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Climate change-induced reduction in agricultural land suitability of West-Africa's inland valley landscapes

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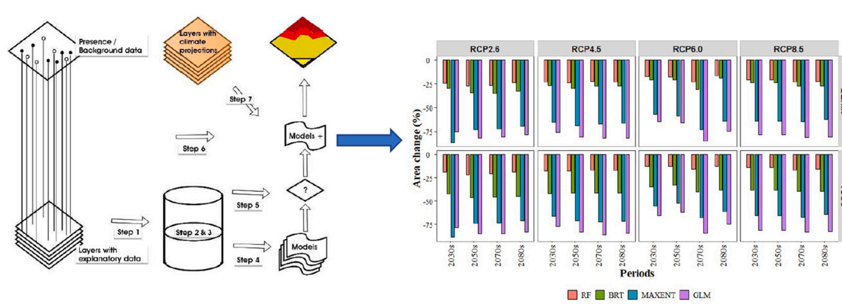
HIGHLIGHTS

- West Africa's agenda for rice self-sufficiency remains uncertain under climate change conditions.
- The potential of inland valleys for rain-fed rice cultivation under future climate change uncertainties was assessed.
- Significant losses of suitable areas due to changes in the day to night temperatures oscillations were found.

GRAPHICAL ABSTRACT



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ABSTRACT

CONTEXT: Although rice production has increased significantly in the last decade in West Africa, the region is far from being rice self-sufficient. Inland valleys (IVs) with their relatively higher water content and soil fertility compared to the surrounding uplands are the main rice-growing agroecosystem. They are being promoted by governments and development agencies as future food baskets of the region. However, West Africa's crop production is estimated to be negatively affected by climate change due to the strong dependence of its agriculture on rainfall.
OBJECTIVE: The main objective of the study is to apply a set of machine learning models to quantify the extent of climate change impact on land suitability for rice using the presence of rice-only data in IVs along with bioclimatic indicators.
METHODS: We used a spatially explicit modeling approach based on correlative Ecological Niche Modeling. We deployed 4 algorithms (Boosted Regression Trees, Generalized Linear Model, Maximum Entropy, and Random Forest) for 4-time periods (the 2030s, 2050s, 2070s, and 2080s) of the 4 Representative Concentration Pathways (RCP2.6, RCP4.5, RCP6.0, and RCP8) from an ensemble set of 32 spatially downscaled and bias-corrected Global Circulation Models climate data.

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RESULTS AND CONCLUSIONS: The overall trend showed a decrease in suitable areas compared to the baseline as a function of changes in temperature and precipitation by the order of 22–33% area loss under the lowest reduction scenarios and more than 50% in extreme cases. Isothermality or how large the day to night temperatures oscillate relative to the annual oscillations has a large impact on area losses while precipitation increase accounts for most of the areas with no change in suitability. Strong adaptation measures along with technological advancement and adoption will be needed to cope with the adverse effects of climate change on inland valley rice areas in the sub-region.

SIGNIFICANCE: The demand for rice in West Africa is huge. For the rice self-sufficiency agenda of the region, "where" and "how much" land resources are available is key and requires long-term, informed planning. Farmers can only adapt when they switch to improved breeds, providing that they are suited for the new conditions. Our results stress the need for land use planning that considers potential climate change impacts to define the best areas and growing systems to produce rice under multiple future climate change uncertainties.

1. Introduction

Crop productions need to increase to meet global rapid population growth by 2050 and beyond (Tilman et al., 2011; Wise, 2013). Nevertheless, agricultural systems that sustain crop production are subjected to changing climate impacts (Schmidhuber and Tubiello, 2008), which will potentially affect all aspects of food security (Mbow et al., 2017). Climate change is expected to negatively impact crop production in low-latitude countries, especially for major crops such as wheat, maize, and rice (Challinor et al., 2014; Rosenzweig et al., 2014). For instance, global warming will result in plausible rice yield losses if farmers are not provided with tools to allow them to adapt to changing growing conditions (Zhao et al., 2016; van Oort and Zwart, 2018). It is acknowledged that climate change will affect future rainfed farming through increased climate variability and reduced mean annual rainfall (IPCC, 2014). In West Africa, for example, a shift in the total amount of rainfall is the main driver of change in the sorghum yield (Guan et al., 2015). There is evidence of change in precipitation patterns across crop production areas even under the lowest emission of the RCP2.6 scenario (Siabi et al., 2021; Yeboah et al., 2022). Similarly, an analysis of heat stress on crop production showed that wetland rice showed high susceptibility to heat stress (Teixeira et al., 2013).

The impact of climate change on crop production and food security has been mainly assessed through crop yield change (Challinor et al., 2014) including studies for rice (Gupta and Mishra, 2019; van Oort and Zwart, 2018). However, climate change not only impacts crop yields but also the suitability of lands for agriculture (Iizumi and Ramankutty, 2015). In addition to crop yield responses, climate change will also impact sequential cropping, rainfed cropland expansion, and irrigation expansion in tropical Sub-Saharan Africa (SSA) (Duku et al., 2018). In Ghana, for example, it is estimated that about 9.5% of the potentially suitable land will become unsuitable for irrigation in the 2050s, and it is expected to reach 17% in the 2070s due to climate change (Worqlul et al., 2019). For a wide range of crops, climate change will induce shifts in the areas previously suitable for their cultivation (Lane and Jarvis, 2007). Therefore, to ensure better planning and sustainability of the agricultural systems, mapping cropland suitability under climate change conditions is important (Akpoti et al., 2019). In SSA, where the main crop production is based on rainfed systems by smallholder subsistence farmers, the cropland suitability mapping is essential for food security designing and implementing adaptation measures. The cropland suitability assessment is considered the process of identifying the likelihood of a given location or pixel in the spatial landscape to support the optimum growth of the crop, taking into account biophysical and socio-economic factors (Akpoti et al., 2019).

Various approaches can be used in assessing changes in cropland suitability under climate change. The discussion often turns around the use of process-based (mechanistic) or statistical models (including ecological niche models; ENMs) (Akpoti et al., 2019). A meta-analysis of both methods comparing modeling climate change impacts from process-based and statistical crop models has been conducted before (Lobell and Asseng, 2017). The comparison of process-based and statistical models for low levels of warming showed that there are no apparent systematic differences between the predicted sensitivities to temperature change (Lobell and Asseng, 2017). Several other studies compared the ability of mechanistic models (MMs) and ENMs to predict climate change effects on habitat suitability for species. One such study was conducted by Hijmans and Graham, 2006 based on MM and certain climate envelope models such as Bioclim (percentile distributions), Domain (distance metric), GAM (general additive modeling), and MaxEnt (maximum entropy). Results showed that while the Domain model performed poorly, GAM and MaxEnt (both can be considered machine learning methods) were as good as the MM. Machine learning methods thus can be used for climate change impacts on land suitability for specific crops. The MaxEnt model has also been used to model the shifting agricultural suitability of maize and wheat under climate change in South Africa (Bradley et al., 2012). There are three major reasons for the choice of ENMs over MMs. Firstly, MMs are intense data-driven models whose inputs include daily weather data, management practices (e.g., planting date), and soil-related parameters. These types of data are mostly available at field scales but are often missing on a larger scale modeling. Secondly, the spatial distribution of agricultural fields and crop types under rainfed conditions infer sufficient bioclimatic information required for statistical modeling (Akpoti et al., 2021; Estes et al., 2013). Thirdly, rainfed lowland rice is often monoculture and does not need to account for crop species interactions.

ENMs have been used in the past to assess the potential impacts of climate change on species range shifts risk (Remya et al., 2015; Ashraf et al., 2017). A crop suitability assessment based on ENM showed that larger area losses occur in the tropical regions of Africa, and southern and eastern Asia for crops such as rice, sweet potato, and yam (Beck, 2013). The approach was also used to assess the vulnerability to climate change of the cocoa belt in West Africa (Schroth et al., 2017), on Hass avocados across the Americas (Ramírez-Gil et al., 2019), and olive varieties in southern Spain (Arenas-Castro et al., 2020). ENM was also used to assess the impact of past climate change on rice area suitability in China (Liu et al., 2015) and future climate change on rice area suitability in Colombia (Castro-Llanos et al., 2019).

West Africa is considered to have a high potential for rice production, but the region still depends on substantial rice imports. According to the Food and agriculture organization of the united nations (FAO) statistics on crop production (FAOSTAT, 2021), the main crops produced in 2019 in Togo and Benin are cassava, maize, yams, sorghum, seed cotton, oil palm fruit, dry beans, paddy rice. In the case of rice, the production in Togo was 147,053 t with a harvested area of 89,678 ha and an overall yield of 1.6 t/ha. For Benin, the paddy rice production was 406,000 t on a harvested area of 113,719 ha and a yield of 3.6 t/ha. The limitations of the region's rice production are related to biophysical, socio-economic, technological, and eco-environmental factors (Balasubramanian et al., 2007; Saito et al., 2013). Africa's rice ecosystems include dryland, deepwater, mangrove swamp, upland, lowland, and inland valleys (Andriesse and Fresco, 1991). In West Africa, inland valleys are believed

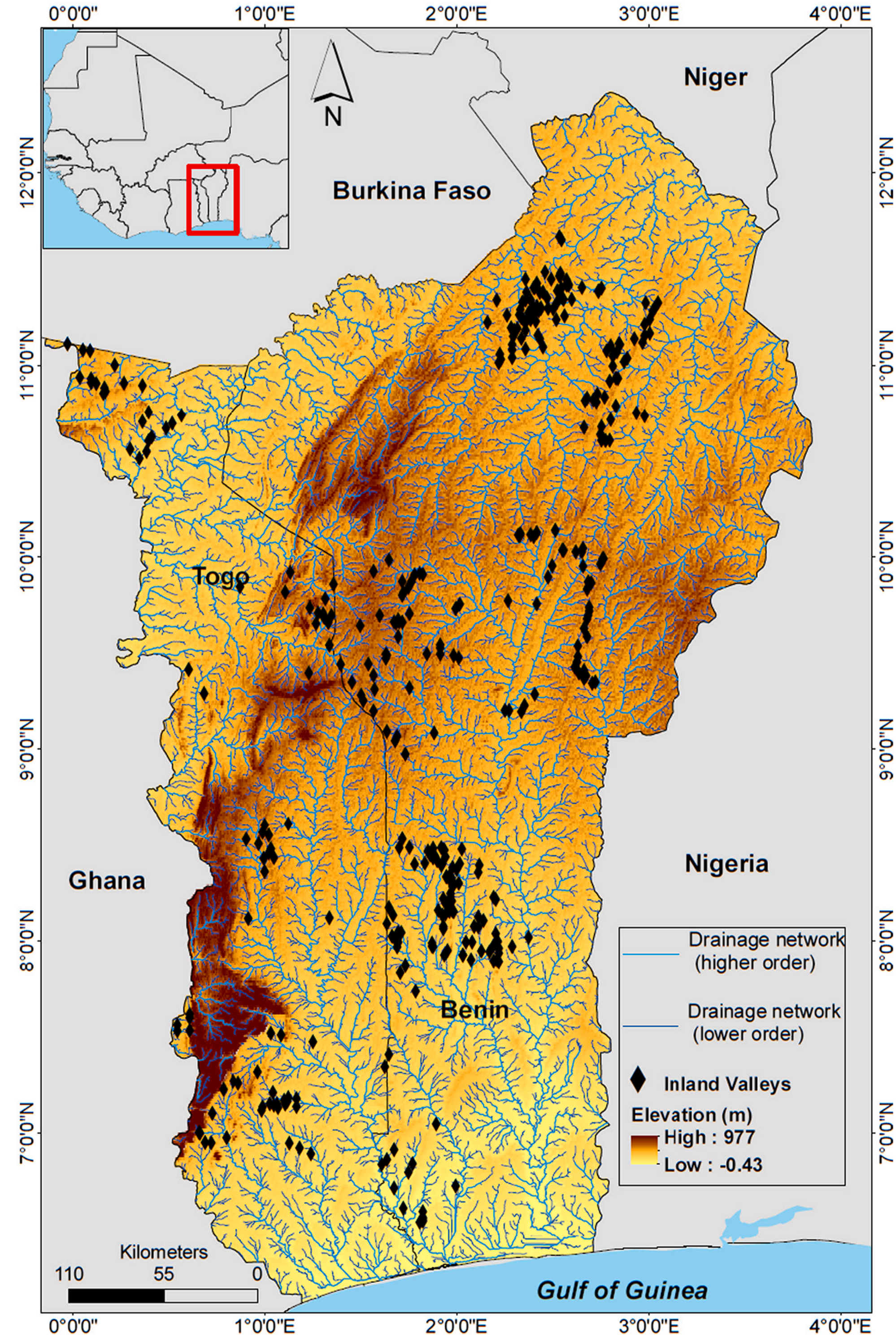

Fig. 1. Study area map of Togo and Benin depicting the location of sampled inland valleys.

to be the future food baskets due to relatively higher water availability and soil fertility than the surrounding uplands (Rodenburg et al., 2014) and they are targeted by many interventions to improve national rice production (Gumma et al., 2009; Sakurai, 2006). In Togo and Benin, inland valley rice production represents more than 60% of the countries' rice cultivated areas (Diagne et al., 2013). However, the impact of future climate change on the suitability of rainfed rice production in inland valleys in terms of direction and magnitude of change remains unclear. In this study, we used a biophysically based assessment to quantitatively map the climate change impact on inland valley rainfed rice area suitability in Togo and Benin. We used an ensemble of ENMs with spatially downscaled climate data from a set of 32 General Circulation Models under 4 expected climate change scenarios as input. We used an ensemble of ENMs with spatially downscaled climate data from a set of 32 General Circulation Models under 4 expected climate change scenarios as input. We specifically address the following question: *How is the extent of inland valleys that are suitable for rainfed rice production changing because of climate change?* The results from this study are to

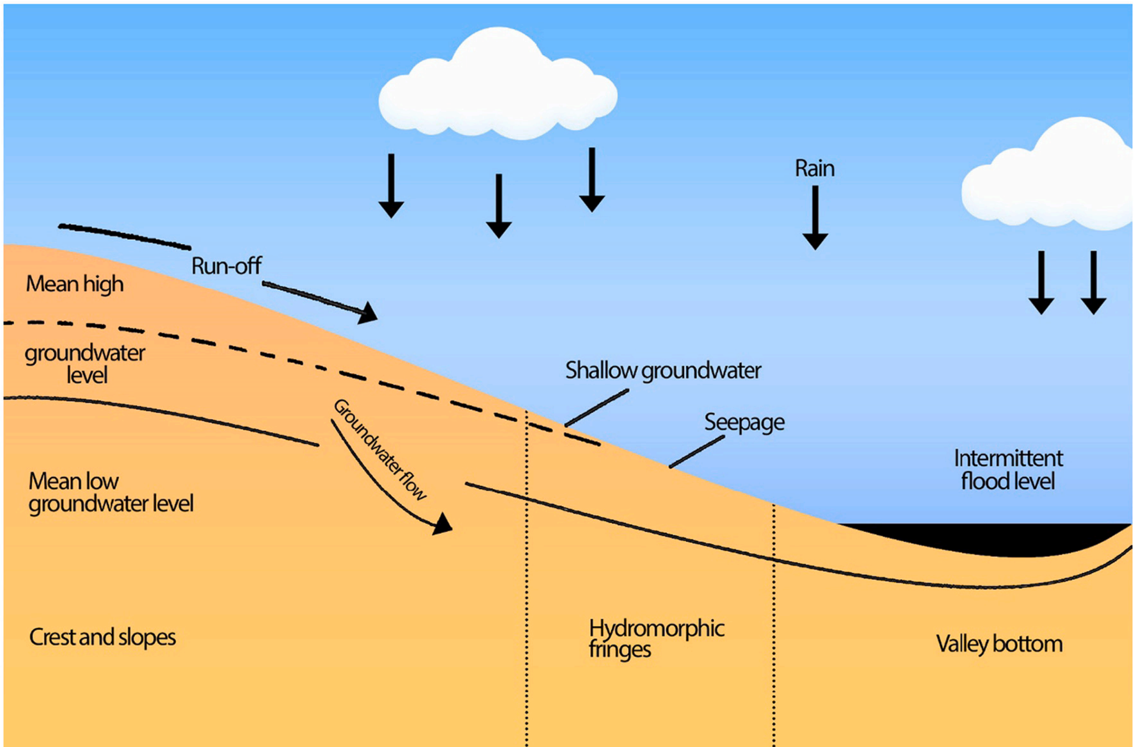

Fig. 2. Flows of water from the upland area to the bottom of the inland valley (adapted from Wopereis et al., 2008). IVs are defined by their upstream position relative to the hydrological network. Characterization of an IV includes crest or upland area, fringes or edges of the valleys, and the area close to the valley bottom or hydromorphic fringes. The catchment area captures the water of the whole hydrological network of an inland valley, from the crest (upland area, without groundwater-table influence on crop growth) through the hydromorphic zone (with shallow groundwater table) to the inland-valley bottom (usually flooded in the wet season) (Wopereis et al., 2008).

guide policy development on climate change adaptation measures, and other development interventions in the rice sector in the region.

2. Materials and methods

2.1. Study area overview

The study area is the national scales of Togo (0°- 2°E, 6° - 11°N) and Benin (0°- 4°E, 6°-13°N), two neighboring tropical countries located along the Gulf of Guinea in West Africa. The surface area of Togo and Benin are respectively about 57,000 km^2 and 115,000 km^2. Elevation relative to sea level across Togo and Benin varies from −0.43 to 977 m (see Fig. 1). Togo is cut across in the center by a chain of hills known as the Togo Mountains. This mountainous chain extends southwestward into Ghana and northeastward into Benin. In Benin, it is known as the Atakora Mountains. The central and southern part of both countries forms a large complex of plateaus covered by a mosaic of vegetation types. The coastal zone of Togo and Benin is characterized by lagoons and marshes formed by rivers. According to the World Bank's Climate Change Knowledge Portal (WBG, 2021), the mean annual temperature and rainfall between 1901 and 2016 for Togo and Benin are respectively 27.0 °C - 1170 mm and 27.5 °C - 1059 mm. The climate in both countries is influenced by the West African Monsoon and the movement of the Inter-tropical Convergence Zone (ITCZ). The south of both countries experiences two rainy seasons: the first between March and July and the second between September and November. Only one rainy season occurs in the north from May to November.

