Parasitic weed density: drivers and management using cultural controls.

By:

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Abstract

Among the most pressing challenges facing agriculture today is the problem of parasitic weeds. A small number of species belonging to the family *Orobanchaceae* result in huge annual losses globally. The magnitude of this problem is likely to increase with climate change and increasing connectedness of global production systems. Research into the ecology of these weeds is therefore urgently needed.

Striga asiatica is one of the most serious parasitic agricultural weeds, disproportionately affecting subsistence farming in Sub-Saharan Africa, exacerbating food insecurity. Farmers frequently lack access to novel technologies, while herbicide is largely ineffective as a control. In addition, there is a paucity of detailed information on distribution, which is required to understand current drivers, better target control efforts, as well as to predict future risks. To address this, we developed a methodology to enable rapid, large-scale monitoring of *Striga* populations. We used this approach to uncover the factors that currently drive the abundance and distribution of *Striga asiatica* in Madagascar.

Two long-distance transects were established across the middle-west region of Madagascar, over which *S. asiatica* abundance in fields was estimated. The resulting dataset indicated the importance of crop variety and legumes in driving *Striga* density. Moreover, the dataset revealed significant effect of precipitation seasonality, mean temperature and altitude in determining abundance. A composite management index indicated the effect of a range of cultural practices on changes in Striga abundance. The findings support the assertion that single measures are not sufficient for the effective, long-term management of Striga. Furthermore, the composite score has

potential as a significant guide of integrated Striga management beyond the geographic range of this study.

Finally, I undertook a meta-analysis of available studies studying the effects of intercropping and rotation cropping on parasitic weed density and crop yields. The meta-analysis comprised 1,525 paired observations from 67 studies across 24 countries. It revealed significant effects of both spatial and temporal crop diversification on parasitic weed density reduction. Furthermore, our results show effects of spatial diversification are stronger in suppressing parasitic weeds than temporal effects. Furthermore, the analysis indicates intercrops, which alter both microclimate and soil chemistry such as Crotalaria, Stylosanthes, Berseem clover and Desmodium are most effective in parasitic weed management.

This thesis overall serves to underline the importance of a range of management controls in the control of *S. asiatica*. Most importantly the study showed the effects of resistant host crops, legume intercrops, crop rotation and combined management in reducing Striga density. The meta-analysis largely supported the findings of the field survey on Striga and further indicated the viability of crop diversification as an important tool in parasitic weed management. In addition, the data from both fieldwork and the meta-analysis indicated the important role of climate in determining parasitic weed densities and possible implications for changing future climate.

Declaration of original authorship

I confirm that this is my own work and the use of all material from other sources has been properly and fully acknowledged.

Donald Scott

Publications

Included in this thesis are two published papers and one paper currently under review for publication, each appropriately formatted for their respective journals. I am the lead author for each, with my supervisory team on both papers and research assistants in Madagascar included in the respective author lists.

Chapter 2: Scott, D., Scholes, J.D., Randrianjafizanaka, M.T., Randriamampianina, J.A., Autfray, P. and Freckleton, R.P., 2020. Mapping the drivers of parasitic weed abundance at a national scale: A new approach applied to Striga asiatica in the mid-west of Madagascar. Weed Research, 60(5), pp.323-333.

Chapter 3: Scott, D., Scholes, J.D., Randrianjafizanaka, M.T., Randriamampianina, J.A., Autfray, P. and Freckleton, R.P., 2021. Identifying existing management practices in the control of Striga asiatica within rice–maize systems in mid-west Madagascar. Ecology and Evolution, 11(19), pp.13579-13592.

Chapter 4: Scott, D. and Freckleton, R.P., 2022. Crop diversification and parasitic weed abundance: a global meta-analysis. Scientific Reports, 12(1), pp.1-12.

Contents

“Whether you think you can, or you think you can't--you're right.”

— Henry Ford

Chapter 1

General Introduction

Arguably, one of the most pressing of the grand challenges facing humanity this century is the need to feed around 10 billion people by 2050 in an environmentally and socio-economically sustainable manner (Searchinger et al. 2014). Intensive agricultural practices have resulting in diminishing soil and water resources, and increased agrochemical pollution and biodiversity loss (Lal 2015, Mancosu et al., 2015, Vitousek et al. 2009, Dudley & Alexander 2017). It is estimated that at present 38% of the world's land cover is under agricultural use (FAO 2020) and that at present resource use is already exceeding the world's capacity to regenerate resources by over 70% (York University 2021). Therefore, future agricultural practices are likely to determine the nature and utility of the world's surface more than any other single factor (Gomiero et al. 2011).

Scientific advances starting in the mid-1960s led to a period of unprecedented growth in agricultural productivity known as the "Green Revolution" (Pingali 2012). However, these advances resulted in a range of unforeseen environmental consequences (Harwood 2020). The introduction of genetically improved, high yielding crop varieties necessitated the increased input of fertilisers (Harwood 2020). The spread of improved varieties worldwide led to increased homogenisation of genetic crop resources, vulnerability to pests and diseases and pesticide use (Gomiero et al. 2011). The increased use of agrochemicals has resulted in serious damage to both the environment and human health (Sharma & Singhvi 2017). Indeed, agriculture at present is the largest contributor to biodiversity loss through pollution and habitat conversion (Dudley & Alexander 2017).

Following the initial increments in crop production initiated by the Green Revolution, growing evidence shows these increases have largely stalled. Crop yields have plateaued in many of the world's most intensive agricultural areas (Grassini et al. 2013). This slowdown is in part attributable to a reduction in efficacy of chemical pest and weed control. Growing levels of pesticide resistance have been recorded amongst crop pests, while their proliferation globally is steadily increasing (Whalon et al. 2008, Bebber et al. 2014). It is estimated that host specific crop pests and pathogens will have fully colonised many agricultural regions by the middle of the century (Bebber et al. 2014).

Crop yield reductions attributable to weeds are approximately 40% globally (Chauhan 2020). Furthermore, it is predicted that production losses from weeds will increase as a result of climate change (Gaudin et al. 2015, Peters et al. 2014, Sharma et al. 2017, Fried et al. 2017). Evidence suggests that key aspects of modern agriculture used to increase yields are now responsible for reduced production. For example, ecological selection has caused increasing instances of herbicide resistance among a growing range of weed species globally (Heap 2020). As with the effect of reduced crop genetic diversity on pests and diseases, simplification of cropping systems has been recognised as a driver of increasing weed infestations (Weisberger et al. 2019). Furthermore, the application of inorganic fertiliser, combined with a warming climate has been found to result in increases cereal yield losses due to weeds (Storkey et al. 2021).

Amongst the most significant agricultural weeds exists small number of parasitic species of the genera *Cuscuta* (L), *Orobanche* (L), *Phelipanche* (L), *and Striga* (Lour). These have spread over recent decades, impacting subsistence and increasingly industrial production systems worldwide (Samejima & Sugimoto 2018, Aly 2007, Fernández-Aparicio et al. 2020). Parasitic weed distribution will also likely increase the range for many problematic weed species, further impacting crop production (Mohamed et al. 2006, Rubiales et al. 2018). As with weeds in general, parasitic weeds predominantly affect low-diversity agricultural systems, with large-scale monocultures providing a continuous supply of host plants, facilitating their spread (Ejeta 2007, Fernández-Aparicio et al. 2020). While herbicides can reduce seedbank density over years, host attachment occurs prior to aboveground emergence. Therefore, such treatments are ineffective in reducing the damage to a current year's crops (Aly 2012, Rubiales et al. 2018).

In response to the growing agricultural production bottleneck, new approaches must be found to increase productivity whist reducing reliance on inorganic inputs and conserving soil, water and biological resources. Weed management options, which minimise reliance on agrochemicals, are a fundamental element of more sustainable future production (Korres et al 2019).

Among potential options for more sustainable weed management using crop diversification has received significant focus for both parasitic weeds and weeds as a whole (Rubiales & Fernández-Aparicio 2012, Weisberger et al. 2019). In addition, the use of crop varieties, which are resistant or tolerant to parasitic weeds is an important component of current and future management (Rodenburg et al. 2015, Cissoko et al. 2011). This thesis is an examination of factors affecting parasitic weed density, which relate to cropping practices, utilising crop diversification (rotation and intercropping) and resistant host crop varieties. The weed density datasets herein have also been analysed to determine patterns linked to edaphic (soil NO_3) and climatic conditions and altitude, to elucidate the ecological niches of the parasitic species under investigation.

Thesis Objectives

The principle aim of this study was to gain an understanding of the effect of crop management and climate on determining parasitic weed density. This aim was supported by two objectives:

- To adapt an existing field survey methodology to undertake a multi-year, rapid assessment of landscape-scale density of *Striga asiatica* in the Mid-West of Madagascar to identify drivers of abundance and distribution for *S. asiatica* in terms of management, soil, climate and altitude.
- To undertake a comprehensive meta-analysis to further understand role of crop diversification and climate on annual, economically important parasitic weeds in general.

In chapter 2, I present the findings of the first year of field survey in comprising two long-distance transects were established across the middle-west region of Madagascar in which *Striga asiatica* abundance in fields adjacent to the road was estimated, along with management, crop structure and soil data. Analysis of the data was undertaken using linear models and generalised additive models.

In chapter 3, I present the findings of the first two years' of field data collection (2019-2020) to undertake a more detailed analysis cultural, climatic and edaphic factors driving abundance and distribution of *Striga asiatica* over time. Linear models were used to assess the expanded dataset and a composite management index was produced to analyse the effect of combined cultural practices on changes in Striga abundance.

Madagascar was chosen as the focus of fieldwork as it afforded the opportunity to study the effects of distinct crop management on a single parasitic species (*Striga asiatica*) within a geographically isolated environment.

In chapter 4, I present the results of a comprehensive literature search and analysis of the subsequent dataset for relevant studies of the effect of intercropping and crop rotation on parasitic weed abundance. This included analysis of a range of climatic factors and altitude on naturally occurring densities of parasitic weeds. I calculated effect sizes for comparison between studies and used linear models and linear mixed effects models to determine the relative effects of different management and climatic factors as well as assessing individual host and companion crops.

The rationale driving the choice of undertaking a global meta-analysis of parasitic weeds was to attempt to capture as broad a range of data, both in terms of species and geographic locations. This was in order to identify the overarching factors driving parasitic weeds abundance on a global scale, while providing information on effects of specific factors such as individual crop families and species.

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Chapter 2

Mapping the drivers of parasitic weed abundance at a national scale: a new approach applied to *Striga asiatica* in the Mid-West of Madagascar

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Abstract

The parasitic weed genus Striga causes huge losses to crop production in sub-Saharan Africa, estimated to be in excess of $7 billion per year. There is a paucity of reliable distribution data for Striga, however such data are urgently needed to understand current drivers, better target control efforts, as well as to predict future risks. To address this, we developed a methodology to enable rapid, large-scale monitoring of Striga populations. We used this approach to uncover the factors that currently drive the abundance and distribution of Striga asiatica in Madagascar. Two long-distance transects were established across the middle-west region of Madagascar in which Striga asiatica abundance in fields adjacent to the road was estimated. Management, crop structure and soil data were also collected. Analysis of the data suggests that crop variety, companion crop and previous crop were correlated with Striga density. A positive relationship between within field Striga density and the density of the nearest neighbouring fields indicates that spatial configuration and connectivity of suitable habitats is also important in determining Striga spread. Our results demonstrate that we are able to capture distribution and management data for Striga density at a landscape scale and use this to understand the ecological and agronomic drivers of abundance. The importance of crop varieties and cropping patterns is significant, as these are key socio-economic elements of Malagasy cropping practices. Therefore, they have the potential to be promoted as readily available control options, rather than novel technologies requiring introduction.

Keywords: weed survey, weed management, parasitic weeds, *Striga asiatica,* NERICA rice varieties, legumes, Madagascar

Introduction

Among the most economically damaging agricultural weeds are parasitic plants belonging to the family *Orobanchaceae* (Joel et al. 2007). The most agriculturally damaging weed genera in this family are *Striga, Rhamphicarpa and Alectra* species in sub Saharan Africa (SSA) and *Orobanche* and *Phelipanche* species in the Mediterranean region, eastern Europe and north Africa (Mohamed et al. 2006, Spallek et al. 2013, Parker 2013). Of the suite of economically significant parasitic weeds, the genus *Striga* is among the most problematic (Mohamed et al 2006, Parker 2009). The genus comprises over 30 recognised species, with the greatest damage caused by *Striga hermonthica* (Del.) Benth and *S. asiatica* (L) Kuntze (Mohamed et al. 2001). This is due to the significant economic losses caused by these two species to a staple cereal crops grown in SSA (Runo and Kuria 2018). The *Striga* problem is recognised as an increasingly serious limiting factor on crop production in SSA, primarily affecting rural smallholder farmers (Cairns et al. 2012, Parker 2012). Reductions in fallow periods and increased monocropping deplete soil organic matter and nitrogen and increase soil erosion; creating conditions favourable for the proliferation of *Striga* (Franke et al. 2006, Parker 2012).

Striga has resulted in reported yield losses of between 35 - 80% in rice (Rodenburg et al. 2016), 50 - 100% for sorghum (Abunyewa and Padi, 2003) and losses of maize of between 21 - 74% (De Groote et al. 2007). Estimates of economic losses from *Striga* range from between $111 and $300 million per year for rice (Rodenburg et al. 2016) and $383 for maize (Woomer and Sabala 2008). Estimates of areas affected vary between 50–100 million ha annually (FAO, http://www.fao.org/). The uncertainty represented by this variance in estimated extent reveals that robust methods for estimating the spatial extent of infestations are lacking.

Resistance of host crops has long been identified as a key management tool for control of *Striga* (Scholes and Press 2008; Hearne 2009). Ongoing research is being conducted on resistance in rice; specifically, the NERICA (NEw RIce for Africa) group of varieties. Broad variation in the resistance of NERICA varieties to *S. asiatica* has been demonstrated from laboratory experiments by Cissoko et al (2011) and in field trials by Rodenburg et al (2015, 2017).

Recent work undertaken by Randrianjafizanaka et al (2018) in Madagascar indicates the potential importance of cropping practices and rice variety in the management of *S. asiatica*. NERICA-9 and NERICA-4 reduced *S. asiatica* infection levels by 57% and 91% respectively, compared with levels of infection on variety B22. In addition, *S. asiatica* densities were reduced by 20 and 60% in maize grown after planting NERICA-9 and NERICA-4 respectively, compared to B22. In the same study, intercropping with legumes (*Vigna unguiculata, Mucuna pruriens, Vigna umbellata and Stylosanthes guianensis*) resulted in significant reductions in *S. asiatica* infection levels and delays in emergence.

Upland rainfed rice in Madagascar is sown directly following tillage and is grown as a mono-crop or in a mixture with other food crops. Farmers generally do not have access to inorganic fertilizers or herbicides and weeding is done manually. Therefore, *Striga* management options available to farmers are limited to cropping practices and use of suitable varieties.

It is hypothesised that leguminous crops reduce levels of *Striga* germination via nitrogen fixation, causing germination or *Striga* without host root attachment, or that they alter soil surface conditions to interfere in germination (Khan et al 2002). Continuous monocropping without rotation has been shown to increase levels of infestation and build ups of *Striga* seed within the soil seed bank (Ejeta 2007).

Successful management of any weed relies on strong predictive systems, underpinned by accurate distribution data, together with a sound understanding of the ecological niche of the target species (Mohamed et al. 2006). The variance and reliability of estimates of the geographic extent of *Striga* is a knowledge gap requiring urgent attention (Parker 2009). The paucity of accurate distribution data also prevents accurate estimates of economic losses (Rodenburg 2016, De Groote 2007), which serves to justify increased investment to address the problem.

Madagascar has been identified as a priority country for parasitic weed research (Rodenburg et al. 2016). This is because of the scale of *Striga* infestation and the lack of current distribution and agroecological data available to address the problem. Fig.1 provides representations of the topography, climate and soil types of Madagascar. Very few studies of *Striga* have been undertaken in Madagascar (Eliot et al. 1993, Geiger et al. 1996). Herbaria records are also scant, with just one new record submitted since 2014 (see Fig. 2).

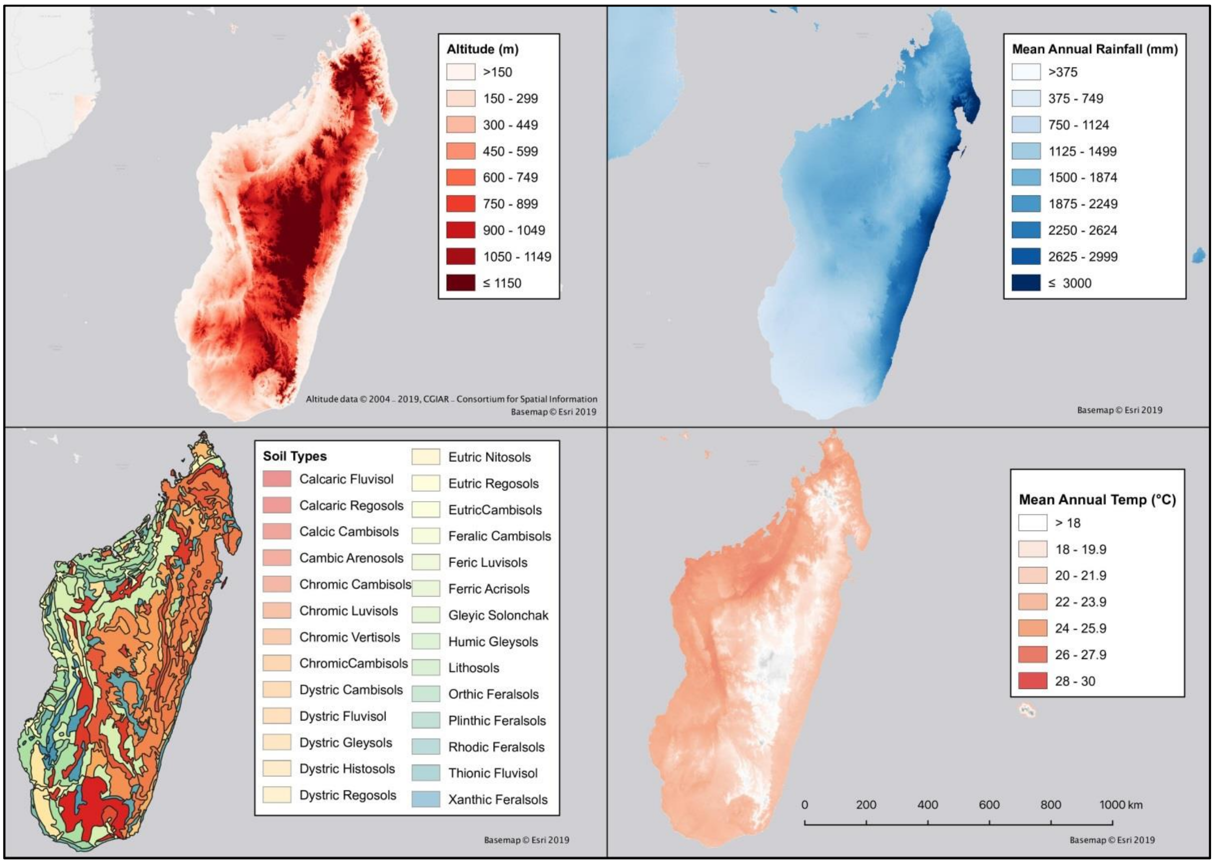

Fig. 1. Distribution of altitude (CGIAR-CSI 2019), mean annual rainfall (Fick and Hijmans, 2017), soil type (FAO 2007) and mean annual temperature (Fick and Hijmans, 2017) across Madagascar.

The first introductions of *S. asiatica* to Madagascar occurred over a century ago (Fig.2.), resulting in the spread and establishment of separate populations which exist today. Within infested areas, losses can vary from between 20 -100% (Joyeux 2014) and 30 - 90% (Geiger et al. 1996). In many instances, losses resulting from *Striga* infestation have caused farmers to abandon fields or, in some instances, entire settlements (Geiger et al. 1996, Andrianaivo et al. 1998).

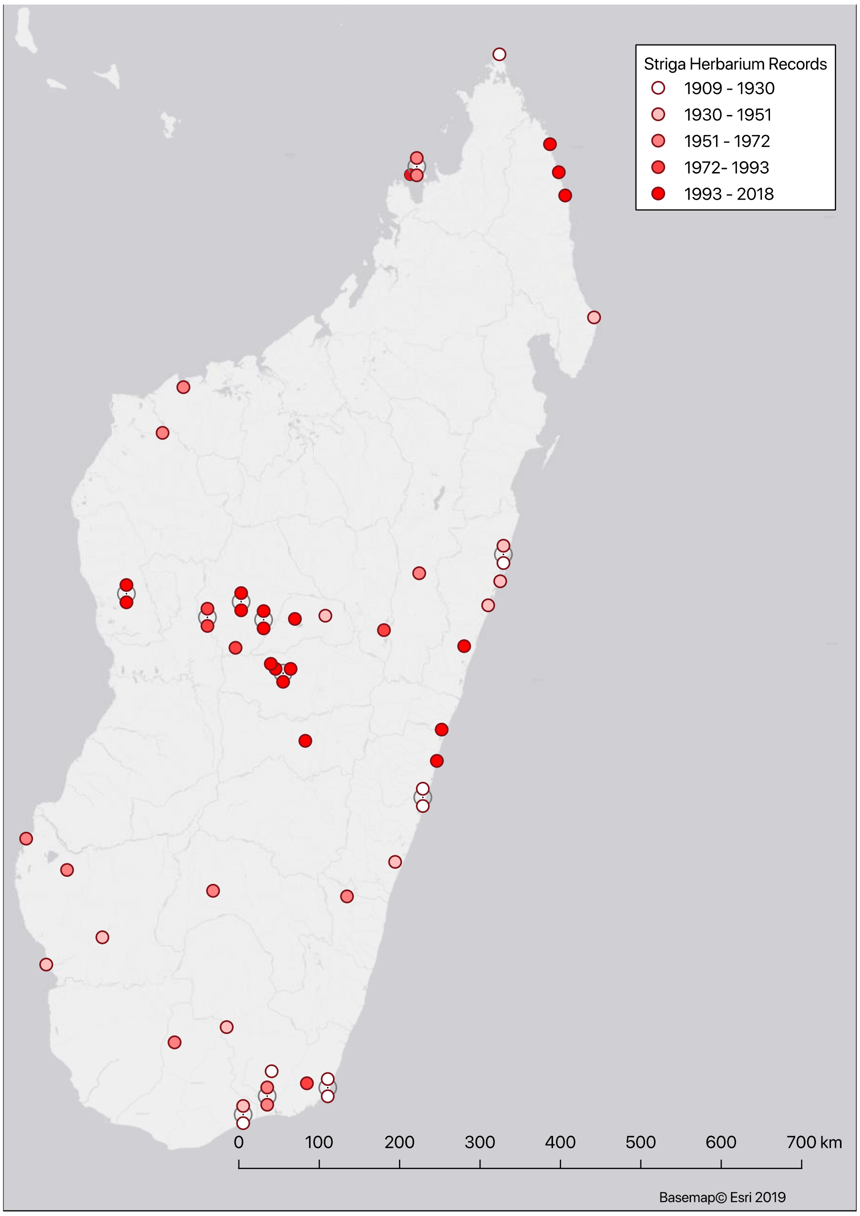

Fig. 2. Herbarium records for Striga asiatica (Rodenburg et al., 2016).

The majority of weed population studies have been conducted on single sites using small (≤ 1m^2) quadrats (Rew and Cousens 2001, Freckleton and Stephens 2009, Queenborough et al. 2011). This approach is inherently labour-intensive and results in coverage of very small spatial extents (Rew and Cousens, 2001). This small scale limits the ability of data to inform predictions of the effects of large-scale environmental change or management on weed population dynamics (Freckleton and Stephens 2009, Treddennick et al. 2017). The use of small quadrats will also almost certainly result in weed patches being missed, creating complications for subsequent statistical analysis (Rew and Cousens, 2001). Large-scale coarse-resolution datasets can be used effectively for distribution modelling on macro scales; for example, using presence data from herbaria or historical records (e.g. Kriticos et al. 2003, Mohamed et al. 2006). However, analyses based on presence data alone will not provide information on weed population dynamics in response to changing abiotic or land management factors.

To address the lack of data at the appropriate scale, collection methods to enable such analyses; density-structured techniques, have been developed (Queenborough et al. 2011, Freckleton et al. 2011). These methods enable the relatively rapid collection of comprehensive data on weed densities with a small team and limited resources. This approach enables the production of regional and national-scale mapping of distributions and abundances, including relating population abundances to environmental drivers (Mieszkowska et al 2013) and management (Freckleton et al 2018).

Here we analyse the factors driving the abundance and distribution of *Striga* at a large scale. We used ecological surveys to obtain landscape-scale distribution data alongside detailed agroecological information for *S. asiatica*. The objectives were to (i) develop a rapid and repeatable methodology that would permit the mapping of this weed at a national scale; (ii) test the role of management (crop and cropping history) in driving increases in abundance; (iii) analyse the impact of variation in soil nutrients in explaining differences in the distribution of *Striga*.

Materials and Methods

Surveys were undertaken by employing a methodology originally developed for the survey of the weed *Alopecurus myosuroides* in the UK (Freckelton et al, Manuscript in preparation). The method permitted the rapid and accurate assessment of black grass densities at a landscape scale, and robust statistical analyses to identify drivers of abundance. This methodology was modified to take account of morphological differences in detectability between *A. myosuroides* and *Striga* and associated detectability.

Study system

Field surveys were undertaken between February and March 2019 in the mid-west of Madagascar, one of the six major rice growing regions in the country (Fujisaka, 1990). The mid-west covers 23,500 km2 with an elevation between 700 m and 1000 m above sea level. The climate is semi-humid tropical, with a warm, rainy season from November to April and a cool, dry season from May to October. Mean annual rainfall ranges from 1100mm to 1900 mm with a mean temperature of 22 ^{o}C.

Large-scale transects

Field sampling involved undertaking two long-distance, driven transects along which *S. asiatica* abundance was estimated in fields adjacent to the road. These comprised a transect of 116 km along the RN34 (T1, n=153) and one of 70 km along the RN1 (T2, n=83). T1 was located within Vakinakaritra province, between the towns of Betafo and Morafeno and T2 was located within Itasy and Bongolava provinces, approximately 3km east of Sakay and the outskirts of Tsiroamandidy (Fig. 3).

Fig. 3. Location of transects T1 and T2 in Vakinakaritra, Itasy and Bongolava provinces of mid-west Madagascar.

The location and orientation of transects was based on expert advice and previous work undertaken by agricultural researchers familiar with the historic distribution of *S. asiatica* in the mid-west of Madagascar. Fieldwork was undertaken with local technicians or guides.

Within-field sampling

One field was surveyed on adjacent sides of the road every kilometre. In the absence of fields in the immediate vicinity of a given 1 km section, the next available field was surveyed. Prior to undertaking the survey, pilot work was undertaken in order to ensure consistency of scoring between observers, and measure the detectability of the Striga within fields. This work was undertaken within an experimental field station maintained by French agricultural research organisation: CIRAD, located at Ivory (Lat: 46.411254, Long: -19.552421). Systematic density scoring was undertaken by principal field surveyors within three rice fields possessing highly varied levels of Striga infestation.

Fields were divided into pairs of 10 × 20-m quadrats, in which two observers simultaneously recorded Striga density, by walking at a steady pace along a central transect, and scanning 5 m to either side; in fields >1200m2, data were recorded from a maximum of three pairs of quadrats (Fig. 4). A field corner was randomly selected as the point to begin survey, and *Striga* density was estimated using a six-point, density structured scale, ranging from absent (0) to very high (5). Based on available information, crop type, rice variety, companion crop, previous crop, estimated mean crop height, and percentage cover data were collected. In addition, information on fertiliser addition and any other pertinent information on the general area were recorded (where available). Mean density score, average crop height and cover, and other weed cover for a quadrat was called and entered on the mobile app prior to moving to a subsequent quadrat. If no *Striga* was found in a quadrat, a thorough walk throughout the entire field was undertaken to verify that *Striga* was truly absent.

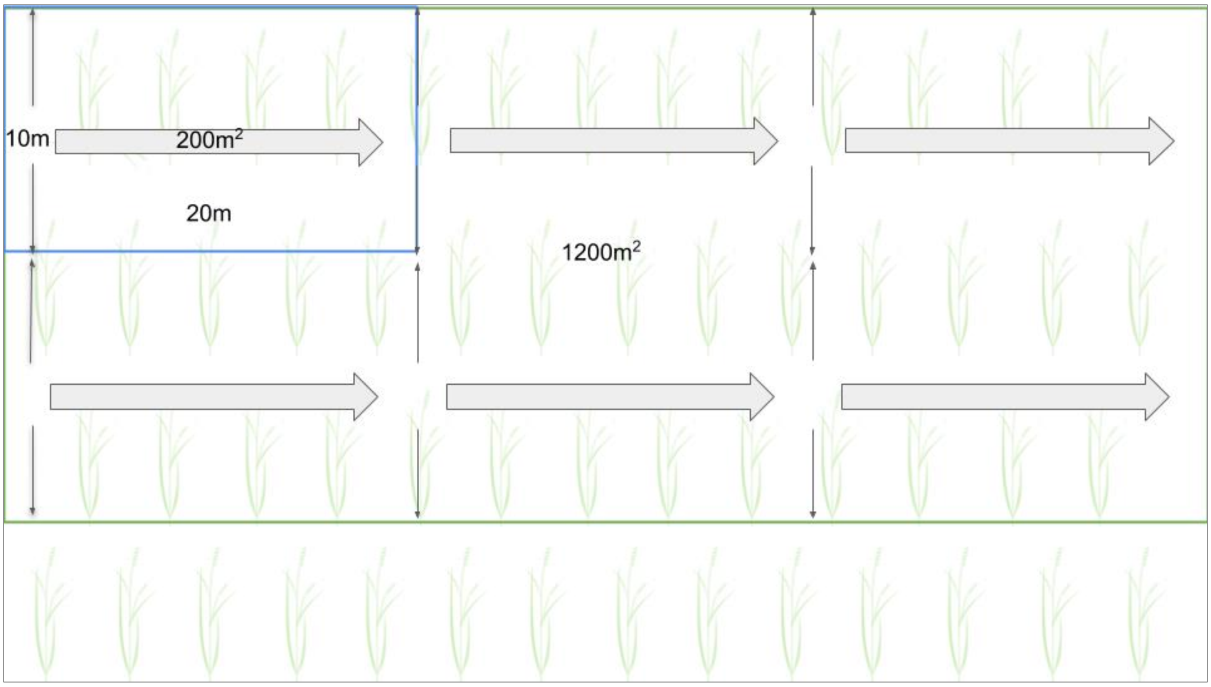

Fig. 4. Illustration of Striga density estimation, where two observers simultaneously surveyed 10 × 20-m quadrats in a field; there was a maximum of three pairs of quadrats in fields >1200 m2.

