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PII: S2211-4645(16)30124-5
DOI: http://dx.doi.org/10.1016/j.envdev.2016.09.001
Reference: ENVDEV303

To appear in: *Environmental Development*

Received date: 31 May 2016
Revised date: 6 September 2016
Accepted date: 6 September 2016

Hydro-climatic variability and agricultural production on the shores of Lake Chad

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Abstract

The purpose of this study is to present and analyze previously unpublished quantitative agricultural data for the area on the shores of Lake Chad in Chad, and explore its relations to hydro-climatic factors (lake levels, rainfall and temperature). This is a rural area with livelihoods based on agropastoral and fishing activities, which are directly dependent on the region's high-varying hydro-climate. By using regression analysis on data from 1988-2012 this study was able to establish correlations between the latter and agricultural output. These correlations were used to build multivariate models to explore the predictive capacities of hydro-climatic factors with regards to the agricultural data. The selected models were able to account for considerable proportions of the agricultural dynamics. Some 5 of the 10 multivariate models tested had cross-validated R^2s of 0.50 or more. Thus, there were still noteworthy unexplained variations in the agricultural data, which likely stem from technological, behavioral, economic and pest factors that were not explored in this study due do data limitations. Additional studies are called for to build on results presented here and further examine these relationships.

Keywords: Lake Chad, agricultural production, hydro-climatic variability, multivariate regression, time series

1. Introduction

The Sustainable Development Goals (SDGs) adopted in 2015 by the United Nations General Assembly will see implementation in the coming years. The ultimate purpose of the SDGs is to bolster well-being globally across 17 goals until 2030 (UN, 2015). The goals are diverse and include to "End poverty in all its forms everywhere" (Goal 1) as well as to "Ensure availability and sustainable management of water and sanitation for all" (Goal 6). Each goal is accompanied by targets, 169 in total, which should specify the goals in more detail. For example, for Goal 1, target 1.1. states that “by 2030, eradicate extreme poverty for all people everywhere, currently measured as people living on less than $1.25 a day”. However, there are also less specific targets, e.g. “by 2020, protect and restore water-related ecosystems, including mountains, forests, wetlands, rivers, aquifers and lakes”. A detailed review of targets can be found in ICSU and ISSC (2015) but what all targets have in common is the recommendation to set up and develop baselines where they do not exist, to “address this gap in data collection so as to better inform the measurement of progress” (SDG point 57). Furthermore, as stated in the SDG, the “targets […] are integrated and indivisible” and therefore essentially have to be seen within a systems perspective for complex relationships to be disentangled and concrete actions identified. This is also in line with the Sendai Framework for Disaster Risk Reduction (UN, 2015) with its emphasis on the need to collect and share data for monitoring and evaluation of risk reduction strategies.

The Lake Chad region, the case study analyzed in this paper, is a good example of the complex challenges which lie ahead in regards to data gathering and disentanglement of relationships in extremely poor and insecure areas. However, it also shows the benefits of such an analysis, by empirically tackling issues of agricultural production risk in regards to hydro-climatic variability and identifying approaches to reduce poverty or the risk of hunger. In fact, the Lake Chad Basin is unique in many respects. It stretches over Central and Western Africa and has gone through extensive hydro-climatic changes since the 1960s. In this period, the annual maximum flooded area of the endorheic Lake Chad has varied from 25,000 km^2 to a minimum of 1,800 km^2 in the 1980s, after which it increased to its current level of around 10,000 km^2 (Bader et al., 2011; Lemoalle et al., 2012; WMO & LCBC, 2005). The communities around the lake are mostly based on traditional small-scale agropastoral and fishing livelihoods, and are thus highly dependent on water availability from the lake and local rainfall. Due to the fluctuating hydro-climatic conditions over the recent decades, inhabitants have been forced to develop flexible livelihood strategies. However, given the population increase, ongoing armed conflicts in adjacent areas, low economic development, and expected further hydrological variations due to global climate change, these communities are facing an increasingly difficult situation. There is an urgent need to confront these issues, and one front on which this can be done is to better understand the relationships between the hydro-climatic variability and the rural economy, thereby supporting the early detection of agricultural production shortfall and food insecurity, and by identifying adaptation measures. If well established, such relationships can also be used for food security outlooks based on seasonal weather forecasts and long term climate projections, thereby creating opportunities for long term planning and climate change impact assessments (see e.g. Dasgupta et al., 2013; Tachie-Obeng et al., 2013). Seasonal outlooks have particularly high potential for the Sahel which experiences a positive skew in seasonal weather forecast accuracy for both rainfall and temperature (Barnston et al., 2010). Despite its importance for rural development, this field of research is generally poorly developed (UNEP, 2012), and certainly so for this region. Some explanations for this are that it is a context specific, transdisciplinary, dynamic and complex topic, where groups and households can display wide differences in vulnerabilities and coping strategies (Adeniji-Oloukoi et al., 2013; Adimassu et al., 2014; Rajesh et al., 2014). Added to this, the overall data availability in this region is low, especially regarding its socio-economical aspects.

Development organizations and various government bodies have been addressing this data shortage by conducting assessments and carrying out data collection projects on food security, demographics and vulnerabilities (e.g. FEWS NET, 2011, 2005; RdT, 2009;

INSEED, 2012, 1993; WFP, 2013, 2009, 2005). Hydrological analyses have received considerable attention due the drastic changes experienced by Lake Chad. Models have been developed to analyze past and future scenarios and inter-basin water transfers, (e.g. Bader, Lemoalle, & Leblanc, 2011; Bastola & Francois, 2012; Lemoalle et al., 2012). More transdisciplinary topics have been investigated recently, e.g.: climate change impacts on fishing communities (De Young et al., 2011), social conflicts due to competition over land and water on the Chadian side (Ndadoum, 2010), structures of traditional fishing management systems on the Nigerian side (Neiland et al., 2005), and adaptations to altered lake levels by Nigerian and Nigerien small-scale fishers (Kiari Fougou, 2014; Luxereau et al., 2012; Sarch and Charon, 2000). Some studies have also engaged with more general assessments of the area's socio-environmental conditions, e.g. an overview of the lake's ecosystem services and their economic values (Eberschweiler, 2011) and three comprehensive syntheses of hydrological, socio-economic and political developments around the lake (EU and BMZ, 2015; Lemoalle and Magrin, 2014; Magrin et al., 2015). While these previous studies provide a wide coverage of the area, none of them include quantitative agricultural data for the Chadian side of the lake presented for the first time in this study, due to local collaborations and archival research. This analysis therefore complements previous studies by presenting these new datasets and exploring their relationships to hydro-climatic variability on the Chadian side of Lake Chad. A unique feature of this case study is the inclusion of two separate hydrological systems, lake levels and rainfall. More specifically, the study investigates the correlations and predictive capacities of lake, rainfall and temperature variability to inter-annual variations in the harvested area and the yield for the two main crops in the region, maize and millet. It does so by using multivariate regression analysis of time series for 1988-2012 on a sub-regional level. By coupling and analyzing these datasets, this study is able to improve the data availability and knowledge on their dynamics for this area and time period. As indicated, this data could be used to set up baseline estimates of agricultural production risk and possible monitoring of SDG targets over time.

1.1. Agricultural climate vulnerability and time series analysis

Statistical time series analysis, which this study employs, is commonly used to establish relationships between climatic and agricultural systems, compared to process based crop models which usually require experimental trials and extensive datasets (Lobell and Burke, 2010). The analysis is based on regression equations of historical data for specific areas and thus covers all dynamics of the agricultural system, not just the direct crop responses. Besides possible issues regarding data quality, one drawback is that it uses historical relationships to infer future outcomes, thereby assuming a certain stationarity to these relationships over time. Extrapolation beyond the historical data therefore needs to be done with sensitivity to any relevant factors external to the analysis. Another issue concerns choice of climate variables to include in the regression analysis. This is on the one hand limited by data availability, however inclusion of more variables increases the risk of over-fitting (Lobell, 2010). Models with a high variable-to-observations ratio necessarily need to address this by validation using independent datasets. However, where there are a small number of observations, it might not be feasible to leave some observations for validation, in which case a leave-one-out cross-validation might be more useful, as it is a robust method for validating predictability in models with few observations (Michaelsen, 1987). Finally, climate variables for the same area often tend to covary, which reduces the possibility of distinguishing the effects of different variables included in a model. However, covariance among variables will not affect overall model performance and need to be approached differently depending on the purpose of the analysis.

