Open Access Earth System Science Data Discussions

An in-situ daily dataset for benchmarking temporal variability of groundwater recharge

Pragnaditya Malakar[1,2], Aatish Anshuman[1], Mukesh Kumar[1], Georgios Boumis[1], T. Prabhakar Clement[1], Arik Tashie[1], Hitesh Thakur[1], Nagaraj Bhat[1], Lokendra Rathore[1]

5   [1]Department of Civil, Construction, and Environmental Engineering, University of Alabama, Tuscaloosa, AL, USA

[2]Department of Geological Sciences, Jadavpur University, Kolkata, India

Correspondence to: Mukesh Kumar (mkumar4@eng.ua.edu) and Pragnaditya Malakar (pragnadityamalakar@gmail.com)

Abstract. Accurate estimate of groundwater recharge is crucial for prediction of groundwater table dynamics and dependent eco-hydrological processes. Despite its importance, benchmark data for groundwater recharge at fine (~ daily) temporal

10   resolution is lacking. We present a first-of-a-kind daily groundwater recharge per unit specific yield (RpSy) data over periods of 2 – 38 years at 485 groundwater monitoring wells in the US. The RpSy data for these locations are calculated from the daily groundwater table time series using the water table fluctuations (WTF) method. Although direct validation of the data is not possible, since it is the first of its kind, we compare the RpSy data with the monthly USGS product to identify similarities and differences. The RpSy dataset may serve as a benchmark for validating the temporal consistency of recharge

15   products and daily simulation results from land surface and integrated hydrologic models.

1 Introduction

Groundwater is the largest distributed inland freshwater storage. It sustains human water consumption and acts as a buffer during droughts (Famiglietti, 2014; Seo et al., 2018; Taylor et al., 2013b). In the US, it is estimated that groundwater supplies approximately 60% of irrigation and 40% of the public water (Russo and Lall, 2017). Furthermore, more than 40 million

20   people in the US, a majority of them in rural areas, rely on domestic boreholes for their drinking water demands (Alley et al., 1999; Wu et al., 2021). Alarmingly, mismanagement of freshwater resources, climate variability and change, rapid population growth, and changes in land use due to urbanization and agricultural expansion has put significant stress on groundwater resources. For example, recent studies have shown that the cumulative volume of groundwater in the US has decreased by almost 1,000 km^3 between 1900 and 2008 (Konikow, 2015). In certain locations, such as the Mississippi embayment section

25   of the Gulf Coastal Plain, the rate of groundwater depletion has occurred at the high rate of 1.2 km^3/yr (Konikow, 2015).

To sustainably manage groundwater resources and for conducting more accurate aquifer vulnerability assessment, it is of critical importance that stakeholders and policy managers are informed of the present and future trends of groundwater recharge (GWR), a flux describing the volume of water infiltrating into an aquifer, per unit area, per unit time, [L/T]). Despite the importance of GWR in controlling groundwater level (GWL) dynamics, its accurate estimation remains a challenge. This

30   is in part because GWR is influenced by a range of variables, such as climate forcings, topography, hydrogeology, land cover, land-use patterns, pumping, and antecedent groundwater/soil states (Berghuijs et al., 2022; Chen et al., 2020; Kumar and Duffy, 2015). Furthermore, GWR varies temporally at multiple temporal scales, ranging from event to inter-annual durations (Crosbie et al., 2005; Scanlon et al., 2006; Varni et al., 2013; Squeo et al., 2006; Valois et al., 2020). Depending on the dominant processes and their trends, GWR may show site-specific variations. For example, studies in both humid (Tashie et

35   al., 2016) and arid (Thomas et al., 2016) settings showed that at the event scale, the intensity of extreme precipitation events changes the ratio of precipitation that contributes to recharge. Others showed that groundwater resources in East Africa is

sustained by anomalously intense seasonal and monthly rainfall (Taylor et al., 2013a). Intense episodic precipitation has been observed to produce a large GWR in sub-Saharan Africa (Cuthbert et al., 2019). Analogous efforts from India indicate that in the southern part of the country, GWR is driven by high-intensity precipitation (Asoka et al., 2018), while higher recharge in

40   the northern fertile Indus-Ganges-Brahmaputra aquifer is due to higher precipitation and pumping-induced GWR (Bhanja et al., 2019; Lapworth et al., 2015; Malakar et al., 2021a, b, c). Past evidence from the Northern High Plains in the US indicates that antecedent soil moisture conditions indeed play a vital role in determining GWR in conjunction with extreme rainfall (Zhang et al., 2016). Given that antecedent soil moisture is also strongly affected by variations in meteorological forcing from daily to longer time scales (Ghannam et al., 2016), so can be expected of event recharge as well. Recharge is also likely to

45   vary with seasonal, inter-annual, and decadal variations in rainfall, temperature, and vapor pressure deficit, which influence evapotranspiration (Liu et al., 2017, 2020; Milly and Dunne, 2016; Mueller and Seneviratne, 2014) and its partitioning (Raghav et al., 2022). An increase in temperature increases evaporative demand and decreases soil moisture (Raghav and Kumar, 2021), which could lead to a reduction in recharge (and aquifer replenishment) (Condon et al., 2020), consequently resulting in groundwater depletion (Singh and Borrok, 2019). In summary, GWR is an integrated response of a range of forcings, processes,

50   and local physiographic properties which are crucial for groundwater sustainability.

There has been a general call to action for improving recharge and baseflow processes in large-scale hydro and Land Surface Models (LSMs) for some time (e.g., (Fan et al., 2019)). The need to improve recharge estimates is further underscored by recent studies such as that by Berghuijs et al. (2022), wherein, based on the global recharge dataset by Moeck et al. (2020), it was reported that LSMs tend to systematically underestimate recharge by a factor of about 2. Gnann et al. (2023) also

55   demonstrated that theoretical and empirically based functional relationships between drivers of recharge and the recharge flux differ significantly across global water models. This underscores the alarming potential of divergent responses from models under future projected changes in drivers. An accurate dataset for GWR can not only assist with the assessment of changes in local hydrologic responses but can also help manage emerging threats to food and water security. Furthermore, it can help benchmark models used for estimating GWR.

60   Despite its importance, what is currently lacking in the scientific record is a continuous, ground-truthing dataset of GWR at monthly or as fine as a daily resolution. Past efforts have mostly focused on obtaining coarser time-resolution groundwater recharge. For example, base flow discharge (Hung Vu and Merkel, 2019; Meyboom, 1961) and isotopic or chemical tracers (Lapworth et al., 2015; McMahon et al., 2011; Scanlon et al., 2010) have been used to estimate recharge over months to decadal scales. These data have formed the basis for several studies that focused on mapping recharge rates at

65   regional to global scales (Moeck et al., 2020). However, these data provide limited to no information related to event-scale or daily resolution variations in recharge (Tashie et al., 2016). While seepage meters (Scanlon et al., 2002), lysimeters (Gong et al., 2021; Xu and Chen, 2005), and heat tracers (Blasch et al., 2007; Healy, 2010) are capable of calculating recharge over a fine temporal resolution, they are expensive and complicated leading to difficulty in the development of continuous datasets at a large number of locations (Tashie et al., 2016). A useful approach for estimating GWR at a fine temporal resolution is

70   based on the water budget method. However, this approach often does not account for the subsurface storage change and is impacted by uncertainties associated with water budget components such as ET and/or quick flow (Reitz et al., 2017a; Reitz and Sanford, 2019a). Furthermore, basin-scaled empirical relationships modelled for recharge estimation oftentimes do not capture finer spatial resolution variations (Gonzalez et al., 2023). An alternative promising option is to obtain GWR estimates using the water table fluctuation (WTF) method (Bhanja et al., 2019; Healy and Cook, 2002; Nimmo et al., 2015).

75   The WTF method based on the master recession curve (MRC) yields GWR at a fine temporal resolution while only needing available well hydrograph data, meteorological data, and specific yield (Boumis et al., 2022). Studies have highlighted its applicability for benchmarking recharge estimates from models (Crosbie et al., 2015), and for further understanding recharge variations and its implications on water resources in diverse hydroclimatic regions (Delin et al., 2007; Nimmo et al.,

2015; Nimmo and Perkins, 2018; Tashie et al., 2016). One major challenge with the WTF method for estimating recharge is
its reliance on specific yield data, which is not commonly accessible and involves a high level of uncertainty. In a study by
Boumis et al. (2022), it was suggested that groundwater recharge may have been overestimated due to specific yield values
obtained at locations where the water table is near the land surface. In a study by Crosbie et al. (2019), it was noted that
improving estimates of specific yield is crucial for addressing the overestimation of recharge. To circumvent the challenge
posed by uncertain specific yield on recharge estimation from WTF method, here we instead generate a benchmark dataset
that provides recharge per unit specific yield, also referred to as RpSy henceforth. We generate this dataset after performing
detailed quality control to identify well locations that are suited for yielding high-fidelity long-term RpSy estimates. Finally,
we compare the estimated RpSy with published monthly recharge estimates provided in other published studies (Reitz and
Sanford, 2019a) and assess RpSy variations vis-à-vis its primary hydrometeorological influencers.

