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Accounting for correlation among environmental covariates improves delineation of extrapolation suitability index for agronomic technological packages

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ABSTRACT

This paper generates an extrapolation suitability index (ESI) to guide scaling-out of improved maize varieties and inorganic fertilizers. The best-bet technology packages were selected based on yield gap data from trial sites in Tanzania. A modified extrapolation detection algorithm was used to generate maps on two types of dissimilarities between environmental conditions at the reference sites and the outlying projection domain. The two dissimilarity maps were intersected to generate ESI. Accounting for correlation structure among covariates improved estimate of risk of extrapolating technologies. The covariate that highly limited the suitability of specific technology package in each pixel was identified. The impact based spatial targeting index (IBSTI) identified zones that should be prioritized to maximize the potential impacts of scaling-out technology packages. The proposed indices will guide extension agencies in targeting technology packages to suitable environments with high potential impact to increase probability of adoption and reduce risk of failure.

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Big data; novel correlation; priority setting; risk of failure; spatial targeting

1. Introduction

Food insecurity is a prevalent problem in sub-Saharan Africa (SSA) and the situation is worsened by rapidly increasing population (van Ittersum et al. 2016). Sustainable intensification is one of viable policy options for increasing food production from existing farmland while conserving natural resource capital (Tilman et al. 2002; Vanlauwe et al. 2011; Garnett et al. 2013; Stevenson et al. 2013). This ensures that the capacity of the future generation to produce food is not undermined. Sustainable intensification in smallholder agriculture promotes scaling out of integrated technological packages such as improved maize varieties and good agronomic practices (Ajayi et al. 2007; Kassie et al. 2013; Fisher et al. 2015). Adoption of improved maize varieties that are high yielding and tolerant to multiple stresses (drought, poor soils, pests and diseases) is promoted to increase food production and reduce

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poverty (Asfaw et al. 2012; Kassie et al. 2014; Fisher et al. 2015; Tesfaye et al. 2016). Improved maize varieties are promoted together with relevant good agronomic practices that synergistically increase productivity (Adu-Gyamfi et al. 2007; Kimaro et al. 2009; Vanlauwe et al. 2011).

Maize is a major staple providing over 60% of dietary calories in Tanzania. It is cultivated on over 2 million hectares that comprise over 45% of total cultivated land and 75% of cereal production (Kassie et al. 2014). The area under maize cultivation has increased at an average rate of 8% for the last 20 years (Mourice et al. 2014) mainly due to expansion into marginal rangelands (Stevenson et al. 2013; van Ittersum et al. 2016). However, yields remain low, averaging 1.15 Mt/ha for the period between 2000 and 2010 (Kassie et al. 2014). Although recent initiatives have bred over 160 improved maize cultivars (Fisher et al. 2015; Abate et al. 2017), their adoption in Tanzania ranges from 18 to 26% (Smale et al. 2013; Lyimo et al. 2014; Beyene and Kassie 2015). Soil fertility depletion is another main biophysical factor that limits maize productivity in Tanzania. Soils in Tanzania experience a negative soil nutrients balance since the rate of nutrient depletion is estimated to be five times higher than replenishment (Bekunda et al. 2004; Adu-Gyamfi et al. 2007; Kihara et al. 2014; Simtowe 2015). Studies estimate that only 5–15% of farmers apply chemical fertilizers in Tanzania (Bekunda et al. 2004; Kassie et al. 2014; Kihara et al. 2014). Increased adoption of improved maize varieties and inorganic fertilizers work synergistically to reduce yield gap and improve soil health (Vanlauwe et al. 2011).

Maize varieties and fertilizer type and application rates are suited for specific agro-ecologies. Their impact on productivity and potential societal impacts can be accentuated if they are disseminated in their suitable biophysical environments (Fisher et al. 2015; Notenbaert et al. 2016; Tesfaye et al. 2016). Therefore, spatial targeting is necessary when scaling out improved maize varieties and mineral fertilizers. Maize breeders have developed general guidelines for determining suitability of maize varieties based on altitude and length of growing period (TOSCI 2016). These recommendations are largely imprecise due to heterogeneity of the growing conditions and therefore they require timely updates to account for climate change and variability (Mtongori et al. 2015). Similarly, fertilizer recommendations currently used in Tanzania were largely developed in 1990s (Mowo et al. 1993). Therefore, they need to be verified and updated. Existing recommendations are biased to diammonium ammonia phosphate (DAP) and urea fertilizers that aggravate soil acidity. Over-reliance on the two fertilizers may limit maximizing yield and economic returns (Simtowe 2015). Manufacturers are producing new fertilizer blends with additional macro and micro nutrients to address multiple nutrient deficiencies in soils e.g. minjingu mazao fertilizer is manufactured from locally available phosphate rocks and therefore cheaper (Jama and Van Straaten 2006). However, their recommendation zones are not clearly known. Moreover, there is tendency to recommend fertilizers based on administrative boundaries rather than agro-ecological zones (Mowo et al. 1993). Previous attempt for fertilizer recommendations are biased towards high potential agricultural zones only (Marandu et al. 2014).

The variety and fertilizer recommendations can be improved using recent data from multilocational trials. One of main challenge is lack of relevant tools to guide spatial targeting of new technologies especially in data limited and heterogeneous environments in Africa (Kumar and Jhariya 2015; Tesfaye et al. 2016). Recently, the application of geospatial tools to generate extrapolation domains for agronomic technologies has been accentuated by increased availability of big spatial data on climate, soils and topography and robust modelling algorithms (Akıncı et al. 2013; Elsheikh et al. 2013; Hyman et al. 2013). Most studies, for generating extrapolation domains for agronomic technologies apply a top-down geospatial approach that utilize machine learning algorithms to classify gridded environmental variables to relatively similar non-contiguous zones (e.g. Williams et al. 2008; Herrera Nuñez et al. 2011; García et al. 2014; Costantini et al. 2016; Muthoni et al. 2017). This approach is largely explorative and more applicable in situations with no or limited *in-situ* knowledge on performance of the candidate technologies (Muthoni et al. 2017). Alternatively, a bottom-up approach is used to calculate dissimilarity between environmental variables in reference sites where a technology package was tested and found to be successful, with those representing a larger extrapolation domain that is targeted for out-scaling (e.g. Setimela et al. 2005; Rubiano et al. 2016). Application of the bottom-up

approach is based on assumption that adoption rates are likely to be higher in areas with similar biophysical conditions to trial sites (Rubiano et al. 2016).

Bottom-up geospatial approach for delimiting extrapolation domains involve a degree of extrapolation beyond the limits of observed covariate space due to spatial-temporal biases in trial site data and environmental heterogeneity (Elith et al. 2010; Zurell et al. 2012; Ranjitkar et al. 2016). Two types of extrapolation can occur: (1) the range of values (minimum/maximum) for individual predictors in the projection domain are beyond that in the reference sites (Novelty type 1, NT1); or (2) predictors exhibit unique combinations (novel correlation structure) not observed in the reference domain (Novelty type 2, NT2) (Zurell et al. 2012; Owens et al. 2013; Mesgaran et al. 2014). Recent studies have used reference trial sites data to generate extrapolation domains for out-scaling maize varieties in southern African region (Setimela et al. 2005), water programmes in Andes (Otero et al. 2006), agroforestry systems in Central America (Rubiano et al. 2014) and water-efficient rice technologies globally (Rubiano et al. 2016). All these studies accounted for extrapolation type one (NT1) but none considered extrapolation type 2 (NT2). These studies assumed that the correlation among variables remains the same even in the extrapolated space which is rarely the case (Farber and Kadmon 2003; Dormann et al. 2012; Zurell et al. 2012; Owens et al. 2013). Extrapolation can occur within the range of univariate variation but which exhibits novel combinations between covariates (Mesgaran et al. 2014). To solve this problem, Mesgaran et al. (2014) developed a novel extrapolation detection (ExeDet) method that calculates Mahalanobis dissimilarity between environmental variables in reference trial sites and the projection domains while accounting for both the deviation from the mean univariate range (NT1) and the correlation between covariates (NT2).

The objective of this paper is to apply a modified ExeDet algorithm to generate spatially explicit indices depicting the risk of extrapolating best-bet technological packages comprising of improved maize varieties and mineral fertilizers in Tanzania. We postulated that uncertainties related to extrapolation of a technology from reference sites to the projection domain are better accounted by considering both dissimilarity from univariate range and changes in correlation structure among covariates. Moreover, it is expected that accounting for correlation structure among covariates contribute additional information that improves mapping risk of extrapolating technology packages from their trial sites to wider projection domain. Therefore, the most suitable zones in the projection domain for scaling-out a particular agronomic technology package are those exhibiting the lowest univariate environmental dissimilarity to the reference trial sites (NT1 equal or close to zero) and without novel correlations among covariates (NT2 values less than 1). This is based on ecological niche theory (Hutchinson 1957), that posits that every species (crop variety) has an optimum range of environmental conditions that they can survive and grow, the fundamental niche. The mean of all environmental conditions in the reference sites is regarded as optimal environment for each technology package. Therefore, increasing environmental dissimilarity with respect to both univariate range and correlation change of covariates compared to conditions in the reference sites, indicates increasing risk of failure of agronomic technology packages. Improved knowledge on environmental dissimilarity between reference sites and the potential projection area for agronomic technologies significantly reduce uncertainty that can increase likelihood of adoption (Rubiano et al. 2016). We also postulated that the potential impacts of a technology package are not uniformly distributed within the derived suitable zone. Therefore, it is necessary to prioritize interventions to zones where potential impacts can be maximized to rationalize use of limited resources. Furthermore, it is expected that determining the distribution of the limiting factors (MIC) in the projection domain will provide useful information to guide extension agents to spatially target remedial interventions for addressing the factor that largely constrain a particular technology to achieve full potential in specific localities. The indices developed in this paper are expected to guide development and extension agents in targeting technology packages in suitable environments to increase probability of adoption and reduce risk of failure.

