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A probabilistic approach to assess agricultural drought risk

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Introduction

The classical approach of drought analysis consists of its characterization from meteorological, hydrological, or agricultural points of view. These characterizations imply a certain temporal component in their analysis. For example, a meteorological drought at a given location is commonly defined using quantiles based on the rainfall data for short periods of a few days to a month. Likewise, the hydrological droughts are characterized by events ranging from months to years that impact hydrological variables like reservoir storages, river flows, and soil moisture depending on the location. However, in the case of agricultural drought, the practice to date has been to use meteorological drought characterizations in the interpretation of the associated reduction in crop vigor and yields. Currently, a novel approach of mainstreaming of disaster risk reduction of drought risk is being adopted in the field of agricultural drought analysis. This new approach involves stochastic analysis of the spatio-temporal vulnerability of crops in an attempt to quantify the frequency of events impacting the crop production. Stochastic analysis of natural hazards in general and droughts in particular, is the basic paradigm of mainstreaming drought risk reduction (Benson et al., 2007). Event-likelihoods corresponding to different magnitudes of crop production losses caused by historical and simulated droughts are used to profile the agricultural drought characteristics of a region.

The core of mainstreaming drought risk management philosophy consists of four analytical components – hazard, exposure, vulnerability, and risk (Benson et al. 2007). The hazard component examines the event that leads to the outcomes studied in mainstreaming. Drought results from abnormally deficient rainfall in a given region. This has a cascading effect on surface and subsurface water storages, stream and river flows, lower soil water storages for agricultural areas and pastures, reduced water availability for human consumption and livestock and beyond. Drought hazard analysis consists of selecting an appropriate hydro-meteorological index to describe intensity, spatial and temporal characteristics. Long-term rainfall records and ancillary hydrologic data inform relevant hazard indices to depict the drought characteristics in a given region.

Drought hazard indices in the past have been constructed using deficiencies in rainfall averaged over periods ranging from fortnights, months, to several years or even decades, depending on the drought characteristics of the region (GAR 2011). In 2009, the World Meteorological Organization (WMO) recommended the use of the Standardized Precipitation Index (SPI) (McKee et al., 1993) as the global standard hazard index to measure droughts via the 'Lincoln Declaration on Drought Indices' (Hayes et al., 2010). The SPI is computationally easy and facilitates transferability across temporal and spatial scales. The main obstacle in using the SPI is that it needs long-term rainfall data (at least 30 years of error-free data) to establish distribution parameters that capture the meteorological droughts in a given region. The SPI, in view of its computational ease, has also been used as an agricultural drought indicator (E.g. for irrigated rice in Philippines[1], and rainfed maize in Malawi and Mozambique[2]). The inherent drawback in using the SPI as an agricultural drought hazard index lies in its presumption of a direct consequence of crop production losses in a given region and that it does not account for the role played by the soil in regulating moisture in the crop root zone.

The most relevant agricultural drought hazard index capturing crop vulnerability to droughts is the gap between the crop water demand and the water available in the root zone, especially for rain fed crops. The variables that influence the corresponding crop losses include the climatic water demand, the soil fertility, water holding capacities and storages, and crop characteristics (type, variety, drought susceptibility, etc.). These variables can be used to model the seasonal changes in the root zone soil water balance to derive the net antecedent conditions that affect the crop and its productivity potential at different phenological growth stages. These soil moisture availability hazard indices can be used to interpret both the spatial as well as the year-to-year crop yield variability.

The exposure component of mainstreaming identifies the facet of society, and the associated value, affected by the hazard. Exposure in the context of earthquakes consists of buildings (both residential and commercial), infrastructure damaged, and population affected. In the context of floods, exposure refers to low-lying infrastructure such as bridges, roads, buildings and crop areas along with the corresponding affected population. Exposure analysis in the context of agricultural droughts consists of historical crop area and production statistics in a given region. At least 20 to 30 years of continuous exposure or 6 to 7 actual event-loss data from the field is needed to conduct objective probabilistic drought risk analysis[1, 2]. In the absence of the above data, an alternative approach consists of using simulated event-losses.

Vulnerability analysis captures the damage or loss suffered at the intersection of exposure and hazard; it represents the resiliency to exposure. It is related to the capacity of the exposed asset to predict, withstand, and recover from the deleterious effects of the hazard. Vulnerability may be deduced either by crop process models using high resolution, high frequency agro-hydro-meteorological field data; or estimated using statistical relationships between coarse resolution drought hazard and the historical crop production losses.

The risk component quantifies the physical damage caused by the hazard in physical and in monetary loss terms. Risk is typically expressed in two ways – graphic and numeric. The *loss exceedance probability* (LEP) curve is a graphical portrayal of the likelihood of specific physical or monetary losses. Numeric loss data is tabulated as the probabilities associated with exceeding discrete levels of loss, referred to as the *return period* losses.

The UNISDR (United Nations International Strategy for Disaster Reduction) publishes a Global Assessment Report (GAR) addressing all types of disaster risk reduction, including drought. The GAR 2011 report observed that the global standards for assessing drought hazard are currently being established. In some of the most drought vulnerable areas of the world there are significant difficulties in getting data to develop risk models, especially from the famine and drought affected countries in Africa. The above report also highlighted that in the absence of a credible drought risk model there is a need to understand agricultural drought impacts and losses using appropriate soil moisture based drought hazard indices. The UNISDR and the Famine Early Warning Systems Network (FEWS NET) have initiated a collaborative study to identify, develop and validate a probabilistic agricultural drought risk methodology. Using satellite estimated rainfall-to drive a basic crop model and develop a hazard index, this work leverages FEWS NET data products which are operationally produced to monitor food insecurity in the drought and famine affected countries in Africa.

