A 3D geological soil-modelling workflow using AEM data – A case study from Gotland, Sweden

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SUMMARY

This study presents a workflow allowing 3D geological soil modelling using a combination of AEM data, borehole information, and soil maps. The workflow aims at utilizing all available information in a time effective way.
The overall goal of the workflow is to define a bedrock surface and in turn model the geology between terrain and this model, conditioned on the available information; soil map, boreholes, and airborne electromagnetic (AEM) data.

The workflow consists of two parts – Inside and outside the areas where AEM data is obtained.
Within the AEM surveys, the AEM data both allow for a more detailed mapping of the bedrock surface and allow for more informative lithological interpretation.
The AEM data, in combination with borehole information, also allow automatic mapping of the bedrock surface using a machine learning approach called Smart Interpretation. The comparison of the results from the automatic approach and a manually interpreted model, show that a fully automatized mapping of the bedrock surface can be a good alternative, and allow a better priority of the modelling resources.

The results from this study suggest an efficient workflow to make 3D geological soil models with combined use of AEM data, borehole data, and soil map information.
All modelling is done in the geological modelling software GeoScene3D.

Key words: AEM Data, 3D modelling, case study, Smart Interpretation, GeoScene3D

INTRODUCTION

Gotland is an island of 3184 square kilometres located in the south Baltic Sea. The high tourist activity during the summer months result in periodic shortage of the groundwater supplies on the island. To meet these problems, 37 % of the island distributed on 8 survey blocks were mapped with helicopter-borne time-domain electromagnetic (AEM) data acquired by SkyTEM Aps in 2013 and 2015 (see Figure 1). The total survey cover 1176 square kilometres with a line spacing of 200m. The data was processed in the Aarhus Workbench Software and inverted using the spatially constrained inversion (SCI) developed by Viezzoli et al. (2009). A smooth inversion with 30-layer models has been used in the presented interpretation process. Based on this dataset, a 3D resistivity grid with a 2m depth discretization down to a depth of 76 m below sea level and a cell size of 100m is interpolated to be used in the modelling.

This study is part of an extensive interpretation work of this AEM data, in combination with a range of other data, to develop a 3D geological model with the aim of finding new fresh groundwater resources. The island of Gotland is dominated by carbonate, mainly lithified, bedrock geology covered by a thin layer of mainly glacial sediments. The workflow presented in this paper focus on this thin soil layer, which varies in thickness from 0 m to approximately 25 meters throughout the island. The full geological model is presented in Jørgensen et al. (this volume).

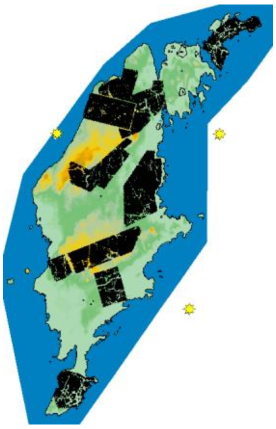

Figure 1. The study area on Gotland. The black lines show the AEM flight lines.

In addition to the inverted AEM data, the workflow in this study utilizes borehole data from the Swedish state oil company's (OPAB) database, a high number of water well boreholes, and a detailed surface geology map (soil map). The total number of boreholes used to condition the soil model developed in this study is 5410.

THE METHODS AND WORKFLOW

The full 3D geological model on Gotland is defined within a regular 3D grid consisting a total of 74,503,800 100m x 100m x 2m voxels (3D grid cells) covering the whole island in an elevation level from 76 m below to 84 m above sea level.
The soil model developed in this study, only covers the voxels between terrain and the surface defining the depth to bedrock. On Gotland, the deepest depth to bedrock lies at 14.8 m below sea level.

As the AEM data doesn't cover the whole study area, two different modelling approaches was applied; inside and outside the AEM data, respectively. The overall steps of the workflow are:

Outside AEM data:

1) Develop a bedrock surface
2) Assign all voxels with the lithology represented by the overlying soil map
3) Condition all voxels with the information from boreholes.

Inside AEM data:

1) Develop a bedrock surface
2) Assign all voxels a lithology based on information from the AEM data
3) Condition the upper 1 or 2 voxels to the overlying soil map
4) Condition all voxels with the information from boreholes.

