



Cairo University

CONDITIONING GROUNDWATER FLOW SIMULATION USING GENERALIZED LIKELIHOOD UNCERTAINTY ESTIMATION (GLUE)

By

Mennatullah Tarek Attia Elrashidy

A Thesis Submitted to
the Faculty of Engineering at Cairo University
In Partial Fulfillment of the
Requirements for the Degree of
MASTER OF SCIENCE

In

IRRIGATION AND HYDRAULICS ENGINEERING

FACULTY OF ENGINEERING, CAIRO UNIVERSITY
GIZA, EGYPT
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GLUE; Monte Carlo; Uncertainty Estimation; Groundwater Flow Modelling; Conditioning.

Summary:

Generalized Likelihood Uncertainty Estimation (**GLUE**) is a statistical approach which is used for decreasing the uncertainty bounds for the outputs resulted from any model. In this study, GLUE technique is used on the output of a groundwater model which simulates an aquifer in KSA which called Wadi Noaman. The study divided into three stages (calibration, verification and prediction). The model is in a stochastic module and simulates the aquifer using 100 realizations of different values for the input parameters R (Recharge) and H (Hydraulic conductivity). The results illustrate the effect of using different likelihood measures and different shape factor values. Also, the model is used to address the expected head values till the year 2037.

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Abstract

Uncertainty estimation is typical of groundwater problems which cause major difficulties in accurately predicting subsurface flow and transport quantities. Uncertainty stems from several sources, some types of uncertainty may be reducible via collecting more data, such as the parametric uncertainty. Data scarcity is the major factor that leads to the great level of uncertainty in groundwater models. When calibration data is limited and the input parameters are uncertain, the model output contains a large degree of uncertainty. In such a case, quantifying the uncertainty of model predictions through more quantitative use of the "limited" calibration data becomes crucial. A variety of methods exist for achieving this purpose, among which are the generalized likelihood uncertainty estimation (GLUE).

GLUE methodology rejects the idea of one single optimal solution and adopts the concept of equifinality of models and parameters. In the GLUE methodology, the results obtained by Monte Carlo simulations built upon a calibrated model are assigned different weights according to some chosen measure of likelihood for each realization. Identifying the appropriate likelihood measure and its shape factor is the key feature of GLUE. This research aims to apply the GLUE methodology to a deterministically developed, calibrated and verified groundwater management model to address the previous issues. The model that will be used in this research for demonstrating the use of GLUE to condition groundwater modeling simulation is a groundwater model of the aquifer of Wadi Noaman, Saudi Arabia. A conceptual groundwater model was developed and was assumed to be composed of two geologic layers; an alluvium layer and a weathered rock layer. The model was then converted to a numerical model using the tools provided in the Groundwater Modeling System (GMS). The model was calibrated using recharge and the aquifer hydraulic conductivity as calibration parameter sets and head observations as calibration data. The model was verified using transient pumping data and was then used as a management tool to a) address the impact of a proposed underground dam on groundwater levels, b) select the location and safe pumping rates of a well field to provide domestic water.

This study addresses uncertainty propagation and quantification in all stages of model development, calibration, and verification. The study relies on using steady calibration data and transient verification data within a GLUE framework to constrain model prediction and uncertainty range. The study implements different methods of data utilization in the GLUE framework with emphasis on the interplay between the steady state calibration and the transient verification data. The impact of these methods on the management model outputs is quantified and compared. Conditioning on the available filed data using GLUE seems to constrain uncertainty and leads to significantly different results than those obtained by typical Monte Carlo averaging.

Chapter 1 : Introduction

1.1. Preamble

Uncertainty in groundwater models is one of the major problems which cause difficulty in describing subsurface flow and transport. Uncertainty problems come from several sources such as numerical errors (which are caused by model limitations), conceptual uncertainty, spatial variability, boundary uncertainty and parametric uncertainty. Some types may be reducible like the parametric uncertainty which is mainly caused by data scarcity. Limited and scarce calibration data lead to a model with highly uncertain output.

