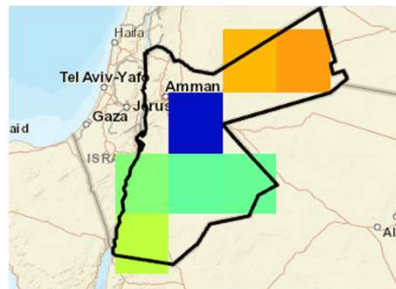
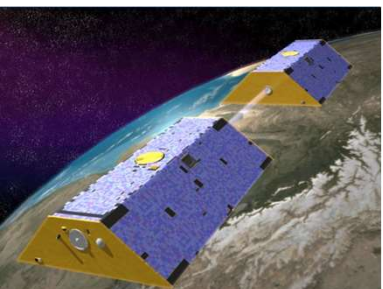


# Performing a GRACE groundwater analysis in small basins

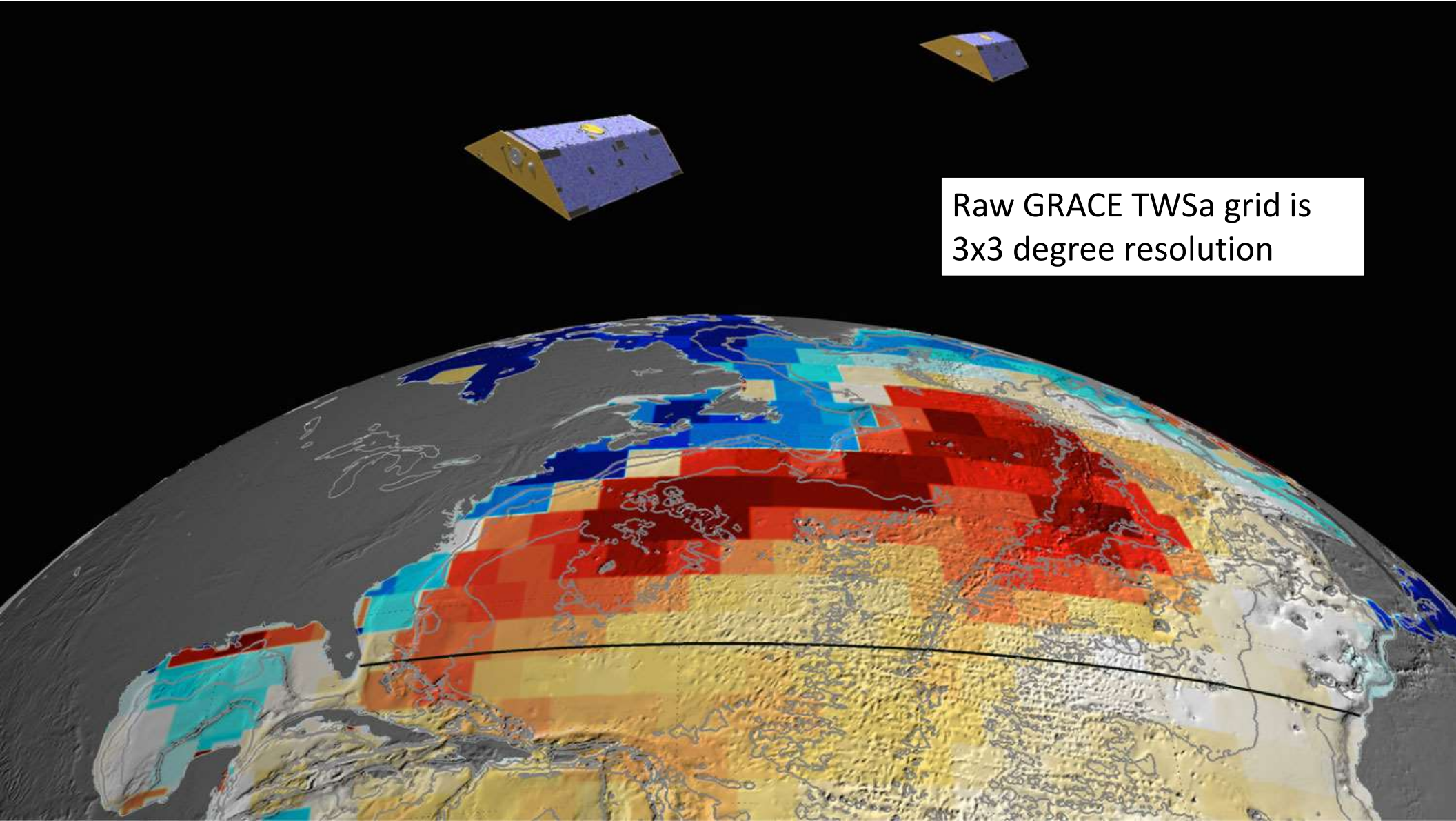
Use of the Gravity Recovery and Climate Experiment (GRACE) mission to monitor groundwater storage change: National workshop for Jordan and State of Palestine