Bedrock surface

The first step in developing a soil model is to develop a surface for the bedrock. Whether the modelling takes place outside or inside the regions with AEM data, two different approaches are applied. The only information about the soil thickness where AEM data is not obtained comes from boreholes. In these areas, the bedrock surface is made by spatially interpolating between the depths to lithologic units indicating bedrock (such as limestone, marl, sandstone, etc) extracted from boreholes. In the areas where AEM data is obtained, however, the resistivity information can be used to obtain a more accurate bedrock surface. Figure 2 shows a cross section through the AEM grid, together with borehole information and the interpreted base of bedrock.

The combination of AEM data and borehole information also allow for an automatized computation of the bedrock surface like (Gulbrandsen et al., 2017a). This methodology is based on the Smart Interpretation (SI) algorithm (Gulbrandsen et al., 2017b). In addition to a manually interpreted bedrock model, we make a SI assisted model for comparison.
The SI algorithm is developed as a polynomial linear regression technique aiming at building a model describing the statistical relation between a set of interpretation points and a set of geophysical attributes. When this relation is established it can be used to perform predictions of new interpretation points, given a new set of the geophysical attributes.
In this study, the depth to bedrock is extracted from all boreholes and used as input to the SI algorithm together with a set of attributes form the 1D inverted AEM data. Each point from the borehole is "paired" with the closest geophysical sounding from which a set of attributes is extracted. The attributes can in principal be any kind of quantifiable information, however in the GeoScene3D software, the attributes used are the resistivity and elevation of all the geophysical layers in the 1D model, together with the terrain-elevation and the geographical coordinates. The relations between each depth to bedrock and their paired set of attributes are used in the SI algorithm to compute a statistical model. This model is then used to predict the depth to bedrock
at each 1D geophysical model throughout the survey.
The automized bedrock surface is not necessarily meant to be the final model, but can be used as a starting point for the geologist, allowing a better prioritising of the resources. In this study the manual model was made in approximately 120 hours, whereas the SI assisted model was made in about one hour. Figure 3 displays the difference between the manual and the SI interpreted bedrock surface, respectively, and show an overall consistency between the surfaces. The SI interpreted bedrock surface is also shown together with the manual one in Figure 2. Due to the time and effort invested in the manual bedrock surface, this is probably a more accurate representation of the real bedrock surface, than the SI assisted model. However, it is a reasonable assumption that an equally adequate bedrock surface could have been made much faster if the SI assisted model was provided as a starting point prior to the manual modelling.

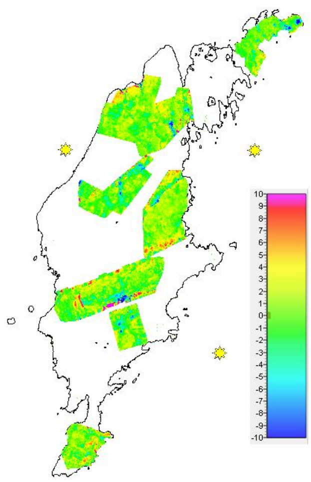

Figure 3. The difference between the manually interpreted bedrock surface and the model made with the SI algorithm, respectively. The colorbar represents the difference in meters.

Lithology from resistivity data

The available resistivity data, indirectly contains information on lithology. Porosity, permeability, saturation, pore water resistivity, clay content etc. all contribute to how well a material leads currents, and hence the resistivity of the material. In this workflow, the information on how resistivity and lithology is connected, is computed and represented through a so-called transfer function. The lithological information from boreholes are compared to the resistivity values from the interpolated resistivity to compute the statistical relation between lithology and resistivity through the transfer function. Figure 4 displays the transfer function computed in the AEM survey on the southernmost part of Gotland. Assuming local variations of the resistivity-lithology relations, we have chosen to compute the transfer function within each AEM survey separately, and not on the whole island at once. The transfer function is computed for two lithological categories, sand/gravel and clay/till, and shows the probability of the two categories for different resistivity values. The transfer function in Figure 4 is computed for resistivity values in bins of 30 Ohm m at a time. From the transfer function a cut-off value, i.e. the resistivity value where one category becomes more probable and the other, can be found. The transfer function in Figure 4 have a cut-off value of 86 Ohm m. All voxels with a resistivity value lower than 86

Ohm m will be assigned the lithological category corresponding to clays and till, whereas voxels with resistivity values above 86 Ohm m will be assigned the category gravel and sand.