Several studies on historic statistical relationships between agricultural output and hydro-climatic variables have been carried out in the Sahel on both national and multinational levels, while regional (sub-national) and sub-regional levels of analysis are generally scarce. They usually focus on yield, and do not include harvested area unlike this study. A unique aspect of this case study is that it includes two separate hydrological systems (lake levels and rainfall), while most other studies only include rainfall. Summaries from five studies in nearby areas using time series and multivariate regression analysis, of both maize and millet, with average temperature and monthly rains as climate variables, give adjusted coefficients of determination (adjusted R^2) in the span of 0.1-0.6 (Akinseye et al., 2013; Lobell and Burke, 2008). As most of these studies are on a multinational level it is expected that the more detailed analysis which this study brings should have at least the R^2s in this range by finding further local dynamics. One of them is however of a Nigerian case which is comparable both in terms of scale, and geographical and socio-economic conditions, however the results have not been verified with independent datasets which raises the possibility of over fitting (adjusted $R^2 = 0.6$).

2. Case Study Area

The area around the Chadian part of Lake Chad is administratively covered by the 'Lake region' which is one of Chad's 22 regions. It has around 430,000 inhabitants (INSEED, 2012) and agriculture is the biggest sector in terms of source of revenue (25%) and rate of active population (41%), followed by fishing, pastoralism and smaller commercial activities (RdT, 2009). One recent study found food insecurity to be at 33%, defined by the Food and Agriculture Organization of the United Nations (FAO) as people not having access to 1.715 kcals per day (RdT, 2009). Both rainfed and lake recession farming are practiced, and most farming systems are family-based, small-scale and with low irrigation and infrastructure usage (RdT, 2009). Water availability for agriculture is thus mainly dependent on the lake levels and local rainfall. The lake levels are not distinctly affected by the local rainfall but are rather determined by the inflow through the Chari-Logone River which originates in the Central African Republic. Water availability in this sense relies on two quite independent hydrological systems: lake levels and local rainfall. A detailed map of land use in the region is given in Figure 1 (P-SIDRAT, 2013). According to this map, lake recession farming (shown in orange) is mostly located in the eastern and western archipelagos. Other sources have indicated that the extent of lake recession farming varies with the lake levels, but that it is practiced in most of the archipelagos around the region capital Bol and towards the eastern and south-eastern shores (Magrin et al., 2015; Yahmed and Houstin, 2012). The only distinguishable irrigation areas on the map (purple) are those surrounding Bol, while other sources report irrigation along the shore between Baga Sola and Bol (Magrin et al., 2015). Rainfed farming (shown in light purple) is scattered in areas next to settlements and villages (black dots), further away from the lake. The agricultural year is divided into a rainy (Jun-Sep) and a dry season (Oct-May) (FEWS NET, 2011). Each season is used for different crops and strategies, with maize and millet as the main rainy season crops which together make up 80-90% of the total annual production (SODELAC, 2014). Production from the dry season, even though small on an annual comparison, still provides important contributions to the stability of the livelihoods over an annual cycle. Maize is mostly grown on the receding lake beds, with or without irrigation, while millet is more rainfall dependent (SODELAC, 2014). One reason for this division is that maize requires more water than millet (Critchley and Siegert, 1991). Throughout the year, people generally engage in different kinds of livelihoods, but due to data limitations, this study will only focus on the agricultural sector, where data have been collected routinely by the local development organization Société de Développement du Lac (SODELAC).

3. Methodology

The main aim of this study was to empirically explore the predictive capacities of hydro-climatic variability on agricultural production in three sub-regions of the Lake region in Chad using the newly developed dataset. The quantitative data used were; seasonal crops (harvested area and yield), monthly rainfall, daily lake levels and daily temperature for each of the sub-regions. Qualitative socio-economic assessments were used to inform the selection of relevant hydro-climatic variables, as well as to interpret the statistical outputs. Data was collected from development organizations and government institutions during field studies in Chad in 2014. SODELAC works specifically with development in the Lake region and provided the most detailed agricultural data through their annual reports of 1988-2012 (SODELAC, 2014). Further information on livelihoods was collected from the Chadian offices of the FAO, the World Food Programme (WFP) and the Famine Early Warnings Systems Network (FEWS NET).

The correlations between agriculture and hydro-climatic variability were explored by bi- and multivariate regression analyses in MatLab. The purpose of this methodology was to find combinations of hydro-climatic variables that were able to explain variations in the agricultural data, and to find potential causalities behind those relationships based on other sources from the area.

3.1. Data overview and selection of hydro-climatic variables

3.1.1. Agriculture

Agricultural data from the SODELAC reports covered all crops and all three growing seasons per year (one rainy season and two off-seasons) for each village in the region. This study looked at maize and millet production from the rainy season, as these accounted for the majority of total annual production (80-90%) (SODELAC, 2014). Villages were put into three sub-regions according to the SODELAC reports: Bol, Ngouri and Doum-Doum. Bol also covered Liwa, as data for Liwa was sometimes reported separately and sometimes together with Bol (see Figure 1 for village locations within the region). Maize and millet were grown in two sub-regions (Bol and Doum-Doum), while only millet was grown in Ngouri, resulting in five different crop datasets. The different sub-regions were expected to have different relationships with the hydro-climatic variables. For instance, Bol and Doum-Doum are both in the direct vicinity of the lake, while Ngouri is located around 20 km east of the eastern shores of the lake. This also explains why Ngouri does not have any maize production, as maize is mostly grown on lake beds in the other areas. Besides crop data, the SODELAC reports also analyzed the agricultural performance of each year and identified difficulties. Together with the quantitative crop data, this provided valuable insights into the agricultural sector in the Lake region.

An issue with this dataset was the potential discrepancy between actual and reported production. The data obtained were gathered by local officers of SODELAC in the region for each growing season over the period 1988-2012. These were in turn based on estimates from local farmers and farmers' associations (SODELAC, 2014). However, as the production systems are small-scale, dispersed throughout the region, and without much centralized monitoring, these estimates were likely to contain errors. To verify the SODELAC data, data were aggregated for the whole region and compared with official agricultural data provided by the Chadian Ministry of Agriculture (ONDR) for the period 1989-2012 (DPSA, 2014, 1996; DSEED, 1999). However, the two organizations usually share data between them, which reduces the potency of such a verification, but also gives credibility to the SODELAC data. Pearson correlation coefficients between these two datasets were 0.96 for maize and 0.83 for millet (student's t-test p-value ≤ 0.01), indicating near perfect linear correlations. The small discrepancies between them were probably due to the use of different estimation sources for some years, different post-harvest loss estimations, or data entry errors. As the SODELAC data were in agreement with the official ONDR data, they were assumed to be accurate.

The agricultural data were broken down by harvested area and yield, and are presented in section 4.1. In the SODELAC reports, some years had data on planted area, but this was not consistently reported throughout the time period and could not be used in the analysis. With five different crop datasets and two agricultural variables per crop (harvested area and yield), 10 agricultural variables were used. As the harvested area and the yield were expected to have distinct relationships with the hydro-climatic conditions, they were analyzed separately and together explain the production, (which was not analyzed on its own). The harvested area is, for instance, initially affected by the farmers' decisions as to where and when to plant their crops. Part of these decisions will be related to hydro-climatic variables, such as the lake levels and the rainfall before and during the planting period, and other parts will be related to socio-economic conditions, e.g.; available seeds, land rights, economic and human resources, and political decisions, which due to data limitations were not included in this study. Furthermore, the harvested area is dependent both on the amount of crops planted and on the crop survival rate over the growing season, which is affected by the hydro-climate, management and pests. Yield on the other hand has a greater dependency on such conditions throughout the growing stages.

3.1.2. Rainfall

Observed rainfall data from weather stations in each of the sub-regions had been collected by SODELAC for monthly total amounts and number of rainy days (SODELAC, 2014). This enabled an analysis of both the monthly amounts of rainfall and their distribution, unlike most studies which only look at total seasonal amount (Lodoun et al., 2013). Daily data would have allowed even more precise dynamics to be analyzed. However, such observations were not available. Daily rainfall data were however available from re-analysis datasets but these were deemed to be less accurate than the observed monthly ones. Figure 2 gives an overview of the monthly and seasonal distribution of rainfall in the region for the studied time period (1988-2012). The rainy season for this period averaged 300 mm, spanned May to October, peaked in July/August, and had only occasional rains in April. Rainfall in July, August and September had the highest variations between the years. Agricultural output was thus expected to be more sensitive to variations during these months than in the others. As this is a semi-arid zone with low levels of irrigation and low ground water usage, rainfall was generally expected to have a positive relationship to both the harvested area and the yield. There were however reports of flooding in the area (SODELAC, 2014), indicating that there were periods of intense rainfall and unusually high lake levels. Both the timing and distribution of rainfall over the growing season were relevant to both how farmers take decisions and how crops are affected directly. In order to discern all such potential relationships, the rainfall variables outlined in Table 1 were created for the regression analysis. With a rainy season spanning from May to October (6 months), this resulted in 22 rainfall variables for each sub region.

