01 Apr 2023

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Recommended Citation

R. G. Smith et al., "Estimating Aquifer System Storage Loss with Water Levels, Pumping and InSAR Data in the Parowan Valley, Utah," *Water Resources Research*, vol. 59, no. 4, article no. e2022WR034095, Wiley; American Geophysical Union, Apr 2023.
The definitive version is available at https://doi.org/10.1029/2022WR034095

AGU ADVANCING EARTH AND SPACE SCIENCE

Water Resources Research

RESEARCH ARTICLE
10.1029/2022WR034095

Special Section:
Hydrogeodesy: Understanding changes in water resources using space geodetic observations

Estimating Aquifer System Storage Loss With Water Levels, Pumping and InSAR Data in the Parowan Valley, Utah

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Key Points:

- New method developed to estimate groundwater storage loss using InSAR, groundwater-level and pumping data
- Fine-grained layers account for most aquifer storage loss in confined aquifers
- Water lost from fine-grained layers is a significant but unsustainable source of water for confined aquifers

Supporting Information:

Supporting Information may be found in the online version of this article.

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Citation:

Smith, R., Li, J., Grote, K., & Butler, J. (2023). Estimating aquifer system storage loss with water levels, pumping and InSAR data in the Parowan Valley, Utah. *Water Resources Research*, *59*, e2022WR034095. https://doi.org/10.1029/2022WR034095

Received 10 NOV 2022
Accepted 29 MAR 2023

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Conceptualization: Ryan Smith, Katherine Grote, Jim Butler
Data curation: Ryan Smith, Jiawei Li
Formal analysis: Ryan Smith, Katherine Grote, Jim Butler
Funding acquisition: Ryan Smith
Investigation: Katherine Grote, Jim Butler
Methodology: Ryan Smith

Abstract

In the Parowan Valley of Utah, groundwater levels have declined by as much as 30 m over the past 50 years with accompanying subsidence rates of up to 5 cm/year. Traditional methods to estimate groundwater storage change use a combination of groundwater level and storativity estimates, but there is often considerable uncertainty in these. In this study, we demonstrate a new method that relies on a combination of geodetic data from InSAR, as well as groundwater level and pumping data, to estimate both the total groundwater storage loss and the percentages of storage loss in fine- and coarse-grained layers within an aquifer system. We find that when aggregated over all of Parowan Valley, fine- and coarse-grained layers account for roughly equal portions of the total groundwater storage loss. However, in confined aquifers, fine-grained layers account for most of the storage loss. This has important implications on the source of groundwater in depleting aquifer systems, as many models do not account for fine-grained layers as a source of water. We find that in the Parowan Valley, the aquifer depletion is roughly 12.5% of the volume of pumped groundwater, meaning that the remainder of pumped groundwater is sourced from net inflow. This study presents the first method that combines geodetic and in situ groundwater data to provide estimates of groundwater storage change that account for both coarse- and fine-grained intervals, which are typically present in significant amounts in the major unconsolidated aquifer systems of the world.

Plain Language Summary

As surface water becomes more scarce, groundwater represents an important source of freshwater. However, it is being depleted in many basins of the western US and world. The Parowan Valley, in southwest Utah, has seen groundwater levels decline by as much as 30 m over the past 50 years. This has resulted in subsidence rates of up to 5 cm/year. Monitoring groundwater storage loss is critical for implementing sustainable groundwater management plans. Subsidence can be measured with a satellite data set called InSAR (Interferometric Synthetic Aperture Radar) with high accuracy. This can then be coupled with ground-based measurements to improve our understanding of groundwater storage loss. We implement this method in the Parowan Valley, and find that roughly half of the estimated groundwater storage loss comes from consolidation of fine-grained materials within the aquifer, which are typically ignored in groundwater budgets. We also find that groundwater depletion is roughly 12.5% of the volume of pumped groundwater, meaning that if pumping were reduced by that amount, depletion of groundwater would likely cease. However, changing recharge and inflow of groundwater could result in renewed depletion in the future (5–10 years), and re-assessing the water budget regularly is crucial for effective management.

1. Introduction

Water resources are being stressed globally as population growth, land use transitions and climate change combine to increase demand for often scarce water supplies (Margat & Van der Gun, 2013). Groundwater basins across the globe are being depleted as a result of these trends. In the western United States, many groundwater basins that have been over-exploited for decades are beginning to see restrictions on groundwater withdrawals (Babbit et al., 2018). One of the primary objectives in reducing withdrawals is to reach a level of withdrawals that does not result in further depletion of the aquifer system.

To implement solutions that achieve this goal, the relationship between groundwater withdrawals and groundwater storage loss must be known. While many methods exist to estimate storage change in aquifers (Konikow, 2013), there is significant uncertainty in traditional storage change estimates. The traditional approach for estimating the groundwater storage change, ΔGWS, is given by:

Resources: Ryan Smith
Software: Ryan Smith
Validation: Ryan Smith
Visualization: Ryan Smith
Writing – original draft: Ryan Smith
Writing – review & editing: Ryan Smith, Katherine Grote, Jim Butler

$$\Delta \mathrm{GWS} = S \Delta h A, \tag{1}$$

where Δh is the change in head [L], A is the area experiencing a given change in head [L^2], S is the storativity [unitless], given in confined aquifers by $S_s b$, where S_s is the specific storage [L^{-1}] and b is the thickness of the aquifer [L]. While this equation is well-established, there is much uncertainty in these parameters. Thus, in practice, estimates using this approach have a high degree of uncertainty except in regions with extensive hydrogeologic data.

Butler et al. (2016) developed an approach to estimate change in groundwater storage using total yearly groundwater withdrawals and average annual change in groundwater levels over a specified region. The advantage of this approach is that it can be used to estimate bulk aquifer storativity that is representative of a large region from known groundwater fluxes (withdrawals) and water-level changes. In this paper, we describe that method as the water balance approach.