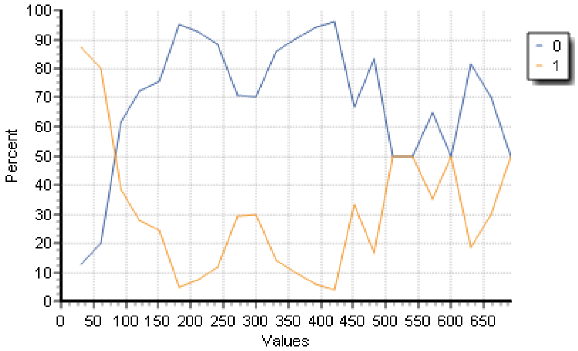

Figure 4. The transfer function showing the probability of the geological categories 0 and 1 (see Table 1) on the southernmost survey on Gotland. The transfer function is based on the inverted AEM data and lithologic information from boreholes.

Conditioning the model to hard data

A detailed geological soil map covering the whole island is available. This map represents the different geological settings as seen at the surface. For simplicity in the modelling, the soil map and hence the soil model is divided into five categories (see Table 1)

Category	Lithology
0	Sand, Gravel
1	All clays and till
2	All organic soils
3	Fillings
4	Water

Table 1. The different geological categories of the soil model and their corresponding lithological units.

In the regions with no available AEM data, the soil map and the boreholes are the only sources of direct geological information. In these parts of the study area, all voxels between terrain and the bedrock is assigned the lithology corresponding to the lithology in the overlying soil map, and in turn all voxels being penetrated by a borehole will get the lithology corresponding to the lithologic content of that borehole at that depth.

Within the regions of available AEM data, all voxels are already assigned a lithology based on the transfer function described above. The soil map is, in addition to be more detailed, also considered as hard data, i.e. assumed to represent the truth. Therefore, the uppermost voxels are 'stamped' with the same lithologic content as the overlying soil map. For the lithologic categories sand/gravel, clay/till, and filling, one voxel (2m) are conditioned on the soil map, whereas for water and organic soil the uppermost 2 voxels (4m) are conditioned. As for the regions outside AEM data, voxels inside AEM data are also conditioned on lithologic information from boreholes.

DISCUSSION AND FUTURE WORK

The presented workflow aims at achieving a geological model in an automized, effective and pragmatic way. This workflow is however incomplete in the sense that the soil model can be improved in several ways, which will be carried out in the future work on the model on Gotland.

One important part of improving the soil model, is to keep the bedrock surface updated. When e.g. a new set of boreholes are digitalized or drilled, the bedrock surface, and in turn the 3D model, should be updated accordingly. This could either be done by manual adjustment or by adding the new points to the Smart Interpretation procedure.

Another way to improve the soil model could be by improving the way the transfer function is computed in the current workflow. One approach could be to compute a spatially varying transfer function, allowing computation of locally varying resistivity cut-off values within the AEM surveys. Another approach, could be to include the uncertainty on the resistivity data, to improve the validity of the statistical relation between resistivity and lithology.

No matter the quality of the transfer function or the bedrock surface it is important for the quality of the geological model that a geological expert with knowledge of the geological settings of the specific region, go through the model and make sure it matches his or her geological expert knowledge. That could for instance be to make sure layers that should be connected are so in the final model.

Mapping geology using cut-off values from a computed transfer function as described in this workflow is an approach to obtain *one* geological model. However, based on the available information and their related level of uncertainty, several geological models could probably be made and still satisfy the available data. A different modelling approach would be to make the geological modelling using a Multiple Point Statistics (MPS) approach. MPS is a simulation strategy to statistically integrate different sources of information and to provide a suite of geologically realistic geological model (see e.g. Høyer et al., 2017 and Hansen et al., 2018). It is outside the scope of this paper to describe such a workflow in detail, but combining AEM data, borehole information, and geological background knowledge (through a so-called training image - a conceptual geological model representing the area being modelled) it would be possible to present a 3D model containing the most probable lithology in each voxel, together with its uncertainty (under the given assumptions). MPS could also be used in combination with the workflow described in this paper, e.g. by just applying the MPS methodology outside the AEM regions, to get a better representation of the potential variability in these regions.

