Evaluating water scarcity in the Southern African Development Community (SADC) region by using a climate moisture index (CMI) indicator

M. S. Malisawa and C. J. deW. Rautenbach

ABSTRACT

Increasing water scarcity in the Southern African Development Community (SADC) region has underscored the need to improve our understanding of the management of water resources. Using total evapotranspiration (TET) and precipitation (P) data of the past 16 years this study used a modified version of the climate moisture index (CMI) in order to evaluate water scarcity throughout the SADC region, by examining the relative importance of P and TET on the variability of the CMI. The CMI value for the Democratic Republic of Congo (CMIDRC = 0.347) as well as for Angola (CMIAngola = 0.351), ranged between 0.25 and 1, characteristic of a humid region, whereas CMI values for Botswana (CMIBotswana = 0.027) and South Africa (CMISouth Africa = 0.075) ranged between −0.6 and 0 or 0 and 0.25, characteristic of semi-arid to sub-humid regions. Namibia (CMINamibia = −0.125) has been experiencing drier conditions. The findings of this linear correlation analysis confirm a strong and significant relationship between DRC-Angola (r = 0.837), and a weak but significant relationship between Botswana–Namibia (r = 0.554) and South Africa–Namibia (r = 0.445) with regard to CMI, and suggest the possibility of transferring water from wetter to drier regions in the SADC study area.

Key words | climate moisture index, precipitation, Southern African Development Community, total evapotranspiration, water scarcity

INTRODUCTION

Globally, water is available in abundance; however, it is not always located where it is needed. Water scarcity is expected to become an escalating problem in the Southern African Development Community (SADC) region (Wolfe & Brooks 2003; Rijsberman 2006). Precipitation (P) is not evenly distributed throughout the SADC region, leading to remarkable temporal and spatial variability of water resources in the region, and any changes in P impact on hydrology and water resources (Meigh & Fry 2004; Oki & Kanae 2006). For instance, Namibia is the driest country in the SADC region, with sparse rainfall of approximately 285 mm per year (FAO 2010). On the other hand, Botswana and South Africa receive annual rainfalls of 416 and 495 mm, respectively, and Angola and the Democratic Republic of Congo (DRC) receive more than 1,000 mm of rainfall every year (FAO 2010).

Most of the major deserts in the world including the Namib Desert and Kalahari Desert in the SADC region are likely to experience decreased amounts of P and runoff with increased global warming (Vörösmarty et al. 2000, 2005). In addition, both semi-arid and arid areas are expected to experience a decrease in the amount of rainfall and will face water scarcity (Seckler et al. 1999).

Water scarcity describes an environment in which water demand for domestic, agricultural and industrial purposes will exceed its availability (Seckler et al. 1999; Wolfe & Brooks 2003; Meigh & Fry 2004). Of the eight Millennium Development Goals (MDGs), Goal 7 (Ensure Environmental Sustainability) focuses on water; due to water scarcity in the SADC region, the main challenge to achieve the target of access to safe drinking water is the very real...
problem of inequitable distribution of water resources where cheap water may be available to the rich while the poor have to seek out supplies and tend to lose out in competition for scarce resources (UNDP 2006).

Coping with increasing water scarcity is a challenge in the 21st century and a new approach is needed to face the challenge and to alleviate water scarcity in the region. The critical choice for water management is to take up the new challenge and to promote potentially useful new technological solutions to meet the needs of society (Vörösmarty et al. 2000; Wolfe & Brooks 2005). As the world’s population has swollen to well over 6 billion, some countries have already reached the limits of their water resources (UNDP 2006).

However, in terms of projections of future climate change and its impact on water resources, water scarcity has been identified by several studies as a major area of interest that is facing the SADC as well as the African continent (Wolfe & Brooks 2005; Douglas et al. 2006; Oki & Kanae 2006). Rainfall variability will be amplified in many places as a result of climate change and it is likely that water shortage will be among the world’s most pressing problems, linking issues as diverse as food security and poverty alleviation by 2025 in the SADC region (Vörösmarty et al. 2000; Douglas et al. 2006; Oki & Kanae 2006).

