



Green water availability and water-limited crop yields under a changing climate in Ethiopia

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Abstract. Climate change is expected to influence future agricultural water availability, posing particular challenges in rainfed agricultural systems. This study aims to analyze the climatology of green water availability and water-limited attainable yield (AY) – the maximum crop yield achieved with available green water under optimal soil nutrient and crop management, considering four major cereal crops (teff, maize, sorghum, and wheat) produced in Ethiopia. An agro-hydrological modeling framework was developed to simulate climatic–hydrological–crop interactions. The model was applied to a reference period (1981–2010) and a future period (2020–2099) under scenarios of low, intermediate, and high greenhouse gas emissions with the following aims: (i) evaluate the current green water availability and AY potential, (ii) assess their climate-driven changes, and (iii) analyze the sensitivity of changes in AY to changes in rainfall and atmospheric evaporative demand. With regional variations based on climatic regimes, the main growing season (*Meher*, May to September) has an average AY of 79 % of a fully irrigated potential yield, with an average soil moisture deficit of 29 % of moisture content at full water-holding capacity. AY of the short growing season (*Belg*, February to May) is, on average, 37 % of the potential yield, with a soil moisture deficit of 56 %. Under the future climate, *Meher* is expected to experience small changes in AY the range of ± 5 %, with dominantly positive trends in the 2030s and decreases in the 2060s and 2080s, mainly driven by changes in the atmospheric evaporative demand due to rising temperatures. The *Belg* regions are expected to experience increased AY that is dominantly controlled by increases in rainfall. On the other

hand, a substantial yield gap is identified between actual and water-limited yields. This points to the need for combining green water management practices with nutrient and tillage management, plant protection, and cultivar improvement to close the yield gaps and to build up the climate resilience of farmers.

1 Introduction

Green water, the infiltrated part of rainfall that is stored in the soil root zone and returns to the atmosphere in the form of evapotranspiration (Falkenmark and Rockström, 2006), is the sole source of moisture in rainfed agriculture (RFA) systems (Rockström, 1999). Green water accounts for an estimated 80 % of the global agricultural evapotranspiration fluxes, and RFA systems produce ~ 60 % of the global food (Mekonnen and Hoekstra, 2011; Molden et al., 2011; Rockström et al., 2010; Sposito, 2013). The reliance on green water varies across regions, with sub-Saharan Africa (SSA) being particularly dependent on this water resource, with close to 95 % of croplands being under rainfed agriculture practices (SIWI, 2018; Laderach et al., 2021). Due to the highly dynamic nature of green water availability (GWA), influenced by climatic and biophysical factors that vary in space and time, RFA systems are strongly climate-sensitive under moisture-limited conditions (Kang et al., 2009; Meng et al., 2023; Park et al., 2022). Climate change presents an additional major challenge to the system, undermining crop production, with

potential consequences of food insecurity, livelihood losses, and economic crises (FAO, 2022).

Previous global-scale assessments have highlighted the challenges posed by climate change in relation to agriculture, both in the past and the future, leading to regionally varying intensification of agricultural water scarcity and a decrease in crop yields (e.g., Borgomeo et al., 2020; Jägermeyr et al., 2021; Lobell et al., 2011b; Rosenzweig et al., 2014). This is particularly evident across the tropics, including the highly climate-vulnerable SSA countries (Burke et al., 2009; Kummu et al., 2021; Müller et al., 2011; Rezaei et al., 2023; Rosenzweig et al., 2014; Schlenker and Lobell, 2010). Adaptation actions tailored to specific contexts are now a top priority for mitigating the impacts of climate-change-induced water scarcity in rainfed agriculture (RFA) systems, primarily at the national scale through the implementation of National Adaptation Plans (NAP) under the auspices of the United Nations Framework Convention on Climate Change (UNFCCC, 2021) and other programs.

Ethiopia is one of the countries committed to formulating and implementing the NAP, including in agriculture, the sector which the country and its population heavily rely on (FDRE, 2019). In fact, climate adaptation is a much-needed action in Ethiopian smallholder agriculture, of which $\sim 95\%$ is dependent on GWA, and, at the same time, it is an indispensable activity supporting the food and income of nearly 80% of the population. The NAP and its implementations are, in principle, based on analyses of climate change impacts and vulnerability, along with relevant adaptation actions (UNFCCC, 2021; Warren et al., 2018). Previous studies on the crop yield impacts of climate change in Ethiopia have mainly focused on local case studies (e.g., Abera et al., 2018; Araya et al., 2015; Degife et al., 2021; Hadgu et al., 2015; Kassie et al., 2014; Markos et al., 2023; Moges and Gangadhara, 2021), making them patchy and insufficient as a comprehensive guide for the NAP. Here, we propose a framework that allows for a regional comprehensive analysis of agrohydrological responses to climate change across the RFA region of Ethiopia.

This framework builds on the key factors that influence GWA and their cascading effects on crop yield to guide appropriate agricultural water management planning, decisions, and actions. Several factors influence GWA. While rainfall amount and distribution fundamentally determine the green water supply, rainfall event characteristics such as intensity, frequency, and duration, combined with surface biophysical conditions (mainly soil, land cover, terrain slope, and roughness), govern the partitioning of rainfall into overland flow and infiltration (Rockström and Gordon, 2001; Schuel et al., 2008). Soil properties (e.g., textural composition, organic matter content, thickness, and salinity) determine the rainfall partitioning into infiltration and runoff, the subsurface flow, green water storage capacity, and plant accessibility, while potential evapotranspiration driven by air temperature, radiation, wind, relative humidity, and vegeta-

tion controls the return flow of green water to the atmosphere (Ringersma et al., 2003).

In moisture-limited regions, crop yield is proportional to the magnitude of the evapotranspiration flux, which is constrained by moisture availability (Hatfield and Dold, 2019; Steduto et al., 2012). The maximum yield that can be achieved with the available green water under the best nutrient input and crop management conditions in RFA systems is considered to be the *water-limited attainable yield* (van Ittersum et al., 2013; Lobell et al., 2009). In conditions where water is not a limiting factor, like in RFA systems in humid agroecologies and in fully irrigated systems in dry agroecologies, the maximum achievable crop yield is limited by energy and, thus, is called *energy-limited yield potential*.

Quantification of the complex interactions between climate, soil, and cultivar and crop management is commonly done with mechanistic crop models, for example, APSIM (Holzworth et al., 2014), AquaCrop (Raes et al., 2009; Steduto et al., 2009), CROPSYST (Stöckle et al., 2003), DSSAT (Jones et al., 2003), EPIC (Williams, 1990), and WOFOST (van Diepen et al., 1989), which are used to simulate crop growth and yields at the field scale. These models combine hydrological models that simulate hydroclimatic processes to estimate water availability in the root zone and crop growth models that simulate the crop physiological responses to the agro-environmental and management conditions (Foster and Brozović, 2018; Siad et al., 2019). Model complexity and associated issues such as high input data and parameter requirements and computational demands are major constraints of mechanistic crop models, especially when applied in a distributed setting to a large geographic domain, which necessitates a compromise between the level of complexity and the purpose of the modeling (Adam et al., 2011; Ramirez-Villegas et al., 2017).

Here, we employ a simplified agrohydrological modeling framework to assess the impacts of climate change on GWA and the subsequent effects on major cereal crops (teff, maize, sorghum, and wheat) produced in the entire RFA region of Ethiopia. We address three research questions that are relevant for future agricultural water management planning and decision-making in Ethiopia: (i) what is the current green water availability and how will it change under the future climate across the RFA region? (ii) How will these changes affect water-limited attainable crop yield (AY)? (iii) Which hydroclimatic factor (rainfall or evapotranspiration) dominantly drives these changes and where? We base our assessment on crop response conditions where all crop growth factors except water are unlimited so that we can capture the effects of climate-driven changes in crop yields in a relative manner. Furthermore, we critically discuss the implications of the changes for water management in the NAP and similar agricultural development initiatives. We also present the workflow of our modeling framework to ensure its robust application in addressing similar or related agrohydrological research questions elsewhere.

2 Methods

2.1 Study area

The study area covers the entire rainfed arable parts of Ethiopia (hereafter RFA region), as mapped in previous land use analysis (Kassawmar et al., 2018), encompassing an area of about 667 000 km² (59 % of the landmass of Ethiopia; see the blue outline in Fig. 1a). The climate of the RFA region ranges from humid to semi-arid (Fig. 1c), with mean annual potential evapotranspiration ranging from 700 mm in the highland regions to 1800 mm in the western lowland part of the RFA region. The mean annual rainfall of the RFA region ranges from 270 mm in the eastern part to 2100 mm in the western and southwestern parts (Fig. 1b). The rainfall has unimodal patterns in the central, western, northern, and northeastern parts, with the highest rainfall in July–August, depending on the location (Segele and Lamb, 2005; Wakjira et al., 2021). This rainy season typically spans from May to September, coinciding with the main growing season, locally known as *Meher*, during which approximately 88 % of the total annual crop harvest occurs (CSA, 2007). The southern and eastern parts of the RFA region, on the other hand, largely experience a bimodal pattern with two rainy seasons in spring and autumn. The spring (February–May) rainy period is considered to be the second and shorter growing season, locally known as *Belg*, in the southern and southeastern part of the RFA region. Cereals account for about 80 % of the crops produced, with teff, maize, sorghum, wheat, and barley being the top varieties, also serving as the main staple food crops in the country (CSA, 2007, 2010).

2.2 Data

Daily rainfall data for the reference period (1981–2010) were obtained from the Climate Hazards Infrared Precipitation with Station (CHIRPS) dataset (Funk et al., 2015), which is available at 0.05° × 0.05° spatial resolution. Maximum and minimum daily 2 m air temperature data consist of the bias-corrected and downscaled ERA5 Land (BCE5) dataset (Wakjira et al., 2022, 2023), which is also available at 0.05° × 0.05° spatial resolution. Other climate variables (solar radiation, wind speed, and dew point temperature) were retrieved from ERA5 Land (Muñoz-Sabater et al., 2021) and were disaggregated to a resolution of 0.05° × 0.05° using a bilinear interpolation method.

Future climate data were derived by downscaling multiple global circulation model (GCM) projections, i.e., 26 for precipitation and solar radiation and 21 for maximum and minimum daily temperatures (listed in Table S2 in the Supplement), from their native coarse resolution to 0.05° × 0.05° grid resolution using a change factor (delta) approach (e.g., Anandhi et al., 2011; Teutschbein and Seibert, 2012). The future climate scenarios include three Shared Socioeconomic Pathways (SSPs) (Meinshausen et al., 2020; O'Neill

et al., 2016), namely SSP1-2.6 (low greenhouse gas emissions), SSP2-4.5 (intermediate emissions), and SSP5-8.5 (high emissions).

Gridded soil texture and organic carbon content data were retrieved from SoilGrids (Poggio et al., 2021). Although the SoilGrids soil data are available at 250 m grid resolution, we upscaled the data to 0.05° (~ 5 km) to harmonize the spatial resolution with that of the climate datasets. Curve number (CN) values for agricultural land use were obtained from the USDA (1986) lookup table according to the hydrologic soil group dataset developed by Ross et al. (2018).

