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Using the water balance approach to understand pool dynamics along non-perennial rivers in the semi-arid areas of South Africa

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ABSTRACT

Study region: The Touws River in the Klein Karoo region of South Africa
Study focus: This study sought to improve the understanding of pool dynamics along non-perennial rivers (NPRs) by utilising the water balance approach to assess the water fluxes that influence pool dynamics in the Touws River. The water balance model made use of various in-situ and satellite-derived data.
New hydrological insights: The analysis of the water losses from the pool showed that most of the water was lost through evaporation. The interaction between the pool and groundwater is dependent on the water levels, as the pool loses water to the subsurface up to a certain depth then it starts gaining. When the Wolverfontein 2 pool is full, it can retained water for approximately 258 days without having a surface water inflow. A water balance model was established, and it simulated the water levels with a high correlation of 0.9. This model was also evaluated in the neighbouring pools, and while it simulated the water levels of the upstream pool well, this was not the case for the downstream pool. When remote sensing-derived rainfall and evaporation data were used in the model, the simulated water levels had a slightly lower correlation of 0.7 with the observed water levels. Overall, the remotely sensing-based monthly fluxes estimates could not provide the detailed pool information that was required for the water balance. Errors may have arisen, or they may have been inherited, from any of the three remotely-sensed parameters, namely, the surface area, the rainfall or the evaporation. Although remote sensing did not provide detailed information, it is worth noting that it provides baseline information on the pool dynamics. Overall, this work underscores the relevance of multisource data and the water balance, it helps to better understand the pool dynamics and it will help with the better management of NPRs.

1. Introduction

Non-perennial rivers (NPRs) comprise all rivers that cease to flow for certain periods of the year. These occur globally and across all climatic zones and biomes (Messager et al., 2021), and their occurrence is increasing due to climate change, social-economic uses, and land-use effects. For some of the NPRs, when flows cease water occurs in pools along these rivers. These pools are of importance for

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aquatic life as refugia and surrounding communities as a source of water for livestock, garden watering and domestic use (Maswanganye et al., 2022). Pools occurring along NPRs have been recognised for their ecological importance (Ilhéu et al., 2020; Marshall et al., 2016; Sheldon et al., 2010). There is a relationship between the ecological state of pools and their hydrology. For example, Bonada et al. (2020) found that larger pools tend to have a higher species richness and abundance. Because of this, pools are often considered when determining environmental flows. There is, however, limited information about the nature and causes of spatio-temporal variations of water storage in pools (Bonada et al., 2020; Bourke et al., 2020; Shanafield et al., 2021). This knowledge gap constrains the formulation of appropriate management measures. Consequently, management decisions are made by extrapolating knowledge based on the spatiotemporal variations of water storage in lakes (Bonada et al., 2020; Maswanganye et al., 2021). Shanafield et al. (2021) recommended the need to improve the understanding of the persistence of pools and how they are impacted by climatic shifts and groundwater abstractions. Furthermore, the communities that utilise these pools need information for allocation and planning purposes; for example, how long will it take for them to dry up (Ali et al., 2015).

Routine monitoring of water storage in pools along NPRs has not been included in most national hydrological monitoring systems, partly because these systems are often considered to have low value (Rodríguez-Lozano et al., 2020), and due to the absence of adequate financial resources. There are also physical limitations, as some of these pools are not easily accessible, and some may disappear after flow events, depending on river-bed material (Hattingh, 2020; Maswanganye et al., 2022). However, very few studies have shown that remote sensing can provide useful information about these pools, including their spatial distribution and size (Maswanganye et al., 2021; Seaton et al., 2020). Maswanganye et al. (2022) found that river flows are the major controlling factor of pool dynamics and suggested that rainfall is important for delaying the drying out of pools in the semi-arid and arid environments of South Africa. However, the study also expressed that there is a need to assess pools in detail, in order to gain a better understanding of their hydrodynamics.

Several methods can be applied for assessing the pool water fluxes. These methods include direct measurements (LaBaugh et al., 2016), as well as linear and multiple regression (Stasik et al., 2020). Although direct measurements are accurate, the limited availability of data on some components remains challenging, due to the complexity associated with field measurements and monitoring. For instance, it is challenging to quantify the interaction between groundwater and pools. The linear and multiple regression methods also require data and are easy to use, but difficulties are experienced with non-linear and non-stationary systems (Li et al., 2016; Seo et al., 2015). To overcome this issue, more complex process-based models are used, such as deterministic and stochastic models, while Artificial Intelligence (AI) and machine learning have also been used to assist with the complexity of the water systems (Seo et al., 2015). These models may have difficulty estimating beyond the data ranges that are used for training and they may be difficult to

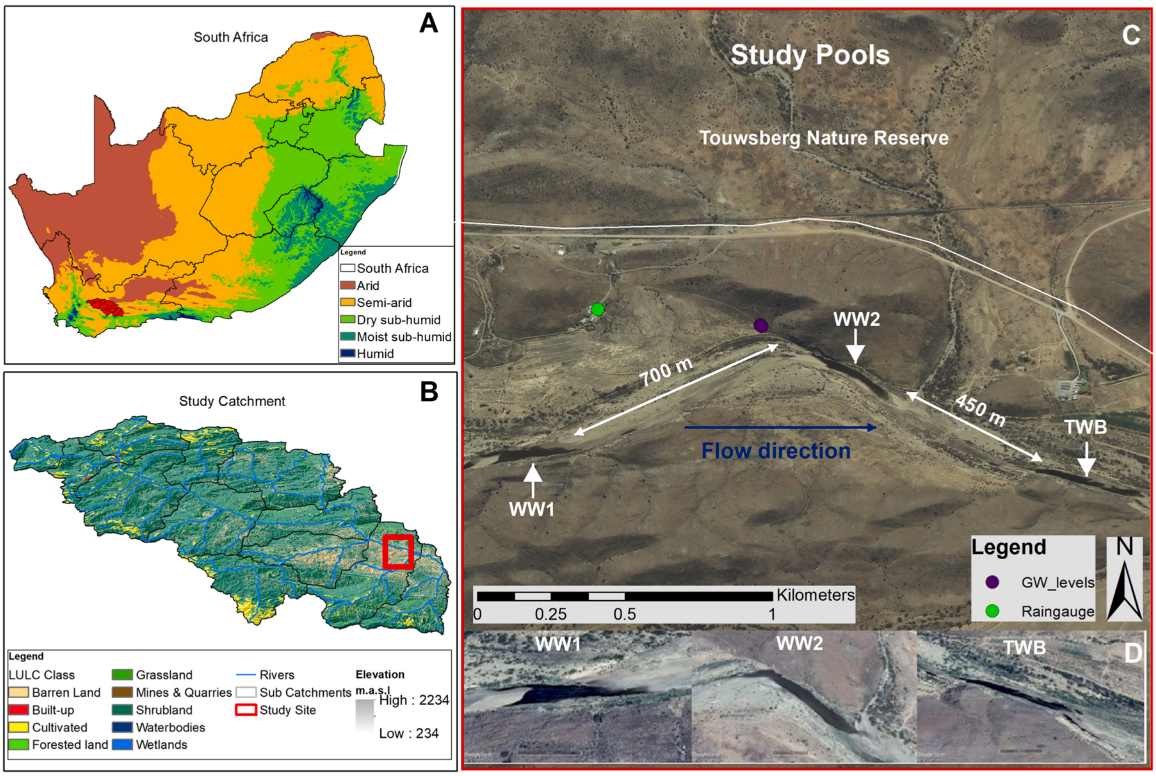


Fig. 1. Location of the study catchment (red) within South Africa (a), the location of the study pools in the study catchment (b), the location of the three pools along the river [National Geo-Spatial Information, South Africa] (c), while the bottom images provide a closer view of the three pools [Google Earth Satellite Imagery] (d).

interpret, due to hidden processes (layers) (Talebizadeh and Moridnejad, 2011). While environmental tracers can also be used to qualify the water sources in a pool (as in Hamilton et al., 2020), in some cases, water types cannot be separated by a hydrochemical analysis (Bourke et al., 2020).

The water balance approach has been widely used to represent and predict changes in water storage of water bodies (Ali et al., 2015). This approach is based on the law of conservation and has been used to understand water fluxes that influence water body dynamics and simulate the water availability in hydrological systems, such as lakes and wetlands (Gronewold et al., 2020; Mbanguka et al., 2016). The water balance, like other methods, requires data or estimates of each of the hydrological components (evaporation, precipitation, surface water in- and outflows and groundwater in- and outflows). However, the advantage of the water balance is that it can be used to estimate an unknown component of the water balance equation. This component is usually the groundwater in- and outflows, which are difficult to measure directly (e.g. Xiao et al., 2018). For instance, Parsons and Vermeulen (2017) found that ~16.9 % and 83.1 % of the water lost by the Groenvlei Lake were due to groundwater outflows and evaporation, respectively. In addition, the water balance method can be used to predict the responses of pools to changes in inputs or outflows. This information can also be used to predict how development, for example, building a dam, will alter the hydrology of a water body.

Although the water balance has been applied to understand the dynamics of water bodies across the globe, it has not been used to understand pools along NPRs. Maswanganye et al. (2022) and Bourke et al. (2020) suggest that the water balance approach can assist in improving the understanding of pool dynamics, which could be useful in the management of NPRs and their contributing catchments. Therefore, this study aims to improve the understanding of pool dynamics or water storage changes in pools along non-perennial rivers (NPRs) in the semi-arid environments of the Karoo region of South Africa. The study uses the water balance method to assess water fluxes that influence the pool dynamics. In addition, because most areas with these pools may not have the required data for the water balance approach, this study also explores the potential of using open-access, remotely-sensed data in the water balance model.