2. Material and methods

2.1. Study area

The study was conducted within five administrative regions of Tanzania (Figure 1), covering approximately 277,743 km² (31.9°E, -3.4°S; 38.5°E, -10.6°S). A technology scaling intervention is being implemented in this area by a consortium of researchers in partnership with a consortium of development partners, to accelerate adoption of sustainable intensification technologies. A basket of technology packages are disseminated through a mother-baby demonstration approach in the intervention villages. Geospatial technology is integrated within the programme to guide spatial targeting of technologies to suitable biophysical and socio-economic environments.

Annual precipitation ranges from 500 to 2500 mm and altitude ranges from 35 to 3000 m above sea level. Soils are largely acidic with pH ranging from 0.4 to 0.6. Land cover is diverse ranging from open grasslands, cropland, shrubland, miombo woodlands, plantation and natural forests. Agriculture is the main economic activity, mainly cultivating maize and rice. Other major food crops are finger millet, sorghum and pearl millet. Livestock keeping dominate in the rangelands.

2.2. Maize and fertilizer demonstration sites

Demonstration plots measuring 10 × 10 m were established during the 2015–2016 growing seasons in Kongwa, Kiteto, Mbozi and Kilolo districts (Figure 1). Treatments combining improved maize varieties and inorganic fertilizers (Table 1) were laid out in a split-plot design at different demonstration sites (Figure 1) based on maize variety requirements (Table 1; TOSCI 2016) and existing fertilizer recommendations (Marandu et al. 2014; Mkoma 2015). This resulted in an imbalanced design. The demonstration plots are hereinafter referred to as technology trial sites. Staha is an open-pollinated variety (OPV) but all the other maize varieties are hybrids. Staha variety is targeted to resource-poor farmers who cannot afford buying hybrid seed every year (Lyimo et al. 2014).

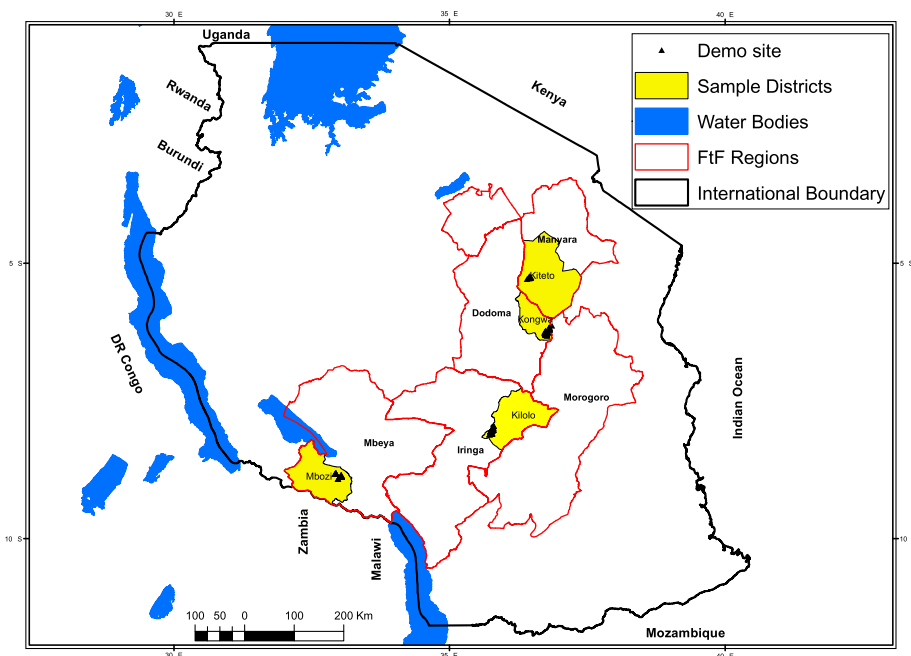


Figure 1. The location of demo sites for improved maize varieties and mineral fertilizers in Tanzania.

Table 1. Characteristics of improved maize varieties and fertilizers treatments.

Variety	Potential yield (t/ha)	Optimal altitude (m)	Maturity (days)	Fertilizer applied	Treatment ID	Original n
HB614	7	>1500	180–190	DAP + Urea	Var1Fer1	11
				Minjingu Mazao+MTD	Var1Fer2	12
				YaramilaCereal + YaraBelaSulfan	Var1Fer4	4
PAN691	7	>1500	103	DAP + Urea	Var2Fer1	10
				Minjingu Mazao+MTD	Var2Fer2	7
				YaramilaCereal	Var2Fer3	20
				YaramilaCereal + YaraBelaSulfan	Var2Fer4	5
UH6303	10-Sep	1200–1800	92	DAP + Urea	Var3Fer1	22
				YaramilaCereal	Var3Fer3	7
				YaramilaCereal + YaraBelaSulfan	Var3Fer4	5
H625	6.0–8.0	1500–2400	180–240	DAP + Urea	Var4Fer1	4
H628	9.0–12.0	150–180	150–180	DAP + Urea	Var4Fer3	13
				YaramilaCereal	Var5Fer1	13
SC719	7–10	800–1500	145–153	DAP+ Urea	Var5Fer3	21
				YaramilaCereal + YaraBelaSulfan	Var6Fer1	5
UH615	8.0–9.0	1200–1800	85–92	DAP+ Urea	Var6Fer4	4
				YaramilaCereal + YaraBelaSulfan	Var7Fer1	5
MERU513	11	800–1200	100–110	DAP + Urea	Var7Fer4	5
				YaramilaCereal + YaraBelaSulfan	Var8Fer1	5
Staha	4.0–5.0	0–900	120	DAP + Urea	Var8Fer4	5
				YaramilaCereal + YaraBelaSulfan	Var9Fer3	59
				Minjingu Mazao + Urea	Var9Fer5	6
				NAFAKA plus + MTD	Var9Fer6	64

Notes: Minjingu Mazao = N (10%), P (8.8%), S (5%), Zn (0.5%), Cu (0.5) and B (0.1%). Minjingu top dressing (MTD) = N (27%), P₂O₅ (10%), Cao (15%). NAFKA plus = N (9%), P₂O₅ (16%), K (6%), MgO (2%), Cao (15%), S (5%) and. YaraMilaCereal = N (23%), P₂O₅ (20%), K (5%), MgO (3%), S (3%) and Zn (0.3%). YaraBelaSulfan = N (24%) and S (6%). DAP = N (18%) and P₂O₅ (46%). Urea = N (46%).

Fertilizer application rates varied for the four sample districts based on existing recommendations as follows; Mbozi (120 kg N/ha and 20 kg P/ha), Kilolo (120 kg N/ha and 20 kg P/ha), based on recommendations by Marandu et al. (2014). Application rates in Kongwa and Kiteto districts was 60 kg N/ha and 30 kg P/ha following Mkoma (2015). The fertilizer treatment (Fer1) with DAP for basal application and urea as top-dressing represented the farmers practice, although this combination is known to accentuate soil acidity (Amuri et al. 2012). The rest of fertilizer treatments (Table 1) comprised of relatively new fertilizer blends that provide macro- and micro-nutrients to address multiple nutrient deficiencies in the soils. The base cations in the new fertilizer blends reduce acidification effect compared to application of DAP and urea. YaraMilaCereal was applied in two equal splits at planting and top-dressing to meet the recommended rate for each site.

During harvesting, maize grains were sampled from the inner plot area, leaving at least two border rows on both sides of the plot. The grain samples were weighed in the field using digital portable mass balance. A sub-sample was oven dried at 60 °C to achieve 12% moisture content. Grain yield per plot was estimated from the ratio of dry-to-fresh weights and extrapolated to one hectare based on yield recorded in the sub-sample.