Amman Jordan, February 25-26



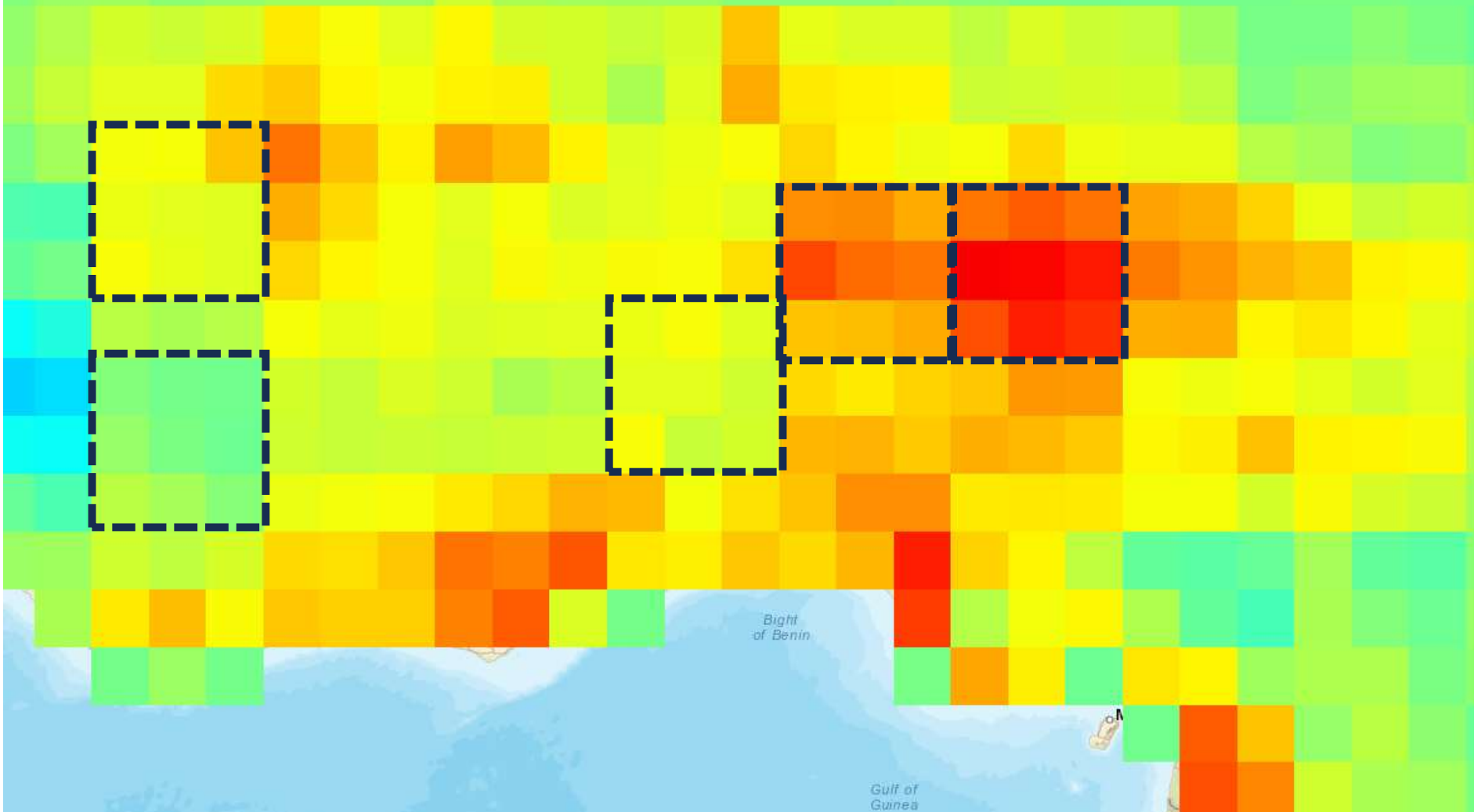
Shared Prosperity Dignified Life



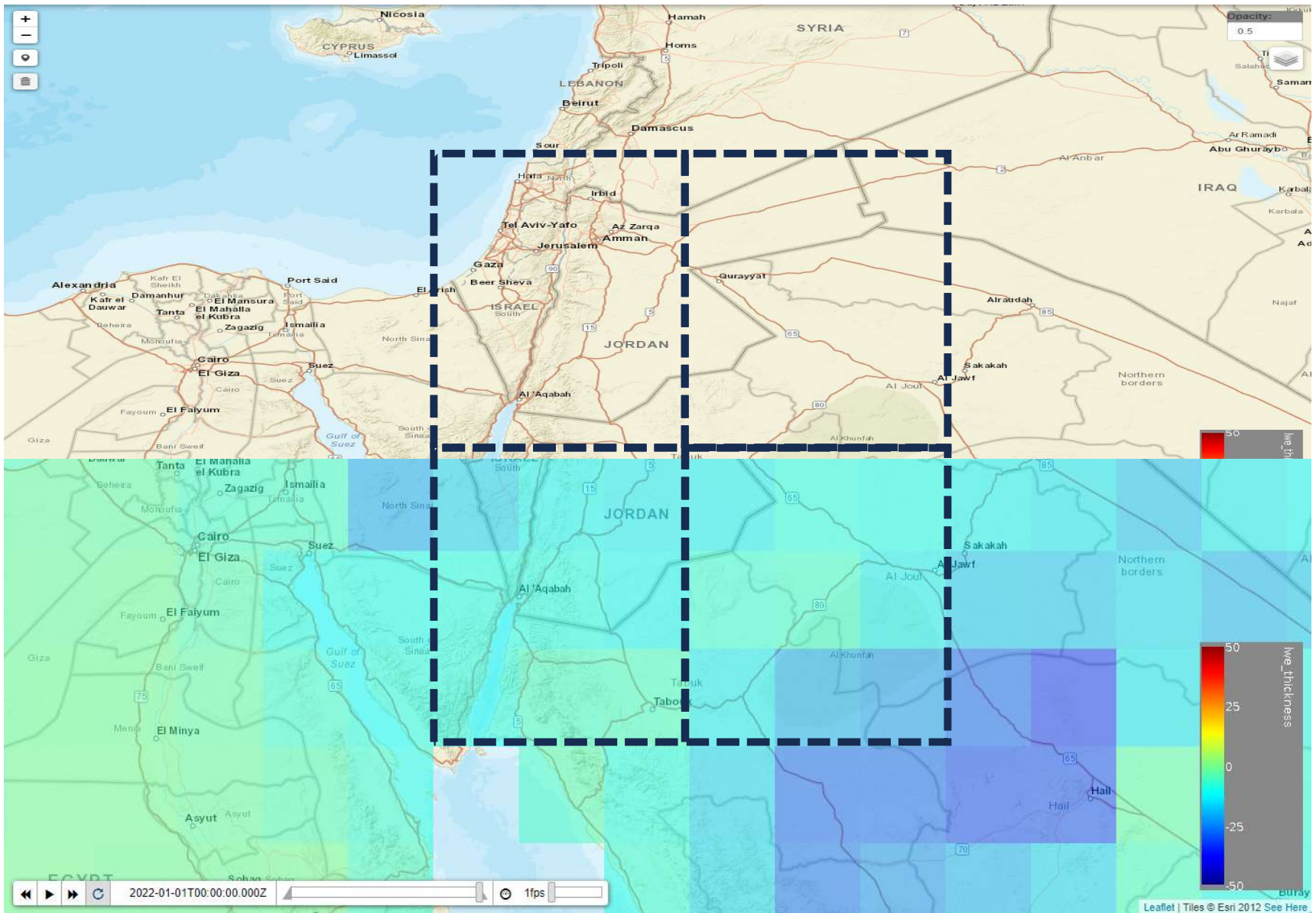


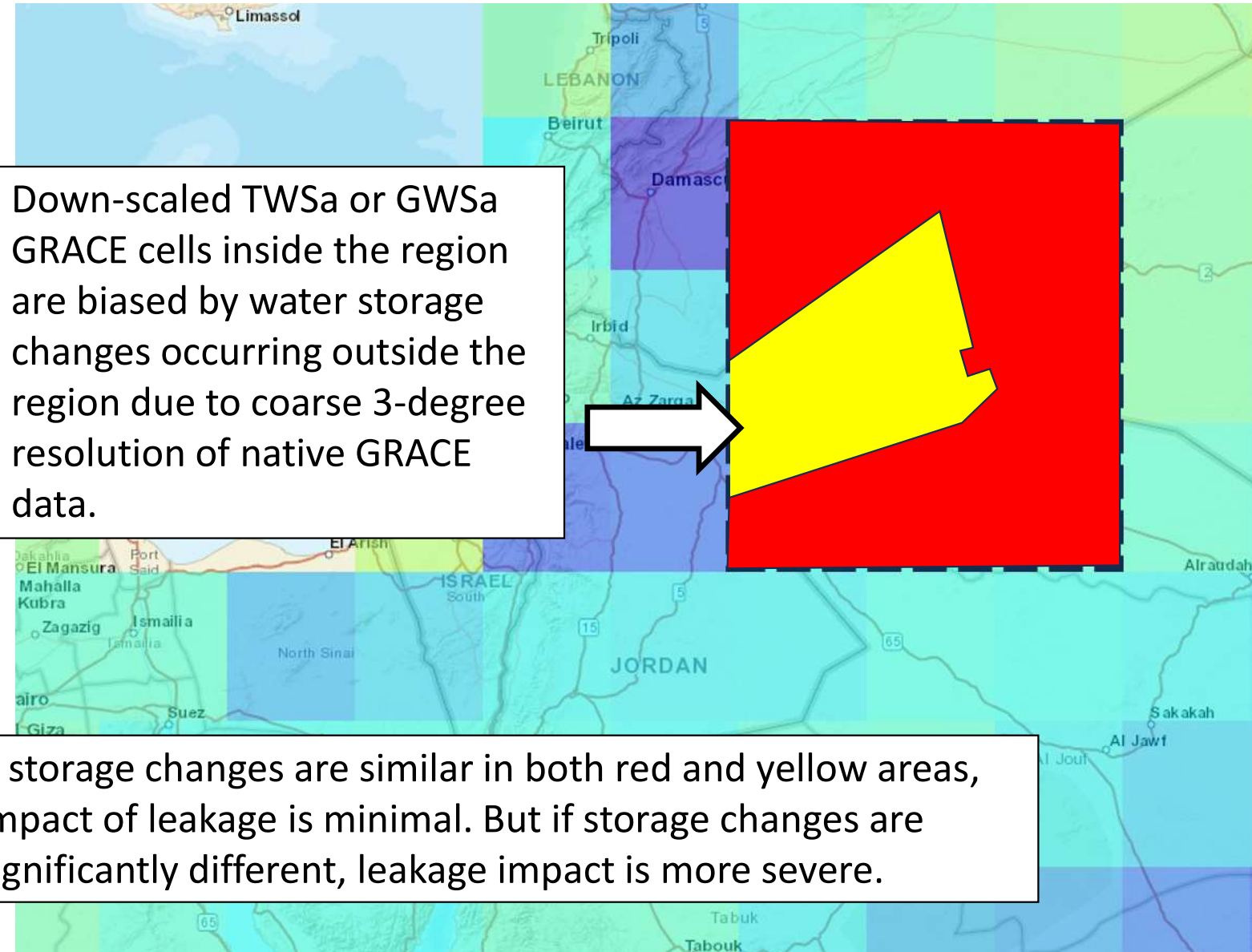
Raw GRACE TWSa grid is  
3x3 degree resolution

NASA distributes down-scaled TWSa grid at 0.5-degree resolution. Derived GWSa is at 1-degree resolution. However, results are still biased by native 3-degree resolution









Down-scaled TWSa or GWSa GRACE cells inside the region are biased by water storage changes occurring outside the region due to coarse 3-degree resolution of native GRACE data.

If storage changes are similar in both red and yellow areas, impact of leakage is minimal. But if storage changes are significantly different, leakage impact is more severe.



# CASE STUDY - Central Valley California

Return to Home

**Region Map**

Select a Region  
California Central Valley

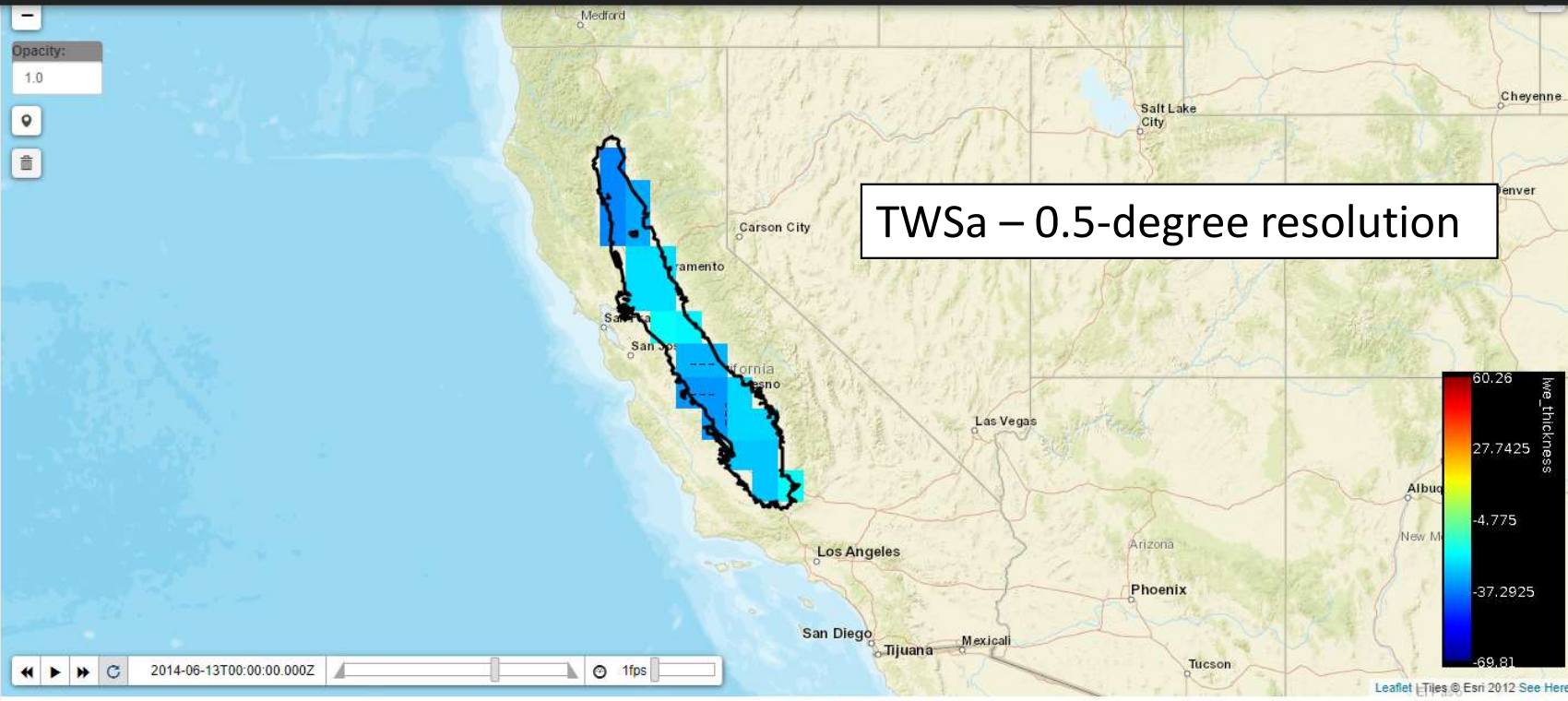
Select Storage Component  
Total Water Storage (GRACE)

Select a day  
2002 April 17

Min:  
-69.81

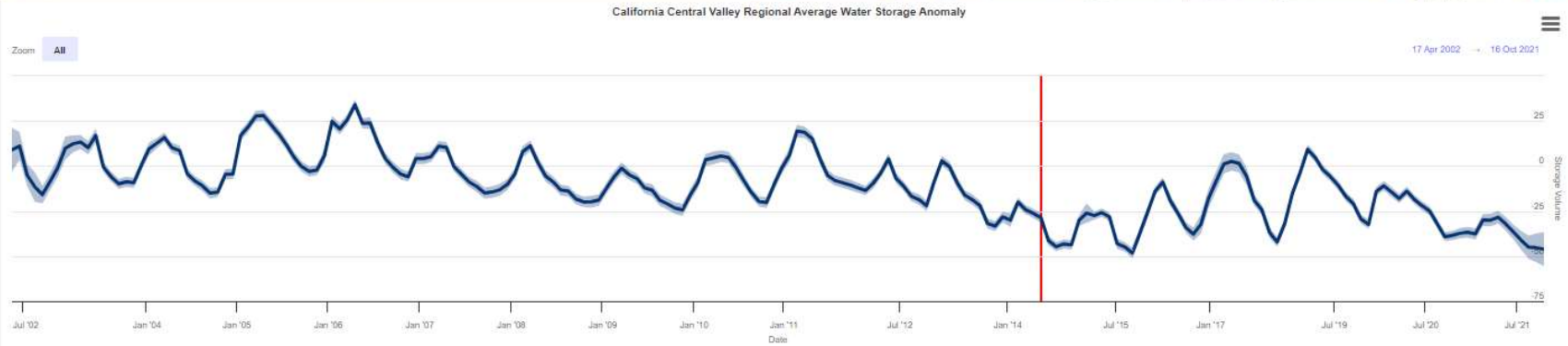
Max:  
60.26

Select Style  
GRACE



**Time Series Generator**

To generate a time series for a specific location, click on the **Marker icon** on left side of the map. Then place the marker at the location for which you wish to extract a time series from the current map layer.





Return to Home

**Region Map**

Select a Region  
California Central Valley

Select Storage Component  
Groundwater Storage (Calculated)

