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The potential for expansion of irrigated rice under alternate wetting and drying in Burkina Faso

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- The potential for irrigated rice in Burkina Faso was estimated at 21.10 x 10^5 ha
- All dekads in the dry season are suitable for Alternate Wetting and Drying (AWD)
- About 25 to 100% of wet season dekads are suitable for AWD
- Soil percolation was the main driver of land suitability to AWD in the wet season

Abstract

Achieving rice self-sufficiency in West Africa will require an expansion of the irrigated rice area under water-scarce conditions. However, little is known about how much area can be irrigated and where and when water-saving practices could be used. The objective of this study was to assess potentially irrigable lands for irrigated rice cultivation under water-saving technology in Burkina Faso. A two-step, spatially explicit approach was developed and implemented. Firstly, machine learning models, namely Random Forest (RF) and Maximum Entropy (MaxEnt) were deployed in ecological niche modeling (ENM) approach to assess the land suitability for irrigated rice cultivation. Spatial datasets on topography, soil characteristics, climate parameters, land use, and water were used along with the current distribution of irrigated rice locations in Burkina Faso to drive ENMs. Secondly, the climatic suitability for alternate wetting and drying (AWD), an irrigation management method for saving water in rice cultivation in irrigated systems, was assessed by using a simple water balance model for the two main growing seasons (February to June and July to November) on a dekadal time scale. The evaluation metrics of the ENMs such as the area under the curve and percentage correctly classified showed values higher than 80% for both RF and MaxEnt. The top four predictors of land suitability for irrigated rice cultivation were exchangeable sodium percentage, exchangeable potassium, depth to the groundwater table, and distance to stream networks and rivers. Potentially suitable lands for rice cultivation in Burkina Faso were estimated at 21.1 x 10^5 ha. The whole dry season was found suitable for AWD implementation against 25–100% of the wet season. Soil percolation was the main driver of the variation in irrigated land suitability for AWD in the wet season. The integrated modeling and water balance assessment approach used in this study can be applied to other West African countries to guide investment in irrigated rice area expansion while adapting to climate change.

Keywords: Alternate wetting and drying, climatic suitability, ecological niche modeling, predictors, water balance

1. Introduction

Rice consumption has steadily increased in Sub-Saharan Africa while domestic rice production hardly meets the demand. In Burkina Faso for example, the national rice self-sufficiency ratio was 30% between 2008-2018 (Africa Rice Center, 2018). Nonetheless, Burkina Faso's National Rice Development Strategy (NRDS) emphasizes intensification and expansion of irrigated rice production systems to achieve rice self-sufficiency (BFNRDS, 2011). There is potential for enhancing rice production through increasing rice yield on existing land (intensification), improving rainfed lowland rice areas, and expanding areas under irrigation through diffusion and adoption of technologies (Seck et al., 2010). Among the five rice cropping systems in West Africa, i.e. rainfed upland, rainfed lowlands, irrigated lowlands, deepwater and mangrove swamps (Balasubramanian et al., 2007), the irrigated rice systems hold a promising future for several reasons: firstly, the average rice yield in irrigated lowland of 3.8 t/ha is higher than yields in rainfed lowland (2.6 t/ha), and rainfed upland (1.7 t/ha) (Dossou-Yovo et al., 2020). Secondly, due to temperature changes, rainfall variability and expected future climate change impacts in rainfed rice systems (van Oort & Zwart, 2018; Singh et al., 2017; Li et al., 2015), improvements in farmers' adaptive capacity due to the expansion of irrigation facilities may reduce rice production losses (Birthal et a., 2015). Although irrigated rice holds tremendous potential in fulfilling many West African countries' agendas of becoming rice self-sufficient, geospatial analysis to assess potentially irrigable land is often not explored. It is therefore relevant to quantify "where" and "how much" land is potentially suitable for irrigated rice cultivation under water-saving technologies.

Previous studies assessed the suitability of lands to crop cultivation at the regional and continental scales (Gumma et al., 2014; Hentze et al., 2016; Lobell & Asner, 2004; Xiong et al., 2017; Pittman et al., 2010). While these studies significantly improved our understanding of the general pattern of agricultural land, they mostly focused on the current planted areas based on satellite imagery. More holistic approaches for suitability analysis took into account the crop requirement for optimal allocation in the context of future cropland expansion. Such possibilities have been widely assessed through agricultural land suitability analysis (ALSA), a global land-use planning approach for land resources allocation in line with Sustainability Development Goals (SDGs) of the United Nations (Akpoti et al., 2019). One such approach used qualitative and parametric methods to evaluate land suitability for irrigated rice in West African Sahel based on soil units, soil fertility, and water management (Dondeyne et al., 1995). West African rice development environment has been characterized based on climate, soil, topography, land types, and rice systems with an emphasis on inland valleys (Andriesse & Fresco, 1991; Windmeijer & Andriesse, 1993; Andriesse et al., 1994). Other studies used Multi-Criteria Evaluation (MCE) to estimate map suitability for irrigation potential under current and future climate change in Ghana and Ethiopia (Schmitter et al., 2018; Worqlul et al., 2019). These methods are broadly classified as deductive which rely on physiology and other biophysical requirements.

New advances in inductive methods such as ecological niche models have provided means to take advantage of spatial big data for estimating the potential for agricultural development. A recent approach has used ecological niche modeling to map quantitatively inland valleys' suitability for rice production using machine learning methods (Akpoti et al., 2020). The approach, based on geospatial predictive modeling, uses rice occurrence along with environmental biophysical predictors of rice. Contrary to Asian conditions, where large-scale rice-growing areas can be mapped by coarse-scale MODIS data (Peng et al., 2011; Sakamoto et al., 2005; Salmon et al., 2015; Xiao et al., 2006, 2005), West African rice areas are sparse in a heterogeneous environment. Thus, the application of the ecological niche modeling approach, which not only has the advantage to predict the current distribution of irrigated rice areas but also identify suitable areas for development, can aid in sustainable irrigated area expansion.

Many irrigation schemes are inefficient and irrigation water productivity is low in Burkina Faso (Dembele et al., 2012; Sawadogo et al., 2020). To improve water-use efficiency through the reduction of irrigated water use, many technologies have been introduced including alternate wetting and drying (AWD). Alternate wetting and drying is a water-saving technology developed by the International Rice Research Institute (IRRI) and is based on the fact that continuous flooding is not required for rice fields to achieve high yields (Bouman et al., 2007). Once the transplanted seedlings are well established, the field water depth can fall to a threshold depth below the soil surface for a certain period before the field is irrigated. Implementation of AWD among farmers particularly in Asia has been very site-specific in terms of the timing, frequency, and duration of the non-flooded periods. In some regions of Asia, rice fields are flooded every 6 – 8 days or 4 – 5 days depending on the soil texture (Howell et al., 2015; Norton et al., 2017; Yao et al., 2012). The IRRI's recommendations of "safe" AWD consist of three key elements: a) flooding for 2 weeks to avoid transplanting shock and suppress weeds, b) flooding during the flowering stage to avoid yield reduction due to water stress at this sensitive stage of rice development, and c) AWD during all other periods with irrigation applied to 5 cm above the soil surface whenever water table falls to 15 cm below the soil surface (Lampayan et al., 2015). A meta-analysis of AWD applications showed that on average AWD reduced water input by 25% and increased water productivity by 24% without a yield penalty (Carrijo et al., 2017). In addition to the aforementioned benefits, AWD reduced methane emission by 53% on average (Jiang et al., 2019) and therefore has the potential to reduce water input, and greenhouse gas emission while maintaining rice yields. Studies showed that AWD can be applied in a dry environment such as the Sahelian environment of West Africa (de Vries et al., 2010; Djaman et al., 2018). These assessments showed that AWD can be deployed in both dry and wet seasons with comparable rice yields (Djaman et al., 2018) and, in some cases, better than in continuously flooded fields (de Vries et al., 2010).

Understanding the potentially irrigable land area while at the same time optimizing irrigation water use was identified as one of the priority actions in the Burkina Faso National Rice Development Strategy (BFNRDS, 2011). Thus, the objective of this study was to assess potentially irrigable lands for rice cultivation under water-saving technology in Burkina Faso. To achieve this objective, an integrated approach of two principal steps was developed and implemented. Firstly, an ensemble of models was used to assess the land suitability for irrigated rice cultivation. Secondly, a simple water balance approach was adopted to estimate the climatic suitability of AWD for water-saving. The results will provide policy makers and the development sector more insight into future suitable

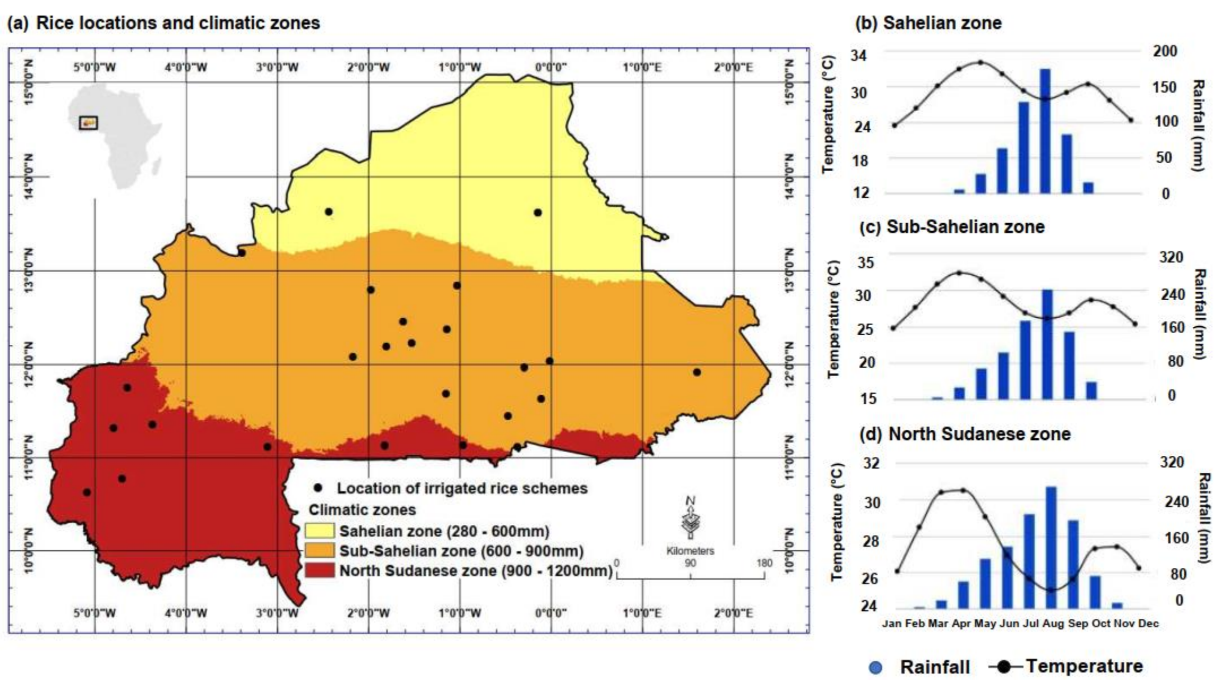

Figure 1. Locations of irrigated rice schemes and climatic zones of Burkina Faso: (a) monthly average temperature and total rainfall in the Sahelian zone, (b) Sub-Sahelian zone, (c) North Sudanese zone, and (d) Temperature and rainfall data of the period 1970–2000 were derived from WorldClim Version2 (Fick & Hijmans, 2017).

areas and opportunities for introducing AWD in irrigated rice systems development.

2. Materials and methods

2.1. Study area

This study was conducted in Burkina Faso (6°W and 3°E, 9°N and 15°N), a landlocked country in West Africa. The topography of the country is mainly characterized by a low relief plain with a gently undulating landscape (elevation between 142 m and 705 m). The country has two main seasons: one rainy season from June to September and one dry season from October to May. Burkina Faso is divided into three main climatic zones: Sahelian zone (280-600mm), Sub-Sahelian zone (600-900), and North-Sudanese zone (900-1200mm) (see Figure 1).

Burkina Faso's economy mainly relies on rainfed agriculture with the majority of the workforce in the agricultural sector. Cereals are the main food resource for the population and are produced on smallholder farmland of less than 5 ha with rice being the fourth most cultivated cereal in terms of both land area and production. In 2018, the cereals harvested area was 4,505,001 ha with a production of 4,991,259 tons of which harvested area paddy rice was 170,158 ha while the production was 160,949 tons (FAO, 2019). Three main cropping systems for rice are used in Burkina Faso, including rainfed upland, rainfed lowland, and irrigated system. According to the Burkina Faso national rice development strategy report, lowland is the main rice ecology across all regions in the country (BFNRDS, 2011). It accounts for 67% of the rice land area and supplies 42% of national rice production, with average yields from 1.3 t/ha to 2.5 t/ha. Also, rainfed rice-growing represents about 10% of the rice land area and provides 5% of national rice production at an average yield of 1 t/ha. Some irrigated areas of minor extent can be found mainly in the direct vicinity of dammed lakes. Between 1984–2009, irrigated rice-growing accounted for an average of 23% of the rice land area and provided nearly 53% of national rice production (BFNRDS, 2011).

2.2. Framework for mapping potentially

2.2.1. irrigable lands for rice cultivation under water-saving technology

We deployed a two-step, spatially explicit integrated approach to map potential areas for irrigated rice expansion under alternate wetting and drying (AWD) conditions (see Figure 2). In the first step, we used the ecological niche modeling concept (Elith & Franklin, 2013; Peterson, 2006) that relates the known location of irrigated rice to relevant predictors and projected suitable unvisited areas. The approach is widely used for species distribution modeling (Crimmins et al., 2013; Evangelista et al., 2008; Guisan & Zimmermann, 2000) and is now applied to agricultural suitability mapping (Akpoti et al., 2020; Estes et al., 2013; Heumann et al., 2011; Nabout et al., 2012; Ramírez-Gil et al., 2018). We developed the modeling procedure in the Software for Assisted Habitat Modeling (SAHM) (Morisette et al., 2013) using two machine learning algorithms; namely Maximum Entropy (MaxEnt) and Random Forest (RF). In the second step, we followed Nelson et al., (2015) to define the suitability for AWD using a water balance approach by defining excess water balance and deficit water balance.

2.2.2. Potential for irrigated rice mapping

Irrigated rice geographical locations data

Data on irrigated rice area locations were derived from the System of Rice Intensification (SRI) International Networks and Resources Center website (http://sri.ciifad.cornell.edu/countries/burkinafaso/index.html). The data comprises the coordinates of the rice fields, the village name, and other administrative attributes. The data represents 31 locations distributed across the 3 climatic zones of Burkina Faso and were used as reference (See Figure 1a). We used Google Earth Pro high-resolution images to inspect each of the rice locations and to digitize the polygons of the rice areas. We further used each of the polygons to randomly generates 10 points within the digitized area. To minimize the oversampling of each polygon which may induce model overfit, we filtered the points by random sampling so that no pairs of points were below 1.5 km. We also dropped any one pair of the sites which were too close in the initial dataset. Finally, points that fell within waterways and other undesired features were removed. The overall irrigated rice occurrence datasets resulted in a total of 226 points.

Environmental predictors selection of land suitability for irrigated rice cultivation

A set of environmental predictors (see Table 1 & Figure 3) was used to characterize the biophysical conditions of irrigated rice systems. The predictors correspond to climate conditions, surface and groundwater, water and energy fluxes, vegetation conditions, soil physical and chemical properties, and topography. The candidate environmental predictors were pre-selected based on previous suitability mapping for rice (Akpoti et al., 2020; Danvi et al., 2016; Heumann et al., 2011; Masoud et al., 2013) and agricultural cropland irrigation potential (Schmitter et al., 2018; Worqlul et al., 2019).