Projected climate trends in Togo showed that the mean annual temperature will increase between 1.2 °C and 2.7 °C in 2040–2059 (RCP 8.5, Ensemble), by 1.0 to 3.1 °C by the 2060s, and by 1.5 °C to 5.3 °C by the 2090s(WBG, 2021). The projected temperature rise in Togo is expected to be pronounced in the north compared to the coastal zone. Contrary to the clear temperature increase projections, projected changes in rainfall are uncertain, with huge variability, with climate circulation models predicting both increases and decreases, with an estimation of an increase in the frequency of intense rainfall events and longer periods of drought (WBG, 2021). As in the case of Togo, Benin's mean annual temperature will increase between 1.3 °C and 2.9 °C in 2040–2059 (RCP 8.5, Ensemble), 1.0–3.0 °C by the 2060s, with the northern regions of Benin experiencing the most rapid increase, while rainfall projections remain uncertain (WBG, 2021). More generally, mean annual temperatures over West Africa are projected to increase by 3 °C to 6 °C by the end of the 21st century under RCP4.5 and RCP8.5 with many CMIP5 models projecting mean precipitation over West Africa to increase during the rainy season with a small delay to the start of the rainy season (WBG, 2021).

2.2. Inland valley delineation

SSA wetlands comprise 1) coastal plains — including deltas, estuaries, and tidal flats, 2) inland basins which consist of extensive drainage depressions, 3) river floodplains characterized by recent alluvial deposits bordering rivers and 4) inland valleys. It is estimated that inland valley wetlands represent 36% of the total wetland land area in SSA (~ 85 million ha) with only 10–15% of the inland valley area used for agriculture (Balasubramanian et al., 2007). Inland valleys are seasonally flooded wetlands comprising valley bottoms and hydromorphic fringes. A single inland valley is a toposequence of a valley bottom that includes hydromorphic edges, dryland slopes, and crests that contribute to runoff and seepage in the valley bottom (Wopereis et al., 2008; Balasubramanian et al., 2007) (see Fig. 2). inland valleys are widespread in West Africa's undulating landscape. Their high agricultural production potential is due to several reasons among which are a) proximity to river water, b) soil fertility, c) water availability even in the dry season, and d)

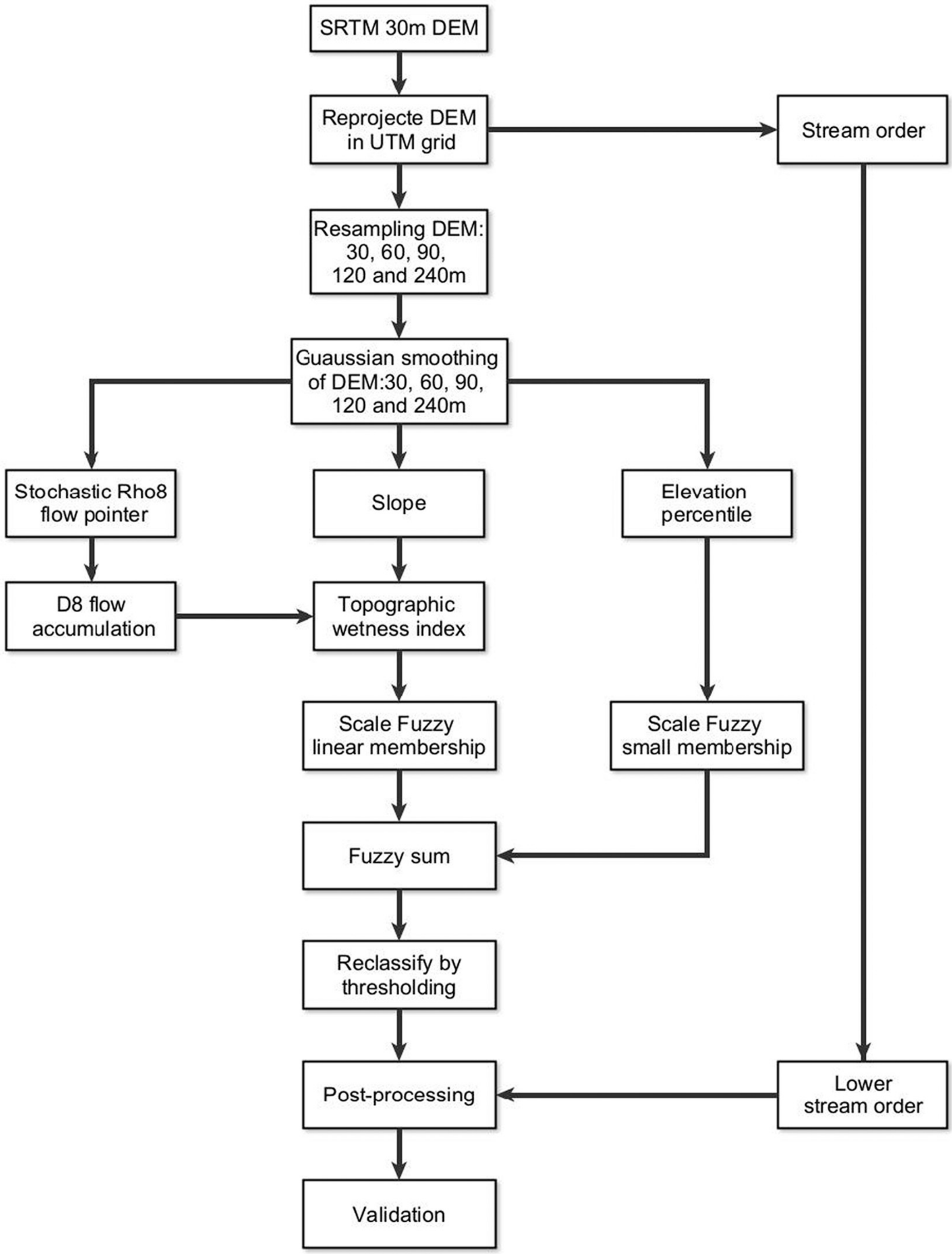

Fig. 3. A methodological framework for inland valleys delineation.

contribution of groundwater lateral flow to water availability (Masoud et al., 2013). Inland valley ecosystems are favorable for rice production, as rice fields are flooded during all or part of the growing period. Selecting the most suitable inland valley for rice production is a determinant of good yield, low-risk areas with ongoing exploitation, or new areas (Rodenburg et al., 2014).

To delineate inland valleys for the rainfed rice potential modeling, two morphometric indices i.e. the Topographical Wetness Index (TWI) and elevation percentile were combined following the methodological framework reported in Fig. 3. We used the 30 m Digital Elevation Model (DEM) in a projected coordinate system, from which 30 m, 60 m, 90 m, 120, and 240 m were resampled to delineate all sizes of inland valleys in the landscape. The four DEMs were then smoothed using the *raster.gaussian.smooth* function of the Spatial Analysis and Modeling Utilities (*spatialEco*) package in R (Evans et al., 2020). This process allows the final inland valley products to have a continuous shape. Elevation percentile, which is the ranking of each cell's elevation relative to all other cells in the landscape that fall within a circular window of a given radius, is a robust index that contrasts the local topography by differentiating between lowland and the upland (Gallant and Dowling, 2003). For each of the DEMs, the elevation percentile was computed based on a size 11 × 11 filter kernel in the x and y directions using the function *wbt_elev_percentile* of the *Whitebox* package in R (Lindsay, 2016). The percentile products were first normalized using the fuzzy small membership then combined using the fuzzy sum membership function in ArcGIS. TWI products were derived using the *wbt_wetness_index* function in the Whitebox package in R as defined in Eq. 1. The TWI of each pixel in the study area is a function of the upslope area (A) per unit contour length and the local slope (tanB) as:

$$TWI = ln\left(\frac{A}{tan(B)}\right) \tag{1}$$

The TWI were further normalized using fuzzy linear membership function in ArcGIS, then combined using fuzzy sum. TWI is one of the key determinants of soil moisture spatial variability based on the assumption that in sloped terrain, topography controls the movement of water (Schmidt and Persson, 2003). The final elevation percentile product and TWI were combined to form inland valleys by setting a threshold. The combination of inland valley products from 30 m and 60 m indices resulted in too many details where small depressions are captured, which were further removed from the final inland valley delineated data. Sensitivity analysis of various threshold values was conducted. A cut-threshold of 0.9 was finally considered with values greater than this threshold defined as inland valleys. The threshold of 0.9 was validated by comparing the tracked inland valleys on the ground with the delineated inland valleys, with an accuracy of 0.8. To exclude river floodplains from inland valleys, we used stream order networks where higher streams are considered flood plains while lower-order streams are generally inland valleys. The total estimated inland valley area for Togo and Benin are 450,000 ha and 860,000 ha respectively. The suitability modeling of inland valleys for rice production was conducted within the delineated inland valleys buffer.

2.3. Inland valleys survey data

The suitability assessment of inland valley landscapes for rainfed rice production systems is based on ecological niche modeling and requires the use of rice occurrence data, meaning the geo-location of agricultural fields where rice is grown in IVs. Between April and September 2017, the Africa Rice Center, and its partners in Togo and Benin implemented a field campaign under the framework of the project "Efficient Targeting and Equitable Scaling of Rice Technologies in Togo and Benin (ETES-Rice)". As reported in Akpoti et al. (2020), 3 main steps were used in the field data: 1) a workshop was organized with country experts and agronomic extension services to define criteria for rainfed lowland including but not limited to the spatial distribution of the inland valleys relevant for ecological niche modeling, such that not all sampled inland valleys are located along major roads or near towns, the diversity of land use in inland valleys concerning presence or absence of rice agro-ecological and climatic zones in both countries; 2) and an exploratory phase to pre-locate the candidate inland valleys to be surveyed was conducted with the assistance of informants and farmers at the village level and the use of topographic maps and Google Earth; 3) and the survey with a data collection unit which consisted of a specific inland valley area users' group and a systematically recording of inland valleys geo-locations using handheld GPS. In addition to location data, other relevant information was collected including 1) hydrological data (flooding duration in inland valley fringe and valley bottom, maximum flow accumulation, duration and frequency, water source in the inland valley, emerging and shallow water table at the firings, and valley bottoms, and duration), 2) topography and climate information in the inland valley, 3) soil information (physical and chemical properties), 3) socio-economic and accessibility environment (proximity to roads, towns, market places, rice mill, inputs, land ownership, gender, etc.) and farm management practices (crop other than rice, total inland valley used for rice, yield in the previous years, mode of exploitation of the inland valleys, water management practices, etc.). The structure of the dataset, which contains more than 50 variables was previously published by Djagba et al. (2019), and the dataset was used to define the predictors that define the potential of inland valleys for rice production (Djagba et al., 2018). The final database contained 408 and 436 inland valleys where rice was grown under rainfed conditions, respectively in Togo and Benin.

2.4. Predictors

2.4.1. Baseline climate characterization

To represent the current climate in our models, a set of bioclimatic predictors were considered from the WorldClim Version2 database (http://worldclim.org/version2, Fick and Hijmans, 2017). The bioclimatic dataset includes 19 bioclimatic predictors derived from average monthly temperature and precipitation throughout 1970–2000 at 1 km^2 spatial resolution. This period was referred to as the baseline climate. The bioclimatic predictors represent an annual average, seasonal, and intra-seasonal as well as limiting environmental factors (O'Donnell and Ignizio, 2012). These predictors are related to plant physiological processes and have been widely used in species distribution modeling (Remya et al., 2015; Hijmans and Graham, 2006) and in cropland suitability mapping including rice (Läderach et al., 2013; Beck, 2013; Liu et al., 2015). Most of the 19 bioclimatic predictors are highly correlated, which may represent a major source of error in the correlative models (Braunisch et al., 2013). Pearson's correlation coefficient value $|r| = 0.75$ was used as a cut-off threshold to exclude any one of the paired highly correlated predictors. Only the climatic predictors that are considered most relevant for rice suitability (see Akpoti et al., 2020) are maintained in the final predictors' list including isothermality (BIO3), annual precipitation (BIO12), precipitation seasonality (BIO15), precipitation of wettest quarter (BIO16) and precipitation of warmest quarter (BIO18). According to O'Donnell & Ignizio, (2012), these predictors are defined as follows:

- Precipitation of the wettest quarter (BIO16) and precipitation of the warmest quarter (BIO18) are defined as the quarterly index approximates of the total precipitation that prevails during the wettest and the warmest quarter respectively.
- Isothermality is defined as quantifying how large the day to night temperatures oscillate relative to the annual oscillations. Isothermality is derived by calculating the ratio of the mean diurnal range to the annual temperature range as:

$$BIO3 = \frac{\left[\sum_{i=1}^{i=12}(Tmax_i - Tmin_i)\right]\Big/12}{max(Tmax_1, \dots, Tmax_{12}) - min(Tmin_1, \dots, Tmin_{12})} \times 100 \tag{2}$$

- Annual precipitation is the sum of all total monthly precipitation values as:

$$BIO12 = \sum_{i=1}^{i=12} PPT_i \tag{3}$$

- Precipitation Seasonality (Coefficient of Variation) is a measure of the variation in monthly precipitation totals over the year as:

$$BIO5 = \frac{SD(PPT_i, \dots, PPT_{12})}{1 + \left(\sum_{i=1}^{i=12} PPT_i\right)\Big/12} \tag{4}$$

Where i = month, Tmax = monthly mean of daily maximum temperatures (°C), Tmin = monthly mean of daily minimum temperatures (°C), PPT = total monthly precipitation (mm), and SD = standard deviation.

2.4.2. Future climate scenarios

General Circulation Models (GCMs) climate projections come at coarse resolution (typically 70 km by 70 km for the latest assessment; IPCC, 2014) while climate change impact studies require finer-scale data (Gharbia et al., 2016). Therefore, spatially downscaled and bias-corrected climate data obtained from the CGIAR Research Program on

Table 1
List of CMIP5 Global Climate Models used in the modeling (Navarro-Racines et al., 2020).

Model	Institution	Country	RCP 2.6	4.5	6.0	8.5
BCC_CSM1.1	Beijing Climate Center	China	–	x	x	x
BCC_CSM 1.1 (m)	Beijing Climate Center	China	–	x	x	x
BNU-ESM	Beijing Normal University	China	x	x	–	x
CCCma CanESM2	Canadian Centre for Climate Modeling and Analysis	Canada	x	x	–	x
CESM1(BGC)	Community earth system model/ National Center for Atmospheric Research	USA	–	x	–	x
CESM1(CAM5)	National Center for Atmospheric Research	USA	x	x	x	x
CSIRO-ACCESS1–0	Commonwealth Scientific and Industrial Research Organization/ Australian Community Climate and Earth System Simulator	Australia	–	x	–	x
CSIRO-ACCESS1.3	Commonwealth Scientific and Industrial Research Organization	Australia	–	x	–	x
CSIRO-Mk3.6.0	Commonwealth Scientific and Industrial Research Organization	Australia	x	x	x	x
FIO-ESM	State Oceanic Administration (SOA)	China	x	x	x	x
EC-Earth	European Centre for Medium-Range Weather Forecasts (ECMWF)	Europe-wide consortium	–	–	–	x
GFDL-CM3	NOAA Geophysical Fluid Dynamics Laboratory	USA	x	x	x	x
GFDL-ESM2G	NOAA Geophysical Fluid Dynamics Laboratory	USA	x	x	x	x
GFDL-ESM2M	NOAA Geophysical Fluid Dynamics Laboratory	USA	x	x	x	x
GISS-E2-H	NASA Goddard Institute for Space Studies	USA	x	–	x	x
GISS-E2-H-CC	NASA Goddard Institute for Space Studies	USA	–	x	–	–
GISS-E2-R	NASA Goddard Institute for Space Studies	USA	x	x	x	x
GISS-E2-R-CC	NASA Goddard Institute for Space Studies	USA	–	x	–	–
INM-CM4	Institute of Numerical Mathematics of the Russian Academy of Sciences	Russia	–	x	–	x
IPSL-CM5A-LR	Institut Pierre Simon Laplace	France	x	x	x	x
IPSL_CM5A_MR	Institut Pierre Simon Laplace	France	x	x	–	x
LASG FGOALS-G2	Institute of Atmospheric Physics, Chinese Academy of Sciences	China	x	x	–	x
MIROC-ESM	Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology	Japan	x	x	x	x
MIROC-ESM-CHEM	University of Tokyo, National Institute for Environmental Studies and Japan Agency for Marine-Earth Science and Technology	Japan	x	x	x	x
MIROC MIROC5	University of Tokyo, National Institute for Environmental Studies and Japan Agency for Marine-Earth Science and Technology	Japan	x	x	x	x
MOHC HadGEM2-CC	Met Office Hadley Centre	UK	–	x	–	x
IPSL-CM5B-LR	Institut Pierre Simon Laplace	France	–	–	–	x
MOHC HadGEM2-ES	Met Office Hadley Centre	UK	x	x	x	x
MPI-ESM-LR	Max Planck Institute for Meteorology	Germany	x	x	–	x
MPI-ESM-MR	Max Planck Institute for Meteorology	Germany	x	–	–	x
MRI-CGCM3	Max Planck Institute for Meteorology	Germany	x	x	x	x
NCAR CCSM4	National Center for Atmospheric Research	USA	x	x	x	x
NCC NorESM1-M	Bjerknes Centre for Climate Research, Norwegian Meteorological Institute	Norway	x	x	x	x
NIMR-HadGEM2-AO	National Institute of Meteorological Research, Korea Meteorological Administration	South Korea	x	x	x	x
TOTAL			25	30	19	32

(x) = GCM is included, (–) = GCM not included.

Climate Change, Agriculture and Food Security (CCAFS) data portal (http://www.ccafs-climate.org/data_spatial_downscaling/; Navarro-Racines et al., 2020) was used. These data have been used previously in climate change impact on rice yield, cropland suitability, and ecological niche modeling (Zwart, 2016; van Oort and Zwart, 2018; Ashraf et al., 2017). We used 32 GCMs of the Coupled Model Intercomparison Project, Phase 5 (CMIP5) models included in the IPCC's Fifth Assessment Report (AR5) for 4 expected climatic scenarios, the Representative Concentration Pathways (RCP 2.6, 4.5, 6.0 and 8.5; see Table 1 for the complete list of models used). We applied a simple average as an ensemble approach to the GCMs to minimize the regional variability and uncertainties associated with these models. In addition to the base period

Table 2
List of predictors.

