Application of Artificial Neural Network (ANN) for Downscaling Ground Storage changes- Case studies from Central Valley

Vibhor Agarwal[1], CK Shum[1], Orhan Akyilmaz[2], Metehan Uz[2], Chaoyang Zhang[1], Wei Chen[1]

[1]Division of Geodetic Science, School of Earth Sciences, The Ohio State University [2]Department of Geomatics Engineering, Istanbul Technical University, Turkey

THE OHIO STATE UNIVERSITY GEODETIC SCIENCE A DIVISION OF THE OSU SCHOOL OF EARTH SCIENCE

ABSTRACT

This study focuses on retrieving high-resolution groundwater storage (GWS) changes from coarse resolution GRACE satellite and other data utilizing Artificial Neural Network (ANN).

Study region Central Valley aquifer has undergone extensive human pumping of groundwater.

Quantifying ground water storage changes at high resolution is important for water resource management. However groundwell-based monitoring of groundwater storage changes are less efficient.

Further, the applicability of GRACE satellite to more localized Groundwater studies is limited by their low spatial resolution at ~100,000 km2. With the aid of Machine Learning and ANN, we establish regression model between GRACE data, climate, environmental, and hydrological data and available ground-based groundwater level data acquired from US Geological Survey (USGS) over the period 2003–2016. The modeled relationship is used to quantify the groundwater storage changes across the study area at a higher resolution than what can be acquired from GRACE and field data alone.

DATASETS USED

The study period is between October 2002-October 2016

CSR GSM GRACE L2 CSR RL06 datasets (coarse resolution ~300 km)

- Monthly 2.5 min resolution precipitation and temperature data from PRISM (PRISM Climate Group)
- 8 day 500 m MOD16 evapotranspiration (ET) –
- Percent Slope from 90 m SRTM DEM
- 4 km Permeability map from Gleeson et al., 2014
- Monthly GW well observations data from USGS

METHODS

Grace was processed according to analysis

$$\Delta EWH = \frac{R\,\rho_{ave}}{3} R \sum_{l=0}^{lmax} \sum_{m=0}^{l} W_l\, \bar{P}_{lm}(\cos\theta)\, [\Delta\bar{C}_{lm}\cos(m\Phi) + \Delta\bar{S}_{lm}\sin(m\Phi)]\, \frac{2l+1}{1+k}$$

