

Note

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To For information

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Date
7 October 2026

Subject Property mapping in ThermoGIS v3.1

Attachment(s)

1. What are the 'property maps'?

To assess the geothermal potential of an aquifer we require estimates of the following 6 aquifer properties:

- Top depth – The depth beneath the surface to the top of the aquifer
- Thickness – The thickness of the aquifer
- Temperature – The temperature of the aquifer
- Net-to-gross – The ratio of sand to shale in the aquifer
- Porosity – The fraction of pore space in the aquifer
- Permeability – The ability of water to flow through the aquifer

Together the top depth and thickness describe the *geometry* of an aquifer.

The temperature is modelled using a combination of borehole temperature observations and a physics based approach.

Net-to-gross, porosity and permeability are modelled using borehole measurements of these properties combined with maps of max burial (the maximum depth an aquifer has been buried). They are the properties which have the greatest uncertainty and unfortunately have the greatest influence on the geothermal potential of an Aquifer. Together these are called the 'property maps'.

2. What has changed?

The past two years there has been a significant effort to improve our maps of net-to-gross, porosity and permeability and, crucially, to improve the statistical basis on which we make the maps to improve the uncertainty assessment.

To achieve this, we have developed a rock properties database, to be able to better track and store what data we use to make our property maps.

Likewise, a new quality-control methodology has been developed so we can better select which data we utilise.

Finally, we have improved the interpolation methodology, we now use universal Kriging with drift to create our estimates of the property maps and to improve the statistical basis and reproducibility of the maps.

3. What data can we use to make property maps?

Making the property maps is complex; for the geometries (top-depth and thickness) we can utilise seismic surveys to 'see' where certain geological layers exist in the subsurface.

For properties there is no such trick; the only information we have comes from boreholes. Boreholes are drilled usually for exploration (such as the SCAN project) or to extract resources such as oil, gas, salt or heat.

As part of a drilling operation data will be collected in the form of logs and core plugs. Logs are indirect measurements of properties of the subsurface, such as resistivity, radiation or sonic velocity. Core plugs are when actual samples of the subsurface geology are extracted and can then be tested in the lab.

Logs are (relatively) cheap, while taking core plugs is expensive as it is time consuming.

Petrophysicists can then use a combination of logs and core plugs to make estimates of net-to-gross, porosity and permeability (additionally permeability can be measured with a well test which is a much more accurate assessment of the permeability of an entire formation).

This means the 'data' we use to make our property maps are themselves closer to an interpretation or model rather than raw data. This explains also why rock property data can differ strongly on a short spatial scale; the choices, interpretation and data available to the petrophysicist can strongly alter the property interpretation.

Our database of property data is large and diverse and represents a collection of interpretations that have been made by numerous operators over past 70 years. This also means that the interpretations are often heterogeneous. It became clear that we needed a process to inspect and remove datapoints before making our maps.