2.3. Environmental and socio-economic layers

Ten gridded biophysical layers were selected as input variables based on their known effect on limiting growth of the maize varieties and efficiency of mineral fertilizers (Table 2). Information on biophysical requirements for maize cultivars was obtained from variety release reports from relevant government agency (TOSCI 2016). Four climatic grid layers with 1 km resolution were obtained from the Worldclim database (Hijmans et al. 2005). The elevation layer was obtained from a 30-m-resolution Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) Digital Elevation Model Version 2 (DEM-V2; METI and NASA 2011). The slope in degrees was extracted from DEM. Gridded layers for soil chemical properties (Table 2) with a resolution of 250 m were downloaded from the World Soil Information database (ISRIC 2015). The soil layers were generated using an automated mapping framework based on random forests (Hengl et al. 2017). These soil layers were estimated at seven standard depths. The average value of top soil (0–30 cm) was used as it represents average effective rooting depth of maize. The selected four soil variables represented the rooting conditions, toxicities, nutrient availability and retention capacity. Before analysis, the DEM and soil grid layers were resampled to 1 km resolution to match the climatic layers. Grid raster with Pearson's r above 0.7 (Bio1, slope and BLD) were removed to avoid multicollinearity.

The remaining seven grid layers were clipped to the extent of the five administrative regions in Tanzania (Figure 1) to delineate the projection domain. Considering that only a few trial sites were available for each treatment (Table 1), a three kilometres buffer was created around the selected demonstration sites for each treatment. Following Rubiano et al. (2016), the resulting buffer polygon was used as a mask for extracting the reference grid layers. The buffer polygon ensured that sufficient local variation of site conditions was captured to avoid over-targeting; although it may cause slight loss of precision (Rubiano et al. 2016). This is justifiable since agronomic technologies suitable for a specific location are generally applicable in the immediate surroundings.

Gridded layers for total population, poverty index, women of childbearing age and children under five years were obtained from Worldpop database (WorldPop 2016). Total population is a proxy for availability of markets and labour as well as level of intensification in small holder farms (Tesfaye et al. 2015). The poverty index layer represented the percentage of total population living below the

Table 2. Input biophysical grid layers.

Code	Variable name	Original Resolution	Reference
<i>Biophysical</i>			
Bio1	Annual mean temperature (C°)	1 km	(Hijmans et al. 2005)
Bio4	Temperature seasonality	"	"
Bio12	Annual precipitation (mm)	"	"
Bio15	Precipitation seasonality (C.V)	"	"
DEM	Elevation (m)	30 m	ASTER (METI and NASA 2011)
Slope	Slope (degrees)	30 m	Generated from DEM
BLD	Bulk density (fine earth) t m ⁻³	250 m	(Hengl et al. 2017)
CEC	Cation Exchange Capacity (cmol ⁺ /kg)	"	"
SOC	Soil organic carbon (fine earth) (g kg ⁻¹)	"	"
pH	Soil pH	"	"
<i>Socio-economic</i>			
Poptot	Total human population	100 m	(WorldPop 2016)
Pov	Poverty index (< \$1.25)	100 m	"
PopPov	Population living below poverty line (< \$1.25)	100 m	Generated from Poptot*Pov
WOCBA	Women of childbearing age (WOCBA)	100 m	"
CU5	Children under 5 years	100 m	"
<i>Auxilliary data</i>			
LULC	Land use land cover (cultivated area, wetlands, water-bodies)	30 m	(Chen et al. 2015)
Prot	Protected areas	–	UNEP-WCMC (2015)
Admin	Administrative data (Level 1–3)	–	TNBS (2016)

poverty line (less than \$1.25 per day). A grid layer representing the number of poor population in each pixel was derived as product of poverty index and total population grid layers. Cultivated land was derived from Globeland30 LULC database (Chen et al. 2015). These data-sets were used to estimate the potential impact of scaling-out best-bet technologies.

2.4. Auxiliary data

A shapefile for Tanzania administrative boundaries was obtained from Tanzania Bureau of Statistics (TNBS 2016). Environmental variables were cropped to the extent of the five administrative regions of interest (Figure 1). A shapefile for protected area boundaries was acquired from World Database of Protected Areas (UNEP-WCMC 2015). The extent of wetlands and large waterbodies was derived from Globeland30 LULC database (Chen et al. 2015).

2.5. Statistical analysis

2.5.1. Selecting best-bet technology package and reference demo sites

The workflow for delineating risk of extrapolating improved maize varieties and fertilizer technological packages is summarized in Figure 2. Analyses were conducted using a modified extrapolation detection (ExeDet) algorithm in R for statistical computing (R Core Team 2017) largely using the ‘raster’ (Hijmans 2015) and ‘BiodiversityR’ packages (Kindt and Coe 2005). Boxplots were generated for visual comparison of the mean and variability of grain yields for different treatments. The trial sites for each technology package should be conducted in sites with relatively homogenous environment to enable comparison of yields. Therefore, environmental variables for all sites for each technology package were tested for multivariate homogeneity of variances using ‘betadisper’ function in ‘Vegan’

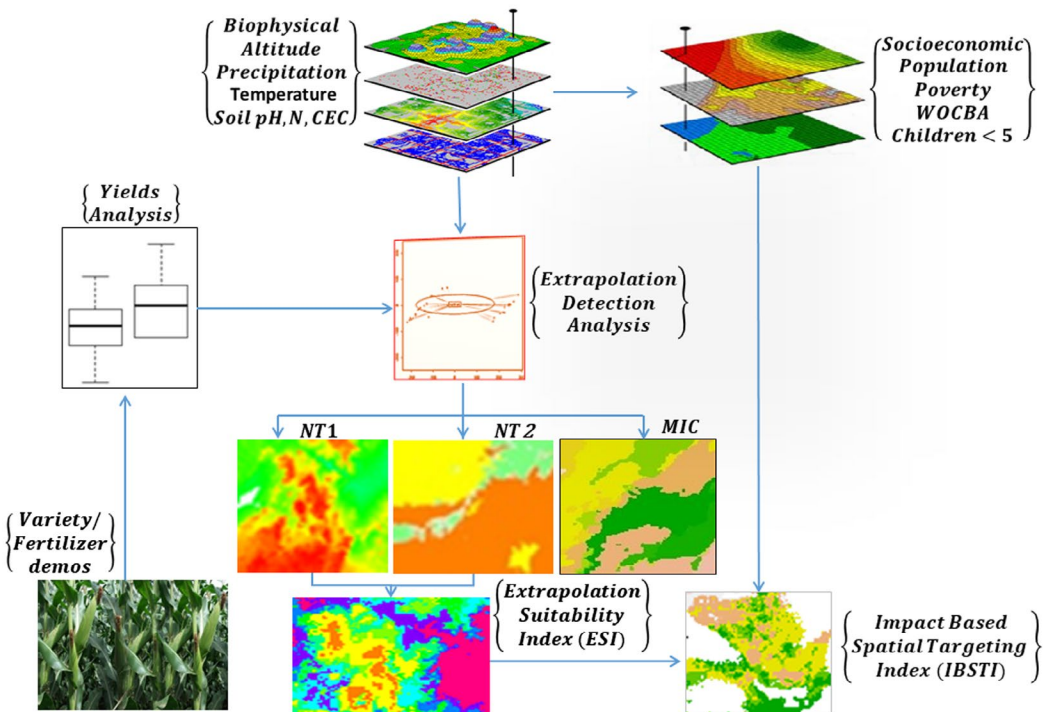


Figure 2. Procedure for delineating extrapolation suitability index (ESI) and impact based spatial targeting index (IBSTI) for estimating risk of extrapolating improved maize varieties and mineral fertilizers.

package (Oksanen et al. 2016). This multivariate tool calculated the Euclidean distance to centroid of the environmental space for cloud of points for each treatment. Sites with multivariate environmental space greater than one standard deviation of data ellipse were identified as outliers and removed. The mean grain yield for the remaining sites for each treatment was calculated and plotted against the yield gap. The suitability of each technology package was evaluated in terms of yield gap calculated as the difference between potential yield for particular variety (Table 1; TOSCI 2016) and observed mean grain yields. Technology packages with lowest yield gap were selected as the best-bets for extrapolation.

2.5.2. Extrapolation detection

A modified extrapolation detection (ExeDet) algorithm (Mesgaran et al. 2014) was used to calculate the environmental dissimilarity between the reference trial sites and the projection domain representing the entire five administrative regions in Tanzania. ExeDet is a multivariate statistical tool that uses Mahalanobis distance to measure the dissimilarity in environment between reference site(s) and a projection domain by accounting for both the deviation from the mean and the correlation between variables (Mesgaran et al. 2014). The projection domain is the search region that is targeted for extrapolating target technological package. The method return maps on two sources of dissimilarity (novelty); the novel univariate range (NT1) and the novel combinations of covariates (NT2). NT1 map indicate the magnitude at which the environmental conditions at any particular location in the projection domains fall outside the range of values observed in the reference sites (Mesgaran et al. 2014). NT1 ranges from zero to an infinite negative value with zero indicating no extrapolation beyond the univariate coverage of reference data. The lower the value is from zero, the more the environmental conditions of a location are dissimilar to that observed in the reference site.

