

# 1 Accounting for interannual variability in 2 agricultural intensification: the potential of crop 3 selection in Sub-Saharan Africa

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10 **Keywords:** Climate change; Yield; LPJ-GUESS; Crop Model; Modern Portfolio Theory

## 11 **Abstract**

12 Providing sufficient food for a growing global population is one of the fundamental global  
13 challenges today. Crop production needs not only to be increased, but also remain stable over  
14 the years, in order to limit the vulnerability of producers and consumers to inter-annual  
15 weather variability, especially in areas of the world where the food consumed is mainly  
16 produced locally (e.g. Sub Saharan Africa (SSA)).

17 For subsistence agriculture, stable yields form a crucial contribution to food security. At a  
18 regional to global scale dynamical crop models can be used to study the impact of future  
19 changes in climate on food production. However, simulations of future crop production, for  
20 instance in response to climate change, often do not take into account either changes in the  
21 sown areas of crops or yield interannual variability. Here, we explore the response of  
22 simulated crop production to assumptions of crop selection, also taking into account

23 interannual variability in yields and considering the response of agricultural productivity to  
24 climate change. We apply the dynamic global vegetation model LPJ-GUESS, which is  
25 designed to simulate yield over large regions under a changing environment. Model output  
26 provides the basis for selecting the relative fractions of sown areas of a range of crops, either  
27 by selecting the highest yielding crop, or by using an optimization approach in which crop  
28 production is maximized while the standard deviation in crop production is kept at below  
29 current levels.

30 Maximizing simulated crop production for current climate while keeping interannual variability  
31 in crop production constant at today's level generates rather similar simulated geographical  
32 distributions of crops compared to observations. Even so, the optimization results suggest that  
33 it is possible to increase crop production regionally by adjusting crop selection, both for current  
34 and future climate, compared to assuming the same cropland cover as today. For future climates  
35 modelled production increase is >25% in more than 15% of the grid cells. For a small number  
36 of grid cells it is possible to both increase crop production while at the same time decreasing its  
37 interannual variability. Selecting the highest yielding crop for any location will lead to a large  
38 potential increase in mean food production, but at the cost of a very large increase in variability.

39

## 40 **1 Introduction**

41 Global food security is a fundamental challenge for Earth's current and future population.  
42 Currently around 840 million people in the world are under-nourished (Food and Agricultural  
43 Organisation, 2013). Due to an increasing global population and changes in food consumption  
44 patterns, it is expected that crop production needs to double by 2050, for which several  
45 options exist in principle. On the production side this entails either increasing the extent of  
46 agricultural land or increasing production on existing cropland. In this context, reducing the

47 difference between actual and potential yield (closing the so-called yield gap) through  
48 improved management (including irrigation and fertilizer use) and by selection of appropriate  
49 cultivars (Foley et al., 2011; Licker et al., 2010; Mueller et al., 2012) is fundamental.

50 A second option, somewhat less discussed, would be to select different crop *species* (as  
51 opposed to different cultivars of the same crop) that give a higher yield locally (Franck *et al.*,  
52 2011; Koh *et al.*, 2013). For example, Koh et al. (2013) found that global cereal crop  
53 production could increase by 46% when selecting the highest yielding cereal (in terms of  
54 mass) for each location. But selecting the highest yielding crop in all locations is not rational  
55 if one wishes to ensure stability in the global crop production. Already the risk of an  
56 increasing volatility, as a consequence of agricultural systems becoming more homogenous, is  
57 being debated, since a few dominating crops can be vulnerable to episodic events such as  
58 extreme weather or disease (Khoury *et al.*, 2014). Moreover, in many parts of the developing  
59 world, such as in Sub-Saharan Africa (SSA), people are largely dependent on local crop  
60 production for their sustenance and lack the means to compensate for years of poor  
61 production by buying food on global markets (Devereux and Maxwell, 2001; Funk and  
62 Brown, 2009). This means that local crop production is a critical aspect for establishing local  
63 food supply (Garrity *et al.*, 2010) but making local population highly vulnerable to the effects  
64 of extreme weather events and crop failure. In addition, SSA is also a region where the effects  
65 of climate change on agriculture are expected to be most adverse (Barrios *et al.*, 2008; Kotir,  
66 2011), including an increased vulnerability in the majority of the region's rain-fed cropland  
67 area, which constitutes 97% of the total cropland area (Rockström *et al.*, 2004).

68 In regions where food security is closely linked to local food production, the inter-annual  
69 variability in yields also needs to be taken into account. In a changing future climate, one key  
70 question is whether farmers in a more variable future climate will still aim to “optimise

71 productivity under increased climate variability or adopt strategies and management practices  
72 that are more risk averse, and aim to achieve consistent, but potentially lower, productivity”  
73 (Matthews *et al.*, 2013). In theory, crops could thus be selected in order to maximize crop  
74 production while keeping interannual variability in production at an acceptable level.

75 Although it must be considered that in reality, other factors also affect the selection of the  
76 crops sown, such as food preferences and market drivers.

77 To study potential future changes in regional to continental and global crop production, large-  
78 scale agricultural models have become useful tools for predicting future changes in crop yield  
79 over large regions (Berg *et al.*, 2011; Bondeau *et al.*, 2007; Deryng *et al.*, 2011; Di Vittorio *et*  
80 *al.*, 2010; Drewniak *et al.*, 2013; Gervois *et al.*, 2004; Lindeskog *et al.*, 2013; Lokupitiya *et*  
81 *al.*, 2009; Sus *et al.*, 2010; Tao *et al.*, 2009). For example, many of these models have been  
82 applied within the Agricultural Model Intercomparison and Improvement Project (AgMIP)  
83 (Rosenzweig *et al.*, 2013b) including a model intercomparison study where the effect of  
84 global change on future crop yield globally was simulated using a large number of crop  
85 models (Rosenzweig *et al.*, 2013a). However, to date most analyses have concentrated on the  
86 impact of climate on mean yields, while studies that have also investigated the effect of  
87 climate change on changes in yield variability are rare. Despite often being described as tools  
88 to support adaptation strategies, relatively few examples of studies in which crop models have  
89 been applied to these types of questions can be found in the literature (Webber *et al.*, 2014).

90 The Modern Portfolio Theory (MPT) (Markowitz, 1959) is a theory within economics for  
91 selecting a portfolio of stocks taking into account not only the monetary return of the portfolio  
92 of these stocks, but also risk aversion. This has been extended into the realm of agriculture,  
93 looking at the return of a portfolio of different crop varieties of wheat and rice (Nalley *et al.*,  
94 2009; Nalley and Barkley, 2010). We broaden this approach here further by combining MPT

95 with simulated yields for SSA from an agrological global dynamic vegetation model (LPJ-  
96 GUESS; Smith et al., 2001, Lindeskog et al. 2013). Rather than looking at maximizing  
97 financial return we here instead maximize the number of calories produced. In this study we  
98 explore the potential to increase crop production through crop selection for SSA while also  
99 taking into account interannual variability in production. This study is a stylised experiment,  
100 and not intended to represent the decision making of individual farmers, which is determined  
101 by many economic aspects beyond climate effect on yields such as food preference, market  
102 value, or access to markets.

103 The focus of the study is the potential increases in crop production that could be attained  
104 through crop selection whilst constraining to an acceptable level of variance in production.

105 The increase in production in this study is thus assessed without extending agricultural land or  
106 through increased irrigation or fertilizer use.

107 Using the same acceptable level of crop production for future yield means that this study also  
108 takes into account limited climate adaptation. While performing the analysis we generate  
109 optimized relative cropland cover for each crop and grid cell.

110 The main purpose of the study is to:

- 111 1) Explore the potential to increase crop production through crop selection for SSA while  
112 also taking into account interannual variability in production using simulated yield and  
113 an optimization approach.
- 114 2) Explore changes in the optimized cropland fractions over time for a range of crops.
- 115 3) Compare the optimized geographical distributions of crops to observed distributions  
116 for current climate.

117

## 118 **2 Methods**

119 Here we use a state-of-the art agrological global dynamical vegetation model LPJ-GUESS  
120 (Lindeskog et al., 2013; Smith et al., 2001) to simulate current and future potential crop  
121 production in SSA. Simulated yields are then used as the basis for two different optimizations.  
122 The first one is to select the single highest yielding crop. The second option is based on MPT  
123 and here the relative sown areas for a range of crops are adjusted in order to maximize the  
124 number of calories produced while at the same time keeping the variance at a minimum level.

### 125 **2.1 Model description**

126 LPJ-GUESS is a deterministic, process-based dynamic global vegetation model designed to  
127 simulate patterns and dynamics of natural vegetation and corresponding fluxes of carbon and  
128 water (Lindeskog et al., 2013; Smith et al., 2001). It is driven by daily temperature,  
129 precipitation and short wave radiation and runs at a daily time scale, typically with a spatial  
130 resolution of 0.5°. Model processes include photosynthesis, respiration, water uptake,  
131 evapotranspiration, and carbon allocation and growth. The model has been evaluated against  
132 a broad range of observations, including for carbon fluxes in European forest ecosystems  
133 (Morales *et al.*, 2005), seasonality of vegetation greenness in cropland regions in Africa  
134 (Lindeskog et al., 2013), interannual variability of terrestrial carbon uptake (Ahlström *et al.*,  
135 2012), CO<sub>2</sub> fertilisation response (Hickler *et al.*, 2008), and yields and soil carbon response  
136 after land-use change (Pugh *et al.*, 2015). Cropland processes have been recently introduced  
137 into LPJ-GUESS, with crops represented through 11 typologies of crops named Crop  
138 Functional Types (CFTs; Bondeau et al., 2007). Carbon allocation to various yield organs  
139 depends on summed heat units (degree-days above a crop-specific base temperature), also  
140 calculated at a daily time step. A dynamic Potential Heat Unit (PHU) sum needed to reach full  
141 maturity is calculated for each grid cell and each CFT based on the mean temperature of the

142 last 10 years (Lindeskog et al., 2013). This approach means that the model assumes that  
143 varieties with growing periods adapted to the prevailing climate are always available and  
144 selected. As such, it represents the opposite approach to that commonly employed in global  
145 crop models of no cultivar adaptation to climate whatsoever (e.g. Rosenzweig et al., 2013). A  
146 new sowing algorithm based on Waha *et al.*, (2012) was also introduced where the timing of  
147 sowing depends on the variability in temperature or precipitation, rather than being specified  
148 from external datasets. Disturbance and mortality through extreme weather, pests and  
149 diseases are presently not yet accounted for in crops. Yields of CFTs are simulated separately  
150 for irrigated and rain-fed crops. Except for sowing and irrigation, crops are assumed to be  
151 grown under similar conditions regarding management, nutrients and pests across all grid  
152 cells in the model.

