Disentangling deep and shallow causes of subsidence

Subsidence is an important social issue in the Netherlands and elsewhere. Some of the anthropogenic causes, like construction of buildings, roads and tunnels, oxidation of peat, clay compaction and withdrawal of groundwater, occur at or near the surface. Others primarily affect the deep subsurface: extraction of hydrocarbons, salt mining and geothermal production. Until now inversion programs, which aim to quantify the subsurface processes based on subsidence measurements, have focused on either deep or shallow causes. If contributions from these processes are comparable, however, neglecting one of them may lead to erroneous parameter estimations. We have therefore devised a procedure to objectively disentangle the shallow and deep causes of surface movement. The procedure employs the Bayesian approach of parameter estimation for the combined effect of the deep and shallow causes of subsidence. Additional information is added, such as knowledge about the expected compaction levels and spatial correlations.

**Inverse Model**

With an appropriate forward model, subsidence can be calculated from given compaction levels. The subsidence is the sum of the contributions due to deep and shallow causes, but the range of influence of deep causes is larger than the range of influence of shallow causes (Figure 1). The inverse problem of the compaction determination from subsidence can be formulated as the search for the compaction levels with the largest likelihood, given the subsidence data and the a priori knowledge. This a priori knowledge is instrumental because without it the inverse process is usually ill-conditioned: small changes in the data result in large variations in the calculated compaction. We have created a tool in which the a priori knowledge is incorporated in the form of a combination of the expected compaction, the variance in it and the covariance. The covariance gives information about spatial correlations within and between compaction levels.

**Demonstration of the Method**

In the first artificial example we combined the effects of a shallow and a deep compaction grid. The shallow compaction consisted of a linearly increasing, regional east-west trend (Figure 2a). This may be considered to represent compaction of an idealized eastward-thinning peat layer that pinches out at the eastern area boundary. The shallow compaction was modelled with a combination of peat oxidation and shallow compaction. The pre-defined deep compaction grid resembled a rectangular-shaped gas reservoir with sharp boundaries (Figure 2b), as may be the case in faulted areas. As a forward model, we used a linear, semi-analytic approach designed to account for layering. With the two forward models, the calculated surface movement was a combination of the east-west trend induced by the shallow compaction and a subsidence bowl related to deep compaction (Figure 2c). In the central part of the area surface movement was controlled to approximately the same extent by shallow and deep compaction.

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**Figure 1. Sketch of shallow and deep causes of compaction (m) resulting in surface subsidence (d). Arrows denote the area of influence of individual compaction sources (m).**
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**Figure 2.** Forward calculation – a) Shallow compaction (40x30 grid) increases linearly from 0 cm at the eastern boundary to 50 cm at the western boundary; b) Deep compaction (25x25 grid) of 1 m within the rectangular shaped reservoir; c) Resulting surface movement prediction (20x20 grid).

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**Figure 3.** Inverse calculation results assuming only deep compaction. Top: Best estimate of deep compaction for a $\sigma^2$ of the initial deep compaction of 0.01, 0.1 and 1 respectively. Bottom: Original subsidence data (mesh) and the best estimate of the subsidence (dots at locations where synthetic subsidence data are available), based on forward modelling using the deep compaction estimates shown in the top row.

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**Figure 4.** Forward calculation of shallow compaction (40x30 grid) of 1 particular realisation after 15 years in which clay thickness decreases from 0.5 m to 0.24 m. The inversion is based on the synthetic measurements in the dots. B and C: Difference between inverse calculation results and original compaction for the best estimate of shallow compaction using the median of the Monte Carlo simulation (Fig. 5C). In B, the full covariance matrix is used; in C only the variance.
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In practice only a rather small number of measurements are available to constrain the movement of the surface. The error created by neglecting shallow compaction (Figure 2a) is demonstrated in cases where the initial model of the deep compaction was correct (Figure 2b) and known within different degrees of certainty. Assuming a small variance in the a priori compaction data (Figure 3, left), the difference in subsidence displayed a clear east-west trend. Such a clear and deviating trend should serve as a warning that a significant process (shallow compaction) has been overlooked. If, on the other hand, the initial deep compaction model was assumed very uncertain (Figure 3, right), this effect was small, whereas the estimated deep compaction did extend well beyond expected reservoir boundaries and displayed a clear east-west trend: subsidence that was caused by shallow compaction was now attributed erroneously to deep compaction.

**Inversion using Monte Carlo simulation**

To demonstrate the strength of the incorporation of the spatial correlation with the covariance we created a more complex artificial case of shallow compaction (Figure 4a). It is a model with two polder units, separated along an east-west dike. The phreatic level in both polders was lowered by 0.3 m and the hydraulic head of the aquifer was lowered by 0.5 m. The subsurface consisted of peat that was covered by a layer of clay. At one boundary the clay thickness was 0.5 m, the opposite boundary had a clay thickness of 0.24 m. The resulting subsidence movement was resampled to provide a random set of 40 subsidence data points, Figure 4b. This set was used as input in the inversion.

In the inversion it was assumed that the setup of the model was known. However, clay thickness was highly uncertain at the second boundary: it could be between 0 and 1 m thick. Fifty Monte Carlo simulations were performed to derive a priori estimates for the shallow compaction, its variance...
and covariance at every grid point. Alternatively, one could choose to simply use the realization of the expected average clay thickness of 0.5 m as the a priori estimate and then allow for a large variance in the model.

Inversion results of both alternatives are shown in Figure 4. Clearly, inversion using the Monte Carlo results approached the original compaction (Figure 4b) best. The result is remarkably smooth given the absence of a smoothness constraint. This is due partly to the reasonable a priori estimate and partly to the introduction of non-zero covariances. The non-zero covariance quantifies expected relations between grid points. In this particular case the grid points were sharing the same groundwater regime or had a similar clay cover thickness. In effect, each data point updated (at least partially) all other grid points with which it shared a non-zero covariance.

Simply using average clay thickness in combination with a high variance produced a lot of spikes and completely failed to reproduce the abrupt change in compaction in one of the polder units (Figure 4c).

Conclusions
We have successfully created and tested a Bayesian inversion scheme that disentangles the deep and shallow causes of subsidence. Assumptions on the shape of the subsidence bowl are not necessary, even when there is considerable uncertainty in the measurements. When the contributions to subsidence of deep and shallow compaction have a similar order of magnitude, the neglect of one of them leads to faulty conclusions. This has been demonstrated using a realistic artificial example.

A priori information and spatial correlations have been introduced through Monte Carlo simulations. Using Monte Carlo simulations for defining a priori estimates is clearly worthwhile. The explicit use of the covariance can be particularly advantageous in optimization problems: adding only a few more data points at carefully chosen locations which share a high covariance with many other grid points will significantly improve the solution.

Monte Carlo simulations can also be applied to compaction in depleting gas reservoirs. There is often knowledge available about spatial correlations, even when the absolute values of the a priori compaction data are quite uncertain. Then, the explicit incorporation of known a priori spatial correlations significantly improves the result.

Outlook
The method is suitable for monitoring reservoir behaviour and depletion zones lacking pressure measurements, such as lateral aquifers or undrilled reservoir blocks. Our method can also be applied in areas where the subsidence signal of reservoir depletion is distorted by unrelated shallow compaction.

Geo energy and Geo information
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