Using Multiple Points Statistics in Indian Wells Valley, California to estimate the aquifer storage capacity

Introduction

Drought and depletion of groundwater have long been an issue in California, USA. In 2014 the state passed a Sustainable Groundwater Management Act (SGMA), that required groundwater agencies to develop groundwater sustainability plans (GSP). The GSP had to include sections on basin setting, groundwater conditions and hydrogeological conceptual models. This led to the birth of the Stanford Groundwater Architecture Project (GAP). It was a two-year program designed to define the optimal workflow using advanced geophysical and computational methods for the development of hydrogeological conceptual models (HCMs) in California. Focus was to support the development of more detailed and improved HCMs. The project was led by Stanford University and the HCM was conducted by I-GIS A/S and Ramboll Denmark A/S. The major project funding partners were The Danish Environmental Technology Development and Demonstration Program (MUDP), the California Department of Water Resources (DWR), and State Water Resources Control Board (SWRCB). Three local agencies and corresponding local basins were selected, with one of them being Indian Wells Valley (IWV).

The basin of IWV is categorized by DWR as subject to critical conditions of overdraft (DWR 2016) and is categorized as a High Priority Basin under the SGMA.

The basin is located at the southeast terminus of the Sierra Nevada Mountain Range. The size of the basin is approx. 1546 square kilometres and is considered a closed internally drained basin, bounded by outcrops of igneous and metamorphic basement rock complexes. It has the Sierra Nevada Mountains as the western bounds, the Coso Range as the Northern bounds, the Argus Range as the eastern bounds and the El Paso Mountains as the southern bounds. The basin is largely filled with unconsolidated sediments, such as clays, sands, silts, and gravels extending to depths of over 600 meters through most of the basin. The basin consists of two areas, the China Lake, being a perennial playa lake situated in the central north-eastern valley, and the El Paso area to the southwest (See Figure 1). A series of mostly active faults are controlling the basin structurally. An unnamed fault separates the China Lake area hydrogeologically from the El Paso area to the southwest. The China Lake is the primary natural groundwater discharge point and the target of this study.

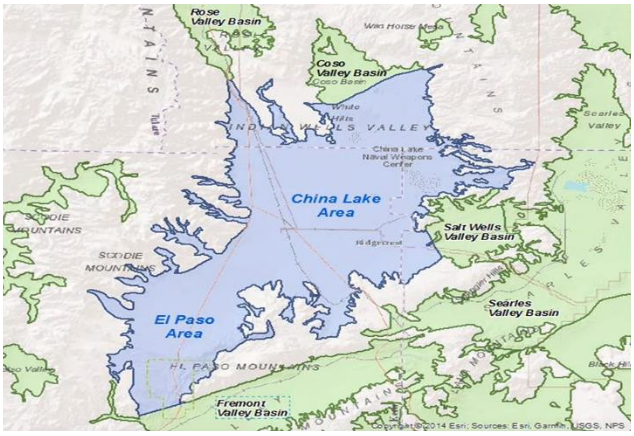

Figure 1 *The groundwater basin of Indian Wells Valley is shown in blue, with the China Lake area in the northern part, being the primary groundwater resource, and the El Paso Area in the southern part of the area.*

Groundwater accounts for more than 95 percent of the water used in IWV with pumping being the largest discharger for over 50 years. Average annual inflows have been estimated to approx. 9.4 to 13.5M cubic meters, with average annual precipitation in the valley varying from approx. 50 to 150 mm. Some years no precipitation falls at all. The pumping is estimated to 29.2M cubic meters pr. year (Todd 2014), resulting in an annual storage change of approx. 20.1M cubic meters, giving chronic groundwater level declines of 0.3 to 0.6 meters per year. Furthermore, the continuous groundwater decline also has a negative effect on the water quality, due to an increased concentrations of total dissolved solids (TDS) in the groundwater (Todd 2014).

The overuse over several decades has resulted in increased pumping costs, degraded water quality and shallow wells running dry. Potentially this will cause land subsidence over time, although this is not evident in IWV yet (Thorn, et al. 2019). This continuous overuse has also defined an urgent need to get a better hydrogeological understanding of the area, and to estimate the potential storage capacity. A more detailed and refined HCM can be used to support this.

