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ABSTRACT

During 1990s, disaster risk reduction emerged as a novel, proactive approach to managing risks from natural hazards. The World Bank, USAID, and other international donor agencies began making efforts to mainstream disaster risk reduction in countries whose population and economies were heavily dependent on rain-fed agriculture. This approach has more significance in light of the increasing climatic hazard patterns and the climate scenarios projected for different hazard prone countries in the world. The Famine Early Warning System Network (FEWS NET) has been monitoring the food security issues in the sub-Saharan Africa, Asia and in Haiti. FEWS NET monitors the rainfall and moisture availability conditions with the help of NOAA RFE2 data for deriving food security status in Africa. This paper highlights the efforts in using satellite estimated rainfall inputs to develop drought vulnerability models in the drought prone areas in Malawi. The satellite RFE2 based SPI corresponding to the critical tasseling and silking phases (in the months of January, February, and March) were statistically regressed with drought-induced yield losses at the district level. The analysis has shown that the drought conditions in February and early March lead to most damage to maize yields in this region. The district-wise vulnerabilities to drought were upscaled to obtain a regional maize vulnerability model for southern Malawi. The results would help in establishing an early monitoring mechanism for drought impact assessment, give the decision makers additional time to assess seasonal outcomes, and identify potential food-related hazards in Malawi.

1. Introduction

The World Meteorological Organization [29] observed that over 70% of natural disasters are partially or totally related to weather and climate in combination with economic, social and political forces. Mainstreaming natural disaster risk reduction is a novel strategy initiated in the late 1990s as a proactive approach toward managing natural hazards. This approach consists of the following sequence of steps—quantify hazard (use an index to represent the occurrence of drought, its severity, and persistence), define exposure (analyze the area and yields

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of principal crops), determine vulnerability (ascertain the response of crops to drought events of different severities), quantify risk metrics (assess the loss in crop productivity in terms of yields and monetary value), and compute average and long term losses through probabilistic analysis of historical events. The analytical results are then used in the development of appropriate institutional and sectoral strategies, policies, and in the design of mitigation measures in the hazard-prone countries [3].

In the context of world agriculture and food security, drought vulnerability analysis is critical, especially in light of the increasing climatic hazard patterns and the potential projected climate scenarios for different hazard prone countries in the world. The U.S. Agency for International Development (USAID) Famine Early Warning Systems Network (FEWSNET) manages an information system designed to identify problems in the food supply system that lead to food-insecure conditions in sub-Saharan Africa, Afghanistan, Central America, and Haiti. FEWSNET also provides access to a range of geo-spatial data, satellite image products, and derived data products in support of the monitoring needs throughout the world as a part of the Early Warning and Environmental Monitoring Program. The FEWSNET system conceptualizes its functioning in accordance to three well defined levels—vulnerability identification and impact assessment, development of appropriate contingency plans, and design and implementation of timely disaster relief packages. The success of the above program depends significantly on understanding the vulnerability of principal crops to droughts and famines of hydro-meteorological origin [8].

1.1. Drought hazard

The first step in the drought vulnerability analysis is the evaluation of drought hazard characteristics in the study area. Drought hazard represents the nature of the drought event that culminates in lowered crop productivity at the end of the crop season. A drought hazard index has to satisfy three characteristics—capture the incidence, assess its severity and persistence, and indicate the probability of future occurrences. A review of various conventional and remote sensing based drought indices are discussed in [1,7,10,15].

The state of art of drought definitions and indices indicates that the varying agro-climatic regions of the world lead to many definitions of drought [9]. While a meteorological drought can be capably characterized by established rainfall-deviation statistic(s) however an agricultural drought has to include agro-climatic indicators (e.g., evapotranspiration-ET, soil moisture) because of the complex soil–atmosphere–vegetation regimes involved. In this context, remote sensing inputs are also used to supplement [11] and increase the effectiveness of drought indices. Consequently, a multitude of definitions and indices for agricultural droughts taking into climate, soil, and crop characteristics are currently in practice. Drought hazard analysis was deemed far more nuanced than just understanding drought vulnerability because of the various agricultural and non-agricultural factors that lead to poor food production [28].

An Inter-Regional Workshop on Indices and Early Warning Systems for Drought (sponsored by the School of Natural Resources of the University of Nebraska, the U.S. National Drought Mitigation Center, the World Meteorological Organization (WMO), the U.S. National Oceanic and Atmospheric Administration (NOAA), the U.S. Department of Agriculture (USDA), and the United Nations Convention to Combat Desertification (UNCCD)). One of the principal recommendations emanating from this Workshop consisted of encouraging the use of the SPI [17] as a standard meteorological index to characterize meteorological droughts as well as development of a corresponding comprehensive user manual [10].

SPI is a commonly used meteorological drought indicator as it is solely based on precipitation. Further, it facilitates comparison of precipitation deficits at multiple time and spatial scales. SPI is used in research or operational mode in over 60 countries. It is to be noted that reliable SPI data series needs at least 30 years of continuous precipitation records. Moreover SPI at time scales less than 1 month and longer than 24 months may be unreliable [22]. In the present study SPI has been used as the drought hazard index in the development of the vulnerability model.

1.2. Drought vulnerability assessment

The scientific literature on drought vulnerability assessment toward modeling crop response to drought was reviewed by [27] and it was reported that the agricultural droughts were very dynamic phenomena as they were influenced by land-use and management practices, farm policies, market demands, resilience, and other societal factors. It is important to note that the crop yields have been used as proxy drought indices [13,16] because of the close relationship between water stress and crop yields in assessing the agricultural drought risk.