No	Predictor Name	Predictor definition	Native spatial resolution/Unit
1	BIO3	Isothermality[a]	1 km (%)
2	BIO12	Annual precipitation[a]	1 km (mm)
3	BIO15	Precipitation seasonality[a]	1 km (%)
4	BIO16	Precipitation of wettest quarter[a]	1 km (mm)
5	BIO18	Precipitation of warmest quarter[a]	1 km (mm)
6	AETI	Actual evapo-transpiration and interception[b]	250 m (mm)
7	GBWP	Gross biomass Water productivity[b]	250 m (kg/m^3)
8	WWP	Available soil water capacity[b]	250 m (%)
9	ECN	Electrical conductivity[c]	250 m (dS/m)
10	PH	Soil pH in Water[c]	250 m (index)
11	BSP	Base saturation percentage[d]	250 m (%)
12	ESP	Exchangeable sodium percentage[e]	250 m (%)
13	TPHOS	Total Phosphorus[f]	250 (mg/kg)
14	SILT	Soil texture fraction silt[c]	250 m (%)
15	CLAY	Soil texture fraction clay[c]	250 m (%)
16	BLD	Bulk density[c]	250 m (kg/m^3)
17	DEPTH	Depth to bedrock[c]	250 m (cm)
18	DEM	Elevation[g]	30 m (m)
19	FACC	Flow accumulation[h]	30 m (factor)
20	SLOPE	Slope[h]	30 m (%)
21	SAVI	Soil adjusted vegetation index[i]	500 m (index)
22	POP	Population density[j]	1 km (persons/km2)
23	ACCESS	Travel time to cities or accessibility[k]	1 km (min)
24	EUCDIST	Euclidian distance of road network[l]	2 km (m)

Sources: [a]www.worldclim.org, [b]FAO Water Productivity Open Access Portal (WaPOR)(https://wapor.apps.fao.org/home/1), [c]AfSoilGrids250m of Africa Soil Information Services (AfSIS) (Hengl et al., 2015), [d]Computed in ArcGIS based on total exchangeable bases and cation exchange capacity, [e]Computed in ArcGIS based on exchangeable sodium and cation exchange capacity, [f]AfSoilGrids250m of Africa Soil Information Services (AfSIS) (Hengl et al., 2017), [g]Shuttle Radar Topography Mission (SRTM) elevation data(https://earthexplorer.usgs.gov/), [h]Derived from DEM in SAGA, [i]Derived from MODIS data using MODIStsp: A Tool for Automatic Preprocessing of MODIS Time Series in R (Busetto and Ranghetti, 2016), [j]Socioeconomic Data and Applications Center (SEDAC) Gridded Population of the World (GPW) Version 4 (CIESIN, 2015), [k]A global map of travel time to cities to assess inequalities in accessibility in 2015 (Weiss et al., 2018), [l]Computed using Euclidean distance tool in ArcGIS and the road network data.

1970–2000, 4 future periods were considered including 2030s: 2020–2049, 2050s: 2040–2069, 2070s: 2060–2089 and 2080s: 2070–2099. The bioclimatic predictors used in the baseline climate characterization were considered for all future scenarios. The future predictors change and variabilities relative to the baseline period are shown in supplementary material 1.

2.4.3. *Other predictors*

In addition to the bioclimatic predictors, other biophysical determinants for inland valley suitability for rice cultivation (Akpoti et al., 2020) were considered including soil physical and chemical properties, topographical indices, vegetation, water availability (see Table 2). In addition, socio-economic variables such as population density, travel time to cities, and distance to the road are also included.

2.5. *Ecological niche modeling (ENM)*

2.5.1. *Overview of the Software for Assisted Habitat Modeling (SAHM)*

The Software for Assisted Habitat Modeling (SAHM v 2.0.1) was developed by the United States Geological Survey (USGS) Fort Collins Science Center (https://www.usgs.gov/centers/fort) (https://www.usgs.gov/software/software-assisted-habitat-modeling-package-vistrails-sahm-vistrails-v1, Morisette et al., 2013) for running multiple Species Distribution Models (SDMs). SAHM is developed as a package or an ensemble of add-on tools in the open-source scientific workflow software VisTrails (Freire et al., 2006) with the capability of handling input data, pre- and post- processing tasks including the execution of algorithms, the evaluation of models, and the display of the spatial, graphical and textual results (Talbert et al., 2013). A key pre-processing feature in the SAHM software is the automated reprojection, aggregation, resampling, and sub-setting of predictors data to match predefined spatial characteristics — modeling grid or spatial resolution, study area extent, and projection system stored in a referenced or template layer. SAHM executes SDMs frameworks by combining spatial predictors layers, also referred to as environmental predictors — climate, soil, vegetation, etc., and field observation or sampling of a given species represented by their geographic locations to drive statistical machine learning algorithms. Five machine learning algorithms are implemented in SAHM, including boosted regression tree (BRT), generalized linear models (GLM), multivariate adaptive regression splines (MARS), random forest (RF), and maximum entropy (MaxEnt). SAHM has the advantage of maintaining the records of the different input data, pre- and post-processing steps, and modeling options during models building (Morisette et al., 2013), model diagnostics including the generation of response curves that graphically represent the relationships between predictors and responses that are represented in models as well as the ability of modelers to recreate any exploratory step and transfer final models to other interested users (Piekielek et al., 2015; West et al., 2017). SAHM software also includes the transferability function into space (calibrated models can also be applied to other regions without collection of new species data) and time (calibrated models can be used for climate change impact studies based on future scenarios analysis) using the “ApplyModel” module.

2.5.2. *Model set up*

We used a correlative ENM approach (Peterson, 2006) that links rice crop occurrence in inland valleys with geospatial environmental predictors. The rainfed rice fundamental niche consists of the set of all conditions (predictors) that allow for its long-term survival in terms of biophysical conditions such as soil, climate, topography, management practices, socio-economic conditions, etc. To model the extent of the fundamental niche, we used the realized niche (rainfed rice fields), which is a subset of the fundamental niche.

Studies showed that there is no single best correlative ecological niche model (Qiao et al., 2015; Pearson et al., 2006). Regardless of similarities in model performances, important variations occur when distributional responses to environmental gradients are assessed through different algorithms (Akpoti et al., 2022; Beaumont et al., 2016). Thus, many modelers advocated for ensemble predictive models to identify the uncertainties and biases associated with a single modeling approach when considering climate change analysis (Hao et al., 2019). Therefore, we developed the inland valley suitability models by fitting four algorithms in the SAHM software: Generalized Linear Model (GLM), Boosted Regression Tree (BRT), Random Forest (RF), and Maximum Entropy (MaxEnt). A detailed description of the modeling approach is presented in Akpoti et al. (2020). The modeling process followed 7 main steps, and are visualized in Fig. 4:

Step 1 – Input data preparation: This step corresponds to the creation of the training and testing data used by the machine learning algorithms for training and testing. The SDMs work by considering both locations where the species occurs (here, rice field locations in inland valleys) and locations where rice is not found, referred to as absence data. The 844 inland valleys geolocation dataset where rice is grown was split in the ratio of 70% and 30% for calibration (training) and validation (testing) respectively. In the present case, because true absence data was not collected, the SAHM background surface generator module was used to establish a surface mask of inland valleys using adhoc bandwidth selection based on the Kernel density estimation method (Duong, 2015). Thus, 15,000 randomly generated background points or pseudo-absence

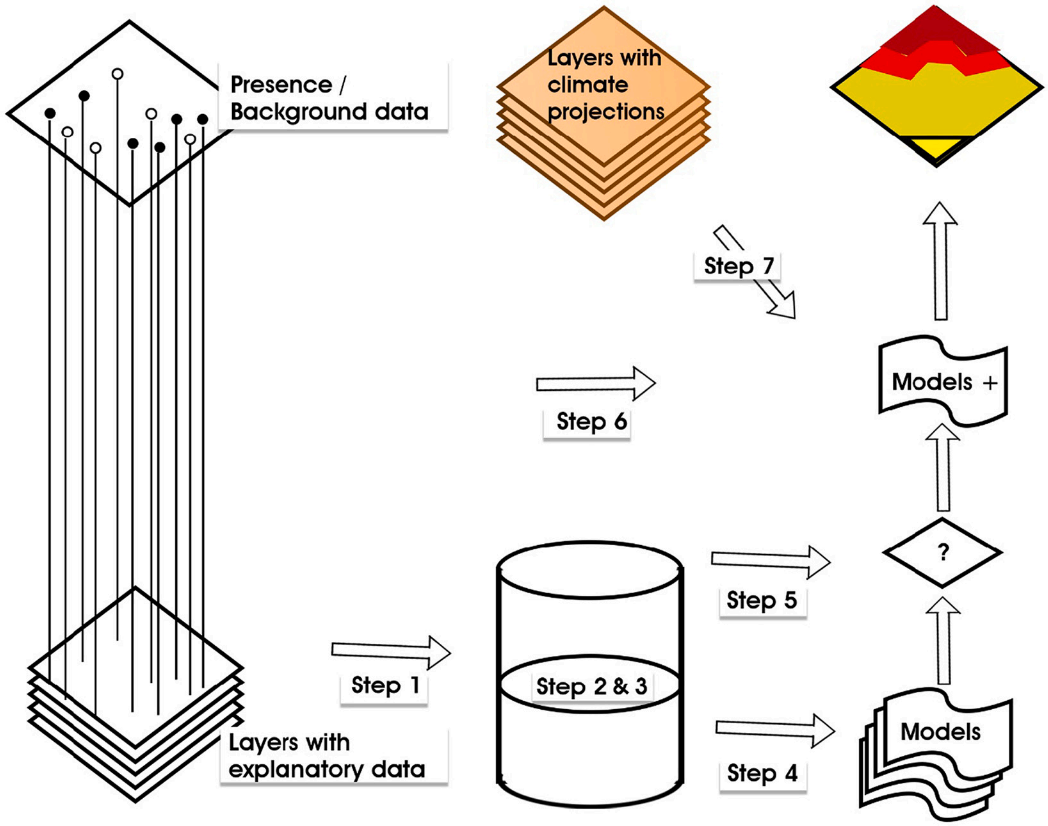

Fig. 4. Summary of modeling steps. Step 1, dataset creation (training/validation); step 2, data exploration (record selection/exclusion); step 3, collinearity analysis (predictors selection/exclusion); step 4, model fitting; step 5, model validation/selection; step 6, interpolate over the whole region of interest; step 7, interpolate with new climate data over the region of interest.

points were considered with the inland valley's surface mask, meaning that these points were generated within the same delineated inland valley buffer as the rice locations points. The SAHM Merged Data Set (MDS) module was then used to combine rice location points data, extracted values at each point for each predictor, and the pseudo-absence points.

Step 2 – Data pre-processing: SAHM data pre-processing stage is useful for formatting and standardizing data from disparate sources. The main tool for this process is the PARC (Projection, Aggregation, Resampling, and Clipping) module. The PARC tool was used to harmonize the various spatial grids of 30 m to 1 km in the predictors' dataset (see Table 2). The predictors were aggregated and resampled to a grid with 90 by 90-m grid cells using the nearest neighbor method. This grid size was selected to match the smallest grid size of the delineated inland valleys.

Step 3 – Collinearity analysis. This step consisted of data exploration of predictors correlation and selection. The step allows selection and/or exclusion of any variables that may exhibit a high correlation with others based on how well each predictor explains the distribution of the sampled data points. Pearson's correlation coefficient value $|r| = 0.75$ was used as a cut-off threshold.

Step 4 – Model Fitting. The four models were fitted in step 4 namely boosted regression trees (BRT), generalized linear models (GLM), random forest (RF), and maximum entropy (MaxEnt):

- Boosted regression trees (BRT), also called stochastic gradient boosting is a machine learning algorithm that uses models that relate a response to their predictors by recursive binary splits (regression trees) and adaptive methods that combines many simple models to improve predictive performance (boosting) (Elith et al., 2008). Three main parameters are used to improve BRT performance: 1) the maximum number of splits (tree complexity) for fitting each regression tree defines the depth of the tree and the maximum level of interaction between the predictor variables, the number of iterations (number of trees), and the model regularization (or shrinkage) parameter (Müller et al., 2013). Besides, internal cross-validation, which limits model growth based on predictive accuracy on independent portions of the data is used to avoid overfitting. In the present case, BRT was fitted with 5000 trees with a simplification method of 10-fold cross-validation with a bag fraction of 0.75. To avoid overfitting, a small learning rate of 0.006 was used following Jarnevich et al., 2017.
- Generalized linear models (GLMs) are mathematical extensions of linear models and allow for non-linearity and non-constant variance structures in the data. They are based on an assumed relationship using the logit link function between the mean of the response variable and the linear combination of the explanatory variables (Guisan et al., 2002). For inland valleys' rainfed rice suitability mapping, we allowed for a second-order polynomial term and interactions in the model. We used the Akaike Information Criterion (AIC) to identify the best model.
- Random Forest (RF) is a tree-based ensemble machine learning algorithm with each tree node depending on a collection of random variables using binary recursive partitioning trees. The RF modeling as implemented in the SAHM was developed based on the package 'randomForest' in R (Breiman et al., 2011). Three main training hyperparameters were specified: the number of trees to grow in the forest (ntree), the number of randomly selected predictor variables at each node (mtry), and the minimal number of observations at the terminal nodes of the trees (node size). We considered 1000, 10, and

Table 3
Definition of the evaluation metrics.

Evaluation metric	Explanation
Overall accuracy	Percentage of training records that was correctly predicted to be either suitable or unsuitable.
Sensitivity	Percentage of training records that was correctly predicted to be suitable from all records that were known to be suitable
Specificity	Percentage of training records that was correctly predicted to be unsuitable from all records that were known to be unsuitable.
Kappa statistic	Percentage of training records that was correctly predicted to be either suitable or unsuitable corrected for the probability of making a correct prediction by chance
True Skill Statistics	The sum of sensitivity and specificity, rescaled between −1 and 1

5 of these parameters respectively as similarly adopted in modeling by Were et al. (2015).

- Maximum Entropy (MaxEnt)(Phillips et al., 2006) is a general-purpose machine learning method, which is defined as probability density estimation where the presence data (here, rice fields point data) are assumed to be drawn from some probability distribution over the study region. The modeling task of the inland valley rainfed rice suitability is to estimate that distribution. To this end, the default settings in the MaxEnt model were considered with a maximum iteration of 5000, except for the 15,000 background samples, as used for the three other models.

Step 5 – Model validation/selection. Consisted of model validation with inspection of evaluation metrics, and assessment of residual surfaces and Receiver Operation Characteristics (ROC) plots.

Step 6 – Interpolate over the whole region of interest. In step 6, the models were interpolated over the entire region of interest, i.e., Togo and Benin.

Step 7 – Interpolate with new climate data over the region of interest. In this step, the final calibrated models (Step 1 to 6) were maintained with the exception that the baseline climate predictors were replaced with future climate predictors under the four climate scenarios (RCPs 2.6, 4.5, 6.0, and 8.0), and the 4-time steps (the 2030s, 2050s, 2070s, and 2080s) using the "ApplyModel" module in SAHM.

2.5.3. Model performance evaluation

Ecological niche models are usually evaluated by comparing the predictions with a set of validations sites using a confusion matrix (Allouche et al., 2006). To construct the matrix from the continuous probability surfaces (on a scale of 0 to 1), a threshold is needed to transform the continuous prediction into binary (suitable, unsuitable). To avoid the subjectivity associated with the choice of a threshold, the area under the receiver operating characteristic (ROC) curve (AUC), is often considered as a standard method to assess the predictive capacity of models by summarizing overall model performance over all possible thresholds (Jiménez-valverde, 2012). According to Swets (1988), AUC values >0.8 indicate high accuracy. In addition to the threshold-independent metric of AUC, multiple threshold dependent performance evaluation metrics exist and will be reported on including the rate of correctly classified cells (overall accuracy), probability of actual presences predicted (Sensitivity), probability of actual absences predicted (Specificity), the kappa statistic and the true skill statistic (TSS) (Allouche et al., 2006) were considered (see Table 3).

2.5.4. Threshold definition

To convert the continuous suitability predictions into discrete binary maps that indicate suitable and non-suitable areas for rainfed rice production, we used the "sensitivity equals specificity" threshold which has performed well in comparison to other thresholds (Liu et al., 2005). In this threshold, there is an equal accuracy in predicting suitabilities (Sensitivity) as there is to predict non-suitabilities (specificity). The threshold was defined based on test data using the presence-absence analysis package in R (Freeman and Moisen, 2008) as implemented in SAHM.

2.5.5. Ensemble prediction

Studies showed that predictions of alternative models can be variable and the use of multiple models within an ensemble forecasting framework is recommended (Crimmins et al., 2013). The ensemble prediction approach represents a single prediction that provides a measure of central tendency across a suite of individual models thus, providing a means to overcome the issue of variability in predictions (Marmion et al., 2009). In the present case, a simple average was applied to the suitability produced by the 4 algorithms.

2.5.6. Statistical analysis of suitability changes

Basic statistics (minimum, maximum, mean, and standard deviation) of the continuous predicted suitability maps and area suitability of the binary maps from the baseline period models and future scenarios models were derived. The approach allowed the evaluation of the magnitude of changes in the predicted areas. Suitable inland valley rice area extent was computed under the baseline condition as well as suitable future rice area by thresholding the predicted probabilities of the models. Furthermore, the changes in future suitable inland valleys area extent for each country (i.e., Togo and Benin) relative to the baseline were computed. To evaluate the statistical difference of future suitable rice area change, compared to the baseline area for a given model (e.g. GLM), the non-parametric one-sample Wilcoxon signed-rank in R (R Development Core Team, R, 2011) was used. This test is used to determine whether the median of the sample (the various prediction of the models over the various periods) is equal to a known standard value (i.e., a theoretical value which represent the baseline prediction). The use of this non-parametric test is justified by the fact that the data series formed by the baseline data and the future projection of each model is not normally distributed. Also, we compared the statistical difference between future suitable area predictions of any paired models (e.g., GLM & MaxEnt or MaxEnt &RF). In this case, the non-parametric unpaired two-sample Wilcoxon test (also known as Wilcoxon rank-sum test or Mann-Whitney test) was applied. The non-parametric Wilcoxon statistics have been previously used to compare model predictions in ecological niche modeling (Zimmermann et al., 2009; Václavík and Meentemeyer, 2009). The non-parametric tests, which were used to compare the significant differences among models further justified the use of the ensemble of the multi-model approach over the single model.

2.5.7. Modeling assumptions

The fundamental assumption in correlative ENMs is that such models estimate the conditions (or some subset of the conditions) within which a species can survive and reproduce (Warren, 2012). In the context of this paper, inland valley wetland ecology where rice is mostly grown in West Africa under rainfed conditions was considered. Although management practices, land tenure, and other factors are relevant for rice cultivation, these factors were not directly included in the modeling. In the potential impacts of climate change on inland valleys' suitability for rainfed rice cultivation assessment, the biophysical factors such as topographical, vegetation, soil physical, and chemical properties were kept constant. Also, the population density and accessibility are likely to change in the future but are assumed constant in the current analysis. The focus of this study was to assess the impact of climate change without the additional (possibly interactive) effect of population growth, infrastructure development, and management practices.