Independent soil moisture (SM), actual evapotranspiration (ET_a), surface runoff, and crop data were utilized to evaluate the agrohydrological model simulations. Four satellite- and model-based global SM datasets, ESA CCI (Dorigo et al., 2017), GLDAS 2.1 (Rui and Beaudoin, 2020), LPMR-TMI (Teng and Parinussa, 2021), and SGD-SM (Zhang et al., 2022), were considered in the evaluation. ET_a estimates were retrieved from five products – SSEBop (Senay et al., 2020), PML-v2 (Zhang et al., 2019), MOD16A2 (Mu et al., 2019), GLDAS 2.1 (Rui and Beaudoin, 2020), and TerraClimate (Abatzoglou et al., 2017), covering the period 2003–2010. Surface runoff data were collected from published runoff plot measurements at 20 locations (Table S3 in the Supplement) across the RFA region of Ethiopia. Regarding the crop data, paired water-limited (Y_w) and potential-yield (Y_p) data were collected from published case studies that are based on field trials and calibrated crop model simulation experiments conducted at 26 locations and from the Global Yield Gap Atlas, GYGA (GYGA, 2024), based at 19 additional locations across the study area (refer Table S4 in the Supplement for more details). In addition to the yield data, total cereal production (TCP), consisting of the sum of all cereals (maize, teff, sorghum, wheat, barley, millet, oat, and rice) produced in Ethiopia, which was derived from the annual Agricultural Sample Survey (AgSS) reports (e.g., CSA, 2010) gridded by Wakjira et al. (2021) for the period 1995–2010, was also utilized in the evaluation.

2.3 Agrohydrological modeling

The agrohydrological modeling framework (Fig. 2) that interlinks climate–hydrological–crop (CHC) interactions was developed to simulate the effects of climate change on green water fluxes and its cascading influences on crop yield. The CHC model consists of three modules for climate, hydrology, and crops.

2.3.1 Climate module

The climate module uses climatic variables to compute the daily reference evapotranspiration ET_o [mm d⁻¹] using the FAO Penman–Monteith equation considering a hypothetical

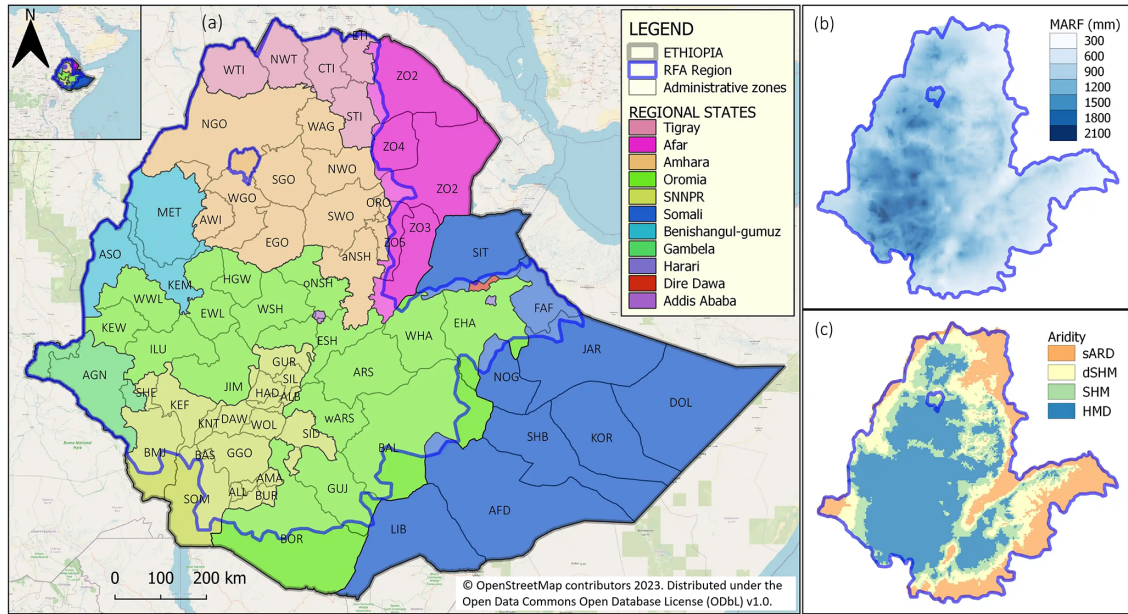


Figure 1. (a) Map of Ethiopia, showing the spatial extent of the rainfed agricultural region (blue outline, Kassawmar et al., 2018) and administrative zones (designated by short names) in the nine regional states. The complete list of the zones with full names is given in Table S1 in the Supplement. (b) Mean annual rainfall (MARF) of the RFA region for the period 1981–2010, based on CHIRPS. (c) Climatic regimes (aridity) of the RFA region (classification based on Spinoni et al., 2015). Abbreviations: sARD denotes semi-arid, dSHM denotes dry sub-humid, SHM denotes sub-humid, and HMD denotes humid.

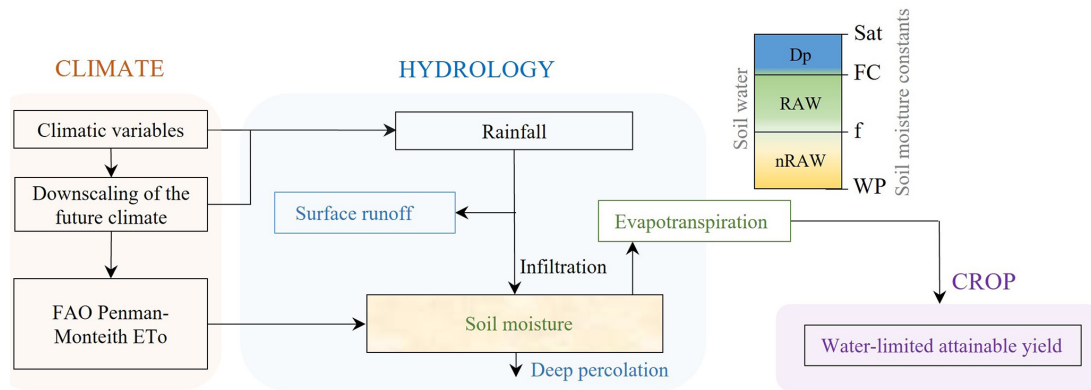


Figure 2. The CHC model used for the assessment of climate-driven changes in green water availability and water-limited attainable yields. Dp denotes deep percolation, RAW denotes readily available water, nRAW denotes non-readily-available water, Sat denotes saturation, FC denotes field capacity, WP denotes wilting point, and *f* denotes critical moisture depletion factor.

reference grass (Allen et al., 1998):

$$ET_0 = \frac{0.408\Delta(R_n - G) + \gamma \frac{900}{T+273} u_2 (e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)}, \quad (1)$$

where R_n [MJ m^{-2}] is net radiation at the crop surface, G [MJ m^{-2}] is soil heat flux, T [$^{\circ}\text{C}$] is 2 m mean daily air temperature, u_2 [m s^{-1}] is 2 m daily wind speed, $e_s - e_a$ [kPa] is the saturation vapor pressure deficit, Δ [$\text{kPa } ^{\circ}\text{C}^{-1}$] is the slope of the vapor pressure curve, and γ [$\text{kPa } ^{\circ}\text{C}^{-1}$] is the psychrometric constant.

2.3.2 Hydrology module

The hydrology module simulates the dynamic soil water balance without lateral surface and subsurface routing. A conceptual (bucket) water balance model is applied to the soil hydrological fluxes, namely surface runoff Q [mm], actual evapotranspiration ET_a [mm], deep percolation D_p [mm], and changes in soil moisture ΔSM [mm] from rainfall input P [mm] at a daily time step t :

$$\Delta SM_t = P_t - Q_t - ET_{a,t} - D_{p,t}. \quad (2)$$

Surface runoff is simulated according to the US Soil Conservation Service (SCS) curve number method (USDA, 1986):

$$Q_t = \begin{cases} \frac{(P_t - I_{a,t})^2}{(P_t - I_{a,t}) + S_{20,t}}, & \text{if } P_t > I_a \\ 0, & \text{otherwise} \end{cases}, \quad (3)$$

where I_a [mm] is an initial abstraction, and S [mm] is the maximum surface retention after runoff begins. We chose the SCS curve number method because it provides a reliable estimate of surface runoff with a reduced number of model parameters. This method accounts for soil hydrologic properties, land use, and antecedent soil moisture condition (AMC) to partition rainfall into infiltration and surface runoff. For this reason, the soil water balance components of widely applied crop models such as DSSAT (Jones et al., 2003), AquaCrop (Hsiao et al., 2009; Raes et al., 2009; Steduto et al., 2009), APSIM (Holzworth et al., 2014), CROPSYST (Stöckle et al., 2003), EPIC (Williams, 1990), and SWAT+ (Bieger et al., 2017; Čerkasova et al., 2023), among others, are either entirely built on the SCS curve number method or provide it as a simpler alternative to infiltration-based models.

In the original SCS curve number model, the initial abstraction ratio of 20% was assumed so that I_a is 20% of S (indicated by the subscript in Eq. 3). However, recent insights have led to an update in the abstraction ratio to 5%, which yielded higher runoff prediction performance of the SCS model. A proposed conversion function from S_{20} to S_{05} is expressed by Hawkins et al. (2020):

$$S_{05} = 1.42S_{20}. \quad (4)$$

S is determined by the land surface conditions, including soil characteristics as represented by the hydrologic soil group, land use land cover (in our case, agricultural land), and antecedent soil moisture, all of which are parameterized as a dimensionless curve number (CN) value. We estimated S as follows:

$$S_{20} = 254 \left(\frac{100}{\text{CN}} - 1 \right). \quad (5)$$

CN is updated daily for AMC, which are often categorized as dry, normal, and wet. The CN values obtained from the USDA lookup table correspond to the normal AMC. Accordingly, we estimated the CN values for the dry and wet AMC following Raes et al. (2022) and Smedema and Rycroft (1983):

$$\begin{aligned} \text{CN}_{\text{dry}} &= 16.91 + 1.348\text{CN} - 0.01379(\text{CN})^2 \\ &\quad + 0.0001172(\text{CN})^3, \\ \text{CN}_{\text{wet}} &= 2.5838 + 1.944\text{CN} - 0.014216(\text{CN})^2 \\ &\quad + 0.000045829(\text{CN})^3. \end{aligned} \quad (6)$$

We then adjusted CN at every time step by linearly interpolating between CN and CN_{dry} or CN_{wet} depending on the soil moisture condition, assuming the soil moisture content corresponds to θ_{WP} for CN_{dry} , $\theta_{0.5(\theta_{\text{FC}} + \theta_{\text{WP}})}$ for CN, and θ_{FC} for CN_{wet} . Note that θ_{FC} [$\text{m}^3 \text{m}^{-3}$] and θ_{WP} [$\text{m}^3 \text{m}^{-3}$] are volumetric moisture contents at field capacity and wilting point, and they were estimated using the widely used pedotransfer function developed by Saxton and Rawls (2006).

