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RESEARCH ARTICLE

Limits to adaptation: Agroforestry buffers but does not offset climate change impacts on maize yields in Dodoma, Tanzania

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Abstract

Agricultural productivity in the semi-arid region of central Tanzania is low and projected to further decrease due to climate change, exacerbating the already high levels of food insecurity among the rural population. Agroforestry is actively promoted in the region as an adaptation strategy due to its multiple biophysical and socio-economic benefits, but whether it can buffer future climate change impacts on maize yields has not yet been quantified. Previous modelling studies in central Tanzania focused either on maize monocropping or on agroforestry under current climate. Moreover, it remains unclear whether yield gains from agroforestry constitute genuine adaptation. Here, we show for the first time how a comprehensive evaluation framework can be used to disaggregate projected yield changes into four distinct indicators: climate change impact, agroforestry impact, agroforestry adaptation effect, and climate change impact with adaptation. The Agricultural Production Systems Simulator was used to simulate maize yields at six sites in Dodoma under current climate conditions and under a low- and a high-emission scenario (shared socio-economic pathways 1-2.6 and 5-8.5) for two periods centred on 2030 (2016–2045) and 2050 (2036–2065). Above-ground agroforestry effects were represented by 10% and 20% shading, associated temperature reductions, and tree litter input. Without adaptation, climate change is projected to reduce maize yields by 23–33%. Agroforestry increased yields under all climate conditions, and the agroforestry adaptation effect grew towards 2050, with 20% shade being most effective. However, the climate change impact with adaptation shows that agroforestry buffers but does not offset yield losses: under the high-emission scenario, yields remained below the baseline at both shade levels, with losses increasing towards 2050. These results demonstrate both the potential and the limits of agroforestry as an adaptation strategy in semi-arid Tanzania.

Keywords Crop modelling · APSIM · Semi-arid regions · Tree shading · *Grevillea robusta*

1 Introduction

Climate change poses a significant threat to agriculture and food security across sub-Saharan Africa (Omokpariola et al. 2025), where the livelihoods of approximately 70% of the population depend on rain-fed agriculture. Multiple biophysical, socio-economic, and political challenges heighten the region's vulnerability, while limiting its adaptive capacity (Connolly-Boutin and Smit 2016). These pressures are particularly pronounced in Tanzania, where high temperatures and variable rainfall have already contributed to significant crop yield losses in the past (Afifi et al. 2014; Mkonda and He 2018; Tarnavsky et al. 2018) and further declines are expected if no appropriate adaptation measures are taken (Rowhani et al. 2011; Tumbo et al. 2020). For instance, maize yields in central Tanzania are projected to decrease by 5–25% toward the end of the century (Msongaleli et al. 2015). As the majority of households practice small-scale rainfed agriculture primarily for subsistence and income generation (National Bureau of Statistics 2017), such yield losses are likely to deepen food insecurity and poverty across the region (Ahmed et al. 2011; Gebre and Rahut 2021), a concern reflected in the fact that currently

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approximately 60% of Tanzania's total population is already moderately or severely food insecure (FAO et al. 2025). These challenges are most acute in the semi-arid agroecosystems of central Tanzania, where low and erratic rainfall, combined with high temperature stress, leave smallholder farmers with particularly limited capacity to cope with ongoing and future climate change (Mdemu 2021; Randell et al. 2022; FAO et al. 2023).

Consequently, adaptation of semi-arid agroecosystems to current and future climate conditions is needed. In that context, the promotion of agroforestry has been proposed (Rosenstock et al. 2019; Skole et al. 2021; Terasaki Hart et al. 2023). Agroforestry refers to "land-use systems and technologies where woody perennials [...] are deliberately used on the same land management unit as agricultural crops and/or animals, in some form of spatial arrangement or temporal sequence" (Lundgren and Raintree 1983; Nair et al. 2021). Potential biophysical and socio-economic benefits of agroforestry systems include the creation of microclimates with lower mean air temperatures (Villani et al. 2022), less soil erosion and improved soil fertility (Macedo et al. 2024), enhanced biodiversity (Zemp et al. 2023), the provision of income through food and wood production (Quandt 2020), and synergies with climate change mitigation through carbon sequestration (Zomer et al. 2016; Smith et al. 2020). However, negative impacts are also possible when trees and crops compete for water and nutrients or when trees diminish the amount of light accessible to crops, thereby affecting their photosynthetic activity (Sanou et al. 2012; Sida et al. 2018a).

A meta-analysis of studies comparing agroforestry and non-agroforestry practices in sub-Saharan Africa revealed that, compared with controls, agroforestry significantly increased crop yield, total soil nitrogen, soil organic carbon, and available phosphorus (Kuyah et al. 2019). The analysis also showed that agroforestry practices reduced surface runoff and soil loss and improved infiltration rates and soil moisture content, making it a viable strategy for adapting to climate change. A review of ecosystem services provided by parklands in the Sahel of West Africa showed that these agroforestry systems are capable of buffering climate risks and sustaining agricultural production (Bayala et al. 2014). An increase in vegetation cover is associated with an increase in the total carbon content, highlighting the potential of agroforestry for carbon sequestration and for reducing greenhouse gases (Bayala et al. 2020). Similarly, *Faidherbia albida (F. albida)* trees, which are common in parklands, can buffer wheat against climate extremes in the Central Rift Valley of Ethiopia (Sida et al. 2018b). In the Dodoma region of Tanzania, high tree canopy cover was associated with a reduction in land surface temperature (Villani et al. 2022). In addition, a survey of 900 small-scale farmers in the Dodoma and Morogoro regions in Tanzania revealed that adopters of climate-smart strategies, such as agroforestry, are more food secure (Brüssow et al. 2017). Fig. 1 shows a *Gliricidia sepium* - maize agroforestry system in Dodoma, Tanzania.

Although agroforestry is promoted as a potential climate change adaptation strategy, studies modelling tree−crop interactions in African agricultural systems are relatively rare. Major challenges in modelling agroforestry systems include the diverse arrangements of trees and crops, the interactions between different system components, and the long lifespan of the tree component (Luedeling et al. 2016). According to a study on the climate change mitigation potential of alley cropping (walnut with wheat) in southern France, agroforestry systems are able to reduce the expected increases in heat, drought, and nitrogen stress by 20–35% compared to monoculture (Reyes et al. 2021). In a virtual experiment on the effect of *F. albida* on millet growth in Senegal, the presence of *F. albida* was found to significantly increase millet yields due to higher organic nitrogen contents in the topsoil (Sow et al. 2024). Similarly, Chemura et al. (2021) demonstrated that 20% shading in Ethiopia could reduce maize yield losses from climate change by 11%. An analysis of the profitability of gliricidia-maize agroforestry systems in Dodoma, Tanzania, based on simulated yields, concluded that these systems can contribute to increased income and food security (Swamila et al. 2021).

While previous modelling studies in central Tanzania focused on maize monocropping (Msongaleli et al. 2015; Volk et al. 2021) or on agroforestry profitability under current climate (Swamila et al. 2021), no study has quantified whether agroforestry can buffer future climate change impacts in Dodoma, nor whether its yield benefits constitute genuine adaptation in the sense of Lobell (2014). According to Lobell (2014), a practice only qualifies as adaptation if it reduces negative (or enhances positive) climate change impacts, i.e., if it performs better under climate change than under current conditions. Closing this gap is of practical relevance, as agroforestry is actively promoted in Dodoma through governmental and non-governmental programmes (Moore et al. 2020; Ngongolo and Kilonzo 2022; Gayo 2023). This study addresses these gaps by applying, for the first time, a comprehensive evaluation framework that disaggregates the combined effects of climate change and agroforestry on maize yields into four distinct components: (1) climate change impact, (2) agroforestry impact, (3) agroforestry adaptation effect, and (4) climate change impact with adaptation. This disaggregation enables a more nuanced understanding of the individual and interactive effects of agroforestry and climate change on crop performance. Accordingly, we seek to answer the following research question: "What is the impact of climate change on maize yields in Dodoma, Tanzania, and how can agroforestry help to mitigate these impacts?"



