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Review article

Conventional and futuristic approaches for the computation of groundwater recharge: A comprehensive review

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Abstract: Groundwater recharge is a critical hydrologic component that determines groundwater availability and sustainability. Groundwater recharge estimation can be performed in a variety of ways, ranging from direct procedures to simulation models. The optimal strategy for recharge estimation depends on several factors, such as study objectives, climatic zones, hydrogeological conditions, data availability, methodology, and temporal and spatial constraints. Groundwater recharge is influenced by uncertainties in weather and hydrology. This study discusses conventional recharge estimation techniques and their application for optimal recharge calculation, and it also offers an overview of recent advances in recharge estimation methods. Most methods provide direct or indirect estimation of recharge across a small region on a point scale for a shorter time. With recent technological advancements and increased data availability, several advanced computational tools, including numerical, empirical, and artificial intelligence models, have been developed for efficient and reliable computation of groundwater recharge. This review article provides a thorough discussion of the techniques, assumptions, advantages, limitations, and selection procedures for estimating groundwater recharge.

Keywords: Groundwater recharge; Groundwater balance; Groundwater flow; Machine learning; Deep learning

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Introduction

Groundwater is a dynamic, replenishable, and precious resource of limited extent, especially in semi-arid countries with tropical climatic conditions. While global climate discussions highlight the importance of water, ground-level users face significant challenges such as scarcity, excess, contamination, and a lack of reliable information. These issues hinder sustainable freshwater use and future sustainability. Excessive resource utilization, uncontrolled urban and industrial discharges, and agricultural intensification are causing widespread degradation of aquifers (Kemper, 2004). Extensive groundwater withdrawal in excess of natural replenishment results in a progressive lowering of the water table, making a sustainable water supply increasingly difficult. Indiscriminate extraction of aquifers can also lead to a decline in the physical and chemical quality of water, saline water intrusion in coastal aquifers, and land subsidence, causing the fresh water table to recede at alarming rates. Proper management of the groundwater system is essential to maintaining a hydrological balance between the water pumped and the water recharged into the aquifer.

Groundwater recharge refers to the process by which water enters the water table through unsaturated zones below rooting depth, thereby contributing to aquifers (De Vries and Simmers, 2002). This process can be categorized into direct or diffuse recharge, localized recharge, and indirect or non-

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diffuse recharge, based on the sources and mechanisms of recharge. The fraction of groundwater recharges depends on natural factors such as land cover, terrain characteristics, rainfall frequency and intensity, subsurface geology, soil properties, irrigation water use, depth to an aquifer, aquifer storage capacity, and the presence of adjacent water bodies (Simmers, 1998; De Vries and Simmers, 2002; Asoka et al. 2018).

Quantifying the current rate of groundwater recharge is essential for efficient and sustainable groundwater resource management in semi-arid and arid areas, where these resources are often key to economic development (De Vries and Simmers, 2002). Assessing recharge helps determine whether abstraction and recharge are well balanced in an aquifer, which is crucial for water resources management. Recent climate change, population growth, altered precipitation patterns, and land use changes significantly impact groundwater replenishment (Kumar, 2012; Sun et al. 2020; Hughes et al. 2021). Numerous studies worldwide have characterized and compared recharge estimation techniques (Sihag et al. 2020; Mohan and Pramada, 2023), with reviews conducted by researchers like Scanlon et al. (2002), Healy (2010), Ali and Mubarak (2017), and Kumar et al. (2021).

Despite the growing demands on groundwater resources and escalating hydrologic stresses complicating groundwater management, these challenges have led to the development of innovative management techniques. Ensuring sustainable groundwater management in the context of climate change remains a global challenge. A deeper understanding of recharge mechanisms in various hydrological zones is required for optimal water resource management and recharge process design. To address the uncertainty and data shortages, particularly in developing countries, machine learning techniques can enhance the modelling efforts. Therefore, sustainable groundwater management necessitates the assessment of aquifer recharge using appropriate methods (Shu and Wang, 2005).

Research on surface–subsurface water exchange processes expanded significantly during the 1990s, focusing on hydrological and biogeochemical processes. However, challenges in quantifying water fluxes between groundwater and surface water persist due to heterogeneity and scale issues (Sophocleous, 2002). Most hydrologic modeling studies have used one-dimensional or two-dimensional models, overlooking the three-dimensional nature of flow dynamics. Improvements in analytical and numerical methods are required to better simulate observed field conditions and understand stream-aquifer processes. Characterizing subsurface heterogeneity and developing operational hierarchies for upscaling from reaches to watersheds remain significant research challenges. A multidisciplinary and multiscale approach is needed, incorporating multiple techniques such as in-situ and remote sensing observations, GIS technology, numerical models, and statistical analyses to study groundwater-surface water exchanges.

The uniqueness of the study lies in its comparison of traditional recharge measurement techniques with cutting-edge approaches, emphasizing key variables and influential factors along with their reliability. This paper critically evaluates current and future groundwater recharge estimation methods, assessing their strengths and weaknesses in light of climate change, land use changes, data availability, economic considerations, and technological advancement. It highlights crucial elements when selecting a methodology, including space and time scales, reliability, and factors that promote or limit their use. This comprehensive evaluation aims to support groundwater users in adapting their active aquifer management strategy.

1 Groundwater recharge estimation techniques

Accurate quantitative analysis of recharge is crucial for managing groundwater resources under diverse climatic conditions. Conventional methods for understanding and quantifying the water that percolates through the soil to replenish aquifers have been widely used for decades in groundwater recharge assessment. These methods rely on empirical, analytical, and numerical approaches, each with its own strengths and limitations. To overcome these limitations, futuristic methods leveraging advanced technologies and data analytics are being developed. Groundwater recharge estimation techniques are categorized into conventional and futuristic methods based on factors such as technology, data requirements, scalability, accuracy, complexity, and cost/labor intensity. This categorization aids in selecting the most suitable approach for specific applications.

1.1 Conventional Methods

Conventional methods for recharge estimation are further categorized into physical, chemical, and numerical modelling approaches.

Physical methods: Physical methods are commonly used to measure recharge from precipitation by measuring or estimating soil physical parameters and applying soil physical principles. These methods are simple, easy to quantify, and inexpensive. However, they are not accurate in arid and semi-arid locations due to the low rates of recharge fluxes, which vary significantly with the immeasurable vadose zone physical parameters and the extreme temporal variability in arid climates (Hendrickx, 1992).

Chemical methods: Chemical approaches assess recharge indirectly, identify recharge sources, and calibrate transport models by using water-soluble compounds such as chloride or isotopic tracers (McConville et al. 2001; Jasechko, 2019). Tracers, which include ions, isotopes, or gases, move with water and can be found in the atmosphere, surface water, and groundwater. These tracers are classified into three types: Applied tracers, historical tracers, and natural ambient tracers.

Numerical models: Numerical modeling techniques account for regional variations in physical parameters, transient flows, and storage changes, offering recharge estimates as a residual term through a numerical relationship between water balance components (Scanlon et al. 2002; Kumar et al. 2021). Integrated models offer enhanced precision in recharge estimation (Chen et al. 2012; Abraham and Mohan, 2019). An effective groundwater recharge model necessitates a thorough understanding the mechanisms governing recharge rates. However, other models, such as those using the Richards equation or hydrological models combining infiltration or precipitation with analytical or numerical parameters, may be less effective due to their complexity and extensive information requirements.

These conventional methods typically requires extensive, high-quality data, which can be challenging to obtain or measure accurately. They often rely on simplifying assumptions, such as homogeneity and steady-state conditions, which may not fully capture the complexities of natural systems. Additionally, many of these techniques are also computationally demanding and require significant expertise, which can limit their routine application. Field methods, while offering direct measurements, are often labor-intensive, costly, and may not provide representative data for larger areas. Consequently, these limitations can lead to imprecise or inaccurate recharge estimates, particularly in heterogeneous or data-scarce environments. Physical and chemical methods have long been used for recharge estimation, but they struggle to accurately model the non-linearity of the groundwater systems and their response to climatic conditions. Traditional decision-making approaches are also inadequate for modeling the interactions between climate, surface water, and both unsaturated and saturated zones due to the massive data requirements and high costs involved (Osman et al. 2021).

1.2 Futuristic methods

Futuristic methods for groundwater recharge estimation offer the potential for more accurate and comprehensive recharge estimates, which are crucial for effective water resource management amid global challenges.

