Review

Groundwater Level Resources Management Modelling: A Review

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Abstract: Globally, groundwater is the largest distributed storage of freshwater that plays an important role in an ecosystem's sustainability in addition to aiding human adaptation to both climatic change and variability.   However, this resource is not unlimited and its sustainability is highly dependent on its prudent use. Thus, efficient management of groundwater resources to prevent overexploitation, scarcity and drought has become a major challenge for researchers as well as water managers. To solve these challenges, many solutions such as simulation and optimisation models have been proffered through the use of historical data. Therefore, this has made efficient data gathering essential to maintain data-driven groundwater level resource management models from the observation site. The global evolution of the Internet of Things (IoTs), has increased the nature of data gathering for the management of groundwater resources. Recently, a number of research challenges such as the lack of computational efficiency and scalability due to uncertainties from input parameters to the groundwater level resource model have been revealed in the management of groundwater level resources. In addition, efficient data-driven groundwater level resource management relies hugely on information relating to changes in groundwater resource levels as well as its availability. At the moment, the groundwater managers lack an efficient and scalable groundwater management system to gather the required data. The literature revealed that the existing methods of collecting data lack efficiency to meet computational model requirements and meet management objectives. Although the IoTs enabled automated data processing systems are in existence by transmitting the generated data from IoT enabled devices into the cloud through the Internet. However, traditional IoT Internet is not scalable and efficient enough to process the generated vast IoT data. Thus, it is necessary to have an efficient and scalable IoT system to extract valuable information in real-time for groundwater level resource management. Unlike previous surveys which solely focussed on particular groundwater issues related to simulation and optimisation management models, nonetheless, this paper seeks to highlight the current groundwater level resources management models as well as the IoT contributions.

Keywords: Internet of Things (IoTs), Groundwater Level Resource, Groundwater Management Model, Groundwater Measurement, Optimisation, Remote Sensing, Sensor Network, Simulation

1.   Introduction

About approximately one-third of the global freshwater consumption depends on groundwater resources thus, it has become an important source of freshwater globally [1]. It is also one of the most valuable unlimited natural resources in the world. Statistically, the freshwater resource is approximately about 4 % of the total water available on earth out of which the remaining 96 % is salty, in the seas and oceans [2]. Meanwhile, only about 0.001 % is available as a groundwater resource that is hidden underground, while 75 % is ice and about 25 % is liquid water [3]. Therefore, groundwater resources constitute approximately 98 % of all fresh liquid water available on the earth [4].   Consequently, groundwater resources are often ignored and easily forgotten in the water cycle. Since both plants and animals depend on water, therefore, the interaction between surface water systems and groundwater

resources is essential for basic life on the earth. This makes groundwater the largest distributed storage of freshwater which plays an important role in an ecosystem's sustainability as well as in aiding human adaptation to both climatic change and variability [5]. Human beings largely depend on groundwater resources as a major supply of their drinking water. Thus, efficient measurement and estimation of groundwater levels are crucial to ensure its future sustainability. Nonetheless, human activities and lack of planning on these activities has led to groundwater quantity shortage in the aquifer, land subsidence, saltwater intrusion, high cost of water production, overexploitation, unhygienic and quality contamination (Erban et al., 2013, Yang et al., 2015, Yeh, 2015, Castellazzi et al., Conway, 2016, Mani et al., 2016, Raju and Varma, 2017, Montevalli et al., 2018, Yin and Tsai, 2018, Liu et al., Yin and Tsai, 2019)

Also, the management and sustainability of groundwater resources is a global critical issue. This is in line with Goal 6 of the Sustainable Development Goals (SDGs) adopted by the United Nations General Assembly which seeks to achieve a universal reduction in water scarcity, sustainable water management, and to substantially increase the efficiency of water usage by 2030 [6]. Thus, understanding groundwater resource's potential is decisive in order to ensure its sustainable usage. Therefore, groundwater models are crucial to ensure a sustainable future without water scarcity, overexploitation, and to improve water efficiency usage. This has made groundwater level measurement very important because it is the principal source of information for groundwater resources management modelling. Depending on a region, replenishing a pumped-out groundwater resource is typically low, thus leading to a reduction in the level of resources. In addition to usage, as a result of high non-linear and non-stationary natures of groundwater resources in time series, its efficient management depends on various complex factors such as precipitation, groundwater aquifers, and other environmental factors [7]. Consequently, it is of vital importance that an effective management model for accurate groundwater level management model be developed [8, 9]

Measurement of groundwater level is important to avoid depletion of the groundwater resource as earlier stated [2]. Groundwater level measurement assists in determining the hydrological stress acting in an aquifer and provide data for efficient management. For a long-time forecast, and management, groundwater level measurement supplies data to develop a groundwater model [10]. Therefore, this has made groundwater level management models become a standard instrument used by water managers and professionals to solve most groundwater-related problems. These have been achieved by utilizing a wide-ranging number of simulation and optimization modelling methods separately. Likewise, many researchers have combined both simulation and optimization modelling methods to manage groundwater levels [11]. However, it is important to understand the nature and characteristics of groundwater levels to be able to efficiently measure or model groundwater. Additionally, the nature of groundwater level measurement in time series was described to be non-stationary and non-linear which depends on various complex surrounding agents such as precipitation, intervening aquitards, groundwater aquifers, and other hydrogeological characteristics of the aquifers involved [12]. Also, the groundwater aquifers systems' interaction with groundwater-surface at different temporal-spatial scales was described as intrinsic heterogeneous systems that are strained by a knotty hydrogeological state [13, 14]. Thus, the processes and the physical attributes that form groundwater flow within an aquifer are very heterogeneous [15]. To effectively take into consideration all these properties of groundwater resources, various groundwater management models warrant complex and highly distributed models in time series. Previously, the tendency in groundwater resources management through distributed modelling was to increase the numerical resolution, include many physical attributes, as well as to enlarge the model's domain using either a finite difference approximation or a finite element method [16-19]. Although the application of either the finite element or finite difference methods to groundwater resources management have enabled real-world and complex systems to be modelled, this has led to an increase in model runtimes and the number of factors.

Due to the depletion of groundwater resources globally as a result of an increase in usage, groundwater resources measurement has become important. Thus, there are many solutions to groundwater quantity management challenges. Thus, measurement and data gathering from an observation well, are the

principal source of data for groundwater resource management modelling. Hence, data gathering is essential to maintain a data-driven groundwater resources management modelling and to perform crucial water-related functions [20]. Besides, efficient data-driven groundwater resources management modelling relies hugely on data measurements relating to changes in groundwater levels as well as their availability. In many instances, groundwater levels are manually measured using a data logger coupled with a pressure transducer, electrical probes or a graduated steel tape dipper [2, 20]. Although these techniques are simple and easy to use, they are prone to human errors, are unreliable, and inefficient. Furthermore, depending on a region, replenishing a pumped-out groundwater resource is typically low, thus leading to a reduction in the levels. In addition to usage, as a result of high non-linear and non-stationary natures of groundwater resources in time series, its efficient management depends on various complex factors such as precipitation, groundwater aquifers, and other environmental factors [7].

