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Mapping suitability for rice production in inland valley landscapes in Benin and Togo using environmental niche modeling

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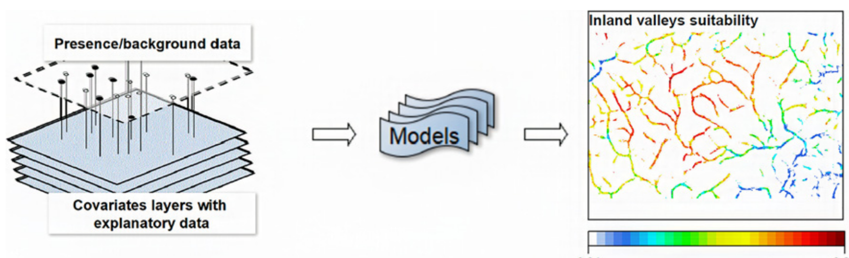
HIGHLIGHTS

- We used environment niche modeling (ENM) to map rainfed inland valleys suitability for rice in Togo and Benin
- We estimated that 155,000-225,000 Ha of inland valleys are suitable for rice production Togo
- Benin has an estimated 351,000-406,000 Ha suitable inland valleys for rice production
- Distance to roads, travel time, climate, available soil water capacity, bulk density among others are important predictors
- ENM is an effective tool for agricultural land use planning

GRAPHICAL ABSTRACT



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ABSTRACT

Inland valleys (IVs) in Africa are important landscapes for rice cultivation and are targeted by national governments to attain self-sufficiency. Yet, there is limited information on the spatial distribution of IVs suitability at the national scale. In the present study, we developed an ensemble model approach to characterize the IVs suitability for rainfed lowland rice using 4 machine learning algorithms based on environmental niche modeling (ENM) with presence-only data and background sample, namely Boosted Regression Tree (BRT), Generalized Linear Model (GLM), Maximum Entropy (MAXNT) and Random Forest (RF). We used a set of predictors that were grouped under climatic variables, agricultural water productivity and soil water content, soil chemical properties, soil physical properties, vegetation cover, and socio-economic variables. The Area Under the Curves (AUC) evaluation metrics for both training and testing were respectively 0.999 and 0.873 for BRT, 0.866 and 0.816 for GLM, 0.948 and 0.861 for MAXENT and 0.911 and 0.878 for RF. Results showed that proximity of inland valleys to roads and urban centers, elevation, soil water holding capacity, bulk density, vegetation index, gross biomass water productivity, precipitation of the wettest quarter, isothermality, annual precipitation, and total phosphorus among others were major predictors of IVs suitability for rainfed lowland rice. Suitable IVs areas were estimated at 155,000–225,000 Ha in Togo and 351,000–406,000 Ha in Benin. We estimated that 53.8% of the suitable IVs area is needed in Togo to attain self-sufficiency in rice while 60.1% of the suitable IVs area is needed in Benin to attain self-sufficiency in rice. These results demonstrated the effectiveness of an ensemble environmental niche modeling approach that combines the strengths of several models.

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1. Introduction

In Africa, rice production has generally increased over the last decade but still covers only 50% of consumers' needs (David-Benz and Lançon, 2007). Thus, rice yield growth alone cannot keep track of growth in consumption, suggesting that rice area expansion will be needed (Van Oort et al., 2015). Spatially detailed and context-specific assessments based on quantitative methods are required to estimate the potential for agricultural land expansion in Africa.

Agricultural land suitability analysis (ALSA) is one of the quantitative tools used to identify the optimal use of available land for crop production. There are different methods used in ALSA that have their specific advantages and disadvantages (Akpoti et al., 2019). The increasing processing power of computers and developments in machine learning algorithms provide new opportunities and such methods are becoming more popular. These methods are well established in ecological niche modeling (Astorga et al., 2018; Freeman et al., 2019; Raghavan et al., 2019; Simões and Peterson, 2018) and agricultural spatial predictive analytic can benefit from such developments (Beck, 2013). Recent advances in environmental niche modeling have focused on novel methods for characterizing the environment that use presence/absence and/or presence-only data and machine-learning algorithms to predict the likelihood of species occurrence (Elith and Leathwick, 2009). Species habitat suitability is mainly evaluated with empirical models also known as environmental or ecological niche-, bioclimatic suitability-, habitat suitability- or species distribution models (Beale and Lennon, 2012). These models are also associated with a number of caveats including potentially biased samples, predictors variables with no biological meaning (Jarnevich et al., 2015). Most of the algorithms are computationally-intensive. Lack of occurrence data and changes in ecological niche parameters are among the major drawbacks (Peterson, 2003). The use of a single algorithm in most cases is also considered as a limitation as different algorithms often provide different results for the same modeling problem (Qiao et al., 2015). Thus, the choice of model selection and parameters specification are important for building a model (Jarnevich et al., 2015).

A recent study in West Africa used Random Forest, a classification tree-based on machine learning method to determine which predictors best explain the presence of rice in inland valleys (Djagba et al., 2018); while Dossou-Yovo et al. (2019) used the same approach to model the determinants of drought in inland valley landscapes. In Colombia and across the Americas, ecological niche modeling based on maximum entropy approach has been used to assess the suitability of land for Hass avocados (Ramírez-Gil et al., 2018; Ramírez-Gil et al., 2019). In Asia, the Random Forest method has been applied to characterize areas currently under paddy cultivation and to predict which other areas are suitable for paddy (Laborte et al., 2012). The maximum entropy method was used to map lowland paddy rice and upland field crop suitability (Heumann et al., 2011). Likewise, Artificial Neural Network has been used for rice suitability mapping in Indonesia (Wang, 1994).

The application of high-performance computing algorithms that can support the modeling of high potential agro-ecological systems such as inland valleys for rice production in Africa is key. Inland valleys are considered as Africa's future food baskets due to their high agricultural potential (Rodenburg et al., 2014). Despite the growing interest in inland valleys rice production in Africa, they are still poorly developed (TNRDS, 2010). In West Africa, most studies focused on the biophysical determinant of the rice yield gap based on statistical analysis and machine learning approaches (Niang et al., 2018; Niang et al., 2017; Tanaka et al., 2017). From pioneering work in the early 90s by Windmeijer and Andriesse (1993) and Andriesse and Fresco (1991) that biophysically characterize the agro-ecological environment of West African inland valleys, a gradual interest is being put on the contribution of the predictors of suitable inland valleys to the choice of agricultural lowland use strategies (Erenstein et al., 2006; Dossou-Yovo et al., 2017). Only few suitability mapping studies have been conducted in West Africa especially for rice production. Therefore, the main objective of the present study is to apply an ensemble environmental niche modeling approach to map land suitability for rice at the national scale in Benin and Togo based on presence-only data in inland valleys. We hypothesized that the current distribution of cultivated inland valleys (IVs) is a “good” indicator of lowland rice ecological requirements.

2. Materials and methods

2.1. Study area description

The present study area corresponds to the national scale of Togo (56,785 km^2) and Benin (114,763 km^2) (see Fig. 1. While Togo encompasses rolling hills including the Chaîne du Togo in the north and southern plateau with low coastal plain and extensive lagoons and marshes, Benin is primarily flat with the exception of the Atakora Mountains rising along the northeastern border of Togo. Togo and Benin exhibit similar climatic conditions with bimodal rainfall pattern in the south and unimodal rainfall regime from the mid-latitudes to the north. According to Diagne et al., 2013, the lowland rice production in Benin and Togo represents 60.8% and 77.6% of both countries' rice cropped areas, respectively.

2.2. Inland valley survey and database

A survey was conducted in Togo and Benin between April and September 2017 to assess inland valleys. These valleys are known in French as *bas-fonds* and are defined as the upper parts of river drainage systems with a complete toposequence from the interfluves to the valley bottom with its seasonally waterlogged depression (Windmeijer and Andriesse, 1993). The data collected includes geolocation, biophysical and socioeconomic characteristics as well as management practices resulting in >50 variables in the dataset. The structure of the dataset and the and variables in the dataset have been previously described by Djagba et al. (2019) and Dossou-Yovo et al. (2018).

The sampling of IVs was based on 3 main steps. Firstly, workshops were held to define the criteria for selecting inland valleys during the surveys. Key considerations for selection were: 1) spatial distribution of the IVs so that not all are located along major roads or near towns, 2) the diversity of land use in IVs with respect to presence or absence of rice and 3) agro-ecological and climatic zones in both countries. These steps were important as niche models are sensitive to both sample size and biases in the distribution of data (Araújo and Guisan, 2006). Secondly, an exploratory phase was conducted to pre-locate the candidates IVs to be surveyed by including leaders and key informants at the village level along with the use of topographic maps and Google Earth. Finally, a survey was conducted with a data collection unit consisting of a specific inland valley area users' group while the location of the surveyed IVs is systematically recorded using handheld Garmin GPS receiver with ± 5 m positional accuracy. The surveys were conducted in 408 and 436 IVs respectively in Togo and Benin. The dataset was complemented with IVs data by Djagba et al. (2019) containing similar information. The database resulted in an occurrence of 1091 IVs.

2.3. Environmental covariates selection

The covariates selection can be based on 3 steps. The first involves the selection from a predefined set of environmental covariates. This step is driven by ecological, biophysical and socio-economic determinants of the crop presence. In the specific context of lowland rice cultivation, predictors were selected based on previous studies and expert knowledge considering both rice species physiology and empirical best fit (Djagba et al., 2018; Niang et al., 2017; Laborte et al., 2012; Heumann et al., 2011; Sys et al., 1993; Sys et al., 1991). A total of 60 covariates were considered and grouped under 6 categories: climatic variables, agricultural water productivity and soil water content variables,

