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A review on sources of uncertainties for groundwater recharge estimates: insight into data scarce tropical, arid, and semiarid regions

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ABSTRACT

Successful sustainable groundwater management requires accurate information on recharge for a given aquifer system. However, recharge estimates are usually used in relative terms rather than an absolute sense. A review of available studies on groundwater recharge estimate uncertainty as well as tools for uncertainty analysis was conducted. Nonetheless, except for the handful of studies that have conducted proper uncertainty analysis, most were inclined to implement multiple methods as an indication of the range of uncertainty. The global trend indicates that considering the significant number of methods for recharge estimation, very little has been done to assess the uncertainty of each method. Therefore, more attention should be given to the individual uncertainty analysis of selected methods as much as using multiple methods recommended for investigating uncertainty. Insight from the review indicates that, when used carefully, tracer-based analysis can be effective and coupling is required for uncertainty analysis. Furthermore, spatial uncertainty due to input data could potentially be minimized by using input data from multiple sources. Better conceptualization of the hydrogeological process can reduce the uncertainty of numerical modelling. This review is limited to widely used methods and excludes uncertainty due to inappropriate method implementation and controlled experimental uncertainties.

Key words: groundwater, recharge, review, uncertainty

HIGHLIGHTS

- The review article summarizes the uncertainties in estimating recharge using widely applied methods.
- The review article highlights methods for investigating the related uncertainties.
- This review highlights exertions made to quantify the uncertainty of recharge estimation globally.

1. INTRODUCTION

Groundwater supplies drinking water for 25–40% of the world's population (Vrba & van der Gun 2004), and shares an important role in the largest food supply produced by irrigation, which is about 38% of irrigated areas worldwide (Siebert *et al.* 2010). Therefore, accurate estimates of recharge would enable us to sustainably manage the resources and be crucial to maintain reliable drinking water and food supply. Recharge has been given more attention as it is considered to be the main controlling factor in sustainable groundwater resource management. The general rule of conservation, when talking about sustainable use, is to limit the extraction rate by the natural recharge rate, even though there is are reservations regarding its applicability (Gorelick & Zheng 2015). Another important factor requiring investigation of recharge is the growing risk of groundwater contamination (Scanlon *et al.* 2002). However, usually due to its complexity, the need for estimation is limited to the range of recharge, i.e. the lower and higher limit, where actual recharge representation is the lower limit and potential recharge is the higher limit. In recharge estimation, it is never easy to use the term 'accurate' to indicate the level of estimates (Healy 2010). Therefore, it is rather better explained with uncertainty analysis. Here, it should be outlined that uncertainty infers the parameter, model structure, model input data or model initialization, and boundary conditions (Ajami *et al.*

2005; Moges *et al.* 2021). Nevertheless, the recharge estimates for a given area should be presented with an uncertainty level or reliability level of estimates.

Nowadays, the numerical modelling tools offer different algorithms to assess the level of uncertainty. A study by Abraham *et al.* (2022) assessed uncertainty contribution of land use land cover data to recharge estimation of Tikur Wuha River using the SUFI-2 algorithm (Khalid *et al.* 2016), which is integrated into the SWAT model. Different recharge estimation techniques are analysed using the generalized likelihood uncertainty estimator (GLUE) (Muñoz *et al.* 2014; Moges *et al.* 2021). Since certain uncertainty assessment tools are better at capturing the contributions of individual uncertainty sources and others at capturing the total uncertainty, choosing one tool over another should be given an emphasis. For instance, tools like IBUNE (Ajami *et al.* 2005) and BATEA (Kavetski *et al.* 2003) are more capable of capturing the uncertainty due to input. Recent advancements have relied on techniques that use Bayesian statistics to investigate the uncertainty in estimates (Moges *et al.* 2018).

Input data from different sources can contribute different magnitudes of uncertainty in recharge estimation. Point measurements of different input data have significant quality over spatial measurements (Crosbie *et al.* 2018). However, ground measurements using different tools have higher uncertainty in representing the spatial representation (De Vries & Simmers 2002), as diffused recharge is a spatial phenomenon. Another source of uncertainty arises from the attempts of representation of the physical phenomenon using a simplified parameter (Kurylyk & MacQuarrie 2013). In addition, in an attempt at model structuring, simplifying natural phenomena can cause significant uncertainty in estimates of recharge (Delin *et al.* 2007). Furthermore, the complexity of groundwater recharge and related hydrogeological components will contribute to the uncertainty of estimate (Heppner *et al.* 2007). The use of multiple recharge estimates as a means of gaining comparative results as an indication to the range of uncertainty in estimation is practiced by most researchers (Heppner *et al.* 2007; Berehanu *et al.* 2017). Globally, there are very few studies which have focused on investigating the ranges of individual uncertainty estimates using a single recharge estimation method. However, this review will encompass studies that have focused on the uncertainty analysis for a single method or multiple methods with individual uncertainty assessment.

Ensuring the reliability level of the estimate could benefit the decision-making in different ways. For instance, successful implementations of managed aquifer recharge projects rely on the accurate spatial and temporal estimates of recharge. Such practices are very helpful in creating a groundwater resource resilient to climate change and variability (Ebrahim *et al.* 2020). As most contaminant sources are diffused, reliable spatial estimates of recharge are useful for the management of head waters upstream of extraction wells (Kurylyk & MacQuarrie 2013; Ebrahim *et al.* 2020). Nevertheless, most recharge estimates lack an uncertainty analysis. Xie *et al.* (2018) found that the main reason, in addition to the complexity of the analysis, is that recharge estimates are used relatively rather than in an absolute sense. Nevertheless, the importance of uncertainty analysis of the recharge estimation method is undeniable. Therefore, the objective of this review is to summarize exertions on recharge uncertainty analysis and possibly point out future directions.

In this review, recharge uncertainty sources for widely used methods such as chloride mass balance (CMB), stable isotopes methods, numerical modelling, water table fluctuation (WTF) method, and base flow separation are discussed. These methods are selected mainly due to limitations in the number of exclusive studies of uncertainty assessment for other recharge quantification methods. In addition, the study aims to present insight into recharge uncertainty sources for the cases of data-scarce regions.