2 Methods

2.1 RpSy estimation using the WTF method

GWL fluctuations recorded at monitoring wells are used to estimate recharge based on the water table fluctuation (WTF)
method (Healy and Cook, 2002; Healy, 2010). The general principle of the method is to use the water table rise and fall
dynamics to compute recharge in a continuous fashion (Heppner and Nimmo, 2005). Quantitatively, GWR within a specific
time interval (daily time scale is used in this study) is evaluated in m/d unit as the product of depth to water level rise occurring
in a day (ΔH) and specific yield (Sy) (Figure 1a):

$$GWR = \Delta H \times Sy, \tag{1}$$

Here, ΔH is the water table rise relative to the predicted water level in the absence of recharge. The water level in the absence
of recharge is predicted based on the MRC (Nimmo et al., 2015; Nimmo and Perkins, 2018), which captures the characteristic
recession pattern, i.e., the relation between water table elevation (H) and its rate of decline (dH/dt) (Figure 1b). Accurate MRC
calculation requires careful identification of the slope element – a short enough interval that can be considered as pure
recession. Because of the uncertainty inherent in defining a pure recession interval, we consider a range of slope element
lengths equal to 4, 6, 8, and 10 days (Boumis et al., 2022). Similarly, multiple minimum interval durations, viz. 2, 4, 6, and 8
days, between precipitation and the start of recession are also considered. Daily precipitation amount smaller than 0.5 mm
precipitation is considered negligible while deriving the MRC (Nimmo and Perkins, 2018). For any given site, the slope
element and the minimum interval duration length that provides the maximum MRC correlation is used for ensuing analysis.

Although Sy is a primary constituent in GWR estimation using the WTF method (see Eqn. 1), accurate estimates of
Sy are unavailable across the US (Li and Rodell, 2015). The feasibility of obtaining Sy for a large number of locations, given
the large spatial heterogeneity in its magnitude, is impractical. Hence, here we evaluate RpSy, instead of GWR, as a
benchmarking product. RpSy is calculated as the ratio GWR/Sy using Eqn. 1.

2.2 Data Sources and well selection criteria

Groundwater level (GWL) records for the last four decades (1983-2022) are retrieved from the US Geological Survey's (USGS)
National Water Information System web interface (link: https://waterdata.usgs.gov/nwis/gw). The data has a temporal
resolution of 1 day and are based on observations at the monitoring wells. The following primary criteria are used to narrow
down the stations:

a) Wells that have never and/or are not prone to going dry (Cunningham et al., 2007).

3

Earth System
Science
Data
Open Access
Discussions

b) Wells with at least two years of continuous daily GWL observations with limited data gaps.

c) Groundwater wells that primarily reflect event-scale GWL changes in response to meteorological forcings. To select wells that likely experience event GWR response to precipitation signals, i.e., where the WTF method is valid, we only select the top 75 percentile wells based on the maximum lag correlation coefficient between RpSy and precipitation time series.

120 Selection of 75th percentile as a threshold is subjective and is obtained after trial and error. The goal is to use a threshold that ensures that wells in the lower percentile of maximum lag correlation coefficient correspond to GWR response that is not event based. Example of a selected and a rejected observation well based on this selection criteria is illustrated in Figure S1.
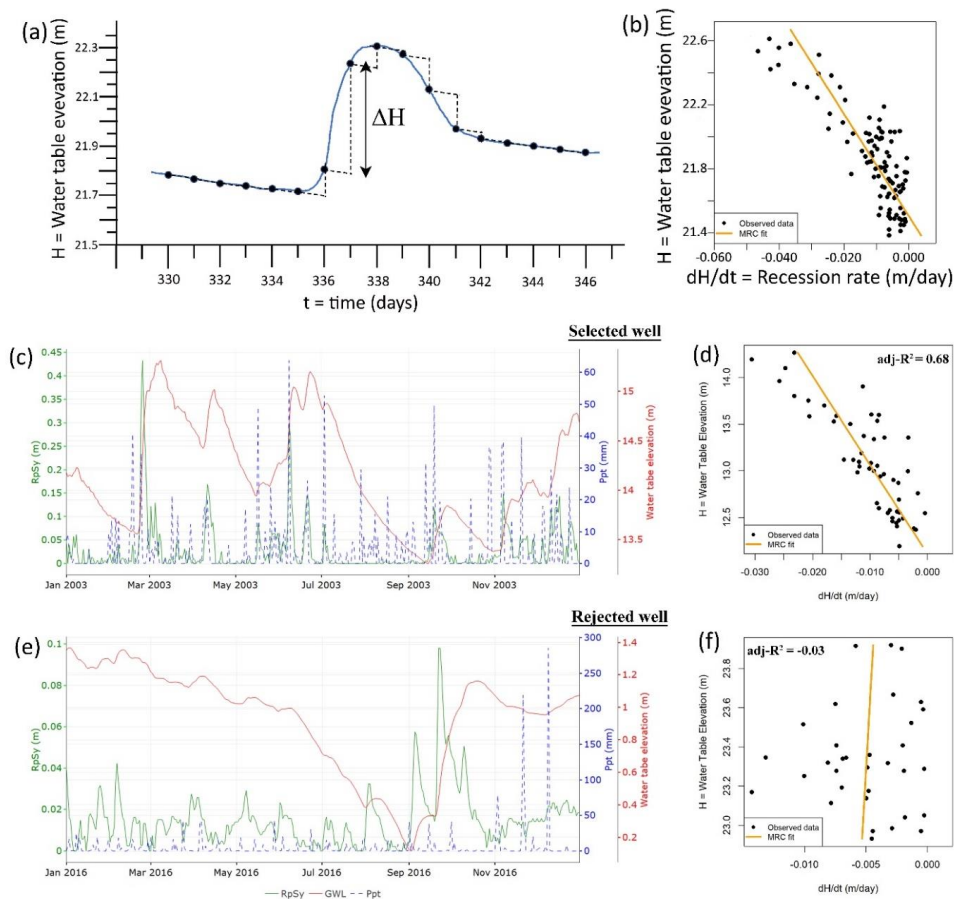
125 Figure 1: (a) Schematic representation of ΔH evaluation in the WTF method, which is then used to obtain daily groundwater recharge using Eqn 1, (b) a typical dH/dt vs. H plot used to derive the MRC. The hydrographs (c) and (e) show daily groundwater level (GWL), precipitation (Ppt), and estimated recharge per unit specific yield (RpSy, discussed later) for a selected and a rejected well, respectively. Here selection/rejection is based on representativeness of the MRC, which here is determined based on an adj-R2 value of 0.2. (d) and (f) show the dH/dt vs. H plot for the corresponding selected and rejected wells, respectively.

Next, we further screened the data selected based on the above criteria to develop a subset of wells that met the following secondary criteria including:

i) Well datasets with a characteristic functional relation between H and dH/dt are needed to develop an MRC. To ensure this, an adj-R2 value of 0.2 for the MRC curve fit is used as a threshold. Only the wells with a correlation coefficient

135 above this threshold are considered. It's important to note that sites with high adj-R² values not only confirm the applicability of the WTF method but also help filter out sites with pumping impacts, which can cause variable recession rates. However, this threshold is not foolproof and cannot completely guarantee the absence of groundwater pumping effects.

ii) Finally, since MRC is expected to exhibit a negative slope, only such wells are used in the proceeding analyses.

