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HOW THE BLACK SWAN DAMAGES THE HARVEST: STATISTICAL MODELLING OF EXTREME EVENTS IN WEATHER AND CROP PRODUCTION IN AFRICA, ASIA, AND LATIN AMERICA

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How the Black Swan damages the harvest: statistical modelling of extreme events in weather and crop production in Africa, Asia, and Latin America

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Abstract

Climate change constitutes a rising challenge to the agricultural base of developing countries. Most of the literature has focused on the impact of changes in the means of weather variables on mean changes in production and has found very little impact of weather upon agricultural production. Instead, a more recent stream of literature showed that we can assess the impact of weather on production by looking at extreme weather events. Based on this evidence, we surmise that there is a missing link in the literature consisting of relating the extreme events in weather with extreme losses in crop production. Indeed, extreme events are of the greatest interest for scholars and policy makers only when they carry extraordinary negative effects. We build on this idea and for the first time, we adapt a conditional dependence model for multivariate extreme values to understand the impact of extreme weather on agricultural production. Specifically, we look at the probability that an extreme event drastically reduces the harvest of any of the major crops. This analysis, which is run on data for six different crops and four different weather variables in a vast array of countries in Africa, Asia and Latin America, shows that extremes in weather and yield losses of major staples are associated events.

1. Introduction

This paper investigates the effect of temperature and precipitation extremes on major staple crops in different regions of Asia, Africa, and Latin America. We provide two key contributions to the literature. First, we adopt a conditional dependence model for multivariate extreme values developed by Heffernan and Tawn (2004). Although this modelling approach already has some applications in environmental or food chemicals studies, see e.g. (Keef et al., 2009; Paulo et al., 2006), there has been no previous attempt to use the model in the context of extremes in weather and crop production losses. Secondly, we provide evidence that these extreme events are associated and we are able to estimate their dependence structure.

The relation between climate and agriculture is a highly debated issue. By focusing on the agricultural sector of countries in Latin America, Africa and/or Asia, numerous studies have found historic evidence and/or have predicted the future effects of weather variables on basic food production (Jones and Thornton, 2003; Lobell and Field, 2007; Kristensen et al., 2011; Lobell et al., 2011a; Rowhani et al., 2011; Welch et al., 2010; Knox et al., 2012). For example, Lobell et al. (2011b) found both positive and negative impacts of temperature and precipitation trends for different major crops at the global level. Specifically, trends in temperature affect mainly yield, whereas precipitation influences inter-annual changes in crop production.

A stream of research, using linear regression models, focuses on the mean effects of weather on average crop production (Kucharik and Serbin, 2008; Tao et al., 2008; Lobell et al., 2011b). The results of, e.g., Schlenker and Lobell (2010) reveal that time constant country-fixed effects and

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time trends explain most of the variation in yields of different agricultural products. Regional characteristics such as soil quality or crop management and country-specific trends, e.g., technological progress in crop production or warming, are the most crucial factors, whereas annual mean changes in weather provide only a minor explanation of the overall variation. This approach suggests that the relation between weather and production is non-linear and difficult to model with linear regression analysis. Burke et al. (2015) discuss the importance of non-linear responses to temperature in agricultural and non-agricultural production for both rich and poor countries. Production peaks at an annual average temperature of 13 degrees Celsius and decreases substantially at higher temperatures. However, the average temperature is higher in poor countries, which leads to stronger effects of temperature on production in these countries. Projections suggest that further warming will reduce productivity and income in countries with high average temperatures.

The assessment of weather impacts on crop production includes not only the focus on changes in the mean values of weather variables but also on the probability, frequency, and severity of extreme events, which substantially influence yields (Wheeler et al., 2000; Moriondo et al., 2011; Lesk et al., 2016). Several empirical works, such as Ciais et al. (2005) in European countries, Schlenker and Roberts (2006) in the United States, Semenov (2007) in the UK, and van der Velde et al. (2012) in France show a substantial impact of extreme weather events on the yields for major crops. Moreover, changes in the frequency of extreme weather events also determine the quality of the crop harvest (Porter and Semenov, 2005). This evidence deserves worth a deeper analysis, since both the frequency and the magnitude of extreme weather events such as heat-waves are likely to rise due to warming climate conditions (Semenov, 2007). Looking at countries globally, Deryng et al. (2014) find extreme heat events to be unfavourable for major producing regions and lower income countries and, according to Semenov (2007), extreme high and low temperature can seriously harm crops or even cause plant death, whereas intensive precipitation can lead to contamination of ground water and soil erosion. In addition to the direct effects of heat, drought, and flooding, extreme events indirectly affect crops through pests, changing soil processes and nutrient dynamics (Rosenzweig et al., 2001). Similarly, Lesk et al. (2016) analyses the damages of extreme weather disasters on crop production and find that drought and extreme heat significantly harm national staple crop production worldwide.

Based on these studies, we surmise that the missing piece in the literature consists of relating the extreme events in weather with substantial losses in production. Indeed, extreme events are of the greatest interest for scholars and policy makers when they have extraordinary negative impacts (Taleb, 2010); otherwise the extreme events are irrelevant. In the remainder of the paper, we model the conditional extreme dependence of extraordinary yields losses and four different weather variables for six different staple crops, separately for different regions in Asia, Africa and Latin America.

2. Data

This study covers countries in Africa, Asia, and Latin America ranging from low to upper middle income countries (UN, 2014) and includes annual data observations from 1961 to 2002. The staple crops of interest are wheat, rice, maize, soybeans, barley, and sorghum which constitute the six most commonly cultivated crops worldwide (Lobell and Field, 2007). Country-level data on yields are available from the FAO website[1].

We make use of Lobell et al. (2011c)'s precipitation and temperature data; the authors constructed weather data based both on Sacks et al. (2010)'s crop calendar to derive the growing season of each crop and on the agricultural maps of Monfreda et al. (2008) to identify the growing

[1] http://faostat3.fao.org

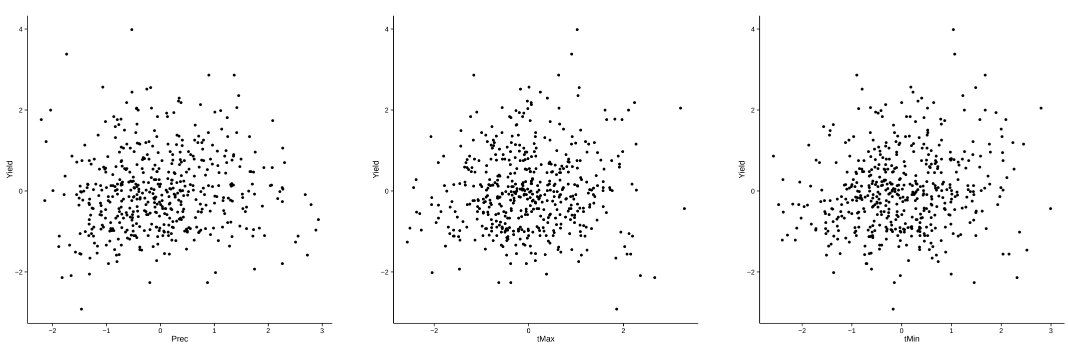
regions of each crop. Lobell et al. (2011c) extracted growing season- and region-specific weather data from the CRU TS 2.1 historical climate data set (Mitchell and Jones, 2005) and created national precipitation and temperature aggregates for each year. Different growing regions and different growing seasons among countries result in different precipitation and temperature data by crop and by country. Table 1 gives an overview of the variables.

The initial sample consists of 42 yearly observations for each country and each variable of analysis. We omit year-country pairs when data are missing for one of the variables. Because 42 observations constitute a small sample to conduct an analysis of extreme values, we pool countries into regions based on the UN Statistics Division composition of geographical regions [2]. Table 2 summarizes the geographical areas, which consist of countries geographically related but still not identical in terms of economic and weather conditions. To account for this heterogeneity within each pool of countries, we standardize the production and weather data independently for each country, subtracting the country-specific mean and dividing by the country-specific standard deviation. This standardization ensures comparability and avoids missing extremes for some countries when pooling data.

Table 1: *Overview of variables*

Variable	Description
Yield	Total production divided by area (hg/ha)
Prec	Total growing season precipitation in millimeters
tMin	Average minimum daily growing season temperature in degree Celsius
tMax	Average maximum daily growing season temperature in degree Celsius

Figure 1 shows scatter plots of the standardized yields *(Yield)*, precipitation *(Prec)*, maximum temperature *(tMax)* and minimum temperature (*tMin*), using maize data in Eastern Africa as a representative example of the data. Figure 1 shows that a regression analysis is not a convenient option because there are no grounds to assume a clear positive or clear negative dependence of the yield and any of the weather variables. Instead, we model the extremes, that is for instance, the set of observations in the bottom right corner of Figure 1a.



(a) **(b)** **(c)**

Figure 1: *Annual standardized yield and precipitation (1), maximum temperature (2), and minimum temperature (3), using maize data in Eastern Africa (1961-2002)*

We define extreme events in precipitation, temperature, and yield as the values of the corre-

[2] http://unstats.un.org/unsd/methods/m49/m49regin.htm

Table 2: *Geographical regions*

Region	Countries
South America	Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Guyana, Paraguay, Peru, Suriname, Uruguay, Venezuela
Central America & Caribbean	Belize, Costa Rica, Cuba, Dominican Republic, El Salvador, Guatemala, Haiti, Honduras, Jamaica, Mexico, Nicaragua, Panama, Trinidad and Tobago
Western Africa	Benin, Burkina Faso, The Gambia, Ghana, Guinea, Ivory Coast, Liberia, Mali, Mauritania, Niger, Nigeria, Senegal, Sierra Leone, Togo
Eastern Africa	Burundi, Comoros, Djibouti, Eritrea, Ethiopia, Kenya, Madagascar, Malawi, Mozambique, Rwanda, Somalia, Sudan, Uganda, United Republic of Tanzania, Zambia, Zimbabwe
Middle & Southern Africa	Angola, Botswana, Cameroon, Central African Republic, Chad, Congo, Gabon, Lesotho, Namibia, South Africa, Swaziland
South & South-Eastern Asia & Melanesia	Bangladesh, Brunei, Bhutan, Cambodia, Indonesia, India, Fiji, Laos, Malaysia, Myanmar (Burma), New Caledonia, Papua New Guinea, Philippines, Solomon Islands, Thailand, Vanuatu, Vietnam

sponding variable above (below) a threshold value, so that the observations subject to the analysis are located in the upper (lower) tail of the distribution (Coles et al., 2001). We are mostly interested in the effect that extremely high or low temperatures and high or low precipitations have on the probability of observing severe yield losses.

3. Methods

Let $X = (X_1, \ldots, X_d)$ be a vector variable with unknown distribution function $F(x)$, and marginal distribution functions F_{x_i}, with $i = 1, \ldots, d$. The idea is to model the joint tail of $F(x)$ and, more specifically, the conditional distribution of $X_{-i}|X_i > x$ when x is large, where X_{-i} denotes the vector X excluding the i^{th} component. In this framework, we follow Heffernan and Tawn (2004), who proposed a semi-parametric model $\hat{F}_{x_i}$ for the marginal distributions based on the generalized Pareto distribution (GPD),

$$\hat{F}_{x_i} = \begin{cases} 1 - \{1 - \tilde{F}_{x_i}(u_{x_i})\}\{1 + \xi_i(x - u_{x_i})/\beta_i\}_+^{-1/\xi_i} & x > u_{x_i} \\ \tilde{F}_{x_i}(x) & x \leq u_{x_i} \end{cases}$$

where (β_i, ξ_i) are the scale and shape parameters of a GPD for the exceedances over the threshold u_{x_i} and $\tilde{F}_{x_i}$ is the empirical distribution of X_i.