3.1.3. Lake levels

Daily data on lake levels in one of the villages (Bol) were collected from the Chadian National Meteorological and Hydrological Department (DREM, 2014) and complemented with data from SODELAC (2014), Lemoalle et al. (2012) and LACBO (2013). The relationship between water depth and water surface area had been previously established by Bader et al. (2011) as being as fairly linear. In this study, only water depth was analyzed and was, as such, taken as a proxy for both the surface area and the soil moisture of the lake beds. As mentioned previously, lake area has changed considerably in the recent past with annual maximum area decreasing from around 25,000 km^2 to its current extension of around 10,000 km^2. Figure 3 presents the daily lake levels for 1986-2012 at Bol on the eastern shores of the lake. Both inter- and intra-annual variations can be seen in Figure 3. It is worth noting that the intra-annual variations can reach 250 cm, which considerably alters the lake recession farming potential. Planting is carried out at different stages in areas where the lake is receding, and harvesting is done at crop maturity or before the lake starts increasing again. Depending on the location, this planting-to-harvest cycle over the rainy season usually takes place between June-October (SODELAC, 2014). The lake recession farming is also done with different intensities throughout the year, but this study only looked at the rainy season as this accounted for the majority of the annual production. The lake levels affect the lake recession farming most directly through land availability and soil moisture, where higher lake levels up until the planting dates will decrease the land availability but at the same time increase the soil moisture. To capture such dynamics, the lake variables presented in Table 2 were created.

3.1.4. Temperature

Temperature was expected to primarily affect the yield but also the harvested area through its effect on the survival rates of the crops. There was no complete dataset of observed temperature from the region, and the closest observations were from the capital N'Djamena approximately 200 km to the south, and then only on a monthly basis. As the relationships between crop development and temperature were expected to be sensitive to sub-monthly variations, reanalysis data with daily coverage were used instead of the observed monthly data. The ERA-interim dataset, which is a global atmospheric reanalysis dataset from 1979 available down to 0.1º resolution (ECMWF, 2015) was chosen. Minimum, mean and maximum temperatures at 6 h intervals were used on the nearest 0.5º to the center of each of the three selected sub-regions. Figure 4 gives an overview of the distribution of the rainy seasons' monthly and seasonal averages based on daily averages for Bol, as given by the ERA-interim dataset. As the three sub-regions were located within 40-50 km of each other, they had only slight temperature differences. June had the highest daily averages and August and September had the widest distribution. Seasonal averages varied between 28 and 32 ºC. The temperature variables were created from this data based on the temperature preferences of maize and millet in the Sahel. USAID (2014) specify six different development stages for the two crops with varying temperature preferences, which were assumed to overlap with the six months of the rainy season in the region. Monthly temperature variables were thus created. Both average monthly temperatures and days, and degree days beyond the given temperature preferences (above maximum and below minimum) calculated from daily averages, minimums, and maximums of each month were used. The same temperature preferences were used for all growing stages to simplify the analysis. For maize the temperature preferences were set to 21 to 35 ºC and for millet 21 to 36 ºC (USAID, 2014). Table 3 summarizes the temperature variables created. The variables of days and degree days beyond the set preferences were created based on how many consecutive days the minimum, average and maximum temperatures were beyond the set preferences. These variables were calculated with thresholds of 1-6 consecutive days. This was done to include the effects of longer periods beyond the set temperature preferences. With variables based on minimum, average and maximum temperatures for each of the six months of the rainy season, a total of 150 temperature variables were created for each sub-region, totaling 191 variables together with the lake and the rainfall variables.

3.2. Regression analysis

The hydro-climatic variables were first tested in bivariate regressions against the agricultural data (harvested area and yield for each crop and sub-region). Long term linear trends in the agricultural data were de-trended using first-order differences, i.e. each data point was given as the difference from the previous year, which is commonly used in time-series analysis (Lobell, 2010). To assess a wide range of potential correlations, the equations presented in Table 4 were used. Quadratic was the highest polynomial order included, as higher orders were deemed superfluous for these relationships. For each variable, the regression with the highest adjusted R^2 was selected. If the p-value of the f-statistics of the selected regression was below 0.05, it was included in the multivariate model selection. But as this was essentially a data mining process with a large number of independent variables (191) and a small number of observations (25 years), there was a risk that some variables would have significant correlations by chance only, without any notable relationships outside the analyzed time period. To take this into account, only variables that were significant and complied with the local dynamics as described by other sources and studies of the area were included (e.g. FEWS NET, 2011; Magrin et al., 2015; SODELAC, 2014). A limitation of such an approach was that some variables with real but seemingly implausible relationships might have been wrongfully excluded, thus reducing the explanatory power of the models, or that relationships without real relationships were included, thus overfitting the models.

For the multivariate model selection, only linear multivariate models were evaluated, as higher polynomials had already been incorporated in the bivariate selection process. To avoid overfitting, the selection of variables was limited by only accepting variables with positive coefficients in the multivariate model (negative coefficients would mean that the selected variable had an opposite relationship to that found in the bivariate analysis). Also, as for the bivariate selection, only coefficients and combinations of variables which corresponded to descriptions by other studies were included. Interaction terms between variables were examined but were excluded due to their low significance, which substantially reduced the number of potential combinations and also reduced the risk of over fitting. Colinearity among selected variables was neglected as this only affects coefficient accuracy within a model and not the overall model performance. The purpose of this analysis was to find multivariate models with the highest predictive capacity, and not necessarily to explore the effect of each included variable. Lastly, the adjusted R^2s of multivariate regression models tend to overestimate the predictive capacity, and especially so if based on few observations. To improve the predictive capacity, 'leave-one-out' cross-validation was applied. The significance of the R^2 from the cross-validation was calculated based on a bootstrap pairwise sampling methodology of 1000 random selections.

4. Analysis

4.1. Agricultural data analysis

Figure 5 presents the agricultural production, the harvested area and the yield for maize and millet for each of the three sub-regions (Bol, Doum-Doum, Ngouri) for the rainy seasons of 1988-2012, as compiled from the SODELAC reports (SODELAC, 2014). No substantial amount of maize was reported for Ngouri and it was therefore not included in the analysis. Both maize and millet production showed high inter-annual variations, with especially high similarities for the millet sub-regions. After the late 1990s, maize production had a positive trend with Bol having a noteworthy jump from 1998, which was partly explained by increases in harvested area. This was explained in the SODELAC reports by the newly constructed dams around the Bol, which held water from the receding lake levels and made more land available for maize farming (SODELAC, 2014). This dam construction was taken into account in the regression analysis by using a dummy variable. The harvested area for the other crops seemed to vary around the same levels throughout the whole time period, showing high inter-annual variations but no apparent trends. The yields also showed high inter-annual variations with high similarities between the sub-regions. Maize consistently had higher yields than millet and there was a strong positive trend in the maize yield after the early 2000s, and a weaker one for millet from around the same time. Investments in modern maize polders since the early 2000s was one factor behind this increase in the yield (Magrin et al., 2015), and other factors could be general farming inputs such as new seeds, fertilizers and farm machinery. There were unfortunately not much data on these input and technological factors. To be able to discern the influence of the inter-annual hydro-climatic variability on the yield, linear trends were removed using first-order differences, as described previously. The yield datasets for all sub-regions showed some long-term trends and were de-trended using this method.

4.2. Regression analysis

This section presents the hydro-climatic variables included in the multivariate models, both by bivariate regression fits and causality analysis, for each sub-region and agricultural variable. Only hydro-climatic variables selected for the multivariate models are presented. It should be noted that several other hydro-climatic variables had significant (f-test p-value $\leq$ 0.05) bivariate correlations to the agricultural data. Summaries of the statistical outputs with fitted regression equations can be found in the appendix.

4.2.1. Bol

For the harvested area of maize, a dummy variable was included to account for the previously mentioned dam construction in the area. Besides this, the variable "Lake Harvest Low Y-1" (the lowest lake level during the previous year's harvest) was selected for the multivariate model. Its relationship to harvested area is presented in Figure 6. A quadratic relationship had the highest correlations. This could be interpreted as that an increased lowest lake level during the previous year's harvest had a decreasingly positive relationship on the harvested area of the upcoming year. The physical component behind this is related to increased soil moisture due to increased lake levels. This might be directly related to the lowest lake level or through its correlation with other lake dynamics. For instance, it had significant negative Pearson correlations (student's t-test p-value $\leq$ 0.05) both to when the lake started increasing before the current season (-0.54, indicating an earlier increase of lake levels) and the rate of that increase (-0.55, indicating lower daily increases), while it had a positive Pearson correlation to the lowest level of the current harvest season (0.59, indicating higher lake levels). Taken together, these correlations suggest which factors could be involved in this relationship. The bivariate regression analysis of the dummy variable for the dam construction showed that there was a highly significant (f-test $p \leq 0.01$) increase (18,000 ha) in the average harvested area after dam construction. As no other persistent area increasing changes were mentioned in the SODELAC reports for that year, this increase could be attributed to the dam construction. The multivariate model with these two variables had a cross-validated R^2 of 0.63 (bootstrap significance ≤ 0.01), thereby accounting for the majority of variation in harvested area over this time period.