The probabilistic approach of drought risk assessment in this study consists of conducting a frequency analysis of the gaps between water demand and availability in the crop root zone during the crop season, constructing appropriate drought vulnerability models, and deriving loss exceedance curves and return period losses for selected crops in drought prone countries of Africa. Specifically, the objectives of this study include (a) generation of LEP curves for maize in Kenya, Malawi, and Mozambique, and millet in Niger, and (b) generation of return period loss maps and statistics for the above crops in the above countries.

Method

Agricultural drought risk assessment is predicated by a reduction in crop area, a loss in crop yields or both as a result of deficient moisture conditions during the crop growing season. Deficient rainfall during the early part of the crop season leads to abnormal sowing operations resulting in reductions in sown area. Further into the crop season, deficient rains lead to stunted crop growth resulting in reduced yield potentials. Rainfall shortages impact crop growth most significantly if they happen during critical flowering or grain formation stages. Regardless of the timing, agricultural drought is defined by a loss in crop production as a result of shortages in water availability.

The U.S. Agency for International Aid (USAID) created FEWS NET in mid 80s with the goal of mitigating the agro-meteorological shocks on the vulnerable populations, especially in the food insecure countries of Africa and Latin America. The objectives of the FEWS NET system are three-tiered (Funk and Verdin 2010): vulnerability identification and impact assessment, development of appropriate contingency plans, and design and implementation of timely disaster relief packages. The US Geological Survey (USGS), National Aeronautics and Space Administration (NASA), the National Oceanic and Atmospheric Administration along with the regional experts in the above countries participate in helping FEWS NET meet these objectives.

FEWS NET monitoring of drought conditions is based on a number of remotely sensed products. Satellite rainfall estimates (RFE2) (Xie and Arkin 1997), which combine satellite thermal infrared measurements with microwave and stations, are used to drive many products such as the SPI, crop models (Senay and Verdin 2003; Verdin and Klaver 2002), soil moisture and runoff (Artan et al. 2001) models. Satellite observed normalized difference vegetation index (NDVI) provides critical information about vegetation health, seasonal progression, and has also been linked to food production estimates (Funk and Budde 2009). More peripherally, FEWS NET may use remotely sensed information to estimate snow extent, prevailing global climate conditions, local soil conditions, national level crop calendars, and topography.

FEWS NET uses the water requirement satisfaction index[3] (WRSI) as a primary agricultural drought hazard index. FAO (Frere and Popov 1979, da Mota 1983, Victor et al. 1988) proposed WRSI as a proxy for crop performance as it could be related to crop production using linear yield-reduction functions. Senay and Verdin (2001) and Verdin and Klaver (2002) demonstrated that the WRSI algorithm could be used to depict the root zone soil water conditions in a gridded cell-based modeling environment.

The gridded WRSI is generated by customized software called GeoWRSI (Magadzire 2009). GeoWRSI is developed to use gridded estimates of satellite rainfall (Xie and Arkin 1997, Huffman et al. 2007), potential evapotranspiration (PET) using the Penman-Monteith equation (Shuttleworth 1992), soil water holding capacity and crop-specific characteristics such as the length of growing season, and crop coefficients (K_c) (Doorenbos and Pruitt 1977). The main difference between GeoWRSI and the software like the FAO AgroMetShell (Mukhala and Hoefsloot 2004) is that the GeoWRSI determines the water balance on a cell-by-cell basis using input grid values rather than a spatially interpolated result of WRSI results calculated for station data (Verdin and Klaver 2002). In the following sections, the agricultural drought risk assessment modules adopted in the present study have been described.

2. a Hazard analysis

In the present study, the end-of-season WRSI (EOS WRSI) output from the GeoWRSI software (Magadzire 2009) has been selected as the agricultural drought hazard index. In its simplest form, the EOS WRSI represents the ratio of the seasonal actual crop evapotranspiration to the seasonal crop water requirement. The EOS WRSI deficits in the water available for crop growth and has been proven as a proxy crop yield index (Frere and Popov 1986; Senay and Verdin 2003; Syroka and Nucifora 2010, Patel et al. 2011). Normal crop yields are associated with WRSI value of 100 as they represent a situation of “no deficit” while a value less than 100 is associated with reduced crop yields. A seasonal WRSI value less than 50 is regarded as a crop failure condition (Smith 1992).

The actual evapotranspiration (AET) represents the actual soil water extracted used by the crop from its root zone. In this regards GeoWRSI used the crop coefficients published by FAO[5] - maize (corn), sorghum, millet, wheat, etc. Soil water accounting in the crop root zone in GeoWRSI consists of assessing the water supply using satellite estimated rainfall (Xie and Arkin 1997), the pre-existing soil water conditions in the root zone, the crop water demand (satellite estimated PET in conjunction with FAO[4] crop coefficients), and the actual evapotranspiration on a 10-day basis.

The iterative water budgeting exercise in the crop root zone is initiated when the first dekad with more than 25 mm of rain is followed by two dekads with a total rainfall of at least 20 mm. The above criterion signifies the onset of the crop season (start of season or SOS) by filling the crop root zone to its field capacity and ensures most favorable soil moisture conditions for crop emergence. The water budgeting process continues on a dekad time-interval till the end of the crop phenological cycle as identified by the length of the growing period (LGP). This water budgeting continues till the end-of-season (EOS) is attained by adding LGP to the SOS dekad for each grid cell. The computational methods used in grid cell soil water accounting, the data used, and the underlying assumptions in GeoWRSI[3] are described in Magadzire (2009).

This study used the FEWS NET LGP information provided as part of the GeoWRSI software package, which blend available FAO products with information from field representatives who work closely with national agricultural services in Africa. The GeoWRSI program was run using default settings for field information (length of growing season, crop type, and crop season) and was run over the study areas for the last 10 years (2001 to 2010).Each dekadal WRSI as well as the EOS WRSI statistics have been spatially averaged over each of the second sub-national districts (18 districts in the Rift Valley province in Kenya; 35 districts in Malawi; 132 districts in Mozambique excluding the urban districts; and 30 Departments in Niger). The resulting statistics generate district and regional WRSI profiles helping to understand the drought incidence and persistence in each location.