## 153 **2.2 Modelling crop yield using LPJ-GUESS**

154 Here we used the simulated rain-fed yield from the LPJ-GUESS model runs from the model  
155 intercomparison study performed as a part of AgMIP (Rosenzweig *et al.*, 2013b). The model  
156 was driven by bias corrected climate forcing data from 5 General Circulation Models (GCMs)  
157 (GFDL-ESM2M, HadGEM2-ES, IPSL-CM5A-LR, MIROC-ESM-CHEM, NorESM1-M)  
158 obtained from the Coupled Model Intercomparison Project Phase 5 (CMIP5) archive (Taylor  
159 *et al.*, 2012). Seven of the LPJ-GUESS CFTs (Table 1) were applied in this analysis for SSA  
160 (<15.5 °N). In this paper we focused on the results using climate data from one Representative  
161 Concentration Pathway (RCP 6.0) (Meinshausen *et al.*, 2011) analysing the results for current  
162 (1996-2005) and two future climates (2056-2065 and 2081-2090). The RCP 6.0 was selected  
163 as this represents one of the “middle of the road” scenarios.

164

165 *Table 1 List of group of crops, or Crop Functional Types (CFT), included in the study. Listed*  
 166 *are also which crops belong to each CFT.*

CFT name	Crops included in CFT
Temperate Cereals	Winter wheat, Spring wheat, Rye, Barley, Oats
Temperate Maize	Corn/Maize
Temperate Pulses	Beans and other pulses
Temperate Tubers	Potatoes, Sugar beet
Tropical Cereals	Millet, Sorghum
Tropical Rice	Rice
Tropical Tubers	Maniok/Cassava, Sweet potatoes

167

### 168 **2.3 Scaling simulated yield to observed values**

169 Since the simulated output from LPJ-GUESS does not account for regional differences in  
 170 management actions such as fertilisation and pest control, but rather the potential response  
 171 due to weather/climate and atmospheric CO<sub>2</sub> concentration, simulated yields were first scaled  
 172 against observed values to correct for this spatial variability. To do this a conversion  
 173 coefficient ( $k$ ) representing the difference in simulated and reported yield was first calculated  
 174 for each CFT ( $c$ ) and grid cell ( $i$ ):

$$175 \quad k_{i,c} = 1 - \frac{Y_{o,i,c}}{\overline{Y_{p,i,c}}} \quad (1)$$

176 where  $\overline{Y_p}$  is mean simulated yield ( $Y_p$ ) (kg m<sup>-2</sup> dry weight) for the current time period (1996-  
 177 2005) and  $Y_o$  is actual yield (kg m<sup>-2</sup> dry weight) for the same time period. Observed yields  
 178 ( $Y_o$ ) were taken from the Spatial Production Allocation Model (SPAM) dataset (You *et al.*,



179 2013). The SPAM dataset is a gridded product of crop yield and area compiled from a range  
180 of datasets centred at the year 2000 and disaggregated to a 5 arc-minute spatial. As the spatial  
181 resolution of LPJ-GUESS is  $0.5^\circ$  we aggregated the SPAM dataset to that same spatial  
182 resolution. Also, as SPAM reports wet weight, the yields were converted into dry weight  
183 using crop specific values for grain/tuber water content (Wirsenius, 2000). SPAM reports  
184 yield separately for high and low input of nutrients as well as subsistence farming. As  
185 subsistence farming can be said to be dominating for most parts of SSA and as this type of  
186 farming is also the focus of this study, subsistence yields were selected to represent observed  
187 yield in this study. For CFTs representing more than one crop, we selected the crop giving the  
188 highest dry yield from the database. This represents a form of optimization in itself where  
189 yield is maximized within each CFT containing more than one crop. In order to avoid getting  
190 unrealistically large or small values of  $k$  we excluded CFTs ( $c$ ), in a grid cell ( $i$ ) from this  
191 analysis if either observed ( $Y_o$ ) or mean simulated yield ( $\overline{Y_p}$ ) were zero or close to zero  
192 ( $<0.01$  kg dry weight  $m^{-2}$ ). For these CFTs we instead assigned  $k$  a “gap-filled” value ( $k_{gap}$ )  
193 based on a distance weighted interpolation using yield data from grid cells that were within  
194 the same agro-ecological zone (AEZ) (Fischer *et al.*, 2012):

$$195 \quad k_{gap,i,c} = \frac{\sum_{j=1}^n \frac{k_{j,c}}{d_{i,j}}}{\sum_{j=1}^n \frac{1}{d_{i,j}}} \quad (2)$$

196 where  $d_{i,j}$  is the distance (in degrees) between cell  $i$  (the grid cell for which  $k_{gap}$  is calculated)  
197 and any cell  $j$  which has existing values of  $k$  for CFT ( $c$ ), belonging to the same AEZ as grid  
198 cell ( $i$ ), and is within a  $2.5^\circ$  distance from  $i$ . In the case no  $k$  values could be found within  $2.5^\circ$   
199 from grid cell  $i$   $k_{gap}$  was set to 1.0.

200 Simulated scaled annual yield ( $Y_s$ ) in  $\text{kg m}^{-2}$  dry weight for each year was calculated using  
201 simulated yield ( $Y_p$ ) and the conversion coefficient ( $k$ ) for each CFT ( $c$ ), grid cell ( $i$ ) and year  
202 ( $t$ ):

$$203 \quad Y_{s,c,i,t} = Y_{p,i,c,t}(1 - k_{i,c}) \quad (3)$$

204  $Y_s$  was converted from  $\text{kg m}^{-2}$  to  $\text{kcal m}^{-2}$  ( $Y_{cal}$ ) ( $1 \text{ kcal} = 4184 \text{ J}$ ) by using values for calorie  
205 content for each crop from the Food and Agricultural Organization (FAO) (2001) as  
206 suggested by Franck *et al.* (2011).

## 207 **2.4 Observed CFT fractions**

208 Total observed areas for each crop were also taken from the SPAM dataset. (You *et al.*,  
209 2013). In contrast to yields, this dataset contains only the *total* cropland area for each crop  
210 rather than separating areas into different types of management and including both rain-fed  
211 and irrigated crops. Observed CFT fractions ( $\omega_o$ ) were calculated as the summed area of each  
212 CFT, divided by the total area of the 7 CFTs within each grid cell for all cells with at least one  
213 CFT present. For example, if three CFTs were present the fraction for one of these was  
214 calculated as the area of that CFT divided by the summed area of all three CFTs.

## 215 **2.5 Modern Portfolio Theory**

216 The approach in this study using Modern Portfolio Theory (MPT) (Markowitz, 1959) was  
217 based on Nalley *et al.* (2009); and Nalley and Barkley (2010) but instead of optimizing  
218 variance in yield or profit from selecting different varieties of wheat or maize the focus was  
219 on optimizing crop production by selecting different crop species.

220 The two variables used in MPT are the mean return of the portfolio, or in the case for crops in  
221 this study, the area weighted mean yield for the total cropland area in each grid cell over the  
222 selected time period ( $Y_{pf}$  in  $\text{kcal m}^{-2}$ ), and the variance ( $\sigma_{pf}^2$  in  $\text{kcal}^2 \text{ m}^{-4}$ ) in the same yield

223 over the same time period.  $Y_{pf}$  was calculated as the area-weighted decadal mean yield of all  
 224 CFTs in each grid cell ( $i$ ), for each optimization period:

$$225 \quad Y_{pf,i,t} = \frac{\sum_{t=1}^a \sum_{e=1}^b \omega_e Y_{cal,e,t}}{a} \quad (4)$$

226 where  $t$  is year number in the optimization period,  $e$  is the CFT index (a number between 1-7  
 227 where each number represents one CFT),  $a$  is number of years of the optimization time  
 228 period,  $b$  is number of CFTs, and  $\omega_e$  is the cropland fraction of CFT  $e$ .

229 The portfolio mean variance ( $\sigma^2_{pf}$ ) is the area-weighted sum of the variance in crop yield  
 230 calculated as:

$$231 \quad \sigma^2_{pf,i,t} = \sum_{e=1}^b \sum_{f=1}^b \omega_e \omega_f \rho_{e,f} \quad (5)$$

232 where  $e$  and  $f$  are CFT indices used in the equation to represent all combinations of CFTs. The  
 233 variable  $\rho$  is the covariance in crop yield of the two corresponding CFTs over the optimization  
 234 period when  $e \neq f$  and the variance of CFT  $e$  (or  $f$ ) when  $e = f$ .

235 Modern Portfolio identifies two optimization options based on the variables described in Eq. 4  
 236 and 5. The first option (A) is to find an optimum portfolio of crops to maximize crop  
 237 production ( $Y_{pf}$ ) while keeping standard deviation ( $\sigma_{pf}$ ) below a maximum value. The  
 238 second option (B) is to find the optimum portfolio of crops to minimize standard deviation (  
 239  $\sigma_{pf}$ ) while keeping crop production ( $Y_{pf}$ ) above a minimum value. This type of optimization  
 240 problem needs to be solved numerically. In this study we used the optimization tool  
 241 implemented in the Financial Toolbox in Matlab (release 2013b) (MathWorks Inc., 2013).  
 242 The Matlab script uses standard deviation ( $\sigma$ ) rather than variance ( $\sigma^2$ ) in the optimization,  
 243 and as this measure is easier to relate to for most readers we use this in both the analysis and

244 the presentation of the results. In addition to the thresholds for  $Y_{pf}$  or  $\sigma_{pf}$  the optimization  
245 algorithm requires an initial state of cropland fractions.