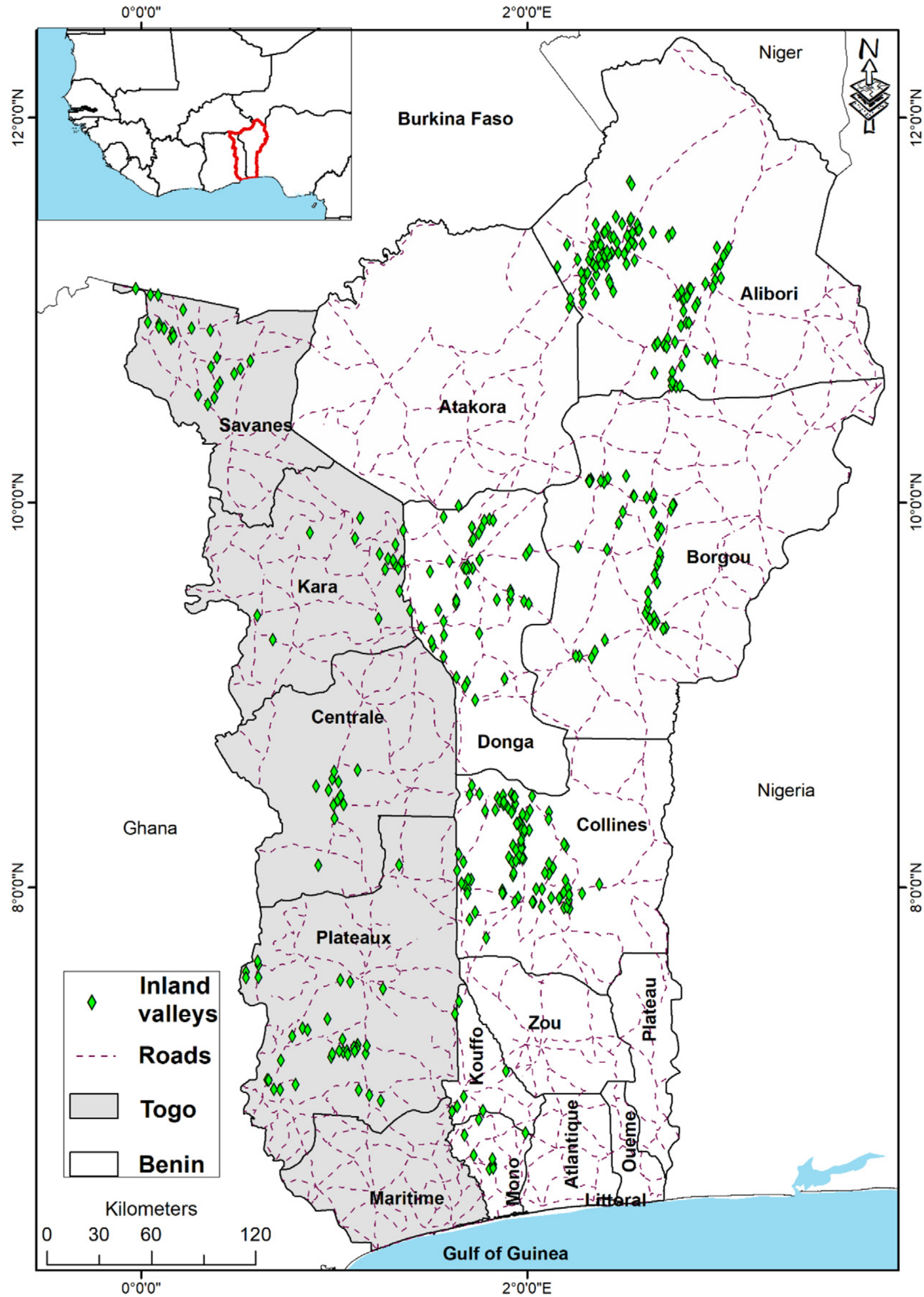

Fig. 1. Study area map showing the locations of the surveyed inland valleys where rice is grown in Togo and Benin.

soil chemical properties variables, soil physical property variables, land use and land cover variables and socio-economic variables (see Table A1 in Appendix 1 for the full list of covariates and Fig. 2 for a display of some selected covariates). Secondly, we used a cut-off threshold of $|r| > 0.75$ to determine and exclude one of any pair of highly correlated variables. Finally, we implemented a stepwise removal of the least contributing variables (Zeng et al., 2016).

We considered 19 bioclimatic variables from the WorldClim version 2 database (Fick and Hijmans, 2017). An average of 9 years of data of agricultural water productivity predictors was obtained from the FAO Water Productivity Open-access portal (WaPOR). Soil water content variables, soil chemical properties as well as some soil physical properties were aggregated from SoilGrids250 m and AfSoilGrids250 m (AfSIS) (Hengl et al., 2015; Hengl et al., 2017a, 2017b) by considering the topsoil layer (0–30 cm) due to the shallow-rooting-type of lowland rice. Also, we included two frequently soil chemical properties predictors used in land suitability analysis such as exchangeable sodium percentage (ESP) and base saturation percentage (BSP) as computed in Eqs. (1) and (2):

$$ESP = \frac{EXNA \times 100}{CEC} \quad (1)$$

$$BSP = \frac{EXB \times 100}{CEC} \quad (2)$$

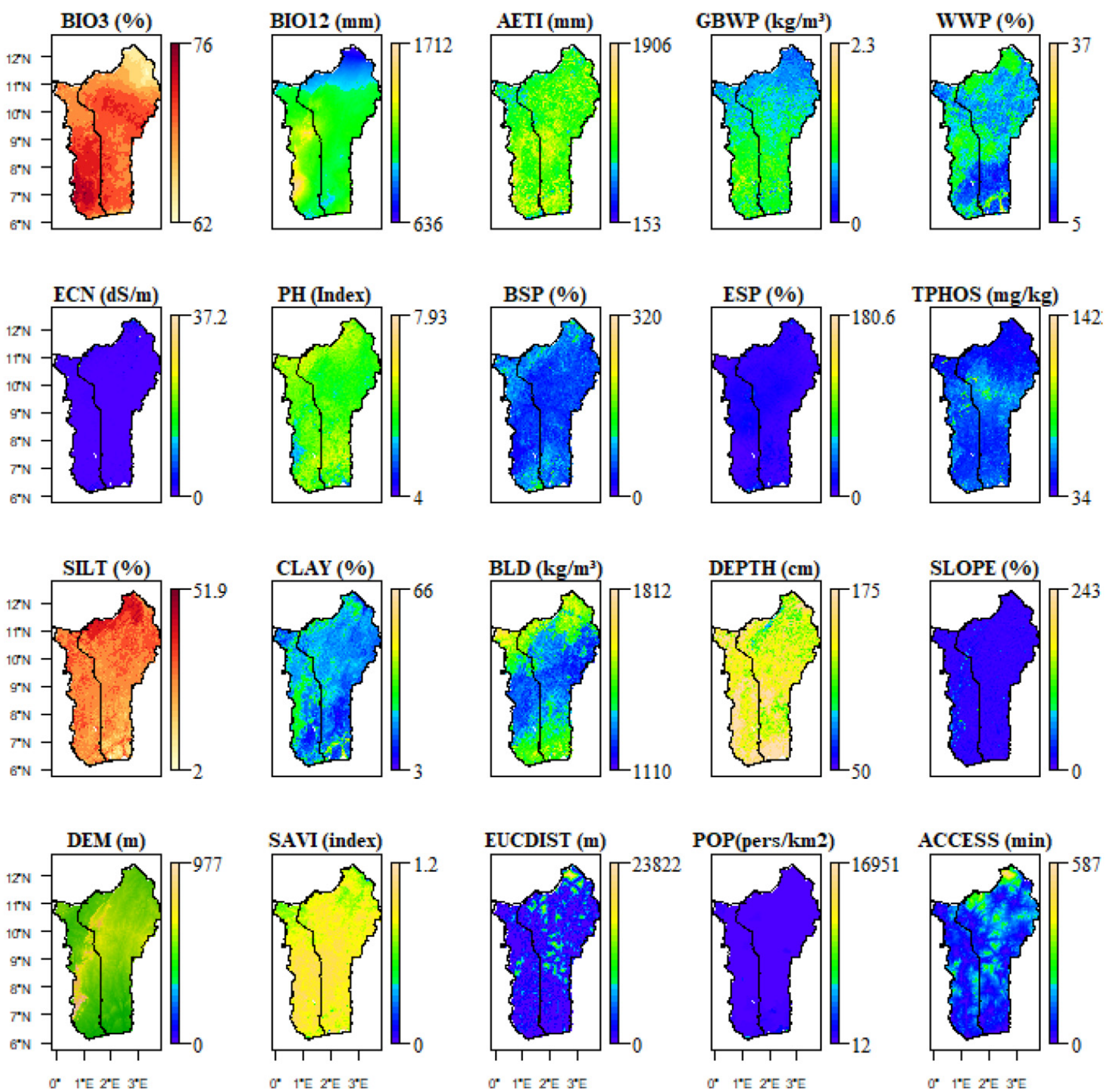

Fig. 2. Example of selected 20 covariates included in the suitability mapping. Isothermality (BIO3), annual precipitation (BIO12), actual evapo-transpiration and interception (AETI), gross biomass water productivity (GBWP), available soil water capacity (volumetric fraction) until wilting point (WWP), electrical conductivity (ECN), Soil pH (PH), base saturation percentage (BSP), exchangeable sodium percentage (ESP), total phosphorus (TPHOS), soil texture fraction silt (SILT), soil texture fraction clay (CLAY), bulk density (BLD), depth to bedrock (DEPTH), slope (SLOPE), elevation (DEM), soil adjusted vegetation index (SAVI), Euclidian distance of road network (EUCDIST), population density (POP), travel time to cities (ACCESS).

where EXNA and EXB and CEC are respectively the soil exchangeable sodium, the total exchangeable bases, and cation exchange capacity. Besides, other parameters of soil physical properties variable were derived from elevation data. A Normalized Difference Flood Index (NDFI) was computed based on Eq. (3), following (Boschetti et al., 2014):

$$NDFI = \frac{(RED - SWIR2)}{(RED + SWIR2)} \tag{3}$$

Where RED band (630–690 nm) and Short-wave-infrared – SWIR2 band (2090–2350 nm) are cloud-free MYD13A1 - MODIS/Aqua Vegetation Indices 16-Day L3 Global 500 m products. A five-year average of data (2013–2017) was downloaded and the index was computed directly using MODIStsp package, a tool for automatic preprocessing of MODIS time series in R (Busetto and Ranghetti, 2017). To represent vegetation dynamics in our model, we considered the Soil-Adjusted Vegetation Index (SAVI) following Eq. (4), computed similarly to the NDFI:

$$SAVI = \frac{(NIR - RED)}{(NIR + RED + 0.5)}(1 + 0.5) \tag{4}$$

where RED (630–690 nm), Near-infrared -NIR (780–900 nm) MODIS products. Recent studies on lowlands diversity and drivers for rice cultivation in West Africa showed the relevance of socio-economic factors (Djagba et al., 2018; Dossou-Yovo et al., 2017). In the present study, we used travel time to the nearest city (accessibility) data from Weiss et al. (2018), Euclidean distance to the nearest road and population density as proxies for socioeconomic factors.

2.4. Suitability modeling development

The environmental niche models (ENMs) link species locations with environmental conditions and then geographically project where the species are likely to be found based on suitable environmental conditions (Beale and Lennon, 2012). For the present study, we develop our IVs suitability models in the Software for Assisted Habitat Modeling (SAHM) package (Morisette et al., 2013). We used SAHM package to fit IVs distribution models using Generalized Linear Model (GLM), Boosted Regression Tree (BRT), Random Forest (RF), and Maximum Entropy (MAXENT) that also compute the related performance metrics. SAHM have been widely used in environmental niche modeling (Jarnevich et al., 2017; West et al., 2016a, 2016b; Hayes et al., 2015; Chang et al., 2014). We followed 6 fundamental steps in our model formulation as shown in Fig. 3. In the first step, we considered covariates and IVs valleys geolocation data as described in Sections 2.2 and 2.3. A temple layer with a pixel size of 90 m in a geographic coordinate system was specified and propagated to the subsequent modeling. The second step consisted of synchronizing all layers by Projection, Aggregation, Resampling and Clipping (PARC) to match the template layer properties. We used the nearest neighbor method for resampling while the mean and majority filter methods were used for aggregation for continuous and categorical covariates, respectively. Also, we used the SAHM background surface generator module to create a surface mask using ad hoc bandwidth selection based on Kernel Density Estimation (KDE) method (Duong, 2007). In addition, 15,000 randomly generated background points were considered in the Merged Data Set (MDS) Builder module. The third step was a preliminary analysis consisting of data splitting. We used 70% of the data for training and 30% for testing. Step 4 consisted of tuning hyperparameters for the individual algorithms as described below.

2.4.1. Generalized Linear Model (GLM)

GLM is a linear regression method adapted to binary data which selects in SAHM covariates by a bidirectional stepwise procedure (Talbert and Talbert, 2012). Thus, a covariate is selected to be included or dropped from the considered set of covariates based on a predefined Akaike Information Criterion (AIC). A likelihood can be increased by adding more parameters but this may result in overfitting. AIC attempts to minimize the overfitting by introducing a penalty term when the number of covariates in the model increases (Cohen, 2006). The overall procedure starts with a null model, then covariates with the best criterion scores are added while also considering the change in criterion when covariates present in the model are dropped; and the modeling ends when no further improvement can be made in AIC (Talbert and Talbert, 2012).

