

Quantifying uncertainty in groundwater recharge due to spatiotemporal rainfall and temporal evapotranspiration variability

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ABSTRACT

The sustainable management of public supply wells relies to a significant degree on groundwater recharge estimates. Accuracy of these estimates will depend on the uncertainty within the largest components of the water budget, including precipitation and evapotranspiration. Quantifying this uncertainty and understanding the effect it may have on regional water balances is challenging. To examine the relative contribution of spatiotemporal rainfall variability (SRV) and annual actual evapotranspiration (AET) variability to groundwater recharge uncertainty, a method was developed to calculate a watershed stochastic vadose zone water budget within a Monte Carlo framework. The method incorporates rainfall time series generated through a semi-parametric approach that is constrained by observed local spatial rainfall correlation coefficients. Stochastic annual AET estimates are generated based on Penman-Monteith potential evapotranspiration (PET) estimates and observed variation about the Budyko curve for selected US MOPEX watersheds with $\overline{PET}/\bar{P}$ ratios similar to the study area. Overland flow is estimated using streamflow records and hydrograph separation results for the study watershed. The method was applied to the Alder Creek watershed (78 km²) in southern Ontario, Canada, over a 46-year period. Results suggested that 84 % of the uncertainty in recharge was related to SRV while 16 % was related to AET. This method could be used to estimate uncertainty in recharge as a context for numerical groundwater modelling and to project changes in this uncertainty based on possible climate-change induced reductions in rainfall correlation.

1. Introduction and background

Sustainable groundwater management requires an accurate historical and ongoing account of the dynamic components of the water budget. One of the main challenges is to quantify groundwater recharge, a vital component of the flow system that is often solved for as the residual of a water budget (e.g., Wiebe and Rudolph, 2020). Recharge rates are an important factor for the renewability of groundwater resources (Cuthbert et al., 2023), the dynamic spatial extent of well capture zones (Rock and Kupfersberger, 2002; Rayne et al., 2014), and the mass flux of contaminants to the water table (Malekani et al., 2018). Contaminant mass loadings, in turn, influence concentrations experienced at public supply wells, water treatment requirements, and the exposure time of wells to contaminants (Frind et al., 2006).

Precipitation (P) heterogeneity is potentially the dominant contributor to groundwater recharge uncertainty and thus may hinder accurate estimations of the temporal and spatial recharge distribution for a

watershed. Precipitation is generally the largest component of the water budget (Dingman, 2015) and likely contributes most of the uncertainty in groundwater recharge estimates (Wiebe and Rudolph, 2020). Though the influence of spatial variation in precipitation has frequently been studied in streamflow models (Andréassian et al., 2001; Bell and Moore, 2000; Faurès et al., 1995; Obled et al., 1994; Zhao et al., 2013), few studies have looked at its contribution to groundwater recharge uncertainty. Sapriza-Azuri et al. (2015) showed that recharge rates could differ by a factor of 2 between simulations with a fully distributed model of a 16,000 km² watershed in Spain, if stochastic rainfall was applied at different spatial scales over several decades. Mileham et al. (2008) found that recharge rates calculated using a semi-distributed model for a 2,100 km² watershed in SW Uganda were highly sensitive to the precipitation interpolation method employed. Wiebe and Rudolph (2020) suggested that mean annual recharge rates could vary by up to 44 % when spatially distributed precipitation was accounted for within a coupled and fully distributed watershed model (68 km²) over several

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years. Numerical groundwater models have often addressed issues such as subsurface heterogeneity that affect groundwater recharge rates (e.g., Hansen et al., 2014; Refsgaard et al., 2012; Rojas et al., 2010), but few studies have assessed the influence of regional heterogeneity in precipitation beyond the ones mentioned above.

Actual evapotranspiration (AET) uncertainty could also contribute substantially to recharge uncertainty because AET is frequently a large water budget component. AET estimates at the watershed scale over long time periods are difficult to obtain from in situ field sensors, particularly due to questions about the degree to which a measurement site represents its surroundings (Hess et al., 2016). AET estimation methods using approaches such as Eddy covariance, the Bowen Ratio energy balance, scintillometry, or weighing lysimetry have disadvantages such as requiring expensive field instruments, relying on complex data analysis, or having a lack of energy budget closure (Moorhead et al., 2017). Derived AET estimates at individual locations may not be representative of the entire watershed (Wilson et al., 2001) and may be prohibitively expensive to obtain by monitoring throughout a watershed (e.g., Martel et al., 2018). Therefore, AET is usually estimated with semi-empirical methods such as the Penman-Monteith method coupled with a crop coefficient (Allen et al., 1998; Martel et al., 2018), or with the Kristensen and Jensen (1975) mechanistic method in numerical models (e.g., HydroGeoSphere – Goderniaux et al., 2009; Aquanty Inc, 2015; and MIKE SHE – DHI, 2017). AET may also be estimated based on empirical relationships, as described below.

The Budyko curve (Budyko, 1961) illustrates trends between annual P , potential evapotranspiration (PET), and streamflow (Q) that exist despite variability in precipitation, geography, and spatial scale (Gentine et al., 2012). It is a commonly used empirical tool for conceptualizing the relationship between the ratio of long-term average actual evapotranspiration ($\overline{AET}$) to long-term average total precipitation ($\overline{P}$) as a function of the average index of aridity, defined as the ratio of long-term average potential (“reference”) evapotranspiration ($\overline{PET}$ or $\overline{ET_0}$) to $\overline{P}$ (Gentine et al., 2012). Though the curve was originally developed (Budyko, 1961) using 1,200 watersheds with areas $> 1,000$ km², it was subsequently shown to hold for more than 400 watersheds with sizes between 60 and 11,000 km² and is an example of an empirical hydrological relationship whose causal mechanism is not completely understood (Gentine et al., 2012). Such patterns may be useful for overcoming the challenges of estimating AET at the watershed scale.

Uncertainty analysis for a water budget component is often conducted by exploring the range of possible outcomes from an ensemble containing multiple scenarios (e.g., McIntyre et al., 2005). In this process, hydrological patterns or signatures (Shafii and Tolson, 2015) such as those derived through the Budyko curve, for example, may be used to constrain the set of scenarios based on regionally reasonable values (Kapangaziwiri et al., 2012). The classic numerical techniques (e.g., finite difference, finite element) employed by conventional, fully distributed groundwater models that can be used to assess recharge rates tend to be computationally expensive (Joodavi et al., 2017), which hinders their use for ensemble uncertainty analysis, especially if many scenarios are needed. In contrast, stochastic water budget simulations that generate an ensemble of possible results may require fewer data.

The objective of this study is to develop and apply a stochastic method that quantifies the uncertainty in long-term average groundwater recharge estimates at the watershed-scale, and assesses the relative contributions to this from daily spatiotemporal rainfall variability (SRV) and annual AET variability. It was hypothesized for one case study that greater uncertainty in recharge would be associated with SRV rather than AET, testing the relative importance of these two sources of uncertainty. The method outlined below is a modified version of the technique described by Wiebe (2020).

2. Methods

2.1. Quantitative analysis

The method proposed in the current study is intended to quantify the uncertainty in watershed groundwater recharge based on SRV and AET estimates using a Monte Carlo framework. A vadose zone water budget with synthetic daily rainfall time series and annual AET estimates is used to calculate average annual watershed recharge over several decades. Fig. S1.1 in the supplementary materials document provides an overview of the components of the method.