The NT2 map indicates the magnitude at which the combinations of observed values of covariates in the projection domain are different from that in the reference sites (novel correlation structure). NT2 ranges from zero to an infinite positive value. NT2 values ranging from 0 to 1 indicate similarity in terms of univariate range and multivariate combination among covariates, with values closer to zero being more similar (Mesgaran et al. 2014). The original NT2 was designed to take care of scenario that the univariate variables can be within the range observed in the reference sites ($NT1 = 0$) but they exhibit novel correlations in the projection domain that may render crop varieties to respond differently to particular environmental stimuli. Locations with NT2 values ranging between 0 and 1 indicates that the correlation (interactions) among covariates are similar to that recorded in the reference sites and therefore the most suitable for out-scaling the target technology. Values larger than one are indicative of novel combinations of environmental variables beyond that observed in reference sites and therefore depict increasing risk of failure if technologies are extrapolated.

ExeDet tool also generate a map of the most influential covariate (MIC) that identify the environmental variable that exert the highest limit to suitability of a particular technology package in each pixel in the projection domain (Mesgaran et al. 2014). The MIC map is derived by identifying where any particular covariate has the most extreme univariate ranges (NT1) or its highest contribution to the largest correlation distortion (NT2).

NT1 maps were generated in R as per the original ExeDet algorithm. However to generate NT2 map, the ExeDet algorithm was modified in R so that it generates NT2 maps for entire projection domain compared to original algorithm that derived NT2 for only the area that was within the range of reference data (Mesgaran et al. 2014). The NT2 map generated by modified ExeDet algorithm is similar to applications of Mahalanobis distance in species distribution models to identify potential geographical distribution of species based on environmental conditions observed in limited reference occurrence points (e.g. Farber and Kadmon 2003; Duan et al. 2014). This Mahalanobis distance is advantageous since it accounts for correlation among covariates and is scale independent. NT1 and NT2 maps were classified into five suitability classes for each technology package; the first class represented the zone where all univariate covariates were within the reference range ($NT1 = 0$) and where covariates were within the univariate range but with unique combination $NT2 < 1$). This zone is generally similar to the conditions in reference site (Mesgaran et al. 2014). The other four classes in each map were derived

by dividing the range of values into four quantiles. NT1 and NT2 maps returned a diverse range of values with different polarity; values of NT1 ranged from zero to negative infinity while NT2 map ranged from zero to positive infinite number. Therefore, quartile classification was done to ensure that the resulting index is simple to use and interpret by extension agencies. The quartile method is an objective statistical classifier that considers the distribution of all available values in the data to determine the breakpoints as opposed to widely used subjective classification that depends on expert judgement (e.g. Notenbaert et al. 2013; Tesfaye et al. 2015). The resulting five classes for two maps were cross-tabulated using 'compareClassification' function in 'greenbrown' R package (Forkel et al. 2015). This returned a map and a contingency table showing producer accuracy to measure agreement between classes from the two classified maps. The function also returned Kappa index of agreement to measure overall agreement between classified NT1 and NT2 maps. Kappa index ranges from 0 to 1 with 1 signifying perfect agreement while a Kappa of 0 indicates agreement equivalent to chance. Following Fleiss (1981), Kappa index values were interpreted as poor (≤ 0.4), fair to good (0.4–0.75) and high agreement (> 0.75). The level of agreement between NT1 and NT2 maps measured using Kappa index determined if accounting for correlation structure among covariates contributed significant information to improve delineation of suitability of technology packages. High agreement between classified NT1 and NT2 maps would indicate that accounting for correlation structure among covariates does not contribute additional information in defining the suitability of the technology packages.

The product of class matrices in the contingency table after cross-tabulating values of the two classified maps was used to derive an index for suitability referred to as extrapolation suitability index (ESI). For example, if a pixel is in class 2 of the classified NT1 map and class 3 in classified NT2 map, the ESI value was derived by multiplying 2 by 3 resulting to 6. The resulting ESI values for all technology packages ranged from 1 to 25 (the product of maximum number of classes in classified NT1 and NT2 maps ($5 \times 5 = 25$)). The lower the ESI value higher the suitability for a particular technology. The Zone with ESI = 1 is perfectly similar to the reference area for particular technology and therefore is the most suitable for scaling out the candidate technology.

2.5.3. Priority setting within extrapolation suitability zones

The potential impacts of a scaling-out a particular technology are defined in advance and may include a variety of socio-economic factors. The zones defined by ESI represent the biophysical suitability and therefore they may exhibit heterogeneity when considering the potential socio-economic impacts of scaling a particular technology. Therefore, spatial prioritization is needed to identify areas within defined suitability clusters that can be targeted to maximize the potential impact of adopting a technology. The impact based spatial targeting index (IBSTI; Muthoni et al. 2017) was used to identify priority clusters in zones that are highly suitable for the specific technology package (with low ESI values). The IBSTI was developed assuming that the aim of a scaling out sustainable intensification intervention in a given area is to disseminate technology packages to the highest possible proportion of total human population, poor population, women of childbearing age and children under age of five years (Muthoni et al. 2017). The target populations should be located absolutely within the currently cultivated land and outside the critical ecosystems such as protected areas and wetlands to maintain provision of ecosystem services. However, the index is flexible so that other relevant impact variables can be included.

The shapefiles for the wetlands, large waterbodies and protected areas (game and forest reserves) were used to mask out these critical ecosystems to ensure that agricultural expansion does not hamper provision of ecosystem services. The grid layers representing total human population, poor population, women of childbearing age and children under age of five years were reclassified into four classes based on quartiles. The quartile classes were allocated weighted scores of 1–4 (value 1 for the lowest quartile and value 4 for upper most 25% quartile). The upper most quartiles were allocated higher scores depicting higher potential impact because total population is a proxy for food demand and availability of labour (Tefaye et al. 2015). Moreover, agronomic technology packages should be targeted for adoption by highest possible number of poor farmers to uplift their livelihoods. Reaching

the highest possible number of WOCBA was prioritized since they constitute the majority of the rural agricultural labour force (Palacios-Lopez et al. 2017). The cultivated land layer was allocated scores of zero for non-cultivated area and four for cultivated portion. IBSTI was generated by summing the scores of the all the five impact variables. It was assumed that all impact variables contributed equal weight to the index. However, stakeholder consultation process can be used to elicit information on distribution of weight depending on target outcomes of specific technology package (Notenbaert et al. 2016). IBSTI values range from one to an infinite positive value, with higher values indicating more potential impact from a scaling intervention. First, a suitable zone for a candidate technology package was selected based on low ESI values (Section 2.5.2) before calculating the IBSTI values for that particular zone.

3. Results

3.1. Selecting the best-bet technology package

Seven technology packages had yield gap below 2 t/ha. These are Var1Fer2, Var2Fer2, Var6Fer4, Var9Fer5, Var9Fer3, Var9Fer6 and Var2Fer3 (in order of increasing yield gap) (Figure 3). Four of these packages (Var1Fer2, Var2Fer2, Var6Fer4 and Var9Fer3) were selected to demonstrate mapping of the risk of extrapolating from reference sites to the wider projection domain (Sections 3.2). Yield gap for the three treatments for variety 9 was almost similar but Var9Fer3 was selected as representative because it had lower variance in grain yields and more samples ($n = 55$) compared to Var9Fer5 which revealed slightly lower yield gap.

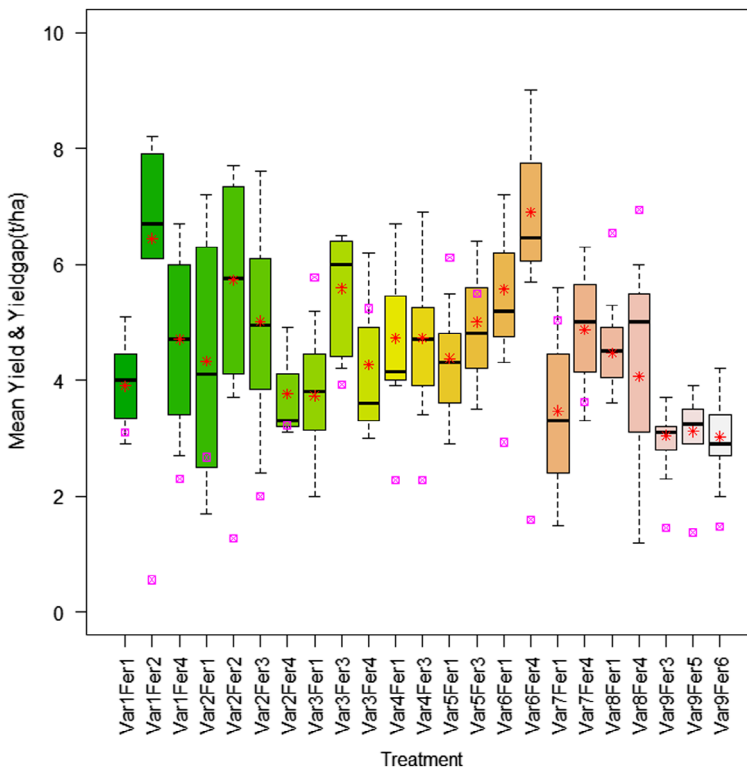


Figure 3. Boxplot showing mean (red star) grain yield and yield gap (magenta points) for technology packages comprising of nine improved maize varieties and six fertilizers.

Note: Yield gap is the difference between the potential and observed mean grain yield.

