Jordan Journal of Civil Engineering, Volume **17**, No. **2**, **2023**
DOI: https://doi.org/10.14525/JJCE.v17i2.11

Drought Assessment of a Data-scarced Watershed – Quetta Valley, Pakistan

Syed M.F. Abdullah[1], Syed Imran Ahmed [2),3)], Etikaf Husain[2),4)]*, Farah Hasan[1)] and Shoaib Ahmed [2)]

[1)] Department of Urban Engineering, NED University of Engineering & Technology, Karachi, Pakistan.
[2)] Department of Civil Engineering, NED University of Engineering & Technology, Karachi, Pakistan.
[3)] School of Engineering, University of Guelph, Ontario, Canada.
[4)] Queensland University of Technology, Centre of Accident Research & Road Safety – Queensland (CARRS-Q), Brisbane, Australia. * Corresponding Author. E-Mail: e.hussain@qut.edu.au

ABSTRACT

Pakistan continuously remains under the threat of drought, as approximately 88% of its area falls under arid and semi-arid regions. The most affected province due to drought is Balochistan, facing migration, scarcity, famine and economic strain. The insufficiency of meteorolgical and hydrological data in the area intensifies the problem because of the late or non-diagnosis of drought. Therefore, this study proposes a methodology to quantify the drought in a watershed with inadequate meteorological and hydrological data. This study aims to design a method to find the extent and duration of drought conditions for watersheds where only basic meteorological data is available. For this purpose, Quetta Valley, Balochistan, Pakistan, is chosen as the study area. First, the hydrological components of water balance for the watershed are calibrated for 10 years using a distributed hydrological model (MIKE-SHE). The modeling results and other observed meteorological data are then used to evaluate eight drought indices to assess the existence and extent of drought, including those which use the hydrological parameters as input from MIKE-SHE. Reconnaissance drought and Palmer drought severity indices, which use detailed hydrological parameters, are found to provide more accurate results coupled with early drought detection of historical events. The results showed that the proposed method could be effectively used to determine the secondary parameters from the hydrological model, which in turn gives more realistic drought conditions for such regions.

KEYWORDS: Meteorological drought indices, Hydrological modeling, MIKE SHE, Drought, Palmer drought severity index.

INTRODUCTION

Drought is a water-oriented event that involves wide-reaching consequences for agriculture and water availability in a region. Uncertainties in future projections of drought arise from several sources. Understanding sources' uncertainty and their contribution to future drought projection is essential (Siddiqui et al., 2012).

Although drought is not a new research problem, the literature on the estimation of drought severity and its time of initiation is still evolving, resulting in a better understanding of drought and its wide-ranging impacts. More than fifty drought severity indices have been established in the literature (Svoboda and Fuchs, 2016). Some of the popular indices are; the Palmer Drought Severity Index (PDSI) (Palmer, 1965), the Deciles Index (DI) (Gibbs and Maher, 1967), the Bhalme–Mooley index (BMI) (Bhalme and Mooley 1979), the Standardized Precipitation Index (SPI) (McKee et al., 1993), the Effective Drought Index (EDI) (Byun and Wilhite, 1999), the Percent of Normal (PN), China-Z Index (CZI) (Wu et al., 2001), Modified CZI (MCZI), the *Z*-Score, the Reconnaissance Drought Index (RDI) (Tsakiris and Vangelis, 2005), the Soil Moisture Drought Index (SMDI) (Narasimhan and Srinivasan, 2005), the Standard Precipitation Evaporation Index (SPEI) (Vicente-Serrano et al., 2010) and the Modified Reconnaissance Drought Index (RDIe) (Tigkas et al.,

---

Received on 2/10/2022.
Accepted for Publication on 13/2/2023.

2016). Out of eight indices; namely, SPI, PDSI, SMDI, EDI, PN, CZI, RDI and Moving Average (MA) analysis, used in the study, two indices, PDSI and RDI, use multiple inputs, whereas the single input for SMDI is soil moisture. For the other five, SPI, PN, CZI, EDI and MA analysis, precipitation is used as a single input for drought assessment.

The drought indices are calculated based on the recorded meteorological and hydrological parameters. Many indices use only precipitation as input (Bhalme and Mooley, 1979; McKee et al., 1993; Wu et al., 2001; Chen et al., 2018). However, some of the indices require more parameters, such as temperature, evapotranspiration (actual and/or potential), soil moisture, etc., for detailed and accurate analysis (Palmer, 1965; Narasimhan and Srinivasan, 2005; Tsakiris and Vangelis, 2005; Li et al., 2019; Marini et al., 2019). The results of these indices are widely accepted and used for drought assessment worldwide. Moreover, the requirement of the temporal resolution also varies from very fine, daily, to coarser, yearly, which can significantly affect the drought-assessment results (Zuo et al., 2018).

Zuo et al. (2018) used SPEI to investigate the temporal and spatial variation of drought in China. The study used SPEI at different temporal resolution data. The results suggested that as the time scale increased, the frequency and area of extreme and severe drought also increased. Li et al. (2019) did a similar work for Tarim river basin in China. Nam et al. (2015) used SPI, SPEI and self-calibrating PDSI for drought evaluation in South Korea and concluded that, at a different scale, each indicator shows a significant increase in drought. In another study, a framework is proposed based on a precipitation-based index and drought-vulnerability index to measure drought and reflect its socio-economic magnitudes (Kim et al., 2015). In a study, Vu et al. (2017) evaluated the drought for Central Vietnam in climate-change scenarios by first using MIKE SHE to simulate river discharge. The study then used SPI and Standardized Runoff Index (SRI) to assess the region’s drought. The study concluded that more severe and extreme droughts are expected in the future despite more rain and high temperature. Meshram et al. (2018) analyzed the drought for the Tons River basin in India by calculating SPI on a 3-month scale and summarized that drought in the said basin depends on the monsoon rainfall.

