Climate Change Impacts on Crop Production in Busia and Homa Bay Counties, Kenya

by

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1. Introduction

Climate change is expected to impact crop production in the Lake Victoria Basin, yet little quantitative information is available on the extent and direction of these impacts. Without such quantitative information, however, developing appropriate adaptation strategies is difficult. While it may seem to make sense to promote measures that make farmers less vulnerable to climatic variability, such measures may not be economically recommendable. For example, putting in place irrigation infrastructure makes crops less vulnerable to water shortages, but this is only appropriate if there is a current or future risk of drought. If there is no such risk, purchasing expensive irrigation equipment would be a bad investment for most farmers.

It is therefore important to anticipate effects of future climate change as accurately as possible and identify those climatic factors that represent the greatest risk of compromising food security. Once these factors have been identified, appropriate and quantitatively informed adaptation strategies can be devised. This study attempts to accomplish this for two counties on the Kenyan shore of Lake Victoria, Busia and Homa Bay, as well as for surrounding areas. The current and future suitability of this region for major agricultural crop was evaluated using a range of methods.

Doing such an analysis is impaired by a striking shortage of necessary input data. Except for isolated rainfall data, there are essentially no long-term weather records for either district. This means that even current climate cannot be reliably characterized, placing constraints on the accuracy, with which the future can be projected. Targeted climate change projections for the study region have also been scarce, for the same reasons. Observations of local weather are needed for calibrating climate models, and where no records are available, the accuracy of climate models is questionable. Similarly, soil information for the study region is scarce, yet soil data is an essential input into any crop model. Finally, information on what crop varieties farmers grow, how these respond to climate, and how exactly they are managed, is unavailable. Some of this information could be obtained through detailed fieldwork, and recommendation will be made on how to go about improving the site-specific validity of modeling efforts. For the purposes of the current study, however, best-bet proxy datasets were used to arrive at the conclusions presented here. This study therefore provides a rough indication of the impacts of climate change on the production of major crops in the study region. It also presents an evaluation of which climatic factors are the most likely constraints for production of the various crops. Yet the results of this study should not be taken as completely accurate, because of the host of unknowns about essentially all important factors of climate, soils and cropping systems.

2. Methodology

2.1. Historic weather data

Reliable climate data for the target region is scarce and of limited usefulness for climate change projection. Long-term weather station records from stations within the study area are only available for rainfall, whereas temperature records are limited to a small number of years, long in the past. Outside the study region, consistent weather records exist for a few stations, such as Kisumu, Kakamega and Kisii. While these stations lie in the geographic vicinity of the study counties, they are not necessarily climatically comparable, due to their positions directly at the lakeshore (Kisumu), or at higher elevation (Kisii and Kakamega). In addition to limited suitability as a proxy for climate in Busia and Homa Bay, station records also had gaps and were lacking information on radiation, both of which reduce their suitability for subsequent analysis steps.

As an alternative source of climate information, the SLATE dataset produced by the HarvestChoice project was used in this study (White et al., 2008). This dataset combines daily observational records from the NASA-POWER dataset (for 1997-2008 at 1 degree resolution) with the results of climate model runs from the Climate Research Unit at the University of East Anglia (for 1901-2006, at 0.5 degree resolution), resulting in a 100-year (1906-2005) record of daily weather information (temperature extremes, rainfall and radiation) for all of Sub-Saharan Africa at 0.5 degree resolution. The SLATE dataset was used for all subsequent downscaling steps.

2.2. Climate change projections

Three climate models were chosen for the analysis. Due to the short project duration, inclusion of more models was not possible, because model runs could not have been completed for a larger array of scenarios. The following three General Circulation Models were selected:

HADCM3 - Hadley Centre Coupled Model, version 3

CCCMA CGCM2 - Canadian General Circulation Model 2 by the Canadian Centre for Climate Modelling and Analysis

CSIRO Mk2 - CSIRO Atmospheric Research Mark 2b

For all models, the statistically downscaled versions provided by the CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS; http://ccafs-climate.org/download_allsres.html) were used for analysis. These projections have a spatial resolution of 2.5 min (approx. 25 km in the study region), and are available for two IPCC greenhouse gas emissions scenarios (A2a - 'business as usual' emissions; and B2a - reduced emissions), and three points in time (2020s, 2050s and 2080s). CCAFS also provides baseline climatology for the time span 1950-2000 (Hijmans et al., 2005), which was used as a reference scenario.

2.3. Downscaling methodology

All climate scenarios used only provide monthly means of important weather variables, which are not sufficient for capturing variation in crop production due to climate variability.

Consequently, models were temporally downscaled using the LARS-WG weather generator (Semenov, 2008). This tool uses daily weather data for a particular location to estimate climatic site parameters, which statistically describe rainfall, temperature extremes and radiation at the location, with separate distributions for wet and dry spells. Based on these parameters, LARS-WG can then be used to generate synthetic weather records, with the same characteristics as the original record. It is also possible to modify this process by including changes to monthly means of all climate variables extracted from climate change projections. The results can then be used to simulate climate change effects on biological processes at high resolution (e.g. Luedeling et al., 2011a; Luedeling et al., 2011b)

Weather generator parameters were computed from all locations from the SLATE database, located within a rectangular area spanning 3.75°S - 3.75°N and 31.25°E to 38.75°E. For all 200 stations, site parameters were calculated from SLATE's 100 years of daily weather. The spatial resolution of this dataset is only 0.5 degrees, so that only about 3 sites would have been located in the vicinity of Homa Bay and Busia counties (and only 2 in the counties). To enhance the resolution, each site parameter produced by the weather generator was extracted from the generated site files and spatially interpolated using the Kriging technique. The almost 6000 resulting grids were then sampled at selected locations within the study area, and LARS-WG parameter files were assembled for each location. The resulting set of 36 stations covered the entire study region at a spatial resolution of 0.2 degrees, corresponding to approximately 20 km.

Climate scenarios for downscaling were obtained by sampling all monthly layers of minimum temperature, maximum temperature and precipitation for the three GCMs, for the A2a and the B2a greenhouse gas emissions scenarios. A2a is the 'business-as-usual' scenario, whereas B2a includes a gradual transition towards a low emission society. Consequently, climatic changes are typically greater in the A2a than in the B2a scenario. For each combination of GCM and greenhouse gas emissions scenario, projections for three time slices were used: the 2020s, the 2050s and the 2080s. Additionally, a climatic baseline was obtained from the WorldClim database. This data layer was generated with the same technique as CCAFS' climate projections, ensuring a cohesive dataset. From the resulting set of climate parameters, LARS-WG scenario files were prepared for all 684 combinations of site and climate scenario. Based on these files and the reassembled site parameter sets for each location, the weather generator was used to produce 25 years of synthetic daily weather data for each scenario. These 25-year records are not time series. They rather constitute 25 replicates of a given year's weather, spanning the range of weather situations that can plausibly be expected. Variation in these records is introduced by a random seed, ensuring that weather is variable, but within the confines dictated by the site parameters and climate scenarios.

2.4. Soil data

As with weather data, soil data for Kenya is scarce. Some surveying work has been done within the Fertilizer Use Recommendation Project, but this effort only included 6 sites within the study districts (Bukiri-Buburi and Alupe in Busia and Rodi Kopany, Rongo, Homa Bay and Oyugis-Ober in South Nyanza). This small selection surely does not cover the full range of soil types in the region. Closing this knowledge gap would require an extensive soil survey covering the full expanse of the study region, which was not possible in this study. Instead, globally available soil

data from the ISRIC WISE database was used for the modeling of crop production (Batjes and Bridges, 1995). This database provides soil information on a 0.5*0.5 degree grid. For each such grid cell, up to 10 soil types are given in the database, with the respective share of the cell that is covered by this type. For the three most important soil types per grid cell, the FAO soil classification code was extracted, and information about the soil extracted from ISRIC's soil profile collection (Batjes, 2009). This database contains information from more than 10,000 soil profiles from around the world, with data on soil properties at different depth that is detailed enough for a process-based crop model that includes multiple soil layers. For all soil types in the database, and for all soil properties, the median values for the distributions were calculated. From the results, a typical profile for the respective soil type was constructed. The number of soil layers was determined as the number of layers present in more than two thirds of profiles from the database, for each soil type separately.

2.5. Crop modeling

Robust crop modeling requires detailed knowledge of a host of factors that influence cropping systems, such as the crop variety planted, sowing densities, fertilization regimes etc. In particular the crop variety needs to be defined not only by name, but with a comprehensive set of crop attributes describing crop phenology (timing of development stages in response to weather), photosynthetic rate etc. If all these factors are known, and reliable weather and soil information is available, crop yields can be simulated quite reliably, with several available models.

In this study, most of the required information was not available, and the time frame of the study did not allow collecting sufficient data for the host of crops that were to be modeled. The crop modeling thus relied on a range of assumptions about pertinent factors. This will be sufficient for getting a general impression of climate change effects on major crops, but for yield projections to be accurate, field collection of relevant data and a repeat of the model runs are recommended.

2.5.1. Annual crops

For modeling the production of annual crops, the Agricultural Production Systems sIMulator (APSIM) was selected (Keating et al., 2003; McCown et al., 1996). This crop model is a robust, process-based model that provides sophisticated modules for a host of important field crops. Unlike more empirically based models, a process-based model can differentiate between different phases of crop development, which may be impacted by weather in different ways. It thus produces a good estimate of how and when crops are susceptible to adverse weather. While developed initially for modeling Australian crop production systems, APSIM has been applied successfully in many countries, across diverse climatic zones. An important feature of APSIM is that it has not only an easy-to-use user interface; it also provides the option of running models in 'command line' mode (directly from the operating system), which is necessary for implementing the batch processing needed for this study.

For preparing APSIM simulations, the user interface was used to design appropriate crop management systems, and the instructions for running the simulation were then modified to accommodate different sets of weather records and soil types. For choosing the most

appropriate crop variety, the number of degree days available during each growing season was calculated according to equations used by APSIM. The number of degree days required by each crop variety given in APSIM's database was also calculated. Based on these calculations, the most appropriate variety was selected as the one that best matched the available number of thermal units, while being slightly below the available amount for each rainy season. To ensure comparability of modeling results, the variety selected for the majority of sites was then chosen for all locations.

APSIM was run for each combination of site, major local soil type, rainy season and climate scenario. Crop yields for all years of the 25-year simulations were extracted from APSIM's output files, and plotted as cumulative distributions for each site, soil and climate scenario.

2.5.2. Rainy seasons

One important input parameter for a crop model is the time of planting the crop. This time invariably varies within the study region, depending on the exact onset date of the rainy season. While farmers' intuition may tell them reliably when the rainy season begins and ends, automatic extraction of these dates from the weather records generated in this study required defining a formalized decision rule. This rule must be able to reproduce the dominant pattern of long and short rains for most of the study region. To achieve this, all rainfall records were first subjected to a 7-day running mean, i.e. the rainfall of each day was replaced by the average rainfall of the period starting 3 days before and ending 3 days after the respective date. All days for which this running mean was above 4 mm were classified as rain days. Since it does not rain every day even during the rainy season, a tolerance of up to 7 days of non-rain days was built into the rule, meaning that periods of up to 7 consecutive days that were not classified as rainy did not signify the end of the rainy season. Finally, a minimum duration of the rainy season of 30 days was used as a threshold. Rainy spells that were shorter than 30 days were not considered to constitute a rainy season.

Applying this rule to averaged annual rainfall records for all years of the baseline scenario produced the following rainy season pattern for the 36 sites chosen for more detailed crop modeling: For all sites, the algorithm found at least 1 rainy season, running from mid-March to the beginning of June. On average, this season lasted for 82 days, with a standard deviation of 6 days. This rainy season is what is commonly referred to as the 'long rains'. The second rainy season, the 'short rains', were detected for 27 out of 36 sites. This means that for 9 sites, this season was not recognized, including the north-eastern half of Homa Bay County. Where it existed, this season lasted for about 45 days (±10 days), spanning October and November. For two sites in Northern Busia, a third rainy season was found, following two to three weeks after a rather short second rainy season. In effect, this additional season is probably part of the short rains, and represents insecure rainfall towards the end of this season. The third rains will thus not be discussed separately.

All crop modeling was done separately for each rainy season, with the detected beginning of the season determining planting dates. The exact date was determined based on available soil moisture, but planting was only allowed during a time window starting 20 days before the average beginning of the rains, and 20 days after this date. For cotton, which is grown as a relay crop in the study region, the planting window was shifted backwards by 30 days.

2.5.3. Perennial crops

With few exceptions, perennial crops cannot be modeled with APSIM, and for most crops, no process-based models exist. Modeling yields of perennial crops could thus only be achieved via empirical correlations of yields with certain environmental factors. However, since empirical models are not based on a thorough understanding of climate responses of all the processes that lead to crop yields, model validity under different climate regimes or in a different location would be questionable. The physiological processes of most annual crops are much better understood, allowing process-based modeling. As another important difference between annual and perennial crops, productivity of a tree crop is determined not only by environmental conditions and management decisions in the current year, but also by conditions and decisions in all years leading up to the current year. A range of factors, such as the pruning regime, alternate bearing or previous exposure to drought or heat stress can have strong effects on yield. But even the applicability of empirical models is quite limited by low availability of productivity data for perennial crops in locations comparable to the study districts.

For perennial crops, as well as for sweet potato and cassava, for which no APSIM modules were available, climate change impact projection was thus based on climatic crop requirements published in FAO's ECOROP database (http://ecocrop.fao.org/ecocrop/srv/en/home). ECOCROP consists of a collection of 2568 crops, for which minimum, maximum and optimum rainfall and temperatures are collated. For perennial crops included in the study, these requirements were extracted from the database. Projected climate conditions for all future scenarios and the baseline were then evaluated, with respect to their suitability for the given crops.

In the evaluation, weights were assigned for monthly minimum and maximum temperatures, depending on how high monthly values were compared to the optimal range. The weighting scheme is illustrated in Figure 1. For either minimum or maximum temperature in the optimal temperature range, a weight of 1 was assigned for the respective month. For values outside the absolute temperature range, the month received a value of 0. For temperatures within the absolute temperature range but not within the optimal range, weights were scaled linearly. For example, where the absolute maximum temperature is 35°C and the upper end of the optimal range is 30°C, a monthly maximum temperature of 32.5°C would receive a weight of 0.5, whereas a minimum temperature of 28°C would receive a weight of 1. Weights were calculated in this manner for minimum and maximum temperature layers for all months of all climate scenarios, and the average per scenario calculated from all scores, for each grid cell of the climate layers that were within the study region. Wherever temperatures fell below the absolute minimum thresholds, or exceeded the absolute upper thresholds, weights for that location were set to 0, since ECOCROP indicates that the site is poorly suited for the crop. For rainfall, only annual totals are given in the database, which precluded taking full account of intra-annual variation. Annual rainfall sums were evaluated against crop requirements in the same way as temperatures (Figure 1). Suitability weights for temperature were then multiplied by weights for rainfall to arrive at a final suitability score for the crop for each map pixel and climate scenario. These were mapped to allow assessment of climate change impacts on crop suitability.
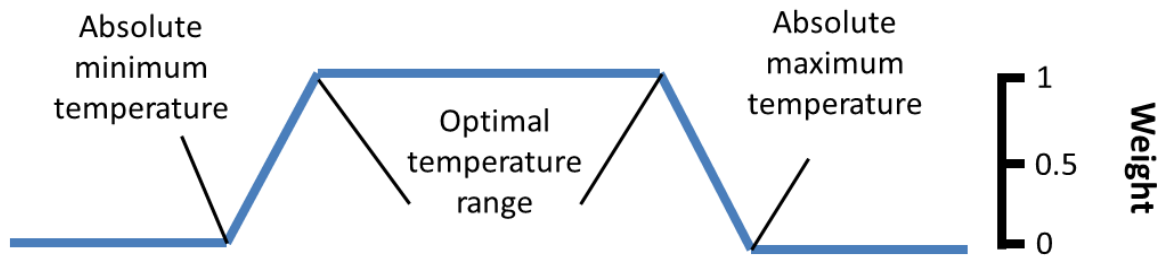
Figure 1. Illustration of the weight function applied to temperature variables in the suitability modeling algorithm. For temperatures in the optimal range for the crop, a weight of 1 was assigned. For temperatures outside the absolute range, 0 was given. For temperatures between the optimal and absolute thresholds, weights were scaled linearly. This scheme was applied to monthly means of daily minimum temperatures, monthly means of daily maximum temperatures and for annual rainfall totals.

2.6. Effects of weather on crop yields

Providers of weather insurance products must know the kind of climatic conditions that impact crop yields. From these conditions, weather indices can be defined. Evidently, these conditions will vary across crops, crop varieties, soil types and management practices. Insurance companies must ensure that the set of indices they use captures the site-specific crop vulnerability situation of their clients. Establishing the details of this vulnerability situation requires collection of a host of site-specific factors, including most importantly data about crop yields, as well as detailed descriptions of crop varieties. Since this information is not currently available, the analysis in the present study was restricted to screening of modeled crop yield patterns for phases and weather parameters that were strongly correlated with either high or low crop yields. This was done by Projection-to-Latent-Structures Regression (PLS), which has recently been shown to be an effective tool for analyzing the way, in which plant performance depends on climate (Luedeling and Gassner, under review; Yu et al., 2010). Unlike most regression approaches, PLS can handle daily weather records as independent input variables, making it suitable for the present study.

Essentially, PLS produces two major outputs: the Variable Importance Plot (VIP) indicates how well certain variables are correlated with crop yields (Wold, 1995). VIP values are computed for each input variable (i.e. minimum and maximum temperatures and rainfall for each day of the growing season). Typically, a threshold value of 0.8 is adopted, with VIP scores above this threshold indicating that the variable is important. The second output is the model coefficient plot, which conveys the strength and the direction of the effect. All effects are measured relative to mean weather conditions at the site that the analysis is done for.

The way PLS outputs must be interpreted is best illustrated using an example: For maize, the 1st of June may have VIP scores of 0.6 for minimum temperature, 1.0 for maximum temperature and 1.2 for rainfall. This means that variation in maximum temperature and rainfall on 1st June should be considered important for explaining crop yields. Model coefficients for the respective days are +0.5 for minimum temperature, -1 for maximum temperature and +0.3 for rainfall. This would mean that high maximum temperature on 1st June has a strongly negative effect on yield

(negative sign of the coefficient), whereas high rainfall on that day has a positive effect. The influence of high minimum temperature is also positive, but this effect is not considered important due to a low VIP score. Combinations of weather parameter and day that have high VIP scores and negative model coefficients are those that are of most concern to crop producers, because high values for the respective combination are associated with low yields.

PLS analyses were run for all combinations of field crops that could be modeled with APSIM and for all major soil type in the study area. Dependent input variables were crop yields generated by APSIM, for all climate scenario years for the climate baseline and the 2020s scenarios. Later results were not included in the final analysis, because the 2050s and 2080s are beyond the planning horizon of most insurance companies. Moreover, due to a strong tendency towards lower yields in most climate change scenarios and for most crops, low yields were associated with higher temperatures during all days of the year. This was not considered realistic, and reflects Luedeling and Gassner's (under review) assertion that all input data for a PLS analysis must be from approximately the same 'climate domain', for the PLS analysis to work.

In the outputs of the PLS procedure, all VIP values above the threshold were marked in blue, for easier interpretation. A VIP threshold of 1.0 was adopted to highlight variables of particular importance. For the model coefficients, all those combinations of weather parameter and year, for which high values had a positive effect on yields were marked in green, whereas those with negative effects are drawn in red.

3. Results

The various model runs done in this study produced a large number of maps, which cannot all be presented in a written report. Therefore, all maps are organized in a series of HTML pages, which is provided as a digital attachment to the report. These maps can be accessed by a standard web browser.

3.1. Soil types

Among the map units of the ISRIC soils database that spanned the study region, a total of 7 soil types were among the three most prevalent soils of the cells. That is, these soils ranked either first, second or third in importance for any of the map units of the ISRIC database that covered the study region. Among these soils were Humic Andosols, Orthic and Plinthic Acrisols, as well as Orthic, Plinthic, Rhodic and Xantic Ferralsols. Andosols are of volcanic origin, with high plant nutrient contents, but potential limitations in water availability and a risk of aluminum toxicity. Acrisols are clay-rich soils of the humid tropics, with low soil fertility and high aluminum contents. Ferralsols are highly weathered soils of the humid tropics, with very low soil fertility. All results presented in this report are for these soils. Modeling yields for all soil types listed in the database was not possible, because model runs could not have been completed during the time available for the study with the available computing infrastructure.

3.2. Climate change projections

3.2.1. Temperature

Among the three climate models used, all scenarios for both emissions scenarios showed a strongly increasing temperature trend (Figure 2). Mean annual temperatures in the study counties were around 22°C in the lower areas, and about 20°C in areas at higher elevations. For the B2a scenario, mean annual temperatures rose to 25°C in the lowlands and 23°C at higher elevations by the 2080s. In the A2a emissions scenario, mean annual temperatures in the lowlands reached 27°C, and even the higher regions of Homa Bay had 25°C as annual mean temperature. Among the three climate models, temperature increases were strongest for the HadCM3 model (third row in Figure 2), while the CCCMA and CSIRO models had similar results. Monthly temperatures were in line with the annual temperature (not shown, but included in the digital supplement).
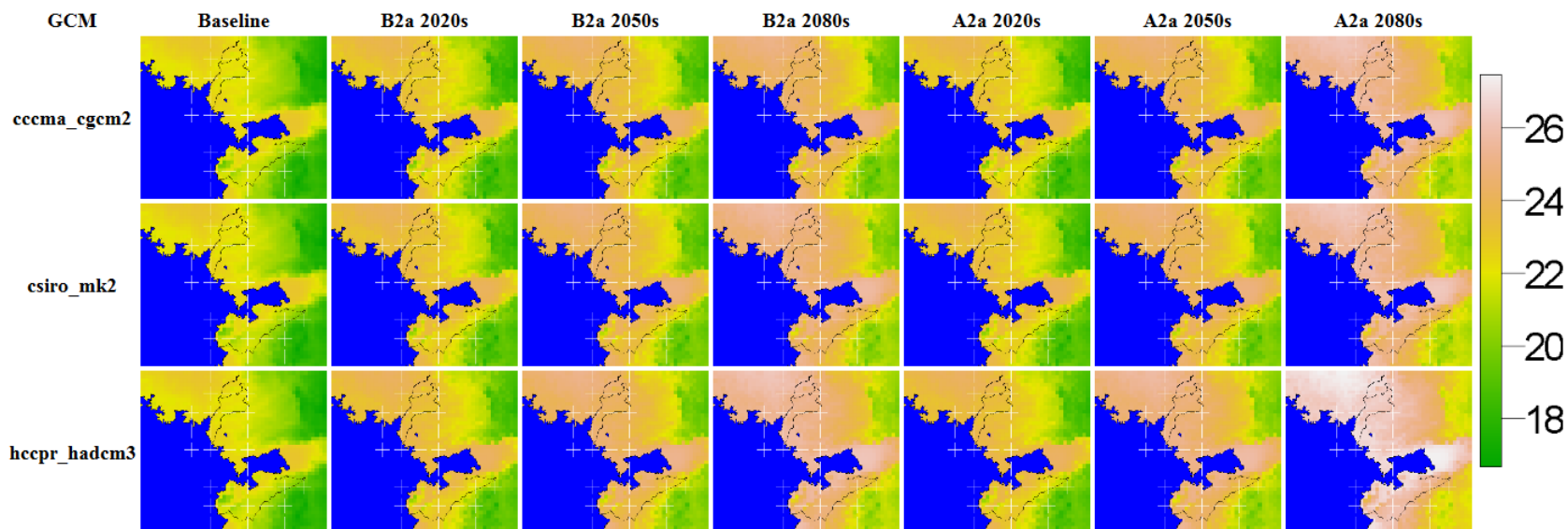
Mean annual temperature (°C)

Figure 2. Mean annual temperature (°C) for the study region projected for the current situation (baseline; first column), and 18 future scenarios. Rows across are projections with the same climate model. The second to fourth column show projections for the 2020s, 2050s and 2080s for the B2a greenhouse gas emissions scenario (low emissions), whereas the last three columns are for the A2a (higher) scenario.

The maps of changes relative to the baseline scenario illustrate projected temperature increases clearly (Figure 3). Projected increases were homogeneous across the study region, but differed across scenarios. Projected temperature rise by the 2020s was around 1°C in all GCMs and emissions scenarios. For the 2050s and 2080s, increases were strongest for the HadCM3 model, which predicted up to 5°C warmer conditions than presently. Projections were more moderate for the other two models, indicating temperature rise by 2-3°C for the B2a scenario by the 2080s, and about 4°C for the A2a scenario.
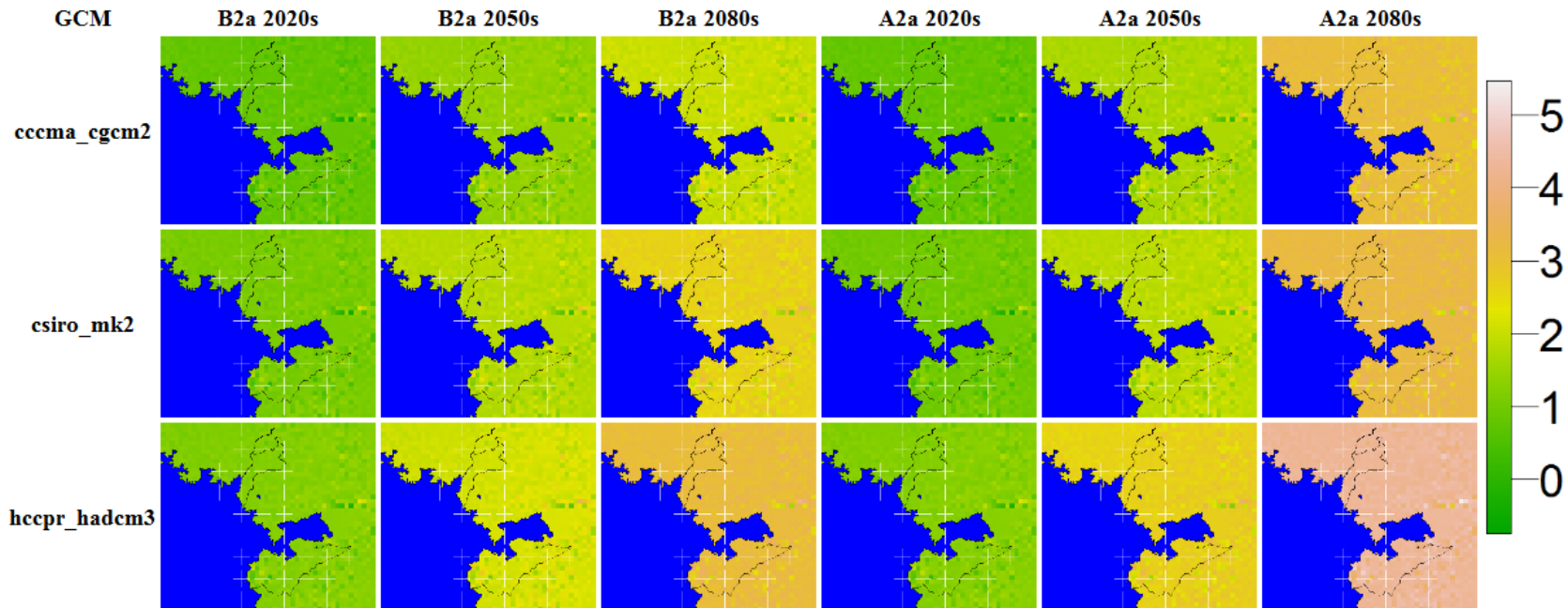
Changes in mean annual temperature
(°C)

Figure 3. Changes in the mean annual temperature (°C) for the study region projected for the current situation, relative to baseline climate, for 18 future scenarios. Rows across are projections with the same climate model. The second to fourth column show projections for the 2020s, 2050s and 2080s for the B2a greenhouse gas emissions scenario (low emissions), whereas the last three columns are for the A2a (higher) scenario.

