2 x 2	178	178	10835,68
Prepeat.CK_GC_UT	482188	2 x 2	238	455	4239,02
Prepeat.RK_A_T	482188	2 x 2	238	455	4239,02
Prepeat.OK_G	482188	2 x 2	60	277	6963,00
Prepeat.RK_G	482188	2 x 2	60	277	6963,00
Prepeat.OK_G_T	482188	2 x 2	60	277	6963,00

5.5. APPLICABILITY

Important for this methodology is that the bog landscape has bog remnants. That way the pre-peat landscape can be reconstructed by subtracting peat depth from the current surface level elevation. This can be the case for comparable bogs in the Netherland, but that is not a real requirement. Streefkerk and Casparie (1989) name several ombrotrophic bogs comparable to the Bargerveen that also consist of bog remnants. They name amongst others the Deurnse Peel (Northern Brabant), Engbertdijksvenen (Overijssel), Fochterloërveen (Drenthe/Friesland), Meerstalblok (another area than the case study area within the Bargerveen) and the Odoornerveen (Drenthe). The latter is like the Bargerveen part of the former Bourtangerveen, stretching in Groningen, Drenthe and North-Western Germany (Casparie, 1993). However, for the methodology it should not necessarily be in the Netherlands. It could (and does) also work in Hatfield and Thorne Moors (Chapman and Gearey, 2013), but with this research it is shown that the research can also be done on a much smaller (10x) resolution. Moreover, in large parts of North-West Europe ombrotrophic mires can be found. A belt with these mires can be found from Ireland, via Great Britain, Northern France, Belgium, the Netherlands, Germany, Poland and Scandinavia up to the European parts of the former Soviet Union (Eurola et al., 2013). Besides, it should hypothetically also be applicable to other bog remnants found in the world. The type of bog found in the remnants should not matter for this sake. What does matter for reconstructing another bog, is the availability of a digital elevation model. For bogs in The Netherlands this will not form a problem due to the availability of the AHN for the whole Netherlands. But when reconstructing outside The Netherlands, a digital elevation model should be available with at least the resolution of the desired reconstruction. Another possibility is to use legacy data points with surface level elevations recorded, or to record the surface level elevations in the field. Both ways will probably not be as accurate as the AHN.

The spatial scale is also variable. The methodology can be applied on very small scale, but also on very large scale. But it should be kept in mind that when extending the spatial scale, the resolution should decrease. Computers limitations should be kept in mind here too, increasing the spatial scale increases the calculation time and load proportionally, while at smaller scale the resolution may be increased to handle the calculations with the same time and load. Increasing or decreasing the sample density does somewhat influence the reconstruction. From the assessment it is visible that the legacy kriged data is a little worse than using legacy and GPR data points combined explainable by the sample density of the legacy data which is twice as low as the sample density of the legacy and GPR data combined. It is arguable that when the sample density decreases, that the uncertainty will increase. Kriging errors occur mostly due to errors made in variogram fitting, both model selection as nugget fitting (Brooker, 1986). When data points are far apart, the distance from the observation point to prediction point is also larger. The farther the prediction point is from the observation point, the larger the interpolation error will be (Burgess et al., 1981). Hence, when the sampling density changes, variograms will be influenced as well and consequently the kriging predictions and kriging variances. This high kriging variance for a low sampling density is well visible in the standard deviation maps of the ordinary- and regression kriged untransformed legacy data: Figure 10.86 and Figure 10.95. These predictions have the lowest sampling density, and the highest standard deviation apart from the reconstructions with transformed data. A low sampling density is not advisable, but neither is a high. As the sampling density becomes higher, sampling covariances increase leading to a less accurate variograms, but on the other hand this can be corrected (Tran, 1994).

FIGURE 5.8: PHOTO OF THE GOUGE PROFILE AT CP24B.

6. DISCUSSION

6.1. RESEARCH QUESTIONS

6.1.1. METHODOLOGY DEVELOPMENT

SELECTING CASE STUDY AREA

Selecting a case study area was the objective in this research. The first choice of case study area were the Engbertdijksvenen. Unfortunately the ranger could not give permission to do more external research: "Currently there are a lot of vulnerable processes around the measures taken to realise the set goals within the management plan of the Natura2000. To preserve the peace in the area it is not desirable to conduct extra research besides the researches that are executed from the management plan." (A. Hollander, email contact, 03-11-2017). Nevertheless the Bargerveen was also a potential interesting area, but somewhat too large to cover completely with GPR measurements. Therefore a smaller area was selected within the Bargerveen. Although careful selecting the case study area, surface water turned out to be an issue. Where it was possible to walk the first fieldwork day (8 Nov 2017), there was water just below knee level during the second day of fieldwork (30 Jan 2018, Figure 6.1). Despite the area is not reclaimed, there were traces of human interference in the case study area. In the north of the area, just outside the case study a new road was built. As well as presence of other roads and the panorama viewpoint (Figure 6.2), at the end of line 30 (see also Figure 5.2), in the north of the case study area.

FIGURE 6.1: PHOTO TAKEN DURING SECOND FIELDWORK WITH THE SURFACE WATER IN THE BARGERVEEN JUST BELOW KNEE LEVEL.

Available data for the Bargerveen that could directly be used (and for most other potential case study areas) were a shapefile extracted from the Natura2000, AHN tiles containing surface level elevations above sea level and legacy data points from the DINOloket and the BIS. The amount of available legacy data presented in Table 4.1 is not the actual amount of used legacy data, because in the table only unprocessed BIS data points were used. Only when preparing the databases for kriging, the data points were processed and only points that had another recorded mineral layer underneath the peat base were used. This is because when this layer is not present underneath the peat layer, exclusion whether the depth of that peat base is really the depth of the peat base or whether it is the end of the recording with the peat possibly reaching deeper, is impossible. The actual amount of legacy data points used was 178 (91 from DINO data and 87 from BIS data). Another implementation that was done with optimizing the databases is the cutoff parameter. This cutoff was used for peat layers that are identified at depths that do not make sense to relate to the other identified peat layers. These "outliers" can be excluded from the database. The identified peat layers can be explained as peat developed during the Saalien, as also mentioned in Paragraph 4.4.

FIGURE 6.2: PHOTO TAKEN IN THE BARGERVEEN, NEAR CP31A. ON THE RIGHT SIDE THE VIEWPOINT, JUST LEFT OF THE VIEWPOINT A SAND DEPOSIT FOR THE ROAD WORK. THE ROAD FOLLOWS THE LANE OF TREES IN THE BACK.

GEOSTATISTICAL TECHNIQUES

To find out which geostatistical technique was most appropriate, several factors have been tested for reconstructing the pre-peat landscape. These factors were checking which data (GPR, legacy or combined) and which kriging method should be used (ordinary-, co- or regression kriging), whether transforming the data was useful and whether peat depth (underneath surface level) or peat height (above sea level) had to be used for reconstructing the pre-peat landscape.

KRIGING TECHNIQUE

The best results was obtained when both legacy and GPR data were used, when using co-kriging with legacy data as covariable. The second best reconstruction was obtained when assuming equal measurement errors for all databases, but then the reconstruction were less precise. Regression kriging with the AHN as regression data and legacy and GPR data combined is better than ordinary kriging with this combined data (third best). As a result precision, accuracy and standard deviation deteriorate minimally.

TRANSFORMING DATA

All seven reconstructions with transformed data ended in the bottom of the assessment. Expected was that transformed data was better for reconstructing than untransformed data, but in this research it appeared not to be. This is due to the fact that the transformed data was normalized, so it had a distribution with a standard deviation of 1. Compared to all standard deviations, 1 is the largest. Therefore untransformed data is better for predicting the pre-peat landscape.

PEAT DEPTH VS. PEAT HEIGHT

Whether peat depth or peat height is better for kriging cannot be determined in advance, this really depends on the dataset and should be determined with use of the variogram function. A lower nugget and sill give better kriging parameters. Overall it is most appropriate to use untransformed combined GPR and legacy data with co-kriging.

6.1.2. QUALITY ASSESSMENT

ADDITION OF DATA

The reconstructions were assessed on MSD (Mean Standard Deviation), ME (Mean Error) and RMSE (Root Mean Square Error). Looking at the ME only, additional data decreased the quality of the reconstruction a little bit, the error increased with more or less 0,03m. Contrary the RMSE and the MSD were slightly improved by adding the additional data. The RMSE was halved relative using legacy data alone. When adding extra data the RMSE decreased with more or less 0,3m and the MSD was decreased by more or less 0,25m. So from adding extra data the standard deviation improved, the accuracy decreased slightly but the precision and accuracy combined improved again. Overall, the addition did improve the quality, but the differences were very minimal so it did not improve significantly.

BEST ACCURACY

The best accuracy that was reached was by regression kriging transformed legacy data. Accuracy cannot be expressed in numbers, but by measures of the ME, as indication for the accuracy, calculations showed an error of 0,017. By measures of the RMSE, as indication of the accuracy and precision combined, calculations showed a minimum error for regression kriging with GPR data alone. But this reconstruction was declassified because it was shown that predictions should have been higher compared to observations of legacy data, if these observations were taken along the RMSE and ME would have been worse for the reconstruction based on GPR data alone. Neglecting these reconstructions, the best accuracy by measures of the RMSE is the RMSE of the best assessed reconstruction: of co-kriging with legacy data as covariable: 0,037m. The ME of the best assessed reconstruction is 0,058m.

RESOLUTION

The best obtained resolution and support were also for co-kriged GPR data with legacy data as covariable: 482188 grid cells of 2 x 2 m and 455 data points used for kriging.

It is possible to even increase the resolution. The used AHN has grid cells of half a meter by half a meter, the current resolution could be adjusted to this, now the AHN is resized to grid cells of two by two meter. Of course this can also be done the other way. However, computer limitations should be taken into account. The computer used for the kriging stalled multiple times, depending on running programmes. When halving the grid cell size twice, there are 16 times more grid cells to be predicted, causing a calculation time to increase 16 times and also calculations become heavier. So taking computer limitations into account, the best possible resolution is using grid cells of half by half a meter. If computer limitations allow a smaller grid cells, a better resolution can be obtained. But to get a significant better reconstruction, probably GPS accuracy should also increase to get obtain a GPS position accurate on a cm scale. Furthermore it should be taken into account that when the grid cell size decreases by 16 times to half a meter by half a meter, the area that one observation should cover increases by 16 times, meaning that with the used set of data one observation should cover 67824,25 m^2, doing this the uncertainty in the prediction will also increase, leading to lower accuracy and precision and higher kriging variances and consequently higher kriging standard deviations. The sample density changes in this case, see also Paragraph 5.5.

6.2. ERROR DISCUSSION

LEGACY DATA

There is an uncertainty in the identified peat depths in the used data points. For the legacy data this is an uncertainty in measurement error. Although all data is checked before it is added to the DINO/BIS databases, it is not traceable how large the measurement errors are and it has multiple original sources since everyone who has data available may submit this data. Most of the peat depths are rounded to 10 cm, leading to a measurement error of maximal 5 cm. Also some records are over 40 years old, dating from times when GPS technology was less accurate than nowadays. So true locations might deviate from the recorded locations of the data points. Even with the used GPS it is doubtful whether the GPS is accurate enough position the location on meters accurate (which is the used grid cell size for reconstructing).

GPR PROCESSING

Furthermore, not at every ten meters a GPR record could be registered, for example at line 24 (Figure 10.21). The measurement was too disturbed to correctly identify a transition border between the peat and the cover sand. At these distances the record has been left out. Also at some locations the there was no peat, for example at line 30 (Figure 10.27). For these records the peat depth could also not been registered and has been set to 0 m. In the optimize database function also records might be left out. If the Euclidean distance between 2 records is less than the grid cell size, only the first recorded record is used. Using both records is not possible since one grid cell can only have one value, so two values (in case of two records) is not possible.

FIGURE 6.3: PHOTO OF THE GOUGE PROFILE AT CP25A. WOOD DEBRIS WAS ENCOUNTERED AT THIS LOCATION.

GPR TRAVEL VELOCITY

For the GPR data there is also an uncertainty, the travel time can be read very accurate, but the conversion to depth is less accurate. In line 27 the GPR travel time has been calculated with use of a parabola: 0,061 m/ns. When using this travel velocity all depths of the transition border were estimated much deeper than they actually were. Therefore an average traveling velocity of 0,0244 m/ns is used. Because the average is used there is already a small error between the recorded and calculated depth. Logically this is continuing throughout all depth calculations. In Table 5.3 the differences between recorded and calculated depths can be found. This differences may be due to different field conditions. If the water or organic matter content in the peat changes, the GPR transmittance also changes. From the loss on ignition results, Table 5.4, it becomes clear that there are quite some differences in organic matter content in the peat.

In Appendix A GPR travel velocities can be found for different materials. The calculated GPR velocity that turned out to be incorrect lies in the range of clays and wet/saturated sands. Peat and organic soils have a travel velocity of 0,04, indicating that the travel velocity should be lower than the calculated travel velocity. On the other hand, the used, average, travel velocity is lower than the indicated travel velocity and comes closer to the travel velocity of fresh and salt water. Knowing that the peat was very wet, and even completely saturated at some measurement locations, it is not inevitable that the travel velocity is lower than that of sand (the parent material) and peat/organic soils. Moreover, it is expected that used travel velocity is lower than the calculated velocity, but anyway, this difference is larger than expected on forehand.

LOSS ON IGNITION

In Paragraph 5.2 it is already shown that there is a clear boundary between the peat and the underlying cover sand layer. There is a large loss on ignition difference both. As noticed in Paragraph 3.4.3 , iron oxides can influence the loss on ignition. There are iron oxides observed in the cover sands just outside the Bargerveen, but it cannot be said whether the iron oxides are also present in the peat and/or underlying cover sands, but in case it is; it will not have much influence on the organic matter content (OM). It might be just a little bit higher or lower depending whether the iron oxides are present in the cover sand (higher OM), peat (lower OM) or both (higher and lower OM both possible).

FIGURE 6.4: PHOTO OF LOCAL HEIGHT DIFFERENCE NEAR CP24B, VISUALIZED WITH HELP OF THE GOUGE AND BLUE LINES INDICATING THE SURFACE ELEVATION.

LOCAL ELEVATION DIFFERENCES

The local height differences (Figure 6.4) can have quite some negative impact on the reconstruction because the pre-peat landscape can be about 20 cm higher or lower at that location while this is not noticed in the standard deviation or cross validation because the assessment is based on the record, which is incorrect in the described hypothetical situation.

SURFACE LEVEL CORRECTION

Another measurement error that occurred in the database is the correction for surface elevation. Some records (including some old records) contained a surface level elevation. Due to peat settling this elevation can have changed over the years, meaning that the peat layer has become thinner. When reconstructing the peat height above sea level it is easy to compensate this by subtracting the depth of the transition border from the known surface level. The height above sea level does not change over time (assuming the underlying sand layer does not settle). But this gives inaccuracies when comparing these reconstructions to reconstructions of which the peat depth is predicted for all locations is subtracted from the current surface level. To overcome this inaccuracy, all known surface levels are removed from the data base and set to "Unknown", forcing the optimize database function to replace these values by the current AHN values. Another benefit of this is that whenever the surface level elevation has not correctly filled out in the database, the optimize database function now does extract the AHN height for this location (which only happens when the surface level elevation is set to "Unknown". In addition to that, previously the horizontal accuracy of GPS material was already questioned, for vertical accuracy it goes the same. So it is questionable whether the recorded surface level elevation in the available data is as accurate as the AHN surface level elevation.

SUBSETTING DATA

Also, deliberately ignoring data may lead to errors, as is done by subsetting data. For subsetting data randomly five points are picked from a transect. A seed is set to let every subset contain the same five points. Using a different subset of data points will lead to different results. When randomly selecting five points and by coincidence these points are all at the start of a transect and hypothetically that transect ascents at the end, this ascending is missed leading to an error. But from earlier created reconstructions it became clear that when the data is not subsetted, errors in the prediction and variance are even larger due to the strong local coherence between the points on each transect. A possible reason for these errors are the difficulties faced with normalizing data. As seen in the results it is very beneficial to transform the data to normality, but because of the low peat depths at and the length of walked line 30, there was very large bin at the lowest peat depth values, making it impossible to normalize data to a very low skewness as is reached with the executed methods. The errors that turned out during the research are much lower than the errors that would have turned out when the data is not subsetted. By bypassing the local coherence in transforming the data and fitting the variogram functions, the final reconstructions have improved tremendously.

BACK TRANSFORMATIONS

When taking the inverse Box-Cox transformation with a non-zero lambda parameter (Equation 9), lambda is multiplied by the transformed kriging variance (which should be back transformed). When the outcome of this multiplication is lower than -1 (1 is added to the multiplication outcome), rooting is impossible because a the root is taken of a negative number and `NaNs` are produced. As a consequence these `NaN` values are not taken into account when calculating the standard deviation. If this occurs it should be checked how many `NaN` values are produced and whether this will have influence on the reconstruction

ASSESSMENT

Due to the back transformation of normalized data, many standard deviations are (close to) 1. When ranking these standard deviations, equal values got equal scores. Where scoring 9th would be most appropriate when reconstructions 9 up till 12 have the same mean standard deviation, in the assessment these reconstruction got ranked 12th, missing 3 points this way. For the final ranking this is not of influence, because these reconstructions with transformed data will not come close to the top with these extra points and all these reconstructions are ranked bottom of the total assessment.

Some reconstructions of the pre-peat landscape have a higher elevation than the AHN, within this research that is not possible since the peat base of bog remnants is reconstructed, therefore the reconstructed pre-peat landscape should always be below the actual surface level elevation.

AHN INFLUENCE

Last, the AHN has major influence on the reconstruction, because the pre-peat landscape is reconstructed based on the current positioning in the landscape. The influence is e.g. very well visible in the 3D reconstruction, where there is a high point in the north. The pre-peat landscape does not have such a peak, but the peat base is much deeper at that location. This is missed in all reconstructions created. On every prediction map in Appendix G2 there is a high point visible at this location. Not only the viewpoint is affected by this, but also e.g. the roads are. As already stated before, these are due to human inference.

6.3. RECOMMENDATIONS

After having done the research and writing this thesis, I have a couple of recommendations for comparable and/or continuation research. The first recommendation is not to add DINO data to the BIS data and optimize the databases to find the actual amount of data points used for kriging for every potential case study, as this takes a lot of time and it is questionable whether this really influences the decision on case study area selection, since the choice for the Engbertdijksvenen or Bargerveen was mainly based on area size and absence of bog remnants.

Secondly, I would recommend not to conduct the fieldwork mid-winter. Due to the timing of the second fieldwork (end of January), some of the in advance determined calibration points were not accessible due to the wet field conditions. Because of this some of the walked transects did not have a calibration to check whether the transition border has been drawn on the right depth. Also it would have been better to check during the second fieldwork on iron spots in the soil. It is an easy and fast way to say something about the iron oxides within the Bargerveen.

Next, the length of the distance walked with the GPR did not correspond with the length of the GPS transects in ArcGIS. This required some recalculations of the lengths. For every transect another length recalculation was required. Due to the accurate length recalculations and adjusting the selection intervals in ArcGIS during the processing, no errors have occurred with this. But it is something I recommend to keep an eye on when working with GPX data (the GPS converted data). The same counts for projecting data between RDNew and WGS84, like has been done during the processing.

Furthermore, for any continuation research, it might be interesting to do further research on the superficial geology of the mineral layer underlying the bog remnants. This cover sand layer is relevant for the future landscape evolution studies on spatio-temporal bog development through its influence on groundwater hydrology and consequently on peat growth. With the database optimization function this layer (or layers if there are more) can be identified. This function is developed in such way that also details, like for example the sand median, can be used as identifying layer.

Also a spatial stochastic simulation might be interesting to do for the reconstruction. A spatial stochastic simulation is made to see the error in the landscape evolution model (from the Home Turf project) when the input, the reconstructed DEM, is not perfectly correct. A spatial stochastic simulation can be used for uncertainty propagation. One of the most used spatial stochastic simulations for digital elevation models is the sequential Gaussian simulation (Kyriakidis et al., 1999). With this simulation, at every predicted location of the kriged DEM, local ordinary kriging is used to estimate a localized mean and variance based on the neighbourhood values. A normal distribution is based on this and from this normal distribution randomly new values are selected. These values replace the DEM predictions. This process is continued until all predicted values are replaced and there are only observed and new simulated values in the DEM (Mowrer, 1997). This can be done in R with the `predict()` function in the *gstat* package (Pebesma, 2017e).

7. CONCLUSION

A smaller area within the Bargerveen turned out to be a suitable pilot area for this research. For this case study area DEM reconstructions were created from legacy (DINO- and BIS data) and newly collected GPR data. It was showed that collecting data does improve, but not significantly improve, the quality of the reconstruction, providing that untransformed data is used with co-kriging with legacy data as covariable. Reconstructing with ordinary kriging with combined legacy and GPR data or regression kriging this data with the AHN as regression data also gave a good representation and is qualitatively comparable to reconstructions using co-kriging, despite the possible different degrees in uncertainty. The method should be applicable to all bogs in the world, as long as there are bog remnants and an accurate digital elevation model available.

FIGURE 7.1: PHOTO OF THE VIEW OVER THE BARGERVEEN FROM THE VIEWPOINT IN THE NORTH OF THE AREA. TREE IN THE FRONT ALSO ALSO VISIBLE IN FIGURE 6.2.

8. ACKNOWLEDGEMENTS

The following people and institutions have had an important contribution to this thesis and have made the research possible. I am grateful for their time, help and information they provided me in order to conduct the research and finish my thesis. First of all Folkert de Vries from Wageningen Environmental Research for providing the BIS data points. Secondly to Ronald Koomans and Silke Ceulemans, both from Medusa, for their hospitality for receiving me at- and showing me around in their office and providing information about GPR measurements in general. Major thanks go to Wouter de Vlieger, ranger of Staatsbosbeheer in the Bargerveen, for providing permits to enter the Bargerveen, providing information about the accessibility and quick responses and flexibility concerning the permits. Furthermore, this research could not have been done without a GPR. For that I am very grateful to Joep Storms from the TU Delft for lending the GPR materials and software to read out the GPR. With this I want to thank Jasper Candel from the Wageningen University as well for arranging the GPR, processing the GPR data in Delft and providing very useful information for GPR measurements and suggestions for several geostatistical techniques. Also I want to thank Gerard Heuvelink, from ISRIC and Wageningen University for his help with the geostatistical techniques and improving the methodology in order to get more reliable results. Last, but not least, big thanks go to Cindy Quick and Roy van Beek, both from Wageningen University for helping me during the first fieldwork and for their monitoring and helping in the form of suggestions and correcting to enhance the quality of this thesis.

FIGURE 8.2: PHOTO OF ROY VAN BEEK DOING GPR MEASUREMENTS.

FIGURE 8.2: PHOTO OF CINDY QUIK DOING GPR MEASUREMENTS. PHOTO CREDITS: ROY VAN BEEK.

9. REFERENCES

AHN, 2018. *Over AHN*. Available at http://www.ahn.nl/common-nlm/over-ahn.html, accessed on 25-4-2018.

ArcGIS, 2017. *AHN2 - Download Kaartbladen*. Available at http://www.arcgis.com/home/webmap/viewer.html?useExisting=1, accessed on 20-11-2017.

Avenza, 2018. *Avenza Maps*. Available at https://www.avenza.com/avenza-maps/, accessed on 22-04-2018.

Bachmaier, M., Backes, M., 2011. *Variogram or semivariogram? Variance or semivariance? Allan variance or introducing a new term?* Mathematical Geosciences, vol: 43, 735-740.

Beets, D.J., van der Spek, A.J.F., 2000. *The Holocene evolution of the barrier and the back-barrier basins of Belgium and the Netherlands as a function of late Weichselian morphology, relative sea-level rise and sediment supply*. Netherlands Journal of Geosciences, vol: 79, 3-16.

Box, G.E., Cox, D.R., 1964. *An analysis of transformations*. Journal of the Royal Statistical Society. Series B (Methodological), 211-252.

Bristow, C.S., Jol, H.M., 2003. *An introduction to ground penetrating radar (GPR) in sediments*. Geological Society, London, Special Publications, vol: 211, 1-7.

Brooker, P., 1986. *A parametric study of robustness of kriging variance as a function of range and relative nugget effect for a spherical semivariogram*. Mathematical Geology, vol: 18, 477-488.

Burgess, T., Webster, R., McBratney, A., 1981. *Optimal interpolation and isarithmic mapping of soil properties. IV Sampling strategy*. European Journal of Soil Science, vol: 32, 643-659.

Candel, J.H.J., Makaske, B., Storms, J.E.A., Wallinga, J., 2017. *Oblique aggradation: a novel explanation for sinuosity of low-energy streams in peat-filled valley systems*. Earth Surface Processes and Landforms.

Casparie, W., 1993. *The Bourtanger Moor: endurance and vulnerability of a raised bog system*, Netherlands-Wetlands. Springer, p. 203-215.

Casparie, W., Tonnis, W., de Vries, J., 2008. *Bargerveen: de veengroei in het natuurreservaat Bargerveen*. Staatsbosbeheer Regio Noord.

Chapman, H.P., Gearey, B.R., 2013. *Modelling Archaeology and Palaeoenvironments in Wetlands: the hidden landscape archaeology of Hatfield and Thorne Moors, eastern England*. Oxbow Books.

Cressie, N., 1990. *The origins of kriging*. Mathematical geology, vol: 22, 239-252.

Daniels, D.J., 2005. *Ground penetrating radar*. Wiley Online Library.

de Brabantse Kempen, 2017. *Natuurgebied de Moeren*. Available at https://www.tipdebrabantsekempen.nl/nl/natuur-omgeving/item/90-natuurgebied-de-moeren, accessed on 12-10-2017.

De Zeeuw, J.W., 1978. *Peat and the dutch golden Age*. The historical meaning of energy attainability, vol: 21, 3-31.

Deforce, K., Bastiaens, J., Ameels, V., 2007. *Peat re-excavated at the Abbey of Ename (Belgium): archaeobotanical evidence for peat extraction and long distance transport in Flanders around 1200 AD*. Environmental Archaeology, vol: 12, 87-94.

DINOloket, 2017. *Aanleveren Booronderzoek*. Available at https://www.dinoloket.nl/aanleveren-booronderzoek, accessed on 07-09-2017.

Eurola, S., Hicks, S., Kaakinen, E., 2013. *Key to Finnish Mire Types*, in: Moore, P.D. (Ed.), European mires. Academic Press, p. 11-118.

European Environment Agency, 2017. *Natura 2000 End 2016 - Shapefile*. Available at https://www.eea.europa.eu/data-and-maps/data/natura-8/natura-2000-spatial-data/natura-2000-shapefile-1, accessed on 11-10-2017.

Finlay, P.I., Parry, N.S., Proskin, S.A., Mickle, R.J., 2008. *An overview of ice profiling using Ground Penetrating Radar (GPR)*, at 21st EEGS Symposium on the Application of Geophysics to Engineering and Environmental Problems.

Foster, D., Wright Jr, H., Thelaus, M., King, G., 1988. *Bog development and landform dynamics in central Sweden and south-eastern Labrador, Canada*. The Journal of Ecology, 1164-1185.

Gerding, M., 1995. *Vier eeuwen turfwinning. De verveningen in Groningen, Friesland, Drenthe en Overijssel tussen 1550–1950. AAG Bijdragen 35.*

Gobin, A., Campling, P., Feyen, J., 2001. *Soil-landscape modelling to quantify spatial variability of soil texture*. Physics and Chemistry of the Earth, Part B: Hydrology, Oceans and Atmosphere, vol: 26, 41-45.

Google Developers, 2017. *KML Tutorial*. Available at https://developers.google.com/kml/documentation/kml_tut, accessed on 02-06-2018.

Goulard, M., Voltz, M., 1992. *Linear coregionalization model: tools for estimation and choice of cross-variogram matrix*. Mathematical Geology, vol: 24, 269-286.

GPSVisualizer, 2018. *Convert a GPS file to plain text or GPX* Available at http://www.gpsvisualizer.com/convert_input, accessed on 19-01-2018.

Griffin, S., Pippett, T., 2002. *Ground penetrating radar*. Geophysical and Remote Sensing Methods for Regolith Exploration. CRC LEME Open File report, vol: 144, 80-89.

Heiri, O., Lotter, A.F., Lemcke, G., 2001. *Loss on ignition as a method for estimating organic and carbonate content in sediments: reproducibility and comparability of results*. Journal of paleolimnology, vol: 25, 101-110.

Hengl, T., Heuvelink, G.B., Stein, A., 2004. *A generic framework for spatial prediction of soil variables based on regression-kriging*. Geoderma, vol: 120, 75-93.

Kleijnen, J.P., 2009. *Kriging metamodeling in simulation: A review*. European journal of operational research, vol: 192, 707-716.

Komunjer, I., 2009. *Global identification of the semiparametric Box–Cox model*. Economics Letters, vol: 104, 53-56.

Kyriakidis, P.C., Shortridge, A.M., Goodchild, M.F., 1999. *Geostatistics for conflation and accuracy assessment of digital elevation models*. International Journal of Geographical Information Science, vol: 13, 677-707.

Lamentowicz, M., Gałka, M., Obremska, M., Kühl, N., Lücke, A., Jassey, V., 2015. *Reconstructing climate change and ombrotrophic bog development during the last 4000years in northern Poland using biotic proxies, stable isotopes and trait-based approach*. Palaeogeography, palaeoclimatology, palaeoecology, vol: 418, 261-277.

LANUV NRW, 2013. *Naturschutzgebiet Zwillbrocker Venn (BOR-008)*. Available at http://nsg.naturschutzinformationen.nrw.de/nsg/de/fachinfo/gebiete/gesamt/BOR_008, accessed on 12-10-2017.

Lark, R., Papritz, A., 2003. *Fitting a linear model of coregionalization for soil properties using simulated annealing*. Geoderma, vol: 115, 245-260.

Lechler, P., Desilets, M., 1987. *A review of the use of loss on ignition as a measurement of total volatiles in whole-rock analysis*. Chemical Geology, vol: 63, 341-344.

Leenders, K.A.H.W., 2014. *Verdwenen venen. Een onderzoek naar de ligging en exploitatie van thans verdwenen venen in het gebied tussen Antwerpen, Turnhout, Geertruidenberg en Willemstad 1250-1750. Herz. dr*. Pictures Publishers.

Leopold, M., Völkel, J., 2003. *GPR images of periglacial slope deposits beneath peat bogs in the Central European Highlands, Germany*. Geological Society, London, Special Publications, vol: 211, 181-189.

LNV, 2018. *Natura 2000-gebieden per provincie*. Available at https://www.synbiosys.alterra.nl/natura2000/gebiedendatabase.aspx?subj=n2k&groep=0, accessed on 02-06-2018.

Lowry, C.S., Fratta, D., Anderson, M.P., 2009. *Ground penetrating radar and spring formation in a groundwater dominated peat wetland*. Journal of Hydrology, vol: 373, 68-79.

Lunt, I., Hubbard, S., Rubin, Y., 2005. *Soil moisture content estimation using ground-penetrating radar reflection data*. Journal of Hydrology, vol: 307, 254-269.

Miller, D.M., 1984. *Reducing transformation bias in curve fitting*. The American Statistician, vol: 38, 124-126.

Montanarella, L., Jones, R.J., Hiederer, R., 2006. *The distribution of peatland in Europe*. Mires and Peat, vol: 1, 1-11.

Mowrer, H.T., 1997. *Propagating uncertainty through spatial estimation processes for old-growth subalpine forests using sequential Gaussian simulation in GIS*. Ecological Modelling, vol: 98, 73-86.

Myers, D.E., 1982. *Matrix formulation of co-kriging*. Journal of the International Association for Mathematical Geology, vol: 14, 249-257.

Neal, A., 2004. *Ground-penetrating radar and its use in sedimentology: principles, problems and progress*. Earth-science reviews, vol: 66, 261-330.

NWO, 2017. *Home Turf. An integrated approach to the long-term development, cultural connections and heritage management of Dutch raised bogs*. Available at https://www.nwo.nl/onderzoek-en-resultaten/onderzoeksprojecten/i/49/26749.html, accessed on 06-09-2017.

Osborne, J.W., 2010. *Improving your data transformations: Applying the Box-Cox transformation*. Practical Assessment, Research & Evaluation, vol: 15, p.2.

Pebesma, E., 2017a. *R Documentation: fit.lmc*. Available at https://www.rdocumentation.org/packages/gstat/versions/1.1-6/topics/fit.lmc, accessed on 19-12-2017.

Pebesma, E., 2017b. *R Documentation: fit.variogram*. Available at https://www.rdocumentation.org/packages/gstat/versions/1.1-4/topics/fit.variogram, accessed on 12-09-2017.

Pebesma, E., 2017c. *R Documentation: krige*. Available at https://www.rdocumentation.org/packages/gstat/versions/1.1-5/topics/krige, accessed on 12-09-2017.

Pebesma, E., 2017d. *R Documentation: krige.cv*. Available at https://www.rdocumentation.org/packages/gstat/versions/1.1-5/topics/krige.cv, accessed on 12-09-2017.

Pebesma, E., 2017e. *R Documentation: predict*. Available at https://www.rdocumentation.org/packages/gstat/versions/1.1-5/topics/predict, accessed on 12-09-2017.

Pebesma, E., 2017f. *R Documentation: spplot*. Available at https://www.rdocumentation.org/packages/sp/versions/1.2-5/topics/spplot, accessed on 12-09-2017.

Perron, T.J., Fagherazzi, S., 2012. *The legacy of initial conditions in landscape evolution*. Earth Surface Processes and Landforms, vol: 37, 52-63.

Pingoruines, 2017. *Zeijen | 1646 | Bollenveen*. Available at http://www.pingoruines.nl/diversen/locaties/zeijen-1646/, accessed on 12-10-2017.

Pîrnău, R.G., Mihu-Pintilie, A., Bodi, G., Asăndulesei, A., Niacșu, L., 2014. *Ground penetrating radar as noninvasive method used in soil science and archaeology*. Soil Forming Factors and Processes from the Temperate Zone, vol: 13, 15-31.

Proulx-McInnis, S., St-Hilaire, A., Rousseau, A.N., Jutras, S., 2013. *A review of ground-penetrating radar studies related to peatland stratigraphy with a case study on the determination of peat thickness in a northern boreal fen in Quebec, Canada*. Progress in Physical Geography, vol: 37, 767-786.

R Studio, 2016. *R Markdown*. Available at https://rmarkdown.rstudio.com/, accessed on 01-05-2018.

Refaeilzadeh, P., Tang, L., Liu, H., 2009. *Cross-validation*, Encyclopedia of database systems. Springer, p. 532-538.

Rossiter, D.G., 2012. *Technical note: co-kriging with the gstat package of the R environment for statistical computing*

Sarkar, D., 2018. *R documentation: 3d Scatter Plot and Wireframe Surface Plot*. Available at https://www.rdocumentation.org/packages/lattice/versions/0.20-35/topics/B_07_cloud, accessed on 16-04-2018.

Schoorl, J., Sonneveld, M., Veldkamp, A., 2000. *Three-dimensional landscape process modelling: the effect of DEM resolution*. Earth Surface Processes and Landforms, vol: 25, 1025-1034.

Segal, S., 1966. *Ecological studies of peat-bog vegetation in the north-western part of the province of Overijsel (The Netherlands)*. Wentia, vol: 15, 109-141.

Staatsbosbeheer, 2017a. *De Pelen - Over De Pelen*. Available at https://www.staatsbosbeheer.nl/natuurgebieden/de-pelen/over-de-pelen, accessed on 12-10-2017.

Staatsbosbeheer, 2017b. *De Pelen - Toegankelijkheid*. Available at https://www.staatsbosbeheer.nl/natuurgebieden/de-pelen/toegankelijkheid, accessed on 12-10-2017.

Staatsbosbeheer, 2017c. *Drentse Aa - Over de Drentse Aa*. Available at https://www.staatsbosbeheer.nl/natuurgebieden/drentsche-aa/over-de-drentsche-aa accessed on 12-10-2017.

Staatsbosbeheer, 2017d. *Drentse Aa - Toegankelijkheid*. Available at https://www.staatsbosbeheer.nl/natuurgebieden/drentsche-aa/toegankelijkheid, accessed on 12-10-2017.

Staatsbosbeheer, 2017e. *Kempen - Toegankelijkheid*. Available at https://www.staatsbosbeheer.nl/Natuurgebieden/kempen/Toegankelijkheid, accessed on 12-10-2017.

Staatsbosbeheer, 2017f. *Twente - Over Twente*. Available at https://www.staatsbosbeheer.nl/natuurgebieden/twente/over-twente, accessed on 12-10-2017.

Staatsbosbeheer, 2017g. *Twente - Toegankelijkheid*. Available at https://www.staatsbosbeheer.nl/natuurgebieden/twente/toegankelijkheid, accessed on 12-10-2017.

Staatsbosbeheer, 2017h. *Veenland - Over het Veenland*. Available at https://www.staatsbosbeheer.nl/natuurgebieden/veenland/over-het-veenland accessed on 12-10-2017.

Staatsbosbeheer, 2017i. *Veenland - Toegankelijkheid*. Available at https://www.staatsbosbeheer.nl/natuurgebieden/veenland/toegankelijkheid, accessed on 12-10-2017.

Statistics How To, 2018. *What is a Box-Cox Transformation?* Available at http://www.statisticshowto.com/box-cox-transformation/, accessed on 22-03-2018.

Stein, M.L., 2012. *Interpolation of spatial data: some theory for kriging*. Springer Science & Business Media.

Streefkerk, J., Casparie, W., 1989. *The hydrology of bog ecosystems*. Guidelines for management. Staatsbosbeheer, The Netherlands.

Svensson, G., 1988. *Bog development and environmental conditions as shown by the stratigraphy of Store Mosse mire in southern Sweden*. Boreas, vol: 17, 89-111.

Temme, A., Armitage, J., Attal, M., Gorp, W., Coulthard, T., Schoorl, J., 2017. *Developing, choosing and using landscape evolution models to inform field-based landscape reconstruction studies*. Earth Surface Processes and Landforms.

Tran, T.T., 1994. *Improving variogram reproduction on dense simulation grids*. Computers & Geosciences, vol: 20, 1161-1168.

Van Beek, R., Maas, G., Van den Berg, E., 2015. *Home Turf: an interdisciplinary exploration of the long-term development, use and reclamation of raised bogs in the Netherlands*. Landscape History, vol: 36, 5-34.

Van Beek, R., Paulissen, M., Quik, C., 2017. *Home Turf - An integrated approach to Dutch raised bogs*. Available at http://www.wur.nl/nl/project/Home-Turf.htm, accessed on 06-09-2017.

Van Geel, B., Buurman, J., Waterbolk, H.T., 1996. *Archaeological and palaeoecological indications of an abrupt climate change in The Netherlands, and evidence for climatological teleconnections around 2650 BP*. Journal of Quaternary Science, vol: 11, 451-460.

Van Hoof, B.I., 2014. *Drie locaties nabij het Bargerveen, gemeente Emmen; archeologisch vooronderzoek: een bureauonderzoek en verkennend veldonderzoek*

Verhoeven, J.T.A., 2013. *Fens and bogs in the Netherlands: vegetation, history, nutrient dynamics and conservation*. Springer Science & Business Media.

Wageningen Environmental Research, 2017a. *Bodemkundig Informatie Systeem (BIS) Nederland*. Available at http://www.wur.nl/nl/Expertises-Dienstverlening/Onderzoeksinstituten/Environmental-Research/Faciliteiten-Producten/Bodemkundig-Informatie-Systeem-BIS-Nederland.htm, accessed on 04-09-2017.

Wageningen Environmental Research, 2017b. *GeoDesk*. Available at http://www.wur.nl/nl/Expertises-Dienstverlening/Onderzoeksinstituten/Environmental-Research/Faciliteiten-Producten/GeoDesk.htm, accessed on 13-07-2017.

Warner, B.G., Nobes, D.C., Theimer, B.D., 1990. *An application of ground penetrating radar to peat stratigraphy of Ellice Swamp, southwestern Ontario*. Canadian Journal of Earth Sciences, vol: 27, 932-938.

Xie, Y., 2018. *R documentation: saveGIF*. Available at https://www.rdocumentation.org/packages/animation/versions/2.5/topics/saveGIF, accessed on 09-05-2017.

Xie, Y., Yu, L., 2017. *Convert images to a single animation file (typically GIF) using ImageMagick or GraphicsMagick*. Available at https://yihui.name/animation/example/savegif/, accessed on 09-05-2018.

Zwillbrock Biologische Station, 2017. *Betreuung von Schutzgebieten*. Available at http://www.bszwillbrock.de/biologische-station/betreute-gebiete/, accessed on 12-10-2017.

10. APPENDICES

Appendix A GPR PARAMETERS FOR DIFFERENT MATERIALS

TABLE 10.1: GPR VELOCITY TABLE AND ANALYSIS OF VELOCITY, DIELECTRIC CONSTANTS, ATTENUATION AND CONDUCTIVITY FOR MATERIALS FROM VARIOUS SOURCES (GPR RENTAL, 2018).

Material	Dielectric constant K	Conductivity (mS/m)	GPR velocity (m/ns)	Attenuation (dB/m)
Air	1	0	0.3	
Air			0.31	
Air	1	0	0.3	
Air	1	0	0.3	0
Air	1	0	0.3	0
Air	1	0		
Asphalt	3 to 5		0.173 to 0.134	
Asphalt			0.14	
Asphalt (dry)	3	.001 to .01		
Asphalt (wet)	9	.01 to .1		
Basalt (Wet)			0.11	
Bauxite (Dry)			0.06	
Clay (Dry)			0.15	
Clay (saturated freshwater)	8 to 12		.09 to 0.11	
Clay (wet)	8 to 12	100 to 1000	0.106 to 0.087	
Clay (Wet)			0.06	
Clay (wet)	10	100 to 1000		
Clayey Soil (dry)	2.4	0.27		
Clayey Soil (wet)	15	50		
Clays	5 to 40	2 to 1000	0.06	1 to 300
Clays	5 to 40	2 to 1000	0.06	1 to 300
Coal	4 to 5		0.15 to 0.134	
Coal			0.14	
Concrete	5 to 10		0.134 to 0.095	
Concrete (Dry)			0.13	
Concrete (dry)	7	.001 to .01		
Concrete (Wet)			0.09	
Concrete (wet)	15	0.01 to 0.1		
Dolomite	6 to 8		0.122 to 0.106	

Dry Salt			0.13	
Dry Salt	5 to 6	0.01 to 1	0.13	
Dry Salt	5 to 6	0.01 to 1	0.13	.01 to 1
Dry, sandy, flat coastal land	10	2	0.095	
Dry, sandy, flat coastal land	10		0.09	
Granite	4 to 6	0.01 to 1	0.13	0.01 to 1
Granite	4 to 6	0.01 to 1	0.13	0.01 to 1
Granite (dry)	5	0.00001	0.134	
Granite (Dry)			0.14	
Granite (Wet)			0.12	
Granite (wet)	7	1		
Ice			0.15	
Ice	3 to 4	0.01	0.16	
Ice	3 to 4	0.01	0.16	0.01
Ice	4	1		
Ice Fresh Water	4	0.1 to 10	0.15	
Limestone	4 to 8	0.5 to 2	0.12	0.4 to 1
Limestone	4 to 8	0.5 to 2	0.12	0.4 to 1
Limestone (dry)	7 to 9	0.000001	0.113 to 0.1	
Limestone (Dry)			0.13	
Limestone (dry)	7		0.11	
Limestone (Wet)			0.11	
Limestone (wet)	8	25		
Loamy Soil (dry)	2.5	0.11		
Loamy Soil (wet)	19	21		
Loamy/Clayey Soils (Dry)			0.19	
Mineral/Sandy Soils (Dry)			0.13	
Mixed soil components saturated	5 to 15		0.08 to 0.13	
Organic Soils			0.04	
Peats			0.04	
Permafrost	4 to 8	0.01 to 10	0.15 to 0.106	
Permafrost	6	0.01 to 10		
Permafrost Frozen Soil			0.13	
Potash Ore			0.13	
PVC, Epoxy, Polyesters, Vinyls, Rubber	3		0.173	
Quartz	4		0.15	
Rock (dry)	5	0.00001		

Sand & Gravel (Dry)			0.13	
Sand & Gravel Frozen			0.14	
Sand (dry)	4 to 6	0.0001 to 1	0.15 to 0.12	
Sand (Dry)			0.15	
Sand (Dry)	3 to 5	0.01	0.15	0.01
Sand (Dry)	3 to 5	0.01	0.15	0.01
Sand (dry)	4.5	0.0001 to 1		
Sand (dry)	4 to 6		0.12 to 0.15	
Sand (dry) Quartz	1.8 to 6		0.12 to 0.22	
Sand (saturated freshwater)	30		0.05	
Sand (wet)	25	0.1 to 1	0.055	
Sand (Wet)			0.08	
Sand (Wet)	20 to 30	0.1 to 1.0	0.06	0.03 to 0.3
Sand (wet)	25	0.1 to 10		
Sand (wet) Quartz, and kaolinite, illite and smectite clays, saturated freshwater	9 to 67		0.04 to 0.10	
Sand and mixed soil components, dry	2 to 6		0.12 to 0.21	
Sand Saturated			0.06	
Sand Saturated	20 to 30	0.1 to 1.0	0.06	0.03 to 0.3
Sandstone (Wet)			0.13	
Sandstone (wet)	6	40		
Sandy Soil (dry)	2.6	0.14		
Sandy Soil (wet)	25	6.9		
Sandy Soils (Wet)			0.06	
Sea Ice	4 to 12		0.15 to 0.087	
Sea Water	70	400	0.033	
Sea Water	80	3000	0.01	1000
Sea Water	80	3000	0.01	1000
Sea Water	81	4000		
Sea Water	81		0.03	
Shale	5 to 15	1 to 100	0.09	1 to 100
Shale (wet)	7	100		
Shales	5 to 15	1 to 100	0.09	1 to 100
Silt (saturated)	10		0.09	
Silt (wet)	10	1 to 10	0.095	
Silt (wet)	10	1 to 100		

Silts	5 to 30	1 to 100	0.07	1 to 100
Silts	5 to 30	1 to 100	0.07	1 to 100
Snow			0.25	
Snow	1.4	0.001 to 0.01		
Syenite Porphyry			0.13	
Tills			0.09	
Travertine			0.11	
Volcanic Ash			0.09	
Water			0.03	
Water Distilled	80	0.01	0.033	0.002
Water Distilled	80	0.01	0.033	0.002
Water Fresh	81	0.10 to 30	0.033	
Water Fresh	81		0.03	
Water Fresh	80	0.5	0.033	0.1
Water Fresh	80	0.5	0.033	0.1
Water Fresh	80	0.5		

Appendix B ARCGIS TOOLBOX MODELS

B1. EUCLIDEAN DISTANCE

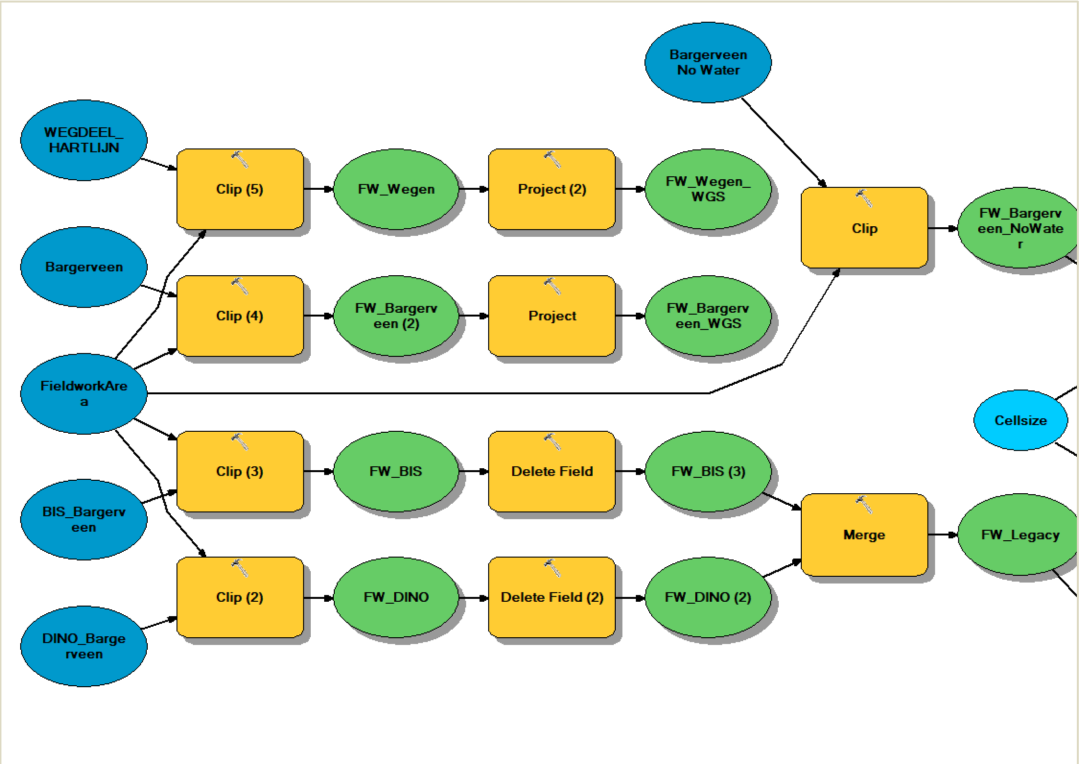

FIGURE 10.2: ARCGIS TOOLBOX MODEL FOR CREATING A SAMPLING STRATEGY (EUCLIDEAN DISTANCE CALCULATION AND REPROJECTION OF THE SHAPEFILES, PART 1.

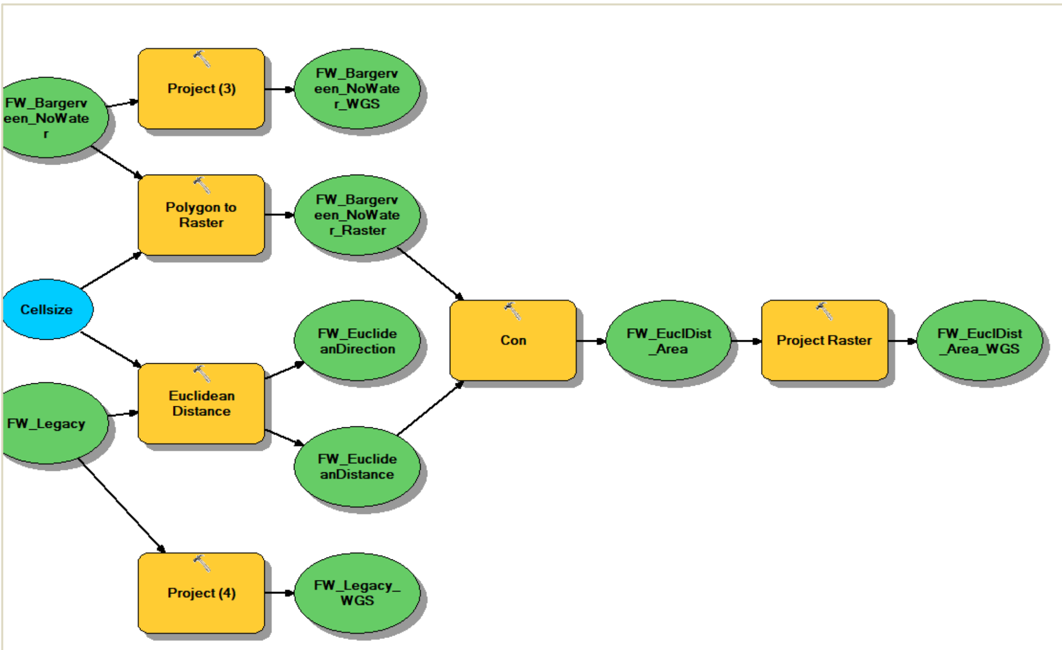

FIGURE 10.1: ARCGIS TOOLBOX MODEL FOR CREATING A SAMPLING STRATEGY (EUCLIDEAN DISTANCE CALCULATION AND REPROJECTION OF THE SHAPEFILES, PART 2

B2. IMPORT KML

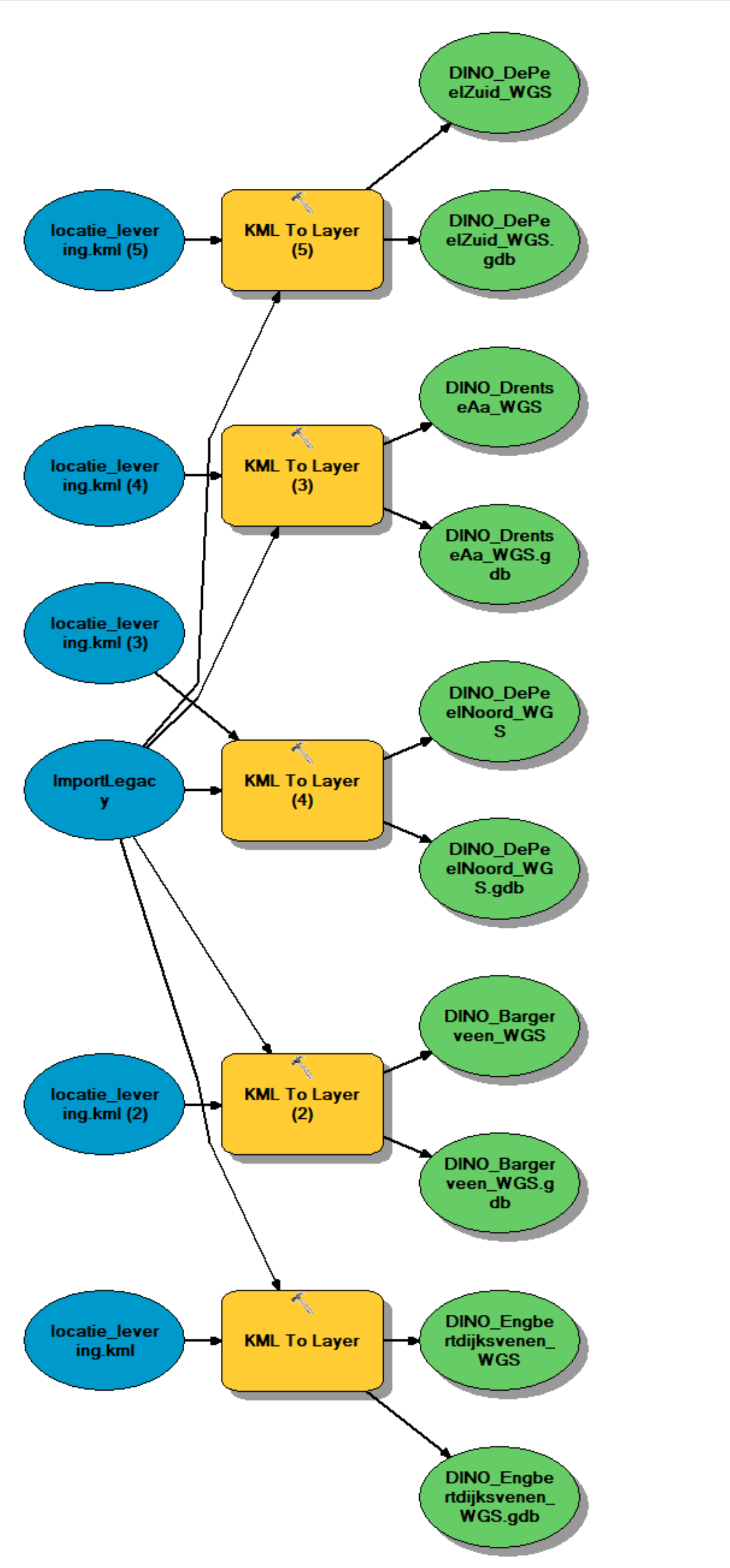

FIGURE 10.3: ARCGIS TOOLBOX MODEL FOR IMPORTING KML FILES.

B3. PREPARE DINO

FIGURE 10.4: ARCGIS TOOLBOX MODEL FOR PREPARING DINO LOCATIONS PER AREA

B4. PREPARE BIS

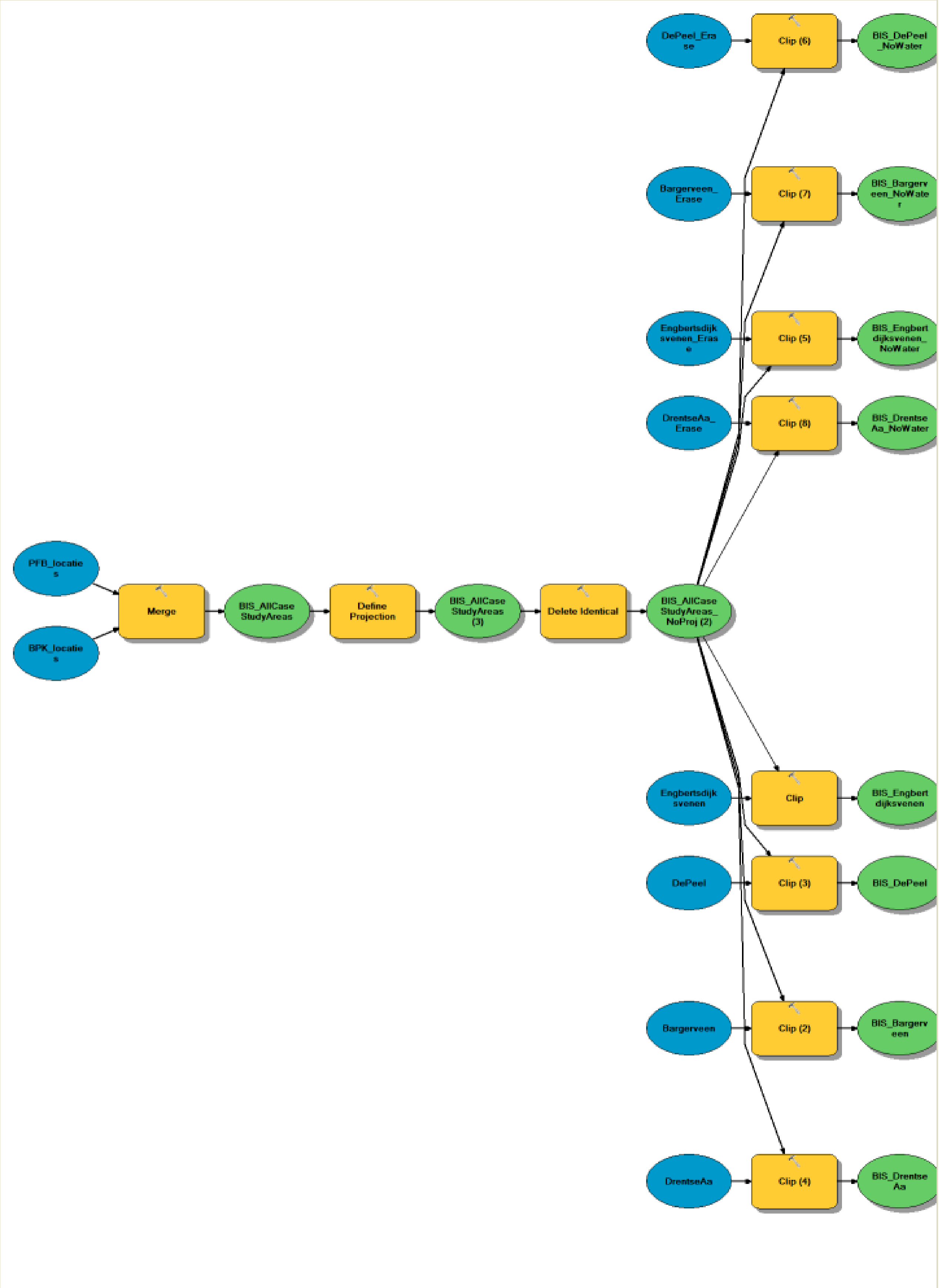

FIGURE 10.5: ARCGIS TOOLBOX MODEL FOR PREPARING BIS LOCATIONS PER AREA, PART 1.

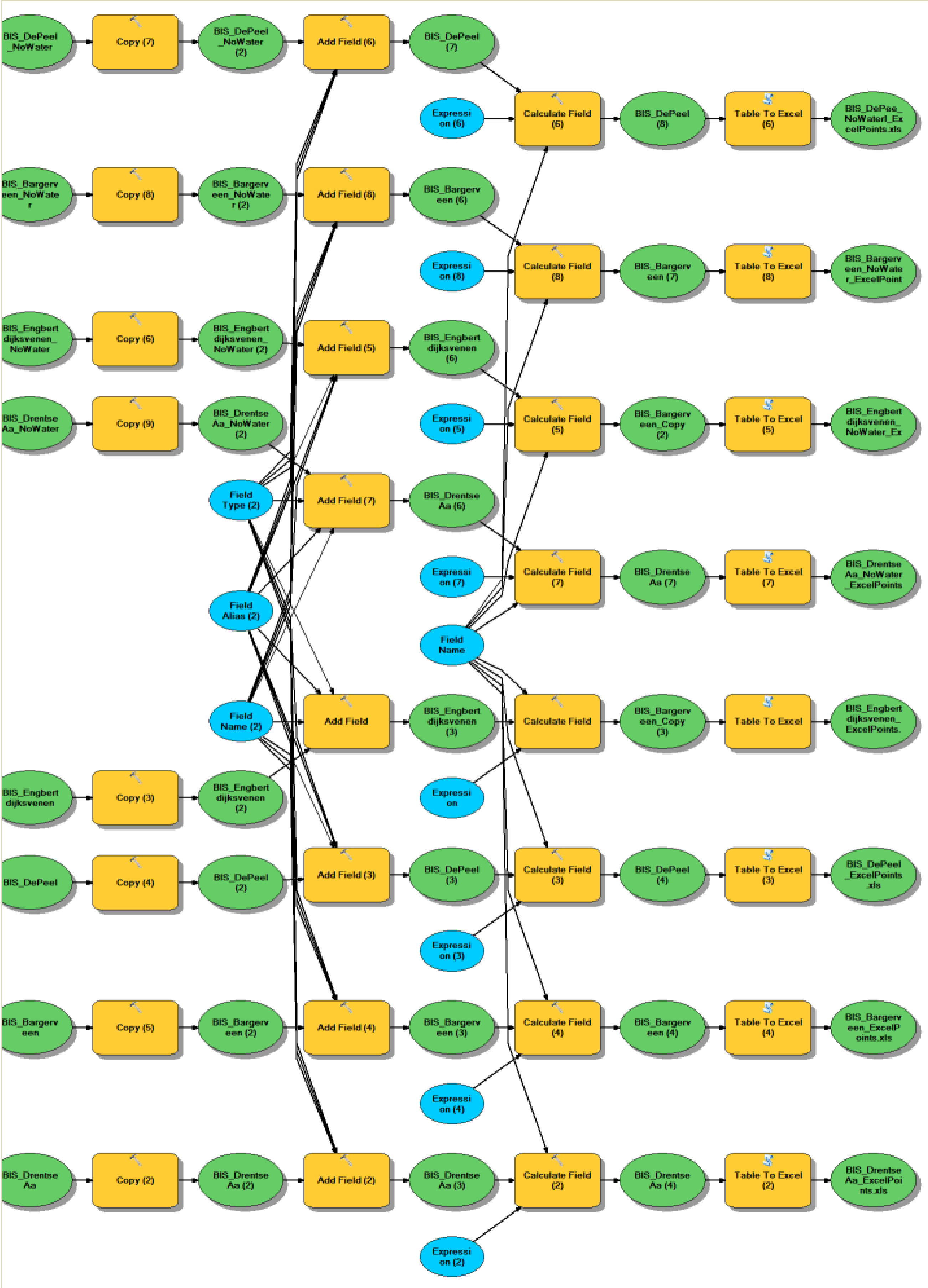

FIGURE 10.6: ARCGIS TOOLBOX MODEL FOR PREPARING BIS LOCATIONS PER AREA, PART 2.