Following Keef et al. (2013), we use the estimated distributions $\hat{F}_{x_i}$ to transform X componentwise to follow Laplace marginal distributions:

$$Y_i = \begin{cases} \log\{2F_{X_i}(X_i)\} & \text{for } X_i < F_{X_i}^{-1}(0.5) \\ -2\log\{2[1 - F_{X_i}(X_i)]\} & \text{for } X_i \geq F_{X_i}^{-1}(0.5). \end{cases} \quad (1)$$

The aim is to model the distribution of $Y_{-i}|Y_i = y$ for y large. For that purpose, univariate extreme value theory is extended to a multivariate context. Assume that there exist normalizing functions $a_{|i}(x)$, $b_{|i}(x)$: $\mathbb{R} \rightarrow \mathbb{R}^{d-1}$ / $\forall$ fixed $z \in \mathbb{R}^{d-1}$ and any sequence of y_i values such that $y_i \rightarrow \infty$ (i.e., high enough):

$$lim_{y_i\rightarrow\infty}[Y_{-i} \leq a_{|i}(y_i) + b_{|i}(y_i)z_{|i}|Y_i = y_i] = G_{|i}(z_{|i}). \tag{2}$$

Denote by G_i the i^{th} marginal distribution of $G_{|i}$, a non-degenerate distribution function with $lim_{z\rightarrow\infty}\{G_i(z)\}$=1 $\forall i$. The method assumes that the limiting distribution holds $\forall$ $y_i > u_{Y_i}$ for a suitable high threshold u_{Y_i}. When $Y_i = y_i$, with $y_i > u_{Y_i}$, the (standardized) random variable $Z_{|i}$ is defined as:

$$Z_{|i} = \frac{Y_{-i} - a_{|i}(y_i)}{b_{|i}(y_i)} \tag{3}$$

and the limiting distribution of $Z_{|i}$:

$$lim_{y_i\rightarrow\infty}P(Z_{|i} \leq z_{|i}|Y_i = y_i) = G_{|i}(z_{|i}). \tag{4}$$

Under this assumption, conditionally on $Y_i > u_{Y_i}$, as $u_{Y_i} \rightarrow \infty$, the variables $Y_i - u_{Y_i}(> 0)$ and $Z_{|i}$ are independent in the limit and their limiting marginal distributions are exponential and $G_{|i}(z_{|i})$, respectively (Keef et al., 2013).

The extremal dependence behaviour is characterized by $a_{|i}(y)$, $b_{|i}(y)$ and $G_{|i}$; hence estimates of the three are needed to derive the conditional distribution. To do so, Heffernan and Tawn (2004) propose a semi-parametric model. The parametric part involves estimating $a_{|i}(y)$ and $b_{|i}(y)$ using the regression model:

$$Y_{-i} = a_{|i}(y) + b_{|i}(y)Z_{|i} = a_{|i}y + y^{b_{|i}}Z_{|i}. \tag{5}$$

Specifically, $a_{|i}(y)$ and $b_{|i}(y)$ are expressed in terms of y as $a_{|i}(y) = a_{|i}y$ and $b_{|i}(y) = y^{b_{|i}}$, with the restrictions $(a_{|i}, b_{|i}) \in [-1, 1]^{d-1} \times (-\infty, 1)^{d-1}$. Further joint constraints on the parameters have been imposed by Keef et al. (2013) to avoid problems of inconsistent inferences with respect to the marginal distributions and parameter identification. Positive and negative dependence are defined by $a_{j|i}$, the component of $a_{|i}$ linked to Y_j and large Y_i, being $0 < a_{j|i} \leq 1$ and $-1 \leq a_{j|i} < 0$ respectively (Keef et al., 2013). Assuming that $(a_{|i}, b_{|i})$ are known, $G_{|i}$ can be estimated non-parametrically using the empirical (or kernel smoothed) distribution of replicates of the random variable $\hat{Z}_{|i}$:

$$\hat{Z}_{|i} = \frac{Y_{-i} - \hat{a}_{|i}(y_i)}{\hat{b}_{|i}(y_i)}$$

for $Y_i = y_i > u_{Y_i}$. Pseudo-samples can then be generated using the fitted model to estimate the conditional probability of interest. Confidence intervals can be obtained using bootstrap methods, see Heffernan and Tawn (2004) for computational details.

4. Empirical analysis

In the case of *Prec*, we consider both extreme high and low precipitation values. Because Heffernan and Tawn (2004) model the upper tail of the distribution, for extreme low precipitation, we consider the reflection of the variable *Prec*, defined as *PrecRefl*. The same procedure applies to *Yield* because we are interested in yield losses and we therefore consider the reflection *YieldRefl*. For each crop, we define four two-dimensional vectors $X = (X_1, X_2)$ with unknown distribution function $F(x)$, where X_1 is always *YieldRefl* of the specific crop and X_2 is one of the four weather variables. We thus model the extreme values in a bivariate context and run a separate analysis for each pair of crop and weather variables. To illustrate the procedure of fitting the dependence model, we report results of the two variables *YieldRefl* and *Prec* using maize data of Eastern Africa from 1961 to 2002 [3]

We first fit a generalized Pareto distribution separately for each variable and then transform X component-wise following equation (1) to obtain identical Laplace marginal distributions. The fitting of the GPD requires an appropriate selection of the threshold above which the GPD model is valid. For this reason, linearity of the mean residual life plots has to be ensured, which is already the case for very low thresholds of *Prec* and *YieldRefl* for maize data in Eastern Africa. However, probability, quantile and return level plots suggest that the estimated distribution function is a reasonable estimate of the theoretical function only above the threshold of the 80 th percentile (Coles et al., 2001), which we then choose as the threshold for *Prec* and *YieldRefl*.

Based on these marginal variables with identical Laplace distributions, we describe the dependence structure of the variables. We explore the behaviour of the variable *YieldRefl* conditional on extreme values of the variable *Prec*. We choose the threshold u_{Y_i} over which the limiting distribution holds by examining the threshold stability of the estimated parameters $a_{|i}$ and $b_{|i}$ of the dependence model (5) using the 50^{th} to 90^{th} quantiles of the conditioning variable *Prec* as potential thresholds. The 90^{th} quantile was found to be adequate, leading to parameter estimates $\hat{a}_{j|i} = 0.355$ and $\hat{b}_{j|i} = -0.394$. Imposing the ordering constraints to the values of the parameters as explained in Section 3, parameter estimates can be sensitive to the initial value of the optimization procedure for the estimation (Southworth et al., 2013). However, constrained dependence parameter estimates are located in the maximum of the profile likelihood surface, as shown in Figure 2. With $\hat{a}_{j|i} = 0.355$, the variables *YieldRefl* and *Prec* exhibit positive extremal dependence (Keef et al., 2013). Using maize data from Eastern Africa, we see that the form of dependence between *YieldRefl* and the weather variables varies. In contrast to *YieldRefl* and *Prec*, the pair *YieldRefl* and *PrecRefl* shows an extremal negative dependence with an $\hat{a}_{j|i} = -0.6265$. The results of the other regions and for the other crops show that the dependence structure does not only change for different conditioning variables but also for different crops and regions. The uncertainty of the parameter estimates was evaluated by means of bootstrapping, see Heffernan and Tawn (2004) for details.

Finally, plotting $Z_{|i}$ against Y_i for values of Y_i over the threshold chosen to fit the model, we conclude that the standardized variable and the conditioning variable are independent. Moreover, the fitted quantiles of the conditional distribution and the observations on the original scale match indicating that the model fits well.

4.1. Extrapolation

The semiparametric model fitted in the previous section is used to simulate from the joint distribution of $(YieldRefl, Prec)$ conditional on $Prec > qu_{Prec}$, where qu_{Prec} is the 91^{st} to $99{,}99^{th}$ quantile of the conditioning variable *Prec*. We simulate 1000 observations, which are then used to calculate the conditional probabilities $P(YieldRefl > qu_{YieldRefl} | Prec > qu_{Prec})$, where $qu_{YieldRefl}$ is always set as the 90^{th} quantile of the variable *YieldRefl*. Thus, we are interested in the change of the probability of high losses in basic food production given rising extremes in precipitation. The uncertainty of each point estimate is assessed by creating 95 % confidence intervals of the conditional probabilities based on 100 bootstrap samples.

[3]Results for the set of specifications with different marginal weather variables and for different crops or regions are available on request. The analysis was conducted using the `R` packages `texmex` (Southworth, 2013), `evd` (Stephenson, 2015), `ggplot2` (Wickham, 2015) and `rworldmap` (?).

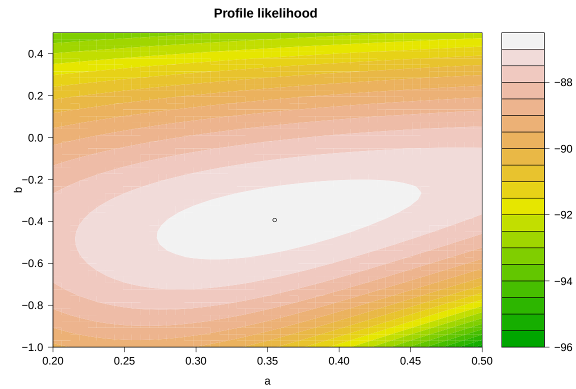


Figure 2: *Constrained dependence parameter estimates* $\hat{a}_{j|i}$ ***(a)*** *and* $\hat{b}_{j|i}$ ***(b)*** *of the conditional distribution of* $(YieldRefl|Prec)$ *conditional on* $Prec > qu_{Prec}$*, with* qu_{Prec} *being the* 91^{st} *to* $99{,}99^{th}$ *quantile of the conditioning variable Prec, correspond to the maximum of the profile likelihood surface using maize data of Eastern Africa.*

Figure 3 contains conditional probabilities and the corresponding confidence intervals of high losses in maize production given a range of thresholds, i.e., from 91^{st} to 99.99^{th} quantiles, for high precipitation. The plots in Figure 3 cover all considered regions in Asia, Africa and Latin America. In Middle & Southern Africa, the conditional probabilities or lower confidence interval bounds are equal to zero, indicating no evidence of an association between extremes in high precipitation and high yield losses. The probability of high losses in maize production given increasing extremes in high precipitation increases sharply up to 94 % in Eastern Africa but with widening confidence intervals. Eastern Africa aside, the probabilities do not change significantly with increasing thresholds of the conditioning variable *Prec* among the different regions and are mostly below 25%. For the opposite case of extremes in low precipitation, Figure 6 (Annex) plots the conditional probabilities for all regions. South America is affected more than the other regions because losses in its maize production are more likely to occur given extremely low rainfall. Point estimates up to 74 % show higher uncertainties, although the confidence intervals do not include zero. In Central America & Caribbean, the lower confidence interval bounds of the conditional probabilities are equal to zero. The conditional probabilities for Eastern Africa are approximately 25 % and are less than 25 % for the other regions.

In the case of extremes in minimum temperature, see Figure 7 (Annex), the lower confidence interval bounds are equal to zero in South America, Western Africa and South & South-Eastern Asia & Melanesia. The other regions do not show remarkable differences. In Central America & Caribbean and Eastern Africa, the conditional probabilities slightly increase with higher extremes in minimum temperature. However, the point estimates are around or below 25 %. The picture looks similar for the maximum temperature as the conditioning variable, which is shown in Figure 8 (Annex). The conditional probabilities rarely exceed 25 %, and the lower confidence interval bounds are equal to zero in Western Africa and South & South-Eastern Asia & Melanesia. The conditional probability plots for barley, rice, sorghum, soy and wheat also reveal a mixed picture and are shown in the supporting material in the supporting material in appendix. Production losses due to weather extremes are not equally likely among the regions. Depending on the crop, the weather extreme and the region, the occurrence of severe production losses is more or less likely. The results emphasize the complexity of interaction factors.