2. Material and methods

2.1. Study area description

The study was conducted in the pools occurring along the Touws River, which is located in the Karoo region in South Africa (Fig. 1). The Touws River is 140 km long and with channel widths of about 200 m. The channel has a sandy-gravel substrate above the Adolpaspoort shale formation. The entire catchment is 6 280 km^2, but this study is confined to a site where the catchment area is ~5750 km^2. The catchment is covered mainly in natural vegetation, predominantly shrubland and fynbos, with some parts of the floodplain being used for agricultural purposes. The mean annual rainfall is 244 mm/year (Grenfell et al., 2021). However, the study site received rainfall amounting to 112 mm/year in 2018, 91 mm/year in 2019, and 182 mm/year in 2020. There is no distinct wet/dry seasons (Maswanganye et al., 2022). According to Petersen et al. (2017), the catchment has a Mean Annual Runoff (MAR) of 16.32 Mm^3/year or 2.5 mm/year. The available observed flow data for the Touws River shows that the river can go for years without having a flow (Fig. 2).

2.2. Pool description

The study investigated three pools located along a 1.2 km stretch of the Touws River in the Plathuis area at Wolverfontein (Fig. 1). The pool on the upstream end referred to as Wolverfontein 1 (WW1) is located at 33.641726° S and 20.965985° E, and had a maximum area of 10,045 m^2. The second pool, Wolverfontein 2 (WW2) is 700 m downstream of WW1, located at 33.639076° S and 20.975719°

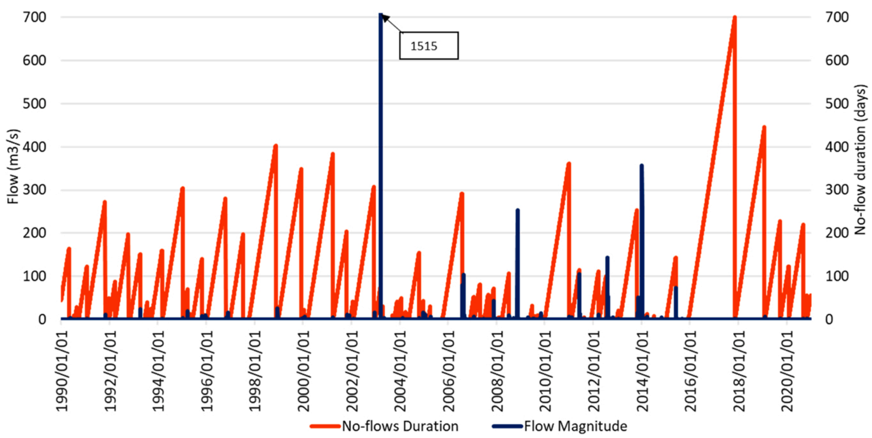


Fig. 2. Flow data (dark blue line) and the number of no-flow days (red line) of the Touws River [Department of Water and Sanitation, Station J1H018].

E, and with a maximum area of 17,742 m^2. The third pool is 450 m downstream of WW2 at 33.642918° S and 20.982405° E, and is referred to as Touwsberg (TWB). This third pool had a maximum area of 15,722 m^2. The study focuses mainly on Wolverfontein 2 (WW2) pool which is situated along the left bank that is hilly with exposed bedrock while the right bank has a sparsely vegetated floodplain (Fig. 1C and D). According to Hattingh (2020), the WW2 pool has a substrate of predominantly fine sand. This pool has a maximum depth of 1.7 m. The WW2 pool nearly dried up during the 2016–2019 drought. During flow events, these pools connect, they are accessible and they persist for long enough to sustain some form of life (aquatic vegetation and animal community), as described in Zacharias and Zamparas (2010). Furthermore, these pools are located close to the flow occurrence, rainfall and groundwater level observation points.

2.3. Data collection and analyses

2.3.1. In-situ data

A water balance analysis of water storage in pools requires data on rainfall, evaporation rates, pool storage, inflows and outflows of both river water and groundwater. The surface area data were obtained from the Global Positioning System (GPS) measurements collected along the edges of the pools, using a hand-held GPS, and a staff gauge was used to measure the water levels during the field visits (Table 1). A Solinst water level logger (M3001, M5, and logging at hourly intervals) was installed in each pool to measure water levels. Water levels in WW2 were measured for two years (2019–2021), while this was done for a year (2020–2021) in WW1 and TWB pools. Data from this rain gauge were used for water balance analysis. Two boreholes for monitoring changes in the depth to the water table were drilled on the left bank, 200 m upstream of WW2. This site was the closest to WW2 that a drilling rig could access because of the hilly terrain adjacent to WW2. The two boreholes had depths of 25 m and 60 m. A water level data logger (logging at hourly intervals) was installed in each borehole. Weather data were required for estimating evaporation rates using the Penman method. Data from the closest weather station owned by the Agricultural Research Council were used. This station is located 27 km south-east of the study pools. Rainfall and flow occurrence obtained from the Citizen Science monitoring programme, whereby farmers neighboring the pools collected these data. The rainfall data were collected using non-recording rain gauges (manual), notes on flow occurrence (absence and presence) were recorded by event. One farmer is located within the study site, 600 m from the WW2 pool (Fig. 1), and the other is located one km upstream of the study site.

The relationship (rating curves) between the surface area, depth and volume were determined, in order to be able to convert between these measurements. The volume of the pool was estimated based on the following equations, which were derived using 3D analyst on ArcGIS and by using the Differential Global Positioning System (DGPS) points and continuous water level measurements (Eq. 1 and 2). The following relationships were specifically derived and used for the WW2 pool.

$$H = 0.00009\,A;\ R = 0{\cdot}99 \tag{1}$$

$$V = 0{\cdot}00005A^2 + 0{\cdot}1415\,A + 18{\cdot}83;\ R = 0{\cdot}99 \tag{2}$$

Where H is the depth of water in a pool in metres, V is the volume of water stored in m^3 and A is the area of the pool in m^2.

2.3.2. Remote sensing data

Since in-situ data on water balance components of non-perennial pools are often unavailable, the study explored the use of readily- and freely-available remotely-sensed data for water balance analysis of water storage in pools along Touws River. Evaporation data were obtained from the Moderate Resolution Imaging Spectroradiometer (MODIS) 16 PET product, as described by Mu et al., (2011, 2007). The data were downloaded from the AppEARS website (https://lpdaacsvc.cr.usgs.gov/appeears/). MODIS 16 evapotranspiration data are widely and commonly used, and Jovanovic et al. (2015) found that MODIS 16 evapotranspiration and potential evapotranspiration estimates over South Africa's landscape were satisfactory; however they cautioned that the spatial resolution can limit its potential for small-scale use. Some studies have argued that MODIS 16-derived PET is suited for small-scale application (Astuti et al., 2022). Bugan et al. (2020) utilised the MODIS 16 dataset in a hydrological model at a catchment level and concluded that the dataset has the potential to be used in data-scarce regions. Based on the findings of these previous studies, the study explored the use of this, it was assumed that MODIS 16 PET would provide the closest satellite-derived and freely-accessible estimates. Satellite derived rainfall estimates were obtained from the Climate Hazards InfraRed Precipitation with Stations (CHIRPS) product, as described by

Table 1
Size of the three pools (WW1, WW2 and TWB) during the site visits.

	WW1 Pool		WW2 Pool		TWB Pool	
Date	Surface Area (m^2)	Water Level (m)	Surface Area (m^2)	Water Level (m)	Surface Area (m^2)	Water Level (m)
2019/07/31			13,242	1.2		
2019/10/01			16,742	1.7		
2020/12/14	6821	0.5	10,836	1.1	16,557	0.8
2021/03/30	6538	0.5	12,891	1.1	15,722	0.76
2021/08/10	10,045	0.7	15,339	1.4	25,789	1
2021/12/01	3500	0.4	8913	0.75		

*Blank spaces indicate no observation.

Funk et al. (2015), which was downloaded from the climate engine website (https://app.climateengine.com/climateEngine#). Many studies, such as those of Maswanganye (2018), Plessis and Kibii (2021) and Pitman and Bailey (2021), have suggested that CHIRPS can be used in the absence of in-situ data.

To obtain the surface area of the pool from remote sensing data, Sentinel-2 images were downloaded, and the Modified Normalized Difference Water Index (MNDWI) was computed to distinguish the water areas (pixels) from the non-water areas. Shadows in the imagery were classified using the Random Forest technique and were used to mask out their effect on the derived MNDWI water pixels (Maswanganye et al., 2022). Twenty-four-monthly Sentinel-2 images close to the end of each month, from August 2019 to August 2021 were used. The relationship between the surface area and the water depth obtained from the bathymetric survey (presented in the in-situ data analysis section) was used to convert the remotely-sensing-derived surface area to water depth, and then compared with the observed water levels.