Moreover, Ashraf and Routray (2015) proposed SPI as a suitable index for investigating meteorological drought over the Balochistan region. Mishra and Singh (2010) and Soro et al. (2014) explained the versatility of SPI in both short-term and long-term water resources’ management based on its efficiency in distinguishing dry and wet spells. Abdulla and Malkawi (2020) evaluated drought by calculating SPI at four different temporal resolutions ranging from 1 month to 12 months for present and future climate conditions. Tarawneh et al. (2008) studied drought severity in arid regions of central Jordan by using precipitation data only. Hammouri and El-Naqa (2007) assessed drought for a basin in Jordan using SPI and the Normalized Difference Vegetation Index by employing precipitation and satellite data. The study suggested combinations of various indices for better understanding and monitoring drought conditions for semi-arid basins.

Naz et al. (2020) studied drought trends in Balochistan using Mann-Kendall Test and Standard Precipitation Index (SPI) by analysing 37 years of rainfall data from 10 stations in the Balochistan province at a 3-month timescale. The study identified extreme drought events in six years. One of the stations was identified as the most frequently experienced extreme to severe drought events, with the most prolonged drought spanning over 22 months. Hina and Saleem (2019) studied the applicability of 3 drought indices in terms of severity and magnitude for Pakistan. The study analysis is based on 38 years of data from 30 climate stations across Pakistan.

Various free-source and commercial models are available for hydrological modeling to obtain desired outputs, such as streamflow, soil moisture, etc., which can be employed to estimate the drought indices using more detailed methods. Some of the renowned models are Hydrological Engineering Systems–River Analysis Simulation (HEC- RAS) (US Army Corps, 2006), Hydrological Simulation Program–Fortran (HSPF) (Bicknell et al., 1997) and MIKE SHE (Danish Hydraulic Institute, DHI) (Zhang et al., 2008).

In a study, Ahmed et al. (2019) calibrated and validated a hydrological model to assess the flood and drought of the Porali basin, Pakistan. Three meteorological stations and 2-gauged stream data were available for input into the hydrological model. The study did not apply any of the drought indices to assess drought in the area. In another study, Sagintayev et al. (2012) used remote-sensing data to calibrate the hydrologic and model in an arid and inaccessible watershed in Pishin, Pakistan. The study concluded that their methodology could not be used as a substitute for state-of-the-art methods; however, it can be used to get first-order information about the situation.

In all the above-cited studies, drought severity is calculated by employing different indices where the required data for analysis are available. Therefore, this study proposes a methodology that addresses the problem of hydro/climatic data scarcity at a watershed scale. This study emphasizes drought estimation in a data-scarce watershed where the only data source is meteorological data.

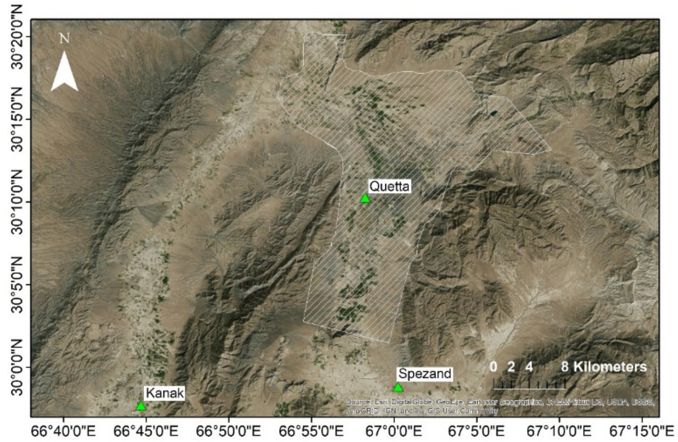
To address the above-mentioned problem, MIKE SHE (DHI, 2017), a deterministic, physics-based, distributed model, is used to perform watershed hydrological modelling. MIKE SHE has been employed by earlier studies to efficiently determine the stream flow, water-table depth and soil moisture content (Dai et al., 2010). The model can also determine 1D and 2D overland flow (Zhang et al., 2008).

The calibrated model of the study area is used to estimate the hydrological parameters, which are required as input for the calculation of detailed drought-severity indices, such as PSI, PDSI, etc. However, for more accurate analysis, eight drought indices; i.e., SPI, PDSI, SMDI, EDI, PN, CZI, RDI and MA analysis, are computed and compared in this study. Estimating different indices would suffice the results of drought severity from PDSI, which uses MIKE SHE output parameters. The parameters include soil moisture content, evapotranspiration, potential evapotranspiration and run-off. These variables are helpful in detecting areas where moisture deficiencies affect the growth of vegetation.

Previous studies tend to rely on the available stream and moisture data to determine sophisticated indices, such as SMDI and PDSI. This study proposes a novel method to estimate these indices by first predicting the required variables from a hydrological model using more traditional meteorological parameters, for instance, temperature and precipitation, which are usually available. The objective of this study is to analyze and model drought scenarios for a watershed with limited data availability. The developed methodology is applied to Quetta Valley, an arid, densely populated area and the largest watershed of Balochistan, Pakistan. In addition, there is very little or no meteorological and hydrological data available for drought assessment. The comparison of different indices is made to test the use of hydrological-model data for drought indices' computation.

MATERIALS AND METHODS

Quetta Valley lies in the Balochistan province of Pakistan. It is highly arid, as the area receives occasional rainfalls, approximately 200 mm/year. Its longitude and latitude are 66°58'E, 30°10'N and the average elevation above sea level is 1,680 m (Figure 1). It has an area of 400 km^2 and a population of approximately 1.1 million people.



Source: Esri, DigitalGlobe, GeoEye, Earthstar Geographics, CNES/Airbus DS, USDA, USGS, AeroGRID, IGN, and the GIS User Community

Figure (1): A view of the study area – Quetta valley

Data is of prime importance in performing hydrological analysis. To achieve the historical meteorological data to analyze or model any current or future scenario, the data acquired for this study is listed as follows:

The meteorological data required for modeling is taken from the National Geophysical Data Center (NGDC)- National Oceanic & Atmospheric Administration (NOAA) website, which has 40 years of data for Quetta (1973 to 2012). The data includes mean temperature, maximum temperature, minimum temperature, dew-point temperature, wind speed and precipitation. Among the obtained data, 11-year data (January 2000 to December 2010) was used to calibrate the MIKE SHE hydrological model. There is no observed evapotranspiration (ET) data; therefore, ET is calculated by the FAO Penman-Monteith method (Allen et al., 1998).