B5. ADD AREA NAME TO LAYER INFORMATION BIS DATA

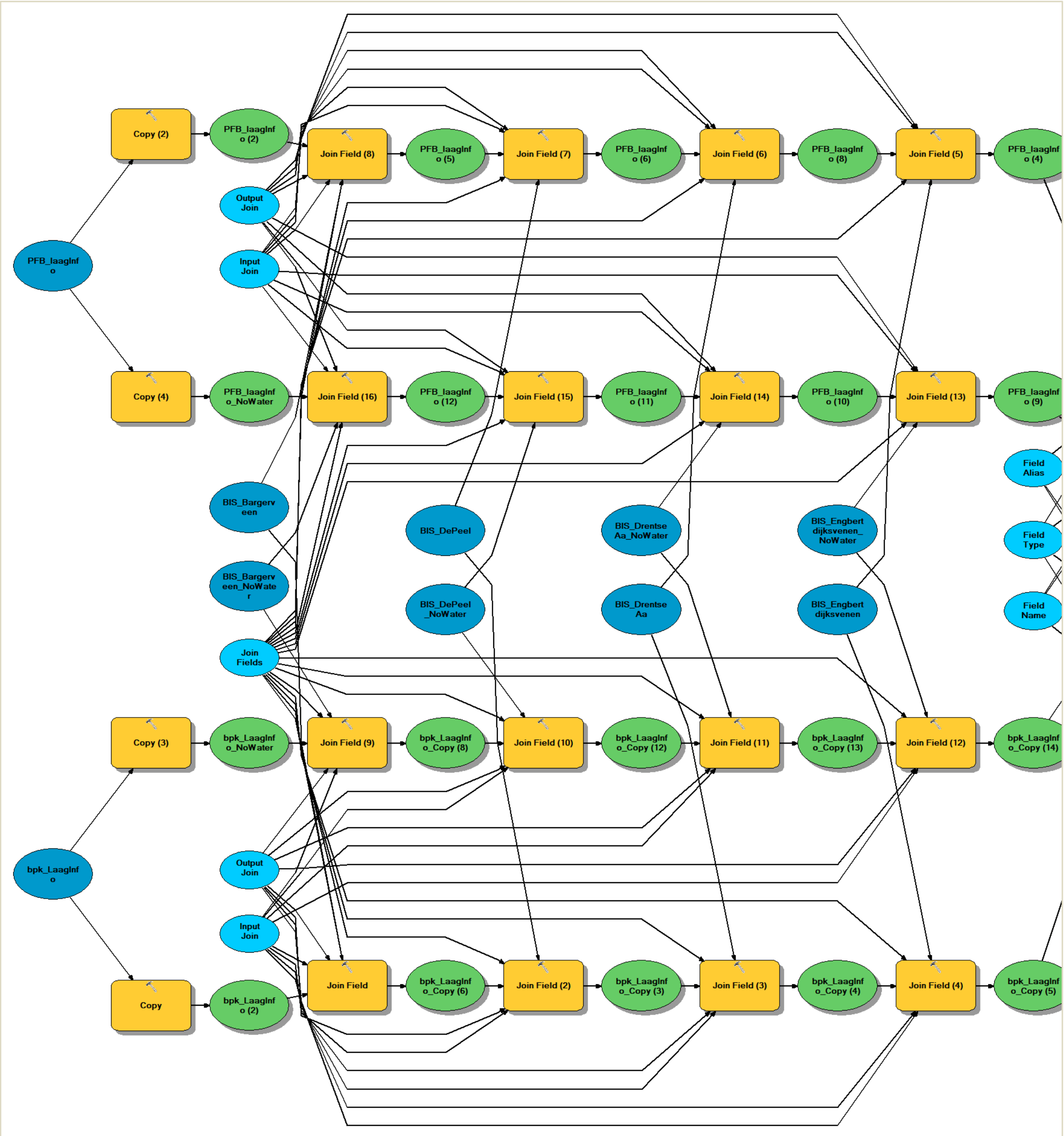

FIGURE 10.7: ARCGIS TOOLBOX MODEL FOR ADDING THE POTENTIAL CASE STUDY AREA NAME TO THE BIS LAYER INFORMATION DATA, PART 1.

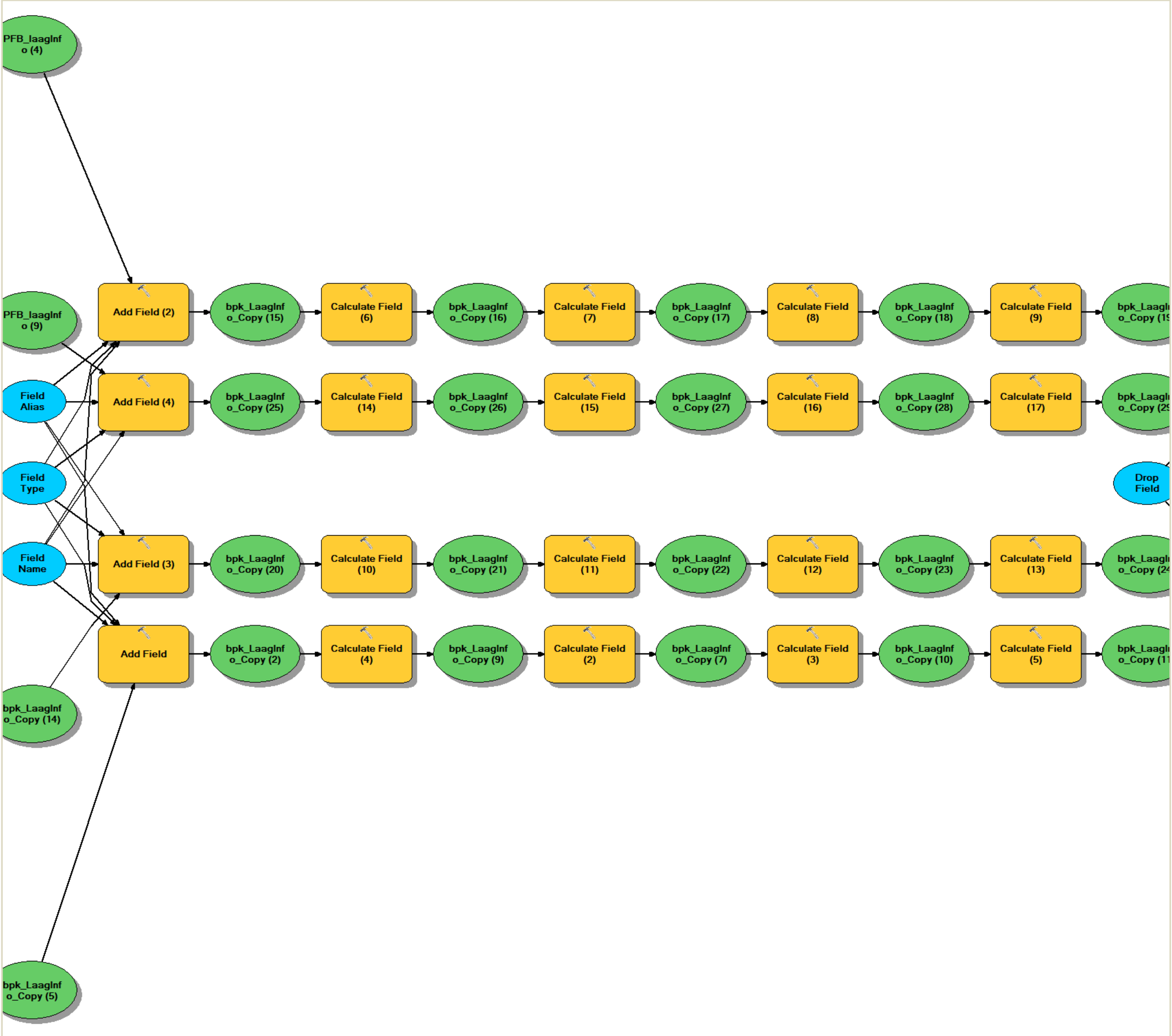

FIGURE 10.8: ARCGIS TOOLBOX MODEL FOR ADDING THE POTENTIAL CASE STUDY AREA NAME TO THE BIS LAYER INFORMATION DATA, PART 2.

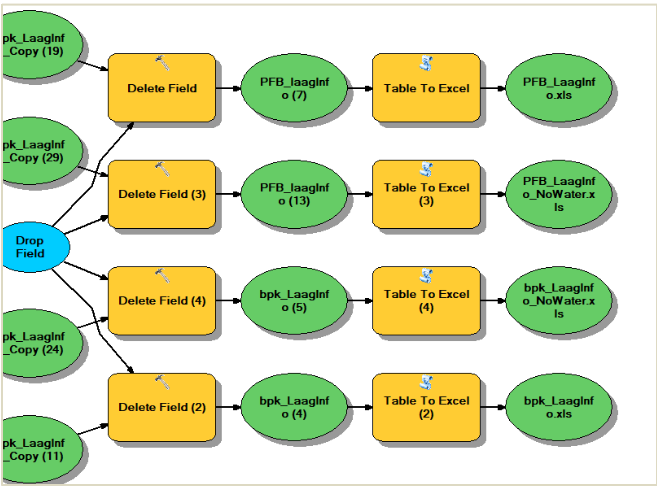

FIGURE 10.9: ARCGIS TOOLBOX MODEL FOR ADDING THE POTENTIAL CASE STUDY AREA NAME TO THE BIS LAYER INFORMATION DATA, PART 3.

B6. CREATE CASE STUDY AREA AND ASCII FILE

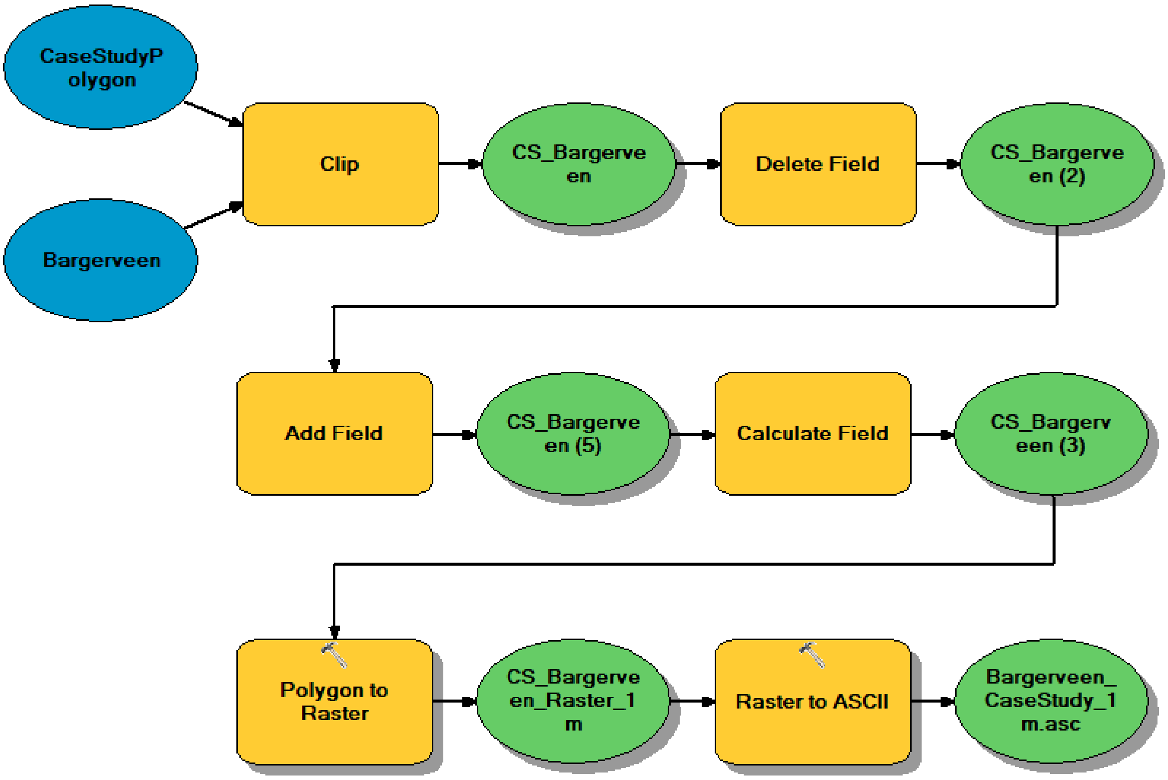

FIGURE 10.10: ARCGIS TOOLBOX MODEL FOR CREATING A SMALLER CASE STUDY AREA AND EXPORTING AN ASCII FILE OF THIS.

B7. CREATING LINES FROM THE .GPX DATA

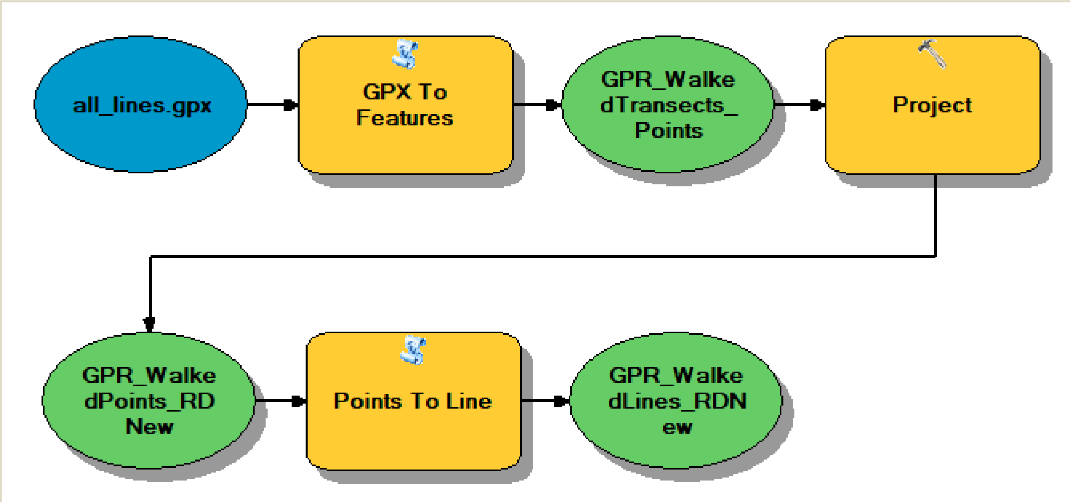

FIGURE 10.11: ARCGIS TOOLBOX MODEL FOR CREATING LINES OF THE WALKED GPR TRANSECTS FROM THE .GPX DATA

B8. CREATE AND EXPORT GPR POINTS

A new point feature class was created and a column was added for the Name of the point. The editor was started and the new feature class was edited. The corresponding created line (the GPR transects for which the calibration point was created) was selected. With the editor points were constructed and the distance was set to the distance of calibration points (in case more than one points were created the first point is highlighted). A distinction was made between “single” and “double” points. The single points were points that are not included in the 10 meter interval, the double points were also points found on the 10 meter interval (so the distance of the calibration point is a multiple of 10). The names of the points were added manually. The single and double calibration points were selected and two new layers were created from the selections. The singles and doubles were merged in order to display all calibration points at once and then sorted on name.

To find the coordinates of the 10 meter intervals used for the transition border depth determination, the same procedure as above was repeated, but instead of using the distance of the first calibration point, the distance was now set to 10 meters. All points on the line were selected and a new layer was created from this. Names of the points were calculated based on the ObjectID (ObjectID * 10 = distance of interval). Once this was done for all lines, all created points were merged. The “single” calibration points were also added to the merge. The points were sorted on name and the X and Y coordinates were calculated. Unused fields were deleted and all points were exported to Microsoft Excel

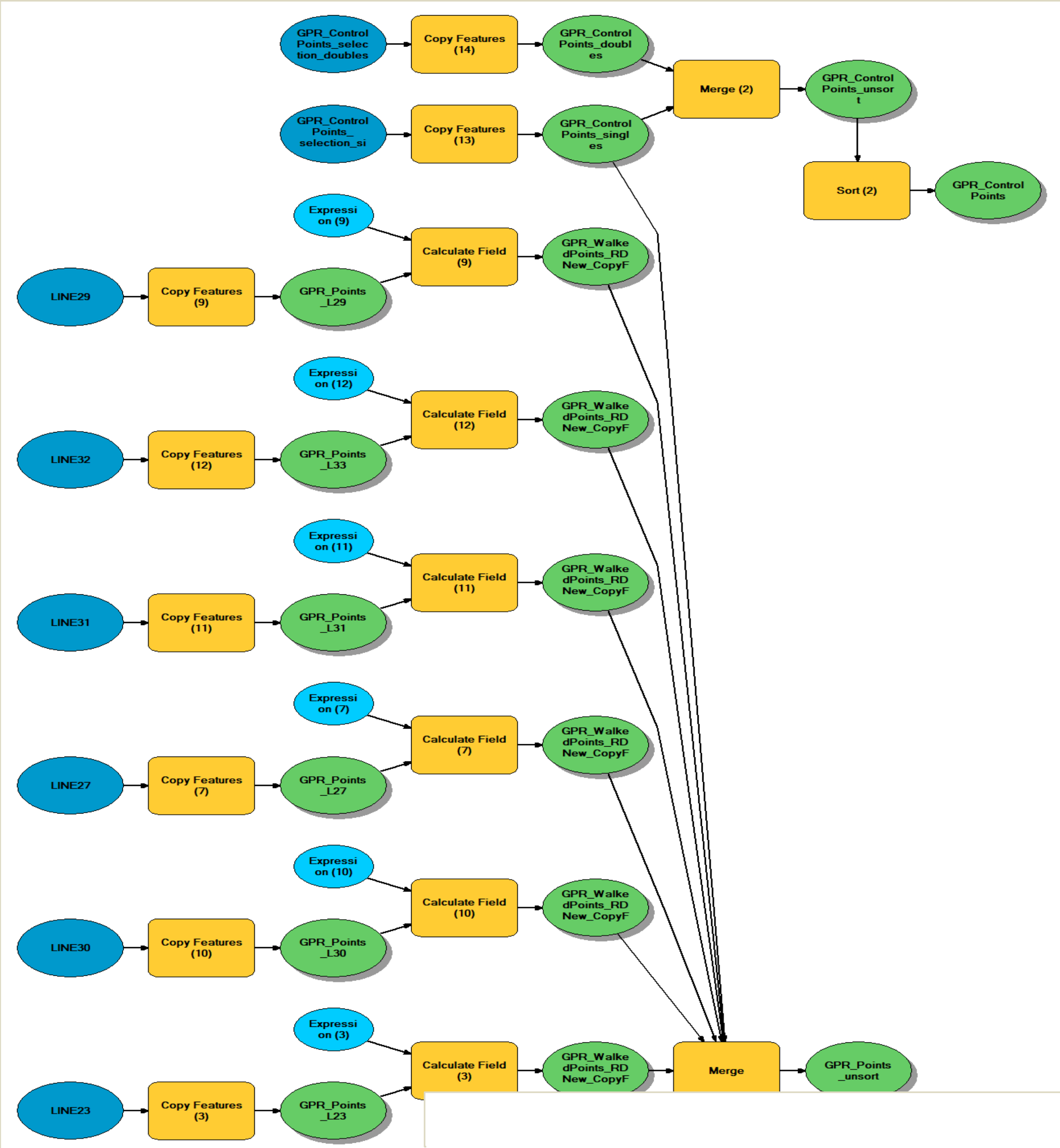

FIGURE 10.12: ARCGIS TOOLBOX MODEL FOR CREATING AND EXPORTING GPR POINTS, PART 1.

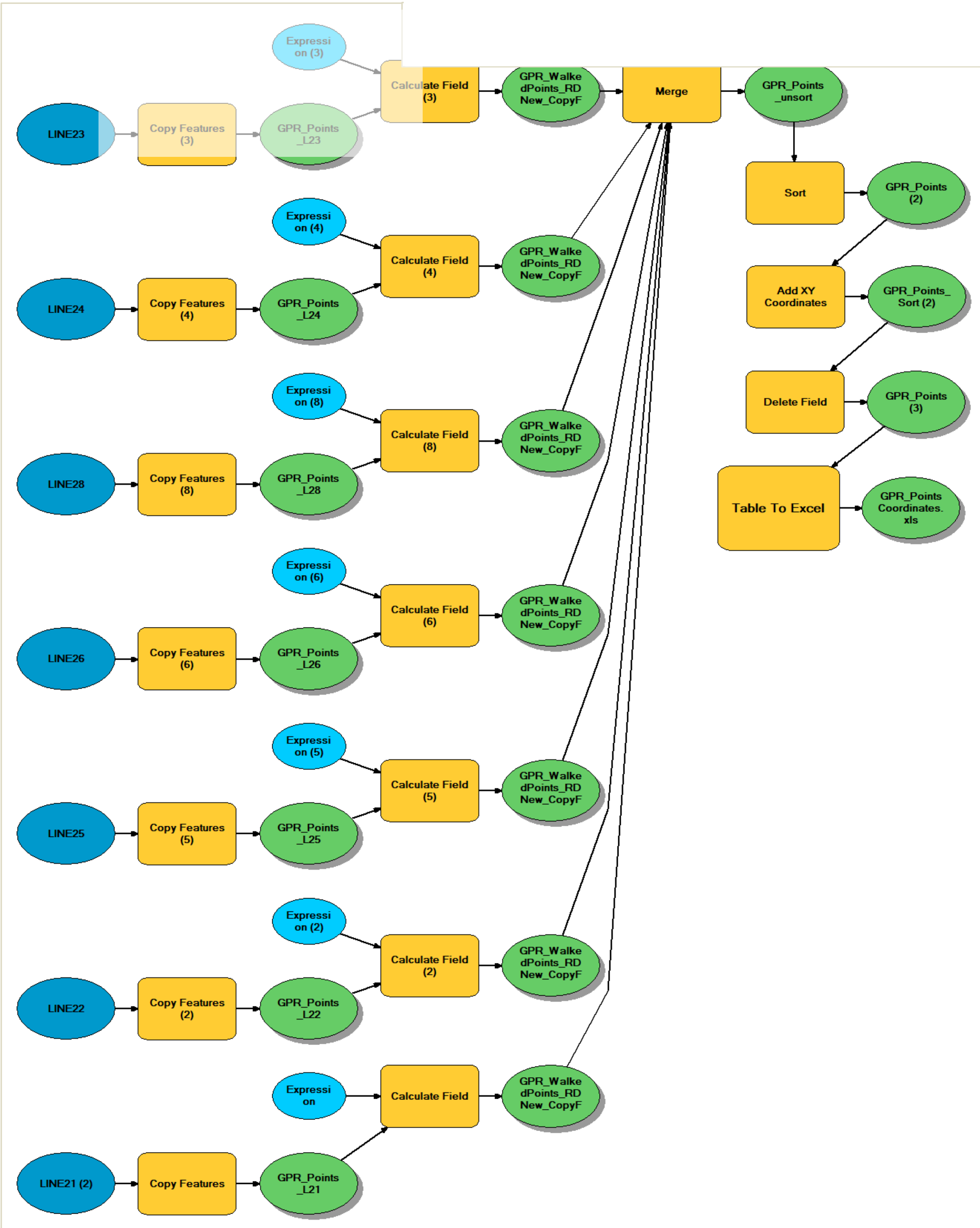

FIGURE 10.13: ARCGIS TOOLBOX MODEL FOR CREATING AND EXPORTING GPR POINTS, PART 2.

B9. CREATE SHAPEFILES POTENTIAL CASE STUDY AREAS

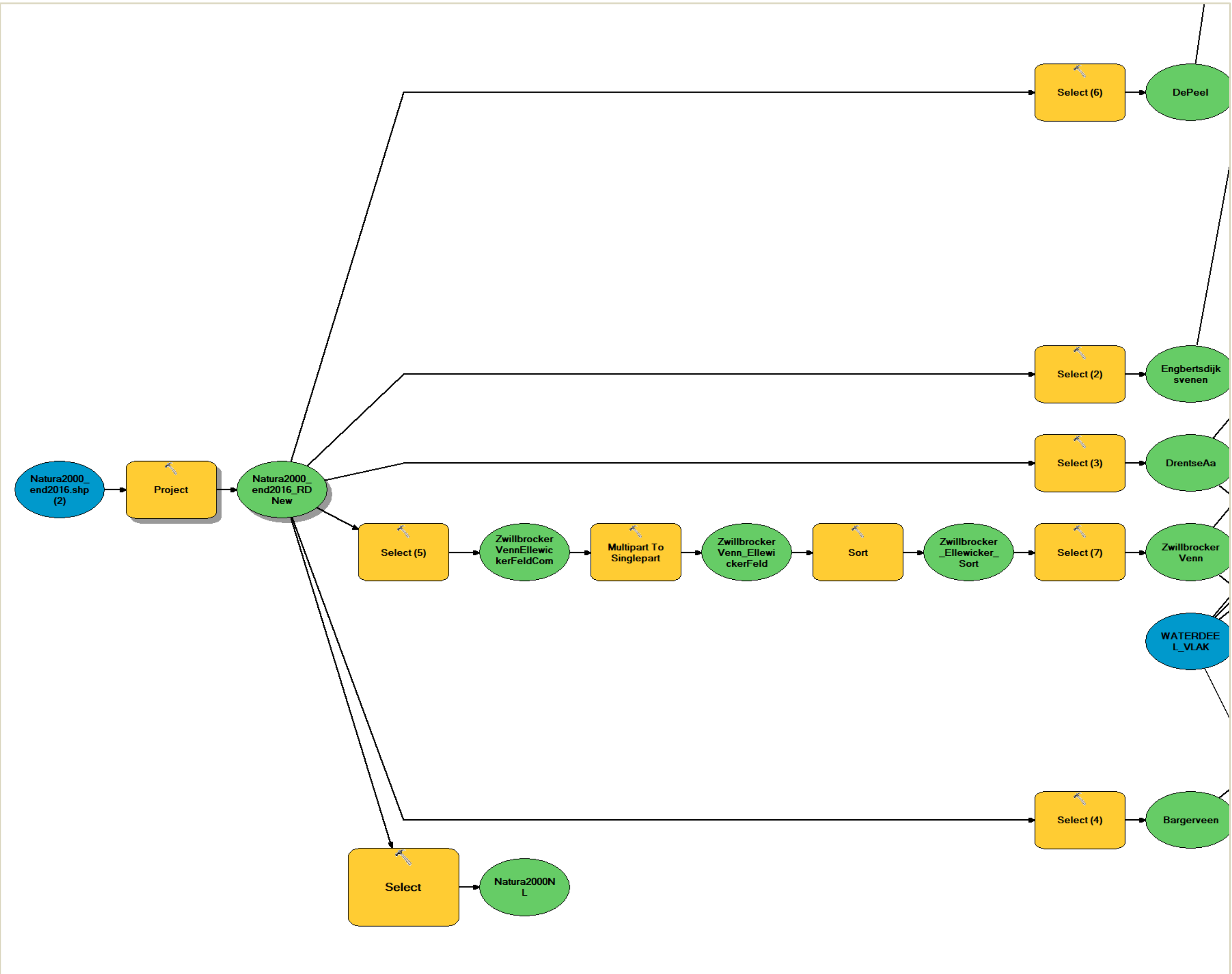

FIGURE 10.14: ARCGIS TOOLBOX MODEL FOR CREATING SHAPEFILES OF THE POTENTIAL CASE STUDY AREAS, PART 1.

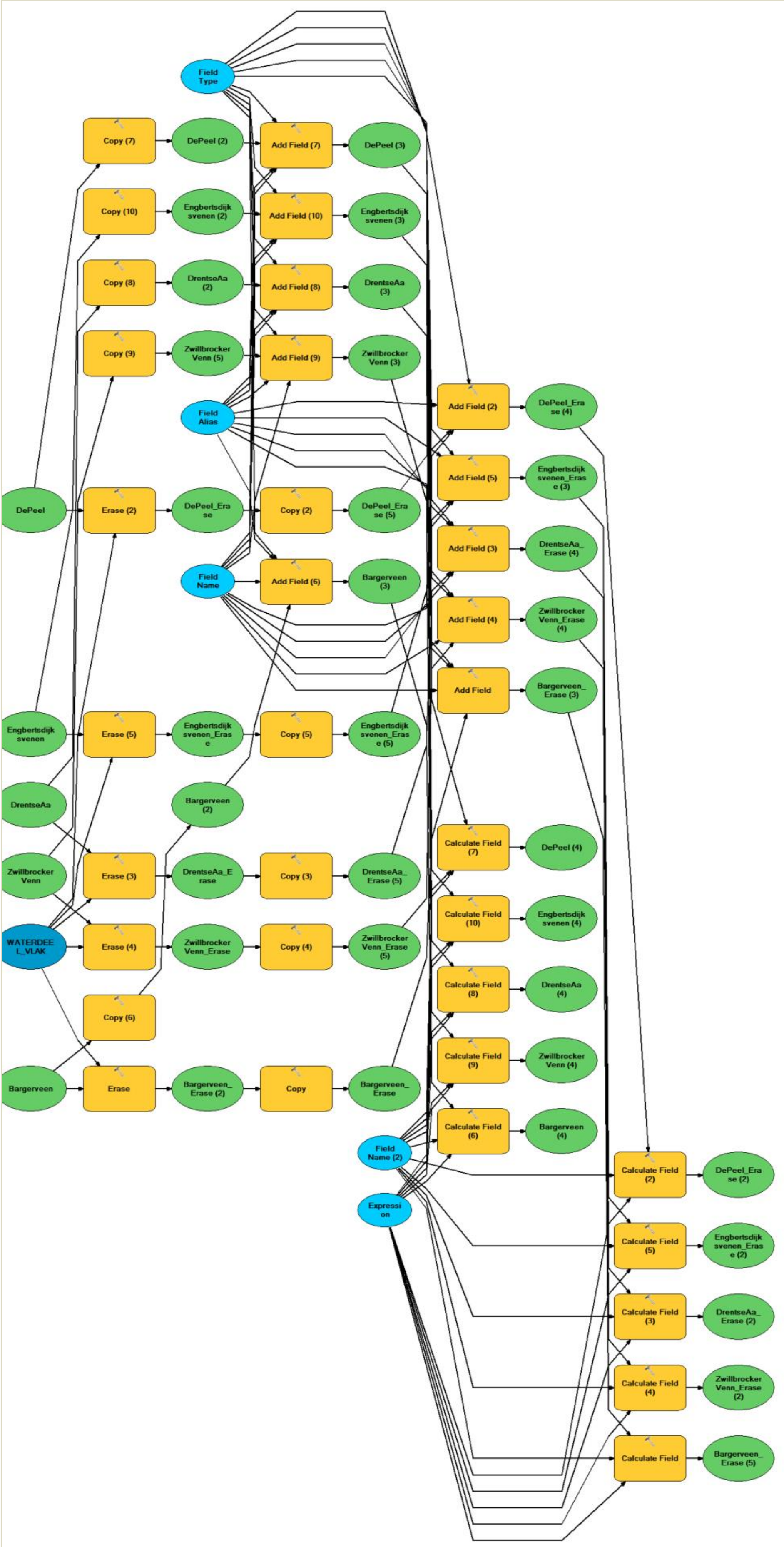

FIGURE 10.15: ARCGIS TOOLBOX MODEL FOR CREATING SHAPEFILES OF THE POTENTIAL CASE STUDY AREAS, PART 2.

Appendix C AREA MEASUREMENT BOLLENVEEN & REUSELSE MOEREN

FIGURE 10.16: AREA DETERMINATION OF THE BOLLENVEEN AND BOLLENVEEN WATER USING GOOGLE MAPS.

FIGURE 10.17: AREA DETERMINATION OF THE REUSELESE MOEREN USING GOOGLE MAPS.

Appendix D RADARGRAMS

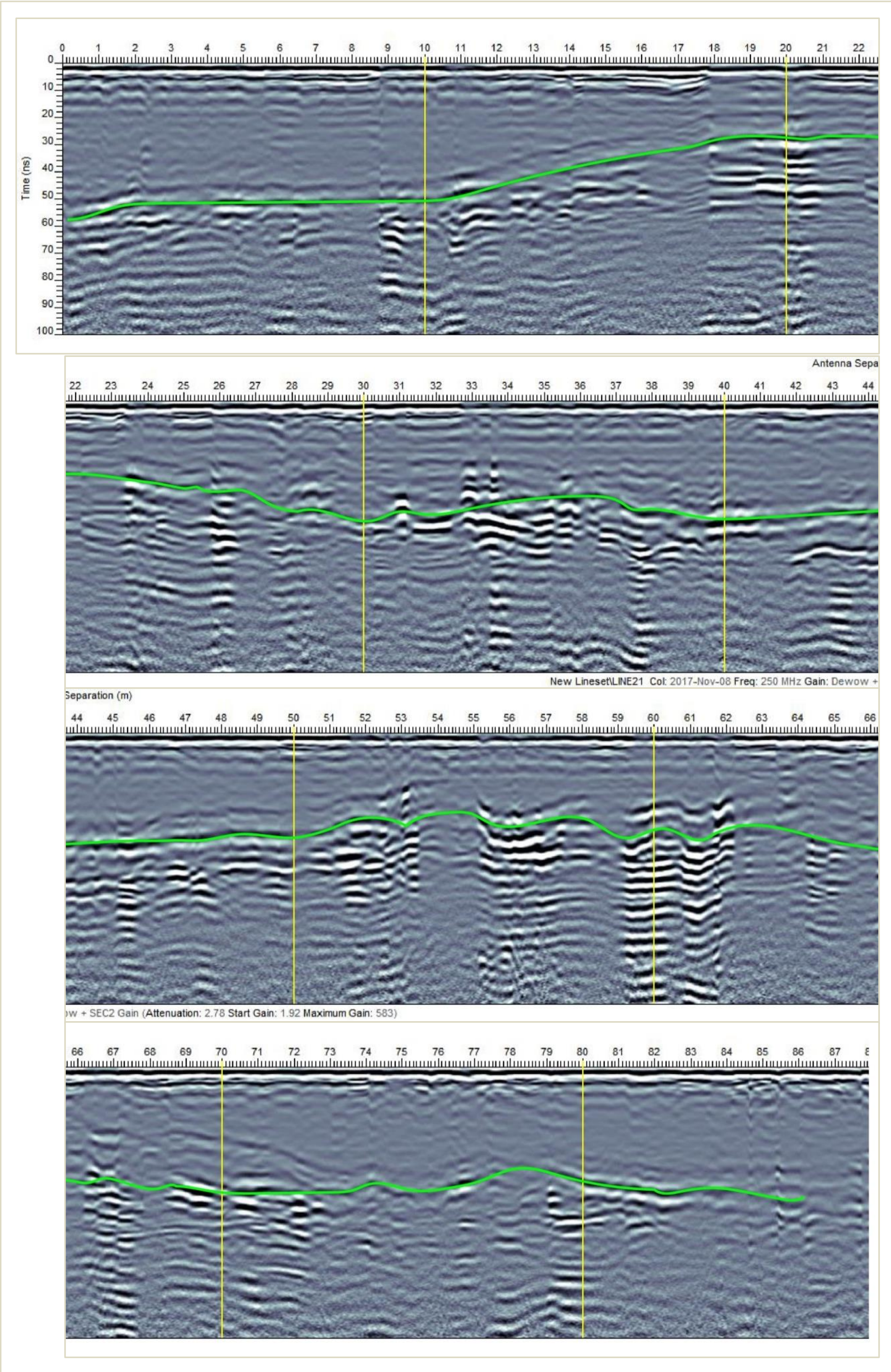

FIGURE 10.18: RADARGRAM LINE21. GREEN: TRANSITION BORDER AND YELLOW: 10M INTERVAL POINTS.

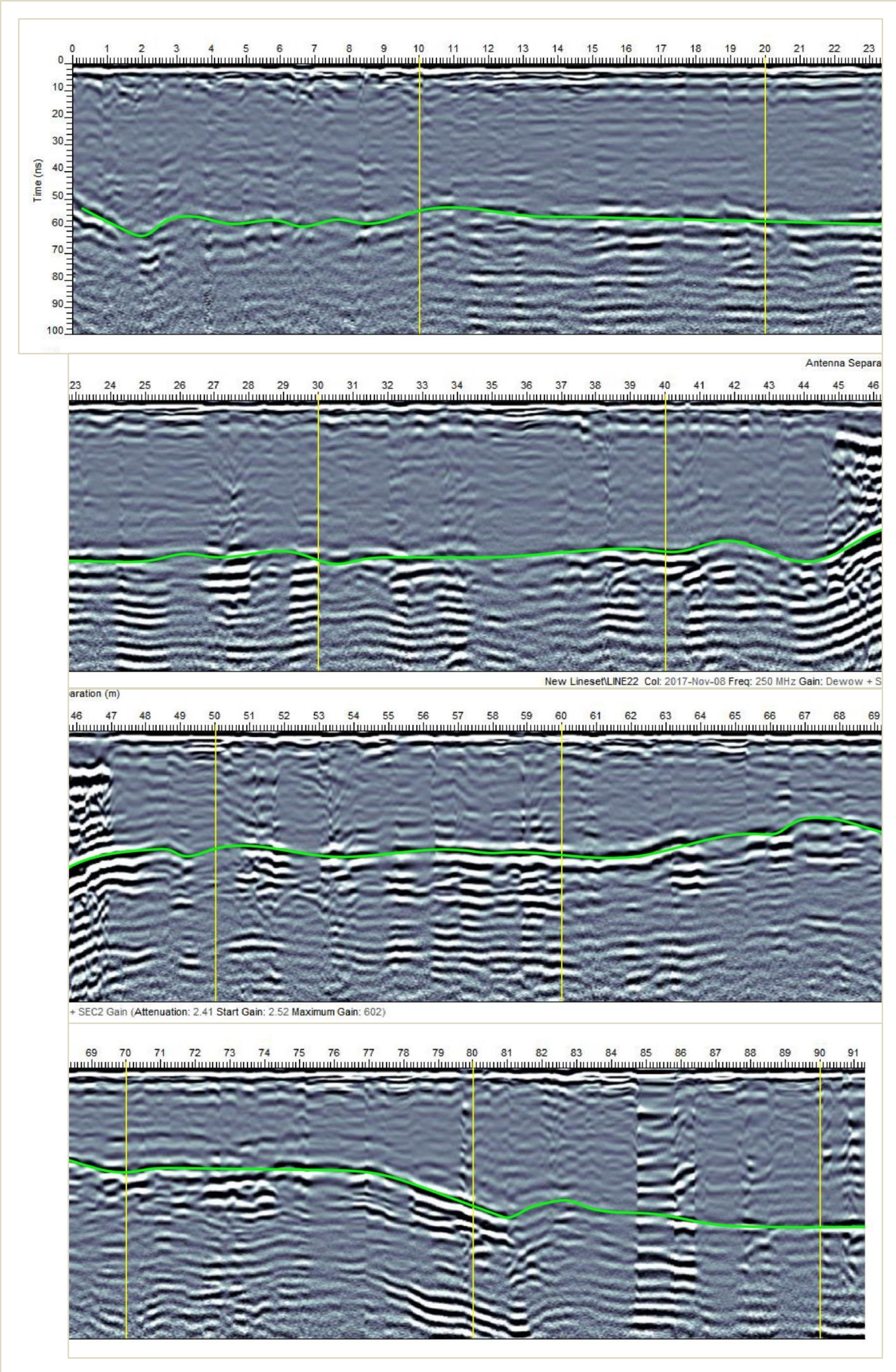

FIGURE 10.19: RADARGRAM LINE22. GREEN: TRANSITION BORDER AND YELLOW: 10M INTERVAL POINTS.

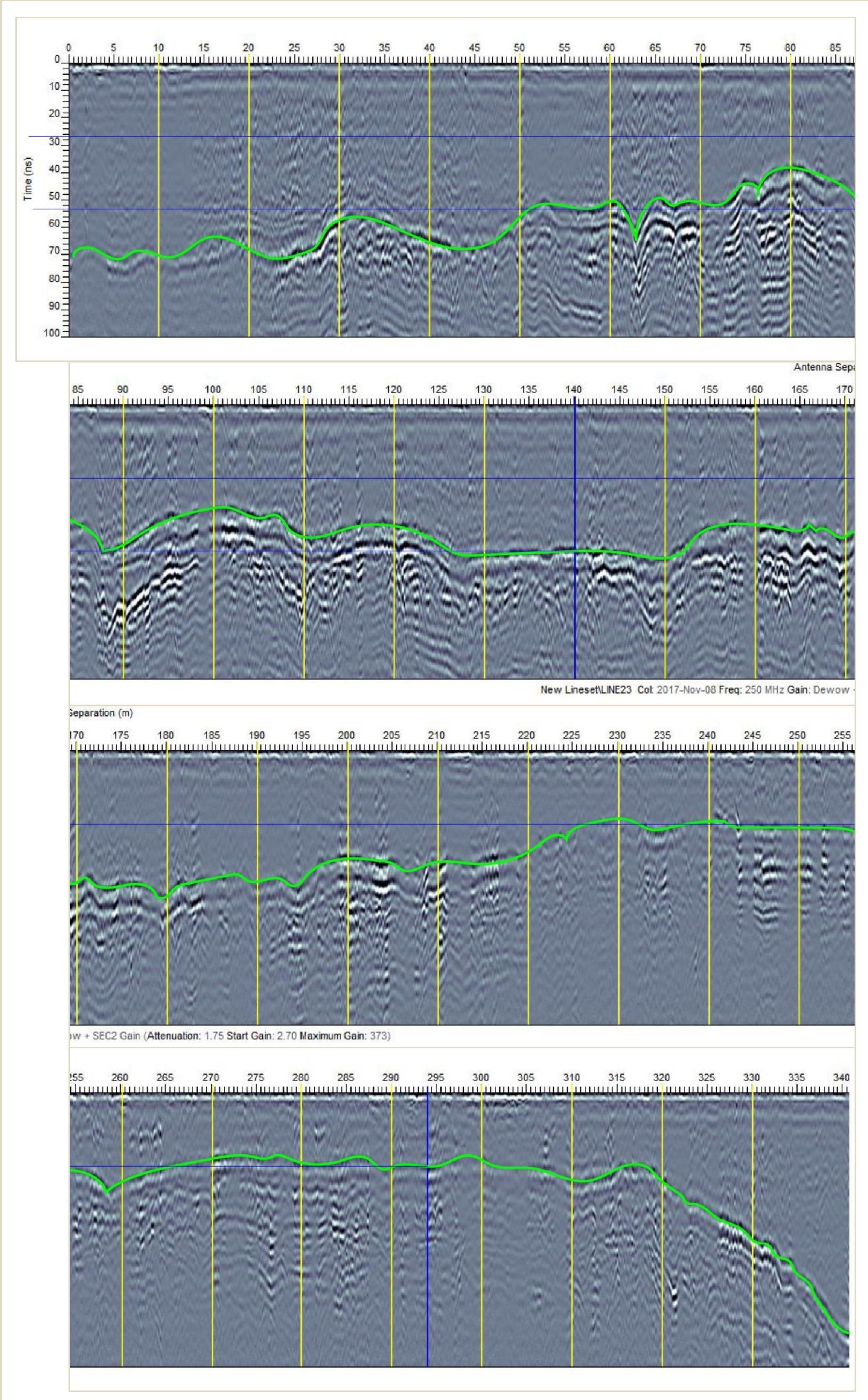

FIGURE 10.20: RADARGRAM LINE23. GREEN: TRANSITION BORDER, BLUE: VISITED CALIBRATION POINTS AND YELLOW: 10M INTERVAL POINTS.

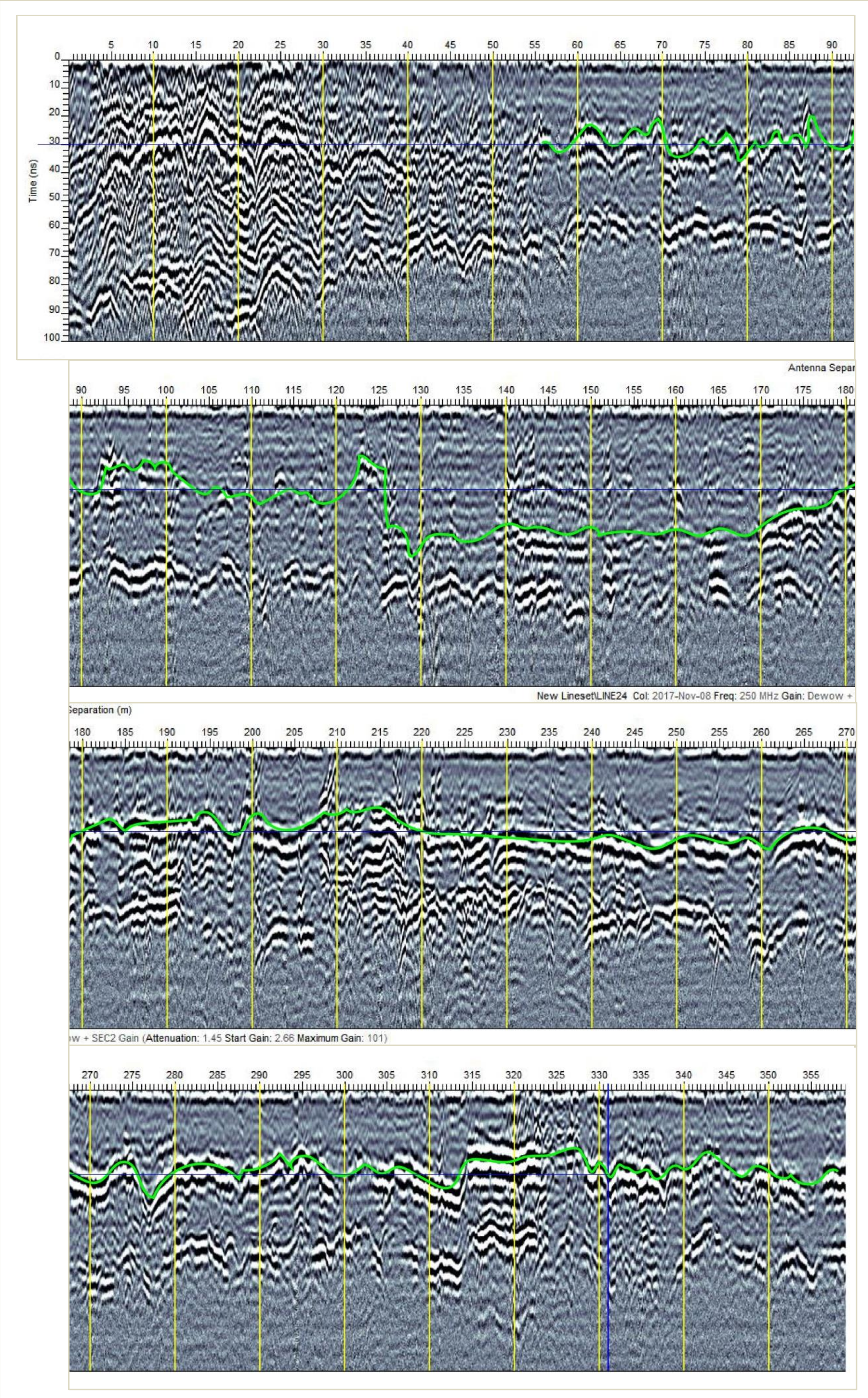

FIGURE 10.21: RADARGRAM LINE24. GREEN: TRANSITION BORDER, BLUE: VISITED CALIBRATION POINT AND YELLOW: 10M INTERVAL POINTS.

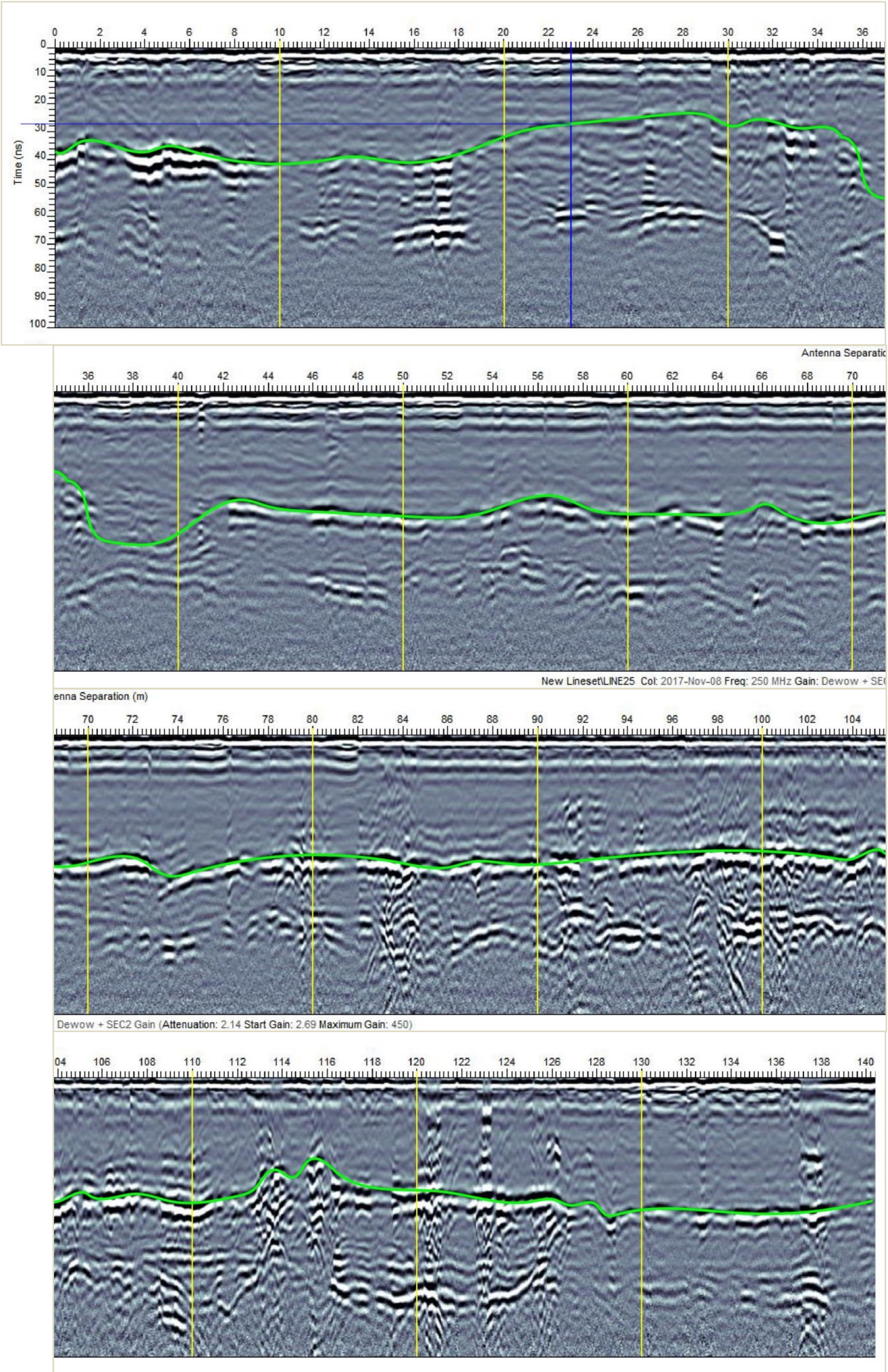

FIGURE 10.22: RADARGRAM LINE25. GREEN: TRANSITION BORDER, BLUE: VISITED CALIBRATION POINT AND YELLOW: 10M INTERVAL POINTS.

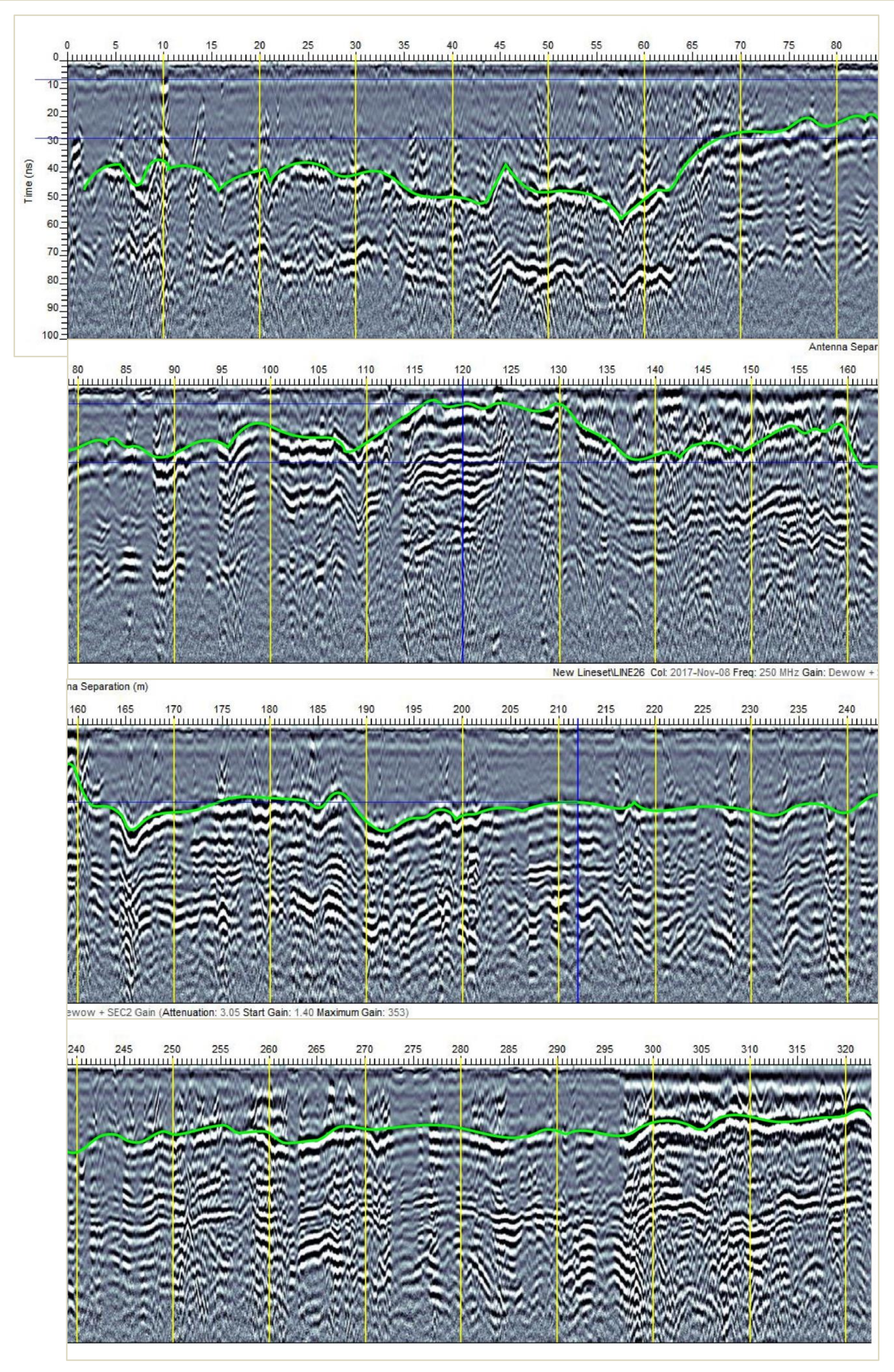

FIGURE 10.23: RADARGRAM LINE26. GREEN: TRANSITION BORDER, BLUE: VISITED CALIBRATION POINTS AND YELLOW: 10M INTERVAL POINTS.

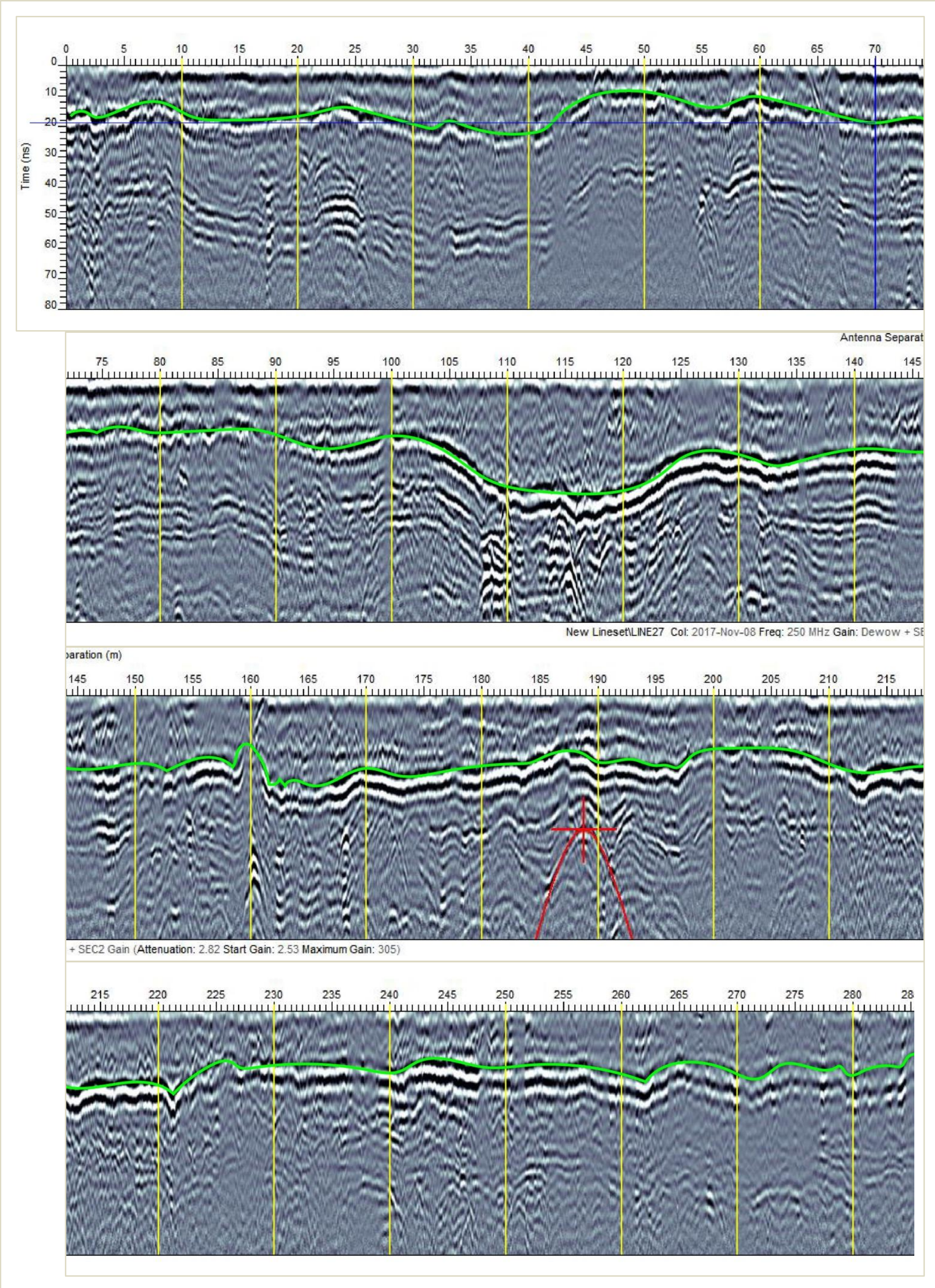

FIGURE 10.24: RADARGRAM LINE27. GREEN: TRANSITION BORDER, BLUE: VISITED CALIBRATION POINT AND YELLOW: 10M INTERVAL POINTS.

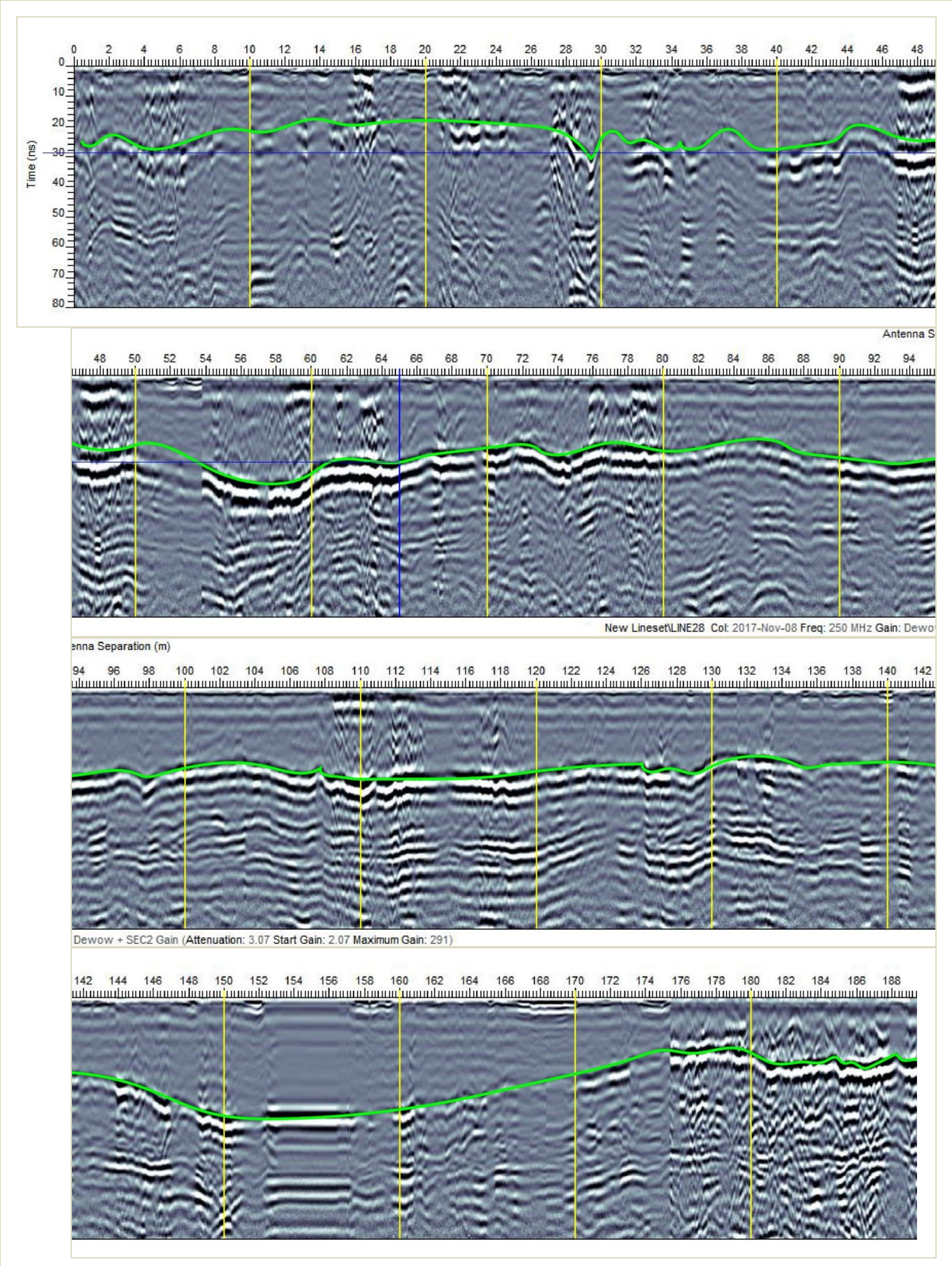

FIGURE 10.25: RADARGRAM LINE28. GREEN: TRANSITION BORDER, BLUE: VISITED CALIBRATION POINT AND YELLOW: 10M INTERVAL POINTS.

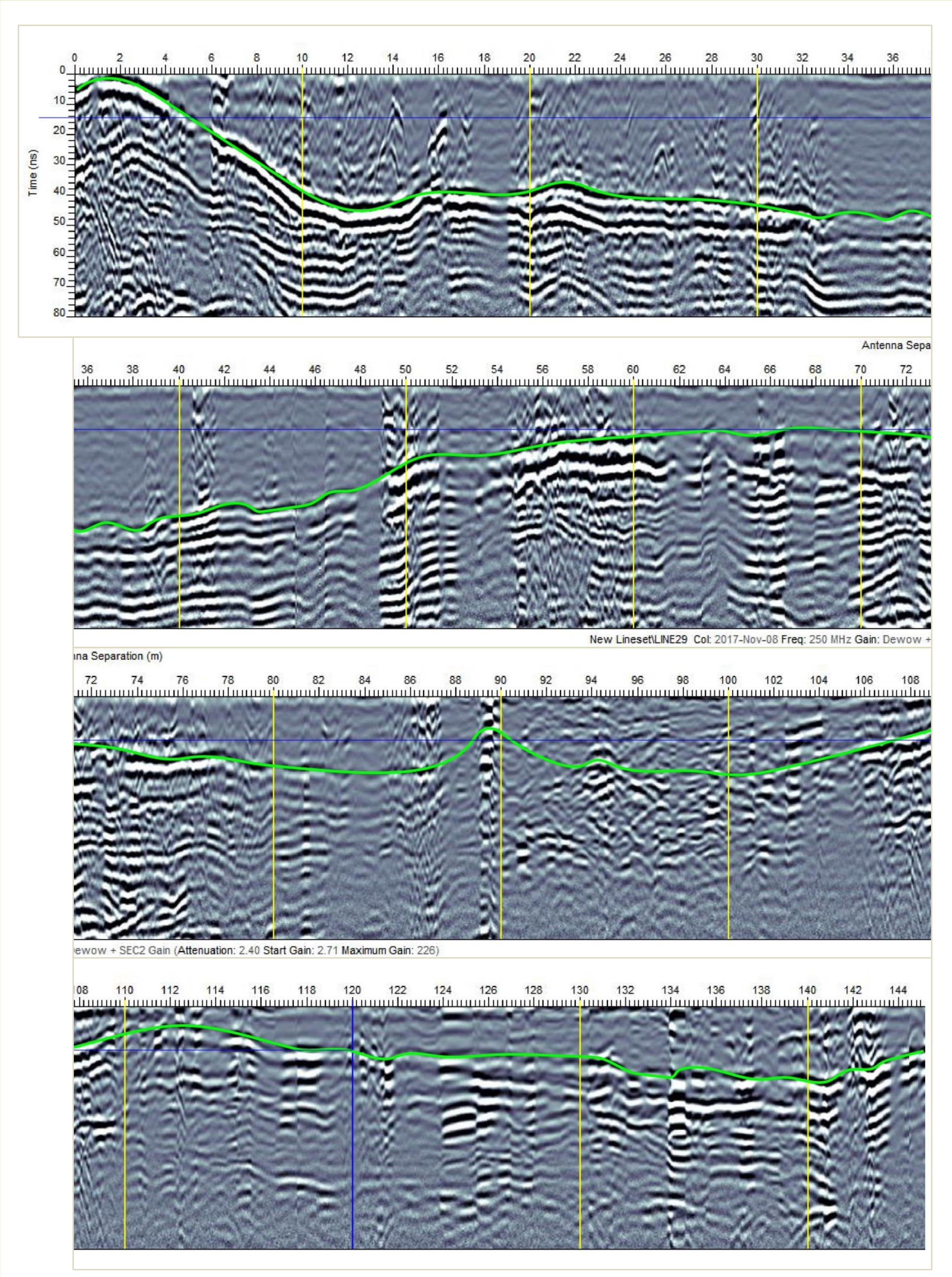

FIGURE 10.26: RADARGRAM LINE29. GREEN: TRANSITION BORDER, BLUE: VISITED CALIBRATION POINT AND YELLOW: 10M INTERVAL POINTS.

