Methods for Characterizing Groundwater Resources with Sparse In-Situ Data

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Methods for Characterizing Groundwater Resources 

with Sparse In-Situ Data

Ren Nishimura

A thesis submitted to the faculty of 
Brigham Young University
in partial fulfillment of the requirements for the degree of

Master of Science

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Groundwater water resources must be accurately characterized in order to be managed sustainably. Due to the cost to install monitoring wells and challenges in collecting and managing in-situ data, groundwater data is sparse in space and time especially in developing countries. In this study we analyzed long-term groundwater storage changes with limited time-series data where each well had only one groundwater measurement in time. We developed methods to synthetically create time-series groundwater table elevation (WTE) by clustering wells with uniform grid and k-means-constrained clustering and creating pseudo wells. Pseudo wells with the WTE values from the cluster-member wells were temporally and spatially interpolated to analyze groundwater changes. We used the methods for the Beryl-Enterprise aquifer in Utah where other researchers quantified the groundwater storage depletion rate in the past, and the methods yielded a similar storage depletion rate. The method was then applied to the southern region in Niger and the result showed a ground water storage change that partially matched with the trend calculated by the GRACE data. With a limited data set that regressions or machine learning did not work, our method captured the groundwater storage trend correctly and can be used for the area where in-situ data is highly limited in time and space.

Keywords: groundwater, aquifer, sustainable water resource management, sustainable water development, sparse data, temporal interpolation, spatial interpolation
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# TABLE OF CONTENTS

| Section                                      | Page |
|----------------------------------------------|------|
| ABSTRACT                                     | ii   |
| ACKNOWLEDGEMENTS                             | iii  |
| TABLE OF CONTENTS                            | iv   |
| LIST OF TABLES                               | v    |
| LIST OF FIGURES                              | vi   |
| 1 Introduction                               | 1    |
| 1.1 Previous Work                            | 3    |
| 1.2 Study Location and Background            | 4    |
| 1.3 Research Objective                       | 7    |
| 2 Data                                       | 8    |
| 3 Methods                                    | 13   |
| 3.1 Grid Clustering                          | 14   |
| 3.2 K-Mean-Constrained Clustering            | 15   |
| 3.3 Temporal Interpolation                   | 17   |
| 3.4 Spatial Interpolation with Kriging       | 24   |
| 3.5 Calculation of Aquifer Storage Change    | 25   |
| 4 Results                                    | 27   |
| 4.1 Utah                                     | 27   |
| 4.2 Niger                                    | 29   |
| 4.2.1 Storage Change Analysis with Grid Clustering | 29 |
| 4.2.2 Storage Change Analysis with K-Means-Constrained Clustering | 32 |
| 5 Discussion                                 | 35   |
| 6 Conclusions                                | 37   |
| References                                   | 38   |
LIST OF TABLES

Table 4-1: Summary of storage depletion rate calculation statistics using 500 random data sets in each column in the table. .................................................................................... 28
### LIST OF FIGURES

Figure 1-1: The location of Niger and its adjacent countries in the African continent .................. 4

Figure 2-1: (a) The locations of the wells and the aquifer in Niger for this research and (b) the distribution of the well measurements in years. ................................................................. 9

Figure 2-2: (a) The spatial distribution of the wells and (b) the temporal distribution of the measurements in years for the Beryl-Enterprise aquifer in Utah. ................................................. 11

Figure 3-1: A synthetic time series formed by aggregating WTE values from wells in the vicinity of a pseudo well............................................................................................................. 13

Figure 3-2: Well clusters and pseudo wells for the grid method with (a) 0.1-degree cells and (b) 0.05-degree cells. ............................................................................................................. 15

Figure 3-3: Creating synthetic WTE time series using the k-means-constrained clustering method. ......................................................................................................................... 16

Figure 3-4: Well clusters and pseudo wells for the k-means-constrained method with (a) 25 wells and (b) 50 wells. ............................................................................................................. 17

Figure 3-5: The synthetic WTE time series at two pseudo wells with irregular time interval and length. ......................................................................................................................... 18

Figure 3-6: Temporal interpolation with the univariate spline that showed (a) a smooth fitted curve and (b) an extreme overshoot and undershoot. ................................................................. 20

Figure 3-7: Temporal interpolation with PCHIP and 96-month window moving average and with the univariate spline ......................................................................................................... 21

Figure 3-8: The synthetic WTE time series at the pseudo well (a) when the univariate spline interpolation was selected and (b) when the PCHIP with the moving average interpolation was select-ed ............................................................................................................. 22

Figure 3-9: The matrix of the pseudo wells in columns and date in rows (a) before and (b) after the missing WTE cells are filled with the last available WTE value ............................................. 23

Figure 3-10: Model variogram created at each time step ................................................................ 24

Figure 4-1: Summary of storage depletion rate calculations using 500 random data sets in each whisker and box plot ......................................................................................................... 29

Figure 4-2: Using 0.05-degree square grid clustering, (a) Spatial distribution of the pseudo wells, (b) groundwater storage change comparison against the GGST GWSa, and (c) synthetic WTE time series of each pseudo well ............................................................................................................. 30

Figure 4-3: Using 0.1-degree square grid clustering, (a) Spatial distribution of the pseudo wells, (b) groundwater storage change comparison against the GGST GWSa, and (c) synthetic WTE time series of each pseudo well ............................................................................................................. 31