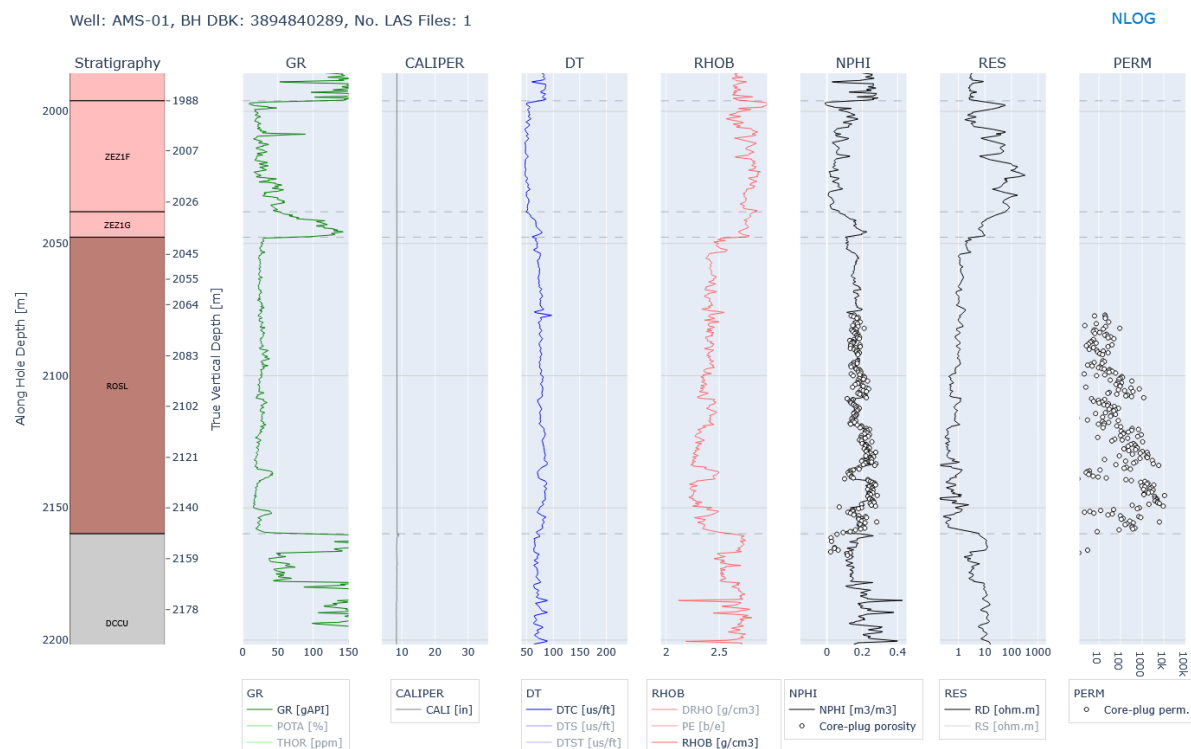


Figure 1 An example of the log and core plug data for the Lower-Slochteren in the AMS-01 well, drilled during the SCAN programme by EBN and available from www.nlog.nl.

4. Data quality control

Due to the heterogeneity of our property database there are frequently conflicting interpretations of net-to-gross, porosity and permeability for the same aquifer. This makes for a complex problem; to use all the data available to us introduces significant uncertainty and artefacts in our maps but to start selecting which data we use requires a system to identify potential erroneous data, inspect the data and track which data points we have inspected and decided to remove.

Through a combination of automatic anomaly detection, manual inspection and the development of specific software to facilitate this process we were able to develop an effective and traceable QC process.

For release v3.1 we have successfully done this for 8 aquifers, which represent the most promising aquifers for geothermal in the Netherlands:

1. Nieuwerkerk Formation, Alblasserdam Member (SLDNA)
2. Nieuwerkerk Formation, Delft Sandstone Member (SLDND)
3. Main Buntsandstein, Hardeggen Formation (RBMH)
4. Main Buntsandstein, Upper Detfurth Sandstone Member (RBMDU)
5. Main Buntsandstein, Lower Detfurth Sandstone Member (RBMDL)
6. Main Buntsandstein, Upper Volpriehausen Sandstone Member (RBMVU)
7. Rotliegend (Upper) Slochteren Formation (ROSL, ROSLU)
8. Rotliegend Lower Slochteren Formation (ROSL)

Work is continuing to complete this data QC process for all the aquifers of interest within ThermoGIS and this will be a part of a future ThermoGIS release.

5. SCAN Data

The SCAN programme by EBN is an effort to reduce uncertainties in the subsurface of the Netherlands through collected seismic data and drilling boreholes in previously un surveyed areas. This makes the SCAN data particularly valuable as there is a large suite of modern measurements made in regions which are relatively data poor.

In ThermoGIS version 3.1 we are for the first time utilizing data from the SCAN wells:

Well	Stratigraphy	NTG	Porosity	Permeability
AMS-01	ROSL_ROSLU	0.91	18.3	152
ASD-01	ROSL_ROSLU	0.998	15.9	42
BLT-01	ROSL_ROSLU	1	16	45.6
EDE-01	ROSL_ROSLU	1	26.5	1546
ORO-01	NLDOBR	0.884	36.1	141
ORO-01	NMRUBE	0.956	33.2	
SVG-01	NLLAOR	0.341	18.6	

This represents a fraction of the property information available due to the new SCAN wells.

6. Interpolation Method

To make our property maps (which are 2D planes) from the property data (which are points) we require an interpolation method; ThermoGIS has previously utilised Kriging along with empirical relationships of porosity-max burial and porosity-permeability.

We have updated and improved our methodology; we still utilise Kriging, but now we use universal Kriging with drift. Instead of prescribing an empirical relationship between porosity-max burial and porosity-permeability we use an integrated workflow to convert from max-burial to porosity and from porosity to permeability while Kriging the residuals between these drift fields.

To do so we have utilized and extended the package **gstools** and developed our own python workflow to do so.