2.1.1. Water budget

The first step of the proposed method is to derive an equation to estimate long-term recharge rates from a combination of measured and stochastically generated synthetic hydrological data. Many studies have used a water budget approach coupled with stochastic methods to estimate recharge uncertainty (e.g., Baalousha, 2009; Crosbie et al., 2018; Scibek and Allen, 2006; Sene, 1996). Consider a vadose zone (VZ) water budget for the region of a watershed between the ground surface and the water table (Eqn. (1)):

$$\Delta S_{VZ} = I - AET_{VZ} - R, \quad (1)$$

where ΔS_{VZ} is the storage change in the vadose zone, I is infiltration, AET_{VZ} is actual evapotranspiration from the vadose zone, and R is recharge flux across the water table. I is equivalent to the difference between precipitation (P) and overland flow (Q_{OL}), where Q_{OL} is the surface runoff portion of total streamflow that excludes net groundwater discharge (baseflow). All terms have units of mm, i.e., volume normalized by watershed area, and represent watershed-wide spatial averages. Components such as AET above the vadose zone, changes in surface storage, and lateral flow within the vadose zone are considered negligible, while AET occurring directly from the saturated zone is considered as described below. Substituting $P - Q_{OL}$ for I and rearranging for recharge (Eqn. (2)):

$$R = P - AET_{VZ} - Q_{OL} - \Delta S_{VZ} \quad (2)$$

Fig. 1 illustrates this water budget. Assuming that quasi steady state conditions can be approximated within a watershed after multiple decades, and that the cumulative storage changes approach zero (e.g., Dingman, 2015) (Eqn. (3)):

$$R_{tot} = \sum_{yr=1}^n (P_{yr} - AET_{VZ, yr} - Q_{OL, yr}), \quad (3)$$

where R_{tot} [mm] is the total, cumulative recharge over the watershed

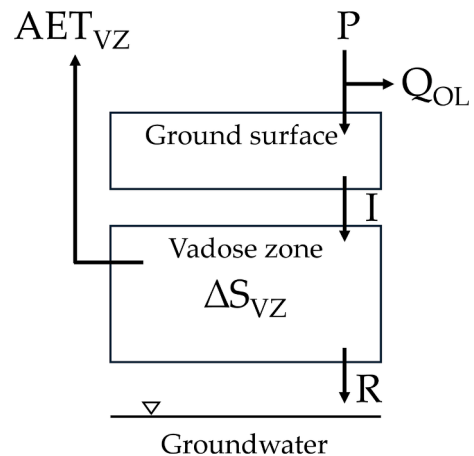


Fig. 1. Vadose zone water budget.

over n years, and yr is the index of the year. Re-writing in terms of the ratio of AET_{VZ}/P , expressing the overland flow fraction of total runoff in terms of the baseflow index (BFI, i.e., the net groundwater discharge fraction of total streamflow), and calculating the annual average (Eqn. (4)):

$$\bar{R}_i = \frac{1}{n} \sum_{yr=1}^n \left(\left(1 - \frac{AET_{VZ, yr}}{P_{yr}} \right) P_{yr} - (1 - BFI_{yr}) Q_{tot, yr} \right), \quad (4)$$

where all terms relate to the watershed spatial mean, $\bar{R}_i$ is the spatially lumped annual average recharge for Monte Carlo realization i , and BFI_{yr} is an annual estimate of baseflow index derived from total streamflow ($Q_{tot, yr}$) recorded at a stream gauge at the outlet of the watershed. The precipitation term (P_{yr}) here is the annual average precipitation for the watershed, calculated from stochastic precipitation time series. The annual AET_{VZ}/P ratios are correlated with P_{yr} via annual PET/P ratios as described later. In this method, the intention is to estimate the uncertainty in $\bar{R}$ via constrained estimates of the variability in P , AET_{VZ}/P , and BFI using annual values of measured Q_{tot} and estimated PET without uncertainty. This method assumes that: 1) vadose zone storage change over the n years is negligible; 2) a time period of n years is sufficient to capture the interannual variability in P and PET estimates; 3) the watershed is close to its natural state and anthropogenic influences are minor, justifying the use of the Budyko curve to estimate the ratio of total AET to precipitation, i.e., AET_{tot}/P ; 4) variation in annual AET_{tot}/P ratios may be reasonably represented by synthetic values generated from the observed distribution of AET/P ratios for a set of reference watersheds (discussed below); and 5) a reasonable (constant) correction factor for the relationship between vadose zone AET and total AET ($\overline{AET_{VZ}/AET_{tot}}$) may be estimated (also discussed below).

2.1.2. Stochastic rainfall and spatial rainfall correlation

Stochastic models have often been employed in the analysis of rainfall (e.g., Wilks and Wilby, 1999). Both parametric and non-parametric approaches have been used for stochastic rainfall generation (Basinger et al., 2010; Sharma and Mehrotra, 2010) by constructing a sequence of rainy and non-rainy days and then generating rainfall amounts (e.g., Lall et al., 1996; Sharma and Mehrotra, 2010). Parametric approaches assume that the relative frequency (i.e., probability) distribution of observations follows a particular curve (e.g., exponential or gamma), require fitting a curve to the data (e.g., Vu et al., 2018), and are simple (Wilks, 1998) though somewhat less portable to other watersheds than non-parametric approaches (Basinger et al., 2010). Non-parametric approaches do not make assumptions about the probability distribution of local rainfall amounts and instead use techniques such as K-nearest neighbour for resampling historical data (Verdin et al., 2015). However, it is difficult to find an approach that performs well across different climates (Vu et al., 2018).

A semi-parametric approach to stochastic rainfall generation is used here, though many methods are available and the selection would depend on the characteristics of local precipitation. Daily time series are generated by using (non-parametric) first-order Markov chain transition probabilities for modelling the occurrence of rainfall, and a (parametric) mixed exponential model to represent the probability distribution of observed rainfall amounts. The transition probabilities between rainy and dry days (i.e., the probability that the next day will be rainy or not) and vice versa are calculated for each day of the year from the set of all 30-day rainfall occurrence (1 if rain > 0 mm, 0 otherwise) vectors that are centred on each Julian Day for the time period with available data, following the process described by Basinger et al. (2010). Each time series of synthetic daily rainfall amounts is constructed by drawing random numbers from the uniform distribution to decide whether each subsequent day is rainy or dry based on the state of the previous day and the transition probabilities. The first day in each time series is assigned to be rainy or dry based on the overall probability of a rainy day from

local rainfall statistics. Though somewhat arbitrary, a moving 30-day window provides a larger sample size than the set of values observed on a particular Julian Day while also reasonably incorporating seasonality (Basinger et al., 2010). The mixed exponential model is used to describe non-zero rainfall amounts (Li et al., 2013) (Eqn. (5)):

$$f(x) = \frac{p}{\beta_1} \exp\left(\frac{-x}{\beta_1}\right) + \frac{1-p}{\beta_2} \exp\left(\frac{-x}{\beta_2}\right), \quad (5)$$

where $f(x)$ is the relative frequency, x is a daily rainfall amount, β_1 and β_2 are the scale parameters ($\beta_i > 0$) for two different exponential distributions, and p is the mixing probability distinguishing the weight of the distribution associated with β_1 ($0 \leq p \leq 1$). This approach is similar to the one presented by Rodriguez-Iturbe et al. (1999), except that a mixed exponential model is suggested here instead of an exponential model. A mixed exponential model has the advantage of representing both large and small extremes of the range of rainfall amounts (Li et al., 2013; Wilks, 1998). The values of p , β_1 , and β_2 are determined by fitting the probability distribution of daily rainfall amounts using non-linear optimization. Rainfall amounts are binned by integer values (e.g., the bin for 1 mm includes all rainfall amounts, r , such that $0 \text{ mm} < r \leq 1 \text{ mm}$, etc.). Amounts are then generated randomly via (Li et al., 2013) (Eqn. (6)):

$$x_t = \begin{cases} -\beta_1 \cdot \ln(v_t), & \text{if } v_t < p \\ -\beta_2 \cdot \ln(v_t), & \text{if } v_t \geq p \end{cases}, \quad (6)$$

where x_t is the rainfall amount at time t , and v_t is a uniform random number ($0 < v_t < 1$). The second step of the proposed method uses Eqn. (6) to generate a large number (thousands) of synthetic daily rainfall time series of several decades in length.

