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# Assessment of CHADFDM satellite-based input dataset for the groundwater recharge estimation in arid and data scarce regions

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## Abstract

Aquifer natural recharge estimations are a prerequisite for understanding hydrologic systems and sustainable water resources management. As meteorological data series collection is difficult in arid and semiarid areas, satellite products have recently become an alternative for water resources studies. A daily groundwater recharge estimation in the NW part of the Lake Chad Basin, using a soil–plant–atmosphere model (VisualBALAN), from ground- and satellite-based meteorological input dataset for non-irrigated and irrigated land and for the 2005–2014 period is presented. Average annual values were 284 mm and 30°C for precipitation and temperature in ground-based gauge stations. For the satellite-model-based Lake Chad Basin Flood and Drought Monitor System platform (CHADFDM), average annual precipitation and temperature were 417 mm and 29°C, respectively. Uncertainties derived from satellite data measurement could account for the rainfall difference. The estimated mean annual aquifer recharge was always higher from satellite- than ground-based data, with differences up to 46% for dryland and 23% in irrigated areas. Recharge response to rainfall events was very variable and results were very sensitive to: wilting point, field capacity and curve number for runoff estimation. Obtained results provide plausible recharge values beyond the uncertainty related to data input and modelling approach. This work prevents on the important deviations in recharge estimation from weighted-ensemble satellite-based data, informing in decision making to both stakeholders and policy makers.

KEYWORDS
CHADFDM data set, ground-satellite meteorological data, groundwater recharge modelling, Lake Chad Basin

## 1 | INTRODUCTION

Scarce precipitation, interannual dry periods, marked seasonal and spatial variability and extreme rainfall events are the main features of arid and semiarid zones that condition groundwater recharge (Lerner et al., 1990). Therefore, reliable rainfall and temperature data in these areas are extremely important for accurately assessing both soil water balance and aquifer recharge (Wu et al., 1996). Beyond inherent uncertainties to available in situ data, that is, from ground-based weather stations, one of the main difficulties is field data scarcity (Bhowmik & Costa, 2014; Dumolard et al., 2007). Meteorological stations are generally scarce, unevenly distributed, and may operate during short periods or imply major gaps. This can, in turn, lead to problems if long-term values are required when only short dataset periods are available (Lerner et al., 1990). Data and information are also often scattered among different agencies with limited access, which makes it difficult to obtain complete records. This generally results in information that is not very suitable for practical needs. To overcome this challenge, researchers have traditionally increased data availability using different statistical methods (Wagner et al., 2012), especially by bridging gaps in time series, interpolating between data points, introducing uncertainties given rainfall intermittency and large distances between observation points.

An alternative and complementary source of information comes from satellite products (e.g., TRMM, CMORPH, TMPA, PERSIANN), which can provide meteorological data series over large areas, and are useful for making multiple applications in hydrology (Beck, van Dijk, et al., 2017; Beck, Vergopolan, et al., 2017; Habib et al., 2008; Mzirai et al., 2005; Sheffield et al., 2018; Velpuri & Senay, 2013). For example, these sources of information have been used to develop large-scale drought monitoring systems with also the goal of stakeholders use in mind, which monitor in near real-time the terrestrial water cycle based on remote sensing data and land surface hydrological modelling (Sheffield et al., 2014).

Given the general ground data scarcity in arid and semiarid zones, satellite remote sensing products are a potentially useful direct or indirect data source of most hydrological cycle components. Nevertheless, satellite products use is influenced/limited by uncertainties resulting from its wide space–time coverage and spatial resolution, which is especially relevant in these regions due to the high spatial and temporal variability of surface meteorology and elevation-dependent biases (Bitew & Gebremichael, 2010). In some cases, satellite sensors may overestimate precipitation given its ability to identify events not recorded by gauge data (Milewski et al., 2009). Besides, satellite-based physical sensor limitations (Knoche et al., 2014; Prigent, 2010) or changes in sensors that lead to temporal non-homogeneity are also challenges as to their use. To understand/verify the utility of such products for hydrological studies, it is necessary to compare satellite data with ground-based data in order to indicate the hydrologic system response to these inputs and a range of predictions. Much work has been done especially on precipitation, (e.g., Beck, van Dijk, et al., 2017; Beck, Vergopolan, et al., 2017; Haile et al., 2015; Jiang, Yu, et al., 2016; Jiang, Zhou, et al., 2016; Lu, Sun, et al., 2016; Lu, Wang, et al., 2016; Nogueira et al., 2018). For groundwater recharge quantifications based on the water balance equation, the use of field and satellite products has been assessed in similar climate areas, ranging between less than 100 km$^2$ and 10$^4$ km$^2$, as summarized by Coelho et al. (2017). Most approaches generally use rainfall and evapotranspiration inputs for studies conducted in the Guarani aquifer (Lucas et al., 2015), Pakistan (Usman et al., 2015) and in the West Bank (Khalaf & Donoghue, 2012); the lately also incorporates irrigation data parameters and surface water input. For arid Northern Brazil, the work of Coelho et al. (2017) considers spatially varying runoff and soil moisture in the water balance equation, along with ancillary land use/land cover data. Wu et al. (2019) determined the aquifer annual and long-term recharge trend at regional scale with GRACE and GLDAS in the semiarid region of the Ordos Basin, China. There was no obvious long-term trend observed, and the annual recharge can be explained by the variability in precipitation. For modelling purposes, several physically based distributed numerical codes, found in different water balance approaches such as SAHYSMOD (ILRI, 2005), VisualBALAN (Samper et al., 2005), TOPOG (CSIRO, 2008) or SWB2 (Westenbroek et al., 2018), among others, are currently applied. The generally available requested input data, estimated reasonably accurately, and the facility to modify or substitute different input datasets, make VisualBALAN an excellent candidate for recharge calculations. VisualBALAN v2.0 offers an intermediate level of difficulty. This model code estimates a sequential water balance for the soil, the unsaturated zone and the aquifer, and has proven successful in calculating groundwater recharge in various hydrogeological conditions (Samper et al., 1999; Espinha-Marques et al., 2011; Touhami et al., 2013).

The quantification of natural groundwater recharge is a basic requirement for efficient water resources management. The diffuse recharge is a complex function that results from the coupling of several factors: precipitation (volume, intensity, duration), air temperature, topography, vegetation (cropping pattern, rooting depth) and evapotranspiration, soil and subsoil types, flow mechanisms in the unsaturated zone, bedrock geology and available groundwater storage (Scanlon et al., 2002). Of these, precipitation and evapotranspiration are the system's driven forces. Depending on relief, not concentrated recharge from runoff and ponding may be also dominant mechanisms in arid environments. Several reviews on aquifer recharge quantification based on different methods have been conducted in the past, and have focused primarily on arid and semiarid regions (de Vries & Simmers, 2002; Moeck et al., 2020; Scanlon et al., 2002; Scanlon et al., 2006). Although the spatio-temporal distribution of precipitation is the most critical factor (Wu et al., 1996), the chosen method can make estimations highly variable (Leduc et al., 2000). For regional scale studies, the soil water balance method is widely used due to its versatility to estimate spatially and temporally distributed aquifer recharge. This analysis calculates the temporal (e.g., daily) response over a wide area based on a physically robust recharge estimate process, taking into account the conditions of the land cover and the rainfall and irrigation contributions. With regard other methods, it presents more complexity as it also takes into account further information from different sources on climatic, soil data, vadose zone/aquifer parameters and vegetated areas.