Efforts to balance supply and demand, and plans for sustainable future water resources in the SADC region are severely hampered by the lack of reliable information (Douglas et al. 2006). Studies of water resources leading to meaningful assessments have been found to be realistic only if conducted on a regional or local basis (Douglas et al. 2006; Oki & Kanae 2006). There may be further variance due to the fact that the distribution of water resources over the SADC region is uneven (Vörösmarty et al. 2000). Due to these complexities and constraints attempts have been made to increase available water resources in water-scarce areas by transferring water from relatively wetter regions to drier regions, e.g. inter-basin water transfers. Attempts have also been made to decrease evapotranspiration by altering vegetation management scenarios, and sometimes even through genetic manipulation (Milly et al. 2002; Oki & Kanae 2006).

Around 1.2 billion people face physical water scarcity, while another 1.6 billion people, or almost one quarter of the world’s population, live in developing countries and face economic water shortage (Seckler et al. 1999; UNDP 2006). In addition, the number of people facing varying degrees of water scarcity might increase by 1.8 billion and if so, it will push 600 million people into malnutrition by the end of the 21st century due to the impacts of climate change, inter alia rainfall variation, floods, heat waves, droughts and sea level rise (UNDP 2006).

Projections of changes in annual P indicate that increases are likely in the tropics and at high latitudes, while decreases are likely in the sub-tropics, especially along its poleward edge (Douglas et al. 2006). Thus, latitudinal variation is likely to affect the distribution of water resources. With rapid population growth in these sub-tropical regions, water resources are likely to become more stressed in these areas, especially as climate change intensifies (Alcamo & Henrichs 2002; Douglas et al. 2006).

The climate moisture index (CMI) is used in a wide variety of climate studies to integrate the effects of evapotranspiration and precipitation (P) (Fedema 1994; Suzuki et al. 2006). Typically, the CMI is a ratio of the total evapotranspiration (TET) and P in a given area. It can be derived from commonly available data like annual TET and annual P, and thus is suitable for long-term studies. In this study, a modified version of the CMI, the TET and P data over the past 16 years, have been used to evaluate water scarcity throughout the SADC region, by examining the relative importance of P and TET on the variability of the CMI. Finally, the CMI is used to assess water scarcity throughout the SADC study area in order to determine the feasibility of increasing water availability in a water-scarce region by transferring water from a wetter region.

DATA AND METHODOLOGY

Dataset availability

The CMI responds rapidly to changing conditions, and it is weighted by location and time. The input data used to propel the model comprise P and TET data estimates. Monthly P and TET data computed using the CMI were obtained from the Global Precipitation Climatology Project (GPCP) data products established by the World Climate Research Programme at http://disc2.nascom.nasa.gov/Giovanni/tovas/ (Xie et al.
and the Global Land Data Assimilation System (GLDAS) available at http://gdata1.sci.gsfc.nasa.gov/daac-bin/G3/gui.cgi?instance_id=GLDAS10_M, by exploring the National Centers for Environmental Prediction/Oregon State University/Air Force/Hydrologic Research Lab (NOAH) model. This dataset is well suited for this type of project and has been used widely in climate studies (Douglas et al. 2006).

It should be noted that one problem with the dataset is that the GPCP and GLDAS do not specify P and TET by each country boundary, but only by latitude/longitude range. The dataset for each study area (Figures 1 and 2) was generated by the Integrated Land Water Information System (ILWIS). With a geographic information system (GIS) package, ILWIS can allow the researcher to manage, analyse and present geographical data in order to generate information on the specific study area. The latitude [36S, 10N] and longitude [0, 52E] were selected as spatial coverage in order to estimate the P (mm/year) and TET (kg/m² s) for the selected study area from 1994 to 2009. The TET value estimated by this method was converted to mm/year from kg/m² s in order to calculate the CMI.

These particular methods were selected for several reasons. Firstly, available potential evapotranspiration (PET) data were not found for this particular study area and the methods developed for determining PET are complex. Secondly, TET and P were estimated for this project because they rely on data that are available for the study area, often with longer record-keeping periods. Thirdly, this dataset has been widely tested, used and validated worldwide (Hulme et al. 1992). Of course, the usefulness of this method depends on the suitability of the ILWIS software.

