PAPER 13

Developing Geo-information Based Selection Algorithms to Identify Water Resource Interventions

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ABSTRACT

The Southern African region is subject to frequent droughts which contribute to crop failures, famines and epidemics, often coupled with devastating socio-economic impacts. To encourage proactive planning in securing water for drought prone areas, the Southern African Development Community Groundwater Management Institute (SADC-GMI) implemented the project: Assessment of Groundwater Resources Development Priority Intervention Areas in the Southern African Development Community Region.

As part of the analyses undertaken to identify drought-prone areas, existing geospatial, hydrological and hydrogeological global datasets were researched and analysed according to their validity and applicability to the region. Global datasets were interrogated to produce several risk indices representative of surface water availability, groundwater availability and population vulnerability, which were weighted and combined to identify so-called hotspot areas within the SADC region which are most vulnerable to drought.

To mitigate the potential impacts of drought in the identified hotspot areas, different types of interventions were conceptualised and evaluated. These include boreholes, sand dams, managed aquifer recharge, surface water dams, rainwater harvesting, stormwater harvesting as well as desalination and water reuse. Selection criteria were developed for each intervention type by means of a typology matrix, which took into consideration a number of physical criteria which had to be satisfied for the intervention to be considered feasible. The criteria were further refined in workflow diagrams to aid incorporation of algorithms and decision-making methodologies in a GIS environment. By using these geo-information based selection algorithms, a suite of possible technically feasible interventions was identified, on a geographic grid by grid basis, for each hotspot area through spatial analyses.

The different types of interventions identified in each hotspot area were evaluated by performing high-level analyses taking into account reliability of supply, population served, level of technical skills required for maintenance and operation, energy requirements and associated capital and operational costs. Finally, after assessing institutional and environmental factors, a list of targeted interventions per hot spot area was compiled, which typically included a combination of large scale and local scale interventions aiming to strengthen water resources diversity and to improve water resilience in communities within the SADC region. The targeted suite of interventions, which was presented at stakeholder workshops, constitute sustainable water supply investments in drought susceptible regions and can assist relevant organisations in these regions in making informed decisions with regard to water resources investments.

INTRODUCTION

Water availability in the Southern African Development Community (SADC) varies greatly in space and time, giving rise to unevenly distributed water resources compared to population and settlement patters. The northern and eastern parts of the region experience significant precipitation in the tropical and sub-tropical climate zones, while the southern region and the western region experience highly seasonal rainfall and are classified as semi-arid and arid climates. The SADC region is prone to recurring droughts, having undergone a series of severe droughts during the 2015/2016 and 2016/2017 summer rainfall seasons (Archer, et al., 2017). In the past, droughts were driven by natural climate variability, however with increasing anthropogenic influences, the characteristics of droughts have shifted and are changing to include a type of drought that has a rapid onset and short duration. Generally, droughts in the SADC region are associated with increased risks to vulnerable communities due to crop failure, food shortages, famine and epidemics.

According to Wilhite & Glantz (1985), droughts are defined by the degree of dryness and the duration of dryness which can have far reaching consequences. Meteorological droughts can arise from a range of hydrometeorological drivers which suppress precipitation and/or limit surface water and groundwater availability, causing significantly drier conditions than normal, and leading to water shortage (Svoboda & Fuchs, 2016).

Drought indices are typically used to quantify hydrometeorological information and to ultimately identify locations, severity and duration of droughts (Nagarajan, 2009). To assess and quantify the severity and duration of droughts requires regional analysis of spatial and time-series data. Long-term trend analysis as well as weighted index methodologies are increasingly applied when assessing data with high spatial and temporal variability (Villholth, et al., 2013).

Water management is a pivotal instrument in managing the widely distributed water resources in an environmentally sustainable way, while providing for the increasing water requirements of communities. To account for geographic, climatic and socio-economic factors within the SADC member states; water resources sharing has been implemented in fifteen transboundary river basins as well as the transboundary aquifers (SADC Secretariat, 2019). Water resources interventions which are gaining increasing traction within the African continent include the conjunctive use of a diverse suit of interventions. Interventions such as sand dams, new surface water storage dams, desalination, stormwater and rainwater harvesting, managed aquifer recharge, new boreholes, as well as water reuse and desalination are considered part of the suit of interventions.

To encourage proactive planning in securing water supply during periods of drought, the Southern African Development Community Groundwater Management Institute (SADC-GMI) is implementing the project: Assessment of Groundwater Resources Development Priority Intervention Areas in the Southern African Development Community (SADC) Region (SADC GMI-GDRI). The project aims to identify and map areas prone to drought based on groundwater and surface water availability and population vulnerability. Moreover, the project provides guidance and recommendations on possible future water resources interventions to enhance water resilience and diversify the current water resources as well as identify possible infrastructure investment opportunities to secure water supply in drought conditions.