This work focuses on the Lake Chad Basin, an arid region in which surface water is not enough to fulfil urban and rural population needs, and groundwater is the main water supply. Natural recharge (diffuse) for the region, which is widely variable on spatial and temporal scales, still remains uncertain. In the last 40 years, much attention has been paid to improve recharge estimations in this area, generally by local research. Methods for recharge estimation mainly included isotopic studies (Djoret & Travi, 2001; Edmunds et al., 1998; Gaultier, 2004; Goni, 2006; Leduc et al., 2000; Ngounou Ngatcha, Mudry, Aranyossy, et al., 2007; Njitchoua & Ngounou Ngatcha, 1997; Tewolde et al., 2019) and mathematical modelling for different hydrologic objectives (Babama'aji, 2013; Leblanc, 2002). Main findings indicate maximum values in the southern part of the Lake Chad Basin (South of 14th parallel) and in northern boundary part of the Lake, while it is almost inexistent in the northern part of the Basin. Different research studies have applied remote sensing data (e.g., Meteosat thermal data), combined with hydrogeological data, for groundwater research purposes. Leblanc (2002) and Leblanc et al. (2007) worked at the basin level to identify surface indicators of recharge and discharge areas for groundwater modelling. Buma et al. (2016) inferred the effect of rainfall on water storage on the basin by applying remote sensing datasets from the Gravity Recovery and Climate Experiment (GRACE) and Global Land Data Assimilation System (GLDAS) for water storage and soil moisture, respectively. Subsurface water variations were compared with groundwater outputs from a global hydrological model that showed a similar pattern.

The main objective of this work was to explore changes in groundwater diffuse recharge; that is, performance evaluation of climate data inputs in a generated daily water budget from a soil–plant-atmosphere model based on the water balance by considering two meteorological data sources and existent agricultural irrigation: (i) available ground-based meteorological data from local stations stored in the Trans-African Hydro-Meteorological Observatory, TAHMO (Van de Giesen et al., 2014); (ii) satellite-based rainfall from the Multi-Source Weighted-Ensemble Precipitation (MSWEP, Beck, van Dijk, et al., 2017; Beck, Vergopolan, et al., 2017; Beck et al., 2018; Beck et al., 2019) and air temperature data from the Princeton Global Forcing (PGF, Sheffield et al., 2006) provided by the Lake Chad Basin Flood and Drought Monitor System platform (CHADFDM; Amani et al., 2021; Sheffield et al., 2014). The CHADFDM was developed for hydrologic applications by Princeton University in collaboration with ICIWaRM (International Center for Water Resources Management) and UNESCO-IHP.

The ultimate goal is to assess the suitability of satellite products (based in a user-friendly platform CHADFDM) to develop spatially and temporally estimates of groundwater recharge for regional management studies with the goal of stakeholder use in mind. This analysis essentially provides 'a controlled experiment' to assess the effects of changes driven only by running the model varying data input from the two sources. The recharge estimations were carried out for the 2005–2014 period. he reliability and uncertainty of the estimated recharge values in the non-irrigated area from the two data sources as regards climate and soil parameters were evaluated by a sensitivity analysis of the model parameters.

## 2 | STUDY AREA

The study area is located in the north-western part of the Lake Chad basin system, which covers an area of about 155 000 km$^2$ of the basin in Chad, Niger and Nigeria (Figure 1). The Lake Chad size is highly variable across seasons and years explained by rainfall variations over its basin, which lead to a wide variability in river flows and lake input, particularly over the Chari-Logone River Basin, which may account for about 95% of the water inflows to the lake. At regional level, aquifer exchanges with surface water and diffuse recharge constitute the main control mechanism of groundwater level. This region is categorized as arid to semiarid, with a main rainfall season between April and September. Average annual precipitation ranges from 20 to 600 mm, daily temperatures between 8 and 45°C, and mean annual potential evaporation exceeds 2000 mm (LCBC-GIZ, 2016; Mahmood & Jia, 2018). A succession of dry periods in the last 100 years has led to a severe depletion of the lake area from 22 000 km$^2$ to 8 000 km$^2$ today, which has drastically reduced the extension of seasonally inundated river plains. The associated impact on infiltration and groundwater recharge remains unknown, but is likely important.

The region is relatively flat with gentle slopes (10%) from the highlands in the NW towards the SE. Land cover is grassland (65%), bare land (20%), sparse vegetation (5% e.g., acacias) and croplands (rain fed and irrigated, 10%) (LCBC-GIZ, 2016). Non-irrigated crops are millet, sorghum, corn and rice. In the studied area, crop irrigation (5000 mm/yr, mainly peppers; LCBC-IRD, 2016) is done by combining groundwater and surface water from Yobe river and covers approximately 21 295 km$^2$.

On the regional scale, the geology of the study area consists of materials from the Precambrian, Mesozoic (Cretaceous), and Plio-Quaternary (BRGM, 1994; Burke, 1976; Schneider, 1989; Schneider & Wolff, 1992). The Cretaceous is predominantly continental and, along with Miocene formations, it is known as the Continental Terminal. Plio-Quaternary deposits comprise fluvio-lacustrine, fluvio-deltaic and aeolian material. Outcrops of igneous rocks complete the geology in the region. From a hydrogeological point of view, three aquifers are distinguished in the area (Schneider & Wolff, 1992), Quaternary, Lower Pliocene and Continental Terminal, and are mainly confined. Only the groundwater recharge to the Quaternary upper unconfined aquifer is the objective of this research work (Figure 1).

## 3 | METHODOLOGY

A soil water balance modelling approach was applied to estimate the groundwater diffuse recharge to the Quaternary unconfined aquifer for the 2005–2014 period. For modelling purposes, the model was set up and the values of the plant–soil-hydrologic parameters remained

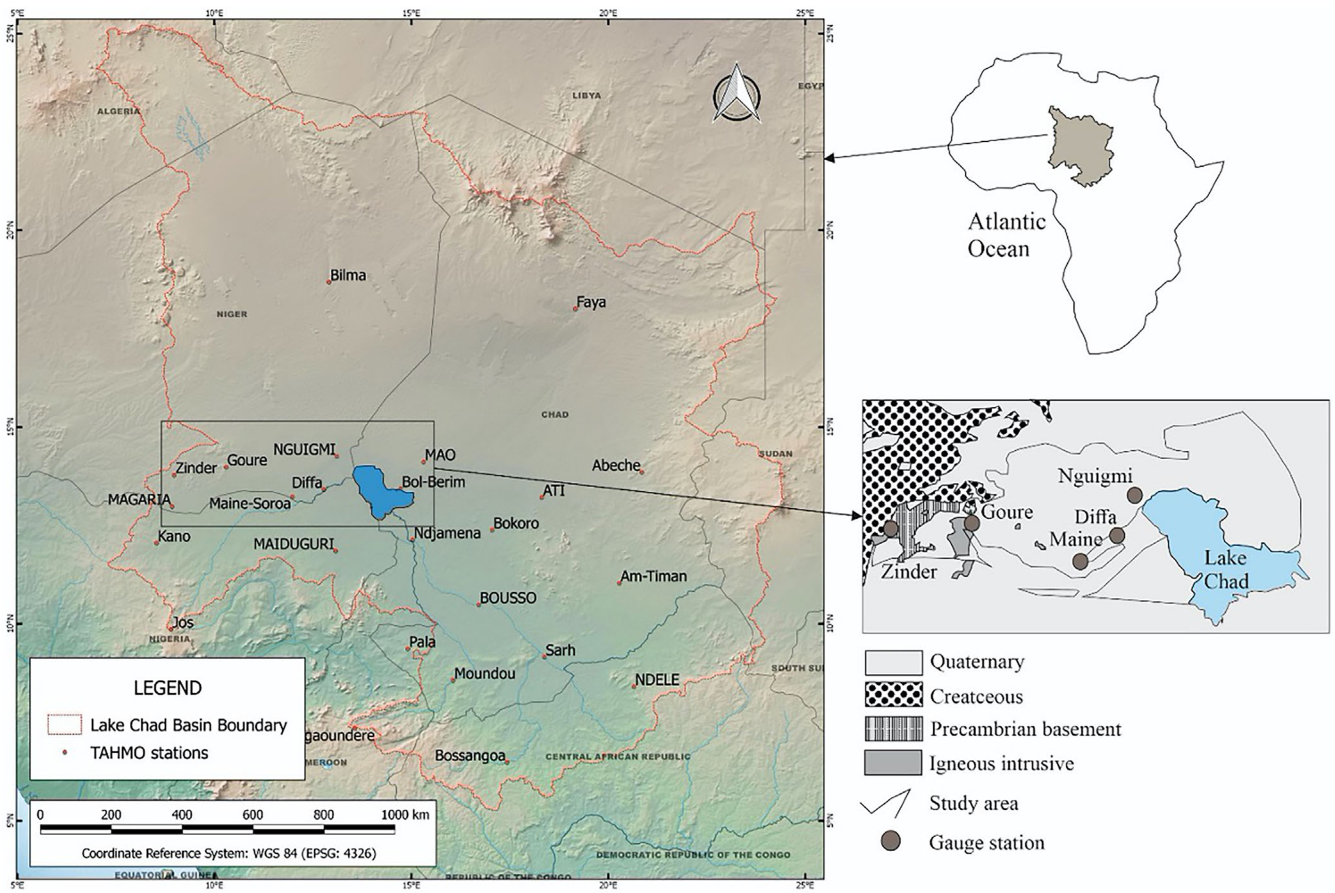


**FIGURE 1** The Lake Chad Basin and location of the study area. Existing ground-based meteorological stations are indicated on the map