Methodology

The CMI indicator used for assessing water scarcity throughout the SADC study area is based on the one formulated in Thornthwaite & Mather (1955) but adapted by Willmott & Feddema (1992). It is an indicator that is delimited from −1 to +1. Positive values indicate a wet region showing a surplus of water in the study area and will be determined by Equation (1), while negative values indicate a dry region where precipitation is not sufficient to meet water demands and will be demonstrated by Equation (2):

\[
CMI = 1 - \frac{TET}{P} \quad \text{when } P \geq TET
\]
or

\[
\text{CMI} = \frac{P}{\text{TET}} - 1 \quad \text{when } P < \text{TET}
\]  

where CMI is the climate moisture index; P is precipitation; TET is total evapotranspiration.

In this study, the CMI is computed from annual P and annual TET data over the period 1994–2009. These equations will be used for the first time and the results will be compared to the results previously obtained. An analysis of P and TET data estimates was generated by ILWIS and computed with SPSS Statistics 17.0. Descriptive analysis and linear correlation were considered for statistical analysis. The results are depicted in the figures and tables given.

RESULTS AND DISCUSSION

Analysis of P, TET and CMI

P and TET are two of the key elements in defining a CMI. Prolonged exposures to TET, P and CMI beyond critical thresholds adversely affect the durability of the assessment of water scarcity in the SADC study area. In effect, using climate change scenarios in the SADC region, it was shown that most water scarcity is caused by the reduction in P and enhancement of TET. This occurs when a community’s demands for freshwater for social, economic and environmental functions exceed the available water supply (Kabat et al. 2004). Figures 1 and 2 highlight the variability of the P and TET between SADC regions over a period of 16 years by showing the wet and dry areas of the study area.

Figures 3 and 4 show an increase in P and a decrease in TET in the wet and dry regions in the SADC study area, compared to annual values obtained in several other studies (Malisawa 2007; FAO 2010). The next section will show how the use of TET in the equation has changed over time in response to changes in the coefficient of variation (CV) for the CMI and its influence on the assessment of water scarcity over the SADC region.

The CMI is an aggregate measure of potential water availability imposed exclusively by climate (Feddema 1994). The relative importance of integrating the effects of P and TET in order to explain trends in the CMI was assessed using GPCP and GLDAS data products. These climate divisions were selected from within each of the areas with cohesive patterns of statistically significant trends in the CMI.

Table 1 illustrates the annual average P, TET and CMI of nearly 95% of the study area showing wet regions \([P > \text{TET}, \text{Equation (1)}]\) and 5% for dry regions \([\text{TET} > P]\). The differences in TET/P published in our work, compared to results obtained in previous studies, are illustrated in Figures 1, 5–8 (Vörösmarty et al. 2005; Douglas et al. 2006; GWSP Digital Water Atlas 2008a, b). In the Republic of Botswana, Namibia and South Africa, a decrease in TET will increase the CMI by reducing water availability and increasing water demand in the water-scarce region. By contrast, the warmer conditions in these regions increased TET.

![Figure 3](https://iwaponline.com/wst/article-pdf/12/1/45/416732/45.pdf)

Figure 3 | Annual averages TET for SADC study areas from 1994 to 2009.
leading to more demand for water and thus a decrease in the CMI. In other areas like Angola and the DRC, TET and P have opposing influences on CMI (see Figures 1 and 2).

Positive CMI values show annual average of P in excess of annual average of TET in the study areas like Angola, Botswana, DRC and South Africa (Table 1, Figures 1, 2 and 8). Nevertheless, Figures 1 and 6 show humid/sub-humid regions by illustrating the large area in the wettest part of the central Congo basin (UNEP 2004; Vörösmarty et al. 2005), and showing Namibia with a negative value of CMI (−0.125) as the driest region by displaying relatively low rainfall. The positive CMI value of Botswana (0.027) and South Africa (0.075) represent 7.56 and 7.78%, respectively, of the CMI value of Angola (0.351) and the DRC (0.347), whereas the CMI value of South Africa represents 21.33 and 21.61% of the same order of the CMI values of Angola and the DRC.