Where scores varied in excess of one density point between surveyors, a discussion was undertaken as to why the quadrat had been scored as such in order to standardise density estimates between observers.

During the pilot work, it was agreed between surveyors that reliable detection of S. asiatica within typically planted, rainfed upland rice fields was possible at distances up to 5 m on either side of each surveyor. As a 10 x 10m quadrat per surveyor would have negatively affected the speed of repeatability, quadrat dimensions of 200m2 (10x20m) were agreed. Definitions of density states were determined, and a table was produced with narrative descriptors of the scale used.

Data were recorded using a GPS-enabled smartphone with the mobile application ‘Fulcrum’ (Fulcrumapp.com, 2019, version 2.31.1) to allow geo-referencing and rapid data entry. Accurate location of the fields will permit the sites to be subsequently resurveyed.

Soil Samples

The role of available nitrogen in determining *S. asiatica* densities was addressed through collecting and analysing soil samples for NO_3. These samples were collected in pairs from quadrats with contrasting *Striga* densities within the same field. The aim was to collect equal numbers of paired samples for all combinations of *Striga* density. However, a paucity of very high *Striga* densities during survey resulted in an unbalanced composition of density pairs (see Appendix 3). The soil samples comprised: 47 pairs representing differing densities and nine single samples from individual fields lacking any *Striga*. Soil samples were obtained from the centre of each chosen quadrat using a 20 mm diameter, hand-held, tubular soil sampler to a depth of approximately 20 cm. Soil samples were subsequently air dried for analysis.

NO_3 analysis was undertaken using a LAQUAtwin NO_3-11 nitrate meter (Horiba Scientific, Japan). Owing to low levels of NO_3 within the soil, it was necessary to dilute the standard solution supplied with the meter. Therefore, calibration was undertaken between 15 and 150 ppm NO_3 to improve sensitivity. One gram of dried soil was mixed with one millilitre of water and ground in a pestle and mortar. The resultant solution was then placed on the sensor of the meter. This procedure was repeated a minimum of two times per soil sample. If agreement between the first two readings was observed (i.e.: between +/- 5 ppm NO3 between readings), then the readings were taken, and the mean of the readings was used. If the readings did not concur, then sampling was repeated until stabilisation of readings.

Soil pH was measured on the soil samples using a Hanna Instruments HI99121 pH meter (Hanna Instruments Ltd, UK). For each sample, 20 g of soil were mixed with 50 ml of soil preparation solution for 30 seconds. After 5 minutes the soil pH was measured using the meter.

Statistical Methods

The first set of analyses tested the roles of crop variety, weeding, previous crop, companion crop and field area in determining the density of *Striga.* A second set examined the potential effect of climatic and edaphic factors (mean annual temperature, mean annual rainfall, altitude, pH and NO_3) on *S. asiatica* density. Within-field *Striga* density was also plotted against that of neighbouring fields. A final set of analyses used *Striga* density as the independent variable and mean crop height, crop cover and other weed cover as response variables; to examine potential effects of *Striga* on crops and any covariation with cover for other weeds present.

Diagnostic plots (density plots, QQ plots and histograms) were produced for each model. Statistics were calculated using R 3.5.1 (R Core Team, 2018) and the packages: dplyr (v0.8.0.1; Wickham, François, Henry & Müller, 2019), mgcv (Wood 2011), lme4 (v067.i01, Bates, Maechler, Bolker, & Walker, 2015), lmerTest (Kuznetsova , Brockhoff & Christensen 2017), MASS (Venables & Ripley 2002), DescTools (v 0.99.28, Signorell et mult. al. 2019). and psych (Revelle 2018, v1.8.12). The full reproducible code is available in Appendix 1.

Striga density was log (x+1) transformed owing to the presence of large numbers of zero densities. Polynomial contrasts were applied to categorical variables incorporated into models (crop variety, previous crop, companion crop). Linear models and generalised additive models (GAMs) were used to test significance of independent variables. Linear regression analyses are robust against moderately high degrees of collinearity among independent variables (Freckleton 2011) and violation of normality assumptions for distribution of residuals (Fitzmaurice, Laird & Ware 2004). GAMs were also chosen due to their flexibility in dealing with non-normal distributions and ability to handle non-linear relationships between response and explanatory variables (Guisan et al 2002).

To test the effects of previous crops, two sets of analyses were undertaken. The first was to examine the effect if the previous crop was a legume or non-legume (dichotomous, yes / no). For this analysis, Shapiro-Wilk tests were undertaken to check for normality of distribution for the two levels of *Striga* density. A Welch Two Sample t-test was subsequently performed on these data. To enable comparison with the study of Randrianjafizanaka et al. (2018) a Welch Two Sample t-test for mean *Striga* density and rice varieties B22 and NERICA-4 was also undertaken. The second analysis examined any effects of specific crop or crop combinations on *Striga* density. Linear models and GAMs for previous crop and *Striga* density with latitude and longitude included as smoothed terms were performed (see Appendix 1). Crop-crop combinations with fewer than two records were omitted from these analyses. An additional model testing for autocorrelation between *Striga* density and latitude / longitude was also performed.

Preliminary model testing for collinearity between climatic and edaphic factors indicated strong correlation between altitude and mean temperature (f=1860, df=2, 239, R^2=0.93, p < 2.2e-16, VIF: 16.56). Potential correlation between mean rainfall and altitude and mean temperature was less evident (f=3.40, df=2, 239, R^2= 0.03, p = 0.04, VIF=1.03). However, this interaction was anticipated and is commonplace amongst analyses using climatic and edaphic data and was therefore not considered a constraint to the analysis undertaken. Smoothed lines fitted to scatterplots for (pH, NO_3, field area, altitude, mean rainfall, mean temperature) indicated potential non-linear relationships with *Striga* density; providing additional justification for the use of GAMs in the analyses (see Appendix 2).

Results

Management Factors

Analysis of management data suggests that rice variety had a significant effect on *Striga* density (linear model F=1.72, df=20, 102, p=0.04, GAM F=11.14, df=21, 102? p <2e-16p), most notably with NERICA-10 and NERICA-4. NERICA-10 exhibited greater resistance than NERICA-4, which was associated with consistently higher *Striga* densities (see Fig. 5 A). A Welch Two Sample t-test for mean *Striga* density and previous crop legume (yes/no, Fig. 5 B) indicated significant differences of means (t=2.05, df=141.08, p=0.02). The t-test for B22 and NERICA-4 did not indicate significant differences of means (μ: B22=0.85, NERICA-4=1.15, t=2.05, df=141.08, p=0.02) although the mean *Striga* density was lower for B22 than for NERICA-4. The effect of previous crop type or variety on mean *Striga* density (Fig. 5 C) was not significant for a linear model (F=1.08, df =25, 159, p= 0.369) but was significant for the associated GAM (F=15.84, df=21, p<2e-16). Specifically, the effects of previous cropping with bambara groundnut (*Vigna subterranea*) and rice / Bambara groundnut were correlated with significantly lower mean *Striga* density.

There was a positive relationship between within field *Striga* density and the density of the nearest neighbouring fields (F=9.015 df=1, 242, p=0.01 and GAM (F=10.91, df=1, p=0.01). This suggests that spatial factors could be important in determining *Striga* distribution and spread (see Fig. 6). No significant results were obtained from the analyses of mean *Striga* density used as an explanatory variable for mean crop height ($F=0.83$, $df=1, 223$, $p=0.36$) crop cover ($F=2.329$ $df=1, 223$, $p=0.13$) and other weed cover ($F=0.08$ $df=1, 151$, $p=0.77$).

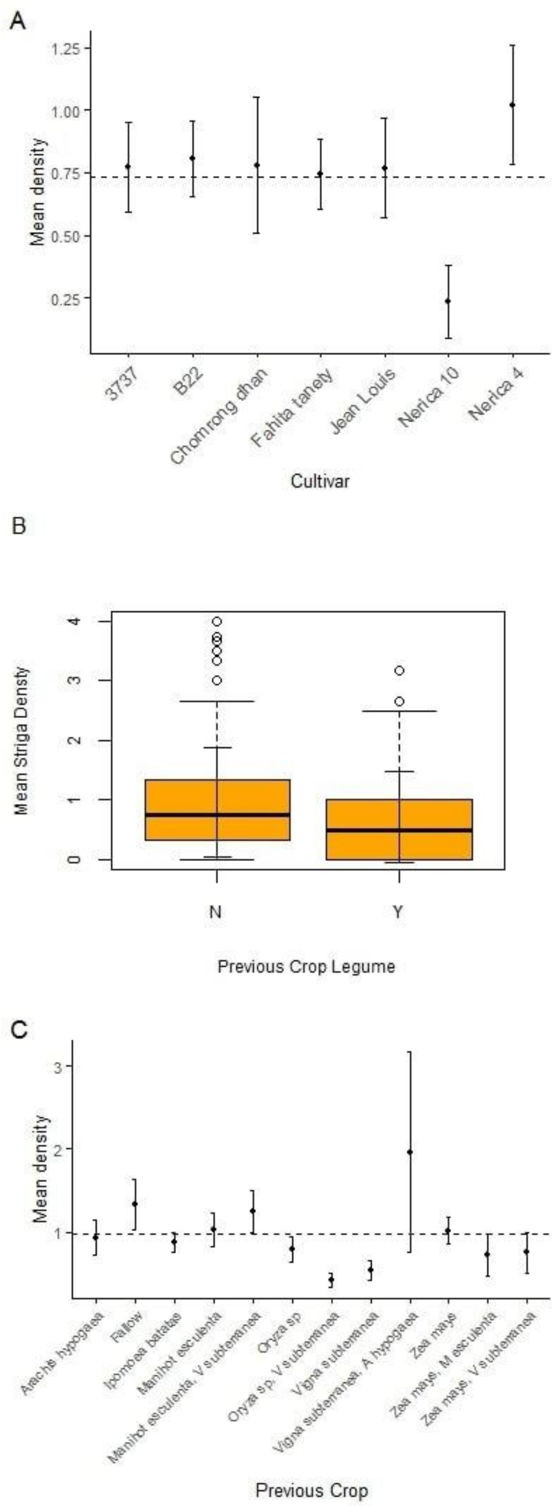

Fig. 5. A: Mean ±SE Striga density in principal rice varieties (overall mean is dashed line) (3737: n=4; B22: n=28; Chomrong dhan: n=11; Fahita tanety: n=2;, Jean Louis: n=2; NERICA-10: n=8; and, NERICA- 4: n=28); B: Mean ±SE Striga density of previous crop types (legume: n=65; non-legume: n=120); and, C: Mean ±SE Striga density of previous crop types and varieties recorded (grand mean is dashed line) (Arachis hypogaea; n=18; Fallow: n=14; Ipomoea batatas: n=4; Manihot esculenta: n=25; M. esculenta, Vigna subterranean: n=2; Oryza sp: n=34; Oryza sp, V. subterranean: n=2; V. subterranean: n=35; V. subterranean, A hypogaea: n=2, Zea mays: n=34; and, Z. mays, M. esculenta: n=7). Analyses indicated significant effects of rice variety, leguminous and individual previous crops.

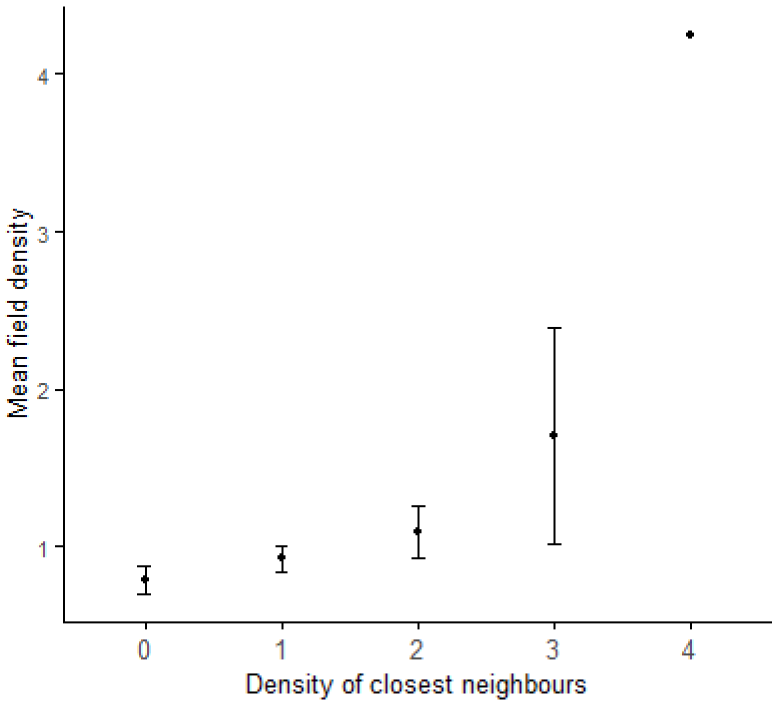

Fig. 6. Within-study field and neighbouring field mean ±SE Striga density. The effect of density in neighbouring fields on within-field mean Striga density was significant for the linear model and GAM.

Climatic and Edaphic Factors

A linear model and GAM combining climatic and edaphic factors to predict *Striga* density (mean rainfall, mean temperature and altitude) did not produce significant results (linear model: f = 1.39, df= 3, 238., p=: 0.25, GAM f =1.297 df= 14.38 p =0.19). A linear mixed model and GAM examining the effects of soil pH and NO3 on *Striga* density did not produce significant results (linear model: pH: t= 0.72, df= 92.58., p=: 0.48, NO_3 : t= -1.12, df= 89.33, p=: 0.27., GAM pH: X^2 = 0.72, df= 1., p=: 0.39, NO_3 : X^2 = 0.48, df= 1., p=: 0.49).

Comparison of variables between transects indicated a high degree of homogeneity (see Table 1). Mean *Striga* density by transect was similar (T1=0.89, σ=0.93 and T2=1.01, 1.01 σ=0.97). Mean rainfall and temperature also showed little variation between transects. Ranges for NO3 were also very similar. Ranges for pH were greater for T1, consistent with a greater distance covered.

Table 1. Mean Striga density (±SD), field area, temperature, rainfall and altitude range for the two transects.

Transect	Mean Striga density	Mean Temperature (°C)	Mean Rainfall (mm)	pH Range	NO-3 Range (ppm)
T1	0.89 (σ=0.93)	21.5	124	4.16 - 6.43	15 – 135
T 2	1.01 (σ=0.97)	22.3	122	4.51 - 5.81	18 – 130

Discussion

This paper describes a systematic, landscape-scale agroecological study of the factors driving the occurrence and abundance of Striga. The methodology enabled the rapid collection of statistically-robust distribution data to reveal key agroecological factors influencing Striga density. Our study demonstrates the role of crop variety, companion crop and crop rotation in determining Striga density and highlights the importance of densities within adjacent fields; providing evidence of the localised nature of Striga dispersal.

Previous *Striga* distribution studies have used a number of other census methods including: whole field plant counts (Dugje et al 2006), plant counts from small quadrats (Kamara et al 2013), questionnaires (Goodwin et al 2008) or preliminary species inventory (Gworgwor et al 2001). Comparable field-level density estimate methods have been previously used (Kabiri et al 2015); although these were undertaken on the scale of a few kilometres, without the use of statistical methods to identify ecological factors in determining *Striga* distribution. Where such statistical analysis has been used the study employed the much more labour-intensive method of plant counts from multiple quadrats per field (Kamara et al 2013).

Cropping practices

There was a significant role of rice variety on *Striga* density, and this was in line with previous studies which analysed the resistance of (NERICA) rice varieties. During the current study NERICA-10 was found to be more resistant than NERICA-4. This is significant as it is consistent with other studies undertaken in the laboratory by Cissoko et al (2011) and during field trials by Rodenburg et al (2015). Cissoko et al. (2011) found that NERICA-10 was more resistant to both *S. asiatica* and S. hermonthica than NERICA-4. This resistance was demonstrated in terms of numbers and mean height of attached Striga plants. Similarly, field trials by Rodenburg et al (2015) in Tanzania found the NERICA-10 was significantly more resistant to *S. asiatica* than NERICA-4. This resistance was expressed by maximum emerged Striga per m2. However additional field trials by Rodenburg et al (2017), -also in Tanzania- indicated similar levels of emerged *S. asiatica* between NERICA-10 and NERICA-4.

Randrianjafizanaka et al. (2018) identified significantly lower Striga infection levels for NERICA-4 than variety B22. During the current study, similar mean Striga density was recorded for B22 and NERICA-4, with means which were not statistically different. NERICA-4 was the worst performing of all rice varieties recorded in terms of Striga density, which is the inverse of the findings of Randrianjafizanaka et al. (2018). However, NERICA-9, used in the study by Randrianjafizanaka et al. (2018), was not recorded, preventing a complete comparison. The results of Randrianjafizanaka et al. (2018) are consistent with regards to the significant effect of previous crop and legumes in reducing Striga infestation. This effect has also been found in other research (e.g. Kureh et al 2006).

The variance in observed resistance of rice varieties between these two studies could be due to several reasons. Firstly, high degrees of genetic variability have been identified between separate populations of *S. asiatica* (Mohamed et al 2007) to the extent that even proximate populations can be considered as separate ecotypes (Botanga et al. 2002). Such variation also appears to be positively related to time since introduction to a region or locality (Gethi et al 2005), which influences the degree of *Striga* virulence and levels of host infection (Cissoko et al 2011).

Secondly, the higher level of complexity associated with open systems could also account for observed variation with controlled studies in a geographically discreet locality. Indeed, the effect of the inherently greater complexity of agroecological systems on resistance of rice cultivars to *Striga* is largely unknown (Rodenburg 2015, 2017). Interactions of environmental factors such as soil composition, nutrients, microclimate, slope, aspect, can interact to influence the expression of host resistance. Interactions of these factors with the phenotypic expression of *Striga* ecotypes may also be responsible. Observations of resistance to *Striga,* due to the factors detailed above, therefore vary greatly according location. This may account for differences between the findings of a study concerning single population, when compared with those aggregated over several populations across a large geographic extent.

Dispersal

The correlation between within-field *Striga* density and that of nearest neighbouring fields suggests that there is transfer between adjacent, suitable habitat patches. Studies of the dispersal of *S hermonthica* (Berner et al 1994, van Delft 1997) and *S asiatica* (Sand et al 1990) also suggest localised seed dispersal to adjacent patches of suitable habitat, as opposed to long-distance, random dispersal via wind or water.

Contamination of seed is responsible for initial introductions between countries or regions (Berner et al 1994, Gethi et al 2005). This assertion is supported by herbarium records for Madagascar (see Fig.2.), which show the earliest records around the country's principal historical ports. Once initial introduction has occurred, the evidence for localised dispersal of *Striga* suggests that a spatially explicit approach to management would be most appropriate (Minor and Gardiner 2011).

Crop Productivity

The absence of any observed relationship between mean *Striga* density and crop height / cover could be attributable to the fact that emerged (aboveground) weed density often does not represent total attached *Striga* plants. In the case of *Striga*, density of plants can actually be lower in the event of high levels of host attachment (Hearne 2009). This is caused by an increased delay in emergence, as greater numbers of attached *Striga* plants compete for the same host nutrient source. This is different to the effect of most weeds, where visible weed biomass is related to crop performance (Rajcan & Swanton 2001). Some previous studies have demonstrated a direct effect of numbers of emerged *Striga* plants on crop performance (Rodenburg et al 2017, Mumera & Below 1993). However, these studies controlled for soil nutrient levels, so the role of *Striga* infection on plant growth could be isolated. It is however considered that poor soil nutrient levels observed during the current study represented an overriding limiting factor in crop performance, rather than *Striga* density.

Climatic and Edaphic Factors

Climatic and edaphic factors were not significantly correlated with Striga density. This was consistent with previous studies, as S asiatica has been found to be unresponsive to temperature (Patterson et al 1990, Rodenburg et al 2011). Mean rainfall variation within the study area was low (min: 114mm, max: 134mm), which is well within the 50–150mm range tolerated by Striga species (Mohamed et al 2006). Similarly, the altitudes encompassed by the current study (713–1301m) were well within the cited range of occurrence for S asiatica (0–2400m) (Agnew & Agnew 1994). In order to detect effects of climatic or edaphic factors on Striga density, it would be necessary to collect data across a wider section of the above-cited ranges. It is most likely that such factors do not solely influence spread or density of S asiatica. If such data were collected, these would require combination as factors within a more complex, future modelling framework.

Conclusions

The results of this study provide a number of important, wider implications for the study and management of economically important Striga species. These implications arise from both the methodology employed and the results obtained. The successful implementation of this novel methodology provides a basis to address the paucity of distribution and open system agroecological data for parasitic weeds. These are two significant concerns, which represent major impediments to the successful management of parasitic weeds. The methodology was successfully adapted from blackgrass, which is a morphologically and ecologically very different species. This demonstrates that the methodology can be further adapted to survey other important parasitic weed species. This simple methodology can be readily communicated to new field surveyors and the rapid, yet accurate nature of data collection is cost-effective. Therefore, surveys can potentially be expanded to regional or national scales as required.

The fact that rice variety and leguminous crops are shown to be significant determinants of Striga density on a landscape scale is highly significant. The identification of NERICA-10 as a highly resistant variety supports several previous studies. NERICA-4 has significantly lower resistance to *Striga* than NERICA-10 and other varieties and landraces. This observation is highly relevant to policy makers, agricultural researchers, extension workers, NGOs, and farmers in Madagascar. NERICA-4 is widely planted within the mid-west of Madagascar, possibly due to it being *Striga* resistant and a high-yield variety. The use of resistant crop varieties is the most widespread seed-based control option available to subsistence farmers with limited capital. However, in light of these findings, it is recommended that alternative varieties are promoted which exhibit greater resistance within this agroecological context.

Lower *Striga* densities recorded in association with planting of legumes also supports a number of previous studies. The use of leguminous companion / rotation crops is already widely practised within farming systems in this region. This control option does not require introduction of novel, unfamiliar crops whose uptake may be subject to potential resistance from farmers. The use of legumes within rotational and intercropping systems should therefore also be promoted in situations where limited access to capital precludes the use of herbicides, fertilisers or other technologies.

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Conflict of Interest Statement

The authors declare that there is no conflict of interest.

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Chapter 3

Identifying existing management practices in the control of *Striga asiatica* within rice–maize systems in mid-west Madagascar

Running Head: Practices to control Striga in Madagascar

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Abstract

Infestations by the parasitic weed genus Striga result in significant losses to cereal crop yields across sub-Saharan Africa. The problem disproportionately affects subsistence farmers who frequently lack access to novel technologies. Effective Striga management therefore requires the development of strategies utilising existing cultural management practices. We report a multi-year, landscape-scale monitoring project for Striga asiatica in the mid-west of Madagascar, undertaken over 2019-2020 with the aims of examining cultural, climatic and edaphic factors currently driving abundance and distribution. Long-distance transects were established across the middle-west region of Madagascar, over which Striga asiatica abundance in fields was estimated. Analysis of the data highlights the importance of crop variety and legumes in driving Striga density. Moreover, the dataset revealed significant effect of precipitation seasonality, mean temperature and altitude in determining abundance. A composite management index indicated the effect of a range of cultural practices on changes in Striga abundance. The findings support the assertion that single measures are not sufficient for the effective, long-term management of Striga. Furthermore, the composite score has potential as a significant guide of integrated Striga management beyond the geographic range of this study.

Keywords: integrated weed management, parasitic weeds, sustainable agriculture, witchweeds, cultural control, legumes

Introduction

Species of the genus *Striga*, which belongs to the parasitic plant family Orobanchaceae (Joel et al. 2007), are among the most economically significant weeds affecting food security within sub-Saharan Africa (SSA), and cause severe losses in many staple crops (Scholes & Press 2008). *Striga* has resulted in reported yield losses of between 35 - 80% in rice (Rodenburg et al. 2016), 50 - 100% for sorghum (Abunyewa & Padi, 2003) between 21 - 74% for maize (De Groote et al. 2007). Estimates of economic losses from *Striga* range from between $111 and $300 million per year for rice (Rodenburg et al. 2016) and $383 for maize (Woomer & Sabala 2008). Estimates of the size of the areas affected vary between 50–100 million ha annually (FAO, http://www.fao.org/).

Several aspects of *Striga* biology contribute to their invasiveness, persistence and economic impact. Most significantly, *Striga* species produce exceptionally large numbers of minute seeds (Joel 2013), resulting in the establishment of high population densities over short periods of time (Gressel & Joel 2013). Seeds can remain dormant within the seed bank for many years, often remaining viable for decades, enabling long-term persistence in affected areas (Parker 2013).

In contrast with weed control in high intensity agriculture, levels of herbicide use in Sub Saharan Africa (SSA) remain at very low levels, due to limited access to capital (Grabowski & Jayne 2016). A recent, comprehensive study of herbicide use within rice production in SSA recorded a mean herbicide frequency of 34% among farmers surveyed (Rodenburg et al. 2019). This study also found low levels of product regulation and frequent sub-optimal timing and application techniques. In some SSA countries surveyed, herbicide use was almost non-existent. For example, in Madagascar only 2% of farmers surveyed used any herbicide (Rodenburg et al. 2019).

Integrated *Striga* management is an initiative that has been promoted by several agencies in different regions of SSA, and uses a combination of approaches to *Striga* control (Baiyegunhi et al. 2019). Integrated *Striga* management incorporates technologies including *Striga* or herbicide resistant cultivars (Kanampiu et al. 2003), mycoherbicidal biocontrol (Schaub et al. 2006), arbuscular mycorrrhizal inoculates (Lendzemo 2004), improved tillage, fertiliser inputs (Grenier 2004) and intercrops with legumes (Schulz et al. 2003, Kamara 2008).

In regions where novel technologies promoted by integrated *Striga* management are unavailable, cultural methods to control *Striga* include crop rotation, fallow and intercropping. Continuous monocropping without rotation leads to increasing levels of infestation and accumulation of *Striga* seed within the soil seed bank (Ejeta 2007). Increasing the diversity of cropping systems can also contribute to management of conventional weeds whilst reducing the reliance on chemical inputs, and maintaining crop yields and ecosystem services (Davis et al. 2012). Cultural methods for weed control such as rotation and cultivar selection are well-established in many agricultural systems in SSA (Rodenburg & Johnson 2009). Alongside hand weeding, or weeding with hand tools, these are the predominant approaches to weed management in SSA (Lee & Thierfelder 2017). The use of legumes by intercropping (Bationo & Ntara 2000), crop rotation, fallow and agroforestry are also traditionally used to manage soil fertility with respect to N_2-fixation (Dakora & Keya 1997).

The incorporation of legumes for cultural management of parasitic weeds in SSA has been documented in a number of studies, and shown to be potentially effective. For example, the use of the N_2-fixing, woody legume *Sesbania sesban* in fallow in Kenya resulted in seedbank reductions of 50% of *Striga hermonthica* (Oswald et al.1996). *Cajanus cajan* grown in rotation with maize also resulted in a halving of the density of *Striga asiatica* (Oswald & Ransom 2001). A study of rice / maize rotations within a no-till cropping system with permanent soil coverage by a range of legume intercrops found *Striga asiatica* infestations were reduced for all rice/ maize/ legume combinations (Randrianjafizanaka et al. 2018). It is hypothesised that varying rates of N_2-fixation by different legume crops could influence the ability of a legume crop to control *Striga*. N_2 fixation alters N availability in soil for host crops. Depletion of soil minerals, including N has been shown to influence the exudation of root exudates known as strigolactones, which stimulate *Striga* germination and subsequent levels of host infection (Jamil et al. 2011, Yoneyama et al. 2007).

Additionally, legume intercrops can act as 'trap' plants and could be important for the reduction of *Striga* seedbanks (Oswald & Ransom 2001). When intercropped with maize and sorghum, *Glycine max* and *Vigna subterranea* have been shown to cause suicidal germination of *S. hermonthica* seeds, reducing the seedbank (Sauerborn 1999). This effect has also been observed in *Striga asiatica* with intercrops of *V unguiculata* (Ejeta & Butler, 1993).

An further property of intercrops, (including legumes) is their ability to shade soils (Carsky et al. 1994). The shading of intercrops can potentially reduce soil temperatures below optimum ranges required for *Striga* germination (e.g. Hsiao et al. 1988, Patterson et al. 1982) Shading by intercrops can also inhibit *Striga* plant development through reduced evapotranspiration rates, which reduce water and nutrient extraction rates from host crops (Stewart & Press 1990). For instance, field trials using leguminous intercrops of *Vigna unguiculata* and *Glycine max* with maize in Kenya recorded suppression of *S hermonthica* germination.

The use of resistant and tolerant crop varieties has also been shown to be an effective method to control *Striga* (e.g. Cissoko et al. 2011, Rodenburg et al. 2015, Randrianjafizanaka et al. 2018). Mechanisms of host resistance to *Striga* can be categorised as either occurring pre or post attachment to the host root system. Pre-attachment resistance is determined by a reduction in strigolactones, reducing subsequent levels of host infection (Jamil et al 2011). Strigolactones are signalling compounds, which stimulate the germination of *Striga* (Xie et al. 2010, Jamil et al 2011). Post attachment resistance refers to the degree in which the haustorium, upon penetrating the host root cortex, then penetrates the endodermis to form a host–parasite xylem connection resistance (Cissoko et al 2011). In addition, host crop genotypes have been identified which exhibit high degrees of tolerance to *Striga* infection, in terms of photosynthesis, plant height and yield (Rodenburg et al 2017).