2.4.2. Boosted Regression Tree (BRT)

This is an ensemble forecasting method based on decision trees that partition the parameter space into the most homogeneous subsets in terms of the response (Araújo and New, 2007). The model is in a form of logistic regression that models the probability of an occurrence, $y = 1$, at a location with covariates X, $P\ (y = 1\ |X)$ (Elith et al., 2008). The BRT starts with a single decision tree, then adds a tree that best explains the residual error in the first tree, and so on (Talbert and Talbert, 2012). The complexity of our models varies from 5000 trees to 10,000 trees. We used a simplification method of 10-fold cross-validation with a bag fraction of 0.75.

2.4.3. Random Forest (RF)

Random forests are a collection of tree-structured classifiers of covariates such that each tree depends on the values of independent identically distributed random vectors sampled independently and with the same distribution for all trees in the forest (Breiman, 2011). Each tree casts a unit vote for the most popular class at the input of a given covariate (Breiman, 2011). We used 1000 decision trees to grow the forest with proximity calculated only on out-of-bag (OOB) data. The RF method uses bootstrap aggregation or bagging for sampling the data. Some observations are not used when building the trees and are known as OOB (Cutler et al., 2012). We used 10 as the randomly selected covariates at each node and 5 as a minimal number of observations at the terminal nodes of the trees.

2.4.4. Maximum Entropy (MAXENT)

Maxent is a prediction method that models the distribution that is the most spread out, i.e. closest to uniform while considering the limits of the environmental covariates of the presence data (Phillips et al., 2006). The Maxent model has been widely used for species distribution modeling (e.g. Qin et al., 2017; West et al., 2016a, 2016b; Evangelista et al., 2008) with various discussions on the model methodological decisions and interpretations (Jarnevich et al., 2017; Zeng et al., 2016; Halvorsen et al., 2016). We considered the default setting of Maxent in SAHM except for the number of background point that was set to 15,000 and with a maximum 5000 iterations.

2.5. Evaluation of models' predictions

We use the area under the receiver operating characteristic (ROC) curve (AUC), a standard statistical method widely used to assess the accuracy of species distribution models (Jiménez-valverde, 2012). Spatial predictive models are also often evaluated based on a confusion matrix (Table 1) from which evaluation metrics are derived (Table 2).

2.6. Threshold selection

A defined threshold is needed to convert the continuous probability maps into binary maps that identify suitable and unsuitable inland valleys for rice development. Defining the threshold level is critical as different thresholds can result in a dissimilar estimate of species suitable range (Liu et al., 2005). Thus, the end-use of model outputs should guide in the selection of thresholds (Jarnevich et al., 2015). Various threshold selection methods have been applied in various ecological

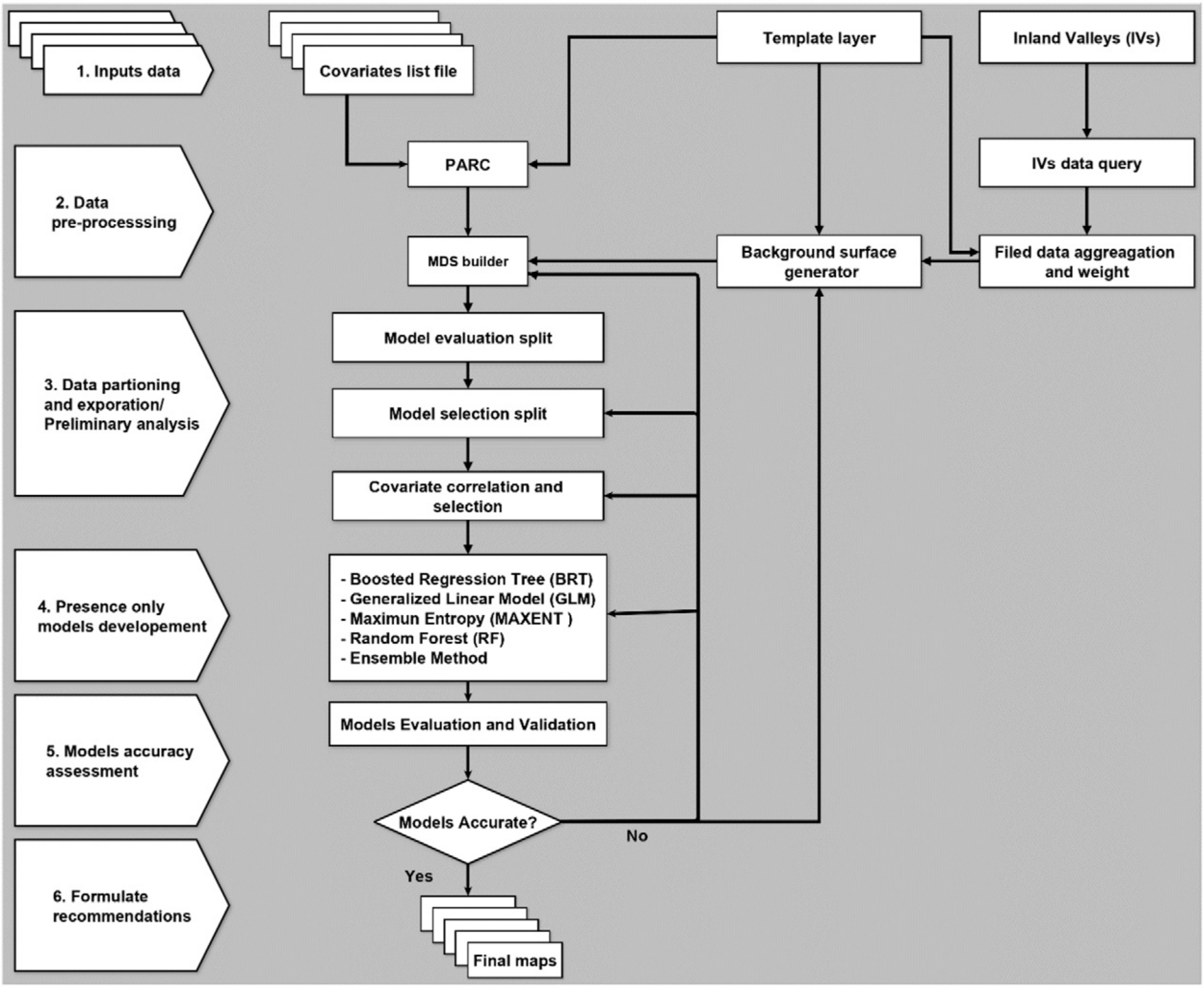

Fig. 3. Flowchart of the inland valleys suitability potential modeling in the Software for Assisted Habitat Modeling (SAHM) package. PARC is a module for Projection, Aggregation, Resampling, and Clipping while MDS is a module for Merging Data Set (MDS). The "Yes" arrow represents the accepted models based on the designed model flow. If results are not satisfactory, the "No" arrows indicate the steps that can be modified to improve model accuracy.

niche modeling (Merow et al., 2013; Cordeiro et al., 2016; García-Callejas and Araújo, 2016). Nine threshold methods were implemented in SAHM: threshold = 0.50, sensitivity = specificity, maximizes (sensitivity + specificity)/2, maximizes Cohen's Kappa, maximizes PCC (percent correctly classified), predicted prevalence = observed prevalence, observed prevalence, mean predicted probability and minimizes distance between ROC plot and (0,1). We tested these nine methods to optimize the modeling. Ultimately, we used the sensitivity = specificity as it a much more commonly used threshold (Dormann et al., 2008; Stohlgren et al., 2010; West et al., 2016a, 2016b). Our approach is based on the test data threshold as it better-discretized predictions in binary data. The approach of sensitivity = specificity based test data was applied before in the studies by Stohlgren et al. (2010).

Table 1
Confusion matrix. a - number of cells for which presence was correctly predicted by the model; b - number of cells for which the species was not found but the model predicted presence; c - number of cells for which the species was found but the model predicted absence; d - number of cells for which absence was correctly predicted by the model. Adapted from Allouche et al. (2006).

		Observed data	
		Presence	Absence
Predicted data	Presence	a (true positive)	b (false positive)
	Absence	c (false negative)	d (true negative)

3. Results

3.1. Models development and evaluation

Based on the correlation matrix (Fig. A1, Appendix 1) and elimination of least contributing covariates, the initial set of 60 variables (Table A1, Appendix 1) was reduced to only 21 bio-physical and 3 socio-economic covariates. The predictive performance across models for both training and testing are reported in Table 3. Results showed that all models performed better than random (AUC > 0.5) with all AUCs >0.8. Also, all models produced PCC > 75%. Models BRT, MAXENT, RF, and GLM showed in that order higher predictive performance for training and validation. However, in term of algorithms showing consistent evaluation metrics between training and testing, RF, and GLM produced better generalizability compared to MAXENT and BRT.

3.2. Covariates importance

Fig. 4 shows the ranking of most important variables by BRT, MAXENT, and RF for the modeling suitability of inland valleys for rice development. Although the rank of each covariate differs from one algorithm to another, there is a consistent prediction of most important covariates across models. These include travel time from IVs to the major cities or accessibility (ACESS), Euclidian distance of IVs to the nearest road (EUCDIST), land elevation (DEM), available soil water capacity (WWP), bulk density (BLD), soil adjusted vegetation index (SAVI),

Table 2
Model evaluation metrics. Overall accuracy: rate of correctly classified cells. Sensitivity: the probability of actual presences predicted. Specificity: probability of actual absences predicted. The kappa statistic and TSS normalize the overall accuracy by the accuracy that might have occurred by chance alone.
Adapted from Allouche et al. (2006).

Evaluation metric	Mathematical formulation	Equation number
Overall accuracy	$(a + d)/n$	5
Sensitivity	$a/(a + c)$	6
Specificity	$d/(b + d)$	7
Kappa statistic	$(\frac{a+d}{n}) - \frac{\frac{(a+b)(a+c)+(c+d)(d+b)}{n^2}}{1-\frac{(a+b)(a+c)+(c+d)(d+b)}{n^2}}$	8
True Skill Statistics	Sensitivity + Specificity − 1	9

n = a + b + c + d.

precipitation of the warmest quarter (BIO18), gross biomass water productivity (GBWP), precipitation of the wettest quarter (BIO16), precipitation seasonality (BIO15), annual precipitation (BIO12) and total phosphorus (TPHOS) as the top 12 most important variables. The jackknife resampling technique applied to the area under the curve (AUC) from the MAXENT model confirmed the importance of the aforementioned variables (Fig. 5). Covariates that have the highest AUC gain when used in isolation are population density (POP) followed by ACCESS. This showed the strong influence of socio-economic drivers on the IVs development for rice production. Also, environmental variables that have the highest AUC gain when used in isolation are SAVI, BLD, WWP, GBWP, and BIO3. These predictors appear to have important information by themselves useful for IVs rice development. Also, the covariates that decreased the AUC gain the most when omitted in the modeling are BIO3, ACCESS, and EUCDIST. In addition to some of the previously mentioned important variables, the GLM also captured exchangeable sodium percentage (ESP), base saturation percentage (BSP), soil texture fraction (SILT) and soil depth to bedrock (DEPTH) as important predictors (Table 4).

