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Testing the Appropriateness of Lumped Hydrological Model in Groundwater Recharge Estimation for a Small Catchment in Karnataka, India

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Abstract: Groundwater recharge, being a major factor monitoring groundwater resources, should be carefully analyzed in order to establish the quantities of water that are available for pumping without dangerously depleting groundwater reserves, but also to determine the groundwater vulnerability. And hence, Quantification of groundwater recharge is a major problem in many water resource investigations. It is a complex function of meteorological conditions, physiographic characteristics and properties of the geological material within the paths of flow. To estimate the groundwater recharge a physically-based lumped hydrological model is developed for modeling groundwater levels in response to precipitation time-series and groundwater abstractions by pumping. The model performance is assessed by comparing predicted and observed groundwater levels. In any modeling exercise their being a need for parameter optimization, Generalized likelihood Uncertainty Estimation methodology (GLUE) is widely-used for quantifying uncertainty in groundwater recharge mapping. In order to improve the reliability and performance of the lumped- hydrological model, in this study a general approach for the assessment of performance in the simulation of groundwater recharge estimation is proposed. Sensitivity analysis results indicate that the groundwater recharge is more sensitive to parameters related to climatic conditions, soil characteristics and land use.

Keywords: Generalized likelihood uncertainty estimation (GLUE); Latin Hypercube Sample (LHS); Parameter optimization; Sensitivity analysis

1. 1. INTRODUCTION

Water is needed in all aspects of life, difficult to purify, expensive to transport and impossible to substitute. Renewable fresh water is an increasingly scarce commodity and the amount of fresh water actually available to people is finite. Although our earth is called the 'Blue Planet' as 70% of the earth is covered by water, yet only 2.5% of the world's water is fresh, while 97.5% is saline being oceans. Of this small percentage of freshwater, only 0.3% of this freshwater is available from rivers, lakes and reservoirs, 30% from the groundwater, while the rest is stored in distant glaciers, ice sheets, mountainous areas, places that we can hardly access. This is the scenario of global water distribution when no intervention is anticipated. As we are aware that numerous interventions are taking place every day in the total environment, and thus actual freshwater availability in the form of surface water and groundwater resources are much different to what it appears from the global water distribution.

The demand of water from various water users, namely, domestic, municipal, agricultural, horticultural, recreation, power and industrial sectors are increasing, and this has put tremendous pressure on the water resources systems. The growing water pollution problems for both surface water as well as groundwater have aggravated the water availability problem. The hydrological uncertainty, the development activities, heterogeneities in land, soil, climate, terrain and anthropogenic activities along with temporal variability and social dimensions has accentuated the water availability problems. The real life complexities, reducing freshwater availability and sustainability of water resources have raised many water issues at local, regional and global scales. The time has come to have a retrospect view on the water use and misuse, to take serious viewpoints towards water management including quality and quantity aspects together.

Water availability in Indian scenario: The geographical area of India is about 329 million hectares (2.45 % of the earth's land mass) and its population is 1,027 million based on the 2001 census, which is about 16% of that of the world. The renewable freshwater resources of the country are 1,869 km^3 $year^{-1}$, which are only about 4% of those of the world. As in many other countries, water resources of this country are not evenly distributed in space and time. Although some water is received from the upstream countries, precipitation is the main source of water availability. The annual rainfall varies from more than 10,000 mm in parts of Meghalaya in the north-east to less than 500mm in semi-arid parts of Rajasthan and Gujarat. In arid regions, it is even less than 100mm. Much of the water is received during monsoon season, about four months in a year and more crucial is that it occurs in about 100 hours of the rainy days. [1]Precipitation is the natural recharging source for the surface water resources and it also maintain the hydrological cycle. Rivers are the major source of water in India. The utilizable annual surface water in rivers of the country is 690 km^3. Groundwater resource recharge from the precipitation mostly in the monsoon season in India. Canal irrigation and other form of irrigation systems also contribute to the recharging of the groundwater. The annual potential of natural groundwater recharge from rainfall in India is about 342.43 km^3, which is 8.56% of total annual rainfall of the country. The annual potential groundwater recharge augmentation from canal irrigation system is about 89.46 km^3

Management of Groundwater systems and role of recharge estimation: Groundwater recharge, being a major factor maintaining groundwater resources, should be carefully analyzed in order to establish the quantities of water that are available for pumping without dangerously depleting groundwater reserves, but also to determine the groundwater vulnerability. Low groundwater resources can be an effective obstacle for industrial and social development, or at least significantly reduce its pace. In many countries, the management of groundwater basins has therefore high priority. In the estimation of groundwater recharge, in particular, in arid and semi arid regions, it is essential to (i) recognize and understand the complexity of the geological formations and the flow processes that occur therein; (ii) the high degree of variability, poor distribution and uncertainty of precipitation and its role in generating recharge; (iii) improvement in the data collection; and (iv) improvement in the recharge estimation methods.

1.1 Recharge estimation through hydrological models

A model is a simplified representation of real world system. The best model is the one which give results close to reality with the use of least parameters and model complexity. Models are mainly used for predicting system behaviour and understanding various hydrological processes. A model consists of various parameters that define the characteristics of the model. The two important inputs required for all models are rainfall data and drainage area. Along with these, watershed characteristics like soil properties, vegetation cover, watershed topography, soil moisture content, characteristics of ground water aquifer are also considered. Hydrological models are now a day considered as an important and necessary tool for water and environment resource management. Rainfall-runoff models are classified based on model input and parameters and the extent of physical principles applied in the model. It can be classified as lumped and distributed model based on the model parameters as a function of space and time and deterministic and stochastic models based on the other criteria. Deterministic model will give same output for a single set of input values whereas in stochastic models, different values of output can be produced for a single set of inputs. The parameters used in the lumped model represent spatially averaged characteristics in a hydrological system and are often unable to be directly compared with field measurements. In general, lumped models use simple bookkeeping procedures to quantify physical processes by simulating the temporal variation of various physical processes in a hydrological system. The advantage of these models over physically based models is that the conceptual parameterization in the models is simple and computation is efficient. With the availability of spatially distributed digital and remotely sensed data sets of

[1] Source: *Water resources of India, Current Science, Vol. 89, No. 5, 10 September 2005,* by Rakesh Kumar, R. D. Singh and K. D. Sharma

features such as precipitation, elevation, vegetation, etc., many distributed lumped models have been developed in recent years. These kinds of models have been widely used in most climate and meteorological studies to model hydrological processes "*Seiller et al. (2012)*".