For maize yield the variables selected were "Lake Harvest Low" (lowest lake level during the harvest) together with two temperature variables: "Temp SepMaxDays3" (number of days in September included in periods with daily maximum temperatures above the set threshold for at least 3 consecutive days) and "Temp JulMaxDays4", as seen in figure 7. It should first be noted that the correlations presented here are of the first-order differences as the yield data had a long-term linear trend. "Lake Harvest Low" had a rather flat relationship up until 0, after which it was increasingly negative. This can be interpreted as follows; reductions compared to the previous years did not have any influence on yield, but increases correlated with decreased yields. One possible explanation for this is that increased lowest lake levels either flooded already planted crops, or that it decreased the land available for planting. "Temp SepMaxDays3" had a decreasingly positive relationship to yield. September coincided with the later stages of the crop development, which generally had temperature preferences of 21-33 ºC (USAID, 2014). It is surprising that an increase in the no. of days with beyond threshold maximum temperatures would be positively correlated with the yield. There are however at least two other possible explanations for this relationship. First, September had a wide distribution of temperatures (Figure 4), and temperatures in the upper span of this spread could be beneficial to yield. Secondly, the variable had significant (student's t-test p-value ≤ 0.05) linear correlations to both higher September daily average averages (Pearson correlation = 0.65) and September daily minimum averages (0.51). A further factor could be that it covaried with September rainfall, but no significant correlations were found when checking for this. "Temp JulMaxDays4" had a negative linear relationship to the yield, which is explained by how higher July temperatures had negative impacts on the early growing stages of maize. The multivariate cross-validated R^2 was 0.50 (bootstrap significance ≤ 0.01), slightly lower than 0.63 for harvested area.

For the harvested area of millet, "Rain Season" and "Temp SepMax5" (degree days in September included in periods with daily maximum temperatures above the set threshold for at least 5 consecutive days) were selected, both with quadratic relationships (Figure 8). "Rain Season" had a decreasingly positive relationship but with a large scatter of the observation points. Underlying factors could be that the amount of rainfall over the season increased both planting by the farmers, as they considered the rainfall to be favorable, and crop survival rate, but that too much rainfall caused flooding. "Temp SepMax5" had an initially horizontal relationship up until around 40 degree days, after which it became increasingly positive, probably due to the same reasons as given above for the temperature variable in the Bol maize yield section. The cross-validated multivariate R^2 was 0.36 (bootstrap significance ≤ 0.01) which was lower than for the previous models and indicated a higher influence of non-hydro-climatic factors.

For the millet yield, combined rainfall in August and September was selected together with "Temp JunMax5", both with quadratic relationships as displayed in figure 9. The slight decrease in the upper ends of the rain variable can be explained by flooding at elevated rainfall amounts. "Temp JunMax5" had a decreasingly negative relationship which would be explained by crops being stressed by increased temperatures, but with increases after a certain threshold having no apparent additional effect. The multivariate model had a cross-validated R^2 of 0.50 (bootstrap significance $\leq$ 0.01), same as for Bol's maize yield.

4.2.2. Doum-Doum

"Rain Oct" and "Temp OctMaxDays3" were selected for the harvested area of maize. Both these relationships were however fairly weak due to the concentration of data around a few values. Even though there were high and significant adjusted R^2s in these relationships, they should not be relied upon as established and should be interpreted and used carefully. The multivariate model with these relationships had a cross-validated R^2 of 0.39 (bootstrap significance $\leq$ 0.03).

For the maize yield, four bivariate correlations were selected and are presented in Figure 10. The August rainfall variable had an increasingly positive correlation with yield, which can be explained in the same way as for the previous rainfall variables. "Rain Season / Rain Season Std" (seasonal amount divided by seasonal standard deviation, the latter measuring spread from the mean and indicating instability) generally had a positive correlation with yield but is described here with a quadratic curve, which seems to be explained by two outliers in the bottom right corner. Presumably a high seasonal rainfall and a low standard deviation would be beneficial to the yield, and a positive correlation would thus be expected. The two outliers could be due to flooding, or other factors that were not accounted for, e.g. pests. Delayed onset of the increase of lake levels compared to last year ("Lake Time Increase" > 0) generally had a positive correlation to yield. One explanation for this is that a later increase also means a later first planting data, which could be beneficial for farmers as it might clash less with other livelihoods activities. Another possible effect could be seen in the correlation between a delayed onset of the lake increase with lower lake levels in general, both through peaks (Pearson correlation = -0.63) and levels during harvest (-0.64), both increasing land availability and decreasing flooding. Finally the average temperature in October had a positive linear correlation but with a low adjusted R^2 and quite dispersed data point. It was probably relevant for the yield due to how it increased otherwise relatively low temperatures in October. With a multivariate cross-validated R^2 of 0.45 (bootstrap significance $\leq$ 0.01) this model was also thought of as reliable.

For the harvested area of millet, three rainfall variables and one lake variable were selected (Figure 11). The "Rain May Days" variable had a slightly lower correlation than the other variables, and its correlations seemed to be undermined by the gathering of data at a few points. A negative relationship suggested that issues such as flooding or an unusually high amount of rainy days disrupted planting procedures. The August rainfall variable, with its increasingly positive correlation in its upper span, was mostly explained by one outlier and is also weak. Some positive trends could still be seen after the 150 mm mark if neglecting this outlier. The other two variables ("Rain May+Jun" and "Lake Harvest Low") had better supported correlations and both indicated relationships that have been explained previously. The multivariate cross-validated R^2 was 0.67 (bootstrap significance $\leq$ 0.01) and was thus able to explain a large proportion of the variation in the agricultural data.

The millet yield also included four variables, all with well-supported correlations, as seen in Figure 12. April to July rainfall was increasingly positive. Higher seasonal rainfall standard deviation ("Rain Season Std") would presumably be detrimental to the yield as it indicates instability, contrary to the correlation given in this figure. This positive correlation most likely occurred due to its significant correlations (student's t-test p-value $\leq$ 0.05) with several other rainfall variables, such as “Rain August” (Pearson correlation = 0.91), “Rain July+Aug” (0.89), “Rain Aug+Sep” (0.76) and “Rain Season” (0.63). In this sense, a higher standard deviation also meant higher overall rainfall. The June temperature variable was negatively correlated up to a certain point after which it became positive. The negative correlation could be related to temperature stress, and the positive turn at the upper end of the data span is probably explained by exogenous factors or covariance with other variables with a more direct relationship. The last September temperature variable had a decreasingly positive correlation as for maize yield in Bol. The multivariate performance was similar to that of harvested area with a cross-validated R^2 of 0.66 (bootstrap significance ≤ 0.01).

4.2.3. Ngouri

Ngouri is located in the eastern part of the region, further away from the lake shores than the other two sub-regions and therefore did not have any significant production of maize. Figure 13 shows the selected variables for the harvested area of millet. Both “Rain Season Days” and “Rain Season” had straight positive correlations, which is due to increased water availability. The average temperature in June had a negative correlation for the first half of the value span, which then flattened out, as did several previous agricultural variables. Put together, they had a cross-validated R^2 of 0.43 (bootstrap significance ≤ 0.01). Lastly, the millet yield had three variables selected, as outlined in Figure 14. The “Rain Season” variable had a strong positive correlation with yield. “Temp JulMax2” was decreasingly negatively correlated, which could be explained by July already having high temperatures and increased maximum temperatures stressing the crops. “Temp SepMaxDays2” on the other hand had a positive correlation, as did the other September temperature variables. The cross-validated R^2 for this model was 0.49 and was similar to both the Bol maize and millet yield (bootstrap significance ≤ 0.01).

5. Discussion

The relationships established here are relevant to risk management in the region both as observed hydro-climatic indicators of agricultural performance and as input for outlooks based on seasonal weather forecasts. It must first be noted that when using these relationships to infer outcomes in agricultural seasons which are outside of the time period studied (1988-2012), the effects of other major changes to the agricultural system must be assessed, e.g. armed conflicts which have struck the region in the past two years. By adding updated data to these results, opportunities for such analyses are now opened up. This would also enable improved assessments of the impacts of such conflicts. One way of applying these results to risk management is by categorizing the variables based on their correlations and time of observation in relation to the crop harvest. Table 5 shows how such a framework could be presented based on the results of this study. The cross-validated R^2s of the 10 multivariate models are between 0.36-0.66, with 5 of them above 0.50, which is probably the level of usefulness for management purposes in the area. For the five agricultural variables with values below 0.50, more factors need to be included to be able to account for larger amounts of the variations. With Table 5, one can see that most of the established relationships hinge on observations close to the harvest, which limits their potential as indicators for early planning for the harvest outcome, unless they are incorporated into seasonal weather forecasts.

