Modelling the impacts of water harvesting and climate change on rainfed maize yields in Senegal

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Abstract

Senegalese agriculture is threatened by climate change effects, affecting rainfall variability both at interannual and interdecadal timescales. Using FAO's AquaCrop crop-growth model, we tested the efficiency of an *in-situ* water harvesting technique - tied ridges - for maize cropping in the Fatick region in Senegal in response to changes in temperature and precipitation with different fertility levels and different soils. Results showed that tied ridges did not significantly impact maize yields considering the current climate and soil fertility. The rainfall amount was enough for maize production and to avoid water stress during the cropping season. Under perturbed climates and, especially in years with low average rainfall amounts, high losses in yield were registered under optimal fertility conditions (up to 80%). The most substantial effect was obtained when tied ridges were simulated on clay soil, enhancing yields by 5.6% and 13% at actual and optimal fertility conditions, respectively. Our results highlighted how the current maize production in the Fatick region in Senegal is not significantly water constrained in the current climate scenario, while it could be potentially impacted by climate change in the near future. In a pessimistic climate change scenario, *in situ* water harvesting can potentially avoid excessive crop losses.

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Introduction

Due to combined threats, African food production will face great challenges in the near future. The highly vulnerable smallholder farmers will be the most impacted since food security is disproportionally undermined where inequalities are greater (FAO, 2020). Climate change is expected in many regions to increase temperature, alter rainfall patterns, and escalate extreme events, such as floods and droughts (Arias *et al*., 2021). Another significant challenge is represented by the demographic growth of most African countries that will continue in the following decades (Samir and Lutz, 2017). The combined impacts of climate change and population growth suggest an alarming increase in water scarcity in sub-Saharan Africa (Cooper *et al*., 2008). Currently, it is estimated that 50 million people in cropland and pastureland are exposed to water shortages, representing a real threat to their food security and nutrition (FAO, 2020). By 2050, increasing temperatures, more frequent extreme weather, and climate events will have pronounced effects on the agricultural sector of Africa. Heat waves, droughts, pest damages, and floods will affect agricultural production systems with regional and crop variability, and under the Representative Concentration Pathway 8.5 scenario, a general reduction in yield of 13% is expected in West and Central Africa (WMO, 2020).

Senegal is a West African country that will likely be affected by severe climate change effects. From the climatic point of view, it is characterised by three climate bands from North to South: the warm desert, warm semi-arid, and tropical savanna climates (Peel *et al*., 2007). The national agriculture economy accounts for approximately one-sixth of the national Gross Domestic Production, the production has increased by 70%, and the population has quadrupled, reaching 16.3 million people over the past 30 years (D'Alessandro *et al*., 2015), inevitably increasing the stress on limited natural resources. Smallholder farmers characterise the agricultural economy; the most cultivated subsistence crops are millet, sorghum, maize, and rice, while the main cash crops are groundnut and cotton (FAO/GIEWS Country Cereal Balance sheet, 2020). Senegal counts less than 5% of irrigated land, and the national agriculture strictly depends on the rainy season lasting from mid-June to mid-October (CIAT and BFS/USAID, 2016). The significant variability of rainfall, both on interannual and interdecadal timescales, represents the critical risk in agriculture, with more than 40% of the variation in national crop yields that can be ascribed to the rainfall variation (D'Alessandro *et al*., 2015). Climate projections agree on the future increase in temperature in West Africa, while the magnitude and direction of change are less clear for precipitation and other correlated variables such as aridity, drought, and extreme events (Arias *et al*., 2021; Roudier *et al*., 2011). This uncertainty range is also reported in the Senegal climate change country profile by McSweeney *et al*. (2008), which indicates decreasing mean annual and wet season rainfall, but with a range of change within -41 to +48% by the 2090s. The decreasing trend in annual precipitation with reductions of 10-20% by the end of the century is also reported in the analysis of Sarr and Sultan (2022). Given these uncertain climate projections, yield changes in West Africa also show a large dispersion from -50% to +90%, with a median negative impact of -18% predicted for the Sudano-Sahelian countries (Roudier *et al*., 2011). As changes in rainfall patterns occur, as well as extreme events such as dry (wet) spells, which are episodes when precipitation is abnormally low (high) compared to the usual climatology (Fall *et al*., 2021), the smallholder farmers get more vulnerable and the need to make agricultural systems more resilient has become clear.

Water harvesting (WH) is described as the process of collecting runoff and storing it for productive purposes (Oweis and Hachum, 2006). It is an adaptation strategy that can help increase rural communities' resilience in the context of climate change. WH plays a vital role in improving small-scale rainfed productions, stabilising the yields, and increasing productivity (Rockström and Falkenmark, 2000; Wallace, 2000). Since the 1980s, WH practices have been strongly promoted in many African regions by non-governmental and development organisations (Rockström and Falkenmark, 2000). Nevertheless, there is significant potential to increase WH application throughout the world. Piemontese *et al*. (2020) identified social-ecological regions worldwide covering 19% of current global croplands in which the adoption of WH can increase yields up to 60-100% in countries such as Uganda, Burundi, Tanzania, and India. Although the importance of water conservation practices is recognised worldwide, further efforts must be applied to include these practices in investment strategies and development policies (Rockström and Falkenmark, 2015).

The WH soil and water conservation practices can be broadly categorised into macro-catchment and micro-catchment WH (Oweis and Hachum, 2006). Tied ridging is among the most promising micro-catchment WH techniques, also referred to as in situ WH (Biazin and Stroosnijder, 2012). Tied ridges (TR) are designed to trap water runoff from small areas (10-500 m^2) with a wide range of land slopes. The structure consists of furrows dug in the soil to hold water, facilitating infiltration and storage in the root zones (Biazin and Stroosnijder, 2012). Brhane *et al*. (2006) showed the effectiveness of TR in reducing surface runoff, improving soil water content, delaying water depletion, and increasing yields. Hunink *et al*. (2010) analysed different green water credit management practices through the SWAT model in Kenya. They underlined the contribution of TR on maize in preventing sediment losses, reducing it by 32%, and in implementing reservoir inflow, increasing it up to 27% compared to standard management. Madalcho *et al*. (2015) found that TR significantly influenced the sorghum biomass in Ethiopia in both fertilized and non-fertilised conditions and minimised fertiliser loss. Similarly, Sibhatu *et al*. (2017) report an increase in yields when TR was dug and optimal results in terms of biomass when coupling this WH technique with the addition of fertilizers. Biazin and Stroosnijer (2012) examined the potential benefits of rainwater harvesting using TR through field experimentation and FAO's AquaCrop model and reported changes in the effectiveness at different water regimes and fertility conditions.

