Assessing water balance and yields in Malawian cropping systems

Maize soybean and maize Gliricidia systems resilience against climate change

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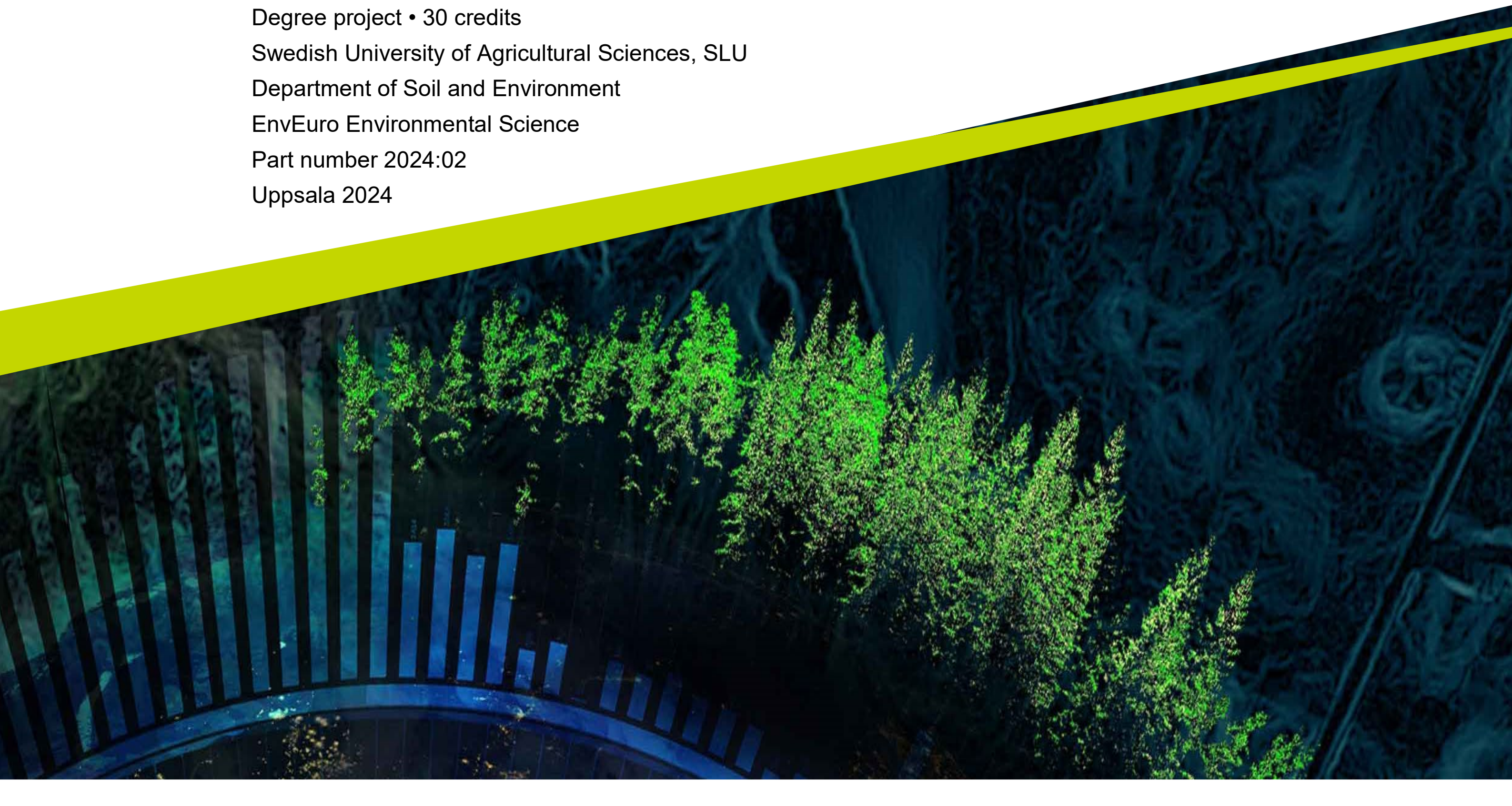

Assessing water balance and yields in Malawian cropping systems: Maize soybean and maize Gliricidia systems resilience against climate change

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Abstract

In Malawi, maize monocultures are increasingly susceptible to extreme weather patterns, causing considerable yield reduction and heightened food insecurity for smallholder farmers dependent on rainfed subsistence agriculture. Diversifying cropping systems is crucial for ensuring yield resilience. The aim of this thesis was to explore water balances and yields across legume maize intercropping and agroforestry systems in rural Lilongwe, Malawi, under current and projected climate change scenarios. Hereby, the Agricultural Production Systems sIMulator (APSIM) maize and soybean baseline models were calibrated, using yield, management, and soil data from the International Institute of Tropical Agriculture (IITA) station trials conducted from 2018 to 2022 at the Chitedze Agricultural Research Station. Maize soybean intercropping and maize Gliricidia agroforestry systems were modelled in a present and three climate change scenarios using the Statistical Downscaling Model (SDSM). Climate prediction data was sourced from an ensemble of the Coupled Model Intercomparison Project Phase 6 (CMIP6) models. Main output parameters were single component and whole system water productivity, evaporative stress index and yields. While intercropped maize yields were higher by 2 t ha^{-1} compared to the monoculture system in the present scenario, long-term maize yields were higher by 1 t ha^{-1} in the agroforestry. This pattern was also observed in maize water productivity, which was higher in the long-term agroforestry system by 1 kg ha^{-1} mm^{-1}. Soybean yields, and evaporative stress index were highest in the intercropping system across all scenarios with an average difference of 0.8 t ha^{-1} in soybean yields and 2.5 mm mm^{-1} in evaporative stress index compared to the sole soybean system. Therefore, I conclude that agroforestry maize systems will show higher yield and water productivity resilience under a long-term climate change scenario. Additionally, results suggest that maize soybean intercropping is more beneficial for water allocation and soybean yields than a mono cropped soybean system. More research and data collection needs to be done in the field of crop agroforestry to solidify presented modelling results.

Keywords: crop modelling, APSIM, Malawi, maize, soybean, Gliricidia, agroforestry, legume intercropping, climate predictions, climate adaptation, SDSM

Popular science summary

In Malawi, smallholder farmers provide a big share of the food consumed in the country. Their main staple crop is maize. Because of changing climate, maize crop yields became more variable, with different yield outcomes every year. This is mainly caused by rainfall behaviour and water availability during the growing season. The type of cropping system plays a major role in the yield reaction of the crop to dry and wet periods and intense rainfall. Therefore, it is important to look into different cropping systems besides monocultivated maize, which is often practiced in Malawi.

What are different cropping systems, you may wonder. There are many diverse systems out there, but in my thesis, I concentrated on two types, always including maize. Intercropping maize with soybean plants was one of them. This approach is very promising since soils in this region are often lacking nutrients. And the fact, that soybeans can fix nitrogen, a substantially important nutrient for plant growth, comes in handy. Additionally, soybean is a trendy crop at the moment, which can easily be commercialized and sold for profit. On top of that, it is a protein source and thus diversifies not only the farmers land but also what ends up in people's plates.

Besides the soybean maize intercropping system, I also analysed a combination of maize with trees, which is called an agroforestry. For this system I used a special tree species which is also able to fix nitrogen in the soil, just as soybeans do. Additionally, since trees grow leaves which tend to shed, leafy biomass can be incorporated into the soil as additional fertilizer. How convenient! On top of that trees provide more shade which results in lower soil evaporation losses and can store water more effectively because of their deep root system.

To understand whether these two cropping systems would support maize yields against changing weather patterns I used a crop modelling software. With the right input parameters, which included climate, soil, and plant management data the tool helped me to create simulations of a cropping series. I modelled four simulations, one for each cropping system including monocultivations of maize and soybean, a maize soybean intercropping system and a maize Gliricidia agroforestry. These four simulations were run under present climatic conditions and a long-term climate change scenario. To create the weather for the latter, I used the results from multiple climate simulation and prediction models from the Coupled Model Intercomparison Project. Comparing virtual yields from the present and future scenario revealed a shift in most beneficial cropping systems across time periods. That is, the intercropping system was more efficient in water allocation and had higher yield outcomes in the present scenario, whereas the same was found for the agroforestry in the climate change scenario. This shows a clear picture of the potential benefits of multiple component systems under present and future climatic conditions. These include maize stability across years and an increase from which smallholder farmers benefit immensely.

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Abbreviations

APSIM	Agricultural Production Systems sIMulator
DUL	Drained upper limit (field capacity)
ESI	Evaporative stress index
ESW	Extractable soil water, plant available water
ESW450	Extractable soil water up to 450 mm soil depth
ETa,p	Actual and potential evapotranspiration
Evapo	Evaporation
GM	Gliricidia maize agroforestry
IITA	International Institute of Tropical Agriculture
KL	Fractional water extraction
KS	Saturated hydraulic conductivity.
LL15	Drained lower limit (wilting point)
SDSM	Statistical Downscaling Model
SM	Soybean maize intercropping
SW	Soil water
Ta	Actual transpiration
WP	Water productivity
WS	Total water stored
WS 450	Water stored within the first 450 mm soil depth

1. Introduction

There are approximately 2 million smallholder farmers in Malawi, who cultivate 80% of food consumed within the country on less than 1 hectare of land per household. Main crops cultivated are maize, cassava and legumes, however 60-70% of cropland is used for maize, the main staple food of the country (CIAT & World Bank, 2018). As on most of Sub-Saharan agricultural land, soils in Malawi tend to be nutrient depleted and only possess poor water storing capacities (Akinnifesi et al., 2007; Swamila et al., 2022). Additionally, low input of nitrogen and phosphorus fertilizers in smallholder farming systems as well as poor soil management such as monocropping leads to higher soil degradation and erosion. This causes limited crop growth and ultimately higher yield gaps in smallholder farming systems (Mueller et al., 2012). In fact, current average yields for maize and soybean in Malawi amount to 1.8 t ha^{-1} and 0.9 t ha^{-1} (National Statistical Office of Malawi, 2022). With population growth and soil fertility decreasing the already precarious food security situation in Malawi becomes even more critical in the next decades (CIAT & World Bank, 2018; Smethurst et al., 2017; Swamila et al., 2022).

Climate change induced weather patterns have a high impact on cereal produce as well. Maize yields are prognosed to be reduced by 10% in a business-as-usual scenario until 2050 (CIAT & World Bank, 2018). 80% to 90% of agricultural systems in Malawi are rainfed which makes them considerably more vulnerable to dry spells and high intensity rainfall events. Both have become more frequent causing critical damage to crops and increase water limited yield gaps. In order to close water yield gaps, water productivity has to be improved (Kahinda et al., 2007).

1.1 Climate change adaptation strategies in smallholder farming systems

For climate change adaptation, restoration of fertility and soil water holding capacity several management strategies are already practiced in Malawi. To make plants more resistant to water stress and increase water productivity (WP), the efficiency with which plants use water for biomass accumulation, a high rainfall infiltration rate, soil water storage, redistribution capacity and accessibility within soil layers are crucial. WP is commonly defined as the ratio of above ground biomass or grain yield to evapotranspired or transpired water (Mudenda, 2015). The main levers for increasing WP are the decrease of evaporative losses and or increase of yield levels (Kahinda et al., 2007). In Malawi, several practices are introduced to increase WP and yields. These target among other the reduction of evaporation through intercropping and higher leaf canopy density or focus on increasing total water availability by introducing multiple species and using plants which can extend their roots deeper (Mudenda, 2015). This leads to lower evaporation and percolation losses and an increase in infiltrated water uptake, resulting in lower yield gaps (Guilpart et al., 2017).

Restoring fertility and getting nitrogen into the soil is conventionally done by solely adding organic and mineral fertilizer. An alternative approach is the additional implementation of nitrogen fixing legumes as a component of intercropping systems. Recently, especially soybean has become more popular in Malawi and is increasingly cultivated by smallholder farmers (Omondi et al., 2023) . Diversifying crop systems with soybeans has multiple benefits. Besides an increase in soil fertility and, improvement of nutrition and income stability, in Malawi soybean yields are prognosed to increase by 2% until 2050 (CIAT & World Bank, 2018). Further, soybean has high market potential as demands raise globally and within Malawi. In Southern Africa its mainly cultivated for commercial production of meat substitutes and feed. National demand for soybean amounts to 2 million Mt whereas inland production can only cover about a fourth of it (Nyagumbo et al., 2022).

Using legume trees in an agroforestry system is another practice implemented in Malawi, to improve microclimatic conditions for understory crops. A legume tree often incorporated in these systems is Gliricidia sepium. Its leafy biomass acts as an additional fertilizer, complementing the nitrogen fixed by its roots (CIAT & World Bank, 2018). It has been proven in numerous studies that using fertilizer trees in intercropped systems has multiple benefits for the crop. Higher accumulation of above and below ground biomass leads to increased levels in soil organic matter, nitrogen and phosphorus (Swamila et al., 2022). Additionally, intercropping Gliricidia with maize is advantageous due to low below ground competition for nutrients and soil water. This results from its low root density in the first 30 cm compared to other legume tree species, whereas maize roots are most dense within this layer (Makumba et al., 2006). Multiple studies showed that in Gliricidia maize intercropping systems, maize yields were higher than in monocropped fields when prunings were incorporated into the soil (Makumba et al., 2006; Smethurst et al., 2017; Swamila et al., 2022). Swamila et al. 2022 found that it takes around five years for a Gliricidia maize intercropping system to have significant yield advantages over monocropped maize systems using conventional fertility practices.

1.2 Water balance parameters in agricultural systems to track climate change adaptation

In water stressed regions, in which water demand is higher than plant available water, it can be helpful to look into the Evaporative Stress Index (ESI) in case of substantial water limiting conditions. The ESI indicates how much of the potentially available water is actually available for plants. Potential and actual available water is measured as potential and actual evapotranspiration (ETp, ETa) Hereby, ESI describes whether water limitations drive yield reduction and is therefore also called water yield gap. In Sub-Saharan Africa (SSA) there is a considerable gap between ETa of commodity crops such as maize and soybean and ETp leading to significant water yield gaps. Average maize yields in semi-arid regions in SSA amount to 1t ha^{-1} whereas the global achievable yield is approximately four to five times higher (Kahinda et al., 2007). Soybean yields in Malawi are 3.8 times lower than achievable yields (Omondi et al., 2023).

Furthermore, it is important to consider WP when focussing on climate change adaption of agricultural systemsBlack et al. investigated the benefits of intercropping systems in the semi-arid tropics, where a high amount of precipitation is lost through evaporation. They suggested that WP can be considerably improved in intercropping systems (Black & Ong, 2000) Morris et al. 1993 found that the increase in WP in diversified cropping systems originates among other factors from overlapping canopies modifying the microclimate. This can lead to higher transpiration rates, humidity and lower windspeed due to windbreaks (Morris & Garrity, 1993). After studying water dynamics in Gliricidia maize intercropping systems Chirwa et al. 2007 concluded that a significant increase in WP can be traced back to the much higher above ground biomass production of incorporated trees. Further, they stated that seasonal fluctuations in water availability are unchanged across different cropping systems and overall availability doesn't change considerably across treatments (Chirwa et al., 2007). They also found volumetric water content being lower in monocropped maize systems below 30cm soil depth.

In conclusion, ESI and WP are helpful indicators when trying to track the decrease of water yield gaps and increase in water use efficiency through different cropping management strategies in water stressed regions.

1.3 Objective of this thesis

The aim of the project was to assess which agricultural systems are most adaptable to a change in climatic conditions in the rural surroundings of Lilongwe, Malawi. Therefore, the main focus lied on water balance and yield shifts across maize and soybean monocropping, soybean maize intercropping and Gliricidia maize agroforestry systems in current and future climate change scenarios. The main research questions were:

1. Does shifting production systems from monocropping to legume and legume tree intercropping reduce water yield gaps and increase water productivity of maize and the whole system?

2. Do soybean intercropped and Gliricidia agroforestry maize systems better resist climate change impacts on water productivity and yields compared to maize monocultivations?

In order to answer these, the Agricultural Production Systems sIMulator (APSIM) was used to model the four described cropping systems in a present and three future climate scenarios for the selected location. For model calibration and parameterization local input data, such as yields, and plant management information was obtained from the International Institute of Tropical Agriculture (IITA) Chitedze database. Meteorological data was obtained from the nearest weather station to the Chitedze Research Station. Additionally, on site water infiltration measurements were conducted and soil samples were collected for physical and chemical soil analysis.

The main output parameters to compare across cropping systems and simulated time periods were two water-based parameters, water productivity and evaporative stress index and yields. Sub-components such as transpiration and evaporation as well as belowground water storage and plant available water were looked into in order to better interpret modelling results. In addition, variability of extreme rainfall parameters such as length of dry and wet spells were analysed and compared to yield variability.

2. Methods and materials

2.1 Site description

Field studies were conducted at the Chitedze Research Station, 15 km west of Lilongwe (13.98°S, 33.64°E). Malawi is divided into three agro-ecological zones, based on soil factors, altitude, rainfall and temperature patterns. Chitedze is located in the mid-altitude plateau and highlands at an altitude of 1151 m (CIAT & World Bank, 2018). Soils in this agro-ecological zone are classified as Ferralsols and have a sandy-loam to sandy clay loam texture with a medium-to-coarse-sized particle-structure(FAO & IIASA, 2023). The region is gently sloping (2%), resulting in low yearly erosion (Ministry of Agriculture Government of Malawi et al., 2021).. Soil organic carbon in the area averages between 0.8% and 1.5%. Soils can be more than 1m deep and are well drained (Li et al., 2017; FAO & IIASA, 2023). This type of soil is mostly used for maize cropping in this region. Tab. 1 lists chemical and textural parameters measured at Chitedze Research Station during the Malawi Land Resources Evaluation Project, conducted from 1987 to 1991. (Kamanga, 2002; Makumba et al., 2006; Ministry of Agriculture Government of Malawi et al., 2021; Ministry of Natural Resources and Climate Change Malawi - DCCMS, 2023).

Tab. 1: Chemical and physical soil parameters measured at Chitedze Research Station during the Malawi Land Resources Evaluation Project, conducted from 1987 to 1991 (Ministry of Agriculture Government of Malawi et al., 2021).

Soil depth [cm]	0-15	15-30	30-45	45-60	60-80	80-100	100-120	120-140	140-160
pH	5.8	5.8	5.9	5.9	6.2	6.0	6.2	6.5	6.4
Silt %	7	6	8	8	8	8	9	7	8
Clay %	10	14	16	17	17	21	16	16	16
Sand %	83	80	76	75	76	71	75	77	76
Tot C %	1.41	1.40	0.78	0.76	0.20	0.94	na	na	na
Tot N %	0.11	0.10	0.07	0.07	0.03	na	na	na	na
P [ppm]	5.00	2.07	2.14	2.33	2.00	4.00	na	na	na

The climate is between semi-arid and sub-humid. Malawi has a wet and a dry season.The wet season spans from November to April during which 95% of annual rainfall takes place. During this period the growing season takes place as well. Precipitation patterns are unimodal. During the historic study period from 2001-2020 the wettest and driest months were January, 233 mm, and July, 0 mm respectively. Mean annual rainfall amounted to 823 mm. Potential evapotranspiration ranged from 110 mm in June to 181 mm in October with a yearly mean of 1686 mm. Monthly minimum and maximum temperatures didn't vary over the 20 year series with the hottest and coldest months being November 31°C and July 10°C respectively (see Fig. 1 and Fig. 2) (Roger Stern, 2010).

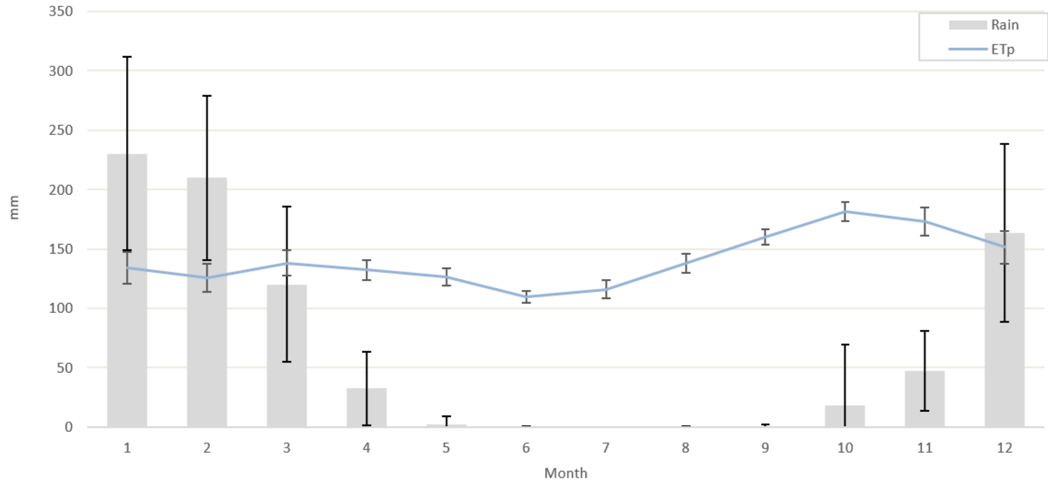


Fig. 1: Average monthly precipitation and evapotranspiration across four agricultural systems from 2001 to 2020. Error bars show standard deviation. Data source: Roger Stern, 2010.

