Disentangling shallow and deep sources of subsidence on a regional scale in the Netherlands

M.A.M. Verberne[1,2], K. Koster[3], T. Candela[2] and P.A. Fokker[2]

1 Utrecht University, Geosciences, Utrecht, The Netherlands
2 Department Applied Geosciences, TNO – Geological Survey of the Netherlands, Utrecht, the Netherlands
3 Department Geomodelling, TNO – Geological Survey of the Netherlands, Utrecht, the Netherlands
Contact: manon.verberne@tno.nl
Session: Coastal Areas, Mining and Resource Extraction

Introduction

Subsidence is often the sum of contributions at multiple depths (Candela and Koster, 2022; Shirzaei et al., 2021). Near surface causes of subsidence can be related to construction of infrastructure and buildings, land use and phreatic water level management, and the withdrawal of groundwater at various depths (Koster et al., 2018). Deep subsurface causes are related to the extraction of hydrocarbons (Chaussard et al., 2013), salts (Mancini et al., 2009), and geothermal production (Massonnet et al., 2009). Most studies are only focusing on potential subsidence processes at single depth levels, although subsidence processes at different depths have been observed in several areas (Candela and Koster, 2022 Shirzaei et al., 2021). Neglecting the contribution of various subsidence processes that influence the total signal of subsidence, potentially leads to erroneous interpretations of the physical process driving the subsidence (Schroot et al., 2005).

We have combined the exhaustive datasets of the shallow subsurface of the Netherlands (TNO-GSN, 2022), that previously has been implemented in a regional lithological and groundwater model, with reservoir data to model gas extraction related subsidence to arrive at a regional multi-depth subsidence model. We introduce a workflow to regionally forecast subsidence originating from causes at multiple depths in the Netherlands, with the use of a forward model optimized in a data assimilation approach. This workflow is subsequently tested with realistic complex synthetic data. We test how well subsidence can be estimated, given the a-priori expected contribution and noise levels.

Materials and methods

Figure 1 shows the overview of the proposed workflow. The first step is to combine subsidence from deep and shallow causes, to arrive at subsidence predictions. These subsidence predictions are benchmarked with measured subsidence, or, in this paper, with synthetic data. A new subsidence prediction is formed with refined parameters. The refinement of the subsidence predictions is done in multiple subsequent steps, gaining confidence with each step. The used data, the forward models and data assimilation approach are further explained in the sections below.

(Synthetic) data sets

To arrive at a realistic synthetic model of subsidence, we used actual subsurface models for lithology and groundwater. For the deep processes a pressure depletion model is used over a period of 5 years inspired by data from a small gas field in the north of the Netherlands. The modelled subsidence region is 20 by 20 kilometers.

GeoTOP is a 3-D geological subsurface model with a x,y,z resolution of 100 x 100 x 0.5 meters. The model schematizes the voxels with 100 realizations of the lithology (grainsize composition), following the statistical probability of the interpolation. GeoTOP was constructed based on digital borehole logs, cone penetrations tests and digitized geological maps, available in the database of the Geological Survey of the Netherlands (Stafleu et al., 2011; TNO-GSN, 2022). For this study we have used the upper 5 meters of the GeoTOP model. For the lithology one of the 100 realizations is taken. Figure 2A shows the lithological map of the area at a depth of 5 meters with respect to NAP (NAP is the Dutch ordnance datum approximating mean sea level).

We used the groundwater model Groundwatertools, with the same spatial extent and resolution as the GeoTOP model. The groundwater model is the result of interpolation of data available at the online portal of TNO-GSN, 2022. The model includes a monthly estimate of the phreatic surface level (Dabekaussen et al., 2020; Zaadnoordijk et al., 2018). For this study we have taken the average slope (m/month) and phreatic surface height from the monthly data over a modelled period of 20 years at a random point in time. Figure 2B shows the average height of the phreatic surface at t=0 with respect to NAP.