In November 2017 the area was mapped with the SkyTEM 312 system (SkyTEM Surveys 2017) and the Stanford Groundwater Architecture Project started. A new HCM was made using the newly gathered airborne electromagnetic (AEM) data together with other existing information such as borehole data, ground based TEM data, seismics, geophysical logs, TDS, and water level measurements.

The HCM in the China Lake area of the IWV groundwater basin resulted in four different hydrogeologic zones (HGZ). HGZ 1 as the shallowest zone consisting primarily of unconsolidated sand and gravel. HGZ 2 follows and consists primarily of clay and silt deposits with embedded lenses of coarser material. HGZ 3 is a deeper zone consisting of unconsolidated to semi-consolidated sand and gravel. HGZ 4 is situated directly on the basement and consists predominately of consolidated deposits.

The sand lenses embedded in HGZ 2 is also an important source for groundwater in IWV. Therefore, it was important to be able to estimate the amount of sand deposits within HGZ 2 to estimate the total storage capacity. These sand bodies are evident in the collected AEM data, but as they vary in extent, and the distance between the AEM flight lines are 1250 m and 2500 m, the location of these sand bodies was associated with too much uncertainty to be mapped in the regular HCM (Thorn, et al. 2019). Instead, an approach to compute the probability of having sand within HGZ 2 using Multiple Point Statistics (MPS) was carried out. The MPS results were, in turn, used to estimate the storage capacity in HGZ 2.

Method and Theory

All geoscience disciplines face the problem of having too little information to allow complete confidence of the problem at hand. It is possible to obtain direct information about the subsurface through borehole drillings, but this only provide point-wise information and is often associated with high costs. It is impossible to know how the geology varies between the boreholes. Therefore, geoscientists often obtain different types of geophysical data, like e.g., electromagnetics, GPR, seismic, etc., to get additional, indirect, information about the subsurface - through their different physical properties. This kind of data is associated with different uncertainties, and it is not possible to map these geophysical measurements directly to geology with complete certainty. Making a geological representation/model is therefore highly underdetermined, i.e., several models fit the information at hand. Instead of making one geological model associated with varying uncertainty, Multiple Point Statistics (MPS) is a methodology allowing to generate/simulate a series of different geological models consistent with the available information.

The general idea of MPS is to integrate different sources of (independent) information and simulate the different models fitting the data. If the different sources of information are independent, the posterior probability distribution of the unknown earth-parameters (model parameters ***m***) is proportional to the product of the different sources of information. Mathematically, this can be formulated as:

$$f_I(\overline{m}) \propto \prod_i f_{I_i}(\overline{m}) \ \propto \ f_{I_{TI}}(\overline{m})\, f_{I_{hard}}(\overline{m}) f_{I_{soft}}(\overline{m}) \qquad (1)$$

Where, *I* referrers to Information, *TI* to Training Image, and *hard* and *soft* to hard data and soft data, respectively. In a typical MPS set up, the different sources of information are represented by these three probability distributions.

The Training image (TI) represents the geological prior knowledge. This is a (3D) representation of the geoscientist's background knowledge of the problem. The TI should represent what we know about the geological structures and patterns and will allow the realisations to have realistic earth structures.

The soft data is data associated with uncertainty and is often representing the geophysical information. The soft data probability distribution is in practice represented by a (3D) model with probabilities of the different earth parameters. This probability model is generated by, first, inferring a function mapping the (geo)physical measurements to the earth model parameters. This function is often referred to as a transfer function or a rock physics model.

Hard data is data representing the 'truth'. If there are no uncertainty associated with a data point, it is treated as hard data. This could be applied to some borehole lithologic logs, but it is worth discussing whether hard data really exists. Borehole information associated with uncertainty is treated as soft data.

There exist several different MPS algorithms, that in different ways simulate ***f(m)***. In this study we have utilized the SNESIM algorithm available through GeoScene3D (www.geoscene3d.com) and MPSLIB (Hansen et al. 2016).

