



FACCE MACSUR

XC8 Extreme events - Final report

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Summary

Following a MACSUR Workshop a joint working paper preliminary titled "More than a change in crop production: metrics and approaches to understand the impacts of extreme events on food security" is now in an advanced stage.

A conference paper based on an M.Sc. thesis by Christoph Buschmann, titled "A model-based economic assessment of future climate variability impacts on global agricultural markets" has been presented and the International Conference of Agricultural Economists, 2015. We are working on a journal publication at the moment.

Based on a B.Sc. thesis by Patrick Jeetze, we have submitted an abstract and held a presentation at the GlobalFood Symposium 2017, 28-29 April 2017 at Georg-August-University of Goettingen, Germany. Title: "Implications of future climate variability on food security: A model-based assessment of climate-induced crop price volatility impacts" We are currently working on a journal publication on this.

Finally, we contributed one section to MACSUR's Research Gap Report (H0.1-D).



A model-based economic assessment of future climate variability impacts on global agricultural markets

By Christoph Buschmann, Hermann Lotze-Campen, Susanne Rolinski and Anne Biewald

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Abstract

Climate change not only entails gradual changes, but also climate variability is predicted to increase. Extreme weather events are expected to affect food security, among other things because yield losses lead to rising food price volatility. We project the potential effect of heat-stress induced yield losses on food price volatility and global economic welfare. For this purpose we use a non-linear partial equilibrium trade model with which we assess global maize, rice, soy and wheat markets. Maize and rice are affected the most, with partially dramatic price volatility increases. In the case of soy, the increase is lower, but still considerable. For wheat, results are mixed. Depending on the scenario, price volatility slightly decreases or significantly increases. Consequences for global economic welfare also strongly depend on the scenario. Losses either increase moderately or they about double.

Keywords

JEL codes: Q02, Q11, Q54



1. Introduction

Climate change not only entails gradual changes of climate elements such as air temperature and precipitation, but also changes in their variability. Extreme weather events like heat waves or floods are predicted to increase both in their intensity and frequency. These extreme events are expected to affect food security, among other things because yield losses lead to rising food price volatility.

However, despite a great number of studies projecting climate change induced long-run food price trends, there have been only few scientific examinations of changing price volatility risks. With the aim of contributing to this under-explored area of research, the present article assesses to what extent future climate variability might impact price volatility on global agricultural markets.

At first, a literature review (chapter 2) summarizes current studies projecting future extreme weather events and yield variability. Further, the chapter points out the multitude of factors influencing price volatility on global agricultural markets. Chapter 3 presents the methodology of the global partial equilibrium trade model with which we assess the research question. The model initially reproduces world market price fluctuations of wheat, maize, rice and soybeans that occurred between 1961 and 2009 (*baseline scenario*). This simulation then serves as a basis for what-if scenarios projecting future price volatility that results from predicted heat stress for crops. The model relates to wheat, maize, rice and soybean markets because of the four crops' high importance for global food supply. Together they amount to more than 40% of human calorie intake (FAOSTAT, 2014). Wheat is the most important grain in temperate regions; maize is the major staple food in parts of Africa and it is the most important raw material for biofuel production in the United States. Rice is the main staple food through most of Asia and soybeans are important both as an animal feedstock and to produce vegetable oil.

Chapter 4 presents model results: world market price fluctuations for different future what-if scenarios in comparison to the *baseline scenario*. In addition the chapter presents welfare changes on a global level and in different world regions. Finally, results are discussed and the whole article is concluded in chapters 5 and 6.

2. Literature review

2.1. Future climate and yield variability

The literature review at first summarizes current studies projecting future extreme weather events and yield variability. Extreme weather events are for example heat waves, precipitation extremes, droughts, heavy storms or extreme sea levels. But we concentrate on extremes concerning temperature, droughts and precipitation since our trade model's future scenarios relate to heat stress.

According to the Intergovernmental Panel on Climate Change (IPCC)'s Fifth Assessment Report it is "virtually certain" (99-100% probability) that more hot and less cold extremes are expected due to global temperature rise (Collins et al., 2013, p.1065). However, not only the severity of temperature extremes is presumed to change but also their length and frequency. Following the IPCC report it is "very likely" (90-100% probability) that heat waves will be longer and occur more often (Collins et al., 2013, p.1066). Sillmann et al. (2013, p. 2476 ff) project the strongest increases of warm spells for the tropics where temperature variability is low. This means that for the tropics the rise of the mean temperature has greater consequences for the tails of the temperature distribution than for the extra-tropics.

Coumou and Robinson (2013) also project the lengthening of future warm spells. They analyze extremes exceeding thresholds at different levels defined by local historically observed natural variability (sigma). This variability is expressed in standard deviations and relates to the reference period 1951-1980. Temperatures that exceed these standard deviations by three times (3-sigma events) or five times (5-sigma events) respectively are regarded as proxies for heat waves. Projections refer to the low emission scenario RCP2.6 and the high emission scenario RCP8.5. Similarly to Sillmann et al. the tropics are most severely affected, which Coumou and Robinson also attribute to the low natural temperature variability. Here even under the low emission scenario, 3-sigma events are expected to be the standard with about half of the summer months affected. But also 5-sigma events will not be unusual since they affect about 20% of the summer months. Extra-tropical regions will only partially experience 3-sigma events in the low emission scenario, for example Western Europe with about 20% of the summer months. However, under the high emission scenario also large parts of the extra-tropics (Mediterranean, Middle East, parts of Western Europe, Central Asia and the US) are projected to experience temperatures above 3-sigma events frequently with more than 70% of the summer months affected. Furthermore 5-sigma events will occur on a regular basis (Coumou and Robinson, 2013, p. 2ff).

Moreover the variability of precipitation events is assumed to experience some changes. Compared to temperature variability, projections are less robust on a regional scale concerning the extent of changes. But their direction and the large geographical patterns are consistent among climate models. More intense precipitation in the wet seasons is expected for the most part of land areas, particularly in the Northern hemisphere and in the global monsoon regions. At the same time, most of the model simulations project longer dry periods for the subtropics and the semi-arid regions of the mid-latitudes (Collins et al., 2013, p. 1082 ff).

The anticipated changes in extreme weather events are expected to have an impact on yield variability which could be even more of a threat to global food security than changes of mean crop yields. This is because adaptation to extreme weather events is more difficult or even impossible (Gornall et al., 2010, p. 2975). For example droughts can cause plants to wither or heavy rainfall may bring about water

logged soils and soil erosion. However the quantification of extreme events' impact is more difficult than modeling long-term mean trends. That is why only few studies project future yield variability. Some of these studies' results are summarized in the IPCC's Fifth Assessment Report (Porter et al., 2014, p.80). They are expressed in percentage changes towards a baseline period ¹ in coefficient of variation (CV) of yield. All in all results are mixed and they refer to different sites, mostly in China. Regarding wheat, the highest CV increases are 50% (for the 2080's). But another study projects CV decreases of up to 25% in the year 2020 and the 2050's. In the case of maize the CV is predicted to increase up to 150%, for rice up to 300% (both in the 2080's). For soy there are no results projected.

Out of the different weather extremes inducing yield variability we take a closer look at the impact of heat stress because it is one of the best researched extremes. We examine the results of Teixeira et al. (2013), which is the basis for one of our future model scenarios. The study looks at the impact of future crop exposure to critical high temperatures during the plant's reproductive period. Plants are particularly sensitive to high temperatures during their reproductive period when heat stress for example "reduces the number of flowers/plant, impairs pollen tube development, limits pollen release and diminishes both pollen viability and flower fertility" (Teixeira et al., 2013, p. 207). In consequence, final yields can largely be reduced or totally lost.

Teixeira et al. project a heat stress intensity index on a global scale both for the period 1971-2000 (baseline climate) and for the period 2071-2100 under the A1B emissions scenario for wheat, maize, rice and soybeans. The index reflects the number of reproductive days over a critical temperature threshold and the intensity of heat stress. Regarding rice, high heat stress intensity is already projected in the baseline climate especially in South Asia. Heat stress increases in the future climate are expected in Central and East Asia, North America and Central South America. Among the crops under consideration, wetland rice is most severely affected by heat stress. This is because with irrigation, farmers grow the crop in warm periods with stronger solar radiation in order to obtain the highest yields. But in these periods the risk of overlaps between critical high temperatures and the reproductive phase is the highest. In the case of maize, however, projected heat stress for the baseline climate is low. It rises considerably in the future climate especially in Northern India, the Sahel region and Central South America. For soy, low to median results are projected under the baseline climate. Increases occur in Central North America, Brazil, Central and East Asia. Regarding wheat, Central Asia, East Asia and North America are affected, but only little changes are predicted between the baseline and the future climate. In some parts of North America and Central Asia the situation even improves in the A1B scenario. For a minor part this is due to a decrease in areas affected. For the most part, however, the decline is the result of changing crop cycle lengths and sowing dates because of a changing seasonal climate leading to a shift of the reproductive

¹Baseline periods differ in the different studies, but they are all in the second half of the 20th century.

period. This shift in turn potentially reduces the intensity and frequency of heat stress (Teixeira et al., 2013, p. 208ff).

A different paper by Gourджи et al. (2013) projects the impact of future crop exposure to heat stress for 2050. Their results are partly similar to those of Teixeira et al.. Main differences exist for maize where Gourджи et al. predict more affected areas for example in South Africa, Latin America and Southern Europe. In the case of soy, however, less areas are affected. Moreover Gourджи et al. do not expect the partly decline of heat stress for wheat. Considering rice, few more areas in West Africa and Latin America are anticipated to suffer from critically high temperatures (Gourджи et al., 2013, p. 5).

