

UPSCALING THE BENEFITS OF PUSH-PULL TECHNOLOGY FOR SUSTAINABLE AGRICULTURAL INTENSIFICATION IN EAST AFRICA

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D2.2:

Report on how soil fertility, landscape structure and climatic region determine the efficacy of current push-pull

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1 Introduction

Work Package 2 (WP2) of the UPSCALE project focuses on the identification and optimization of target regions for the application of push-pull technology within different biophysical settings. The main tasks within WP2 involve the analysis of suitability of field sites across the five East-African study countries of Ethiopia, Kenya, Rwanda, Tanzania, and Uganda, that are representative for the implementation of push-pull technology across different environmental gradients, including climate variables, land-use patterns, and soil fertility. For the task reported here, we developed a 'nestedscales' experiment allowing to assess the determinants of push-pull effectiveness across farms, landscapes and climatic zones. We especially focus on assessing how soil fertility and landscape structure determine the efficacy of push-pull in different climatic regions.

In this report, we present preliminary statistical analyses focusing on the effects of cropping systems (push-pull vs. maize monocrop) and environmental factors on maize yield and crop damage from the 16 field pairs located in Rwanda and Uganda, respectively (Figure 1). Using piecewise structural equation models (piecewise SEM), we examined the cascading effects of cropping systems, grassland cover, and seasonality on maize damage and subsequent yield impacts. Using principal component analysis (PCA), we explored covariation of soil properties, differentiated into chemical and physical components. These components were then analysed for their effects on the *Striga* weed seed bank and maize yield.

2 Methods

2.1 Field site selection

Regional and Field Selection Process: The process started with the selection of study regions based on variables such as land cover, soil fertility, altitude. Following this, a moving window analysis was employed to calculate landscape variables within a 1 km radius around push-pull and monocrop fields to identify areas with uncorrelated gradients of grassland cover and soil fertility.

GIS and Ground Truthing: Geographic Information Systems (GIS) were employed to layer information about existing push-pull fields and assist in the selection process. Ground truthing further refined this selection by verifying the actual conditions of these preselected fields, ensuring they align with the biophysical data used in the selection process.

Criteria for Field Selection: The fields were selected to maximize environmental gradients while keeping these gradients independent of each other. The selection was tailored to ensure a representative sample of soil fertility levels and grassland cover across the study regions. Preselection included 30 push-pull and monocrop field pairs per country for WP2, which were narrowed down to 16 pairs per country after ground truthing. See deliverable D2.1 for a more detailed description of the field selection procedure.

Figure 1: Locations of the joint study design for WP2, 3 and 4 (Jie Zhang, UWUE). The field sites in Rwanda and Uganda analysed in this report are marked with red circles.

2.2 Land cover maps for analysis of landscape context

In Rwanda and Uganda, land cover maps of the study area, incorporating detailed crop classification, are derived from Sentinel-2 and Planetscope satellite data. The classification is based on field data collected in June of 2022. MaxNDVI image composite was created and random forest classification was applied. This results in the creation of the most recent, high-resolution land cover map, essential for spatial analyses (https://www.upscale.biozentrum.uniwuerzburg.de/Download/ShowXml.aspx?DatasetId=11800, https://www.upscale.biozentrum.uniwuerzburg.de/Download/ShowXml.aspx?DatasetId=11840). In our landscape composition analysis, different spatial scales are applied ranging from 250 to 2000 meters buffer area around study plots, incremented in 250-meter intervals. However, due to incomplete coverage of our land cover maps within the 2000-meter buffer area, ESA World Cover map 2021 (© ESA WorldCover project [https://doi.org/10.5281/zenodo.5571936\)](https://doi.org/10.5281/zenodo.5571936) is utilized to fill in the area beyond the extent of our classification map. We have harmonized and reclassified these maps into 8 distinct land cover types (Bare soil, Built-up, Cropland, Forest, Grassland, Shrubland, Flooded vegetation, water) and calculated the landscape composition using software ESRI ArcGIS pro 3.2.0 (https://www.upscale.biozentrum.uni-wuerzburg.de/Download/ShowXml.aspx?DatasetId=12500, https://www.upscale.biozentrum.uni-wuerzburg.de/Download/ShowXml.aspx?DatasetId=12480). The resulting landscape composition, including percentages of grassland and cropland within each spatial buffer area, constitute essential components of the deliverable.

In the current analysis we focused on the effects of grassland and cropland cover within 1 km radius of each field plot.