2. b Exposure analysis

Exposure data has been collected from the respective Ministries of Agriculture in Kenya, Malawi, Mozambique and Niger. The collected data provides an inconsistent record of cropped area and production in that they are not available for many years in the above countries. The maize area and yield statistics are available from 1984 to 2009 in Malawi; from 2000 to 2009 in Mozambique; however are available only from 2000 up to 2006 in Kenya. The millet area and yield statistics are available from 1984 to 2009 in Niger. Mapping these statistics provides spatial context to the tabular data, and gives the user a sense for the major cropping zones within a country.

Clarke (2012) cited the World Bank report[5] observed that there have been 6 major drought events in Malawi during 1982 to 2008 period. Pauw (2010) evaluated the economywide impacts of extreme hydro-meteorological events on crop production in Malawi and Mozambique. Adopting an ex-post analytical approach, the crop production losses during the crops seasons of 1986/87, 1991/92, 1993/94, 2003/04 and 2004/05 were analyzed to evaluate the direct and indirect economic losses. The World Bank report[5] observed that the drought impact on crop production in Malawi was reflected more prominent in the rain-fed crop yields than area planted.

2.c Vulnerability analysis

Drought vulnerability is best expressed as a statistical relationship between EOS WRSI and drought related reduction in crop production in the study areas. Developing an objective and reliable vulnerability model requires 20 to 30 years of continuous and error-free crop area and production data[1, 2] along with EOS

WRSI data for the corresponding years, ideally capturing at least six to seven drought events. However, the research presented here is limited to the overlapping period of available crop statistics and the RFE2 database, which limits the work to data from 2001 to 2009 for Malawi, Mozambique and Niger, and 2001 to 2006 for Kenya. The vulnerability analysis using the above data has been used to generate simulated event-losses by applying it to synthetic drought events as explained in section 3.

In the present study, modeling of the vulnerability relationships has been based on the FAO guidelines for determining relative yield deficit and relative evapotranspiration deficit[4]. The steps followed in establishing the vulnerability model in the present study are as follows:

- Calculate spatially averaged EOS WRSI statistics for the selected administrative zones.
- Determine the relative evapotranspiration deficit by calculating (1-EOS WRSI/100).
- Analyze crop production data to determine the drought incidence according to reductions in crop production as identified by corresponding EOS WRSI. This subset of selected years of drought related losses by district are the events used in maize drought risk analysis.
- Select a reference yield ($Y_{reference}$) using the crop yield corresponding to the most temporally proximate season which is neither affected by drought nor flood. The reference yield represents the crop yield obtained in the absence of drought during the drought affected season at that location.
- Calculate the relative yield loss ($1-Y_{actual}/Y_{reference}$) corresponding to the identified drought years for the identified events.
- Develop a statistical relationship between the relative yield deficits with the corresponding EOS WRSI for each event.
- Estimate the total drought-induced loss in crop production using the potential crop area in the selected district. Potential crop area is the amount of land likely to be sown in the absence of drought in the region.

The procedure described above was followed to develop the drought vulnerability models for maize in the Rift Valley province in Kenya, Malawi, and Mozambique, and for millet in Niger. A summary of the drought vulnerability models for each country is presented in Table 1, which list the slope, intercept and r^2 between the modeled relative evapotranspiration deficit and relative yield loss based on the identified drought events.

Table 1: Details of statistical regression between relative-yield deficit with relative evapotranspiration deficit for maize and millet

Country	Crop	Slope	Intercept	r^2
Kenya	Maize	1.115	+0.0034	0.52
Malawi	Maize	1.311	+0.0956	0.72
Mozambique	Maize	0.777	+0.0392	0.62
Niger	Millet	1.906	+0.64	0.64

Maize yield-loss function

The slope of the yield-loss function (K_y) indicates the rate at which the crop loses its yields due to the soil moisture deficits in its root zone. The greater the slope value, the larger the anticipated losses per unit of water deficit (Doorenbos and Kassam 1979). Stan and Naescu (1997) indicated that the value of K_y varied between 0.66 and 0.86 depending on its drought-resistance. Popova et al. (2006) reported that the K_y for drought susceptible maize varied 1.0 to 1.10 while Yazer et al. (2009) reported a value of K_y of 0.98 for irrigated maize. Popova et al. (2006) reported that the maize variety that was less-resistant to water-stress reflected steeper K_y when compared to a more drought-resistant maize hybrid variety. Najarchi et al. (2011) reported a K_y value of 0.91 for maize under deficit irrigation and observed that a steeper slope of the yield-reduction function indicated greater drought-susceptibility while shallower slopes indicated greater drought-resistance in maize and wheat. Djaman (2011) reviewed the literature available on the maize yield loss functions and indicated that in addition to the drought resistance of a given crop variety, the slope of the yield reduction function was also influenced by the fertilizer, salinity, pests and diseases, and agronomic management practices.

It can be observed from Table 1 that the slopes of K_y for maize among the countries are different, indicating different rates of yield losses due to drought. Initial observations indicate that the average slope of the drought yield-loss function for maize in Kenya and Malawi is near 1.25, which conforms to that specified for the entire crop growing season for maize by the FAO[4]. However, the slope of loss function for maize in Mozambique is 0.78, which is nearly half of that defined by FAO[4].

Typically a WRSI less than 50 corresponds to conditions nearing total crop failure (Smith 1992; Senay and Verdin 2002). It can be observed from insets (a) and (b) in Figure 1 that the maize vulnerability relationship does not show any data points corresponding to WRSI below 50 in Kenya and Malawi. However, the maize yield losses in Mozambique (Inset d in Figure 1) do not conform to this condition as maize yields are observed even when WRSI goes below 40. This highlights an increased range of WRSI sensitivity to capture maize yield losses especially in drought prone areas.