2. REVIEW OF UNCERTAINTY IDENTIFICATION

Over the years, different methods have been introduced to quantify recharge. But it should be noted that recharge definition is necessary whenever a particular method is referenced. Scanlon *et al.* (2002) categorized the methods based on the hydrological source/zone as saturated zone, unsaturated zone, and surface water. The classification was further subdivided as physical methods, tracer methods, and numerical methods (Scanlon *et al.* 2002). Such classification may depend on the purpose of classification, for instance, the aforementioned classification was made to distinguish methods based on the spatial and temporal range with associated reliability (Scanlon *et al.* 2002). In addition, recharge estimation from all zones can also be achieved using some methods like basin water balance (BWB), numerical modelling, empirical rainfall–recharge relationships, and others (Walker *et al.* 2019).

Inherent to their assumptions and structural nature, each method is limited both spatially and temporally, and they can only detect a range of recharge magnitudes (Scanlon *et al.* 2002). For further detail, readers are referred to Healy (2010), Lorentz *et al.* (2003), and Scanlon *et al.* (2002). Numerous studies have been conducted on the uncertainty analysis of different recharge estimation methods. In this review, special focus has been given to the methods applied most frequently. The uncertainty in recharge estimates is sometimes from the lack of understanding assumptions for a specific method or not meeting the data requirement and error created during data collection (Healy 2010). However, such sources of uncertainty will not be covered in this review as these types of error cannot be used to deduce the method.

2.1. Tracer-based estimation methods

The general rule of tracer application for estimating recharge (i.e. mass balance approach) follows the fractioning of concentration of selected tracer element from different sources. That means the concentration of tracer elements will be measured in the rainfall, and it will be compared to the concentration of tracer element in the groundwater or other point of measurement such as springs. Tracer-based groundwater recharge estimation methods can be classified further as experimental (applied tracer), historical, and environmental tracer based methods (Healy 2010). The experimental method usually depends on the judgement of the researcher, which implies investigation of the uncertainty related to this method, and one should collect all the assumptions, field setups, data collection process, and other factors (Meyer *et al.* 1997). This could potentially vary from research to research making the generalization of the method difficult. Therefore, the review intends to discuss the uncertainty related to the application of environmental tracer element application. In the following section, widely applied methods such as CMB and stable isotope profiling are discussed in detail.

2.1.1. Model structure uncertainty

The CMB method is one of the widely applied methods (Scanlon *et al.* 2006), and it is used for testing uncertainty in different parts of the world. The conventional method estimates the diffused recharge by assuming that the only source of chloride is from the environment (Healy 2010). Essentially, this means point recharges and other sources of chloride are ideally negligible. The method's mathematical representation as referenced by Marei *et al.* (2010) is as follows:

$$R = P \times \frac{\mathrm{Cl}_p^-}{\mathrm{Cl}_{\mathrm{gw}}^-}$$

where R is recharge; P is precipitation; and Cl_p^- and $\mathrm{Cl}_{\mathrm{gw}}^-$ are chloride concentration in precipitation and ground water, respectively. It is indubitable that the aforementioned simple model will have uncertainty if other sources of chloride (Figure 1) are not included.

But one could assume that the cost and time to collect and analyse all sources is unmatchable to the result gained from reducing (not eliminating) model uncertainty of CMB. For regions where concentrated recharge cannot be neglected, such as in karst aquifers (Ahmet *et al.* 2020), updates have been made to include point recharge (Somaratne & Smettem 2014). Deng *et al.* (2013) assessed the uncertainty of the traditional CMB model by considering the effect of canopy on the surface deposition of chloride. The result indicates 28 and 89% chloride deposition enhancement for eucalyptus and pine dominant areas compared to open fields. This clearly indicates the uncertainty in the model structure.

Some researchers argue that stable water isotopes are a good indicator of a recharge process and source, but less efficient when used for estimation (Scanlon *et al.* 2002; Walker *et al.* 2019). Nevertheless, the analysis has been applied for both purposes and reported to contain uncertainty. The uncertainty of this method when applied for source identification or process understanding is challenged when there are multiple sources (Solder & Beisner 2020). That means different sources can have similar isotopic signature. In such cases, it is recommended to use multiple types of isotopes and apply mixing models (Yu *et al.* 2018). In general model uncertainty decreases as the types of isotopes used in the model increases. However, applying multiple isotopes and using mixing models can sometimes be source of uncertainty (Vázquez-Suñé *et al.* 2010; Zhang *et al.* 2018b; Solder & Beisner 2020).

Other forms of tracer are the historical tracers, which are used to estimate the age of groundwater, while inferring to recharge (McCallum *et al.* 2015). McCallum *et al.* (2015) found that the use of lumped parameter models to derive mean transit times and multi-tracers reduces model uncertainty. On the contrary, Turnadge & Smerdon (2014) argued that numerical transport modelling allows direct and bias comparison with observation, unlike other methods which require apparent age bias correction.

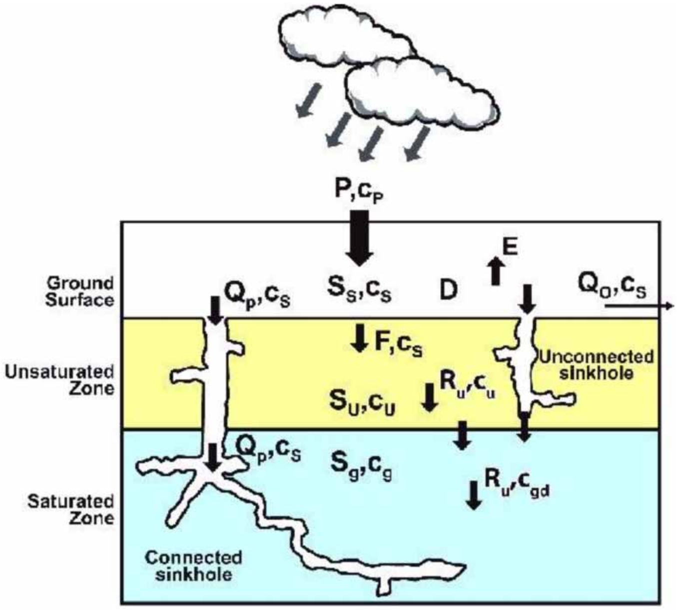

Figure 1 | Schematic diagram for applying chloride mass balance to a control volume (Somaratne & Smettem 2014). *Note*: S_s, surface storage; C_s, Cl^- concentration of surface storage; P, average annual precipitation; C_p, Cl^- concentration of rainfall; D, dry deposition; E, evapotranspiration; Q_p, runoff to sinkholes; Q_o, runoff out of catchment; F, infiltration; S_u, unsaturated storage; C_u, Cl^- concentration in recharge water; R_u, diffuse recharge through the soil profile; S_g, groundwater storage; C_g, Cl^- concentration of groundwater; C_{gw}, Cl^- concentration of diffused groundwater recharge.