Generally, the effectiveness of micro-catchment WH techniques like TR is based on farmers' experience. Compared to other adaptation practices, such as supplemental irrigation, the application of numerical models to study these techniques is still underdeveloped.

The use of models could help promote these practices and optimally locate the regions in which they would be more successful. Nowadays, many crop models are being used for various purposes, including identifying adaptation strategies to reduce climate change impacts on future crop production (Kephe *et al*., 2021). Among the various models used, Aquacrop is one of the most applied to study adaptation strategies and climate change impacts. For example, Bird *et al*. (2016) investigated the effect of climate change on rainfed wheat in Italy and irrigated tomato production in Tunisia and possible adaptation strategies. Alvar-Beltrán *et al*. (2021) assessed the impacts of two climate change scenarios on soil evaporation and transpiration rates, crop water productivity, and yield of wheat and sugarcane under different irrigation schedules along the Indus River Basin, Pakistan. Alvar-Beltrán *et al*. (2023) also evaluated the impact of two climate change scenarios on millet, sorghum, and cowpea in two agroclimatological regions in the Republic of Niger. Regarding WH modelling, Biazin and Stroosnijer (2012) applied the Aquacrop model to simulate TR in Ethiopia. In the same country, Wolka *et al*. (2021) modelled the effects of soil bunds on surface runoff and maize yield, while Villani *et al*. (2018) performed a water productivity analysis of maize in a sand dam irrigation scheme. Lastly, Renzi *et al.* (2023) simulated the hydro-agrological effect of Marab water harvesting technology on barley production in Jordan.

Climate change is primarily included in General Circulation Models simulation studies, usually statistically or dynamically downscaled with Regional Climate Models. Even if these models are widely used in research, they present significant uncertainties and biases (Christensen *et al.,* 2008; Laux *et al*., 2021). An interesting alternative methodology to study adaptation strategies in different plausible climates without using climate models is represented by adaptation response surface (ARS) methodology (Ruiz-Ramos *et al.,* 2018). ARS methodology builds on previous research on impact response surfaces (IRS) (Pirttioja *et al.,* 2015), which are created by perturbing historical weather time series by changing temperature and precipitation within plausible ranges, hence evaluating the sensitivity of crop yield to systematic changes of climate variables.

Due to the lack of literature on the role of WH in many areas of the African continent, particularly in Senegal, the present study focused on determining how the runoff collection with TR can effectively reduce water stress, thus increasing yields. For this scope, we simulated the maize crop cycle in the Fatick region in Senegal with and without TR. The effectiveness of TR in terms of increased yields was studied with the historical climate and applying the ARS methodology, and considering different soil types and management scenarios. This study also further demonstrates the potential of numerical models to understand the processes of micro-catchment WH better. These models can be conveniently applied to perform exploratory analysis, even if the role of field experiments remains crucial.

Materials and Methods

Study area

Fatick region is located in the Sudan Sahelian climatic zone of Senegal and covers an area of 6,685 km² (Figure 1). It is part of the groundnut basin, an area of 46,367 km² well known for the rainfed groundnut production for staple and cash purposes (Faye and Du, 2021). The rural population represents 85% (ANSD, 2014). The region is characterised by a dry season lasting seven months and a wet season of five months, from June to October (Figure 2). The annual mean minimum temperature is 20°C while the mean maximum temperature reaches nearly 37°C. Annual rainfall ranges between 500 and 900 mm based on the historical period 1980-2013 (D'Alessandro *et al*., 2015). Fatick is one of Senegal's most rainy regions with millions of cubic metres of water lost due to a lack of water retention structures (Department of Agriculture and Rural Development Central West Region, 2003). Four different soil types constitute the pedologic picture, which is associated with four ecological zones: tropical ferruginous soils, hydro soils, halo morphic soils, and the soils of mangroves (ANSD, 2014). In agriculture, the crop rotation is characterised by the two most cultivated crops, millet and groundnut (36.5% and 26.9% of parcels, respectively). Other major crops representing an interesting source of diversification for subsistence agriculture are maize, cowpea, and rice (DAPSA, 2020). In the last decades, the Senegalese government promoted large-scale actions to increase the productivity of maize and rice, which are considered fundamental for food security (Diakhate, 2014; Gueye, 2021). The two crops require more inputs, such as fertilisers, and are more vulnerable to drought than groundnut and pearl millet (Okuyama *et al*., 2017).

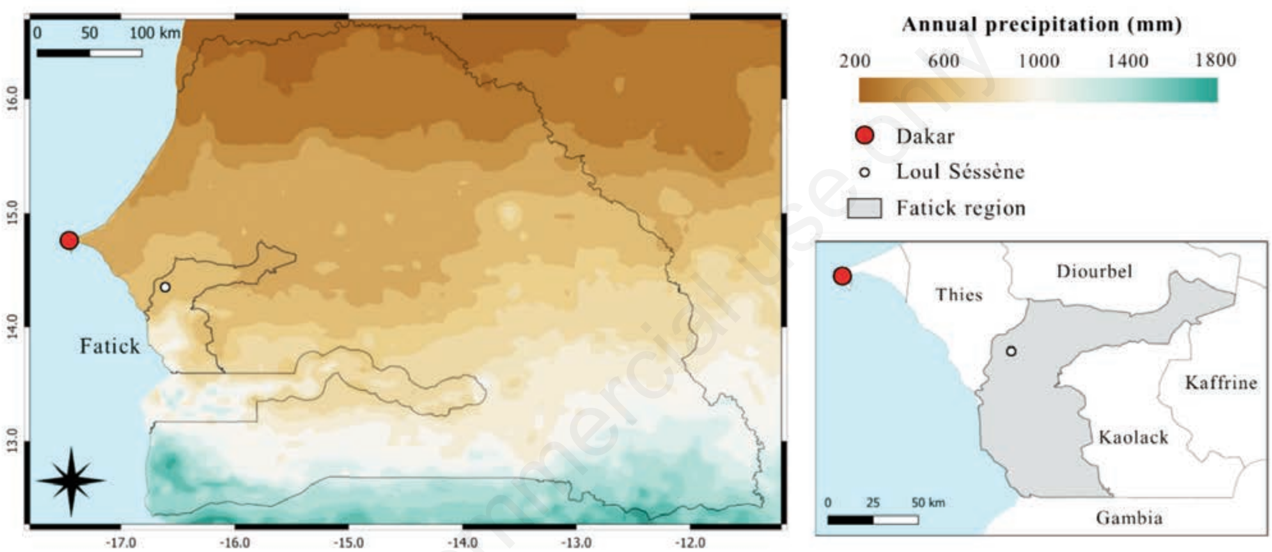

Figure 1. Map of the Fatick region in Senegal and the location of Loul Séssène. Data of the mean annual precipitation retrieved on the World Association for Public Opinion Research portal for the period 2009-2019.