Millet yield-loss function

Figure 1 (inset d) depicts the statistical relationships between drought-induced millet yield losses with WRSI. The slope defining the loss function for millet is much steeper than those for maize. This is related to the increased sensitivity of millet to shortages in water availability. The drought vulnerability model for millet in Niger shows that WRSI value of 40 corresponds to more than 60% loss in millet yield which again indicates almost total loss of crop yield.

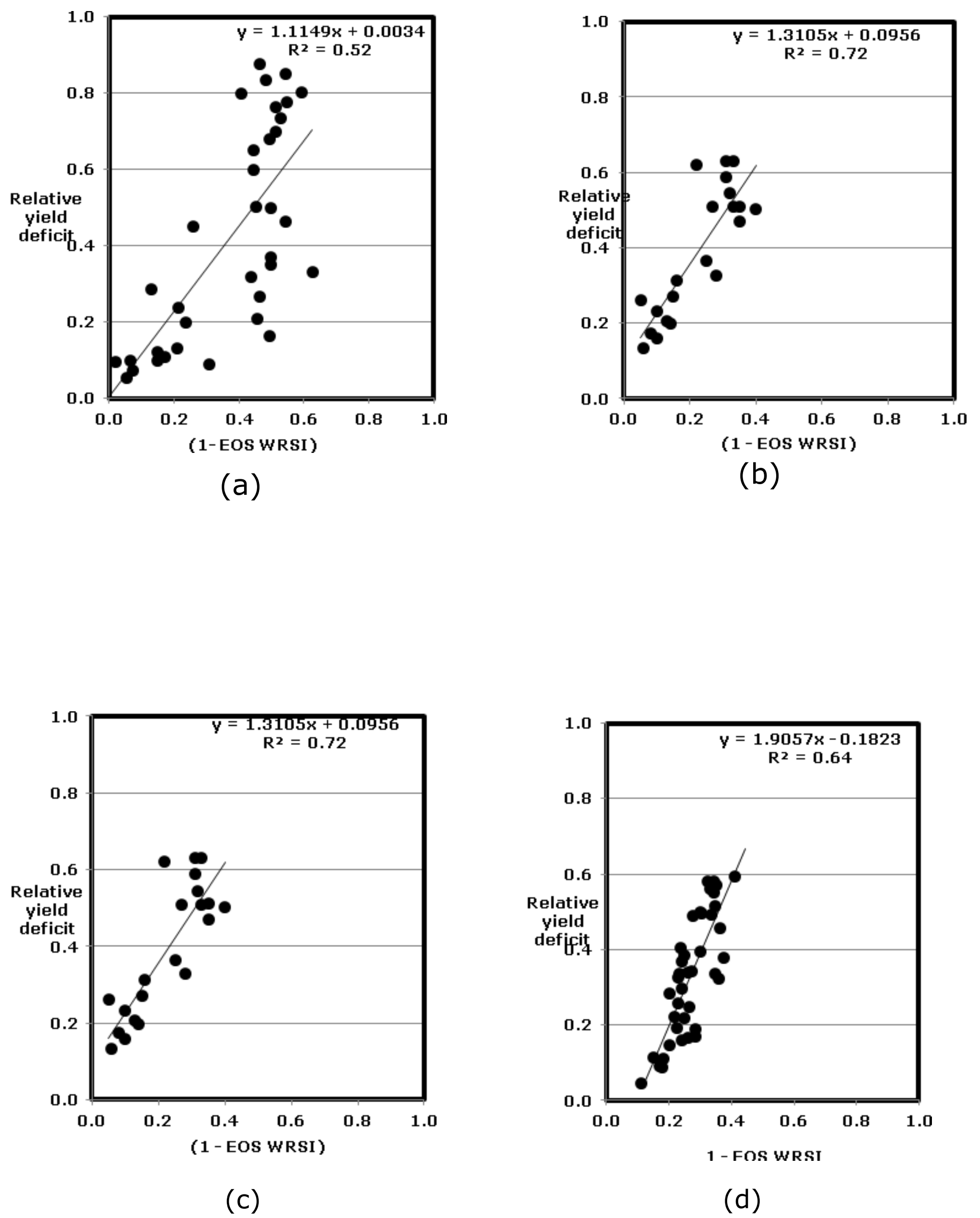


Figure 1: Drought vulnerability model for maize in the (a) Rift Valley province, Kenya, (b) Malawi, (c) Mozambique and for (d) millet in Niger. The relative yield decrease ($1-Y_a/Y_m$) relation with the relative evapotranspiration deficit (1- EOS WRSI) over its total growing period.

3. Agricultural drought risk analysis

Estimating the frequency and severity of drought events is best done by estimating a statistical distribution to a set of observed events. Such distributions serve as the basis for evaluating the likelihood of particular events occurring, and are critical to metrics such as the SPI (McKee et al. 1993). An accurate estimation of the statistical distribution of RFE2 accumulations is difficult given the relatively short timescale (March 2000 – present). Estimating seasonal totals can be done fitting statistical distributions to the available data. However, that doesn't provide the within season variability that is critical to calculating the WRSI.

An approach was developed to leverage the available RFE2 records to create a longer time series, allowing for a more complete estimate of seasonal totals and WRSI outcomes. Combining sequential dekads from randomly selected year's results in an array of synthetic seasons, which can be used to drive the GeoWRSI, along with climatologic conditions for other inputs such as PET, and create a suite of WRSI totals (Husak, in review). The statistical distribution of seasonal totals for the 500 scenarios used in the research presented here is not statistically different from the distribution of the RFE2 seasonal totals. However, it should be noted that with the limited historical record of the RFE2, tails of the distribution may be poorly defined, indicating that caution should be used for analysis of drought events less than the 10^{th} percentile. The resulting synthetic scenarios assist in better defining the likelihood of seasonal WRSI outcomes by allowing for within season variability to be expressed and incorporated in the model. With this suite of outcomes, it was possible to determine the likelihood of a specific loss event being exceeded. The yield loss function calculates the loss associated with each WRSI, and with the synthetic seasons it is possible to estimate the probability of that WRSI value, or one less than it, occurring.