Applying the conversion from Eq. (4) for S_{05} and then expressing I_a in terms of S_{20} in Eq. (3), the expression for Q can be rewritten as follows:

$$Q_t = \begin{cases} \frac{(P_t - 0.071S_{20,t})^2}{(P_t + 1.349S_{20,t})}, & \text{if } P_t > 0.071S_{20} \\ 0, & \text{otherwise} \end{cases}. \quad (7)$$

The rainfall that is in excess of Q (Eq. 7) infiltrates into the soil and refills the available soil storage V_t [mm] = $1000Z(\theta_{\text{sat}} - \theta_{t-1})$, where θ_{sat} [$\text{m}^3 \text{m}^{-3}$] and θ_{t-1} [$\text{m}^3 \text{m}^{-3}$] are volumetric soil moisture content at saturation on the previous day (respectively), and Z [m] is the soil depth. We assumed the top 60 cm of soil to be a homogeneous layer containing the majority of the root biomass (e.g., Fan et al., 2016; Mthandi et al., 2013), and hence, this is the agrohydrological active soil depth Z for the major crops. ET_a is determined by moisture availability (green water) relative to the readily available water: RAW [mm] = $1000Zf(\theta_{\text{FC}} - \theta_{\text{WP}})$, where f [-] is a critical depletion factor that represents the soil moisture level below which plants experience moisture stress. For all four cereal crops studied, the value of f was set to 0.55 following Allen et al. (1998). ET_a was computed as $\text{ET}_a = K_{s,t}\text{ET}_{o,t}$, where $K_{s,t}$ [-] is the soil moisture stress coefficient (Allen et al., 1998):

$$K_{s,t} = \begin{cases} \frac{\text{SM}_t}{\text{RAW}}, & \text{if } \text{SM}_t < \text{RAW} \\ 1, & \text{if } \text{SM}_t > \text{RAW} \end{cases}. \quad (8)$$

If the soil is saturated, the infiltrated water which exceeds the soil field capacity percolates into deeper soil layers at the rate $\text{Dp}_t = 1000Z(\theta_t - \theta_{\text{FC}})$.

2.3.3 Crop module

The crop module simulates water-limited attainable yield (AY) based on the FAO water production function (Doorenbos and Kassam, 1979). The FAO water production function is a well-established relationship between climate and crop yield, explaining relative yield as a function of the evapotranspiration ratio, i.e., the ratio of actual to potential evapotranspiration on a seasonal scale. It is widely applied to assess the effects of water scarcity and climate change impacts on crop yields to inform agricultural water management planning and decision-making (e.g., Fischer et al., 2021; Foster and Brozović, 2018; Geerts and Raes, 2009; He et al., 2022; Sapino et al., 2022; Smilovic et al., 2016). The function assumes a linear relationship between relative crop yield losses

and seasonal evaporative stress (deficits in crop water use) under water-limited climatic conditions:

$$1 - \frac{Y_w}{Y_p} = K_y \left(1 - \frac{ETa}{ETo} \right), \quad (9)$$

where Y_w [tha^{-1}] and Y_p [tha^{-1}] are water-limited and energy-limited potential yields, respectively, and K_y [-] is the yield response factor that accounts for the complex crop characteristics that determine the crop water use. We re-defined AY, the ratio of the water-limited yield Y_w to the potential yield Y_p as a function of evaporative stress index $ESI = 1 - ETa/ETo$:

$$AY = 100(1 - K_y ESI). \quad (10)$$

The recommended K_y values were set to 1.25 for maize, 0.9 for sorghum, and 1.15 for wheat, obtained from the FAO irrigation and drainage paper 66 (Steduto et al., 2012), and to 1.04 for teff (Araya et al., 2011).

2.3.4 Model evaluation

The CHC modeling framework was not explicitly calibrated, meaning all parameters were taken from the literature and global datasets. Due to the limited availability of observed data, we could not conduct a formal validation of the model. However, we compared the simulated values of the agrohydrological variables Q , SM, and ETa, as well as the water-limited attainable yield AY, with independent data. In our comparisons, we focused on the differences and correlations between the simulated and independent values using the root-mean-square difference (RMSD) and the Pearson correlation coefficient (ρ).

The simulated mean annual Q was compared to published mean annual runoff observations from 20 sites within the RFA region (Table S3). We compared the annual cycles and interannual variabilities of the CHC-simulated SM and ETa with those of independent satellite- and model-based products (hereafter referred to as global datasets) for the period 2003–2010 across the four climatic regimes: semi-arid, dry sub-humid, sub-humid, and humid. For AY, we compared the simulated AY with the ratio of Y_w to Y_p estimates obtained from published field trials, calibrated crop model simulations, and the GYGA database at a total of 45 locations across the RFA region (Table S4). Additionally, we examined how temporal variations in AY explain variabilities in seasonal crop production. For this, we correlated AY and total cereal production (TCP) at each computation grid during the period 1995–2010.

2.4 Assessment of green water availability and its yield potential

We evaluated the climatology of GWA and AY during two growing seasons, *Meher* (May to September) and *Belg*

(February to May), based on the simulations for the reference period 1981–2010. We used soil moisture deficit (SMD) as a metric to evaluate GWA:

$$\text{SMD} = 100 \left(1 - \frac{\theta_{\text{clim}}}{\theta_{\text{FC}}} \right), \quad (11)$$

where θ_{clim} [$\text{m}^3 \text{m}^{-3}$] is the climatological mean seasonal soil moisture. SMD [%] is a dimensionless metric ranging from 0 % (no moisture deficit) to 100 % (maximum moisture deficit). The yield metric, AY [%], which was determined using Eq. (10), is also a relative quantity that explains the percentage of the energy-limited potential yield that can be viably attained under the actual water-limited conditions when all other agro-environmental factors such as nutrients are not limiting the yield; thus, its values range from 0 % (no yield) to 100 % (water-unlimited potential yield).

2.5 Future changes and climate sensitivity analysis

We applied the modeling framework to quantify changes in GWA and its implications for AY under climate change. We investigated the changes for three future periods, namely 2020–2049 (2030s), 2045–2074 (2060s), and 2070–2099 (2080s), under SSP1-2.6 (low), SSP2-4.5 (intermediate), and SSP5-8.5 (high) greenhouse gas emission scenarios. The impact assessments presented here are based on the median of downscaled multiple-GCM projections of future changes in rainfall, air temperature, and solar radiation. Other climatic variables were assumed to remain unchanged (Peleg et al., 2019). The impact analyses compare SMD and AY during the three future periods with the reference period (1981–2010) for the two growing seasons, *Meher* and *Belg*, and for the four major crops grown in Ethiopia (teff, maize, sorghum, and wheat).

We also examined the sensitivity of AY to changes in rainfall (green water supply) and atmospheric evaporative demand (AED) as represented by ETa. We determined the rainfall and AED sensitivity metrics, $\beta_{\text{RF}} = \frac{\% \Delta \text{AY}(\text{RF})}{\% \Delta \text{RF}}$ [-] and $\beta_{\text{ED}} = \frac{\% \Delta \text{AY}(\text{ED})}{\% \Delta \text{ETa}}$ [-], as the ratio of the percent change in AY to the percent change in rainfall or ETa based on the one-at-a-time sensitivity analysis approach (Hamby, 1994), where the CHC modeling framework was forced by the future RF and ETa (computed considering the future temperature and radiation) for all three emission scenarios and all three future periods. We determined the relative influences of the future changes in rainfall and AED on AY using the sensitivity ratio $\beta_{\text{ratio}} = \frac{\beta_{\text{RF}}}{\beta_{\text{ED}}}$. The values of β_{ratio} [-] range from zero to infinity, with values less than 1 indicating that temperature sensitivity dominates and values greater than 1 indicating that AED sensitivity dominates. This assumes that changes in rainfall and ETa are independent, which was confirmed by the low dependency ($R^2 = 0.098$) between rainfall and ETa computed for the period 2020–2099 for the three SSPs at every grid point.

3 Results

3.1 Evaluation of the CHC model

We first evaluate the simulated runoff (Q), soil moisture (SM), actual evapotranspiration (ETa), and water-limited attainable yield (AY) against other independent data. The comparison of simulated and observed mean annual Q (Fig. 3a) at the 20 field locations demonstrates a solid performance ($\rho = 0.91$ and RMSD = 52 mm) of the hydrological module in estimating the annual surface runoff from croplands. It is important to note that this comparison involves a point-to-grid value, and a perfect match cannot be expected due to this scale difference. The model underestimates the simulated Q at the two most humid locations.

The comparison for SM is illustrated in Fig. 3b. The scatterplot of the area-averaged CHC-simulated annual SM (2003–2010) versus the median of the global SM datasets demonstrates that the simulated SM closely follows the interannual variabilities in the median of the global datasets, with Pearson's ρ ranging from 0.69 in humid climate to 0.92 in semi-arid climate. Likewise, the annual cycles of the simulated and global SM datasets are also highly comparable, as shown in Fig. S1 in the Supplement. However, the simulated SM estimates are (systematically) lower than those from the global SM datasets in all climatic regimes (see also Fig. S3a and b in the Supplement). These differences decrease from semi-arid (RMSD = $0.075 \text{ m}^3 \text{ m}^{-3}$) to humid areas (RMSD = $0.041 \text{ m}^3 \text{ m}^{-3}$), as shown in Fig. 4b. In semi-arid and dry sub-humid areas, these discrepancies can be partly attributed to the fact that satellite-based global SM datasets are informed, in one way or another, by vegetation conditions (e.g., Dorigo et al., 2017; Rodell et al., 2004; Teng and Parinussa, 2021), which carry soil moisture signatures from deeper soil layers compared to the top 60 cm layer considered in this study. But, in general, the differences observed in the present analysis are consistent with findings from a previous study by Jimma et al. (2023), which revealed that the global satellite-based soil moisture products (FLDAS, ERA5 Land, ESA CCI, and GLDAS2) significantly overestimate soil moisture over Ethiopia. Similarly, Teferi et al. (2023) also reported that soil moisture estimates derived from two satellite products – the Advanced Scatterometer (ASCAT) and Soil Moisture Active Passive (SMAP) – overestimate the in situ-measured soil moisture at a monitoring site in the Upper Blue Nile.

The simulated annual ETa correlates well with the median of the global ETa datasets in all climatic regimes, with Pearson's ρ ranging from 0.80 in sub-humid regions to 0.93 in humid regions (Fig. 3c). The annual cycles of the simulated ETa also closely match those of the global ETa datasets (Fig. S2 in the Supplement). However, during the dry months (December to February), the simulated ETa is lower compared to the global ETa across all climatic regimes. From the scatterplot presented in Fig. 3c (see also the spatial patterns in Fig. S3c

and d), it is evident that the differences are more pronounced in semi-arid (RMSD = 61 mm) and dry sub-humid (31 mm) climates. Like in the case of SM, this can be attributed to the absence of vegetation representation in the CHC modeling framework, unlike in the global ETa datasets considered.

The comparisons of the simulated AY (at 45 locations) with three categories of the independent AY estimates are shown in Fig. 3d. The green category (scatters) represents the simulated AY versus the corresponding independent AY estimates from field trials and calibrated crop modeling experiments at 20 locations in different years within the reference period (1981–2010) for various crops. These exhibited a good correlation ($\rho = 0.79$), and the smallest difference (RMSD = 7.1 %) compared to the other categories. The blue category represents the simulated AY versus AY estimates from field trials at six locations, conducted outside the reference period in later years (post-2010), which we plotted against the average simulated AY over the later years of the reference period (2007–2010). This category also showed a similar correlation to the green category but with higher differences (RMSD = 9.4 %). The orange category, representing the simulated versus GYGA-derived AY at 19 locations, showed a weaker correlation ($\rho = 0.39$) and the highest difference (RMSD = 14.3 %). Note that these independent data (both from field trials and model simulations) have their own uncertainties. For example, most of the field trials from which the paired Y_w and Y_p were derived were conducted to evaluate crop yields under supplementary irrigation and not explicitly to determine Y_w and Y_p . Therefore, the AY values derived from these field trials are only rough estimates. Nevertheless, on average, the CHC-simulated AY is still highly comparable to the independent AY data. The average simulated AY across the 45 locations is 84.2 %, which is slightly lower than the average AY estimate from the independent data, which stands at 86.2 %.