3. Results

3.1. Baseline models' performance evaluation

All models show good performance with AUC $>$ 0.84 and PCC $>$ 75%

Table 4
Baseline models performance evaluation for both training (70%) and testing (30%) of the data. Area Under the Curves (AUC), Overall accuracy or Percentage Correctly Classified (PCC), Sensitivity, Specificity, Kappa statistic, True Skill Statistics for the 4 algorithms.

Evaluation metrics	BRT		GLM		MAXENT		RF	
	Train	Test	Train	Test	Train	Test	Train	Test
AUC	0.998	0.915	0.850	0.845	0.938	0.892	0.898	0.905
PCC	98.0	83.9	76.0	75.6	86.75	83.0	81.73	82.2
Sensitivity	0.975	0.840	0.755	0.756	0.877	0.832	0.823	0.823
Specificity	0.980	0.839	0.760	0.756	0.867	0.830	0.817	0.822
Kappa	0.744	0.209	0.115	0.116	0.259	0.196	0.179	0.185
TSS	0.954	0.680	0.510	0.512	0.744	0.662	0.640	0.646

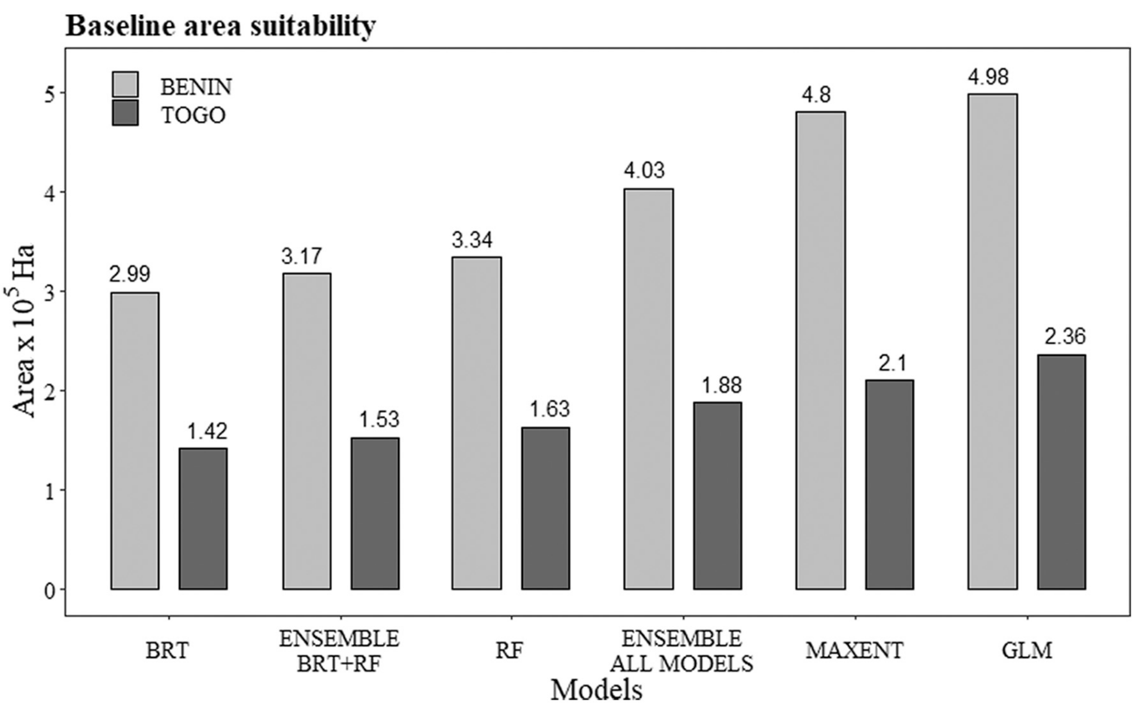

Fig. 5. Baseline area suitability. The ensemble represents the simple mean on the binary suitability produced by the 4 algorithms. The ensemble of BRT and RF is also reported as they are the only two models used in the future scenarios' analysis.

for both training and testing simulations (Table 4). Other performance metrics values confirm the ability of the models to accurately predict inland valleys' suitability for rice production. However, BRT showed some level of overfitting as demonstrated by the notable difference between training and testing values of the performance statistics compared to the consistency in the values related to GLM, MaxEnt, and RF. Overall, evaluation metrics values for training and testing data are similar in GLM and RF.

3.2. Potential distribution of the baseline suitability

For both Togo and Benin, the GLM predicted the highest suitable areas in the baseline followed by MaxEnt, RF, and BRT (Fig. 5). The two extreme positions of the predicted areas occupied by GLM, and BRT may be explained by both models' complexity. BRT put more constraints on covariates data than GLM which is simpler in structure. The ensemble suitability that includes the 4 models produced an estimated suitable area of 4.03×10^5 ha in Benin, which represents 46.7% of the total available inland valleys. Similarly, the ensemble estimated area of suitable inland valleys represents 1.9×10^5 ha in Togo, corresponding to 41.8% of the total available inland valleys in Togo. Also, the predicted areas suitable for rice production are located throughout the study with marginal suitable areas along the coastal zones compared to other parts of both countries.

Table 5
Suitability area (x10^5Ha) in Togo for all scenarios, time periods and models (N-non-suitable, S-suitable).

Scenarios-Periods	BRT		GLM		MAXENT		RF	
	N	S	N	S	N	S	N	S
BASELINE	7.01	1.42	6.09	2.36	6.33	2.10	6.80	1.63
RCP2.6 2030s	7.61	0.82	7.94	0.51	8.19	0.24	7.11	1.32
RCP2.6 2050s	7.66	0.77	8.09	0.36	7.88	0.55	7.15	1.28
RCP2.6 2070s	7.66	0.77	8.09	0.36	7.87	0.56	7.13	1.30
RCP2.6 2080s	7.65	0.79	8.05	0.40	7.82	0.62	7.11	1.32
RCP4.5 2030s	7.60	0.83	7.90	0.54	7.72	0.71	7.09	1.34
RCP4.5 2050s	7.59	0.84	8.05	0.40	7.81	0.62	7.09	1.34
RCP4.5 2070s	7.59	0.84	8.11	0.33	7.84	0.60	7.07	1.36
RCP4.5 2080s	7.59	0.84	8.08	0.37	7.83	0.60	7.08	1.35
RCP6.0 2030s	7.50	0.93	7.63	0.82	7.49	0.94	7.01	1.42
RCP6.0 2050s	7.47	0.96	7.55	0.90	7.43	1.00	7.01	1.42
RCP6.0 2070s	7.57	0.86	8.07	0.38	7.74	0.69	7.05	1.38
RCP6.0 2080s	7.55	0.88	7.85	0.60	7.61	0.82	7.00	1.43
RCP8.5 2030s	7.55	0.88	8.01	0.44	7.71	0.72	7.03	1.40
RCP8.5 2050s	7.55	0.88	8.01	0.44	7.71	0.72	7.03	1.40
RCP8.5 2070s	7.57	0.86	8.05	0.40	7.74	0.69	7.07	1.37
RCP8.5 2080s	7.56	0.87	8.03	0.42	7.69	0.75	7.05	1.38

Table 6
Suitability area (x10^{5}Ha) in Benin for all scenarios, time periods and models (N-non-suitable, S-suitable).

Scenarios-Periods	BRT		GLM		MAXENT		RF	
	N	S	N	S	N	S	N	S
BASELINE	13.34	2.99	11.35	4.98	11.53	4.80	12.99	3.34
RCP2.6 2030s	14.23	2.10	15.11	1.25	15.67	0.65	13.80	2.52
RCP2.6 2050s	14.36	1.97	15.45	0.90	15.04	1.29	13.90	2.43
RCP2.6 2070s	14.38	1.94	15.40	0.96	14.98	1.35	13.88	2.45
RCP2.6 2080s	14.31	2.01	15.27	1.09	14.87	1.46	13.79	2.54
RCP4.5 2030s	14.13	2.19	15.16	1.20	14.65	1.68	13.75	2.58
RCP4.5 2050s	14.24	2.09	15.38	0.97	14.82	1.50	13.80	2.53
RCP4.5 2070s	14.15	2.18	15.45	0.91	14.74	1.59	13.72	2.60
RCP4.5 2080s	14.15	2.18	15.45	0.90	14.69	1.64	13.75	2.57
RCP6.0 2030s	13.96	2.37	14.58	1.78	14.27	2.06	13.57	2.76
RCP6.0 2050s	13.95	2.38	14.63	1.73	14.34	1.99	13.58	2.75
RCP6.0 2070s	14.27	2.06	15.61	0.74	15.04	1.29	13.75	2.58
RCP6.0 2080s	13.90	2.43	15.10	1.26	14.61	1.72	13.54	2.79
RCP8.5 2030s	14.05	2.28	15.25	1.10	14.60	1.73	13.68	2.65
RCP8.5 2050s	14.05	2.28	15.25	1.10	14.60	1.73	13.68	2.65
RCP8.5 2070s	14.16	2.17	15.42	0.93	14.61	1.71	13.75	2.57
RCP8.5 2080s	14.15	2.18	15.40	0.96	14.53	1.80	13.74	2.59

3.3. Models transfer, future suitability distribution, and changes

Future scenarios results showed a significant difference relative to the baseline predicted areas when considering individual models based on the non-parametric one-sample Wilcoxon signed-rank (*p*-value <0.05). Also, the unpaired two-sample Wilcoxon test across all pairs of models showed a significant difference between models' predictions of future scenarios (p-value <0.05). This suggests that predictions of suitable inland valleys varied from one model to another (see details of the individual's predictions under all RCPs and periods for Togo and Benin respectively reported in Table 5 and Table 6).

In the future scenario's predictions, MaxEnt and GLM showed grossly high area losses (50–60%) while BRT and RF showed relatively lower area losses compared to the baseline (17–32%). Thus, in the subsequent results, only an ensemble of BRT and RF are used in area change analysis. The spatial disaggregation of the ensemble suitability of future predictions in terms of areas that remained stable (no change), areas with suitability losses, and areas with suitability gains are reported in Fig. 6 with zoom in selected windows in Fig. 7. The disaggregation is further reported as a percentage shared for all RCPs and periods in Fig. 8. Overall, stable areas varied from 59% to 63% with higher values in the 2030s and lower values in the 2080s. Only 2080s of RCPs 2.6 have higher suitability of stable areas (62%) compared to 2030s prediction among all 4 RCPs. In Togo, stable areas are located along with the mountainous areas (Southwest-northeast direction) and the extreme north of the country (which is also a hilly zone). The stable areas in Benin are also located at high altitudes (see Fig. 1 for topographical profile) between 9-degree north and 11-degree north latitude, the central part of the country. Comparatively, area losses increased with time and emission scenarios, varying from 29% to 37%. Only marginal new suitable area gain has been observed representing 3% to 9%. The newly suitable areas, although located across both countries (see Fig. 9 for area suitability per administrative units), tends to be more pronounced in the southern and coastal zones of both countries.

The estimated future changes of inland valleys area suitable for rice production relative to the baseline predictions were quantified for Togo and Benin across all four algorithms (Fig. 10). Results show small variability between the different RCP scenarios and large variability between the models; but overall, all scenarios and model realizations suggest a loss of suitable area for inland valley rice production because of climate change when no mitigating measures are taken. More specifically, on average, results show that in Togo, area losses varied from 29.8% to 32.1% while Benin area losses varied from 27% to 30.6% under RCP 2.6. A similar trend is shown for other RCPs with slightly lower values compared to RCP 2.6. These lower values are exceptionally noticeable under RCP 6.0 where area losses varied from 21.0% to 26.8% in Togo and 17.5% to 26.7% in Benin. This exception may be explained by the spatial difference in rainfall under RCP6.0 in both countries compared to other RCPs. Under RCP6.0, annual rainfall increased more in Benin compared to Togo (see Fig. S1.4, supplementary material 1). A similar trend can be observed in the precipitation of the wettest quarter (Fig. S1.6, supplementary material 1). Also, annual, and wettest quarter precipitation increased more under the 2070s, and 2080s compared to the 2030s and 2050s of RCP6.0. Meanwhile, predictors response curves showed that the probability of suitable conditions increased with increased values of precipitation-related predictors while the opposite is observed with temperature.

3.4. Area losses, gain, and stables related to predictors changes

We linked the area suitability changes to the variability of future predictors values based on stable areas, area losses, and area gains. Area gains (Fig. 11), no change (Fig. 12), and losses (Fig. 13) appeared to be linked to both changes in future temperature (isothermality) and precipitation values. Area gains seem to be influenced by higher precipitation values. Most of the points in area gains appear to be above the 1:1 line for the annual precipitation (BIO12), precipitation coefficient of variation (BIO15), and precipitation of the wettest quarter (BIO16) (Fig. 11). Most area gains felt above 1000 mm, 60 mm, and 400 mm respectively for BIO12, BIO15, and BIO6. For area gains, no clear trend is shown for isothermality (BIO3) as equal points appeared to be above and below the 1:1 line. For the precipitation of the warmest quarter (BIO18), area gains are either on the 1:1 line or below. In areas with no change (stable areas) and area losses (Figs. 9 & 10), most points are below the 1:1 line for BIO3; which suggests that future high temperatures influence the suitability of area losses and stability. In both cases, most of the points are above either follow or above the 1:1 line for BIO12, BIO16, and BIO18. Area losses and stability seem not to be impacted by BIO15.

4. Discussion

4.1. Inland valleys' suitability changes under multiple climate change scenarios

Our results demonstrate the potential impacts of climate change on rainfed agriculture in tropical inland valleys. Changing climate, expressed here as changes in the bioclimatic predictors represented in our models as annual trends (precipitation-BIO12), seasonality (Isothermality-BIO3, precipitation seasonality-BIO15), and limiting

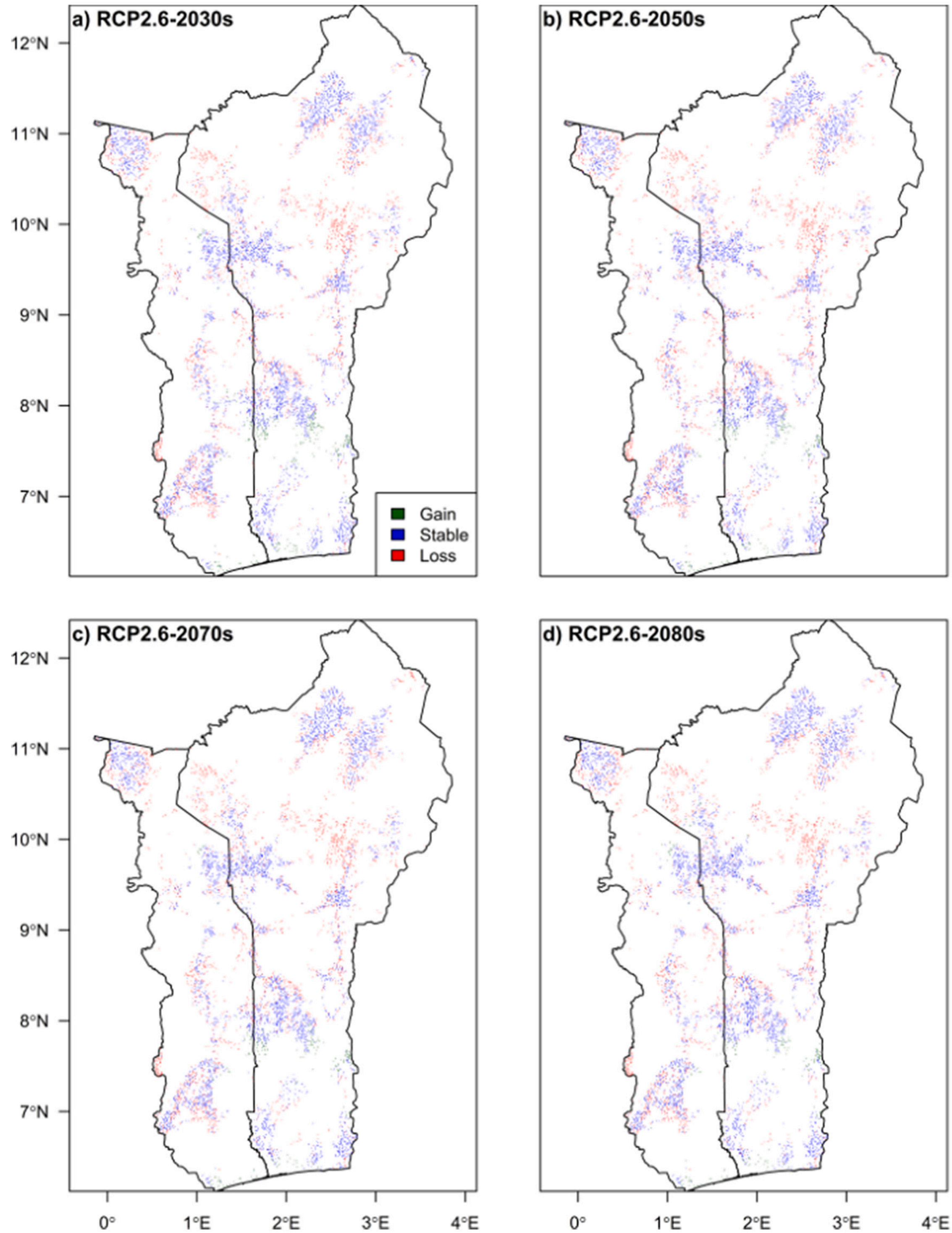

Fig. 6. Spatial disaggregation of the ensemble suitability (BRT and RF) of future predictions for RCP 2.6 in terms of area that remained stable (no change), area with suitability losses, and area with suitability gains.

environmental predictors (precipitation of wettest quarter-BIO16 and precipitation of warmest quarter-BIO18), strain important impact over suitability for rainfed rice production in inland valleys, a process often overlooked by studies that focus on climate change impact on rice yield. The results indicated a reduction in inland valleys' suitability for rice production under the future climate in Togo and Benin. Our results are in support to other similar studies which showed that agricultural lands will face major constraints under future climate change uncertainties (Lamboll et al., 2017), notably in tropical countries expecting the significant losses of suitable cropland (Bradley et al., 2012; Beck, 2013). A previous study on the effect of changing climate on rice yields in Africa, assuming no adaptation to these conditions, showed an average lowest yield decline of −9% under RCP 2.6 and the highest decline of −24% in RCP 8.5 relative to the base year yield (van Oort and Zwart, 2018). A similar study in India showed that despite the increase in rice yield under RCP 2.6, there is a decline in rice yield for higher RCPs (Gupta and Mishra, 2019). Thus, climatic change is expected to impact croplands as demonstrated for rice areas in this study as well as in other