Select a day  
2002 April 01

Min:  
-38.36

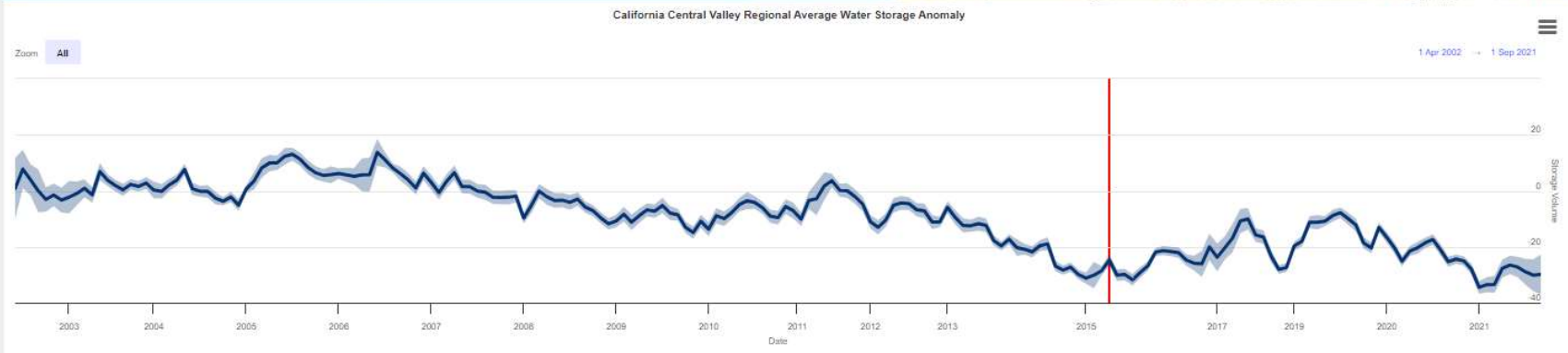
Max:  
16.76

Select Style  
GRACE



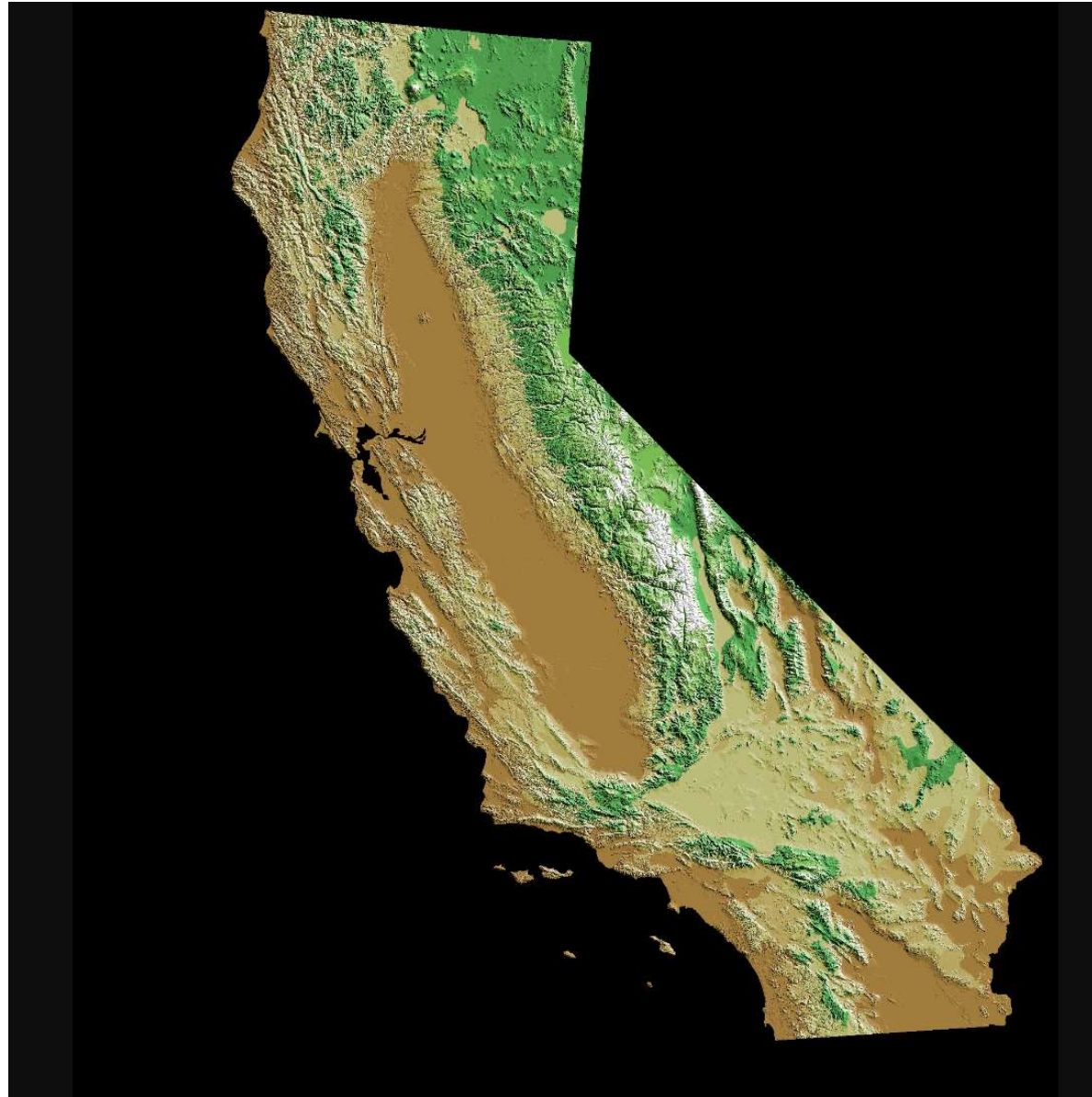
**Time Series Generator**

To generate a time series for a specific location, click on the **Marker Icon** on left side of the map. Then place the marker at the location for which you wish to extract a time series from the current map layer.





Groundwater pumping in the Central Valley is highly concentrated relative to surrounding areas, thus amplifying the leakage effect with GRACE data.





## STRATEGY #1

Most researchers deal with the Central Valley leakage problem by performing a GRACE analysis on the larger hydrographic basin containing the central valley aquifer, and then using the GWSa from that analysis and assuming that the GW pumping is almost all confined to the aquifer.

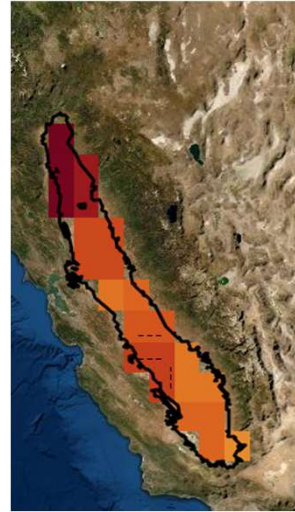
$$GW\_Vol_{\text{aquifer}} = LWE_{\text{basin}} * Area_{\text{basin}}$$

I.e., entire GWSa from basin is assumed to apply to aquifer

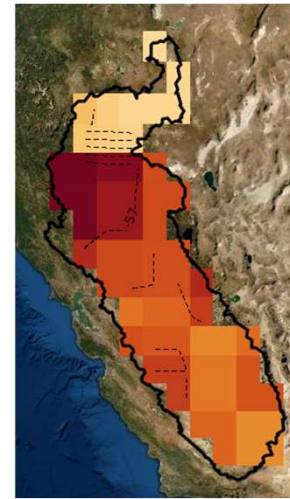
# GRACE Basin Comparison

GRACE **TWSa**  
0.5° Resolution

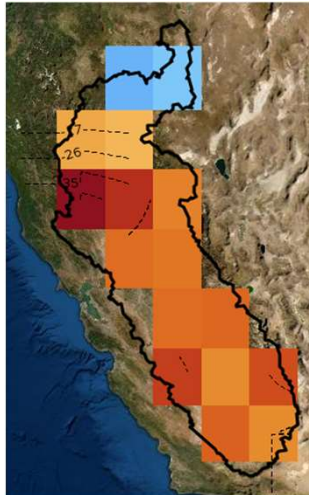
Central Valley



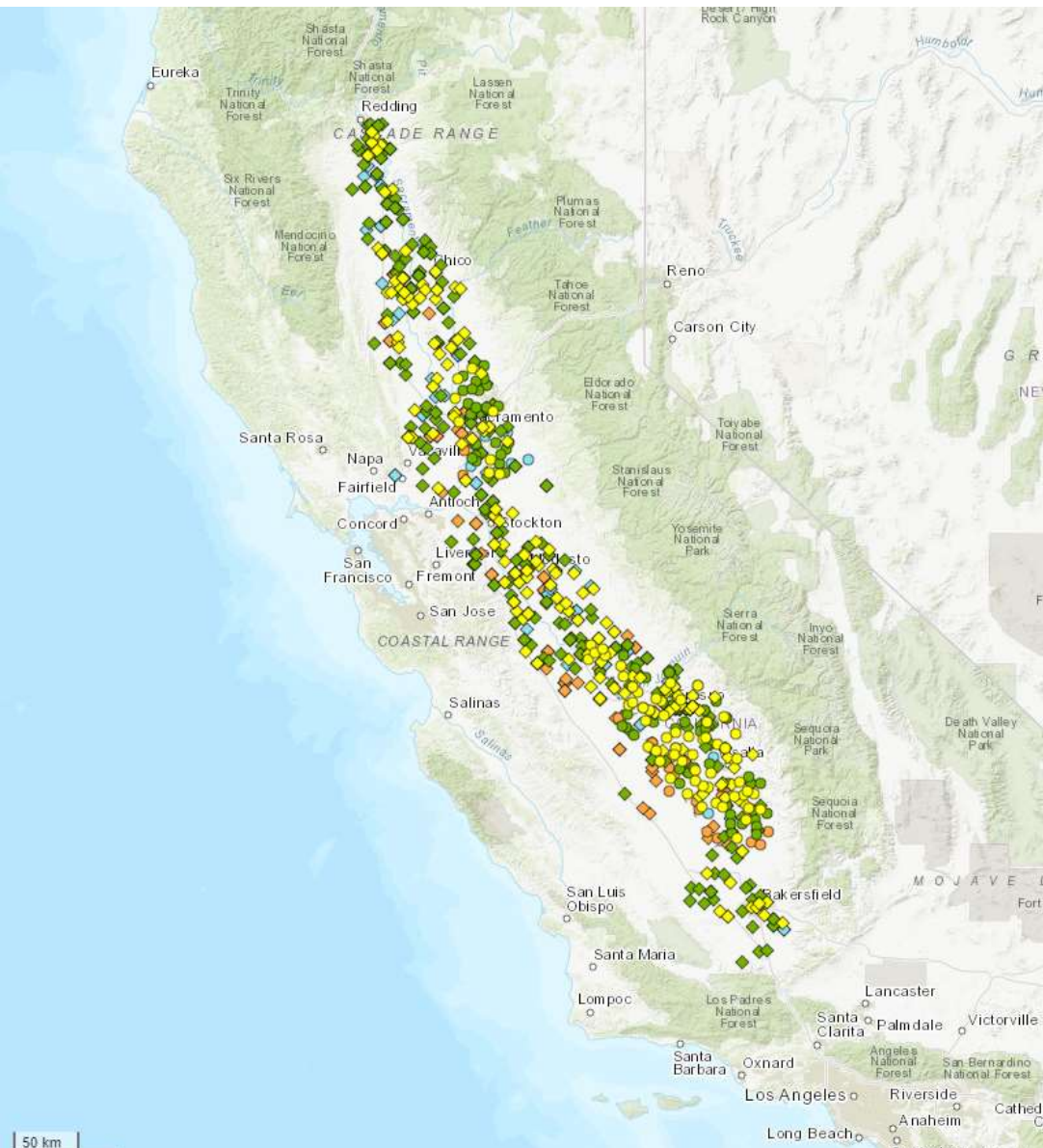
Sacramento / SJ  
River Basins



GRACE-derived **GWa**  
1° Resolution





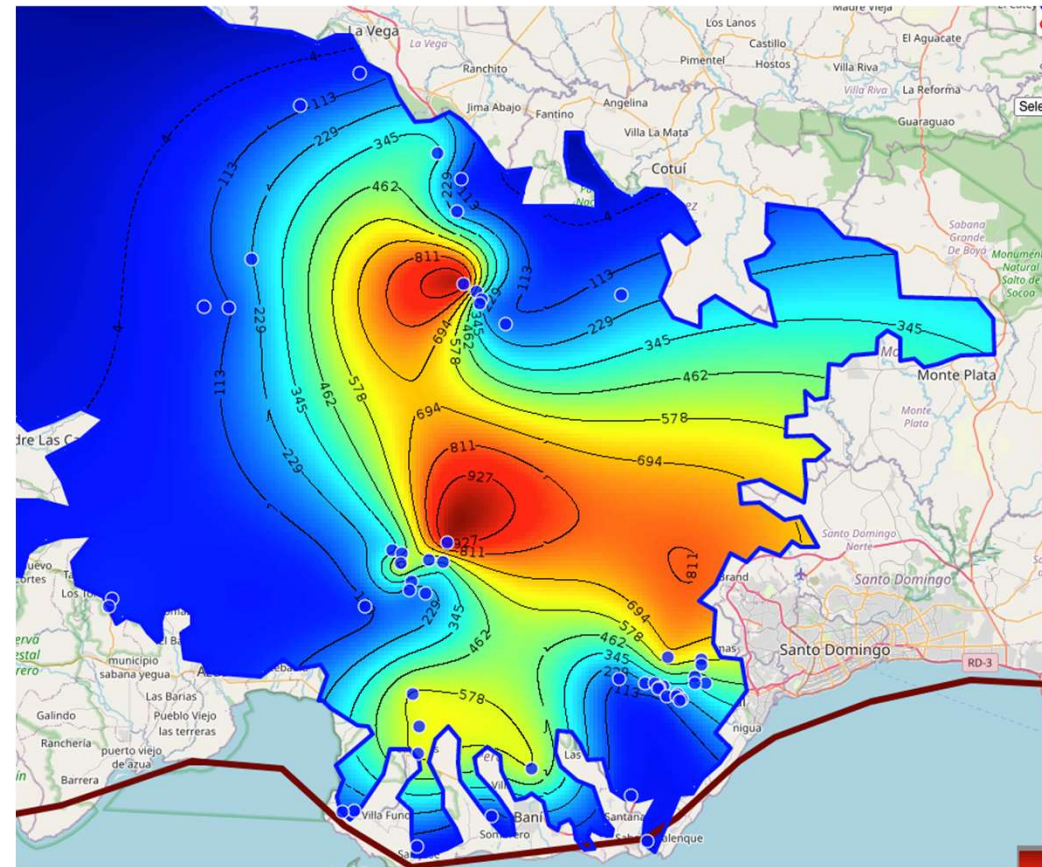


## STRATEGY #2

Analyze in situ well data and look at long-term groundwater level changes to estimate groundwater storage change (GWSa) over the entire region over the same time period as GRACE data. Compare GWSa from both GRACE and in situ method and calculate a scaling ratio to apply to GRACE GWSa to account for leakage.