3.2. ESI for best-bet technology packages

The values of grid layers for the projection domain exhibited higher variance compared to similar grids for the reference site (Figure 4). For Var6Fer4, the annual precipitation in the reference site ranged from 1160 to 1180 mm compared to 500–2500 mm in the projection domain (Figure 4). The derived NT1 maps revealed a gradient of increasing environmental dissimilarity between the reference sites and the projection domain. NT1 maps were reclassified into five risk zones with values ranging 1–5 (Figure 5). Zone 1 coincides with the area where values of univariate covariates were similar to the reference sites for particular technology package. The higher the value in reclassified NT1 maps, the higher the environmental dissimilarity from the reference sites. Zone 5 in reclassified NT1 maps is the most dissimilar to the reference site and therefore poses the highest risk for extrapolating a technology package.

The correlation matrix revealed presence of unique combinations of covariates in the projection domain compared to that in the reference domain. For instance, the correlation between DEM and Bio12 in reference grids of the four technology packages was positive but negative in projection domain. For Var1Fer2 package, the correlation between DEM and Bio12 changed from -0.68 in the reference grids to -0.12 in the projection domain grids (Table 3). The NT2 maps were generated to quantify the degree at which the environmental conditions in the projection domain exhibited novel combinations of covariates compared to reference site. The generated NT2 maps for the four technology packages

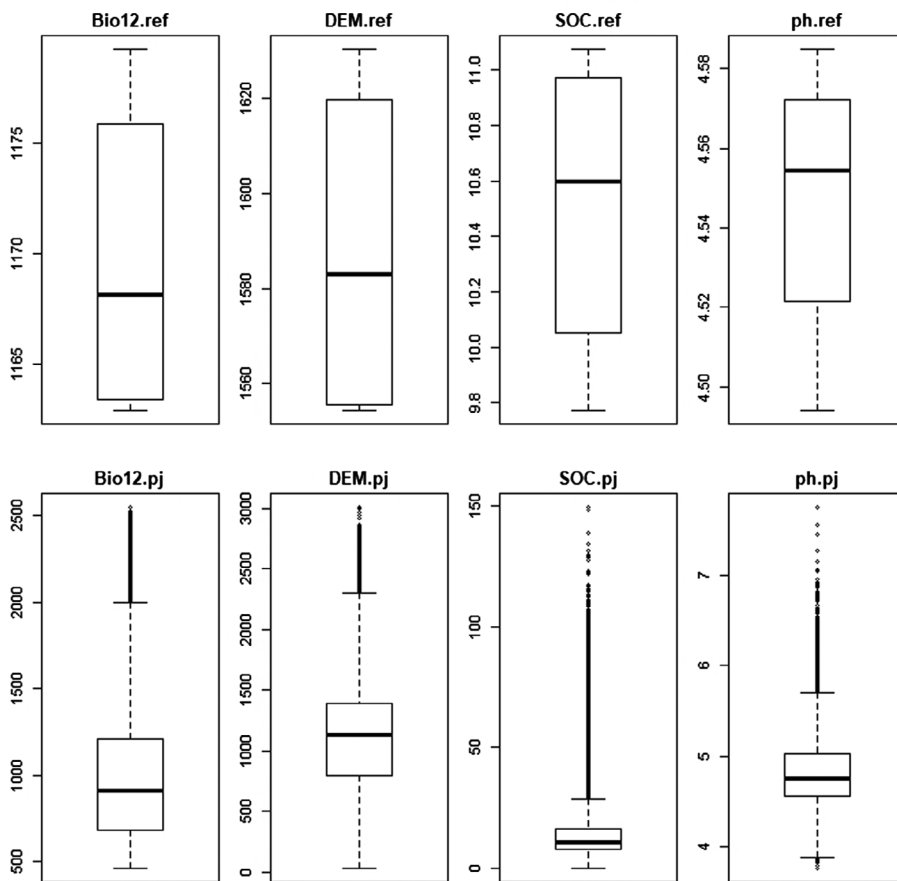


Figure 4. Boxplot reflecting variance in Bio12 (annual precipitation), DEM (elevation), SOC (soil organic carbon) and pH (soil pH) for the reference sites (.ref) and projection domain (.pj) for Var6Fer4 technology package.

Notes: Values of grid layers representing the projection domain exhibited higher variance in environmental space compared to grids for the reference sites.

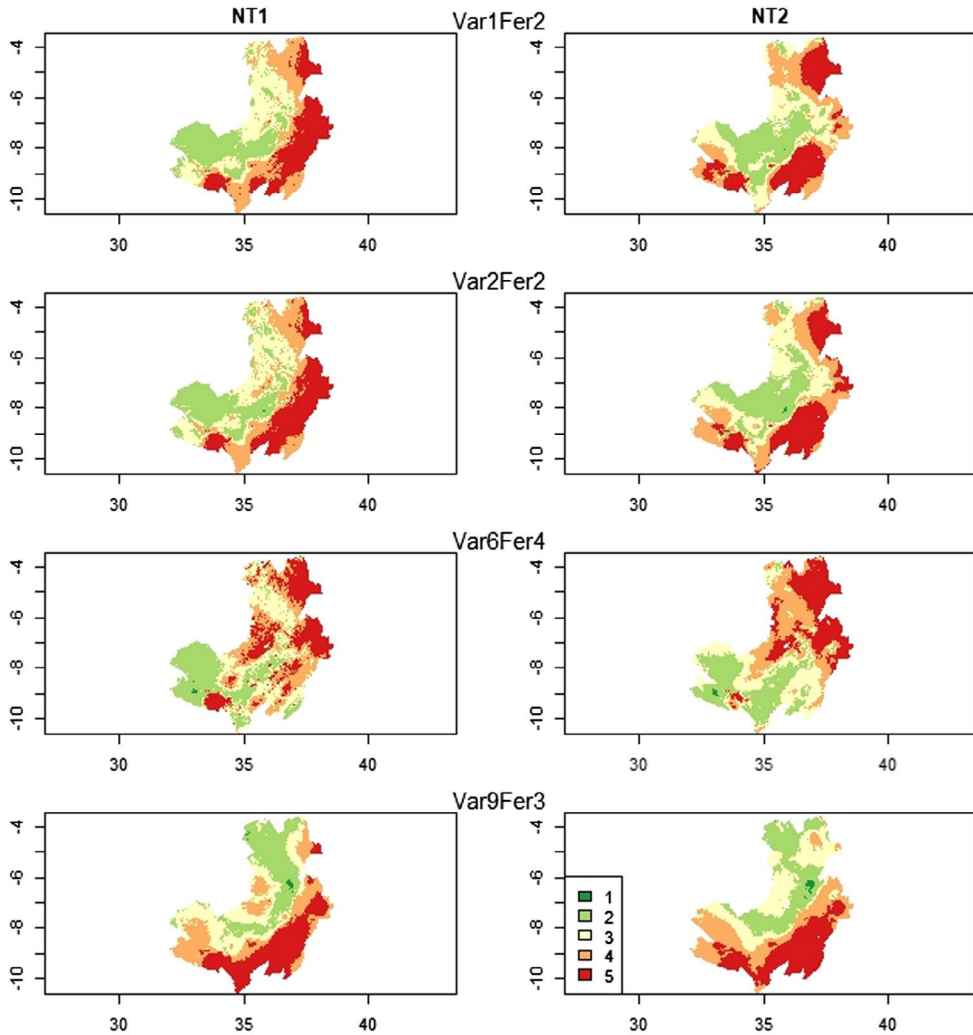


Figure 5. Maps for four best-bet packages reclassified into five suitability classes based on dissimilarity from univariate range (NT1) and degree of unique combination of covariates (NT2).

Notes: Class 5 is the most dissimilar from reference sites represented by class 1. Extrapolating a technology package in zone 5 poses the highest risk of failure.

revealed that only less than 1% of the area in NT2 dissimilarity maps had values less than 1 (Table S1), indicating high prevalence of novel multivariate combination of covariates in the projection domain. NT2 map was reclassified into five classes representing the degree of unique combination of covariates (Figure 5). NT2 class 1 represents the area with no unique combinations of covariates (largely the reference area) while NT2 class 5 is the most dissimilar to the reference sites.

Intersecting the reclassified NT1 and NT2 maps (Figure 5) produced a map and a contingent table showing classification agreement (Figure 6). The overall Kappa index of agreement between reclassified NT1 and NT2 maps for all technology packages except Var9Fer3, was poor (≤ 0.35). Kappa index of agreement for Var9Fer3 was 0.57.

The ESI for a specific technology package was generated as a product of cross-tabulated class matrices in the resulting contingency table (Figure 6). ESI values ranged from 1 to 25 (Figure 7) with lower values indicating high suitability and therefore lower risk for extrapolating a particular package.

Table 3. Pearson's correlation coefficients (r) for covariates in the reference area (upper diagonal cells) and in projection domain (lower diagonal cells).