3.2.2. Rainfall

Mean annual rainfall in the study region ranged from 1000 to 2000 mm in the baseline scenario (Figure 4). It is highest in the hilly areas north of Kisumu and east of Homa Bay. The least rainfall falls along the lake shore. This general pattern persisted in all future projections, but the three models differed significantly in projections of future rainfall. The HadCM3 and the CCCMA models showed rainfall patterns similar to the baseline for all future scenarios. Only the CSIRO model projected a marked increase in rainfall, reaching more than 2500 mm in the highlands.
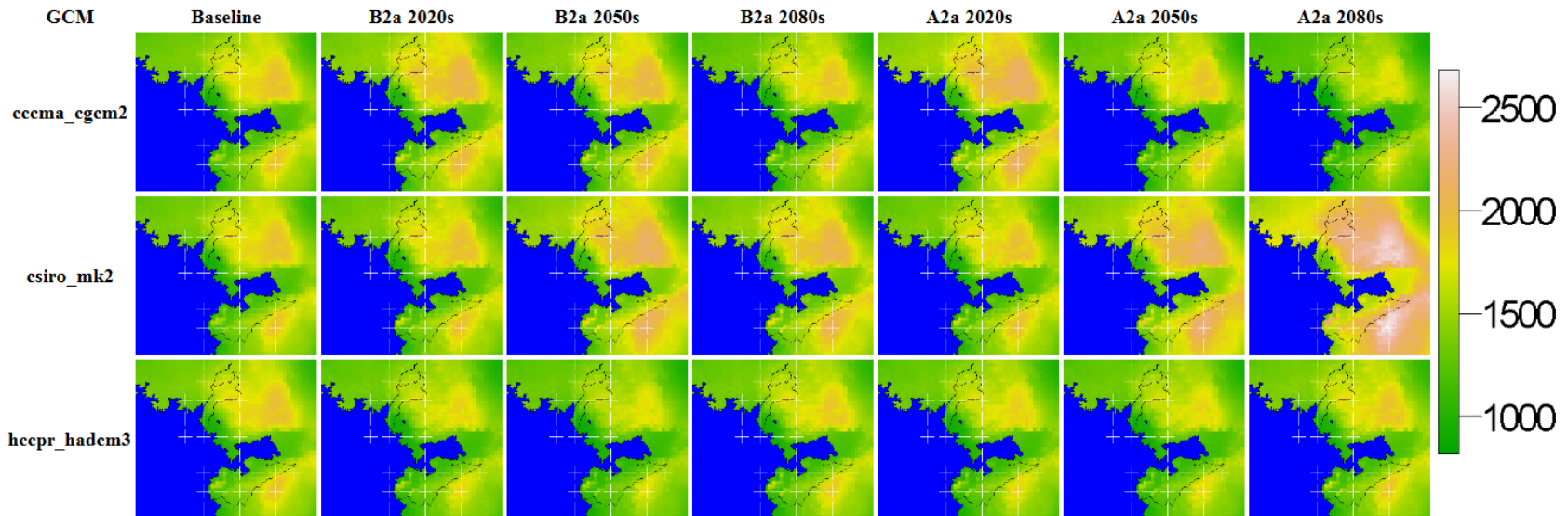
Mean annual rainfall (mm)

Figure 4. Mean annual rainfall (mm) for the study region projected for the current situation (baseline; first column), and 18 future scenarios. Rows across are projections with the same climate model. The second to fourth column show projections for the 2020s, 2050s and 2080s for the B2a greenhouse gas emissions scenario (low emissions), whereas the last three columns are for the A2a (higher) scenario.

Maps of projected changes in rainfall (Figure 5) show these trends more clearly. No projection indicated annual rainfall decreases of more than 200 mm, while up to 800 mm more were projected for the 2080s for the CSIRO model and the A2a emissions scenario. Judging by annual rainfall alone, changes in the study counties should not pose big problems for agriculture. However, gains and losses in rainfall differed throughout the year, with less rainfall projected for some regions for May and June, and substantial gains for October through April.
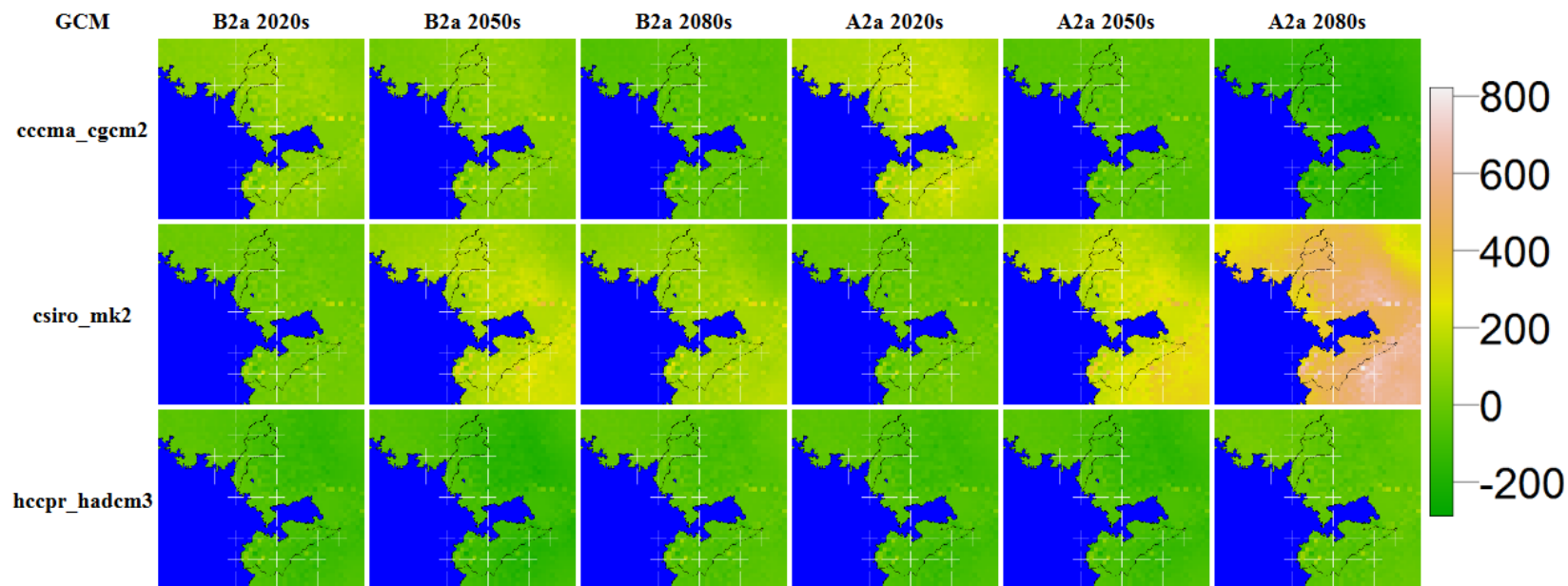
Changes in mean annual rainfall
(mm)

Figure 5. Changes in the mean annual rainfall (mm) for the study region projected for the current situation, relative to baseline climate, for 18 future scenarios. Rows across are projections with the same climate model. The second to fourth column show projections for the 2020s, 2050s and 2080s for the B2a greenhouse gas emissions scenario (low emissions), whereas the last three columns are for the A2a (higher) scenario.

3.2.3. Length of the rainy season

Changes in seasonal rainfall had some effect on the duration of the rainy seasons, as defined by the decision criteria described in the Materials and Methods section. This information is derived from more detailed, daily weather records, so that not the entire area shown on the previous maps was covered. The following maps also only show data for locations, where the clear pattern of two rainy seasons still persisted in future scenarios. This was not the case everywhere in the study region. Especially for the CSIRO model, which projected strongly increasing rainfall, the long and short rains merged for some sites. These locations are not shown on the maps, because their inclusion would have shifted the legend scale so much that other differences could no longer have been distinguished. The start of the long rains, which currently happens around early to mid-March in the study region, was projected to

shift in many climate projections (Figure 6). Interestingly, significant differences were present between climate models, with the CCCMA model projecting a delay by about 10 days already by the 2020s for the B2a scenario. However, the A2a scenario, which is typically associated with greater changes, showed almost unchanged conditions at that time. This emissions scenario only showed such strong changes by the 2080s. The CSIRO model predicted an advanced beginning of the long rains by up to 20 days by the 2080s. For earlier time slices, changes were smaller but pointed in the same direction. The HadCM3 model also showed a clear advance of the long rains.

Beginning of the long rains (day of year)
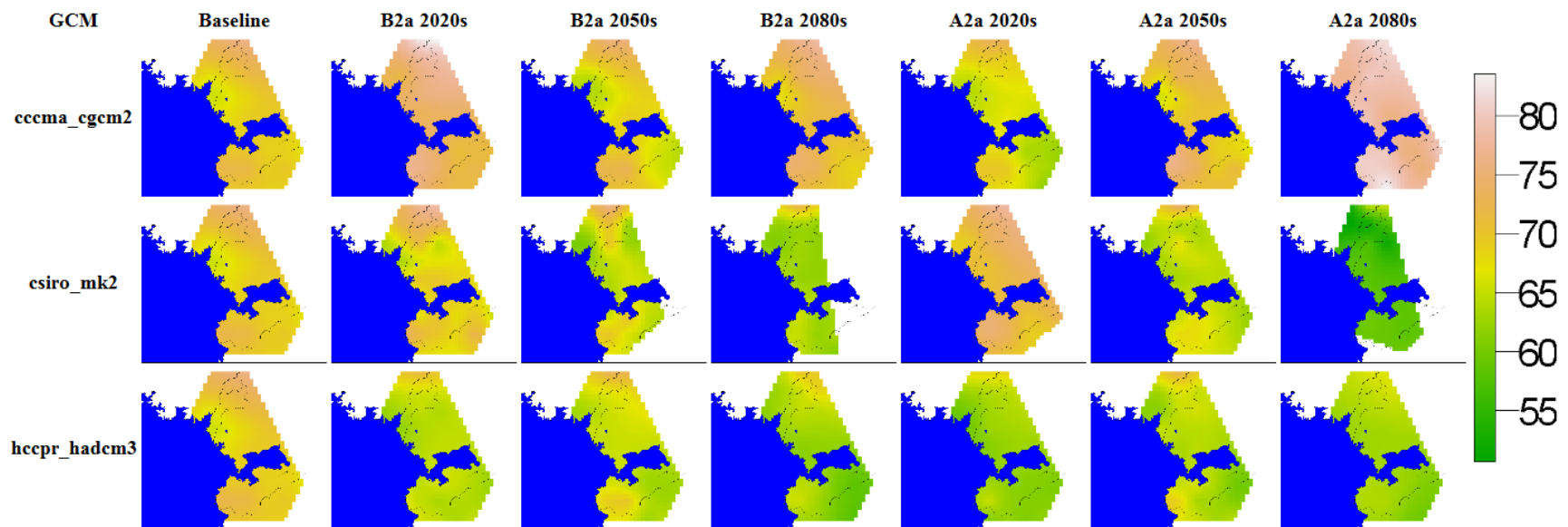
Figure 6. Mean beginning of the long rains (day of year) for the study region projected for the current situation (baseline; first column), and 18 future scenarios. The second to fourth column show projections for the 2020s, 2050s and 2080s for the B2a greenhouse gas emissions scenario (low emissions; the last three columns are for the A2a (higher) scenario.

Not all earlier starts of the long rains translated into longer rainy seasons. In spite of the earlier beginning, the HadCM3 actually projected a shortening of the long rains by up to 20 days (Figure 7). In contrast, CCCMA indicated a mostly unchanged length of the long rains, whereas the CSIRO model showed longer long rains. Among scenarios, changes in the length of the long rains were much less linear along the time progressions than other weather parameters. For the 2020s scenarios, all projections except the

CCCMA model run for the A2a scenario, presented a slight decrease in the length of the rains, which in most cases was compensated later.

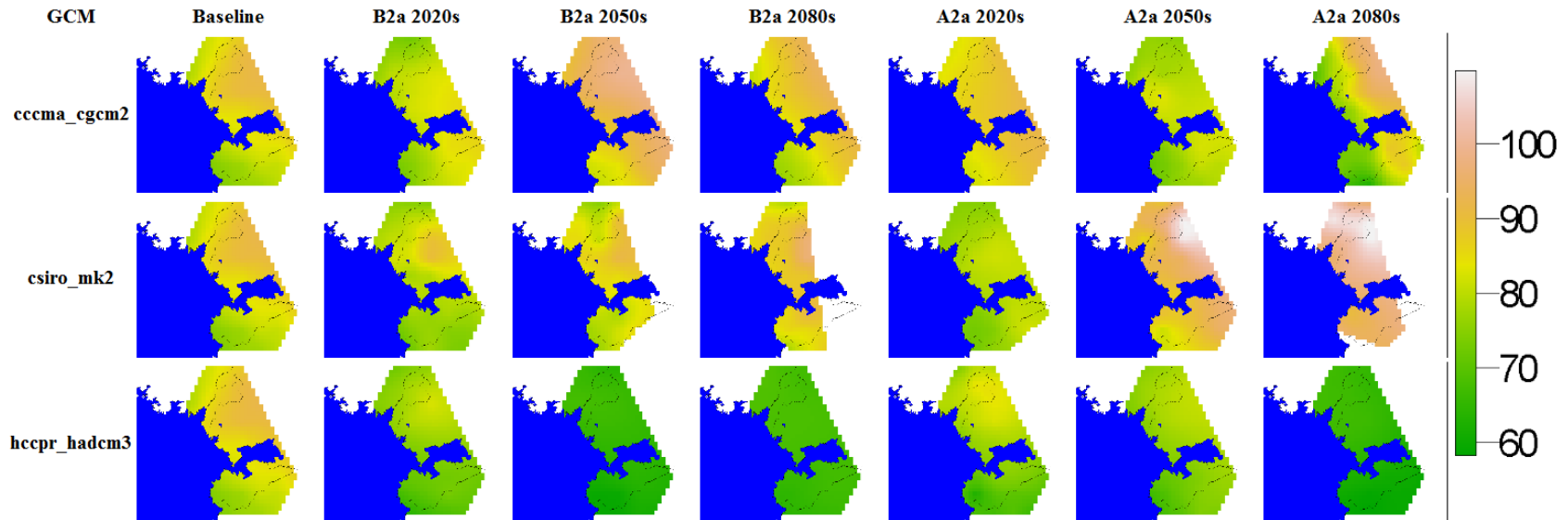## Length of the long rains (days)

Figure 7. Length of the long rains (days) for the study region projected for the current situation (baseline; first column), and 18 future scenarios. The second to fourth column show projections for the 2020s, 2050s and 2080s for the B2a greenhouse gas emissions scenario (low emissions; the last three columns are for the A2a (higher) scenario.

On average, the short rains started between the end of September and the end of October throughout the study region, with only the very north-eastern corner starting earlier, around mid-August (Figure 8). The CCCMA climate model showed a tendency towards slightly earlier short rain onsets until the 2020s, but then went back to close to the baseline situation. The area of earlier rain onset in the northeast experienced a month or more delay in the beginning of the short rains. The CSIRO model, which projected substantial rainfall increases, saw earlier onset of the short rains throughout the study region. For many stations, the short rains even merged with the long rains, so that the rainy season detection algorithm no longer recognized a separate short rainy season. The HadCM3 model showed relatively stable rain onset dates for the short rains, with some advances only recognizable by the 2080s, for both emissions scenarios.
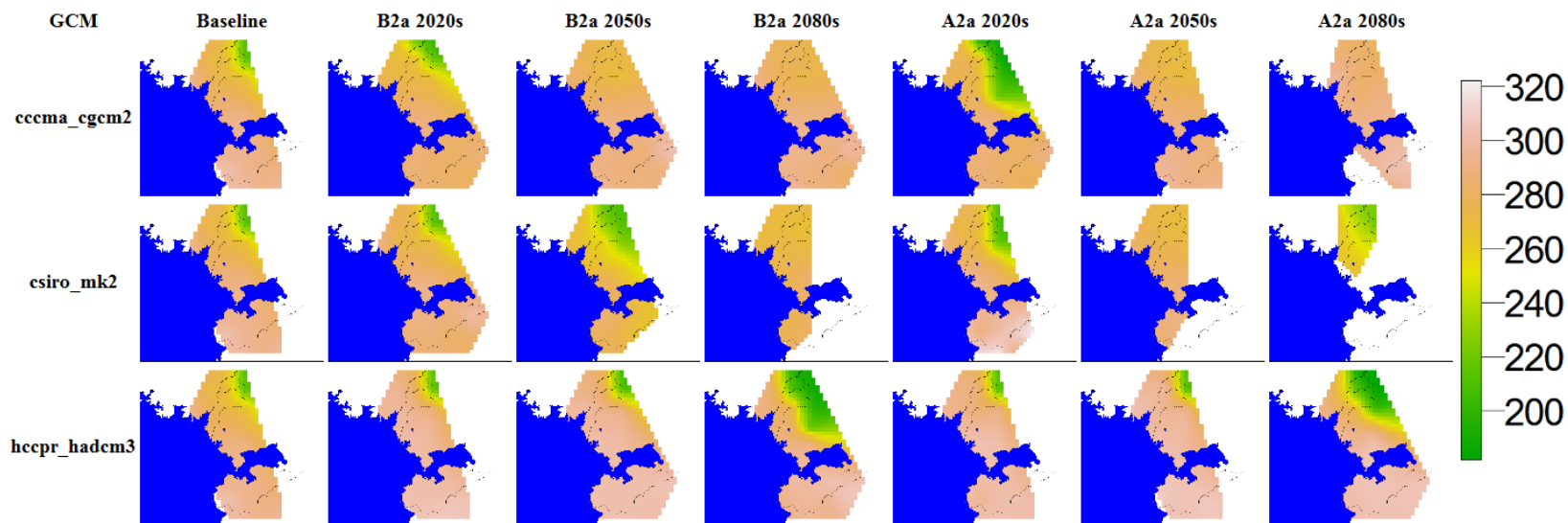
Beginning of the short rains (day of year)

Figure 8. Mean beginning of the short rains (day of year) for the study region projected for the current situation (baseline; first column), and 18 future scenarios. The second to fourth column show projections for the 2020s, 2050s and 2080s for the B2a greenhouse gas emissions scenario (low emissions; the last three columns are for the A2a (higher) scenario.

Changes in the length of the short rains were relatively small for most scenarios. Only the CSIRO GCM projected substantial changes, indicating a lengthening of the short rains. This went so far, that at many of the modeled sites, the short rains essentially merged with the long rains, forming one long rainy season, rather than two distinct ones (Figure 9). For these locations, no data are shown in the maps. While also relatively small, projected changes according to the HadCM3 model may be significant, because the rainy season is already quite short for many crops. Further shortening by up to 20 days, as projected by this GCM, may therefore be a concern.
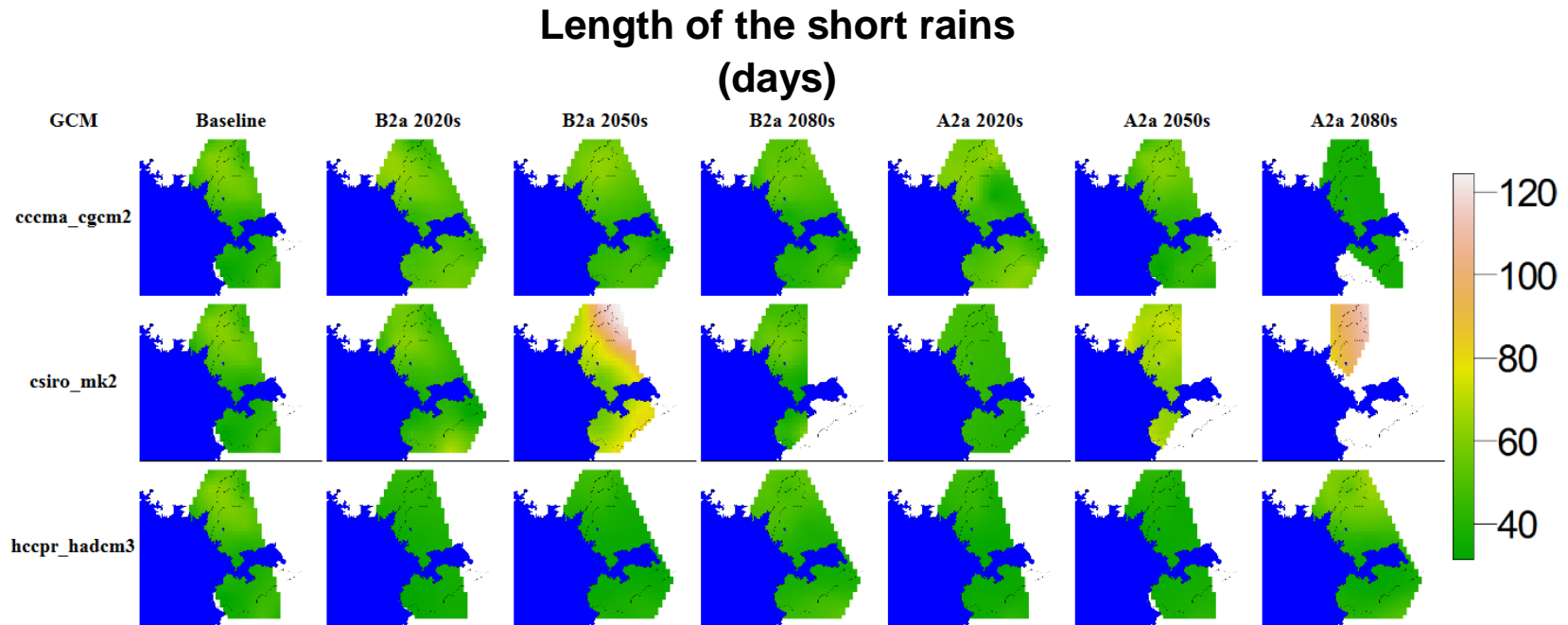
Length of the short rains (days)

Figure 9. Length of the short rains (days) for the study region projected for the current situation (baseline; first column), and 18 future scenarios. The second to fourth column show projections for the 2020s, 2050s and 2080s for the B2a greenhouse gas emissions scenario (low emissions; the last three columns are for the A2a (higher) scenario.

3.3.   Projected performance of annual crops

Yields of annual crops for 25 years were calculated for each crop, climate scenario, site and major soil type present in the vicinity of the site. For each combination of site, soil and crop, this resulted in 19 sets of 25 yield estimates. For taking full account of the effects of weather variability on crop production, the entire population of these 25 years' yields must be evaluated, rather than simply calculating means. This is best accomplished by showing yield distribution functions. These plots show the likelihood of yields exceeding a certain level for each climate scenario, based on the empirical distribution of yields produced by the model. In these plots, yields for each climate scenario are shown as lines, with the black line showing the baseline scenario, and the colored lines the results of the climate projections. Figure 10 shows an example of such a cumulative yield frequency plot. The x-axis of the figure shows cotton yields at one of the modeling sites, as a percentage of the maximum yield that was modeled in the study region. The y-

axis shows the probability of yield exceeding a certain level. The lines in the plot area indicate the distribution of yields for all modeled scenarios. The black line is the baseline scenario, while the colored lines are future projections. The following kinds of information can be extracted from the figure:

1) The point where the right-most line meets the bottom of the figure is the best yield obtained in any model run, relative to the highest in the region. In this case, this site's production potential is only about 80% of that at the region's best site, meaning that other places in the study region have a higher yield potential.
2) Some lines intersect with the left edge of the plot. This means that there is a risk of complete crop failure all climate scenarios. This risk is relatively low, with the highest risk among all scenarios at 4% (intersection with the left edge at 96%).
3) Rather than going relatively straight down, most lines are rather diagonal. This indicates highly variable crop yields.
4) Most, but not all colored lines are to the left of the black line. This means that for most climate scenarios, yield expectation decreases. However, for the lines to the right of the black line, climate change is projected to improve crop yields.
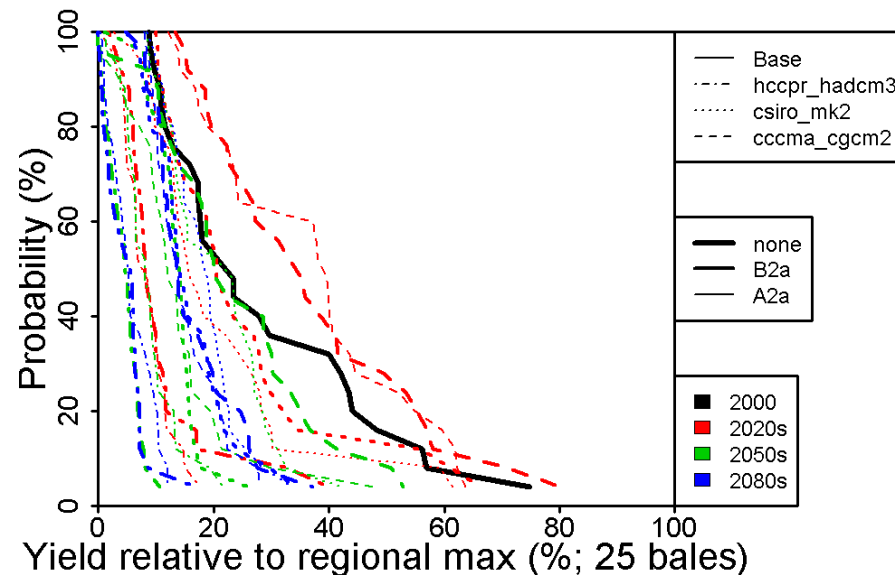

Figure 10. Example of a crop performance plot. The x-axis shows projected yields relative to the maximum yield observed in the study region (given in the axis title), whereas the y-axis shows the probability of harvesting less than a given yield level. Separate lines for each climate scenario show yield profiles for each scenario, as a distribution over 25 modeled years. Results are presented for 3 Global Climate Models (distinguished by line styles), two greenhouse gas emissions scenarios (line thickness) and three future points in time (line color). A baseline scenario representing current conditions (drawn in black) is also presented.

Modeled yield of most crops differed considerably between soil types, and no reliable map of the distribution of soils in the region was available. Consequently, the point estimates of yield profiles could not be interpolated into maps. The following presentation of results will thus rely on selected cases that span the spectrum of results that were obtained.

3.3.1. Maize

Long rains

During the long rains, modeled maize yields were quite stable, with surprisingly little variation. Figure 11 shows typical yield projection profiles. Most lines are almost vertical, indicating that yields during the long rains are quite stable. Projected yields for the climate change scenarios were mostly related to the time slice, showing a steady decline as time progressed. At this point, it should be noted that these profiles only reflect *direct* effects of weather on production. Other factors, such as pest and disease incidence are not captured in this analysis.
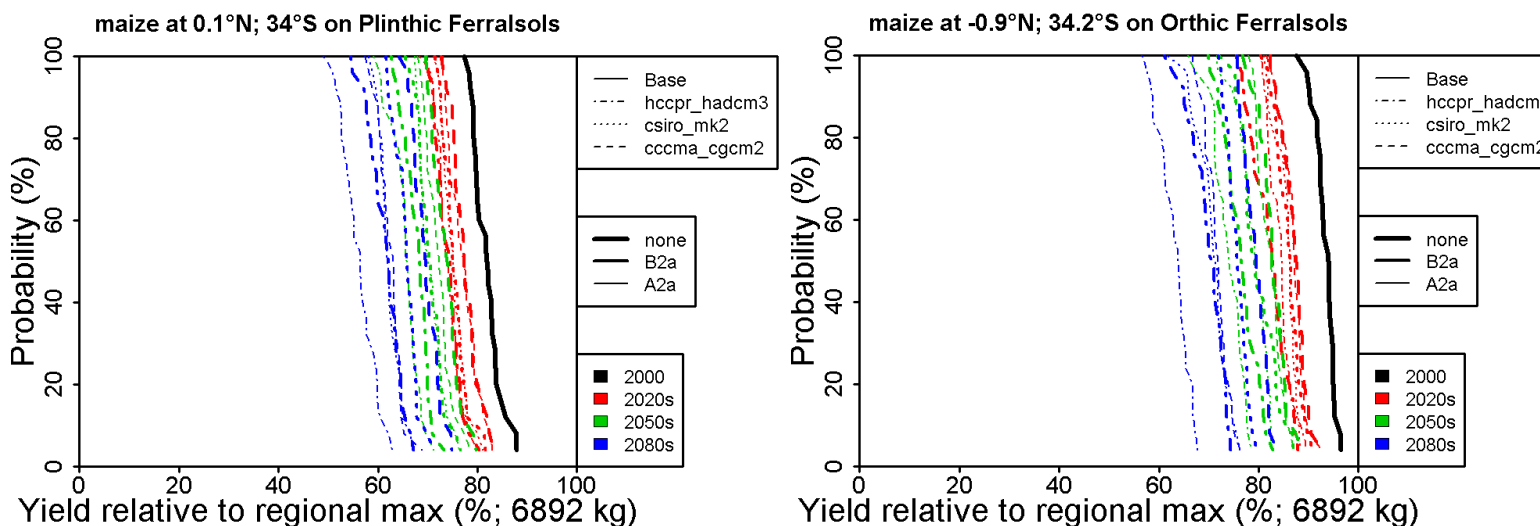

Figure 11. Selected crop performance profiles for maize during the long rains, for all climate scenarios.