We also evaluated the simulations of AY [%] in terms of their correlation to variations in detrended total cereal production, TCP [t yr^{-1}], as depicted in Fig. 4. The rationale here is that, in some regions, TCP will follow the climate-driven attainable yield (high correlation), while in others, the non-climatic factors, including nutrient input, improved cultivars, and pest and weed management, will play a role (low or negative correlation). Because TCP in the RFA region of Ethiopia exhibited an average increase of $0.36 \text{ t ha}^{-1} \text{ yr}^{-1}$ during the studied period (1995–2010), despite an almost constant AY, we conducted the correlation analysis on detrended TCP, thereby removing some of the effects of the non-climatic component of the variabilities in TCP (Kukul and Irmak, 2018; Mohammadi et al., 2023; Wakjira et al., 2021). The correlation analysis between detrended TCP and AY anomalies reveals mostly positive correlations (median Pearson's $\rho = 0.37$), particularly in the northern half of the RFA region (Fig. 4).

Some areas, primarily in the humid and sub-humid regions of the southern and southwestern parts and, to a lesser ex-

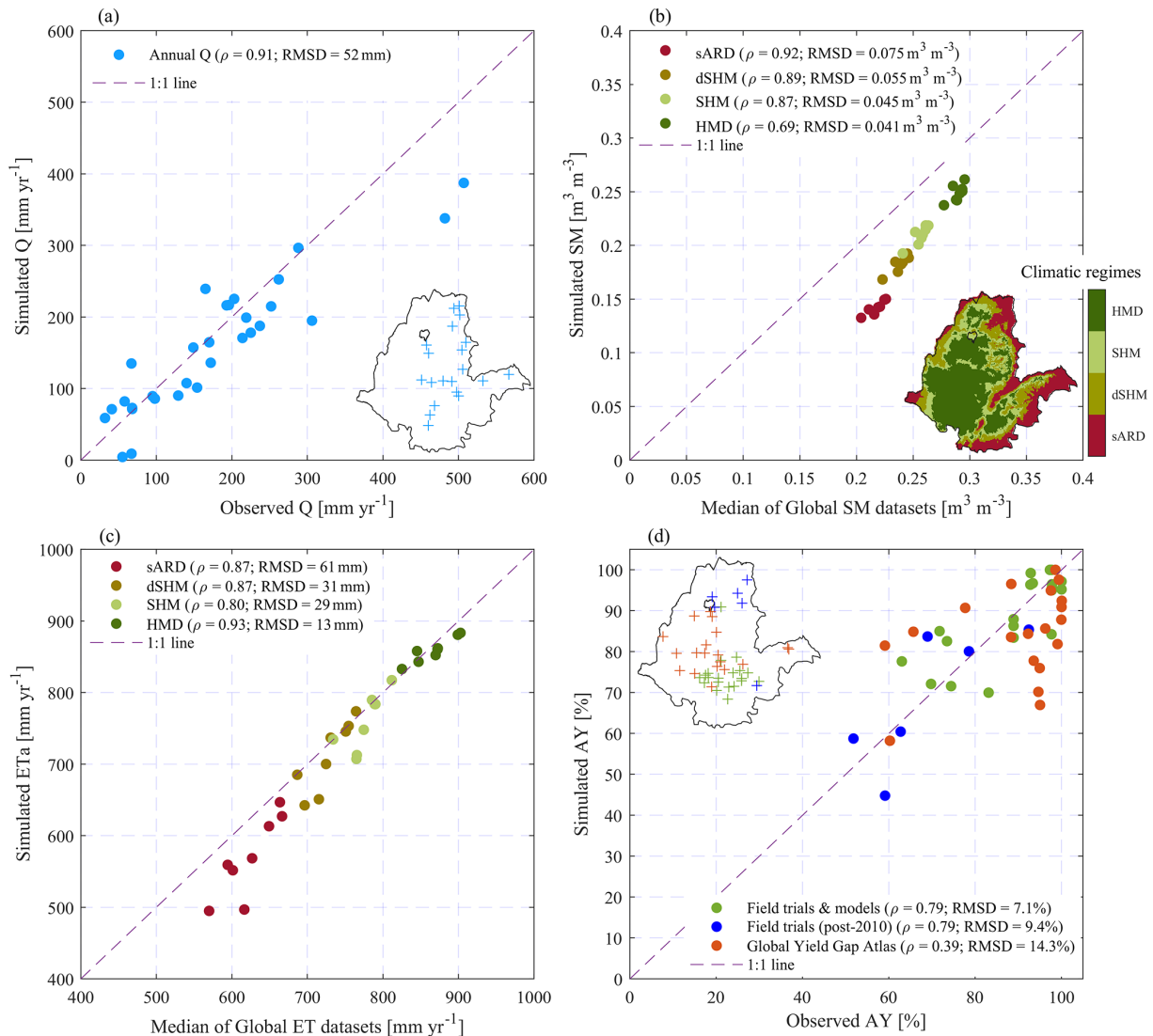


Figure 3. (a) Simulated versus observed yearly or mean annual runoff (Q), measured over varying years at 20 locations (shown on the inset map), collected from published studies across the RFA region (Table S3). This is a grid-to-point comparison. (b) Simulated versus median of four satellite- and model-based annual (2003–2010) soil moisture (SM) products (Sect. 2.2) spatially averaged over the four climatic regimes – semi-arid (sARD), dry sub-humid (dSHM), sub-humid (SHM), and humid (HMD) – shown by the inset map (from Fig. 1). Each circle represents area-averaged (over each climatic regime) SM for each year (2003–2010), and the colors indicate the climatic regimes. (c) The same as in (b) but for actual evapotranspiration (ETa) considering the median of the five global datasets. (d) Simulated water-limited attainable yield (AY) and the observed ratio of water-limited (rainfed) (Yw) to fully irrigated (Yp) collected from published field trials and crop modeling experiments at 29 locations across the RFA region indicated on the inset map.

tent, in the western and southeastern parts of the RFA region, exhibited negative correlations between TCP and AY. This can be attributed to climatic regimes, land use, and socio-economic practices. Two main factors may govern the AY-TCP correlation with climate. In less water-limited humid areas like the southwestern part, the linear relationship assumed in the crop yield response to water availability (Eq. 9) does not hold as AY is weakly dependent on rainfall. Additionally, in these humid climates and areas with poor soil drainage (e.g., areas marked as E1 in Fig. 4), crop yield can

be adversely affected by saturated soil conditions, leading to waterlogging problems. Concerning land use and socio-economic practices, the majority of areas with evident negative correlation are forest and/or agroforestry ecoregions (see E2 and E3 in Fig. 4) (Kassawmar et al., 2018), while other areas are agropastoral (E4), where seasonal crop production is an optional practice. Thus, interannual variabilities in TCP depend largely on how much farmers opt for cereal production in a given production year.

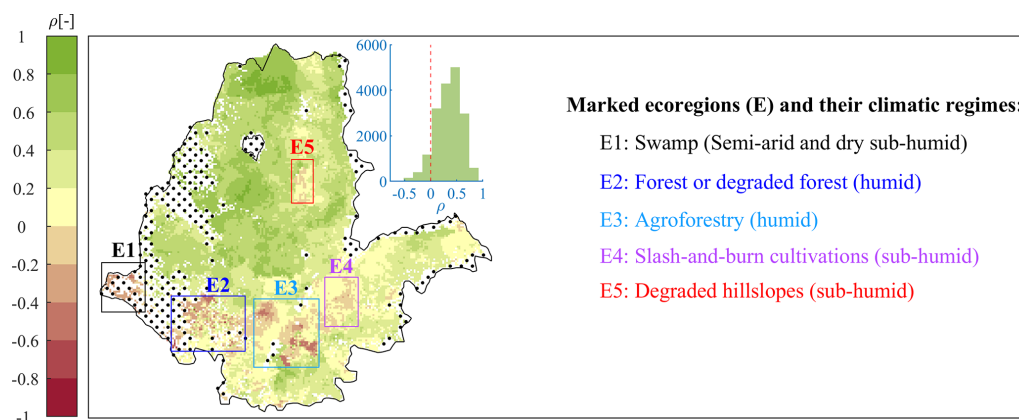


Figure 4. Map of Pearson's correlation coefficient (ρ) of detrended total cereal production (TCP) and AY for the period 1995–2010. TCP represents the sum of all cereals produced during the *Meher* growing season, with average values ranging from 28 to 24 000 t yr^{-1} across the RFA region. The dots show uncultivated areas based on cropland cover fraction data from Copernicus Land Services (Buchhorn et al., 2020). The inset histogram shows the distribution of ρ . The rectangular marks (E1–E5) show ecoregions where the correlations are weak or negative.

3.2 Green water availability and attainable crop yields

The reference climatology of growing-season GWA and water-limited yield across the RFA region based on the computed SMD and AY values is presented in Fig. 5, considering the reference alfalfa grass ($K_y = 1.1$, Allen et al., 1998). During the *Meher* growing season, the southern and southwestern humid areas of the RFA region exhibit a low soil moisture deficit, with values of less than 10 % of θ_{FC} (see Fig. 5a). Moving from the southwestern areas, the *Meher* SMD gradually increases in the northern and northeastern directions. In the peripheral semi-arid regions in the northeast, east, and southeast, the deficit reaches as high as 60 %–70 %. Notably, areas with SMD values below 20 % largely have $AY > 90$ %. In other words, the water-limited yield gap of less than 10 % of the potential yield achievable under unstressed moisture conditions (equivalent to a fully irrigated system) can be attained in the south-central, southwestern, and eastern highland parts of the RFA region (Fig. 5b). As expected, low AY (mostly less than 40 %) is evident in the southern and southeastern semi-arid parts of the RFA region during the *Meher* growing season. In summary, the median *Meher* SMD values are 17 %, 30 %, 37 %, and 53 % in humid, sub-humid, dry sub-humid, and semi-arid climates, respectively, while the corresponding median AY values are 93 %, 80 %, 68 %, and 46 % (Fig. 5e and f).

In the *Belg* season, the median SMD is mostly below 40 % across the major *Belg* region in the south (see Fig. 5c), with AY of up to 80 % in the humid areas in the southwestern part (Fig. 5d). In the central and eastern parts of the RFA region, which constitute other *Belg* regions, SMD is higher, reaching up to 60 %, resulting in a correspondingly lower AY of 40 %–60 %. The northern and northwestern parts of the RFA are dry during the *Belg* season; thus, SMD is very high. Unlike in the

Meher season, the differences in SMD among the climatic regimes are less pronounced in the *Belg* season, with median SMD ranging from 56 % in humid areas to 62 % in semi-arid regions (Fig. 5e).

In Fig. 6, we presented attainable yield (Y_w / Y_p) in a Budyko-like space (Budyko, 1974) and included paired Y_w (blue diamonds) and Y_a (actual yield, orange squares) estimates for 14 locations from previous studies across the RFA region (Table S5 in the Supplement), highlighting the gaps between these two yield levels for maize. In the *Meher* season, green water has the potential to produce more than 80 % of Y_p across 52 % of the *Meher*-producing regions of Ethiopia (highlighted by the shaded area in Fig. 6). Only about 27 % of the *Meher* region is moisture-limited ($P/ET_o < 1$). Y_a averages only 36 % of Y_w at the 14 locations, indicating significant potential for yield improvement through enhanced management practices. Notably, there are areas where the seasonal rainfall is greater than the atmospheric evaporative demand, but AY is still low. This discrepancy explains the non-linearity of the relationship between AY and SMD (shown in Fig. S4 in the Supplement), which is primarily linked to the combined effects of climatic and soil characteristics that influence rainfall–runoff partitioning and green water storage capacity. For example, a low AY for a given SMD can be associated with sandy soil in a dry climate, while a high AY for the same SMD can be linked to loam soil in a humid climate. From a management perspective, there may be limited options to address inherent soil physical properties like textural composition apart from measures such as amendment with organic matter, which might, to some extent, improve infiltration and green water storage capacity (Hartmann and Six, 2023).