Both studies predict the highest heat stress increases for rice and maize. Geographically both papers expect heat stress hot-spots mainly in Central, South and East Asia. Additionally both North and South America are partly affected. This means that hot-spot regions overlap with important agricultural areas such as Eastern China, the Northern United States, South-Western Russia and South Canada (Teixeira et al., 2013, p. 208ff) (Gourджи et al., 2013, p. 5,9).

2.2. Crop price volatility

Changing yield variability is expected to impact future crop price volatility. However, price formation is influenced by numerous other factors. With the aim of briefly introducing some of these factors, we exemplary take a brief look at the reasons for the two great food price crises in the early 1970's and in the late 2000's. The crisis in the 1970's was rooted in an extensive drought in 1972 that severely diminished rice crops in South-East Asia. Additionally wheat and maize yields have been negatively affected by the drought, leading to price jumps. Effects on the rice market further intensified because Thailand - the main global rice exporter - stopped its exports in 1973. In consequence the world rice market came to a standstill and experienced an enormous price increase in 1974 when it reopened (Timmer, 2010, p. 2).

The food-price crisis in the late 2000's did have various causes. Following Headey and Fan (2008) there have been both crop-specific and general developments that together led to a "near perfect storm" (p. 382). Starting with crop-specific explanations, the rice price jump was mainly connected with export restrictions. In the case of rice, they usually have an immediate effect on world market prices because - in comparison to other staple crops - only a small share of the global rice production is traded. That is why the free world market is more volatile than other crop markets (Gilbert and Morgan, 2010, p. 3030). In 2007, first India imposed export restrictions reacting on a world price increase. This restriction has triggered a chain reaction on the world market. Prices increased rapidly so that Vietnam, Cambodia and Egypt also introduced export bans which in turn intensified the price surge (Headey and Fan, 2008, p. 379).

The maize price increase since the mid-2000's has been mainly attributed to the enlarging production of biofuels. To a lesser extent the connection between increasing biofuel demand and rising prices also exists for soybeans since they are used for the production of biodiesel. Regarding wheat there have been poor harvests in 2006 in the United States and Australia caused by weather shocks. But overall, global wheat production only declined by 5% from 2006 to 2007, which is within the normal range of production fluctuation. However, this small decline may still have triggered price increases because of low wheat stocks and a sensitive market (Headey and Fan, 2008, p. 379f).

General explanations for the 2008 food price crisis include firstly the rising oil price, which does have an impact on crop prices because it is an important production factor. Oil is used for the operation of agricultural machinery, for crop transportation and for fertilizer production. Secondly the depreciation of the U.S. dollar from 2002 to 2007 meant that U.S. agricultural exports became cheaper for the rest of the world, leading to a higher demand on world agricultural markets. This stiffened price increases (Headey and Fan, 2008, p. 380f).

Other more controversial explanations for the crisis are the decline in stocks and financial speculation. Stocks have declined in the 2000's especially for wheat and maize, but according to Headey and Fan there is no convincing argument that declines could have set off the crisis. However, other authors such as Gilbert and Morgan (2010) assume that low stocks may still have amplified the price movements. Regarding financial speculation both studies presume that even if their rise coincided with price increases, there is no causal relationship. But similarly to the decline in stocks, financial speculations may have exacerbated price jumps (Headey and Fan, 2008, p. 377 ff) (Gilbert and Morgan, 2010, p. 3028 f).

Overall this brief retrospective view on the two greatest food price crises since the 1960's demonstrates that weather is only one of many factors influencing crop price volatility. But weather extremes and their impact on yield variability are expected to increase considerably with climate change. Thus the question arises to what extent increasing weather extremes will influence future crop price volatility. The quantification of this effect has been hardly examined on a global scale (Gilbert and Morgan, 2010, p. 3029) (Willenbockel, 2012, p. 4). One exception is Willenbockel (2012) who calculates the potential impacts of a number of extreme weather event scenarios in 2030 for each of the main exporting regions for rice, maize and wheat. Here fore he simulates extreme weather induced productivity shocks, that have been observed in the past. According to Willenbockel's results, a drought in North America comparable to the historical drought in 1988 would temporarily lead to a maize price increase of 140%. For wheat the price increase would be 33%.² Moreover, if bad harvests occur simultaneously in India and East Asia, the rice price will increase by about 26% (Willenbockel, 2012, p. 4, 27f).

²Prices refer to average world market export prices.

Tran et al. (2012) also project climate change induced commodity price volatility and price level on a global scale. For this purpose they forecast 1600 hypothetical yield paths from 2000 to 2080 for wheat, maize, rice and soybeans and then they aggregate the four series into one series of global caloric yield. Thereafter they simulate 1600 stochastic-equilibrium price paths by using a dynamic competitive storage model and compare these price paths under climate change with a baseline path of stable prices. According to the results, world crop price volatility will increase fivefold between 2000 and 2080, i.e. the standard deviation of the simulated price paths increases fivefold in this period of time.

But what has not been examined so far is the overall change of the frequency distribution of price fluctuations induced by increasing extreme weather events. This change is what we will project with our market model in different what-if future scenarios, separately for each of the world's four most important crops.

3. Methodology and data

3.1. Description of the model

The aim of the model is to initially reproduce world market price fluctuations of wheat, maize, rice and soybeans like they actually occurred between 1961 and 2009. This chapter first of all explains the technical functioning of the model. Chapter 3.2 describes how fluctuations are created. Thereafter chapter 3.3 explains how the model is calibrated so that it sufficiently corresponds to the real price fluctuations. The reproduction of past price fluctuations then serves as a basis for future scenarios which are described in chapter 3.4.

For calculations of the market model, we use a General Algebraic Modeling System (GAMS) implementation of a simple non-linear partial-equilibrium trade model. It includes four agricultural commodities (wheat, maize, rice, soybeans) and covers ten world regions (Sub-Saharan Africa (AFR), Centrally-Planned Asia (CPA), Europe (EUR), Former Soviet Union (FSU), Latin America (LAM), Middle East and North Africa (MEA), North America (NAM), Pacific member states of the Organisation for Economic Co-operation and Development (PAO), Pacific Asia (PAS), South Asia (SAS)).³

Exogenous model inputs are first of all supply and demand quantities ($q_{i,j}^{s0}$, $q_{i,j}^{d0}$) for each commodity (i) and region (j). Data base on the year 2005 and they are taken from the Food and Agriculture Organization of the United Nations (FAO) (FAOSTAT, 2013). Secondly real world market prices (p_i^0) for each commodity are from the World Bank (The World Bank, 2013). Prices are measured in U.S. dollar per ton and also refer to 2005. Thirdly supply and demand elasticities ($e_{i,j}^s$, $e_{i,j}^d$) for each commodity and region

³Figure 1 shows the geographic distribution of the applied model regions.

are provided by the Food and Agricultural Policy Research Institute (FAPRI) (FAPRI, 2013).

The basis of the market model are isoelastic supply and demand functions, which are power functions with the constant elasticity as exponent and with the price as base. If these are further multiplied by the supply constant $a_{i,j}$ or the demand constant $b_{i,j}$, the supply quantity $q_{i,j}^{s0}$ or the demand quantity $q_{i,j}^{d0}$ can be determined respectively. The supply and demand constants are technical terms that influence the slope of the functions.

$$q_{i,j}^{s0} = a_{i,j} * (p_i^0)^{e_{i,j}^s}, \forall i = 1, \dots, n \quad \forall j = 1, \dots, m \quad (1)$$

$$q_{i,j}^{d0} = b_{i,j} * (p_i^0)^{e_{i,j}^d}, \forall i = 1, \dots, n \quad \forall j = 1, \dots, m \quad (2)$$

with $e_{i,j}^s > 0$ and $e_{i,j}^d < 0$

In a first stage, the model creates an initial market situation for each commodity (i) and region (j) based on the exogenously given elasticity data and the 2005 data for supply and demand quantities and world market prices. Subsequently consumers' utility and producers' costs, as well as producer and consumer surplus and welfare are calculated.

After the creation of the initial market situation, we simulate supply and demand shocks by introducing exogenous shift parameters per commodity and region into the supply and demand functions. The shifts are expressed in percentages. Hence for example a supply shift (s_shift) of -0.20 stands for a 20% decrease in production, leading to a shift of the supply curve. The shift calculation will be described in chapter 3.2.

$$q_{s_{i,j}} = a_{i,j} * (1 + s_shift_{i,j}) * (p_i)^{e_{s_{i,j}}}, \forall i = 1, \dots, n \quad \forall j = 1, \dots, m \quad (3)$$

$$q_{d_{i,j}} = b_{i,j} * (1 + d_shift_{i,j}) * (p_i)^{e_{d_{i,j}}}, \forall i = 1, \dots, n \quad \forall j = 1, \dots, m \quad (4)$$

The difference to the initial market situation is that both supply and demand quantities ($q_{s_{i,j}}$, $q_{d_{i,j}}$) and world market prices (p_i) are now endogenous variables and not exogenously fixed values such as $q_{i,j}^{s0}$, $q_{i,j}^{d0}$ and p_i^0 . The endogenous variables are used to find a new market equilibrium by means of a non-linear optimization process. The goal of this process is to maximize welfare.

After having computed the new market equilibrium with new supply and demand quantities and prices, the new producer and consumer surplus and welfare are calculated. Finally price and welfare changes between the initial and the new market situation are determined. They represent the key output of the model and the whole article.

3.2. *Implementation of supply and demand shifts*

3.2.1. Approach A

The generation of shifts, which serve as model input, is based on global supply and demand data (1961 to 2009) from FAOSTAT (2013). They are aggregated on the model regions described above. Starting with the production data, we create a nine-year moving average for each of the four crops and each region. For methodological reasons we choose a moving average with an odd number of years. The moving average is only calculated for 41 years because for the first and last few years of the time series (1961-2009) not enough data are available to calculate the average. For example for 1961 one cannot determine an average since there are no data for 1959 and 1960.