Figure 4-4: Using 0.25-degree square grid clustering, (a) Spatial distribution of the pseudo wells, (b) groundwater storage change comparison against the GGST GWSa, and (c) synthetic WTE time series of each pseudo well ............................................................................................................. 32
Figure 4-5: Using the k-means-constrained clustering with 13 minimum cluster size, (a) Spatial distribution of the pseudo wells, (b) groundwater storage change comparison against GRACE GWSa, and (c) synthetic WTE time series of each pseudo well.................................................................................................................... 33

Figure 4-6: Using the k-means-constrained clustering with 25 minimum cluster size, (a) Spatial distribution of the pseudo wells, (b) groundwater storage change comparison against GRACE GWSa, and (c) synthetic WTE time series of each pseudo well.................................................................................................................... 34
1 INTRODUCTION

Groundwater is a precious resource and is increasingly in demand. Groundwater is used for multiple purposes including but not limited to drinking water, agriculture, mining, or industry [1–3]. Approximately 30% of the earth’s freshwater exists as groundwater while only 1.2% is surface water such as lakes, rivers, and streams [4]. Because of climate changes and severe droughts, water managers are shifting from surface water to groundwater [5]. The average groundwater pumping rate for the entire world has gradually increased and is estimated to be 600 - 1000 km³ per year and expected to increase even more due to population growth [6].

Understanding long-term groundwater level changes is essential for sustainable groundwater management; however, groundwater is often pumped out of aquifers without consideration of sustainability. In the past half century, the groundwater storage in various places has been depleted [7]. Theis [8] explained that groundwater extraction is initially derived from removal of water in storage, but in the long-term, the source of groundwater extraction shifts from the storage to decrease in discharge and/or increase in recharge. No additional water is removed from storage when a new equilibrium is reached. When groundwater extraction exceeds natural recharge, the system cannot reach a new equilibrium resulting in perpetual groundwater mining [9]. For example, Central Valley, California experienced 80 km³ (65,000,000 ac-ft) of groundwater storage depletion due to lack of sustainable groundwater management and over pumping since the 1960’s [10]. The Beryl-Enterprise aquifer in Escalante Valley, Utah was also
studied and it was estimated that the net groundwater depletion rate is approximately 65,000 ac-
ft per year, resulting in substantial water level declines [11].

Understanding groundwater is more important than ever due to increasing pressure for
sustainable water resource management. In recent years, there have been many regulatory
requirements initiated to protect the groundwater resources in the United States. Several states
require water agencies to characterize groundwater resources and implement management plans
for sustainable groundwater development and management. For example, California issued the
Sustainable Groundwater Management Act (SGMA) to help protect groundwater resources over
the long term [12,13]. The SGMA requires the formation of groundwater sustainability agencies
(GSAs) for the high and medium priority basins and for the GSAs to develop and implement
groundwater sustainability plans to avoid over usage of groundwater resources and to mitigate
the over-usage [14]. In Utah, groundwater management plans were created to promote wise use
of the groundwater, protect existing water rights, and address water quality issues and over-
pumping of groundwater.

Because of higher demand, increased pumping, and the regulatory requirements of
groundwater, understanding and characterizing long-term groundwater storage changes is critical
to sustainably manage aquifers, but it is technically challenging. First, groundwater is not
directly visible and it has to be physically measured at discrete locations to determine water table
elevations. Groundwater generally requires wells or piezometers to measure water table
elevations but they need to be spatially distributed throughout aquifers. Not only is it expensive
to physically sample wells on a consistent basis but it also requires manpower to log long periods
of records to accurately characterize the condition of aquifers [15,16]. Because of these
difficulties, groundwater level data is spatially or temporally sporadic, especially in developing countries [17].

1.1 Previous Work

Several researchers have developed techniques to address the issue of sparse data. Researchers have used in-situ data driven models to predict groundwater levels using generic programming [18], principal component regression [19], and artificial neural networks [20]. Other researchers have incorporated remote sensing data to address the temporal data scarcity. Evans et al. [21] used soil moisture data from the Global Land Data Assimilation System (GLDAS) developed by the National Oceanic and Atmospheric Administration along with an Extreme Learning Machine algorithm to impute missing groundwater measurement at a given well. Seo and Lee [22] used multiple satellite data together with long short term memory (LSTM) and convolutional neural network LSTM for groundwater data imputation.

Spatial data scarcity is often addressed by spatial interpolation techniques such as Kriging [23]. Gundogdu and Guney [24] analyzed multiple semivariogram models of kriging for the groundwater table estimation and comparison in Mustafakemalpasa in Turkey. Ruybal et al. suggested that three-dimensional interpolation with space and time, called spatiotemporal interpolation, yields more realistic temporal and spatial changes in water levels relative to spatial interpolation [25]. These methods are useful but require a significant amount of in-situ groundwater measurements to temporally impute time-series data or spatially interpolate the groundwater elevations at a given time. Challenges remain for developing countries where available groundwater measurements are sparser than what is necessary to perform the temporal and spatial interpolation methods described above.
1.2 Study Location and Background

Niger is located between latitude 11 to 24 degree North and longitude 0 to 16 degree East as shown in Figure 1-1. It is a landlocked country in West Africa and covers an area of 1,270,000 km², which makes it the largest country in West Africa, and 80% of its area is part of the Sahara desert [26]. Niger has distinct wet and dry periods where the northern area has longer dry periods. The wet period starts around June to October for five months with the average precipitation of 700-1100 mm in the southern part and July to August in the northern desert area of Niger [27]. The Niger River is the only permanent river in the country whereas the other rivers are ephemeral, called “wadi” in Niger. There are also internal drainage ponds and dammed reservoirs for surface water storage [28].