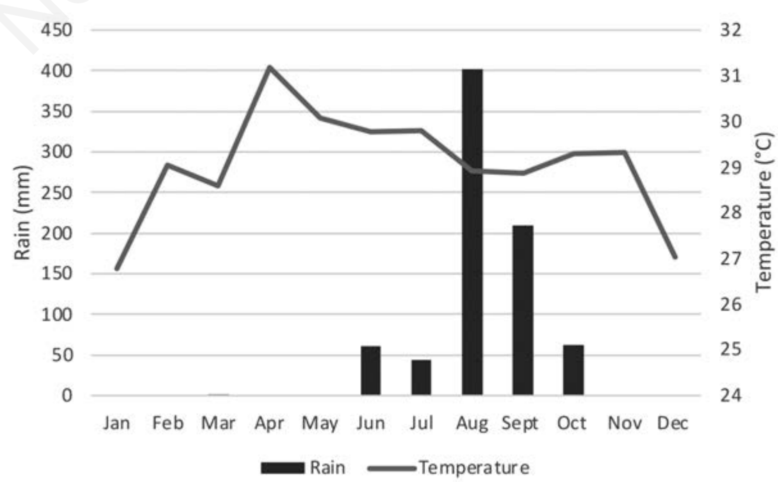

Figure 2. Monthly mean rainfall and temperature in the Fatick region. The data source is the World Association for Public Opinion Research portal, and the period considered is 2009-2019.

The AquaCrop model

The AquaCrop water productivity model, developed by FAO (Hsiao *et al*., 2009), was used to simulate maize yield variation in relation to climate change and the adoption of water harvesting. The model has been validated for many crops in different locations and was declared non-cultivar specific and applicable to a wide range of conditions (Hsiao *et al*., 2009). This study focuses on maize crop because AquaCrop's performance in simulating maize growth and yield is considered good in comparison with other crops, as it has been tested in stress and non-limiting water conditions and with good geographical coverage (Raes *et al*., 2018b). The AquaCrop model is considered robust; it can be used with limited data availability and as a management tool to develop strategies to maximise water productivity through crop and management practices such as WH (Raes, 2017). The model simulates, with a daily time step, soil water balance, crop development, soil evaporation and crop transpiration, aboveground biomass, and biomass partitioning into yields (Raes, 2017). Key equations used by AquaCrop are:

$$B = WP^{*} \times \Sigma \left[\frac{Tr_i}{ET0_i}\right] \tag{1}$$

$$Y = B \times HI \tag{2}$$

where B is the total biomass (g m^{-2}), WP^{*} is the water productivity (g m^{-2} mm^{-1}) normalised for atmospheric evaporative demand and CO_2 concentration (Raes, 2017), Tr_i is the daily amount of water transpired (mm day^{-1}), and $ET0_i$ is the reference evapotranspiration for that day. Y is the final yield (g m^{-2}), and HI is the actual harvest index (%), obtained by adjusting the reference harvest index with an adjustment factor for water and temperature stress effects (Raes, 2017). Regarding the AquaCrop crop parameters, it is essential to differentiate between conservative and non-conservative ones. The former does not change with time and cultivating conditions, while the latter must be modified based on the selected cultivar or environmental conditions (Raes, 2017).

To simulate the effect of TR on runoff, the curve number (CN) is modified. CN is the parameter that describes the interaction between rainwater and soil, it is dimensionless, and it is influenced by hydrologic soil group, soil cover type, land use, hydrologic condition, and antecedent moisture condition. The CN is used to determine the total amount of runoff from a rainfall event in a specific area through the CN method with Eq. 3 (Raes *et al*., 2022). It ranges from 0 to 100, and the higher the value, the higher the runoff; therefore, the lower is water infiltration. Eq. 4 expresses the potential maximum retention after runoff begins, needed in the CN equation.

$$Q = \frac{(P-\gamma S)^2}{[P+(1-\gamma)S]} \tag{3}$$

$$S = 254\left(\frac{100}{CN}-1\right) \tag{4}$$

where Q is the total amount of runoff in mm, P is the total rainfall in mm considered in the time frame, and S is the potential maximum retention after runoff begins and multiplied by the value γ (0.20) gives the initial abstraction of the soil. AquaCrop assigns a CN value on the basis of the saturated hydraulic conductivity of the soil top horizon; the values refer to averages of the hydrologic soil groups for small grains soil cover complex with good hydrologic conditions given by the United States Department of Agriculture (Raes *et al.,* 2022). Furthermore, since the type of crop and the soil management can affect the CN, AquaCrop allows further adjustment of the CN based on the selected crop (if different from small grain) or soil management.

AquaCrop does not simulate the nutrient cycles and balances but considers the effect of soil fertility stress on the canopy cover and biomass production expressed as a percentage. Limited soil fertility results in a biomass water productivity (WP) decrease and a smaller canopy cover during the growing cycle (Raes, 2017). The weed competition is expressed by the relative cover of weeds, which is the ratio between the ground area covered by leaves of weeds and the total canopy cover of weeds and crops.

Climate data

The climate input data required to run AquaCrop are the daily maximum and minimum temperature, the daily rainfall, the daily reference evapotranspiration, and the mean annual CO_2 concentration in the atmosphere. To calculate daily reference evapotranspiration, several methods are available. Since we did not dispose of air humidity, wind speed, and solar radiation data, ET_0 was manually calculated through the Hargreaves method, as described in Allen *et al*. (1998).

Baseline climate data

The observed values of the CO_2 atmospheric concentration measured by Mauna Loa Observatory Hawaii, available as default in AquaCrop, were used for the baseline climate data collection. Rainfall data for the Loul Séssène area (14°18'00'- 16°36'00') obtained from the Climate Hazards Group Infrared Precipitation with Stations dataset (Funk *et al*., 2015) were downloaded through the FAO WaPOR portal. Values of the maximum, minimum, and average daily temperatures were retrieved from the National Oceanic and Atmospheric Administration climate dataset, a quality-controlled dataset providing daily data recorded worldwide. In our case, the reference station of Kaolack was selected because of its nearness to the study area. Due to the limited climate data availability, ET_0 was calculated following the Hargreaves method with Eq. 5:

$$ET_o = 0.0023 \times (T_{mean} + 17.8) \times (T_{max}\text{-}T_{min})^2 \times Ra \tag{5}$$

where T_{mean}, T_{min}, and T_{max} are the daily mean, minimum and maximum temperatures (°C), and Ra is the daily extra-terrestrial radiation (MJ m^{-2} day^{-1}). Ra was determined for the geographic location following the procedure described by Allen *et al*. (1998). The daily ET_0 results have been compared with an 11-year data series retrieved on the WaPOR portal to evaluate its consistency.