3.3. Covariates response curves

Figs. 6 graphically depicted the shape and the magnitude of the covariates across models in which they were captured. The graphs displayed the link between the values of the covariates and the IVs suitability according to the predictions of the four algorithms. We only highlight the shape and direction of the most important predictors in each category of the covariates that includes climate (BIO3, BIO16 and BIO18), agricultural water productivity and soil water content (GBWP and WWP), soil chemical properties (BSP, ESP), soil physical properties (DEM, BLD, DEPTH), vegetation cover (SAVI) and socio-economic variables (ACCESS, EUCDIST and POP).

Climatic covariates indicate that Isothermality (BIO3) has a positive linear response curve with suitability. The results indicate a smaller level of temperature variability within an average month relative to the year. Precipitation of warmest quarter (BIO18) right-skewed bell-shaped response curves as with maximum suitability between 100 and 200 mm. Precipitation of wettest quarter (BIO16) shows the highest suitability between 500 and 900 mm for at least two of the models. Gross biomass water productivity (GBWP) exhibits a sigmoid response curve with the highest values between 1 and 2 kg/m^3. Available soil water capacity (WWP) shows a truncated positively skewed Gaussian response with an optimum value of 10% beyond which suitability decreased. The chemical properties of IVs described a truncated positively skewed Gaussian response for base saturation percentage (BSP) with an optimum value of 50% beyond which suitability decreased. Exchangeable sodium percentage (ESP) describes normal distribution between 0 and 10% with maximum suitability at 5%. Beyond ESP value of 10%, suitability decreases or remains constant except for MAXENT that shows an increasing response curve. Elevation showed a normal distribution between 0 and 500 m with highest suitability corresponding to 350 m. Bulk density showed for most of the model, a trapezoidal shape with the plateau curve corresponding 1300–1800 kg/m^3. Linear to a positive exponential curve represents the gradient of soil depth with high soil depth corresponding to increasing suitability. Results show that SAVI has a negative linear relationship with suitability. Lower SAVI values (<0.6) exhibits higher suitability while SAVI values >0.9 are unsuitable for lowland rice cultivation.

Travel time to the major cities and distance to the nearest road both showed negative exponential distribution, implying that the shorter the travel time and the distance, the economically viable become the IVs for rice production. The travel time of 100 min is the critical value beyond which a given IV becomes economically unsuitable. Similarly, the critical nearest distance to the road is 5 km.

Table 3
Evaluation metrics for both training (70%) and testing (30%) of the data split. The evaluation measures are: Area Under the Curves (AUC), Overall accuracy or Percentage Correctly Classified (PCC), Sensitivity, Specificity, Kappa statistic, True Skill Statistics for the four algorithms.

Evaluation metrics	BRT		GLM		MAXENT		RF	
	Train	Test	Train	Test	Train	Test	Train	Test
AUC	0.999	0.873	0.866	0.816	0.948	0.861	0.911	0.878
PCC	98.6	78.6	78.3	74.1	89.6	77.9	83.4	81.4
Sensitivity	0.980	0.783	0.783	0.747	0.898	0.778	0.833	0.803
Specificity	0.986	0.786	0.783	0.741	0.896	0.780	0.834	0.815
Kappa	0.822	0.153	0.150	0.113	0.340	0.146	0.214	0.184
TSS	0.966	0.569	0.565	0.488	0.794	0.557	0.668	0.618
Threshold	0.930	0.440	0.570	0.510	0.340	0.190	0.530	0.500

3.4. Modeling spatial distributions of IVs suitability and evaluation

Results of the spatial explicit distributions of the suitability of IVs predicted by the four algorithms are shown in Fig. A2 (Appendix 2). Also, the average suitability from the models and habitat suitability scores indicating the number of the four optimized models that classified a given pixel as having suitable conditions for IVs rice cultivation are reported. Results of the spatial distribution of the suitability over the study show some level of variation across models but also consistent predictions of new areas as suitable. The continuous probability maps were converted into binary maps (suitable, unsuitable) based on the threshold method of the probability that the model correctly classifies a suitable area is the same as the probability that the model correctly classifies unsuitable area (Sensitivity = Specificity). The results of the discretization maps are shown in Fig. 7. The coastal zone of both countries shows less suitable IVs for rice productions.

The area coverage of the potentially suitable IVs areas in Benin and Togo are further analyzed in Fig. 8. In Benin, the predicted suitable IVs occupy 351,000–406,000 Ha corresponding to 40.8–47.2% of the total

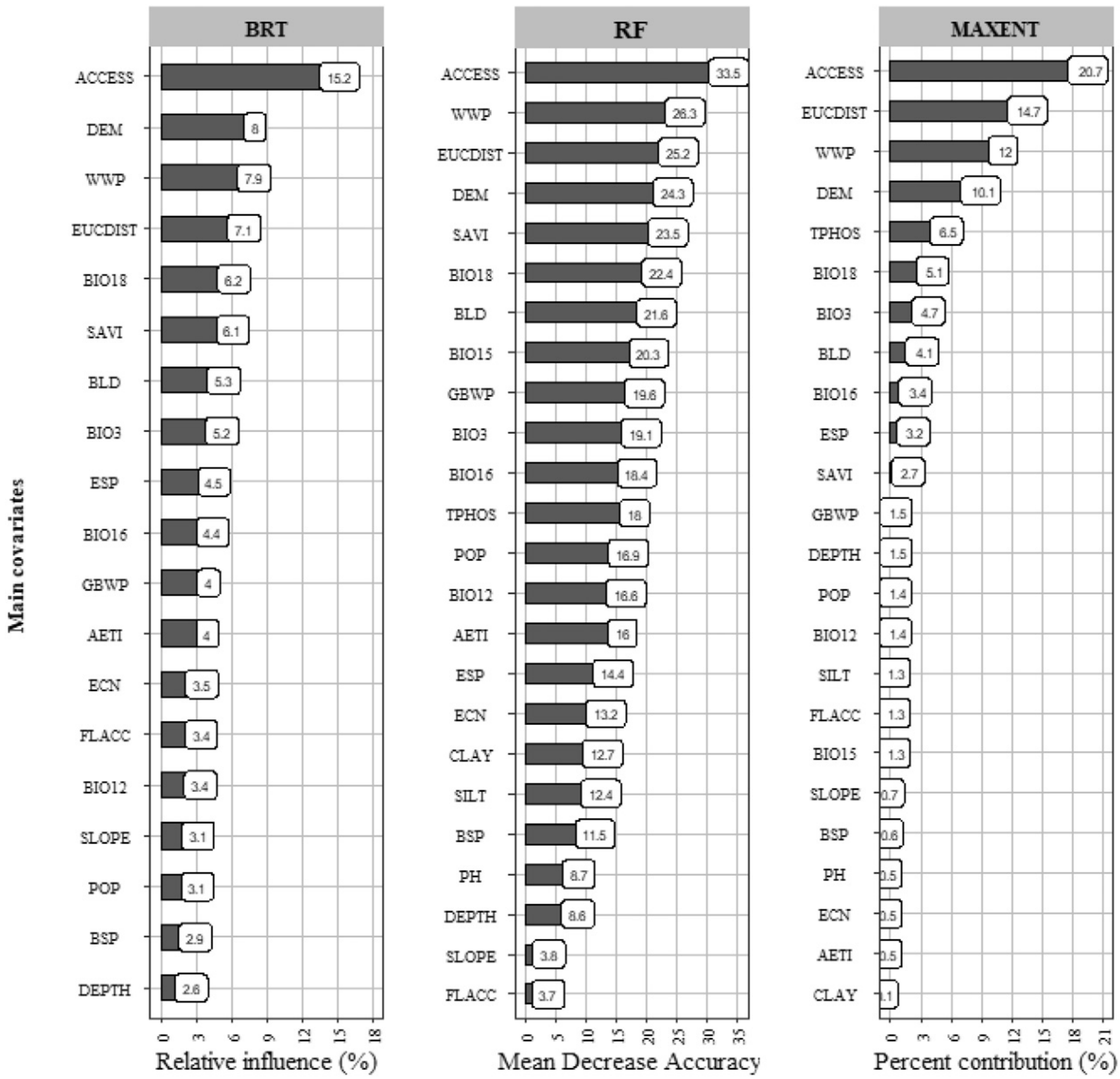

Fig. 4. Covariates importance. Only the ranking among covariates is compared, not the absolutes values because the estimation of the covariates' importance differed across algorithms.

inland valley area in Benin.[1] In Togo, suitable IVs area coverage represents 147,000–225,000 Ha corresponding to 32.6–50% of the total estimated inland valley area in Togo.[2]

Also, we evaluate the prediction of our models with known points distribution of IVs where rice is grown and the delineated IVs at 4 different locations in Togo and Benin (Fig. 9). Results show strong agreement with IVs locations as well as matching between the delineated IVs and our predictions. These results are in support of our initial hypothesis that the current distribution of cultivated inland valleys is a "good" indicator of lowland rice ecological requirements.

4. Discussion

Previous studies focused on the spatial characteristics of croplands at varying scales and for different agro-ecosystems, which included rainfed and irrigated rice systems (Salmon et al., 2015; Samasse et al., 2018; You et al., 2014; Beck, 2013). While these studies advanced our understanding of the factors determining land suitability to rice cultivation, major challenges remain as to the level of uncertainties due to missing data, misregistration, gridding errors, topographical effects, and classifier error (Salmon et al., 2015). In this study, we developed a spatially explicit inland valleys (IVs) suitability mapping approach for rice cultivation in Togo and Benin using four environmental niche models. We assume that the current distribution of the cultivated IVs represents the "best bet" ecology for lowland rain-fed rice cultivation. The result is the spatial distribution and suitability level for lowland rice along with the evaluation of the predictive power of the models considered, the covariates importance and the response curve of rice to the covariates' gradients (see Supplementary material 1 for additional results).

4.1. Covariates selection and model's evaluation

We used the Area Under the Curves (AUC), Percentage Correctly Classified (PCC), Sensitivity, Specificity, Kappa statistic, and True Skill Statistics to evaluate the performance of four models: Boosted Regression Tree (BRT), Generalized Linear Models (GLM), Maximum Entropy (MAXENT) and Random Forest (RF). Consistently, BRT and MAXENT

[1] A total estimated inland valley area in Benin = 860,000Ha according to AfricaRice report.
[2] A total estimated inland valley area in Togo = 450,000 Ha according to AfricaRice report.