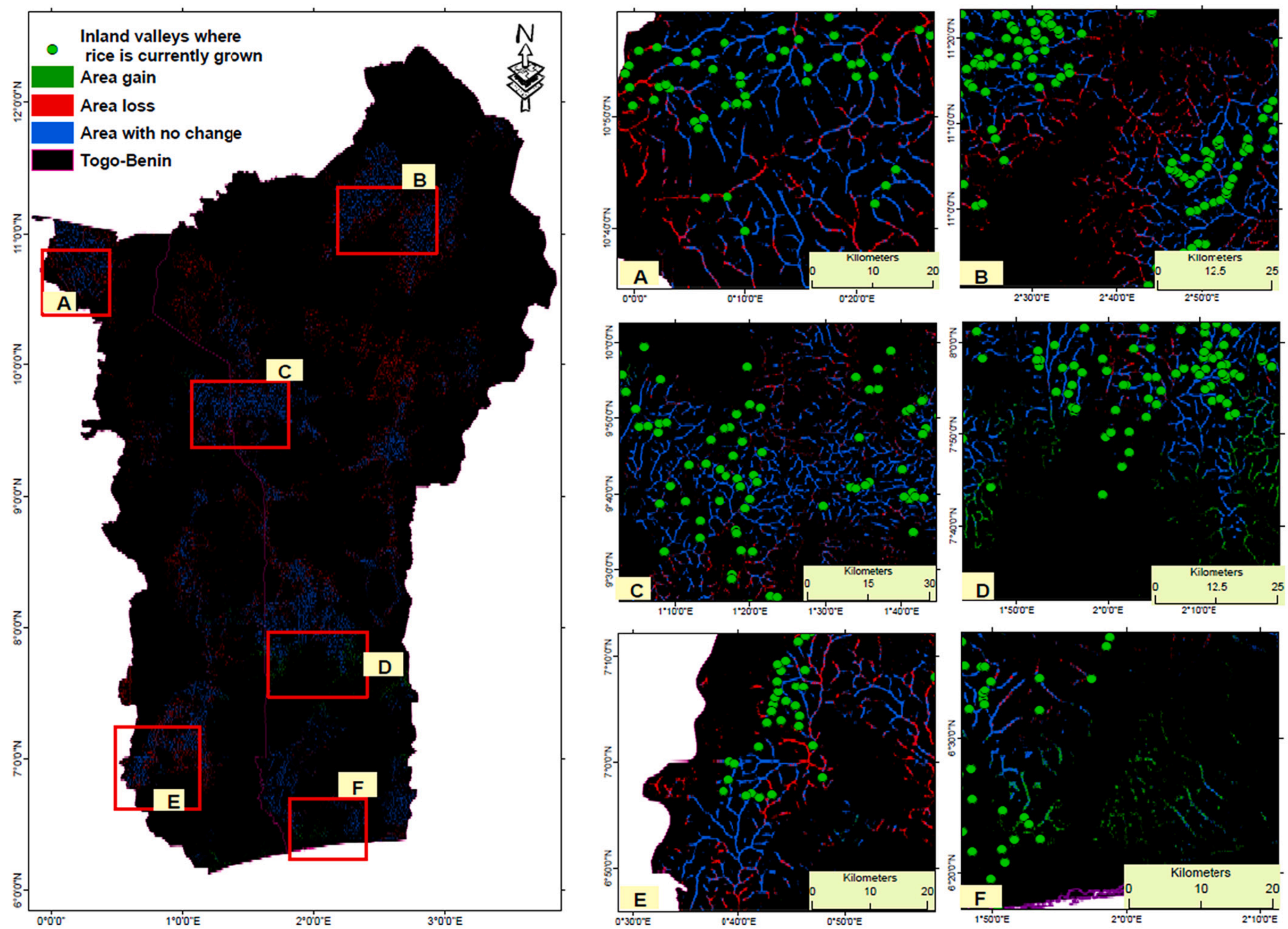

Fig. 7. Zoom into six selected windows (A-F) in Togo and Benin to show details of the spatial disaggregation of the ensemble suitability of future predictions for RCP 2.6 (2030s) in terms of area that remained stable (no change), area with suitability losses, and area with suitability gains.

studies (Iizumi and Ramankutty, 2015; Liu et al., 2015).

Under RCP 2.6, the scenario leading to the lowest greenhouse gas concentration levels through a "peak-and-decline" succession for 2050 and 2100, that aims to keep global warming likely below 2 °C above pre-industrial temperatures (IPCC, 2014), we still found a significant decline in land suitability in both countries for rainfed rice (29.8% to 32.9% in Benin and 27% to 30.6% in Togo). Similar trends were observed for the intermediate scenarios (RCP 4.5 and 6.0) with slightly higher losses (see Figs. 6 & 7). With the scenario, RCP 8.5, leading to high greenhouse gas concentration levels through rising radiative forcing, inland valleys landscape suitability showed higher losses up to 27% in Benin and 25% in Togo by the end of the century. These projections suggest that lowland rice production will be severely affected by climate change, with serious implications for food security in the region. Existing research in Colombia, using the MaxEnt model, showed that climate change could reduce the area that is suitable for rice production by 60% (Castro-Llanos et al., 2019), a magnitude of suitable area losses supported by our results. Also, the same study demonstrated that lowland rice production regions may be the most affected by changing climate while higher altitudes may become more favorable for rice production. Similarly, our predicted suitability maps showed that inland valleys areas that were suitable in the baseline and located along with the mountain ranges in Togo and Benin (see Fig. 1 for the topographical profile of the study area) and other high-altitude areas remained mostly suitable along the same gradient (see Fig. 10). Also, other studies showed that rice area's suitability shifts in China match climate change patterns in the country (Liu et al., 2015), showing that future agricultural land use planning should consider changing environment scenarios.

GCMs forecasted substantial changes in the bioclimatic predictors over the study regions (see supplementary material 1) which limits the potential gains in suitability for rainfed rice production and drives the predicted suitability decreases over the study area. Although changes in the predictions among RCPs remained subtly small, the analysis of the suitable inland valleys area reductions showed trends compatible with the severity of emission scenarios where lower emissions resulted in lower area losses while higher emissions were associated with extreme climate conditions and the highest area suitability losses. We showed this through the assessment of the spatio-temporal bio-climatic predictors' anomaly by comparing the future predictors to the baseline climate conditions (1970–2000). The mean anomaly over the study areas showed isothermalitity (BIO3) variation between −10% to +8%, corresponding to an annual mean temperature (BIO1) increase between +0.5 °C in the 2030s (RCP2.6) to more than +4.5 °C by 2080s (2080s) (Fig. S1.1, supplementary material 1). The modeling showed that inland valley suitability decreased with increasing temperature. Heat stress, which results from a combination of higher temperatures and lower humidity, reduces rice yield through reduced grain quality (spikelet sterility) due to transpiration cooling induced by high daytime temperatures and reduced assimilated accumulation due to increased nighttime temperature (Wassmann et al., 2009; van Oort and Zwart, 2018). The magnitude of warming is a function of CO_2-equivalent concentration i.e., higher RCPs represent higher warming. The spatial

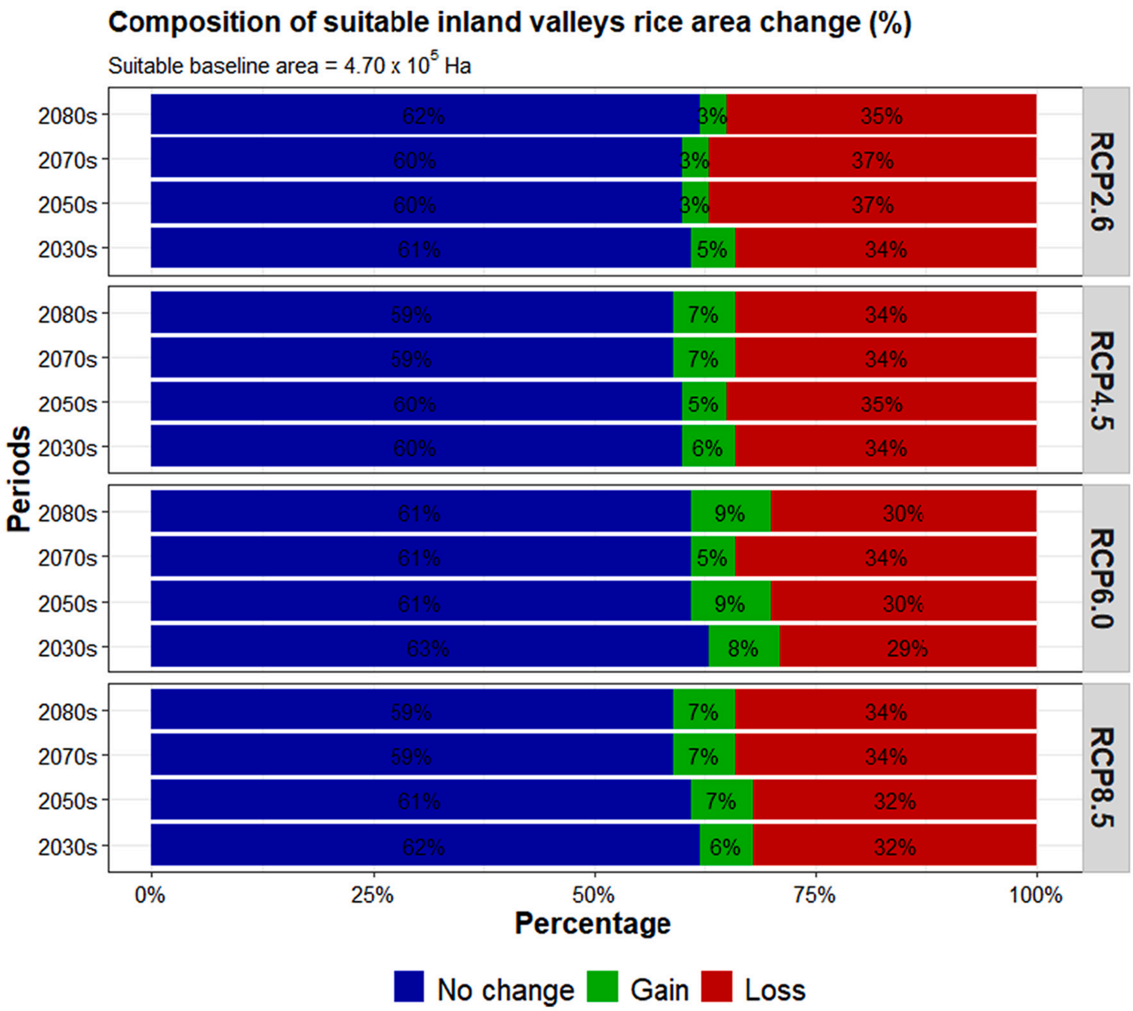

Fig. 8. Inland valleys suitability share by area gain, loss, and no change over Togo and Benin based on the ensemble of BRT and RF.

variations of BIO1 showed noticeable warming from the south to the north in both Togo and Benin (Fig. S1.2, supplementary material 1). This can also be inferred by the fact that the points in Fig. 11 (also see supplementary material 1), for BIO3 lay considerably below the 1:1 line. The distance between these points and the 1:1 line indicates the temperature (Isothermality) difference. Rice, as a C3[1] crop, may benefit from higher CO_2 concentration which could enhance photosynthesis. However, this advantage could be limited by an average air temperature increase at the same time (Wassmann et al., 2009), a trend predicted under all RCPs scenarios for this region. The mean anomaly of isothermality (BIO3) showed a decline in the day to night temperature compared to annual temperature oscillations (Fig. S1.3, supplementary material 1). In terms of spatial variations, the BIO3 anomaly showed negative values in the southern part of both Togo and Benin while northeast of Benin and northwest of Togo displayed positive values. In general, the southern part of both countries' BIO3 regime will show a higher level of temperature variability within an average month relative to the year while the northern part of both countries will undergo the opposite phenomenon.

The mean anomaly over the study area of the annual precipitation (BIO12) showed that precipitation will increase in the future under all RCPs compared to the present condition with the highest precipitation occurring under RCP6.0 (Fig. S1.4, supplementary material 1). Spatially, BIO12 will increase mainly in northeast Benin and southwest Togo. However, the spatial variations of the BIO12 anomaly showed selected hotspots of future rainfall deficits mainly in the coastal zone of both countries, some parts of central and northern Togo, and northwest of Benin. Also, the central part of Togo and northern Benin showed a reduction in seasonal rainfall (BIO15) compared to other parts of the countries. Precipitation of the wettest quarter (BIO16) anomaly showed a similar pattern as BIO12 while future precipitation of the warmest quarter (BIO18) showed a reduction compared to the baseline. These trends showed that changing climate may not be homogenous, conditions that may adversity impact food security (Misra, 2014). Drought is already a reality in West African inland valleys, causing low agricultural profitability and crop production vulnerability (Dossou-Yovo et al., 2019). Besides, climate change may significantly impact inland valleys water yields in West Africa (Danvi et al., 2018), which in turn, will jeopardize their ability to support rainfed rice systems.

4.2. *Climate change impacts on the agricultural sector in the region and options for adaptation*

The agricultural sector in West Africa is vulnerable to climate change due to high climate variability, high reliance on rain-fed agriculture, and limited economic and institutional capacity to respond to climate variability and change (Sultan and Gaetani, 2016). Changing climate in the

[1] C3 plants are plants in which the initial product of the assimilation of carbon dioxide through photosynthesis is 3-phosphoglycerate, which contains 3 carbon atoms (https://www.sciencedirect.com/topics/earth-and-planetary-sciences/c3-plant/pdf)

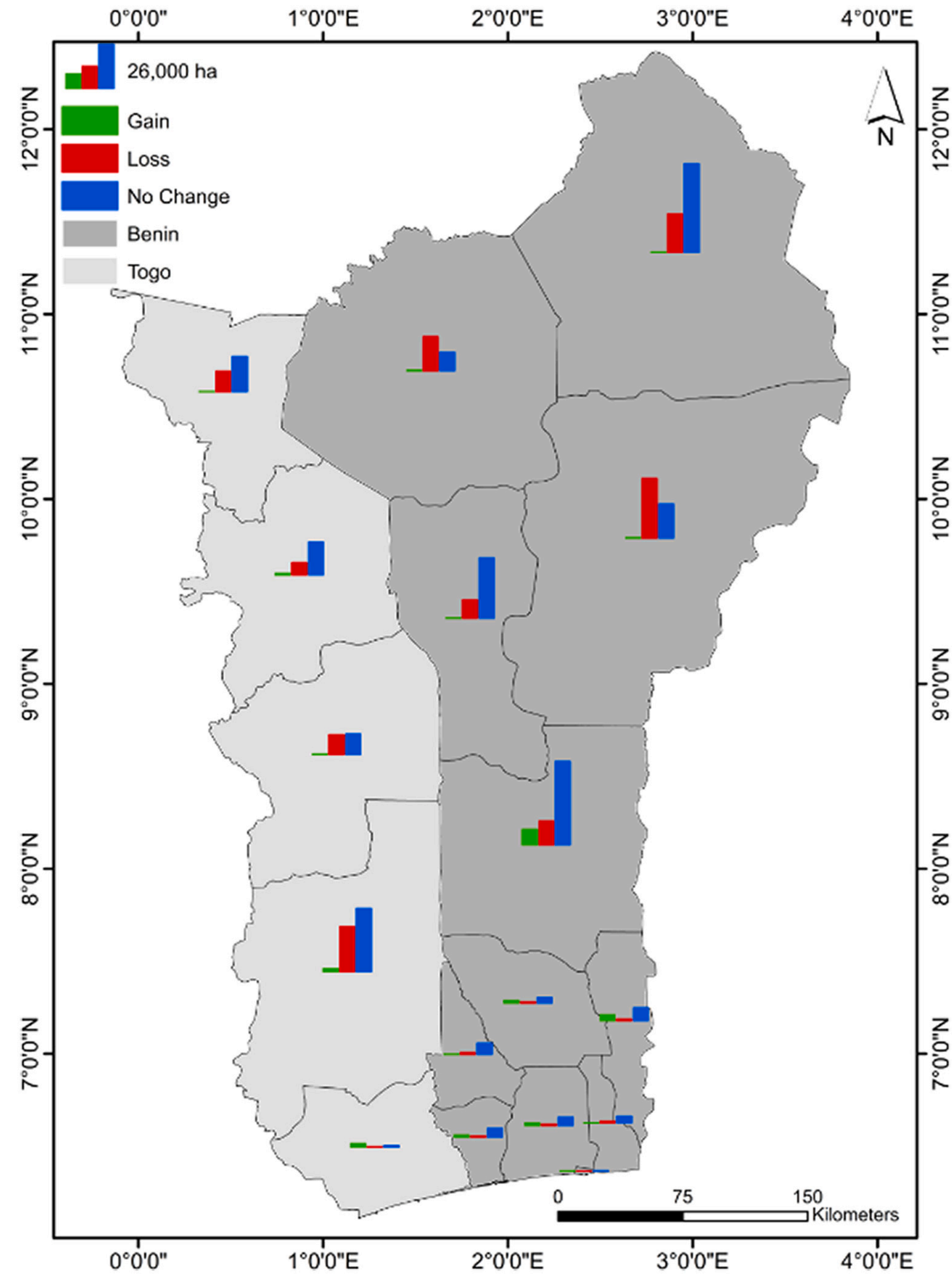

Fig. 9. Inland valleys suitability share by area gain, loss, and no change over administrative units in Togo (Regions) and Benin (Departments) for the period 2030s of RCP2.6.

region results in late-onset and early cessation dates of rainfall, reduction of length of the growing period, frequent drought, heat stress (Sarr, 2012), the reduced potential of the suitable land to support crop among others with a need for strong support to research on adaptation to climate change (Rhodes et al., 2014). It is projected that global climate change effects such as temperature increases and changes in rainfall patterns and distribution could result in significant changes in land and water resources for rice production as well as in the productivity of rice crops grown (Nguyen, 2002). Thus, the primary land class for rice and other crops grown in the tropical areas would decline by between 18.4 and 51% by the end of the century due to global warming, figures which are in support of the results from this study (Nguyen, 2002).