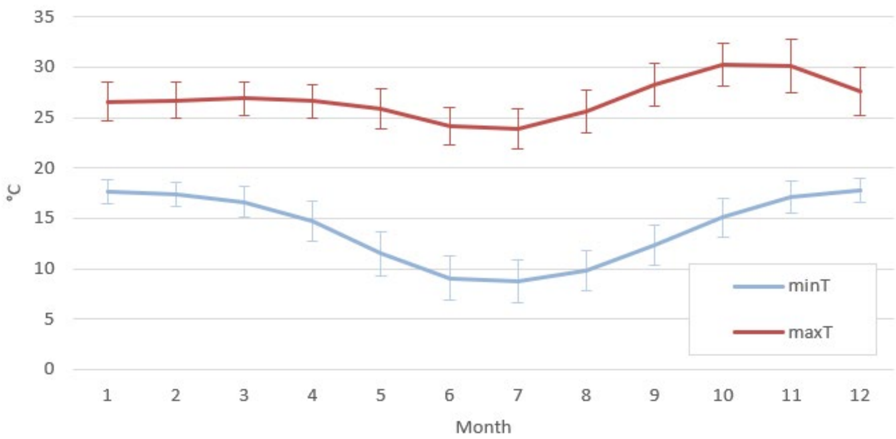


Fig. 2: Average monthly minimum and maximum temperature from 2001 to 2020. Error bars show standard deviation. Data source: Roger Stern, 2010.

2.2 Experimental design, methods for field data collection

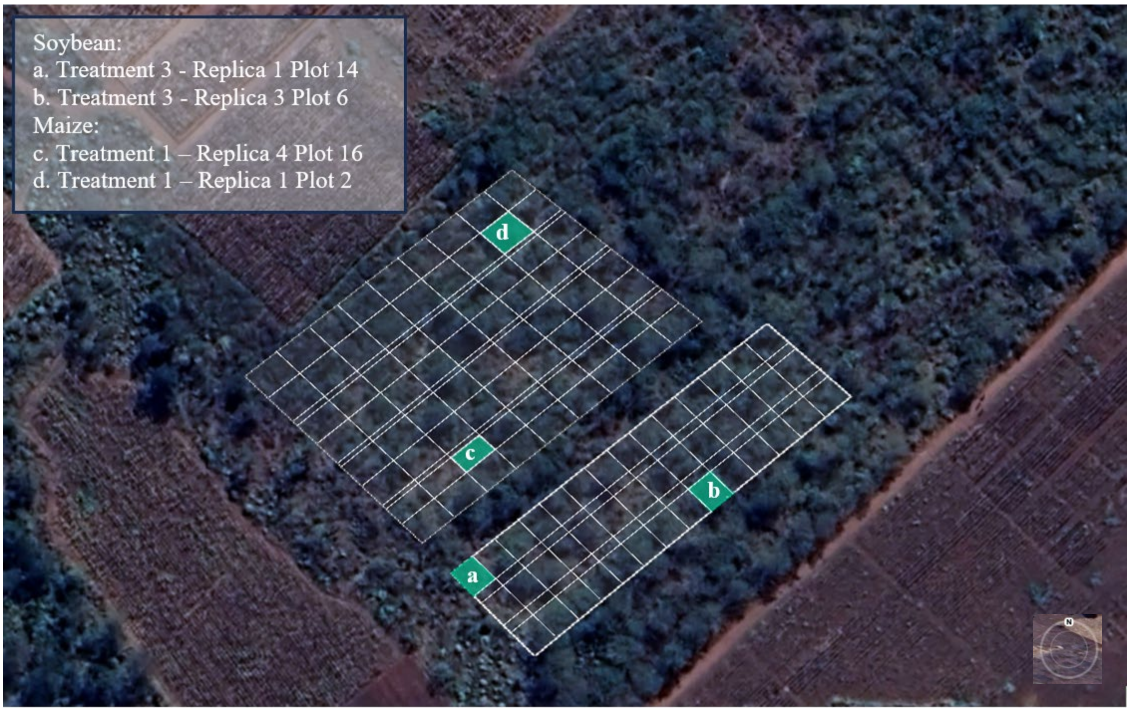


Fig. 3: Two sampling plots in maize (above) and soybean (below) trails: green fields show selected plots for infiltration measurements and soil sampling. Bulk density tests were conducted at plot a. and c (Google Earth Pro 2022).

For the conducted field work described below, trials from the Excellence in Agronomy initiative were made accessible (CGIAR 2020). The trials chosen contained continuous maize and soybean plots under various fertilizer treatments. Sampling plots were chosen to represent fertilizer conditions found in the cropping systems for which yield, and management data were obtained from the IITA database. Therefore, two monocropped maize and soybean plots extending to 42 m² and 12 m² respectively were selected (see Fig. 3). The exact plot management and fertilizer application of selected fields can be seen in Tab. 2. Units are the same as in APSIM. The cultivation on these plots started in 2022, before that the area was uncultivated and covered by natural vegetation.

*Tab. 2: Management practices and fertilizer application of the Excellence in Agronomy trials accessed for onsite measurements. *Sources for P and N content of fertilizers: Incitec Pivot Fertilisers, 2021.*

Plots	Crop (Cultivar)	Crop density [n m^{-2}]	Soil management	Fertilizer [kg ha^{-1}]
Treatment 3 - Replica 1 Plot 14	Soybean (Tikolore)	60 – 80 kg ha^{-1} (seed rate, 5 cm between seeds)	No groundcover, planted on ridges	4.3 N, 24.2 P (NPK, TSP*)
Treatment 3 - Replica 3 Plot 6				
Treatment 1 – Replica 4 Plot 16	Maize (MH43A)	5.3 (75 cm between rows and 25 cm between seeds)	No groundcover, conventionally tilled, planted in furrows, manual weeding	46 N, 20 P (NPK) at planting 92 N (urea*) 4-5 weeks after planting
Treatment 1 – Replica 1 Plot 2				

Infiltration measurements with double ring infiltrometers

Due to lack of data on soil water parameters on site, soil surface infiltration measurements were conducted in order to obtain the saturated hydraulic conductivity (Ksat) as input parameter for APSIM. Therefore, two measurement locations per plot were selected, resulting in a total of eight experiments. The implementation of all measurements took 5 days from the 14th to the 21st of April 2023, every day two measurements were completed. Measurements were done between the outer two crop rows on opposite sides of one field. The outer and inner ring were dimensioned with diameters of 57 cm and 28 cm respectively and a height of 25 cm. The rings were driven 12 cm deep into the soil, as shown in Fig. 4. Before starting the measurements, the soil was pre-wetted by filling both rings completely with water and waiting 30 minutes before starting. After this time period both rings were filled up to 2.5 cm from the top and the time recorded. In the first hour head hight was recorded every ten minutes and every 30 minutes thereafter. For measuring head height, a ruler was used. After every measurement

Fig. 4: Infiltration measurement with double ring infiltrometer at IITA Chitedze.

both rings were filled up to the same starting height, in order to keep a constant head. One experiment lasted for two to three hours, depending on how fast the infiltration rate became constant. At the end of an infiltration experiment a compound gravimetric soil sample was taken for soil moisture content analysis.

For calculating the infiltration rates and the saturated hydraulic conductivity (Ks) from the measurements taken, the Philips equation was used (Philip, 1969). It describes the infiltration rate v in cm min^{-1} as

$$v(t) = 0.5St^{0.5} + A \qquad (1)$$

where S is the sorptivity and A is gravity-driven flow. A second equation is given by using the accumulated infiltration rate i in cm min^{-1}

i(t)=St^0.5+At *(2)*

A can lie between 0.38Ks to 0.66Ks (Philip, 1969). For very long time series A can be approximated as Ks. According to Rahmati et al. double ring infiltrometers produce 1D - flow conditions for which A can be approximated as 0.33Ks (Rahmati et al., 2018).

In order to obtain S and A, linear regression analysis of the accumulated infiltration rate against √t were done in Minitab, using equation (2), to, in a next step, calculate Ks and v with equation (1) (Minitab, LLC, 2021).

Soil samples for bulk density, physical and chemical soil analysis

As additional input parameter for APSIM and to calculate volumetric soil water content bulk density measurements were done. For bulk density sampling, two soil profiles were dug, one in a maize the other one in a soybean field, in which infiltration measurements were done (see Fig. 5). Therefore, three shelves at different heights, topsoil at 2-7 cm, compaction layer at 15-20 cm, and deeper layer at 35-40 cm, were prepared and pre-wetted one day before sampling. Four soil core samples were taken at every height to obtain an average. For analysing soil texture and chemical properties, compound auger samples (see Fig. 6) from four holes were taken at every infiltration measurement site at three depths corresponding to the depths of the bulk density soil samples, from 0-10 cm, 10-20 cm and 30-40 cm.

Fig. 5, Fig. 6: Soil profile for soil bulk density sampling (left) Auger compound soil sampling (right)

Soil analysis were done at the governmental Chitedze Agricultural Research Station laboratory under the Department of Agricultural Research Services. For gravimetric and bulk density analysis, collected samples were dried at 105°C for 92 hours and weighed afterwards. For soil texture analysis the hydrometer method was used. Therefore, soil samples were prepared, sieved, and weighed before mixed with sodium hexametaphosphate and shaken. Hydrometer values were taken 40 seconds and 2 hours after shaking. For chemical analysis soils were finely sieved and weighed. Components measured were pH, total nitrogen, organic carbon and organic matter. pH was measured in water, nitrogen was extracted by the Merlich 3 Method and organic carbon was obtained by the Walkley-Black Method. From organic carbon the fraction of organic matter was calculated by multiplying it with a factor of 1.724 according to (Chilimba, 2007).

2.3 Modelling approach

2.3.1 Description of the main APSIM models

For crop simulation and modelling the Agricultural Production Systems sIMulator (APSIM) was used. APSIM is an agricultural modelling framework developed by the Agricultural Production Systems Simulator Initiative. The core processes are driven by five main modules which can be seen in Fig. 7.

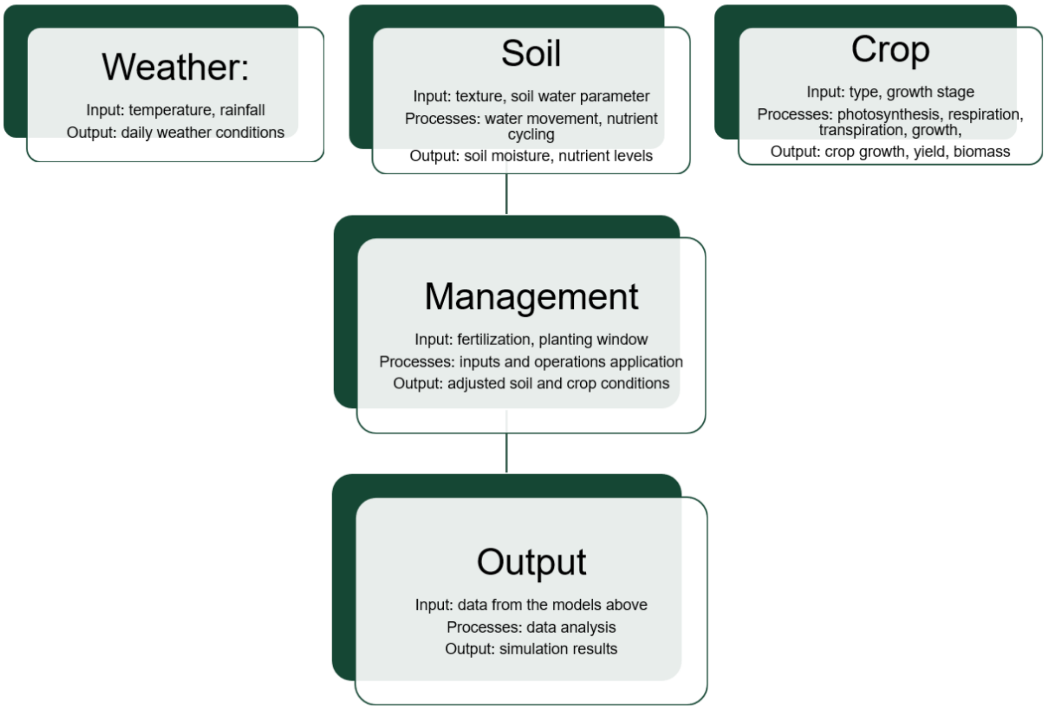


Fig. 7: Schematic structure of the main models in APSIM.

Each model contains input parameters determined by the user, processes and the final output which is then used in the next model (Holzworth et al., 2020).

Four different crop systems were parametrised in the APSIM modelling structure including monocropped maize, monocropped soybean, maize soybean intercropped (SM) and maize Gliricida agroforestry (GM). Input parameters for the various models are described in depth in the next paragraph.

2.3.2 Output parameters

Evaporative Stress Index (ESI) and Water Productivity based on one component yields for maize or soybean (WP1) and on aboveground biomass, including grain and straw for crops and stem and leaves for trees, of the whole system (WP2) are the main output parameters looked into for the water balance analysis. ESI describes availability of water for plants for transpiration in comparison to the potentially available water, whereas WP defines the efficiency of available water usage by plants. WP1 and WP2 are calculated seasonally and yearly respectively in kg ha^{-1} mm^{-1}. ESI is calculated yearly in mm mm^{-1} for the total system. They are calculated as follows:

$$ESI = \frac{ET_a}{ET_p} \qquad (3)$$

$$WP_1 = \frac{Yield_{Maize\ or\ Soybean}}{ET_a} \quad (4)$$

$$WP_2 = \frac{Aboveground\ biomass_{tot}}{ET_{a,tot}} \quad (5)$$

Potential evapotranspiration is calculated by APSIM using the Penman-Monteith equation which is based on climatic parameters including vapor pressure, wind speed, radiation and ambient temperature, among other. To better understand outcomes, components including actual transpiration (Ta), actual evaporation (Evapo_a), total (total WS, total ESW) and up to 450 mm depth water storage (WS450) and extractable soil water (ESW450) as well as yields are looked into. Transpiration in APSIM is calculated in several steps including soil water supply, plant water demand, efficiency of transpiration, water stress and biomass partitioning. This can vary for different crop species. Soil evaporation is described in two stages, when soil water content is sufficiently high for reaching potential evaporation and when soil moisture is too low to reach potential evaporation. Water storage defines the total soil water content in the soil whereas extractable soil water describes plant available soil water. 450 mm were chosen to cover the root length of maize and soybean crops. This is done by calculating percentage of change (Δ) based on the baseline monocropped models and their intercropping systems (Akinnifesi et al., 2007).

$$\Delta y_{bi} = \frac{(y_i - y_b)}{y_b} * 100 \quad (6)$$

Percentage of change Δy_{bi} describes an averaged parameter y in an intercropping system i compared to the averaged baseline parameter yb.dditionally, seasonal extreme weather patterns are analysed, looking into mean and maximum length of monthly wet and dry spells during the growing season in winter (December to February) and spring (March to May). This is analysed with the weather generator the Statistical Downscaling Model (SDSM), which is described below, by calculating the number of consecutive days on which precipitation is lower or higher than 1mm which describes the length of a dry or wet spell. For the obtained rainfall parameters Coefficient of variation (CV) for the above rainfall parameters and yields across cropping systems are then calculated to analyse yield sensitivity towards rainfall variability. CV is calculated by the ratio of standard deviation and mean:

$$CV = \frac{\sigma}{\mu} * 100 \quad (7)$$

2.3.3 Parameterization and calibration

Maize and soybean baseline models were parameterized using data from the IITA database from monocropped maize and soybean plots from 2018 to 2022. Data not available on site, such as soil water information was calibrated based on the comparison of observed and simulated maize and soybean yields for four and three seasons respectively. Thereafter, based on the calibrated simulations four 19-year-long time series from 2001 to 2020 were modelled as the present scenarios, one for each cropping system. Since no yields were obtained in the simulation in the starting year 2001, yield analysis is always done starting from 2002.

Plant management and sowing design

Plant management input parameters for APSIM are sowing window, planting density, rainfall accumulation prerequisites and fertilizer regime. For the maize and soybean baseline scenarios all the necessary data as well as yield data was taken from the IITA database as mentioned above. For the intercropping and the agroforestry scenarios fertilizer amounts were kept the same as in the baselines for better comparison whereas plant density and coppicing schedules were taken from literature. Planting densities for maize and soybean amounted to 5.3 and 40 plants per m^2 respectively. For the intercropping system soybean density was halved while maize density remained the same. In the agroforestry system maize densities increased by one plant per m^2 while 0.74 Gliricidia trees per m^2 were planted.

The sowing window for maize and soybean was the same, ranging from mid-December to beginning of January. Nitrogen fertilizer was applied on both crops and amounted to 9 kg/ha and 10 kg/ ha for maize and soybean respectively. Phosphorus was only applied on soybean plants with 24 kg/ha. Gliricidia trees were pruned three times per year, in October, December and February.

All plant management parameters and values across the four cropping systems are described in Appendix 2.

Meteorological data

Weather data from 2001 to 2022 was taken from the local meteorological station at Chitedze and included daily values in minimum and maximum temperature, and rainfall. This data was used for the calibration process as well as for the 19-year-long simulations. Radiation data was obtained from the National Aeronautics and Space Administration (NASA) Langley Research Center (LaRC) Prediction of Worldwide Energy Resource (POWER) Project funded through the NASA Earth Science/Applied Science Program. The data was obtained from the POWER Project's Hourly Beta v2.0.12 version on on 2023/08/04.

Local cultivar

Based on data availability two local cultivars, SC 719 for maize and SC Safari for Soybean, were used for modelling crop yields. SC 719 is a late maturing improved hybrid with a yield potential up to 13 t ha^{-1}. In Malawi more improved varieties are being adapted by smallholder farmers since the introduction of the Farm Input Subsidy Program (FISP) in 2005 (Audet-Bélanger et al., 2016). SC Safari is a long duration variety with a growing period longer than 120 days. Its potential yields amount to 4.5 t ha^{-1} (Omondi et al., 2023). Root depth for both crops was set to 0.45 m soil depth. For maize on site root length measurements were available whereas literature values were taken for rooting depth of soybean plants in this area.

For the baseline models, parameterization of local cultivars was done with on-site data and literature on crop phenology. Locally used maize and soybean cultivars, SC719 and SC Safari respectively, were modelled in APSIM by calculating thermal time needs for various phenological stages. Therefore, daily thermal time was calculated using mean (Tmean) and base temperature (Tbase) during the growing seasons 2018/2019 (for maize) 2019/2020 (for soybean) (Jones & Kiniry, 1986). Tbase describes the lower limit temperature until which plant growing processes can still take place. According to literature Tbase for maize and soybean were set as 6.2°C and 4°C (Covell et al., 1986; Sánchez et al., 2014).

$$TT = T_{mean} - T_{base} \qquad (8)$$

If Tmin is below Tbase TT is calculated using eight interpolations of air temperature (Tinter,i), resulting in eight three-hour estimates of TT (i=1 to 8):

$$TT_{T_{min}<T_{base},i} = T_{inter,i} - T_{base} \qquad (9)$$

The eight Tinter values are obtained through a correction factor (Tcorr,i), calculated for every three-hour temperature value (I = 1 – 8)

$$T_{inter} = T_{min} + T_{corr} * (T_{max} - T_{min}) \qquad (10)$$

$$T_{corr} = 0.931 + 0.114 * I - 0.0703 * I^2 + 0.0053 * I^3 \qquad (11)$$

The eight three-hour estimates $TT_{T_{min}<T_{base}}$ are finally averaged to calculate the daily TT value.

A table listing calculated TT needs using on site data for days until flowering, maturity, harvesting and literature for emergence and juvenile time periods can be found in Appendix 2.

Soil water parameter calibration

Most yield-sensitive crop soil water parameters, wilting point, field capacity, airdry and volumetric water content at saturation were manually calibrated based on yield data from 2019-2022. Therefore, value intervals were created for each parameter based on regional and literature across Southern-Africa. Various parameter value combinations were itinerated multiple times until best fit between observed and simulated data was found. Therefore, wilting point and airdry slightly differ for maize and soybean baseline models. For the SM these two parameters had to be averaged from both baseline models. For the GM model soil parameters were the same than for monocropped maize. To see an overview of all soil water input parameters see Appendix 2. Tab. 3 describes calibration data sources.

Tab. 3: Calibration data sources, locations and climate.

