# Annex: Climate risk analysis for adaptation planning in Cameroon's agricultural sector

## Methodology

### Climate projections

The basis for the evaluation of the current and near-past climate in this study is the climate observational dataset W5E5 (Cucchi et al., 2020; Lange et al., 2021), a dataset based on a combination of simulations from global weather models, satellite data and in-situ observations. The dataset covers the time period 1979–2016 at daily temporal resolution and the entire globe at 0.5° × 0.5° grid spacing (corresponding to approximately 55 km × 55 km in Cameroon).

Future climate projection data simulated by Global Climate Models (GCMs) was obtained from ISIMIP3b (phase 3b of the Inter-Sectoral Impact Model Intercomparison Project; Lange, 2019; Lange & Büchner, 2021). Historical simulations cover the years 1850–2014 and future projections under both greenhouse gas emissions scenarios cover the years 2015–2100. W5E5 is the observational reference dataset used for bias adjustment and statistical downscaling of ISIMIP3b. The GCMs included in ISIMIP3b are CanESM5 (short: Can), CNRM-ESM2-1 (short: CNES), CNRM-CM6-1 (short: CNCM), EC-Earth3 (short: EC), GFDL-ESM4 (short: GFDL), IPSL-CM6A-LR (short: IPSL), MIROC6 (short: MIROC), MPI-ESM1-2-HR (short: MPI), MRI-ESM2-0 (short: MRI) and UKESM1-0-LL (short: UKE) (Lange, 2019; Lange & Büchner, 2021).

GCMs cannot perfectly represent the current and future climate. They naturally show slightly different projections in modelling the climate, even if they are driven by the same emissions scenario. Differences among the models indicate the range of uncertainty and the multi-model mean provides a conservative estimate of possible climatic changes. Thus, in this report, the multi-model mean is shown in figures and maps and an uncertainty range based on all GCM results is either shown or discussed. Climate change analyses are based on 20-year averages[1], meaning that the mean annual temperature in e.g. 2030 is calculated as an average over the mean temperature between 2021 and 2040. Changes in the past are analysed by comparing the W5E5 data from 2000–2019 with 1979–1998. The reference climate, used as the baseline in this study, refers to the climate in 2004 (1995–2014) as the period is included in the historical simulations of ISIMIP3b. The projected climate data is evaluated for the periods 2030 (2021–2040), 2050 (2041–2060) and 2090 (2081–2099) in differentiation to the baseline (2004) for each model and scenario.

The indicators analysed in this study are the annual average mean air temperature, the number of very hot days per year (maximum temperature above 35 °C), the number of hot nights per year (minimum temperature above 25 °C), the mean annual precipitation sum, the heavy precipitation intensity, and the rainy season onset, cessation and length.

The indicator for heavy precipitation intensity is defined as the value of the 95th percentile considering only days with precipitation (>0.1 mm).

We used the method of percentage cumulative mean rainfall for determining rainfall onset and cessation dates. The method was adopted from Liebmann et al. (2012) objective, and well-tested methodology. Onset is defined as occurring when daily precipitation consistently exceeds its local annual daily average and ends when precipitation systematically drops below that value. Wet season length, rate, and total are then determined. Much of Africa is characterized by a single summer wet season, with a well-defined onset and end, during which most precipitation falls. Exceptions to the single wet season regime occur mostly near the equator, where two wet periods are usually separated by a period of relatively modest precipitation. Another particularly interesting region is the semiarid to arid eastern Horn of Africa, where there are two short wet seasons separated by nearly dry periods. Chiefly, the summer monsoon spreads poleward from near the equator in both hemispheres, although in southern Africa the wet season progresses northwestward from the southeast coast. Composites relative to onset are constructed for selected points in West Africa and in the eastern Horn of Africa. In each case, onset is often preceded by the arrival of an eastward-propagating precipitation disturbance. Comparisons are made with the satellite-based Tropical Rainfall Measuring Mission (TRMM and it has been successfully applied to the complete African continent. The certainty level of future climate projections is determined by the percentage of models agreeing on the trend (with significance level of 0.05) (compare IPCC, 2014). ≥ 90 %: very high; ≥ 80 %: high; ≥ 50 %: medium; ≤ 50 %: low.

1) Climate variables (such as temperature and precipitation) show high annual variability. In order to analyse long-term climatic changes instead of annual variabilities, means of climate variables over 20–40 years are compared with one another.