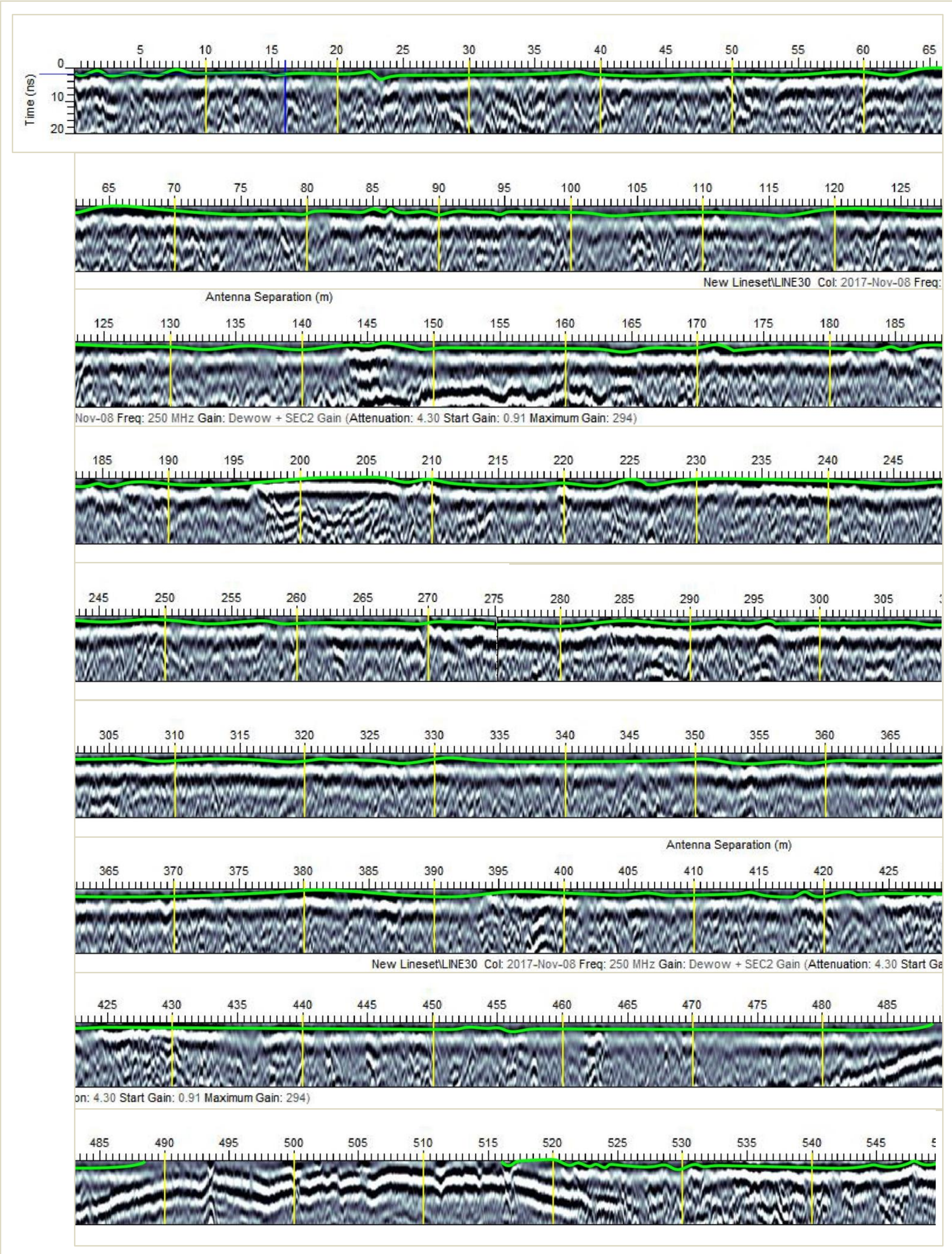

FIGURE 10.27: RADARGRAM LINE30. GREEN: TRANSITION BORDER, BLUE: VISITED CALIBRATION POINT AND YELLOW: 10M INTERVAL POINTS.

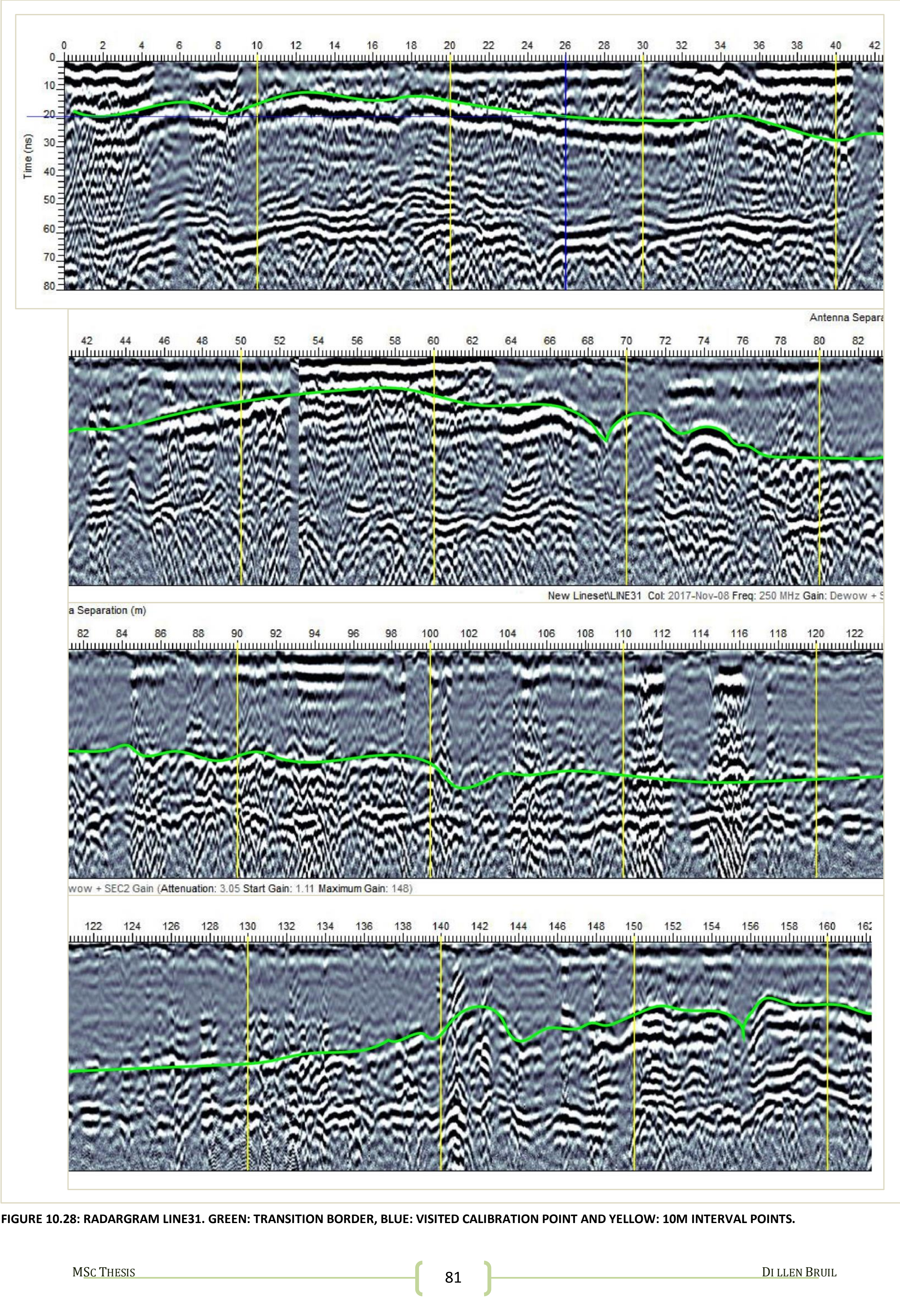

FIGURE 10.28: RADARGRAM LINE31. GREEN: TRANSITION BORDER, BLUE: VISITED CALIBRATION POINT AND YELLOW: 10M INTERVAL POINTS.

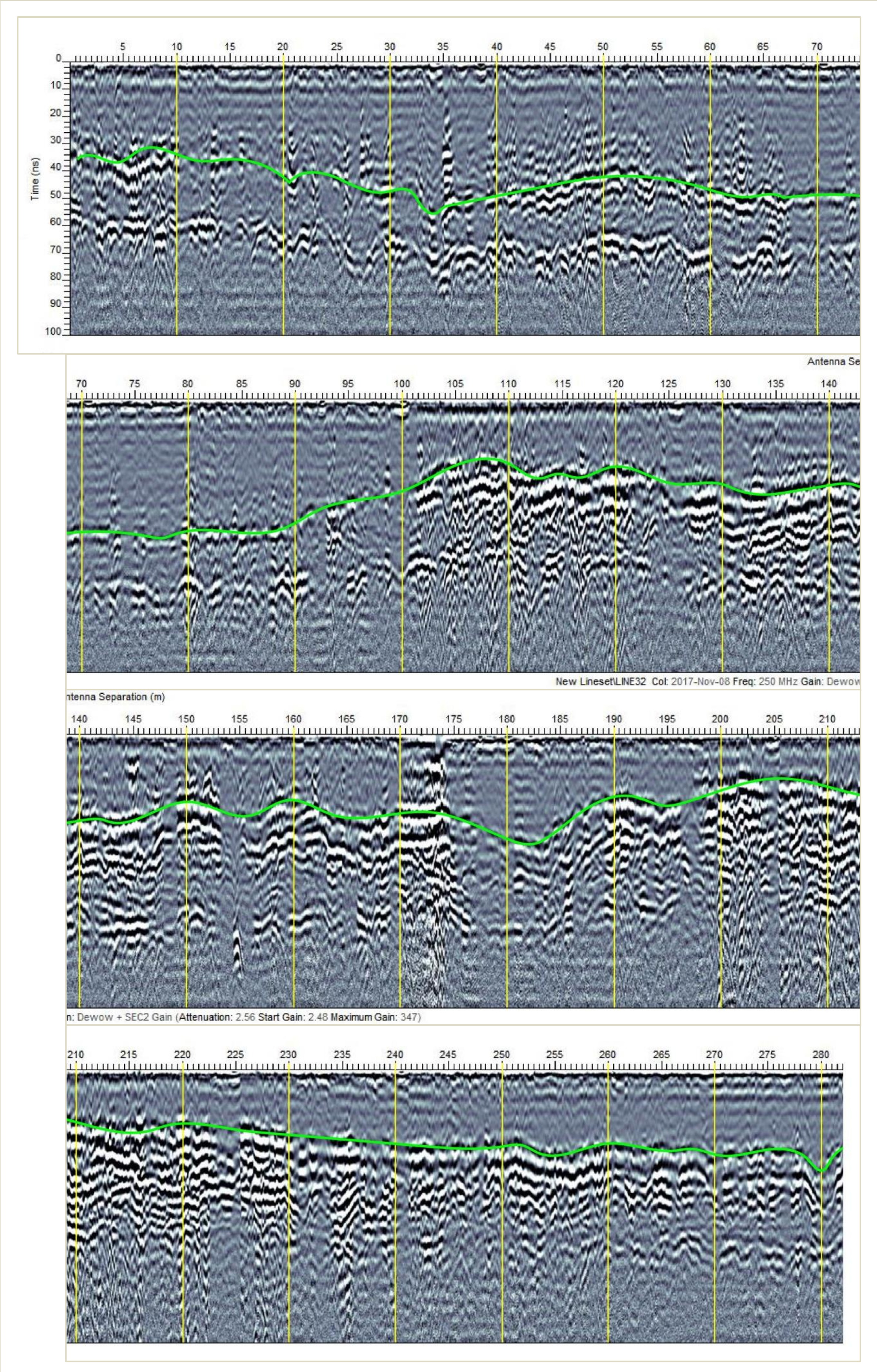

FIGURE 10.29: RADARGRAM LINE32. GREEN: TRANSITION BORDER AND YELLOW: 10M INTERVAL POINTS.

Appendix E GPR RECORDED PEAT DEPTHS

TABLE 10.2: ESTIMATED TRAVEL TIMES AND CALCULATED PEAT DEPTHS FOR EVERY GPR INTERVAL OF 10 METER BASED ON AN AVERAGE TRAVEL VELOCITY OF 0,0244 M/NS.

Line	Distance transect	Estimated Travel time [ns]	Calculated peat depth [m]	Line	Distance transect	Estimated Travel time [ns]	Calculated peat depth [m]
21	10	51	1,24	28	10	21,5	0,52
21	20	27,5	0,67	28	20	20	0,49
21	30	44,5	1,09	28	30	24,5	0,60
21	40	44	1,07	28	40	27,5	0,67
21	50	38,5	0,94	28	50	23	0,56
21	60	36	0,88	28	60	32,5	0,79
21	70	46,5	1,13	28	65	29,00	0,71
21	80	42	1,02	28	70	24	0,59
22	10	54,5	1,33	28	80	25	0,61
22	20	58	1,41	28	90	27,5	0,67
22	30	59	1,44	28	100	27	0,66
22	40	56	1,37	28	110	30,5	0,74
22	50	43	1,05	28	120	28	0,68
22	60	47,5	1,16	28	130	26	0,63
22	70	38,5	0,94	28	140	25	0,61
22	80	51	1,24	28	150	39,5	0,96
22	90	58,5	1,43	28	160	36,5	0,89
23	10	70,5	1,72	28	170	25,5	0,62
23	20	68	1,66	28	180	20	0,49
23	30	57,5	1,40	28	190	20,5	0,50
23	40	65,5	1,60	29	10	39,5	0,96
23	50	51	1,24	29	20	38,5	0,94
23	60	50,5	1,23	29	30	43,5	1,06
23	70	50,5	1,23	29	40	43	1,05
23	80	38	0,93	29	50	25,5	0,62
23	90	51	1,24	29	60	18,5	0,45
23	100	38	0,93	29	70	15	0,37
23	110	48	1,17	29	80	23	0,56
23	120	44	1,07	29	90	12	0,29
23	130	54,5	1,33	29	100	26	0,63
23	140	53,00	1,29	29	110	9	0,22
23	150	56	1,37	29	120	14,50	0,35
23	160	44	1,07	29	130	18,5	0,45
23	170	48	1,17	29	140	24,5	0,60
23	180	53	1,29	30	10	1,5	0,04
23	190	48	1,17	30	16	2,00	0,05
23	200	39,5	0,96	30	20	2	0,05
23	210	40,5	0,99	30	30	2	0,05
23	220	39	0,95	30	40	2	0,05
23	230	25	0,61	30	50	2	0,05
23	240	26	0,63	30	60	1,5	0,04
23	250	28	0,68	30	70	1,5	0,04
23	260	32,5	0,79	30	80	2,5	0,06
23	270	24	0,59	30	90	2,5	0,06
23	280	25,5	0,62	30	100	2	0,05
23	290	27	0,66	30	110	2	0,05
23	294	26,50	0,65	30	120	1	0,02
23	300	24,5	0,60	30	130	1,5	0,04

23	310	32	0,78	30	140	2,5	0,06
23	320	32,5	0,79	30	150	2	0,05
23	330	54	1,32	30	160	2	0,05
24	60	27,5	0,67	30	170	2	0,05
24	70	24,5	0,60	30	180	2	0,05
24	80	33	0,80	30	190	2	0,05
24	90	30,5	0,74	30	200	0	0,00
24	100	20,5	0,50	30	210	0,5	0,01
24	110	32	0,78	30	220	1,5	0,04
24	120	33,5	0,82	30	230	0	0,00
24	130	50	1,22	30	240	0,5	0,01
24	140	42,5	1,04	30	250	1	0,02
24	150	43,5	1,06	30	260	2	0,05
24	160	42,5	1,04	30	270	2	0,05
24	170	42	1,02	30	280	3	0,07
24	180	30	0,73	30	290	2	0,05
24	190	26,5	0,65	30	300	2	0,05
24	200	24,5	0,60	30	310	2,5	0,06
24	210	24	0,59	30	320	2,5	0,06
24	220	30	0,73	30	330	2	0,05
24	230	32	0,78	30	340	2,5	0,06
24	240	32,5	0,79	30	350	2	0,05
24	250	32,5	0,79	30	360	2,5	0,06
24	260	35	0,85	30	370	2,5	0,06
24	270	32,5	0,79	30	380	0,5	0,01
24	280	29	0,71	30	390	2,5	0,06
24	290	29	0,71	30	400	1,5	0,04
24	300	30,5	0,74	30	410	2	0,05
24	310	32	0,78	30	420	2,5	0,06
24	320	25,5	0,62	30	430	1,5	0,04
24	330	26	0,63	30	440	2	0,05
24	331	30,00	0,73	30	450	2	0,05
24	340	29	0,71	30	460	2	0,05
24	350	29	0,71	30	470	2	0,05
25	10	41,5	1,01	30	480	2	0,05
25	20	32	0,78	30	490	0	0,00
25	23	27,00	0,66	30	500	0	0,00
25	30	28	0,68	30	510	0	0,00
25	40	51	1,24	30	520	0	0,00
25	50	44,5	1,09	30	530	2,5	0,06
25	60	48	1,17	30	540	2	0,05
25	70	45,5	1,11	31	10	15	0,37
25	80	45	1,10	31	20	14	0,34
25	90	48,5	1,18	31	26	19,50	0,48
25	100	42	1,02	31	30	20,5	0,50
25	110	45	1,10	31	40	27,5	0,67
25	120	40,5	0,99	31	50	16	0,39
25	130	49,5	1,21	31	60	13,5	0,33
26	10	36	0,88	31	70	20,5	0,50
26	20	39,5	0,96	31	80	35,5	0,87
26	30	41	1,00	31	90	37,5	0,91
26	40	49	1,20	31	100	40	0,98
26	50	47	1,15	31	110	44	1,07
26	60	49	1,20	31	120	45,5	1,11
26	70	26	0,63	31	130	42,5	1,04

26	80	22	0,54
26	90	24,5	0,60
26	100	15	0,37
26	110	20,5	0,50
26	120	6,5	0,16
26	130	6,5	0,16
26	140	25	0,61
26	150	22	0,54
26	160	20	0,49
26	170	31	0,76
26	180	26,5	0,65
26	190	34,5	0,84
26	200	32,5	0,79
26	210	28	0,68
26	212	28,00	0,68
26	220	31	0,76
26	230	31	0,76
26	240	31,5	0,77
26	250	25	0,61
26	260	24,5	0,60
26	270	23	0,56
26	280	23	0,56
26	290	24	0,59
26	300	20,5	0,50
26	310	18,5	0,45
26	320	18	0,44
27	10	15	0,37
27	20	16,5	0,40
27	30	19,5	0,48
27	40	22	0,54
27	50	8,5	0,21
27	60	10	0,24
27	70	19,50	0,48
27	80	17,5	0,43
27	90	20,5	0,50
27	100	19,5	0,48
27	110	35	0,85
27	120	39	0,95
27	130	25	0,61
27	140	23,5	0,57
27	150	22	0,54
27	160	16,5	0,40
27	170	24	0,59
27	180	23	0,56
27	190	22	0,54
27	200	17,5	0,43
27	210	22,5	0,55
27	220	24	0,59
27	230	17,5	0,43
27	240	20	0,49
27	250	20,5	0,50
27	260	20,5	0,50
27	270	20,5	0,50
27	280	21	0,51
31	140	32,5	0,79
31	150	25,5	0,62
31	160	22	0,54
32	10	34	0,83
32	20	42,5	1,04
32	30	47,5	1,16
32	40	49	1,20
32	50	42	1,02
32	60	47	1,15
32	70	48,5	1,18
32	80	48,5	1,18
32	90	45,5	1,11
32	100	34	0,83
32	110	24	0,59
32	120	25	0,61
32	130	31,5	0,77
32	140	31,5	0,77
32	150	25	0,61
32	160	24	0,59
32	170	29	0,71
32	180	38	0,93
32	190	23	0,56
32	200	20,5	0,50
32	210	19	0,46
32	220	19,5	0,48
32	230	24	0,59
32	240	27	0,66
32	250	28	0,68
32	260	27	0,66
32	270	31	0,76
32	280	37,5	0,91

Appendix F USED DATABASES

Underneath the databases are presented. Because of the size of the databases, the databases are cut into smaller pieces. In Figure 10.30 an overview of the database representation can be found and how to recognize where in the database particular pages fit. The borders of the database all have a thicker green border. Each page contains the datapoint names (indicated with a "*n*"), followed by the corresponding data. First all the rows in the first columns are presented, then the rows are continued with the next columns, ending with the rows in the last columns.

Each of the following pages show part of the databases. The databases are presented the way they are used as input for the reconstruction. This means that empty rows occur when no data is recorded (which means for the legacy data that the end of the record has already been reached).

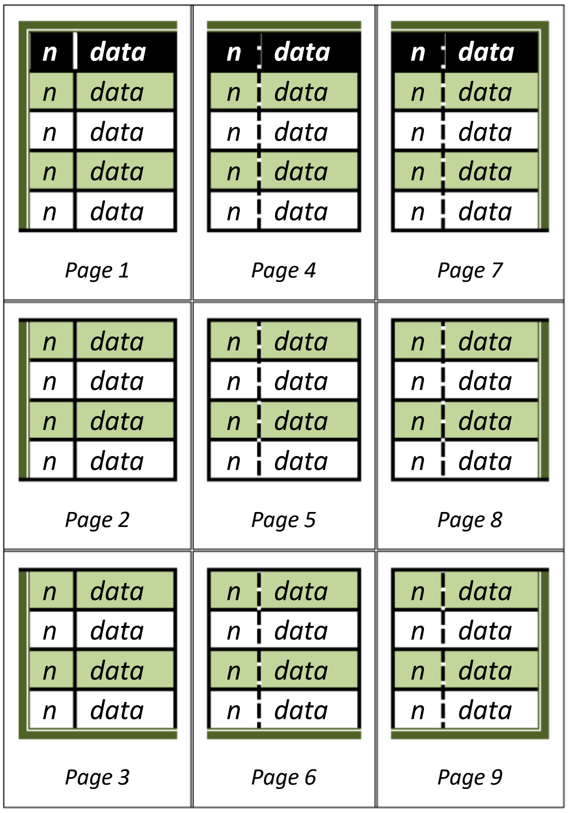

FIGURE 10.30: OVERVIEW OF THE REPRESENTATION OF THE DATABASES ON DIFFERENT PAGES.

The legacy data consists of three databases: the DINO data (Table 10.3) and the BIS data divided into BPK (Table 10.4) and PFB (Table 10.5). The databases are found on the next pages.

F1. LEGACY DATA: DINO DATABASE

TABLE 10.3: LEGACY DATA: DINO DATABASE

Name	X.Coord	Y.Coord	SurfaceLevel	Layer1 Depth	Layer1 Deposit	Layer1 Details	Layer2 Depth	Layer2 Deposit	Layer2 Details	Layer3 Depth	Layer3 Deposit	Layer3 Details	Layer4 Depth	Layer4 Deposit	Layer4 Details	Layer5 Depth	Layer5 Deposit	Layer5 Details
DINO_B18C0227	265830	525070	19,18	2,20	Peat		2,40	Clay		5,10	Sand	Very Fine						
DINO_B18C0228	265440	525280	17,80	0,90	Peat		1,50	Sand	Moderate Fine	1,90	Sand	Very Fine	7,00	Sand	Moderate Fine			
DINO_B23A0015	266950	523420	15,82	13,00	Sand	Unknown	15,00	Sand	Moderate Coarse									
DINO_B23A0024	266970	523325	16,80	0,55	Sand	Moderate Coarse	1,50	Peat		3,50	Sand	Very Fine	6,50	Sand	Moderate Fine	13,50	Sand	Moderate Coarse
DINO_B23A0025	268084	523477	18,75	0,30	Sand	Unknown	2,70	Peat		18,00	Sand	Moderate Fine	19,70	Sand	Moderate Coarse	20,80	Sand	Very Coarse
DINO_B23A0026	266630	520000	16,98	0,80	Sand	Unknown	2,00	Sand	Moderate Fine	9,00	Loam		10,50	Sand	Extreme Coarse	10,80	Sand	Moderate Fine
DINO_B23A0028	265660	522480	20,40	3,00	Peat		3,50	Sand	Fine	11,50	Sand		12,00	Sand	Fine	27,00	Sand	Unknown
DINO_B23A0030	266516	523327	18,02	1,00	Sand	Moderate Fine	2,00	Sand	Very Fine	3,00	Sand	Moderate Fine	7,00	Sand	Very Fine	16,00	Sand	Moderate Fine
DINO_B23A0034	266840	521530	18,53	0,20	Sand	Moderate Fine	2,50	Peat		4,25	Sand	Moderate Fine	5,80	Sand	Very Fine	8,25	Clay	
DINO_B23A0216	266970	523330	16,38	0,20	Unknown		1,60	Peat		2,00	Sand	Unknown						
DINO_B23A0223	263660	520360	15,41	2,00	Sand													
DINO_B23A0234	265256	524345	20,44	4,00	Peat		0,90	Unknown		2,30	Peat		2,50	Sand	Very Fine	3,00	Sand	Moderate Fine
DINO_B23A0259	266956	524191	17,67	0,50	Peat		1,30	Sand	Moderate Fine	1,80	Peat		2,30	Sand	Very Fine	4,00	Sand	Moderate Fine
DINO_B23A0277	266065	522583	17,63	0,50	Peat		0,80	Sand	Very Fine	2,40	Sand	Moderate Fine	2,60	Loam				
DINO_B23A0398	266009	523776	19,49	0,15	Sand	Moderate Fine	2,90	Peat		3,50	Sand	Moderate Fine	3,60	Sand	Very Fine	5,20	Sand	Moderate Fine
DINO_B23A0400	268005	522336	18,88	0,20	Peat		0,70	Unknown		2,80	Peat		3,00	Sand	Moderate Fine	3,70	Sand	Very Fine
DINO_B23A0401	267938	520877	18,42	2,60	Peat		2,70	Sand	Moderate Fine	2,90	Sand	Very Fine	5,00	Sand	Moderate Fine			
DINO_B23A0404	267388	523849	20,17	1,50	Peat													
DINO_B23A0406	265691	522134	18,77	0,90	Peat		1,10	Clay		2,00	Sand	Moderate Fine	7,20	Clay				
DINO_B23A0407	264930	523850	19,73	0,10	Sand	Moderate Fine	1,25	Peat		1,70	Sand	Very Fine	2,90	Sand	Moderate Fine	3,70	Clay	
DINO_B23A0409	264352	521208	18,53	2,90	Peat		3,10	Sand	Very Fine	3,60	Sand	Moderate Fine	5,70	Clay		6,20	Sand	Moderate Coarse
DINO_B23A0410	264165	520492	17,98	2,55	Peat		2,70	Clay		2,90	Sand	Very Fine	3,60	Sand	Moderate Fine	4,15	Clay	
DINO_B23A0412	263008	520601	18,20	3,10	Peat		3,30	Sand	Moderate Fine	3,60	Sand	Very Fine	5,60	Sand	Moderate Fine			
DINO_B23A0419	265828	520439	18,36	1,75	Peat		1,90	Clay		2,15	Sand	Very Fine	3,00	Sand	Moderate Fine	3,50	Sand	Very Fine
DINO_B23A0423	266484	524443	19,49	1,10	Peat													
DINO_B23A0426	266281	524463	20,54	1,10	Peat													
DINO_B23A0427	266055	524422	20,02	1,10	Peat													
DINO_B23A0447	266900	523360	17,64	2,70	Peat		3,50	Sand	Very Fine	5,00	Sand	Moderate Fine						
DINO_B23A0452	264696	523388	18,25	0,60	Sand		0,80	Loam		1,00	Peat		1,00	Sand	Very Fine	1,60	Sand	Moderate Fine
DINO_B23A0461	265869	520676	19,15	1,80	Peat		2,30	Sand	Very Fine	2,40	Sand	Moderate Fine	2,80	Sand	Very Fine	4,20	Sand	Moderate Fine
DINO_B23A0462	264814	520114	17,42	2,10	Peat		2,20	Sand	Moderate Fine	2,40	Sand	Very Fine	2,90	Sand	Moderate Fine	6,20	Loam	
DINO_B23A0463	266610	524711	19,05	3,30	Peat		4,50	Sand	Very Fine	5,30	Sand	Moderate Fine						
DINO_B23A0464	265789	521498	20,04	0,20	Sand	Very Fine	2,40	Peat		2,50	Sand	Moderate Fine	3,00	Sand	Very Fine	3,80	Sand	Moderate Fine
DINO_B23A0466	266016	523783	19,46	1,55	Peat													
DINO_B23A0467	263992	522898	16,73	0,80	Peat		1,50	Sand	Moderate Fine	1,70	Sand	Very Fine	3,00	Sand	Moderate Fine			
DINO_B23A0468	266271	524463	20,59	1,10	Peat													
DINO_B23A0469	266419	524459	19,56	1,10	Peat													
DINO_B23A0470	266415	524290	19,53	1,10	Peat													

DINO_B23A0471	267393	520284	18,27	1,40	Peat		1,50	Sand	Very Fine	4,60	Sand	Moderate Fine	11,90	Loam		14,00	Loam	
DINO_B23A0472	266859	524435	18,93	1,10	Peat													
DINO_B23A0473	266684	524455	18,97	1,10	Peat													
DINO_B23A0475	266420	524452	19,54	1,10	Peat													
DINO_B23A0476	266423	524279	19,52	1,10	Peat													
DINO_B23A0479	266177	519982	17,94	1,60	Peat		2,00	Sand	Very Fine	5,30	Sand	Moderate Fine	7,90	Loam		9,00	Sand	Moderate Fine
DINO_B23A0500	265780	519890	17,20	0,20	Peat		0,60	Sand	Unknown	0,80	Peat		1,00	Sand	Very Fine	1,20	Sand	Unknown
DINO_B23A0501	265680	519900	17,50	0,40	Sand	Unknown	0,80	Peat		3,00	Sand	Very Fine	3,10	Sand	Unknown	3,40	Loam	
DINO_B23A0504	266160	519950	16,70	0,10	Sand	Unknown	1,30	Sand	Moderate Fine	1,90	Sand	Very Fine						
DINO_B23A0513	262400	520520	17,63	2,10	Peat		2,30	Clay		3,20	Sand	Moderate Fine	3,50	Clay				
DINO_B23A0514	263020	520600	18,18	3,30	Peat		3,50	Clay		6,20	Sand	Moderate Fine						
DINO_B23A0516	263790	520800	15,69	0,60	Peat		2,70	Sand	Moderate Fine	3,80	Loam		6,80	Sand	Moderate Fine			
DINO_B23A0518	264000	520330	18,00	2,60	Peat		3,20	Sand	Very Fine									
DINO_B23A0519	264800	520470	18,37	2,10	Peat		2,35	Clay		4,70	Sand	Moderate Fine						
DINO_B23A0522	265460	520460	19,20	2,30	Peat		3,00	Sand	Moderate Fine									
DINO_B23A0524	266500	520500	18,70	0,60	Peat		2,30	Sand	Moderate Fine	3,00	Loam							
DINO_B23A0525	266360	520000	19,20	2,20	Peat		2,90	Loam		3,40	Sand	Moderate Fine						
DINO_B23A0527	267500	520500	17,70	0,80	Peat		0,90	Sand	Extreme Coarse	5,00	Sand	Moderate Fine						
DINO_B23A0531	262950	521600	15,91	0,15	Sand	Very Fine	1,55	Peat		1,70	Clay		4,50	Sand	Moderate Fine			
DINO_B23A0534	263200	521150	17,48	2,70	Peat		2,80	Clay		6,00	Sand	Moderate Fine						
DINO_B23A0538	264960	521220	18,79	2,40	Peat		2,60	Sand	Extreme Fine	3,70	Sand	Moderate Fine	3,90	Sand	Moderate Coarse	6,40	Loam	
DINO_B23A0539	265470	521550	19,00	0,40	Sand	Moderate Fine	2,00	Sand	Very Fine	2,70	Sand	Moderate Fine						
DINO_B23A0540	265020	521600	18,40	1,00	Peat		1,40	Sand	Very Fine	2,40	Sand	Extreme Fine	3,00	Loam				
DINO_B23A0541	266700	521220	19,75	2,50	Peat		2,65	Clay		2,95	Sand	Moderate Fine	3,70	Clay		4,05	Sand	Moderate Fine
DINO_B23A0542	266000	521540	20,00	1,60	Peat		3,20	Sand	Moderate Fine									
DINO_B23A0543	266100	521500	19,40	0,50	Sand	Very Fine	0,60	Peat		0,70	Sand	Moderate Fine	1,90	Peat		2,40	Sand	Moderate Fine
DINO_B23A0544	266600	521450	18,60	0,20	Sand	Unknown	1,40	Peat		2,60	Sand	Moderate Fine	2,80	Sand	Very Fine	3,10	Sand	Moderate Fine
DINO_B23A0545	266490	521490	18,90	2,10	Peat		2,30	Sand	Unknown	2,70	Sand	Moderate Fine	6,30	Loam		7,80	Sand	Very Coarse
DINO_B23A0546	267480	521540	17,00	2,50	Peat		2,70	Sand	Moderate Fine	3,10	Sand	Very Fine	3,60	Loam		3,80	Sand	Moderate Fine
DINO_B23A0547	267000	521470	19,00	2,40	Peat		2,90	Sand	Moderate Fine									
DINO_B23A0548	267070	521540	19,00	0,10	Sand	Unknown	2,30	Peat		2,60	Sand	Very Fine	2,70	Sand	Moderate Fine			
DINO_B23A0559	264420	522510	17,40	0,40	Sand	Unknown	0,50	Sand	Very Fine	1,00	Sand	Moderate Fine	1,10	Loam		1,40	Sand	Moderate Fine
DINO_B23A0561	265480	522480	18,80	2,80	Peat		3,40	Sand	Moderate Fine									
DINO_B23A0563	266500	522400	19,20	2,95	Peat		3,60	Sand	Moderate Fine									
DINO_B23A0564	266170	522750	17,43	0,60	Peat		0,85	Clay		2,20	Sand	Very Fine	2,30	Clay		3,60	Sand	Very Fine
DINO_B23A0565	267360	522500	18,00	3,20	Peat		3,60	Sand										
DINO_B23A0566	267100	522360	18,18	2,10	Peat													
DINO_B23A0585	265849	523381	18,40	0,65	Sand	Moderate Fine	1,80	Peat		3,90	Sand	Moderate Fine	4,50	Sand	Very Fine			
DINO_B23A0586	265439	523391	18,30	4,00	Sand	Moderate Fine												
DINO_B23A0587	266210	523480	17,49	1,20	Peat		1,40	Clay		3,50	Sand	Very Fine						
DINO_B23A0588	266180	523120	17,50	0,65	Peat		0,80	Clay		3,60	Sand	Very Fine						
DINO_B23A0589	266854	523365	18,00	2,95	Peat		3,30	Sand	Moderate Fine	4,00	Sand	Very Fine						
DINO_B23A0590	266299	523387	18,00	2,30	Peat		2,70	Sand	Moderate Fine	2,80	Loam		3,00	Sand	Moderate Fine	4,00	Sand	Very Fine
DINO_B23A0591	267510	523470	16,40	1,80	Peat		2,00	Sand	Very Fine	4,00	Sand	Moderate Fine						

DINO_B23A0592	267380	523870	20,01	3,80	Peat		3,90	Clay		4,65	Sand	Moderate Fine	6,50	Sand	Very Fine			
DINO_B23A0593	267900	523780	19,21	3,05	Peat		3,15	Clay		5,70	Sand	Very Fine						
DINO_B23A0609	265530	524290	19,80	2,00	Peat		7,00	Sand	Moderate Fine									
DINO_B23A0610	266050	524480	20,14	4,70	Peat		4,90	Sand	Moderate Fine	5,70	Sand	Very Fine						
DINO_B23A0611	266040	524380	20,12	4,70	Peat		5,50	Sand	Moderate Fine	6,00	Sand	Very Fine						
DINO_B23A0612	266050	524290	20,05	4,10	Peat		6,50	Sand	Very Fine									
DINO_B23A0613	266600	524730	17,30	0,90	Peat		4,00	Sand	Moderate Fine									
DINO_B23A0614	267400	524300	19,09	2,90	Peat		3,05	Clay		6,00	Sand	Very Fine						
DINO_B23A0615	267000	524400	16,50	0,70	Peat		7,00	Sand	Moderate Fine									
DINO_B23A0740	262677	520503	17,12	0,50	Sand	Moderate Fine	1,60	Sand	Very Fine	2,20	Peat		3,10	Sand	Very Fine	4,20	Sand	Moderate Fine
DINO_B23A0741	264052	521298	18,31	0,70	Sand	Moderate Fine	1,70	Peat		2,55	Sand	Very Fine	5,20	Loam		7,00	Sand	Moderate Fine
DINO_B23A0743	263810	521527	17,67	2,50	Sand	Very Fine	3,10	Loam										
DINO_B23A0746	263274	521609	16,76	1,35	Peat		2,20	Sand	Very Fine	3,50	Sand	Moderate Fine						
DINO_B23A0747	262542	521624	16,85	0,40	Sand	Moderate Fine	2,10	Peat		3,30	Sand	Very Fine	4,20	Sand	Moderate Fine			
DINO_B23A0748	267015	522381	18,10	3,00	Peat		4,50	Sand	Very Fine									
DINO_B23A0749	262313	520558	17,58	2,10	Peat		3,40	Sand	Very Fine	3,55	Sand	Unknown						
DINO_B23A0753	267287	520024	18,29	1,30	Peat		3,60	Sand	Very Fine	6,10	Loam		7,90	Clay		22,30	Sand	Very Fine
DINO_B23A0754	265340	519951	17,22	1,50	Peat		2,40	Sand	Very Fine	5,50	Loam		28,70	Sand	Very Fine	28,90	Loam	
DINO_B23A0761	264834	520542	18,12	2,40	Peat		3,10	Sand	Very Fine	5,50	Loam		6,00	Sand	Moderate Fine	7,00	Sand	Very Fine
DINO_B23A0762	268004	523812	19,05	3,00	Peat		3,80	Sand	Very Fine	4,20	Sand	Moderate Fine	5,60	Sand	Very Fine			
DINO_B23A0763	267390	523857	20,00	4,40	Peat		6,10	Sand	Very Fine									
DINO_B23A0764	265686	522132	18,76	1,10	Peat		2,00	Sand	Very Fine	7,20	Loam		8,00	Sand	Very Coarse	8,10	Gravel	
DINO_B23A0765	265255	524339	20,43	2,60	Peat		3,10	Sand	Moderate Fine	5,50	Loam		5,90	Sand	Extreme Fine	6,10	Loam	
DINO_B23A0766	263004	520603	18,00	3,20	Peat		4,00	Sand	Very Fine	6,00	Sand	Moderate Fine						
DINO_B23A0767	264159	520493	17,74	2,50	Peat		3,20	Sand	Very Fine	4,20	Loam		6,10	Sand	Very Fine			
DINO_B23A0768	266485	524446	19,32	0,55	Roots		1,00	Peat		1,50	Unknown		4,00	Peat		6,30	Sand	Very Fine
DINO_B23A0769	266687	524453	19,19	0,45	Unknown		3,95	Peat		5,50	Sand	Very Fine	6,40	Sand	Moderate Fine			
DINO_B23A0770	266420	524459	19,44	0,20	Roots		0,60	Peat		1,50	Unknown		4,20	Peat		4,50	Sand	Very Fine
DINO_B23A0771	266860	524438	19,19	0,80	Unknown		3,60	Peat		3,80	Sand	Very Fine	6,00	Sand	Moderate Fine			
DINO_B23A0772	266282	524465	20,41	0,50	Roots		5,00	Peat		5,20	Sand	Moderate Fine	7,00	Sand	Very Fine			
DINO_B23A0773	266056	524418	20,05	0,30	Roots		4,50	Peat		6,55	Sand	Very Fine						
DINO_B23A0775	267079	521479	18,17	2,35	Peat		2,80	Sand	Very Fine	5,10	Sand	Moderate Fine						
DINO_B23A0776	267451	521483	17,83	2,35	Peat		3,45	Sand	Very Fine	5,00	Sand	Moderate Fine						
DINO_B23A0777	267816	521469	17,92	2,30	Peat		3,60	Sand	Moderate Fine	5,01	Sand	Very Fine						
DINO_B23A0780	265339	520164	19,19	2,80	Peat		4,00	Sand	Very Fine	4,10	Sand	Extreme Fine	4,20	Loam				
DINO_B23A0781	266188	523177	17,43	0,40	Peat		1,10	Sand	Moderate Fine	5,00	Sand	Very Fine						
DINO_B23A0783	268012	522332	Unknown	1,50	Peat													
DINO_B23A0784	267937	520872	Unknown	1,50	Peat													
DINO_B23A0785	268001	523812	Unknown	1,00	Peat													
DINO_B23A0786	265256	524337	Unknown	1,20	Peat													
DINO_B23A0787	263003	520602	Unknown	1,50	Peat													
DINO_B23A0788	264158	520493	Unknown	1,50	Peat													

Name	Layer6 Depth	Layer6 Deposit	Layer6 Details	Layer7 Depth	Layer7 Deposit	Layer7 Details	Layer8 Depth	Layer8 Deposit	Layer8 Details	Layer9 Depth	Layer9 Deposit	Layer9 Details	Layer10 Depth	Layer10 Deposit	Layer10 Details	Layer11 Depth	Layer11 Deposit	Layer11 Details
DINO_B18C0227																		
DINO_B18C0228																		
DINO_B23A0015																		
DINO_B23A0024	14,50	Sand	Very Coarse	15,50	Sand	Extreme Coarse	16,50	Sand	Moderate Fine	17,30	Sand	Very Fine	17,60	Sand	Fine	18,20	Peat	
DINO_B23A0025	25,00	Sand	Moderate Coarse	37,80	Sand	Moderate Fine	38,00	Sand	Moderate Coarse	38,70	Sand	Very Coarse						
DINO_B23A0026	12,00	Sand	Very Coarse	21,20	Sand	Moderate Fine	24,30	Clay		32,00	Sand	Moderate Fine	32,50	Sand	Moderate Coarse	38,20	Sand	Extreme Coarse
DINO_B23A0028	42,00	Clay		43,00	Sand	Fine	51,00	Sand	Moderate Coarse	54,00	Sand	Moderate Fine						
DINO_B23A0030	22,00	Sand	Moderate Coarse	37,00	Sand	Moderate Fine	48,00	Sand	Moderate Coarse	61,00	Sand	Moderate Fine						
DINO_B23A0034	11,50	Sand	Very Fine	13,10	Clay		19,50	Sand	Very Fine	22,50	Sand	Moderate Fine	24,45	Clay		31,00	Sand	Very Fine
DINO_B23A0216																		
DINO_B23A0223																		
DINO_B23A0234	3,10	Loam																
DINO_B23A0259																		
DINO_B23A0277																		
DINO_B23A0398																		
DINO_B23A0400	4,90	Sand	Moderate Fine	5,00	Sand	Very Fine												
DINO_B23A0401																		
DINO_B23A0404																		
DINO_B23A0406																		
DINO_B23A0407	3,95	Sand	Moderate Fine	4,90	Clay		5,30	Sand	Moderate Fine	6,20	Sand	Very Fine						
DINO_B23A0409	7,50	Sand	Moderate Fine															
DINO_B23A0410	5,70	Sand	Very Fine															
DINO_B23A0412																		
DINO_B23A0419	3,80	Clay																
DINO_B23A0423																		
DINO_B23A0426																		
DINO_B23A0427																		
DINO_B23A0447																		
DINO_B23A0452	2,00	Sand	Moderate Fine	3,80	Loam		4,00	Sand	Moderate Fine	6,10	Sand	Very Fine						
DINO_B23A0461	4,30	Loam																
DINO_B23A0462	8,50	Sand	Moderate Fine															
DINO_B23A0463																		
DINO_B23A0464	4,00	Loam																
DINO_B23A0466																		
DINO_B23A0467																		
DINO_B23A0468																		
DINO_B23A0469																		
DINO_B23A0470																		

DINO_B23A0471																		
DINO_B23A0472																		
DINO_B23A0473																		
DINO_B23A0475																		
DINO_B23A0476																		
DINO_B23A0479																		
DINO_B23A0500	2,00	Sand	Very Fine															
DINO_B23A0501																		
DINO_B23A0504																		
DINO_B23A0513																		
DINO_B23A0514																		
DINO_B23A0516																		
DINO_B23A0518																		
DINO_B23A0519																		
DINO_B23A0522																		
DINO_B23A0524																		
DINO_B23A0525																		
DINO_B23A0527																		
DINO_B23A0531																		
DINO_B23A0534																		
DINO_B23A0538	7,00	Sand	Extreme Coarse	7,80	Sand	Moderate Coarse												
DINO_B23A0539																		
DINO_B23A0540																		
DINO_B23A0541	4,80	Clay		5,20	Sand	Moderate Fine	6,70	Sand	Moderate Fine									
DINO_B23A0542																		
DINO_B23A0543	2,60	Sand	Very Fine	4,50	Loam													
DINO_B23A0544	3,70	Sand	Extreme Coarse	4,80	Sand	Extreme Fine												
DINO_B23A0545	8,80	Sand	Moderate Fine															
DINO_B23A0546																		
DINO_B23A0547																		
DINO_B23A0548																		
DINO_B23A0559	2,80	Loam		3,00	Sand	Moderate Fine												
DINO_B23A0561																		
DINO_B23A0563																		
DINO_B23A0564																		
DINO_B23A0565																		
DINO_B23A0566																		
DINO_B23A0585																		
DINO_B23A0586																		
DINO_B23A0587																		
DINO_B23A0588																		
DINO_B23A0589																		
DINO_B23A0590																		
DINO_B23A0591																		
DINO_B23A0592																		

DINO_B23A0593																		
DINO_B23A0609																		
DINO_B23A0610																		
DINO_B23A0611																		
DINO_B23A0612																		
DINO_B23A0613																		
DINO_B23A0614																		
DINO_B23A0615																		
DINO_B23A0740																		
DINO_B23A0741																		
DINO_B23A0743																		
DINO_B23A0746																		
DINO_B23A0747																		
DINO_B23A0748																		
DINO_B23A0749																		
DINO_B23A0753	25,90	Clay		30,00	Sand	Very Fine												
DINO_B23A0754	32,00	Sand	Very Fine	33,50	Sand	Moderate Fine												
DINO_B23A0761																		
DINO_B23A0762																		
DINO_B23A0763																		
DINO_B23A0764																		
DINO_B23A0765	7,40	Sand	Moderate Fine															
DINO_B23A0766																		
DINO_B23A0767																		
DINO_B23A0768																		
DINO_B23A0769																		
DINO_B23A0770	6,30	Sand	Moderate Fine															
DINO_B23A0771																		
DINO_B23A0772																		
DINO_B23A0773																		
DINO_B23A0775																		
DINO_B23A0776																		
DINO_B23A0777																		
DINO_B23A0780																		
DINO_B23A0781																		
DINO_B23A0783																		
DINO_B23A0784																		
DINO_B23A0785																		
DINO_B23A0786																		
DINO_B23A0787																		
DINO_B23A0788																		

Name	Layer12 Depth	Layer12 Deposit	Layer12 Details	Layer13 Depth	Layer13 Deposit	Layer13 Details	Layer14 Depth	Layer14 Deposit	Layer14 Details	Layer15 Depth	Layer15 Deposit	Layer15 Details	Layer16 Depth	Layer16 Deposit	Layer16 Details	Layer17 Depth	Layer17 Deposit	Layer17 Details
DINO_B18C0227																		
DINO_B18C0228																		
DINO_B23A0015																		
DINO_B23A0024	18,70	Sand	Very Fine	19,25	Peat		20,10	Sand	Moderate Coarse	21,10	Loam		25,35	Sand	Very Coarse			
DINO_B23A0025																		
DINO_B23A0026	39,70	Gravel		49,00	Sand	Extreme Coarse	50,20	Sand	Moderate Fine									
DINO_B23A0028																		
DINO_B23A0030																		
DINO_B23A0034	31,20	Clay		32,20	Sand	Moderate Fine	34,00	Clay		37,80	Sand	Moderate Fine	40,60	Sand	Moderate Coarse	41,00	Sand	Very Coarse
DINO_B23A0216																		
DINO_B23A0223																		
DINO_B23A0234																		
DINO_B23A0259																		
DINO_B23A0277																		
DINO_B23A0398																		
DINO_B23A0400																		
DINO_B23A0401																		
DINO_B23A0404																		
DINO_B23A0406																		
DINO_B23A0407																		
DINO_B23A0409																		
DINO_B23A0410																		
DINO_B23A0412																		
DINO_B23A0419																		
DINO_B23A0423																		
DINO_B23A0426																		
DINO_B23A0427																		
DINO_B23A0447																		
DINO_B23A0452																		
DINO_B23A0461																		
DINO_B23A0462																		
DINO_B23A0463																		
DINO_B23A0464																		
DINO_B23A0466																		
DINO_B23A0467																		
DINO_B23A0468																		
DINO_B23A0469																		
DINO_B23A0470																		

DINO_B23A0471																		
DINO_B23A0472																		
DINO_B23A0473																		
DINO_B23A0475																		
DINO_B23A0476																		
DINO_B23A0479																		
DINO_B23A0500																		
DINO_B23A0501																		
DINO_B23A0504																		
DINO_B23A0513																		
DINO_B23A0514																		
DINO_B23A0516																		
DINO_B23A0518																		
DINO_B23A0519																		
DINO_B23A0522																		
DINO_B23A0524																		
DINO_B23A0525																		
DINO_B23A0527																		
DINO_B23A0531																		
DINO_B23A0534																		
DINO_B23A0538																		
DINO_B23A0539																		
DINO_B23A0540																		
DINO_B23A0541																		
DINO_B23A0542																		
DINO_B23A0543																		
DINO_B23A0544																		
DINO_B23A0545																		
DINO_B23A0546																		
DINO_B23A0547																		
DINO_B23A0548																		
DINO_B23A0559																		
DINO_B23A0561																		
DINO_B23A0563																		
DINO_B23A0564																		
DINO_B23A0565																		
DINO_B23A0566																		
DINO_B23A0585																		
DINO_B23A0586																		
DINO_B23A0587																		
DINO_B23A0588																		
DINO_B23A0589																		
DINO_B23A0590																		
DINO_B23A0591																		

DINO_B23A0592																		
DINO_B23A0593																		
DINO_B23A0609																		
DINO_B23A0610																		
DINO_B23A0611																		
DINO_B23A0612																		
DINO_B23A0613																		
DINO_B23A0614																		
DINO_B23A0615																		
DINO_B23A0740																		
DINO_B23A0741																		
DINO_B23A0743																		
DINO_B23A0746																		
DINO_B23A0747																		
DINO_B23A0748																		
DINO_B23A0749																		
DINO_B23A0753																		
DINO_B23A0754																		
DINO_B23A0761																		
DINO_B23A0762																		
DINO_B23A0763																		
DINO_B23A0764																		
DINO_B23A0765																		
DINO_B23A0766																		
DINO_B23A0767																		
DINO_B23A0768																		
DINO_B23A0769																		
DINO_B23A0770																		
DINO_B23A0771																		
DINO_B23A0772																		
DINO_B23A0773																		
DINO_B23A0775																		
DINO_B23A0776																		
DINO_B23A0777																		
DINO_B23A0780																		
DINO_B23A0781																		
DINO_B23A0783																		
DINO_B23A0784																		
DINO_B23A0785																		
DINO_B23A0786																		
DINO_B23A0787																		
DINO_B23A0788																		

F2. LEGACY DATA: BIS DATABASE (BPK)

TABLE 10.4: LEGACY DATA: BPK DATABASE

Name	X.Coord	Y.Coord	SurfaceLevel	Layer1 Depth	Layer1 Deposit	Layer1 Details	Layer2 Depth	Layer2 Deposit	Layer2 Details	Layer3 Depth	Layer3 Deposit	Layer3 Details	Layer4 Depth	Layer4 Deposit	Layer4 Details
BPK_25587	262810	520403	Unknown	0,10	Peat		0,65	Peat		0,95	Peat		1,00	Peat	
BPK_25588	262939	520652	Unknown	0,10	Peat		0,45	Peat		0,70	Peat		1,35	Peat	
BPK_25589	262966	520488	Unknown	0,10	Peat		0,45	Peat		0,80	Peat		1,00	Peat	
BPK_25590	263130	520390	Unknown	0,10	Peat		0,50	Peat		1,50	Peat				
BPK_25591	263117	520639	Unknown	0,10	Peat		0,30	Peat		1,50	Peat				
BPK_25592	263328	521038	Unknown	0,10	Peat		0,20	Peat		0,70	Peat		1,50	Peat	
BPK_25593	263387	520408	Unknown	0,15	Peat		0,50	Peat		1,50	Peat				
BPK_25594	263580	520422	Unknown	0,25	Unknown		0,40	Unknown		1,10	Peat		1,30	Unknown	
BPK_25595	263561	520721	Unknown	0,15	Peat		0,30	Peat		0,70	Peat		0,80	Peat	
BPK_25596	263559	521141	Unknown	0,15	Peat		0,30	Peat		0,50	Peat		0,65	Peat	
BPK_25597	263749	521303	Unknown	0,35	Peat		0,75	Peat		1,20	Peat		1,60	Peat	
BPK_25598	263879	521374	Unknown	0,15	Peat		0,25	Peat		0,60	Peat		1,00	Peat	
BPK_25599	263709	521059	Unknown	0,20	Peat		0,45	Peat		0,80	Peat		2,00	Peat	
BPK_25600	263731	520887	Unknown	0,20	Peat		0,35	Peat		0,50	Peat		1,55	Peat	
BPK_25601	263511	521295	Unknown	0,20	Peat		0,45	Peat		0,90	Peat		2,00	Peat	
BPK_25602	263604	521607	Unknown	0,40	Unknown		0,65	Peat		0,80	Peat		1,25	Peat	
BPK_25603	263347	521247	Unknown	0,25	Peat		0,60	Peat		2,00	Peat				
BPK_25604	263432	521522	Unknown	0,10	Peat		0,30	Peat		0,50	Peat		1,00	Peat	
BPK_25605	263133	521467	Unknown	0,15	Peat		0,30	Peat		0,90	Peat		1,40	Peat	
BPK_25606	263252	521615	Unknown	0,15	Peat		0,50	Peat		0,90	Peat		1,30	Peat	
BPK_25607	261929	520456	Unknown	0,35	Unknown		0,50	Unknown		1,50	Unknown				
BPK_25608	261976	520760	Unknown	0,20	Peat		0,80	Peat		1,50	Peat				
BPK_25609	262339	521485	Unknown	0,20	Unknown		0,70	Peat		1,35	Peat		1,50	Unknown	
BPK_261398	267403	520093	Unknown	0,15	Peat		0,95	Peat		1,50	Peat				
BPK_261399	267371	520207	Unknown	0,05	Peat		0,90	Peat		1,50	Peat				
BPK_261400	267453	520196	Unknown	0,05	Peat		0,85	Peat		1,50	Peat				
BPK_262370	265403	519963	Unknown	0,10	Peat		0,65	Peat		1,50	Peat				
BPK_262371	264170	521514	Unknown	0,15	Unknown		0,40	Peat		0,70	Peat		0,80	Peat	
BPK_262372	264860	521294	Unknown	0,20	Peat		0,60	Peat		1,30	Peat				
BPK_262373	266554	520106	Unknown	0,10	Peat		0,45	Peat		0,90	Peat		1,50	Peat	
BPK_262384	267702	520313	Unknown	0,15	Unknown		0,40	Peat		0,70	Peat		1,10	Peat	
BPK_262396	267771	520130	Unknown	0,20	Unknown		0,40	Peat		1,00	Peat		1,50	Peat	
BPK_262397	267781	520384	Unknown	0,15	Peat		0,50	Peat		1,20	Peat		1,50	Peat	
BPK_262398	267795	520514	Unknown	0,15	Peat		0,70	Peat		0,90	Peat		1,50	Peat	
BPK_262786	263204	520827	Unknown	0,05	Peat		0,35	Peat		1,50	Peat				
BPK_262787	263569	520977	Unknown	0,20	Peat		0,30	Peat		0,50	Peat		0,70	Peat	
BPK_262788	263720	521443	Unknown	0,35	Unknown		0,50	Peat		0,85	Peat		1,20	Unknown	
BPK_262789	263299	521414	Unknown	0,10	Peat		0,40	Peat		0,70	Peat		2,00	Peat	
BPK_263069	263707	520363	Unknown	0,25	Peat		0,70	Peat		1,20	Peat		1,50	Peat	
BPK_263070	263768	520577	Unknown	0,20	Peat		0,50	Peat		0,70	Peat		1,50	Peat	
BPK_263071	264678	520239	Unknown	0,45	Peat		1,50	Peat							
BPK_263072	264723	520109	Unknown	0,15	Peat		0,45	Peat		1,00	Peat		1,50	Peat	
BPK_263073	265128	520072	Unknown	0,10	Peat		0,60	Peat		1,50	Peat				
BPK_263074	265535	520035	Unknown	0,25	Unknown		1,00	Peat		1,40	Peat		1,50	Peat	
BPK_263075	263887	520958	Unknown	0,25	Peat		0,60	Peat		0,75	Peat		0,85	Peat	
BPK_263077	264278	521162	Unknown	0,15	Peat		0,45	Peat		1,50	Peat				
BPK_263078	264305	521477	Unknown	0,25	Peat		0,45	Peat		1,50	Peat				
BPK_263079	264072	521247	Unknown	0,15	Peat		0,60	Peat		1,50	Peat				
BPK_263080	264659	521088	Unknown	0,10	Peat		0,85	Peat		1,50	Peat				
BPK_263081	264763	521458	Unknown	0,15	Peat		0,45	Peat		1,50	Peat				
BPK_263082	264810	521083	Unknown	0,10	Peat		0,40	Peat		1,00	Peat		1,50	Peat	
BPK_263083	265024	521397	Unknown	0,10	Peat		0,40	Peat		1,20	Peat		1,50	Peat	
BPK_263084	265154	521321	Unknown	0,40	Unknown		0,70	Peat		1,20	Peat		1,50	Peat	
BPK_263085	265241	521405	Unknown	0,10	Peat		0,35	Peat		1,50	Peat				
BPK_263086	265379	521382	Unknown	0,15	Peat		0,30	Peat		1,50	Peat				
BPK_263087	265583	521210	Unknown	0,15	Peat		0,75	Peat		0,90	Unknown		1,20	Unknown	
BPK_263088	266554	520453	Unknown	0,10	Peat		0,90	Peat		1,50	Peat				
BPK_273054	262447	521491	Unknown	0,20	Peat		0,45	Peat		1,10	Peat		1,50	Peat	
BPK_273055	262199	521140	Unknown	0,25	Unknown		0,70	Unknown		0,70	Peat		1,40	Unknown	
BPK_273056	261900	520596	Unknown	0,20	Peat		0,50	Peat		0,95	Peat		1,10	Unknown	
BPK_273057	262271	520751	Unknown	0,20	Unknown		0,70	Unknown		0,70	Peat		1,00	Unknown	
BPK_273058	262536	521372	Unknown	0,20	Unknown		0,50	Peat		1,10	Peat		1,50	Peat	
BPK_273059	262340	520618	Unknown	0,15	Peat		0,40	Peat		0,70	Peat		1,50	Peat	
BPK_273060	262607	521106	Unknown	0,10	Peat		0,70	Peat		1,50	Peat				

BPK_273155	267368	520078	Unknown	0,15	Peat		0,90	Peat		1,50	Peat				
BPK_273164	267611	520215	Unknown	0,15	Peat		0,85	Peat		1,50	Peat				
BPK_273165	267719	520458	Unknown	0,20	Unknown		0,75	Peat		1,50	Peat				
BPK_273166	267797	519999	Unknown	0,15	Peat		0,85	Peat		1,50	Peat				
BPK_273212	262472	520481	Unknown	0,15	Peat		0,70	Peat		1,50	Peat				
BPK_273213	262651	520909	Unknown	0,05	Peat		0,65	Peat		1,50	Peat				
BPK_273214	262796	521211	Unknown	0,10	Peat		0,60	Peat		1,50	Peat				
BPK_273215	262971	521554	Unknown	0,10	Peat		0,60	Peat		1,50	Peat				
BPK_273216	263023	521405	Unknown	0,10	Peat		0,70	Peat		0,90	Peat		1,00	Unknown	
BPK_273217	262846	520938	Unknown	0,60	Peat		0,80	Peat		1,00	Unknown		1,50	Unknown	
BPK_273218	262681	520677	Unknown	0,15	Peat		0,70	Peat		1,50	Peat				
BPK_273219	262995	520836	Unknown	0,60	Peat		1,50	Peat							
BPK_273220	263124	521434	Unknown	0,12	Peat		0,70	Peat		1,50	Peat				
BPK_273221	263413	521448	Unknown	0,15	Peat		0,75	Peat		1,50	Peat				
BPK_273222	263308	521153	Unknown	0,15	Peat		0,70	Peat		1,50	Peat				
BPK_273223	263093	520533	Unknown	0,10	Peat		0,65	Peat		1,50	Peat				
BPK_273224	262734	520427	Unknown	0,25	Unknown		1,00	Peat		1,20	Unknown		1,35	Unknown	
BPK_273225	263224	520447	Unknown	0,15	Peat		0,70	Peat		1,50	Peat				
BPK_273226	263360	520644	Unknown	0,10	Peat		0,60	Peat		1,50	Peat				
BPK_273227	263448	521089	Unknown	0,15	Peat		0,70	Peat		1,50	Peat				
BPK_273228	263704	521340	Unknown	0,20	Peat		0,40	Peat		0,85	Peat		1,50	Peat	
BPK_273229	263526	520847	Unknown	0,25	Unknown		0,95	Peat		1,50	Peat				
BPK_273230	263399	520429	Unknown	0,20	Unknown		0,50	Peat		1,00	Peat		1,50	Peat	
BPK_273231	263649	520691	Unknown	0,10	Peat		0,80	Peat		1,30	Peat		1,45	Unknown	
BPK_273232	263754	521037	Unknown	0,15	Peat		0,40	Peat		0,90	Peat		1,50	Peat	
BPK_273233	263812	520468	Unknown	0,15	Peat		0,70	Peat		1,50	Peat				
BPK_273234	264050	520738	Unknown	0,50	Peat		1,50	Peat							
BPK_273235	264035	520983	Unknown	0,50	Peat		1,50	Peat							
BPK_273236	264117	521336	Unknown	0,15	Peat		0,70	Peat		1,50	Peat				
BPK_273237	264188	521150	Unknown	0,10	Peat		0,75	Peat		1,50	Peat				
BPK_273238	264351	521141	Unknown	0,10	Peat		0,65	Peat		1,50	Peat				
BPK_273239	264275	520756	Unknown	0,10	Peat		0,65	Peat		1,50	Peat				
BPK_273240	264175	520513	Unknown	0,10	Peat		0,70	Peat		1,50	Peat				
BPK_273241	263981	520340	Unknown	0,15	Peat		0,75	Peat		1,50	Peat				
BPK_273242	264317	520307	Unknown	0,70	Peat		0,90	Peat		1,00	Unknown		1,30	Unknown	
BPK_273243	264377	520645	Unknown	0,70	Peat		1,00	Peat		1,10	Unknown		1,40	Unknown	
BPK_273244	264520	520972	Unknown	0,70	Peat		1,10	Peat		1,30	Peat		1,40	Unknown	
BPK_273245	264550	521307	Unknown	0,70	Peat		0,85	Unknown		1,00	Unknown		1,30	Unknown	
BPK_273246	264692	521226	Unknown	0,15	Peat		0,85	Peat		1,50	Peat				
BPK_273247	264618	520762	Unknown	0,10	Peat		0,70	Peat		1,50	Peat				
BPK_273248	264513	520404	Unknown	0,10	Peat		0,65	Peat		1,50	Peat				
BPK_273249	264625	520113	Unknown	0,20	Peat		0,85	Peat		1,50	Peat				
BPK_273250	264708	520397	Unknown	0,15	Peat		0,70	Peat		1,50	Peat				
BPK_273251	264944	520888	Unknown	0,15	Peat		0,65	Peat		1,50	Peat				
BPK_273252	264982	521225	Unknown	0,12	Peat		0,70	Peat		1,50	Peat				
BPK_273253	265358	521289	Unknown	0,15	Peat		0,90	Peat		1,50	Peat				
BPK_273254	265223	521035	Unknown	0,10	Peat		0,80	Peat		1,50	Peat				
BPK_273255	265134	520645	Unknown	0,10	Peat		0,75	Peat		1,50	Peat				
BPK_273256	265039	520322	Unknown	0,10	Peat		0,65	Peat		1,50	Peat				
BPK_273257	264970	520070	Unknown	0,15	Peat		0,85	Peat		1,50	Peat				
BPK_273258	265429	519995	Unknown	0,10	Peat		0,70	Peat		1,50	Peat				
BPK_273259	265464	520356	Unknown	0,10	Peat		0,70	Peat		1,50	Peat				
BPK_273260	265478	520747	Unknown	0,40	Peat		0,70	Peat		1,50	Peat				
BPK_273261	265612	521156	Unknown	0,15	Peat		0,80	Peat		1,50	Peat				
BPK_273262	265784	520705	Unknown	0,10	Peat		0,90	Peat		1,50	Peat				
BPK_273263	265765	520372	Unknown	0,05	Peat		0,65	Peat		1,50	Peat				
BPK_273264	265750	519973	Unknown	0,15	Peat		0,75	Peat		1,50	Peat				
BPK_273265	266074	520127	Unknown	0,80	Peat		0,90	Unknown		1,10	Unknown		1,50	Unknown	
BPK_273266	266114	520414	Unknown	0,70	Peat		1,35	Peat		1,50	Unknown				
BPK_273267	266190	520779	Unknown	0,80	Peat		0,90	Unknown		1,10	Unknown		1,50	Unknown	
BPK_273268	266475	520786	Unknown	0,80	Peat		0,95	Unknown		1,15	Unknown		1,50	Unknown	
BPK_273269	266412	520302	Unknown	0,80	Peat		0,90	Unknown		1,10	Unknown		1,50	Unknown	
BPK_273270	266556	520106	Unknown	0,12	Peat		0,85	Peat		1,50	Peat				
BPK_273271	265635	521398	Unknown	0,25	Unknown		0,60	Unknown		0,60	Peat		1,10	Unknown	
BPK_273272	265940	521363	Unknown	0,05	Peat		0,70	Peat		1,50	Peat				
BPK_273273	265873	521067	Unknown	0,10	Peat		0,80	Peat		1,50	Peat				
BPK_273274	266171	521377	Unknown	0,70	Peat		0,90	Peat		1,05	Unknown		1,25	Unknown	
BPK_273275	266510	521374	Unknown	0,50	Peat		0,80	Peat		0,90	Unknown		1,15	Unknown	
BPK_273276	266207	521014	Unknown	0,70	Peat		1,00	Peat		1,10	Unknown		1,30	Unknown	