Efforts have also been made to establish drought vulnerability models through statistical regressions between SPI and crop yields for wheat [21,33], corn [23,31,34], cereals and pulses [20], and sorghum and wheat [24]. While Ref. [2] recommended using SPI for short term drought forecasting at regional and continental scales, Ref. [18] highlighted the ability of SPI to provide information about the probable initiation or establishment of a drought, its continuity and its probable termination. The global patterns of droughts were mapped by using SPI to examine their impacts at different spatial scales and maps of hydro-meteorological and social vulnerabilities were compiled by integrating the available global data sets [6]. The authors identified that the African continent lagged behind in drought preparedness and the agricultural economies were highly vulnerable to the adverse impacts of meteorological droughts.

Droughts have a major impact on the African populations as the climate significantly influences their agriculture-driven economies. Almost three-fourths of the African population resides in rural areas and is employed as labor in agriculture, livestock, forestry, and fishery that contribute anywhere from 10% to 70% of GDP [19,25]. The current state of the practice for food security

related monitoring of rainfall conditions in Africa relies on the NOAA RFE2 [32]. Drought conditions are operationally monitored through the analysis of SPI, the duration of dry spells, seasonal rainfall totals and the water requirement satisfaction index (WRSI).

Decision makers need objective drought impact information as early as possible, either during or immediately following the season. Advanced warning allows mitigation efforts to reduce the negative impacts of widespread disasters, or possibly eliminate the effects associated with minor disasters. The main aim of the present study was to develop a drought vulnerability model for maize in the drought prone districts of southern Malawi using the available satellite estimates of rainfall. The present research provides an objective tool to quantify the drought impacts in terms of loss of crop productivity. Efforts were made to use satellite RFE2 based SPI to construct a regional maize drought vulnerability model. The monthly SPI during critical milking and tasseling phenological stages were statistically regressed with end-of-season maize yields for normal and drought years in the drought prone districts of southern Malawi. The district-level drought-induced losses in maize yields were up scaled to obtain regional yield loss function for the three types of maize in the study area. The results show that a reliable statistical estimate of drought induced maize yield loss can be obtained using the satellite rainfall estimates. A regional drought vulnerability curve for maize was determined for the drought-prone districts of southern Malawi.

2. Materials and method

2.1. Study area description

Malawi is a landlocked country in southeast Africa, bordered by Tanzania to the northeast; Mozambique on its east, south, and west; and Zambia to its northwest (Fig. 1a). The drought prone area in the southern Malawi lies to the south of Lake Malawi between 14°–18° S; and 34°–36° E and comprises the following districts—Balaka, Blantyre, Chikwawa, Chiradzulu, Machinga, Mangochi, Mulanje, Mwanza, Neno, Nsanje, Ntcheu, Phalombe, Thyolo, and Zomba.

The spatial variations in annual rainfall and temperature (maximum and minimum) in Malawi are depicted in Fig. 1 (b and c). Malawi has a sub-tropical climate with three general seasons. The winter season is between May and August characterized by cool, dry conditions with mean temperatures ranging 17°–27 °C. This is followed by a hot and dry season between September and mid-October, during which the average temperatures range between 25° and 37 °C with an average humidity of 50%. Finally, the main rainfall season is between November and April and the corresponding rainfall accounts for nearly 95% of the annual precipitation. The north region of Malawi receives 1050 mm of rainfall annually, the central region receives about 1025 mm, and the south receives 925 mm rainfall during the above period.

The Malawian economy is dependent on agriculture as it contributes one-third of the GDP, accounts for 90% of foreign earnings, and supports 85% of domestic employment [30]. Rain-fed maize occupies 52% of the total agricultural crop area in Malawi. Other important food crops are pulses (18.4%), groundnut (8.2%), and cassava (5.3%). Droughts and floods are the major natural disasters that significantly affect the Malawian food production and thus the economy, with droughts having a more pronounced influence than the latter [31].

Maize is grown in temperate–tropic climates during the period when the mean daily temperatures are above 15 °C and frost-free (http://www.fao.org/nr/water/ cropinfomaize.html accessed on October 20, 2012). The duration of maize growing period in this region mostly matches the rainy season (November–April), and is also significantly dependent on the farmers' ability to purchase seed, choice of the variety, and preference of economic returns of its cultivation [7]. The length of growing period for maize is 140 days: 25 days for establishment; 35 days for vegetative growth; 20 days for tasseling and silking stages; 45 days for (yield) grain formation and hardening; and the last 15 days for ripening (http://www.fao.org/nr/water/20cropinfomaize.html accessed on October 20, 2012), personal communication with the Department of Ministry of Agriculture and Food Security, (Government of Malawi). The average start of the cultivation season occurs during the second and third dekads of November in this area. Consequently, the vegetative phase extends till mid-January; tasseling and silking occurs at the end of January; the yield formation occurs between February and mid-March, and the ripening of grains is completed by the last fortnight of March and in the first fortnight of April in the study area.

2.2. Data used

This study utilizes the NOAA RFE2 [32] as the input rainfall estimate and it is standard for rainfall monitoring and food security monitoring in Africa by the FEWS NET (http://earlywarning.usgs.gov/fews/africa/index.php accessed on October 20, 2012). The RFE2 blends together microwave, infrared, and gauge observations via a set of weights minimizing the overall root mean squared error to generate 0.1° daily rainfall estimates which are then aggregated to dekadal or monthly time intervals.