Examples of selected and rejected observation wells based on the secondary selection criteria are illustrated in Figure 1. After

140 implementation of all these filtering and post-processing criteria, 485 daily observation wells out of 2136 are finally found suitable for our analysis (Figure 2). Most selected wells fall within the eastern part of the US. Precipitation data from PRISM (Daly et al., 2008) are used to obtain the estimates of the MRC characteristics curve. The PRISM data has a temporal resolution of 1 day and a spatial resolution of 800 m. Evapotranspiration data that has been used in the technical validation (discussed later) is obtained from the Global Land Evaporation Amsterdam Model (GLEAM) (Martens et al., 2017; Miralles et al., 2011).
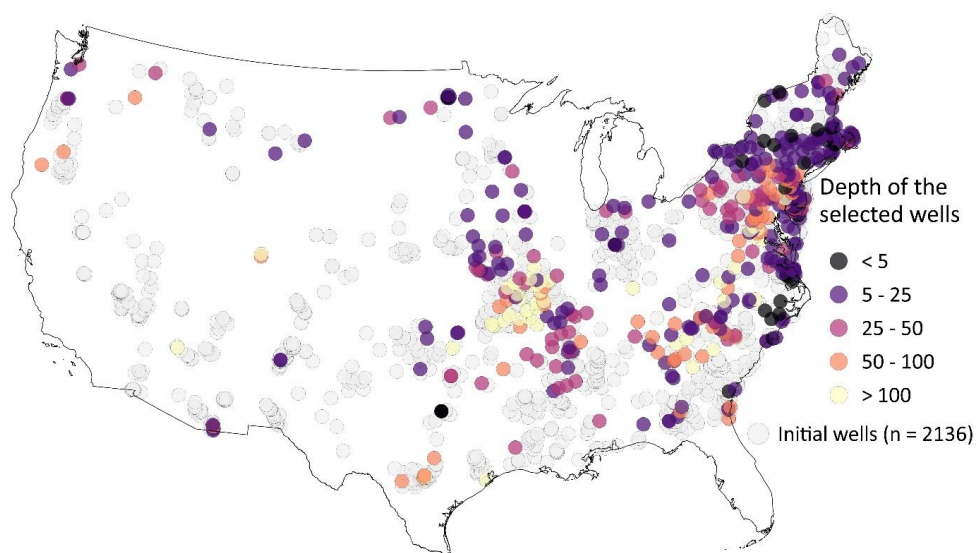
145

Figure 2: Location of all the available observation wells with (> 2 years) daily data and the final selected wells (shown in color) with their screen depths in meters.

2.3 Influence of water table depth variations and nearby streams on RpSy

Although the RpSy dataset may not provide direct estimate of recharge, but it can still capture the temporal consistency of

150 groundwater recharge. This assumes that the specific yield (S_y) varies minimally in time, as has been considered in numerous groundwater studies (Maréchal et al., 2006; Gumuła-Kawęcka et al., 2022; Ala-Aho et al., 2015; Gehman et al., 2009; Varni et al., 2013). Under this assumption, temporal variations of recharge and RpSy time series are expected to be the same. However, several studies (Lv et al., 2021; Shah and Ross, 2009) have pointed out the temporally varying nature of specific yield depending on water table depth, time of drainage, and other influencing factors, many of which indirectly affect water

155 table variations and drainage rate. We perform additional analysis to evaluate the role of groundwater depth variations on S_y and, consequently, on RpSy. To this end, time varying S_y is evaluated using the method derived in Crosbie et al. (2005), where a constant ultimate specific yield (S_{yu}) is dynamically modified using the equation

$$\frac{S_y}{S_{yu}} = 1 - \frac{1}{\{1+(\alpha d)^n\}^{1-\frac{1}{n}}} \tag{2}$$

Here, d is the groundwater depth. The van Genuchten drainage parameters, α and n are obtained from POLARIS data (Chaney et al., 2019).

160

We also specifically identify wells where the likelihood of groundwater dynamics, and consequently recharge, being significantly affected by nearby streams is minimal. To this end, we filter out wells that are either farther than a threshold distance from the stream, or has groundwater depth in it being higher than the river level or have a small volume (or bankfull width < 5m). The difference in groundwater and river elevations follow the procedure in Jasechko et al. (2021). Notably, Jasechko et al. (2021) considered threshold distances of 250 m and 1 km, though determining distance thresholds to demarcate influence of streams on groundwater dynamics remains challenging. While using a threshold of 250 m and other criteria, 420 wells are selected (Supplementary text S1, Figure S2, S3, Table S1). Users may consider just these wells for benchmarking. Despite these efforts to ensure good quality data, there is still a possibility of some contamination to recharge derived from the WTF method at the selected sites.

165

3 Data Assessment

170

Given that the presented dataset is first of its kind in providing an observational data-based recharge equivalent at a daily resolution, a direct validation is not possible. However, a comparison of the presented data series to recharge estimates from USGS is performed to understand the similarities and differences between these two products. Furthermore, to qualitatively test the physical plausibility of the results, the presented data is also assessed vis-à-vis the direct influencing variables, i.e., precipitation and evapotranspiration. But, before performing the aforementioned evaluations, we first inter-compare the RpSy estimates using both constant and variable Sy (i.e., RpSyu). Results indicate a correlation higher than 0.8 between the two methods in 94% of the sites (Figure S4). Given the similarity of the two data sets, and considering that using variable Sy requires soil drainage parameters (see Eqn. 2), which are inherently uncertain (Gupta et al., 2022; Dai et al., 2019), we proceed with RpSy obtained from constant Sy for the subsequent analysis.

175

3.1 Comparison against USGS recharge estimates

180

We compare the long-term RpSy for selected observation wells against the USGS monthly recharge estimates (Reitz et al., 2017a; Reitz and Sanford, 2019a) available at 1 km × 1 km resolution between October 2003 and December 2015 for the Conterminous United States. The USGS dataset has been developed through data analysis on water budget components from
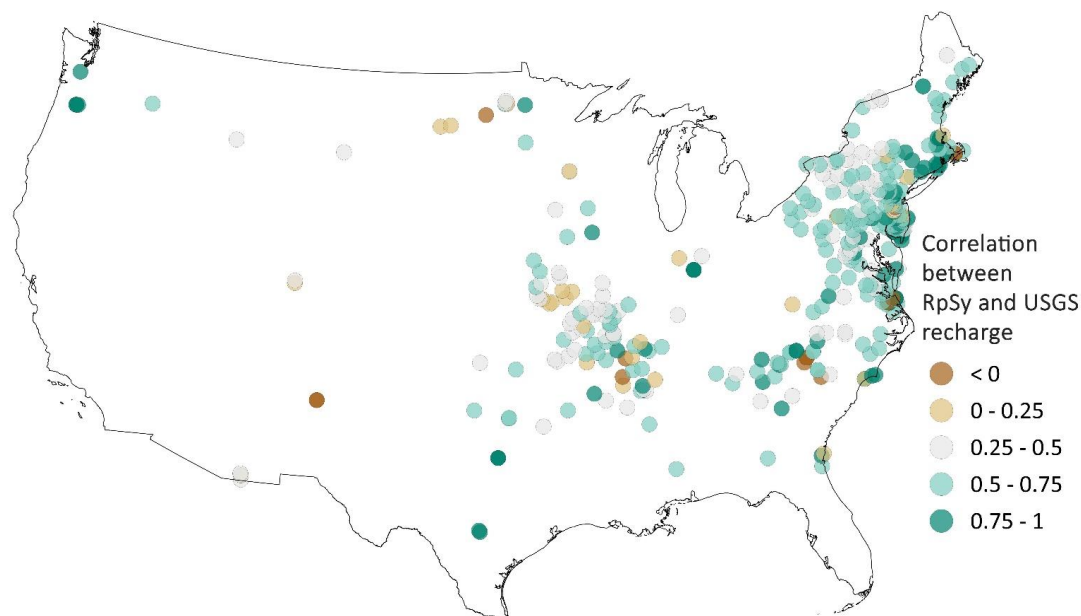
Figure 3: Spatial variation of temporal correlation between RpSy and USGS recharge.

