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ORIGINAL PAPER

Impact of droughts on child mortality: a case study in Southern African countries

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Abstract

Natural hazards like floods and droughts affect many aspects of life. The study in particular examined the impacts of droughts on under-five mortality rate in Southern Africa, adjusting for gross domestic product (GDP) and literacy rate. Despite drought and child mortality being key public health concerns in Southern Africa over the past few decades, there have hardly been any studies examining the relationships between them. The study used publicly available data from 1980 to 2012. The Standard Precipitation Index (SPI) was calculated for 3-, 6-, 9-, and 12-monthly time scales for ten southern African countries. The wetter and drier states are represented by positive and negative SPI values, respectively. SPI, GDP, and literacy rate were considered for predicting child mortality rate using both Multiple Linear Regression techniques and nonlinear methods (Generalized Additive Model), on a leave-one-year-out cross validation approach for model evaluation. Child mortality increased as the drought worsened for five countries in this region, namely Angola, Malawi, Mozambique, Namibia, and Zambia. We found that child mortality can be predicted with a high degree of accuracy using three predictor variables—drought index, GDP and literacy rate. Statistical modelling based on early warning system can complement regional capacities for drought response systems to increase child survival rate in drought-prone areas

Keywords Drought · Standard Precipitation Index · Child mortality · Southern Africa · GDP · Literacy rate · Generalized Additive Model

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1 Introduction

Natural hazards affect our life in many different ways. For example, floods cause billions of dollars of damage globally in each year (Haddad and Rahman 2013). Drought is a creeping natural disaster, which causes famines and deaths. In fact, many of the past famines are related to droughts. This study focuses how droughts affect child mortality.

Over the decades, the primary concern of international public health and development agenda has been on reducing child mortality. The United Nations Millennium Development Goal (UN MDG) 4 was intended to lower the under-five mortality rate by 67% during the MDG monitoring period (between 1990 and 2015). The 2015 UN MDG final global report noted that the under-five mortality rate reduced globally by 52%, from 90 to 43 deaths per 1000 live births during 1990–2015 (United Nations 2015). This notable success in lowering child mortality is closely linked to improvement in immunization and sound health-sector investments. For example, it is estimated that investment in health-sector accounted for about 50% reduction in mortality for children below five years during 1990–2010 (Kuruvilla et al. 2014), while measles vaccination alone helped preventing death of about 15.6 million during 2000–2013 (United Nations 2015).

However, child survival has remained at the heart of the post-2015 United Nations Sustainable Development Goals (UN SDGs). UN SDG 3 focuses on healthy lives and promoting well-being for all people at all ages, and one of its targets is to stop preventable deaths of newborns and children lower than 5 years of age by 2030 (UN SDG3, Target 3.2; https://sustainabledevelopment.un.org/sdg3). It has been estimated that there are currently 79 countries with an under-five mortality rate well above 25 per 1000 live births. Of these, 47 countries have a trend suggesting that they may not achieve the set UN SDG target of $\leq$25 deaths per 1000 live births by 2030 (World Health Organization 2017b).

Impacts of natural hazards on children's health are significant and one way to reduce child mortality is to invest in policies, programs and management systems that reduce environmental risks. For example, more than a quarter (26%) of deaths and 25% of the disease load in children younger than 5 years are attributable to unhealthy environments (World Health Organization 2017a) In addition, there is a global consensus that natural disasters such as droughts and floods which are linked with El Niño phenomenon present the single biggest threat to international development agenda, especially targets related to reducing child mortality (Rowling 2016). The UN SDG 13 demands immediate action to tackle climate change and its effects (United Nations 2016). Southern Africa represents a region that has been disproportionally impacted by natural disasters in frequency and intensity with huge damages to humanity (United Nations 2016). Major disasters in the region have intensified since the 1990s, peaking between 1992 and 1996, 2002–2005, and 2015–2016 (Masih et al. 2014; Renzaho and Kamara 2016).

It has been reported that climate change is precipitating the intensity and effect of El Niño as evidenced by the disruption of normal weather patterns characterized by heavy rains, worsening floods, and drought (Fasullo et al. 2018; Wang et al. 2019). For example, the 2015–2016 El Niño occurrence, which came immediately after the 2014–2015 poor rainfall season, caused the lowest recorded rainfall in at least 35 years (Masih et al. 2014). Data by the United Nations Office for the Coordination of Humanitarian Affairs indicate that the 2015–2016 El Niño-created drought resulted in over half a million cases of acute malnutrition in children in the Southern Africa region, while 3.2 million children have experienced reduced availability of safe drinking water and associated increases in disease outbreaks and declines in medical care as clinics and hospitals run dry due to lack of water (The United Nations Office for the Coordination of Humanitarian Affairs 2017). The drought also undermined the region's efforts to address poverty causing major economic downturns.