## Land cover change

Mapping areas of forest cover change is essential for developing locally adapted strategies to control these dynamics better (de Wasseige et al., 2014). To carry out such monitoring, remote sensing is a less-expensive method that has proven its effectiveness for the assessment of forest cover dynamics and degradation over several decades and at different scales (Loveland et al., 2012; Hansen et al., 2013; Nagendra et al., 2013; Mukete et al., 2018).

Mbam and Kim region were analyzed using Sentinel satellite imagery with its high spatial resolution and multispectral capabilities for land use classification. The images were preprocessed to ensure cloud-free data. Relevant spectral, textural, and contextual features were extracted from the preprocessed imagery using a training dataset. The model was then trained using the training data samples and their corresponding features to classify land use classes. The trained model was used to classify each pixel or image segment into land use classes. Accuracy assessment was carried out using independent reference data and expert opinion to validate the results. Post-classification processing and analysis were conducted to refine the land use classification results using post-processing techniques. The classified land use map was analyzed and interpreted to extract meaningful information about forest areas, land cover changes, and ecological patterns. The assessment of the accuracy and thus confidence level is based on data from training sets and expert opinion.

## Grasland productivity

The analysis is relevant for major grazing animals including cattle, sheep and goat. The dynamic global vegetation model LPJmL (Lund-Potsdam-Jena with managed land) has been used, which was mainly developed at PIK (Schaphoff et al., 2018; Von Bloh et al., 2018). LPJmL simulates key ecosystem processes such as photosynthesis, plant and soil respiration, carbon allocation, evapotranspiration and phenology of natural as well as managed vegetation, as coherently linked through their carbon, water and nitrogen fluxes (Schaphoff et al., 2018; Von Bloh et al., 2018). Dynamic global vegetation models are often used to study the impact of climate change on vegetation cover. In addition to natural vegetation dynamics, LPJmL features a representation of different grassland management schemes, enabling it to simulate the impacts of grazing on managed grasslands (Rolinski et al., 2018).

Daily forage requirements vary by animal type. To make them comparable, animal types can be converted to a generic Tropical Livestock Unit (TLU) based on their live weight using example conversion factors as shown in Table 10. One TLU corresponds to one animal with a live weight of 250 kg. A daily forage requirement of 6.25 kg dry matter per TLU is assumed (MINEPIA, 2022), and no distinction between specific animal types is made in the following analysis.

| Livestock species | Number of TLUs |
|---|---|
| Cattle | 0.73 |
| Sheep | 0.12 |
| Goat | 0.12 |

Table 1: Conversion factors for different types of animals to Tropical Livestock Units (TLUs) (based on Ziébé, Thys & De Deken, 2005).

In the model simulations, grazing lands are assumed to be covered by grass only, hence with no trees or shrub species. The model does not distinguish between different grass species. The daily forage requirement of 6.25 kg/TLU is set relatively high to account for variations in forage digestibility that cannot be captured by the model. The effect of grazing by livestock is represented as a daily partial removal of the leaf biomass of grasses. Grazing is assumed to always leave a minimum stubble height of about 1 cm. On the demand side, the amount of removed biomass depends on the density of grazing animals (number of TLUs per hectare). On the supply side, available biomass changes between seasons and between years in response to weather, but also in response to previous grazing and the long-term land-use history. Continuous grazing at high livestock densities leads to a deterioration of soil carbon and soil nitrogen stocks in the model with negative effects on grassland productivity over time. Other negative side effects of overgrazing such as soil erosion are not represented in the model. Soil carbon and nitrogen stocks and biomass supply are also affected by fire. Wildfires are simulated by the SPITFIRE model included in LPJmL (Drüke et al. 2019). SPITFIRE distinguishes lightning-caused and human-caused "ignition events", but fire only occurs if ignitions meet with sufficient fuel loads that are also sufficiently dry.

There are no spatially and temporally explicit data available for the actual livestock grazing density in Cameroon for the historical period. Land-cover products vary substantially in their estimates of areas covered by different land-cover types, due to uncertainties in the classification algorithms. For example, grasslands are estimated to cover between 1.34 and 2.69 million ha in Cameroon during 2015–2019 (Table 11). Estimating grazing demand at sub-annual scale is complicated by the practice of transhumance, which involves seasonal movement of herds over often large distances.