This paper highlights the main aspects of producing a drought risk map for the SADC region, which included surface water, groundwater and population vulnerability assessments, with a specific emphasis on surface water resources assessment aspects. In addition, the approach towards the identification and evaluation of potential interventions through typology matrices and geo-information-based selection algorithms is presented. As such, this paper provides findings on some of the available hydrological time-series global datasets, the processing of such 'large' datasets as well as the weighted index approach to overlay these datasets. Furthermore, it presents a decision-based methodology to assess the technical viability and suitability of surface and groundwater interventions within the SADC region on a grid-by-grid basis.

The methodologies developed during this project could be applied to smaller study areas and potentially aid decision making processes.

APPROACH AND METHODOLOGY

The project essentially entailed two main tasks: Firstly, the identification and mapping of SADC areas prone to drought based on groundwater and surface water availability and population vulnerability. Secondly, the development of a pragmatic approach to guide and recommend possible future water resources engineering interventions to mitigate drought risk and enhance water resilience in the identified drought-prone areas where high population vulnerability and drought risk coincides. The approach and methodologies associated with these two tasks are briefly described in this section.

THE IDENTIFICATION OF DROUGHT RISK HOTSPOT AREAS

As mentioned above, in order to identify drought risk areas (hotspots) within the SADC region, three separate maps were produced, namely surface water drought risk, groundwater drought risk and population vulnerability, which were subsequently overlaid and weighted to identify hotspot areas for further consideration of drought mitigation interventions. To assess groundwater drought risk, the current SADC Groundwater Drought Risk (GDR) map (Villholth, et al., 2013) was revised to identify areas that are prone to groundwater drought in the SADC region (SADC-GMI, 2020). In parallel, population vulnerability within the SADC region was mapped based on a number of criteria (SADC-GMI, 2020).

Although mention is made in this paper on how the surface water risk map was integrated with the groundwater risk map and the population vulnerability map, the focus of this paper, in relation to drought risk, is the assessment of surface water drought risk.

SURFACE WATER DROUGHT RISK MAP

A surface water resources assessment informed the mapping of surface water availability and variability across the study area. Existing spatial data, catchment characteristics derived from satellite imagery and global DEMs as well as readily available time-series data were utilised for this assessment.

Figure 1 presents the process followed to assess surface water resources. Existing time-series global datasets were reviewed, and surface water risk indices were determined to quantify the availability and variability of these long-term historical datasets. Subsequently, the surface water risk indices underwent a process of normalisation and were then weighted to produce a combined surface water risk index which was used to produce the surface water risk map.

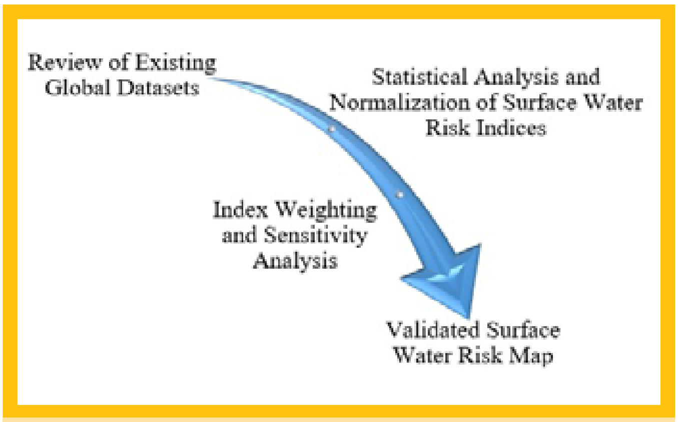


FIGURE 1: Surface water risk map process overview

Generally, surface water data are presented at varying scales. Given the need for a uniform scale across the surface water data layers in order to compare the different datasets and considering the 'catchment-nature' of surface water, catchment unit polygons were used as spatial unit to ensure uniformity for the analyses. **Hydro**logical data and maps based on **SH**uttle **E**levation **D**erivatives at multiple Scale (HydroSHEDS) is a mapping product that provides hydrographic information for regional and global-scale applications. HydroBASINS presents a sub dataset of HydroSHEDS and entails a series of polygon layers derived from HydroSHEDS data at 15 arc-second resolution depicting watershed boundaries and sub-basin delineations at a global scale (Lehner, 2014). These sub-basins provide a global coverage of consistently sized and hierarchically nested catchment areas at different scales. A level 1 catchment distinguishes the continents, level 2 splits the continents into 9 sub-units and at level 3 the largest river basins of each continent start to break out. From level 4 onwards the largest river basins are broken down into the tributaries using high resolution elevation data (Lehner, 2014) up to level 12. A level 8 catchment unit was applied during this project, providing a total of 15 202 catchment units over the SADC region.