Perturbed climate data

The synthetic climate scenarios were created following Ruiz-Ramos *et al*. (2018) by perturbing the baseline climate data. The intervals of change were based on projections of annual precipitation and temperature for Senegal up to 2090s provided by McSweeney *et al*. (2008). The mean annual temperature is projected to increase by 1.7 to 4.9°C, with a faster warming rate in the interior regions than in coastal areas. Annual rainfall is projected to decrease, particularly in the wet season, with the change ranging between -41 to +48%. The perturbation involved only precipitation (P) and temperature (T), while CO_2 concentration was not varied since we aimed to evaluate the effect of TR only on P and T variables and exclude any yield variations caused by CO_2 concentration change. The variation deltas were defined from 0 to 5°C at 1°C intervals for T and from 0 to -50% at 10% intervals for P (Table 1). The increase in rainfall percentages was not considered to restrict the study to contexts of water scarcity in which WH techniques can better express their function. As a result of the process, 36 different climate series with perturbed T and P were generated.

Soil and crop management data

The’ Soil Grids’ database was used to retrieve the soil texture and the chemical properties of two representative soils of the Fatick region (Poggio *et al*., 2021). Soil Grids is a high-resolution soil-mapping system providing soil properties data of the globe, with a spatial resolution of up to 250 m, already used in crop-growth model application studies in Senegal (Jha *et al*., 2021). Sandy soil prevails in the Fatick region, and a sample was selected in the Loul Séssène area (14.3030 N, –16.6036 E). We also selected clay soil in the Ndofene area (14.2475 N, –16.3492 E) to investigate the impact of tied ridges with different textures. In this case, the chosen sample, also from SoilGrids, was based on observed data from the WoSIS database, explaining the different thicknesses of layers. The texture classes of the two representative soils for all the layers were imported into the software ‘Soil Water Characteristic’ (Saxton and Willey, 2006). This software is a hydraulic properties calculator developed by the US Department of Agriculture and Washington State University. It calculates hydraulic properties based on soil texture, organic matter, gravel content, salinity, and compaction using the pedo-transfer functions of Saxton and Rawls (2006) as in Raes *et al*. (2021). The outputs are presented in Table 2.

In AquaCrop, soil fertility is not simulated based on the nutrient balance, but it is estimated based on the effects it has on canopy development and biomass production. For instance, poor soil fertility results in a smaller canopy cover and a decrease in biomass WP during the growing cycle (Raes, 2017). AquaCrop considers the optimal fertility status as the condition found on a well-watered field with no soil fertility stresses, in which the crop can express its maximum canopy cover development and water productivity; meanwhile, due to the lack of canopy cover data, the actual fertility conditions of the soil under scope were estimated on the base of literature information about the soil condition of the area. Land degradation in the Fatick region was estimated from ‘light’ to ‘strong’ in the analysis of Sonneveld *et al*. (2016), and other studies reported limited fertility conditions (Gueye, 2021; Laminou *et al*., 2020). The 2020 Rapport de l’Enquête Agricole Annuelle of Disease Activity in PSoriatic Arthritis (DAPSA) highlighted how many constraints strongly limit agricultural production, and the most frequent in agriculture of Senegal is the loss of soil fertility, which involves 35% of the plots concerned by the analysis. In addition the gap between actual and potential yield at the national level is also explained by poor management practices, and the doses of NPK fertilizers applied on the field recorded by the DAPSA are below the recommended by the competent organism. In addition the data collection across the West Central region of Senegal conducted by Hernández *et al*. (2021) was taken as a reference to define the fertility status of the area. The study observed a low quantity of total carbon content across the whole region, reporting a mean value of 0.30% between all the 825 samples collected. Finally, we assigned ‘poor’ soil fertility conditions, and so the soil fertility stress on the crop development was set at 62% by the model as in Raes *et al*. (2021). The soil fertility reduction is consistent also with the study of Jha *et al*. (2021). The weed management was also assumed to be ‘poor’ considering that weeding is largely performed with animal traction and hand hoes in small-scale farms (Okuyama *et al*., 2017). Hence, the weed relative cover was set at 45% by the model. Furthermore, the first soil CN assigned by the model was 61 for the sandy soil and 72 for the clay soil, and it was increased to 73 and 86, respectively, after specifying the adoption of row crop management. To simulate the TR effect of slowing down or

Table 1. Simulations performed in the study considering different climate scenarios, including the range of change, tied ridges (TR, No-TR), the soil fertility level, and texture.

Climate	Range of change (climate)	Tied ridges	Fertility level	Soil
Baseline	-	No-TR, TR	PF, OF	Sandy, clay
Perturbed	0% to -50% (P) 0° to 5°C (T)	No-TR, TR	PF, OF	Sandy, clay

P, precipitation; T, temperature; TR, tied ridges; No-TR, without tied ridges; PF, poor fertility; OF, optimum fertility.

Table 2. The two soils considered in the study, with the hydraulic properties for the whole soil profile.

Layer	Thickness (m)	Texture	TAW (mm/m)	PWP (vol %)	FC (vol %)	SAT (vol %)	Ksat (mm/day)
Sandy soil							
1st	0.3	Sandy loam	85	12.6	21.1	43.3	622.6
2nd	0.6	Sandy clay loam	92	14.9	24.4	43.2	390.5
3rd	0.6	Sandy clay loam	94	15.5	25	43	347
Clay soil							
1st	0.4	Clay loam	130	24	37	47.2	64.8
2nd	0.12	Sandy clay loam	116	20.4	32	44.6	117.1
3rd	0.12	Clay	119	30.9	42.8	49.6	18
4th	0.4	Sandy loam	79	9.8	17.7	44.1	1041

The hydraulic properties are total available water (TAW, mm/m), permanent wilting point (PWP, vol%), field capacity (FC, vol %), saturation (SAT, vol%), saturated hydraulic conductivity (Ksat, mm/day). Source: https://soilgrids.org stopping the runoff, the CN value was zeroed as recommended by Raes *et al*. (2018a). For this study, crop parametrisation was defined based on information from local experts and literature (Table 3). The maize variety chosen for the study is a medium-cycle length variety (Diakhate, 2014). Plant density was set to 30.000 plants/ha to simulate a common value adopted in semi-arid areas by smallholder farmers. Biazin and Stroosnijder (2012) also describe crop densities adopted in semi-arid areas as usually less or equal to 3 plants/m^2. Based on the local information regarding the maize phenological phases provided by the International Rain Water Harvesting Alliance technicians, the 2nd of July was selected as the common sowing date for every simulation year.