For each region Figure 4 displays the highest point estimates and 95 % confidence intervals of the probability of observing a high loss in yield, i.e., $YieldRefl$ above its 90^{th} quantile, conditional

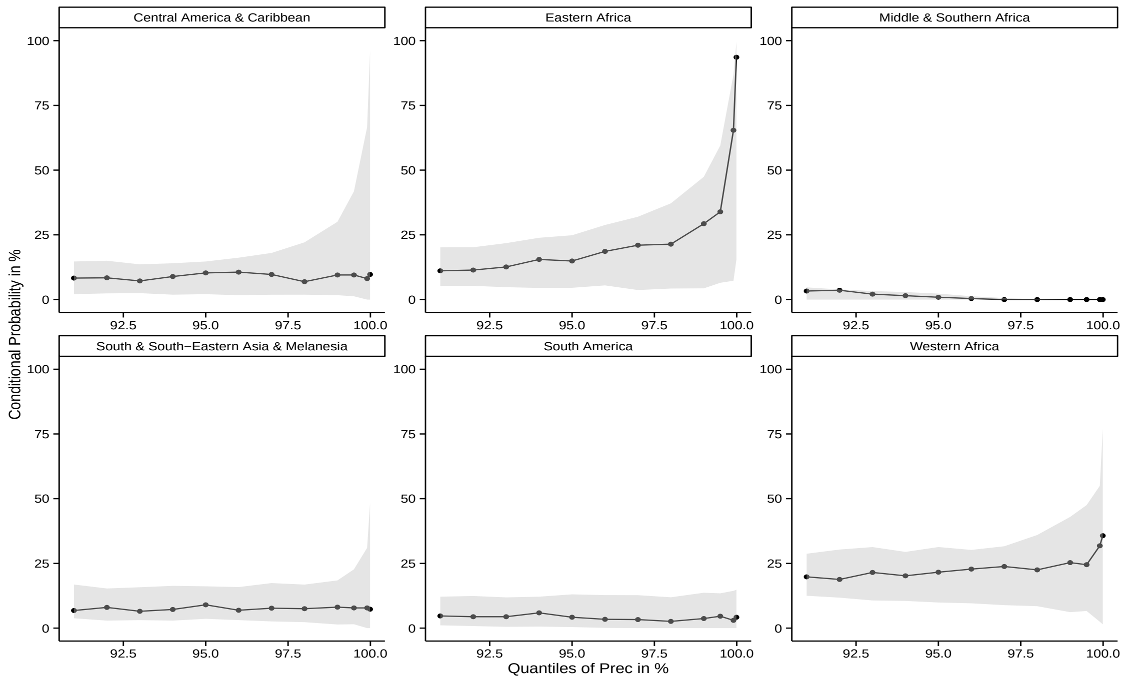


Figure 3: *Point estimates and 95 % confidence intervals of the conditional probability $P(YieldRefl > qu_{YieldRefl}|Prec > qu_{Prec})$, where $qu_{YieldRefl}$ is always set as the 90^{th} quantile of the variable YieldRefl and qu_{Prec} is the 91^{st} to $99{,}99^{th}$ quantile of the conditioning variable Prec. Estimation is done using maize data from 1961 to 2002. In Eastern Africa conditional probabilities sharply increase with widening confidence intervals for high thresholds of the conditioning variable. In Middle & Southern Africa the conditional probabilities or the lower confidence interval bounds are zero indicating no evidence of an association between extremes in high precipitation and high yield losses.*

on extremes in weather. Weather includes either $Prec$, $PrecRefl$, $tMin$, or $tMax$. For the sake of clarity, we denote $Prec$ and $PrecRefl$ as $HighPrec$ and $LowPrec$ respectively to indicate that precipitation is extremely high, i.e., above its 98^{th} quantile, or that precipitation is extremely low, i.e., below its 2^{nd} quantile. The variables $tMin$ and $tMax$ are both extreme high, i.e., above their 98^{th} quantile.

Figure 4 shows that each of the considered regions is likely to have severe losses in its production of staple food due to extreme weather events. However, the effect of extreme weather varies among regions depending on the crop and the type of weather extreme. Sorghum, which is the main staple in Africa, has the highest risk of severe yield losses for different weather extremes in the three African regions. Extreme high maximum temperature and low precipitation are the main weather conditions leading to extraordinary yield losses, which is in line with the distribution of sorghum in arid regions in Africa or in regions where precipitation is erratic and characterized by short periods of high precipitation (Taylor, 2003). In Eastern and Western Africa severe reduction in sorghum yield are given extreme high minimum temperature. High losses in maize production are due to extreme high minimum temperature in Middle & Southern Africa and are due to extreme high precipitation in Eastern Africa. Noteworthy because of the importance of rice, which is a main staple in Western Africa (Maclean et al., 2013), high losses in rice production are likely to occur with extreme events in high precipitation.

Central America & Caribbean exhibits the highest conditional probabilities due to weather extremes for rice and maize, whereas South America shows it for barley and soybean which are

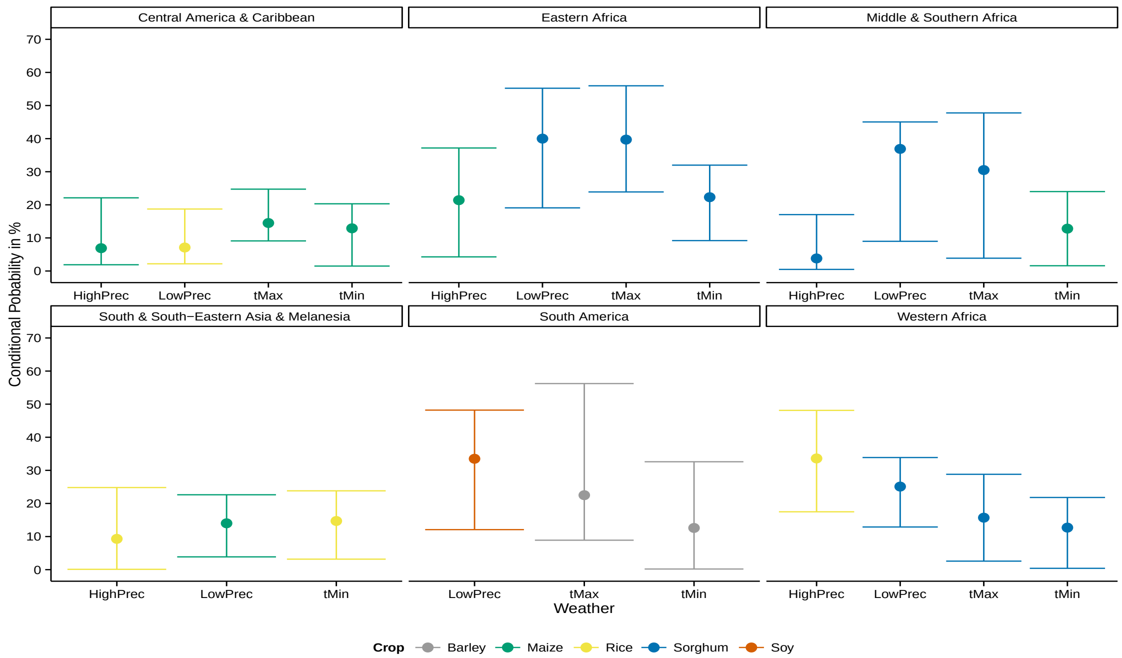


Figure 4: *Highest point estimates of the conditional probabilities, i.e. the probabilities of yield losses above the 90th quantile given minimum temperature, maximum temperature or high precipitation extremes above the 98th quantile or low precipitation extremes below the 2nd quantile. If the 95 % confidence interval includes zero, the conditional probabilities are not shown.*

among the most important staple crops in the regions. Weather patterns are diverse in Latin America. Whereas South America experiences rising temperature and changing precipitation patterns leading to mixed effects on agriculture, an increase in temperature severely damages agricultural output in Central America. Moreover, even though Central America is marked by a decline in precipitation, floods remain among the most frequent extreme weather events (Galindo and De Miguel, 2010). The estimated conditional probabilities suggest that in Central America & Caribbean maize production reacts mainly to extremes in high precipitation and temperature and rice production reacts to extreme low precipitation. In South America, barley and soybean production losses are likely to increase with extremes in temperature and low precipitation respectively.

In Asia a main staple crop is rice where 90 % of rice production and consumption is concentrated (Maclean et al., 2013). The dependency on rice is reflected by the fact that we obtain the highest conditional probabilities for rice in South & South-Eastern Asia & Melanesia. Losses in rice production are likely due to extreme high minimum temperature. The finding is in line with Maclean et al. (2013) who state that higher minimum temperatures become increasingly a major cause of yield losses of rice in Asia. On the other side, the occurrence of very low rice yields is likely due to high precipitation. Only in South Asia yield losses of rice due to floods are about 4 million t per year (Maclean et al., 2013). Interestingly, the probability of production losses given extreme low precipitation is the highest for maize in the tropical region of South & South-Eastern Asia & Melanesia. The finding is plausible as maize production is predominantly rain-fed in South and South-Eastern Asia (Wani et al., 2009).

The point estimates of conditional probabilities shown in Figure 4 are at maximum 40 %, which

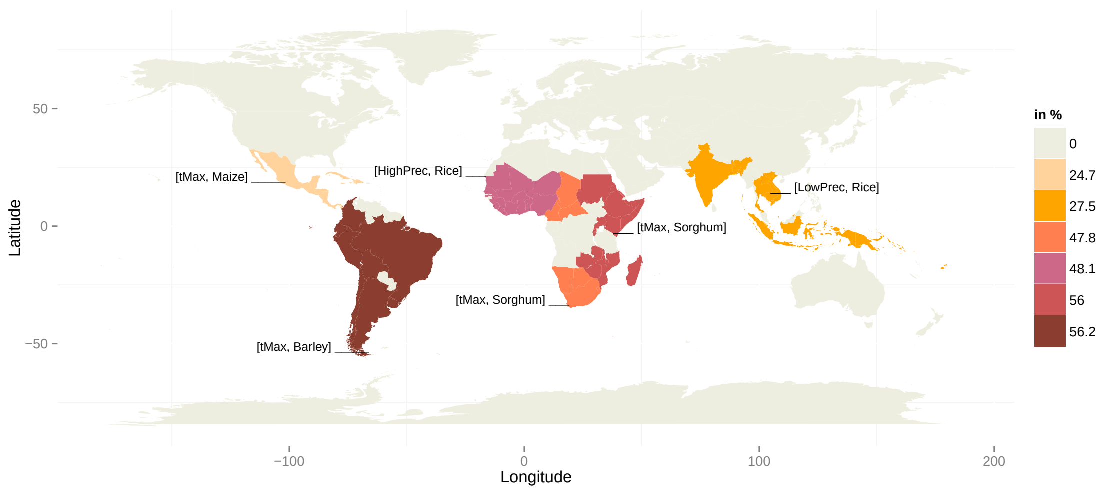


Figure 5: *Worst-case scenario: the maximum upper bound of the 95 % confidence interval of the conditional probability estimates, i.e. the probability estimates of yield losses above the 90^{th} quantile given minimum temperature, maximum temperature or high precipitation extremes above the 98^{th} quantile or low precipitation extremes below the 2^{nd} quantile.*

is the case for sorghum in Eastern Africa given extreme low precipitation. Overall, the highest conditional probabilities given different weather extremes are in Eastern and Middle & Southern Africa as well as in South America. In contrast, the conditional probabilities are less than 30 % for all types of weather extremes in Central America & Caribbean and South & South-Eastern Asia & Melanesia. Western Africa shows mixed results, which change depending on the weather extreme.

Summing up the results, we find that, first, maize and sorghum have the highest conditional probabilities of extreme high losses in crop production given the occurrence of extreme weather conditions. Second, extreme low precipitation and extreme high maximum temperature are the defining weather extremes, except for Latin America and Western Africa. In Latin America, the probabilities do not change significantly among different conditioning variables, and in Western Africa, the highest conditional probability is due to extreme high precipitation in the case of rice. Third, losses in staple crop production given extreme weather events are more likely in the African regions and South America.

Finally, Figure 5 shows the worst-case scenario by displaying the maximum upper bound of the 95 % confidence interval of the conditional probability estimates, i.e., the probability estimates of yield losses above the 90^{th} quantile given the minimum temperature, maximum temperature or high precipitation extremes above the 98^{th} quantile or low precipitation extremes below the 2^{nd} quantile. The maximum upper bound of the 95 % confidence interval is chosen from all of the weather variables and crops in a region. Each region has a different worst-case scenario, i.e., a different crop and weather variable for which we obtain the maximum upper confidence interval bound. In Central America & Caribbean, South America, Eastern Africa and Middle & Southern Africa, extreme high temperature is the condition that leads to the highest production losses. Whereas in the African regions, the associated crop is sorghum, the associated crop is maize in Central America & Caribbean and barley in South America. The worst-case scenario for Western Africa constitutes high losses in rice yields due to extremes in high precipitation. In the Asian region, extremes in low precipitation is the defining weather variable in the worst-case scenario and rice is the affected crop. The worst-case scenarios occur with different probability in the different regions. The probability ranges from around 25 % in Central America & Caribbean and South & South-Eastern Asia & Melanesia to 56 % in Eastern Africa and South America, whereas probabilities of approximately 50 % are found in Western and Middle & Southern Africa.