Most methods for estimating changes in groundwater storage, including the water balance approach described above, have a strong bias for changes in storage within coarse-grained intervals, while a significant amount of the total storage change occurs within clay layers. The schematic shown in Figure 1 represents a hypothetical unconsolidated sedimentary aquifer with interbedded sands and clays. Most wells are perforated in the most permeable (typically coarse-grained) portions of the aquifer; most well measurements thus represent the head in the coarse-grained portions of the aquifer system. Furthermore, estimates of S_s used in Equation 1 typically are taken for coarse-grained materials, which have S_s values one to two orders of magnitude lower than clays (Riley, 1969; Sneed, 2001).

We refer to the coarse-grained sands and gravels within an aquifer system, which can include both confined and unconfined aquifers, as the primary aquifer, and the whole aquifer system as the entire vertical profile containing clays, sands and gravels. In this study, we estimate the relative contributions of the primary aquifer and clay layers to total aquifer system storage change. We do this with a combination of an in situ, water-level based method (water balance approach), which is used to estimate storage change in the primary aquifer, and a deformation-based approach, which is used to estimate storage change in clay layers. The water balance approach produces an estimate of storage loss that is aggregated over both confined and unconfined "primary" aquifers. We validate the results with water-level and storativity estimates derived from the literature, which also allows us to spatially disaggregate the storage change estimates. Our results show that in the confined aquifer system of our study area, most storage loss occurred in clays, while in the unconfined aquifer portion, most storage loss occurred in sands. These results highlight the need to account for clay storage, particularly in confined aquifers.

2. Study Area

The Parowan Valley is an agricultural region, roughly 360 km^2 in area, in southwest Utah. The valley has a thick (up to 600 m) package of water-bearing unconsolidated sediments beneath it. Figure 2 shows the study area, as well as the watershed surrounding it. The catchment area includes mountains to the southeast and northeast, as well as highlands to the northwest, and drains toward the Little Salt Lake, a dry lakebed/playa. Historically, water flowed from the Little Salt Lake through the Parowan Gap, but interception of water for irrigation from the streams that flowed into the Little Salt Lake reduced flow into or out of the lake. The valley is now a closed basin, with all surface water infiltrating, evaporating, or ultimately reaching the Little Salt Lake. The Parowan Valley has extensive fine-grained layers, resulting in confined conditions over the majority of the aquifer system (Li et al., 2023; Marston, 2017). Groundwater is the primary source of irrigation water in the valley, and extensive pumping for roughly 50 years has dramatically lowered the potentiometric surface (Marston, 2017), resulting in widespread land subsidence (R. Smith & Li, 2021).

3. Methods

We make use of a combination of geodetic data sets from InSAR, in situ measurements of groundwater levels, and estimates of groundwater withdrawals. The description of the InSAR processing methods is given in Section 3.1. These data sets are used to estimate the change in groundwater storage in the primary aquifer and in the fine-grained intervals using a data-driven approach (Section 3.2), and a storativity-based validation (Section 3.3).

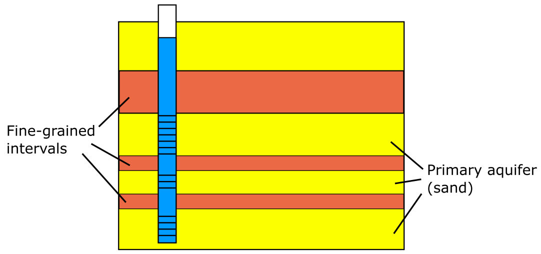

Figure 1. Schematic of aquifer system. The horizontal lines within the well indicate the well screens, which are usually located within the coarse-grained portions of the aquifer.

3.1. InSAR Processing

The InSAR data were processed using the approach described in R. Smith and Li (2021). To cover the entire Parowan Valley from 29 Nov. 2014, to 27 Dec. 2020, a total of 155 SAR scenes acquired by the Sentinal-1A satellite, descending along path 100, frames 464 and 465 with an average latency (time between acquisitions) of 12 days were downloaded from the Alaska Satellite Facility (ASF). Table S4 shows a list of all SAR images used in our processing workflow. Interferogram generation, topography correction, geocoding, unwrapping and small baseline subset (SBAS) were done using the GMTSAR package (Sandwell et al., 2011). Interferogram pairs were selected from scene pairs with less than 50 day temporal baseline (time between acquisitions) and less than 100 m perpendicular baseline (perpendicular distance between repeat orbital tracks), resulting in a total of 404 interferograms. Signals from pixels with a spatial coherence of less than 0.1 were considered noise and masked out. Coherent pixels were then interpolated using the nearest neighbor algorithm. Times series of deformation were derived from these interferograms using the SBAS method (Berardino et al., 2002; Lanari et al., 2004). The deformation result was converted from line-of-sight (LOS) direction to the vertical direction by dividing the deformation value by the cosine of the incidence angle. This approach assumes horizontal deformation is low, which was corroborated by comparing LOS velocities in ascending and descending tracks. The tropospheric noise was corrected by removing the signal of the reference point set in the city of Parowan, which has a similar tropospheric pattern to the rest of the valley, and where little to no deformation occurred during the research time period (R. Smith & Li, 2021). The resulting subsidence rate over the period of this study is shown in Figure 3.

3.2. Estimating Change in Storage With Head, Pumping, and InSAR Data

3.2.1. Estimating Primary Aquifer Storage Change With the Water Balance Approach

The premise of the water balance approach is that groundwater levels and withdrawals over large regions will be linearly correlated if certain assumptions hold. The primary assumptions are that the storativity of the aquifer and net inflow, defined as the difference between total inflow and total outflow minus pumping, do not change significantly over time. Net inflow can also be described as the sum of recharge, groundwater inflow and natural groundwater discharge. A schematic showing these different water balance components is shown in Figure 4. These assumptions tend to hold in many regions (Butler et al., 2016), and the water balance approach has been used successfully to both estimate changes in groundwater storage and determine the reduction in withdrawals necessary to halt groundwater storage loss over the short to moderate term (Butler et al., 2023).