Our aim is to generate supply shifts, that is why we want to simulate short term supply behavior. In consequence we are not interested in the long-term trend, i.e. the nine-year moving average, but in the deviations from this average. For this purpose we determine the difference between the average and the production data.

In the next step, we test with the Shapiro-Wilk test, explained in Royston (1995), whether the deviations are normally distributed. If this is the case, we create a Gaussian distribution based the deviations' mean and standard deviation. Then one value is randomly drawn from the Gaussian distribution. This value serves as a supply shift for the market model. By using the Gaussian distribution, the pool of possible shifts is much bigger in comparison to drawing one value out of the observed deviations. However, if data are not normally distributed, we draw one value out of the 41 observed deviations.

Both changes in production and demand behavior and their interaction determine the formation of prices. That is why demand deviations are equally generated and inserted into the model. Demand behavior is represented by domestic supply data from FAOSTAT (2013). Domestic supply data are the balance of

Production - Exports + Imports + Changes in storage.

3.2.2. Approach B

In the above described approach A the supply and demand shifts for each crop and region are randomly drawn from different years. For instance the supply shift for wheat in AFR could be from 1975, whereas the demand shift for maize in CPA is from 1990. Thus causalities and patterns between regions, crops and supply and demand behavior are not covered in this approach.

That is why we use approach B as sensitivity analysis, where all supply and demand shifts for all regions and the four crops are drawn from the same year. For example supply shifts for wheat in AFR and demand shifts for rice in PAS are drawn from 1988. Additionally shifts are only drawn from the observed deviations from nine-year moving average and there are no drawings from a Gaussian distribution. So possible influences - for example between regions - are included, at least those that occurred within one year.

3.3. Calibration of the model

In the next step, randomly drawn supply and demand shifts are implemented into the market model according to the explanations above. After implementing the shifts, a new world market price for each crop is generated and the difference between the new and the initial market price is determined (see chapter 3.1). The process is repeated 1000 times, each time with a new drawing of supply and demand shifts so that a distribution of 1000 simulated world market price deviations comes into being. Then we compare these deviations with with real world market price deviations, i.e. deviations from nine-year moving average based on real world market prices from 1961-2009 (The World Bank, 2013). The Kolmogorov-Smirnov test (KS-test), explained in Wang et al. (2003), shows that simulated and real price deviations do not match sufficiently.

The observed deviations from nine-year moving average based on real prices reflect relative short-term behavior. However, in our market model, changes in supply and demand are influenced by elasticity data from FAPRI that refer to long-term market behavior. This difference is assumed to be the reason for the mismatch between simulated and observed price deviations. In order to adjust the market model, we reduce both supply and demand elasticities so that they reflect short-term behavior. We multiply the initial elasticity data for wheat by 0.3, maize by 0.4, rice by 0.25 and soybean by 0.5. In the case of rice supply, calibration by simply reducing elasticities does not lead to a sufficient match between observed and simulated data. This is not surprising since the observed rice price development is more volatile than the other crops' price development. We additionally have to calibrate the model by using a multiplier of the supply shifts, so that rice supply shifts are multiplied by 1.8 in each of the 1000 models runs. We use the same calibration parameter for model variations with approach A and B. The KS-test now shows positive results, so that observed and simulated distributions match sufficiently.

To conclude, by means of the calibrated market model we are now able to reproduce the observed price changes between 1961 and 2009 adequately so that we can use this simulation as our *baseline scenario*. It implicitly simulates those effects that had an influence on crop price volatility in the past: among others oil price, currency fluctuations and political interventions such as export restrictions. This scenario serves

as a basis for the projection of future developments. The next chapter explains two scenarios simulating the effect of future yield variability on world market prices and global welfare.

3.4. Implementation of future scenarios

3.4.1. Main scenario

The main scenario (*scenario_main*) refers to the normalized production damage index (f_{dmg}) results calculated in Teixeira et al. (2013) that has been introduced in chapter 2.1. The index is a proxy for the extent of produce loss caused by heat stress. Since it is normalized, with values between 0 and 1, it only serves as a relative measure to compare different situations. Global f_{dmg} results show the relative extent and annual variability of heat stress induced yield losses during the projected 30-year baseline period (1971-2000) and the 30-year future period (2071-2100) under A1B emissions scenario.⁴ Yield variability increases for maize, rice and soybeans. Maize is affected the most, which is in accordance with the projected great difference between heat stress intensity index (f_{HS}) levels in the baseline and in the A1B scenario. In the case of wheat, global yield variability decreases in the A1B scenario, which is attributed to the decline of heat stress variability in certain regions such as Central Asia and North America as explained in chapter 2.1 (Teixeira et al., 2013, p. 211f).

For the modelling of *scenario_main* we are particularly interested in the full range of the variability distributions since we want to simulate the effect of extremes. That is why we look at the distance between the 5th and 95th percentile of global f_{dmg} results for each 30-year period in the baseline climate and the future climate.⁵ By comparing the distances between the two 30-year periods, the variability's increase and decrease can be read respectively. Table 1 lists the distances between the 5th and 95th percentiles in columns 4 and 7 and shows the percentage increases or decreases in column 8.

Increases are partly very high, particularly for maize with about 1650%. The literature review in chapter 2.1, however, has shown that the few studies concerned with yield variability indicate lower future changes. But these changes are given for a CV. That is why we need to calculate a CV for the results of Teixeira et al. in order to make them comparable. For this purpose we firstly require a measure representing yield. Since the yearly production damage values f_{dmg_n} range between 0 and 1 and represent global production damage, we simply calculate $1-f_{dmg_n}$. Thus these values stand for global yield in each year. In the second step we calculate the CV of these values for the baseline period and the future period. Thirdly the percentage change of CV between the two time periods is determined. Calculations and results are

⁴See Figure 7, p. 211 in Teixeira et al. (2013). Variability is indicated by the distance between the 10th and 90th percentiles (whiskers) in the boxplot depiction. The calculations' methodology is explained in p. 208.

⁵The global f_{dmg} values for each year have been provided by Teixeira.

given in Table 2. Results confirm the impression that the variability changes given in Teixeira et al. are unusually high. Increase of CV for maize is 2080%, whereas the highest CV change in the literature review is 150%. For rice the difference is a bit less extreme: the calculated CV increase is 1230% in comparison to 300% in the literature review. In the case of wheat, the literature review gives a range of changes between a decrease of 25% and an increase of 50%. The calculated CV decrease based on Teixeira et al.'s results is about 60%. For soy the CV increase is about 600% with no comparative value from the literature review.

The remarkably high values in Teixeira et al. may be attributed to some pragmatic simplifications in their methodology. Heat stress intensity (f_{HS}) calculation assumes a linear relationship between the degree of daytime temperature and heat stress intensity for the plant, where interactions are in fact more complex and non-linear. Moreover production damage calculation (f_{dmg}) by multiplying a grid cell's potential yield by the heat stress intensity index is a rough representation of reality (Teixeira et al., 2013, p. 208). For these reasons, variability changes given in Table 1 (column 8) only serve as clue for *scenario_main*. Against the background of the above given arguments and the comparison with the results from the literature review, less severe variability changes can be assumed. Therefore values are reduced to one third of the initial values as given in column 9 of Table 1. These reduced values are used for the calculations in *scenario_main*.

3.4.2. Alternative scenario

The alternative scenario (*scenario_alt*) also relates to heat stress, but the effect on yields is translated in a qualitative way. It draws on changes in spatial patterns of heat waves for 2080 to 2099 (A1B emissions scenario) towards 1980 to 1999 projected by Tebaldi et al. (2006) and presented in the IPCC's Fourth Assessment Report (IPCC, 2007, p. 786f). The changes are expressed in standard deviations and divided into three categories given in column 1 of Table 3(a). These categories are then assigned to three different assumed increases in yield variability (column 2). For example a standard deviation of 3.75 and higher is assigned to a 100% increase in yield variability. Finally model regions are allocated to the different levels of yield variability increases in accordance with the projected standard deviations in the regions (see Table 3(b)). The lowest impacts are observed for PAS, corresponding to a 25% increase in yield variability. Increases of up to 50% are expected in AFR, EUR, FSU, LAM and PAO, whereas MEA, NAM and SAS will face heat waves implicating a 100% increase in yield variability.

3.4.3. Technical implementation of future scenarios

The technical implementation of the future scenarios works just like the implementation of the *baseline scenario* described in chapters 3.2 and 3.3. The only difference is that the supply shifts are now increased by a certain percentage factor. For example in *scenario_main* we assume that the variability of maize production will increase by 549% (see Table 1, column 9) in comparison to the *baseline scenario*. So the supply shifts referring to maize are increased by 549% in each of the ten model regions. In some cases the increased negative shifts become lower than -100%. For instance if an initial shift of -20% is increased by 549%, the final shift will be -130%. This does not make sense because it would mean that the supply quantity becomes negative. That is why in these cases the shifts are set to -100%. For wheat, we assume a decline in production variability by 14.27% so that the corresponding supply shifts are reduced. Just the same as in the *baseline scenario* we run the model 1000 times, only that now the supply shifts for wheat, maize, rice and soy are modified. Because of the modified supply shifts, a new market equilibrium and new price changes are projected in each of the 1000 model runs so that a new frequency distribution of price changes comes into being.

The technical implementation of *scenario_alt* is similar, only that now supply shifts are modified for each world region. For example for AFR we assume an increase of production variability of 50% (see Table 3b). So the supply shifts referring to AFR are increased by 50% for wheat, maize, rice and soybean. Again we run the model 1000 times and a new frequency distribution of price changes is created.

