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A Genetic Algorithm Approach for Location-Specific Calibration of Rainfed Maize Cropping in the Context of Smallholder Farming in West Africa

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Abstract

Smallholder farming in West Africa faces various challenges, such as limited access to seeds, fertilizers, modern mechanization, and agricultural climate services. Crop productivity obtained under these conditions varies significantly from one farmer to another, making it challenging to accurately estimate crop production through crop models. This limitation has implications for the reliability of using crop models as agricultural decision-making support tools. To support decision making in agriculture, an approach combining a genetic algorithm (GA) with the crop model AquaCrop is proposed for a location-specific calibration of maize cropping. In this approach, AquaCrop is used to simulate maize crop yield while the GA is used to derive optimal parameters set at grid cell resolution from various combinations of cultivar parameters and crop management in the process of crop and management options calibration. Statistics on pairwise simulated and observed yields indicate that the coefficient of determination varies from 0.20 to 0.65, with a yield deviation ranging from 8% to 36% across Burkina Faso (BF). An analysis of the optimal parameter sets shows that regardless of the climatic zone, a base temperature of 10˚C and an upper temperature of 32˚C is observed in at least 50% of grid cells. The growing season length and the harvest index vary significantly across BF, with the highest values found in the Soudanian zone and the lowest values in the Sahelian zone. Regarding management strategies, the fertility mean rate is approximately 35%, 39%, and 49% for the Sahelian, Soudano-sahelian, and Soudanian zones, respectively. The mean weed cover is around 36%, with the Sahelian and Soudano-sahelian zones showing the highest variability. The proposed approach can be an alternative to the conventional one-size-fits-all approach commonly used for regional crop modeling. Moreover, it has the potential to explore the performance of cropping strategies to adapt to changing climate conditions.

Keywords

Smallholder Farming, AquaCrop, Genetics Algorithm Optimization, Maize, Burkina Faso

1. Introduction

West Africa is characterized by a tropical climate that varies from humid conditions in the coastal areas to arid and semi-arid conditions in the Sahel region [1] [2]. In this region, agriculture plays a central role in food security. The importance of agriculture in West Africa goes beyond food production since it also encompasses income generation, employment opportunities, and its contributions to economic stability and rural development [3] [4]. Food production comes essentially from smallholder farmers, making them essential for food security and rural livelihoods [5]. Indeed, smallholder farming system is predominantly based on indigenous farming practices. Although the primary objective of this agricultural system is to produce for consumption needs of the families, the surplus may be sold to generate additional income for their livelihood [6]. However, smallholder farmers in West Africa face numerous challenges, including limited access to seeds, fertilizers, pesticides, modern mechanization as well as lack of useful agricultural climate services making them more vulnerability to climate change and variability [3] [7].

Smallholder farming systems are predominantly rainfed with mixed cropping and shifting cultivation areas. Therefore, they are strongly influenced by climate change and variability with the strongest impact in the Sahel region [8]. This region is experiencing a high rainfall variability and climate change with changing precipitation patterns, and droughts. Consequently, this is leading to water scarcity for food production. In light of this climate context and the population growth, the Sahel is facing severe and structural food security challenges. To address food production challenges, it is urgent to develop and implement effective climate adaptation strategies and promote sustainable farming practices [7] [9] [10]. Among adaptation strategies, agricultural decisions such as when to start planting are essential tools that can be beneficial for smallholder farmers [11] [12].

Smallholder farming practices are thus mainly influenced by local climate and farmers' incomes. They rely on locally available crop seeds for planting and availability of machines and labor for farming actions such as sowing, ploughing, and harvesting [13] [14]. Due to the lack of local climate information for the ongoing season, smallholder farmers rely on indigenous knowledge to sharpen their farming practices. In order to support this agricultural system, it is crucial to develop approaches which can support the development of local climate information aiming to help farmers prepare for and respond to climate-related challenges [15] [16].

Efforts have been made to provide tailored agricultural information but the availability of small-scale information remains a challenge for researcher. For instance, in the Sahel, smallholder farmers rely on seasonal climate forecasts for planting and harvesting schedules [17] [18]. These forecasts provide information about expected rainfall patterns, such as the onset and the duration of the rainy season, and the risk on long dry spell occurrence [19] [20]. However, these climate services issued by the West African regional climate outlook forums are still not tailored for sub-district scale uses, particularly in the context of smallholder farming system [21] [22]. Also, it is quite uncommon to find sub-district crop monitoring and crop yield forecast information provided by Regional Climate Centers and National Meteorological Services [23] [24]. The main contributing factor to this issue is the lack of adequate crop and management data at finer spatial scale. This emphasizes the pressing need to obtain crop information at the sub-district scale, which can be further served as valuable input for models in agricultural impact studies or tools aiming at generating crop and location-specific information to support smallholder farming in West Africa.

Burkina Faso's economy and food production are primarily based on rainfed agriculture [25]. More than 70% of the population, mainly from rural areas, is engaged in subsistence farming with millet, sorghum, and maize as the main staple crops [26] [27]. In addition, it serves as the main source of income for the rural population, therefore, ensuring food security is the main challenge for the country [28].

Using Burkina Faso as a regional focus, this study aims to support agrometeorological decision making in West Africa by proposing an approach to derive sub-district crop and location-specific information for impact studies in agriculture. Our approach combines a genetic algorithm (GA) with a dynamic crop model and observed maize yields to determine suitable crop and management parameters at a 0.44˚ grid resolution. This work provides a reliable framework for optimizing location-specific cultivation parameters across the region's agroecological zones. The paper structure is as follows: Section 2 describes the study area, data, and methodology; Section 3 presents the results; and Section 4 discusses these results and summarizes the key findings.

2. Material and Methods

2.1. Study Area

Burkina Faso (BF) is a landlocked country in West Africa. It is located between 9˚20' and 15˚05' North latitude, 5˚30' West longitude, and 2˚20' East longitude (**Figure 1**). It is bordered by six countries: Mali to the north, Niger to the east, Benin to the southeast, Togo and Ghana to the south, and Côte d'Ivoire to the southwest. Located in the Sahel region, it experiences a distinct wet season and dry season driven by the West African Monsoon [29].

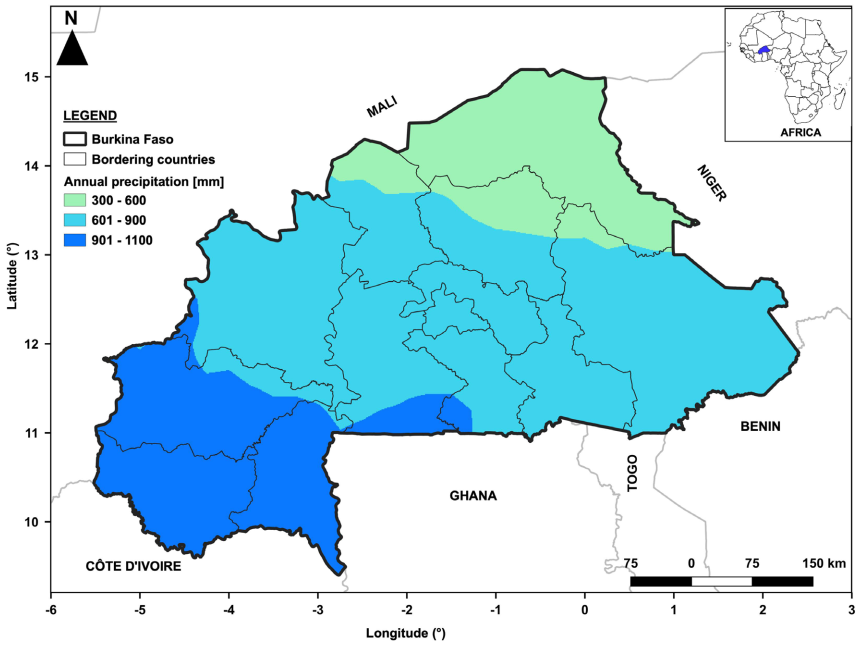


Figure 1. Study domain and spatial distribution of the annual precipitation of the period 1991-2020 (data source: ANAM-BF, 2022).

The timing and intensity of the monsoon strongly affect rainfall patterns during the wet season. The aforementioned occurs from May to October and lasts three months in the North and up to six months in the South. The annual cumulative rainfall varies between 300 mm in the North and less than 1200 mm [30] with three climatic zones: Sahelian zone (rainfall less than 300 mm), Soudano-sahelian zone (rainfall between 300 mm and 900 mm), and Soudanian zone (rainfall greater than 900 mm). The irregular distribution of rainfall has consequences for rainfed agriculture. In fact, the observed changes in planting dates, the occurrence of long dry spells, and the limited water availability for crop growth are the climate-related limiting factors for food production [31].

2.2. AquaCrop Model

Crop models are developed to address various challenges and objectives in the field of crop production and management. Efforts have led to the development of more advanced models, some of which are more focused on the plot-plant scale, while others, like AquaCrop, are more focused on the canopy-level scale and serve as management tools to assist in decision making.

The AquaCrop model has been developed by the Food and Agriculture Organization (FAO) of the United Nations [32]. It is specifically designed to simulate and optimize crop production, with a particular emphasis on water management in agriculture, particularly for water-sensitive crops [32]. The model considers various factors, such as planting date, climate, available soil water, field management, and crop-specific parameters, in order to simulate crop growth and development. Climate data used in the model typically includes daily rainfall, minimum (Tn) and maximum (Tx) air temperature, reference crop evapotranspiration (ETo), and mean annual carbon dioxide concentration (CO_2). By making adjustments to parameters such as planting date, agronomic practices, and crop-specific location parameters, users can determine the most efficient strategies for enhancing crop yields and water use efficiency [33]. The following AquaCrop chart illustrates the key elements of the soil-plant-atmosphere continuum and the parameters that influence phenology, canopy cover, transpiration, biomass production, and yield (**Figure 2**). In this study, the open-source AquaCrop Fortran code from the FAO website (available at https://www.fao.org/aquacrop/software/aquacrop-gisen#c518675) has been compiled on a Unix-like operating system and then used for simulation at the grid cell resolution of 0.44˚ × 0.44˚ across BF.