5. Conclusion

Standard approaches for assessing the impact of weather on crops have largely focused on the mean values. In line with a recent stream of research on extreme weather events, we do not focus on the mean but on the tails of the distributions. We find systematic evidence that extreme losses in production of major food staples are likely to occur in times of extreme conditions in weather and the probability depends on the type of weather extreme, the crop, and the region. The alleged increase in the number of extreme events should be taken seriously because the potential damage can be extraordinary. We provide a measure of risk for each region, that is specific to both the crop and the weather event. This outcome can also be used as a form of resilience of a region and to help policy makers to intervene and set priorities. In the short run, a country cannot change the risk of incurring high losses due to weather events. However, the resilience of a country depends on many factors, such as the adoption of advanced irrigation technology, the diffusion of fertilizer, and the introduction of new and resistant crops, which can be highly influenced by the policy makers.

This work leaves some questions unanswered due to data availability. Specifically, the same type of weather extremes can lead to different crop responses based on the time of the year and the crop growth stage (van der Velde et al., 2012). The use of growing-season national aggregates of weather to account for weather extremes instead of using precise weather data is critical because growing-season aggregates do not to capture inter-annual ups and downs and extremes within a growing period. The drawback occurs because extreme weather conditions are particularly harmful in certain stages of plant growth (Porter and Gawith, 1999). In addition, studies that focus on the occurrence of extreme weather events have to be accompanied by studies that also include the severity of extremes, such as the length of heatwaves or floods. The main constraint for a large fraction of countries worldwide is the lack of access to long-term weather data with high time and spatial resolution (Easterling et al., 2000), which are now available for case studies limited in time and space. We try to mitigate this problem by looking at aggregates of weather in the growing season and for different growing regions and we analyse the occurrence of periods of extreme hot, dry or wet conditions from a long-term perspective. The value of this paper is to provide an indication of the probability of extreme losses in basic food production due to extreme weather events in a specific region under historic climate conditions. This analysis provides a perspective that is complementary to more detailed localized studies focusing on one particular region with higher time and spatial resolution data.

To conclude, studying weather changes and the impacts on agricultural production remains a challenging task. To evaluate crop production responses the uncertainty of weather changes needs to be further addressed. The uncertainty in the evaluation of current and future impacts of weather on agricultural production stems from uncertainties that arise in the estimation of crop responses to changes in average growing season temperature and precipitation (Lobell and Burke, 2008). We believe that the uncertainties also come from the extreme events that are by nature difficult to model. Given that future climate is likely to be prone to a higher frequency of extreme weather events, our results contribute to this discussion by providing the probabilities of severe staple crop production losses conditioned on extremes in temperature and precipitation.

References

Marshall Burke, Solomon M Hsiang, and Edward Miguel. Global non-linear effect of temperature on economic production. *Nature*, 2015.

Ph Ciais, M Reichstein, Nicolas Viovy, A Granier, Jérôme Ogée, V Allard, Marc Aubinet, N Buchmann, Chr Bernhofer, A Carrara, et al. Europe-wide reduction in primary productivity caused by the heat and drought in 2003. *Nature*, 437(7058):529–533, 2005.

Stuart Coles, Joanna Bawa, Lesley Trenner, and Pat Dorazio. *An introduction to statistical modeling of extreme values*, volume 208. Springer, 2001.

Delphine Deryng, Declan Conway, Navin Ramankutty, Jeff Price, and Rachel Warren. Global crop yield response to extreme heat stress under multiple climate change futures. *Environmental Research Letters*, 9(3):034011, 2014.

David R Easterling, JL Evans, P Ya Groisman, TR Karl, K E_ Kunkel, and P Ambenje. Observed variability and trends in extreme climate events: a brief review*. *Bulletin of the American Meteorological Society*, 81(3):417–425, 2000.

Luis Miguel Galindo and Carlos J De Miguel. Economics of climate change in latin america and the caribbean: summary 2010. 2010.

Janet E Heffernan and Jonathan A Tawn. A conditional approach for multivariate extreme values (with discussion). *Journal of the Royal Statistical Society Series B*, 66(3):497–546, 2004.

Peter G Jones and Philip K Thornton. The potential impacts of climate change on maize production in africa and latin america in 2055. *Global environmental change*, 13(1):51–59, 2003.

Caroline Keef, Jonathan Tawn, and Cecilia Svensson. Spatial risk assessment for extreme river flows. *Journal of the Royal Statistical Society: Series C (Applied Statistics)*, 58(5):601–618, 2009.

Caroline Keef, Ioannis Papastathopoulos, and Jonathan A Tawn. Estimation of the conditional distribution of a multivariate variable given that one of its components is large: Additional constraints for the heffernan and tawn model. *Journal of Multivariate Analysis*, 115:396–404, 2013.

Jerry Knox, Tim Hess, Andre Daccache, and Tim Wheeler. Climate change impacts on crop productivity in africa and south asia. *Environmental Research Letters*, 7(3):034032, 2012.

Kristian Kristensen, Kirsten Schelde, and Jørgen E Olesen. Winter wheat yield response to climate variability in denmark. *The Journal of Agricultural Science*, 149(01):33–47, 2011.

Christopher J Kucharik and Shawn P Serbin. Impacts of recent climate change on wisconsin corn and soybean yield trends. *Environmental Research Letters*, 3(3):034003, 2008.

Corey Lesk, Pedram Rowhani, and Navin Ramankutty. Influence of extreme weather disasters on global crop production. *Nature*, 529(7584):84–87, 2016.

David B Lobell and Marshall B Burke. Why are agricultural impacts of climate change so uncertain? the importance of temperature relative to precipitation. *Environmental Research Letters*, 3(3): 034007, 2008.

David B Lobell and Christopher B Field. Global scale climate–crop yield relationships and the impacts of recent warming. *Environmental research letters*, 2(1):014002, 2007.

David B Lobell, Marianne Bänziger, Cosmos Magorokosho, and Bindiganavile Vivek. Nonlinear heat effects on african maize as evidenced by historical yield trials. *Nature Climate Change*, 1(1): 42–45, 2011a.

David B Lobell, Wolfram Schlenker, and Justin Costa-Roberts. Climate trends and global crop production since 1980. *Science*, 333(6042):616–620, 2011b.

David B Lobell, Wolfram Schlenker, and Justin Costa-Roberts. Climate trends and global crop production since 1980. *Science*, 333(6042):616–620, 2011c.

Jay Maclean, Bill Hardy, and G Hettel. *Rice Almanac: Source Book for One of the Most Important Economic Activities on Earth*. IRRI, 2013.

Timothy D Mitchell and Philip D Jones. An improved method of constructing a database of monthly climate observations and associated high-resolution grids. *International Journal of Climatology*, 25(6):693–712, 2005.

Chad Monfreda, Navin Ramankutty, and Jonathan A Foley. Farming the planet: 2. geographic distribution of crop areas, yields, physiological types, and net primary production in the year 2000. *Global biogeochemical cycles*, 22(1), 2008.

M Moriondo, C Giannakopoulos, and M Bindi. Climate change impact assessment: the role of climate extremes in crop yield simulation. *Climatic Change*, 104(3-4):679–701, 2011.

MJ Paulo, H Van der Voet, JC Wood, GR Marion, and JD Van Klaveren. Analysis of multivariate extreme intakes of food chemicals. *Food and chemical toxicology*, 44(7):994–1005, 2006.

John R Porter and Megan Gawith. Temperatures and the growth and development of wheat: a review. *European Journal of Agronomy*, 10(1):23–36, 1999.

John R Porter and Mikhail A Semenov. Crop responses to climatic variation. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 360(1463):2021–2035, 2005.

Cynthia Rosenzweig, Ana Iglesias, XB Yang, Paul R Epstein, and Eric Chivian. Climate change and extreme weather events; implications for food production, plant diseases, and pests. *Global change & human health*, 2(2):90–104, 2001.

Pedram Rowhani, David B Lobell, Marc Linderman, and Navin Ramankutty. Climate variability and crop production in tanzania. *Agricultural and Forest Meteorology*, 151(4):449–460, 2011.

William J Sacks, Delphine Deryng, Jonathan A Foley, and Navin Ramankutty. Crop planting dates: an analysis of global patterns. *Global Ecology and Biogeography*, 19(5):607–620, 2010.

Wolfram Schlenker and David B Lobell. Robust negative impacts of climate change on african agriculture. *Environmental Research Letters*, 5(1):014010, 2010.

Wolfram Schlenker and Michael J Roberts. Nonlinear effects of weather on corn yields. *Applied Economic Perspectives and Policy*, 28(3):391–398, 2006.

Mikhail A Semenov. Development of high-resolution ukcip02-based climate change scenarios in the uk. *Agricultural and Forest Meteorology*, 144(1):127–138, 2007.

Harry Southworth, Janet E Heffernan, and Maintainer Harry Southworth. Package texmex. 2013.

Janet Southworth, Harry; Heffernan. texmex: Statistical modelling of extreme values. *R package Version 2.1*, 2013.

Alec Stephenson. evd: Functions for extreme value distributions. *R package Version 2.3*, 2015.

Nassim Nicholas Taleb. *The black swan: The impact of the highly improbable fragility*, volume 2. Random House, 2010.

Fulu Tao, Masayuki Yokozawa, Jiyuan Liu, Zhao Zhang, et al. Climate-crop yield relationships at provincial scales in china and the impacts of recent climate trends. *Climate Research*, 38(1):83–94, 2008.

JRN Taylor. Overview: Importance of sorghum in africa. In *Proceedings of AFRIPRO Workshop on the Proteins of Sorghum And Millets: Enhancing Nutritional and Functional Properties for Africa, Pretoria, South Africa*, volume 9, 2003.

UN. World economic situation and prospects 2014. Technical report, 2014.

Marijn van der Velde, Francesco N Tubiello, Anton Vrieling, and Fayçal Bouraoui. Impacts of extreme weather on wheat and maize in france: evaluating regional crop simulations against observed data. *Climatic change*, 113(3-4):751–765, 2012.

Suhas Pralhad Wani, Johan Rockström, Theib Yousef Oweis, et al. *Rainfed agriculture: unlocking the potential*, volume 7. CABI, 2009.

Jarrod R Welch, Jeffrey R Vincent, Maximilian Auffhammer, Piedad F Moya, Achim Dobermann, and David Dawe. Rice yields in tropical/subtropical asia exhibit large but opposing sensitivities to minimum and maximum temperatures. *Proceedings of the National Academy of Sciences*, 107(33): 14562–14567, 2010.

Timothy R Wheeler, Peter Q Craufurd, Richard H Ellis, John R Porter, and PV Vara Prasad. Temperature variability and the yield of annual crops. *Agriculture, Ecosystems & Environment*, 82 (1):159–167, 2000.

Winston Wickham, Hadley; Chang. ggplot2: An implementation of the grammar of graphics. *R package Version 2.0*, 2015.