With this relationship in mind, groundwater withdrawals for each year are plotted on the x axis, and changes in groundwater levels are plotted on the y axis. The best-fit line can be used to estimate the storage parameter as well as the net inflow into the aquifer (Butler et al., 2016, 2023). The net inflow is estimated as the value of withdrawals at which the average annual change in groundwater levels is 0, or the negative intercept of the best-fit line divided by its slope. As this approach relies on groundwater levels taken within primarily coarse-grained intervals to estimate the storage change from the change in groundwater levels, it is primarily sensitive to changes in storage within the coarse-grained units, and any long-term (greater than 1 year) flux into those units (including flux from clays that are located within the vertical profile of the aquifer system) are considered net inflow to the aquifer. Thus, storage change estimated using this method does not account for storage

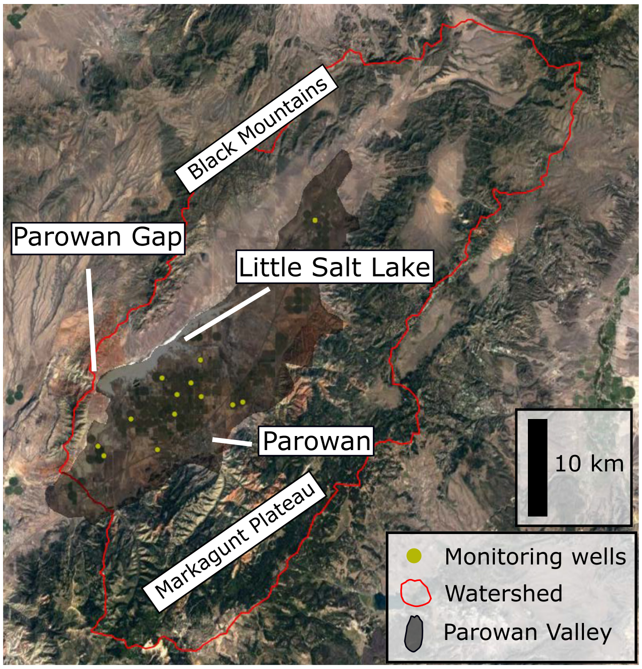

Figure 2. Overview of the Parowan Valley. The valley portion, outlined in gray, is relatively flat with an elevation of ~1,740 m, and surrounded by the Markagunt Plateau on the southeast, which reaches an altitude of ~3,300 m on the southeast edge of the watershed, and the Black Mountains on the north, which reach an elevation of ~2,200 m on the north edge of the watershed.

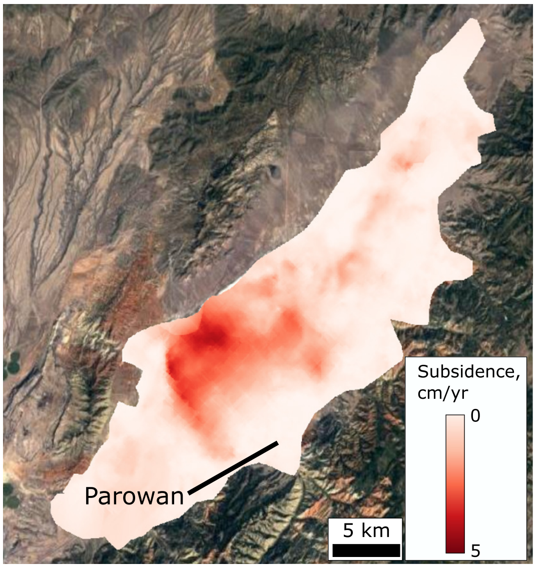

Figure 3. Subsidence rate (cm/year) from 2014 to 2020 in Parowan Valley, as estimated from InSAR data.

loss in fine-grained units, which can be significant in confined and unconfined aquifers. The former is often accompanied by measurable subsidence, while the latter often is not, with some exceptions (Bouwer, 1977; Leake & Galloway, 2007), because the pore pressure decline is typically much lower.

We used the approach described above in Parowan Valley to estimate storage change in the primary aquifer. Groundwater withdrawal data were used from Marston (2017), who compiled USGS estimates of withdrawals over Parowan Valley from 1994 to 2013. These estimates were derived from energy consumption records that were calibrated to groundwater withdrawals measured at specific wells. Since the calibration parameters changed over time, the USGS made visits roughly every 3 years from 1997 to 2008 to re-calibrate their water use model. After 2008, no site visits were made until 2013, when 86 wells in the valley were calibrated to power consumption records using instantaneous flow measurements from an ultrasonic flowmeter. The power consumption coefficients produced from this were used to estimate groundwater withdrawals, which were then compared to total withdrawals measured with totalizing flowmeters at 13 wells. The power consumption estimates compared well with totalizing flowmeter data, with an r^2 of 0.91. For this reason, we consider the water use estimates from 1997 to 2008 to be reasonably accurate and 2013 to be the most accurate. There are still likely some inaccuracies in the years 1997–2008, as the calibration was not done every year during this time period (Marston, 2017).

Groundwater level (head) data were taken from available USGS wells (Table S1 in Supporting Information S1). We only used wells that had annual spring water level measurements taken every year of our available withdrawal data (1997–2008, 2013), which left us with 14 wells. While the magnitude of change in groundwater levels varied spatially, generally years with higher water demand due to a combination of lower snowpack and lower spring and growing-season precipitation showed decreasing groundwater levels, while the opposite was observed during years of low water demand.