Parameter Optimization Technique: Routine availability of hydrological, geological, and other physiographic data today allows us to obtain a priori estimates of hydrologic model parameters prior to explicit model calibration. When informative a priori estimates of model parameters are available, the problem of hydrologic model calibration becomes one of filtering, i.e. improving the a priori estimates based on observations of input and output to and from the hydrologic system, respectively, rather than one of bounded global optimization based solely on the input and output data as in traditional model calibration "*kuzim et al. (2007)*". The equifinality problem has been universally found in hydrological models. The Generalized Likelihood Uncertainty Estimation methodology (GLUE) is widely used to quantify the parameter uncertainty in a variety of hydrological models "*André Fonseca et al. (2013)*". This study makes a comprehensive discussion about the sources of equifinality in a distributed conceptual hydrological model "*LI LU et al. (2009)*". However, the subjective nature of GLUE involving the definition of the likelihood measure and the criteria for defining acceptable *versus* unacceptable models can lead to different results in quantifying uncertainty bounds *"Jung et al. (2014)"*. The approach of Water Table Fluctuation (WTF) method as given by "*Park and Parker (2007)*", further stated as P&P model in this paper is adopted to estimate groundwater recharge. The objective of this paper is to perform a sensitivity analysis [2]of the effect of the choice of likelihood measures and cut-off thresholds used in selecting behavioral and non-behavioral models in the GLUE methodology.

2. MATERIALS AND METHODS

2.1 Hydrogeological setting of India

Rainfall is the important element of Indian economy. Although the monsoons affect most part of India, the amount of rainfall varies from heavy to scanty on different parts. There is great regional and temporal variation in the distribution of rainfall. Over 80% of the annual rainfall is received in the four rainy months of June to September. The average annual rainfall is about 125cm, but it has great spatial variations.

The hydrogeological setting of groundwater defines the potential of groundwater resource and its vulnerability to irreversible degradation. This setting in India can be divided into following categories, which are described below:

Hard-rock aquifers of peninsular India: These aquifers represent around 65% of India's overall aquifer surface area. Most of them are found in central peninsular India, where land is typically underlain by hard-rock formations. These rocks give rise to a complex and extensive low-storage aquifer system, where in the water level tends to drop very rapidly once the water table falls by more than 2-6 meters. Additionally, these aquifers have poor permeability which limits their recharge through rainfall. This implies that water in these aquifers is non- replenishable and will eventually dry out due to continuous usage.

Alluvial aquifers of the Indo-Gangetic plains: These aquifers, found in the Gangetic and Indus plains in Northern India have significant storage spaces, and hence are a valuable source of fresh water supply. However, due to excessive groundwater extraction and high salinity and elevated arsenic concentrations exist in parts of the basin limiting the usefulness of the groundwater resource. Saline water predominates in the Lower Indus, and near to the coast in the Bengal Delta, and is also a major concern in the Middle Ganges and Upper Ganges. Arsenic severely impacts the development of shallow groundwater in the fluvial influenced deltaic area of the Bengal Basin leading to low recharge rates.

Data availability for groundwater recharges estimation: Monitoring of groundwater regime is an effort to obtain information on groundwater levels. The important attributes of groundwater regime monitoring are groundwater level, groundwater quality and temperature. Groundwater levels are being measured four times

[2] "Sensitivity Analysis - Investopedia." http://www.investopedia.com/terms/s/sensitivityanalysis.asp. Accessed 27 Oct. 2017.

a year during January, April/ May, August and November. The regime monitoring started in the year 1969 by *Central Ground Water Board*. At present a network of 15640 observation wells located all over the country is being monitored *"CGWB Report (2011)"*. The *Ministry of Water Resources* regularly monitors groundwater level through a wide network of groundwater observation wells located all over the Country. Water level is measured four times in a year i.e., in the month of January, April/May, August and November and groundwater quality samples are collected once in a year i.e., during April/May. The *Groundwater Wing of the Department of Mines and Geology* is carrying out monitoring of groundwater levels in the State, monitoring of groundwater quality and assessment of groundwater resources once in five years as per guidelines of *Ministry of Water Resources, Government of India*. The available data series are point data series and hence suitable would be lumped model. The parameters used in the lumped model represent spatially averaged characteristics in a hydrological system and are often unable to be directly compared with field measurements. The advantage of these models over physically based models is that the conceptual parameterization in the models is simple and computation is efficient.
This work pertains to use a lumped hydrological model "*Park and Parker (2007)*" momentarily stated as P&P model, which when applied to the data sets of a groundwater level series and incorporating the groundwater pumping series for the study area would yield the groundwater recharge estimates of the area which are then represented as recharge maps.

2.2 Study area

Berambadi Watershed : The Berambadi watershed (84 km^2) located in the hard – rock aquifers of peninsular India, belongs to Gundlupet town in Chamarajanagar district of Karnataka state in South India as shown in Fig 2.1. The watershed lies in semi-arid climate zone with a mean annual dominant South-West monsoon rainfall of 800 mm, regionally; the climate is dominated by a monsoon regime that generates a strong precipitation gradient with decadal trends and strong inter-annual variability, with recurrent droughts *"Sekhar et al. (2011)"*.