Maize yield data for the period 1984–2008 was collected from the Department of Agriculture and Food Security, Government of Malawi. Historically there are three types of maize (LMA, HYV, and COM) cultivated in Malawi, and Fig. 2 depicts the time series of LMZ, HYV and COM maize yields in the study area.

2.3. Methodology

2.3.1. Standardized precipitation index

SPI is a tool developed for the identification, and monitoring the severity and persistence, of drought derived from the long term historical rainfall records in a given place [17]. Gamma distribution parameters are fit to the historical rainfall distributions (at fortnightly, monthly, quarterly, half yearly or annual intervals) using maximum likelihood estimates [14,26] to determine the normalized distribution of probabilities of exceedance. Drought is characterized by a rainfall event with low

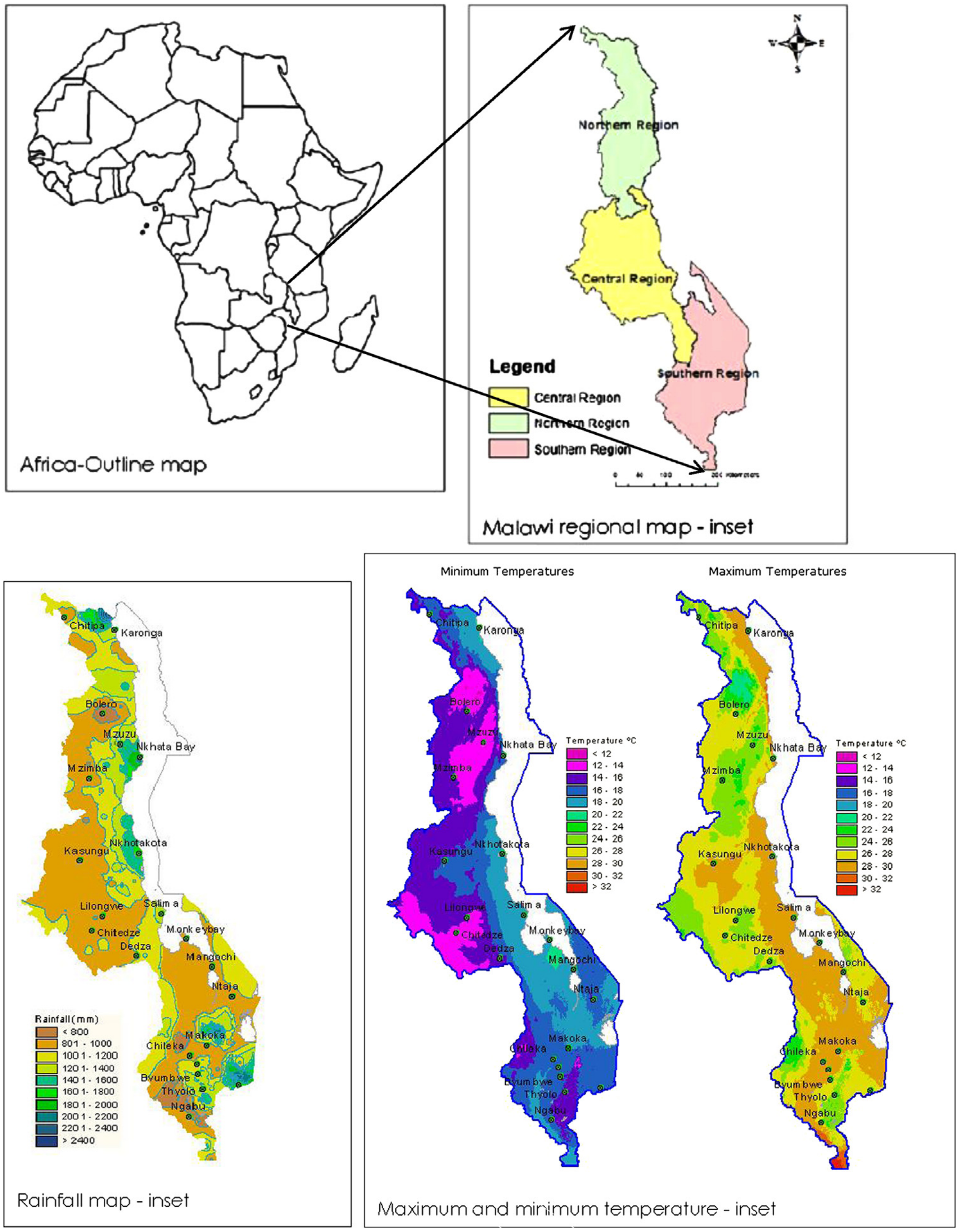

Fig. 1. Map showing (a) study area (districts) in southern Malawi, (b) annual rainfall and (c) maximum and minimum temperature variations in Malawi. (*Source*: http://www.MetMalawi.com)

probability while a flood event is indicated by high probability on the transformed cumulative probability function. SPI is the number of standard deviations that the observed value would deviate from the long-term mean. Drought is represented by a value less than zero; greater the negative number more severe is the drought. WMO has recommended that a drought event begins when the SPI is continuously negative for a period of 2–3 weeks, and ends when it turns positive (http://www.irinnews.org/Report.aspx?ReportId=87442 accessed on October 20, 2012). In the present analysis, in order to understand the variability of maize yields during typical rainfall conditions, a district averaged SPI less than 0.2 in January, February and March with no incidence of flood in the preceding or the following months was considered to capture the characteristic response of maize to reduced rainfall in the study area.