Likewise, many researchers have combined both simulation and optimization modelling methods to manage groundwater resources [11, 21-27]. In the past decades, researchers in the field of water engineering have developed various management models using numerical simulation and optimisation methods to help in evaluating groundwater resources. Also, different groundwater resource management models have been developed to minimize groundwater resources scarcity [7, 12-14, 28-46]. Also, there are many models, for example, data-driven models, numerical models as well as nonlinear models that are used for groundwater resources management [47-49]. Chang et al developed a numerical groundwater resource model from a conceptual model but failed to capture the computational complexities nature of the groundwater aquifer system while focusing only on the fundamental as well as the main principles [13]. This is because it is difficult to formulate both groundwater flow equations and prove the hydrogeological parameters for conceptual models due to computation complexity. Additionally, there are uncertainties and difficulties in obtaining long time series data for groundwater levels using numerical modelling processes [12, 31, 50]. Thus, making long time series models time-consuming, laborious, unscalable, and costly [35]. However, it is important to achieve an acceptable groundwater resources model performance efficiency. But, previous information was not often available because most government agencies in charge of water often collect these data just once or twice a year during the agricultural season [45]. Also, the majority of traditional groundwater models are process-based [34]. This means much supplementary spatial data on the aquifer's hydrological and geological properties is mandatory. Further challenges occur in groundwater level management due to the complexity of hydrogeology subsurface as well as spatiotemporally variable in societal pumping activities [46].

Furthermore, as identified in most literature, there are many efforts developed previously to profer solutions to groundwater level management. Some of these solutions are through linear and nonlinear programming of simulation and optimisation techniques which are driven solely by a data acquisition [21, 23, 26, 27, 35-37, 51-54]. Data-driven classification models such as Genetic Programming (GP), Artificial Neutral Networks (ANNs), Fuzzy Logic, as well as Support Vector Machines (SVMs), and time-series techniques such as Autoregressive Integrated Moving Average (ARIMA) and Autoregressive Moving Average (ARMA) are proven alternatives to conceptual models [7, 28, 31, 32]. However, they are not scalable enough when there is a change in dynamic groundwater level with time as well as when available data is insufficient to give accurate results [34]. Furthermore, Husna et al and Kenda et al observed that the majority of groundwater level resource management models have failed to capture computation efficiency and scalability [33, 34]. Despite the huge improvements in the existing groundwater resource management models, researchers pointed out lack of efficiency and scalability as a result of considerable uncertainty, over-dependent on unavailable additional datasheets and potential substantial errors [55-59].

Over the years, the concept of the Internet of Things (IoT) has been embraced in areas including smart water, smart healthcare, smart agriculture, smart climate, and so on [60, 61]. This concept of the IoT refers to a phenomenon in which there is a connection of many smart things such, sensors, mobile phones, utility and industrial components through networks and possess data analytics capabilities. Thus, smart sensors and pressure transducers have found their usage in groundwater level management using the traditional

IoT architecture for data acquisition and processing. In a traditional IoT architecture, the IoT data generated by the smart devices are transmitted into the remote cloud through the internet [62]. As a result of huge data transferring from IoT devices into the cloud, the traditional IoT internet architecture has become inefficient for analysing and processing the collected data [61]. This is because this computation process exerts pressure on the cloud computing linked network, hereby, causing untold stress. Furthermore as identified in most literature, the cloud is not efficient and scalable entirely to sustain IoT big data in real-time due to its communication latency and network bandwidth [60-64].

Furthermore, the use of IoT in the management of groundwater levels as well as in the development of groundwater data-driven models has been instrumental in detecting areas of groundwater resources quantity reduction. However, the sensing instruments deployed into the observation wells have too low resolution and too indirect to be of use for local regional assessments in geodetic methods [55, 58, 59, 65]. Consequently, improvements in IoT technology in combination with improved geophysical modelling and data-assimilation are needed to meet computation efficient and scalable IoT architecture needs for groundwater resources management models.

While previous surveys have solely focussed on particular groundwater issues related to mathematical modelling and simulation models, this current review seeks to provide an IoT based inclusion perspective as it relates to groundwater resources management. Therefore, this paper aims to present a review of groundwater existing models, their limitations and the current challenges as well as IoT (remote sensing and geographic information system) inclusion.

The arrangement of this paper is as follows; section 2 discusses the overview and organisation of groundwater level management models. The groundwater management and IoT are presented in section 3, while section 4 contains the conclusion and thereafter references and acknowledgement.

2.   Overview and Organisation of Groundwater Level Management Models

This section aims to provide an overview and organisation of the groundwater level management model hierarchy.

2.1. *Overview of Groundwater Management Models*

A groundwater management model is a powerful mathematical aquifer management tool that utilises optimisation and simulation methods such as linear and quadratic programming with a combination of groundwater governing flow and transport equations to solve groundwater management problems [66-74]. Therefore, a traditional simulation model is utilized to answer "what if" related questions while an optimisation model provides a solution to "what is the best" under given limiting boundaries [11]. Over the years, groundwater hydrogeologists have attempted to evaluate groundwater resources using numerical simulation models. The application of numerical simulation models by the researchers in the field of groundwater hydrology has assisted them to increase their understanding of regional aquifers functions about a particular facet of groundwater systems as well as testing of the hypotheses [11, 15, 21, 23, 40, 41, 55, 75, 76], Therefore, modelling of real and complex groundwater systems have been made possible via the use of finite difference and finite element simulation models. Furthermore, this has enabled the idea for evaluation and conception framework towards effective management of groundwater resources, including impacts of chemical contaminants, surface water interaction, and its withdrawal. In a real-world groundwater resources management scenario, the groundwater management problems are multi-dimensional and hence single objective simulation management methods are not adequate.