There have been few studies on the impacts of droughts on child mortality. For example, the Ethiopia Child Survival Survey 2004 examined the impact of 2002–2003 droughts in Ethiopia which covered 4816 households and found that child mortality rate was higher in drought affected areas than non-drought affected areas (De Waal et al. 2006). Hoddinott and Kinsey (2001) examined the impacts of droughts on child health in rural Zimbabwe and found that children aged 12 to 24 months lose 1.5–2 cm of growth after a drought event. Kudamatsu et al. (2012) examined the impact of weather fluctuations on child mortality in 28 African countries and found that children had a greater chance to die due to droughts in arid areas. Lazzaroni and Wagner (2016) reported that the occurrence of drought in 2009 and 2011 in Senegal explained about 25% and 44% of the pooled 'weight-for-age' standard deviation of children's anthropometry outcomes (Lazzaroni and Wagner 2016).

The above available evidence suggests droughts generally affect child health; however, there has been limited research on the assessment of explicit relationship between child mortality and droughts. Therefore, the aim of the study is to assess the link between droughts and under-five child mortality in Southern African countries along with two other major socio-economic factors, Gross Domestic Product (GDP) and literacy rate. We hypothesized that rate of child mortality in in southern African countries increased as the drought worsened during the study period.

2 Data and method

In this study, the maximum length of the analysis period was 1980–2012 since the necessary data (rainfall and child mortality) were publicly available over this period. For estimating the Standard Precipitation Index (SPI), we needed monthly precipitation data, which were obtained from Climate Change Knowledge Portal of the World Bank Group (World Bank 2017). The child mortality data were sourced from Our World in Data (OWID) (OWID 2017). The gross domestic product (GDP) data were obtained from databases of

Fig. 1 Location of Southern African Countries

International Monetary Fund (IMF) (IMF 2015) and literacy rate data from United Nations Educational Scientific and Cultural Organization (2017).

Ten out of the sixteen countries which are members of the Southern African Development Community were included in this study because they had reliable publicly available data (Fig. 1). Generally the rainfall shortfall over different timescales was quantified by SPI (McKee et al. 1993). SPI is generally used to identify meteorological drought on different timescales. When the timescale is short, the SPI is linked with soil moisture. For longer time span, SPI may be linked with groundwater and water storage in reservoir (National Centre for Atmospheric Research 2018). In this study, we estimated the SPI for 3-, 6-, 9-, and 12-monthly time scales. In essence, SPI at a given location was determined using precipitation data the specified period. The SPI was scaled to zero mean using a normal distribution at a given location (Edward and McKee 1997). When SPI is positive, it indicates a wetter condition. Conversely, negative SPI values indicated lower than median precipitation i.e. a drier condition. Thus, when SPI is continuously negative, with values smaller than -1.0, it indicates a drought event. Accordingly, a drought event is ended when the SPI value became positive. To test the relationship between child mortality and drought, we estimated value of Pearson correlation coefficient between child mortality and SPI. While estimating the correlation between SPI and under 5 child mortality, we considered only 3-, 6-, 9-, and 12-monthly SPI. For each data set, the minimum SPI value over a year for a country was applied to correlate yearly child mortality rate of that country.

In addition to drought index, GDP and literacy rate were also considered for predicting child mortality rate. We applied multiple linear regression (MLR) and the nonlinear methods such as the Generalized Additive Model (GAM). For independent testing of the developed models, on a leave-one-year-out cross validation technique was applied (Haddad et al. 2013). For example, if we considered year 2010 and wanted to predict child mortality rate for this year, we left this year out in the model building step and pulled out information for SPI, GDP and literacy rate from other years in the dataset which were 1980—2009 and 2011—2012. Thereafter, the developed model was applied to year 2010 to predict the child mortality rate, and the procedure was repeated for each of the years. MLR/GAM was applied to develop relationship between a dependent variable and a set of explanatory variables using a linear model (Eq. 1) or a nonlinear model (Eq. 2). GAM (Wood 2006) is used to account for the nonlinearity of the explanatory variables on the dependent variable and has been applied in the public health and epidemiological research and environmental studies e.g. (Bayentin et al. 2010; Clifford et al. 2011; Haddad et al. 2012).

In our case, predictors were SPI, GDP and literacy rate, whereas, child mortality was the dependent variable. For each of the observed years, we had data for the dependent and predictors variables e.g. 1980—2009 and 2010—2011 and thus a regression equation could be developed, which could then be used to predict child mortality in year 2010. The procedure was repeated until child mortality was predicted for each of the years. Then, the coefficient of determination (R^2) was estimated by considering the observed and predicted child mortality over all the years. The R^2 reflects how well the predicted values match with the observed data, when R^2 is equal to 1.00, it represents a perfect model, and when R^2 is 0.00, it represents zero correlation between dependent and explanatory variables.

The MLR model can be expressed by:

$$Y = \mathrm{b}_0 + \mathrm{b}_1 X_1 + \mathrm{b}_2 X_2 + \cdots + \varepsilon \tag{1}$$

where Y is dependent variable (child mortality in this study); X_1, X_2 … are predictor variables (GDP and literacy rate here); b_0, b_1, b_2, … are regression coefficients, which have been found by ordinary least squares in this study; and ε is the error term.