The continuous distribution of simulated drought-induced losses has been used to derive drought frequency maps of the study areas. The count (number of times) of drought-incidence over the 500-year has been used to establish the agricultural-proneness maps in Kenya, Malawi, Mozambique and Niger.

4. Results and Discussion

The simulated WRSI time series were then converted to estimate loss based on the equations established from Table 1. With each synthetic season attached to a given loss, it is possible to determine the LEP in an empirical manner. These results are shown in the Figure 2 (insets a - d) for each of the four study areas. On the y-axis in each plot is the probability of exceedance and the x-axis shows the loss in production in terms of metric tons. Normalizing the production loss by total production, it is possible to put these in a relative measure of the percent of production lost. Figure 3 (insets a - d) depict the normalized LEP curves expressed in terms of percentage loss of total crop production in the Rift Valley in Kenya, Malawi, Mozambique and Niger respectively.

The return period losses provide magnitudes of anticipated drought severity in terms of production losses in metric tons. Tables 2 to 5 list the return period losses for the average annual loss, 1 in 5, 10, 20, 50 and 100 years (both in terms of tons of crop production loss as well as percentage of total crop production) caused by drought in the Rift Valley in Kenya, entire country of Malawi, province-wise in Mozambique, and by Department in Niger.

The agricultural drought frequency maps showing the drought-proneness at district-level in the Rift Valley in Kenya, Malawi, Mozambique, and Niger are depicted in figure 4 (insets a to d).

Table 2: Return period losses for maize in Rift Valley, Kenya

RP (years)	Loss (MT)	Loss w.r.t 2006 production (%) in Rift Valley province
100	201,257	11.0
50	176,322	9.7
20	135,172	7.4
10	113,632	6.2
5	78,277	4.3
AAL	34,923	2.3

Table 3: Return period losses for maize in Malawi

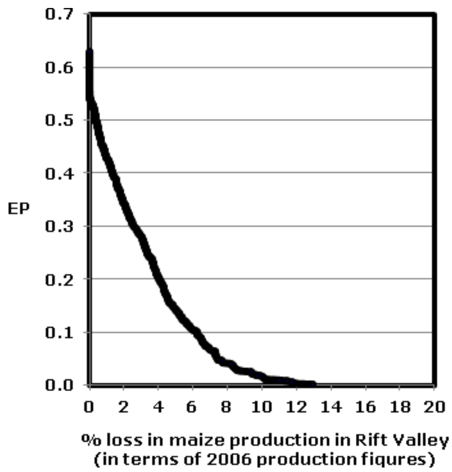
RP (years)	Loss (MT)	Loss w.r.t 2008 maize production in Malawi (%)
100	52,652	8.9
50	42,816	7.2
20	28,912	4.9
10	21,126	3.6
5	13,719	2.3
AAL	6,266	1.2

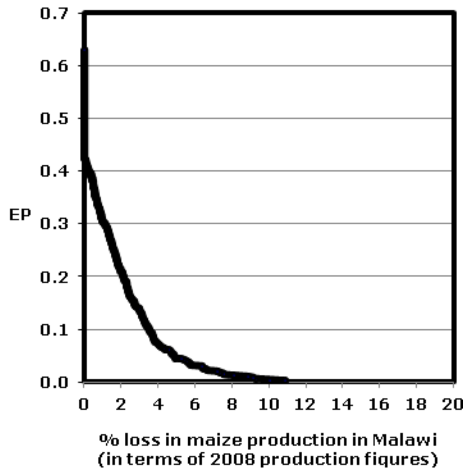
Table 4: Return period losses for maize in Mozambique

Province	AAL	1 in 10 years	1 in 20 years	1 in 50 years	1 in 100 years	AAL as a % of production (2008)
Cabo Delgado	396	-	869	6,144	13,232	0.24
Nampula	623	1,008	3,121	8,811	17,202	0.35
Niassa	816	-	3,496	13,815	24,848	0.33
Manica	11,266	51,724	74,556	81,933	88,571	3.99
Sofala	4,042	16,790	20,550	25,227	27,313	5.06
Tete	2,206	6,926	11,420	16,165	25,563	1.07
Zambezia	3,677	13,638	24,388	36,444	44,046	1.11
Inhambane	4,006	15,132	19,578	23,573	25,013	8.63
Gaza	10,009	28,759	30,607	32,297	33,515	17.96
Maputo	5,462	16,841	17,717	18,405	18,994	16.04

Table 5: Return period losses for millet in Niger

	Millet production losses (MT)						
Department	1 in 5	1 in 10	1 in 20	1 in 25	1 in 50	1 in 100	AAL
Goure	3,166	15,780	22,511	24,108	27,265	31,337	3,378
Magariya	-	12,871	26,155	30,239	30,239	52,429	3,336
Matamey	-	2,273	11,261	13,466	18,469	22,369	1,288
Mirriah	-	16,828	35,447	38,797	45,798	55,547	4,383
Tanout	313	11,483	17,568	19,331	23,989	29,177	2,462
Filingue	-	8,361	26,280	30,813	43,891	46,842	3,036
Kollo	-	19,508	32,060	34,470	42,235	48,093	4,073
Oullaum	3,102	20,224	33,282	34,047	40,076	45,613	4,529
Say	-	426	7,578	7,992	12,822	17,799	834
Tera	-	11,327	34,787	37,789	49,361	52,797	3,662
Tillaberi	2,456	15,930	21,457	22,853	26,054	27,524	3,210
Diffa	4,665	11,637	13,292	13,691	15,454	16,339	2,346
Maine-soroa	4,505	12,078	13,503	14,538	16,862	17,795	2,436
Boboye	-	-	2,723	4,291	14,321	21,294	703
D'doutchi	-	-	14,998	19,153	36,114	42,790	1,928
Dosso	-	-	-	-	-	10,364	271
Gaya	-	-	-	-	-	9,555	167
Loga	-	-	3,669	4,662	9,659	11,706	510
Aguie	-	10,983	21,858	24,955	32,961	38,021	2,676
Dakoro	-	16,542	29,637	35,053	45,910	60,353	4,148
G'roumdji	-	24,424	38,019	42,114	52,979	57,292	4,989
M'rounfa	3,444	26,430	37,082	42,268	51,097	60,138	5,516
Mayahi	-	5,571	15,757	19,172	28,905	40,360	2,013
Tassoua	-	14,634	33,127	43,506	60,112	66,527	4,321
B'konni	-	18,779	35,207	40,372	46,691	58,558	4,433
Bouza	-	16,111	24,241	26,630	34,801	37,651	3,332
Illela	-	28,355	41,549	43,322	52,119	64,249	5,197
Keita	5,401	30,113	38,769	40,782	48,382	51,452	5,718
Madoua	-	13,723	22,480	24,437	36,081	41,952	3,080
Tahoua	-	24,077	30,059	32,546	39,062	41,959	4,524