Although simulation as a tool is often utilised by groundwater managers, nonetheless, it fails to capture critical functional and physical restrictions while also sideling the management goals. Therefore, the use of the simulation method only will not be able to provide the optimal management objective because determining the proper objective function of a groundwater system is very challenging, but can not be ignored. Consequently, a combination of simulation and optimisation management models is needed. An

optimisation-based groundwater management model aims to provide a solution to a specified goal in the best possible manner within the various limiting boundaries. These limiting boundaries emanate from both the physical patterns of the groundwater system and the manager's requirements. In addition, optimisation as a simple tool employs the capabilities of both nonlinear and linear formulations in order to solve a given complex mathematical problem. Therefore, simulation-optimisation groundwater management models in optimisation formulation merge aquifer simulation models in exchange for constraints. Thus, optimisation and simulation groundwater models have been developed for various utilisation like management of groundwater resource policies, restoration of surface and groundwater resources, control of aquifer flows and aquifer simulation simultaneously [11, 77-81].

2.2. The organisation of groundwater management models

The groundwater management models can be classified into two main groups. These are the physical classification models and data-driven classification models [45], Furthermore, studies have shown that the combination of optimisation and simulation management techniques which are data-driven models that could be organised into two groups; groundwater hydraulic management models and groundwater policy evaluation and allocation models [11, 12, 75, 78, 82]. Figure 1 shows the organisation of groundwater management models into groups.
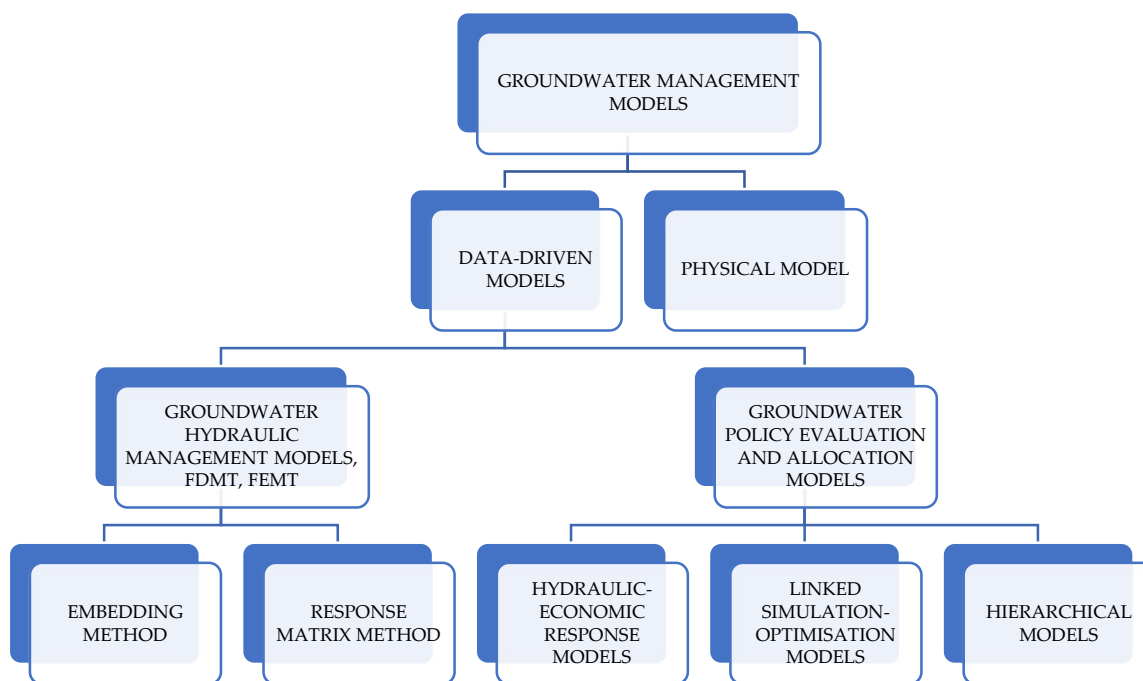

Figure 1. The organisation of groundwater level resource management models adapted from [75]

The physical classification models are based on the use of physical parameters of the groundwater bed to determine any changes in the water level. However, these models are difficult to execute, expensive, and need to be partitioned to obtain numerical information [43]. Furthermore, although groundwater management models are essential tools to examine the negative effects of human activities on the dynamic nature of groundwater resources, be as it may, the physical and the hydrogeological surroundings require reliable data [83, 84]. The aquifer of the physical groundwater management models aquifer's surrounding includes the topography, soil, climate, land use, agricultural practise, demand for groundwater usage, drainage and canals ditches. Whereas, the hydrogeological surrounding refer to the groundwater dynamism, the hydraulic parameters for each of the aquifer layers, aquifer system parameters, as well as aquifer boundary conditions. This hydrogeological surrounding varies in time and space [30, 85]. Above

all, to achieve accurate modelling results from a physical model, it is essential to have a calibration of the model using accurate data. To achieve an efficient computation is open research that must be explored.

Data-driven models' groups are differentiated on the objective function where the decision is based solely on groundwater hydraulics functions and the other whose management decision is based on evaluation of policy as well as an allocation of groundwater economy. Thus, the former is aimed at the management of groundwater stresses like rechargings as well as dischargings, well costs, and aquifer hydraulics. These groundwater hydraulic management models groups treat both the hydraulic heads and stresses as direct management objective function decision variables. On the other hand, the groundwater policy evaluation and allocation models group are aimed to solve groundwater management problems by examining the complex relationship between groundwater as well as surface water and their economic interactions. These evaluations form the base of regional groundwater policy [65, 77, 78]. The data-driven groundwater model in its primitive structure possess four basic components: it is nonlinear concerning its decision variables; requires the solution of nonlinear partial differential equations to describe the transport as well as the flow of groundwater; it is stochastic as its primary uncertain source is associated with the aquifer simulation mode, and; it is a mixed-integer programming decision because it contains discrete and continuous objective functions [54, 86]. Therefore, generally, these models are identified by their multiple objectives optimisation characteristics and possess robust economic management units.

In all these groups of optimisation and simulation groundwater management models, a set of different differential mathematical equations are used to describe the groundwater flow. Thus, a mathematical model is formed as a result of the combination of these different differential equations with their boundaries as well as initial conditions. The basis of groundwater modelling is governed by the combination of Darcy's law and conservation of mass law through an anisotropic nonhomogeneous porous medium [87-89]. The combine flow equation is represented by equation (1);

$$\frac{\partial}{\partial x}\left(T_x \frac{\partial h}{\partial x}\right) + \frac{\partial}{\partial y}\left(T_y \frac{\partial h}{\partial y}\right) + W = S\frac{\partial h}{\partial x} \tag{1}$$

where h is the hydraulic potential (L), $x, and\ y$ are cartesian coordinates (L), $T_x\ and\ T_y$ are the components of the transmissivity tensor (L^{2}T^{-1}), W is a general source/sink term (LT^{-1}), while S is the storage coefficient, and t is time (T). The efficient measurement of groundwater level (head) is important to improve the model usage. Hence, various non-linear time-series mathematical models have been proposed to measure groundwater levels in one as well as two-dimensional flow. However, many physical management model parameters should be treated in three dimensions. Consequently, the three-dimensional management application method is an open research management method for groundwater resources management discussion.