A. Annex

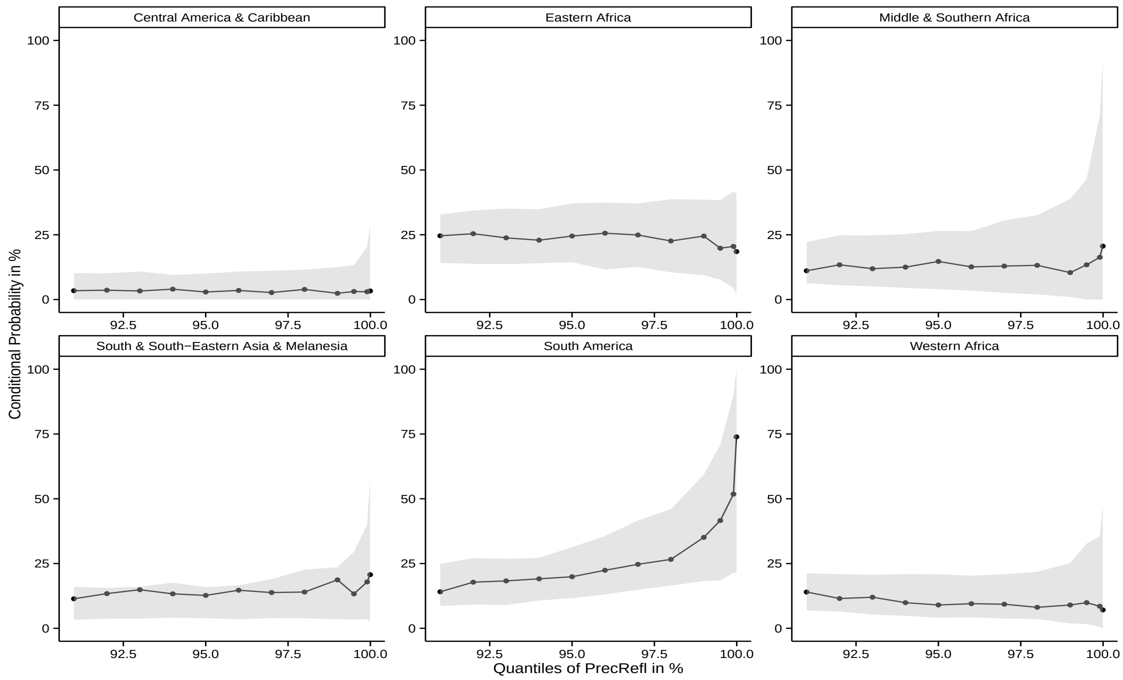


Figure 6: *Point estimates and 95 % confidence intervals of the conditional probability $P(YieldRefl > qu_{YieldRefl}|PrecRefl > qu_{PrecRefl})$, where $qu_{YieldRefl}$ is always set as the 90^{th} quantile of the variable YieldRefl and $qu_{PrecRefl}$ is the 91^{st} to $99{,}99^{th}$ quantile of the conditioning variable PrecRefl. Estimation is done using maize data from 1961 to 2002. In Central America & Caribbean the lower confidence interval bounds of conditional probabilities are equal to zero.*

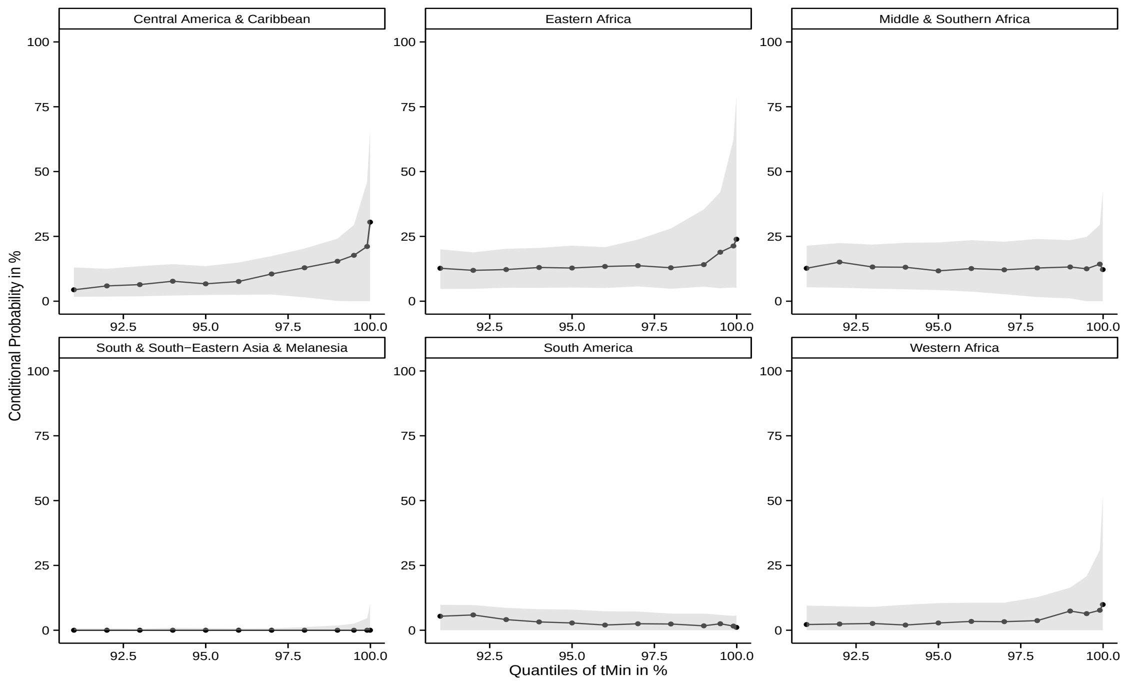


Figure 7: *Point estimates and 95 % confidence intervals of the conditional probability* $P(YieldRefl > qu_{YieldRefl}|tMin > qu_{tMin})$*, where* $qu_{YieldRefl}$ *is always set as the 90*th *quantile of the variable YieldRefl and* qu_{tMin} *is the 91*st *to 99,99*th *quantile of the conditioning variable tMin. Estimation is done using maize data from 1961 to 2002. In South America, Western Africa and South, South-Eastern, and Eastern Asia & Melanesia the conditional probabilities or the lower confidence interval bounds are zero indicating no evidence of an association between extremes in minimum temperature and high yield losses.*

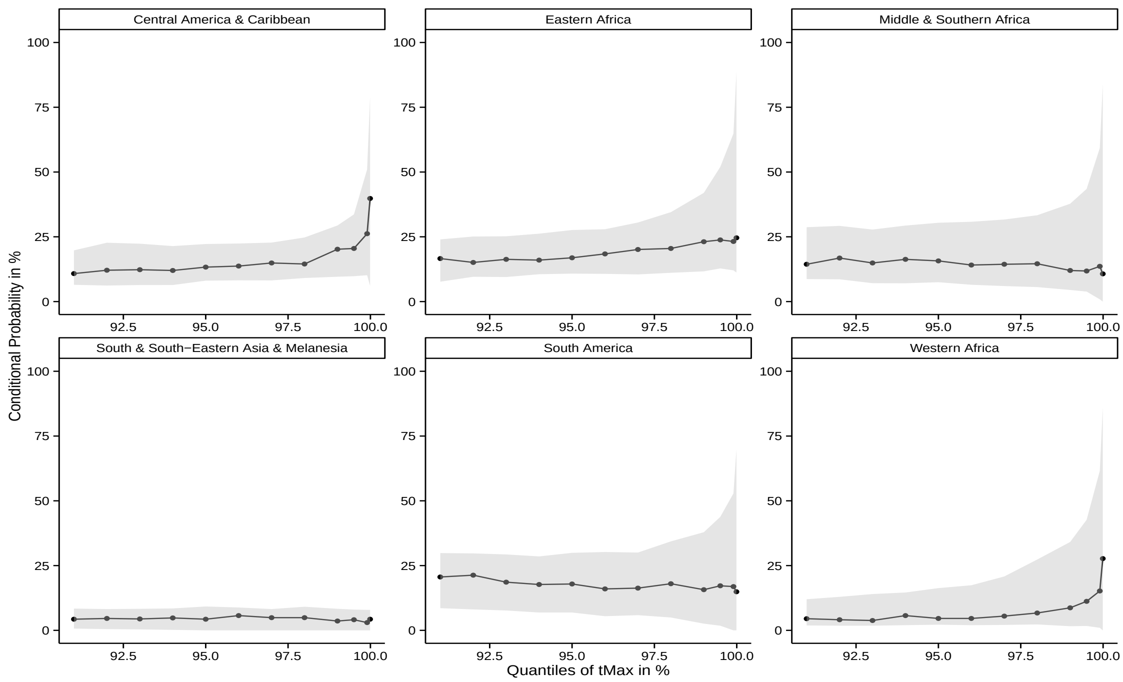


Figure 8: *Point estimates and 95 % confidence intervals of conditional probability $P(YieldRefl > qu_{YieldRefl_i} = 90\%|tMax > qu_{tMax_i})$ per region i. Estimation done using maize data from 1961 to 2002. In South & South-Eastern Asia & Melanesia the lower confidence interval bounds of conditional probabilities are equal to zero.*

Supporting Material for: How the Black Swan damages the harvest: statistical modelling of extreme events in weather and crop production in Africa, Asia and Latin America

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The supporting material contains the conditional probability plots for different regions and weather variables. The conditional probability plots are grouped by crop. We show plots for the conditional probabilities $P(YieldRefl > qu_{YieldRefl}|Weather > qu_{Weather})$, where $qu_{YieldRefl}$ is always set as the 90 % quantile of the dependent variable *YieldRefl* and $qu_{Weather}$ is the 91 to 99,99% quantile of the conditioning variable *Weather*, i.e. *Prec*, *PrecRefl*, *tMax*, or *tMin*. We are interested in the change of the probability of high losses in yield, i.e. above the 90 % quantile, given rising extremes in weather. For some crops and weather variables we do not plot conditional probabilities as these samples do not contain sufficient observations to evaluate the conditional probabilities. Table 1 contains the considered countries for each region [1].

[1]Countries are pooled into regions based on the UN Statistics Division composition of geographical regions http://unstats.un.org/unsd/methods/m49/m49regin.htm

Table 1: *Geographical regions*

Region	Countries
South America	Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Guyana, Paraguay, Peru, Suriname, Uruguay, Venezuela
Central America & Caribbean	Belize, Costa Rica, Cuba, Dominican Republic, El Salvador, Guatemala, Haiti, Honduras, Jamaica, Mexico, Nicaragua, Panama, Trinidad and Tobago
Western Africa	Benin, Burkina Faso, The Gambia, Ghana, Guinea, Ivory Coast, Liberia, Mali, Mauritania, Niger, Nigeria, Senegal, Sierra Leone, Togo
Eastern Africa	Burundi, Comoros, Djibouti, Eritrea, Ethiopia, Kenya, Madagascar, Malawi, Mozambique, Rwanda, Somalia, Sudan, Uganda, United Republic of Tanzania, Zambia, Zimbabwe
Middle & Southern Africa	Angola, Botswana, Cameroon, Central African Republic, Chad, Congo, Gabon, Lesotho, Namibia, South Africa, Swaziland
South & South-Eastern Asia & Melanesia	Bangladesh, Brunei, Bhutan, Cambodia, Indonesia, India, Fiji, Laos, Malaysia, Myanmar (Burma), New Caledonia, Papua New Guinea, Philippines, Solomon Islands, Thailand, Vanuatu, Vietnam

Conditional probabilities Rice

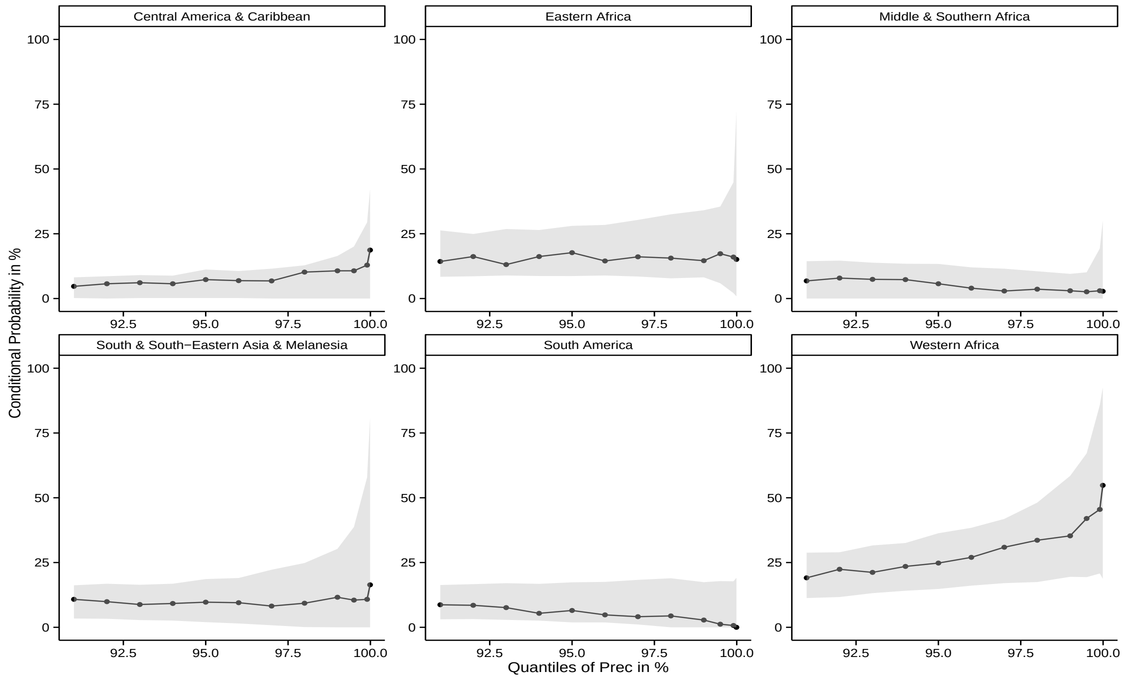

Figure 1: *Point estimates and 95 % confidence intervals of the conditional probability $P(YieldRefl > qu_{YieldRefl}|Prec > qu_{Prec})$, where $qu_{YieldRefl}$ is always set as the 90^{th} quantile of the variable YieldRefl and qu_{Prec} is the 91^{st} to $99{,}99^{th}$ quantile of the conditioning variable Prec. Estimation is done using rice data from 1961 to 2002. Note that some conditional probabilities and/or lower confidence interval bounds are equal to 0.0000. It is especially evident in Central America & Caribbean and Middle & Southern Africa. In Western Africa conditional probabilities of high yield losses given extreme high precipitation are highest.*