246 As  $Y_{pf}$  is the area weighted yield of all crops and since the total cultivated area of crops does  
247 not change over time for any grid cell, maximizing  $Y_{pf}$  for any grid cell also means  
248 maximizing the number of calories produced for that grid cell and we therefore use  $Y_{pf}$  as a  
249 measure of crop production for any grid cell  $i$ .

## 250 **2.6 Maximizing crop production through crop selection**

251 In order to study the impact of crop selection for maximizing crop production we performed  
252 two optimizations per time period (current climate: 1996-2005 and the two future time  
253 periods: 2056-2065 and 2081-2090), GCM and grid cell where the first is based on MPT:

### 254 *Low risk (LR)*

255 Here the first MPT optimization option (A) was used, that is to maximize  $Y_{pf}$ , while  
256 keeping  $\sigma_{pf}^2$  below a maximum threshold. This optimization represents a low risk  
257 scenario where the interannual variability in crop production is not allowed to be  
258 higher than simulated crop production using current cropland cover. The value of this  
259 threshold is calculated using Eq. 5, based on simulated  $Y_{cal}$  values for the current time  
260 period (1996-2005) and assuming current observed cropland fractions (as described  
261 above). The optimization was made for all CFTs that are currently grown in a given  
262 grid cell according to the SPAM dataset. The initial state for the cropland fractions ( $\omega$ )  
263 for all CFTs in the optimization was assumed to be equal to the observed fractions  
264 ( $\omega_o$ ). Although the optimization is made at a grid cell level this optimization could be  
265 seen as a risk aversion strategy for a farmer in a region with local markets and high  
266 level of local sustenance.

267 *High risk (HR)*

268 As a comparison to the LR scenario we also selected the highest yielding CFT (in  
269 calories) of the ones that are currently growing in each grid cell. Crop production for  
270 that grid cell is thus equal to the yield of the highest yielding CFT. This optimization  
271 represents a high risk scenario where the crop production is maximized without taking  
272 into account climate-related interannual variability in productivity. This optimization  
273 is more closely related to commercial agricultural systems where one bad harvest one  
274 year can be compensated for by large harvests in “typical” years.

275

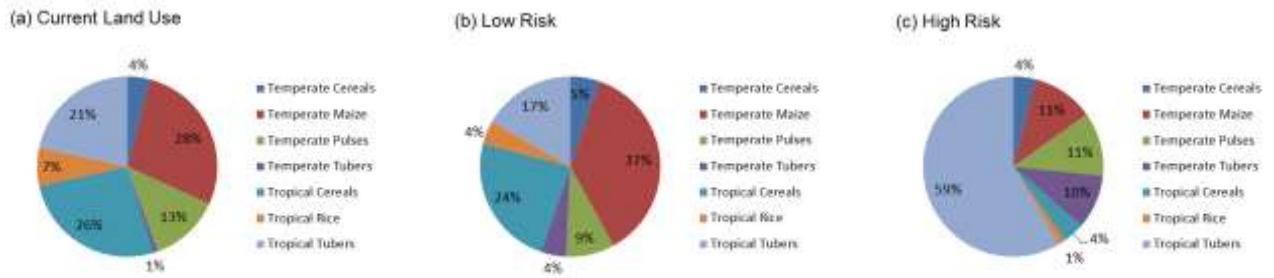
276 The optimizations were made separately for each GCM. The results below are presented as  
277 the mean of all five GCMs.

## 278 **3 Results**

### 279 **3.1 Optimized CFT fractions**

280 By performing the two optimizations for current climate we generated different sets of  
281 optimal CFT fractions ( $\omega_{opt}$ ) for each grid cell, optimization and time period. The unweighted  
282 grid cell mean  $\omega_{opt}$  values for current climate were compared with the observed fractions ( $\omega_o$ )  
283 taken from the SPAM dataset (Fig. 1). This comparison could at least partly be seen as a form  
284 of validation, in a sense that if these patterns agree there is an indication that current  
285 cropland cover to some extent follows the assumptions in the optimization. The  $\omega_{opt}$  values  
286 from the LR optimization were relatively similar to the  $\omega_o$  values, whereas for HR  $\omega_{opt}$   
287 differed greatly from  $\omega_o$ , with Tropical Tubers being the dominating crop in the simulated  
288 case, covering nearly 60% of the crop area, rather than the ca. 20% observed (Fig. 1). For LR  
289 some differences can be seen for Temperate Maize, Temperate Pulses, Temperate Tubers and

290 Tropical Tubers where grid cell mean  $\omega_{opt}$  for Temperate Maize and Temperate Tubers was  
 291 larger than  $\omega_o$  and smaller than  $\omega_o$  for Temperate Pulses and Tropical Tubers (Fig. 1)



292 *Figure 1. Current grid cell mean CFT fractions (a) as well as optimized CFT fractions (Low*  
 293 *Risk: (b) and High Risk: (c)) for current climate.*

294 Latitudinally, both  $\omega_o$  and  $\omega_{opt}$  (LR and HR) for the three most important groups of crops in  
 295 SSA (based on number of calories produced (FAOSTAT)) varied strongly (Fig. 2) with the  
 296 latitudinal fraction for LR reproducing the data-based observed patterns quite well. A strong  
 297 positive correlation ( $p < 0.001$ ) was found between the latitudinal mean values of  $\omega_o$  and  $\omega_{opt}$   
 298 for the LR-optimization (Table 2) for all CFTs except for Tropical Rice, indicating that  
 299 current crop selection is close to optimum calculated based on the LR scenario. As correlation  
 300 does not take into account the bias between predicted and observed values, the Modelling  
 301 Efficiency (ME) (Janssen and Heuberger, 1995) was also calculated (Table 2). A negative ME  
 302 value indicates a very poor fit whereas a value close to unity indicates a good fit. Of the CFTs  
 303 with significant correlations between  $\omega_o$  and  $\omega_{opt}$  the ME values were positive for all CFTs  
 304 except for Temperate Pulses and Temperate Tubers (Table 2).

305 For the HR scenario the latitudinal pattern of  $\omega_{opt}$  differed greatly from that of  $\omega_o$  for all CFTs  
 306 (Fig. 2 and Fig. S1). Still, there was a significant correlation ( $p < 0.001$ ) between  $\omega_o$  and  $\omega_{opt}$   
 307 for Temperate Pulses, Temperate Tubers, Tropical Tubers and Tropical Cereals (Table 2).

308 However, looking at the ME, none of the CFTs generated positive values, indicating a poor fit  
 309 between  $\omega_o$  and  $\omega_{opt}$ . The ME values was smaller for HR compared to LR for all CFTs.

310 *Table 2. Pearson's correlation (R) and Modelling Efficiency (ME) between observed and*  
 311 *optimized latitudinal CFT fractions (High or Low Risk) of cropland cover for all Crop*  
 312 *Functional Types (CFTs). Significant correlations ( $p < 0.001$ ) and positive values for ME are*  
 313 *marked in bold.*

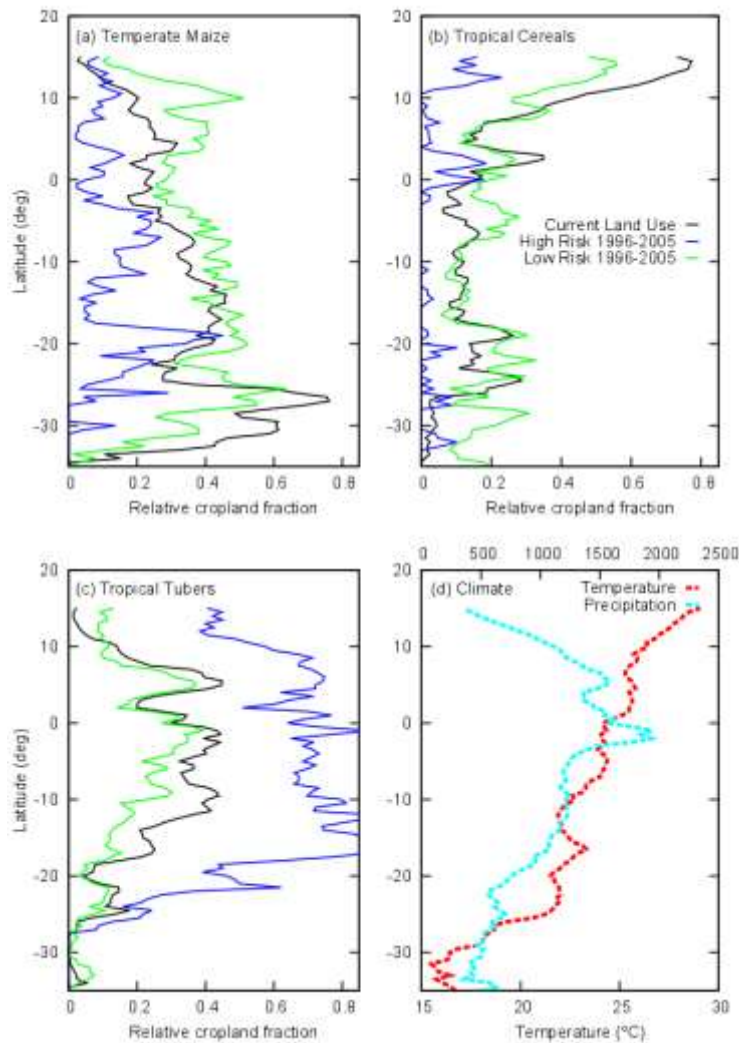
CFT	Low Risk (LR) Scenario		High Risk (HR) Scenario	
	R	ME	R	ME
<i>Temperate Cereals</i>	<b>0.91</b>	<b>0.81</b>	-0.09	-0.15
<i>Temperate Maize</i>	<b>0.61</b>	<b>0.26</b>	0.03	-2.01
<i>Temperate Pulses</i>	<b>0.42</b>	-0.48	<b>0.35</b>	-1.82
<i>Temperate Tubers</i>	<b>0.34</b>	-5.67	<b>0.69</b>	-297.14
<i>Tropical Rice</i>	0.26	-0.39	0.02	-1.25
<i>Tropical Tubers</i>	<b>0.92</b>	<b>0.70</b>	<b>0.81</b>	-4.49
<i>Tropical Cereals</i>	<b>0.84</b>	<b>0.65</b>	<b>0.59</b>	-0.49

314

315 For the LR optimization some regions stood out in relation to where  $\omega_{opt}$  of CFTs differed  
 316 from  $\omega_o$ . The  $\omega_{opt}$  values were much higher than the  $\omega_o$  for Tropical Cereals in the regions  
 317 south of 25°S; and for Temperate Tubers in the regions around 10°S (Fig. 2 and Fig. S1). For  
 318 Tropical Rice,  $\omega_{opt}$  was much lower than  $\omega_o$  for the region between 15 and 25°S (Fig. S1).