2.3. *Data-Driven Classification Models*

The latest data-driven classification models such as Artificial Neural Network (ANN) technique, Genetic programming (GP), Adaptive Neuro-Fuzzy Inference System (ANFIS), and support vector machine (SVM) as well as time series methods such as Autoregressive Integrated Moving Average (ARIMA), Multiobjective Function Approach, and Autoregressive Moving Average (ARMA) are proven alternatives to physical models. They are treated as nonlinear standard estimators that can overcome difficulties associated with physical models and are less costly. However, they are less accurate with insufficient data availability and when the focus of research is not based on a physical mechanism [32]. Furthermore, there are numerical groundwater models developed from a conceptual model. However, these models often neglect the complexities while focusing only on the main fundamental principles of the groundwater systems [13]. Meanwhile, finding long time-series data for a numerical model is exceedingly difficult and challenging during the modelling processes.

2.4. Data-Driven Mathematical Models for Groundwater Resources Management

The groundwater level resources prediction model is described as a regression problem [34, 90, 91]. This means the goal is to forecast, predict and manage any changes in the groundwater level resources on any particular day according to the available data. Thus, data-driven mathematical models use previous data based on the underlying process behind particular phenomena to learn the best forecast result. Thus, the goal of this section is to provide insight into the mathematically formulated for managements of groundwater level resource

2.4.1.   Sequential Gradient Restoration Algorithm (SGRA) Model

The Sequential Gradient Restoration Algorithm (SGRA) is a dual-phase path to solve non-linear programming (NLP) problems. Beginning from a feasible design point of view, the gradient phase decreases the value of the objective function while at the same time fulfilling the obligation of the linearized active constraints. This will lead to constraints violation of the nonlinear active constraints. Consequently, the restoration phase catalyses the design to feasibility which may produce a new as well as a distinct set of constraints. This process of two phases cycle is repeated until the optimum is achieved [92]. This technique incorporates a decent property with each cycle. The SGRA uses an active constraint strategy just like other algorithms. This method has been favourably compared to the generalized reduced gradient (GRG) and the gradient projection method. However, in comparison, the SGRA combines the two phases [92, 93].

The SGRA assumes the inequality constraints of the form by equation (2);

$$g_j(X) \geq 0; \ j \ = 1,2,\dots,m \tag{2}$$

The general problem is defined as

$$\text{Minimize } f(X), \ [X]_n \tag{3}$$

Subject to:

$$[h(X)]_t = 0 \tag{4}$$

$$[g(X)]_m \leq 0 \tag{5}$$

$$X^{low} \leq \ X \ \leq X^{up} \tag{6}$$

Only active inequality constraints are of interest in the SGRA. Although equality constraints are always active. Active inequality constraints also include violated constraints. If 'v' indicates the set of active constraints, equation (4) and equation (5) can be combined into a vector of active constraints (Φ);

$$\Phi(X) \ = \ \begin{bmatrix} h(X) \\ g(X) \geq 0 \end{bmatrix}_v \tag{7}$$

The number of active inequality is v-l. The Lagrangian for the problem can be expressed in terms of the active constraints alone (since the multipliers for the $g_f(X) \ < \ 0$ will be set to zero as part of KT conditions]. The KT conditions are then expressed by equations 8a to 8c.

$$\nabla_X F(X,\lambda^v) = \ \nabla_x f(X) + [\nabla_x \Phi]\lambda^v \tag{8a}$$

$$\Phi(X) = 0 \tag{8b}$$

$$\lambda_{v-t} \geq \ 0 \tag{8c}$$

where $[\nabla_x \Phi] = [\nabla_x \Phi_1 \ \nabla_x \Phi_2 \dots \nabla_x \Phi_v]; \quad \lambda^v \ = \ [\lambda_1 \ \lambda_2 \dots \ \lambda_v]^{\mathrm{T}}$

Gradient phase: Given a feasible design X^i, the neighbouring gradient point can be expressed as

$$\tilde{X}_g = X^i + \Delta X \tag{9}$$

where δf < 0 and δΦ = 0. By imposing a quadratic constraint on the displacement ΔK in equation (9), the problem can be set up as an optimization subproblem whose KT conditions are determined as given in eqaution (10)

$$\Delta X = -a\nabla F_x(X^i, \lambda^v) = aS \tag{10}$$

In this model, the search direction is directly proportioning to the gradient of the Lagrangian, which is an improved and model feature. To solve the Lagrangian, the Lagrange multipliers must be computed. This is solved by solving a system of v linear equations given in equation (11);

$$[\nabla_X\Phi(X^i)]^T\nabla_Xf(X^i) + [\nabla_X\Phi(X^i)]^T[\nabla_X\Phi(X^i)]\lambda^v = 0 \tag{11}$$

Stepsize for gradient phase: The stepsize calculation is based on driving the optimality conditions in (8a) to zero. Therefore, if the

$$\tilde{X}_g = X^i - \alpha\nabla F_X(X^i, \lambda^v)\nabla_X F(X, \lambda^v) = \nabla_xf(X) + [\nabla_X\Phi]\lambda^v \tag{12}$$

thus, the optimum $\alpha^{\wedge*}$ is solved by cubic interpolation while trying to satisfy the condition in (13)

$$\nabla_X F(\tilde{X}_g, \lambda^v)^T\nabla_X F(X^i, \lambda^v) = 0 \tag{13}$$

However, an adequate step must be taken that this stepsize does not cause significant constraint violation. This is can be ensured by capping the squared error in the constraints by a suitable upper bound which is set up as

$$\Phi(\tilde{X}_g)^T\Phi\tilde{X}_g \leq P_{max} \tag{14}$$

Furthermore, the Pmax is related to another performance index Q, which is the error in the optimality conditions [82]. Thus,

$$Q = \nabla F_X(\tilde{X}_g, \lambda^v)^T\nabla F_X(X^i, \lambda^v) \tag{15}$$

Restoration Phase: After the end of the gradient phase, it is assumed the function will have decreased but there would be some infeasible constraints (supposing at the initial stage of the gradient phase, there were at least more than one nonlinear active constraint). In the restoration phase, a feasible solution within the neighbour would be established. This is achieved by making sure that the linearized constraints are feasible. However, before this, the active constraint set has to be updated (v⁻) since the initial feasible constraints could have become infeasible (and previously infeasible constraints could have become feasible) as a result of the change in design caused by the gradient phase. Thus, the design vector and the changes in design for this restoration phase can be written as