Field trials are effective in demonstrating the effectiveness of alternative management options at small scales. However, such trials are typically conducted at single sites with limited ranges of variation in environmental conditions. Consequently, there is a question about the effectiveness of various alternatives, when applied in real systems, and across large numbers of farms that vary in terms of soil, history and management (Rew & Cousins 2001, Freckleton et al. 2018). In the case of *Striga*, to address this a landscape-scale study of the drivers of *Striga asiatica* distribution was conducted within rice –maize systems in the mid-west region of Madagascar (Scott et al, 2020).

This previous study demonstrated the importance of cultural practices in determining large-scale distributions of *Striga*, in terms of crop variety, companion crop and previous crop as well as *Striga* density of the nearest neighbouring fields. However, this previous analysis was a static ‘snapshot’ of field densities based on one year’s *Striga* density data, without providing information on changes in relation to any management practices. Ideally, tests of the effectiveness of management factors on weed control should use dynamic data that can also account for such temporal variability. Moreover, our previous study did not address the role of several key integrated *Striga* management tools, namely crop rotation and overall crop diversity.

The overall objective of this paper is to test the degree to which existing integrated *Striga* management practices could contribute to the management of *Striga* in the absence of widespread availability of chemical control. Here we measure the effect of cultural management practices on *Striga* density. These cultural practices include variation in crop variety, intercropping and use of legumes. In many parts of SSA, this suite of practices represents the main options for cultural weed management. We resurveyed fields over successive years to provide three years of crop management data and corresponding changes in weed density between 2019 and 2020.

Methods

Study system

Field surveys were undertaken during March 2020, supplementing initial surveys undertaken between February and March 2019. The surveys were undertaken in the mid-west of Madagascar, one of the six major rice-growing regions in the country (Fujisaka 1990). The mid-west covers 23,500 km^2, with an elevation between 700 m and 1000 m above sea level. The climate is tropical semi-humid, with a warm, rainy season from November to April and a cool, dry season from May to October. Mean annual rainfall ranges from 1100mm to 1900 mm with a mean temperature of 22 ^{o}C.

Large-scale transects

The aim of the sampling was to estimate the abundance of *Striga* within fields that varied in terms of their management. Because access to fields is limited by the absence of good roads, we structured our survey program around the main road system. Field sampling was based around two long-distance driven transects along which *Striga* abundance was estimated in fields adjacent to the road. These comprised a transect of 129 km along the RN34, and one of 25 km along the RN1b. A total of 221 fields were surveyed (transect 1: n=174, transect 2, n=47). Transect 1 was located within Vakinakaritra province, between the towns of Betafo and Morafeno and transect 2 was located within Itasy and Bongolava provinces, approximately 6km east of Ambohimarina and the outskirts of Tsiroamandidy (Fig. 1). Rice-maize cropping systems are largely employed within the study areas, with incorporation of legumes, - mainly cowpea (*Vigna unguiculata*), ricebean (*Vigna umbellata*), soybean (*Glycine max*) and groundnut (*Arachis hypogaea*), and manioc (*Manihot esculenta*).

Fieldwork was undertaken with support from local technicians and guides who were familiar with the locality and field history. Prior to commencing work within a locality, the Chef Fokotany (local administrative head) was sought in order to present ourselves and detail the work we were undertaking.

Within-field sampling

One field was surveyed on adjacent sides of the road every kilometre. During the initial surveys in 2019, it was quickly established that detection of *S. asiatica* was possible within rainfed upland rice and maize fields of typically planted densities at distances up to 5 m on either side of each surveyor. Quadrat dimensions of 200m^2 (10 m x 20 m) were agreed based on a trade-off between speed of data capture, and accuracy of measurement. Fields were divided into pairs of 10 m × 20 m quadrats, in which two observers simultaneously recorded *Striga* density, by walking at a steady pace along a central transect, and scanning 5 m to either side; in fields >1200 m^2, data were recorded from a maximum of three pairs of quadrats. A field corner was randomly selected as the starting point for each field survey. *Striga* density was estimated using a six-point, density structured scale, ranging from absent (0) to very high (5). Definitions of density states were determined during fieldwork in 2019, and a table with narrative descriptors of the scale used alongside representative photographs for each density state was produced (see Appendix 1).

Information was collated on crop type, rice variety, companion crop and previous crop. In addition, mean crop height, and percentage crop cover was estimated for each quadrat. Mean density score for *Striga*, average crop height and cover, and other weed cover for a quadrat was entered on a mobile application prior to moving to a subsequent quadrat. If no *Striga* was found in a quadrat, a thorough walk throughout the entire field was undertaken to verify that *Striga* was truly absent. If *Striga* was then located, density was estimated for this area which replaced a quadrat with a zero record on the data sheet.

To measure changes in *Striga* density between years, fields surveyed in the first year (2019) were relocated using a GPS-enabled smartphone. Data were recorded using a smartphone with the mobile application ‘Google Sheets’ (Google LLC, 2020, Version 1.20.492.01.45) to allow rapid and paperless data entry. Where new fields were surveyed, geo-referencing was undertaken using ‘Google My Maps’ (Google LLC, 2020, Version 2.2.1.4).

In a small number of instances, it was not possible to verify the exact location of previously surveyed fields. This was a consequence of GPS error, resulting in coordinates being located in margins between small fields, or being clearly erroneous (e.g. centred on a road, non-agricultural location). In these instances, the field was omitted (n=19). In instances where the resurveyed field contained a current non-host (i.e. non-cereal) crop, the field was surveyed but was omitted from analyses of *Striga* density (n=55). An adjacent, substitute field containing a cereal crop was surveyed and added to the dataset. Of the resurveyed non-cereal crop fields, only three were found to contain low, residual levels of *Striga.*

Our initial intention was to extend both transects in order to capture a greater degree of altitudinal and climatic heterogeneity. However, owing to logistic constraints imposed by the COVID 19 situation it was only possible to extend transect 1 by 16 kilometres east. It was also not possible to either resurvey the entirety of fields originally surveyed in 2019 or to extend transect 2.

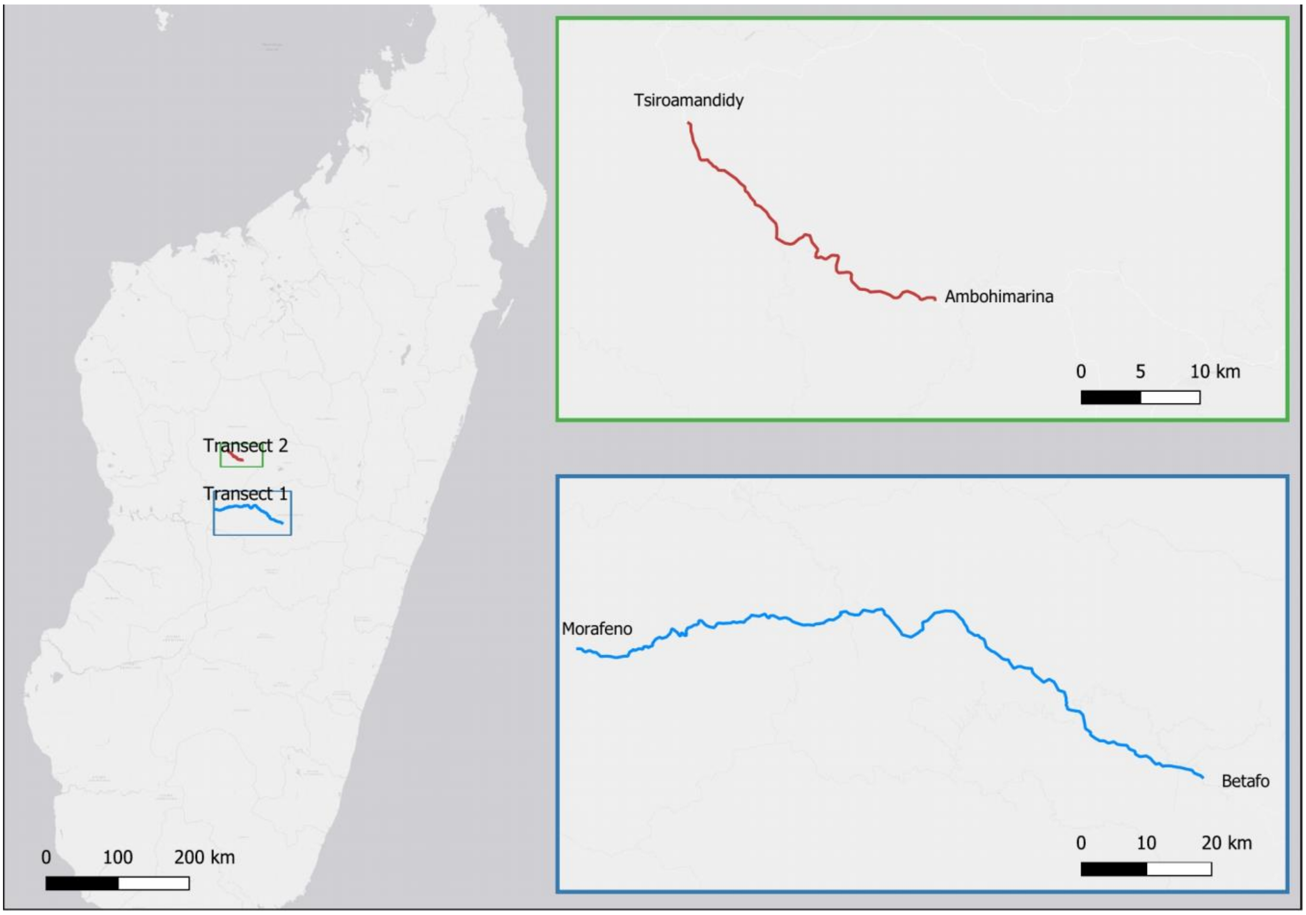

Fig 1. Location of transects 1 and 2, within the Vakinakaritra, Itasy and Bongolava provinces in the mid-west of Madagascar.

Soil Samples

Alongside the impact of cropping, the role of available nitrogen in determining *Striga* densities was addressed through collecting and analysing soil samples for NO_3. These samples were collected in pairs from quadrats with contrasting *Striga* densities within the same field. Samples comprised 23 pairs representing differing densities from absent to very high. These were analysed immediately following collection, with data added to those of the 98 samples collected in 2019 for the purposes of analysis.

Soil samples were obtained from the centre of each selected quadrat using a 20 mm diameter, hand-held, tubular soil sampler to a depth of approximately 20 cm. Soil samples were subsequently air dried for analysis.

NO_3 analysis was undertaken using a LAQUAtwin NO_3-11 nitrate meter (Horiba Scientific, Japan). Owing to low levels of NO_3 within the soil, it was necessary to dilute the standard solution supplied with the meter. Therefore, calibration was undertaken between 15 and 150 ppm NO_3 to improve sensitivity. One gram of dried soil was mixed with one millilitre of water and ground in a pestle and mortar. The resultant solution was then placed on the sensor of the meter. This procedure was repeated a minimum of two times per soil sample. If agreement between the first two readings was observed (i.e. between +/- 5 ppm NO_3 between readings), then the readings were taken, and the mean of the readings was used. If the readings did not concur, then sampling was repeated until stabilisation of readings.

Climate and Altitude

Climate data were obtained from the WorldClim2 dataset (Fick & Hijmans 2017). Climatic parameters included in the analyses were mean annual rainfall and mean annual temperature. Precipitation seasonality was included as an additional climatic factor. This was obtained by calculating the coefficient of variation (CV) of mean monthly precipitation, which is the ratio of the standard deviation of the monthly total precipitation to the mean annual precipitation (O'Donnell, & Ignizio, 2012). Invasion risk modelling has identified the seasonality of precipitation as one of the most significant bioclimatic variables influencing the occurrence of *Striga asiatica* (Mudereri et al. 2020). Seasonality is the chief driver of variation in monthly rainfall through the year. Therefore, the CV of monthly precipitation is an appropriate measure of seasonal variation. Altitudes for surveyed sites were obtained from CGIAR - Consortium for Spatial Information (CGIAR-CSI 2019).

Statistical Methods

Linear Models were used to test the effects of management (rice variety, previous crop and companion crop) and climatic predictors (mean annual temperature, mean annual rainfall, altitude). Soil sample data from 2019 and 2020 were analysed, using NO_3 as a predictor of *Striga* density. Within-field *Striga* density was also plotted against that of neighbouring fields. Year was also included in interaction with all predictors in order to test for any differences in patterns between the two years.

Striga density was log (x+1) transformed owing to the presence of large numbers of zero densities. Categorical variables incorporated into the models included crop variety, previous crop, companion crop. We included and tested terms sequentially (using Type I Sums of Squares): specifically, the interaction between year and the main effects was included, and tested as the final variable in the model to maintain the principle of marginality.

Statistics were calculated using R 3.6.3 (R Core Team, 2020) and the packages: dplyr (v0.8.0.1; Wickham, François, Henry & Müller, 2019), mgcv (Wood 2011), lme4 (v067.i01, Bates, Maechler, Bolker, & Walker, 2015), lmerTest (Kuznetsova , Brockhoff & Christensen 2017), MASS (Venables & Ripley 2002), DescTools (v 0.99.28, Signorell et mult. al. 2019). and psych (Revelle 2018, v1.8.12). The full reproducible code is available in Appendix 2.

Tests for collinearity between climatic factors indicated strong correlation between mean temperature and precipitation seasonality (f=1768.9, df=1, 406, R^2=0.81, p <

2.2e-16, VIF: 5.36, see plot, Appendix 3). This is because higher temperatures are correlated with greater variation in seasonal rainfall. Owing to this correlation, these terms were included in separate models.

Legume Crops

We tested the effects of the incorporation of legumes into crop rotation, as well as to examine effects of individual legume crops on *Striga* density. This analysis used data from all fields surveyed in 2019-2020, in which either a current legume companion crop or a previous legume crop was recorded. Firstly, a linear model was used to determine binary effects of the presence or absence of legumes in rotation using log-transformed mean *Striga* density. Secondly, an analysis was undertaken to examine the effects of individual legume crops on *Striga* density using mean *Striga* density (log transformed) as the response for a linear model.

Management and change in Striga density

In the set of analyses described above, the objective is to determine which factors correlate with the density of *Striga.* However, this does not tell us whether the correlates of static density measures are able to predict the impact of management on the *change* in density from one year to the next. Therefore, we tested whether models fitted to static density data could predict changes in *Striga* density.

Based on the outcome of the models described above, we tested the combined effects of a suite of management factors thought to individually affect *Striga* density, specifically inclusion of fallow, number of years of cereal cultivation, number of years of legume crop cultivation, and crop diversity (see Table 1). This analysis used cropping data obtained from field survey combined across 2019 and 2020, and included the previous crop for 2019, therefore, giving a three-year sequence of crop rotation data.

Table 1. Management scores for individual practices, calculated from verifiable 2-year dataset including previous crop for 2019. These measures were scaled using coefficients derived from a linear model including all four factors and summed to produce an overall *Striga* "management score" for each field.

Variable	Range	Coefficient
Fallow	0-1	-0.2018*n*
Years of cereal planting	2-3	-0.09133n
Years of legume planting	0-3	-0.36512*n*
Crop diversity	1-5	-0.26289*n*

We fitted a single linear model using the four individual factors (fallow, years of cereal cultivation, years of legume crop cultivation, crop diversity) as predictors of *Striga* density. The resultant values were then summed to produce a composite score (Table 1). Example calculations for fields with different indicator scores are provided in table 2. The composite scores were then used as the independent variable in a linear model of change in mean *Striga* density between 2019 and 2020 as the response.

Table 2. Example calculations for fields with differing composite scores. FL_YR = Fallow included in 3 year rotation, CR_YR = Number of years of cereal planting in 3 year rotation, LM_YR = Number of years in which legumes have been planted in 3 year rotation, NC = Number of different crops planted in 3 year rotation.

FL_YR	Score	CR_YR	Score	LM_YR	Score	NC	Score	Total
No	0	2	-0.18266	1	-0.36512	3	-0.78867	-1.33645
Yes	-0.2018	2	-0.18266	2	-0.73024	4	-1.05156	-2.16626
No	0	2	0.18266	2	-0.73024	4	-1.05156	-2.16626
Yes	-0.2018	2	0.18266	1	-0.36512	4	-1.05156	-1.80114
No	0	3	-0.27399	0	0	2	-0.52578	-0.79977

The score for legume crops included fields containing *Mimosa diplotricha.* Though this appeared to be an incidental weed species, its properties as an N-enriching green manure species are well-established (Yogaratnam et al. 1984, Thomas & George 1990). To simplify, and based on the results of models fitted to statistic density data, no differentiation was made between legume species. However, different rice varieties were considered as separate crops, owing to their observed influence on *Striga* density (Scott et al. 2020, Cissoko et al 2011, Rodenburg et al 2015, Randrianjafizanaka et al. 2018).

Results

The importance of the rice variety and whether the previous crop was leguminous were evident in this dataset (Table 3, Fig.2). Rice variety NERICA 10 was associated with lowest mean *Striga* densities (see also Scott et al. 2020). Several locally improved varieties (FOFIFA/SCRiD) and landraces are associated with higher *Striga* densities.

Fields previously planted with legumes had significantly lower densities than those that had not (Table 3 & Fig. 2.C). The linear model using individual legume crops as the independent variable for *Striga* density did not indicate any significance for this factor, with the majority of variation explained by the effect of year. However, figure 3 indicates varying levels of *Striga* infestation associated with different legume crops.

Impacts of Management Diversity

Patterns of rotation of main crops between years are shown in Table 4. Crop rotations were dominated by cereal (rice/maize) accounting for 44.5% of all combinations; comprising continuous maize (15%), continuous rice (10%), followed by maize / rice or rice / maize (19%). Following this was rice / maize and Bambara groundnut (13%), rice / maize and manioc (10%) rice / maize and groundnut (7%) and rice / maize and fallow(6%). Soya and other legumes were less widely recorded as a main crop, but were more frequently recorded as an intercrop.

Results for the analyses of the composite management score indicated significant effects on change in *Striga* density (F=9.06, df=1, 76, p=0.0035). Figure 4 indicates a clear positive relationship between the composite of management index scores for fields and mean change in *Striga* density between 2019 and 2020. The strong effect of *Striga* abundance of neighbouring fields suggests that this is a very strong predictor of within-field density (see Fig.5.A, Table 3.). This reinforces previous results (Scott et al. 2020), and suggests that spatial factors are important in determining *Striga* distribution and spread.

Significant effects for precipitation seasonality, altitude and temperature were indicated: with distinct trends in density observable along individual gradients (Fig.5.C-E). Soil analyses produced similar results with no significance of probabilities, in line with analysis of 2019 data alone.

Year emerged as significant term in the majority of models (companion crop, previous crop legume, legume crop, mean rainfall, precipitation seasonality, altitude and mean temperature, and other weed density) and as an interaction term in models for rice variety, previous crop, neighbouring density and mean rainfall (Table 3).

Table 3. Summary of models relating density of *Striga* to a range of management and ecological predictors. Precipitation seasonality (coefficient of variation for rainfall) is included as an additional test for the combined dataset. Resurvey in 2020 included a subset of original fields with additional fields. Updated analyses used combined dataset for both years.

Variable	Year	(df)	P	Effect	(df)	P	Year x effect	(df)	P
(a) Management variables									
Rice Variety	0.57	(1, 164)	0.450	2.02	(27, 164)	**0.004**	1.90	(9, 164)	**0.054**
Previous Crop	3.25	(1, 238)	0.073	1.02	(23, 238)	0.434	2.21	(6, 238)	**0.043**
Companion Crop	11.52	(1, 209)	**0.001**	1.13	(25, 209)	0.315	0.48	(6, 209)	0.822
Previous Legume	4.33	(1, 316)	**0.038**	6.39	(1, 316)	**0.012**	0.02	(1, 316)	0.885
Legume Crop	8.69	(1, 133)	**0.004**	1.82	(6, 133)	0.099	2.37	(3, 133)	0.073
(b) Ecological variables									
Neighbor density	3.04	(1, 338)	0.082	5.83	(1, 338)	**0.016**	6.32	(1, 338)	**0.012**
Mean rainfall	5.94	(1, 411)	**0.015**	1.84	(1, 411)	0.162	14.29	(1, 411)	**0.000**
Precipitation seasonality	5.87	(1, 411)	**0.016**	8.78	(1, 411)	**0.003**	3.13	(1, 411)	0.078
Altitude	5.56	(1, 409)	**0.019**	9.20	(1, 409)	**0.003**	0.51	(1, 409)	0.478
Mean Temperature	5.89	(1, 411)	**0.016**	12.61	(1, 411)	**4.3×10^{-4}**	0.58	(1, 411)	0.448
NO3	0.293	(1, 69)	0.590	0.10	(1, 69)	0.752	0.19	(1,69)	0.663
Other Weed Cover	5.69	(1, 337)	**0.018**	1.46	(1, 337)	0.227	0.10	(1, 337)	0.750

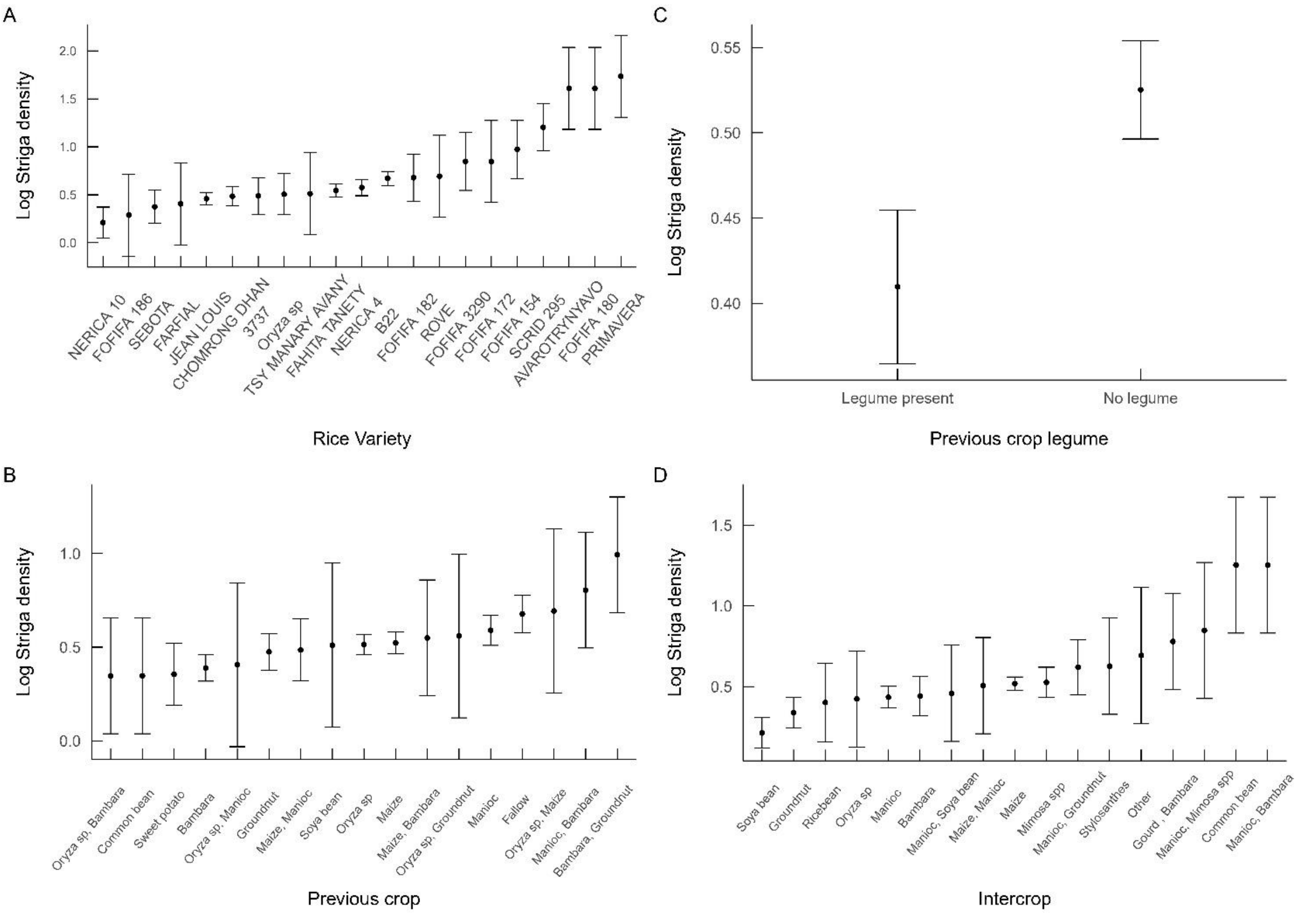

Fig 2. A: Log *Striga* density for rice variety ±SE , NERICA-10 n=10, FOFIFA 186 n=1, SEBOTA n=6, FARFIAL n=1, JEAN LOUIS n=44, CHOMRONG DHAN n=18, 3737 n=5, Oryza sp n=4, TSY MANARY AVANY n=1, FAHITA TANETY n=43, NERICA- 4 n=33, B22 n=41, FOFIFA 182 n=4, ROVE n=1, FOFIFA 3290 n=2, FOFIFA 172 n=1, FOFIFA 154 n=2, SCRID 295 n=3, AVAROTRYNYAVO n=1, PRIMAVERA n=1), **B:** Log *Striga* density for previous crop ±SE , (Onion n=1, Oryza sp / Bambara groundnut n=2, Common bean n=2, Sweet potato n=7, Oryza sp / Manioc n=1, Groundnut n=20, Maize / Manioc n=7, Soya bean, n=20, Oryza sp n=70, Maize n=59, Maize / Bambara groundnut n=2, Oryza sp / Groundnut n=1, Manioc n=29, Fallow n=19, Oryza sp / Maize n=1, Manioc / Bambara groundnut n=2, Bambara groundnut / Groundnut n=2. **C:** Log *Striga* density for previous crop type ±SE (-legume / non- legume). **D:** Mean *Striga* density for companion crop ±SE (Soya bean n=20, Groundnut n=20, Ricebean n=4, Oryza sp n=2, Manioc n=40, Bambara groundnut n=13, Manioc / Soya bean n=2, Maize / Manioc, n=2, Maize n=101, Mimosa spp n =20, Manioc / Groundnut n=6, Stylosanthes n=2, Other n=2, Gourd / Bambara groundnut n=2, Manioc / Mimosa spp n=1, Common bean n=1, Manioc / Bambara groundnut n=1 ±SE .

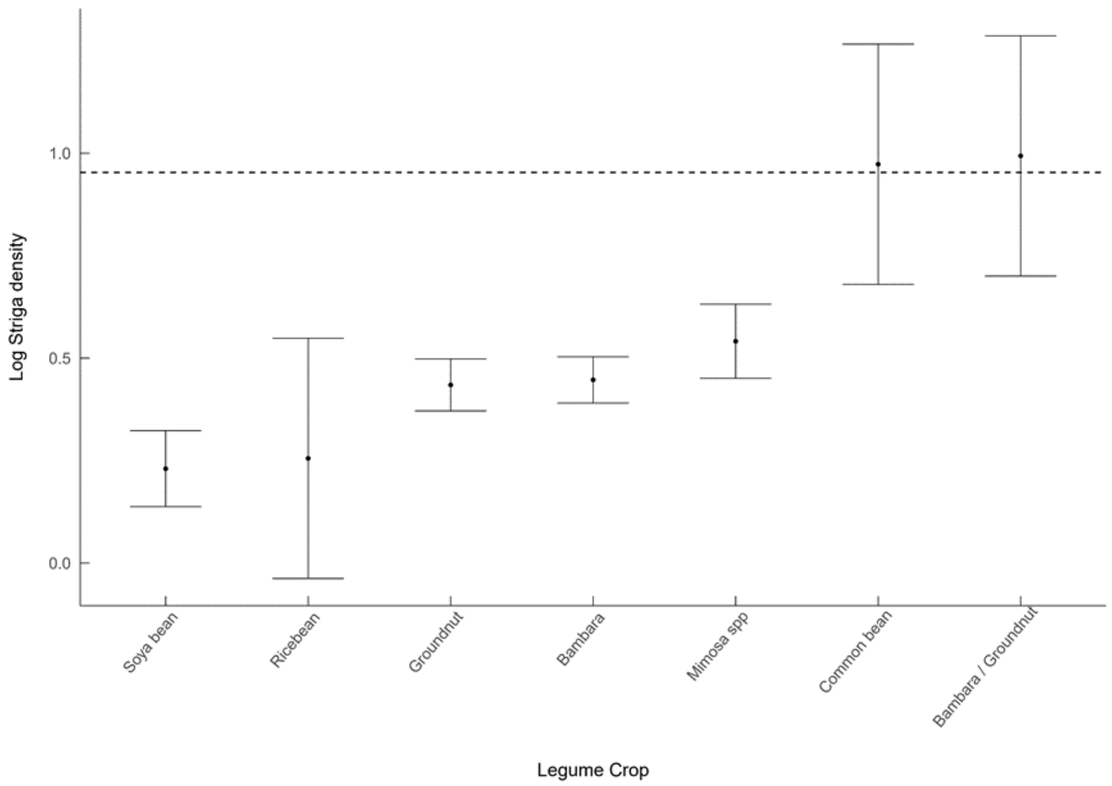

Fig 3. Log *Striga* density for fields planted with either a current legume companion crop or previous legume crop ±SE and grand mean (dashed line), Soya bean n=20, AH, VU Ricebean n=2, Groundnut n=42, Bambara groundnut n=54, *Mimosa spp* n=21, Common bean n=2, Bambara groundnut / Groundnut n=2.

Table 4. A transition matrix illustrating rotations for main crops recorded for the study between 2020/2019 and previous main crops recorded in fields for 2019. The number in each cell is the number of fields for each rotation. The colour represents the number of fields in each observed rotation. Asterisk denotes legume crop.