The results of this study present an opportunity to develop new avenues of research to adapt rainfed rice systems in inland valleys in the region. Our results stress the need for land use planning that considers potential climate change impacts to define the best areas and growing systems for the production of rice under multiple future climate change uncertainties. The relationship between changes in inland valley suitability and isothermality suggested that breeding programs should focus on the development of high nighttime temperature and heat tolerant rice varieties. The extension services should also support farmers with knowledge and early warning systems about changing the planting date and proving varieties that have shorter duration to avoid the heat during the sensitive growth phases. Improvement in water control and soil management in the rice field is considered as one of the adaptation measures to climate change, especially in the context of inland valleys rice production (Dossou-Yovo et al., 2022). To improve water control and soil management and increase the productivity of local rice

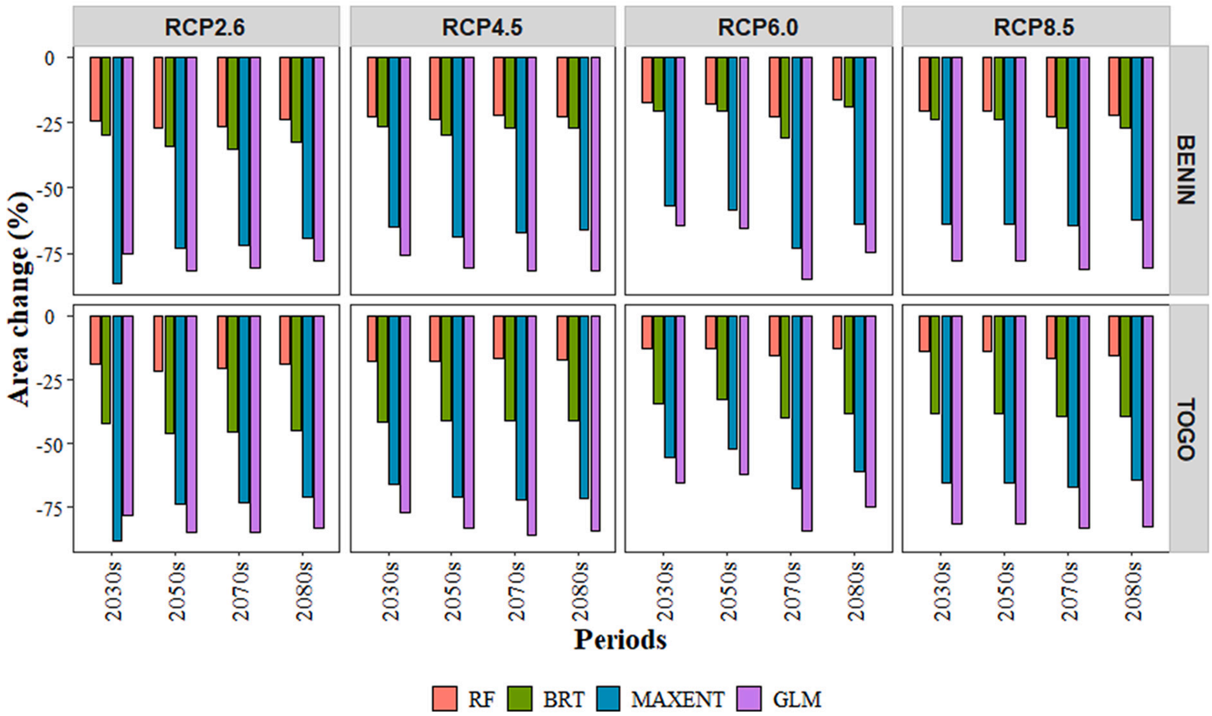

Fig. 10. Area changes relative to the baseline (1970–2000) in Togo (1.53×10^5 ha) and Benin (3.17×10^5 ha) for the four algorithms.

production in the context of climate change, a new technology (smart-valley approach) was introduced in Benin and Togo in 2010. The Smart-valley approach entails good agricultural practices such as land leveling, bunding, and puddling in combination with good water management, which leads lead to greater water storage in the fields and less field run-off through bunding and drainage facilities (Arouna and Akpa, 2019). In practice, the smart-valley approach is based on three pillars such as drainage canals, irrigation infrastructure (where water resources are available), and bunded and leveled rice fields in the inland valleys (Arouna and Akpa, 2019). The smart valley approach allows adaptation under actual local conditions to meet farmers' demands and the climate change risks for farmers, such as drought and flooding are reduced (Arouna and Akpa, 2019). Also, irrigation is considered as a means of adaptation to climate change in Africa in addition to the intensification of existing rice land, and the introduction of rice cultivation into highly suitable environments (Wassmann and Dobermann, 2007).

In the general context of West Africa, there is a need to tackle the impact of climate change on crop production and agricultural land through innovation. For example, new models to allow access to land, inputs, credit, and markets are needed, which in turn can influence the level of adaptation of the small-scale farmers. Drought-tolerant varieties are needed to cope with future climate uncertainties. Early warning systems (including those using sensors and mobile apps), new methods, and tools to guide farmers on when and where to farm are all relevant to the collective effort for adaptation. To this end, is important to include these efforts in the agricultural research for development agenda.

4.3. Caveats of correlative modeling

Limitations and areas of caution in correlative modeling for native species distribution have extensively been discussed in the past, including but not limited to sampling issues, clustering of observations, choice of predictors and autocorrelation, ecological niche models selection, models evaluations metrics, result interpretations, applications of concepts and theories, conceptual flaws in landscape analyses, and challenges in models transferability among others (Dormann, 2007; Li and Wu, 2004; Peterson et al., 2018; Sillero and Barbosa, 2021; Yates et al., 2018). For cultivated species such as rice, most of the above limitations still hold when designing an ecological modeling framework (Nabout et al., 2012). As discussed in the previous section, we tried to minimize the pitfalls by adopting the best practices. Still, some aspects warrant further discussions.

The models relate descriptors of climate to inland valley rice locations empirically and processes can be implicit (Asse et al., 2020) and are estimated by response curves (Dormann, 2007). However, a previous study showed that response curves to both climatic and other biophysical predictors of inland valleys rainfed rice cultivation have a reasonable ecological explanation (Akpoti et al., 2020). The models may also seem to suggest that the farmers of inland valley rice crops have adopted the best management practices for optimal rice crop development. This is not always true however as water, weed and pest control in inland valleys have been a major limiting factor in rice cultivation in Africa (Rodenburg et al., 2014) and this is not explicitly captured in our models.

Peterson et al. (2018) reported three main limitations that could impact the transfer of correlative models in climate change impact studies. Firstly, the effects of niche truncation on model transfer to future climate conditions are important. To train and evaluate the predictive skills of the 4 models we used a total of 844 inland valleys covering all agroclimatic zones in Benin and Togo. Although not all inland valley hydrological regimes or soil and topographical profile may be represented in the initial sample, we believe it provides sufficient basis for reliable predictions. Further data collection could improve the overall predictions of suitable and not suitable inland valleys. Secondly, the effects of model selection procedures on future-climate transfers of ecological niche models have a clear impact on results. In the present study, we used 4 different correlative models. While the direction and distribution of change in future inland valley suitability were unanimously captured by all models, the potential magnitude of change is different among the models; providing some level of uncertainties in quantifying how much area loss should be expected from climate change. Thus, we strongly support the view that multi-model predictions should be adopted to provide a large view of what could be expected under multiple future climate uncertainties. Thirdly, the relative

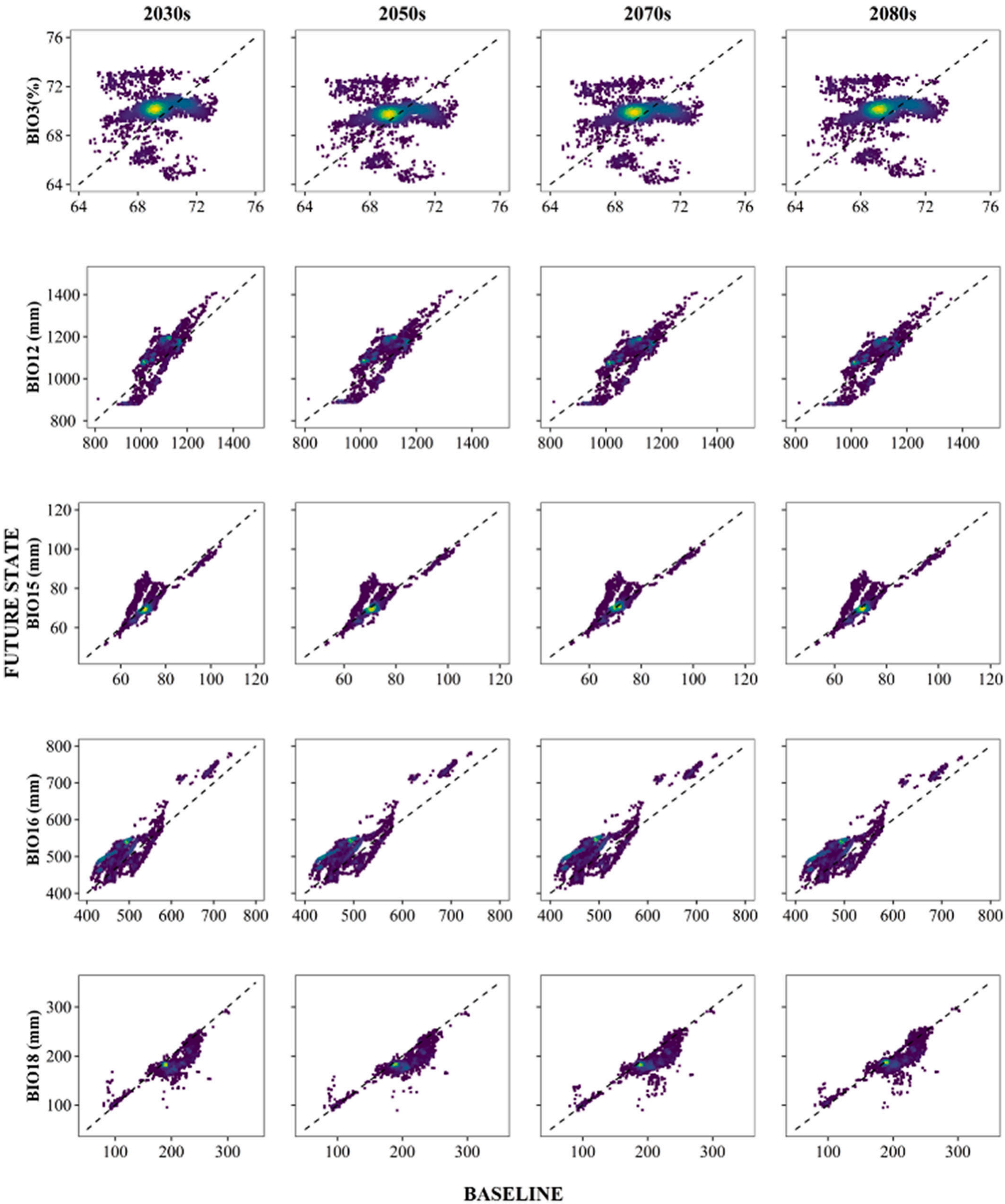

Fig. 11. Relationship between baseline and future state of bioclimatic predictors values in areas presenting gains, in terms of suitability for inland valley rice under RCP2.6 for 4 time periods (the 2030s, 2050s, 2070s, and 2080s). The dashed lines represent 1:1 line (no change in the predictor's future values). BIO3, Isothermality; BIO15, precipitation seasonality (Coefficient of Variation); BIO12, annual precipitation; BIO16, precipitation of wettest quarter; BIO18, precipitation of warmest quarter.

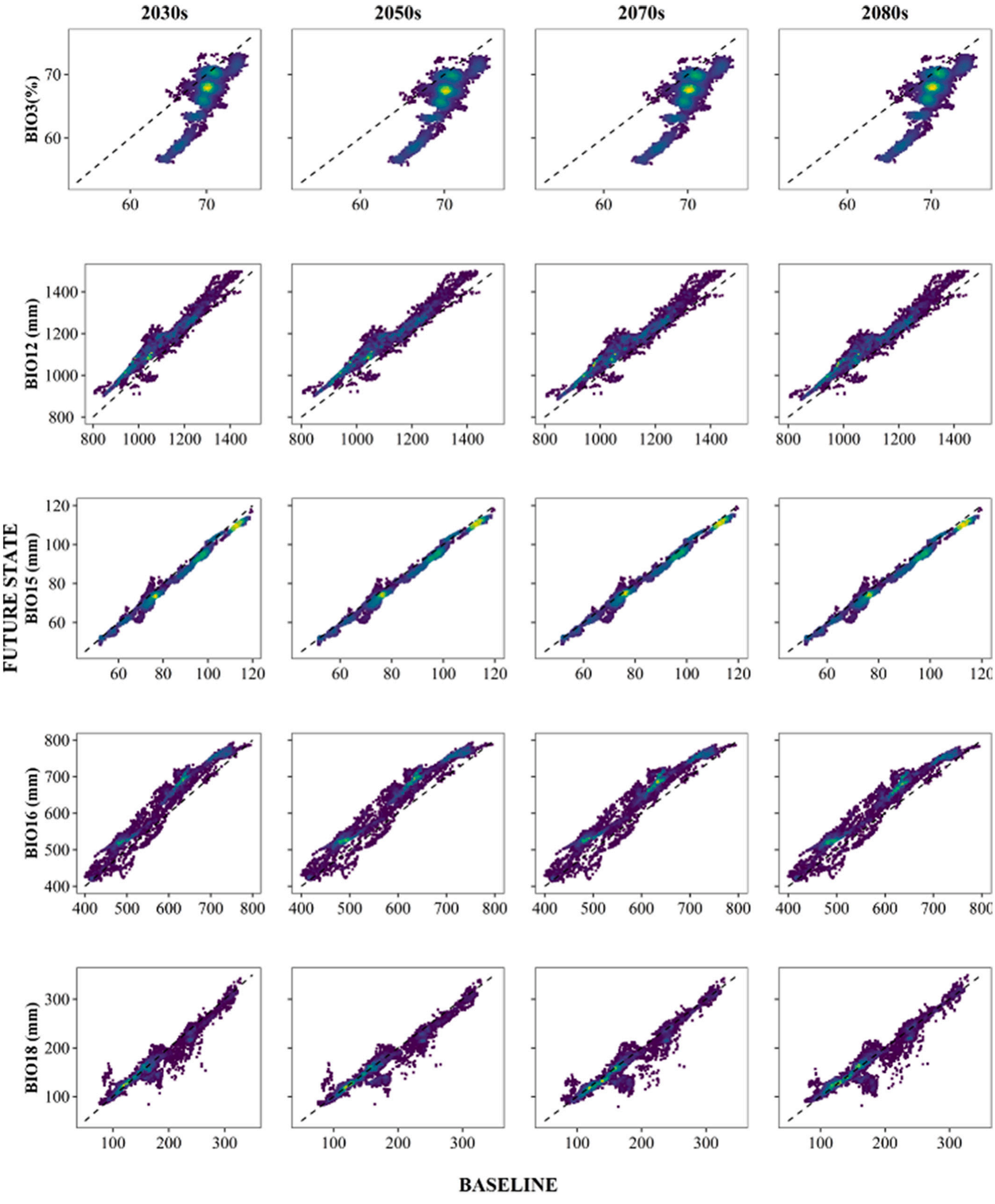

Fig. 12. Relationship between baseline and future state of bioclimatic predictors values in areas presenting no change, in terms of suitability for inland valley rice under RCP2.6 for 4 time periods (the 2030s, 2050s, 2070s, and 2080s). The dashed lines represent 1:1 line (no change in the predictor's future values). BIO3, Isothermality; BIO15, precipitation seasonality (Coefficient of Variation); BIO12, annual precipitation; BIO16, precipitation of wettest quarter; BIO18, precipitation of warmest quarter.

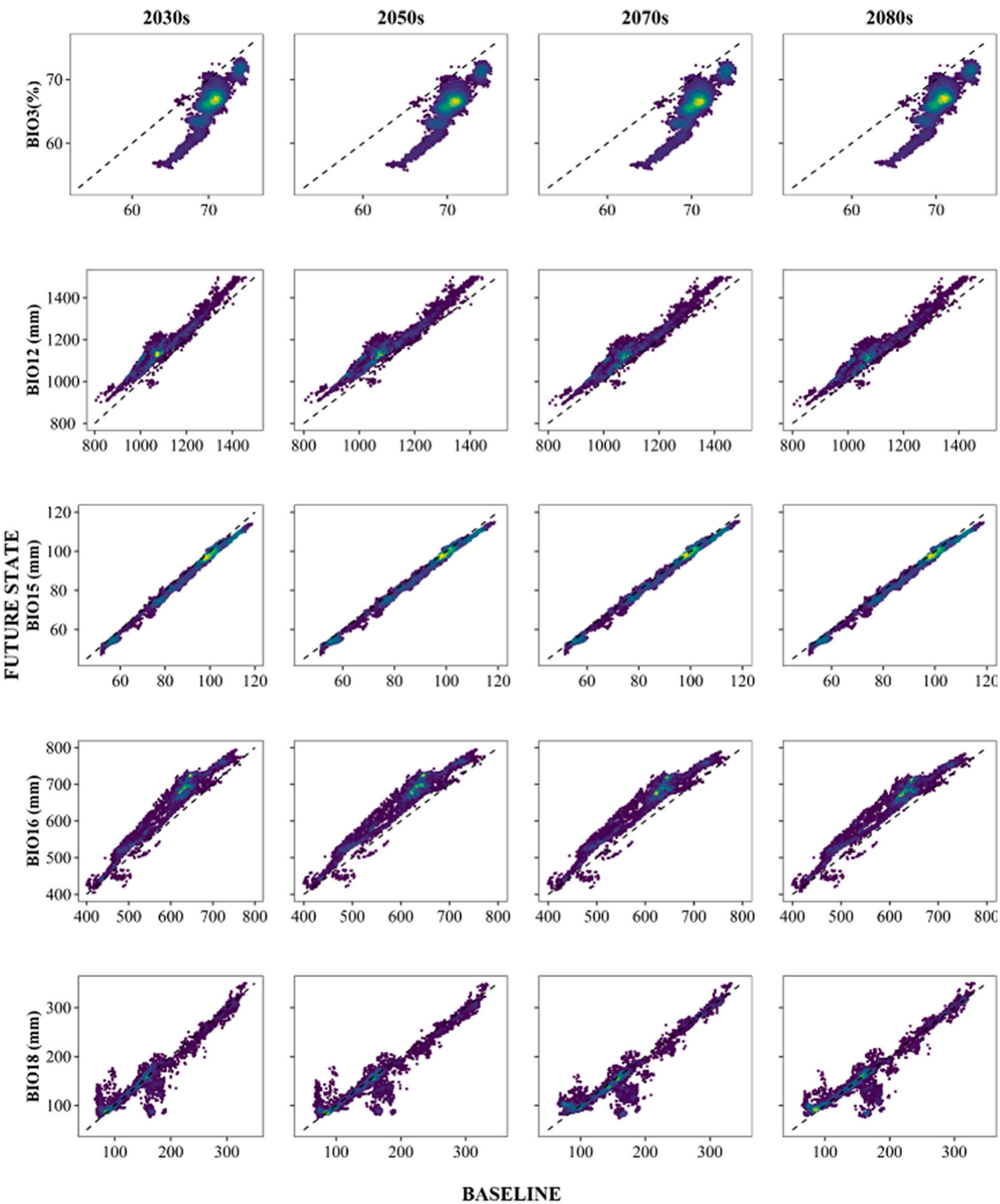

Fig. 13. Relationship between baseline and future state of bioclimatic predictors values in areas presenting losses, in terms of suitability for inland valley rice under RCP2.6 for 4 time periods (the 2030s, 2050s, 2070s, and 2080s). The dashed lines represent a 1:1 line (no change in the predictor's future values). BIO3, Isothermality; BIO15, precipitation seasonality (Coefficient of Variation); BIO12, annual precipitation; BIO16, precipitation of wettest quarter; BIO18, precipitation of warmest quarter.

contributions of several factors were not considered in the present study. The replicate of samples of point data, the individual general circulation models, and alternative model parameterizations to overall variance in models' outcomes are not presented. We are aware that doing so will quantify the source of uncertainties in models results and should be considered in subsequent modeling efforts.