4. Results

4.1. Price changes

Results are presented in the form of frequency distributions of price changes for the *baseline scenario* and the two future scenarios. They refer to both approach A and B of drawing supply and demand shifts. The figures additionally show the 75th, 90th and 95th percentiles as we are most interested in the distributions extreme values.

4.1.1. Wheat

Figure 2a shows the frequency distribution of price changes in the *baseline scenario* (approach A), where changes of up to 51% occur. With a probability of 95% they are not higher than 18%. In *scenario_main* (Figure 2b) the maximum price change is a mere 44% because a future decrease in wheat yield variability

is assumed. The 95th percentile is at about 15%. Notably in *scenario_alt* (Figure 2c) - assuming an increase in variability - the highest price change is 81% and the 95th percentile is more than two times greater than in *scenario_main* with 35%.

Frequency distributions projected with approach B (Figures 2d, e, f) have a distinctly different shape than the ones projected with approach A. Firstly price changes are less diverse. Out of the 1000 model runs only 41 different price changes are projected, whereas with approach A there are nearly 1000 different price changes. Secondly results are more irregular. For example in the *baseline scenario* one can observe a very high frequency (162) of price changes of -7% and -6%, whereas all other price changes are much less frequent. Thirdly results are not as broad. For instance all maximum price changes are significantly smaller than the maximum price changes projected with approach A.

However, the 75th, 90th and 95th percentiles in the three scenarios (Figures 2d, e, f) are similar to those in Figures 2a, b, c depicting results for approach A. For example in *scenario_main* the 95th percentile lies at a price change of 13% and in *scenario_alt* it lies at 32% (with approach A: 15% and 35%).

4.1.2. Maize

With regard to results for maize (Figure 3), there are overall great differences between the *baseline scenario* and the two future scenarios. For example the price change value at the 75th percentile (approach A) increases 9 fold in *scenario_main* (45%) compared to the *baseline scenario* (5%). In *scenario_alt* it more than doubles from 5% to 11%. Especially results for *scenario_main* are high. In 10% of all cases, prices more than triple and in 5% of all cases, prices increase more than four times. The maximum price change is 2660%.

Regarding results for approach B, frequency distributions are again less broadly distributed and more irregular than with approach A. But overall, the 75th, 90th and 95th percentiles are similar.

4.1.3. Rice

Figures 4a and d depict the distributions of price changes for rice in the *baseline scenario*. In accordance with the observed high rice price volatility, these *baseline scenarios* have the broadest distributions in comparison to the other crops. Again we observe considerable increases between the baseline and the future scenarios. For example in the *baseline scenario* (approach A) the 75th percentile is at a price change of 4%, whereas in *scenario_main* it is at a price change of 47% and in *scenario_alt* it is at 21%.

Similarly to the results for maize, price changes are particularly high for *scenario_main* (Figure 4b). One

in every ten changes leads to a price increase of more than 140%. At every 20th change, the price more than triples. The maximum price increase is 1749%.

With approach B, increases between scenarios are similarly high. For instance at the 75th percentile, price changes between the *baseline scenario* and *scenario_alt* increase 4.8 fold with approach B (from 4% to 19%). With approach A the increase is 5.3 fold (from 4% to 21%).

4.1.4. Soybeans

For soy (Figure 5) price change increases between the *baseline scenario* and *scenario_main* are more modest than in the case of maize and rice. However, they are still considerably high. For instance for approach A, the 90th percentile increases from a price change of 19% to a price change of 54%, i. e. the value more than doubles. Results for *scenario_alt* are again more modest. For example the price increase at the 90th percentile is 36% .

When shift inputs have been drawn from the same year (approach B) (Figures 5d, e, f), price change increases between scenarios are more pronounced. For example the above mentioned price change between the *baseline scenario* and *scenario_main* at the 90th percentile not only doubles but nearly quadruples (from 10% to 38%).

4.2. Welfare changes

The productivity shocks projected in the two future scenarios also lead to changes in global and regional welfare. Global changes are depicted in Figure 6. Here, the 25th, 10th and 5th percentiles are in the center of interest since welfare changes are predominantly negative.

The differences between the *baseline scenario* and *scenario_main* are considerably high, whereas they are moderate between the *baseline scenario* and *scenario_alt*. For example in the *baseline scenario* projected with approach A the highest 10% of welfare losses are higher than 47 bn USD. However, in *scenario_main* the highest 10% are higher than 88 bn USD, so the percentile nearly doubled. In *scenario_alt* the highest 10% of losses are higher than 51 bn USD, which means only an increase of 8.5% towards the *baseline scenario*. Additionally *scenario_main* shows more extreme results, the highest loss is 382 bn USD and the highest gain is 108 bn USD. In contrast, results of *scenario_alt* merely range between a minimum of -126 bn USD and a maximum of 78 bn USD. To have a comparative value, the global gross domestic product (GDP) is 50895 bn USD (for 2010 in 2005 exchange rates), the world agricultural GDP is about 1578 bn USD (3.1% of GDP) (The World Bank, 2014a) (The World Bank, 2014b).

When looking at regional results (Table 4)⁶, South Asia (SAS) and North America (NAM) are the most affected.⁷ In SAS - including India - fluctuations increase the most, especially in *scenario_main*. The fifth percentile increases 3.8 times from a loss of 18.5 to 69.8 bn USD. This means a loss of 4.4% of the regional GDP in *scenario_main* in comparison to 1.2% in the *baseline scenario* (The World Bank, 2014b). In *scenario_alt* the fifth percentile increases by about 70% leading to a loss of 2% of the regional GDP. Changes in NAM are also high, since the 5th percentile increases 3.4 times in *scenario_main* and by 20% in *scenario_alt*, but this only amounts to 0.7% or 0.2% of the regional GDP (The World Bank, 2014b).

5. Discussion

5.1. Price and welfare changes

Price fluctuations for wheat decrease in *scenario_main* since according to Teixeira et al. (2013) wheat will overall be less affected by heat stress, leading to a decline in global yield variability. This is because in some important regions of cultivation, the crop's sensitive reproductive period may be shifted away from periods of high heat stress due to adaptation measures.

Regarding maize, price change increases for *scenario_main* are very high. This is overall in accordance with Teixeira et al.'s projections showing a low heat stress impact in the baseline climate and a drastic future heat stress increase both in the area affected and in intensity. However, there are some extreme outliers, for example the highest price increase is 2660%, i.e. the price increases more than 27 times. In order to understand how these extreme values may come about, one has to call to mind the methodology of *scenario_main* and the approach A of drawing shifts. In each of the 1000 model runs, supply shifts are randomly drawn and then increased by 549%. In consequence, severe supply shifts of up to -100% may come about. This is what leads to the above mentioned dramatic price increase of 2660%: the important maize cultivation regions EUR, LAM and NAM are affected by severe negative supply shifts from -72% to -100%. This leads a yield loss of 416 million tons which accounts for about 58% of the global maize supply (711 million tons in 2005) (FAOSTAT, 2013). With the dramatic and hypothetical assumption of more than 50% global yield loss, it becomes apparent that this extreme price increase and other comparably high values should be interpreted as hypothetical.

With regard to rice, the *baseline scenario* is most broadly distributed in comparison to the other crops. This is in accordance with the observed high rice price volatility. Price fluctuation increases towards

⁶For the sake of simplification, regional results have only been calculated with approach A.

⁷Figure 1 shows the geographic distribution of the applied model regions.

scenario_main are high, but overall not as high as in the case of maize. This is consistent with Teixeira et al.'s assumption that rice will be most severely affected by heat stress, because the risk of an overlap between critical high temperatures and the sensitive reproductive period is the highest. However, the future increase of heat stress impact is not as severe as in the case of maize, because rice is already much affected in the baseline climate.

In the case of soybeans, the increase of price fluctuations in *scenario_main* is more modest than the ones for maize and rice, which is consistent with Teixeira et al.'s heat stress projections. But the increase is still considerably high. For example the price change at the 90th percentile nearly triples towards the *baseline scenario* (approach A).

Scenario_alt works on the assumption that the yield variability of all crops increases by the same extent. Moreover, increases are 100% at the most. In consequence, price fluctuation increases for *scenario_alt* are more modest than the ones for *scenario_main* and the differences between the crops are much lower. But there are still some differences: in the case of wheat and soy, price fluctuations in the 95th percentile about double towards the *baseline scenario*, with regard to maize they increase 3.8 times and for rice they triple (approach A).

Results projected with approach B, which is considered as a sensitivity analysis, confirm those of approach A. Overall, percentiles and increases between scenarios are similarly high. However the distributions are not as diverse and broad since there are only 41 different solutions. This difference in result diversity can be attributed to the different ways of drawing shifts. With approach B only 41 different shift combinations are possible, because all shifts are drawn from the same year (see chapter 3.2). In consequence there are only 41 different results.

Generally, price change results are greater than the ones projected in Willenbockel (2012) (see chapter 2.2). The maximum maize price increase in Willenbockel is 140%. This is in the 87th percentile of *scenario_main* and in the 96th percentile of *scenario_alt* (approach A). For rice the difference is greater, since the maximum price increase of 26% in Willenbockel is in the 69th percentile of *scenario_main* and in the 78th percentile of *scenario_alt*. In the case of wheat, the results are close to each other. The maximum price increase in Willenbockel is 33%, which is in the 100th percentile of *scenario_main* and the 94th percentile of *scenario_alt*. The partial differences in the results make sense since Willenbockel refers to extreme weather events that occurred in the past and projects price volatility for 2030. The present article, however, refers to the impact of future heat stress that is expected for 2071-2100 (*scenario_main*) and 2080-2099 (*scenario_alt*).