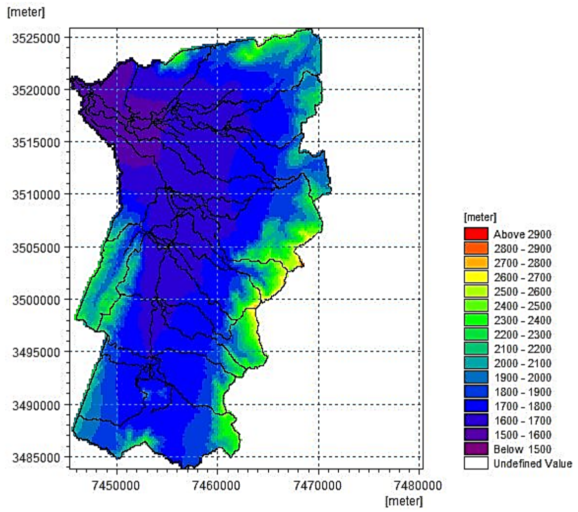


Figure (2): Digital elevation model used in the study for Quetta valley

A free-source Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) of 30m×30m resolution is used for the analysis, as shown in Figure 2. A soil map is acquired from a previous study (Sagintayev et al., 2012). The soil layer is developed through the MIKE SHE dfs2 grid creator by assigning integers to each grid. It has seven different types of soil, Chiltan limestone, Urak group (sandstone and shale), Ghazij shale, older alluvium (gravel, sand and clay-unconsolidated), piedmont, Spintangi limestone and shale.

The vegetation layer is developed by superimposing the Google Earth image over a shapefile of the catchment and marking cultivated areas. The study area is characterised by sparse cultivation; i.e., small patches of cultivated areas, which are marked manually and crop labelling is carried out using field knowledge. The crops found in the study area are wheat, maize, apple, apricot, orchard, coriander shrubs and lentils. The values for critical parameters, such as root depth and Leaf Area Index (LAI) used in the MIKE SHE model, are specified in Table 1.

To set up the model, temperature, evapotranspiration and precipitation data is converted into Data File Systems (dfs$_0$) time series, which is a DHI's binary file format. Furthermore, the soil and vegetation layers are converted into the model's acceptable format.

Calibration of MIKE SHE

The observed streamflow data is not available to calibrate the MIKE SHE model for hydrological processes in the study area. Therefore, calibration for this particular study is based on the trial-and-error method until the required water balance fractions are achieved. Calibration values are then cross-referenced with those found in the MIKE SHE guides and relevant scientific literature available for the study area and the surrounding. The parameters that significantly impact the model's prediction along with the selected values are mentioned in Table 2.

Table 1. Values of LAI and root depth of various vegetation types

Vegetation type	**Bare soil**	**Apple and apricot orchards**	**Wheat and maize**	**Onion and potato**	**Grain and sorghum**	**Coriander shrubs and lentils**
LAI	0	2.2	4	4	3	1.5
Root Depth (mm)	0	1500	1050	500	800	200

Table 2. Values of calibrated parameters of the hydrological model

Processes	Calibrated parameters	Selected value
Unsaturated Zone (K_s in m/s)	Chiltan Limestone	1.6×10^{-7}
	Urak Group; Sandstone and Shale	1×10^{-7}
	Ghazij Shale	1×10^{-7}
	Older Alluvium (gravel, sand, silt and clay; unconsolidated)	3.16×10^{-6}
	Piedmont	3.8×10^{-7}
	Spintangi Limestone and Shale	3.3×10^{-7}
	Dune Sand	1.19×10^{-6}
Overland Flow	Manning Number M (1/n)	30
	Detention Storage (mm)	0
	Initial Water Depth (mm)	0
Saturated Zone	Horizontal Hydraulical Conductivity (m/s)	1.38×10^{-7}
	Vertical Hydraulical Conductivity (m/s)	1.38×10^{-7}
	Specific Yield	0.1
	Storage Coefficient (1/m)	5×10^{-5}
	Leakage Coefficient	1×10^{-6}
Snow Melt	Melting Temperature	0 °C
	Degree Day Coefficient	2.5 mm°C^{-1}d^{-1}
	Minimum Snow Storage	5 mm
	Max Wet Snow Fraction	0
	Initial Total Snow Storage	0
	Initial Wet Snow Fraction	0

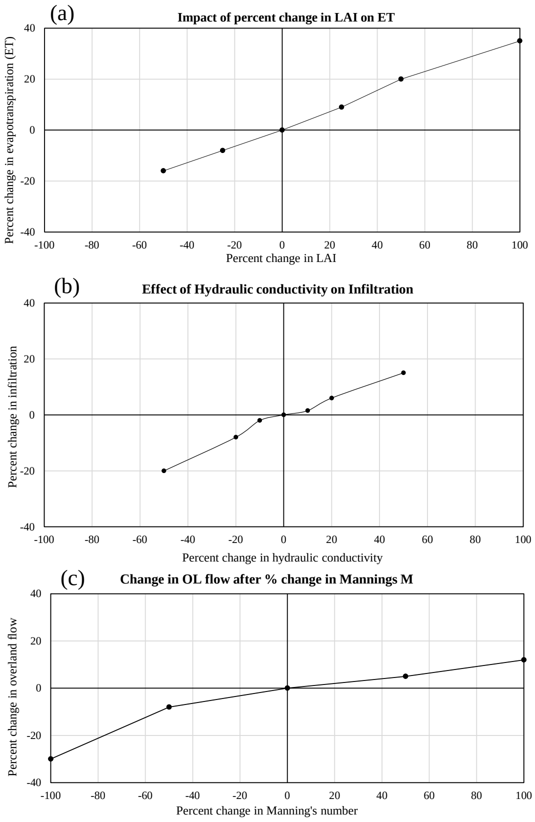


Figure (3): Sensitivity analysis of (a) Effect of precent change of LAI on ET, (b) Effect of hydraulic conductivity (Ks) on infiltration and (c) Manning's M effect on overland flow

Sensitivity Analysis of Input Parameters

A sensitivity analysis is performed by identifying the sensitive parameters to quantify their effect on the model's results. Firstly, by taking different values of leaf area index (LAI) against ET, it is observed that an increase in LAI increased the value of ET, as shown in Figure 3(a). Vertical hydraulic conductivity (K_v) is sensitive to infiltration (Figure 3(b)) and the value of Overland Flow (OL) is found to be sensitive to Manning's M (increase in M leads to increase OL) (Figure 3(c)).