4.4. Other uncertainties and limitations

In climate change impacts studies on agricultural systems, the use of a single GCM prediction to characterize future climate profiles and no bias-correction and spatial downscaling assessment of the products have been acknowledged as limitations (Zhang et al., 2017). Our approach avoided such drawbacks by including the spatial downscaled and bias-corrected the full range of changes in climatic variables as projected by the total ensemble of the 32 GCMs of the CMIP5 experiment included in the CCAFS database (Navarro-Racines et al., 2020). This approach is considered good practice in spatial modeling (Lutz et al., 2016). Still, there are major uncertainties in the GCMs predictions, especially for rainfall in the region (WBG, 2021). Also, limitations in data used in our approach may be related to soil and other topographic parameters, which we maintained as constant throughout future predictions. Meanwhile, poor agricultural practices that result in land degradation and soil losses, as well as climate change and its effects on hydrological processes, may affect soil properties in the next decades (Zhang et al., 2017) with subsequent impacts on food security (Brevik, 2013). Currently, we are not aware of any spatial data available on climate change impacts on soil properties that can be used in land suitability modeling. Studies suggested that future population growth may imply competing use of resources, including land for agriculture (Hall et al., 2017). This aspect was not considered in our modeling, as population density was kept constant.

Aside from data-associated limitations, there are uncertainties in the models' predictions. Results showed a small extent of variability between the different RCP scenarios but large differences among the four algorithms. Still, the trend across all algorithms is clear, suggesting that climate change will induce a significant reduction in inland valleys suitable for rainfed rice production if no adaptation and mitigation efforts are put in place. In the same line, other studies suggest that, despite the uncertainties in the magnitude of impacts, the climate will negatively affect agricultural production in Sub-Saharan Africa (Kotir, 2011).

5. Conclusion and future research

In the present study, we carefully analyzed the future inland valleys' suitability for rice production under 4 different climate scenarios and 4 time periods by explicitly addressing the questions of the magnitude of suitable area changes. The modeling showed a significant loss in potentially suitable inland valley areas as early as the 2030s up from 37% under RCP2.6 to about 34% losses by the end of the century under RCP8.5. The suitable inland valleys areas which will remain unchanged varied from 61% in the 2030s of RCP2.6 to 59% in the 2080s of RCP8.4. There were marginal gains of suitable inland valley areas from 3% to 9% across scenarios which tend to be located south and coastal areas in both Togo and Benin. The suitability changes are both linked to changes in temperature and precipitation regimes. Area losses may be explained by higher warming while area stability and gain may be linked to increased precipitation and lower temperatures. With current rice production far from meeting national demands, coupled with rapid population growth and dietary shifts, strong adaptation measures along with technological advancement and adoption are needed to cope with the adverse effects of climate change on inland valley rice fields. Although our modeling made use of the current most comprehensive datasets, uncertainties remain. Future research may also consider future population dynamics in the modeling as well as infrastructure development and their potential impacts on inland valleys' agricultural development. The results from this study should be interpreted in the context of no adaption scenarios. We recommend that subsequent studies may consider adaptation options, for example, better field-scale management, the adoption of extreme tolerant rice varieties among others. The present results could guide researchers, development agencies, and policymakers in the future sustainable planning and use of wetlands for food security.

Declaration of Competing Interest

The authors declare that they have no known competing of interest.

Acknowledgment

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.agsy.2022.103429.

References

Akpoti, K., Kabo-bah, A.T., Zwart, S.J., 2019. Agricultural land suitability analysis: state-of-the-art and outlooks for integration of climate change analysis. Agric. Syst. 173 (February), 172–208. https://doi.org/10.1016/j.agsy.2019.02.013.

Akpoti, K., Kabo-bah, A.T., Dossou-Yovo, E.R., Groen, T.A., Zwart, S.J., 2020. Mapping suitability for rice production in inland valley landscapes in Benin and Togo using environmental niche modeling. Sci. Total Environ. 709 https://doi.org/10.1016/j.scitotenv.2019.136165.

Akpoti, K., Dossou-Yovo, E.R., Zwart, S.J., Kiepe, P., 2021. The potential for expansion of irrigated rice under alternate wetting and drying in Burkina Faso. Agric. Water Manag. 247, 106758. https://doi.org/10.1016/j.agwat.2021.106758, 31 March 2021.

Akpoti, K., Higginbottom, T.P., Foster, T., Adhikari, R., Zwart, S.J., 2022. Mapping land suitability for informal, small-scale irrigation development using spatial modelling and machine learning in the Upper East Region, Ghana. Sci. Total Environ. 803, 149959 https://doi.org/10.1016/j.scitotenv.2021.149959.

Allouche, O., Tsoar, A., Kadmon, R., 2006. Assessing the accuracy of species distribution models : prevalence, kappa and the true skill statistic (TSS). J. Appl. Ecol. 43 (6), 1223–1232. https://doi.org/10.1111/j.1365-2664.2006.01214.x.

Andriesse, W., Fresco, L.O., 1991. A characterization of Rice growing environments in West Africa. Agric. Ecosyst. Environ. 33 (4), 377–395. https://doi.org/10.1016/0167-8809(91)90059-7.

Arenas-Castro, S., Gonçalves, J.F., Moreno, M., Villar, R., 2020. Projected climate changes are expected to decrease the suitability and production of olive varieties in southern Spain. Sci. Total Environ. 709, 136161 https://doi.org/10.1016/j.scitotenv.2019.136161.

Arouna, A., Akpa, A.K.A., 2019. Water management technology for adaptation to climate change in rice production: Evidence of smart-valley approach in west africa. In: Sustainable Solutions for Food Security: Combating Climate Change by Adaptation. Springer, Cham, pp. 211–227. https://doi.org/10.1007/978-3-319-77878-5_11.

Ashraf, U., Peterson, A.T., Chaudhry, M.N., Ashraf, I., Saqib, Z., Ahmad, S.R., Ali, H., 2017. Ecological niche model comparison under different climate scenarios: a case study of Olea spp. in Asia. Ecosphere 8 (5), 1–13. https://doi.org/10.1002/ecs2.1825.

Asse, D., Randin, C.F., Bonhomme, M., Delestrade, A., Chuine, I., 2020. Process-based models outcompete correlative models in projecting spring phenology of trees in a future warmer climate. Agric. For. Meteorol. 285–286 (January), 107931 https://doi.org/10.1016/j.agrformet.2020.107931.

Balasubramanian, V., Sie, M., Hijmans, R.J., Otsuka, K., 2007. Increasing rice production in Sub-Saharan Africa: challenges and opportunities. Adv. Agron. 94 (06), 55–133. https://doi.org/10.1016/S0065-2113(06)94002-4.

Beaumont, L.J., Graham, E., Duursma, D.E., Wilson, P.D., Cabrelli, A., Baumgartner, J.B., Hallgren, W., Esperón-Rodríguez, M., Nipperess, D.A., Warren, D.L., Laffan, S.W., VanDerWal, J., 2016. Which species distribution models are more (or less) likely to project broad-scale, climate-induced shifts in species ranges? Ecol. Model. 342, 135–146. https://doi.org/10.1016/j.ecolmodel.2016.10.004.

Beck, J., 2013. Predicting climate change effects on agriculture from ecological niche modeling: who profits, who loses? Clim. Chang. 116 (2), 177–189. https://doi.org/10.1007/s10584-012-0481-x.

Bradley, B.A., Estes, L.D., Hole, D.G., Holness, S., Oppenheimer, M., Turner, W.R., Beukes, H., Schulze, R.E., Tadross, M.A., Wilcove, D.S., 2012. Predicting how adaptation to climate change could affect ecological conservation: secondary impacts of shifting agricultural suitability. Divers. Distrib. 18 (5), 425–437. https://doi.org/10.1111/j.1472-4642.2011.00875.x.

Braunisch, V., Coppes, J., Arlettaz, R., Suchant, R., Schmid, H., Bollmann, K., 2013. Selecting from correlated climate variables : a major source of uncertainty for predicting species distributions under climate change. Ecography 36 (9), 1–13. https://doi.org/10.1111/j.1600-0587.2013.00138.x.

Breiman, L., Cutler, A., Liaw, A., Wiener, M., . Package randomForest. In Software available at. *http://stat-www.berkeley.edu/users/breiman/RandomForests*. https://doi.org/10.1023/A.

Brevik, E.C., 2013. The potential impact of climate change on soil properties and processes and corresponding influence on food security. Agriculture 3 (3), 398–417. https://doi.org/10.3390/agriculture3030398.

Busetto, L., Ranghetti, L., 2016. MODIStsp: An R package for automatic preprocessing of MODIS Land Products time series. Comput. Geosci. 97, 40–48. https://doi.org/10.1016/j.cageo.2016.08.020.

Castro-Llanos, F., Hyman, G., Rubiano, J., Ramirez-Villegas, J., Achicanoy, H., 2019. Climate change favors rice production at higher elevations in Colombia. Mitig. Adapt. Strateg. Glob. Chang. 24 (8), 1401–1430. https://doi.org/10.1007/s11027-019-09852-x.

Challinor, A.J., Watson, J., Lobell, D.B., Howden, S.M., Smith, D.R., Chhetri, N., 2014. A meta-analysis of crop yield under climate change and adaptation. Nat. Clim. Chang. 4 (4), 287–291. https://doi.org/10.1038/nclimate2153.

CIESIN, S., 2015. Gridded population of the world, version 4 (GPWv4): population density. Center for International Earth Science Information Network-CIESIN-Columbia University. NASA Socioeconomic Data and Applications Center (SEDAC). https://doi.org/10.7927/H4DZ068D.

Crimmins, S.M., Dobrowski, S.Z., Mynsberge, A.R., 2013. Evaluating ensemble forecasts of plant species distributions under climate change. Ecol. Model. 266 (1), 126–130. https://doi.org/10.1016/j.ecolmodel.2013.07.006.

Danvi, A., Giertz, S., Zwart, S.J., Diekkrüger, B., 2018. Rice intensification in a changing environment: impact on water availability in inland valley landscapes in Benin. Water (Switzerland) 10 (1), 74. https://doi.org/10.3390/w10010074.

Diagne, M., Amovin-Assagba, E., Futakuchi, K., 2013. Estimation of cultivated area, number of farming households and yield for major rice-growing environments in Africa. In: CABI (Ed.), Realizing Africa's Rice Promise, pp. 35–45. https://doi.org/10.1079/9781845938123.0035.

Djagba, Justin Fagnombo, Sintondji, L.O., Kouyaté, A.M., Baggie, I., Agbahungba, G., Hamadoun, A., Zwart, S.J., 2018. Predictors determining the potential of inland valleys for rice production development in West Africa. Appl. Geogr. 96 (August 2017), 86–97. https://doi.org/10.1016/j.apgeog.2018.05.003.

Djagba, Justin F., Kouyaté, A.M., Baggie, I., Zwart, S.J., 2019. Data in brief a geospatial dataset of inland valleys in four zones in Benin, Sierra Leone and Mali. Data Brief 23, 0–5. https://doi.org/10.1016/j.dib.2019.103699.

Dormann, C.F., 2007. Promising the future? Global change projections of species distributions. Basic Appl. Ecol. 8 (5), 387–397. https://doi.org/10.1016/j.baae.2006.11.001.

Dossou-Yovo, E.R., Devkota, K.P., Akpoti, K., Danvi, A., Duku, C., Zwart, S.J., 2022. Thirty years of water management research for rice in sub-Saharan Africa: Achievement and perspectives. Field Crops Res. 283 (1 July 2022), 108548. https://doi.org/10.1016/j.fcr.2022.108548.

Dossou-Yovo, E.R., Zwart, S.J., Kouyaté, A., Ouédraogo, I., Bakare, O., 2019. Predictors of drought in inland valley landscapes and enabling factors for rice farmers' mitigation measures in the Sudan-Sahel zone. Sustainability 11 (1). https://doi.org/10.3390/su11010079.

Duku, C., Zwart, S.J., Hein, L., 2018. Impacts of climate change on cropping patterns in a tropical, sub-humid watershed. PLoS One 13 (3), 1–21. https://doi.org/10.1371/journal.pone.0192642.

Duong, T., 2015. ks : kernel density estimation and kernel discriminant analysis for multivariate data in R. J. Stat. Softw. 21 (7) https://doi.org/10.18637/jss.v021.i07.

Elith, J., Leathwick, J.R., Hastie, T., 2008. A working guide to boosted regression trees. J. Anim. Ecol. 77 (4), 802–813. https://doi.org/10.1111/j.1365-2656.2008.01390.x.

Estes, L.D., Bradley, B.A., Beukes, H., Hole, D.G., Lau, M., Oppenheimer, M.G., Schulze, R., Tadross, M.A., Turner, W.R., 2013. Comparing mechanistic and empirical model projections of crop suitability and productivity: implications for ecological forecasting. Glob. Ecol. Biogeogr. 22 (8), 1007–1018. https://doi.org/10.1111/geb.12034.

Evans, J., Murphy, M.A., Ram, K., 2020. Package "spatialEco." Cran.R-Project. https://cran.r-project.org/web/packages/spatialEco/index.html.

FAOSTAT, 2021. FAO & Crops Production. Food and Agriculture Organization of the United Nations. http://www.fao.org/faostat/en/#data/QC.

Fick, S.E., Hijmans, R.J., 2017. WorldClim 2: new 1-km spatial resolution climate surfaces for global land areas. Int. J. Climatol. 37 (12), 4302–4315. https://doi.org/10.1002/joc.5086.

Freeman, E.A., Moisen, G., 2008. PresenceAbsence: an R package for PresenceAbsence analysis. J. Stat. Softw. 23 (11), 1–31. https://doi.org/10.18637/jss.v023.i11.

Freire, J., Silva, C.T., Callahan, S.P., Santos, E., Scheidegger, C.E., Vo, H.T., 2006. Managing rapidly-evolving scientific workflows. In: L, F.I. Moreau (Ed.), Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), vol. 4145 LNCS. Springer, pp. 10–18. https://doi.org/10.1007/11890850_2.

Gallant, J.C., Dowling, T.I., 2003. A multiresolution index of valley bottom flatness for mapping depositional areas. Water Resour. Res. 39 (12) https://doi.org/10.1029/2002WR001426.

Gharbia, S.S., Gill, L., Johnston, P., Pilla, F., 2016. Multi-GCM ensembles performance for climate projection on a GIS platform. Model. Earth Syst. Environ. 2 (2), 1–21. https://doi.org/10.1007/s40808-016-0154-2.

Guan, K., Sultan, B., Biasutti, M., Baron, C., Lobell, D.B., 2015. What aspects of future rainfall changes matter for crop yields in West Africa? Geophys. Res. Lett. 42 (19), 8001–8010. https://doi.org/10.1002/2015GL063877.

Guisan, A., Edwards Jr., T.C., Hastie, T., 2002. Generalized linear and generalized additive models in studies of species distributions: setting the scene. Ecol. Model. 157, 89–100. https://doi.org/10.1016/S0304-3800(02)00204-1.

Gumma, M., Thenkabail, P.S., Fujii, H., Namara, R., 2009. Spatial models for selecting the most suitable areas of rice cultivation in the Inland Valley Wetlands of Ghana using remote sensing and geographic information systems. J. Appl. Remote. Sens. 3 (1), 033537 https://doi.org/10.1117/1.3182847.

Gupta, R., Mishra, A., 2019. Climate change induced impact and uncertainty of rice yield of agro-ecological zones of India. Agric. Syst. 173 (October 2018), 1–11. https://doi.org/10.1016/j.agsy.2019.01.009.

Hall, C., Dawson, T.P., Macdiarmid, J.I., Matthews, R.B., Smith, P., 2017. The impact of population growth and climate change on food security in Africa: looking ahead to 2050. Int. J. Agric. Sustain. 15 (2), 124–135. https://doi.org/10.1080/14735903.2017.1293929.

Hao, T., Elith, J., Guillera-Arroita, G., Lahoz-Monfort, J.J., 2019. A review of evidence about use and performance of species distribution modelling ensembles like BIOMOD. Divers. Distrib. 25 (5), 839–852. https://doi.org/10.1111/ddi.12892.

Hengl, T., Heuvelink, G.B., Kempen, B., Leenaars, J.G., Walsh, M.G., et al., 2015. Mapping soil properties of Africa at 250 m resolution: Random forests significantly improve current predictions. PloS one 10 (6), e0125814. https://doi.org/10.1371/journal.pone.0125814.

Hengl, T., Leenaars, J.G.B., Shepherd, K.D., Walsh, M.G., Heuvelink, G., Mamo, T., 2017. Soil nutrient maps of Sub-Saharan Africa: assessment of soil nutrient content at 250 m spatial resolution using machine learning. Nutr. Cycl. Agroecosystems 109 (1), 77–102. https://doi.org/10.1007/s10705-017-9870-x.