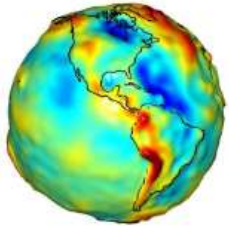
Our BYU research team recently completed a study to do this.

# Groundwater Level Mapping and Storage Analysis





## Apps Library



Grace  
Groundwater  
Subsetting Tool



Groundwater  
Data Mapper






**Ground Water Data Mapper**  
latest

Search docs

**TABLE OF CONTENTS**

- Home
- Overview
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  - Tethys Application
  - Regions, Aquifers, and Well Data
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  - Displaying Rasters
  - Admin Control Panel
  - Documentation and Tutorials
- Data Preparation
  - Data Preparation Scripts
  - Importing Data
  - Groundwater Level Mapping
  - Installing the GWDM Application



**No-code Payments Integration** Add new features without the need to code from scratch **Try For Free**

Ad by EthicalAds · 1

<https://gwdm.readthedocs.io/>

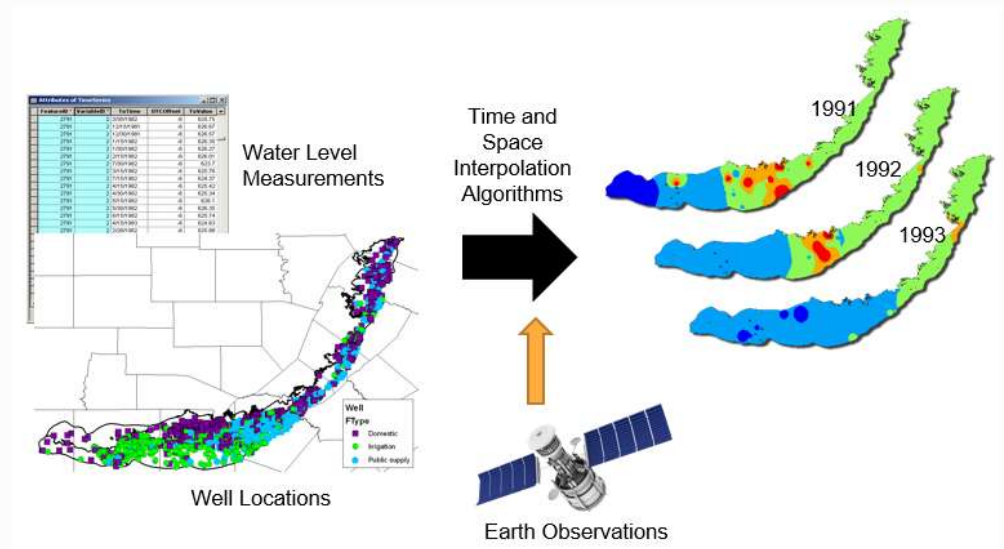
## Overview

Select Language ▼  
Powered by Google Translate

Water managers in Western Africa and around the world face the daunting task of managing freshwater resources in the face of increased demand from industry, agriculture, climate change, and population growth. As surface water resources become fully allocated, groundwater is increasingly targeted to make up surface water deficits, particularly during periods of drought. As a result, many of our aquifers are not being managed in a sustainable fashion, resulting in reduced water quality, land subsidence, increased pumping costs, and in some cases, the complete exhaustion of an aquifer and the loss of groundwater as a buffer during times of drought.

## Mapping Algorithm

Even when water managers have access to large data sets of historical groundwater level measurements, at any individual well these measurements often exhibit significant time gaps. Aggregating and synthesizing these well measurements to provide information that supports a holistic assessment of aquifer level sustainability can be a challenging task. In partnership with NASA SERVIR, we have developed a series of algorithms that use these existing well measurements combined with Earth Observation data to analyze changes in water tables and characterize aquifer storage over time. Our approach involves collecting data describing well locations and any historical water level measurements in an aquifer. To evaluate aquifer behavior, we need to impute missing data at each well location so that we have data at each time step for analysis. To impute (or estimate) missing measurements at each well, we use a machine learning approach that trains models to use Earth observation data. Using this approach, we generate a time series for each well and use these data to spatially interpolate the water table at each time step.



These interpolated water table maps can be used to evaluate the sustainability of the aquifer by looking at the changes to aquifer storage over time. We

Go Home

Region Name:  
Niger\_PreWorkshopTes

Select a Region  
Niger

Select an Aquifer  
Korama

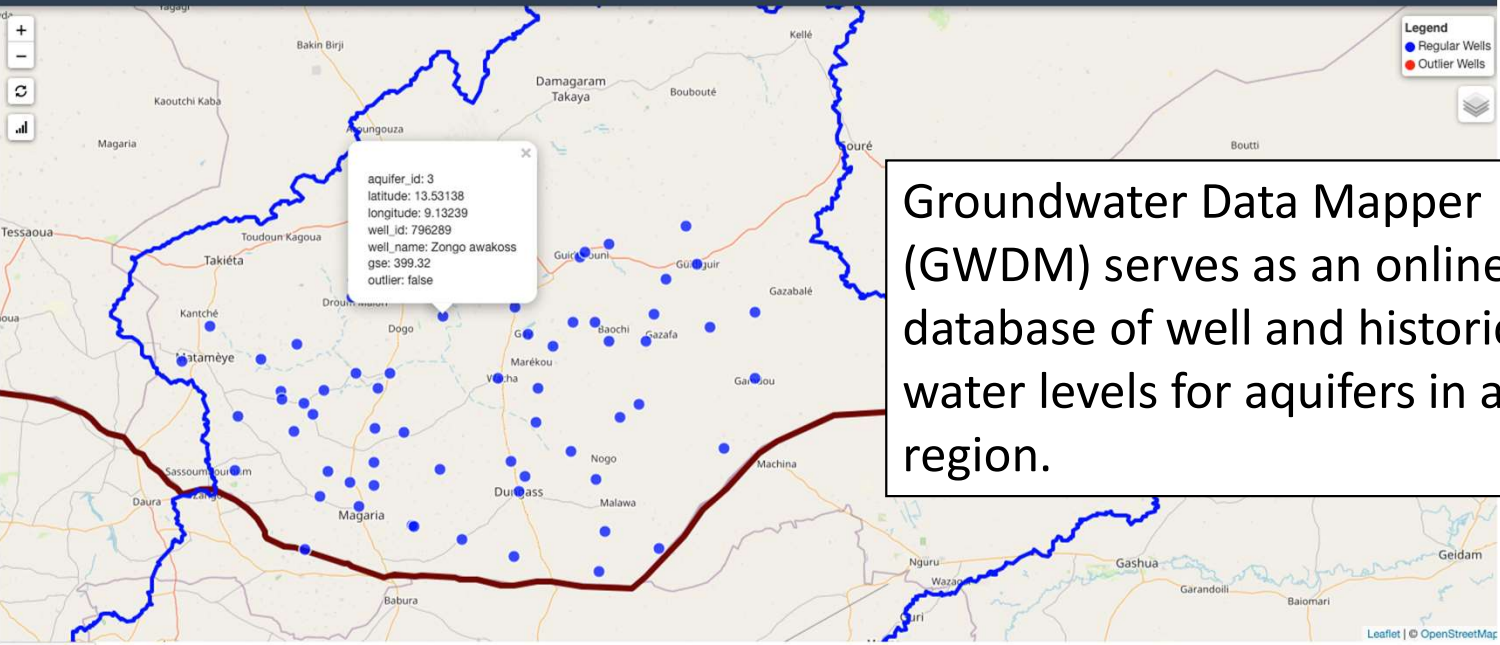
Select Variable  
Water table elevation, m

Interpolation Layer  
Select a Layer

Cluster Wells

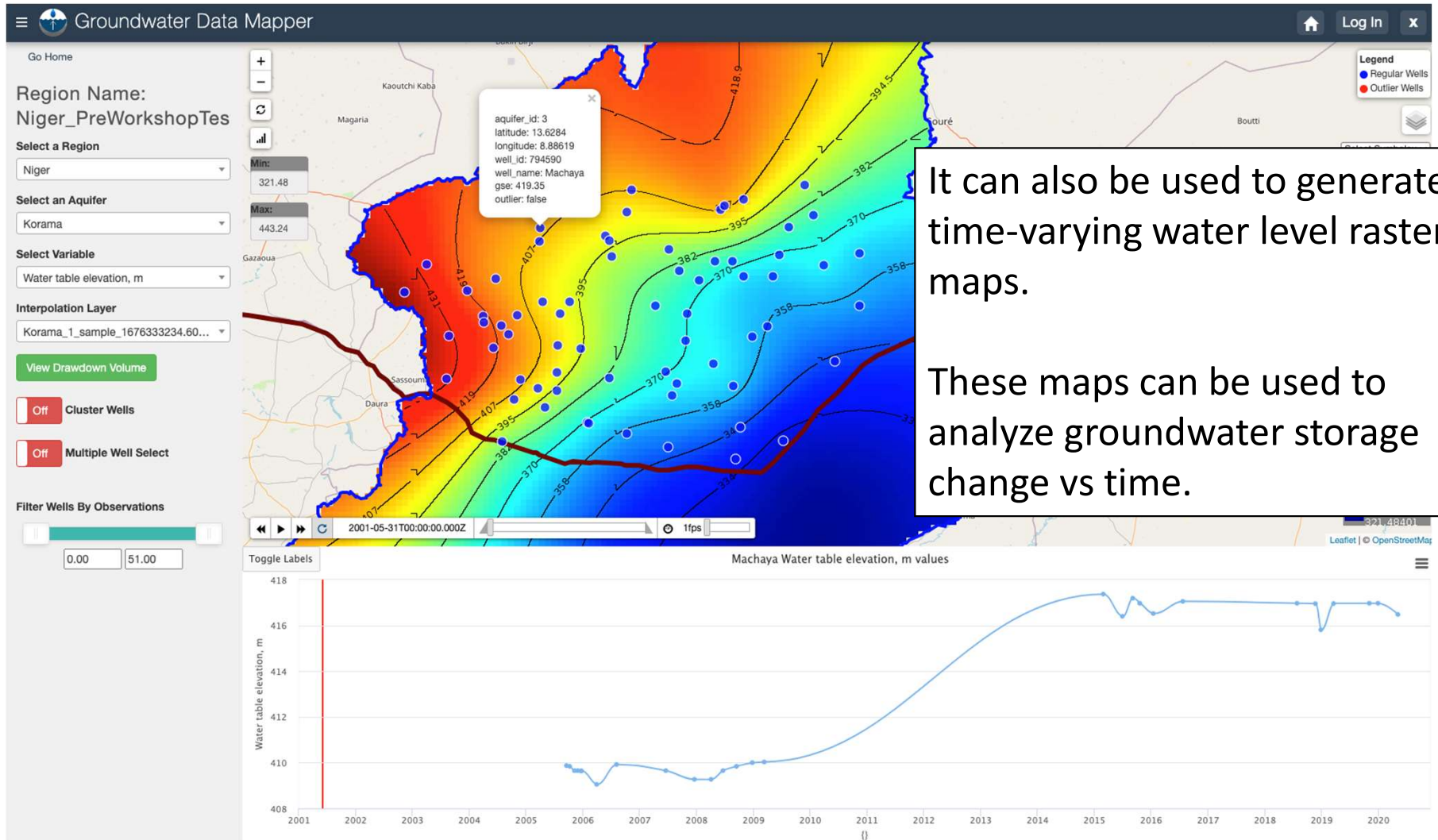
Multiple Well Select

Filter Wells By Observations  
0.00 51.00



Groundwater Data Mapper (GWDM) serves as an online database of well and historical water levels for aquifers in a region.





It can also be used to generate time-varying water level raster maps.

These maps can be used to analyze groundwater storage change vs time.