Model calibration and validation

Due to data constraints, a simplified calibration process was applied based on the Fatick yield data recorded by the DAPSA in 2018. Calibration was performed through trials and errors by changing AquaCrop non-conservative parameters, specifically maximum canopy cover and harvest index, so that the model output corresponded to the observed value. The validation was conducted utilising regional yield data for 2015, 2016, 2017, and 2019. To compare the simulated yields with the recorded data, we applied the Normalized Root Mean Square Error (NRMSE) calculated with Eq. 6:

$$NRMSE = 100 \times \frac{1}{\bar{O}} \sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_i - O_i)^2} \tag{6}$$

where P and O are simulated and observed values expressed in kg/ha, and n is the number of observations.

NRMSE is used to measure the error of a model in predicting quantitative data and gives information on the differences in percentage between the observed and the simulated values. It was considered a good performance of the model if NRMSE was lower than 15% and highly performant if lower than 5% (Raes *et al*., 2018a). Furthermore, the mean absolute difference (AD), calculated by averaging the differences between yields obtained with and without TR, indicated the impact of TR.

Simulations

To assess the impact of TR on the baseline climate, the model was run from 2009 to 2019 for both soil types, firstly considering the standard CN and afterwards equal to zero. Also, each round of simulations was run under optimal (OF) and poor (PF) fertility conditions.

In the present study, the ARS method was used (Ruiz-Ramos *et al.,* 2018) to evaluate the maize yield response under the perturbed climate variables and, in these conditions, to understand how TRs act as an adaptation measure. The 36 perturbed climate files were uploaded on the AquaCrop model and tested with the different CN values, soil types, and fertilization levels. The yields were simulated for each year, and each variable combination considering the biomass developed at the simulated conditions and the calibrated HI value. The IRS were constructed by plotting the average final yield of the 11 years as contour lines along the axes of P and T. IRS are surface plots that represent the response of an impact variable to changes in two independent variables (Pirttioja *et al*., 2015; Ruiz-Ramos *et al*., 2018), in our case represented by the maize yields and the two variables T and P.

Unadapted and Adapted IRS were generated by plotting the simulated yields without and applying TR, respectively. To verify if TR had any influence on yields, the difference between the yields obtained, at the same climate conditions, with and without TR, was calculated and plotted in a new contour plot, the ARS, as represented in Eq. 7. In this case, the isolines are expressed in percentage of yield change.

$$\textit{Adapted IRS} - \textit{Unadapted IRS} = \textit{ARS} \tag{7}$$

To better identify the simulations for each climate scenario, in Table 1, the combinations and relative codes are reported.

Results

Calibration and validation of the model

The fine-tuning of the crop parameters resulted in a maximum effective rooting depth of 0.8 m and the HI at 34%, similar to the one reported by Raes *et al*. (2021) for maize in Gambia. The mean regional yield taken as a reference is 1326 kg/ha, and simulated grain yields of 1323 kg/ha and 1340 kg/ha were obtained after the

Table 3. The AquaCrop crop user-specific parameters used in the study.

User-specific parameters (calibrated)	Value	Units/meaning
Harvest index	34	%
Maximum effective rooting depth	0.8	m
Effect of canopy cover in late season	50	(%) CC effect on soil evaporation
Number of plants per hectare	30000	Ha^{-1}
Canopy decline coefficient	0.932	per day % CC decrease
Time from sowing to emergence	6	Calendar days
Time from sowing to maximum rooting depth	108	Calendar days
Time from sowing to start senescence	107	Calendar days
Time from sowing to maturity	132	Calendar days
Time from sowing to flowering	66	Calendar days
Length of the flowering stage	13	Calendar days
Building up of harvest index	61	From flowering (days)

calibration of the model for sandy and clay soil, respectively. The validation assessed the accuracy of the model in simulating maize grain yield; the recorded average of the regional yields from 2016 to 2019 was taken as a reference, and the model simulated the final yields for each soil type with good relative errors between simulated and observed yields (Table 4).

The mean relative difference between simulated and observed yield data was 7.0% for the sandy soil and 6.0% for the clay soil, while the mean AD resulted in 80.5 kg/ha and 76 kg/ha for the sandy and clay soil, respectively. The total relative magnitude of the differences, expressed by NMRSE, was 9.99%; thus, being the value lower than 15%, it was considered a good result in terms of model performance (Raes *et al*., 2018a). Overall, the model simulated the mean regional yield well and the results were considered satisfactory.

Simulations

Tied ridges impact simulation under the baseline conditions

As shown in Table 5, the comparison between yields under current climate conditions showed no significant changes when simulating the implementation of TR for sandy and clay soils. At PF condition, using TR, the average yield on both sandy and clay soils did not vary. Regarding the simulations conducted at OF condition, the mean yield did not show any significant changes; values ranged from 2894 to 2902 kg/ha for sandy and 3009 to 3036 kg/ha for clay soil. Also, no differences exceeding 27 kg/ha of mean AD were observed. The standard deviation (Stdev) was calculated for the yield values of the 9-year series, and minor differences at PF condition for both soils after TR application were found. On the other hand, at OF condition, the Stdev resulted much higher; the use of TR did not significatively influence the values in the case of sandy soil, while for clay soil it was observed a decrease from 518 to 346 kg/ha, thus indicating TR application may reduce the interannual yield variability in clay soils.

Tied ridges impact simulation using adaptation response surface methodology

The analysis of IRS consisted in interpreting the IRS contour plots for PF and OF conditions for sandy (Figure 3) and clay soils (Figure 4). The two independent variables, T and P, are displayed on the X and Y axes, respectively, and the contour lines represent the yield response to T and P joint changes.

The mean yield reported by IRSs at PF condition for sandy soil (Figure 3, PF) ranges from 1019 and 1350 kg/ha for the non-adapted scenarios and from 1029 to 1351 kg/ha for the adapted. Contour lines tend to be horizontal, meaning that yields are stable when increasing T and decrease in function of P changes. This behaviour expresses the main limiting effect that rainfall has on yield variation. The major impact is identified at high T and reduced P on the right-down corner of the graph. Furthermore, in both adapted and not adapted scenarios, relevant decreases in yields were recorded only in years with rainfall below the average value of 526 mm (2011, 2014, 2016, 2017, 2018, 2019), and the maximum observed loss was -50%. At OF condition, IRS plots (Figure 3, OF) showed a similar contour lines behaviour of the IRSs-PF. Differences were found in the magnitude of the impact; more specifically, the influence of T increase and P reduction generated higher yield losses with an observed peak of 70%. Differently from the PF condition scenario, the yield reduction in OF condition was more diffuse over the years and not limited to the below-average rainy seasons.