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a)

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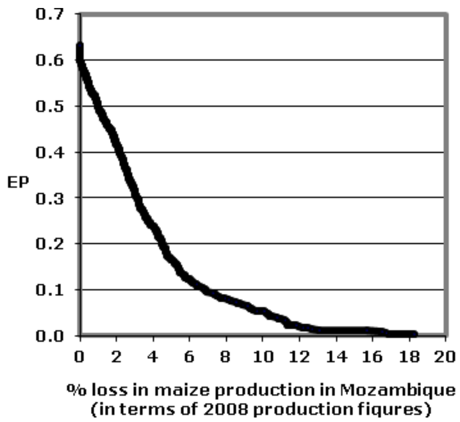

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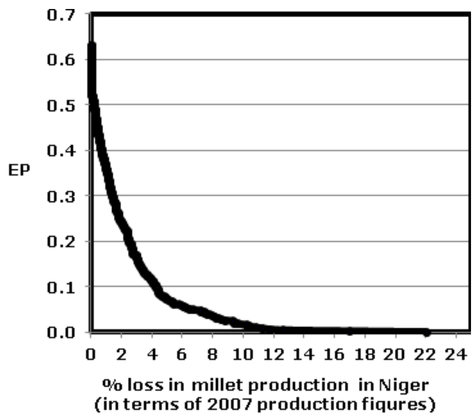

(d)

Figure 3: Loss exceedance probability curve for maize in (a) the Rift Valley province, Kenya, (b) Malawi, (c) Mozambique and for (d) millet in Niger. The losses are expressed in percentage of total loss in crop production.