The third step assigns these time series to virtual stations located in or around the watershed and adjusts sets of time series (one set per Monte Carlo realization) to ensure more realistic spatial and temporal correlation between synthetic rainfall based on field data. Virtual rain gauge station locations are chosen, and the watershed is subdivided into representative regions for interpolation (Thiessen polygons). Then the range of observed spatial correlation coefficients representing daily rainfall at multiple stations in and around the watershed of interest is calculated. This requires data from multiple stations within the area of interest over a suitable time period (≥ 3 years). Spatial correlation between daily rainfall observations at local weather stations is characterized via the Pearson Product Moment correlation coefficient and the Spearman Rank correlation coefficient (e.g., Gibbons and Chakraborti, 1992). The Iman and Conover (1982) method is subsequently used to ensure that correlation between sets of stochastic rainfall time series is within the observed range of Pearson and Spearman Rank correlation coefficients (Tarpanelli et al., 2012). This is done by rearranging the order of the synthetic rainfall values so that the Spearman Rank correlation coefficient matrix of the synthetic time series matches that of the observed. Advantages of the Iman and Conover (1982) method include its simplicity and its lack of dependence on any particular rainfall distribution (Tarpanelli et al., 2012).

2.1.3. AET, streamflow partitioning, and snowfall

Two analyses applied slightly different techniques to estimate AET in order to include or minimize AET variability for comparison with the contribution from SRV. Analysis 1 generated AET estimates empirically by using the US MOPEX experiment dataset (Duan et al., 2006; Troch et al., 2018). Plotting the annual pairs of AET/P and PET/P ratios for US MOPEX watersheds yields a cloud of points in Budyko space (Fig. 2). MOPEX watersheds similar to the study watershed are selected by choosing watersheds with $\overline{PET/P}$ within a small range (± 0.05) of the ratio for the study watershed. Because the variability of annual points varies along the Budyko curve (Budyko, 1961), PET/P ratios are binned into ranges and treated separately. In Analysis 1, annual AET/P ratios are drawn from a normal distribution representing the MOPEX points for

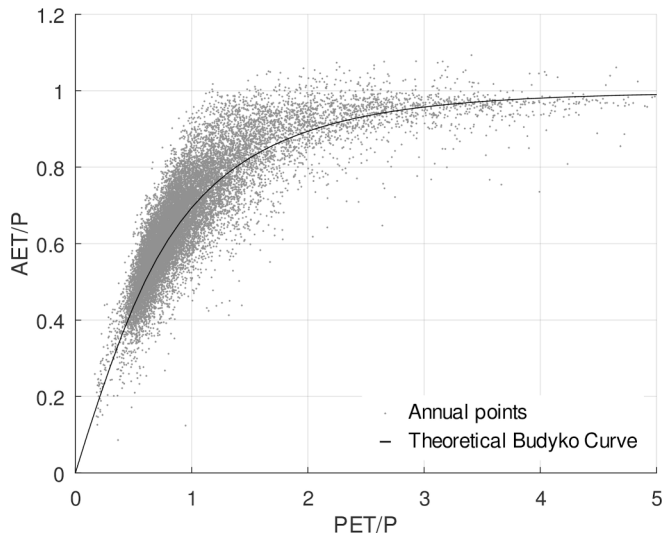


Fig. 2. Budyko curve and US MOPEX data (Duan et al., 2006; Troch et al., 2018; after Gentile et al., 2012).

each range of PET/P ratios. Conversely, Analysis 2 is performed to assess the uncertainty in recharge that is associated solely with precipitation uncertainty. Analysis 2 assigns each annual AET_{tot}/P ratio to the long-term value from the Budyko curve ($\overline{AET_{tot}/P}$) with no random component. Both procedures correlate the ratio of synthetic AET to synthetic P with the ratio of estimated PET to synthetic P, and Analysis 1 attempts to capture the variability in the empirical, annual scatter of points in Budyko space. The AET/P estimates derived from either the MOPEX dataset or the Budyko curve were adjusted using a correction factor to reconcile AET_{tot} with the AET_{VZ} component required in the vadose zone water budget (Eqn. (1) based on the proportion of the watershed area where the water table could be expected to be at or close to ground surface. The correction factor ($\overline{AET_{VZ}/AET_{Tot}}$) was calculated via (Wiebe, 2020) (Eqn. (7)):

$$\frac{\overline{AET_{VZ}}}{\overline{AET_{Tot}}} = 1 - \frac{A_{highWT}}{A_{tot}} \cdot \frac{\overline{PET}}{\overline{AET_{Tot}}} \quad (7)$$

where $\overline{AET_{VZ}}$ is the spatially lumped, long-term average actual evapotranspiration from the vadose zone, $\overline{AET_{Tot}}$ is the total actual evapotranspiration calculated from the Budyko curve, A_{highWT} is the area of the watershed that is composed of wetlands and similar areas with a high water table or open water, A_{tot} is the total watershed area, and $\overline{PET}$ is the spatially lumped, long-term average potential evapotranspiration. Multiplication of $\overline{AET_{Tot,yr}}$ values by the correction factor yields the adjusted $\overline{AET_{VZ,yr}}$ values.

In order to partition total streamflow into its overland and baseflow components and thereby estimate infiltration ($I = P - Q_{OL}$), BFI values must be estimated. Annual BFI values for the stream of interest are estimated with the PART (Barlow et al., 2014) hydrograph separation method. The PART method excludes the interflow component of streamflow, thus lumping it with the overland flow component. Synthetic BFI values are then generated during each realization using the mean and standard deviation of a normal distribution approximating the distribution of BFI values about the trend line between observed rainfall and the BFI estimates.

Snowfall is assumed to be spatially uniform across the watershed of interest, which maintains focus on SRV within the method. The timing of snowmelt and its tendency to either infiltrate or flow overland is incorporated into the method indirectly via use of the annual BFI estimates. Synthetic snowfall amounts are generated by using the mean and standard deviation of a normal distribution that approximates the observed annual snowfall amounts.

2.1.4. Simulation conclusion criterion and relative component contributions

Finally, total recharge is calculated via Eqn. (4) for each set of spatially correlated synthetic rainfall time series. The total number of realizations is determined from the stability of the calculated overall average annual watershed recharge, $\bar{R}$, over recent realizations (i.e., the last 1000). Stability suggests that the simulation has likely explored the range of possible combinations of parameters to provide a reasonable confidence interval (e.g., 95 %) for $\bar{R}$. Stability is defined as the absolute value of percent change in metric being < 0.01 % with an additional 1000 realizations.