High spatial resolution of bioclimatic variables were obtained from WorldClim version 2.1 climate data (https://worldclim.org/; Fick & Hijmans, 2017). These climatic predictors profiled long term (1970-2000) annual trends, climate seasonality, and limiting environmental predictors. Irrigated rice cultivation relies on water availability. We used distance to stream networks as a proxy for access to surface water. High-density stream networks were first derived from Digital Elevation Model (DEM); then Euclidian distance was computed. Groundwater was represented in the modeling with the depth to groundwater table data obtained from Fan et al., (2017), and two categorical raster data of groundwater storage and groundwater yield obtained from MacDonald et al., (2012). Groundwater variables are important as they are linked to climate, aquifer types and porosity, proximity to rivers, and borehole yields under different hydrogeological conditions (MacDonald et al., 2012).

Water and energy fluxes were represented by long-term mean (1970-2000) of annual potential evapotranspiration based on the Penman-Monteith Evapotranspiration (PET) equation for reference crop obtained from (Trabucco & Zomer, 2018) and solar radiation from WorldClim database. These predictors are related to quantitative measures for deficit or surplus of water balance (Liu et al., 2016) and the production of biomass and crop yield (Zhi-peng et al., 2017).

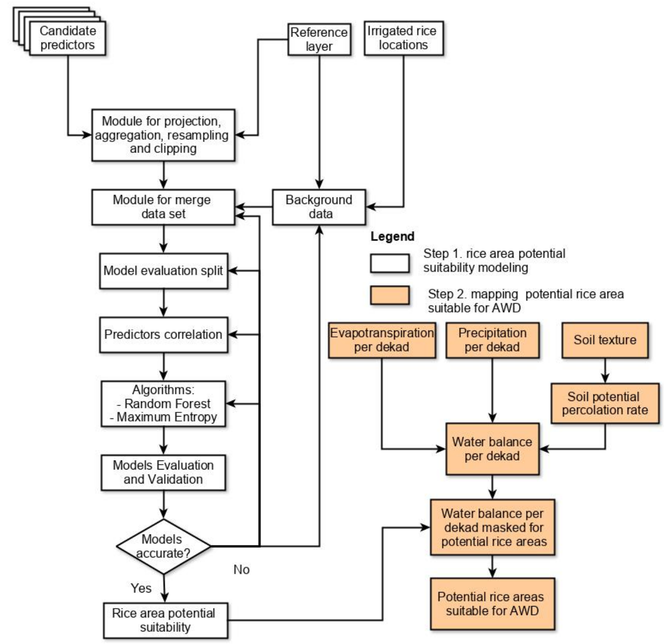

Figure 2. An integrated approach for mapping the potential for expanding irrigated rice under alternate wetting and drying conditions. Step 1, rice area potential suitability mapping was modified from Akpoti et al., (2020) and implemented in the Software for Assisted Habitat Modeling (SAHM) (Morisette et al., 2013). The reference layer corresponds to a template layer in which properties of spatial resolution and projection are transferred to predictors layers in the subsequent analysis. In the present case, a spatial resolution of 90 m x 90 m and geographic coordinate systems (WGS 84) were adopted. The Projection, Aggregation, Resampling, and Clipping (PARC) module prepares raster layers so that all predictors have coincident pixels, the same coordinate system, and the same geographic extent as defined in the reference layer. The Merged Data Set module extracts the values of each predictor layer to the irrigated rice locations. The Model Selection Split partitions the data in training and testing (here 60% and 40%). The predictors' correlation module helps explains the distribution of the sampled data points and removes any one highly correlated predictor. Step 2 shows the workflow of AWD climatic suitability assessment as modified from Nelson et al., (2015).

Table 1. Predictors used in the rice irrigation potential mapping.

No	Predictor	Predictor definition	Spatial Resolution	Units	Included (Yes/No (Reason for exclusion))
1	BIO1	Annual mean temperature [a]	1 km	°C	Yes
2	BIO3	Isothermality [a]	1 km	%	No (Least contributing)
3	BIO12	Annual Precipitation [a]	1 km	mm	No (Correlated with AET — r = 0.99, and OCS — r =0.83)
4	BIO16	Precipitation of Wettest Quarter [a]	1 km	mm	No (Correlated with AET — r = 0.88)
5	BIO17	Precipitation of Driest Quarter [a]	1 km	mm	No (Correlated with AET — r = 0.92)
6	BIO18	Precipitation of Warmest Quarter [a]	1 km	mm	Yes
7	SRD	Solar radiation [a]	1 km	kJ m^{-2} day^{-1}	No (Correlated with AET — r = 0.92)
8	AET	Mean annual Actual evapotranspiration [b]	1 km	mm	Yes
9	WWP	Available soil water capacity (volumetric fraction) [c]	250 m	%	Yes
10	CEC	Cation exchange capacity of the soil [c]	250 m	cmol/kg	Yes
11	ECN	Electrical conductivity	250 m	dS/m	No (Least contributing)
12	ESB	Exchangeable bases total	250 m	cmol/kg	No (Least contributing)
13	ESK	Exchangeable potassium	250 m	cmol/kg	Yes
14	ESNa	Exchangeable sodium	250 m	cmol/kg	No (Least contributing)
15	EXT_K	Extractable potassium [e]	250 m	ppm	No (Least contributing)
16	EXT_NA	Extractable sodium [e]	250 m	ppm	No (Least contributing)
17	OCD	Organic carbon density [c]	250 m	Kg/dm^3	No (Correlated with AET — r =0.88)
18	SOC	Soil organic carbon content in the fine earth fraction [c]	250 m	g/kg	No (Correlated with AET — r = 0.85)
19	OCS	Organic carbon stocks [c]	250 m	kg/m^2	Yes
20	NTO	Total nitrogen [c]	250 m	ppm	No (Least contributing)
21	PH	Soil pH [c]	250 m	pH	No (Least contributing)
22	BSP	Base saturation percentage [c]	250 m	%	No (Least contributing)
23	ESP	Exchangeable sodium percentage [c]	250 m	%	Yes
24	CRFVOL	Volume fraction of coarse fragments (>2mm)	250 m	%	Yes
25	TPHOS	Total phosphorus [e]	250 m	ppm	Yes
26	SILT	Proportion of silt particles in the fine earth fraction [c]	250 m	%	Yes
27	CLAY	Proportion of clay particles in the fine earth fraction [c]	250m	%	Yes
28	BLD	Bulk density of the fine earth fraction [c]	250 m	Kg/dm^2	Yes
29	DEPTH	Depth to bedrock [c]	250 m	cm	Yes
30	TWI	Topographic Wetness Index [d]	30 m	-	Yes
31	STRDIST	Distance to stream network [d]	250 m	m	Yes
32	SLOPE	Slope [d]	30 m	%	No (Least contributing)
33	DEM	Elevation [d]	30 m	m	No (Least contributing)
34	WTD	Water table depth [f]	1 km	m	Yes
35	STORAGE	Groundwater storage [h]	5 km	mm	Yes
36	GWYIELD	Groundwater productivity [h]	5 km	l/s	No (Least contributing)
37	NDFI	Normalized difference flood index [g]	1 km	-	Yes
38	SAVI	Soil adjusted vegetation index [g]	1 km	-	Yes

[a] www.worldclim.org; [b] Trabucco & Zomer, 2018; [c] Hengl et al., 2015; [d] Derived from Shuttle Radar Topography Mission DEM data; [e] https://files.isric.org/soilgrids/data/recent; [f] MacDonald et al., 2012; [g] Derived from MODIS data in R (Busetto and Ranghetti, 2017); [h] Fan et al., 2017.

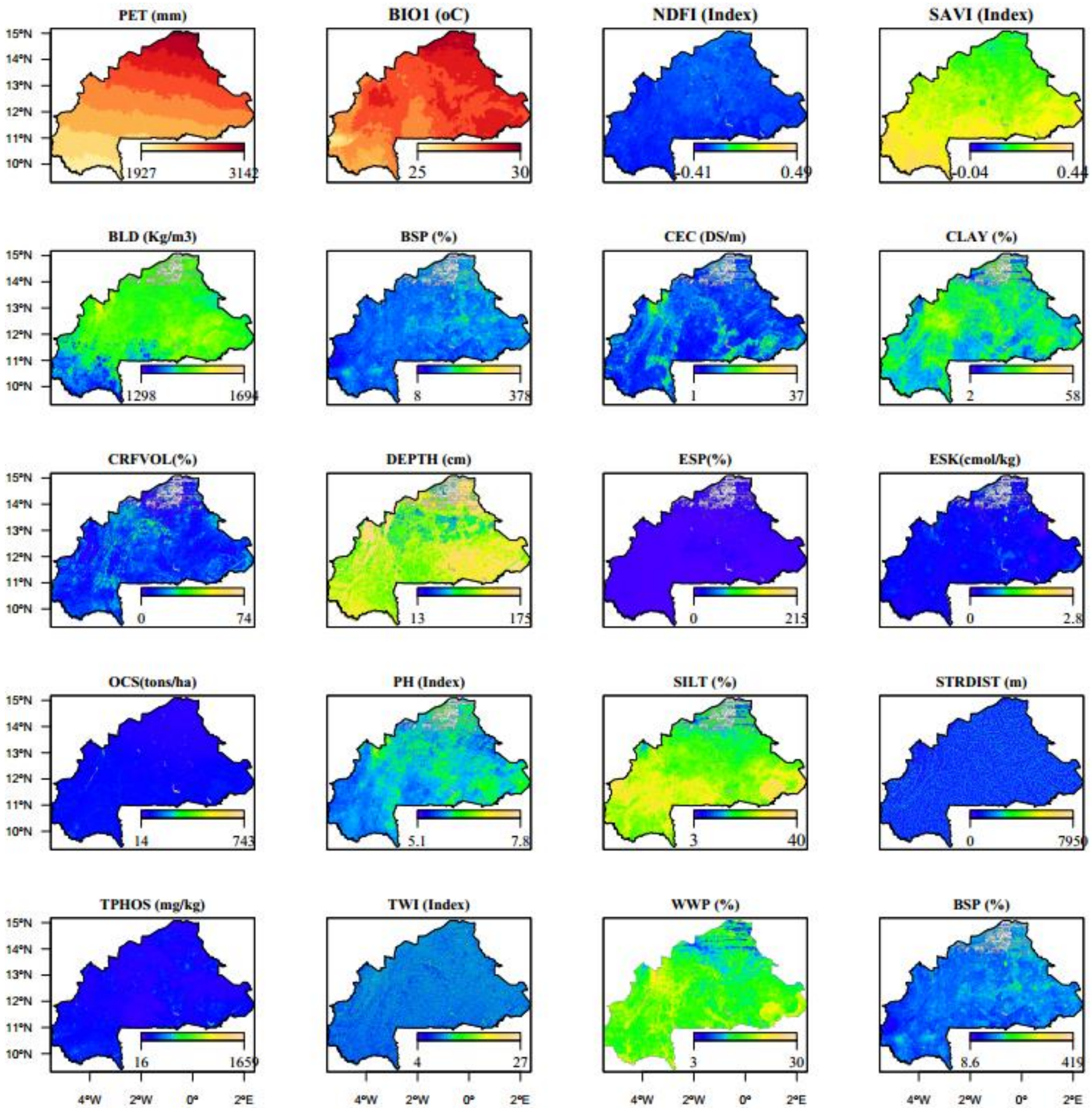

Figure 3. Selected predictors layers maps. PET—annual potential evapotranspiration, BIO1—annual mean temperature, NDFI—normalized difference flood index, SAVI—soil adjusted vegetation index, BLD—depth to bedrock, BSP—base saturation percentage, CEC—cation exchange capacity of the soil, CLAY—proportion of clay particles in the fine earth fraction, CRFVOL—volume fraction of coarse fragments, DEPTH—depth to bedrock, ESP—exchangeable sodium percentage, ESK—exchangeable potassium, OCS—organic carbon stocks, PH—soil pH, SILT— proportion of silt particles in the fine earth fraction, STRDIST— distance to stream network, TPHOS— total phosphorus, TWI— topographic wetness index, WWP— available soil water capacity (volumetric fraction), BSP—base saturation percentage.

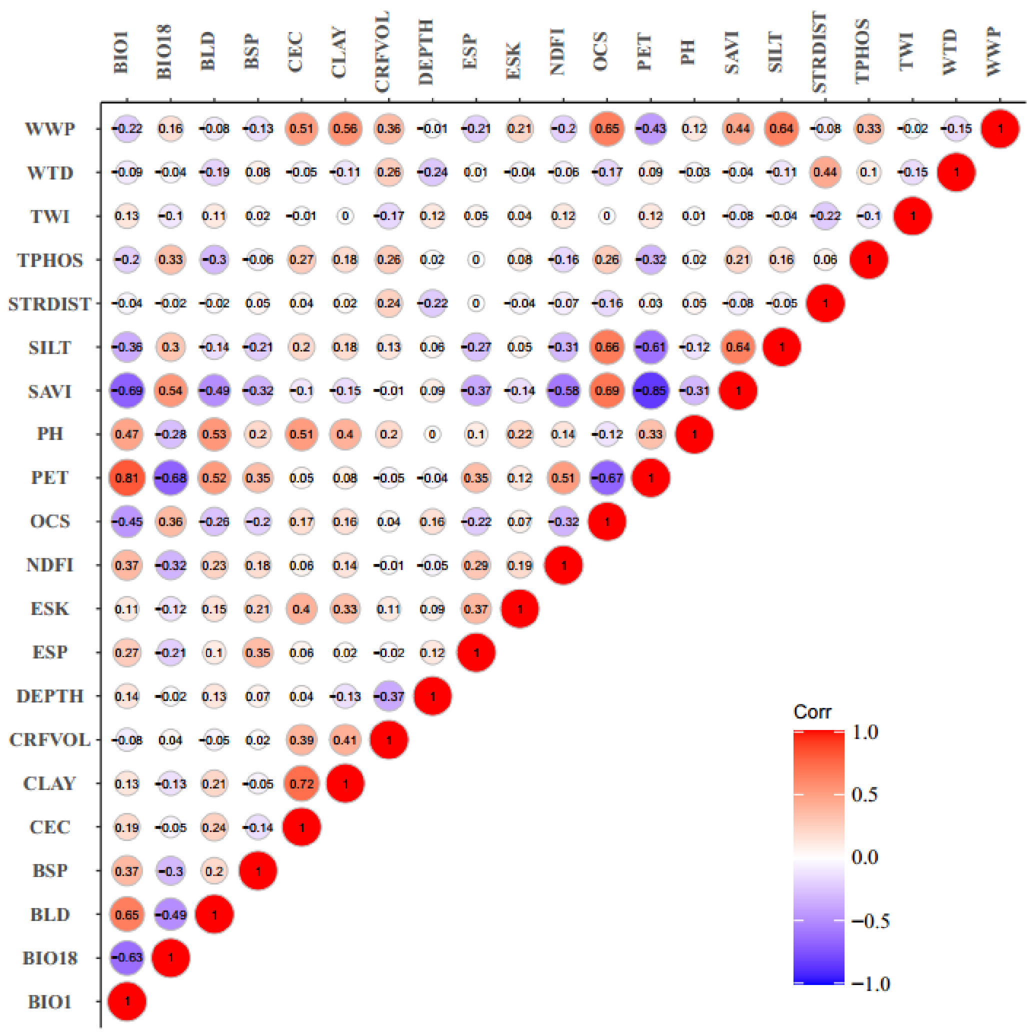

Figure 4. Paired Pearson correlation between predictors. BIO1—annual mean temperature, BIO18—Precipitation of Warmest Quarter, BLD—bulk density, BSP—base saturation percentage, CEC—cation exchange capacity of the soil, CLAY—proportion of clay particles in the fine earth fraction, CRFVOL—volume fraction of coarse fragments, DEPTH—depth to bedrock, ESP—exchangeable sodium percentage, ESK—exchangeable potassium, NDFI—normalized difference flood index, OCS—organic carbon stocks, PET—annual potential evapotranspiration, PH—soil pH, SAVI—soil adjusted vegetation index, SILT— proportion of silt particles in the fine earth fraction, STRDIST— distance to stream network, TPHOS— total phosphorus, TWI— topographic wetness index, BSP—base saturation percentage, WTD—Water table depth, WWP— available soil water capacity (volumetric fraction).