Table 1 | Annual average for P, for TET and for CMI over 16 years

<table>
<thead>
<tr>
<th>SADC study area</th>
<th>Average precipitation</th>
<th>Average total evapotranspiration</th>
<th>Climate moisture index</th>
</tr>
</thead>
<tbody>
<tr>
<td>Angola</td>
<td>1010.583</td>
<td>656.0821</td>
<td>0.351</td>
</tr>
<tr>
<td>Botswana</td>
<td>480.7775</td>
<td>467.7184</td>
<td>0.027</td>
</tr>
<tr>
<td>D.R. Congo</td>
<td>1555.126</td>
<td>1016.048</td>
<td>0.347</td>
</tr>
<tr>
<td>Namibia</td>
<td>336.2744</td>
<td>384.238</td>
<td>−0.125</td>
</tr>
<tr>
<td>South Africa</td>
<td>591.7481</td>
<td>547.1498</td>
<td>0.075</td>
</tr>
</tbody>
</table>

Figure 4 | Annual averages P for SADC study areas from 1994 to 2009.

Figure 5 | Annual averages for P, TET and CMI of the studied SADC area.
These areas also display a low rainfall and show the potential for climate-based water scarcity for resident populations, and these CMI values are included in the universal medium of CMI value (UNEP 2004) and are located in the semi-arid region.

Coefficient of Variation (CV) of CMI

CV of CMI variability over DRC and Angola for 16 years

Another important consideration is whether there has been any change in the variability of the CMI from one period to another. The CV for the CMI was computed for each study area during the 1994–2009 periods. The variability of CMI, crucial to determining the reliability of water supplies, especially in the water scarce SADC countries, is measured by CV, defined as the amount of annual variation of CMI over the 16 years of the study period. Angola and DRC show moderate variability (0.25 < DRC\textsubscript{CV,CMI} < 0.75) as reflected in the worldwide standard (Table 2 and Figure 8).

As illustrated in Table 2, Figures 8 and 9 based on the mean values for each country, Angola and the DRC appear to be similar with the highest mean values, followed by Botswana and South Africa, which also appear to be similar. This is an indication that Angola and the DRC provide the best fit in terms of CMI and water abundance based on 1994–2009 data. The findings above confirm that the DRC and Angola appear to be most consistent in terms of climate variability with the smallest standard deviation, while Namibia with the highest standard deviation appears to be the worst affected by increasing water demand in the driest region (Table 2).

CV of CMI variability over Botswana, Namibia and South Africa for 16 years

Figures 8 and 9 show the CVs for CMI values for Botswana (Botswana\textsubscript{CV,CMI} = 11.8361 > 0.75), South Africa (South Africa\textsubscript{CV,CMI} = 2.0072 > 0.75) and Namibia (Namibia\textsubscript{CV,CMI} = -2.0234 < -0.75) that fall above 0.75 for Botswana and South Africa or below -0.75 for Namibia, as illustrated in Figure 7 and calculated for the African continent using PET (Vörösmarty et al. 2005; Douglas et al. 2006; UNEP 2004). Botswana and South Africa have high CVs for CMIs and are considered to have high variability (Botswana\textsubscript{CV,CMI} and South Africa\textsubscript{CV,CMI} > 0.75) due to the smallest mean values (Table 2); this confirms the difference between TET and PET for our work compared to the worldwide standard (0.75; -0.75) (UNEP 2004 and Vörösmarty et al. 2005). Climate variability in the SADC region, known as a water scarce area, indicates the largest fluctuation and least predictability of water in 16 years of study.

Namibia is confirmed as being located in a dry area of the SADC region by showing a negative CV value for the climate variability in the area.
CMI and low variability in climate (Namibia\textsubscript{CV-CMI} < −0.75, −0.25) (Table 2). Nevertheless, Namibia generates water resources with low variability as do Botswana and South Africa, when their local surface runoff is discharged into river corridors. This buffering capacity is particularly apparent when a large proportion of the groundwater resource is not hydraulically connected to the river system, the base flow of the rivers is usually low, and the overlap between surface water and groundwater is negligible (UNEP 2004). The CV for the CMI is a useful measure for identifying regions with highly variable climates as potentially vulnerable to periodic water scarcity. It is also a statistical measure of variability in the allocation of water demand to P. Increased CV for CMI often occurs along the interface between the humid and dry areas in the study area known for water stress and water scarcity.