In GAM, a predictor variable can be a nonlinear function and additivity of the model can be maintained for multiple predictor variables (Hastie 1992). This is implemented by using a smooth nonlinear function $f_j(x_{ij})$ for each linear component in Eq. 1. A GAM is expressed by:

$$y_i = \beta_0 + \sum_{j=1}^{p} f_j(x_{ij}) + \varepsilon_i = \beta_0 + f_1(x_{i1}) + f_2(x_{i2}) + \cdots + f_p(x_{ip}) + \varepsilon_i \tag{2}$$

In GAM a nonlinear function f_j is fitted to X_j. This helps to avoid many different manual transformation of individual explanatory variable in real-world model development. In GAM, it is possible to examine the effect of each X_j on Y separately due to the additive nature of the GAM. Here degrees of freedom are used to express the smoothness of f_j for X_j. GAM allows to use exponential or a quasi-likelihood approaches in model development (Wood 2006). In GAM, f_j can be estimated by a spline such as cubic splines. Here, thin plate regression splines were applied since these facilitated quicker calculation without selecting the location of the knot and provided an optimal solution.

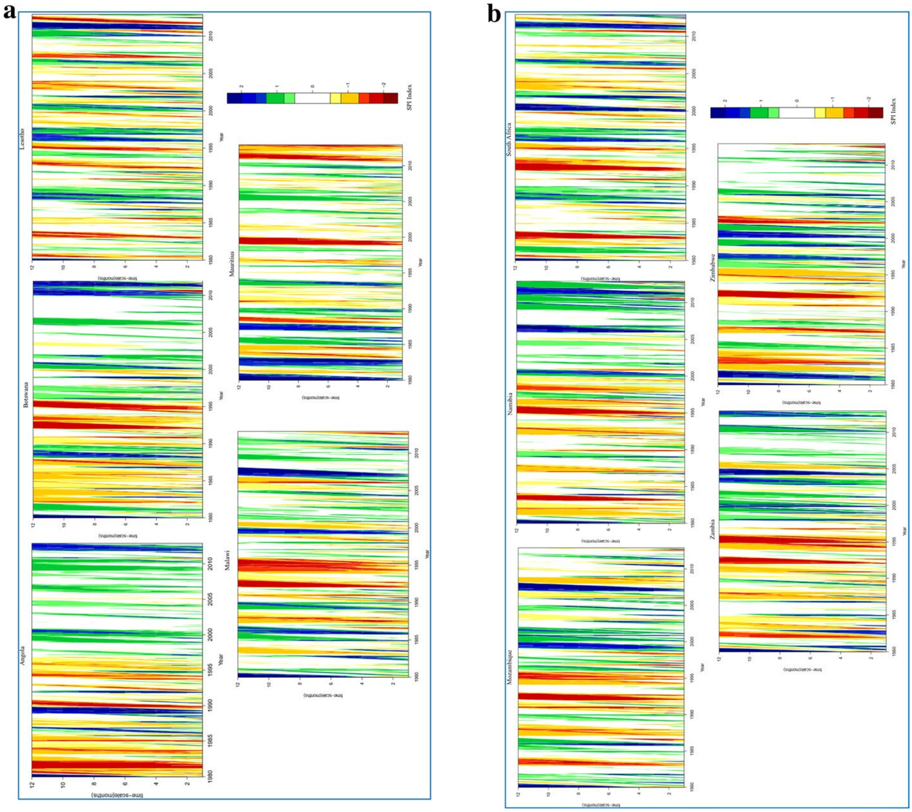

Fig. 2 **a** Standard Precipitation Index (SPI) over the Southern African Countries for the period 1980–2012. **b** Standard Precipitation Index (SPI) over the Southern African Countries for the period 1980–2012

3 Results and discussion

In this study, the drought event and its intensity over a country were expressed by SPI resulting from the long-term shortfall of precipitation over multiple time scales. SPI was considered as a standard measure of monitoring wetter and drier climates and its extent. Figure 2a, b shows the calculated SPI values over all the 10 countries in the Southern Africa covering 1980—2012. We limited the analysis to this period because of the availability of rainfall and child mortality data for the included ten countries. Drought prevailed over the period 1980—1997 except for the years 1987–1988 in Angola. Similarly, unbroken longer drought events were recorded for Botswana, Namibia, Zambia, and Zimbabwe over the years 1983—1996, 1981—2000, 1982—1997, and 1982–1996, respectively, having few exceptions. In Malawi, South Africa and Mauritius, severe droughts were identified for the phases 1992—1996, 1992—1995, and 2010 -2012. In case of Mozambique, few drought events were observed during 1983, 1987—1988 and 1992—1995. The dry and wet climatic conditions occurred side by side in Lesotho over the entire analysis period (1980—2012).