319 When performing the optimizations for future climate,  $\omega_{opt}$  differed only to a relatively small  
 320 degree in absolute terms compared to the optimizations made for current climate. The largest

321 difference in relative fractions between 2081-2090 and 1996-2005 was a decrease by nearly  
322 50% for Tropical Tubers (LR) and Temperate Maize (HR) (Fig. S1).



323

324 *Figure 2. Optimized latitudinal mean CFT fractions for the current climate (1996-2005)*  
325 *(High Risk solid blue lines; Low Risk solid green lines) and observed CFT fractions (black*  
326 *lines) for the three most common crops in SSA: Temperate Maize (a), Tropical Cereals (b),*  
327 *and Tropical Tubers (c). The bottom right panel (d) represents latitudinal mean total annual*  
328 *precipitation (mm) (dotted cyan line) and mean annual temperature (°C) (dotted red line).*

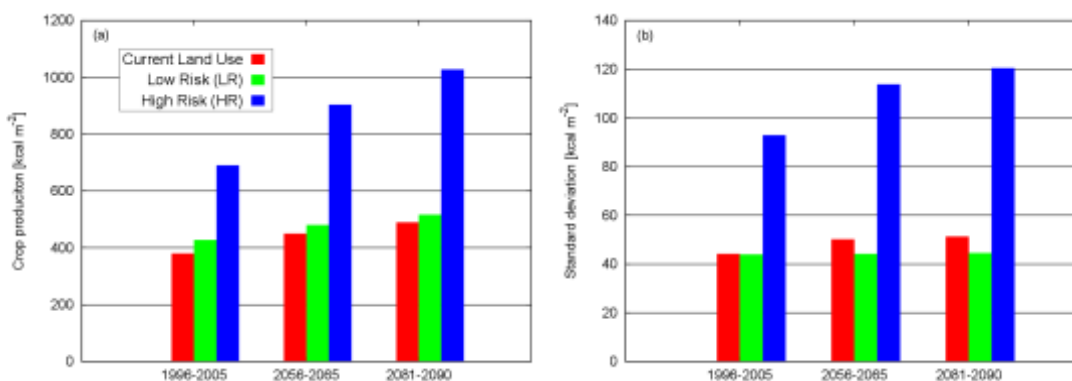


### 329 3.2 Spatial and temporal differences in crop production and its interannual variability

330 For future climate we compared the optimized crop production and its standard deviation  
331 against a “business as usual” situation which assumed the same CFT fractions as today  
332 ( $Y_{pf,BAU}$  and  $\sigma_{pf,BAU}$ ). Optimized crop production and its standard deviation were therefore  
333 compared against  $Y_{pf}$  and  $\sigma_{pf}$  calculated using simulated values of  $Y_{cal}$  for current (1996-2005)  
334 or future (2056-2065 and 2081-2090) climate, maintaining current observed cropland  
335 fractions ( $\omega_o$ ).

#### 336 3.2.1 Current cropland cover: Business as usual (BAU)

337 The grid cell median annual value of  $Y_{pf,BAU}$  for current climate was 380 kcal m<sup>-2</sup> with a  
338 median value for  $\sigma_{pf,BAU}$  of 45 kcal m<sup>-2</sup> (Fig. 3). Reflecting simulated yield increases in the  
339 future, a result mostly in response to enhanced atmospheric CO<sub>2</sub> levels (Rosenzweig et al.,  
340 2013), there was an increase in  $Y_{pf,BAU}$  over time (Fig. 3a; Fig. S3a-b). From 1996-2005 to  
341 2081-2090 there was an increase in the grid cell median  $Y_{pf,BAU}$  by 30%. For the majority of  
342 the grid cells (~65%), there was also an increase in  $\sigma_{pf,BAU}$ , leading to an increase in grid cell  
343 median  $\sigma_{pf,BAU}$  over time (Fig. 3b) of around 15%.



344  
345 *Figure 3. Grid cell median crop production (kcal m<sup>-2</sup>) (a) and standard deviation (b) (kcal*  
346 *m<sup>-2</sup>) for current (BAU) and optimized CFT fractions.*

347 Geographically, the largest increases in  $Y_{pf,BAU}$  over time occurred in Somalia, Botswana and  
348 South Africa (Figure S3a-b). The largest increase in  $\sigma_{pf,BAU}$  occurred in the same regions but  
349 also for large parts of West Africa and Sudan (Figure S3c-d). For some regions (e.g. large  
350 parts of South Africa and Angola)  $\sigma_{pf,BAU}$  instead decreased over time (Figure S3c-d) .

### 351 3.2.2 The High Risk Scenario (HR)

352 Selecting the highest yielding crop (HR) meant that for current climate, optimized  $Y_{pf}$  was by  
353 definition equal to or higher than  $Y_{pf,BAU}$ . The grid cell median  $Y_{pf}$  was ~70% higher than the  
354 grid cell median  $Y_{pf,BAU}$ . Optimized  $Y_{pf}$  was >25% larger than  $Y_{pf,BAU}$  for ~80 % of the grid  
355 cells for both current and future climate (Table 3; Fig. S4). The grid cells with the highest  
356 potential to increase crop production through selecting the highest yielding CFT are mainly  
357 located in the Sahel, Angola and in the South Eastern parts of Africa (Fig. S4). The associated  
358  $\sigma_{pf}$  was also much higher than  $\sigma_{pf,BAU}$  for the majority of grid cells (with a difference >25% for  
359 ~80% of the grid cells: Table 3) and with the median value for  $\sigma_{pf}$  being 110% larger than  
360  $\sigma_{pf,BAU}$  (Fig. 3b). For a small number of grid cells (for current and future climate) selecting the  
361 single highest yielding crop actually produced a  $\sigma_{pf}$  that was smaller than  $\sigma_{pf,BAU}$  (Fig. S5). But  
362 the number of grid cells where this difference was larger than 25% was less than 1% of the  
363 total (Table 3).

### 364 3.2.3 The Low Risk Scenario (LR)

365 For current climate, the set of assumptions made in LR meant that optimized  $Y_{pf}$  was larger  
366 than  $Y_{pf,BAU}$  across the entire simulation domain, with the grid cell median value being ~12%  
367 larger than  $Y_{pf,BAU}$ . There was an increase over time in the grid cell median optimized  $Y_{pf}$  (Fig.  
368 3a), but as the increase in  $Y_{pf,BAU}$  was even larger, the relative difference of the grid cell  
369 median optimized  $Y_{pf}$  and  $Y_{pf,BAU}$  became smaller for future climate (~5% for 2081-2090).

370 Patterns of change were spatially very variable. The largest potential to increase  $Y_{pf}$  whilst  
 371 keeping a  $\sigma_{pf}$  at current level could be found in Senegal, parts of the Sahel, Tanzania, Angola  
 372 and parts of Mozambique and South Africa (Fig. 4a-c). In total ~10% of the grid cells  
 373 displayed a  $Y_{pf}$  that was at least 25% above  $Y_{pf,BAU}$  for current climate, and 16-20% for future  
 374 climates and CO<sub>2</sub> (Table 3). Following the assumption that the optimization is made against  
 375  $\sigma_{pf,BAU}$  values for current climate, and the fact that  $\sigma_{pf,BAU}$  increases over time for some grid  
 376 cells, optimized  $Y_{pf}$  actually became lower than  $Y_{pf,BAU}$  (Fig. 4b-c) for future climates. These  
 377 grid cells are mainly located in regions where  $\sigma_{pf,BAU}$  in crop production displayed the largest  
 378 increase over time (Fig. S3c-d). For ~5% of the grid cells optimized  $Y_{pf}$  was more than 25%  
 379 below  $Y_{pf,BAU}$  for future climates (Table 3).