1.2. Problem Definition

Limited calibration data and highly uncertain input parameters lead to model output with high degree of uncertainty. The major factor that leads to the great level of uncertainty in groundwater models is data scarcity. We can overcome the problem of scarce data via collecting more data. When collecting more data is not feasible for time and budgetary constraints, one should employ one of the various techniques that are used to quantify the uncertainty. One of those methods is the Generalized Likelihood Uncertainty Estimation (GLUE) which was originally developed by Beven and Binley (1992). GLUE methodology rejects the idea of one single optimal solution and updates the model output to account for the level of correspondence between model predictions and observed system attributes. The bolts and nuts of the GLUE approach are that the results obtained from Monte Carlo simulations are assigned different weights according to some chosen measure of likelihood for each simulation or realization. A realization is defined as a set of input parameters for which the model can be run producing the corresponding output. This model output is compared to the observed system behavior and the degree of correspondence between them gives rise to the weight assigned to that realization. The measure of likelihood updates the prior knowledge about the uncertain model parameters to a posterior probability for each one of those parameters. Briefly and concisely, the GLUE procedure is an extension of Monte Carlo random sampling to incorporate the goodness-of-fit of each simulation.

In groundwater management models, the calibrated model is used to achieve management objectives (e.g., selection of sites for well fields, determining safe yield, developing wellhead protection zone, etc.). Through future and scenario simulations, the model is commonly used to assess the impact of any management scheme on the groundwater system. This is commonly achieved using a deterministically calibrated version of the model. Incorporating goodness of fit measures and the effectuation of

quantitative use of the "limited" calibration data have not been thoroughly addressed. It is of importance to assess the effect of propagating the goodness of fit results of the calibration (through GLUE) into these management simulation results. Also, incorporating GLUE for transient calibration and verification of models has received little attention in the groundwater community. Therefore, this study attempts to fill this gap and addresses the use of the GLUE methodology in model calibration, verification, and future prediction and assessment of management scenarios.

1.3. Research Objectives

The main objective of this research is to assess the impact of using GLUE in groundwater management models and in models where observed data are used for calibration and verification. To achieve this main objective, the following specific objectives are considered:

1. Assessing the effects of using calibration data only for GLUE conditioning, using verification data only, or using a combination of calibration and verification data on the model prediction and uncertainty range
2. Assessing the sensitivity of the results of the groundwater flow model to the choice of the GLUE likelihood measure
3. Assessing the impacts of GLUE conditioning on the results (the uncertainty bounds) of the management model

1.4. Dissertation Scope and Methodology

To assess the effect of using GLUE technique an already developed and calibrated site-specific groundwater model is used. The model was used previously to simulate an aquifer existing in Saudi Arabia called Wadi Noaman aquifer. Wadi Noaman aquifer model was developed in a deterministic framework and without attention to uncertainty. In this study, the same model is used but in a stochastic framework to address the use of the GLUE methodology in reducing the overall prediction uncertainty.

The general stages of the methodology can be envisioned to include:

1. Developing prior probability distributions for input parameters (e.g., hydraulic conductivity, recharge) related to the case study of Wadi Noaman based on previous studies and in particular the extensive program of topographical, hydrological, geophysical, hydro-geological, engineering, and field investigations that were conducted during the 1990s for devising an approach to retrieve the groundwater levels in the aquifer to their original high level.

2. Simulating the aquifer of Wadi Noaman using the groundwater modeling system (GMS) under uncertain input using the prior distributions devised in the previous stage to obtain the unconditional output parameter distributions
3. For each selection of a likelihood measure and/or conditioning data, develop the uncertainty bounds and the posterior distributions using the GLUE methodology
4. Assessing and comparing the uncertainty bounds for the different cases of using calibration data only, verification data only, and both data sets combined
5. Comparing between different outputs and different uncertainty bounds when the model is used for assessing management scenarios

1.5. Thesis Outline

Chapter (1) gives an introduction including problem definition, objectives of the study, thesis scope and methodology, and thesis outline.

Chapter (2) presents a brief background on GLUE technique and reviews past studies that were devoted to addressing the use of the GLUE methodology in hydrological models in general and groundwater models in particular.

Chapter (3) discusses the methodology and the model setup for Wadi Noaman and the approach used to assess the effect of applying GLUE technique on the model results.

Chapter (4) presents the results of the different study stages including calibration, verification and prediction under both steady and transient conditions. Various likelihood measures are used, and the parameters controlling each likelihood measure are changed to assess their effect on the uncertainty bounds.

Chapter (5) presents a summary of the work conducted in this study, the general conclusions drawn from the results, and some recommendations for future research work.