First Crop

Second Crop	Rice	Maize	Fallow	Manioc	Bambara*	Cowpea*	Groundnut*	Soya*	Sweet.potato
Rice	29	37	8	9	5	0	0	2	1
Maize	16	43	2	0	0	0	0	0	0
Bambara*	28	9	0	1	0	0	0	0	0
Manioc	16	13	0	1	0	1	0	0	0
Fallow	12	6	0	0	1	0	0	0	0
Common bean*	1	1	0	0	0	0	0	0	0
Groundnut*	9	11	0	0	0	0	0	0	0
Maize / Manioc	2	5	0	0	0	0	0	0	0
Manioc/Bambara*	1	1	0	0	0	0	0	0	0
Rice / Bambara*	2	0	0	0	0	0	0	0	0
Soya*	1	0	0	0	0	0	0	0	0
Sweet potato	3	4	0	0	0	0	0	0	0

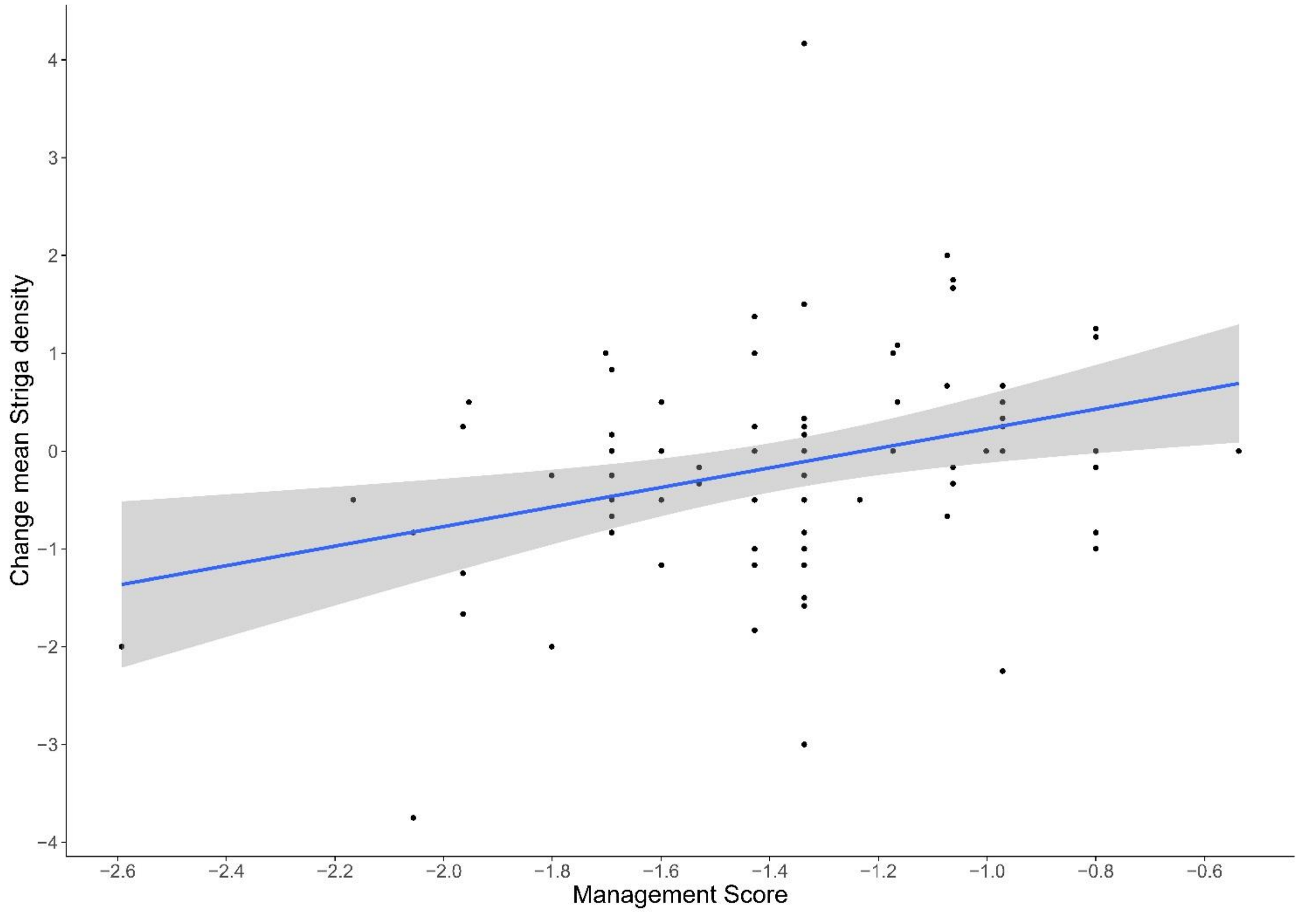

Fig 4. Change in mean *Striga* density and composite management score. Score comprised: years of fallow, number of years of cereal cropping, number of years of legume cropping and number of different crops planted. Values were weighted using coefficients derived from a linear model containing each factor as individual terms. As all coefficients were negative, a higher score is associated with increases in *Striga* density. The effect of management score on change in mean *Striga* density was significant for both the linear model.

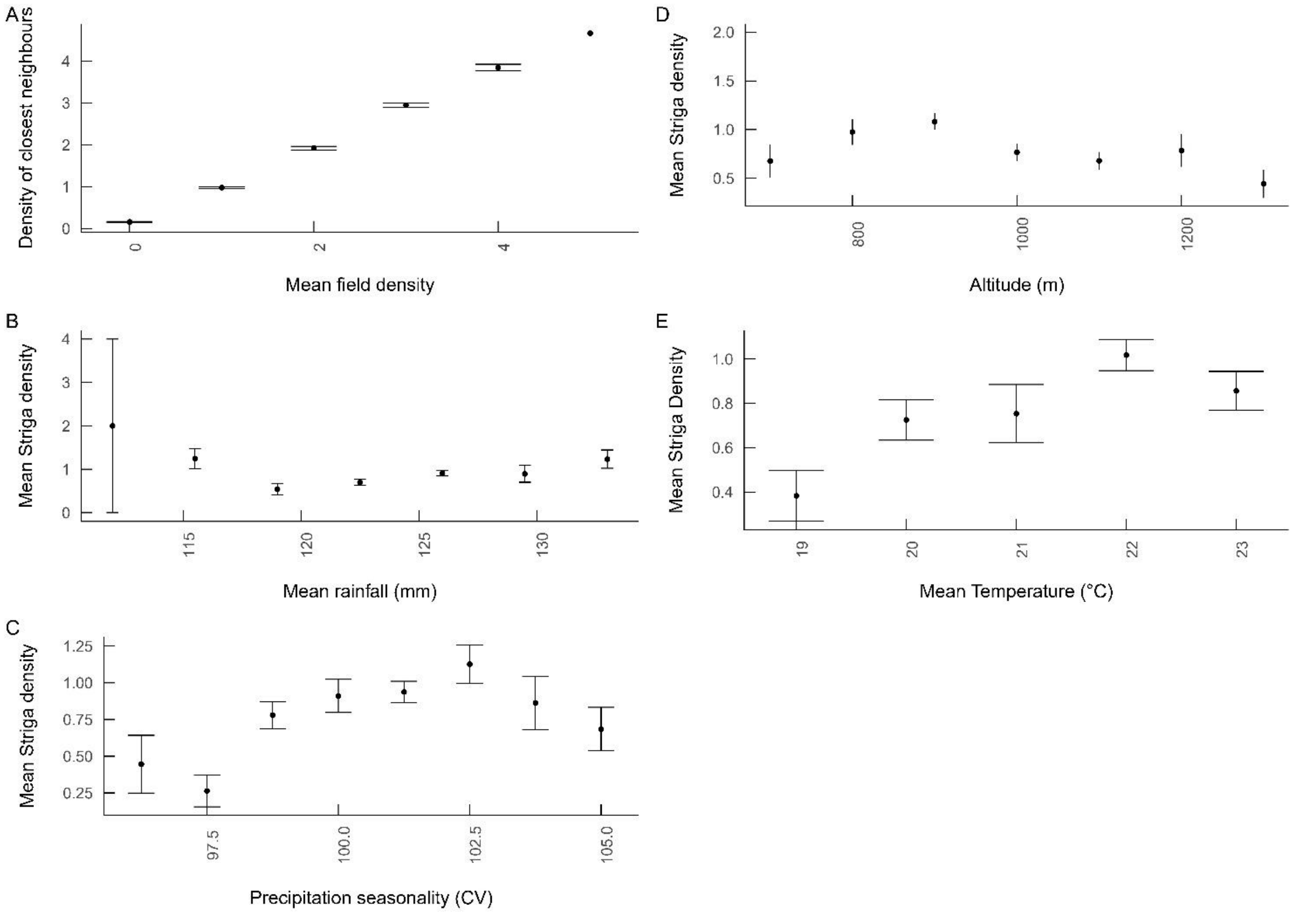

Fig 5. A: Mean within-field *Striga* density and *Striga* density within closest neighbouring fields ±SE, B: Mean *Striga* density and mean annual rainfall ±SE, C Mean *Striga* density and precipitation seasonality (coefficient of variation for rainfall) ±SE, D: Mean *Striga* density and altitude ±SE, E: Mean *Striga* density and mean annual temperature ±SE. The effects of both neighbouring densities, precipitation seasonality, altitude and mean temperature on mean *Striga* density were significant for linear models (see Table 3).

Discussion

This study provides evidence of the effect of a wide range of individual factors on *Striga* abundance at a landscape scale over multiple years. Given the importance of rice variety, legume crops and *Striga* density within adjacent fields, we provide evidence to contribute to the multifactor approach to *Striga* through integrated *Striga* management. The identification of year as a consistently significant effect across models illustrates the importance of inter-annual variability of *Striga* density. Strong inter-annual variation in *Striga* density has also been observed by other multi-year studies of cropping practices on *Striga* density (Reda et al. 2005, Khan et al. 2007, Midega et al. 2014, Randrianjafizanaka et al. 2018).

The work presented here advances our previous work in several respects. Firstly, the expansion of ranges encompassed by the 2020 surveys showed the significance of climatic and altitudinal factors in determining *Striga* density, not revealed in the analysis of the 2019 alone. Secondly, recording interannual variability in *Striga* density allowed for the assessment of the effects of a number of combined cultural factors. This is significant from a management perspective as it provides evidence of measures which can be implemented to control this problematic weed.

Climate and Altitude

The significant effect of precipitation, seasonality and mean temperature in our data concurs with ecological niche modelling, field surveys and laboratory tests undertaken elsewhere. Mudereri et al (2020) used a range of models including bioclimatic variables to determine the ecological nice of *Striga asiatica* in Zimbabwe. Precipitation seasonality was consistently identified as a key factor within all models. Niche based modelling prediction undertaken by Ronald et al. (2017) also identified precipitation variation as a major determinant of future spread. An association between regions with erratic, savannah-type rainfall patterns and high rates of *Striga* infestation has also been noted from field surveys (Dugje et al. (2006). The role of moisture variation in *Striga* seed conditioning and germination has also been demonstrated in laboratory studies (e.g. Babikar et al. 1987, Hsiao et al. 1987, Mohamed et al. 1998).

A minimum seed conditioning and germination temperature of 20^{o}C for *Striga asiatica* was observed by Hsiao et al. (1988) and Patterson et al. (1982). Patterson (1990) suggested that *Striga asiatica* requires a mean temperature of 22^{o}C to reach maturity, with an optimum temperature of 32 ^oC. While there are a few observations from this study, which fall below these thresholds; the general trend supports the assertion of these temperature ranges.

The significance of altitude as a predictor of *Striga* density is evident. Fig.5.D shows fields with highest infestation rates occurring at intermediate altitudes. Rodenburg et al. (2014) also observe that *S. asiatica* is particularly problematic at altitudes between 800-1100 m a.s.l within the region of Vakinakaritra, which serves to confirm this observation.

Soil NO3

Striga density was not found to be related to NO_3 levels in the soil. There are several potential reasons for this. Firstly, the literature suggests contradictory effects of the role of nitrogen on *Striga* emergence. For example, although Osman et al. (1991) recorded a significant increase in emerged *S. asiatica* between plots with applied nitrogen versus nitrogen-poor controls, no significance was found in numbers of emerged *Striga* between N treatments. However, Mumera and Below (1993) found decreases of *Striga hermonthica* with increased rates of applied N, although inter annual variability was considerable.

A second factor in the lack of observed impact of NO_3 is the timing of sampling. NO_3 samples were collected just before harvest at the end of the growing season. Soil N rates in rainfed rice are highest at the time of crop planting, with plant uptake and leaching decreasing over the duration of the growing season (Ranaivoson et al. 2019). Timing of sampling is therefore a possible factor in the lack of recorded effects of NO_3 on *Striga* density.

Legumes

The results of this study demonstrate the effect of legumes cropping systems on *Striga* density on a number of levels. Firstly, the effect of legumes in general was demonstrated by the lower mean *Striga* density associated with the previous planting of legumes versus other crop types (Fig.2.C). The generalised effect of legumes was further supported by the significance of the composite management score, which includes number of legumes planted over a three-year rotation as a component (Fig.4). Although individual legume crops show varying mean *Striga* densities in figure 4, these differences were not significant; with Significance within this model apportioned to year.

The individual effects of legume crops on *Striga* density also varies between other comparable studies. For example, Randrianjafizanaka et al. (2018), recorded significant effects of a cowpea, Mucuna, ricebean and *Stylosanthes* intercrops on *S. asiatica* density in both rice and maize. A study by Khan et al. (2007), using common bean, cowpea, *Crotalaria, Desmodium,* mung bean and groundnut, only found a significant effect for *Desmodium* intercrop. Midega et al. (2014) only found significant differences among some legumes in certain cropping seasons, while Reda et al. (2005) found no significance for a suite of legume intercrops.

Management

The analysis of the management score indicates a significant relationship between the combined factors and inter-annual variation in *Striga* density. While these variables when assessed individually may not demonstrate significant effects due to their coarse resolutions, their combined effect on change in *Striga* density is considerable from a farm management viewpoint. Indeed, the importance of an integrated *Striga* management approach, combining multiple methods has been demonstrated in several other studies (e.g.: Tesso and Ejeta 2011, Randrianjafizanaka et al. 2018).

Effective dissemination of novel technologies associated with integrated Striga management requires functional and accessible extension services to maximise farmer's awareness and education (Ellis-Jones et al. 2004, Emmanuel et al. 2016). Increased costs associated with implementing novel integrated Striga management technologies are also related to adoption rates; with larger commercial farmers showing significantly higher levels of adoption in other areas of SSA (Baiyegunhi et al. 2019). Both these factors represent significant barriers to both diffusion and adoption of new integrated Striga management technologies in Madagascar.

Extension services are not sufficient to effectively support widespread diffusion of other novel technologies (Harvey et al. 2014). In addition, around 70% of farmers in Madagascar practice subsistence agriculture (INSTAT 2011), while the average farm area for upland rice for Madagascar is 1.28ha (Zeller et al. 1999). Agriculture is also subject to frequent extreme weather events and pest and disease infestations (Rakotobe et al. 2016). Coupled to this is an absence of financial safety nets and widespread food insecurity for at least part of the year (Harvey et al. 2014). These factors result in an understandably high degree of risk-aversion towards adopting new technologies, even when they are available (Moser & Barrett 2003). Therefore, the adaption of existing practices, combined with available resistant crops is considered a more viable approach to *Striga* management within this context.

Because of the complexity of the information included, we simplified by developing a management score designed to represent the complexity and diversity of crops used. The use of composite indices is an effective means of aggregating often-disparate individual indicators into a single summary value (Foster et al. 2013, Greco et al. 2019). Such indices have the potential to summarise systems in ways not directly measurable (Dobbie & Dail 2013). They have been widely used within ecological and environmental assessment. For example, to measure biotic integrity of freshwater and riparian habitats (Karr 1981, Munné et al. 2003), assess habitat suitability for protected species (Oldham et al. 2000), as well as measuring global biodiversity trends (Collen et al. 2009) and national-level environmental performance (Srebotnjak 2014)).

Conclusion

The findings of this study further demonstrate the influence of a range of individual cultural factors on *Striga*. Moreover, the influence of individual legume crops on *Striga* density provides additional insight into observations of overall effects of legumes in general. Further study of the degree to which these effects are attributable to either the habit or N fixing properties of different legume crops is recommended to obtain a deeper understanding of the specific roles of different legume crops.

The analysis shows however that no single factor influences *Striga* density to the degree that it can be considered a panacea for control. Indeed, it is widely accepted that single measures are not sufficient for the effective, long-term management of *Striga*. The influence of the composite management score in reducing *Striga* densities is of potential relevance to farmers and extension workers in regions without access to novel control technologies. The scoring system provides an indication of the way in which several, easily measurable factors combine to result in significant reductions in *Striga* density between years. With annual monitoring, the index could be employed as an adaptive management tool, providing feedback on changes in infestation and options to adapt cropping accordingly. If used as a complementary method, alongside locally-effective resistant crop varieties and legume intercrops, the composite score has potential as a significant component of integrated *Striga* management beyond the geographic range of this study.

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Julie Diane Scholes: Conceptualization (Supporting); Funding acquisition (Equal); Investigation (Supporting); Methodology (Supporting); Project administration (Supporting); Resources (Supporting); Supervision (Supporting); Validation (Supporting); Writing-review & editing (Supporting).

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Conflict of Interest

The authors have no conflicts of interest to declare.

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Data availability statement

The datasets and code generated during and/or analyzed during the current study are available in the Dryad repository: (doi:10.5061/dryad.4qrfj6qb3).

Chapter 4

Crop diversification and parasitic weed abundance: a global meta-analysis

Running Head: Crop diversification and parasitic weed abundance

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Abstract

Parasitic weeds cause huge annual losses to food production globally, affecting both industrial and subsistence agriculture. A small number of species from the genera Cuscuta, Orobanche, Phelipanche and Striga have proliferated across many agroecological zones. Their control is compromised due to the lack of efficacy afforded by conventional, herbicide based approaches and their rapid adaptation to new resistant crop cultivars. A broad range of studies suggest consistent reductions in parasitic weed densities owing to increased spatial (intercropping) and temporal diversity (rotation cropping). However, to date, no synthesis of this body of research has been published. Here we report the results of a meta-analysis using 1,525 paired observations from 67 studies across 24 countries, comparing parasitic weed density and crop yields from monocrop and more diverse cropping systems. We found both spatial and temporal crop diversification had a significant effect on parasitic weed density reduction. Furthermore, our results show effects of spatial diversification are stronger in suppressing parasitic weeds than temporal effects. Furthermore, the analysis indicates intercrops, which alter both microclimate and soil chemistry such as Crotalaria, Stylosanthes, Berseem clover and Desmodium are most effective in parasitic weed management. This analysis serves to underline the viability of crop diversification as a tool to enhance food security globally.

Keywords: integrated weed management, parasitic weeds, sustainable agriculture, agrodiversity, legumes

Introduction

Weeds currently represent the most significant factor limiting agricultural production, with crop yield reductions attributable to weeds measured at approximately 40% globally (Chauhan 2020, Oerke 2006). Amongst the most serious weeds, a small number of parasitic plants of the genera *Cuscuta, Orobanche, Phelipanche* and *Striga* have proliferated, impacting food production worldwide (Samejima & Sugimoto 2018, Aly 2007, Fernández-Aparicio et al. 2020). Parasitic weeds disproportionately affect subsistence farming in the developed world (Rodenburg et al. 2016), exacerbating food insecurity and confounding poverty alleviation initiatives. Simplification of cropping systems has been recognised as a key driver of agricultural weeds in general (Weisberger et al. 2019). This is also the case for parasitic weeds, which predominantly affect low-diversity agricultural systems, with large-scale monocultures providing a continuous supply of host plants, facilitating their spread (Ejeta 2007, Fernández-Aparicio et al. 2020).

It is widely acknowledged that production losses from weeds will increase as a result of climate change (Gaudin et al. 2015, Sharma et al. 2017, Fried et al. 2017), with predicted infestations of parasitic weeds also increasing (Mohamed et al. 2006, Rubiales et al. 2018). Growing levels of herbicide resistance have been recorded among an increasing number of weed species globally (Heap 2020). Similarly, herbicide use to control noxious parasitic weeds is largely ineffective (Aly 2012, Rubiales et al. 2018). Weed management options, which minimise herbicide reliance, are increasingly viewed as a more sustainable solution (Korres et al 2019). In particular, weed management using crop diversification has received significant focus for both parasitic weeds and weeds as a whole (Rubiales & Fernández-Aparicio 2012, Weisberger et al. 2019).

Agrodiversity describes diversity within varieties and species of cultivated crops, crop-management systems and techniques, as well as insect and soil biodiversity (Netting & Stone 1996, Pimentel et al.1992). This diversity is important because it enhances the provision of ecosystem services by mitigating and reducing environmental risk, particularly with respect to climatic variations (Isaac 2012, Di Falco & Veronesi, 2013). An important component of agrodiversity is the diversity of cultivated crop species

(Khoshbakht & Hammer 2008) as well as genetic diversity at the varietal and landrace level (Hajjar et al. 2008).

Crop management diversification has been promoted to enhance sustainable agricultural development, environmental management, and poverty alleviation; thereby enhancing the overall agroecological resilience of production systems (FAO, 2012, Peterson et al. 2018). Studies have demonstrated that under a broad range of conditions it is possible to maintain yields whilst reducing the use of chemical fertilisers and herbicides (Raseduzzaman & Jensen 2017; Davis et al. 2012). Furthermore, diversification has been shown to stabilise and increase yields when compared with less diverse systems (Himmelstein et al. 2017). Such effects have been demonstrated on field, landscape and national scales (Davis et al. 2012, Abson et al. 2013, Renard & Tilman 2019) as well as across climatic gradients (Gaudin et al. 2015, Bowles et al. 2020).

Techniques used to enhance diversity include crop rotation (He et al. 2019), intercropping (Ofori & Stern 1987), cover cropping (Hartwig & Ammon 2002) and the use of cultivar mixes of the same species (Hajjar et al. 2008). There are several ways in which crop diversification has been shown to enhance food security. The principal effects are via control of plant pests (insects, pathogens and weeds) (de Vallavieille-Pope 2004, He et al. 2019), enhancement of soil macronutrients (Davis et al. 2012, Haugaard-Nielsen et al. 2001, Zhang & Li 2003), soil mycorrhizae and other plant growth resources (Haugaard-Nielsen & Jensen 2005). There is also evidence, albeit more limited; suggesting crop diversification provides enhanced pollination (Kubisova & Haslbachova 1991, Pywell et al. 2005).

Several mechanisms have been suggested by which intercropping results in increased crop yields. Crop diversity enhances the efficiency of crop resource use through niche complementarity or resource partitioning. This is due to variation in resource requirements, occupation of differing soil horizons and canopy heights resulting in more efficient use of available resources (Van der Meer 1992, Bybee-Finley & Ryan 2018). The facilitative production principle suggests that the interaction of beneficial traits between two crops results in increased productivity (Van der Meer 1992, Brooker et al. 2015). Intercropping also provides enhanced crop yield stabilisation through the compensation principle, (Raseduzzaman & Jensen 2017). Planting of more diverse suites of crops has been shown to reduce the likelihood of total crop failure in the event of extreme weather or pest outbreak (Rao & Willey 1980, Altieri et al. 2012).

Intercropping also helps to limit the proliferation of pests and diseases (Raseduzzaman & Jensen 2017). This is achieved by reducing susceptible crop densities, thereby reducing the pool of available hosts and reducing transmission (Burdon & Chilvers 1982). In addition, disease dispersal can also be disrupted by changes in microclimates due to the structural diversity afforded by crops of differing habits (He et al. 2019). Diversification of crop rotations has also been shown to have a significant effect on weed control (Chauhan et al. 2012, Nichols et al. 2015). For example, a recent and comprehensive meta-analysis undertaken by Weisberger et al (2019) found an average weed density reduction of 49% in diverse crop rotations, as compared with monocropping. Similarly, the role of intercrops in the suppression of weeds has been demonstrated across a wide range of crop types within both tropical and temperate biomes (e.g. Banik et al. 2006, Workayehu & Wortmann, 2011, Haugaard-Nielsen et al. 2001, Jensen 2006). However, in some studies this effect has been less evident, with significant variability in results between crops, years and locations (e.g. Arlauskienė et al. 2014, Szumigalski & Van Acker 2005, Stoltz & Nadeau 2014).

Increased resource use efficiency by intercrops has been shown to suppress weeds through several mechanisms. The effect of niche complementarity has been observed in intercrops, particularly for cereal-legume combinations, because legumes facilitate increased input of fixed N_2 cropping systems whilst not affecting uptake N uptake for the associated cereal crop (Anil et al. 1998). Increased resource use efficiency by intercrops through differing nutrient requirements between crops has also been shown to assist in weed suppression. For example, Haugaard-Nielsen et al. (2001) found enhanced interception of N by when intercropped with pea, compared to barley monocrop, which resulted in reduced weed incidence. Another important mechanism is the allelopathic effects of some crops on weeds when grown in rotation (e.g. Mamolos & Kalburtji 2001, Khan et al. 2005).

Crop damage begins when parasitic weeds attach to the host plant, and before they are visible above ground. This is because parasitic weeds are distinct from other weed species due to the presence of a specialised organ called the haustorium. This rootlike structure penetrates the host plant's vascular system and allows the parasite to assimilate nutrients and water (Sauerborn et al. 2007). Host plant attachment reduces the photosynthetic requirements of parasitic weeds either completely in the case of holoparasites such as *Cuscuta* or partially in the case of hemiparasites such as *Striga* and hemi-parasites such as *Orobanche* (Sauerborn et al. 2007).

Conventional weed management typically targets secondary growth such as herbicide application and mechanical weeding are frequently ineffective when applied to parasitic weeds. Methods of parasitic weed control must therefore focus on the reduction of germination and primary growth. Mechanisms to reduce parasitic weed recruitment include alteration of soil chemistry (Jamil et al. 2011, Yoneyama et al. 2007), germination in the absence of available hosts (suicidal germination) (Sauerborn 1999, Ejeta & Butler, 1993) and altering soil microclimate (Carsky et al. 1994, Hsiao et al. 1988, Patterson 1990, Stewart & Press 1990).

Additional methods also help mitigate yield losses, such as the use of resistant crop varieties (Cissoko et al. 2011, Rodenburg et al. 2015, Randrianjafizanaka et al. 2018) and post attachment tolerance of parasitic weeds by host crops (Rodenburg et al 2017). Combinations of crops, intercrops, rotation crops and varieties thereof may therefore manage or mitigate the effects of parasitic weeds in any number of ways listed above.

Meta-analyses have been undertaken to examine the broader effect of plant diversity on biomass production (Cardinale et al. 2007, Wang et al. 2021). More specifically, the effect of intercropping on crop yield stability (Raseduzzaman & Jensen 2017), suppression of weeds in general (Weisberger et al. 2019), woody crops (agroforestry) on pest, disease and weed control (Pumariño et al. 2015), crop yield and provision of ecosystem services (Kuyah et al. 2019), farmer income, and integrated pest management effects (Himmelstein et al. 2017). However, to our knowledge, no analysis has been undertaken of the effects of rotation and intercropping on economically significant parasitic weeds.

Here we present the results of a meta-analysis of the effects of crop diversity on parasitic weeds using an extensive data set derived from laboratory, field, farm and landscape studies. This represents the first quantitative synthesis of the effects of crop diversification on parasitic weeds and associated crop yields. We address the following questions:

- Does crop diversity, expressed as the incorporation of additional crops within a system, affect parasitic weed density or crop yield?
- In terms of management factors, what are the strongest predictors of variation in parasitic weed density and crop yield?
- Which are the best-performing combinations of crops/intercrops and /or rotation crops in terms of weed reduction and yield increase?
- An ancillary analysis, we address the effect of climate and altitude on reported, unmanipulated weed densities.

Meta-analysis methods

Pilot Study

A pilot study was undertaken using a combination of provisional terms in conjunction with the genera: *Striga* and *Orobanche* (being among the most economically significant parasitic weed genera). The number of returns for each search combination, accompanied by an assessment of relevance based on the title of each study, indicated their relevance. This determined the final list of terms for inclusion, as some terms were too broad and returned too many unrelated results. Search combinations returning very high (e.g. >400) numbers of records with a very large proportion of non-relevant studies indicated that the term was too broad and was omitted from the main search (e.g.: “Taxon” AND inter*, “Taxon” AND Legum*).

The choice of taxa for inclusion in the main search was determined by a review of economically significant parasitic plants using several sources (Nickrent & Musselman 2004, Sauerborn et al. 2007, Parker 2012). The list was then subject to triage, based on the nature of their parasitism, removing weeds not affecting annual crops planted in the soil. Genera which returned no results for the 12 search combinations were removed from the main search. In the case of genera containing high numbers of economically important species (e.g.: *Cuscuta, Striga*), the genus was included as a search term alone without going to the species level. Widely adopted synonyms at the family and genus level were also included. Appendix 1 details search combinations used for the pilot, results, list of taxa, synonyms, and full search methodology.

Main Search

The electronic databases, Web of Science, Scopus and AGRICOLA were searched using a range of Boolean search terms. Searches were performed in February 2021 on the complete range of references available at that time.

Search terms were constructed as follows: taxon name (*Aeginetia, Alectra, Christisonia, Cuscuta, Grammica, Orobanche, Phelipanche, Scrophulariaceae, Striga*) AND cover AND crop, taxon name AND Intercrop, taxon name AND trap*, taxon name AND push AND pull, taxon name AND companion, taxon name AND conservation AND agriculture *, taxon name AND integrated weed management, taxon name AND cultural AND control, taxon name AND suicidal*, taxon name AND legume, taxon name AND no AND till, taxon name AND zero AND till.

Additional searches were performed between May 2021 and February 2022 by manually searching for citations within relevant sections of 20 review studies of control methods for all economically significant parasitic weed taxa. Experts in the field of parasitic weed agronomy were also contacted to identify possible sources of data (including primary data) and to verify the thoroughness of our literature coverage. The list of studies and subsequent data were updated periodically as additional sources became available.

Criteria for Inclusion of Studies

Studies were included if they fulfilled the following relevance criteria:

Subjects studied: Any annual parasitic weed species, host crop and intercrop combinations

Treatment used: Intercropping or rotation cropping

Study type: Any primary studies with appropriate comparators, continuous data with means, information on sample sizes, available/calculable measures of variance or sufficient information to impute values. Range of studies comprised: Landscape-level assessment, laboratory, field trials, farm trials, pot, bag and rhizotron experiments.

Response(s): Host yield (t ha^{-1}/kg ha^{-1}), stover yield (t ha^{-1}), weed dry weight (t ha^{-1}/g pot/ g plant/ gm^2), weed / weed seed density (per petri dish / pot / plant / M^2/ $\log_{10}M^2$ / density / severity score), percentage weed reduction / ratio (versus control / from original density).