2.1.2. Input data uncertainty

The CMB method gives point estimation of a given location, whereas recharge is a spatial phenomenon. As cited by Crosbie *et al.* (2018), the pioneer studies assumed the estimate to be representative of an area, but later works like Bresciani *et al.* (2014) argued the estimate to be an integration of an area up-gradient of the sample location. This leads to spatial uncertainty in the process of up scaling point estimates. A study conducted in Uley South Basin, South Australia, using WTF, CMB, and isotope analysis indicated the uncertainty level by providing the range of estimate (i.e. high and low), and attributed the uncertainty caused to the input data (Ordens *et al.* 2012). Ordens *et al.* (2012) concluded that decreasing the uncertainty from other sources of chloride, influence of vegetation, and proximity to the ocean could potentially reduce such uncertainty.

Alcalá & Custodio (2014) suggested that using short-term chloride concentration records (1–5 years) will induce uncertainty in the estimation of long-term average recharge estimation. In this study, the input variable error propagation method was used to estimate the natural uncertainty and spatial uncertainty using the ordinary kriging up scaling technique. The study also concluded that better data coverage reduces the up scaling uncertainty. Davies & Crosbie (2018) used 291 measurements and a regression (chloride concentration and distance to the coast) in data-scarce areas. Then, ordinary kriging interpolation was applied to create a continental chloride concentration map for Australia. The uncertainty analysis was done during the calibration by creating 1,000 maps using the Monte Carlo sampling technique. The uncertainty analysis suggested that higher uncertainty was observed in data-scare regions, which supports the findings of Alcalá & Custodio (2014).

2.1.3. Parameter uncertainty

The CMB method is susceptible to uncertainty generated from unknown long-term deposition of chloride in the atmosphere, even though one could manage to meet all the assumptions and requirements of the method (Custodio 2010). This could also be because chloride concentration in surface runoff and chloride concentration in groundwater are not exactly known. A work by Crosbie *et al.* (2018) improved up scaling point estimation by using regression kriging and applied global regression using gridded rainfall with geology in data-scarce areas. The parameter uncertainty was analysed using 1,000 stochastic replica of chloride deposition of rainfall, the chloride exported in runoff, the chloride concentration of the groundwater, and the regression equations used to perform the up scaling. In addition, a qualitative uncertainty analysis was done to ensure that the assumptions of the method are consistent for the study basin.

Conversely, one of the reasons for stable isotope performance to be minimum in recharge estimation is linked to the susceptibility of ions to sorption, evaporation, dispersion, and adsorption or other geochemical or biochemical processes (Healy 2010; Cartwright *et al.* 2017). Adomako *et al.* (2010) applied three estimation methods, which included the peak shift method where the difference in groundwater isotope peak is compared to the seasonal rainfall peak. The main assumption of the method is that vertical permeability is much higher than horizontal permeability, which neglects the dispersive flow (Adomako *et al.* 2010). A soil depth profile sample from the selected representative location was analysed to acquire the hydraulic parameters of the depth profile and isotope profile of the soil water, where the result was used to profile additional requirements (hydraulic conductivity and isotope dispersivity) for transient flow and transport modelling. The uncertainty analysis was conducted by varying hydraulic conductivity and other soil retention parameters, where the result illustrated >5% uncertainty level.

2.2. Numerical modelling

The numerical modelling method is applicable to estimate recharge in all hydrological zones (i.e. surface water, unsaturated zone, and saturated zone) (Walker *et al.* 2019). Furthermore, they provide different scale recharge estimation techniques: point-scale from simulations of water flow through the unsaturated zone (e.g. HYDRUS-1D (Simunek *et al.* 2005), UNSAT (Fayer 2000), Soil Water Atmosphere Plant (SWAP) (Kroes *et al.* 2017)), and large-scale from catchment models (e.g. SWAT (Neitsch *et al.* 2002), MIKE-SHE (Refshaard & Storm 1995)).

2.2.1. Input data uncertainty

Despite their range of applicability, these methods need to be checked for reliability using field observations (such as lysimeter data, tracers, water content, and temperature/evaporation) (Scanlon *et al.* 2002). A usual approach to deal with the uncertainty of these methods is to assess the input data uncertainty and deduce the result to output uncertainty. The spatial uncertainty of recharge estimation can be done by creating gridded input data or by creating similar regions of input data (Szilagyi *et al.* 2012; Xie *et al.* 2018).

Xie *et al.* (2017) argued that while using water balance analysis for the estimation of potential groundwater recharge, the related uncertainty could be reduced by 50%, if one can produce a more accurate field-based evapotranspiration time series data. On the contrary, he discussed that the use of field-measured moisture time series to reduce the uncertainty in recharge estimation is unsatisfactory. Xie *et al.* (2018) performed the uncertainty analysis of recharge estimates using the Water Vegetation Energy and Solute Modeling (WAVES) model (Zhang & Dawes 1998) to compare modelled evapotranspiration to Moderate Resolution Imaging Spectroradiometer (MODIS) evapotranspiration data, by applying the Monte Carlo method together with the Latin-hypercube sampling technique on 13 predefined zones. Each zone was represented by the WAVES model for unsaturated zone analysis. The study has highlighted that the Moderate Resolution Imaging Spectroradiometer Evapotranspiration (MODIS ET) can be used to reduce uncertainty. Another work by Westerhoff *et al.* (2018) introduced a large-scale recharge estimation model for New Zealand by using high-resolution satellite data and ground observation map. The study achieved a 17% uncertainty level and concluded that ground observation rainfall data and geological map lead to the highest uncertainty. The method implemented in the analysis of the uncertainty was a propagation of variance and covariance of all input data (Westerhoff *et al.* 2018).