2.3.2. Maize drought vulnerability model

A drought vulnerability model for maize essentially consists of establishing a functional relationship between the maize yield reductions that are consequent to different drought severities. Yield reductions were computed with respect to the closest unaffected seasonal yield (absence of any natural or human intervention that had mitigated the normal seasonal crop growth progress) in the study area.

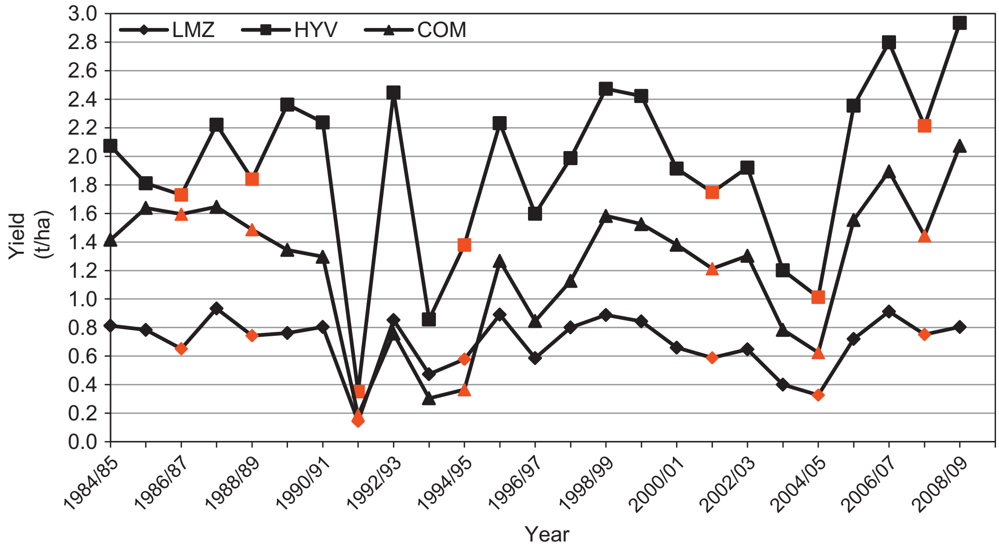

Fig. 2. Time series of maize yield in southern Malawi. The red markers indicate maize yields during drought years. (For interpretation of references to color in this figure legend, the reader is referred to the web version of this article.) (*Source*: Ministry of Agriculture and Food Security, Government of Malawi)

The vegetative, flowering (tasseling and silking) and yield formation (grain formation and filling) stages of maize have been reported to be the most sensitive to water deficits [5]; and when the water deficits occur during the above stages the maize yield gets affected. These would correspond to January (vegetative and flowering), and February until mid-March (grain formation and filling) in the study area.

The available time series of local maize (LMZ), high yield variety (HYV), and composite (COM) maize yields were analyzed and the respective drought-induced yield reductions were estimated. A total of 92 district-based drought events were identified during concurrent period of satellite RFE2 and yield data available during 2001–2007. Statistical regressions were performed between the satellite RFE2 based SPI of January, February, and March, January–February (Jan–Feb), February–March (Feb–Mar), and January–February–March (JFM) with the drought-induced reductions in maize yields. As the occurrence of drought in a district would not be independent of its occurrence in the adjacent districts, the drought-induced yield reductions in all the districts for every drought event in a season were up scaled to obtain the regional drought vulnerability curve for maize in the study area.

3. Results

The frames in Fig. 3 highlight the statistical regressions between the LMZ yield reductions with corresponding average SPI for January, February, March, bimonthly (Jan–Feb and Feb–Mar) and 3-month (Jan–Feb–Mar) SPI in the study area.

The frames in Fig. 3 show that the drought induced LMZ yield reduction is best correlated (r-squared = 0.73) with the March SPI in the study area. This is followed by the average Feb–Mar SPI with r-squared of 0.71. An r-squared of about 0.64 is obtained in the regression of LMZ yield reduction with February SPI. The strength of the regression of LMZ yield loss is the least correlated with January SPI and most correlated with March SPI. Although the best r-squared is obtained with March SPI, however the data for March lacks a consistent distribution between -1.25 and 0.

It can also be observed from Fig. 3 (frame b) that the slope associated with February SPI has the largest absolute value thus indicating that the relative yield loss is more sensitive to the February SPI than with SPI of any other months or combinations thereof. It is deduced that more severe the meteorological drought in the month of February, larger is the maize yield reduction in the area.

The frames in Fig. 4 highlight the statistical regressions between the HYV maize yield reductions with SPI at selected monthly, bimonthly and three-month intervals in the study area.

It can be seen from the frames in Fig. 4 that the drought induced HYV maize yield reduction is best correlated (r-squared = 0.84) with the Jan–Feb–Mar SPI in the study area. This is followed by the average Feb–Mar SPI with r-squared of about 0.8. An r-squared of about 0.73 is also obtained in the regression of HYV maize yield reduction with March SPI and an r-squared of 0.58 with February SPI. The HYV maize responses to drought are similar to those observed in the vulnerability graphs for LMZ maize. The slope of February SPI is largest and corresponds with most HYV yield losses during drought years. As in the case of LMZ maize, although the regression of March SPI has highest r-squared, the data distribution of HYV maize yield losses is not consistent.