invariant as only the climatological data inputs were modified. Two sources of precipitation (*P*) and air temperature (*T*) data were used: (i) ground-based data from the selected local meteorological stations; (ii) satellite-based rainfall and air temperature data downloaded from the CHADFDM (Amani et al., 2021; Sheffield et al., 2014) for the same time period and geographical location (coordinates) of the field stations. The *P* and *T* data downloaded from the CHADFDM platform are always referred to as satellite data throughout the text.

The exploratory inspection for the 9-year series of meteorological daily data of each data source involved an analysis with simple descriptive statistics (mean, median, mode, standard deviation). Out-of-sample testing was conducted to assess if the statistical analysis results could be generalized to an independent dataset. The *P* and *T* data deriving from the CHADFDM were checked against the ground data to evaluate temporal hydrological patterns, to validate assumptions and to compare the results. A dependence assessment (correlation) between the two datasets was made with a regression analysis and goodness-of-fit was assessed by the coefficient of determination ($R^2$) to identify the possible presence of trends. Annual precipitation as cumulative deviation from the mean was calculated. Finally, a statistical data analysis was carried out with the EXCEL Analysis Toolpack 2013 (Microsoft®). A sensitivity analysis was also carried out on the aquifer recharge estimations for the non-irrigated area.

### 3.1 | Soil water balance model description

Aquifer recharge was calculated using VisualBALAN v.2.0 (Samper et al., 2005), a numerical model to simulate water balance in soil, vadose zone and aquifer with a user-friendly modular design. It requires specific information on climate, land use, land cover and topography to simulate recharge process. This numerical tool has been successfully applied in different areas (e.g., Candela et al., 2016; Jiménez-Martínez et al., 2010, among many others).

The model is divided into three sub models (Figure 2), which considers the processes in: (i) the upper part of soil (root zone) to solve the critical interactions of the soil–plant–atmosphere continuum; (ii) the vadose or unsaturated zone (below the root zone); (iii) the saturated zone (aquifer). The water balance (in water depth) for a vegetated soil is represented by:

$$P + Ir - In - Es - ETa - R = \Delta\theta.$$

where *P* (mm) represents precipitation, *Ir* (mm) irrigation, *In* (mm) canopy interception, *Es* (mm) runoff, *ETa* (mm) actual evapotranspiration, *R* (mm) potential recharge to the vadose zone and $\Delta\theta$ variation in soil water storage (mm).

Precipitation (*P*) and irrigation (*Ir*) are distributed between surface runoff and infiltration. The *In* volume is a fraction of the precipitation intercepted by vegetation (leaves, branches, trunks) to deal with water

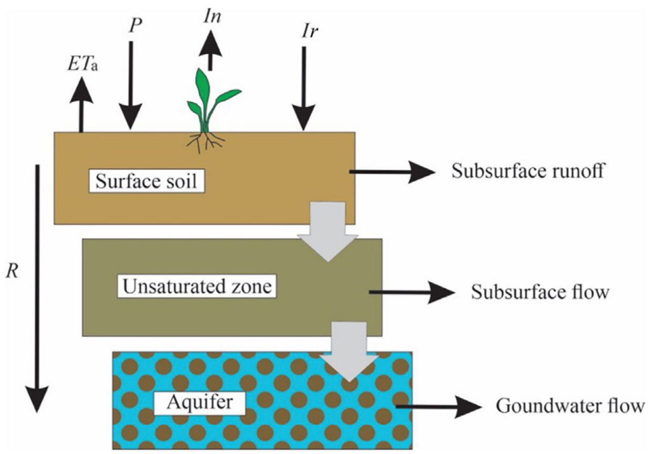


**FIGURE 2** VisualBALAN conceptual model (adapted after Samper et al., 2005), where the nomenclature denotes: *P* precipitation, *Ir* irrigation, *In* interception, *ET*a actual evapotranspiration, *R* aquifer recharge

loss by evaporation. The residual water after evapotranspiration, infiltration term *I* (mm), was included in the water balance equations as:

$$I - (ETa - R) = \Delta\theta$$
$$P + Ir - In - Es = I$$

Part of infiltration comes back to the atmosphere by evapotranspiration (*ET*a), another part increases the water content in soil and the rest contributes to potential recharge, the water input in the unsaturated zone. In this zone, flow direction can present a horizontal component as interflow, or can vertically percolate to the aquifer (*R*) (Figure 2).

The code allows the water balance to be solved in a multicell pattern by considering the defined zones, assumed homogeneous in relation to soil parameters land use, aquifer and meteorological data. The model simulates the temporal differences (between initial, $t_i$, and final time, $t_f$, $\Delta t = t_f - t_i$) of the actual evapotranspiration and groundwater recharge. The model outputs are the water balance components (runoff, interflow, vegetal interception, *ET*a, groundwater recharge) expressed as daily rates. The recharge is estimated according to the assumption of homogeneity and isotropy of soil. In the aquifer, the groundwater level is estimated for each $\Delta t$ by considering the entry of water by vertical flow. It also allows parameter calibration by comparing between the measured (observations) and estimated groundwater levels. A comprehensive explanation of the conceptual model and its corresponding parameters can be found in Jiménez-Martínez et al. (2010).

### 3.1.1 | Model setup

The current model requires some input parameters which include: geographical coordinates, daily precipitation and air temperature, vegetation types and spatial distribution, crops and irrigation provisions (i.e., time and volume), maximum root-depth (m), evapotranspiration (mm), physical soil characteristics like thickness (m), porosity (%), saturation ($m^3/m^3$), field capacity ($m^3/m^3$), wilting point ($m^3/m^3$), and vertical hydraulic conductivity (m/day) and Curve Number (*CN*, non-dimensional). The state variable is water volume, expressed as volume per surface unit (e.g., L/$m^2$ or $m^3/m^2$) or equivalent height of water (e.g., mm). For instance, the water volume in soil is the product of saturation and soil thickness.

Surface components daily irrigation (*I*) and precipitation (*P*) rates are the main input variables. The water needs of each crop were extracted from Allen et al. (1998). Runoff, *Es*, is estimated from the Curve Number method (Soil Conservation Service, 1975) based on loss and precipitation ratios; the *CN* values, directly selected from the VisualBALAN data base on *CN*s for most general land-cover and hydrologic soil group, and from existing spatial information of topography and vegetation cover in the study area. Interception, *In*, derived from the method of Horton. Daily potential evapotranspiration (*ET*p) was computed by the Thornthwaite method (Thornthwaite & Holzman, 1939), suitable for data scarcity regions because of its very low data demanding character (Yang et al., 2017). Note that potential evapotranspiration estimated with the Thorthwaite formula tend to be short in vegetated arid environments (Tukimat et al., 2012).

Model parameterization uses datasets on topography, land cover and soil type. Soil-aquifer parameters (porosity, hydraulic conductivity, storage coefficient, field capacity, wilting point, soil depth) and plant parameters (height, interception coefficient) complete the system as main inputs. Processes in the saturated zone (aquifer) were not included by assuming that the infiltrated water through the vadose zone reached a depth beyond the action of roots and evaporation, which becomes direct infiltration to the aquifer.