Machine learning algorithms: Machine Learning (ML) represents a significant advancement in recharge estimation by utilizing sophisticated data analytics to enhance accuracy, adaptability, and scalability. Unlike traditional methods, which are often region-specific, ML models are data driven and can quickly process new information once trained, providing real-time predictions and improving computational efficiency. ML algorithms excel at analyzing complex and large datasets, offering more precise predictions of groundwater recharge rates. Key steps in applying machine learning for recharge estimation include data collection, preprocessing, training, evaluation, prediction, interpretation, and uncertainty analysis. While ML holds promise for refining recharge estimation, challenges such as data quality and availability, model complexity, and interpretability need to be addressed. However, machine learning has the potential to significantly improve the precision and reliability of recharge estimates, ultimately leading to better water resource management and planning (Osman et al. 2021; Ahmadi et al. 2022).

Recharge estimation methods are further categorized based on the hydrologic sources or zones from which data are collected, including surface water zone, unsaturated zone, and saturated zone techniques (Lerner, 1990; Allison et al. 1994; Sophocleous, 2002). Techniques based on surface water and the unsaturated zone estimate potential recharge, representing the water that infiltrates but may not necessarily reach the groundwater. In contrast, methods focused on saturated zone provide actual recharge estimates by measuring the water that replenishes the saturated groundwater zone.

This review explores various methods for recharge estimation, including physical methods, chemical methods, numerical models, and machine learning algorithms. It highlights the significance of selecting appropriate techniques based on the range, spatial and temporal scales, and consistency required for accurate assessment.

1.3 Physical methods

1.3.1 Surface water zone

The interaction between surface water and subsurface systems significantly influences the extent of groundwater recharge associated with surface water bodies (Sophocleous, 2002). Streamflow data is widely utilized to estimate recharge rates, particularly in humid and sub-humid regions, due to its relative data abundance and the availability of sophisticated computer programs for analysis (Healy, 2010). In humid environments, surface waters often contribute to groundwater recharge through gaining streams, where water from the surface flows into the groundwater system. Conversely, in arid regions, surface water bodies may frequently disappear due to thick unsaturated zones, and they often serve as sources for groundwater recharge. By analyzing the accumulation and loss of surface water bodies, recharge rates can be predicted in these environments.

Channel water balance: Channel water balance technique is used to estimate groundwater recharge by evaluating transmission loss or flow loss between the upstream and downstream levels using river gauge data. The water balance for a channel is described as follows (Lerner, 1990; Scanlon et al. 2002):

$$R = Q_{upward} - Q_{downward} + \sum Q_{in} - \sum Q_{out} - E_a - \frac{\Delta S}{\Delta t} \tag{1}$$

Where: R *is* rate of recharge;

Q_{upward} and $Q_{downward}$ is flows at the upstream and downstream ends of the channel reach;

Q_{in} and Q_{out} is inflow and outflow of the tributary along the channel reach;

E_a is Evaporation from the surface water or the river bed;

ΔS is Change in unsaturated zone channel storage over time (Δt).

This technique calculates recharge rates by analyzing transmission losses using gauge data and tributary flows. Transmission losses can indicate potential recharge due to levee retention, aquifer development, or aquifers unable to accommodate recharge.

Seepage meter: A seepage meter is a device designed to directly measure the rate of water exchange between the sediment-water interface, surface water zone and the underlying aquifer (Lee and Cherry, 1979). The recharge rate R (depth/time-m^3/m^2/hr) is calculated as:

$$R = \frac{V_s}{TXA} \tag{2}$$

Where: V_s is the volume of water lost (m^3), T is the time interval (hour), and A is the area enclosed (m^2).

Research shows that the assuming seepage rates remain steady is often inaccurate because seepage can be highly variable, influenced by factors such as temperature, evapotranspiration, rainfall and other environmental conditions (Wang and Tang, 2024). Flowmeters have been used to improve the accuracy and consistency of measurements. Combining direct seepage meter data with additional measurements, such as vertical hydraulic gradients and temperature profiles, provides a more comprehensive understanding of groundwater and surface water exchange processes (Rosenberry et al. 2020).

Base-flow discharge/Hydrograph separation method: The base-flow discharge or hydrograph separation method estimates groundwater recharge by analyzing base flow, particularly in basins with gaining streams and shallow water table, where recharge is assumed to equal base flow. This method is rooted in water balance techniques that relate recharge to runoff. However, hydrographic analysis methods based on steady-state water balance equations are often considered too subjective and empirical to provide precise quantitative estimates (Sophocleous, 2002). Various techniques for baseflow hydrographic analysis include tracer-based methods, graphical methods, filter methods, recession-curve displacement method, and digital filtering (Nathan and McMahon, 1990).

$$\begin{aligned} \mathrm{R} = {} & \text{pumpage} + \text{evapotranspiration} + \\ & \text{underflow} + \text{base flow} \end{aligned} \tag{3}$$

Baseflow discharge is not always synonymous with recharge, as factors like pumpage, evapotranspiration, and underflow to deep aquifers can also play significant roles. These components should be estimated independently. Furthermore, baseflow discharge does not consistently measure potential recharge and is often unsuitable for large-basins due to the challenges associated with separating flow components from bank storage effects, which may lead to over-estimation (Chapman, 1999; Eckhardt, 2008).

1.3.2 Unsaturated zone

Research on unsaturated zone processes focuses on calculating potential recharge based on drainage rates underneath the vadose zone. Approaches related to the unsaturated zone are primarily utilized for recharge calculations in semi-arid and arid regions characterized by naturally thick unsaturated zones (Zhang et al. 2002; Healy, 2010). These calculations are particularly relevant to smaller spatial scales compared to those used in groundwater or surface water approaches.

Lysimeter method: The lysimeter method is used to measure soil water exchanges within the lysimeter zone, including parameters such as evapotranspiration, irrigation, evaporation, and other parameters to provide a field estimate of the rate of aquifer renewal (Zhang et al. 2002; Chen et al. 2008). The residual of the water budgeting equation, known as deep percolation, is then calculated to determine the recharge component. Percolate collected by lysimeters has been shown to accurately estimate the amount of recharge reaching the water table. The equation for this calculation is as follows:

$$R = P + I - [(ET/E) \pm \Delta S] \tag{4}$$

Where: P is precipitation; ET is evapotranspiration, I is irrigation, E is evaporation.

It is important to consider evaporation instead of evapotranspiration when there is no crop or vegetation present. The term ΔS represents change in soil water storage within the lysimeter zone. Percolation at the root zone can be measured using deep drainage-type and weighing-type lysimeters (Gee and Hillel, 1988; Zhang et al. 2024).

Zero Flux Plane (ZFP) Method: ZFP method is employed to estimate potential groundwater recharge by delineating water-movement zones with a plane that exhibits zero hydraulic gradients. In this method, soil water flows downward to reach the ZFP, and any water located below this depth is considered to contribute to recharge at the water table (Cooper et al. 1990; Khalil et al. 2003). The depth of the ZFP can vary from a few centimeters to several meters below the soil surface and is not constant throughout the year.

Accurate determination of ZFP requires meticulous care and specialized equipment. Measurements of soil matric potential and soil water content are essential for identifying the ZFP position and estimating changes in storage. Tensiometers are typically used to measure matric potential, while neutron probes are used to determine moisture content. The flux (q), which represents the movement of water across a unit area per unit time, is described by Darcy's law.

$$q = -K(\varphi)\frac{\partial H}{\partial z} \tag{5}$$

Where: $K(\varphi)$ is unsaturated hydraulic conductivity, h is matric potential (negative), H is total water potential $[h(\varphi) - z]$, z is depth below the surface and φ is moisture content.

The depth of the ZFP is identified through the inversely calculated matric potential derived from measured soil water content. The ZFP approach underscores the importance of careful field handling of equipment, necessitating high instrument density and frequency for accurate and direct soil measurements (Khalil et al. 2003).

Unsaturated water flux estimation using Richards equation: Water-budget techniques based on the Richards Equation, as proposed by Richards (1931), can effectively estimate soil water balance in unsaturated zones. This approach involves measuring water pressure and hydraulic conductivity at ambient moisture content (Feddes et al. 1988). By utilizing unsaturated hydraulic conductivity and water retention data, the soil moisture flux in the subsurface zone can be calculated by solving the Richards Equation. The formula governing one-dimensional water movement in a partially saturated porous medium, as described in Equation (6), is an enhanced version of Richards equation:

$$\frac{\partial \theta}{\partial t} = \frac{\partial}{\partial z}\left[K(\psi)\left(\frac{\partial \psi}{\partial z} + 1\right)\right] - S(h) \tag{6}$$

Where: ψ is the water pressure head (L), θ is the volumetric moisture content (dimensionless), t is time (T), z is the vertical coordinate axis (L) and $S(h)$ is the sink /source term in the flow equation (T^{-1}) which corresponds to the root water uptake, calculated using the Feddes equation (Feddes et al. 1976).