380

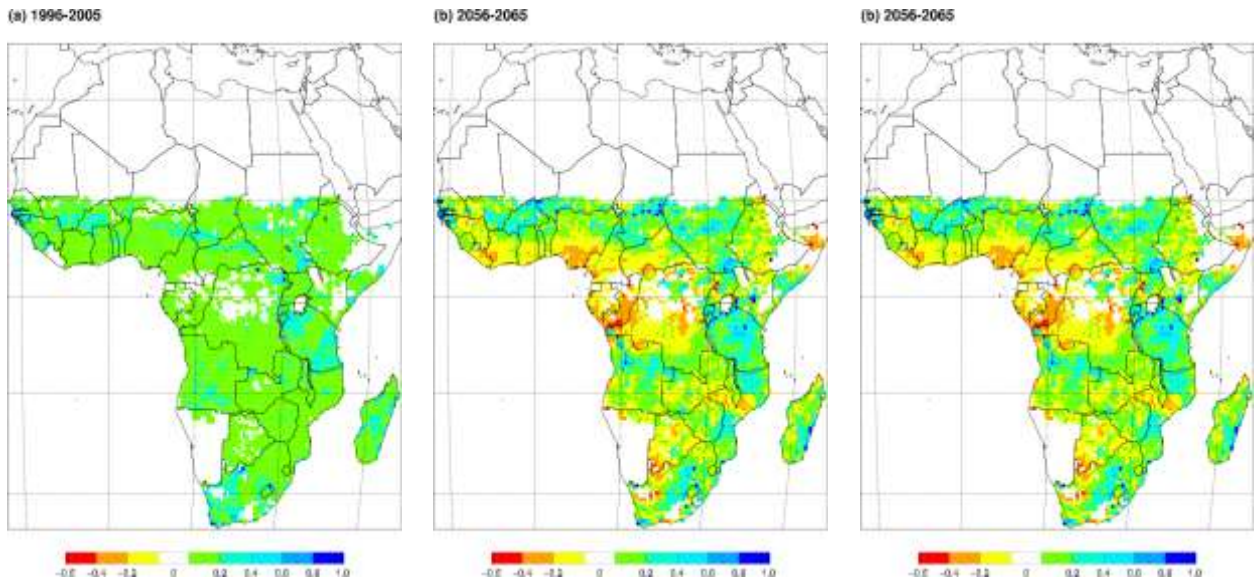
381 *Table 3. Percent of grid cells where the optimized crop production (or standard deviation) is*  
 382 *at least 25% larger (or smaller) compared to using observed CFT fractions (BAU) for the two*  
 383 *optimizations and three time periods.*

	Low Risk (LR) Scenario			High Risk (HR) Scenario 384		
	1996- 2005	2056- 2065	2081- 2090	1996- 2005	1996- 2005	1996- 2005 <sup>385</sup>
Grid cells with increase in yield >25%	9%	16%	20%	77%	80%	81% <sup>386</sup>
Grid cells with increase in standard deviation >25%	0%	4%	7%	0%	0%	0% <sup>387</sup>
Grid cells with increase in standard deviation >25%	0%	5%	7%	80%	82%	83% <sup>388</sup>
Grid cells with decrease in standard deviation >25%	<1%	18%	24%	<1%	<1%	<1% <sup>389</sup>

391

392 Following the optimization criteria, optimized grid cell median  $\sigma_{pf}$  changes little over time  
393 (Fig. 3b) and for current climate  $\sigma_{pf}$  was smaller than or equal to  $\sigma_{pf,BAU}$  for all grid cells (Fig.  
394 S6a). Even if there was virtually no change in optimized  $\sigma_{pf}$  over time in absolute terms, the  
395 change could be either positive or negative in relative terms compared to  $\sigma_{pf,BAU}$ . This resulted  
396 in optimized  $\sigma_{pf}$  being at least 25% higher than  $\sigma_{pf,BAU}$  for ~5% of the grid cells and at least  
397 25% lower for ~20% of the grid cells (Table 3) for future climates. The highest potential to  
398 decrease  $\sigma_{pf}$  can be found in western Africa whereas the largest increase in the relative  
399 difference of  $\sigma_{pf}$  compared to  $\sigma_{pf,BAU}$  can be found in the Sahel, Angola and parts of  
400 Mozambique and South Africa (Fig. S6).

401



402 *Figure 4. Relative difference in optimized crop production compared to assuming current*  
403 *land use fractions (BAU) for the Low Risk optimization for the time periods: 1996-2005 (a),*  
404 *2056-2065 (b) and 2081-2090 (c).*

405 From the results above (Table 3) it can be seen that for LR, it was potentially possible to  
406 simultaneously increase  $Y_{pf}$  by 25% and to decrease  $\sigma_{pf}$  by the same figure for the two future  
407 time periods compared to the business as usual scenario ( $Y_{pf,BAU}$  and  $\sigma_{pf,BAU}$ ) for a number of  
408 grid cells. However, the number of grid cells for which both these criteria were met was <1%.  
409 If instead looking at the possibility to increase  $Y_{pf}$  by 10%, whilst decreasing  $\sigma_{pf}$  by the same  
410 magnitude, the number of grid cells for which this occurred increased to ~7%. The grid cells  
411 for which it is possible to increase  $Y_{pf}$  while at the same time decreasing  $\sigma_{pf}$  are mainly located  
412 in the eastern parts of SSA (Fig. S7).

#### 413 **4 Discussion**

414 The agreement between observed and simulated relative cropland cover of the LR optimisation  
415 for present-day suggests that cropland cover depends on both yield and interannual variability  
416 in yield in a way that makes it possible to recreate the existing spatial patterns for a range of  
417 CFTs using simulated yield with LPJ-GUESS and MPT. This pattern relies on assuming  
418 simulated interannual variability in crop production of current CFTs as the acceptable level.  
419 This agreement is remarkable and implies that in SSA under present-day conditions, crop  
420 selection with respect to calorific value is relatively optimal on average, accounting for given  
421 interannual variability in weather. Both temperature and precipitation vary notably with latitude  
422 (Fig. 2). As climate is the main driver of which CFTs are favoured regionally both in reality  
423 and in the optimization it is not surprising that there is a strong correlation between the relative  
424 sown areas of CFTs and climate (Table S1). For the observed fractions the strongest correlation  
425 with climate was found for temperature for all CFTs (with negative correlations for Temperate  
426 Maize, Temperate Tubers and Temperate Cereals) except for Tropical Tubers where the  
427 strongest correlation was with precipitation. The correlation between the optimized CFT  
428 fractions and climate for LR were of the same direction and order of magnitude for all CFTs

429 except for Temperate Maize. The lack of correlation for Temperate Maize follows a larger  
430 optimized fraction in the Sahel compared to the observed (Fig. 2).

431 The optimizations were made under the assumption that all crops were rain-fed. The reported  
432 areas used in this study do however also include some irrigated crops. While for most crops  
433 the irrigated area is negligible in SSA, for the two countries with the highest rice production  
434 (Nigeria and Madagascar) 15% and 50% of all harvested area is irrigated, respectively  
435 (Balasubramanian *et al.*, 2007). This could explain the large underestimation in optimized  
436 fractions of rice (Tropical Rice) for the region between 17 and 25°S where Madagascar is  
437 located. Furthermore, the CFTs in LPJ-GUESS are not affected by pests, such that yields  
438 respond to climatic, but not biotic stresses. This might play a role particularly for potatoes  
439 (Temperate Tubers) for which a large amount of pesticides are required compared to other  
440 crops in order to protect against, for example, late blight, a fungus responsible for large yield  
441 losses in unsprayed fields (Sengooba and Hakiza, 1999) with reported yield losses in central  
442 Africa of more than 50% (Oerke, 2006). The expense of these pesticides could partly explain  
443 the difference between optimized and observed Temperate Tubers cover.

444 In the regions south of 25 °S the LR optimization generated larger fractions of Tropical  
445 Cereals than the observed and lower fractions of Temperate Maize. These latitudes are  
446 dominated by South Africa, a country where commercial agriculture is practiced on 86% of  
447 total cropland (Anon., 2012). By contrast, our study addresses subsistence farming which is  
448 the dominating form of agriculture in SSA, and the optimization assumptions are that two  
449 important features of agriculture are to maximize the number of calories produced and to  
450 ensure a stable production. Other drivers such as maximization of profit (rather than the  
451 number of calories), or national to local policies were thus not considered. Regional  
452 differences in these drivers could explain the lack of agreement in non-subsistence regions.

453 Given the overall strong correlation between observed and optimized crop fractions for  
454 current climate, the optimizations made for future climate could be seen as scenarios of  
455 changes in crop fractions in regions where agriculture is focused on local sustenance. These  
456 types of scenarios could be alternatives to assuming no change in land use and crop fraction  
457 which is frequently done in impact studies that focus on changes in yields (Liu et al., 2008;  
458 Müller et al., 2010; Rosenzweig et al., 2013a; Schlenker and Lobell, 2010). Earlier studies  
459 looking at trends in crop selection have mostly done so from the perspective of societal  
460 demand for various crops (e.g. Wu *et al.*, 2007). Our study instead focus on the supply side  
461 but taking into account also aspects of crop production stability, thus offering a  
462 complementary alternative to demand-driven study designs.

463 For the HR scenario we identified the single-highest yielding crop of each grid-cell for current  
464 and future climate (You *et al.*, 2013). By contrast to Tropical Tubers in our study, Franck *et*  
465 *al.*, (2011), using the model LPJmL, found the highest simulated yield for Temperate Tubers  
466 (in their study named sugar beet) followed by Temperate Maize. The chief reason for these  
467 differences is likely that Franck et al (2011) computed maximum (potential) yield by  
468 assuming agricultural intensification, and did not scale simulated yield against observed  
469 (actual subsistence) yield as we did for our optimizations. In the study by Koh *et al.*, (2013)  
470 the highest yielding cereal (choosing between barley, maize, millet, rice, sorghum and wheat)  
471 for each 5 min grid cell was selected based on yield data from Monfreda *et al.*, (2008). Their  
472 results gave an increase in crop production by 68% in eastern Africa and 87% in central  
473 Africa when selecting the highest yielding crop compared to current crop fraction. The  
474 relative increase in production from selecting the highest yielding crop in their study is lower  
475 than the one found in our study (HR). Their study however was confined to cereals and also  
476 did not take into account any difference in dry weight and calorific contents of the different  
477 crops. Moreover, in their study, some crops would be grown under intensive farming whereas

478 our study compared yield of crops grown under today's existing management practices  
479 (subsistence farming). Neither of the above studies (Franck et al., 2011; Koh et al., 2013)  
480 therefore compare to our HR approach. Regardless of different approaches to estimate  
481 increases in crop production, as can be seen from our results, selecting the highest yielding  
482 crop generated not only a large increase in crop production compared to current crop fraction  
483 but also an even larger increase in interannual variability.

484 By contrast to the HR approach, in the LR optimization, we investigated the ability to  
485 increase yield for a portfolio of crops while keeping standard deviation in crop production  
486 constant at the current level. We performed the analysis at the grid scale discussing the  
487 potential to increase crop production at regional to continental scale, in contrast to previous  
488 work that applied MPT for the selection of crop varieties more locally (Nalley *et al.*, 2009;  
489 Nalley and Barkley, 2010). For a range of experimental sites in Arkansas, USA the potential  
490 to increase profit in rice production was up to 23% while keeping its standard deviation  
491 constant (Nalley *et al.*, 2009). Applying this method for different crop species rather than  
492 varieties of rice and for a larger spatial area we find that it is possible to regionally increase  
493 crop production by a similar figure.