For the model setup, the land surface topography (elevation and slope) was obtained from a 30 × 30 m Digital Elevation Model-DEM (ASTER GDEM 2.0) from NASA Earthdata (GDEM2). The digital elevation model (DEM) is used for slope and elevation. Land use and land physical coverage were supplied by The European Space Centre (ESA, CCI land cover – S2 prototype land cover 20 M map of Africa, 2016). Soil-related information (e.g., clay and silt content, hydrological soil group) was acquired from the European Soil Data Centre (ESDAC), European Commission – Joint Research Centre (Jones et al., 2013) and the literature. Homogeneous loamy sand was considered the main soil type, according to the United Sates Department of Agriculture–USDA Soil Textural Classification (Gaultier, 2004; LCBC-IRD, 2016). Soil-aquifer parameters were obtained from the works of Leblanc (2002), Gaultier (2004) and Zaïri (2008).

Finally, six digital base maps were produced (climate, slope, land cover, cultivated crops, aquifers, soil attributes) and overlaid using GIS tools to create a final base map for recharge calculations by solving the water balance equation in a multicell pattern.

## 3.2 | Climate datasets

The meteorological data inputs for the period 2005–2014 for the model were the daily air temperature (°C) and precipitation (mm) time series reported from five ground stations in the study region (Diffa, Goure, Maine, Nguigmi, Zinder) and CHADFDM data (satellite-based) for the same locations and period.

#### 3.2.1 | Ground data

Ground-based time series from local meteorological stations were directly compiled from the TAHMO platform (Figure 1). For the historic data record (1973–2018), the study period (2005–2014) was chosen as that presenting the fewest gaps ( ≤ 20%) in the precipitation and air temperature time series. The 9-year length of the dataset enabled the variability in daily precipitation and air temperature in the region to be captured.

The representativeness of the available dataset included: assessment of missing values, accuracy of measurements (inaccuracy of the amount of precipitation), stationarity and homogeneity (changes to stations, relocation of stations, among others). To complete the missing rainfall data, Inverse Distance Weighting was applied, based on four rain-gauge stations in the vicinity of the analysed station (Lam, 1983). Thiessen Polygon was used to estimate the average rainfall over the area.

#### 3.2.2 | Satellite-based rainfall and air temperature data from the CHADFDM

The Multi-Source Weighted-Ensemble Precipitation (MSWEP v2.1; Beck et al., 2018), a fully global historic precipitation dataset developed by Princeton University, was selected as the source for the satellite-based data, based on the data availability for the region of interest. MSWEP is produced as 3-hourly and monthly data, 0.1-degree, by merging a set of about 12 satellite and reanalysis datasets; 0.1-degree is the highest resolution that is presently supportable from these datasets and is typical of other similar satellite-based datasets that range from about 0.05-degree (e.g., CHIRPS, PERSIANN-CCS) to 0.25-degree (e.g., TMPA). MSWEP provides reliable rainfall estimates by taking advantage of the complementary strengths of gauge, satellite, and reanalysis-based data (Beck et al., 2019). The dataset includes daily gauge corrections, and systematic biases (e.g., from the orographical enhancement of precipitation) are corrected using readily available gauge data observations (about 25 gauges in the Lake Chad Basin) with enough quality (long record, filtered for spurious values, adjusted for reporting times, and no step changes) and by comparing to other satellite-based products (Beck et al., 2018; Beck, van Dijk, et al., 2017; Beck, Vergopolan, et al., 2017). Air temperature data is taken from the Princeton Global Forcing dataset (PGF, Sheffield et al., 2006), which merges satellite, reanalysis and gridded gauge data to produce a 0.25-degree, 3-hourly, global product. Both datasets were downloaded from the CHADFDM.

### 3.3 | Sensitivity analysis

Knowledge of the model parameters, and their statistical variability and correlation structure, is a key aspect to quantify the effect of uncertainties on recharge estimates according to the used data source to define the boundary condition, that is, ground- or satellite-based. The importance of the parameter uncertainties on recharge can be evaluated as the objective function by a sensitivity analysis (Jiménez-Martínez et al., 2010). To this end, several simulations were run on individual model parameters modified by a given amount of perturbation ($\pm$25% of the original value), and by estimating the groundwater recharge for both sources of precipitation and air temperature used to define the boundary condition.

## 4 | RESULTS

### 4.1 | Ground- versus satellite-based datasets

For the selected 2005–2014 time period, three of the five ground-based stations (Figure 1; Nguigmi, Zinder and Maine) had complete daily air temperature and precipitation records, while Goure and Diffa presented 3.3% and 2.5% missing precipitation values, respectively. Occasionally, one station can have higher precipitation values than nearby stations for one particular year when most annual amounts fall during one rainfall event or two.

On a daily scale, the rainfall measured at the five meteorological ground stations presented less variability in the recorded amount than the satellite-based data at the same locations (Earth coordinates) (Figure 3). The maximum rainfall occurs during the June–October period, with the values recorded at gauges being the highest. For the 2005–2014 period (Table 1), the satellite-based mean annual precipitation (417 mm) was 46% higher than the ground observations (284 mm). However, the air temperature values for both time series (TAHMO and satellite) well agreed, and ranged between 15°C and 40°C (average 29°C).

At the monthly scale, the satellite data generally overestimated the amount of ground-based precipitation (Figure 4), except for the two heavy (extreme) rain events recorded at the Diffa (August 2008: 440 mm) and Zinder (August 2011: 411 mm) weather stations. A similar effect, but with generally higher values for satellite records compared to the ground data, have been reported by some authors (McCollum et al., 1999; Mehran & AghaKouchak, 2013; Nogueira et al., 2018; Young et al., 2014).

Between the ground- (gauged) and satellite-based data sources, annual rainfall varies according to location, and wet and dry condition distribution appears to be different (Figure 5(a),(b)). The wettest and driest years of the period took place in 2008 (600 mm) and 2006 (10 mm) for the ground data, and in 2006 (920 mm) and 2011 (200 mm) for the satellite data, respectively. An inspection of the cumulative deviation of precipitation from the mean (Figure 5(c),(d)) revealed no significant trend on the annual scale.

For the months with continuous rainfall (July to September), the ground-based rainfall versus satellite-based, average daily data and average monthly data, are plotted in Figure 6. On a daily basis, the ground and satellite rainfall data relation analysis (Figure 6(a)) did not present any correlation ($R^2 = 0.06$) between datasets; a poor regression fit may arise from high scatter in data by considering all the recorded values throughout the hydrologic year. By arranging datasets