The function $K(h)$ and $\theta(h)$ can be determined using the Maulem's model equation, where soil water content is a function of pressure head (Van Genuchten, 1980). A key advantage of this approach over the Fokker-Planck equation is that h is a continuous function across boundaries between distinct soils or sediments, whereas θ is discontinuous at the boundary between two media with different physical characteristics. In scenarios involving heterogeneous porous media, such as layered media or simultaneous saturated-unsaturated flow, the Richards equation has proven to be the most effective option (Giudici, 2023).

1.3.3 Saturated zone

Methods based on saturated zone studies are essential for estimating recharge points, providing indications of actual recharge, while unsaturated zone methods typically offer drainage or potential recharge estimates over larger areas.

Water Table Fluctuation (WTF) method: WTF method is based on the premise that increased Groundwater Levels (GWL) in unconfined aquifers result from recharge water entering the water table (Healy and Cook, 2002; Park, 2012; Kuruppath et al. 2018). This approach is grounded in the principle of volume balancing, utilizing hydrographs and aquifer yield characteristics to calculate recharge. Recharge is calculated as:

$$R = S_y \frac{\Delta h}{\Delta t} \tag{7}$$

Where: S_y is specific yield (unitless), Δh is rise in water table (m), Δt is time within which rise Δh takes place (d).

The WTF method assumes that subsurface flows are uniformly distributed and that water levels respond instantly without interference from other connected aquifers. However, the accuracy of water table data is influenced by several factors, including aquifer diffusivity, the arrangement of abstraction wells, air entrapment, and evapotranspiration by deep-rooted vegetation, which can vary significantly between basins (Scanlon, 2000).

Research indicates that obtaining a depth-dependent specific yield by measuring soil moisture content from various profiles across all water table depths can yield more reliable recharge estimates than using a constant specific yield derived from pumping tests or saturated soil moisture contents (Cheng et al. 2020; Gong et al. 2021). Sophocleous (1991) introduced the hybrid water table fluctuation method to predict groundwater recharge in flat areas with shallow water tables by introducing the concept of transient fillable porosity.

However, limitations of this method include the need to ensure that fluctuations are indeed due to recharge, difficulties in determining specific yield, and challenges encountered in fractured-rock aquifers. Accurate quantification of recharge is vital, and future research should focus on addressing uncertainties and exploring alternative models (Healy and Cook, 2002).

Regional Level Empirical equations: Estimating groundwater recharge involves various strategies, each with advantages and disadvantages. One common method is the use of empirical formulas, such as $R = K_1(P-K_2)^a$ where P stands for precipitation, K_1 , K_2 and a represent localized constants.

These empirical expressions exhibit varying effectiveness, but they are particularly useful for formulating hypotheses about recharge in areas with high annual recharge rates (>50 mm). Some representative formulas for estimating annual natural groundwater recharge from rainfall are provided in Table 1.

Soil moisture budget method: The soil moisture budgeting method estimates recharge by considering precipitation and evapotranspiration. In contrast, the water balance equation employs a residual method to estimate recharge, except for soil water storage, and determines the water required for soil saturation by balancing inflow and outflow. This can be expressed as:

$$R = [P + I - (ET\ or\ E) - R_0 \pm \Delta S] \tag{8}$$

Where: P is precipitation; ET is evapotranspiration; I is irrigation; E is evaporation.

It is important to note that evaporation should be considered instead of evapotranspiration in certain contexts. Variable R_0 in the equation is runoff and ΔS represents change in soil water storage in lysimeter zone. Additionally, large areas may require different input parameter values, which can introduce uncertainty and inaccuracy into the estimates. The soil moisture budget method was originally developed by Thornthwaite in 1948 and has since been refined by various scholars.

Groundwater Balance Method: Groundwater balance estimation is a systematic approach for estimating groundwater recharge by considering the variations in inflow, outflow, and storage. (Lerner, 1990; Nimmo et al. 2005; Kumar et al. 2021). The equation is

$$(P + GW_{in}) - (Q + ET + GW_{Out}) = \Delta S \tag{9}$$

Where: GW_{in} is groundwater inflow, Q is discharge, P is precipitation, ET is evapotranspiration, ΔS is change in storage and GW_{out} is groundwater outflow. This method integrates all water sources in both the surface and subsurface environments.

Table 1 Empirical equations for recharge estimation

Formula Name	Equation (s)	Parameter definition
Chaturvedi Formula (Chaturvedi, 1973) Ganga-Yamuna doab region	$R= 2(P-15)^{0.4}$	
Modified Chaturvedi Formula - Ganga-Yamuna doab region	$R = 1.35(P-14)^{0.5}$	
Sehgal Formula (1973)- Punjab region	$R = 2.5\ (P-16)^{0.5}$	P = rainfall (inch)
Kumar and Seethapathi (2002) - Upper Ganga Canal command area	$R = 0.63\ (P-15.28)^{0.76}$	R = recharge (inch)
Mohan and Abraham (2010)- Cuddalore basin , Tamil Nadu	$R = 3.55\ (P-40)^{0.42}$	P and R (cm)

1.4 Chemical methods

1.4.1 Surface water zone

Heat tracer: The heat tracer method is employed in groundwater surveys to measure surface water infiltration and flow, particularly in ephemeral rivers. This technique serves as an alternative to traditional flow measurements, especially in semi-arid regions where water flow can be intermittent. By measuring temperature variations, researchers can estimate recharge rates from streams and steady drainage rates at various depths within heterogeneous media (Lapham, 1989; Stonestrom and Constantz, 2003).

The method involves using transient and steady-state analytical solutions to one-dimensional conduction-advection differential equations, which are inverted to estimate vertical flow rates (Kurylyk et al. 2017). Diurnal temperature fluctuations, along with matric potential recorded by heat dissipation sensors or thermistors, are input into a variably saturated flow model. This model employs inverse modelling techniques to estimate the hydraulic conductivity of sediments, ultimately allowing for the calculation of percolation rates.

Isotopic tracers: Isotopic tracers, provide valuable insights into groundwater flow patterns, age, recharge zones, losses, and interactions with surface waters as described by Coplen (1993). This method involves analyzing the concentrations of conservative stable isotopes, such as $^{18}O/^{2}H$, in precipitation, soil water, and groundwater. Such analyses help in understanding subsurface flow processes, recharge environment and the cycle characteristics of groundwater (Zhao et al. 2021). Thermo Finnegan Delta isotope mass spectrometry is utilized for measuring soil water isotope concentrations (Wood and Sanford, 1995; Adomako et al. 2010). Groundwater recharge rates can be derived from the measured soil water isotopic profiles using methods like the approximate peak shift method (Leibundgut et al. 2009) and transport modelling approaches (Simunek et al. 2005).

1.4.2 Unsaturated zone

Environmental tracer: Environmental tracers, including isotopes such as oxygen-18 (^{18}O), deuterium (^{2}H), nitrogen-15 (^{15}N), tritium (^{3}H), carbon-14 (^{14}C), and chloride-36 (^{36}Cl), are effective tools for studying groundwater recharge due to their affordability and availability. Among these, chloride is particularly favored as an environmental tracer because it is inexpensive and effectively reflects atmospheric inputs (Chen et al. 2006).

A widely used approach for estimating recharge is the Chloride Mass Balance (CMB) method. This method operates under the assumption that environmental chloride is the sole source of chloride in groundwater (Allison and Hughes, 1983; Edmunds and Gaye, 1994). It presumes that precipitation water infiltrates the aquifer through deep percolation without surface drainage, and that there is no additional chloride input from human activities, vegetation, or agricultural practices. The recharge can be estimated using the following equation: (Allison and Hughes, 1983).

$$R = (PC_{wp} + C_{dd}) / C_{st} \tag{10}$$

Where: C_{wp} is weighted average chloride concentration in rainfall P;

C_{dd} is chloride concentration of dry deposition;

C_s is average chloride concentration over interval 't' of interstitial water in the unsaturated zone.

The CMB method provides a precise approximation of recharge rates, as there is an inverse relationship between chloride concentration and drainage in the unsaturated zone (Scanlon, 2000; Huang et al. 2019; Kumar et al. 2021).