Figure 1-1: The location of Niger and its adjacent countries in the African continent
Niger experienced a severe drought in the early 1980’s together with desertification and needed alternative reliable water sources [29]. Aquifers in Niger were intensively studied starting around 1980 by various donors and groundwater wells were developed [30]. There are studies in the past that found increases in groundwater storage even though the area experienced severe drought. Leduc et al. [31] concluded that the increases were due to changes of land use and increase in the groundwater recharge patterns. Although groundwater has been periodically studied in Niger, a challenge still exists to sustainably manage the groundwater resources over the long term because the legal and organizational groundwater management frameworks are fragmented, inconsistent, and sometimes incomplete in the region [32,33]. As a result, there are very few historical groundwater measurements to accurately characterize the long-term changes.

The SERVIR program operated by the National Aeronautics and Space Administration (NASA) assists developing countries addressing sustainability and environmental issues incorporating Earth Observations to assess, analyze, and manage natural resources, including groundwater, to improve human lives [34]. This research was funded by NASA SERVIR and we worked with the West Africa hub that was one of the five NASA SERVIR regional hubs. The West Africa hub is partnered with an organization called AGRHYMET located in Niamey, Niger and who had provided the data for this research. The objective of our research was to assist water managers and local stakeholders to analyze and characterize local groundwater conditions.

We use two approaches to assess groundwater storage changes in Niger. The GRACE Groundwater Subsetting Tool (GGST) calculates groundwater storage anomalies for a user-defined area using data from the NASA Gravity Recovery and Climate Experiment (GRACE) missions [35]. We derive groundwater storage anomalies by subtracting terrestrial water storage anomalies simulated by GLDAS from the total water storage anomalies provided by the GRACE
mission. This method does not require in-situ data and can be used to analyze the changes of groundwater storage in data-poor areas from 2002 to the present time. Barbosa et al. [36] studied the groundwater storage changes in two regions in Niger using the GGST and identified a significant increase in groundwater storage volume from 2011 to present. While this approach is relatively simple and doesn’t require in-situ data, the native resolution of the GRACE grids is 3 degrees x 3 degrees so it can only be applied to large regions.

The Groundwater Data Mapping Tool (GWDM) displays historical groundwater level measurements at monitoring wells on an interactive map [37]. It can also be used to analyze groundwater storage changes through a three-step process. First, a temporal interpolation is performed to sample the water level time series for each well at selected intervals (2 years, 5 years, etc.). Prior to this step, the GWDM uses a machine learning algorithm to impute gaps in the water level times series using correlations with Earth observations. In the second step, the water levels from the wells are interpolated spatially at each time interval to create a raster of the water level that is clipped to the aquifer boundary. Finally, the volume between each subsequent pair of rasters is computed and multiplied by a storage coefficient to derive a curve of groundwater storage change vs time. Unlike the GRACE method, this approach can be applied to aquifers of any size as long as sufficient water level data is available.

To assess groundwater resources in Niger using the GWDM approach, we obtained groundwater data from the AGRHYMET Regional Centre in Niamey, Niger [38]. AGRHYMENT is a research center associated with the Permanent Interstate Committee for Drought Control in the Sahel (CILSS), and organization dedicated to achieving food security and increased agricultural production in the region. Unfortunately, while there are some wells in Niger with historical measurements, they are extremely rare. Most wells are not sampled after
they are constructed. We were able to obtain data for three aquifers but only for a small set of
wells and the measurements only covered a short period of time. However, we did obtain the
well inventory containing 15,688 wells scattered throughout southern Niger, and the water level
at the time of construction was measured for many of these wells. The GWDM method requires
a time series of measurements at each well, so we can’t directly apply this method, but the data
set does provide information on how water levels have changed over time.

1.3 Research Objective

The objective of this study is finding a way to harness these single-value well records and
calculate groundwater storage change over selected regions. To do this we created pseudo-wells
and aggregated the water table elevations (WTE) values from individual wells into the pseudo-
wells to synthetically create the time series. We then calculated groundwater storage changes
over time by incorporating the impute-interpolate steps similar to the GWDM method. We tested
the methods on the wells in the Beryl-Enterprise Aquifer in Utah as a test case and the resulting
groundwater storage rates were compared to values found by other researchers. The methods
were then used to analyze the groundwater storage changes in selected regions in Southern
Niger.
2 DATA

The data used in this research was provided by AGRHYMET and included a well file that contained 15,688 rows of well information with dates ranging from 1947 to 2010, well locations in degree latitude and longitude, depth to water table in meters, and several other columns. We filtered out the wells missing critical information, such as date or location, and 4,835 wells out of the original 15,688 wells remained for further analysis.