Hijmans, R.J., Graham, C.H., 2006. The ability of climate envelope models to predict the effect of climate change on species distributions. Glob. Chang. Biol. 12 (12), 2272–2281. https://doi.org/10.1111/j.1365-2486.2006.01256.x.

Iizumi, T., Ramankutty, N., 2015. How do weather and climate influence cropping area and intensity? Glob. Food Secur. 4, 46–50. https://doi.org/10.1016/j.gfs.2014.11.003.

IPCC, 2014. Climate change 2014 synthesis report summary chapter for policymakers. In: Climate Change 2014: Synthesis Report. Summary for Policymakers. IPCC, 2014.

Jarnevich, C.S., Talbert, M., Morisette, J., Aldridge, C., Brown, C.S., Kumar, S., Manier, D., Talbert, C., Holcombe, T., 2017. Minimizing effects of methodological decisions on interpretation and prediction in species distribution studies: an example with background selection. Ecol. Model. 363, 48–56. https://doi.org/10.1016/j.ecolmodel.2017.08.017.

Jiménez-valverde, A., 2012. Insights into the area under the receiver operating characteristic curve (AUC) as a discrimination measure in species. Glob. Ecol. Biogeogr. 21 (4), 498–507. https://doi.org/10.1111/j.1466-8238.2011.00683.x.

Kotir, J.H., 2011. Climate change and variability in Sub-Saharan Africa: a review of current and future trends and impacts on agriculture and food security. Environ. Dev. Sustain. 13 (3), 587–605. https://doi.org/10.1007/s10668-010-9278-0.

Läderach, P., Martinez-Valle, A., Schroth, G., Castro, N., 2013. Predicting the future climatic suitability for cocoa farming of the world's leading producer countries, Ghana and Côte d'Ivoire. Clim. Chang. 119 (3–4), 841–854. https://doi.org/10.1007/s10584-013-0774-8.

Lamboll, R., Stathers, T., Morton, J., 2017. Climate change and agricultural systems. In: Agricultural Systems: Agroecology and Rural Innovation for Development. Elsevier Inc., Second, pp. 441–490. https://doi.org/10.1016/B978-0-12-802070-8.00013-X.

Lane, A., Jarvis, A., 2007. Changes in climate will modify the geography of crop suitability: agricultural biodiversity can help with adaptation. SAT Ejournal 4 (1), 1–12.

Li, H., Wu, J., 2004. Use misuse landscape metrics. Landsc. Ecol. 19, 389–399 papers2://publication/uuid/F819F009-DF8E-4AA8-A817-05D74B1E6148.

Lindsay, J.B., 2016. Whitebox GAT: a case study in geomorphometric analysis. Comput. Geosci. https://doi.org/10.1016/j.cageo.2016.07.003.

Liu, C., Berry, P.M., Dawson, T.P., Pearson, R.G., 2005. Selecting thresholds of occurrence in the prediction of species distribution. Ecography 3 (December 2004), 385–393.

Liu, Z., Yang, P., Tang, H., Wu, W., Zhang, L., Yu, Q., Li, Z., 2015. Shifts in the extent and location of rice cropping areas match the climate change pattern in China during 1980–2010. Reg. Environ. Chang. 15 (5), 919–929. https://doi.org/10.1007/s10113-014-0677-x.

Lobell, D.B., Asseng, S., 2017. Comparing estimates of climate change impacts from process-based and statistical crop models. Environ. Res. Lett. 12 (1), 015001 https://doi.org/10.1088/1748-9326/015001.

Lutz, A.F., ter Maat, H.W., Biemans, H., Shrestha, A.B., Wester, P., Immerzeel, W.W., 2016. Selecting representative climate models for climate change impact studies: an advanced envelope-based selection approach. Int. J. Climatol. 36 (12), 3988–4005. https://doi.org/10.1002/joc.4608.

Marmion, M., Parviainen, M., Luoto, M., Heikkinen, R.K., Thuiller, W., 2009. Evaluation of consensus methods in predictive species distribution modelling. Divers. Distrib. 15 (1), 59–69. https://doi.org/10.1111/j.1472-4642.2008.00491.x.

Masoud, J., Forkuor, G., Namara, R., Ofori, E., 2013. Modeling inland valley suitability for rice cultivation. ARPN J. Eng. Appl. Sci. 8 (1), 9–19.
Mbow, H.O.P., Reisinger, A., Canadell, J., O'Brien, P., 2017. Special report on climate change, desertification, land degradation, sustainable land management, food security, and greenhouse gas fluxes in terrestrial ecosystems (SR2). In: Background report for the Scoping Meeting (Issue February).
Misra, A.K., 2014. Climate change and challenges of water and food security. Int. J. Sustain. Built Environ. 3 (1), 153–165. https://doi.org/10.1016/j.ijsbe.2014.04.006.
Morisette, J.T., Jarnevich, C.S., Holcombe, T.R., Talbert, C.B., Ignizio, D., Talbert, M.K., Silva, C., Koop, D., Swanson, A., Young, N.E., 2013. VisTrails SAHM: visualization and workflow management for species habitat modeling. Ecography 36 (2), 129–135. https://doi.org/10.1111/j.1600-0587.2012.07815.x.
Müller, D., Leitão, P.J., Sikor, T., 2013. Comparing the determinants of cropland abandonment in Albania and Romania using boosted regression trees. Agric. Syst. 117, 66–77. https://doi.org/10.1016/j.agsy.2012.12.010.
Nabout, J.C., Caetano, J.M., Ferreira, R.B., Teixeira, I.R., de Alves, S.M.F., 2012. Using correlative, mechanistic and hybrid niche models to predict the productivity and impact of global climate change on maize crop in Brazil. Natureza a Conservacao 10 (2), 177–183. https://doi.org/10.4322/natcon.2012.034.
Navarro-Racines, C., Tarapues, J., Thornton, P., Jarvis, A., Ramirez-Villegas, J., 2020. High-resolution and bias-corrected CMIP5 projections for climate change impact assessments. Sci. Data 7 (1), 7. https://doi.org/10.1038/s41597-019-0343-8.
Nguyen, N.V., 2002. Global climate changes and rice food security. In: Executive Secretary, International Rice Commission. FAO, Rome, Italy.
O'Donnell, M.S., Ignizio, D.A., 2012. Bioclimatic predictors for supporting ecological applications in the conterminous United States. U.S Geol. Surv. Data Ser. 691, 10. https://doi.org/10.1016/j.mimet.2011.04.001.
Pearson, R.G., Thuiller, W., Araújo, M.B., Martinez-Meyer, E., Brotons, L., McClean, C., Miles, L., Segurado, P., Dawson, T.P., Lees, D.C., 2006. Model-based uncertainty in species range prediction. J. Biogeogr. 33 (10), 1704–1711. https://doi.org/10.1111/j.1365-2699.2006.01460.x.
Peterson, A.T., 2006. Uses and requirements of ecological niche models and related distributional models. Biodivers. Inform. 3 (0), 59–72. https://doi.org/10.17161/bi.v3i0.29.
Peterson, A.T., Cobos, M.E., Jiménez-García, D., 2018. Major challenges for correlational ecological niche model projections to future climate conditions. Ann. N. Y. Acad. Sci. 1429 (1), 66–77. https://doi.org/10.1111/nyas.13873.
Phillips, S.J., Anderson, R.P., Schapire, R.E., 2006. Maximum entropy modeling of species geographic distributions. Ecol. Model. 190 (3–4), 231–259. https://doi.org/10.1016/j.ecolmodel.2005.03.026.
Piekielek, N.B., Hansen, A.J., Chang, T., 2015. Using custom scientific workflow software and GIS to inform protected area climate adaptation planning in the Greater Yellowstone Ecosystem. Ecol. Inform. 30, 40–48. https://doi.org/10.1016/j.ecoinf.2015.08.010.
Qiao, H., Soberón, J., Peterson, A.T., 2015. No silver bullets in correlative ecological niche modelling: insights from testing among many potential algorithms for niche estimation. Methods Ecol. Evol. 6 (10), 1126–1136. https://doi.org/10.1111/2041-210X.12397.
R Development Core Team, R, 2011. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing. https://doi.org/10.1007/978-3-540-74686-7.
Ramírez-Gil, J.G., Cobos, M.E., Jiménez-García, D., Morales-Osorio, J.G., Peterson, A.T., 2019. Current and potential future distributions of Hass avocados in the face of climate change across the Americas. Crop & Pasture Sci. 70 (8), 694–708. https://doi.org/10.1071/CP19094.
Remya, K., Ramachandran, A., Jayakumar, S., 2015. Predicting the current and future suitable habitat distribution of Myristica dactyloides Gaertn. using MaxEnt model in the Eastern Ghats, India. Ecol. Eng. 82, 184–188. https://doi.org/10.1016/j.ecoleng.2015.04.053.
Rhodes, E.R., Jalloh, A., Diouf, A., 2014. Review of research and policies for climate change adaptation in the agriculture sector in West Africa. In: Future Agricultures Working Paper (No. 90; Issue May).
Rodenburg, J., Zwart, S.J., Kiepe, P., Narteh, L.T., Dogbe, W., Wopereis, M.C.S., 2014. Sustainable rice production in African inland valleys: seizing regional potentials through local approaches. Agric. Syst. 123, 1–11. https://doi.org/10.1016/j.agsy.2013.09.004.
Rosenzweig, C., Elliott, J., Deryng, D., Ruane, A.C., Müller, C., Arneth, A., Boote, K.J., Folberth, C., Glotter, M., Khabarov, N., Neumann, K., Piontek, F., Pugh, T.A.M., Schmid, E., Stehfest, E., Yang, H., Jones, J.W., 2014. Assessing agricultural risks of climate change in the 21st century in a global gridded crop model intercomparison. Proc. Natl. Acad. Sci. U. S. A. 111 (9), 3268–3273. https://doi.org/10.1073/pnas.1222463110.
Saito, K., Nelson, A., Zwart, S.J., Niang, A., Sow, A., Yoshida, H., Wopereis, M.C.S., 2013. Towards a better understanding of biophysical determinants of yield gaps and the potential for expansion of the rice area in Africa. In: CABI (Ed.), Realizing Africa's Rice Promise, pp. 190–192. https://doi.org/10.1079/9781845938123.0000.
Sakurai, T., 2006. Intensification of rainfed lowland rice production in West Africa: present status and potential green revolution. Dev. Econ. 44 (2), 232–251. https://doi.org/10.1111/j.1746-1049.2006.00015.x.
Sarr, B., 2012. Present and future climate change in the semi-arid region of West Africa: a crucial input for practical adaptation in agriculture. Atmos. Sci. Lett. 13 (2), 108–112. https://doi.org/10.1002/asl.368.
Schmidhuber, J., Tubiello, F.N., 2008. Global food security under climate change. Proc. Natl. Acad. Sci. U. S. A. 104 (50), 19703–19708. https://doi.org/10.1073/pnas.0701424104.
Schmidt, F., Persson, A., 2003. Comparison of DEM data capture and topographic wetness indices. Precis. Agric. 4 (2), 179–192. https://doi.org/10.1023/A:1024509322709.
Schroth, G., Läderach, P., Martinez-Valle, A.I., Bunn, C., 2017. From site-level to regional adaptation planning for tropical commodities: cocoa in West Africa. Mitig. Adapt. Strateg. Glob. Chang. 22 (6), 903–927. https://doi.org/10.1007/s11027-016-9707-y.
Siabi, E.K., Kabobah, A.T., Akpoti, K., Anornu, G.K., Amo-Boateng, M., Nyantakyi, E.K., 2021. Statistical downscaling of global circulation models to assess future climate changes in the Black Volta basin of Ghana. Environ. Chall. 5 (August), 100299 https://doi.org/10.1016/j.envc.2021.100299.
Sillero, N., Barbosa, A.M., 2021. Common mistakes in ecological niche models. Int. J. Geogr. Inf. Sci. 35 (2), 213–226. https://doi.org/10.1080/13658816.2020.1798968.
Sultan, B., Gaetani, M., 2016. Agriculture in West Africa in the twenty-first century: climate change and impacts scenarios, and potential for adaptation. Front. Plant Sci. 7 (AUG2016), 1–20. https://doi.org/10.3389/fpls.2016.01262.
Swets, J.A., 1988. Measuring the accuracy of diagnostic systems. Science 240 (4857), 1285–1293.
Talbert, C., Talbert, M., Morisette, J., Koop, D., 2013. Data management challenges in species distribution modeling. Bull. IEEE Comput. Soc. Tech. Committee Data Eng. 36 (4), 31–40.
Teixeira, E.I., Fischer, G., Van Velthuizen, H., Walter, C., Ewert, F., 2013. Global hot-spots of heat stress on agricultural crops due to climate change. Agric. For. Meteorol. 170, 206–215. https://doi.org/10.1016/j.agrformet.2011.09.002.
Tilman, D., Balzer, C., Hill, J., Befort, B.L., 2011. Global food demand and the sustainable intensification of agriculture. Proc. Natl. Acad. Sci. U. S. A. 108 (50), 20260–20264. https://doi.org/10.1073/pnas.1116437108.
Václavík, T., Meentemeyer, R.K., 2009. Invasive species distribution modeling (iSDM): are absence data and dispersal constraints needed to predict actual distributions? Ecol. Model. 220 (23), 3248–3258. https://doi.org/10.1016/j.ecolmodel.2009.08.013.
van Oort, P.A.J., Zwart, S.J., 2018. Impacts of climate change on rice production in Africa and causes of simulated yield changes. Glob. Chang. Biol. 24 (3), 1029–1045. https://doi.org/10.1111/gcb.13967.
Warren, D.L., 2012. In defense of "niche modeling.". Trends Ecol. Evol. 27 (9), 497–500. https://doi.org/10.1016/j.tree.2012.03.010.
Wassmann, R., Dobermann, A., 2007. Climate change adaptation through rice production in regions with high poverty levels. SAT Ejournal 1 (4), 133–136.
Wassmann, R., Jagadish, S.V.K., Heuer, S., Ismail, A., Redona, E., Serraj, R., Singh, R.K., Howell, G., Pathak, H., Sumfleth, K., 2009. Chapter 2 climate change affecting rice production. The physiological and agronomic basis for possible adaptation strategies. In: Advances in Agronomy, , 1st ed.vol. 101, Issue 08. Elsevier Inc. https://doi.org/10.1016/S0065-2113(08)00802-X
WBG, 2021. Climate Change Knowledge Portal: For Development Practiioners and Policy Makers. https://climateknowledgeportal.worldbank.org/.
Weiss, D.J., Nelson, A., Gibson, H.S., Temperley, W., Peedell, S., Lieber, A., et al., 2018. A global map of travel time to cities to assess inequalities in accessibility in 2015. Nature 553 (7688), 333–336. https://doi.org/10.1038/nature25181.
Were, K., Bui, D.T., Dick, Ø.B., Singh, B.R., 2015. A comparative assessment of support vector regression, artificial neural networks, and random forests for predicting and mapping soil organic carbon stocks across an Afromontane landscape. Ecol. Indic. 52, 394–403. https://doi.org/10.1016/j.ecolind.2014.12.028.
West, A.M., Evangelista, P.H., Jarnevich, C.S., Kumar, S., Swallow, A., Luizza, M.W., Chignell, S.M., 2017. Using multi-date satellite imagery to monitor invasive grass species distribution in post-wildfire landscapes: an iterative, adaptable approach that employs open-source data and software. Int. J. Appl. Earth Obs. Geoinf. 59, 135–146. https://doi.org/10.1016/j.jag.2017.03.009.
Wise, T.A., 2013. Can We Feed the World in 2050? A Scoping Paper to Assess the Evidence, 13(4). Global Development and Environment Institute, pp. 1–38.
Wopereis, M.C.S., Defoer, T., Idinoba, P., 2008. Curriculum for Participatory Learning and Action Research (PLAR) for Integrated Rice Management (IRM) in Inland Valleys of Sub-Saharan Africa:Techincal Manual. In: WARDA Training Series. Africa Rice Center.
Worqlul, A.W., Dile, Y.T., Jeong, J., Adimassu, Z., Lefore, N., Gerik, T., Srinivasan, R., Clarke, N., 2019. Effect of climate change on land suitability for surface irrigation and irrigation potential of the shallow groundwater in Ghana. Comput. Electron. Agric. 157 (August 2018), 110–125. https://doi.org/10.1016/j.compag.2018.12.040.
Yates, K.L., Bouchet, P.J., Caley, M.J., Mengersen, K., Randin, C.F., Parnell, S., Fielding, A.H., Bamford, A.J., Ban, S., Barbosa, A.M., Dormann, C.F., Elith, J., Embling, C.B., Ervin, G.N., Fisher, R., Gould, S., Graf, R.F., Gregr, E.J., Halpin, P.N., Sequeira, A.M.M., 2018. Outstanding challenges in the transferability of ecological models. Trends Ecol. Evol. 33 (10), 790–802. https://doi.org/10.1016/j.tree.2018.08.001.
Yeboah, K.A., Akpoti, K., Kabo-bah, A.T., Ofosu, E.A., Siabi, E.K., Mortey, E.M., Okyereh, S.A., 2022. Assessing climate change projections in the Volta Basin using the CORDEX-Africa climate simulations and statistical bias-correction. Environ. Chall. 6 (August 2021), 100439. https://doi.org/10.1016/j.envc.2021.100439.
Zhang, Y., Wang, Y., Niu, H., 2017. Spatio-temporal variations in the areas suitable for the cultivation of rice and maize in China under future climate scenarios. Sci. Total Environ. 601–602 (19), 518–531. https://doi.org/10.1016/j.scitotenv.2017.05.232.
Zhao, C., Piao, S., Wang, X., Huang, Y., Ciais, P., Elliott, J., Huang, M., Janssens, I.A., Li, T., Lian, X., Liu, Y., Müller, C., Peng, S., Wang, T., Zeng, Z., Peñuelas, J., 2016.

Plausible rice yield losses under future climate warming. Nat. Plant 3 (December), 1–5. https://doi.org/10.1038/nplants.2016.202.

Zimmermann, N.E., Yoccoz, N.G., Edwards, T.C., Meier, E.S., Thuiller, W., Guisan, A., Schmatz, D.R., Pearman, P.B., 2009. Climatic extremes improve predictions of spatial patterns of tree species. Proc. Natl. Acad. Sci. 106 (Supplement_2), 19723–19728. https://doi.org/10.1073/pnas.0901643106.

Zwart, S.J., 2016. Projected Climate Conditions for Rice Production Systems in Africa. AfricaRice GIS Report – 1.