To demonstrate the relationship between climate and water demand, and to identify potential data outliers, we estimated both change in head and withdrawals as a function of growing-season precipitation, spring precipitation and maximum seasonal snowpack. Growing-season precipitation from 1 May to 1 September was estimated for

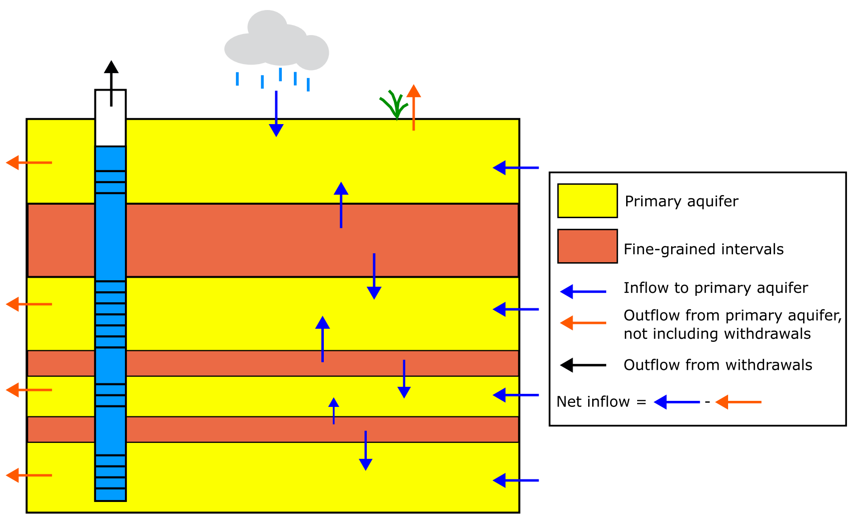

Figure 4. Schematic showing the various components of the water budget relative to the primary aquifer. Net inflow as defined here comprises the sum of all fluxes entering the primary aquifer, less the sum of all fluxes except withdrawals leaving the primary aquifer. When the change in head in the primary aquifer is 0, there is no change in storage, so net inflow is equal to withdrawals.

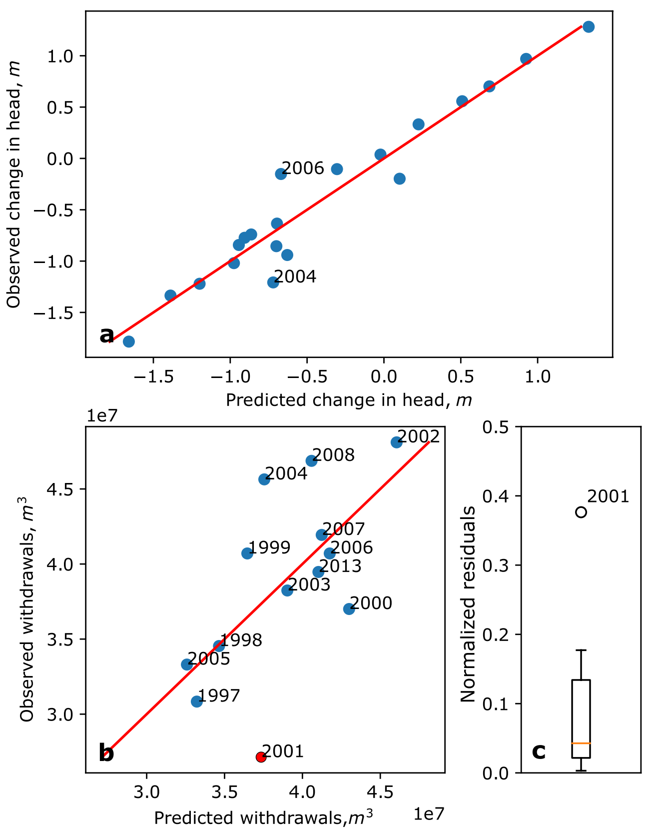

Figure 5. Fit of multivariate linear predictions of (a) average basin change in head, (b) withdrawals for years with calibrated withdrawal data, and (c) normalized residuals from predicted and observed (from Marston (2017)) withdrawals. Predictors in both multivariate regressions were growing-season precipitation, spring precipitation, and maximum annual snowpack.

each year from PRISM (Daly et al., 1997); spring precipitation (1 March–1 May) was taken from the same data set; and maximum seasonal snowpack was taken from the Midway Valley SNOTEL site (https://wcc.sc.egov.usda.gov/nwcc/site?sitenum=626). We used these as predictor variables in two linear predictions, one estimating change in head, averaged over the basin from the 14 wells described earlier (Figure 5a) and one estimating groundwater withdrawals (Figure 5b).

Change in head had a strong positive relationship, as indicated by positive t-values and low to moderately low p-values, with growing-season precipitation, spring precipitation, and maximum seasonal snowpack. The spring precipitation has a p-value of 0.06, which is slightly above the typical 0.05 threshold, but is still relatively low. The coefficients, t-values and p-values are shown in Supporting Information S1 (Table S2). Since each of the explanatory variables represents a positive water flux, the strong positive correlation demonstrates that periods of higher surface water availability result in higher groundwater levels, due to some combination of a reduction in groundwater demand and an increase in recharge. The linear regression predicting change in head had no obvious outliers and resulted in an r^2 of 0.93. These results give us confidence in the yearly head estimates.

The coefficients, p-values and t-values for the model estimating groundwater withdrawals are shown in Supporting Information S1 (Table S3). Groundwater withdrawals had a negative relationship with growing-season precipitation, spring precipitation and maximum seasonal snowpack, likely for the same reasons as described in the previous paragraph. While there were no clear outliers in the change in head data set, the withdrawal predictions had a clear outlier in 2001. The year 2001 had a very low observed discharge, but a low snowpack, as well as low spring and growing-season precipitation, all of which are expected to cause a higher discharge. The box plot shown in Figure 5c demonstrates that the normalized residual (divided by observed withdrawals) of predicted and observed withdrawals for 2001 was well above the whisker threshold indicating outliers. This established 2001 as a clear outlier, and it was removed from the data set. After removing 2001, the r^2 changed from 0.41 to 0.53. While this is an improvement, it shows that climate factors only explain 53% of the variance in groundwater withdrawals while Figure 5a and the statistics accompanying it indicate that it should be much higher, a likely sign that there is significant uncertainty in the groundwater withdrawal data set. Because of the poor model fit, p-values for all climate predictors are not sufficiently low to indicate statistical significance in the climate predictors.