The frames in Fig. 5 highlight the statistical regressions between the COM maize yield reductions with the SPI at the selected time intervals in the study area. The drought induced COM maize yield reduction is best correlated (r-squared = 0.67) with the average March SPI in the study area. This is followed by the average Jan–Feb–Mar SPI

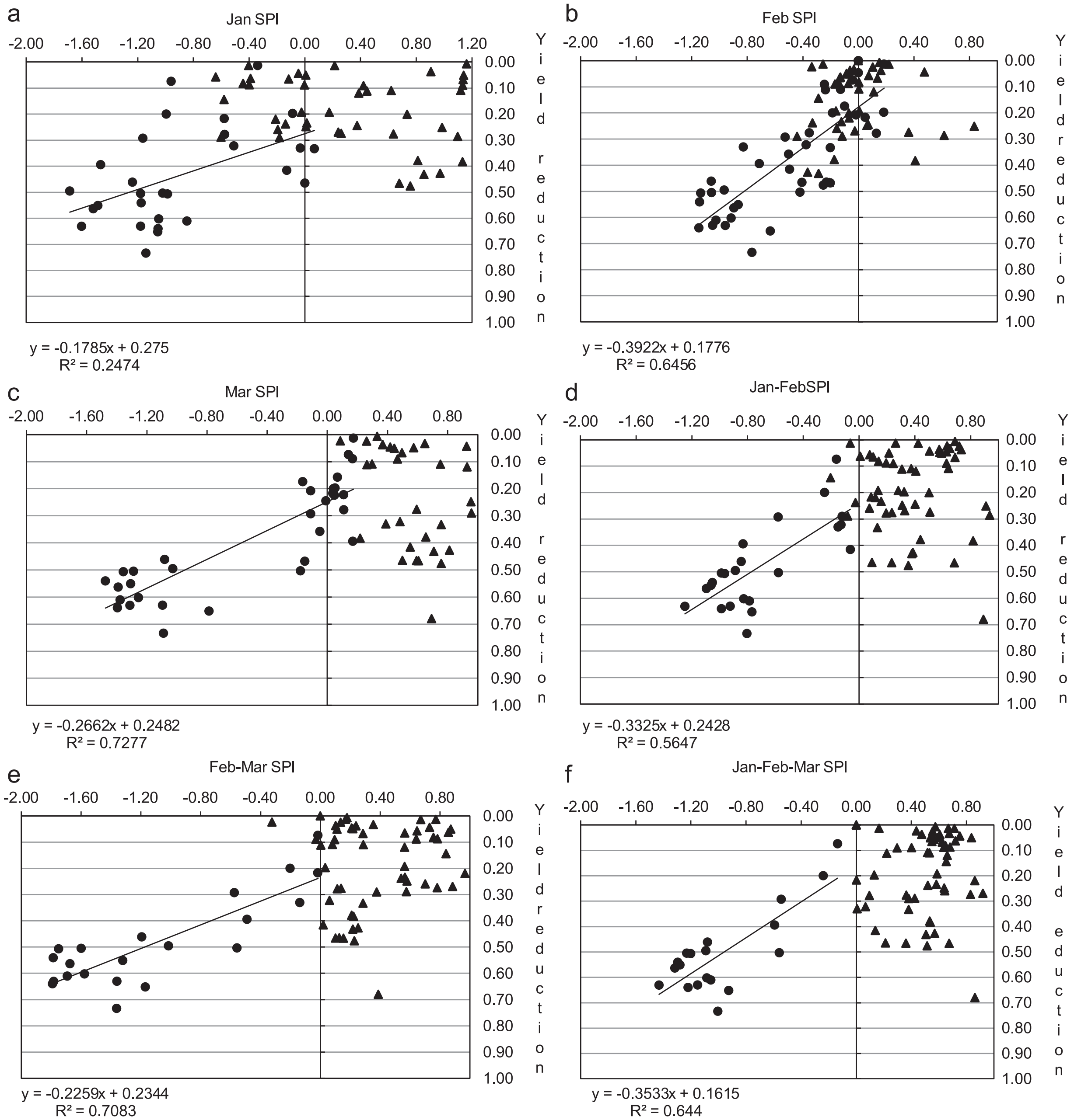

Fig. 3. Statistical regression plots between satellite RFE data-based SPI of (a) January, (b) February, (c) March, (d) Jan–Feb, (e) Feb–Mar, and (f) Jan–Feb–Mar with drought-induced LMZ yield reductions in the selected districts of southern Malawi between 2001 and 2007. The dots indicate yield reduction because of drought (SPI $<$ 0.2) while the triangles indicate yield reduction because of non-drought factors (SPI $>$ 0.2).

with *r*-squared of about 0.66 and an *r*-squared of about 0.54 with Feb SPI.

The SPI of March shows highest strength of correlation and January shows the least strength of statistical correlation with COM maize yield losses. However, the distribution of March SPI was observed to be uneven in terms of occurrences and in magnitude (comparison of frames c in Figs. 3 and 4). This is mainly because of less frequency of drought incidence in March, and maize being in maturity stage (hence less vulnerable to droughts).