The relative uncertainty in average annual recharge is quantified using via (e.g., Dingman, 2015) (Eqn. (8)):

$$\varepsilon_{\bar{R}} = \pm \frac{1.96 \cdot \sigma_{\bar{R}}}{\bar{R}}, \quad (8)$$

where $\sigma_{\bar{R}}$ is the standard deviation of $\bar{R}$, and $\varepsilon_{\bar{R}}$ is the uncertainty associated with the 95 % confidence interval. The relative contribution (φ) of SRV (determined in Analysis 2) to the combined uncertainty resulting from both SRV and annual AET variability (determined in Analysis 1) is obtained by the ratio of the standard deviations of $\bar{R}$ from the two analyses (Eqn. (9)):

$$\varphi = \frac{\sigma_{\bar{R},2}}{\sigma_{\bar{R},1}}. \quad (9)$$

3. Case study

3.1. Field site

Alder Creek is a tributary to the Nith River within the larger Grand River basin (6,800 km²; OMNRF, 2016). The Alder Creek watershed has an area of 78 km² and is located on the Waterloo Moraine outside of Kitchener-Waterloo, Ontario (Fig. 3). The Waterloo Moraine consists of inter-bedded sand/gravel layers and silt/clay layers, resulting in a complex stratigraphic system with discontinuous aquifers and aquitards (Bajc et al., 2014; Martin and Frind, 1998), where coarse-grained sand and gravel deposits are present at the ground surface over about half of the watershed area (CH2MHILL and SSPA, 2003; OGS, 2010; Wiebe and Rudolph, 2020). Groundwater recharge to the underlying glaciofluvial

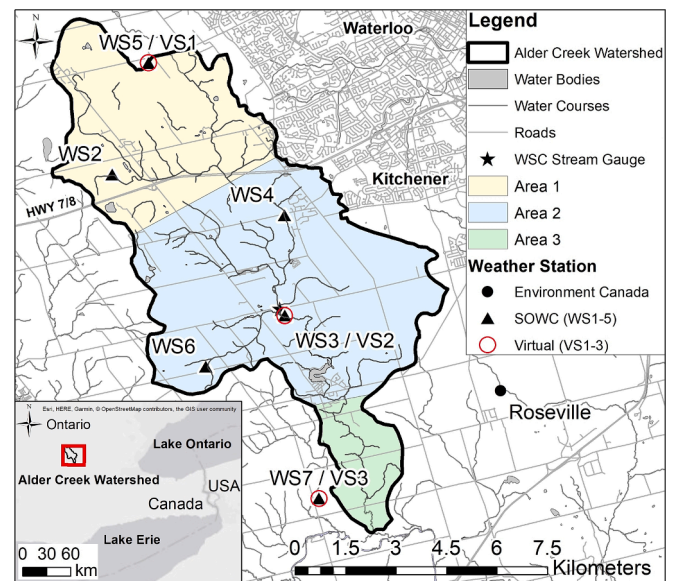


Fig. 3. Study site and Thiessen polygons (Areas 1 – 3) for virtual rain gauges (DMTI, 2011; Esri, 2019 [Sources: Esri, HERE, Garmin, © OpenStreetMap contributors, the GIS user community]; Government of Canada, 2019; GRCA, 1998; WSC, 2019; Wiebe, 2020).

aquifers in the watershed provides source water for to up to seven well fields operated by the Regional Municipality of Waterloo (Brouwers, 2007). Regionally averaged recharge rates have been estimated to range between 210 mm (CH2MHILL and SSPA, 2003) and 321 mm (M.H. Brouwers, pers. comm., 2017, Matrix and SSPA, 2014a) per year. About 23,000 m³/d is pumped by the wells located directly within the watershed on average (Matrix and SSPA, 2014b), which is a non-trivial amount (~10 % of average annual precipitation volume) that should be included in the water budget.

Land use in the watershed is predominantly agricultural; however, urbanization has been occurring at a relatively rapid pace in the area (Poulin, 2009). Total average annual precipitation in the region is approximately 900 mm per year, with 15 % in the form of snow on average as observed at the Roseville Environment Canada weather station situated near the watershed (Government of Canada, 2019; Fig. 3). PET at the Roseville station is around 780 mm per year on average (Wiebe, 2020). Total streamflow at a Water Survey of Canada (WSC) stream flow gauge in the middle of the watershed equates to 141 mm per year on average for the area of the watershed upstream of the gauge (Fig. 3; WSC, 2019).

A network of six local rain gauge stations (WS2 to WS7; Fig. 3) was installed in and around the watershed by the Southern Ontario Water Consortium (SOWC) to provide greater spatial resolution on rainfall amounts in the area. Rainfall data (Wiebe et al., 2019) were recorded via tipping bucket rain gauges surrounded by Alter-type wind screens. Data were collected from 2014 to 2016 on a 15 min time scale and were aggregated up to daily scale for the correlation analysis described below. Snowfall was not recorded continuously at these stations, so annual sums of the daily snowfall amounts from the Roseville weather station were used (Government of Canada, 2019). Infrequent manual measurements of snowpack thickness near WS4 (Fig. 3) were within 2 cm of the Roseville measurements (Government of Canada, 2019), and the average difference between Roseville measurements and the average from sonic snow depth observations (Wiebe et al., 2019) at all six local stations was 2.0 cm during the 2014 to 2015 winter season (Nov 2014 to Mar 2015; Wiebe, 2020). Monthly precipitation data from the SOWC network are presented in various forms within Wiebe et al. (2019), Wiebe (2020), and Wiebe and Rudolph (2022).

This watershed has been numerically modelled many times because of its importance as a municipal water supply (e.g., CH2MHILL and SSPA, 2003; Martin and Frind, 1998; Matrix and SSPA, 2014a,b; Sousa et al., 2013). The current study seeks to build upon previous work by assessing the ranges of plausible variability in P and AET across the watershed and the resulting long-term recharge uncertainty. An increased understanding of this hydrologic uncertainty in recharge could assist groundwater management in the area.

3.2. Application of the method

Scripts were written for the scientific computation program GNU Octave (Eaton et al., 2024) to perform the calculations for the stochastic water budget analysis (Wiebe, 2024). The Roseville Environment Canada weather station (Government of Canada, 2019) was used as the source of long-term precipitation records (46 years). The Markov chain transition probabilities were calculated from daily data from this station.

The range of observed spatial correlation coefficients among daily rainfall totals was calculated for six local weather stations (five within the Alder Creek watershed, and one < 0.5 km outside; Wiebe et al., 2019) and the Roseville national weather station (< 3 km outside the watershed). Months with missing data (Jan to Jun 2014 at WS5) or anomalous data (June to Dec 2016 at WS2 and WS6) were omitted from the correlation analysis. Gaps in the Roseville precipitation record (daily rainfall and snowfall; about 10 missing days per year on average) were filled prior to analysis based on nearby weather stations (Government of Canada, 2020a, 2020b; Seglenieks, 2020), as explained in AquaResource

Inc (2008) and Supplementary Materials Document S1. In summary, filled values were predicted by scaling observations made at other stations by ratios between Roseville precipitation and the nearby stations' precipitation that were derived from at least eight years of data. The revised dataset is referred to as the "observed" rainfall or snowfall or total precipitation for Roseville in the following analysis.

The third step of the analysis involved the generation of around 30,000 daily rainfall time series of 46 years in length. Fig. 4 shows the observed and fitted probability distributions of rainfall amounts for the Roseville station. Ensuring spatial correlation similar to that observed from the local data was facilitated using 3- or 4-year subsets of six synthetic time series plus the Roseville time series for consistency with the length of the observed local rainfall records (3 years), from which the observed correlation matrices were calculated. A total of seven time series was required for consistency with the observed correlation matrix (7 × 7) within the Iman and Conover (1982) method. Maximum and minimum Spearman Rank correlation coefficients for the adjusted six random time series were calculated for each 3- or 4- year subset and sets of three time series with coefficients within the observed range were selected.