Source	Location	Time period of collection	Climate
Smethursta et al. 2017	Makoka, Malawi	1992 - 2003	sub-humid to sub-tropical annual rainfall 1024 mm mean daily temperature 16 to 24 °C.
Mante 2019	Limpopo Province, South Africa	2016/2017	semi-arid annual rainfall 400 - 700 mm mean daily temperature 16 to 35°C
Chisanga 2021	Chilanga, Zambia	2016/2017	annual rainfall 930.17 mm mean daily temperature 21.83 ◦C

Limitations and data uncertainty

Fig. 8 gives an overview of the single input data sources for each APSIM module. Most data was needed for the soil module, which was taken from on site measurements, literature for calibration and for filling out gaps, default APSIM settings, from the African soil profile database and fine tuning the model at the end. Due to lack of onsite data, main soil water parameters, field capacity, wilting point, soil water content at saturation and at air dry conditions had to be calibrated. The origin from the input data for the calibration ranged from regional to international. This is a considerable factor of uncertainty concerning modelling results, since these parameters determine plant water uptake and water reallocation in the soil. Furthermore, there was no on-site data for most suitable intercropping and agroforestry configurations for this area available. Therefore, it was also not possible to validate these simulations. Furthermore, sole soybean and maize cropping simulations were validated with national to international data sources, since there were no additional years with yield data available. This represents another flaw in the modelling process.

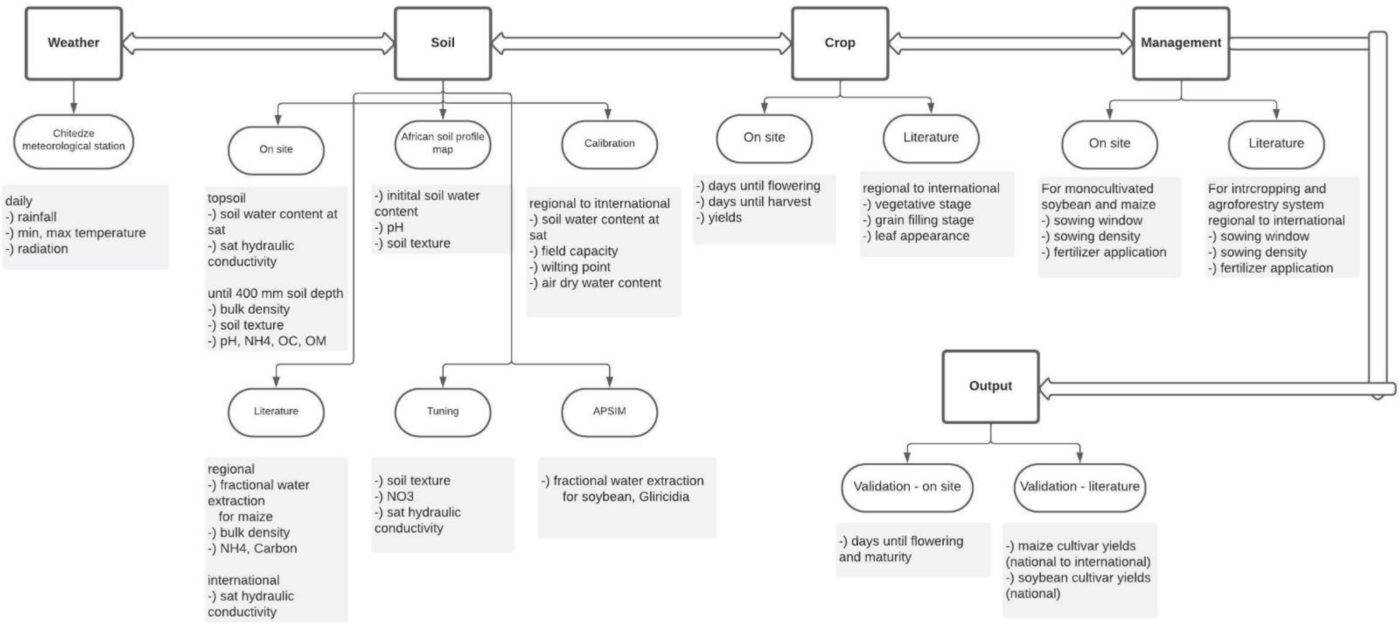


Fig. 8: Flow diagram of data input types parameter and sources for each APSIM module.

2.3.4 Model validation

Average soybean yield data from 2000 to 2022 was used from the National Statistical Office of Malawi (National Statistical Office of Malawi, 2022). Since the used maize cultivar SC 719 is an improved maize variety with high yield potential average maize yields over the country didn’t match the simulated ones. Therefore, observed yields of SC 719 in various studies in Africa were used to compare modelling results of simulated maize yields. Tab. 4 lists all the literature sources.

Tab. 4: Literature sources and description for model validation.

Source	Location	Time period of collection	Climate
Magodo 2007	Harare, Zimbabwe	2006/2007	semi-arid climate annual rainfall 750-1000 mm mean annual temperature 19°C
Malaza et al. 2022	Malkern, Luve, Eswatini	2019/2020	sub–tropical climate annual rainfall 800–1000 mm mean daily temperature 19°C
Mudenda et al 2015	Lusaka, Zambia	2014/2015	sub–tropical climate annual rainfall 800 - 1000 mm average max, min temperatures 15- 28°C
Yusuf et al. 2019	Owode-Egba, Nigeria	2018/2019	tropical humid climate annual rainfall 700–1000 mm average min, max temperature 23°C, 35°C

Further, observed on site phenological characteristics of both cultivars for the years of calibration from 2018/2019 to 2021/2022 were used as well to compare with modelled growth stages.

2.3.5 Statistical Analysis

Field data analysis

A one-sided ANOVA test, including Tukey's range test as multiple comparison method, was done in Minitab to analyse whether and which ones of the various infiltration rate means are significantly different (Minitab, LLC, 2021). The same test was done for soil textures, bulk density, total nitrogen and organic carbon across sampling plots.

For the raw data of the soil sampling analysis boxplots were created in DPlot (Hydesoft Computing LLC, 2023). A pairwise depiction of measured parameters at each soil depth for maize and soybean plots can be seen in Appendix 1.

Modelling results analysis

To determine the fit of simulated to observed yields R^2 and root mean square error (RMSE) were calculated. For model evaluation model efficiency (ME) was also determined. These three parameters were obtained as follows:

First the correlation coefficient r was calculated, with s and o being the simulated and observed value respectively. Thereafter, R^2 was obtained.

$$r = \frac{\sum(s_i - \bar{s})(o_i - \bar{o})}{\sqrt{\sum(s_i - \bar{s})^2 \sum(o_i - \bar{o})^2}} \qquad (12)$$

$$R^2 = r^2 \qquad (13)$$

$$RMSE = \left[\left(\frac{1}{n}\right)\sum_{i=1}^{n}(o_i - s_i)^2\right]^{0.5} \qquad (14)$$

$$ME = 1 - \frac{\sum_{i=1}^{n}(o_i - s_i)}{\sum_{i=1}^{n}(o_i - \bar{o})^2} \qquad (15)$$

Simulations are fitting observed data the best when R^2 and ME are close to 1 and RMSE is low.

For analysing differences in average maize yields across the three agricultural systems and monthly wet and dry spells a one-sided ANOVA test, including

Tukey's range test as multiple comparison method, was done using Minitab. A two-sided ANOVA was implemented to, in a next step, estimate the combined effects of dry and wet spells on yields dependent on agricultural systems and the other way around.

2.3.6 Statistical Downscaling Model – Climate change scenarios

The Statistical Downscaling Model (SDSM) is a weather generator and weather pattern analysis tool (Dawson, 2023). It is important to underline that SDSM is not a climate prediction tool and that future climate change scenarios are synthesised for the purpose of analysing responses of several components to changed climatic conditions. For this work, SDSM-DC 6.1 was used to generate four time series, one in the past from 2001-2020 and three future climate change scenarios from 2021-2040, 2041-2060 and from 2081-2100.

For generating future climate scenario weather files for APSIM, NCEP reanalysis predictor variables were downscaled with observed daily weather data from 1949 to 2009 from Chitedze weather station, available on the APSIM platform (Roger Stern, 2010). Gridded NCEP values were taken from the SDSM website, available under *https://sdsm.org.uk/sdsmmain.html*. Different NCEPs were chosen for the parameters precipitation, minimum and maximum temperature. Tab. 5 lists all used NCEP variables. The selection was done by the variable screening process during which monthly and partial correlation analysis were conducted to estimate which variables were best suited for generating new values of a weather parameter. On average, four to six variables were chosen for each, precipitation, and temperature in reference literature (Dorji et al., 2017; Wilby & Dawson, 2007).

Tab. 5: Predictor variables used for downscaling for each weather parameter synthesized.

Precipitation	Minimum temperature	Maximum temperature
Vorticity near the surface Near surface specific humidity Near surface air temperature	Near surface specific humidity Near surface air temperature Direct shortwave radiation Relative humidity at 500 hPa heigh	Vorticity at 850 hPa Geostrophic airflow velocity near the surface Near surface air temperature Precipitation total

With the downscaled NCEP variables a synthetic weather series was generated producing daily values for precipitation, minimum and maximum temperature from 1990 to 2009 with twenty ensemble members, as suggested by literature (González-Rojí et al., 2019; Wilby & Dawson, 2007). This weather series was then used for producing future climate weather files. In SDSM-DC it is possible to create own climate change scenarios by changing several parameters. Tab. 6 summarizes the changes for all weather parameters and climate change scenarios.

Tab. 6: Parameter settings for generating future climate scenarios. CDD = Consecutive dry days, RIX = 1-day-maximum rainfall

Weather parameter	Variable changed	2021–2040	2041–2060	2081-2100
Precipitation	Occurrence of CDD [%]	5.51	13.15	20.59
	Variance of RX1 [%]	38.67	38.37	57.46
Minimum temperature	Mean of Tmin, absolute value	4.67	6.54	6.03
	Variance of Tmin [%]	4.5	-24.02	-3.32
Maximum temperature	Mean of Tmax, absolute value	2.15	4.75	8.08
	Variance of Tmax [%]	14.63	5.08	8.72

In order to obtain values for variance and occurrence changes, future weather data following the SSP 2-4.5 was downloaded from the IPCC Interactive Atlas, based on the 6[th] Assessment Report (AR6) generated by an ensemble of up to 32 CMIP6 model ensembles. Precipitation, min, max temperature and used variables such as consecutive dry days (CDD) and 1-day-maximum rainfall (RX1) data were downloaded for the three future climate scenarios time periods. RX1 and CDD were included to generate precipitation while considering changes in extreme weather patterns. Since weather patterns differed the most under the long-term climate change scenario from 2081 to 2100 (see Fig. 9 and Fig. 10) results are shown for only this time period. Diagrams for the short- and mid-term scenario can be seen in Appendix 4.

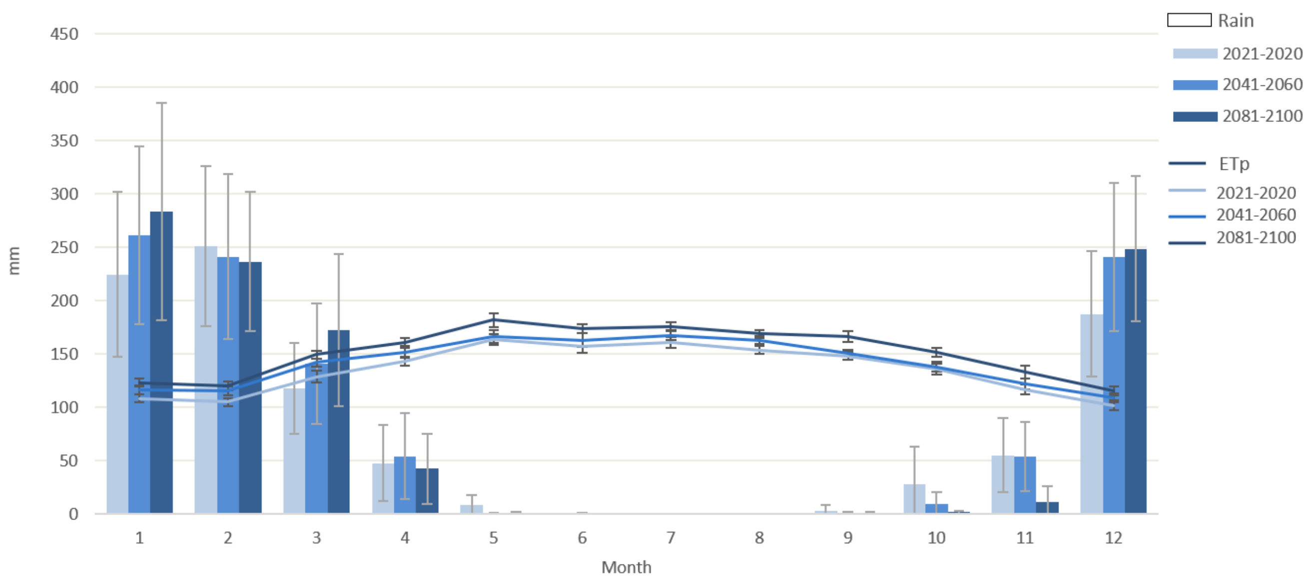


Fig. 9: Average monthly rainfall and potential evapotranspiration across all three climate change scenarios.

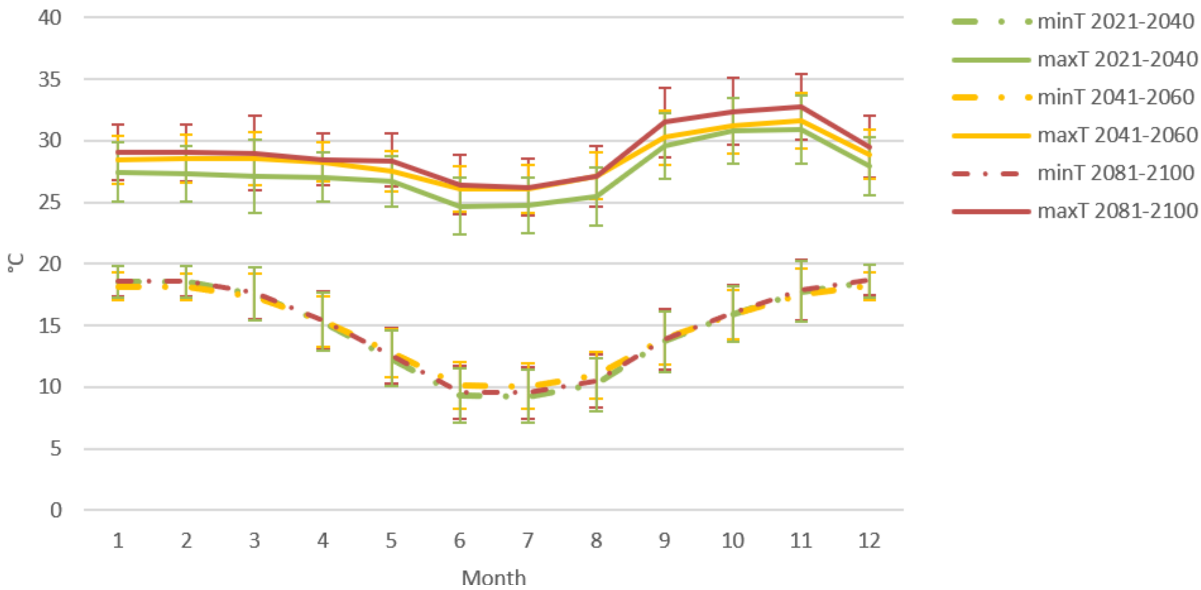


Fig. 10: Average monthly minimum and maximum temperature across all three climate change scenarios.

3. Results

3.1 Field data collection for APSIM model input

Tukey's range test resulted in all means of the infiltration rates being significantly different from one another (P = 0). Therefore, for determining Ksat and plotting infiltration rates, total means across all four measured plots were calculated (see Fig. 11). A diagram of all eight infiltration rates can be seen in Appendix 1.

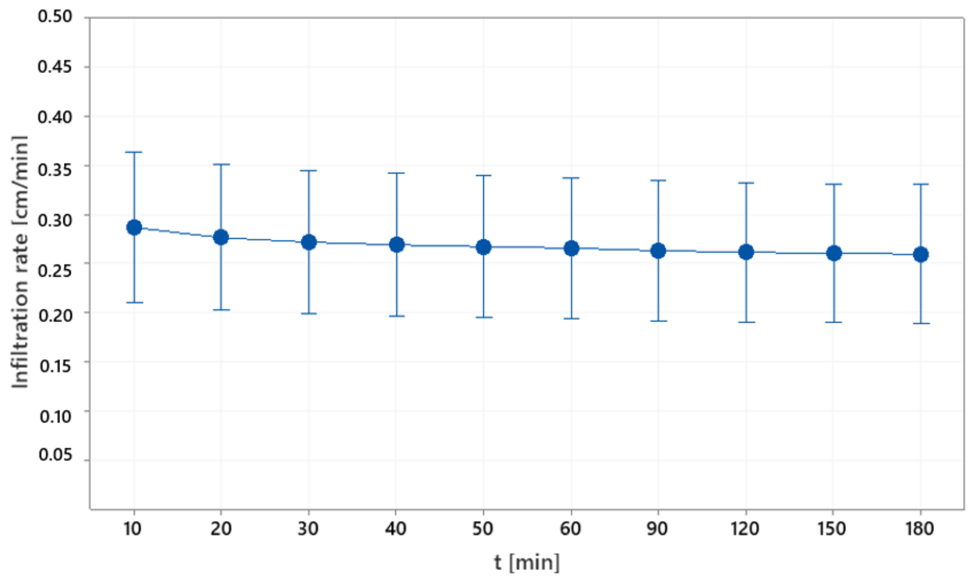


Fig. 11: Mean infiltration rate across all plots

Tab. 7 lists all the measured soil parameters across three soil depths.

Tab. 7: Physical and chemical soil analysis results across three soil depths.

Depth [cm]	0-10	10-20	30-40
BD [g/cm³]	1.36 ± 0.11	1.44 ± 0.09	1.24 ± 0.10
Clay %	17 ± 2	24 ± 3	27 ± 5
Silt %	15 ± 5	8 ± 2	10 ± 3
Sand %	68 ± 5	68 ± 4	63 ± 2
pH	5.19 ± 0.08	5.27 ± 0.09	5.36 ± 0.14
OC %	2.6 ± 0.17	2.04 ± 0.50	2.17 ± 0.45
OM %	4.49 ± 0.30	3.52 ± 0.87	3.74 ± 0.77
N tot %	0.23 ± 0.02	0.18 ± 0.05	0.19 ± 0.05
Sat volum water cont %	0.51 ± 0.04	/	/
KS [cm/min]	0.28 ±0.08	/	/

For soil texture the ANOVA analysis resulted in not significantly different means across all eight sampling locations, thus the null hypothesis of all samples sharing the same mean wasn't rejected (P=0.822). Therefore, the overall means for soil texture of all three depths were used as APSIM input parameters for clay, silt and sand (see Fig. 12).

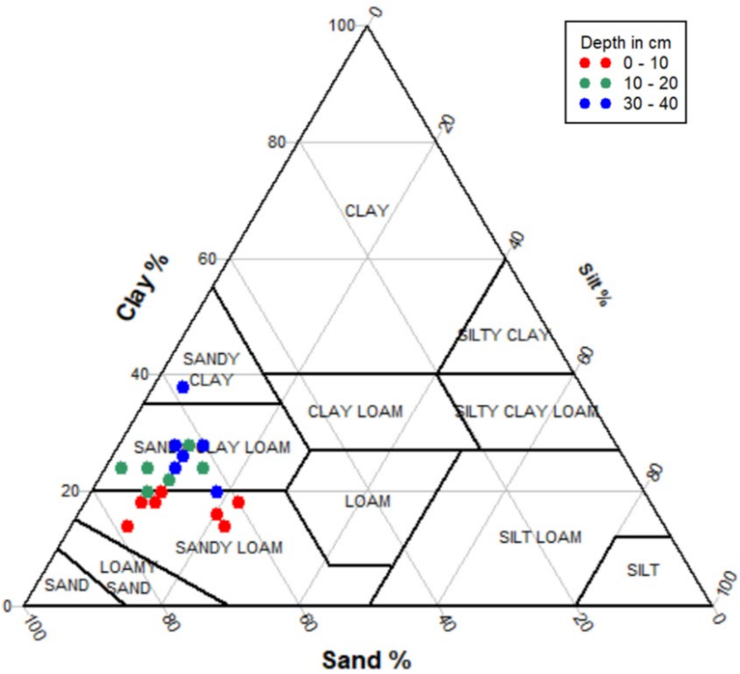


Fig. 12: Soil texture means across all sampling sites at three depths.

The same results were found for the two bulk density testing sites (P=0.583) as well as for nitrogen (P=0.451) and organic carbon (P=0.410) analysis (see Fig. 13). One outlier of bulk density measurements was found at the maize plot at a depth of 15-20 cm at the 5% level of significance. Plotted data for all the sampling locations are listed in Appendix 1.