BPK_273277	266808	521360	Unknown	0,60	Peat		0,80	Peat		0,90	Unknown		1,10	Unknown	
BPK_273278	266771	520981	Unknown	0,70	Peat		0,85	Unknown		1,10	Unknown		1,30	Unknown	
BPK_273279	266693	520763	Unknown	0,70	Peat		1,00	Peat		1,15	Unknown		1,35	Unknown	
BPK_273280	266676	520410	Unknown	0,65	Peat		1,00	Peat		1,15	Peat		1,30	Unknown	
BPK_273281	266714	520134	Unknown	0,65	Peat		1,30	Peat		1,40	Unknown		1,50	Unknown	
BPK_273282	267169	520157	Unknown	0,75	Peat		1,40	Peat		1,50	Unknown				
BPK_273283	267021	520340	Unknown	0,70	Peat		1,20	Peat		1,35	Peat		1,50	Unknown	
BPK_273284	267006	520807	Unknown	0,70	Peat		1,10	Peat		1,25	Unknown		1,40	Unknown	
BPK_273285	267103	521346	Unknown	0,75	Peat		1,20	Peat		1,30	Unknown		1,45	Unknown	
BPK_273286	267399	521300	Unknown	0,65	Peat		1,00	Peat		1,15	Unknown		1,30	Unknown	
BPK_273287	267429	520925	Unknown	0,75	Peat		1,20	Peat		1,35	Unknown		1,50	Unknown	
BPK_273288	267383	520536	Unknown	0,70	Peat		1,30	Peat		1,50	Unknown				
BPK_273289	267772	520636	Unknown	0,80	Peat		0,90	Unknown		1,10	Unknown		1,30	Unknown	
BPK_273290	267737	521015	Unknown	0,70	Peat		0,85	Unknown		1,00	Unknown		1,30	Unknown	
BPK_273291	267740	521326	Unknown	0,70	Peat		0,90	Peat		1,05	Unknown		1,25	Unknown	
BPK_307032	265170	523540	Unknown	0,10	Peat		0,40	Peat		0,50	Unknown		0,70	Unknown	
BPK_307033	265498	523801	Unknown	0,12	Peat		0,60	Peat		1,50	Peat				
BPK_307034	265753	523712	Unknown	0,05	Peat		0,60	Peat		1,00	Peat		1,50	Peat	
BPK_307035	265572	524324	Unknown	0,05	Peat		0,60	Peat		1,50	Peat				
BPK_307036	265319	524968	Unknown	0,05	Peat		0,50	Peat		1,50	Peat				
BPK_307037	264809	523660	Unknown	0,10	Peat		0,50	Peat		1,00	Peat		1,50	Peat	
BPK_307040	265213	524507	Unknown	0,10	Peat		0,50	Peat		0,80	Peat		1,50	Peat	
BPK_307041	264932	524046	Unknown	0,10	Peat		0,40	Peat		1,00	Peat		1,50	Peat	
BPK_307042	265627	524869	Unknown	0,05	Peat		0,90	Peat		1,50	Peat				
BPK_307043	265920	524530	Unknown	0,07	Peat		0,35	Peat		0,70	Peat		1,50	Peat	
BPK_307044	266261	524286	Unknown	0,05	Peat		0,50	Peat		1,00	Peat		1,50	Peat	
BPK_307045	266687	524180	Unknown	0,05	Peat		0,45	Peat		1,50	Peat				
BPK_307046	266553	523770	Unknown	0,05	Peat		0,50	Peat		1,00	Peat		1,50	Peat	
BPK_307047	266085	523800	Unknown	0,10	Peat		0,50	Peat		0,70	Peat		1,50	Peat	
BPK_307048	265908	523434	Unknown	0,10	Peat		0,60	Peat		1,00	Peat		1,50	Peat	
BPK_307049	266313	523360	Unknown	0,10	Peat		0,50	Peat		1,50	Peat				
BPK_307050	266757	523503	Unknown	0,10	Peat		0,50	Peat		1,50	Peat				
BPK_307051	267319	524261	Unknown	0,20	Unknown		0,40	Peat		0,50	Peat		0,60	Unknown	
BPK_307052	266872	524425	Unknown	0,60	Peat		1,50	Peat							
BPK_307053	266141	524668	Unknown	0,30	Peat		1,50	Peat							
BPK_307056	268078	524717	Unknown	0,50	Peat		0,90	Peat		1,50	Peat				
BPK_307057	267647	524331	Unknown	0,50	Peat		1,00	Peat		1,50	Peat				
BPK_307058	268056	524207	Unknown	0,20	Unknown		0,40	Peat		0,70	Peat		1,50	Peat	
BPK_307059	267872	524016	Unknown	0,15	Unknown		0,45	Peat		0,80	Peat		1,20	Peat	
BPK_307060	267993	523786	Unknown	0,05	Peat		0,40	Peat		0,90	Peat		1,50	Peat	
BPK_307061	267666	523735	Unknown	0,10	Peat		0,50	Peat		0,90	Peat		1,50	Peat	
BPK_307062	267156	523770	Unknown	0,07	Peat		0,40	Peat		0,70	Peat		1,50	Peat	
BPK_307063	267106	523442	Unknown	0,10	Peat		0,50	Peat		0,90	Peat		1,10	Unknown	
BPK_307064	265750	523086	Unknown	0,10	Peat		0,40	Peat		0,60	Peat		0,70	Unknown	
BPK_307065	266130	523140	Unknown	0,12	Peat		0,70	Peat		0,90	Peat		1,40	Peat	
BPK_307066	266873	522956	Unknown	0,40	Peat		0,60	Peat		1,50	Peat				
BPK_307067	266189	522529	Unknown	0,70	Peat		1,20	Peat		1,50	Unknown				
BPK_307068	265761	522725	Unknown	0,12	Peat		0,55	Peat		0,65	Unknown		0,85	Unknown	
BPK_307069	267854	523057	Unknown	0,45	Peat		0,65	Peat		1,15	Peat		1,25	Peat	
BPK_307070	267587	522804	Unknown	0,55	Peat		0,80	Peat		1,30	Peat		1,50	Unknown	
BPK_307071	267965	522463	Unknown	0,10	Peat		0,45	Peat		0,80	Peat		1,10	Peat	
BPK_307072	264574	523295	Unknown	0,07	Peat		0,50	Peat		0,50	Peat		0,70	Peat	
BPK_307073	264610	522977	Unknown	0,10	Peat		0,40	Peat		0,55	Unknown		0,85	Unknown	
BPK_307074	265543	522884	Unknown	0,07	Peat		0,30	Peat		0,60	Peat		0,70	Peat	
BPK_307075	265268	522570	Unknown	0,07	Peat		0,35	Peat		0,80	Peat		0,90	Peat	
BPK_307076	264700	522637	Unknown	0,10	Peat		0,50	Peat		0,70	Peat		0,80	Peat	
BPK_307077	264244	523016	Unknown	0,12	Peat		0,45	Peat		0,55	Peat		0,75	Peat	
BPK_307078	264035	523342	Unknown	0,10	Peat		0,70	Peat		1,20	Peat		1,50	Peat	
BPK_307079	263562	522764	Unknown	0,20	Peat		0,40	Peat		0,60	Peat		0,80	Peat	
BPK_307080	263863	522745	Unknown	0,10	Peat		0,70	Peat		0,90	Peat		1,10	Peat	
BPK_307081	265050	522258	Unknown	0,12	Peat		0,35	Peat		0,50	Unknown		0,70	Unknown	
BPK_307082	265421	522335	Unknown	0,10	Peat		0,45	Peat		0,75	Peat		1,15	Peat	
BPK_307083	265156	522065	Unknown	0,15	Peat		0,50	Peat		0,65	Peat		0,70	Peat	
BPK_307084	265597	521605	Unknown	0,15	Peat		0,35	Peat		0,45	Peat		0,85	Peat	
BPK_307085	265015	521854	Unknown	0,15	Peat		0,40	Peat		0,80	Peat		0,95	Unknown	
BPK_307086	264718	522097	Unknown	0,10	Peat		0,60	Peat		0,70	Peat		0,80	Unknown	
BPK_307087	265860	522338	Unknown	0,12	Peat		0,50	Peat		0,65	Peat		0,70	Peat	
BPK_307088	265720	522114	Unknown	0,10	Peat		0,45	Peat		0,80	Peat		0,95	Peat	
BPK_307089	265786	521794	Unknown	0,12	Peat		0,45	Peat		0,90	Peat		1,00	Peat	

BPK_307090	266106	521612	Unknown	0,10	Peat		0,60	Peat		0,90	Peat		1,30	Peat	
BPK_307091	266671	521759	Unknown	0,60	Peat		0,90	Peat		1,25	Peat		1,35	Peat	
BPK_307092	266276	521856	Unknown	0,10	Peat		0,45	Peat		0,75	Peat		0,95	Peat	
BPK_307095	265876	524199	Unknown	0,10	Unknown		0,50	Peat		0,60	Unknown		0,90	Unknown	
BPK_307096	264773	520590	Unknown	0,10	Unknown		0,55	Peat		0,80	Peat		1,95	Peat	
BPK_307097	263810	520952	Unknown	0,20	Peat		0,90	Peat		1,50	Unknown				
BPK_307098	263653	520838	Unknown	0,10	Peat		0,60	Peat		1,10	Peat		2,00	Peat	
BPK_307099	263878	520858	Unknown	0,15	Peat		0,65	Peat		1,70	Peat		2,00	Unknown	
BPK_307100	263804	520583	Unknown	0,10	Peat		0,30	Peat		0,60	Peat		2,00	Peat	
BPK_307101	265530	525215	Unknown	0,40	Unknown		1,50	Peat							
BPK_307140	263859	522392	Unknown	0,10	Peat		0,50	Peat		0,90	Peat		1,50	Peat	
BPK_308111	266849	522495	Unknown	0,10	Peat		0,70	Peat		1,20	Peat		1,50	Peat	
BPK_308112	267972	523462	Unknown	0,12	Peat		0,30	Peat		0,65	Peat		1,50	Peat	
BPK_308113	265257	523297	Unknown	0,10	Peat		0,45	Peat		0,60	Unknown		0,80	Unknown	
BPK_308114	265050	523029	Unknown	0,10	Peat		0,40	Peat		0,90	Peat		1,05	Peat	
BPK_308115	264218	522655	Unknown	0,10	Peat		0,40	Peat		0,70	Peat		0,80	Peat	
BPK_308116	263904	523188	Unknown	0,10	Peat		0,90	Peat		1,30	Peat		1,50	Peat	
BPK_308117	264691	522335	Unknown	0,15	Peat		0,80	Peat		0,95	Peat		1,00	Peat	
BPK_308118	265532	521961	Unknown	0,10	Peat		0,50	Peat		0,60	Peat		0,70	Unknown	
BPK_308119	264747	521708	Unknown	0,05	Peat		0,40	Peat		0,60	Peat		0,65	Peat	
BPK_308120	265969	522155	Unknown	0,10	Peat		0,40	Peat		0,70	Peat		0,80	Peat	
BPK_308121	266607	521580	Unknown	0,10	Peat		0,60	Peat		0,90	Peat		1,25	Peat	
BPK_308122	266132	520862	Unknown	0,13	Peat		0,45	Peat		0,60	Peat		0,65	Peat	
BPK_308123	265899	521400	Unknown	0,05	Peat		0,30	Peat		0,80	Peat		2,00	Peat	
BPK_308124	263757	520760	Unknown	0,20	Peat		0,70	Peat		0,90	Unknown		1,30	Unknown	
BPK_308125	265046	524956	Unknown	0,10	Unknown		0,50	Peat		1,10	Peat		1,50	Peat	
BPK_315704	266547	520051	Unknown	0,10	Peat		0,30	Peat		0,60	Peat		1,50	Peat	
BPK_315798	265319	521748	Unknown	0,12	Peat		0,45	Peat		0,60	Unknown		1,00	Unknown	
BPK_317076	265072	522596	Unknown	0,20	Peat		0,60	Peat		0,90	Peat		1,20	Unknown	
BPK_317077	264664	523381	Unknown	0,20	Unknown		0,45	Peat		0,70	Peat		0,80	Peat	
BPK_317078	267913	523315	Unknown	0,25	Peat		1,25	Peat		1,35	Unknown				
BPK_317081	264909	522919	Unknown	0,30	Peat		0,40	Peat		0,50	Peat		0,80	Unknown	
BPK_317082	267684	524462	Unknown	0,10	Peat		0,25	Peat		1,50	Peat				
BPK_317083	265116	523783	Unknown	0,45	Peat		0,55	Peat		0,70	Peat		0,80	Unknown	
BPK_317084	265035	522613	Unknown	0,50	Peat		0,70	Peat		1,20	Unknown				
BPK_317085	264840	523587	Unknown	0,30	Peat		0,55	Peat		1,00	Peat		1,20	Unknown	
BPK_318608	263111	520887	Unknown	0,20	Peat		2,01	Peat							
BPK_326516	265064	523721	Unknown	0,05	Peat		0,10	Peat		0,95	Peat		1,60	Peat	
BPK_329398	263570	520352	Unknown	0,15	Peat		0,75	Peat		1,50	Peat				
BPK_329399	263847	520828	Unknown	0,15	Peat		0,65	Peat		1,90	Peat		2,00	Peat	
BPK_329400	264273	521427	Unknown	0,12	Peat		0,70	Peat		1,70	Peat		1,85	Peat	
BPK_329401	264265	521298	Unknown	0,12	Peat		0,70	Peat		1,70	Peat		1,80	Peat	
BPK_329402	264200	521141	Unknown	0,12	Peat		0,25	Peat		0,70	Peat		1,80	Peat	

Name	Layer5 Depth	Layer5 Deposit	Layer5 Details	Layer6 Depth	Layer6 Deposit	Layer6 Details	Layer7 Depth	Layer7 Deposit	Layer7 Details	Layer8 Depth	Layer8 Deposit	Layer8 Details	Layer9 Depth	Layer9 Deposit	Layer9 Details
BPK_25587	1,15	Unknown		1,25	Unknown		1,50	Unknown							
BPK_25588	1,50	Peat													
BPK_25589	1,50	Peat													
BPK_25590															
BPK_25591															
BPK_25592															
BPK_25593															
BPK_25594	1,50	Unknown													
BPK_25595	1,30	Peat		1,50	Peat										
BPK_25596	0,80	Peat		1,20	Peat		2,00	Peat							
BPK_25597															
BPK_25598	2,00	Peat													
BPK_25599															
BPK_25600	1,70	Peat		1,75	Peat		1,85	Unknown		2,00	Unknown				
BPK_25601															
BPK_25602	1,30	Unknown		1,40	Unknown		1,50	Unknown							
BPK_25603															
BPK_25604	1,10	Peat		1,30	Unknown		1,50	Unknown							
BPK_25605	1,60	Peat		1,90	Peat		2,10	Peat							
BPK_25606	1,60	Peat		1,70	Peat		2,00	Unknown							
BPK_25607															
BPK_25608															
BPK_25609															
BPK_261398															
BPK_261399															
BPK_261400															
BPK_262370															
BPK_262371	1,20	Unknown		1,50	Unknown										
BPK_262372															
BPK_262373															
BPK_262384	1,50	Peat													
BPK_262396															
BPK_262397															
BPK_262398															
BPK_262786															
BPK_262787	1,40	Peat		1,50	Peat										
BPK_262788	1,50	Unknown													
BPK_262789															
BPK_263069															
BPK_263070															
BPK_263071															
BPK_263072															
BPK_263073															
BPK_263074															
BPK_263075	1,15	Unknown		1,40	Unknown		1,50	Unknown							
BPK_263077															
BPK_263078															
BPK_263079															
BPK_263080															
BPK_263081															
BPK_263082															
BPK_263083															
BPK_263084															
BPK_263085															
BPK_263086															
BPK_263087	1,50	Unknown													
BPK_263088															
BPK_273054															
BPK_273055	1,50	Unknown													
BPK_273056	1,30	Unknown		1,50	Unknown		1,60	Unknown							
BPK_273057	1,50	Unknown		1,60	Unknown										
BPK_273058															
BPK_273059															
BPK_273060															

BPK_273155															
BPK_273164															
BPK_273165															
BPK_273166															
BPK_273212															
BPK_273213															
BPK_273214															
BPK_273215															
BPK_273216	1,50	Unknown													
BPK_273217															
BPK_273218															
BPK_273219															
BPK_273220															
BPK_273221															
BPK_273222															
BPK_273223															
BPK_273224	1,50	Unknown													
BPK_273225															
BPK_273226															
BPK_273227															
BPK_273228															
BPK_273229															
BPK_273230															
BPK_273231	1,50	Unknown													
BPK_273232															
BPK_273233															
BPK_273234															
BPK_273235															
BPK_273236															
BPK_273237															
BPK_273238															
BPK_273239															
BPK_273240															
BPK_273241															
BPK_273242	1,50	Unknown													
BPK_273243	1,50	Unknown													
BPK_273244	1,50	Unknown													
BPK_273245	1,50	Unknown													
BPK_273246															
BPK_273247															
BPK_273248															
BPK_273249															
BPK_273250															
BPK_273251															
BPK_273252															
BPK_273253															
BPK_273254															
BPK_273255															
BPK_273256															
BPK_273257															
BPK_273258															
BPK_273259															
BPK_273260															
BPK_273261															
BPK_273262															
BPK_273263															
BPK_273264															
BPK_273265															
BPK_273266															
BPK_273267															
BPK_273268															
BPK_273269															
BPK_273270															
BPK_273271	1,40	Unknown		1,50	Unknown										
BPK_273272															
BPK_273273															
BPK_273274	1,50	Unknown													
BPK_273275	1,20	Unknown		1,50	Unknown										
BPK_273276	1,50	Unknown													

BPK_273277	1,50	Unknown													
BPK_273278	1,50	Unknown													
BPK_273279	1,50	Unknown													
BPK_273280	1,50	Unknown													
BPK_273281															
BPK_273282															
BPK_273283															
BPK_273284	1,50	Unknown													
BPK_273285	1,50	Unknown													
BPK_273286	1,50	Unknown													
BPK_273287															
BPK_273288															
BPK_273289	1,50	Unknown													
BPK_273290	1,50	Unknown													
BPK_273291	1,50	Unknown													
BPK_307032	0,90	Unknown		1,30	Unknown		1,50	Unknown							
BPK_307033															
BPK_307034															
BPK_307035															
BPK_307036															
BPK_307037															
BPK_307040															
BPK_307041															
BPK_307042															
BPK_307043															
BPK_307044															
BPK_307045															
BPK_307046															
BPK_307047															
BPK_307048															
BPK_307049															
BPK_307050															
BPK_307051	0,85	Unknown		1,25	Unknown		1,50	Unknown							
BPK_307052															
BPK_307053															
BPK_307056															
BPK_307057															
BPK_307058															
BPK_307059	1,30	Peat		1,50	Unknown										
BPK_307060															
BPK_307061															
BPK_307062															
BPK_307063	1,30	Unknown		1,50	Unknown										
BPK_307064	0,95	Unknown		1,10	Unknown		1,50	Unknown							
BPK_307065	1,50	Unknown													
BPK_307066															
BPK_307067															
BPK_307068	1,20	Unknown		1,50	Unknown										
BPK_307069	1,35	Unknown		1,50	Unknown										
BPK_307070															
BPK_307071	1,20	Peat		1,40	Unknown		1,50	Unknown							
BPK_307072	0,85	Unknown		1,00	Unknown		1,20	Unknown		1,35	Unknown		1,50	Unknown	
BPK_307073	1,50	Unknown													
BPK_307074	1,00	Unknown		1,40	Unknown		1,50	Unknown							
BPK_307075	1,05	Unknown		1,20	Unknown		1,50	Unknown							
BPK_307076	0,90	Unknown		1,00	Unknown		1,20	Unknown		1,50	Unknown				
BPK_307077	0,85	Peat		0,95	Unknown		1,10	Unknown		1,30	Unknown		1,50	Unknown	
BPK_307078															
BPK_307079	0,90	Peat		1,00	Unknown		1,15	Unknown		1,35	Unknown		1,50	Unknown	
BPK_307080	1,25	Peat		1,35	Unknown		1,50	Unknown							
BPK_307081	1,00	Unknown		1,50	Unknown										
BPK_307082	1,30	Peat		1,50	Unknown										
BPK_307083	0,80	Unknown		1,05	Unknown		1,30	Unknown		1,50	Unknown				
BPK_307084	1,50	Peat													
BPK_307085	1,10	Unknown		1,30	Unknown		1,50	Unknown							
BPK_307086	0,95	Unknown		1,20	Unknown		1,50	Unknown							
BPK_307087	0,80	Unknown		1,00	Unknown		1,30	Unknown		1,50	Unknown				
BPK_307088	1,05	Unknown		1,20	Unknown		1,50	Unknown							
BPK_307089	1,10	Unknown		1,30	Unknown		1,50	Unknown							

BPK_307090	1,40	Peat		1,50	Unknown										
BPK_307091	1,50	Unknown													
BPK_307092	1,20	Peat		1,35	Unknown		1,50	Unknown							
BPK_307095	1,10	Unknown		1,50	Unknown										
BPK_307096	2,00	Peat													
BPK_307097															
BPK_307098															
BPK_307099															
BPK_307100															
BPK_307101															
BPK_307140															
BPK_308111															
BPK_308112															
BPK_308113	1,00	Unknown		1,40	Unknown		1,50	Unknown							
BPK_308114	1,20	Unknown		1,40	Unknown		1,50	Unknown							
BPK_308115	0,90	Unknown		1,20	Unknown		1,40	Unknown		1,50	Unknown				
BPK_308116															
BPK_308117	1,10	Unknown		1,25	Unknown		1,35	Unknown		1,50	Unknown				
BPK_308118	0,80	Unknown		1,20	Unknown		1,50	Unknown							
BPK_308119	0,80	Unknown		1,20	Unknown		1,50	Unknown							
BPK_308120	0,90	Unknown		1,15	Unknown		1,35	Unknown		1,50	Unknown				
BPK_308121	1,35	Peat		1,50	Unknown										
BPK_308122	0,75	Unknown		0,95	Unknown		1,25	Unknown		1,50	Unknown				
BPK_308123															
BPK_308124	1,45	Unknown		1,50	Unknown										
BPK_308125															
BPK_315704															
BPK_315798	1,50	Unknown													
BPK_317076															
BPK_317077	1,30	Unknown													
BPK_317078															
BPK_317081	1,00	Unknown													
BPK_317082															
BPK_317083	1,20	Unknown													
BPK_317084															
BPK_317085															
BPK_318608															
BPK_326516	1,70	Unknown		1,80	Unknown		1,90	Unknown							
BPK_329398															
BPK_329399	2,20	Unknown													
BPK_329400	2,00	Unknown		2,40	Unknown		2,50	Unknown							
BPK_329401	1,95	Unknown		2,40	Unknown		2,50	Unknown							
BPK_329402	1,90	Peat		2,05	Unknown		2,20	Unknown		2,50	Unknown				

F3. LEGACY DATA: BIS DATABASE (PFB)

TABLE 10.5: LEGACY DATA: PFB DATABASE

PFB_3473	266860	520080	Unknown	0,40	Peat		0,88	Peat		1,46	Peat		1,93	Peat	
PFB_3474	267025	523250	Unknown	0,46	Peat		0,69	Peat		1,21	Peat		1,47	Peat	
PFB_4975	265800	523800	Unknown	0,12	Peat		0,60	Peat		0,90	Peat		1,20	Peat	
PFB_4976	264900	520600	Unknown	0,08	Peat		0,80	Peat		1,20	Peat				

Name	Layer5 Depth	Layer5 Deposit	Layer5 Details	Layer6 Depth	Layer6 Deposit	Layer6 Details	Layer7 Depth	Layer7 Deposit	Layer7 Details
PFB_3473	2,50	Peat							
PFB_3474	2,33	Peat		2,68	Peat		2,80	Peat	
PFB_4975									
PFB_4976									

F4. GPR DATABASE

From the data collected with the GPR, the GPR database is completed (Table 10.6).

TABLE 10.6: GPR DATA: GPR DATABASE

Name	X.Coord	Y.Coord	SurfaceLevel	Layer1 Depth	Layer1 Deposit	Layer1 Details	Layer2 Depth	Layer2 Deposit	Layer2 Details
FW_L21D10	265455	523062	Unknown	1,24	Peat			Other	
FW_L21D20	265446	523063	Unknown	0,67	Peat			Other	
FW_L21D30	265439	523062	Unknown	1,09	Peat			Other	
FW_L21D40	265430	523063	Unknown	1,07	Peat			Other	
FW_L21D50	265420	523065	Unknown	0,94	Peat			Other	
FW_L21D60	265411	523067	Unknown	0,88	Peat			Other	
FW_L21D70	265404	523072	Unknown	1,13	Peat			Other	
FW_L21D80	265399	523080	Unknown	1,02	Peat			Other	
FW_L22D10	265386	523081	Unknown	1,33	Peat			Other	
FW_L22D20	265385	523071	Unknown	1,41	Peat			Other	
FW_L22D30	265379	523066	Unknown	1,44	Peat			Other	
FW_L22D40	265370	523064	Unknown	1,37	Peat			Other	
FW_L22D50	265362	523062	Unknown	1,05	Peat			Other	
FW_L22D60	265357	523057	Unknown	1,16	Peat			Other	
FW_L22D70	265349	523051	Unknown	0,94	Peat			Other	
FW_L22D80	265339	523050	Unknown	1,24	Peat			Other	
FW_L22D90	265332	523045	Unknown	1,43	Peat			Other	
FW_L23D10	265338	523017	Unknown	1,72	Peat			Other	
FW_L23D100	265425	523013	Unknown	0,93	Peat			Other	
FW_L23D110	265435	523012	Unknown	1,17	Peat			Other	
FW_L23D120	265445	523012	Unknown	1,07	Peat			Other	
FW_L23D130	265455	523011	Unknown	1,33	Peat			Other	
FW_L23D140	265465	523011	Unknown	1,29	Peat			Other	
FW_L23D150	265474	523010	Unknown	1,37	Peat			Other	
FW_L23D160	265484	523010	Unknown	1,07	Peat			Other	
FW_L23D170	265494	523009	Unknown	1,17	Peat			Other	
FW_L23D180	265504	523008	Unknown	1,29	Peat			Other	
FW_L23D190	265513	523007	Unknown	1,17	Peat			Other	
FW_L23D20	265347	523017	Unknown	1,66	Peat			Other	
FW_L23D200	265522	523004	Unknown	0,96	Peat			Other	

Name	X.Coord	Y.Coord	SurfaceLevel	Layer1 Depth	Layer1 Deposit	Layer1 Details	Layer2 Depth	Layer2 Deposit	Layer2 Details
FW_L28D100	264192	523226	Unknown	0,66	Peat			Other	
FW_L28D110	264201	523229	Unknown	0,74	Peat			Other	
FW_L28D120	264210	523234	Unknown	0,68	Peat			Other	
FW_L28D130	264218	523238	Unknown	0,63	Peat			Other	
FW_L28D140	264227	523241	Unknown	0,61	Peat			Other	
FW_L28D150	264236	523246	Unknown	0,96	Peat			Other	
FW_L28D160	264243	523248	Unknown	0,89	Peat			Other	
FW_L28D170	264250	523255	Unknown	0,62	Peat			Other	
FW_L28D180	264258	523261	Unknown	0,49	Peat			Other	
FW_L28D190	264265	523266	Unknown	0,50	Peat			Other	
FW_L28D20	264136	523179	Unknown	0,49	Peat			Other	
FW_L28D30	264140	523187	Unknown	0,60	Peat			Other	
FW_L28D40	264145	523195	Unknown	0,67	Peat			Other	
FW_L28D50	264152	523201	Unknown	0,56	Peat			Other	
FW_L28D60	264160	523205	Unknown	0,79	Peat			Other	
FW_L28D65	264164	523208	Unknown	0,71	Peat			Other	
FW_L28D70	264167	523212	Unknown	0,59	Peat			Other	
FW_L28D80	264176	523216	Unknown	0,61	Peat			Other	
FW_L28D90	264184	523221	Unknown	0,67	Peat			Other	
FW_L29D10	264289	523297	Unknown	0,96	Peat			Other	
FW_L29D100	264295	523380	Unknown	0,63	Peat			Other	
FW_L29D110	264295	523389	Unknown	0,22	Peat			Other	
FW_L29D120	264295	523399	Unknown	0,35	Peat			Other	
FW_L29D130	264294	523408	Unknown	0,45	Peat			Other	
FW_L29D140	264293	523417	Unknown	0,60	Peat			Other	
FW_L29D20	264292	523306	Unknown	0,94	Peat			Other	
FW_L29D30	264293	523315	Unknown	1,06	Peat			Other	
FW_L29D40	264294	523325	Unknown	1,05	Peat			Other	
FW_L29D50	264294	523334	Unknown	0,62	Peat			Other	
FW_L29D60	264294	523344	Unknown	0,45	Peat			Other	

FW_L23D210	265532	523004	Unknown	0,99	Peat			Other	
FW_L23D220	265541	523005	Unknown	0,95	Peat			Other	
FW_L23D230	265550	523005	Unknown	0,61	Peat			Other	
FW_L23D240	265558	523006	Unknown	0,63	Peat			Other	
FW_L23D250	265566	523005	Unknown	0,68	Peat			Other	
FW_L23D260	265575	523005	Unknown	0,79	Peat			Other	
FW_L23D270	265584	523006	Unknown	0,59	Peat			Other	
FW_L23D280	265591	523006	Unknown	0,62	Peat			Other	
FW_L23D290	265600	523006	Unknown	0,66	Peat			Other	
FW_L23D294	265604	523007	Unknown	0,65	Peat			Other	
FW_L23D30	265357	523016	Unknown	1,40	Peat			Other	
FW_L23D300	265609	523007	Unknown	0,60	Peat			Other	
FW_L23D310	265618	523011	Unknown	0,78	Peat			Other	
FW_L23D320	265627	523010	Unknown	0,79	Peat			Other	
FW_L23D330	265636	523012	Unknown	1,32	Peat			Other	
FW_L23D40	265367	523016	Unknown	1,60	Peat			Other	
FW_L23D50	265377	523015	Unknown	1,24	Peat			Other	
FW_L23D60	265387	523015	Unknown	1,23	Peat			Other	
FW_L23D70	265396	523015	Unknown	1,23	Peat			Other	
FW_L23D80	265406	523014	Unknown	0,93	Peat			Other	
FW_L23D90	265416	523014	Unknown	1,24	Peat			Other	
FW_L24D100	264555	522610	Unknown	0,50	Peat			Other	
FW_L24D110	264546	522610	Unknown	0,78	Peat			Other	
FW_L24D120	264537	522611	Unknown	0,82	Peat			Other	
FW_L24D130	264528	522610	Unknown	1,22	Peat			Other	
FW_L24D140	264520	522612	Unknown	1,04	Peat			Other	
FW_L24D150	264511	522614	Unknown	1,06	Peat			Other	
FW_L24D160	264501	522614	Unknown	1,04	Peat			Other	
FW_L24D170	264492	522614	Unknown	1,02	Peat			Other	
FW_L24D180	264485	522620	Unknown	0,73	Peat			Other	
FW_L24D190	264477	522623	Unknown	0,65	Peat			Other	
FW_L24D200	264471	522630	Unknown	0,60	Peat			Other	
FW_L24D210	264466	522637	Unknown	0,59	Peat			Other	
FW_L24D220	264460	522644	Unknown	0,73	Peat			Other	
FW_L24D230	264453	522651	Unknown	0,78	Peat			Other	
FW_L24D240	264448	522658	Unknown	0,79	Peat			Other	
FW_L24D250	264446	522667	Unknown	0,79	Peat			Other	
FW_L24D260	264440	522674	Unknown	0,85	Peat			Other	
FW_L24D270	264436	522683	Unknown	0,79	Peat			Other	
FW_L24D280	264432	522691	Unknown	0,71	Peat			Other	
FW_L24D290	264432	522700	Unknown	0,71	Peat			Other	
FW_L24D300	264435	522709	Unknown	0,74	Peat			Other	
FW_L24D310	264438	522717	Unknown	0,78	Peat			Other	
FW_L24D320	264441	522726	Unknown	0,62	Peat			Other	
FW_L29D70	264292	523353	Unknown	0,37	Peat			Other	
FW_L29D80	264290	523362	Unknown	0,56	Peat			Other	
FW_L29D90	264294	523371	Unknown	0,29	Peat			Other	
FW_L30D10	264305	523423	Unknown	0,04	Peat			Other	
FW_L30D100	264392	523418	Unknown	0,05	Peat			Other	
FW_L30D110	264401	523417	Unknown	0,05	Peat			Other	
FW_L30D120	264411	523417	Unknown	0,02	Peat			Other	
FW_L30D130	264420	523417	Unknown	0,04	Peat			Other	
FW_L30D140	264430	523416	Unknown	0,06	Peat			Other	
FW_L30D150	264440	523415	Unknown	0,05	Peat			Other	
FW_L30D16	264310	523423	Unknown	0,05	Peat			Other	
FW_L30D160	264450	523415	Unknown	0,05	Peat			Other	
FW_L30D170	264459	523415	Unknown	0,05	Peat			Other	
FW_L30D180	264469	523414	Unknown	0,05	Peat			Other	
FW_L30D190	264479	523413	Unknown	0,05	Peat			Other	
FW_L30D20	264314	523422	Unknown	0,05	Peat			Other	
FW_L30D200	264488	523412	Unknown	0,00	Peat			Other	
FW_L30D210	264498	523412	Unknown	0,01	Peat			Other	
FW_L30D220	264508	523411	Unknown	0,04	Peat			Other	
FW_L30D230	264517	523410	Unknown	0,00	Peat			Other	
FW_L30D240	264527	523410	Unknown	0,01	Peat			Other	
FW_L30D250	264537	523409	Unknown	0,02	Peat			Other	
FW_L30D260	264547	523408	Unknown	0,05	Peat			Other	
FW_L30D270	264556	523408	Unknown	0,05	Peat			Other	
FW_L30D280	264566	523407	Unknown	0,07	Peat			Other	
FW_L30D290	264576	523406	Unknown	0,05	Peat			Other	
FW_L30D30	264324	523422	Unknown	0,05	Peat			Other	
FW_L30D300	264585	523406	Unknown	0,05	Peat			Other	
FW_L30D310	264595	523405	Unknown	0,06	Peat			Other	
FW_L30D320	264605	523405	Unknown	0,06	Peat			Other	
FW_L30D330	264614	523404	Unknown	0,05	Peat			Other	
FW_L30D340	264624	523403	Unknown	0,06	Peat			Other	
FW_L30D350	264634	523403	Unknown	0,05	Peat			Other	
FW_L30D360	264644	523402	Unknown	0,06	Peat			Other	
FW_L30D370	264653	523401	Unknown	0,06	Peat			Other	
FW_L30D380	264663	523401	Unknown	0,01	Peat			Other	
FW_L30D390	264673	523400	Unknown	0,06	Peat			Other	
FW_L30D40	264334	523421	Unknown	0,05	Peat			Other	
FW_L30D400	264682	523399	Unknown	0,04	Peat			Other	
FW_L30D410	264692	523399	Unknown	0,05	Peat			Other	
FW_L30D420	264702	523398	Unknown	0,06	Peat			Other	
FW_L30D430	264712	523397	Unknown	0,04	Peat			Other	
FW_L30D440	264721	523397	Unknown	0,05	Peat			Other	
FW_L30D450	264731	523396	Unknown	0,05	Peat			Other	

FW_L24D330	264446	522733	Unknown	0,63	Peat			Other	
FW_L24D331	264447	522734	Unknown	0,73	Peat			Other	
FW_L24D340	264452	522741	Unknown	0,71	Peat			Other	
FW_L24D350	264458	522747	Unknown	0,71	Peat			Other	
FW_L24D60	264590	522599	Unknown	0,67	Peat			Other	
FW_L24D70	264582	522603	Unknown	0,60	Peat			Other	
FW_L24D80	264574	522607	Unknown	0,80	Peat			Other	
FW_L24D90	264564	522608	Unknown	0,74	Peat			Other	
FW_L25D10	264463	522763	Unknown	1,01	Peat			Other	
FW_L25D100	264402	522812	Unknown	1,02	Peat			Other	
FW_L25D110	264395	522818	Unknown	1,10	Peat			Other	
FW_L25D120	264388	522824	Unknown	0,99	Peat			Other	
FW_L25D130	264382	522831	Unknown	1,21	Peat			Other	
FW_L25D20	264461	522772	Unknown	0,78	Peat			Other	
FW_L25D23	264459	522774	Unknown	0,66	Peat			Other	
FW_L25D30	264456	522780	Unknown	0,68	Peat			Other	
FW_L25D40	264451	522788	Unknown	1,24	Peat			Other	
FW_L25D50	264444	522794	Unknown	1,09	Peat			Other	
FW_L25D60	264435	522798	Unknown	1,17	Peat			Other	
FW_L25D70	264426	522798	Unknown	1,11	Peat			Other	
FW_L25D80	264418	522801	Unknown	1,10	Peat			Other	
FW_L25D90	264410	522807	Unknown	1,18	Peat			Other	
FW_L26D10	264372	522848	Unknown	0,88	Peat			Other	
FW_L26D100	264388	522928	Unknown	0,37	Peat			Other	
FW_L26D110	264391	522937	Unknown	0,50	Peat			Other	
FW_L26D120	264392	522946	Unknown	0,16	Peat			Other	
FW_L26D130	264393	522956	Unknown	0,16	Peat			Other	
FW_L26D140	264394	522965	Unknown	0,61	Peat			Other	
FW_L26D150	264397	522974	Unknown	0,54	Peat			Other	
FW_L26D160	264400	522983	Unknown	0,49	Peat			Other	
FW_L26D170	264402	522992	Unknown	0,76	Peat			Other	
FW_L26D180	264403	523002	Unknown	0,65	Peat			Other	
FW_L26D190	264405	523011	Unknown	0,84	Peat			Other	
FW_L26D20	264370	522857	Unknown	0,96	Peat			Other	
FW_L26D200	264407	523020	Unknown	0,79	Peat			Other	
FW_L26D210	264407	523030	Unknown	0,68	Peat			Other	
FW_L26D212	264407	523030	Unknown	0,68	Peat			Other	
FW_L26D220	264408	523039	Unknown	0,76	Peat			Other	
FW_L26D230	264410	523048	Unknown	0,76	Peat			Other	
FW_L26D240	264411	523058	Unknown	0,77	Peat			Other	
FW_L26D250	264410	523067	Unknown	0,61	Peat			Other	
FW_L26D260	264411	523076	Unknown	0,60	Peat			Other	
FW_L26D270	264409	523086	Unknown	0,56	Peat			Other	
FW_L26D280	264411	523095	Unknown	0,56	Peat			Other	
FW_L30D460	264741	523395	Unknown	0,05	Peat			Other	
FW_L30D470	264750	523395	Unknown	0,05	Peat			Other	
FW_L30D480	264760	523394	Unknown	0,05	Peat			Other	
FW_L30D490	264770	523394	Unknown	0,00	Peat			Other	
FW_L30D50	264343	523421	Unknown	0,05	Peat			Other	
FW_L30D500	264779	523393	Unknown	0,00	Peat			Other	
FW_L30D510	264789	523392	Unknown	0,00	Peat			Other	
FW_L30D520	264799	523391	Unknown	0,00	Peat			Other	
FW_L30D530	264809	523391	Unknown	0,06	Peat			Other	
FW_L30D540	264818	523392	Unknown	0,05	Peat			Other	
FW_L30D60	264353	523420	Unknown	0,04	Peat			Other	
FW_L30D70	264363	523419	Unknown	0,04	Peat			Other	
FW_L30D80	264372	523419	Unknown	0,06	Peat			Other	
FW_L30D90	264382	523418	Unknown	0,06	Peat			Other	
FW_L31D10	264823	523340	Unknown	0,37	Peat			Other	
FW_L31D100	264909	523332	Unknown	0,98	Peat			Other	
FW_L31D110	264919	523331	Unknown	1,07	Peat			Other	
FW_L31D120	264928	523330	Unknown	1,11	Peat			Other	
FW_L31D130	264937	523331	Unknown	1,04	Peat			Other	
FW_L31D140	264947	523332	Unknown	0,79	Peat			Other	
FW_L31D150	264956	523334	Unknown	0,62	Peat			Other	
FW_L31D160	264965	523332	Unknown	0,54	Peat			Other	
FW_L31D20	264833	523339	Unknown	0,34	Peat			Other	
FW_L31D26	264839	523338	Unknown	0,48	Peat			Other	
FW_L31D30	264843	523338	Unknown	0,50	Peat			Other	
FW_L31D40	264852	523339	Unknown	0,67	Peat			Other	
FW_L31D50	264862	523340	Unknown	0,39	Peat			Other	
FW_L31D60	264871	523339	Unknown	0,33	Peat			Other	
FW_L31D70	264881	523335	Unknown	0,50	Peat			Other	
FW_L31D80	264890	523334	Unknown	0,87	Peat			Other	
FW_L31D90	264900	523333	Unknown	0,91	Peat			Other	
FW_L32D10	264971	523323	Unknown	0,83	Peat			Other	
FW_L32D100	264928	523288	Unknown	0,83	Peat			Other	
FW_L32D110	264918	523290	Unknown	0,59	Peat			Other	
FW_L32D120	264909	523288	Unknown	0,61	Peat			Other	
FW_L32D130	264902	523283	Unknown	0,77	Peat			Other	
FW_L32D140	264893	523279	Unknown	0,77	Peat			Other	
FW_L32D150	264885	523274	Unknown	0,61	Peat			Other	
FW_L32D160	264878	523269	Unknown	0,59	Peat			Other	
FW_L32D170	264874	523261	Unknown	0,71	Peat			Other	
FW_L32D180	264868	523255	Unknown	0,93	Peat			Other	
FW_L32D190	264863	523247	Unknown	0,56	Peat			Other	
FW_L32D20	264974	523314	Unknown	1,04	Peat			Other	
FW_L32D200	264857	523240	Unknown	0,50	Peat			Other	

FW_L26D290	264414	523104	Unknown	0,59	Peat			Other	
FW_L26D30	264373	522866	Unknown	1,00	Peat			Other	
FW_L26D300	264415	523113	Unknown	0,50	Peat			Other	
FW_L26D310	264411	523122	Unknown	0,45	Peat			Other	
FW_L26D320	264409	523131	Unknown	0,44	Peat			Other	
FW_L26D40	264376	522875	Unknown	1,20	Peat			Other	
FW_L26D50	264379	522884	Unknown	1,15	Peat			Other	
FW_L26D60	264379	522894	Unknown	1,20	Peat			Other	
FW_L26D70	264380	522903	Unknown	0,63	Peat			Other	
FW_L26D80	264378	522913	Unknown	0,54	Peat			Other	
FW_L26D90	264383	522920	Unknown	0,60	Peat			Other	
FW_L27D10	264400	523135	Unknown	0,37	Peat			Other	
FW_L27D100	264310	523140	Unknown	0,48	Peat			Other	
FW_L27D110	264301	523141	Unknown	0,85	Peat			Other	
FW_L27D120	264291	523142	Unknown	0,95	Peat			Other	
FW_L27D130	264281	523144	Unknown	0,61	Peat			Other	
FW_L27D140	264271	523145	Unknown	0,57	Peat			Other	
FW_L27D150	264261	523145	Unknown	0,54	Peat			Other	
FW_L27D160	264251	523144	Unknown	0,40	Peat			Other	
FW_L27D170	264242	523145	Unknown	0,59	Peat			Other	
FW_L27D180	264232	523146	Unknown	0,56	Peat			Other	
FW_L27D190	264222	523147	Unknown	0,54	Peat			Other	
FW_L27D20	264390	523135	Unknown	0,40	Peat			Other	
FW_L27D200	264212	523147	Unknown	0,43	Peat			Other	
FW_L27D210	264202	523148	Unknown	0,55	Peat			Other	
FW_L27D220	264192	523148	Unknown	0,59	Peat			Other	
FW_L27D230	264182	523149	Unknown	0,43	Peat			Other	
FW_L27D240	264173	523151	Unknown	0,49	Peat			Other	
FW_L27D250	264163	523154	Unknown	0,50	Peat			Other	
FW_L27D260	264153	523154	Unknown	0,50	Peat			Other	
FW_L27D270	264144	523155	Unknown	0,50	Peat			Other	
FW_L27D280	264135	523158	Unknown	0,51	Peat			Other	
FW_L27D30	264380	523135	Unknown	0,48	Peat			Other	
FW_L27D40	264370	523135	Unknown	0,54	Peat			Other	
FW_L27D50	264360	523135	Unknown	0,21	Peat			Other	
FW_L27D60	264350	523136	Unknown	0,24	Peat			Other	
FW_L27D70	264340	523137	Unknown	0,48	Peat			Other	
FW_L27D80	264330	523139	Unknown	0,43	Peat			Other	
FW_L27D90	264320	523139	Unknown	0,50	Peat			Other	
FW_L32D210	264851	523232	Unknown	0,46	Peat			Other	
FW_L32D220	264847	523224	Unknown	0,48	Peat			Other	
FW_L32D230	264844	523215	Unknown	0,59	Peat			Other	
FW_L32D240	264841	523206	Unknown	0,66	Peat			Other	
FW_L32D250	264837	523199	Unknown	0,68	Peat			Other	
FW_L32D260	264832	523191	Unknown	0,66	Peat			Other	
FW_L32D270	264827	523182	Unknown	0,76	Peat			Other	
FW_L32D280	264821	523175	Unknown	0,91	Peat			Other	
FW_L32D30	264975	523304	Unknown	1,16	Peat			Other	
FW_L32D40	264974	523295	Unknown	1,20	Peat			Other	
FW_L32D50	264971	523286	Unknown	1,02	Peat			Other	
FW_L32D60	264964	523279	Unknown	1,15	Peat			Other	
FW_L32D70	264955	523282	Unknown	1,18	Peat			Other	
FW_L32D80	264946	523283	Unknown	1,18	Peat			Other	
FW_L32D90	264937	523286	Unknown	1,11	Peat			Other	

Appendix G RECONSTRUCTION SCRIPT

RECONSTRUCTING PRE-PEAT LANDSCAPES

Dillen Bruil
2 June 2018

This script reconstructs and assesses several reconstructions of a pre-peat landscape, if desired it can also be used to reconstruct other layers. Most steps are automated with use of functions (found directly underneath). But some manual input is required in the main script (where indicated). The main reconstruction script is continued directly after the used functions.

G1. USED FUNCTIONS

PACKAGE LOADER

Function to load, and if necessary install, all packages.

Input can be either a package name (as string) or a vector with the names of the packages (as string). If a package does not exist or is not available for this version of R. the function will be aborted and a warning with an error will be displayed.

```
packageloader <- function(packages){

# Run the function for every desired package.
  for (x in packages){

# Test if package is allready installed.
    if (!(x %in% rownames(installed.packages()))) {

# If not, install the package.
      lapply(x, FUN=install.packages)
    }

# Load the package.
    lapply(x, FUN=library, character.only=T)

# print the loaded packages.
    print(paste0("The package '", x, "' is loaded."))
  }
}
```

OPEN ASCII FILES

Function to open an ASCII files and adding the RD New projection to it.

Loading (and if necessary installing) packages.

```
packages <- c("rgdal")
packageloader(packages)
```

Inputs for the function are:

- The filename of the to be opened ASCII file,
- The directory where the ASCII file can be found,
- The projection of the ASCII file.

```
OpenASCII <- function(filename, directory, projection){

# Define full path to open the ASCII file.
  fullpath <- paste0(directory, "/", filename, ".asc")

# Open ASCII file.
  ASCIIfile <- readGDAL(fullpath)

# Define projection.
  proj4string(ASCIIfile) <- projection

# Return ASCII file.
  return(ASCIIfile)
}
```

OPEN AHN

Function to load and merge all AHN (.TIF) tile files in a folder

.TIF tiles of the AHN are available at: http://www.arcgis.com/home/webmap/viewer.html?webmap=ac6b6ecd42424e33bd0e6fa09499c563.

Loading (and if necessary installing) packages.

```
packages <- c("raster")
packageloader(packages)
```

Input of the function is the name of the directory that contains all the to be merged .TIF tiles.

```
open_ahn <- function(data_directory_name) {

# Set proper paths.
  data_dir  <- paste0(data_directory_name, "/")
  data_file <- dir(data_dir)


# In case only 1 file is present in the folder, merging is not possible:
  if (length(data_file) == 1){
    message(paste("There is", length(data_file), "AHN file in the selected direc
tory"))
    ahn <- raster(paste0(data_dir, data_file[1]))
    message("The AHN raster is created")
  }

# In case more than 1 file is present in the folder:
  if (length(data_file) > 1){

# Set initial conditions for while loop.
    i <- 1
```

```
    message(paste("There are", length(data_file), "AHN files in the selected dir
ectory."))

# While loop to merge all files in the folder.
    while (i <= length(data_file)){

# First merge, starting with the first two .TIF files listed.
      if (i == 1){
        print(paste0("Merging AHN files ", i, " and ", i+1,"."))

# Before merging, a raster should be made from the .TIF files.
        ahn <- merge(raster(paste0(data_dir, data_file[i])),
                     raster(paste0(data_dir, data_file[i+1])))

        print(paste("AHN files", i, "and", i+1, "have merged."))

# Merging is done for file 1 and 2 listed, so the loop can skip the second
.TIF file listed.
        i <- 2
      }

# Merging continues by adding the next .TIF file (starting with the third)
to the already merged file. Also here a raster should be made from the the
.TIF file before merging.
      if (i > 2){
        print(paste("Adding AHN file", i, "to the previous merged AHN files."))
        ahn<- merge(ahn, raster(paste0(data_dir, data_file[i])))
        print(paste("AHN file", i, "is added to the merged AHN."))
      }

# Continue tot the next file in the folder.
      i <- i + 1
    }
  }

# Return the AHN when all files in the folder have been merged.
  message("The AHN raster is created")
  return(ahn)
}
```

OPTIMIZE DATABASES

Function that optimizes and complements databases in order to use them for the kriging

Inputs for the function are:

- The identifier of the layer that needs to be reconstructed,
- Optionally details if details are preferred above the identifier, e.g. sand median (default is FALSE)
- A database in the correct setup,
- A raster heightfile,
- The projection of the used coordinate system,
- Optionally a cutoff (the column with the last plausible depth of the identifier) (default is no cutoff)
- Size of the rastercells of the final reconstruction

The correct setup of the database:

```
(df <- data.frame("Name" = c("Name_1", "Name_2", "Name_n"),
                  "X.Coord" = c("X-Coord_1", "X-Coord_2", "X-Coord_n"),
                  "Y.Coord" = c("Y-Coord_1", "Y-Coord_2", "Y-Coord_n"),
                  "SurfaceLevel" = c("SurfaceLevel_1", "SurfaceLevel_2", "SurfaceLe
vel_n"),
                  "Layer1 Depth" = c("Depth of Layer 1_1", "Depth of Layer 1_2", "D
epth of Layer 1_n"),
                  "Layer1 Deposit" = c("Layer1_Deposit_1", "Layer1_Deposit_2", "Lay
er1_Deposit_n"),
                  "Layer1 Details" = c("Sand Median_1", "Sand Median_2", "Sand Medi
an_n"),
                  "Layer2 Depth" = c("Depth of Layer 2_1", "Depth of Layer 2_2", "D
epth of Layer 2_n"),
                  "Layer2 Deposit" = c("Layer2_Deposit_1", "Layer2_Deposit_2", "Lay
er2_Deposit_n"),
                  "Layer2 Details" = c("Sand Median_1", "Sand Median_2", "Sand Medi
an_n"),
                  "Layer'n' Depth" = c("Depth of Layer n_1", "Depth of Layer n_2",
"Depth of Layer n_n"),
                  "Layer'n' Details" = c("Layer'n'_Deposit_1", "Layer'n'_Deposit_2"
, "Layer'n'_Deposit_n"),
                  "Layer'n' Deposit" = c("Sand Median_1", "Sand Median_2", "Sand Me
dian_n")
))

##     Name   X.Coord   Y.Coord   SurfaceLevel       Layer1.Depth
## 1 Name_1 X-Coord_1 Y-Coord_1 SurfaceLevel_1 Depth of Layer 1_1
## 2 Name_2 X-Coord_2 Y-Coord_2 SurfaceLevel_2 Depth of Layer 1_2
## 3 Name_n X-Coord_n Y-Coord_n SurfaceLevel_n Depth of Layer 1_n
##     Layer1.Deposit Layer1.Details       Layer2.Depth   Layer2.Deposit
## 1 Layer1_Deposit_1  Sand Median_1 Depth of Layer 2_1 Layer2_Deposit_1
## 2 Layer1_Deposit_2  Sand Median_2 Depth of Layer 2_2 Layer2_Deposit_2
## 3 Layer1_Deposit_n  Sand Median_n Depth of Layer 2_n Layer2_Deposit_n
##   Layer2.Details     Layer.n..Depth   Layer.n..Details Layer.n..Deposit
## 1  Sand Median_1 Depth of Layer n_1 Layer'n'_Deposit_1    Sand Median_1
## 2  Sand Median_2 Depth of Layer n_2 Layer'n'_Deposit_2    Sand Median_2
## 3  Sand Median_n Depth of Layer n_n Layer'n'_Deposit_n    Sand Median_n
```

The database is optimized for kriging in five main steps. These steps are indicated with a double hashtag in front of the comment. The output is a spatial points data frame.

```
optim_database <- function(identifier, details = FALSE, database, heightfile,
                           projection, cutoff = FALSE, rastersize){

  name <- deparse(substitute(database))


## Add empty columns and rearrange columns:
  database["Peatdepth"]  <- NA
  database["Peatheight"] <- NA
  col_Peatdepth  <- grep("Peatdepth", names(database))
  col_Peatheight <- grep("Peatheight", names(database))
  database <- database[, c((1:4),col_Peatdepth, col_Peatheight,(7:ncol(database))-
2)]
```

```r
## Calculate max peat depth under surface level:

# Set Start row and column for finding max peat depth.
  colnr <- 8
  rownr <-1

# If cutoff is FALSE, make the cutoff the max column number.
  if (!cutoff){
    cutoff <- length(names(database))
  }

# If details are provided look for details as identifier and loop through d
etails column.
  if (details){
    identifier = details
    colnr <- 9
  }

# Loop over all columns that describe the layer (Name =  "LayerX").
  while (colnr <= length(colnames(database))){

# Continue loop over all rows.
    while (rownr <= length(row.names(database))){

# Only use cells that are not NA and skip outliers by setting a cutoff (too
deep to be realistic part of the reconstructed pre-peat landscape, this can
be checked with the printed statements, indicicating which rows and columns
match the identifier).
      if (!is.na(database[rownr, colnr]) & colnr <= cutoff){

# Only use cells that that have the identifier.
        if ((database[rownr,colnr]) == identifier){
          print(paste(identifier, "layer at rownumber:", rownr, "and column numbe
r:", colnr))

# Replace peatdepth by the depth of the peath of this layer.
          database$Peatdepth[rownr] <- database[rownr,colnr-1]
        }
      }

# Continue to the next row (next sample location).
      rownr <- rownr + 1
    }

# Continue to the next LayerX column --> Layer(X+1) and Reset the rownumber
s to start at the first sample location again.
    colnr <- colnr + 3
    rownr <- 1
  }

# Assumption made that no peat has depth 0. Set NA to 0 for peat depth.
  for (i in seq(row.names(database))){
    if (is.na(database$Peatdepth[i])){
      database$Peatdepth[i] <- 0
```

```
    }
  }


## Check whether all depths have a deeper layer to make sure the depth is really t
he bottom of the layer and not only the end of the measurement:

# Set initial values and add 2 empty columns at the end to make the loop po
ssible in case the identifier is identified in the last column.
  rownr <- 1
  database$Extra1 <- as.factor("")
  database$Extra2 <- as.factor("")

# Loop through all rows
  while (rownr <= length(row.names(database))){

# Only loop when there is a Peat layer.
    if (database$Peatdepth[rownr] != 0){

# Find out wichh columnnumber has the deepest layer.
      match <- which(database$Peatdepth[rownr] == database[rownr,])

# Take the last matching depth and add 4 to see which layer is underneath.
      match <- tail(match, n = 1) + 4

# If there is no layer, the Peatdepth should be set to NA.
      if (database[rownr, match]  == "" | is.na(database[rownr, match])){
        database$Peatdepth[rownr] <- NA
      }
    }

# Continue to next row.
    rownr <- rownr + 1
  }

# Remove extra created columns.
  database$Extra1 <- NULL
  database$Extra2 <- NULL

# Remove all data points with NA values for the Peat depth and only continu
e if there is still data left, otherwise return NULL.
  database <- database[complete.cases(database$Peatdepth),]

  if (is.na(database[1,1])){
    message("No data in the database is suited.")
    message(paste("There is no layer underneath the", identifier,"layer."))
    message("An empty variable will be returned.")
    database <- NULL
  }

  if (!is.null(database)){


## Extract heights from heightfile raster:
```

```
# Create new dataframe with x and y coordinates of the data to extract the
surface level heights from the heightfile raster.
    ahncoords <- data.frame(x = database$X.Coord, y = database$Y.Coord)
    ahnheight <- extract(heightfile, ahncoords)

# Add the heightfile heights to the levels in the surface level column of t
he dataframe and replace all "Unknown" surface level heights with the heigh
ts extracted from the raster heightfile.
    levels(database$SurfaceLevel) <- c(levels(database$SurfaceLevel), ahnheight)

    for (i in seq(length(rownames(database)))){
      if (database$SurfaceLevel[i] == "Unknown"){
        database$SurfaceLevel[i] <- ahnheight[i]
      }
    }

# Remove all data points with NA values for the surface level and only cont
inue if there is still data left, otherwise return NULL.
    database <- database[complete.cases(database$SurfaceLevel),]

    if (is.na(database[1,1])){
      message("No data in the database is suited.")
      message("The datapoints do not have a surfacelevel height and are not locat
ed on the heightfile")
      message("An empty variable will be returned.")
      database <- NULL
    }

    if (!is.null(database)){


## Calculate peat depth above sea level:

# Make surface level numeric and replace comma's by dots.
      database$SurfaceLevel <- as.numeric(gsub("\\,", ".", database$SurfaceLevel)
)

# Calculate Peat depth above sealevel.
      database$Peatheight <- database$SurfaceLevel - database$Peatdepth

# Make spatial points data frame and add projection.
      coordinates(database) <- ~ X.Coord + Y.Coord
      proj4string(database) <- projection

# Remove duplicate points within [the rastersize] meter.
      database <- remove.duplicates(database, zero = rastersize, remove.second =
T)

      message(paste(name, "has successfully been optimized for use."))
    }
  }

# Return database.
  return(database)
}
```

OPTIMAL LAMBDA (FOR BOXCOX TRANSFORMATION)

Function to find the most optimal lambda in order to get the least skewed histogram of the dataset Or to find the most optimal, universal lamda, for two datasets

If "forecast" is not yet installed, install it. Do not load it because gstat will give problems

```
if (!("forecast" %in% rownames(installed.packages()))) {
  install.packages("forecast")
}
```

Inputs are two datasets, of which the combined most optimal lambda is calculated, to get the lowest skewness average of both BoxCox transformed datasets. If for only 1 dataset the most optimal lambda should be calculated in order to get the least skewed transformation, dataset 1 should be used for dataset 2 as well (default).

```
OptimLambda <- function(dataset1, dataset2 = dataset1){

# Create empty data frame.
  lambda        <- c()
  abs.meanskew <- c()
  abs.BC1skew  <- c()
  abs.BC2skew  <- c()

  lambdadf <- data.frame(lambda, abs.BC1skew, abs.BC2skew, abs.meanskew)
  lambdadf <- lambdadf$lambda
  lambdadf <- lambdadf$abs.BC1skew
  lambdadf <- lambdadf$abs.BC2skew
  lambdadf <- lambdadf$abs.meanskew

# set parameters.
  i <- 1
  series <- seq(-5, 5, 0.01)

# Loop through every value in the series used for lambda.
  for (uselambda in series){

# The used lambda.
    lambdadf$lambda[i]       <- uselambda

# Calculate absolute skewness value for BoxCox transformation.
    lambdadf$abs.BC1skew[i]  <- abs(skewness(try(forecast::BoxCox(dataset1, lamb
da = uselambda), silent = T)))
    lambdadf$abs.BC2skew[i]  <- abs(skewness(try(forecast::BoxCox(dataset2, lamb
da = uselambda), silent = T)))

# Calculate average of both skewnesses.
    lambdadf$abs.meanskew[i] <- mean(c(lambdadf$abs.BC1skew[i], lambdadf$abs.BC2sk
ew[i]))

# Continue to next value in the serie.
    i <- i + 1
  }
```

```
# Find the belonging lambda value of the minimum avareage absolute skewness
.
  optimlambda <- lambdadf$lambda[which(min(na.omit(lambdadf$abs.meanskew))==lambd
adf$abs.meanskew)]

# Retaurn the most optimal lambda.
  return(optimlambda)
}
```

TRANSFORM DATA

Function that tells if a transformation of the data is advisable, if yes it transforms the data

If "forecast" is not yet installed, install it. Do not load it because gstat will give problems, and loading (and if necessary installing) timeDate package.

```
if (!("forecast" %in% rownames(installed.packages()))) {
  install.packages("forecast")
}

packages <- c("timeDate")
packageloader(packages)
```

Inputs for the function are:

- Dataset1: the data that that needs to be checked on distribution and needs to be transformed to become the least skewed,
- Dataset2: only use to find the best transformation based on two datasets; used to get the same lambda for BoxCox transformation.
- Transformdata is data to be transformed, use if the to be transformed data is different than the data on which the distribution is based. Default is dataset 1. if draw=TRUE, it is adviced to use dataset1 here instead of calling on dataset1 as default (if not done the title will contain "dataset1" instead of the name of dataset1),
- Transformation: choose a specific transformation (default is "All"). Choose between:
  - "All"
  - "No"
  - "Natural logarithmic"
  - "Logarithmic"
  - "Square root"
  - "Exponential"
  - "BoxCox"
- Draw: choose to plot the histogram. Default is to plot it (TRUE)

```
DoTransform <- function(dataset1, dataset2 = dataset1, transformdata = dataset1,
                        transformation = "All", draw = T){

# Copy transformation in order to properly check all transformations and se
lect a transformation based on that checkup and correctly inform the user o
n the transformation.
  Trans <- transformation

# Identify most likely transformations.
```

```
  lambda <- OptimLambda(dataset1, dataset2)

  NoTrans     <- dataset1
  NatLogTrans <- log(dataset1)
  Log10Trans  <- log10(dataset1)
  SqrtTrans   <- sqrt(dataset1)
  ExpTrans    <- exp(dataset1)
  BCTrans     <- forecast::BoxCox(transformdata, lambda = lambda)

# Create dataframe with most likely transformations and the skewness.
  Transdf <- data.frame("Transformations"= c("No", "Natural logarithmic", "Logari
thmic",
                                              "Square root", "Exponential", "BoxCox
"),
                        "Skewness"= c(skewness(NoTrans), skewness(NatLogTrans),
skewness(Log10Trans),
                                        skewness(SqrtTrans), skewness(ExpTrans), s
kewness(BCTrans)))

  if (transformation == "All" |
      transformation == "No" |
      transformation == "Natural logarithmic" |
      transformation == "Logarithmic" |
      transformation == "Square root" |
      transformation == "Exponential" |
      transformation == "BoxCox"){

# If transformation = All, check all transformations and use the least skew
ed transformation.
    if (Trans == "All"){

# Find least skewed transformation and rename Trans.
      LeastSkew <- min(abs(na.omit(Transdf$Skewness)))
      LowTrans  <- which(LeastSkew == abs(Transdf$Skewness))[1]
      Trans     <- Transdf$Transformations[LowTrans]
    }

# If no transformation is needed: do nothing.
    if(Trans == "No"){
      newData <- NoTrans

# Inform user what is done.
      message(paste(Trans, "transformation is advised and data is left unchanged"
))
      message(paste("The skewness of the data is", skewness(newData)))

# Plot histogram of the distribution and add the skewness to the plot if dr
aw = TRUE.
      if (draw == T){
        hist(newData, xlab = "Untransformed Height of layer", ylab = "Frequency",
             main = paste("Histogram of", deparse(substitute(transformdata))),
             sub  = paste("Skewness is", skewness(newData)))
      }
    }

# If a transformation is needed: transform data.
```

```
    if (Trans != "No"){

      if(Trans == "Natural logarithmic"){
        newData <- NatLogTrans
      }
      if(Trans == "Logarithmic"){
        newData <- Log10Trans
      }
      if(Trans == "Square root"){
        newData <- SqrtTrans
      }
      if(Trans == "Exponential"){
        newData <- ExpTrans
      }
      if(Trans == "BoxCox"){
        newData <- BCTrans
      }

# Inform user what is done if a transformation advice is given.
      if (transformation == "All"){
        message(paste(Trans, "transformation is advised and executed"))
        message(paste("The skewness of the transformed data is", skewness(newDat
a)))
      }

# Inform user what is done if the user choose the transformation.
      if (transformation != "All"){
        message(paste(Trans, "transformation is executed"))
        message(paste("The skewness of the transformed data is", skewness(newDat
a)))
      }

# Plot histogram of the new distribution and add the skewness to the plot i
f draw = TRUE.
      if (draw == T){
        hist(newData, xlab = "Transformed height of layer", ylab = "Frequency",
             main = paste("Histogram of a", Trans, "transformation of", deparse(s
ubstitute(transformdata))),
             sub = paste("Skewness is", skewness(newData)))
      }
    }
  }

# In case the wrong "transformation" is given.
  else {
    warning('Incorrect input for "transformation" , please use one of the followi
ng statements:
  "All", "No", "Natural logarithmic", "Logarithmic", "Square root", "Exponential"
or "BoxCox"')
    newData <- NoTrans
  }

# Return the new data.
  return(newData)
}
```

BEST FIT VARIOGRAM MODEL

Function that returns the variogram with the lowest sum of square error of all available variogram types ("vgm()")

Loading (and if necessary installing) packages.

```
packages <- c("gstat")
packageloader(packages)
```

Input for the function is a variogram of a gstat object, skip allows to skip one variogram type.

```
optim_vgm_model <- function(vg, skip = F){

# Set parameters and initial (empty) vectors and dataframe.
  i         <- 1
  skipnr    <- which(vgm()$short == skip)
  VgmType   <- c()
  VgmSSErr  <- c()
  df        <- data.frame(VgmType, VgmSSErr)
  df        <- df$VgmType
  df        <- df$VgmSSErr

# Loop through all variogram types.
  while (i < length(vgm()$short)){

# vgm() is of class data.frame. For every row the type should be selected a
nd only the short code for the variogram type should be used when autofitti
ng the variogram. Not all variogram types can be used, some throw errors so
fitting the variogram should be suppressed with a Try(). Warnings are suppr
essed.
    VgmType[i] <- unlist(strsplit(as.character(vgm()$short[i]), " "))
    suppressWarnings(try(vgmX <- fit.variogram(vg, vgm(VgmType[i]), fit.kappa =
T), silent = T))


# Find the belonging sum of squared errors.
    VgmSSErr[i] <- attr(vgmX, "SSErr")


# Store data in the dataframe.
    df$VgmType[i]  <- VgmType[i]
    df$VgmSSErr[i] <- VgmSSErr[i]

# Continue to the next row
    i <- i + 1

# If the next row is the vgm type that should be skipped, continue to secon
d next row.
    if (skip %in% vgm()$short){
      if (i == skipnr){
        i <- i + 1
      }
    }
  }
```

```
# Find variogram type with minimum sum of squared errors, if multiple vario
grams have the lowest sum of squared errors, the first one is used.
  minSSErr     <- min(na.omit(df$VgmSSErr))
  minSSErrRow  <- which(df$VgmSSErr == minSSErr)[1]
  minSSErrFull <- factor(vgm()$short[minSSErrRow])
  print(paste("The best fitted variogram type is:", minSSErrFull))
  minSSErrType <- toString((factor(df$VgmType[minSSErrRow])))

# Return the fitted variogram with the lowest sum of squared errors.
  vgm <- fit.variogram(vg,vgm(minSSErrType))
  return(vgm)
}
```

BEST VARIOGRAM MODEL

Function that tells which of two variogram models is best for kriging, meaning: which variogram model has the lowest sill and the lowest nugget.