With an understanding of relationships between climate and water demand, we return to the analysis of change in groundwater storage within the primary aquifer. To evaluate the water balance, we plotted observed values for total groundwater withdrawals against average annual water-level change in the Parowan Valley (Figure 6). We removed 2001, which appears as a clear outlier in this plot as well, based on our earlier analysis. The strong linear trend in Figure 6 indicates that the Butler et al. (2016) approach can be used to estimate the aquifer storativity, $S_{aq} = \frac{-1}{A \times m}$, where A is the areal extent of the aquifer (same as A in Equation 1), and m is the slope of the best-fit line produced by the linear regression (black line). The storativity and areal extent of the aquifer can then be used with the change in head to estimate change in primary aquifer storage, $\Delta S = S_{aq} \times \Delta h \times A$. The storage change estimated by this approach is given in Figure 8.

While removing the year 2001 from our analysis reduced some of the noise in our data, there is still significant uncertainty in the withdrawal estimates. Notably, the years 2000 and 2003 have much greater water level decline than expected based on their estimated withdrawals. We used a bootstrapping approach that quantifies the uncertainty in our S_{aq} estimates introduced by uncertainty in groundwater withdrawal estimates and produces a range of possible S_{aq} values. The bootstrapping method was performed by sampling (with replacement) 30 value pairs from our data set of total annual discharge and average annual water level change, estimating the slope and

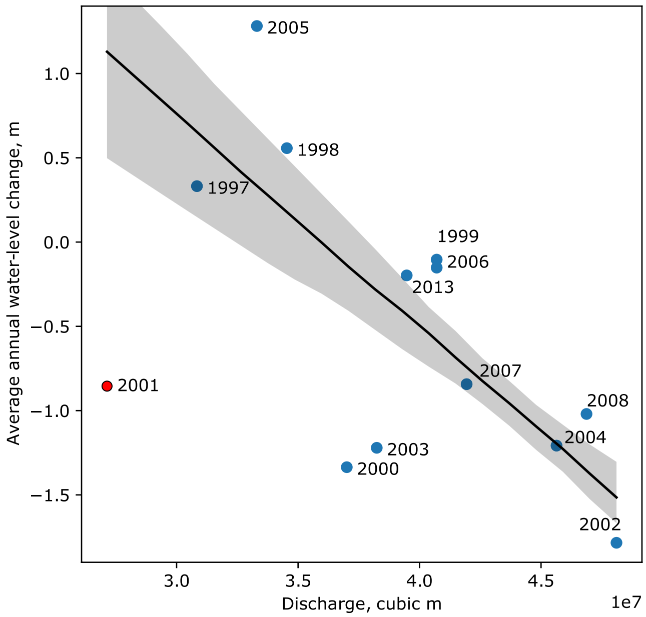

Figure 6. Total discharge (pumping) plotted against average annual water-level change in Parowan Valley, with 2001 outlier shown in red; best-fit line shown after removing 2001, 5th and 95th percentiles of bootstrap regression analysis shown as a shaded Gy bar. The 5th, 50th, and 95th percentiles of S_{aq} estimates produced in the bootstrap analysis were 0.018, 0.022, and 0.30, respectively.

intercept of the best-fit line using linear regression, and iterating the process. We iterated a total of 100 times, producing 100 estimates of slope and intercept. The 5th and 95th percentiles of data produced from these slopes and intercepts are shown as the shaded gray region in Figure 6. These ranges of values were then used to estimate a range of possible primary aquifer storage changes. The 5th, 50th, and 95th percentiles of S_{aq} estimates produced in the bootstrap analysis were 0.018, 0.022, and 0.30, respectively.

As noted previously, the years 2000 and 2003 appeared to potentially have anomalous withdrawal data. To understand their influence on primary aquifer storage change estimates, we performed a test in which we removed them from the storage change analysis. If these years are removed from the climate-based multivariate linear regression, the resulting discharge estimates have an overall improved fit, with an r^2 of 0.84, compared with an r^2 of 0.54 when those years are not held out (Figure S1a in Supporting Information S1). The resulting storage change estimates are shown in Supporting Information S1 (Figure S1b). Although it is possible that removing years 2000 and 2003 would be justified, they were not identified as outliers in our climate-based analysis (Figure 5c), and removing them does not significantly change the results of aquifer storage change (Figure S1b in Supporting Information S1). For this reason, we choose not to remove them for our analysis.

3.2.2. Estimating Fine-Grained Storage Change With InSAR Data

While in situ water level and discharge measurements are crucial for estimating the water balance, additional insights can be gained from integrating these with remotely sensed and modeled estimates of storage change in fine-grained units. Here, we relate modeled deformation data that were calibrated with InSAR data to primary aquifer storage change estimates produced using the methods in Section 3.2.1.

R. Smith and Li (2021) produced an estimate of deformation across Parowan Valley derived from a process-based model of deformation from 1984 to 2020 at one location in Parowan Valley. This model is representative of the region with the most subsidence in the valley. We also have a regional map of average long-term subsidence over the entire valley from 2014 to 2020 produced from InSAR, and shown in Figure 3 (Li et al., 2023; R. Smith & Li, 2021). We calculated a scaling factor to extend our point-based estimate of subsidence to valley-wide subsidence from 2004 to 2020. We chose to exclude the first 20 years of our deformation model because the model was calibrated to data from 2014 to 2020, and the model spin-up period is likely less accurate due to the delayed response in fine-grained layers to changes in head within aquifers (i.e., Lees et al., 2022; R. Smith & Knight, 2019). The scaling factor was determined as the ratio of average yearly subsidence from 2014 to 2020 across the entire valley to the average yearly subsidence at the location with the modeled point-based estimates. This ratio was then multiplied by the modeled annual point-based subsidence for each year of our study period. The basic assumption is that as annual subsidence at our point-based location varies, the valley-wide subsidence also varies. Since groundwater levels, which drive the subsidence signal, are correlated across the valley and strongly tied to local climate variations (Figure 5a), and because the location of drawdown, which is closely tied to the location of withdrawals, has not changed significantly since 1970 (Marston, 2017) we consider this a reasonable assumption.