2.3 Soil variables for analysis of soil context

We assessed 20 variables related to soil fertility. Most of these were nutrients included in a soil analysis package. Complementary analyses were carried out at another laboratory, and some variables were also measured directly in the fields.

In each field, 20 evenly distributed soil cores were collected from the topsoil using a soil corer (inner ϕ 25 mm, depth 20 cm), and combined to one pooled sample per field (Figure 2). The samples were air dried at ambient temperature. When completely dry, soil aggregates (if present) were crushed and the soil sieved through 2mm mesh. The fine fraction (i.e. particles < 2mm) was thoroughly homogenised and subsampled for analysis at the two laboratories.

One set of subsamples was sent to Crop Nutrition Laboratories Ltd, Nairobi, Kenya and analysed according to their Complete Soil Analysis package where they follow the protocols by Pansu and Gautheyrou (2006). pH and the electrical conductivity (EC) were thus determined in soil:water 1:2, organic matter by the Walkley and Black method, and total nitrogen by Kjeldahl digestion. 'Plantavailable' phosphorus was determined after Olsen extraction, while 'plant-available' potassium, calcium, magnesium, sulphur, sodium, iron, manganese, boron, copper and zinc were determined after Mehlich 3 extraction. The carbon-to-nitrogen ratio was calculated from the analytical data.

The other set of subsamples was sent to the soil laboratories of Makerere University, Kampala, Uganda. There, soil texture was determined by the hydrometer method (Bouyoucos, 1962).

In addition to the laboratory analyses of soil samples, soil water infiltration and the soil penetration resistance were measured directly in the field (Figure 2). The method for measuring infiltration rate followed that of the International Centre for Tropical Agriculture (CIAT). Measurements were done in three replicates per field using single-ring infiltrometers with a soil bund replacing the outer ring of a double-ring infiltrometer. The water levels were topped-up as required, depending on the infiltration rate of the soils and measurements continued to constant rate. Data for the last three readings for the three replicates were averaged to provide one value per plot.

Wile penetrometers were used to assess depths within which the penetration resistance in the soil fell within three general suitability classes (good, reasonable and poor for root development). We also determined the depth of the exploitable soil profile below which it was not possible to penetrate using hand power, and where we assumed bedrock or a hardened soil horizon was present. The measurements were repeated 10 times across the plot and an average depth calculated for each field. **D2.2 Report on how soil fertility, landscape structure and climatic region determines the efficacy of push-pull**

Figure 2: WP2 Fieldwork in Rwanda 2022-2023.

2.4 *Striga* **seed bank, crop damage and crop yield**

We investigated how landscape context and soil context impacted the effect of cropping system on 1) the *Striga* seed bank (seeds and husks), 2) leaf damage by pests (essentially stemborers and fall army worm (FAW)) and 3) crop yield.

Striga seeds and husks were determined in the soil-sub samples that were analysed by Makerere University. It was done through wet sieving followed by flotation in sucrose solution according to Berner et al. (1997), and finally counting of the isolated seeds and husks at 30X magnification.

We assessed leaf damage caused by FAW and stemborers on maize plants within the push-pull and non-push-pull fields (Figure 2). Three parallel transects were set up in each field at standardised distances from the field edge. Seven maize plants were selected along each transect, totalling 21 plants per field. Every third plant per transect was tagged to ensure systematic sampling. We conducted leaf damage assessments by recording damage on all the leaves of each selected plant, with the leaf at the bottom of the plant designated as leaf number 1. Leaf damage was scored using a simple scale ranging from 1 to 5, as outlined by Toepfer et al. (2021). Additionally, any damage caused by other factors such as wilting, breakage, livestock feeding, or other insect infestations was also recorded. We estimated leaf damage attributable specifically to FAW and stemborers as the main damage, and leaves damaged by other causes were excluded from the analysis. We averaged the leaf damage scores for each plant separately for the first and second sampling rounds. Subsequently, we averaged leaf damage across the 21 plants to determine average leaf damage per plant per plot.

To assess crop yield, we collected the 21 tagged plants per field, with each cob/cobs per plant stored separately in bags and labelled correctly with the plotID, date of harvest, transect and plant number and collector. If a tagged plant was missing, we recorded and replaced it with a nearby plant from the same transect next to the initial missing plant. We recorded plant biomass and height at harvest, as well as the fresh cob weight per plant in grams (Figure 2). We air dried the maize cobs for 7 days, and then weighed them to obtain the dry weight of each cob per plant. Yield per plant was recorded as the dry weight of the maize cob. In cases where a plant had more than one maize cob, we combined the weight of the cobs. Subsequently, we averaged the dry weight of the maize cobs from the 21 plants to determine the average yield per plant per plot in grams.