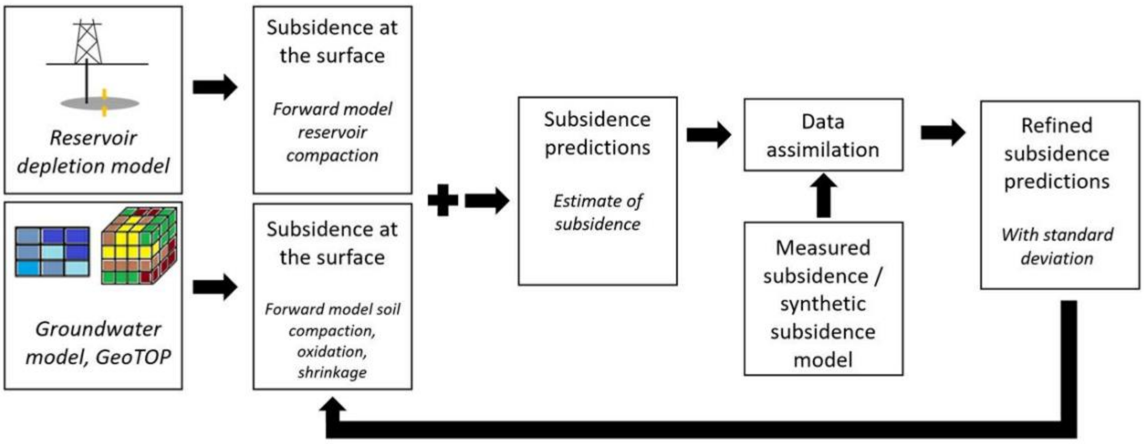

Figure 1 Overview of workflow. Shallow and deep causes of subsidence are combined into one subsidence prediction. This prediction is checked against the observational data to refine the subsidence predictions by optimization of the parameters. This process is repeated multiple times. Image adapted after Candela et al., 2020.

For the pressure field related to reservoir depletion in the deep subsurface, a 2-D grid was constructed. The data contains a yearly value of pressure over the 2-D reservoir grid, a value for the average reservoir depth, and a value for the grid block volume. Figure 2C shows the total pressure depletion over the study time, for the extent of the gas field, with coordinates in the same synthetic system as the GeoTOP and groundwater model. As realistic for reservoirs, there are multiple centers of increased pressure depletion, which results in two subsidence bowls (see Fig 2C).

Forward model

A forward model is a schematized representation of the physics driving the subsidence processes. The subsidence is calculated as the combined effect of the deep and shallow causes. The models are kept simple to compare the influence of each process and not dive in the details the modelling. The pressure depletion is defined as the drop in pressure between two consecutive timesteps. To calculate reservoir compaction from pressure depletion we used a linear elastic compaction model (Candela et al., 2022). Cm,, the compaction coefficient of the reservoir is the single value to optimize in this study. To calculate surface movement from reservoir compaction, an influence function (Green's function) was used (see Geertsma, 1973).

Shallow causes of subsidence are compression, oxidation and shrinkage of peat and clay beds. Compression models often follow a logarithmic equation (e.g. Den Haan, 1996) while oxidation (and sometimes shrinkage) follows an exponential decay function (Van den Akker, 2008; Fokker et al., 2019). We have chosen to only account for an exponential decay function to calculate the subsidence, with variable parameters for peat and clay. This is justified by the length of the study: for a 5 year period logarithmic equation for compression can be estimated with a linear function. Hence equation 1 is assumed to account for subsidence of compression, oxidation and shrinkage.

The equation calculates the subsidence for the part of the layer that is susceptible to subsidence. The effects of swelling are ignored. For a completely dry layer we can determine the fraction of a layer susceptible to subsidence hst=ht- R*h0 where R is the residual height, the fraction of the layer that is left after the full process of subsidence and h0 the original layer thickness. The groundwater variation in time is taken into account by calculating the fraction of the layer above the phreatic surface for each timestep, assuming no subsidence takes place below the phreatic surface. Over time the subsidence for a single layer can be calculated as:

$$\Delta h = (1 - e^{-V\,\Delta t})(h(t) - h_{wet} - R\,[h_0 - h_{wet}]) \qquad (1)$$

In which V is the rate of subsidence and h_{wet} the height of the phreatic surface within the layer.