2.2.2. Model structure uncertainty

Many studies have been done on uncertainty of numerical models due to input data uncertainty as well as parameter uncertainties. Even though the uncertainty of model structure could match the combined effect of the aforementioned uncertainties, little has been done to investigate model uncertainty (Højberg & Refsgaard 2005). To some extent, the problem is related to data requirement and method of analysis. Land cover type is one of the controlling factors of recharge. Ampe *et al.* (2012) used two land use classification approach and implemented the Monte Carlo simulation to assess the uncertainty due to the classification method. Results illustrated that regional classification yielded lower uncertainty compared to pixel-based classification.

Ye *et al.* (2010) applied the model averaging method to assess model uncertainty using the five recharge estimation method. From the recharge controlling factor, geology was combined with these five models and categorized into 25 discrete models. The study concluded that the model uncertainty was higher than parameter uncertainty. Model uncertainty induced during calibration of parameters (parameterization process) was assessed by Zhu *et al.* (2020). In this study, hydrological simulation was conducted using three models, and the RORA model (Rutledge 2007) was used for recharge estimation, whereas the uncertainty interval and coverage probability were used to assess the uncertainty. Results showed that parameterization can be a source of uncertainty when estimating diffused recharge from the simulated stream flow.

Manna *et al.* (2019) implemented water balance analysis using a spatially distributed numerical model (MIKE-SHE; Refshaard & Storm (1995)) to map the spatio-temporal distribution of recharge in upland catchment on fractured sandstone upland catchment near Los Angeles, California. In his investigation, he incorporated the analysis of stable water isotopes as a validation of his result. Qualitative uncertainty analysis was conducted by comparing with analysis results from water isotope. The research also concluded that using fine-gridded (and fine temporal resolution) data will necessarily reduce the model uncertainty level.

2.3. Physical-based methods

Over the year, multiple physical-based methods are developed to investigate groundwater recharge. The widely practiced WTF method and base flow separation method are reviewed and discussed in the succeeding section.

2.3.1. Parameter uncertainty

The main cause of uncertainty for the WTF method emanates from the uncertainty of specific yield (Healy & Cook 2002; Jeong & Park 2017). There are many ways of determining the specific yield presented in the literature. Readers are referred to the study by Healy (2010) for more details. One of these methods of investigating specific yield is soil core sample analysis. Even though this method is expensive, especially on heterogeneous geology, it is one of the reliable methods with minimum uncertainty (Kim *et al.* 2010). Delottier *et al.* (2018) used the aquifer test with the WTF method to investigate the uncertainty due to parameter of the method. The experimental setup in this study consists of one pumping well, and at a distance of 6.8 m from this well is the observation well. The uncertainty was conducted on the estimated specific yield and effective water level change. Collected data from the experiment were used to assess the uncertainty of Sy using Moench's, Neuman's, and Theis' models, where the Markov chain Monte Carlo method was used to sample the data. Result showed that most of the uncertainty in this method is due to uncertainty in the parameters.

Another study by Crosbie *et al.* (2019) treated the specific yield as an unmeasurable variable and tried to assess the uncertainty by applying the rejection sampling approach using probabilistic estimates of net recharge from two methods. The study was applied in four different catchments, where the result has proved that constraining specific yield in recharge estimate provides consistent output.

Parameter uncertainty related to base flow separation conducted using two-parameter recursive digital filter was investigated by He *et al.* (2022). In the study, the uncertainty due to two parameters, namely, recession constant and the maximum base flow index (BFI), was investigated. The study deduced that optimized values of the BFI and time-scaled recession constants can be used to reduce the uncertainty in base flow separation (He *et al.* 2022). Sensitivity of the BFI was investigated by Yang *et al.* (2019), by base flow separation by the two-component hydrograph separation method with conductivity as a tracer. The study deduced that the uncertainty in the BFI can be reduced by half when considering mutual offset of the measurement errors in conductivity and stream flow (Yang *et al.* 2019).

2.3.2. Model structure uncertainty

The WTF method of recharge estimation has shown very reliable estimation compared to other methods (Heppner & Nimmo 2005; Delottier *et al.* 2018). The method assumes that recharge to an unconfined aquifer is proportional to the change in the water level in the saturated zone (Scanlon *et al.* 2002; Healy 2010). The method is related to the volume of fillable porosity or drainable porosity volume (Park 2012). Also, falling water table analysis should be treated with drainable porosity as the storage parameter, while fillable porosity is for WTF analysis of the rising water table. The simplified mathematical representation of this method (Equation (1)) is as follows (Park 2012):

$$R = \mathrm{Sy}\frac{\mathrm{dh}}{\mathrm{dt}} \tag{1}$$

where Sy is the specific yield and dh/dt is the change in groundwater table over time.

In the aforementioned simple model, the effect of delayed recharge flux, unsaturated drainage, and other important futures of groundwater table level time series are not well represented (Park 2012). The delay from rainfall event to water table response and delayed gravitational flow from unsaturated zone to the saturated zone can cause undetectable recharge rate

(Jeong & Park 2017). Another controversial concept of time variant-specific yield was also tested using field observation as a model uncertainty reduction measure (Crosbie *et al.* 2005). When using the WTF method, another source of uncertainty is caused by air entrapment and water table recession due to the lateral flow of water (Walker *et al.* 2019). One way of reducing such problems is by using effective water table rise (Cuthbert 2010; Delottier *et al.* 2018).

The base flow separation method can be applied only in gaining streams (Rutledge 2007). Usually to identify losing or gaining section of a river additional modelling or assessment is required. There are also reservations regarding this method even when following a reliable separation technique. At some reaches of the stream bank when the water level is high enough, water is stored in the bank and discharged when it is low, which cannot be accounted as recharge (Walker *et al.* 2019). The uncertainty level will also be higher if we do not include extraction, evapotranspiration, and underflow to deep aquifers (Scanlon *et al.* 2002). Scanlon *et al.* (2002) state that the reliability of this method entirely depends on the validity of assumptions and good estimation of the source.