### Comparing the CMI between the SADC countries

A useful application of statistics involves comparing two samples to examine whether a difference between them is significant or likely to have been a chance finding. This

<table>
<thead>
<tr>
<th>SADC study area</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Coefficient of variation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Angola</td>
<td>0.3394</td>
<td>0.12186</td>
<td>0.3590</td>
</tr>
<tr>
<td>Botswana</td>
<td>0.0144</td>
<td>0.17044</td>
<td>11.8361</td>
</tr>
<tr>
<td>D. R. Congo</td>
<td>0.3395</td>
<td>0.10315</td>
<td>0.3038</td>
</tr>
<tr>
<td>Namibia</td>
<td>−0.0984</td>
<td>0.19910</td>
<td>−2.0234</td>
</tr>
<tr>
<td>South Africa</td>
<td>0.0655</td>
<td>0.13147</td>
<td>2.0072</td>
</tr>
</tbody>
</table>
lends itself well to analysis of experimental data such as shown in Table 3. This approach will be dealt with using the following hypotheses: The null hypothesis (H0): There is no difference in terms of CMI between countries and the alternative (H1); the difference exists between countries in terms of CMI. The \( t \)-distribution was used and the significant \( p \)-value < 0.05 indicates that the CMI conditions of the two countries are not the same. In the case of Angola–Botswana and Angola–Namibia a \( p \)-value (0.000) less than 0.05 (see Table 3) is rejected at the 5% (significance) level; we can therefore reject the null hypothesis (H0) in favour of the alternative (H1). In contrast, the comparison between Angola–DRC (\( p \)-value = 0.994) and Botswana–South Africa (\( p \)-value = 0.074) does not reject the null hypothesis (H0) in favour of the alternative hypothesis (H1) as is shown in Table 3 (\( p \)-value > 0.05); the \( t \)-test is also significant at 5%. This significance criterion can also be confirmed by the confidence interval when zero lies outside of the confidence limits.

Additionally, a correlation is a way to index the degree to which two or more variables are associated with or related to each other. This concept of relationship is fundamental to understanding research design and statistical analysis; bivariate correlation measures the relationship between two variables. The Pearson correlation coefficient

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**Table 3** | Paired sample test of the similarity of the CMI between the study areas

<table>
<thead>
<tr>
<th>SADC study area</th>
<th>Lower</th>
<th>Upper</th>
<th>( t )-test</th>
<th>( p )-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Angola–Botswana</td>
<td>0.24766</td>
<td>0.40234</td>
<td>8.957</td>
<td>0.000</td>
</tr>
<tr>
<td>Angola–DRC</td>
<td>–0.03571</td>
<td>0.03546</td>
<td>0.007</td>
<td>0.994</td>
</tr>
<tr>
<td>Angola–Namibia</td>
<td>0.33647</td>
<td>0.53915</td>
<td>0.208</td>
<td>0.000</td>
</tr>
<tr>
<td>Botswana–South Africa</td>
<td>–0.10788</td>
<td>0.00563</td>
<td>–1.920</td>
<td>0.074</td>
</tr>
</tbody>
</table>

**Figure 9** | Mean, standard deviation and CV for CMI of the studied SADC area.
(r) indexes the extent to which a linear relationship exists between two quantitatively measured variables. In a study of this nature it is therefore necessary to decide on which variables are related so that one may be sure about the choice of countries with the information relative to the CMI being the only variables of the correlations. The mathematical formulation of the functions to this subject must be one which will generate the correlations among data points in the study areas. At its extreme, a correlation of 1 or –1 means that the two variables are perfectly correlated, meaning that one can predict the values of one variable from the values of the other variable with perfect accuracy; the larger the value of r, ignoring the sign, the stronger the association between the two variables and the more accurately one can predict one variable from knowledge of the other variable.

The findings show that significant relationships exist between the two variables examined. The association is significant between Angola and the DRC (r = 0.837) (Table 4), which illustrates that Angola and the DRC are positioned in the sub-humid/humid region as shown in Table 1 and in Figures 1, 7 and 8. Aquifers underlying those countries, especially in the DRC, are hydraulically connected to the river system and groundwater and constitute almost the entire base flow of rivers in the SADC region. Thus, overlap is more or less equal to the groundwater resources. A moderate association was found between Angola and South Africa (r = 0.664) and between Angola and Botswana (r = 0.550) (Table 4). The correlation coefficient was found to be significant between Botswana and South Africa (r = 0.781) and between the DRC and South Africa (r = 0.639). The quantity of water leaving the Republic of Botswana is less than the quantity of water flowing into the country (Malisawa 2007).

