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Downscaling GRACE data to estimate groundwater use at the aquifer scale

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Abstract.

Sustainable groundwater management requires an operational in situ monitoring network. Concerning groundwater quantity, the EU Water Framework Directive (WFD) requires groundwater level and abstraction monitoring so as to ensure that changes in groundwater storage do not exceed the natural replenishment of the groundwater system. However, there are cases, e.g. Greece, where WFD monitoring program has not yet become fully operational due to various constraints which are more evident during the recent economic crisis. Over the last few decades, satellites have provided useful information to hydrologists, not only concerning surface water resources but also concerning groundwater conditions. The present study aims at quantifying groundwater use at the aquifer scale by using Gravity Recovery and Climate Experiment (GRACE) satellite data in combination with available meteorological data of the study area. To achieve this goal, gridded GRACE Total Water Storage data were statistically downscaled using an Artificial Neural Network (ANN). The methodology was applied in an aquifer in Thrace region (NE Greece) during the time period 2005 - 2014. Results showed that monthly quantity of water extracted from a certain aquifer can be efficiently estimated offering an inexpensive alternative when in situ observations are not available.

Keywords: Groundwater use, statistical downscaling, Artificial Neural Networks, GRACE, Thrace Greece

1. Introduction

It is widely accepted that groundwater constitutes a resilient source of drinking and irrigation water in many parts of the world. Recent studies have shown that the global groundwater abstraction rate has doubled during the last five decades and that groundwater depletion is a major threat for many aquifers all over the world (Wada *et al.*, 2010). Climate changes are expected to pose additional stress to groundwater resources especially in areas defined as "Hot Spots" regarding their vulnerability or their climate response to climate changes, like the Mediterranean countries (Giorgi, 2006). In order to protect groundwater systems around Europe, EU has set up several requirements from Member States, as described in the Water Framework Directive (WFD) (European Union, 2000) and the daughter Groundwater Directive (European Union, 2006). Concerning the quantitative status of groundwater resources EU Member States should have established by the end of 2006 an operational monitoring network so as to ensure a balance between abstraction and recharge of groundwater. In cases where this balance is disrupted, Member States should have taken all necessary measures to restore the affected groundwater systems at least by the end of 2015. Decisions regarding the state of a groundwater system traditionally rely on in situ observation networks which however demonstrated a decline of coverage in recent years (Sun, 2013), resulting in loss of precious information for many aquifers. It should be also admitted that establishing and maintaining a fully operational groundwater monitoring network is both cost and effort demanding, especially during the period of recent economic crisis. A typical example is that of Greece, which is behind due dates concerning the establishment of an operational groundwater monitoring network. The lack of monitoring data in combination with the complex administrative system and the sharing of responsibilities to many authorities resulted in serious delays regarding the submission of the required by the WFD River Basin Management Plans and the implementation of measures to restore water resources (European Commission, 2015). While in situ observations offer valuable information, the role of remote sensing in offering the required hydrological information is more and more appreciated, especially in poorly gauged areas where there is no monitoring network or monitoring provides only sparse data (Lakshmi, 2004). It has been shown that it is possible to overcome data availability restrictions in various hydrologic applications using remotely sensed data (Fang and Lakshmi, 2014; Gemitzi *et al.*, 2017; Lakshmi, 2016; Richey *et al.*, 2015; Sun, 2013). Concerning the quantity of groundwater resources, it is not possible to measure groundwater storage changes by any of the current remote sensing technologies (Brunner *et al.*, 2007). During the last decade the Gravity Recovery and Climate Experiment (GRACE) (Tapley *et al.*, 2004) has been a focus point for many hydrologists, as it provides measurements of the changes in Total Water Storage (TWS). Although GRACE cannot provide measurements of the individual hydrologic components, various methods for isolating the TWS components from GRACE signal using supplementary data sets, either as modeled values or as in situ observations, are developed (Richey *et al*., 2015; Sun, 2013; Zaitchik *et al*., 2008). It has also been shown that GRACE changes in TWS, i.e. ΔTWS may serve as predictor for changes in water level, which is especially useful when the monitoring network cannot provide continuous in situ observations (Sun, 2013). The objective of this study is to develop a statistical downscaling model for GRACE ΔTWS that will be used along with meteorological data in order to predict the abstracted water quantities form a certain aquifer. Performance of the model was assessed in an aquifer in Thrace (NE Greece). It is expected that the developed model will be very useful in case where monitoring network fails to provide water level and abstracted quantities and will help towards highlighting overexploited aquifers.