Short rains

For the short rains, the situation was quite similar, once again with little yield variation among soil types and sites. Also for the short rains, climate change projections indicated a steady decline of yield levels, but with relatively stable yields for each climate scenario (Figure 12).
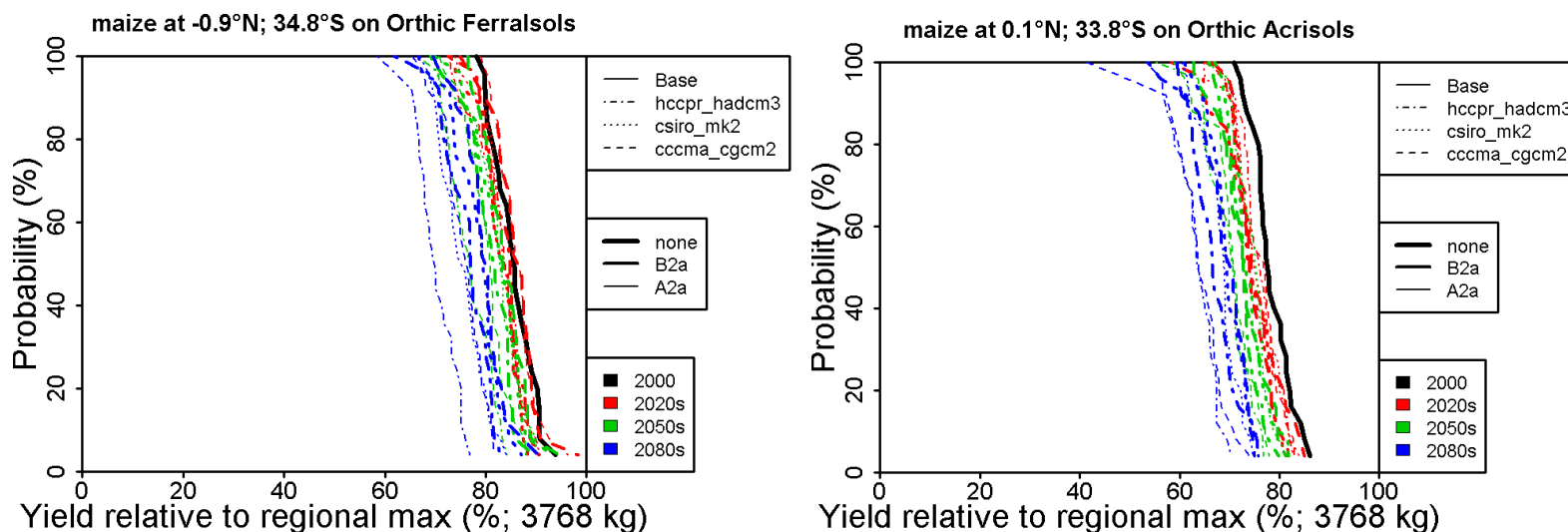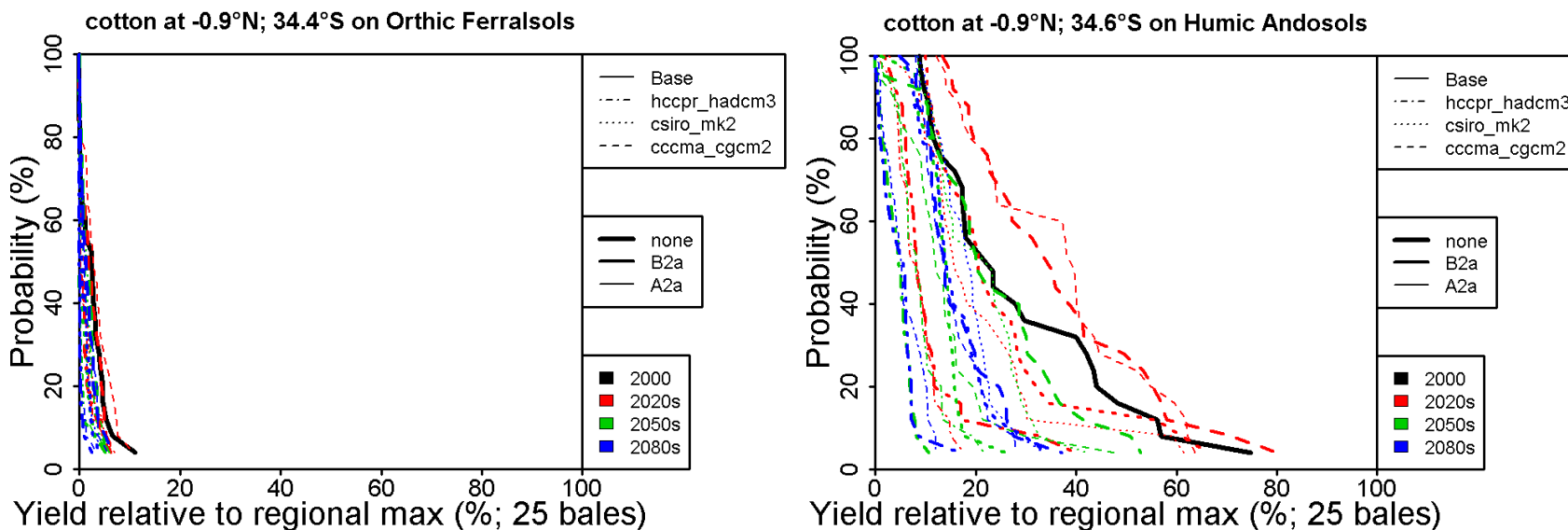

Figure 12. Selected crop performance profiles for maize during the short rains, for all climate scenarios.

The clustering of yield projection curves for each time slice indicated that climate change impacts on maize yields are quite predictable. In other words, the point in time had a stronger effect on yield levels than the climate model or the greenhouse gas emissions scenario. This indicates that future yield levels can be anticipated with relative certainty. The likely trajectory is a gradual decline in yield levels.

3.3.2. Cotton

Long rains

Modeled cotton yields depended primarily on the soil type. Among the soils modeled in this study, most were virtually unsuitable for cotton (Figure 13, left). Only on Humic Andosols, cotton production was possible (Fig. 13, right), and even there yields were highly

variable, as indicated by the diagonal orientation of most lines in the figure. In the example shown here, which was typical of the yield patterns obtained for all sites that had this soil type, yield varied between 15% and 85% of the maximum yield in the region, even for the baseline scenario, and obtaining yields close to the mean of this distribution was no more likely than any other yield. This signifies that even under current climate, cotton yields are highly variable. Two climate scenarios for the 2020s actually improved yield expectations, but for all other scenarios projected yields were substantially lower than baseline yields. Even for some 2020s projections, very low yields were obtained.

Figure 13. Selected crop performance profiles for cotton during the long rains, for all climate scenarios.

Short rains

For the short rains, modeled yields for all soil types except Humic Andosols were also negligible. Among the Humic Andosols (two examples shown in Figure 14), projected yield patterns were similar to those for the same soil during the long rains. In contrast to those, however, some projections for the 2050s and 2080s indicated higher yields than the baseline.
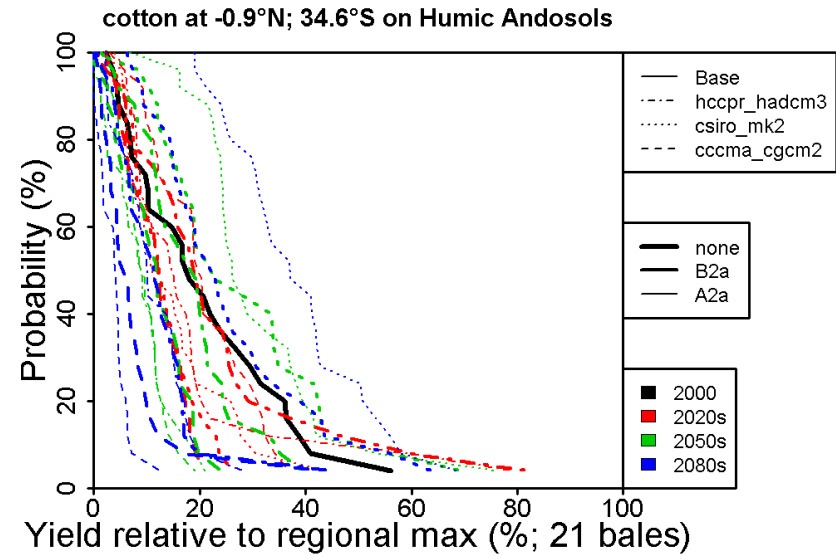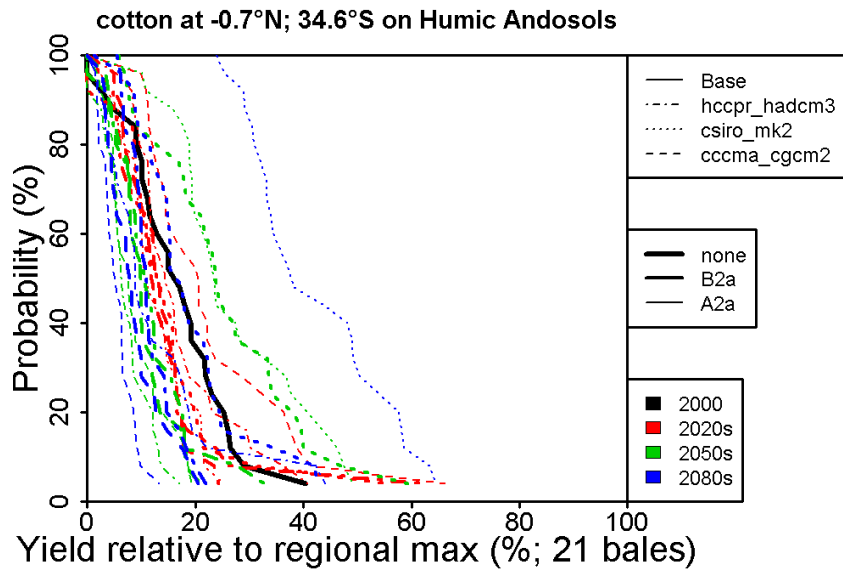
Figure 14. Selected crop performance profiles for cotton during the short rains, for all climate scenarios.

3.3.3. Sorghum

Long rains

Similar to maize, sorghum yields during the long rains showed little variation for most sites (Figure 15). For most sites, climate change effects in all scenarios were relatively small, but with a slight tendency towards decreasing yields. Only for a few sites, impacts were stronger, accompanied by an increase in yield variability, as illustrated in the right plot. These effects, however, only manifested themselves in the 2050s and 2080s scenarios.
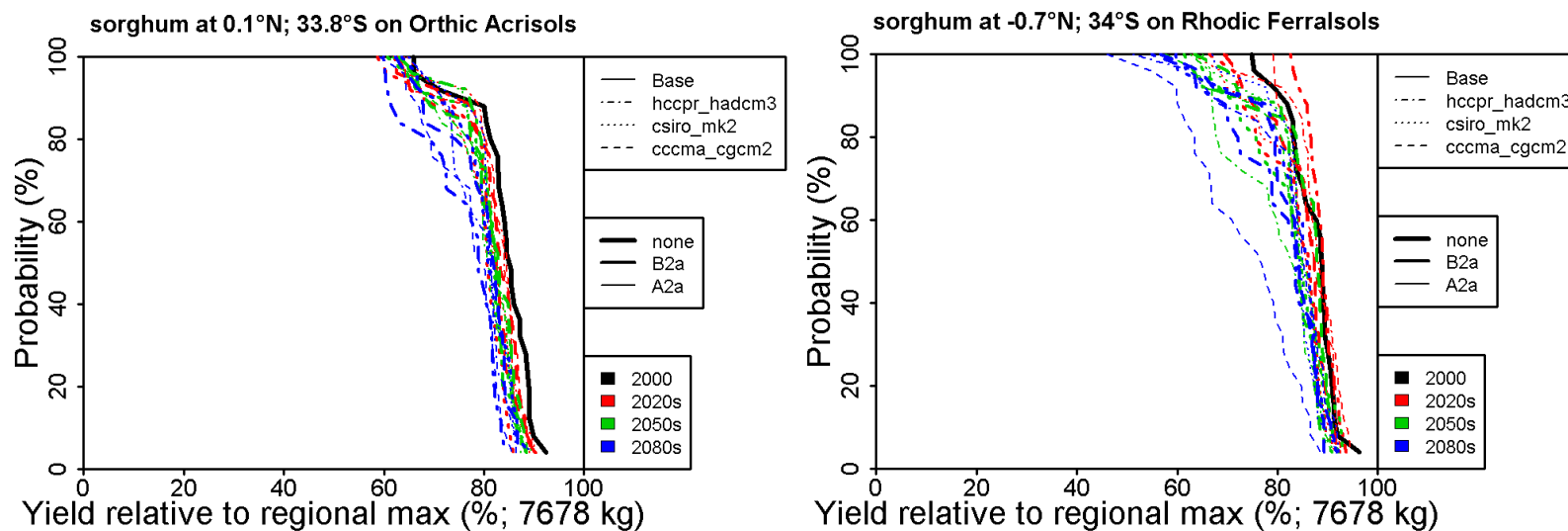

Figure 15. Selected crop performance profiles for sorghum during the long rains, for all climate scenarios.

Short rains

During the short rains, sorghum yields were more variable, and climate change impacts differed markedly. The four plots in Figure 16 illustrate this variability. For sorghum, the soil type had a major influence on yields. On Humic Andosols, yields were very stable, while on all other soils, yield variation was greater. Again, most climate changes scenarios indicated a decrease in yields, but a few exceptions existed (top left figure). By the 2050s and 2080s, several of the climate scenarios showed a clear decline in yield levels.
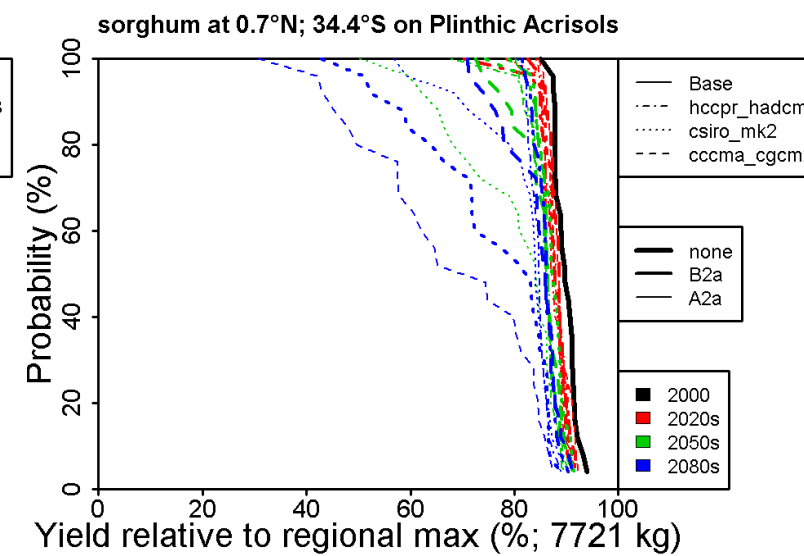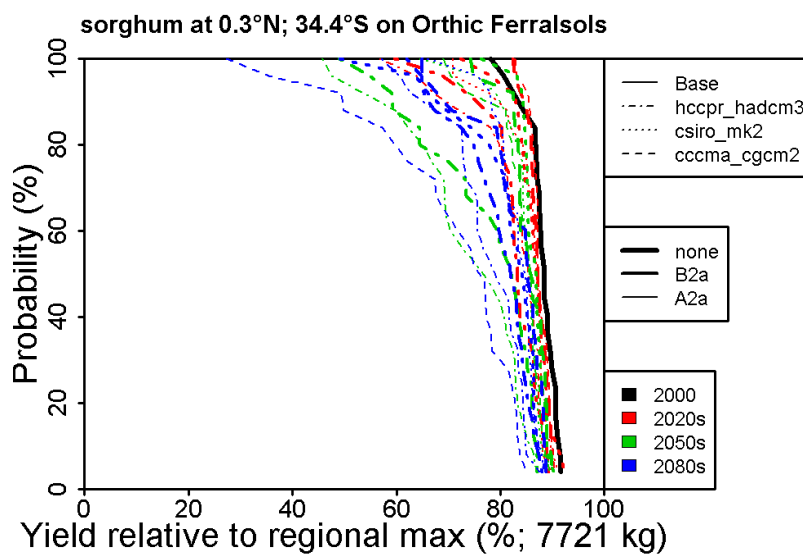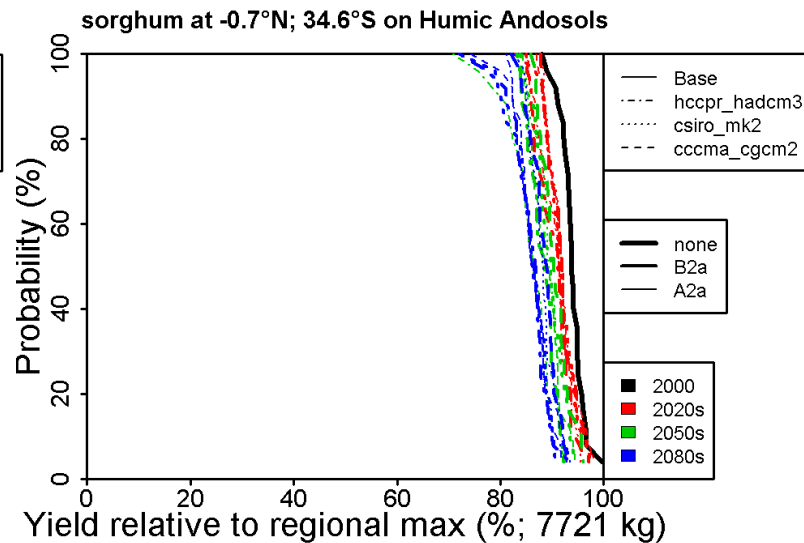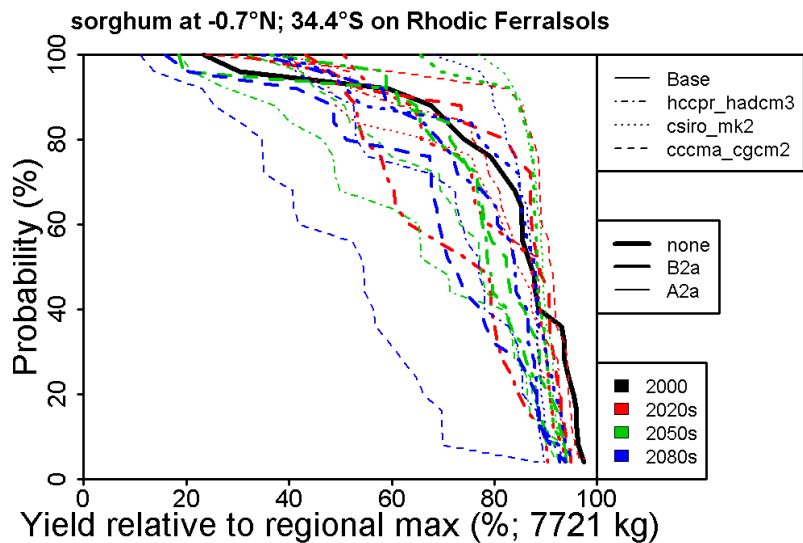
Figure 16. Selected crop performance profiles for sorghum during the short rains, for all climate scenarios.

3.3.4. Greengram

Long rains

Greengram yields in the long rains were relatively stable for the baseline scenario, for all sites and all soils. However, all climate change scenarios projected a strong decline in yields (Figure 17). Already by the 2020s, the amount of greengrams that could be harvested declined by more than 10% in most future scenarios. These losses became increasingly severe for the later time slices. As for maize and sorghum, the time slice was the most important determinant of yield, whereas climate model and greenhouse gas emissions scenario were of lesser importance.
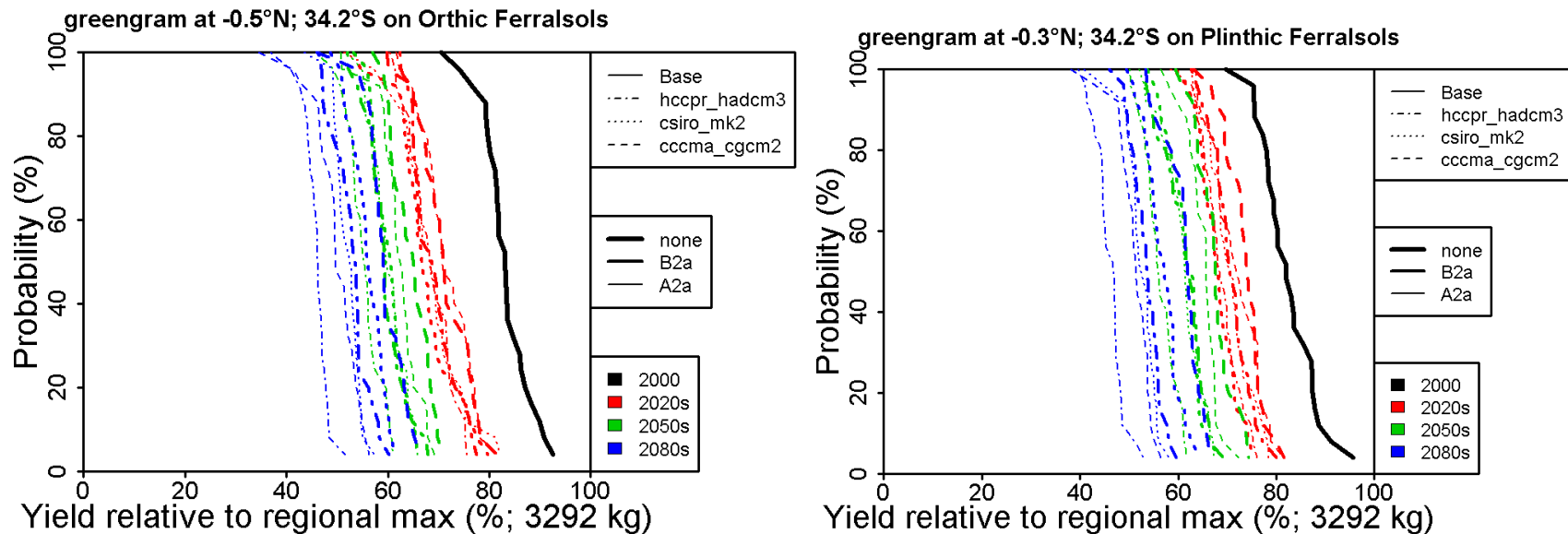

Figure 17. Selected crop performance profiles for greengram during the long rains, for all climate scenarios.

Short rains

For many sites, yield patterns of greengram during the short rains were similar to those for the long rains (Figure 18 right). For some locations, however, variability was quite high in the baseline scenario, and some climate scenarios showed a slightly decreasing risk of obtaining very low yields (Figure 18 left).
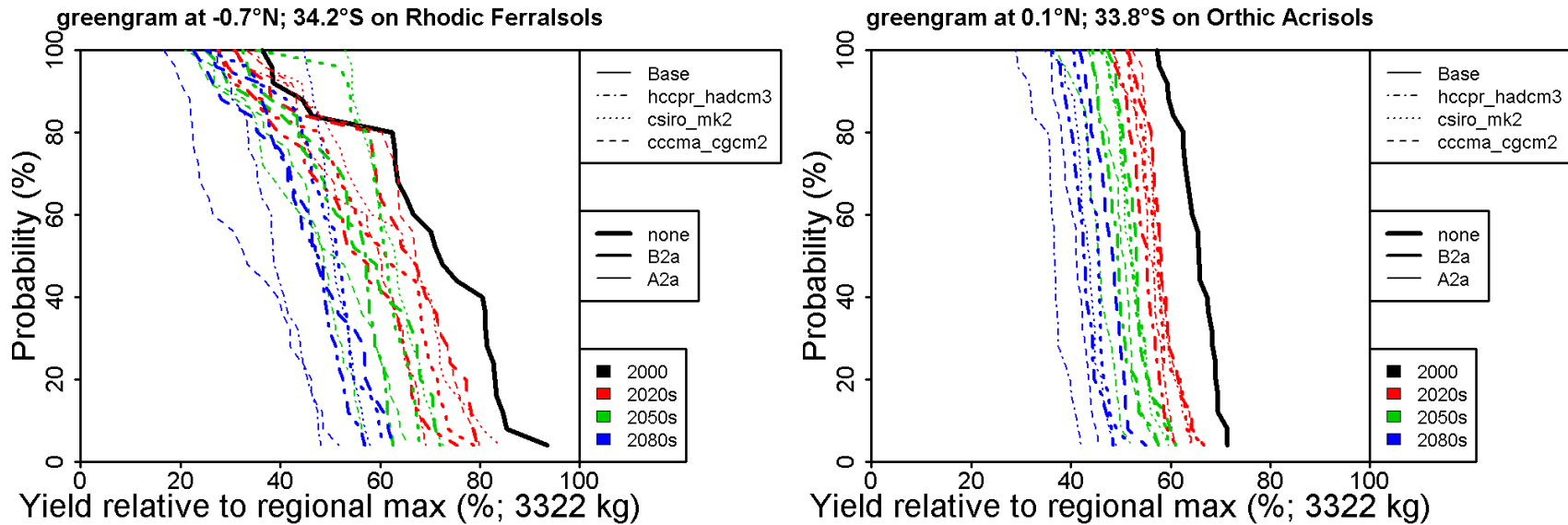

Figure 18. Selected crop performance profiles for greengram during the short rains, for all climate scenarios.