Fig. 1 Gliricidia sepium – maize agroforestry system in Dodoma, Tanzania. Photocredit: Anna Hampf.

2 Materials and methods

2.1 Study area

The Dodoma region, situated in central Tanzania, East Africa (Fig. 2a), covers an area of 41,310 km^2 and includes the country's capital. Most of the region has a hot semi-arid climate, with a long dry season spanning from late April to early December and a short rainy season from late December to early April (Mayaya et al. 2015; Villani et al. 2022). The yearly average precipitation reaches 570 mm, with 85% of the rainfall occurring during the rainy season, while the average maximum and minimum temperatures are 31 °C and 18 °C, respectively (id.).

The primary land cover types in Dodoma are grassland, shrubland, and cropland. Only 8.5% of the area is

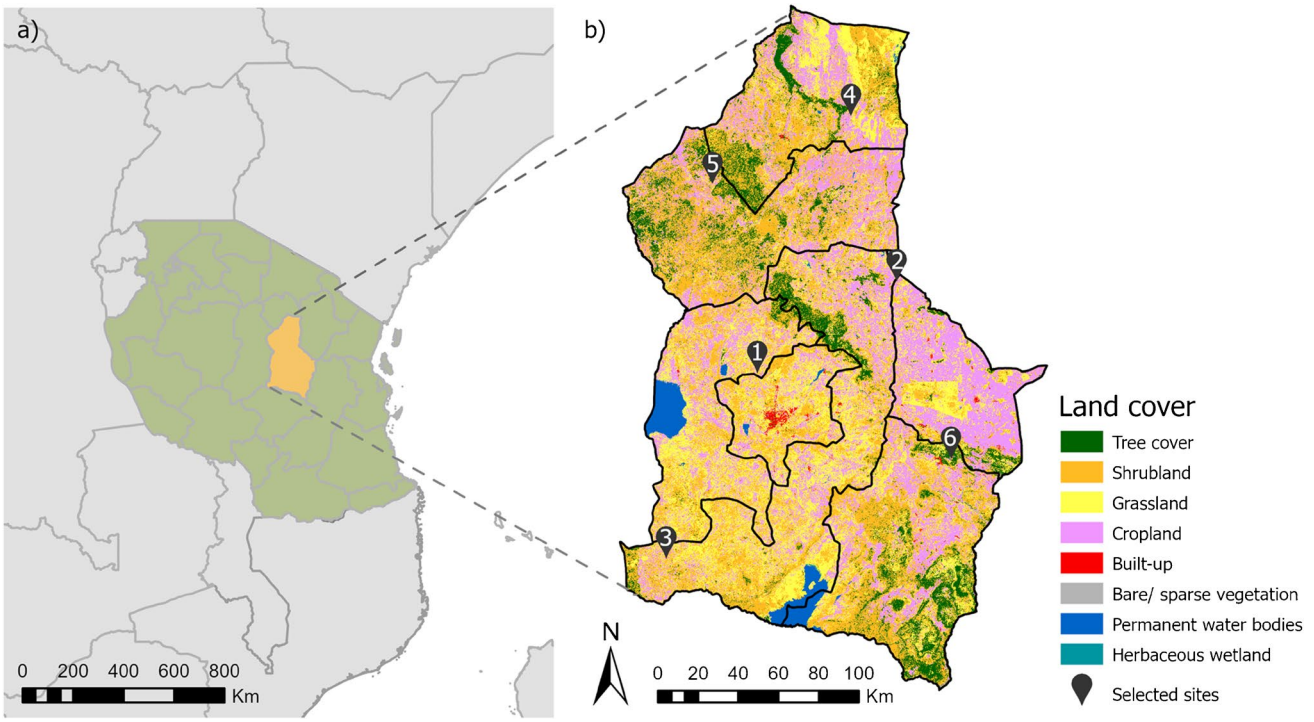


Fig. 2 **a** Location of Dodoma within Tanzania and (**b**) land cover map of Dodoma with location of selected study sites. Data source for map (**b**): ESA WorldCover project 2021/Contains modified Copernicus Sentinel data (2021) processed by the ESA WorldCover consortium.

covered by trees (Fig. 2b). Although Dodoma holds the largest share of land dedicated to agricultural activities within Tanzania, productivity is low, with maize yields falling 30% behind the national average (National Bureau of Statistics 2021). The reasons for low productivity are heavy land degradation and frequently occurring droughts (Moore et al. 2020). Mono- or mixed cropping are the dominant farming practices, and maize is the most widely planted crop. Other important food crops include sorghum, millet, cassava, sweet potato, groundnuts, beans and cowpea. The key cash crops are sunflower and sesame (National Bureau of Statistics 2021). The average farm size in Dodoma is 3 ha, and the farm is managed manually mainly by using hand hoes, swords and, to a much lesser extent, animals (draft animals, ox ploughing) and tractors (id.). Inorganic fertilizers are almost absent from Dodoma (< 1% of farmers), while 17.5% of the farmers use organic fertilizers during the long rainy season (id.). The predominant soil types in Dodoma are luvisols, cambisols, and lixisols (Poggio et al. 2021).

To ensure broad geographic representation of the region, six sites across the non-urban districts of Dodoma were selected for crop growth and agroforestry simulations (Fig. 2b). Each district contributed one site, and all locations were verified for active agricultural land use through visual inspection of Google Maps imagery (2025). Geographic coordinates and a summary of agro-climatic conditions for each site are provided in the Supplementary Information (SI-Table 1 and SI-Fig. 1).

2.2 Agroforestry systems in Dodoma and selection of tree species

In Dodoma, approximately 10% of farmers actively plant trees or practice agroforestry (Jha et al. 2021). Common agroforestry systems in Dodoma include tree intercropping, contour planting, boundary trees, woodlots and farmer-managed natural regeneration (Awoke et al. 2023). Utilized tree species are diverse and include mango, eucalyptus, *Gliricidia sepium* and *Grevillea robusta (G. robusta)*, among others. A comprehensive overview of tree species commonly utilized in Tanzanian semi-arid agroforestry systems and their primary uses is given in the Supplementary Information (SI-Table 2). For the purpose of this study, we decided to mimic the effects of *G. robusta,* a popular non-native tree species that was promoted by governmental forestry programmes since the 1970 s, and perceived by rural households as an innovation associated with environmental improvement, landownership and wealth (Yasu 1999; Charles et al. 2013; von Hellermann 2016). It is an evergreen tree and fast-growing member of the Proteaceae family, that can reach heights of 12–25 meters**,** with a relatively open canopy in its early years (Orwa et al. 2009). Although not fixing atmospheric nitrogen, it is considered to be suitable

for use in agroforestry systems as its deep rooting system causes little interference with shallow-rooted crops (Ong et al. 2000; Wajja-Musukwe et al. 2008). In addition, its timber is suitable for flooring and the manufacture of plywood and light furniture, providing an additional source of income.

Constraints to agroforestry implementation include barriers to knowledge about suitable trees and their management, lack of awareness, deficits in tenure security, high implementation costs and little access to input and output markets for agroforestry products (Muthee et al. 2022). Farmers who are part of a project, who have access to seedlings, who are able to rent land and who perceive the land to be relatively fertile are more likely to adopt agroforestry (Jha et al. 2021). Agroforestry and afforestation efforts in Dodoma have been supported by the Tanzanian government since the 1970 s (Gayo 2023), including the provision of free tree seedlings (Yasu 1999) and more recently the launch of a regreening programme (Ngongolo and Kilonzo 2022). In addition, non-governmental organizations have contributed to vegetation restoration by promoting practices such as farmer-managed natural regeneration and rainwater harvesting (Moore et al. 2020).

2.3 Model selection and evaluation

The Agricultural Production Systems sIMulator (APSIM) next generation (APSIMX, v2022.11.7125.0, Holzworth et al. 2014, 2018) was used to simulate climate change and agroforestry impacts on maize yields across Dodoma. Among several models available to simulate agroforestry systems (e.g. Hi-sAFe, EPIC, and WaNuLCAS), we selected APSIMX, as it covers the largest number of ecosystem properties relevant for climate change and agroforestry assessments (Kraft et al. 2021). The framework for simulating agroforestry using APSIMX was introduced by Huth et al. (2002) and was further developed by Smethurst et al. (2017), who showed that APSIMX is capable of accurately simulating crop yields and water content in gliricidia-maize agroforestry systems in Kenya and Malawi. Since then, APSIMX has been applied in several other agroforestry studies (Dilla et al. 2020; Chemura et al. 2021), which showed that the model can be reliably employed to simulate maize productivity in agroforestry systems with up to 50% shading (Dilla et al. 2018).