The selected rainfall variables generally had positive relationships except for a few examples of potential flooding, while lake levels and temperature had both positive and negative relationships. Temperature variables were also marked by differences across the season, where earlier variables were negatively related and later ones positively. The mixed relationships found for lake levels are noteworthy as lake dynamics are rarely incorporated in food security outlooks for the region, which usually focus on rainfall forecasts and also assume a straightforward relationship between increased water resources and agricultural production. Issues of flooding from both rainfall and lake levels indicate that water storage infrastructure has the potential to even out water availability across the season. The different sub-regions also showed some noteworthy differences. For maize in Bol, only lake and temperature variables were selected, indicating higher dependence on lake levels than rainfall for crop water demands and planting strategies. The relationship established for the harvested area of maize is especially relevant as the “Lake Harvest Low Y-1” is based on the previous year’s lake levels and can be accurately measured well before the upcoming agricultural season, contrary to the yield which needs later observations. Millet in Bol on the other hand seems to be more dependent on rainfall than on lake levels, as expected given the distance of millet areas from the lakeshores. Doum-Doum had variables selected from all three hydro-climatic categories, not including the harvested area of maize which was discarded due to poorly established correlations. Finally, in similarity with Bol, millet in Ngouri had only rainfall and temperature variables selected, once again affirming millet’s dependence on rainfall. These results are relevant to the Sustainable Development Goals as they enable baseline assessments of agricultural production in the Lake region of Chad and they outline the hydro-climatic relationships with the agricultural sector on a sub-regional level. By building on these datasets and results, sustainable management of hydrological resources can be advanced through early indications of agricultural output and seasonal outlooks, which can guide adaptation strategies to respond to production shortfalls, and stabilize and increase agricultural production, thereby improving food security and economic development in the region.

6. Conclusion

This study investigated the role of hydro-climatic variability in relation to the agricultural system around Lake Chad in Chad by using regression analysis on sub-regional datasets. Given that this is a rural region with traditional farming systems, low technological development and high hydro-climatic variability, it was assumed that this variability would have significant impacts on the agricultural system. The methodology focused on finding the highest cross-validated multivariate correlations, and there were therefore many relevant hydro-climatic variables that were not included in the multivariate models. However, the selected multivariate models were the combinations of variables that had the highest explanatory power, making them the most relevant when it came to infer agricultural performance based on hydro-climatic variability. The cross-validated R^2s of the 10 multivariate models were between 0.36-0.66, with five of them above 0.50, which is probably the level of usefulness for predictive management purposes in the area. A major constraint was that, due to data limitations, only hydro-climatic variables were included in the regression analysis. Other qualitative data sources were however used to create the relevant variables and to assess the reliability of their correlations. The agricultural system in this region is certainly dependent on other factors, such as socio-economic conditions, management practices, pests and policy. But as this methodology focused on exploring the agricultural system’s inter-annual variations, the relevance of factors with more stability over time (such as economic development and population growth) was reduced. The occurrence of pests and the impacts of certain development projects, factors with high inter-annual influence, were omitted. Consideration of these factors would probably enhance the analysis.

Acknowledgments

The authors would like to thank the Chadian institutions that provided data used in this study, most notably: Société de Développement du Lac (SODELAC), Institut National de la Statistique, des Études Économiques et Démographiques (INSEED), the Lake Chad Basin Commission (LCBC), and the Famine Early Warning Systems Network (FEWS NET), all based in N'Djamena. The analytical part of this study was developed at the Young Scientist Summer Program 2015 at the International Institute of Applied Systems Analysis. Funding was provided by the Swedish Research Council, the Swedish Research Council-Formas, and the Crafoord Foundation.

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Tables

Table 1 – Rainfall Variables

Rainfall variable	**Relationship to crops**
Monthly total amounts	Positive with potential peak
Monthly number of rainy days	"
Dual and triple combinations of monthly amounts (e.g. May + June)	"
Total seasonal amount	"
Coefficient of variation for the season (of monthly amounts)	Even distribution (low variation) expected to have positive relationship
Standard deviation for the season (of monthly amounts)	"
Total seasonal amount / Standard deviation	Positive, as both high total amount and an even distribution (low std) are expected to be beneficial for yield

Table 2 – Lake Variables

Lake variable	**Relationship to crops**
Peak during previous year's season	Higher levels during the previous year are expected to increase current year's soil moisture
Lowest level during previous harvest	"
Annual average during the previous season	"
Peak during current year	Higher levels during planting are expected to decrease land availability, increase flooding and increase soil moisture
Lowest level during current harvest	"
Peak during current year + lowest level during current harvest	"
Time of peak before planting	Earlier peaks before planting could make farmers anticipate lower levels, and alter the land availability/soil moisture relationship
Time when lake starts increasing	"

after previous harvest	
Rate of pre-peak increase	Farmers might make planting decisions as they start noticing changes to the lake

Table 3 – Temperature Variables

Temperature variable	**Relationship to crops**
Monthly and seasonal averages for the rainy season (June to October)	Positive within the set thresholds, negative beyond
Degree days & number of days beyond set minimum and maximum thresholds per month and season	"
Degree days & number of days in periods of 1-6 consecutive days beyond set minimum and maximum thresholds per month and season	"

Table 4 – Regression equations

Type	**Regression equation**	**Relationship**
Linear	$y = \beta_0 + \beta_1 x$	Linear
Exponential	$y = \beta_0 + \beta_1 \exp(\beta_2 x)$	Increasing intensity
Logarithmic	$y = \beta_0 + \beta_1 \log(x)$	Decreasing intensity
Quadratic	$y = \beta_0 + \beta_1 x + \beta_2 x^2$	Threshold

Table 5 – Hydro-climatic risk management framework

AGRICULTURAL VARIABLE		HYDRO-CLIMATIC VARIABLE * > 3 months	HYDRO-CLIMATIC VARIABLE * 1-3 months	HYDRO-CLIMATIC VARIABLE * < 1 month	PREDICTIVE CAPACITY (R^2)
Bol Maize	Area	Lake Harvest Low Y-1			0.63
Bol Maize	Yield		Temp JulMaxDays4 Lake Harvest Low	Temp SepMaxDays3	0.50
Bol Millet	Area			Temp SepMax5 Rain Season	0.36
Bol Millet	Yield		Temp JunTmax5	Rain Aug + Sep	0.50
Doum-Doum Maize	Area				
Doum-Doum Maize	Yield	Lake Time Increase	Rain Aug	Temp OctAve Rain Season / Season Std	0.45
Doum-Doum Millet	Area	Rain May Days	Rain May + Jun Rain Aug	Lake Harvest Low	0.66
Doum-Doum Millet	Yield		Temp JunMax2 Rain Apr to Jul	Temp SepMax5 Rain Season Std	0.66
Ngouri Millet	Area		Temp JunAve	Rain Season Days Rain Season	0.43
Ngouri Millet	Yield		Temp JulMax2	Temp SepMaxDays2 Rain Season	0.49

TIME TO HARVEST FROM OBSERVATION

* Green = positive correlation, red = negative correlation. Dual colors in the same box indicate shifts in correlations with increasing values. The vertical size of the boxes are proportionate to their share of the multivariate correlation. The equations behind each relationship can be found in the appendix. All multivariate R^2s have bootstrap significances ≤ 0.01.

Fig. 1 - Land use in Lake region (authors' translation to English and editing for readability) (P-SIDRAT, 2013)

Fig. 2 - Monthly rain boxplot (region average)

Fig. 3 - Lake Chad water depth measured at Bol 1988-2012 (daily)

Fig. 4 – Distribution of monthly average temperatures in Bol

Fig. 5 – Production, Harvested Area and Yield for maize & millet per rainy season and sub-region

Fig. 6 - Bol Maize Harvested Area Bivariate Correlation

Fig. 7 - Bol Maize Yield Bivariate Correlations (1st-order difference)

Fig. 8 - Bol Millet Harvested Area Bivariate Correlations

Fig. 9 - Bol Millet Yield Bivariate Correlations (1st-order difference)