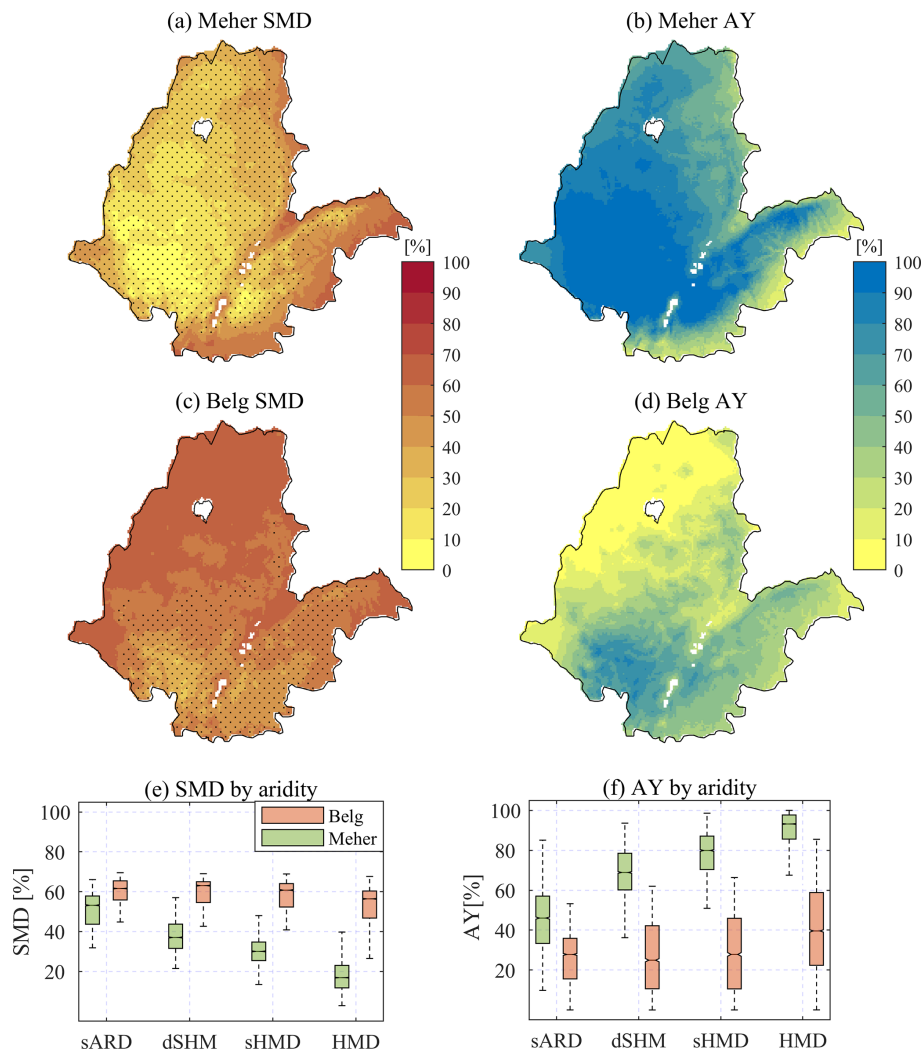


Figure 5. Climatological SMD during *Meher* (a) and *Belg* (c), AY for alfalfa grass ($K_y = 1.1$) during *Meher* (b) and *Belg* (d), SMD in different climatic regimes by aridity (e), and AY in different climatic regimes during the two growing seasons for the period 1981–2010 (f). Aridity classification is the same as in Fig. 1: sARD denotes semi-arid, dSMD denotes dry sub-humid, sHMD denotes sub-humid, and HMD denotes humid. The dotted areas in (a) and (c) show the *Meher*- and *Belg* regions, respectively, delineated based on the Atlas of Ethiopian Rural Socioeconomy (IFPRI and CSA, 2006).

3.3 Future changes in GWA and AY

3.3.1 Projected changes in growing-season rainfall and temperature

Based on the downscaled multiple-GCM median projection, the growing-season climate across the RFA region is expected to become warmer and wetter in future periods (Fig. 7). The temperature increase is progressive over time, especially under the intermediate- and high-emission scenarios, and shows little spatial variability (e.g., Fig. 7c). However, changes in rainfall patterns vary across regions and depend on the growing seasons. For example, *Meher* regions are likely to experience increased rainfall, while dry seasons are expected to remain unchanged or become even drier (e.g.,

Fig. 7a and b). Similarly, during the *Belg* season, the *Belg* regions in the southern part of the RFA region are expected to become wetter under higher greenhouse gas emissions. In general, a rainfall increase of up to 250 mm (multi-model median with 5th–95th percentile uncertainties ranging from about -150 to $+850$ mm; not shown) is anticipated over a large part of the RFA region during the *Meher* season under the high-emission scenario in the 2060s (Fig. 7a), and an increase of up to 300 mm is expected in the 2080s (not shown). During the *Belg* season, rainfall increases could reach up to 150 mm (5th–95th percentiles of about -60 to 500 mm) under the high-emission scenario in the 2060s. Additionally, the mean annual temperature is projected to rise by up to 3°C in the 2060s and up to 5°C by the end of the century.

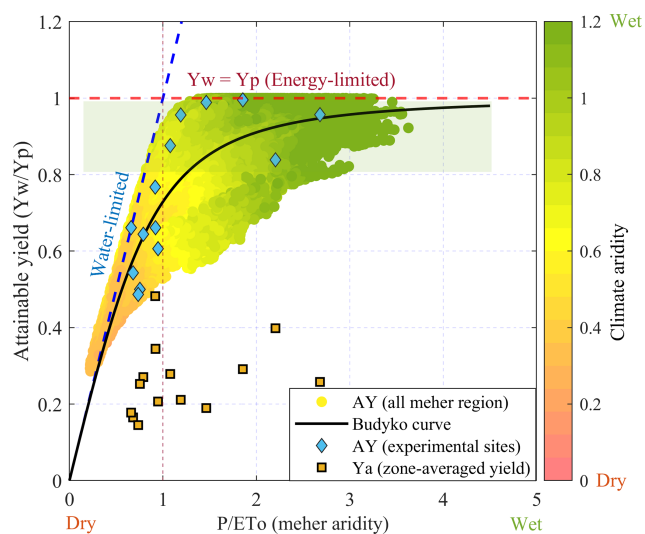


Figure 6. Scatterplot of water-limited attainable maize yield fraction (Y_w / Y_p) against seasonal aridity, showing the energy (dashed red line) and water limitations (dashed blue line). The color gradient shows the climatic aridity of each grid cell (different from the values on the x axis, which are seasonal aridity for *Meher*). The solid line represents the parametric Budyko curve fitted to the point cloud. The blue diamonds show Y_w at 14 locations across the RFA region, derived from published maize Y_p data (fully irrigated, optimally fertilized). The orange squares are the corresponding average actual maize yield (Y_a) in the administrative zone within which the experimental location is found. The shaded area indicates maize $AY > 80\%$.

3.3.2 Future changes in soil moisture deficit

In the face of the expected warmer and mostly wetter climate across the RFA region of Ethiopia, the GWA is likely to increase. Here, we present the expected changes in GWA in *Meher* (Fig. 8) as an estimated 88 % of the total grain production in Ethiopia occurs during this season. The expected changes in *Belg* are shown in Fig. S5 in the Supplement. In *Meher*, SMD is expected to decrease by up to 5 % over a large part of the region in the 2030s under all emission scenarios (Fig. 8). However, in the 2060s and 2080s, SMD is projected to increase by 3 %–15 % over the western, southwestern, and southern parts under the low- and intermediate-emission scenarios. This is expected, given the projected minimal change in rainfall under the warming climate over these regions.

Under the high-emission scenario, soil moisture deficit is likely to decrease over the majority of the region following the increase in rainfall. The central and northeastern parts of the RFA region are generally expected to experience a slight decrease in SMD and, thus, slightly higher GWA under all scenarios in the future. The highest increase in SMD was observed in the southwestern and southern parts of the RFA region, where the *Meher* rainfall mostly remains unchanged (see Fig. 7a). In the *Belg* growing season, soil moisture deficit consistently decreases over the producing regions in the fu-

ture periods under all scenarios (Fig. S5). These increases in GWA are particularly significant across the main *Belg* region in the southwestern part. In these areas, SMD is expected to decrease by up to 6 % in the 2030s (2020–2049) and by over 15 % in the 2080s under the low- and intermediate-emission scenarios. Under the high-emission scenario, GWA across the primary *Belg* regions in the south and southwest is expected to increase by up to 23 % by the end of the century.

3.3.3 Future changes in water-limited crop yields

The likely implications of changes in SMD for attainable yields for the four major cereal crops (teff, maize, sorghum, wheat) cultivated in Ethiopia are presented next. We summarize the changes occurring during the two growing seasons in their respective producing regions (Wakjira et al., 2024) and across the various climatic regimes of the RFA region.

Meher season

In the *Meher* season, minor or no changes in AY are expected, although regional differences exist in both the magnitude and direction of these changes. For example, for the 2060s, the projected changes in AY for teff range from -7.8% to 5.3% under the low-emission scenario and from -12.1% to 10.7% under the high-emission scenario. Similarly, for maize, the expected changes range from -7.8% to 4.7% under the low-emission scenario and from -11.5% to 6% under the high-emission scenario (Fig. 9a). Under the intermediate-emission scenario, the changes are predominantly negative, ranging from -9.3% to 1.8% for teff and from -8.2% to 1.2% for maize. Similar orders of magnitude and directions of change were observed for sorghum and wheat crops (refer to Figs. S6–S9 in the Supplement).

Comparing the near- and long-term future changes, we note a decreasing trend in AY for all crops under all emission scenarios. During the 2030s, the northern parts of the RFA region are likely to experience increases, while decreases are mainly evident in the southern and southeastern parts of the *Meher* regions. Notably, the marginal areas in the south and southeast are likely to experience the most significant decrease in AY for all crops and under all scenarios. By the 2080s, most of the *Meher* regions are expected to witness either no change or a decrease in AY (Figs. S6–S9).

We also examined the water-limited attainable yield responses in different climatic regimes (Fig. 10). In humid areas, the temporal changes and spatial variability in AY are small for all crops under all emission scenarios. This is because these areas rarely have moisture limitations, meaning that an increase in rainfall will have a minimal effect on yield improvement. In contrast, in semi-arid, dry sub-humid, and sub-humid areas, AY is likely to increase in the 2030s and then consistently decrease in future periods under both low- and high-emission scenarios. Under the intermediate scenario, AY is expected to decrease in the 2060s and then

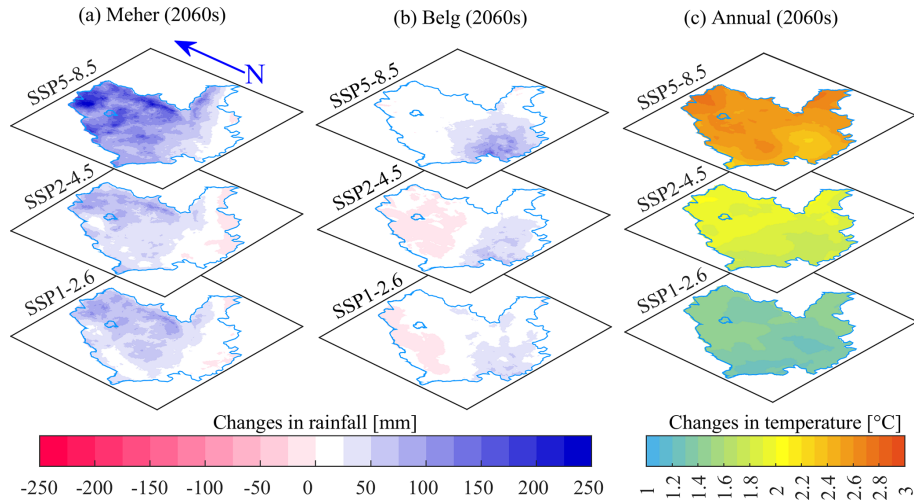


Figure 7. Projected changes in seasonal rainfall in the 2060s during (a) *Meher* (May–September) and (b) *Belg* (February–May) and (c) changes in annual temperature under the three SSPs. The changes presented here are the median of 26 downscaled GCM projections for rainfall and 21 GCM projections for temperature.