RESULTS AND DISCUSSION

Water Balance

By running the model for 11 years (Jan. 2000 to Dec. 2010), water balance is generated multiple times until the results are logically understood with the annual water-balance formula presented in Equation (1).

$$P = ET + SRO + Storage \qquad (1)$$

where P is the annual precipitation, ET is the evapotranspiration and SRO is the surface run-off. In a calibrated model, 70% of the precipitation goes off as ET with surface storage of 2.5% and around 9% of the precipitation annually contributes to run-off. The other modeling studies from the area and overall Balochistan also found similar results (Sagintayev et al., 2012; Ahmed et al., 2019). The water balance for the study area, based on the percentage of precipitation, is shown in Table 3.

Drought Indices

Five drought indices are computed, which use only precipitation data, in addition to three detailed drought indices (PDSI, SMDI and RDI) to assess their performance. The detailed indices, employ the variables from the output of the hydrological model. Therefore, in total, eight drought indices: SPI, PDSI, RDI, EDI, MA, SMDI, PN and CZI, are computed and compared for their performance. An overview of these indices is provided in Table 4. The data, other than precipitation and temperature, is taken from the output of the calibrated hydrological model.

Table 3. Water balance output for Quetta valley, MIKE SHE

Duration	Unit	Precipitation	ET	Run-off	Surface storage	Recharge
11 years	Percent	100	70	8.5	2.5	19
	mm	2038	1426	173	51	388

Table 4. Drought indices and watershed input parameters required to perform tests

Name	Factors used	Time scale	Main concept
PDSI	Precipitation, Temperature, Evapotranspiration, Soil Moisture, Run-off	Monthly	Based on moisture inflow, outflow and storage
PN	Precipitation	Monthly	Dividing actual precipitation by the normal value
SPI	Precipitation	Monthly	Difference of precipitation from the mean for a particular time and dividing it by the standard deviation
SMDI	Soil Moisture	Yearly	Summation of daily soil moisture for a year
RDI	Precipitation and Potential Evapotranspiration	Monthly, Yearly	Precipitation is compared to an arbitrary value of +3 and -3, which is assigned to the mean of ten extreme + and - anomalies of rainfall
CZI	Precipitation	Monthly	Assumes type III Pearson distribution of precipitation, taking monthly values of all years
EDI	Precipitation	Monthly, Yearly	Based on the recovery from the accumulated deficit since the beginning of the drought
MA Analysis	Precipitation	Yearly	Cumulative impact of surplus or deficit

This study analyzes CZI, RDI, EDI and PN for 25 years (i.e., 1985-2010). The graphical illustration of these tests is provided in Figures 6 to 9.

Among the four tests shown in Figures 4-7, the results of PN (Figure 4) indicate drought conditions in Quetta throughout the study period other than February 2005. CZI (Figure 5) and EDI (Figure 6). On the other hand, the results indicate normal climate conditions for most of the years. However, according to RDI (Figure 7), moderate-to- severe drought existed during 1988-1989 and reoccurred in 1996 and 2001-2002. Drought ranges according to all three tests are depicted in Table 5.