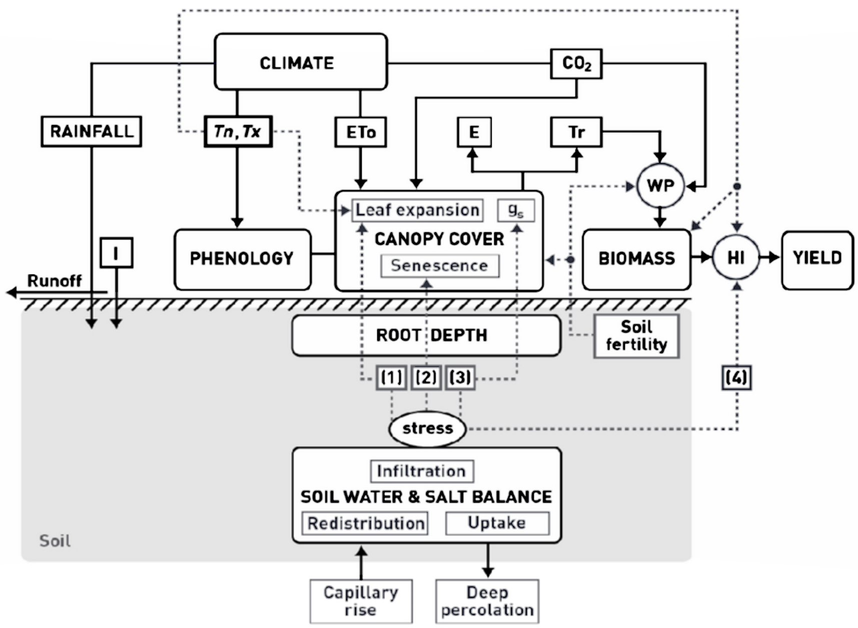


Figure 2. Main components of the soil-plant-atmosphere continuum in AquaCrop (from [34]).

2.3. Climate Data

Daily climate data for the period 1983-2020 are used in this study, including precipitation, minimum and maximum temperature, dew point temperature at 2 m, and surface net solar radiation. Except for precipitation data, climate data were retrieved from ERA5, the fifth generation of global climate reanalysis data from the European Centre for Medium-Range Weather Forecasts [35] [36]. The data are accessible on Copernicus Climate Data Store (https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-single-levels?tab=overview). ERA5 has been widely validated and successfully applied in agricultural climate impact studies [37] [38].

Precipitation data is obtained by merging measurements from rain gauges with satellite precipitation data. In Burkina Faso, the rain gauge network consists of nearly 134 observation stations, which include synoptic, climatological, agrometeorological, and rain gauges that have long-term series of data. To ensure data quality, stations with large data gaps (greater than 5% on a daily basis) for the considered period are removed, resulting in 97 rain gauges for the merging process (**Figure 3**). Satellite data are from the version 3.1 of the Tropical Applications of Meteorology using SATellite data and ground-based observations (TAMSAT v3.1) [39]. Previous research comparing seven satellite precipitation datasets has shown that TAMSAT performed better on a daily basis in Burkina Faso [40]. For merging the precipitation data from the selected rain gauges with TAMSAT data, bias correction and interpolation methods were employed throughout the Climate Data Tools (https://iri.columbia.edu/our-expertise/climate/tools/cdt/), an R-based software developed by the International Research Institute for Climate and Society (IRI). The empirical quantile mapping method [41] was used to compute the bias correction factor between station observations and TAMSAT estimates at the station location, while the regression kriging [42] was used as the interpolation method aiming to capture the spatial dependence of the residuals. These methods have been extensively used for operational applications [43] [44].

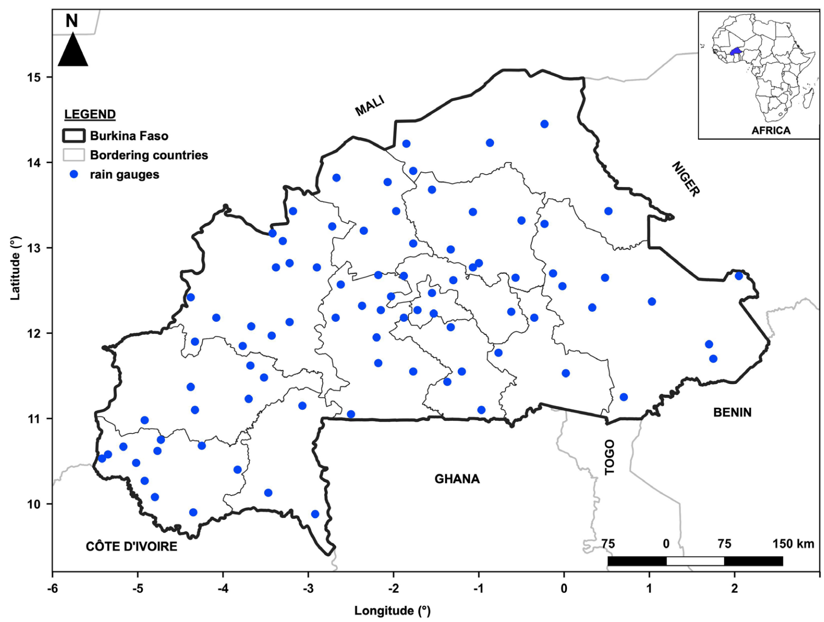


Figure 3. Spatial distribution of the selected rain gauges.

2.4. Deriving Reference Crop Evapotranspiration (ETo)

ETo is a critical parameter for crop water requirement estimation and therefore for the soil water balance of the crop root zone. To estimate ETo, air temperature, relative humidity or dewpoint temperature, solar radiation, wind speed, and elevation data are required [45]. However, in Burkina Faso, only ten weather observation stations (synoptic stations) with long-term data records for these weather parameters are available. To address the specific need of ETo for this study, ERA5 gridded data at a resolution of 0.44˚ × 0.44˚ along with a Digital Elevation Model Data (https://srtm.csi.cgiar.org/srtmdata) have been used to calculate ETo, using the FAO-Penman-Monteith Equation (1) following [45]. ERA5 reanalysis at this resolution provides physically consistent meteorological variables for ETo calculations while aligning with the district-level crop yield data available for model validation.

$$ETo = \frac{0.408 \times \Delta \times \left(R_n - G\right) + \gamma \times \dfrac{900}{T + 273} \times u_2 \times \left(e_s - e_a\right)}{\Delta + \gamma \times \left(1 + 0.32 \times u_2\right)} \quad (1)$$

where: R_n is the net radiation flux density on the crop surface ($MJ \cdot m^{-2} \cdot d^{-1}$); G is the soil heat flux density ($MJ \cdot m^{-2} \cdot d^{-1}$); T is the average daily air temperature (˚C); u_2 is the wind speed at 2 m high ($m \cdot s^{-1}$); e_s is the saturation vapor pressure (kPa); e_a is the actual vapor pressure (kPa); Δ is the slope of vapor pressure-temperature curve ($kPa \cdot {}^\circ C^{-1}$) and γ is the psychometric constant ($kPa \cdot {}^\circ C^{-1}$).

2.5. Soil Information

Soil hydraulic characteristics such as the upper limit of volumetric water holding capacity (FC), the lower limit of water holding capacity (PWD), drainage coefficient (τ), and hydraulic conductivity at saturation (Ksat) are necessary for running AquaCrop. Soil parameters including organic carbon and the fractions of clay, silt, and sand were obtained from the latest version (2.0) of the Harmonized World Soil Database (HWSD) [46]. For a given grid cell at a resolution of 0.44˚ × 0.44˚ in the study area, these retrieved soil parameters were used to calculate textural classes based on the USDA classification, and then summarized to determine the dominant soil texture for each of the soil layers. Computed soil textures are then used to derive soil hydraulic characteristics such as the upper limit of volumetric water-holding capacity (FC), the lower limit of water-holding capacity (PWD), drainage coefficient (τ), and hydraulic conductivity at saturation (Ksat), which are necessary for running AquaCrop [34]. The hydraulic characteristics for the dominant soil texture were based on the FAO database implemented in AquaCrop. In this study, the maximum depth of the soil was set to 1.5m for maize crop rooting, which corresponds to the first six layers in HWSD v2.0.

2.6. Observed Crop Yield

In crop simulation, the availability of observed crop yield data is crucial to ensure that crop models accurately represent local agricultural conditions. We obtained maize crop production and cultivated areas from the Direction Générale des Etudes et des Statistiques Sectorielles of the Burkina Faso Ministry of Agriculture, Animal Resources and Fisheries. These data are available at the province level, covering the 45 provinces in Burkina Faso, and span the period from 2009 to 2022. We performed crop yield calculations (kg/ha) at a resolution of 0.44˚ × 0.44˚. The yield for a specific grid cell is calculated using a composite weighted average that considers all provinces that share the same grid. The cultivated areas of the relevant provinces were used as the weights in Equation (2).

$$Y_{grid}\left(kg \cdot ha^{-1}\right) = \sum_{i=1}^{n} w_i \times Y_{province(i)}\left(kg \cdot ha^{-1}\right) \quad (2)$$

where Y_{grid} (kg/ha) represents the gridded crop yield, $Y_{province(i)}$ represents the crop yield in province i, w_i represents the fraction of cultivated area of province i within the grid cell, and n represents the number of provinces that share the area of the grid cell.