494 A commonly discussed option for increasing crop production is the closing of the so-called  
495 yield gap (Foley et al., 2011; Licker et al., 2010) through agricultural intensification, which  
496 has been estimated for large parts of SSA to lead to yield increases of existing crops by a  
497 factor of ~10 (Licker *et al.*, 2010). There are however large obstacles for increasing yields in  
498 this manner due to high costs of fertilizers and pesticides, and lack of surface water for  
499 irrigation, all of which would need to be applied (Mueller *et al.*, 2012). Switching from one  
500 mix of crops to another to maximize crop production whilst keeping an acceptable level of  
501 standard deviation in crop production, as suggested by this study, could therefore be seen as



502 an additional option to be explored to produce more calories as well as decreasing the  
503 variability in the food production system. Ultimately, what is being sown is determined by  
504 the individual farmer and these decisions are affected by the demand for crops locally that  
505 may or may not reflect the suitability of those crops in the region.

506 It is necessary, however, to consider that from a food security perspective many other factors  
507 than the generation of a large and/or stable number of calories are equally important, such as  
508 access to markets and the nutritional quality and safety of food (Food and Agricultural  
509 Organisation, 2013). Not getting enough calories is only one aspect of the food security  
510 problem. Micronutrient deficiency is a large problem with an estimated 2 billion people being  
511 affected (Tulchinsky, 2010). Also, at the same time as many people still suffer from  
512 malnutrition, obesity is a growing problem in the developing world (Godfray and Garnett,  
513 2014; Steyn and Mchiza, 2014) meaning that people simultaneously can be both nutritionally  
514 undernourished and obese. Our study focused on staple crops but for a fully nutritional diet  
515 these foods need to be complemented by foods which may be richer in minerals, vitamins and  
516 proteins (DeClerck *et al.*, 2011). For example, a maize based diet increases the risk for the  
517 skin disease pellagra generated by vitamin B<sub>3</sub> deficiency (Hegyi *et al.*, 2004).

518 By extending the simulations to future climate we simulated changes in yield taking into  
519 account not only mean yield changes in future climate but also in its interannual variability.  
520 Our projected crop production rates were compared against the “business as usual”-scenario  
521 in which cropland fractions were assumed to be the same as today (a common assumption in  
522 most modelling studies) and our results can thus be interpreted to consider some degree of  
523 climate change adaptation. Model impact studies have traditionally focused on changes in  
524 mean yield, ignoring the effect on interannual variability in yield. Those studies that assessed  
525 changes in future interannual variability in yield (Chavas *et al.*, 2009; Urban *et al.*, 2012)

526 concentrated on a single crop species. Here we take these approaches a step further, looking at  
527 the interannual variability of the total crop production and not only of single crops. Our  
528 results indicate that across large parts of SSA crop selection could generate increased future  
529 crop production using the same total sown areas as today without increasing the interannual  
530 variability in crop production (Fig. 4b-c). Some regions can also be identified where it is  
531 possible to both increase crop production and to decrease interannual variability at the same.  
532 Regions not suitable for growing crops today might become suitable in a changing climate.  
533 The option to increase crop production by extending crops to new regions was however  
534 beyond the scope of this paper as it would require additional analysis on potential and  
535 estimated actual yields in regions where crops are currently not growing.

536 AgroDGVMs, such as the LPJ-GUESS model used in this study, have the advantage of being  
537 able to simulate changes in crop production and its standard deviation over large regions and  
538 for long time periods (Bondeau et al., 2007; Drewniak et al., 2013; Lindeskog et al., 2013;  
539 Rosenzweig et al., 2013a), and furthermore being based on fundamental process-  
540 representations of plant physiology, rather than extrapolations of empirical relationships  
541 beyond their windows of validity. These advantages come at the price of a lack of spatial  
542 detail and therefore several generalizations have to be made (related to e.g. soil types, local  
543 climate and crop management, and the effect of heat stress) (Challinor *et al.*, 2009). There are  
544 also substantial uncertainties related to model input. Earlier evaluation tests for Africa have  
545 however shown the ability of LPJ-GUESS to reproduce interannual variability in yields at the  
546 country level as reported by the FAO (Lindeskog et al., 2013) when applying climate input  
547 based on observations. Our analysis here was made using bias corrected climate data from 5  
548 GCMs and the mean results from these model runs were used. Simulated fluxes of carbon  
549 using LPJ-GUESS have been shown to be highly sensitive to the choice of GCM (Ahlström *et*

550 *al.*, 2012). By contrast to simulated current yield, the standard deviation in yield was not  
551 scaled against measured data as the availability of data in the SPAM database for evaluating  
552 interannual variability in yield is limited. One potentially useful dataset in this regard is the  
553 one recently created by Iizumi *et al.*, (2014) which combines reported data of harvested area  
554 for the year 2000, country yield statistics and satellite-derived net primary production into a  
555 spatio-temporal gridded dataset of yield for a range of crops. However, two issues prevent  
556 comparison of simulated yield against this dataset, grid by grid. Firstly the dataset shows clear  
557 differences in interannual variability between grid cells on opposite sides of political borders,  
558 i.e. yield dynamics are influenced by the reporting of national yields. Secondly, the climate  
559 input data used in this study was based on GCM model runs which cannot represent the actual  
560 time-series of climate variability for an individual grid.

561 In conclusion this study presents a novel approach for simulating the (climate-constrained)  
562 potential to optimize crop selection in order to increase food production but at the same time  
563 keeping a maximum level of interannual variability in crop production. The close  
564 reproduction of the observed latitudinal fractions of most crops in the study implies that,  
565 assuming current level of variability in crop production as the acceptable level, agriculture is  
566 relatively close to the optimum for producing the highest number of calories. Even so, our  
567 results imply that for some regions it is possible to increase the number of calories produced.  
568 Based on extending the optimization to future climate assuming the same acceptable level of  
569 variability in crop production, increasing regional food production appears plausible. Thus the  
570 method demonstrated herein could be seen as a way to introduce climate adaptation into the  
571 simulations of future crop production.

572

573           **Acknowledgements**

574   This work was supported by the ClimAfrica project funded by the European Commission under  
575   the 7th Framework Program (FP7), grant number 244240 (<http://www.climafrika.net/>) and by  
576   the FORMAS Strong Research Environment: Land Use Today and Tomorrow. AA and TAMP  
577   also acknowledge support from the EC 7th Framework Programme LUC4C (grant no. 603542).  
578   This study is a contribution to the Strategic Research Areas BECC and MERGE and to the Lund  
579   University Centre for Studies of Carbon Cycle and Climate Interactions (LUCCI).

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774 **Supplementary**

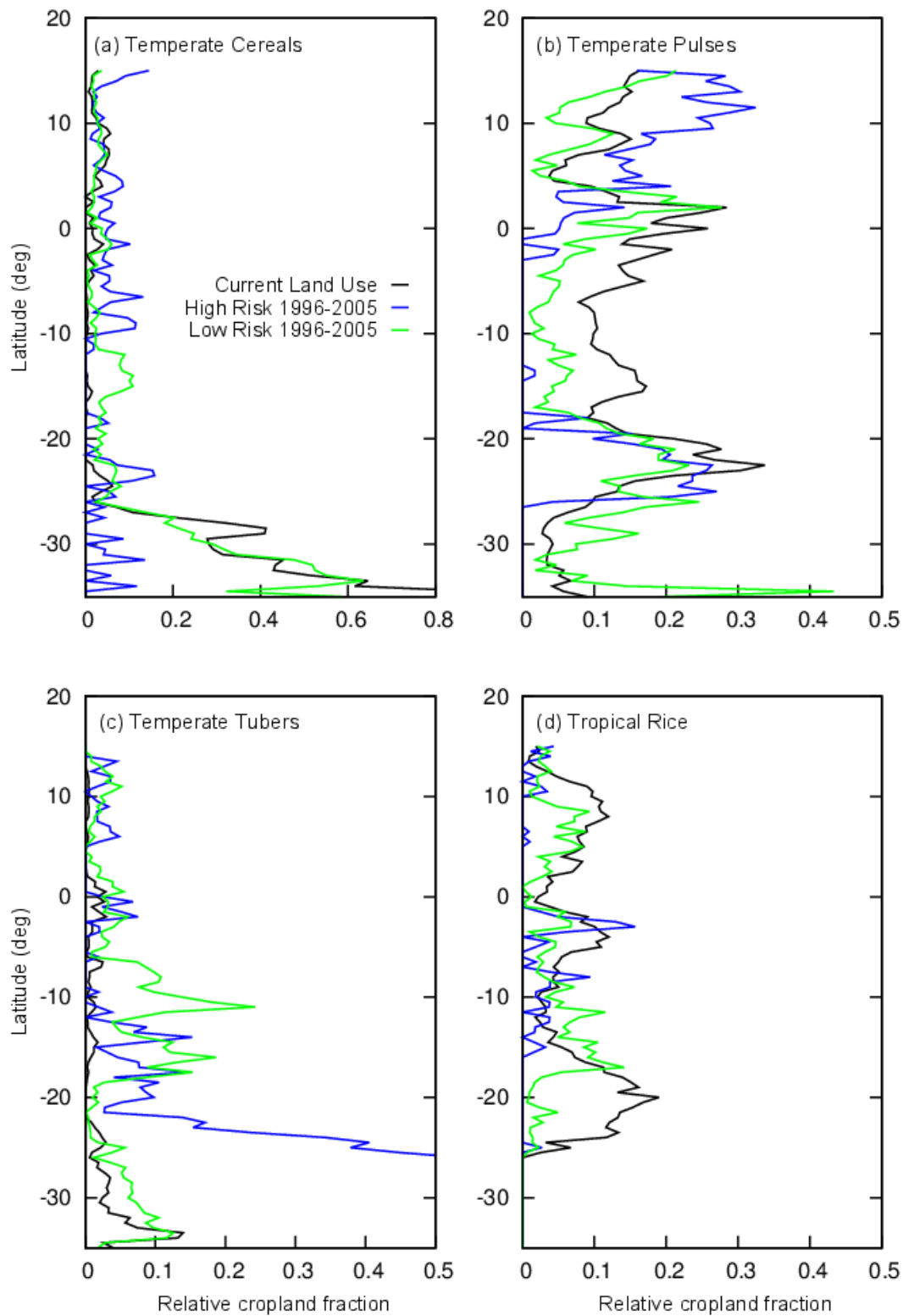
775 *Table S1. Pearson’s correlation between the latitudinal mean of observed (OBS) or optimized*  
 776 *(High or Low Risk) cropland cover and mean annual temperature (Tair) or total annual*  
 777 *precipitation (Prec). Significant correlations ( $p < 0.001$ ) are marked in bold. Colours indicate*  
 778 *degree of correlation as indicated by the colour bar below.*