Review of Existing Global Datasets

Time-series precipitation and surface water runoff datasets were the predominant datasets used to assess surface water availability and variability. Sun et al., (2017) summarised global precipitation and runoff data into three main categories: gauge-based, satellite-based (precipitation) or model-derived (runoff), and reanalysis datasets. All three dataset types are generally presented in the form of multi-dimensional gridded raster files (sometimes referred to as netCDF files). These files store the spatial distribution of the data at a given time step as a separate raster band.

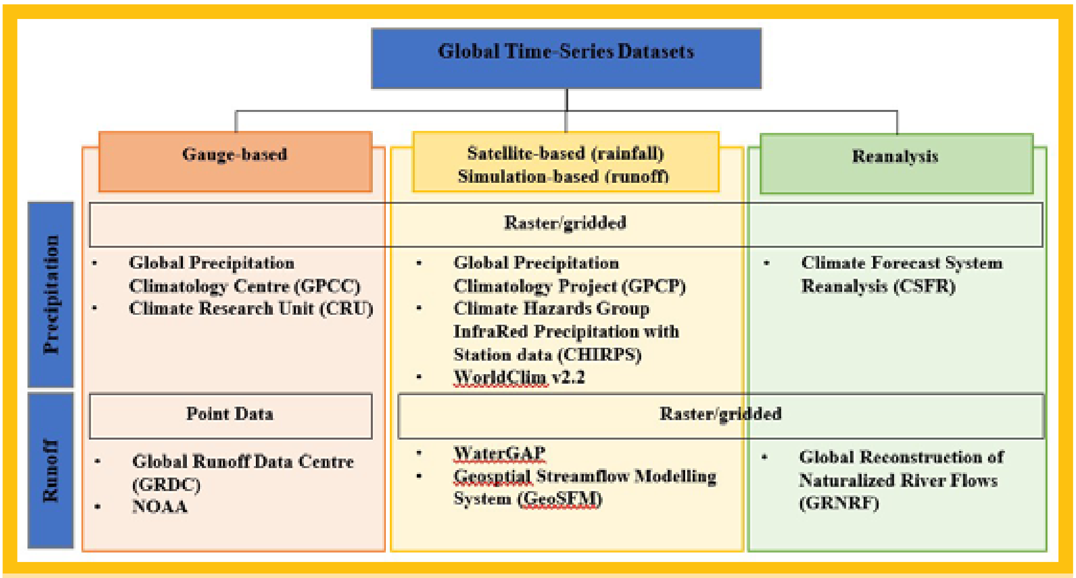


FIGURE 2: Global time-series datasets and possible examples

Figure 2 presents the three main types of global hydromet time-series datasets, as well as identified example datasets that were investigated for potential application Global time-series datasets and possible examples.

Gauge-based precipitation datasets are a collection of historical precipitation data from gauge observations across the world. These observations are generally collected with the assistance of national weather services. As such, these gauges tend to be more prolific in developed areas, causing an irregular distribution of observation stations. Due to the irregular distribution of observation stations, gridding of the data is required for many climate-related applications (Sun, et al., 2017). Weighted empirical interpolation methods are generally applied to extrapolate gauge data to gridpoints so that a gridded precipitation dataset is created (Sun, et al., 2017). Two precipitation gauge-based datasets that have undergone weighted empirical interpolation include the Global Precipitation Climatology Centre (GPCC) and the Climate Research Unit (CRU) datasets.

The Global Runoff Data Centre (GRDC) is an international data centre operating under the auspices of the World Meteorological Organization (WMO). Their dataset is a collection of quality controlled historical mean daily and monthly discharge data. Time series data on river discharge is available for more than 9 900 stations in 159 countries. The Southern Africa Flow Database of SA FRIEND is also available from the GRDC. The National Oceanic and Atmospheric Administration (NOAA) dataset which contains both satellite and point data. Runoff data is available for NOAA stations across Africa, which are often cross referenced and patched and thus provide a good validation dataset.

Satellite data is needed when surface observations of precipitation data is sparse. Data scarcity is often the case in developing countries where infrastructural development is costly and requires high maintenance (Wang, et al., 2019). Sensors onboard satellites measure clouds and related convection to predict the probability and intensity of rainfall. These predictions are typically supported by land-based measurements. Satellite sensors are currently the only method of providing homogenous precipitation measurements on a global scale, but satellite data also contains random errors and biases, and data is only available over a smaller time period. Satellite data is typically merged with rain gauge data to increase the accuracy of the dataset (Sun, et al., 2017). The most widely recognised merged dataset (Sun, et al., 2017) is the Global Precipitation Climatology Project (GPCP) dataset, which is based on sequential combination of microwave, infrared as well as gauge data). The CHIRPS dataset used interpolation techniques and long periods of precipitation estimates based on infrared Cold Cloud Duration observations as well as in-situ station data. Satellite information is incorporated to represent sparsely gauged locations, while daily and monthly Cold Cloud Duration observations are also included from 1981 (Funk, et al., 2015). The WorldClim dataset is considered one of the most popular global datasets providing invaluable data for data-sparse areas (Wango, et al., 2018; Fick & Hijmans, 2017). WorldClim v2.1 contains average monthly climatic gridded data for the period between 1960 to 2018, the CRU was used to perform bias-correction.