Alder Creek watershed was divided into three Thiessen polygon regions (Areas 1 to 3; Fig. 3), which were drawn for three rain gauge locations (WS5, WS3, and WS7). Each polygon was assigned a virtual rain gauge ("VS1", "VS2", and "VS3"; Fig. 3), to which synthetic rainfall time series were assigned. Three gauges were selected based on gauge density recommendations by Schaake et al. (2006). Total annual precipitation was calculated for each station for each year by adding synthetic snowfall generated using the mean and standard deviation of the approximately normal distribution of observed Roseville annual snowfall amounts to the sum of the synthetic daily rainfall amounts.

Estimates of the annual ratios of $AET_{tot,yr}/P_{yr}$ were obtained from the scatter of observed points around the Budyko curve (e.g., Gentile et al., 2012) for 47 US MOPEX watersheds (Duan et al., 2006; Troch et al., 2018; Fig. S1.2) similar to Alder Creek for each realization (i.e., $[\overline{PET}/\overline{P}]_{watershed} - [\overline{PET}/\overline{P}]_{Roseville} \leq \pm 0.05$). Prior to the selection of the 47 watersheds, watersheds that were similar but had < 40 years of data or exhibited anthropogenic influence were removed, following the approach of Gentile et al. (2012). PET_{yr} values for the Roseville station were calculated via the Penman-Monteith method (Allen et al., 1998) from the maximum and minimum daily temperatures (Government of Canada, 2019) using the UNFAO56 ETo Calculator (Raes, 2009), where the average wind speed from seven local weather stations over four

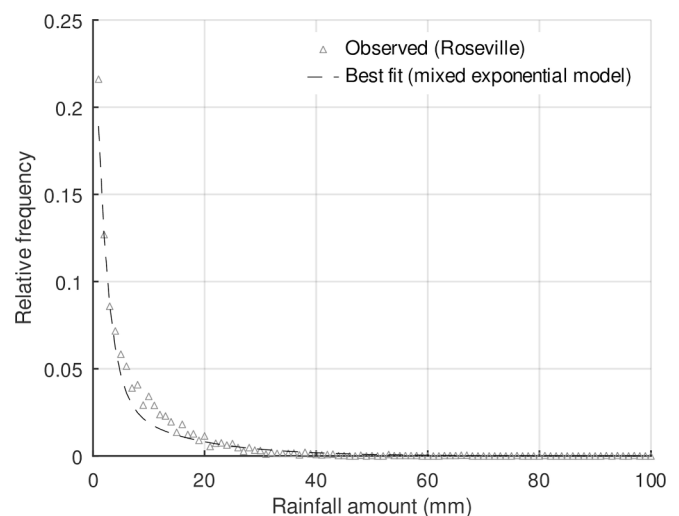


Fig. 4. Probability distribution of rainfall amounts at the Roseville weather station. A mixed exponential model (Eqn. (5); Li et al., 2013) was used with $p = 0.5147$, $\beta_1 = 2.015$, and $\beta_2 = 13.40$.

years was employed (Wiebe, 2020). The observed temperatures and derived set of annual PET_{yr} values were the same in each realization. Six ranges of PET_{yr}/P_{yr} ratios (Fig. 5; Table 1) were used to evaluate the range of possible AET_{yr}/P_{yr} values.

BFI values were calculated based on hydrograph separation analysis of daily WSC streamflow data (1973 to 2018; WSC, 2019) from the gauge within the Alder Creek watershed. The PART method (Barlow et al., 2014) was used to estimate BFI, and the relationship between BFI and precipitation is shown in Fig. S1.3. The slope of the trend line between observed annual rainfall and BFI was used to calculate the mean difference of BFI values from the line and its standard deviation; these were used to generate synthetic annual BFI values based on the approximately normal distribution of values about the trend line (Fig. S1.4). Because the WSC gauge is not located at the outflow of the creek into the Nith River, a scaling factor was derived from long-term water budgets to estimate annual total streamflow at the outflow. The scaling factor (SF) was calculated via (Wiebe, 2020) (Eqn. (10)):

$$\overline{Q_{Tot}} = \overline{P} - \overline{AET_{Tot}} - \overline{Q_{Pump}}, \quad (10.1)$$

$$SF = \overline{Q_{Tot}} / \overline{Q_{Obs}}, \quad (10.2)$$

where $\overline{Q_{Tot}}$ is the estimated average annual streamflow at the watershed outlet, $\overline{AET_{Tot}}$ is estimated based on the Budyko curve, $\overline{Q_{Pump}}$ is the average annual amount extracted by public supply wells, and $\overline{Q_{Obs}}$ is the average annual streamflow for the WSC gauge within the watershed.

4. Results

The results of the spatial correlation analysis of the observed daily rainfall amounts are shown in Fig. 6. Spearman Rank spatial correlation coefficients for the seven rainfall stations varied between 0.52 and 0.83.

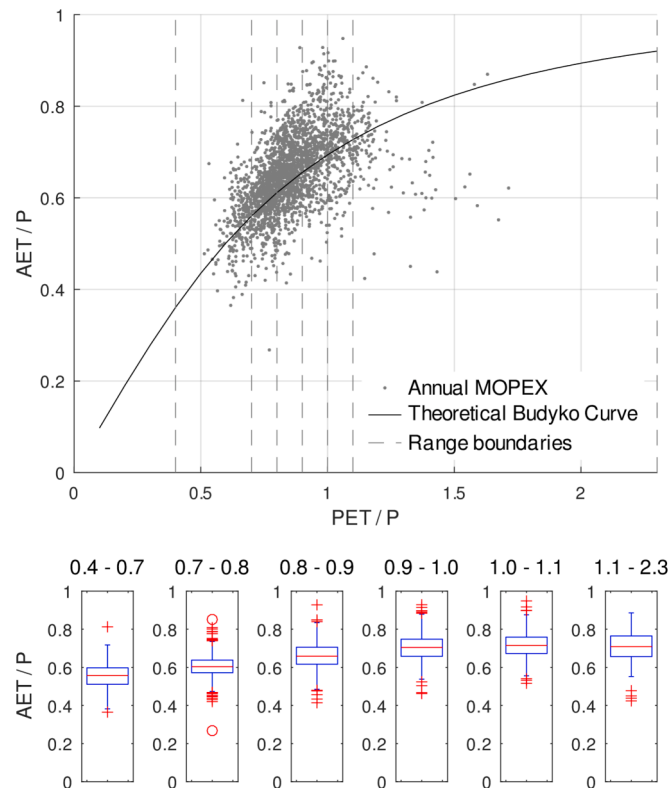


Fig. 5. Observed variation about the Budyko curve (equation from Gentile et al., 2012) for the 47 selected US MOPEX (Duan et al., 2006; Troch et al., 2018) watersheds.

Table 1

Mean and standard deviation for bins of annual points from selected 47 US MOPEX watersheds.