$\bar{P}_{lm}$ are normalized Legendre functions of degree *l* and order *m*

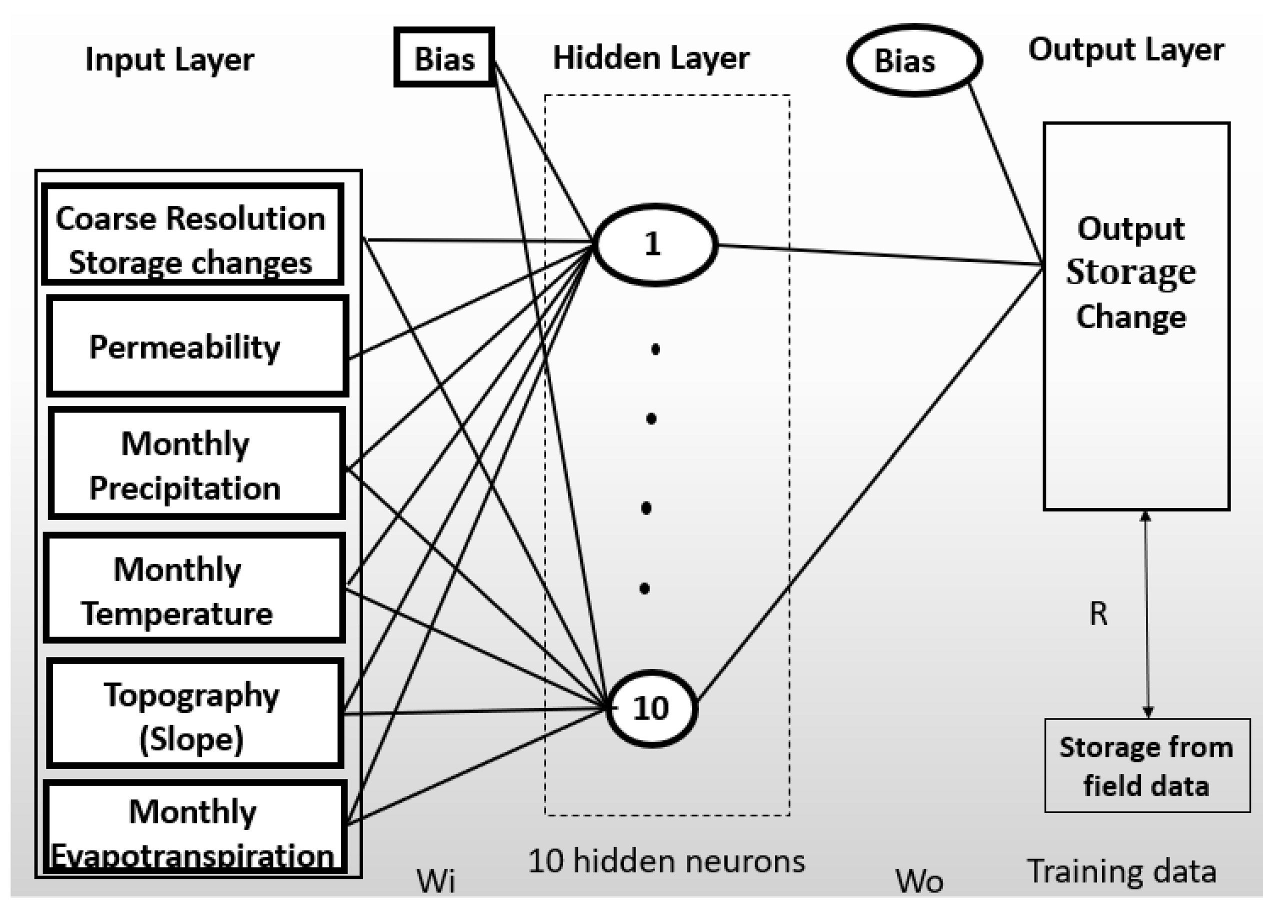
$\Delta\bar{C}_{lm}$ and $\Delta\bar{S}_{lm}$ represent the harmonic coefficients of the time-variable Earth's gravity field relative to a long-term average.

h, *k* and l are the load Love numbers

Destriping based on Swenson et al (2006) was applied on the GRACE data and Gaussian filter of 300 km radius was applied for smoothening. GIA signal was removed based on Geru, A (2012). All the processing was done in GRAMAT software (Wei, 2019)