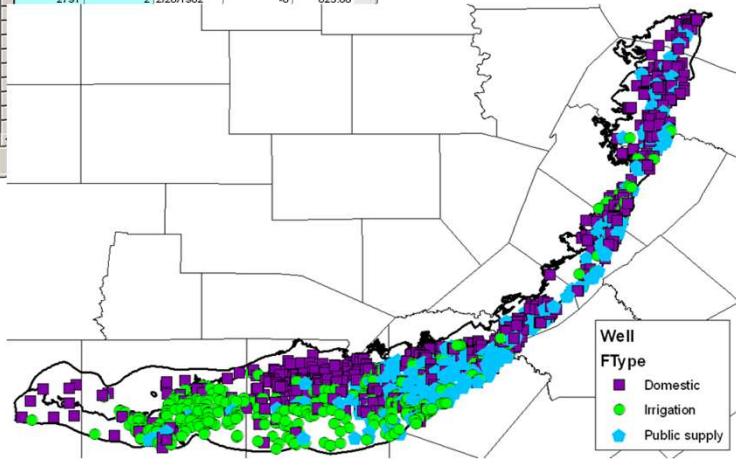
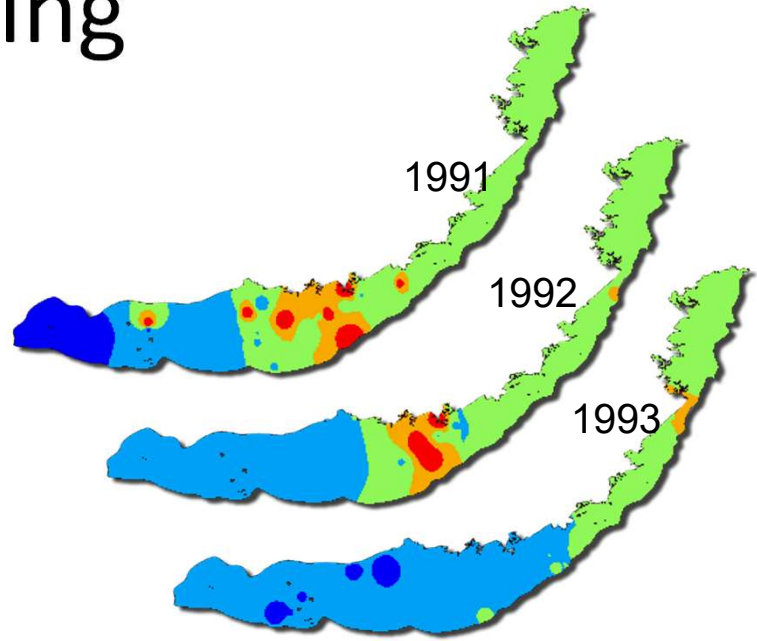
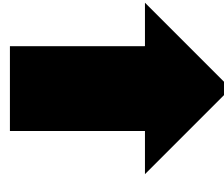


# Groundwater Data Mapping

FeatureID	VariableID	TsTime	UTCOffset	TsValue
2791	2	3/30/1982	-6	625.75
2791	2	12/15/1981	-6	626.67
2791	2	12/30/1981	-6	626.57
2791	2	1/15/1982	-6	626.35
2791	2	1/30/1982	-6	626.27
2791	2	2/15/1982	-6	626.01
2791	2	7/30/1982	-6	623.7
2791	2	3/15/1982	-6	625.76
2791	2	7/15/1982	-6	624.37
2791	2	4/15/1982	-6	625.42
2791	2	4/30/1982	-6	625.34
2791	2	5/15/1982	-6	626.1
2791	2	5/30/1982	-6	626.35
2791	2	6/15/1982	-6	625.74
2791	2	4/15/1983	-6	624.63
2791	2	2/28/1982	-6	625.88

Water Level Measurements

Time and Space Interpolation Algorithms



Well Locations



Earth Observations

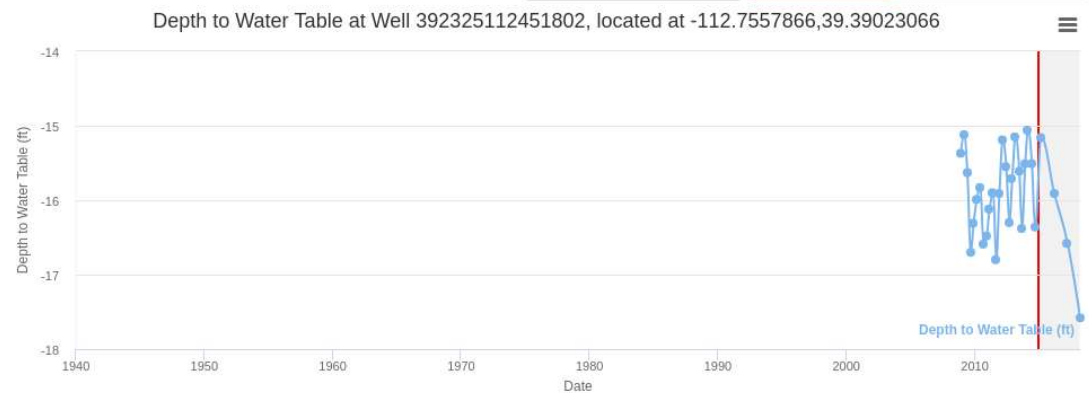
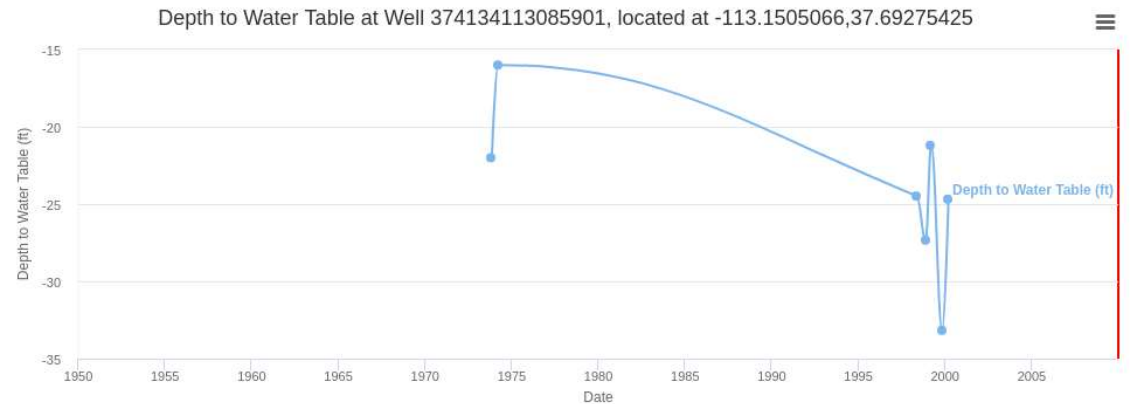
# Step 1

Impute gaps in water level time series using machine learning and Earth observations

# The Challenge - Temporally Sporadic Data

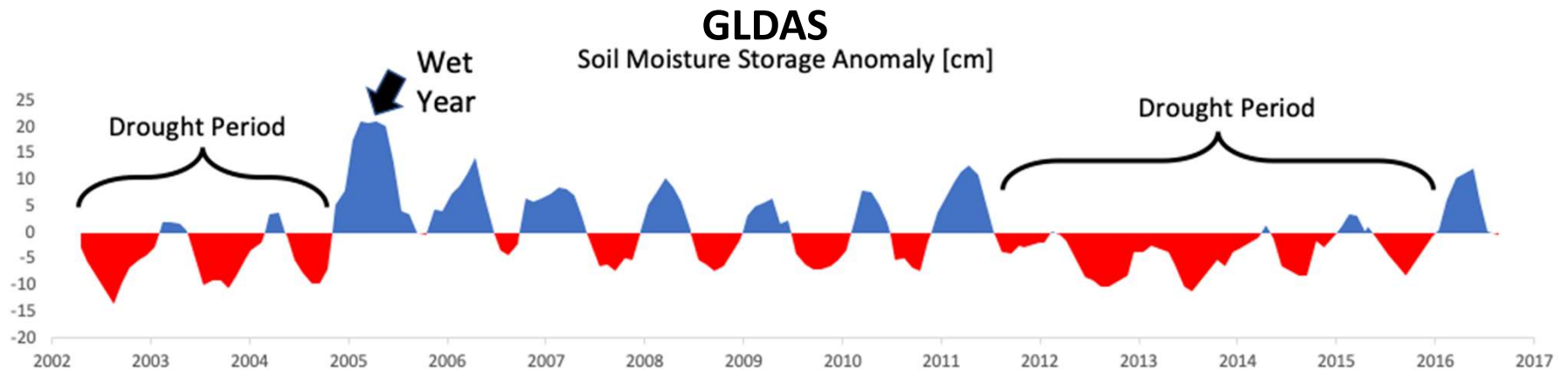
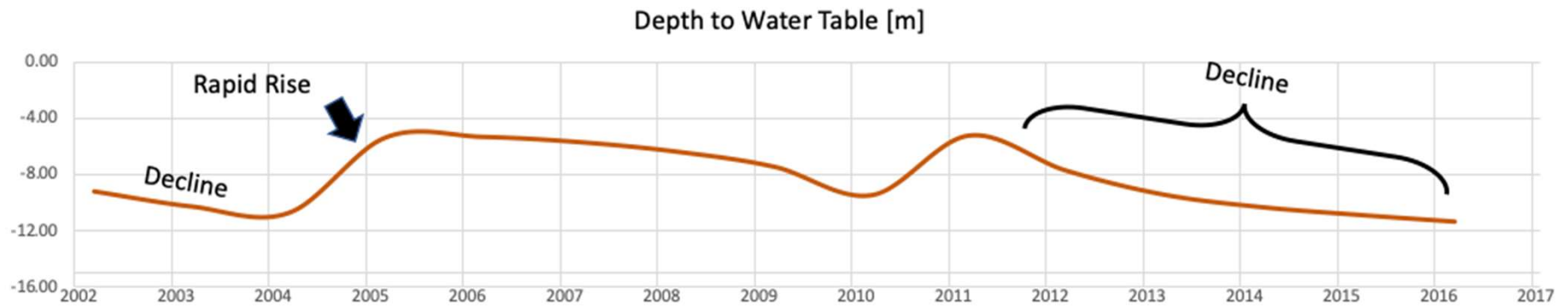
- Well Time series often include large gaps in collected data
- Some wells may only have data for one or two years

We need a more complete water level time series dataset to adequately characterize groundwater storage changes