Normalized difference spectral indices have been widely used for characterizing irrigated rice environments (Gumma et al., 2014; Jeong et al., 2012; Sakamoto et al., 2007; Tornos et al., 2015). We considered the 5-years average (2015-2019) of the Soil Adjusted Vegetation Index (SAVI) and Normalized Difference Flood Index (NDFI) derived from Terra Moderate Resolution Imaging Spectroradiometer (MODIS) Vegetation Indices (MOD13A3) Version 6 monthly L3 Global 1km products. These indices were computed using a tool for automatic preprocessing of MODIS time series, MODIStsp package in R (Busetto and Ranghetti, 2017) as:

$$NDFI = \frac{(RED-SWIR2)}{(RED+SWIR2)} \tag{1}$$

$$SAVI = \frac{(NIR-RED)}{(NIR+RED+0.5)}(1+0.5) \tag{2}$$

where RED, SWIR2, and NIR are respectively cloud-free red band (630–690 nm), the short-wave-infrared band (2090–2350 nm), and near-infrared (780–900 nm) MODIS products.

Selected soil property maps of Africa at 250 m resolution–AfSoilGrids250m (Hengl et al., 2015; Hengl et al., 2017) were aggregated by weighted depth up to 30 cm to represent soil physico-chemical properties in the models. The 30 cm limit was considered as rice roots are usually contained within the puddled layer and muddy topsoil of 10–20 cm (Bouman et al., 2007). We also derived exchangeable sodium percentage (ESP) and base saturation percentage (BSP) computed based on soil exchangeable sodium (ESNa), the total exchangeable bases (ESB), and cation exchange capacity (CEC) as:

$$ESP = \frac{ESNa \times 100}{CEC} \tag{3}$$

$$BSP = \frac{ESB \times 100}{CEC} \tag{4}$$

Topography is one of the key factors that control the spatial pattern of water availability (Grabs et al., 2009). We used a digital elevation model (DEM) from which we derived slopes and topographical wetness index (TWI) to represent topographical variations in the models. 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:

$$TWI = \ ln(A/tan(B)\,) \tag{5}$$

The final selection of the predictors was based on the step-wise elimination of the least contributing variables and collinearity among variables. A threshold of |r| < 80% of Pearson correlation was used to exclude any one of highly paired correlated variables (see Figure 4), a process considered as very important to ensure the independence among the predictors (Jarnevich et al., 2015). Twenty predictors were used in the final modeling.

Maximum Entropy (MaxEnt) and Random Forest (RF) models' settings

MaxEnt is one the most widely used predictive modeling method due to its high predictive accuracy even under a low sample size, along with the user-friendly settings of the model (Halvorsen et al., 2016; Zeng et al., 2016). The MaxEnt model, developed by Phillips et al., (2006), is based on the use of presence-only data and a set of environmental predictors constraints. The model was tuned based on model setting guidelines by Phillips & Dudík, (2008) and Phillips et al., (2009). We maintained the 5,000 iterations in the initial setting while the evaluation metrics stabilized around 11,000 background points.

Also, RF has been used in many presence/backgrounds predictive modeling where the approach outperforms many other models (Mi et al., 2017; Stohlgren et al., 2010). The model is a classification and regression learning method based on an ensemble of decision trees (Breiman, 2011). RF was tuned based on the number of randomly selected predictor variables at each node, the number of trees in the forest, and the smallest node size for splitting as implemented in the package 'randomForest' in R (Breiman et, 2011). In this study, we used 6, 1500, and 5 for the number of randomly selected predictor variables at each node, the number of trees in the forest, and the smallest node size for splitting, respectively.

All the predictors were aggregated and resampled to a 90 m x 90 m grid using the nearest neighbor and majority filter methods for non-categorical and categorical raster datasets respectively. The modeling is based on the irrigated rice occurrence data along with randomly generated absence data as previously used by Akpoti et al., (2020). We used the Kernel density estimate (Duong, 2015) to randomly generate 11,000 background data. Training and testing datasets comprised 60% and 40% of the initial dataset respectively.

Threshold selection

To discriminate between suitable and unsuitable areas from the continuous probability surface of the models' predictions, a threshold that maximizes the (Sensitivity + Specificity)/2 was used. The sum maximizer threshold was shown to be one of the best performing across varying modeling settings (Jiménez-Valverde & Lobo, 2007; Liu et al., 2013). This threshold minimizes the mean of the error rate for irrigated rice locations and the error rate for background samples. We used the consensus forecast approach based on a simple mean to estimate the central tendency across both MaxEnt and RF algorithms (Crimmins et al., 2013).

Model evaluation

To evaluate the models' performance, we considered widely used spatial predictive evaluation metrics including the area under the receiver operating characteristic curve (AUC), the percentage correctly classified (PCC), the sensitivity (i.e. prediction of true presence), specificity (i.e. prediction of background points), the Kappa statistic and the True Skill Statistics (TSS). Together, they provide the level of accuracy of the modeling assignment.

2.3. Climatic suitability assessment of the alternate wetting and drying (AWD)

We followed Nelson et al., (2015) to define the climatic suitability for AWD using a water balance equation (Figure 5 and Eq.(6)):

$$I + Pcp + C = ET + S + D + Pot\_Pc \quad (6)$$

where I is irrigated water supply, Pcp is precipitation, C is capillary rise, ET is potential evapotranspiration of a specific type of well-watered crop, S is lateral seepage, D is a surface inflow or drainage and Pot_Pc is potential percolation.

In farmers' fields, water loss due to seepage (the subsurface movement of water) from one rice field to the other is often compensated by seepage inflow from another field (Schmitter et al., 2015). Therefore, water loss through seepage was neglected in Eq.(6). Irrigated rice fields are surrounded by bunds to store water in the rice fields in Burkina Faso, thus resulting in negligible water loss through drainage. The contribution of capillary rise in meeting water requirements for rice cultivation can be substantial if there is non-flooded (aerobic) soil. However, in flooded rice fields, soil percolation prevents capillary rise into the root zone, and therefore capillary rise is often neglected in the water balance equation. In AWD, capillary rise during the non-flooding period may provide extra-water to the crop in schemes where there is a shallow groundwater table (Bouman et al., 2007). However, water input through capillary rise was not included in the water balance equation due to a lack of spatial datasets on the capillary rise. This might result in a bias in the water balance assessment in schemes with a shallow groundwater table. Based on the above-mentioned assumptions, and following Nelson et al. (2015), the water balance equation was simplified in Eq.(7).

$$I + Pcp = ET + Pot\_Pc$$

$$I + Pcp - (ET + Pot\_Pc) = 0 \quad (7)$$

AWD is an irrigation technology developed to produce rice with less water compared with the conventional approach of continuous flooding (Bouman et al., 2007). Following Nelson et al. (2015), we assumed that AWD is suitable in a given period if there is a deficit water balance (Eq.(8)) and unsuitable otherwise (Eq.(9)).

$$Water\ balance\ deficit\ if\ Pcp - (ET + Pot\_Pc) < 0 \quad (8)$$

$$Water\ balance\ excess\ if\ Pcp - (ET + Pot\_Pc) \geq 0 \quad (9)$$

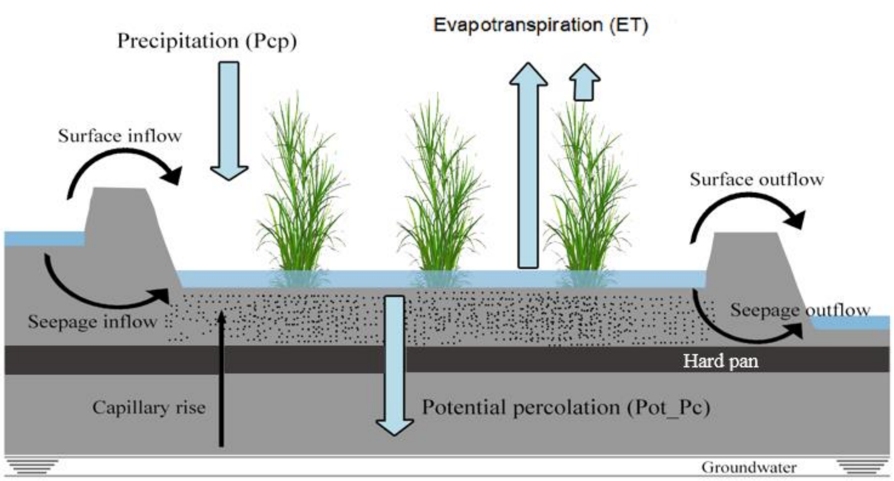

Figure 5. Water balance diagram in flooded rice fields without irrigation. Redrawn with modification from Nelson et al., (2015) and Bouman et al., (2007). Pcp, ET and Pot_Pc are the only water fluxes considered in the simple water balance estimation. Other water fluxes such as surface inflow, surface outflow, seepage inflow, seepage outflow, and capillary rice were not considered.

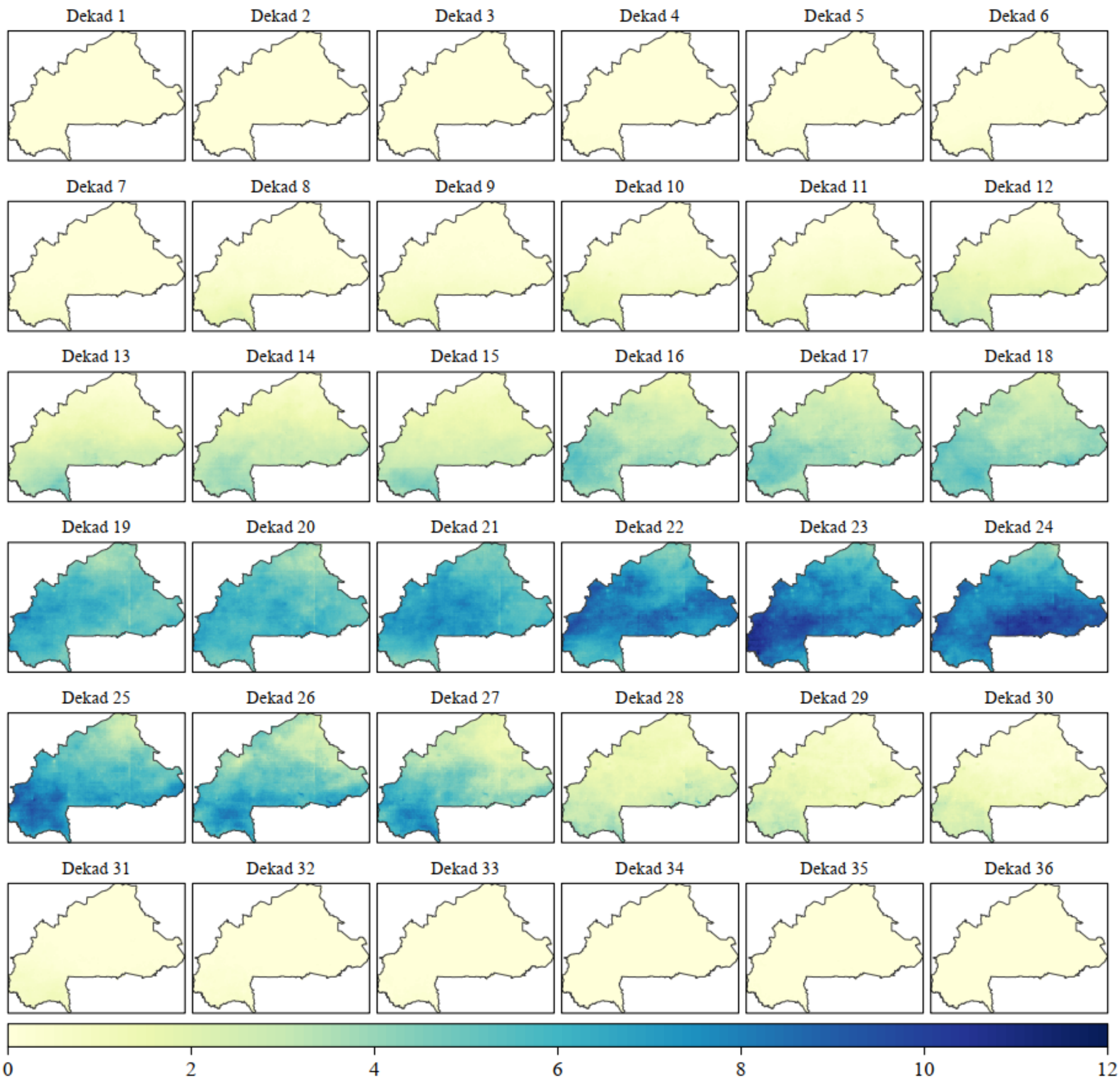

Figure 6. 10-years (2009-2018) average precipitation in mm/day. The data was obtained from FAO-WaPOR portal (https://wapor.apps.fao.org/catalog/WAPOR_2/1/L1_PCP_D).

The water balance was computed based on dekadal time-steps, corresponding to a total of 36 dekads in the year (3 dekads for each month). This temporal resolution is justified by the fact that irrigation or drainage water management decisions are often taken on a weekly or fortnightly basis (Nelson et al., 2015). We used 10-years average (2010-2019) of the dekad (average daily in a dekad, mm/day) precipitation data obtained from the Food and Agricultural Organization of the United Nations (FAO) portal to monitor Water Productivity through Open-access of Remotely sensed derived data (WaPOR) v2 (FAO, 2020). This precipitation product of 5 km resolution is based on the Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) dataset, which is a well-performing satellite rainfall products over Burkina

Faso (Dembélé & Zwart, 2016). The spatial distributions of the dekad precipitation variations are displayed in Figure 6. Similarly, we considered the reference ET dekad product of the WaPOR v2 database (FAO, 2020) (Figure 7). ET is the reference evapotranspiration (dekad, in mm/day), a sum of the soil evaporation (E) and canopy transpiration (T) of a hypothetical reference crop — a well-watered grass surface, which is based on the FAO method (Allen et al., 1998).

Table 2. Potential percolation rates as a function of soil texture.

Texture ID	Soil type	Percolation rate (mm/day)		
		Lower bound	Upper bound	Basic Setting
1	Clay [a]	1	5	3
3	Sandy clay [b]	3	9	6
4	Clay loam [b]	1	6	4
6	Sandy clay loam [c]	3	15	9
7	Loam [c]	2	6	4
9	Sandy loam [c]	3	15	9
11	Loamy sand [b]	4	8	5
12	Sand [c, d]	5	20	12

Source of percolation rates: [a] GRiSP, 2013; [b] setting based on percolation rates of sand, clay, and loam ; [c] Nelson et al., 2015; [d] Humphreys et al., 2015.

Percolation rate on the rice field is influenced by soil factors including soil structure, texture, bulk density, mineralogy, organic matter content, and the salt type and concentration (Bouman et al., 2007). Although the soil structure is changed by the physical action of puddling resulting in a hard pan, there still variation in percolation rates among different soil texture classes. For example, Bouman et al., (2007) reported a value of 1–5 mm/day in heavy clay soils to 25–30 mm/day in sandy and sandy loam. We used the approach developed by Nelson et al., (2015) by defining the percolation rate as a function of soil texture classes (potential percolation, Pot_Pc) which defines the upper limit of the rate of percolation into the subsoil. Due to the uncertainties associated with the texture classes percolation rates, a sensitivity analysis used in the aforementioned research was adopted using 4 main sensitivity categories: First, a lower bound of Pot_Pc as a function of soil texture classes were defined, followed by an upper bound of Pot_Pc. Then, a basic setting, which corresponds to Pot_Pc rates that lie between the lower and the upper bounds (see Table 2). We finally considered fixed values of Pot_Pc for the entire national scale of Burkina Faso of 1, 2, 3, 4, 5, and 10 mm/day. We used the texture data of the soil property maps of Africa at 250 m resolution–AfSoilGrids250m (Hengl et al., 2015). We used aggregation by weighted depth up to 30 cm of the Pot_Pc using the first 3 standard depths. An area coverage description of the texture classes at each depth over Burkina Faso is reported in Table 3, showing the dominance of the sandy loam, sandy clay loam, and clay loam classes.