Given these data limitations, we do not attempt to reproduce the actual grazing regimes found in Cameroon. Instead, we systematically test a range of biomass removal rates (corresponding to livestock densities between 0 and 6 TLU/ha) and select in each grid cell and 20-year time slice the removal rate that produces the highest total annual grass yield. We consider this grass yield a grazing potential but caution that it is not equivalent to a carrying capacity. Since grass yield can vary between individual years in the 20-year period and even

| Land-cover dataset | Grassland [ha] | Herbaceous crops [ha] | Shrub-covered areas [ha] |
|---|---|---|---|
| Area from CCI_LC | 1717542 | 4806836 | 2340560 |
| Area from CGLS | 2692340 | 2476072 | 3655974 |
| Area from MODIS | 1337538 | 6246500 | 1863 |
| **Land-use dataset** | **Arable land [ha]** | **Land under temporary meadows and pastures [ha]** | **Land under permanent meadows and pastures [ha]** |
| FAOSTAT land use | 6200000 | 716073 | 2000000 |
| HYDE grazing land | | | 2676112 |

Table 2: Land-cover estimates for Cameroon for the period 2015 – 2019 based on three different land-cover products and land-use areas reported by FAOSTAT (FAO, 2023d). The category “Land under temporary meadows and pastures” is part of “Arable land” according to FAOSTAT typology. HYDE grazing land taken from the History Database of the Global Environment (HYDE, version 3.2.1, Klein Goldewijk et al. 2017).

seasonally, utilizing the full grazing potential would either require a seasonal adjustment of the livestock density or supplemental fodder from other sources. The grazing potential we calculate acknowledges that both of these management techniques are currently practiced in Cameroon while not explicitly accounting for them quantitatively, as would be required in order to estimate the carrying capacity.

Aggregating grid-cell yield levels to regions or to the national scale requires some assumption on the extent of grazing land in each grid cell. We use a gridded dataset of grazing land from the History Database of the Global Environment (HYDE, version 3.2.1, Klein Goldewijk et al. 2017). The sum of HYDE grazing land across all grid cells in Cameroon (2.68 million ha) matches reasonably well with the sum over temporary and permanent meadows and pastures reported in FAOSTAT (2.72 million ha, Table 11).

Following the spatial resolution of the climate data, LPJmL simulates the land surface as discrete grid cells with a grid size of 0.5° × 0.5°, roughly 55 × 55 km. Simulations of historical and future grassland production under a range of livestock densities are driven by the 10 Global Climate Models (GCMs) and two emissions scenarios as presented in Chapter 1. Future changes in annual grazing potential are presented for three time periods: near future ~2030 (2021–2040), mid-century ~2050 (2041–2060), and end-of-century ~2090 (2081–2100). All changes are in comparison to the historical period 1995–2014. No changes in grazing land are assumed for the future.

## Suitability assessment

Climatic crop suitability models have been applied to assess climate impacts on the potential for maize *(Zea mays)*, cassava *(Manihot esculenta)* and cocoa *(Theobroma cacao)* as individual crops as well as the potential for agroforestry systems as an adaptation option for cocoa production in Cameroon. Crop suitability assessments are based on the understanding that the biophysical parameters (e.g. soil pH) and climatic variables (e.g. total amount of precipitation received in the growing season) play an important role in determining crop production rates, which is true in many tropical areas where agriculture is mainly influenced by weather. A suitability model therefore uses these variables to create a score for each crop, each period and each location depending on how the variables meet the crop requirements or conditions in known current production areas (Evangelista et al., 2013). Replacing the climatic variables with those projected under climate change shows the change in the potentially cultivatable arable land of an area for a specific crop. Thus, crop suitability models are used in assessing climate impacts on the season-long crop production potential for national and local-level adaptation planning.

In this study, we applied the EcoCrop model which calculates the suitability of environments by comparing crop-specific ecological ranges, with climate data for a given environment. The crop-specific parameters and climate data needed for EcoCrop are presented in Table 10. As input data, we used the ISRIC soil data base, future climate projection data simulated by GCMs were obtained from ISIMIP3b (Lange, 2019; Lange et al., 2021). The crop requirements were obtained from the FAO Ecocrop database, adjusted accordingly to Cameroon-specific conditions. The emissions scenarios SSP1-RCP2.6 and SSP3-RCP7.0 for suitability projections in the years 2030 (2021–2040), 2050 (2041–2060), and 2090 (2081–2100). Model validation was done by comparing simulated suitability to reported occurrence of the respective crop in Cameroon using field data and the GBIF data base. A good model fit for maize (accuracy > 0.84), cocoa (accuracy > 0.87) and cassava (accuracy > 0.84) was achieved compared to reported crop occurrence, giving confidence in the application of the model in the climate change impact assessments in Cameroon. Crop suitability varies from 0 (not at all suitable) to 1 (highly suitable). We defined the following thresholds of above the 55th suitability percentile to define areas with no significant limitations to sustained production and stability over time and limited suitability below the 55th percentile based on the approach of Ramirez. After assessing the individual crop suitability for the three crops in Cameroon, we combined the suitability of cocoa with the African plum tree *(Dacryodes edulis)* and mango tree *(Mangifera indica)* to understand which areas are suitable for adaptation through the implementation of agroforestry systems using the method by (Chemura et al., 2020). Changes in suitability proportion and distribution between the current and the projected climatic conditions were assessed by comparing areas between time periods and climatic scenarios.