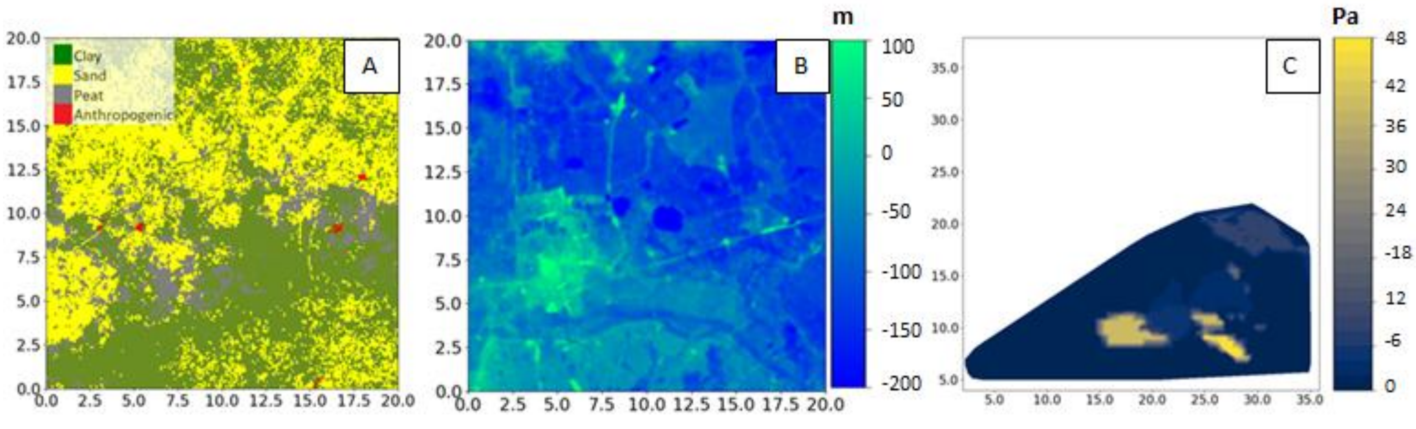

Figure 2 This image shows A) the lithological model of the synthetic area at a depth of 5 meters below NAP in 4 different lithologies, B) the phreatic surface height at t=0 of the synthetic study with respect to NAP and C) the pressure depletion of our 2D upscales gas reservoir over a period of 5 years.

ES-MDA

For the parameter estimation method we used an algorithm often used in parameter estimation studies related to subsidence (e.g. Fokker et al., 2019; Gazzola et al., 2021). ES-MDA stand for Ensemble Smoothing with Multiple Data Assimilation (Emerick and Reynolds, 2016). An ensemble is a collections of members, resulting from a Monte Carlo analysis. Members represent single realizations of the subsidence with specific values for different parameters. A forward model calculates subsidence according to the set of parameters in each member. Subsequently the ES-MDA algorithm minimizes the mismatch between the estimated subsidence and the measured subsidence, by taking multiple steps in which the parameters are modified to reduce mismatch and increase the certainty in the parameter values and standard deviation. For the description of the model see Emerick and Reynolds, 2016 and Fokker et al., 2019.

Experimental set-up

The synthetic subsidence data was created by the sum of the contribution of each subsidence process for 100x100 meter grid cells in the study area for a period of 5 years with monthly timesteps.. From the dataset 1500 random x,y locations were taken. Normally distributed noise was added to the data and functions as input for the covariance of the data. Noise levels and the compaction coefficient are varied. The quality of the estimate is quantified by the absolute error (AE) and absolute ensemble spread (AES) (see Baù et al, 2015).

Results

Figure 3 shows the parameter fit of four different models (A, B, C and D). The variance in fit is related to different noise levels, compaction coefficients and prior ensemble spread, from which the values are given for each model in the figure. Hence, the effects of prior parameter estimates, relative noise and signal contribution are tested. The estimated subsidence rate for peat and clay and the compaction coefficient of the gas reservoir for the prior estimate and each step in the assimilation are plotted on the y axis versus the ensemble member on the x axis. The black line denotes the actual value for that parameter.

Discussion and conclusion

We have introduced a workflow to disentangle the multiple-depth causes of the subsidence signal and identified potential assessment risk for when this method is applied to real data. By comparing four different model outcomes of a realistic synthetic data, we can draw conclusions on what factors should be considered when applying the methodology to real data.

With model A and B of Figure 3 we have compared the influence of noise of the synthetic data to the subsidence fit. The lower the noise level, the lower the spread in our ensemble estimates (AES) and the lower the absolute error (AE) of the estimates. The AE and AES are scaled to the noise level given to the data. With model B and C we have compared the effect of relative influence of the different subsidence processes. In model C, we have chosen a value for Cm as such that the magnitude of subsidence of gas is in the same order as the magnitude of subsidence due to the shallow processes (peat and clay). From this comparison follows that if both multi-depth processes are in the same order, correctly estimating the contributions of the different processes becomes harder. The AES is larger for model C compared to model B, pointing towards a higher uncertainty in the subsidence estimate. From the comparison of model B with model D follows that the initial spread of our parameters has influence on the final estimate of subsidence. The prior spread of the estimate of Cm does not include the true value. As a result, the final Cm is overestimated, although the ensemble spread is reduced with each assimilation step. The estimates of peat and clay in model D are a bit below the true value, to compensate for the over estimation of Cm, resulting in a comparable AE and AES for model B and D.