$$\tilde{X}_r = \tilde{X}_g + \Delta\tilde{X}_r \tag{16}$$

The change in design for this restoration phase $\Delta\tilde{X}$_r can be obtained as a least square error in the design changes subject to the satisfaction of the linear constraints. Thus, equation (17) is used to calculate this change in the design using NLP

$$\Delta\tilde{X}_r = -\nabla_X\Phi(\tilde{X}_g)\sigma^{-v} \tag{17}$$

where σ^(-v) is the V⁻ vector Lagrange multiplier of the quadrantic subproblem. Furthermore, the values for the multipliers are established through the linear equation in equation (18)

$$\mu\Phi(\tilde{X}_g) - \nabla_X\Phi(\tilde{X}_g)^T\nabla_X\Phi(\tilde{X}_g)\sigma^{-v} = 0 \tag{18}$$

where factor μ is a user-controlled parameter to discourage large design changes. The Restoration phase is iteratively applied until equation (19) is feasible

$$\Phi(\tilde{X}_r)^T\Phi(\tilde{X}_r) \leq \varepsilon_1 \tag{19}$$

where ε_1 represent a small number.

After the restoration phase, the constraints are feasible and the next cycle of the Gradient-Restoration phase can be applied again.

2.4.2.   Linear Regression

Linear Regression (LR) is one of the oldest and most widely used groundwater management models. Therefore, LR can be defined by equation (20) [94, 95].

$$y = X\beta + \varepsilon, \tag{20}$$

Where y is the vector of the groundwater level changes values from the observation well, X is the aquifer's independent parameters such as the historic weather data, in a two rows matrix, β is the parameter of forecasting vector that is under the investigation, while ε is the errors' vector. In LR, the goal of applying this model technique is to minimise the validation set errors as well as to learn the vector parameter β. Many parameter estimation model techniques are available, however, the least-squares estimation techniques are most popular [34].

2.4.3.   Regression Tree and Gradient Boosting

Decision making is an important aspect of the linear regression groundwater management model [96-98]. Therefore, decision trees based algorithm known as Regression Trees (RTs) was developed. RTs operate by diving each groundwater resource value into smaller subspaces that are represented by a tree leaf. Thus, the learning samples are obtainable by averaging all the samples as well as by introducing another LR model at the node. The accuracy of this model is a function of introduction ensembles of regression. In environmental data-driven modelling applications, the RTs algorithm is very important as it is easy, fast, and successfully deployed. Gradient Boosting (GB) is the most used method in various fields. This is because the GB make practical and effective use of ensemble weaker trees from the learning set to provide final predictable results, nonetheless, it stacks them additively [99, 100]. Thus, the loss function differentials are approximated in each succeeding stage. Equation (21) is an example of a loss function

$$L(y, F_m(x)) = \frac{1}{2}(y - F_m(x))^2 \tag{21}$$

From (21), the true value is represented by y. $F_m(x)$ is the model's prediction after the m-th stage. As stated earlier, The RTs model prediction $F_m(x)$ combines all the weaker tree's results.

2.4.4.   Artificial Neural Network (ANN) Model

An artificial neural network (ANN) is a black box tool with a resemblance of a human brain's biological neural networks in certain performance characteristics which consist of an enormous equidistant distribution processing system [8, 101, 102]. However, Feed-forward neural networks (FFNN) model are the most commonly used and employed in modelling [12, 103, 104]. A normal ANN model is made up of a three-layer FFNN model of an input layer, hidden layer, and output layer as well as artificial neurons with each layer interwoven with those in the next layer known as Multilayer Perception Network (MLPN). As such, the output of a node layer determined the weight, as well as the type of transform of the sole function of the input it received from the former layer. Therefore, previous research trained the ANN with the Bayesian regularization algorithm and tan-sigmoid transfer function [12, 28, 32, 34]. This is mathematically expressed by equation (22).

$$y_j = f\left(\sum_{i=1}^{N} w_{ji} x_i + b_j\right) \tag{22}$$

where the input vector is x_i, the output is y_j, the bias is b_i, the weight connecting x_i and x_i is x_{ji} the number of nodes is represented by N, while the activation function is f within the presentation layer. The application of ANN by many researchers has proved to be a success. The ANN time series data trained model was used successfully to predict the principal factors affecting algal blooms in a man-made Lake Juam reservoir [105]. Furthermore, ANN models have been applied in various scenarios such as estimation of regional index flood, in an ungauged catchment of the Chindwin River in Myanmar, to evaluate an extreme daily

precipitation's potential in Athens, Greece, for river flow rate and sediment load from Rantau Panjang Station on Johor River [106, 107]. The results showed that ANN models are superior to the conventional regression method.

2.4.5.   Adaptive Neuro-Fuzzy Inference System (ANFIS) Model

An adaptive neuro-fuzzy inference system (ANFIS) model can be described as an adaptive neural hybrid algorithm that is based on a fuzzy inference system. This model was first inaugurated in 1993 by Jang et al [108, 109]. Furthermore, ANFIS has been found to be capable of approximating any continuous and real function in a compact set to an acceptable degree of accuracy universally (Hipni et al., 2013, Awan and Bae, 2014). In the ANFIS model, it is assumed that the fuzzy inference system has two inputs x and y as well as one output f. Thus, it can be expressed by the set of rules in equation (23) and equation (24).

$$Rule\ 1: If\ x\ is\ A_1\ and\ y\ is\ B_1; then\ f_1 =\ p_1 x\ +\ q_1 y\ +\ r_1 \tag{23}$$
$$Rule\ 2: If\ x\ is\ A_2\ and\ y\ is\ B_2; then\ f_2 =\ p_2 x\ +\ q_2 y\ +\ r_2 \tag{24}$$

where x and y are the crisp inputs to the node i, the low, medium or high characterized linguistic labels by the convenient membership functions are represented by A_i and B_i. Parameters of the first-order fuzzy model are represented by p_i, q_i, and r_i (i = 1,2). The ANFIS models have a higher capability for modelling non-linear dynamic hydrology and diverse water resources among all the models, for effective water management. In terms of efficiency and accuracy, the ANFIS was utilised with machine learning for estimation of pan evaporation daily as well as long-term dam inflow water [110-112]. The result showed that the ANFIS model performed better than any traditional empirical techniques. The ANFIS model has been used for rainfall-runoff modelling, groundwater modelling as well as evaporation modelling [12, 113-115].