2. Data and Methods

2.1. GRACE data

GRACE is a joint mission between the National Aeronautics and Space Administration (NASA) in the United States and Deutsche Forschungsanstalt für Luft und Raumfahrt (DLR) in Germany. It launched in March 2002, and its purpose is to map Earth's gravity field. It was found that after removing the ocean and atmosphere effects, GRACE signal approximates changes in terrestrial water storage (ΔTWS) (Tapley *et al*., 2004). Thus, converting observed gravity anomalies into changes of equivalent water height, GRACE data provide measurements of monthly changes in total terrestrial water storage. In this work we acquired Version 5.0 for the Level 2 GRACE data in the form of monthly Total Water Storage (TWS) anomalies from 2005 to 2014, from the CU GRACE data portal (http://geoid.colorado.edu/grace/index.html) developed by the University of Colorado. The data set comprised of gridded GRACE TWS anomalies with spatial resolution of 100 km, scaled applying gridded gain factors according to the methodology described in Landerer and Swenson (2012).

2.2. In situ observations - Description of the study area

In order to develop and verify our model for nowcasting and forecasting of groundwater abstraction quantities, data from Neon Sidirohorion aquifer in Rhodope area (Thrace, NE Greece) were used (Figure 1). The study aquifer is an alluvial one covering an area of 35km^2, with thickness ranging from 50 - 100m. Cotton and corn are the main cultivations of the region. Groundwater abstractions are taking place during summer (June to August) for irrigation purposes causing groundwater level drawdown (Gemitzi and Stefanopoulos, 2011). The following data were used along with GRACE observations from 2005 - 2014 (Table 1):

a) Monthly meteorological data in the form of monthly precipitation and mean monthly temperature acquired from Komotini meteorological station, nearby the study aquifer.

b) Abstraction quantities were determined using the total power consumption for irrigation in the study aquifer (Gemitzi and Stefanopoulos, 2011), based on the equation provided by Faour (2001):

$$P = \frac{Q\ x\ H}{102\ x\ n} \quad (1)$$

where P is the total power required (kW), Q is the flow rate (l/s), H is total pumping head (m), n is the combined effect of pumping efficiency and derating, and 102 is a conversion factor. Derating accounts for efficiency losses between the energy required at the pump shaft and the total energy required. Approximate derating factor for electric motors is 80% and for diesel motors is 75%, (Faour, 2001). Power consumption was provided by the Public Power Corporation in the form of total electric power consumed in the study area per month. Pumping head in Equation (1) was taken to be the mean of monthly groundwater head in eight monitoring points in the study aquifer.

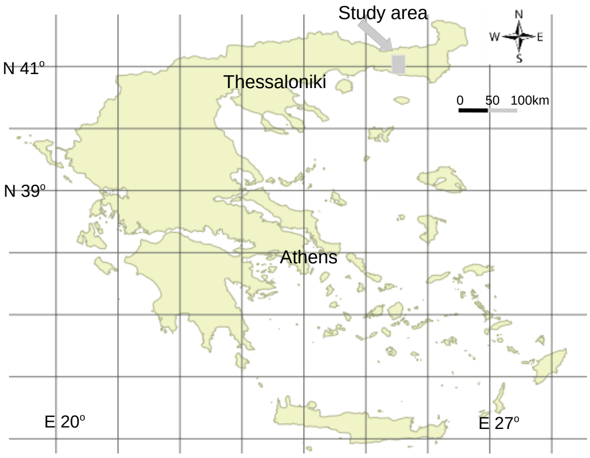

Figure 1. Location map of the study area

2.3. ANN model

ANNs have been widely used in groundwater modeling and forecasting, especially for groundwater level predictions (Chu and Chang, 2009; Coppola *et al*., 2007; Coulibaly *et al*., 2001; Sun, 2013). In our work we developed a Multi Layer Perceptron (MLP) ANN that estimates groundwater quantity abstracted from an aquifer using as input variables mean monthly temperature, mean monthly precipitation, GRACE ΔTWS and monthly abstraction quantity of the same month one year before. Since the abstraction time series demonstrates strong seasonality (Gemitzi and Stefanopoulos, 2011), use of abstraction in the previous year as predictor variable is unavoidable. Given a set of predictor variables x, an ANN evaluates the target variable:

$$y = f(x) + \varepsilon \quad (1)$$

where *f* is a complex non-linear mathematical function that converts input data to a desired output and ε is the noise in the process. Each MLP network consists of the input layer, one or more hidden layers and the output layer. To keep the structure as simple as possible we used a single hidden layer network. Each layer has one or more neurons. Given a set of M predictors $\{x_i\}_{i=1}^{M}$, the hidden layer has K hidden neurons each one computed as a weighted sum of predictors (Sun, 2013):

$$a_k = \sum_{i=1}^{M} w_{ki}^{(1)} x_i + w_{k0}^{(1)}, k = 1, \ldots, K \quad (2)$$

where a_k is a neuron in the hidden layer, $\{w_{ki}^{(1)}\}_{i=1}^{M}$are the unknown weights associated with each one of the input

Table 1. Basic statistics of the parameters used

Parameter	Minimum value	Mean value	Maximum value	Standard deviation
Mean monthly precipitation (mm)	0.0	51.3	241.0	52.2
Mean monthly temperature (^{o}C)	2.2	15.5	29	7.5
GRACE ΔTWS (mm / month)	-107.3	20.6	152.7	57.2
Groundwater abstractions (m^3 x 10^6/month)*	1.2	2.1	3.4	0.58

* Statistics for groundwater abstraction correspond to summer period only

neurons, and $w_{k0}^{(1)}$is the unknown bias term, superscripts denote the layer number. To provide output (o_k) from hidden neurons, a transfer function $g(a_k)$, in applied to a_k:$o_k = g(a_k), k = 1, \dots, K$ (3)

A linear transfer function passes the signal from hidden neurons to the output layer:

$$y_j = \sum_{k=1}^{K} w_{jk}^{(2)} o_k + w_{j0}^{(2)} \qquad (4)$$

in which y_j is the output neuron, $\{w_{jk}^{(2)}\}$ are the unknown weights and $w_{j0}^{(2)}$the bias term. In this study the number of output neurons is one. The development of an ANN model requires two phases, i.e. the training and the testing phase, each one applied to a different portion of the data set. In the present work half of the data set is used for training (2005 - 2009) and the rest half (2010 - 2014) for testing. In the training phase, fitting errors are passed backward to the network so as to obtain weights in each layer that provide best fit to observations. This process is known as backpropagation. Performance of the model is assessed in the testing phase by two criteria, i.e. the scaled Root Mean Square Error (RMSE) denoted as R* = RMSE /standard deviation of observations, and the Nash-Sutcliff efficiency (NSE) (Nash and Sutcliffe, 1970), ranging - ∞ to 1. A model is considered to have very good performance if the resulting NSE is greater than 0.75 and R* is less than 0.50 (Sun, 2013). In order to generalize the model, an ensemble of 100 ANNs was developed applying the initial weight randomization method (Sun, 2013). The Neuralnet tool (Fritsch *et al*., 2016) of the open source software R was used to develop the ensemble of MLP ANNs in this study.

3. Results and discussion

Figure 2 shows the MLP ANN developed, the neurons in each layer, together with neuron weights (in black) and bias terms (in blue). The observed and modelled time series of groundwater abstractions from 2005 to 2014 are shown on Figure 3. Training period corresponds to 2005 - 2009 and testing was performed from 2010 to 2014. Modelled values correspond to means of the ensemble of the 100 ANN models. Performance of the model was assessed in testing period and was found to be very good, with NSE = 0.95 and R* = 0.23. Our results thus, support the initial assumption that GRACE ΔTWS can be downscaled using in situ meteorological data which is in agreement with findings from previous works (Sun, 2013).