We show in our analysis that a combination of noise level, relative importance of multi-depth subsidence processes and the chosen prior spread in the ensemble parameters all influence the ability to estimate subsidence correctly. With synthetic data we have the advantage of the known true values of the parameters, whilst with real data this information is unknown. Hence, it if of imminent importance that the effects of each of the factors is understood correctly. When the methodology is applied to a real multi-source subsidence case study, a range of scenarios with varying ratios of the different influence factors should be tested. This means that parameter estimates outside the original distribution window should lead to critically review the prior values, and when different sources of subsidence contribute to the total subsidence, their potential relative contribution should be reviewed. Additionally, with a low ensemble spread, the noise level of the subsidence measurements should be checked.

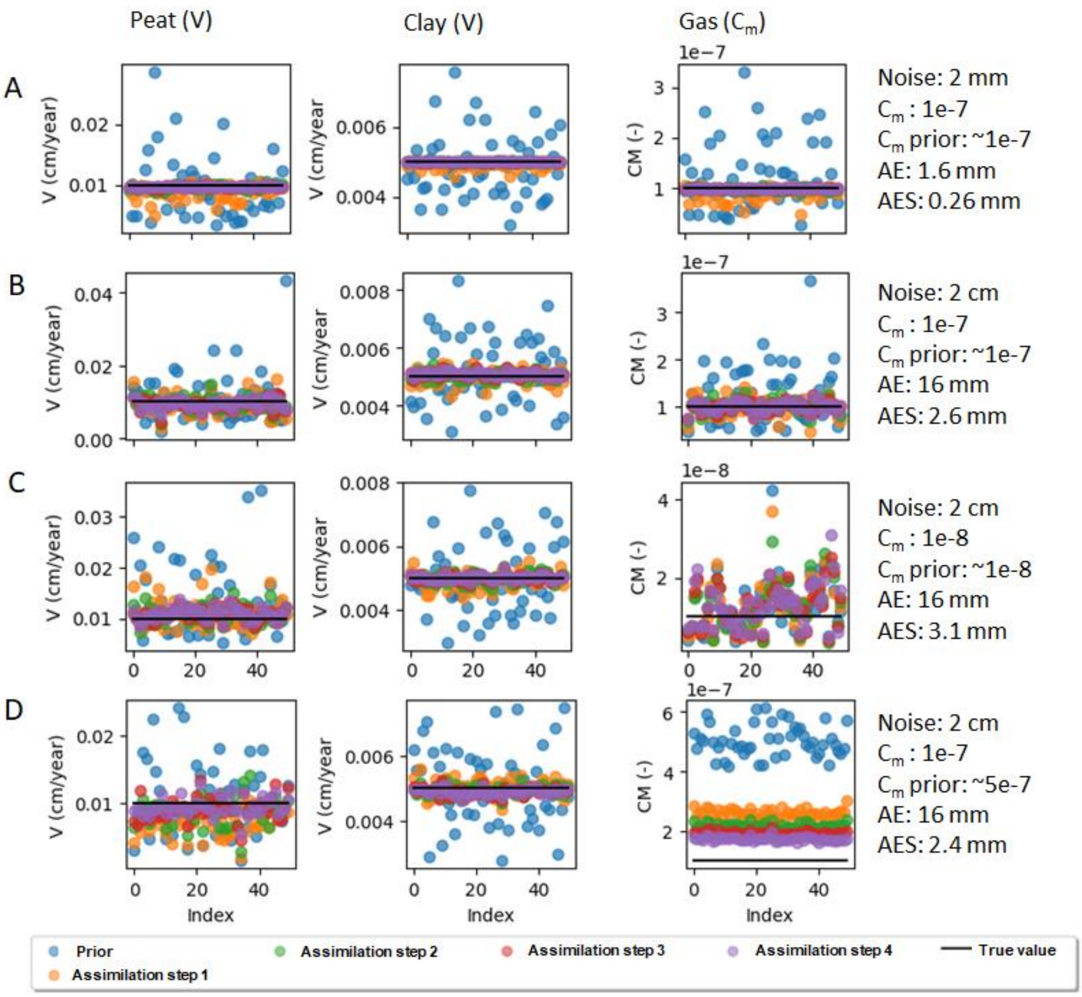

Figure 3 Results of the parameter estimation of 3 different models for 4 assimjlation steps with 50 ensemble members. The estimated parameters for peat and clay (subsidence rate) and gas related subsidence (compaction coefficient) are shown for each assimilation step. Black is the actual parameter value. For each model the noise level, the prior and post estimate chi-square error and the true compaction coefficient are indicated.