One of the widely applied methods of separation is the recession curve displacement method. This method is applicable for watersheds with uniform rainfall and consistent geological formation (Healy 2010). In addition, this method cannot be applied for watershed containing flood control structures (Rutledge 2007). Other methods of separation including the one described earlier and their corresponding structural uncertainty are explained in detail by Healy (2010) and Heppner & Nimmo (2005).

Gallart *et al.* (2007) applied the GLUE uncertainty assessment tool to investigate the impact of understanding and tailoring catchment information to reduce both surface water and base flow simulation uncertainty. The study was conducted using TOPMODEL (Beven 1997). The findings of the study confirmed that the uncertainty level can be reduced by introducing the conditioned water table records and the distribution of parameters obtained from point observations (Gallart *et al.* 2007).

2.4. Regional scale recharge uncertainty

Recharge uncertainty assessment on meso-scale watersheds is a work requiring in-depth knowledge of the hydrogeological processes of the focus area. In developing countries aided by lack of sufficient ground observation, it has been a challenge to investigate/conduct recharge uncertainty assessment. This subsection aims to highlight the impact of data scarcity on recharge uncertainty in spite of the difference in hydrometeorology of the selected watersheds. Contrasting watersheds where multiple recharge estimations are attempted using different methods are selected to illustrate the impact of data scarcity. Generally, as discussed in Section 1, very little has been done to investigate groundwater recharge uncertainty in meso-scale watersheds of Ethiopia. A very good summary of research on groundwater recharge conducted in Ethiopia is presented by Walker *et al.* (2019). In this study, nine methods of estimation were implemented to give an insight about uncertainty characterization in three catchments in the Blue Nile River basin (Walker *et al.* 2019). The study emphasized assessing the discrepancies caused by lack of recharge interpretation and uncertainties due to inherent assumptions of a specific method. The uncertainty result was presented with a higher and lower limit of actual recharge and noted that the type of recharge should be inferred to each method.

The uncertainty in most studies is presented by implementing multiple methods at a site and providing the range of recharge. But as noted by Walker *et al.* (2019), in addition to the inherent assumptions and recharge type estimated by each method, the data-driven selection procedure followed by uncertainty analysis results in incomparable outputs. In the upper Awash basin, implementation of four methods (of which two are estimated actual recharge and the rest potential recharge) has resulted in comparable outcomes (Berehanu *et al.* 2017). Similarly, the study has highlighted that the result gained cannot be used as an uncertainty range descriptor. Such an approach when implemented properly can give good insight into the range of recharge uncertainty, but lacks ability to identify the uncertainty in neither individual method or input data.

Inevitable uncertainties in estimation can be illustrated by observing multiple estimations (Table 1) in a particular region. This table presents estimations of different regions by different methods and multiple scholars. In order to address the reasons for the disparities in recharge estimates, the Lake Hawassa Watershed's recharge estimations are chosen. The main similarity between the below tabulated multiple estimations for similar watersheds using different methods (Table 1) is that all locations suffer from data scarcity and inadequacy of available data for accurate recharge estimation.

The review of previous studies focusing on assessing the recharge to Densu River basin indicates that the average annual potential recharge reaches up to more than 10% of the annual average rainfall (Akurugu *et al.* 2022). However, Akurugu *et al.'s* (2022) similar BWB approach has yielded a smaller magnitude of mean annual potential recharge for the same

Table 1 | Variability of recharge estimates for similar study area using multiple methods

Publication	Recharge type	Method	Recharge (mm/year)	Annual precipitation (mm/year) (year)	Basin	Remark	Country
Zemedagegnehu (2020)	Potential	BWB	211.5	1,039.35 mm (1991–2010)	Lake Hawassa	Basin average	Ethiopia
Kebede (2013)	Minimum	BFS	50–150	NA		Basin average	
Lin (2020)	Potential	NM	138.8	671.50 mm (2006–2016)		Basin average	
Ayenew & Tilahun (2008)	Actual	SWB and BWB	17.9–80.3	1,030 mm (1970–2004)		For 200 m resolution (variable recharge)	
Yeneneh (2014)	Potential	NM	19.63% of AP	818–1,117 mm (1969–2013)		Basin average	
Lemlem (2008)	Minimum	BFS	90–190	1,038 mm (1970–2004)		Basin average	
Adomako *et al.* (2010)	Potential Average Potential	NM IPS BWB	182 110 135	1,310 mm (2006–2008)	Densu River at sample site Ayikae Doblo	Isotope concentrations (O18 and H2) were sampled from soil depth profile and rainfall for both seasonal peak shift and numerical modelling, whereas nearby measurements where used for calculating simplified water balance	Ghana
Adomako *et al.* (2010)	Potential Average Potential	NM IPS BWB	94 120 75	1,310 mm (2006–2008)	Densu River at sample site Teacher mante		
Adomako *et al.* (2010)	Potential Average Potential	NM IPS BWB	101 250 21	1,737 mm (2006–2008)	Densu River at sample site Adwumuko		
Akurugu *et al.* (2022)	Potential	BWB	120–153	1,700 mm (NA)	Densu River	WB for different geological formations	
	Potential	BWB	172.2			Basin Average	
Berehanu *et al.* (2017)	Potential	BWB	131	1,170 mm (NA)	Upper Awash	Basin average by considering subsurface inflow	Ethiopia
	Potential	CMB	135			Basin average	
	Potential	NM	157			Basin average using HYDRUS-1D	
	Minimum	BFS	91.25			Basin average	
Tolera & Chung (2021)	Potential	BWB	179	1,207 mm (1988–2004)		Basin average using SWAT	
Eilers (2018)	Potential	CMB	20–27 40–53		Verlorenvlei catchment	Upper valley subcatchment Subcatchments of mountain ranges	SA
Watson *et al.* (2020)	Potential	CMB	4.2–5.6% of MAP 11.4–15.1% of MAP			Upper valley subcatchment Subcatchments of mountain ranges	

Note: BWB, basin water balance method; BSF, base flow separation method; NA, Not Available; SWB, soil moisture balance method; AP, annual precipitation; MAP, mean annual precipitation; CM, chloride mass balance; NM, numerical modelling; IPS, isotope peak shift; SA, South Africa; WB, Water Balance; WTF, Water Table Fl actuation.

watershed. This illustrates that recharge uncertainties increase where field observations are scarce. Furthermore, the importance of coupling different recharge estimation methods for data-scarce regions was illustrated by Adomako *et al.* (2010). In addition, discrepancies between the estimates using different methods for similar regions highlight the importance of appropriate selection of methods for specific objectives. The similar deduction can be drawn by observing the discrepancies in the Verlorenvlei catchment recharge estimation.