Applied tracer: Applied or artificial tracers are used in recharge calculation by enhancing their natural concentrations in the environment. The distribution of these applied tracers in the subsurface is determined through methods such as by digging trenches or drilling sampling holes. The minimal soil water flux can be calculated based on the time interval between application of the tracer and its sampling, as well as the root zone depth (Scanlon et al. 2002; Ali, 2017; Ali and Islam, 2020). The vertical distribution of the tracer is employed to calculate both the recharge rate (R) and the velocity of water movement (v), as described by the equation:

$$R = v\theta = \frac{\Delta z}{\Delta t}\theta \tag{11}$$

Where: Δz is elevation of tracer peak, Δt is elapsed time between the tracer application and sampling and θ is the volumetric moisture content. To avoid complexities associated with the root zone, it is recommended to apply the tracer below the root zone.

Historical tracers: Historical tracers, such as ^{3}H and ^{36}Cl, are derived from by human activities and past events, including pollution spills or nuclear testing, and are found in the atmosphere. These tracers offer advantages such as minimal additional hazards and reduced costs (Nativ et al. 1995). They can be particularly effective for estimating higher recharge rates when the water table is deeper. However, challenges may arise in soil sampling and accurately locating the tracer peak.

Historical tracers provide point estimates of water flux over the past 50 years. Nonetheless, they come with limitations, including uncertainty regarding the location and concentration of the tracer, difficulties in sampling at greater soil depths, and the potential for overestimation of water flux due to evapotranspiration effects in the root zone. Water fluxes can be calculated using Equation (11).

1.4.3 Saturated zone

Groundwater dating/Groundwater Aging: Groundwater age can be determined using tritium, a radioactive tracer known for its shorter half-life compared to other tracers (Kinzelbach and Aeschbach, 2002). The age of the groundwater can be calculated from the ratio of tritium to tritio-genic-helium ($^3H/^3He$) using the following equation:

$$t = -\frac{1}{\lambda} ln\left[1 + \frac{3_{He_{trit}}}{3_H}\right] \tag{12}$$

Where: λ is the decay constant (ln $2/t^{1/2}$), $t^{1/2}$ is the half-life of ^3He (12.43 years), and He_{trit} is the tritio-genic-^3He (Ali and Mubarak, 2017).

The primary assumption in this method is that the groundwater system is closed. Factors such as porosity, geological structure, and recharge rates significantly influence groundwater aging in unconfined aquifers (Cook and Bohlke, 2000). Groundwater ages can be estimated with a precision of 2 to 3 years using $^3H/^3He$ and chlorofluorocarbons for groundwater that is up to about 50 years old. For older groundwater, the radioactive decay of ^{14}C can be used to estimate ages ranging from 200 years to 20,000 years (Cook and Solomon, 1995). The decay equation for estimating groundwater residence duration is given by.

$$\text{Age} = ln\left(\frac{A}{A_0}\right)8266.7 \tag{13}$$

Where: A_0 is the initial radiocarbon concentration of water.

$$\text{R} = \frac{L\varphi_e}{T} \tag{14}$$

Where: L is flow path length, φ_e is the effective porosity, and T is age of the groundwater at the distance L.

Understanding groundwater ages significantly enhance the accuracy of recharge rate estimates, which can be integrated into automated inverse-modeling exercises. Baseflows estimates provide Darcian flux, while travel times help estimate seepage flux. Both types of flux data are essential for effective porosity estimation. Additionally, carbon-14-based ages can also be used to estimate paleo-recharge rates in certain cases (Sanford, 2002).

1.5 Numerical models

Watershed model: Watershed models are essential for predicting recharge rates across extensive regions, providing estimates as a residual factor in the water-budget equation (Ali and Mubarak, 2017). The spatial resolution of these models varies; some provide lumped estimates of recharge for the entire catchment, while others divide basins into hydrologic-response units (Flint et al. 2002). The precision of recharge approximation depends on the accuracy of various water balance components. Notable watershed models include MIKESHE, SWAT, and HSPF, which integrate all hydrologic components and offer advanced capabilities for parameter estimation and water budget studies (Daniel et al. 2011).

Unsaturated zone model: Recent advancements in computational algorithms have significantly enhanced the feasibility of conducting long-term simulations of aquifer recharge (Shamsi et al. 2020; Zeinali et al. 2020). Unsaturated zone modeling enables the estimation of potential recharge; however, drainage rates in deep unsaturated zones may not accurately reflect real recharge rates at the water table, as infiltrated water may not completely reach the groundwater. The Richards equation, governing unsaturated flow, is addressed through various methods, including numerical solutions, techniques for routing soil-water storage, and quasi-analytical methods. Several software packages facilitate the analysis of unsaturated flow by solving the Richards equation, including SWIM (Ross, 1990); VS2DI (Hsieh et al. 2000); WASH123D (Yeh et al. 2006); Feflow (Trefry and Muffles, 2007); FEHM (Zyvoloski, 2007); Hydrus-1D, 2D/3D (Simunek et al. 1998, 2005); Hydrogeosphere (Brunner and Simmons, 2012). Despite these advancements, uncertainties associated with hydraulic conductivity and non-linear interactions often make this approach more suitable for small-scale analyses.

Groundwater flow models: Groundwater flow models are essential for mathematically describing groundwater flow and forecasting aquifer conditions. The most widely used numerical groundwater flow model is MODFLOW, developed by the United States Geological Survey (McDonald and Harbaugh, 1988). It employs a block-centered finite difference approach for the saturated zone. Other models used for recharge measurements include HST3D, MODFLOW SURFACT, MODFLOWT, MOC, VAM2D, WHI Unsat Suite (Kumar, 2004). These models estimate the impact of withdrawal or recharge rates on aquifer water levels, supporting research on groundwater supplies and pollutant transport. While most models focus on the saturated zone, some sophisticated models can replicate both unsaturated and saturated zone flow. Groundwater modeling results are subject to various uncertainties, including parameter, conceptual, and measurement uncertainties, primarily due to the challenges in monitoring hydrodynamic parameters and variables across the aquifer.

A semi-coupled modeling approach computes the spatio-temporal variability of groundwater recharge where the net recharge from unsaturated flow models is used as input to groundwater flow models (Sophocleous and Perkins, 2000). Additionally, groundwater models coupled with Soil Vegetation Atmospheric Transport (SVAT) models help assess the impact of land use, soil type, and climate on groundwater budget. SVAT models simulate hydrologic process in the vadose zone, using governing equations for moisture and energy movement in vertical direction, applicable at various soil profile levels. The recharge output from the deep soil level is then input into the groundwater flow model (Facchi et al. 2004).

However, predicting groundwater recharge in watersheds with hydrological and geographic variability presents challenges. Geographic Information Systems (GIS) can assist in resolving these issues by employing physical-based coupled water balance-groundwater flow models (Batelaan and De Smedt, 2007; Dereje and Nedaw, 2019). These models requrie inputs related to the watershed system, the physical rules governing its behavior, and the boundary and initial conditions. Nonetheless, conventional methods used in this approach are computationally intensive, necessitating substantial data and calibration efforts (Daniel et al. 2011).

Groundwater models incorporate recharge based on the process controlling it and the modelling objectives. In arid regions, recharge is primarily influenced by climate and soil conditions, while in wetter regions, it is determined by the aquifer system's ability to transmit water. Mixed-type boundary conditions are used for accurate simulation. Groundwater models estimate regional recharge rates largely based on water level information and aquifer permeability distribution. Variably saturated subsurface flow models, like integrated surface and subsurface hydrologic models, simulate water movement across surface water, saturated, and unsaturated zones, relying on climate data. However, their outputs may be less meaningful in certain situations due to storage dynamics in the capillary fringe above the water table (Gong et al. 2023).

Inverse Model: Inverse modeling is a technique used to determine appropriate values for model parameters by comparing model outputs with field measurements. This approach is commonly applied in calibrating models for forecasting natural systems in fields such as hydrology, meteorology, and climatology. In the context of groundwater flow modeling, outputs typically include hydraulic heads, drawdown, groundwater age, surface water gains and losses, and travel times. The most widely used approach in inverse aquifer modeling is parameter estimation, which seeks the optimal solution based on available measurements. Inverse modeling is employed to identify factors affecting a physical system by using observations from measured hydraulic heads/field data, and to predict recharge rates through numerical approximation of the two-dimensional groundwater flow equation (Kendy et al. 2003).