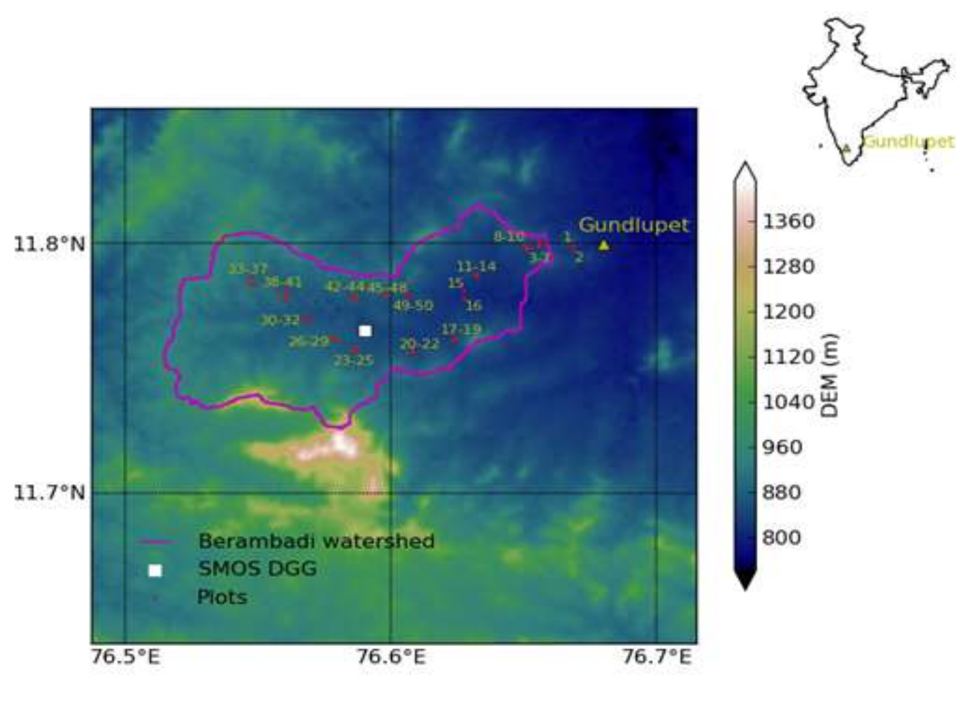

Fig 2.1. Location of Berambadi watershed inside India (shown in inset) and Digital Elevation Model (DEM). Location of 50 soil moisture measurement plots is also shown.

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The Berambadi watershed is a representative Southern Indian catchment in terms of overexploitation of its hard-rock aquifer, its cropping, rural socio-economy and agricultural practices. The watershed comprises of 12 villages, the borewells in use in each village is as shown in Fig 2.2.

The number of borewells in the watershed has been drastically increased over the years (Fig 2.2) which has lead to the exploitation of groundwater in the area. Overexploitation occurs as far as groundwater abstraction exceeds available groundwater recharge from precipitation or surface water contribution in the study area. India, with hard rock constituting more than two-thirds of the total surface, is a great example of the nexus between water scarcity and the occurrence of hard-rock aquifers. The groundwater boom during the Green revolution of the seventies has lead to a complete inversion of the irrigation scenario, with groundwater now sustaining almost 60% of irrigated land *"Roy and Shah (2002)"*. It is generally assumed that specific yield varies with depth – especially in hard-rock aquifers where fracture density and porosity change with depth, namely between the different layers constituting the aquifer "*Mare´chal et al. (2004)*" which ranges between (0.0138 – 0.0140) ± 0.0027 and hence specific yield of 0.01 is adopted in the study.

The groundwater levels for the study area were collected from *Indian Institute of Science (IISc)*, Bangalore, for 205 observation wells from 2010-2015 as shown in Fig 2.3. and also water yield data for the wells in berambadi were collected from *Ashoka Trust for Research in Ecology and The Environment(ATREE)*, Bangalore.

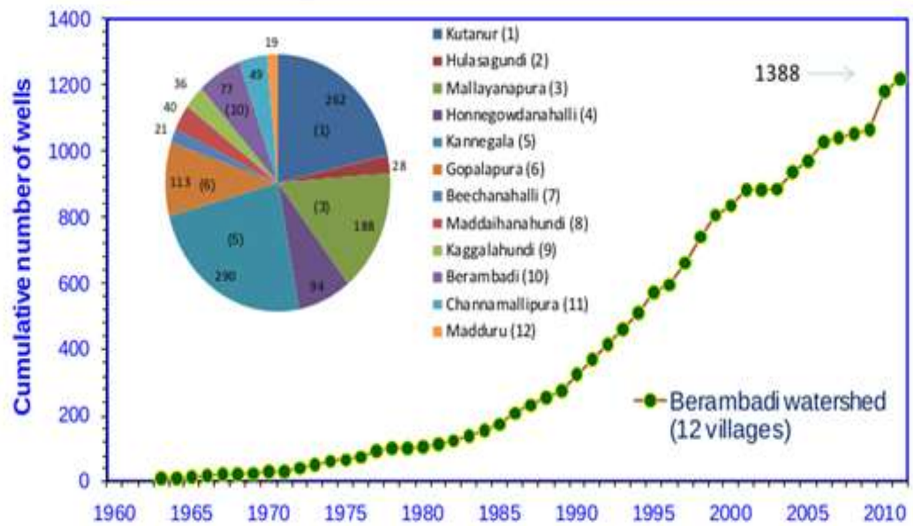

Fig 2.2 Borewells in the villages in the watershed

Out of 205 observation wells, 24 wells were considered Fig 2.4 *(Spatial distribution of borewell locations selected under study in the Berambadi watershed)*. The rainfall data for the Berambadi rain gauge station was collected from Indian Institute of Science (IISc), Bangalore which comprises of monthly rainfall data during the year 2010 -2015.