Over the years, many studies have been done on surface and subsurface hydrological processes of the Lake Hawassa watershed. The results of each research have significant implications for recharge in the basin. Significant discrepancy can be observed from previous studies (Table 1) on recharge values in the basin. Among the factors affecting recharge, land use/cover spatial and temporal distribution has been assessed in the Hawassa watershed. The implication of temporal land use dynamics to the environment (Degife *et al.* 2019), to groundwater recharge (Lemlem 2008), to the catchment hydrology (Orkodjo 2014), and to soil erosion (Degen 2016) are some of the focus areas. The common agreement of these studies is that forest cover, shrub land cover, and wet land have drastically decreased, while covers like urban cover, bare land cover, and agriculture have increased (Degen 2016; Degife *et al.* 2019), and there has been a significant change in the hydrological process.

However, the meteorological data analysis presented declining and constant trends of evapotranspiration and temperature, respectively (Lemlem 2008; Orkodjo 2014). Such results have contradicting inferences for recharge. Land use land cover studies (Eshete 2009; Degen 2016; Degife *et al.* 2019) in the basin have highlighted that there is a significant change from forest/shrub land to bare land and agricultural land. Such change results in an increase in recharge (Pan *et al.* 2011; Owuor *et al.* 2016); on the contrary, a study by Lemlem (2008) suggested the declining recharge trend over 3 decades (i.e. until the year 2000) in Hawassa Lake Catchment. Sources of uncertainty can be accredited to input data as well as parameter uncertainty and model structural uncertainty.

For aquifers with higher permeability, recharge is highly sensitive to the rainfall amount (Xie *et al.* 2018). Recent fluctuation on the lake level of Hawassa has been related to the impact of El-Nino and La-Nina (Belete *et al.* 2016; Belete *et al.* 2017). However, others relate the scenario to a significant interaction of overland flow and groundwater with the lake level fluctuation (Ayenew & Becht 2008; Ayenew & Tilahun 2008). The preceding argument is challenged by the scarce meteorological data record (Belete *et al.* 2017), while the second statement is vulnerable to scanty spatial distribution of other input data and modelling uncertainty (Ayenew & Tilahun 2008). From both studies, one can infer that significant recharge causes lake level fluctuation, or the lake level fluctuation is assisted by increased surface runoff (Tessema 2004) and recharge. However, there is a gap in identifying the contribution of surface runoff and subsurface process for the fluctuation.

Environmental stable isotope studies are being used to better understand the hydrological and hydrogeological process in Ethiopia (Tekleab *et al.* 2014; Tolke & Ayenew 2019). In one of the Main Ethiopian Rift (MER) sub-basins (i.e. Abaya-Chamo Basin), Tolke & Ayenew (2019) implemented environmental isotopes and geochemical analysis for characterization of recharge source, type, and hydrogeological system of the basin. The study presented well-depicted insights into the recharge mechanism and subsurface flow for the basin. A significant contribution to creating better understanding hydrogeology of Lake Hawassa was presented by Tessema (2004), using isotopic and geochemical investigation. This study concluded that the recharge elevation for the basin was 2,000 m.a.s.l. and highlighted that the lake receives inflow from eastern, western, and southern shorelines, while losing in the northern shoreline. As far as this review is concerned, no research has been done to investigate recharge uncertainty using isotopic analysis in the basin.

3. UNCERTAINTY ASSESSMENT TOOLS

Uncertainty has been a challenging task in many recharge estimation efforts by different researchers. Concepts like unpredictability, imprecision, and variability are used to describe uncertainty in modelling (Contreras *et al.* 2018). Unpredictability can be due to natural trends in inputs and errors in observation, whereas inaccuracy of boundary conditions, model simplification through parameter reduction, and other similar sources of uncertainty are related to the imprecision concept (Moges *et al.* 2021). Spatial and temporal uncertainties are usually best described with the variability concept and are usually difficult to quantify (Contreras *et al.* 2018). Model initialization can also be a source of uncertainty (Yu *et al.* 2019). Uncertainty sources like parameter, structure, and input are inclusive of some of the sources of uncertainty discussed earlier. Further discussion on reviewed literature focusing only on parameter, model structure, and input uncertainty evaluation tool is presented as follows. The objective of this section is not to stress on or discuss available methods or to repeat previous reviews, but rather to highlight available methods.

Recent development in the field of uncertainty analysis is the implementation of deep learning algorithms. The parameter uncertainty assessment using Bayesian long short-term memory through the Bayesian sampling approach called the stochastic variational inference has been proven to perform better over the traditional Bayesian linear regression model (Li *et al.* 2021). Another deep learning tool for uncertainty assessment is the Monte Carlo dropout with an input-dependent data noise term (MCD + N) (Gal & Ghahramani 2016). Fang *et al.* (2020) implemented MCD + N to investigate the parameter uncertainty in soil moisture prediction.

3.1. Input uncertainty

From simple water balance to a complex modelling method requires meteorological, hydrological, topographic, geological, and other types of input data. However, very few methods are available to explicitly quantify the uncertainty from such inputs (Ajami *et al.* 2005). A method introduced by Huard & Mailhot (2006), as well as methods like BATEA (Kavetski *et al.* 2003) and IBUNE (Ajami *et al.* 2005), can explicitly assess input uncertainty (Balin *et al.* 2010). The majority of input uncertainty studies have focused on precipitation uncertainty assessment (Moges *et al.* 2021). Nevertheless, when considering especially the subsurface hydrological process assessing other inputs such as the land use/cover, evapotranspiration, and others also need to be considered. Scarce calibration data are also another challenge while assessing such uncertainty (Muñoz *et al.* 2014). Simple multiplicative error models have also been studied to decrease uncertainty in mean aerial rainfall (Balin *et al.* 2010; McMillan *et al.* 2011). McMillan *et al.* (2011) highlighted that such a simple method is better at capturing the tail distribution compared to lognormal multiplier distribution. However, approaches like this are limited in capturing the 'true' rainfall distribution (Moges *et al.* 2021).