The function reports it when no choice can be made. An eye should be kept on the difference in range, with a high range difference the sill might look better on small scale.

Inputs are two variogram models.

```
bestvgm <- function(vgm1, vgm2){

# Calculate the difference in range.
  rangedif <- abs(vgm1$range[2] - vgm2$range[2])

# Check if variogram model 1 is best and set variogram model 1 for use.
  if (vgm1$psill[1] < vgm2$psill[1] & vgm1$psill[2] < vgm2$psill[2]){
    use <- vgm1
    message(deparse(substitute(vgm1)), " is best suited for kriging")
    message(deparse(substitute(vgm1)), " is the returned variogram model")
    message("MIND: the range difference is: ", rangedif)
  }

# Check if variogram model 2 is best and set variogram model 2 for use.
  if (vgm1$psill[1] > vgm2$psill[1] & vgm1$psill[2] > vgm2$psill[2]){
    use <- vgm2
    message(deparse(substitute(vgm2)), " is best suited for kriging")
    message(deparse(substitute(vgm2)), " is the returned variogram model")
    message("MIND: the range difference is: ", rangedif)
  }

# If the nugget and sill both are not the best option.
  if (!(vgm1$psill[1] < vgm2$psill[1] & vgm1$psill[2] < vgm2$psill[2]) &
      !(vgm1$psill[1] > vgm2$psill[1] & vgm1$psill[2] > vgm2$psill[2])){
    use <- NULL
    message("Cannot choose the best variogram model, manual selection is required
")
    message("No variogram model is returned")
  }

# Return the variogram model set for use.
```

```
  return(use)
}
```

REVERSE BOXCOX TRANSFORMATION

Function that reverses (back transforms) BoxCox transformed data

If "forecast" is not yet installed, install it. Do not load it because gstat will give problems.

```
if (!("forecast" %in% rownames(installed.packages()))) {
  install.packages("forecast")
}
```

Inputs for the function are:

- BoxCox transformed dataset,
- Original dataset to calculate the optimal lambda used,
- In case two datasets are compared, the second dataset to calculate the combined most optimal lambda,
- Variance of the transformed dataset

```
revBoxCox <- function(BCTransformedData, OriginalData1, OriginalData2 = OriginalDa
ta1, variance){

# Calculate lambda based on the original input data for the transformation.
  lambda   <- OptimLambda(OriginalData1, OriginalData2)

# Back transformation to expected values.
  normdata <- forecast::InvBoxCox(BCTransformedData, lambda = lambda, biasadj = T
, fvar = variance)

  return(normdata)
}
```

CALCULATE RECONSTRUCTION STATISTICS

Function that returns an asked statistic of input reconstructions and layers

All inputs as character vectors:

- One statistic method (e.g. min, max, mean),
- Multiple reconstructions to be compared,
- One selectable layer that all reconstructions contain.

```
reconstruction_stat <-function(reconstructions, layer, stat){

# Set parameters.
  i      <-1
  value <- c()
  df     <- data.frame(value)
  df     <- df$value

# Loop through all reconstructions.
  for (recons in reconstructions){
```

```
# Calculate the asked statistic of the selected layer of the reconstruction
.
    df$value[i] <- eval(parse(text = paste0(stat, "(", "na.omit(", recons, "$", l
ayer,"))")))

# Continue to the next reconstruction.
    i <- i +1
  }

  return(df$value)
}
```

OPTIMIZED BARGERVEEN CASE STUDY PLOT

Function to automatically plot figures with correct settings, optimized for the Bargerveen case study area.

Loading (and if necessary installing) packages.

```
packages <- c("sp")
packageloader(packages)
```

Inputs for the function are:

- The dataset of class extending Spatial-Class,
- The character (column) that needs to be plotted (zcol from sp package),
- Title of the plot,
- Optional observation data points that are used for kriging,
- Minimum value to be scaled,
- Maximum value to be scaled.

```
BargerveenCasePlot <- function(data, sp_zcol, title, pts = NULL, minval, maxval) {

# North Arrow.
  arrow    <- list("SpatialPolygonsRescale", layout.north.arrow(type=2),
                   offset = c(264900, 522115), scale = 92)
  arrowlab <- list("sp.text", c(264990, 522160), "N", cex = 1.05)

# Scalebar of the plot and accompanying numbers.
  scalebar       <- list("SpatialPolygonsRescale", layout.scale.bar(),
                         offset = c(263670,522115), scale = 1000,
                         fill=c("white","black"))
  scalebartext.l <- list("sp.text", c(263670, 522200), "0", cex = 0.7)
  scalebartext.r <- list("sp.text", c(264670, 522200), "1000 m", cex = 0.7)

# Data points displayed as green circle with a white outline, not displayed
if pts = NULL.
  pts1 <- list("sp.points", pts, pch = 20, col = "white", cex = 1.2)
  pts2 <- list("sp.points", pts, pch = 20, col = "dark green")


# Create variables to add to the spplot layout in case data points are give
n as input (pts != NULL).
  if (!is.null(pts)){
```

```
# Box around the extra information
    poly <- list("sp.polygons",
                 SpatialPolygons(list(Polygons(list(Polygon(cbind(
                   c(263625, 265635, 265635, 263625), c(522225, 522225, 522100, 52
2100)))), "bg"))),
                 fill = "lightgrey")

# Label for the data points in the box, it's location and the symbol in fro
nt of the text.
    ptslab     <- list("sp.text", c(265400, 522167), "Data Points", cex = 0.9)
    ptslabloc  <- data.frame("x"= 265200, "y"= 522160) ; coordinates(ptslabloc)
<- ~x+y
    ptslabsym1 <- list("sp.points", ptslabloc, pch =20, col="white", cex = 1.2, fi
rst = F)
    ptslabsym2 <- list("sp.points", ptslabloc, pch =20, col="dark green", cex = 1,
first = F)
   }


# Create variables to add to the spplot layout in case no data points are g
iven as input (pts = NULL).
  if(is.null(pts)){

# Box around the extra information
    poly <- list("sp.polygons",
                 SpatialPolygons(list(Polygons(list(Polygon(cbind(
                   c(263625, 265100, 265100, 263625), c(522225, 522225, 522100, 52
2100)))), "bg"))),
                 fill = "lightgrey")

# Empty label/symbol for the legend, so it is not displayed.
    ptslab     <- NULL
    ptslabsym1 <- NULL
    ptslabsym2 <- NULL
    }


# Creating the plot.
  figure <- spplot(obj    = data,
                   zcol   = sp_zcol,
                   main   = title,
                   scales = list(draw = T),
                   xlim   = c(data@bbox[1,1] - 100, data@bbox[1,2] + 100),
                   ylim   = c(data@bbox[2,1] - 300, data@bbox[2,2] + 100),
                   xlab   = "X coordinates",
                   ylab   = "Y coordinates",
                   at     = seq(minval, maxval, by= (maxval-minval)/100),
                   sp.layout = list(poly, arrow, arrowlab, scalebar, scalebartext.
l, scalebartext.r,
                                    pts1, pts2, ptslab, ptslabsym1, ptslabsym2),
                   as.table  = T
  )

# Displaying the plot.
  print(figure)
```

```
# Returning the plot.
  return(figure)
}
```

CROSS VALIDATION WITH NO CLUSTERING

Function to do a cross validation without influence of local clustering by predicting all clustered observation data using all other available observation data that is not clustered. Clustered data should be identified by a similar identification in one of the columns of the spatial points data frame).

The cross validation happens in three steps, first a hold-out cross validation is done for the first cluster, than a hold-out cross validation is done for the remaining clusters (if present) and last a leave-one-out cross validation is done for the non-clustered data (if present). All cross validations are combined. In the output, the "$fold" column indicates the hold-out cross validation (fold = 1), and the leave-one-out cross validation (fold > 1).

Inputs for the function are:

- The right cross validation method, depending on kriging method used. Choose between: "gstat.cv" or "krige.cv"
- A vector with the cluster identifiers
- Character name of the column where the clusters can be identified
- Character name of the Spatial points data frame with locations to be cross validised

- When using "gstat.cv" method: gstat object
- When using "krige.cv" method: gstat formula for cross validation
- When using "krige.cv" method: gstat model for cross validation

```
cv.nocluster <- function(method, clusters, ID_column, data_cv, object_cv, formula_
cv, model_cv){

# Check if method is correct
  if (method == "gstat.cv"){
    message("gstat.cv has been chosen as method")
  }
  if (method == "krige.cv"){
    message("krige.cv has been chosen as method")
  }
  if (method != "gstat.cv" & method != "krige.cv"){
    stop('Wrong method chosen, choose "gstat.cv" or "krige.cv"')
  }

# Select first cluster ID and make selection of all other cluster ID's
  select1 <- clusters[1]
  select2 <- clusters[2:length(clusters)]

## Start cross validation for first cluster:
  message(select1)

# Find location of cluster in the spatialpointdataframe
  foldclass <- which(grepl(select1, eval(parse(text = paste0(data_cv, "$", ID_co
lumn)))))

# Create vector with "folds": 1 if location is in cluster, 2 if not in clus
ter
```

```
  foldvect  <- c()

# Loop through all rows in the data and check if the rownumber matches a lo
cation in the cluster
  for (i in eval(parse(text = paste0(data_cv, "$", ID_column)))){

# In cluster --> fold 1
    if (which(eval(parse(text = paste0(data_cv, "$", ID_column))) == i) %in% fol
dclass){
      foldvect <- c(foldvect,1)
    }

# Not in cluster --> fold 2
    if (!(which(eval(parse(text = paste0(data_cv, "$", ID_column))) == i) %in% f
oldclass)){
      foldvect <- c(foldvect,2)
    }
  }

# Holdout cross validation, depending on selected method
  if (method == "gstat.cv"){hocv <- gstat.cv(object  = object_cv,  nfold = foldve
ct)}
  if (method == "krige.cv"){hocv <- krige.cv(formula = formula_cv, eval(parse(te
xt = data_cv)),
                                               model    = model_cv,    nfold = foldvec
t)}

# Select the cross validated data in the cluster (fold = 1)
  combcv <- hocv[hocv$fold== 1,]


## If there are more than one cluster, continue:
  if (length(clusters) > 1){

# Loop through all other clusters
    for (select in select2){

# Start cross validation for remaining clusters
      message(select)

# Find locations of clusters in the spatialpointsdataframe
      foldclass <- which(grepl(select, eval(parse(text = paste0(data_cv, "$", ID
_column)))))

# Create vector with "folds": 1 if location is in cluster, 2 if not in clus
ter
      foldvect  <- c()

# Loop through all rows in the data and check if the rownumber matches a lo
cation in the cluster
      for (i in eval(parse(text = paste0(data_cv, "$", ID_column)))){

# In cluster --> fold 1
        if (which(eval(parse(text = paste0(data_cv, "$", ID_column))) == i) %in%
foldclass){
```

```
          foldvect <- c(foldvect,1)
        }

# Not in cluster --> fold 2
        if (!(which(eval(parse(text = paste0(data_cv, "$", ID_column))) == i) %i
n% foldclass)){
          foldvect <- c(foldvect,2)
        }
      }

# Holdout cross validation, depending on selected method
      if (method == "gstat.cv"){hocv <- gstat.cv(object  = object_cv,  nfold = fo
ldvect)}
      if (method == "krige.cv"){hocv <- krige.cv(formula = formula_cv, locations
= eval(parse(text = data_cv)),
                                                model    = model_cv,   nfold = fol
dvect)}

# Select the cross validated data in the cluster (fold = 1) and add to prev
ious selected cross validated cluster data.
      combcv <- rbind(combcv, hocv[hocv$fold == 1,])
    }
  }


## Continue if there is more data that is not clustered:
  if (length(combcv) != length(eval(parse(text = data_cv)))){

# Start cross validation for first cluster
    message("Remaining, non clustered data")

# Find locations of nonclustered data in the spatialpointsdataframe
    foldclass <- c()

# Loop through all clusters
    for (cluster in clusters){

# Find locations per cluster
      singclust <- which(grepl(cluster, eval(parse(text = paste0(data_cv, "$", I
D_column)))))

# Store cluster locations in vector
      foldclass <- c(foldclass, singclust)
    }

# Create vector with "folds": 1 if location is in cluster, 2 if not in clus
ter
    foldvect  <- c()

# Loop through all rows in the data and check if the rownumber matches a lo
cation in the cluster
    for (i in eval(parse(text = paste0(data_cv, "$", ID_column)))){

# In cluster --> fold 1
      if (which(eval(parse(text = paste0(data_cv, "$", ID_column))) == i) %in% f
```

```
oldclass)){
        foldvect <- c(foldvect,1)
      }

# Not in cluster --> fold 2
      if (!(which(eval(parse(text = paste0(data_cv, "$", ID_column))) == i) %in%
foldclass)){
        foldvect <- c(foldvect,2)
      }
    }

# Copy spatialpointsdatframe and create new column with the fold (1 or 2)
    remain <- eval(parse(text = data_cv))
    remain$foldvect <- foldvect

# Only keep rows with fold is 2 (non clustered data)
    remain <- remain[remain$foldvect == 2, ]

# Leave one out cross validation, depending on selected method
    if (method == "gstat.cv"){loocv <- gstat.cv(object  = object_cv,  nfold = fol
dvect)}
    if (method == "krige.cv"){loocv <- krige.cv(formula = formula_cv, locations =
remain,
                                                model    = model_cv,    nfold = nrow
(remain))}

# Add 1 to the fold number in order to maintain unique fold number when com
bining all crossvalidations
    loocv$fold <- loocv$fold + 1

# Add to holdout cross validated cluster data
    combcv <- suppressWarnings(rbind(combcv, loocv))
  }

# Return all cross validated data
  return(combcv)
}
```

G2. MAIN RECONSTRUCTION SCRIPT

GENERAL SETUP AND GLOBAL PARAMETERS USED FOR RECONSTRUCTING

Loading (and if necessary installing) packages.

```
packages <- c("raster",
              "sp",
              "gstat",
              "timeDate",
              "lattice",
              "animation"
)
packageloader(packages)
```

Creating a projection variable (RD New).

```
projection <- CRS("+init=epsg:28992")
```

Setting the resolution (m).

```
resolution_CS <- 2
```

Open ASCII file of the area with the locations that need to be predicted.

```
CaseStudy <- OpenASCII(paste0("bargerveen_casestudy_", resolution_CS, "m"), "ASCI
I", projection)

## ASCII/bargerveen_casestudy_2m.asc has GDAL driver AAIGrid
## and has 556 rows and 1112 columns
```

Open AHN for case study area.

```
ahn <- open_ahn("AHNdata")
```

Creating a reconstruction of the surfacelevel with the same resolution as the final reconstruction by creating a spatial points data frame with all locations (coordinates) in the casestudy area and assign values from one to the length of the casestudy area.

```
area_recon <- SpatialPointsDataFrame(coordinates(CaseStudy), data.frame(ID=1:l
ength(CaseStudy)))
```

Extract data of the ahn for all locations in the area reconstruction

```
ahndata_recon <- extract(ahn, area_recon)
```

Create Spatial grid data frame for the case study area with all the locations of the casestudy area and data extracted from the ahn.

```
ahn_area <- SpatialGridDataFrame(CaseStudy, data.frame(SurfaceLevel = ahndata_r
econ), proj4string = projection)
```

DATABASE SETUP

Set path.

```
csvpath <- "Databases/"
```

Open csv files with database data.

```
BPKcsv  <- "Bargerveen_BPK.csv"
DINOcsv <- "Bargerveen_DINO.csv"
PFBcsv  <- "Bargerveen_PFB.csv"
GPRcsv  <- "Bargerveen_GPR.csv"
```

Create dataframes from csv files

```
BPKdf  <- read.csv2(paste0(csvpath,  BPKcsv), header = T)
DINOdf <- read.csv2(paste0(csvpath, DINOcsv), header = T)
PFBdf  <- read.csv2(paste0(csvpath,  PFBcsv), header = T)
GPRdf  <- read.csv2(paste0(csvpath,  GPRcsv), header = T)
```

There are two ways of reconstruction the peat height:

- Kriging: (surface level - peatdepth) --> peatheight reconstruction
- Surface level - (Kriging: peatdepth) --> peatdepth reconstruction

The optim_databases() function replaces all "Unknown" surface level heights. In order to have the same surfacelevel heights for both ways of reconstructing, all known surface levels are replaced by ahn surface level heights.

Make all surfacelevels "Unknown".

```
for (i in seq(DINOdf$SurfaceLevel)){DINOdf$SurfaceLevel[i] <- "Unknown"}
```

Create databases.

```
BISdf    <- merge(PFBdf, BPKdf,  all = T)
Legacydf <- merge(BISdf, DINOdf, all = T)
Alldf    <- merge(Legacydf, GPRdf, all =T)
```

Optimize databases.

```
GPR    <- optim_database("Peat", details = F, GPRdf,    ahn, proj = projection,
                         cutoff = F,  rastersize = 1)

## GPRdf has successfully been optimized for use.

Legacy <- optim_database("Peat", details = F, Legacydf, ahn, proj = projection,
                         cutoff = 26, rastersize = 1)

## Legacydf has successfully been optimized for use.

All    <- optim_database("Peat", details = F, Alldf,    ahn, proj = projection,
                         cutoff = 26, rastersize = 1)

## Alldf has successfully been optimized for use.
```

Subsetting the walked transect lines with the GPR.

```
L21GPR <- subset(GPR, grepl("FW_L21", GPR$Name)); L21All <- subset(All, grepl("F
W_L21", All$Name))
L22GPR <- subset(GPR, grepl("FW_L22", GPR$Name)); L22All <- subset(All, grepl("F
W_L22", All$Name))
L23GPR <- subset(GPR, grepl("FW_L23", GPR$Name)); L23All <- subset(All, grepl("F
W_L23", All$Name))
L24GPR <- subset(GPR, grepl("FW_L24", GPR$Name)); L24All <- subset(All, grepl("F
W_L24", All$Name))
```

```
L25GPR <- subset(GPR, grepl("FW_L25", GPR$Name)); L25All <- subset(All, grepl("F
W_L25", All$Name))
L26GPR <- subset(GPR, grepl("FW_L26", GPR$Name)); L26All <- subset(All, grepl("F
W_L26", All$Name))
L27GPR <- subset(GPR, grepl("FW_L27", GPR$Name)); L27All <- subset(All, grepl("F
W_L27", All$Name))
L28GPR <- subset(GPR, grepl("FW_L28", GPR$Name)); L28All <- subset(All, grepl("F
W_L28", All$Name))
L29GPR <- subset(GPR, grepl("FW_L29", GPR$Name)); L29All <- subset(All, grepl("F
W_L29", All$Name))
L30GPR <- subset(GPR, grepl("FW_L30", GPR$Name)); L30All <- subset(All, grepl("F
W_L30", All$Name))
L31GPR <- subset(GPR, grepl("FW_L31", GPR$Name)); L31All <- subset(All, grepl("F
W_L31", All$Name))
L32GPR <- subset(GPR, grepl("FW_L32", GPR$Name)); L32All <- subset(All, grepl("F
W_L32", All$Name))
remain1 <- subset(All, grepl("BPK",  All$Name))
remain2 <- subset(All, grepl("DINO", All$Name))
remain3 <- subset(All, grepl("PFB",  All$Name))
```

Select 5 random numbers from the lines (subsetted GPR and All have the same length, so random selection is used for both.

```
set.seed(275); rand21 <- sort(sample(1:length(L21GPR), 5))
set.seed(275); rand22 <- sort(sample(1:length(L22GPR), 5))
set.seed(275); rand23 <- sort(sample(1:length(L23GPR), 5))
set.seed(275); rand24 <- sort(sample(1:length(L24GPR), 5))
set.seed(275); rand25 <- sort(sample(1:length(L25GPR), 5))
set.seed(275); rand26 <- sort(sample(1:length(L26GPR), 5))
set.seed(275); rand27 <- sort(sample(1:length(L27GPR), 5))
set.seed(275); rand28 <- sort(sample(1:length(L28GPR), 5))
set.seed(275); rand29 <- sort(sample(1:length(L29GPR), 5))
set.seed(275); rand30 <- sort(sample(1:length(L30GPR), 5))
set.seed(275); rand31 <- sort(sample(1:length(L31GPR), 5))
set.seed(275); rand32 <- sort(sample(1:length(L32GPR), 5))
```

Select the random data points from the subsetted lines for both GPR and All data.

```
S21GPR <- L21GPR[rand21, ];  S21All <- L21All[rand21, ]
S22GPR <- L22GPR[rand22, ];  S22All <- L22All[rand22, ]
S23GPR <- L23GPR[rand23, ];  S23All <- L23All[rand23, ]
S24GPR <- L24GPR[rand24, ];  S24All <- L24All[rand24, ]
S25GPR <- L25GPR[rand25, ];  S25All <- L25All[rand25, ]
S26GPR <- L26GPR[rand26, ];  S26All <- L26All[rand26, ]
S27GPR <- L27GPR[rand27, ];  S27All <- L27All[rand27, ]
S28GPR <- L28GPR[rand28, ];  S28All <- L28All[rand28, ]
S29GPR <- L29GPR[rand29, ];  S29All <- L29All[rand29, ]
S30GPR <- L30GPR[rand30, ];  S30All <- L30All[rand30, ]
S31GPR <- L31GPR[rand31, ];  S31All <- L31All[rand31, ]
S32GPR <- L32GPR[rand31, ];  S32All <- L32All[rand31, ]
```

Combine the subsetted random points, use to get less disturbance of local clustering in variogram.

```
GPR_subset <- rbind(S21GPR, S22GPR, S23GPR, S24GPR, S25GPR, S26GPR,
                    S27GPR, S28GPR, S29GPR, S30GPR, S31GPR, S32GPR)
All_subset <- rbind(S21All, S22All, S23All, S24All, S25All, S26All,
                    S27All, S28All, S29All, S30All, S31All, S32All, remain1, remai
n2, remain3)
```

The subsetted data is used for variagram fitting and thus for transforming data. The complete dataset is used for the reconstruction. The latter needs the same transformation (and consequently back transformation) as the subsetted data.

Check for distribution, and transform data.

```
All$T_Peatdepth            <- DoTransform(All_subset$Peatdepth,
                                          transformdata = All$Peatdepth,  transfor
mation = "BoxCox")
```

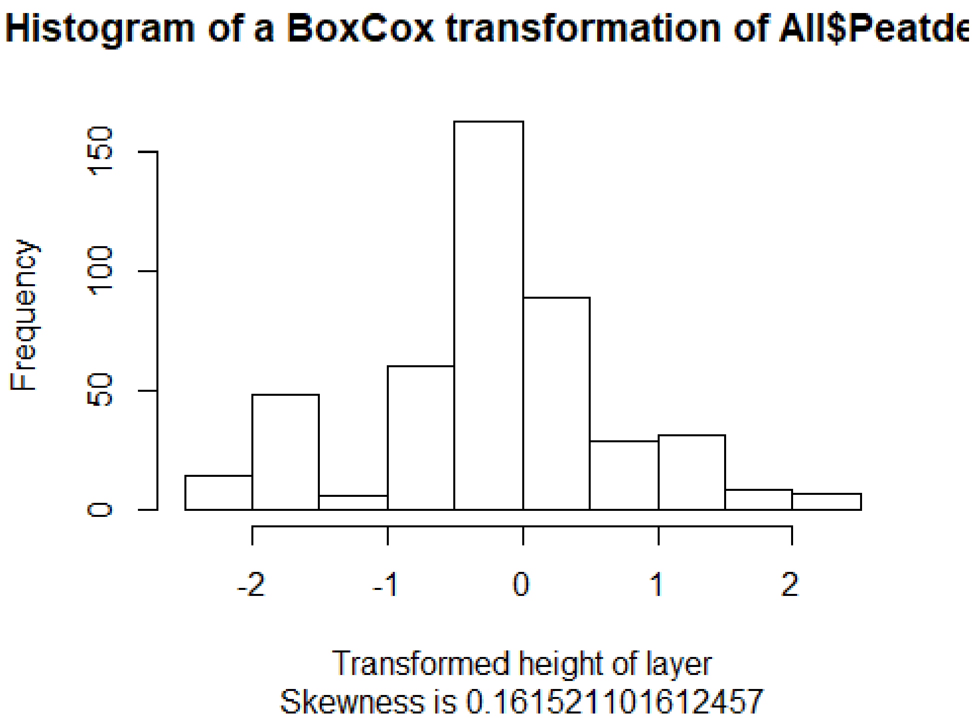

FIGURE 10.31: HISTOGRAM OF A BOX-COX TRANSFORMATION OF ALL$PEATDEPTH.

```
All$T_Peatheight           <- DoTransform(All_subset$Peatheight,
                                          transformdata = All$Peatheight, transfor
mation = "BoxCox")
```

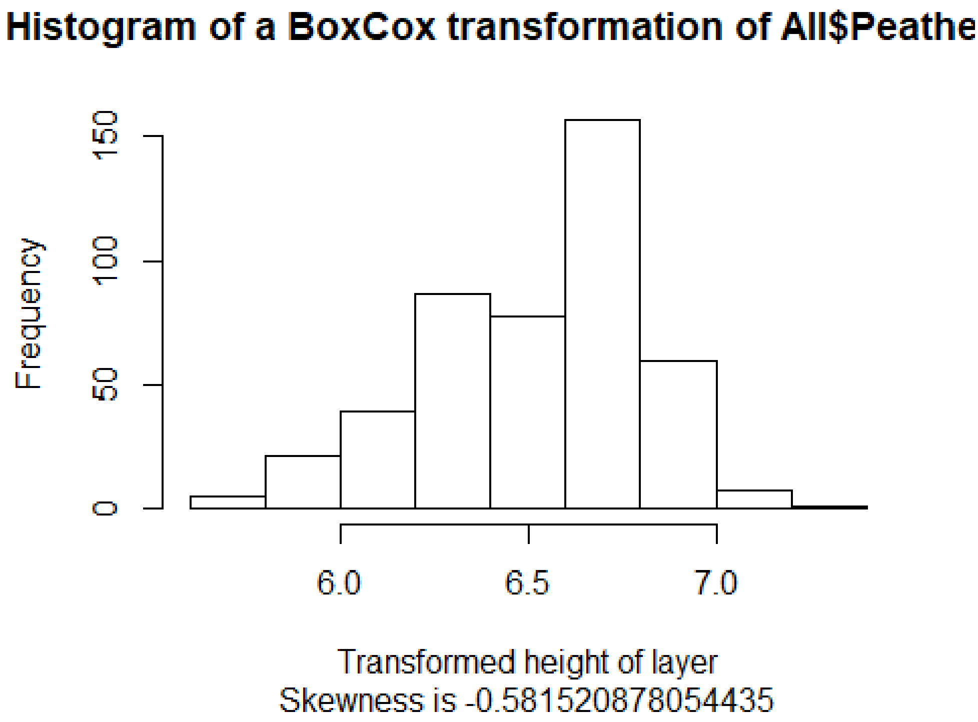

FIGURE 10.32: HISTOGRAM OF A BOX-COX TRANSFORMATION OF ALL$PEATHEIGHT.

```
All_subset$T_Peatdepth     <- DoTransform(All_subset$Peatdepth,  transformdata =
All_subset$Peatdepth)
```

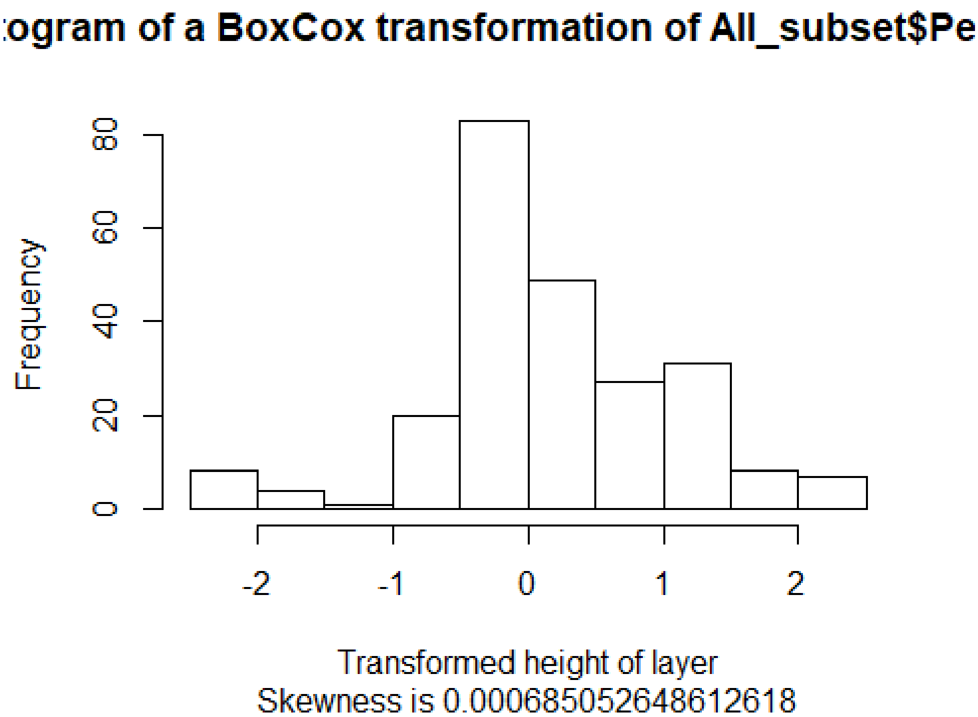

FIGURE 10.33: HISTOGRAM OF A BOX-COX TRANSFORMATION OF ALL_SUBSET$PEATDEPTH.

```
All_subset$T_Peatheight    <- DoTransform(All_subset$Peatheight, transformdata =
All_subset$Peatheight)
```

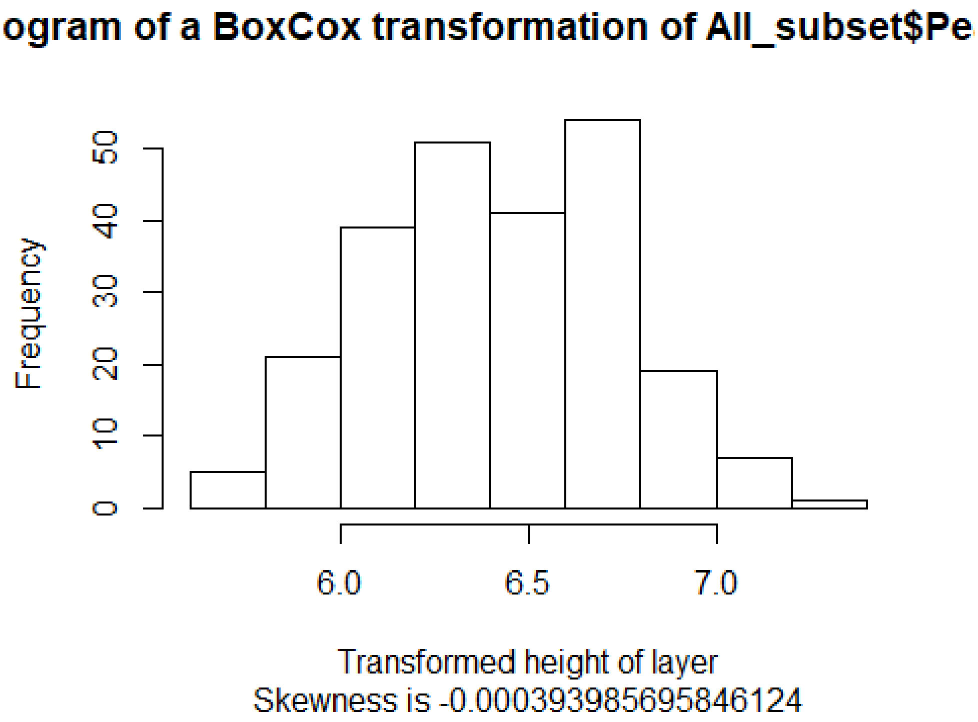

FIGURE 10.34: HISTOGRAM OF A BOX-COX TRANSFORMATION OF ALL_SUBSET$PEATHEIGHT.

```
GPR$T_Peatdepth              <- DoTransform(GPR_subset$Peatdepth,
                                            transformdata = GPR$Peatdepth,   transfor
mation = "BoxCox")
```

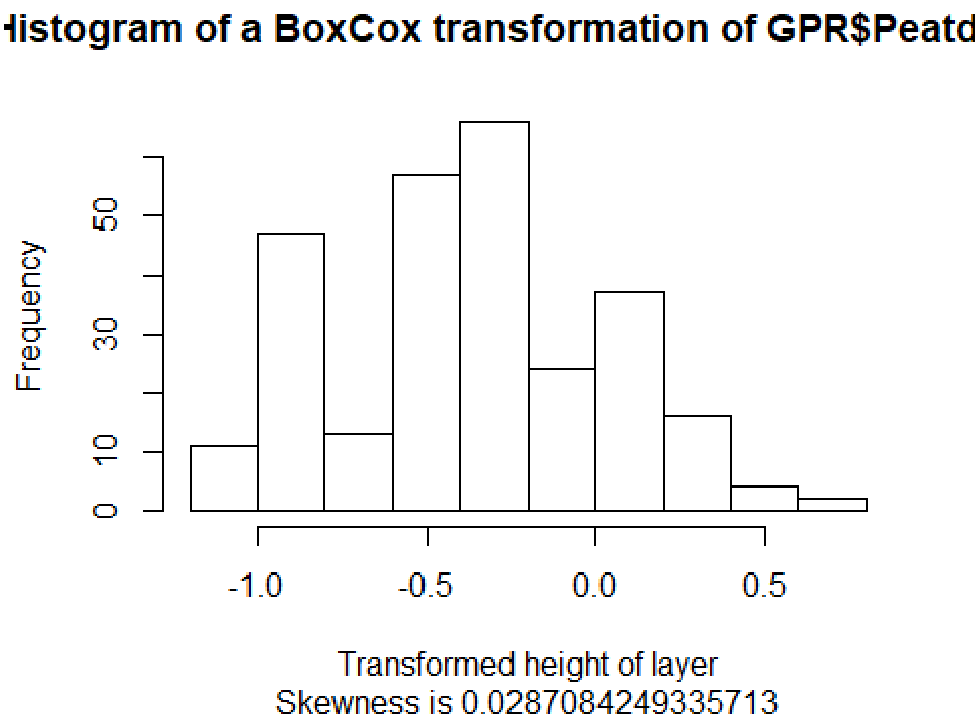

FIGURE 10.35: HISTOGRAM OF A BOX-COX TRANSFORMATION OF GPR$PEATDEPTH.

```
GPR$T_Peatheight             <- DoTransform(GPR_subset$Peatheight,
                                transformdata = GPR$Peatheight, transfor
mation = "BoxCox")
```

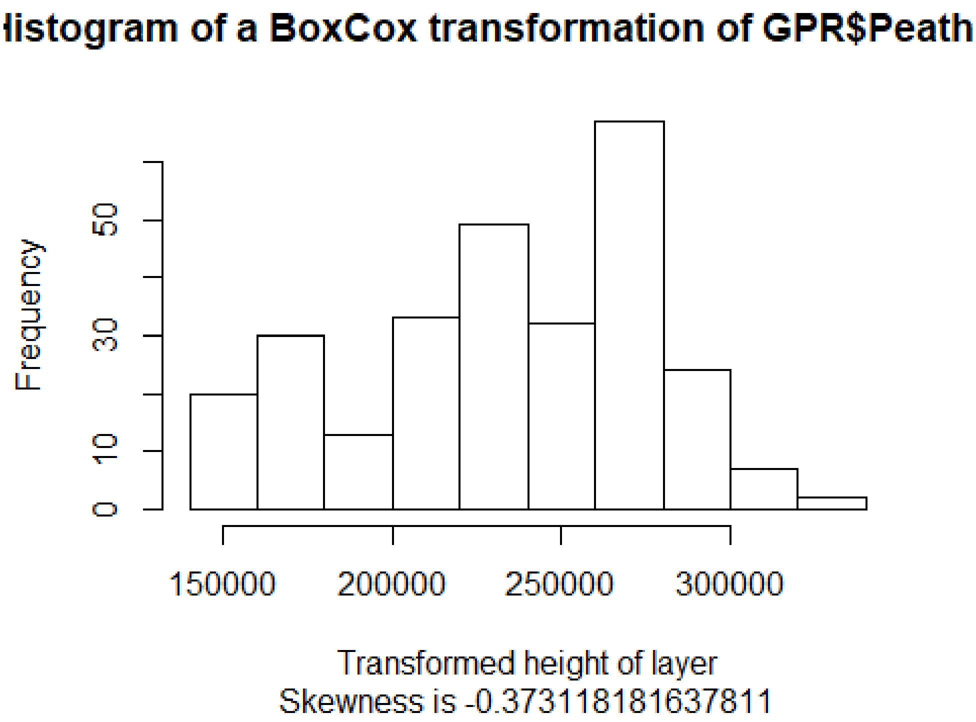

FIGURE 10.36: HISTOGRAM OF A BOX-COX TRANSFORMATION OF GPR$PEATHEIGHT.

```
GPR_subset$T_Peatdepth      <- DoTransform(GPR_subset$Peatdepth,  transformdata =
GPR_subset$Peatdepth)
```

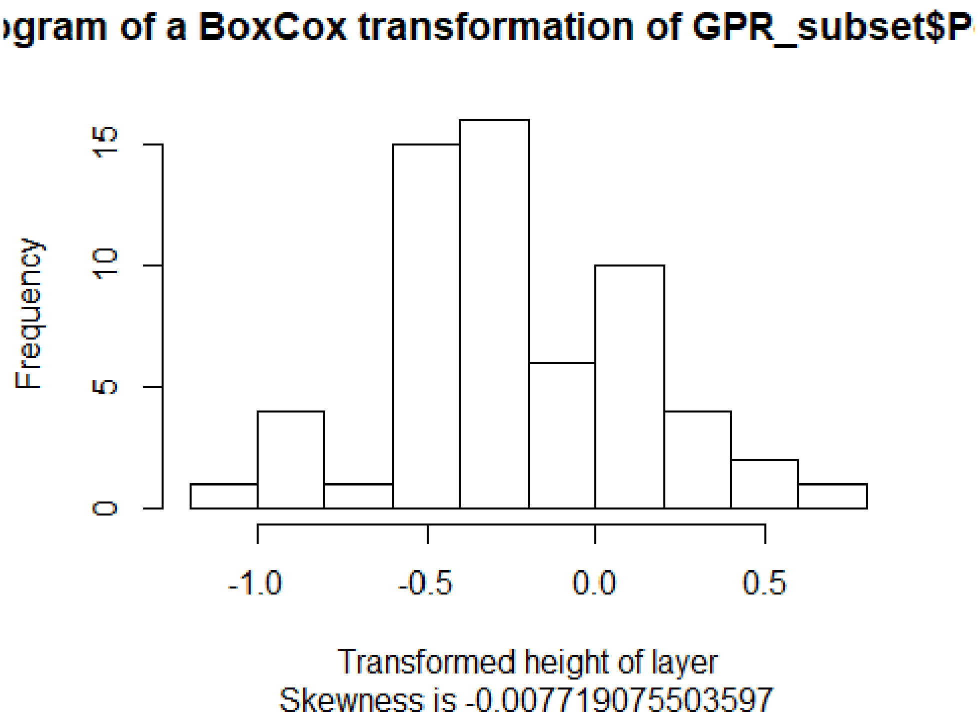

FIGURE 10.37: HISTOGRAM OF A BOX-COX TRANSFORMATION OF GPR_SUBSET$PEATDEPTH.

```
GPR_subset$T_Peatheight    <- DoTransform(GPR_subset$Peatheight, transformdata =
GPR_subset$Peatheight)
```

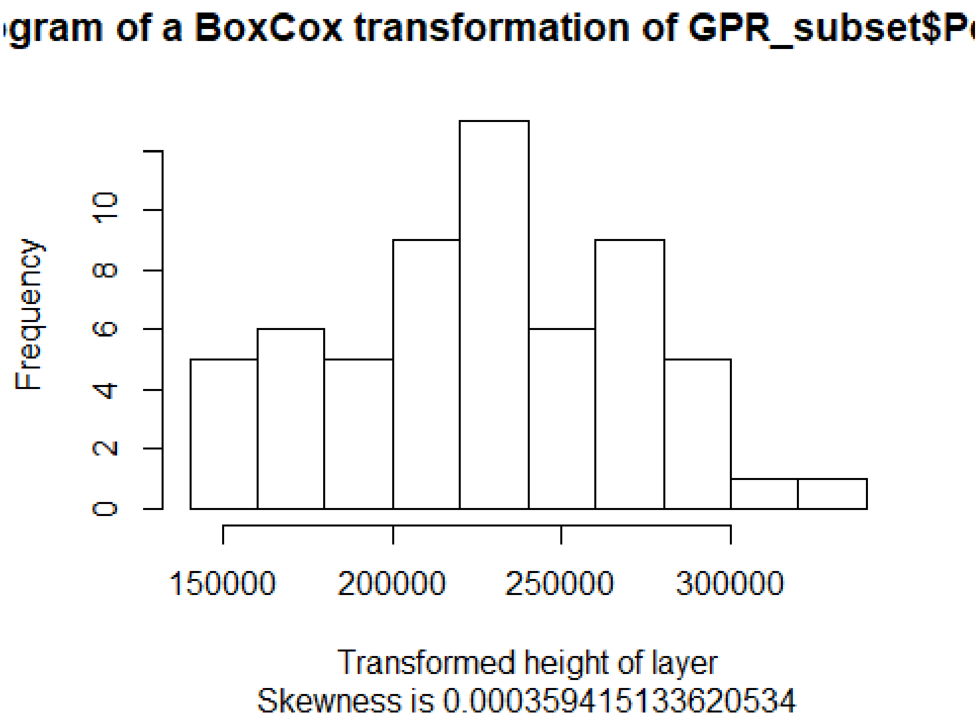

FIGURE 10.38: HISTOGRAM OF A BOX-COX TRANSFORMATION OF GPR_SUBSET$PEATHEIGHT.

```
Legacy$T_Peatdepth          <- DoTransform(Legacy$Peatdepth,  transformdata = Lega
cy$Peatdepth)
```

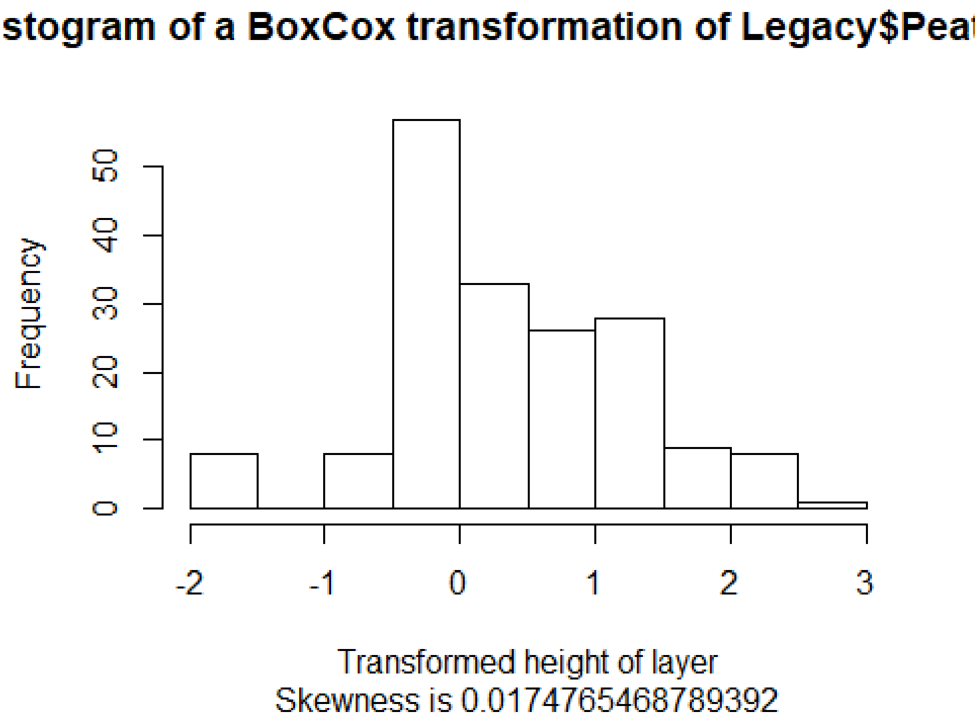

FIGURE 10.39: HISTOGRAM OF A BOX-COX TRANSFORMATION OF LEGACY$PEATDEPTH.

```
Legacy$T_Peatheight          <- DoTransform(Legacy$Peatheight, transformdata = Lega
cy$Peatheight)
```

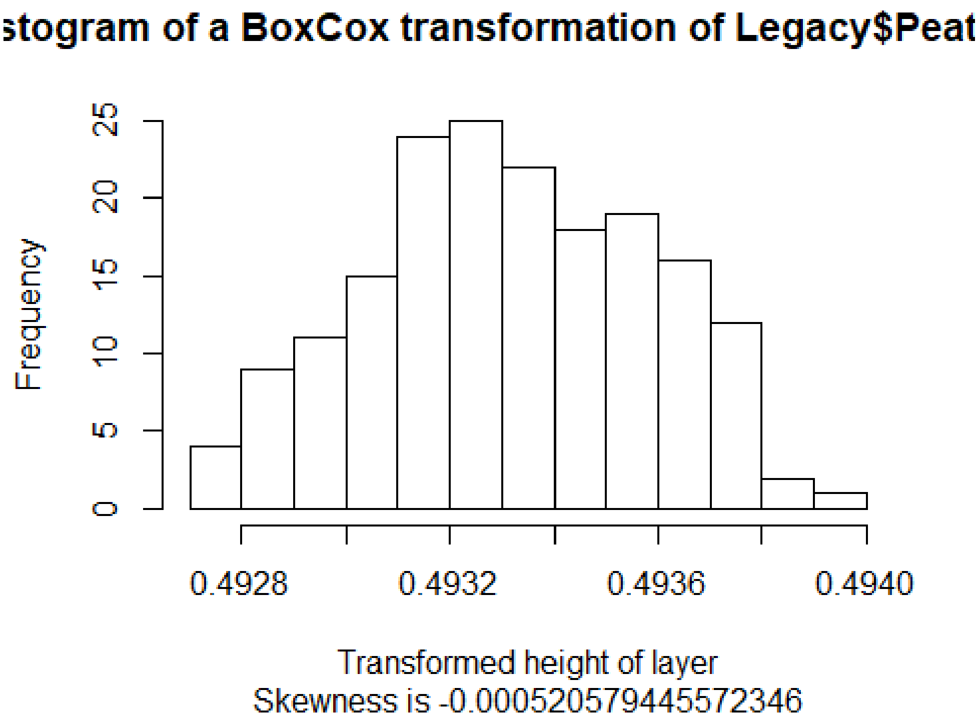

FIGURE 10.40: HISTOGRAM OF A BOX-COX TRANSFORMATION OF LEGACY$PEATHEIGHT.

KRIGING SETUP

ORDINARY KRIGING

Create gstat objects for variogram fitting.

```
g.h.All      <- gstat(id=c("Peatheight"),   formula = Peatheight~1,   data = All_
subset)
g.h.All_T    <- gstat(id=c("T_Peatheight"), formula = T_Peatheight~1, data = All_
subset)
g.h.GPR      <- gstat(id=c("Peatheight"),   formula = Peatheight~1,   data = GPR_
subset)
g.h.GPR_T    <- gstat(id=c("T_Peatheight"), formula = T_Peatheight~1, data = GPR_
subset)
g.h.Legacy   <- gstat(id=c("Peatheight"),   formula = Peatheight~1,   data = Lega
cy)
g.h.Legacy_T <- gstat(id=c("T_Peatheight"), formula = T_Peatheight~1, data = Lega
cy)

g.d.All      <- gstat(id=c("Peatdepth"),   formula = Peatdepth~1,   data = All_su
bset)
g.d.All_T    <- gstat(id=c("T_Peatdepth"), formula = T_Peatdepth~1, data = All_su
bset)
g.d.GPR      <- gstat(id=c("Peatdepth"),   formula = Peatdepth~1,   data = GPR_su
bset)
g.d.GPR_T    <- gstat(id=c("T_Peatdepth"), formula = T_Peatdepth~1, data = GPR_su
bset)
g.d.Legacy   <- gstat(id=c("Peatdepth"),   formula = Peatdepth~1,   data = Legacy
)
g.d.Legacy_T <- gstat(id=c("T_Peatdepth"), formula = T_Peatdepth~1, data = Legacy
)
```

Select most optimal variogram model for kriging and compare whether using peatheight or peatdepth is better for kriging (lower nugget & lower sill give better kriging parameters).

Variogram selection for All data.

```
vgm.h.All       <- optim_vgm_model(variogram(g.h.All))
vgm.d.All       <- optim_vgm_model(variogram(g.d.All))
vgm.All         <- bestvgm(vgm.h.All, vgm.d.All)

## vgm.d.All is best suited for kriging

## vgm.d.All is the returned variogram model

## MIND: the range difference is: 2824.90031478646

plotvgm.height  <- plot(variogram(g.h.All), vgm.h.All, main ="Peatheight")
plotvgm.depth   <- plot(variogram(g.d.All), vgm.d.All, main ="Peatdepth")
plotvgm.height; plotvgm.depth
```

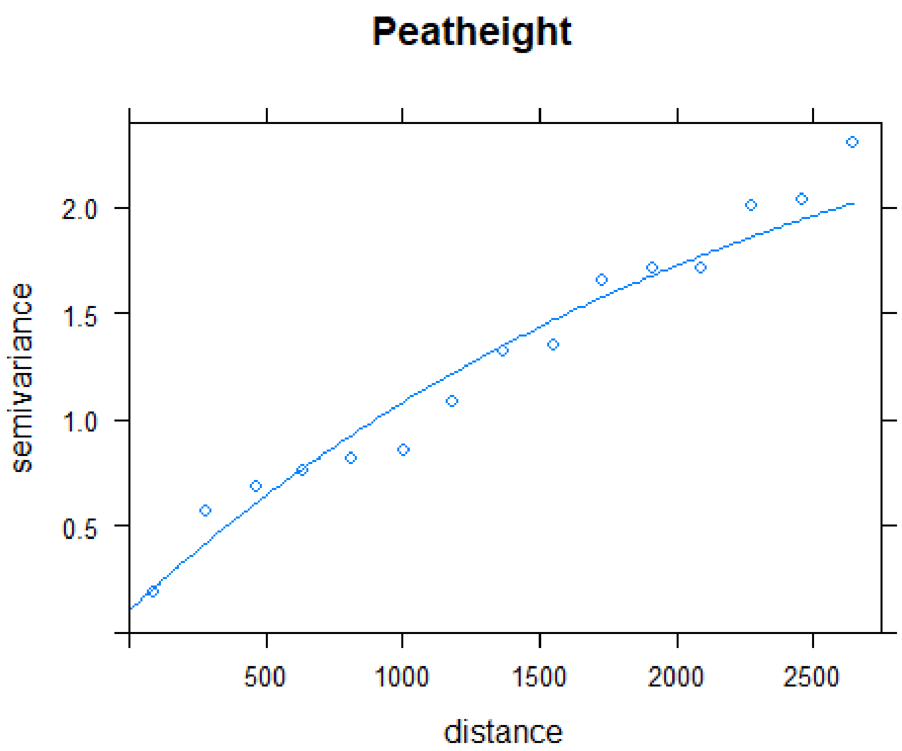

FIGURE 10.41: VARIOGRAM MODEL ORDINARY KRIGING ALL PEATHEIGHT.

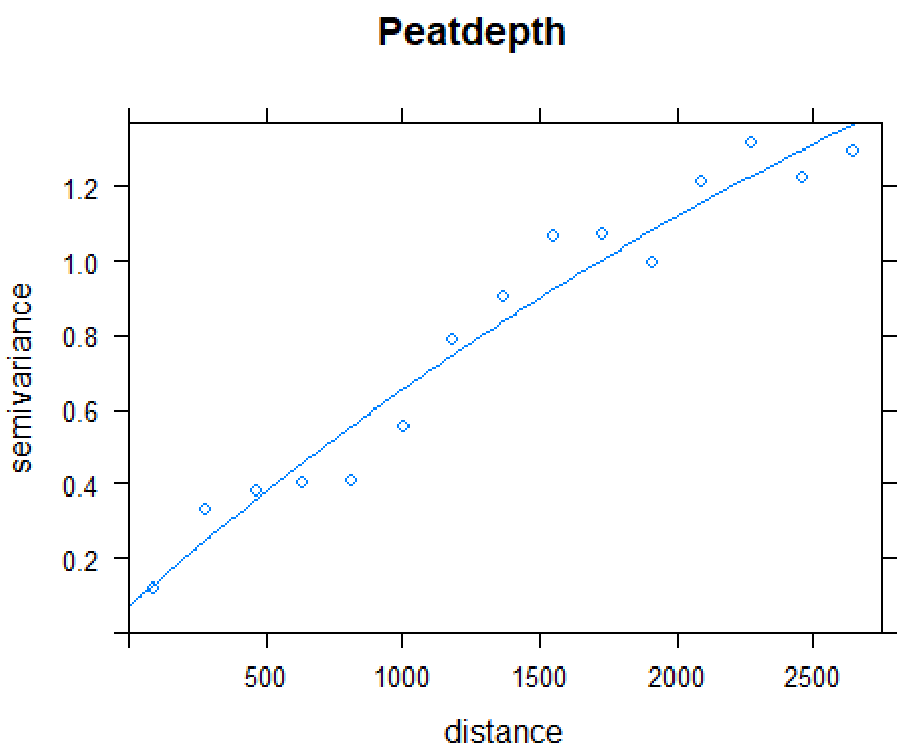

FIGURE 10.42: VARIOGRAM MODEL ORDINARY KRIGING ALL PEATDEPTH.

High range difference, but peatdepth is indeed the best of the two for kriging.

Variogram selection for transformed All data.

```
vgm.h.All_T     <- optim_vgm_model(variogram(g.h.All_T))
vgm.d.All_T     <- optim_vgm_model(variogram(g.d.All_T))
vgm.All_T       <- bestvgm(vgm.h.All_T, vgm.d.All_T)

## Cannot choose the best variogram model, manual selection is required

## No variogram model is returned

plotvgm.height  <- plot(variogram(g.h.All_T), vgm.h.All_T, main ="Peatheight")
plotvgm.depth   <- plot(variogram(g.d.All_T), vgm.d.All_T, main ="Peatdepth")
plotvgm.height; plotvgm.depth
```

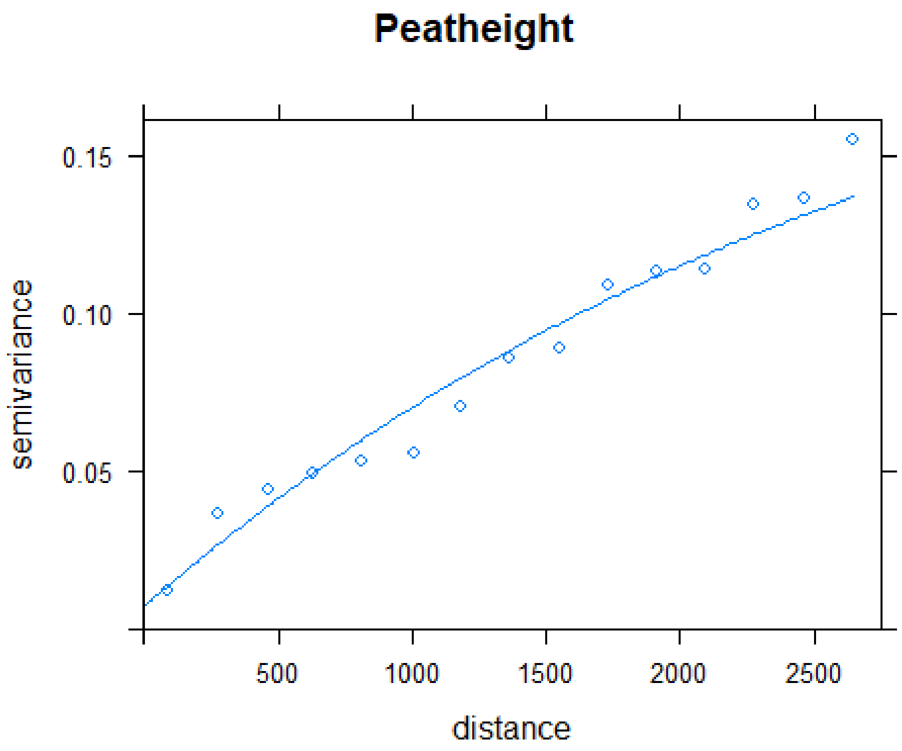

FIGURE 10.43: VARIOGRAM MODEL ORDINARY KRIGING ALL TRANSFORMED PEATHEIGHT.

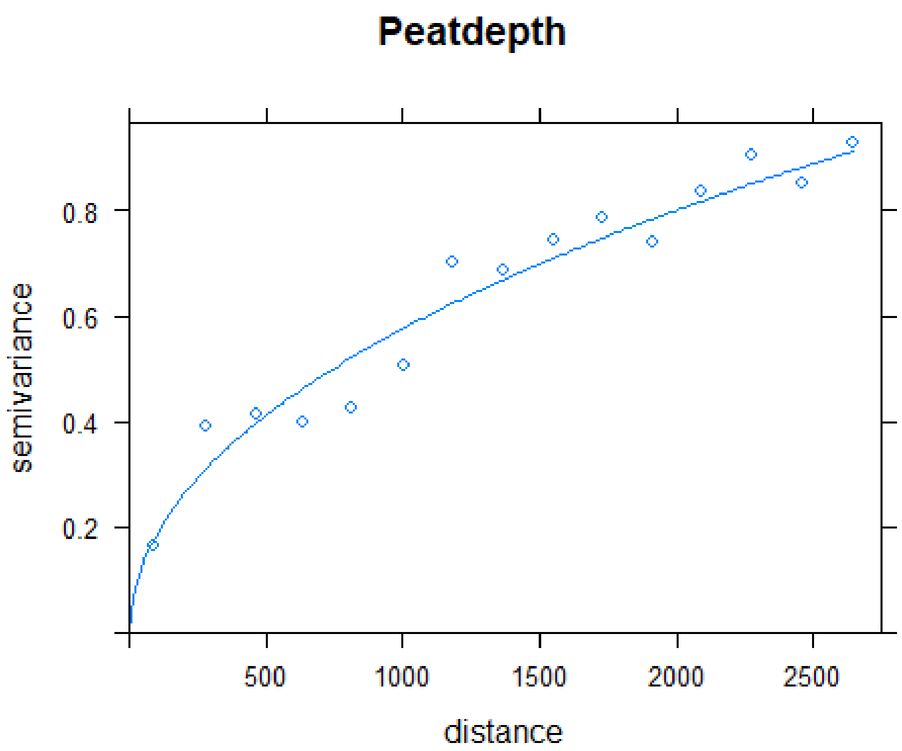

FIGURE 10.44: VARIOGRAM MODEL ORDINARY KRIGING ALL TRANSFORMED PEATDEPTH.