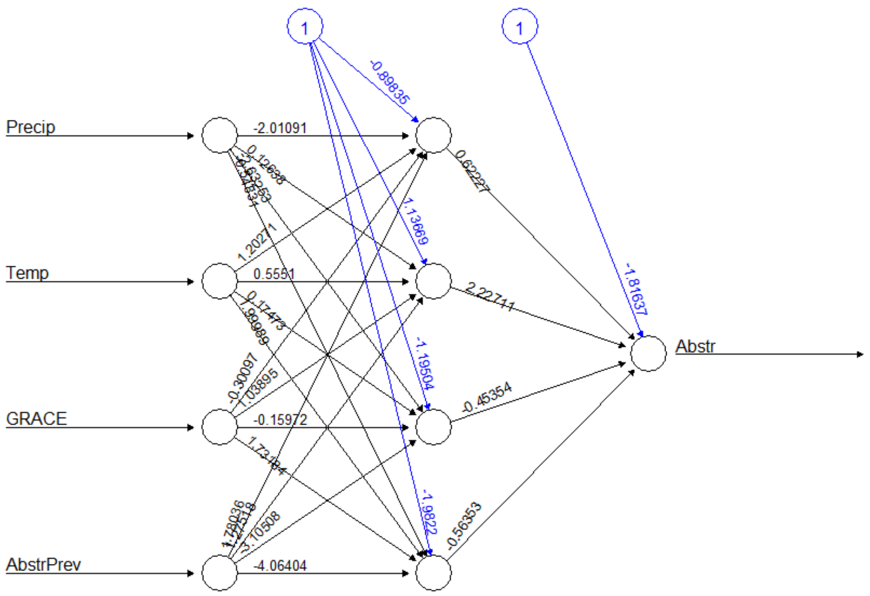

Figure 2. The structure and weights of the ANN. Black lines and numbers correspond to synapse weights. Blue lines and numbers correspond to bias terms. Precip = mean monthly precipitation, Temp = mean monthly temperature, GRACE = monthly ΔTWS and AbstrPrev = monthly groundwater abstractions during the same month of the previous year, Abstr = groundwater abstractions in the current month.

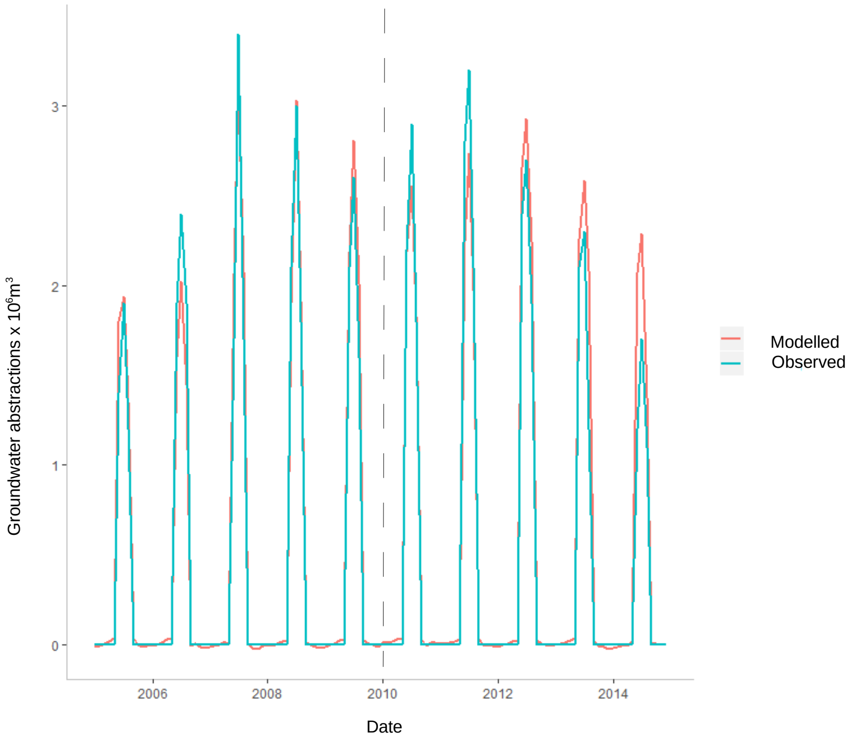

Figure 3. Modelled and observed time series of groundwater abstractions in Neon Sidirohorion aquifer (Thrace, Greece). Black dashed line separates training (2005 - 2009) and testing (2010 - 2014) phases

Additionally, it was shown that GRACE signal can be used as a predictor variable for groundwater abstractions, when a monitoring network has failed to provide required abstracted quantities. Water managers are interested in such information as it helps identifying aquifers being at risk of quantitative stress and enforce measures to ensure balance between abstractions and recharge and restore the groundwater system

4. Conclusions

In the present work an ANN model has been developed to estimate groundwater abstractions from an aquifer, using as input variables meteorological data and GRACE remotely sensed data. Results showed that gridded GRACE ΔTWS can be downscaled and used for estimating abstracted quantities of groundwater. As the whole process requires only easily available meteorological data and remotely sensed GRACE data, it is a reasonable and low cost alternative when the monitoring network fails to provide such information. Although training and testing of an ANN might be time consuming and requires computational skills, it is thereafter a readily available tool for use by water managers. The methodology is especially useful for areas like Greece, where groundwater represents approximately 42% of the total water demand and other analogous cases where groundwater constitutes a major source of water.

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