2.3.3. Pool dynamics data analyses

This study first examined the water depths of the focal pool (WW2) in relation to the water fluxes, in order to gain an insight into the water gains and losses. The time to empty, and the probability of the pool drying out, were then determined. The water balance model was established by using in-situ data, which will be explained in the next section. The water balance model calibrated using WW2 data was tested on the other two pools, WW1 and TWB. Satellite-derived rainfall and evaporation estimates were incorporated into the model by substituting the observed rainfall and evaporation, which resulted in an in-situ and remote sensing hybrid water balance; this model does not consider the groundwater in- and outflows (Fig. 3). The fully remote sensing-based analysis used the changes from the surface area that were obtained from the Sentinel-2 images and the satellite-derived rainfall and evaporation. The performance of all the models was evaluated by using the actual water levels measured of the pools. Fig. 3 illustrates the methodological flow of the analyses.

In this study, the Time to Empty (TE) was defined as the time it takes for a pool to completely drain out the water, from being full. This is based on the water loss rate of the pool and assumes that there are no surface water inflows into the pool.

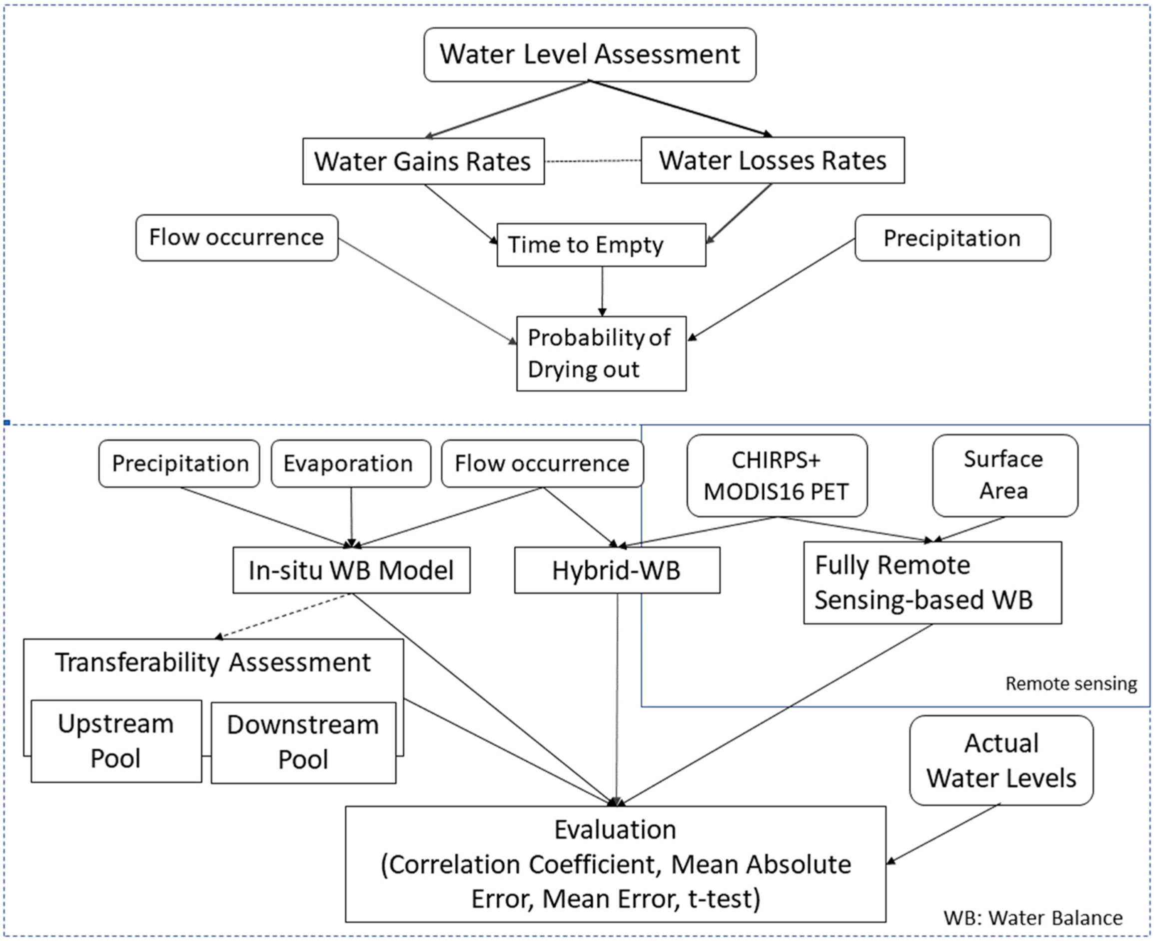


Fig. 3. A flow chart illustrating the methodological procedure that was followed in this study.

$$TE = \frac{S_{max}}{L_{Wl}} \quad (1)$$

Where S_{max} is the maximum water level in meters and L_{wl} is the average water loss per day in meters, which is obtained from assessing the observed water levels. The probability of the pool drying out is the chance of finding the pool dry, which is calculated based on the dry period (no streamflow duration) exceeding the time to empty, while considering that the rainfall over the pool can reduce the number of days that the pool will be dry. In this study, this was calculated by using the 30-year flow occurrence and rainfall data, because there is no long-term data on the other water balance components.

2.3.4. *Water balance analysis*

Water storage in the pool is described by the following water balance Eq. (2) and illustration (4): Fig. 4.

$$S_{(t)} = S_{(t-1)} + P_{(t)} - E_{(t)} + Q_{in(t)} - Q_{out(t)} + G_{in(t)} - G_{out(t)} \quad (2)$$

Where $S_{(t)}$ is storage at the end of time period t, t being a daily interval, $P_{(t)}$ is volume of rainfall over the pool, E(t) is volume of water evaporated from the pool during the day t, $Q_{in(t)}$ is river inflows into the pool, $Q_{out(t)}$ is surface outflow from the pool, $G_{in(t)}$ is groundwater discharge into the pool, $G_{out(t)}$ is groundwater recharge from the pool.

Daily rainfall p(t)) data obtained from the nearby homestead was used to estimate volume of rainfall over the pool using the following relation.

$$P(t) = p(t)A(t) \quad (3)$$

Where A(t) is the surface area of the pool obtained using the relationship between surface area and water storage. Evaporation from the pool (E(t)) was estimated similarly to P(t) with evaporation rates derived using the Penman (1948) method, based on weather station data, as it is a commonly-used method for estimating open water evaporation (Mbanguka et al., 2016; Yihdego and Webb, 2018).

Based on empirical observations, the study assumed that when river inflows are occurring continuously, then the pool fills and during that period inflows will equal outflows from the pool, thus, $Q_{in(t)} = Q_{out(t)}$. During this period, although the pool remains full, some of the inflowing water will contribute to subsurface water around and beneath the pool. The influence of the pool recharging subsurface water will materialise when no surface inflows occur. After the inflows have ceased, the amount of water flowing from the pool into the subsurface material will depend on the area of the pool, or volume of water in storage. Thus $G_{out(t)}$ was assumed to be described by the following relationship.

$$G_{out(t)} = a(S_{(t)} - S_1)^b \quad (4)$$

Where S_1 is the volume of water in the pool below which there will be no positive hydraulic gradient into the subsurface material. The volume of water in the pool can also be represented by the depth of water in the pool. We assumed that $G_{out(t)}$ will be a function of the depth of water in the pool.

$$G_{in(t)} = cH \quad (5)$$

Where c is a coefficient.

The model was built specifically for the WW2 pool by using the above water balance approach, and its equation and assumptions

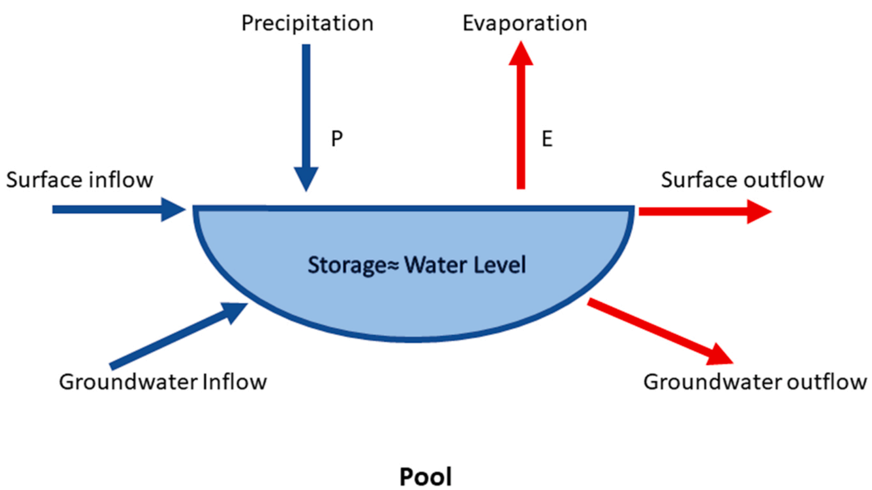


Fig. 4. Concept of the water balance model, with the blue arrows showing the water gains (precipitation, surface and groundwater inflows) and the red arrows showing the water losses (evaporation, surface and groundwater outflows) from the pool.

were transferred to the WW1 and TWB pools. Only two adjustments were made: the initial water level (starting point) and the maximum water level, as these pools were not of equal size. These pools are very close to the WW2 pool; therefore, it was assumed that they have the same hydroclimatic conditions.