No choice has been made by the function, but peatheight is chosen as the best of the two for kriging.

```
vgm.All_T        <- vgm.h.All_T
```

Variogram selection for GPR data.

```
vgm.h.GPR        <- optim_vgm_model(variogram(g.h.GPR))
vgm.d.GPR        <- optim_vgm_model(variogram(g.d.GPR))
vgm.GPR          <- bestvgm(vgm.h.GPR, vgm.d.GPR)

## vgm.d.GPR is best suited for kriging

## vgm.d.GPR is the returned variogram model

## MIND: the range difference is: 142.639744690239
```

Variogram selection for transformed GPR data.

```
vgm.h.GPR_T      <- optim_vgm_model(variogram(g.h.GPR_T))
vgm.d.GPR_T      <- optim_vgm_model(variogram(g.d.GPR_T))
vgm.GPR_T        <- bestvgm(vgm.h.GPR_T, vgm.d.GPR_T)

## vgm.d.GPR_T is best suited for kriging

## vgm.d.GPR_T is the returned variogram model

## MIND: the range difference is: 158.668843780792
```

Variogram selection for Legacy data.

```
vgm.h.Legacy     <- optim_vgm_model(variogram(g.h.Legacy))
vgm.d.Legacy     <- optim_vgm_model(variogram(g.d.Legacy))
vgm.Legacy       <- bestvgm(vgm.h.Legacy, vgm.d.Legacy)

## vgm.d.Legacy is best suited for kriging

## vgm.d.Legacy is the returned variogram model

## MIND: the range difference is: 12839.8904431321

plotvgm.height  <- plot(variogram(g.h.Legacy), vgm.h.Legacy, main = "Peatheight")
plotvgm.depth   <-plot(variogram(g.d.Legacy), vgm.d.Legacy, main = "Peatdepth")
plotvgm.height; plotvgm.depth
```

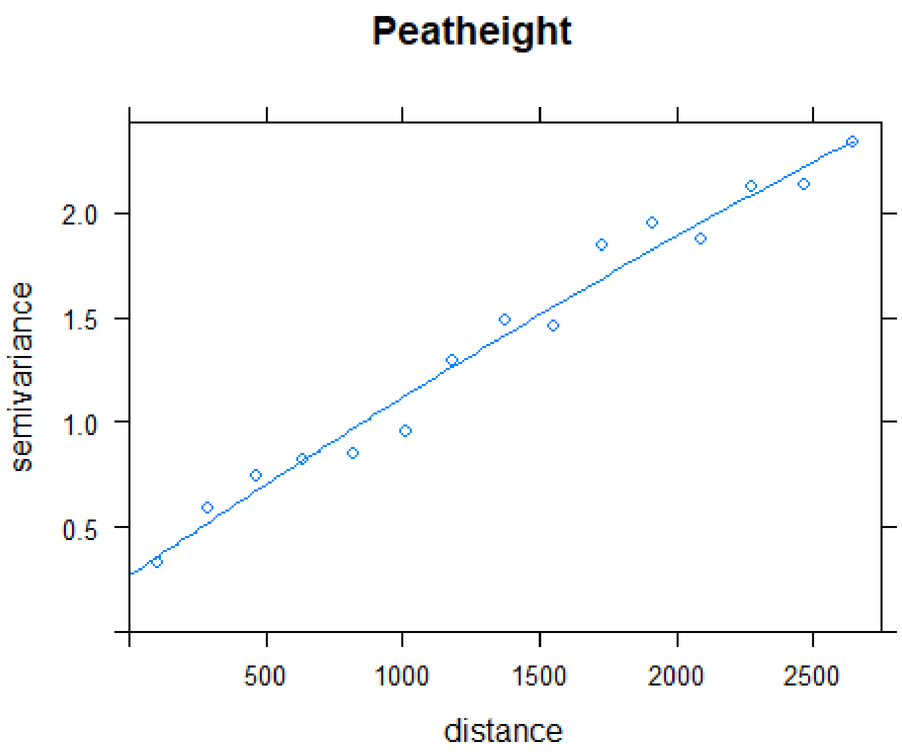

FIGURE 10.45: VARIOGRAM MODEL ORDINARY KRIGING LEGACY PEATHEIGHT.

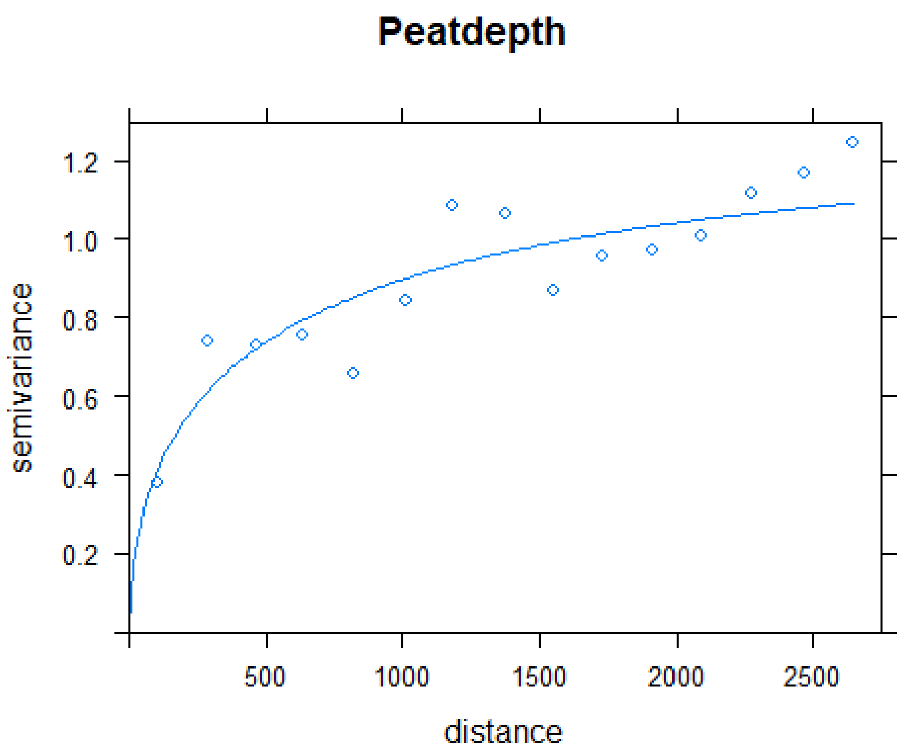

FIGURE 10.46: VARIOGRAM MODEL ORDINARY KRIGING LEGACY PEATDEPTH.

High range difference, but peatdepth is indeed the best of the two for kriging.

Variogram selection for transformed Legacy data.

```
vgm.h.Legacy_T  <- optim_vgm_model(variogram(g.h.Legacy_T))
vgm.d.Legacy_T  <- optim_vgm_model(variogram(g.d.Legacy_T))
vgm.Legacy_T    <- bestvgm(vgm.h.Legacy_T, vgm.d.Legacy_T)

## Cannot choose the best variogram model, manual selection is required

## No variogram model is returned

plotvgm.height  <- plot(variogram(g.h.Legacy_T), vgm.h.Legacy_T, main = "Peatheig
ht")
plotvgm.depth   <- plot(variogram(g.d.Legacy_T), vgm.d.Legacy_T, main = "Peatdept
h")
plotvgm.height; plotvgm.depth
```

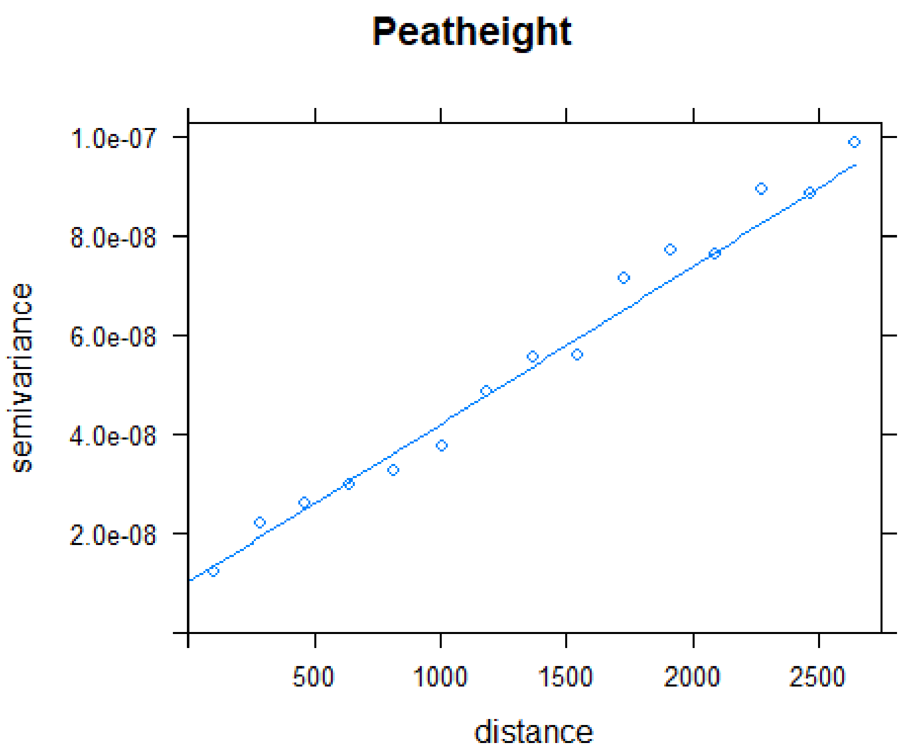

FIGURE 10.47: VARIOGRAM MODEL ORDINARY KRIGING LEGACY TRANSFORMED PEATHEIGHT.

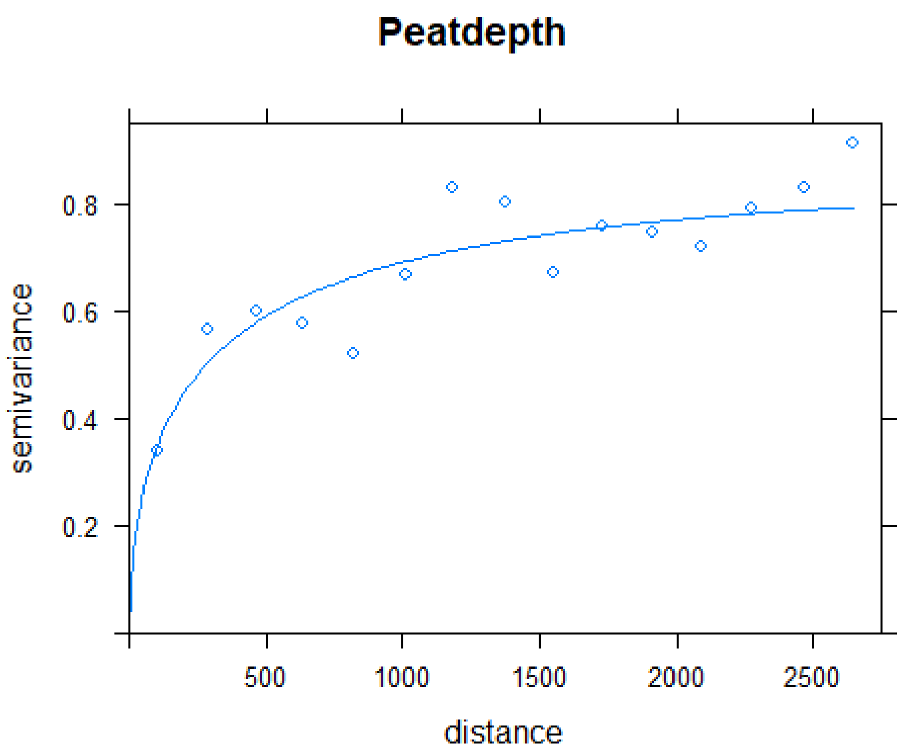

FIGURE 10.48: VARIOGRAM MODEL ORDINARY KRIGING LEGACY TRANSFORMED PEATDEPTH.

No choice has been made by the function, but peatheight is chosen as the best of the two for kriging.

```
vgm.Legacy_T    <- vgm.h.Legacy_T
```

CO-KRIGING

TRANSFORMATIONS

For co-kriging one universal transformation, for both the GPR and Legacy data, is needed. To do so the lowest absolute average skewness of the two databases combined is determined, using both peatheight and peatdepth data.

Identify different transformation cases.

```
cases <- c("No", "Natural logarithmic", "Logarithmic", "Square root", "Exponential
", "BoxCox")
```

Create peatheight skewness dataframe.

```
i <- 1; case.h <- c(); skew.h <- c(); skewdf.h <- data.frame(case.h, skew.h)
skewdf.h <- skewdf.h$case.h; skewdf.h <- skewdf.h$skew.h
```

Find optimal transformation for peatheight.

```
for (case in cases){
  skewdf.h$case.h[i] <- case
  skewdf.h$skew.h[i] <- suppressMessages(mean(c(abs(skewness(DoTransform(GPR_s
ubset$Peatheight,
                                                                       Legacy$Pe
atheight,
                                                                       transform
ation = case,
                                                                       draw = F)
)),
                                                 abs(skewness(DoTransform(Legacy$
Peatheight,
                                                                       GPR_subse
t$Peatheight,
                                                                       transform
ation = case,
                                                                       draw = F)
)))))
  i <- i + 1
}

(Transform.h.optimcombi <- skewdf.h$case.h[which(min(na.omit(skewdf.h$skew.h))==s
kewdf.h$skew.h)])

## [1] "BoxCox"
```

Create peatdepth skewness dataframe.

```
i <- 1; case.d <- c(); skew.d <- c(); skewdf.d <- data.frame(case.d, skew.d);
skewdf.d <- skewdf.d$case.d; skewdf.d <- skewdf.d$skew.d
```

Find optimal transformation for peatdepth.

```
for (case in cases){
  skewdf.d$case.d[i] <- case
  skewdf.d$skew.d[i] <- suppressMessages(mean(c(abs(skewness(DoTransform(GPR_s
ubset$Peatdepth,
                                                                       Legacy$Pe
```

```
atdepth,
                                                                                transform
ation = case,
                                                                                draw = F)
)),
                                                          abs(skewness(DoTransform(Legacy$
Peatdepth,
                                                                                GPR_subse
t$Peatdepth,
                                                                                transform
ation = case,
                                                                                draw = F)
)))))
  i <- i + 1
}

(Transform.d.optimcombi <- skewdf.d$case.d[which(min(na.omit(skewdf.d$skew.d))==s
kewdf.d$skew.d)])

## [1] "BoxCox"
```

Universal transformed data, using the same transformation.

```
GPR_subset$UT_Peatheight <- DoTransform(GPR_subset$Peatheight, Legacy$Peatheight,
                                        transformdata = GPR_subset$Peatheight,
                                        transformation = Transform.h.optimcombi)
```

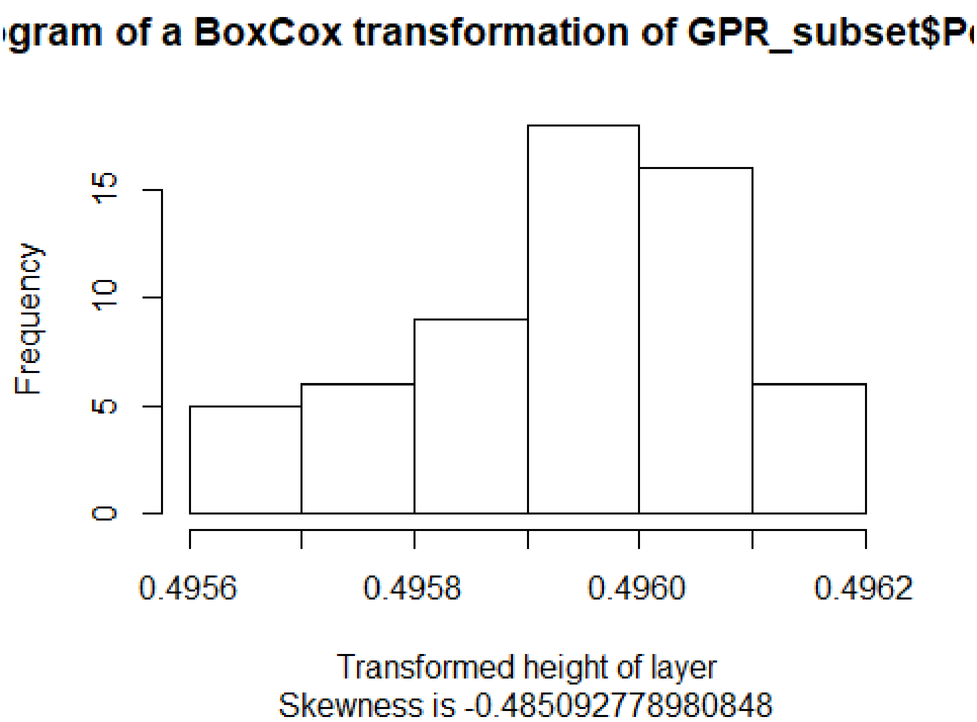

FIGURE 10.49: HISTOGRAM OF A BOX-COX TRANSFORMATION OF GPR_SUBSET$PEATHEIGHT.

```
Legacy$UT_Peatheight     <- DoTransform(GPR_subset$Peatheight, Legacy$Peatheight,
                                        transformdata = Legacy$Peatheight,
                                        transformation = Transform.h.optimcombi)
```

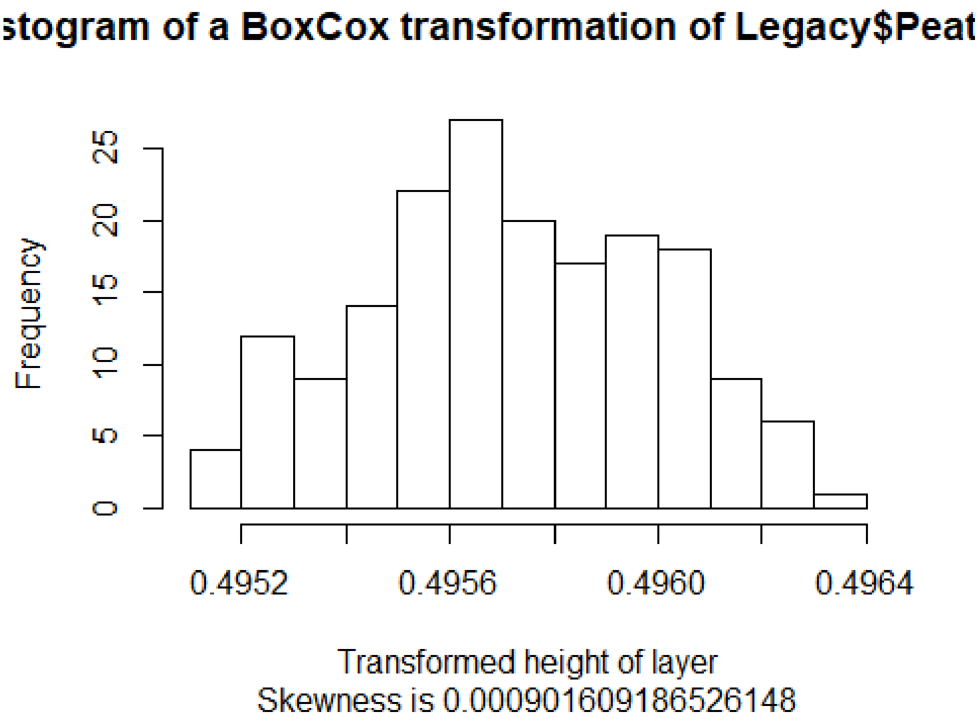

FIGURE 10.50: HISTOGRAM OF A BOX-COX TRANSFORMATION OF LEGACY$PEATHEIGHT.

```
GPR_subset$UT_Peatdepth <- DoTransform(GPR_subset$Peatdepth, Legacy$Peatdepth,
                                       transformdata = GPR_subset$Peatdepth,
                                       transformation = Transform.d.optimcombi)
```

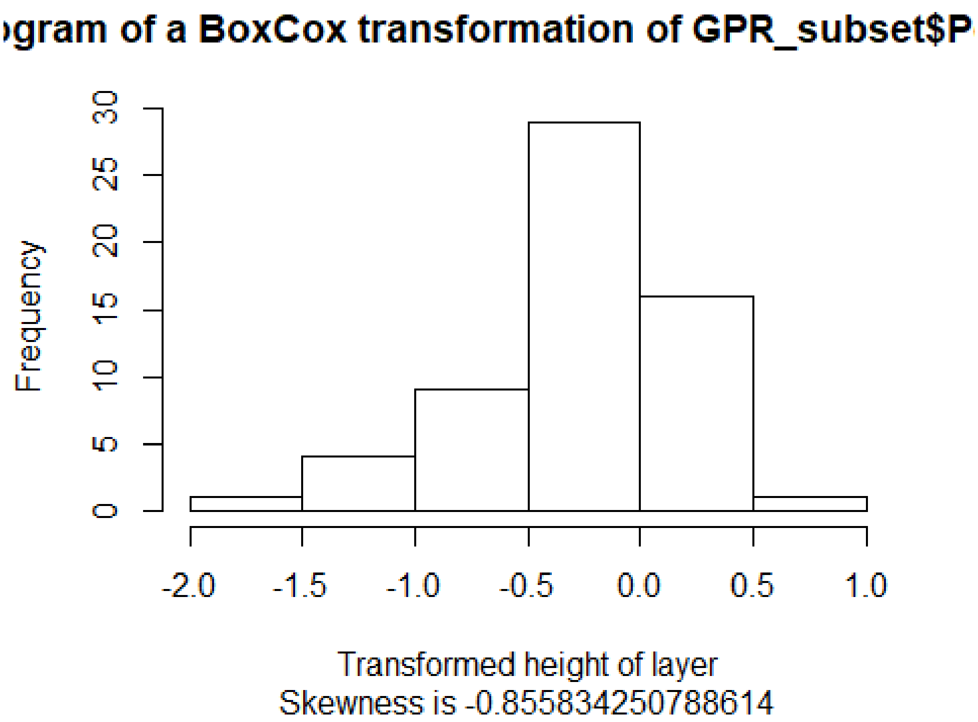

FIGURE 10.51: HISTOGRAM OF A BOX-COX TRANSFORMATION OF GPR_SUBSET$PEATDEPTH.

```
Legacy$UT_Peatdepth     <- DoTransform(GPR_subset$Peatdepth, Legacy$Peatdepth,
                                       transformdata = Legacy$Peatdepth,
                                       transformation = Transform.d.optimcombi)
```

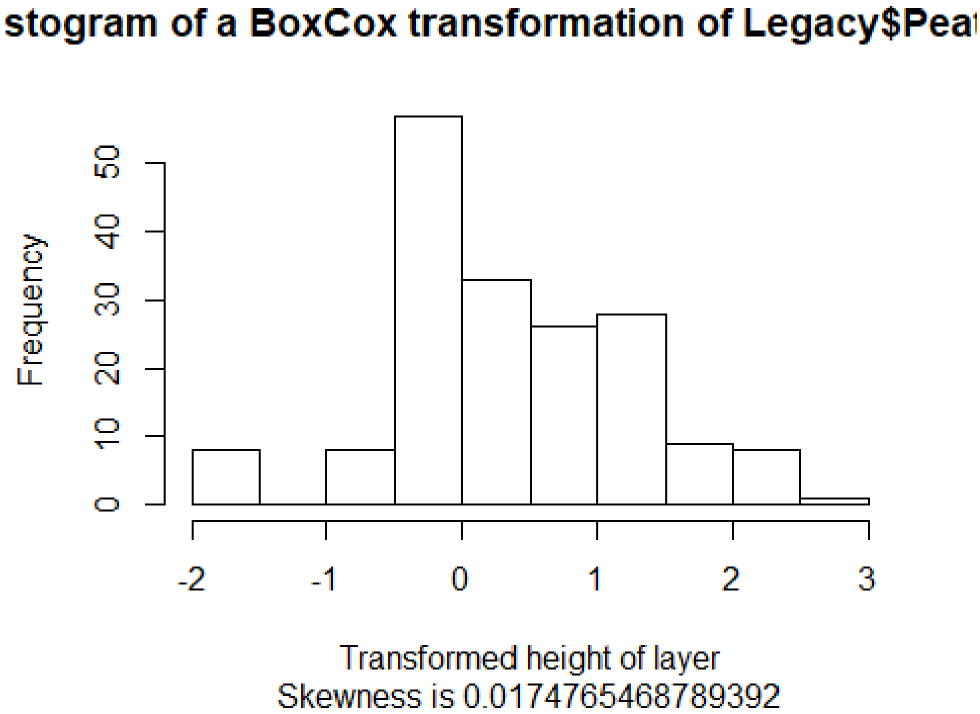

FIGURE 10.52: HISTOGRAM OF A BOX-COX TRANSFORMATION OF LEGACY$PEATDEPTH.

Univeral transformed data for the complete dataset, using subsetted transformed data parameters

```
GPR$UT_Peatheight <- DoTransform(GPR_subset$Peatheight, Legacy$Peatheight,
                                 transformdata = GPR$Peatheight,
                                 transformation = Transform.h.optimcombi,
                                 draw = F)

## BoxCox transformation is executed

## The skewness of the transformed data is -0.782763233308501

GPR$UT_Peatdepth  <- DoTransform(GPR_subset$Peatdepth, Legacy$Peatdepth,
                                 transformdata = GPR$Peatdepth,
                                 transformation = Transform.d.optimcombi,
                                 draw = F)

## BoxCox transformation is executed

## The skewness of the transformed data is -0.604355741048921
```

VARIOGRAM MODELS

For co-kriging one universal variogram model, for both the GPR and Legacy data, is needed. All variograms are created with this model. This is done by looping through all variogram types with fit.variogram and selecting the variogram type with the lowest sum of squared errors (SSErr).

Creating gstat objects.

```
g.h.GPR_UT    <- gstat(id=c("UT_Peatheight"), formula = UT_Peatheight~1, data = G
PR_subset)
g.h.Legacy_UT <- gstat(id=c("UT_Peatheight"), formula = UT_Peatheight~1, data = L
egacy)
g.d.GPR_UT    <- gstat(id=c("UT_Peatdepth"),  formula = UT_Peatdepth~1,  data = G
PR_subset)
g.d.Legacy_UT <- gstat(id=c("UT_Peatdepth"),  formula = UT_Peatdepth~1,  data = L
egacy)
```

Set up variogram dataframe for untransformed peatheight data.

```
SSErr.h <- c(); vgmmodel.h <- c()
i <- 1; vgmdf.h <- data.frame(vgmmodel.h, SSErr.h)
vgmdf.h <- vgmdf.h$vgmmodel.h; vgmdf.h <- vgmdf.h$SSErr.h
```

Find variogram model with lowest SSErr for untransformed peatheight data.

```
for (vgmmod in vgm()$short){
  vgmdf.h$vgmmodel.h[i] <- vgmmod
  vgmdf.h$SSErr.h[i]    <- suppressWarnings(mean(c(attr(try(fit.variogram(vari
ogram(g.h.GPR),
                                                                          vgm(as.
character(vgmmod))),
                                                               silent = T), "SSErr"),
                                                      attr(try(fit.variogram(vario
gram(g.h.Legacy),
                                                                          vgm(as.
character(vgmmod))),
                                                               silent = T), "SSErr"))
))
  i <- i + 1
}

(Vgmmodel.h.optimcombi <- vgmdf.h$vgmmodel.h[which(min(na.omit(vgmdf.h$SSErr.h))
== vgmdf.h$SSErr.h)])

## [1] "Lin"
```

Set up variogram dataframe for untransformed peatdepth data.

```
SSErr.d <- c(); vgmmodel.d <- c()
i <- 1; vgmdf.d <- data.frame(vgmmodel.d, SSErr.d)
vgmdf.d <- vgmdf.d$vgmmodel.d; vgmdf.d <- vgmdf.d$SSErr.d
```

Find variogram model with lowest SSErr for untransformed peatdepth data.

```
for (vgmmod in vgm()$short){
  vgmdf.d$vgmmodel.d[i] <- vgmmod
  vgmdf.d$SSErr.d[i]    <- suppressWarnings(mean(c(attr(try(fit.variogram(vari
ogram(g.d.GPR),
                                                                          vgm(as.
character(vgmmod))),
                                                               silent = T), "SSErr"),
```

```
                                                    attr(try(fit.variogram(vario
gram(g.d.Legacy),
                                                                          vgm(as.
character(vgmmod))),
                                                            silent = T), "SSErr"))
))
  i <- i + 1
}

(Vgmmodel.d.optimcombi <- vgmdf.d$vgmmodel.d[which(min(na.omit(vgmdf.d$SSErr.d))
== vgmdf.d$SSErr.d)])

## [1] "Exc"
```

Set up variogram dataframe for universal transformed peatheight data.

```
SSErr.h <- c(); vgmmodel.h <- c()
i <- 1; vgmdf.h_UT <- data.frame(vgmmodel.h, SSErr.h)
vgmdf.h_UT <- vgmdf.h_UT$vgmmodel.h; vgmdf.h_UT <- vgmdf.h_UT$SSErr.h
```

Find variogram model with lowest SSErr for universal transformed peatheight data.

```
for (vgmmod in vgm()$short){
  vgmdf.h_UT$vgmmodel.h[i] <- vgmmod
  vgmdf.h_UT$SSErr.h[i]    <- suppressWarnings(mean(c(attr(try(fit.variogram(v
ariogram(g.h.GPR_UT),
                                                                          vgm(a
s.character(vgmmod))),
                                                            silent = T), "SSErr
"),
                                                       attr(try(fit.variogram(var
iogram(g.h.Legacy_UT),
                                                                          vgm(a
s.character(vgmmod))),
                                                            silent = T), "SSErr
"))))
  i <- i + 1
}

(Vgmmodel.h.optimcombi_UT <- vgmdf.h_UT$vgmmodel.h[which(min(na.omit(vgmdf.h_UT$S
SErr.h)) ==
                                                          vgmdf.h_UT$SSErr.h)])

## [1] "Lin"
```

Set up variogram dataframe for universal transformed peatdepth data.

```
SSErr.d <- c(); vgmmodel.d <- c();
i <- 1; vgmdf.d_UT <- data.frame(vgmmodel.d, SSErr.d)
vgmdf.d_UT <- vgmdf.d_UT$vgmmodel.d; vgmdf.d_UT <- vgmdf.d_UT$SSErr.d
```

Find variogram model with lowest SSErr for universal transformed peatdepth data.

```
for (vgmmod in vgm()$short){
  vgmdf.d_UT$vgmmodel.d[i] <- vgmmod
  vgmdf.d_UT$SSErr.d[i]    <- suppressWarnings(mean(c(attr(try(fit.variogram(v
```

```
ariogram(g.d.GPR_UT),
                                                                    vgm(a
s.character(vgmmod))),
                                                          silent = T), "SSErr
"),
                                                  attr(try(fit.variogram(var
iogram(g.d.Legacy_UT),
                                                                    vgm(a
s.character(vgmmod))),
                                                          silent = T), "SSErr
"))))
  i <- i + 1
}

(Vgmmodel.d.optimcombi_UT <- vgmdf.d_UT$vgmmodel.d[which(min(na.omit(vgmdf.d_UT$S
SErr.d)) ==
                                                       vgmdf.d_UT$SSErr.d)])

## [1] "Mat"
```

VARIOGRAMS

Select most optimal variogram model for kriging and compare whether using peatheight or peatdepth is better for kriging (lower nugget & lower sill give better kriging parameters).

Variogram selection for GPR data as covariable.

```
vgm.h.CK_GPR    <- fit.variogram(variogram(g.h.GPR),       model = vgm(Vgmmodel.
h.optimcombi))
vgm.d.CK_GPR    <- fit.variogram(variogram(g.d.GPR),       model = vgm(Vgmmodel.
d.optimcombi))
vgm.CK_GPR      <- bestvgm(vgm.h.CK_GPR, vgm.d.CK_GPR)

## vgm.h.CK_GPR is best suited for kriging

## vgm.h.CK_GPR is the returned variogram model

## MIND: the range difference is: 722368.18994377

plotvgm.height  <- plot(variogram(g.h.GPR), vgm.h.CK_GPR, main = "Peatheight")
plotvgm.depth   <- plot(variogram(g.d.GPR), vgm.d.CK_GPR, main = "Peatdepth")
plotvgm.height; plotvgm.depth
```

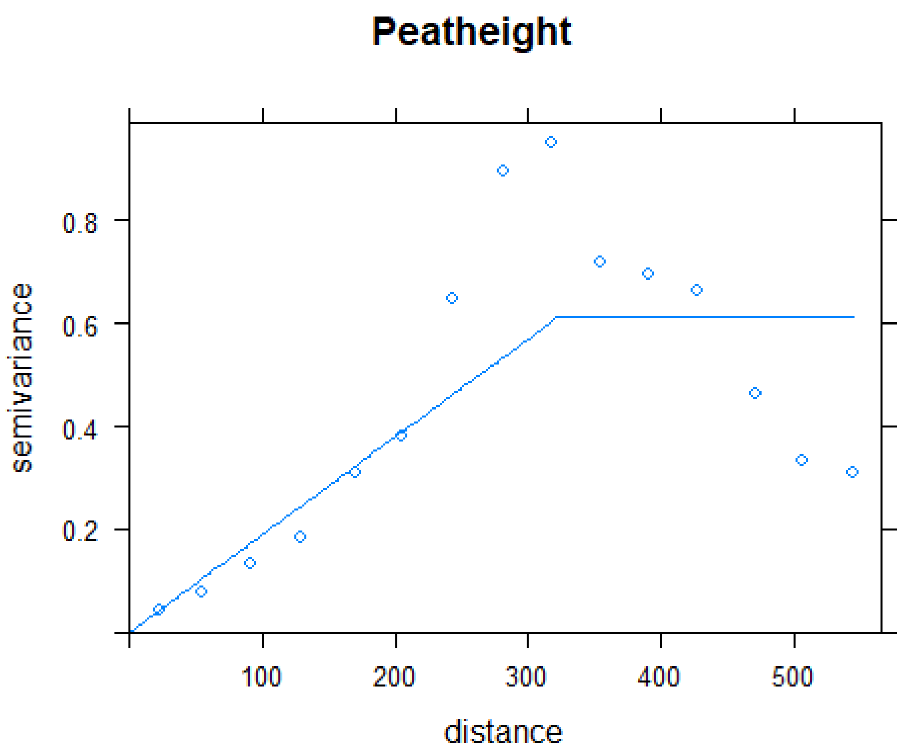

FIGURE 10.53: VARIOGRAM MODEL CO-KRIGING GPR PEATHEIGHT.

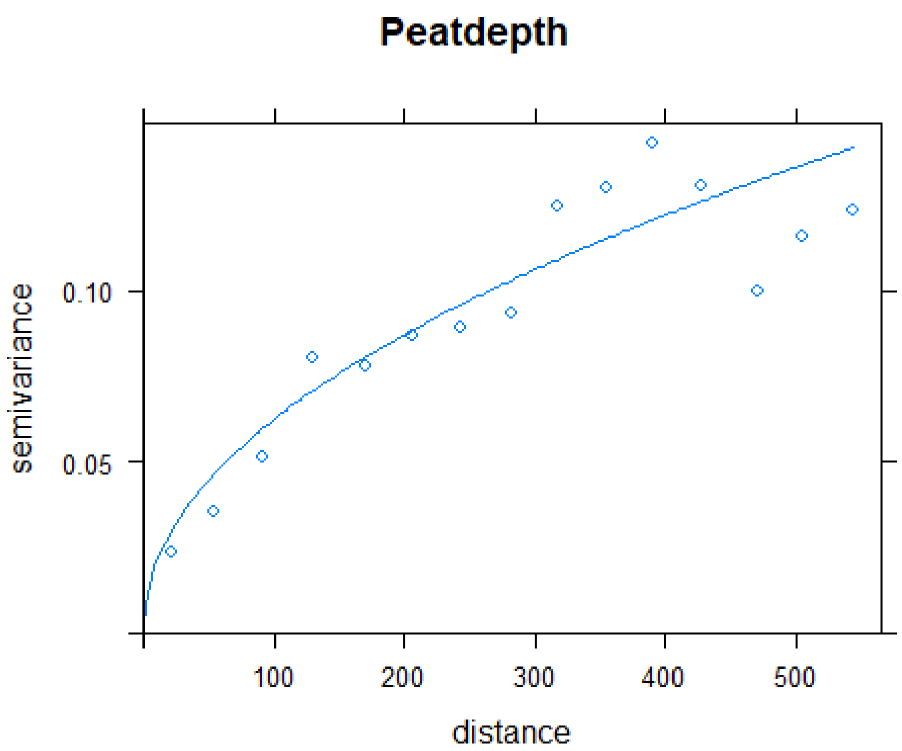

FIGURE 10.54: VARIOGRAM MODEL CO-KRIGING GPR PEATDEPTH

High range difference, but peatdepth is chosen as the best of the two for kriging since the sill is lower at closer distances.

```
vgm.CK_GPR      <- vgm.d.CK_GPR
```

Variogram selection for universal transformed GPR data as covariable.

```
vgm.h.CK_GPR_UT <- fit.variogram(variogram(g.h.GPR_UT),    model = vgm(Vgmmodel.
h.optimcombi_UT))
vgm.d.CK_GPR_UT <- fit.variogram(variogram(g.d.GPR_UT),    model = vgm(Vgmmodel.
d.optimcombi_UT))
vgm.CK_GPR_UT   <- bestvgm(vgm.h.CK_GPR_UT, vgm.d.CK_GPR_UT)

## vgm.h.CK_GPR_UT is best suited for kriging

## vgm.h.CK_GPR_UT is the returned variogram model

## MIND: the range difference is: 4.11432042132395
```

Variogram selection for Legacy data as covariable.

```
vgm.h.CK_Leg    <- fit.variogram(variogram(g.h.Legacy),    model = vgm(Vgmmodel.
h.optimcombi))
vgm.d.CK_Leg    <- fit.variogram(variogram(g.d.Legacy),    model = vgm(Vgmmodel.
d.optimcombi))
vgm.CK_Leg      <- bestvgm(vgm.h.CK_Leg, vgm.d.CK_Leg)

## vgm.d.CK_Leg is best suited for kriging

## vgm.d.CK_Leg is the returned variogram model

## MIND: the range difference is: 1732.85153557267

plotvgm.height  <- plot(variogram(g.h.Legacy), vgm.h.CK_Leg, main = "Peatheight")
plotvgm.depth   <- plot(variogram(g.d.Legacy), vgm.d.CK_Leg, main = "Peatdepth")
plotvgm.height; plotvgm.depth
```

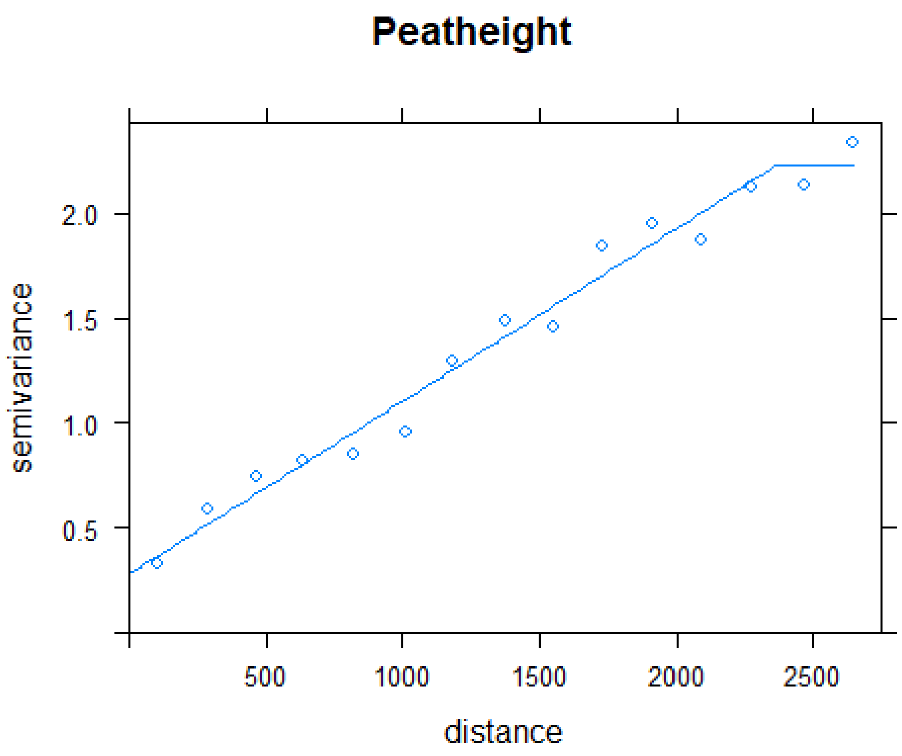

FIGURE 10.55: VARIOGRAM MODEL CO-KRIGING LEGACY PEATHEIGHT.

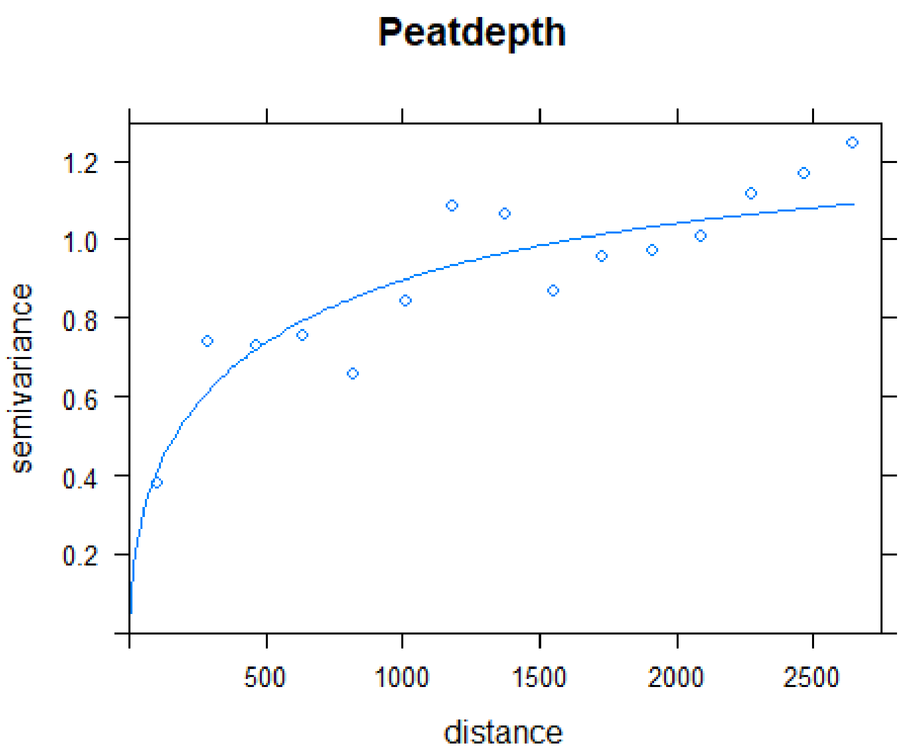

FIGURE 10.56: VARIOGRAM MODEL CO-KRIGING LEGACY PEATDEPTH.

High range difference, but peatdepth is indeed the best of the two for kriging.

Variogram selection for universal transformed Legacy data as covariable.

```
vgm.h.CK_Leg_UT <- fit.variogram(variogram(g.h.Legacy_UT), model = vgm(Vgmmodel.
h.optimcombi_UT))
vgm.d.CK_Leg_UT <- fit.variogram(variogram(g.d.Legacy_UT), model = vgm(Vgmmodel.
d.optimcombi_UT))
vgm.CK_Leg_UT   <- bestvgm(vgm.h.CK_Leg_UT, vgm.d.CK_Leg_UT)

## vgm.h.CK_Leg_UT is best suited for kriging

## vgm.h.CK_Leg_UT is the returned variogram model

## MIND: the range difference is: 1885.84814125982

plotvgm.height  <- plot(variogram(g.h.Legacy_UT), vgm.h.CK_Leg_UT, main = "Peathe
ight")
plotvgm.depth   <- plot(variogram(g.d.Legacy_UT), vgm.d.CK_Leg_UT, main = "Peatde
pth")
plotvgm.height; plotvgm.depth
```

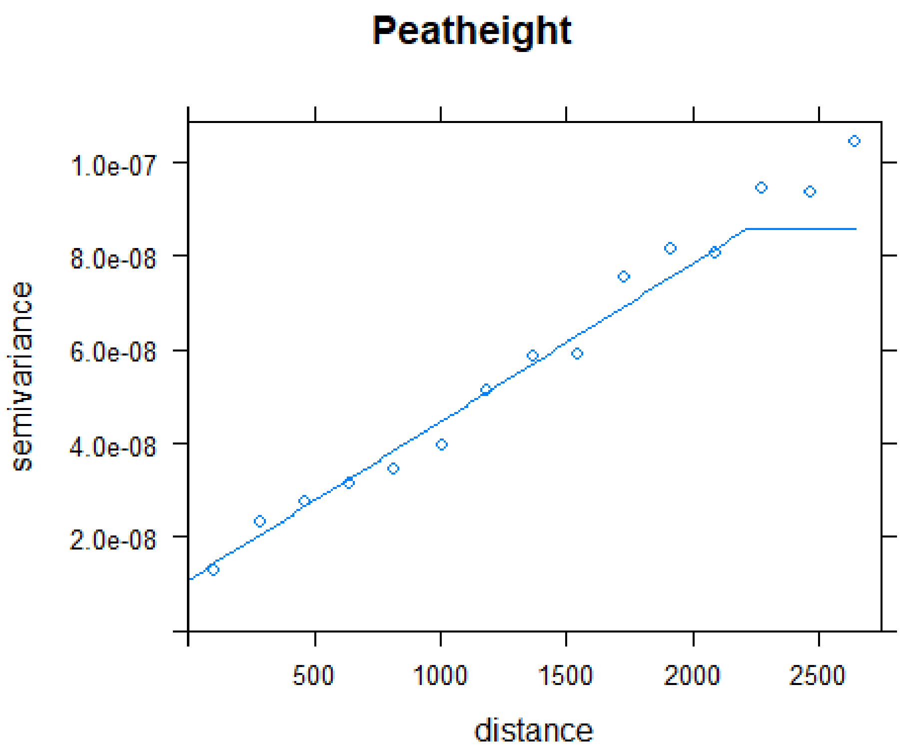

FIGURE 10.57: VARIOGRAM MODEL CO-KRIGING UNIVERSAL TRANSFORMED LEGACY PEATHEIGHT.

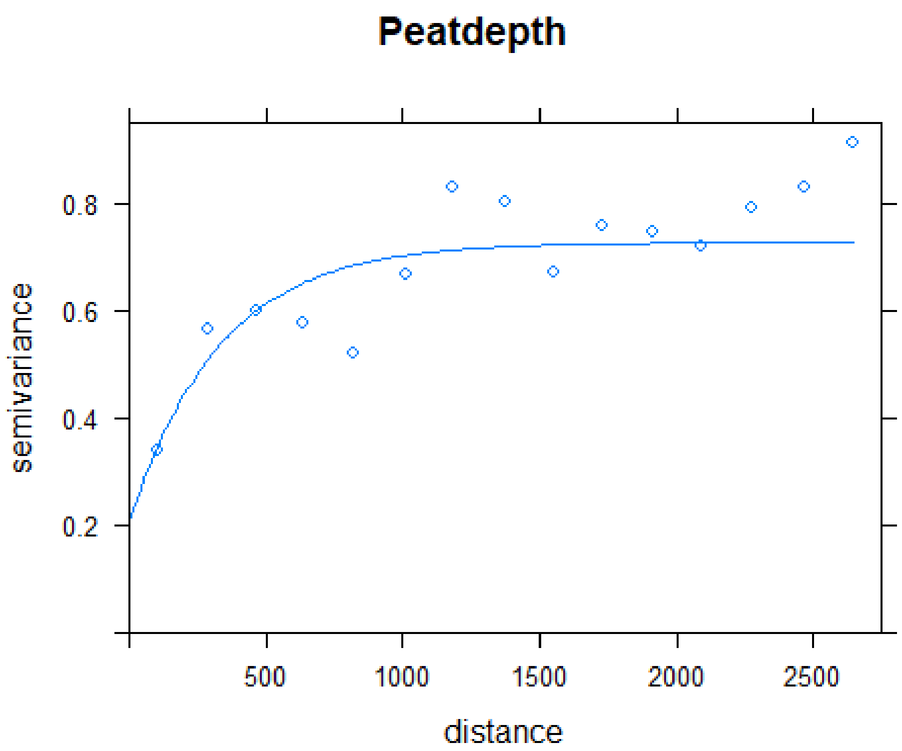

FIGURE 10.58: VARIOGRAM MODEL CO-KRIGING UNIVERSAL TRANSFORMED LEGACY PEATDEPTH.

High range difference, but peatheight is indeed the best of the two for kriging.

Manual fitted variagram for combined data.

```
vgm.GPRLeg     <- vgm(nugget = 0.022,   range = 2280, psill = 1.17,     model = Vgm
model.d.optimcombi)
vgm.GPRLeg_UT <- vgm(nugget = 2e-09,   range = 390,  psill = 4.67e-08, model = Vgm
model.h.optimcombi_UT)
vgm.LegGPR     <- vgm(nugget = 0.0019,  range = 310,  psill = 0.79,     model = Vgm
model.d.optimcombi)
vgm.LegGPR_UT <- vgm(nugget = 1.8e-09, range = 290,  psill = 4.75e-08, model = Vgm
model.h.optimcombi_UT)
```

LINEAR MODELS OF COREGIONALIZATION

The manual fitted variograms (above) are fitted for subsetted data, but the linear model of coregionalization needs to be found for the complete dataset. This manual fitting requires some 'trial and error' until a linear model of coregionalization is found when predicting the data.

Using untransformed GPR data as covariable data

```
g.CK_GC <- gstat(NULL,    id = c("Peatdepth.Legacy"),     formula = Peatdepth~1,
                 data = Legacy,     model = vgm.CK_Leg)
g.CK_GC <- gstat(g.CK_GC, id = c("Peatdepth.GPR_subset"), formula = Peatdepth~1,
                 data = GPR_subset, model = vgm.CK_GPR)
g.CK_GC <- gstat(g.CK_GC, id = c("Peatdepth.Legacy","Peatdepth.GPR_subset"),
                 model = vgm.LegGPR)
plot(variogram(g.CK_GC), model = g.CK_GC$model)
```

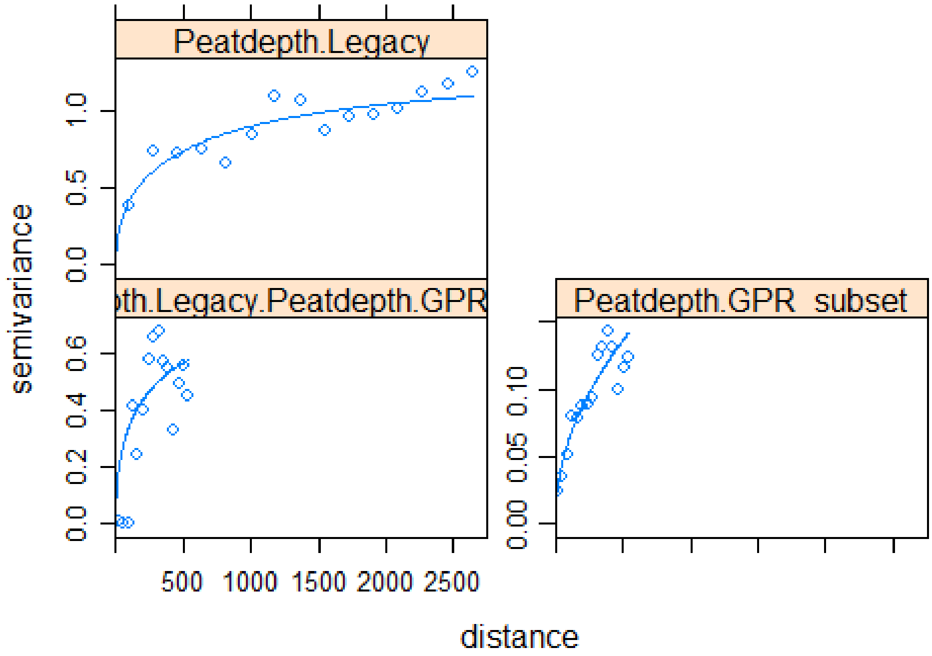

FIGURE 10.59: VARIOGRAM MODELS CO-KRIGING, GPR AS COVARIABLE.

```
g.CK_GC <- gstat(NULL,    id = c("Peatdepth.Legacy"), formula = Peatdepth~1,
                 data = Legacy, model = vgm.CK_Leg)
g.CK_GC <- gstat(g.CK_GC, id = c("Peatdepth.GPR"),    formula = Peatdepth~1,
                 data = GPR,     model = vgm.CK_GPR)
g.CK_GC <- gstat(g.CK_GC, id = c("Peatdepth.Legacy","Peatdepth.GPR"),
                 model = vgm.LegGPR)
fit.CK_GC <- fit.lmc(variogram(g.CK_GC), g.CK_GC, model=vgm.LegGPR, fit.ranges=F
, fit.lmc=T)
```

Using universal transformed GPR data as covariable data

```
g.CK_GC_UT <- gstat(NULL,      id = c("Peatheight.Legacy_UT"),      formula = UT_
Peatheight~1,
                    data = Legacy,     model = vgm.CK_Leg_UT)
g.CK_GC_UT <- gstat(g.CK_GC_UT, id = c("Peatheight.GPR_subset_UT"), formula = UT_
Peatheight~1,
                    data = GPR_subset, model = vgm.CK_GPR_UT)
g.CK_GC_UT <- gstat(g.CK_GC_UT, id = c("Peatheight.Legacy_UT","Peatheight.GPR_sub
set_UT"),
                    model = vgm.LegGPR_UT)
plot(variogram(g.CK_GC_UT), model = g.CK_GC_UT$model)
```

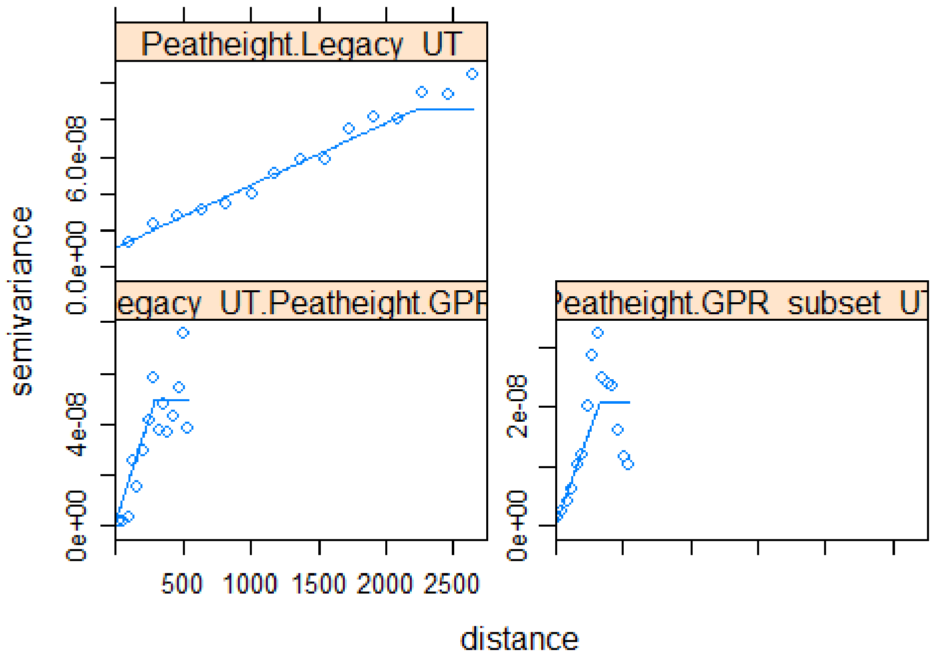

FIGURE 10.60: VARIOGRAM MODELS CO-KRIGING, UNIVERSAL TRANSFORMED GPR AS COVARIABLE.

```
g.CK_GC_UT <- gstat(NULL,       id = c("Peatheight.Legacy_UT"), formula = UT_Peat
height~1,
                    data = Legacy, model = vgm.CK_Leg_UT)
g.CK_GC_UT <- gstat(g.CK_GC_UT, id = c("Peatheight.GPR_UT"),    formula = UT_Peat
height~1,
                    data = GPR,     model = vgm.CK_GPR_UT)
g.CK_GC_UT <- gstat(g.CK_GC_UT, id = c("Peatheight.Legacy_UT","Peatheight.GPR_UT"
),
                    model = vgm.LegGPR_UT)
fit.CK_GC_UT <- fit.lmc(variogram(g.CK_GC_UT), g.CK_GC_UT, model=vgm.LegGPR_UT,
fit.ranges=F, fit.lmc=T)
```

Using untransformed Legacy data as covariable data

```
g.CK_LC <- gstat(NULL,    id = c("Peatdepth.GPR_subset"), formula = Peatdepth~1,
                 data = GPR_subset, model = vgm.CK_GPR)
g.CK_LC <- gstat(g.CK_LC, id = c("Peatdepth.Legacy"),     formula = Peatdepth~1,
                 data = Legacy,     model = vgm.CK_Leg)
g.CK_LC <- gstat(g.CK_LC, id = c("Peatdepth.GPR_subset","Peatdepth.Legacy"),
                 model = vgm.GPRLeg)
plot(variogram(g.CK_LC), model = g.CK_LC$model)
```

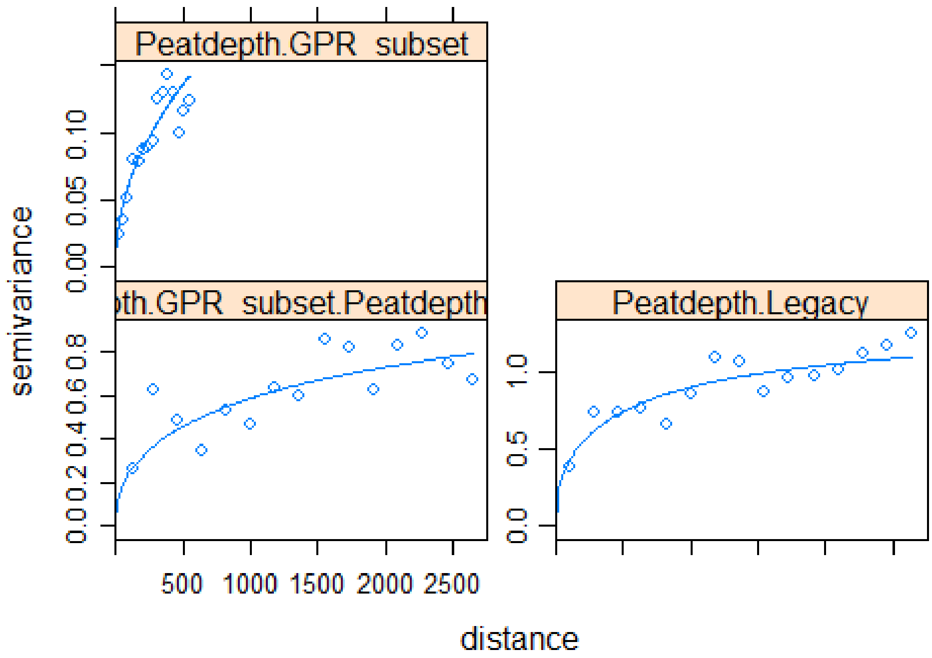

FIGURE 10.61: VARIOGRAM MODELS CO-KRIGING, LEGACY AS COVARIABLE.

```
g.CK_LC <- gstat(NULL,    id = c("Peatdepth.GPR"),    formula = Peatdepth~1,
                 data = GPR,    model = vgm.CK_GPR)
g.CK_LC <- gstat(g.CK_LC, id = c("Peatdepth.Legacy"), formula = Peatdepth~1,
                 data = Legacy, model = vgm.CK_Leg)
g.CK_LC <- gstat(g.CK_LC, id = c("Peatdepth.GPR","Peatdepth.Legacy"),
                 model = vgm.GPRLeg)
fit.CK_LC <- fit.lmc(variogram(g.CK_LC), g.CK_LC, model=vgm.GPRLeg, fit.ranges=F
, fit.lmc=T)
```

Using universal transformed Legacy data as covariable data

```
g.CK_LC_UT <- gstat(NULL,       id = c("Peatheight.GPR_subset_UT"), formula = UT_
Peatheight~1,
                    data = GPR_subset, model = vgm.CK_GPR_UT)
g.CK_LC_UT <- gstat(g.CK_LC_UT, id = c("Peatheight.Legacy_UT"),     formula = UT_
Peatheight~1,
                    data = Legacy,     model = vgm.CK_Leg_UT)
g.CK_LC_UT <- gstat(g.CK_LC_UT, id = c("Peatheight.GPR_subset_UT","Peatheight.Leg
acy_UT"),
                    model = vgm.GPRLeg_UT)
plot(variogram(g.CK_LC_UT), model = g.CK_LC_UT$model)
```

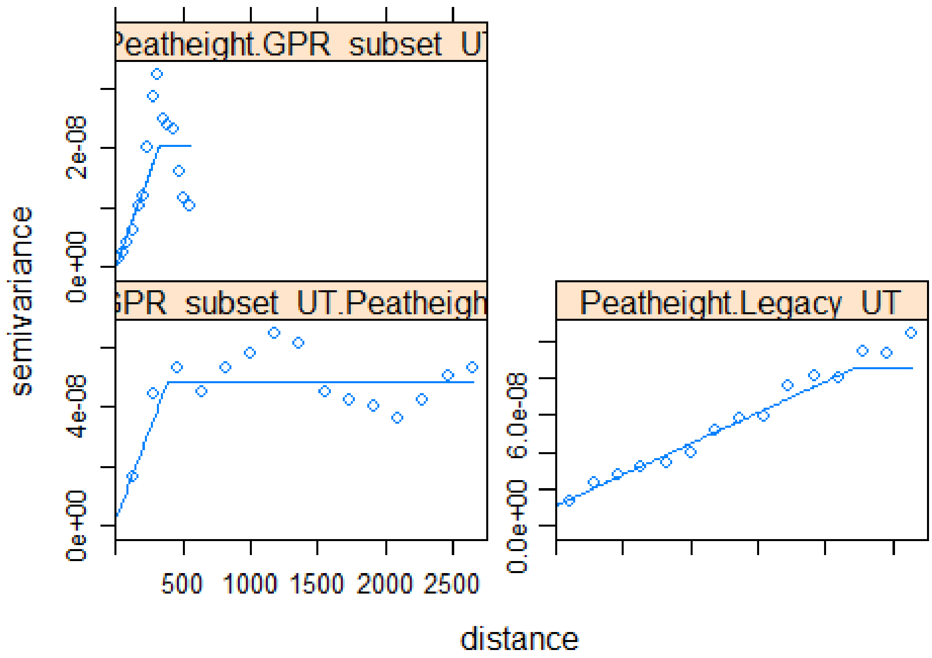

FIGURE 10.62: VARIOGRAM MODELS CO-KRIGING, UNIVERSAL TRANSFORMED LEGACY AS COVARIABLE.

```
g.CK_LC_UT <- gstat(NULL,       id = c("Peatheight.GPR_UT"),    formula = UT_Peat
height~1,
                    data = GPR,     model = vgm.CK_GPR_UT)
g.CK_LC_UT <- gstat(g.CK_LC_UT, id = c("Peatheight.Legacy_UT"), formula = UT_Peat
height~1,
                    data = Legacy, model = vgm.CK_Leg_UT)
g.CK_LC_UT <- gstat(g.CK_LC_UT, id = c("Peatheight.GPR_UT","Peatheight.Legacy_UT"
),
                    model = vgm.GPRLeg_UT)
fit.CK_LC_UT <- fit.lmc(variogram(g.CK_LC_UT), g.CK_LC_UT, model=vgm.GPRLeg_UT,
fit.ranges=F, fit.lmc=T)
```

REGRESSION KRIGING

Regression kriging with using the residuals of a linear model with the surface level as regression data. *Create linear models of the Peatheight and depth with surfacelevel as regression data.*

```
linmod.h.A   <- lm(Peatheight   ~ SurfaceLevel, data = All_subset)
linmod.h.A_T <- lm(T_Peatheight ~ SurfaceLevel, data = All_subset)
linmod.h.G   <- lm(Peatheight   ~ SurfaceLevel, data = GPR_subset)
linmod.h.G_T <- lm(T_Peatheight ~ SurfaceLevel, data = GPR_subset)
linmod.h.L   <- lm(Peatheight   ~ SurfaceLevel, data = Legacy)
linmod.h.L_T <- lm(T_Peatheight ~ SurfaceLevel, data = Legacy)

linmod.d.A   <- lm(Peatdepth   ~ SurfaceLevel, data = All_subset)
linmod.d.A_T <- lm(T_Peatdepth ~ SurfaceLevel, data = All_subset)
linmod.d.G   <- lm(Peatdepth   ~ SurfaceLevel, data = GPR_subset)
linmod.d.G_T <- lm(T_Peatdepth ~ SurfaceLevel, data = GPR_subset)
```

```
linmod.d.L   <- lm(Peatdepth   ~ SurfaceLevel, data = Legacy)
linmod.d.L_T <- lm(T_Peatdepth ~ SurfaceLevel, data = Legacy)
```

Check the summaries of the linear model whether the linear model is relevant for regression kriging.

```
summary(linmod.h.A)

##
## Call:
## lm(formula = Peatheight ~ SurfaceLevel, data = All_subset)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3.0065 -0.5277  0.1841  0.6849  1.6603
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   3.35696    1.01208   3.317  0.00105 **
## SurfaceLevel  0.73977    0.05548  13.334  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.9605 on 236 degrees of freedom
## Multiple R-squared:  0.4297, Adjusted R-squared:  0.4272
## F-statistic: 177.8 on 1 and 236 DF,  p-value: < 2.2e-16
```

There is a very significant relation, and satisfying residual standard error, p-value and (adjested) r squared.

```
summary(linmod.h.G)

##
## Call:
## lm(formula = Peatheight ~ SurfaceLevel, data = GPR_subset)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.87541 -0.26057  0.03058  0.21278  0.75063
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   0.07738    1.36214   0.057    0.955
## SurfaceLevel  0.95404    0.07427  12.845   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.3694 on 58 degrees of freedom
## Multiple R-squared:  0.7399, Adjusted R-squared:  0.7354
## F-statistic:   165 on 1 and 58 DF,  p-value: < 2.2e-16
```

There is a very significant relation, and satisfying residual standard error, p-value and (adjested) r squared.

```
summary(linmod.h.L)

##
## Call:
```

```
## lm(formula = Peatheight ~ SurfaceLevel, data = Legacy)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2.68728 -0.71166  0.05838  0.76141  1.92556
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   3.90510    1.09585   3.564 0.000471 ***
## SurfaceLevel  0.69758    0.06018  11.591  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.9959 on 176 degrees of freedom
## Multiple R-squared:  0.4329, Adjusted R-squared:  0.4297
## F-statistic: 134.4 on 1 and 176 DF,  p-value: < 2.2e-16
```

There is a very significant relation, and satisfying residual standard error, p-value and (adjested) r squared.

```
summary(linmod.h.A_T)

##
## Call:
## lm(formula = T_Peatheight ~ SurfaceLevel, data = All_subset)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.77607 -0.13509  0.05121  0.17736  0.41334
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   2.94072    0.26114   11.26   <2e-16 ***
## SurfaceLevel  0.19096    0.01432   13.34   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2478 on 236 degrees of freedom
## Multiple R-squared:  0.4299, Adjusted R-squared:  0.4275
## F-statistic: 177.9 on 1 and 236 DF,  p-value: < 2.2e-16
```

There is a very significant relation, and satisfying residual standard error, p-value and (adjested) r squared.

```
summary(linmod.h.G_T)

##
## Call:
## lm(formula = T_Peatheight ~ SurfaceLevel, data = GPR_subset)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -55605 -18501   2035  14118  46986
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   -831631      85598  -9.716 8.94e-14 ***
## SurfaceLevel    57792       4668  12.382  < 2e-16 ***
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 23210 on 58 degrees of freedom
## Multiple R-squared:  0.7255, Adjusted R-squared:  0.7208
## F-statistic: 153.3 on 1 and 58 DF,  p-value: < 2.2e-16
```

There is a very significant relation, satisfying p-value and (adjested) r squared.but the residual standard error is not satisfying.

```
summary(linmod.h.L_T)

##
## Call:
## lm(formula = T_Peatheight ~ SurfaceLevel, data = Legacy)
##
## Residuals:
##        Min         1Q     Median         3Q        Max
## -5.440e-04 -1.351e-04  2.899e-05  1.679e-04  3.227e-04
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  4.907e-01  2.227e-04 2203.07   <2e-16 ***
## SurfaceLevel 1.435e-04  1.223e-05   11.73   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.0002024 on 176 degrees of freedom
## Multiple R-squared:  0.4388, Adjusted R-squared:  0.4356
## F-statistic: 137.6 on 1 and 176 DF,  p-value: < 2.2e-16
```

There is a very significant relation, and satisfying residual standard error, p-value and (adjested) r squared.

```
summary(linmod.d.A)

##
## Call:
## lm(formula = Peatdepth ~ SurfaceLevel, data = All_subset)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -1.6603 -0.6849 -0.1841  0.5277  3.0065
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  -3.35696    1.01208  -3.317  0.00105 **
## SurfaceLevel  0.26023    0.05548   4.691 4.61e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.9605 on 236 degrees of freedom
## Multiple R-squared:  0.08528,    Adjusted R-squared:  0.0814
## F-statistic:    22 on 1 and 236 DF,  p-value: 4.614e-06
```

There is a very significant relation, and satisfying residual standard error, p-value and (adjested) r squared.

```
summary(linmod.d.A_T)
```

```
##
## Call:
## lm(formula = T_Peatdepth ~ SurfaceLevel, data = All_subset)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2.41929 -0.53227 -0.03379  0.56894  1.83566
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  -3.16962    0.89068  -3.559 0.000451 ***
## SurfaceLevel  0.18403    0.04883   3.769 0.000207 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.8453 on 236 degrees of freedom
## Multiple R-squared:  0.05678,    Adjusted R-squared:  0.05278
## F-statistic: 14.21 on 1 and 236 DF,  p-value: 0.000207
```

There is a very significant relation, and satisfying residual standard error, p-value and (adjested) r squared.

```
summary(linmod.d.G)

##
## Call:
## lm(formula = Peatdepth ~ SurfaceLevel, data = GPR_subset)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.75063 -0.21278 -0.03058  0.26057  0.87541
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  -0.07738    1.36214  -0.057    0.955
## SurfaceLevel  0.04596    0.07427   0.619    0.538
##
## Residual standard error: 0.3694 on 58 degrees of freedom
## Multiple R-squared:  0.006559,   Adjusted R-squared:  -0.01057
## F-statistic: 0.3829 on 1 and 58 DF,  p-value: 0.5385
```

There is no relation, a satisfying residual standard error, but no satisfying (adjusted) R squared and p value.

```
summary(linmod.d.G_T)

##
## Call:
## lm(formula = T_Peatdepth ~ SurfaceLevel, data = GPR_subset)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.78436 -0.21177 -0.02645  0.26585  0.87351
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  -1.08664    1.38574  -0.784    0.436
## SurfaceLevel  0.04617    0.07556   0.611    0.544
```

```
##
## Residual standard error: 0.3758 on 58 degrees of freedom
## Multiple R-squared:  0.006397,   Adjusted R-squared:  -0.01073
## F-statistic: 0.3734 on 1 and 58 DF,  p-value: 0.5435
```

There is no relation, a satisfying residual standard error, but no satisfying (adjusted) R squared and p value.

```
summary(linmod.d.L)

##
## Call:
## lm(formula = Peatdepth ~ SurfaceLevel, data = Legacy)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.92556 -0.76141 -0.05838  0.71166  2.68728
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  -3.90510    1.09585  -3.564 0.000471 ***
## SurfaceLevel  0.30242    0.06018   5.025 1.23e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.9959 on 176 degrees of freedom
## Multiple R-squared:  0.1255, Adjusted R-squared:  0.1205
## F-statistic: 25.25 on 1 and 176 DF,  p-value: 1.229e-06
```

There is a very significant relation, and satisfying residual standard error, p-value and (adjested) r squared.

```
summary(linmod.d.L_T)

##
## Call:
## lm(formula = T_Peatdepth ~ SurfaceLevel, data = Legacy)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -2.4178 -0.5627  0.0387  0.6605  1.6961
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  -3.64324    0.94124  -3.871 0.000153 ***
## SurfaceLevel  0.22175    0.05169   4.290 2.94e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.8554 on 176 degrees of freedom
## Multiple R-squared:  0.09467,    Adjusted R-squared:  0.08953
## F-statistic:  18.4 on 1 and 176 DF,  p-value: 2.942e-05
```

There is a very significant relation, and satisfying residual standard error, p-value and (adjested) r squared.