Table 1 shows the correlation between child mortality and drought over the ten Southern African countries during 1980–2012 period for the four data series. An absolute value in the table exhibits significant correlation if it is greater than |0.27|. It is shown in Table 1 that a negative correlation exists between SPI and child mortality for the five countries, namely Angola, Malawi, Mozambique, Namibia, and Zambia. This implies that the rate of child mortality in these counties increased as the drought worsened. Furthermore, two of these five countries, i.e. Angola and Zambia had significant and stronger correlation for the four-time series. Thus, considering SPI as a function of child mortality, we performed regression analysis for these two countries. We have achieved a promising result for Angola where $\boldsymbol{R}^2$ was found as high as 0.72 for 12-monthly SPI (Fig. 3). Here $\boldsymbol{R}^2$ increased as SPI time series increased from three to twelve months, which indicates that the longer the drought the higher the child mortality. However, in case of Zambia, the highest $\boldsymbol{R}^2$ was found for 6-monthly SPI which was 0.45 (Fig. 4). On the other hand, the positive correlation between SPI and child mortality existed for the countries—Botswana, Lesotho,

Table 1 Correlation between child mortality and drought (SPI) over the ten countries in Southern Africa for the period 1980–2012

Country	3-month SPI	6-month SPI	9-month SPI	12-month SPI
Angola	−0.54	−0.58	−0.71	−0.77
Botswana	0.42	0.23	0.17	0.15
Lesotho	0.02	0.04	−0.08	−0.13
Malawi	−0.17	−0.18	−0.27	−0.33
Mauritius	0.35	0.24	0.35	0.38
Mozambique	0.02	−0.12	−0.23	−0.28
Namibia	−0.16	−0.36	−0.42	−0.51
South Africa	0.05	0.18	−0.07	−0.12
Zambia	−0.35	−0.69	−0.59	−0.54
Zimbabwe	0.37	0.37	0.27	0.23

An absolute value in the table exhibits significant correlation if it is greater than |0.27|

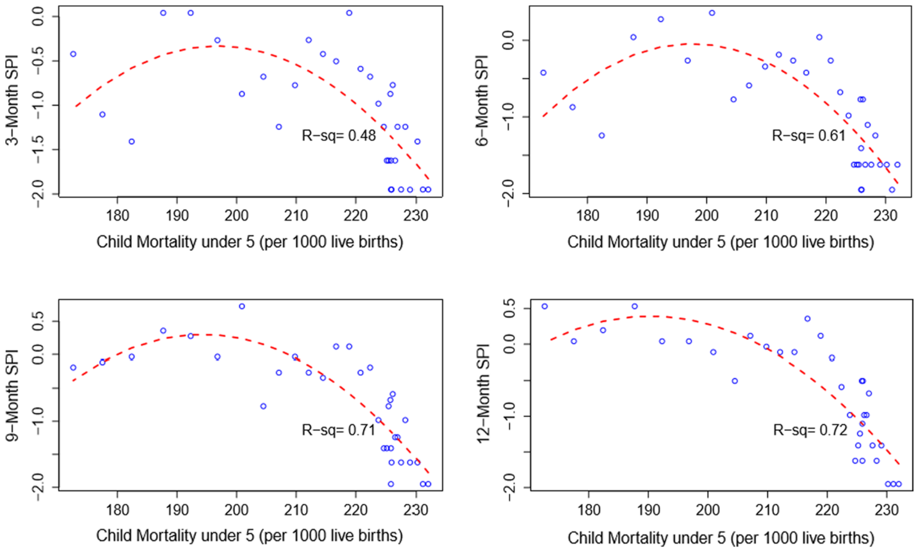

Fig. 3 SPI is a function of child mortality under 5 (per 1000 live births) in Angola for the period 1980–2012

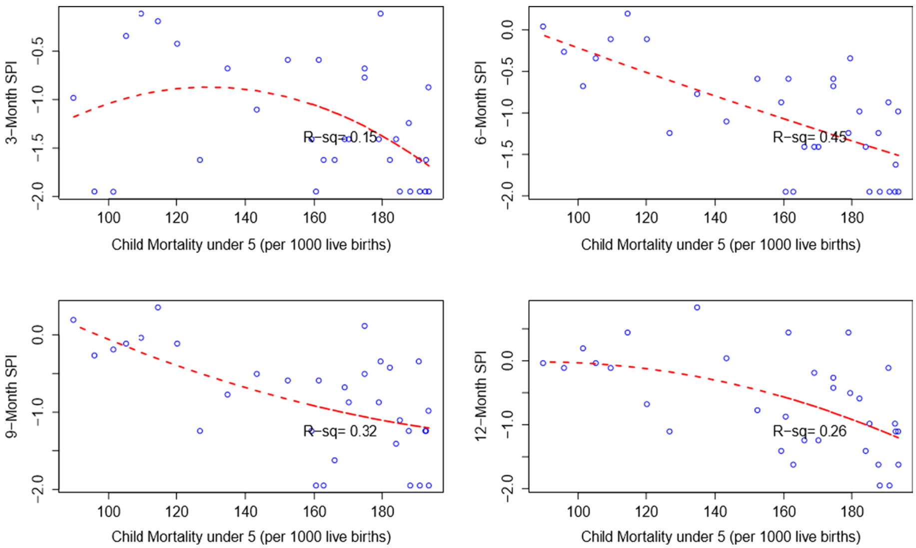

Fig. 4 SPI is a function of child mortality under 5 (per 1000 live births) in Zambia for the period 1980–2012

Mauritius and Zimbabwe, which indicates that child mortality in these countries was not affected by the drought.