Case Study and results

The target of the MPS analysis was to simulate the HGZ 2 in the China Lake area. As the HGZ 2 unit primarily consists of finer sediments (mainly clay) with embedded lenses of coarser material (mainly sand) the MPS model was defined to consist of 2 categories, i.e., sand and clay.

Indian Wells Valley (IWV) is a complex project area with complex (hydro)geological settings. As the MPS algorithm assumes stationary, it was needed to subdivide the China Lake Basin into five independent regions with more similar geological structures. Each region was defined based on differences in sand lens orientation, dip, and size (horizontally and vertically). A TI was created for each individual region. In the MPS simulation, each region was simulated in a successive order, where each region was conditioning to those already simulated. This allows all TIs to be used in each simulation, and at the same time securing continuity between the five regional zones (no boundary effects between the different regions).

The inverted AEM data was interpolated into a 3D Grid and converted into soft data to be used in the MPS simulation. As IWV is heavily dominated by salt/brackish water, which has large impact on the resistivity measurements from the AEM data, the TDS measurements needed to be considered. Three TDS zones were defined, varying both horizontally and with depth. The three TDS zones were defined as freshwater, brackish water, and highly saline water. The AEM data was divided with respect to the TDS zones, resulting in three individual AEM sub-datasets. For each zone a transfer function, mapping resistivity to lithology, specific to the TDS value of that zone, were created and applied to the coherent AEM sub-dataset. The three subsets were merged, resulting in a (soft data) grid representing the probability of having sand and clay, based on the AEM data.

Borehole data was also treated as soft data. The borehole lithologic logs in IWV are considered to have various quality and can not to be used as hard data. A quality system was developed to handle the differences in quality of the individual boreholes. All boreholes were categorized into quality groups based on their lithological description and accuracy of location. Each quality category was assigned a probability. A detailed description of each quality category and their respective category can be found in (Danish Environmental Protection Agency 2021).

Having a soft data representation from AEM data (constrained to TDS data) and borehole information, together with five training images for the five sub-regions, allowed to run the MPS simulations. The simulation was run using the SNESIM algorithm with a preferential path (Hansen et al. 2018).

The result was 75 realizations representing different possible models of HGZ2. From these realizations we computed the probability of having sand and clay. This way we could point out areas with increased probability of having sand within the clay unit (see Figure 2).

The probability grid of sand can also be used to estimate the total storage capacity within HGZ 2. Assuming a 20% pore porosity, the accumulated potential water volume was calculated by weighting the volume of each voxel in the 3D grid with its associated sand probability and sum the total volume for the whole area. This gives an estimated water volume of approx. 6,868 billion m^3. If we only consider the voxels with high confident of having sand (>90% probability), the accumulated water volume is approx.: 345 million m^3.

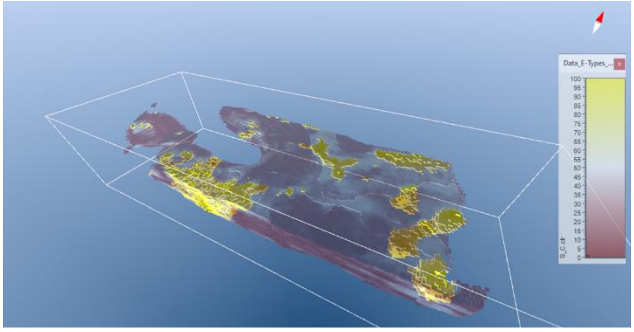

Figure 2 *The probability of having sand (and clay) in one sub-area of the China Lake basin. Transparency is added to probabilities above 67%*

Conclusions

This study presents the work of applying Multiple Point Statistics to allow mapping of coarse material (sand) bodies embedded in larger units of finer materials (clay). These sand bodies act as local aquifers in the study area and are hence important to map. Even though these sand bodies are evident in data, they are associated with too much uncertainty, to be included with enough confinement in regular hydrogeological models. MPS was the solution to this. Using a combination of AEM data, groundwater chemistry, borehole lithologic logs, and geological background knowledge (through training images) we have presented a successful workflow allowing to point out areas with increased probability of having local aquifers, and their potential storage capacity.

Acknowledgements

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