APSIMX has also been extensively used to simulate maize yields and the response of maize growth to climate change factors, showing overall good performance in diverse model intercomparison studies (Bassu et al. 2014; Kimball et al. 2023). The maize cultivar *Katumani* was selected for this study as it is among the most widely grown cultivars in Dodoma (Patrick 2017) and has previously been calibrated for use in APSIM across Tanzania and East Africa (Gurney et al. 2002; Lalani et al. 2025). The performance of APSIMX in simulating maize yields without the effect of trees (see baseline simulation, section 2.4) was assessed by comparing simulated yields to reported ones. Maize yield data at the administrative level of Dodoma for the years 2009–2019 were provided by the Tanzanian Ministry of Agriculture (Laudien et al. 2020) and were complemented with values for the years 2003 and 2008, as published by the Tanzanian government (URT 2012). In sum, maize yield data included 13 records covering the years 2003 and 2008 to 2019. To assess the model performance, several statistical metrics were calculated, such as Root Mean Square Error (RMSE), normalized Root Mean Square Error (nRMSE), Mean Absolute Error (MAE), model efficiency (EF), Willmott's index of agreement (d) and percent bias (pbias). The equations for calculating these metrics are contained in the Supplementary Information.

2.4 Baseline simulations

First, a baseline simulation was set up to represent the predominant farming practice in Dodoma, namely, maize mono-cropping, under recent past climate conditions. The baseline simulation spanned the years 1989 to 2019, with the analysis focusing on the 30-year period from 1990 to 2019. Due to limited availability of observational weather data from local stations, data on minimum and maximum temperatures as well as incoming solar radiation were obtained from the W5E5v2.0 dataset at a spatial resolution of 0.5° (Lange et al. 2021) for all six study sites. Daily precipitation data were obtained from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS), which is available at a fine spatial resolution of 0.05° (Funk et al. 2015).

Site-specific physical and chemical soil characteristics were extracted from SoilGrids (Poggio et al. 2021), which offers data for six soil depth intervals down to 2 meters at a 250 × 250 m resolution. The initial plant available water (PAW) was set to 5%, corresponding to approximately 120 mm of PAW consistent with values reported in Msongaleli et al. (2017) and Gupta et al. (2023). A detailed overview of the physical and chemical soil properties of the six study sites can be found in the Supplementary Information (SI-Table 3 and SI-Table 4).

Surface organic matter was set to 500 kg based on values reported by Mourice et al. (2015), who modelled maize cropping systems in the region using household survey data. The C:N ratio of this residue was defined as 60:1, following measurements from a field experiment in central east Tanzania by Nishigaki et al. (2017). Sowing depth (7 mm), row spacing (75 cm), and plant density (3.3 plants/m^2) were adopted from Lana et al. (2018), who studied the effectiveness of dry-soil planting of maize as an adaptation strategy

to climate change in Dodoma. The sowing window was scheduled over a two-month period beginning January 4th, corresponding to the historical onset of the growing season with a 50% probability (Yonah et al. 2006). Sowing was triggered when 20mm of rainfall accumulated within 10 days and extractable water reached at least 30 mm (ibid.). Due to limited access to synthetic fertilizers (Harou et al. 2022) and the low availability of organic inputs linked to reduced livestock density (Jackson and Mtengeti 2005), a minimal fertilization regime of 500 kg/ha manure with an N content of 1.27% in dry matter (Sileshi et al. 2017) was applied at sowing. Irrigation was not included in the simulations, as farmers mainly practice rainfed agriculture. To isolate the effects of climate variability and change, initial water content, surface organic matter, and soil nutrient levels were reset at the beginning of each growing season.

2.5 Climate change simulations

To project future climate change impacts on maize yields in Dodoma, bias-adjusted climate data at daily resolution from the third round of the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP3b, Lange and Büchner 2021) were obtained for the years 2015–2065. Of these years, two 30-year periods centred on 2030 (2016–2045, near-term future) and 2050 (2036–2065, mid-term future) were analysed. The ISIMIP3b data are bias adjusted with the observational dataset W5E5v2.0 and statistically downscaled to a resolution of 0.5° × 0.5° using the downscaling method ISIMIP3BASD v2.5.0 (Lange 2019).

Of the five GCMs available in ISIMIP3b, the models MRI-ESM2-0 (MRI), IPSL-CM6A-LR (IPSL), and MPI-ESM1-2-HR (MPI) were selected based on their demonstrated performance in simulating key climate variables over Tanzania and East Africa. MRI has been shown to reliably simulate temperatures across Tanzania (Hersi et al. 2023). For precipitation, CMIP6 models show improved performance relative to their CMIP5 predecessors in reproducing observed rainfall patterns over East Africa (Ayugi et al. 2021), with both IPSL-CM6A-LR and MPI-ESM1-2-HR ranking among the nine best-performing CMIP6 models across the region (Makula and Zhou 2022). Climate projections were extracted for two Shared Socio-economic Pathways (SSP) representing low- and high-emission trajectories: SSP1-2.6 and SSP5-8.5 (O'Neill et al. 2014).

2.6 Agroforestry simulations

When modelling crop yield responses to the presence of trees, key interactions to be considered are competition for light, water, and nutrients, as well as alterations to the microclimate and contributions of biomass (Luedeling et al. 2016). Here, we focused on above-ground agroforestry effects, specifically tree shading, associated microclimatic modifications and biomass input from leaf litterfall, following the approach of Chemura et al. (2021). Below-ground competition for water and nutrients was not considered, as *G. robusta* was found to be relatively non-competitive with crops, extracting substantial quantities of water from beneath the crop rooting zone (Wajja-Musukwe et al. 2008).

The level of tree shading on understorey crops depends on a number of factors, such as tree spacing and orientation, canopy structure and pruning practices. Shading also varies with seasonal sun angle and the life-cycle of the tree, as older and taller trees cast larger and denser shadows. As tree growth is not simulated dynamically here, tree shading was implemented in the simulations by reducing incoming solar radiation in the weather files by 10% and 20%. The 10% shade level represents light shading conditions, whereas the 20% shade level approximates the average shade intensity observed under *G. robusta* in a maize-based agroforestry system in semi-arid Kenya (Ong et al. 2000). We opted for rather low shading levels, as the current average of 5% tree cover on agricultural lands in Dodoma suggests that most fields are sparsely shaded, reflecting relatively low tree densities and limited canopy overlap in existing agroforestry systems (Villani et al. 2022).

The effect of shading on the microclimate was implemented in the simulations by quantifying the cooling effect of reduced solar radiation on air temperature. For each study site, a random forest regression was used to relate daily minimum and maximum temperatures to incoming solar radiation based on the baseline climate dataset (see Section 2.4). These relationships were then applied to climate datasets with reduced radiation to estimate the corresponding temperature changes under shaded conditions, for both baseline and future climate scenarios. Model evaluations for each regression are provided in the supplementary information (SI-Fig. 2 and SI-Fig. 3).

While litterfall production varies with tree species, density, age, and management, long-term empirical data across different stages of tree development under field conditions in Dodoma are currently lacking. Therefore, we adopted a simplified approach using a constant annual litter input informed by field measurements. Specifically, annual leaf litterfall and associated nutrient inputs from *G. robusta* were based on a study conducted in Ethiopia, where litterfall traps placed randomly beneath the subcanopy over 12 months recorded an average of 325 kg ha^{-1} yr^{-1} at a tree density of 18.67 trees ha^{-1} (Kassa et al. 2022), corresponding to an N addition of 1.84 kg ha^{-1}. This value was used to represent a 10% shade scenario. For the 20% shade scenario, we assumed a doubling of the litter input (650 kg ha^{-1}), not as a strictly linear biological relationship, but as a scenario-based estimate to reflect a higher but plausible biomass input under denser canopy cover. In both cases, the litter N input was

implemented in the model as an equivalent manure application at sowing, assuming an N concentration of 0.57% in dry matter. Contributions of litterfall to crop P supply were considered minimal and were therefore excluded from the simulation (Nair et al. 1999).