2.4. Statistical analysis

In order to evaluate the performance of the water balance analysis the following statistics were used; the mean error (ME), the mean absolute error (MAE), the correlation coefficient (R) and the paired T-test were used. The Mean Error (ME), which is also called bias, measures the average of the estimation error; this considers the direction of the errors (Eq. 6). The ME ranges from negative infinity to positive infinity and has a perfect score of 0. A positive score indicates that the model is over-estimating, while a negative score indicates that it is under-estimating, on average. However, with the ME, a perfect score can be achieved when the over- and under-estimation compensate each other. Hence, the Mean Absolute Error (MAE) was used to provide a true estimation error (Eq. 7), and the ME was used to derive the direction of the error.

$$ME = \frac{1}{n}\sum_{i=1}^{n}\left(H_{obs,i} - H_{sim,i}\right) \tag{6}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|H_{obs,i} - H_{sim,i}\right| \tag{7}$$

Where $H_{obs,i}$ is the observed water level, $H_{sim,i}$ is the simulated water level, and n is total number of data points.

A t-test (Eq. 8) was used to determine whether there is a significant difference between means of the observed and simulated water levels

$$t = \frac{\sum \mathrm{x} - \mathrm{y}}{\sqrt{\frac{\mathrm{n}\left(\sum \mathrm{x}^2 - \mathrm{y}^2\right) - \left(\sum \mathrm{x} - \mathrm{y}\right)^2}{\mathrm{n} - 1}}} \tag{8}$$

where t is the t-statistic, x is the observed water level mean, y is the modelled water level, and n is the total number of data points. A paired t-test assumes that the data sets are continuous, that they follow a normal distribution, that the mean is a good measure of the central tendency and that the two samples are paired (Helsel et al., 2020).

To assess the relationship between the simulated and observed water levels at different time-steps (daily, monthly), a correlation coefficient (Eq. 9) was used. The correlation ranges from − 1 to + 1, with ± 1 being a perfect relationship, and 0 meaning that there is no relationship between the observed and the simulated values.

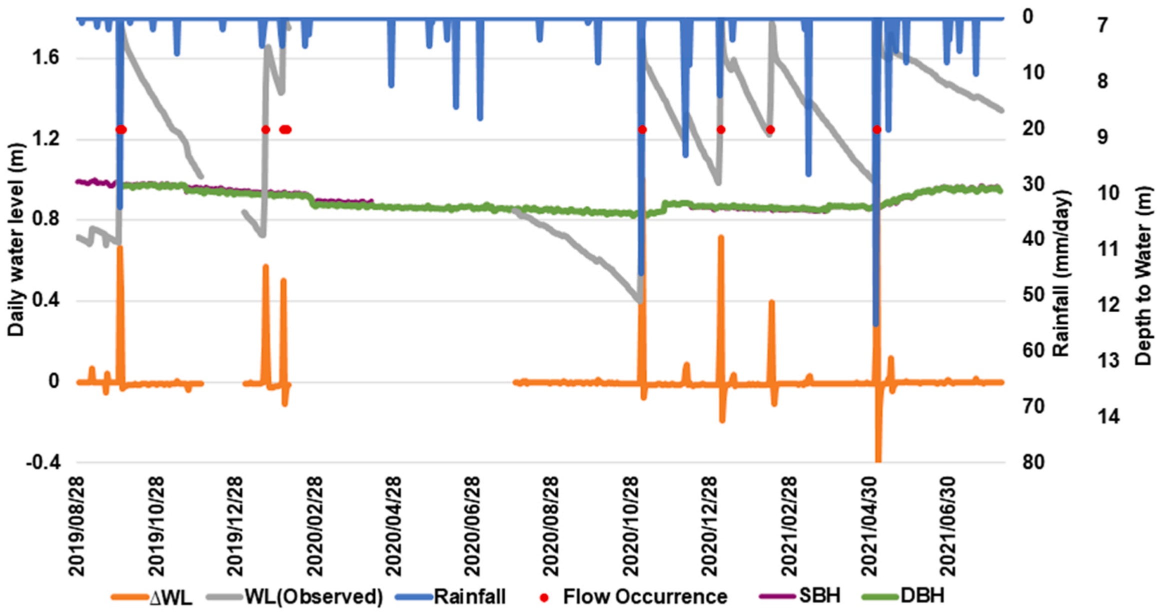


Fig. 5. Changes in water levels of the pool, with negative and positive values indicating the losing and gaining pools, respectively (orange line), the actual water level (grey line), the rainfall over the pool (blue line), and the flow occurrence (red dots), with the depth to water of the shallow pool (purple line) and deep borehole (green line).

$$r = \frac{n \quad (\sum OE) - (\sum O)(\sum E)}{\sqrt{[n\sum O^2 - \sum O)^2 - [n\sum E^2 - (\sum E)^2}} \tag{9}$$

where O is the observed water level measured by a logger, E is the simulated water level, and n is the number of score pairs of scores.

The mean error, mean absolute error, t-test and correlation coefficient were also used to assess the transferability of the model to a pool that is upstream and downstream of WW2.

3. Results

3.1. Water level assessment

The water balance analysis shows that the major gains in water level were due to river flow occurrences, and that the minor gains were due to the rainfall received over the pool (Fig. 5). High losses always followed the high gain episodes, which suggests that water losses might be a function of the water level. The depth to water of the shallow and deep boreholes shows no significant changes in relation to the pool water levels, nor to the occurrence of flows. However, the water level data between 2020/02/07–2020/07/31 was missing, due to a stolen logger during the COVID-19 hard lockdown period.

3.1.1. Assessment of the water losses from the pool

The observed pool water level data from August 2019 to August 2021, suggests that the pool loses approximately 0.2 m per month or 2.4 m per year. The losses are high during the southern hemisphere summer (~0.29 m/month) and low during the winter months (~0.09 m/month) (Fig. 6). This indicates that when the pool is full, it can last, on average, for ~258 days (8.5 months) without any inflows. This pool loses 0.7 m/year more than the estimated Penman evaporation rates. The difference may be attributed to water lost through seepage into the subsurface material (Fig. A2 in supplementary material). When the volume of water in storage or the water surface area of the pool is large, evaporation losses will be large. Similarly with a large pool bed covered with water, and if the underlying subsurface material is unsaturated, seepage will also be large. Since the water depth increases with volume of water in storage or pool surface area, water losses from the pool will increase with water depth.

3.1.2. Probability of the pool drying out

Based on the observed losses and time to empty, the river flow and rainfall data from 1990 to 2020 were used to establish the chances of the pool drying out. There is only a 10 % chance of finding the pool dry, as the pool was likely to have dried out 11 times in 30 years, or it could have potentially dried out for 1115 days out of 11322 days (30 years) (Table 2). This is based on the no-flow and no-rain days exceeding 258 days. Rainfall reduces the number of potential pool dry days; for instance, 52 mm during the no-flow period can delay the drying of the pool by eight days. These estimates suggest that the most prolonged period with no water was 411 days during the 2015–2017 drought, assuming that it did not receive any water from the groundwater.

3.2. The water balance model

Based on the understanding of the pool, the water balance approach was used to simulate its water levels. The water balance satisfactorily predicted the water levels (ME=−0.03 m; MAE=0.05 m; r = 0.96) and there was no significant difference between the

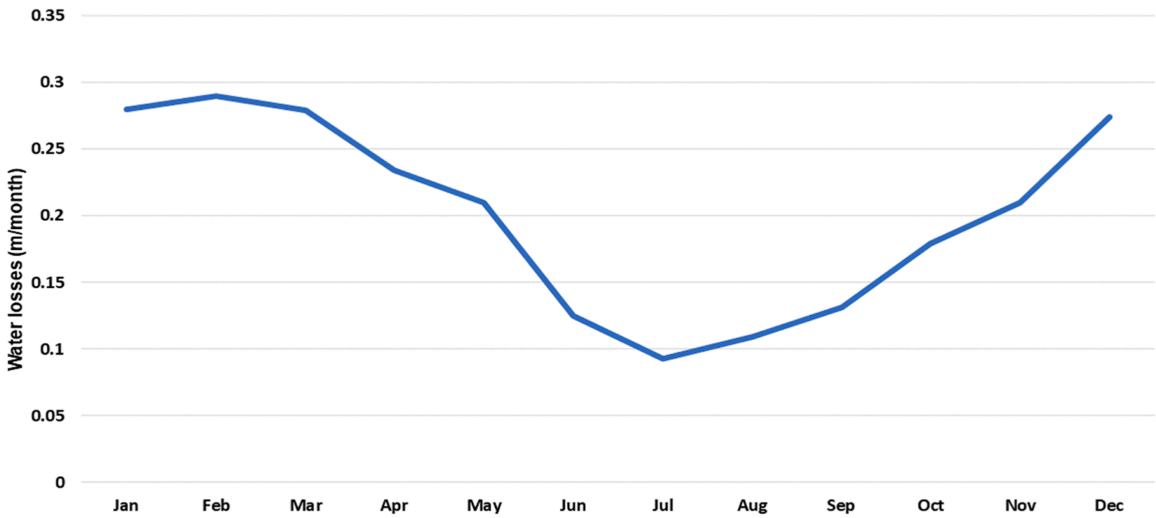


Fig. 6. Average monthly water losses from the WW2 pool for the study period.

Table 2
Drying out of the pool based on the estimated time to empty, using data from 1990 to 2020.