Regarding the clay soil simulation (Figure 4), IRS shows the same contour lines behaviour observed for the sandy soil, and it confirmed the higher limitation effect that P exercises on maize yields compared to the T variable. Clay soil increased the sensitivity to precipitation changes; the highest losses are observed primarily in years with rainfall under the average value, and the maximum observed reduction peak is 80%.

The ARS plots (Figure 5) represent the adaptation response from using TR, expressed in % of yield change, and consider soil type and fertility condition. At PF condition, on sandy soil (Figure

Table 4. Comparison analysis of observed and simulated yields in the model validation.

	D (%)	AD (kg/ha)	RMSE (kg/ha)	NRMSE (%)
Sandy	7.00	80.5	134.1	9.99
Clay	6.00	76	131.4	9.82

Performances are indicated for the mean relative difference (D), mean absolute difference (AD), root mean square error (RMSE), and normalized root mean square error (NRMSE).

Table 5. Simulated yields (kg/ha) under the baseline without tied ridges and with tied ridges for two soil types and at two different soil fertility levels, poor fertility level and optimum fertility level.

	PF No-TR / TR	OF No-TR / TR
Sandy soil		
Mean	1350 / 1351	2894 / 2902
Stdev	13 / 13	432 / 429
AD	0.7	7.5
Clay soil		
Mean	1344 / 1329	3009 / 3036
Stdev	14 /10	518 / 346
AD	-15	27

Results are reported considering the average yield (Mean), standard deviation (Stdev), and mean absolute difference (AD) between tied ridges (TR) and without tied ridges (No-TR). PF, poor fertility; OF, optimum fertility.

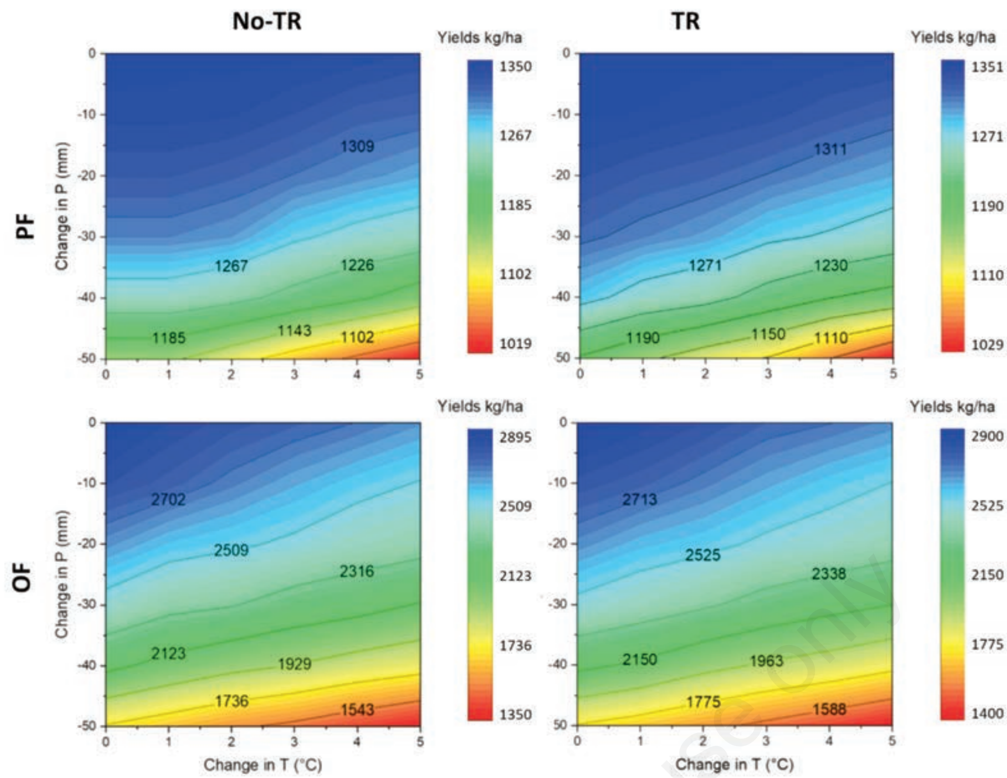

Figure 3. Impact response surface plots for sandy soil, considering two soil fertility levels, namely poor fertility (PF) and optimum fertility (OF), with tied ridges (TR) and without tied ridges (No-TR).

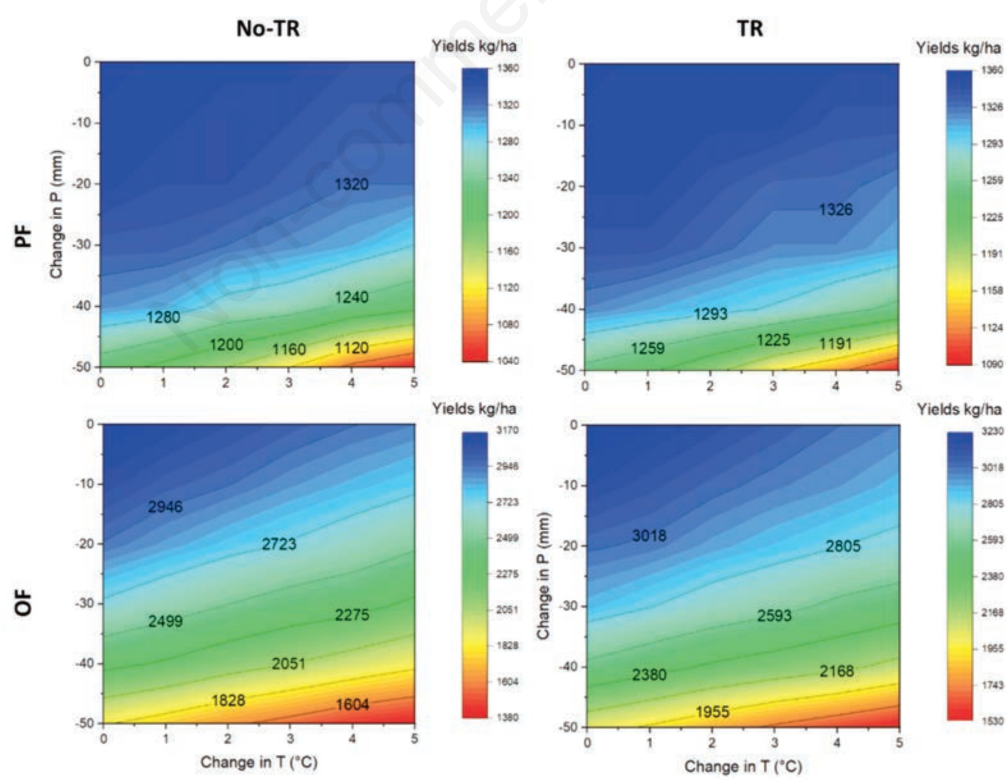

Figure 4. Impact response surface plots for clay soil, considering two soil fertility levels, namely poor fertility (PF) and optimum fertility (OF), with tied ridges (TR) and without tied ridges (No-TR).