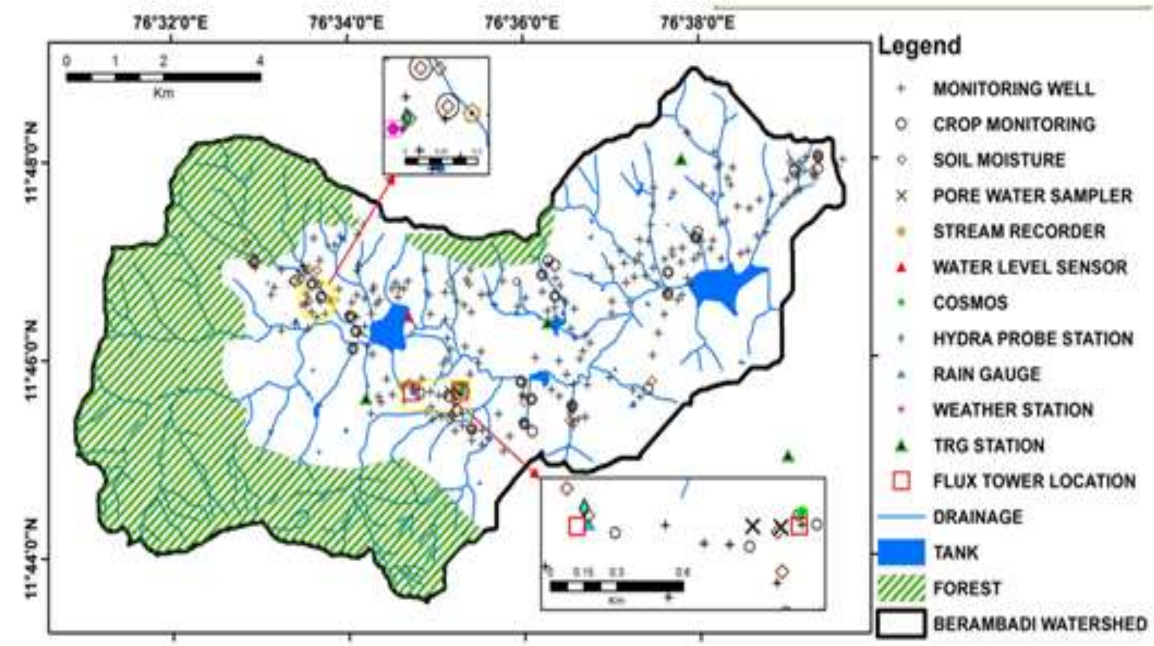

Fig 2.3 Spatial distribution of monitoring locations in the Berambadi watershed

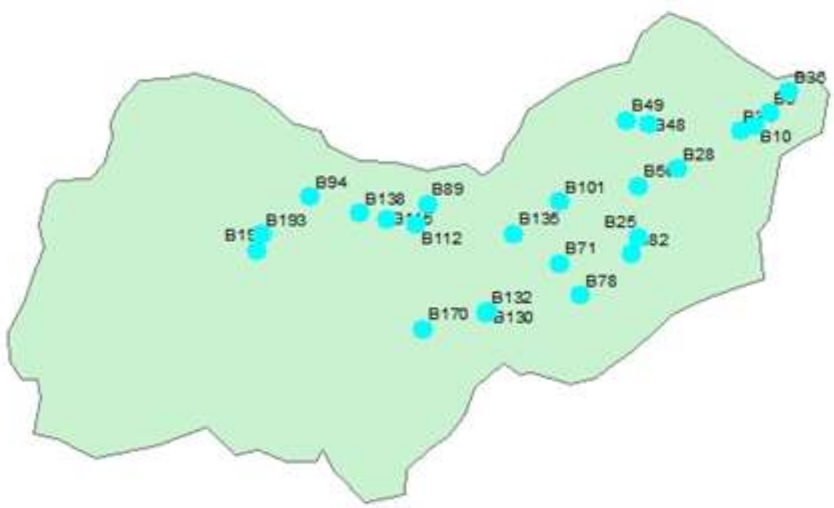

Fig 2.4 Spatial distribution of borewell locations selected under study in the Berambadi watershed

2.3 Methodology

The methodology for groundwater recharge estimation is modeled based on the lumped hydrological model given by "*Park and Parker (2007)*". The model henceforth can be called as P&P model. Optimization of parameters is done by adopting Generalized Likelihood Uncertainty Estimation (GLUE) technique and the results obtained through GLUE are then used for uncertainty and sensitivity analysis. The framework for the methodology is presented in the form of flowchart as shown in Figure 2.5 below

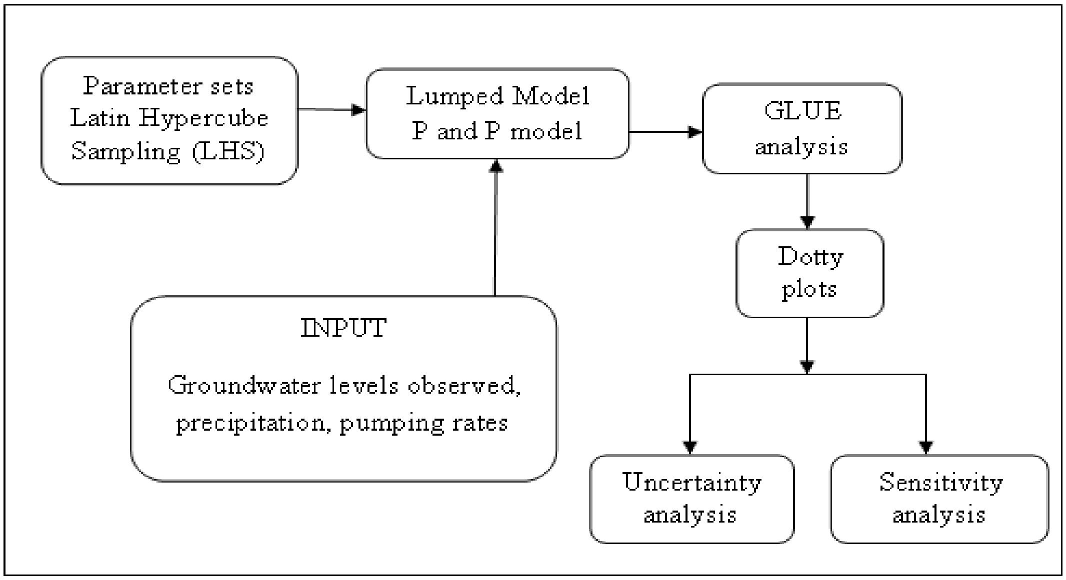

Figure 2.5 Flowchart representing the methodology adopted in this work

The lumped hydrological model and its development:

The lumped hydrological model, which was developed by "Park and Parker (2007)" (P&P model), has been applied in the Berambadi watershed with further small modifications. The primary equations of the model are presented in the model development section below.