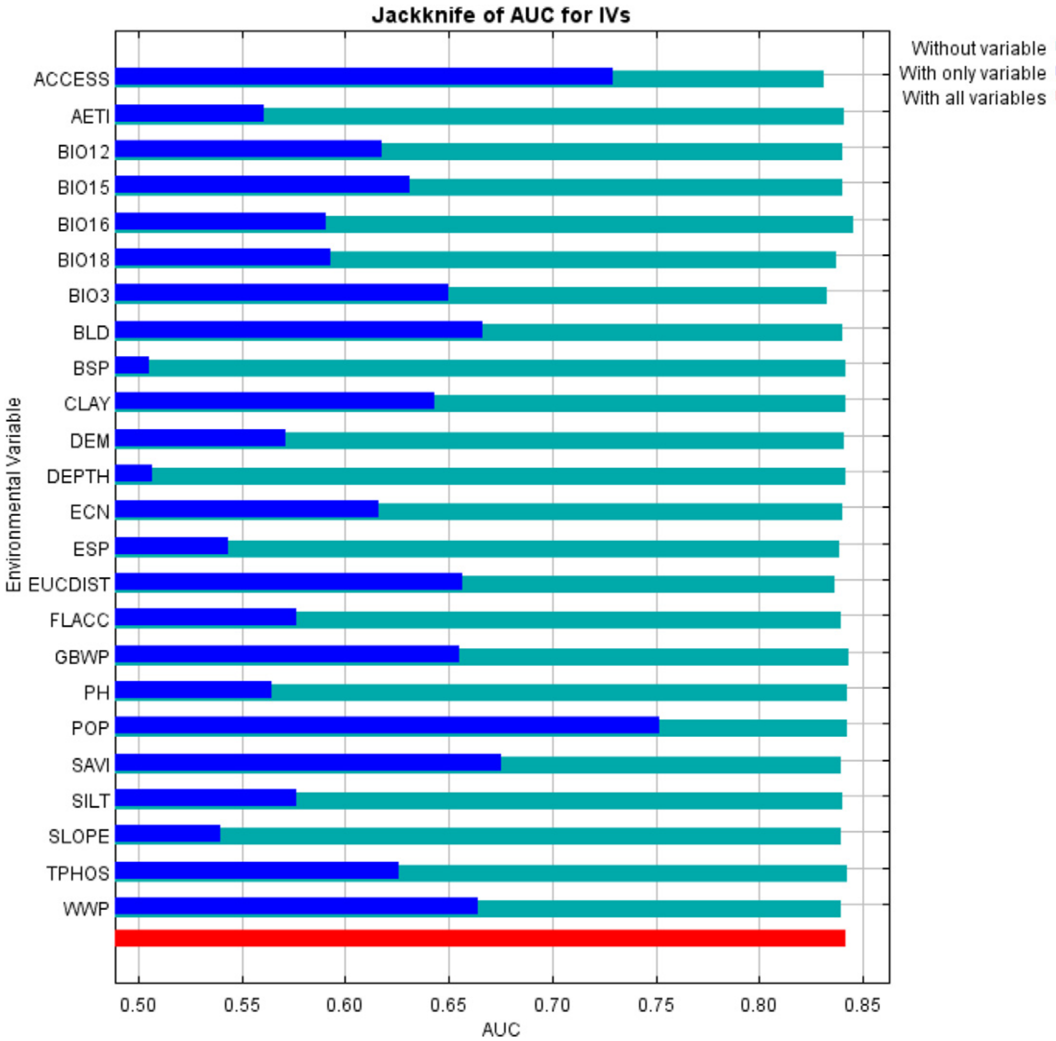

Fig. 5. Jackknife test for AUC of individual covariates importance (blue bars), all the remaining variables (light blue) and all environmental variables (red bar).

and RF were top-performing models while GLM showed lower performance irrespective of the covariates included. Previous studies reported a lower performance of the GLM compared to a machine learning model (Jarnevich et al., 2017). The differences in models' performances are often associated with the model's complexity. The model complexity is related to computation time for fitting models (García-Callejas and Araújo, 2016). Models with longer run time seem to produce higher evaluation metrics. In our case, BRT, RF, MAXENT, and GLM showed in that order higher computation time. Also, the properties of IVs with presence of rice data and their relationship with the environment are strong predictors of model success (García-Callejas and Araújo, 2016). Thus, the covariates involved in the modeling process influence strongly the model performance. In our IVs suitability modeling, the models that included only biophysical factors showed a lower performance compared to the models that included both biophysical and socio-economic factors indicating the importance of combining both biophysical and socio-economic covariates in assessing IVs suitability for rice cultivation. Nevertheless, the success of a predictive model also depends on its ability to produce high evaluation metrics both at training and validation stage, an effect known as model generalizability. Our modeling shows that RF and GLM produced better generalizability compared to MAXENT and BRT. This characteristic makes these models better predictive algorithms for unvisited locations as shown by GLM in a study by Duque-Lazo et al., 2016.

Table 4
GLM model variables importance.

Response ~ ACCESS + ACCESS:EUCDIST + EUCDIST + EUCDIST:BLD + BLD + BLD^2 + BIO15^2 + BIO3^2 + WWP + DEPTH^2 + BSP + GBWP^2

Coefficients:	Estimate	Std. error	z value	Pr(>|z|)	Sign.
Intercept	−60.000	21.400	−2.799	0.005	**
ACCESS	−0.016	0.004	−4.010	0.000	***
ACCESS:EUCDIST	0.000	0.000	−1.836	0.066	.
EUCDIST	−0.005	0.002	−2.808	0.005	**
EUCDIST:BLD	0.000	0.000	2.822	0.005	**
BLD	0.057	0.028	2.023	0.043	*
BLD^2	0.000	0.000	−1.900	0.057	.
BIO15^2	0.001	0.000	5.969	0.000	***
BIO3^2	0.004	0.001	4.434	0.000	***
WWP	−0.241	0.061	−3.956	0.000	***
DEPTH^2	0.000	0.000	2.747	0.006	**
BSP	−0.031	0.011	−2.909	0.004	**
GBWP^2	1.380	0.553	2.496	0.013	*

Signifiance codes : 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.

4.2. Covariates importance and response curves

Rice-growing environments in Africa are highly diverse (Saito et al., 2013; Diagne et al., 2013); even within the same ecology like IVs as shown in recent studies in West Africa (Djagba et al., 2018; Dossou-Yovo et al., 2017). Thus, the challenges to area expansion and

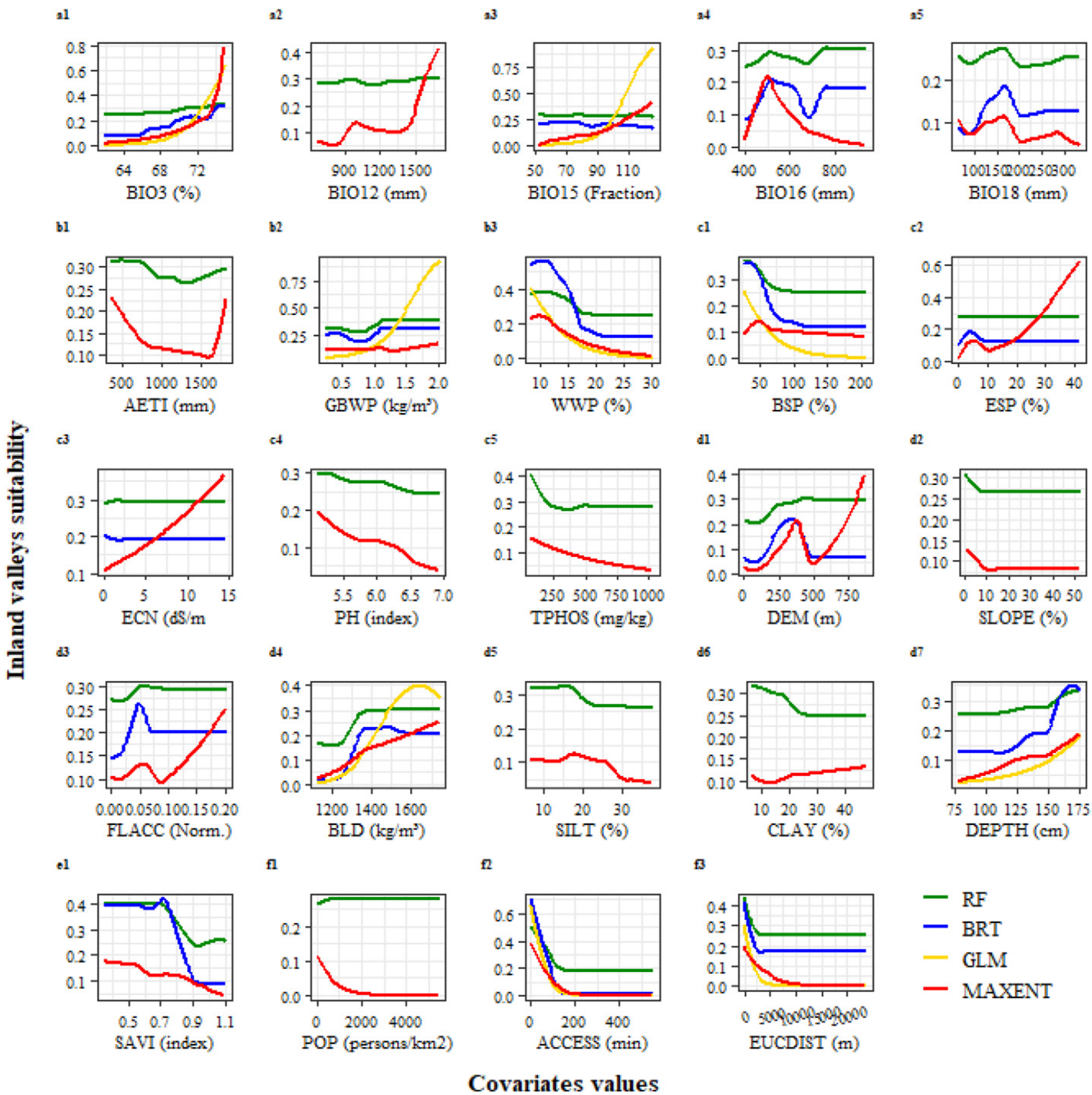

Fig. 6. The response curve of the covariates. The covariates represent the reduced set in the final models for each modeling algorithm such as BRT, GLM, MAXENT, and RF. The x-axis represents the covariates observed values in the complete training dataset while the y-axis shows the corresponding suitability rank with 0 as not suitable and 1 for maximum suitability. Covariates in the final models are represented by figure a1–a5 for climatic variables, b1–b3 for the agricultural water productivity and soil water content variables, c1–c5 for the soil chemical properties variables, d1–d7 for soil physical properties, and e1 vegetation index and f1–f3 for socio-economic variables. The abbreviation Norm. corresponds to the normalization of the covariate using the fuzzy linear method.

intensification widely vary by ecology (Niang et al., 2017) with opportunities for increasing rice production depending, to a large extent, on biophysical and socio-economic environments. In our spatially explicit characterization of the biophysical and socio-economic suitability of IVs ecology for rice production, 25 covariates were considered in the final model setting.