Long-term subsidence signals are typically dominated by deformation in fine-grained units, because fine-grained units are one to two orders of magnitude more compressible than coarse-grained units, and deform inelastically much more readily (Riley, 1998). Thus, deformation at annual and longer time scales typically represents loss of storage from fine-grained units (R. G. Smith & Majumdar, 2020), and we can use our estimate of valley-wide deformation to approximate loss of storage from fine-grained units within the aquifer system.

As water flows out of clay layers, it flows into the coarse-grained intervals, representing a positive flux in storage for the primary aquifer. Given the time it takes for clays to release the water, the Butler et al. (2016) approach considers this flux to be part of net inflow as defined in Section 3.2.1. Thus, the storage loss in fine-grained units

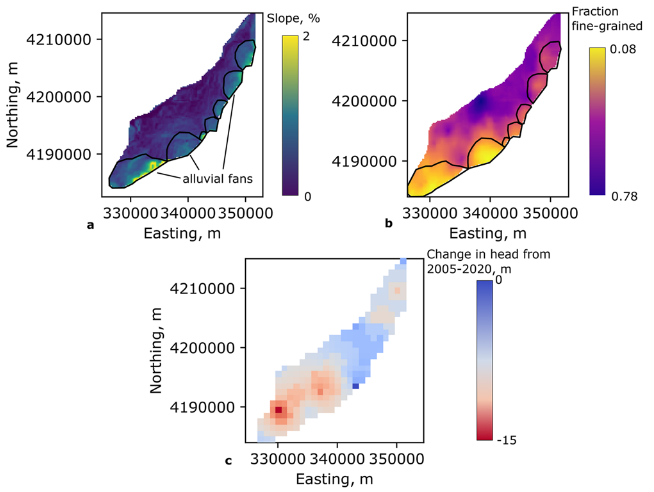

Figure 7. (a) Map of slope compared with delineated alluvial fans, (b) map of fraction fine-grained material from Li et al. (2023) compared with delineated alluvial fans, and (c) total change in head interpolated from 14 wells (locations in Figure 2 and Table S1 in Supporting Information S1) from 2005 to 2020, in *m*.

is not accounted for in the primary aquifer storage change calculated based on groundwater withdrawal estimates. Estimation of the total storage change in the aquifer system (including both the primary aquifer and the fine-grained units) requires summing the storage change from the fine-grained units and the primary aquifer.

3.3. Validation of Storage Change With Head and Storativity Estimates

While the approach outlined in Section 3.2.1 has been implemented successfully in studies of the High Plains aquifer (Butler et al., 2016, 2023), here we use a traditional approach to validate the estimates produced in that section. The traditional approach relies on spatially distributed estimates of changes in head, Δh, and storativity, S, and computing the change in storage using Equation 1. While this approach is well-established, its uncertainty is high due to uncertainty in the spatial distribution of both S and Δh. We also note that this approach, like that used in Section 3.2.1, produces estimates of storage change within the coarse-grained intervals of the aquifer. To implement this validation in our study area, we produced interpolated grids of change in head for each year from 2004 to 2021 using ordinary kriging with an exponential variogram. We used the same set of wells as for our previous analyses (locations shown in Figure 2 and Table S1 in Supporting Information S1). We summed the change in head for each year to estimate the total change in head over that time period.

To estimate the storativity of the primary aquifer, we first divided the aquifer spatially into two distinct regions: alluvial fans, which are found near the foothills of the southeast portion of the valley, and which we consider to be unconfined, and the valley portion of the aquifer, which we consider to be confined. The justification for this approach is guided by both conceptual understanding of depositional environments and available data on confining conditions of the aquifer. Bjorklund et al. (1978) performed multiple aquifer tests in the valley portion of the aquifer. These aquifer tests resulted in storativity estimates that ranged from 7×10^{-5} to 0.02, with a geometric mean of 1×10^{-3}. The geometric mean of these values is within the range of typical storativities in confined aquifers. Marston (2017) also indicated that most of the valley was a confined system.

Li et al. (2023) computed the fraction of material that is fine-grained in over 200 wells in the Parowan Valley, and interpolated these estimates throughout the valley to produce a map of fraction of fine-grained material. While the valley itself was mapped to have extensive (50% or higher) fractions of fine-grained material, alluvial fans were mapped to have very few fine-grained deposits, which is expected based on their high-energy depositional environment. We thus assume that these regions do not have extensive confining layers and are unconfined. Since the map of fine-grained deposits from Li et al. (2023) had a limited number of wells in some regions, we used a combination of their map and a map of slope derived from the Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) over the region to map the presence of alluvial fans, and delineated these zones as unconfined. All other regions were considered to be confined. Figures 7a and 7b show the delineated alluvial fans compared with slope and fraction of fine-grained material, respectively, and Figure 7c shows the map of total change in head from 2005 to 2020, in *m*.

The storativity for the confined aquifer was taken from the geometric mean of the estimates of Bjorklund et al. (1978), 1×10^{-3}. No aquifer tests over the unconfined aquifer were available, so we used the specific yield estimate from the model of Brooks (2017), who calibrated a groundwater model over the Parowan Valley and estimated the specific yield to be 0.07.

4. Results and Discussion

Here we evaluate the storage change estimates from the approaches described in Sections 3.2 and 3.3, as well as model-derived storage change estimates from Brooks (2017), then discuss the implications of these results on groundwater budgets and models.