Comparator: Appropriate controls: experimental units in which no intercrop was grown with the host crop, or monocrop / fallow / bare earth in the case of rotation studies.

Data Extraction

Weed density and yield data were standardised to m^{-2} or t ha^{-1}, respectively. Where reported, the long or short rainy season was also recorded. In the case of data presented in graph form, numeric data were extracted using data extraction software ('im2graph'; Shai Vaingast 2014). Data from studies were recorded to either intercrop or rotation cropping systems, as the mechanisms of impact of these on both parasitic weed density and yield are ecologically distinct.

Coordinates for study locations were directly extracted where available, or were estimated based on central coordinates of place names and extracted using Google maps (Google Maps, 2022). In a handful of instances where it was not possible to determine separate coordinates for locations very close together (e.g. villages), data were aggregated and mean values calculated.

Studies in which there were no reported controls for the main treatment, or where data were not presented in a useable form were rejected. However, measures of variance were not reported in 53% of intercrop and 50% of rotation studies. Rejection of this proportion of studies due to missing variance risks the loss of significant volumes of data (Kambach et al. 2020). Furthermore, such omission can result in both losses of statistical power and errors in parameter estimates (Nakagawa & Freckleton 2008) as well as a risk of bias toward studies that report significant results (Idris & Robertson 2009). We, therefore, imputed missing variances as this has been shown to improve the reliability of meta-analysis (Kambach et al. 2020). Imputation was undertaken using the "mice" package in R using the predictive mean matching method (van

Buuren & Groothuis-Oudshoorn, 2011). This method was chosen as it selects values from the complete studies in the dataset predicted to be closest to values which are missing (van Buuren 2018). Other methods produced imputed values which were either not realistic or were negative (e.g. Random sample, Linear regression). Imputed values were estimated by averaging across ten iterations undertaken for each missing variance.

Climate and Altitude

Climate data were obtained from the WorldClim2 dataset (Fick & Hijmans 2017). Climate variables recorded were mean annual rainfall, mean annual temperature and precipitation seasonality. Precipitation seasonality is defined as the coefficient of variation of mean monthly precipitation (O'Donnell, & Ignizio, 2012). Altitudes for individual study sites were obtained from the SRTM 90m Digital Elevation Database v4.1 (Reuter et al. 2007, (CGIAR-CSI 2004 – 2021) and were extracted using QGIS (QGIS Development Team, 2020).

Statistical Methods

Analyses were undertaken using linear models and linear mixed effect models, adjusted to account for the differences in variance of effect sizes among studies. Linear models were used to test the overall effects of the cropping system on weed density and yield across studies. Linear models were also used to determine the effect of rainfall CV, mean annual temperature, mean annual rainfall, and altitude on parasitic weed density and crop yield. This second group of analyses were done by using a subset of studies where initial weed density had not been manipulated (i.e.: farm, field trial or landscape).

Linear mixed-effect models were used to identify the effect of management factors on weed density and yield across studies. Two groups of factors were included in these models with effect size as the response (weighted by the study variance), and study ID included as a random effect. The effect size was estimated as Hedge's g and its variance (standardised mean difference). This was done by calculating the difference between the treatment and control (weed density, weed dry weight or host yield) divided by the pooled standard deviation using the “compute.es” package in R (Del Rey 2013).

Statistics were calculated using R 3.6.3 (R Core Team, 2020) and the packages: dplyr (v0.8.0.1; Wickham, François, Henry & Müller, 2019), lme4 (v067.i01, Bates, Mächler , Bolker, & Walker, 2015), lmerTest (Kuznetsova , Brockhoff & Christensen 2017). The fully reproducible code is available in Appendix 2.

Results

Meta-analysis search

A total of 3,722 bibliographical references were retrieved using our search strategy. An initial assessment of the relevance of each study was made based on the title and abstract of each paper. This reduced the list to 83 original studies directly relating to the effect of either intercrops or rotation crops on parasitic weed density. After examining the full text of these papers, 67 were deemed to fulfil the inclusion criteria and provide all information needed. The remaining 16 were rejected as having either no experimental control or insufficient detail regarding the effects of response variables. The full list of studies included in the meta-analysis is included in appendix 2.

The final dataset encompassed research across 24 countries and 89 localities (Figure 1) and yielded 1,525 individual data points. In terms of weed and crop diversity, it included 11 parasitic weed species, 70 varieties across 18 host crops and 115 intercrop rotation varieties across 105 trap crops (Appendix 3). Contingency tables for both intercrops and rotation crops are shown in Appendix 4.

The studies are predominantly located across sub-Saharan Africa, with a smaller number in North Africa and the Middle East, the Indian subcontinent and China and only three conducted in the United States and Europe. This distribution reflects the severity of the problem of parasitic weeds affecting annual crops across these regions, driving research efforts in search of solutions.

Figure 1: Maps of weed species locations for studies used for this meta-analysis. As the majority of studies focus on sub-Saharan Africa, the lower map has been used to further identify their distribution within this region. Basemap: Open Street Map Basic base map (obtained through QuickMapServices QGIS plugin), Map data © OpenStreetMap contributors.

Cropping System

Our analysis reveals strong overall effects of both intercropping and crop rotation on weed density reduction and crop yields (Table 1). Consistent reductions in weed densities are associated with the use of intercrops across a diverse range of crops. Crop yields are also generally higher within a smaller range of intercrops (Fig 3A & 3B). The use of multiple crops in the rotation has a consistently negative effect on weed density for a comparably large range of crops (Fig 3C). Crop rotation also has a more marked effect on yields, for a greater range of crops than intercropping.

Analysis of effect sizes (Hedges g) indicated broadly similar mean effect sizes for both systems, with marginally greater weed reduction for rotation cropping and yield increase for intercropping (Fig 2A & 2B). The number of crops used in rotation, denoted as diversity, did not have any significant effect on the percentage change in weed density for the linear model (Table 1). Similarly, the mixed effect model for diversity did not show significant differences in weed reduction effect size between the numbers of rotation crops used (Table 2).

Management Factors

The linear mixed-effects models did not detect significant differences in effect sizes for the majority of factors (Table 2). This does not mean the rotation had no effect on the responses, but that effect sizes did not differ greatly enough between the factors. Mean effect sizes for both weed reduction and yield were in fact greater than 0.5 for over 75% of factors tested (Table 2).

Our models indicated that weed, crop and intercrop species, as well as intercrop variety, had significant effects on weed density effect sizes in intercropping systems. Weed and intercrop species also had a significant effect on yield effect sizes in intercropping systems (Figures 4A & B). Mixed-effects models for crop rotation also indicated significant effect sizes for weed and host crop species and host crop variety. Notable effects on weed reduction included, inter alia, *Desmodium* and *Stylosanthes* in intercropping and maize, wheat and cotton in rotations. Mixed effect models for factors pertaining to yield in rotation systems did not indicate any individual significance for effect sizes.

Table 1. Summary of linear models testing overall effects of cropping system reported across studies. Climatic factors and altitude were tested against non-manipulated, initial weed densities from intercropping and rotation studies in open systems (farm, field trials and landscape). Yield data were obtained from studies with no manipulation of climatic conditions.

Cropping System	Response	Variable	Effect	(df)	P
Intercropping	weed density	Control / Treatment	1235.1	1,628	**< 2.2e-16**
	yield	Control / Treatment	51.2	1,393	**4.07e-12**
Crop Rotation	weed density	Control / Treatment	187.9	1,366	**< 2.2e-16**
	% Change in weed density	Crop Diversity	0.1363	3,365	0.9383
	yield	Control / Treatment	235.7	1,128	**< 2.2e-16**
Combined	weed density	Rainfall CV	13.6	1,701	**0.0002**
		Mean Rainfall	32.6	1,701	**1.7e-08**
		Mean Temperature	0.4	1,701	0.5182
		Altitude	14.8	1,701	**0.0001**
	yield	Rainfall CV	4.7	1,488	**0.0311**
		Mean Rainfall	6.9	1,488	**0.0084**
		Mean Temperature	14.5	1,488	**0.0002**
		Altitude	6.8	1,488	**0.0096**

Table 2: Summary of linear mixed-effects models relating parasitic weed density and crop yield to a range of management and ecological predictors with significant probabilities reported in bold. These were used to determine which management factors explained the most variance within models and were, therefore, most significant in influencing both weed density and crop yields.

Cropping System	Response	Variable(s)	Effect	(df)	P
Intercropping	weed density	Weed Species	3.1	7,56	**0.0086**
		Host Crop	3.7	9,203	**0.0002**
		Intercrop	3.7	34,170	**7.6e-09**
		Host Crop Variety	3.7	21,2	0.2339
		Intercrop Variety	0.9	38,2	0.6436
	yield	Weed Species	2.7	5,36	**0.0339**
		Host Crop	0.4	3,43	0.7629
		Intercrop	1.7	23,65	**0.0410**
		Host Crop Variety	1.2	9,103	0.2745
		Intercrop Variety	1.1	19,103	0.4510
Crop Rotation	weed density	Weed Species	2.1	8,10	0.1255
		Host Crop	1.9	7,15	0.1320
		Rotation crop 1	1.1	81,217	0.2596
		Crop Diversity	0.1	1, 181	0.8965
		Host Crop Variety	2	15,43	**0.0439**
		Rotation Crop Variety 1	0.5	42,43	0.9826
	yield	Weed Species	1	6,69	0.4346
		Host Crop	0.1	3,69	0.9441

		Rotation crop 1	0.6	52,69	0.9824
		Crop Diversity	0.5	1,125	0.503
		Host Crop Variety	1.5	7,8	0.2772
		Rotation Crop Variety 1	0.5	18,8	0.8637

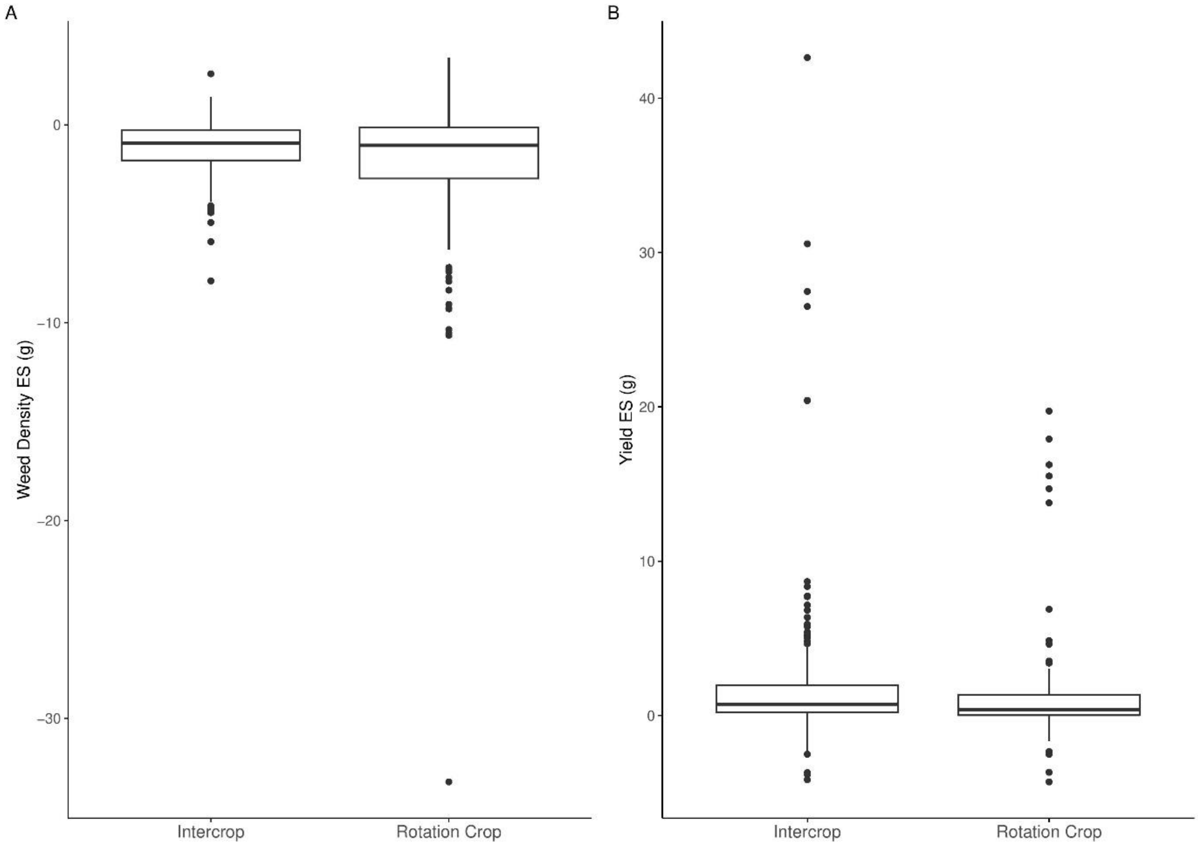

Fig 2A: The effect of cropping system (intercrop / rotation) on weed density. Fig 2B: The effect of cropping system (intercrop / rotation) on crop yield with crops grouped by family. Effect size (ES) expressed by Hedges g, multiplied by -1 to aid interpretation.

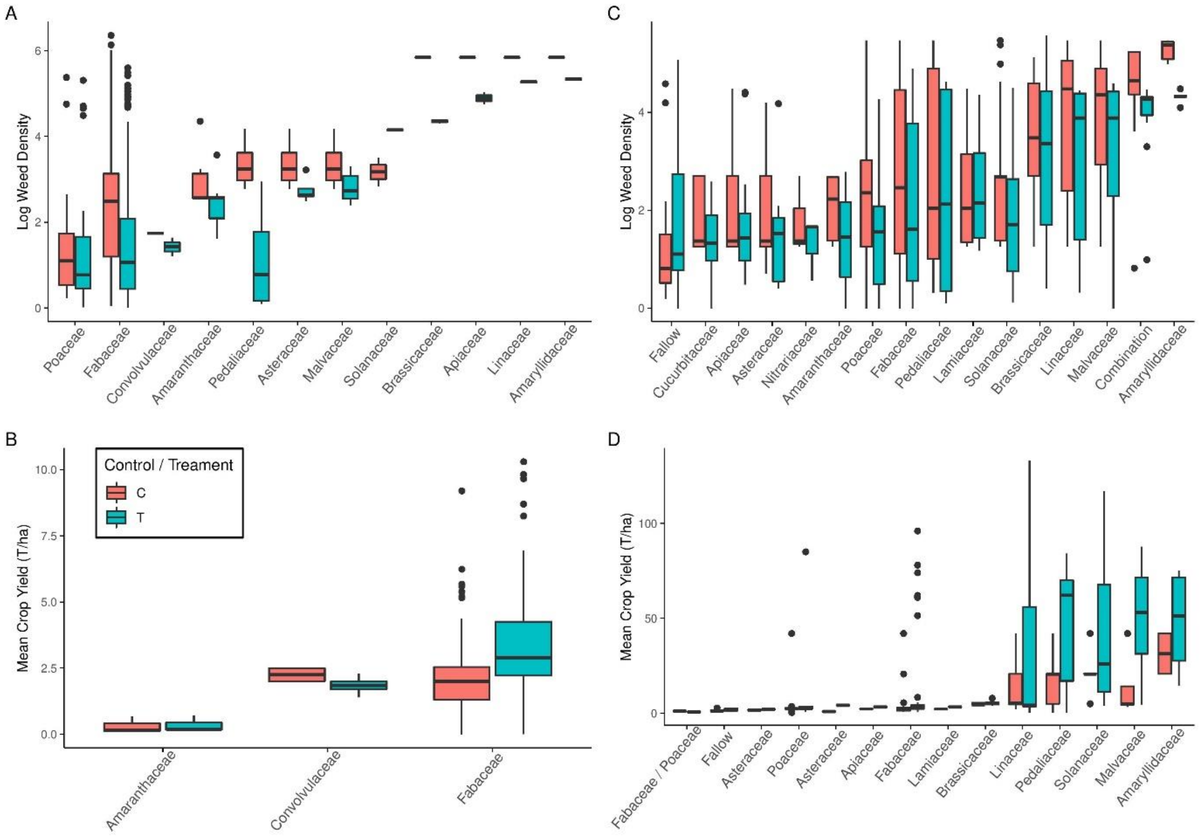

Fig 3A: Log weed densities in intercrops grouped by family, Fig 3B: Mean crop yields in intercrops, Fig 3C: Log weed densities in crop rotation and Fig 3D: Mean crop yields in rotation crops. Fallow is also included. The same set of figures grouped by crop species are included in appendix 4.

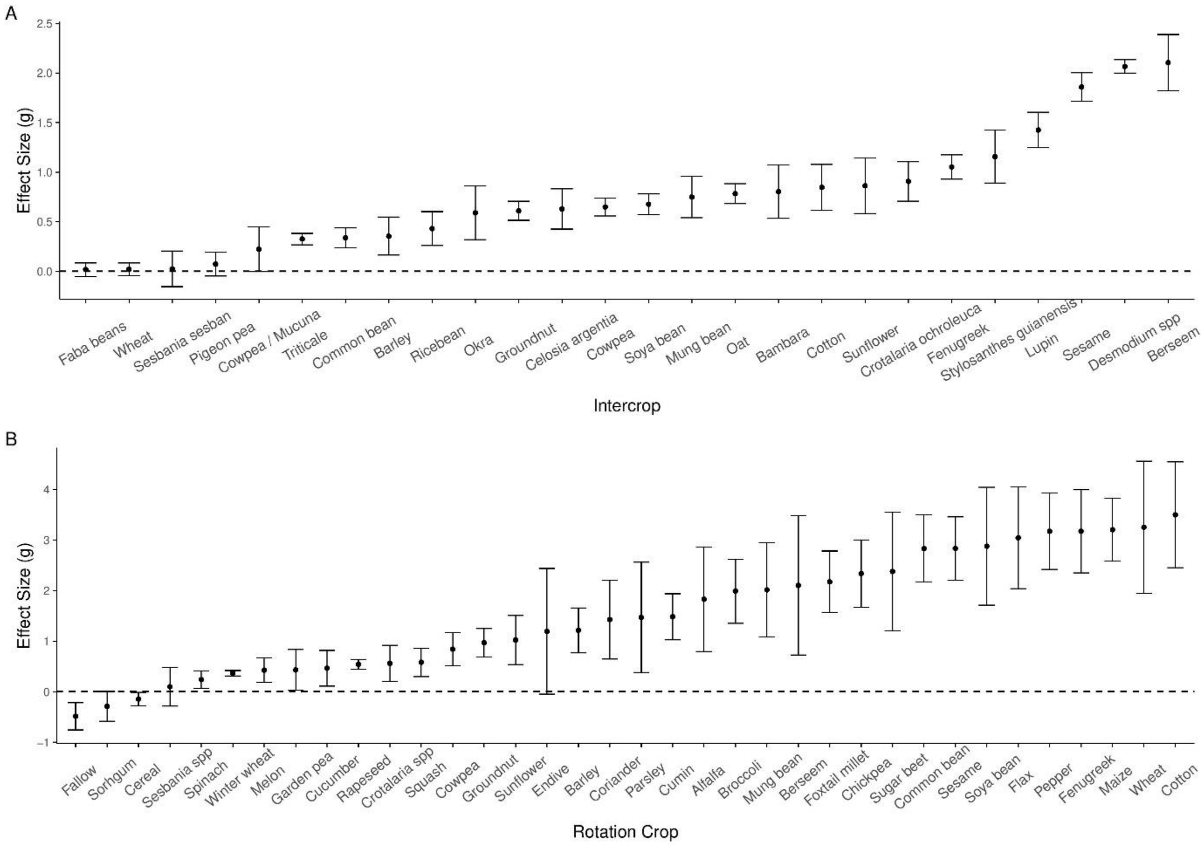

Fig 4A: Intercrop effects on weed density ordered by effect size ±SE. Faba beans: n=4, Wheat n=30, *Sesbania sesban* n=6, Pigeon pea n=6, Cowpea / *Mucuna* n=8, Triticale n=9, Common bean n=27, Barley n=7, Ricebean n=8Okra n=4, Groundnut n=54, *Celosia argentia* n=8, Cowpea n=66, Soya bean n=21, Mung bean n=24, Oat n=21, Bambara n=9, Cotton n=4, Sunflower n=4, *Crotalaria ochroleuca* n=24, Fenugreek n=27, *Stylosanthes guianensis* n=8, Lupin n=5, Sesame n=4, *Desmodium spp* n=204, Berseem n=23. Fig 4B: The effects of rotation crops on crop on weed density ordered by effect size ±SE. Fallow n=11, Sorhgum n=7, Cereal n=9, *Sesbania spp* n=11, Winter wheat n=6, Garden pea n=4, Rapeseed n=8, *Crotalaria spp* n=4, Cowpea n=10, Groundnut n=14, Sunflower n=4, Barley n=4, Coriander n=4, Cumin n=4, Alfalfa n=6, Broccoli n=5, Mung bean n=4, Berseem n=6, Foxtail millet n=6, Chickpea n=4, Sugar beet n=6, Common bean n=8, Sesame n=10, Soya bean n=30, Flax n=8, Pepper n=13, Fenugreek n=6, Maize n=22, Wheat n=4, Cotton n=6. Effect size (ES) expressed by Hedges g. Crops with ≤ 3 data points were omitted for concise presentation.

Climatic Factors

In terms of climatic factors, rainfall seasonality (CV), mean annual rainfall and altitude were significant factors for both weed density and yield for intercropping systems (See Table 1 and Figs 5A & 5B). For rotation cropping, rainfall seasonality, mean annual rainfall, mean temperature and altitude were significant factors in determining weed density. Mean annual rainfall and mean temperature were significant factors for yields.

A clear negative relationship is seen between log weed density and mean rainfall (Fig 5A). In addition, an increase in rainfall variability is linked to increases in weed density up to an intermediate level, beyond which densities appear to drop off (Fig 5B). There are two clear peaks in weed density around zero and 1,250 metres above sea level, relating generally to the distribution of *Orobanche* and *Striga* species respectively.

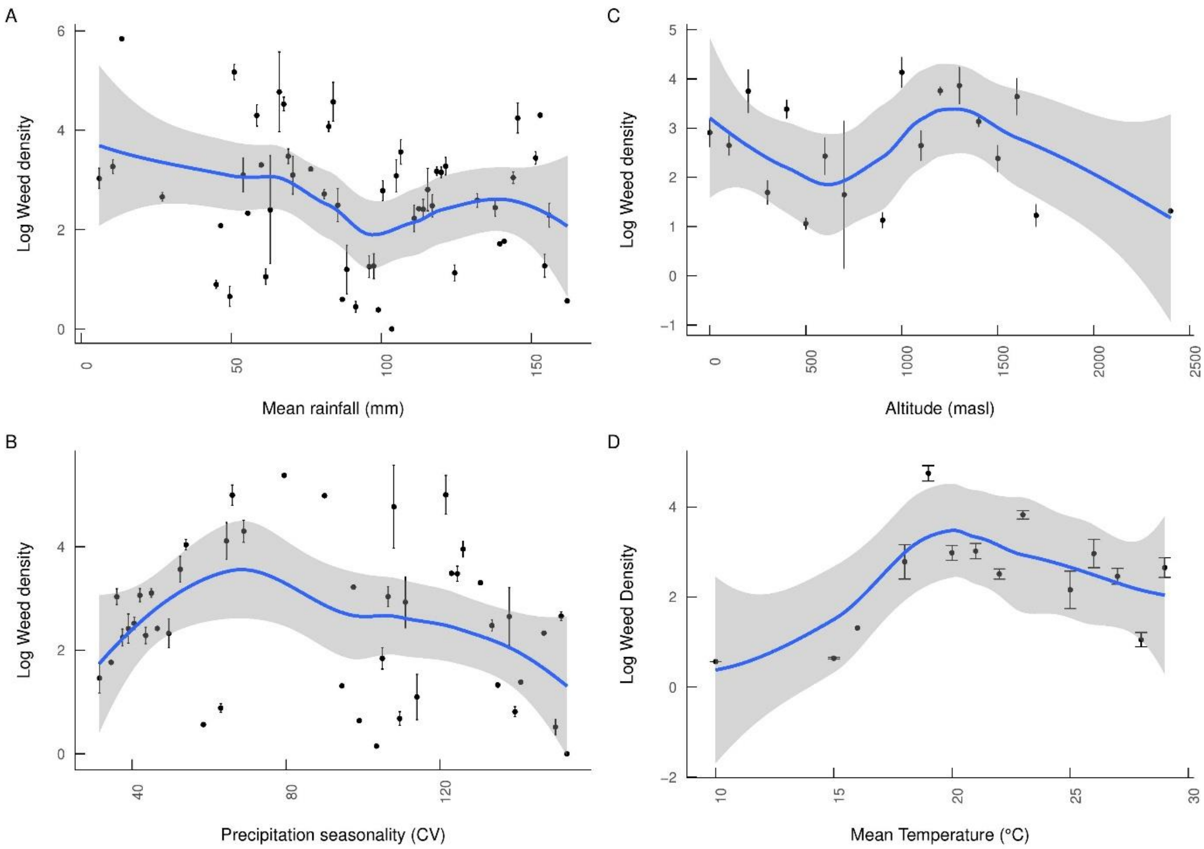

Fig 5A: Parasitic weed densities and mean annual rainfall ±SE, B: Weed densities and precipitation seasonality (coefficient of variation for rainfall) ±SE, C: Weed densities and altitude ±SE, D: Weed densities and mean annual temperature ±SE. The effects of climatic altitude and altitude on weed densities were significant for several linear models (see Table 2). Data were obtained from non-manipulated initial weed densities in field / farm trials or landscape studies.

Publication Bias

Egger's tests for funnel plot asymmetry indicated a significant degree of heterogeneity within the effect sizes of the data set (random-effects model: p= < .0001, mixed-effects meta-regression model p = 0.0449). This indicates that the distribution of effect sizes for studies included in this meta-analysis differs sufficiently from that expected to suggest a bias in the reporting of results. The additional fail-safe N test undertaken indicated however that the impact of any potential bias within the data was low (Rosenberg significance Level= <0.0001, fail-safe N: 311129, Rosenthal significance Level= <0.0001, fail-safe N: 447309), Orwin fail-safe N= 1517.

Discussion

Our results demonstrate that crop diversification has consistent effects in reducing parasitic weed density and increasing crop yield. Effects are significant for increases in both spatial (intercropping) and temporal (rotation cropping) crop diversification, though there are notable differences between the two systems. The linear models show the greater effect of weed suppression for intercrops, while the effect for yield is stronger for rotation crops.

The significant effect of crop diversification on weed density is supported by several comparable meta-analyses. For example, in reductions of weed densities in general (Liebman, & Dyck, 1993, Weisberger et al. 2019), increased crop yields due to intercropping (Himmelstein et al. 2017) and improved yield stability (Raseduzzaman & Jensen 2017) noted that intercropping. Meta-analyses of agroforestry (which can also be considered a form of diversification) have also found reductions in parasitic and non-parasitic weeds (Pumariño et al. 2015), and crop yield increases (Kuyah et al. 2019).

A recent, meta-analysis of weed responses to crop diversification by Weisberger et al. (2019) found that weed reduction correlated with temporal diversity expressed as the variance of sowing dates between different crops. The metric of temporal crop diversification can encompass elements of intercropping (such as relay cropping) as well as rotation cropping. However, our results suggest that the effects of spatial diversification are stronger than temporal in suppressing parasitic weeds.

Our results further suggests that soil microclimate and host crop pre-attachment resistance effects may be stronger than effects more clearly attributable to rotation such as alteration of soil N_2. Suicidal germination and allelopathy can occur within both intercropping and rotation cropping systems and could therefore be equally important mechanisms. Different combinations of crops and intercrops will produce different combinations of effects influencing weed density. Intercrops combining strong shading properties and favourably affect soil N_2 show particularly strong effects in reducing parasitic weed density here, such as *Crotalaria ochroleuca*, *Stylosanthes*, Berseem clover and Lupin. Likewise, crops affording shade with allelopathic properties, antagonistic to parasitic weeds, such as Fenugreek (Evidente et al. 2007) have large effect sizes in both rotation and intercropping studies. *Desmodium* is effective in three ways, shading, enhancing N_2 and stimulating suicidal germination by root exudates (Khan et al. 2002, Evidente et al. 2007), reflected by its' significant effect size in this analysis.

Publication bias, in particular the potential over-reporting of significant results, can compromise the validity of the results of meta-analyses (Nakagawa et al. 2022). The Egger's tests undertaken indicated a significant level of potential publication bias within the dataset, supported by the strong concurrence of results from a wide combination of systems, crops and weed species in terms of general trends. Although caution should be exercised in the inference of fail-safe N values, the results of the fail-safe N tests indicate that the data are sufficiently robust in terms of the impact of potential bias (Nakagawa et al. 2022).

Management

Effect sizes for both weed reduction and yield were significant (i.e. nonzero) for all models, and greater than 0.5 for over 75% of factors tested. The most notable effects were those of host crop and host crop variety, intercrop, and to a lesser extent rotation crop. Caution should be exercised with a simplistic, interpretation of effect sizes in terms of small, medium and large in quantitative studies (Bakker et al. 2019). However, these results clearly show individual crops which perform better than others. The notable effects of crop variety on parasitic weed density support studies of individual parasitic weeds (Cissoko et al. 2011, Rodenburg et al. 2015, Randrianjafizanaka et al. 2018, Scott et al. 2020, Scott et al. 2021). This effect also supports the rationale of a broader effort to identify and breed crop varieties resistant or tolerant to a wide range of parasitic weed pests (Aly 2007, Rubiales & Fernández-Aparicio 2012).

Our models did not detect significant differences in effect sizes for the majority of management factors. This does not indicate these factors should be discounted, but just that effect sizes did not differ greatly enough between the individual elements of these factors. The effects of management factors on yield may not be directly related to weed density, as there is no way to demonstrate the link in this analysis. Other factors are likely involved in influencing yields, as it is clearly understood that different crops, intercrops and crop varieties produce different yields independently of weed density.