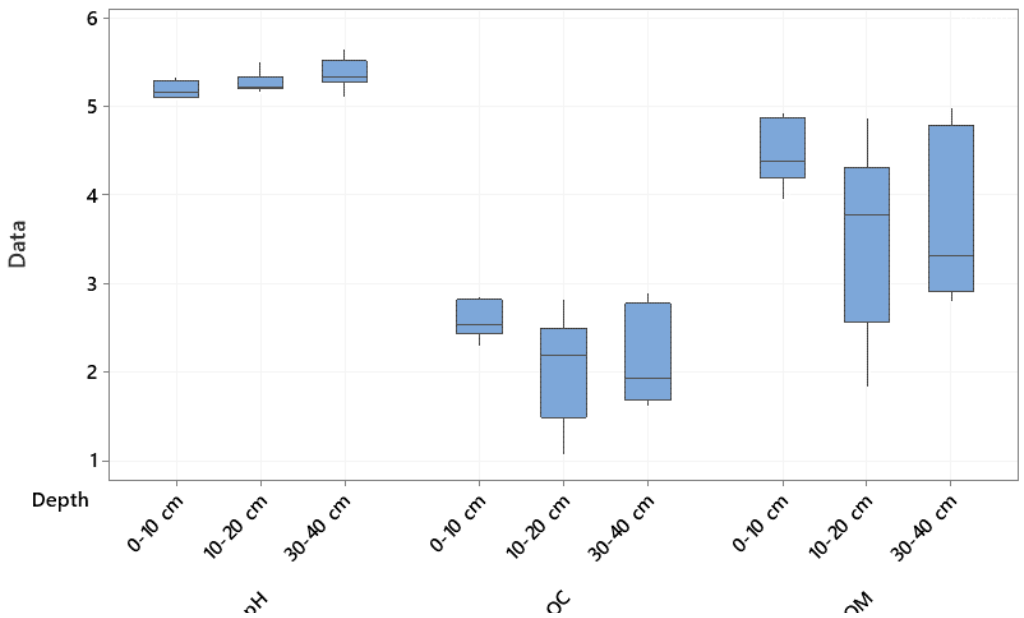


Fig. 13: Organic carbon, organic matter and pH results for all the measurements at three depths.

Bulk density was highest in the compaction layer from 15 cm to 20 cm soil depth, which also showed the lowest variability in measurement results, which can be seen in Fig. 14.

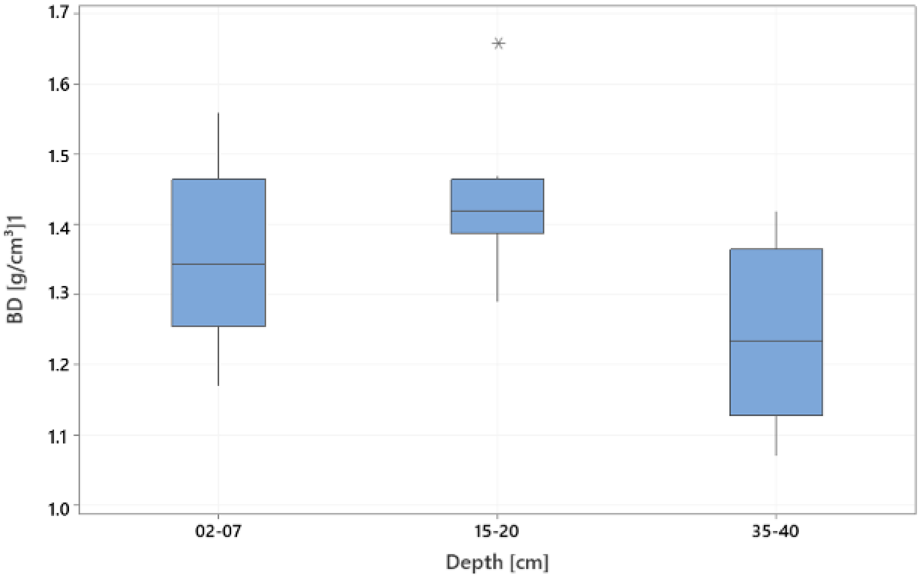


Fig. 14: Bulk density across all plots at three soil depths.

3.2 APSIM calibration for maize and soybean models

In Tab. 8 the calibration data intervals and values for initial calibration and best fit are shown. Parameters differing in the maize and soybean baseline model are Airdry and Field capacity. Values marked with * were tuned during the calibration process and differ slightly from value ranges.

Tab. 8: Calibration data intervals and sources. LL15=wilting point, DUL=field capacity, SAT=soil water content at saturation.

[mm/mm]	Simulation	0 - 15 [cm]	15 - 30	30 - 45	45 - 60	60 - 80	80 - 100	100 - 120	120 - 140	140 - 160	160 - 180	180 - 200	Source
Airdry	Literature intervals	0.04-0.16	0.08-0.17	0.13-0.17	0.13-0.18	0.13-0.20	0.13-0.23	0.23	0.26	0.27	0.28	0.28	(1), (2)
	Initial calibration	0.100	0.125	0.150	0.155	0.165	0.180	0.230	0.260	0.265*	0.265*	0.260*	
	Best fit Maize	0.040	0.080	0.130	0.130	0.130	0.130	0.230	0.260	0.270	0.280	0.280	
	Best fit Soybean	0.150	0.160	0.160	0.170	0.190	0.220	0.230	0.260	0.260*	0.250*	0.240*	
LL15	Literature intervals	0.15-0.29	0.18-0.29	0.18-0.29	0.18-0.30	0.18-0.24	0.18-0.35	0.25	0.27	0.27	0.29	0.29	(1) - (3)
	Initial calibration	0.175	0.215	0.215	0.215	0.210	0.215	0.250	0.270	0.270	0.290	0.270*	
	Best fit Maize	0.180	0.180	0.200	0.200	0.200	0.200	0.250	0.270	0.270	0.290	0.290	
	Best fit Soybean	0.190	0.240	0.240	0.240	0.230	0.240	0.240*	0.270	0.270	0.290	0.250*	
DUL	Literature intervals	0.23-0.41	0.27-0.41	0.27-0.41	0.27-0.42	0.28-0.36	0.28-0.47	0.28 - 0.34	0.29 - 0.33	0.30 - 0.32	0.3	0.29	(1) - (3)
	Initial calibration	0.307	0.325	0.325	0.320	0.320	0.315	0.310	0.310	0.310	0.300	0.290	
	Best fit Maize	0.230	0.270	0.270	0.270	0.280	0.280	0.280	0.290	0.300	0.300	0.290	
	Best fit Soybean	0.230	0.270	0.270	0.270	0.280	0.280	0.280	0.290	0.300	0.300	0.290	
SAT	Literature intervals	0.5	0.4-0.47	0.41-0.47	0.41-0.47	0.41-0.45	0.41-0.49	0.44	0.44	0.44	0.44	0.44	(1) - (3)
	Initial calibration	0.487	0.423	0.440	0.428	0.450	0.425	0.440	0.440	0.440	0.440	0.440	
	Best fit Maize	0.487	0.400	0.410	0.410	0.410	0.410	0.440	0.440	0.440	0.440	0.440	
	Best fit Soybean	0.487	0.400	0.410	0.410	0.410	0.410	0.440	0.440	0.440	0.440	0.440	

Source Codes	Place
(1) Smethursta et al. 2017	Malawi
(2) Mante 2019	South Africa
(3) Chisanga 2021	Zambia

In Fig. 15 observed yields are compared to first calibration and best fit after several iterations of parameter value combinations. In some years there were several plots from which observed yields were available. In these, observed yields are shown as a range. It is clear that initial parameter calibration overestimated soybean and underestimated maize yields whereas best fit follows the yield trends from year to year and always stays within the yield range. Observed maize yields in 2022 were considerably lower due to a change of planting location to one with poorer soil and low fertility. Therefore, this year's yield was not taken into account during the calibration phase.

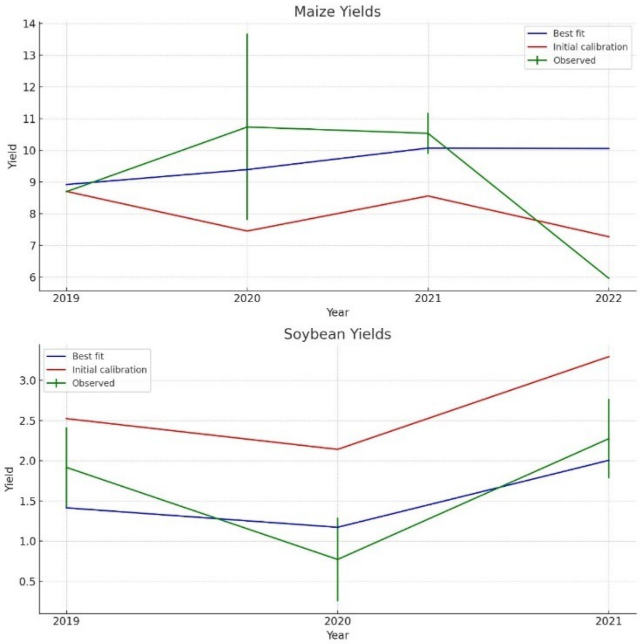


Fig. 15: Best fit, initial calibration and observed yields from 2019 to 2021 for soybean and maize.

3.3 Model validation

Maize baseline model

Observed and simulated maize and soybean yields can be seen in Fig. 16.

Tab. 10 shows SC 719 yields from literature described above for various years and averaged yield across all seasons. Simulated maize yields in the according years are shown as well as average yield over the 2001-2020 simulation period. Tab. 9 shows average days until flowering and maturity over the 2001 to 2020 simulation period for maize and soybean. It is clear that simulated day span until harvest for soybean is much longer than for observed time spans. Days until flowering is overestimated for soybean and underestimated for maize in the simulation. Tab. 11 shows statistical parameters describing calibration quality. R^2 is low, showing that there is not much correlation between observed and simulated yields. ME shows similar results, whereby differences in simulated and observed maize yields fit better the observed variation than simulated soybean ones. RMSE is not within the range of 0.2 to 0.5 which indicates that the model is not predicting the data accurately. It has to be indicated that observed validation data was taken from national averages and are not reflecting on the exact agroecological zone of Malawi nor the fact that cultivars can make a considerable difference in yields.

Tab. 10: SC 719 yields from literature and simulation results in t ha^{-1}.

Season	Simulated	Observed	Source
2006/2007	5.02	7.45	(1)
2014/2015	6.16	5.50	(2)
2018/2019	6.72	6.35	(3)
2019/2020	6.42	7.49	(4)
Average	6.43	6.70	

(1) Magodo 2007
(2) Mudenda 2015
(3) Yusuf et al. 2019
(4) Malaza et al. 2022

Tab. 9: Observed and simulated phenology data for maize and soybean.

	Observed		Simulated	
	Maize	Soybean	Maize	Soybean
Days to flowering	64-67	47-54	52-61	59-68
Days to harvest	150-160	124-130	135-162	177-211

Tab. 11: Statistical parameters describing accuracy of simulated yield data for calibration.

	Soybean	Maize
RMSE	0.66	1.38
ME	-7.91	-1.77
R^2	0.12	0.16

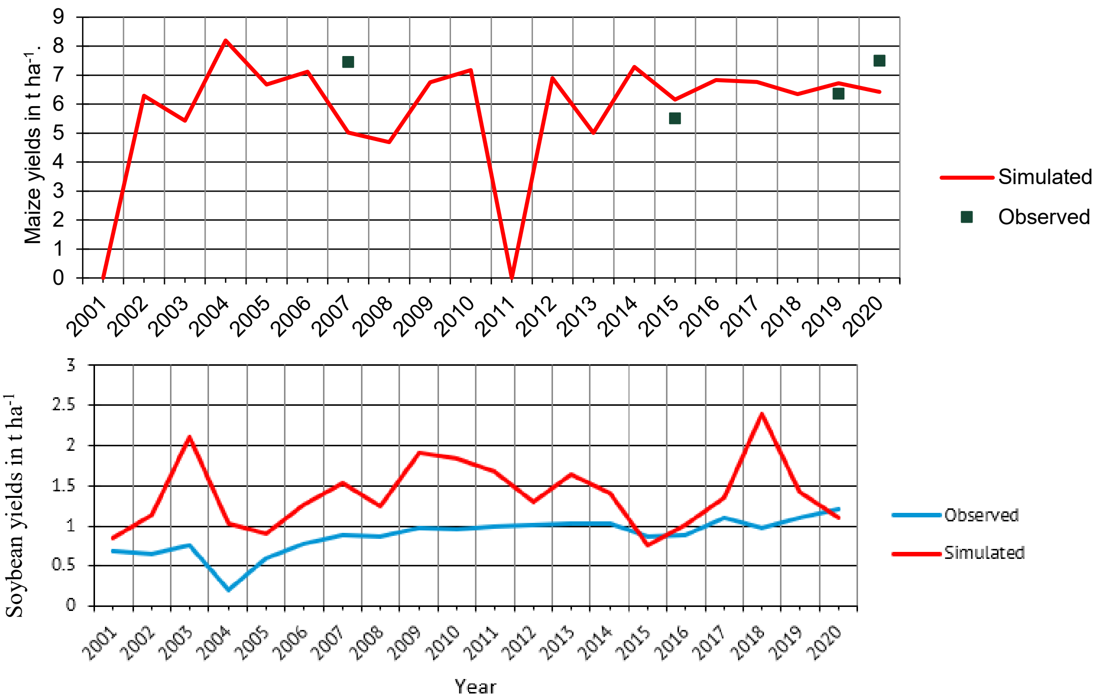


Fig. 16: Observed and simulated maize (above) and soybean (below) yields from 2001 – 2020.

3.4 Water balance assessment for four crop systems during 2001-2020

Grain yield and total aboveground biomass

Fig. 17 shows yields across all cropping systems and yearly rainfall from 2002 to 2020. Planting densities stayed the same across the sole and intercropping system for maize with a decrease by one plant m^{-2} in the agroforestry system. Soybean planting density decreased in the intercropping system by a third compared to the soybean monocultivation. For exact values see Appendix 2. The SM system had the highest maize and soybean yield outcomes across all years for maize and most years for soybean with an average across all years of 8.1 t ha^{-1} and of 1.7 t ha^{-1} respectively. Average yield increase in the SM system compared to the baseline models amounted to 28 % ± 12 % and 15 % ± 42 % for maize and soybean respectively, averages across years being 6.4 t ha^{-1} and 1.4 t ha^{-1}. For most years maize yields were lowest in the GM system with an average yield decrease of 8 % ± 32 % amounting to an average of 5.8 t ha^{-1}. The high standard deviations in both intercropping systems for Soybean and Maize in the SM and the GM system respectively are caused by high yield variability across years.

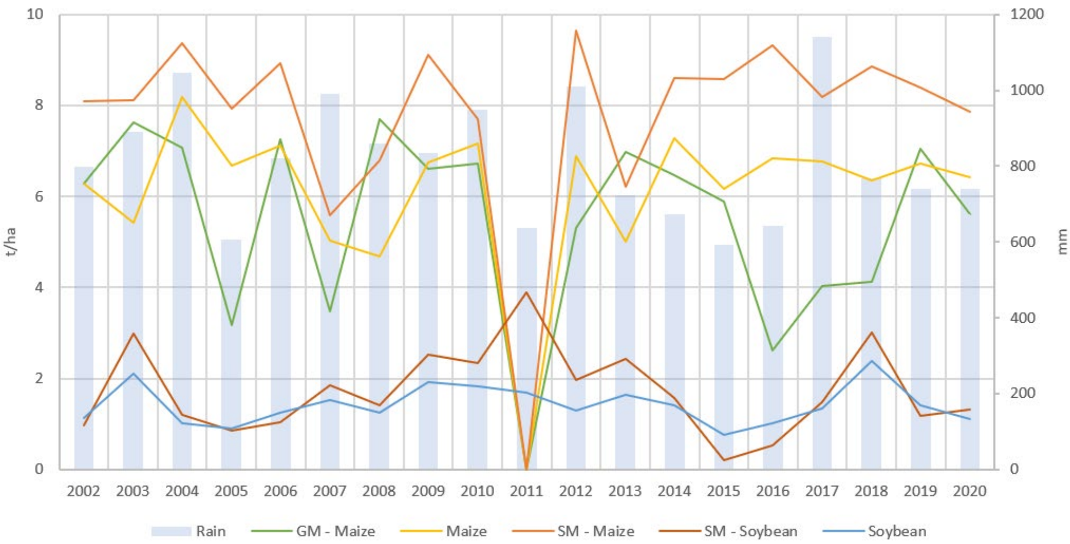


Fig. 17: Yields and yearly rainfall from 2002 to 2020 for all cropping systems. GM=Gliricidia maize agroforestry, SM=soybean maize system.

The extend of yield variability can also be seen in Fig. 18, which shows yield ranges from 2002 to 2020. Maize and Soybean baseline models are much less variable in yields than the intercropping systems. Yield variability and CV results are discussed in detail below. In the GM system average Gliricidia biomass is four times lower than maize biomass. This is due to heavy tree pruning three times per year. Across all systems maize wasn't sown in 2011 due to not fulfilled accumulated rainfall requirements three days before sowing. Thus, 2011 wasn't included in the following maize yields analysis and diagrams.

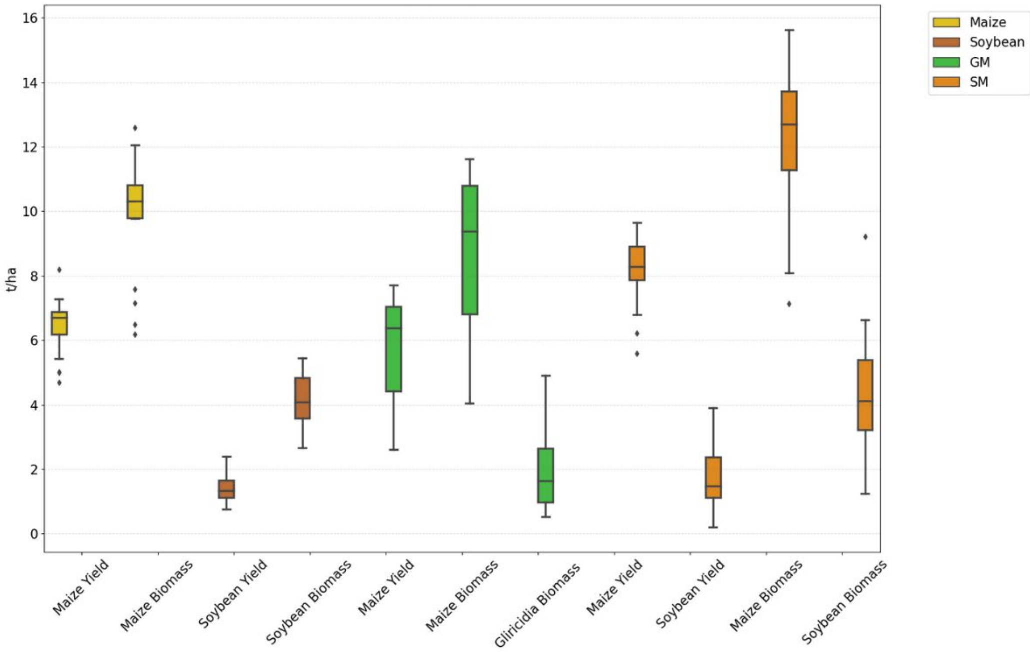


Fig. 18: Boxplots of grain yield and above ground biomass of all cropping components in the four cropping systems.

Water balance

Fig. 19 visualizes transpiration, evaporation and biomass development over the growing season for all cropping systems. Over the growing season the SM system had the lowest monthly evaporation losses (211 mm) whereas the baseline maize model had the highest (282 mm). For both crops Ta was highest in the SM simulation (about 195 mm). Maize Ta was lowest in the GM system (116 mm) and lower than Gliricidia Ta (158 mm), however the latter showed high monthly variability with a standard deviation of up to 18 mm. Aboveground biomass accumulation was highest for maize in the SM system with an average increase from the baseline of 2 t ha^{-1} whereas in the GM system maize biomass decreased by 4 t ha^{-1}. Soybean showed higher biomass accumulation in the baseline system and a decrease by 2 t ha^{-1} in the intercropping one. Gliricidia showed approximately constant average biomass accumulation due to heavy pruning and therefore had the lowest values ranging between 1 and 3 t ha^{-1}. However, differences across years are high, indicated by a high standard deviation throughout the growing season.