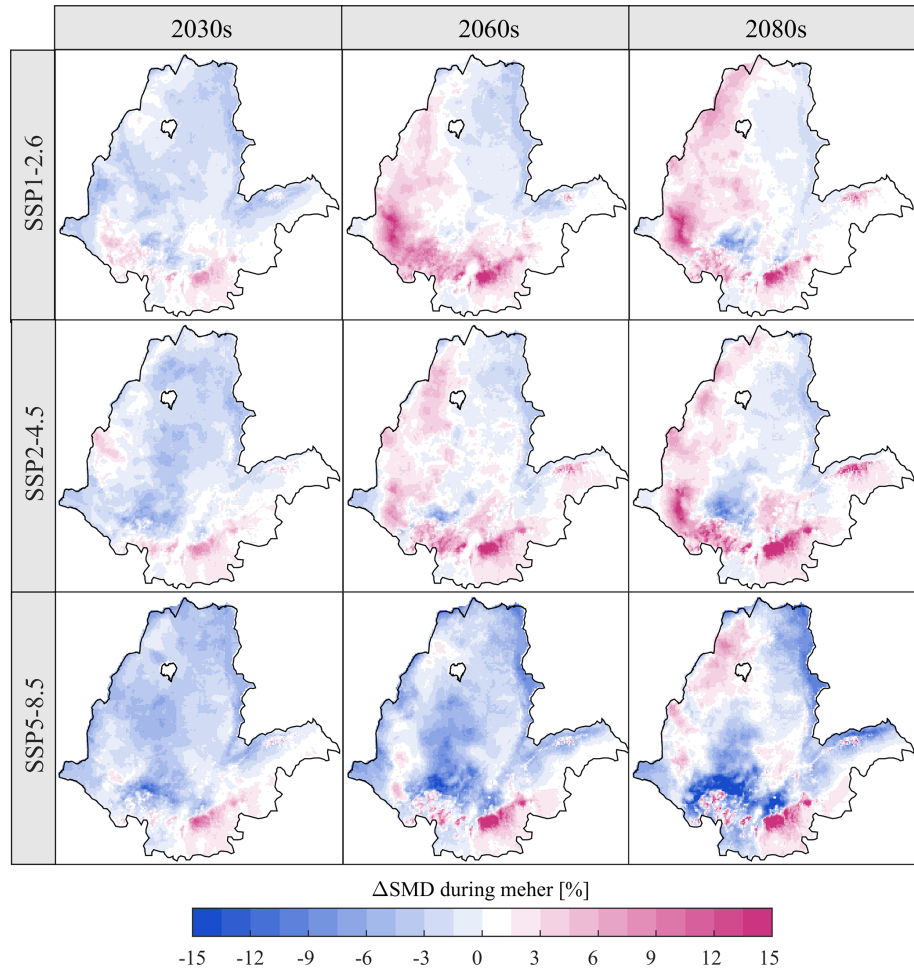


Figure 8. Projected changes in soil moisture deficit (SMD) across the rainfed agricultural region of Ethiopia during the *Meher* growing season under the SSP1-2.6, SSP2-4.5, and SSP5-8.5 scenarios in the 2030s, 2060s, and 2080s.

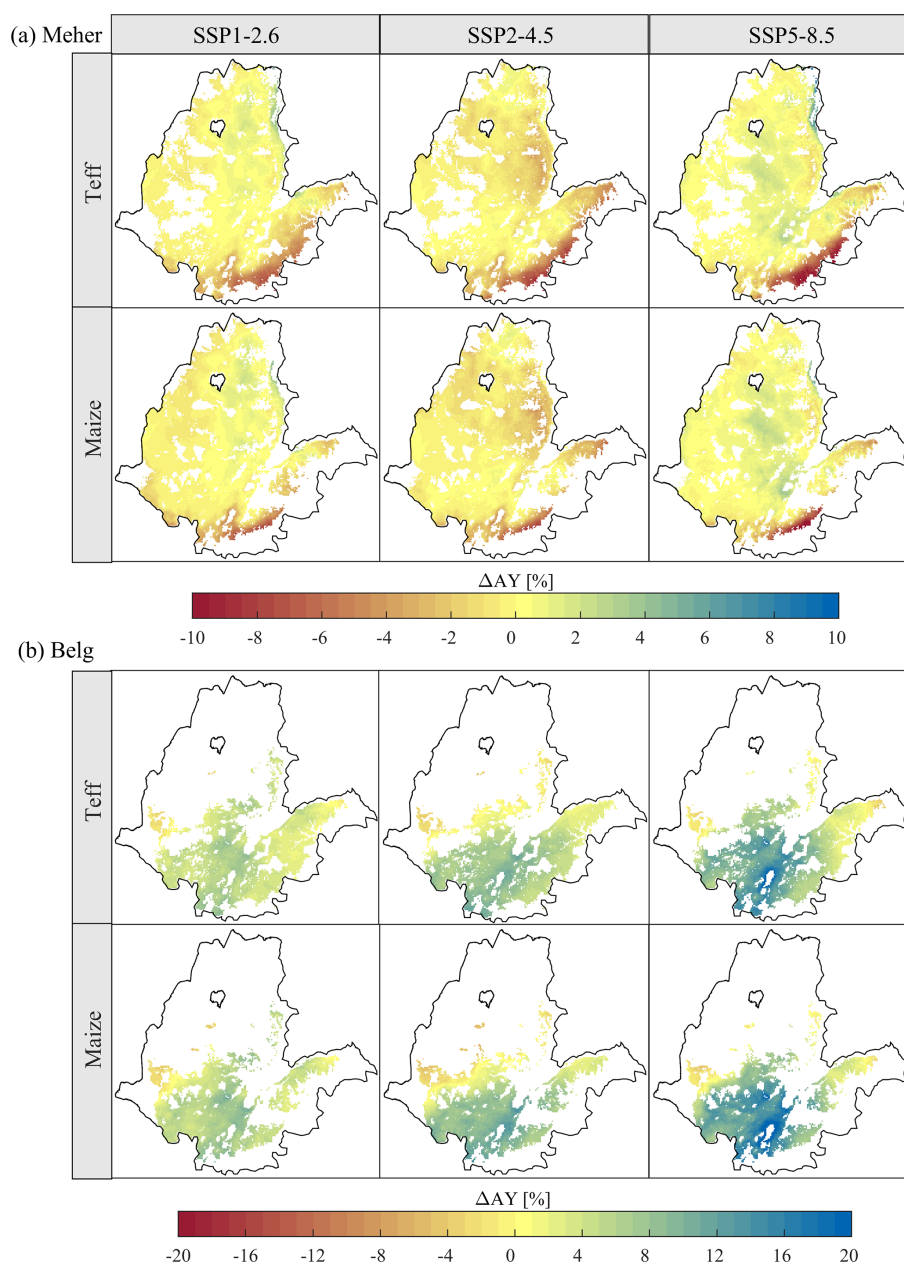


Figure 9. Projected changes in water-limited attainable yield for teff and maize in *Meher* (a) and *Belg* (b) during the 2060s under SSP1-2.6, SSP2-4.5, and SSP5-8.5. The RFA region was masked using cropland suitability maps (Wakjira et al., 2024) to restrict the analysis to areas potentially suitable for each crop. The non-producing areas during both seasons were also masked out following the Atlas of Ethiopian Rural Socioeconomy (IFPRI and CSA, 2006).

increase in the 2080s. Spatial variations are particularly high for teff, especially in semi-arid areas, with changes ranging from -10% to $+5\%$ in the 2060s.

Belg season

Following the increased rainfall and the subsequent rise in GWA, AY is projected to increase significantly and progressively over the major parts of the *Belg* regions in fu-

ture periods. However, a few areas will experience small decreases (Fig. 9b). For teff, the expected changes in the 2060s range from -3.5% to 8.8% under the low-emission scenario and from -3.6% to 21.7% under the high-emission scenario. Similarly, for maize, the changes range from -5.9% to 10.6% under the low-emission scenario and from -4.7% to 27.6% under the high-emission scenario. These positive changes are expected to intensify, particularly under the high-emission scenario, with the majority of the *Belg* region expe-

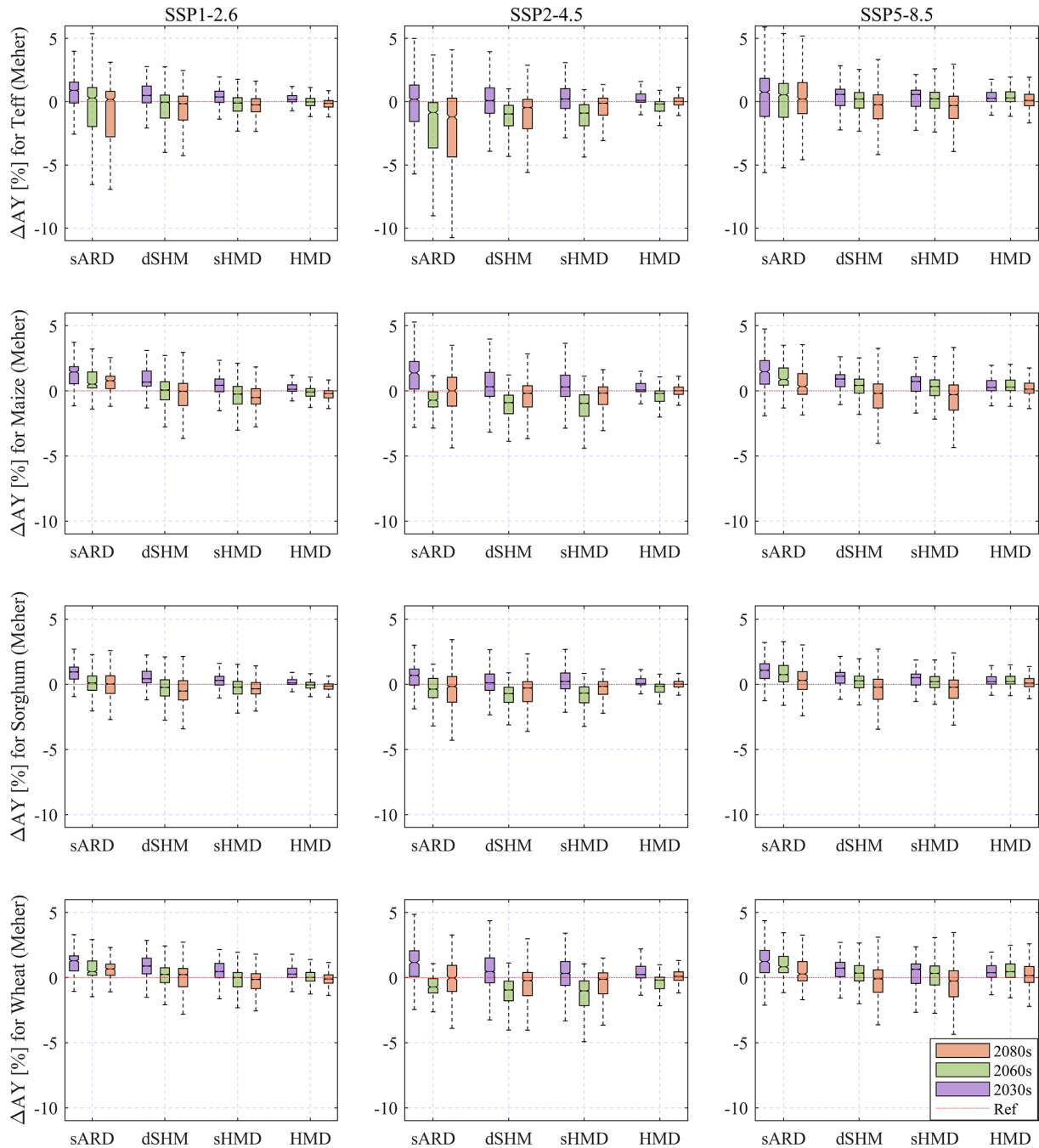


Figure 10. Boxplots of the projected changes in water-limited yields (AY) of the four major cereal crops produced in Ethiopia under different climatic regimes under the three SSPs for the three future periods during the *Meher* growing season. Each boxplot represents the distribution of AY changes within *Meher* regions for all grid cells in the respective climatic regime. Outlier values have been excluded.