Var1Fer2							
Variables	Bio4	Bio12	Bio15	CEC	DEM	SOC	pH
Bio4	1	0.88	-0.88	0.46	0.33	0.56	-0.28
Bio12	0.3	1	-0.85	0.27	0.68	0.43	-0.39
Bio15	-0.45	-0.15	1	-0.39	-0.3	-0.41	0.29
CEC	0.1	0	-0.22	1	-0.14	0.73	-0.22
DEM	-0.32	-0.12	0.26	0.14	1	0.08	-0.25
SOC	0.22	0.5	-0.2	0.39	0.35	1	-0.2
pH	0.2	-0.28	-0.44	0.53	-0.21	0.04	1
Var2Fer2							
Bio4	1	0.88	-0.91	0.3	-0.03	0.08	0.42
Bio12	0.3	1	-0.88	0.29	0.26	0.08	0.34
Bio15	-0.45	-0.15	1	-0.29	0.09	-0.03	-0.46
CEC	0.1	0	-0.22	1	-0.12	0.57	0.19
DEM	-0.32	-0.12	0.26	0.14	1	0.12	-0.31
SOC	0.22	0.5	-0.2	0.39	0.35	1	-0.11
pH	0.2	-0.28	-0.44	0.53	-0.21	0.04	1
Var6Fer4							
Bio4	1	0.42	-0.32	0.23	0.79	0.21	0.03
Bio12	0.3	1	-0.77	0.31	0.06	0.09	-0.3
Bio15	-0.45	-0.15	1	-0.23	-0.44	-0.26	0.46
CEC	0.1	0	-0.22	1	0.1	0.15	0.05
DEM	-0.32	-0.12	0.26	0.14	1	0.33	-0.1
SOC	0.22	0.5	-0.2	0.39	0.35	1	0.17
pH	0.2	-0.28	-0.44	0.53	-0.21	0.04	1
Var9Fer3							
Bio4	1	0.58	-0.93	-0.49	0.1	-0.17	0.41
Bio12	0.3	1	-0.61	-0.34	0.81	0.27	-0.07
Bio15	-0.45	-0.15	1	0.4	-0.1	0.19	-0.45
CEC	0.1	0	-0.22	1	-0.19	-0.15	0.17
DEM	-0.32	-0.12	0.26	0.14	1	0.63	-0.44
SOC	0.22	0.5	-0.2	0.39	0.35	1	-0.4
pH	0.2	-0.28	-0.44	0.53	-0.21	0.04	1

Note: Bold values indicate that correlation between DEM and Bio12 in reference grids was positive but negative in projection domain.

Table S1 shows the area for zones with similar ESI value in the projection domain for each technology package. The area with ESI = 1 has environmental conditions similar to the reference sites for specific technology package since they are within the reference range of univariate variables and capture similar combinations of covariates. This is the most suitable zone for scaling the candidate technology package. The zone with ESI = 2 represents the area where environmental conditions are within the univariate range but with novel combinations of covariates. Over 99% of the area of the projection domain for the four technology packages had ESI values greater than two (Table S1) indicating that at least one covariate has a value that is outside the reference range or covariates had unique correlation structure.

The zone with ESI = 4 was third in suitability and covered over 13% of total area of projection domain of each technology package (Figure S1, Table S1). To demonstrate the ability of the proposed methodology in priority setting, IBSTI was calculated for zone with ESI = 4. The resulting IBSTI values ranged from 4 to 20 (Figure 8; Table S2) with higher values indicating higher potential impact for scaling a technology package. The zone with IBSTI of 20 had the maximum potential impact for scaling out particular technology package. Var9Fer3 technology package had the largest area with IBSTI = 20 (11,956 Km²; Table S2).

Zonal means of the MIC map revealed that except for Var1Fer2, the suitability of the other three technology packages in the largest area of projection domain was mainly limited by one factor (Figure 9, Table S3). Zonal mean for the limiting covariates revealed that except for Var9Fer3, the values of the dominant MIC were lower than that observed in the reference sites (Figure 9). Suitability of VarFer2 in

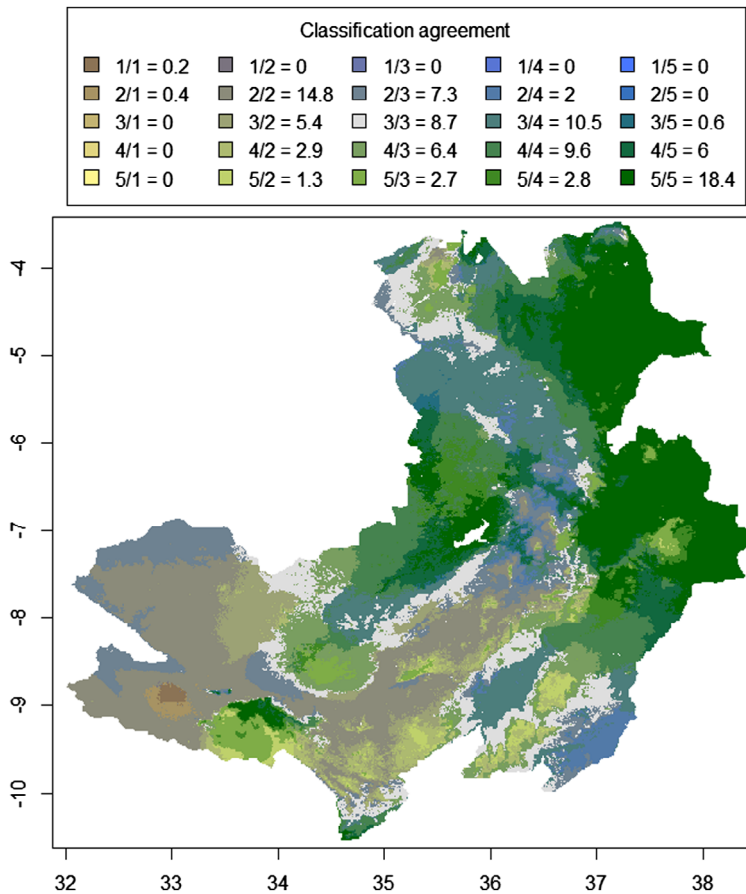


Figure 6. Classification agreement for NT1 and NT2 maps for Var6Fer4 technology package.

Notes: Relatively low agreement between classes reveals that each dissimilarity map had significant contribution to suitability of the technology package. Extrapolation suitability index was computed as product of class matrices from the contingency table.

54% of the projection domain was limited by lower DEM (857.6) compared to reference area (1791.9; Table S3). Suitability of Var6Fer4 in 60.3% of the projection domain was limited by lower mean annual precipitation (Bio12; 807.7 mm) compared to 1181 mm in the reference site. In contrast, suitability of Var9Fer3 in 61.4% of the projection domain was limited by higher mean annual precipitation (1096.7 mm) compared to 765.9 mm in the reference sites (Table S3). Another 8.1% of the area in the projection domain the suitability of Var6Fer4 package was limited by extremely high SOC (mean = 37 g kg⁻¹) compared to 10.7 g kg⁻¹ in the reference site (Table S3). This zone was located in southern highlands in Iringa region (mean elevation = 1662 m a.s.l).

4. Discussion

4.1. Generating ESI

This paper generates a simple and easy method for visualizing risk associated with extrapolating technologies beyond the environmental conditions observed in the trial sites. Results generate ESI map for four best-bet agronomic technology packages comprising of improved maize varieties and new mineral fertilizer blends in Tanzania. ESI maps were derived using a novel extrapolation detection method that account for the magnitude at which the univariate environmental variables in the

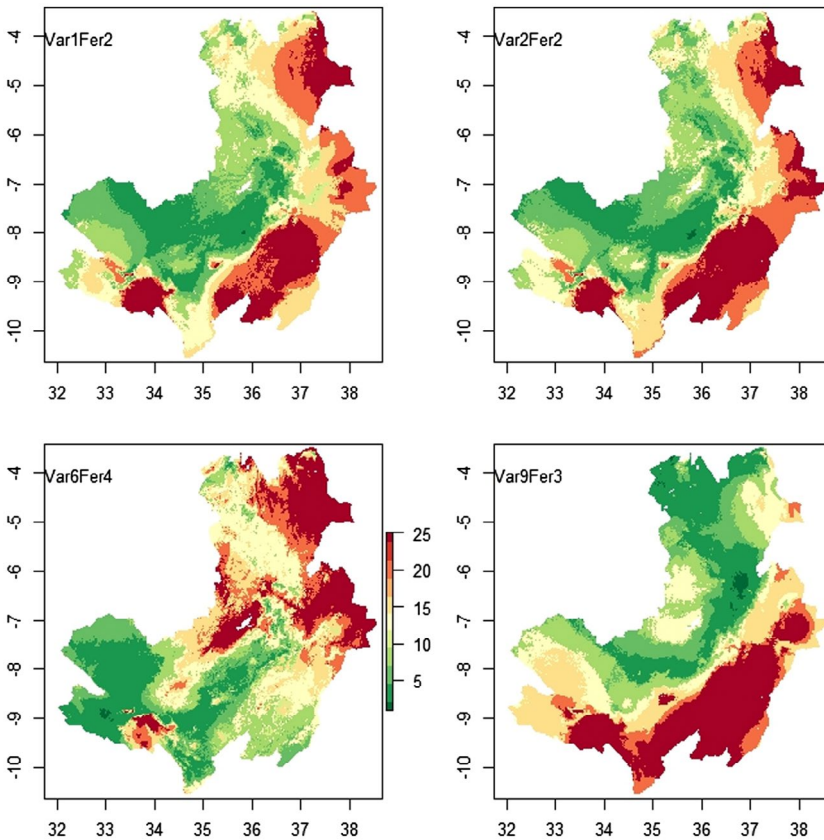


Figure 7. The ESI values for four promising technology packages.