various sources such as PRISM precipitation (Daly et al., 2008), SNODAS snow water equivalent (Snow Data Assimilation System (SNODAS) Data Products at NSIDC, Version 1 | National Snow and Ice Data Center, 2022), SSEBop-WB evapotranspiration (Reitz et al., 2017b), USGS groundwater-sourced irrigation map (Reitz et al., 2017a) and monthly surface runoff (Reitz and Sanford, 2019b). Figure 3 highlights the spatial variation of temporal correlations between RpSy and USGS recharge. The average spatial Pearson's correlation between RpSy and USGS recharge at the observation wells is R = 0.54, with ~1/5 of the wells having R > 0.75. We find positive correlations in 95% of all the selected wells, with the highest correlation of 0.99 and the lowest correlation of -0.8. Higher correlations are generally observed in the moist northeastern US, while correlations are lower in the midwestern US. It is conjectured that the relatively poor performance at several wells in the mid-western states is attributable to the uniform distribution of county-scaled groundwater-sourced irrigation water use data in the assessment of USGS recharge (Reitz et al., 2017a). In contrast, wells selected for RpSy derivation are expected to be not influenced by irrigation. The disagreement also could be due to the scale mismatch between the RpSy, which provides recharge equivalent estimates at a point scale (near the wells), and the gridded USGS product. An additional source of mismatch could be linked to the USGS product neglecting the change of storage in the water balance approach and the inherent uncertainties in their model structure (Reitz et al., 2017a). It is to be noted that RpSy essentially captures the recharge flux reaching the groundwater table, while the recharge estimate in USGS product's is the water flux leaking below the root zone. These two fluxes can be different, especially in settings where significant moisture deficit exists in the soil column between the root zone and the groundwater table.
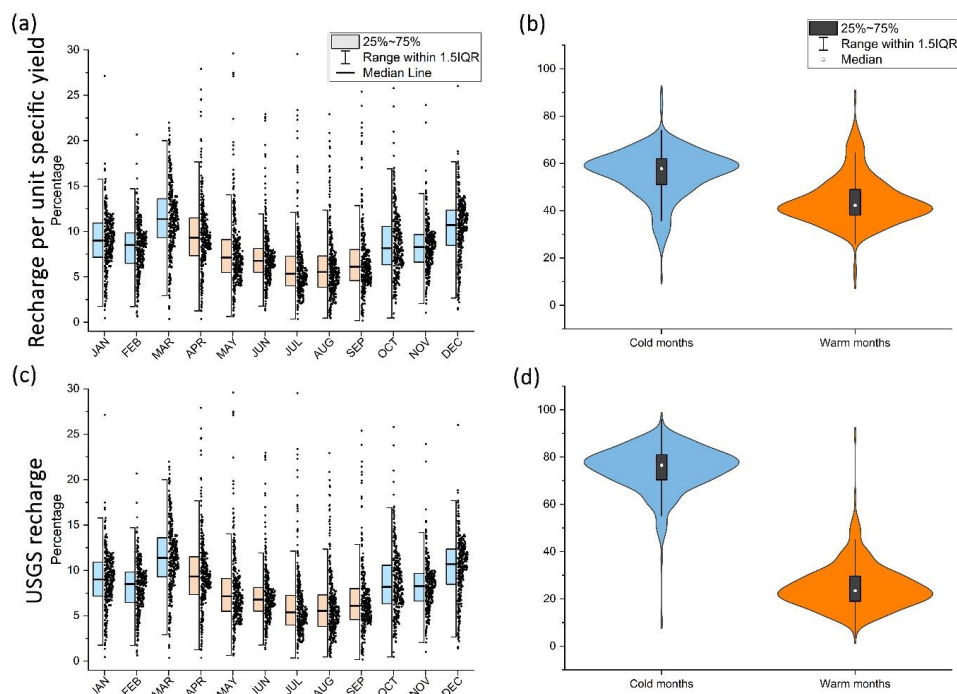
Figure 4: Fraction of recharge in different months and seasons (i.e., Cold seasons (Oct to Mar), Warm-season (Apr to Sept)) relative to the total recharge(/equivalents) for RpSy (top, a and b) and USGS (bottom, c, and d) recharge products. In this plot, USGS recharge data for the grids with RpSy estimates are used. IQR indicates the interquartile range.

To investigate the temporal agreement of the two products, we calculate the fraction of recharge in different months and seasons (i.e., colder months (Oct to Mar) and warmer months (Apr to Sept)) relative to the total recharge equivalent in the respective dataset. The temporal recharge fraction suggests that USGS and RpSy show larger fractions in cold months. The USGS product shows a higher recharge fraction in cold months than RpSy, resulting in a lower fraction in warm months. The lowest monthly fraction is observed around July for USGS recharge and in August for RpSy. The USGS recharge also seems to peak earlier (in December) than RpSy (in March) (Figure 4).

3.2 RpSy variations with Precipitation (Ppt) and Evapotranspiration (ET)

Next, we assess the inter-annual and intra-annual variations in RpSy vis-à-vis Ppt and (Ppt-ET). Evaluation of inter-annual variations includes comparisons of normalized annual recharge fraction (normRpSy, henceforth) with normalized annual precipitation (normP, henceforth) or normalized annual precipitation minus evapotranspiration (normP-ET, henceforth). Here, the normalized variables (e.g., normRpSy) are calculated as the ratio of its annual magnitude for each year, and the overall mean over all the data years. A plot of the normRpSy and normP in Figure 5a shows that the inter-annual variation of normRpSy is much larger than precipitation fractions. This points to the ratio of recharge to precipitation being generally much higher in wetter years than in drier years. In contrast, the inter-annual variation of normRpSy is relatively muted with respect to (Ppt-ET), highlighting that the ratio of recharge to (Ppt-ET) is relatively smaller in wetter years than in drier years (Figure 5b).
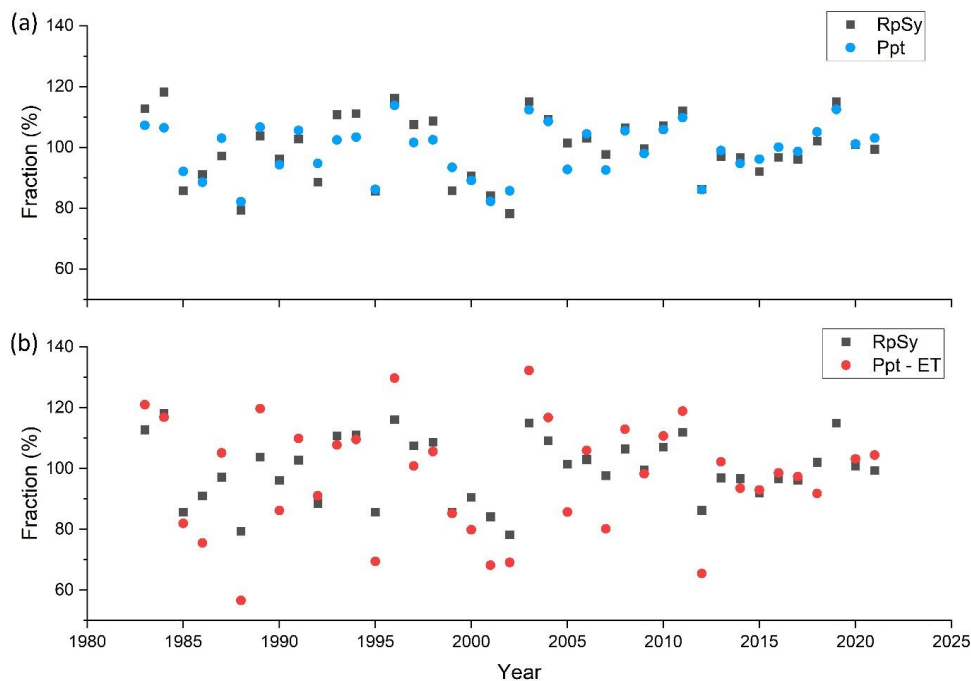
Figure 5: Inter-annual variation of normalized annual recharge (normRpSy, shown using solid squares), precipitation (normP, blue dots), and Ppt-ET (normP-ET, red dots).

To assess the intra-annual variation of RpSy vis-à-vis Ppt and Ppt-ET, we evaluate the centroid, which is the center of mass of the mean time series. The centroid date is calculated by first obtaining the cumulative time series of the variables (i.e., RpSy, Ppt, Ppt-ET) and then identifying the date on which the cumulative value is half of the yearly total in a water year (1 October to 30 September). We find that centroid (Ppt-ET) < centroid RpSy < centroid Ppt (Figure 6). The centroid (Ppt-ET) < centroid RpSy is likely due to a larger runoff ratio during the winter period. For example, for a shallow well in New Jersey, we notice centroid (Ppt-ET) on 4 February, which is relatively earlier than the centroid of RpSy and Ppt, which are on 24 March and 5 April, respectively (Figure 6d). It is to be noted that an overestimation in ET (especially during winter) can lead to (Ppt-ET) centroid being earlier as well. The centroid RpSy < centroid Ppt is because of larger ET losses in summer.

9
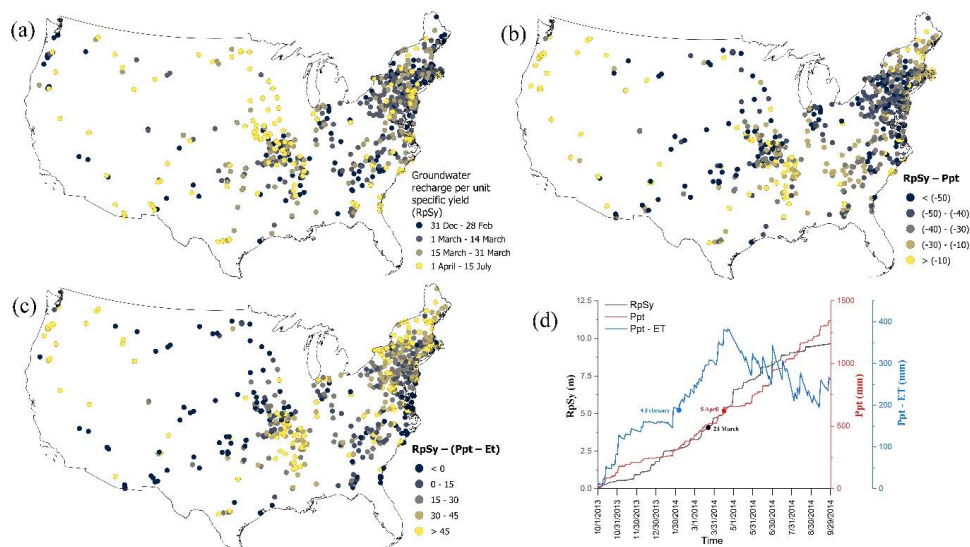
Figure 6: Centroid date for RpSy (a). Distance between centroidal date of RpSy and Ppt (b), and (Ppt-ET) (c). A negative (positive) value indicates a later (earlier) centroidal date for the variable with respect to that of RpSy. Day 1 is the start of the water year, i.e., Oct. 1. Also shown in d is a representative example of cumulative time series and all estimated centroids for a shallow well (Well ID: 400232074213201) in New Jersey.