The IVs suitability for rice production in West Africa largely depends on the interaction between biophysical factors including climate, soil types and, hydrology (Niang et al., 2017; Tanaka et al., 2017). Rainfed ecosystems represent 70% of the rice production area in Africa while rainfed lowlands account for 38%. As such, climatic conditions play a vital role and influence other biophysical factors such as hydrology and soil conditions (Touré et al., 2009; Tsubo et al., 2006). Considering the climatic covariates, the prediction of our models for annual precipitation (BIO12) as (Unsuitable <1000 mm; Marginally suitable—1000–1250 mm; moderately suitable—1250–1500 mm; highly suitable—1500–1750 mm) agreed on overall with the Sys et al. (1991, 1993) suitability ranges (Unsuitable <900 mm; Marginally suitable—950–1100 mm; moderately suitable—1200–1400 mm; highly suitable >1400) for rainfed lowland rice. The temperature parameter is indirectly incorporated in the modeling through the Isothermality predictor (BIO3) that is computed based on the minimum and maximum

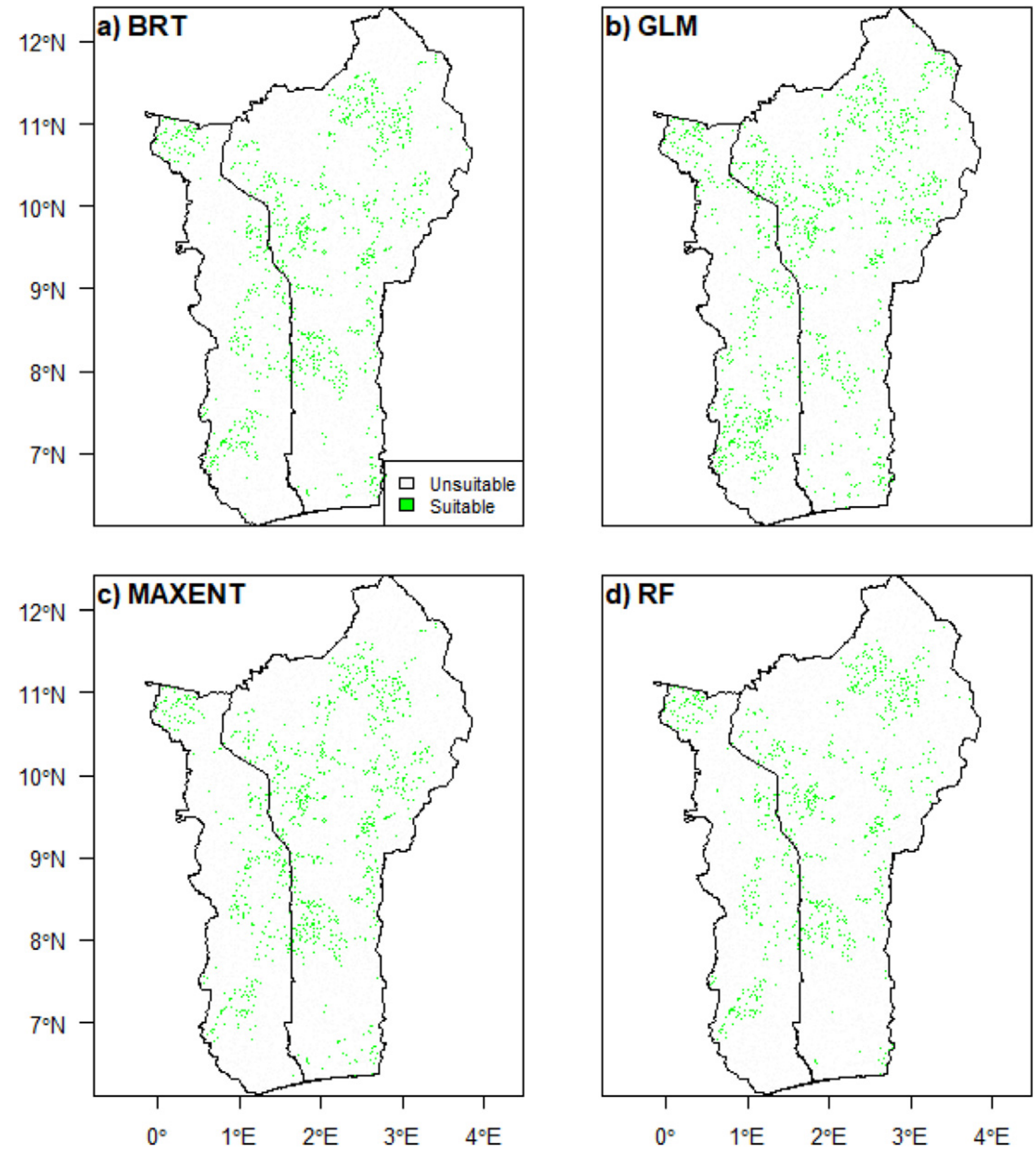

Fig. 7. Binary maps showing predicted suitability of inland valleys for rice production. The binary maps are discretization from the continuous probability maps based on the threshold optimization method (sensitivity = specificity). The thresholds are 0.44, 0.51, 0.19 and 0.50 respectively for BRT, GLM, MAXENT, and RF.

temperatures. IVs suitability increased with isothermally in the study area with a maximum value of 75%. This indicates a smaller level of variability in annual temperature in the study region, but a large variability between the daytime and nighttime temperature that affects inland valley rice cultivation (Dingkuhn et al., 2015). The Isothermality covariate was constantly selected as one of the main predictors for both biophysical and socio-economic models. The precipitation of the warmest quarter (BIO 18) and the precipitation of wettest quarter (BIO16) were among important predictors in most cases. However, the optimum values for BIO18 (100–200 mm) were lower compared to the optimum values for BIO16 (500–900 mm) because rainfed rice, as opposed to irrigated rice, is not cultivated during the warmest quarter.

In the case of rain-fed lowland rice production ecology, studies showed that the toposequence effects on hydrological variability can lead to differences in yield (Touré et al., 2009; Tsubo et al., 2006). Also, local topographical variations are shown to be a greater determinant of drought risk in rainfed lowlands than soil variations (van Oort, 2018; Dossou-Yovo et al., 2018). In the present study, elevation was constantly among the main predictors for all models increasing suitability up to an optimum value of 350 m. This could be explained by a reduced flooding risk with an increase in elevation. But since both studied countries exhibit a decrease in rainfall and an increase in elevation patterns following the gradient south-north, regions located above the elevation 350 m presented marginal climatic conditions for rice cultivation. Conversely, the slope was not important predictors across models with decrease suitability to slope value of 10%. Beyond this value, suitability remains marginal or present unsuitable condition for rice cultivation. A similar study on lowland suitability in Laos using RF showed similar response curve for slope with values <5% representing higher suitability (Laborte et al., 2012). The difference in the threshold could be explained by the overall difference in topography as Laos is hilly and mountainous while Togo and Benin are relatively flat. Therefore, a lower value of slope in Benin and Togo could be similar to higher flooding risk. The flow accumulation covariate, a cumulative count of

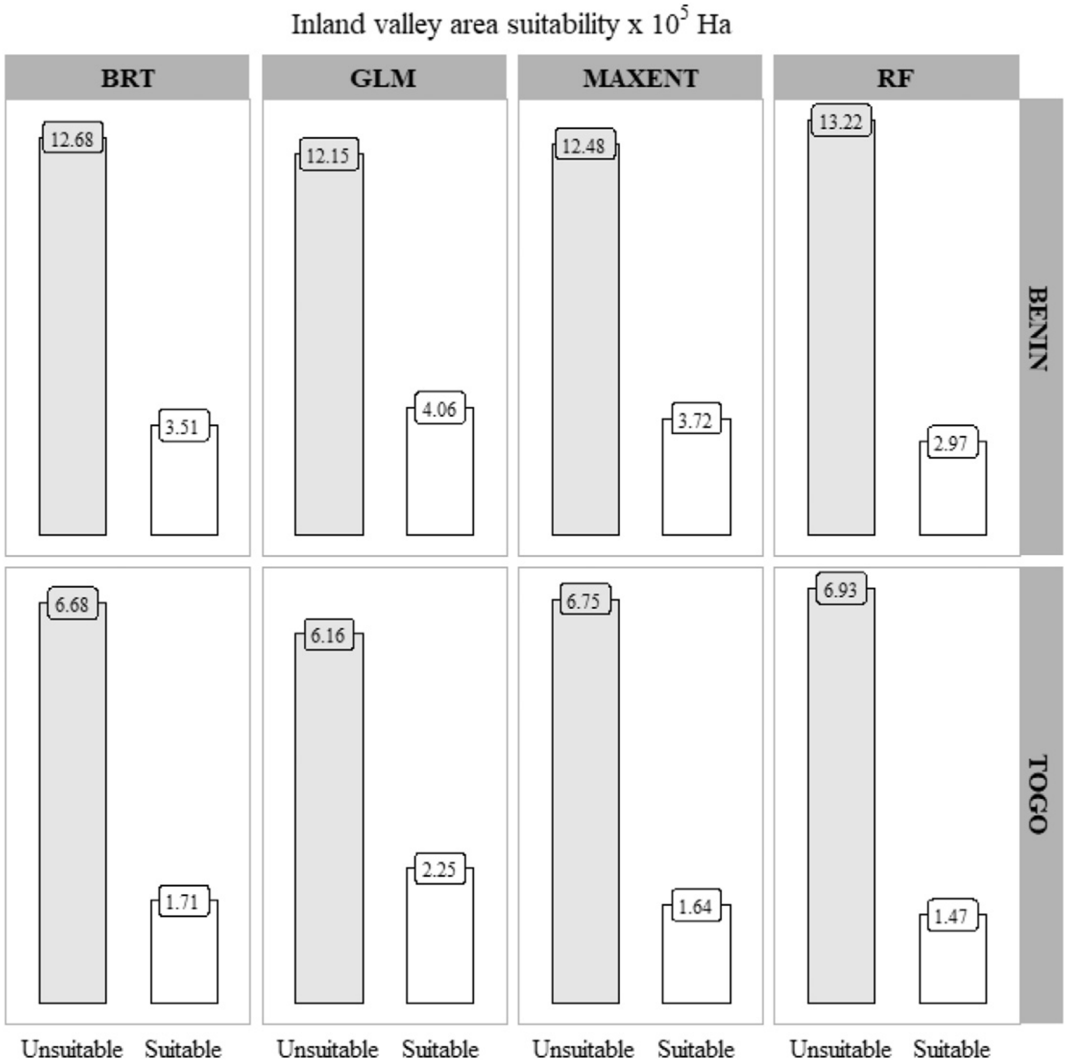

Fig. 8. Area coverage of the suitability classes for Benin and Togo as predicted by each model.

the number of pixels that naturally drain into outlets, obviously showed increased suitability with higher values with similar results by Laborte et al. (2012).

The use of socio-economic covariates provided the means to include in our modeling the market opportunities for IVs rice production. The importance of the accessibility captured by the travel time to urban centers (ACESS), the Euclidian distance to the road network (EUCDIST). The suitability of IVs decreased exponentially with longer travel time with critical values varying between 100 and 200 min beyond which the IVs becomes unsuitable. Similarly, the suitability showed an exponential decrease with EUCDIST with a critical range of 1.25 to 5 km. Similar response curves were found for covariates related to distance by Laborte et al. (2012). A study on the drivers of household food availability in sub-Saharan Africa suggested that targeting poverty through improving market access is a better strategy to increase food security (Frelat et al., 2016) in the contest of crop production. Albeit the importance of these socio-economic predictors for IVs suitability, a study showed that geography cannot explain, on its own, the agricultural use of IVs ecology (Dossou-Yovo et al., 2017). As discussed in the latter study, about 40% of the inland valleys abandoned by farmers were located in relatively high population-density areas close to the main road and to the market. Meanwhile, biogeography elements including soil fertility status, hydrological regimes among others are strong players in the agricultural land use of the IVs.

4.3. IVs spatially explicit distribution and its implications for Togo and Benin rice self-sufficiency

While most African countries are far from being self-sufficient in their rice consumption, area expansion will play a major part in filling that gap (Van Oort et al., 2015). There is an estimated 450,000 Ha of IV in Togo while Benin has 860,000 Ha of IV. Our modeling resulted in 155,000–225,000 Ha suitable IV in Togo; corresponding to 34.4–50.0% of the total IV area. Using rice area, production and yield data from FAO statistics (FAO STAT, 2017) on the various rice ecology in combination with 2016 rice consumption data in Togo, we estimated that 53.8% of the suitable IV area (121,133 Ha) is needed to attain self-sufficiency in rice (see Supplementary material 2). Thus, the remaining 103,866.6 Ha can be safeguarded for other purposes. Alike Togo, Benin suitable IV represents 351,000–406,000 Ha corresponding to 40.8–47.2% of the total inland valley area. We estimated that 60.1% of the Benin suitable IV area (244,149 Ha) is needed to attain self-sufficiency in rice while 161,850 can be used for other purposes.