Table 3. Area of texture classes for 6 standard soil depth.

Texture ID	Soil type	Area of texture classes ($x10^4$Ha)		
		0-5 cm	5-15 cm	15-30 cm
1	Clay	4.95	8.08	17.8
3	Sandy clay	0.27	1.14	8.97
4	Clay loam	129	194	382
6	Sandy clay loam	1026	1348	2033
7	Loam	373	313	123
9	Sandy loam	1168	842	147
11	Loamy sand	20.5	16.0	10.4
12	Sand	0.18	0.11	0.03

Two growing seasons for irrigated rice exist in Burkina Faso that coincide with the dry and the wet seasons. The first rice growing season extends from February to June, referred to as dry-season rice, and the second season from July to December referred to as wet-season rice. Rice cannot be cultivated from January to mid-February due to low temperatures brought by the dry air Harmattan winds blowing from the Sahara. We computed the AWD climatic suitability based on the two growing seasons. We then masked the AWD climatic suitability with the potential suitability for irrigated rice cultivation as previously described.

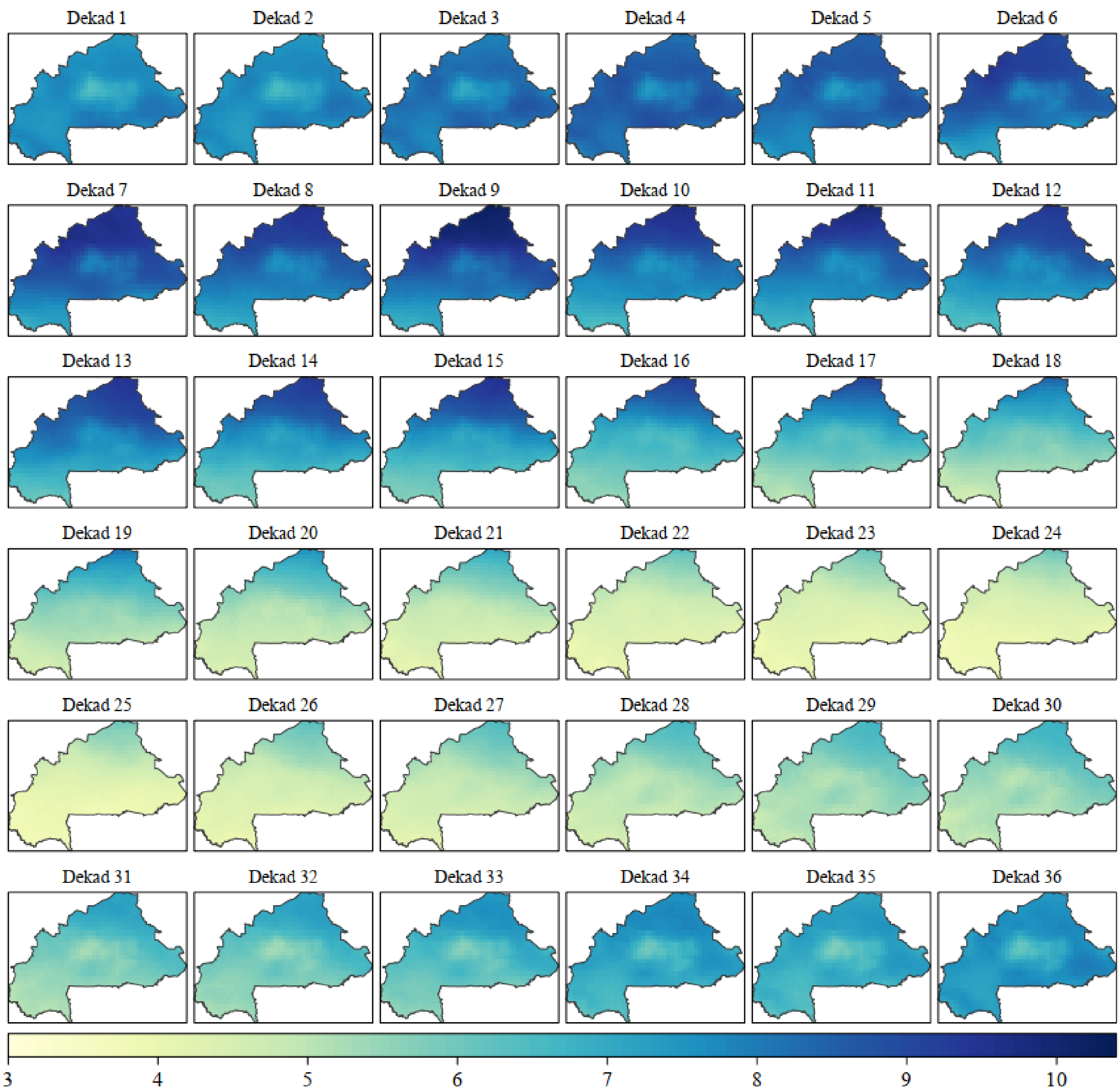

Figure 7. 10-years (2009-2018) average of reference evapotranspiration in mm/dekad. obtained from FAO-WaPOR portal (https://wapor.apps.fao.org/catalog/WAPOR_2/1/L1_RET_D).

3. Results

3.1. Rice suitability assessment

3.1.1. Evaluation of irrigated rice ecological niche models

Evaluation of the two models (i.e. MaxEnt and RF) of the potential suitability distribution of irrigated rice in Burkina Faso shows high performing metrics with AUC and PCC on training data higher than 92% and PCC > 90%, respectively. Similarly, the models depict high performance when applied on independent test data with AUC equals to 92% and PCC > 81%. Overall, RF showed higher consistency in the evaluation metrics compared with MaxEnt with both models performing better than random (AUC > 50%) (see Table 4). RF evaluation metrics showed a smaller difference between training and testing which may represent an advantage in predicting unvisited suitable conditions for irrigated rice.

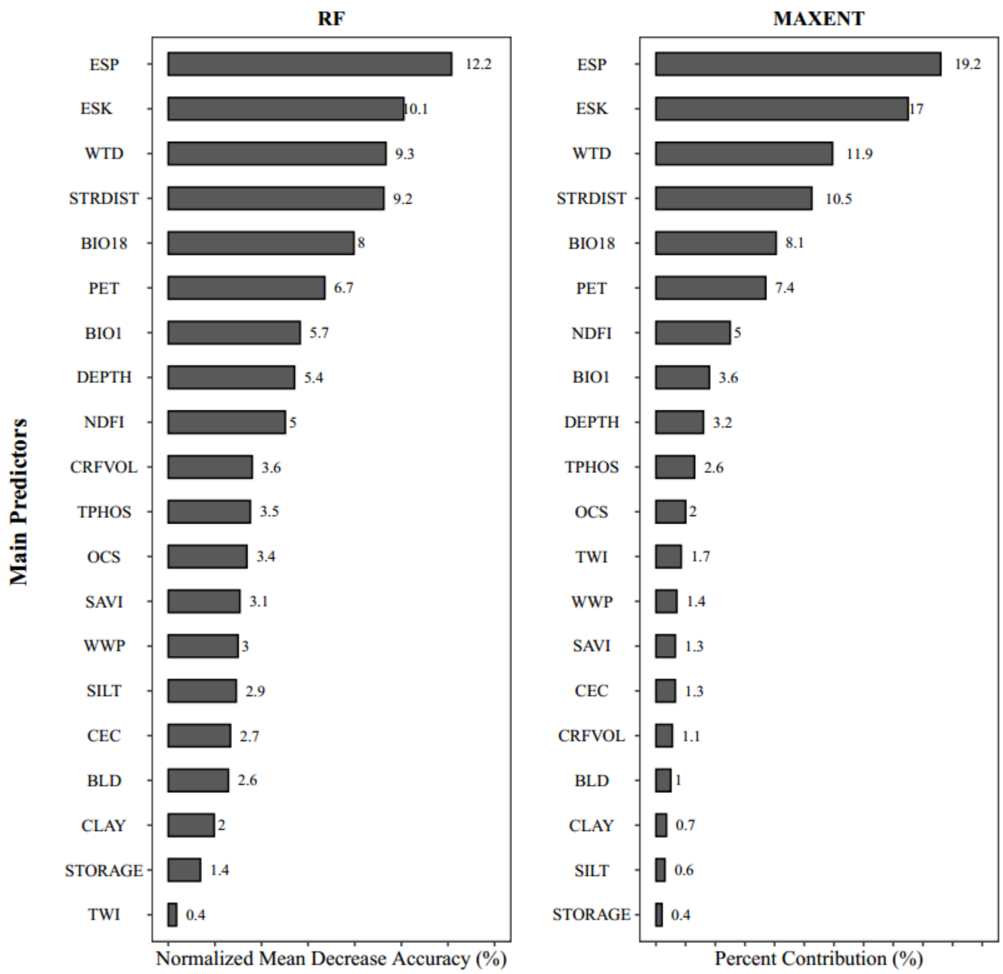

Figure 8. Contribution of each of the predictors in the modeling of potential suitability for irrigated rice. ESP—exchangeable sodium percentage, ESK—exchangeable potassium, WTD—Water table depth, STRDIST—distance to stream network, BIO18—precipitation of warmest quarter, AET—annual mean evapotranspiration, NDFI—normalized difference flood index, BIO1—annual mean temperature, DEPTH—depth to bedrock, TPHOS— total phosphorus, OCS—organic carbon stocks, CRFVOL—volume fraction of coarse fragments, WWP— available soil water capacity (volumetric fraction), SAVI—soil adjusted vegetation index, CEC—cation exchange capacity of the soil, BLD—bulk density, SILT— proportion of silt particles in the fine earth fraction, CLAY—proportion of clay particles in the fine earth fraction, TWI— topographic wetness index, Storage (L, <1,000mm; LM, 1,000-10,000mm; H, 25,000-50,000mm; VH, >50,000mm).

Table 4. Final evaluation of potential suitability of irrigated rice distribution model performance. Models included Maximum Entropy (MaxEnt) and Random Forests (RF). AUC represents the area under the receiver operating characteristic curve; PCC represents percentage correctly classified; Sensitivity represents the probability of observed irrigated rice locations that are predicted as such; Specificity is the probability of observed non-irrigated rice areas that are predicted as such; TSS (Sensitivity + Specificity – 1) represents True Skill Statistic.

Evaluation metrics	MAXENT		RF	
	Train	Test	Train	Test
AUC	0.96	0.92	0.92	0.92
PCC	90	81	91	83
Sensitivity	0.91	0.87	0.80	0.90
Specificity	0.90	0.81	0.91	0.83
TSS	0.81	0.68	0.71	0.73

3.1.2. Predictors importance and excluded variables

From the final model settings, exchangeable sodium percentage (ESP), exchangeable potassium (ESK), groundwater table depth (WTD), Euclidean distance to stream networks (STRDIST) and precipitation of the warmest quarter (BIO18) represent in that order the top 5 predictors for both RF and MaxEnt (Figure 8). The results show that soil salinity, fertility and water availability for irrigated rice including groundwater and surface water along with rainfall were key predictors of irrigated rice. The five next top predictors were evapotranspiration (ET), the normalized difference flood index (NDFI), annual mean temperature (BIO1), soil depth (DEPTH), and total phosphorus (TPHOS). Other predictors, which were initially considered in the model development were finally excluded either due to their least contribution to the models or their high correlation with other predictors (Table 1). For example, groundwater productivity, although important to measure groundwater availability for irrigation, was dropped from the models due to its weak contribution. On the other hand, solar radiation, although important for rice plant growth, was excluded due to its high collinearity with AET (r =0.92). In total, 18 predictors were excluded (See Table 1).

3.1.3. Relationship between the most relevant predictors and land suitability for irrigated rice

Figure 9 shows the response curves of the most important predictors of land suitability for irrigated rice cultivation. Exchangeable sodium percentage (ESP) shows a positively skewed distribution with a maximum value of 9%. ESP response curve suggests that irrigated rice suitability decreases with soil salinity where ESP is higher 9%. A similar right-skewed curve is shown for soil organic carbon stock (OCS) with a peak value of 75 tons/ha, soil bulk density (BLD) with a maximum value of 1,250 kg/m^3, and soil clay content of around 20% for maximum suitability. AET shows a negatively skewed response with a peak value of 850 mm. Warmest quarter precipitation (BIO18) shows the highest suitability between 100-150 mm in a bell-shaped response curve. However, the annual mean temperature shows a complex and positively skewed response curve with maximum suitability around 27.5 °C. A similar response shape is shown for available soil water capacity (WWP) with maximum suitability around 17.5%. Results show that irrigated rice suitability increases with exchangeable potassium (ESK), soil depth (DEPTH), normalized difference flood index (NDFI), soil adjusted vegetation index (SAVI), and cation exchange capacity (CEC) in an exponential, convex, truncated normal distribution, linear response curves, respectively. Predictors such as depth to groundwater table (WTD), distance to stream network and soil silt content decrease with higher suitability. Land suitability for irrigated rice increased with groundwater storage value although no change in suitability is observed above the value of 1,000 mm.

3.1.4. Spatial prediction of potential suitability for irrigated rice cultivation

The potential for a suitable irrigable rice area is estimated at 25.0 x 10^5 ha for MaxEnt and 20.7 x 10^5 ha for RF. The consensus estimate of the suitable rice area is 21.1 x 10^5 ha. The spatial distribution of predicted suitability is mapped in Figures 10. The results show that suitable lands are mostly located within the latitudes (10°N-12.5°N) from the West to East of the country. This domain corresponds to the sub-Sahelian climatic zone and the north Sudanese climatic zone (see Figure 1 for the climatic zones of Burkina Faso). Within the aforementioned domain, three main clusters can be observed: The first cluster corresponds to the location (5.5°W-2.7°W, 10°N-12°N) in the north Sudanese climatic zone. The second cluster corresponds to (2.7°W-0°, 11°N-12.5°N) which falls mostly within the sub-Sahelian climatic zone. The third cluster of suitable land is located around the 11.5°N-2°E of the sub-Sahelian climatic zone. In general, the Sahelian climatic zone is marginally suitable for irrigated rice compared with the two other climatic zones. The validation of the modeled suitable areas by comparison between the digitalized rice based on satellite imagery and modeled data showed a good agreement (Figure 11), confirming the PCC >81% previously reported and the potential for expansion.