1.6 Machine learning algorithms

Machine learning techniques have proven effective in predicting groundwater system behavior by analyzing data from various hydrological zones, such as recharge areas, water levels, and water quality, and applying algorithms to predict future trends. These algorithms employ available data to identify the optimal function for classification, forecasting, or detection of specific outputs, thus qualifying them as empirical models (Ahmadi et al. 2022). Artificial Intelligence (AI) approaches have facilitated the probabilistic calculation of groundwater balance components by examining correlations and causal relationships with other hydrological, climatic, and geospatial variables (Tao et al. 2022). Linear regression, logistic regression, decision trees, support vector machines, Naive Bayes, K-means clustering, Random Forest, gradient boosting, and adaptive boosting are some of the commonly used ML methods. Below are some of them used in this field.

Multivariate Linear Regression (MLR): MLR is a statistical method used to model the relationship between input parameters and outcome measures, quantifying the correlation between input and output variables (Mogaji et al. 2015). It is valuable for forecasting GWL, modeling trends, and predicting recharge rates by correlating recharge values with other groundwater conditioning factors or predictor variables to build the reservoir prediction regression model. MLR also assesses the impact of climatic and environmental variables on groundwater recharge using time series data (Huang et al. 2019; Tao et al. 2022).

Random Forest (RF): The RF approach uses multiple decision trees for classification and prediction by aggregating the votes for selecting the prediction (Breiman, 2001). It handles complex datasets effectively by combining classification and regression trees with randomization and utilizing random variables for node splitting. RF improves prediction accuracy by expanding decision trees without pruning based on the number of trees and predictor variables (Di Salvo, 2022). Its small parameter set makes it suitable for water resources applications (Liaw et al. 2002). The RF regression algorithm predicts groundwater recharge using multiple hydrogeological attributes as input predictor variables such as precipitation, evapotranspiration, soil moisture, aridity index, vegetation indices, and so on. The algorithm is built using the training dataset from experimental/field data or from recharge values estimated using numerical or physical based methods (Sihag et al. 2020).

Extreme Gradient Boosting (EGB): EGB is an ensemble learning technique that uses gradient boosting algorithm for prediction. It builds tree type predictors sequentially and focuses on residuals from earlier learners to reduce errors. It is flexible and compatible with various programming languages but requires technical expertise. However, it is complex, memory-intensive, and lacks transparency. XGB regression modeling uses climatic variables and GWL data to predict GWL behavior (Osman et al. 2021; Tladi et al. 2023).

Support Vector Machine (SVM) and Support Vector Regression (SVR): SVMs are statistical learning techniques that utilize structural risk minimization and kernel functions to transform data into a high-dimensional space for optimal classification and regression (Naghibi et al. 2017). SVR is a variant of SVM, used for regression problems. SVM enhances its generalization ability and prediction accuracy by minimizing empirical error and model complexity simultaneously, focusing on testing error rather than training error (Di Salvo, 2022; Anh et al. 2023). SVM can predict GWL fluctuations over various periods by approximating nonlinear process using different kernel functions (Tao et al. 2022).

Gaussian Process Regression (GPR) and Gaussian Mixture Models (GMM): GPR is a non-parametric, kernel-based probabilistic method, which can be used for preferential learning, regularization of parameters, uncertainty handling and probabilistic predictions. GMMs assume that data points result from a combination of Gaussian distributions with unknown characteristics (Zeng et al. 2008; Reynolds, 2009). GPR models, regulated by covariance functions, offer robustness and reliability, often outperforming other ML models in GWL prediction (Ahmed et al. 2022).

Deep learning algorithms: Deep learning is a branch of ML in which millions of data are given as input that uses neural networks with multiple layers to analyze and emulate complex nonlinear patterns by building relationships with the variables and enhancing the stability of the whole system. Annual/Regional groundwater extraction data calculated using chemical methods or physical methods and the groundwater predictor variables are used to train the network. The recharge values are then calculated using the input potential variables based on the trained network parameters (Huang et al. 2023). The top ten popular deep learning algorithms include Convolutional Neural Networks (CNNs), Long Short-Term Memory Networks (LSTMs), Recurrent Neural Networks (RNNs), Generative Adversarial Networks (GANs), Radial Basis Function Networks (RBFNs), Multilayer Perceptrons (MLPs), Self-Organizing Maps (SOMs), Deep Belief Networks (DBNs), Restricted Boltzmann Machines (RBMs), and Auto encoders. Deep learning has been utilized to predict parameters in the numerical homogenization of Richards equation (Stepanov et al. 2023). Artificial Neural Networks (ANNs) are self-learning algorithms that mimic the brain's structure and operation through interconnected processing units, can simulate complex processes like pattern creation and decision-making. Fuzzy logic and neuro-fuzzy models integrate ANNs with Fuzzy Logic (FL) to leverage the strengths of both methodologies (Sharafati et al. 2020). The ANFIS model is frequently used in hydrology for GWL prediction, using meteorological parameters as inputs (Bak and Bae, 2019).

In extensive research areas, while ML models cannot replace numerical models, they offer cost-effective tools that can enhance groundwater forecasts for specific locations. ML models improve numerical model calibration, predict head errors, and aid in variables selection, thus refining decision-making procedures. Nevertheless, they have limitations like uncertainty quantification, short forecast time frames, and challenges in handling non-spatial data sources (Huang et al. 2019).

ML models, which are often bottom-up and data driven, face challenges with lengthy calibration and prediction time. Bottom-up models, requiring spatially sensitive data, struggle with interpolating and upscaling spatio-temporal behaviour in areas with sparse sampling data. For spatio-temporal groundwater recharge prediction, deep learning models with top-down approach outperform other approaches due to their superior prediction performance, long term forecasting capabilities, interpolation, upscaling, minimal training time, and strong generalization ability (Huang et al. 2023).

Machine learning applications in forecasting groundwater and climate variables have demonstrated accuracy comparable to or exceeding traditional numerical models. These methods require fewer input parameters and bypass the typical model building and parameter estimation stages, offering a viable alternative for models with lengthy computational times. ML techniques reduce processing times without compromising the accuracy of GWL forecasting (Banerjee et al. 2024), addressing errors from multiple sources without assumptions about error distribution. They also allow for the integration of diverse input data, enhancing the prediction capabilities of physically-based models under varying conditions. Table 2 illustrates the diverse range of machine learning algorithms utilized in recent groundwater level and recharge prediction research. ML algorithms effectively address the challenges in modelling complex hydrogeological processes, capturing the nonlinear and dynamic characteristics of systems without explicit mathematical descriptions, as demonstrated in studies by Ahmadi et al. (2022), Derbela and Nouiri (2020), Di Salvo (2022), and Osman et al. (2021).

Despite limitations such as overtraining and dependency on training data, ML methods offer simplicity, high-speed processing, and reasonable accuracy without requiring a deep understanding of the problem's physics. However, these methods often overlook the spatial correlation of target variables (Reichstein et al. 2019) and are opaque, lacking physical mechanisms, which can increase uncertainty in simulation outcomes. To mitigate this uncertainty, various studies has employed the Bayesian optimization algorithm to fine-tune model hyperparameters, thereby reducing simulation uncertainty to a certain degree.

Limitations in modelling nonlinear and non-stationary processes in AI models have led to the development of hybrid modeling approaches, combining different AI methods at various stages of the modeling process. Hybrid methods integrate AI-based models, computational machine learning models, and traditional regression models to enhance performance accuracy or achieve optimal outcomes. These hybrid approaches can be applied in prediction or optimization stages depending on their intended goals, are proven to be more dependable and capable of surpassing single models in terms of modeling accuracy. Various hybrid models, particularly those integrating Artificial Neural Networks (ANNs), have demonstrated significant improvements in GWL prediction (Tao et al. 2022). Wavelet-AI model, Genetic programming-AI model, AI-Kriging, Wavelet-ANN and Wavelet-ANFIS models are coupled to leverage their combined potential for spatio-temporal simulation of GWL (Rajaee et al. 2019). Integrating AI with conceptual-numerical models to create integrated modular models, eg. ANN-MODFLOW (Abd-Elmaboud et al. 2021), can effectively addresses the limitation of each approach. Predictive error of physically-based groundwater models are frequently prone to random and systematic errors due to deficiencies in model structure, parameter, and data. Such errors can be effectively reduced using coupled numerical models with data driven models from machine learning algorithms. Combining local data, remote sensing, and GIS with AI improves our understanding of recharge (Tao et al. 2022).