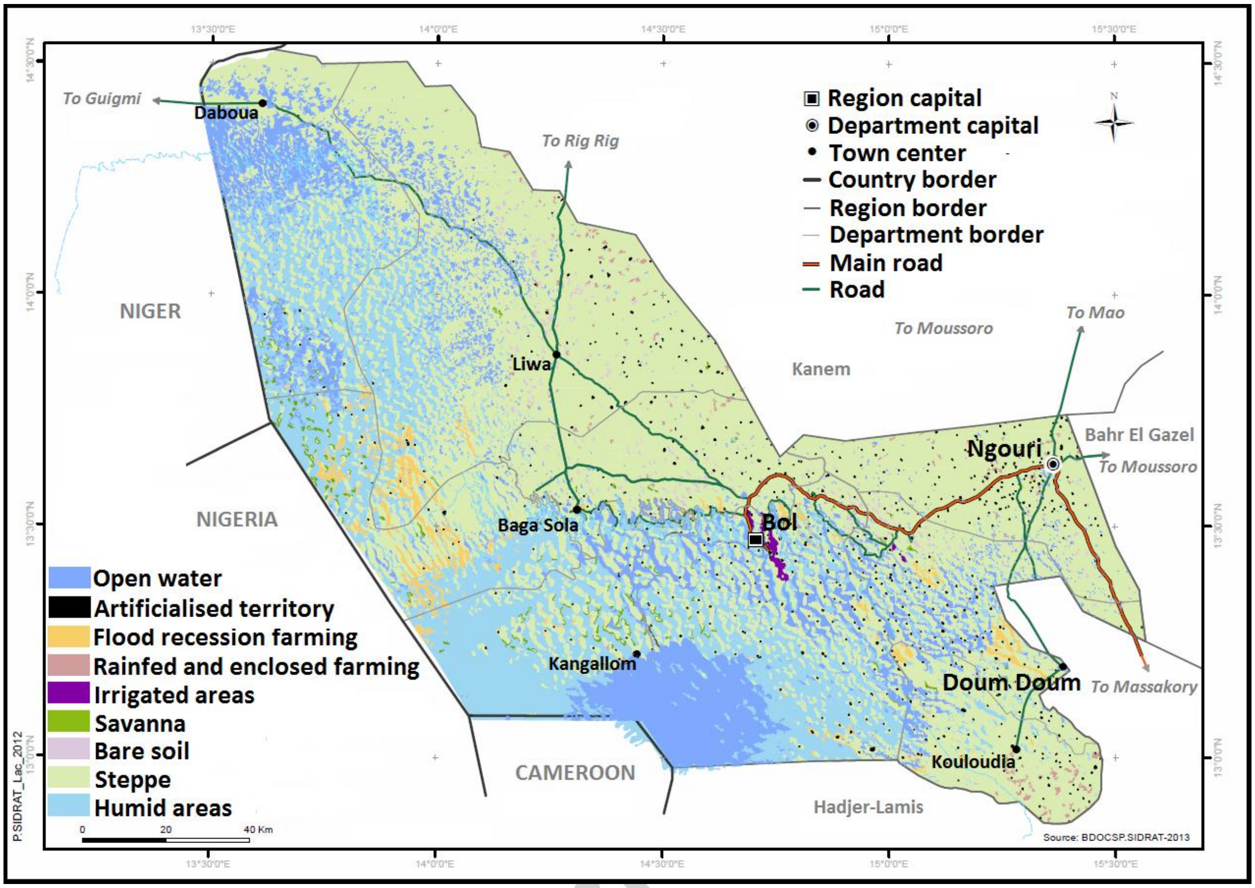
Fig. 10 - Doum-Doum Maize Yield Bivariate Correlations (1st difference)

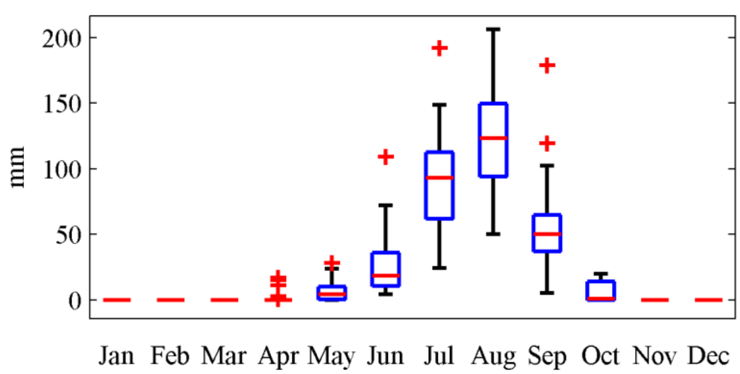
Fig. 11 - Doum-Doum Millet Harvested Area Bivariate Correlations

Fig. 12 - Doum-Doum Millet Yield Bivariate Correlations (1st-order difference)

Fig, 13 – Ngouri Millet Harvested Area Bivariate Correlations

Fig. 14 – Ngouri Millet Yield Bivariate Correlations (1st-order difference)


Region capital
Department capital
Town center
Country border
Region border
Department border
Main road
Road
To Guigmi
Daboua
To Rig Rig
NIGER
Liwa
Kanem
To Moussoro
To Mao
Bahr El Gazel
Ngouri
To Moussoro
NIGERIA
Baga Sola
Bol
Kangallom
Doum Doum
To Massakory
Kouloudia
CAMEROON
Hadjer-Lamis
Open water
Artificialised territory
Flood recession farming
Rainfed and enclosed farming
Irrigated areas
Savanna
Bare soil
Steppe
Humid areas
P.SIDRAT_Lac_2012
0
20
40 Km
Source: BDOCSP.SIDRAT-2013


mm
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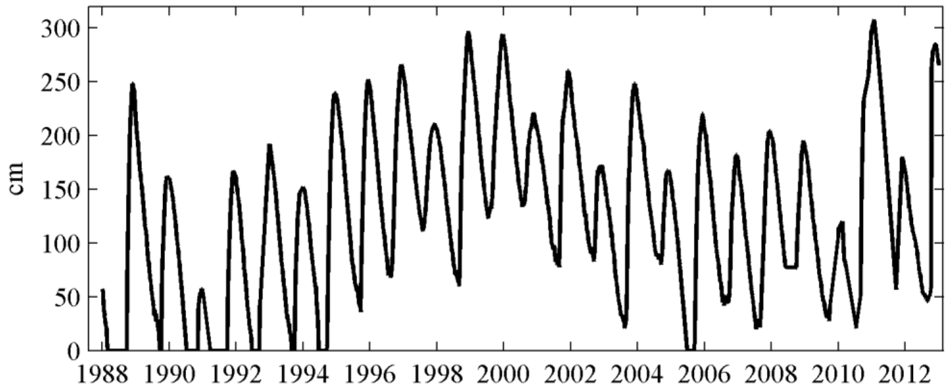
cm
300
250
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1988
1990
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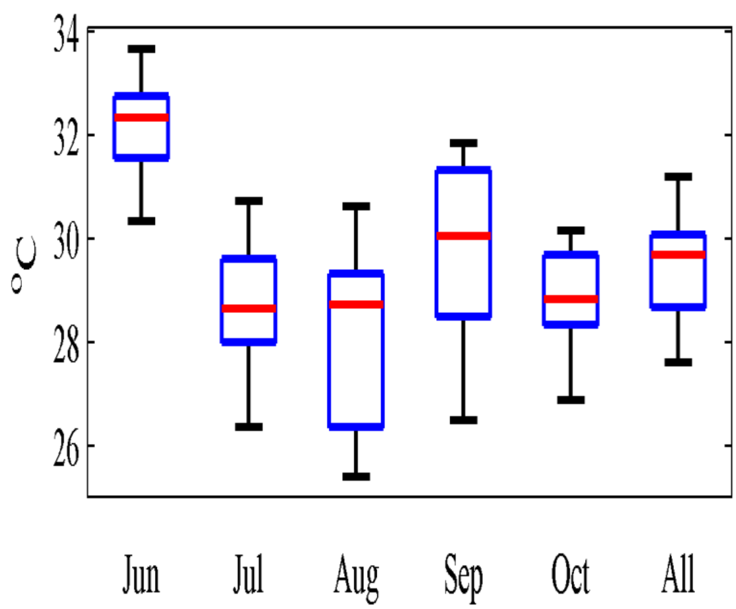
2010
2012