Simulation-based or model-based runoff datasets make use of rainfall data and typically model a catchment response to simulate runoff data. WaterGAP v2.2 is a global water assessment model consisting of two main components, namely: the Global Water Use model and the Global Hydrology model. The Water Use model considers basic socio-economic factors that lead to domestic, industrial and agricultural water use, while the Hydrology model incorporates physical and climate factors that lead to runoff and groundwater recharge based on the computation of daily water balances of the soil and canopy. A further model-based runoff dataset is generated with the Geospatial Streamflow Model (GeoSFM). The geospatial streamflow modeling system is parameterised with global terrain, soils and land cover data and runs with satellite-derived precipitation and evapotranspiration datasets (Asante, et al., 2008).

Reanalysis data are generated by using advanced numerical modelling techniques to combine observations from multiple sources. Observational data and numerical weather prediction and runoff model products are typically fused and integrated by data assimilation systems to produce reanalysis datasets (Wang, et al., 2019). The result is usually a synthesised estimate of rainfall across a uniform grid that is spatially and temporally homogenous (Sun, et al., 2017). A further reanalysis runoff dataset is the Global Reconstruction of Naturalized River Flows (GRNRF) dataset. The GRNRF is classified as a reanalysis dataset rather than a model-based dataset, as is the case with GRUN, because a merged precipitation dataset consisting of gauge, satellite as well as reanalysis-based datasets is used in the GRNRF. The dataset is a reconstruction of daily and monthly streamflow records ranging from 1979 to 2014, covering the spectrum of stream orders (Lin, et al., 2019).

Based on a comprehensive review of the above datasets, surface water indices capturing variability (annual, seasonal) were derived from the selected datasets for the period 1971 to 2016 at a temporal resolution of monthly and a spatial resolution of 0.5°x 0.5° for the purpose of the surface water analyses undertaken as part of this study. WorldClim v2.1 was used as primary rainfall dataset and WaterGAP v2.2 was selected as primary runoff dataset. Both datasets were validated against gauge-based datasets such as NOAA and the GRDC respectively. Note that for some of the island states within the SADC region only precipitation data and no runoff data were available. Consequently, for these islands, surface water drought risk was determined based solely on precipitation data.

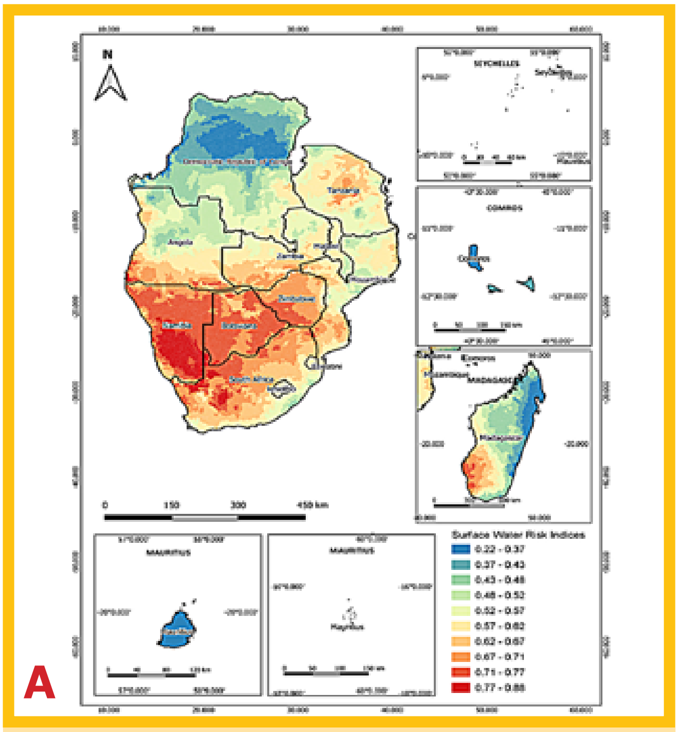
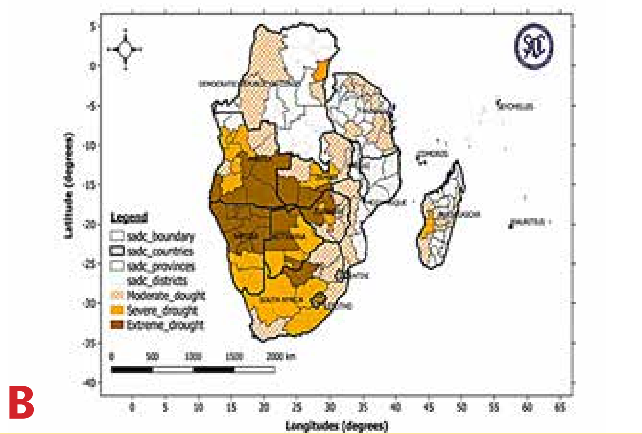
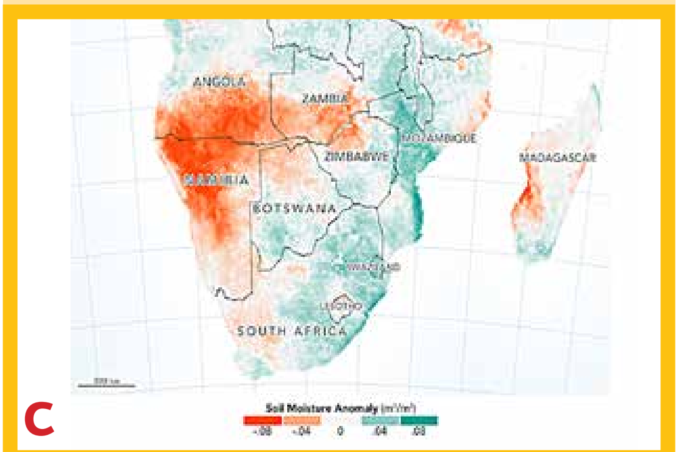