2.4.6.   Support Vector Machine (SVM) Model

The support vector machine (SVM) is a machine learning approach characterized by the statistical learning principle [116, 117]. Therefore, its solution is obtainable via an optimization algorithm using a regression hyperplane. Although, in a regression SVM model, an insensitivity loss function, as well as a regression hyperplane, is a convex dual optimization problem. In addition, the Sequential Minimal Optimisation (SMO) algorithm is often used to provide a solution to problems involving dual optimisation of the SVM. Mathematically, the SVM deterministic function is expressed as shown in equation (25).

$$f(x) = w \cdot \phi(x) + b \tag{25}$$

where w_i is a weight vector, while b is a bias, the high-dimensional feature space x is mapped by a non-linear transfer function ϕ. This SVM model has been deployed by many researchers in the field of engineering to solve hydrogeology and hydrology drawbacks. The results showed that the SVM model performed better than the ANN model. Limited climatic data were used to evaluate daily evapotranspiration using the SVM model in an extremely arid region [118]. Of the four models used, the SVM model proved to be the best. Also, the SVM model assembled with quantum behaved particles warm optimisation SVM-QPSO model was used to forecast streamflow every month [119]. The result showed that the SVM model ensures a high prediction degree of streamflow reliability and accuracy. In addition, several researchers applied the SVM model to predict, estimate, and evaluate the streamflow as well as, water level of Lake Van in Turkey [50, 120-122]. The results showed that the SVM model outperformed the regression and ANN models.

2.4.7.   Empirical Mode Decomposition (EMD)

Empirical mode decomposition (EMD) is a data-adaptive full algorithm technique used for analysing signals that are non-linear as well as non-stationary [123]. Thus, for EMD to perform its basic function of decomposing an original signal to a various number of intrinsic mode functions (IMFs), two conditions must be met: (a) number of extrema and zero crossings must be equal or differ at most by one, and ; (b)

functions are symmetric and the mean value of the upper, as well as lower envelopes, should be zero. However, mode mixing has been identified as the major shortcoming of EMD implementation [124]. Mathematically, the EMD can be obtained using equation (26).

$$x[x] = \sum_{k=1}^{K} IMF_k[n] + R[n], \qquad (26)$$

where the corresponding residue to the signal approximation at the lowest resolution is represented by $R[n] = m_K[n]$ and $IMF_k[n]$ is the k-th IMF. It is however widely claimed that the EMD, as well as the Ensemble EMD (EEMD), are computationally intensive to run. Over the past years, both the EMD and EEMD have demonstrated higher effectiveness in comparison to the Fourier techniques. Thus, it has been extensively deployed in various disciplines such as image analysis, the health sector for diagnosis, biomedicine and big data logging.

Table 1 shows a summary of the latest data-driven groundwater resources management methods of modelling.

Table 1: Summary of data-driven groundwater resource management modelling methods

Authors	Methods	Objectives	Shortcoming
Valipour et al [44, 125]	Improved Random Forest Regression With A Combination Of Random Features	These authors provide the application of simulation modelling methods in groundwater resource management.	The effectiveness of these methods and solutions could not be established by these authors with a field experiment. This is due to costs and time constraints, increase in computational complexity as well as needs partitioning
Xuanhui et al[37, 45]	Canonical correlation forest algorithm with a combination of the random features simulation model and neuro-particle swarm optimisation and neuro-differential evolution methods	These authors proposed this method to solve the problem of data scarcity on a site and low-dimensional data	The accuracy of this method is instantaneous. Hence, this makes it unsuitable for groundwater level resource prediction over a long period.
Emamgholizadeh et al [28, 31-33, 42]	Artificial Neural Network (ANN) based	The objective of this method was to provide accurate predictions without an increase in costly computational time.	ANN models are prone to incur the problems of local minima and overfitting.
Yoon et al [35, 42, 45, 50, 126, 127]	Super Vector Machine Method (SVM)	The objective of this method is to overcome the variation in groundwater level prediction	Although SVM is robust for groundwater resource prediction as highlighted by these authors, it is

			sensitive to redundant and outlier data. Also, it is not scalable enough and requires more time because of trials and errors. SVM also has high parametrization complexity.
Mustafa et al [11, 38, 39, 42, 46, 128]	Groundwater flow model and multiobjective method	The objective of this model was to evaluate the effects of human activities on groundwater dynamics	This model is negatively hampered due to a lack of data in arid and semi-arid regions. Furthermore, this model requires a good quality of evidence-based data for it to be reliable
Kisi et al [29, 37, 38, 42, 44, 115]	Adaptive Neuro-Fuzzy Inference System (ANFIS)	The objective of this model is to overcome challenges with both ANN and SVM models	Although ANFIS has performance acceptability in modelling many environmental and hydrological phenomena, it has many weaknesses such as probable entrapment at local minima and slow convergence makes it ineffective in modelling.

With the advancement in data mining for modelling, optimisation, and simulation techniques for groundwater resources management, the use of finite difference and finite element have increased exponentially. Although the use of the Finite Element Modelling Technique (FEMT) was first instigated by Lee and Cheng in 1974, for seawater encroachment in a coastal aquifer [129]. Likewise, Tyson and Weber, in 1963 advocated the use of electronic computers in the simulation of the dynamic behaviour of groundwater basins using the Finite-Difference Model Technique (FDMT) [130]. Consequently, both the FEMT and FDMT have been used extensively for the Groundwater Flow Model (GWFM), Hydro-Economic Model (HEM), Calibration (C), Sensitivity Analysis, (SA), Water Balance Model (WBM), as well as Validation/Verification (V) [80]. However, the efficacy of these modelling solutions depends largely on their adequate verification. Table 2 is a summary of some of the relevant researchers that have applied these two modelling techniques in groundwater resources management [80].

Table 2 Summary of relevant application of FEMT and FDMT and their purposes

Study	Application	Modelling Technique	Scheme
[131-134]	• GWFM • SWAP • WOFOST • SEBAL • SLURP • SWAP-SWATRE • SIMGRO	• FEMT	• Calibration • Validation/Verification • Simulation
[135], [136]	• MODFLOW • GFLOW • MODPATH	• FDMT	• Calibration • Simulation
[137-141]	• HYDRUS-1D • SWMS-2D • PLASM • MODFLOW • AQUIFEMM-1 • ISOQUAD • SVAT • SIMGRO	• FEMT • FDMT	• Calibration • Validation/Verification • Simulation
[142]	• SGMP	• FDMT	• Calibration • Simulation • Sensitivity Analysis
[138, 139, 143-153]	• MODFLOW • SVAT • SIMGRO • SEAWAT • UCODE • ISOQUAD • MT-3D • UPFLOW • HEM • WBM • MMA • GLUE	• FDMT	• Calibration • Simulation • Validation/Verification

3. Groundwater Management and IoT

This section aims to highlight the relationship and importance of the Internet of Things which comprises Remote Sensing (RS), and Geographic Information Systems (GIS), as it relates to the measurement, monitoring, management, forecasting, and modelling of groundwater resources.