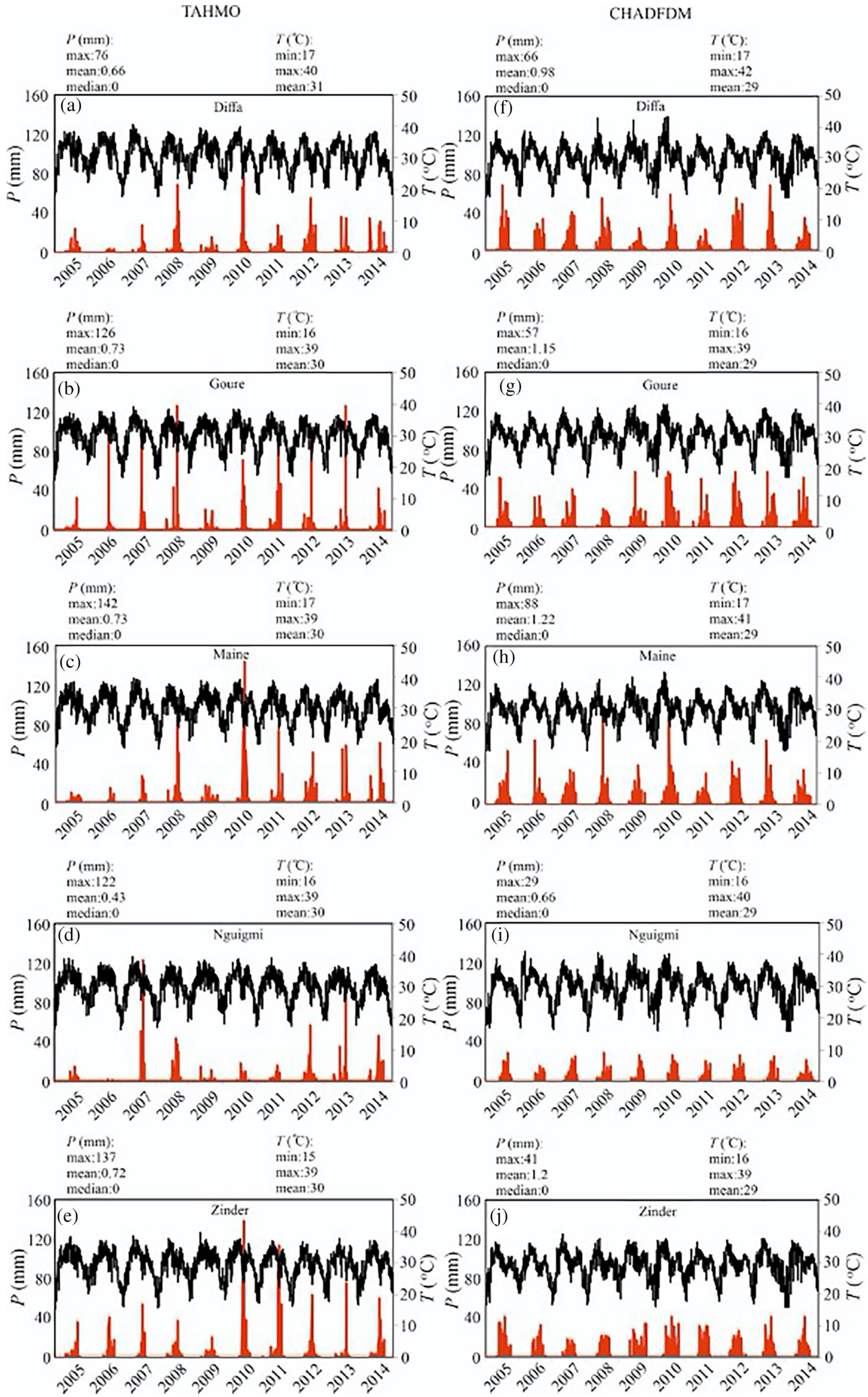


**FIGURE 3** Daily precipitation (*P*, red) and temperature (*T*, black) for the (a–e) five selected ground-based stations, and TAHMO and (f–j) CHADFMD outputs at the same earth coordinate locations (rainfall and temperature data)

**TABLE 1** Annual (mm/yr) and total recharge (*R*, mm) estimates for the study period (2005–2014) from the ground-based stations (TAHMO) and CHADFDM (satellite-based data) in the irrigated and non-irrigated areas. *P* denotes precipitation and *ET*a evapotranspiration

| Data source | Total *P* (mm) | Average *P* (mm/yr) | Total *ET*a (mm) | Average *ET*a (mm/yr) | Total *R* Non-irrigated (mm) | Average *R* Non-irrigated (mm/yr) | Total *R* irrigated (mm) | Average *R* Irrigated (mm/yr)) |
|---|---|---|---|---|---|---|---|---|
| Ground | 2555 | 283.9 | 2244 | 250 | 90.8 | 10.0 | 302.1 | 33.5 |
| Satellite | 3754 | 417.1 | 3363 | 375 | 132.7 | 14.7 | 374.4 | 41.6 |
| % of ground gauges | +46 | +46 | +33 | +33 | +46 | +46 | +23 | +23 |

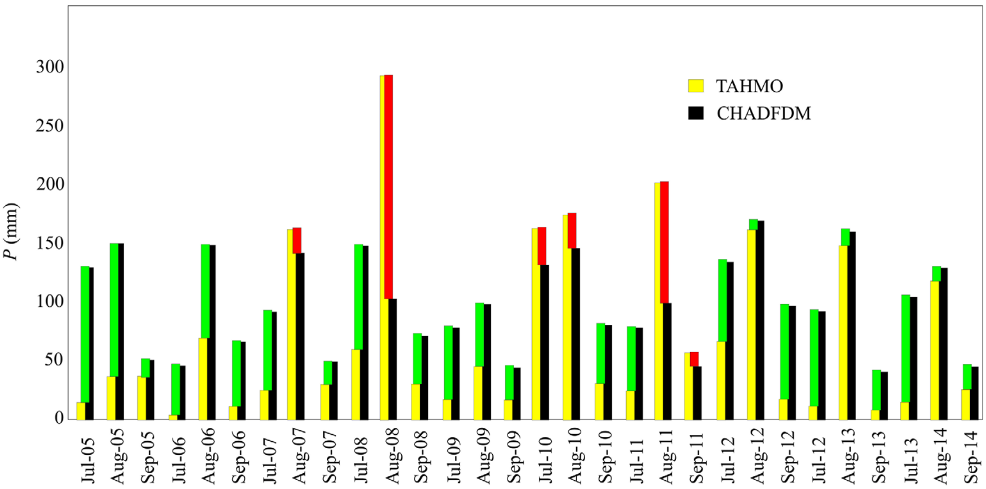


**FIGURE 4** Monthly average precipitation (mm) from both ground-based stations and satellite-based data at the same locations (earth coordinates). Red bars indicate months with higher TAHMO values than CHADFDM ones. Green bars depict the opposite

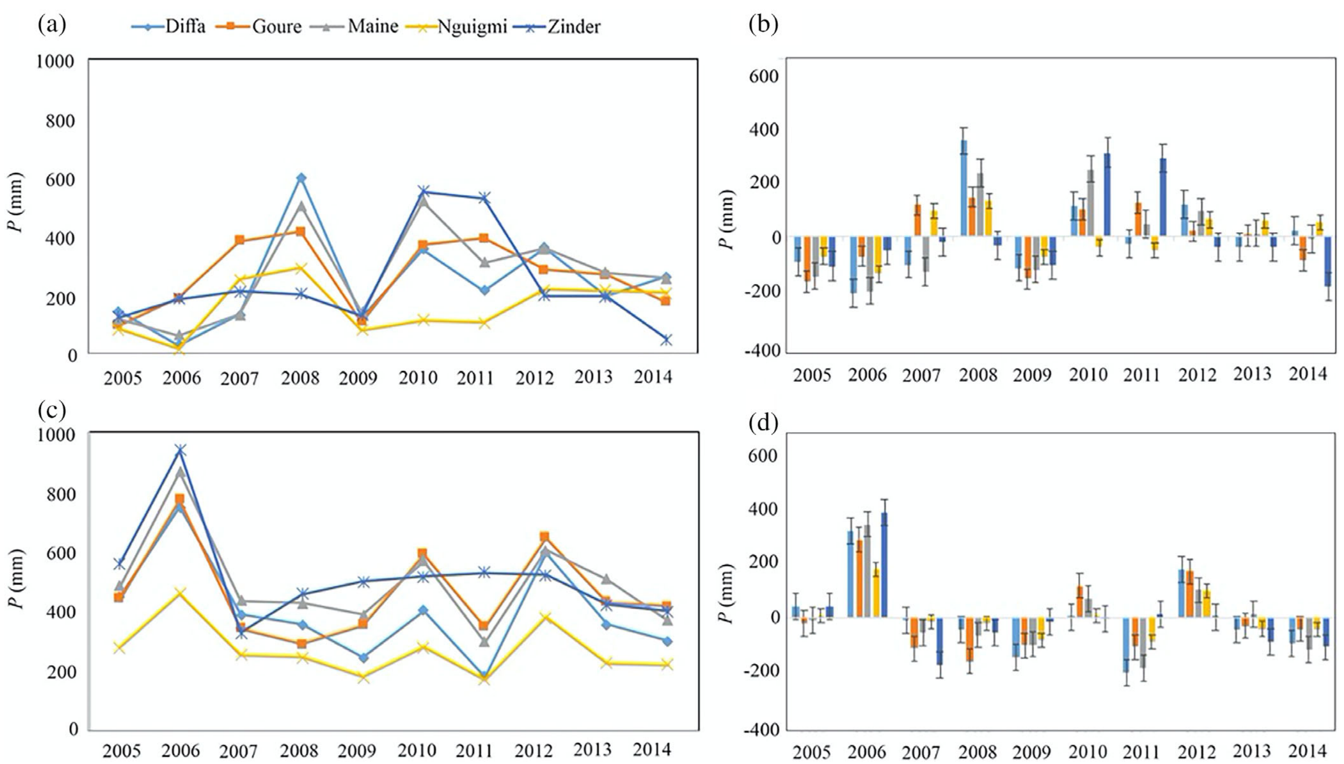


**FIGURE 5** Annual precipitation (left) and cumulative deviation from the mean (right) for ground (a–b, TAHMO) and satellite-based (c–d, CHADFDM) data (2005–2014 period)