FIGURE 3: Surface water drought risk map and validation maps



Drought situation over SADC region for 2019/2019 rainfall season (https://www.sadc.int/files/5615/5991/5186/SADC_DROUGHT_MONITOR_2018-19_SEASON_JUNE_2019.pdf)



Soil moisture anomaly February 2019 (https://earthobservatory.nasa.gov/images/144704/drought-harms-corn-crops-in-southern-africa)

Statistical Analysis and Normalisation of Surface Water Risk Indices

Statistical indices based on hydro-meteorological data are commonly used to quantify droughts on the landscape for any given period (Svoboda & Fuchs, 2016) and provide numerical representations of drought severity. For the purpose of this surface water resources assessment, statistical indices were calculated at catchment unit scale and represented and/or included long-term mean annual values, seasonality indices, indices of seasonal variability, coefficients of variation as well as runoff coefficients.

Index normalization was undertaken to standardise the different index values to values between 0 and 1, and to allow comparison and integration of a number of indices. Normalisation techniques which were considered include the percentage of a maximum, percentage of range and unit vector techniques. There is no one single method that can prove itself to be the globally acceptable approach for normalisation. Rather, characteristics of various indicators and parameters were evaluated in selecting a normalisation technique able to support comparison of various parameters at an appropriate scale. A direction for each index was selected based on how the index impacts drought risk, such that the drought risk is maximized. The statistical indices as well as the normalisation technique applied are summarised in Table 1. (Note that maximum drought risk is represented by a value of 1 and minimum drought risk by a value of zero).

TABLE 1: Surface water risk indices and normalization

Index	Definition	Direction: Drought Risk	Normalization
Mean Annual Values	Mean annual values, provide an indication of average long-term precipitation, discharge and runoff averaged over the available time series length and per catchment unit.	Max as 0; Min as 1 The higher the rainfall, the lower the drought risk	Percentage of Max
Index of Seasonal Variability	The index of seasonal variability indicates the extent of intra-annual (month-to-month) fluctuation of rainfall and streamflow over a single year (Pitman, et al., 2008). It is calculated by using a mass curve method.	Max as 1, Min as 0 The higher the index of seasonal variability, the greater the drought risk.	Percentage of Range
Coefficient of Variation	The coefficient of variation of mean annual precipitation or discharge provides an index of climatic risk, indicating the likelihood of fluctuations from year to year (inter-annually).	Max as 1, Min as 0 The higher the coefficient of variation, the more variable is the inter-annual variability and the greater the drought risk.	Percentage of Range
Runoff Coefficient	The runoff coefficient is a dimensionless factor that relates the amount of surface water runoff from a catchment to the amount of precipitation received.	Max as 0; Min as 1 A high runoff coefficient may indicate flash flooding areas during storms.	Percentage of Max

Surface Water Index Weighting

A surface water risk index was produced by combining the surface water indices determined for rainfall, discharge and runoff. Runoff (often measured in mm) is a result of precipitation (e.g. rainfall), after infiltration has taken place, that moves along the surface of the earth and subsequently drains to low lying areas where it accumulates to flow into or form rivers and streams. The discharge in a river (often measured as a flow rate in m^3/sec) is the flow in a river as a result of both surface water and groundwater (baseflow).