Results by Tran et al. (2012, p. 25) indicate a confirmation of *scenario_main*. They show a fivefold increase of global crop price volatility (from 2000 to 2080) under climate change, i.e. the standard deviation

of the simulated price paths increases fivefold (see chapter 2.2). When comparing the standard deviation of price fluctuations in the *baseline scenario* with the one in *scenario_main*, we observe an increase by 11.4 times for maize, 6.5 times for rice and 2.5 times for soy. In the case of wheat, the standard deviation decreases by about 9%. The average of these standard deviation changes amount to a fivefold increase.⁸ Regarding *scenario_alt*, standard deviation changes are smaller, they increase by three times for maize, 2.4 times for rice and 1.6 times for soy. In the case of wheat, the standard deviation increases by about 60%.

Welfare change results show that *scenario_main* has a strong impact and *scenario_alt* has a moderate effect. For example the welfare loss at the tenth percentile nearly doubles in *scenario_main* in comparison to the *baseline scenario*, whereas in *scenario_alt* it only increases by 9% (approach A). We again observe high outliers in *scenario_main*, for example the highest loss is 382 bn USD (approach A). These outliers can be ascribed to the few model runs that assume extreme yield losses in important cultivation regions as described above.

To compare our results with welfare change results in Tran et al. (2012), we take a look at their projected mean increase of welfare loss of 34 bn USD between 2010 and 2080 (p. 17, 29). The increase of mean welfare loss between our *baseline scenario* and *scenario_main* is only 17.7 bn USD, between the *baseline scenario* and *scenario_alt* it is 3.8 bn USD. The difference to Tran et al. may be attributed to the fact that they project welfare loss caused by both the level and volatility changes of commodity prices under climate change. We, however, only calculate welfare losses caused by price volatility.

With regard to regional welfare changes, NAM and SAS are hot-spot regions where welfare losses more than triple in *scenario_main* compared to the *baseline scenario*. This may well be attributed to the fact that - according to the projections - maize and rice are the most affected by future price volatility. NAM is the most important maize producing region and moreover maize demand in NAM is very high. SAS is a key rice producing region with also a very high demand.

5.2. Overall interpretation

Overall the projected price and welfare changes should only be interpreted as the result of what-if scenarios. Firstly this is because the input data are subject to uncertainty. *Scenario_main* is based on projections on future heat stress and yield variability that only represent one possibility of potential outcomes. Other studies, however, project different results. Moreover only globally averaged data on future yield variability were used in our market model. In *scenario_alt*, projected heat stress intensification is translated

⁸For the average calculation we apply a simple approach and ignore different crop quantities.

into increases in yield variability in a purely qualitative way. The accuracy of calculated price and welfare changes could be improved in future when more sophisticated predictions on yield variability exist, especially if they may project results for different crop species and different world regions.

Secondly our model does not explicitly account for important factors influencing price volatility, such as substitution effects between crops, storage of crops or export restrictions. These factors are only implicitly simulated by reproducing the past price volatility with the *baseline scenario*. In the future scenarios we only change weather induced price variability, all other influencing factors remain the same. So the implicit assumption is that these other factors will be the same in the future.

Despite the limitations of the input data and the market model, results still show which great effect extreme weather events can have on future crop price volatility and welfare losses. To make matters worse, these effects will happen against the background of a trend of increasing crop prices and climate change induced yield decreases. Higher crop price volatility is likely to have an effect on global food security and poverty even if world market prices are only one of many influencing factors. Effects on local communities depend on the extent of transmission from global commodity to domestic food prices. According to Kalkuhl (2014) about 90% of the global poor live in countries with a significant price transmission of 10% or higher. So the vast majority of the global poor may suffer from an increasing world market price volatility. Potential consequences comprise mainly two elements: firstly sudden price changes can lead both consumers and smallholders into long-term poverty traps. Consumers often can not absorb sudden price increases and smallholders might not be able to compensate for abrupt price decreases of the crops they want to sell. These short-term shocks may have a permanent effect, when for example parents must take their children out of school during high price periods. Secondly high price volatility lowers the willingness of farmers to make productive investments especially if they tie up capital for a long period of time (FAO, 2011) (Porter et al., 2014, p. 5).

6. Conclusion

Weather extremes and their impact on yield variability are expected to increase considerably with climate change. It is thus reasonable to assume that they will increasingly impact crop price volatility, even though weather is only one of many influencing factors. However the quantification of this effect has been hardly examined on a global scale. With the aim of contributing to this under-explored area of research, this article assesses climate variability impacts on price volatility of global agricultural markets by means of a non-linear partial equilibrium trade model that projects a baseline and two future scenarios. In the *baseline scenario* the model reproduces world market price fluctuations of wheat, maize, rice and soybeans that occurred between 1961 and 2009. *Scenario_main* is built on the results of Teixeira et al.

(2013) that predicts future heat stress (A1B emissions scenario, 2071-2100) and its effects on globally averaged yields. *Scenario_alt* bases on the anticipated changes in global spatial patterns of heat waves for a future climate (A1B emissions scenario, 2080-2099) towards a baseline climate (1980 to 1999) presented in the IPCC's Fourth Assessment Report.

For maize and rice there is a dramatic increase of volatility in *scenario_main*. The 75th percentile of results increases nine and 11 times respectively. The change in *scenario_alt* is strong (75th percentile increases 2 and 5 times respectively). In the case of soy, the increase is lower in both future scenarios but still considerable (75th percentile increases 2.6 and 1.7 times respectively). For wheat, price volatility slightly decreases in *scenario_main* but it increases significantly in *scenario_alt* (75th percentile more than doubles).

Alterations in price volatility lead to changes in global welfare which strongly increase in *scenario_main* towards the *baseline scenario*. For example the 10th percentile of results nearly doubles. However, *scenario_alt* only has a moderate effect, the 10th percentile merely increases by 9%. With regard to regional results, NAM and SAS are hot-spot regions with great changes in *scenario_main* towards the *baseline scenario*.

Overall, the predicted changes should only be interpreted as the result of what-if scenarios. They base on projections and simplifying assumptions on future heat stress, yield variability and market behavior that are subject to uncertainty. Nonetheless, results show which great effect extreme weather events can have on future crop price volatility and economic welfare. Effects that are likely to have an impact on global food security and poverty which is different from the impact of gradual price increases. Evidently adaptation measures are in need to fight high price volatility, such as higher crop stocks and increasing research in more heat tolerant crop varieties. It is reasonable to assume that these measures would moderate the partly dramatic extent of results. Moreover other measures could alleviate the consequences of high price volatility such as micro-insurances against price risks for smallholders.

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Table 1: Changes in global f_{dmg} variability (Compiled by the author, underlying data have been provided by Teixeira).

Crop	Baseline climate			A1B climate			Difference	
	5th percentile	95th percentile	Distance	5th percentile	95th percentile	Distance	Distance change (in %)	1/3 Distance change (in%)
Rice	0.050	0.134	0.084	0.284	0.914	0.630	+647.95	+215.98
Maize	0.004	0.038	0.034	0.159	0.751	0.592	+1646.07	+548.69
Soybean	0.014	0.191	0.177	0.194	0.959	0.765	+332.96	+110.99
Wheat	0.213	0.925	0.712	0.202	0.609	0.407	-42.80	-14.27

Table 2: Change in yield variability (CV) based on production damage index (f_{dmg}) data provided by Teixeira (Source: Author).

Crop	Climate	Standard deviation of $1-f_{dmg_n}$	Mean of $1-f_{dmg_n}$	CV of $1-f_{dmg_n}$	CV change (in %)
Wheat	Baseline	0.23	0.44	0.51	-57.45
	A1B	0.13	0.62	0.22	
Maize	Baseline	0.02	0.98	0.02	2078.22
	A1B	0.21	0.55	0.38	
Rice	Baseline	0.03	0.91	0.03	1232.47
	A1B	0.18	0.40	0.46	
Soy	Baseline	0.06	0.94	0.07	594.24
	A1B	0.22	0.47	0.47	

Table 3: Classification of regions according to heat wave induced yield variability (IPCC (2007, p. 786 f) adapted from Tebaldi et al. (2006)).

(a) Classification of yield variability according to standard deviations of heat waves.

Range of standard deviations	Yield variability (in%)
>3.75	100
1.5 - 3	50
0 - 1.5	25

(b) Classification of model regions according to yield variability.

Region	Standard deviation	Yield Variability (in %)
AFR	3.00	50
MEA	3.75	100
EUR	3.00	50
FSU	3.00	50
NAM	3.75	100
LAM	3.00	50
CPA	3.75	100
PAS	1.50	25
PAO	3.00	50
SAS	3.75	100

Table 4: Data summary of regional welfare changes (in bn USD) projected with approach A (Source: Author; regional GDP from The World Bank (2014b)).