°C
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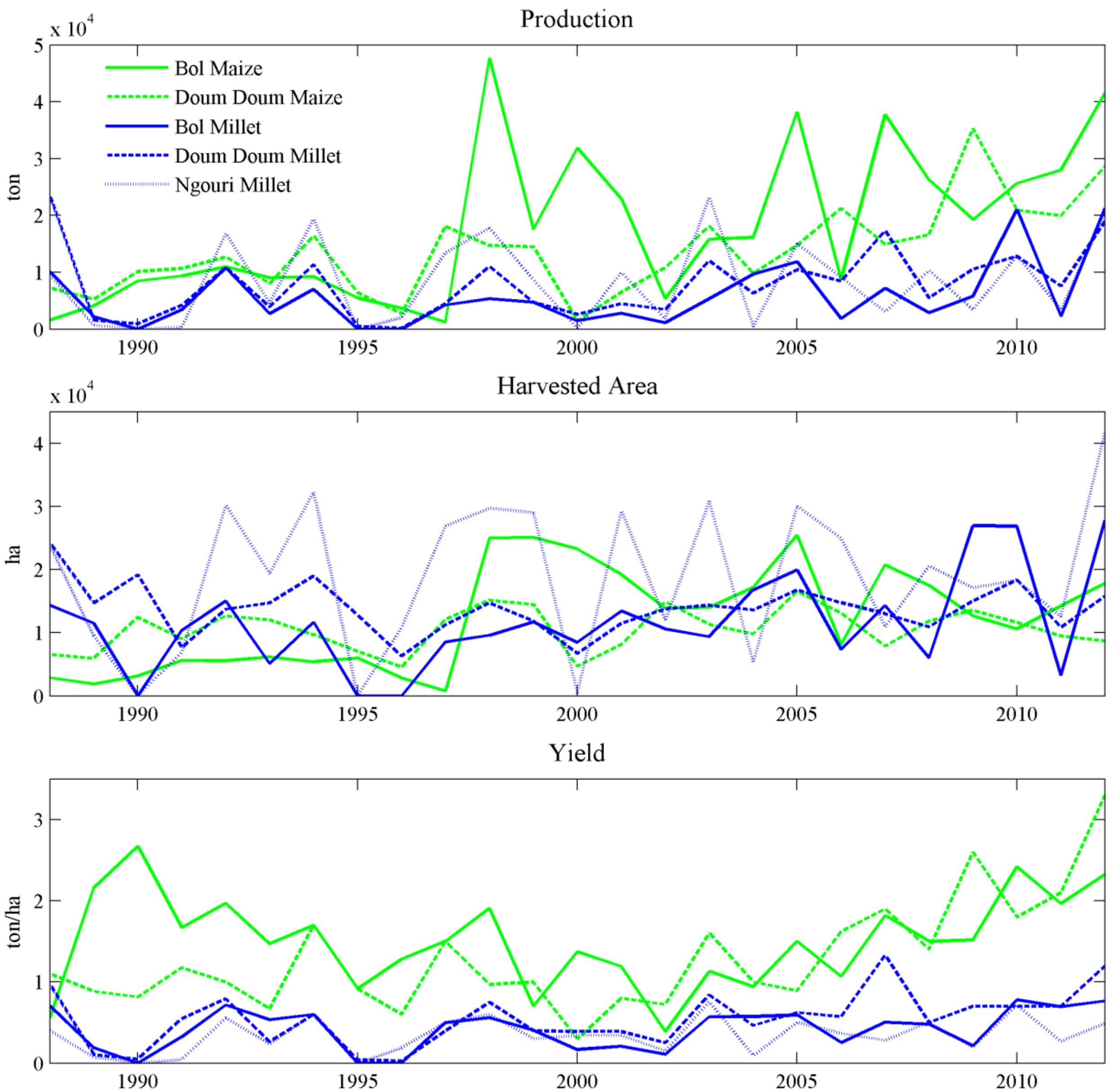
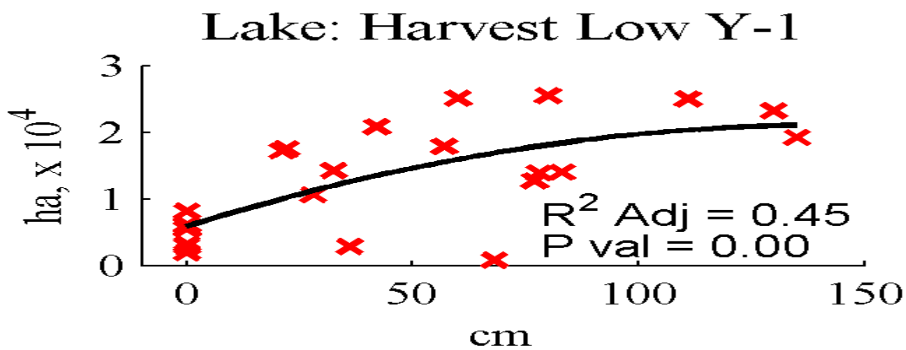
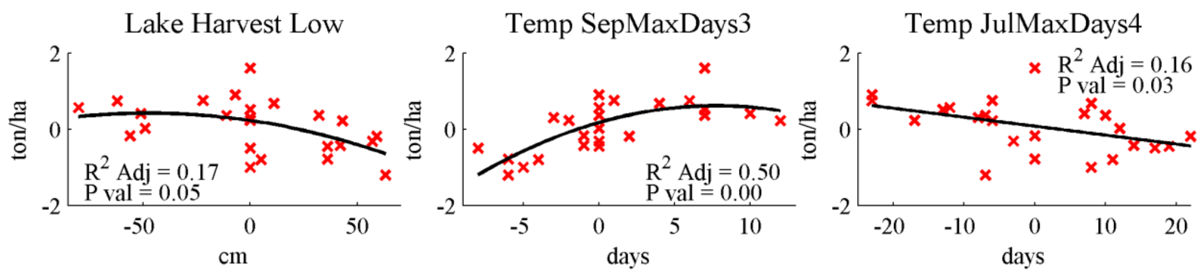
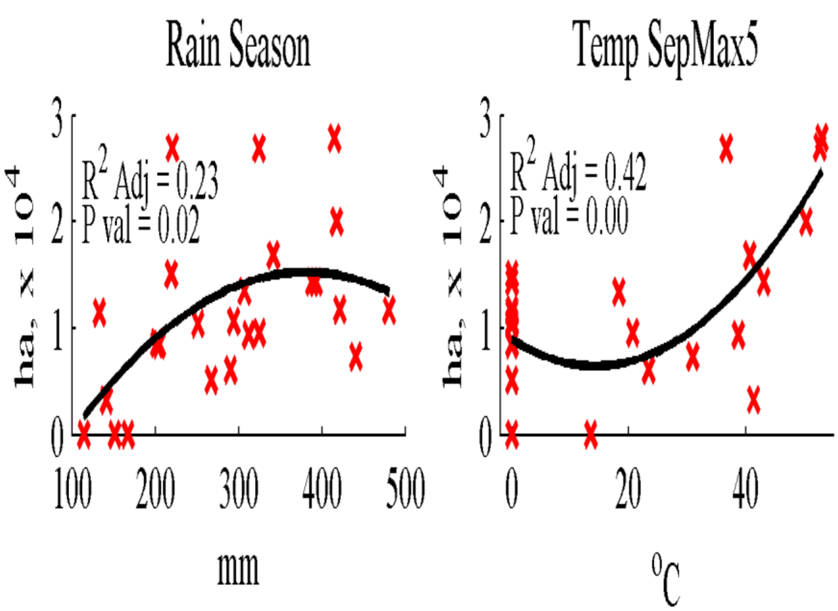
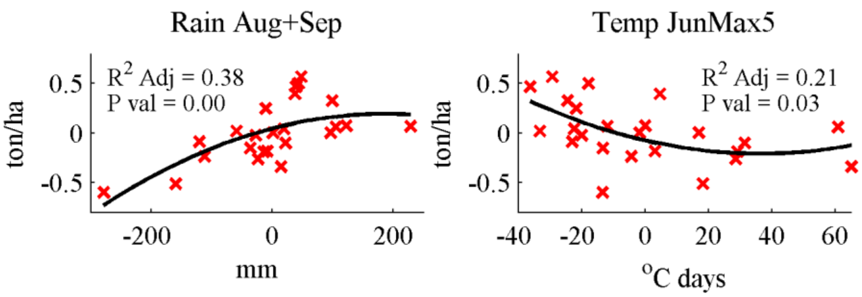
32
30
28
26
Jun
Jul
Aug
Sep
Oct
All

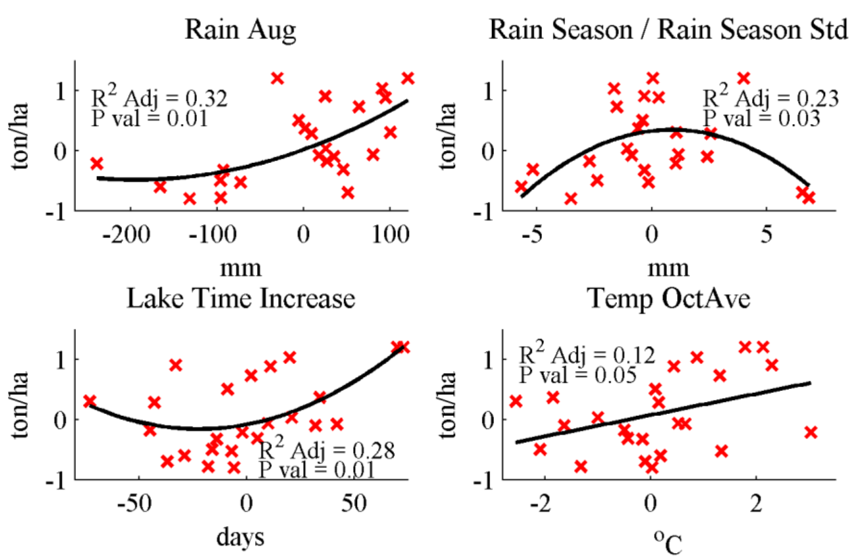

Production
x 10^4
ton
Bol Maize
Doum Doum Maize
Bol Millet
Doum Doum Millet
Ngouri Millet
Harvested Area
x 10^4
ha
Yield
ton/ha
1990
1995
2000
2005
2010