2.7. The Parameter Set for Calibration

Calibration is a systematic process of optimizing model parameters to minimize the difference between simulated outputs and observed data, thereby improving model accuracy for specific environmental conditions. For crop models, this process involves adjusting biophysical parameters and management practices to better reflect local farming conditions. In this study, we employed a Genetic Algorithm optimization approach to calibrate selected maize crop and management parameters. The calibration methodology combines mathematical optimization with local agricultural knowledge. Specifically, the parameter selection and boundaries were driven by the specific challenges of Sahelian agriculture and constrained by local maize varieties and well-documented agronomic practices from the Institut de l'Environnement et de Recherches Agricoles (INERA) in Burkina Faso (Olaoye *et al.*, 2009).

The crop parameters were initially drawn from the generic maize crop file in AquaCrop [32], while the growing period durations were established based on the main maize cultivar categories in use in Burkina Faso: short-duration (75 - 80 days), medium-duration (90 - 100 days), and long-duration (105 - 120 days) varieties [47] [48]. Similarly, plant density parameters computed based on row spacing and plant spacing along rows were established based on comprehensive field surveys on agronomic practices of the main cultivars used in smallholder farming systems across Burkina Faso [49] [50]. As sowing stratey, row spacing was fixed at 0.80 m, while plant spacing along rows varied from ~0.25 m to 0.50 m according to cultivars. The phenological development stages, which determine the length of the growing period, were parameterized according to [32] and [51]. Among management parameters, we prioritized the calibration of relative weed cover and soil fertility stress coefficients, as these factors show high spatial and temporal variability in smallholder farming systems and significantly impact crop water productivity [52]. The following **Table 1** summarizes the key parameter set selected for calibration. The calibration approach ensures that our optimized parameters represent not just mathematically optimal solutions but also practically viable recommendations grounded in local agricultural reality.

Table 1. Selected crop and management parameters.

Types	Parameters	Minimum values	Maximum values
Crop	Growing period length	80 days	120 days
	Base temperature	8	12
	Upper temperature	30	35
	Number of plants	25,000 plants/ha	45,000 plants/ha

Continued

Crop	Length of building up of Harvest Index	20 days	40 days
	Reference Harvest Index (HIo)	20%	45%
Management	Soil fertility rate	20%	80%
	Relative cover of weed	10%	80%

2.8. The Genetic Algorithm (GA) Approach

Genetic algorithms (GAs) are adaptive heuristic search algorithms inspired by the principles of natural selection. They are based on genetic mechanisms such as selection, crossover, and mutation [53] [54]. Unlike traditional search methods, they are particularly suitable for global optimization problems that involve finding the best solution within a large and complex space [55]. However, the performance of GAs is heavily influenced by a number of factors, one of the most pivotal being the objective function used [56]. In this study, the genetic algorithm (GA) is combined with a designed objective function (fobj) to optimize parameter sets for location-specific calibration of maize crops. The calibration process through the objective function performs simulations at a grid cell resolution of 0.44˚ × 0.44˚ using AquaCrop's open-source Fortran code as a subroutine within the GA. For each grid cell, climate and soil data remain constant across GA iteration steps, while selected crop and management parameters are optimized according to the objective function.

The objective function takes into account two performance metrics, namely the coefficient of determination (R2) and the Relative Absolute Error (RAE). These two statistics are calculated based on the observed yield and the simulated yield using the AquaCrop model. R2, RAE and fobj are expressed as the following Equation (3). To ensure the significance of the Pearson linear correlation (R), the p-value has been set to a maximum of 5%. These statistical measures guide the GA in optimizing location-specific crop and management parameters for maize cultivation across Burkina Faso. Ultimately, the success of a GA requires a thorough understanding of the problem landscape and depends on the careful combination of multiple objective functions to achieve a balanced approach for the optimization tasks [57].

$$R = \frac{\sum_{i=1}^{n}\left(O_i - O_{avg}\right)\left(P_i - P_{avg}\right)}{\sqrt{\sum_{i=1}^{n}\left(O_i - O_{avg}\right)^2 \sum_{i=1}^{n}\left(P_i - P_{avg}\right)^2}}$$

$$RAE = \frac{\sum_{i=1}^{n}\left|O_i - P_i\right|}{\sum_{i=1}^{n}\left|O_i - O_{mean}\right|} \tag{3}$$

$$f_{obj} = \begin{cases} -\left|\left(RAE\right)\right|^{\left(1-R^2\right)} & \text{if } R^2 > 0.2 \text{ and } p\text{-value} < 5\% \\ -\infty & \text{if } R^2 \le 0.2 \text{ and } p\text{-value} > 5\% \end{cases}$$

where O_i and P_i represent the observed and simulated yields for the i-th cropping season, respectively. O_{avg} and P_{avg} indicate the mean values of observed and simulated yields for the n cropping seasons of the simulation.

In this study, the optimization process aims to maximize f_{obj}. The highest values of f_{obj} correspond to those close to zero (dark blue area), as depicted in **Figure 4**. Hence, a set of optimal parameter swill yield an RAE close to zero and R^2 close to one.

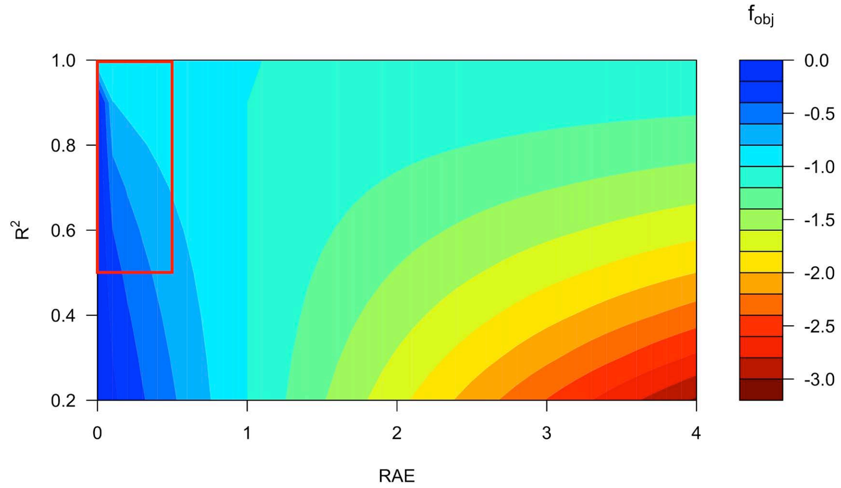


Figure 4. Values of the objective function. The red rectangle represents the area of the optimal solution.

The flowchart in **Figure 5** depicts the different steps in the process of location-specific crop calibration using a GA. A member of a GA population of candidate solutions is a vector of eight crop and management parameters. For each member, once the growing duration parameter is known through the GA selection process, it is used to derive the comprehensive phenology of the crop. This step completes the user-defined parameters set required to set up the crop file essential for AquaCrop simulation.

3. Results

3.1. Inputs Data Analysis

Different types and sources of data have been preprocessed to obtain the required input data for AquaCrop runs. From the soil data, the soil fraction of silt, clay, sand, and organic content has been transformed into soil textural classes. The results shown in **Figure 6** indicate that there are a total of 7 USDA soil textural classes across Burkina Faso. Sandy loam, sandy clay loam, and clay are the dominant soil textures for all the layers considered, with sandy loam being the most prevalent in the northern half of the country while sandy clay loam and clay dominate the south and southwest regions. The soil depth less than 60 cm is more heterogeneous compared to the layers ranging from 80 cm to 150 cm.

Daily ETo has been computed based on the FAO-Penman-Monteith method and using ERA5 reanalysis data and further re-gridded at a resolution of 0.44˚ × 0.44˚. The results on the long-term mean (period 1981-2020) spatial variation of ETo indicate that it ranges from 5 mm/day to 8 mm/day throughout the country (Figure 7(a)). It shows a North-South gradient, with the highest values observed in the northern part and the lowest values in the southern part of the country.

Maize crop yields for the 45 provinces in Burkina Faso from 2009 to 2022 have been re-gridded and used for the calibration process. The average crop yields across the country range from 0.5 t/ha to 2.5 t/ha (Figure 7(b)). The lowest yields are located in Northern half of BF, while the highest are found in the southwestern part of Burkina Faso.