3.3.5. Soybean

Long rains

During the long rains, most sites, for which yields were modeled, had very low yields, compared to a few sites in lower Busia (Figure 19 left). For these sites, high baseline yield potential was identified, but climate change effects promised to be quite severe. For all other locations, yield potential was very low, in most cases below 1000 kg per ha (Figure 19 right).
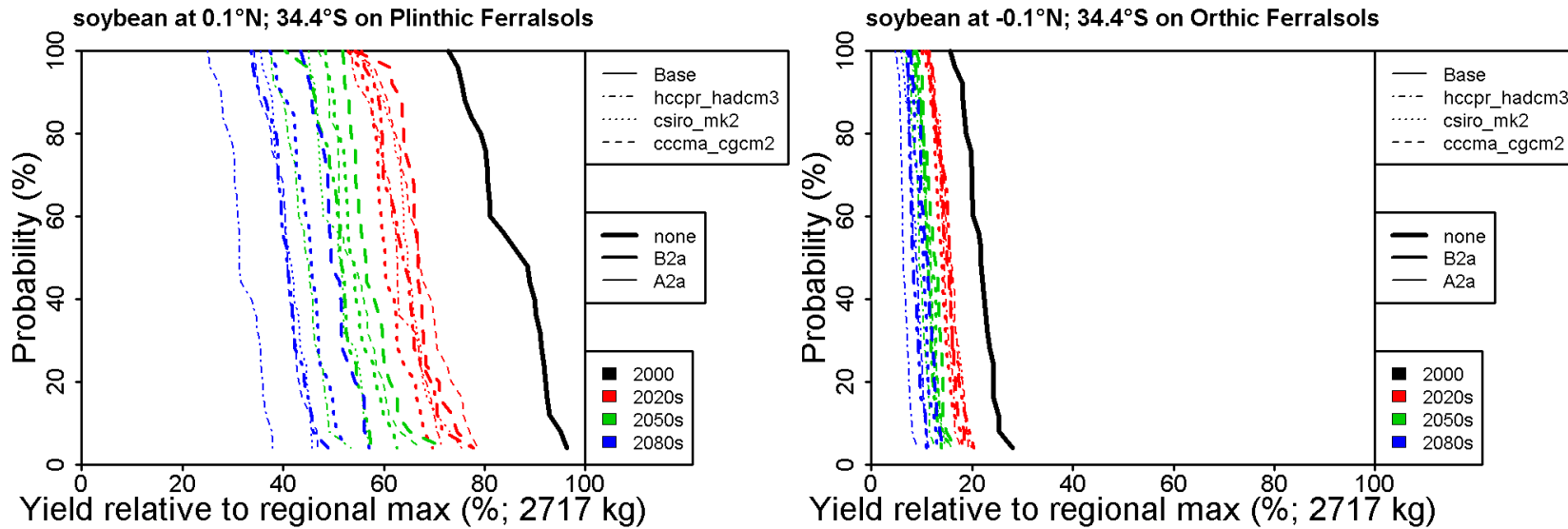

Figure 19. Selected crop performance profiles for soybean during the long rains, for all climate scenarios.

Short rains

For the short rains, yield potential of soybeans was low for all modeled sites, and climate change impacts were severe (Figure 20). The highest modeled yield for the short rains was only about one third of the maximum yield of the long rains. Many climate change scenarios reduced these yields to half of this amount or less.
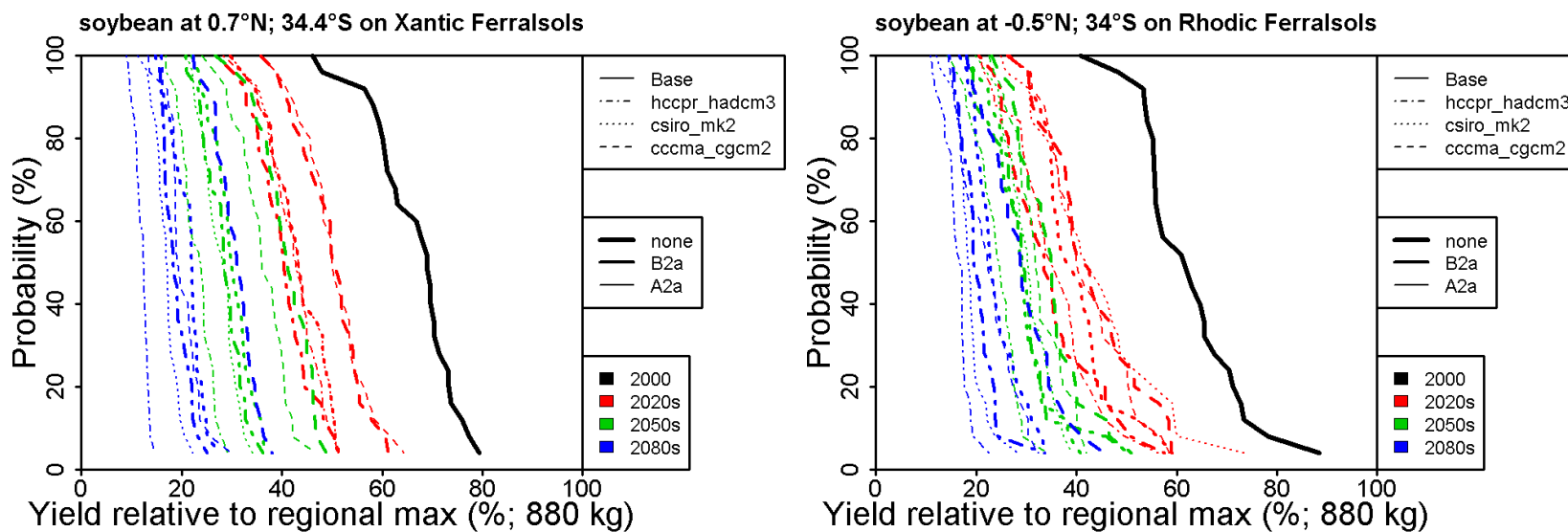
Figure 20. Selected crop performance profiles for soybean during the short rains, for all climate scenarios.

3.3.6. Groundnut

Long rains

Groundnut yields during the long rains were quite high for all of the study region, but at risk from climate change impacts (Figure 21). In all climate change scenarios, yields were quite a bit lower than at present, and yield losses increased as time went on.

Figure 21. Selected crop performance profiles for groundnut during the long rains, for all climate scenarios.

Short rains

For some locations, the yield patterns during the short rains were quite similar to those of the long rains, though at a slightly lower level (Figure 22 left). However, a few stations showed a pattern as shown in Figure 22 right, in which climate change lowered attainable yield, but for some climate scenarios reduced the risk of obtaining very low yields. For some of these sites, all future scenarios had more consistent (though lower) yields than the baseline.
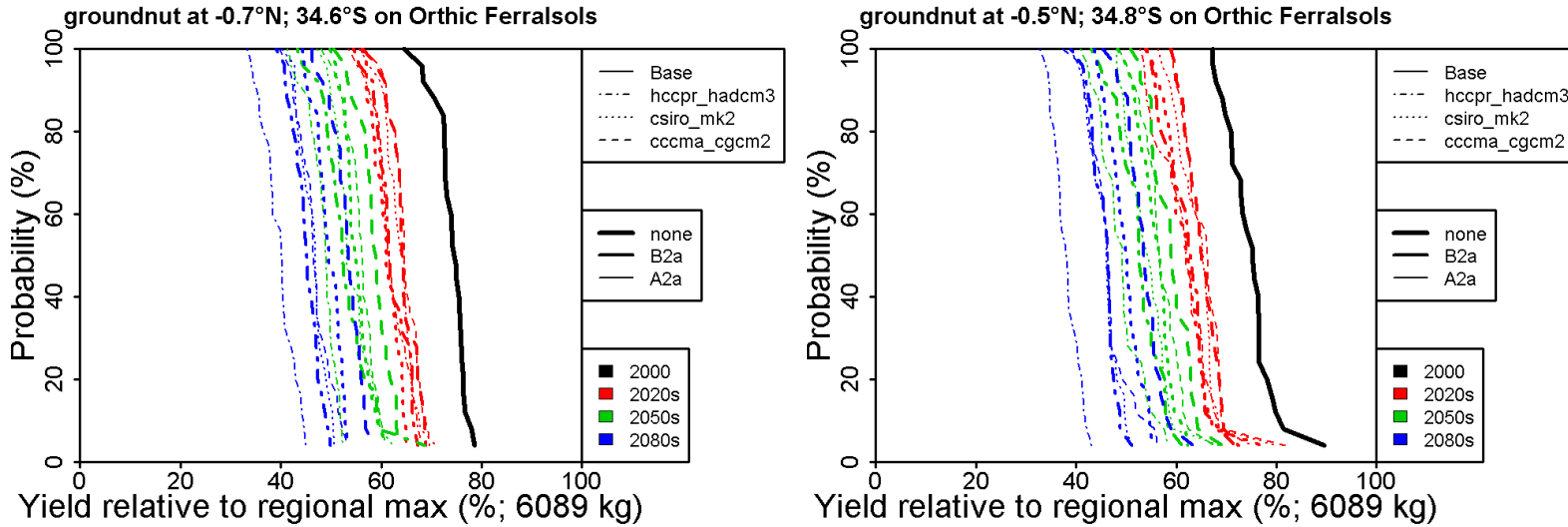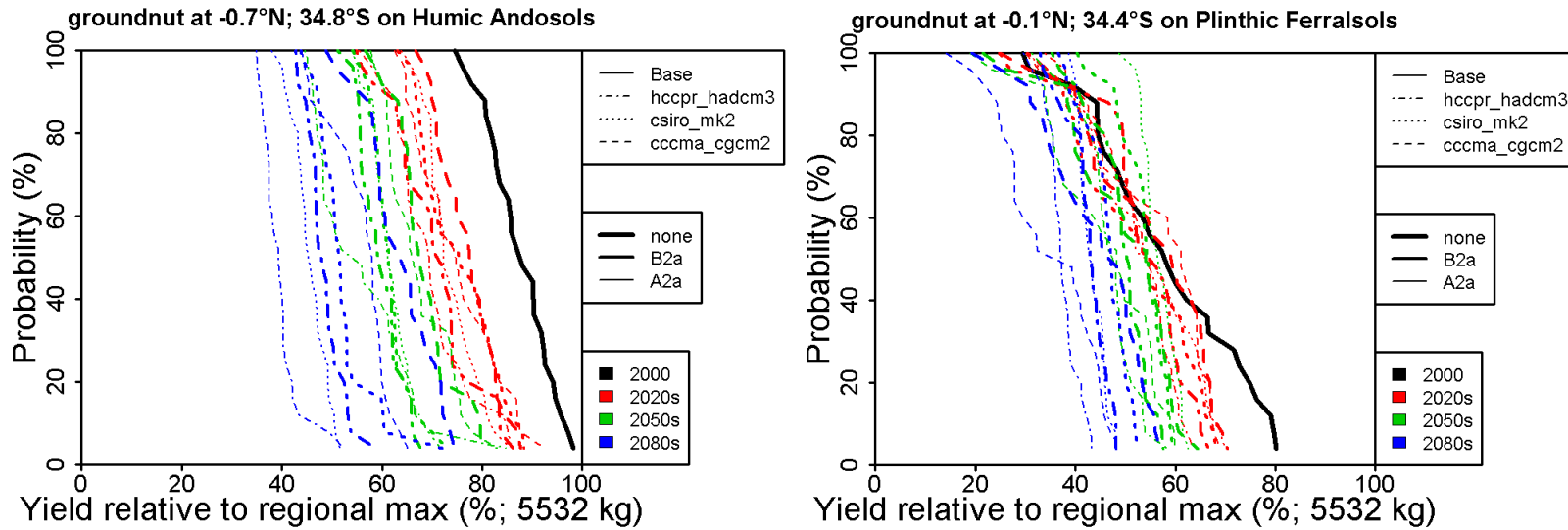

Figure 22. Selected crop performance profiles for groundnut during the short rains, for all climate scenarios.

3.3.7. Cowpea

Long rains

Cowpea yields during the long rains were fairly stable within climate scenarios. Once again, the main factor that determined yield levels for future scenarios was the time slice, with a steady decline in productivity projected as time went on. While yield levels varied among sites and soils, the general pattern shown in the two presented examples (Figure 23) was evident for all simulations.
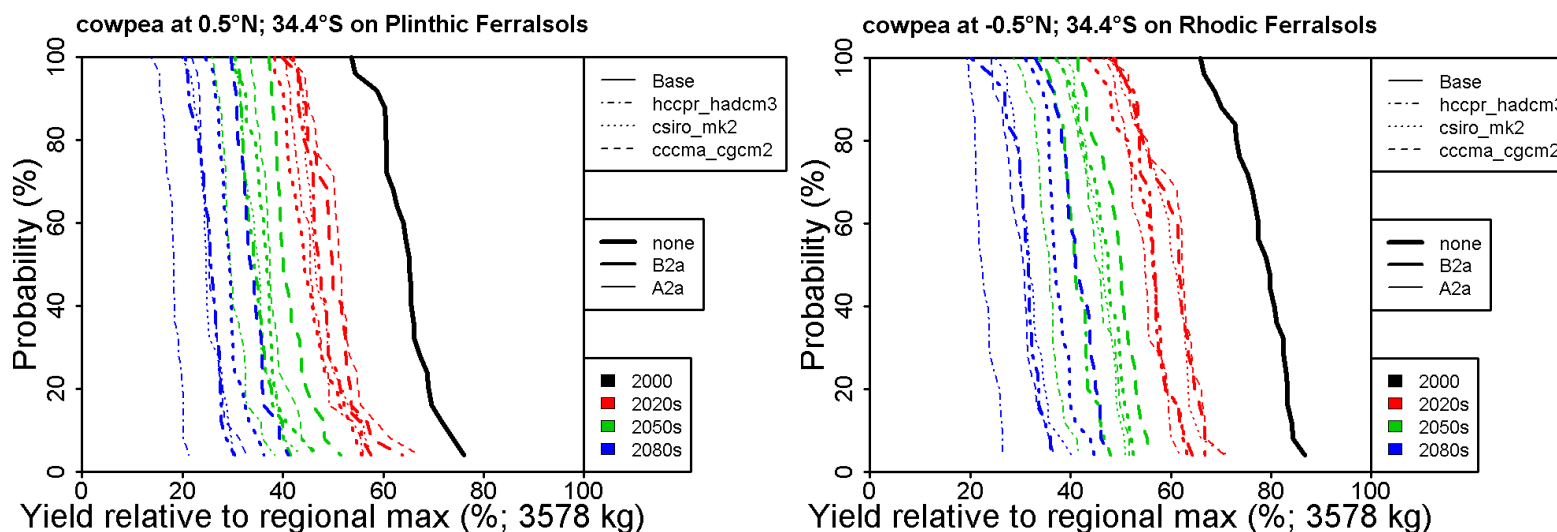

Figure 23. Selected crop performance profiles for cowpea during the long rains, for all climate scenarios.

Short rains

During the short rains, two types of yield patterns were observed. For many sites and soils, simulated yields and changes projected for climate change scenarios resembled those for the long rains (Figure 24 left). However, some locations exhibited a different behavior, which featured higher yield variability for the baseline scenario (Figure 24 right). At these sites, climate change reduced yield levels, but also reduced variability (more vertical lines in the figure). Yields thus became lower but more predictable. This is probably due to the brevity of the short rains, which appear barely long enough to reliably produce a cowpea crop. For some future scenarios, the rainy season increased in length, but the effect shown here may also be related to faster accumulation of thermal time due to higher temperatures. The optimum temperature for cowpea development (not for yield) in APSIM's cowpea module is quite

high at 35°C and growth only ceases at 44°C, so that temperature increases within the range projected for the future should accelerate growth. This makes the crop harvestable at an earlier date, making it less vulnerable to short growing seasons.
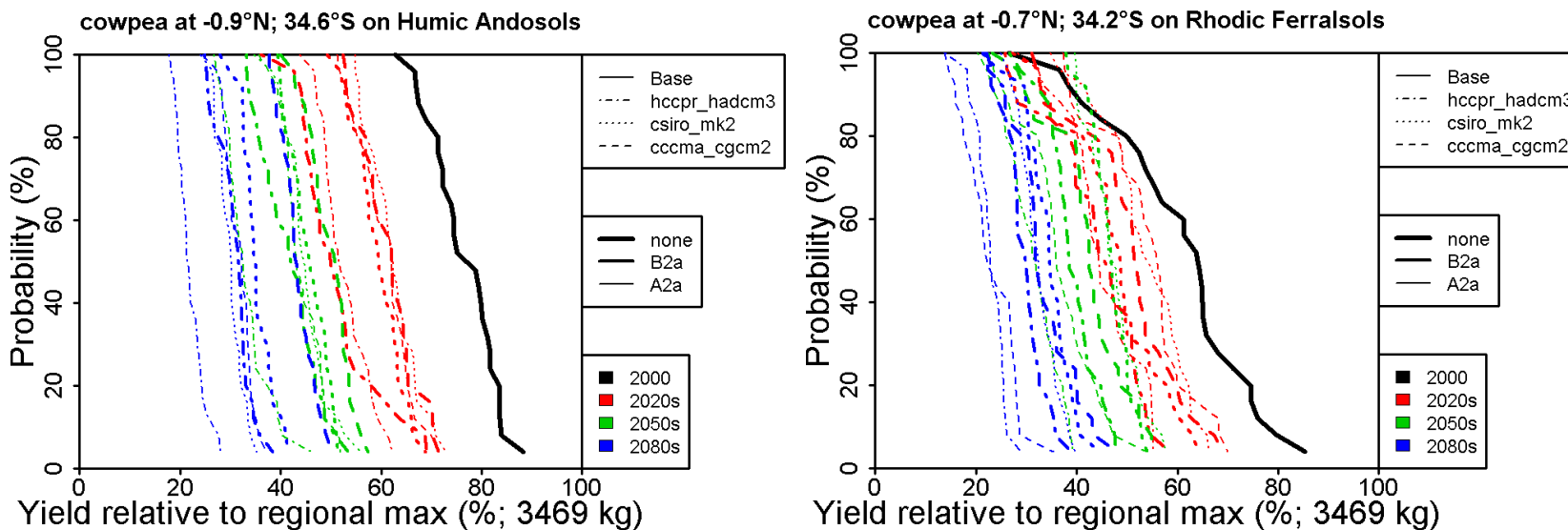

Figure 24. Selected crop performance profiles for cowpea during the short rains, for all climate scenarios.

3.3.8. Fababean

Long rains

During the long rains, modeled yields of fababean were quite high and reliable in the baseline scenario at most locations (Figure 25 left). In all climate change scenarios, a clear decline in yields was visible, with again the time being the major determinant of yield levels. A second type of yield pattern was also observed in the study region. Here, yields were also quite stable, but with a 10-20% probability of getting much lower yields. This risk was preserved in some, but not all, of the climate scenarios (Figure 25 right)
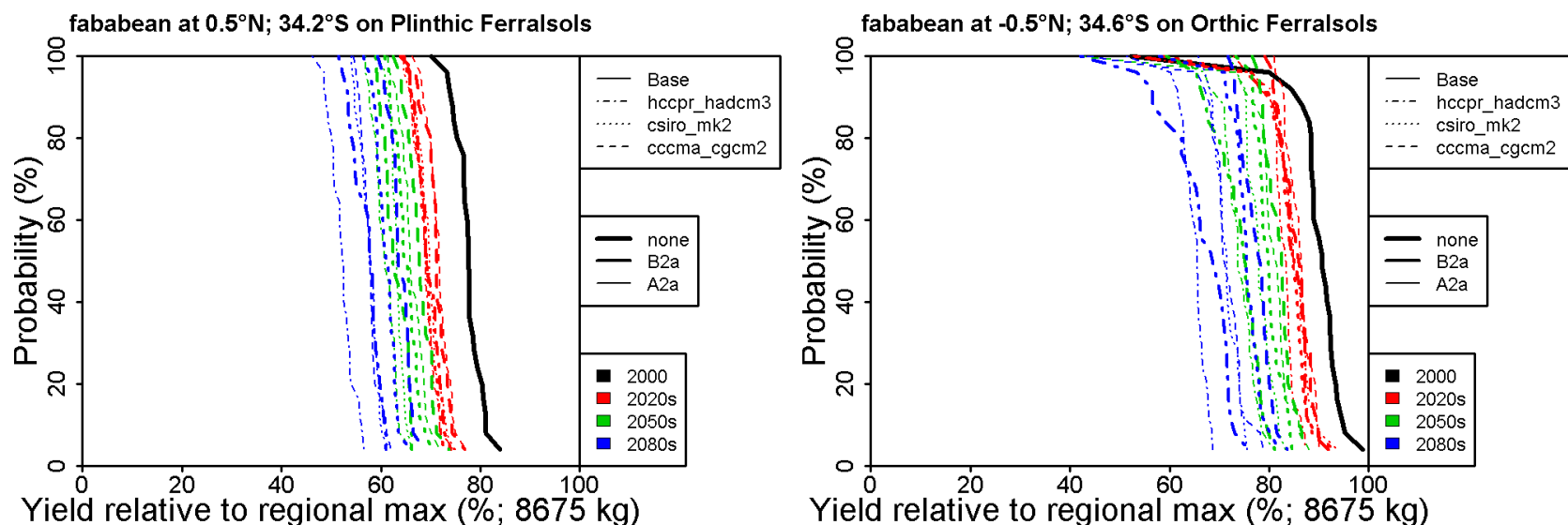
Figure 25. Selected crop performance profiles for fababean during the long rains, for all climate scenarios.

Short rains

The duration of the short rains was not enough to ensure reliable fababean yields in most places. While the maximum yield observed in the study region was similar to the long rains, yield variability was much higher, ranging in the example from 25 to 85% of the maximum (Figure 26 left). This was mainly related to the length of the growing season, and since changes to this parameter differed among climate scenarios, responses to climate change were less clear-cut than for the long rains. Some scenarios indicated yield increases and lower risks, while others showed lower yields and similarly high variability as in the baseline scenario. Only in the more

humid highland areas were yields more predictable, but even here a certain probability of low yields persisted. In these areas, effects of climate change were predominantly negative (Figure 26 right).
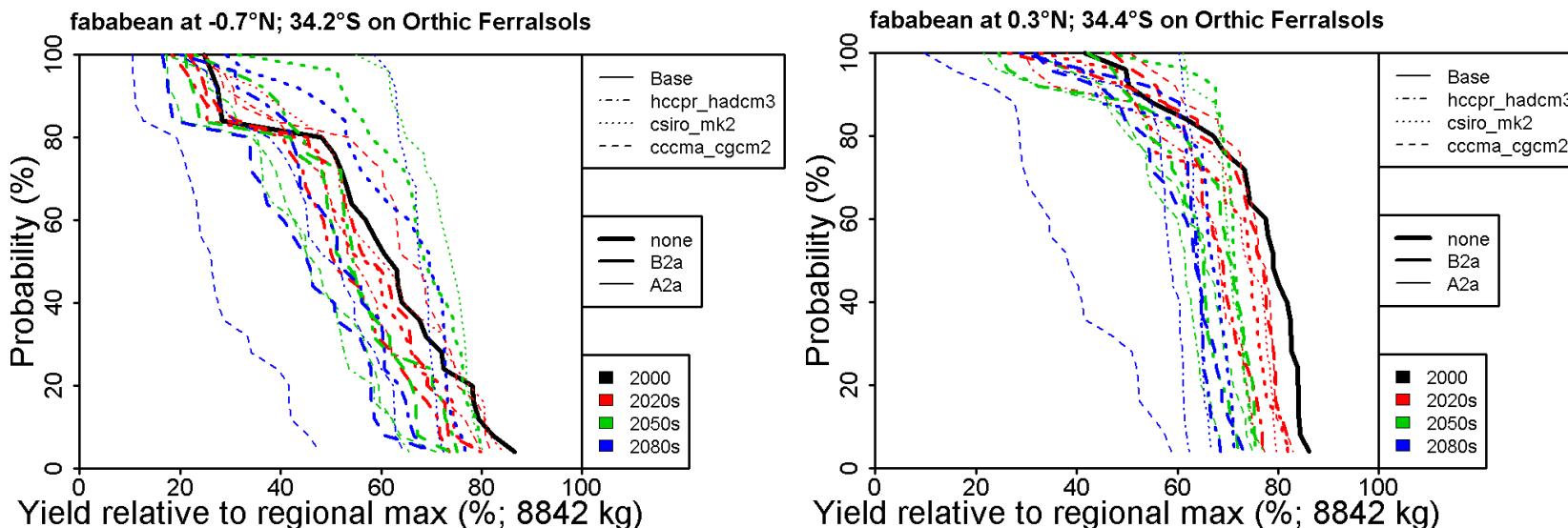
Figure 26. Selected crop performance profiles for fababean during the short rains, for all climate scenarios.

3.4. Projected performance of perennial crops (and crops not included in APSIM)

3.4.1. Mango

Most of the study region was highly suitable for mango production. While the maximum suitability score of 1.0 was not reached anywhere for any climate scenario (Figure 27), much of Busia and Homa Bay had scores above 0.6 for all scenarios. Most future projections saw slightly increasing suitability, because some months of the baseline scenario were slightly cooler than would be ideal for mango production. Only the CSIRO model, which projected strong increases in rainfall, showed declining suitability in the future.

Suitability for mango

Figure 27. Suitability of the study region for production of mango, according to crop requirements from FAO's ECOCROP database. A score of 1.0 indicates optimal conditions, whereas 0.0 means unsuitable for the crop. Suitability is shown for the current situation (baseline; first column), and 18 future scenarios. Rows across are projections with the same climate model. The second to fourth column show projections for the 2020s, 2050s and 2080s for the B2a greenhouse gas emissions scenario (low emissions), whereas the last three columns are for the A2a (higher) scenario.

3.4.2. Sugarcane

Figure 28. Suitability of the study region for production of unirrigated sugarcane, according to crop requirements from FAO's ECOCROP database. A score of 1.0 indicates optimal conditions, whereas 0.0 means unsuitable for the crop. Suitability is shown for the current situation (baseline; first column), and 18 future scenarios. Rows across are projections with the same climate model. The second to fourth column show projections for the 2020s, 2050s and 2080s for the B2a greenhouse gas emissions scenario (low emissions), whereas the last three columns are for the A2a (higher) scenario.

Suitability for sugarcane for the baseline scenario was quite high for Busia, but low for most of Homa Bay (Figure 28). This was predominantly because rainfall requirements of sugarcane could not be met. For all future scenarios, the region became more suitable for this crop. For some of the 2080s projections, almost the whole region was very well suited for sugarcane. It should be noted that these projections are only valid for sugarcane that is not irrigated and has no access to shallow groundwater. Especially the latter, however, is certainly the case in some of the lakeshore areas, probably enhancing suitability substantially.