5, Sandy-PF), the yield increase generated by the adoption of TR is +3.1%; it occurred at low changes in T (0°C to +1°C) and at high P reductions (-40% to -50%). At the same soil fertility condition, the adaptation response was higher for clay soil (Figure 5, Clay-PF), generating a +5.6% of yield at high changes in T (+4°C to +5°C) and P (-40% to -50%). Furthermore, for clay soil, the adaptation effect on yields is higher along the whole graph; contour lines adopted a more regular behaviour and appeared parallel within each other and with horizontal tendency, identifying P as the major influencing variable.

By improving the fertility status of the soil, the adaptation effect of TR further increased; ARS showed a maximum average value of gained yield equal to 3.8% for sandy soil at strong reductions in P (-40% to -50%) and low increases in T (+1 to +2°C). Meanwhile, in the same condition on clay soil, TR generated the highest maximum value obtained from the ARS analysis; the adaptation strategy generated a 13% gained yield produced in condition of high reduction in P (-40 and -50%) and T (+4 to +5°C).

Overall, the TR adaptation response was accentuated by fertilization which increased the maximum gained yield value of 0.7% for sandy soil and 7.4% for clay soil. The clay soil showed a higher response for both fertility conditions than the sandy soil, increasing the maximum value of gained yield obtained on sandy soil by 2.5% at the PF condition and by 9.2% at OF condition. The clay soil plots showed contour lines with a more regular behaviour compared to the sandy soil, identifying P as the major factor influencing the TR adaptation effect, while the T variable showed to slightly affect the TR performance since low increases of yield were recorded at the same P amount.

Discussion

Numerical modelling, and in particular the use of the AquaCrop model, is a useful tool to study the effectiveness of TR under different climates, management, and soil textures. Crop calibration and validation were based on a few years of maize yield data available for the Fatick region. Indeed, a higher number of yield data and field-measured crop parameters would have been useful to conduct a more precise calibration and validation. Despite these limitations, the simulated yield matched well with the observed ones, and we consider the model validated for the exploratory analysis performed. Simulated yields were slightly higher compared to those reported by Raes *et al*. (2021) for maize in Gambia, on the border of the Fatick region of Senegal. Other studies in Senegal reported lower (Diouf *et al*., 2020; Gueye, 2021; Okuyama *et al*., 2017) and similar (Jha *et al*., 2021) maize yields. Instead, in the field experiment by Laminou *et al.* (2020) in the Thies region, maize yield in the control treatment was higher (1.8 tons/ha). In the same experiment, maize with optimal fertilisation reached more than 3 tons/ha with a maximum of 4.1 tons/ha, comparable to our results at optimal fertility. The ARS analysis proved useful since it allowed us to evaluate the effectiveness of TR without considering the uncertainty in future projections as predicted by climate models. However, in our analysis, the projected increase in radiative forcing was not considered, and the concentration of CO_2 was considered constant. Increased CO_2 concentration in the atmosphere tends to increase the photosynthesis rate and, consequently, the yields. Therefore, if CO_2 concentration increases were included in the perturbed climate files, we would

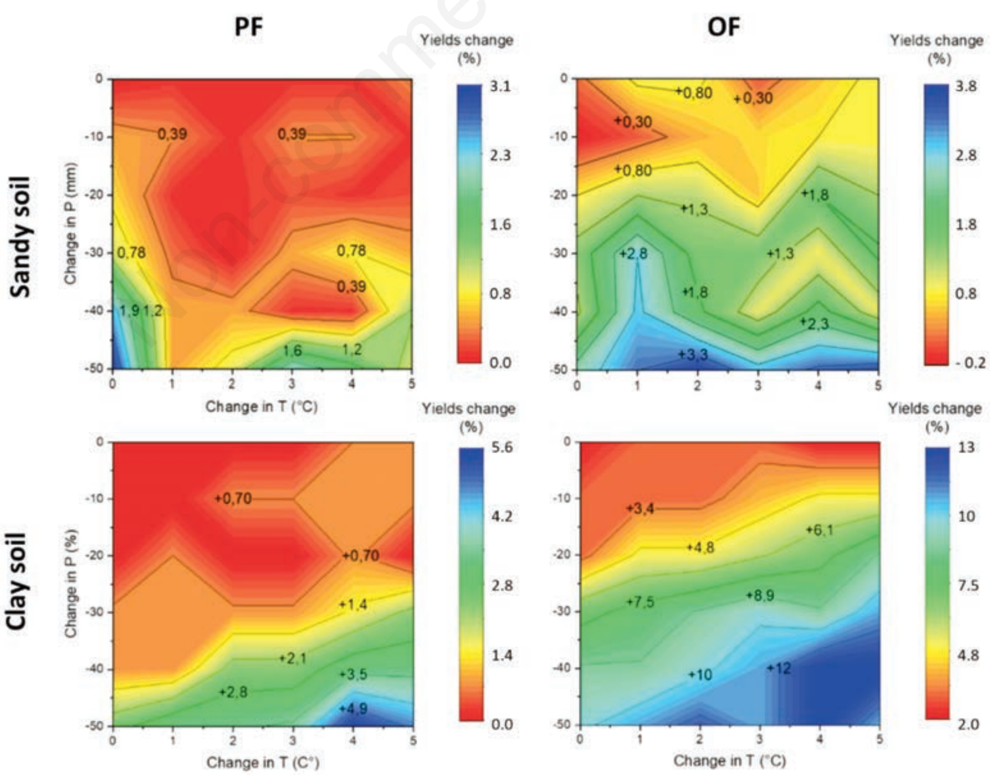

Figure 5. Adaptation response surface plots for clay and sandy soil types at two fertility conditions, poor fertility (PF) and optimum fertility (OP).

have expected higher yields and, possibly, lower losses due to the combined effect of T and P variation and higher CO_2. Another aspect related to ARS methodology is that the joint variation of T and P has no physical basis; thus, the consistency between climate variables such as temperature and precipitation is not preserved since they are modified without considering feedback as climate models do (Roudier *et al*., 2011). However, it does not affect the reliability of the results and so the response of the model to different combinations of T and P. Also, for the ET_0 estimation, it was not considered important climate variables such as solar radiation, wind speed, and relative humidity.