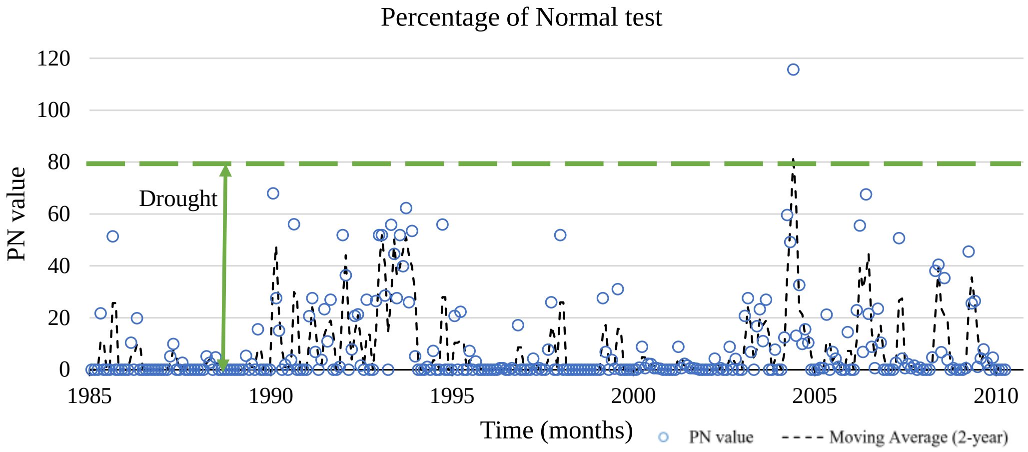


Figure (4): Percentage of normal (PN) test results

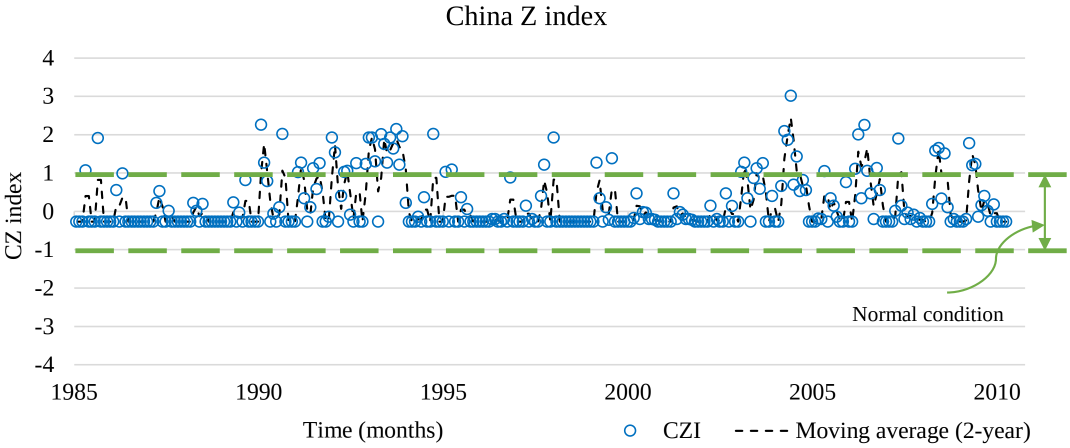


Figure (5): China Z-index (CZI) test results

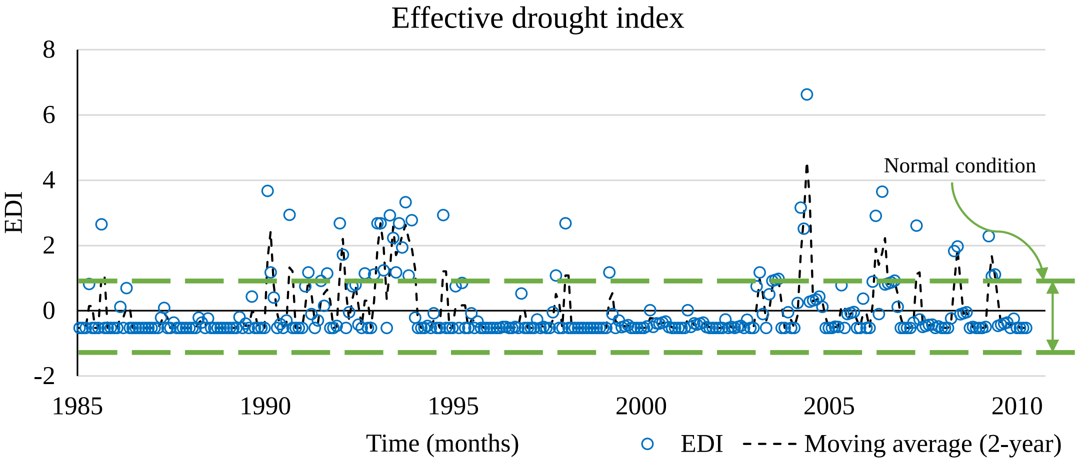


Figure (6): Effective drought index (EDI) results

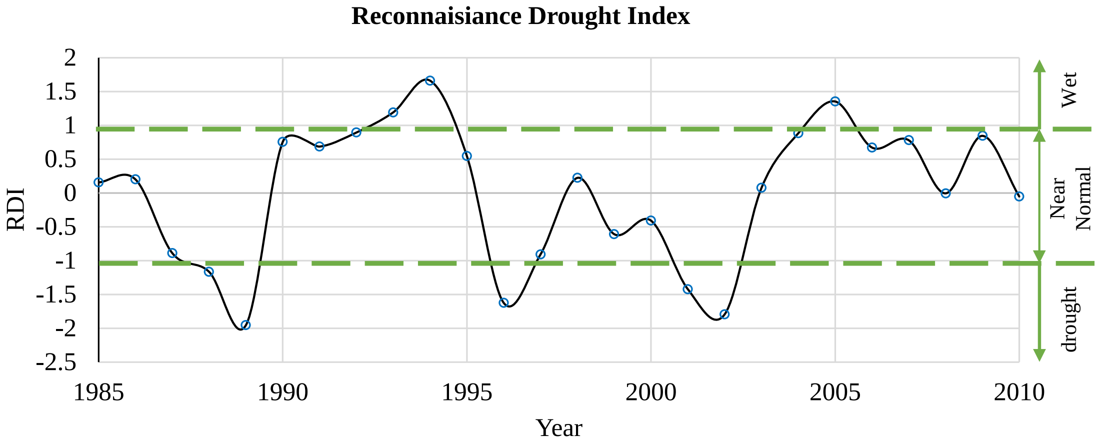


Figure (7): Reconnaissance drought index (RDI) test results

Table 5. Categories and reference range for different drought indices

Category	**PN range**	**CZI range**	**EDI range**	**RDI range**	**SPI range**	**PDSI range**
Extremely wet		≥ 2.00		≥ 2.00		> -4.00
Very wet		1.50 to 1.99		1.50 to 1.99		3.00 to 3.99
Moderately wet		1.00 to 1.49		1.00 to 1.49		2.00 to 2.99
Slightly wet						1.00 to 1.99
Incipient wet spell						0.50 to 0.99
Near-normal			-1.0 to 1.0	−0.99 to 0.99		0.49 to -0.49
Normal	> 80	−0.99 to 0.99				
Incipient dry spell						-0.50 to -0.99
Mild drought					0 to -0.99	-1.00 to -1.99
Moderate drought	55 to 80	−1.00 to −1.49	-1.50 to -1.00	−1.00 to −1.49	-1.00 to -1.49	-2.00 to -2.99
Severe drought	40 to 55	−1.50 to −1.99	-2.0 to -1.5	−1.50 to −1.99	-1.5 to -1.99	-3.00 to -3.99
Extreme drought	< 40	≤ -2.00	< -2.00	≤ -2.00	≤ -2.00	≤ -4.00

SPI (Figure 8) illustrates a mild-to-moderate drought for the years 1987, 1989, 1993, 1996, 1998-2004 and 2008-2009 (for SPI range, refer to Table 5). It also shows that out of 26 years, 13 years are normal, while for the other 13 years, Quetta Valley faced mild-to-moderate drought.