Model development

It is assumed that the modeled aquifer region is relatively small and the hydraulic gradient inside domain is approximately constant. Further assuming that there is no groundwater pumping and no significant evapotranspiration, the following mathematical model is given-

$$h = h_0 \exp(kt) + \alpha P \; ((\exp(k)-1))/((k*s)) \qquad (2.1)$$

where h is the groundwater level, h_0 is the initial groundwater level, P is the precipitation data series for the study area, α is the recharge factor. Based on the above equation, an algorithm is given as where h_i is taken to be h_o for the first time-step (i = 1) and the groundwater elevation at the end of the time -step is computed from the average precipitation rate P_i for the period as

$$h_{(i+1\,)} = h_i \exp(k\Delta t)+(\alpha P(\exp(k\Delta t)-1))/kn \qquad (2.2)$$

Where h_{i+1} is the groundwater level calculated at time step i+1 after the time step Δt. Also, P now is the precipitation in the time interval Δt. From then on, the groundwater level for the next time step is computed using the previous groundwater level h and the precipitation in the respective time step. It is observed in Eqn.2.2 that the first term of the right hand side lead to a constant fall in the groundwater level in the case when there is no precipitation. If there is precipitation in the time period Δt, then the second term of the right hand side of the Eqn.2.2 leads to a corresponding rise in groundwater level.

In Eqn.2.2 there are three parameters- parameter k controls the fall in the groundwater level whereas parameter α in combination of parameter n (and implicitly along with k) controls the rises in groundwater level. It is observed from Eqn.2.2 that the second term is exclusively taking care of the influence of the precipitation on the groundwater level fluctuation. Extending this understanding a little further, the output through pumping from the system can be logically integrated as given-

$$h_{(i+1)} = h_i \exp(k)+((rP-P_m\,)(\exp(k)-1))/((k*s)) \qquad (2.3)$$

Where h_{i+1} is the groundwater level calculated at the time step i+1, h_i is the groundwater level of the time step i, P_m is the pumping data series of the study area, P is the precipitation data series of the study area, r is the recharge factor, k is the falling parameter and s is the specific yield. The term $(P\text{-}P_m)$ can be now considered as net input which can be either positive or negative based on the relative magnitudes of P and

P_m. Then knowing groundwater level of the previous month, and knowing the precipitation and pumping value of the same month, the groundwater level of the month can be calculated. The above equation is the primary equation on which the lumped model is based.

Implementation of P&P model in MATLAB

The P&P model as represented by Eq2.3 is implemented in MATLAB, to generate the simulated groundwater levels by optimizing the model parameters such as the recharge factor (r) and the falling parameter (k) by using the Nash Sutcliffe (NS) coefficient as the objective function and GLUE technique of parameter estimation.

Generalized Likelihood Uncertainty Estimation (GLUE)

Parameter optimization

A critical review of the application of physically based distributed modeling "*Beven, (1996)*" with multiple distributed parameters, led to the recognition that, rather than a single globally optimal parameter set, a large number of parameter sets could show equivalent behavior in terms of the objective function used in calibration. This recognition is the basic principle of the GLUE procedure, where the likelihood that any possible parameter set is a good simulator of the system is expressed in terms of how well the model performs with that parameter set, given the available data. The model parameters r and k are calibrated by adopting the Nash-Sutcliffe values as the objective function which helps in determining the model performance, where the NS values itself is taken as the likelihood measures further for the parameter uncertainty estimation.

Uncertainty analysis

The NS values obtained from the P&P model is taken as the likelihood measures. For each of the model parameters, a prior distribution is defined. Parameter sets are sampled randomly from this prior distribution. In most of the reported applications of the GLUE procedure "*Beven and Binley (1992)*"; "*Aronica et al. (1998)*"; "*Uhlenbrook et al. (1999)*", little prior information was available as to the distribution of each parameter, and a non-informative uniformly distributed prior is selected. Thus the obtained number of parameter sets (N_{MC}) was sampled using the Monte-Carlo technique from the prior parameter distributions (say 1000 samples). The model is then run using these parameter sets and the model outcome of each run is compared to the observed values using the selected objective function (NS values). Based on the value of this objective function, a likelihood value is assigned to the parameter set. The distribution of the likelihood function (NS values) is then normalized to create a proper posterior distribution of likelihoods "*Romanowicz et al. (1996)*". All parameter sets performing below a preselected threshold 0.75 are considered non-behavioral and thus removed.

The likelihood values of the behavioral parameter sets are normalized such that the distribution function is again proper and a new threshold of 0.80 is set. Subsequent predictive model runs using the remaining parameter sets are weighted according to the likelihood value of the parameter used, and from this ensemble the weighted mean and uncertainty bounds of model outcome can be derived.

Quantification of Uncertainty and sensitivity: The behavioral parameter sets and the corresponding NS values having the threshold value >= 0.8 are used for the quantification of uncertainty and sensitivity. The NS values itself are considered as the likelihood measures which are then normalized by dividing each value of likelihood measure by its total value, which gives the relative frequency of values of each parameter as typically shown in Table 2.1.