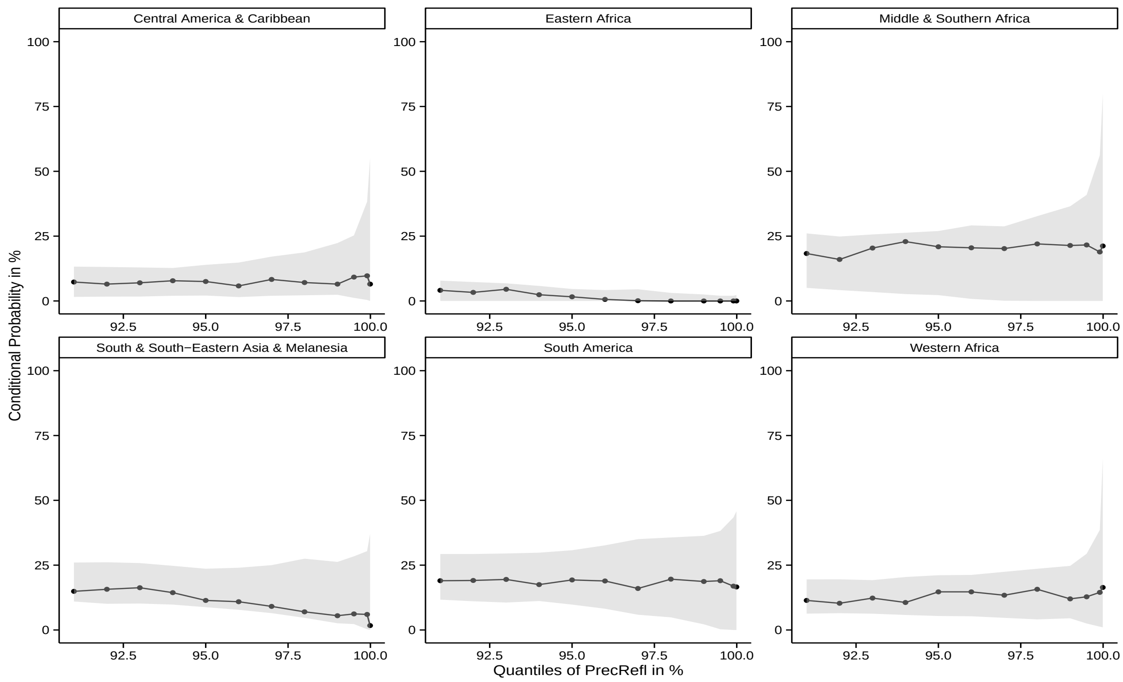

Figure 2: *Point estimates and 95 % confidence intervals of the conditional probability* $P(YieldRefl > qu_{YieldRefl}|PrecRefl > qu_{PrecRefl})$*, where* $qu_{YieldRefl}$ *is always set as the* 90^{th} *quantile of the variable YieldRefl and* $qu_{PrecRefl}$ *is the* 91^{st} *to* $99{,}99^{th}$ *quantile of the conditioning variable PrecRefl. Estimation is done using rice data from 1961 to 2002. Some conditional probabilities and/or lower confidence interval bounds are equal to 0.0000 especially in Eastern Africa.*

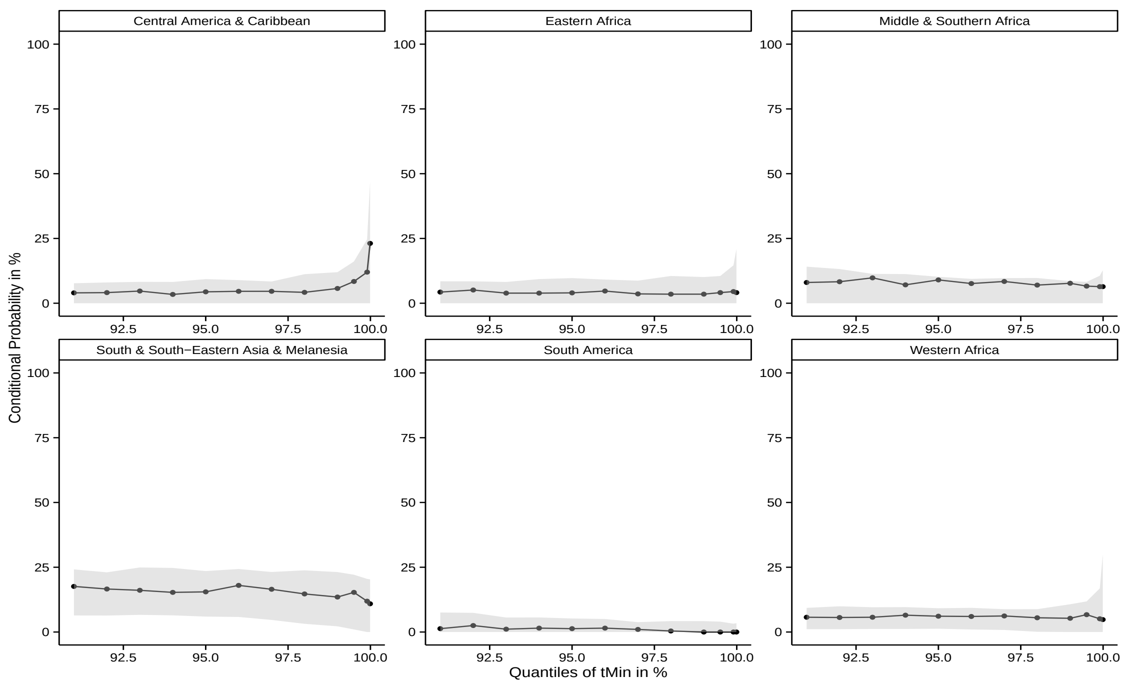

Figure 3: *Point estimates and 95 % confidence intervals of the conditional probability $P(YieldRefl > qu_{YieldRefl}|tMin > qu_{tMin})$, where $qu_{YieldRefl}$ is always set as the 90^{th} quantile of the variable YieldRefl and qu_{tMin} is the 91^{st} to $99{,}99^{th}$ quantile of the conditioning variable tMin. Estimation is done using rice data from 1961 to 2002. Note that in all regions, except South & South-Eastern Asia & Melanesia, most conditional probabilities and/or lower confidence interval bounds are equal to 0.0000.*

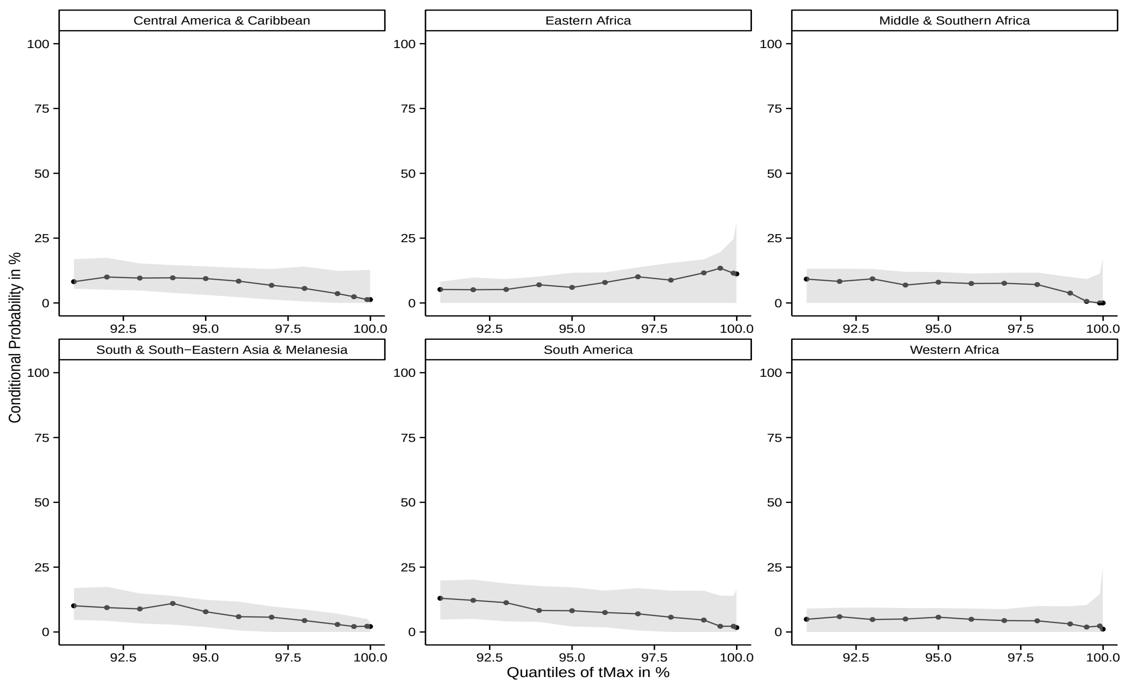

Figure 4: *Point estimates and 95 % confidence intervals of the conditional probability $P(YieldRefl > qu_{YieldRefl}|tMax > qu_{tMax})$, where $qu_{YieldRefl}$ is always set as the 90^{th} quantile of the variable YieldRefl and qu_{tMax} is the 91^{st} to $99{,}99^{th}$ quantile of the conditioning variable tMax. Estimation is done using rice data from 1961 to 2002. In all African regions conditional probabilities and/or lower confidence interval bounds are equal to 0.0000*

Conditional probabilities Sorghum

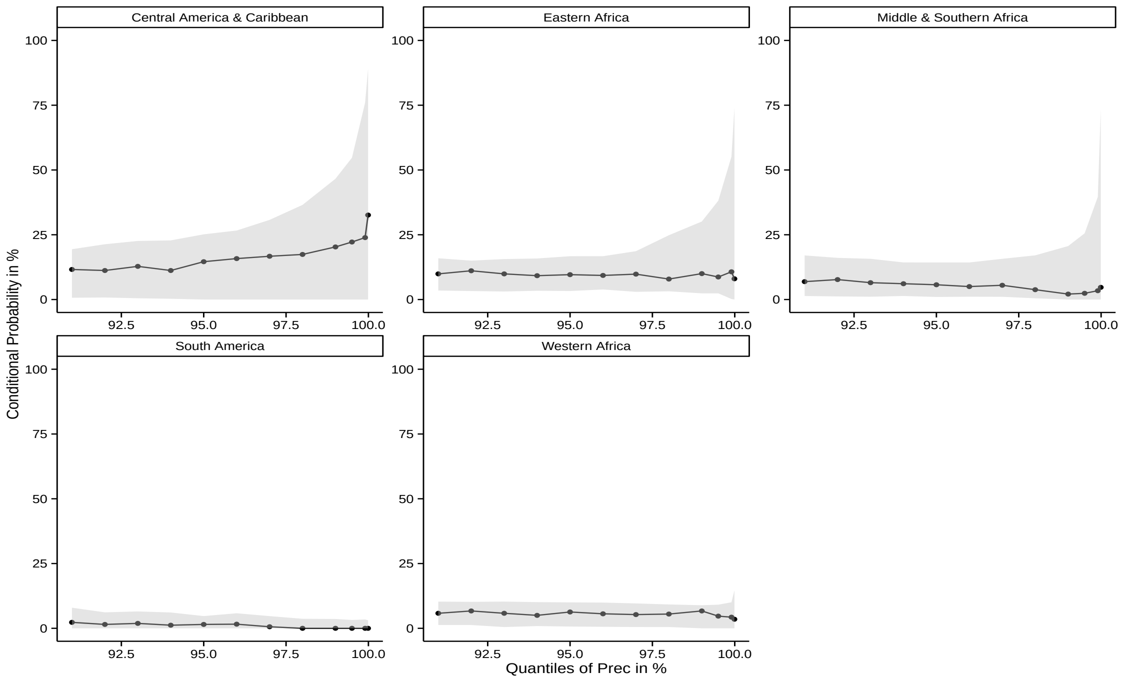

Figure 5: *Point estimates and 95 % confidence intervals of conditional probability $P(YieldRefl > qu_{YieldRefl}|Prec > qu_{Prec})$, where $qu_{YieldRefl}$ is always set as the 90^{th} quantile of the variable YieldRefl and qu_{Prec} is the 91^{st} to $99{,}99^{th}$ quantile of the conditioning variable Prec. Estimation is done using sorghum data from 1961 to 2002. Except for Eastern Africa, conditional probabilities and/or lower confidence interval bounds are mostly equal to 0.0000. The conditional probability plot of South & South-Eastern Asia & Melanesia is not shown as the sample of the region does not contain sufficient observations to evaluate the conditional probabilities.*