3.4.3. Pineapple

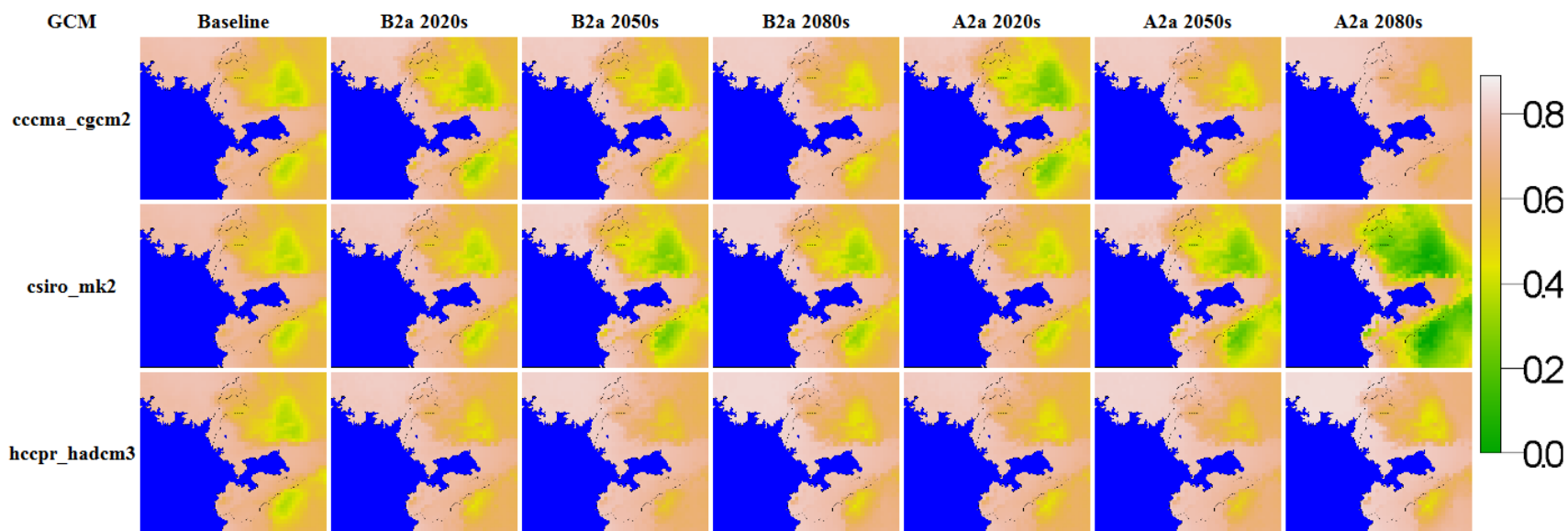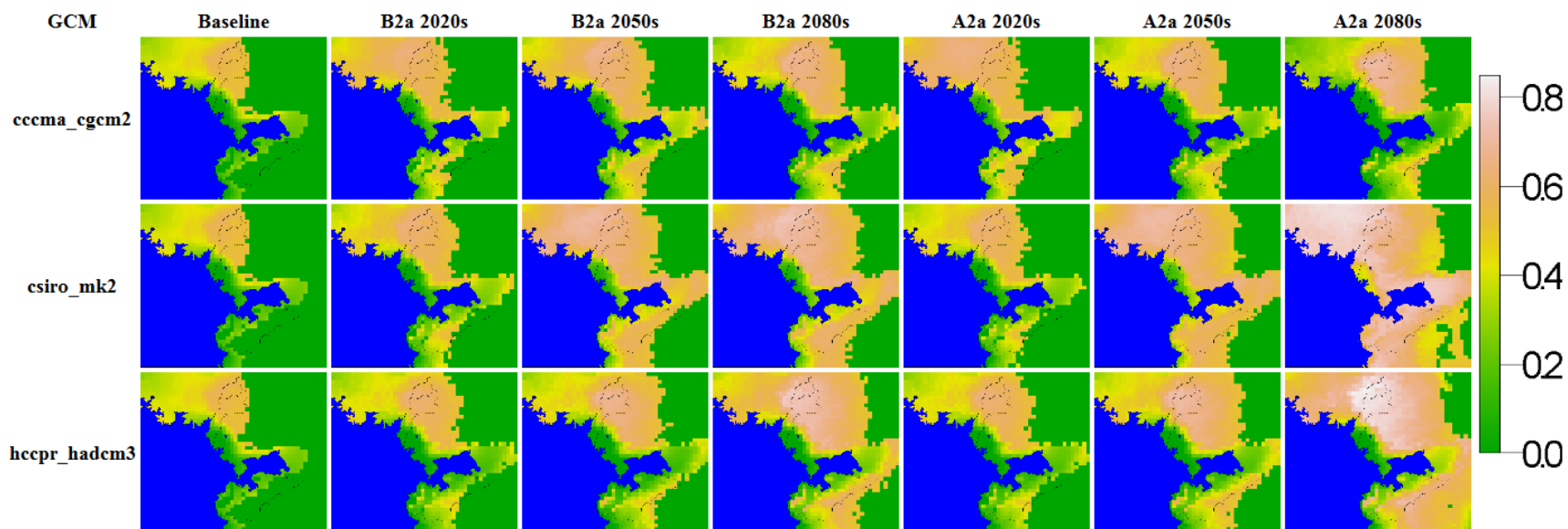## Suitability for pineapple

Figure 29. Suitability of the study region for production of pineapple, according to crop requirements from FAO's ECOCROP database. A score of 1.0 indicates optimal conditions, whereas 0.0 means unsuitable for the crop. Suitability is shown for the current situation (baseline; first column), and 18 future scenarios. Rows across are projections with the same climate model. The second to fourth column show projections for the 2020s, 2050s and 2080s for the B2a greenhouse gas emissions scenario (low emissions), whereas the last three columns are for the A2a (higher) scenario.

Essentially the whole study region was classified as suitable for pineapple production (Figure 29). Only in a small area in the northeast, minimum temperatures constrained pineapple production for scenarios up to the 2020s. For all later times, this constraint was lifted. In general, all future climate trajectories indicated further increases in suitability for pineapple.

3.4.4. Banana

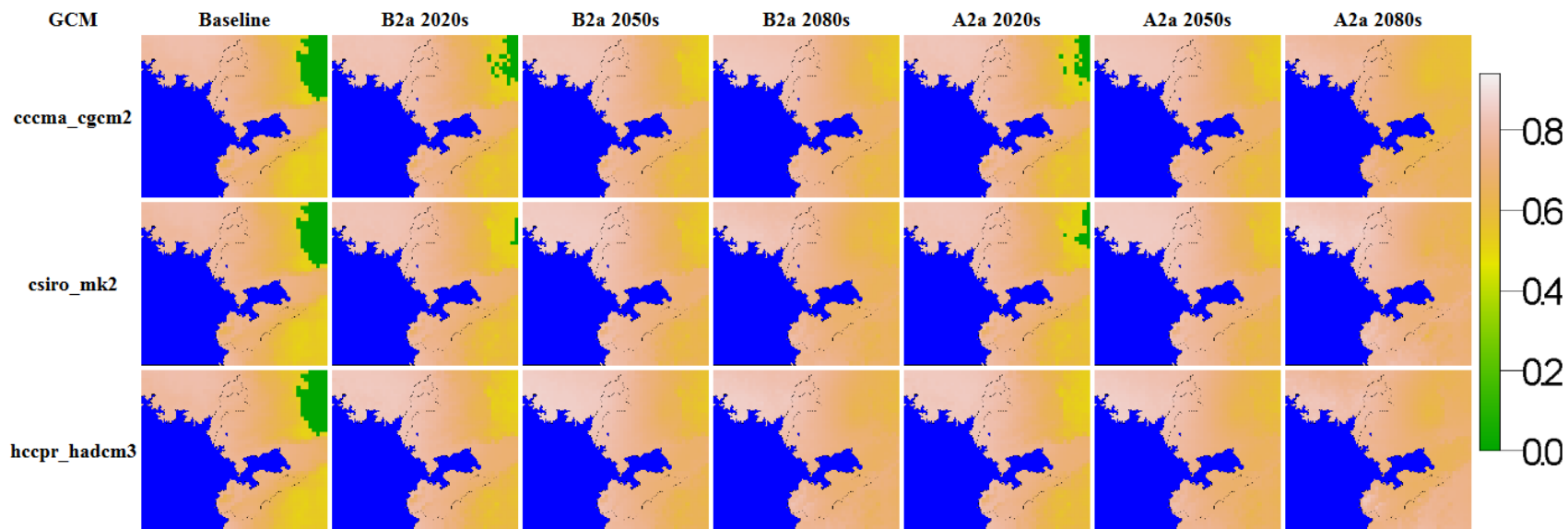Figure 30. Suitability of the study region for production of banana, according to crop requirements from FAO's ECOCROP database. A score of 1.0 indicates optimal conditions, whereas 0.0 means unsuitable for the crop. Suitability is shown for the current situation (baseline; first column), and 18 future scenarios. Rows across are projections with the same climate model. The second to fourth column show projections for the 2020s, 2050s and 2080s for the B2a greenhouse gas emissions scenario (low emissions), whereas the last three columns are for the A2a (higher) scenario.

With the exception of highland areas, the whole study region was suitable for banana. For all future scenarios, suitability increased, until by the 2080s, conditions were almost ideal in much of the study region (Figure 30).
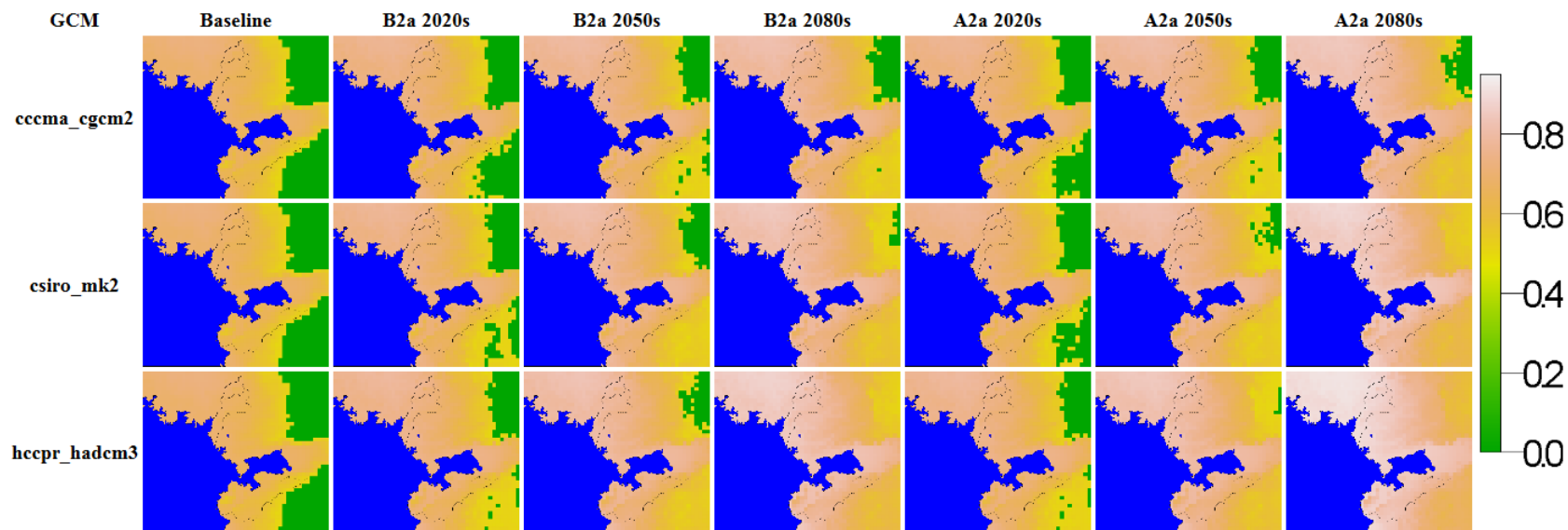
3.4.5. Cassava

Suitability for cassava

Figure 31. Suitability of the study region for production of cassava, according to crop requirements from FAO's ECOCROP database. A score of 1.0 indicates optimal conditions, whereas 0.0 means unsuitable for the crop. Suitability is shown for the current situation (baseline; first column), and 18 future scenarios. Rows across are projections with the same climate model. The second to fourth column show projections for the 2020s, 2050s and 2080s for the B2a greenhouse gas emissions scenario (low emissions), whereas the last three columns are for the A2a (higher) scenario.

Also for cassava, conditions were quite favorable for the baseline scenario, but became very suitable almost everywhere in the region by the 2050s (Figure 31). The few areas that are currently unsuitable for production became suitable in the course of the model runs.

3.4.6. Sweet potato

Figure 32. Suitability of the study region for production of sweet potato, according to crop requirements from FAO's ECOCROP database. A score of 1.0 indicates optimal conditions, whereas 0.0 means unsuitable for the crop. Suitability is shown for the current situation (baseline; first column), and 18 future scenarios. Rows across are projections with the same climate model. The second to fourth column show projections for the 2020s, 2050s and 2080s for the B2a greenhouse gas emissions scenario (low emissions), whereas the last three columns are for the A2a (higher) scenario.

Because the climatic requirements of sweet potato are somewhat similar to those of cassava, projections for sweet potato (Figure 32) are not very different from those for cassava. Because of slight differences in optimal and tolerable high temperatures, suitability was slightly higher for sweet potato than for cassava.

3.4.7. Common bean
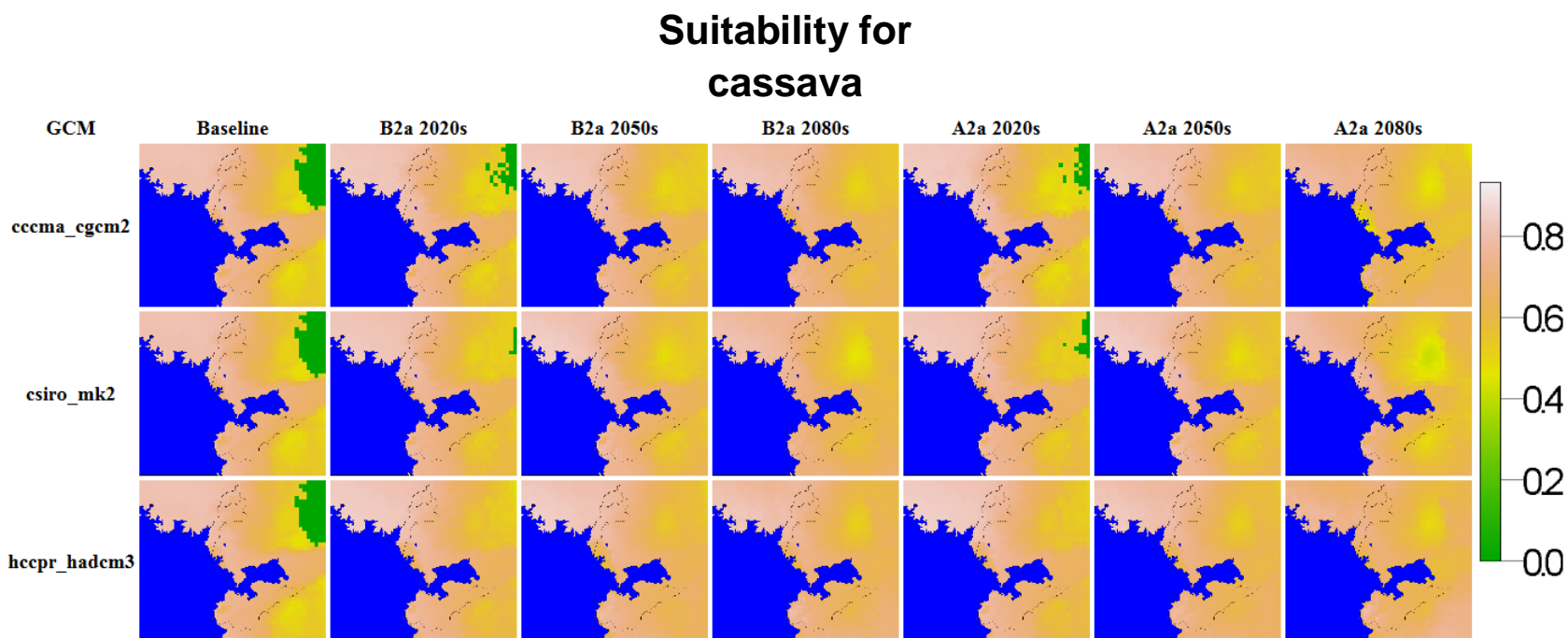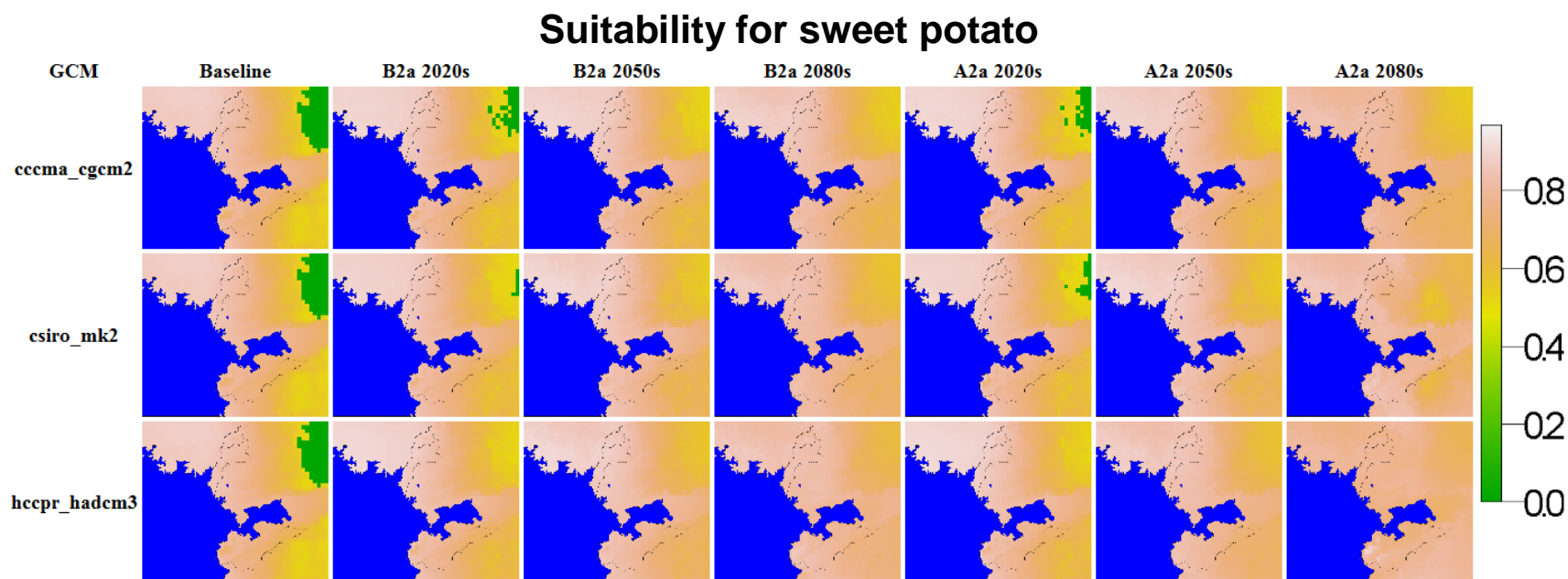
Suitability for common bean

Figure 33. Suitability of the study region for production of common bean, according to crop requirements from FAO's ECOCROP database. A score of 1.0 indicates optimal conditions, whereas 0.0 means unsuitable for the crop. Suitability is shown for the current situation (baseline; first column), and 18 future scenarios. Rows across are projections with the same climate model. The second to fourth column show projections for the 2020s, 2050s and 2080s for the B2a greenhouse gas emissions scenario (low emissions), whereas the last three columns are for the A2a (higher) scenario.

In the baseline scenario, conditions were very favorable for common beans, and such good conditions were projected to continue for all 2020s scenarios (Figure 33). However, from the 2050s scenarios onward, suitability gradually declined. By the 2080s, peak temperatures in much of the study region could be above the absolute temperature range of common beans. This probably signifies severe yield reductions.

3.4.8. Finger millet
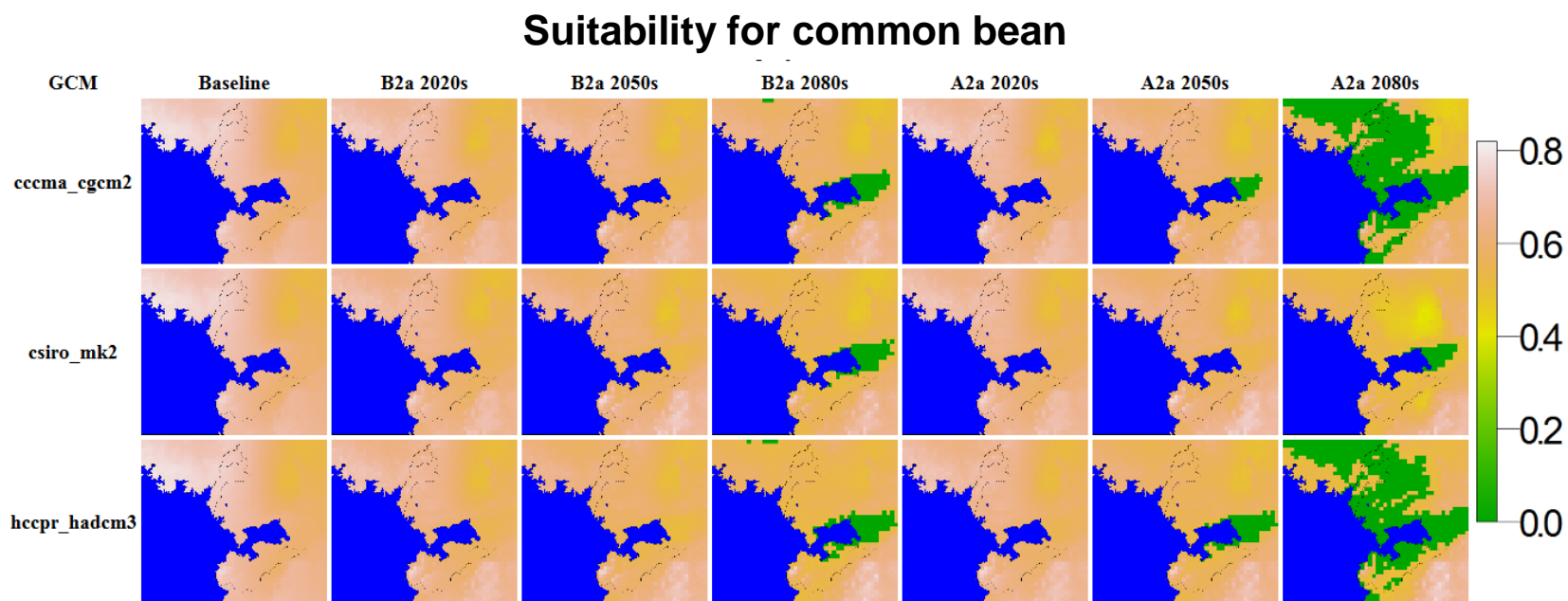
Suitability for finger millet
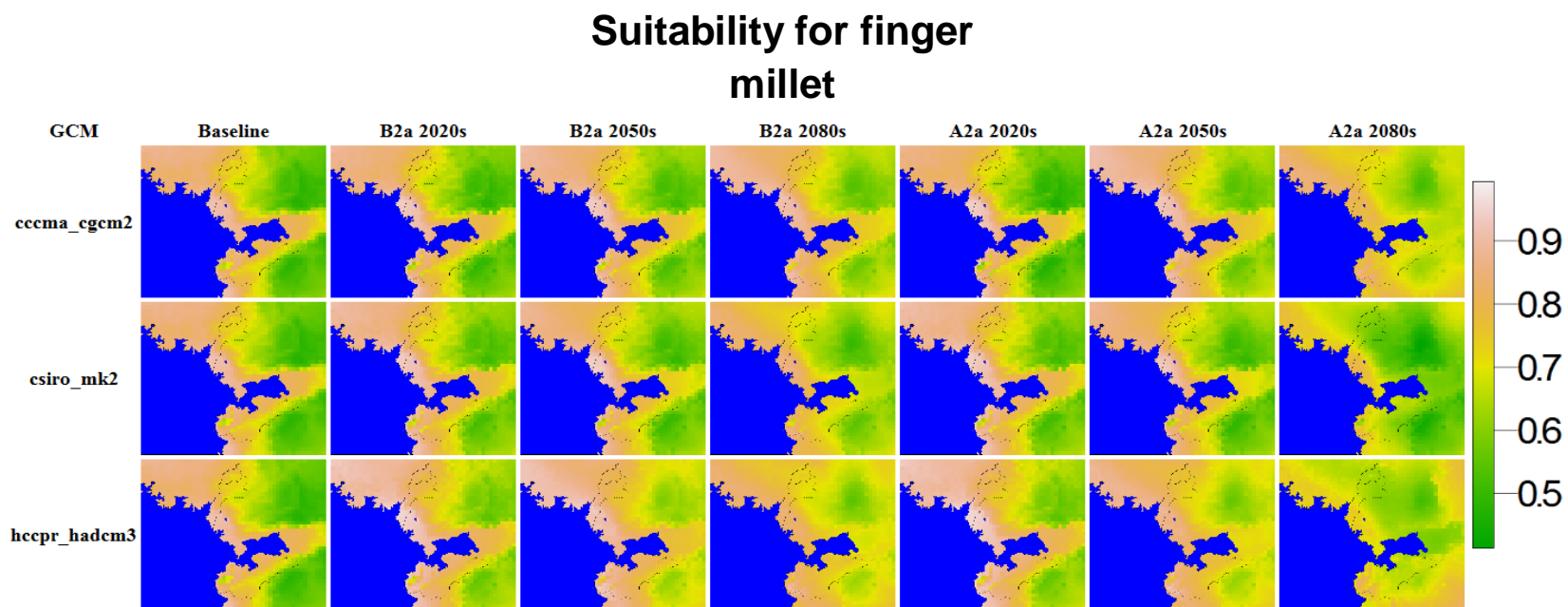
Figure 34. Suitability of the study region for production of finger millet, according to crop requirements from FAO's ECOCROP database. A score of 1.0 indicates optimal conditions, whereas 0.0 means unsuitable for the crop. Suitability is shown for the current situation (baseline; first column), and 18 future scenarios. Rows across are projections with the same climate model. The second to fourth column show projections for the 2020s, 2050s and 2080s for the B2a greenhouse gas emissions scenario (low emissions), whereas the last three columns are for the A2a (higher) scenario.

According to the ECOCROP database, favorable conditions for finger millet can currently only be found along the lakeshore (Figure 34). This was projected to persist throughout the 2020s and 2050s scenarios. By the 2080s, however, conditions were much less favorable, probably due to higher temperatures.

3.5. Effects of weather on crop yields

The second set of outputs for each crop comes from the analysis of weather effects on crop yields, accomplished by PLS regression. This procedure generated three plots each for minimum temperature, maximum temperature and rainfall. The example below, for the response of a crop to minimum temperatures, shows how these results can be interpreted (Figure 35).

Figure 35. Example of PLS analysis output. The Variable-Importance-Plot (left) shows the importance of a variable for explai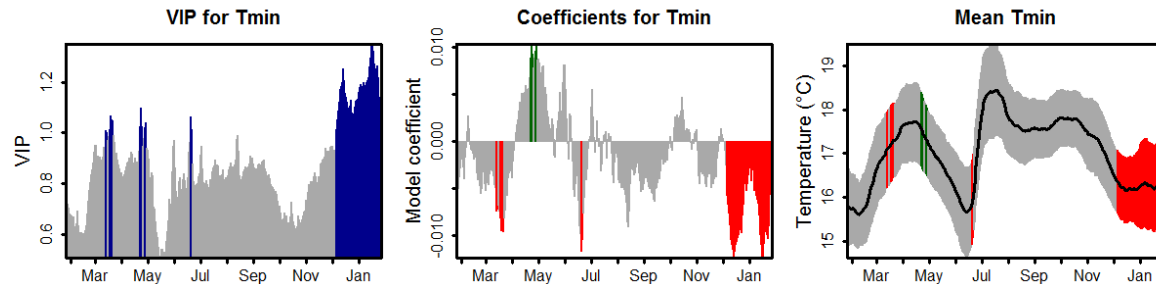ning variation in crop yields. Blue bars indicate days, for which the VIP score for the respective climate parameter exceeded the threshold value of 1, indicating importance for the explanatory model. The model coefficient plot (middle) shows the direction, in which high values for the respective climate parameters and day influence yields. Positive values (green, when also important) indicate that high Tmin causes high yields; negative values (red, when also important) mean the opposite. The plot of the right shows the information from the middle plot in the context of modeled values for the climate parameter. The black line in this plot is the mean for the respective date, the grey bars are the standard deviation.

The x-axis for each plot shows the time between about 20 days before the beginning of the planting window and the date, when 90% of the cotton crops of all model runs had been harvested. The first plot shows the variable importance statistic, which evaluates whether or not minimum temperature during certain days has an important effect on crop yields. This is the case for all days, for which the bars are blue, i.e. for short phases in March, April and June, and for a long period between December and February. The middle plot, showing the coefficients of the PLS model, shows the direction, in which high minimum temperature during these phases pushes yields. Red bars indicate that high minimum temperatures lead to lower yields, green bars signify a yield increase. The plot shows that during a short phase in April, high minimum temperatures have a significant positive effect on yields. During short phases in March and June, the opposite effect occurs. The main effect, however, is the negative effect of high minimum temperatures on yield, for the end of the growing season. The third plot shows the same results in the context of modeled temperatures. The black line in this figure shows the mean minimum temperature of the respective dates among all scenarios for the 2020s and the baseline. The gray, red or green bars are the standard deviation of Tmin for these dates. The coloring is the same as in the middle plot. In this case, the figure shows that minimum temperatures in December, January and February are relatively low, compared to earlier in the season. However, the modeled crop still reacted strongly to Tmin, with warmer conditions having a fairly strong negative effect on yields. Overall these results show that the modeled crop is relatively insensitive to minimum temperatures within the range observed in the modeled scenarios, during most of the growing season. Only during the last few months before harvest is there a strong effect of

this climate parameter, with conditions at the cooler end of what can be expected being optimal for yields.