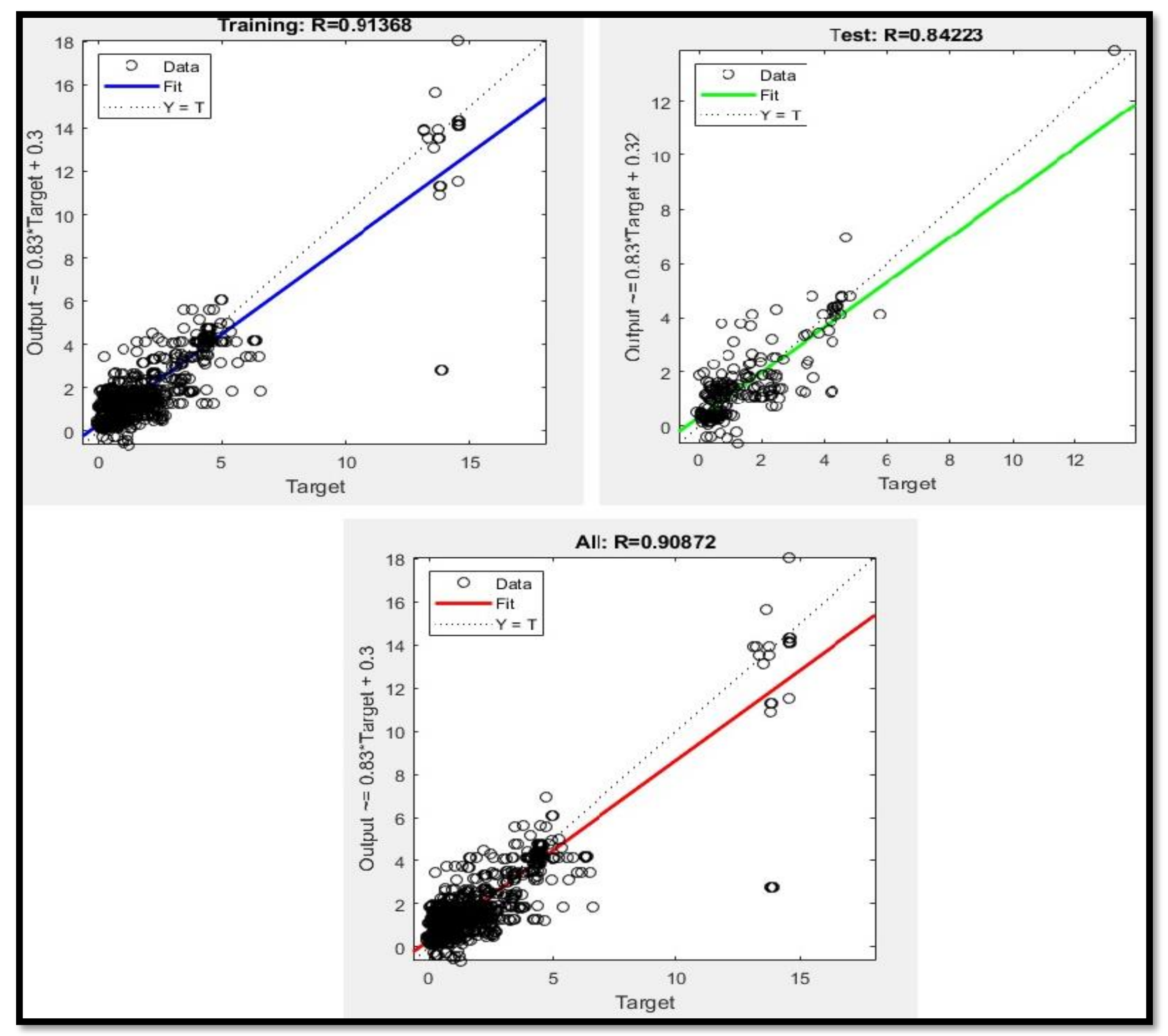
Before the ANN processing, Grid all the input data to the same Target Resolution, 8 km.

Set up the Artificial Neural Network (ANN) Architecture in **MATLAB Deep Learning Toolbox**