Start of no flow	End of no flow	No. of days the pool could be dry (excluding rainfall)	Rainfall (mm)	No. of days the pool could be dry (including rainfall)
1991/01/29	1991/10/29	15.0	54.0	6.8
1994/03/14	1995/01/12	46.0	52.0	38.1
1996/01/15	1996/10/22	23.0	34.0	17.9
1997/10/11	1998/11/18	145.0	89.0	131.6
1998/12/26	1999/12/09	90.0	79.0	78.1
2000/03/14	2001/04/01	125.0	80.0	112.9
2002/02/05	2002/12/10	50.0	110.0	33.4
2005/10/12	2006/07/31	34.0	187.0	5.7
2010/01/03	2010/12/31	104.0	97.0	89.3
2015/12/14	2017/11/13	442.0	203.0	411.3
2017/11/14	2019/02/02	187.0	111.5	170.2
Total		**1283.0**	**1096.5**	**1115.3**
Probability		**0.113**		**0.099**

means (t = −4.5) over the assessed period (2019/08/25–2021/08/10) (Fig. 7). Besides the inputs (rainfall and evaporation), the model was supplied with a maximum water level of 1.7 m (which is also the cease-to-flow level) and the initial water level. Moreover, the model was able to predict the water levels during the period where no observed data were available (February-July 2020). The model shows that when the pool has more water, the water is rapidly lost via seepage into the subsurface strata or aquifer, and that the seepage ranged from 0 to 0.005 m/day and was defined as 0.003 of the water level of the pool (Fig. A2 in supplementary materials). Rainfall delays the drying of the pool. The pool is sensitive to the flow occurrence, and the assumption that every flow will fill the pool to capacity is correct and drives the model. After the river flow has ceased, evaporation dominates the water losses. The model suggests that seepage into the subsurface material occurs when the water depth exceeds ~1.1 m. Seepage out of the pool does not occur below this water depth. Instead, groundwater discharge into the pool occurs when the water depth is less than 1.1 m. This proposed behavior could be that the water level in the pool will be greater than the local water table around the pool when the water depth exceeds 1.1 m. Hence, groundwater recharge occurs from the pool. With a water depth below 1.1 m, the local water table will be above the pool water level, hence groundwater discharges into the pool. Fig. A3 in the supplementary material shows the model that does not take the above behavior into consideration.

3.2.1. Transferability of the water balance to the surrounding pools

The simulated water levels of the WW1 pool were in good agreement with the observed water level (ME=−0.02 m; MAE=0.04 m; r = 0.96) (Fig. 8). The only changes made from the original water balance model from the WW2 pool was the maximum water level, which was adjusted, by trial and error, to be 0.95 m for the WW1 pool and the initial observed water level. Water lost to groundwater was estimated in the same way as for the WW2 pool (0.003 of the water depth). However, the model overestimated the water lost by

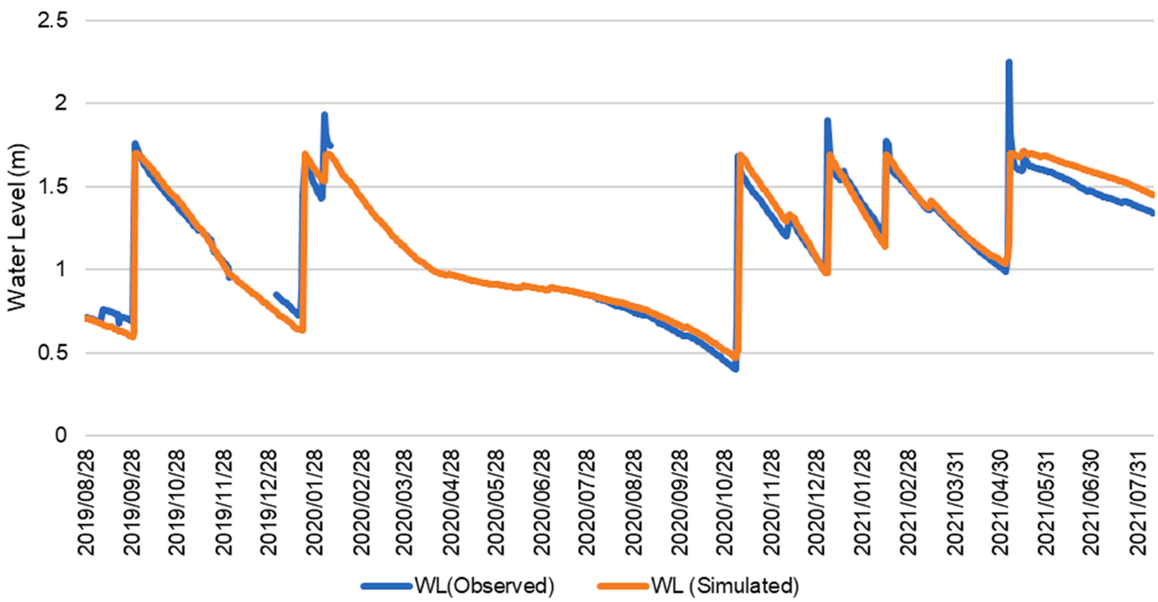


Fig. 7. The water balance model of water levels of the WW2 pool in the Touws River. The blue line indicates the observed water level, and the orange line indicates the simulated water level, using in-situ inputs.

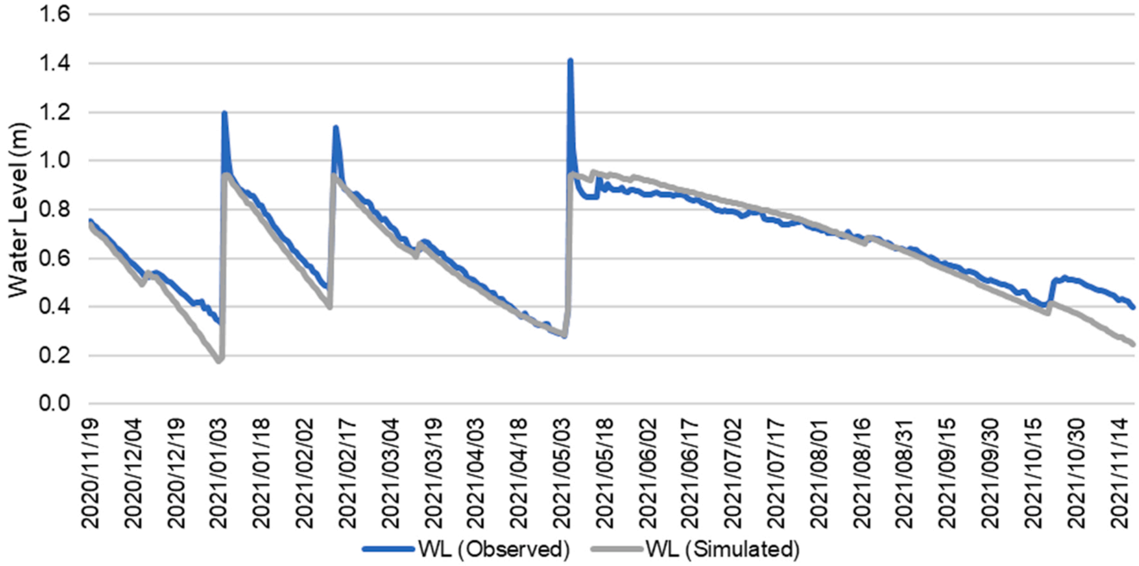
the pool between December 2020 and November 2021, which resulted in the lowest predicted level of 0.2 m, compared to the observed level of 0.35 m. For the TWB pool, which is 450 m downstream of the WW2 pool, the model did not perform as well as the WW1 pool ; (ME=0.02 m; MAE=0.06 m; r = 0.86), which suggests that the pool varies significantly from the focus pool (WW2). During a field visit, seepage into the pool was observed. The constant water level of the pool between June and August 2021 suggests that it probably receives substantial sub-surface inflows, in order to maintain such water levels.

The paired *t*-test (t = 8.3) showed that, at a 5 % significance level, there is no significant difference between the observed daily mean water level (0.64 m) and the simulated mean (0.62 m) for the WW1 pool. There was, however, a significant difference (t = 1.9) between the modelled mean water level (0.89 m) and the observed mean (0.91 m) of the TWB pool.

3.3. Water balance analysis using remote sensing data

3.3.1. Comparison of the remote sensing and observed inputs of the model

In terms of comparing the inputs, the CHIRPS rainfall estimates compared well with the observed rainfall data (r = 0.6). However, it has errors during some periods, such as July to August 2020 (Fig. 9). Although the remotely-sensed evaporation rates from MODIS 16



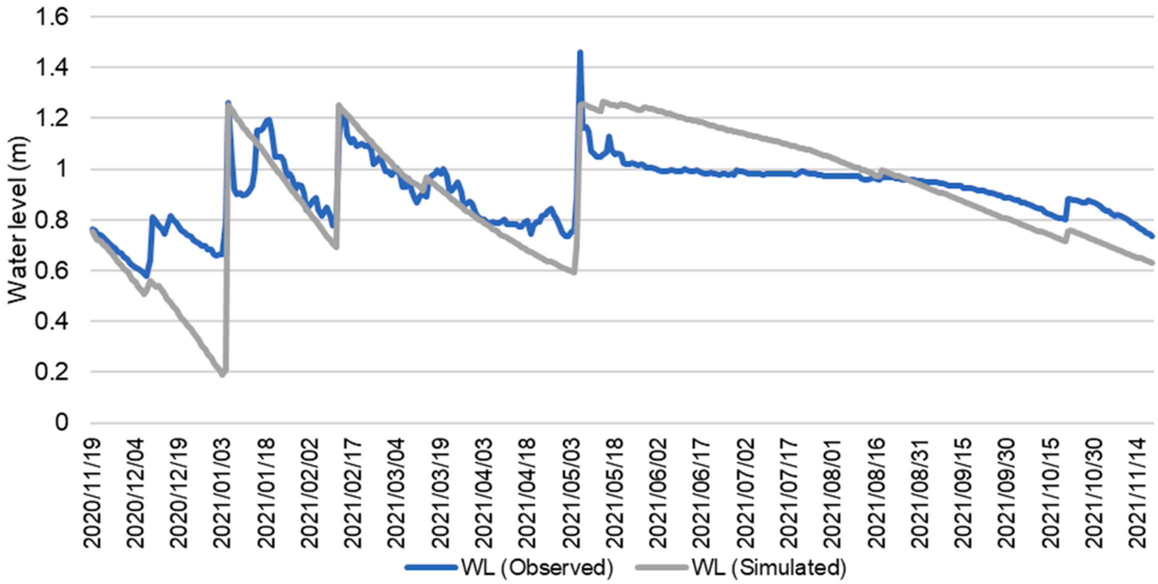


Fig. 8. Observed (blue line) and simulated (grey line) water levels for the WW1 pool (top) and the TWB pool (bottom).