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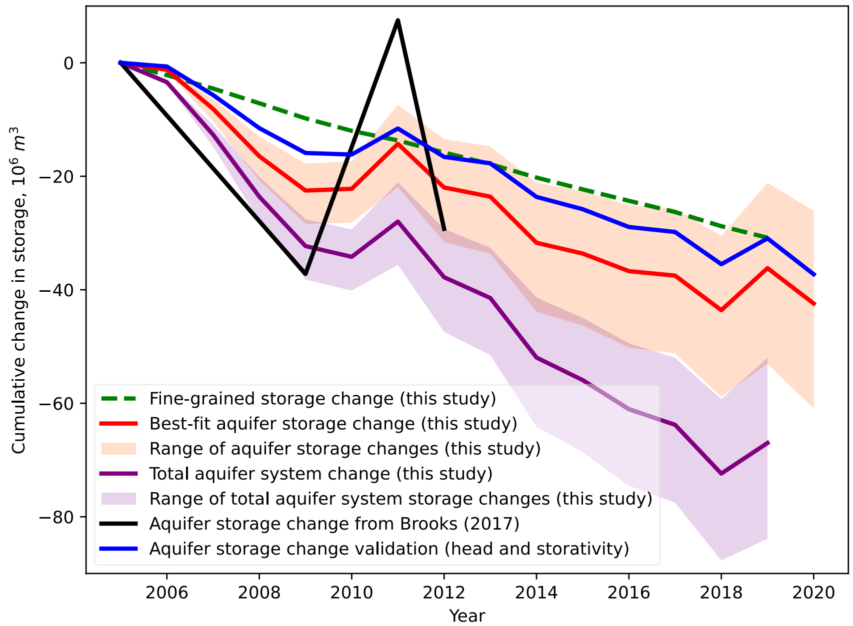

Figure 8. Cumulative storage change from the primary aquifer (red, blue, and black lines), from fine-grained intervals (dashed green line) and from the total aquifer system, obtained by summing this study's aquifer storage change and fine-grained storage change (purple line). Shaded regions indicate a 5th–95th percentile uncertainty in the primary aquifer from bootstrapping. Note that due to the low permeability of fine-grained units, which are draining into the primary aquifer, their storage change is relatively constant over time, while the primary aquifer storage change fluctuates annually with varying climate.

4.1. Storage Change Results

We first discuss the results of our two approaches for estimating aquifer system storage change. The storage change estimate for the primary aquifer, derived from the Butler et al. (2016) method, and the storage change estimate for fine-grained units, derived from 1D deformation modeling calibrated with InSAR data, described in Sections 3.2.1 and 3.2.2, respectively, are shown in Figure 8. The red shaded region is bounded by the 5th and 95th percentiles of the bootstrapped estimates of storage change in the primary aquifer. The total aquifer system storage change is defined as the sum of both the primary aquifer and fine-grained interval storage changes, and is also shown in Figure 8. For both the primary-aquifer and fine-grained intervals, negative values indicate a decline in total storage. The storage change in fine-grained units is consistently declining each year, while the primary-aquifer storage change varies much more, with some years showing increases but an average annual decreasing storage trend whose magnitude is similar to the storage change from clays.

To validate our estimates, we compare them with aquifer storage change estimates from the groundwater model of Brooks (2017) and with the storativity-based approach described in Section 3.3. We find that both validation data sets show aquifer storage loss that is within the range of primary aquifer storage loss estimates produced by our water balance approach (the red shaded region in Figure 8). As traditional storage change estimates (both modeling and storativity-based) use groundwater level data, which represents storage in the primary aquifer, as the driver of storage change, it is expected that they would more closely match our primary aquifer storage change estimates.

While the magnitudes of the storage loss occurring in the primary aquifer and fine-grained units are similar, they are a product of distinct processes and represent individual components of the total aquifer system storage loss. In confined aquifers, storage loss occurs due to a combination of loss of pore space due to consolidation, and expansion of water. In compressible unconsolidated systems such as Parowan Valley, most of the storage loss occurs due to consolidation, as compressibility of unconsolidated sediments is significantly larger than the compressibility of water (Fetter, 2001; Sneed, 2001). Since the majority of consolidation occurs in clays and other compressible fine-grained material, the storage loss in fine-grained units is a first-order estimate of confined aquifer storage

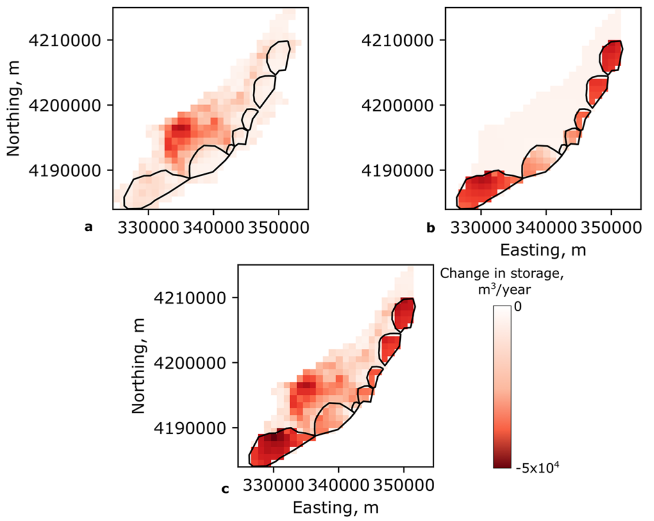

Figure 9. Average annual storage loss from 2015 to 2020 in (a) fine-grained intervals, (b) primary aquifer, and (c) the aquifer system (sum of fine-grained intervals and primary aquifer).

loss. However, our results indicate that a roughly equivalent volume of water is being lost from the primary aquifer and from the fine-grained units.