In addition to SPI, we included GDP and literacy rate as predictor variables. Figures 5, 6 and 7 show the predicted child mortality under 5 (per 1000 live births) in Angola, Malawi and Zambia over the period 1980—2012. Here, Child mortality was estimated as

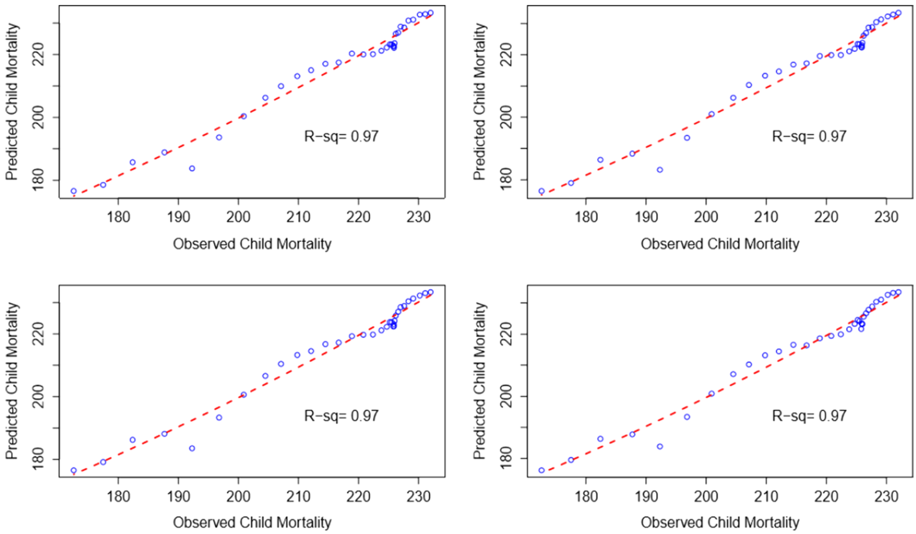

Fig. 5 Multiple Linear Regression (MLR) technique: predicted child mortality under 5 (per 1000 live births) in Angola over the period 1980–2012. Here Child mortality is estimated as a function of GDP, literacy rate and SPI on a leave-one-year-out cross validation technique. Having same GDP and literacy rate, 3-month, 6-month, 9-month and 12-month SPIs are applied on top-left, top-right, bottom-left and bottom-right figures, respectively

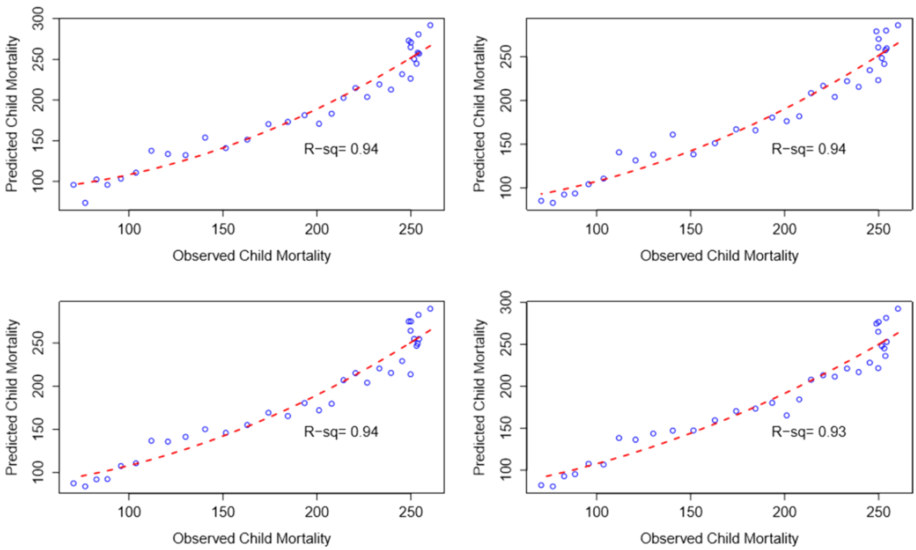

Fig. 6 Multiple Linear Regression (MLR) technique: Predicted child mortality under 5 (per 1000 live births) in Malawi over the period 1980–2012. Here child mortality is estimated as a function of GDP, literacy rate and SPI on a leave-one-year-out cross validation technique. Having same GDP and literacy rate, 3-month, 6-month, 9-month and 12-month SPIs are applied on top-left, top-right, bottom-left and bottom-right figures, respectively