4 Data availability

The final product we provide is a continuous daily RpSy time series data estimated using the WTF method for all 485 observation wells (Figure 2). Additionally, we also provide data of daily RpSy time series (RpSyu) while considering a groundwater depth-dependent S_y. Furthermore, we also identify the observation wells that are less likely to be affected by water leakage from nearby streams based on the criteria outlined in section 2.3. These data files, provided in the .csv format, consist of three columns for each observation well, with the first column listing the local time while the second and third columns provide the RpSy and RpSyu time series, respectively. The file containing site information for all the selected wells has four columns that detail the USGS ID of the groundwater well, its latitude (Lat), longitude (Long), and screen depth (depth) (Figure S5). We also provide the van Genuchten drainage parameters (i.e., α and n) used to derive RpSyu and nearest stream attributes used to evaluate nearby streams' impact for each observation wells. The data file can be opened in most text editors and spreadsheets. The data can be found online at Zenodo: https://doi.org/10.5281/zenodo.13323242 (Malakar et al., 2024).

5 Code Availability

We performed all steps, including data processing, MRC analysis, and RpSy calculations in R; and RpSyu and nearest stream attributes calculations in Python. All the codes, along with sample input datasets, can be found at the following link: https://doi.org/10.5281/zenodo.13323242 (Malakar et al., 2024).

6 Limitations

RpSy estimate from WTF method can be affected by temporal variation in S_y. Although a sincere effort has been made to explicitly account for the influence of water table depth on S_y and consequently on RpSy (see section 2.3), influences on S_y

from other factors (Lv et al., 2021) remain unaccounted for. RpSy evaluation using the WTF method can also be influenced by several other factors, including stage variations in a nearby surface water body, barometric pressure shifts, abstraction, groundwater pumping in the vicinity, and lateral flow contributions from uplands. As mentioned in section 2.2, only sites with a good MRC curve fit are used. This ensures the applicability of the WTF method and helps filter out sites with significant pumping impacts. However, the method is not foolproof and cannot completely guarantee the absence of groundwater pumping effects. We also identify a smaller subset of sites where the contribution to recharge from nearby surface water bodies is expected to be minimal, but the methodology cannot ensure zero contribution.

Recharge estimate from WTF method may also be affected by Lisse effect, which is characterized by large water level rise than expected for an infiltration amount due to trapped air in the unsaturated zone following a sudden high-intensity rain event (Crosbie et al., 2005; Cuthbert, 2010). Since Lisse effect occurs under very specific conditions of intense rainfall, fine-textured soil, and shallow groundwater table, it is expected to be less frequent. Irrespectively, as there is no sure short method for detecting and eliminating the Lisse effect from groundwater levels without using additional data subsurface moisture or potential, which are generally unavailable at most groundwater well sites, some influence of the Lisse effect may still be present in the derived RpSy data.

7 Conclusions

The study presents a novel benchmark dataset of groundwater recharge per unit specific yield (RpSy) at daily temporal resolution. The estimates are based on WTF and MRC methods and only require readily available precipitation and GWL data to obtain the recharge equivalents. The output data (i.e., RpSy) are available for download from the zenodo.com platform (Malakar et al., 2024). The datasets for continuous daily RpSy, well locations, and time are provided for end-user use. Given that the presented data set is first of its kind in providing an observational data-based recharge equivalent at a daily resolution, a direct validation is not possible. However, a comparison of the presented data series to recharge estimates from USGS is performed. To qualitatively assess the physical plausibility of the results, the presented data is also studied vis-à-vis the direct influencing variables, i.e., precipitation and evapotranspiration. While there is no available dataset that demonstrates the actual recharge time series at daily resolution, a comparison of the presented data series to monthly recharge estimates from USGS is performed for users of the data. Further analyses highlight that the RpSy product shows physically plausible temporal variations vis-à-vis the variations in Ppt and ET at both inter- and intra-annual scales.

While the RpSy data does not offer direct recharge estimates, it still captures the variations and changes in groundwater recharge over time at daily to coarser temporal resolution. Hence, despite the limitations, uncertainty, and associated caveats discussed in section 2, the RpSy dataset can be used to validate temporal consistency of recharge estimates derived from empirical methods (Reitz et al., 2017a; Reitz and Sanford, 2019a), physically-based land surface models (Anurag and Ng, 2022; Li et al., 2021; Niraula et al., 2017) or integrated hydrologic models (Kumar and Duffy, 2015; Kollet and Maxwell, 2006; Kumar et al., 2009; Therrien et al., 2010). Furthermore, the data may also be used to validate the functional relationship between recharge and associated factors as represented in land surface and global hydrologic models. Gnann et al. (2023) demonstrated that theoretical and empirically based functional relationships for recharge differ significantly from global water models. Even when a model produces highly accurate predictions, it may still poorly simulate the strength of functional process couplings. In other words, it may produce right results for wrong reasons. Such models are likely to underperform during periods when the forcing characteristics are different than those in the training data. The derived benchmark RpSy data, along with forcing variables, can be used to validate the functional relationships represented in models of recharge, using one of the several diagnostic methods such as information theory (Ruddell et al., 2019), causality mapping (Barnett and Seth, 2014; Runge et al., 2019; Runge, 2018), and convergence cross mapping (Ye et al., 2015). The RpSy data

may also be used to temporally downscale long-term recharge estimates from observations, thus facilitating generation of recharge inputs for groundwater models (Kim et al., 2008). Additionally, the data may be used for improved understanding

300 of the role of different forcing and antecedent hydrologic conditions on groundwater recharge and help manage groundwater aquifers under water-stress conditions.

Author contribution

MK conceived the study and provided project administration and supervision. MK and PC acquired funding to support the project. PM compiled the data, developed relevant codes for analyses and visualizations, and generated results. AA developed

305 and implemented code to obtain modified RpSy that accounts for the influence of water table depth on S_y. AA also identified the gauging stations with smaller likelihood of influence on groundwater dynamics from nearby streams. PM and MK designed the methodology, performed data analyses, and drafted the manuscript. PC and AT provided thoughtful inputs. All authors edited the manuscript and helped improve it.

Competing interests

310 The authors declare no competing interests.

References

320 Ala-Aho, P., Rossi, P. M., and Kløve, B.: Estimation of temporal and spatial variations in groundwater recharge in unconfined sand aquifers using Scots pine inventories, Hydrol. Earth Syst. Sci., 19, 1961–1976, https://doi.org/10.5194/hess-19-1961-2015, 2015.

Alley, W. M., Reilly, T. E., and Franke, O. L.: Sustainability of groundwater resources, US Dep. Inter. US Geol. Surv., 1186, 1999.

325 Anurag, H. and Ng, G. H. C.: Assessing future climate change impacts on groundwater recharge in Minnesota, J. Hydrol., 612, 128112, https://doi.org/10.1016/J.JHYDROL.2022.128112, 2022.

Asoka, A., Wada, Y., Fishman, R., and Mishra, V.: Strong linkage between precipitation intensity and monsoon season groundwater recharge in India, Geophys. Res. Lett., 45, 5536–5544, https://doi.org/10.1029/2018GL078466, 2018.

330   Barnett, L. and Seth, A. K.: The MVGC multivariate Granger causality toolbox: A new approach to Granger-causal inference, J. Neurosci. Methods, 223, 50–68, https://doi.org/10.1016/j.jneumeth.2013.10.018, 2014.

Berghuijs, W. R., Luijendijk, E., Moeck, C., Velde, Y. van der, and Allen, S. T.: Global Recharge Data Set Indicates Strengthened Groundwater Connection to Surface Fluxes, Geophys. Res. Lett., 49, e2022GL099010, https://doi.org/10.1029/2022GL099010, 2022.