With the commitment of Togo and Benin to double their domestic rice production (BNRDS, 2011; TNRDS, 2010), it appears that at least 50% of the highly suitable areas in both countries could be used to attain this objective while the remaining can be safeguarded for other ecological services. A study showed that with improved water and weed management, Africa could be self-sufficient in rice with <10% of the total inland valley area (Rodenburg et al., 2014).

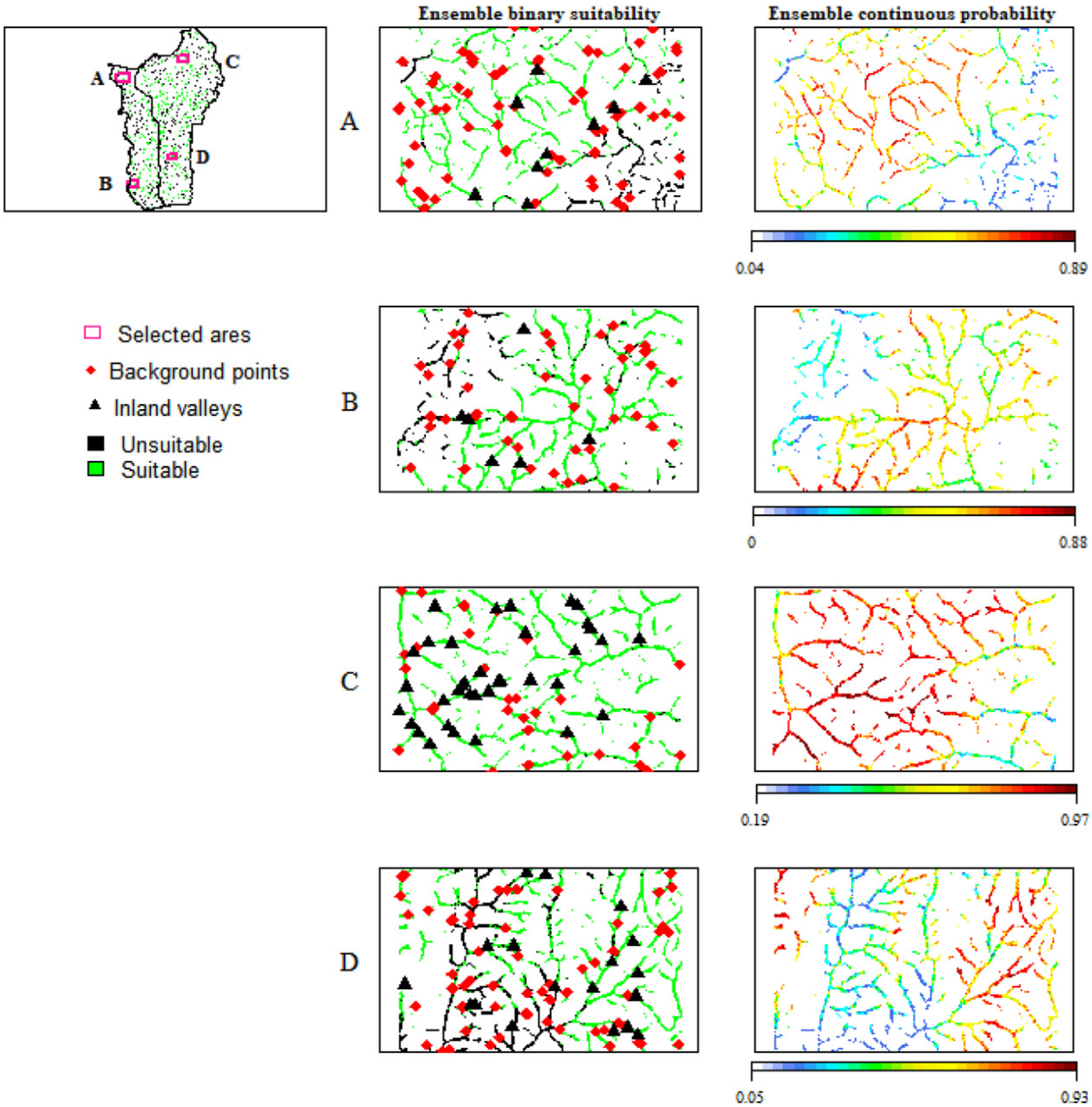

Fig. 9. Predicted ensemble binary suitability of IVs rice shown in the left window and a zoom on 4 selected areas: two in Togo (A, B) and in Benin (C, D) at a finer scale - 1:215,781 for which we showed binary suitability and continuous probability maps.

5. Special use of ENM in agriculture and uncertainties

Some discussions on the use of Environmental Niche Models (ENMs) in agriculture tend to compare correlative species distribution and mechanistic models and in some cases the combination of both (Estes et al., 2013; Nabout et al., 2012). Most of these studies showed that mechanistic models often require more time, effort, resources and data to construct and validate (Kearney and Porter, 2009) compared to correlative models. Nabout et al., 2012 and Estes et al., 2013 showed that correlative models can produce the same or better accuracy as mechanistic models for predicting both crop suitability and productivity. Correlative species distribution models as used in the present work relate known geographical locations of species (e.g. here inland valley rice) with environmental predictors to estimate suitability gradient (Peterson, 2006). However, Elith and Leathwick, 2009 described 4 issues in the use of these models related to ENM theory: 1) non-environmental factors that may impact occurrence data, (2) the assumption of niche conservatism, (3) the interaction with other species, and (4) the environmental migration of species to adapt to environmental changes. In the context of crop suitability mapping, these uncertainties may be introduced by the rate of adoption of novel techniques and the introduction of new crop varieties in crop production systems, the economic activities, and trade that influence crop production (Beck, 2013). Therefore, high demand for rice commodities in West Africa coupled with technological adoption and introduction of new rice varieties may influence where rice is planted and thus introduce uncertainties in rainfed rice correlative suitability mapping. Thus, the effort to introduce new spatial explicit predictors data related technological adoptions, new varieties could significantly improve the correlative models' predictive power.

Although our modeling exercise was complex in terms of covariates choice, models parameter tuning in order to get the best results possible, our results are not beyond criticism. Such caveats are related to known limitations of ecological niche modeling (Jarnevich et al., 2015; Beale and Lennon, 2012; Araújo and Guisan, 2006) including but not limited to incomplete and potentially biased sampling, the quality of predictors used as well as missing of potential important predictors. This study made use of 1091 geo-located IVs of which 818 were with the presence of rice, it is not clear whether this sampling is complete enough to be representative of all environmental gradient present in the study area especially those related to soil properties. Thus we are in support of the fact that these results should be treated as a hypothesis to be tested and validated with additional sampling and modeling (Jarnevich et al., 2015). The soils related covariates used are themselves model prediction with subsequent related limitations including undersampled locations in Africa (Hengl et al., 2017a, 2017b; Hengl et al., 2015) and is certainly reflected in our modeling results. As an example, the initial models' results showed that total nitrogen (TNO) was one of the top predictors but resulted in decreasing suitability with increasing values of NTO. The result showed the opposite of what was expected, and the variable was further removed from the final model setting. However, these datasets are the best available owing to the lack of national spatially-explicit soil data. Other important predictors of IVs used for rice production such as presence of rice mill, percentage of female farmers in the inland valley (Justin Fagnombo Djagba et al., 2018) as well as ethnicity and land tenure status as noted by Laborte et al. (2012) are missing in our model.

6. Conclusions and outlook

This study is the first step toward a detailed spatially explicit understanding of the rainfed lowland rice system in West Africa. Differences in the models' predictions suggest that the multi-model approach and consensus modeling is the best way to increase confidence in the results. Our modeling showed that BRT and MAXENT produced higher evaluation metrics compared to RF and GLM. Topographical variables, climate covariates as well as soil water content parameter are major predictors' suitable inland valley condition for rainfed rice cultivation. Also, our results showed that proximity of inland valleys to roads and urban centers provide an additional suitable condition for rice production. This study shows that Togo and Benin have enough IVs suitable to meet their domestic rice production. The study provides an important insight into the spatially explicit potentials of IVs of both countries, but only represent the first stage of a more complex evaluation. A local and participatory approach to assess the detailed feasibility to implement rice production in currently uncultivated areas would be required. Future research should also consider the specificity of rice varieties and technological advancements in rice suitability modeling. Besides, the suitability of the IVs ecology for rainfed rice under climate change scenarios needs to be further explored.

Declaration of competing interest

The authors declare that there is no conflict of interest.

Acknowledgments

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Appendix 1. Covariates data

Table A1
Covariates considered in the IVs suitability models including the covariate name, covariates definition, steps taken to create the covariates and/or the source of the original data, the spatial native resolution, and unit, the covariate inclusion in the final models.

No	Covariate name	Covariate definition	Creation step/source	Native spatial resolution/unit	Included (yes/no)
Climatic variables					
1	BIO1	Annual mean temperature	www.worldclim.org	1 km (°C)	No
2	BIO2	Annual mean diurnal range	www.worldclim.org	1 km (°C)	No
3	BIO3	Isothermality	www.worldclim.org	1 km (%)	Yes
4	BIO4	Temperature seasonality	www.worldclim.org	1 km (°C)	No
5	BIO5	Maximum temperature of warmest month	www.worldclim.org	1 km (°C)	No
6	BIO6	Minimum temperature of the coldest month	www.worldclim.org	1 km (°C)	No
7	BIO7	Annual temperature range	www.worldclim.org	1 km (°C)	No
8	BIO8	Mean temperature of wettest quarter	www.worldclim.org	1 km (°C)	No
9	BIO9	Mean temperature of driest quarter	www.worldclim.org	1 km (°C)	No
10	BIO10	Mean temperature of warmest quarter	www.worldclim.org	1 km (°C)	No
11	BIO11	Mean temperature of coldest quarter	www.worldclim.org	1 km (°C)	No
12	BIO12	Annual precipitation	www.worldclim.org	1 km (mm)	Yes
13	BIO13	Precipitation of wettest month	www.worldclim.org	1 km (mm)	No
14	BIO14	Precipitation of driest month	www.worldclim.org	1 km (mm)	No
15	BIO15	Precipitation seasonality	www.worldclim.org	1 km (%)	Yes
16	BIO16	Precipitation of wettest quarter	www.worldclim.org	1 km (mm)	Yes
17	BIO17	Precipitation of driest quarter	www.worldclim.org	1 km (mm)	No
18	BIO18	Precipitation of warmest quarter	www.worldclim.org	1 km (mm)	Yes
19	BIO19	Precipitation of coldest quarter	www.worldclim.org	1 km (mm)	No
Agricultural water productivity and soil water content variables					
20	AETI	Actual evapo-transpiration and interception	https://wapor.apps.fao.org/home/1	250 m (mm)	Yes
21	GBWP	Gross biomass Water productivity	https://wapor.apps.fao.org/home/1	250 m (kg/m^3)	Yes
22	NBWP	Net biomass water productivity	https://wapor.apps.fao.org/home/1	250 m (kg/m^3)	No
23	AWCH	Available soil water capacity	AfSoilGrids250m	250 m (%)	No
24	AWCTS	Saturated water content (porosity)	SoilGrids250m	250 m (%)	No
25	WWP	Available soil water capacity (volumetric fraction) until wilting point	SoilGrids250m	250 m (%)	Yes
26	NDFI	Normalized difference flood index	Derived from MODIS data using MODIStsp	500 m (index)	No
Soil chemical property variables					

Table A1 (*continued*)