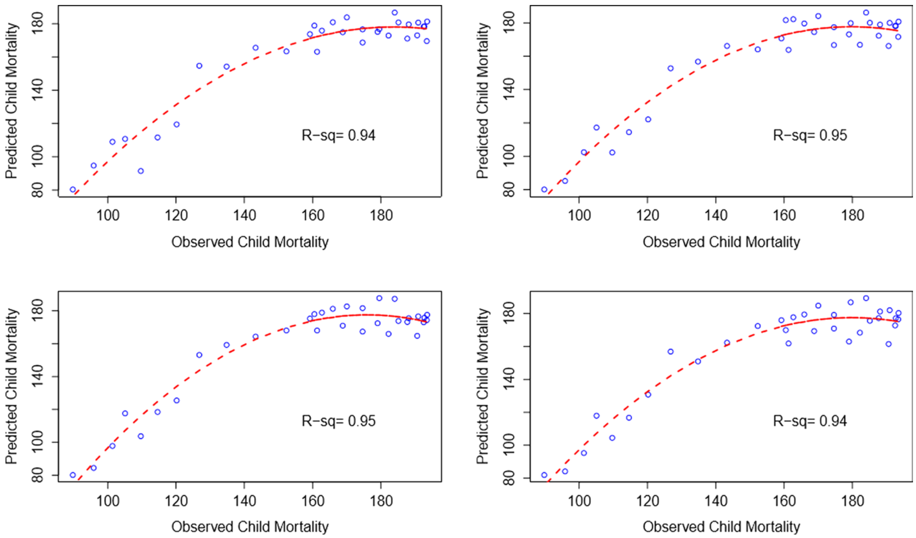

Fig. 7 Multiple Linear Regression (MLR) technique: predicted child mortality under 5 (per 1000 live births) in Zambia over the period 1980–2012. Here child mortality is estimated as a function of GDP, literacy rate and SPI on a leave-one-year-out cross validation technique. Having same GDP and literacy rate, 3-month, 6-month, 9-month and 12-month SPIs are applied on top-left, top-right, bottom-left and bottom-right figures, respectively

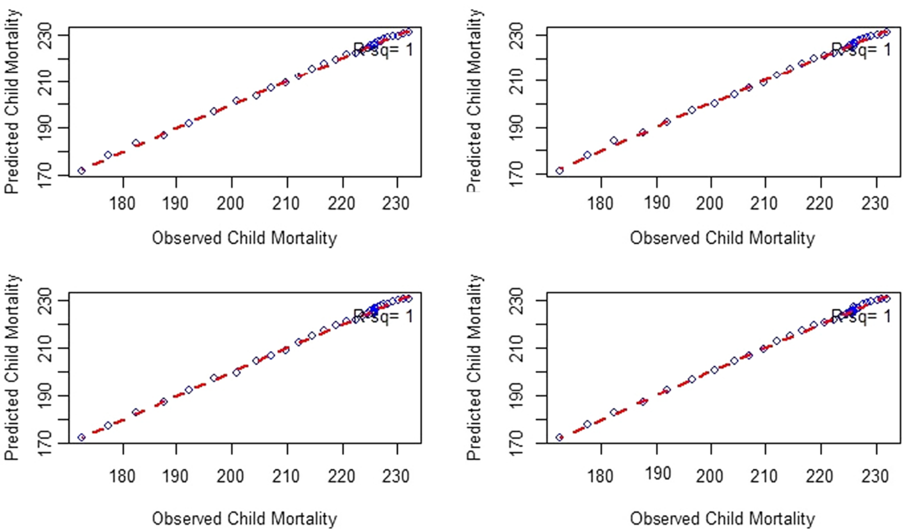

Fig. 8 Generalized Additive Model (GAM) technique: predicted child mortality under 5 (per 1000 live births) in Angola over the period 1980–2012. Here child mortality is estimated as a function of GDP, literacy rate and SPI on a leave-one-year-out cross validation technique. Having same GDP and literacy rate, 3-month, 6-month, 9-month and 12-month SPIs are applied on top-left, top-right, bottom-left and bottom-right figures, respectively