Notes: Low ESI values indicate higher suitability for extrapolating particular technology package. The zone with ESI value 1 has environmental conditions similar to the reference site and therefore represents the most suitable zone for scaling the candidate technology package.

projection domains fall outside the range of values in the reference sites (Mesgaran et al. 2014). It also accounts for the change in the correlation structure of covariates in the projection domain compared to that observed in the reference sites. An impact based spatial targeting index (IBSTI) was used to identify high impact zones within the delineated suitable zones. Scaling-out technology packages in the delineated high-impact zones would maximize potential impacts and rationalize limited resources. A map of the most important covariate (MIC) was generated to guide extension agencies on spatial distribution of the biophysical limiting factor for a particular technology at different locations of the projection domain.

Higher variances in grids for the projection domain compared to that in the reference sites indicate that scaling out the best-bet technology packages involved a degree of extrapolation beyond the values of individual predictors observed in the reference site (Figure 4). This extrapolation type 1 was accounted for in terms of univariate dissimilarity computed using NT1 map (Figure 5(a)). A number of studies on species suitability account for univariate dissimilarity among covariates by restricting extrapolation to areas where predictors are within the reference range of individual covariates (Li et al. 2016; Ranjitkar et al. 2016). The multivariate environmental similarity surfaces (MESS; Elith et al. 2010) is one of widely used algorithm to identify the areas in the projection domain where values of at least one individual covariate are beyond the reference range (Li et al. 2016; Ranjitkar et al. 2016). However, MESS is limited because it only accounts for the range of individual variables thus overlooking the multivariate combinations of covariates (Mesgaran et al. 2014).

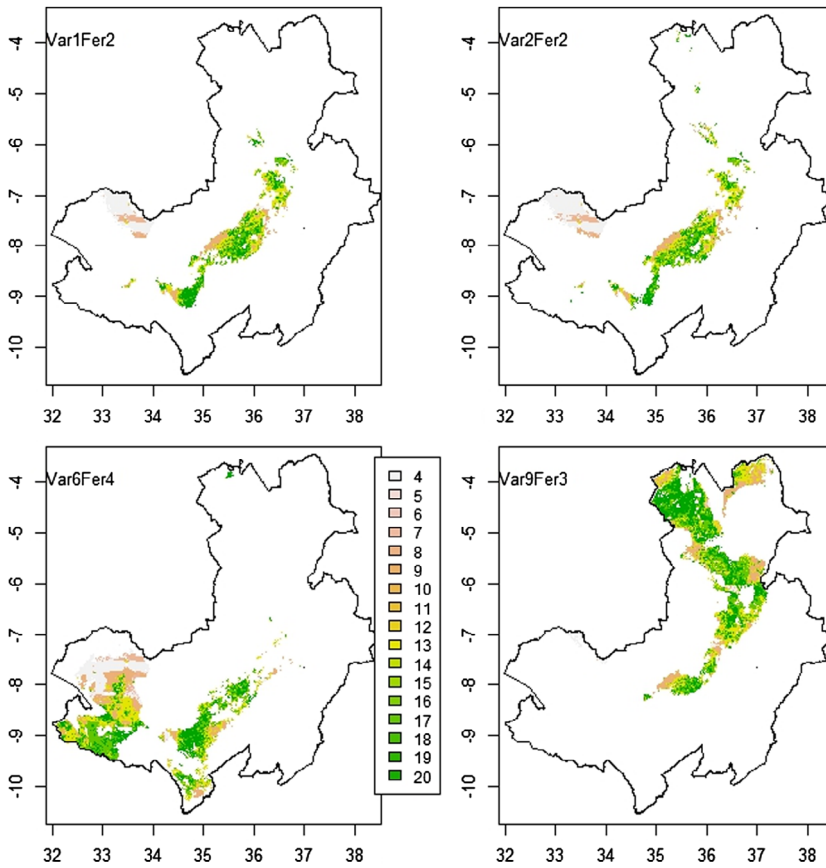


Figure 8. The Impact Based Spatial Targeting index (IBSTI) values in the largest most suitable zone with ESI = 4.

Notes: Higher IBSTI value indicates more potential impact for scaling a technology package. Zones with high IBSTI of 20 should be prioritized for scaling specific technology package to maximize potential impact. Table S2 shows the area for zones with different IBSTI values.

Results further revealed that over 99% of the projection domain for the four technology packages had NT2 values greater than one, indicating that covariates exhibited unique combinations relative to that in the reference grids (Figure 5(a)). For instance, the correlation coefficient between elevation (DEM) and annual precipitation (Bio12) was -0.56 in the reference grids for Var1Fer2 and changed to -0.12 in the projection domain (Table 3). Such changes in correlation structure between covariates can significantly alter the response of a particular crop variety to environmental cues and management practices. The Kappa index of agreement between NT1 and NT2 for all packages except Var9Fer3 was poor (below 0.35) indicating that the two maps contributed unique information for delineating suitability of the technology packages. Failure to account for unique combinations may result to scaling of technologies to unsuitable environments (Zurell et al. 2012). Previous studies on mapping extrapolation domains for agronomic technologies assumed that combinations of variables in reference sites is similar to that in the projection domain (e.g. Otero et al. 2006; Ramírez-Villegas et al. 2011; Pfeifer et al. 2014; Rubiano et al. 2014, 2016). To the best of our knowledge, this is the first time that novel correlation among covariates is accounted for while generating extrapolation domains for agronomic technologies. Recently, Zurell et al. (2012) demonstrated that overlooking multivariate combinations of environments reduces transferability of species distribution models. Moreover, the relatively low classification agreement between NT1 and NT2 maps (Figure 6) suggests that the two dissimilarity maps contributed different information for quantifying the risk of extrapolating technologies from reference sites. Therefore, this paper improves estimation of risk of extrapolating technologies in

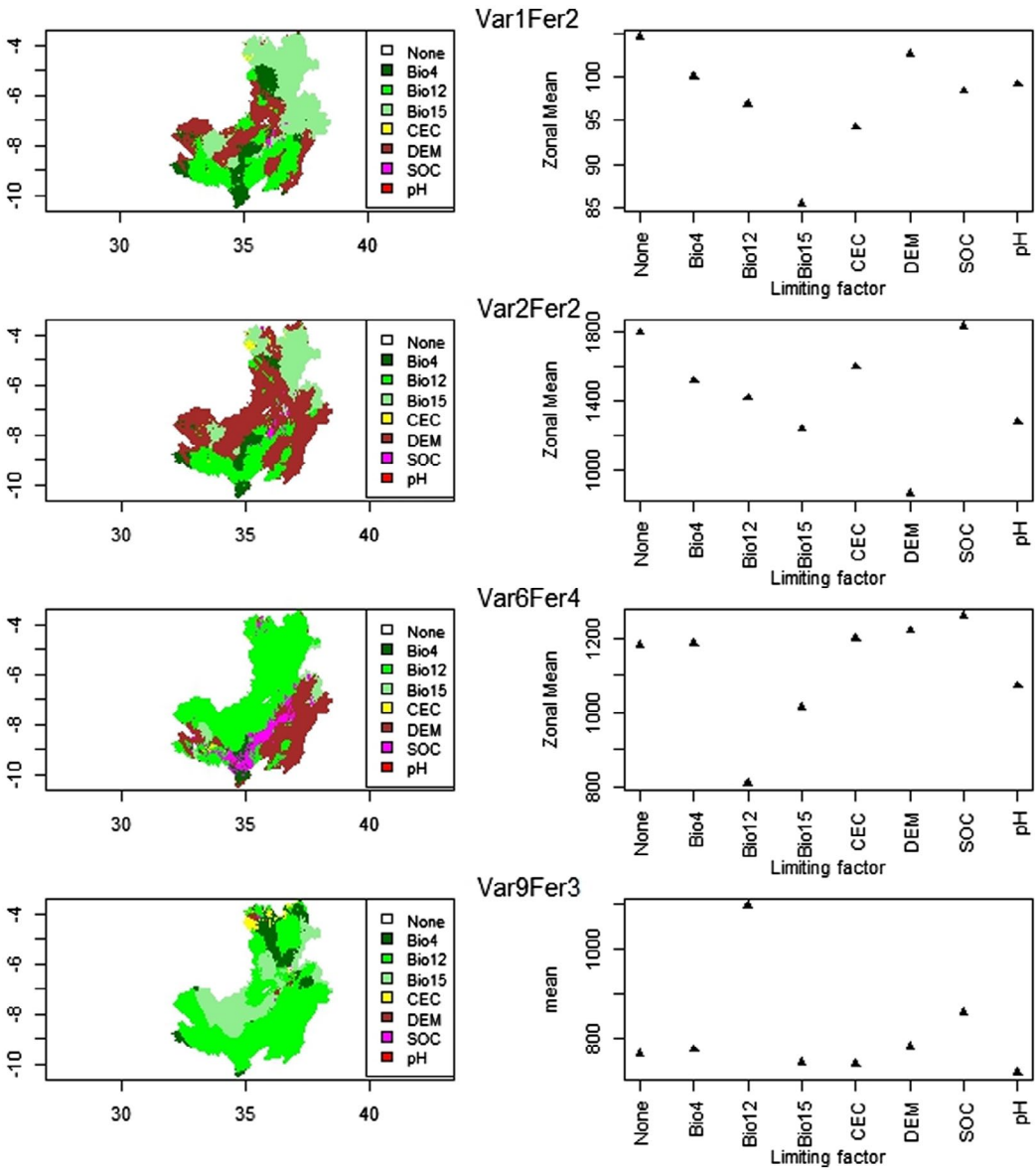


Figure 9. Map of the most important covariate (MIC) and plot for zonal mean for the covariate that was most limiting in the largest section of the projection domain (right) for four technology packages.