3.1. Introduction

Effective groundwater resource management, as well as modelling, is a function of the availability of good quality data pertaining to the information of the observation well. This is because the groundwater resource measurements are the most basis supporting existence for evaluating the information of the quantity of groundwater resources stored within the aquifer [10]. The information about the aquifer's properties may include, and not limited to changes in groundwater level, storage, flow rate, recharge as well as discharge rates. But these data are not collected automatically. Furthermore, Calderwood et al stated that the negative impact of overexploitation, as well as reduction in recharge of groundwater resources, are often unknown, even after years have passed, due to data limitations [20]. In addition, groundwater resources information is strenuous to collect and use due to lack of proper integration between the equipment deployed, irrelevant and inconsistent data as a result of lack of stationary large-scale flow rate hindrances, un-automated groundwater analysis process, and lack of interoperability in the previous systems [154-159]. Consequently, these limitations are causing untold strains in groundwater resources management. Additionally, most groundwater resources management models can not provide any reliable decision or support without the required data input. Hence, there is a need for a contemporary, scalable, and real-time IoT-based management system solution for groundwater resources management.

There are various groundwater level monitoring systems. These systems vary in technology, monitoring and management tasks, scalability, the solution they render, and the cost implications. Historically, the traditional technique of measuring groundwater levels involves the use of a manual tape rule. Furthermore, there are emerging threats that the majority of groundwater level measuring networks are been regularly abandoned due to a decline in global groundwater monitoring [160]. Consequently, groundwater level resources are inadequately monitored often, despite the fact that they are needed for calibration and validation of groundwater resources models [161, 162]. These aforementioned challenges can be solved through the use of the Internet of Things (IoTs) techniques [154].

3.2. IoT and Groundwater Level Measurement Techniques

In recent years, the internet has changed the way human lives. Therefore, the Internet of Things (IoT) as a facet of the internet has become the ultimate layer on which several things such as smart gadgets are interconnected. This concept of the IoT has been embraced in many areas of human endeavours including smart water and groundwater level management. Thus, IoTs techniques are used to collect, transfer, and analysis the required groundwater level data. The major advantage of IoT deployment is its ability to be able to combine with several technologies such as wireless sensors, cloud computing, ubiquitous computing, RFIP, and software [163]. Thus, the groundwater level data management in an IoT environment involves the combination of smart technologies such as sensors to collect data, over a network area, with a combination of software IDE into the cloud server.

Remote sensing (RS) is an example of a classical way of obtaining the much needed hydrological data for groundwater level measurements using the internet [164]. However, this can only provide point data. Thus, the challenge remains on how to navigate from point data alone to regionally distributed data. Although the RS can be used to obtain certain groundwater resources parameters, these parameters are not often useful for groundwater management modelling. Consequently, another model will be required to manipulate the acquired data into usable or verifiable data as an input in spatially distributed models [165]. Furthermore, the data acquired via the RS are prone to noise. The substantial and most relevant data for groundwater resource management modelling are the recharge and discharge information. Of these two, recharge is very crucial for the sustainability of groundwater level management. Application of RS for groundwater level modelling was carried out by Dams et al, for mapping out impervious surface changes for hydrological modelling [166]. More researchers also applied the RS technique for the management of groundwater resources [164, 167-169]. To solve these challenges, the IoTs and machine learning techniques can be employed. Apart from RS, groundwater level managements are using situ networks in many aquifer systems around the world. But the difference in each monitoring well depends on the technology used as

well as the frequency of the measuring data [170-172]. The situ technique assists in the management of groundwater level by estimating the changes in (groundwater) storage, provide the user's information, flow model calibration, and general up to date system information [172-174].

The IoTs and machine learning techniques involve the acquisition, processing, transfer and analysis of groundwater level data interconnected using intelligent nodes. This combined with the evolution of web techniques has been used in many works of literature. The application of IoTs for monitoring the groundwater level daily variations and safety quality in the mining environment was carried out by Reddy et al, using sensor technologies [175]. Also, Neyens et al monitored groundwater quality and quantity from a desktop using the IoTs-enabled Environmental data Management Interface (EMI) technique [176]. This same technique was also applied to saltwater intrusion monitoring. A low cost IoT-based real-time groundwater level resource management system was built for monitoring a community-based network consisting of eleven wells sited in Nova Scotia, Canada [177]. Also, an automated low-cost sensor network for monitoring groundwater levels was designed at the South American Subbasin Groundwater Observatory (GWO), in a real-time scenario [20]. Botta et al presented the IoTs based sensor network review for both quality and quantity measurement of water in a smart city [178]. It should be noted that with big groundwater level data collected from many deployed sensors, there is a new challenge of how to process, store and deal with them. This is an open research bottleneck that needs to be unravelled.

Starting from the evolution of the web technique in the year 1993, several database managers have started to develop web-based Geographic Information Systems (WebGIS) to store the collected real-time and fast data streams [179, 180]. The GIS as an example of Database Management Systems (DBMS) is embedded with the topography, geology, geometry, as well as coordinates data to assist in storage, explanation, location, and manipulation of input as well as the corresponding output data information [181]. Therefore, the WebGIS technique performs better in terms of user' quality of service (QoS), can be used by multiple users, cost reduction, global reach, as well as cross-platform compatibility [182].

There has been exponential growth in the development of groundwater level measurement IoT based management techniques with a combination of relevant WebGIS. The GIS software known as ARCVIEW and the groundwater model (MODFLOW) were combined for numerical modelling of groundwater resources by Chenini and Mammou [183]. This combination was used in the central region of Tunisia. Similarly, the Managed Aquifer Recharge (MAR) and International Groundwater Resources Assessment Centre's Global Groundwater Information Service (IGRAC's GGIS) combination was successfully implemented using an enhanced historical data from approximately 1200 site studies in about 62 nations [184]. The results showed an increase in groundwater resource storage, good recharging levels, and improved water distribution management. In Table 3, a few other existing groundwater level IoT-based management techniques are presented. Most of the highlighted studies combined both web browser and GIS software, and support multiple users as well as tasks.