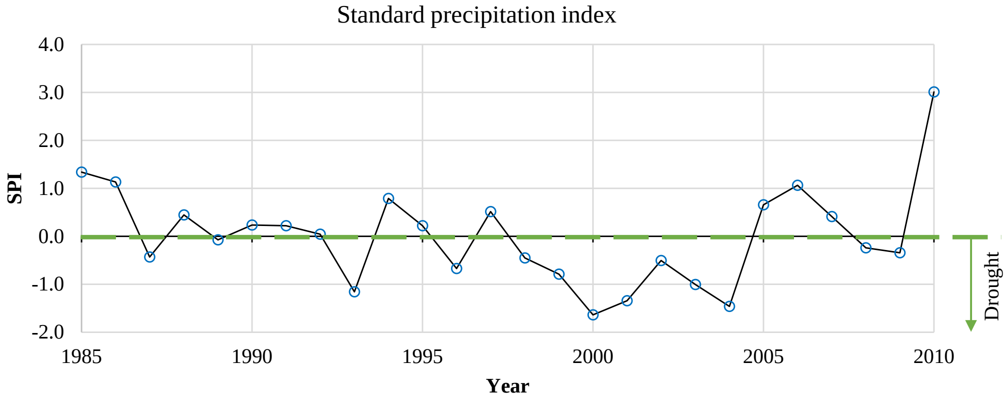


Figure (8): Standard precipitation index (SPI) test results

PDSI is computed from January 2000 to December 2009. According to PDSI, almost the entire year 2000 was under moderate-drought conditions, whereas the month of April, from 2000 to 2008, faced severe drought with similar reoccurring patterns every year. The drought conditions in Quetta Valley prevailed for 99 months out of 120 months (10 years). The corresponding drought-range classification is shown in Table 5.

SMDI follows a similar drought range as PDSI (Table 5). SMDI is computed for 10 years (2000-2009). Figure 10 shows that it does not detect any drought and indicates no drought conditions for any period.

The final test carried out is the moving average. This analysis depends on rainfall and it is performed on the yearly scale for the 26 years of data; i.e., 1985 to 2010. The long-term average (LTA) of 26 years, the 5-year average and the average raw values for each year are plotted together in Figure 11. The long-term average of 26 years of precipitation is 192 mm. The annual sum of the precipitation (raw data in Figure 11) shows that out of 26 years, 11 years received above-average rainfall. Hence, the rainfall is below average for the rest of the 15 years, suggesting drought conditions 58% of the time in the study area. Also, the 5-year moving average depicts 12 normal years (1993-1998 and 2005-2010) compared to 10 dry years.