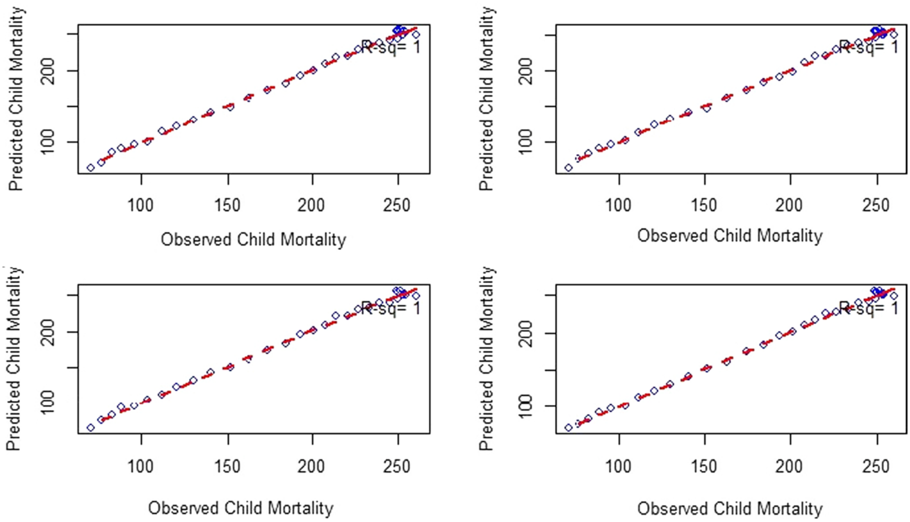

Fig. 9 Generalized Additive Model (GAM) technique: predicted child mortality under 5 (per 1000 live births) in Malawi over the period 1980–2012. Here child mortality is estimated as a function of GDP, literacy rate and SPI on a leave-one-year-out cross validation technique. Having same GDP and literacy rate, 3-month, 6-month, 9-month and 12-month SPIs are applied on top-left, top-right, bottom-left and bottom-right figures, respectively

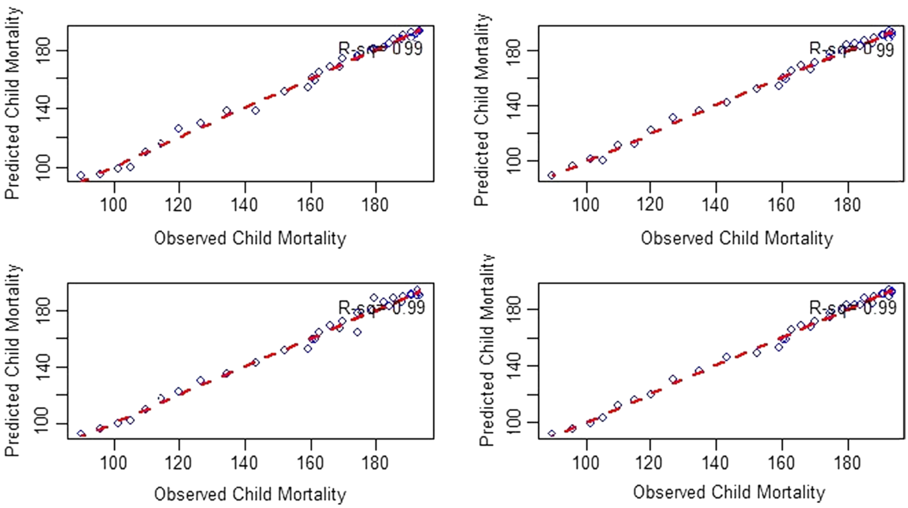

Fig. 10 Generalized Additive Model (GAM) technique: predicted child mortality under 5 (per 1000 live births) in Zambia over the period 1980–2012. Here child mortality is estimated as a function of GDP, literacy rate and SPI on a leave-one-year-out cross validation technique. Having same GDP and literacy rate, 3-month, 6-month, 9-month and 12-month SPIs are applied on top-left, top-right, bottom-left and bottom-right figures, respectively

a function of GDP, literacy and SPI following a leave-one-year-out cross validation technique (Sect. 3). GDP and literacy rate were associated with child mortality in Southern African countries. For Angola, Malawi and Zambia, the developed prediction equations exhibited very high R^2 values (above 0.92). This suggests that the child mortality rate of these countries can be estimated from the developed prediction equations using three predictor variables—SPI, GDP and literacy rate with very high degree of accuracy. Very promising $\boldsymbol{R^2}$ values and negative correlations for these countries indicate that GDP and literacy rate were associated with child mortality. The results from GAM (Figs. 8, 9, 10) show a better prediction than MLR ($\boldsymbol{R^2} \sim 1$). Similar results were also obtained for other countries.