2.7 Framework for disaggregating climate change impacts, agroforestry and adaptation

The impacts of climate change and agroforestry on maize yields in Dodoma were disaggregated into four different indicators: 1) climate change impact, 2) agroforestry impact, 3) agroforestry adaptation effect and 4) climate change impact with adaptation (Fig. 3). These indicators are calculated as outlined below with the following symbols: $\bar{y}$ refers to the long-term mean yield calculated as the mean of a 30-year simulation, and the subscript i refers to a specific combination of management and climate. i is further specified in some cases by i_{BC}, a simulation employing baseline climate, or i_{CC}, a simulation using climate projections. Management is specified by i_{BM} for a simulation with baseline management or i_{AF} for a simulation with agroforestry management. An asterisk (*) refers to a combination of those.

The impact of climate change on yields is quantified by the climate change impact (Eq. 1, Fig. 3a). It is evaluated only under baseline management and defined as the percentage difference in the long-term mean yield between the baseline and climate change simulations (Lobell 2014). A negative climate change impact implies yield losses relative to the baseline climate.

$$\text{Climate change impact} = \frac{\bar{y}_{iCC*BM} - \bar{y}_{iBC*BM}}{\bar{y}_{iBC*BM}} \times 100 \quad (1)$$

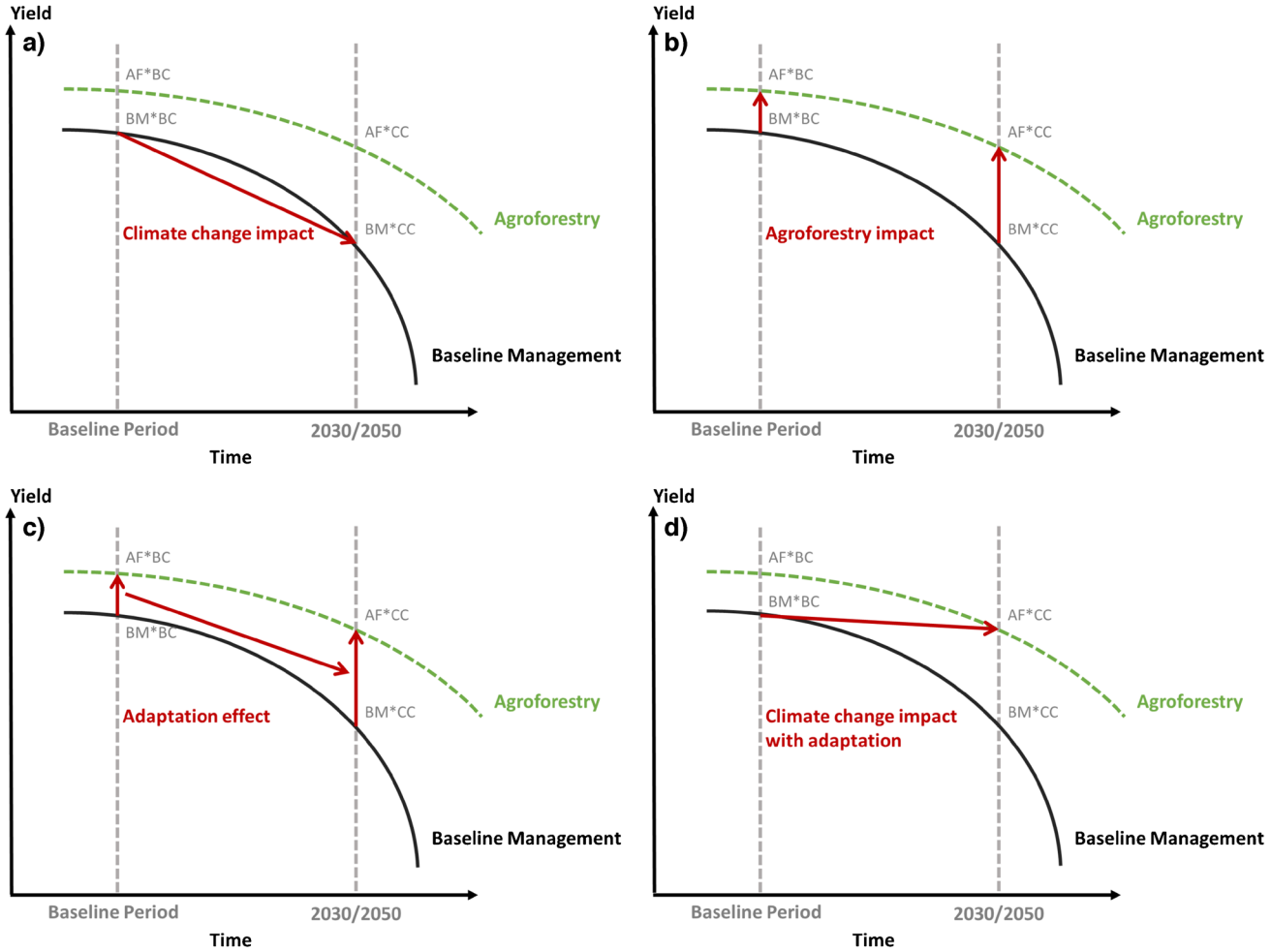


Fig. 3 Conceptual visualization of the four indicators used to disaggregate climate change and agroforestry impacts on maize yields, based on the adaptation concept of Lobell (2014): **a** Climate change impact, (**b**) Agroforestry impact, (**c**) Adaptation effect, and (**d**) Climate change impact with adaptation. Curves show yields over time under baseline management (BM, solid black line) and agroforestry (AF, dashed green line). BC denotes baseline climate (baseline period), and CC denotes projected climate change; e.g. AF*CC refers to yields with agroforestry under projected climate. Red arrows and red labels indicate the yield comparisons underlying each indicator.

The effect of agroforestry on yields is depicted by the agroforestry impact (Eq. 2, Fig. 3b). It compares the long-term mean yield between the baseline and agroforestry management under the same climate. A positive agroforestry impact indicates yield gains due to agroforestry relative to the baseline management.

$$\text{Agroforestry impact} = AFI_{i_{AF}} = \frac{\bar{y}_{iAF} - \bar{y}_{iBM}}{\bar{y}_{iBM}} \times 100 \quad (2)$$

Adaptation through agroforestry is quantified by the agroforestry adaptation effect (Eq. 3, Fig. 3c). This is the percentage difference between the agroforestry impact under baseline and projected climates relative to the yield under baseline climate with the respective agroforestry management practices. Positive values denote a greater agroforestry impact under climate change than under the baseline climate, which implies climate change adaptation (Lobell 2014).

$$\text{Agroforestry adaptation effect} = \frac{AFI_{i_{AF*CC}} - AFI_{i_{AF*BC}}}{\bar{y}_{iAF*BC}} \times 100 \quad (3)$$

Yield changes under climate change with agroforestry are quantified by the climate change impact with adaptation (Equ. 4, Fig. 3d). Here, long-term mean yields under climate change and agroforestry are compared to the baseline long-term mean yield. A value of 0 implies full preservation of baseline yields under climate change due to agroforestry. Negative values indicate climate change-induced yield losses despite the adoption of agroforestry, while positive values point toward yield gains.

$$\text{Climate change impact with adaptation} = \frac{\bar{y}_{iCC*AF} - \bar{y}_{iBC*BM}}{\bar{y}_{iBC*BM}} \times 100 \quad (4)$$

3 Results

The following section presents the main results of the model performance assessment, projected changes in temperature and precipitation, and the results of the climate change and agroforestry impact simulations. The underlying data and code used to produce these results are openly accessible in a Zenodo repository (https://doi.org/10.5281/zenodo.20627984).