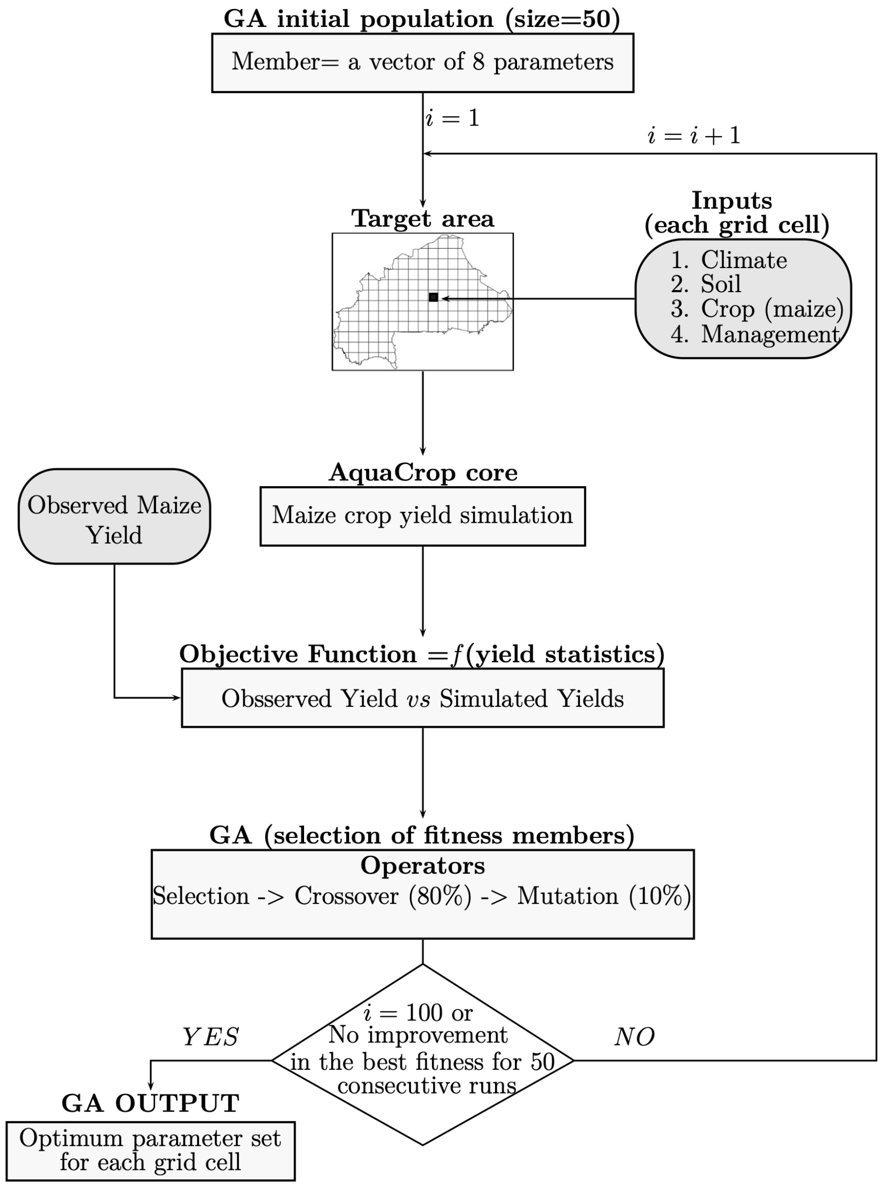


Figure 5. Flowchart illustrating the steps in location-specific maize crop calibration using a GA.

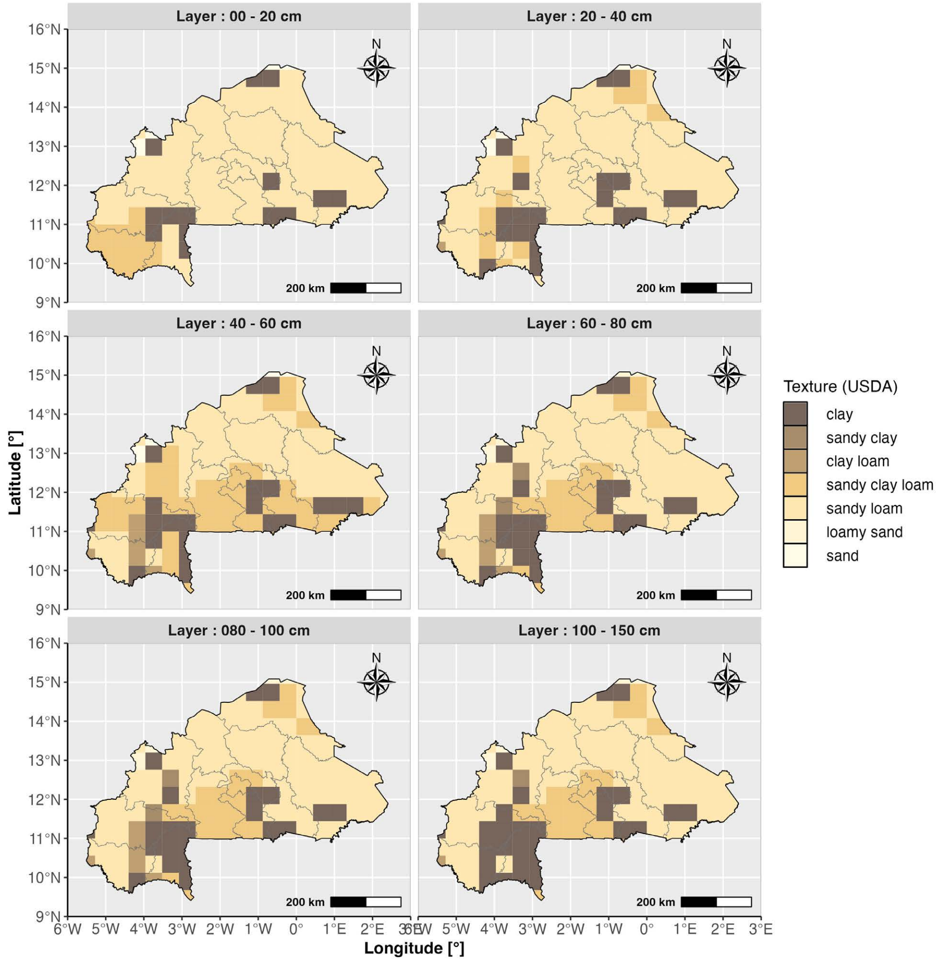
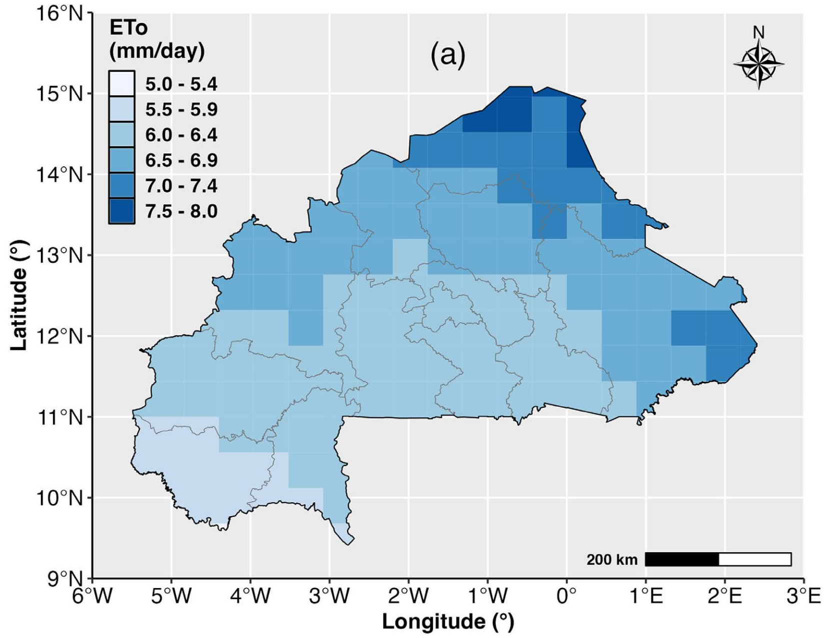


Figure 6. Soil textural classes for the six (6) soil layers. The dominant soil texture is shown at 0.44˚ grid-cell resolution.



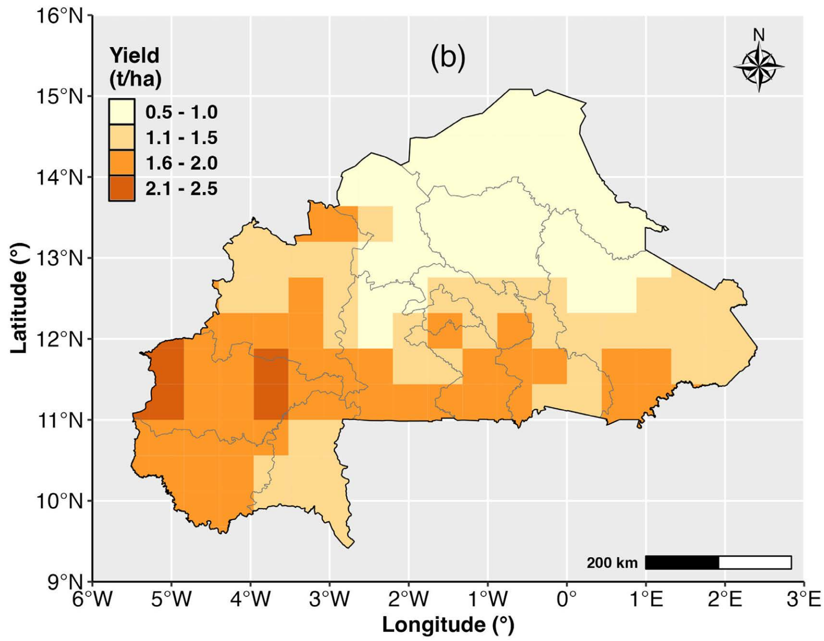
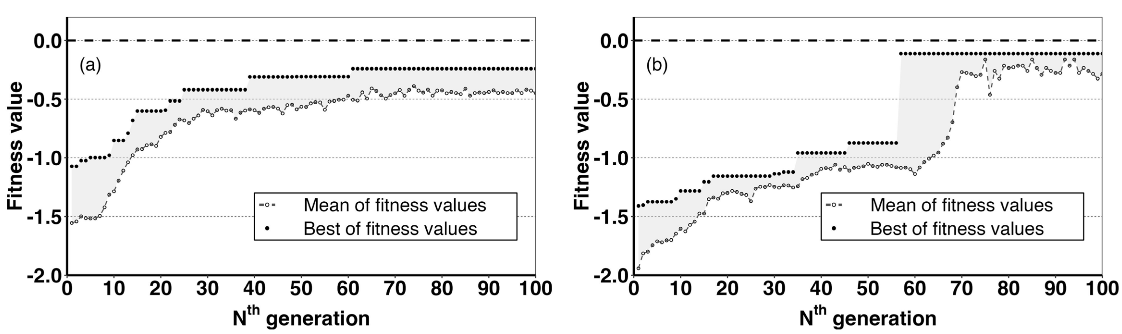


Figure 7. Spatial distribution of ETo (a) and maize crop yield (b) in BF at grid cell resolution.