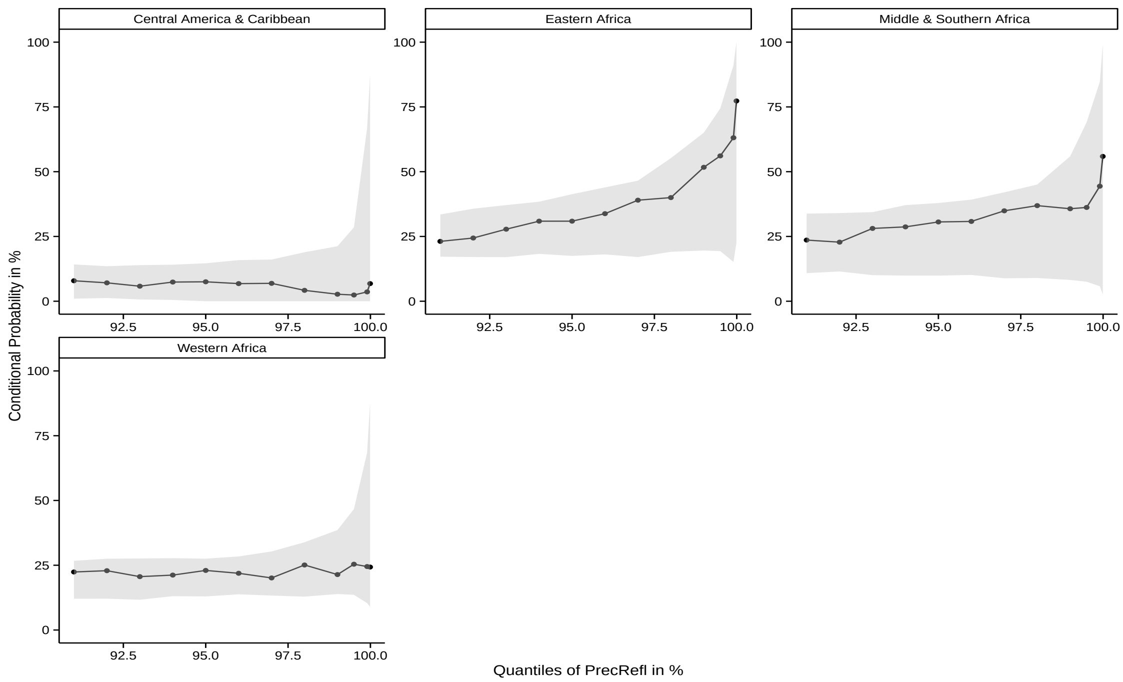

Figure 6: *Point estimates and 95 % confidence intervals of the conditional probability* $P(YieldRefl > qu_{YieldRefl}|PrecRefl > qu_{PrecRefl})$*, where* $qu_{YieldRefl}$ *is always set as the* 90th *quantile of the variable YieldRefl and* $qu_{PrecRefl}$ *is the* 91st *to* 99,99th *quantile of the conditioning variable PrecRefl. Estimation is done using sorghum data from 1961 to 2002. The conditional probability plots of South America and South & South-Eastern Asia & Melanesia are not shown as the sample of the region does not contain sufficient observations to evaluate the conditional probabilities. Especially in Eastern Africa but also in Middle & Southern Africa the conditional probabilities sharply increase (with widening confidence intervals) for high thresholds of the conditioning variable. Note that the conditional probabilities and/or lower confidence interval bounds are mostly equal to 0.0000 in Central America & Caribbean and Southern, South-Eastern, and Eastern Asia & Melanesia.*

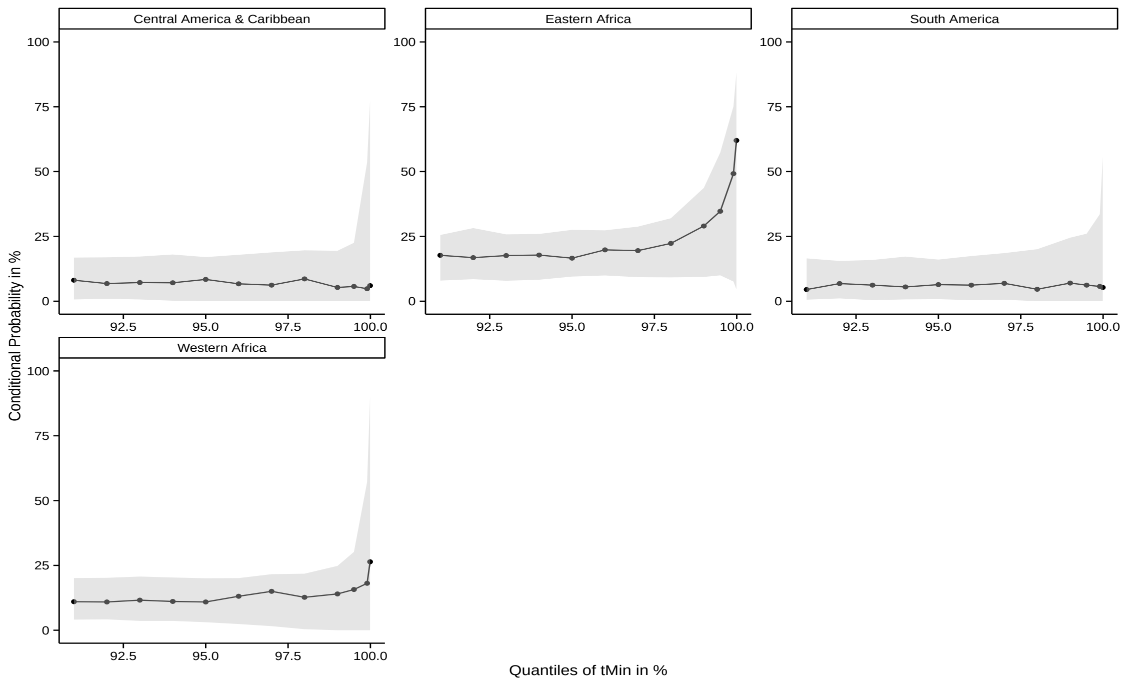

Figure 7: *Point estimates and 95 % confidence intervals of conditional probability $P(YieldRefl > qu_{YieldRefl} = |tMin > qu_{tMin})$, where $qu_{YieldRefl}$ is always set as the 90^{th} quantile of the variable YieldRefl and qu_{tMin} is the 91^{st} to $99{,}99^{th}$ quantile of the conditioning variable tMin. Estimation is done using sorghum data from 1961 to 2002. The conditional probability plots of South America and South & South-Eastern Asia & Melanesia are not shown as the sample of the region does not contain sufficient observations to evaluate the conditional probabilities. The conditional probability sharply increases for high thresholds of $tMin$ in Eastern Africa. Note that some conditional probabilities and/or the lower confidence interval bounds are equal to 0.0000, especially in Central America & Caribbean and South America.*

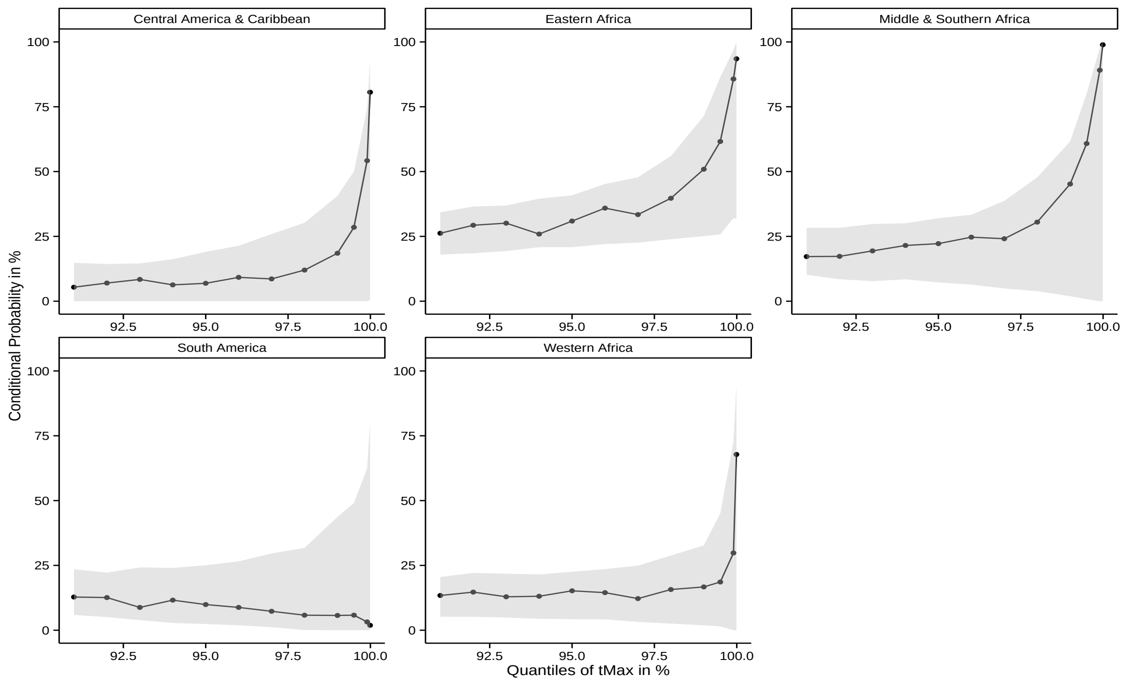

Figure 8: *Point estimates and 95 % confidence intervals of the conditional probability $P(YieldRefl > qu_{YieldRefl}|tMax > qu_{tMax})$, where $qu_{YieldRefl}$ is always set as the 90^{th} quantile of the variable YieldRefl and qu_{tMax} is the 91^{st} to $99{,}99^{th}$ quantile of the conditioning variable tMax. Estimation is done using sorghum data from 1961 to 2002. Note that there are conditional probabilities and/or the lower confidence interval bounds equal to 0.0000, which is especially the case in Central America & Caribbean. On the other side, in all African regions, remarkably in Eastern Africa with tighter confidence intervals than in the other African regions, conditional probabilities exhibit a steep increase for extreme values of $tMax$. The conditional probability plot of South & South-Eastern Asia & Melanesia is not shown as the sample of the region does not contain sufficient observations to evaluate the conditional probabilities.*