2 Selection of suitable recharge estimation methods

Sustainable groundwater extraction faces challenges due to limited knowledge and tools for understanding groundwater dynamics. Accurate groundwater recharge projections are crucial for assessing the impacts of climate change on groundwater resources and for effective planning and management. With the increasing water demands of irrigated agriculture, precise recharge estimation methods become crucial. Current methods for modelling groundwater dynamics often focus on time series data analysis, neglecting spatial components due to challenges in capturing both temporal and spatial similarity of recharge variables (Sena and Nagwani, 2016). Errors and uncertainties in recharge estimations arise from spatio-temporal variations in processes and parameter values, measurement errors, and the validity of underlying assumptions (Healy and Cook, 2002; Sanford, 2002). The selection of estimation method depends on factors such as the study's purpose, required accuracy level, the area under study, and history of recharge monitoring. Table 3 provides a summary

Table 2 Details of machine learning algorithms utilized in recent studies for groundwater level and recharge predictions.

References	Machine learning models	Predictive evaluation metrics	Input data	Target prediction
Emamgholizadeh et al. 2014	Artificial Neural Network (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS)	Root-Mean-Square-Error (RMSE) and determination coefficient (R^2)	Rainfall recharge, irrigation returned flow and pumping rates from water wells	Groundwater level (GWL)
Pandey et al. 2020	ANN optimized with a Genetic Algorithm (GA-ANN)	Coefficient of determination (R^2), coefficient of efficiency (CE), correlation coefficient (r), Mean Absolute Deviation (MAD), RMSE, Coefficient of Variation of Error Residuals (CVER), Absolute Prediction Error (APE) and Performance Index (PI)	Groundwater recharge, groundwater discharge and previous groundwater level data	Seasonal groundwater table depth
Derbela and Nouiri, 2020	ANN	RMSE, R^2, Nash–Sutcliffe (NASH) efficiency coefficient	Monthly rainfall, evapotranspiration and initial water table level	Monthly water table levels
Dadhich et al. 2021	Time series forecasting models (Simple Exponential Smoothing, Holt's Trend Method, ARIMA) and ANN	Root-Mean-Square-Error (RMSE) and determination coefficient (R^2)	Groundwater data	GWL and quality parameters
Pham et al. 2022	Random Tree (RT), Random Forest (RF), decision stump, M5P regression algorithm, Support Vector Machine (SVM), locally weighted linear regression (LWLR), and reduce error pruning tree (REP Tree)	RMSE, Mean Absolute Error (MAE), Relative Absolute Error (RAE), Root Relative Squared Error (RRSE), Correlation Coefficient (CC), and Taylor diagram	Historical GWL, mean temperature, rainfall, and relative humidity datasets	Groundwater level (GWL)
Huang et al. 2023	Top-down deep learning model (s-LSTM), bottom-up machine learning models (m-Linear, m-MLP, and m-LSTM)	Root-Mean-Square-Error (RMSE), absolute errors between calibrated and predicted data	Groundwater extraction, mean number of wet days per year, seasonal minimum temperature, seasonal rainfall, and seasonal actual evaporation	Groundwater recharge
Banerjee et al. 2024	Linear Regression model to the intricate Extreme Gradient Booting (xgboost)	Inversive correlation and *k*-fold cross-validation	Precipitation, Land Use Land Cover (LULC), soil type, land slope, temperature, potential evapotranspiration, and aridity index	Groundwater recharge pattern under different climate change scenarios
Ramadan and Boubaker, 2024	SVM, RF, Linear Regression (LR), and Gradient Boosting (GB)	Mean Squared Error (MSE), R-squared (R^2), Mean Absolute Error (MAE), Explained Variance Score (EVS), Mean Absolute Percentage Error (MAPE), and Median Absolute Error (medae)	Weather data	Water consumption, groundwater recharge
Fahim et al. 2024	Multiple Linear Regression (MLR), regression trees, SVM, Gaussian Process Regression (GPR), and ANN	Overall correlation coefficient (R) and MSE	Groundwater storage (GWS) gridded data from the Global Land Data Assimilation System (GLDAS) and other data sources such as population, rainfall, temperature, irrigation, and elevation	Groundwater level (GWL)

Table 3 Brief outline of the various methods of estimation of groundwater recharge with their advantages, disadvantages and scope of application

Zones	Methods	Climatic regions	Advantages	Disadvantages	Scope of application
	Physical methods				
Surface water zone	Channel Water Balance	All Climatic Regions	Analyzes recharge Rate based on transmission losses; Provides potential recharge values.	Uncertainty issues due to inherent fluctuations in hydrologic cycle and related measurement mistakes; Overestimation due to bank storage/evapotranspiration/perched aquifer effects.	Represent average recharge values over the reach between gauging stations; Temporal scales range from event scale to long-term summation of individual events.
	Seepage Meters	All Climatic Regions	Direct, Fast Measurement; Simple computation; Affordable; Rational on-site implementation.	Point estimates of fluxes; Requires multiple measurements.	Localized Recharge Estimation providing actual recharge values; Time scales range from individual events to days; Wide application range.
	Hydrograph Separation Method	Humid	Simple recharge estimator; No sophisticated instrument required; Estimates recharge over longer times by summing shorter time estimates.	Not suitable for large basins with high pumpage, evapotranspiration, deep aquifer underflow and losing stream; Difficulty in separating flow components from bank storage effects.	Watershed/catchment/regional level estimation providing net recharge values; Time scales range from months to years; Best for shallow water-table regions with gaining streams.
Unsaturated zone techniques	Lysimeter Method	All Climatic Regions	Percolate gathered by lysimeters closely approximates the recharge reaching the water table.	High costs and impracticability in non-identical soils, drainage areas, deep rooted vegetation condition and sidewall flow. Overestimation due to changes in surface and subsurface flow routes; Point-estimate of recharge.	Measures aquifer renewal rate; Used for local estimation at point scales; Temporal scale ranges from minutes to years, depending on drainage accuracy and lysimeter surface area; Wide application range.
	Zero Flux Plane Method	All Climatic Regions	Direct point estimation of potential groundwater recharge.	Costly requires expensive devices and data; Fails with sufficient infiltration due to a positive hydraulic gradient; ZFP depth is not fixed and fluctuates throughout the year, ranging from a few centimeters to a few meters below the soil surface; Accurate determination requires special care and sensitive instruments, making it difficult to measure; Not applicable in wet areas.	Applicable in areas with FP and deep water table; Cannot be used when water fluxes are downward or when water storage grows; Downward movement of a wetting front can obscure the zero-flux plane.
	Unstaurated Zone Flux Estimation Using Richards Eqution	Arid/Semi-arid	Water draining below the root zone (or passing through unsaturated zone) contributes to recharge.	Difficulties in measuring soil-water potential gradient at deeper layer/profile; Variabilities in hydraulic properties of field soil, field measured data of hydraulic properties, etc; Point estimate of recharge over a wide range of time; Does not indicate total recharge as it only accounts for diffuse or matrix flow.	The minimum recharge rate that can be estimated using Richards equation depends on the accuracy of hydraulic conductivity and head gradient measurement.

Table 3 (continued)

Zones	Methods	Climatic regions	Advantages	Disadvantages	Scope of application
Saturated Zone Techniques	Water Table Fluctuation Method	All Climatic Regions	Widely used method for estimating groundwater recharge based on groundwater levels; Applicable in arid and semiarid regions with shallow WT; Most promising and attractive approaches due to its accuracy, ease of use and low application cost in semiarid areas; Effective for analyzing short-term fluctuations in water levels in shallow water tables and for determining long-term recharge changes induced by climate or land-use change.	Not suitable for deep aquifers due to the delayed rise in WT; Time intervals for recording/ measurement should consider wet/dry spell length, aquifer depth, and recharge estimation objective; Accumulated errors from other fluxes can lead to significant mistakes.	Applicable to unconfined aquifer only; Used for local to catchment/regional level estimation providing actual recharge values; Rates for recharge range from tens to hundreds or thousands of meters; Time spans range from event scale to hydrographic record length.
	Chemical methods				
Surface Water Zone	Heat Tracer	Arid/Semi-arid	Measures surface water infiltration and flow through ephemeral rivers; Alternative to flow measurements in semi-arid regions prone to erosion.	Point estimate of recharge.	Uses a variably saturated flow model to estimate sediment hydraulic conductivity and percolation rates based on temperature fluctuations and matric potential from heat dissipation sensors.
	Isotopic Tracer	All Climatic Regions	Direct method for field surveys; Accurate results without absorption or tracer loss; Requires only one-time sampling, allowing for smaller flux estimates; Doesn't require frequent field visits.	Radioactive material may not be permitted in all areas due to environmental protection laws; Requires costly instruments for reading samples and technical operation; Point estimates of recharge require multiple measurements; Difficulties in soil sampling at greater depths and locating tracer peak; Water content within root zone is underestimated due to evapotranspiration.	Application of tracer at multiple sites and appropriate averaging of the results can give more realistic value of recharge; Understanding groundwater flow patterns, age, recharge zones, losses, and interactions with surface waters.
Unsaturated Zone Techniques	Environmental Tracer	Arid/Semi-arid	Chloride Mass Balance (CMB) Model for Recharge Rate Estimation; Cost-effective and environmentally friendly; Accurately estimates recharge rates; Conserves atmospheric inputs; Provides integrated value.	Ambiguity in determining chloride concentration in wet/dry deposition; Extreme rainfall affects concentration; CMB method relies on runoff for Cl concentration causes errors in humid regions;	Provides precise recharge rate approximation for a few years to longer periods; Used for local to catchment/regional level estimation providing potential estimates if withdrawals greater than recharge.