The different indices were combined through a simple linear algorithm and associated weighting scheme based on the relative importance of various indices to derive a spatially distributed surface water risk map across the SADC region. The indices include average values representing absolute precipitation, discharge or runoff in mm, as well as dimensionless indices e.g. seasonal variability, coefficient of variation and runoff coefficient. A sensitivity analysis was also undertaken to determine the most appropriate combination of the respective indices. The sensitivity analysis confirmed the importance of not assigning too great a weight to absolute values as this could potentially skew the resulting surface water risk index.

The final indices used to determine the combined surface water risk index and their associated weightings are presented in Table 2.

TABLE 2: Surface water risk indices and normalization

	Surface Water Indices	Final Weightings
Rainfall	Average rainfall (mm)	0.11
	Seasonality	0.06
	Index of Seasonality	0.06
	Coefficient of variation (%)	0.15
Discharge	Average discharge (mm)	0.11
	Seasonality	0.06
	Index of Seasonality	0.06
	Coefficient of variation (%)	0.15
Runoff	Mean annual runoff (mm)	0.11
	Runoff coefficient (%)	0.15

Validation of Surface Water Drought Risk Map

The surface water risk map, which was developed during this study, as presented in Figure 3a, was validated qualitatively with existing maps and information indicating frequent drought prone areas in the SADC region.

For example, the SADC Climate Services Centre (2018/2019) indicated extreme drought being experienced over most of the south-western parts of SADC due to below average rainfall during the 2018/2019 rainfall season (Figure 3b). Extreme drought conditions were prevalent over southern Angola, southern Zambia, northern Zimbabwe, northern Botswana, north-western South Africa and most of central-northern Namibia. Moderate to severe drought is also affecting most of Angola, Namibia, Botswana, Zimbabwe, South Africa, Lesotho and Zambia. Pockets of dryness also occurred over most of Tanzania, western and eastern DRC, Eswatini, southern Mozambique and western Madagascar. Most of these areas concur with the identified drought areas of the surface water drought risk map.

Similarly, the map in Figure 3c depicts soil moisture anomalies during February 2019 based on remote information as monitored by the U.S. Geological Survey for the Famine Early Warning System Network, showing areas with more (green) or less (red) water in the upper soil layers for the month (Stevens & Hansen, 2019). Namibia and southern Angola and southern Zambia, northern Botswana and norther Zimbabwe as well as western Madagascar showed especially dry soils. The areas characterised by low soil moisture to a large extent coincide with similar regions as identified in the surface water drought risk map.

MAP OVERLAY AND HOTSPOT IDENTIFICATION

The surface water drought risk map (Figure 3a) was subsequently overlaid with the groundwater drought risk and population vulnerability maps (Figure 4) to identify hotspot areas for further consideration of drought mitigation interventions. A final number of 26 hotspots were identified within the SADC region.

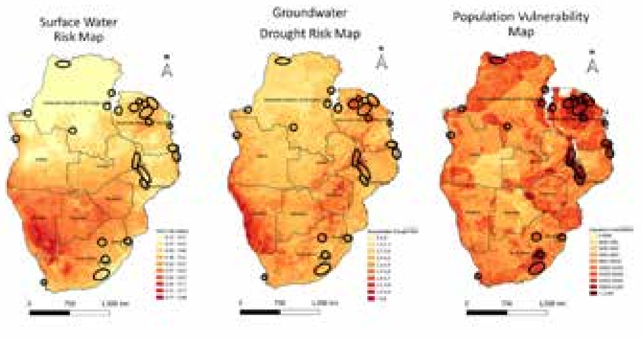


FIGURE 4: a) Population Vulnerability Areas of Priority, identified for consideration of interventions, b) Population Vulnerability Areas of Priority overlaid with the GDR map, c) Population Vulnerability Areas of Priority overlaid with the surface water risk map for SADC mainland.

DOMESTIC WATER SUPPLY INTERVENTIONS

A key component of this project related to identifying feasible and cost-effective domestic water supply interventions for water demand centres which are most at risk i.e., located in the hotspot areas identified above. The list of interventions which has been proposed provide a roadmap for further water supply development in SADC, and a starting point for more detailed feasibility studies.

CONCEPTUAL APPROACH

The conceptual methodology is summarized in Figure 5 and discussed in the following paragraphs.