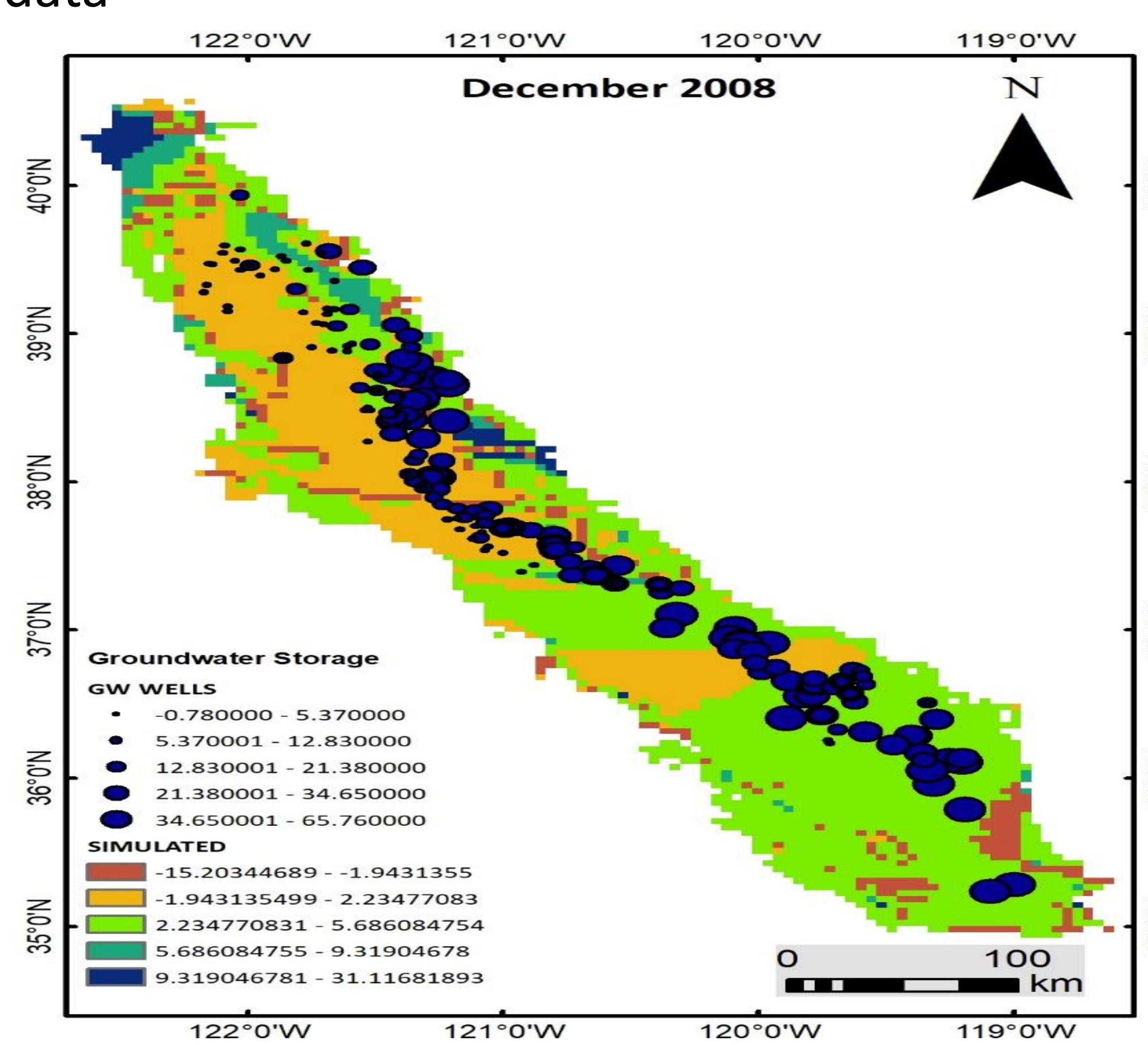


RESULTS

ANN is a powerful tool for modeling complex non-linear relationships. The following chart represent correlation coefficient between actual and modeled data after Training and Testing following Bayesian Regularization approach in ANN.



Following is the simulated Groundwater Storage computed at 8 km resolution compared with field data



DISCUSSION

The **predictive power** of ANN model is defined by **Nash–Sutcliffe efficiency (NSE)**

$$NSE = 1 - \frac{\sum_{t=1}^{T}(Q_m^t - Q_o^t)^2}{\sum_{t=1}^{T}(Q_o^t - \overline{Q_o})^2}$$

Value obtained: 0.83 (Excellent predictions)

Q_m and Q_o represent simulated and observed data respectively, whereas $\overline{Q_o}$ represent mean of observed data .

Order of importance of variables (Olden et al., 2004

1. GRACE 2. Permeability 3. Precipitation
4. Evapotranspiration 5. Temperature

SUMMARY AND CONCLUSIONS

ANN is a statistical downscaling approach viable for applications such as downscaling and can include multiple variables during modeling.

The accuracy of the model can be improved by Feature Engineering (such as Seasonality correction), ensemble modeling and Bayesian ANN which will be considered in future.

REFERENCES

Wei (2019). fengweiigg/GRACE_Matlab_Toolbox (https://www.github.com/fengweiigg/GRACE_Matlab_Toolbox), GitHub. Retrieved July 27, 2019.

Olden, J.D., Joy, M.K., Death, R.G. 2004. An accurate comparison of methods for quantifying variable importance in artificial neural networks using simulated data. Ecological Modelling. 178:389-397.

Gleeson, T., Moosdorf ,N., Hartmann,J. and van Beek, L.P.H.(2014) A glimpse beneath earth's surface: GLobal HYdrogeology MaPS (GLHYMPS) of permeability and porosity. Geophyscial Research Letters, 41: 2014GL059856 doi: 10.1002/2014gl059856

ACKNOWLEDGMENTS

We are thankful to FOH to provide us funding for 27th General Assembly of International Union of Geodesy and Geophysics in Montreal Canada.