2.5 Statistical analyses

For Rwanda, we conducted separate analyses of i) the interactive effects of cropping system and landscape composition on pest damage and crop yield, and ii) the interactive effects of soil conditions and cropping system on *Striga* seed bank and crop yield. This analysis structure was motivated by the fact that landscape composition often affects arthropod pests, whereas *Striga* is known to be affected by soil conditions. For Uganda, data on plant damage and crop yield were not yet available so we analysed the effects of soil variables and cropping system on *Striga* seed bank.

For Rwanda, initial generalized linear mixed models (GLMMs) showed no effect of cropland cover in the surrounding landscape (1 km radius) on crop damage and crop yield. We therefore focused on the effects of grassland cover in subsequent analyses. We built a piecewise structural equation model (piecewise SEM; Lefcheck, 2016) to examine the cascading effects of cropping system, grassland cover, and their interaction, on maize yield via maize damage. The piecewise SEM was built by combining two models. In the first, we related cropping system, grassland cover, and their interaction, to damage, and in the second, we related cropping system and damage to yield (Figure 3). Season was added as a fixed effect in both models because data were collected in two seasons. Damage and yield measurements were modelled with gaussian GLMMs, and the coding for maize and push-pull plot pairs was added as a random effect to account for spatial proximity of paired plots.

Figure 3: Causal hypotheses for the SEM assessing the effect of landscape context and cropping system on pest damage and crop yield in Rwanda. Arrows pointing to and away from the black dot represent effects before and after an interaction, respectively.

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To identify the most parsimonious SEM, we simplified each GLMM using the "dredge" function in package MuMIn (Bartón, 2023). The models with the lowest Akaike information criterion corrected for small sample sizes (AICc) were included in the final piecewise SEM. We also calculated variance inflation factors (VIFs) in package CAR (Fox and Weisberg, 2019) to check for collinearity between predictors in the GLMMs. All VIFs were under 3, which suggests no collinearity problems. The goodness-of-fit of the SEM was assessed with a test of directed separation (D-separation test) on Fisher's C statistic. This tests the assumption that all the variables are conditionally independent (i.e., there are no missing paths between unconnected variables) (Shipley, 2009). A test with $P > 0.05$ indicates that no additional paths improve the model's explanatory power. The importance of the explanatory variables was compared by standardising model coefficients, which involved scaling them by the standard deviation of the predictor variable over the standard deviation of the dependent variable (Lefcheck, 2016).

The effects of cropping system, soil properties, and their interaction, on maize yield via *Striga* seed bank, were also assessed with a piecewise SEM. Because of the large number of soil properties measured, we first summarized these data with a principal component analysis (PCA) using the "prcomp" function in package stats. The PCA revealed partial separation between chemical and physical soil properties, with the first component being more associated with the chemical properties and the second with the physical properties. Both principal components were thus included in the analysis to represent gradients of soil chemistry and of soil physics. The piecewise SEM also combined two models. The first related cropping system, soil chemistry and soil physics to the *Striga* seed bank, and included interaction terms between cropping system and soil chemistry, and between cropping system and soil physics (Figure 4). In the second we included the same set of predictors along with *Striga* weed abundance, and analysed their effects on maize yield (Figure 4). We modelled *Striga* seed bank and maize yield with Poisson and gaussian GLMMs, respectively. As above the coding for maize and push-pull plot pairs was also included as a random effect.

Figure 4: Causal hypothesis for the SEM assessing the soil context of cropping system on Striga seeds and husks and crop yield in Rwanda. Arrows pointing to and away from the black dots represent effects before and after an interaction, respectively.

We used the same procedures as those described above to simplify the GLMMs, to rule out collinearity between predictors (all VIFs were < 3), to assess the goodness-of-fit of the SEM, and to standardize model coefficients.

As yield data were not yet available for Uganda, we examined the effects of cropping system, soil properties (PC1, PC2), and their interaction, on the *Striga* seed bank. We used a Poisson GLMM as the data were counts, and simplified the model using the "dredge" function. All GLMMs were fitted using package lme4 (Bates et al. 2015) and the piecewise SEMs using package piecewiseSEM (Lefcheck, 2016). Analyses were performed in R 4.2.1 (R Core Team 2022).