Notes: MIC map shows the spatial distribution of the most dissimilar covariate in the projection domain. The zone where none of the covariates was limiting coincides with the reference sites of particular technology package. Suitability of Var1Fer2 in the projection domain was largely limited by Bio15 (precipitation seasonality). The area for each zone is tabulated in Table S3.

heterogeneous landscapes by explicitly accounting for correlation structure among covariates. The method of generating ESI is easily replicable provided that representative crop trial data and appropriate environmental grids indicating the success criteria for a candidate technology are available.

4.2. Priority setting with IBSTI

The goal of out-scaling agronomic technologies is to maximize adoption by farmers to achieve pre-determined societal impacts or outcomes. These impacts include, for example, lifting a set percentage

of poor population from poverty (Asfaw et al. 2012; Kassie et al. 2014). The generated IBSTI maps revealed that the potential impact zones within the suitable areas for each technology package were heterogeneously distributed (Figure 8). IBSTI identified the high potential impact zones for prioritisation within the suitable zone, to reduce cost and time spent to achieve the target impacts at scale. This ex-ante impact assessment can support decision on whether it is worth investing in scaling out a particular technology package in a particular region (Notenbaert et al. 2016).

4.3. Relevance of the research to technology scaling

Spatial targeting of zones with highest suitability to scale out agronomic technologies reduces the risk of failure (Kalcic et al. 2015). Previous studies have demonstrated that targeting improved varieties to GIS generated domains lead to increased crop yields (Annicchiarico et al. 2006). The ESI and IBSTI indices generated in this paper are useful for not only identifying the suitable regions for a particular technology package but also in pinpointing areas within the suitable zone where the maximum potential impact for scaling out can be achieved. Application of these indices would facilitate rational investment of available resources to achieve maximum potential impact at scale. Investing SAI technologies in suitable zones lowers cost of production due to reduced requirement for inputs such as fertilizers and water for irrigation (Vanlauwe et al. 2006, 2011). The ESI map can guide seed companies and agro-dealers involved in production or distribution of improved seeds and fertilizers to target appropriate supplies to specific regions where their technologies are suitable or have the highest potential impact. Based on the size of suitable zone for a particular technology package, the demand for improved seeds and fertilizers can be estimated in advance before the planting season (Annicchiarico et al. 2005; Tesfaye et al. 2016). This is expected to improve the input supply systems that is one of the main bottlenecks hindering adoption of improved varieties (Fisher et al. 2015). Furthermore, seed companies can utilize the ESI and IBSTI maps to target suitable and high-impact zones for disseminating market and advisory services to promote adoption of particular technology package (Teskaye et al. 2016).

The MIC map identified the environmental variable that mostly limits the suitability of a technology package at every location in the projection domain. Understanding constraints to suitability or adoption of a technology can stimulate appropriate interventions to address the barrier or introduce incentives (Notenbaert et al. 2016). Extension agents can use the MIC map to target technological interventions to ameliorate the most significant biophysical factor that hinder a technology to achieve its full potential. For example, the large zone where low precipitation (mean = 762.4) was the most limiting factor could be targeted for disseminating drought tolerant maize varieties. Moreover, the MIC map is a useful guide to crop breeders interested in establishing multilocation trials for cultivars adapted to tolerate specific limiting factor such as drought, soil N deficiency and salinity (Setimela et al. 2005; Annicchiarico et al. 2006).

Results revealed that except for Var8Fer1, the yield for all the other trials treated with DAP and urea was lower compared to other fertilizer blends. This is despite the fact that this farmer's practice aggravates soil acidity (Amuri et al. 2012). New fertilizer blends such as YaramilaCereal and Minjingu Mazao contains micro and macro nutrients (Table 1) that address multiple deficiencies in soil. The two fertilizers have less acidification effect due to presence of base cations. The ESI is not only useful in targeting appropriate type fertilizer for specific localities, but also the appropriate application rate of application to reduce losses incurred by farmers after applying high doses based on old recommendations.

The method generated in this paper can be replicated for scaling out any technological package provided that relevant data are available. This is beneficial in assessing changes in suitability of agronomic technology packages in response to climate change and habitat fragmentation. Another possible potential for replication is in delineation of suitability zones for technologies in large mega-environments that cut across administrative boundaries (Setimela et al. 2005). This could foster international collaboration in dissemination of high-potential technologies such as disease-tolerant varieties to control spread that is otherwise difficult to eradicate in absence of regional coordination. This could foster

regional cooperation in research and dissemination for technologies of common interest requiring fast and coordinated efforts, for example, control of maize lethal necrosis disease (MNLD; Kiruwa et al. 2016). The generated ESI maps are aimed at reducing recommendations of agronomic technologies based on administrative boundaries (Mowo et al. 1993; Marandu et al. 2014). They also address over-reliance on broad AEZ's with fuzzy boundaries such as the. The ESI maps revealed the widely referred to 'southern highlands' comprise complex heterogeneous agro-ecologies.

4.4. Limitations

The trials to identify the best performing technology package were conducted in one growing season. Nevertheless, Annicchiarico et al. (2005) demonstrated that extrapolation domains generated using one season data increased durum wheat yield by 7%. Moreover, Rubiano et al. (2016) used only 20 trial sites to generate a global map for extrapolating aerobic rice technologies. Certainly, the precision of generated ESI map could be validated or enhanced by incorporating yield data from multiple seasons trials (e.g. Setimela et al. 2005). Multiseason yield data can be obtained from ongoing or historical trials. Many trials for maize varieties have been conducted in Tanzania, (Lobell et al. 2011). However, long-term data are not easily accessible since there are no data sharing platforms. Moreover, trials are conducted by different entities following different protocols that hinder inter-comparison. Moreover, the geographical coordinates for trial sites data are often held outside public domain or are imprecise thus leading to error propagation in spatial models (Hyman et al. 2013). Establishing a platform to harmonize protocols for maize trials data collection, archiving and open sharing would greatly improve delineation of extrapolation domains.

Grain yield was the only criterion used to evaluate the suitability of the technology packages. Other important qualities that significantly affect acceptability and adoption a particular maize variety include seed availability, cost, drought resistance, resistant to pests, nutrient content and grain poundability (Smale and Olwande 2014; Waldman et al. 2016). The importance of these qualities varies by location and intended use of the grain maize. Moreover, only biophysical variables are used to delineate the extrapolation domains although suitability of maize varieties is influenced by a variety of socio-economic factors such access to market, cultural practices, income and education levels of farmers (Kassie et al. 2013; Notenbaert et al. 2013; Tesfaye et al. 2015). However, limited availability of reliable socio-economic grid layers at appropriate scale and resolution hinder their inclusion in the analysis (Hyman et al. 2013). Moreover, the LULC map that was used to generate IBSTI does not capture inter-seasonal changes in cultivated area which may lead to under or over-estimate of potential impact of a given technology package. This limitation can be solved by using seasonal time series LULC maps generated using recently developed automated cropland mapping algorithm (ACMA) for rapid mapping of season-after-season crop land extent, cropping intensities and crop types (Xiong et al. 2017).

4.5. Conclusions

This paper generates ESI map as a simple and quick method for visualizing risk associated with extrapolating technologies beyond the environmental conditions observed in the trial sites. The generated ESI improves estimation of risk of extrapolating technologies in heterogeneous landscapes as it explicitly account for correlation structure among covariates. The impact based spatial targeting index (IBSTI) was used to identify high-impact zones for targeting to maximize potential impacts in out-scaling interventions. The ESI and IBSTI indices generated in this paper are useful in guiding extension agencies to prioritize scaling intervention based on both biophysical suitability and potential impact of particular technology package. A map of the most important covariates was generated to identify the environmental variable that mostly limits the suitability of a technology package at every location in the projection domain. Extension agents can utilize the MIC map to spatially target

specific management interventions to ameliorate the most significant biophysical factors that hinder a technology to achieve its full potential.

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