Table 3 (continued)

Zones	Methods	Climatic regions	Advantages	Disadvantages	Scope of application
	Historical Tracer	Arid/Semi-arid	No extra hazard; No extra cost of tracer; Historical tracers provide point estimates of water flux over the last 50 years.	Uncertainties regarding tracer location and concentration; Difficulties of soil sampling at greater depths and locating tracer peaks in areas with higher recharge rate; Water fluxes estimated from tracers within the root zone can overestimate water fluxes below the root zone due to evapotranspiration.	Historical tracers or event markers such as bomb-pulse tritium (^3H) has been widely used in the past in both unsaturated and saturated zones to estimate recharge.
	Applied Tracer	Humid	No environmental hazard; Easy to apply and sampling; Low cost; Visual observation is possible for visible dyes; Provides precise recharge estimations as they are unaffected by surface runoff and other water balance component and driven only by recharge component.	Observed recharge rate will be higher than actual due to preferential pathways; Negligible concentration towards greater depth with insufficient initial concentration; Tracers don't directly measure water flow, leading to over- or under-estimation; Issues with secondary tracer inputs, mixing, and dual flow mechanisms; Technique yields point estimates of recharge through soil matrix only; Low recharge rate calculation due to the slow movement of tracer through root zone.	Calculated recharge rates represent the time between application and sampling; Used for local to catchment/regional level estimation providing potential estimates if withdrawals exceed recharge.
Saturated Zone Techniques	Ground Water Dating/ Aging	All Climatic Regions	Easy to implement if the instrument for reading the sample is available; No additional field setting/experiment is needed.	Costly instrument; Variation of isotopic signature with depth may occur due to various reasons; Multiple sampling throughout the depth up to aquifer is needed; Neoconservative nature; Lack of mass balance research; Affected by contamination; High cost, and specialized personnel requirements.	Used for local to catchment/regional level estimation giving actual recharge values; Range is not limited; The temporal scales represented by the recharge values range from years to long term average.
Numerical models					
All Hydrological Zones	Numerical Modelling	All Climatic Regions	Requires less data; Can model large areas and complex conditions; Can provide the missing information; Calibrated models can assess spatial and temporal distribution and Scenarios; Can provide a predictive tool to quantify impacts on the system; Higher generalization ability than AI models.	Computationally intensive due to iterative techniques; Simulation models may display errors in parameter estimation, measurement errors, and application scale due to inherent assumptions and validation processes; Complexity in model preparation, realistic problem description and result evaluation.	Numerical relationship between basic components in the water budget method is used; Provides the recharge estimate as a residual term; Used for catchment to regional level estimation; Range is medium to large basins; Temporal scales represented by the recharge values range from months to years.

Table 3 (continued)

Zones	Methods	Climatic regions	Advantages	Disadvantages	Scope of application
Machine learning algorithms					
All Hydrological Zones	Machine Learning/ Deep Learning	All Climatic Regions	Improves calibration of numerical models; Requires fewer input parameters, reducing computational times without sacrificing accuracy of detail; Easy to use with reasonable accuracy without needing to understand the system's physics; Deep learning models are robust, relying on significant predictors, so eliminating any predictor doesn't affect the system.	Lack of understanding the underlying physical process; Lower generalization ability due to overtraining; Require a high number of models runs for optimization, sensitivity / uncertainty analysis; Lengthy calibration and prediction time; Spatial recharge dynamics is not covered as it is data intensive; Short forecast time period; Not suitable for large research areas.	Effective for groundwater management when used in combination with numerical models; Machine learning models can improve numerical models especially with limited field data, enabling accurate prediction at specific locations using various codes and software.

of various methods, outlining their advantages, disadvantages, and applications.

Climatic geomorphology: Recharge estimation methods vary significantly across different climatic regions and often rely on limited historical monitoring data (Delin et al. 2000; Kumar et al. 2021). Historical tracers are useful in unsaturated zones in humid regions, where watershed modelling approaches offer higher accuracy due to perennial surface-water flow for calibration. In contrast, arid and semiarid regions typically use unsaturated-zone techniques more frequently, though interpreting groundwater hydrographs and water-table rises can be challenging in these areas, particularly where the water table is deep.

Spatial and temporal scale: Surface-water and groundwater techniques generally offer regional recharge estimates, while unsaturated-zone methods provide point-based or small-scale estimates. Recharge rates can vary significantly depending on the time scale of the study, with surface-water methods offering short-term or event-based estimates, while unsaturated and saturated-zone techniques provide estimates ranging from event scales to multiple years. Numerical modelling can predict recharge over extended periods, though estimation based on climate data are typically constrained to around 100 years. Tracer techniques, such as those using ^{36}Cl, ^{3}H, $^{3}H/^{3}He$, CFCs, ^{14}C, and Cl, can offer comprehensive long-term estimations.

Cost and time requirement: The cost and time requirements for various approaches vary considerably. Tracer techniques are advantageous for quick recharge estimations, as a single sampling is often sufficient for chemical and isotopic tracers, potentially costing less than short-term monitoring, which requires monitoring equipment and continuous data collection and analysis. Numerical and ML models, on the other hand, require significant investment in terms of time and cost during the design process. Deep learning models, in particular, are expensive to train, necessitate high-quality data, and are often considered "black boxes" due to their high computational costs (Hussein et al. 2020).

Accuracy: Saturated-zone techniques typically provide more reliable recharge estimates by measuring actual recharge, while surface-water and unsaturated-zone techniques estimate potential recharge. In arid and semi-arid regions, where recharge constitutes a small portion of the water budget, inaccuracies in water-budget techniques can accumulate, making them less accurate compared to humid regions. Variability in hydraulic conductivity affects the accuracy of approaches using this data, such as unsaturated and saturated zone techniques. Properly applied ML techniques can yield more accurate predictions compared to some traditional physical models.

Uncertainty in data: Uncertainties in hydraulic conductivity are more pronounced in unsaturated systems due to the nonlinear relationship between hydraulic conductivity and water content. Tracer data estimations also carry uncertainties related to tracer concentrations measurements, estimated inputs, and assumptions about tracer transport processes, though these are generally less than those associated with water-budget approaches or hydraulic-conductivity data. Physically based numerical models are subject to inherent uncertainties from structural errors, parametric calibration, and input data inaccuracies. AI models also face uncertainties throughout the stages of training, learning, prediction, preprocessing, and data collection. Addressing uncertainty measurements in different AI and numerical models is essential, Suggesting an iterative approach to recharge estimation that employs multiple techniques to account for these uncertainties (Scanlon et al. 2002; Nimmo et al. 2005; Kumar et al. 2021). Hybrid models, which integrate multiple techniques, often outperform single models in terms of effectiveness, and addressing various issues associated with individual techniques (Tao et al. 2022).