3 Results

3.1 Effects of landscape context

In Rwanda, the proportion of grassland cover within a 1 km radius of each plot ranged between 0.045 and 0.552. Crop damage in non-push-pull sites was on average 1.744 in Season 1 and 1.551 in Season 2, and in push-pull sites 1.705 in Season 1 and 1.195 in Season 2 (damage score 1 represents no damage and 2 represents low damage). Crop yield in non-push-pull sites was on average 67.9 g per plant in Season 1 and 113.9 g per plant in Season 2, and in push-pull sites it was 92.4 g per plant in Season 1 and 103.6 g per plant in Season 2.

As expected, push-pull significantly reduced crop damage (especially in Season2) and had a nonsignificant, but positive direct effect on crop yield (Figure 5, Table 1). Grassland cover did not moderate the effects of push-pull on crop damage, but had a negative and non-significant direct effect on crop damage. Crop damage was generally low but had a marginally positive effect on crop yield. Cropping season had a strong effect on both crop damage and crop yield. The long rainy season (Season 2) had lower crop damage but higher crop yield than the short rainy season (Season 1) (Figure 5, Table 1).

Figure 5: Final SEM assessing the effects of landscape context and cropping system on pest damage and crop yield in Rwanda. Thickness of arrows is proportional to the standardised model coefficients.

Table 1: Statistical output from the SEM assessing the effects of landscape context and cropping system on pest damage and crop yield in Rwanda. For each model, the response variable, predictors retained after model simplification, the coefficient estimate (Estimate), standard error (Std. Error), degrees of freedom (DF), standardised estimate (Std. Estimate) and P value, are specified.

3.2 Effects of soil context

In Rwanda, the number of *Striga* seeds and husks per 50g⁻¹ soil was on average 6.2 in non-push-pull plots and 4.4 in push-pull plots. In Uganda the average number of seeds and husks was also higher in non-push-pull (5.2) than in push-pull plots (3.2). The variation in the soil fertility variables is presented in Table 2.

We found that the soils´ *Striga* seed bank was affected by an interaction between cropping system and soil physical properties (Soil PC2); the number of seeds and husks decreased in push-pull plots with more favourable soil physical conditions, but this effect was not found in non-push-pull plots where the number of seeds and husks remained similar across the range of soil physical properties (Figures 6 and 7, Table 3). Crop yield was in turn marginally negatively correlated with the *Striga* seed bank. The cropping system did not show any significant additional effect on maize yield. The SEM analysis further showed that Soil PC1 (soil chemical properties) marginally increased maize yield, but did not affect the *Striga* seed bank (Figure 6, Table 3).

Figure 6: Final SEM assessing the effect of soil context and cropping system on pest damage and crop yield in Rwanda. Arrows pointing to and away from the black dots represent effects before and after an interaction, respectively. Thickness of arrows is proportional to the standardised model coefficients.

Table 3: Statistical output from the SEM assessing the effect of soil context and cropping system on Striga seeds and husks and crop yield in Rwanda. For each model, the response variable, predictors retained after model simplification, the coefficient estimate (Estimate), standard error (Std. Error), degrees of freedom (DF), standardised estimate (Std. Estimate) and P value, are specified.

Response	Predictor	Estimate	Std. Error	DF	P value	Std. Estimate
Striga	Plot P	-0.393	0.160	35.000	0.014	-0.235
Striga	PC ₂	0.032	0.073	35.000	0.663	0.019
Striga	Plot P * PC2	-0.268	0.101	35.000	0.008	-0.161
Avg yield_per_plant	Plot P	-4.482	19.260	17.144	0.819	-0.036
Avg yield_per_plant	PC ₁	7.510	4.279	27.920	0.090	0.362
Avg yield per plant	PC ₂	9.452	6.694	27.888	0.169	0.290
Avg yield per plant	Striga	-3.751	1.923	25.157	0.062	-0.313
Avg_yield_per_plant	Plot P * PC1	-10.768	6.522	17.376	0.117	-0.320
Avg yield per plant	Plot $P * PC2$	-1.595	10.548	21.411	0.881	-0.030

Figure 7: Interactive effect of cropping system and Soil PC2 on Striga seed bank (seeds and husks) in Rwanda. P: push-pull plots, M: non-push-pull plots.