Add relevent residiuals to data

```
All_subset$residuals.h   <- linmod.h.A$residuals
All_subset$T_residuals.h <- linmod.h.A_T$residuals
GPR_subset$residuals.h   <- linmod.h.G$residuals
Legacy$residuals.h       <- linmod.h.L$residuals
Legacy$T_residuals.h     <- linmod.h.L_T$residuals

All_subset$residuals.d   <- linmod.d.A$residuals
All_subset$T_residuals.d <- linmod.d.A_T$residuals
Legacy$residuals.d       <- linmod.d.L$residuals
Legacy$T_residuals.d     <- linmod.d.L_T$residuals
```

Create variogram models

```
g.resid.h.A   <- gstat(id=c("residuals.h"),   formula = residuals.h~1,   data = A
ll_subset)
g.resid.h.A_T <- gstat(id=c("T_residuals.h"), formula = T_residuals.h~1, data = A
ll_subset)
g.resid.h.G   <- gstat(id=c("residuals.h"),   formula = residuals.h~1,   data = G
PR_subset)
g.resid.h.L   <- gstat(id=c("residuals.h"),   formula = residuals.h~1,   data = L
egacy)
g.resid.h.L_T <- gstat(id=c("T_residuals.h"), formula = T_residuals.h~1, data = L
egacy)

g.resid.d.A   <- gstat(id=c("residuals.d"),   formula = residuals.d~1,   data = A
ll_subset)
g.resid.d.A_T <- gstat(id=c("T_residuals.d"), formula = T_residuals.d~1, data = A
ll_subset)
g.resid.d.L   <- gstat(id=c("residuals.d"),   formula = residuals.d~1,   data = L
egacy)
g.resid.d.L_T <- gstat(id=c("T_residuals.d"), formula = T_residuals.d~1, data = L
egacy)
```

Select most optimal variogram model for kriging and compare whether using peatheight or peatdepth is better for kriging (lower nugget & lower sill give better kriging parameters).

Variogram selection for All data. A "Linear" model gives no kriging output, so linear may be skipped.

```
vgm.resid.h.A   <- optim_vgm_model(variogram(g.resid.h.A), skip = "Lin")
vgm.resid.d.A   <- optim_vgm_model(variogram(g.resid.d.A), skip = "Lin")
vgm.resid.A     <- bestvgm(vgm.resid.h.A, vgm.resid.d.A)

## vgm.resid.d.A is best suited for kriging

## vgm.resid.d.A is the returned variogram model

## MIND: the range difference is: 1.30439912027214e-06
```

Variogram selection for transformed all data. A "Linear" model gives no kriging output, so linear may be skipped.

```
vgm.resid.h.A_T <- optim_vgm_model(variogram(g.resid.h.A_T), skip = "Lin")
vgm.resid.d.A_T <- optim_vgm_model(variogram(g.resid.d.A_T), skip = "Lin")
vgm.resid.A_T   <- bestvgm(vgm.resid.h.A, vgm.resid.d.A_T)
```

```
## Cannot choose the best variogram model, manual selection is required

## No variogram model is returned

plotvgm.height  <- plot(variogram(g.resid.h.A_T), vgm.resid.h.A_T, main="Peatheig
ht")
plotvgm.depth   <- plot(variogram(g.resid.d.A_T), vgm.resid.d.A_T, main="Peatdept
h")
plotvgm.height; plotvgm.depth
```

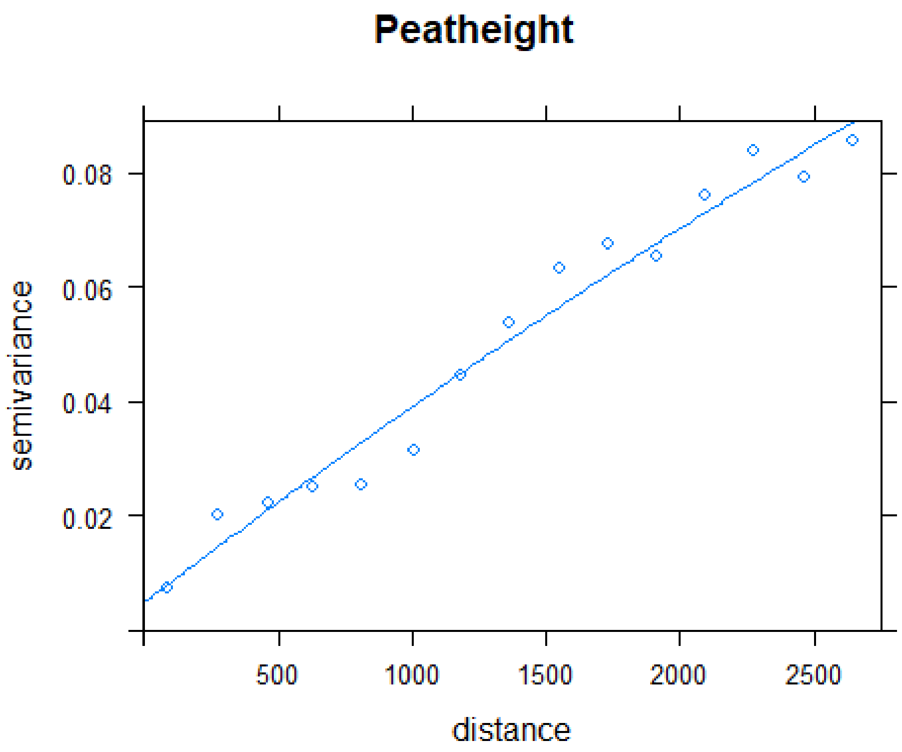

FIGURE 10.63: VARIOGRAM MODELS RESIDUALS TRANSFORMED ALL PEATHEIGHT.

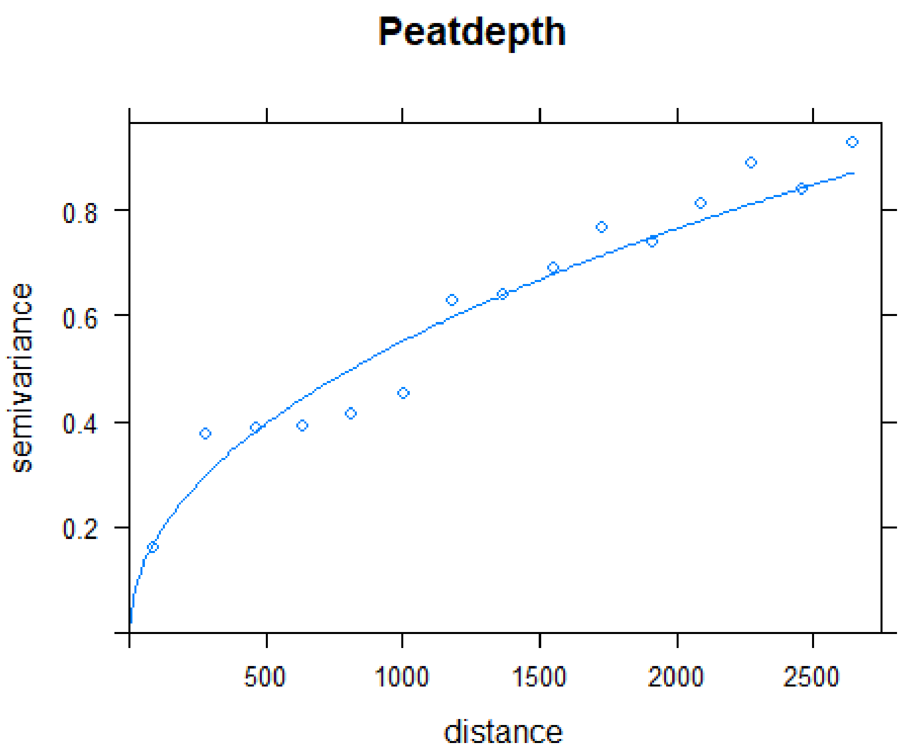

FIGURE 10.64: VARIOGRAM MODELS RESIDUALS TRANSFORMED ALL PEATDEPTH.

No choice has been made by the function, but peatheight is chosen as the best of the two for kriging.

```
vgm.resid.A_T   <- vgm.resid.h.A_T
```

Variogram selection for GPR data.

```
vgm.resid.G     <- optim_vgm_model(variogram(g.resid.h.G))

## [1] "The best fitted variogram type is: Mat"
```

Variogram selection for Legacy data.

```
vgm.resid.h.L   <- optim_vgm_model(variogram(g.resid.h.L))
vgm.resid.d.L   <- optim_vgm_model(variogram(g.resid.d.L))
vgm.resid.L     <- bestvgm(vgm.resid.h.L, vgm.resid.d.L)

## vgm.resid.d.L is best suited for kriging

## vgm.resid.d.L is the returned variogram model

## MIND: the range difference is: 3.7708377931267e-07
```

Variogram selection for transformed Legacy data.

```
vgm.resid.h.L_T <- optim_vgm_model(variogram(g.resid.h.L_T))
vgm.resid.d.L_T <- optim_vgm_model(variogram(g.resid.d.L_T))
vgm.resid.L_T   <- bestvgm(vgm.resid.h.L_T, vgm.resid.d.L_T)
```

```
## vgm.resid.h.L_T is best suited for kriging

## vgm.resid.h.L_T is the returned variogram model

## MIND: the range difference is: 2023.35253785549

plotvgm.height  <- plot(variogram(g.resid.h.L_T), vgm.resid.h.L_T, main="Peatheig
ht")
plotvgm.depth   <- plot(variogram(g.resid.d.L_T), vgm.resid.d.L_T, main="Peatdept
h")
plotvgm.height; plotvgm.depth
```

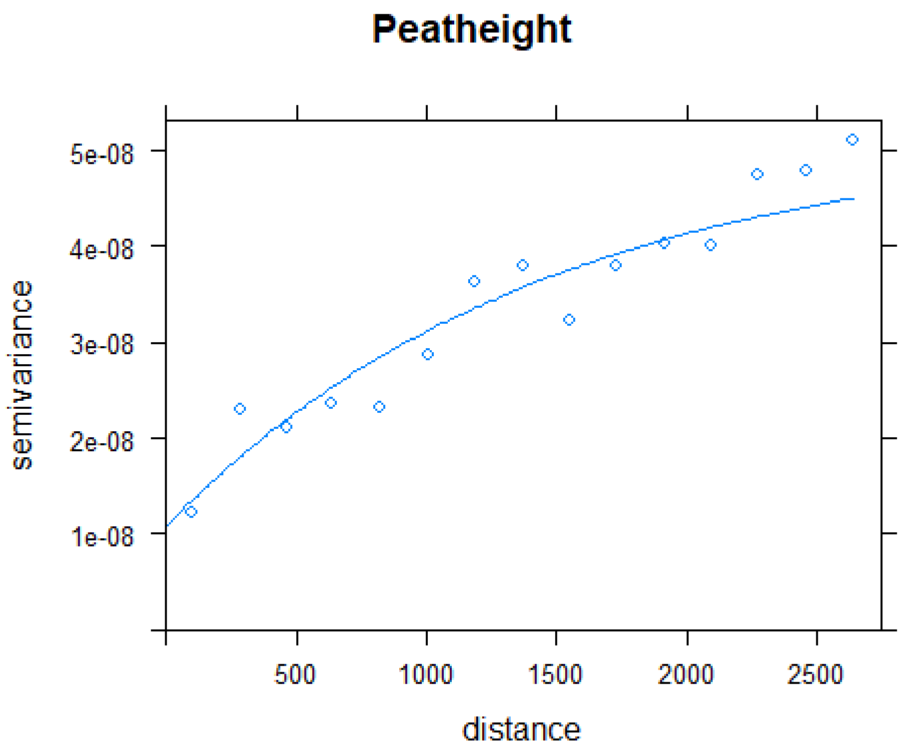

FIGURE 10.65: VARIOGRAM MODELS RESIDUALS TRANSFORMED LEGACY PEATHEIGHT.

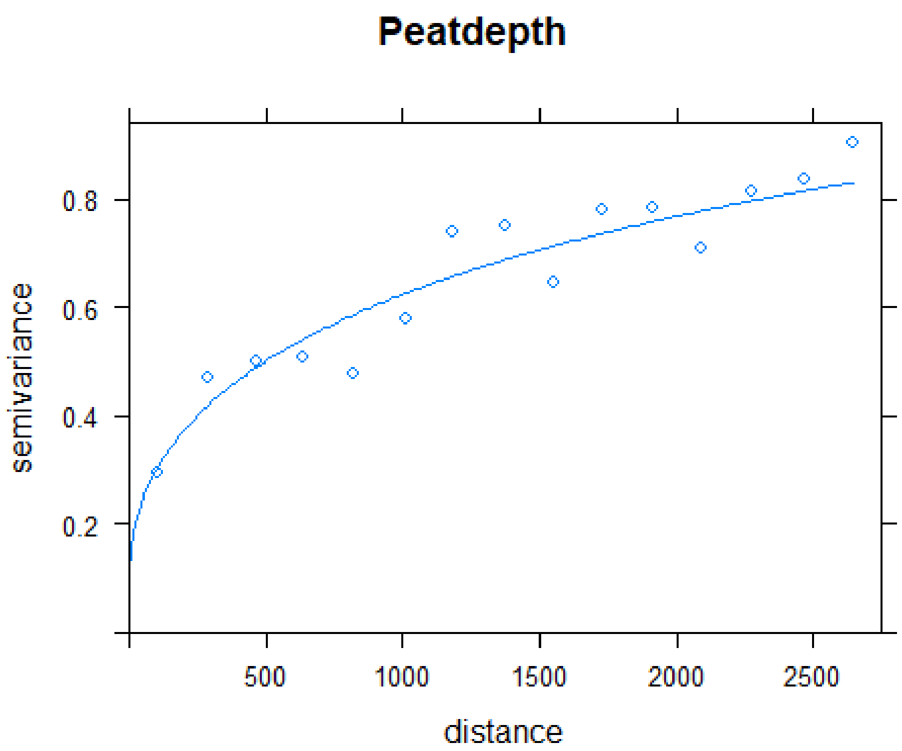

FIGURE 10.66: VARIOGRAM MODELS RESIDUALS TRANSFORMED LEGACY PEATDEPHT.

High range difference, but peatheight is indeed the best of the two for kriging.

KRIGING

Ordinary Kriging.

```
Peatdepth.OK_A     <- krige(formula = Peatdepth~1,     locations = All,
                            newdata = CaseStudy, model = vgm.All)
Peatheight.OK_A_T <- krige(formula = T_Peatheight~1, locations = All,
                            newdata = CaseStudy, model = vgm.All_T)
Peatdepth.OK_G     <- krige(formula = Peatdepth~1,     locations = GPR,
                            newdata = CaseStudy, model = vgm.GPR)
Peatdepth.OK_G_T  <- krige(formula = T_Peatdepth~1,  locations = GPR,
                            newdata = CaseStudy, model = vgm.GPR_T)
Peatdepth.OK_L     <- krige(formula = Peatdepth~1,     locations = Legacy,
                            newdata = CaseStudy, model = vgm.Legacy)
Peatheight.OK_L_T <- krige(formula = T_Peatheight~1, locations = Legacy,
                            newdata = CaseStudy, model = vgm.Legacy_T)
```

Co - kriging.

```
Peatdepth.CK_LC      <- predict(object = fit.CK_LC,    newdata = CaseStudy)
Peatheight.CK_LC_UT <- predict(object = fit.CK_LC_UT, newdata = CaseStudy)
Peatdepth.CK_GC      <- predict(object = fit.CK_GC,    newdata = CaseStudy)
Peatheight.CK_GC_UT <- predict(object = fit.CK_GC_UT, newdata = CaseStudy)
```

Regression kriging

```
Peatdepth.RK_A     <- krige(formula = Peatdepth~SurfaceLevel,     locations = All,
                             newdata = ahn_area, model = vgm.resid.A)
Peatheight.RK_A_T <- krige(formula = T_Peatheight~SurfaceLevel,  locations = All,
                             newdata = ahn_area, model = vgm.resid.A_T)
Peatheight.RK_G    <- krige(formula = Peatheight~SurfaceLevel,    locations = GPR,
                             newdata = ahn_area, model = vgm.resid.G)
Peatdepth.RK_L     <- krige(formula = Peatdepth~SurfaceLevel,     locations = Legac
y,
                             newdata = ahn_area, model = vgm.resid.L)
Peatheight.RK_L_T <- krige(formula = T_Peatheight~SurfaceLevel,  locations = Legac
y,
                             newdata = ahn_area, model = vgm.resid.L_T)
```

Back transforming data.

```
Peatheight.OK_A_T$prediction   <- revBoxCox(Peatheight.OK_A_T$var1.pred, All_subs
et$Peatheight,
                                            variance = Peatheight.OK_A_T$var1.var)
Peatheight.OK_A_T$variance     <- revBoxCox(Peatheight.OK_A_T$var1.var,  All_subs
et$Peatheight,
                                            variance = Peatheight.OK_A_T$var1.var)
Peatdepth.OK_G_T$prediction    <- revBoxCox(Peatdepth.OK_G_T$var1.pred,  GPR_subs
et$Peatdepth,
                                            variance = Peatdepth.OK_G_T$var1.var)
Peatdepth.OK_G_T$variance      <- revBoxCox(Peatdepth.OK_G_T$var1.var,   GPR_subs
et$Peatdepth,
                                            variance = Peatdepth.OK_G_T$var1.var)
Peatheight.OK_L_T$prediction   <- revBoxCox(Peatheight.OK_L_T$var1.pred, Legacy$P
eatheight,
                                            variance = Peatheight.OK_L_T$var1.var)
Peatheight.OK_L_T$variance     <- revBoxCox(Peatheight.OK_L_T$var1.var,  Legacy$P
eatheight,
                                            variance = Peatheight.OK_L_T$var1.var)
Peatheight.CK_GC_UT$prediction <- revBoxCox(Peatheight.CK_GC_UT$Peatheight.Legacy
_UT.pred,
                                            GPR_subset$Peatheight, Legacy$Peatheig
ht,
                                            variance = Peatheight.CK_GC_UT$Peathei
ght.Legacy_UT.var)
Peatheight.CK_GC_UT$variance   <- revBoxCox(Peatheight.CK_GC_UT$Peatheight.Legacy
_UT.var,
                                            GPR_subset$Peatheight, Legacy$Peatheig
ht,
                                            variance = Peatheight.CK_GC_UT$Peathei
ght.Legacy_UT.var)
Peatheight.CK_LC_UT$prediction <- revBoxCox(Peatheight.CK_LC_UT$Peatheight.GPR_UT
.pred,
                                            GPR_subset$Peatheight, Legacy$Peatheig
ht,
                                            variance = Peatheight.CK_LC_UT$Peathei
ght.GPR_UT.var)
Peatheight.CK_LC_UT$variance   <- revBoxCox(Peatheight.CK_LC_UT$Peatheight.GPR_UT
.var,
                                            GPR_subset$Peatheight, Legacy$Peatheig
ht,
```

```
                                            variance = Peatheight.CK_LC_UT$Peathei
ght.GPR_UT.var)
Peatheight.RK_A_T$prediction   <- revBoxCox(Peatheight.RK_A_T$var1.pred, All_subs
et$Peatheight,
                                            variance = Peatheight.RK_A_T$var1.var)
Peatheight.RK_A_T$variance     <- revBoxCox(Peatheight.RK_A_T$var1.var,  All_subs
et$Peatheight,
                                            variance = Peatheight.RK_A_T$var1.var)
Peatheight.RK_L_T$prediction   <- revBoxCox(Peatheight.RK_L_T$var1.pred, Legacy$P
eatheight,
                                            variance = Peatheight.RK_L_T$var1.var)
Peatheight.RK_L_T$variance     <- revBoxCox(Peatheight.RK_L_T$var1.var,  Legacy$P
eatheight,
                                            variance = Peatheight.RK_L_T$var1.var)
```

Changing names so all PrePeat reconstructions have the same parameters.

```
names(Peatdepth.OK_A)[1]  <- "prediction"
names(Peatdepth.OK_A)[2]  <- "variance"
names(Peatdepth.OK_G)[1]  <- "prediction"
names(Peatdepth.OK_G)[2]  <- "variance"
names(Peatdepth.OK_L)[1]  <- "prediction"
names(Peatdepth.OK_L)[2]  <- "variance"
names(Peatdepth.CK_GC)[1] <- "prediction"
names(Peatdepth.CK_GC)[2] <- "variance"
names(Peatdepth.CK_LC)[1] <- "prediction"
names(Peatdepth.CK_LC)[2] <- "variance"
names(Peatdepth.RK_A)[1]  <- "prediction"
names(Peatdepth.RK_A)[2]  <- "variance"
names(Peatheight.RK_G)[1] <- "prediction"
names(Peatheight.RK_G)[2] <- "variance"
names(Peatdepth.RK_L)[1]  <- "prediction"
names(Peatdepth.RK_L)[2]  <- "variance"
```

Make a multiplier from the ahn for the peatheight data, to get the same "gaps"/NA values in the peatheight data as in the peatdepth data.

```
multiplier <- ahn_area$SurfaceLevel / ahn_area$SurfaceLevel
```

Prediction variables for prepeat landscape reconstruction. Regression kriged reconstructions are also multiplied by the casestudy ASCII file (with values of '1') to get the same area as other predictions

```
Prediction.OK_A     <- ahn_area$SurfaceLevel - Peatdepth.OK_A$prediction
Prediction.OK_A_T   <- multiplier            * Peatheight.OK_A_T$prediction
Prediction.OK_G     <- ahn_area$SurfaceLevel - Peatdepth.OK_G$prediction
Prediction.OK_G_T   <- ahn_area$SurfaceLevel - Peatdepth.OK_G_T$prediction
Prediction.OK_L     <- ahn_area$SurfaceLevel - Peatdepth.OK_L$prediction
Prediction.OK_L_T   <- multiplier            * Peatheight.OK_L_T$prediction
Prediction.CK_GC    <- ahn_area$SurfaceLevel - Peatdepth.CK_GC$prediction
Prediction.CK_GC_UT <- multiplier            * Peatheight.CK_GC_UT$prediction
Prediction.CK_LC    <- ahn_area$SurfaceLevel - Peatdepth.CK_LC$prediction
Prediction.CK_LC_UT <- multiplier            * Peatheight.CK_LC_UT$prediction
Prediction.RK_A     <- ahn_area$SurfaceLevel - Peatdepth.RK_A$prediction      * Ca
```

```
seStudy$band1
Prediction.RK_A_T   <- multiplier            * Peatheight.RK_A_T$prediction   * Ca
seStudy$band1
Prediction.RK_G     <- multiplier            * Peatheight.RK_G$prediction     * Ca
seStudy$band1
Prediction.RK_L     <- ahn_area$SurfaceLevel - Peatdepth.RK_L$prediction      * Ca
seStudy$band1
Prediction.RK_L_T   <- multiplier            * Peatheight.RK_L_T$prediction   * Ca
seStudy$band1
```

Prepeat landscape reconstructions.

```
Prepeat.OK_A     <- SpatialGridDataFrame(CaseStudy, data.frame(Prediction.OK_A)
,     proj4string = projection)
Prepeat.OK_A_T   <- SpatialGridDataFrame(CaseStudy, data.frame(Prediction.OK_A_
T),   proj4string = projection)
Prepeat.OK_G     <- SpatialGridDataFrame(CaseStudy, data.frame(Prediction.OK_G)
,     proj4string = projection)
Prepeat.OK_G_T   <- SpatialGridDataFrame(CaseStudy, data.frame(Prediction.OK_G_
T),   proj4string = projection)
Prepeat.OK_L     <- SpatialGridDataFrame(CaseStudy, data.frame(Prediction.OK_L)
,     proj4string = projection)
Prepeat.OK_L_T   <- SpatialGridDataFrame(CaseStudy, data.frame(Prediction.OK_L_
T),   proj4string = projection)
Prepeat.CK_GC    <- SpatialGridDataFrame(CaseStudy, data.frame(Prediction.CK_GC
),    proj4string = projection)
Prepeat.CK_GC_UT <- SpatialGridDataFrame(CaseStudy, data.frame(Prediction.CK_GC
_UT), proj4string = projection)
Prepeat.CK_LC    <- SpatialGridDataFrame(CaseStudy, data.frame(Prediction.CK_LC
),    proj4string = projection)
Prepeat.CK_LC_UT <- SpatialGridDataFrame(CaseStudy, data.frame(Prediction.CK_LC
_UT), proj4string = projection)
Prepeat.RK_A     <- SpatialGridDataFrame(CaseStudy, data.frame(Prediction.RK_A)
,     proj4string = projection)
Prepeat.RK_A_T   <- SpatialGridDataFrame(CaseStudy, data.frame(Prediction.RK_A_
T),   proj4string = projection)
Prepeat.RK_G     <- SpatialGridDataFrame(CaseStudy, data.frame(Prediction.RK_G)
,     proj4string = projection)
Prepeat.RK_L     <- SpatialGridDataFrame(CaseStudy, data.frame(Prediction.RK_L)
,     proj4string = projection)
Prepeat.RK_L_T   <- SpatialGridDataFrame(CaseStudy, data.frame(Prediction.RK_L_
T),   proj4string = projection)
```

Change names.

```
names(Prepeat.OK_A)     <- "prediction"
names(Prepeat.OK_A_T)   <- "prediction"
names(Prepeat.OK_G)     <- "prediction"
names(Prepeat.OK_G_T)   <- "prediction"
names(Prepeat.OK_L)     <- "prediction"
names(Prepeat.OK_L_T)   <- "prediction"
names(Prepeat.CK_GC)    <- "prediction"
names(Prepeat.CK_GC_UT) <- "prediction"
names(Prepeat.CK_LC)    <- "prediction"
```

```
names(Prepeat.CK_LC_UT) <- "prediction"
names(Prepeat.RK_A)     <- "prediction"
names(Prepeat.RK_A_T)   <- "prediction"
names(Prepeat.RK_G)     <- "prediction"
names(Prepeat.RK_L)     <- "prediction"
names(Prepeat.RK_L_T)   <- "prediction"
```

Vector with all reconstructions.

```
reconstructions <- c("Prepeat.OK_A",
                     "Prepeat.OK_A_T",
                     "Prepeat.OK_G",
                     "Prepeat.OK_G_T",
                     "Prepeat.OK_L",
                     "Prepeat.OK_L_T",
                     "Prepeat.CK_GC",
                     "Prepeat.CK_GC_UT",
                     "Prepeat.CK_LC",
                     "Prepeat.CK_LC_UT",
                     "Prepeat.RK_A",
                     "Prepeat.RK_A_T",
                     "Prepeat.RK_G",
                     "Prepeat.RK_L",
                     "Prepeat.RK_L_T")
```

Minimum and maximum prediction values used for scaling the reconstruction maps.

```
(low_AHN  <- min(na.omit(ahndata_recon)))

## [1] 14.96

(high_AHN <- max(na.omit(ahndata_recon)))

## [1] 24.61

## Minimum and maximum prediction values used for scaling the reconstruction maps
predmins     <- reconstruction_stat(reconstructions, "prediction", "min")
predmin      <- min(predmins)
comp_AHN_low <- predmins < low_AHN
for (i in seq(comp_AHN_low)){if(comp_AHN_low[i]){comp_AHN_low[i] = "Lower than AHN
"}
  else{comp_AHN_low[i] = "Higher than AHN"}}

predmaxs      <- reconstruction_stat(reconstructions, "prediction", "max")
predmax       <- max(predmaxs)
comp_AHN_high <- predmins < high_AHN
for (i in seq(comp_AHN_high)){if(comp_AHN_high[i]){comp_AHN_high[i] = "Lower than
AHN"}
  else{comp_AHN_high[i] = "Higher than AHN"}}


(Pred.df <- data.frame(reconstructions, predmins, comp_AHN_low, predmaxs, comp_AH
N_high))
```

```
##     reconstructions predmins    comp_AHN_low predmaxs  comp_AHN_high
## 1        Prepeat.OK_A 13.99061  Lower than AHN 24.29180 Lower than AHN
## 2      Prepeat.OK_A_T 15.47256 Higher than AHN 18.76183 Lower than AHN
## 3        Prepeat.OK_G 14.22666  Lower than AHN 24.33659 Lower than AHN
## 4      Prepeat.OK_G_T 14.22624  Lower than AHN 24.34136 Lower than AHN
## 5        Prepeat.OK_L 13.98010  Lower than AHN 23.74534 Lower than AHN
## 6      Prepeat.OK_L_T 15.73332 Higher than AHN 18.44945 Lower than AHN
## 7       Prepeat.CK_GC 13.91339  Lower than AHN 24.08770 Lower than AHN
## 8    Prepeat.CK_GC_UT 14.75795  Lower than AHN 19.98649 Lower than AHN
## 9       Prepeat.CK_LC 14.28441  Lower than AHN 24.26407 Lower than AHN
## 10 Prepeat.CK_LC_UT 16.07515 Higher than AHN 19.67128 Lower than AHN
## 11       Prepeat.RK_A 14.80655  Lower than AHN 21.48253 Lower than AHN
## 12     Prepeat.RK_A_T 14.86733  Lower than AHN 21.68824 Lower than AHN
## 13       Prepeat.RK_G 14.31440  Lower than AHN 24.12368 Lower than AHN
## 14       Prepeat.RK_L 14.97576 Higher than AHN 20.87845 Lower than AHN
## 15     Prepeat.RK_L_T 15.27232 Higher than AHN 22.34892 Lower than AHN
```

2D MAPS

Data points.

```
All.pts    <- as.data.frame(All@coords);    coordinates(All.pts)    <- ~X.Coord
+ Y.Coord
GPR.pts    <- as.data.frame(GPR@coords);    coordinates(GPR.pts)    <- ~X.Coord
+ Y.Coord
Legacy.pts <- as.data.frame(Legacy@coords); coordinates(Legacy.pts) <- ~X.Coord
+ Y.Coord
```

Vectors of the characteristics of the different reconstructions: used data points, used kriging method, used data type, and a title for the maps:

```
plotpts  <- c("All.pts", "All.pts", "GPR.pts", "GPR.pts", "Legacy.pts", "Legacy.pt
s",
              "All.pts", "All.pts", "All.pts", "All.pts", "All.pts", "All.pts",
              "GPR.pts", "Legacy.pts", "Legacy.pts")
method   <- c(rep("Ordinary kriging",6), rep("Co-Kriging",4), rep("Regression kri
ging",5))
datatype <- c("All data", "All data (transformed)", "GPR data", "GPR data (transfo
rmed)",
              "Legacy data", "Legacy data (transformed)", "GPR data as covariate d
ata",
              "GPR data as covariate data (universal transformed)", "Legacy data a
s covariate data",
              "Legacy data as covariate data (universal transformed)", "All data",
              "All data (transformed)", "GPR data", "Legacy data", "Legacy data (t
ransformed)")
```

Create 2D maps of the prediction of all reconstructions.

```
title_pred <- "Bargerveen Case Study Area: Predicted pre-peat landscape \n"

for (i in seq(reconstructions)){
  BargerveenCasePlot(data   = eval(parse(text = reconstructions[i])), sp_zcol =
```

```
"prediction",
                          pts    = eval(parse(text = plotpts[i])),
                          title  = paste0(title_pred, method[i], ", ", datatype[i]),
                          minval = predmin, maxval = predmax)
}
```

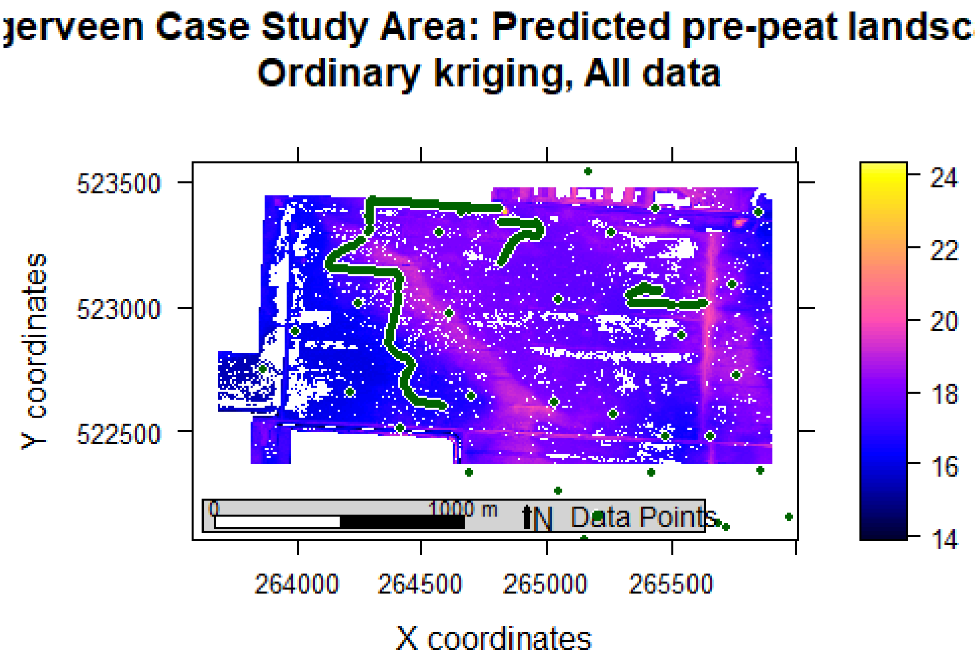

FIGURE 10.67: BARGERVEEN CASE STUDY AREA: PREDICTED PRE-PEAT LANDSCAPE. ORDINARY KRIGING, ALL DATA.

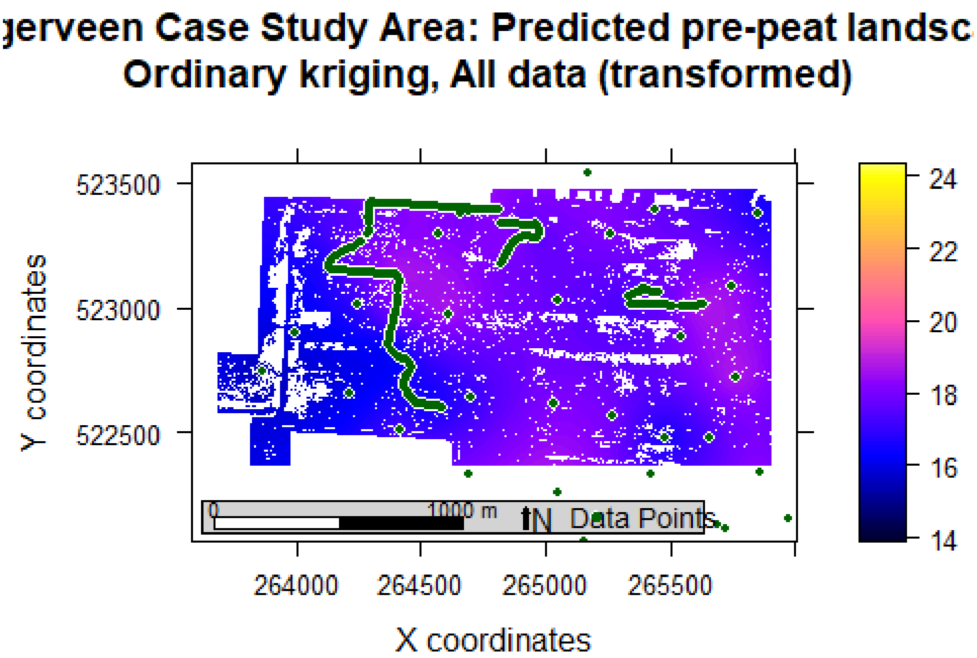

FIGURE 10.68: BARGERVEEN CASE STUDY AREA: PREDICTED PRE-PEAT LANDSCAPE. ORDINARY KRIGING, ALL DATA (TRANSFORMED).

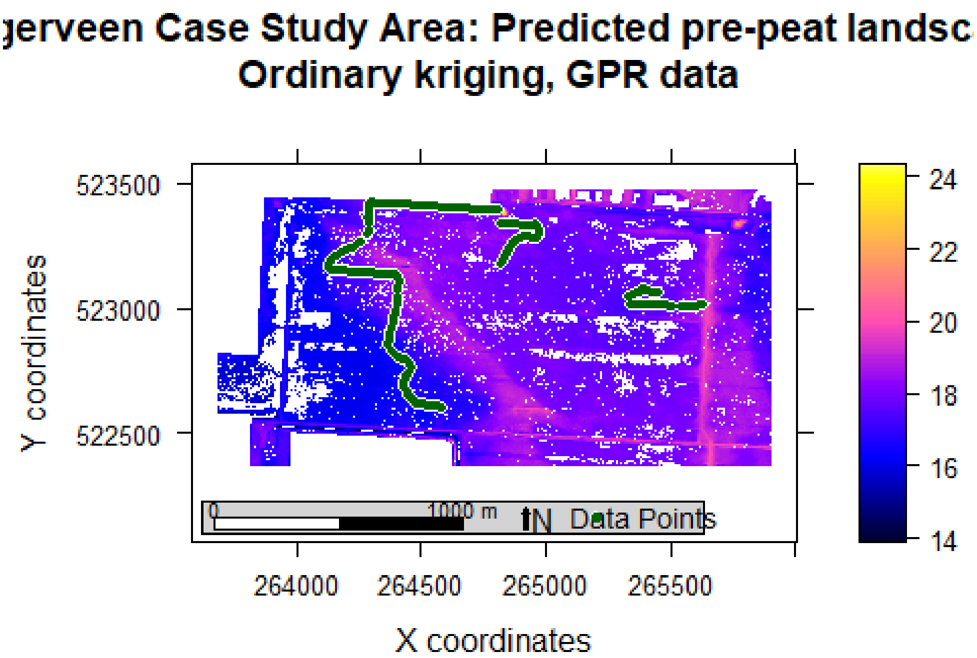

FIGURE 10.69: BARGERVEEN CASE STUDY AREA: PREDICTED PRE-PEAT LANDSCAPE. ORDINARY KRIGING, GPR DATA.

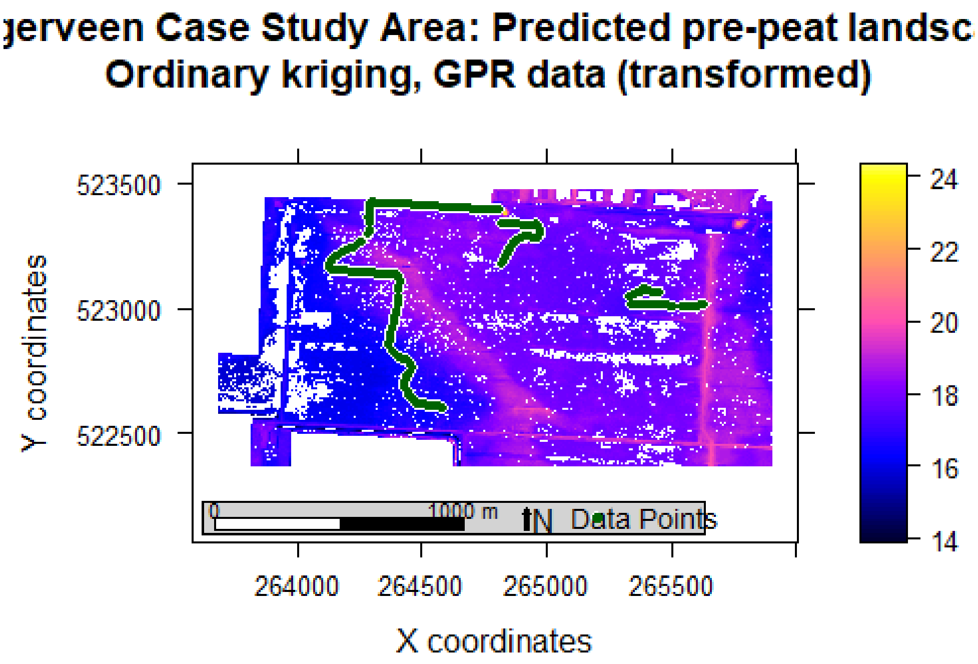

FIGURE 10.70: BARGERVEEN CASE STUDY AREA: PREDICTED PRE-PEAT LANDSCAPE. ORDINARY KRIGING, GPR DATA (TRANSFORMED).

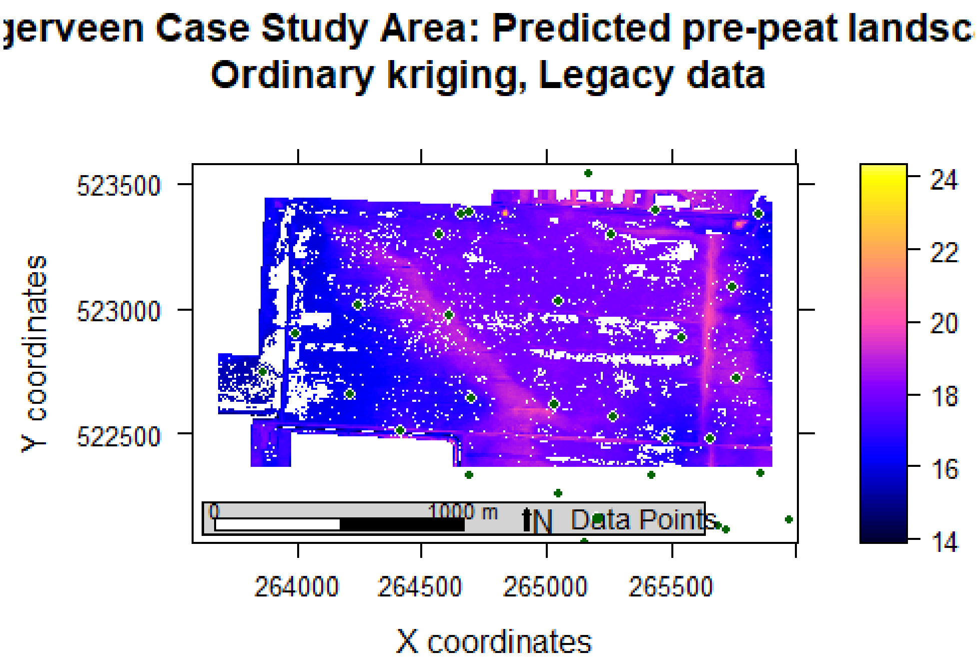

FIGURE 10.71: BARGERVEEN CASE STUDY AREA: PREDICTED PRE-PEAT LANDSCAPE. ORDINARY KRIGING, LEGACY DATA.

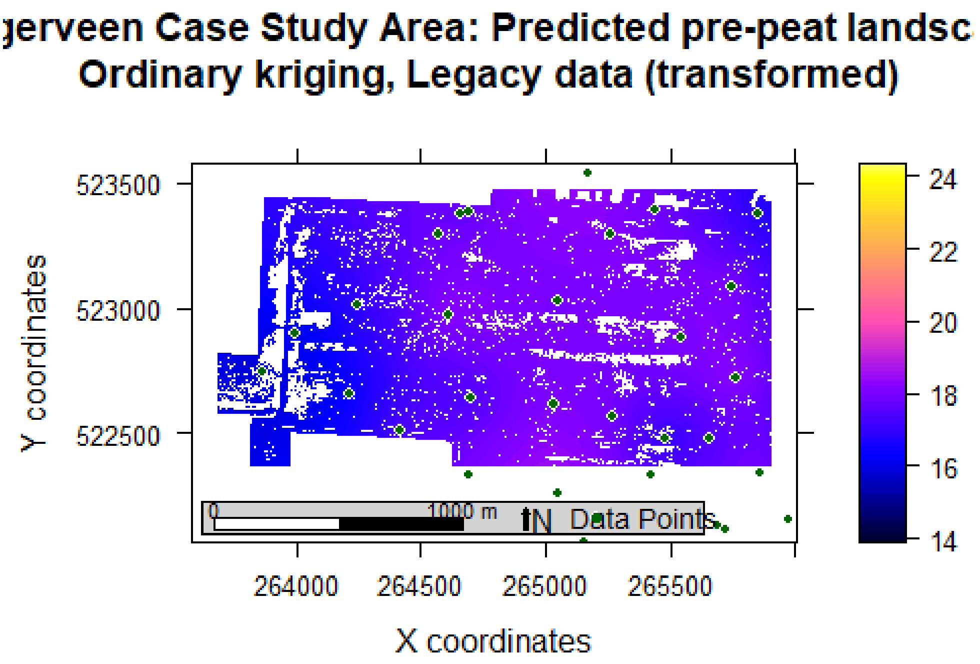

FIGURE 10.72: BARGERVEEN CASE STUDY AREA: PREDICTED PRE-PEAT LANDSCAPE. ORDINARY KRIGING, LEGACY DATA (TRANSFORMED).

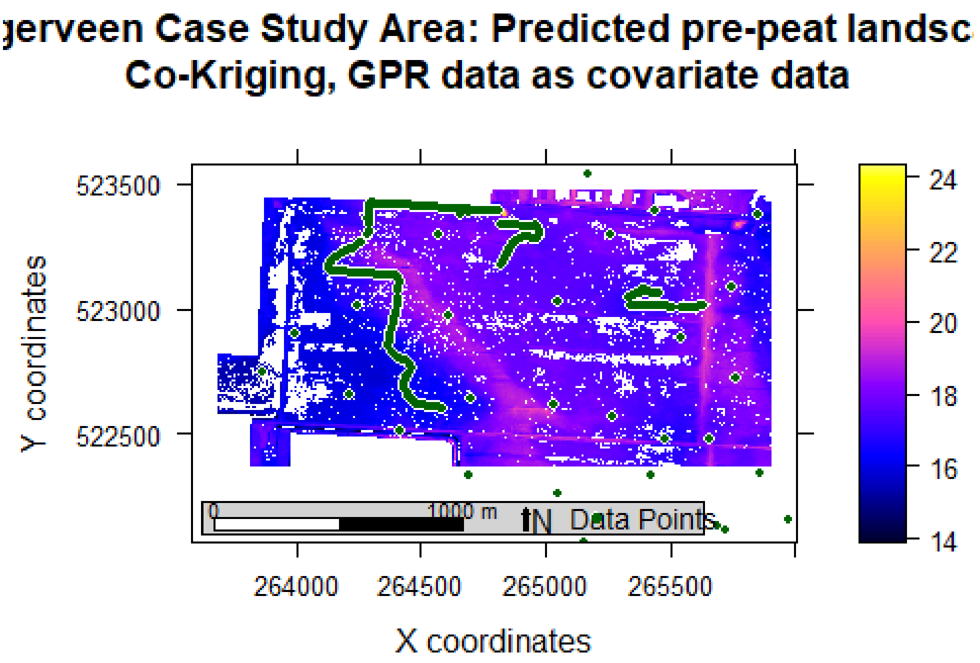

FIGURE 10.73: BARGERVEEN CASE STUDY AREA: PREDICTED PRE-PEAT LANDSCAPE. CO-KRIGING, GPR DATA AS COVARIATE DATA.

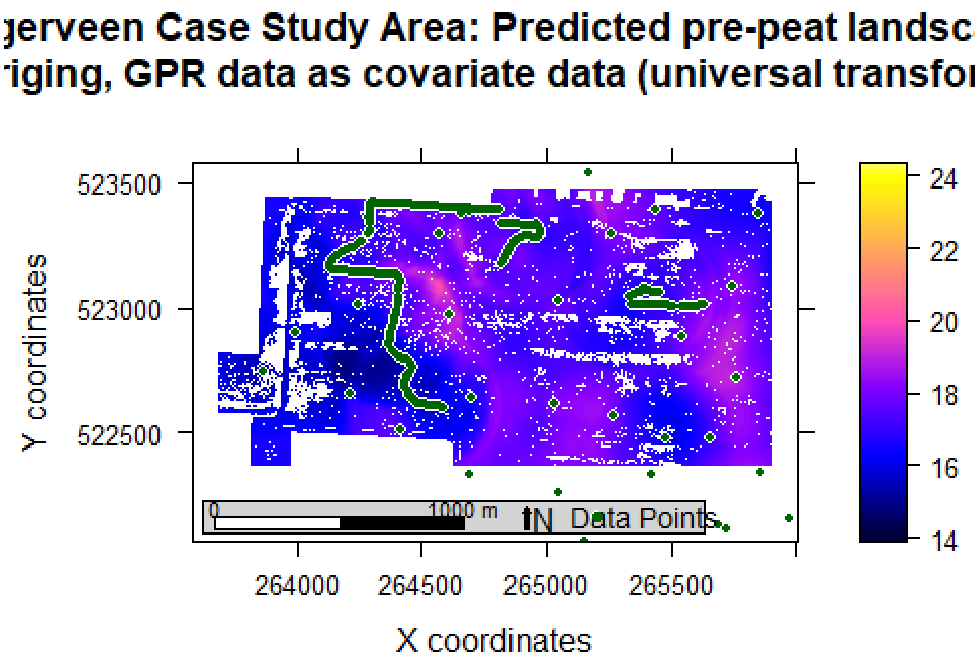

FIGURE 10.74: BARGERVEEN CASE STUDY AREA: PREDICTED PRE-PEAT LANDSCAPE. CO-KRIGING, GPR DATA AS COVARIATE DATA (UNIVERSAL TRANSFORMED).

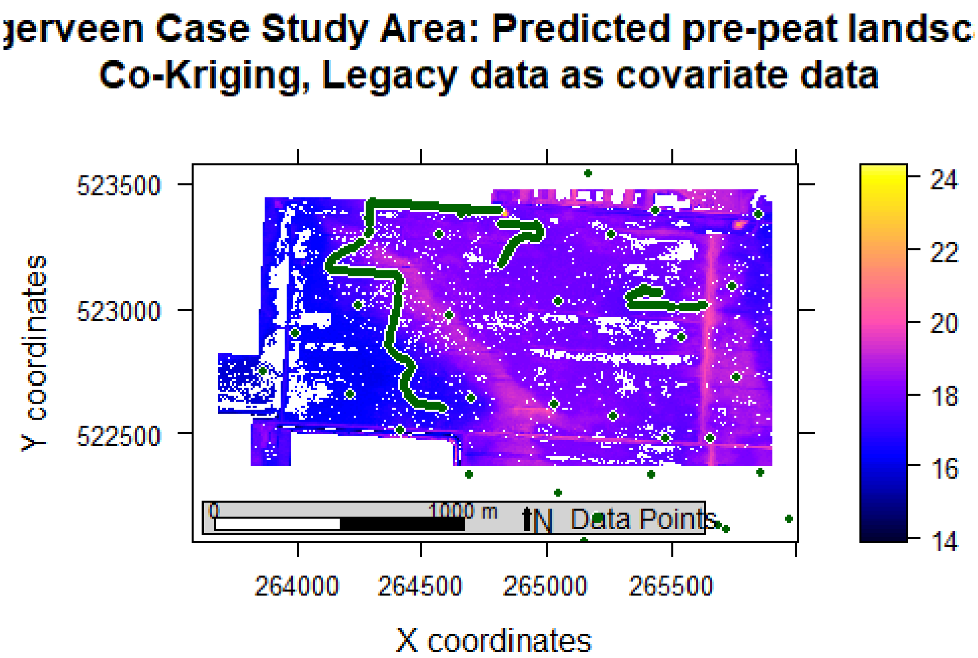

FIGURE 10.75: BARGERVEEN CASE STUDY AREA: PREDICTED PRE-PEAT LANDSCAPE. CO-KRIGING, LEGACY DATA AS COVARIATE DATA.

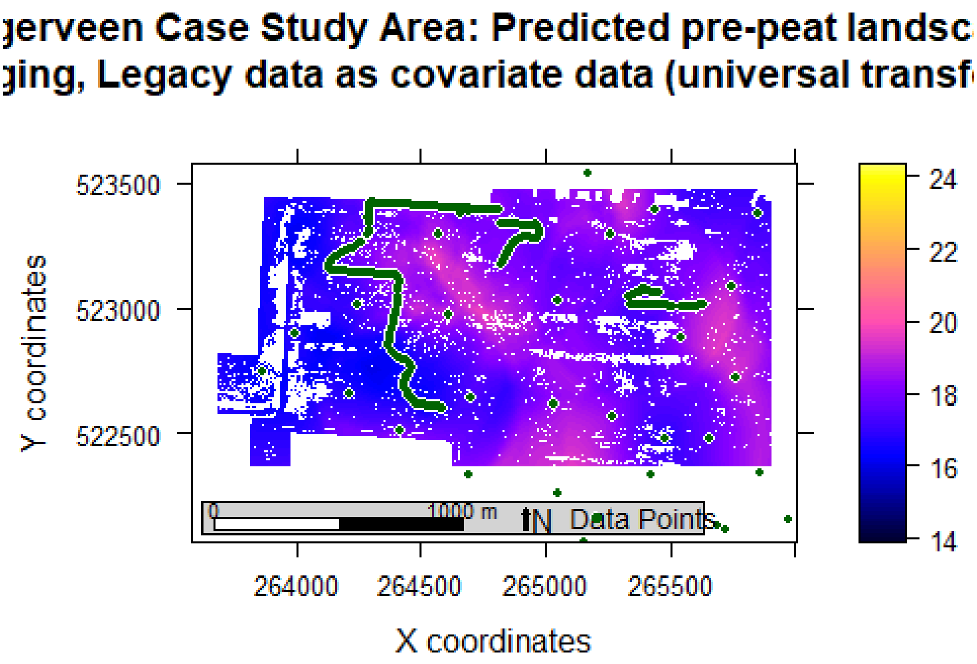

FIGURE 10.76: BARGERVEEN CASE STUDY AREA: PREDICTED PRE-PEAT LANDSCAPE. CO-KRIGING, LEGACY DATA AS COVARIATE DATA (UNIVERSAL TRANSFORMED).

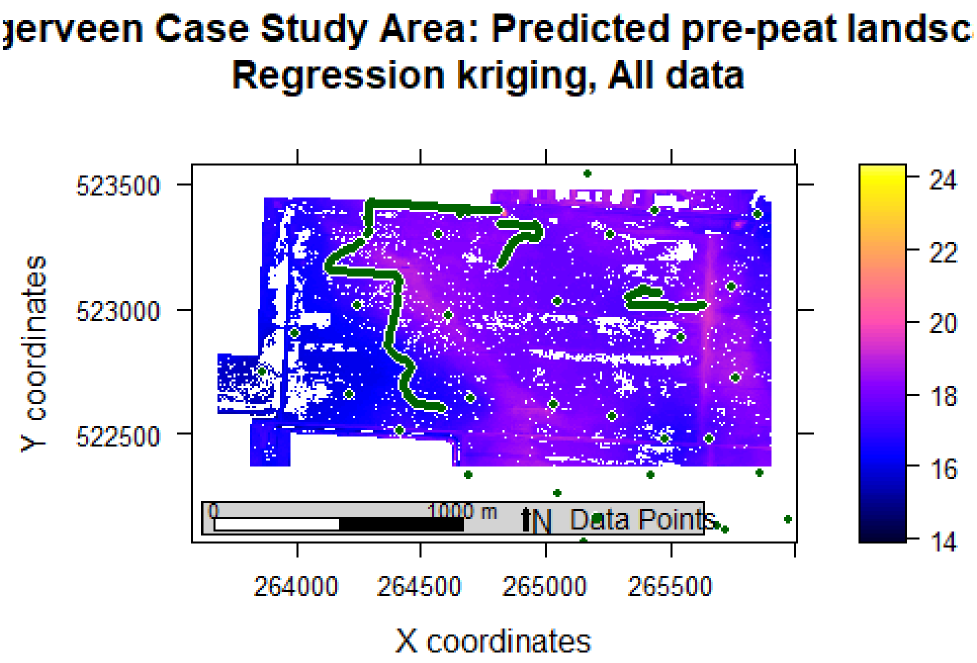

FIGURE 10.77: BARGERVEEN CASE STUDY AREA: PREDICTED PRE-PEAT LANDSCAPE. REGRESSION KRIGING, ALL DATA.