6.1. Synthetic 1D Example

Take the following 1D example on Figure 2;

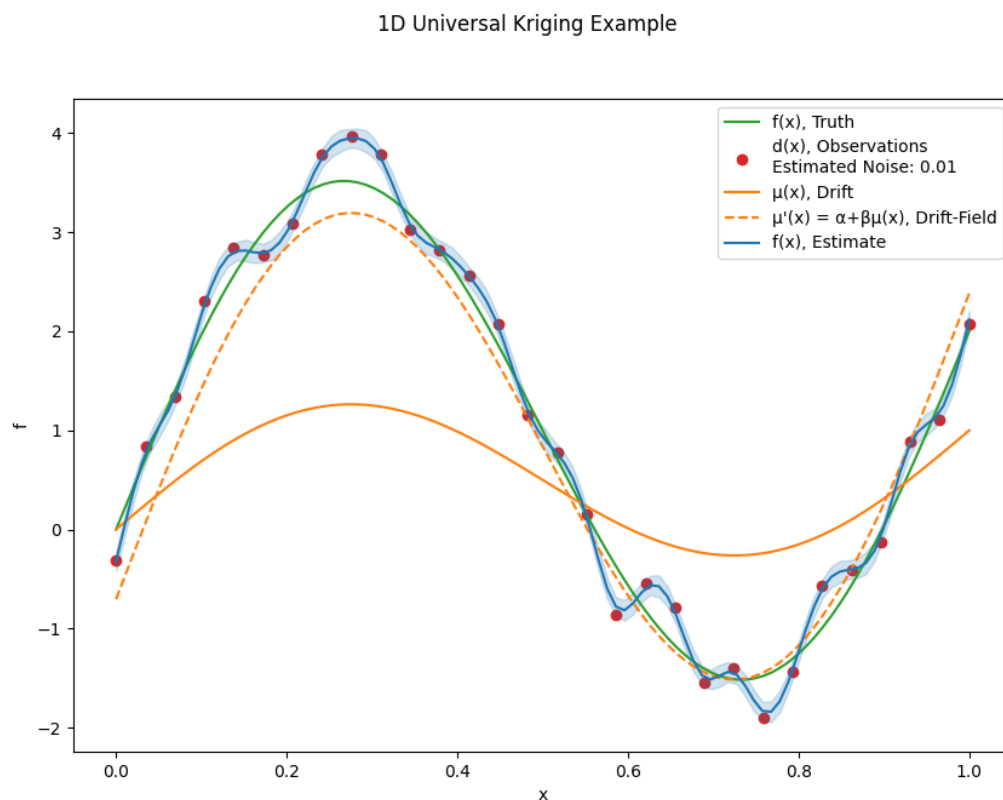


Figure 2 1D example of Universal Kriging with Drift

The green line $f(x)$ is the true function that we are trying to estimate, in this synthetic example we know the function:

$$f(x) = 3 \sin(2x\pi) + 2x$$

The red points are the observed data, which have noise added to them; this noise represents random uncertainty due to imperfect measurements. Uniform random noise between -0.5 and +0.5 has been added to the True function.

The filled orange line $\mu(x)$ is the drift function, which is provided by the user (or fitted to data if no other option is available). The user believes that this function is correlated to the true function. In this example the function is:

$$\mu(x) = \sin(2x\pi) + x$$

(Note how $\mu(x)$ has the same form, but different coefficients to $f(x)$)

The Universal Kriging algorithm will first fit coefficients to $\mu(x)$ to estimate the drift field:

$$\mu'(x) = \alpha + \beta\mu(x)$$

Then the residual between the observed data and the drift field is calculated, a variogram is fitted automatically (Figure 2) and the residual is Kriged and added back to the drift field, providing a local improvement on the drift. See chapter below on automatic variogram fitting.