3 Challenges and progressions in recharge estimation

Recharge estimation methods have inherent limitations and are often dependent on specific problems and scales. Accurate groundwater recharge estimation is an iterative process that involves ongoing data collection and evaluation of aquifer responses. Field measurements are crucial for capturing realistic recharge processes, as they provide data that cannot be solely derived from modeling. Models used for recharge estimation must accurately represent essential flow mechanisms to ensure reliability. Recharge processes are influenced by both climatic factors and surface and subsurface conditions, which may not always align with lithology and climate conditions. Geological factors such as regolith, duricrust, and karst formations significantly impact recharge and are shaped by historical geological processes (De Vries and Simmers, 2002; Dang and Zhang, 2008). Over time, various methods have been developed for evaluating recharge, including basin water balance, numerical modeling, empirical rainfall-recharge relationships (Beyene et al. 2024). Each method is constrained spatially and temporally by its underlying assumptions and structural features, thus limiting the range of detectable recharge magnitudes (Scanlon et al. 2002). Recharge estimation involves field measurements, heavily influenced by climate, surface, and subsurface conditions. Challenges include the influence of vegetation, soil properties, and precipitation characteristics, and the difficulty of direct observation. Recharge-precipitation relationships exhibit spatial heterogeneity and temporal variability, with varying lag times due to hydrological impacts and urban development. Numerical modelling and tracer methods are sensitive to boundary conditions and require reliable parameters. Tracer methods, such as chloride mass balance, offer valuable insights into recharge sources but rely on assumptions of system steadiness. While tracer approaches can yield reliable estimates, they require careful interpretation to account for localized and regional variability (Moeck et al. 2020). Physical methods, such as lysimeters, offer high temporal resolution for recharge estimation, through direct and indirect measurements such as the zero-flux plane and the WTF method. However, accurately applying the WTF method is challenging due to its dependence on factors like time, water table depth, and soil texture. Exploring newer techniques with local specificity is recommended.

Geological complexities and low precipitation further challenge the estimation of spatial recharge distribution. In arid environments, site-scale recharge models are essential for predicting net surface infiltration and nonuniform recharge at the water table (Flint et al. 2002). Physically based models are commonly employed in quantitative groundwater flow and solute transport analysis, but their accuracy diminishes as field observations, computer capacity, and hydrogeological systems expand. Practical limitations include the need for extensive data and input parameters, as well as the difficulty of obtaining accurate model parameter estimates across study areas.

The groundwater study process involves gathering geological and hydrological data on the basin, including surface and subsurface geology, water tables, precipitation, and land use. In cases where data are lacking, fieldwork is necessary to build a conceptual model, which is validated with physical and hydrological stress data to outline inflow and outflow. Results are typically presented through maps and cross-sections. For numerical modelling, contour maps of aquifer boundaries and characteristics are essential, aided by auxiliary maps. Studies require comprehensive data on physical and hydrogeologic frameworks, encompassing geological and topographic maps, water table data, and hydraulic conductivity distributions. Gathering data for groundwater modelling can be challenging, especially when information about the study area is limited. While some data may be available from existing reports, additional fieldwork is often needed. Collected data may not always match the required format and may contain inaccuracies, necessitating validation. Estimating hydrological stresses such as groundwater pumping is relatively straightforward, whereas inferring evapotranspiration from land use and potential evapotranspiration data is feasible. Aquifer characteristics are typically determined through pumping or laboratory tests, although lab values may underestimate field values due to sample constraints.

Modelling anisotropic media requires data on hydraulic conductivity components, which can be derived from stratigraphic details or estimated during model.

4 Data challenges in developing countries

Developing nations often lack extensive monitoring systems for groundwater levels, precipitation, and soil moisture, which hinders accurate recharge estimation. This lack of infrastructure results in sparse data coverage, particularly in rural or remote areas, making it difficult to capture the variability of recharge processes across different regions and hydrogeological settings. Data inconsistencies and incompleteness are common, often due to outdated measurement techniques, lack of quality control measures, or insufficient data sharing and integration efforts. Limited resources for data collection and management, including financial, technical, and institutional constraints, further impede effective data collection, management, and analysis. Additionally, a lack of technical expertise for groundwater monitoring, data management, and analysis exacerbates these issues. Addressing these challenges requires a multi-faceted approach involving infrastructure investments, capacity building, collaboration, and policy support to ensure sustainable groundwater resource management. An important development in addressing data scarcity issues is the use of Basin Characterization Model (BCM) (Stern et al. 2021) in water balance modelling. BCM offers a thorough understanding of groundwater recharge and runoff dynamics by integrating local and global datasets in a seamless manner, especially in areas with restricted data availability. This method improves estimating precision by utilizing remote sensing technologies and climate data (Mekonen et al. 2023).

The Global Land Data Assimilation System (GLDAS) gridded Groundwater Storage (GWS) data presents a cost-effective alternative to establishing an extensive groundwater monitoring network. By employing advanced data assimilation techniques and land surface modelling, GLDAS GWS data has proven effective in various regions, serving as a viable substitute for in-situ data (Fahim et al. 2024). GIS technologies are well-suited for groundwater studies due to their ability to handle both locational and attribute data simultaneously. GIS technology facilitates the integration of diverse datasets, such as topographic maps, lithological maps, and water level data, which need to be integrated for coherent interpretation. Advances in computer technology have improved GIS's capacity to process large volumes of data quickly and accurately, leading to higher accuracy and repeatability of results compared to manual methods.

This review has focused on conventional and machine learning techniques for recharge estimation, highlighting their scope of application. Future research should emphasize hybrid AI models and coupled numerical models for optimal evaluation of water storage, withdrawal, and groundwater reservoir operations.

Developing a management action plan to accelerate groundwater recharge is essential for maximizing the natural underground reservoir for water storage and stormwater collection. Managed projects could enhance recharge by capturing water from streams during high flows and directing it to recharge sites where it can infiltrate into the groundwater reservoir. Without reliable recharge estimates, it is challenging to assess optimal withdrawal rates from an aquifer/wellfield or predict how an aquifer will respond to different management plans over time. Stormwater management and managed aquifer recharge, when properly designed, can achieve high stormwater recharge efficiency by using estimated recharge capacities and understanding recharge mechanisms (Abraham and Mohan, 2019). Many countries have introduced groundwater management policies to sustainably manage groundwater resources and implement rain water harvesting, storm water management and recharge programs. To address these needs, simulator-optimizer models should be employed for groundwater reservoir operations, combining prediction and exploitation policies. Zheng and Huang (2023) suggest that these models represent a crucial direction for future research, integrating advanced simulation and optimization techniques to ensure sustainable groundwater management. Future directions also include ensuring high-quality data availability for model training, enhancing model interpretability, fostering interdisciplinary collaboration, and integrating machine learning with Internet of things and big data for real-time groundwater monitoring and management.

5 Conclusion

Groundwater is a valuable but limited resource facing numerous challenges such as scarcity, contamination, and lack of reliable data. Effective groundwater recharge estimation is critical for sustainable water resource management. Recharge estimation methods fall into two broad categories: Conventional approaches and advanced techniques such as machine learning algorithms. Conventional methods include physical, chemical, and numerical models, while advanced techniques leverage machine learning to enhance predictive accuracy. Based on hydrologic sources or zones from which data are gathered, recharge estimation methods are further classified as surface water, unsaturated, and saturated zone techniques. Surface water and unsaturated zone techniques typically estimate potential recharge, while saturated zone methods provide actual recharge estimates. Physical methods, although simple and cost-effective, often lack accuracy in arid regions. Chemical methods use tracers for indirect assessment, and numerical models offer detailed recharge estimates by modelling water balance elements and accounting for regional variations and transient flows.

The choice of the method depends on factors such as spatial and temporal scales, as well as the consistency of recharge estimates. Machine learning algorithms represent a modern approach, analyzing complex datasets and predicting groundwater behaviour using techniques like multivariate linear regression, random forest, extreme gradient boosting, support vector machines, Gaussian process regression, and deep learning. These algorithms address the limitations of traditional modelling approaches by providing faster, more accurate predictions and enhancing understanding.

Future research should focus on evaluating the significant impacts of external factors such as climate change, land use changes, and groundwater extraction. Developing climate-driven recharge models to assess future changes in recharge rates is crucial. Additionally, integrating AI models to predict groundwater level time series, including lag considerations, is vital for advancing groundwater management practices. Exploring various hybrid AI models to improve prediction accuracy, employing deep learning methods to address missing groundwater data, and integrating nature-inspired algorithms with machine learning for optimal parameter adjustment are essential research avenues. The development of hybrid AI models and coupled hydrologic models that integrate groundwater, surface water, and atmospheric processes can address the challenges of predicting nonlinear relationships between input and output variables in groundwater recharge. It is advisable to combine different methodologies, such as merging numerical methods with physical or tracer-based approaches and AI techniques, rather than applying them separately within a single watershed. Additionally, investigating input data assimilation is essential for reducing uncertainty associated with spatial estimation.

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