CONCLUSIONS

This study presents a workflow allowing integration of AEM data, soil maps, borehole information and geological knowledge to make a 3D geological soil model. The workflow focuses on being effective and to some extent automized, allowing all available data to be considered in the modelling. The results suggest that this workflow is able to provide a high quality initial model, allowing valuable resources to be used on the most important parts of the model, such that these areas can get an increased level of attention.

ACKNOWLEDGMENTS

We wish to acknowledge the Gotland County Administration Board for funding the Gotland mapping campaign, and the Innovation Fund Denmark for financing part of the work behind this study (ref: 7039-00006B)

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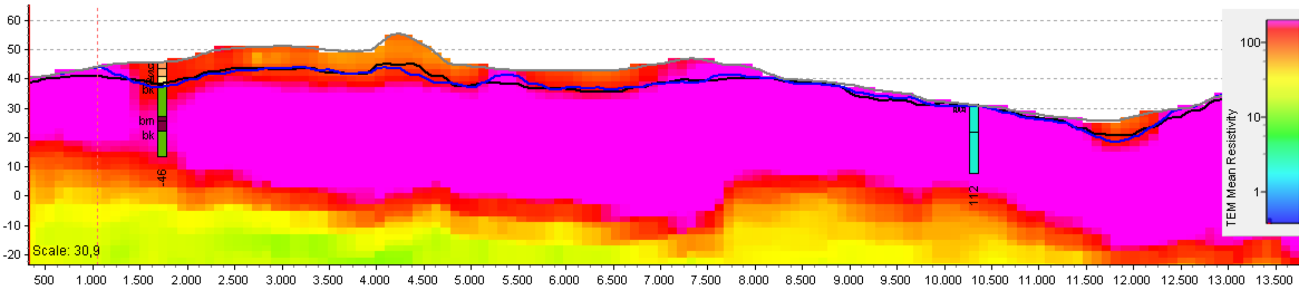

Figure 2. A cross section through the 3D resistivity grid, showing terrain (grey line), boreholes, and the interpreted depth to bedrock (blue line). The black line represents the SI interpreted depth to bedrock and the colorbar represents the resistivity values in Ohmm.

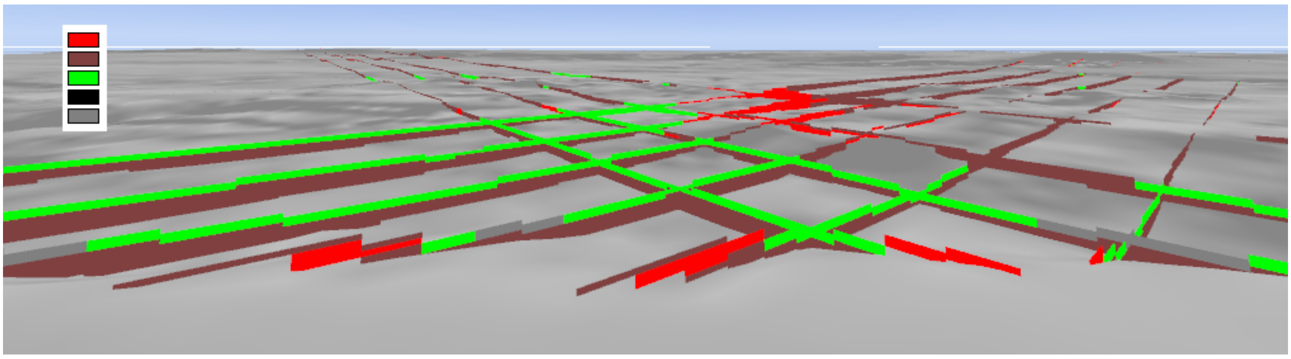

Figure 5. A 3D view of a part the final soil model on Gotland. The colours represent the different geological categories and in the same order as described in Table 1 (red is sand/gravel, brown is clays and till etc.) The bedrock surface is seen in grey.