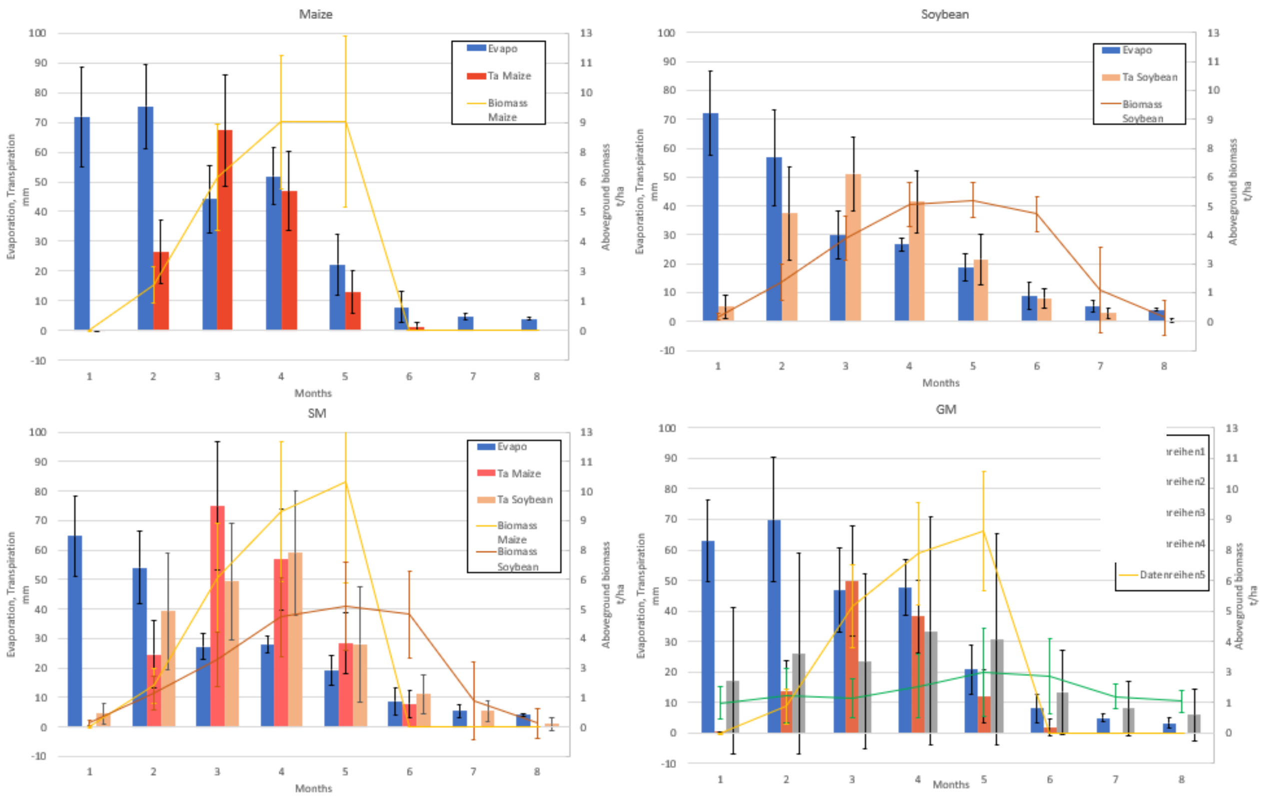


Fig. 19: Evaporation, transpiration, and above ground biomass over the growing season for all cropping systems and system components.

In Fig. 20 water balance changes from the baseline to the intercropping systems for maize and soybean are shown. Evaporation losses were reduced in the SM (21% for maize and 3% for soybean) and the GM (10% for maize) system for both crops, reductions were highest for maize in the SM system. Ta increased for both crops in the intercropping system by 21% and 17% for maize and soybean respectively and decreased for maize in the agroforestry model by a quarter. Variation of the latter suggests that yearly differences in Ta decrease are considerable. The same is valid for Soybean Ta in the SM system.

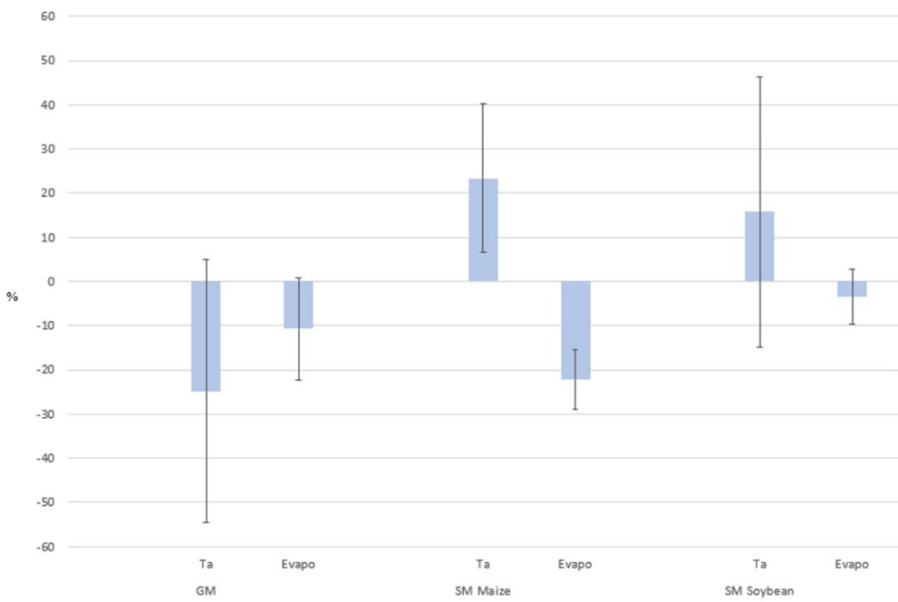


Fig. 20: Average percentage change in actual transpiration (Ta) and evaporation (Evapo) in the multiple component systems compared to the baseline models from 2002-2020.

Looking into belowground water storage, total maize available water decreased by 60% in the agroforestry system (see Fig. 21). Both crops benefited from higher water availability in the intercropping system. Hereby, a three to four time increase of extractable soil water within the first 450 mm was seen for soybean, with a high variation across years. For maize the same parameter increased almost by double. However, across all systems total available soil water didn't change.

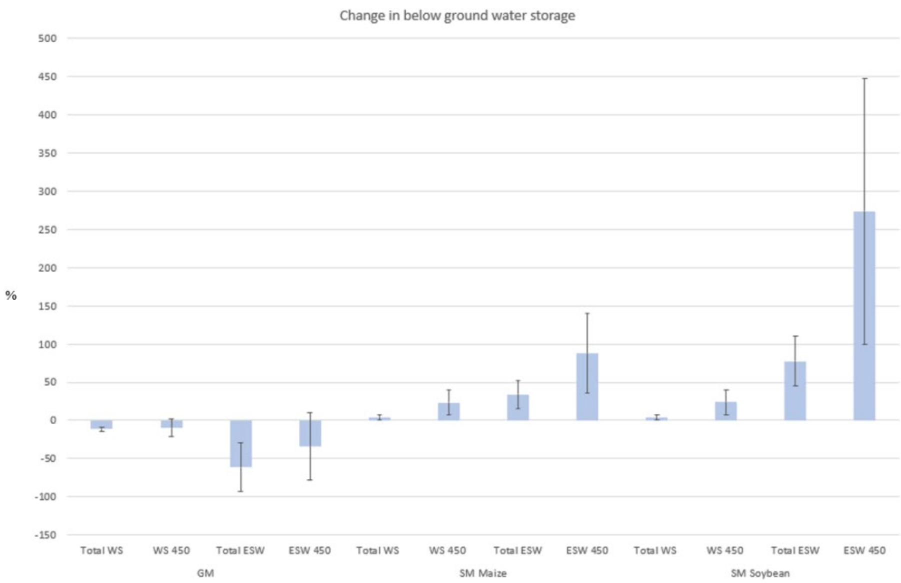


Fig. 21: Average percentage change in total below ground water storage (Total WS) and extractable soil water (Total ESW) and until 450 mm of soil depth (WS 450, ESW 450) in the multiple component systems compared to the baseline models from 2002-2020.

Evaporative Stress Index

As can be seen in the Fig. 22, monthly ESI was the highest in both intercropping simulations with the SM system showing overall highest values with an average of 0.65 compared to the GM system with an ESI of 0.56. Monocropped maize (0.31) showed slightly better results than soybean (0.25). However, variability was highest on both intercropping systems, whereas in the baseline models ESI didn't vary considerably across years.

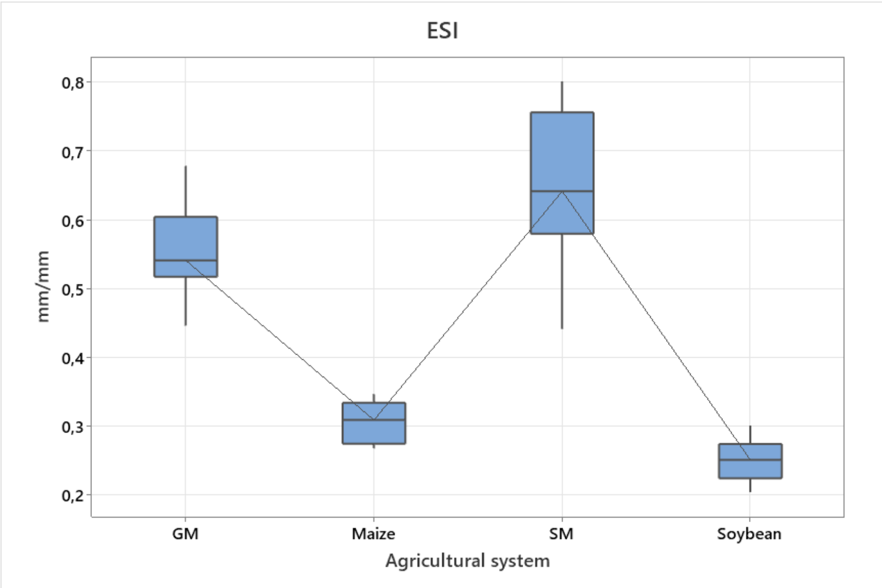


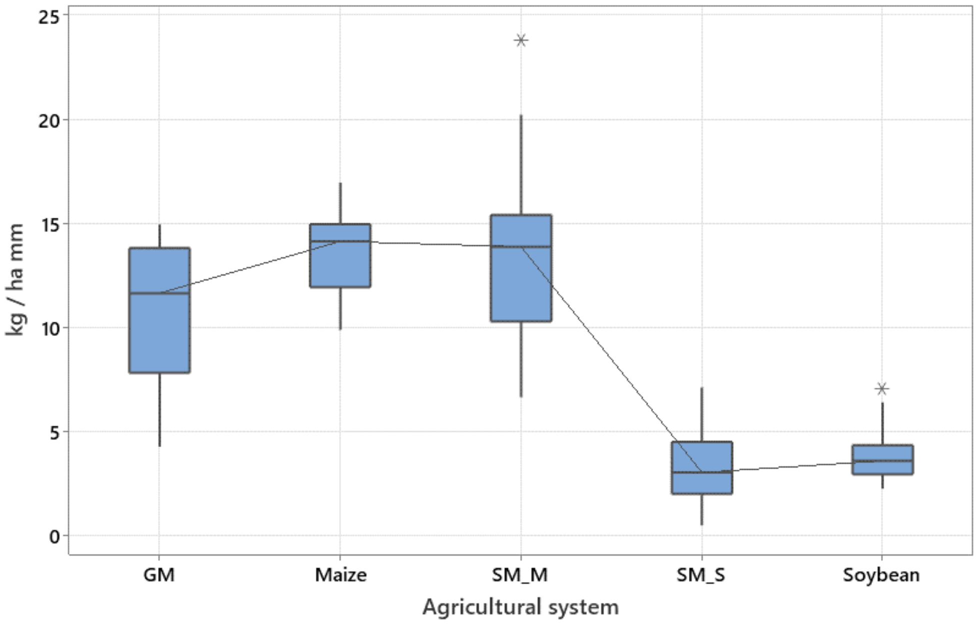
Fig. 22: Averaged monthly ESI for all cropping system from 2001-2020.

Water productivity

Fig. 23 shows boxplots for WP1 and WP2 across all systems from 2002-2020. Yield-based water productivity was highest for all maize including cropping systems, the highest values were achieved in the monocropping and intercropping simulations with an average of 13.5 kg yield ha^{-1} mm^{-1}. The agroforestry system only obtained an average of 10.9 kg yield ha^{-1} mm^{-1}, owing to lower maize yields. For soybean, values were slightly higher in the monocultivation with 3.8 kg yield ha^{-1} mm^{-1} than in the intercropping one with 3.2 kg yield ha^{-1} mm^{-1}. Different to WP1, sole maize showed by far the highest biomass-based water productivity values with an average of 16.6 kg yield ha^{-1} mm^{-1}, while the other maize based systems obtained WP2 values of 10.5 kg yield ha^{-1} mm^{-1}. WP1 averages across all years were mostly lower than WP2 for all systems and the lower 50% of values were higher for WP2. Average WP2 was slightly higher than WP1 in the maize baseline by 3 kg $ha^{-1}mm^{-1}$, whereas 50% of WP2 values in the maize baseline are considerably higher, reaching up to 10 $ha^{-1}mm^{-1}$ more than WP1. This is due to high variation in increase of yearly compared to seasonal ETa ranging from 17 mm to

130 mm and the same for yearly biomass accumulation compared to yields from 1.5 t ha^{-1} to 5 t ha^{-1}.

However, for maize in the SM system average WP1 was higher or equal than WP2 by 3 kg $ha^{-1}mm^{-1}$. Average WP2 was much higher than WP1 for monocropped soybean and soybean in the SM system with a difference of about 6.5 kg $ha^{-1}mm^{-1}$ for both systems. In the GM system on the other hand, both, average WP1 and WP2 stayed the same whereas minimum values increased for WP2 compared to WP1.



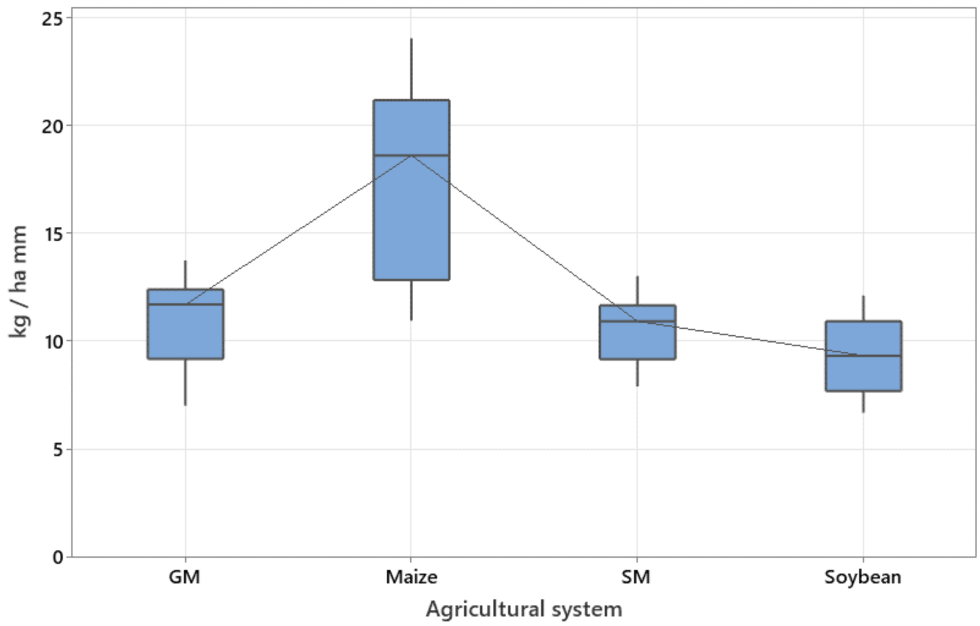


Fig. 23: Yield-based (WP1, above) and biomass-based (WP2, below) water productivity across all cropping systems from 2002-2020. SM_M, SM_S = Maize and soybean respectively in the intercropping system.

Rainfall patterns and yield response

Looking into CV in Tab. 12, a higher value for yearly rainfall than for the monocropped maize system and maize in the SM system suggests yield resilience towards variance in rainfall patterns. Whereas CV values for soybean in both cropping systems as well as for maize in the agroforestry system indicate a higher crop sensitivity to variability in rainfall.

Tab. 12: Coefficient of variation (CV) for rainfall parameters and yields from 2002-2020. DS=dry spell, WS=wet spell, GM=Gliricidia-maize system, SM=soybean-maize.

CV % - Rainfall

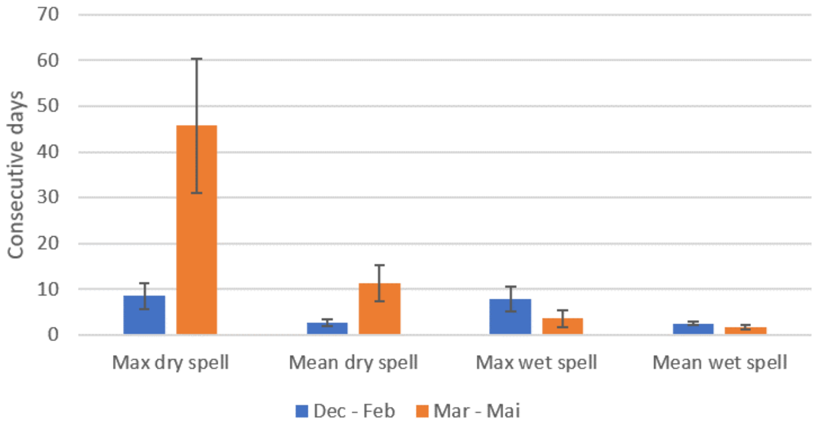
	Sum	Max DS	Max WS	Mean DS	Mean WS
Dec-Feb	19.6	32.3	34.3	25.0	15.3
Mar-Mai	53.7	32.1	49.6	34.4	32.7
Annual	19.4	16.4	34.3	12.4	16.4

CV % - Agricultural systems

Maize	Soybean	GM	SM - Maize	SM - Soybean
14.0	29.9	28.0	13.3	54.6

Further, Fig. 24 indicates that the duration of maximum wet and dry spells are more variable than mean duration of these events, and hereby suggests higher unpredictability of extreme weather patterns. Hereby, maximum wet spells are more variable than maximum dry spells. Further, CV of total rainfall over spring, thus during maturing and ripening time, is considerably higher than over winter.

Fig. 24: Maximum and mean monthly dry and wet spells during winter and spring averaged over the present simulation period from 2002-2020



The one-way ANOVA test showed that there were significant differences in maize yields across agricultural systems (P=0.0019) but not across monthly wet and dry spells. Exceptions were maximum dry spells in April (P=0.03) and December (P=0.0029) as well as maximum wet spells in December (P=0.0021). This suggests that during the period from sowing to emergence both crops and during reaching maturity maize is most sensitive to rainfall patterns.

The two-way ANOVA showed that the effects of monthly maximum dry spells in April (P= 0.932) and December (P=0.978) and wet spells in December (P=0.443) on yields didn't depend significantly on the agricultural system in place.

3.5 Water balance assessment for 4 crop systems for the long-term climate scenario

Grain yield

Fig. 25 shows yields and yearly rainfall across all cropping systems from 2082-2100. The GM system resulted in the highest maize yield outcomes across all years except of the years 2086 and 2090 on average amounting to 6.5 t ha^{-1} with an increase of 15% ± 19% compared to the mono cropped maize. The SM system showed the highest soybean yields across all years with an average of 2.8 t ha^{-1}. Average yield increase in the SM system compared to the soybean baseline model amounted to 40% ± 10%. For the majority of years maize yields were lowest in the SM system with an average yield decrease of 4% ± 20% amounting to an average of 5.5 t ha^{-1}. The high standard deviations in both the GM and the SM maize system are caused by high yield variability across years.

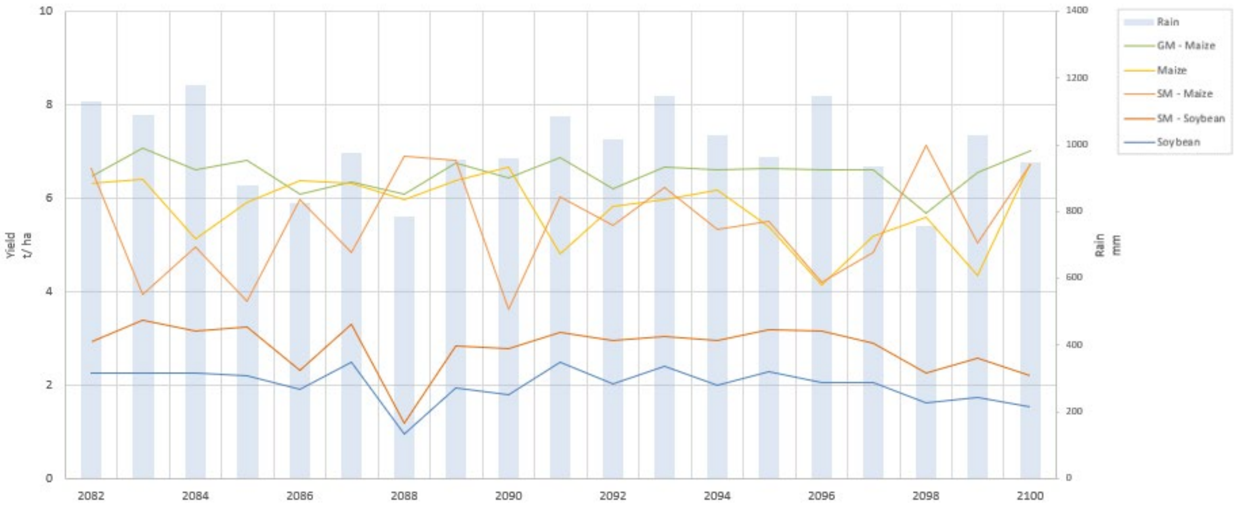


Fig. 25: Yearly yields and rainfall under the long-term climate prediction scenario from 2082 to 2100.