3.2. Global Optimum Search in the GA Process

The combination of AquaCrop and a Genetic Algorithm (GA) has been implemented in a total of 156 grid-cells. The main objective is to find the global optimum in the search space, thereby maximizing the fitness. The fitness values are calculated through the fitness function which is based on a specific set of parameters heuristically chosen at each step of the GA. Figure 8 illustrates the GA process for a randomly selected set of grid cells. Overall, the results indicate that the global optimum is achieved after at least the 20th generation. The value of the global optimum obtained through the GA process ranges from −0.65 to −0.15 (Figure 8(b) and Figure 8(c)), whereas theoretically, the optimal value should be zero, indicating a perfect match between simulated and observed yield. Figure 8(c) demonstrates a scenario of rapid convergence towards the global optimum, while Figure 8(a) and Figure 8(d) depict slower convergence. Figure 8(b) represents a hybrid case with slow convergence until the 60th generation, followed by rapid convergence.



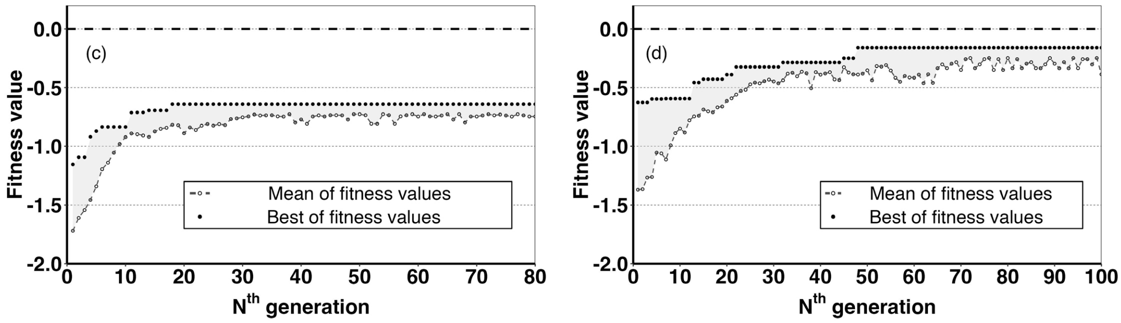


Figure 8. GA process for a selected set of grid cells. The dotted line represents the maximum fitness value computed from the 50 ensemble members at each generation of the GA, while the dash-dotted line represents the ensemble mean for each generation.

3.3. Performance Metrics of AquaCrop Calibration for Maize Cropping in BF

For a given grid cell, the coefficient of determination (**Figure 9(a)**) and the relative absolute error (**Figure 9(b)**) were calculated using pairwise simulated and observed yield data for the period 2009-2022. The simulated yield was performed using AquaCrop in combination with the optimal crop and management location-specific parameter sets obtained throughout the GA crop calibration processes. Our findings reveal that the coefficient of determination (R2) varies from 0.20 to 0.65, whereas the yield deviation (RAE) varied from 8% to 36% across the country. Notably, the southwestern part of the country exhibits the highest R2 values, while the northern part exhibits the lowest values. Among the 156 grid cells, approximately 60% show yield deviations within the range of 21% to 30%.

3.4. Set of Calibrated Parameters Across the Climatic Zone in BF

Crop and management parameters derived from the GA process of location-specific calibration for maize cropping have been analyzed for the three climatic zones in BF. The results show that regardless of the climatic zone, a base temperature of 10˚C and an upper temperature of 32˚C are required for at least 50% of grid cells (**Figure 10(a)** and **Figure 10(b)**). The duration of the growing season (**Figure 10(c)**) and the harvest index (**Figure 10(f)**) vary significantly among the three climatic zones, with the highest values found in the Soudanian zone and the lowest values in the Sahelian zone. The mean plant sowing density (**Figure 10(d)**) is approximately 31,000 plants per hectare, but there is considerable variability within each climatic zone. The flowering duration (**Figure 10(j)**) is consistent across the three climatic zones, lasting about 2 to 3 weeks. Crop development stages (**Figure 10(g)**, **Figure 10(h)** and **Figure 10(i)**) show a similar trend in variability as the duration of the growing season. In terms of management strategies, the overall fertility rate parameters range from 20% to 55%, with mean values of 35%, 39%, and 49% for the Sahelian, Soudano-sahelian, and Soudanian zones, respectively (**Figure 10(e)**). The mean weed cover (**Figure 10(e)**) is approximately

36%, with the Sahelian and Soudano-sahelian zones showing high variability and the Soudanian zone showing low variability.

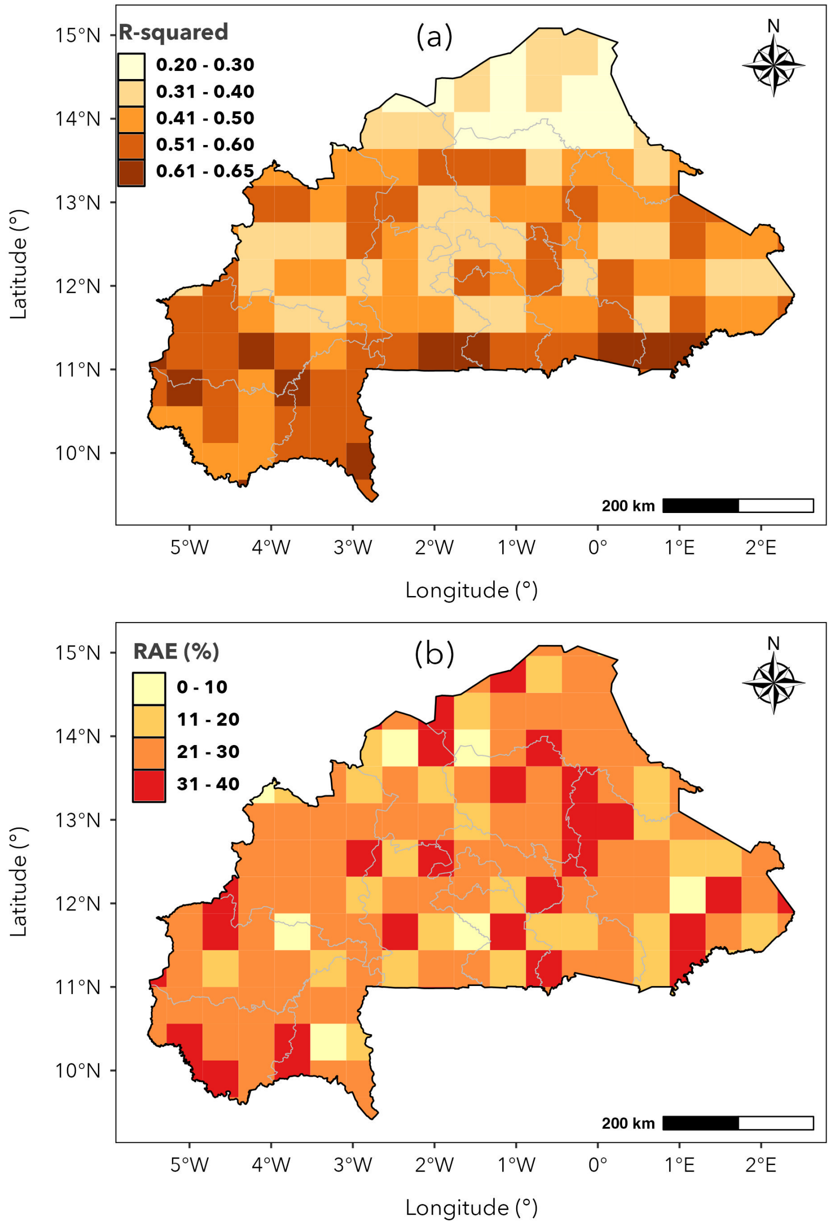
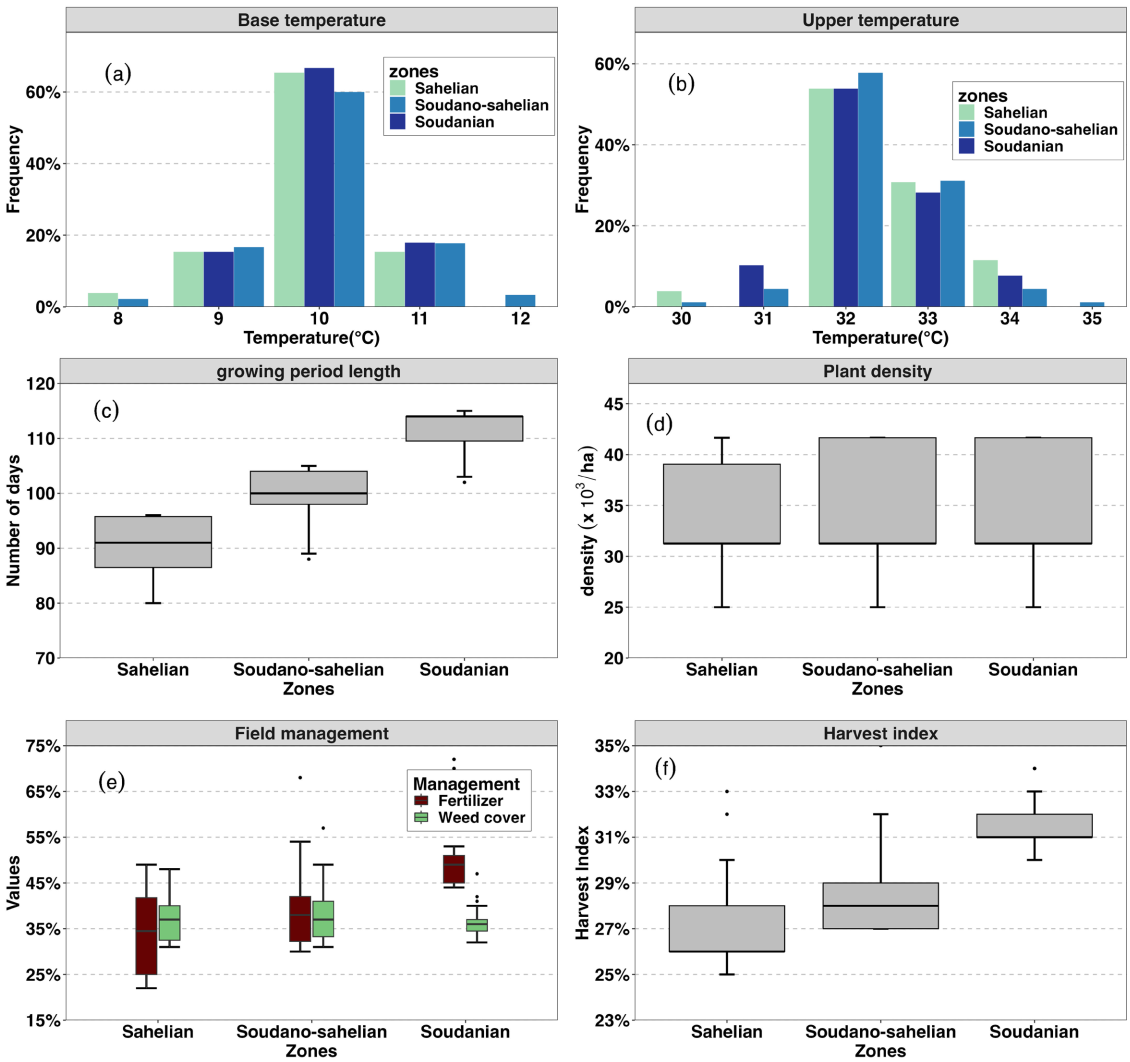