| Crop-specific parameters | Climate data |
|---|---|
| Critical minimum temperature | Monthly minimum temperature |
| Minimum temperature | Monthly mean temperature |
| Minimum optimum temperature | Monthly total precipitation |
| Maximum optimum temperature | |
| Maximum temperature | |
| Minimum precipitation | |
| Minimum optimum precipitation | |
| Maximum optimum precipitation | |
| Maximum precipitation | |
| Crop growing period<br>Crop specific soil pH | |

Table 3: Crop-specific parameters and climate data used in EcoCrop.

## Yield loss assessment

Crop yield is a specific plant response to weather and soil variables and other field inputs determined by agronomic practice. These interactions can be formalised as equations representing a specific crop cultivar's physiological response to environmental variables (Jones et al., 2003). Biophysical crop simulation models simultaneously incorporate interacting soil, plant, and field inputs as well as weather information. In this study we used APSIM which simulates crop growth as affected by temperature, radiation, soil moisture and nutrient supplies. The model requires daily weather data, soil profile parameters, detailed crop management information, and genetic coefficients of the chosen crop variety as inputs to simulate crop growth. APSIM calculates plant-available water, soil nitrogen, phosphorus, and carbon balances, as well as the vegetative and reproductive development of crops at a daily time step.

We simulate production at grid level with 0.5° spacing (approx. 55 km x 55 km) over Cameroon under current and future climate projections. In line with Chapters 1 and 2, we use the emissions scenarios SSP1-RCP2.6 and SSP3-RCP7.0 for yield projections in the years 2030 (2021–2040), 2050 (2041–2060), and 2090 (2081–2100). Future climate projection data simulated by GCMs were obtained from ISIMIP3b (Lange, 2019a, 2019b).

For the assessment, we assume rain-fed conditions and no fertiliser application as a default management strategy. For maize, the cultivar hybred511 was used as the default cultivar due to its similarity to CMS8704, the most commonly grown maize cultivar in Cameroon. For cassava, a custom cultivar was parametrised to match observed yield levels in the country. The sowing date is automatically set by the model when the 5-day rainfall sum exceeds 20 mm in predetermined sowing time windows by AEZ based on the agricultural calendar of Cameroon (ONACC, 2021). Simultaneously, harvest dates are also automatically calculated by ASPIM, indicating when the crop has reached maturity. For maize, sowing depth was set to 6 cm, row spacing to 90 cm, and plant density to 2 plants/m², according to common practice in Cameroon (IFATI & MINEFOP, 2022). For the assessment on cassava, we used various sources to parameterise and calibrate the model. We modelled cassava yields under rain-fed smallholder conditions as this is the dominant system for cassava production in Cameroon. Planting dates, harvest dates, planting depth, row spacing and plant density were obtained by Temegne et al. (2015) and ISRIC soils were used as soil profiles for each level. We rely on yield statistics provided on province level by the Ministry of Agriculture in Cameroon for model calibration of cassava as well as the Global Dataset of Historical Yields GHDY for the maize model (Iizumi, 2019).

The maize model has produced a good agreement at the grid level between long-term (1984–2014) average observed and simulated yields (a correlation of Pearson's r=0.53 & Willmott's index of agreement d=0.74). Regarding the inter-annual variability from 1984–2014, the model has produced a correlation of r=0.45 and an index agreement of d=0.68 between observed and simulated yields at a national scale, indicating a sufficient model fit for analysing future scenarios.

In contrast to suitability models that typically use an empirical model to measure the general seasonal, long-term climate conditions (employed in the previous section), this section uses biophysical mechanistic modelling of climate change impacts on agricultural yield. Yield is thereby calculated from the daily, possibly non-linear response to weather variables and other field inputs such as soil and farmer's practices.

# Cost-benefit analyses

## Improved seeds for maize

In two CBAs, we compare the costs and benefits of investing in heat-tolerant hybrid maize seeds with the costs and benefits of producing maize with conventional hybrid varieties until 2050.

**Scenario 1 and baseline: Non-adaptation (no action, climate impacts)**
The baseline of the calculation is a non-adaptation scenario in which a farmer produces rainfed maize with conventional hybrid maize varieties (CMS8704 und CMS8806). The model assumes extensive management without fertilisation and irrigation in order to represent smallholder farming systems. The market revenues of this production system are extrapolated until 2050 assuming a climate impact under a SSP1-RCP2.6 scenario and a SSP3-RCP7.0 scenario.