Table 2.1 Normalized Uncertainty measure

Par 1	NS(Likelihood measure)	Normalized likelihood measure
Value 1	Value 4	=value4/(value4+value5+value6)
Value 2	Value 5	=value5/(value4+value5+value6)
Value 3	Value 6	=value6/(value4+value5+value6)

In first row, normalized likelihood measure calculated as shown in the Table 2.1 gives the relative frequency of value 1 of Par 1. Likewise the normalized likelihood measures are calculated for the rest of the values for Par1. which are then used to get the histogram, where the area under the histogram is 1 and hence is equivalent to a probability density function (PDF). The normal distribution is fitted to the histogram to derive the PDF. From the PDF, the CDF is derived and the plot of CDF is typically as shown in Figure 2.6. From the CDF, 0.05 quantile ($Q_{0.05}$), 0.5 quantile ($Q_{0.5}$) and 0.95 quantile ($Q_{0.95}$) are read.

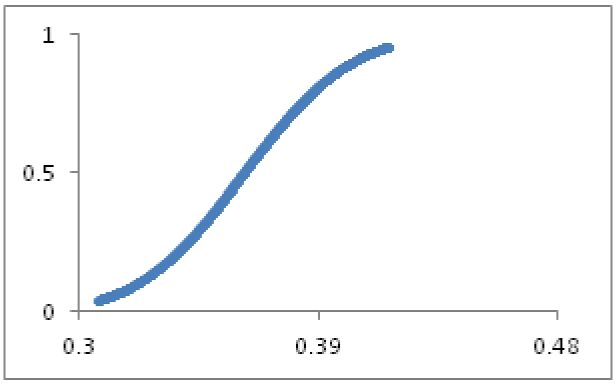

Fig 2.6 CDF of Par 1

The uncertainty bound is then obtained as,

$$UB = Q_{0.95} - Q_{0.05} \quad (2.4)$$

Where, UB = Uncertainty Bound

$Q_{0.95}$ = 0.95 quantile of the parameter

$Q_{0.05}$ = 0.05 quantile of the parameter

The uncertainty bound obtained are then normalized as shown below to compare the uncertainty of the model parameters.

$$\text{Normalized Uncertainty Bound} = (Q_{0.95} - Q_{0.05})/Q_{0.5} \quad (2.5)$$

The sensitiveness of model parameter is then quantified by dotty plots. If the dotty plot of the parameter is peaked (may be also asymmetric), then the parameter is said to sensitive; otherwise it is relatively less sensitive which is typically as shown in Figure 2.7.

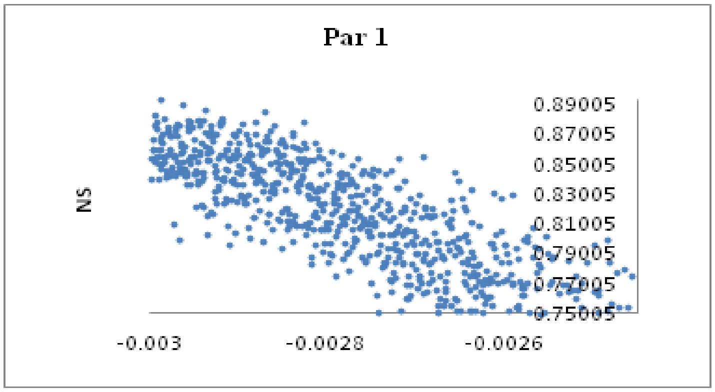

Fig 2.7 Dotty plot for Par 1

The dotty plot of Par 1 represents that the Par 1 is sensitive to the model response, as the scatter plot is peaked (may be also asymmetric), more likely aligning towards left.

3. Results and Discussions

The results referring to the implementation of lumped hydrological model (P&P model) are given in this section. Also, Optimization of model parameters by GLUE technique involves Latin Hypercube Sampling (LHS) and the obtained parameter values are then used to quantify uncertainty and sensitivity of the parameters. The model parameters considered under study i.e., the single falling parameter k and yearly recharge parameters (r1, r2, r3, r4, r5, r6) over the period of 5 years (2010-2015), the number of samples for which the program has to generate the parameter values i.e., 1000 samples, and the specified range of values for each parameter as mentioned is given as input to the Latin Hypercube Sampling (LHS) program. The LHS vector obtained, thus is given as input to the lumped model (P&P model), along with the other input variables such as groundwater levels observed, the precipitation values for every month for the period of 5 years (2010-2015) and also the pumping values having same units of measurements as precipitation for the same month. The model is thus run for 1000 times and the simulated groundwater levels are calculated by using the Eqn. 2.3 which is programmed in MATLAB. Thus, the outputs from P&P model after the model simulations are (a) the simulated groundwater levels and (b) an array of 1000 NS values. Then the model parameters are segregated as behavioral and non behavioral parameters by sorting the parameter set with the corresponding NS value >= 0.75 as threshold. The parameter sets corresponding to NS values, whose threshold is less than 0.75 is discarded as non behavioral parameters.

From the obtained behavioral parameter sets, the refined range of values of each parameter is then generated by plotting NS values versus model parameters. This refined range for all the model parameters act as input to the LHS program, to get a new 1000 sample values of refined range of each parameter. The simulated groundwater levels are then generated using the Eqn. 2.3. with the parameter values for k, r1, r2, r3, r4, r5, r6 taken as the average of upper bound (ub) and lower bound (lb). Further, the simulated groundwater levels are then obtained for all the borewells considered under study with the same procedure as mentioned above. The goodness of fit of P&P model is then represented by comparing the simulated groundwater levels and the groundwater levels observed as typically represented for a borewell in the study area in Figure 2.8.