Climate

The significant negative effect of precipitation on parasitic weeds is the most notable climatic effect revealed within the analysis undertaken here. There was also some evidence of a role for precipitation variation. The importance of rainfall and soil moisture is also shown across reviews of future weed distribution trends (e.g. Bir et al. 2014), niche modelling (Mohamed et al. 2007, Mandumbu et al. 2017, Mudereri et al. 2020) and landscape-scale studies of parasitic weeds (Scott et al. 2021). Drier, warmer climates across many areas of Eurasia, South and North America, combined with more erratic rainfall patterns will favour the spread of many of the most problematic parasitic weeds such as *Striga* and *Orobanche*. This underlines the importance of monitoring and biosecurity measures to prevent or contain the introduction into currently uninfested agricultural zones.

Conclusion

This meta-analysis underlines the important role that temporal and spatial crop diversification has in the reduction of economically important parasitic weeds. This effect is consistent across a wide range of geographic locations, crops, varieties and weed species. There is also strong evidence of the positive effect of diversification on crop yield, although this may involve factors other than weed reduction. This analysis further serves to underline the viability of crop diversification as a tool to enhance global food security. This will become increasingly relevant given projections of the future proliferation of many parasitic weeds to areas currently not under infestation driven by globalisation and climate change.

The concentration of studies undertaken in sub-Saharan Africa indicates, however, that crop diversification is still largely focused on subsistence farmers in low and middle income countries. While this is an entirely valid concentration of efforts, increased research should focus on the effects of diversification on the industrial production of staple crops within agroecological zones possessing Mediterranean climates globally. This will likely happen in response to the evolution of global patterns of weed distributions. However, proactive research strategies informed by predictive risk modelling could help in gaining the upper hand in the crop-weed “arms race”.

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General Discussion

The aim of this thesis was primarily to develop, implement, assess and refine a rapid density survey of *Striga asiatica* in the mid-west of Madagascar in order to identify the drivers of landscape-level distribution. The resultant dataset demonstrated the usefulness of the survey methodology in mapping *Striga* denstities and, importantly, in using the dataset to identify drivers of abundance spatially and between years.

Chapters two and three examined the roles of cropping practices, soil NO3 and climate in determining Striga abundance. These chapters showed the varying effects of a range of factors on *Striga* density. These ranged from individual crops to combined management, climatic factors and the influence of neighbouring densities. The fourth chapter applied the findings of chapter two and three to undertake a meta-analysis of the most ecomonically-significant parasitic weeds. The most fundamental point orienting this meta-analysis was that *Striga* densities were strongly influenced by cropping practices. Static farms are, of course restricted by their climate and altitude. However, cropping can be actively managed by farmers to influence infestations of parasitic weeds. Chapters two and three show that this can be done without recourse to agrochemical inputs. Given this basic observation, the main aim of chapter four was to examine the effects of cropping diversification on the density of all annual parasitic weeds for which primary studies were available. This study also provided an opportunity to quantify and compare the effects of crop families, individual hosts and companion crops.

Here I provide an overall discussion of the findings of this thesis as a whole, whilst avoiding replication of previously stated implications for the management of the species under investigation. I will also discuss the merits of the approach and provide some pointers for directions of future work.

The strong relationship between attached and aboveground *Striga* has been demonstrated in field plot study conditions (Rodenburg et al. 2005). If such a relationship holds true across the landscape scale, the method represents a novel, easily replicatable means of determining *Striga* density across large areas. This method can therefore be utilised to provide much needed distribution data in a rapid, cost effective manner.

However, the relationship between emerged weeds and the density of a seedbank may not be easily predictable (Smith & Webb 1996). Therefore, soil seed counts need to be done to determine interannual variation in the seedbank. Unfortunately, direct observation of seedbank density is time consuming and are unsuitable for rapid assessment.

There is always an inherent tradeoff between survey effort and accuracy, which must be acknowleged in assessing the validity of the field survey methodology (eg.: Leujak & Ormond, 2007, Del Vecchio et al., 2019). The results of the field surveys do show however that the performance of a wide variety of host varieties, rotation and intercrops, while indicating the effects of climate. Therefore, despite the potential inaccuracies inherent in rapid assessment in general, this thesis provides sufficient evidence to validate its' utility in measuring *Striga* and potential extension to other annual parasitic weeds.

The meta-analysis undertaken here represents the first published study of the effects of management on parasitic weed density, drawn from a wide geographic, taxonomic and methodological sources. It provides important insights into the role of both spatial and temporal crop diversity, while providing details of the relative effects of specific crops and climatic variables.

The field study did not measure the direct effect of monocrops versus intercrops or crop rotation on *Striga* density. As this basic dichotomous division was not measured, it was not possible to draw direct comparison between the resuts of chapters two, three and the meta-analysis of chapter four. Despite this, there remains a high degree of congruence between the field findings of field survey and the broader meta-analysis.

The effects of individual rotation and intercrops on weed density are notable across the field survey and meta-anaylysis. Likewise, the effect of rice and host crop variety in chapters two, three and four respectively is of comparable significance. Also, the effect of incorporating legumes into cropping systems is notable across the analyses. This serves to underline the fundamental importance of host crop, variety and companion crop in parasitic weed management. The importance of these elements is also reflected in other studies (Berner et al., 1996, Rodenburg et al., 2006, Tesso et al., 2007, Jamil et al., 2021) Optimal combinations will depend on the specific weed, and agroecological conditions however.

Finally, the effect of altitude and precipitation seasonality on both *Striga* and parasitic weeds in general was clear across analyses. This observation is perhaps more relevant to regional invasion risk modelling and assessment, than farm managers. It is nonetheless of note as it both accords with and complements the observations of other climatic studies available (Aflakpui et al., 1998, Hsiao et al., 1988, Mohamed et al., 2007, Mandumbu et al., 2017, Mudereri et al., 2020,).

However, a differentiation of parasitic weeds with respect to the climatic data in the meta-analysis would have provided specific insights into the respective profiles of separate species. A paucity of data would have provided poor resolution for some species however. In addition, the high level on which the meta-analysis was framed also resulted in a loss of resolution of representation of specific host / parasite / co-cropping effects.

Options for further research could be to apply the rapid assessment methods developed in this thesis to replicate the study within other areas of *Striga* infestation, where either less diverse or signiffcantly different cropping practices are employed. This could serve to undertake a more comprehensive comparative analysis and further elucidate the optimal means of weed management. Additionally, these methods could also be employed in conjunction with post-harvest yield measurements. This could provide indications of the interaction between management, weed density and crop productivity on a landscape scale.

Parasitic weeds are easily dispersed and rapidly adaptable in response to crop resistance, creating highly dynamic infestation states at local and regional levels (Goldwasser & Rodenburg 2013). Therefore, management responses must be equally adaptable and employ concepts of diversity found elsewhere in biology to counter their threat to global food security. Overall, I believe that this thesis shows that diversity is not only important for maintenance of functional populations of organisms, human societies and institutions and natural environments but is hugely important in combatting seemingly intractable problems such as the scourge of parasitic weeds in agriculture.

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Appendices

Chapter 2 Appendices

Appendix 1: Model details, outputs and R scripts

<table>
<tr><th>Model</th><th>#</th><th>Code</th><th>Result</th></tr>
<tr><td>Mean crop height v Log striga density +1</td><td>LM1</td><td>ALOM1<-group_by(AD_1, R_M_O)

lm1 <- lm(MCH ~ log(AvDen + 1), data = ALOM1)</td><td>Analysis of Variance Table

Response: MCH
Df Sum Sq Mean Sq F value Pr(>F)
log(AvDen + 1) 1 3767 3766.9 0.8295 0.3634
Residuals 223 1012696 4541.2
>
Coefficients:
Estimate Std. Error t value Pr(>|t|)
(Intercept) 99.03 7.36 13.454 <2e-16 ***
log(AvDen + 1) 9.87 10.84 0.911 0.363

Residual standard error: 67.39 on 223 degrees of freedom
(19 observations deleted due to missingness)
Multiple R-squared: 0.003706, Adjusted R-squared: -0.0007618

F-statistic: 0.8295 on 1 and 223 DF, p-value: 0.3634</td></tr>
<tr><td>Mean crop height v Log striga density +1 + S(Lat-Lon)</td><td>GAM 1</td><td>gam1 <- gam(MCH ~ log(AvDen + 1) + s(Lat, Lon), data = ALOM1)</td><td>Parametric Terms:
df F p-value
log(AvDen + 1) 1 0.511 0.475

Approximate significance of smooth terms:
edf Ref.df F p-value
s(Lat,Lon) 8.187 10.745 1.788 0.0586

Parametric coefficients:
Estimate Std. Error t value Pr(>|t|)
(Intercept) 100.217 7.212 13.896 <2e-16 ***
log(AvDen + 1) 7.663 10.717 0.715 0.475

Approximate significance of smooth terms:
edf Ref.df F p-value
s(Lat,Lon) 8.187 10.75 1.788 0.0586 .

R-sq.(adj) = 0.0693 Deviance explained = 10.7%
GCV = 4423.6 Scale est. = 4223.3 n = 225</td></tr>
<tr><td>Mean crop cover v Log striga density +1</td><td>LM2</td><td>lm2 <- lm(MCC ~ log(AvDen + 1), data = ALOM1)</td><td>Analysis of Variance Table

Response: MCC
Df Sum Sq Mean Sq F value Pr(>F)
log(AvDen + 1) 1 637 637.16 2.3293 0.1284
Residuals 223 60999 273.54

Call:
lm(formula = MCC ~ log(AvDen + 1), data = ALOM1)

Coefficients:</td></tr>
</table>

			Estimate Std. Error t value Pr(>|t|) (Intercept) 50.769 1.806 28.105 <2e-16 *** log(AvDen + 1) -4.059 2.660 -1.526 0.128 --- Residual standard error: 16.54 on 223 degrees of freedom (19 observations deleted due to missingness) Multiple R-squared: 0.01034, Adjusted R-squared: 0.0059 F-statistic: 2.329 on 1 and 223 DF, p-value: 0.1284
Mean crop cover v Log striga density +1 + S(Lat-Lon)	GAM 2	gam2 <- gam(MCC ~ log(AvDen + 1) + s(Lat, Lon), data = ALOM1)	Parametric Terms: df F p-value log(AvDen + 1) 1 2.819 0.0947 Approximate significance of smooth terms: edf Ref.df F p-value s(Lat,Lon) 17.27 21.63 1.685 0.0344 Parametric coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 50.970 1.758 28.997 <2e-16 *** log(AvDen + 1) -4.433 2.640 -1.679 0.0947 . --- Approximate significance of smooth terms: edf Ref.df F p-value s(Lat,Lon) 17.27 21.63 1.685 0.0344 * --- R-sq.(adj) = 0.123 Deviance explained = 19.5% GCV = 263.8 Scale est. = 241.21 n = 225 >
Mean other weed cover v Log striga density +1	LM3	lm3 <- lm(MWC ~ log(AvDen + 1), data = ALOM1)	Analysis of Variance Table Response: MWC Df Sum Sq Mean Sq F value Pr(>F) log(AvDen + 1) 1 45 45.05 0.0847 0.7714 Residuals 151 80320 531.92 Call: lm(formula = MWC ~ log(AvDen + 1), data = ALOM1) Residuals: Min 1Q Median 3Q Max -22.425 -20.773 -8.733 14.012 59.227 Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 30.773 3.127 9.843 <2e-16 *** log(AvDen + 1) 1.319 4.531 0.291 0.771 --- Residual standard error: 23.06 on 151 degrees of freedom (91 observations deleted due to missingness) Multiple R-squared: 0.0005605, Adjusted R-squared: -0.006058 F-statistic: 0.08469 on 1 and 151 DF, p-value: 0.7714
Mean crop cover v Log striga density +1 + S(Lat-Lon)	GAM 3	gam3 <- gam(MWC ~ log(AvDen + 1) + s(Lat, Lon), data = ALOM1)	Parametric Terms: df F p-value log(AvDen + 1) 1 0.218 0.641 Approximate significance of smooth terms: edf Ref.df F p-value s(Lat,Lon) 2 2 4.636 0.0111 arametric coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 30.353 3.064 9.906 <2e-16 *** log(AvDen + 1) 2.077 4.448 0.467 0.641 --- Approximate significance of smooth terms: edf Ref.df F p-value s(Lat,Lon) 2 2 4.636 0.0111 * --- R-sq.(adj) = 0.0402 Deviance explained = 5.91%

<table>
<tr><td></td><td></td><td></td><td>GCV = 521.1 Scale est. = 507.48   n = 153</td></tr>
<tr><td>Mean crop height, crop cover and other weed cover as combined response v striga density</td><td>LM4</td><td>lm4 <- lm(MCH + MCC + MWC ~ log(AvDen + 1), data = ALOM1)</td><td>Analysis of Variance Table

Response: MCH + MCC + MWC
Df Sum Sq Mean Sq F value Pr(>F)
log(AvDen + 1)   1   4878 4877.7 0.8778 0.3503
Residuals   151 839024 5556.5
> summary(lm4)

Coefficients:
Estimate Std. Error t value Pr(>|t|)
(Intercept)   176.34   10.10 17.451   <2e-16 ***
log(AvDen + 1)   13.72   14.64   0.937   0.35

Residual standard error: 74.54 on 151 degrees of freedom
(91 observations deleted due to missingness)
Multiple R-squared: 0.00578, Adjusted R-squared: -0.0008043
F-statistic: 0.8778 on 1 and 151 DF, p-value: 0.3503</td></tr>
<tr><td>Mean crop height, crop cover and other weed cover as combined response v striga density</td><td>GAM 4</td><td>gam4<- gam(MCH + MCC + MWC ~ log(AvDen + 1) + s(Lat, Lon), data = ALOM1)</td><td>Parametric Terms:
df   F p-value
log(AvDen + 1) 1 0.44   0.508

Approximate significance of smooth terms:
edf Ref.df   F p-value
s(Lat,Lon) 2.001 2.001 4.331 0.0148
> summary(gam4)

Parametric coefficients:
Estimate Std. Error t value Pr(>|t|)
(Intercept)   178.651   9.922 18.006   <2e-16 ***
log(AvDen + 1)   9.555   14.405   0.663   0.508

Approximate significance of smooth terms:
edf Ref.df   F p-value
s(Lat,Lon) 2.001 2.001 4.331 0.0148 *

R-sq.(adj) = 0.0415   Deviance explained = 6.04%
GCV = 5464.4 Scale est. = 5321.5   n = 153</td></tr>
<tr><td>Mean crop height of RICE ONLY v Log striga density +1</td><td>LM5</td><td>lm5 <- lm(MCH ~ log(AvDen + 1), data = AD_1, subset = which(R_M_O == "Rice")))</td><td>Response: MCH
Df Sum Sq Mean Sq F value Pr(>F)
log(AvDen + 1)   1   41   40.89 0.1291 0.7201
Residuals   106 33587 316.86
> summary(lm5)

Residuals:
Min   1Q Median   3Q   Max
-40.129 -9.944 -1.415   6.422 60.980

Coefficients:
Estimate Std. Error t value Pr(>|t|)
(Intercept)   60.129   2.737 21.971   <2e-16 ***
log(AvDen + 1)   -1.599   4.452 -0.359   0.72

Residual standard error: 17.8 on 106 degrees of freedom
(15 observations deleted due to missingness)
Multiple R-squared: 0.001216,   Adjusted R-squared: -0.008206
F-statistic: 0.1291 on 1 and 106 DF, p-value: 0.7201</td></tr>
<tr><td>Mean crop height RICE ONLY v Log striga density +1 + S(Lat-Lon)</td><td>GAM 5</td><td>gam5 <- gam(MCH ~ log(AvDen + 1) + s(Lat, Lon), data = AD_1, subset = which(R_M_O == "Rice")))</td><td>Parametric Terms:
df   F p-value
log(AvDen + 1) 1 0.091   0.763

Approximate significance of smooth terms:
edf Ref.df   F p-value
s(Lat,Lon) 11.07 14.37 1.36   0.187
> summary(gam5)

Family: gaussian
Link function: identity</td></tr>
</table>

<table>
<tr><td></td><td></td><td></td><td>Parametric coefficients:
Estimate Std. Error t value Pr(>|t|)
(Intercept) 59.988 2.615 22.943 <2e-16 ***
log(AvDen + 1) -1.307 4.322 -0.302 0.763

Approximate significance of smooth terms:
edf Ref.df F p-value
s(Lat,Lon) 11.07 14.37 1.36 0.187

R-sq.(adj) = 0.126 Deviance explained = 22.5%
GCV = 312.43 Scale est. = 274.61 n = 108
></td></tr>
<tr><td>Previous crop legume v previous crop not legume?</td><td>ttest1</td><td>AD1<- (AD_1$AvDen+2)#Adds 2 to the zeros to allow log transformation without excessive zeros

ADL<- log(AD1) # Then log transforms data

AD_1$ADL<-ADL

Make two vectors subsetting if previous crop was legume or not

PCLY = AD_1$ADL[AD_1$PCL=="Y"]

PCLN = AD_1$ADL[AD_1$PCL=="N"]

Plot histogram for each subset with nice normal distribution line

plotNormalHistogram(PCLY)

plotNormalHistogram(PCLN)

ttest1 <-t.test(PCLN, PCLY, "greater")</td><td>Welch Two Sample t-test

data: PCLN and PCLY
t = 2.0485, df = 141.08, p-value = 0.02118
alternative hypothesis: true difference in means is greater than 0
95 percent confidence interval:
0.01590524 Inf
sample estimates:
mean of x mean of y
1.0444077 0.9614534</td></tr>
<tr><td>Welch Two Sample t-test Companion crop legume v previous crop not legume?</td><td>ttest 2</td><td>CCLY = AD_1$ADL[AD_1$CCL=="Y"]

CCLN = AD_1$ADL[AD_1$CCL=="N"]

ttest1<- t.test(CCLN, CCLY, "greater")</td><td>Welch Two Sample t-test

data: CCLN and CCLY
t = -0.51946, df = 89.595, p-value = 0.6976
alternative hypothesis: true difference in means is greater than 0
95 percent confidence interval:
-0.1715704 Inf
sample estimates:
mean of x mean of y
0.5239577 0.5648124</td></tr>
<tr><td>Shapiro Wilk Test for normal distribution</td><td>SW1, SW2</td><td>sw1<-shapiro.test(PCLN)

sw2<-shapiro.test(PCLY)</td><td>Shapiro-Wilk normality test

data: PCLN
W = 0.93023, p-value = 9.952e-06

Shapiro-Wilk normality test

data: PCLY
W = 0.88964, p-value = 2.924e-05</td></tr>
<tr><td>Independent 2-group Mann-Whitney U Test As data looks non normal</td><td>UT1</td><td>wilcox.test(PCLN,PCLY, "greater")</td><td>Wilcoxon rank sum test with continuity correction

data: PCLN and PCLY
W = 4605.5, p-value = 0.02053
alternative hypothesis: true location shift is greater than 0</td></tr>
<tr><td>Welch Two Sample t-test NERICA4 and B22

As The results of Randrianjafizanaka et al. compared these two varieties</td><td>ttest 3</td><td>ttest3<- t.test(NERICA4, B22, "greater")</td><td>Welch Two Sample t-test

data: NERICA4 and B22
t = 1.0121, df = 53.34, p-value = 0.158
alternative hypothesis: true difference in means is greater than 0
95 percent confidence interval:
-0.07241114 Inf
sample estimates:
mean of x mean of y
0.6640107 0.5532828</td></tr>
</table>

Linear model Striga density v previous crop	LM6	options(contrasts = c("contr.sum","contr.poly")) lm6 <- lm(log(AvDen + 1) ~ PC, data = AD_1)	Analysis of Variance Table Response: log(AvDen + 1) Df Sum Sq Mean Sq F value Pr(>F) PC 25 4.6514 0.18606 1.082 0.369 Residuals 159 27.3413 0.17196 Multiple R-squared: 0.1454, Adjusted R-squared: 0.01102 F-statistic: 1.082 on 25 and 159 DF, p-value: 0.369
GAM Striga density v previous crop	GAM 6	gam6 <- gam(log(AvDen + 1) ~ PC -1 + s(Lat, Lon), data = AD_1)	Family: gaussian Link function: identity Formula: log(AvDen + 1) ~ PC - 1 + s(Lat, Lon) Parametric Terms: df F p-value PC 21 15.84 <2e-16 Approximate significance of smooth terms: edf Ref.df F p-value s(Lat,Lon) 2.126 2.247 0.708 0.457 > summary(gam6) Family: gaussian Link function: identity Formula: log(AvDen + 1) ~ PC - 1 + s(Lat, Lon) Parametric coefficients: Estimate Std. Error t value Pr(>|t|) PCArachis hypogaea 0.591496 0.106648 5.546 1.17e-07 *** PCArachis hypogaea, Manihot esculenta 0.068891 0.417409 0.165 0.869114 PCArachis hypogaea, Solanum lycopersicumes -0.009785 0.420001 -0.023 0.981442 PCCucumis sativus -0.082705 0.418120 -0.198 0.843447 PCFallow 0.721657 0.112531 6.413 1.50e-09 *** PCGlycine max 0.504852 0.416996 1.211 0.227780 PCIpomoea batatas 0.621659 0.209986 2.960 0.003534 ** PCManihot esculenta 0.640039 0.085632 7.474 4.61e-12 *** PCManihot esculenta, Vigna subterranea 0.828340 0.293686 2.820 0.005395 ** PCOryza sp 0.483489 0.072564 6.663 4.00e-10 *** PCOryza sp, Arachis hypogaea 0.547073 0.420556 1.301 0.195164 PCOryza sp, Manihot esculenta 0.416930 0.414682 1.005 0.316194 PCOryza sp, Vigna subterranea 0.316803 0.293555 1.079 0.282107 PCOryza sp, Zea mays 0.786737 0.420889 1.869 0.063398 . PCPhaseolus vulgaris 0.685005 0.418282 1.638 0.103434 PCVigna subterranea 0.347235 0.070044 4.957 1.79e-06 *** PCVigna subterranea, Arachis hypogaea 1.019209 0.293910 3.468 0.000672 *** PCZea mays 0.595244 0.073236 8.128 1.07e-13 *** PCZea mays, Manihot esculenta 0.524288 0.159370 3.290 0.001231 ** PCZea mays, Vigna subterranea 0.698396 0.414674 1.684 0.094069 . PCZea mays, Voanjo 0.396548 0.417749 0.949 0.343909 --- Approximate significance of smooth terms:

			edf Ref.df F p-value s(Lat,Lon) 2.126 2.247 0.708 0.457 R-sq.(adj) = 0.016 Deviance explained = 67.4% GCV = 0.19554 Scale est. = 0.1711 n = 185
Linear model Striga density v mean temp, mean rainfall and altitude	LM7	lm7 <- lm(log(AvDen + 1) ~ MeanRF + MeanTA + Alt, data = AD_1) anova(lm7)	Analysis of Variance Table Response: log(AvDen + 1) Df Sum Sq Mean Sq F value Pr(>F) MeanRF 1 0.171 0.17083 0.8905 0.34629 MeanTA 1 0.572 0.57172 2.9803 0.08558 . Alt 1 0.057 0.05727 0.2985 0.58532 Residuals 238 45.656 0.19183 --- Call: lm(formula = log(AvDen + 1) ~ MeanRF + MeanTA + Alt, data = AD_1) Residuals: Min 1Q Median 3Q Max -0.66661 -0.34131 -0.01941 0.24838 1.10644 Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) -1.3746946 3.5007288 -0.393 0.695 MeanRF -0.0088361 0.0080381 -1.099 0.273 MeanTA 0.1166316 0.1222766 0.954 0.341 Alt 0.0005012 0.0009172 0.546 0.585 Residual standard error: 0.438 on 238 degrees of freedom (2 observations deleted due to missingness) Multiple R-squared: 0.01722, Adjusted R-squared: 0.004829 F-statistic: 1.39 on 3 and 238 DF, p-value: 0.2465
GAM Striga density v mean temp, mean rainfall and altitude	GAM 7	gam1 <- gam(log(AvDen + 1) ~ MeanRF + MeanTA + Alt + s(Lat, Lon), data = AD_1) anova(gam1)	Family: gaussian Link function: identity Formula: log(AvDen + 1) ~ MeanRF + MeanTA + Alt + s(Lat, Lon) Parametric Terms: df F p-value MeanRF 1 0.045 0.832 MeanTA 1 0.649 0.421 Alt 1 0.046 0.830 Approximate significance of smooth terms: edf Ref.df F p-value s(Lat,Lon) 10.72 14.38 1.297 0.191
Linear model Striga density v rice variety	LM8	options(contrasts = c("contr.sum","contr.poly")) lm2 <- lm(log(AvDen + 1) ~ CV, data = AD_1, subset = which(R_M_O == "Rice")) anova(lm2) summary(lm2)	lm(formula = log(AvDen + 1) ~ CV, data = AD_1, subset = which(R_M_O == "Rice")) Residuals: Min 1Q Median 3Q Max -0.6753 -0.2743 0.0000 0.2105 1.1398 Coefficients: Estimate Std. Error t value Pr(>|t|) (Intercept) 0.64723 0.07299 8.867 2.59e-14 *** CV1 -0.09334 0.21212 -0.440 0.6608 CV2 0.96221 0.40497 2.376 0.0194 * CV3 -0.12445 0.11350 -1.096 0.2755 CV4 -0.16463 0.14054 -1.171 0.2442 CV5 -0.15229 0.11057 -1.377 0.1714 CV6 -0.64723 0.40497 -1.598 0.1131 CV7 -0.24177 0.40497 -0.597 0.5518 CV8 0.96221 0.40497 2.376 0.0194 * CV9 -0.24177 0.40497 -0.597 0.5518 CV10 -0.17764 0.11198 -1.586 0.1158 CV11 -0.46397 0.19251 -2.410 0.0177 * CV12 -0.05733 0.11696 -0.490 0.6250 CV13 0.55674 0.40497 1.375 0.1722 CV14 0.02808 0.24128 0.116 0.9076 CV15 0.04591 0.40497 0.113 0.9100 CV16 1.01100 0.40497 2.496 0.0141 *

<table>
<tr><td></td><td></td><td></td><td>CV17 0.10320 0.24128 0.428 0.6698
CV18 -0.13641 0.40497 -0.337 0.7369
CV19 0.12596 0.40497 0.311 0.7564
CV20 -0.64723 0.40497 -1.598 0.1131

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.4188 on 102 degrees of freedom
Multiple R-squared: 0.2522, Adjusted R-squared: 0.1055
F-statistic: 1.72 on 20 and 102 DF, p-value: 0.04175</td></tr>
<tr><td>GAM Striga density v rice variety</td><td>GAM 8</td><td>gam2 <- gam(log(AvDen + 1) ~ CV -1 + s(Lat, Lon), data = AD_1, subset = which(R_M_O == "Rice"))
anova(gam2)</td><td>Family: gaussian
Link function: identity

Parametric Terms:
df F p-value
CV 21 11.14 <2e-16

Approximate significance of smooth terms:
edf Ref.df F p-value
s(Lat,Lon) 2 2 0.934 0.396</td></tr>
<tr><td>Linear model Striga density v density of nearest neighboring field</td><td>LM9</td><td>AD_1$nCat <- as.factor(round(AD_1$N_dens))

nsummary <- AD_1 %>% group_by(nCat) %>%
summarise(avDens = mean(AvDen), se = stderr(AvDen))

lm3 <- lm(log(AvDen + 1) ~ N_dens, data = AD_1)
anova(lm3)</td><td>Analysis of Variance Table

Response: log(AvDen + 1)
Df Sum Sq Mean Sq F value Pr(>F)
N_dens 1 1.679 1.67911 9.0152 0.002958 **
Residuals 242 45.073 0.18625

Call:
lm(formula = log(AvDen + 1) ~ N_dens, data = AD_1)

Residuals:
Min 1Q Median 3Q Max
-0.75064 -0.34077 -0.01308 0.25523 1.10064

Coefficients:
Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.44773 0.04573 9.792 < 2e-16 ***
N_dens 0.11725 0.03905 3.003 0.00296 **

Residual standard error: 0.4316 on 242 degrees of freedom
Multiple R-squared: 0.03592, Adjusted R-squared: 0.03193
F-statistic: 9.015 on 1 and 242 DF, p-value: 0.002958</td></tr>
<tr><td>GAM Striga density v density of nearest neighboring field</td><td>GAM 9</td><td>gam3 <- gam(log(AvDen + 1) ~ N_dens + s(Lat, Lon), data = AD_1)
anova(gam3)</td><td>Family: gaussian
Link function: identity

Parametric Terms:
df F p-value
N_dens 1 10.91 0.0011

Approximate significance of smooth terms:
edf Ref.df F p-value
s(Lat,Lon) 4.608 6.045 1.311 0.253</td></tr>
<tr><td>Linear model Striga density v pH and NO3</td><td>Lm10</td><td>nutrData$FN <- as.factor(nutrData$FN)
model <- lmer(Den ~ pH + NO3 + (1|FN), data = nutrData)
summary(model)</td><td>Linear mixed model fit by REML. t-tests use Satterthwaite's method ['lmerModLmerTest']
Formula: Den ~ pH + NO3 + (1 | FN)
Data: nutrData

REML criterion at convergence: 389.7

Scaled residuals:
Min 1Q Median 3Q Max
-1.4520 -0.7703 -0.1183 0.7171 1.8717

Random effects:
Groups Name Variance Std.Dev.
FN (Intercept) 0.3169 0.5629
Residual 2.1968 1.4822
Number of obs: 102, groups: FN, 55

Fixed effects:
Estimate Std. Error df t value Pr(>|t|)
(Intercept) 0.944720 1.943948 90.538263 0.486 0.628
pH 0.277479 0.386763 92.589360 0.717 0.475
NO3 -0.007826 0.007011 89.327229 -1.116 0.267</td></tr>
</table>

<table>
<tr><td></td><td></td><td></td><td>Correlation of Fixed Effects:
(Intr) pH
pH -0.983
NO3 0.094 -0.258</td></tr>
<tr><td>GAM Striga density v pH and NO3</td><td>GAM 10</td><td>model2 <- gam(Den + 1 ~ pH + NO3 + s(latitude, longitude) + s(FN, bs = "re"), family = "ocat(R = 6)", data = nutrData)
anova(model2)</td><td>Family: Ordered Categorical(-1,0.08,0.76,1.89,3.53)
Link function: identity

Formula:
Den + 1 ~ pH + NO3 + s(latitude, longitude) + s(FN, bs = "re")