Range of PET/P values per bin	No. of points	Mean AET/P ratio (–)	Standard Deviation, σ (–)
$0.4 < x \leq 0.7$	236	0.55349	0.067327
$0.7 < x \leq 0.8$	565	0.60459	0.061807
$0.8 < x \leq 0.9$	711	0.66018	0.066929
$0.9 < x \leq 1.0$	449	0.70346	0.075305
$1.0 < x \leq 1.1$	240	0.71596	0.076412
$1.1 < x \leq 2.3$	125	0.70525	0.086968

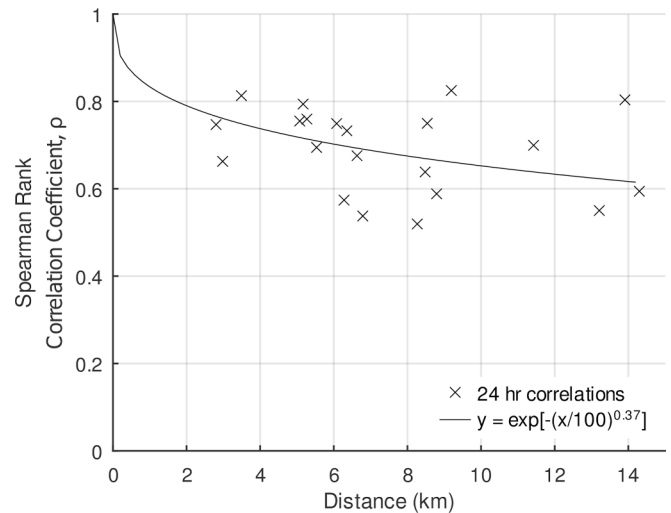


Fig. 6. Spearman Rank correlation between six local rain gauges and the nearest national station for the Alder Creek watershed (Government of Canada, 2019; Wiebe et al., 2019). Curve fitting of the exponential function employed (following Villarini et al., 2008, 2010) was performed using a non-linear optimization function in GNU Octave (Eaton et al., 2024).

For context, if Pearson Product-Moment Correlation among the Alder Creek rain gauges is compared with the few rainfall correlation studies available in the literature, Alder Creek rainfall is better correlated than rainfall in Florida and Brazil, where intense, convective storms are prevalent (Krajewski et al., 2003), and less well correlated than rainfall in Oklahoma (Villarini and Krajewski, 2007), where frontal rainfall is more common. Alder Creek would be expected to experience a mix of convective and frontal storm systems in the southern Ontario climatic context (e.g., Paixao et al., 2015). The overall probability of a rainy day was 29 %, while the transition probability for a rainy day followed by a rainy day ranged from 28 % to 52 % (mean: 44 %) throughout the year, and the probability that a day with no rain was followed by a day with no rain ranged from 66 % to 93 % (mean: 77 %).

Baseflow separation with PART (Barlow et al., 2014) yielded a range of annual BFI values from 0.37 to 0.72 with a mean value of 0.56. Because the creek has been hypothesized to receive increased baseflow into its lower reaches downstream of the WSC gauging station (CH2MHILL and SSPA, 2003), the average value seems reasonable when compared with the minimum estimate from the nearby Upper Grand River basin (0.6) in a study by Neff et al. (2005). The average annual streamflow for the watershed, $\overline{Q_{Tot}}$, was estimated to be 236 mm based on the average total streamflow derived from the daily WSC gauge data (WSC, 2019) and the estimated scaling factor, 1.68.

Table 2 summarizes the results of the two Analyses. Each analysis reached its stability criterion after around 9000 realizations, each of which has a corresponding set of three selected time series for the virtual stations and one time series of watershed AET_{VZ} estimates. The average

Table 2
Stochastic water budget results for Alder Creek case study.

Category	Analysis	
	A1 [†]	A2
Simulation		
No. of realizations	9,482	9,466
Vadose Zone Water Budget		
$\bar{P}$	923 mm	923 mm
$\overline{AET_{VZ}}$	542 mm	529 mm
$\bar{Q}_{OL}$	103 mm	103 mm
$\bar{R}^*$	276 mm	290 mm
Statistics		
0.025-quantile annual watershed recharge	249 mm	267 mm
0.975-quantile annual watershed recharge	305 mm	314 mm
$\sigma_{\bar{R}}$	14 mm	12 mm
$\epsilon_{\bar{R}}^{\dagger}$	± 28 mm	± 23 mm

* Mean recharge over entire 46-year time period, across all realizations.

[†] Uncertainty in $\bar{R}$ associated with 95% confidence interval.

[‡] Analysis A1 results are shown in Figs. 7 to 9.

recharge is higher in Analysis 2 because the AET_{VZ}/P ratios are lower on average than in Analysis 1 due to the skew of the distribution of annual MOPEX points relative to the Budyko curve.

The observed mean annual precipitation at the Roseville station from 1973 to 2018 (Fig. 7b) was 926 mm (standard deviation: $\sigma = 127$ mm), and the simulated mean annual watershed-averaged precipitation over all realizations was 923 mm ($\sigma = 124$ mm) (Fig. 7c; Table 2). The annual observed precipitation at Roseville ranged from 651 to 1237 mm per year, and the simulated (interpolated) annual total precipitation ranged from 692 to 1173 mm over the 95 % confidence interval. Mean annual total precipitation values for the individual virtual stations ranged from 664 to 1214 mm over the 95 % confidence interval, and σ was approximately 140 mm in each case. Fig. 7a shows an example for VS1; frequency distributions for the other virtual stations were similar. Averaging simulated total precipitation for the watershed over 46 years resulted in a much smaller 95 % confidence range (893 to 953 mm, $\sigma =$

15 mm; Fig. 7d). Overall, the simulations represented the observed mean total precipitation and range of annual values well.

The long-term average ratio of $\overline{PET}/\bar{P}$ at Roseville was estimated to be 0.84 using the Penman-Monteith method for PET. Application of the Budyko curve equation from Gentile et al. (2012) resulted in a long-term average $\overline{AET_{tot}}/\bar{P}$ ratio of 0.63. Fig. 8 shows the $\overline{AET_{tot}}/\bar{P}$ estimate and range derived from the average of the PET/P values calculated for Roseville (Fig. 8a) and the simulated annual AET_{VZ} (Fig. 8b) and overall average $\overline{AET_{VZ}}/\bar{P}$ (Fig. 8c and 8d) values for Analysis 1. The distribution of annual AET_{VZ} values across all realizations had a standard deviation of 70 mm. The $\overline{AET_{VZ}}/\bar{P}$ ratios within the 95 % confidence interval varied between 0.57 and 0.63 (Fig. 8c and 8d), after applying the correction to remove saturated zone AET. The mean ratio of $\overline{AET_{VZ}}/\bar{P}$ for the watershed was 0.59 (Fig. 8b). The area of the watershed covered by wetlands and other features where the water table was expected to be at or close to ground surface was 7 % of the total area (OMNR, 2008; ROW, 2010; Wiebe, 2020), and the $\overline{AET_{VZ}}/\overline{AET_{tot}}$ correction factor was calculated to be 0.91 ± 0.02 by applying $\overline{PET}$ to this fraction of the watershed area. The 95 % confidence interval for the magnitude of $\overline{AET_{VZ}}$ varied between 523 and 561 mm, with a mean value of 542 mm and $\sigma = 9.8$ mm (Table 2). Thus, the uncertainty in $\overline{AET_{VZ}}$ was about 35 % smaller than that associated with $\bar{P}$, according to their standard deviations.