3.1 Evaluation of model performance

The performance of APSIMX in simulating maize yields without agroforestry (baseline simulations) in Dodoma, Tanzania, was deemed acceptable (d > 0.75 and EF > 0), with a Willmott's index (d) of 0.77 and a model efficiency (EF) of 0.12. The RMSE was 247 kg/ha, with an nRMSE of 31.9%, indicating considerable deviations between the simulated and observed annual mean yields in individual years, which partly reflect the comparison of site-based simulations with yield statistics at the administrative level. A graphical comparison of the simulated and reported values revealed high correspondence in some years but deviations above the RMSE value for three years (2010, 2015 and 2017; Fig. 4). The mean error, as expressed by MAE, was 183 kg/ha. Overall, the model's tendency to either overestimate or underestimate yield was low, with a pbias of −0.1%, as overestimations and underestimations in individual years largely offset each other. Based on these performance metrics, it is concluded that the baseline simulation satisfactorily reproduced the mean maize yield level of Dodoma, although deviations occurred in individual years, and thus provides a suitable reference for the relative comparison of scenarios.

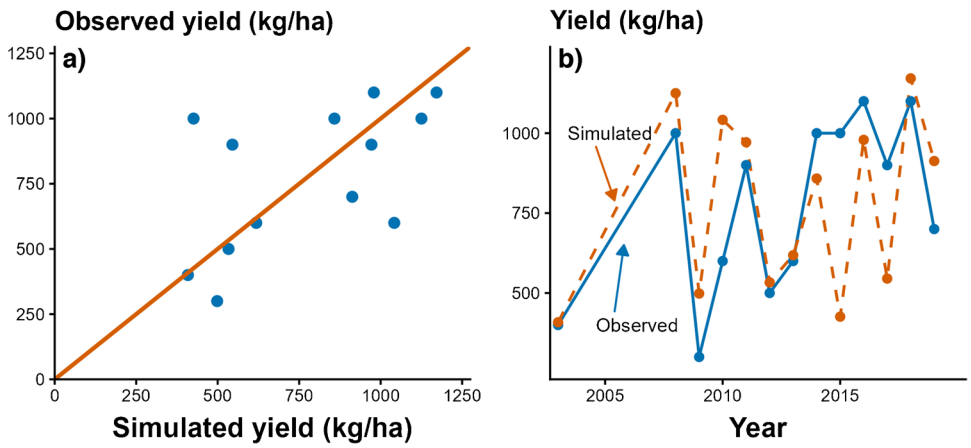


Fig. 4 Comparison of observed and simulated mean yields at the administrative level in Dodoma, Tanzania. Years included are 2003 and 2008–2019. **a** Scatter plot of simulated versus observed yields; **b** simulated and observed yields as a time series.

3.2 Projected climate change in Dodoma

Compared to the baseline period (1990–2019), with an annual precipitation of 623 mm, a mean minimum temperature of 16.5°C, and a mean maximum temperature of 28.3°C, all future scenarios indicate increased temperatures and variable precipitation patterns. Depending on the SSP, minimum temperatures are projected to rise by 0.8–2.0°C by 2050, while maximum temperatures are expected to increase by 0.5–2.2°C, with the highest warming occurring under SSP5-8.5 by 2050, reaching up to 30.5°C. All models and scenarios consistently project warming, with greater increases associated with the high-emission pathway. In contrast, changes in annual precipitation are more uncertain, with projections ranging from approximately 572 mm to 725 mm, reflecting both increases and decreases relative to the baseline. For example, IPSL suggests a notable increase in precipitation under SSP5-8.5 by 2050 (an increase of 102 mm, or around 16%), whereas MRI indicates a potential decline (a reduction of 51 mm, or about 8%). These divergent trends highlight the uncertainty in future rainfall patterns across models and scenarios. A summary of the projected mean daily minimum and maximum temperature and annual precipitation for the near- and mid-term periods, under both SSPs and across all three GCMs, is provided in the Supplementary Information (SI-Table 5).

3.3 Simulated climate change impact on maize yields

Simulation results indicate that climate change is likely to have a negative impact on maize yields in Dodoma. When averaged across all three GCMs, the baseline long-term mean yield of 763 kg ha^{-1} is projected to decrease by 23–24%, regardless of the SSP and period considered, with the exception of SSP5-8.5 in 2050, where the projected decline reaches 33% (Fig. 5). The magnitude of climate change impacts and the dynamics between SSPs and periods differ among GCMs, however. Simulations based on IPSL and MRI project a growing negative impact from 2030 to 2050, whereas MPI-based results suggest the opposite, particularly under SSP1-2.6. Nevertheless, all three GCMs consistently project negative impacts of climate change on maize yields across both SSPs and time periods, indicating that the direction of the finding is robust despite uncertainty in its magnitude.

3.4 Simulated agroforestry impact on maize yields

Simulated above-ground agroforestry effects increased maize yields by 15% and 14% under baseline climate conditions under 10% and 20% shade, respectively (Fig. 6). Under future climate conditions, a positive agroforestry impact persists and strengthens, with yield gains of 25–42% across all climate change simulations relative to baseline management. The benefits of agroforestry are greater with 20% shade, with additional yield increases of 8% under SSP1-2.6 and 4–6% under SSP5-8.5, depending on the period. The agroforestry impact generally increases from 2030 to 2050 and from the low- to the high-emission scenario, with the exception of MPI-based simulations under SSP1-2.6, where the impact stagnated between 2030 and 2050 under 10% shade and declined until 2050 under 20% shade. In summary, agroforestry is projected to have a positive impact on maize yields under both baseline and future climate conditions, with its effectiveness increasing over time and under more severe emission scenarios.

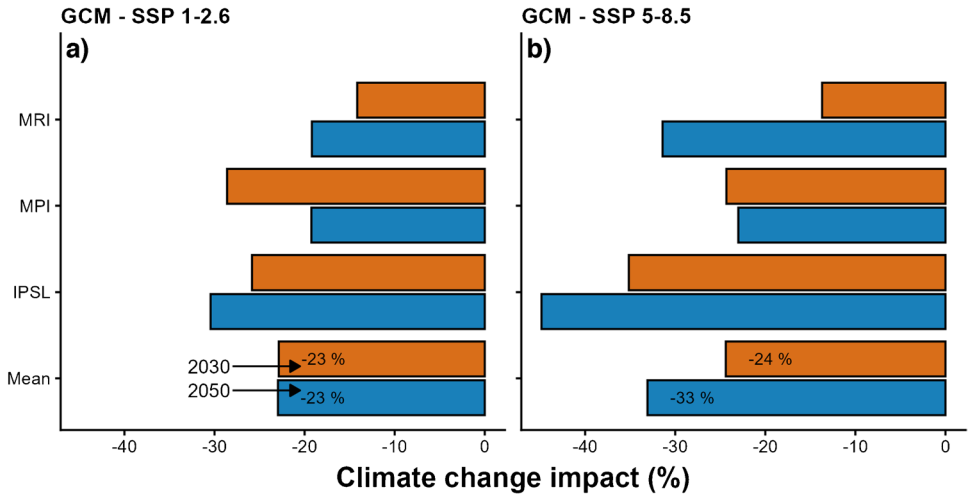


Fig. 5 Simulated climate change impacts on maize yields (%) under baseline management across six sites in Dodoma, Tanzania. **a** Shared socio-economic pathway SSP 1–2.6 and (**b**) SSP 5–8.5, each for two future periods, 2030 (orange) and 2050 (blue). Results are shown for three general circulation models (GCMs): MRI (MRI-ESM2-0), MPI (MPI-ESM1-2-HR) and IPSL (IPSL-CM6A-LR), and for the mean across the three GCMs (Mean).