Bhanja, S. N., Mukherjee, A., Rangarajan, R., Scanlon, B. R., Malakar, P., and Verma, S.: Long-term groundwater recharge
335   rates across India by in situ measurements, Hydrol. Earth Syst. Sci., 23, 711–722, https://doi.org/10.5194/hess-23-711-2019, 2019.

Blasch, K. W., Constantz, J., and Stonestrom, D. A.: Thermal Methods for Investigating Groundwater Recharge, Prof. Pap., https://doi.org/10.3133/PP17031, 2007.

Boumis, G., Kumar, M., Nimmo, J. R., and Clement, T. P.: Influence of Shallow Groundwater Evapotranspiration on
340   Recharge Estimation Using the Water Table Fluctuation Method, Water Resour. Res., 58, e2022WR032073, https://doi.org/10.1029/2022WR032073, 2022.

Chaney, N. W., Minasny, B., Herman, J. D., Nauman, T. W., Brungard, C. W., Morgan, C. L. S., McBratney, A. B., Wood, E. F., and Yimam, Y.: POLARIS Soil Properties: 30-m Probabilistic Maps of Soil Properties Over the Contiguous United States, Water Resour. Res., 55, 2916–2938, https://doi.org/10.1029/2018WR022797, 2019.

345   Chen, X., Kumar, M., deB Richter, D., and Mau, Y.: Impact of gully incision on hillslope hydrology, Hydrol. Process., 34, 3848–3866, https://doi.org/10.1002/HYP.13845, 2020.

Condon, L. E., Atchley, A. L., and Maxwell, R. M.: Evapotranspiration depletes groundwater under warming over the contiguous United States, Nat. Commun., 11, 1–8, https://doi.org/10.1038/s41467-020-14688-0, 2020.

Crosbie, R. S., Binning, P., and Kalma, J. D.: A time series approach to inferring groundwater recharge using the water table
350   fluctuation method, Water Resour. Res., 41, 1–9, https://doi.org/10.1029/2004WR003077, 2005.

Crosbie, R. S., Davies, P., Harrington, N., and Lamontagne, S.: Ground truthing groundwater-recharge estimates derived from remotely sensed evapotranspiration: a case in South Australia, Hydrogeol. J., 23, 335–350, https://doi.org/10.1007/s10040-014-1200-7, 2015.

Crosbie, R. S., Doble, R. C., Turnadge, C., and Taylor, A. R.: Constraining the Magnitude and Uncertainty of Specific Yield
355   for Use in the Water Table Fluctuation Method of Estimating Recharge, Water Resour. Res., 55, 7343–7361, https://doi.org/10.1029/2019WR025285, 2019.

Cunningham, W. L., Geiger, L. H., and Karavatis, G. A.: U.S. Geological Survey Groundwater Climate Response Network, US Department of the Interior, US Geological Survey Fact Sheet 2007-3003, 4 pp., https://doi.org/10.3133/fs20073003, 2007.

360   Cuthbert, M. O.: An improved time series approach for estimating groundwater recharge from groundwater level fluctuations, Water Resour. Res., 46, 9515, https://doi.org/10.1029/2009WR008572, 2010.

Cuthbert, M. O., Taylor, R. G., Favreau, G., Todd, M. C., Shamsudduha, M., Villholth, K. G., MacDonald, A. M., Scanlon, B. R., Kotchoni, D. O. V., Vouillamoz, J. M., Lawson, F. M. A., Adjomayi, P. A., Kashaigili, J., Seddon, D., Sorensen, J. P. R., Ebrahim, G. Y., Owor, M., Nyenje, P. M., Nazoumou, Y., Goni, I., Ousmane, B. I., Sibanda, T., Ascott, M. J.,
365   Macdonald, D. M. J., Agyekum, W., Koussoubé, Y., Wanke, H., Kim, H., Wada, Y., Lo, M. H., Oki, T., and Kukuric, N.:

Observed controls on resilience of groundwater to climate variability in sub-Saharan Africa, Nat. 2019 5727768, 572, 230–234, https://doi.org/10.1038/s41586-019-1441-7, 2019.

Dai, Y., Xin, Q., Wei, N., Zhang, Y., Shangguan, W., Yuan, H., Zhang, S., Liu, S., and Lu, X.: A Global High-Resolution Data Set of Soil Hydraulic and Thermal Properties for Land Surface Modeling, J. Adv. Model. Earth Syst., 11, 2996–3023,
370   https://doi.org/10.1029/2019MS001784, 2019.

Daly, C., Halbleib, M., Smith, J. I., Gibson, W. P., Doggett, M. K., Taylor, G. H., Curtis, J., and Pasteris, P. P.: Physiographically sensitive mapping of climatological temperature and precipitation across the conterminous United States, Int. J. Climatol., 28, 2031–2064, https://doi.org/10.1002/JOC.1688, 2008.

Delin, G. N., Healy, R. W., Lorenz, D. L., and Nimmo, J. R.: Comparison of local- to regional-scale estimates of
375   groundwater recharge in Minnesota, USA, J. Hydrol., 334, 231–249, https://doi.org/10.1016/J.JHYDROL.2006.10.010, 2007.

Famiglietti, J. S.: The global groundwater crisis, Nat. Clim. Chang., 4, 945–948, https://doi.org/10.1038/nclimate2425, 2014.

Fan, Y., Clark, M., Lawrence, D. M., Swenson, S., Band, L. E., Brantley, S. L., Brooks, P. D., Dietrich, W. E., Flores, A., Grant, G., Kirchner, J. W., Mackay, D. S., McDonnell, J. J., Milly, P. C. D., Sullivan, P. L., Tague, C., Ajami, H., Chaney,
380   N., Hartmann, A., Hazenberg, P., McNamara, J., Pelletier, J., Perket, J., Rouholahnejad-Freund, E., Wagener, T., Zeng, X., Beighley, E., Buzan, J., Huang, M., Livneh, B., Mohanty, B. P., Nijssen, B., Safeeq, M., Shen, C., van Verseveld, W., Volk, J., and Yamazaki, D.: Hillslope Hydrology in Global Change Research and Earth System Modeling, Water Resour. Res., 55, 1737–1772, https://doi.org/10.1029/2018WR023903, 2019.

Gehman, C. L., Harry, D. L., Sanford, W. E., Stednick, J. D., and Beckman, N. A.: Estimating specific yield and storage
385   change in an unconfined aquifer using temporal gravity surveys, Water Resour. Res., 46, https://doi.org/10.1029/2007WR006096, 2009.

Ghannam, K., Nakai, T., Paschalis, A., Oishi, C. A., Kotani, A., Igarashi, Y., Kumagai, T., and Katul, G. G.: Persistence and memory timescales in root-zone soil moisture dynamics, Water Resour. Res., 52, 1427–1445, https://doi.org/10.1002/2015WR017983, 2016.

390   Gnann, S., Reinecke, R., Stein, L., Wada, Y., Thiery, W., Müller Schmied, H., Satoh, Y., Pokhrel, Y., Ostberg, S., Koutroulis, A., Hanasaki, N., Grillakis, M., Gosling, S. N., Burek, P., Bierkens, M. F. P., and Wagener, T.: Functional relationships reveal differences in the water cycle representation of global water models, Nat. Water 2023 112, 1, 1079–1090, https://doi.org/10.1038/s44221-023-00160-y, 2023.

Gong, C., Zhang, Z., Wang, W., Duan, L., and Wang, Z.: An assessment of different methods to determine specific yield for
395   estimating groundwater recharge using lysimeters, Sci. Total Environ., 788, 147799, https://doi.org/10.1016/J.SCITOTENV.2021.147799, 2021.

Gonzalez, M. O., Preetha, P., Kumar, M., and Clement, T. P.: Comparison of Data-Driven Groundwater Recharge Estimates with a Process-Based Model for a River Basin in the Southeastern USA, J. Hydrol. Eng., 28, 04023019, https://doi.org/10.1061/JHYEFF.HEENG-5882, 2023.

400   Gumuła-Kawęcka, A., Jaworska-Szulc, B., Szymkiewicz, A., Gorczewska-Langner, W., Pruszkowska-Caceres, M., Angulo-Jaramillo, R., and Šimůnek, J.: Estimation of groundwater recharge in a shallow sandy aquifer using unsaturated zone modeling and water table fluctuation method, J. Hydrol., 605, https://doi.org/10.1016/j.jhydrol.2021.127283, 2022.

Gupta, S., Papritz, A., Lehmann, P., Hengl, T., Bonetti, S., and Or, D.: Global Soil Hydraulic Properties dataset based on legacy site observations and robust parameterization, Sci. Data, 9, https://doi.org/10.1038/s41597-022-01481-5, 2022.

405   Healy, R. W.: Estimating groundwater recharge, Cambridge University Press, 1–245 pp., https://doi.org/10.1017/CBO9780511780745, 2010.