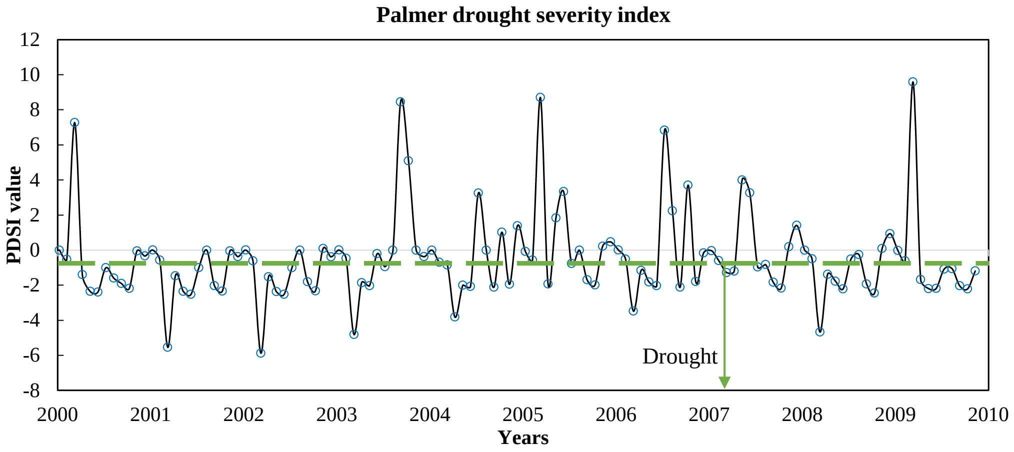


Figure (9): Palmer drought-severity index (PDSI) test results

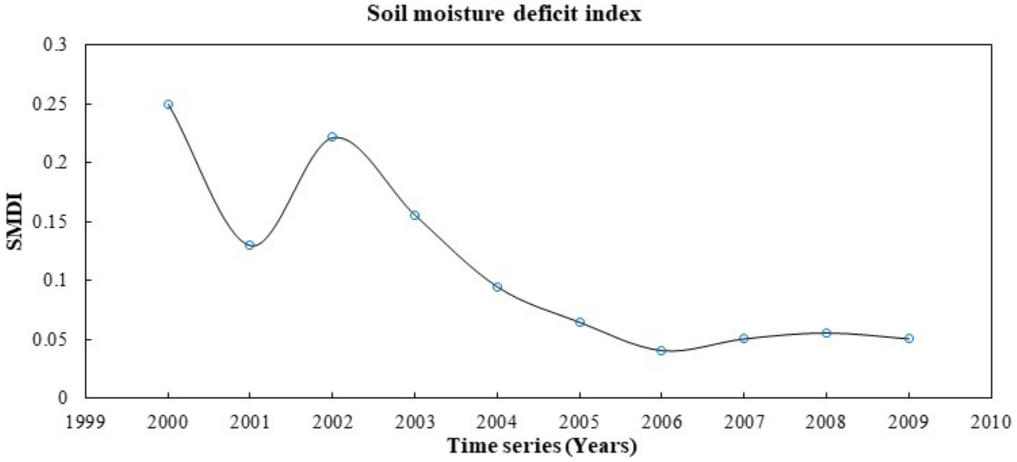


Figure (10): Soil moisture deficit index (SMDI) test results

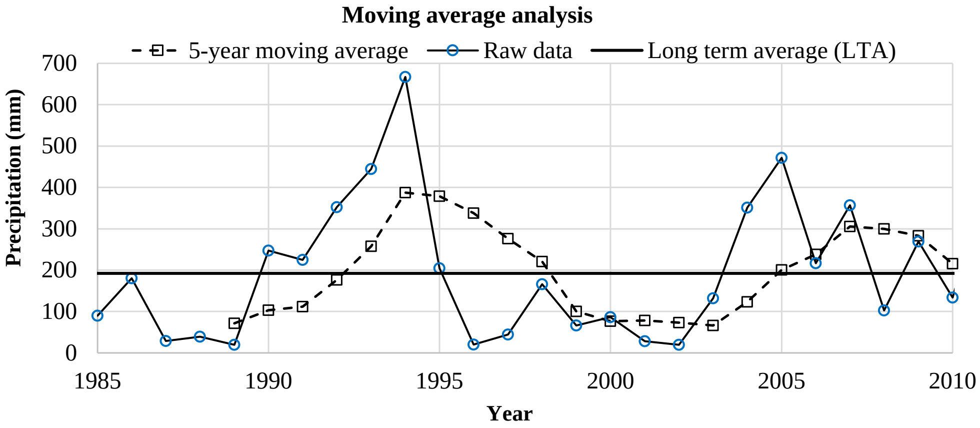


Figure (11): Moving-average analysis results

Among eight drought indices computed in this study, five tests (SPI, PDSI, RDI, PN and MA) proved the drought conditions for Quetta Valley. It is crucial to note that SPI and MA patterns are similar. SPI is based on the actual precipitation versus the probabilistic precipitation. MA takes the long-term average and observes the raw or actual rainfall events *versus* the long-term precipitation. One more similarity between these tests is that they take into account the precipitation data only. The tests indicate that most of Quetta Valley's precipitation is less than the average long-term rainfall, depicting drought conditions.

Input parameters of PDSI and RDI include precipitation and potential evapotranspiration. As Quetta is an arid region, there is more ET (around 70%, which is also evident by the simulated water balance of the model); therefore, both tests show drought conditions. PDSI, being a multi- parametric test, gives more insight into the drought at a finer temporal resolution.

The study results are aligned with the reported drought spells in the Balochistan province. For instance, Ahmad et al. (2004) and GoB (2007) reported that Balochistan province was severely affected by a persistent multi-year drought during 1998–2002, ending almost 80% of fruit orchards, affecting 22 districts out of 29 in the province. Ashraf and Routray (2015) also revealed with field-survey results that about 63.3 % of the farmers perceived 1998–2004 as a severe-drought period in terms of severe consequences on their livelihood. Similar results are obtained from PDSI and RDI, advocating their use in drought detection. Surprisingly, the 5-year moving average and SPI, which are relatively easier and less technical tests, also highlighted the same duration (i.e., 1998-2004) as drought. However, drought detection might be late when employing 5-year moving average as compared to RDI and PSI.

CONCLUSIONS

This study is carried out on a densely populated, water- and data-deficient valley. The data deficiency proves vital, because the drought periods are not sensed earlier. Therefore, we are unable to provide in-time measures required to mitigate the impact of the said phenomenon. MIKE SHE model for the simulation for Quetta basin proved to be a better choice in predicting the existing scenario. Therefore, it enables us to use more sophisticated methods for drought detection. The simulated water balance showed that precipitation is distributed as 70% to evapotranspiration, leaving only 18% recharge in the form of infiltration, which is stored in groundwater.

Using the model outputs and running drought tests, the following findings are made: i) Among eight drought indices, six tests showed the drought conditions for Quetta Valley from 1998 to 2004, being the most prolonged dry spells. PDSI and RDI, being detailed tests, can give more insight into the drought-duration estimation; ii) The 5-year moving average has also identified the drought conditions effectively; iii) Because of the continuous dry spells and according to the present situation, the Quetta Valley is under considerable economic stress which is expected to rise if the existing climatic conditions continue along with more population in the future, which will cause significant social and environmental impacts.

Acknowledgement

The authors would like to thank Shahzad Shaikh and Awais Ali Kalwar who initially contributed to this idea, including data curation.

REFERENCES

Abdulla, F.A., and Malkawi, D.A.H. (2020). "Potential impacts of climate change on the drought conditions in Jordan". Jordan Journal of Civil Engineering, 14 (1).

Ahmad, S., Hussain, Z., Qureshi, A.S., Majeed, R., and Saleem, M. (2004). "Drought mitigation in Pakistan: Current status and options for future strategies". IWMI.

Ahmed, S., Ahmed, S.I., Maqsood, H., and Lakhani, B. (2019). “Modeling flood & drought scenario for water management in Porali river basin, Balochistan”. International Journal of Economic and Environmental Geology, 1-9.

Allen, R. G., Pereira, L. S., Raes, D., and Smith, M. (1998). “Crop evapotranspiration: Guidelines for computing crop water requirements-FAO irrigation and drainage paper 56”. Fao, Rome 300 (9): D05109.

Ashraf M., and Routray, J. K. (2015). “Spatio-temporal characteristics of precipitation and drought in Balochistan province, Pakistan”. Natural Hazards, 77 (1), 229-254.

Bhalme, H., and Mooley, D. (1979). “On the performance of modified Palmer index”. Archiv für Meteorologie, Geophysik und Bioklimatologie, Serie B, 27 (4), 281-295.

Bicknell, B.R., Imhoff, J.C., Kittle Jr, J.L., Jobes, T., and Donigian Jr, A. (1997). “Hydrological simulation program-FORTRAN”. User’s Manual for Release, 11.

Byun H.-R., and Wilhite, D.A. (1999). “Objective quantification of drought severity and duration". Journal of Climate, 12 (9), 2747-2756.

Chen, H., Wu, W., and Liu, H.-B. (2018). “Assessing the utility of meteorological drought indices in monitoring summer drought based on soil moisture in Chongqing, China”. Theoretical and Applied Climatology, 132 (1), 587-597.