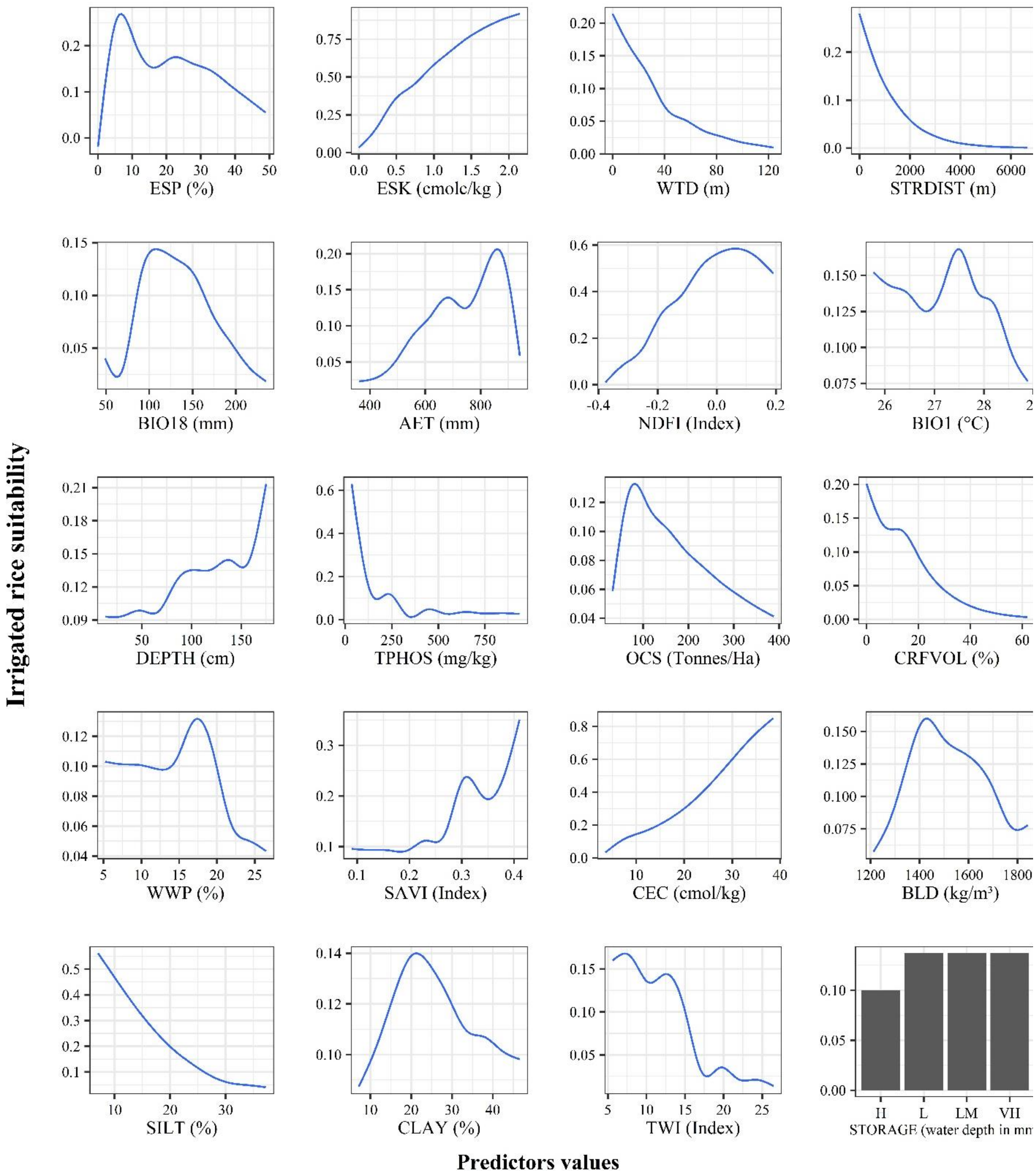

Figure 9. Response curves showing the relationship between MAXENT predicted suitability of occurrence of irrigated rice and predictors. ESP—exchangeable sodium percentage, ESK—exchangeable potassium, WTD—Water table depth, STRDIST— distance to stream network, BIO18—precipitation of warmest quarter, AET—annual mean evapotranspiration, NDFI—normalized difference flood index, BIO1—annual mean temperature, DEPTH—depth to bedrock, TPHOS— total phosphorus, OCS—organic carbon stocks, CRFVOL—volume fraction of coarse fragments, WWP— available soil water capacity (volumetric fraction), SAVI—soil adjusted vegetation index, CEC—cation exchange capacity of the soil, BLD—bulk density, SILT—proportion of silt particles in the fine earth fraction, CLAY—proportion of clay particles in the fine earth fraction, TWI—topographic wetness index, Storage (L, <1,000mm; LM, 1,000-10,000mm; H, 25,000-50,000mm; VH, >50,000mm).

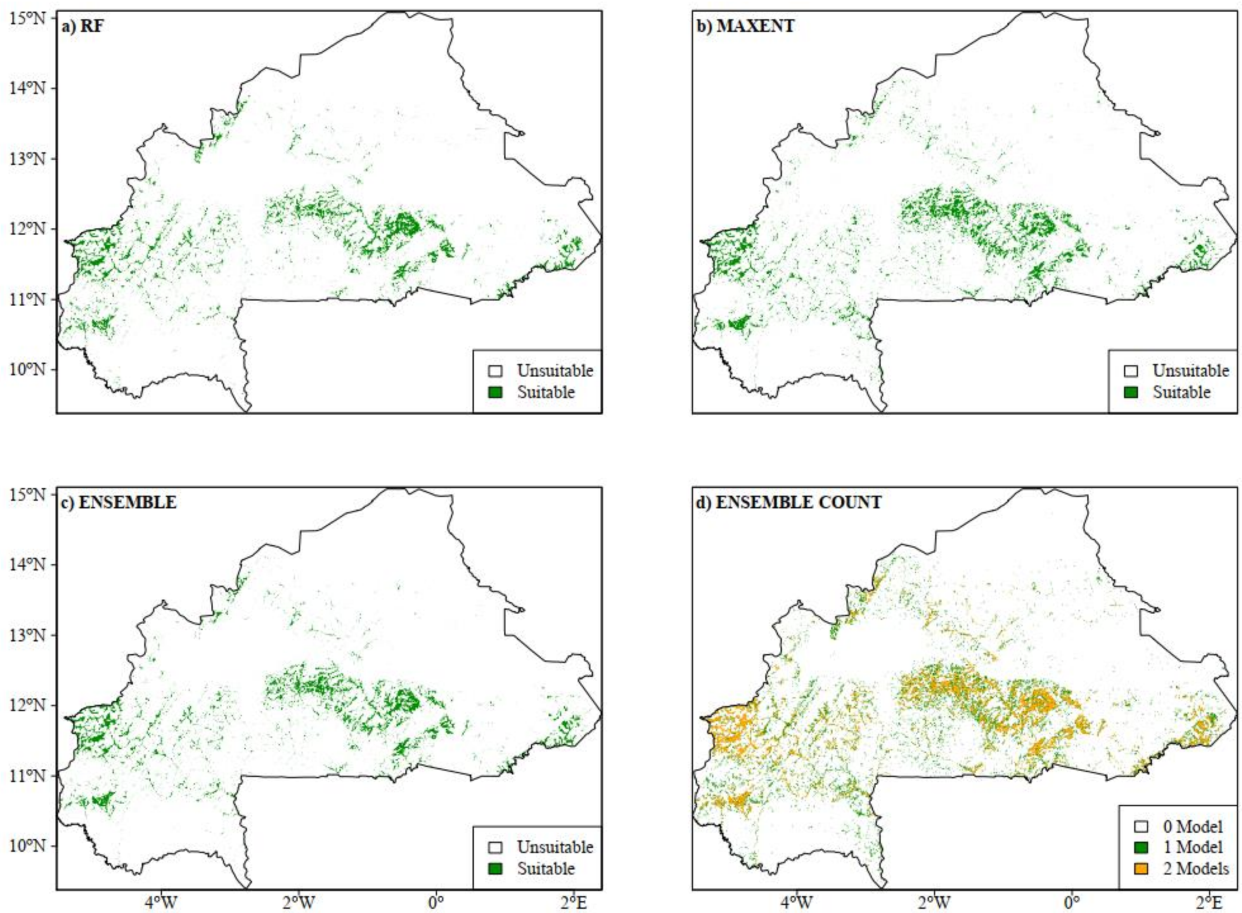

Figure 10. Predicted suitability maps. The maps illustrate the binary predictions and the ensemble count showing the number of models that agree on a given pixel as suitable.

3.2. Climatic suitability of alternate wetting and drying (AWD)

The totality of the dekads in the dry season are classified as suitable for AWD. The dry season AWD results are expected due to low precipitation (0-6mm/day) (see Figure 6) and high reference evapotranspiration (5-10 mm/day) (see Figure 7). Even at the onset of the wet season in the north Sudanese climatic zone where the precipitation values are close to 6 mm/day, any combination of (ET + Pot_Pc) always exceeds Pcp which results in a water balance deficit for the entire areas classified as potentially suitable for AWD.

The AWD climatic suitability during the wet season (July to October) under fixed values of Pot_Pc is reported in Figure 12 while AWD climatic suitability where Pot_Pc is a function of the soil texture (see Table 2) is depicted in Figure 13. Results show that for all fixed values of Pot_Pc, the month of July (dekads 19 to 21) is mostly suitable for AWD where Pcp values are less than 4 mm/day. This, in the exception of the last dekad of July under Pot_Pc of 1 and 2 mm/day where Pcp values of 4-5 mm/day exceed in some areas the combination of both 1 mm/day Pot_Pc and the PET values of 3-6 mm/day. The temporal variability of water balance excess and deficit is explained by the precipitation pattern with slow onset in June and maximum precipitation values in August-September with a slow decrease toward October (dekads 25-27). AWD suitability also follows the precipitation pattern for relatively higher fixed values of Pot_Pc such as 4 and 5 mm/day. In general, with increasing Pot_Pc, only peaking precipitation months become unsuitable for AWD such that for Pot_Pc of 10 mm/day or higher, the entire area potentially suitable for irrigated rice also becomes suitable for AWD. Overall, taking into account the full length of the wet season, 25% (dekads

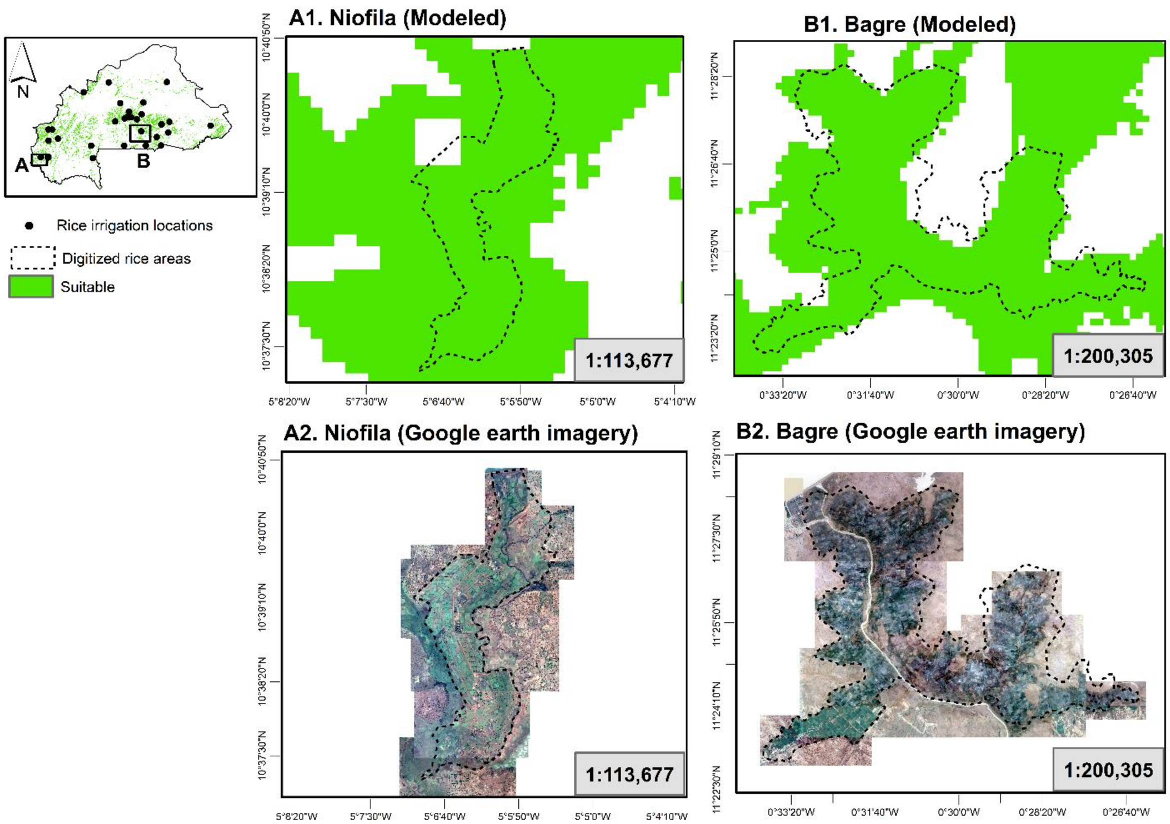

Figure 11. A zoom on selected locations of Burkina Faso where rice is irrigated comparing digitized rice schemes at Niofila and Bagre and modelled suitability.

28 to 30), 58% (dekads 19 to 20 & 26 to 30), 67% (dekads 19 to 21 & 26 to 30), 75% (dekads 19 to 21 % 25 to 30), 83% (dekads 19 to 22 & dekads 25 to 33) and 100% of the dekads are suitable for AWD for Pot_Pc values of 1, 2, 3, 4, 5, and 10mm/day, respectively (see supplementary material). Dekads that are partly suitable are mostly located in the central, South-East (Sub-Sahelian climatic zone) and the north (Sahelian zone) (see Figure 14)).

The AWD under low boundary settings shows that 58% of the dekads (26-33) are suitable in the wet season (Figure 15). The upper boundary settings show that 100% suitability for AWD (supplementary material). Similarly, AWD is suitable in all months except for short periods between August-September for basic settings (supplementary material).

4. Discussions

4.1. Potential for irrigated rice expansion

Many publications showed that there is a scope for irrigated rice expansion in Africa (Xie et al., 2014; You et al., 2011; Lançon & Erenstein, 2002) owing to the small fraction of agricultural land irrigated at present and considerable unused water sources (Wiggins & Lankford, 2019). It is estimated that investment in new irrigation schemes can raise the share of irrigated rice in domestic production from less than 10% on average presently to more than 50% in the coming year (Seck, 2008).

This article used a comprehensive ecological niche approach to estimate the potential for irrigated rice cultivation in Burkina Faso based on two machine learning methods including MaxEnt and RF. It was estimated that 20.7 x 10^5 ha to 25.0 x 10^5 ha are potentially suitable for irrigated rice cultivation in Burkina Faso. These estimates were 9 to 11-folds higher than the existing potential for irrigation of 233,500 ha as reported in many documents including the Burkina Faso national rice development strategy report (BFNRDS, 2011). This figure was rather close to the 350,000 ha potentially irrigable land for rice as reported in Barghouti & LeMoigne, (1990) and FAO, (1986) while others reported a higher value of 720,000 ha (Biswas, 1986). The discrepancies between the

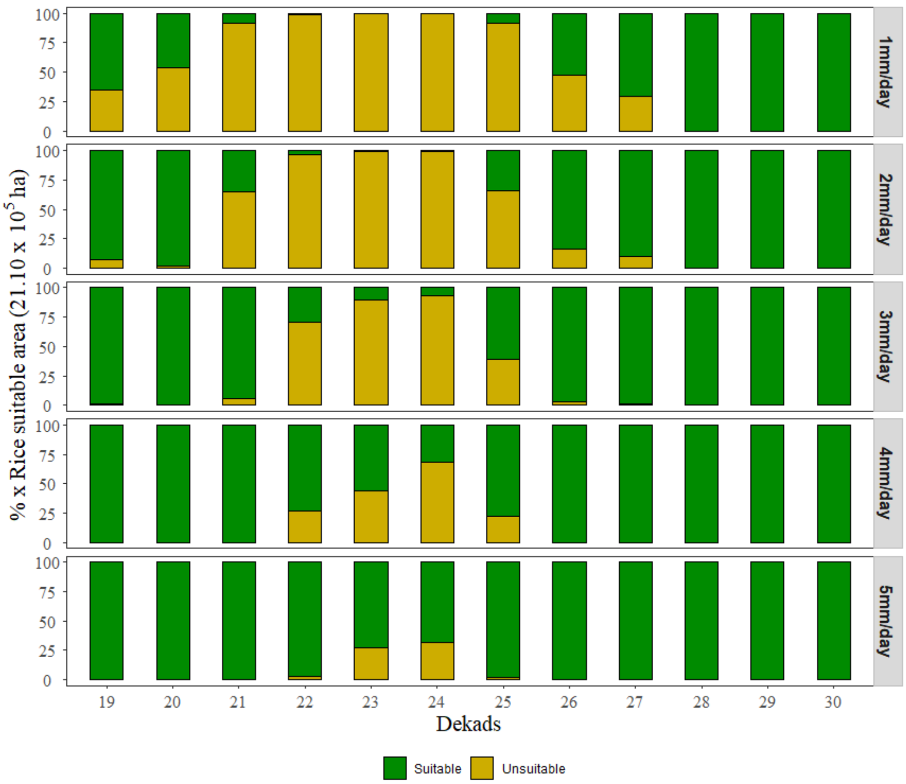

Figure 12. AWD climatic suitability in the wet season (July-October) showing the sensitivity analysis for fixed values of soil percolation of 1, 2, 3, 4, and 5 mm/day.