3.5.1. Maize

Long rains

Maize is normally planted at the beginning of the rainy season and matures after the rains have stopped. Its productivity is thus not very susceptible to the length of the rainy season, unless rains are very short. This is reflected in the crop weather profile (Figure 36), which shows very few days, during which rainfall had a significant effect on crop yields. Both minimum and maximum temperature, in contrast, had strong effects, with warm conditions during most developmental stages impacting yields negatively, while heat never benefitted the crop. The pattern shown in Fig. 34 for Orthic Ferralsols was also apparent for all other soils.

Figure 36. Results of the PLS analysis for maize during the long rains on all Orthic Ferralsols. For a more detailed explanation, see text.

Short rains

For the short rains, maize also responded strongly negatively to high temperatures (Figure 37). For this rainy season, however, the shorter duration of humid conditions was reflected in greater yield response to variation in rainfall. For example, maize grown on a Xantic Ferralsol responded favorable to extraordinarily moist conditions until mid October. After this time, effects of high rainfall were mixed, with both negative and positive impacts detected.

Other soils, most notably Plinthic Ferralsols, did not show a positive response of maize yields to high rainfall.

Figure 37. Results of the PLS analysis for maize during the short rains on all Xantic Ferralsol. For a more detailed explanation, see text.

3.5.2. Cotton

Among the soils, for which cotton production was modeled, only Humic Andosols deserve a closer look. On all other soils, yields were negligible, and while for some sites, influential factors can be identified, overcoming the associated constraints would probably still not make production worthwhile.

Long rains
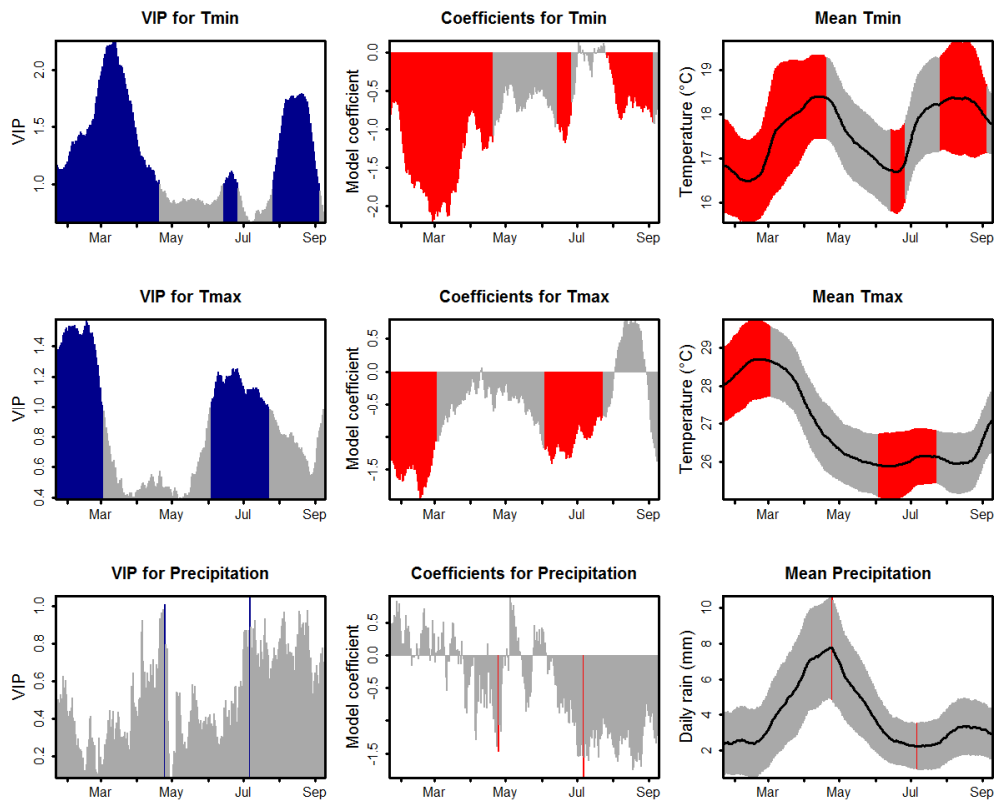

Figure 38. Results of the PLS analysis for cotton during the long rains on all Humic Andosols. For a more detailed explanation, see text.

On Humic Andosols, the growing period of cotton ranged from March through September to October, for most sites (Figure 38). However, in some cases, cotton was only harvested in January. Unlike maize, cotton production was strongly impacted by rains, with high rainfall in the second half of the long rains and first half of the short rains impacting yields positively. Between the rainy seasons, the impact was lower in spite of relatively low rainfall, reflecting a low water requirement of cotton during the corresponding development phases. The second phase of high rainfall influence is after most of the cotton has already been harvested. Effects of temperature were only manifest for maximum temperatures. High maximum temperatures after the long rains and during the short rains led to low yields.

Short rains
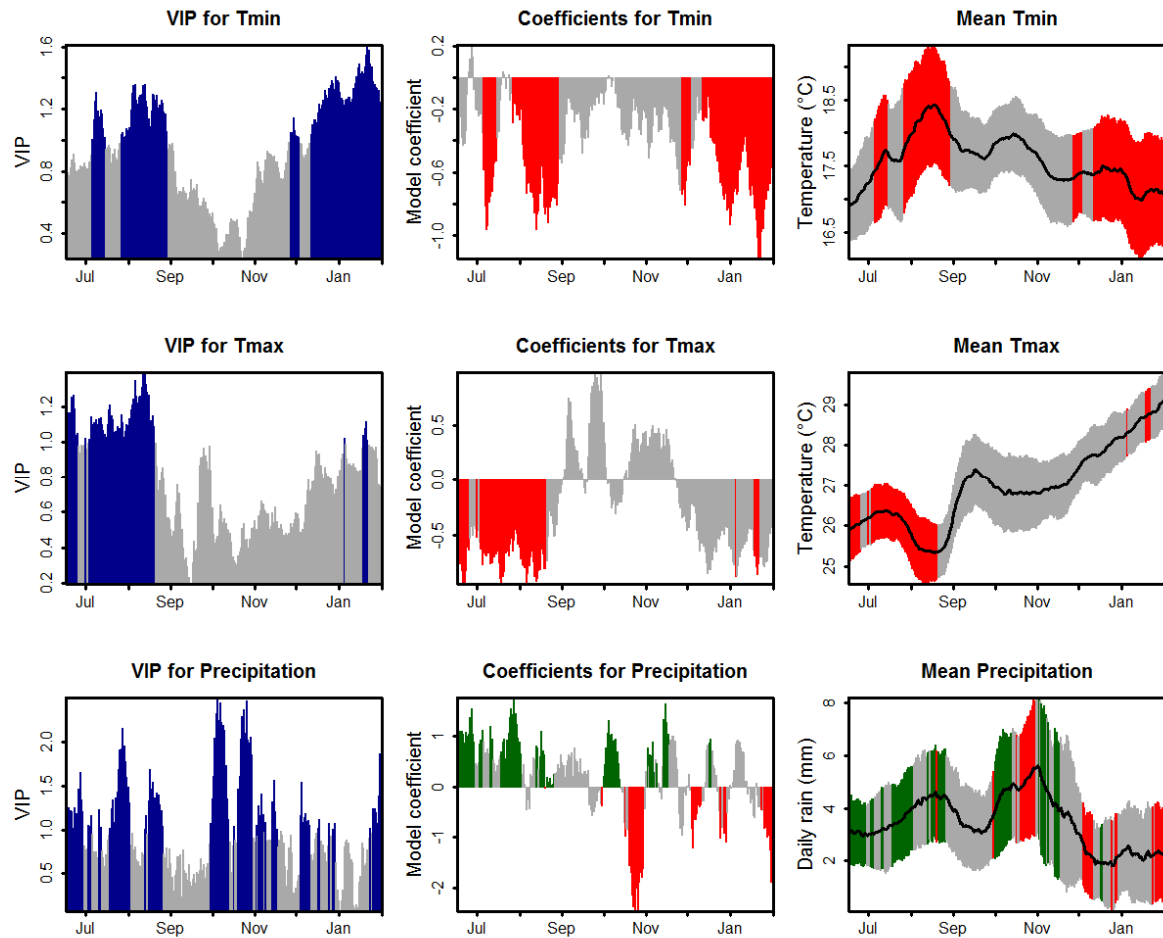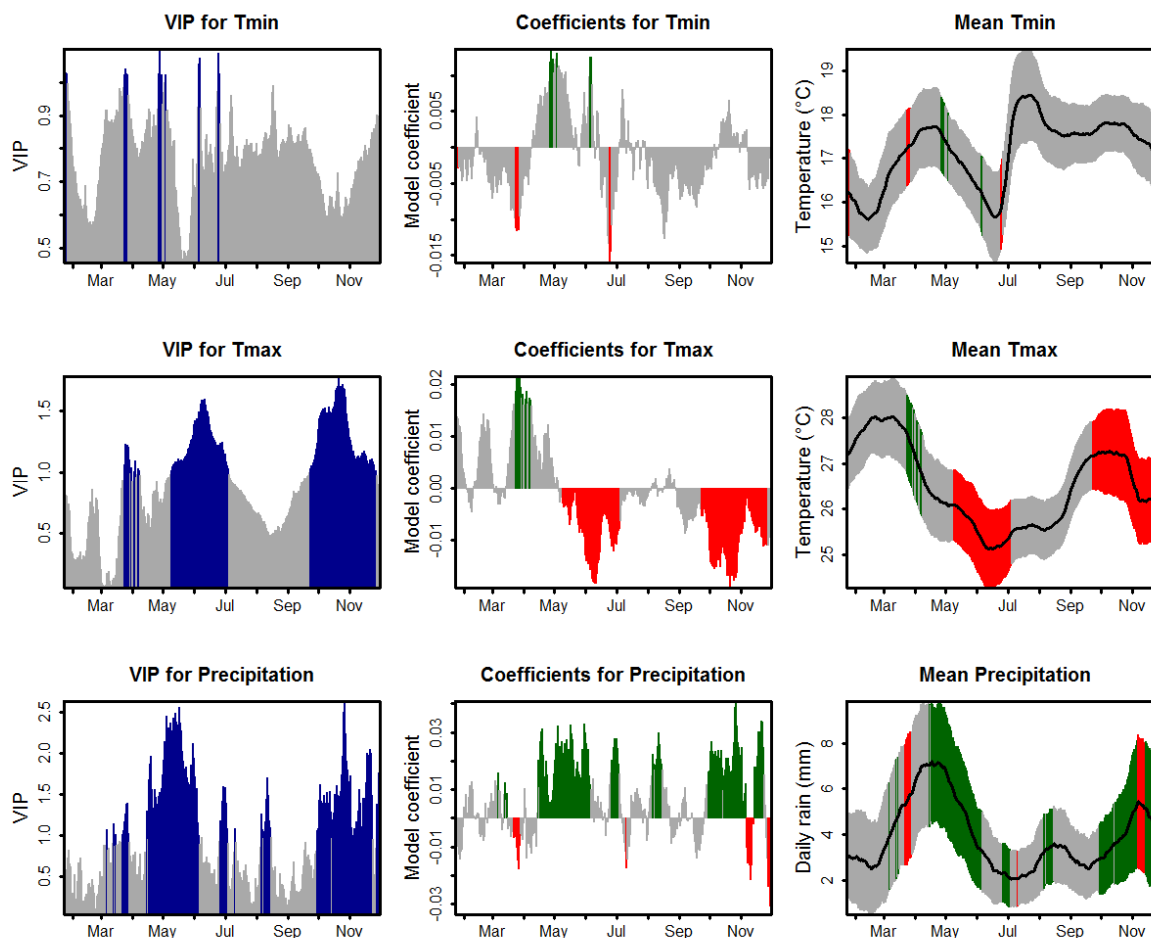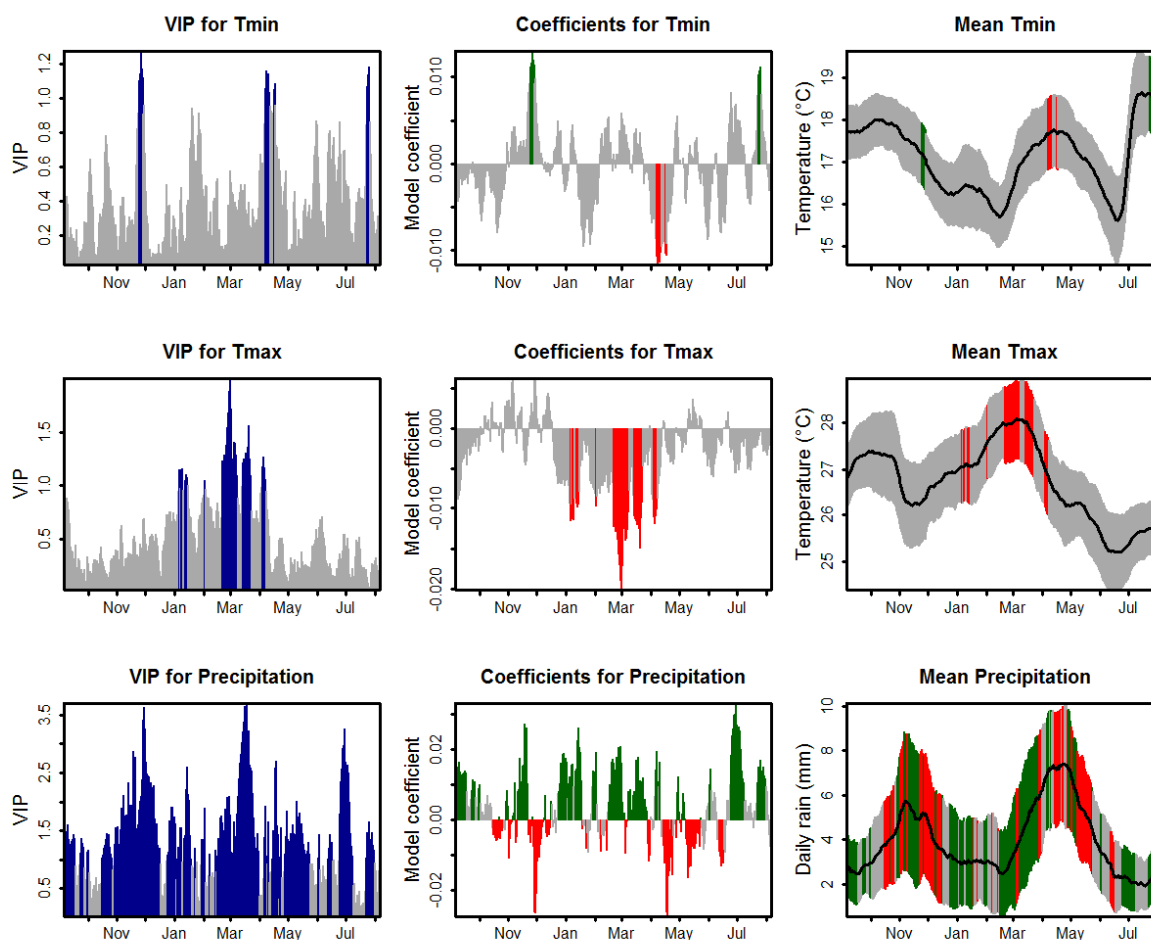

Figure 39. Results of the PLS analysis for cotton during the short rains on all Humic Andosols. For a more detailed explanation, see text.

Also for cotton planted during the short rains, rainfall was the dominant factor impacting yields (Figure 39). The emerging pattern was somewhat less clear than for the long rains, but in general, high rainfall during the drier seasons had a positive effect on yields, whereas relatively low rainfall was beneficial during the wettest phases of the rainy seasons. Harvest dates for cotton ranged between May and August for the baseline scenario, with most of the yields coming in between June and August, after the end of the long rains. For many future climate scenarios, harvest dates advanced, so that cotton harvest occurred between March and May. While the crop model did not simulate cotton quality, this advance in harvest dates may be a concern, because rainfall just before and during harvest diminishes cotton quality. With most of the simulated cotton growing season ending during the long rains, the value of the harvested product may thus decline.

3.5.3. Sorghum

Long rains
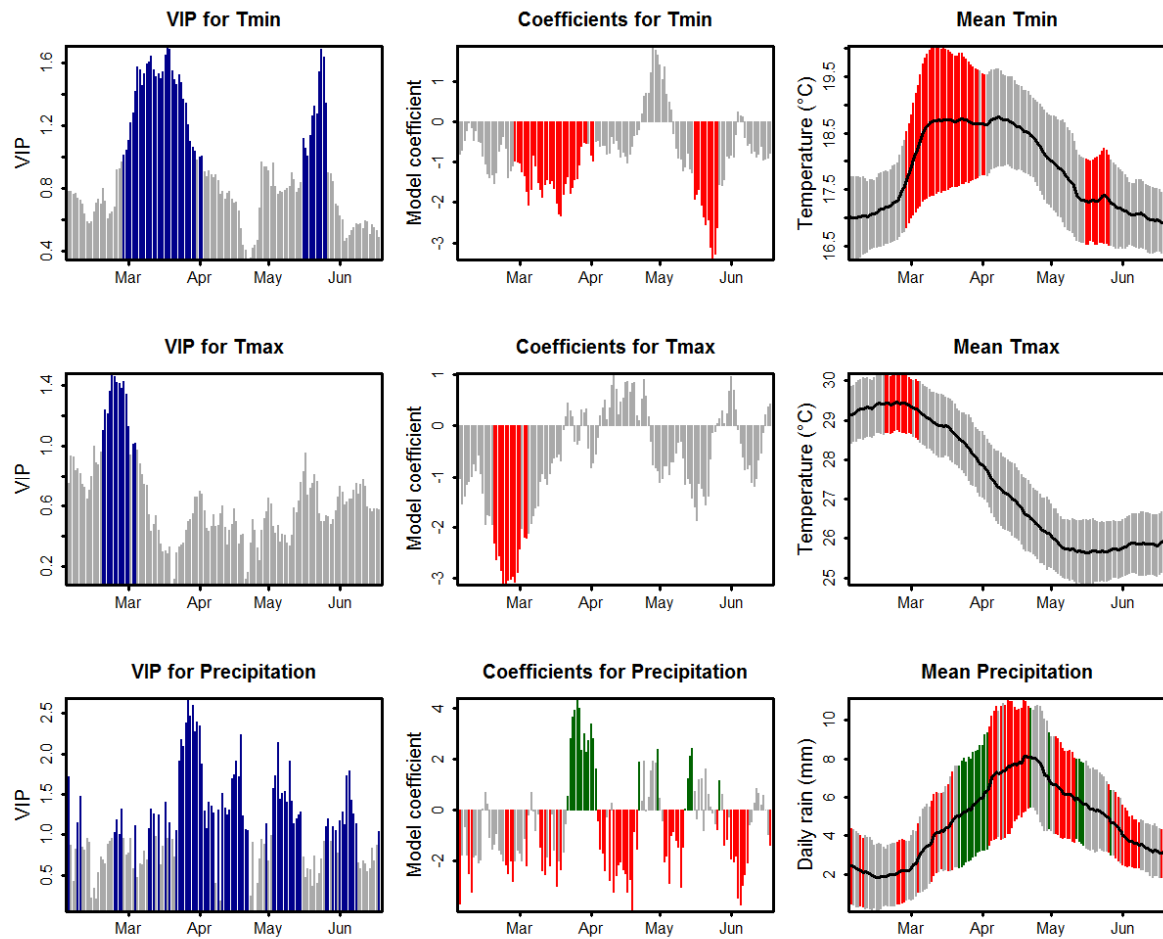
Figure 40. Results of the PLS analysis for sorghum during the long rains on all Plinthic Acrisols. For a more detailed explanation, see text.

Weather variables with significant impacts on sorghum yields during the long rains were identified among all three main climate parameters (Tmin, Tmax and Rainfall; Figure 40). Significant effects of high temperatures were always negative. This was particularly the case at the beginning of the long rains. Yields were much more susceptible to high minimum than to high maximum temperatures. Effects of rainfall were mixed, with high rainfall having a positive effect on yields during some phases, and a negative effect during others. This may reflect sorghum's sensitivity to soil water levels. Water supply must be sufficient, but the crop is also sensitive to waterlogging, which may happen if too much precipitation occurs. Observed crop response patterns to weather were similar for all soil types.

Short rains

Figure 41. Results of the PLS analysis for sorghum during the short rains on all Plinthic Ferralsols. For a more detailed explanation, see text.

During the short rains, crop responses to weather were a bit more complicated than for the long rains (Figure 41). Effects of high temperature were still predominantly negative, but some phases that showed a positive effect of heat on crop yields were also seen, for some soil types. Effects of high precipitation were mixed again, with negative and positive impacts on yield found in the model output.

3.5.4. Greengram

Long rains

Figure 42. Results of the PLS analysis for greengram during the long rains on all Humic Andosols. For a more detailed explanation, see text.

Greengram yields responded primarily to temperature, with high values for Tmin and Tmax impacting yields negatively (Figure 42). In particular, high minimum temperatures had a strongly negative effect almost during the entire growing period. Rainfall effects were less pronounced, except for high moisture near the end of the growing season. This indicates that greengram benefits from a slightly longer rainy period than is normal in the study region.

Short rains
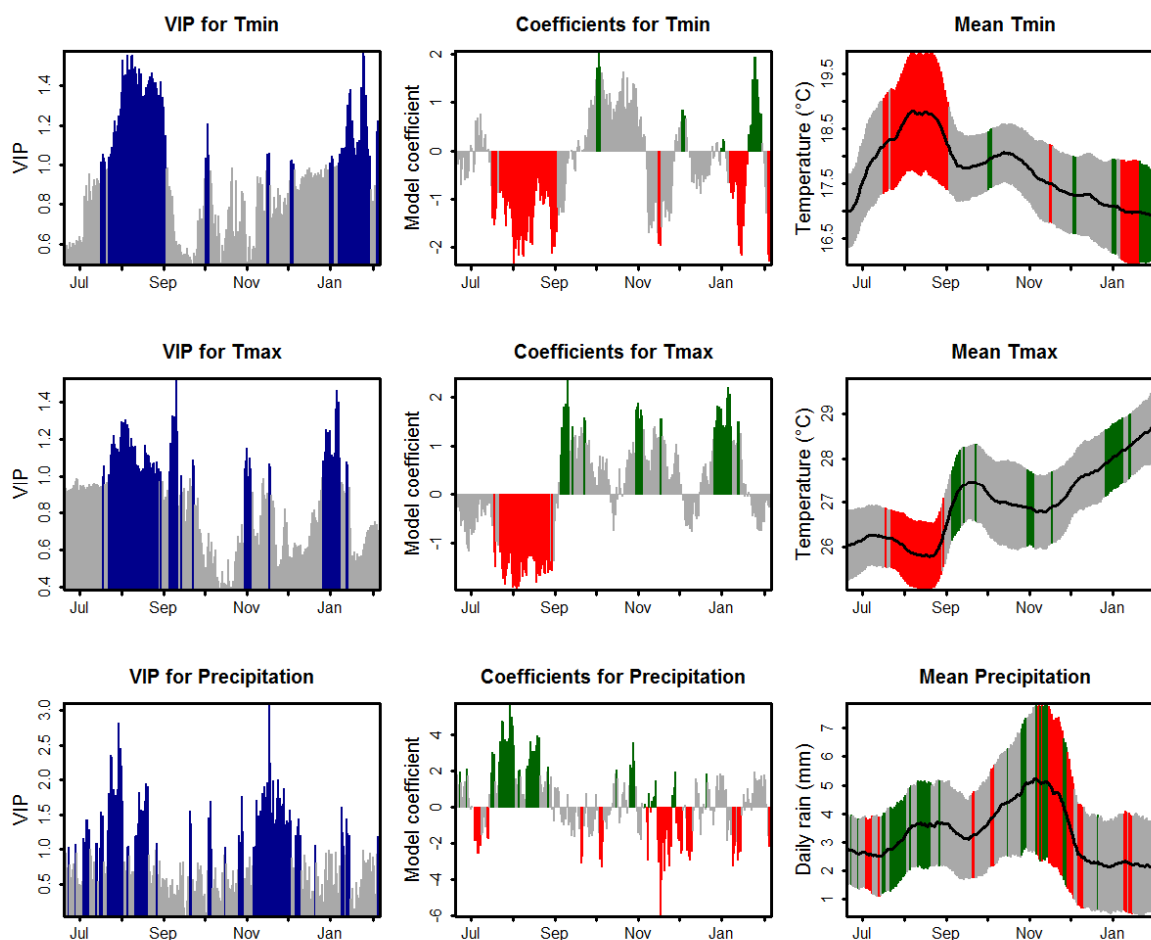

Figure 43. Results of the PLS analysis for greengram during the short rains on all Humic Andosols. For a more detailed explanation, see text.

Also for the short rainy season, weather effects on greengram yield were dominated by adverse heat effects (Figure 43). High precipitation had a positive impact during certain parts of the growing season. The response of greengram to weather varied among soil types (see digital attachment).

3.5.5. Soybean

Long rains

Soybean responded to weather in a rather inconclusive way. For example, high minimum temperatures had a strongly negative effect for some soils, but a strongly positive effect for other soils. A representative PLS profile could therefore not be identified. The reason for this pattern is probably that soybean yields were only high in the highlands, yet soils there were similar as in the lowlands (according to the global database used). In the PLS analysis, all sites for a given soil type were analyzed together. For soybean, however, differences between the sites may have been greater than acceptable for the analysis method.
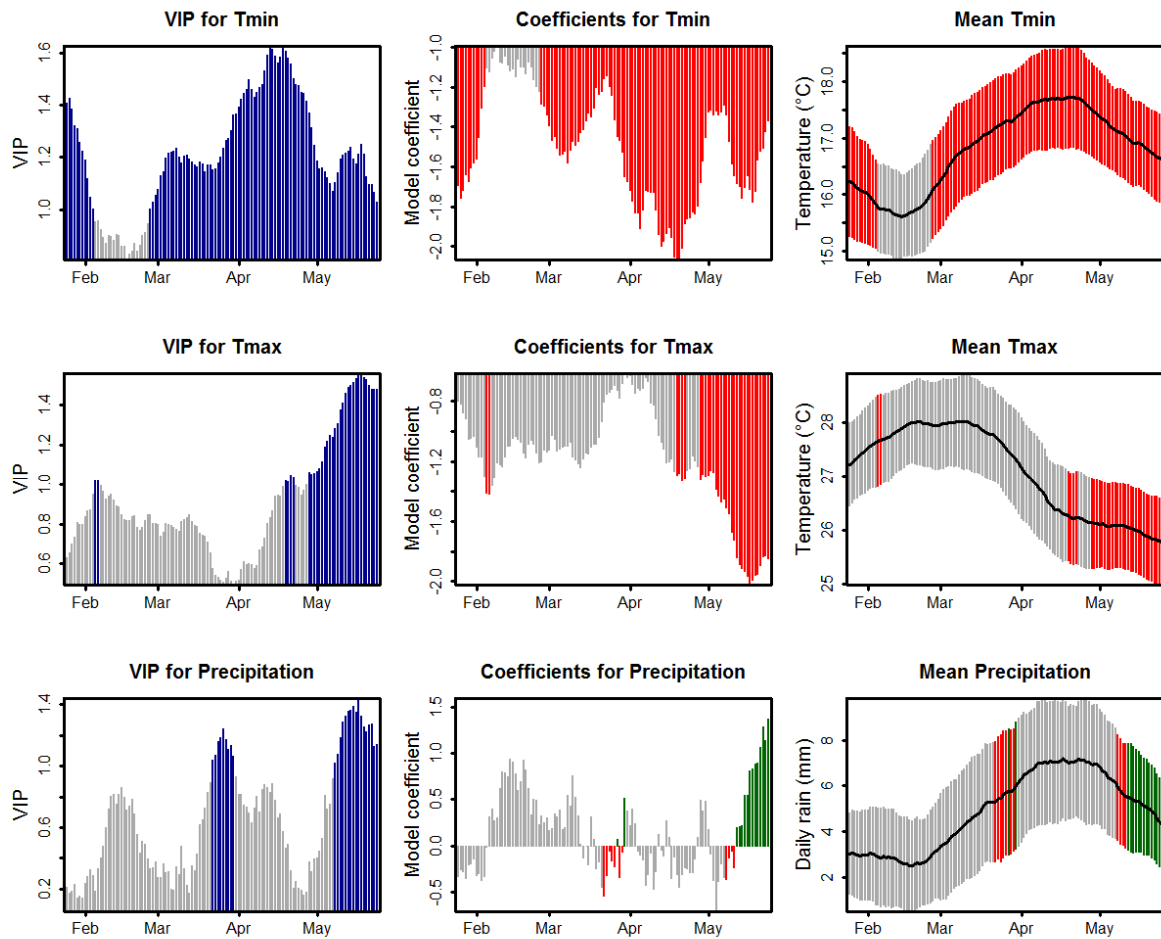
Short rains

Figure 44. Results of the PLS analysis for soybean during the short rains on all Humic Andosols. For a more detailed explanation, see text.