Acknowledgements

The research presented in this paper is part of the project Living on soft soils: subsidence and society (grantnr.: NWA.1160.18.259). This project is funded through the Dutch Research Council (NWO-NWA-ORC).

References

Baù, D., Ferronato, M., Gambolati, G., Teatini, P., and Alzraiee, A. (2015). Ensemble Smoothing of Land Subsidence Measurements for Reservoir Geomechanical Characterization. Int. J. Numer. Anal. Meth. Geomech. 39 (2), 207–228

Candela, T., Koster, K., Stafleu, J., Visser, W. and Fokker, P. (2020) Towards regionally forecasting shallow subsidence in the Netherlands. *Proc. IAHS*, 382, 427-431

Candela, T. and Koster, K. (2022). The many faces of anthropogenic subsidence. *Science, 376*(6600), 1381-1382.

Chaussard, E., Amelung, F., Abidin, H., & Hong, S. H. (2013). Sinking cities in Indonesia: ALOS PALSAR detects rapid subsidence due to groundwater and gas extraction. *Remote sensing of environment*, 128, 150-161.

Dabekaussen, W., Lourens, A. and Zaadnoordijk, W.J. (2020), Simulation of groundwater heads for the Think or Sink project. TNO report, Unpublished. pp. 12

Den Haan, E. (January 1996). A compression model for non-brittle soft clays and peat. Géotechnique, 46(1), 1–16.

Fokker, P. A., Gunnink, J. L., Koster, K., & de Lange, G. (2019). Disentangling and parameterizing shallow sources of subsidence: Application to a reclaimed coastal area, Flevoland, the Netherlands. *Journal of Geophysical Research: Earth Surface, 124*(5), 1099-1117.

Gazzola, L., Ferronato, M., Frigo, M., Janna, C., Teatini, P., Zoccarato, C., ... & Mantica, S. (2021). A novel methodological approach for land subsidence prediction through data assimilation techniques. *Computational Geosciences, 25*(5), 1731-1750.

Geertsma, J. (1973). Land subsidence above compacting oil and gas reservoirs. *Journal of petroleum technology, 25*(06), 734-744.

Mancini, F., Stecchi, F., Zanni, M., & Gabbianelli, G. (2009). Monitoring ground subsidence induced by salt mining in the city of

Tuzla (Bosnia and Herzegovina). *Environmental Geology, 58*(2), 381-389.

Massonnet, D., Holzer, T., & Vadon, H. (1997). Land subsidence caused by the East Mesa geothermal field, California, Observed using SAR interferometry. *Geophysical research letters, 24*(8), 901-904.

Schroot BM, Fokker PA, Lutgert JE, Van der Meer BGH, Orlic B, Scheffers BC, Barends FBJ (2005) Subsidence induced by gas production: an integrated approach. In: Proc SISOLS’05, special volume, geodelft, Millpress Rotterdam, pp 121–135

Shirzaei, M., Freymueller, J., Törnqvist, T. E., Galloway, D. L., Dura, T., & Minderhoud, P. S. (2021). Measuring, modelling and projecting coastal land subsidence. *Nature Reviews Earth & Environment, 2*(1), 40-58.

Stafleu, J., Maljers, D., Gunnink, J. L., Menkovic, A., & Busschers, F. S. (2011). 3D modelling of the shallow subsurface of Zeeland, the Netherlands. *Netherlands Journal of Geosciences, 90*(4), 293-310.
TNO-GSN (2022) DINOloket, https://www.dinoloket.nl/

Van den Akker, J.J.H., Kuikman, P.J., De Vries, F., …, Kwakernaak, C., 2008. Emission of CO2 from agricultural peat soils in the Netherlands and ways to limit this emission. In: Farrell, C., Feehan, J. (Eds.), Proc. of the 13th Int. Peat Congr., , pp. 1–6.

Zaadnoordijk, Willem J., et al. "Automated time series Modeling for piezometers in the National Database of The Netherlands." Groundwater 57.6 (2019): 834-843.