Parametric Terms:
df Chi.sq p-value
pH 1 0.754 0.385
NO3 1 0.479 0.489

Approximate significance of smooth terms:
edf Ref.df Chi.sq p-value
s(latitude,longitude) 5.290 6.769 7.519 0.337
s(FN) 7.050 54.000 8.568 0.110</td></tr>
<tr><td>Linear model Striga density v companion crop</td><td>Lm11</td><td>options(contrasts = c("contr.sum","contr.poly"))
lm11 <- lm(log(AvDen + 1) ~ CC, data = AD_1)
anova(lm11)
summary(lm11)</td><td>Analysis of Variance Table

Response: log(AvDen + 1)
Df Sum Sq Mean Sq F value Pr(>F)
CC 18 2.0619 0.11455 0.6131 0.8829
Residuals 111 20.7395 0.18684</td></tr>
<tr><td>GAM Striga density v companion crop</td><td></td><td>options(contrasts = c("contr.sum","contr.poly"))
gam11 <- gam(log(AvDen + 1) ~ CC - 1 + s(Lat, Lon), data = AD_1)
anova(gam11)
summary(gam11)</td><td>Family: gaussian
Link function: identity

Formula:
log(AvDen + 1) ~ CC - 1 + s(Lat, Lon)

Parametric Terms:
df F p-value
CC 19 11.61 <2e-16

Approximate significance of smooth terms:
edf Ref.df F p-value
s(Lat,Lon) 4.071 5.331 0.88 0.493
> summary(gam11)

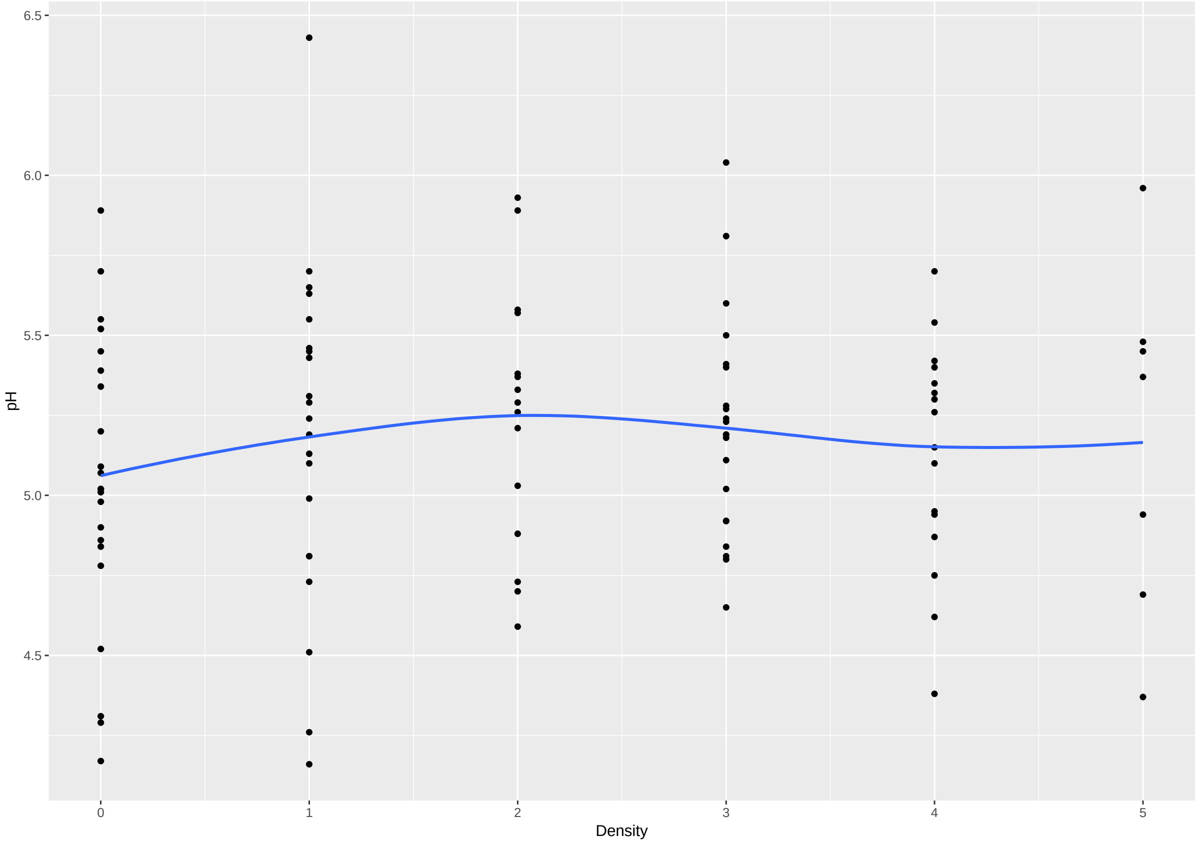
Family: gaussian
Link function: identity

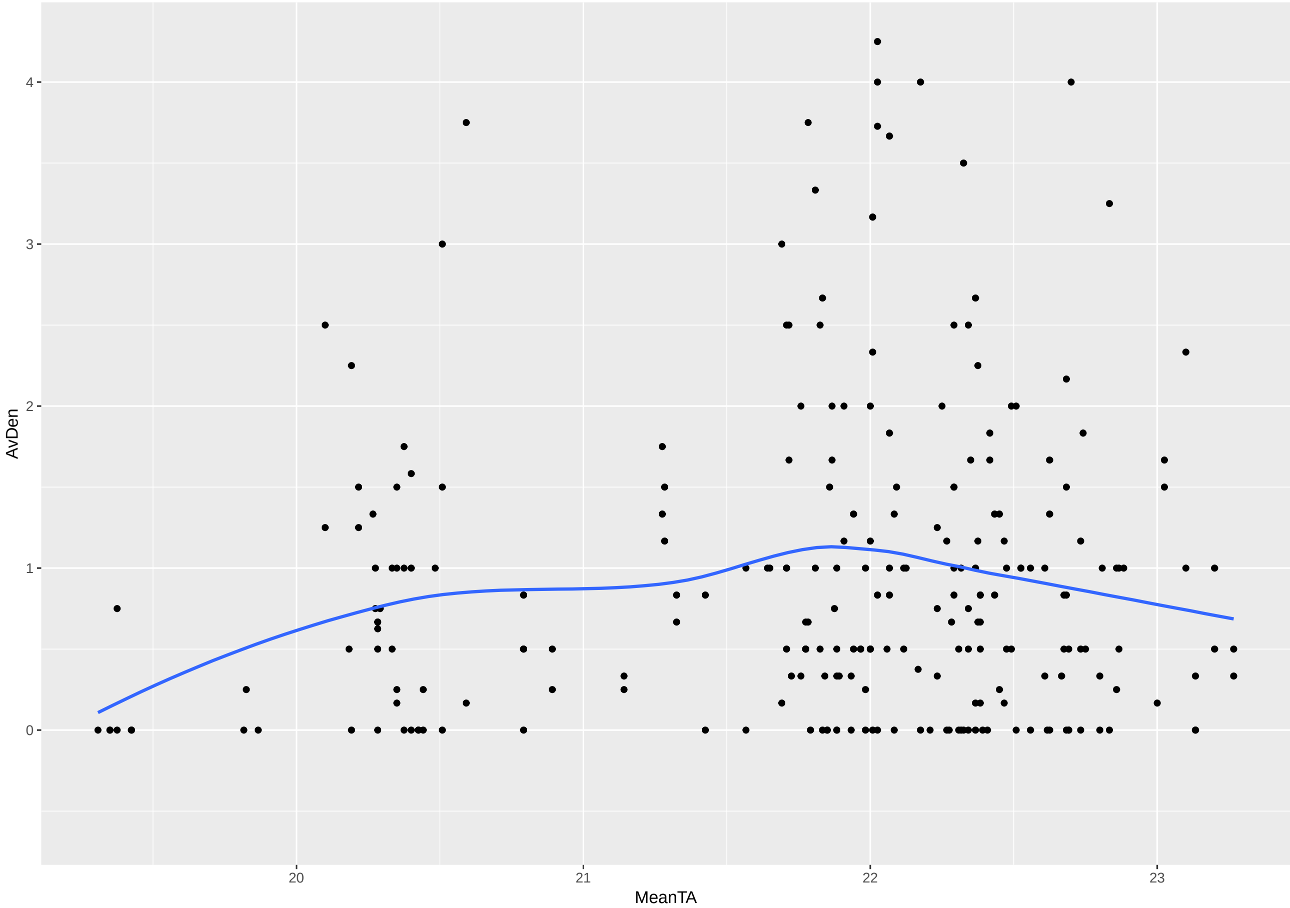
Formula:
log(AvDen + 1) ~ CC - 1 + s(Lat, Lon)

Parametric coefficients:
Estimate Std. Error t value Pr(>|t|)
CCBalahazo 0.54030 0.11161 4.841 4.37e-06
CCBalahazo, mimosa 0.85393 0.43824 1.949 0.053974
CCBalahazo, soya 0.39466 0.30604 1.290 0.199990
CCBalahazo, voanjobory 1.23788 0.43203 2.865 0.005017
CCBalahazo, voanjolava 0.66420 0.19364 3.430 0.000859
CCMaize 0.51256 0.05292 9.686 2.64e-16
CCMaize, balahazo 0.47971 0.30405 1.578 0.117581
CCMimosa 0.54219 0.14264 3.801 0.000240
CCNiebe 0.04795 0.42896 0.112 0.911211
CCSoya 0.48501 0.16442 2.950 0.003906
CCSoya, voanjobory, balahazo -0.04726 0.43993 -0.107 0.914659
CCStylosanthes 0.65162 0.30707 2.122 0.036140
CCTsaramaso 1.41963 0.43421 3.269 0.001450
CCTsy asisa 0.80957 0.43116 1.878 0.063153
CCVoanjobory 0.51947 0.17553 2.959 0.003795</td></tr>
</table>

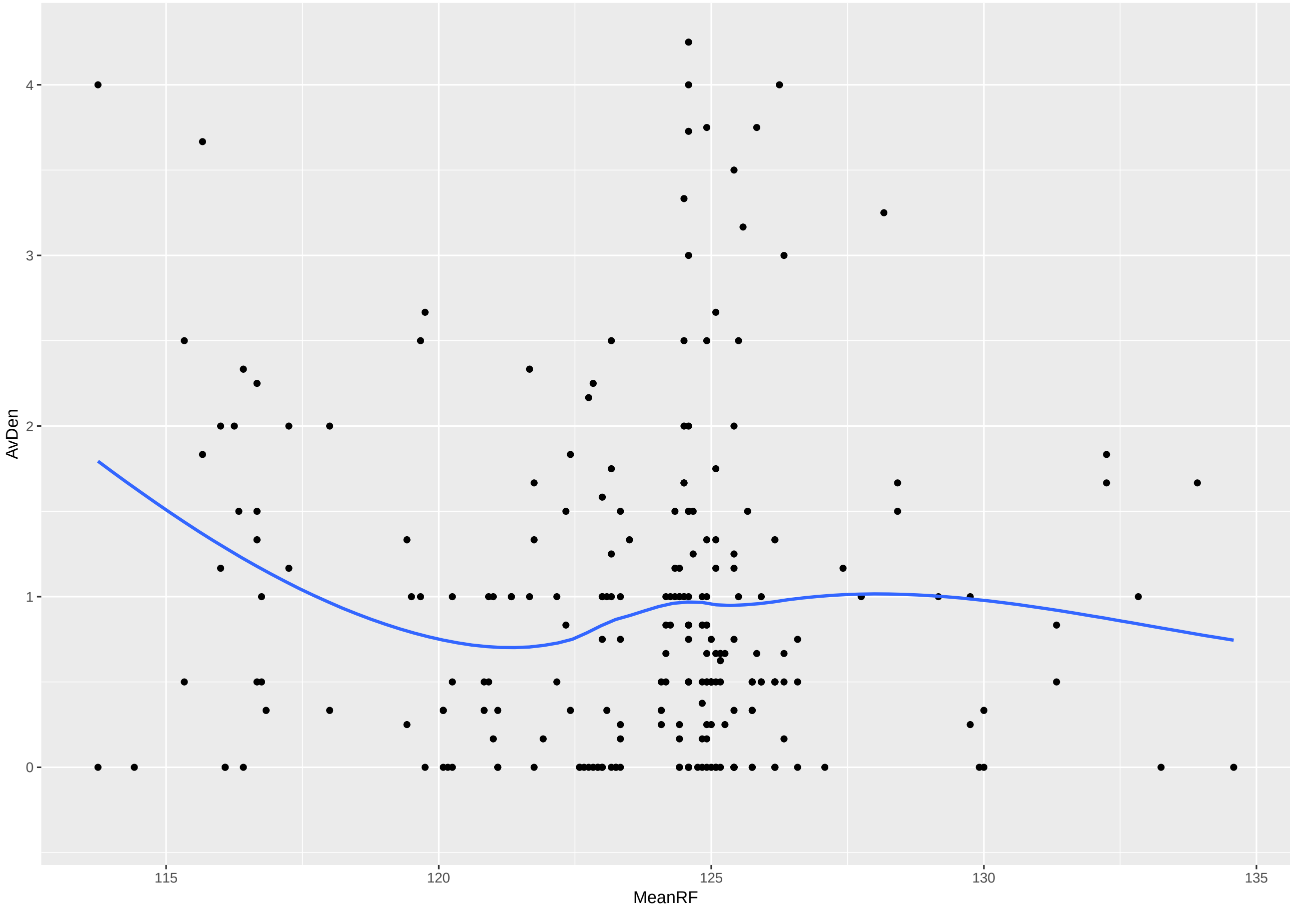
			CCVoanjolava 0.57283 0.20209 2.834 0.005489 CCVoanjolava, balahazo 0.50922 0.43426 1.173 0.243563 CCVoanzobory 0.53340 0.42897 1.243 0.216417 CCVoatavo, voanjobory 0.78297 0.30956 2.529 0.012887 CCBalahazo *** CCBalahazo, mimosa . CCBalahazo, soya CCBalahazo, voanjobory ** CCBalahazo, voanjolava *** CCMaize *** CCMaize, balahazo CCMimosa *** CCNiebe CCSoya ** CCSoya, voanjobory, balahazo CCStylosanthes * CCTsaramaso ** CCTsy asisa . CCVoanjobory ** CCVoanjolava ** CCVoanjolava, balahazo CCVoanzobory CCVoatavo, voanjobory * --- Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 Approximate significance of smooth terms: edf Ref.df F p-value s(Lat,Lon) 4.071 5.331 0.88 0.493 R-sq.(adj) = -0.0257 Deviance explained = 68% GCV = 0.22042 Scale est. = 0.1813 n = 130
Pearson's chi-squared test for independence for Main crop v companion crop	$X^2 1$	chisq.test(AD_1R_M_O,AD_1CC)	Pearson's Chi-squared test data: AD_1$R_M_O and AD_1$CC X-squared = 137.08, df = 19, p-value < 2.2e-16
Pearson's chi-squared test for independence for Main crop v previous crop	$X^2 2$	chisq.test(AD_1R_M_O,AD_1PC)	Pearson's Chi-squared test data: AD_1$R_M_O and AD_1$PC X-squared = 34.394, df = 18, p-value = 0.01126
Cramer's V test to test for the strength of any observed associations from X^2 1test.	C1	CramerV(AD_1R_M_O,AD_1PC)	0.7770854
Cramer's V test to test for the strength of any observed associations from X^2 2test.	C2	CramerV(AD_1R_M_O,AD_1CC)	0.4433248

Appendix 2: Scatterplots for models

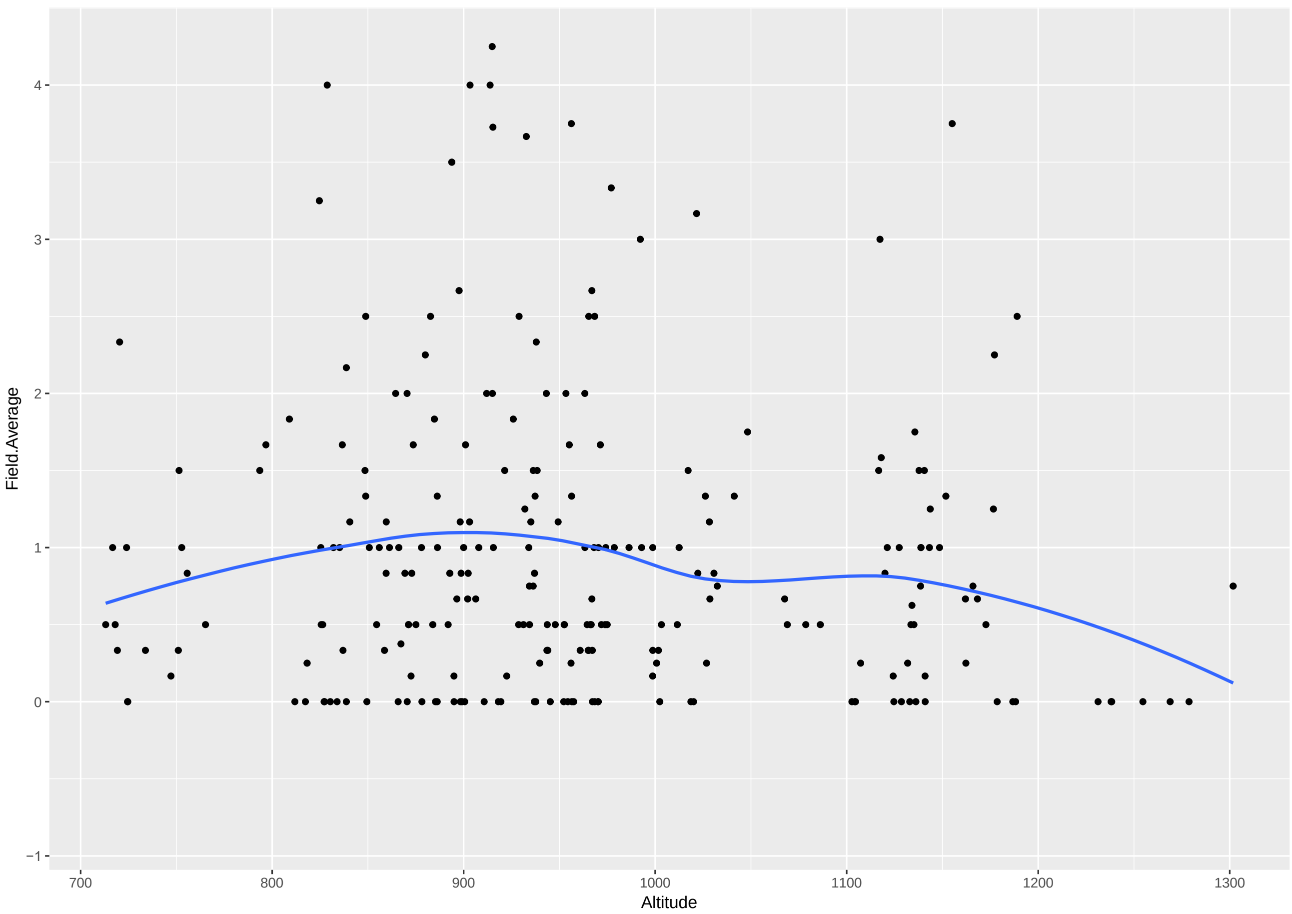




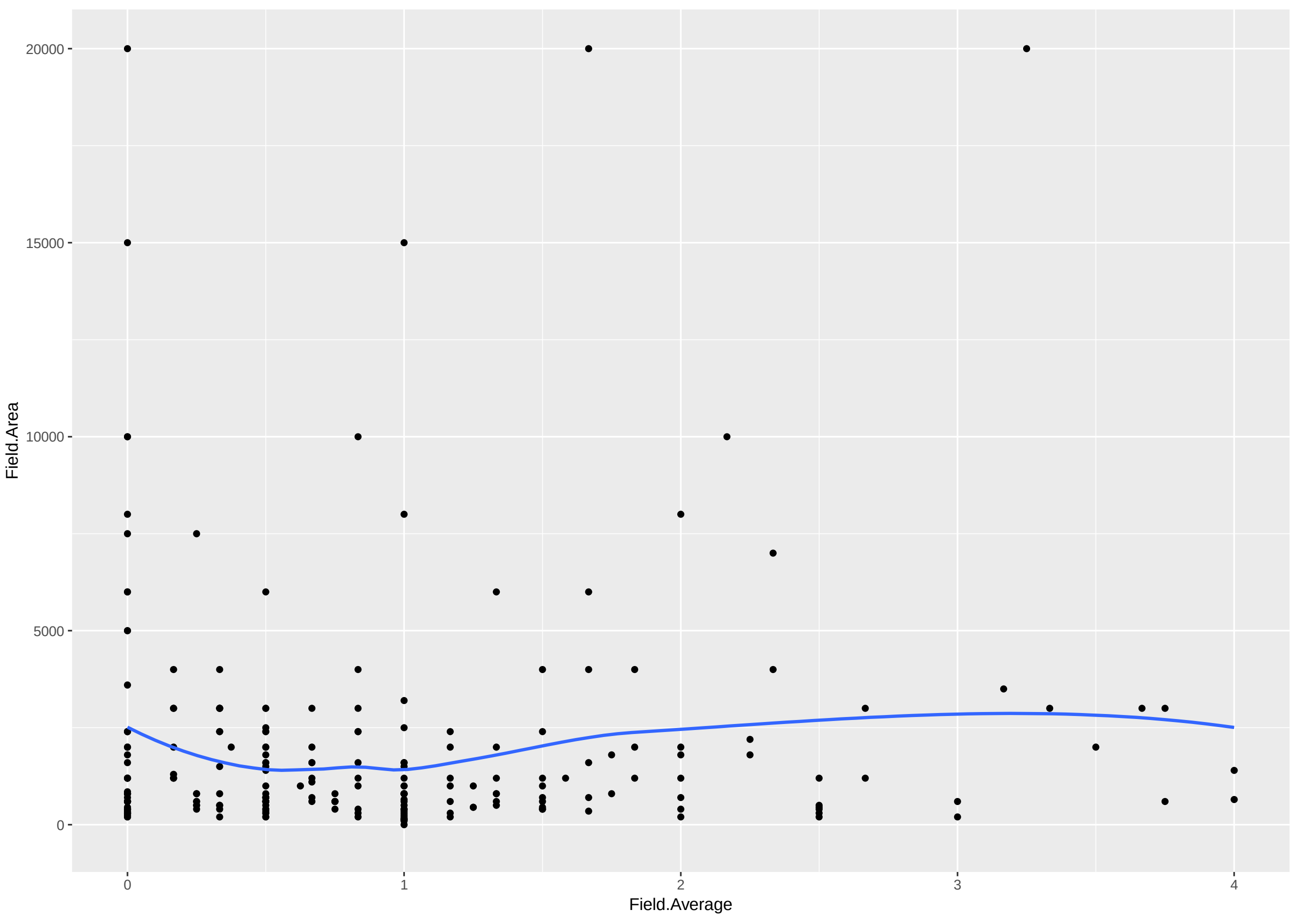
AvDen
4
3
2
1
0
20
21
22
23
MeanTA



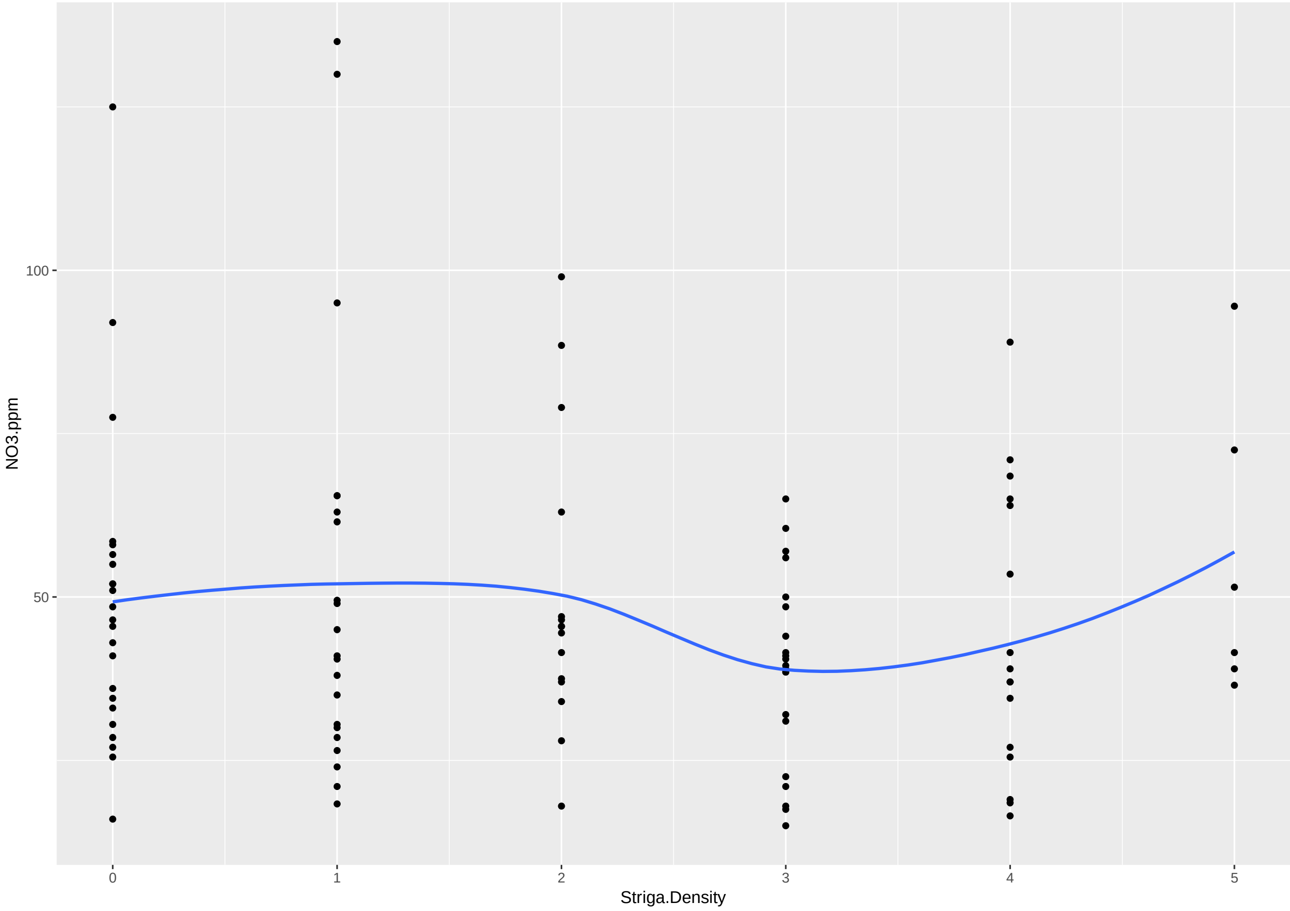
AvDen
4
3
2
1
0
115
120
125
130
135
MeanRF