Figure 9. location-specific performance of maize crop calibration. The coefficient of determination (a) and the Relative Absolute Error (RAE) (b) were calculated pairwise using simulated and observed maize yields.

4. Discussion and Conclusions

In West Africa, smallholder farming is characterized by high rainfall variability and significant variation in crop cultivars and soil conditions. This means that a one-size-fits-all approach is not effective for estimating crop yield. Our paper focuses on calibrating crop maize (as one of the most important staple crops) to account for the diverse agroecological conditions faced by smallholder farmers in this region. At the local level, climate conditions are not uniform, and there are differences in cultivars, soils and cropping practices, resulting in high variability in crop yield. It is important to consider this variability in order to accurately estimate crop yield. Figure 9(a) and Figure 9(b) in this paper demonstrate the spatial variability in simulated crop yield when local climate conditions and management are taken into account. Previous studies have also highlighted the significance of local conditions and management in yield variability [58]-[60]. Accurate yield estimation is crucial for agricultural production, policy-making in food security, and the adoption of cropping technologies.

Furthermore, Figure 10(e) illustrates the predominance of poor to moderate soil fertility, as well as sparse to approximately half weed cover, which are distinct characteristics of smallholder farming in the study area. This cropping context has been observed in West Africa, particularly in the Sahel region, over the past few decades. While large-scale yield estimation provides an overall view of agricultural productivity, it often overlooks the local characteristics of the region, resulting in a lack of understanding of the extent of yield variability [61]. When



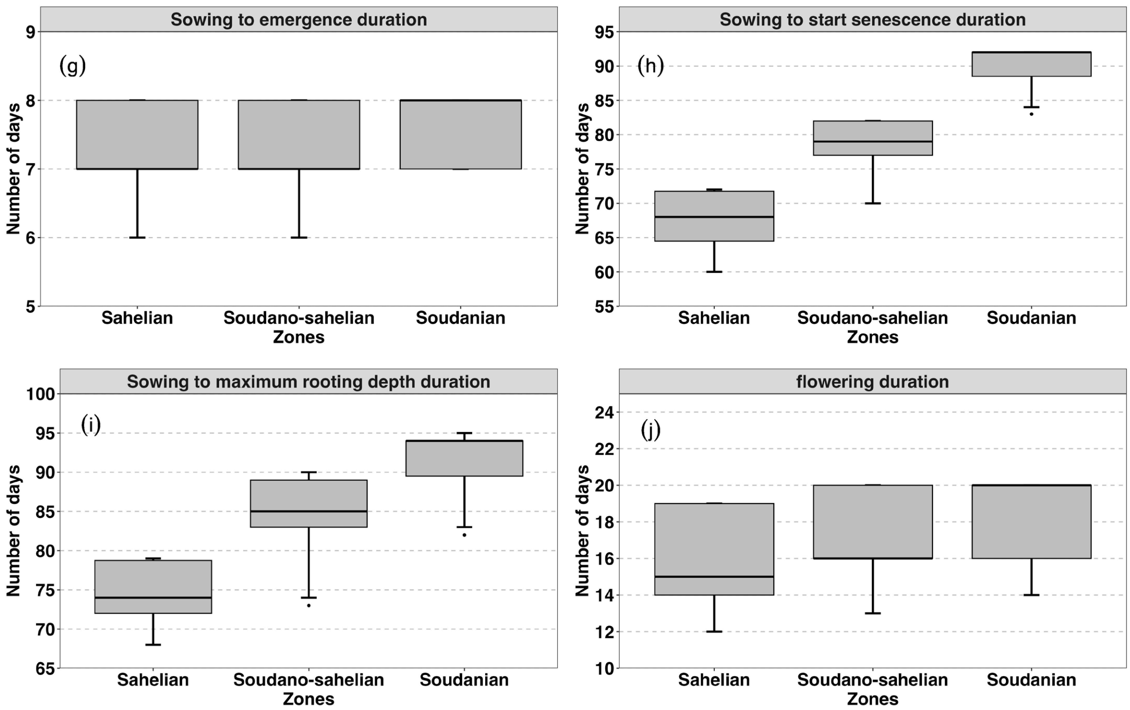


Figure 10. Crop and management optimal parameters for maize cropping in the three climatic zones in Burkina Faso. Statistics for each climatic zone are calculated by considering all grid cells that belong to the respective zone.

ever possible, it is important to take into account tailored crop and management strategies to accommodate the diversity of smallholder farmers and their practices. This finally contributes to better agricultural decision-making.

In this study, the choice of a GA approach is due to its ability to handle complex, non-linear problems with a large solution space [55]. The use of GA allows for the exploration of various combinations of cultivar parameters, soils and crop management, which would be impractical or time-consuming with traditional, manual calibration methods. However, the definition of the objective function is critical in GA since it guides the optimization process. It can vary depending on the specific problem. The optimization process described in this paper is not solely focused on maximizing crop yield. Instead, it aims to simultaneously maximize the pairwise correlation between simulated and observed yield while minimizing the deviation between simulated and observed yield. Previous studies have explored various optimization objectives. Reference [10] investigated maximizing crop yield while minimizing its inter-annual variability. Reference [62] focused on maximizing the sum of relative crop yields, while [56] employed a multi-objective function to enhance crop yield prediction accuracy.

In the agricultural productivity perspective, the GA approach can help identify strategies that optimize cropping resources, aligning with the principles of sustainable agriculture. In addition, it presents a notable reliance on data, including weather data, soil and management information, and crop yield data. This data-driven approach is essential for accurate modeling and optimization, emphasizing the importance of data collection efforts in the fields of agriculture.

Using the dynamic crop model AquaCrop in the core process of the GA approach enables the accounting for complex and nonlinear interactions between various environmental factors, including temperature, precipitation, soil conditions, and management practices. This allows for a more accurate simulation of crop yield in the optimization process. The varying convergence speeds observed across grid cells (**Figure 8**) can be attributed to the spatially heterogeneous nature of three key factors: local climate variability, soil condition complexity, and management practice variations. These factors create distinct optimization landscapes for each grid cell, consequently influencing the algorithm's efficiency in identifying optimal solutions. Despite varying convergence rates, the GA approach demonstrates computational efficiency by achieving parameter optimization within approximately 100 generations for most grid cells, and AquaCrop successfully simulates annual crop yield with a deviation of less than 30% for the majority of the grid cells when using these optimized parameters. However, it is important to note that the quality of input data significantly impacts the success of this approach. In this particular study, the reference maize crop yield is based on the official agricultural survey database at the district level rather than a research experimental field. Additionally, it is worth mentioning that the GA optimization process can be time-consuming, especially when dealing with input data at a finer spatial resolution, leading to a large number of grid cells. However, when computer resources are available, GA can take advantage of parallel processing capabilities, allowing for the execution of multiple simulations simultaneously and reducing the time required to find optimal solutions.