Fig. 9 shows the frequencies of the calculated average recharge estimates over all realizations for Analysis 1. The average annual recharge averaged over all realizations ($\bar{R}$) was 276 mm, and the 95 % confidence interval for $\bar{R}$ ranged from 249 to 305 mm (Table 2), where $\sigma = 14$ mm. These averages are within the range of recharge estimates from previous numerical modelling studies of the watershed (noted in Section 3.1). Table 2 summarizes the uncertainty in recharge due to both SRV and AET variability. The 95 % confidence range of $\bar{R}$ was 56 mm, with an uncertainty of ± 28 mm, or $\epsilon_{\bar{R}} = \pm 10$ % (Table 2). If the impacts of solely SRV were considered and $\overline{AET_{tot}}/\bar{P}$ estimates were not allowed to deviate from the Budyko curve prior to being adjusted by the AET

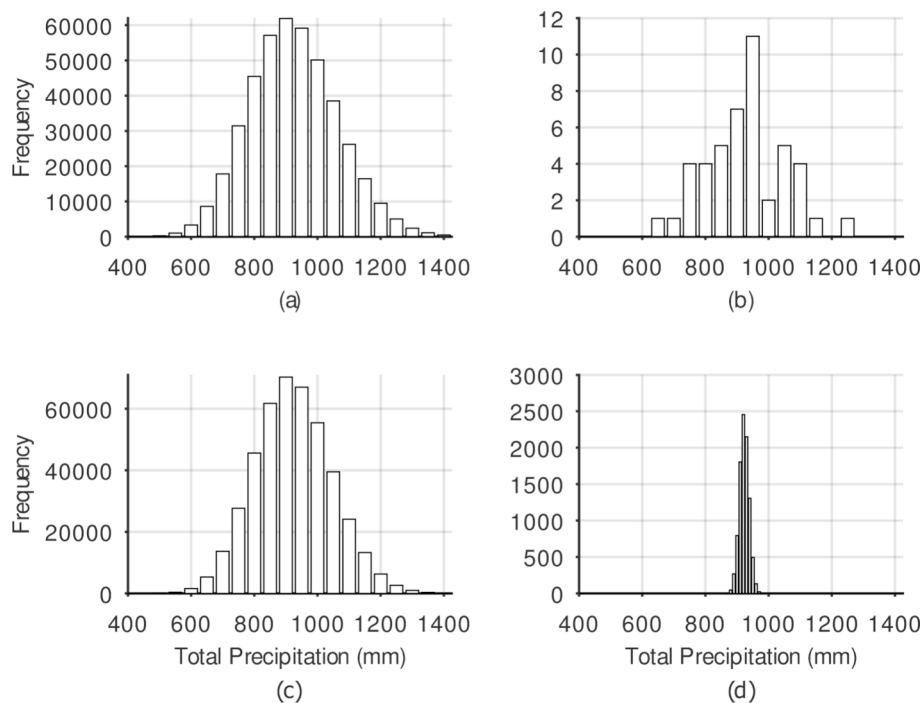


Fig. 7. Frequency distribution of total precipitation for: a) Virtual Station 1 over all realizations (annual values), b) Roseville annual values for 1973 to 2018 (Government of Canada, 2019), c) the watershed, over all realizations and in terms of interpolated annual values, and d) the watershed, where interpolated annual values were averaged over 46 years for each realization. The bin size was 50 mm for a), b), and c), and 10 mm for d).

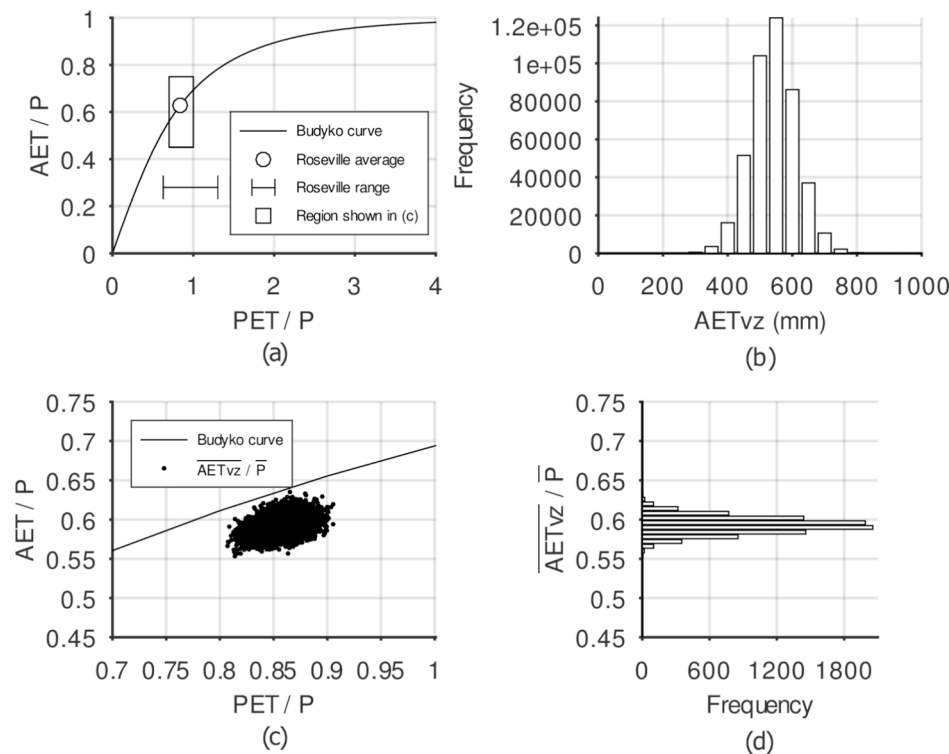


Fig. 8. AET/P and PET/P ratios: a) Roseville long-term average (equation from Gentine et al., 2012) and observed annual variations in PET/P, b) frequency distribution of simulated annual AET_{vz} values (bin size = 50 mm), c) simulated $AET_{vz}/\bar{P}$ ratios, and d) frequency distribution of $AET_{vz}/\bar{P}$ ratios from all realizations (bin size = 0.006).

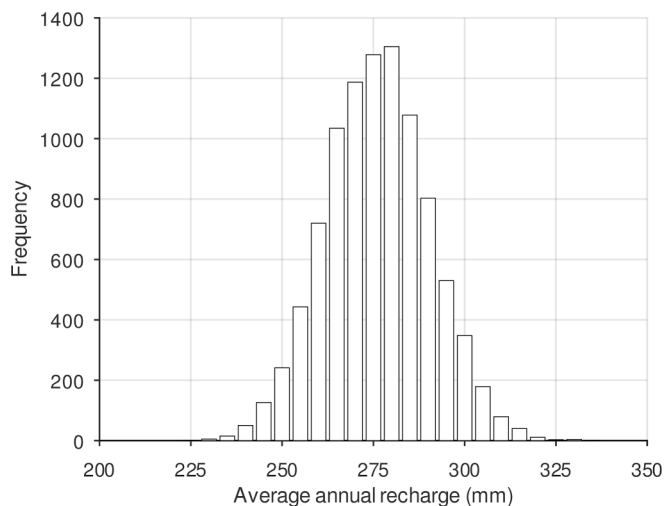


Fig. 9. Frequency of average recharge rates ($\bar{R}$) over all realizations.

correction factor (Analysis 2), then $\bar{R} = 290$ mm, the range of $\bar{R}$ was 47 mm (95 % confidence) and $\sigma = 12$ mm, indicating an uncertainty of $\varepsilon_{\bar{R}} = \pm 23$ mm (Table 2). Comparison of the two standard deviations suggests that SRV contributes $\varphi = 84$ % of the total uncertainty in recharge when both SRV and AET variability are considered.

5. Discussion

The approach used in the current study applies a new combination of existing ideas by using stochastic generation of both rainfall and AET estimates derived based on the Budyko curve to estimate uncertainty in watershed scale recharge rates and the relative contributions of SRV and

AET variability. Advantages of this approach include that it is applicable to the long-term, at the watershed scale, and does not require complex geological information or hydraulic head measurements. This latter information would be useful to generate complementary estimates via numerical simulations. The following discusses the methodology and its potential applications.