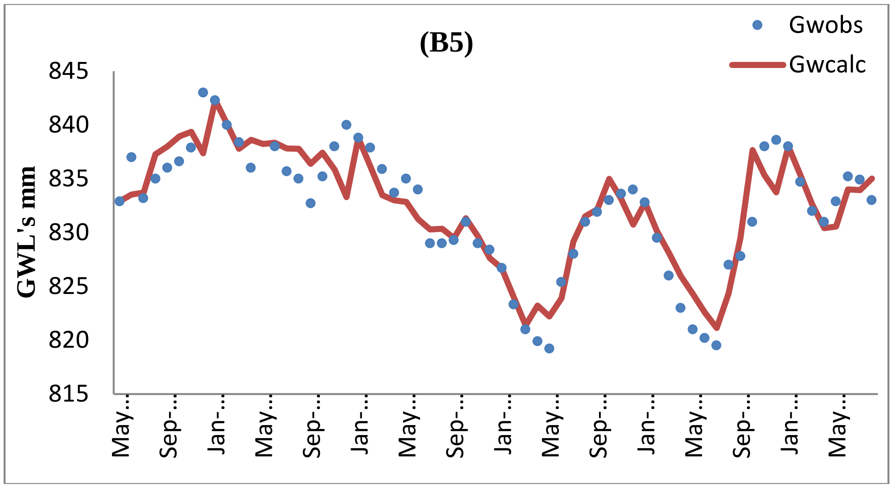

Fig 2.8 Comparison of simulated groundwater levels and observed groundwater levels for 24 borewells

The simulated groundwater levels modeled were very well captured by lumped hydrological model (P&P model) with great goodness of fit except the very few borewells which has relatively low goodness of fit when compared to the other borewells. The goodness of fit mainly depends upon the likelihood measures i.e., NS value and also the cut- off thresholds and also the low goodness of fits are may be due to the reason that a rain gauge is very close proximity to the well is not used. The obtained NS values from P&P model is itself taken as likelihood measures. The likelihood measures are then normalized by dividing each likelihood measure with the sum of likelihood measures with the help of which histograms are obtained.The normal distribution is fitted to the histogram to derive PDF. From, the PDF, the CDF is derived and the code used in MATLAB for the same. The quantiles such as 0.05 quantile ($Q_{0.05}$), 0.95 quantile ($Q_{0.95}$) and 0.5 quantile ($Q_{0.5}$) is noted from the CDF curves for all the borewells considered under study. Then the uncertainty bound for all the parameters in the borewells considered under study is obtained as ($Q_{(0.95\ )}$- $Q_{(0.05)}$) and is represented in the Table 2.2.

Table 2.2 The Uncertainty Bound (UB) of each parameter of 24 borewells considered under study

Borewell no.	UTM(X)	UTM(Y)	Uncertainty Bound						
			r1	r2	r3	r4	r5	r6	k
B5	679790	1304565	0.0435	0.029	0.034	0.028	0.085	0.104	0.00025
B10	679482	1304287	0.106	0.039	0.13	0.092	0.13	0.046	0.00016
B25	677249	1302067	0.096	0.048	0.068	0.078	0.066	0.048	0.0014
B28	678017	1303431	0.048	0.092	0.068	0.062	0.064	0.084	0.0004
B34	679218	1304198	0.088	0.066	0.106	0.102	0.132	0.122	0.00046
B36	680170	1304984	0.098	0.048	0.056	0.017	0.067 8	0.07	0.00014
B48	677434	1304327	0.05	0.0385	0.063	0.0088	0.097 2	0.086	0.0007
B49	677028	1304414	0.02	0.062	0.068	0.106	0.098	0.0194	0.0012

B56	677258	1303088	0.0995	0.07	0.122	0.058	0.126	0.076	0.00085
B71	675713	1301531	0.04	0.098	0.096	0.094	0.03	0.096	0.0013
B78	676116	1300885	0.044	0.038	0.032	0.03	0.03	0.05	0.00028
B82	677123	1301716	0.07	0.096	0.05	0.03	0.098	0.078	0.0009
B89	673160	1302715	0.076	0.078	0.036	0.048	0.074	0.03	0.00036
B94	670889	1302870	0.05	0.074	0.058	0.04	0.086	0.094	0.0008
B101	675732	1302767	0.02	0.022	0.036	0.036	0.028	0.08	0.00018
B112	672958	1302305	0.088	0.08	0.0435	0.059	0.035	0.054	0.000195
B115	672381	1302424	0.0185	0.0028	0.0255	0.016	0.0265	0.0072	0.000072
B130	674324	1300555	0.02	0.0195	0.028	0.082	0.037	0.01495	0.001
B132	674303	1300539	0.017	0.046	0.017	0.064	0.0092	0.056	0.0004
B135	674833	1302129	0.112	0.095	0.164	0.15	0.21	0.12	0.0008
B138	671863	1302540	0.048	0.0635	0.0285	0.08	0.028	0.0086	0.0004
B170	673074	1300202	0.0465	0.0185	0.0465	0.0489	0.064	0.052	0.00762
B191	669881	1301802	0	0.056	0.116	0.058	0.098	0.094	0.0005
B193	669953	1302105	0.019	0.057	0.038	0.01945	0.046	0.0865	0.00095

The normalized uncertainty bound is used to compare the parameter uncertainty across the year (2010-2015) for the borewells considered. It was observed that, even though the parameter uncertainty across the year for the borewells differs, the average parameter uncertainty across the year and across the wells is almost same having the value of 0.27(27% uncertainty). The sensitiveness of each parameter to the model response is quantified by plotting NS values[3] versus each parameter. The parameter is said to be sensitive if the scatter plots are peaked (may be also asymmetric) otherwise it is said to be insensitive. The model parameter sensitiveness and is represented in the Table 2.3 for 24 borewells considered under study.