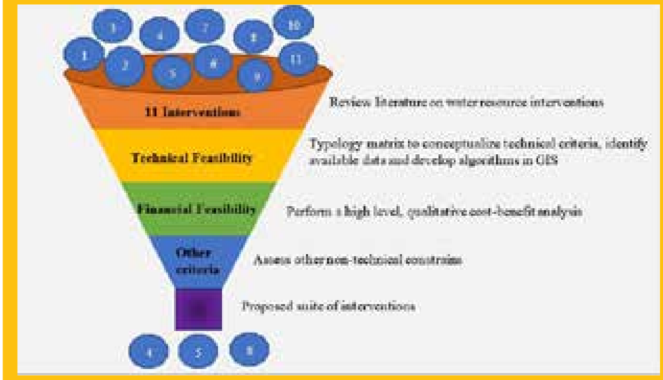


FIGURE 5: Conceptual methodology to assess the suitability of water supply interventions (by process of elimination)

Eleven domestic water supply interventions were considered:

1. Sand dams
2. Rainwater harvesting

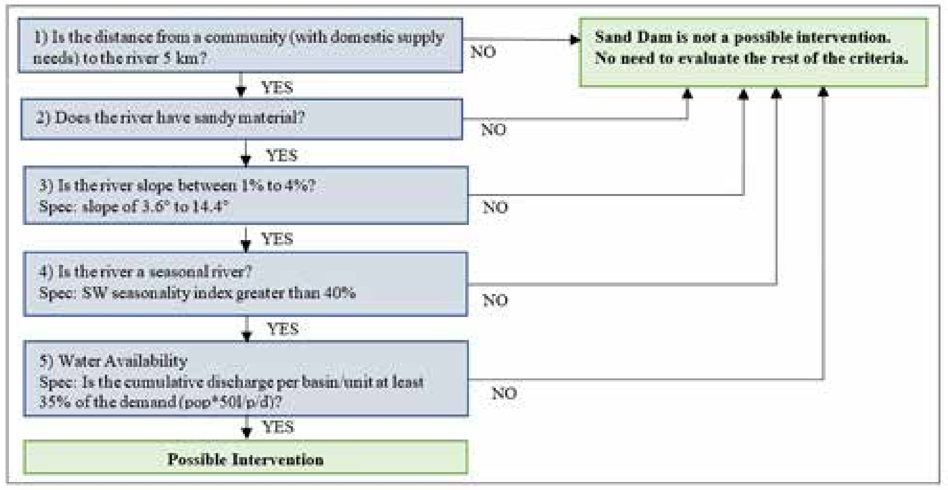


FIGURE 6: Work-flow diagram of sand dams to aid GIS based selection algorithms

3. Stormwater harvesting
4. Surface water reservoirs (dams)
5. Run of river abstraction
6. Desalination
7. Water reclamation and reuse
8. Groundwater reclamation and reuse
9. Managed aquifer recharge
10. Drilling of new boreholes
11. Conjunctive use

The final selection of the most applicable suite of interventions (from the above list) was based on the consideration of:

- the population served by the intervention;
- the technical feasibility of the interventions, for the specific region;
- the financial viability of the intervention within the context of the specific country and region;
- other important considerations, such as environmentally sensitive or protected areas;

The above factors fed into a typology matrix that was used to conceptualise and evaluate the different intervention types based on pre-defined criteria and readily available data, and to ultimately arrive at the most feasible interventions through a process of elimination for each of the 26 hotspots. The evaluation criteria were primarily derived from technical requirements associated with each intervention type.

To accommodate the size of the hotspot areas, and the often significant variability in terms of geophysical characteristics within some of the hotspot areas, the assessment of different intervention types within each hotspot area involved subdividing each hotspot area into uniform grid cells and undertaking the intervention analysis per grid cell through data queries and models in a GIS environment.

For those interventions deemed technically feasible, a high level, qualitative cost-benefit analysis was also used to further refine the suite of technically feasible interventions per hotspot zone.

Finally, to further assess the applicability of the identified interventions, literature studies were conducted to assess whether there might be other, non-technical constraints which could affect the implementation and/or operation and maintenance of the interventions related to political, institutional, environmental or other factors.

IDENTIFYING INTERVENTIONS USING SAND DAMS AS EXAMPLE

To illustrate the methodology (outlined in above Figure 5) sand dams are considered as a show case example intervention. The typology matrix and the development of the technical criteria into workflow diagrams and algorithms for GIS algorithms is discussed below.

A sand dam is a small dam which is built in the riverbed of a seasonal sandy river. The sand from flash floods accumulates behind the dam wall which provides additional storage to the riverbed aquifer (Beswetherick, et al., 2018). The aquifer fills with water during the wet season, resulting from surface runoff and groundwater within the catchment. The riverbed is also recharged through the groundwater flow, which is obstructed by the sand dam, creating additional groundwater storage communities. The typology matrix used to conceptualize technical criteria of sand dams is presented in Table 3. Through research, the criteria identified in the typology matrix were expanded to include specific boundary conditions which were used in GIS software, to aid the GIS-based decision algorithms. Figure 6 presents a workflow diagram for sand dams. A typology matrix and workflow diagrams were conceptualized and developed for all 11 interventions and applied to every grid cell within the hotspot.