Region	Scenario	Mean	Standard Deviation	Min.	Max.	Median	25th percentile	10th	5th	5th perc. % of reg. GDP	regional GDP 2010 in 2005 exchange rates
AFR	Baseline scenario	-0.2	1.5	-5.4	4.4	-0.1	-1.2	-2	-2.5	0.3	840.6
	Scenario_main	0.3	8.1	-50.3	129.3	-0.2	-2.4	-4.8	-7.2	0.9	
	Scenario_alt	-0.1	1.8	-5.3	6.5	-0.1	-1.4	-2.4	-3.0	0.4	
CPA	Baseline scenario	0.5	14.6	-37.5	65.3	-1.1	-8.5	-16.3	-21.3	0.5	4162.0
	Scenario_main	-0.2	23.7	-110.2	122.0	-0.9	-12.6	-25.0	-35.3	0.8	
	Scenario_alt	0.3	15.3	-43.2	62.1	-0.6	-9.6	-18.7	-23.8	0.6	
EUR	Baseline scenario	0.4	6.1	-18.1	19.3	0.7	-3.7	-7.4	-9.6	0.1	15754.3
	Scenario_main	1.4	13.1	-150.1	183.1	0.7	-4.6	-9.1	-12.5	0.1	
	Scenario_alt	0.3	6.2	-20.3	20.8	0.1	-4.0	-7.4	-9.8	0.1	
FSU	Baseline scenario	-0.6	6.5	-22.3	23.0	-0.5	-4.7	-8.5	-11.8	1.0	1203.1
	Scenario_main	0.1	8.1	-29.0	78.5	0.0	-4.9	-9.8	-12.4	1.0	
	Scenario_alt	-0.8	6.9	-25.4	19.5	-0.8	-5.3	-9.3	-11.5	1.0	
LAM	Baseline scenario	-5.2	8.3	-30.0	13.9	-3.8	-10.9	-16.9	-20.5	0.6	3236.6
	Scenario_main	-5.8	14.8	-123.1	75.5	-4.9	-14.0	-22.5	-30.3	0.9	
	Scenario_alt	-5.1	9.1	-34.6	24.4	-3.7	-11.0	-17.9	-21.8	0.7	
MEA	Baseline scenario	-0.4	2.2	-7.8	7.6	-0.4	-2.1	-3.1	-4.0	0.2	1740.1
	Scenario_main	-1.0	3.3	-27.9	7.7	-0.7	-2.6	-4.8	-6.8	0.4	
	Scenario_alt	-0.7	2.6	-10.5	7.6	-0.7	-2.5	-4.0	-4.9	0.3	
NAM	Baseline scenario	-1.2	16.3	-61.8	50.1	-1.3	-12.2	-22.0	-28.6	0.2	14556.5
	Scenario_main	-10.7	41.1	-364.5	56.1	-1.1	-16.5	-66.1	-96.5	0.7	
	Scenario_alt	-1.6	18.8	-74.9	55.2	-0.6	-12.0	-24.3	-34.2	0.2	
PAO	Baseline scenario	0.0	1.4	-4.3	4.5	-0.1	-1.0	-1.8	-2.3	0.0	5597.8
	Scenario_main	-0.9	3.3	-26.9	12.7	-0.4	-2.1	-4.4	-6.4	0.1	
	Scenario_alt	-0.2	2.0	-6.0	5.2	-0.1	-1.4	-2.7	-3.7	0.1	
PAS	Baseline scenario	-0.7	3.5	-11.8	10.7	-0.7	-2.9	-5.4	-6.5	0.3	2206.2
	Scenario_main	0.5	10.7	-49.1	158.2	0.0	-3.2	-7.0	-11.3	0.5	
	Scenario_alt	-0.5	3.7	-10.0	24.8	-0.7	-2.8	-5.0	-6.5	0.3	
SAS	Baseline scenario	-2.4	9.2	-37.2	20.7	-1.9	-7.8	-14.1	-18.5	1.2	1598.2
	Scenario_main	-11.2	33.7	-451.4	66.9	-1.8	-18.7	-42.0	-69.8	4.4	
	Scenario_alt	-5.2	14.0	-67.5	34.1	-3.4	-12.8	-23.4	-31.2	2.0	

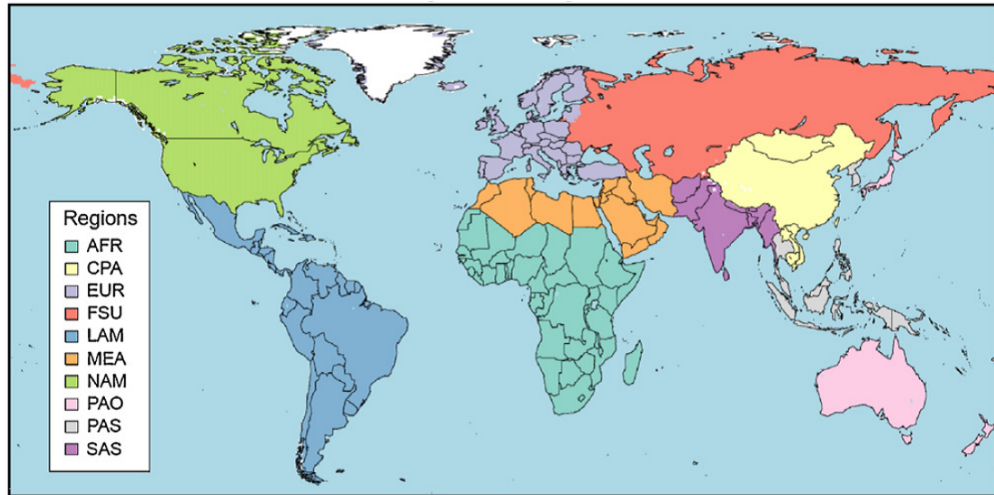
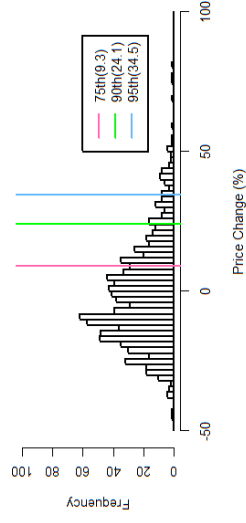
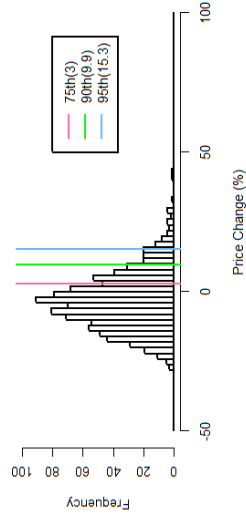


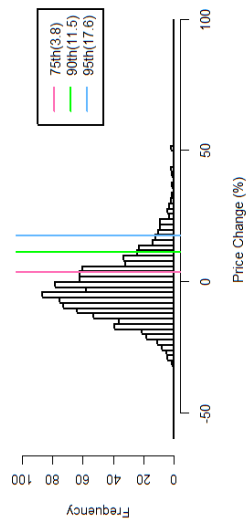
Figure 1: Model regions (Sub-Saharan Africa (AFR), Centrally-Planned Asia (CPA), Europe (EUR), Former Soviet Union (FSU), Latin America (LAM), Middle East and North Africa (MEA), North America (NAM), Pacific member states of the Organisation for Economic Co-operation and Development (PAO), Pacific Asia (PAS), South Asia (SAS)).



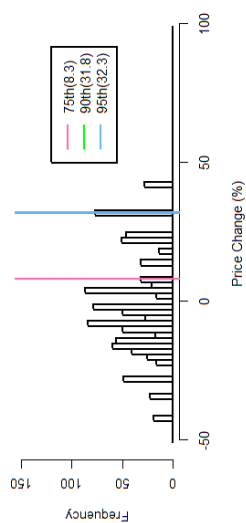
(a) Baseline scenario with approach A



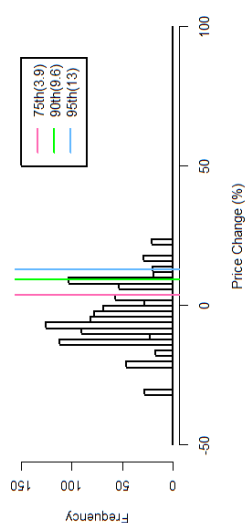
(b) Scenario_main with approach A



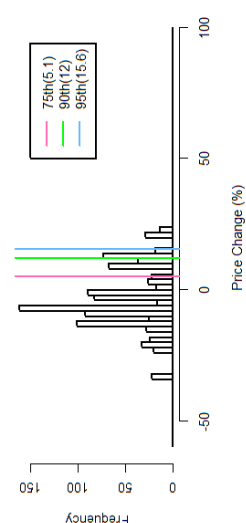
(c) Scenario_alt with approach A



(d) Baseline scenario with approach B

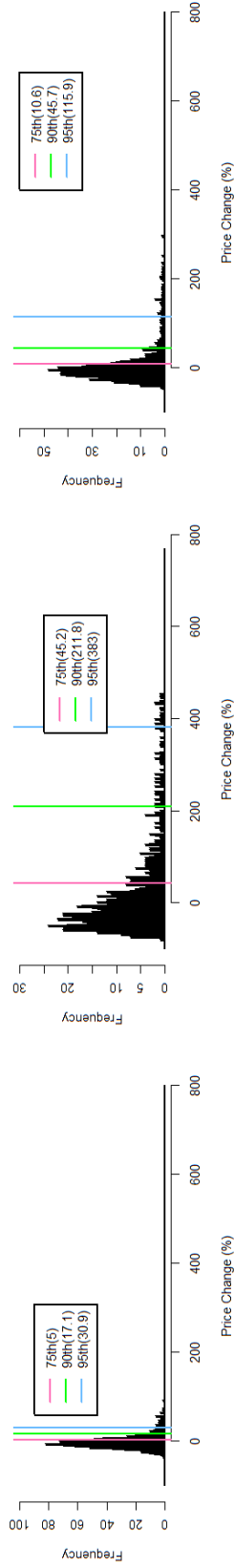


(e) Scenario_main with approach B



(f) Scenario_alt with approach B

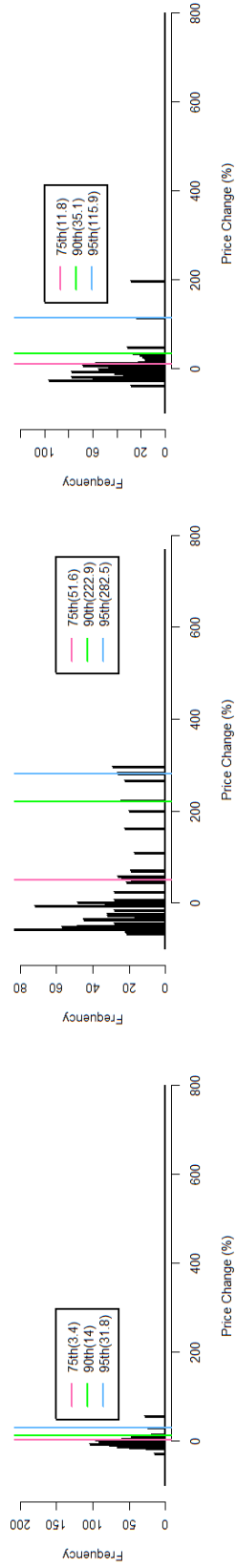
Figure 2: **Wheat:** Price changes in the baseline scenario, scenario_main and scenario_alt for approach A and B (Source: Author).