**Scenario 2: Adaptation (action, climate change impacts)**
In the adaptation scenario, the farmer switches to a heat-tolerant hybrid variety (based on H511), while keeping a rainfed and non-fertilized production system. The yields increase, but the improved seeds must be purchased from special seed companies at higher costs. The market revenues and costs of the investment are extrapolated until 2050 assuming a climate impact under a SSP1-RCP2.6 scenario and a SSP3-RCP7.0 scenario.

**Data input and assumptions**
The input data for this CBA has been obtained from literature and interviews with local key informants and is based on a number of assumptions.

- To calculate the investment costs, the cost delta resulting from the increased costs for the improved seed was used. Therefore, it has been assumed that the farmers in the non-adaptation scenario purchase their seeds for 650 FCFA/kg, while the farmers in the adaptation scenario need to invest 2,000 CFAF per kg for the improved seeds (Centre de Documentation pour le Développement Rural, 2016). To cultivate one hectare an amount of 22.5 kg maize seeds is needed (ANADER, 2017).
- It is further assumed that there are no additional transportation costs related to the purchase of new seeds. The rationale behind this assumption is that these costs depend on the distance between the farming household and the seed suppliers and would, therefore, vary depending on the region and location of assessment.
- *Benefits* are derived from the revenues resulting from the sale of maize and are made up of the producer price at the farm gate and the yields at national level as well as at the level of the Adamawa region, respectively:
  - For the yields, projections for the improved and the traditional variety under different climate change scenarios and at the different regional levels were used. According to these projections, at the national level, the baseline yield for the CMS varieties is approximately 2,000 kg/ha, while the baseline yield of the heat-tolerant variety is assumed to be around 2,500 kg/ha. In the Adamawa region, the baseline yield of the CMA varieties amounts to approximately 2,400 kg/ha, while the baseline yield of the improved variety reaches 2,800 kg/ha. It can be seen from the yield projections that traditional varieties perform better and make greater use of their potential in advantageous natural conditions, as is the case for the Adamawa region.
  - The average producer price for maize at the farm gate is between 10,000 and 15,000 FCFAF per bag of 100 kg (Interview Mesmin Tchindjang). Hence, for the calculation an average producer price of 125 FCFA per kg maize was used.
- It is additionally assumed that the productivity of a farmer's cultivated area increases due to autonomous technological change by 0.33 % per year. This is an extrapolation of previous maize yield increases over the last 30 years in Cameroon (FAOSTAT, 2023a).
- To depict the inflation rate, the exponential growth rate of the gross domestic product per capita of Cameroon from the last 50 years was calculated; its value is 2.15 % (FAOSTAT, 2023b).

## ISFM for cassava

The CBA is based on a model that describes an average small-scale farmer in Cameroon who grows cassava under two different scenarios: a non-adaptation scenario and an adaptation scenario. By comparing the costs and benefits of both scenarios, the CBA assesses whether adaptation makes sense from an economic point of view and in comparison to no adaptation.

**Baseline and scenarios**

**Scenario 1 and baseline: Non-adaptation (no action, climate change impacts)**
The non-adaptation scenario serves as the baseline of this calculation. It assumes a farmer who produces cassava under 'business as usual' without practicing ISFM. The model assumes an extensive management without fertilisation and irrigation in order to represent smallholder farming systems. The market revenues and costs of this system are extrapolated until 2050 assuming a climate impact under SSP1-RCP2.6 scenario and SSP3-RCP7.0 scenario.

**Scenario 2: Adaptation (action, climate change impacts)**
In the adaptation scenario, the cassava farmer switches to the application of ISFM by enriching the soil with leafy materials from *Tithonia diversifolia* and *Mucuna pruriens* residues. The cassava yields are expected to increase, and the market revenues and costs of the production system are extrapolated until 2050 assuming a climate impact under SSP1-RCP2.6 scenario and SSP3-RCP7.0 scenario.

**Input data and assumptions**
The CBA is based on cost and benefit data from literature and interviews with key informants. Where specific data and information are missing, this data is complemented with assumptions.