CFT	Tair			Prec		
	OBS	Low Risk	High Risk	OBS	Low Risk	High Risk
<i>Temperate Cereals</i>	<b>-0.72</b>	<b>-0.80</b>	0.16	<b>-0.50</b>	-0.55	0.04
<i>Temperate Maize</i>	<b>-0.60</b>	0.05	0.21	-0.26	0.16	0.06
<i>Temperate Pulses</i>	<b>0.37</b>	-0.08	<b>0.52</b>	0.19	-0.32	-0.17
<i>Temperate Tubers</i>	<b>-0.65</b>	<b>-0.36</b>	<b>-0.87</b>	<b>-0.36</b>	-0.04	<b>0.81</b>
<i>Tropical Cereals</i>	<b>0.71</b>	<b>0.53</b>	<b>0.36</b>	-0.10	-0.22	<b>-0.66</b>
<i>Tropical Rice</i>	<b>0.38</b>	<b>0.39</b>	0.19	0.25	<b>0.45</b>	-0.06
<i>Tropical Tubers</i>	<b>0.43</b>	<b>0.54</b>	<b>0.68</b>	<b>0.88</b>	<b>0.87</b>	0.29

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Tair/Prec	r	0.0-0.2	0.2-0.4	0.4-0.6	0.6-0.8	>0.8
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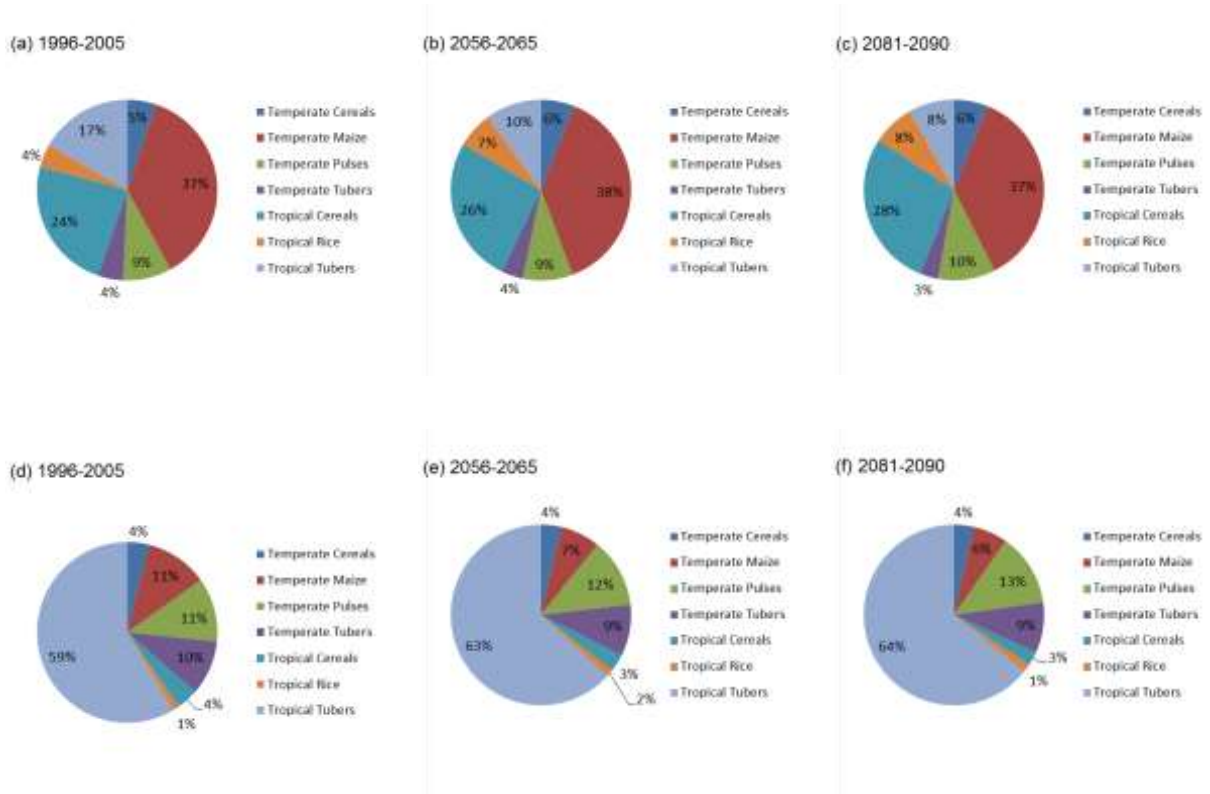
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782 *Figure S1. Optimized latitudinal mean CFT fractions for current climate (1996-2005) (High*

783 *Risk solid blue lines; Low Risk solid green lines) and observed CFT fractions (black lines)*

784 for: Tropical Rice (a), Temperate Cereals (b), Temperate Tubers (c) and Temperate Pulses  
 785 (d). Note the difference in scale for Temperate Cereals.

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787 Figure S2. Optimized cropland fractions for the Low Risk (a-c) and High Risk optimization (d-  
 788 f) for the time periods 1999-2005 (a,d) 2056-2065 (b,e) and 2081-2090 (c,f).

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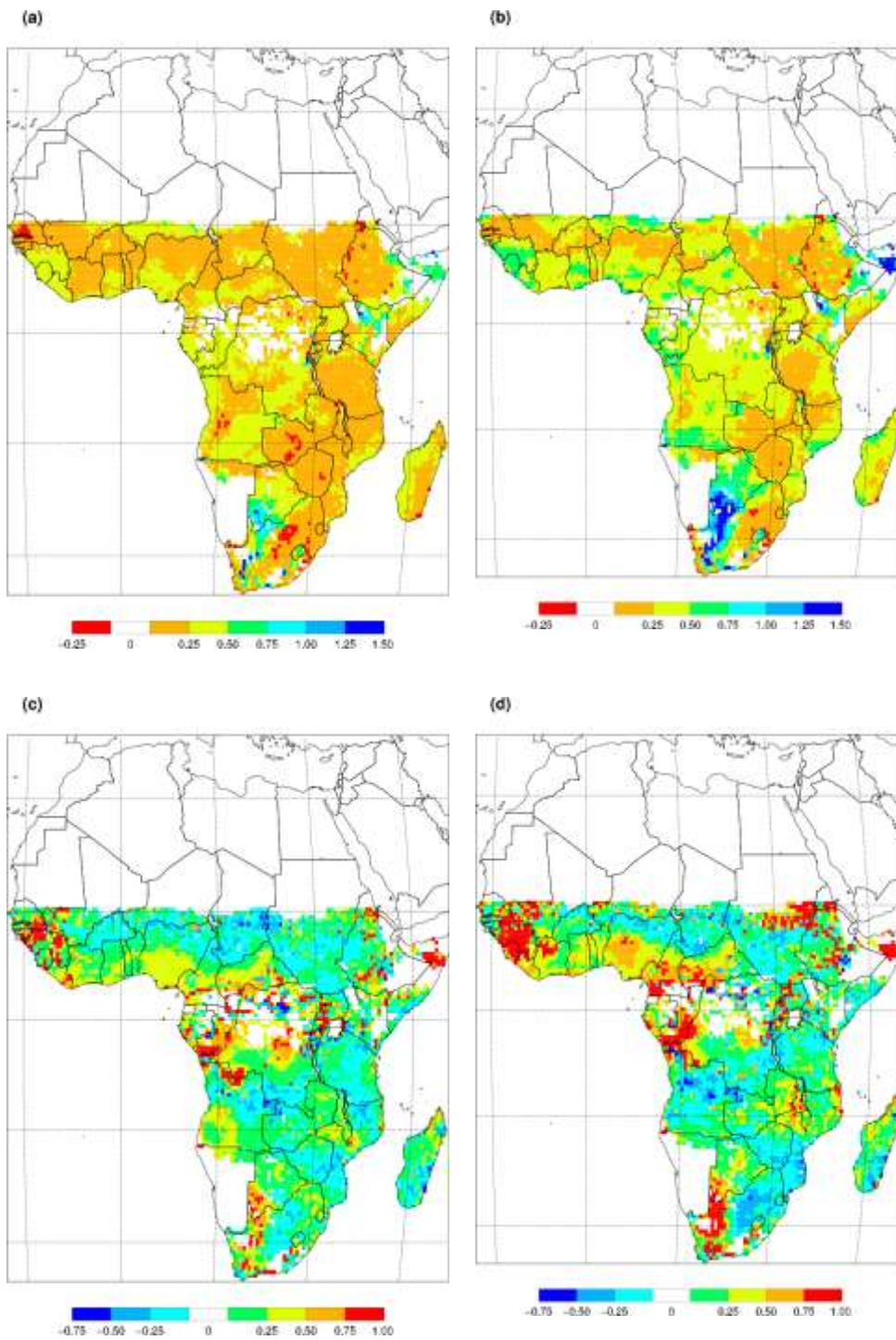
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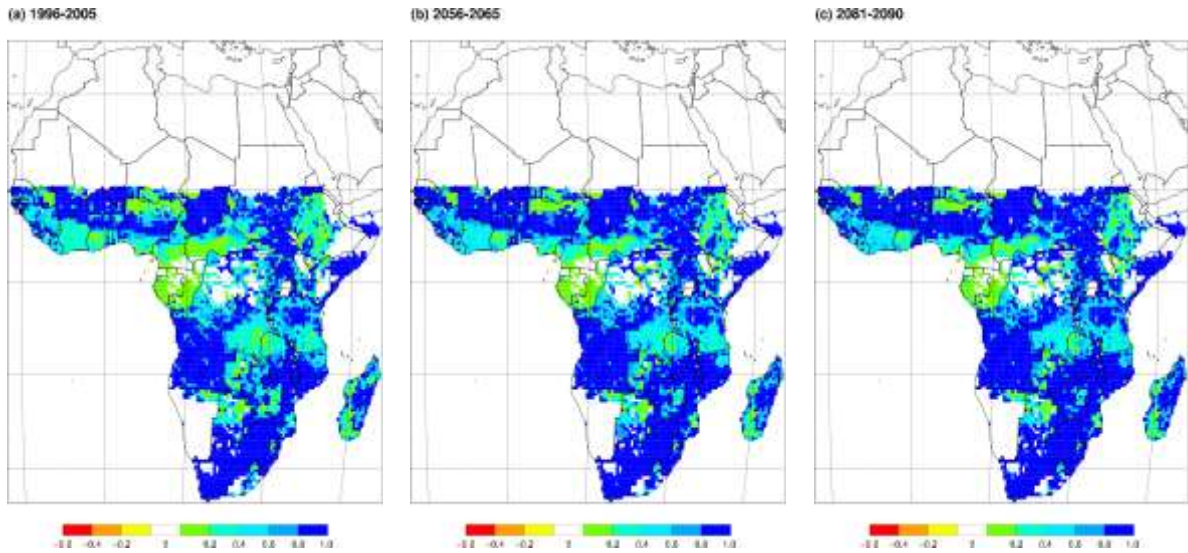
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795 *Figure S3 Relative difference in simulated crop production (a-b) and standard deviation in*  
 796 *production (c-d) compared to current climate (1996-2005) assuming current land use fractions*  
 797 *(BAU) for both future time periods: 2056-2065 (a and c); and 2081-2090 (b and d).*