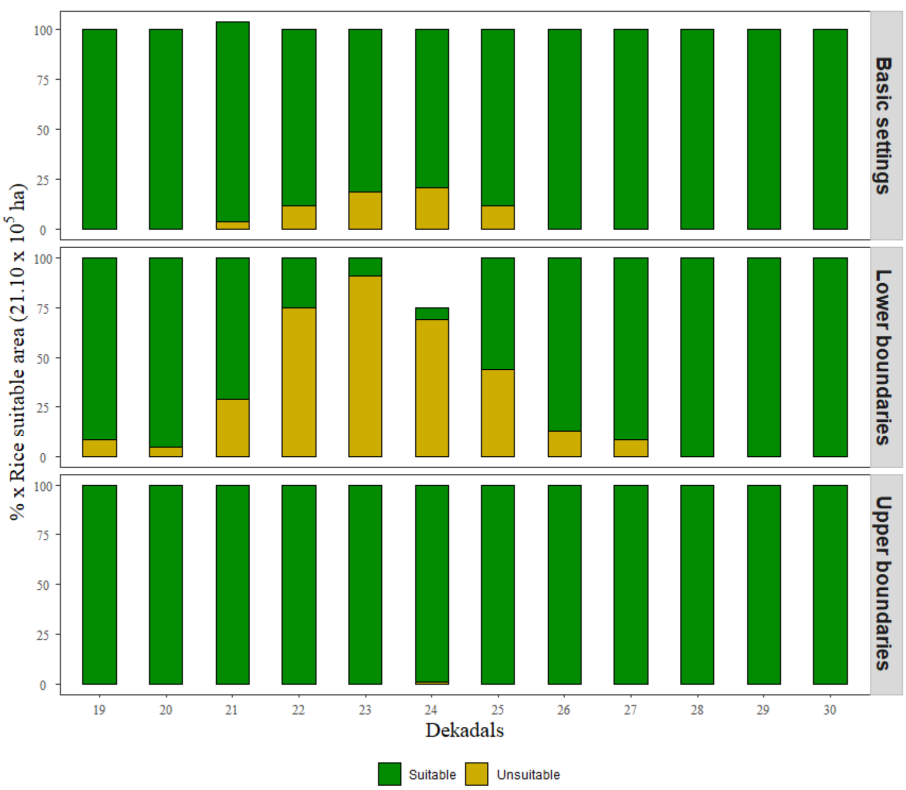

Figure 13. AWD climatic suitability in the wet season (July-October) showing the sensitivity analysis of soil percolation rates as function of soil texture in 3 settings scenarios (lower boundary, upper boundary and basic settings as defined in Table 1).

modeling results and the previous estimates were mainly explained by the methodological approaches. As explained by van der Wijngaart et al., (2019), the estimation of 233,500 ha was based on biophysical and socio-economic methods following a cost-benefit analysis. This approach relies on Spatial Production Allocation Model (SPAM) where national and sub-national agricultural statistics for crop production are downscaled to approximately 10 km × 10 km grid as described in Xie et al., (2017), Xie et al., (2014) and You et al., (2011). On the other hand, the estimated 350,000 ha and 720, 000 ha were based on existing dams and the cost of water delivery to irrigated farmlands Barghouti & LeMoigne, (1990). Thus, these potential irrigable lands are rather based on both biophysical and socio-economic variables and existing irrigation infrastructures. Another estimate based on soil and terrain suitability for surface irrigation showed that Burkina Faso has 5,438,000 ha suitable for rice irrigation (Frenken, 1997). In our approach, we used digitized irrigated rice areas of currently known rice production areas in Burkina Faso to train the models in an inductive approach. These locations are along rivers, river flood plains, lowland (inland valleys and flood plains), which are near small, medium and big reservoirs. Thus, the modeling results infer potential for irrigated rice expansion by implicitly considering the likelihood of water availability and other suitable biophysical conditions, key to future interventions in irrigation infrastructures development for irrigated rice area expansion. The computed difference in the suitability maps for RF and MaxEnt is mainly due to the specification in the threshold's values and methods. RF showed consistency in the evaluation metrics with smaller differences between training and testing data. In other studies, RF has shown the best performance compared with other methods under limited data conditions (Mi et al., 2017). Since we have limited training data, the use of MaxEnt represents an advantage due to its generative learning nature (Phillips et al., 2006).

The distribution of the potential suitability was also explained by the predictors' importance. The modeling shows that exchangeable sodium percentage (ESP) and exchangeable potassium (ESK) were top predictors. The response curve of ESP showed that suitability decreases from an optimum value of 5% toward an upper boundary of 50%. This corresponds to the optimum (less than 20%) and marginal (20-40%) conditions of irrigated rice systems (Frenken, 1997). Previous studies indicated soil salinity as one of the main constraints to irrigated rice cultivation (Abe et al., 2010; Mel et al., 2019). The response curve of ESK showed increasing suitability with increasing ESK values to an upper limit of 2.2 cmol/kg, which is in agreement with previous findings (Saito et al., 2019). The variable importance also shows that depth to groundwater table (WTD) and distance to stream networks and rivers are also top predictors and have decreasing suitability with their increasing values. Both predictors, which are proxies to groundwater and surface water availability for irrigation imply that the estimated distribution of potentially suitable land for rice irrigation corresponds to relatively high-water availability. In the Sahelian context, soil depth is considered as the limiting factor in irrigated rice systems (Dondeyne et al., 1995). The models show that suitability increases with soil depth, probably due to the lower risk of prolonged rice field submergence, which often leads to crop failure (Singh et al., 2009). The overall trends in predictors response curves reconcile well with irrigated rice crop requirements, conferring to the models a strong ecological sense following acceptable ecological niche model development (Hirzel & Le Lay, 2008).

The spatially explicit distribution of potential suitability for irrigated rice shows that the majority of the suitable land lies below latitude 13°N, in three mains clusters around the southwest, central and southeast. The distribution of the suitable land corresponds to the sub-Sahelian climatic zone within the 600 to 900 mm isohyets and the north Sudanese climatic zone within the 900 to 1,200 mm isohyets. Only selected hotspots of suitable areas are located in the Sahelian climatic zone within the 200 to 600 mm isohyets. The southwest spatial distribution of suitable areas is in agreement with irrigated agricultural areas presented in Knauer et al. (2017) based on existing land use and land cover data. Also, the overall potential distribution of irrigable land is in agreement with a map presented in Taverner and Barry (2020).

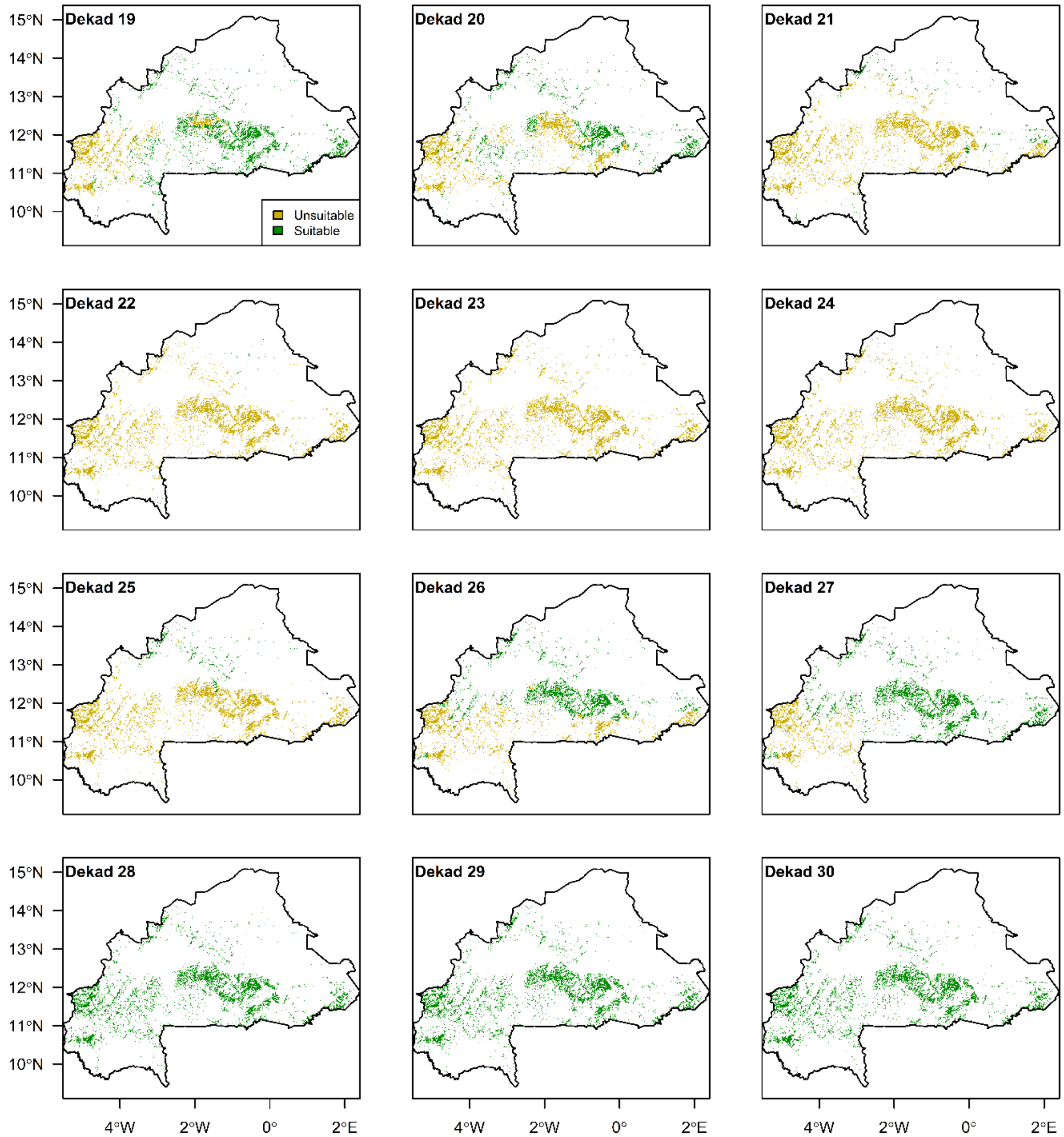

Figure 14. AWD climatic suitability with Pot_Pc equals 1mm/day in the wet season (July-October)

4.2. Suitability of irrigated rice area to the AWD method of irrigation

In the arid and dry-sub humid zone of West Africa, reducing water for irrigation while at the same time keeping good yield is strategic for food security and adapting to water scarcity. In this study, we evaluated the climatic suitability of AWD at the national scale of Burkina Faso during both dry and wet seasons. The results indicated that all dekads in the dry season were deemed suitable for AWD, following similar results found in the Philippines (Nelson et al., 2015).

The application of AWD water-saving technology is challenged by many factors including soil types and climate (Yang, Zhou, & Zhang, 2017) such that Djaman et al., (2018) recommended the testing of AWD under various soil texture conditions and water regimes. Thus, to account for uncertainties associated with potential soil percolation rates (Pot_Pc), a sensitivity analysis was conducted by testing Pot_Pc fixed values of 1, 2, 3, 4, 5 and 10 mm/day and by also

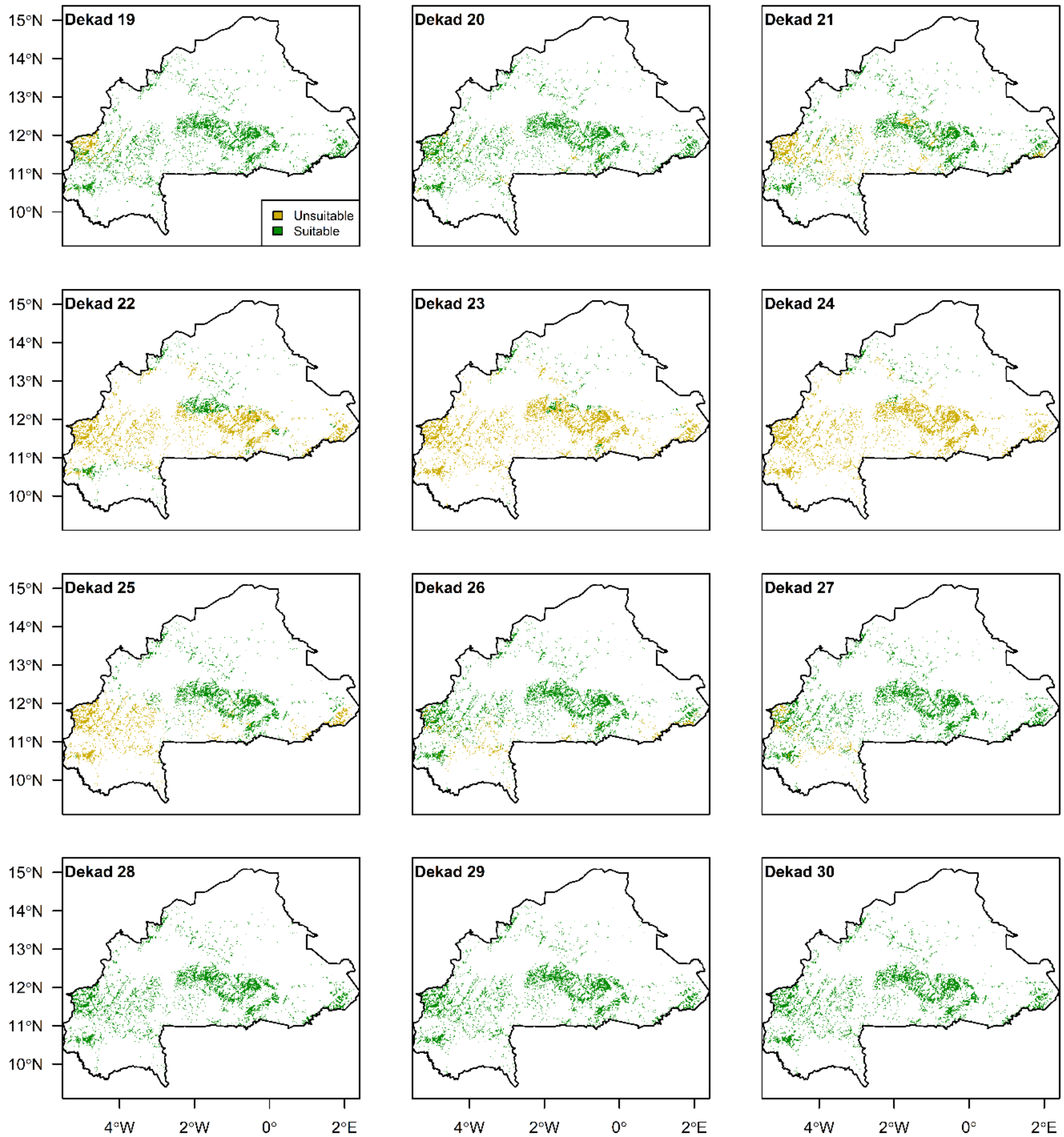

Figure 15. AWD climatic suitability with Pot_Pc as a function of soil texture (lower boundary) in the wet season (July-October)

defining Pot_Pc as a function of texture classes in three different settings namely the low boundaries where Pot_Pc values were set to minimum, the upper boundary where Pot_Pc were grossly high and the intermediate Pot_Pc values. Under fixed Pot_Pc settings, AWD suitability in the wet season was partially or totally suitable in dekads 19 to 21 (July) and in dekads 25 to 30 (September-October). This suggests that AWD is feasible in wet season in Burkina Faso (currently, AWD is not used in the wet season), which might result in reduced water stress and higher rice yield. This is in line with the conclusion that during the wet season in the Sahel, AWD can be implemented (de Vries et al., 2010). Our results also substantiate the findings of Johnson et al, (2020) who assessed the agronomic performance of AWD during four growing seasons (two wet and two dry) in four irrigation schemes in Burkina Faso and reported that AWD can be practiced in the dry and wet seasons with a reduction in the irrigation water use by 32% and

25%, respectively compared with the farmers' conventional practice of irrigation. However, it is also acknowledged that AWD adoption in the rainy season or at least some parts of the rainy season may be limited since rice systems are often in low-lying valleys and it may not be possible to dry the field, especially in high rainfall years (Adhya et al., 2014; Carrijo et al., 2017). This condition is true for Burkina Faso in the dekads 22 to 24 (August-September) where the country receives the peak precipitation following the south-north gradient and in scenarios where Pot_Pc were relatively low (less than 3 mm/day and lower boundary conditions). Irrespective of Pot_Pc spatial variability, the spatial and temporal distributions of precipitation and evapotranspiration were the main drivers of water balance excess and deficit in the wet season.