The Ugandan fields under push-pull cropping also had a smaller *Striga* seed bank than the control fields (Figure 8, Table 4), but the soil properties did not significantly affect the size of the seed bank.

Figure 8: Effect of cropping system on Striga seeds and husks in Uganda. P: push-pull plots, M: nonpush-pull plots.

Table 4: Statistical output from the most parsimonious GLMM assessing the soil context of cropping system on Striga seeds and husks and crop yield in Rwanda. Soil PC1 and PC2 were not retained in the model.

4 Discussion

4.1 Effects of soil and landscape context

As expected, we found that push-pull cropping systems in Rwanda and Uganda had reduced pest damage and reduced *Striga* numbers compared to non-push-pull systems (primarily monocultures). Surprisingly though, we found very little context dependency in these effects. Grassland cover did not moderate the effect of push-pull on pest damage in Rwanda and there was only a small, and nonsignificant, moderating effect of soil fertility (PC2) on the effects of push-pull on *Striga* in Rwanda but not in Uganda. These preliminary results thus indicate that push-pull can be effective across a range of soils with different fertility and across landscapes with different amount of grassland.

Yield differences between push-pull and non-push-pull fields was unusually small in Rwanda compared to recent work e.g., from Western Kenya (Luttermoser et al. 2023). Potential reasons for this might be that plot size in Rwanda tends to be smaller than the recommended 10 x 10m size, and that almost all push-pull plots had been recently established (usually less than 3 seasons).

Crop damage was marginally positively related to crop yield. Damage levels were generally low so may not have had a significant negative effect on yield. Positive relationships between pest damage and yield may occur if pests prefer productive crops.

Desmodium spp have previously been shown to induce suicidal germination of *Striga* seeds (e.g. Khan et al., 2006); identifying the effect on the *Striga* seed bank against the large variability of farmers´ fields confirms the robustness of the technology. However, the insignificant effect of the soil chemical properties on the *Striga* seed bank differs from previous findings where low nutrient availability has been shown to promote *Striga* (e.g. Khan et al. 2001). The farmers´ application of manure (and in some cases mineral fertiliser) to all investigated plots may have made the soils´ inherent capacity to supply nutrients less influential on *Striga* germination and emergence, and thus seed production. Earlier published results also have shown that poor water availability during the growing season aggravates infestation by *Striga* (Khan et al. 2001), and our results from Rwanda confirm that soil physical conditions supporting higher crop access to water reduced the *Striga* incidence under push-pull. This was not seen under the non-push-pull system, somewhat surprisingly suggesting that push-pull had a larger effect on the *Striga* seed bank at more conducive soil physical properties; the corresponding analysis of data from the other countries will show if this is a general pattern.

In a previous study in Western Kenya it was found that the number of stemborer larvae and pupae increased with increasing grassland cover and that the effects of push-pull on pests was larger in fields located in landscapes with larger amounts of grasslands (Midega et al. 2014). In our study we found no significant effect of grassland cover on crop damage despite studying a much larger range in grassland cover than Midega et al. (2014). One potential reason for this lack of grassland effect is that FAW nowadays is more common than stemborers and that FAW has a much broader host range. This may have decreased the importance of grassland cover as a predictor of plant damage in our study. Furthermore, crop damage was generally low which might have masked potential effects of landscape composition.

4.2 Next steps

The results reported here constitute a starting point for further analyses in this task. Due to a lack of available data for the other countries we could only analyse context dependency for Rwanda and partially for Uganda. Data is expected to soon be fully available for Uganda, Ethiopia, Tanzania and Kenya and then we will be able to get a fuller picture of the context dependency of push-pull in relation to soil conditions and landscape context. We will also explore soil variables and landscape structure in more detail. For soil we will analyse which variables are affected by push-pull cropping and regarding landscape context we will assess the importance of maize cover and edge density (a metric of landscape configuration) on pest damage in the maize fields. We will also assess effects of landscape context across additional spatial scales (smaller and larger than 1 km radius).

The output from this report and the ongoing analyses are expected to have a large impact on other work packages of UPSCALE and for upscaling of push-pull in general. For example, it provides direct input into the synthesis and suitability mapping conducted in WP5, which leverages the data and results made available through this task. If the results for Rwanda turn out to be general across climatic regions it suggests that push-pull efficacy is less affected by soil conditions and landscape structure than previously thought, which may simplify the process of Upscaling push-pull cropping across East Africa.

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