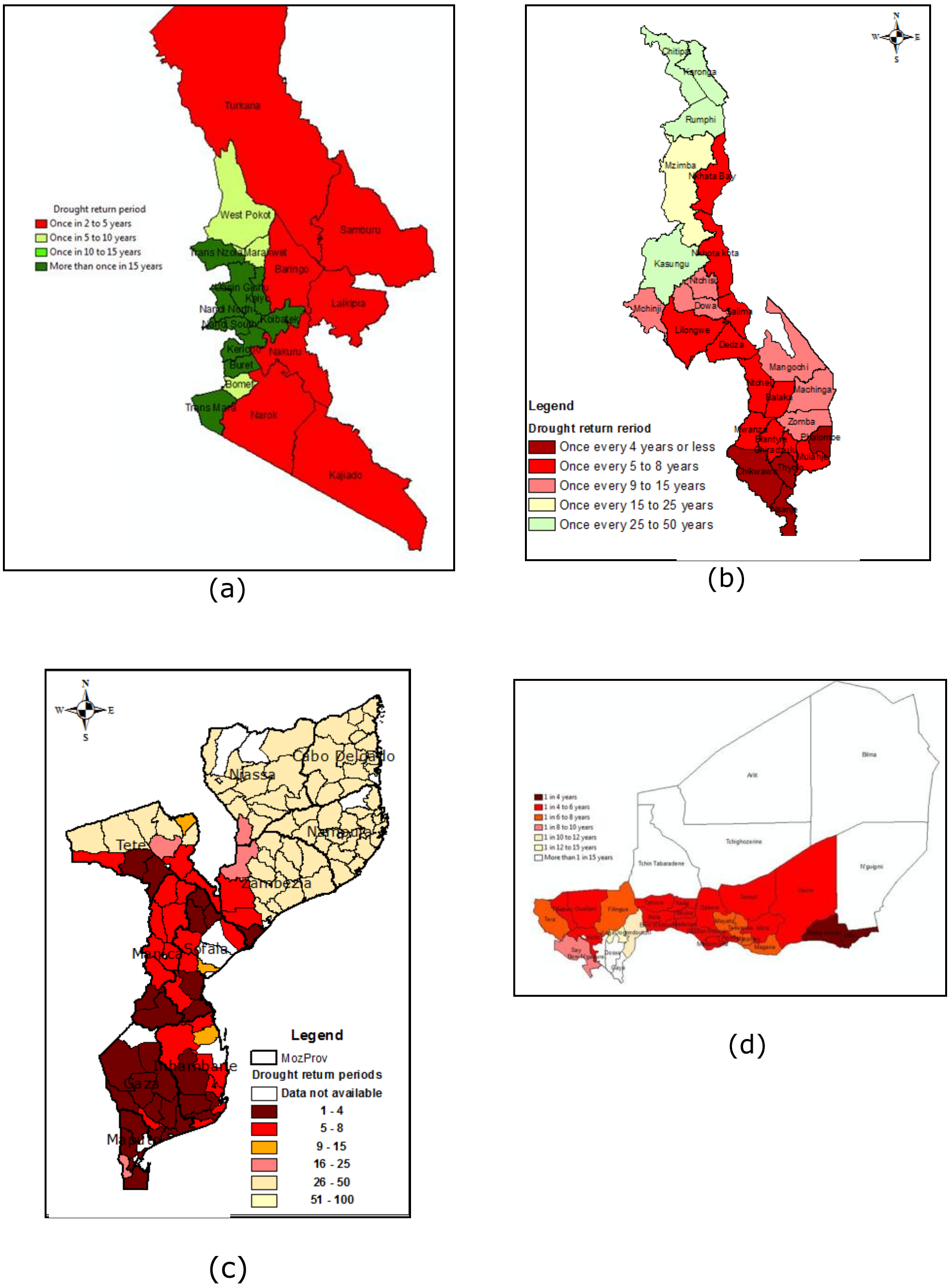

Figure 4: Drought frequency maps for maize in (a) the Rift Valley province, Kenya, (b) Malawi, (c) Mozambique and for (d) millet in Niger.

Kenya

The average annual loss for maize in the Rift Valley is about 35,000 MT (Table 2). This translates to about 2.3% of the total maize production (based on 2006 maize statistics in this Province). Further, it can be deduced from the LEP curve (Figure 2(a)) that drought-induced losses of roughly 50,000 MT occur one on 3 year drought in the Rift Valley, Kenya.

The drought frequency map (Figure 4(a)) established from the simulated drought incidences in the Rift Valley delineates two distinct areas – a more drought prone eastern side and less drought prone western region. The eastern districts have a return period of less than one in five year drought, as indicated by the red shading. These include Baringo, Laikipia, Kajiado, Narok, Nakuru, Samburu and Turkana. The districts on the western fringe namely Buret, Keiyo, Kericho, Koibatek, Nandi (North and South), Trans Mara, Trans Nzoia, and Uasin Gishu have a return period of more than one in 10 year drought (depicted in green color). The central districts of Marakwet and West Pokot are observed to have a drought return period of 5 to 10 years.

The above results can be explained from the understanding of the physiography, the rainfall patterns, the cropping intensities, and the population distributions in this region. The average annual rainfall in the eastern districts varies between 400-600 mm while that in the western districts is between 1000 – 1200 mm and more (Oroda 2004). This agro-ecological system has rendered the eastern districts significantly drought prone and maize yields highly susceptible to droughts in the Rift Valley province.

Malawi

The average annual loss for maize in Malawi is about 6,250 MT (Table 3). This translates to about 1.2% of the total maize production (based on 2008 maize statistics in Malawi). One in 10 year drought in Malawi leads to a loss of about 21,500 MT of maize.

The drought frequency map (Figure 4(b)) in Malawi indicates 3 broad regions of drought-proneness. The North Malawi districts of Chitipa, Karonga, Kasungu, Mzimba and Rumphi have a drought return period of more than one in 15 years. The Central districts in Malawi are susceptible to droughts of one in 5 to 8 years. The Southern Malawi districts of Chikwawa, Nsanje, Phalombe and Thyolo are severely drought-prone with a drought return period of one in 4 years while other districts in this region are susceptible to agricultural droughts at least one in 4 to 8 years. This can again be explained with the help of rainfall patterns and physiography differences in the northern, central and southern Malawian regions. Northern districts receive an annual rainfall of 1000 mm or more while the southern districts receive 600-800 mm rainfall[6].

Mozambique

Table 4 lists the different return period drought losses for each province in Mozambique. It is observed that the highest maize production losses are observed in Gaza, Manica, and Sofala due to intense maize cultivation in these provinces. Figure 2 (c) describes the LEP curve for maize in Mozambique in terms of maize production loss in tons. It is observed that the average annual loss for maize in Mozambique is about 42,500 MT; which translates to approximately 3% of the total maize production in the country. The LEP curve indicates that maize loss of at least 100,000 MT or more occurs one in 10 years in Mozambique.

The drought frequency map (Figure 4(c)) in Mozambique indicates 3 broad regions from a drought perspective. The North regions are relatively less drought prone with a drought return period of more than once in more than 15 years, while the regions in the central provinces are susceptible to droughts once in 5 to 8 years. The southern provinces are most drought-prone with a drought frequency of once in 4 years or less. This is explained again by the rainfall and physiography prevalent in the above regions. Mole (2006) described that the average annual rainfall in the northern Mozambique comprising of Cabo Delgado, Nampula, Niassa, and some regions of Zambezia and Tete province lies in the range of 800 – 1200 mm. The central provinces of Manica and Sofala receive an annual rainfall of 800 to 1000 mm while the southern provinces of Gaza, Inhambane, and Maputo receive an annual rainfall of 600 to 800 mm.

The non-dimensionalized LEP curves, expressed as percentages with respect to the total crop production statistics of a recent year for the maize growing regions in this study have been plotted in Figure 5.