Conditional probabilities Wheat

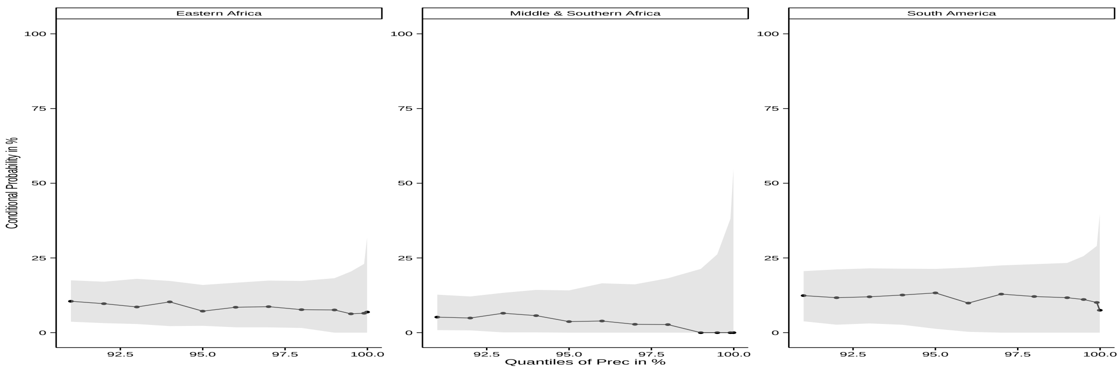

Figure 9: *Point estimates and 95 % confidence intervals of the conditional probability $P(YieldRefl > qu_{YieldRefl}|Prec > qu_{Prec})$, where $qu_{YieldRefl}$ is always set as the 90^{th} quantile of the variable YieldRefl and qu_{Prec} is the 91^{st} to $99{,}99^{th}$ quantile of the conditioning variable Prec. Estimation is done using wheat data from 1961 to 2002. The conditional probability plots of the regions Western Africa, South & South-Eastern Asia & Melanesia and Central America & Caribbean are not shown as the sample of the region does not contain sufficient observations to evaluate the conditional probabilities. The conditional probabilities and/or the lower confidence interval bounds are equal to 0.0000, which is especially the case in Middle & Southern Africa.*

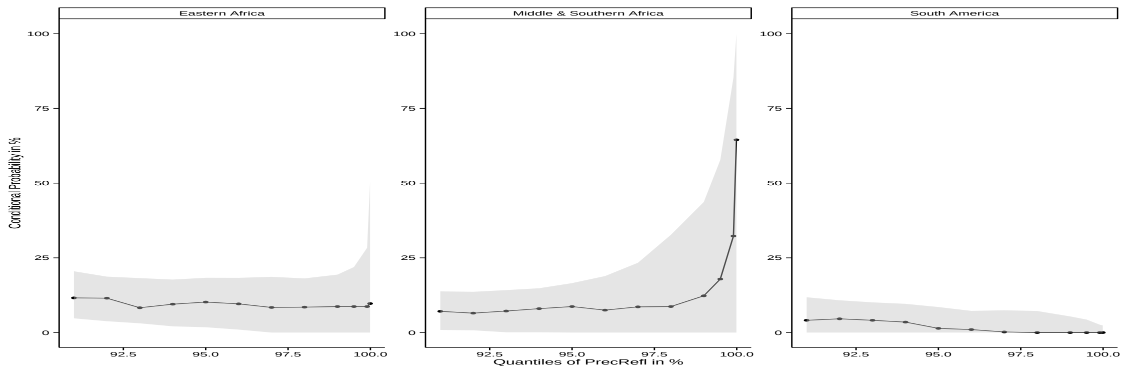

Figure 10: *Point estimates and 95 % confidence intervals of the conditional probability $P(YieldRefl > qu_{YieldRefl}|PrecRefl > qu_{PrecRefl})$, where $qu_{YieldRefl}$ is always set as the 90^{th} quantile of the variable YieldRefl and $qu_{PrecRefl}$ is the 91^{st} to $99{,}99^{th}$ quantile of the conditioning variable PrecRefl. Estimation is done using wheat data from 1961 to 2002. The conditional probability plots of the regions Western Africa, South & South-Eastern Asia & Melanesia and Central America & Caribbean are not shown as the sample of the region does not contain sufficient observations to evaluate the conditional probabilities. The conditional probabilities and/or the lower confidence interval bounds are equal to 0.0000, which is the case in Middle & Southern Africa, South America and for high values of the threshold of the conditioning variable $PrecRefl$ in Eastern Africa.*

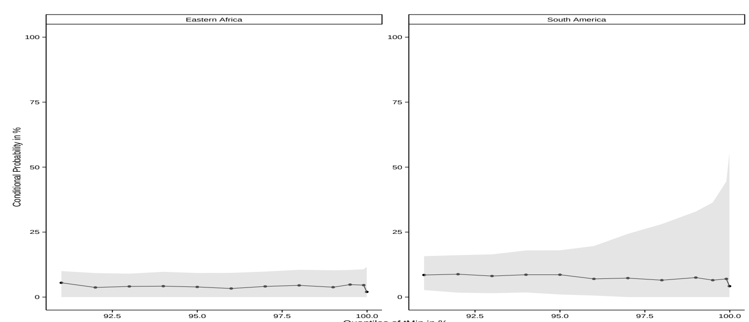

Figure 11: *Point estimates and 95 % confidence intervals of the conditional probability $P(YieldRefl > qu_{YieldRefl}|tMin > qu_{tMin})$, where $qu_{YieldRefl}$ is always set as the 90^{th} quantile of the variable YieldRefl and qu_{tMin} is the 91^{st} to $99{,}99^{th}$ quantile of the conditioning variable tMin. Estimation is done using wheat data from 1961 to 2002. The conditional probability plots of the regions Middle & Southern, Western Africa, South & South-Eastern Asia & Melanesia and Central America & Caribbean are not shown as the sample of the regions does not contain sufficient observations to evaluate the conditional probabilities. In all plotted regions lower confidence interval bounds and/or conditional probabilities are equal to 0.0000 for most thresholds of the conditioning variable.*

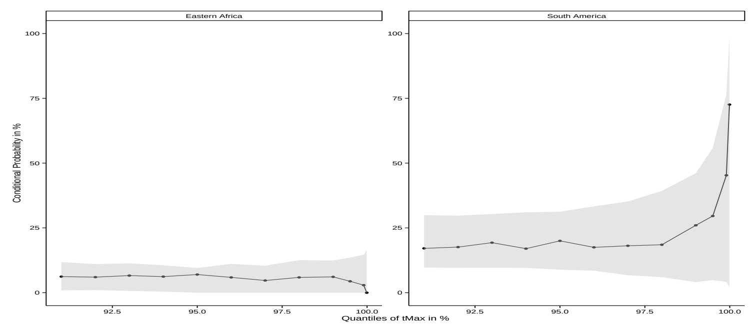

Figure 12: *Point estimates and 95 % confidence intervals of the conditional probability $P(YieldRefl > qu_{YieldRefl}|tMax > qu_{tMax})$, where $qu_{YieldRefl}$ is always set as the 90^{th} quantile of the variable YieldRefl and qu_{tMax} is the 91^{st} to $99{,}99^{th}$ quantile of the conditioning variable tMax. Estimation is done using wheat data from 1961 to 2002. The conditional probability plots of the regions Middle & Southern, Western Africa, South & South-Eastern Asia & Melanesia and Central America & Caribbean are not shown as the sample of the regions does not contain sufficient observations to evaluate the conditional probabilities. In Eastern Africa lower confidence interval bounds are equal to 0.0000. On the other side, conditional probabilities show a steep increase but with widening confidence interval for extreme values of tMax in South America.*

Conditional Probabilities Soy

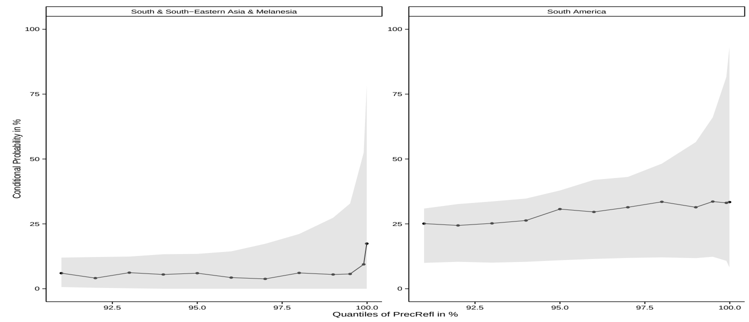

Figure 13: *Point estimates and 95 % confidence intervals of the conditional probability $P(YieldRefl > qu_{YieldRefl}|PrecRefl > qu_{PrecRefl})$, where $qu_{YieldRefl}$ is always set as the 90^{th} quantile of the variable YieldRefl and $qu_{PrecRefl}$ is the 91^{st} to $99{,}99^{th}$ quantile of the conditioning variable PrecRefl. Estimation is done using soy data from 1961 to 2002. The conditional probability plots of all regions, except South America and South & South-Eastern Asia & Melanesia, are not shown as the sample of the regions does not contain sufficient observations to evaluate the conditional probabilities. Note that in South & South-Eastern Asia & Melanesia lower bounds of the confidence interval are equal to 0.0000.*

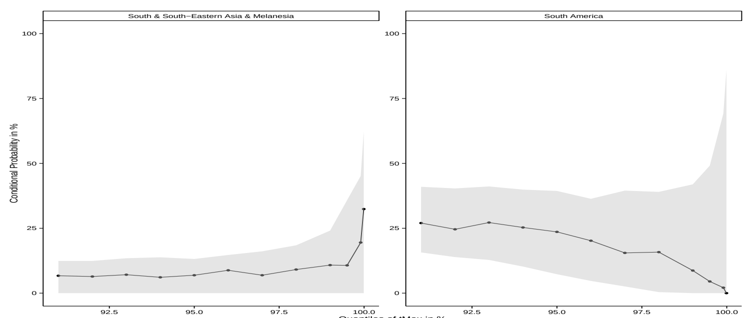

Figure 14: *Point estimates and 95 % confidence intervals of conditional probability $P(YieldRefl > qu_{YieldRefl}|tMax > qu_{tMax})$, where $qu_{YieldRefl}$ is always set as the 90^{th} quantile of the variable YieldRefl and qu_{tMax} is the 91^{st} to $99{,}99^{th}$ quantile of the conditioning variable tMax. Estimation is done using soy data from 1961 to 2002. The conditional probability plots of all African regions and Central America & Caribbean are not shown as the sample of the regions does not contain sufficient observations to evaluate the conditional probabilities. Note that in South & South-Eastern Asia & Melanesia lower bounds of the confidence interval are equal to 0.0000. Interestingly, in South America the conditional probability sharply decreases with widening confidence intervals for high thresholds of the conditioning variable.*

Conditional Probabilities Barley

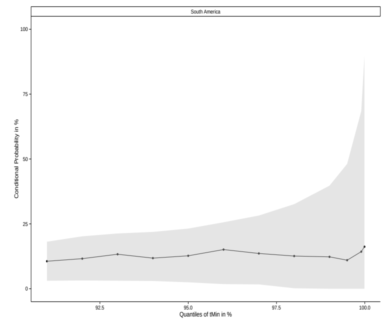

Figure 15: *Point estimates and 95 % confidence intervals of the conditional probability* $P(YieldRefl > qu_{YieldRefl}|tMin > qu_{tMin})$*, where* $qu_{YieldRefl}$ *is always set as the 90*th *quantile of the variable YieldRefl and* qu_{tMin} *is the 91*st *to 99,99*th *quantile of the conditioning variable tMin. Estimation is done using barley data from 1961 to 2002. The conditional probability plots of all African regions, South & South-Eastern Asia & Melanesia and Central America & Caribbean are not shown as the sample of the regions does not contain sufficient observations to evaluate conditional probabilities. Conditional probabilities and/or lower confidence interval bounds are equal to 0.0000 for high thresholds of the conditioning variable for both plotted regions.*

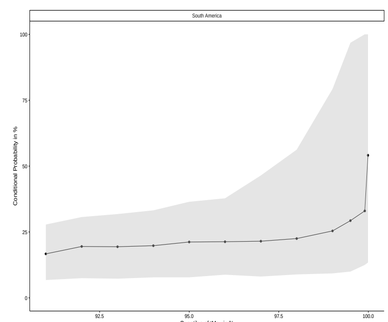

Figure 16: *Point estimates and 95 % confidence intervals of the conditional probability* $P(YieldRefl > qu_{YieldRefl} = 90\%|tMax > qu_{tMax})$*, where* $qu_{YieldRefl}$ *is always set as the 90*th *quantile of the variable YieldRefl and* qu_{tMax} *is the 91*st *to 99,99*th *quantile of the conditioning variable tMax. Estimation is done using barley data from 1961 to 2002. The conditional probability plots are not shown, except for South America, as the sample of the regions does not contain sufficient observations to evaluate conditional probabilities.*