GLUE is also considered to evaluate the uncertainty in point rainfall observations (Muñoz *et al.* 2014). The GLUE approach presents the uncertainty related to the input combined with parameter uncertainty (Muñoz *et al.* 2014; Moges *et al.* 2021).

3.2. Parameter uncertainty

Parameter uncertainty analysis has been given significant focus and has benefited from multiple assessment methods (Moges *et al.* 2021). Uncertainty analysis in recharge estimation methods has also been the main objective of many studies (Delottier *et al.* 2018; Crosbie *et al.* 2019). The shared approach in such analysis is that model realization is created by applying a Monte Carlo simulation on the bounded parameter range (based on prior knowledge) and followed by investigation on the result from the specified objective function. Tools like Glue, and PEST (Doherty *et al.* 2010) mainly rely on Monte Carlo simulation, while others like DREAM rely on Bayesian statistics (Moges *et al.* 2021).

3.3. Model structure uncertainty

Usually, model structural uncertainty arises due to simplification of the natural process (Ajami *et al.* 2005). To this end, very good prior knowledge of the existing condition is an appropriate way to decrease model structure uncertainty (Duan *et al.* 2007). Uncertainty assessment tools like IBUNE are equipped with the model averaging approach (Bayesian model averaging) to reduce the structural uncertainty (Ajami *et al.* 2005). For a detailed discussion of model averaging tools, refer to reviews by Fragoso *et al.* (2018) and Moges *et al.* (2021).

4. DISCUSSION

4.1. Discussion of identified gaps

It is noteworthy to mention that each method has a potential applicability and strength over the other methods. Tracer methods have good quality in acquiring subsurface processes, information that cannot be acquired by other methods (Vitvar *et al.* 2005). Some methods give potential recharge, while others provide actual recharge to the water table. Methods such as CMB and BWB are used to determine potential recharge, while SWB and WTF methods can be used to determine actual groundwater recharge for a given aquifer. Readers are encouraged to refer to studies by Walker *et al.* (2019) and Lorentz *et al.* (2003) for more details on types of recharge for different recharge determination techniques. Using multiple methods is recommended for a reliable estimation of recharge (Scanlon *et al.* 2002). In addition, the research output implementing the tracer method coupled with the base flow separation method has shown good results (Stewart *et al.* 2007). Prior knowledge of the watershed and aquifer property is another good source of information for the qualitative uncertainty analysis (Xie *et al.* 2018). It is also very important to understand the assumptions of a method applied to a specific catchment.

Tracer-based methods are reported to suffer from the inability to capture the contribution of direct recharges in faulty (i.e. geological cracks and fissures) regions (Berehanu *et al.* 2017). Another limitation is the gap in the spatial representation of sampling for the CMB method (Crosbie *et al.* 2018). However, such methods are advantageous in establishing a benchmark point measurement to other preferred methods for spatial recharge estimation such as numerical modelling. The modelling efforts have the disadvantage in structuring, as most models emphasize either surface hydrology over groundwater hydrology and vice versa (Bear *et al.* 2010; Dile *et al.* 2018). Hence, couple models giving equal emphasis to surface and groundwater hydrology are recommended for the future study.

Several studies in different parts of the world were conducted using two of the aforementioned methods reported different magnitudes of recharge (Walker *et al.* 2019). These discrepancies are attributed to the individual assumption of each method as well as spatial and temporal resolution of estimation (Scanlon *et al.* 2002). This means that there are inherent uncertainties in each estimation. Generally, the uncertainty in each method arises from uncertainty of the parameter, model structural, and input data uncertainty.

The uncertainty analysis of this important hydrogeological parameter has spanned from simple range determination (i.e. maximum recharge and minimum recharge), to input parameter uncertainty analysis. There are also significant studies conducted to quantify the spatial uncertainty of estimation (Alcalá & Custodio 2014; Crosbie *et al.* 2018). Considering the importance of mapping recharge for a large area spatial uncertainty needs to be investigated more. In general, the main findings of this review on recharge uncertainty are discussed as follows.

Conceptualization and good prior knowledge of the aquifer as well as the watershed are important before conducting uncertainty analysis (Xie *et al.* 2018; Moges *et al.* 2021). A prior understanding of the physical properties of the watershed is necessary for appropriate model selection due to the disparity in process conceptualization and model assumptions (Gupta *et al.* 2012). Otherwise, misrepresentation/oversimplification of any existing process will result in structural uncertainty (Moges *et al.* 2021). Somaratne & Smettem (2014) have shown the inadequacy of the conventional CMB recharge estimation method for watersheds with deep faults. In addition, parameter uncertainty analysis based on Monte Carlo simulation requires bounded parameter values gained from prior knowledge of the existing condition (Xie *et al.* 2018). Furthermore, prior knowledge is essential in minimizing uncertainties emanating from boundary conditions and model initialization.

Therefore, considering the variability in estimation methods and watershed characteristics, inherent assumptions of available methods need to be further assessed for uncertainty (model structure uncertainty). Structural uncertainty potentially can be reduced by using multiple methods of estimation (Scanlon *et al.* 2002; Berehanu *et al.* 2017). Further, multi-model ensemble and averaging techniques should be investigated in depth. Mustafa *et al.* (2020) introduced the integrated Bayesian multimodel uncertainty estimation framework for analysing uncertainties emanating from alternative conceptual models. Estimates from multi model averaging approaches are far less uncertain compared to single model estimates (Moges *et al.* 2018). Despite the inability to consider all possible model structures, coupling multiple models can be used to assess the uncertainty in the model structure (Moges *et al.* 2021).