riencing an increase in AY of over 20 % for all crops examined. The changes for all crops and future periods have been illustrated in the supplementary material appended to this paper (Figs. S10–S13 in the Supplement).

The changes in AY during the *Belg* season under different climatic regimes are illustrated in Fig. S14 in the Supplement. The variations in overall changes in AY among these

regimes depend on the emission scenario. Under the low-emission scenario, median changes in AY do not vary significantly across climatic regimes, remaining positive throughout the three future periods for all crops examined. In contrast, under the intermediate- and high-emission scenarios, AY tends to increase with climatic wetness (from semi-arid to humid climates). Decreases in AY are mainly noticeable

in semi-arid and dry sub-humid areas in the 2030s, particularly under the intermediate emission scenario. However, during the 2060s and 2080s, median changes in AY are positive and relatively consistent across climatic regimes for all crops. The projected increases in AY are higher for maize and wheat compared to for teff and sorghum. Spatial variability in changes generally increases with climatic wetness and into the future periods under the low-emission scenario, while a decreasing pattern is rarely observed under the intermediate- and high-emission scenarios.

3.3.4 Climate sensitivity of attainable crop yields

The spatiotemporal average relative sensitivities (β_{ratio}) of AY to atmospheric evaporative demand (AED) and rainfall for the four crops under the three SSPs are presented in Fig. 11. The results are averaged for the three future periods for the main growing season, *Meher*, in the administrative agricultural zones of Ethiopia. Results for the *Belg* short growing season are presented in Fig. S15 in the Supplement. The climate sensitivity is reported at a zonal scale rather than at the grid scale to provide zone-specific insights into the relative importance of ETo and rainfall in determining future green water productivity; this information is crucial for agricultural water management planning, service provision, and decision-making at the institutional scale. For the interpretation, we categorize the sensitivity of AY as AED-sensitive ($\beta_{\text{ratio}} \leq 0.8$), AED- and rainfall-sensitive ($0.8 < \beta_{\text{ratio}} < 1.2$), and rainfall-sensitive ($\beta_{\text{ratio}} \geq 1.2$).

During the *Meher* growing season, AY is predominantly AED-sensitive for all crops under all emission scenarios we considered (Fig. 11). The percentage of zones across which AY is, on average, AED-sensitive is 64 % for teff, 50 % for maize, 52 % for sorghum, and 77 % for wheat under low emissions. The influences of AED on AY increase with greenhouse gas (GHG) emissions. Under high emissions, AED dominates the changes in AY in 82 %, 65 %, 73 %, and 92 % of the zones for teff, maize, sorghum, and wheat, respectively. In the remaining zones, the simultaneous influences of rainfall and AED are evident, except for maize, where rainfall has a more significant impact than AED. Notably, changes in rainfall have a low influence on teff and wheat, with AY being rainfall-sensitive in less than 5 % of the zones. These crops are exceptionally more sensitive to AED compared to maize and sorghum, as indicated earlier. Temporal changes in the climate sensitivity of AY are also evident, but the spatial patterns do not change significantly in future periods.

The influences of changes in AED and rainfall on AY are primarily linked to the climatic regimes of the RFA region. In semi-arid and dry sub-humid climates, AY is predominantly AED-sensitive. This is particularly noticeable in the northeastern zones (covering the eastern parts of Tigray and Amhara and the western zones of Afar regions) and the central to eastern zones (including the Shoa, Arsi, and Hararghe

zones of the Oromia region) in the RFA region for all crops under low emissions (left panels in Fig. 11). This influence of AED intensifies in more zones in sub-humid and humid climates under the intermediate and high emissions. The sensitivity of AY to rainfall is largely evident in humid climates, mostly in the central, western, and northwestern zones under low emissions, for all crops except wheat, which is rainfall-sensitive only in the northwestern parts of the RFA region (Western Tigray and North Gondar zones). Maize AY is strongly rainfall-sensitive under all scenarios across the humid zones in the western part of Oromia (Wollega, Jimma, and Illubabor zones), the Sidama region, and most of the zones of the Southern Nations, Nationalities and Peoples' Region (SNNPR) region in the southwestern part.

In contrast to the main growing season, future changes in AY during the *Belg* growing season are primarily influenced by changes in rainfall, particularly in the main *Belg* regions in the southwestern, southern, and southeastern parts of the RFA region for all crops under all SSPs (Fig. S15). There is less spatiotemporal change in the rainfall sensitivity of *Belg* AY. Only under the high-emission scenario does the influence of changes in AED contribute to the influences of rainfall, primarily in the northern half of the RFA region, which remains dry during this season.

4 Discussion

4.1 Future green water limitations and crop yields in Ethiopia

Achieving crop yield at its potential level is not only a matter of adaptation to climate variability and change; it is also a key strategy for eradicating rural poverty and building resilience in heavily agricultural nations like Ethiopia (SIWI, 2018; Tittonell and Giller, 2013). In RFA systems, green water is a major limiting factor, and, thus, Yw defines the rain-fed crop yield potential (van Dijk et al., 2017; van Ittersum et al., 2013). Our analysis sheds a broader light on the potential of green water for crop production, as well as on its spatial variability and temporal changes (at a climatological timescale) in the face of climate change across the RFA region of Ethiopia.

We showed that the likely wetting and warming climate across a large part of the Ethiopian RFA region is expected to enhance green water availability (GWA) slightly in the near future. This is largely consistent with a recent global-scale assessment by Liu et al. (2022), which reported a decrease in agricultural water scarcity of up to 15 % in the RFA region for a comparable future period (2026–2050) and reference period (1981–2005) under the low-emission scenario. However, it is also evident that, in the long term, the effects of climate warming outweigh those of climate wetting, leading to green water scarcity. For example, Setegn et al. (2011), in a SWAT-based evaluation of future agricultural water availabil-

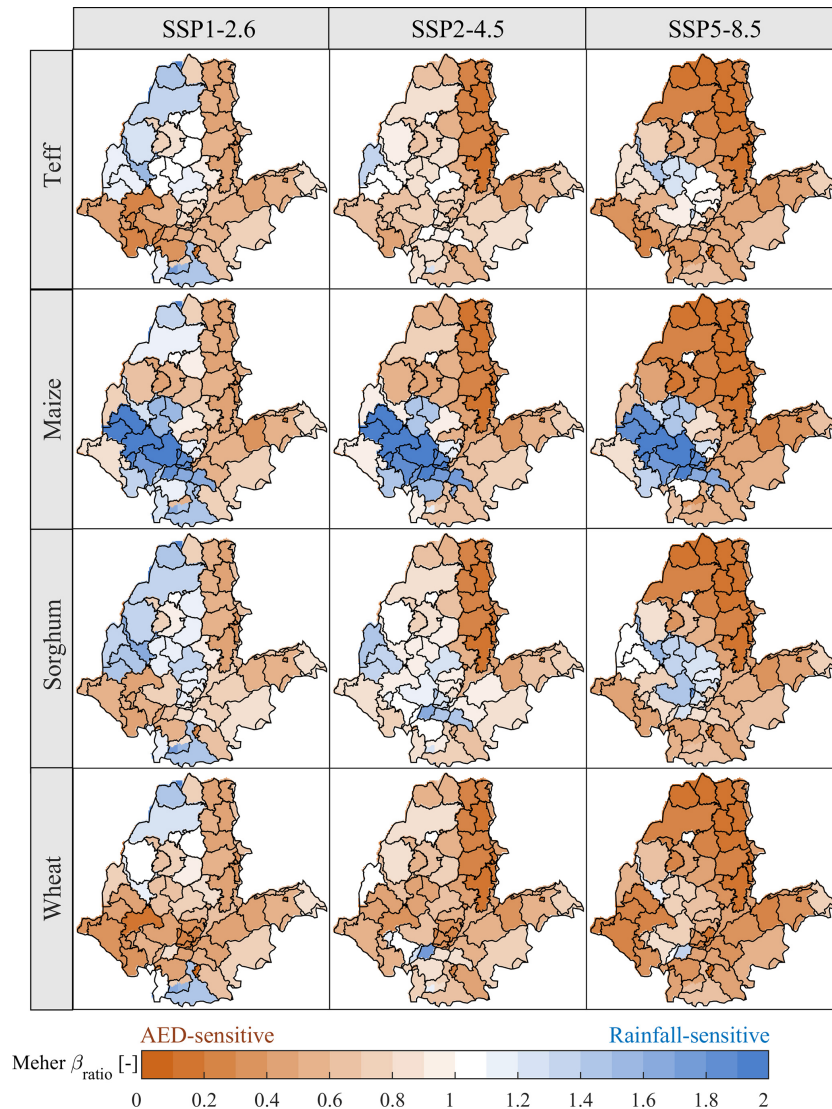


Figure 11. Area-averaged relative sensitivity (β_{ratio}) of water-limited attainable yield (AY) to rainfall and atmospheric evaporative demand (AED) for the *Meher* growing season at the administrative zone level under the low-, intermediate-, and high-emission scenarios. The mapped values represent the average of β_{ratio} of all grid cells within each zone and for all three future periods. The names of the administrative zones are indicated in Fig. 1 and Table S1.

ity in the Lake Tana basin in northern Ethiopia, conducted using four GCMs, revealed a decreasing tendency in soil moisture (by up to -2%) during the middle and end of the century, which aligns with our estimates for that area (-3% to $+1.5\%$, Fig. 8). In the northeastern semi-arid areas, GWA is expected to improve under all emission scenarios, across all future periods, and in both growing seasons. This is consistent (in terms of the direction of change) with another recent assessment based on the SWAT+ model driven by multiple-GCM projections under medium- and high-emission scenarios, which reported substantial increases in GWA in future periods in the Kobo-Golina River catchment (Abate et al., 2024). Similarly, our findings in the central Rift Valley sup-

port those of Muluneh (2020), who reported increases in soil moisture based on the AquaCrop model for maize forced by ensemble GCM projections under the high-emission scenario. The observed decreases in GWA across the southeastern semi-arid areas are the combined effects of the no-change or drying tendency and of temperature warming. Our findings in this area contradict those of Serur (2020), who predicts increases in GWA in the Weyn River catchment.