Important groundwater reserves in South Africa and Botswana can be accessed but are in part not renewable, especially in South Africa (Malisawa 2007 and FAO 2010). This is what could be expected in reality and the equation can be used to generate valuable data.

CONCLUSION

A new approach using TET to compute CMI was introduced in this study in order to assess water scarcity in the SADC region. Substituting TET for PET in Equations (1) and (2) generated information that illustrated the relative importance of P and TET on the variability of the CMI. TET had a significant effect on the determination of wet and dry regions in the study area, compared to the use of PET. It is believed that more accurate near-term and far-term water resource predictions in the SADC water-scarce region can therefore be produced with a slightly enlarged dataset of TET or PET, and with CMI as an aggregate measure of potential water availability imposed solely by climate.

This study has shown that the CMI results for the DRC, Angola and Namibia, as well the CV for CMI for Angola and the DRC from GLDAS and GPCP are quite consistent with those given on the map of the African continent as mentioned, respectively, in Tables 1 and 2, Figures 6 and 7 (UNEP 2004). The correlation values (Table 4) computed between long-term averages for SADC studied areas for CMI confirm a strong and significant relationship between DRC–Angola (r = 0.837), significant between South Africa–Botswana (r = 0.781) and a weak but significant relationship between Namibia–Botswana (r = 0.554) and between Namibia–South Africa (r = 0.445). The results of this study also confirm that the DRC and Angola appear

<table>
<thead>
<tr>
<th>Study area</th>
<th>Angola</th>
<th>Botswana</th>
<th>D. R. Congo</th>
<th>Namibia</th>
<th>South Africa</th>
</tr>
</thead>
<tbody>
<tr>
<td>Angola</td>
<td>1</td>
<td>0.550*a</td>
<td>0.837*b</td>
<td>0.378</td>
<td>0.664*b</td>
</tr>
<tr>
<td>Botswana</td>
<td>0.550*a</td>
<td>1</td>
<td>0.467</td>
<td>0.554*b</td>
<td>0.781*b</td>
</tr>
<tr>
<td>D.R. Congo</td>
<td>0.837*b</td>
<td>0.467</td>
<td>1</td>
<td>0.207</td>
<td>0.639*b</td>
</tr>
<tr>
<td>Namibia</td>
<td>0.378</td>
<td>0.554*b</td>
<td>0.207</td>
<td>1</td>
<td>0.445</td>
</tr>
<tr>
<td>South Africa</td>
<td>0.664*b</td>
<td>0.781*b</td>
<td>0.639*b</td>
<td>0.445</td>
<td>1</td>
</tr>
</tbody>
</table>

*aCorrelation is significant at the 0.05 level (2-tailed).

bCorrelation is significant at the 0.01 level (2-tailed).
to be most consistent in terms of climate variability, while Namibia appears to be the least consistent (Table 2). With regard to the alleviation of water scarcity and improving the availability of water resources in the SADC water-scarce region, the conclusion regarding the feasibility of transferring water from the Congo River will depend on the mathematical formulation of the functions pertaining to this subject as confirmed by the correlation coefficients of the study areas.

The wetness and dryness of the region have been determined by the balance between accumulated rainfall and TET. The results indicate positive CMI trends across all the study areas except for Namibia (Table 1). While the trends are mostly related to variability in P, changes in the demand for water are still needed in areas such as Botswana and South Africa. Thus, one would overestimate or underestimate the wetness of the surface for these regions by excluding TET and considering only P, e.g. it gives a misleading result for Botswana and South Africa in terms of water abundance in the region (CMI > 0). Namibia shows an increase in dryness due to an increase in TET and a decrease in P. This is an interesting region in the study area because it is one of the most water-scarce regions in the SADC where there has been an obvious warming trend, mainly as a result of the high rates of evapotranspiration.

It is particularly useful to compare TET and PET data in order to determine the overall lack of the available water supply per grid cell in the SADC water-scarce region. The limitation is the lack of PET data in the SADC region and the fact that surface water sources and groundwater in this water-scarce region are not hydraulically connected. Due to difficulties in measuring PET in the SADC water-scarce region and the constraints in obtaining Congo River outflow measurements with adequate sampling and accuracy, the task to alleviate water scarcity in particular areas of the region becomes a major undertaking.

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