The data distribution in Figs. 3–5 (frames b) is better populated in February as the frequency of meteorological droughts is relatively higher in the study area. As maize is in tasseling and silking stages which occurs during February hence the crop yields are most vulnerable to water deficits in February [7,12]. In the context of early warning of drought impact on maize yields, the Feb-SPI becomes the most relevant than that of March-SPI as the season would almost be over in the latter half of March. It is interesting to note that the distribution of data points

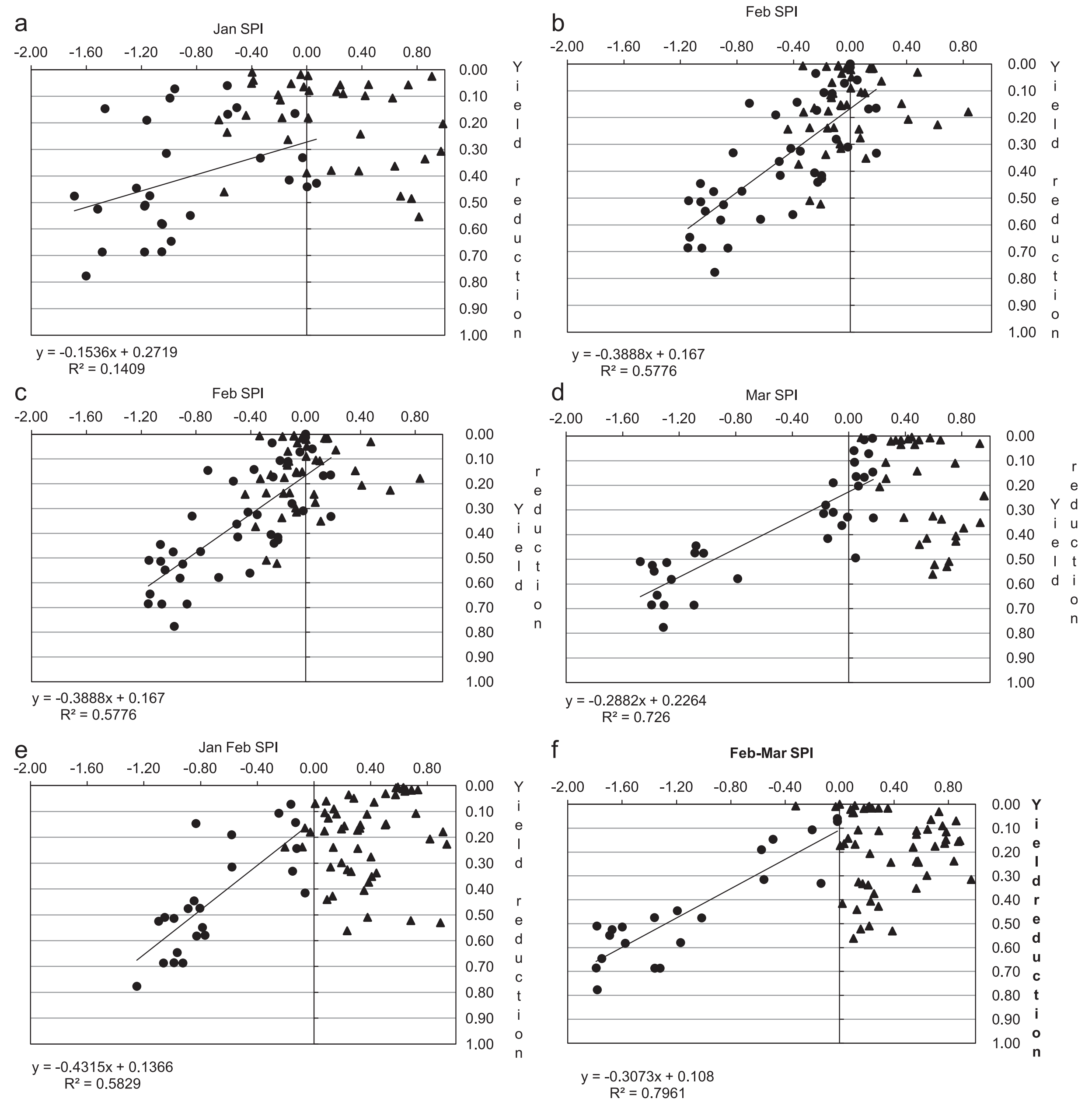

Fig. 4. Statistical regression plots between satellite RFE data-based SPI of (a) January, (b) February, (c) March, (d) Jan–Feb, (e) Feb–Mar, and (f) Jan–Feb–Mar with drought-induced HYV maize yield reductions in the selected districts of southern Malawi between 2001 and 2007. The dots indicate yield reduction because of drought (SPI < 0.2) while the triangles indicate yield reduction because of non-drought factors (SPI > 0.2).

(frames c in Figs. 3–5) are clustered either around SPI of −1.0 or around zero. Although this would give higher *r*-squared, however its use would be limited from early drought impact assessment point of view.

The summary of strengths of the statistical relationships between the relative loss in maize yields with SPI during the months of January, February, March and their combinations are given in Tables 1–3 below:

Tables 1–3 and Figs. 3–5 (frames e) also highlight the strong statistical correlation between the drought-induced losses in the maize yields and the average SPI of February–March. This may be due to the fact that maize would be in the milking–tasseling–grain formation–grain hardening phases during this period. Due to the variability in the onset of rains this critical portion of the maize growing cycle varies in time as well. In a normal year the grain formation stage would occur during February and early March. However when the onset of rains is early, maize would be in silking stage during all of February, while March would most