It has been widely reported that crop yields across the tropics, including East Africa, are likely to be affected negatively by climate change (e.g., Asseng et al., 2015; Jägermeyr et al., 2021; Li et al., 2022; Rosenzweig et al., 2014). We observe overall decreasing tendencies in *Meher* season AY for

the four crops studied, across all climatic regimes, and under all emission scenarios by the middle and end of the century (Fig. 10). In this regard, our results align with a recent study (Yang et al., 2023) which assessed climate-driven changes in maize yields in Ethiopia using the process-based DSSAT model with four GCM projections and similarly indicated a decreasing trend in yields. Our findings also align with the work of Rettie et al. (2022), which used an ensemble of crop models and similarly concluded that there would be decreases in *Meher* maize and wheat yields by the mid-century. Consistently with our findings (Fig. 11), they also reported that maize and wheat yields are more sensitive to temperature changes than to changes in rainfall. In Gambella, western Ethiopia, Degife et al. (2021) observed a decreasing trend in maize yields throughout the 21st century, with temperature playing a strong role in driving the change, which aligns with our findings, except for the 2030s, for which we found no change or a slight increase in that region (Fig. S8). Additionally, the projected slight increases in maize AY in Bako (central west) and the slight decreases in Melkasa (central east) are comparable to those of Araya et al. (2015). However, our findings largely contradict the crop yield projections based on a statistical model forced by two regional climate model projections (Kassaye et al., 2021), which reported substantial increases in teff and maize yields and substantial decreases for sorghum and wheat.

4.2 Uncertainties and limitations

From the model evaluation (Sect. 3.1), it is evident that the CHC modeling framework can reliably estimate the agrohydrological variables at a grid scale with minimal complexity for our stated purpose, which is to inform long-term agricultural water management, climate adaptation, resilience, and rural economic development in Ethiopia. Before we discuss further the practical implications of the GWA and AY conditions across the RFA region, we first highlight the limitations of the CHC model structure, especially the considerations needed when applying the model in different contexts, particularly in terms of purpose and temporal scale.

One of the simplifications in the CHC modeling framework is the use of the CN-based soil water balance model. The main limitation of the method stems from the empirical parameters – namely the curve number and the initial abstraction ratio – used to simulate the vertical soil water balance at the grid scale without routing the surface and subsurface flow. Therefore, these parameters must be properly calibrated for site-specific conditions (Assaye et al., 2021; Qi et al., 2020), particularly when the model is applied at the local scale and a shorter timescale. In our application, calibration over the entire RFA region is rather difficult as this would require large local observation data.

We quantified the uncertainty associated with the CN-based rainfall–runoff partitioning approach (CHC-CN) by comparing it to a water balance model that is based on

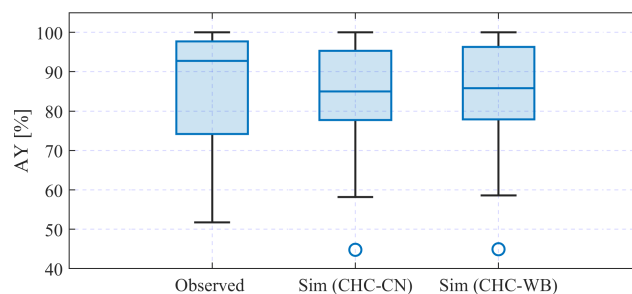


Figure 12. Comparison of CHC-simulated AY using the CN-based and water-balance-based (where WB denotes water balance) rainfall–runoff partitioning methods at 45 locations (Table S4) for which independent (observed) AY data were collected via published field trials, crop model simulations, and GYGA (<https://www.yieldgap.org>, last access: 13 August 2024).

the maximum soil infiltration capacity (CHC-WB), another widely applied concept (e.g., Chiarelli et al., 2020; Hoogeveen et al., 2015; Sishu et al., 2024; Tenreiro et al., 2020). In CHC-WB we assumed that surface runoff events occur when rainfall on a given day exceeds the maximum infiltration capacity (the difference between water content at saturation and soil water content the day before). Comparing the AY simulated using CHC-CN and CHC-WB, we found negligible differences between the models (Fig. 12), with a root-mean-square deviation (RMSD) from the observed AY of 10.98 % for CHC-CN and of 10.86 % for CHC-WB. Similarly, the differences in ETa and SMD simulated by the two models were small (see Fig. S16b and c in the Supplement). The main discrepancy appeared in surface runoff (Q) and deep-percolation (Dp) simulations (Fig. S16a) as the CHC-WB model does not adequately differentiate between surface and subsurface flow, diverting a larger portion of runoff to deep percolation. Although both surface runoff (Q) and deep percolation (Dp) are not the primary variables of interest in our analysis, their accurate estimation is crucial for other agrohydrological applications, such as water harvesting, flood (spate) irrigation design, and agricultural drainage system design, as well as the monitoring of soil and nutrient erosion. When input parameters like rainfall intensity and infiltration characteristics are available and when the model's complexity is manageable, infiltration-based models, such as those using Richards' equation (Richards, 1931), may provide more precise results than the curve-number- and water-balance-based models.

The crop module of the CHC modeling framework estimates relative crop yield only at a seasonal scale using the evaporative stress index (ESI) as a climatic factor and the yield response factor (K_y) to represent the seasonal crop response. In crop and agroecosystem modeling, such models are categorized as crop coefficient models and are primarily used for planning and decision-making (Foster and Brozović, 2018; He et al., 2022; Schwartz et al., 2020). Sub-seasonal

variabilities of stress conditions (water, thermal, light, nutrient, etc.), as well as the crop physiological responses within the growing season, have not been represented in the CHC modeling framework. Therefore, the use of the framework should not aim for accurate simulation of crop growth and yields; such simulations should be based on process-based crop models, which are capable of accounting for the major influences of climate change, such as the negative effects of heat stress and the positive effects of elevated CO₂ on future crop yield (Becker et al., 2023; Lobell et al., 2011a). In our analysis, which focuses on assessing changes on a climatological timescale, we focused on the climate of the rainy seasons (May to September and February to May) instead of accurately defining the growing period from planting to harvest. While the uncertainties associated with the choice of growing period are averaged out at a climatological timescale, an accurate planting date is an important input in process-based crop growth and yield simulations at local and sub-seasonal scales (Lala et al., 2021).

Despite the uncertainties and limitations outlined, the results presented are robust and offer valuable insights for practitioners in planning and policy formulation in Ethiopia. Furthermore, the model developed can be adapted for application in different regions and climates, enhancing its utility for broader decision-making processes.

4.3 Implications for green water management and sustainable intensification

While the changes in water-limited attainable yield vary greatly across the RFA region in terms of both magnitude and direction during the main growing season, the results show that semi-arid and dry sub-humid areas are most likely to experience a reduction in AY. On the one hand, this is attributed to an intensified soil moisture deficit, as is evident, for example, in the northwestern, western, southern, and southeastern semi-arid areas (with low and intermediate emissions in the 2060s and 2080s, as seen in Fig. 8), and, on the other hand, this is also a result of increases in the sensitivity of AY to AED (Fig. 11), particularly in the moisture-limited regions. In these regions, it would be beneficial to implement on-farm water management strategies that maximize green water availability and minimize non-productive green water flows.

Practices that aim to maximize GWA should focus on altering the rainfall–runoff partitioning processes by increasing the opportunity for infiltration during rainfall through various surface management practices. For example, tillage and physical measures like bunds, infiltration trenches, tied ridges, and planting pits, among others (Hurni, 2016; Makurira et al., 2009; Nyakudya et al., 2014), have been successfully evaluated in field experiments and on-farm practices. Other measures like residue retention and cover cropping not only enhance infiltration but also suppress the non-productive evaporation from the soil surface (Rockström,

2003). Additionally, measures that improve infiltration also offer the side benefit of reducing soil erosion by runoff, another critical challenge that contributes to the crop yield gap. Finally, we strongly suggest that the selection of water management practices should be carefully made by evaluating their need and suitability primarily based on climate and soil characteristics. For example, in humid climates with heavy clay soils, such practices may result in waterlogging problems, which is also a major yield-reducing factor in such environments (Manik et al., 2019; Pittelkow et al., 2015).

The projected increase in GWA and AY during the *Belg* season may provide an additional opportunity for farmers to intensify their production during this season. This, however, will need firm stakeholder commitment to plan and mobilize resources for action in the framework of National Adaptation Plans (NAP) and similar initiatives (Conway and Vincent, 2021). Long-term awareness of stakeholders, ranging from the institutional level to farm-level actors, with regard to the expected challenges and opportunities of climate change, supported by climate information services for short-term decisions, is highly important to exploit such opportunities (Grossi and Dinku, 2022). In addition to climate information like the forecast information of the expected onset and cessation of *Belg* rain, extensive support with regard to the proper selection of crop types compatible with the duration of the short growing season is vital to help farmers effectively plan and undertake bi-annual production without compromising the main growing season.

5 Conclusions

We investigated the cascading effects of climate on green water availability and water-limited attainable yield (AY) in the context of the rainfed agricultural region of Ethiopia. We integrated hydroclimatic processes with crop yield response through an agrohydrological modeling framework to assess the current potential, future changes, and climate sensitivity of AY. The AY across the Ethiopian RFA region is on the average 79 % of what could be produced under water-unlimited conditions during the main growing season (*Meher*) and 37 % of what could be produced under water-unlimited conditions during the shorter season (*Belg*) during the reference period (1981–2010), with regional variation depending on the climatic regimes. The soil moisture deficit (percentage of soil moisture content at field capacity) during this period is, on average, about 29 % in *Meher* and 56 % in *Belg*.

The future climate over the RFA region is expected to be warmer and mostly wetter. Under these changes, future changes in green water availability and AY vary across regions, emission scenarios, and future periods, as well as between the two growing seasons. In *Meher*, the expected changes in AY predominantly fall within the ± 5 % range under all scenarios and future periods. Changes during the

2030s are largely positive under all scenarios, but AY shows overall decreases in the 2060s and 2080s. Decreases in AY are mostly evident in semi-arid regions, with teff being the most affected. These changes are dominantly driven by the atmospheric evaporative demand (AED) that is caused by temperature increase, especially in moisture-limited regions. The influence of AED increases under the intermediate- and high-emission scenarios, suggesting the need for due attention to management strategies that suppress evaporative losses in the future. In *Belg*, AY is expected to progressively increase by up to 20 % under the high-emission scenario by the end of the century, providing an opportunity for farmers to expand crop production in this season. These changes are dominantly driven by increases in rainfall, implying that green water management practices that increase water availability would further improve crop yields during this season. Furthermore, our assessment of documented field experiment results and crop yield data from the RFA region reveals a large gap between the actual and water-limited yields. For example, for maize, on average, only 36 % of AY is actually realized under the current practices, suggesting that green water management practices should be combined with other measures that overcome the yield-reducing factors related to soil nutrients, tillage practices, plant protection, and cultivar improvement.

Finally, the CHC modeling framework developed in this study can be applied to conduct similar assessments in other regions. It can also be adopted for various agrometeorological applications, such as estimating seasonal water availability and crop water demand for both irrigated and rain-fed systems, as well as predicting relative yield for management planning and decision-making. The framework minimizes dependence on process-based crop models for such analyses, which often require intensive measurement data for the calibration of several model parameters.

Data availability. The processed data and simulation output will be made available upon request.

Supplement. The supplement related to this article is available online at <https://doi.org/10.5194/hess-29-863-2025-supplement>.

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