The well records had three date-related columns; the date that the well construction started, the date the well construction finished, and the date the well was rehabilitated. For a given well, one or more of these dates could be empty. For wells with multiple dates, we had to determine which date to associate with the corresponding depth to water table value. In consultation with an AGRHYMET representative, priority was given first to the date rehabilitated, then to the date construction finished, and finally to the date construction started. The well locations and dates are shown in Figure 2-1. Most of the wells are located in the southern region of Niger close to the border with Nigeria, and we analyzed the southern region in Niger between 6 to 10 degrees East surrounded in a red line in Figure 2-1. We found a major increase in the number of wells in inventory from 1981 to 1990 and 2003 to 2009. We believe those years are when the wells were constructed or rehabilitated.
Figure 2-1: (a) The locations of the wells and the aquifer in Niger for this research and (b) the distribution of the well measurements in years.

The well inventory had groundwater measurements recorded as depth to groundwater. WTE were calculated by subtracting the depth to groundwater values from the Ground Surface Elevation (GSE). Since the well records did not include GSE data, we interpolated the GSE values for each well based on NASA’s SRTM DEM [39]. The resulting WTE values represent height of groundwater above mean sea level determined by the WGS84 Earth Gravitational Model geoid.
Before applying our technique in Niger, we first need to test it on an aquifer with a more complete set of historical water level data to determine if the resulting storage estimates are sufficiently accurate to be of value. We selected the Beryl-Enterprise aquifer in Utah, the United States because the aquifer has two independent storage change estimates. First, the USGS and the Utah Division of Water Rights studied the groundwater storage change in the past and estimated that the annual depletion rate of this aquifer to be 650,000 acre-feet per year between 2000 to 2012[11,40]. Evans et al. [37] used the GWDM tool and its three-step groundwater storage calculation method and found the annual depletion rate -660,000 acre-feet per year – a value that is remarkably close to the value reported by the Utah Division of Water Rights.

To obtain well data for the Beryl-Enterprise Aquifer, we used the USGS National Water Information System (NWIS) web service. NWIS web service provides online public access to water-resources data collected in the United States. Similar to Niger’s data set, groundwater measurements were reported as depth to groundwater. We also calculated the WTE by the same method. Unlike the Niger data set, most of the wells in the Beryl-Enterprise Aquifer have historical groundwater measurements. The locations of the wells and a histogram of water level sampling frequency for the aquifer is shown Figure 2-2

To replicate the temporal data scarcity characteristic of Niger, a single groundwater measurement was randomly sampled (n=1) from each well in the Beryl-Enterprise Aquifer, and we repeated this 500 times to create 500 different random sample data sets. We used each of these data sets to calculate the annual storage depletion rate using our proposed algorithm and then compared with the known depletion rate in order to validate our methods. The date range of a random sample varies among the 500 data sets depending on which date is picked by random
sampling. The spatial distribution of the wells does not change among the 500 data sets, and each well only has one groundwater measurement.

Figure 2-2: (a) The spatial distribution of the wells and (b) the temporal distribution of the measurements in years for the Beryl-Enterprise aquifer in Utah.
One random sample for each well \((n=1)\) is an ideal data set to replicate the temporal data scarcity in Niger. However, in order to evaluate the impact of data frequency on the spread or uncertainty of the method results, we created three additional data sets where we randomly selected more than one sample per well. We decided to use 5, 15, and 30 random sample sizes \((n=5, 15, 30)\) and created 500 additional random sample data sets per sample size to analyze the variations of resulting estimated depletion rates.
3 METHODS

Our proposed method for dealing with data sets with one historical WTE per well is to group wells from a common geographic location represented by a “pseudo-well” at the centroid of the location. The WTE values for each of the wells associated with the pseudo-well are from a variety of dates, so we aggregate them into a single synthetic WTE time series as shown in Figure 3-1. These time series are then used to perform temporal imputation and then spatial interpolation to get time-varying WTE raster data sets and eventually time series of groundwater storage change for the aquifer. We used two methods to cluster the individual wells into groups: one method based on a uniform grid and another based on modified version of the K-Means clustering algorithm.

![Figure 3-1: A synthetic time series formed by aggregating WTE values from wells in the vicinity of a pseudo well.](image)

Figure 3-1: A synthetic time series formed by aggregating WTE values from wells in the vicinity of a pseudo well.
3.1 Grid Clustering

Our first approach of clustering individual wells employs a uniform grid as shown on the left side of Figure 3-1 and in Figure 3-2. We place a series of equally sized grid cells (black boundaries) over the extent of the individual wells in an aquifer. In each grid, the pseudo-well (red dot) was created at the centroid of the grid and the WTE values from the individual wells (blue dots) within the grid were aggregated to the pseudo-well to create the “synthetic” WTE time series. The theory behind this approach is that groundwater levels tend to be relatively uniform over a certain distance and local variations are acceptable as long as the overall groundwater storage change estimate is reasonably accurate.

An important consideration for this method is selecting the grid height or width. Grid size has a significant impact on the pseudo-wells and the resulting synthetic WTE time series. Larger grid size results in longer synthetic time series or more data points in the time series which gives an advantage in temporal interpolation of the WTE time series. On the other hand, larger grid size produces fewer pseudo-wells in the aquifer and it combines data from wells that may be separated by a substantial distance. Fewer pseudo wells results in a smaller data set to use in the spatial interpolation step. To determine the impact of grid resolution, we tested 0.05-degree and 0.1-degree square grids in the Beryl-Enterprise aquifer as shown in Figure 3-2. For Niger, we tested 0.25-degree grids in addition to 0.05-degree and 0.1-degree grids to compare the effects of different grid sizes in the groundwater storage change analysis.