The ARS analysis also showed how TR effectiveness was affected by rainfall since they generated higher water beneficial use in water scarcity conditions and years with rainfall amount under the average value. Soil texture also influenced the results, and TR performed better on clay soil than sandy soil at both fertility conditions. Due to the higher water holding capacity of clay soil, the retained water decreased the water stress experienced by the crop, increasing transpiration, and so the final yield. Similar evidence was found by Wiyo *et al*. (2000), who used the capacity-based water balance model TIWBM to assess the impact of TR on the soil water balance of maize in Malawi. The model was tested for 5 soils and 12 rainfall regimes, and the results highlighted that TR benefited maize on fined textured soils (clay texture) and not on coarse-textured soils (sandy texture).

The impact of TR did not show significant changes in maize yields during the simulated years for the historical scenario since the rainfall amount was sufficient to satisfy crop water requirements. TR increased the infiltration of water that would runoff by adopting standard soil management; however, most of it was drained, and the additional water collected by WH was not beneficially used. This trend is more accentuated for sandy soils but is also valid for clay soils with the current rainfall. This is consistent with the study of Diakhate (2014) that in the neighbour Kaolack region estimated no yield reductions caused by water stress. Similar results are reported by Wolka *et al*. (2021), who evaluated soil bunds' effect on surface runoff and maize yield in Ethiopia with AquaCrop. The study did not find significant differences between plots with and without WH; water availability was enough or even in excess for maize cropping. In a field-based study, Araya and Stroosnijder (2010) found that TR increased the grain yield of barley in Ethiopia by 44% during below-average rainfall years (600 mm); meanwhile, during equal or above-average rainfall years, no differences were found with the control plots. Other field-based studies also observed a negative effect during above-average rainfall years. For example, Jensen *et al*. (2003) tested TR in a combination with mineral N and P fertilizer on maize in Tanzania; they identified positive effects of tied ridges on yield for the near-optimal rainfall years (500-600 mm), whereas an adverse effect for the years with annual rainfall above 700-900 mm. The limitation of the TR effect due to wet years with rainfall above 900 mm was also observed by Wiyo *et al*. (2000), especially on fine-textured soils, where waterlogging generated aerations stress on maize. Our study focused on contexts of water scarcity in which WH techniques can better express their function, so only the reduction in rainfall was considered for the simulations. Further studies could include rainfall increases to evaluate TR drawbacks such as waterlogging.

Impact assessments should be as integrated as possible by considering socioeconomic aspects and should not be limited to the direct effect on crop yield (*e.g*., Diouf *et al*., 2020). TR also impacted other biophysical aspects, such as the reduction of soil erosion and degradation. For example, Tamagnone *et al*. (2020) tested different rainwater harvesting techniques against meteorological extremes affecting the Sahelian areas; the results underline the effectiveness of WH indigenous techniques in retaining runoff up to 87% and increasing the infiltration. They showed that the crop water stress diminished and eventually allowed an extension of the crop cycle up to 20 days. Therefore, assessing the impacts of TR considering the social and economic aspects and other biophysical impacts are recommended in further research.

The present study also showed a higher impact of TR when the adaptation measure was implemented in conditions of optimum soil fertility both for clay and sandy soils. This trend is frequently reported in the literature. Rockström *et al*. (2002) found that, in drought-prone environments, the simultaneous implementation of water management and fertilization is more effective in increasing yields than implementing a single practice. Biazin and Stroosnijer (2012) found that, in Ethiopia, TR enhanced maize yields from 6.1-6.5 ton/ha to 6.8-7.3 ton/ha and with optimum fertilisation up to 11.0-12.9 ton/ha during the above-average rainfall seasons (280-300 mm). Also, for sorghum and millet in Ethiopia, Nigeria, and China, through a meta-analysis of related literature, Mak-Mensah *et al*. (2021) found that yield increases by 32% by applying TR compared to the standard flat planting, and it further increases by 17% when it is combined with fertilisation. The usefulness of combining fertilisation and tied ridging also emerges in simulated future climate scenarios. Muluneh (2020) found that under projected climate change (2021-2050 and 2066-2095 periods) maize yield decreased by 9%; meanwhile, the combined effect of TR and fertilisation increased yield by 90% in the period 2021-2050 climate period due to the decreased evapotranspiration (3%) and runoff, increase in transpiration (14%), soil fertility and carbon dioxide effect. Applying numerical models to evaluate the benefits of adaptation strategies is promising. In our study, we focused on the effect of TR on maize, but several other crops could be studied in further research. Also, the approach to simulate TR by zeroing the CN is simple and effective, but it is clearly a simplification. Using the outputs of GCMs and RCMs when simulating future conditions is an option that should be considered in further research to assess the effect of TR on crop yield. Furthermore, we modified historical precipitation and temperature in our study, considering interannual variability and not intra-annual one. As climate variability is going to change the frequency and intensity of extreme events, our study provides an overview of the adaptation response of TR in relation to climate changes that could be different in the future. Reproducing rainfall patterns with rainfall synthetic models is an alternative solution to perform simulations with multiple plausible precipitation patterns to test the performance of TR.

Conclusions

The novelty of this study lies in assessing the potential benefit TRs have in Western Africa as an adaptation strategy in the context of climate change. Furthermore, the ARS represents a simple methodology to simulate the adaptive capacity of TR under changes in R and T. To our knowledge, TRs were never modelled in Western Africa with AquaCrop.

The AquaCrop simulations showed that TR limited the runoff but did not significantly impact the maize yields for sandy and clay soil since rainfall was enough for maize production and to avoid high water stresses along the cropping season. Hence, TR potential is not expressed in the current conditions of Fatick.

Under the perturbed climate scenarios, rainfall reduction was the most impacting variable, as it contributed to increasing water stress and reducing biomass and yields. The worse climate condition (-50% and +5°C) generated a maximum peak of yield reduction of 80% compared to the standard condition in years with rainfall under average rainfall seasons. ARS allowed us to evaluate the potential of adaptation strategies in plotted surfaces; TR limited the losses of yield by increasing yields by 3.1% and 3.8% at PF and OF conditions on sandy soil. The adaptation effect was higher when TR was simulated on clay soil, increasing the yield by 5.6% and 13% at PF and OF conditions, respectively.

Integrating TR and fertilisation represents a better strategy to cope with climate change impact rather than adopting a single adaptation measure. Furthermore, by improving the water infiltration and nutrient availability, TR represents a good strategy that can reduce the losses of yield and the probability of crop failure in case of future rainfall reduction.

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