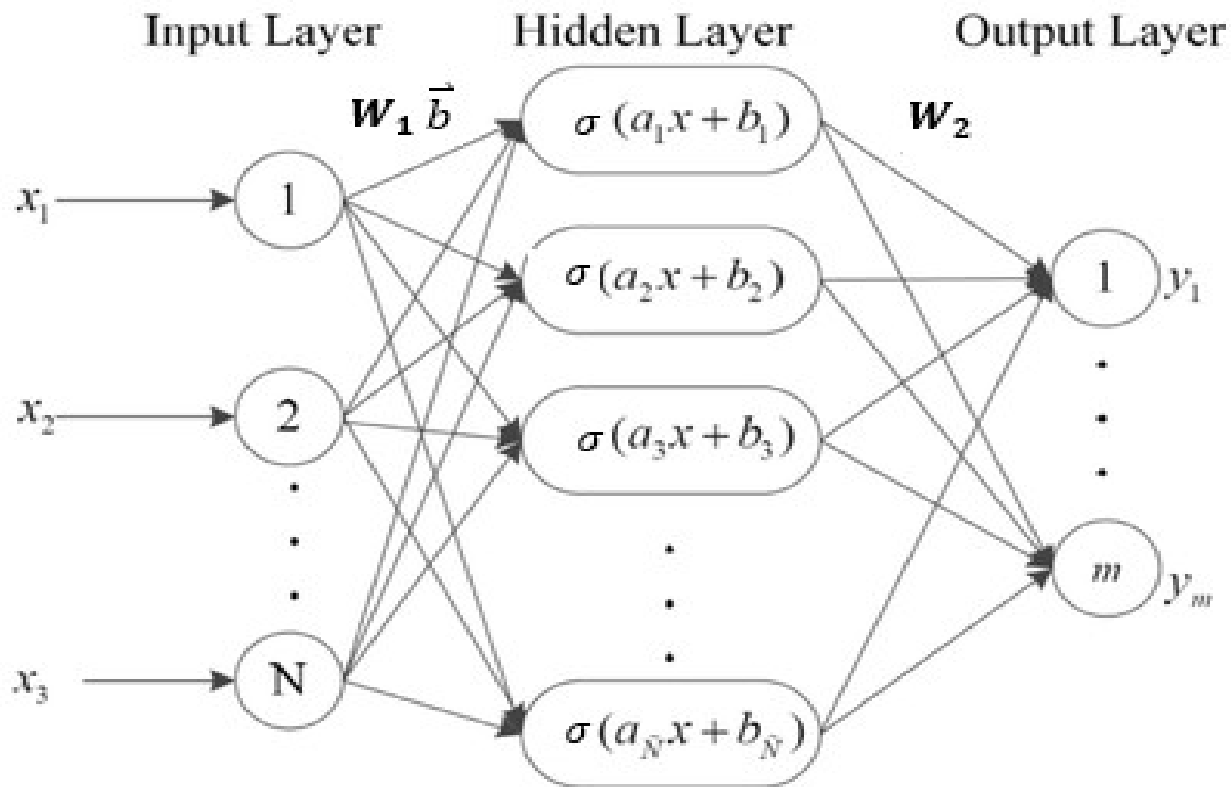




# Correlation with Earth Observations



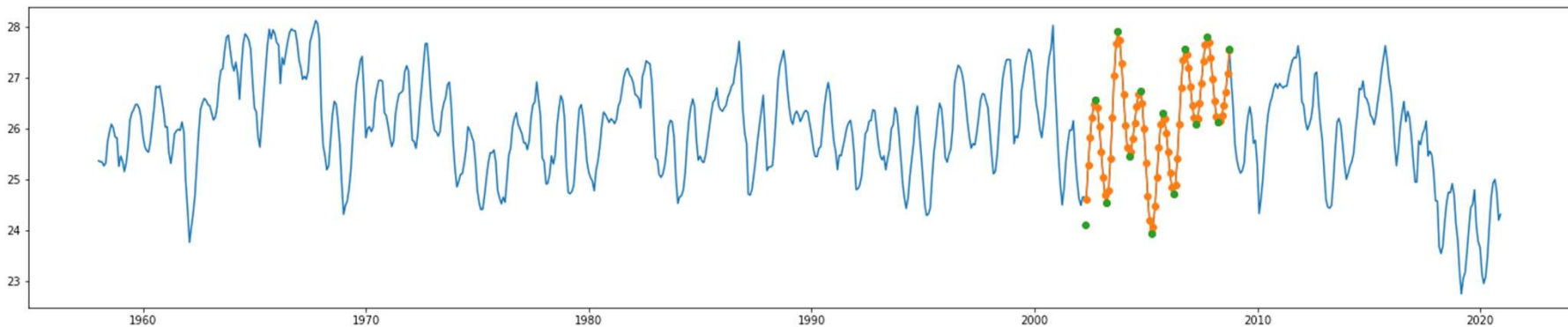
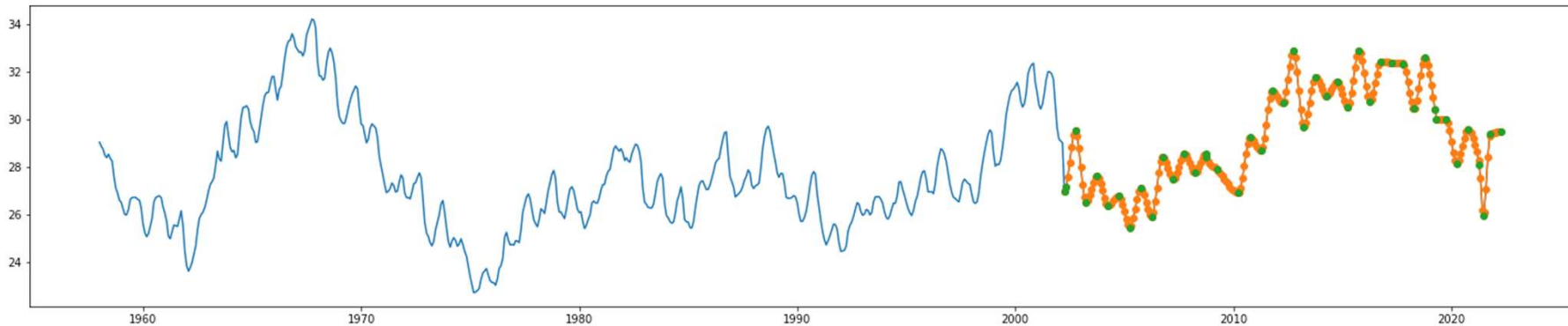
# Extreme Learning Machine



$$\vec{Y} = \mathbf{W}_2 * \sigma(\mathbf{W}_1 \mathbf{X} + \vec{b})$$

$$\sigma(x) = \max(0, x)$$

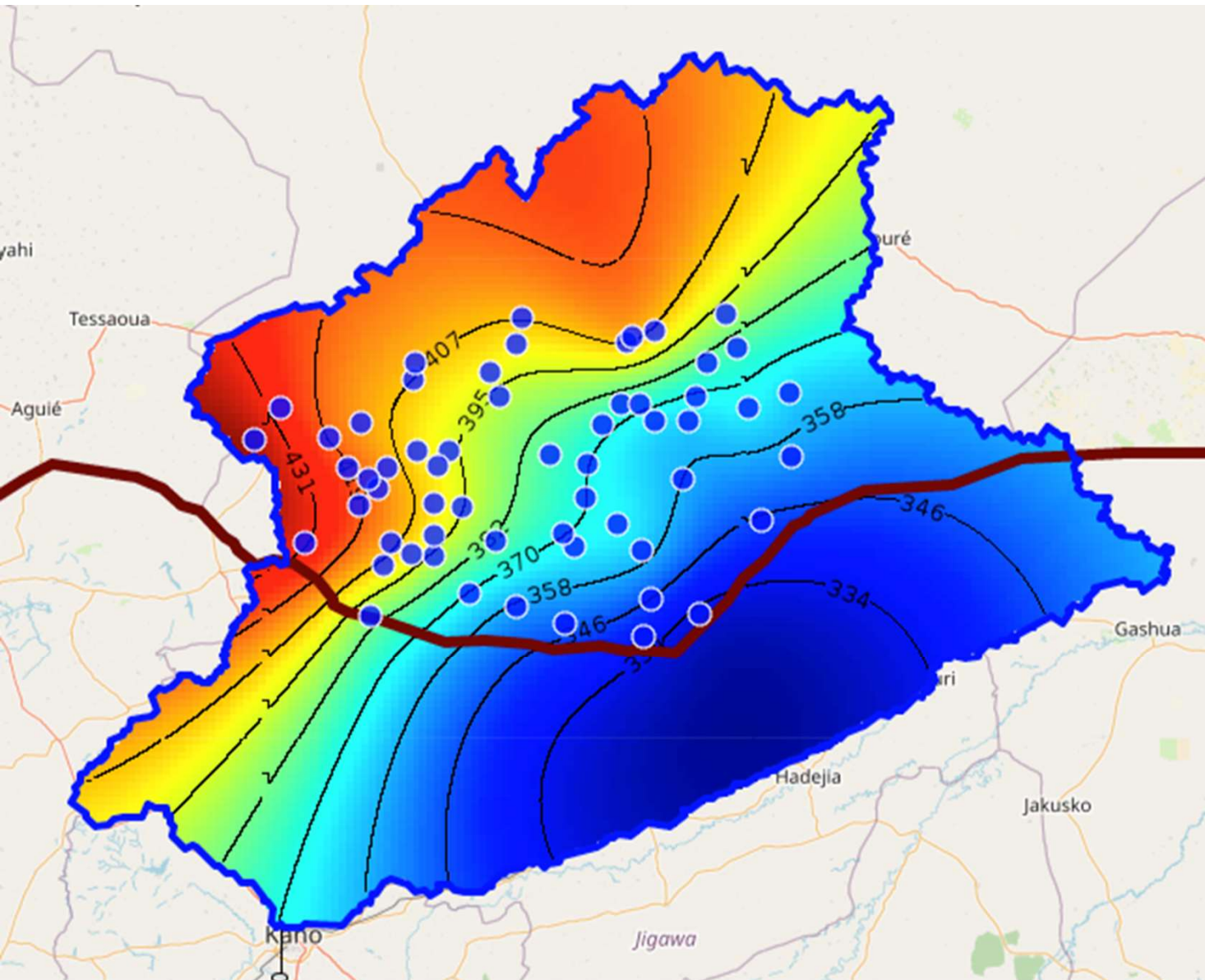
At the end of this step, we have a complete time series for each well over the mapping/interpolation range (one value per month)



# Step 2

Generate rasters by spatially interpolating values from time series at selected points in time

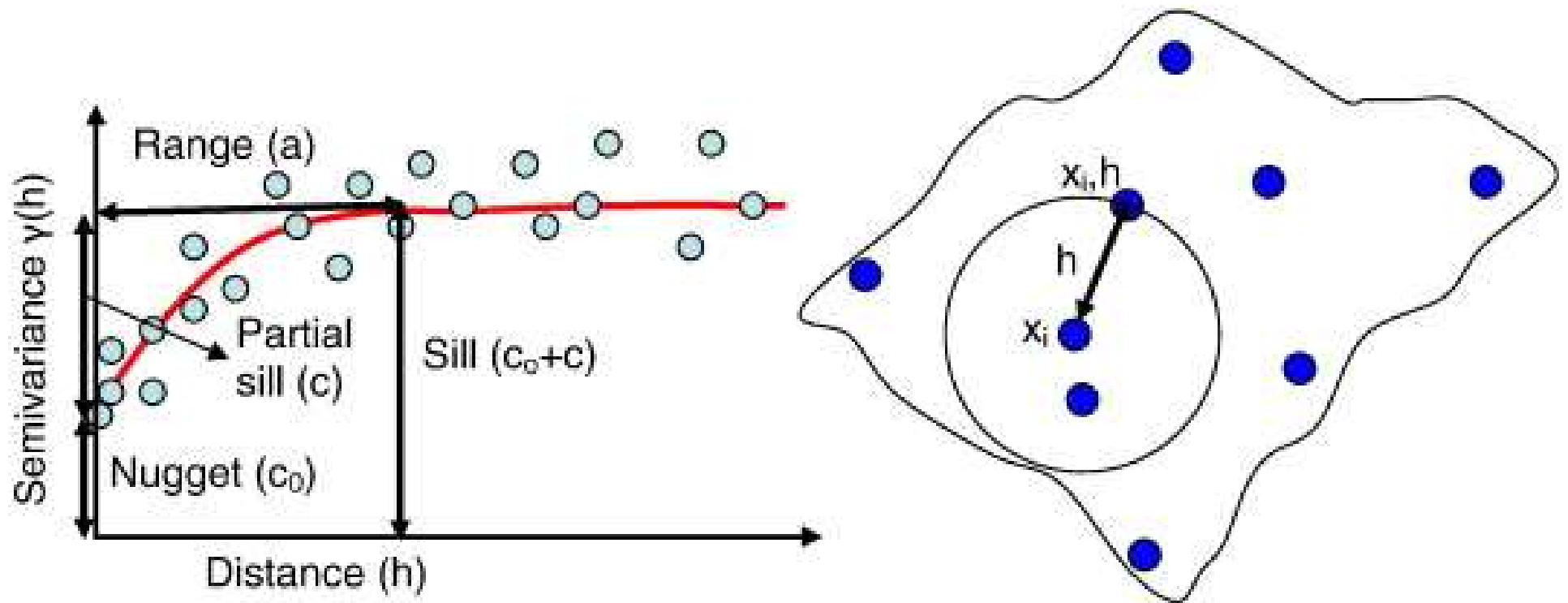




In this step we interpolate from the well locations using water levels at selected time intervals to create one raster for each time interval (2000, 2001, 2002, etc.)

The output is a time-varying array of rasters

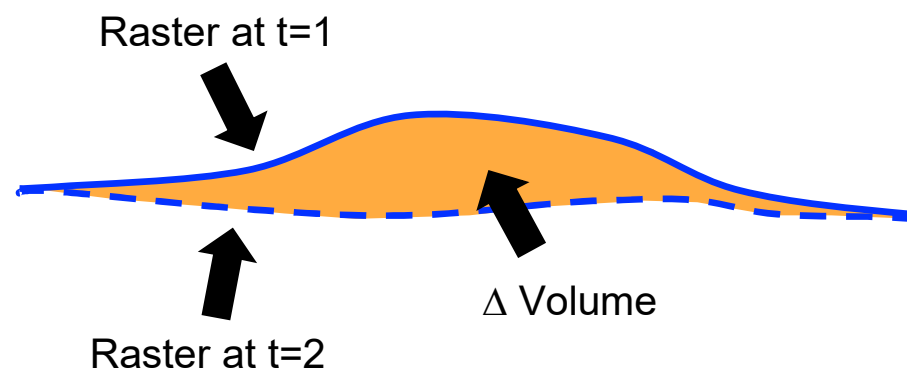
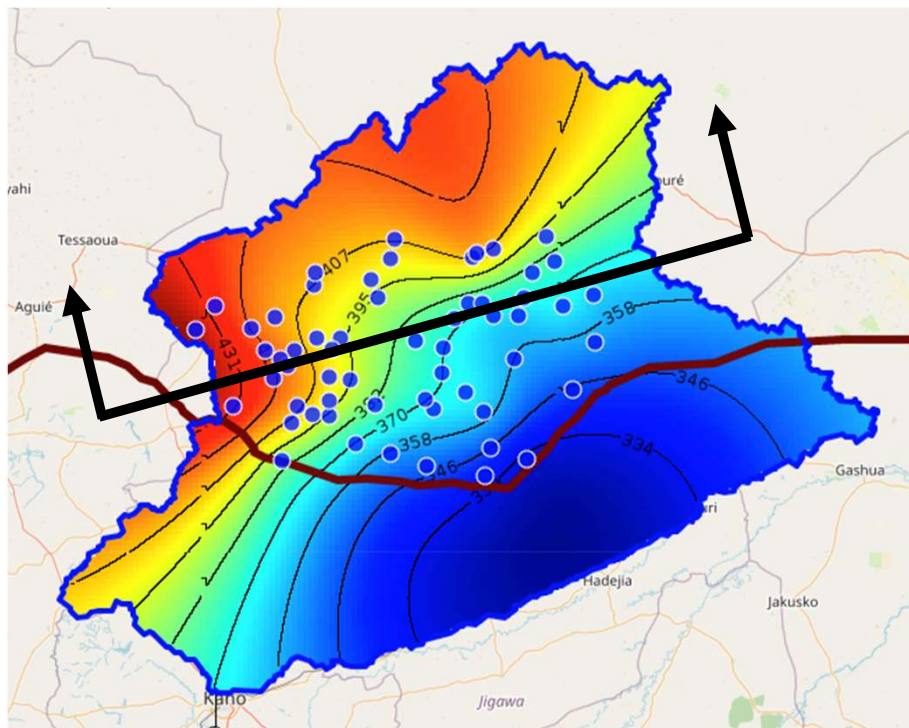
# Kriging Algorithm