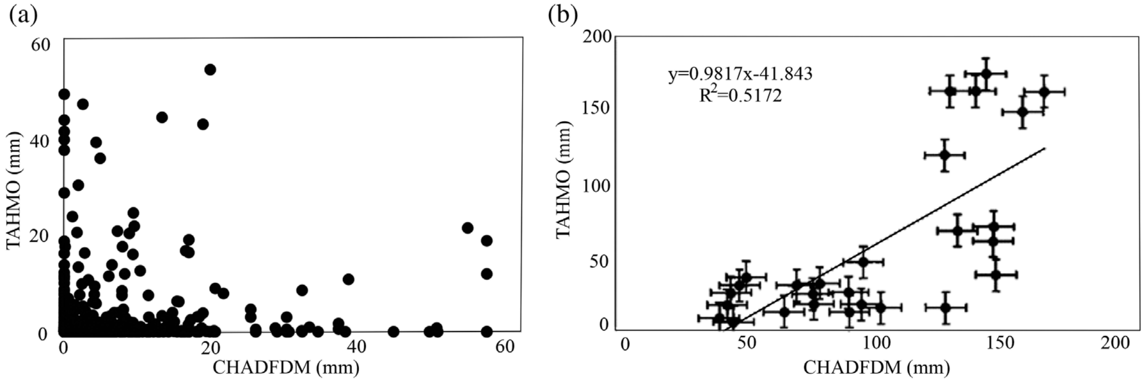


**FIGURE 6** Rainfall data, ground (TAHMO) versus satellite (CHADFDM): (a) average daily data; (b) average monthly data for months with continuous rainfall (July to September)

from daily to monthly scales (change in time interval), and by focusing on months with high precipitation (July–August–September), scatter reduced, while the correlation increased ($R^2 = 0.51$). The data aggregation clearly smooths out the differences between both data sources. Moreover, it was noted that the performance of the products is largely scale and geographic location dependent. Most of the presently applied products showed comparatively good skills on the seasonal scale ($R^2 > 0.90$) rather than at annual scale (Atiah et al., 2020). This indicates that satellite data should be improved taking into account the type of precipitation (i.e., intensity), and for that a minimum of daily resolution is required.

### 4.2 | Recharge estimation

Two groundwater recharge types were assessed in the study area: (i) from precipitation; (ii) resulting from the precipitation and irrigation combination in irrigated areas. Calculated daily recharge and real evapotranspiration for irrigated areas and the study duration (2005–2014) are shown in Figure 7 from both ground-based stations and satellite results. The estimated mean annual recharge from precipitation equalled 10 mm/yr and 14.7 mm/yr for the ground- and satellite-based data, respectively (Table 1). Differences were marked in extremely dry and wet years, such as 2006 (9 and 20 mm/yr for the ground- and satellite-based data, respectively) and 2008 (15 and 12 mm/yr for the ground- and satellite-based data, respectively). The computed mean annual aquifer recharge in the irrigated areas ($P + I$) was 33.5 mm/yr and 41.6 mm/yr for the ground- and satellite-based data, respectively.

To better assess the recharge process, a daily recharge estimation in the area for the non-irrigated and irrigated areas, and from the two *P* and *T* datasets, was calculated for 2012 (Figure 8). Year selection was based on data availability, smallest gaps and amount of precipitation (282 mm), similarly to the average precipitation for all whole 2005–2014 period. In both the non-irrigated and irrigated areas, recharge takes place mainly during the wet season, between June and October. Recharge response to rainfall events was most variable (Figure 8(a),(b)), and somewhat independent of the amount of rainfall and changes over time, but was strongly conditioned by antecedent soil moisture condition, and highly dependent on precipitation distribution over both time and space. For the ground-based calculations, recharge only occurred after one important rainfall episode (more than 100 mm on 2 days, Figure 8(a)) with a peak after 3 days of continuous rainfall. Groundwater recharge differs spatially as a result of climatic and physical characteristics including precipitation pattern, soil type, porosity of vadose zone, depth to groundwater and hydrogeology. In arid and semiarid environments, groundwater recharge appears to occur during intense precipitation events as compared to other environments described as having a mix of constant-rate and episodic behaviours and often conditioned by preferential flow (De Vries & Simmers, 2002).

### 4.3 | Sensitivity analysis

A series of simulations were performed by perturbing (were multiplied by 10%, 15%, 20% and 25% test-factors, from $-25\%$ to $+25\%$ in magnitude) the model parameters. The test included: field capacity, wilting point, soil thickness, soil porosity, soil hydraulic conductivity, curve number and initial conditions (initial soil water content) to evaluate the impact on aquifer recharge estimates. The model was run repeatedly changing each test-factor to evaluate the impact on aquifer recharge estimates by relative change in each input parameter.

For the loamy sand soil in the area, the initially considered parameters were: field capacity, 0.1 ($m^3/m^3$); wilting point 0.05 ($m^3/m^3$); soil thickness, 6 m; soil total porosity, 0.42; soil hydraulic conductivity $2 \times 10^{-5}$ (m/s); curve number (*CN*), 77. The boundary conditions (temperature, precipitation, irrigation) were left at the baseline values. Then the effect of perturbations on estimated aquifer recharge in relation to the baseline estimation was evaluated (Figure 9).

The results showed for both the ground- and satellite-based data that only the changes or uncertainties in field capacity, wilting point, and curve number led to significant changes in the aquifer recharge estimations (Figure 9). A 25% increase in wilting point led to a 1.6%

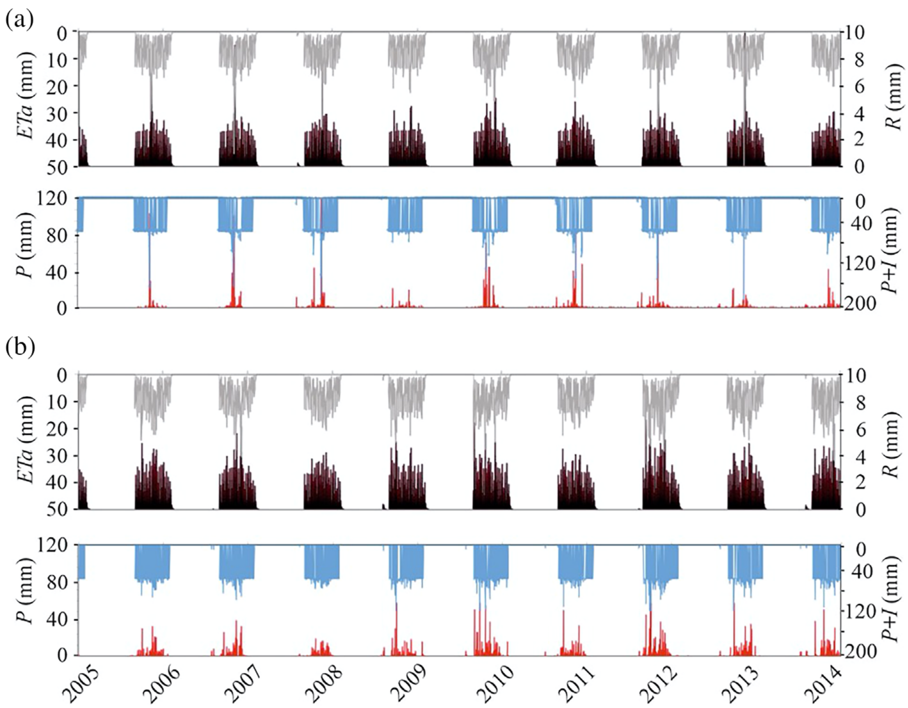


**FIGURE 7** Calculated daily recharge (*R*, black) and actual evapotranspiration (*ETa*, grey) for irrigated areas and the study period (2005–2014) from the (a) ground-based stations and (b) satellite-based data. Daily precipitation (*P*, red) and irrigation (*Ir*, blue) are also shown. The irrigation applied according to crop water needs and data provided for the study area