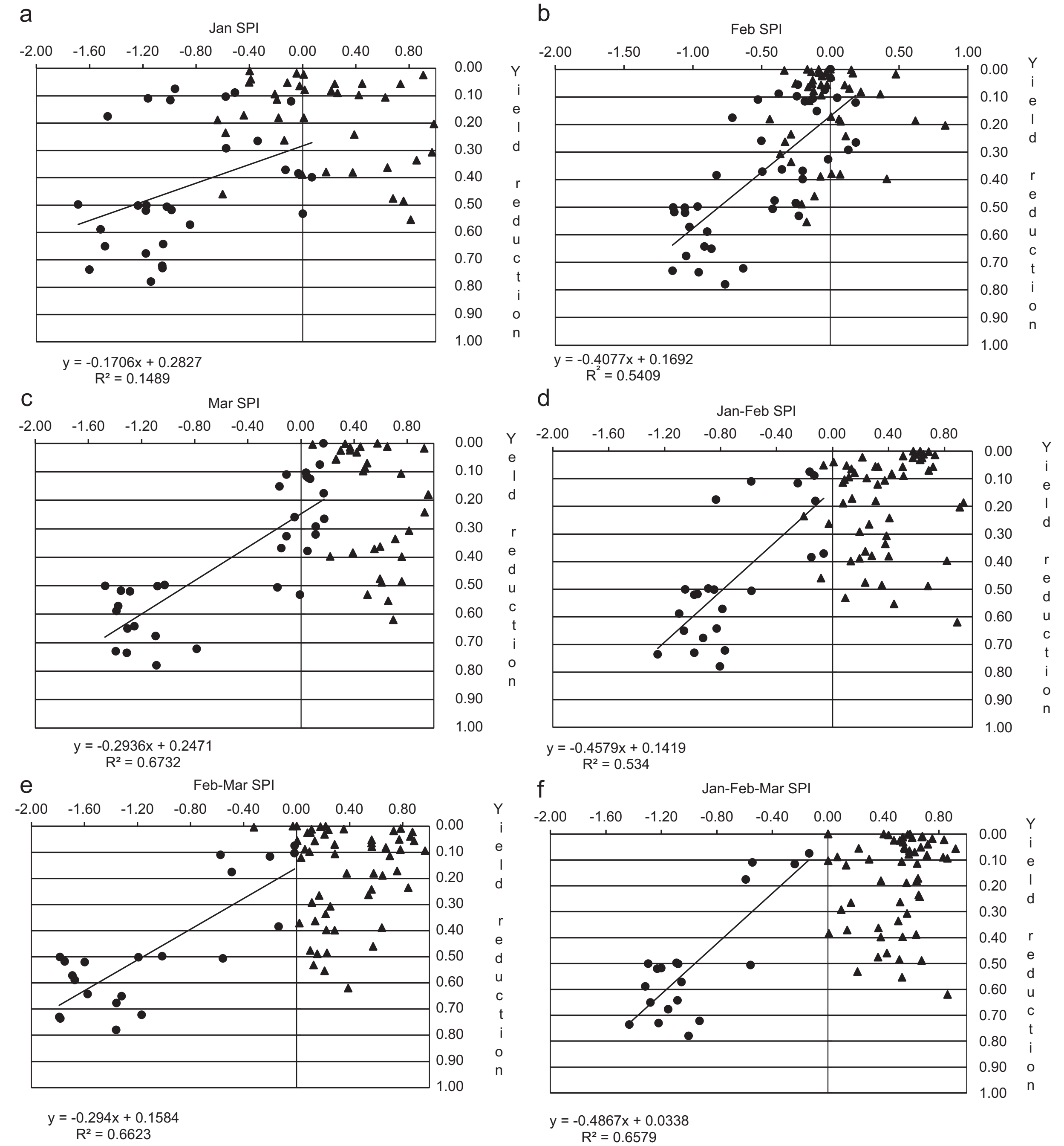

Fig. 5. Statistical regression plots between satellite RFE data-based SPI of (a) January, (b) February, (c) March, (d) Jan–Feb, (e) Feb–Mar, and (f) Jan–Feb–Mar with drought-induced COM maize yield reductions in the selected districts of southern Malawi between 2001 and 2007. The dots indicate yield reduction because of drought (SPI < 0.2) while the triangles indicate yield reduction because of non-drought factors (SPI > 0.2).

likely be excluded. Conversely, in delayed seasons only a portion of February may be covered while all of March would be included. In total, the fact that February is usually entirely, or at least partially, within the grain formation stage, would show that its SPI would be the most reliable indicator of yield reduction. Furthermore, given that the predictability provided by February is not worse than March, using February as the interval of choice allows for an extra month of preparation to respond to consequences resulting from significant yield reductions.

The district-wise drought induced maize yield losses for the three types of maize during the drought-affected season during 2000–2007 using the February SPI were up

Table 1
Details of statistical regression between drought-induced maize yield losses with the SPI of January, February, March and their combinations for LMZ maize.

SPI	Slope	Intercept	*R*-squared	Std. error
Jan	−0.1785	0.275	0.25	0.163
Feb	−0.366	0.1998	**0.62**	**0.121**
Mar	−0.2662	0.2482	**0.73**	**0.107**
Jan–Feb	−0.3325	0.2428	0.56	0.110
Feb–Mar	−0.2259	0.2344	**0.71**	**0.095**
Jan–Feb–Mar	−0.3533	0.1615	**0.64**	**0.101**

Table 2
Details of statistical regression between drought-induced maize yield losses with the SPI of January, February, March and their combinations for HYV maize.