Table 3 Summary of relevant existing groundwater level WebGIS technique

Technique	Numerical Model	Spatial Interpolation	Limitation
Cloud-based MODFLOW [185, 186] ArcGIS	None	Several methods	This is based on the simulation modules only. This limitation does not permit extensive interpolation due to the lack of a numerical model
Collaborative Geographic	Multi hydraulic	Several methods	It is based on the computer's Random

Information Systems (CGIS) ([154, 187]			Access Memory (RAM) size. This causes delays or freezing up during processing
Delft-FEWS [188, 189]	Multi hydraulic	Several methods	It is based on the computer's Random Access Memory (RAM) size. As a result of this limitation, the model experiences low computation memory during operation
FREEWAT developed as a plugging GIS desktop software QGIS (QGIS Development Team 2017) [190-192]	Multi hydraulic	QGIS	The interpolation speed is based on the computer's RAM. This causes a delay in operation
HydroShare [193, 194]	It is based on the user's developed numerical model	Based on the user's upload	It is based on the developed model and lack space and speed.
Tethy [195]	It is based on multi hydraulic models	Several methods	Based on a developed model
MAGNET [196]	It is based on multi hydraulic models	Several methods	It is limited to a 10000 mesh number. Above this number is not possible.

3.2.1.   Overview of Groundwater Level IoTs Based System

Generally, the groundwater level IoTs-based system architecture can be subdivided into three layers. These are the physical layers, the service layer as well as the presentation layer [197]. In the physical layer, the communication equipment, as well as various sensor nodes for basic data acquisition of relevant groundwater level and aquifer information, are built-in. The raw data measured and collected are deployed to the service layer. At the service layer, there are various tools for data analytics. This layer also stores the received data from the physical layer. Both the application and business logic implementation are implemented at this layer, thus making it an important part of the architecture. The presentation layer is the visualisation layer where the users are allowed to interact as well as view the displayed information on a screen monitor.

Figure 2 shows the overview working representation of the workflow of groundwater level IoTs based system. This shows the interconnection of the sensors deployed into the well, the nodes, gateway and the end-user platform. The arrows indicate the direction of the flow of data. The solid line represents the direction of the data received, while the broken lines represent the request sent for data. In this system, the IoTs is combined with the GIS to ensure the real-time uploading of groundwater level data, improve the quality of the database, and provide geographical information about the system. The sensors deployed into the observation wells acquire and send the corresponding measurement of groundwater level parameter to their nodes over the Modbus protocol employed. From the nodes, the data is sent via the Long Range (LoRa) wireless network to the gateway. The data is saved into the Message Queuing Telemetry Transport server (MQTT) platform, which is connected to the No relational Structured Query Language (NoSQL)

database or any other Graphics Processing Unit (GPU) platform for real-time display. Examples of these web-based clients GPU are ArcGIS, API, Google Map API, ThingSpeak and WebGL [187, 198-201].
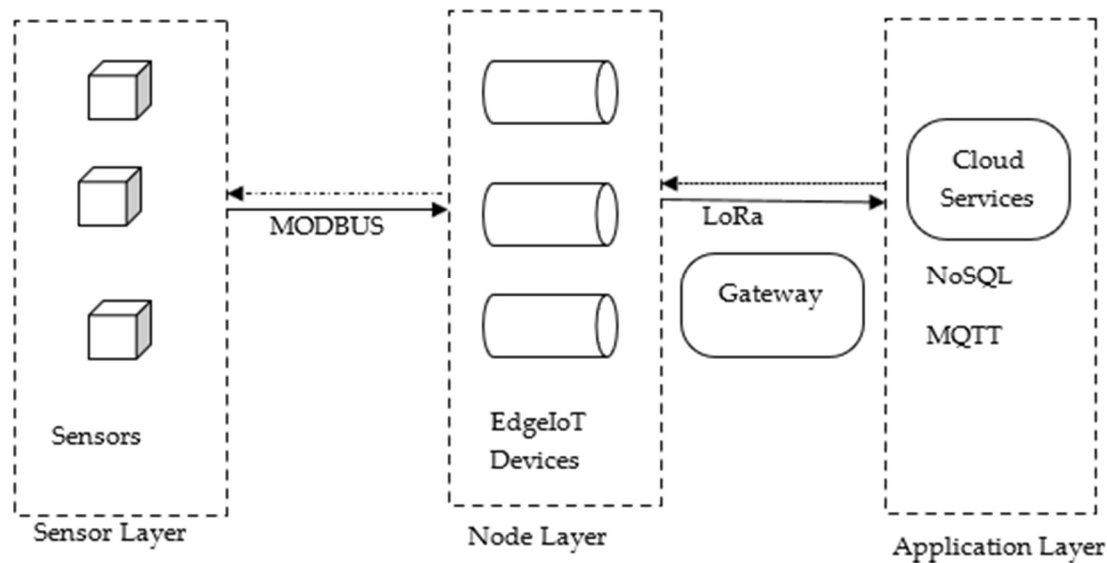
Figure 2. Overview of Groundwater level resource IoTs based system.

4. Conclusion and Future Directions

This review presented and discussed the existing trend in groundwater resources management. In the past, most of the existing groundwater resource management models have been combined with optimisation and simulation techniques using appropriate mathematical programming to proffer solution to challenges within the aquifer. Consequently, the previous surveys have presented a narrow review involving simulation and optimisation management models, however, this review presented a much broader IoTs-enabled management perspective. This is because, for any of the management modelling of groundwater resources to be achieved, the measurement of resource data is important. However, part of the general limitations is the uncertainties from input parameters to the system modelling. Furthermore, despite huge research attention towards solving such problems, little research evidence exists concerning achieving computationally efficient and scalable models for groundwater resources management in real-time operations. Although there are various modelling tools as presented in this review, their field applications must be ascertained.

Furthermore, there has been an unprecedented increase in the amount of data generated by electrical sensors in the Internet of Things (IoT) over the years. The application of groundwater resource IoT-based technique is a very useful tool in data acquisition, monitoring, manipulation and management of groundwater resources. This technique combined with GIS has a huge potential in the field of water management. However, IoT data are mostly processed via a computing resource situated in a farther data centre location using either internet or cloud computing. Consequently, this has led to insecurity in users' privacy, low latency, and scalability problem. Since the IoT big data are transmitted into the cloud in high volumes, it is necessary to have an efficient and scalable IoT platform to extract valuable information in real-time for groundwater resource management.

For future research directions, the challenges of high computational inefficiency and scalability must be addressed. This will enable the groundwater level resource management model to achieve computationally efficiency and scalability. Also, the current IoT-enabled automated data processing systems for

transmitting the generated data from IoT sensors into the centralised cloud are not scalable and efficient. Therefore, there is a need to develop an alternative model for the IoT-enabled groundwater level resources management model. These are open research direction that should be explored.Although this is a review of existing management models for groundwater resources, this is not all-inclusive. Thus, there is a possibility of missing out on some other publications because it is impractical to review them all. Therefore, these gaps could also be filled with more review publications.

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