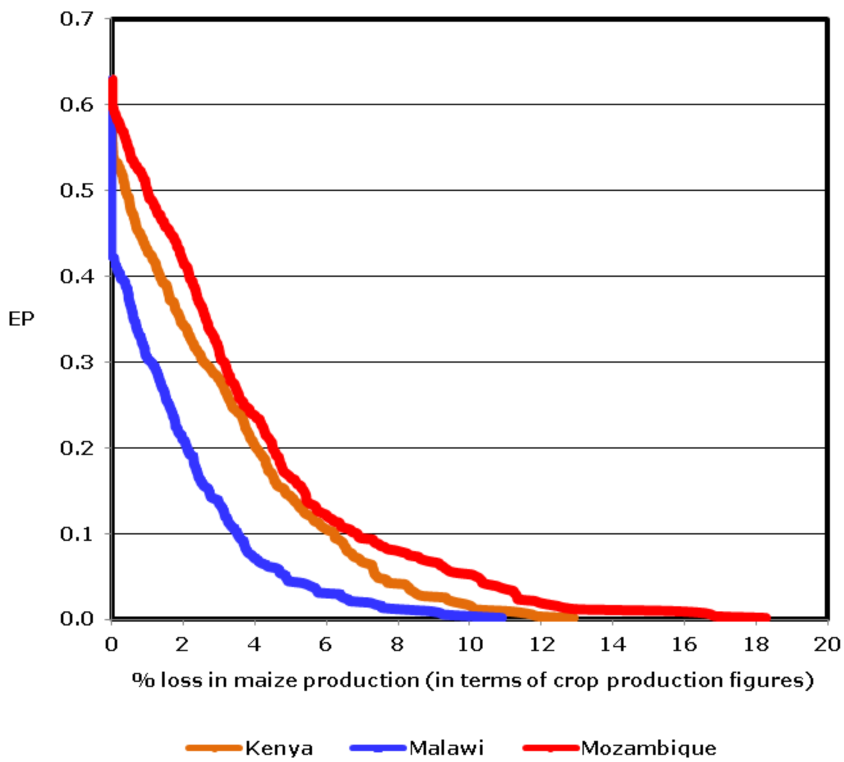

Figure 5: Comparison of LEP curves for maize in Kenya, Malawi and Mozambique. The LEP curves have been non-dimensionalized and expressed as

a percentage of the total crop production corresponding to a reference year statistics.

Figure 5 reveals interesting comparative characteristics of each region and the frequency with which it experiences major events, as well as how regularly it experiences any production loss according to this study. For instance, it becomes apparent that Malawi experiences loss less than half the time, while Mozambique and Kenya experience some loss in more than half the scenarios. It is also observed that the potential loss is much larger in Mozambique and Kenya, than for Malawi. Another way this is expressed is that for the same likelihood-event, the percentage of loss is greater for Mozambique and Kenya than it is for Malawi.

The maize cultivation in the Rift Valley in Kenya suffers a loss of nearly 6% of the total maize production in that province once every 10 years; while the maize cultivation in Mozambique loses up to 7% of the total maize production due to one-in-a-10 year drought. The maize cultivation suffers a 3.8% production loss due to a one-in-a-10 year drought in Malawi.

Millet in Niger

Table 5 lists the Department-wise return period losses for millet affected by droughts in Niger. Figure 2(d) indicates the LEP curve for millet in Niger and it can be seen that drought-induced losses of a magnitude of 150,000 MT occur one in 5 years in Niger. The average annual loss for millet is about 92,500 MT while a one in 10 year drought will cause a loss of about 390,000 MT of millet production loss. Figure 3(d) highlights the LEP curve for millet with the losses expresses in percentages of the total millet production (2008 millet statistics). Figure 4(d) presents the drought frequency map derived using the simulated WRSI statistics in Niger. The Departments of Diffa and Maine-Soroa are highly susceptible to drought with a return period of once in 4 years. The remaining districts are prone to drought at least once in 5 to 8 years except for Birni N'Gaoure, Dosso, Dogondoutchi, Gaya, and Loga which have a drought frequency of once in more than 12 years. This frequency is in line with the overall rainfall patterns, and also with the temperature gradients across the region, which is a critical input to potential evapotranspiration.

Conclusions

Agricultural drought risk profiling is one of the difficult tasks faced by the risk modelers in the World. While many hazards are finite events that present clear outcomes and as such are easy in their hazard mapping, drought incidence is more nuanced and therefore more difficult to capture. This has prompted GAR 2011 to state that the risks associated with droughts are less understood. There are two major approaches to agricultural drought risk modeling – either run a high-frequency high-resolution input based crop process model to monitor the agricultural crop performance or conduct an analysis of the historical drought-induced crop losses to understand the crop response in a given region.

Initial efforts in drought identification and vulnerability analysis looked at the SPI as an indicator. However, the SPI requires identification of the critical rainfall period and analyzes only rainfall sums over that entire period, not the distribution of rainfall within that period. In short, while a valuable indicator for meteorological or hydrological drought, the SPI is not tuned enough to crop characteristics to be valuable as an agricultural drought indicator. An index that is more tuned to agricultural needs and water availability conditions was identified in the WRSI used by FEWS NET.

WRSI has been validated as a proxy for crop productivity and related statistically to crop production using linear yield-reduction functions (Senay and Verdin 2001; Verdin and Klaver 2002; Syroka and Nucifora 2010; Patel et al. 2011). The UNISDR and FEWS NET have initiated a collaborative study to identify, develop and validate a probabilistic agricultural drought risk methodology using satellite estimated rainfall-based WRSI.

In this paper, a probabilistic method for estimating agricultural drought risk for maize in Kenya, Malawi and Mozambique, and for millet in Niger has been proposed. Historical yields have been analyzed to develop drought vulnerability models using the satellite rainfall based-water requirement satisfaction index (WRSI) in the above countries. In view of the limited hazard and exposure data (2000 to present) a bootstrapping technique was used to approximate a long-term rainfall time series (Husak et al., in review). The statistical distribution of seasonal totals for the 500 scenarios used in the research presented here is not statistically different from the distribution of the RFE2 seasonal totals. The resulting synthetic scenarios were used to drive the GeoWRSI model to determine the continuous simulations of LEP curves for the identified regions.

This paper presents graphic and numeric loss profiles for maize and millet crops in select drought prone countries in Africa. Drought frequency maps indicating the drought return interval at district-level have been generated indicating the agricultural drought risk characteristics for the selected crops in the above regions. Differences in vulnerability of the study areas revealed a deeper understanding of the capacity of each region to overcome, or fall victim to, agricultural drought events.

The efforts presented here represent an initial foray of disaster risk reduction mainstreaming into the realm of agricultural drought. The methodology presents promising results based on limited rainfall estimates and crop statistics. Despite these shortcomings, the results allow for insightful analysis, comparisons, and paint a promising future for the characterization of the risk of agricultural drought in vulnerable regions of the world.

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