In contrast to the long rains, clear weather response patterns emerged for the short rains (Figure 44). This is probably because for many of the high potential sites, no short rainy season was identified, because the short rains were projected to merge with the long rains. As for most of the other crops, high temperatures had a strong negative effect on yield levels. High rains during early phases of the growing season had a positive influence.

3.5.6. Groundnut

Long rains

Figure 45. Results of the PLS analysis for groundnut during the long rains on all Rhodic Ferralsols. For a more detailed explanation, see text.

Weather effects on groundnut yields were dominated by an adverse effect of high temperatures (Figure 45). This was similar for minimum and maximum temperatures. In comparison, rainfall effects were relatively small and limited to fairly short time spans at the beginning and end of the rainy season.
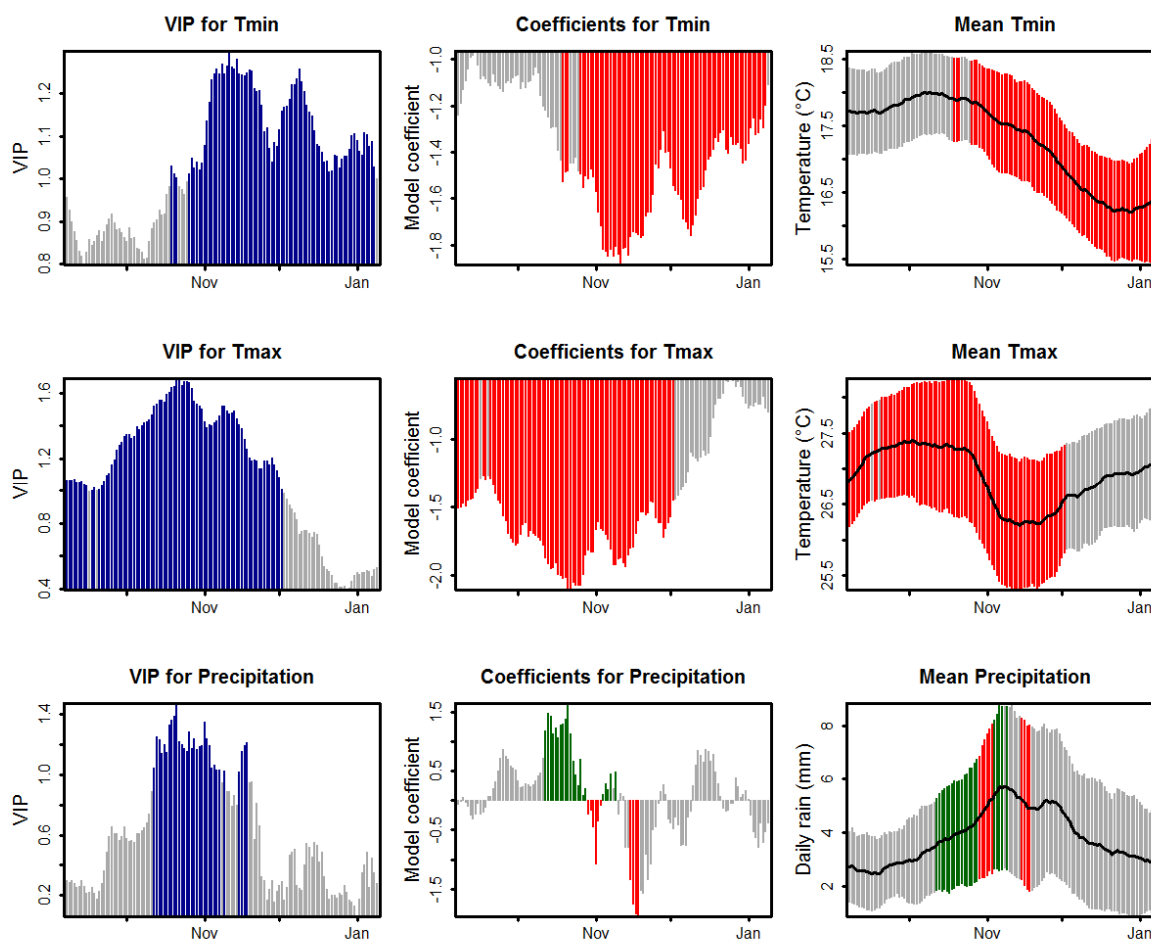
Short rains

Figure 46. Results of the PLS analysis for groundnut during the short rains on all Rhodic Ferralsols. For a more detailed explanation, see text.

For the short rains, high temperature was also the dominant factor influencing groundnut yields (Figure 46). Rainfall also had an effect, with abundant rains at the beginning and end of the rainy season promoting high yields. This indicates that a rainy season slightly longer than the current short rains would benefit groundnuts.
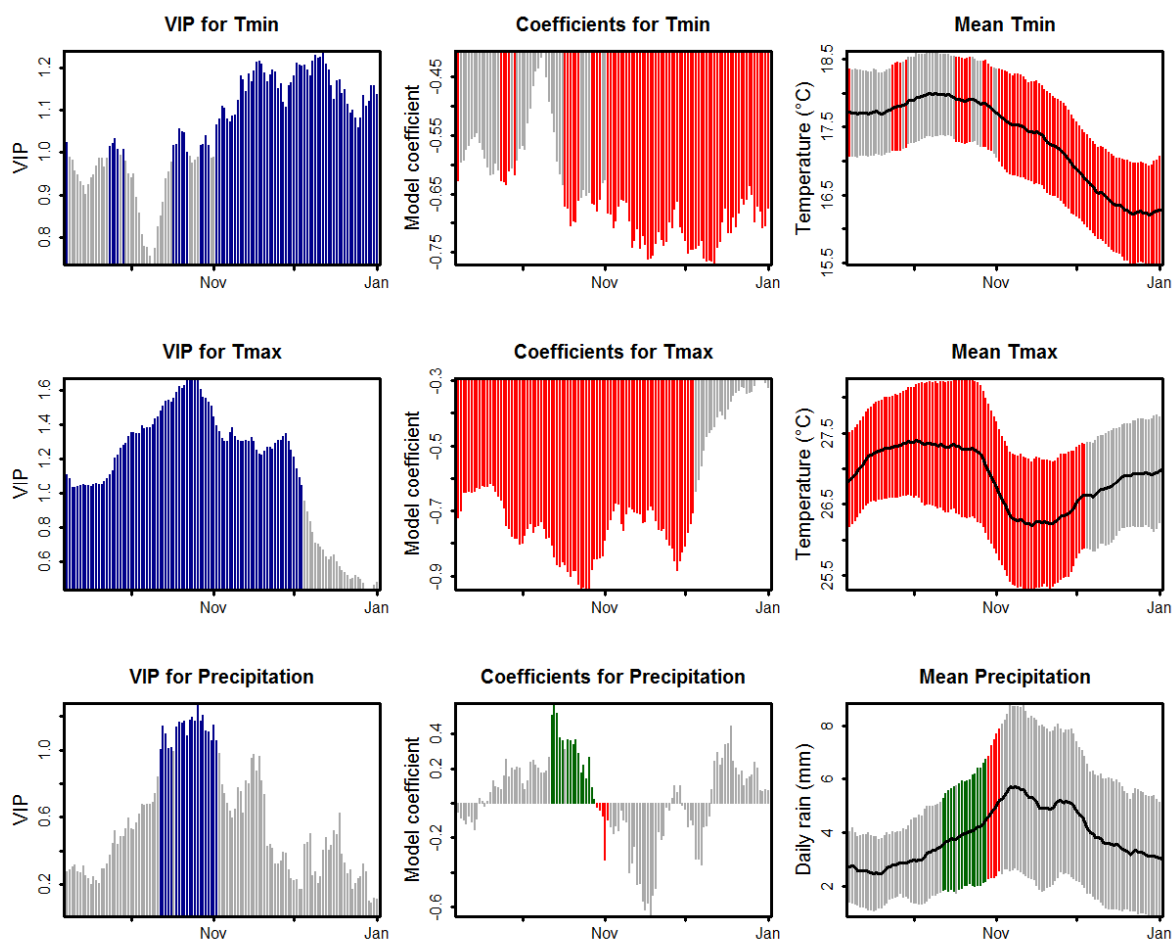
3.5.7. Cowpea

Long rains
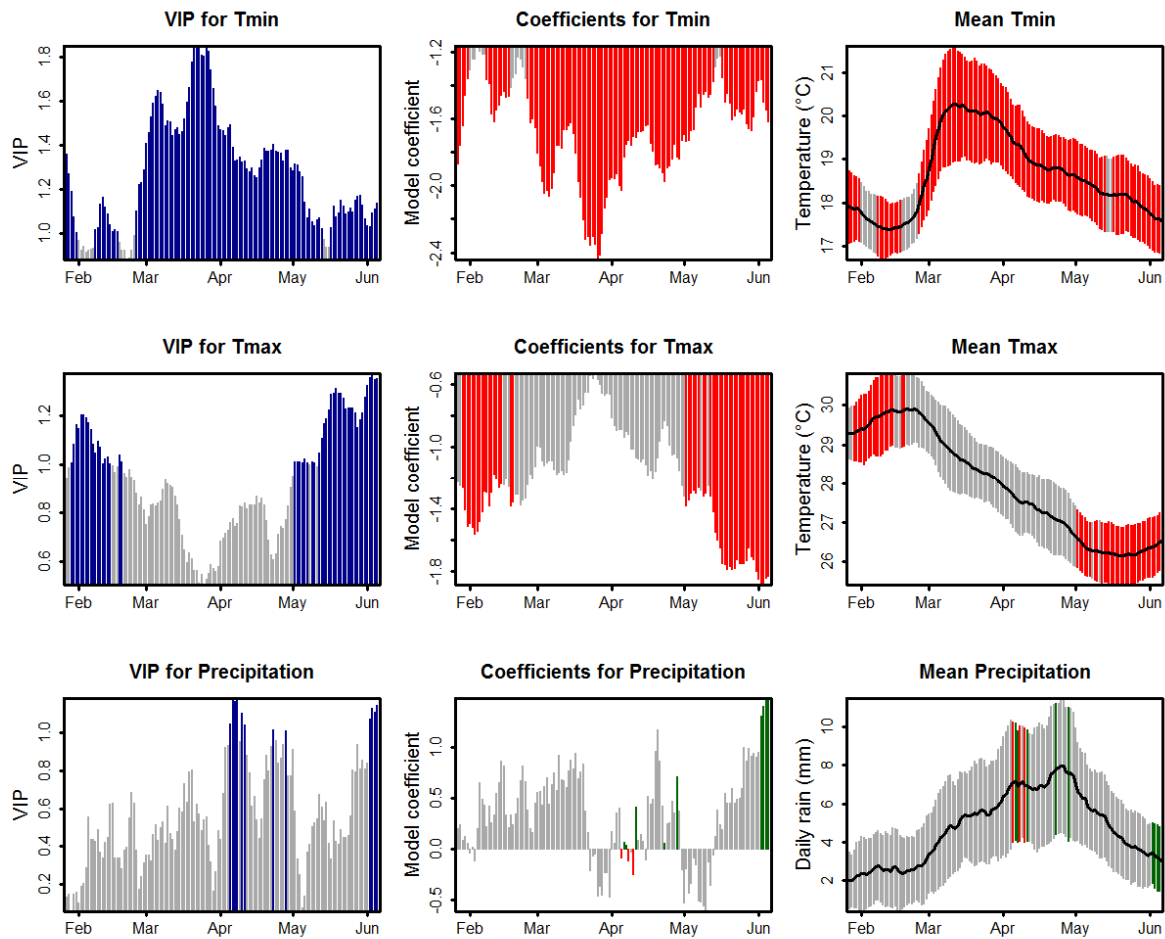
Figure 47. Results of the PLS analysis for cowpea during the long rains on all Orthic Acrisols. For a more detailed explanation, see text.

During the long rains, cowpea responded mainly to high minimum temperature throughout the growing season (Figure 47). High maximum temperatures at the beginning and end of the season also had an effect. For both parameters, impacts were always negative, indicating that cowpea yields were heat-sensitive. Rainfall during the long rains only had a minor effect on cowpea yields.

Short rains
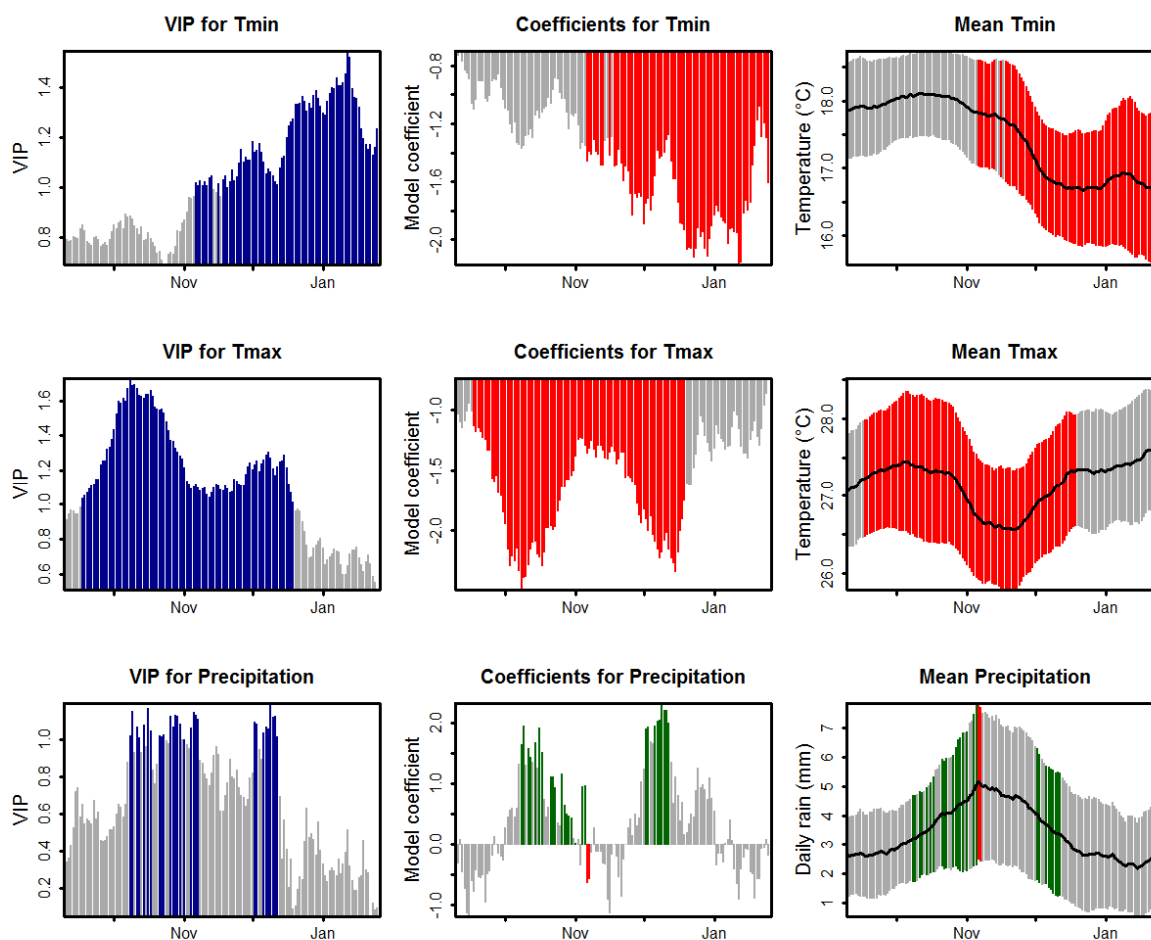
Figure 48. Results of the PLS analysis for cowpea during the short rains on all Rhodic Ferralsols. For a more detailed explanation, see text.

Also during the short rainy season, the main factors influencing cowpea yields was temperature, with high Tmin and Tmax having negative effects, throughout much of the season (Figure 48). Rainfall was of comparatively minor importance, but high rains during certain phases had significant positive impact.

3.5.8. Fababean

Long rains
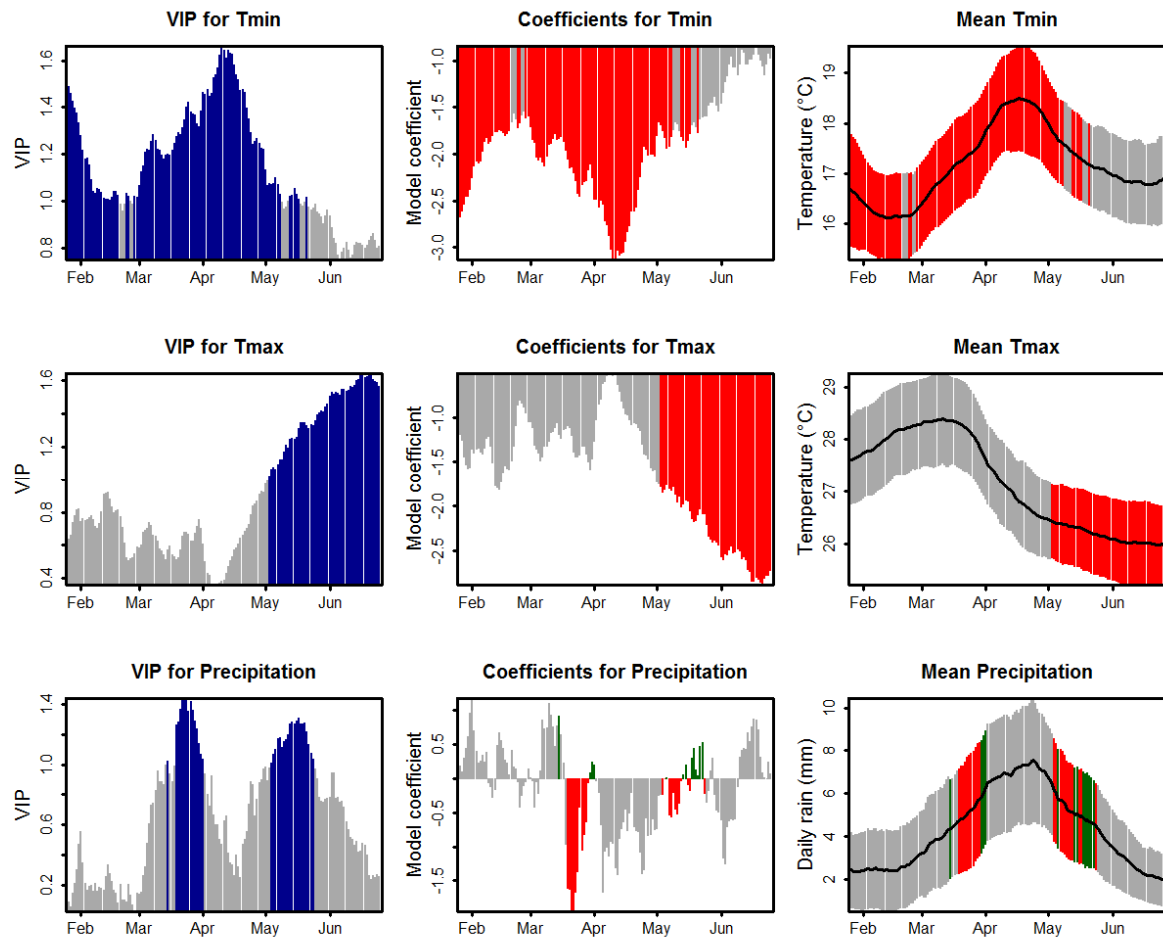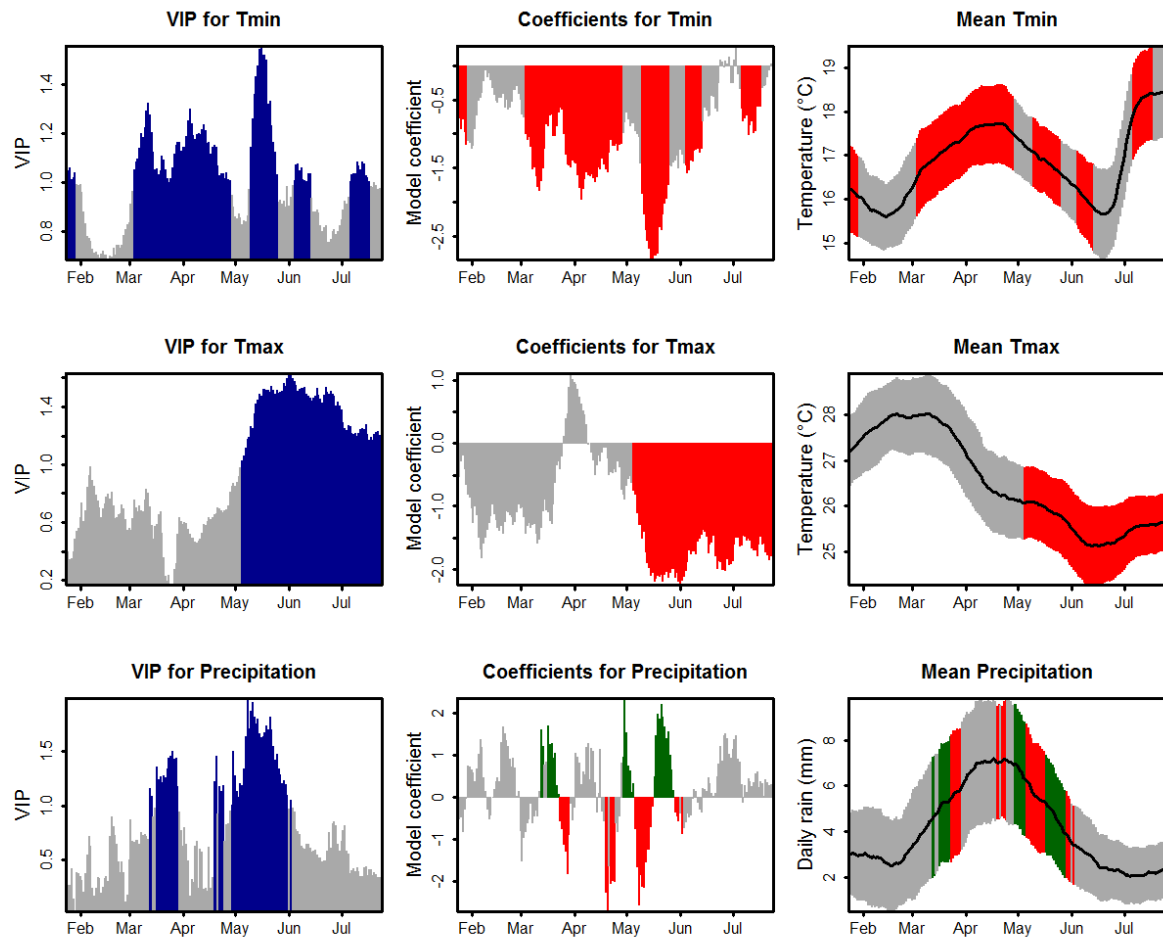

Figure 49. Results of the PLS analysis for fababean during the long rains on all Humic Andosols. For a more detailed explanation, see text.

As most other crops, fababean responded predominantly to high temperatures, with lower yields (Figure 49). High precipitation had a slight effect, where it extended the rainy season.
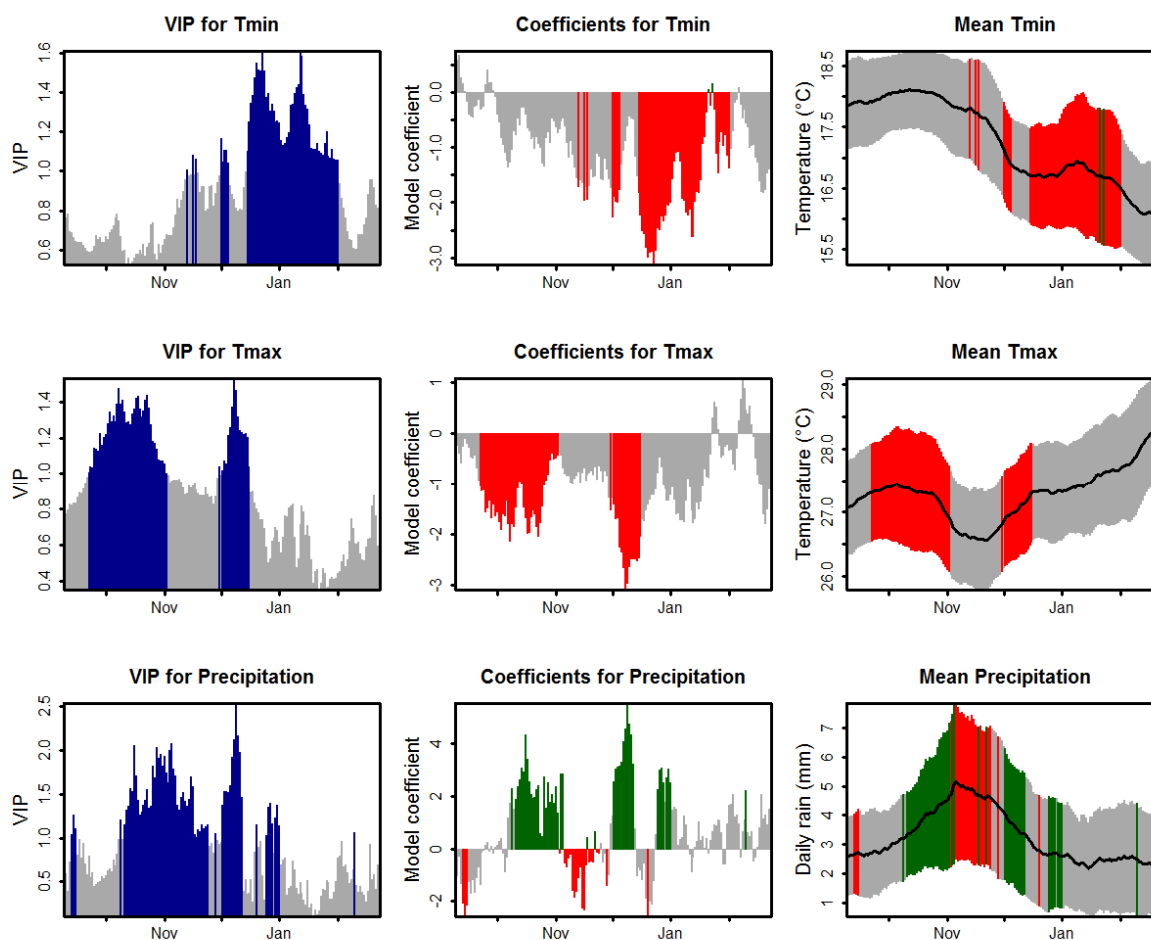
Short rains
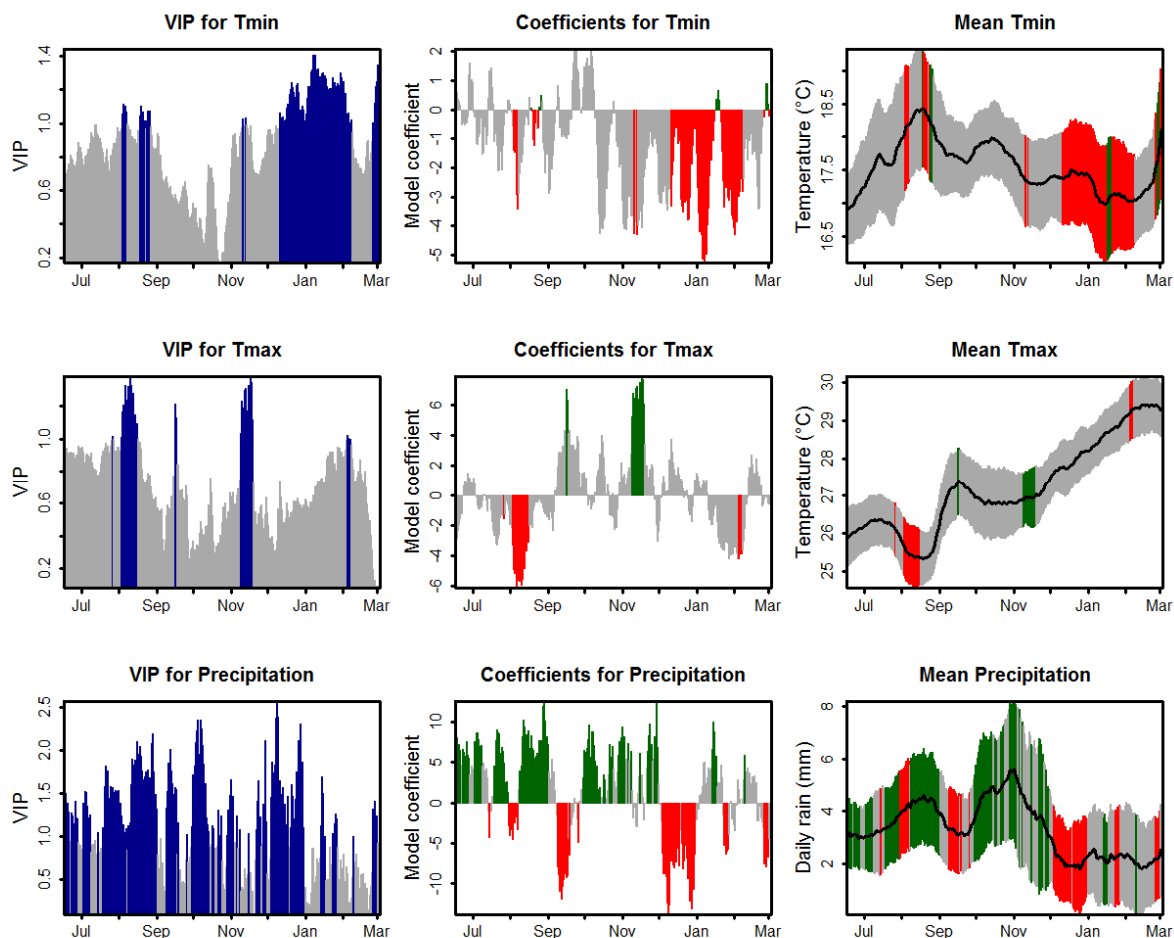
Figure 50. Results of the PLS analysis for fababean during the short rains on all Plinthic Acrisols. For a more detailed explanation, see text.