Under the "safe" AWD recommended by IRRI, rice fields are kept flooded during the first two weeks after transplanting to prevent transplanting shock and suppress weeds, and during the flowering stage to avoid water stress at this sensitive stage and all other growing periods. Our assessment of AWD suitability did not consider such periods where rice fields should be maintained flooded. If all farmers transplanted rice seedlings in dekad 4 using a 120 days rice variety, then dekads 4 and 5 (two weeks after transplanting) and decades 11 to 13 (flowering stage) will be considered unsuitable for AWD. However, not all farmers transplant rice seedlings in the same decade. Therefore, our study provides a window for AWD application on a national scale. Soil properties that favor AWD yield and promote low water use relative to continuous flooding were previously reported (Carrijo et al., 2017). Yield losses with AWD compared with CF were found to be pronounced in soils with pH ≥ 7, soil organic carbon $< 1\%$, and clay soil (Carrijo et al., 2017). Besides, soil salinity might increase with AWD in schemes with a deeper groundwater table due to capillary rise (Letey et al., 2011). Although our AWD suitability assessment did not specifically include soil properties and groundwater depth, we used these variables to identify suitable land for irrigated rice areas and evaluate AWD suitability in the identified potentially suitable land.

4.3. Viewpoints on other water-saving strategies in irrigated rice systems

The increased water scarcity for crop productions requires methods and best water management practices that result in less water usage in irrigated rice systems. These water-saving strategies try to reduce the unproductive water losses through seepage, percolation, and evaporation at the irrigated rice field scale. While the full discussion on the water-saving strategies in irrigated rice schemes is beyond the scope of this paper, we presented here a brief of such strategies that may be promoted or may need further research in West Africa for more sustainable irrigated rice production:

a. **Aerobic rice systems:** These systems are characterized by rice cultivation in non-flooded and non-saturated soil with supplemental irrigation when needed (Bouman et al., 2005). Aerobic rice leads to the lowest water consumption compared with the traditional flooded rice, but also the lowest yield, while the risk of crop failure due to drought is high (Nie et al., 2012; Peng et al., 2006). The low yield in aerobic systems represents the main limitation to its widespread adoption by small-scale farmers (Nie et al., 2012). Besides, for Sahelian conditions such as in Burkina Faso, a thorough understanding of the opportunities and threats is still needed in the viewpoints of knowledge, labor, and energy requirements.

b. **Ground Cover Rice Production System (GCRPS) or Mulching:** Mulching is another water-saving technology through the reduction of runoff and soil water evapotranspiration, which increases soil moisture retention by covering the ground with straw, other crop residues, or plastic sheets (Jabran et al., 2015). Studies showed that mulching improved both soil moisture and yields (Dossou-Yovo et al., 2016) while controlling weeds germination and development (Liu et al., 2013; Qin et al., 2006) and pest and diseases (Erenstein, 2003; Ngosong et al., 2019). However, in an irrigated system, the performance of mulching is limited by the high soil moisture that limits the decomposition of organic matter and generates high methane emission (Kreye et al., 2007). Besides, in the Sahelian environment such as in Burkina Faso, mulch availability is often limited, contributing to the poor adoption of this technology by small scale farmers (Erenstein, 2003).

c. **The System of Rice Intensification (SRI):** SRI is an ensemble of rice systems management practices based on 4 principles: wide spacing, young seedling, use of organic fertilizer and AWD (See Satyanarayana et al., 2007 for review on SRI and its historical development). Experiments conducted on SRI demonstrated its benefits on water saving, yield increase and soil fertility improvement (Dobermann, 2004; McDonald et al., 2006; Sheehy et al., 2004). However, SRI has not been widely adopted by small-scale farmers due to several reasons including high labour requirement, and organic fertilizer, often limiting, particularly in the Sahelian environment where rainfall is too low and livestock production requires organic matter.

Among the water-saving technologies, AWD has been widely advocated for its potential to reduce water consumption, methane emission, while maintaining rice yield compared with the traditional approach of conventional flooding. However, more research is needed on the effects of AWD on labour requirements and soil fertility.

4.4. Outlooks

Several studies showed the greenhouse gas emissions (GHGs) reduction potential of the AWD with large reductions in methane emissions reported in compared to continuous flooding (Clements et al., 2011; LaHue et al., 2016; Wang et al., 2020). This aspect is critical in the West African situation where rice area expansion is unavoidable to meet the national rice self-sufficiency agenda while keeping the promise of sustainable intensification goals. A study on a biophysical suitability mapping for AWD in the Philippines and Thailand demonstrated an approach to quantify GHGs at the national scale (Sander et al., 2017; Prangbang et al., 2020). Given this context, it is important to deploy this method in West Africa to support GHG inventory in the national communications to the United Nations Framework Convention on Climate Change (UNFCCC) in the rice sectors. In a large agricultural water management context, especially in a transboundary watershed (e.g. the Volta Basin), it is recommended a general adoption of the water-saving concept. A detailed spatial explicit mapping and quantification of irrigation water use and its productivity from field scale to regional scales while considering AWD is a prerequisite for planning, improving, and managing irrigation systems (Lampayan et al., 2015). Future research may also consider how socio-economic factors may influence the adoption of AWD among smallholder rice farmers (Howell et al., 2015).

5. Conclusion

To achieve rice self-sufficiency in West Africa, governments and the private sector need to invest in area expansion of irrigated rice production. Climate change is expected, however, to negatively affect water resource availability. Thus, planning and development of new rice areas must be done conjunctively with the adoption of water-saving irrigation management technologies. To develop policies, plan investment, and make informed decisions, accurate and reliable spatial information on irrigated rice potential for sustainable development is essential. To fill this gap and support policymakers, planners, and other stakeholders in Burkina Faso, we developed a spatially explicit and integrated approach to map the potential areas for irrigated rice expansion under the water-saving alternate wetting and drying (AWD) water management technology. We assessed that between 20.7 x 10^5 ha and 25.0 x 10^5 hectares are potentially suitable for irrigated rice in Burkina Faso. The major predictors for irrigated rice potential were exchangeable sodium percentage, exchangeable potassium, depth to groundwater table, and distance to stream networks and rivers. This indicated the importance of soil chemical properties as well as groundwater and surface water importance for irrigated rice. Given that the ecological niche approach used in this study infers optimum conditions from observed irrigated rice areas, the method offers a tool that is robust for planning sustainable agricultural development by providing a major predictor of optimum location and their partial response to the suitability level of that location. The climatic suitability for AWD indicated that about all dekads of the dry season was deemed climatically suitable for AWD. Besides, an additional 25–100% of the wet season was found climatically suitable for AWD. Soil percolation rate was the main driver of AWD suitability during the wet season. The framework used in this study can guide investment in irrigated rice expansion and AWD scaling for water-saving, greenhouse gas mitigation, and ecosystem services preservation, all unknown in the West African region. Further studies should evaluate the boundary conditions in irrigation systems that are required for large-scale adoption of AWD. This study did not consider the cost of water delivery to potentially irrigable rice areas. Future studies may consider this option in cost-benefit analysis. Also, future research may include water storage – reservoirs, and/or dams as predictors and their impact on the spatial distribution of potentially suitable irrigable lands.

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Supplementary materials: AWD climatic suitability in the wet season (July to October)