Another consideration of the grid clustering method is the uneven number of the individual wells in each grid cell. The grid cells with fewer individual wells result in temporally shorter or more sporadic time series at the pseudo-well. Our temporal interpolation step requires
at least five unique WTE values per synthetic time series and therefore pseudo-wells with less than five individual wells are filtered out.

Figure 3-2: Well clusters and pseudo wells for the grid method with (a) 0.1-degree cells and (b) 0.05-degree cells.

3.2 K-Mean-Constrained Clustering

To overcome the issue of uneven numbers of the individual wells contributing to the pseudo-wells, we used a modified K-means clustering algorithm to set the minimum number of the individual wells to the pseudo-wells. A K-means algorithm iteratively partitions the data set into a user-defined number of distinct non-overlapping groups ($K$) where each data point belongs to only one group. The algorithm iteratively tries to minimize the sum of the squared distance between the data points and the cluster’s centroid until the assignment of the data points to the clusters no longer changes [41]. This algorithm may still result in an uneven number of data points.
points in each cluster and therefore does not fully resolve our issues of the grid clustering
method. To ensure a more uniform distribution of wells to clusters, we used a modified version
of the K-means algorithm from a Python library called k-means-constrained which is a modified
version of scikit-learn’s KMeans method whereby a minimum and/or maximum cluster member
size can be specified [42].

While a K-means clustering takes only a user input of $K$, the modified K-means
algorithm also takes the minimum size for each cluster and adjusts the number of clusters
accordingly. As a result, each pseudo-well at least has the specified number of individual wells.
After applying the k-means-constrained method we placed pseudo wells at the centroids of the
clusters and aggregated the WTE measurements from individual wells in each cluster to form
WTE time series as shown in Figure 3-3.

![Figure 3-3: Creating synthetic WTE time series using the k-means-constrained clustering
method.](image)

We tested a minimum cluster size of 13 and 25 wells for the Beryl-Enterprise aquifer and
28 and 14 clusters/pseudo-wells were created as shown in Figure 3-4. One advantage of this
method is because each pseudo-well has the minimum number of individual wells, the resulting synthetic WTE time series are more likely to exhibit a similar temporal data distribution. However, unlike the grid clustering method, the spatial size (area) of each cluster is different in this method. In regions where wells are sparser, the cluster must cover more area in order to include the minimum number of wells. On the other hand, in the area where the wells are densely located, this method creates clusters that are spatially smaller as shown in the middle and southern region of the Beryl-Enterprise aquifer in Figure 3-4.

Figure 3-4: Well clusters and pseudo wells for the k-means-constrained method with (a) 25 wells and (b) 50 wells.

3.3 Temporal Interpolation

After the wells were organized into clusters to create pseudo-wells and synthetic time series, at this point the pseudo-wells have WTE values at different dates as shown by the sample WTE vs time plots in Figure 3-5. To perform spatial interpolation and storage change analysis, it
is necessary to fit some kinds of trend line or curve to the WTE values to generate a synthetic WTE time series from which we can impute WTE values at the selected times.

Figure 3-5: The synthetic WTE time series at two pseudo wells with irregular time interval and length.

Prior to generating the synthetic time series for imputation, we identified outlier WTE values at each pseudo-well. Because the WTE values for each pseudo-well are derived from individual wells from various spatial locations and due to data errors, the pseudo-wells often had WTE values that seemed to be outliers. Thus, we removed WTE values at each pseudo-well that were outside of the 3rd standard deviation.
After removing outliers, we then fit a univariate spline curve to the WTE values at each pseudo-well using the Scipy univariate spline, which is a 1D smoothing spline [43]. This method fits a spline equation of degree $k$ ($k=1-5$) to the provided $x$ and $y$ data by specifying a smoothing condition. A smoothing factor $s$ is used to choose the number of knots, and this number is adjusted until the smoothing condition equation (3-1) is satisfactory.

$$\sum (y_i - sp(x_i))^2 \leq s$$  \hspace{1cm} (3-1)

We used the univariate spline because it generates a smooth curve that approximates the trend of the data points. The knot parameters were adjusted to 10,000,000 after visually inspecting the spline fit so that the fitted curves did not create an extreme overshoot and an undershoot. The fitted curve values were then resampled to at monthly intervals. Examples of the univariate spline curves are shown in Figure 3-6.

For time series that have a long gap between clusters of data points as shown in Figure 3-6 (b), the univariate spline will often result in an overshoot and/or an undershoot regardless of the knot parameters. To address this issue, we used the Piecewise Cubic Hermite Interpolating Polynomial (PCHIP) interpolation method [44] and resampled the time-series to a uniform monthly frequency. The PCHIP interpolation is often selected to interpolate and resample environmental data over other methods such as cubic splines or linear interpolation as it provides a continuous curve and does not exceed the local physical data bounds. In other words, the PCHIP interpolation does not create an overshoot or undershoot that commonly occurs with cubic splines. However, it goes through all the data points and the daily WTE values from individual wells can create wide oscillations in the interpolation. To resolve this, we averaged the WTE values at each pseudo-well to unique monthly values and then applied the PCHIP interpolation.
Figure 3-6: Temporal interpolation with the univariate spline that showed (a) a smooth fitted curve and (b) an extreme overshoot and undershoot.