# Step 3

Evaluate changes in rasters over time to calculate groundwater storage time series

# Storage Time Series Calculations

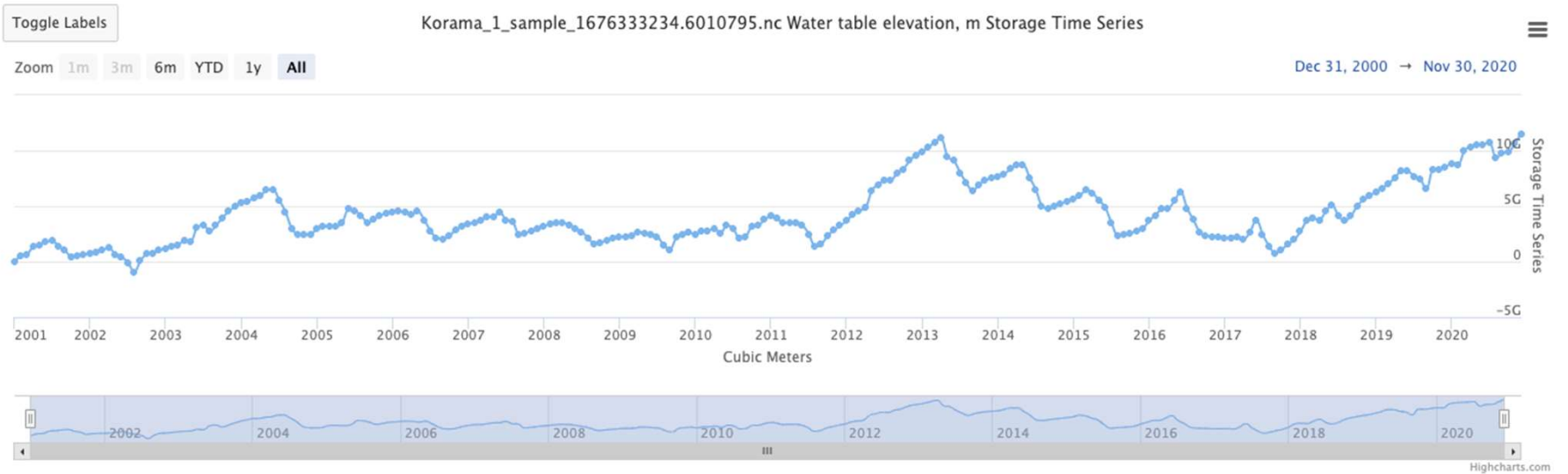


$$\Delta \text{ GW Storage} = S_y * \Delta \text{ Volume}$$



# Storage Change Time Series

Chart



# Mapping Algorithm Python Script – Colab Notebook

Aquifer-Interpolation-Final.ipynb ☆  
File Edit View Insert Runtime Tools Help [Last saved at 8:35AM](#)

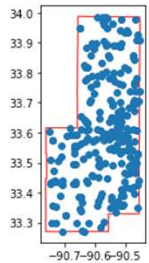
+ Code + Text

```
[ ] 264 335860090334401 133A0089 SUNFLOWER 33.983100 -90.562128 150.53 133
265 335905090343001 133A0054 SUNFLOWER 33.984834 -90.575096 145.00 133
266 335909090353901 133A0052 SUNFLOWER 33.985945 -90.594263 145.00 133
267 rows x 6 columns
```

```
[ ] wells_gdf = gpd.GeoDataFrame(wells, geometry=gpd.points_from_xy(wells["long_dec"], wells["lat_dec"]))
```

```
[ ] import matplotlib.pyplot as plt
fig, ax = plt.subplots()
aquifer.plot(color="none", edgecolor="red", ax=ax)
wells_gdf.plot(ax=ax)
```

<matplotlib.axes.\_subplots.AxesSubplot at 0x7fb7f73b2be0>



```
[ ] upload_timeseries = files.upload()
```

No file chosen Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.  
Saving sunflower\_ts.csv to sunflower\_ts.csv

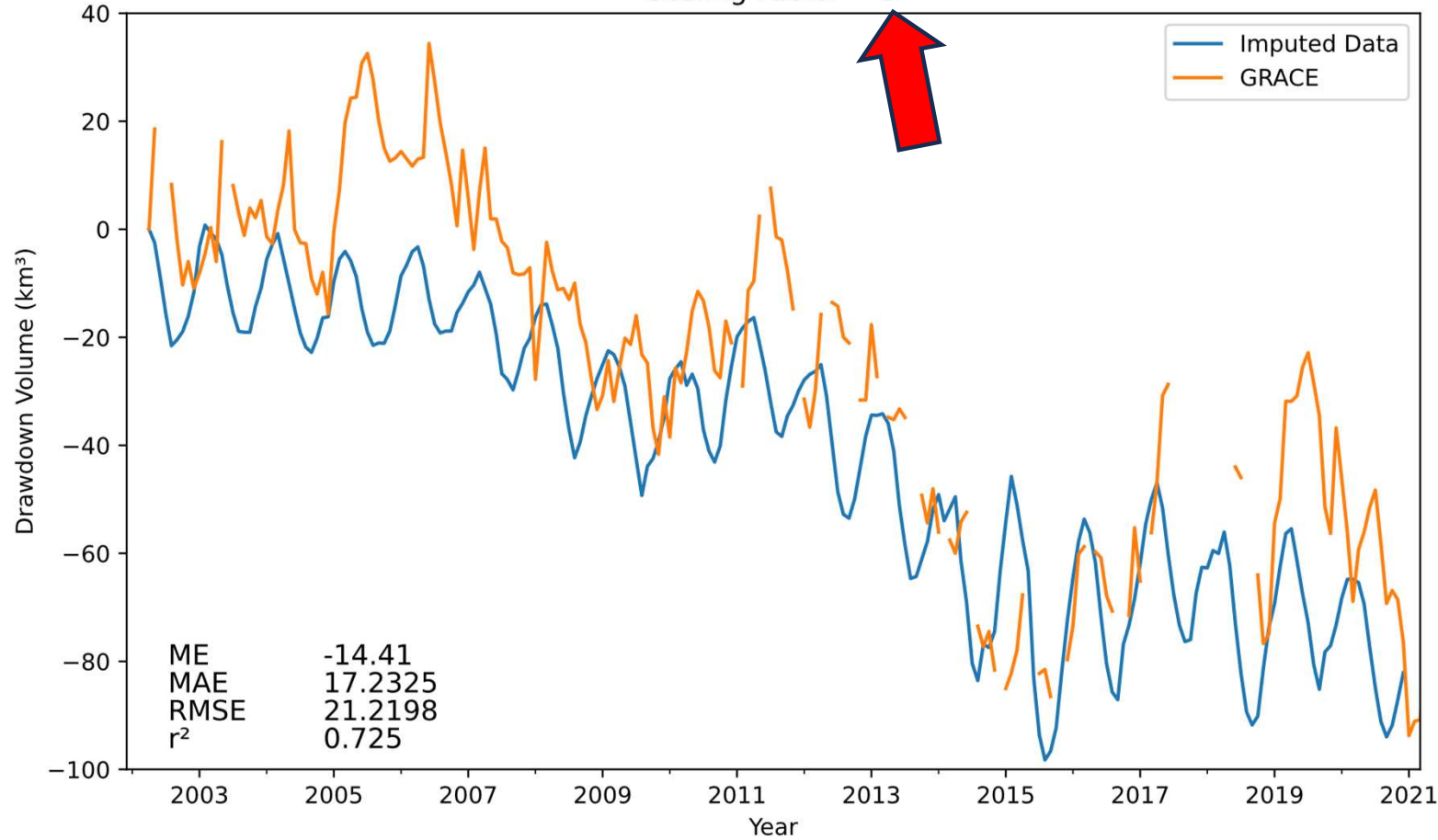
```
[ ] measurements = pd.read_csv(list(upload_timeseries.keys())[0])
measurements
```

Process is executed step-by-step for better control over results

Resulting rasters can be uploaded to GWDM app via admin control panel



Comparison to GRACE  
75 Observation-month Threshold, Iterative Imputation,  
Scaling Factor = 5





# Conclusion

- Good agreement between GRACE GWSa and in situ GWSa after applying scaling factor
- Going forward, GRACE GWSa can be used reliably after applying scaling factor = 5

## Groundwater Storage Loss in the Central Valley Analysis Using a Novel Method based on *In Situ* Data Compared to GRACE-Derived Data

1 Michael D. Stevens<sup>1</sup>, Saul G. Ramirez<sup>1</sup>, Eva-Marie H. Martin<sup>2</sup>, \*Norman L. Jones<sup>1</sup>, Gustavious P. Williams<sup>1</sup>, Kyra H. Adams<sup>3</sup>, Daniel P. Ames<sup>1</sup>, Cedric H. David<sup>3</sup>, J.T. Reager<sup>3</sup>, Sarva T. Pulla<sup>4</sup>

3 <sup>1</sup>Brigham Young University, Department of Civil and Construction Engineering, Provo, UT, USA

4 <sup>2</sup>Eva needs to check what to put here

5 <sup>3</sup>Jet Propulsion Laboratory, California Institute of Technology, Pasadena, CA, USA

6 <sup>4</sup>ArchGeo LLC, Saint Louis, MO, USA

7 \* Correspondence:

8 Norman L. Jones  
9 njones@byu.edu

10 **Keywords:** Machine Learning, Groundwater, Central Valley, Sustainability, GRACE

### 11 Abstract

12 We estimate long-term groundwater storage loss in California's Central Valley (CV) with a novel data  
13 imputation method that uses *in situ* data combined with globally available Earth Observations - the Palmer  
14 Drought Severity Index (PDSI), and the Global Land Data Assimilation System (GLDAS) - to generate  
15 temporally- and spatially-interpolated groundwater elevations which we combine with storage coefficient  
16 maps to produce computed volume changes over time for the valley. We compare our results to groundwater  
17 storage changes we calculated using Gravity Recovery and Climate Experiment (GRACE) mission data and  
18 show that the two storage estimates are significantly correlated. We also compare our results with previously  
19 published groundwater storage changes using GRACE-derived data and show that the trends match well.  
20 However, while correlated, the GRACE-derived storage values are significantly lower than estimates derived  
21 from *in situ* data. This is because the area of the CV is small compared to GRACE pixels and therefore the  
22 GRACE data includes areas without active groundwater changes, in this case the Sierra and coastal mountain  
23 ranges, and GRACE pixels within the CV experience "leakage" where values within a pixel are influenced by  
24 surrounding areas. While other researchers have accounted for leakage by scaling the GRACE results based on  
25 the ratio of the area of the CV to the larger CV hydrographic basin, our method demonstrates a direct method for  
26 calibrating GRACE estimated groundwater change, which can then be applied to future GRACE results with  
27 confidence. This method can be replicated globally at a variety of aquifer scales to account for both pixel size  
28 and leakage affects with minimal *in situ* data.