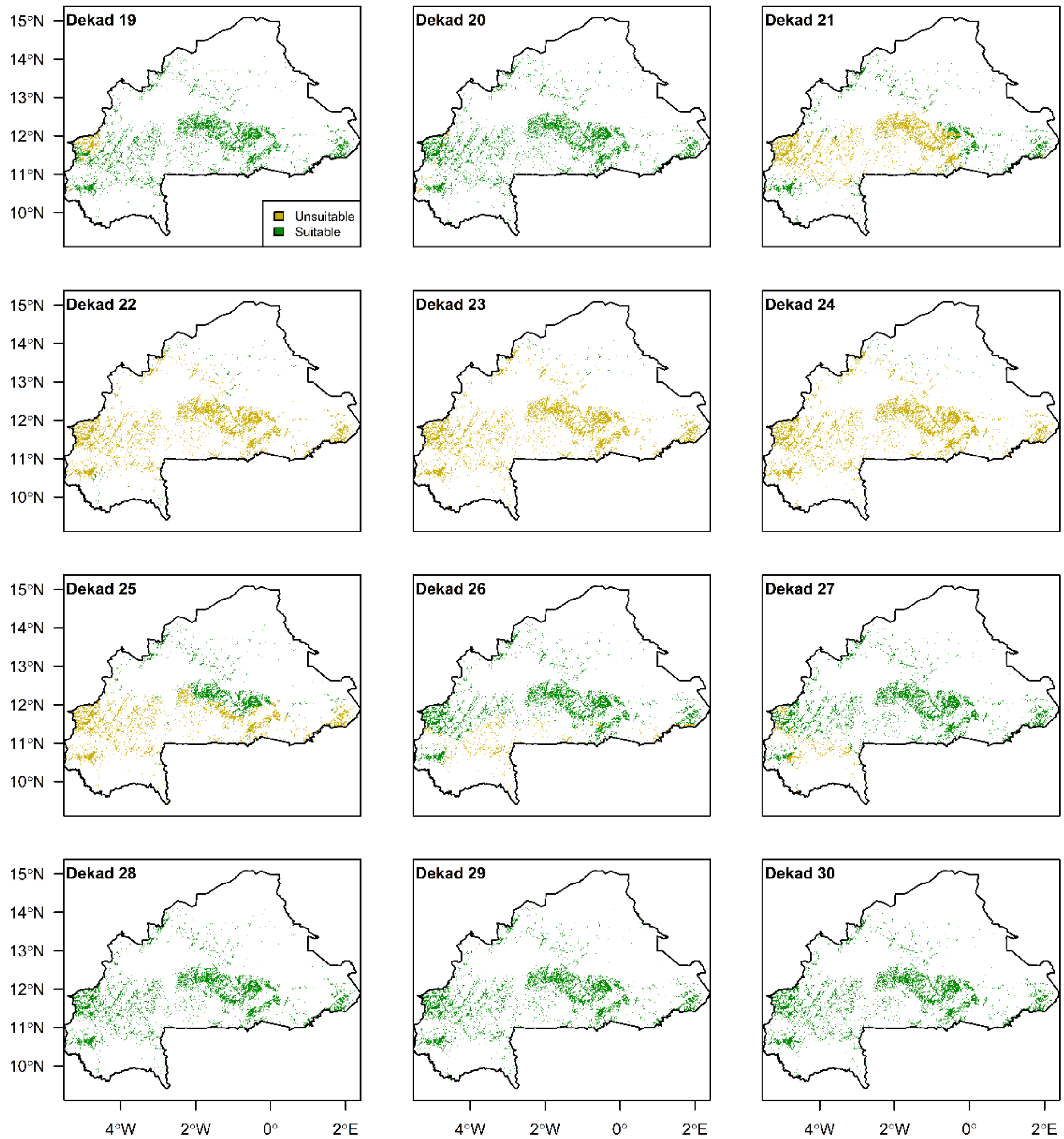

Figure S2_1. AWD with Pot_Pc equals 2mm/day

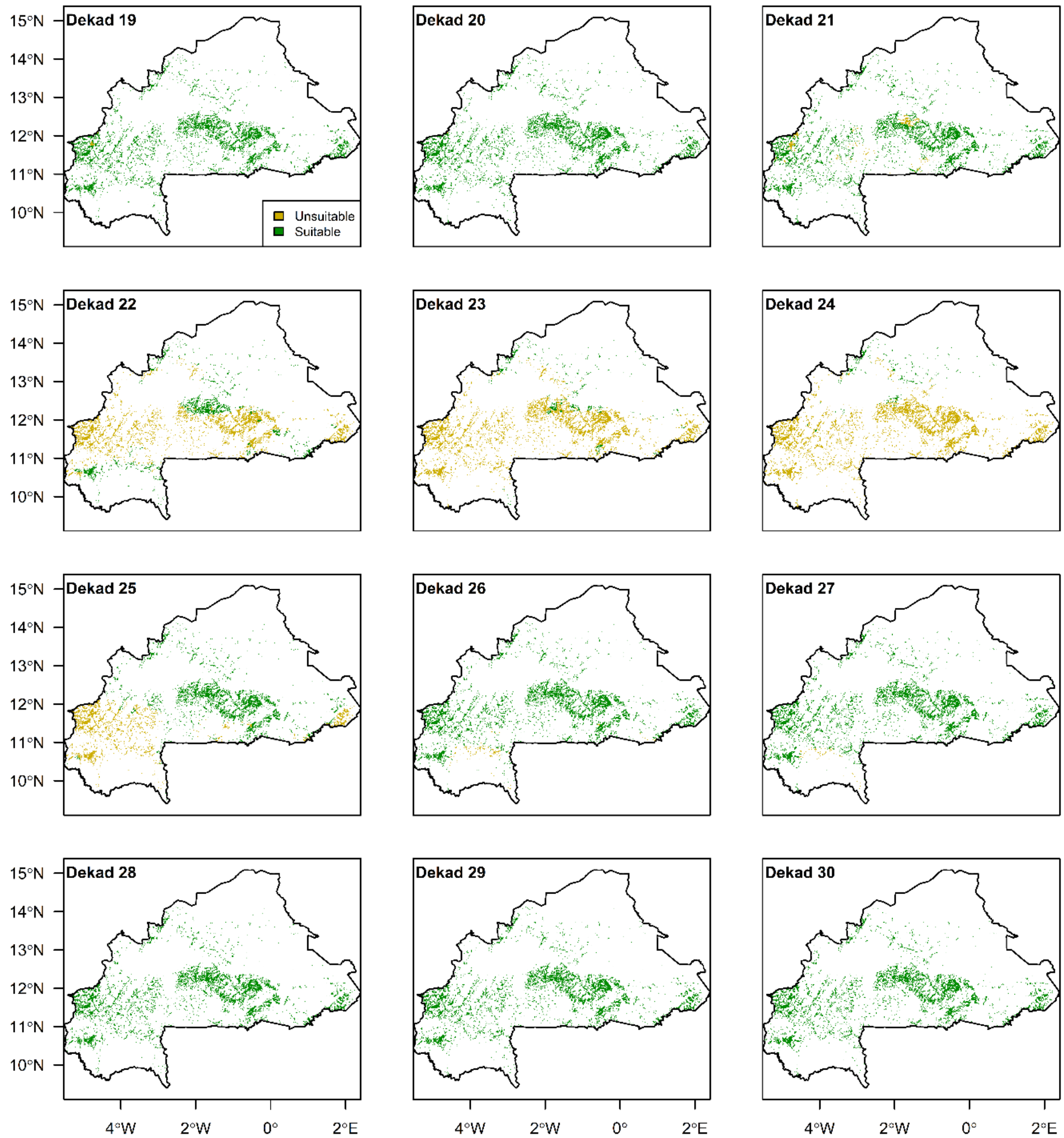

Figure S2_2. AWD with Pot_Pc equals 3mm/day

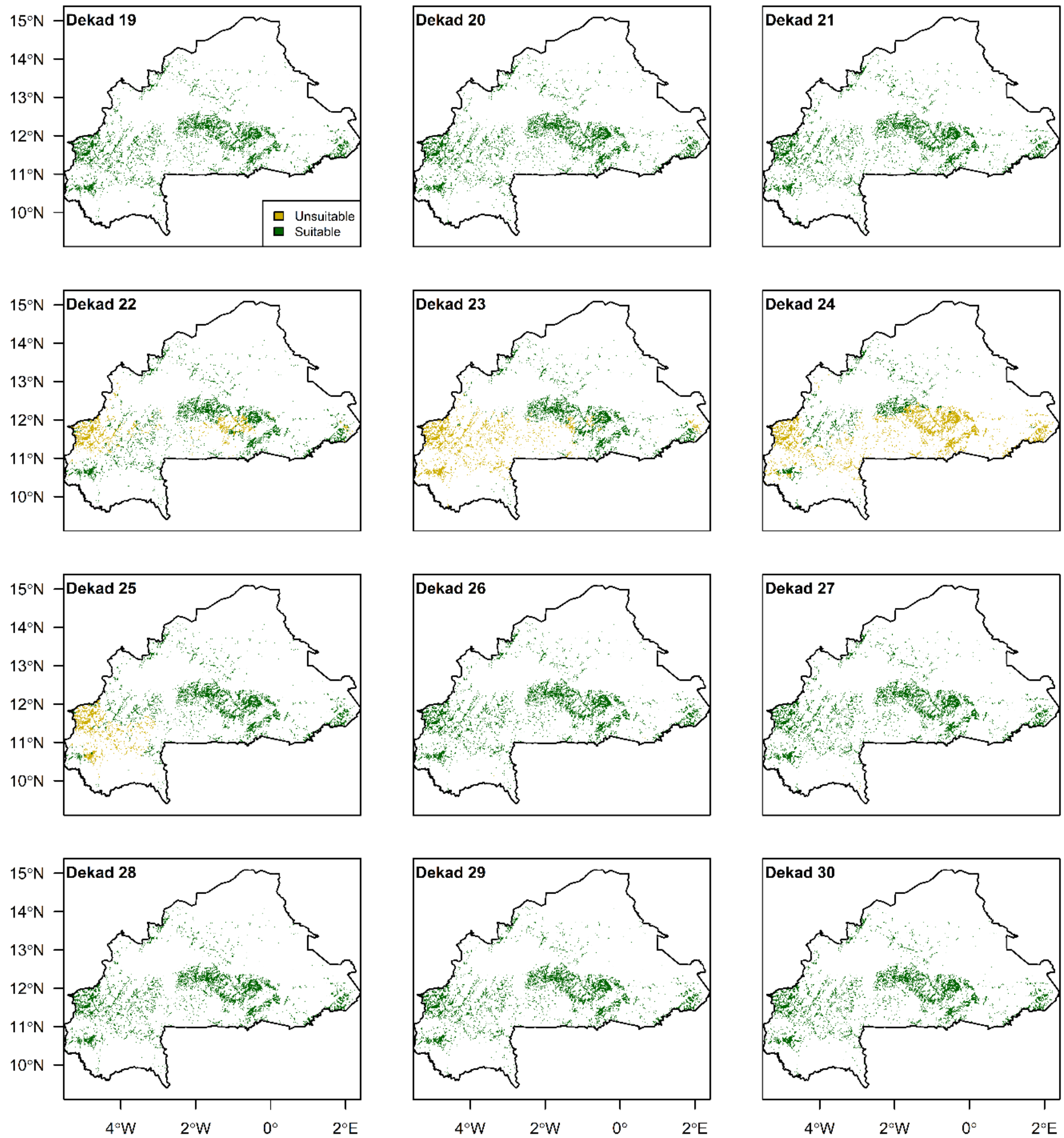

Figure S2_3. AWD with Pot_Pc equals 4mm/day

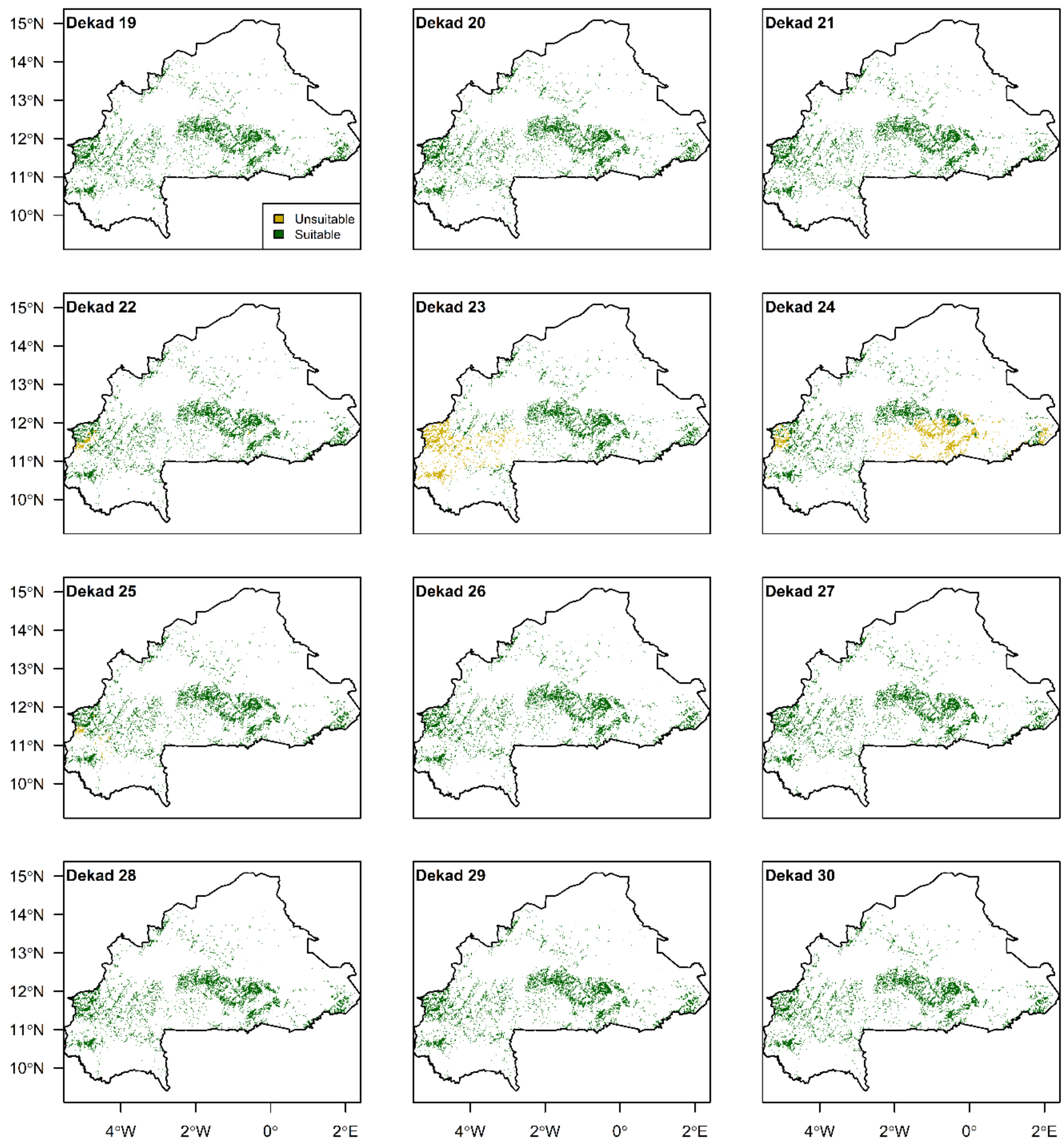

Figure S2_4. AWD with Pot_Pc equals 5mm/day

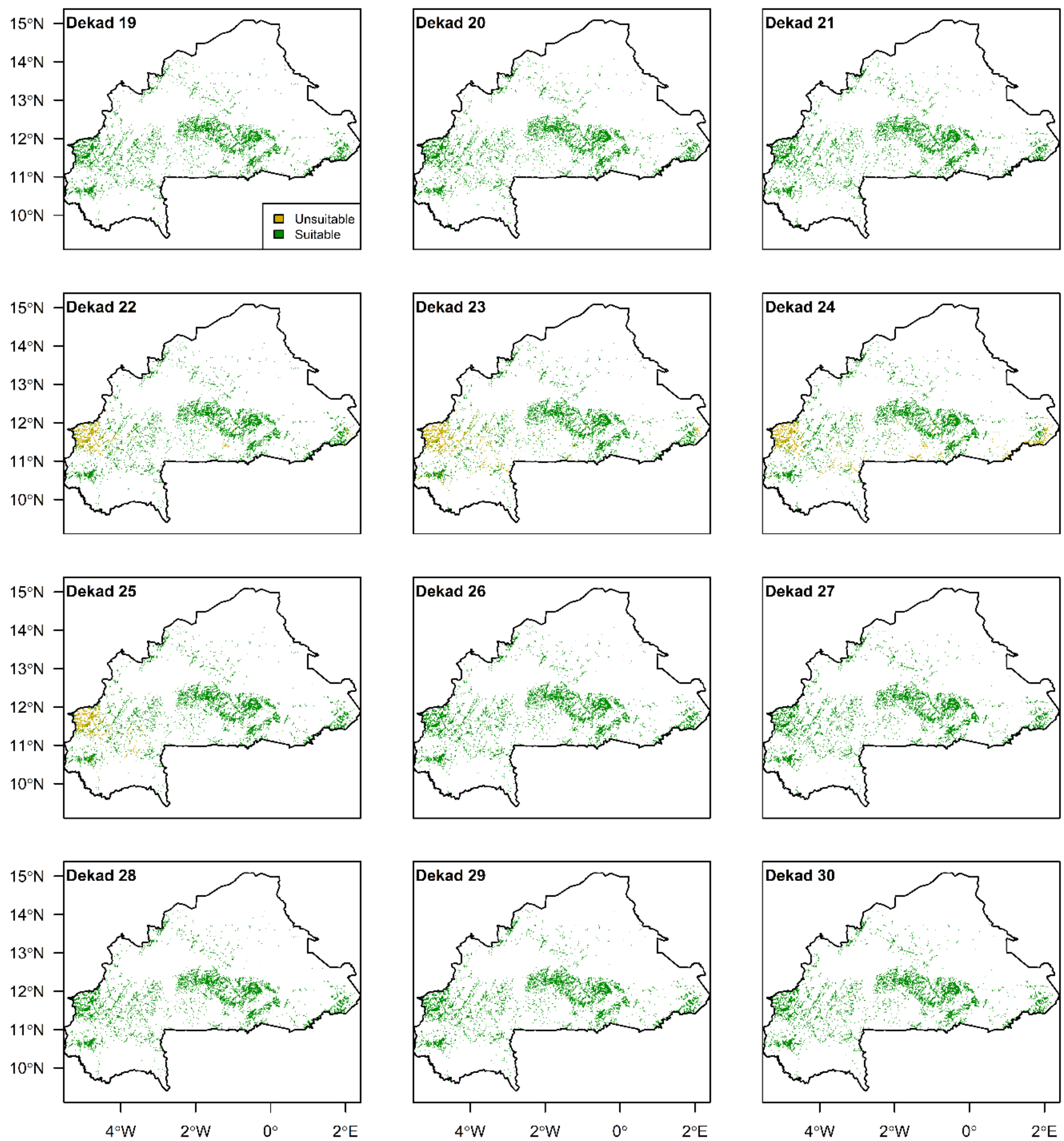

Figure S2_5. AWD with Pot_Pc as function of soil texture (basic settings)

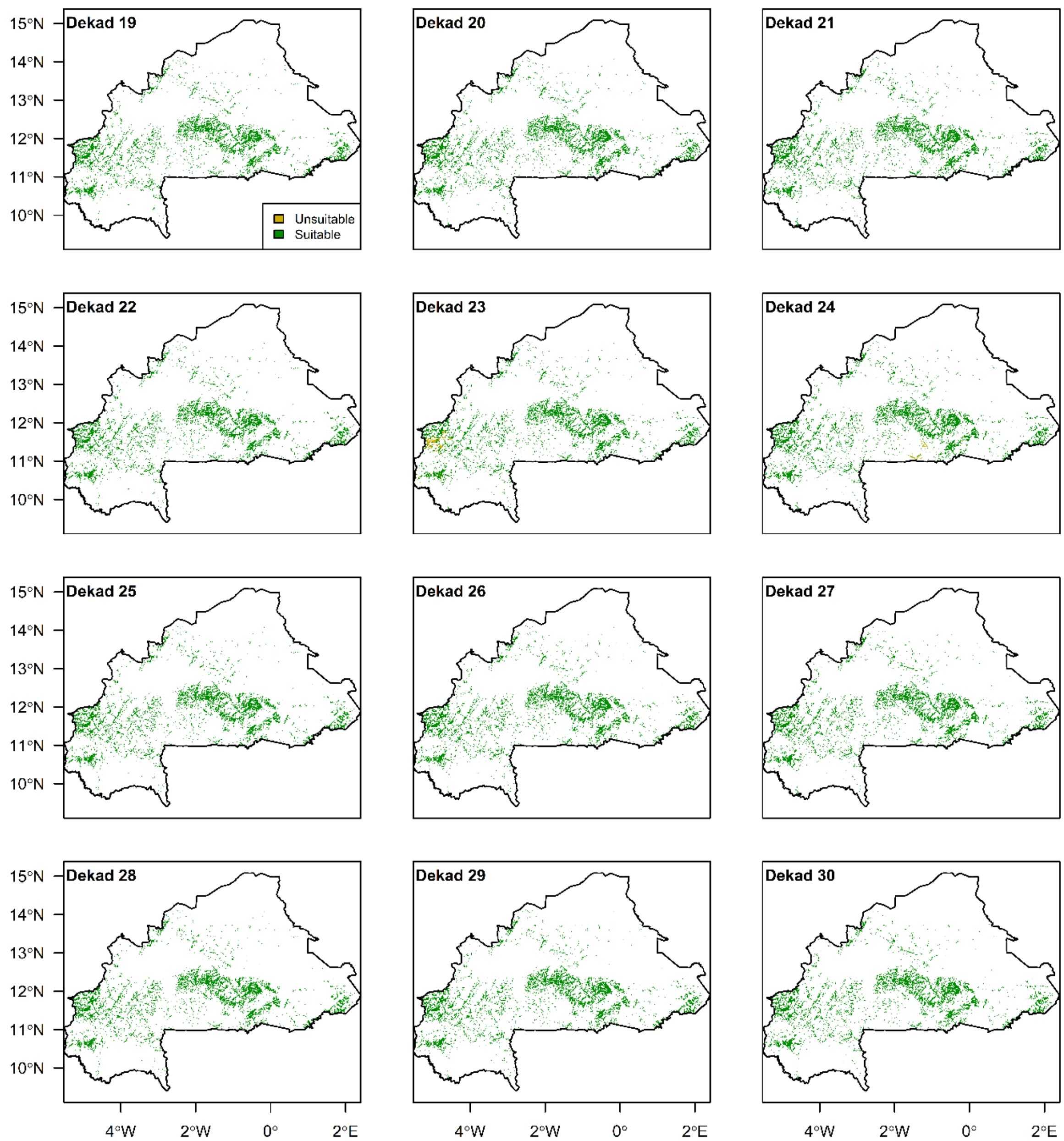

Figure S2_7. AWD with Pot_Pc as function of soil texture (upper bounds)