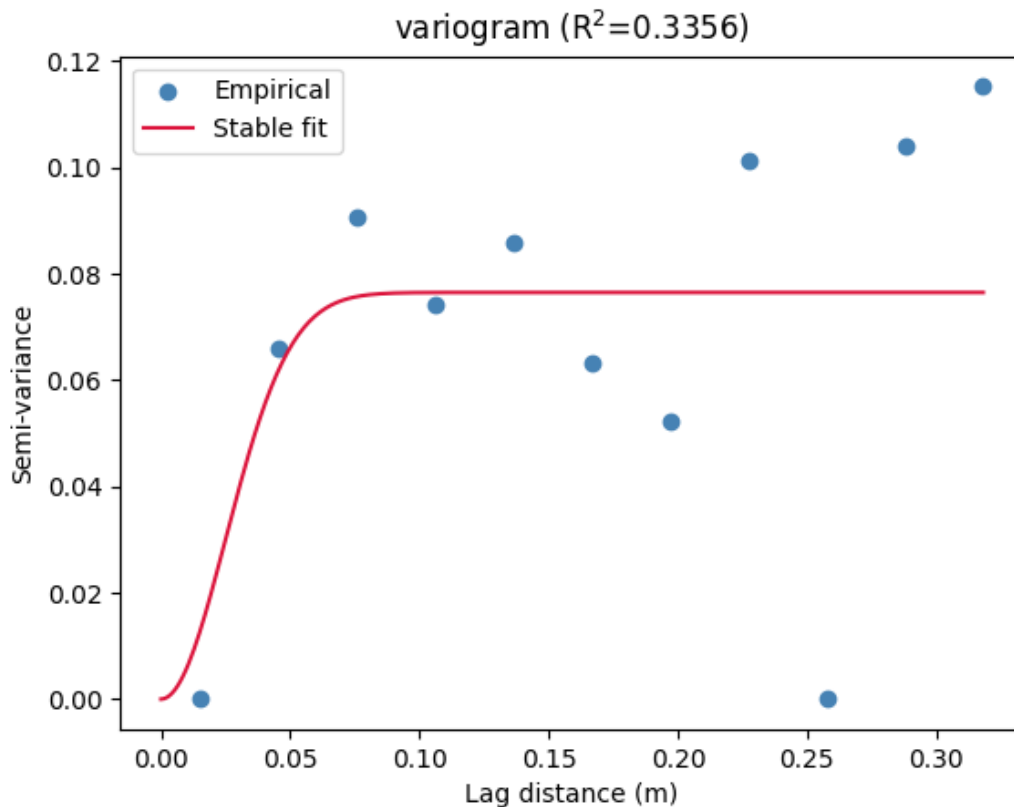


Figure 3 Variogram generated using the residuals of the data from Figure 1

After this process we get an estimate of the true function and an uncertainty on this estimate, which is shown by the blue line on Figure 2. It can be seen that this blue line follows the truth well but is fitting the observations too closely. This is because we have set the observational error too low. In this initial example, the observational error has been set to 0.1 while we know that the true observational error is really 1.0. We have been too confident in our data meaning that the final estimate is overfitting the data.

If we set the observational error to 1.0, we then get the following (Figure 4):

1D Universal Kriging Example

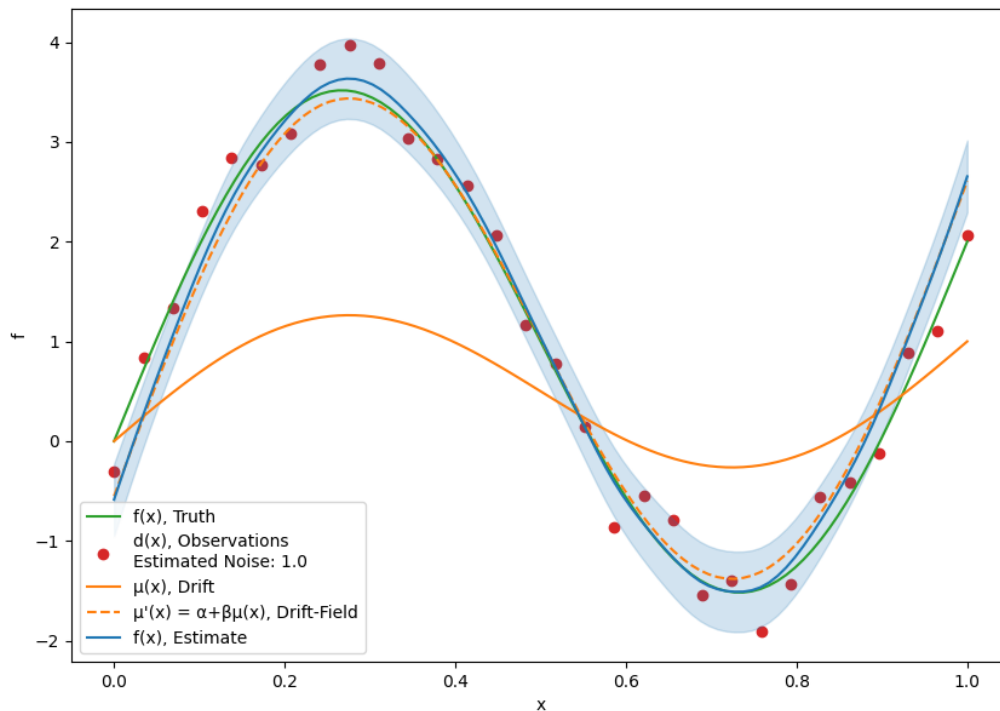


Figure 4 1D example of Universal Kriging with a higher level of data noise than Figure 1.