PET are closely related to the observed evaporation rates that were derived by using the Penman equation (r = 0.98), they overestimated the months with lower evaporation (April to Sept) (Fig. 10). A general assessment of the climatic water balance shows that the remotely-sensed climatic water balance is strongly associated with observed climatic water balance (r = 0.87) (Fig. 11), which suggests that a monthly-based water balance can have errors caused by rainfall and evaporation, but these are likely to be small. The negative climate water balance indicates that the catchment is potentially in a water deficit.

The comparison between the observed water level and the remotely-sensed surface area of the pool is in good agreement (ME= 0.04 m, MAE=0.2 m; r = 0.72) (see Fig. 12). There seem to be more discrepancies, but they are minor when the pool is almost full (water level>1.2 m). Overall, the remote sensing estimated surface water of pool is promising.

Therefore, freely-accessible remote-sensing data were incorporated into the water balance, particularly the CHIRPS and MODIS16 PET data. The initial and maximum water level and flow occurrence were the only inputs used. This also assumes that no information exists about water losses due to subsurface/groundwater. The results show an underestimation of the water losses, as expected (Fig. 13), as losses into the sub-surface are not incorporated.

The surface area of the pool obtained from remote sensing was converted to the water level (Equation 12). The remote sensing-based estimation showed an increase in the water level, in response to the flow occurrence (Fig. 14). The remote sensing-based water balance suggests that 65 % of the water is lost through evaporation; therefore, 35 % is lost to the sub-surface (negative residual), which is higher than the outcomes from the in-situ-based estimation.

4. Discussion

The study focused on improving the understanding of pool dynamics along non-perennial rivers by assessing the water fluxes using the water balance approach. The results showed that one flow event can sustain the pool for 258 days without any inflows, although the probability of such a prolonged no-flow is low (10 %). This suggests that the WW2 pool that was focused upon is semi-permanent to permanent. Pools in South Australia showed a similar persistency i.e. 286 days for the pool, with a maximum water level of greater than 1.6 m (Marshall et al., 2016). The water balance model also supports the fact that the pool is very sensitive to the flow occurrence, as indicated by Maswanganye et al. (2022). The persistence of the pool might change over time, as evaporation increases and as the rainfall declines over the region, due to climate change (Department of Environmental Affairs, 2018). These findings also suggest that if there is dam construction upstream, which reduces the frequency of the river flows, the pools will be impacted and this could lead to the drying out of the pools, which has further implications for the biodiversity found in these pools (Bonada et al., 2020; Larned et al., 2010). Therefore, this information should be considered when proposing any new development, such as the construction of a dam.

The water balance models indicate that there might be groundwater inflow into the pools will occur during the period of low water depth, this might be seasonal, as observed by Bestland et al. (2017). In this case of the current study, this was observed when the pool reached a certain level, as it has been stated that the study catchment has no clear wet and dry season. Maswanganye et al. (2022) found that surface flow and rainfall did not cause a fluctuation in the groundwater levels, hence it was suggested that the groundwater does not feed the pool. The water balance analyses revealed that water losses from the pool into the subsurface is insignificant to cause groundwater level fluctuations. The substrate and the underlying geology of the pool also suggest that there is limited, or no interaction (low conductivity) (Hwang et al., 2017; Mohuba et al., 2020). The interaction might also depend on the gradient between the pool and the water table, as illustrated in Fig. 15. This observation is further supported by the elevation plot, using DGPS measurements, which shows that groundwater usually fluctuates at around 1.1 m of the pool's water level (Fig. 16). Bourke et al. (2020) referred to this kind

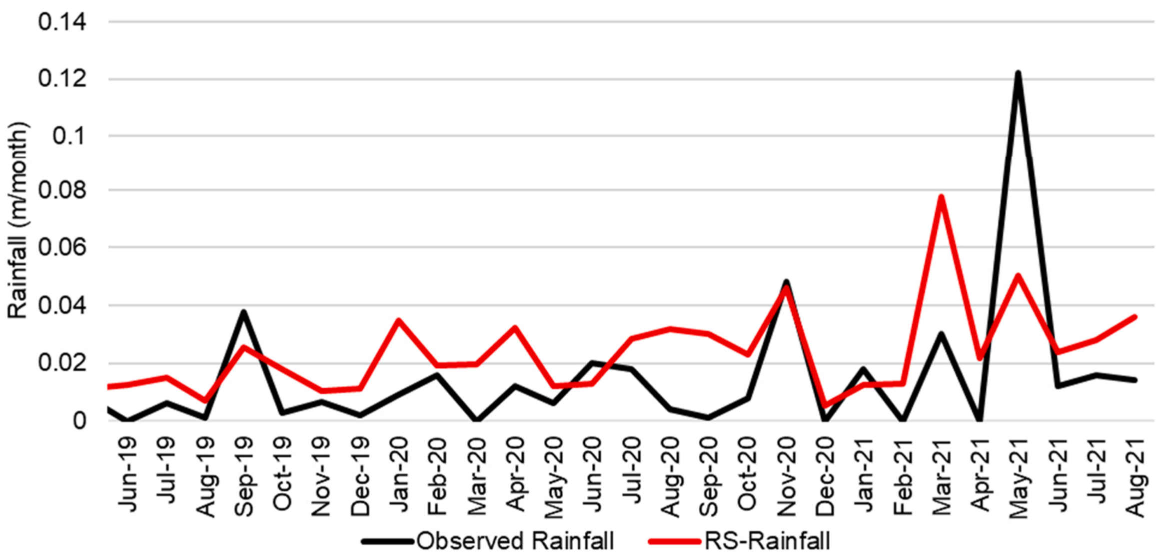


Fig. 9. Comparison of observed (black line) and estimated (red line) rainfall by CHIRPS.

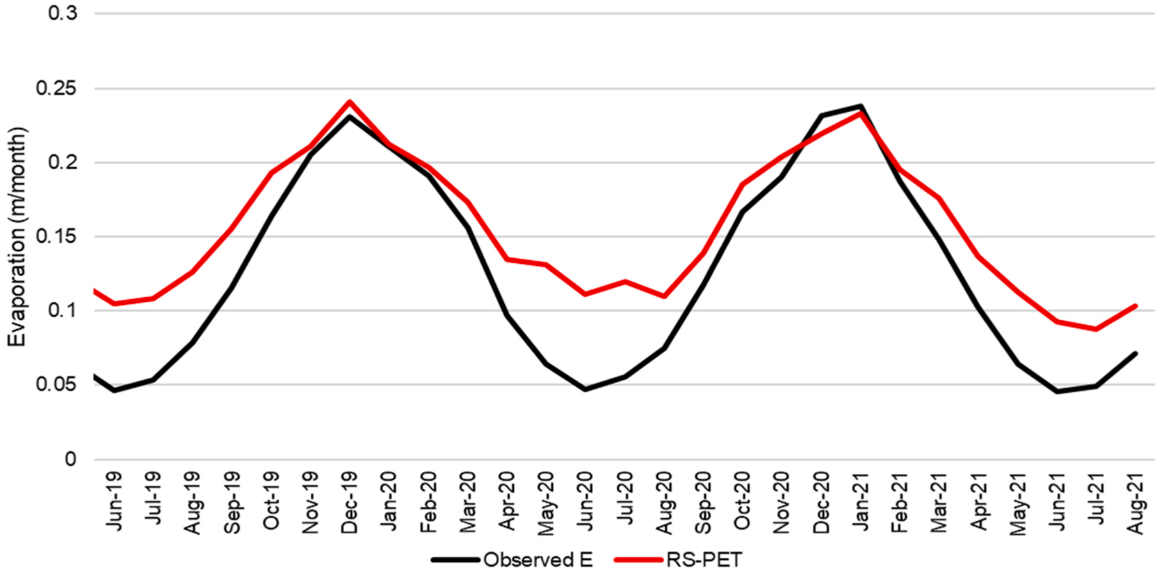


Fig. 10. Comparison of observed evaporation (black line) and estimated potential evaporation (red line) by MODIS 16.