No	Covariate name	Covariate definition	Creation step/source	Native spatial resolution/unit	Included (yes/no)
27	CEC	Cation exchange capacity	AfSoilGrids250 m	250 m (cmol/kg)	No
28	ECN	Electrical conductivity	AfSoilGrids250 m	250 m (dS/m)	Yes
29	EXB	Exchangeable bases total	AfSoilGrids250 m	250 m (cmol/kg)	No
30	EXK	Exchangeable K	AfSoilGrids250 m	250 m (cmol/kg)	No
31	EXNA	Exchangeable Na	AfSoilGrids250m	250 m ()	No
32	NTO	Total nitrogen	AfSoilGrids250 m	250 m (g/kg)	No
33	ORC	Soil organic carbon content	AfSoilGrids250 m	250 m (g/kg)	No
34	PH	Soil pH in water	AfSoilGrids250m	250 m (index)	Yes
35	BSP	Base saturation percentage	Computed in ArcGIS	250 m (%)	Yes
36	ESP	Exchangeable sodium percentage	Computed in ArcGIS	250 m (%)	Yes
37	CFV	Coarse fragments volumetric	AfSoilGrids250 m	250 m (%)	No
38	TPHOS	Total phosphorus	AfSoilGrids250 m	250 (mg/kg)	Yes
Soil physical property variables					
39	SAND	Soil texture fraction sand	AfSoilGrids250 m	250 m (%)	No
40	SILT	Soil texture fraction silt	AfSoilGrids250 m	250 m (%)	Yes
41	CLAY	Soil texture fraction clay	AfSoilGrids250 m	250 m (%)	Yes
42	TEXT	Texture	AfSoilGrids250 m	250 m (factor)	No
43	BLD	Bulk density	AfSoilGrids250 m	250 m (kg/m^3)	Yes
44	DRAIN	Drainage	AfSoilGrids250 m	250 m (factor)	No
45	DEPTH	Depth to bedrock	AfSoilGrids250 m	250 m (cm)	Yes
46	DEM	Elevation	https://earthexplorer.usgs.gov/	30 m (m)	Yes
47	FACC	Flow accumulation	Derived in SAGA	30 m (factor)	Yes
48	SLOPE	Slope	Derived in SAGA	30 m (%)	Yes
49	ASPECT	Aspect	Derived in SAGA	30 m (radians)	No
50	TWI	Topographic wetness index	Derived in SAGA	30 m (index)	No
51	SPI	Stream power index	Derived in SAGA	30 m (index)	No
52	TRI	Terrain ruggedness index	Derived in SAGA	30 m (index)	No
53	TPI	Topographic position index	Derived in SAGA	30 m (index)	No
54	MRVBF	Multiresolution index of valley bottom flatness	Derived in SAGA	30 m (index)	No
55	MRRTF	Multi-resolution ridge top flatness	Derived in SAGA	30 m (index)	No
Land use and Land cover variables					
56	LULC	Land use land cover	http://2016africalandcover20m.esrin.esa.int/	20 m (factor)	No
57	SAVI	Soil adjusted vegetation index	Derived from MODIS data using MODIStsp	(500 m) (index)	Yes
Socio-economic variables					
58	POP	Population density	CIESIN, 2018	1 km (persons/km2)	Yes
59	ACCESS	Travel time to cities or accessibility	Weiss et al., 2018	1 km (min)	Yes
60	EUCDIST	Euclidian distance of road network	Derived in ArcGIS	2 km (m)	Yes

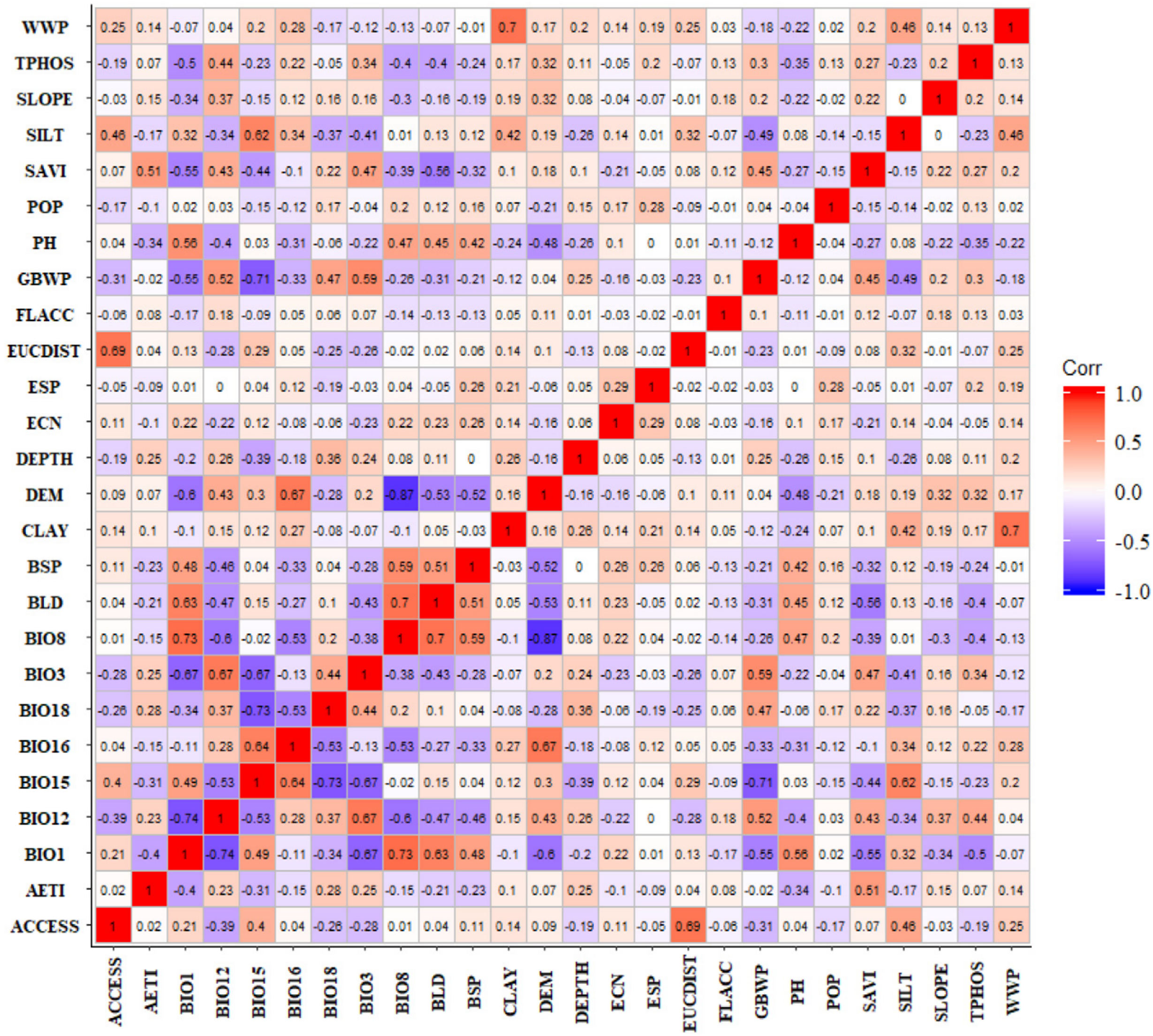

Fig. A1. Paired correlation between 26 selected covariates.

Appendix 2. Predicted suitability maps

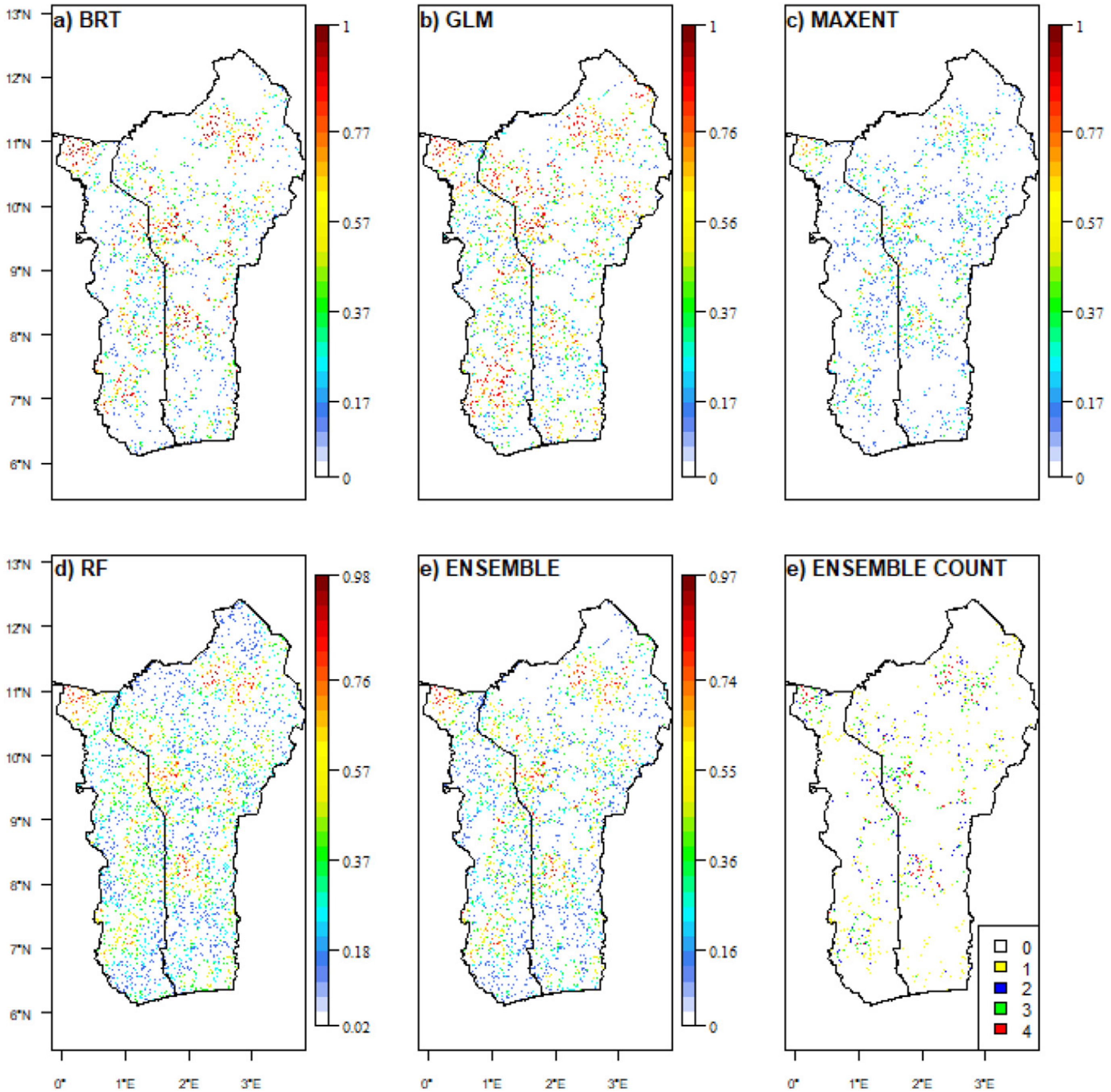

Fig. A2. Predicted suitability maps (a–d) of the four environmental niche models. Panel e showcases the ensemble suitability of the four models while panel f displays the consensus habitat suitability scores indicating the number of the four optimized models that classified a given pixel as having suitable conditions for IVs rice cultivation.

Appendix 3. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2019.136165.

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