Unique monthly data points still created extreme changes in the interpolated WTE values at some pseudo wells as shown in Figure 3-7. To smooth the overall WTE trend further, we applied a centered moving average with a 96-month window. We chose a 96-month window after testing 24, 36, and 96 month windows and visually inspecting the results.
At this point, we had generated both a univariate spline and a PCHIP moving average curve for each of the pseudo-wells. To automate the process of determining which method to use for each pseudo well, we interpolated both curves at a selected interval and calculated the difference between the maximum and the minimum of the interpolated values. The time series with lower maximum-minimum difference were selected to represent the synthetic WTE time-series at the pseudo-well as shown in Figure 3-8.

After the temporal interpolation process, the pseudo-wells have the WTE time series in every month but the time length of the WTE varies. The time length of the WTE time series at the pseudo-well starts from the oldest month to the latest month in which the individual wells had WTE values. To facilitate temporal interpolation over a common time range for all wells, the WTE values were extended forward and/or backward to the time duration of interest by using the first or last available values as shown in Figure 3-9.
Figure 3-8: The synthetic WTE time series at the pseudo well (a) when the univariate spline interpolation was selected and (b) when the PCHIP with the moving average interpolation was selected.
Figure 3-9: The matrix of the pseudo wells in columns and date in rows (a) before and (b) after the missing WTE cells are filled with the last available WTE value.
Spatial Interpolation with Kriging

After the temporal interpolation step, we have WTE data at the pseudo-well locations scattered throughout an aquifer available for every month. We can now use these point data to spatially interpolate WTE levels throughout the entire aquifer at any or all of the time step using kriging. To perform the kriging we used the used the GSTools Python package [45] and used the “stable” option for the model variogram. The model variogram is usually developed by first creating the experimental variogram from the point data set, and then a curve is fit either manually or using a covariance model. However, we needed a method to automatically construct the model variogram at each time interval in a loop. A model variogram requires a nugget, sill, and range. At each monthly time step in which the model variogram is created, we calculated the standard deviation of the WTE values in the time step and set it for the sill. The nugget and the range were fixed throughout all time steps, and we set one tenth of the diagonal length of the aquifer bounding box to the range and used zero for the nugget as shown in Figure 3-10.

![Model variogram created at each time step](image)

**Figure 3-10: Model variogram created at each time step**
The kriging interpolation was then carried out at a selected spatial resolution throughout the aquifer. We set the spatial resolution to be 0.1 degree for both latitude and longitude for both the Utah and Niger regions. The interpolation results were placed in a time-varying NetCDF raster grid [46].

### 3.5 Calculation of Aquifer Storage Change

Once the NetCDF rasters of water levels were generated, the final step is to calculate groundwater storage changes vs time. This is accomplished by performing mathematical operations on \( n \) series of raster data set layers \( R \) of WTE at specific times produced during the spatial interpolation. The first data set, which is corresponding to the earliest time step in the series of our interest, is known as \( R_0 \) and serves as the baseline from which changes in aquifer storage are measured. These changes are found by first calculating the drawdown \( D_i \) from the bases case for each time step in the raster series. The drawdown \( D_i \) is calculated on a cell-by-cell basis by applying Equation (3-2) for each of the \( n \) time steps, resulting in a new set of \( n - 1 \) raster data sets of drawdown.

\[
D_i = R_i - R_0
\]  

(3-2)

The aquifer-wide storage volume change was calculated for each time step by multiplying the aquifer-wide mean drawdown by the average aquifer storage coefficient \( p \) and the aquifer area \( A \). The aquifer area \( A \) was calculated by summing the areas of all grid cells in the aquifer \( A_j \). The area \( A_j \) is not constant for each grid cell over the data set, since the grids are defined at a specified latitude and longitude resolution. Each cell has constant height, but the cell width is dependent on the cell latitude. Cells closer to the equator will have larger widths than the one nearer the poles. The area of each grid cell \( A_r \) in the aquifer is calculated based on the
resolution of the grid $g$, the mean radius of the Earth $R$, and the latitude $\lambda_r$ of the center of each grid cell $j$ as shown in Equation (3-3).

$$A_j = R^2 \sin g \left| \sin \left( \frac{\lambda_j + \frac{g}{2}}{2} \right) - \sin \left( \frac{\lambda_j - \frac{g}{2}}{2} \right) \right|$$  \hspace{1cm} (3-3)$$

For the Niger data set that is in metric units, the mean radius of the Earth $R$ is set 6,371,000 meters [47]. The aquifer storage change is calculated in cubic kilometers (km$^3$), and also WTE and the drawdown $D_i$ were calculated in meters. For the Utah data set, the changes in aquifer storage volume were calculated in acre-feet, which is the volumetric unit used in prior studies of this aquifer by the other researchers. We use a mean Radius of the Earth $R$ of 3,959 miles. In this case, the result of Equation (3-3) is in square mile-ft, which is converted to acre-ft by multiplying by 640.
4 RESULTS

4.1 Utah

The objective of the Utah data set was to use a site with a known storage depletion curve to determine if the pseudo well technique can reasonably predict storage changes in regions with sparse data. To simulate a data-poor environment, we created a sample data set by randomly selecting a single WTE value from each well. We applied the three-step method: 1. temporal interpolation, 2. spatial interpolation, and 3. aquifer storage calculation, and computed the groundwater depletion curve and used the curve to derive an average depletion rate. The results were compared to the storage depletion rate reported by the Utah Division of Water Rights and by Evans et al. which are 66,000 acre-feet/year and 65,000 acre-feet/year in 2000 to 2012. We repeated this process 500 times for each method using a different set of randomly selected WTE values each time. In order to determine the impact of data scarcity on the variance in the results, we repeated the process by randomly selecting 5, 15, and 30 WTE values per well.