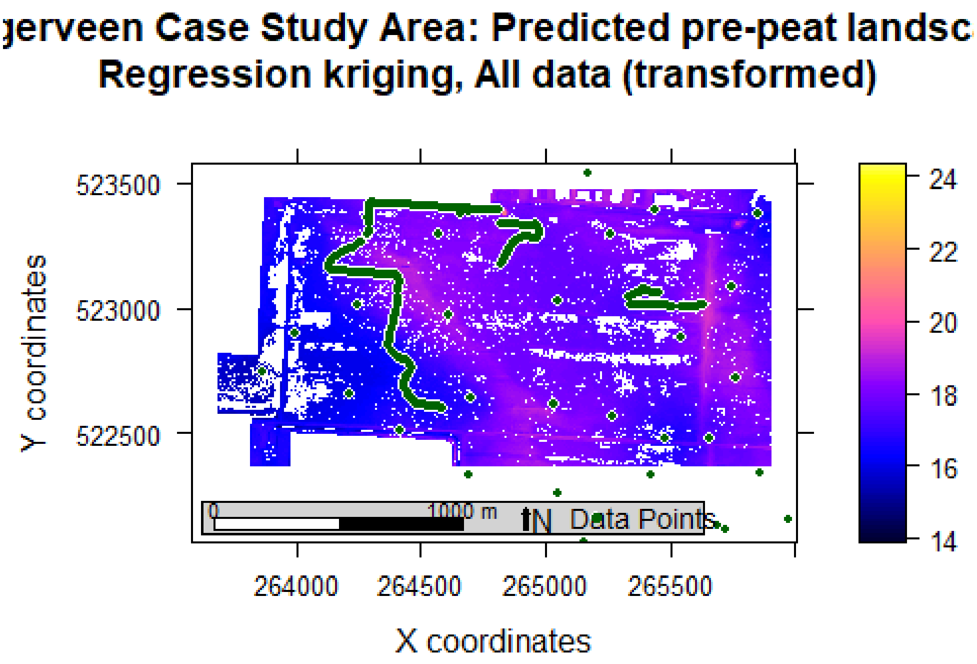

FIGURE 10.78: BARGERVEEN CASE STUDY AREA: PREDICTED PRE-PEAT LANDSCAPE. REGRESSION KRIGING, ALL DATA (TRANSFORMED).

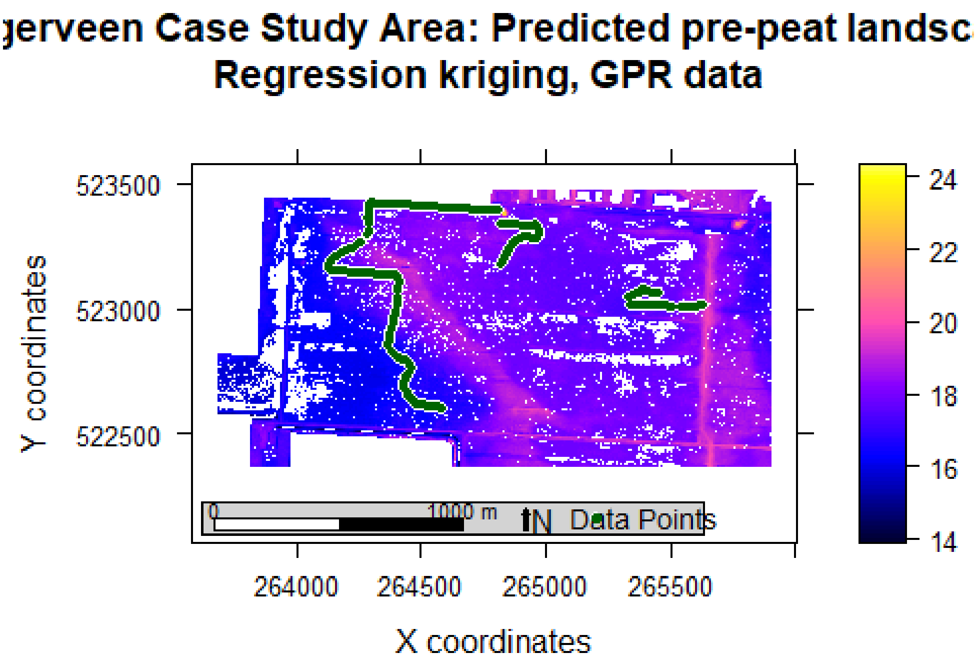

FIGURE 10.79: BARGERVEEN CASE STUDY AREA: PREDICTED PRE-PEAT LANDSCAPE. REGRESSION KRIGING, GPR DATA.

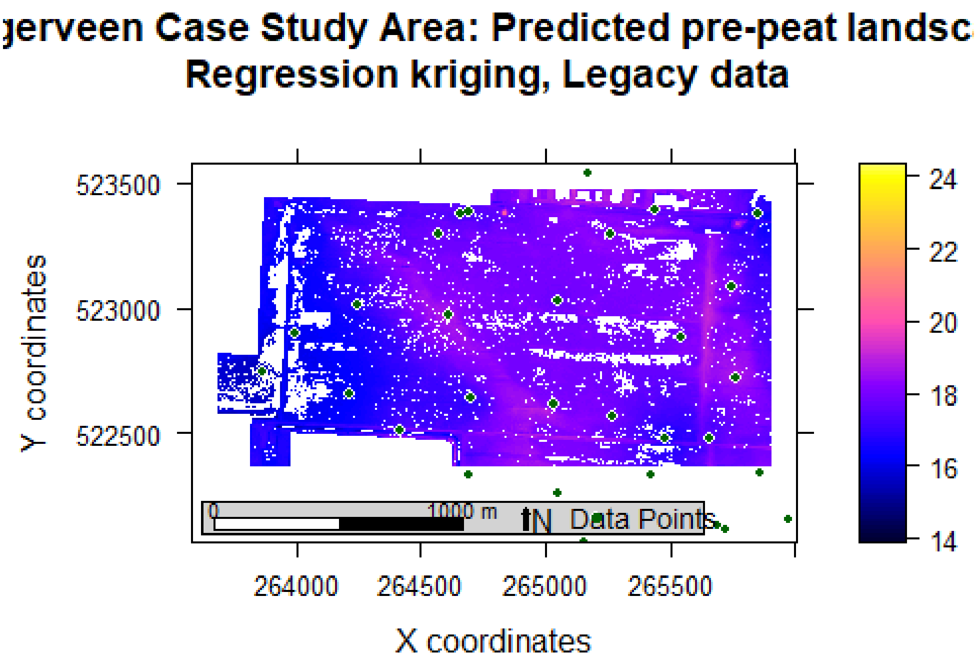

FIGURE 10.80: BARGERVEEN CASE STUDY AREA: PREDICTED PRE-PEAT LANDSCAPE. REGRESSION KRIGING, LEGACY DATA.

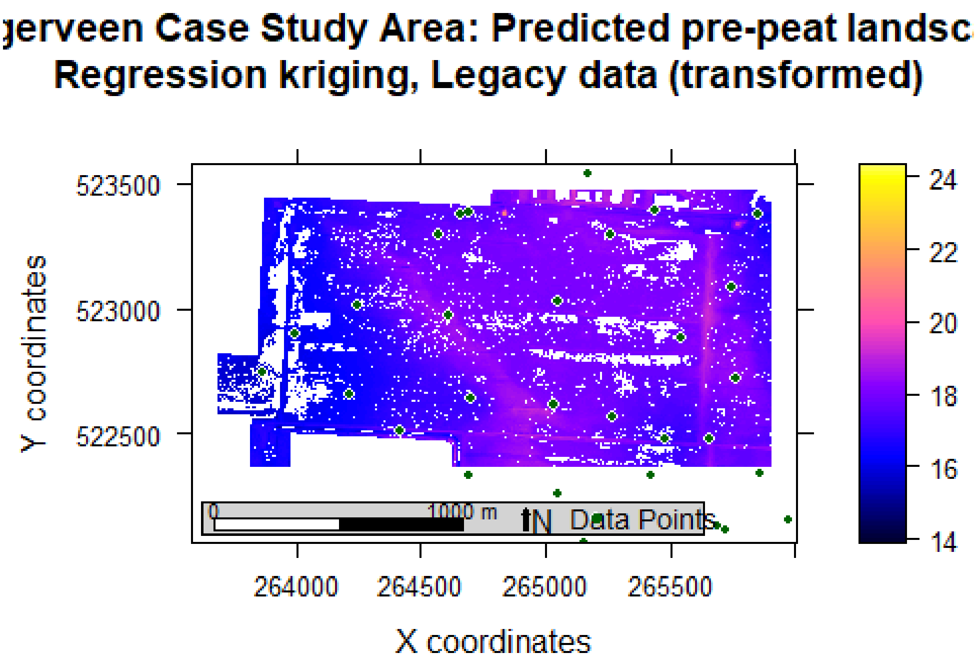

FIGURE 10.81: BARGERVEEN CASE STUDY AREA: PREDICTED PRE-PEAT LANDSCAPE. REGRESSION KRIGING, LEGACY DATA (TRANSFORMED).

ASSESSMENT

KRIGING STANDARD DEVIATION

```
Peatdepth.OK_A$sd       <- sqrt(Peatdepth.OK_A$variance)
Peatheight.OK_A_T$sd    <- sqrt(Peatheight.OK_A_T$variance)
Peatdepth.OK_G$sd       <- sqrt(Peatdepth.OK_G$variance)
Peatdepth.OK_G_T$sd     <- sqrt(Peatdepth.OK_G_T$variance)
Peatdepth.OK_L$sd       <- sqrt(Peatdepth.OK_L$variance)
Peatheight.OK_L_T$sd    <- sqrt(Peatheight.OK_L_T$variance)
Peatdepth.CK_GC$sd      <- sqrt(Peatdepth.CK_GC$variance)
Peatheight.CK_GC_UT$sd <- sqrt(Peatheight.CK_GC_UT$variance)
Peatdepth.CK_LC$sd      <- sqrt(Peatdepth.CK_LC$variance)
Peatheight.CK_LC_UT$sd <- sqrt(Peatheight.CK_LC_UT$variance)
Peatdepth.RK_A$sd       <- sqrt(Peatdepth.RK_A$variance)    * CaseStudy$band1
Peatheight.RK_A_T$sd    <- sqrt(Peatheight.RK_A_T$variance) * CaseStudy$band1
Peatheight.RK_G$sd      <- sqrt(Peatheight.RK_G$variance)   * CaseStudy$band1
Peatdepth.RK_L$sd       <- sqrt(Peatdepth.RK_L$variance)    * CaseStudy$band1
Peatheight.RK_L_T$sd    <- sqrt(Peatheight.RK_L_T$variance) * CaseStudy$band1
```

Vector of all reconstructions with standard deviation calculated.

```
reconstructions.sd <- c("Peatdepth.OK_A",
                        "Peatheight.OK_A_T",
                        "Peatdepth.OK_G",
                        "Peatdepth.OK_G_T",
                        "Peatdepth.OK_L",
                        "Peatheight.OK_L_T",
                        "Peatdepth.CK_GC",
                        "Peatheight.CK_GC_UT",
                        "Peatdepth.CK_LC",
                        "Peatheight.CK_LC_UT",
                        "Peatdepth.RK_A",
                        "Peatheight.RK_A_T",
                        "Peatheight.RK_G",
                        "Peatdepth.RK_L",
                        "Peatheight.RK_L_T")
```

Minimum, minimum average and maximum standard deviation values used for scaling the standard deviation maps and assessing the reconstructions.

```
sdmins <- reconstruction_stat(reconstructions.sd, "sd", "min")
sdmin  <- min(sdmins)
sdavgs <- reconstruction_stat(reconstructions.sd, "sd", "mean")
sdavg  <- min(sdavgs)
sdmaxs <- reconstruction_stat(reconstructions.sd, "sd", "max")
sdmax  <- max(sdmaxs)

(Sd.df <- format(data.frame(reconstructions, sdmins, sdavgs, sdmaxs), scientific
= FALSE))

##     reconstructions    sdmins    sdavgs    sdmaxs
## 1      Prepeat.OK_A 0.2899544 0.4123490 0.6393189
## 2    Prepeat.OK_A_T 1.0051098 1.0112982 1.0276680
## 3      Prepeat.OK_G 0.1270193 0.3234432 0.4075012
## 4    Prepeat.OK_G_T 1.0079381 1.0566233 1.0861299
## 5      Prepeat.OK_L 0.2585649 0.7690972 0.9590929
```

```
## 6    Prepeat.OK_L_T 1.0000000 1.0000000 1.0000000
## 7     Prepeat.CK_GC 0.5996035 0.9587153 1.1229258
## 8  Prepeat.CK_GC_UT 1.0000000 1.0000000 1.0000001
## 9     Prepeat.CK_LC 0.3598494 0.4560307 0.5296123
## 10 Prepeat.CK_LC_UT 1.0000000 1.0000000 1.0000000
## 11     Prepeat.RK_A 0.2926692 0.4003370 0.6070232
## 12   Prepeat.RK_A_T 1.0034438 1.0064923 1.0146510
## 13     Prepeat.RK_G 0.1269510 0.3306926 0.4900378
## 14     Prepeat.RK_L 0.4156591 0.6845412 0.8863981
## 15   Prepeat.RK_L_T 1.0000000 1.0000000 1.0000000
```

Create 2D maps of the standard deviation of all reconstructions

```
title_sd <- "Bargerveen Case Study Area: Standard deviation pre-peat landscape \n"

for (i in seq(reconstructions.sd)){
  BargerveenCasePlot(data   = eval(parse(text = reconstructions.sd[i])), sp_zco
l = "sd",
                     title  = paste0(title_sd, method[i], ", ", datatype[i]),
                     minval = sdmin, maxval = sdmax)
}
```

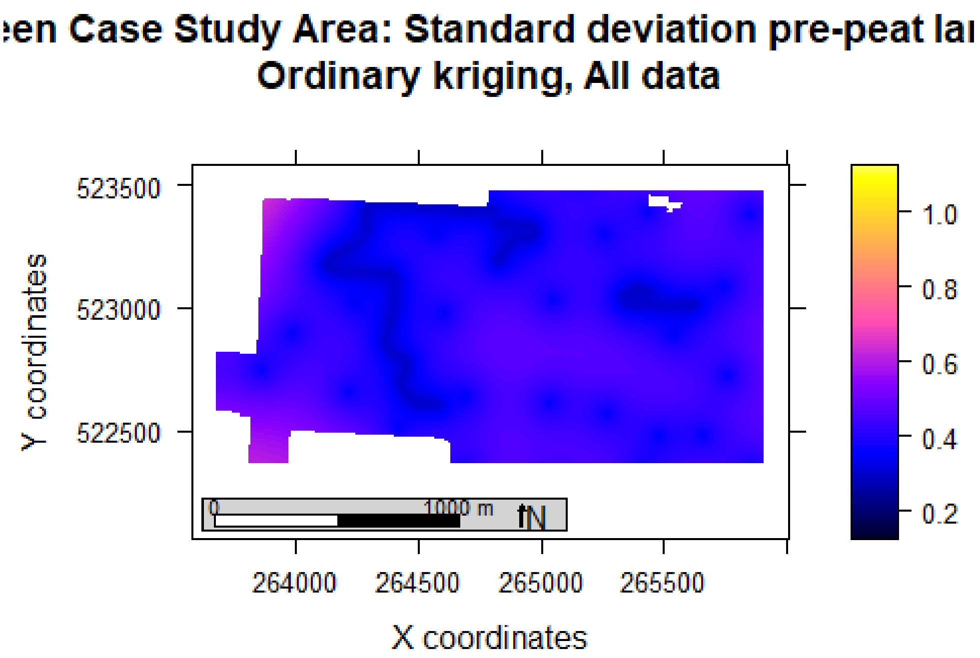

FIGURE 10.82: BARGERVEEN CASE STUDY AREA: STANDARD DEVIATION PRE-PEAT LANDSCAPE. ORDINARY KRIGING, ALL DATA.

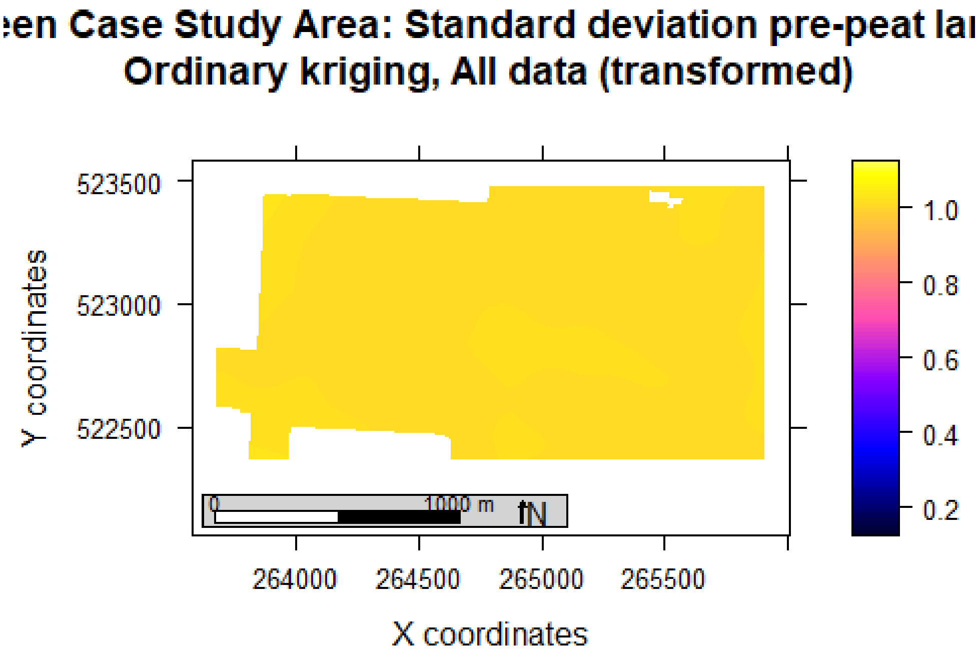

FIGURE 10.83: BARGERVEEN CASE STUDY AREA: STANDARD DEVIATION PRE-PEAT LANDSCAPE. ORDINARY KRIGING, ALL DATA (TRANSFORMED).

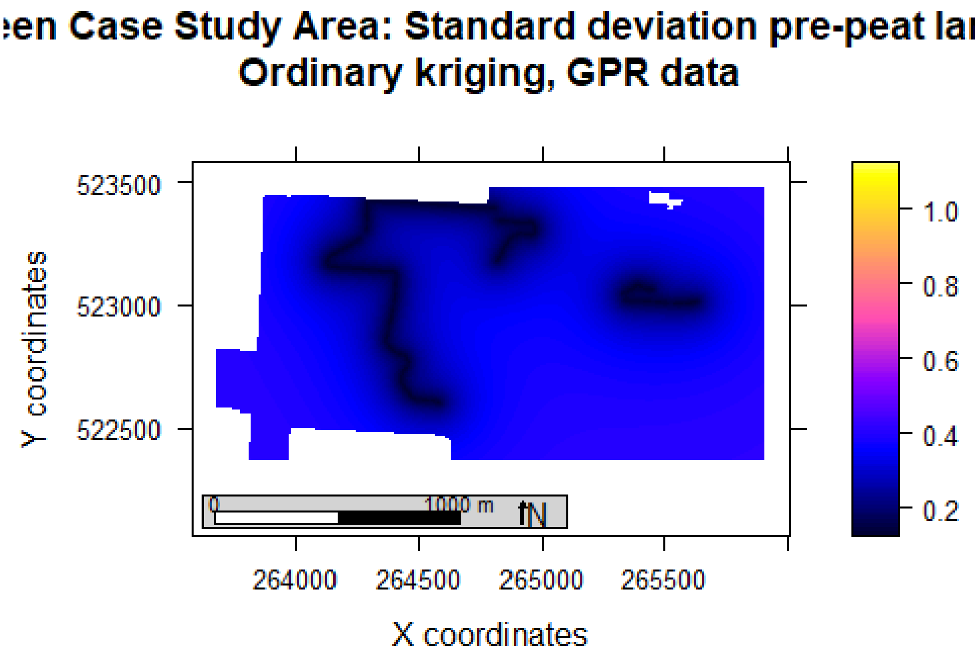

FIGURE 10.84: BARGERVEEN CASE STUDY AREA: STANDARD DEVIATION PRE-PEAT LANDSCAPE. ORDINARY KRIGING, GPR DATA.

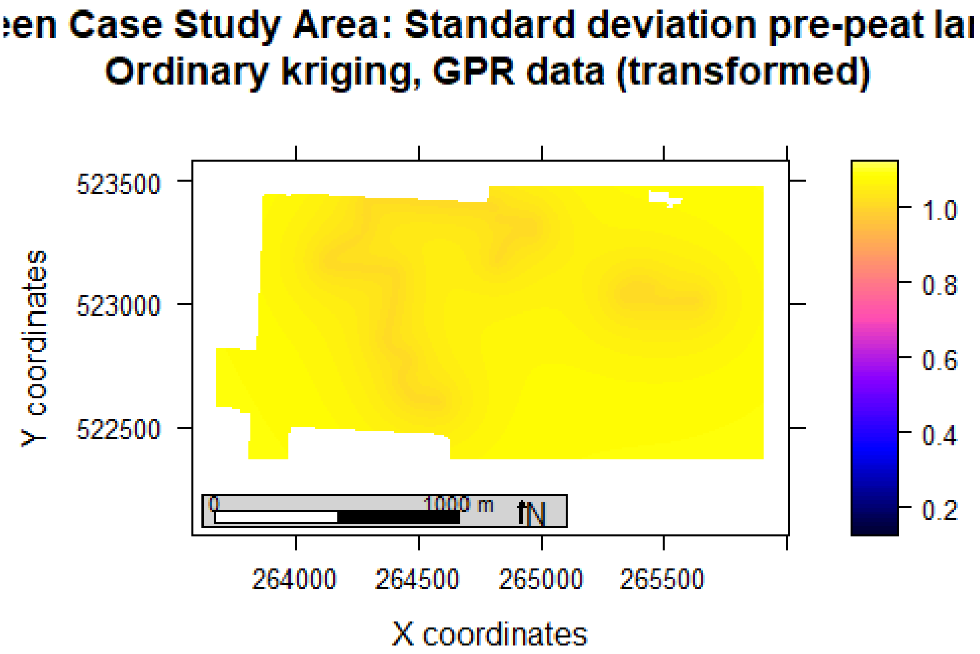

FIGURE 10.85: BARGERVEEN CASE STUDY AREA: STANDARD DEVIATION PRE-PEAT LANDSCAPE. ORDINARY KRIGING, GPR DATA (TRANSFORMED).

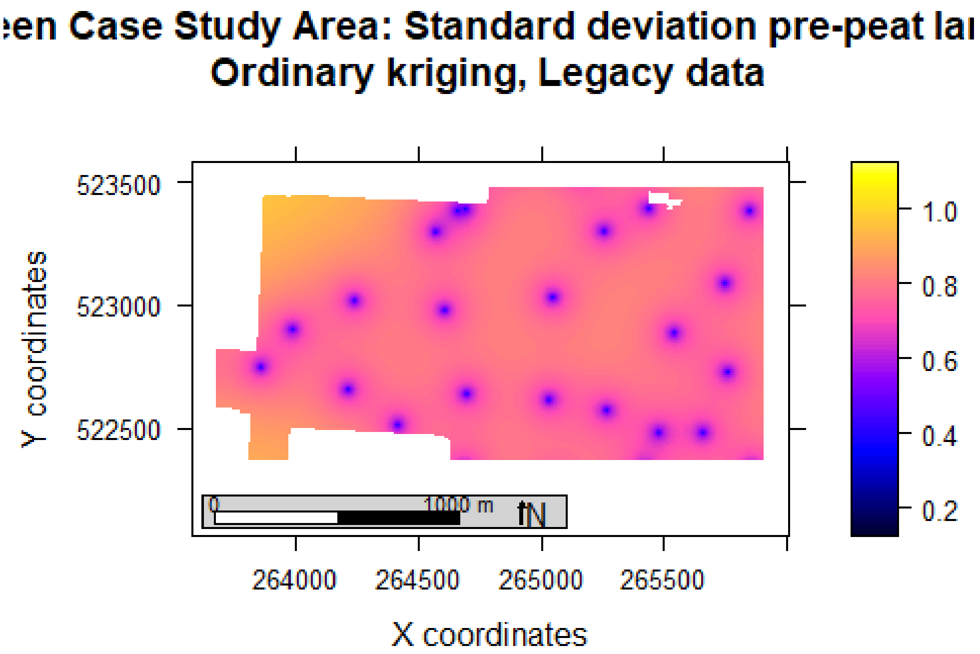

FIGURE 10.86: BARGERVEEN CASE STUDY AREA: STANDARD DEVIATION PRE-PEAT LANDSCAPE. ORDINARY KRIGING, LEGACY DATA.

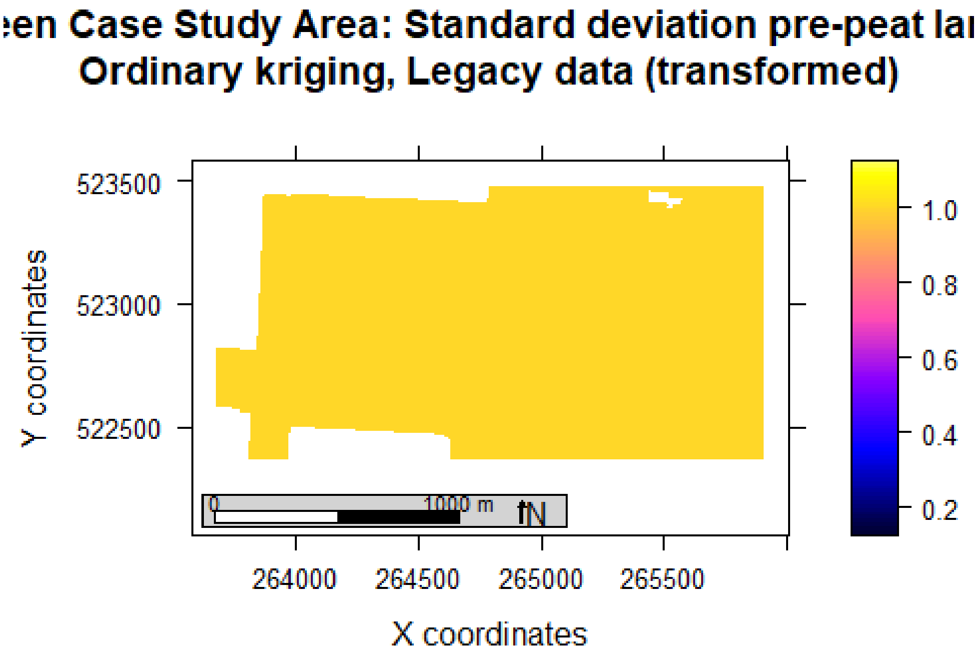

FIGURE 10.87: BARGERVEEN CASE STUDY AREA: STANDARD DEVIATION PRE-PEAT LANDSCAPE. ORDINARY KRIGING, LEGACY DATA (TRANSFORMED).

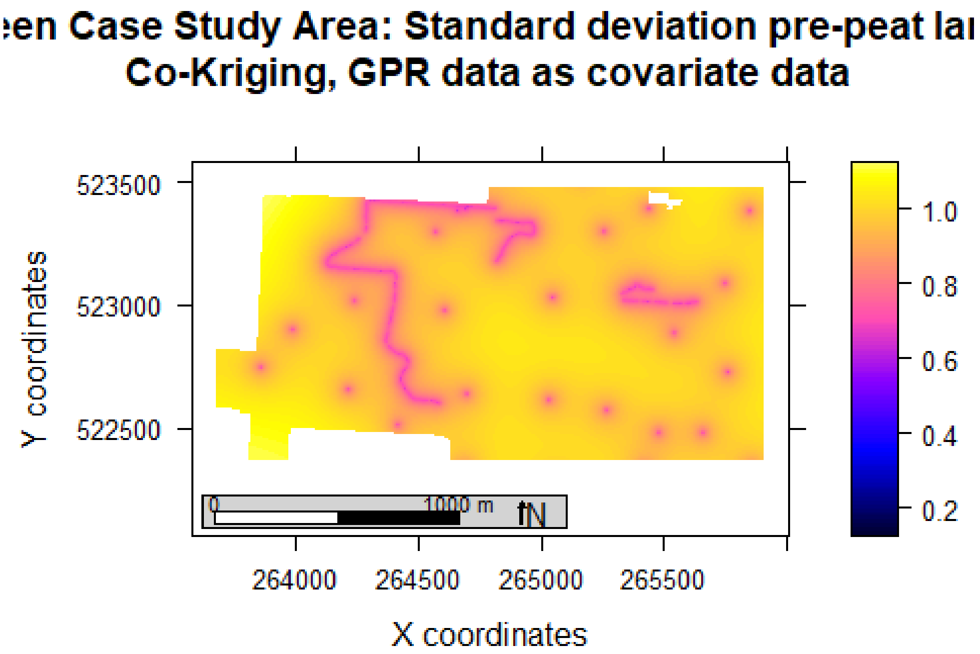

FIGURE 10.88: BARGERVEEN CASE STUDY AREA: STANDARD DEVIATION PRE-PEAT LANDSCAPE. CO-KRIGING, GPR DATA AS COVARIATE DATA.

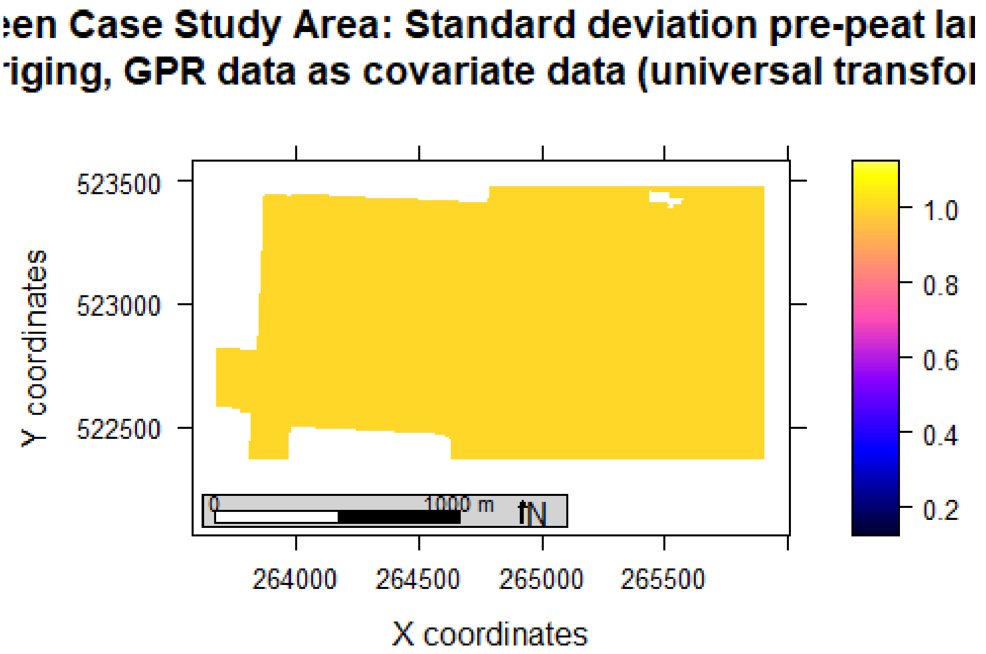

FIGURE 10.89: BARGERVEEN CASE STUDY AREA: STANDARD DEVIATION PRE-PEAT LANDSCAPE. CO-KRIGING, GPR DATA AS COVARIATE DATA (UNIVERSAL TRANSFORMED).

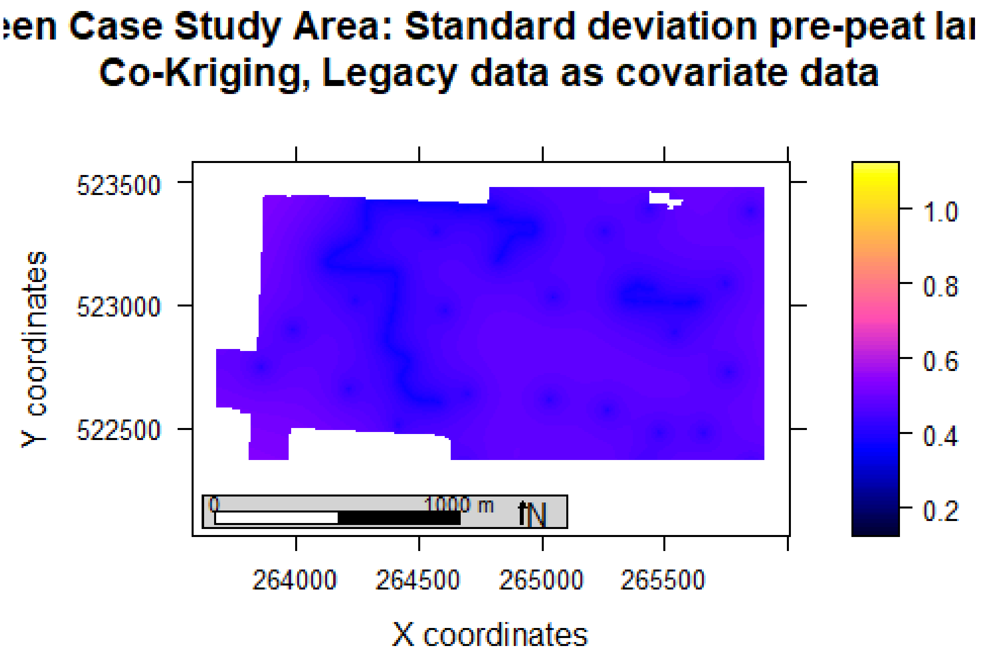

FIGURE 10.90: BARGERVEEN CASE STUDY AREA: STANDARD DEVIATION PRE-PEAT LANDSCAPE. CO-KRIGING, LEGACY DATA AS COVARIATE DATA.

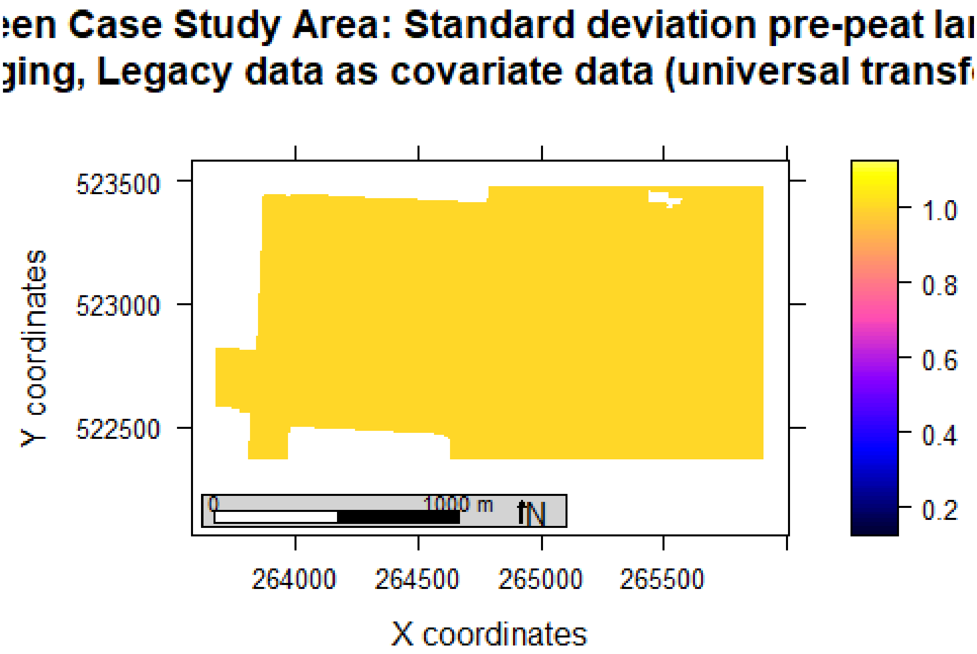

FIGURE 10.91: BARGERVEEN CASE STUDY AREA: STANDARD DEVIATION PRE-PEAT LANDSCAPE. CO-KRIGING, LEGACY DATA AS COVARIATE DATA (UNIVERSAL TRANSFORMED).

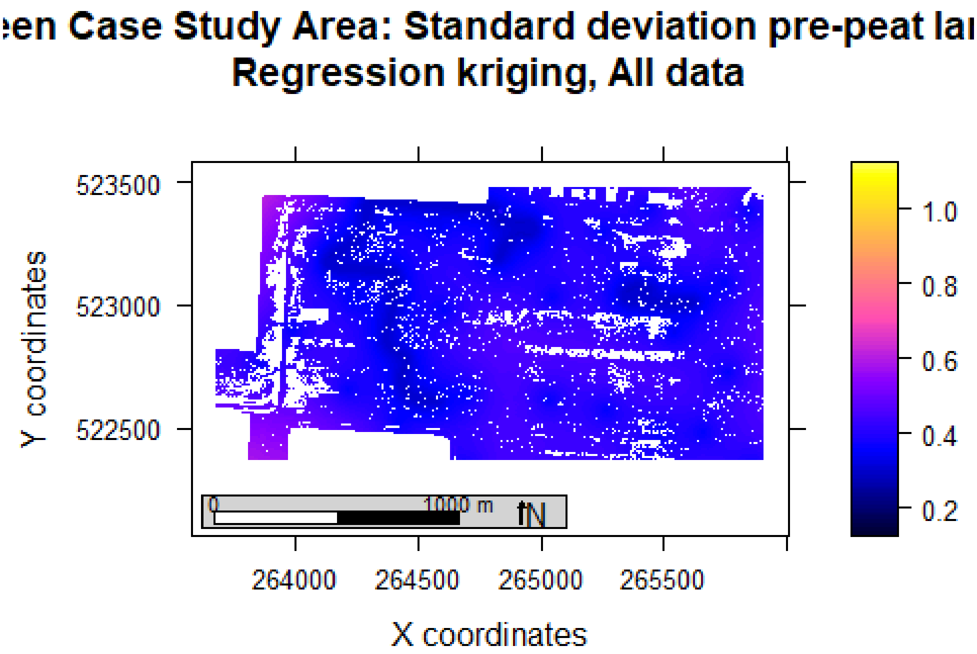

FIGURE 10.92: BARGERVEEN CASE STUDY AREA: STANDARD DEVIATION PRE-PEAT LANDSCAPE. REGRESSION KRIGING, ALL DATA.

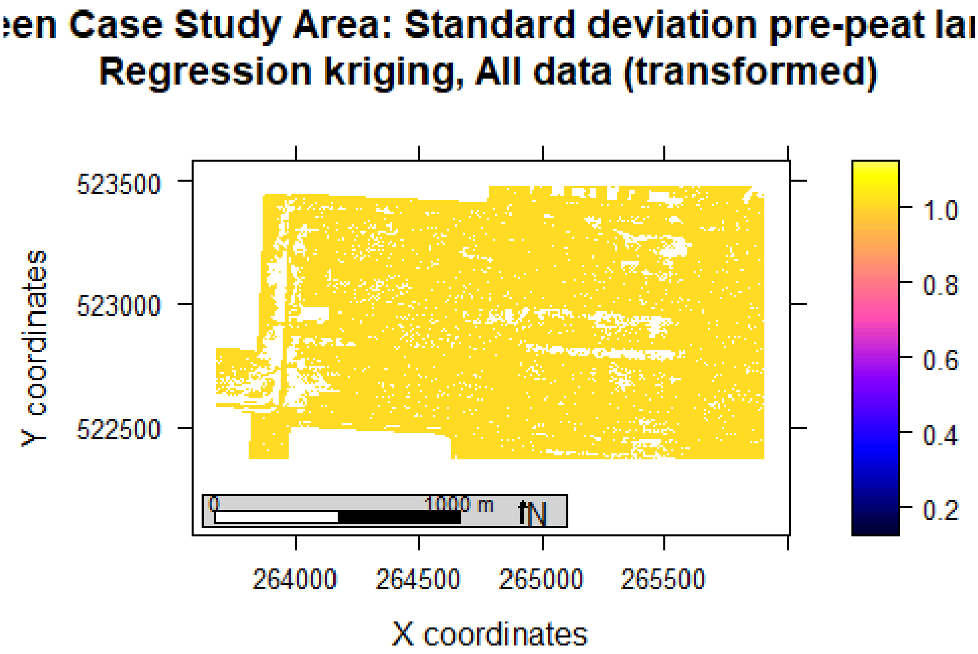

FIGURE 10.93: BARGERVEEN CASE STUDY AREA: STANDARD DEVIATION PRE-PEAT LANDSCAPE. REGRESSION KRIGING, ALL DATA (TRANSFORMED).

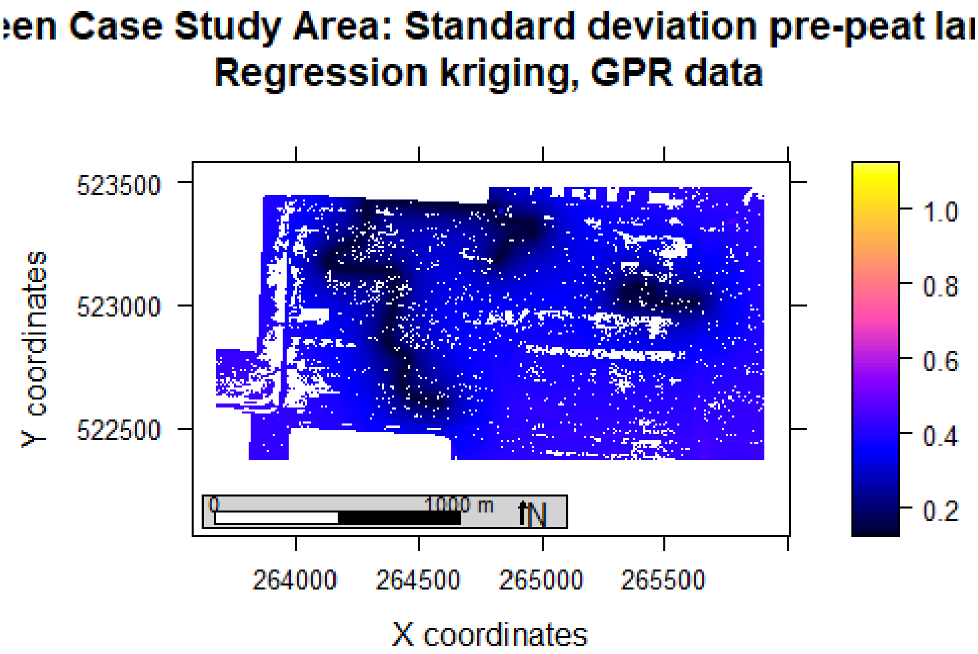

FIGURE 10.94: BARGERVEEN CASE STUDY AREA: STANDARD DEVIATION PRE-PEAT LANDSCAPE. REGRESSION KRIGING, GPR DATA.

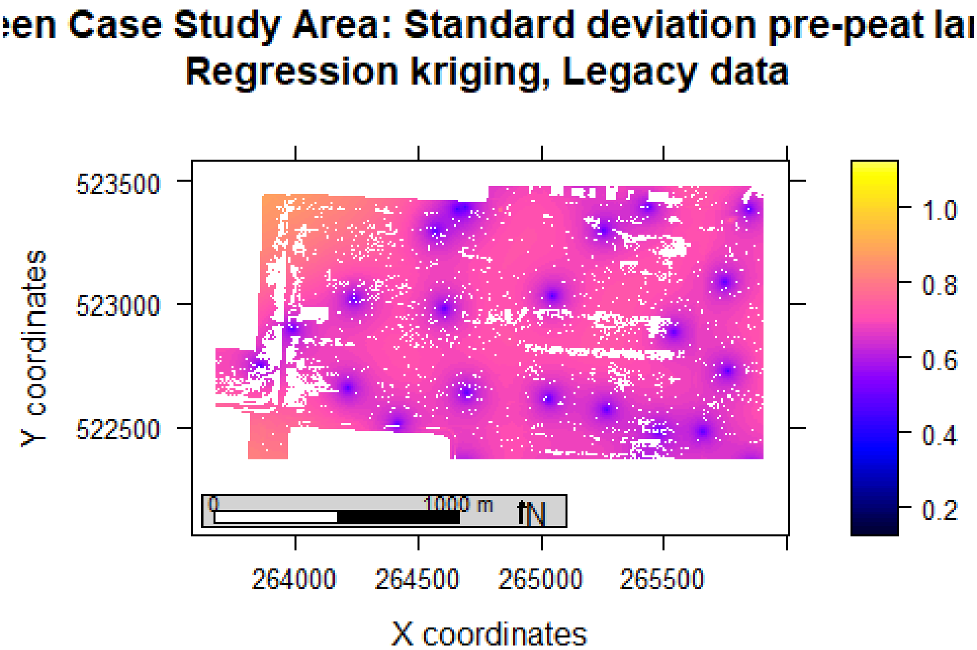

FIGURE 10.95: BARGERVEEN CASE STUDY AREA: STANDARD DEVIATION PRE-PEAT LANDSCAPE. REGRESSION KRIGING, LEGACY DATA.

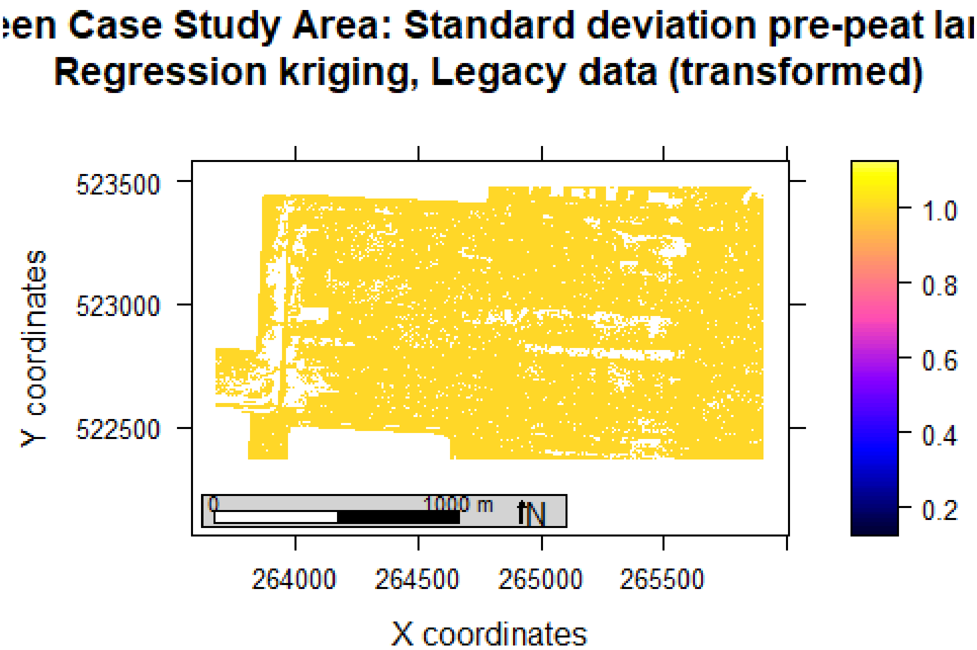

FIGURE 10.96: BARGERVEEN CASE STUDY AREA: STANDARD DEVIATION PRE-PEAT LANDSCAPE. REGRESSION KRIGING, LEGACY DATA (TRANSFORMED).

ACCURACY

Accuracy is calculated by means of the Mean Error and the Root Mean Square Error:

$ME = mean(residuals)\ RMSE = mean(residuals^2)$

The residuals are calculated from a cross validation. For the GPR and All data local coherence of clustering may not have an influence.

Clusters for ross validation

```
clusters <- c("FW_L21", "FW_L22", "FW_L23", "FW_L24", "FW_L25", "FW_L26",
              "FW_L27", "FW_L28", "FW_L29", "FW_L30", "FW_L31", "FW_L32")
```

Cross validation

```
cv.OK_A       <- cv.nocluster(method  = "krige.cv", cluster    = clusters,
ID_column = "Name",
                              data_cv = "All",      formula_cv = Peatdepth~1,    m
odel_cv = vgm.All)
cv.OK_A_T     <- cv.nocluster(method  = "krige.cv", cluster    = clusters,
ID_column = "Name",
                              data_cv = "All",      formula_cv = T_Peatheight~1, m
odel_cv = vgm.All_T)
cv.OK_G       <- cv.nocluster(method  = "krige.cv", cluster    = clusters,
ID_column = "Name",
                              data_cv = "GPR",      formula_cv = Peatdepth~1,    m
odel_cv = vgm.GPR)
cv.OK_G_T     <- cv.nocluster(method  = "krige.cv", cluster    = clusters,
ID_column = "Name",
                              data_cv = "GPR",      formula_cv = T_Peatdepth~1,  m
odel_cv = vgm.GPR_T)

cv.OK_L       <- krige.cv(formula = Peatdepth~1,    locations = Legacy,
                          model   = vgm.Legacy,     nfold = nrow(Legacy))
cv.OK_L_T     <- krige.cv(formula = T_Peatheight~1, locations = Legacy,
                          model   = vgm.Legacy_T,   nfold = nrow(Legacy))

cv.CK_LC      <- cv.nocluster(method  = "gstat.cv", cluster   = clusters, ID_colu
mn = "Name",
                              data_cv = "GPR",      object_cv = fit.CK_LC)
cv.CK_LC_UT   <- cv.nocluster(method  = "gstat.cv", cluster   = clusters, ID_colu
mn = "Name",
                              data_cv = "GPR",      object_cv = fit.CK_LC_UT)

cv.CK_GC      <- gstat.cv(object = fit.CK_GC,    nfold = nrow(Legacy))
cv.CK_GC_UT   <- gstat.cv(object = fit.CK_GC_UT, nfold = nrow(Legacy))

cv.RK_A       <- cv.nocluster(method     = "krige.cv", cluster    = clusters, ID_
column = "Name",
                              data_cv    = "All",      formula_cv = Peatdepth~Surf
aceLevel,
                              model_cv   = vgm.resid.A)
cv.RK_A_T     <- cv.nocluster(method     = "krige.cv", cluster    = clusters, ID_
column = "Name",
                              data_cv    = "All",      formula_cv = Peatheight~Sur
```

```
faceLevel,
                              model_cv    = vgm.resid.A_T)
cv.RK_G       <- cv.nocluster(method      = "krige.cv", cluster     = clusters,
                              ID_column  = "Name",      data_cv     = "GPR",
                              formula_cv = Peatheight~SurfaceLevel, model_cv = vgm
.resid.G)

cv.RK_L       <- krige.cv(formula = Peatdepth~SurfaceLevel,    locations = Legacy
,
                          model    = vgm.resid.L,             nfold      = nrow(Le
gacy))
cv.RK_L_T     <- krige.cv(formula = T_Peatheight~SurfaceLevel, locations = Legacy
,
                          model    = vgm.resid.L_T,           nfold      = nrow(Le
gacy))
```

Back transform the predicted and observed values.

```
cv.OK_A_T$predicted   <- revBoxCOx(cv.OK_A_T$var1.pred, All_subset$Peatheight,
                                   variance = cv.OK_A_T$var1.var)
cv.OK_A_T$observed    <- revBoxCOx(cv.OK_A_T$observed,  All_subset$Peatheight,
                                   variance = cv.OK_A_T$var1.var)
cv.OK_G_T$predicted   <- revBoxCOx(cv.OK_G_T$var1.pred, GPR_subset$Peatdepth,
                                   variance = cv.OK_G_T$var1.var)
cv.OK_G_T$observed    <- revBoxCOx(cv.OK_G_T$observed,  GPR_subset$Peatdepth,
                                   variance = cv.OK_G_T$var1.var)
cv.OK_L_T$predicted   <- revBoxCOx(cv.OK_L_T$var1.pred, Legacy$Peatheight,
                                   variance = cv.OK_L_T$var1.var)
cv.OK_L_T$observed    <- revBoxCOx(cv.OK_L_T$observed,  Legacy$Peatheight,
                                   variance = cv.OK_L_T$var1.var)
cv.CK_GC_UT$predicted <- revBoxCOx(cv.CK_GC_UT$Peatheight.Legacy_UT.pred,
                                   GPR_subset$Peatheight, Legacy$Peatheight,
                                   variance = cv.CK_GC_UT$Peatheight.Legacy_UT.var
)
cv.CK_GC_UT$observed  <- revBoxCOx(cv.CK_GC_UT$observed,
                                   GPR_subset$Peatheight, Legacy$Peatheight,
                                   variance = cv.CK_GC_UT$Peatheight.Legacy_UT.var
)
cv.CK_LC_UT$predicted <- revBoxCOx(cv.CK_LC_UT$Peatheight.GPR_UT.pred,
                                   GPR_subset$Peatheight, Legacy$Peatheight,
                                   variance = cv.CK_LC_UT$Peatheight.GPR_UT.var)
cv.CK_LC_UT$observed  <- revBoxCOx(cv.CK_LC_UT$observed,
                                   GPR_subset$Peatheight, Legacy$Peatheight,
                                   variance = cv.CK_LC_UT$Peatheight.GPR_UT.var)
cv.RK_A_T$predicted   <- revBoxCOx(cv.RK_A_T$var1.pred, All_subset$Peatheight,
                                   variance = cv.RK_A_T$var1.var)
cv.RK_A_T$observed    <- revBoxCOx(cv.RK_A_T$observed,  All_subset$Peatheight,
                                   variance = cv.RK_A_T$var1.var)
cv.RK_L_T$predicted   <- revBoxCOx(cv.RK_L_T$var1.pred, Legacy$Peatheight,
                                   variance = cv.RK_L_T$var1.var)
cv.RK_L_T$observed    <- revBoxCOx(cv.RK_L_T$observed,  Legacy$Peatheight,
                                   variance = cv.RK_L_T$var1.var)
```

Change names of untransformed cross validations in order to properly loop through all cross validations.

```
names(cv.OK_A)[1]  <- "predicted"
names(cv.OK_G)[1]  <- "predicted"
names(cv.OK_L)[1]  <- "predicted"
names(cv.CK_GC)[1] <- "predicted"
names(cv.CK_LC)[1] <- "predicted"
names(cv.RK_A)[1]  <- "predicted"
names(cv.RK_G)[1]  <- "predicted"
names(cv.RK_L)[1]  <- "predicted"
```

Vector with al cross validations.

```
crosvals <- c("cv.OK_A",
              "cv.OK_A_T",
              "cv.OK_G",
              "cv.OK_G_T",
              "cv.OK_L",
              "cv.OK_L_T",
              "cv.CK_GC",
              "cv.CK_GC_UT",
              "cv.CK_LC",
              "cv.CK_LC_UT",
              "cv.RK_A",
              "cv.RK_A_T",
              "cv.RK_G",
              "cv.RK_L",
              "cv.RK_L_T")
```

Set up database for calculation the Mean Error and the Root Mean Squared Error.

```
Reconstruction <- c(); ME <- c(); RMSE <- c(); Error.df <- data.frame(Reconstruct
ion, ME, RMSE)
Error.df <- Error.df$Reconstruction; Error.df <- Error.df$ME; Error.df <- Error.df
$RMSE
```

Create data frame for the ME and RMSE.

```
# Loop through all cross validations
for (i in seq(crosvals)){

# Identify residuals of each cross validation
  obs  <- eval(parse(text = paste0(crosvals[i], "$observed")))
  pred <- eval(parse(text = paste0(crosvals[i], "$predicted")))

  # Calculations
  Error.df$Reconstruction[i] <- reconstructions[i]
  Error.df$ME[i]             <- abs(mean(obs - pred))
  Error.df$RMSE[i]           <- sqrt(mean((obs - pred)^2))
}

Error.df <- format(as.data.frame(Error.df), scientific = FALSE)
```

Replace possible "NaN" character values by NA, to improve assessment ordering.

```
for (i in seq(Error.df[,1])){
  for (j in seq(Error.df[1,])){
    if (suppressWarnings(is.na(eval(parse(text=Error.df[i,j]))))){
      Error.df[i,j] = NA
    }
  }
}
Error.df

##      Reconstruction          ME      RMSE
## 1      Prepeat.OK_A  0.06478488 0.5816011
## 2    Prepeat.OK_A_T  0.05245758 0.5917665
## 3      Prepeat.OK_G  0.08396079 0.3089014
## 4    Prepeat.OK_G_T  1.09377850 1.1359305
## 5      Prepeat.OK_L  0.02784783 0.7822371
## 6    Prepeat.OK_L_T  0.05308218 0.7781694
## 7     Prepeat.CK_GC  0.02631493 0.7899106
## 8  Prepeat.CK_GC_UT  0.14036514 1.0862053
## 9     Prepeat.CK_LC  0.05843319 0.3672137
## 10 Prepeat.CK_LC_UT  0.09943318 0.4469958
## 11     Prepeat.RK_A  0.05629054 0.5275632
## 12   Prepeat.RK_A_T  0.52715985 4.3958718
## 13     Prepeat.RK_G  0.08048023 0.3066633
## 14     Prepeat.RK_L  0.01757814 0.7009223
## 15   Prepeat.RK_L_T  0.05341685 0.6873141
```

ASSESS ALL TOGETHER

Every 'best' assessment gets value 1, so the lowest ME/RMSE/Mean standard deviation gets value 1, the highest gets value 15. All values are added up and the lowest Total is the gets the best assessment based on Mean Error, Root Mean Squared Error and Mean Standard Deviation. Because a good RMSE is preferred over a good ME (so not only accurate, but also precise) the ME values are halved.

Set up data frame to assess the ME, RMSE and Standard deviation.

```
Assess <- data.frame(); Reconstruction <- c(); ME <- c(); RMSE <- c(); SD <- c();
Total <- c()
Assess <- Assess$Reconstrucion; Assess <- Assess$ME; Assess <- Assess$RMSE;
Assess <- Assess$SD; Assess <- Assess$Total
```

Create data frame to assess the ME, RMSE and Standard deviation.

```
for (i in seq(reconstructions)){
  Assess$Reconstruction[i] <- reconstructions[i]

  Sort_ME   <- sort(Error.df$ME)
  Sort_RMSE <- sort(Error.df$RMSE)
  Sort_SD   <- sort(Sd.df$sdavgs)

  Rank_ME   <- which(Sort_ME[i]   == Error.df$ME)
  Rank_RMSE <- which(Sort_RMSE[i] == Error.df$RMSE)
  Rank_SD   <- which(Sort_SD[i]   == Sd.df$sdavgs)

  Assess$ME[Rank_ME]     <- i * 0.5
  Assess$RMSE[Rank_RMSE] <- i
```

```
  Assess$SD[Rank_SD]     <- i
}

Assess$Total <- Assess$ME + Assess$RMSE + Assess$SD
(Assess <- as.data.frame(Assess))

##      Reconstruction  ME  RMSE  SD  Total
## 1      Prepeat.OK_A 3.0    6   4  13.0
## 2    Prepeat.OK_A_T 4.5    7  14  25.5
## 3      Prepeat.OK_G 3.5    2   1   6.5
## 4    Prepeat.OK_G_T 4.0   14  15  33.0
## 5      Prepeat.OK_L 1.5   11   7  19.5
## 6    Prepeat.OK_L_T 5.0   10  12  27.0
## 7     Prepeat.CK_GC 1.0   12   8  21.0
## 8  Prepeat.CK_GC_UT 7.0   13  12  32.0
## 9     Prepeat.CK_LC 2.5    3   5  10.5
## 10 Prepeat.CK_LC_UT 6.5    4  12  22.5
## 11     Prepeat.RK_A 2.0    5   3  10.0
## 12   Prepeat.RK_A_T 7.5   15  13  35.5
## 13     Prepeat.RK_G 6.0    1   2   9.0
## 14     Prepeat.RK_L 0.5    9   6  15.5
## 15   Prepeat.RK_L_T 5.5    8  12  25.5
```

Sorted on total value.

```
Assess[with(Assess, order(Total)),]

##      Reconstruction  ME  RMSE  SD  Total
## 3      Prepeat.OK_G 3.5    2   1   6.5
## 13     Prepeat.RK_G 6.0    1   2   9.0
## 11     Prepeat.RK_A 2.0    5   3  10.0
## 9     Prepeat.CK_LC 2.5    3   5  10.5
## 1      Prepeat.OK_A 3.0    6   4  13.0
## 14     Prepeat.RK_L 0.5    9   6  15.5
## 5      Prepeat.OK_L 1.5   11   7  19.5
## 7     Prepeat.CK_GC 1.0   12   8  21.0
## 10 Prepeat.CK_LC_UT 6.5    4  12  22.5
## 2    Prepeat.OK_A_T 4.5    7  14  25.5
## 15   Prepeat.RK_L_T 5.5    8  12  25.5
## 6    Prepeat.OK_L_T 5.0   10  12  27.0
## 8  Prepeat.CK_GC_UT 7.0   13  12  32.0
## 4    Prepeat.OK_G_T 4.0   14  15  33.0
## 12   Prepeat.RK_A_T 7.5   15  13  35.5
```

BEST METHOD

The best assessed method is co-kriging with legacy data as covariate data, using universal transformed data.

Create data frames of the x (x coordinates), y (y coordinates) and z (reconstructed surface level above sea level) axis, values.

```
x <- as.data.frame(Prepeat.CK_LC)[,2]
y <- as.data.frame(Prepeat.CK_LC)[,3]
z <- as.data.frame(Prepeat.CK_LC)[,1]
```

Plot 3D reconstruction of the best assessed pre-peat landscape reconstruction.

```
wireframe(z ~ x * y,
          shade = TRUE,
          xlab  = list("X coordinates", rot = 25),
          ylab  = list("Y coordinates", rot = -55),
          zlab  = list("height above sealevel (m)", rot = 95),
          main  = "3D plot best assessed pre-spppeat landscape reconstruction",
          scales = list(arrows=FALSE),
          screen = list(z=30, x=-50)
          )
```

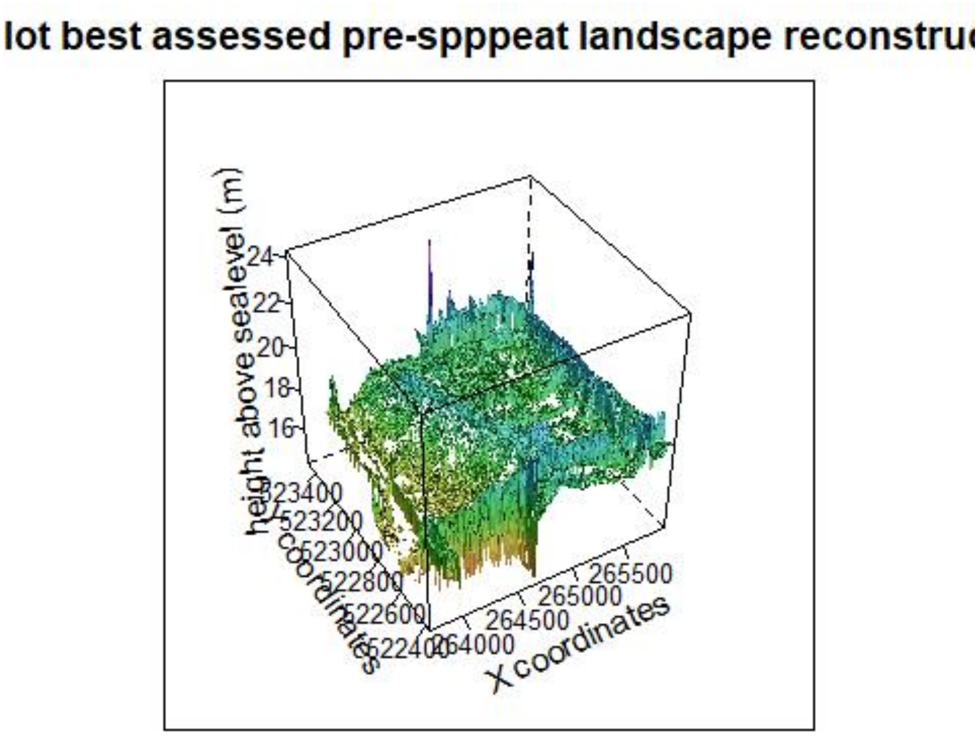

FIGURE 10.97: 3D PLOT OF THE BEST ASSESSED PRE-PEAT LANDSCAPE RECONSTRUCTION (CO-KRIGING WITH LEGACY AS COVARIATE DATA).

For a rotating 3D plot, the free software of ImageMagick should be installed. This can be done via this link: https://www.imagemagick.org/script/download.php, selecting the right download.

Rotating 3D reconstruction of the best assessed pre-peat landscape reconstruction.

```
angles <- seq(from=1,to=360,by=1)

draw.plot <- function(angles){
  for(i in 1:length(angles)){
    print(wireframe(z ~ x * y,
                    shade = TRUE,
                    xlab  = list("X coordinates", rot = angles[i]),
                    ylab  = list("Y coordinates", rot = angles[i] + 90),
                    zlab  = list("height above sealevel (m)", rot = 95),
                    main  = "3D plot best assessed pre-peat landscape reconstructi
on",
                    scales = list(arrows=FALSE),
                    screen = list(z=angles[i], x=-50)
```

```
                        )
            )
  }
}

saveGIF(draw.plot(angles), interval = 60/360, movie.name="3D Rotating plot.GIF",
        ani.height=640,ani.width=640)
```