- In this CBA, two management practices are applied together: the harvest of *Tithonia* biomass mulch from off-farm resources that is transported, dried and then applied to the field; and the application of *Mucuna* biomass mulch that has been cultivated as a cover crop on the same field as cassava (Ngosong et al., 2015).
- Since *Tithonia* grows wild, no costs for seeding, planting and tending incur. However, applying *Tithonia* to the field is labour intense. After the harvest, the leaves and fresh biomass of *Tithonia* are chopped into smaller pieces, dried and dropped into the soil with a hoe a couple of weeks before planting cassava (Bilong et al., 2022). In total, 20 tons of *Tithonia* dry mass are applied to a field of one hectare. The cost for this practice is estimated to be approximately FCFA 693,840 ha-1 (Kimaru-Muchai et al., 2021), based on a daily labour rate of 3,540 FCFA (Mutsonziwa et al., 2018).
- To estimate the costs for cultivating and applying *Mucuna*, a 1:1 intercropping system with cassava is assumed. Hence, for one hectare approximately 15 kg of *Mucuna* seeds are needed (Chakoma et al., 2016; Ngandjui Tchapga et al., 2023). It is further assumed that farmers need to buy *Mucuna* seeds only in the first year of adoption, while in the following years, they produce their own seeds. The cost of *Mucuna* seeds is estimated at 885 FCFA per kg (Ekyaligonza et al., 2022). Since planting is done together with cassava and plants are dried and left directly on the field, no extra labour costs are applied. For harvesting a workload of 21 days per ha was estimated (Ngosong et al., 2015).
- Benefits were estimated by calculating the revenues resulting from the yield delta that is expected from higher cassava productivity in the adaptation scenario. The yield model assumes a baseline yield for the untreated and unfertilized cassava in the non-adaptation scenario of approximately 10 t/ha and a baseline yield of 30,300 t/ha for the ISFM-treated cassava in the adaptation scenario. The baseline yields were then extrapolated until 2050 by applying a climate change effect under a SSP126 and a SSP370 scenario. The average producer price for cassava at farm gate was estimated to be 160 FCFA per kg (FEWS NET, 2022; MINADER & WFP Cameroon, 2022).
- The farmer generates an additional benefit with the cultivation of *Mucuna*, as it is assumed that the farmer sells the share of the seed production that is not used for self-consumption. By assuming a yield of 2,329 kg/ha (Ngandjui Tchapga et al., 2023) and a market price of 400 CFA kg-1 (FEWS NET, 2022), the additional income for the farmer through the selling of *Mucuna* beans was calculated.
- It is assumed that the productivity of the farmer's area increases due to autonomous technological change by 0.26 % per year. This is an extrapolation of previous cassava yield increases over the last 30 years in Cameroon (FAO, 2023a).
- To depict the inflation rate, the exponential growth rate of the GDP per capita of Cameroon from the last 50 years was calculated, its value is 2.15 % (FAO, 2023b).

## Agroforestry for cocoa

**Baseline and scenarios**
We assumed a conventional rainfed cocoa production system which is combined with agroforestry. The introduction of agroforestry fruit trees presents the adaptation measure in this calculation. As the CBA displays the changes made to the initial situation where a cocoa production system already exists, only the additional costs and benefits that are associated with the introduction of the agroforestry system will be analysed and projected until 2050. The goal is to compare the profitability of a conventional cocoa plantation in an agroforestry system with a cocoa plantation without agroforestry. The scenarios are defined as follows:

**Scenario 1 and baseline: Non-adaptation (no action, climate change impacts)**
The baseline assumes a conventional rainfed cocoa production system without agroforestry in Cameroon. The market revenues and costs of the production system are extrapolated until 2050 assuming a climate impact under SSP1-RCP2.6 scenario and a SSP3-RCP7.0 scenario.

**Scenario 2: Adaptation (action, climate change impacts)**
For the adaptation scenario, the rainfed production of cocoa is combined with fruit trees in an agroforestry system in Cameroon. The tested fruit trees are:

- African plum (*Dacryodes edulis; Safou*);
- Avocado tree (*Persea americana*);
- Mango tree (*Magnifera indica*).

The market revenues and costs of the production system are extrapolated until 2050 assuming a climate impact under SSP1-RCP2.6 scenario and a SSP3-RCP7.0 scenario.