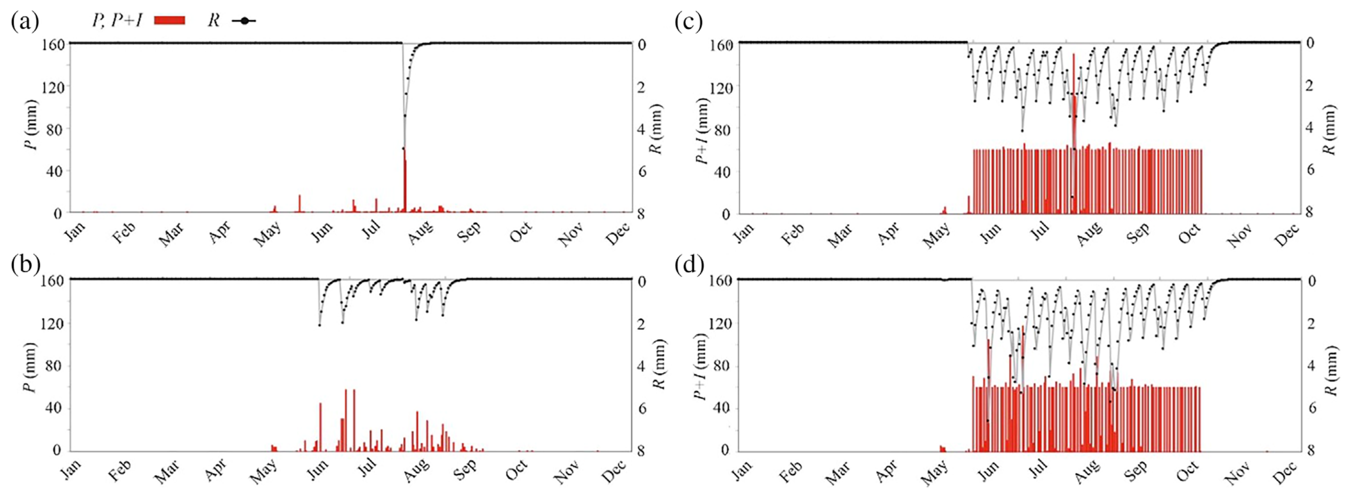


**FIGURE 8** Computed daily recharge (mm) for the non-irrigated (a, b) and irrigated (c, d) areas for 2012 from the ground-based stations (upper row) and satellite-based data (lower row)

increase in recharge for the ground and 4.4% for the satellite data. The perturbation of the curve number resulted in a different magnitude of recharge and differed depending on the magnitude of the perturbation between the ground-based stations and satellite-based data. Changes in porosity (soil thickness and hydraulic conductivity; neither is shown here) had a much less impact on computed recharge.

## 5 | DISCUSSION

Climate forcing functions (precipitation and temperature, important system driving forces), soil and vegetation variables availability and the non-linearity of recharge processes are the most important obstacles for recharge estimations in arid and semiarid areas, where they predominantly concentrated in the short term.

The comparison between the two rainfall dataset sources (ground and satellite) showed that a bigger amount of precipitation and a relatively time-homogeneous precipitation distribution occurred from the satellite data source in relation to the ground data. Satellite derived data estimates may provide uncertain rates even when they contain information on spatial patterns and relative spatial distributions (Lucas et al., 2015). One explanation could be accounting for cloud microphysical processes (liquid water content, effective radius, and radar reflectivity) in the satellite-based data, and the moisture distribution

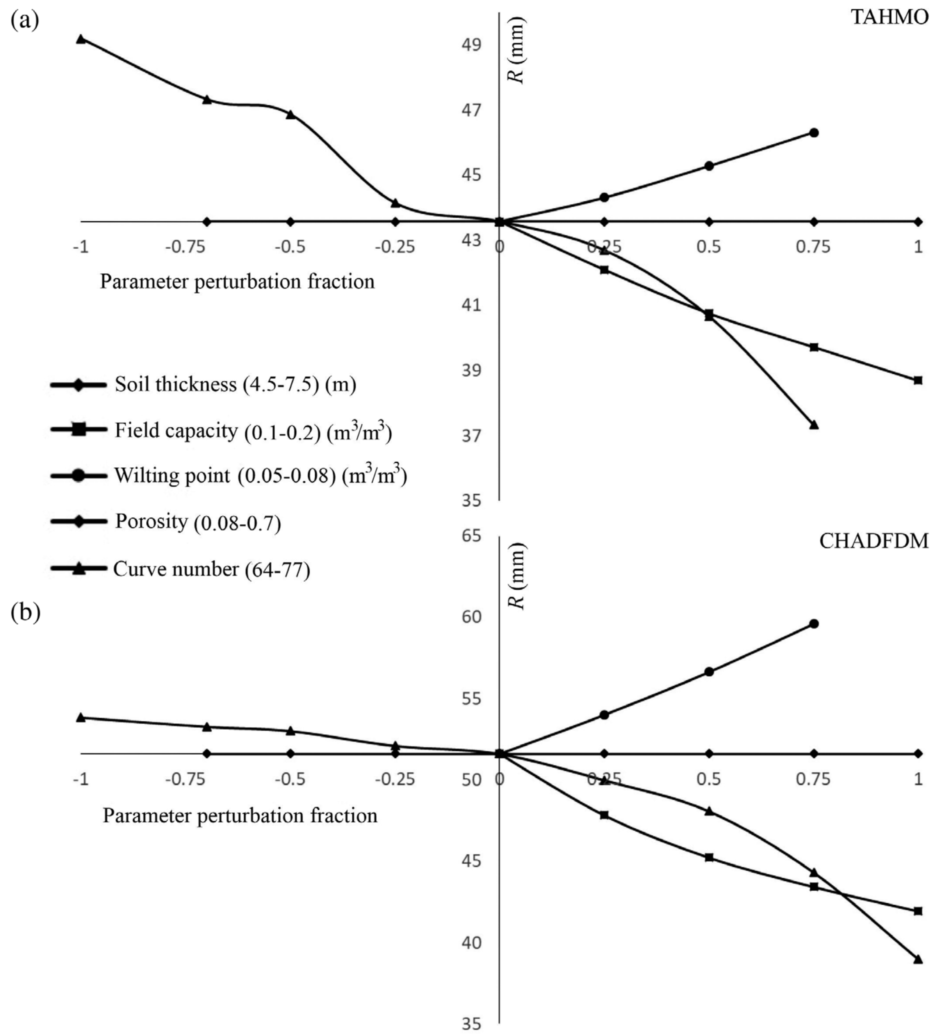


**FIGURE 9** Irrigated area. Sensitivity analysis of aquifer recharge to the soil parameters for the ground-TAHMO (a) and satellite-based-CHADFDM (b) data. The numbers in brackets are the range of variation for parameters

of the environment (Gao et al., 2014; McCollum et al., 1999). In particular, the overestimation by infrared-based satellite retrieval algorithms (which contribute to MSWEP) was attributed to rainless cirrus with a cold cloud-top temperature (Young et al., 2014). For the ground-based data, misleading results cannot be ruled out due to possible changes in observation practices, equipment, and location. Systematic biases are possible in rain gauge-based gridded precipitation products. Wind-induced precipitation under gauge catchment, evaporation losses and wetting losses are examples of estimation biases. In general, the bias due to wind-induced precipitation under catchment is the most important (Masuda et al., 2019). The air temperature from satellite and field observations presented a high degree of similarity.