Water balance

Fig. 26 shows transpiration, evaporation and biomass over the growing season for all cropping systems and system components. Over the growing season the SM and the sole soybean system had the lowest monthly evaporation losses (197 mm to 201 mm) whereas the baseline maize and the GM model had the highest (301 mm to 304 mm). For soybean Ta was higher in the intercropping system by 100 mm amounting to 308 mm, whereas the agroforestry and the sole maize system were most beneficial for maize Ta with 181 mm. Aboveground biomass accumulation was highest for maize in the GM system with an average increase from the baseline of 1.5 t ha^{-1} whereas in the SM system maize biomass decreased by 4 t ha^{-1}. Soybean biomass increased in the SM system by 2 t ha^{-1}. Gliricidia biomass and transpiration was very low, indicating growing issues after planting. This was beneficial for maize development, noticeable by higher transpiration and biomass accumulation values as described above.

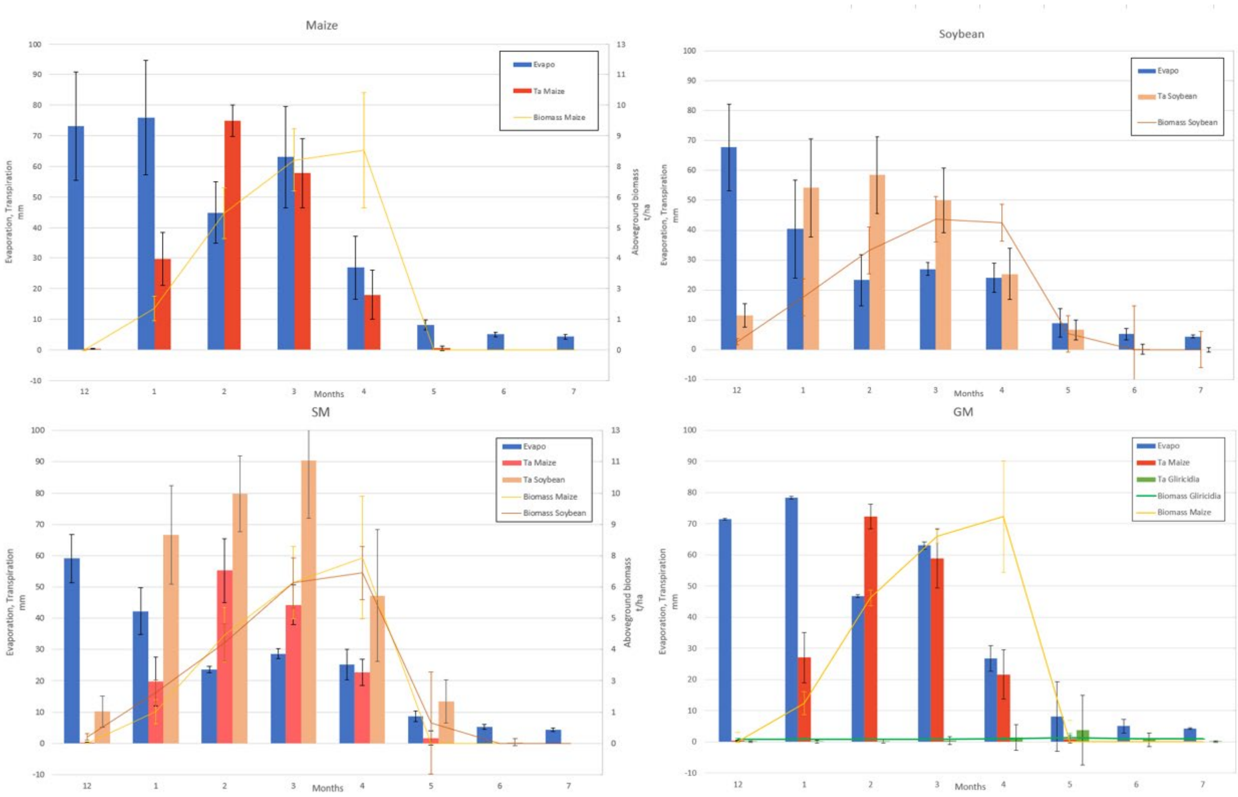


Fig. 26: Evaporation, transpiration, and above ground biomass over the growing season for all cropping systems and system components from 2082-2100.

In Fig. 27 water balance changes from the long-term baseline scenarios to the intercropping systems for maize and soybean are shown. Evaporation losses were reduced in the SM system for both crops (32% for maize and 2% for soybean) and stayed the same for maize in the GM system. Ta increased only for soybean in the SM system by 48% whereas maize Ta decreased by 20% and stayed the same in the GM system. High standard deviation for maize transpiration in the intercropping system indicates maize yield variability across years in the SM system.

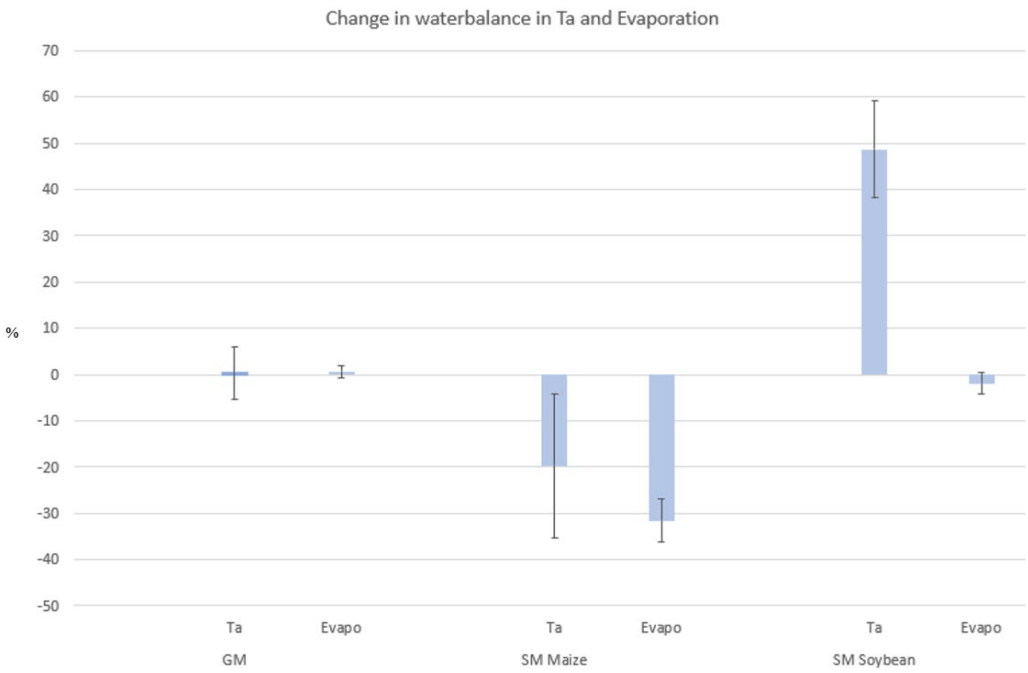


Fig. 27: Average percentage change in actual transpiration (Ta) and evaporation (Evapo) in the multiple component systems compared to the baseline models from 2082-2100.

Water storage and extractable soil water didn't change in the agroforestry system, whereas they increased in the intercropping system for both crops (see Fig. 28). Soybean benefitted the most, with a more than four times increase in ESW within the first 450 mm of soil depth. The respective standard deviation is half of the value showing highly variable changes in plant available water in the soybean monocropped system. ESW450 doubled for maize in the SM system, whereas for both crops water stored within the first 450 mm of soil depth increased by half.

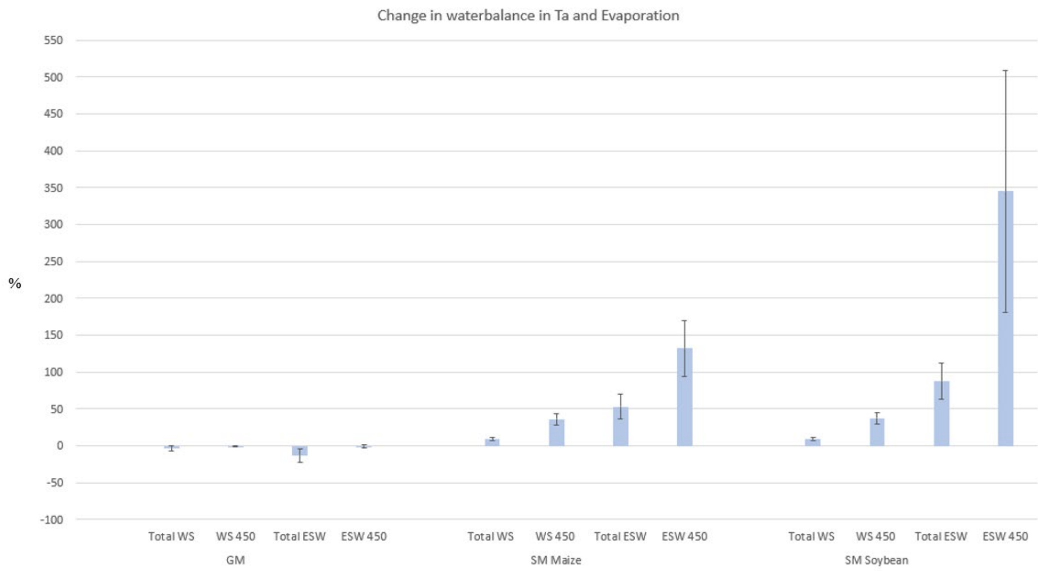


Fig. 28: Average percentage change in total below ground water storage (Total WS) and extractable soil water (Total ESW) and until 450 mm of soil depth (WS 450, ESW 450) in the multiple component systems compared to the baseline models from 2082-2100.

Evaporative Stress Index

Highest ESI values were observed in both, the intercropping and the agroforestry system with averages of 0.59 and 0.42 respectively as can be seen in Fig. 29. Monocropped maize (0.30) showed slightly better results than soybean (0.23). Variability was very low across all systems.

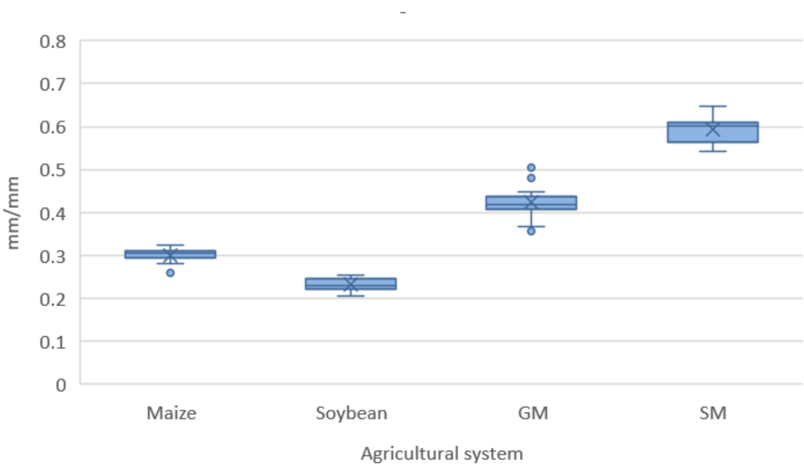


Fig. 29: Average ESI across all cropping systems from 2081-2100.

Water productivity

Overall highest WP1 was achieved in the GM system with an average of 12.88 kg ha^{-1} mm^{-1} compared to the value of 11.71 kg ha^{-1} mm^{-1} in the mono cultivated maize system (see Fig. 30). For soybean WP1 was slightly higher in the mono cropped system with an average of 5.57 kg ha^{-1} mm^{-1} compared to the average in the intercropped system amounting to 5.23 kg ha^{-1} mm^{-1}. Variability was highest for maize in the mono cropped as well as the SM system, whereas for the other models WP1 didn't vary considerably across years.

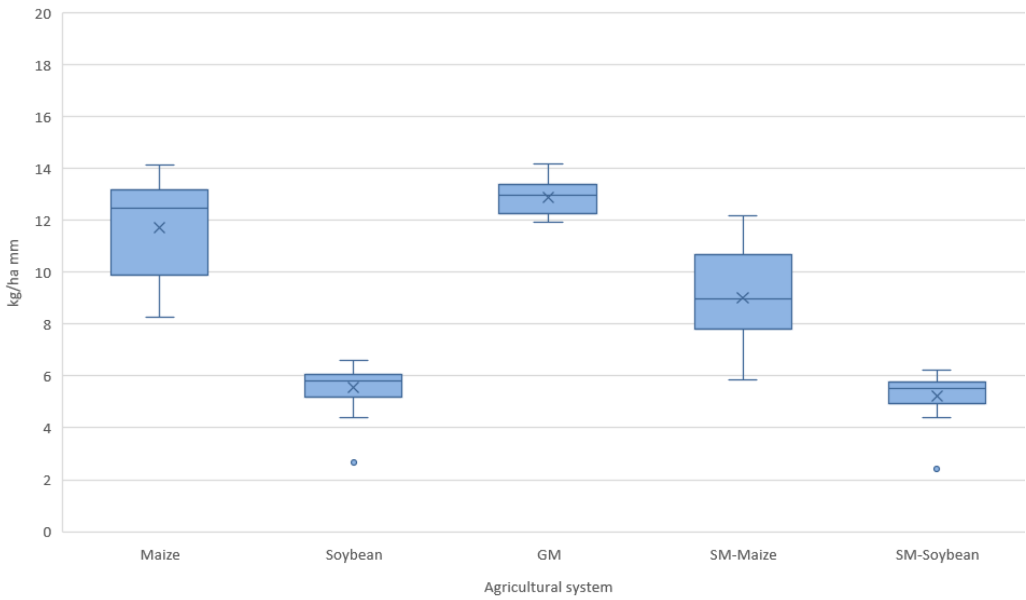


Fig. 30: Single system water productivity boxplots for the long-term scenario from 2081-2100.

WP1 averages and medians across all cropping configurations were lower than WP2 except for the GM system (see Fig. 31). Average WP2 was considerably higher than WP1 in the maize baseline and intercropping system by 4 kg ha^{-1} mm^{-1}. Intercropped soybean WP2 values exceeded WP1 values by 8 kg ha^{-1} mm^{-1}. However, in the GM system, both, average WP1 and WP2 stayed the same with slightly higher WP1 values by 0.3 kg ha^{-1} mm^{-1}.

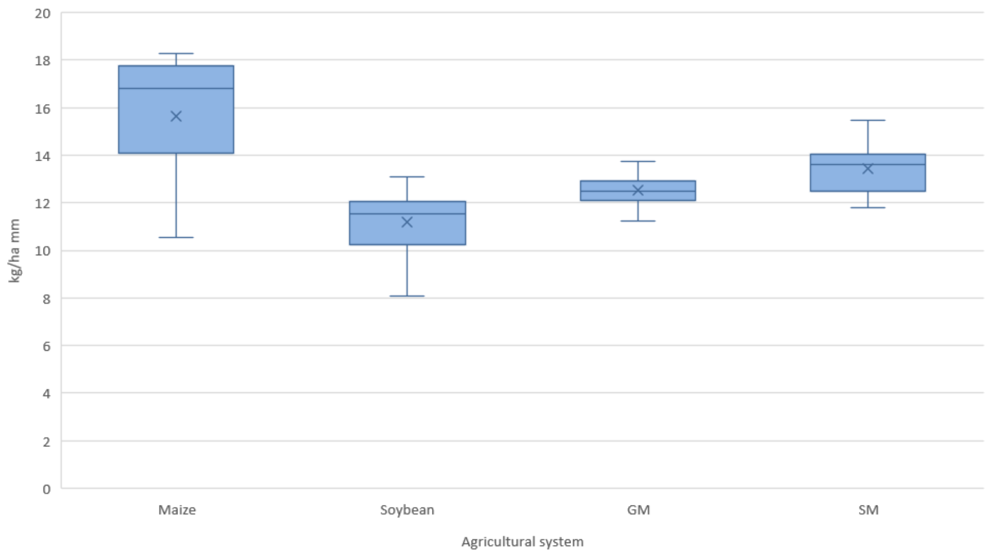


Fig. 31: Whole system water productivity boxplots for the long-term scenario from 2081-2100

Rainfall patterns and yield response

Looking into the coefficient of variation in Tab. 13, the GM system shows by far highest resilience towards variance in rainfall compared to the other cropping configurations. The maize baseline system follows the same pattern, whereas high CV values in the sole soybean and in the intercropping system for both crops suggest a higher crop sensitivity to variability in rainfall.

Tab. 13: Coefficient of variation (CV) for rain parameters and crop yields for the long-term climate scenario from 2081 to 2100. DS=dry spell, WS=wet spell, CV=coefficient, GM=Gliricidia-maize, SM=soybean-maize.

	Sum	Max DS	Max WS	Mean DS	Mean WS
Dec-Feb	23.3	25.0	42.3	22.7	16.0
Mar-Mai	36.4	28.3	31.0	34.1	19.1
Annual	18.7	6.6	42.3	10.6	13.8

CV % - Agricultural systems

	Maize	Soybean	GM	SM - Maize	SM - Soybean
	13.2	18.8	5.2	20.2	18.8

Further, the table shows that the duration of maximum wet spells is more variable than its mean duration, hereby indicating higher unpredictability of extreme rainfall events. On the other hand, maximum and mean dry spells are similar, the prior being slightly higher in the winter and lower in the spring. This suggests that extreme dry spells are less predictable during the wet season. Moreover, CV of total rainfall over spring, thus during maturing and ripening time, is considerably higher than over winter. Fig. 32 shows averages of mean and maximum dry and wet spells during winter and spring seasons. Average values of maximum dry spells are four times higher than mean ones with a period of 38 days compared to 9 days. Maximum consecutive days of wet spells in the wet season amount to 5 days compared to 2 days for mean periods.

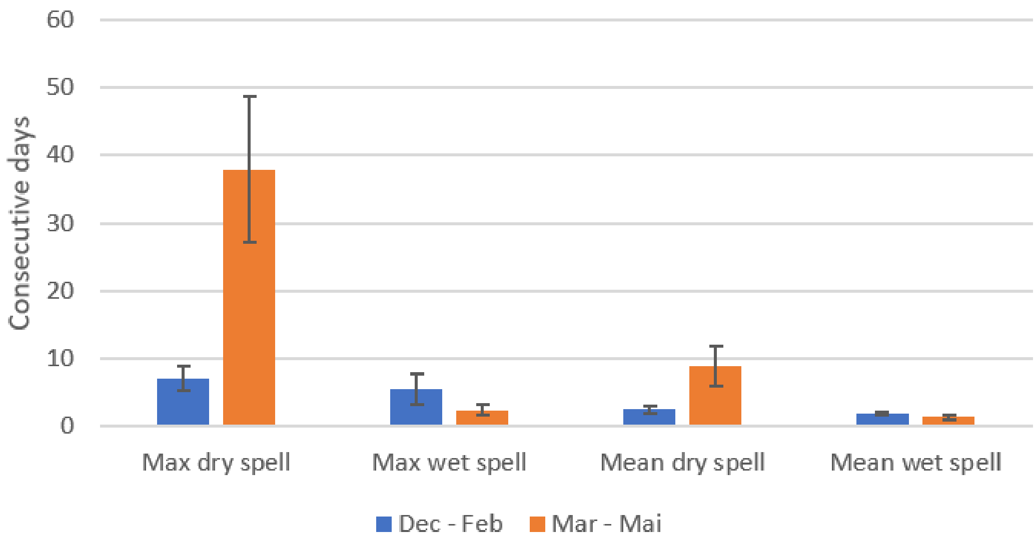


Fig. 32: Maximum and mean monthly dry and wet spells during winter and spring averaged over the present simulation period from 2082-2100.

The one-way ANOVA test showed that there were significant differences in maize yields across agricultural systems (P=0.0). The two-way ANOVA showed that the effects of monthly maximum dry spells during the growing season on yields didn't depend significantly on the agricultural system in place.

4. Discussion

4.1 Results analysis

Baseline simulation from 2001-2020

The intercropping system was the most beneficial one for maize and soybean yields and low evaporation losses. This can be due to beneficial nutrient supply by legume plants, higher compatibility of maize and soybean plants below ground and higher ground cover protecting the soil from evaporation. An increase of extractable soil water availability for both crops in the intercropping system compared to the baseline models indicates the absence of water competition and suggests synergies in below ground rooting patterns and water reallocation. Simulated rowing patterns were similar for both crops, maize and soybean were sown in December, however, while maize was harvested in Mai soybean matured only two months later.