Dai, Z., Li, C., Trettin, C., Sun, G., Amatya, D., and Li, H. (2010). “Bi-criteria evaluation of the MIKE SHE model for a forested watershed on the South Carolina coastal plain”. Hydrology and Earth System Sciences, 14 (6), 1033-1046.

DHI. (2017). “MIKE SHE-Volume 1: User guide”. The Experts in Water Environment, DHI Software.

Gibbs, W., and Maher, J. (1967). “Rainfall deciles as drought indicators". Bureau of Meteorology, Bulletin 48. Commonwealth of Australia: Melbourne, 29.

GoB. (2007). “Provincial disaster risk-management plan". Balochistan Disaster Management Authority Government of Balochistan.

Hammouri, N., and El-Naqa, A. (2007). “Drought assessment using GIS and remote sensing in Amman-Zarqa basin, Jordan”. Jordan Journal of Civil Engineering, 1 (2), 142-152.

Hina S., and Saleem, F. (2019). “Historical analysis (1981-2017) of drought severity and magnitude over a pre-dominantly arid region of Pakistan”. Climate Research, 78 (3), 189-204.

Kim, H., Park, J., Yoo, J., and Kim, T.-W. (2015). “Assessment of drought hazard, vulnerability and risk: A case study for administrative districts in South Korea”. Journal of Hydro-environment Research, 9 (1), 28-35.

Li, C., Wang, J., Yin, S., Bao, Y., Li, Y., and Yu, S. (2019). “Drought-hazard assessment and possible adaptation options for typical steppe grassland in Xilingol League, Inner Mongolia, China”. Theoretical and Applied Climatology, 136 (3), 1339-1346.

Marini, G., Fontana, N., and Mishra, A.K. (2019). “Investigating drought in Apulia region, Italy using SPI and RDI”. Theoretical and Applied Climatology, 137 (1), 383-397.

McKee, T.B., Doesken, N.J., and Kleist, J. (1993). “The relationship of drought frequency and duration to time scales”. Proceedings of the 8th Conference on Applied Climatology, Boston, MA, USA.

Meshram, S.G., Gautam, R., and Kahya, E. (2018). “Drought analysis in the Tons River Basin, India during 1969-2008”. Theoretical and Applied Climatology, 132 (3), 939-951.

Mishra, A.K., and Singh, V.P. (2010). “A review of drought concepts”. Journal of Hydrology, 391 (1-2), 202-216.

Nam, W.-H., Hayes, M.J., Svoboda, M.D., Tadesse, T., and Wilhite, D.A. (2015). “Drought- hazard assessment in the context of climate change for South Korea”. Agricultural Water Management, 160, 106-117.

Narasimhan, B., and Srinivasan, R. (2005). “Development and evaluation of soil moisture deficit index (SMDI) and evapotranspiration deficit index (ETDI) for agricultural drought monitoring”. Agricultural and Forest Meteorology, 133: 69-88.

Naz, F., Dars, G.H., Ansari, K., Jamro, S., and Krakauer, N.Y. (2020). “Drought trends in Balochistan”. Water, 12 (2), 470.

Palmer, W.C. (1965). "Meteorological drought". US Department of Commerce, Weather Bureau.

Sagintayev, Z., Sultan, M., Khan, S., Khan, S., Mahmood, K., Yan, E., Milewski, A., and Marsala, P. (2012). “A remote sensing contribution to hydrological modeling in arid and inaccessible watersheds, Pishin Lora basin, Pakistan”. Hydrological Processes, 26 (1), 85-99.

Soro, G., Anouman, D., Bi, T.G., Srohorou, B., and Savane, I. (2014). “Caractérisation des séquences de sècheresse météorologique à diverses échelles de temps en climat de type soudanais: Cas de l’extrême nord-ouest de la Cote d’Ivoire”. LARHYSS Journal-P-ISSN 1112-3680/E-ISSN 2521-9782(18).

Svoboda, M., and Fuchs, B. (2016). “World meteorological organization (WMO) and global water partnership (GWP), 2016: Handbook of drought indicators and indices”. Integrated Drought Management Programme (IDMP), Integrated Drought Management Tools and Guidelines. Series 2.

Tarawneh, Z., Elgaali, E., and Hamdi, M.R. (2008). “Severity of droughts in arid regions”. Jordan Journal of Civil Engineering, 2 (3), 228-237.

Tigkas, D., Vangelis, H., and Tsakiris, G. (2016). “Introducing a modified reconnaissance drought index (RDIe): Incorporating effective precipitation”. Procedia-Engineering, 162, 332-339.

Tsakiris, G., and Vangelis, H. (2005). “Establishing a drought index incorporating evapotranspiration”. European Water, 9 (10), 3-11.

Vicente-Serrano, S.M., Beguería, S., and López-Moreno, J.I. (2010). “A multi-scalar drought index sensitive to global warming: The standardized precipitation evapotranspiration index”. Journal of Climate, 23 (7), 1696-1718.

Vu, M., Vo, N., Gourbesville, P., Raghavan, S., and Liong, S.-Y. (2017). “Hydro-meteorological drought assessment under climate-change impact over the Vu Gia–Thu Bon river basin, Vietnam”. Hydrological Sciences Journal, 62 (10), 1654-1668.

Wu, H., Hayes, M.J., Weiss, A., and Hu, Q. (2001). “An evaluation of the standardized precipitation index, the China-Z index and the statistical Z-score”. International Journal of Climatology: A Journal of the Royal Meteorological Society, 21 (6), 745-758.

Zhang, Z., Wang, S., Sun, G., McNulty, S. G., Zhang, H., Li, J., Zhang, M., Klaghofer, E., and Strauss, P. (2008). “Evaluation of the MIKE SHE model for application in the Loess Plateau, China”. JAWRA Journal of the American Water Resources Association, 44 (5), 1108-1120.

Zuo, D., Cai, S., Xu, Z., Li, F., Sun, W., Yang, X., Kan, G., and Liu, P. (2018). “Spatiotemporal patterns of drought at various time scales in Shandong province of eastern China”. Theoretical and Applied Climatology, 131 (1), 271-284.