TABLE 3: Sand dams example typology matrix

Implementation Requirements	Data Needed
Distance to river: preferably less than 5 km radius, generally people do not walk further than within a 5km radius to retrieve water.	Rivers with 5 km buffer
Sandy river underlain by impermeable or less permeable bedrock or clay to store water in the sand pores without letting it percolate to lower soil layers.	Regional Geology Map 1:1000000 (1:250000)
Regions sloping 1 to 2%. Highest water storage due to lower gradient of the channel bottom.	Slope map
Seasonal sandy rivers, which experience high siltation during the rainy season (high water runoff, high seasonality)	Discharge Seasonality
Water availability: there should be enough water available in the river during the rainy season to satisfy a significant portion of the water demand in the area.	Mean Annual Discharge

To illustrate the geo-spatial results of this GIS based selection algorithm, an example hotspot with identified technically feasible interventions is presented in Figure 7. In some grid cells, more than one intervention was identified as technically feasible.

Through the high-level cost benefit analysis, which considered amongst others, the financial capacity of cities or towns to implement

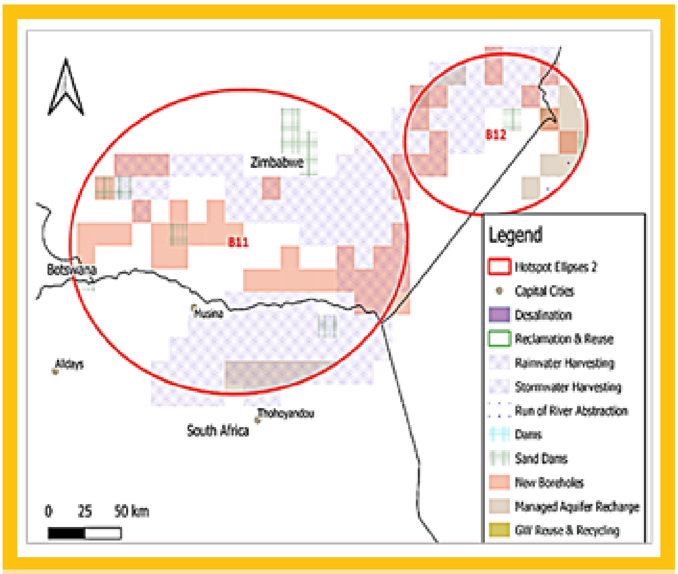


FIGURE 7: Technically feasible interventions

FIGURE 8: Proposed suit of interventions

interventions with a high reliability of supply, which would require specialized and expert skills, as well as potentially high energy consumption as well as the relative capital and operational cost. Contextual research about the area, nature reserves as well as specific aquifer types provided other criteria to further streamline the interventions per gridcell in the hotspot. The resulting proposed suit of interventions is presented in Figure 8. Out of the 11 possible interventions considered for the hotspot area, 6 interventions were identified as technically feasible (Figure 7), while only 4 intervention became part of the final proposed interventions (Figure 8), namely; rainwater harvesting, off-channel dams, sand dams and new boreholes.

RESULTS AND DISCUSSION

Temporal and spatial variability regarding water availability creates a greater need for integrated, diversified water planning and management to create more resilient and sustainable water supply options.

To encourage proactive planning in drought prone areas, the water availability and variability of existing surface and groundwater resources in the SADC region were assessed in conjunction with population vulnerability. Drought risk hotspots were successfully identified by:

- Reviewing existing global time series datasets;
- Identifying the most appropriate datasets to perform a statistical analysis and derive surface water risk indices as well as normalizing these risk indices;
- Weighting the surface water risk indices to produce a surface water risk map;
- Overlaying the population vulnerability map over the groundwater and surface water risk maps resulting in the identification of 26 hotspots.

Furthermore, by using geo-information based selection algorithms, a suite of possible technically feasible interventions was identified, on a geographic grid by grid basis, for each hotspot area through spatial analyses. A process of elimination was applied to identify technical feasible interventions by means of selection based decision algorithms using GIS-software. To this effect, typology matrices were used to conceptualise the interventions and data requirements, whereafter specific criteria were formulated into work flow diagrams and GIS algorithms, making it possible to identify grid-cells in the hotspots which would satisfy the technical evaluation criteria. The identified technically feasible interventions were further refined through high-level cost-benefit analysis as well as other considerations to produce a final suite of interventions.

CONCLUSIONS

This paper demonstrates that readily available demographic, hydrological and hydrogeological global datasets allow the identification of drought-prone areas at regional level using geospatial analyses; and that a typology matrix approach allows the identification and evaluation of a range of possible engineering interventions, at conceptual level, based on technical, economic, institutional and environmental parameters. This can assist relevant organisations within the SADC region in making informed decisions with regard to water resources investments.

The methodologies developed during the study provide a valuable toolset for firstly, understanding the context of an area by using geospatial and temporal data, and secondly, providing a conceptual approach to identifying possible solutions over large geographical areas. Further research can add to the powerful spatial data processing tools that exist and streamline methodologies for various end purposes on both a regional or a more localized scale.

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