**Input data and assumptions**

The CBA calculates the costs and benefits of a model farming system that is based on several assumptions. The input data concerning costs and benefits was collected via literature review as well as from interviews with local farmers and consultants in Cameroon. The following aspects were taken into account:

- Three different fruit tree species – African plum, avocado and mango – are introduced as agroforestry trees into the cocoa farming system. All three trees provide several positive influencing factors for the intercropping system regarding environmental as well as economic aspects. Some of them are, however, difficult to quantify in monetary terms. Yet, all trees produce fruits that can be monetized as relevant by-products.
- The model assumes that the three tree species are equally distributed across the production area. According to local consultants, in the area under investigation, the number of fruit trees per hectare is 20 (seven mango trees, seven avocado trees and six African plums) (see also Jaza Folefack et al., 2021). It is assumed that replanting is not necessary within the time span of this analysis.
- It is further assumed that no cocoa plants have to be removed to make space for the agroforestry trees. Hence, no cocoa yield reduction due to the introduction of the agroforestry trees is occurring.
- The model assumes that no additional machinery or other equipment (like wheelbarrow, hoe, cutlass, boat, etc.) must be purchased for the planting and harvesting of the fruit trees, since these are already needed and available for the maintenance of the cocoa plantation itself.

On the **cost side**, the following cost items were considered in the analysis:

- Establishment costs per tree for the agroforestry system were extrapolated to the system of 20 trees analysed in this CBA. This data has been adjusted for inflation to reflect current cost structures. According to information from interviews with local experts and combined with current market information, we assume an average price for fruit tree seedlings between 1000 and 2000 FCFA (Agriculture au Cameroun, 2023b).
- We included a daily labour rate of 3,540 FCFA to account for the labour needed to establish and maintain the agroforestry system, including planting, pruning and harvesting (Mutsonziwa and Kouame, 2018).

Concerning the **benefit side**, the following benefits were considered in the analysis:

- Based on an adequate management of the agroforestry-cocoa system (including pruning of trees and low planting density), we assume that the shading effect of fruit trees positively impacts cocoa yields from the sixth year onwards, leading to a yield increase of around 12 % (Andres et al., 2016). As mentioned in the introduction, the predicted effects of climate change on cocoa production (in terms of yield output) differ widely between countries and regions (see Schroth et al., 2016; Läderach et al., 2013; Ofori-Boateng, 2012), which is why for this scenario, we neither assume a negative nor a positive effect on cocoa production due to climate change.
- For our calculation, we used national average yields based on FAO data of approx. 400 kg/ha (FAO, 2023a), which was supported by data in the literature (Jaza Folefack et al., 2021; Lescuyer & Bassanaga, 2021). It is assumed that the productivity of the farmer's area increases due to autonomous technological change[2] by 1.06 % per year. This is an extrapolation of previous cocoa yield increases over the last 30 years in Cameroon (FAO, 2023a).
- According to local information, the producer price for one kilogram of cocoa beans in 2022 was between 900 up to 1,300 CFA, depending on the distances of different villages to the next market. In alignment with Jaza Folefack et al. (2021) and Business in Cameroon (2022a, b) and based on the fact that cocoa prices vary a lot between months and regions (Reuters, 2015), we calculated with an average kilogram price for cocoa beans of 1,000 FCFA.
- An additional income stream from the fruits is estimated to be achieved only after five to six years, depending on the species and climatic and edaphic conditions (Agriculture au Cameroun, 2023a). The revenues are based on yields per fruit tree ranging between 100 kg for avocado trees and 200 kg for African plums (Awono et al., 2002; Juma et al., 2019; Rey et al., 2004). Market prices were obtained from Jaza Folefack et al. (2021), according to whom the producer price is 700 FCFA kg-1 for mangos and 500 FCFA kg-1 for avocados. Following Rimlinger et al. (2021) and backed up with local expert information, the producer price for African plums was estimated at 1000 FCFA kg-1. Due to the rapid perishability of fruits, we included post-harvest losses of 24 % for avocados (Dolaso et el., 2023), and applied it to African plums, too, due to the similar physio-chemical characteristics (Fotouo Makouate & Dongmo Lekagne, 2021). For mangos, a reduction of 32 % due to post-harvest losses was included in the calculation (Kamda Silapeux et al., 2021).

2) The autonomous technological change rate is linked to a technological progress induced by improved management or input techniques.

# Annex II: Uncertainties

The results presented in this study are subject to a number of uncertainties and limitations, which have to be thoroughly considered for correct interpretation as well as for drawing policy implications and recommendations. This chapter presents and discusses the uncertainties attached to the different types of analyses in this study and highlights their relevance in the Cameroonian context.