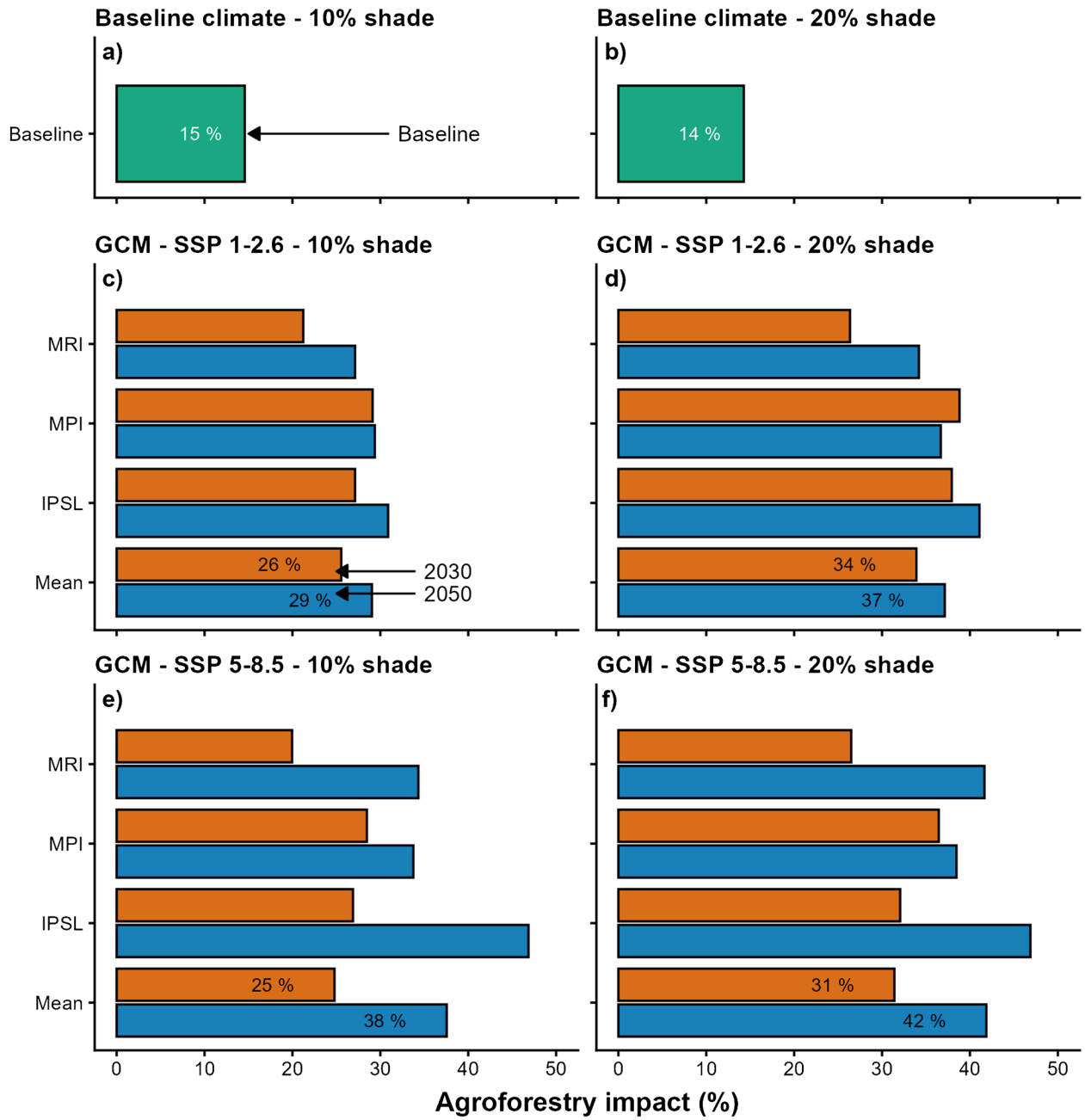


Fig. 6 Simulated agroforestry impact on maize yields (%) across six sites in Dodoma, Tanzania, for 10% and 20% shade. **a** Baseline climate with 10% shade and (**b**) with 20% shade (green). **c**–**f** Projected climate for two future periods, 2030 (orange) and 2050 (blue): **c** shared socio-economic pathway SSP 1–2.6 with 10% shade, (**d**) SSP 1–2.6 with 20% shade, (**e**) SSP 5–8.5 with 10% shade and f) SSP 5–8.5 with 20% shade. Results are shown for three general circulation models (GCMs): MRI (MRI-ESM2-0), MPI (MPI-ESM1-2-HR) and IPSL (IPSL-CM6A-LR), and for the mean across the three GCMs (Mean). Note that agroforestry effects are modelled as static and above-ground only.

3.5 Simulated agroforestry adaptation effect on maize yields

Simulation results indicate a positive adaptation effect for all agroforestry climate change simulations, pointing to a greater agroforestry impact under climate change relative to the baseline climate (Fig. 7). Ensemble means of all GCMs suggest adaptation effects of 4–13%, depending on the shade level, emission scenario and period considered. Adaptation effects are projected to be greater with 20% shade and to increase toward 2050. SSPs affect adaptation effects differently in relation to period and shade

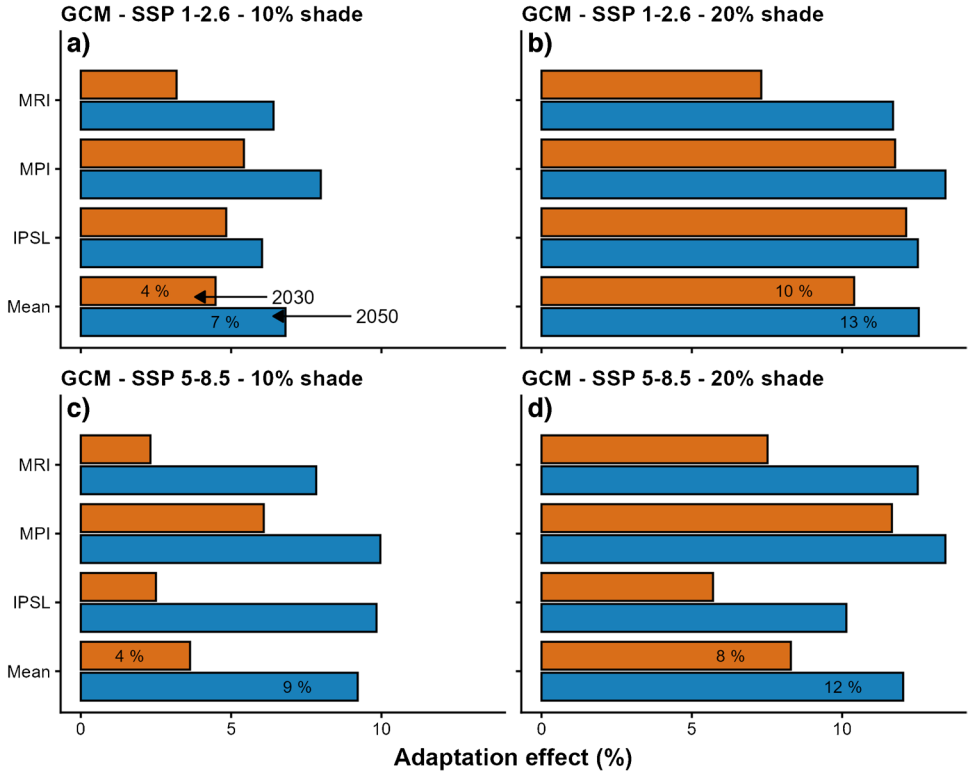


Fig. 7 Simulated adaptation effect of agroforestry on maize yields (%) across six sites in Dodoma, Tanzania, for two future periods, 2030 (orange) and 2050 (blue): **a** shared socio-economic pathway SSP 1–2.6 with 10% shade, (**b**) SSP 1–2.6 with 20% shade, (**c**) SSP 5–8.5 with 10% shade and (**d**) SSP 5–8.5 with 20% shade. Results are shown for three general circulation models (GCMs): MRI (MRI-ESM2-0), MPI (MPI-ESM1-2-HR) and IPSL (IPSL-CM6A-LR), and for the mean across the three GCMs (Mean). Note that agroforestry effects are modelled as static and above-ground only.

level. With 10% shade, the adaptation effects are the same regardless of the SSP in 2030, while they increase with SSP5-8.5 in 2050. At 20% shading, the adaptation effects are slightly lower in SSP5-8.5 than in SSP1-2.6 during both periods. In summary, agroforestry has a positive adaptation effect.