The two clustering methods, grid and k-means-constrained clustering, were used to create the synthetic WTE time series. For the grid clustering method, we created grids at 0.05- and 0.1-degree resolution and for the k-means clustering algorithm, we used minimum cluster sizes of 13 and 25 wells. As shown in Figure 3-2, the grid clustering method created 34 and 13 pseudo-wells after the pseudo-wells with less than 5 unique monthly measurements were filtered out. With the
k-means-constrained clustering method, the minimum cluster size of 13 wells and 25 wells resulted in 28 and 14 clusters (pseudo-wells) respectively as shown in Figure 3-4.

The average storage depletion rate over the designated time range was calculated and compared to the rate found by the other two studies. Table 4-1 and Figure 4-1 summarize the storage change rate calculation results. With the data set of one random sample size (n=1), the grid clustering with 0.1-degree square grids had the closest median estimated, but all medians were reasonably close to the target values. However, all the clustering methods resulted in a wide range of estimates. The storage depletion rate calculations with larger random sample size were also analyzed. In general, as the random sample size increases, the interquartile range gets smaller as shown in Figure 4-1.

### Table 4-1: Summary of storage depletion rate calculation statistics using 500 random data sets in each column in the table.

| Cluster Size | Grid 0.05x0.05 | Grid 0.05x0.05 | Grid 0.05x0.05 | Grid 0.05x0.05 | Grid 0.1x0.1 | Grid 0.1x0.1 | Grid 0.1x0.1 |
|--------------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|
|               | n=1            | n=5            | n=15           | n=30           | n=1            | n=5            | n=15           |
| Max           | -12,557        | -32,000        | -39,841        | -51,017        | 20,477         | -36,373        | -37,233        | 39,774         |
| Upper Quartile| -42,099        | -48,007        | -56,509        | -62,191        | -49,190        | -54,737        | -51,899        | -53,511        |
| Median        | -51,562        | -53,980        | -60,023        | -65,105        | -60,056        | -61,696        | -57,223        | -56,841        |
| Lower Quartile| -63,834        | -60,411        | -63,951        | -68,189        | -73,864        | -67,178        | -62,924        | -60,162        |
| Min           | -167,058       | -97,141        | -88,690        | -79,416        | -150,389       | -92,847        | -81,509        | -70,845        |
| Std           | 19,474         | 9,573          | 6,490          | 4,554          | 19,886         | 9,575          | 7,684          | 5,057          |

| Cluster Size | Cluster 25 Wells in Cluster n=1 | Cluster 25 Wells in Cluster n=15 | Cluster 25 Wells in Cluster n=30 | Cluster 50 Wells in Cluster n=1 | Cluster 50 Wells in Cluster n=15 | Cluster 50 Wells in Cluster n=30 |
|--------------|----------------------------------|----------------------------------|----------------------------------|---------------------------------|----------------------------------|----------------------------------|
| Max          | -20,676                          | -39,399                          | -52,760                          | -56,481                         | -11,651                          | -37,951                          | -40,656                         | -53,889                         |
| Upper Quartile| -45,637                          | -57,130                          | -64,390                          | -68,399                         | -44,551                          | -57,724                          | -64,978                          | -63,739                         |
| Median        | -56,943                          | -63,766                          | -68,105                          | -73,158                         | -55,558                          | -64,213                          | -69,720                          | -67,067                         |
| Lower Quartile| -71,974                          | -71,204                          | -72,681                          | -78,661                         | -69,275                          | -71,093                          | -75,141                          | -70,929                         |
| Min           | -169,959                         | -98,490                          | -106,574                         | -101,237                        | -145,149                         | -114,638                         | -111,425                         | -102,023                        |
| Std           | 19,841                           | 9,863                            | 6,998                            | 7,864                           | 20,636                           | 11,657                           | 8,298                            | 5,534                           |

Unit: Acre-Feet/Year
4.2 Niger

After testing the pseudo well method using the Utah data, we analyzed the Niger data and calculated the groundwater storage change over time. The groundwater storage change results were then compared to the Groundwater Storage Anomaly (GWSa) found using GRACE data via the GGST application.

4.2.1 Storage Change Analysis with Grid Clustering

The uniform grid clustering with 0.05-degree square grids created sparse spatial distribution of the pseudo-wells as displayed in Figure 4-2 (a). This is mainly due to the limited spatial coverage of each grid that the grid did not have more than five unique monthly time-series observations that we set as a filtration parameter. The storage change showed a slight upward trend from 2002 to 2004 and followed by the downward trend to 2010 with 5 cm liquid
water equivalent (LWE) thickness loss shown in Figure 4-2 (b). However, the storage change result is not a good representation of the aquifer state because 1. spatial interpolation relies on the temporally sporadic pseudo-wells and 2. the temporal interpolation created wide oscillation in the synthetic WTE as shown in Figure 4-2 (c).