## Climate model data

Despite vast improvements in recent decades, climate models continue to display substantial uncertainties in simulating the current climate (Tebaldi and Knutti, 2007). To remove the biases in the climate simulations and make the models suitable for our crop analysis, climate data is statistically processed (bias-adjustment) with the help of observational climate data sets (in our case W5E5). This approach has critical limitations (Ehret et al., 2012; Maraun, 2016) as it adjusts the simulated data to fit to the observations without fixing the inability of the models to represent some physical processes of the earth's system. Nevertheless, this step is necessary and does not change the fact that realistic simulations of climate impacts can still be obtained (J. Chen et al., 2013; Teutschbein & Seibert, 2012). We analysed the performance of each climate model to represent the current climate to ensure that none of the models show strong biases. Working with a climate model ensemble can additionally reduce individual model biases. In addition, the observational climate data sets themselves are imperfect, especially in areas with few weather stations. The used data sets are based on re-analysis models, satellite observations and stationary data. Due to the low density of long-term, reliable stationary data in Western Africa, the data sets have strong biases, especially on a fine-gridded scale. The analysis of future climate in this report is based on ten bias-adjusted GCMs produced under phase 3b of the ISIMIP project (https://www.isimip.org/protocol/3/) and is a sub-ensemble of the Coupled Model Intercomparison Project Phase 6 (CMIP6) used for the next IPCC report AR6.

Furthermore, future climate projections come with uncertainties, which can be seen in the diverging temperature and precipitation projections of different climate models. The GCMs project the same temperature trend over Africa, whereas precipitation projections show agreeing trends only in some regions (Niang et al., 2014). For general conclusions on future climate impacts, it is important to select models that cover the whole range of climate model outputs, namely applying models with wet and dry trends in precipitation projections (if applicable) as well as different magnitudes of projected temperature changes in the target region. The diverging trends related to precipitation projections of the ten chosen models show similar patterns as the earlier used complete CMIP5 model ensemble (Niang et al., 2014) and thus we can assume that the models are suitable to cover the range of possible future precipitation in Cameroon.

The ten models cover a wide range of climate sensitivity with equilibrium climate sensitivity (ECS) values of 1.53–5.41 °C (Nijsse et al., 2020). Nevertheless, the selection of models shows a bias towards higher ECS, with five out of ten models having an ECS higher than 4.5 °C, which is, according to various studies, very unlikely (Nijsse et al., 2020). This means that the displayed temperature increases from five models show unlikely high future temperatures under increasing greenhouse gas concentrations and also the multi model median will shows a bias towards warm future projections.

## Crop models

Crop models are used to determine the share of weather-related variation in yields and to project impacts of changing climatic conditions on crop yields. Such analyses can support farmers in taking decisions related to yield stabilisation and crop yield improvement to cope with uncertain climatic conditions in the future.

Crop models are widely used to project these impacts – beyond the observed range of yield and weather variability – of climate change on future yields (Ewert et al., 2015; Folberth et al., 2012; Rosenzweig et al., 2014). However, when employing crop models some limitations need to be considered. For instance, limited data availability may restrict model fitting, such as a lack of information on growing season dates, yields, land use allocation, intercropping or information on fertiliser application (Müller et al., 2016). Also, the quality of soil data contributes to uncertain yield assessments (Folberth et al., 2016). Fragmented and imprecise weather data from regions with few weather stations further increase uncertainty (Van Wart et al., 2013), especially if highly localised weather data is needed as it is for this district study. Moreover, the selection of climate scenario data adds another layer of uncertainty (Müller et al. 2021). There are certain disagreements between the different model types – statistical, machine learning and process based – (Schauberger et al., 2017), but however, these two model types in this case study have been used in past studies and are unlikely to be inapt in general.

## Cost-benefit analysis

The cost-benefit analysis was conducted to evaluate the economic costs and benefits at the farm level of the three selected adaptation strategies. The CBAs considered a representative farmer by taking detailed household data on yields, costs and prices derived from survey samples. In addition, average yield and cost data were used to supplement and verify the household survey, as it is done in many standard CBAs. Such CBAs are, however, limited in terms of shedding light on the distribution of costs and benefits that an adaptation strategy may cause on a spectrum of farm groups, since an adaptation strategy may not necessarily affect all kinds of farm groups in the same way.

Assumptions regarding yields under climate change with and without adaptation were made based on crop yield simulations, which in turn were based on climate data predicted by climate models. Therefore, any uncertainty in climate models and crop models (see above) also translated into the analysis.

Uncertainty on assumptions with regard to future changes in prices and costs and the choice of the discount rate are further increasing the uncertainty of the CBA results. However, the assumptions made in our study are based on studies conducted in comparable socio-economic conditions of Cameroon, different data sources were triangulated, and expert opinion sought. The results of the CBA should not be taken as definite outcomes to expect when implementing the adaptation strategies, but they can guide decision-making and provide case studies for adaptation scenarios. Assumptions regarding yields under climate change with and without adaptation were made based on crop yield simulations, which in turn were based on climate data predicted by climate models. Therefore, any uncertainty in climate models and crop models also translated into the analysis.

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