The annual and total recharges (dryland) estimated on the daily scale by VisualBALAN from the satellite data were 46% higher than the results obtained from ground stations. As expected, the highest rates for the recharge from the satellite-based data were primarily due to more abundant precipitation, while the amount of evapotranspiration was similar, which resulted in much more readily available water to infiltrate. Nevertheless, owing to the episodic aspect of recharge in arid areas, small changes in precipitation rate may affect groundwater recharge (Thomas et al., 2016), besides in non-vegetated areas vapour diffusion in the soil may overcome plant root transpiration. An attempt of recharge estimation after bias-correction of CHADFDM precipitation data set (only one gauge station,Supplementary material) shows that obtained result is 9% greater than the obtained from ground-based data, for Diffa location. As regards the annual ground-based recharge results (Table 1), values ranging between 15 mm/yr and 50 mm/yr have been obtained by other authors who worked in this area (Edmunds et al., 1998; Leblanc, 2002; Ngounou Ngatcha, Mudry, & Sarrot-Reynauld, 2007) mainly based on isotopic and numerical methods. Between 5% and 10% of the rainfall by Leduc and Desconnets (1994), and also from running the numerical groundwater flow model of the Basin for the same time period (WB, 2020). The data also agree with the aquifer recharge estimations (1–30% of precipitation) in arid and semiarid regions worldwide (Carter et al., 1994; de Vries et al., 2000) as found 14.89% and 13.53% of the rainfall in Brazil (Coelho et al., 2017), 10.8% of total rainfall in Iran (Ebrahimi et al., 2016).

In the irrigated areas, with irrigation applied to account for 5000 mm/yr, while the precipitation from the ground- and satellite-based data remained invariant (Table 1), the recharge difference from both datasets was ∼23%, which was much lower than between the precipitation values (46%), a finding that evidences the non-linearity of recharge processes. Although precipitation from the satellite-based data, and therefore $P + I$, were higher, the actual evapotranspiration was almost double compared to the values computed from the ground data (Figure 7; *ET*a, grey). A detailed observation of the process that controlled recharge indicated that most important parameters were irrigation dose and application frequency (Figure 8(c),(d)). Cyclical variability was also observed as a response of irrigation application. The effect of rainfall events was less influential in irrigated than on the -non-irrigated areas.

Previous studies conducted in irrigated zones for semiarid climates have shown that irrigation return can vary between 1% and 25% of the applied water, with an average of ~15% (Scanlon et al., 2006). The values herein obtained fell within this range (1–13%). Genthon et al. (2015) have also demonstrated that this recharge was supposed to take place during the irrigation cycles. The effect of irrigation methods on groundwater recharge is critical and generally under the water conservation methods, only after a very significant rainfall occurrence deep drainage contributing to groundwater recharge occurs (Porhemmat et al., 2018). Under water-saving irrigation systems in arid and semiarid zones, the absence of significant rainfall occurrences between irrigations reduced recharge (Jiménez-Martínez et al., 2010).

Sensitivity analysis identified the effects of different input parameters helping to elucidate potential uncertainties on obtained recharge. Wilting point and field capacity are key parameters of water holding capacity and depending on soil texture. Spatial variability of soil texture (sands or clay-silt soil type) would imply different recharge rates areal distribution. Although changes in the mean annual recharge due to perturbations in wilting point and field capacity were linear and quasi-linear, showing positive and negative slope as perturbation increases, respectively, magnitude was not the same for the ground stations and satellite-based data. Curve number, for runoff estimation, exhibited different behaviour for both data source; recharge dependence on *CN* was higher for the ground-based data characterized by wider precipitation variability and the existence of rainfall events. The Curve Number equation empirically describes the runoff amount from a rainfall event and potential soil water retention. It is based on data collection from different sites, and published values can only approximate actual runoff conditions at field sites being the *CN* appropriate for use at watershed scale (Westenbroek et al., 2018). In the area, gauged watersheds do not exist and field data measurement are not available for runoff validation.

Uncertainties from input datasets could affect model final results. Lack of groundwater level observations in the area to assess the relation between the simulated aquifer recharge and observed groundwater levels did not allowed for model calibration and model performance assessments. Nevertheless, as the vegetation and soil-aquifer parameters remained invariant to run the model independently of the data base, recharge dependence relied on mainly climate parameters (*P* and *T*) and related soil water conditions. Therefore, the obtained results did not invalidate the findings.

## 6 | CONCLUSIONS

Reliable aquifer recharge estimations are crucial for assessing and managing groundwater resources, and their role will become even more important if further climate change and variability impacts restrain increasing demand. Since groundwater is one of the key sources of irrigation in arid and semiarid regions, the recharge estimation is also crucial for ensuring future groundwater supply and usage.

Climate, vegetation and soil-related parameters are the most important parameters to condition groundwater recharge. Precise ground-based daily data on amount of precipitation and temperature are difficult to obtain in some areas, while remote sensing data sources can provide continuous estimates of these variables. However, the differences in precipitation rates and rainfall distribution, and therefore on recharge estimates, between weighted-ensemble satellite-based data and ground-based data indicate that a comparative analysis is needed to establish a range of possible real values; beyond the uncertainty related to the considered model parameters, it may provide initial estimations for groundwater numerical modelling, among other applications.

For the Lake Chad aquifer system, one of the largest aquifers of the world, groundwater has a significant importance as a source for water supply and irrigation, especially in the northern part. For the basin-wide, diffuse recharge of aquifer system from precipitation is the main water source and it mainly takes place on southern margins and in the dune systems. Estimates for the Basin ranges between 0% and 13% of total precipitation (WB, 2020), with important spatial variability. Assessment of the groundwater renewal and vulnerability of the system involves recharge quantification from rainfall to the groundwater system. At regional level, the field data scarcity from unevenly distributed weather ground-based stations, its availability and possible related uncertainties to measured series, make the information from satellite products a useful data source for recharge estimation. As accurate assessment of recharge is limited by uncertainties derived from satellite data in a wide dry region where rainfall is localized and sporadic, development of user-friendly platforms providing relatively wide range of improved observations may constrain associated uncertainty.

In the semiarid Lake Chad Basin part, the analysis focused on understanding how different data sources could affect the amount of recharge because of the highly non-linear behaviour of the recharge process through soil. Aquifer recharge concentrates predominantly during short periods of time (rainy season from June to October) and is controlled mainly by climate factors such as precipitation, evapotranspiration and the few intense rainfall events, together with applied irrigation in agricultural areas. More precipitation does not necessarily imply a proportional increase in recharge as the actual evapotranspiration rate would also rise. As agricultural irrigation is generally carried out from surface water, implying more water availability from an external source, the obtained amount would reflect the combined effect (from dryland recharge plus irrigation return flow). Note that in those areas where water depth was close to the ground, the surface water table could also provide an additional source of water for evapotranspiration. As recharge very much depends on changes in the soil moisture condition over time, the almost uniform rainfall distribution with time from satellites also implies computing higher soil water content and a bigger amount of recharge.

In the Lake Chad Basin region and in other arid zones, where groundwater is the main water resource, accurate recharge estimates are essential for the knowledge of system hydrologic dynamics (input–output) and water availability. Also it is essential for establishing guiding planning and policy water management and ecosystems protection for sustainable long-term water resources management. A better understanding of recharge mechanisms will enormously contribute to the sustainability of groundwater exploitation rates across the basin. This fact is especially important if future land use changes and new agricultural developments require increased surface water and groundwater withdrawal.

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## DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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## SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of this article.

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