Journal article manuscript under development

Go Home

**Region Name: Jordan**

Select a Region  
Jordan

Select an Aquifer  
Dead Sea GW

Select Variable  
Water table elevation, m

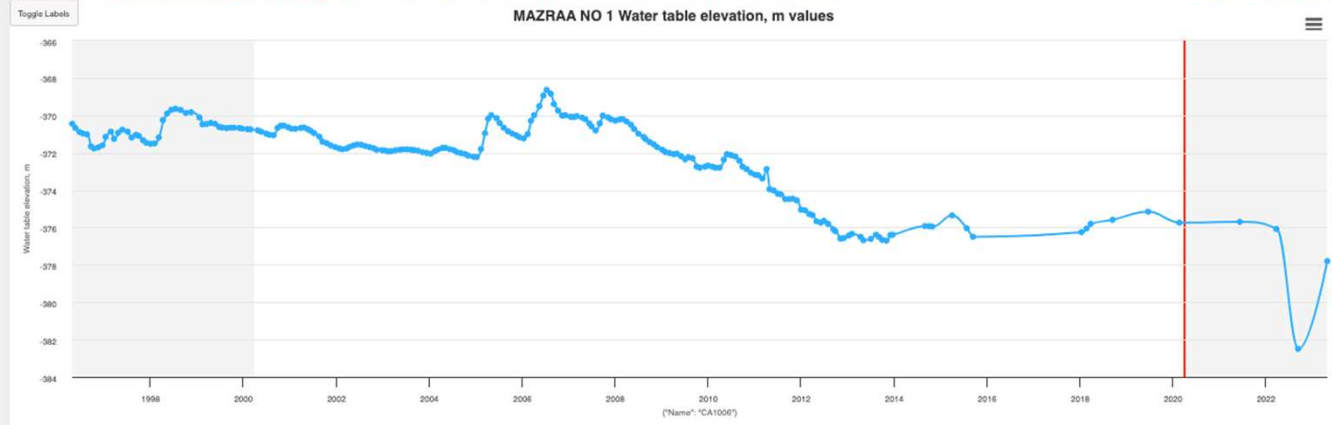
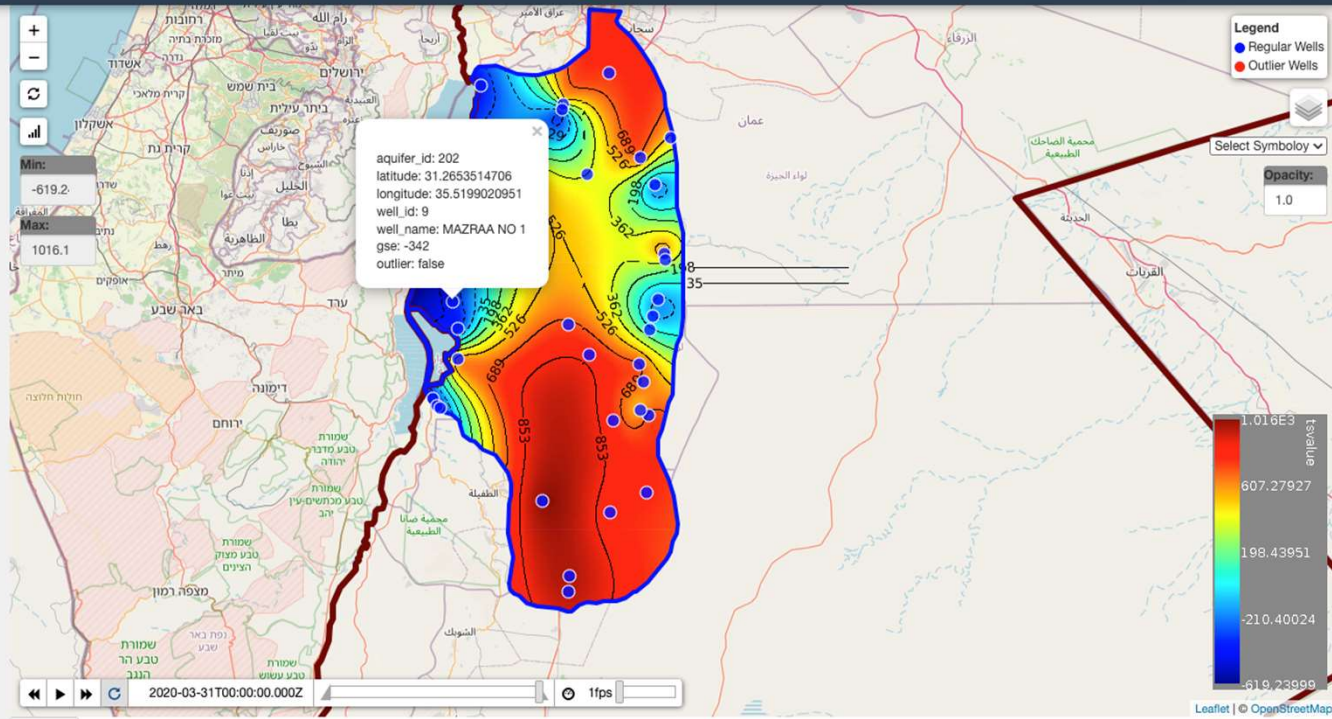
Interpolation Layer  
Dead\_Sea\_GW\_2\_myjordandata\_17...

Cluster Wells

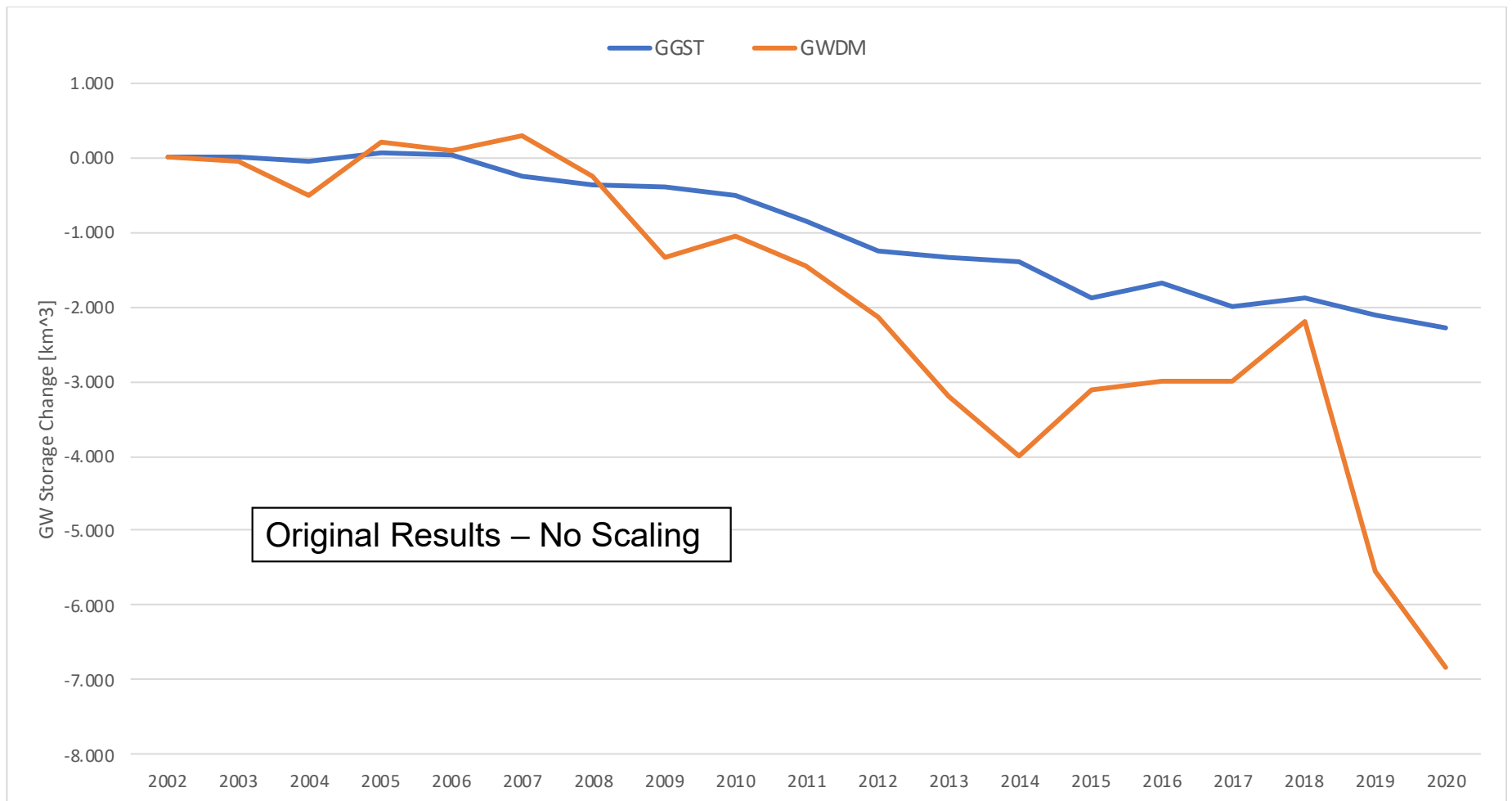
Multiple Well Select

Filter Wells By Observations

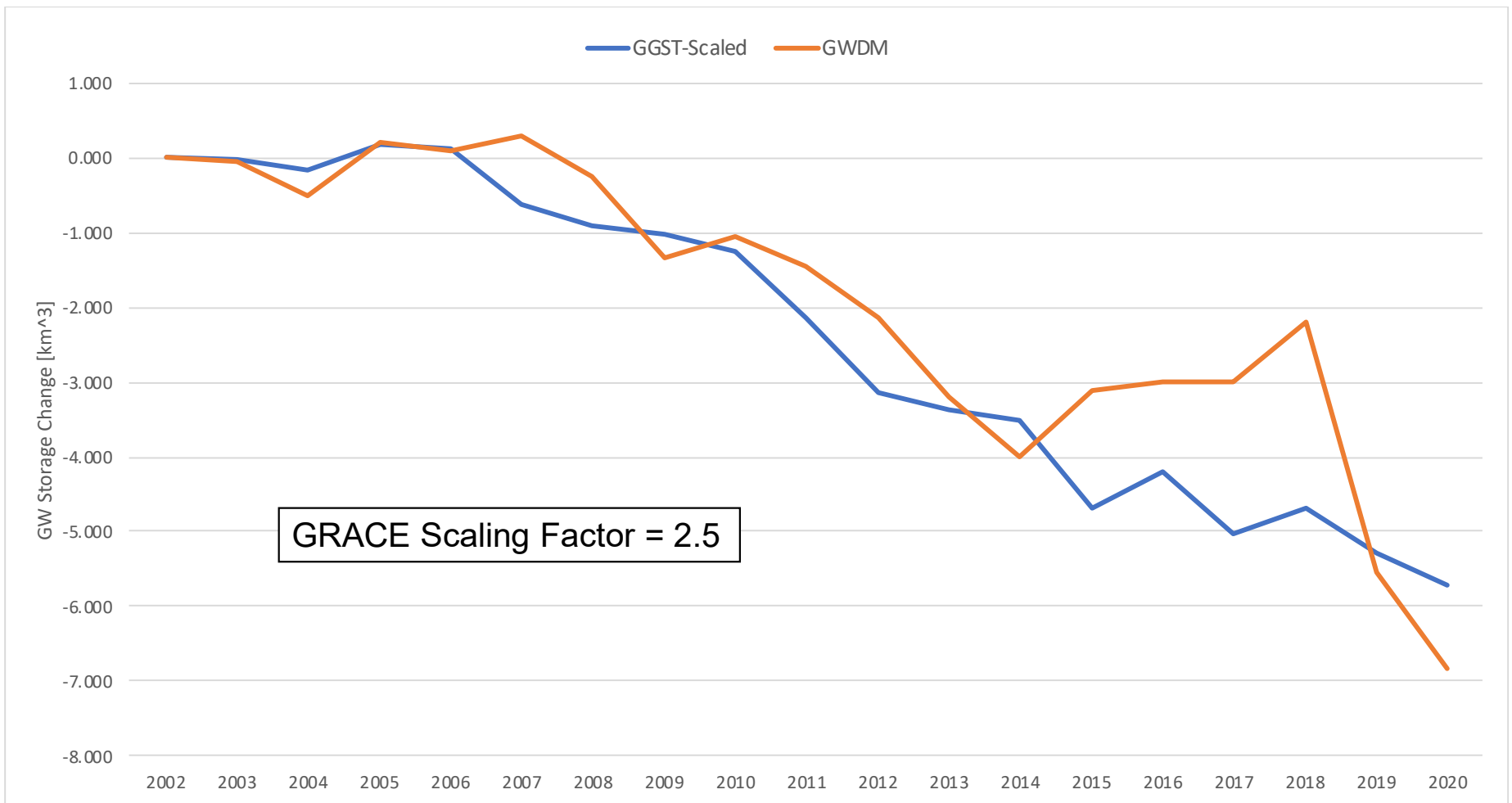
0.00 381.00



# Dead Sea Basin – Groundwater Depletion



# Dead Sea Basin – Groundwater Depletion





# Questions?