In data-scarce areas, spatial uncertainty of recharge is mostly due to uncertainty of input data (Alcalá & Custodio 2014; Crosbie *et al.* 2018; Westerhoff *et al.* 2018). Zhang *et al.* (2018a) have illustrated the influence of spatial rainfall uncertainty on hydrological simulations using the bootstrap method. Similarly, input data of rainfall and geology have been observed to cause more uncertainty in spatial recharge estimates by Westerhoff *et al.* (2018). Other input data such as evapotranspiration and soil moisture have been investigated by Xie *et al.* (2018). The result indicates that input spatial uncertainty could be propagated to simulation outputs (Montanari & Di Baldassarre 2013). Therefore, further investigations are required to fully understand the uncertainty from input data for different hydrological settings and input data.

4.2. Future research directions

Discrepancies between recharge estimation using multiple methods on a single location (Table 1) indicate that more should be done to investigate the root cause of the variation in recharge estimation. The uncertainty analysis on input variables, especially on physical methods, needs more work, since such work will be useful in guiding modellers on which parameter to focus. As discussed earlier, recharge is a spatially variable phenomenon and should be treated as such, which implies that future works on uncertainty analysis of scaling up technique is imperative. In general, from the findings of this review, the following areas are recommended for future studies.

Uncertainty in physical-based recharge estimation is one of the identified focus areas for future research. The review indicates that little has been done to investigate the uncertainty of input data for physical-based methods. A physical-based recharge estimation method of WTF requires water table depth time series data as an input (Heppner & Nimmo 2005; Delin *et al.* 2007; Heppner *et al.* 2007). Despite the advancement in water table depth measuring equipment, continuous calibration of devices is required and lacking in most developing countries (Dile *et al.* 2018). Hence, this requires further investigation to quantify errors induced by such unreliable input data. Furthermore, more research is required to determine how errors spatially propagate and disperse as a result of inadequate representation of observation wells.

Alternatively, current advancement in input data assimilation from multiple sources has proven efficient error reduction for further application (Gebremedhin *et al.* 2021). Implementing a merging technique using two or more rainfall data sources enables the capturing of complementary merits of each source, which could reduce bias in satellite rainfall products (Jongjin *et al.* 2016). Hence, data assimilation/fusion of different sources of meteorological and hydrological input data for spatial uncertainty analysis should be considered in future research. Similarly, more reliable estimates of groundwater recharge can be gained by jointly applying two methods (Gumuła-Kawęcka *et al.* 2022). Gumuła-Kawęcka *et al.* (2022) illustrated the potential to decrease and understand uncertainty by combining two methods using the WTF method, which is susceptible to error both from RISE and master recession curve approaches, and the HYDRUS-1D (Simunek *et al.* 2005) numerical model. This was accomplished by separating rise of water table due to recharge from rise and/or fall of water table level due to outflows to and/or inflow from nearby surface water body, which corrects the misassumption that all rises are caused by recharge in the WTF method. Therefore, future works focusing on coupling of methods for a better understanding of uncertainties in recharge assessment should be considered.

Even though it is out of the scope of this review to discuss the uncertainty related to experimental setups to determine recharge estimation, it is noteworthy to highlight the need to incorporate field experiments to support the accuracy/uncertainty of other conceptual models. Ali Rahmani *et al.* (2018) illustrated this by incorporating in-site experiment-based recharge estimation in the process of advancing the capability of numerical modelling methods to reduce recharge estimation error. Furthermore, current modelling developments focusing on merging surface hydrology with subsurface model have highlighted the uncertainty related to considering one apart from the other (Tolera & Chung 2021). Aside from the pioneering work by Kim *et al.* (2008) on a merged product of SWAT-MODFLOW, many studies (Bailey *et al.* 2016; Molina-Navarro *et al.* 2019) have proven the accuracy of using such fused models in comparison to stand-alone approaches. Therefore, surface hydrology analysis coupled with subsurface modelling using other numerical models should be considered in future works.

Among available methods, one of the widely used methods for estimation is modelling BWB, which is reported to yield rough estimates (Adomako *et al.* 2010; Berehanu *et al.* 2017). The analysis on the uncertainty of input data to determine outputs uncertainty is a never-ending approach, as the efficiency of input data acquiring method progresses. For a more efficient hydrological analysis, existing scarce meteorological data in Hawassa watershed need upgrading using satellite rainfall products. However, from the review of previous studies in the basin, it is clear that there is a gap in quantifying the uncertainty in estimating recharge. Especially, an attempt to correlate surface flow investigation with subsurface flow is lacking. Assessment of event and pre-event water separation using stable isotope analysis with the implication to recharge needs to be investigated. In addition, the need for stipulating uncertainty from scarce rainfall records is observed as a gap, i.e. for recharge estimation.

5. CONCLUSIONS

A review of uncertainty analysis of recharge estimation for widely applied methods is presented in this review. Most uncertainties are likely due to a lack of fully understanding a specific method and difficulty of acquiring desirable well-distributed quality data. Multiple studies have illustrated the importance of uncertainty analysis on input data in unsaturated flow modelling for recharge estimation. A significant reliability level has been gained by assuring the quality of input data. Similarly, the uncertainty analysis on aquifer parameters like specific yield can illustrate their importance on the reliability of recharge estimation.

Despite the importance of uncertainty analysis on spatial scale methods, very little has been done. In addition, it has been noted that the efforts of modifying model structure through uncertainty analysis should be aided with more experimental works. The use of multiple data sources as a means of reducing the uncertainty level is also another observation of this review. Furthermore, tracer-based analysis can be successful if applied with care and requires coupling with other methods for further uncertainty analysis.

Physical-based methods have shown reliable estimation; however, the uncertainty analysis requires extensive data and field observation (because aquifer parameter varies spatially). The uncertainty of numerical modelling relies on the very good conceptualization of the existing condition. In addition, it has been noted that input data to such numerical modelling methods requires a detailed uncertainty analysis. Generally, more has to be done to minimize the difference between the estimation of recharge by understanding the source of uncertainty in each method. In the future, coupling of methods (i.e. numerical methods with physical or tracer methods) instead of using multiple methods in one watershed is recommended. Furthermore, the use of assimilation of input data needs to be investigated to reduce the uncertainty of spatial estimation.

DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

CONFLICT OF INTEREST

The authors declare there is no conflict.

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