Droughts have severely affected Southern African countries over the past few decades. Historical studies on the change of El Niño properties suggest that climate change will significantly increase both the severity and frequency of the extreme El Niño events, translating into worsening floods, severe droughts, and shifting hurricane patter (Wang et al. 2019). However, there have been hardly any studies examining the explicit mathematical relationships between child mortality and droughts. The current study found that child mortality is directly affected by drought for five Southern African countries, Angola, Malawi, Mozambique, Namibia, and Zambia. This study also found a statistically significant and strong correlation between child mortality and SPI in Angola, with a coefficient of determination value (R^2) of 0.74. This implies that drought explains a significant share of child mortality in Angola. However, in some Southern African countries (Botswana, Lesotho, Mauritius and Zimbabwe), child mortality is not affected by droughts. In these countries, there could be other drought-induced causal factors such as water scarcity, poor sanitation, and food insecurity that cause child mortality in these countries other than drought itself. It is well documented that water and rainfall shortage not only lead to delays of the planting season or complete failure and associated decline in food production and acute food shortage, water shortages also lead to decline in industrial production, distorted household consumption patterns, increased likelihood of water-borne diseases, increased livestock diseases and mortality, as well as the reduced capacity of basic services such as hospitals, clinics, and schools to maintain their services (ACAPS 2016; Conway et al. 2015). Notwithstanding, variations in the relationship between child mortality and drought across southern African countries, the findings suggest that in some countries, drought management and control (e.g. drought forecasting, provision of alternative water supply other than rainfall such as groundwater) are needed to reduce the child mortality. This is an area that needs further investigation, which is left for future research efforts.

In addition, two major socio-economic factors i.e. GDP and literacy rate were associated with child mortality in Southern African countries, and the relationship was stronger for Angola, Malawi, Zambia and other countries. The effects of variability in rainfall and temperature on nation-wide economic growth indicators is well established, with various studies showing that drought has a significant effect on GDP per capita growth (Benson and Clay 1998; Brown et al. 2011). Low- and Middle-Income Countries rely on large agricultural sectors for their economic growth, which becomes negatively affected in the presence of any drought. This is because drought affects the economy in many ways, including declines in GDP, reductions in agricultural production and agricultural export earnings, and reductions in employment opportunities and domestic purchasing power and associated losses of income and assets (Benson and Clay 1998). For example, agriculture contributes less than 10% to the economy in Botswana, Swaziland, South Africa, Namibia, Angola and Lesotho, but more than 13% in other Southern African countries. However, the shares of agriculture to the national GDP will increase substantially if agricultural processing and agricultural employment opportunities were included in agricultural GDP (Conway et al. 2015). A meta-analyses of 24 studies found that increasing GDP per capita purchasing power parity by 10% in a country with an infant mortality of 50 per 1000 live births would reduce the infant mortality to 45 per 1000 live births (a 10% reduction) (O'Hare et al. 2013). These findings suggest that protecting and increasing the agricultural GDP through the effective management of vulnerability to drought and enhancing livelihood resilience would increase child survival in drought-prone countries.

Literacy rate remains a good indicator of economic development (Carrão et al. 2016) and there is a significant positive relationship between per capita GDP and rate of literacy (Rahman 2011). Data by the United Nations Educational, Scientific and Cultural Organization suggest that the lowest literacy rates in the world are observed in sub-Saharan Africa (United Nations Educational Scientific and Cultural Organization 2015). However, low literacy rates are associated with poor understanding of drought as well as poor drought management (Habiba et al. 2011). In addition, literacy rate, especially female literacy rate has been found to be a better explanatory variable to predict infant mortality rate (Saurabh et al. 2013). Therefore, increasing the nation's literacy rate not only will reduce its unemployment rate and increase per capita GDP, it will also transform the population into drought-ready communities and increase child survival.

It should be noted that the child mortality data used in this study comes from multiple sources, namely: UN Inter-agency Group for Child Mortality Estimation (comprising UNICEF, WHO, World Bank, UN DESA Population Division) as well as the global burden of diseases (Ahmad et al., 2000). However, regardless of the source of the data, child mortality is estimated using different approaches and sources which vary at a given time, across time, and place. Such sources include civil registration systems, national surveys, and applying indirect estimation techniques based on sample surveys or censuses which tend to be outdated. For example, civil registration systems in most low and middle income countries are still underdeveloped, weak, incomplete and/or dysfunctional. Data from national surveys present their own problems including poor quality data due to substantial errors, recall biases, systematic exclusion (e.g. inaccurate ages at death, omissions of births and deaths such in the case where the mother died hence precluding the children from the study, children who do not live with their natural mother or died outside the recall period etc.). The consequence is the under-estimation of child mortality and distortion of trend.

4 Conclusions

The southern Africa region has historically been severely affected by drought. Our study shows that, in some of the selected countries drought is associated with increased under-five mortality. In order to increase child survival in drought-prone areas, multidimensional strategies to reduce the drought impacts are required. Such strategies are needed to incorporate community-based early prediction and coping methods as well as the strengthening of national and regional capacities for drought response systems. At the national and regional level, establishing coordinated meteorological services that include drought monitoring, information dissemination, and awareness-raising as part of drought response systems would allow policy makers to assess and prioritize policy options to build resilience to drought. At the community level, the development and implementation of appropriate drought risk reduction strategies should include not only information and knowledge management and harnessing traditional coping mechanisms, but they should also include programs that strengthen the communities' adaptation to drought. Possible programs could include irrigation and rainwater harvesting systems, drought resistant seed varieties and grain storage systems for farmers, and supporting existing basic services. The developed method can easily be extended and/or adapted to other countries by adding a greater number of explanatory variables that affect child mortality.

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