AET is the second largest water budget component in settings similar to the case study watershed and is difficult to measure or estimate (Hess et al., 2016). The Budyko curve may be a useful tool for estimating long-term $AET/\bar{P}$ ratios, but guidance is needed on two issues. First, the process of adjusting AET estimates by a correction factor (to remove AET originating in the saturated zone) could be improved. Results may be sensitive to the correction factor in some cases, so verification of the suitability of applying PET to areas where the water table is near ground surface is needed. Second, the variability in the $AET_{tot}/\bar{P}$ ratio with respect to the average, long-term $PET/\bar{P}$ ratio requires further study. The use of the scatter of points about the Budyko curve from the US MOPEX data using watersheds in other geographical contexts with $PET/\bar{P}$ ratios similar to the watershed of interest was proposed above. Verification is needed to constrain the AET/P variability.

The Budyko curve may be a useful tool for many watersheds, but care should be taken. For instance, watersheds in arid regions (Donohue et al., 2007, 2010; Gentine et al., 2012) or areas affected by afforestation or deforestation (Zhang et al., 2001) or peatlands (Hwang et al., 2018) may not conform to the general trend. The use of the Budyko curve requires the assumption that the study watershed behaves similarly to the watersheds employed in its development. This entails assuming that the study watershed exchanges a negligible net flow of groundwater with adjacent basins, and that it has experienced minimal human influence (i.e., no significant alterations such as irrigation or the construction of reservoirs – Gentine et al., 2012 – or extensive groundwater extraction from pumping wells). Agriculture may constitute the largest anthropogenic change to many watersheds, although groundwater

extraction also affects $\overline{AET}$ and streamflow estimates. For instance, $\overline{AET}$ values for the Alder Creek watershed are likely lower than they would be in an undeveloped, naturally vegetated watershed because conventional agriculture is the dominant land use and groundwater withdrawals for public drinking water have lowered the water table in places (e.g., [CH2MHILL and SSPA, 2003](#)). These localized declines in the water table are expected to have a minor impact in this case due to the relative area in question. Groundwater flow to other watersheds is uncertain and poses a larger concern that is potentially reduced by the presence of aquitard layers which slow downward flow to deep overburden aquifers, and by pumping from within the watershed. Despite these issues, the method may still be useful if major factors (e.g., withdrawals) can be accounted for, or if natural baseline conditions are of interest – especially because the uncertainty in recharge is the chief quantity estimated by the method.

The method presented focuses on rainfall and treats snowfall in a simplistic manner. This is likely acceptable for watersheds where rainfall is the dominant precipitation type but can be improved in adaptations of the method for snow dominated watersheds. Field data related to spatially distributed snow water equivalent data can be used to predict spatiotemporal variations in snowmelt. The dynamics of snowpack accumulation, changes in snow water equivalent, and the timing of snowmelt are not considered in the annually lumped water budget employed, but the range of baseflow indices indirectly incorporates information regarding spatially and temporally lumped snowmelt contributions to streamflow.

Climate change poses challenges for the SRV aspect of the method. Climatic change may result in changing trends and statistics (e.g., [DeBeer et al., 2016](#); [Gregersen et al., 2013](#)), including the spatial correlation of rainfall rates and mean annual rainfall. An increase in the number of intense storms would likely be associated with changes in the spatial distribution of rainfall at different scales ([Marvel and Bonfils, 2013](#); [Simonovic et al., 2017](#); [Trenberth, 2011](#)). Ongoing rainfall observation at multiple sites is required for accurate correlation estimates if conditions change. The method could be used to test how possible reductions in spatial rainfall correlation would change uncertainty in groundwater recharge, which could then be compared to correlations derived from such field data.

The method outlined above may be used to compare ranges of recharge rates across watersheds of different scales. Previous studies of the variation of recharge rates due to SRV have reported larger relative differences in recharge rates than those in the Alder Creek case study. The ratio of cumulative recharge under maximum and minimum conditions (here equivalent to the ratio of the 0.975-quantile to the 0.025-quantile of $\bar{R}$) for Analysis 2 (~ 1.2) was less than the factor (~ 2) obtained by [Sapriza-Azuri et al. \(2015\)](#) over a similar time period (43 years) for a watershed in Spain. The difference in values may be related to the differences in the sizes of these watersheds and/or differences in rainfall spatial correlation.

Applications of the method outlined in the current study could include providing recharge estimates for regional hydrologic models, providing context for fully distributed numerical model results, or predicting water budget components. The average recharge or 95 % confidence interval of recharge estimates could be imposed on regional groundwater models as the top surface boundary condition. [Shafii and Tolson \(2015\)](#) recommended the use of multiple hydrological signatures during model calibration, and the range of recharge estimates derived by the method of the current study could be used as a calibration target or during uncertainty analysis. Alternatively, machine learning techniques such as artificial neural networks, which have been used to predict groundwater levels based on factors such as rainfall (e.g., [Yoon et al., 2016](#)), precipitation and temperature ([Coppola et al., 2005](#)), or evaporation/evapotranspiration (e.g., [Tao et al., 2022](#)), could be coupled with the method outlined above to incorporate SRV and AET. A machine learning algorithm capable of successfully downscaling water budget

components (especially stream baseflow and AET) to subwatershed areas or shorter than annual time scales would be particularly useful to extend the scale at which the method outlined in the current study may be applied.

6. Conclusions

The current study outlines a stochastic, Monte Carlo vadose zone water budget method for calculating the potential uncertainty in groundwater recharge due to SRV and temporal AET variability for a watershed over several decades. This uncertainty was derived from the plausible range of long-term recharge rates. Highlights of the method include the use of a mathematical technique to constrain the spatial correlation of stochastic rainfall time series based on field data, and use of the Budyko curve with empirical data from a subset of 47 watersheds from a large dataset (~ 400 watersheds) to estimate potential variability in AET. A case study for the Alder Creek watershed, southern Ontario, Canada, was used to illustrate the method. Results indicated that SRV contributed 84 % of the uncertainty in recharge rates while estimated temporal AET variability contributed the remainder. The uncertainty in average recharge was ± 10 % for the combined SRV and AET variability (95 % confidence interval).

The approach developed in the current study is applicable to watersheds where the Budyko curve is either representative or the influence of land use changes on the curve may be estimated, and where there exist sufficient data from other watersheds with a similar index of aridity for quantification of variability about the Budyko curve. Current limitations of the method include the requirement that the analysis be conducted at the watershed scale on an annual basis, and a simplistic treatment of snow. Future work could use results of the approach to provide a calibration signature range for recharge or predict hydrological variables at time scales shorter than one year and in regions smaller than a watershed.

CRedit authorship contribution statement

Andrew J. Wiebe: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **David L. Rudolph:** Writing – review & editing, Supervision, Resources, Funding acquisition. **James R. Craig:** Writing – review & editing, Conceptualization.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

A supplementary information file (mmc1.docx) includes additional figures and describes the processes for filling in missing precipitation records and for calculating the probability distribution of observed rainfall amounts during the case study. Supplementary data to this article can be found online at <https://doi.org/10.1016/j.jhydrol.2025.133089>.

Data availability

Data from the Alder Creek watershed are available at the Federated Research Data Repository (www.frdr.ca; <https://doi.org/10.20383/101.0178>). The GNU Octave code written to perform the calculations is available at: <https://doi.org/10.17632/stbtg4hnnv9.1>. The US MOPEX data used for the study are available from Troch et al. (2018) at: <http://www.hydroshare.org/resource/99d5c1a238134ea6b8b767a65f440cb7>.

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