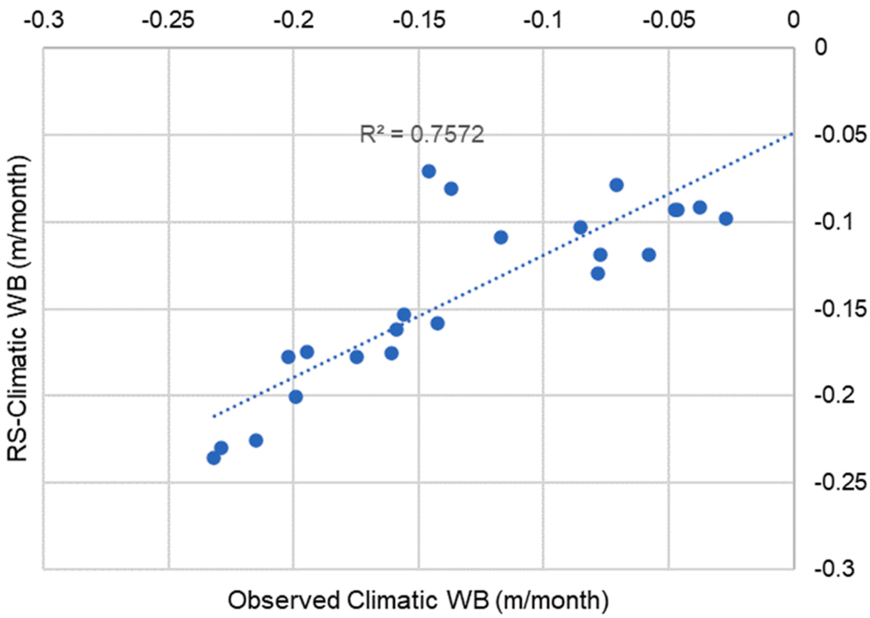


Fig. 11. Correlation between the observed and estimated climate water balance (rainfall-potential evaporation).

of pool as a through-flow pool.

Although the water balance models performed well by using just the flow occurrence, having information about the discharge into and out of the pool could have provided more insight; for instance, how the relationship between the discharge and pool water level affects the water losses. Furthermore, in order to determine whether the pool water losses from upstream are detected downstream (interaction between the pools), some studies have suggested that pools can remain hydrologically connected through shallow groundwater paths, while being disconnected on the surface (Larned et al., 2010).

The water balance model displayed robustness and transferability to the WW1 pool, albeit with minor adjustments to the maximum and initial water level. However, it did not perform as well when evaluated at the TWB pool. This might be due to the pool having a strong subsurface flow impact, which influences the dynamics of the pool. It is also possible that the properties of the TWB pool may differ, for example, the presence of algae and shade over the water, which might significantly reduce evaporation (Trimmel et al., 2018). Furthermore, Seaman et al. (2016) indicated that neighbouring pools along the same reach can differ significantly. The WW1 pool (upstream) was shown to have the same pattern as the WW2 pool; however, it will dry out before the WW2 pool, because it is

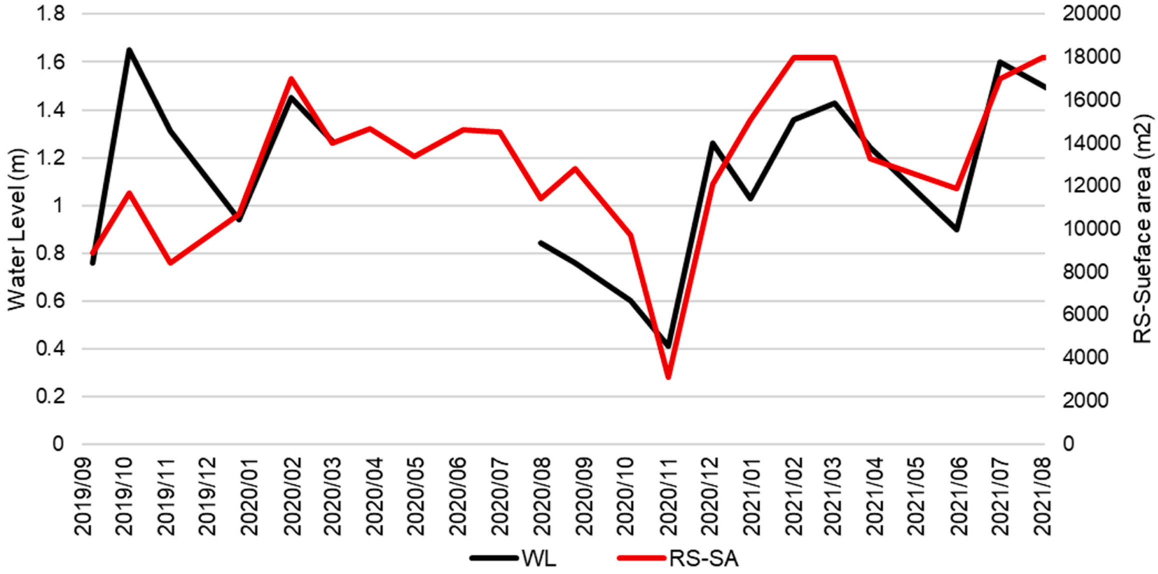


Fig. 12. Comparison between the observed water levels (black line) and remote sensing derived surface area (red line).

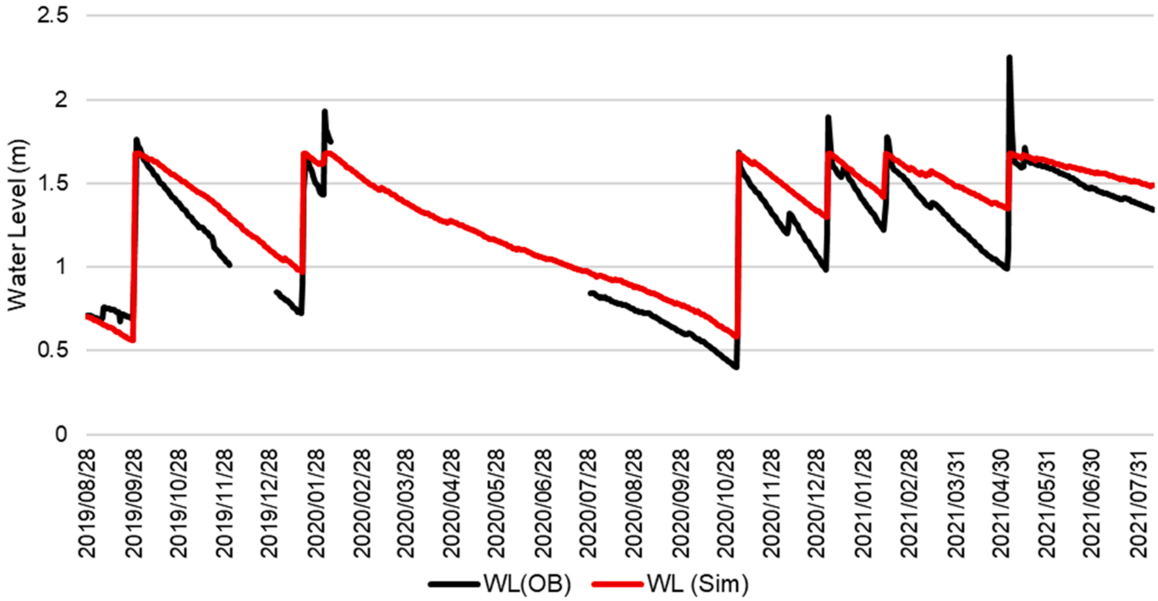


Fig. 13. Observed water level (black line) and simulated water levels based on remotely-sensed estimated climatic variables (rainfall and evaporation) (red line).

smaller in size. The TWB pool (downstream) showed a very distinct pattern in terms of losses, as itsustained its size or water level for longer periods, which suggests that this could be a permanent pool.

Remote sensing detects the pools and provides a general overview of the pool dynamics, as suggested by Maswanganye et al. (2022), as it was able to detect major changes correctly; however, it does not provide detailed information or an understanding of the pool dynamics at the water balance level. This might be due to errors emanating from each of the model input variables. Furthermore, errors may also be caused by the resolution of the remote sensing data, when compared to the size and the temporal dynamics of the pool. When the water balance approach is applied in larger surface bodies, such as large dams and lakes, these errors might be negligible (Chen et al., 2022: Dues et al., 2018). The water balance can also provide a better insight when applied on a long-term basis. However, to improve the remote sensing-based water balance model, there is a need to acquire more information on the flow occurrence. This could be done by detecting flows from satellite images or it can be predicted through rainfall (a runoff-rainfall model). Furthermore, the groundwater information that is required for predicting pool water losses to subsurface stores is still a mystery in the