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799 *Figure S4. Relative difference in crop production compared to assuming current land use*  
 800 *fractions (BAU) for the High Risk optimization, for the years 1996-2005 (a), 2056-2065 (b) and*  
 801 *2081-2090 (c).*

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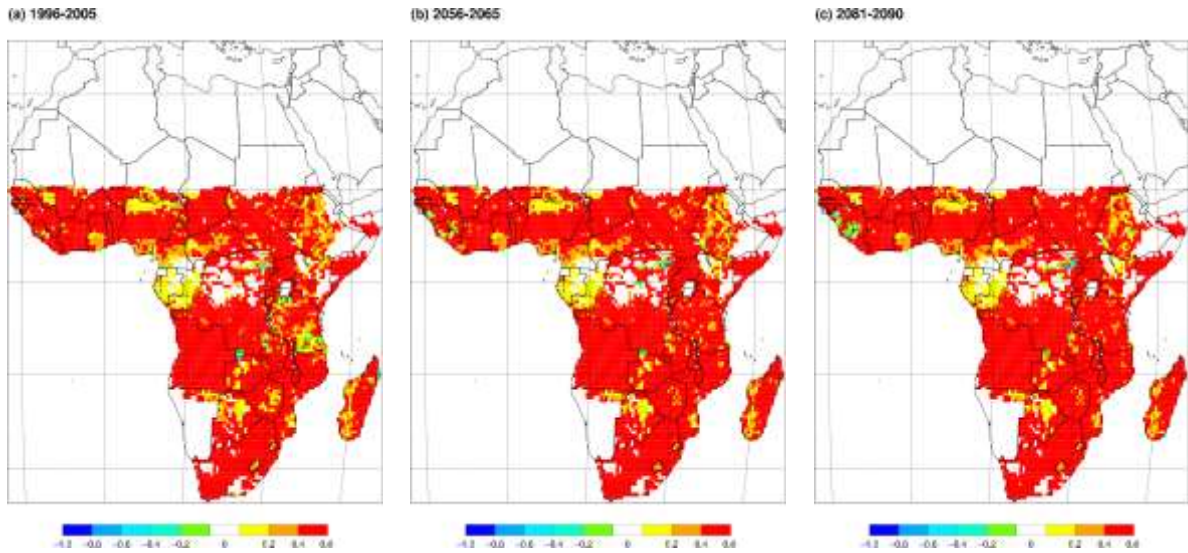
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813 *Figure S5. Relative difference in standard deviation in crop production compared to assuming*  
 814 *current land use fractions (BAU) for the High Risk optimization, for the years 1996-2005 (a),*  
 815 *2056-2065 (b) and 2081-2090 (c).*

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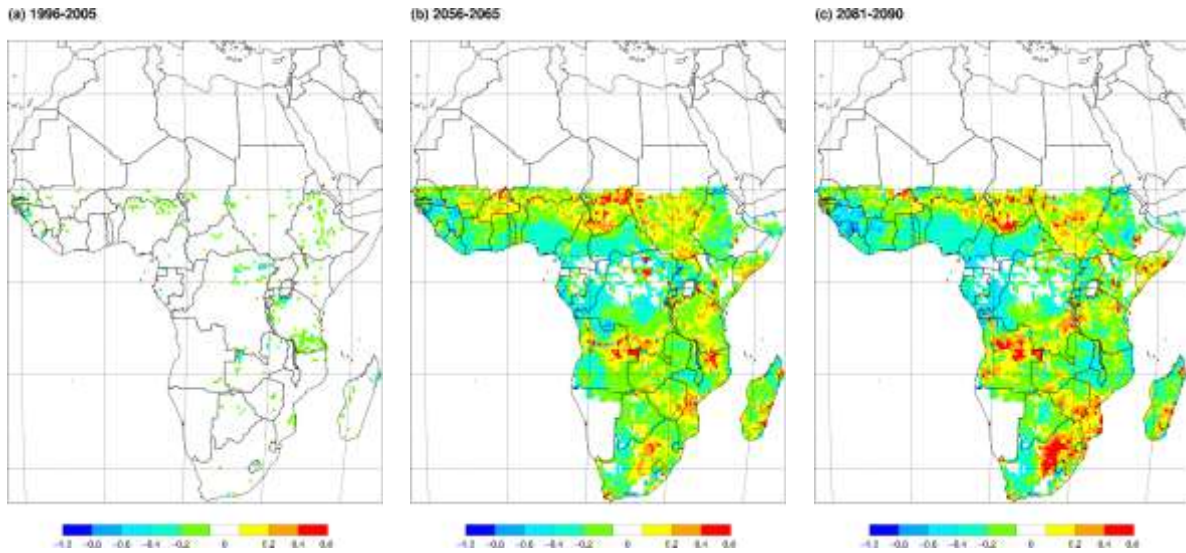
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827 *Figure S6. Relative difference in standard deviation in crop production compared to assuming*  
 828 *current land use fractions (BAU) for the Low Risk optimization, for the years 1996-2005 (a),*  
 829 *2056-2065 (b) and 2081-2090 (c).*

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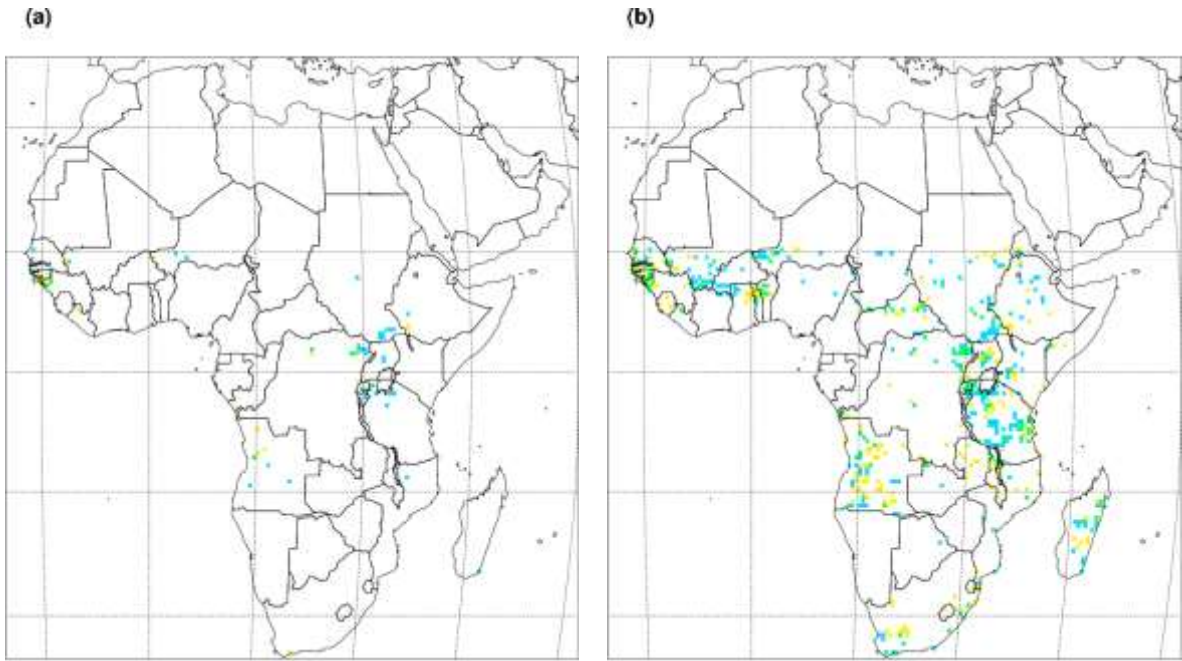
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837 *Figure S7. Grid cells where the Low Risk optimization generated both an increase in crop*  
838 *production and a decrease in the standard deviation in crop production >25% (a) or >10%*  
839 *(b) for the time period 2056-2065 (yellow); 2081-2090 (blue) or both time periods (green).*

840