For the short rainy season, the negative effects of high temperatures were less pronounced, but still present (Figure 50). Rainfall had a higher impact, with high rainfall during much of the growing season having a positive effect. This indicates that in much of the study region, the short rains are shorter than would be ideal for fababean production.

4. Synthesis

4.1. Present and future performance of major crops

4.1.1. Maize

Maize is currently the most important crop in the region, and this analysis confirmed its suitability for the climate of the study region. Current yields were stable and relatively high, and the crop could be reliably produced during both the long and the short rains at every site that was analyzed. Compared to other crops, soil type was of little influence. It appeared that water demand was well attuned to rainfall patterns, with relatively low water needs after the end of the rains, during maturation of the crop.

Future projections indicated declining yields for every site, soil and climate scenario. However, these losses were relatively modest and predictable, and yield levels continued to be stable (though lower) for all future scenarios. The main factor that drove yield variation was temperature, with high minimum and maximum temperatures having a negative impact on maize yields. During the short rains, some sites and soils benefited from rainfall around the beginning and end of the season.

Based on these results, adaptation of maize production to climate change impacts should focus on introducing or developing varieties that can tolerate heat. Farmers could also benefit from introducing measures to influence farm microclimate, e.g. by planting shade trees or introducing other kinds of agroforestry practices.

4.1.2. Cotton

Given local climatic conditions, it was possible to achieve high cotton yields without irrigation, but only rarely and only on certain soils. Among the soils investigated in detail in this study, only Humic Andosols had high potential, whereas for all other soil types, yields were very low. Exploratory further model runs on additional soil types implied that Eutric Histosols and to a lesser extent Chromic Vertisols should be added to this list. For these soils, yield patterns resembled those for Humic Andosols, except that yields on Chromic Vertisols were only about two thirds of those on the other two soils. On all soils that are not in this select group of three, cotton production cannot be recommended.

For the suitable soils, yields were very variable for the baseline scenario and also for all future scenarios. Mean yields were only about half of the maximum yields, and many scenarios showed a certain risk of complete crop failure. Whether cotton production makes sense in such a risky production environment must be evaluated in light of the economics of cotton production and marketing, which were not explored in this study. In any case, the high yield fluctuations would likely be a major constraint on the establishment of a viable cotton industry.

Future scenarios mostly saw a decline in yields, even though in some cases, increases were also projected. In general, future climate scenarios indicated either yield losses or increasing yield variability. High temperatures during certain phases of the growing season had a negative effect on cotton yields, but the dominant factor was rainfall. The growing period of cotton spans both rainy seasons, meaning that much of the active growth occurs between these seasons. Any additional rainfall during this period is thus of great benefit for the crop. As a result, cotton production would benefit from the option to irrigate during the dry season.

Since this is necessary for ensuring stable production levels even under current conditions, this is not only an adaptation strategy for future climates, but also a prerequisite of a viable cotton industry, which currently does not exist in the area.

Quality attributes of cotton were not evaluated in this study, but some concerns resulted from the analysis. Cotton quality depends to a large extent on weather before and during harvest. Rainfall around that time has a detrimental effect. Dry seasons in Kenya's southwest are not as dry as those in other major cotton-producing regions, and some rain can fall at any time of year. Whether cotton from the study region can compete for quality with other supply regions should be explored separately, before investments in cotton production are intensified. Some climate change scenarios also indicated that cotton could complete its life cycle earlier, due to faster accumulation of thermal time. This shifted harvest dates earlier, so that in many cases, harvest occurred in the middle of the next rainy season. This could have a strong negative effect on cotton quality. For cotton, more than for most other crops, yield levels are not the only, and possibly not even the most important, aspect of production, and care should be taken when recommending this crop to farmers.

4.1.3. Sorghum

Like maize, sorghum yields were also very stable throughout the growing region, and the crop grew almost equally well on all soil types. While most sites displayed this behavior in both the long and the short rainy season, some sites had more variable yields during the short rains. For future climate scenarios, most site/soil combinations showed a decline in yields, which however, was much less pronounced than for maize. On soils that had fairly variable yields in the baseline scenario, some future climate scenarios even saw an increase in yields, and sometimes a decrease in yield variability. This pattern indicates that sorghum is sensitive to the length of the short rainy season. The PLS analysis confirmed this impression, showing a strong positive effect of high rainfall at the beginning and end of the short rains for many sites. In addition to this moisture effect, high temperatures negatively impacted sorghum yields. The high yield levels, small variation and low susceptibility to climate change make sorghum appear like a recommendable crop, for the present situation as well as for climate change adaptation. The crop model results indicate that particularly during the long rains, sorghum production represents a good option for farmers.

4.1.4. Greengram

For greengram, yield differences among sites were relatively small. Only a few locations showed notable yield variability for the baseline scenario, and only during the short rains. All future scenarios indicated a yield decline. The main driver of this decline was high temperature. In addition to this strongly negative effect, a positive effect of abundant rainfall at the beginning and end of the short rains was beneficial. This indicates that greengram is better suited for the long rains, while the short rains may at times not be long enough for optimal greengram yields.

4.1.5. Soybean

For soybean, yield varied substantially between sites. Only a few locations came close to the regional yield maximum. For most sites and most soils, yields were insignificant during the long rains and would probably not allow profitable production of this crop. For the short rains, maximum yield across all sites was only about a third of that for the long rains, implying that the short rains are not long enough for soybean production. In spite of the low production

level, yields during the long rains were stable, whereas for the short rains, some sites displayed substantial variability. All climate change scenarios indicated a yield decline. The response of soybean yields to weather variables was mixed, but a general negative impact of high temperatures was detected. As many other crops, soybean would benefit from an extension of the growing season, as implied by positive PLS model coefficients for rains near the margins of the short rains.

4.1.6. Groundnut

For groundnuts, yield differences across sites were relatively small, and most sites had quite high yields. This was particularly true for the long rains. During the short rains, yields were more variable and generally lower. All future scenarios indicated decreasing yields, with quite substantial losses for all time slices. Again, the main driver of this yield decline was high temperature, whereas high rainfall at the beginning and end of the short rains was beneficial.

4.1.7. Cowpea

For cowpea, differences between sites were small. During the long rains, most sites had stable and moderately high yields. Short rain yields were much more variable, but maximum yields during this season were only slightly lower than during the long rains. In all climate change scenarios, yield losses were substantial, with 2050s yields only about half of those for the baseline scenario. Again, it was mainly high temperature that reduced yields, while more rains had a positive effect on yield during the short rainy season.

4.1.8. Fababean

Fababean yields during the long rains were high, and did not vary much between sites and soils, except for a few locations, which had more variable and lower yields than the majority of sites. For most sites, yields were quite stable. During the short rains, yields were much more variable, but still relatively high. Climate change scenarios projected a steady decline in yields over time. For a small number of sites, however, yields during the short rains increased slightly and became less variable for some climate scenarios. Even for those sites, most climate scenarios saw a decrease in yields. Higher temperatures were mainly responsible for the yield decline, while a longer than usual duration of the short rains was beneficial.

4.2. Present and future performance of perennial and non-APSIM crops

4.2.1. Mango

Both counties were classified as suitable for mango production. While yield levels could not be projected with the method used, this should indicate good potential to produce mangoes in the study region. Suitability was not compromised by climate change, with increases in suitability for much of the study region.

4.2.2. Sugarcane

When grown under rainfed conditions without irrigation or access to groundwater, much of the study region was unsuitable for sugarcane. Only the higher reaches of Busia received adequate amounts of rainfall for classifying this region as suitable for the crop. Since the main constraint to production appeared to be rainfall in most of the study region, additional

irrigation could make sugarcane production possible in most of Busia and Homa Bay counties. Likewise, access to groundwater would facilitate sugarcane production. This is already widely practiced, with sugarcane predominantly grown in low-lying areas, where it does not depend on rainfall alone for meeting its water needs.

4.2.3. Pineapple

The whole study region was highly suitable for pineapple production. In future scenarios, conditions improved further.

4.2.4. Banana

With the exception of highland areas, most of the study area was suitable for banana production. Again, climate change seems poised to further improve suitability for this crop.

4.2.5. Cassava

The whole region was classified as suitable for cassava production and projected to remain suitable. There was a slight drop in suitability in some 2080s scenarios, but not to an extent that would warrant concerns.

4.2.6. Sweet potato

Like cassava, sweet potato could be grown throughout the study region. Most of the area was highly suitable for all climate scenarios. By the 2080s, suitability dropped slightly, but remained at high levels.

4.2.7. Common bean

Common beans, a major component of typical farming systems in the region, encountered high suitability in the study region, in the baseline scenario. For future scenarios, however, suitability declined slightly, and by the late 21st century, some parts of the study region had become unsuitable because of high temperature.

4.2.8. Finger millet

The lowland areas near the lake were highly suitable for finger millet in the baseline scenario. High suitability persisted there throughout the 2020s and 2050s. By the 2080s, suitability declined considerably due to high temperatures.

5.   Adaptation recommendations

Among the crops that were modeled, the cereals maize and sorghum performed strongly in the baseline scenario, and losses in climate change projections were moderate. This was particularly true for sorghum. Among the pulses, groundnut and fababean had high yields and were moderately resistant to climate change. Greengrams and cowpeas also produced well, but were very susceptible to climate change. The production potential for soybeans was low, and this crop may not be well adapted to the study region. Many crops, in particular the pulses, benefited from irrigation during the short rains. This rainy season is short, as the name suggests, and if it is further shortened during particularly dry years, it may not be long enough for many crops. Whether establishment of irrigation infrastructure is economically warranted cannot be answered in this study, but additional water at the right time has potential to increase short rain yields. Maize and sorghum appeared to benefit relatively little from such measures.

Cotton production would also benefit from additional water supply, because it has to grow through one dry season. As discussed earlier, producing cotton can be risky, because this crop is vulnerable to factors other than yield. Product quality can be too low to be profitable, if it rains during harvest season.

High potential was identified for cassava and sweet potato. Both of these crops thrive in climates that are warmer than present-day Busia and Homa Bay. They are thus expected to do well in the study region in the future. The same was true for mango, banana and pineapple, for which climatic conditions were almost optimal.

The main climate factor that was responsible for climate-induced yield losses in annual crops was not rainfall but temperature. At the same time, temperature is the climate parameter that is most predictable. All climate models agree that temperature in the study region will rise substantially over the 21st century. The most promising strategy for reducing crop vulnerability to climate change is thus breeding for heat tolerance or introduction of drought tolerant new crop species and varieties. Establishment of multi-strata agroforestry is also a promising adaptation option. Temperatures under an open tree canopy can be several degrees cooler than they would be in full sunlight. As long as competition between trees and crops for water and nutrients can be controlled, or additional production resources provided were they are lacking, such agroforestry systems, which are already present in the study region, could be a viable adaptation option.

For some crops, modeling results indicated high potential for index-based weather insurance. This was particularly true for cotton, as well as for a number of crops during the short rains. For these, rainfall variability had a major effect on yields, and it should be possible to capture this in an index that describes abundance of rainfall at both ends of the rainy season. For cotton, rainfall between the rainy seasons may also be worth considering. While high temperatures also had a strong negative effect on yields, the feasibility of designing an index around temperature variables must be investigated in more detail. This will depend greatly on how accurately APSIM captures crop responses to high temperatures. In the current version of the model, these are built-in constants for each crops, while only the numbers of thermal units required for reaching each crop developmental stage are variety-specific. Yield observations, coupled with actual weather observations are needed for validating the relationship. The best index for use in designing insurance schemes is

probably the projected yield by a crop model, provided that the model is well calibrated for local soils and crops. A crop model integrates all effects of weather on yields, and thus provides a better indicator of yield potentials than a more restricted index would allow.

For evaluating the feasibility of a weather insurance scheme for local conditions in the Lake Victoria Basin, an evaluation of the effects of other drivers of crop yields is recommended. It seems quite likely that the more important climate-related impacts on crop yields will be caused by indirect effects, such as higher pest and disease pressure. Such factors can amplify the effects of climate, or even counteract direct climatic effects. For example, while a cool, moist season may be good for the crops, it may also favor development of fungal diseases, which may eliminate the positive weather effects on crop yields. If these effects are found to be of similar magnitude to the direct effects of weather, designing an insurance scheme around these factors may be more promising than one focused on weather alone.

6. Climate analogues of the study region

One strategy for identifying suitable adaptation options for climate change scenarios is climate analogue analysis. This approach is based on the premise that for most places and most climate projections, an existing place can be found, that currently has that climate. In other words, the objective is to find a place, where the current climate resembles the climate that is projected for the study region in the future. Such locations were identified for one site from each of the target counties. The procedure was based on mean monthly minimum temperatures, mean monthly maximum temperatures and mean monthly rainfall for the selected locations, for all climate scenarios described above. Euclidean distances between these values and the respective values in the baseline scenario were then calculated for each grid cell of the baseline climate grid within East Africa. The location, at which the Euclidean distance between projected future conditions and baseline conditions was lowest, was accepted as the best available climate analogue. In this study it was not possible to physically visit any analogue locations, so that this method could only be used as an illustration tool. The maps below thus simply present the distribution of analogue locations, as well as the distribution of climatically similar sites to selected future scenarios in the study region.
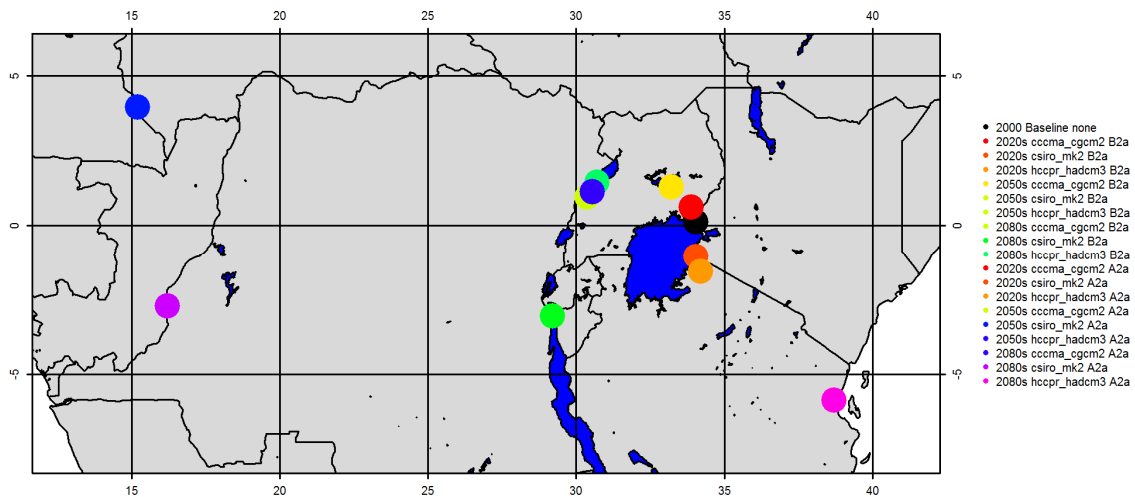
6.1. Climate analogues of Lower Busia

Figure 51. Climate analogue locations of Lower Busia. The black dot indicates the current location of the sites, and the colored dots are the current places that most closely resemble the climate projected for Lower Busia in the future.

Climate analogue locations of Lower Busia were scattered across East Africa (Figure 51). For three long-term climate scenarios, analogue locations were situated as far away as the Congo River (CSIRO A2a 2080s), western Central African Republic (CSIRO A2a 2050s) or the Tanzanian coast north of Dar es Salam (HadCM3 A2a 2080s). Most analogue locations, however, were close to inland water bodies in East Africa, either scattered around Lake

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Victoria, close to Lake Albert at the border between Uganda and the Democratic Republic of Congo (DRC) border or near Lake Tanganyika at the border between Burundi and the DRC. While these sites are much closer to current-day Busia, the climate there is quite different due to lower elevations. While Busia is at roughly 1150 m a.s.l., many analogue sites were several hundred meters lower.

6.2. Climate analogues of Upper Homa Bay

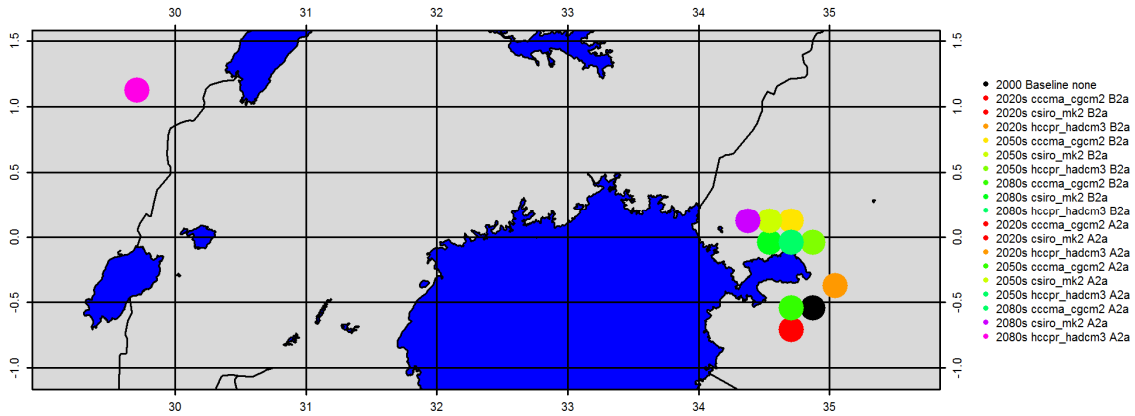# Climate analogues of Upper Homa Bay

Figure 52. Climate analogue locations of Upper Homa Bay. The black dot indicates the current location of the sites, and the colored dots are the current places that most closely resemble the climate projected for Lower Busia in the future.

For Upper Homa Bay, only one climate analogue (for the HadCM3 A2a 2080s scenario) was more than 100 km from the current location of this site (Figure 52). All other analogue locations were around Lake Victoria, but most were at lower elevation than the Baseline location. Depending on the time slice, analogue sites were between 50 and 400 meters lower than the current location. This shows that where a pronounced elevation gradient exists, the most likely climate analogues of high-elevation locations are at lower elevation within the same region. These analogue sites are locations where candidate technologies and crop varieties for climate change could be sourced or tested. The search for adapted technologies could be extended to all places with similar climate, based on the same kind of Euclidean distance approach that was used for identifying the climate analogues shown above (Figure 53).

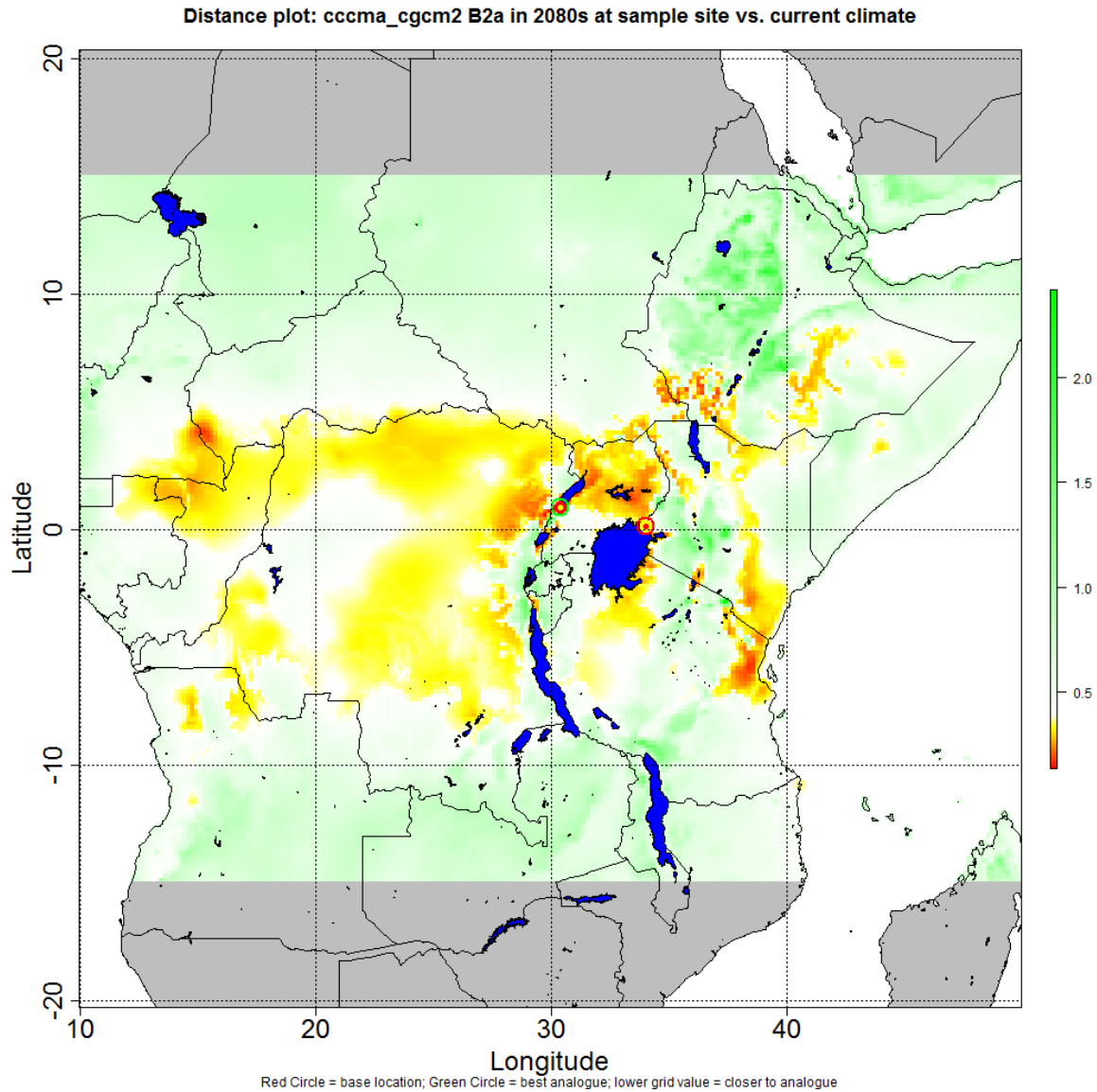**Distance plot: cccma_cgcm2 B2a in 2080s at sample site vs. current climate**

Figure 53. Climatic distance between the projected climate for Upper Homa Bay for the 2080s, according to the CCCMA climate model and the B2a greenhouse gas emissions scenario. The red circle indicates the current location of Upper Homa Bay, whereas the green circle is the best analogue location. Smaller values for the climatic distance indicate closer proximity between projected climate at Upper Homa Bay and current climate at the respective grid cell. All red areas are thus relatively good climate analogues of Upper Homa Bay for this particular climate scenario. The digital attachment to this report contains similar maps for five locations and all climate scenarios.

7. Recommendations for follow-up studies

As mentioned earlier, all results presented in this report, and in the supporting digital materials, were produced from proxy data, and a wide range of assumptions were necessary to arrive at these results. While for the purposes of a rough assessment this seemed like an acceptable strategy, a lot more data would ideally be collected and input into the models, in order to ensure that results are truly site-specific.

Most importantly, information on crop varieties grown in the study counties should be collected. This would include yield levels of all major crops, as well as the thermal time requirements of the various crop stages, which are an important input into the APSIM crop model. Better soil data is also needed. Relying only on global FAO data is too crude an approach for making site-specific decisions. Moreover, for actual adaptation planning or for designing a site-specific crop weather insurance product, knowledge about the distribution of soil types within the region is essential. In collecting soil data, information about soil hydraulic properties is particularly important. Management practices by local farmers should also be assessed, because specifications about crop management are needed by APSIM.

It should also be kept in mind that climate responses quantified in this study only include direct effects of weather on crop yield. Yet much of the yield variability in the region likely stems from indirect effects, or from phenomena that are unrelated to weather. Pests and diseases are a major factor that is influenced by weather. This effect can amplify or compensate the direct weather effects. An assessment of the impact of such factors on crop yields and consideration of including such factors in a potential insurance scheme is thus also recommended.

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Project Brief

Seizing opportunities in a changing climate

Climate change is a reality and is taking place around us. Communities are compelled to adapt to this situation. Therefore we must understand and plan for the potential impact of a changing climate, which is already visible in shifting weather patterns and extremes in droughts or floods. Recognizing the positive opportunities that climate change can offer, and making the most of them, will, contribute to successful adaptation.

Adaptation to Climate Change and Insurance (ACCI) is a bilateral project between the Kenyan and German Governments, funded by the German Federal Ministry for the Environment, Nature Conservation and Nuclear Safety (BMU) and the Government of Kenya. It is implemented by the Kenyan Ministry of Agriculture and GIZ – Deutsche Gesellschaft für Internationale Zusammenarbeit.

The goal of the **ACCI** project is to enable farmers and small-scale enterprises to increase their capacity to adapt to climate change in Homa Bay and Busia County.

ACCI through its partners supports
- ► Systematic collection, analysis and dissemination of information about climate change and related risks
- ► Dissemination of adapted site specific good agricultural practices
- ► Promotion of insurance products as measures to mitigate climate risks
- ► Monitoring of local adaptation capacity to climate change

ACCI collaborates with public and private sectors to provide these services to farmers. The extension structure of the Ministry of Agriculture is the main implementing partner. In addition, local NGOs, CBOs, insurance companies and financial institutions are involved in implementation. The project started at the beginning of 2011 and will run until the end of 2013.

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