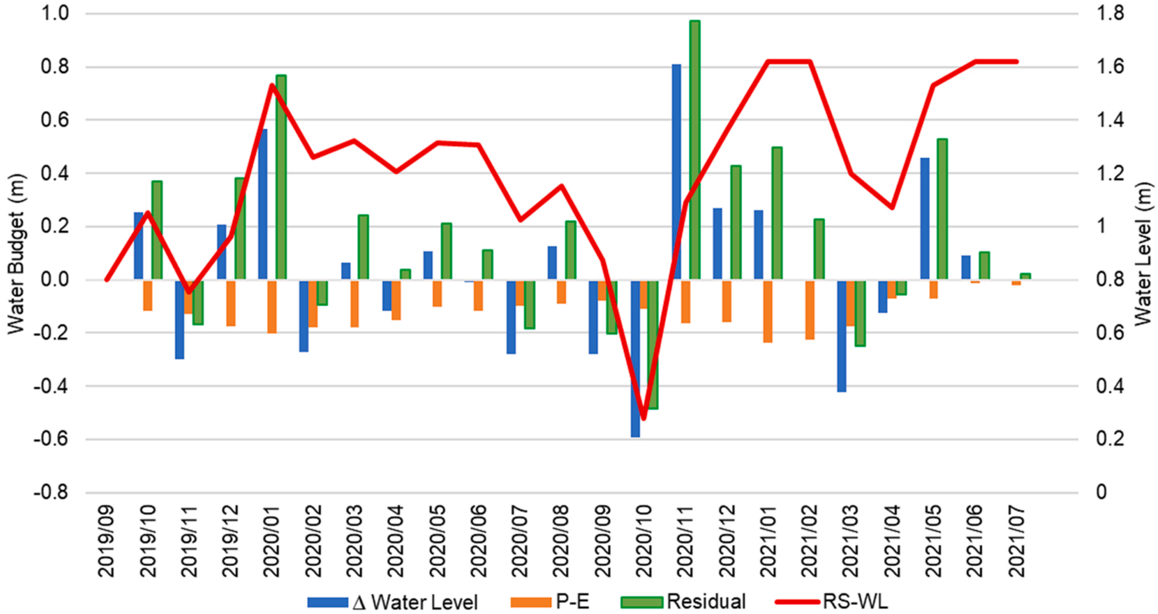


Fig. 14. Remotely-sensed water balance of the pool with the negative and positive values denoting the losing and gaining pools, respectively (blue bar), the estimated water level (red line), the difference between evaporation and rainfall over the pool (orange bar), as well as the residual of water level and the difference between precipitation and evaporation (green bars).

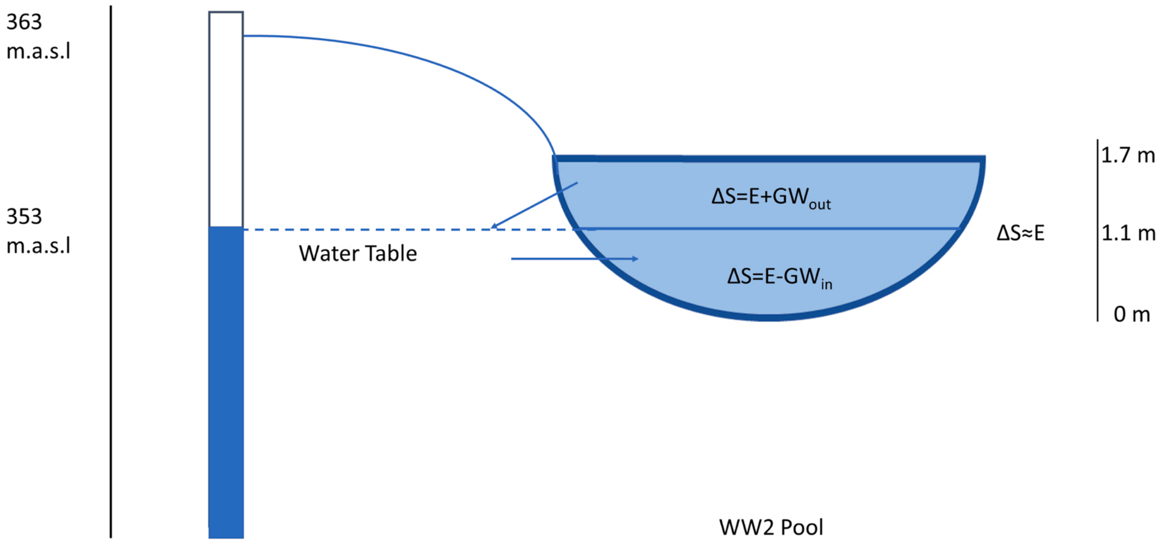


Fig. 15. Conceptual model of the pool, based on water balance simulation.

remote sensing field. This could be predicted by using the climatic variable(s); for instance, groundwater losses could be expressed as function of evaporation. This estimation should take into account the substrate and underlying geology of the area and the fact that the relationship is not linear, as it depends on the size of the pool and the season. Predicting the GW_{in} flow will still be a challenge, as it was shown that it could be function of the groundwater table. The GRACE satellite showed to be useful in larger water bodies (Deus et al., 2013). However, the incorporation of remote-sensing-based climatic variables was shown to be limited by the unknown groundwater-pool interaction. This suggests that remote sensing can used to understand the pool dynamics of pools that are not influenced by groundwater processes.

Overall, the results provided a better understanding of the pool dynamics, and they imply that the water balance approach could be useful for understanding pools along non-perennial rivers. The information derived from the water balance should be incorporated in the water resource management of NPRs and catchments. Water resource managers can determine the water that is available in the pools, by knowing the last day of the flow.

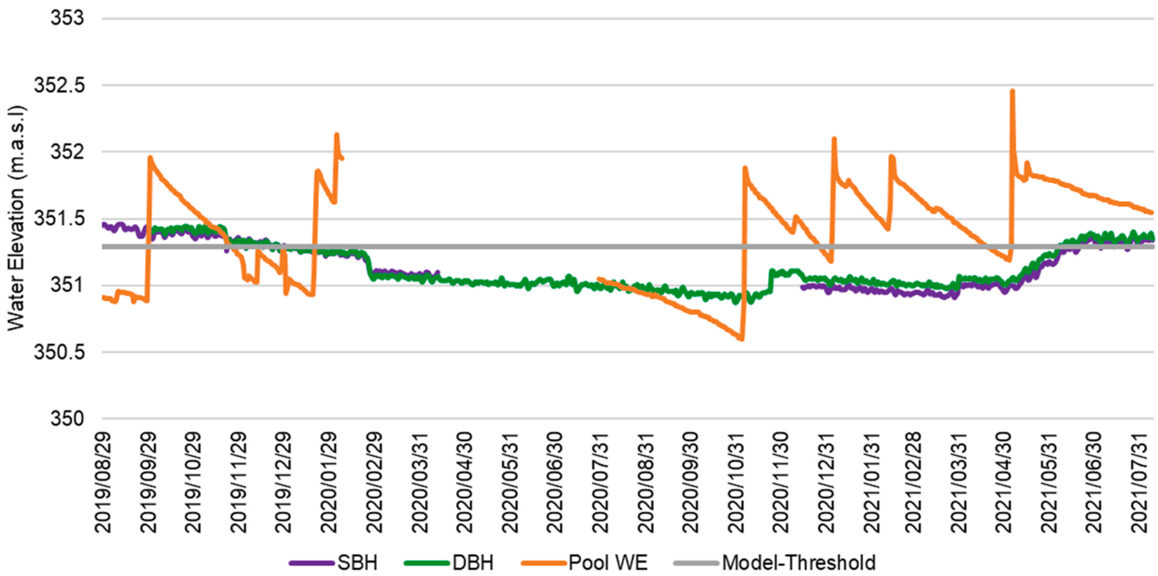


Fig. 16. Water elevation of shallow (purple line) and deep (green line) boreholes, compared to the observed water elevation of the pool (orange line) and the threshold, whereby groundwater could be flowing into the pool, as estimated by using the model (grey line).

5. Conclusion

There are limited studies on the hydrology of pools along non-perennial rivers. Using pools along the Touws River in the Karoo region of South Africa, this study assessed the pool dynamics by using the water balance approach. The study established that Wolverfontein 2 pool is a semi-permanent pool that has little chance of completely drying out. The water balance of the pools was established and modelled with limited data, and the simulated water levels showed a satisfactory performance. The model was transferable to the neighbouring pools, although it required an adjustment of the maximum and initial water levels. The water balance approach that was applied to the pool provided a better insight into the pool dynamics.

The models suggest that there is groundwater-pool interaction at the assessed site. However, the magnitude of the losses seems to be minor, when compared to the losses into the atmosphere via evaporation. The pool has a point where the rate of the loss is less than the evaporation, which indicates that there is a potential gain from the groundwater. These gains and rainfall into the pools delay the drying out of the pools. We assume that the errors in the estimation of water levels are due to the uncertainty related to a full understanding of the pool-groundwater interactions. The use of remotely-sensed climatic variables with a maximum water level can provide temporal dynamics for pools with no groundwater influence, when the flow occurrence is known. If the size of the pool is known, remote sensing can provide an overview of the general behaviour of the pool, but it cannot provide the detailed information that an in-situ observation can provide. However, with all the rapid advancements in the remote sensing field, this gap will soon be closed. This study successfully used the water balance approach to understand the pool dynamics, and the information derived from the water balance models is of significant importance for the management of pools and pool dynamics in semi-arid environments.

CRediT authorship contribution statement

Sagwati E. Maswanganye: Conceptualization, Writing – original draft, Data curation. **Timothy Dube:** Conceptualization, Writing – review & editing, Supervision, Project administration, Funding acquisition. **Nebo Jovanovic:** Writing – review & editing, Supervision, Project administration, Funding acquisition. **Evison Kapangaziwiri:** Writing – review & editing, Supervision, Project administration, Funding acquisition. **Dominic Mazvimavi:** Conceptualization, Writing – review & editing, Supervision, Project administration, Funding acquisition.

Declaration of Competing Interest

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

Data Availability

The authors do not have permission to share data.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.ejrh.2022.101244.

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