Healy, R. W. and Cook, P. G.: Using groundwater levels to estimate recharge, Hydrogeol. J. 2002 101, 10, 91–109, https://doi.org/10.1007/S10040-001-0178-0, 2002.

Heppner, C. S. and Nimmo, J. R.: A Computer Program for Predicting Recharge with a Master Recession Curve, 8, 2005.

410   Hung Vu, V. and Merkel, B. J.: Estimating groundwater recharge for Hanoi, Vietnam, Sci. Total Environ., 651, 1047–1057, https://doi.org/10.1016/J.SCITOTENV.2018.09.225, 2019.

Jasechko, S., Seybold, H., Perrone, D., Fan, Y., and Kirchner, J. W.: Widespread potential loss of streamflow into underlying aquifers across the USA, Nat. 2021 5917850, 591, 391–395, https://doi.org/10.1038/s41586-021-03311-x, 2021.

Kim, N. W., Chung, I. M., Won, Y. S., and Arnold, J. G.: Development and application of the integrated SWAT–
415   MODFLOW model, J. Hydrol., 356, 1–16, https://doi.org/10.1016/J.JHYDROL.2008.02.024, 2008.

Kollet, S. J. and Maxwell, R. M.: Integrated surface-groundwater flow modeling: A free-surface overland flow boundary condition in a parallel groundwater flow model, Adv. Water Resour., 29, 945–958, https://doi.org/10.1016/j.advwatres.2005.08.006, 2006.

Konikow, L. F.: Long-Term Groundwater Depletion in the United States, Groundwater, 53, 2–9,
420   https://doi.org/10.1111/gwat.12306, 2015.

Kumar, M., Duffy, C. J., and Salvage, K. M.: A Second-Order Accurate, Finite Volume-Based, Integrated Hydrologic Modeling (FIHM) Framework for Simulation of Surface and Subsurface Flow, Vadose Zo. J., 8, 873–890, https://doi.org/10.2136/vzj2009.0014, 2009.

Kumar, M. and Duffy, C. J.: Exploring the Role of Domain Partitioning on Efficiency of Parallel Distributed Hydrologic
425   Model Simulations, J. Hydrogeol. Hydrol. Eng., 04, https://doi.org/10.4172/2325-9647.1000119, 2015.

Lapworth, D. J., MacDonald, A. M., Krishan, G., Rao, M. S., Gooddy, D. C., and Darling, W. G.: Groundwater recharge and age-depth profiles of intensively exploited groundwater resources in northwest India, Geophys. Res. Lett., 42, 7554–7562, https://doi.org/10.1002/2015GL065798, 2015.

Li, B. and Rodell, M.: Evaluation of a model-based groundwater drought indicator in the conterminous U.S., J. Hydrol., 526,
430   78–88, https://doi.org/10.1016/J.JHYDROL.2014.09.027, 2015.

Li, B., Rodell, M., Peters-Lidard, C., Erlingis, J., Kumar, S., and Mocko, D.: Groundwater recharge estimated by land surface models: An evaluation in the conterminous United States, J. Hydrometeorol., 22, 499–522, https://doi.org/10.1175/JHM-D-20-0130.1, 2021.

Liu, Y., Parolari, A. J., Kumar, M., Huang, C. W., Katul, G. G., and Porporato, A.: Increasing atmospheric humidity and
435   CO_2 concentration alleviate forest mortality risk, Proc. Natl. Acad. Sci. U. S. A., 114, 9918–9923, https://doi.org/10.1073/pnas.1704811114, 2017.

Liu, Y., Kumar, M., Katul, G. G., Feng, X., and Konings, A. G.: Plant hydraulics accentuates the effect of atmospheric moisture stress on transpiration, Nat. Clim. Chang. 2020 107, 10, 691–695, https://doi.org/10.1038/s41558-020-0781-5, 2020.

440   Lv, M., Xu, Z., Yang, Z. L., Lu, H., and Lv, M.: A Comprehensive Review of Specific Yield in Land Surface and
        Groundwater Studies, J. Adv. Model. Earth Syst., 13, https://doi.org/10.1029/2020MS002270, 2021.

        Malakar, P., Mukherjee, A., Bhanja, S. N., Sarkar, S., Saha, D., and Ray, R. K.: Deep Learning-Based Forecasting of
        Groundwater Level Trends in India: Implications for Crop Production and Drinking Water Supply, ACS ES&T Eng., 1,
        965–977, https://doi.org/10.1021/ACSESTENGG.0C00238, 2021a.

445   Malakar, P., Mukherjee, A., Bhanja, S. N., Ray, R. K., Sarkar, S., and Zahid, A.: Machine-learning-based regional-scale
        groundwater level prediction using GRACE, Hydrogeol. J., 29, 1027–1042, https://doi.org/10.1007/s10040-021-02306-2,
        2021b.

        Malakar, P., Mukherjee, A., Bhanja, S. N., Ganguly, A. R., Ray, R. K., Zahid, A., Sarkar, S., Saha, D., and Chattopadhyay,
        S.: Three decades of depth-dependent groundwater response to climate variability and human regime in the transboundary
450   Indus-Ganges-Brahmaputra-Meghna mega river basin aquifers, Adv. Water Resour., 149, 103856,
        https://doi.org/10.1016/J.ADVWATRES.2021.103856, 2021c.

        Malakar, P., Anshuman, A., Boumis, G., Kumar, M., Clement, P., Tashie, A., Thakur, H., & Rathore, L.: An in-situ daily
        dataset for benchmarking temporal variability of groundwater recharge, https://doi.org/10.5281/zenodo.13323242, 2024.

        Maréchal, J. C., Dewandel, B., Ahmed, S., Galeazzi, L., and Zaidi, F. K.: Combined estimation of specific yield and natural
455   recharge in a semi-arid groundwater basin with irrigated agriculture, J. Hydrol., 329, 281–293,
        https://doi.org/10.1016/j.jhydrol.2006.02.022, 2006.

        Martens, B., Miralles, D. G., Lievens, H., Van Der Schalie, R., De Jeu, R. A. M., Fernández-Prieto, D., Beck, H. E., Dorigo,
        W. A., and Verhoest, N. E. C.: GLEAM v3: Satellite-based land evaporation and root-zone soil moisture, Geosci. Model
        Dev., 10, 1903–1925, https://doi.org/10.5194/GMD-10-1903-2017, 2017.

460   McMahon, P. B., Plummer, L. N., Böhlke, J. K., Shapiro, S. D., and Hinkle, S. R.: A comparison of recharge rates in
        aquifers of the United States based on groundwater-age data, Hydrogeol. J., 19, 779–800, https://doi.org/10.1007/s10040-
        011-0722-5, 2011.

        Meyboom, P.: Estimating groundwater recharge from stream hydrographs, J. Geophys. Res., 66, 1203–1214,
        https://doi.org/10.1029/JZ066I004P01203, 1961.

465   Milly, P. C. D. and Dunne, K. A.: Potential evapotranspiration and continental drying, Nat. Clim. Chang., 6, 946–949,
        https://doi.org/10.1038/nclimate3046, 2016.

        Miralles, D. G., Holmes, T. R. H., De Jeu, R. A. M., Gash, J. H., Meesters, A. G. C. A., and Dolman, A. J.: Global land-
        surface evaporation estimated from satellite-based observations, Hydrol. Earth Syst. Sci., 15, 453–469,
        https://doi.org/10.5194/HESS-15-453-2011, 2011.

470   Moeck, C., Grech-Cumbo, N., Podgorski, J., Bretzler, A., Gurdak, J. J., Berg, M., and Schirmer, M.: A global-scale dataset
        of direct natural groundwater recharge rates: A review of variables, processes and relationships, Sci. Total Environ., 717,
        https://doi.org/10.1016/j.scitotenv.2020.137042, 2020.

        Mueller, B. and Seneviratne, S. I.: Systematic land climate and evapotranspiration biases in CMIP5 simulations, Geophys.
        Res. Lett., 41, 128–134, https://doi.org/10.1002/2013GL058055, 2014.

475   Nimmo, J. R. and Perkins, K. S.: Episodic Master Recession Evaluation of Groundwater and Streamflow Hydrographs for
        Water-Resource Estimation, Vadose Zo. J., 17, 180050, https://doi.org/10.2136/vzj2018.03.0050, 2018.

Nimmo, J. R., Horowitz, C., and Mitchell, L.: Discrete-storm water-table fluctuation method to estimate episodic recharge, Groundwater, 53, 282–292, https://doi.org/10.1111/gwat.12177, 2015.

480 Niraula, R., Meixner, T., Ajami, H., Rodell, M., Gochis, D., and Castro, C. L.: Comparing potential recharge estimates from three Land Surface Models across the western US, J. Hydrol., 545, 410–423, https://doi.org/10.1016/j.jhydrol.2016.12.028, 2017.