SPI	Slope	Intercept	*R*-squared	Std. error
Jan	−0.1536	0.2719	0.14	0.200
Feb	−0.3640	0.1879	0.55	0.141
Mar	−0.2882	0.2264	**0.72**	**0.117**
Jan–Feb	−0.4315	0.1366	0.58	0.138
Feb–Mar	−0.3073	0.1080	**0.80**	**0.102**
Jan–Feb–Mar	−0.5153	−0.0285	**0.84**	**0.087**

Table 3
Details of statistical regression between drought-induced maize yield losses with the SPI of January, February, March and their combinations for COM maize.

SPI	Slope	Intercept	*R*-squared	Std. error
Jan	−0.1706	0.2827	0.15	0.214
Feb	−0.3828	0.1984	0.51	0.161
Mar	−0.2936	0.2471	**0.67**	**0.135**
Jan–Feb	−0.4579	0.1419	0.53	0.162
Feb–Mar	−0.2940	0.1584	**0.66**	**0.138**
Jan–Feb–Mar	−0.4867	0.0380	**0.66**	**0.135**

scaled for the entire southern Malawi region and plotted in Fig. 6.

Fig. 6 highlights a distinct vulnerability pattern of the LMZ, HYV, and COM maize yield reductions due to droughts in southern Malawi. More importantly, the above figure defines a quantitative relationship that can be used to estimate lowering of maize yield using the February SPI during drought years in this region.

It is important to note that confounding factors such as losses in maize yields due to flood events either in the month of January and/or in March, in addition to the drought conditions in the month of February have not been included in the present analysis.

4. Concluding remarks

This study investigates the relationship between water shortages during critical crop stages and their impacts on yields, with an eye toward early indication of food insecurity. Monthly SPI derived from satellite RFE has been shown as an effective tool for assessing the impact of drought on maize productivity in the drought prone areas of southern Malawi. Monthly SPI of January, February and March that overlap the critical tasseling and milking phase of three types of maize (LMZ, HYV, and COM) have been statistically regressed with drought-induced yield losses at district level during 2001–2007 seasons. Statistically significant relations exist between the maize yield losses with the February SPI in the study area. The individual maize yield losses were aggregated to obtain a corresponding regional vulnerability models (for the three maize types) that is primarily dependent on the satellite RFE data. In the context of FEWS NET famine early warning, such regional vulnerability model becomes a very important yield monitoring tool that can be used to ascertain the drought impacts objectively.

The present study confirms a discernable statistical relation between drought-induced maize yield losses and the monthly SPI derived from satellite RFE2 data.

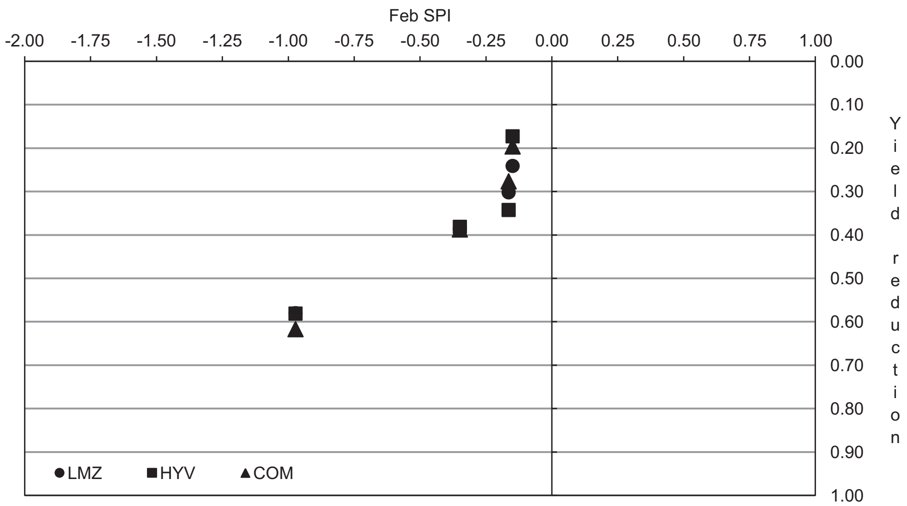

Fig. 6. Regional aggregation of statistical regressions between satellite RFE data-based February SPI with drought-induced (a) LMZ, (b) HYV, and (c) COM yield reductions in southern Malawi between 2001 and 2007.

There are two specific areas where the current model can be further refined. Firstly, the current model is based on a general crop calendar—sowings are assumed between mid-November and mid-December; the critical flowering (anthesis) expected in the month of January, and the grain formation and hardening stages expected to happen in the months of February and March in the study area. As drought years exhibit different phenological crop growth progress from those during normal years, dekadal SPI could be used to assess and define the start-of-the-season more accurately. Once this is accomplished, the most representative SPI could be used accordingly to improve the assessment of drought vulnerability of the maize. Secondly, yield reduction coefficients associated with different maize growth stages could be combined with the SPI to generate a weighted-SPI. This can be used as the impact variable in the regression procedure. Such efforts will most likely increase the accuracy of this approach. Further this research linking maize yield reduction to mid-season rainfall deviations in Malawi can potentially be extended to all of the southern Africa.

Another important factor that has not been accounted for in this study is the impact of changes brought about by the drought management strategies of the Government of Malawi. For instance, the Government of Malawi had taken a strategic decision of providing fertilizer at subsidized rates since 2005/06 season ([4] and personal communication with the Department of Climate Change and Meteorological Services, Malawi and the consequent effect on the crop yields has not been addressed in this paper).

Overall, the identification of the critical monitoring period for a wide area, and a quantitative relationship between estimated rainfall and crop yield impacts, may have widespread effects on food security by giving decision makers additional time to assess the seasonal outcomes and identify potential food-related hazards.

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