Our fine-grained storage loss estimates, combined with our validation data set, allow us to explore the spatial variation in storage loss from both fine-grained intervals and the primary aquifer. In Figures 9a–9c we plot the storage loss in m^3/year from 2015 to 2020 for fine-grained intervals (as described in Section 3.2.2), the primary aquifer (as described in Section 3.3), and the total aquifer system (the sum of fine-grained and primary) respectively. It is noteworthy that outside of the alluvial fans, in the confined aquifer, the primary mechanism for storage loss is consolidation of fine-grained materials, and thus the storage loss from these intervals is much larger than the primary aquifer. Conversely, the alluvial fans have a much higher storativity component from specific yield, and thus experience most of their storage loss within the primary aquifer.

At the scale of the entire valley, the storage loss from the primary aquifer and fine-grained units are roughly equivalent (Figure 8). The average fine-grained storage loss from 2015 to 2020 is 2.23×10^{-6} m^3, the average primary aquifer storage loss from 2015 to 2020 computed with the water balance approach, is 1.76×10^{3} m^3, and the average primary aquifer storage loss from 2015 to 2020 computed with our validation approach (storativity multiplied by change in head) is 2.27×10^{6} m^3, While the magnitude of these numbers is similar, there is significant spatial variation; relatively little storage loss occurs in the primary aquifer in the confined portion of the aquifer, while the opposite is true in the unconfined portion (Figure 9). These results are in agreement with normal confined and unconfined aquifer behavior and also agree with the distribution of clay in confined and unconfined portions of the Parowan Valley. Because fine-grained storage change is approximated here by the long-term deformation rate, Figure 9a is very similar to Figure 3.

The temporal variations in storage loss also provide indications of the mechanisms driving storage change. Figure 8 shows that for the primary aquifer, significant temporal variations occur; these variations are driven primarily by head loss caused by pumping and are linked to variable climatic parameters. For storage loss from the fine-grained units, the rate of storage loss is relatively constant with time. This is consistent with the mechanisms for draining low permeability units within a primary aquifer, where flow from the fine-grained units is driven by the lower head in the adjacent primary aquifer but is primarily controlled by the vertical hydraulic conductivity of the fine-grained materials, which does not change significantly with time.

4.2. Implications for Groundwater Budgets

In this study, we have shown with a combination of data-driven approaches and process models that storage loss in fine-grained units represents a significant portion of total groundwater storage change in confined aquifers. Storage loss from fine-grained units is considered in many models of regions with substantial subsidence (Faunt et al., 2009; Kasmarek, 2012; Siade et al., 2014). However, many other studies model regions with measurable subsidence as a classical coarse-grained system, without consideration of storage change in fine-grained units. In addition, unconsolidated confined aquifer systems, which are common in alluvial basins, may contain low levels of subsidence, but the subsidence volume could still be a significant percentage of total aquifer system storage loss, indicating that the loss of storage from fine-grained units is substantial relative to total groundwater storage loss. In this study, storage loss from fine-grained units represented roughly 46% of total aquifer system storage loss. Neglecting storage loss in fine-grained units may lead to an under-estimation of total groundwater storage loss, or bias in parameters that are constrained to fit head measurements in aquifers without consideration of flow from fine-grained units.

The substantial amount of storage loss occurring in fine-grained units within Parowan Valley indicates that they are a significant source of water for the aquifer system. Groundwater management plans are often tasked with reducing or halting groundwater storage loss by a combination of managed aquifer recharge and reductions in groundwater withdrawals. In our study, we found that the total aquifer system storage loss (the sum of fine-grained and coarse-grained units, shown in Figure 8 as a purple line) is approximately 12.5% of withdrawals. This indicates that if withdrawals are reduced by this amount and net inflow remains constant, there would be no continuing storage loss within the aquifer system. The total storage loss within the coarse-grained aquifer (the red line in Figure 8) is roughly 6.8% of the total withdrawals. If storage loss in the coarse-grained aquifer were the only storage component considered, then it would be assumed that a 6.8% reduction in withdrawals would arrest storage loss in the aquifer system. However, as pumping is reduced, the amount of inflow from the fine-grained units would also be reduced over a time period of years to decades (i.e., Figure 8 in R. Smith & Knight, 2019), resulting in continued aquifer depletion. In either scenario, it is likely that net inflow decreases over longer time periods as management practices are implemented due to changing irrigation practices and inter-basin hydraulic gradients (Butler et al., 2023; Deines et al., 2021). This highlights the need to consider storage loss from all intervals within an aquifer system for aquifer sustainability planning, as well as the need to re-visit inflow estimates and water budgets periodically as sustainability plans are implemented (Butler et al., 2016, 2023).

5. Conclusion

Groundwater scarcity threatens many agricultural and urban communities and is expected to increase due to climate change, population growth and industrialization (Butler et al., 2021). Characterizing groundwater storage change, while critical for sustainable management plans, is challenging and has high uncertainty. In this study, we show the utility in comparing InSAR deformation-based storage change estimates, which are primarily sensitive to storage changes in fine-grained intervals, with in situ and model-derived methods. The independent methods can be used to estimate the relative portion of groundwater storage loss in different components of aquifer systems. In the Parowan Valley, the confined portion of the aquifer experiences the greatest storage loss in fine-grained intervals, while the greatest portion of storage loss occurs in coarse-grained (the primary aquifer) intervals in unconfined portions of the aquifer. These findings are likely to hold for other unconsolidated basins that transition from unconfined to confined conditions. Failing to account for storage change in fine-grained intervals can thus greatly underestimate the total storage loss in these systems.

Data Availability Statement

Groundwater storage loss data sets produced in this study will be made available at https://www.remote-sensing-hydrology.com/datasets upon publication of the manuscript.

Acknowledgments
The authors would like to thank T. Marston for providing valuable feedback on pumping data and general hydrologic conditions in the Parowan Valley. This work was supported in part by NASA Grant number 80NSSC21K0979.

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