An estimate that:

1. Follows a user provided drift function
2. Fits observed data to within (provided) observational error
3. Through Kriging can provide an uncertainty band in the final estimate
4. Utilises automatic variogram fitting to remove subjective model choices and simplify the workflow.

6.2. Automatic Variogram Estimation

Multiple variogram models (Gaussian, Exponential, Spherical, Matern, Stable) are tested and the one which fits the data best is selected. Now with this automated variogram selection algorithm variogram selection is dependent entirely on the data.

gstools provides the algorithms to estimate the bin values and to fit variogram models accordingly, we simply extended this functionality to try multiple types of models and select the one which performs the best.

6.3. Effect of observational uncertainty

With the new framework we are able to add uncertainty to individual data points, this means we can use meta-information on each observed value to produce an estimate of the uncertainty on that observation which can then be included in the Kriging algorithm. The improvement in the final estimate can be seen when comparing Figure 2 to Figure 4.

7. Aquifers with too few data?

In previous ThermoGIS maps, Kriging was utilised even when few data points were available for an aquifer. It was decided that this not statistically valid; and so for aquifers and properties with less than 10 property observations then a mean and standard deviation of the data is taken and a 'flat' map is produced.

For aquifer-properties with less than 5 property observations then the mean and standard deviation of the group data is taken.

Table 1 shows the amount of well data per property, per aquifer and which methodology was utilised.

Table 1 For each aquifer showing the number of wells present with observations of NTG, porosity and permeability and the corresponding spatial interpolation method used.

aquifer	NWells NTG	ntg method	NWells Porosity	poro method	NWells Perm	perm method
DCD	25	Krige	60	Krige	8	Mean and SD Aquifer
DCH	6	Mean and SD Aquifer	29	Krige	20	Krige
SLDNA	40	Krige	52	Krige	38	Krige
SLDND	36	Krige	36	Krige	32	Krige
KNNSL	9	Mean and SD Aquifer	73	Krige	19	Krige
KNGLG_KNGLS	7	Mean and SD Aquifer	42	Krige	11	Krige
KNNSB	25	Krige	33	Krige	14	Krige
KNNSF	32	Krige	117	Krige	25	Krige
KNNSG	4	Mean and SD group	64	Krige	7	Mean and SD Aquifer
KNNSP	10	Mean and SD Aquifer	202	Krige	16	Krige
KNNSR	36	Krige	69	Krige	44	Krige
KNNSY	12	Krige	70	Krige	11	Krige
RBSHN	1	Mean and SD group	1	Mean and SD group	1	Mean and SD group
RBMDL	50	Krige	105	Krige	24	Krige
RBMDU	19	Krige	25	Krige	5	Mean and SD group
RBMH	47	Krige	56	Krige	24	Krige

RBMVL	68	Krige	191	Krige	27	Krige
RBMVU	41	Krige	51	Krige	15	Krige
RNROF	52	Krige	64	Krige	49	Krige
RNSOB	59	Krige	36	Krige	22	Krige
ROSL_ROSLU	267	Krige	543	Krige	220	Krige
ROSL	50	Krige	77	Krige	19	Krige
NLDOBR	15	Krige	17	Krige	16	Krige
NLDOOO	1	Mean and SD group	3	Mean and SD group	0	Mean and SD group
NLLAOR	1	Mean and SD group	1	Mean and SD group	0	Mean and SD group
NLLARE	0	Mean and SD group	0	Mean and SD group	0	Mean and SD group
NMVESO	0	Mean and SD group	1	Mean and SD group	0	Mean and SD group
NMVEVO	0	Mean and SD group	7	Mean and SD Aquifer	5	Mean and SD group
NMRUST	0	Mean and SD group	0	Mean and SD group	0	Mean and SD group
NMRUBE	1	Mean and SD group	4	Mean and SD group	3	Mean and SD group
NUBD	18	Krige	15	Krige	15	Krige
NUBG	18	Krige	17	Krige	17	Krige

8. Results

The resulting changes in the property maps are significant, the combination of improved data quantity, quality and an improved interpolation method has meant that we have more reliable property maps. At the same time, the approach we take to producing maps has changed and for some aquifers and properties we have concluded that we are not as sure as we thought we once were over spatial distribution of the properties. This means that for some aquifer-properties we now have maps with less detail than before. Still, given that we think this better reflects our understanding of the subsurface, we consider these to be better representations of the subsurface.