On the other hand, results indicate high below ground competition between plants in the agroforestry, with a considerable reduction in total extractable soil water and maize transpiration compared to the baseline maize simulation. Literature suggests the contrary, since Gliricidia plants can root deeper and lift inaccessible soil water up to levels reachable for maize roots, plant available soil water should increase for nearby planted crops (Makumba et al., 2006). Above ground competition for sunlight is improbable, since Gliricidia biomass was significantly lower than maize biomass due to heavy pruning.. Further analysis would be necessary to determine deeper lying drivers such as competition for nutrients, planting density, etc. The negative impact of Gliricidia on crop yields is not consistent withfindings of a long-term maize Gliricidia intercropping study in Malawi. in which maize yields amounted to 6 to 7 t ha-1 with a fertilizer input of 48kg N ha-1 and the same planting density used for the thesis. In the mentioned study maize plant density was the same in the monocropping and the agroforestry system and after 11 years maize yields in the latter were 1.9 times higher than in the monocultivation, whereas for this work, maize density was decreased by one plant m-2 in the agroforestry system and yields were 1.1 times higher.

(Akinnifesi et al., 2007; Makumba et al., 2006; Smethurst et al., 2017). Additionally, evaporation reduction was lower in the tree system than in the intercropped one. Usually, agroforestry systems show less evaporation losses due to a large canopy extend (Morris & Garrity, 1993). Since the Gliricidia trees were heavily pruned, as can be seen in the biomass charts, it might have led to insignificant shading not effecting the systems evaporation amounts. Furthermore, the density of the trees might have been too low.

The evaporative stress index was highest for both the intercropping and the agroforestry system, while also showing the highest data ranges. Reasons therefore are the high values for combined actual evapotranspiration of the system components while potential evapotranspiration remains constant. Furthermore, higher standard deviations in average monthly transpiration for intercropped soybean, maize and agroforestry maize than in the sole cropping systems suggests high yield variability during growing seasons and therefore high ranges in evapotranspiration.

The reason for yield-based water productivity being highest for all maize including cropping systems is twofold.. Firstly, average maize yields are generally higher than soybean yields and secondly the used improved maize cultivar has a high yield potential,compared to the chosen more conventional soybean cultivar.

Interestingly, sole maize showed by far the highest biomass-based water productivity values, indicating that plant interaction in both combined systems was affecting aboveground biomass accumulation negatively. Combined with considerably higher evapotranspiration rates of multi-component systems, total system water productivity for the intercropping and the agroforestry systems remained lower. In a field study Mudenda 2015 found that late maturing maize cultivars, such as SC719, have yield- and biomass-based water productivity values of between 3.72 to 13.22 kg yield ha^{-1} mm^{-1} and 13.2 to 52.9 kg ha^{-1} mm^{-1} respectively (Mudenda, 2015). These fit the average simulation values of 13.6 kg yields ha^{-1} mm^{-1} and 16.5 yields ha^{-1} mm^{-1} respectively.

Averages of biomass-based water productivity of the entire system were higher than yield-based ones for both monocropping and the intercropping system for soybean. This aligns with literature suggesting that efficient water use increases in combined plant systems (Black & Ong, 2000). Factors causing the opposite trend in the agroforestry and the intercropping system for maize are substantially higher combined evapotranspiration values as discussed above.

Even though the statistical analysis indicated maize yield indifference across systems towards weather extreme impacts, the intercropping system showed more promising yield results and a slightly higher yield resilience towards rainfall variability than the maize monocultivation.

Long-term climate change scenario and comparison to baseline simulation

Overall, maximum crop yields decreased in the climate change scenario by 1.7 t ha^{-1} for maize and increased by 1.1 t ha^{-1} for soybean compared to the present one. The increase of soybean yields in the climate change simulation is in agreement with the world bank report cited prior in this work, predicting soybean yield increases under future climate scenarios (CIAT & World Bank, 2018). Different to the present simulation, highest maize yields were achieved in the agroforestry system in the long-term scenario.. However, evaporation and maize transpiration didn't increase in the agroforestry system in comparison to the maize baseline model and total extractable soil water even decreased.For maize in the intercropping system, total and extractable soil water within the first 450 mm of soil depth increased whereas transpiration decreased, resultingin slightly lower maize yields than in the sole maize system. .

Soybean yields were highest in the intercropping system.With a decrease in soybean planting density by a third in the intercropping system the yield increase is quite astonishing and realistically doubtable. Drivers might be the increase in soybean transpiration and extractable soil water within the first 450 mm of soil depth in the intercropping compared to sole soybean. However, model components driving this increased need to be analysed more in depth to determine any errors in calibration. . The shift in most beneficial cropping configurations across time periods suggests higher resistance of multiple component systems against climate change effects on crops..

Average yield-based water productivity for sole and intercropped maize decreased by 1.9 kg ha^{-1} mm^{-1} and 4.5 kg ha^{-1} mm^{-1} respectively in the future climate change scenario compared to the present one, owing to lower yields while evapotranspiration remained the same for sole maize and decreased 1.2 times in the future intercropping system. Highest values were obtained in the agroforestry, amounting to 12.9 kg ha^{-1} mm^{-1}, which is an overall decrease in best maize water productivity of 1.3 kg ha^{-1} mm^{-1} compared to the sole maize system in the present scenario. The improvement of agroforestry water productivity from the present to the long-term scenario results from a 1.2 times higher average value for maize transpiration in the present agroforestry and a 1.1 times yield increase in the climate change scenario. Therefore, water use efficiency in the agroforestry was increased in the climate change scenario. For soybean, yield-based water productivity increased in the long-term scenario by 1.7 kg ha^{-1} mm^{-1} and 2 kg ha^{-1} mm^{-1} in the sole and intercropped simulation respectively and obtained slightly higher values in the prior with an average of 5.6 kg ha^{-1} mm^{-1}. This is due to a yield increase in the long-term scenario as described above. Variability decreased in the agroforestry system and stayed the same for sole maize.

These results would suggest that maize agroforestry configurations are more adaptable to extreme weather pattern changes than mono cultivated maize based on the system's ability to efficiently allocate accessible water (Barrios et al., 2012). However, since aboveground accumulation of Gliricidia biomass was significantly low in the long-term scenario, it is likely that maize yields might have been less influenced by the trees resulting in higher crop yields. The exact reasons for Gliricidia trees not growing properly after sowing and emerging are unclear but are undoubtedly connected to differences in climate, since weather parameters were the only variables changed in the present scenarios to obtain the long-term ones. Nevertheless, Gliricidia trees had a visible impact on maize crops since yields were higher in the agroforestry than the sole maize system.

Average biomass-based water productivity of the entire system was highest in the monocultivated maize, following the same pattern of the present scenario with a decrease of 0.8 kg ha^{-1} mm^{-1}. Across the other cropping systems values increased by 1.8 kg ha^{-1} mm^{-1} to 2.9 kg ha^{-1} mm^{-1}, with the intercropping system showing second highest values amounting to 13.4 kg ha^{-1} mm^{-1} followed by the agroforestry with 12.5 kg ha^{-1} mm^{-1}. Whole system water productivity was higher than yield-based one across all systems except for the agroforestry one. This trend was also observed in the present scenario and is due to low aboveground biomass accumulation of Gliricidia trees.

Evaporative stress index didn't change considerably across time periods, with the intercropping system still ranking highest, followed by the agroforestry. As described above, since potential evapotranspiration remains constant across cropping configurations it is apparent that the multiple component systems have a higher evaporative stress index. Even though Gliricidia biomass remained very low evapotranspiration decreased 1.2 times and therefore still amounted to a yearly average of 541 mm. The intercropping system might have the highest values due to the considerable increase in extractable soil water for both crops, indicating below ground synergies, as described above. Sole maize had a slightly higher value than soybean. A slight overall decrease of up to 0.1 was observed in the future scenario. Variability in values of the intercropping systems decreased considerably compared to the present simulation, due to higher yield stability across years, as can be seen in the yield charts.

While the statistical analysis indicates that with long-term climatic conditions, yield reductions due to extreme weather patterns are not improved by changing agricultural systems from monocropping to intercropping ones, the shift of highest maize yields from the intercropping system in the present to the agroforestry system in the long-term scenario suggests otherwise.

Total rainfall variability in winter and spring were 4% lower and 20% higher in the present scenario than in the long-term one whereas annual variability stayed the same. Maximum dry spell variability was lower across all time periods in the long-term simulation, whereas variability of maximum wet spells in winter and spring increased by 10% and decreased by 20 % in the long-term simulation. These findings suggest that wet spells become more variable during the wet season in a long-term climate change scenario and might decrease in the dry season. Average duration of extreme weather events stayed constant across simulated time periods. One exception is the mean duration of maximum dry spells which decrease in spring by 10 days in the long-term scenario.

Field data collection results analysis

For better comparison of the soil analysis on site measurement results to literature Tab. 14 lists measured and published parameters. Values were taken from the Malawi Land Resources Evaluation Project described above and from the ISRIC global soil database published by Omondi et al., 2023 and the Ministry of Agriculture Government of Malawi et al., 2021.

Measured total organic carbon was higher than total soil carbon from literature across all soil depths by approximately 1%, whereby both experiments showed a decreasing tendency with depth. Total nitrogen was slightly higher whereas pH was lower in the measured experiment. Measured texture was similar to literature values. Mean bulk density in 30 cm depth across both measuring locations was considerably lower with 1.24 g cm^{-3}. However, the mean of one only one measuring location amounted to 1.34 g cm^{-3} aligning to the published values, while the mean of the other location was 1.15 g cm^{-3}. Since there weren't outliers and all the values at that depth at this location were low, a mistake while taking the sample is less probable than inaccurate digging and preparation of this soil layer. Measured saturated soil moisture content was 10% higher.

Tab. 14: Measured and published soil physical and chemical parameters.

Depth [cm]	BD [g cm^{-3}]	Cay [%]	Silt [%]	Sand [%]	pH	Tot C [%]	Tot N [%]	Sat volum water cont [%]
Literature								
0-10	1.39	24	14	62	5.9	1.60	0.11	0.39
10-20	1.40	25	14	61	5.8	1.51	0.10	0.39
20-30	1.41	30	13	57	5.8	1.34	0.07	0.40
On site measurements								
0-10	1.36	17	15	68	5.2	2.60	0.23	0.51
10-20	1.44	24	8	68	5.3	2.04	0.18	/
20-30	1.24	27	10	63	5.4	2.17	0.19	/

Average Ks obtained from the infiltration measurements fit literature values for the same soil texture (see Tab. 15). Overall, soybean infiltration rates were lower than maize infiltration rates. See table below for comparison.

Tab. 15: measured and literature Ks values.

	Measured			Literature
Ks	TotMean	SoyMean	MaizeMean	Rahmati et al. 2018
[cm/h]	4.8	2.7	7.2	5.4

The statistical analysis resulted in the infiltration measurements being significantly different from one another, even within the same plot. Underlying factors are unclear since weather conditions were always the same and across plots of the same trial tillage management was always the same. On top of that, bulk density and soil texture measurements were not significantly different across locations, thus there couldn't be found a correlation between infiltration time and soil characteristics of one location.

4.2 Limits and weaknesses of this thesis

The input data quality is a considerable source of uncertainty in the accuracy of the modelling results. Due to limited data availability relevant soil water parameters such as field capacity and wilting point needed to be calibrated with literature values whose origins were regional and international. Further, despite subsidy programs, the maize cultivar used might not be able to represent average small holder farmer maize yields in Malawi, since this is an improved variety with high yield potential.

Concerning modelling results, it is not clear why Gliricidia trees didn't grow properly in the climate change scenario. Lower tree biomass positively influenced the growth of maize crops which affects the authenticity of resulting maize yields in an agroforestry system and reduces the representativeness of the outcomes. Thus, the high maize yield results in the long-term agroforestry simulation need to be analysed carefully keeping this divagation in mind. Further modelling alternations would need to be done to analyse what the underlying cause of the diminished tree growth is. Additionally, it is surprising that soybean yields increased in the intercropping system while planting densities were halved compared to the soybean monocultivation. This could only be explained by the immense increase in available plant water, but it is not certain whether there are other underlying factors.

Moreover, SDSM is a handy and powerful downscaling tool, however the user's knowledge is substantially influencing the outcomes of a generated climate change scenario. This is due to the freedom to modify parameters such as variance and mean of a daily weather series. Even though these parameters were researched carefully there were not substantial differences across the three climate change scenarios, suggesting that parameter values should have been chosen more accurately based on further literature. This also creates an uncertainty around the reliability of the cropping system outcomes in the long-term climate change scenario.

Concerning the quality of climate change data of the CMIP6 ensemble, Ayugi et al. 2021 found that some CMIP6 models overestimate extreme wet days and consecutive wet days and underestimate maximum 5-day precipitation in both seasons (Akinsanola et al., 2021; Ayugi et al., 2021). Additionally, there are still wet and dry modelled biases over the period October to December and March to Mai respectively. Therefore, it has to be considered that these biases might have been reproduced in the generated climate change weather files. Additionally, by using a model ensemble of more than 30 models, it might be that the climate change scenario extremes where averaged, since different prediction models can have considerably different outcomes.

Finally, regarding on site infiltration measurements, due to time constraints it was not possible to conduct more measurements than two per plot. The assumption was made that the soil characteristics are the same across all four plots and therefore statistically analysis would be possible. The results showed that all measurements are significantly different from one another. Thus calculating an average value for the saturated hydraulic conductivity valid across all cropping simulations seemed reasonable.

5. Conclusion

In a present scenario, it was not found that shifting from a maize monocultivation to an agroforestry improved the water productivity, whereas the water yield gap was decreased with higher values of the evaporative stress index. In addition, maize yields were reduced considerably in the agroforestry. However, the hypothesis was fulfilled for the soybean maize intercropping system in which water parameters increased as well as maize and soybean yields. One exception was the biomass-based water productivity which was highest for monocropped maize.

Under a long-term climate change scenario, the agroforestry and the intercropping systems were proven to be the most beneficial ones for closing water yield gaps. Yield-based water productivity and maize yields were highest in the agroforestry, while the biomass-based one was still highest for sole maize. However, it is important to keep in mind that Gliricidia trees were only growing very little and therefore outcome authenticity and representability of the results might be impacted. In conclusion, multicomponent cropping systems seem to be promising adaptation mechanisms towards climate change induced weather patterns.

6. References

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Appendix 1 – Raw data of soil analysis and infiltration rates

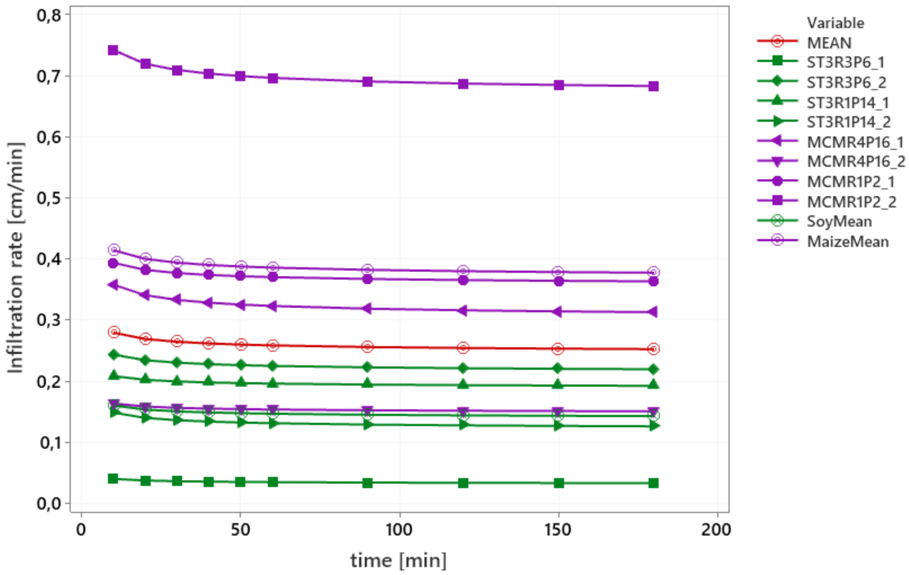

Fig. A 1: Infiltration rates near and at soil saturation at two soybean (S) and two maize (M) plots. T=treatment, R=replica, P=plot.

Tab. A 1: Saturated hydraulic conductivity for all measuring locations. T=treatment, R=replica, P=plot, S=soybean, M=maize.

Ks	[cm min^{-1}]	[cm h^{-1}]
TotMean	0.1	4.8
SoyMean	0.0	2.7
MaizeMean	0.1	7.2
ST3R3P6_1	0.0	0.6
ST3R3P6_2	0.1	4.2
ST3R1P14_1	0.1	3.7
ST3R1P14_2	0.0	2.4
MCMR4P16_1	0.1	5.9
MCMR4P16_2	0.0	2.9
MCMR1P2_1	0.1	7.0
MCMR1P2_2	0.2	13.2

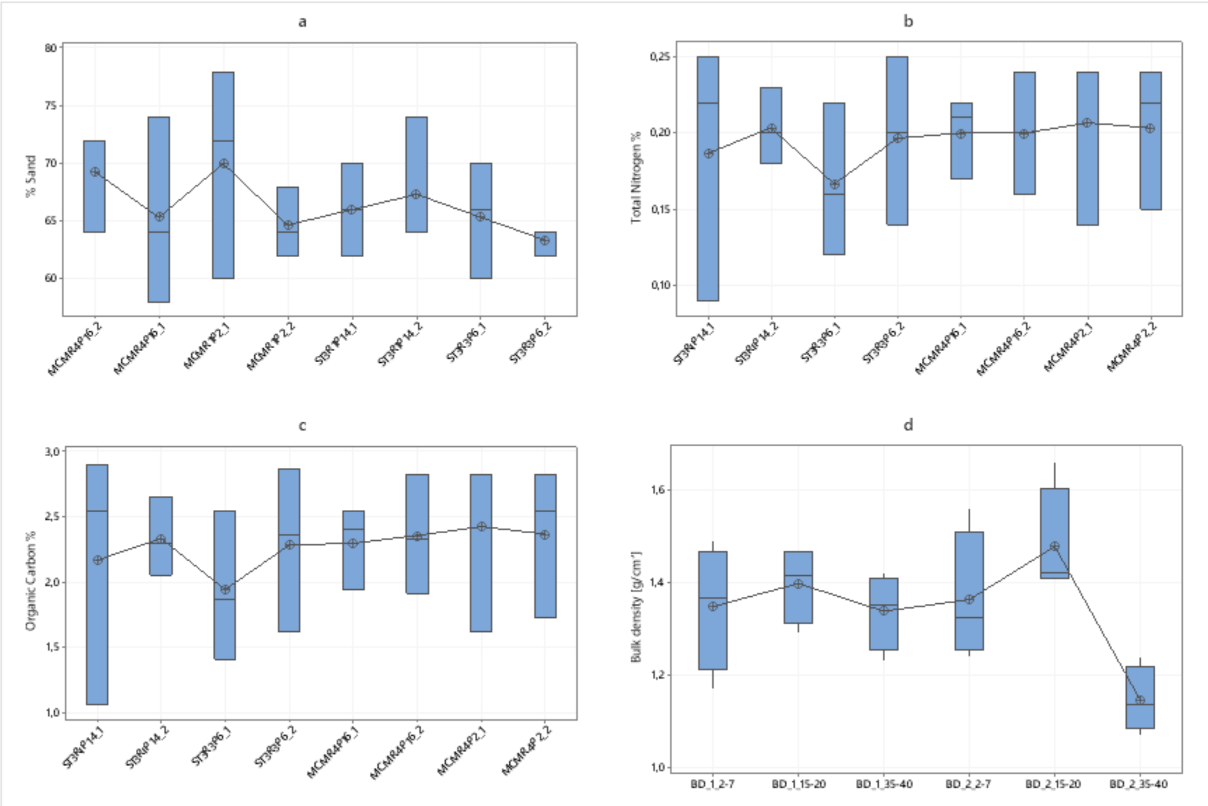

Fig. A 2:Raw data of texture (sand) (a), total nitrogen (b), organic carbon (c) and bulk density (d) across all measurement sites.

Appendix 2 – Calibrated and parameterized input data for APSIM

Tab.A 2: Soil water input parameters for APSIM. KL = Fractional water extraction, LL15 = Drained lower limit (wilting point), DUL = Drained upper limit (field capacity), Ini. SW = Initial soil water, KS = Saturated hydraulic conductivity.