(a) Baseline scenario with approach A

(b) Scenario_main with approach A

(c) Scenario_alt with approach A

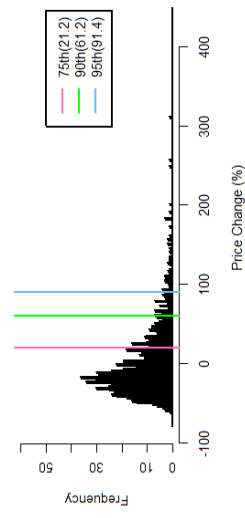


(d) Baseline scenario with approach B

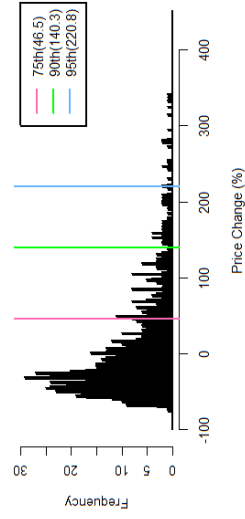
(e) Scenario_main with approach B

(f) Scenario_alt with approach B

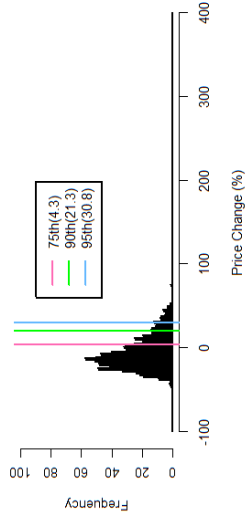
Figure 3: **Maize**: Price changes in the baseline scenario, scenario_main and scenario_alt for approach A and B. In both figures for scenario_main the highest 3% of values are taken out to ensure a clear depiction. However, calculations of percentiles cover all values (Source: Author).



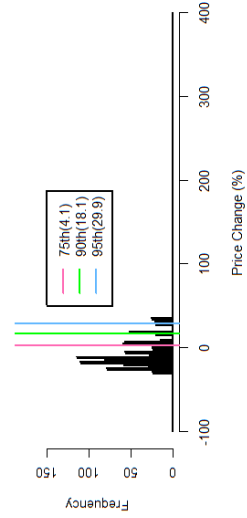
(a) Baseline scenario with approach A



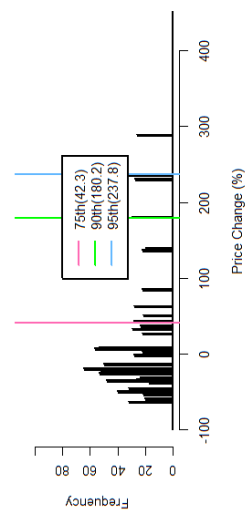
(b) Scenario_main with approach A



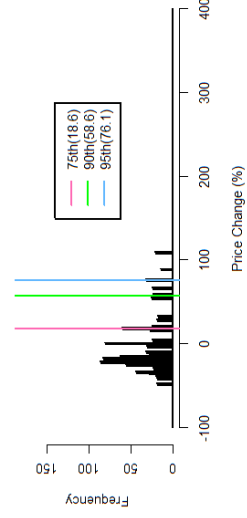
(c) Scenario_alt with approach A



(d) Baseline scenario with approach B

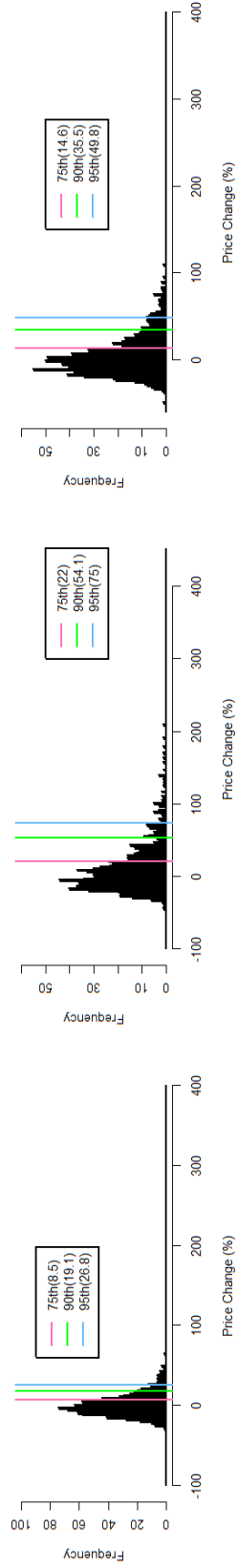


(e) Scenario_main with approach B

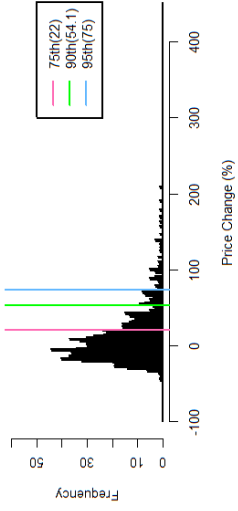


(f) Scenario_alt with approach B

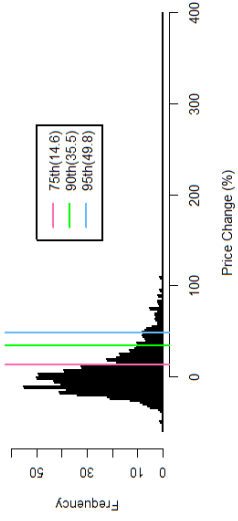
Figure 4: **Rice**: Price changes in the baseline scenario, scenario_main and scenario_alt for approach A and B. In Figure (b) the highest 3% of values are taken out to ensure a clear depiction. However, calculations of the percentiles cover all values (Source: Author).



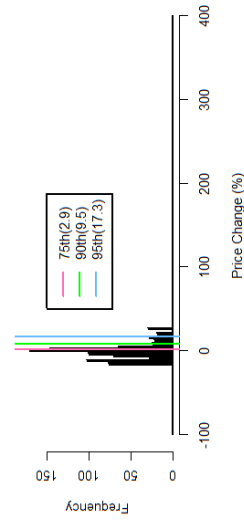
(a) Baseline scenario with approach A



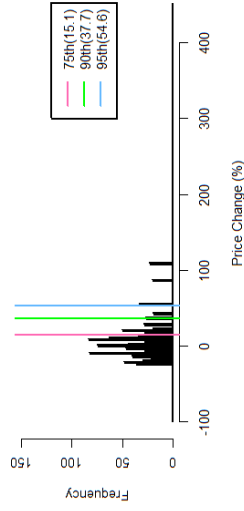
(b) Scenario_main with approach A



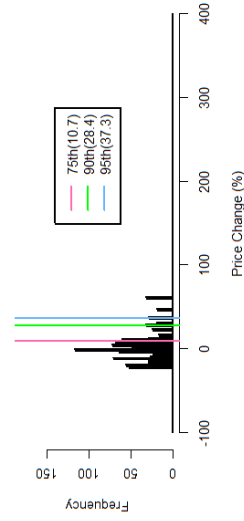
(c) Scenario_alt with approach A



(d) Baseline scenario with approach B

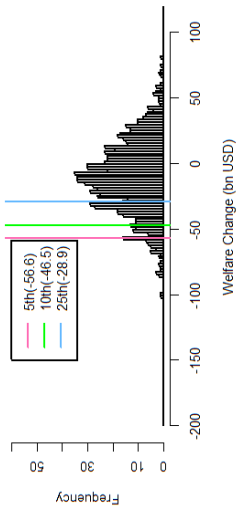


(e) Scenario_main with approach B

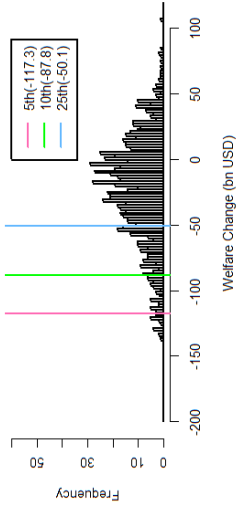


(f) Scenario_alt with approach B

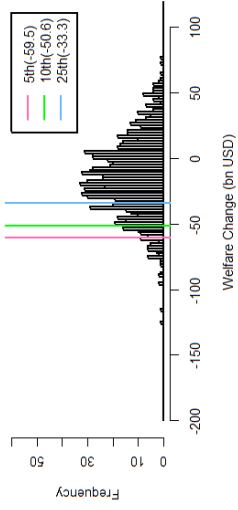
Figure 5: Soybeans: Price changes in the baseline scenario, scenario_main and scenario_alt for approach A and B (Source: Author).