![Graphs and images showing spatial distribution of pseudo-wells and groundwater storage change comparison](image)

**Figure 4-2:** Using 0.05-degree square grid clustering, (a) Spatial distribution of the pseudo wells, (b) groundwater storage change comparison against the GGST GWSa, and (c) synthetic WTE time series of each pseudo well

The grid size was changed to 0.1 degree and the clustering was performed. The pseudo-wells were more spatially distributed as shown in Figure 4-3 (a) compared to the pseudo-wells created by the 0.05-degree grid. The number of the pseudo-wells remaining in the aquifer with 0.1-degree grids increased to 217 from 106 though the total number of cells created by the grid clustering method decreased with increased grid size because fewer cells were eliminated for
having fewer than 5 WTE values. The storage change trend showed an upward trend from 1992 to 2002 and a downward trend from 2002 but are relatively flat in the range between -5 cm to 0 cm LWE (Figure 4-3 (b))

Figure 4-3: Using 0.1-degree square grid clustering, (a) Spatial distribution of the pseudo wells, (b) groundwater storage change comparison against the GGST GWSa, and (c) synthetic WTE time series of each pseudo well

Using a grid cell size of 0.25-degrees created more evenly spatially distributed pseudo wells as shown in Figure 4-4 (a). Despite an improvement in the spatial distribution of the pseudo wells, the groundwater storage change shown in Figure 4-4 (b) follows a similar pattern as the result from the 0.1-degree grid clustering with a steeper downward trend after 2004.
4.2.2 Storage Change Analysis with K-Means-Constrained Clustering

The storage trends calculated with the k-means-constrained clustering with 13 and 25 cluster sizes were analyzed. The clusters with 13 minimums wells created 166 pseudo-wells in the aquifer as shown in Figure 4-5 (a). The spatial distribution of the pseudo-wells is highly dense in the aquifer, and the trend follows a similar pattern of the other trends from the grid clustering methods.
Figure 4-5: Using the k-means-constrained clustering with 13 minimum cluster size, (a) Spatial distribution of the pseudo wells, (b) groundwater storage change comparison against GRACE GWSa, and (c) synthetic WTE time series of each pseudo well

The minimum cluster size of 25 wells created 83 pseudo-wells and the distribution of the pseudo-well is more sporadic in the northern region as shown in Figure 4-6. (a). The storage change shows an upward trend from 1992 to 2002 followed by a downward trend from 2002 shown in Figure 4-6 (b). The trend also follows a similar pattern of the other trends from the grid clustering methods.
Figure 4-6: Using the k-means-constrained clustering with 25 minimum cluster size, (a) Spatial distribution of the pseudo wells, (b) groundwater storage change comparison against GRACE GWSa, and (c) synthetic WTE time series of each pseudo well
5 DISCUSSION

The results from the Beryl-Enterprise aquifer in Utah demonstrated that the pseudo well method with one measurement per well successfully created synthetic WTE time series which then can be used to calculate the aquifer storage change over time. The statistics from the 500 random sample data sets showed that the median estimates were reasonably close to the depletion rate reported by the Utah Division of Water Rights and Evans at et al. However, the results indicated a high degree of variance.

We then analyzed the groundwater storage change in Southern Niger where each well only had one groundwater elevation measurement. Our methods with the grid and k-means-constrained clustering had similar aquifer storage change results which the groundwater storage increases until 2002 and decreases from 2002, and all the methods showed the right magnitude of the groundwater storage change in volume.

Although the groundwater storage trends from our methods did not match with the trend derived from GRACE for the range in time that the data sets overlapped, there are a number of possible explanations for this discrepancy. One issue could be the well-documented “leakage” effect often encountered when applying GRACE data to relatively small regions such as the one used in this study. The native GRACE grid cells are 3 x 3 degrees and the GRACE cells that overlap the region being analyzed extend over into adjacent regions, skewing the results. Our study regions may have experienced a decrease in groundwater storage as shown by our
methods, but neighboring regions may have experienced gradual increase in the storage over
time. Another possible explanation is that many of the wells used in this study were shallow
while the GRACE results measure storage change at a deeper level. Finally, another source of
uncertainty is quality of Niger’s well inventory, especially in the date columns. We determined
that the date when the well was rehabilitated corresponded to the groundwater elevation
measurement if there are multiple date values in the well inventory. If the wells were not
resampled when rehabilitated and if the water table was going up, a low WTE value from an
earlier date when the well was constructed would have been artificially shifted to the later date,
potentially contributing to a downward trend of the groundwater as opposed to the actual upward
trend.
6 CONCLUSIONS

In this research, we developed a method to characterize groundwater resources with extremely sparse in-situ data, in which there was only one groundwater elevation measurement per well. The methods were shown to yield a reasonably accurate estimate but also carry a high level of uncertainty.

Various data imputation methods have developed for temporally sparse groundwater table measurements; however, most of the techniques still require a handful of in-situ measurements to apply regressions or machine learning techniques. Using GRACE data, water managers can analyze the groundwater storage changes without in-situ data; however, the spatial resolution is limited and only large aquifers can be analyzed; furthermore, the data is only available from 2002. With our method, water managers can use well data which may containing as little as one historical groundwater measurement and analyze long-term groundwater storage change in small aquifers before and after 2002. Our method can be an additional tool for water managers to characterize the groundwater storage change over time where in-situ data is highly limited as is frequently the case in developing countries.
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