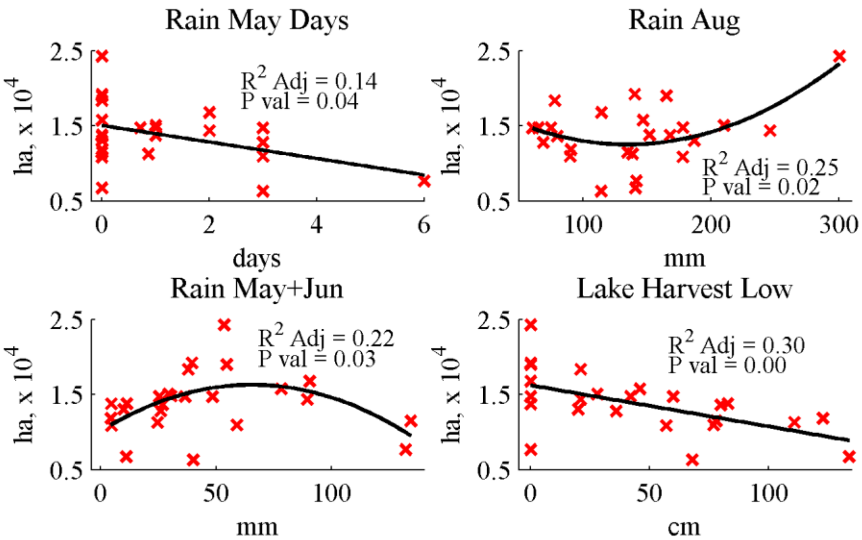

Lake: Harvest Low Y-1
ha, x 10^4
R^2 Adj = 0.45
P val = 0.00
cm

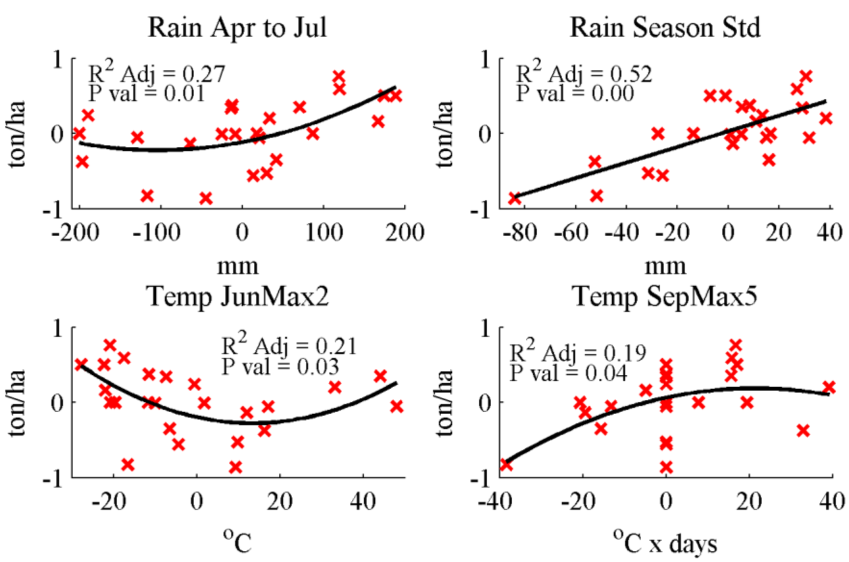

Lake Harvest Low
ton/ha
R^2 Adj = 0.17
P val = 0.05
cm
Temp SepMaxDays3
ton/ha
R^2 Adj = 0.50
P val = 0.00
days
Temp JulMaxDays4
ton/ha
R^2 Adj = 0.16
P val = 0.03
days

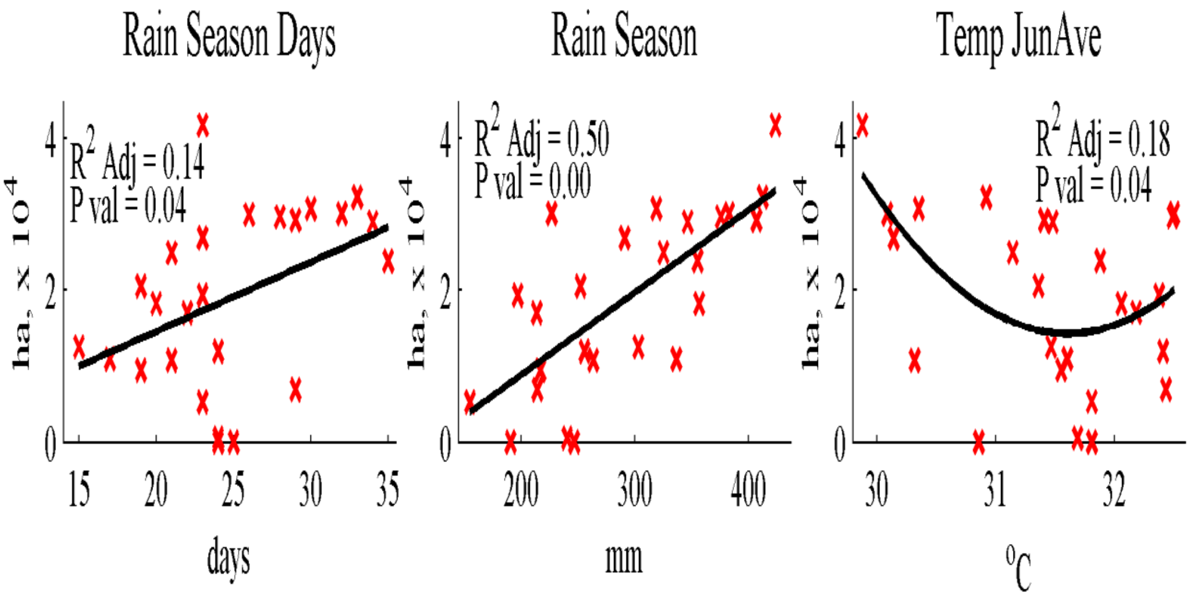

Rain Season
ha, x 10^4
R^2 Adj = 0.23
P val = 0.02
mm
Temp SepMax5
ha, x 10^4
R^2 Adj = 0.42
P val = 0.00
°C

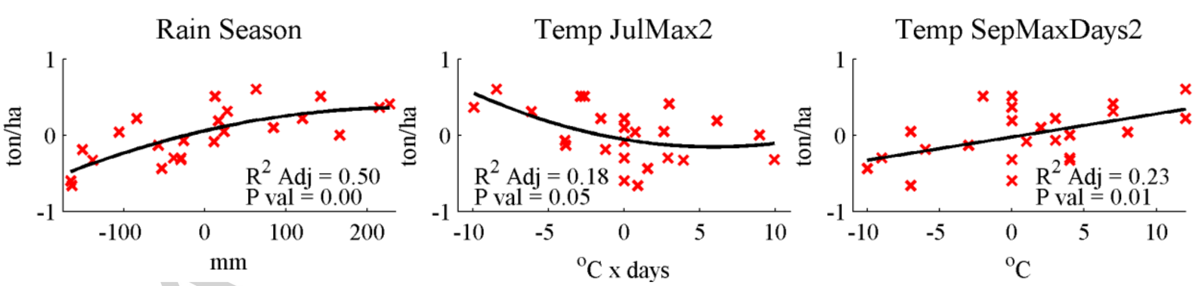

Rain Aug+Sep
R^2 Adj = 0.38
P val = 0.00
ton/ha
mm
Temp JunMax5
R^2 Adj = 0.21
P val = 0.03
ton/ha
°C days


Rain Aug
R^2 Adj = 0.32
P val = 0.01
ton/ha
mm
Rain Season / Rain Season Std
R^2 Adj = 0.23
P val = 0.03
ton/ha
mm
Lake Time Increase
R^2 Adj = 0.28
P val = 0.01
ton/ha
days
Temp OctAve
R^2 Adj = 0.12
P val = 0.05
ton/ha
°C


Rain May Days
ha, x 10^4
R^2 Adj = 0.14
P val = 0.04
days
Rain Aug
R^2 Adj = 0.25
P val = 0.02
mm
Rain May+Jun
R^2 Adj = 0.22
P val = 0.03
mm
Lake Harvest Low
R^2 Adj = 0.30
P val = 0.00
cm


Rain Apr to Jul
ton/ha
R^2 Adj = 0.27
P val = 0.01
mm
Rain Season Std
R^2 Adj = 0.52
P val = 0.00
mm
Temp JunMax2
R^2 Adj = 0.21
P val = 0.03
°C
Temp SepMax5
R^2 Adj = 0.19
P val = 0.04
°C x days


Rain Season Days
Rain Season
Temp JunAve
R^2 Adj = 0.14
P val = 0.04
R^2 Adj = 0.50
P val = 0.00
R^2 Adj = 0.18
P val = 0.04
ha, x 10^4
days
mm
°C


Rain Season
Temp JulMax2
Temp SepMaxDays2
ton/ha
R^2 Adj = 0.50
P val = 0.00
R^2 Adj = 0.18
P val = 0.05
R^2 Adj = 0.23
P val = 0.01
mm
°C x days
°C