Depth [cm]	KL mm mm^{-1} d^{-1}	Air dry mm mm^{-1}	LL15 mm mm^{-1}	DUL mm mm^{-1}	Saturated mm mm^{-1}	Initial Soilwater mm mm^{-1}
			Maize			
0 - 15	0.08	0.04	0.18	0.23	0.487	0.215
15 - 30	0.08	0.08	0.18	0.27	0.4	0.215
30 - 45	0.08	0.13	0.2	0.27	0.41	0.225
45 - 60	0.08	0.13	0.2	0.27	0.41	0.21
60 - 80	0.08	0.13	0.2	0.28	0.41	0.21
80 - 100	0.06	0.13	0.2	0.28	0.41	0.23
100 - 120	0.04	0.23	0.25	0.28	0.28	0.265
120 - 140	0.03	0.26	0.27	0.29	0.29	0.27
140 - 160	0.02	0.27	0.27	0.3	0.3	0.27
160 - 180	0.02	0.28	0.29	0.3	0.3	0.29
180 - 200	0.02	0.28	0.29	0.29	0.29	0.29
Sources	(1)	(1), (5)	(1), (3), (5)	(1), (3), (5)	(1), (3), (5)	(2)
			Soybean			
0 - 15	0.06	0.15	0.19	0.233	0.49	0.215
15 - 30	0.06	0.16	0.24	0.27	0.4	0.215
30 - 45	0.06	0.16	0.24	0.27	0.41	0.225
45 - 60	0.06	0.17	0.24	0.27	0.41	0.21
60 - 80	0.04	0.19	0.23	0.28	0.41	0.21
80 - 100	0.04	0.22	0.24	0.28	0.41	0.227
100 - 120	0.04	0.23	0.24	0.28	0.44	0.265
120 - 140	0.02	0.26	0.27	0.29	0.44	0.265
140 - 160	0.02	0.26	0.27	0.3	0.44	0.242
160 - 180	0.01	0.25	0.29	0.3	0.44	0.261
180 - 200	0.01	0.24	0.25	0.29	0.44	0.261
Sources	(6)	(1)	(1), (3), (5)	(1), (3), (5)	(1), (3), (5)	(2)

MS intercropping						
0 - 15	see M, S BS	0.095	0.19	0.2315	0.4885	0.215
15 - 30	see M, S BS	0.12	0.21	0.27	0.4	0.215
30 - 45	see M, S BS	0.145	0.22	0.27	0.41	0.225
45 - 60	see M, S BS	0.15	0.22	0.27	0.41	0.21
60 - 80	see M, S BS	0.16	0.22	0.28	0.41	0.21
80 - 100	see M, S BS	0.175	0.22	0.28	0.41	0.2285
100 - 120	see M, S BS	0.23	0.25	0.28	0.36	0.265
120 - 140	see M, S BS	0.26	0.27	0.29	0.365	0.2675
140 - 160	see M, S BS	0.265	0.27	0.3	0.37	0.26
160 - 180	see M, S BS	0.265	0.29	0.3	0.37	0.2755
180 - 200	see M, S BS	0.26	0.27	0.29	0.365	0.2755
Sources		(1), (5)	(1), (3), (5)	(1), (3), (5)	(1), (3), (5)	(2)
GM agroforestry						
0 - 15	0.10	0.04	0.18	0.23	0.487	0.215
15 - 30	0.10	0.08	0.18	0.27	0.4	0.215
30 - 45	0.10	0.13	0.2	0.27	0.41	0.225
45 - 60	0.10	0.13	0.2	0.27	0.41	0.21
60 - 80	0.10	0.13	0.2	0.28	0.41	0.21
80 - 100	0.10	0.13	0.2	0.28	0.41	0.23
100 - 120	0.10	0.23	0.25	0.28	0.28	0.265
120 - 140	0.10	0.26	0.27	0.29	0.29	0.27
140 - 160	0.02	0.27	0.27	0.3	0.3	0.27
160 - 180	0.02	0.28	0.29	0.3	0.3	0.29
180 - 200	0.02	0.28	0.29	0.29	0.29	0.29
Sources	(6)	(1), (5)	(1), (3), (5)	(1), (3), (5)	(1), (3), (5)	(2)

On site measurements

Africa Soil Profiles Database

Tuning during calibration

Southern Africa range

Regional

Suggested from APSIM

Source Codes

(1) Smethursta et al. 2017

(2) Leenaars et al. 2014

(3) Chisanga et al. 2021

(4) Makumba et al. 2006

(5) Mante et al. 2019

(6) APSIM

Tab.A 3: Soil physical and chemical input parameters for APSIM for all cropping simulations

Depth [cm]	Clay [%]	Sand [%]	Silt [%]	BD g cm^{-3}	pH	NO3 µg g^{-1}	NH4 µg g^{-1}	C [%]	KS mm d^{-1}
0-15	17	68	15	1.36	5.2	7.4	2.5	2.65	40.3
15 - 30	24	68	8	1.44	5.3	6.4	1	2.04	21
30 - 45	27	63	10	1.24	5.4	6.4	1	2.17	16
45 - 60	26	66	8	1.47	5.6	5.4	0.5	1.2	11
60 - 80	26	66	8	1.31	5.6	4.4	0.1	1.115	15
80 - 100	26	66	8	1.42	6	3.4	0.1	0.86	15
100 - 120	26	66	8	1.38	6.3	2	0.1	0.555	15
120 - 140	26	66	8	1.32	6.3	1	0.1	0.05	15
140 - 160	26	66	8	1.3	6.4	1	0.1	0.05	15
160 - 180	26	66	8	1.31	6.6	0.1	0.1	0.05	15
180 - 200	26	66	8	1.31	6.6	0.1	0.1	0.05	15
Sources	(2)	(2)	(2)	(5)	(4)		(1)	(1), (4)	(3)

On site measurements
Africa Soil Profiles Database
Tuning during calibration
Southern Africa range
Regional

Source Codes
(1) Smethursta et al. 2017
(2) Leenaars et al. 2014
(3) Chisanga et al. 2021
(4) Makumba et al. 2006
(5) Mante et al. 2019

Phenology

Calibrated phenological stages for local Maize and Soybean cultivars. Phenological stages and terms used in APSIM are different for maize and soybean.

Tab.A 4: Days after planting and TT for phenological stages for SC Safari and SC719, based on onsite data, literature, and calculated TT. (Bayer U.S. LLC, 2020; Magodo, 2007; Malaza & Tana, 2023; Mudenda, 2015; Naeve, 2018)

Cultivar	Growth stages	Days after planting	TT [°C]
SC Safari (Soybean)	Vegetative	5-48	774
	Late Grainfilling_complete grainfilling	65-104	694
	Maturing	104-120	280
SC719 (Maize)	Juvenile	4-16	203
	Leaf appearance	17-76	927
	Flagleaf to Flowering	77	10
	Flowering to Grainfilling	78-90	197
	Grainfilling	89-165	1045

Plant management

Tab.A 5:Plant management input data for APSIM for all the cropping simulations.

System	**M**		**S**		**MS**			**MG**		
Plant										
Crop	Maize	Source	Soybean	Source	Maize	Soybean	Source	Maize	Gliricidia	Source
Cultivar	SC719		SC Safari		SC719	SC Safari		SC719	Generic	
Root depth [m]	0.45		0.45	(2)	0.45	0.45	(2)	0.45	2	(1)
Plant management										
Row spacing [m]	0.75		0.5		0.75	0.75	(8)	0.75	1.5	(4)-(7)
Plant population [m²]	5.3		40		5.3	26.6	(8)	4.44	0.74	(4)-(7)
Start - end of sowing window	15.12. - 31.12.		01.12. - 15.01.		15.12. - 31.12.	01.12. - 15.01.		15.12. - 31.12.	15.12.	(4)-(7)
Ini. surface residual type	Maize		/		Soybean			Gliricidia		
Mass of ini. surface residue [kg/ha]	2500		0		3000			5000		(4)-(7)
C:N ratio	75	(3)	/		12		(3)	8		
Fertilizer N kg/ha	92		10		92	10		92	/	(9)
Fertilizer P kg/ha	/		24		/	24		/	/	(9)
Date fertilizer	planting date		planting date		planting date	planting date		planting date	/	(9)
Specific Gliricidia parameters										
First harvest [month]									10	(4)-(7)
Second harvest [month]									12	(4)-(7)
Third harvest [month]									2	(4)-(7)
Leaf removal Wt [g/m²]									0.45	(4)-(7)
Leaf removal N [g/m²]									0.05	(4)-(7)
Harvest age (removal)									11	(7)

Source codes	Colour codes
(1) Smethursta et al. 2017	On site measurements
(2) Mante et al. 2019	Tuning during calibration
(3) Wingeyer 2007	Southern Africa range
(4) Makumba et al. 2006	Regional
(5) Chirwa et al. 2007	Suggested by APSIM
(6) Akinnifesi et al. 2007	International
(7) Ikerra et al. 1999	
(8) Simbine et al. 2018	
(9) Swamila et al. 2021	

Appendix 3 – Percentage change of output parameters

Tab.A 6: Percentage change of monthly water parameters in the present scenario. Ta = actual Transpiration, Evapo_a = actual Evaporation, WS = Water storage, ESW = extractable soil water, ESW / WS 450 = until 450 mm depth.

Year	Ta	Evapo a	Tot WS	WS 450	Tot ESW	ESW 450
GM						
2002	-3	-3	-10	-2	-42	-6
2003	-2	-24	-13	-21	-86	-79
2004	-14	-11	-15	4	-48	10
2005	-56	-24	-6	-9	-36	-22
2006	2	-10	-11	5	-44	16
2007	-51	-30	-4	1	-18	3
2008	17	-8	-15	-15	-77	-59
2009	-20	-24	-10	-2	-42	-5
2010	-8	-2	-13	-5	-58	-18
2011	-35	-22	-14	-19	-80	-54
2012	-36	8	-9	3	-30	8
2013	9	-7	-14	-20	-77	-54
2014	-20	-9	-15	-26	-90	-67
2015	-1	0	-12	-25	-135	-127
2016	-63	-7	-18	-34	-125	-131
2017	-47	13	-10	-2	-35	-8
2018	-59	-22	-11	-2	-43	-5
2019	-1	-4	-10	-5	-41	-11
2020	-26	-17	-9	-12	-50	-31
SM Maize						
2002	41	-19	3	24	23	72
2003	13	-28	5	16	58	83
2004	25	-13	5	43	24	124
2005	25	-17	6	14	52	46
2006	48	-21	6	41	36	152
2007	-8	-29	8	38	46	116
2008	19	-21	4	24	39	122
2009	23	-29	8	35	46	101
2010	14	-20	3	27	29	133
2011	0	-37	6	13	54	53
2012	31	-24	5	44	28	150
2013	3	-26	4	12	39	47
2014	16	-19	1	5	25	27
2015	55	-13	-3	-5	11	9
2016	49	-8	-7	-10	-22	-12
2017	13	-22	7	43	34	167
2018	25	-29	6	39	37	146
2019	32	-22	6	24	39	65
2020	19	-23	5	18	45	63
SM Soybean						
2002	-3	0	2	23	45	139
2003	32	-2	7	17	158	323
2004	-4	-19	8	44	60	228
2005	20	-1	2	11	60	81
2006	-5	-7	6	40	69	329
2007	17	5	4	36	48	201
2008	16	3	4	26	73	553
2009	30	-7	8	34	85	184
2010	12	-2	4	30	67	637
2011	104	6	7	12	133	124
2012	23	-13	6	46	56	353
2013	47	1	5	12	105	122
2014	6	-1	3	10	110	117
2015	-21	-2	-6	-10	36	128
2016	-40	-4	-2	-3	112	516
2017	-10	-4	5	46	46	500
2018	48	-11	8	42	78	397
2019	7	-8	5	23	64	113
2020	18	1	3	19	68	154

Tab.A 7: Percentage change of monthly water parameters. Ta = actual Transpiration, Evapo_a = actual Evaporation, WS = Water storage, ESW = extractable soil water, ESW / WS 450 = until 450 mm depth.

Year	Ta	Evapo a	Tot WS	WS 450	Tot ESW	ESW 450
GM						
2082	-3	-3	-10	-2	-42	-6
2083	-2	-24	-13	-21	-86	-79
2084	-14	-11	-15	4	-48	10
2085	-56	-24	-6	-9	-36	-22
2086	2	-10	-11	5	-44	16
2087	-51	-30	-4	1	-18	3
2088	17	-8	-15	-15	-77	-59
2089	-20	-24	-10	-2	-42	-5
2090	-8	-2	-13	-5	-58	-18
2091	-95	-22	-14	-19	-80	-54
2092	-36	8	-9	3	-30	8
2093	9	-7	-14	-20	-77	-54
2094	-20	-9	-15	-26	-90	-67
2095	-1	0	-12	-25	-135	-127
2096	-63	-7	-18	-34	-125	-131
2097	-47	13	-10	-2	-35	-8
2098	-59	-22	-11	-2	-43	-5
2099	-1	-4	-10	-5	-41	-11
2100	-26	-17	-9	-12	-50	-31
SM Maize						
2082	41	-19	3	24	23	72
2083	13	-28	5	16	58	83
2084	25	-13	5	43	24	124
2085	25	-17	6	14	52	46
2086	48	-21	6	41	36	152
2087	-8	-29	8	38	46	116
2088	19	-21	4	24	39	122
2089	23	-29	8	35	46	101
2090	14	-20	3	27	29	133
2091	0	-37	6	13	54	53
2092	31	-24	5	44	28	150
2093	3	-26	4	12	39	47
2094	16	-19	1	5	25	27
2095	55	-13	-3	-5	11	9
2096	49	-8	-7	-10	-22	-12
2097	13	-22	7	43	34	167
2098	25	-29	6	39	37	146
2099	32	-22	6	24	39	65
2100	19	-23	5	18	45	63
SM Soybean						
2082	-3	0	2	23	45	139
2083	32	-2	7	17	158	323
2084	-4	-19	8	44	60	228
2085	20	-1	2	11	60	81
2086	-5	-7	6	40	69	329
2087	17	5	4	36	48	201
2088	16	3	4	26	73	553
2089	30	-7	8	34	85	184
2090	12	-2	4	30	67	637
2091	104	6	7	12	133	124
2092	23	-13	6	46	56	353
2093	47	1	5	12	105	122
2094	6	-1	3	10	110	117
2095	-21	-2	-6	-10	36	128
2096	-40	-4	-2	-3	112	516
2097	-10	-4	5	46	46	500
2098	48	-11	8	42	78	397
2099	7	-8	5	23	64	113
2100	18	1	3	19	68	154

Appendix 4 – Diagrams of the short- and mid-term climate change scenarios

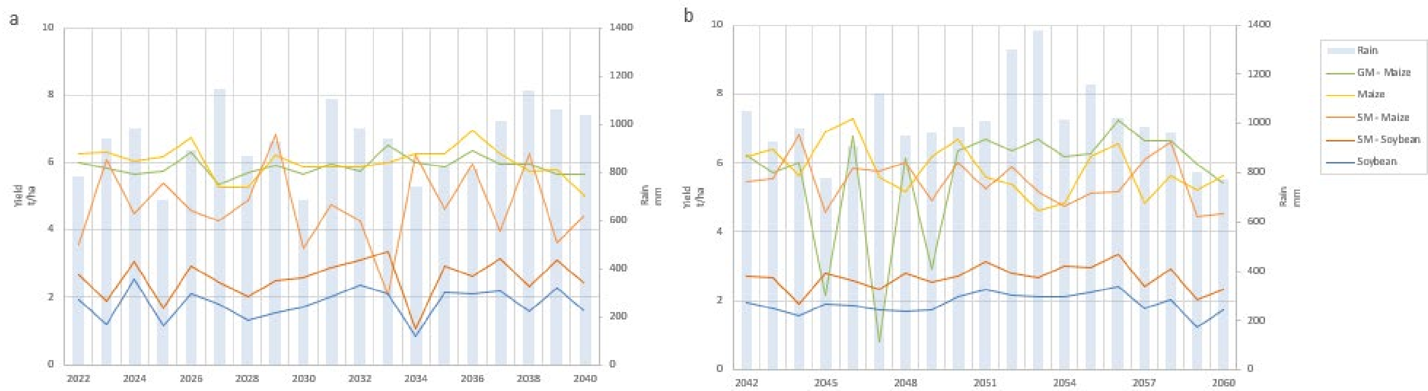

Fig. A 3: Yearly yields and rainfall for the short- and mid-term climate simulations from a) 2021-2040 and b) 2041-2060

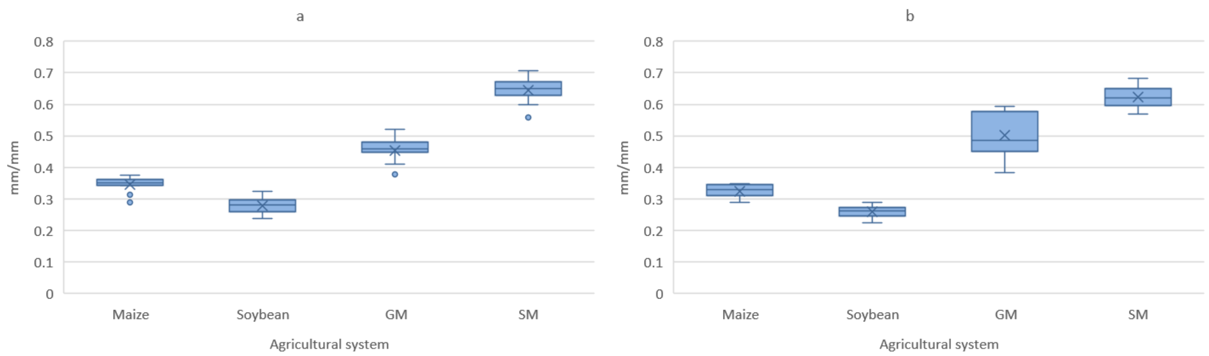

Fig. A 4: ESI for short- and mid-term climate scenarios from a) 2021-2040 and b) 2041-2060.

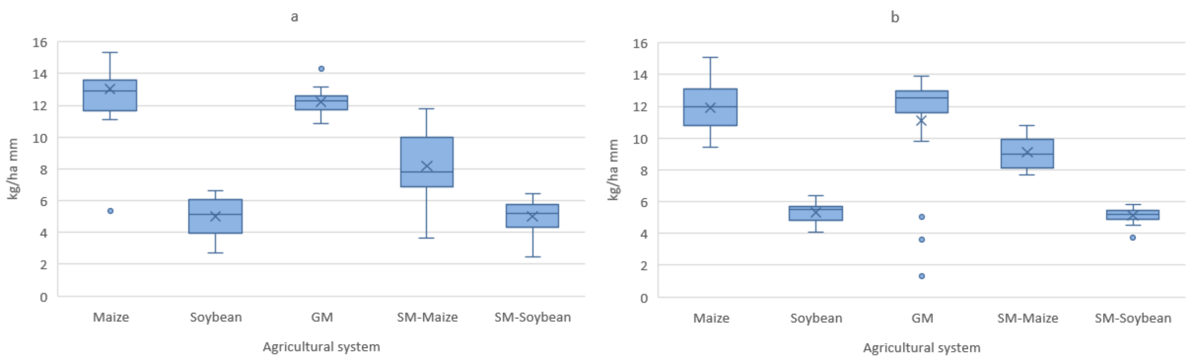

Fig. A 5: WP1 for short- and mid-term climate scenarios from a) 2021-2040 and b) 2041-2060.

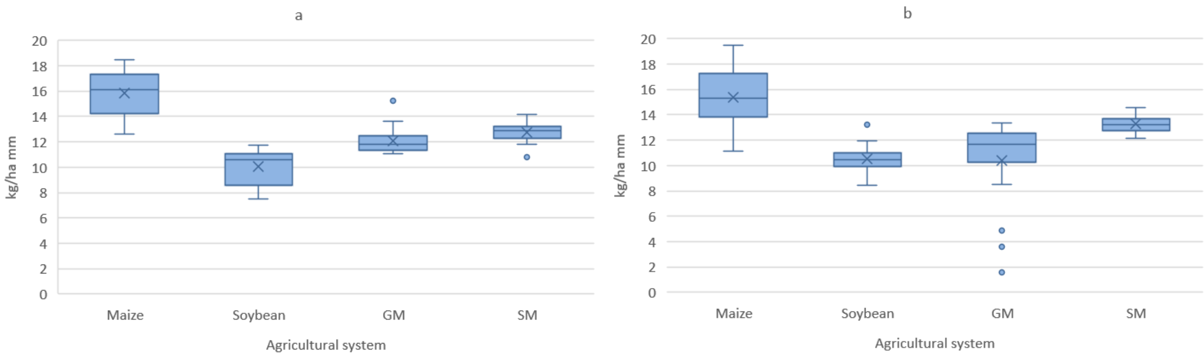

Fig. A 6: WP2 for short- and mid-term climate scenarios from a) 2021-2040 and b) 2041-2060.

Tab.A 8: Coefficient of variation for short- and mid-term climate scenarios from 2021 to 2040 and from 2041 to 2060.

CV % - Rainfall 2021-2040

	Sum	Max DS	Max WS	Mean DS	Mean WS
Dec-Feb	27.3	25.7	42.4	20.0	12.2
Mar-Mai	28.4	33.4	26.9	21.6	12.3
Annual	14.6	12.7	41.4	10.3	8.6

CV % - Agricultural systems

	Maize	Soybean	GM	SM - Maize	SM - Soybean
	8.0	25.2	4.8	25.2	22.8

2041-2060

	Sum	Max DS	Max WS	Mean DS	Mean WS
Dec-Feb	20.2	22.7	41.4	17.9	10.4
Mar-Mai	39.0	25.1	20.4	22.0	18.6
Annual	17.8	10.8	40.3	10.9	10.2

CV % - Agricultural systems

	Maize	Soybean	GM	SM - Maize	SM - Soybean
	12.9	14.8	30.6	12.4	13.4

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