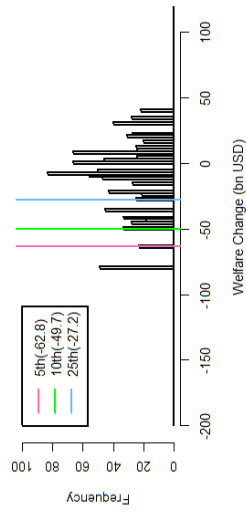
(a) Baseline scenario with approach A



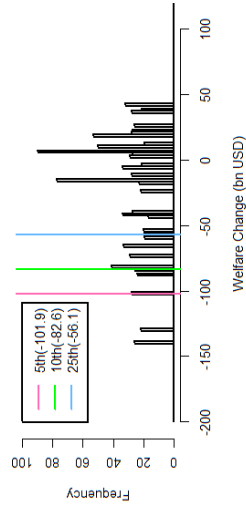
(b) Scenario_main with approach A



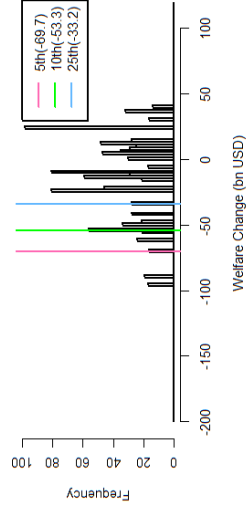
(c) Scenario_alt with approach A



(d) Baseline scenario with approach B



(e) Scenario_main with approach B



(f) Scenario_alt with approach B

Figure 6: **Global welfare changes** in the baseline scenario, scenario_main and scenario_alt for approach A and B. In Figure (b) the lowest 3% of values are taken out to ensure a clear depiction. However, percentile calculations cover all values (Source: Author).

Implications of future climate variability on food security: A model-based assessment of climate-induced crop price volatility impacts

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Introduction

Over the last two decades undernourishment globally has declined by over 44 %, but volatile commodity prices, rising food and energy prices, extreme weather events and natural disasters have frequently produced setbacks [1]. Climate change could further accentuate these setbacks and slow down progress in the reduction of hunger and poverty [2]. As future climate extremes could become more frequent and intense [3], they could pose a severe threat to food security and poverty reduction as the poor are particularly vulnerable to climate-related shocks and stresses [4].

There is only limited literature that directly links the outcome of increased biophysical shocks to hunger risk on a broader scale. Here, we provide a framework that directly links climate-induced price volatility increases to the ‘monetary accessibility’ of grain calories in order to identify changes in the the risk of hunger at distinct probability thresholds.

Methods and Data

Our analysis includes 36 countries from Sub-Saharan Africa (AFR), Centrally-Planned Asia (CPA), Latin America (LAM), Pacific Asia (PAS) and South Asia (SAS), while drawing on a wide range of data sources such as the Global Consumption and Income Project¹ (GCIP), the World Bank’s Global Consumption Database and the FAO GIEWS and WFP VAM domestic price databases in order to depict food consumption patterns and domestic food costs.

Within our model framework we introduce sets of exogenous supply shocks to a global non-linear partial-equilibrium trade model and generate frequency distributions of price shifts for maize, rice, soy and wheat for a historic *baseline scenario* and a future *climate change scenario*. Based on these price shifts we then estimate changes in the *monetary accessibility* of calories in both the baseline and the future scenario. The methodology broadly consists of three stages: (i) We use distributions of real consumption on country level and a non-linear regression model of total consumption to both the share of food (Engel ratio) and grain consumption to predict the real consumption of food and grains (Fig. 1). (ii) A demand weighted domestic grain price index (GPI) is established to estimate the price per calorie derived from grains. (iii) In order to assess changes in the *monetary accessibility* of grain calories in each country, simulated distributions of price shifts are translated to the GPI by using country-specific price transmission elasticities taken from Kalkuhl [5]. For both scenarios we then compute frequencies of the share of people additionally or less falling below a calorie threshold (reference food bundle) and thus become prone to hunger risk.

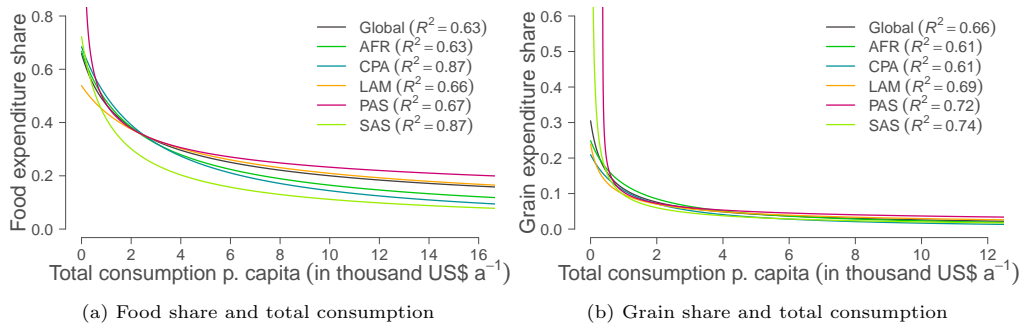


Fig. 1: Global and regional regression models on the relationship between the share of food consumption in total consumption (a) and the share of grain consumption in total consumption (b). The regression analysis is based on data from the World Bank’s ‘Global Consumption Database’.

Results and Discussion

The results indicate that under climate change increased price volatility substantially raises the risk of hunger when compared to the scenario without climate change (Fig 2). Globally, the

¹<http://gcip.info>

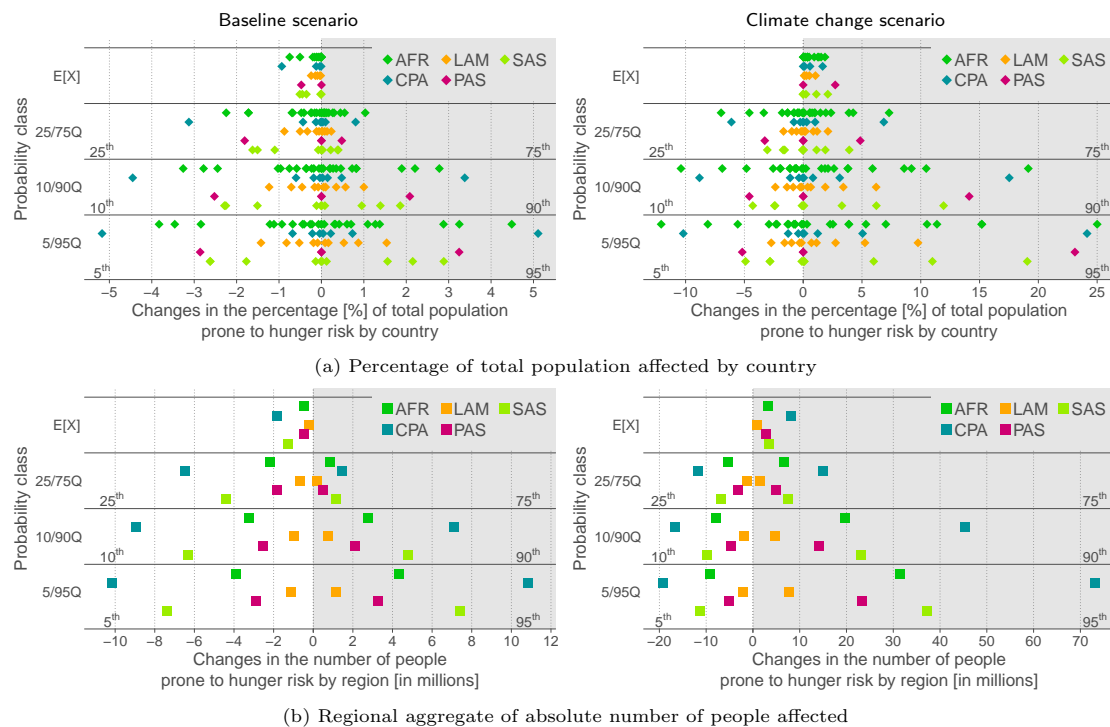


Fig. 2: Probability classes of changes in (a) the percentage of total population (by country) and (b) absolute number of people (regional aggregate) for the *baseline* and the *climate change scenario*. By pairs, the data is split into probability classes which correspond to the 25th and 75th, the 90th and 10th and the 5th and 95th quantile (Q) of simulated hunger impacts. $E[X]$ is the expected value (mean value) of the frequency distribution. Negative values indicate less people affected, while positive values depict additionally affected people due to changing grain prices.

number of people that could additionally become prone to hunger risk in our future scenario is more than 36 million people once in four years and more than 176 million people in a once-in-a-twenty-years occasion. The increment is substantial when compared to our reference scenario in which price changes on average showed a positive effects. The increments of hunger risk are due to the significant rise of the international price volatility of maize and rice in our climate change scenario. In Sub-Saharan Africa, East and South Asia, where large impacts could be found, maize and rice account for large proportions of the staple dietary energy supply. The highest changes to hunger risk could be observed in countries with a high price transmission elasticity. Under future climate conditions, high price transmission could reinforce negative outcomes for hunger risk that are caused by climate-induced price shocks. In our reference scenario, however, high price transmission increased the overall positive effect of changing prices, since prices declined on average.

Our straightforward approach is able to directly link future climate extremes to changes in hunger risk. Yet it also entails some clear limitations. Different outcomes for ‘net consumers’ and ‘net producers’ that could result from price shocks cannot be addressed. Also taking positive income effects into account that result from higher grain prices could improve our results [6]. However, poverty in urban areas is of increasing importance, which could significantly raise the number of poor (net) consumers. By 2050 another 2.5 billion people could be added through population growth and growing urbanisation [7]. While not all of these people are likely to be poor, this trend could exacerbate future food security impacts of sudden food price shocks.

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