In conclusion, this paper presents an approach to address the location-specific calibration of maize crop yield. This is achieved by using a genetic algorithm in combination with the dynamic crop model AquaCrop. The approach yields optimal cultivar parameters and management practices that are tailored to specific locations and can adapt to climate variability. The findings can be used to support better adapted agricultural decisions (e.g., the decision about the planting time), thereby contributing to the promotion of sustainable and resilient agriculture in smallholder farming. Potential extensions of this research should explore cropping strategies to adapt to changing climate conditions. Additionally, it can be further used to explore the local implications in agricultural policies in the Sahel region dominated by smallholder farming.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

References

[1] Janicot, S. (1992) Spatiotemporal Variability of West African Rainfall. Part I: Regionalizations and Typings. *Journal of Climate*, **5**, 489-497. https://doi.org/10.1175/1520-0442(1992)005<0489:svowar>2.0.co;2

[2] Nicholson, S.E. (2013) The West African Sahel: A Review of Recent Studies on the Rainfall Regime and Its Interannual Variability. *ISRN Meteorology*, **2013**, 1-32. https://doi.org/10.1155/2013/453521

[3] Partey, S.T., Zougmoré, R.B., Ouédraogo, M. and Campbell, B.M. (2018) Developing Climate-Smart Agriculture to Face Climate Variability in West Africa: Challenges and Lessons Learnt. *Journal of Cleaner Production*, **187**, 285-295. https://doi.org/10.1016/j.jclepro.2018.03.199

[4] Swinnen, J.F.M., Colen, L. and Maertens, M. (2013) Constraints to Smallholder Participation in High-Value Agriculture in West Africa. In: Elbehri, A., Ed., *Rebuilding West Africa's Food Potential*, FAO/IFAD, 289-313.

[5] Herrero, M., Thornton, P.K., Notenbaert, A.M., Wood, S., Msangi, S., Freeman, H.A., *et al.* (2010) Smart Investments in Sustainable Food Production: Revisiting Mixed Crop-Livestock Systems. *Science*, **327**, 822-825. https://doi.org/10.1126/science.1183725

[6] Kaminski, J., Elbehri, A. and Zoma, J.B. (2013) An Analysis of Maize Value Chain and Competitiveness in Burkina Faso: Implications for Smallholder-Inclusive Policies and Initiatives. In: Elbehri, A., Ed., *Rebuilding West Africa's Food Potential*, FAO/IFAD, 453-478.

[7] Zougmoré, R., Partey, S., Ouédraogo, M., Omitoyin, B., Thomas, T., Ayantunde, A., *et al.* (2016) Toward Climate-Smart Agriculture in West Africa: A Review of Climate Change Impacts, Adaptation Strategies and Policy Developments for the Livestock, Fishery and Crop Production Sectors. *Agriculture & Food Security*, **5**, Article No. 26. https://doi.org/10.1186/s40066-016-0075-3

[8] Biazin, B., Sterk, G., Temesgen, M., Abdulkedir, A. and Stroosnijder, L. (2012) Rainwater Harvesting and Management in Rainfed Agricultural Systems in Sub-Saharan Africa—A Review. *Physics and Chemistry of the Earth*, *Parts A/B/C*, **47**, 139-151. https://doi.org/10.1016/j.pce.2011.08.015

[9] Wall, E. and Smit, B. (2005) Climate Change Adaptation in Light of Sustainable Agriculture. *Journal of Sustainable Agriculture*, **27**, 113-123. https://doi.org/10.1300/j064v27n01_07

[10] Waongo, M., Laux, P. and Kunstmann, H. (2015) Adaptation to Climate Change: The Impacts of Optimized Planting Dates on Attainable Maize Yields under Rainfed Conditions in Burkina Faso. *Agricultural and Forest Meteorology*, **205**, 23-39. https://doi.org/10.1016/j.agrformet.2015.02.006

[11] Laux, P., Jäckel, G., Tingem, R.M. and Kunstmann, H. (2010) Impact of Climate Change on Agricultural Productivity under Rainfed Conditions in Cameroon—A Method to Improve Attainable Crop Yields by Planting Date Adaptations. *Agricultural and Forest Meteorology*, **150**, 1258-1271. https://doi.org/10.1016/j.agrformet.2010.05.008

[12] Waongo, M., Laux, P., Traoré, S.B., Sanon, M. and Kunstmann, H. (2014) A Crop Model and Fuzzy Rule Based Approach for Optimizing Maize Planting Dates in Burkina Faso, West Africa. *Journal of Applied Meteorology and Climatology*, **53**, 598-613. https://doi.org/10.1175/jamc-d-13-0116.1

[13] Coulibaly, A., Motelica-Heino, M. and Hien, E. (2019) Determinants of Agroecological Practices Adoption in the Sudano-Sahelian Zone. *Journal of Environmental Protection*, **10**, 900-918. https://doi.org/10.4236/jep.2019.107053

[14] McGuire, S. and Sperling, L. (2016) Seed Systems Smallholder Farmers Use. *Food Security*, **8**, 179-195. https://doi.org/10.1007/s12571-015-0528-8

[15] Atta-Aidoo, J., Antwi-Agyei, P., Dougill, A.J., Ogbanje, C.E., Akoto-Danso, E.K. and Eze, S. (2022) Adoption of Climate-Smart Agricultural Practices by Smallholder Farmers in Rural Ghana: An Application of the Theory of Planned Behavior. *PLOS Climate*, **1**, e0000082. https://doi.org/10.1371/journal.pclm.0000082

[16] Tapsoba, P.K., Aoudji, A.K.N., Ouédraogo, F., Dassekpo, I.S., Kestemont, M., Kabore Konkobo, M., *et al.* (2023) Understanding the Behavioral Drivers of Smallholder Agro-Ecological Practice Adoption in Benin and Burkina Faso. *Farming System*, **1**, Article ID: 100023. https://doi.org/10.1016/j.farsys.2023.100023

[17] Bombardi, R.J., Pegion, K.V., Kinter, J.L., Cash, B.A. and Adams, J.M. (2017) Subseasonal Predictability of the Onset and Demise of the Rainy Season over Monsoonal Regions. *Frontiers in Earth Science*, **5**, Article 14. https://doi.org/10.3389/feart.2017.00014

[18] Paeth, H. and Hense, A. (2003) Seasonal Forecast of Sub-Sahelian Rainfall Using Cross Validated Model Output Statistics. *Meteorologische Zeitschrift*, **12**, 157-173. https://doi.org/10.1127/0941-2948/2003/0012-0157

[19] Laux, P., Wagner, S., Wagner, A., Jacobeit, J., Bárdossy, A. and Kunstmann, H. (2009) Modelling Daily Precipitation Features in the Volta Basin of West Africa. *International Journal of Climatology*, **29**, 937-954. https://doi.org/10.1002/joc.1852

[20] Siegmund, J., Bliefernicht, J., Laux, P. and Kunstmann, H. (2015) Toward a Seasonal Precipitation Prediction System for West Africa: Performance of CFSV2 and High-Resolution Dynamical Downscaling. *Journal of Geophysical Research*: *Atmospheres*, **120**, 7316-7339. https://doi.org/10.1002/2014jd022692

[21] Bliefernicht, J., Waongo, M., Salack, S., Seidel, J., Laux, P. and Kunstmann, H. (2019) Quality and Value of Seasonal Precipitation Forecasts Issued by the West African Regional Climate Outlook Forum. *Journal of Applied Meteorology and Climatology*, **58**, 621-642. https://doi.org/10.1175/jamc-d-18-0066.1

[22] Hansen, J.W., Mason, S.J., Sun, L. and Tall, A. (2011) Review of Seasonal Climate Forecasting for Agriculture in Sub-Saharan Africa. *Experimental Agriculture*, **47**, 205-240. https://doi.org/10.1017/s0014479710000876

[23] Blundo-Canto, G., Andrieu, N., Soule Adam, N., Ndiaye, O. and Chiputwa, B. (2021) Scaling Weather and Climate Services for Agriculture in Senegal: Evaluating Systemic but Overlooked Effects. *Climate Services*, **22**, Article ID: 100216. https://doi.org/10.1016/j.cliser.2021.100216

[24] Roudier, P., Alhassane, A., Baron, C., Louvet, S. and Sultan, B. (2016) Assessing the Benefits of Weather and Seasonal Forecasts to Millet Growers in Niger. *Agricultural and Forest Meteorology*, **223**, 168-180. https://doi.org/10.1016/j.agrformet.2016.04.010

[25] Tankari, M.R. (2020) Rainfall Variability and Farm Households' Food Insecurity in Burkina Faso: Nonfarm Activities as a Coping Strategy. *Food Security*, **12**, 567-578. https://doi.org/10.1007/s12571-019-01002-0

[26] Laudien, R., Schauberger, B., Waid, J. and Gornott, C. (2022) A Forecast of Staple Crop Production in Burkina Faso to Enable Early Warnings of Shortages in Domestic Food Availability. *Scientific Reports*, **12**, Article No. 1638. https://doi.org/10.1038/s41598-022-05561-9

[27] Ouedraogo, I., Savadogo, P., Tigabu, M., Cole, R., Odén, P.C. and Ouadba, J. (2009) Is Rural Migration a Threat to Environmental Sustainability in Southern Burkina Faso? *Land Degradation & Development*, **20**, 217-230. https://doi.org/10.1002/ldr.910

[28] Alene, A.D., Menkir, A., Ajala, S.O., Badu-Apraku, B., Olanrewaju, A.S., Manyong, V.M., *et al.* (2009) The Economic and Poverty Impacts of Maize Research in West and Central Africa. *Agricultural Economics*, **40**, 535-550. https://doi.org/10.1111/j.1574-0862.2009.00396.x

[29] Dembélé, M. and Zwart, S.J. (2016) Evaluation and Comparison of Satellite-Based Rainfall Products in Burkina Faso, West Africa. *International Journal of Remote Sensing*, **37**, 3995-4014. https://doi.org/10.1080/01431161.2016.1207258