Raghav, P. and Kumar, M.: Retrieving gap-free daily root zone soil moisture using surface flux equilibrium theory, Environ. Res. Lett., 16, 104007, https://doi.org/10.1088/1748-9326/AC2441, 2021.

Raghav, P., Wagle, P., Kumar, M., Banerjee, T., and Neel, J. P. S.: Vegetation Index-Based Partitioning of
485 Evapotranspiration Is Deficient in Grazed Systems, Water Resour. Res., 58, https://doi.org/10.1029/2022WR032067, 2022.

Reitz, M., & Sanford, W.: Modern monthly effective recharge maps for the conterminous US, 2003-2015 | USGS Science Data Catalog, https://data.usgs.gov/datacatalog/data/USGS:5cd0a1b1e4b09b8c0b79a51c, 2019a.

Reitz, M. and Sanford, W. E.: Estimating quick-flow runoff at the monthly timescale for the conterminous United States, J. Hydrol., 573, 841–854, https://doi.org/10.1016/j.jhydrol.2019.04.010, 2019b.

490 Reitz, M., Sanford, W. E., Senay, G. B., and Cazenas, J.: Annual Estimates of Recharge, Quick-Flow Runoff, and Evapotranspiration for the Contiguous U.S. Using Empirical Regression Equations, J. Am. Water Resour. Assoc., 53, 961–983, https://doi.org/10.1111/1752-1688.12546, 2017a.

Reitz, M., Senay, G. B., and Sanford, W. E.: Combining remote sensing and water-balance evapotranspiration estimates for the conterminous United States, Remote Sens., 9, https://doi.org/10.3390/rs9121181, 2017b.

495 Ruddell, B. L., Drewry, D. T., and Nearing, G. S.: Information Theory for Model Diagnostics: Structural Error is Indicated by Trade-Off Between Functional and Predictive Performance, Water Resour. Res., 55, 6534–6554, https://doi.org/10.1029/2018WR023692, 2019.

Runge, J.: Causal network reconstruction from time series: From theoretical assumptions to practical estimation, Chaos, 28, https://doi.org/10.1063/1.5025050, 2018.

500 Runge, J., Bathiany, S., Bollt, E., Camps-Valls, G., Coumou, D., Deyle, E., Glymour, C., Kretschmer, M., Mahecha, M. D., Muñoz-Marí, J., van Nes, E. H., Peters, J., Quax, R., Reichstein, M., Scheffer, M., Schölkopf, B., Spirtes, P., Sugihara, G., Sun, J., Zhang, K., and Zscheischler, J.: Inferring causation from time series in Earth system sciences, Nat. Commun. 2019 101, 10, 1–13, https://doi.org/10.1038/s41467-019-10105-3, 2019.

Russo, T. A. and Lall, U.: Depletion and response of deep groundwater to climate-induced pumping variability, Nat. Geosci.,
505 10, 105–108, https://doi.org/10.1038/ngeo2883, 2017.

Scanlon, B. R., Healy, R. W., and Cook, P. G.: Choosing appropriate techniques for quantifying groundwater recharge, Hydrogeol. J. 2002 101, 10, 18–39, https://doi.org/10.1007/S10040-001-0176-2, 2002.

Scanlon, B. R., Keese, K. E., Flint, A. L., Flint, L. E., Gaye, C. B., Edmunds, W. M., and Simmers, I.: Global synthesis of groundwater recharge in semiarid and arid regions, Hydrol. Process., 20, 3335–3370, https://doi.org/10.1002/hyp.6335,
510 2006.

Scanlon, B. R., Mukherjee, A., Gates, J., Reedy, R. C., and Sinha, A. K.: Groundwater recharge in natural dune systems and agricultural ecosystems in the Thar Desert region, Rajasthan, India, Hydrogeol. J., 18, 959–972, https://doi.org/10.1007/s10040-009-0555-7, 2010.

515   Seo, S. B., Mahinthakumar, G., Sankarasubramanian, A., and Kumar, M.: Conjunctive Management of Surface Water and Groundwater Resources under Drought Conditions Using a Fully Coupled Hydrological Model, J. Water Resour. Plan. Manag., 144, 04018060, https://doi.org/10.1061/(ASCE)WR.1943-5452.0000978, 2018.

Shah, N. and Ross, M.: Variability in Specific Yield under Shallow Water Table Conditions, J. Hydrol. Eng., 14, 1290–1298, https://doi.org/10.1061/(asce)he.1943-5584.0000121, 2009.

Singh, N. K. and Borrok, D. M.: A Granger causality analysis of groundwater patterns over a half-century, Sci. Reports 2019
520   91, 9, 1–8, https://doi.org/10.1038/s41598-019-49278-8, 2019.

Snow Data Assimilation System (SNODAS) Data Products at NSIDC, Version 1 | National Snow and Ice Data Center, https://nsidc.org/data/G02158/versions/1, 2022.

Squeo, F. A., Aravena, R., Aguirre, E., Pollastri, A., Jorquera, C. B., and Ehleringer, J. R.: Groundwater dynamics in a coastal aquifer in north-central Chile: Implications for groundwater recharge in an arid ecosystem, J. Arid Environ., 67, 240–
525   254, https://doi.org/10.1016/j.jaridenv.2006.02.012, 2006.

Tashie, A. M., Mirus, B. B., and Pavelsky, T. M.: Identifying long-term empirical relationships between storm characteristics and episodic groundwater recharge, Water Resour. Res., 52, 21–35, https://doi.org/10.1002/2015WR017876, 2016.

Taylor, R. G., Todd, M. C., Kongola, L., Maurice, L., Nahozya, E., Sanga, H., and Macdonald, A. M.: Evidence of the
530   dependence of groundwater resources on extreme rainfall in East Africa, Nat. Clim. Chang., 3, 374–378, https://doi.org/10.1038/nclimate1731, 2013a.

Taylor, R. G., Scanlon, B., Döll, P., Rodell, M., Van Beek, R., Wada, Y., Longuevergne, L., Leblanc, M., Famiglietti, J. S., Edmunds, M., Konikow, L., Green, T. R., Chen, J., Taniguchi, M., Bierkens, M. F. P., Macdonald, A., Fan, Y., Maxwell, R. M., Yechieli, Y., Gurdak, J. J., Allen, D. M., Shamsudduha, M., Hiscock, K., Yeh, P. J. F., Holman, I., and Treidel, H.:
535   Ground water and climate change, Nat. Clim. Chang., 3, 322–329, https://doi.org/10.1038/nclimate1744, 2013b.

Therrien, R., McLaren, R. G. G., Sudicky, E. A. A., and Panday, S. M. M.: HydroGeoSphere: a three-dimensional numerical model describing fully-integrated subsurface and surface flow and solute transport, Groundw. Simulations Group, Univ. Waterloo, Waterloo, 322p., 2010.

Thomas, B. F., Behrangi, A., and Famiglietti, J. S.: Precipitation intensity effects on groundwater recharge in the
540   southwestern United States, Water (Switzerland), 8, https://doi.org/10.3390/w8030090, 2016.

Valois, R., MacDonell, S., Núñez Cobo, J. H., and Maureira-Cortés, H.: Groundwater level trends and recharge event characterization using historical observed data in semi-arid Chile, Hydrol. Sci. J., 65, 597–609, https://doi.org/10.1080/02626667.2020.1711912, 2020.

Varni, M., Comas, R., Weinzettel, P., and Dietrich, S.: Application of the water table fluctuation method to characterize
545   groundwater recharge in the Pampa plain, Argentina, Hydrol. Sci. J., 58, 1445–1455, https://doi.org/10.1080/02626667.2013.833663, 2013.

Wu, J., Cao, M., Tong, D., Finkelstein, Z., and Hoek, E. M. V.: A critical review of point-of-use drinking water treatment in the United States, npj Clean Water, 4, https://doi.org/10.1038/s41545-021-00128-z, 2021.

Xu, C. Y. and Chen, D.: Comparison of seven models for estimation of evapotranspiration and groundwater recharge using
550   lysimeter measurement data in Germany, Hydrol. Process., 19, 3717–3734, https://doi.org/10.1002/HYP.5853, 2005.

Ye, H., Deyle, E. R., Gilarranz, L. J., and Sugihara, G.: Distinguishing time-delayed causal interactions using convergent cross mapping, Sci. Rep., 5, https://doi.org/10.1038/srep14750, 2015.

Zhang, J., Felzer, B. S., and Troy, T. J.: Extreme precipitation drives groundwater recharge: the Northern High Plains Aquifer, central United States, 1950–2010, Hydrol. Process., 30, 2533–2545, https://doi.org/10.1002/hyp.10809, 2016.

555