Table 2.3 The sensitiveness [Y] and insensitiveness [N] of the parameter across the wells for all the years

1**Borewell no.**	**r1**	**r2**	**r3**	**r4**	**r5**	**r6**	**k**
B5	N	N	N	N	Y	N	Y
B10	N	Y	N	N	N	N	Y

[3] (Note: NS values taken as likelihood measures)

B25	N	Y	N	N	N	N	Y
B28	Y	Y	Y	Y	Y	Y	Y
B34	N	Y	Y	N	Y	N	K
B36	Y	Y	Y	Y	Y	Y	Y
B48	N	N	N	N	Y	N	N
B49	N	N	N	Y	N	N	Y
B56	Y	Y	N	Y	N	N	N
B71	N	Y	N	Y	N	N	N
B78	Y	Y	N	Y	N	N	N
B82	N	Y	N	N	N	N	Y
B89	N	Y	N	N	N	N	Y
B94	N	Y	N	N	N	N	N
B101	Y	Y	Y	N	Y	N	Y
B112	Y	Y	Y	Y	Y	Y	Y
B115	Y	Y	Y	Y	N	N	Y
B130	N	N	N	Y	N	N	N
B132	N	Y	N	Y	N	N	N
B138	N	Y	N	Y	N	N	Y
B170	N	N	N	Y	N	N	Y
B191	N	N	Y	N	N	N	Y
B193	N	Y	N	N	N	N	Y

From Table 2.3 it can be observed that, the sensitivity of the model parameters is not homogenous. The sensitivity of the model parameters vary for different wells may be because of the reason that the rain gauge located in the proximity of the well is not used.

4. CONCLUSIONS AND RECOMMENDATIONS

The use of the lumped hydrological groundwater model proposed by "Park and Parker (2007)" was able to simulate the groundwater levels reasonably well except for the very few borewells. The overall average recharge across the years and across the 24 borewells considered under the study is 0.26 (27%) with the range being 0.09 to 0.63 (9% - 63%). Uncertainty in modeling exercise was studied using GLUE technique and the overall uncertainty of the model parameters is 0.27 (27%). GLUE being the subjective method that involves making decisions on a probability distribution of the uncertain variable and the selection of

likelihood measures and a cut-off threshold to develop the uncertainty bound. Depending on the choices made for the probability distribution, likelihood measure and cut-off threshold, the results may vary. The subjectivity of the GLUE methodology is widely discussed in the literature; a framework to quantify the effect of these subjective decisions on the final result does not exist. This study is an attempt to develop such a framework. Based on the results from the study area we can come to an understanding that the shape of the posterior PDF also changes as the cut-off threshold is changed for different likelihood measures. Usually, the number of datasets used to create an uncertainty bound decreases with tighter thresholds. In order to get a reasonable number of datasets with a tighter threshold for the smooth CDF weighted by behavioral models, a large number of simulations are needed. However, too many simulations can increase the computational burden.
The sensitivity analysis of the model parameters indicates that the sensitivity of the model parameters is not homogenous and hence for any further model implementation, the parameters should be considered for their sensitivity on an individual basis.

5. REFERENCES

[1]. Aronica, G. Nasello C. Tucciarelli, T. (1998), 2D multilevel model for flood wave propagation in flood-affected areas. *J. Water Resour. Plan. Manag*, *124*, 210–217.
[2]. André Fonseca, D P. Ames, P. Yang , C. Botelho , R. Boaventura, V. Vilar, (2013), Watershed model parameter estimation and uncertainty in data-limited environments, Environmental Modelling & Software 5184e93.
[3]. Beven, K.J; Binley, A.M. (1992), The future of distributed models: Model calibration and uncertainty prediction. Hydrol. Process., 6, 279–298.
[4]. Beven, K. J., (1996), A discussion of distributed hydrological modelling, Distributed Hydrological Modelling, Water Science and Technology Library, Vol. 22, Kluwer, Dordrecht, 255–278.
[5]. CGWB report (2011), Ground Water Year Book - India 2011-12, Central Ground Water Board.
[6]. G. Seiller, F. Anctil, and C. Perrin (2012), Multimodel evaluation of twenty lumped hydrological models under contrasted climate conditions, Hydrol. Earth Syst. Sci., 16, 1171–1189.
[7]. Li Lu, Xia Jun, X. Chong-Yu, C. Jianjing & W. Rui (2009), Analyse the sources of equifinality in hydrological model using GLUE methodology, Hydroinformatics in Hydrology, Hydrogeology and Water Resources (Proc. of Symposium JS.4 at the Joint IAHS & IAH Convention, Hyderabad, India, September 2009. IAHS Publ. 331, 2009.
[8]. Mare'chal, J.C., Dewandel, B., Subrahmanyam, K., (2004). Use of hydraulic tests at different scales to characterize fracture network properties in the weathered-fractured layer of a hard rock aquifer. Water Resources Research 40, 11.
[9]. Muddu, S., Javeed, Y., Bandyopadhyay, S., Mangiarotti, S., & Mazzega, P.. (2011). Groundwater management practices and emerging challenges: lessons from a case study in the karnataka state of south india. Groundwater management practices, 57.
[10]. E. Park , J.C. Parker. (2007), A simple model for water table fluctuations in response to precipitation, Journal of Hydrology (2008) 356, 344– 349.
[11]. Romanowicz. R., Beven K and Tason J., (1996), Bayesian calibration of flood inundation models. In: Flood plain processes, M. Anderson, D.E. Walling and P.D. Bates,(Eds), Wiley, Chichester, UK, 333-360.
[12]. Roy A. D., and T. Shah (2002), Socio-ecology of groundwater irrigation in India, in Intensive Use of Groundwater: Challenges and Opportunities, pp. 307– 335, A. A. Balkema, Brookfield, Vt.
[13]. Uhlenbrook. S., Seibert. J., Heibendgest. C. and Rodle. A (1999), Prediction uncertainty of conceptual rainfall-runoff models caused by problems in identifying model parameters and structure, Hydrology. Science, journal-4, 779-797.
[14]. V. Kuzmin, D.J. Seo, V. Koren (2007), Fast and efficient optimization of hydrologic model parameters using a priori estimates and stepwise line search, Journal of Hydrology 353, 109– 128.
[15]. Y. Jung , V. Merwade, S. Kim, N. Kang , Y. Kim, K. Lee, G. Kim and H.S. Kim. (2014),Sensitivity of Subjective Decisions in the GLUE Methodology for Quantifying the Uncertainty in the Flood Inundation Map for Seymour Reach in Indiana, USA, water ISSN 2073-4441.