[30] Ibrahim, B., Waongo, M., Sidibe, M., Sanfo, S. and Barry, B. (2022) Agroclimatological Characteristics of Rainy Seasons in Southwestern Burkina Faso during the 1970-2013 Period. *Atmospheric and Climate Sciences*, **12**, 330-357. https://doi.org/10.4236/acs.2022.122021

[31] De Longueville, F., Hountondji, Y., Kindo, I., Gemenne, F. and Ozer, P. (2016) Long-term Analysis of Rainfall and Temperature Data in Burkina Faso (1950-2013). *International Journal of Climatology*, **36**, 4393-4405. https://doi.org/10.1002/joc.4640

[32] Raes, D., Steduto, P., Hsiao, T.C. and Fereres, E. (2009) Aquacrop—The FAO Crop Model to Simulate Yield Response to Water: II. Main Algorithms and Software Description. *Agronomy Journal*, **101**, 438-447. https://doi.org/10.2134/agronj2008.0140s

[33] Raes, D., Waongo, M., Vanuytrecht, E. and Mejias Moreno, P. (2021) Improved Management May Alleviate Some but Not All of the Adverse Effects of Climate Change on Crop Yields in Smallholder Farms in West Africa. *Agricultural and Forest Meteorology*, **308**, Article ID: 108563. https://doi.org/10.1016/j.agrformet.2021.108563

[34] Steduto, P., Hsiao, T.C., Raes, D. and Fereres, E. (2009) Aquacrop—The FAO Crop Model to Simulate Yield Response to Water: I. Concepts and Underlying Principles. *Agronomy Journal*, **101**, 426-437. https://doi.org/10.2134/agronj2008.0139s

[35] Bell, B., Hersbach, H., Simmons, A., Berrisford, P., Dahlgren, P., Horányi, A., *et al.* (2021) The ERA5 Global Reanalysis: Preliminary Extension to 1950. *Quarterly Journal of the Royal Meteorological Society*, **147**, 4186-4227. https://doi.org/10.1002/qj.4174

[36] Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., *et al.* (2020) The ERA5 Global Reanalysis. *Quarterly Journal of the Royal Meteorological Society*, **146**, 1999-2049. https://doi.org/10.1002/qj.3803

[37] Rolle, M., Tamea, S. and Claps, P. (2022) Climate-driven Trends in Agricultural Water Requirement: An ERA5-Based Assessment at Daily Scale over 50 Years. *Environmental Research Letters*, **17**, Article ID: 044017. https://doi.org/10.1088/1748-9326/ac57e4

[38] Rolle, M., Tamea, S. and Claps, P. (2021) ERA5-based Global Assessment of Irrigation Requirement and Validation. *PLOS ONE*, **16**, e0250979. https://doi.org/10.1371/journal.pone.0250979

[39] Maidment, R.I., Grimes, D., Black, E., Tarnavsky, E., Young, M., Greatrex, H., *et al.* (2017) A New, Long-Term Daily Satellite-Based Rainfall Dataset for Operational

Monitoring in Africa. *Scientific Data*, **4**, Article No. 170063. https://doi.org/10.1038/sdata.2017.63

[40] Garba, J.N., Diasso, U.J., Waongo, M., Sawadogo, W. and Daho, T. (2023) Performance Evaluation of Satellite-Based Rainfall Estimation across Climatic Zones in Burkina Faso. *Theoretical and Applied Climatology*, **154**, 1051-1073. https://doi.org/10.1007/s00704-023-04593-z

[41] Reiter, P., Gutjahr, O., Schefczyk, L., Heinemann, G. and Casper, M. (2017) Does Applying Quantile Mapping to Subsamples Improve the Bias Correction of Daily Precipitation? *International Journal of Climatology*, **38**, 1623-1633. https://doi.org/10.1002/joc.5283

[42] Gia Pham, T., Kappas, M., Van Huynh, C. and Hoang Khanh Nguyen, L. (2019) Application of Ordinary Kriging and Regression Kriging Method for Soil Properties Mapping in Hilly Region of Central Vietnam. *ISPRS International Journal of Geo-Information*, **8**, Article 147. https://doi.org/10.3390/ijgi8030147

[43] Ochoa-Rodriguez, S., Wang, L., Willems, P. and Onof, C. (2019) A Review of Radar-Rain Gauge Data Merging Methods and Their Potential for Urban Hydrological Applications. *Water Resources Research*, **55**, 6356-6391. https://doi.org/10.1029/2018wr023332

[44] Qiu, Q., Liu, J., Tian, J., Jiao, Y., Li, C., Wang, W., *et al.* (2020) Evaluation of the Radar QPE and Rain Gauge Data Merging Methods in Northern China. *Remote Sensing*, **12**, Article 363. https://doi.org/10.3390/rs12030363

[45] Allen, R.G., Pereira, L.S., Raes, D. and Smith, M. (1998) Crop Evapotranspiration—Guidelines for Computing Crop Water Requirements—FAO Irrigation and Drainage Paper 56. Food and Agriculture Organisation.

[46] FAO and IIASA (2023) Harmonized World Soil Database version 2.0 [Internet]. FAO, International Institute for Applied Systems Analysis (IIASA). https://doi.org/10.4060/cc3823en

[47] Dao, A., Sanou, J., Gracen, V. and Danquah, E.Y. (2015) Indentifying Farmers' Preferences and Constraints to Maize Production in Two Agro-Ecological Zones in Burkina Faso. *Agriculture & Food Security*, **4**, Article No. 13. https://doi.org/10.1186/s40066-015-0035-3

[48] Yaméogo, I.S., Ouattara, D., Dabiré, R., Oumsonré, A., Kossi, L., Gnankiné, O., *et al.* (2023) Évaluation de la sensibilité de variétés vulgarisées de maïs à la chenille légionnaire d'automne, Spodoptera frugiperda J.E. Smith à l'ouest du Burkina Faso. *Journal of Applied Biosciences*, **191**, 20186-20202. https://doi.org/10.35759/jabs.191.2

[49] Boro, L.R. (2017) Diffusion de six variétés améliorées de maïs à travers la vitrine-test et les tests démonstratifs dans les cinq régions du Burkina Faso [Internet] [Diplome D'ingenieur du Developpement Rural]. Universite Nazi Boni (UNB).

[50] Segda, Z. (1995) La culture du maïs dans les systèmes de culture pluviaux dans l'ouest du Burkina Faso. Production et valorisation du maïs à' l'échelon villageois en Afrique de l'Ouest, CIRAD.

[51] Badu-Apraku, B. and Fakorede, M.A.B. (2017) Climatology of Maize in Sub-Saharan Africa. In: Badu-Apraku, B. and Fakorede, M.A.B., Eds., *Advances in Genetic Enhancement of Early and Extra-Early Maize for Sub-Saharan Africa*, Springer, 11-31. https://doi.org/10.1007/978-3-319-64852-1_2

[52] Rockström, J. and Barron, J. (2007) Water Productivity in Rainfed Systems: Overview of Challenges and Analysis of Opportunities in Water Scarcity Prone Savannahs. *Irrigation Science*, **25**, 299-311. https://doi.org/10.1007/s00271-007-0062-3

[53] Beasley, D., Bull, D.R. and Martin, R.R. (1993) An Overview of Genetic Algorithms:

Part 1, Fundamentals. *University Computing*, **15**, 56-69.

[54] Holland, J.H. (1992) Adaptation in Natural and Artificial Systems: An Introductory Analysis with Applications to Biology, Control, and Artificial Intelligence. The MIT Press. https://doi.org/10.7551/mitpress/1090.001.0001

[55] Scrucca, L. (2013) GA: A Package for Genetic Algorithms in *R. Journal of Statistical Software*, **53**, 1-37. https://doi.org/10.18637/jss.v053.i04

[56] Guo, D., Olesen, J.E., Pullens, J.W.M., Guo, C. and Ma, X. (2021) Calibrating Aquacrop Model Using Genetic Algorithm with Multi-Objective Functions Applying Different Weight Factors. *Agronomy Journal*, **113**, 1420-1438. https://doi.org/10.1002/agj2.20588

[57] Bagchi, T.P. (2012) Multiobjective Scheduling by Genetic Algorithms. Springer.

[58] Dutta, S., Chakraborty, S., Goswami, R., Banerjee, H., Majumdar, K., Li, B., *et al.* (2020) Maize Yield in Smallholder Agriculture System—An Approach Integrating Socio-Economic and Crop Management Factors. *PLOS ONE*, **15**, e0229100. https://doi.org/10.1371/journal.pone.0229100

[59] Kraaijvanger, R. and Veldkamp, A. (2015) The Importance of Local Factors and Management in Determining Wheat Yield Variability in On-Farm Experimentation in Tigray, Northern Ethiopia. *Agriculture*, *Ecosystems & Environment*, **214**, 1-9. https://doi.org/10.1016/j.agee.2015.08.003

[60] van Loon, M.P., Adjei-Nsiah, S., Descheemaeker, K., Akotsen-Mensah, C., van Dijk, M., Morley, T., *et al.* (2019) Can Yield Variability Be Explained? Integrated Assessment of Maize Yield Gaps across Smallholders in Ghana. *Field Crops Research*, **236**, 132-144. https://doi.org/10.1016/j.fcr.2019.03.022

[61] van Wart, J., Kersebaum, K.C., Peng, S., Milner, M. and Cassman, K.G. (2013) Estimating Crop Yield Potential at Regional to National Scales. *Field Crops Research*, **143**, 34-43. https://doi.org/10.1016/j.fcr.2012.11.018

[62] Sirajul, I. and Bipul, T. (2014) Crop Yield Optimization Using Genetic Algorithm with the CROPWAT Model as a Decision Support System. *CABI Databases*, **7**, 7-11.