3.6 Simulated climate change impacts with adaptation

Ensemble means of the climate change impact with adaptation range from −8% to +6%, indicating that agroforestry can buffer but not fully reverse negative climate change impacts under all conditions (Fig. 8). The effectiveness of agroforestry in reducing climate change impacts is generally greater at the 20% shading level, and the residual negative impact intensifies under the high-emission scenario and in the mid-term future. Notably, under the low-emission scenario with 20% shade, the climate change impact with adaptation turns positive, suggesting that the benefits of agroforestry can outweigh the negative effects of climate change and result in yields exceeding the baseline. Under the high-emission scenario, however, the residual climate change impact remains negative regardless of shading level, demonstrating that agroforestry alone is insufficient to prevent yield losses under severe warming.

4 Discussion

4.1 Climate change impacts on maize yields

Simulation results indicate that climate change is likely to have a negative impact on maize yields, ranging from −23% to −33%, depending on the considered period and SSP. Our findings are in line, though slightly more pessimistic, with other modelling studies that assessed climate change impacts on maize yields in semi-arid central Tanzania. For instance, Tumbo et al. (2020) found that maize yields in the Wami River sub-basin in Tanzania are likely to decrease by 5–41% in a "business-as-usual" scenario by mid-century. Another study on climate change impacts on maize yields in the neighbouring Singida region projected yield losses of 16% in 2020–2060 and 20% in 2061–2099 compared to the 1980–2012 baseline (Volk et al. 2021). Likewise, Msongaleli et al. (2015) found that maize yields are likely to decrease by 5–25% in Singida and Dodoma towards the end of the century. Our results also show that climate change impacts increase notably under the high-emission scenario and in the mid-term future. This finding is in accordance with Volk et al. (2021), who reported a significant increase in negative climate change impacts on maize yields under a high-emission scenario. Temperature increases are likely the primary driver of simulated

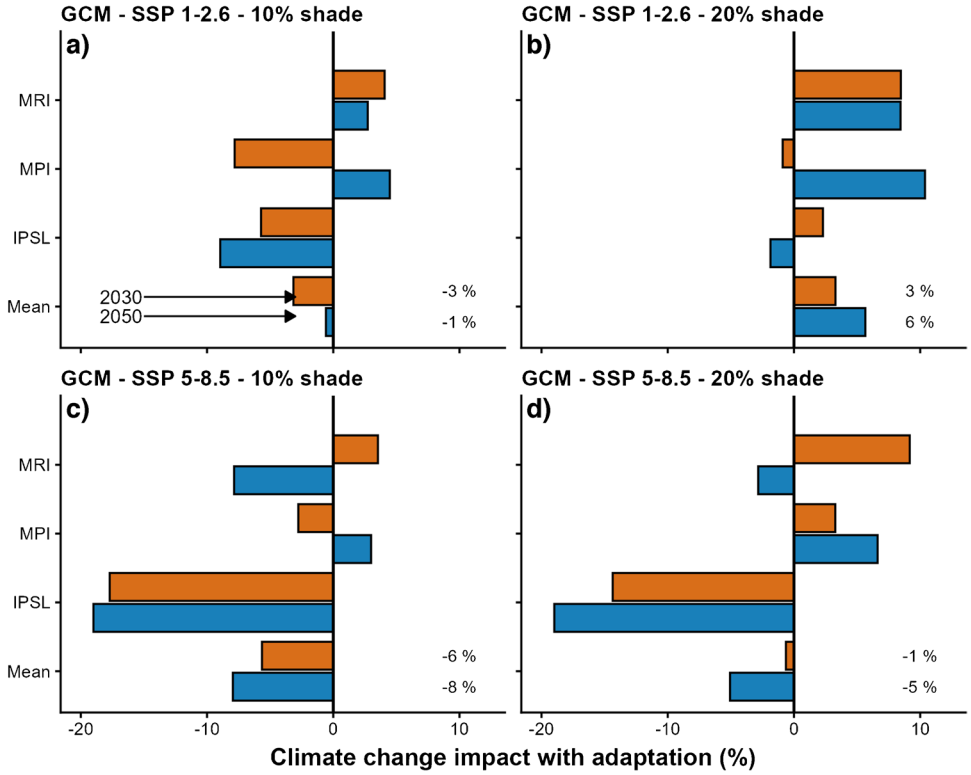


Fig. 8 Simulated climate change impact with adaptation on maize yields (%) across six sites in Dodoma, Tanzania, for two future periods, 2030 (orange) and 2050 (blue): **a** shared socio-economic pathway SSP 1–2.6 with 10% shade, (**b**) SSP 1–2.6 with 20% shade, (**c**) SSP 5–8.5 with 10% shade and (**d**) SSP 5–8.5 with 20% shade. Results are shown for three general circulation models (GCMs): MRI (MRI-ESM2-0), MPI (MPI-ESM1-2-HR) and IPSL (IPSL-CM6A-LR), and for the mean across the three GCMs (Mean). Note that agroforestry effects are modelled as static and above-ground only.

maize yield losses, as rising temperatures accelerate crop development, shorten the grain filling period, and amplify drought and heat stress, all of which reduce final grain yield, as documented for the region (Waha et al. 2013; Volk et al. 2021; Mohammed et al. 2022).

4.2 Agroforestry impacts on maize yields

Simulated above-ground agroforestry effects resulted in average maize yield gains of 14–15% under baseline climate conditions, consistent with the 16% median increase reported for subtropical and tropical regions in a global meta-analysis of agroforestry impacts on maize yield (Baier et al. 2023). However, our simulated gains appear relatively high compared to studies involving non-nitrogen-fixing tree species, which have shown negligible or non-significant yield changes (Tadesse et al. 2021). It is therefore important to note that our simulated yield gains should be interpreted as a best-case scenario. Two key modelling assumptions contribute to this optimistic estimate. First, the relatively low shading levels used in the simulations (10% and 20%) are unlikely to cause light limitation, whereas shading levels above 20% were found to reduce above-ground biomass and yield of millet in *F. albida* parkland systems (Sow et al. 2024). Likewise, Dilla et al. (2020) demonstrated in a field trial that unpruned trees significantly reduced crop biomass and yield compared to partially or fully pruned trees, underscoring the importance of managing tree spacing and pruning to optimize light availability. Second, our simulations did not account for below-ground competition for water and nutrients, which may partially offset positive above-ground effects. Evidence from field experiments is mixed: while Lott et al. (2009) found that below-ground competition outweighed the benefits of tree shading in semi-arid Kenya, yield reductions on the same experimental site were only observed at rainfall below 150 mm (Mungai et al. 2001), a condition not applicable in Dodoma. Moreover, Huxley et al. (1994) observed that *G. robusta* roots reach down to at least 2 m, while maize roots occupied only the upper 1.3 meters of the soil profile, indicating partial root niche differentiation. In addition, management practices such as root pruning can be employed to further minimize potential negative below-ground interactions (Wajja-Musukwe et al. 2008).

4.3 Agroforestry buffers but does not offset climate change impacts

Two key findings emerge from the analysis of the agroforestry adaptation effect and the climate change impact with adaptation. First, simulation results revealed a positive agroforestry adaptation effect ranging from 4–9% with 10% shade and 8–13% with 20% shade, depending on the period and emission scenario considered. These values are consistent with adaptation effects reported for other commonly applied strategies, including optimized planting dates, fertilizer use, and climate-resilient crop varieties (Carr et al.

2022). They also fall within the wide range of agroforestry adaptation effects for maize yields (−39% to 30%) reported for Ethiopia (Chemura et al. 2021). The results further indicate that agroforestry becomes increasingly effective under climate change relative to baseline conditions, with benefits amplifying at the 20% shade level and towards 2050.

Second, the net yield outcome for farmers adopting agroforestry, as expressed by the climate change impact with adaptation, demonstrates that agroforestry can buffer but not fully offset climate change impacts on maize yields. Under the low-emission scenario (SSP1-2.6), ensemble mean yields with agroforestry were −3% and −1% relative to baseline in 2030 and 2050 respectively with 10% shade, but turned positive with 20% shade (+3% in 2030, +6% in 2050). Importantly, under moderate warming and sufficient shading, the positive impacts of agroforestry can outweigh the negative impacts of climate change, resulting in yields that exceed the baseline. Under the high-emission scenario (SSP5-8.5), however, the climate change impact with adaptation remained negative across both shading levels (−6% and −8% in 2030 and 2050 with 10% shade; −1% and −5% with 20% shade), demonstrating that even with agroforestry adoption, substantial yield losses persist under severe warming.

4.4 Agroforestry co-benefits and policy implications

The findings presented above indicate that agroforestry-based adaptation has its limits and will not be sufficient to maintain maize yields in Dodoma, Tanzania, under most future climate conditions. This underlines that climate change mitigation remains indispensable to limit the magnitude of climate change to levels where adaptation strategies such as agroforestry remain effective. Agroforestry can play an important role in this regard, as it offers co-benefits that extend well beyond crop yield improvement, including considerable carbon sequestration potential. In a systematic review on the role of agroforestry in climate change mitigation and adaptation, Abebaw et al. (2025) found that agroforestry systems can sequester an average of 3.5–9.8 Mg CO_2 ha^{-1} $year^{-1}$, depending on tree species, soil type, and climatic conditions. At the global scale, Terasaki Hart et al. (2023) estimate that the expansion of agroforestry could sequester up to 0.31 Pg C yr^{-1}, a mitigation potential comparable to that of reforestation and other prominent natural climate solutions, positioning agroforestry as a cost-effective natural climate solution directly contributing to Sustainable Development Goal (SDG) 13.

Agroforestry also delivers important co-benefits for biodiversity and soil health. Meta-analytic evidence suggests that the integration of trees with crops and livestock can enhance on-farm biodiversity by 25–40% and improve soil organic carbon content by an average of 15% over two decades (Abebaw et al. 2025). The integration of *G. robusta* and other tree species into smallholder farms further provides habitat connectivity in landscapes otherwise dominated by monocultures (Zemp et al. 2023), contributing to SDG 15. Improved soil organic matter and nutrient cycling additionally support more resilient and productive farming systems (Kuyah et al. 2019), advancing SDG 2.

Based on our findings and the potential co-benefits of agroforestry discussed above, several policy recommendations can be derived. First, efforts to promote agroforestry adoption among smallholder farmers should be continued and strengthened, for example through seedling distribution programmes and dedicated extension services that support farmers in establishing and managing agroforestry systems. Second, while *G. robusta* has been widely promoted in the region, greater attention should be given to native and nitrogen-fixing tree species (e.g. *Faidherbia albida, Albizia gummifera*), which have been shown to deliver substantially higher yield benefits than non-nitrogen-fixing species. Third, careful management of tree spacing and pruning practices is essential to ensure that shade levels remain within a range that benefits rather than hinders crop production, as modelling results for millet in *Faidherbia* parklands indicate that shading above 20% can reduce yields (Sow et al. 2024). Finally, the integration of fruit trees such as mango (*Mangifera indica*), avocado (*Persea americana*), banana (*Musa* spp.) and baobab (*Adansonia digitata*) into agroforestry systems should be considered as a complementary strategy, as these species can diversify household diets, improve food security, and generate additional income from fruit sales, thereby enhancing the overall livelihood benefits of agroforestry beyond grain yield alone.

4.5 Limitations and scope for further research

The findings presented here are subject to methodological limitations that should be considered when interpreting the results. A primary limitation is the simplified and static representation of agroforestry within the simulation framework. Tree growth was not modelled dynamically, and several important tree-induced effects on soil properties and water dynamics were omitted. For example, while the positive influence of trees on soil water via reduced evaporation from canopy cooling was included, other potentially beneficial agroforestry effects, such as enhanced cation exchange capacity (Gindaba et al. 2005), improved soil infiltration, and increased water retention (Kuyah et al. 2019) were not represented. These processes are likely beneficial for agroecosystems (Carsan et al. 2014; Dollinger and Jose 2018) and may gain importance under climate change (Allen et al. 2011).

Furthermore, the simulation treated tree effects as static, providing a constant amount of shade and litterfall each year, without accounting for dynamic changes in canopy size, biomass accumulation, or age-related shifts in tree function. In reality, agroforestry species such as *G. robusta* are often harvested for timber or firewood after 15–20 years (Lott et al. 2000), which would reduce long-term agroforestry benefits unless regular replanting is practised. Additionally, trees themselves are susceptible to climate change (Watts et al. 2022), and increasing environmental stress may reduce the success rate of tree establishment and survival, thereby limiting the potential of agroforestry as a climate adaptation strategy.

Uncertainties in simulation results are also inherent to climate change projections. Despite the use of three GCMs here, higher certainty could be achieved through the use of more GCMs and ensemble means (Ma et al. 2021). Likewise, uncertainty arises from reliance on a single crop model. Previous research has shown that different crop models can produce divergent yield projections due to varying internal processes and assumptions (Jägermeyr et al. 2021). The use of multiple crop models could have improved the robustness of our findings (Martre et al. 2015). Additionally, uncertainties in soil data stemming from the use of a gridded soil map rather than in-field measurements may further affect model outputs. Another limitation concerns the spatial generalization of our results. While six sites were selected to represent a range of climatic and soil conditions, local variation in crop management practices and cultivar selection was not captured, although such factors can significantly influence the feasibility and performance of agroforestry interventions.

In light of these limitations, future research should prioritize the dynamic modelling of both crop and tree components in agroforestry systems, capturing seasonal and long-term changes in growth, competition, and resource allocation. It is also essential to explicitly represent belowground competition for water and nutrients, and to collect field-based measurements of soil health indicators such as soil organic carbon, nutrient cycling, and root distribution, which would provide valuable empirical data to complement and validate the modelling approach adopted here. In addition, testing a broader range of shade levels and tree management scenarios, including different pruning intensities, tree densities, and species compositions, would help identify optimal agroforestry configurations for semi-arid environments such as Dodoma. Finally, integrating tree responses to climate change, including the effects of heat and drought stress, will be crucial for assessing the long-term resilience and viability of agroforestry systems under future climate conditions.

5 Conclusion

The objective of this study was to assess the impact of climate change on maize yields in Dodoma, Tanzania, and to evaluate the potential of agroforestry to offset these negative impacts. Simulation results with the crop model APSIM indicate that, without appropriate adaptation measures, maize yields are likely to decline by 23–33%, depending on the emission scenario (SSP1-2.6, SSP5-8.5) and time horizon (2030, 2050), compared to the baseline. By disaggregating the combined effects of climate change and agroforestry into four distinct indicators, the study reveals that agroforestry consistently increases maize yields under all simulated climate conditions and generates a positive adaptation effect under future climate. Both the yield increase and the positive adaptation effect could contribute to securing maize yields in Dodoma and similar semi-arid environments, provided that appropriate management practices such as regular tree pruning and controlled shade management are adopted by farmers, with 20% shade being most effective in our simulations. However, the climate change impact with adaptation demonstrates that agroforestry can buffer but not fully offset climate change impacts, underscoring that there are limits to adaptation and that climate change mitigation remains indispensable to keep impacts within manageable bounds. This is particularly evident under the high-emission scenario (SSP5-8.5), where yield losses persist at both shade levels and increase towards 2050. Finally, the study emphasizes the importance of timely action: as establishing agroforestry systems is a long-term undertaking, early implementation is essential to ensure that its benefits are available when they are most needed, both under current climate conditions and in the face of future climate change.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s13593-026-01158-y.

Authors' contributions All authors contributed to the study conception and design. Material preparation, data collection, and initial analysis were performed by J.S. The first draft of the manuscript was prepared by J.S. A.H. led the substantial revision and restructuring of the manuscript, addressed all comments raised during the review process, prepared the final version of the figures and was responsible for the final version submitted for publication. All authors commented on previous versions of the manuscript and approved the final manuscript.

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Data availability The baseline and projected climate data, the simulated maize yields and the observed yields used for model evaluation

are openly accessible in the Zenodo repository (https://doi.org/10.5281/zenodo.20627984).

Code availability The code used for data preparation, model evaluation and visualization is openly accessible in the Zenodo repository (https://doi.org/10.5281/zenodo.20627984).

Declarations

Ethics approval Not applicable.

Consent to participate Not applicable.

Consent for publication Not applicable.

Competing interests The authors declare that they have no competing interests.

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