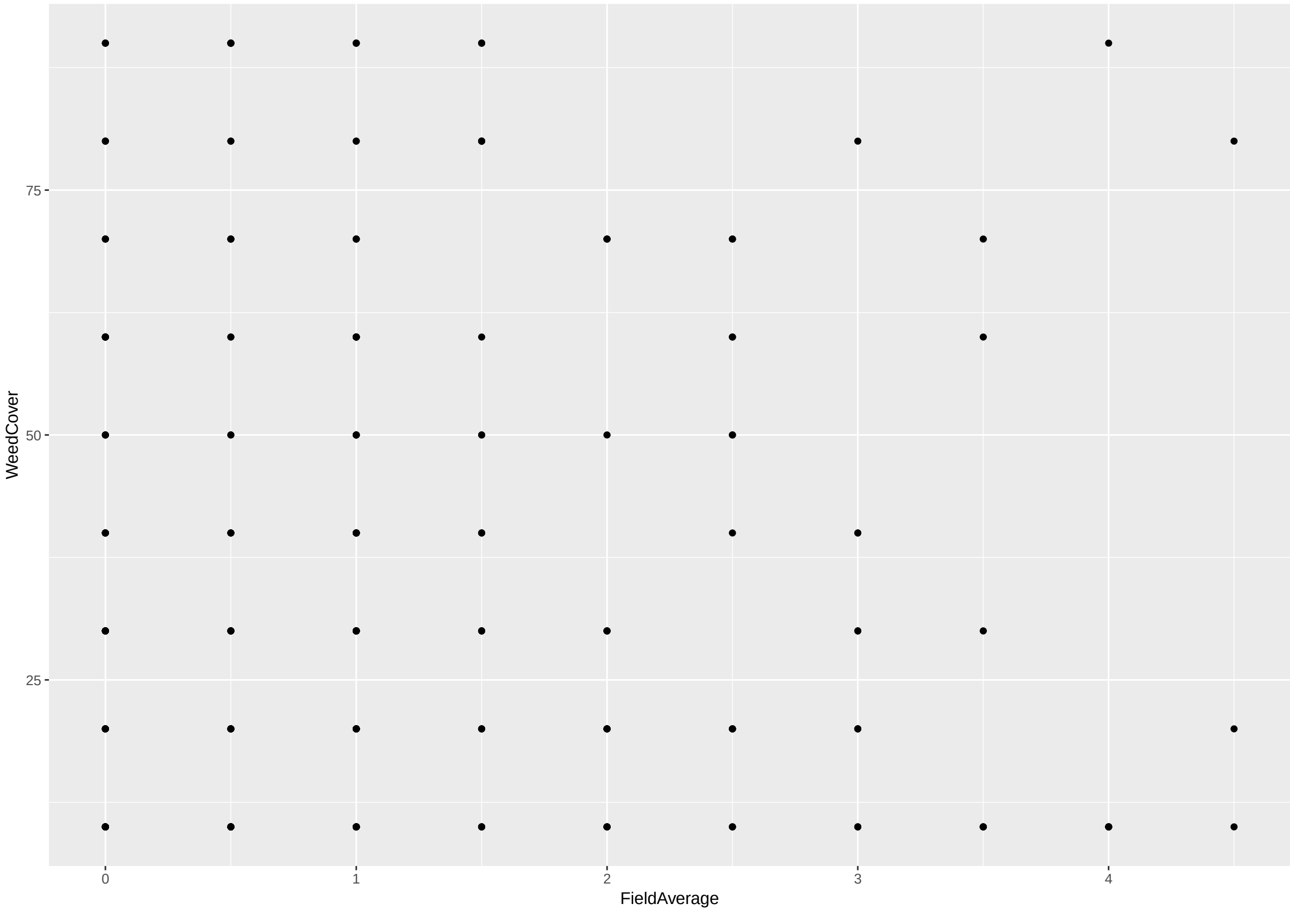


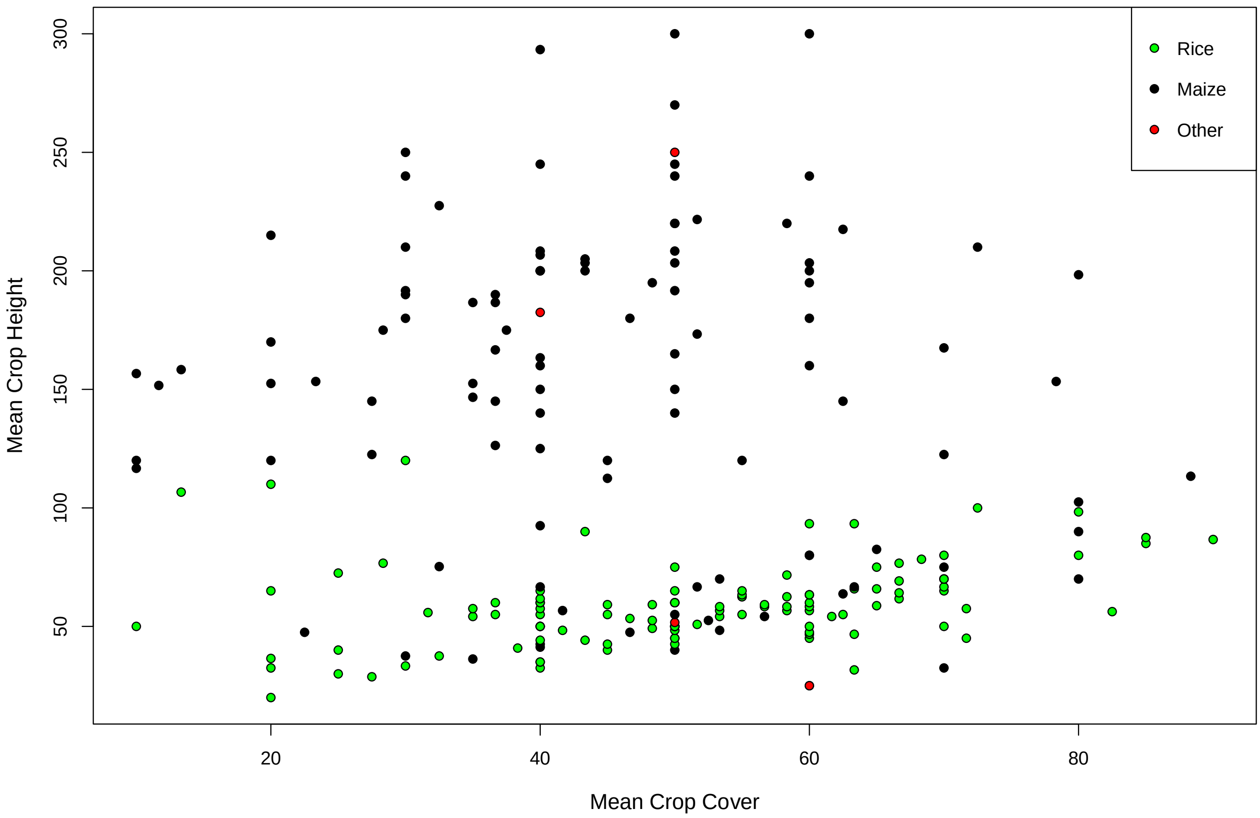
Field.Average
Altitude

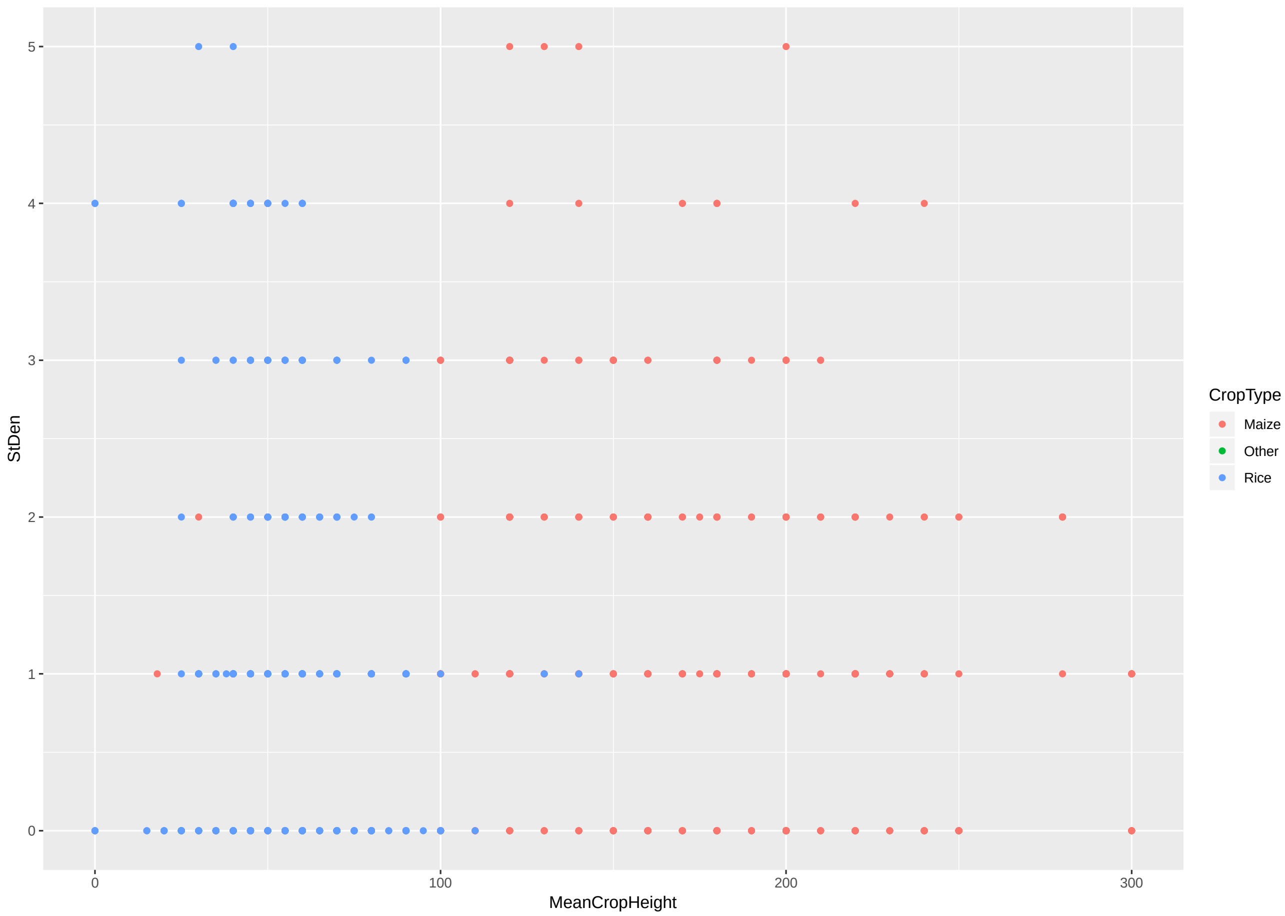


Field.Area
Field.Average


NO3.ppm
100
50
0
1
2
3
4
5
Striga.Density


WeedCover
75
50
25
0
1
2
3
4
FieldAverage


Rice
Maize
Other
Mean Crop Height
Mean Crop Cover
300
250
200
150
100
50
20
40
60
80



Appendix 3: Soil sample (pH and NO3) pairs collected within fields containing differing Striga densities.

***Striga* density Pair**	**Count**
1:0	5
1:2	3
1:3	11
1:4	2
1:5	0
2:0	3
2:3	3
2:4	4
2:5	2
3:0	3
3:4	3

3:5	1
4:0	3
4:5	4
5:0	0
Zero density (single samples)	10
Total	**104**

Chapter 3 Appendices

Appendix 1: Striga Density state guides

Density	Description
0 (Absent)	No *Striga* present either within quadrat or within field (dependent on scale of determination). In case of field scale, extensive search undertaken across entire field to determine absence.
1 (Very Low)	Between one and ten percent of host crop plants infected recorded across the quadrat.
2 (Low)	Between 11 and 25 percent of host crop infected across the quadrat. Crop symptoms unlikely to be easily visible / or attributable to *Striga.*
3 (Moderate)	Between 26 and 50 percent of host crop plants infected across the quadrat. Localised visible stunting, chlorosis, wilting and poor yield most likely attributable to *Striga* damage.
4 (High)	Between 51 and 75 percent of host crop infected across the quadrat. Widespread visible stunting, chlorosis, wilting and visibly poor yield across majority of host crop, directly attributable to *Striga.*
5 (Very High)	Between 76 and 100 percent of host crop plants infected across the quadrat. Stunting, chlorosis and wilting resulting in almost or complete crop failure.

Appendix 1a: Descriptions of Striga asiatica density states from absent to very high Striga infestation.

Appendix 1 b: Indicative photographs for rice field in each estimated state from absent (top left) to very high Striga infestation (bottom right).

Appendix 2: Model details, outputs and R scripts

Model	#	Code	Result

Log Striga density V Year * NO3	LM1	library(mgcv)
		library(lme4)
		library(lmerTest)
		library(ggplot2)
		library(dplyr)
		library(geosphere)
		library(stringr)
		
		#Calculate a standard error
		stderr <- function(x, ...) sd(x, na.rm = TRUE) / sqrt(length(is.na(x == FALSE)))
		
		# Have cleaned the cultivar variable
		fulldata <-
		read.csv("/Users/Ragenaky/Desktop/Striga Madagascar 2020/Completed Sheets/Ecology Data Updated/MASTER_2019_2020_NANC.csv", h = T)
		
		fulldata$YR <- as.factor(fulldata$YR)
		fulldata$FN <- as.factor(fulldata$FN)
		
		# Load NO3 data
		
		NO3 <-
		read.csv("/Users/Ragenaky/Desktop/Striga Madagascar 2020/Completed
			Analysis of Variance Table
			
			Response: log(AvDen + 1)
			Df Sum Sq Mean Sq F value Pr(>F)
			YR 1 0.0690 0.069027 0.2934 0.5898
			NO3 1 0.0236 0.023648 0.1005 0.7522
			YR:NO3 1 0.0450 0.044971 0.1911 0.6634
			Residuals 69 16.2356 0.235299
			> summary(model10)

		Sheets/Ecology Data
		Updated/NO3_2019_2020.csv", h = T)
		colnames(NO3)[1] <- "YR"
		NO3Summary <- NO3 %>%
		  group_by(YR, Field) %>%
		  summarise(NO3 = mean(NO3_ppm),
		avdenCHECK = mean(AvDen))
		NO3Summary <-
		data.frame(NO3Summary)
		
		NO3idx <- apply(fulldata, 1, function(x) {
		idx <- which(NO3Summary$YR == x[1]
		& NO3Summary$Field == x[2])
		ret <- NA
		if(length(idx) >0) ret
		<- NO3Summary[idx,3]
		ret})
		fulldata$NO3 <- NO3idx
		
		# NO3
		model1 <- lm(log(AvDen + 1) ~ YR *
		NO3, data = fulldata)
		anova(model1)	

Log Striga density V Year * Mean other weed cover	LM2	AD_1<-read.csv("MWC_AVDEN.CSV") # Striga Density v Mean other Weed Cover for both years . Lm2 <- lm(AvDen ~ Mean_WC*Year, data = AD_1,) anova(lm2) summary(lm2)	Analysis of Variance Table Response: AvDen Df Sum Sq Mean Sq F value Pr(>F) Year 1 4.452 4.4522 5.6855 0.01766 * Mean_WC 1 1.145 1.1450 1.4622 0.22742 Year:Mean_WC 1 0.080 0.0798 0.1019 0.74976 Residuals 337 263.896 0.7831 --- Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
Log Striga density V Year * Rice Variety	LM3	riceData <- fulldata[which(fulldata$R_M_O == "Rice"),] model3 <- lm(log(AvDen + 1) ~ YR * CVclean , data = riceData) anova(model3)	Analysis of Variance Table Response: log(AvDen + 1) Df Sum Sq Mean Sq F value Pr(>F) YR 1 0.0989 0.09886 0.5655 0.453129 CVclean 27 9.5141 0.35237 2.0157 0.004041 ** YR:CVclean 9 2.9965 0.33294 1.9045 0.054556 . Residuals 164 28.6697 0.17482 --- Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
Log Striga density V Year * Previous crop	LM4	Model4 <- lm(log(AvDen + 1) ~ YR * PC, data = fulldata) anova(model4)	Analysis of Variance Table Response: log(AvDen + 1) Df Sum Sq Mean Sq F value Pr(>F) YR 1 0.595 0.59460 3.2503 0.07268 . PC 23 4.314 0.18757 1.0253 0.43411 YR:PC 6 2.425 0.40415 2.2092 0.04293 * Residuals 238 43.540 0.18294 --- Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1 --- R-sq.(adj) = 0.123 Deviance explained = 19.5% GCV = 263.8 Scale est. = 241.21 n = 225 >
Log Striga density V Year * Previous crop Legume	LM5	Model5 <- lm(log(AvDen + 1) ~ YR * PCL, data = fulldata) anova(model5)	Analysis of Variance Table Response: log(AvDen + 1) Df Sum Sq Mean Sq F value Pr(>F) YR 1 0.809 0.80850 4.3286 0.03828 * PCL 1 1.194 1.19366 6.3907 0.01196 * YR:PCL 1 0.004 0.00389 0.0209 0.88528 Residuals 316 59.023 0.18678 --- Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
Log Striga density V Year * intercrop	LM6	Model6 <- lm(log(AvDen + 1) ~ YR * CC, data = fulldata) anova(model6)	Analysis of Variance Table Response: log(AvDen + 1)

			Df Sum Sq Mean Sq F value Pr(>F) YR 1 2.026 2.02550 11.5209 0.0008233 *** CC 25 4.950 0.19801 1.1262 0.3153817 YR:CC 6 0.507 0.08446 0.4804 0.8225375 Residuals 209 36.744 0.17581 --- Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Log Striga density V Year * Neighboring Striga density	LM7	# Functions to find neighbour densities
		
		findNN <- function(p, pts) {
		  dists <- distm(p, pts, fun = distHaversine)
		  idxN1 <- which(dists == min(dists))
		  idxN2 <- which(dists == min(dists[-idxN1]))
		  idxN3 <- which(dists == min(dists[-c(idxN1, idxN2)]))
		  return(c(idxN2, idxN3))
		}
		
		NNdens <- function(pts, dens) {
		  idxs <- t(apply(pts, 1, function(x) findNN(x, pts)))
		  Ns <- apply(idxs,1, function(idx) mean(dens[idx]))
		  return(Ns)
		}
		
		# Run
		data2019 <- fulldata[which(fulldata$YR == 2019),]
		data2020 <- fulldata[which(fulldata$YR == 2020),]
		
		ptest <- c(data2019$Lon[1], data2019$Lat[1])
		ptstest <- cbind(data2019$Lon , data2019$Lat)
		Neigh2019 <- unlist(NNdens(ptstest, data2019$AvDen))
		
		ptest <- c(data2020$Lon[1], data2020$Lat[1])
		ptstest <- cbind(data2020$Lon , data2020$Lat)
		Neigh2020 <- unlist(NNdens(ptstest, data2020$AvDen))
		
		fulldata$Neigh <- c(Neigh2019, Neigh2020) model7 <- lm(log(AvDen + 1) ~ YR * Neigh, data = fulldata)
		anova(model7)
			Analysis of Variance Table
			
			Response: log(AvDen + 1)
			Df Sum Sq Mean Sq F value Pr(>F)
			YR 1 0.582 0.58238 3.0426 0.08202 .
			Neigh 1 1.115 1.11534 5.8270 0.01631 *
			YR:Neigh 1 1.211 1.21054 6.3244 0.01237 *
			Residuals 338 64.697 0.19141
			--- 	
			Signif. codes:
			0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

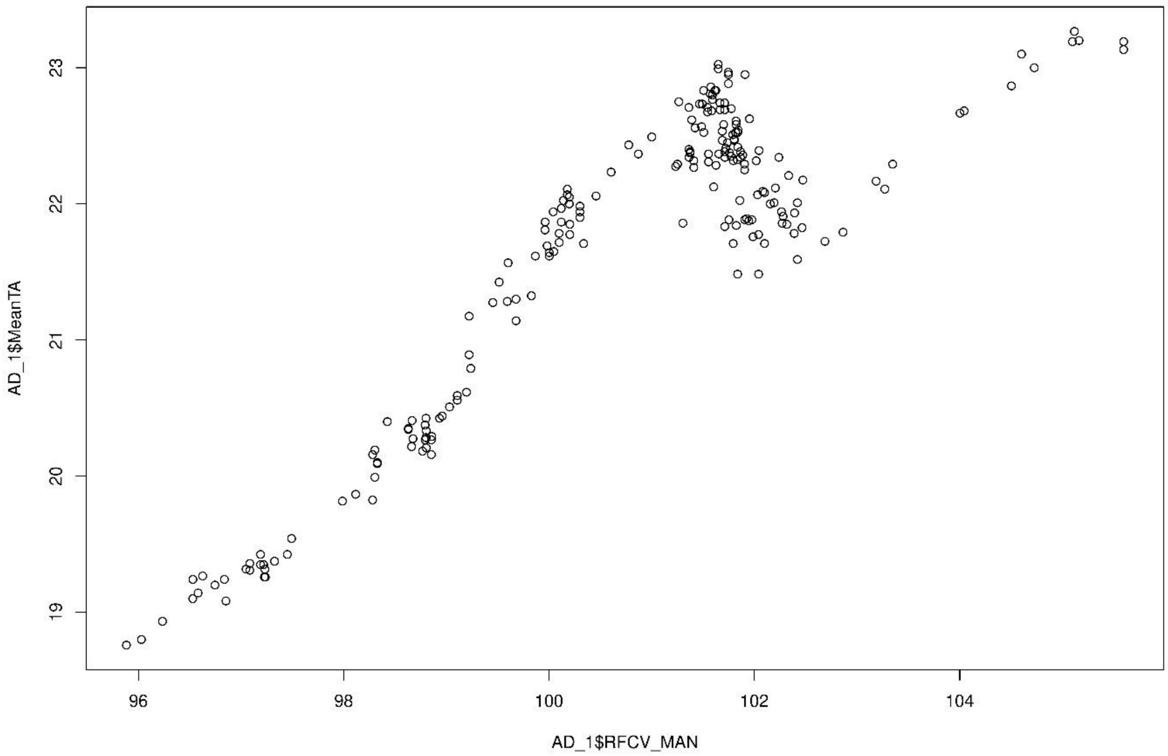
Log Striga density V Year * Mean annual rainfall	LM8	Model8 <- lm(log(AvDen + 1) ~ YR * MeanRF, data = fulldata) anova(model8)	Analysis of Variance Table Response: log(AvDen + 1) Df Sum Sq Mean Sq F value Pr(>F) YR 1 1.159 1.15903 5.9334 0.015281 * MeanRF 1 0.360 0.36001 1.8430 0.175344 YR:MeanRF 1 2.793 2.79326 14.2994 0.000179 *** Residuals 411 80.285 0.19534 --- Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Log Striga density V Year * Precipitation seasonality	LM9	Model9 <- lm(log(AvDen + 1) ~ YR * RFCV_MAN, data = fulldata) anova(model9)	Analysis of Variance Table Response: log(AvDen + 1) Df Sum Sq Mean Sq F value Pr(>F) YR 1 1.159 1.15903 5.8746 0.015791 * RFCV_MAN 1 1.732 1.73222 8.7799 0.003223 ** YR:RFCV_MAN 1 0.618 0.61849 3.1349 0.077375 . Residuals 411 81.088 0.19729 --- Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

			>
Log Striga density V Year * Altitude	LM9	Model10 <- lm(log(AvDen + 1) ~ YR * Alt, data = fulldata) anova(model10)	Analysis of Variance Table Response: log(AvDen + 1) Df Sum Sq Mean Sq F value Pr(>F) YR 1 1.103 1.10319 5.5557 0.018891 * Alt 1 1.827 1.82653 9.1985 0.002576 ** YR:Alt 1 0.100 0.10029 0.5051 0.477691 Residuals 409 81.215 0.19857 --- Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Log Striga density V Year * Mean annual temperature	LM11	Model11 <- lm(log(AvDen + 1) ~ YR * MeanTA, data = fulldata) anova(model1)	Analysis of Variance Table Response: log(AvDen + 1) Df Sum Sq Mean Sq F value Pr(>F) YR 1 1.159 1.15903 5.8923 0.0156356 * MeanTA 1 2.481 2.48108 12.6135 0.0004273 *** YR:MeanTA 1 0.113 0.11345 0.5768 0.4480112 Residuals 411 80.844 0.19670 --- Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Log Striga density V Year * Legume Crop	lm12	LC_1<-
		read.csv("LEGUME_CROP_2019_2020_SINGLE_RECS_REMOVED.CSV")
		
		# (2) Look at effects of different legume crops
		
		# Set contrasts so that we can test against the grand mean.
		options(contrasts = c("contr.sum","contr.poly"))
		lm1 <- lm(log(AvDen + 1) ~ YR * LC, data = LC_1)
		anova(lm12)
		summary(lm12)
			Analysis of Variance Table
			
			Response: log(AvDen + 1)
			Df Sum Sq Mean Sq F value Pr(>F)
			YR 1 1.4086 1.40863 8.6945 0.003772 **
			LC 6 1.7735 0.29558 1.8244 0.098934 .
			YR:LC 3 1.1541 0.38469 2.3744 0.073025 .
			Residuals 133 21.5479 0.16201
			--- 	
			Signif. codes:
			0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Linear model to obtain weighting coefficients for individual management components	Lm13	AD_1<- read.csv("CD_1_With_Score.CSV") # Density change v Total Score (Fallow, Cereal years, legume years,Numer of crops). lm13 <- lm(Change ~ FL_YR + CR_YR + LM_YR + NC, data = AD_1,) anova(lm1)	Analysis of Variance Table Response: Change Df Sum Sq Mean Sq F value Pr(>F) FL_YR 1 0.153 0.1528 0.1196 0.73048 CR_YR 1 0.055 0.0553 0.0433 0.83572 LM_YR 1 8.416 8.4164 6.5880 0.01232 * NC 1 2.498 2.4983 1.9555 0.16623 Residuals 73 93.261 1.2775
Change in average Striga density (2019-2020) v Management score		AD_1<- read.csv("CD_1_With_Score_Using_Coefficients.CSV") # Average Density 2020 v Total Score (Fallow, Cereal years, legume years,Numer of crops). lm1 <- lm(Change ~ Total, data = AD_1,) anova(lm1)	Analysis of Variance Table Response: Change Df Sum Sq Mean Sq F value Pr(>F) Total 1 11.123 11.1228 9.0642 0.003537 ** Residuals 76 93.261 1.2271 --- Signif. code

Appendix 2: Climate Autocorrelation plot



Appendix 4: Legume Fixation Table

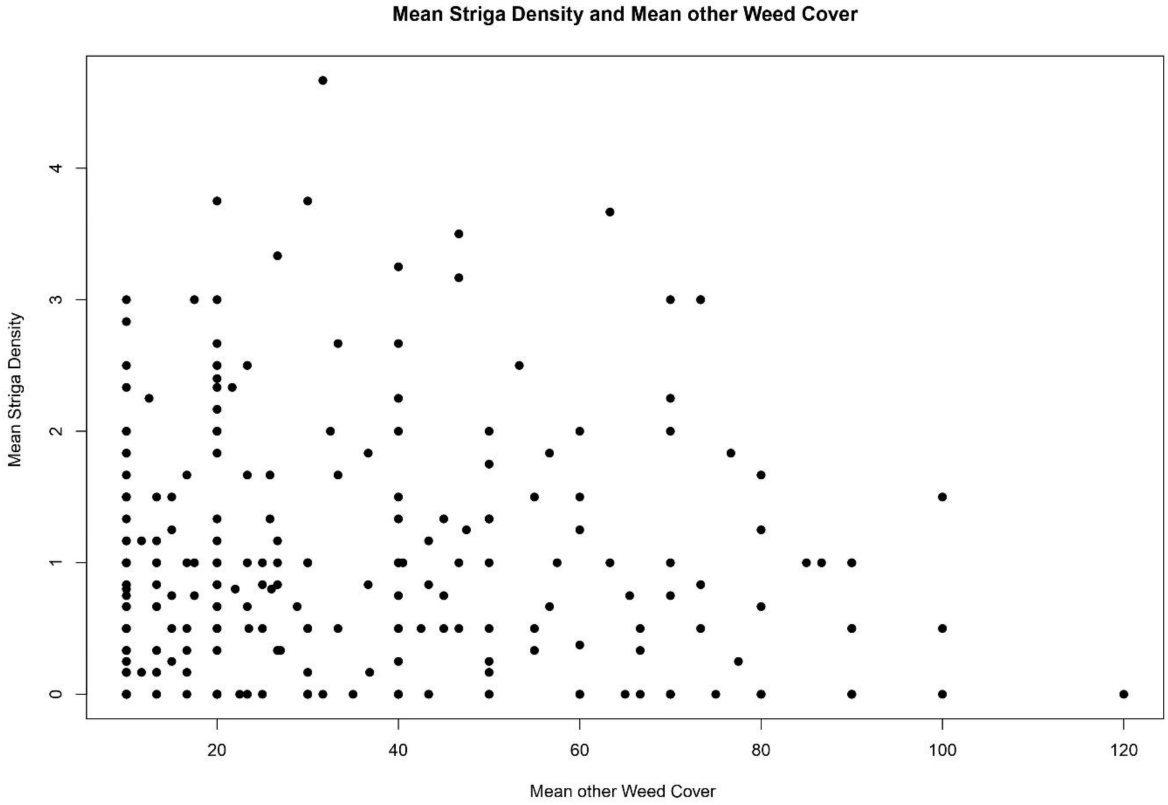
Crop	Mean N Fixation / kg ha^{-1}
Arachis hypogaea[1]	48
Glycine max[a]	193
Mucuna puriens[2]	60
Phaseolus vulgaris[a]	30
Mimosa diplotricha	
Vigna subterranea[3]	63
Vigna umbellata[4]	67

Table …: Mean Nitrogen fixation (kg / ha^{-1}) for legume crops recorded in study area.

All values pertain to studies conducted in Africa except *V umbellata*; conducted in rainfed conditions in northern Thailand. Though no values are available for *M diplotricha*; its use as an N-enriching green manure species is widely documented (e.g.: Yogaratnam *et al* 1984, Tomas & George 1990).

[1] Peoples et al 2009
[2] Houngnandan et al 2000
[3] Bernard et al 2018, Nyemba & Dakora 2010, Pule-Meulenberg & Dakora 2009
[4] Rerkasem and Rerkasem, 1988; Rerkasem et al., 1988

Appendix 5 Mean other Weed Density v Mean Striga



Chapter 4 Appendices

Appendix 1A: Pilot Search Returns Table for Web of Science (Top)&

Appendix 1B: Taxa list for parasitic weeds of economic importance (with notes on biological characteristics, Below)

Term 1	Term 2	Term 3	Term 4	Term 5	Term 6	Term 7	# Refs gross	# Refs net	Notes
Orobanche	AND	Cover	AND	Crop			38	37	
Orobanche	AND	Intercrop					20	18	
Orobanche	AND	Inter*					737	461	Too broad. Only first 500 exported
Orobanche	AND	Trap*					66	47	
Orobanche	AND	Push	AND	Pull			2	1	
Orobanche	AND	Companion					3	1	
Orobanche	AND	Conservation	AND	Agriculture			10	7	
Orobanche	AND	Integrated	AND	Weed	AND	Management	1	1	
Orobanche	AND	Cultural	AND	Control			103	61	Perhaps too broad. Needs triage
Orobanche	AND	Suicid*					40	4	Too focused on biochemical study rather than actual intercrops.
Orobanche	AND	Legum*					644	240	Again could be too broad. Needs triage
Orobanche	AND	Legume					256		
Orobanche	AND	no	AND	till			3	2	
Orobanche	AND	zero	AND	till			1	0	
Striga	AND	Cover	AND	Crop			69	52	
Striga	AND	Intercrop					129	103	
Striga	AND	Inter*					921	195	Too broad. Only first 500 exported
Striga	AND	Trap*					109	27	
Striga	AND	Push	AND	Pull			52	17	
Striga	AND	Companion					16	6	
Striga	AND	Conservation	AND	Agriculture			33	16	
Striga	AND	Integrated	AND	Weed	AND	Management	154	87	
Striga	AND	Cultural	AND	Control			165	52	
Striga	AND	Suicid*					74	48	Too focused on biochemical study rather than actual intercrops.
Striga	AND	Legum*					572	282	Again could be too broad. Needs triage

Striga	AND	Legume					275			
Striga	AND	no	AND	till			2		0	
Striga	AND	zero	AND	till			1		0	
						Total Gross: 4496		**Total Net:** 1765		

Family	**Synonym**	**Genus**	**Synonym**	**Sub genus**	**Synonym**	**Species**	**Included**	**Notes**
Convolvulaceae	Cuscutaceae	Cuscuta		Monogynella		-	No	Robust vines which attack fruit trees. No information when searched.
Convolvulaceae		Cuscuta		Cuscuta		-	Yes	Favour herbaceous hosts. Holoparasites (photosynthetically inactive). Just genus included in search as over 200 species listed with taxonomic ambiguity.
Convolvulaceae		Cuscuta		Grammica		-	No	No evidence of economic significance
Lauraceae		Cassytha				-	No	Perennial / climbers affect woody plants
Orobanchaceae	Scrophulariaceae	Striga				S. asiatica	Yes	
Orobanchaceae		Striga				S.hermonthica	Yes	
Orobanchaceae		Striga				S. gesnerioides	Yes	
Orobanchaceae		Striga				S. hirsuta	Yes	Less likely to attack crops but still cited as a threat
Orobanchaceae		Striga				S. lutea	Yes	Less likely to attack crops but still cited as a threat
Orobanchaceae		Striga				S. forbesii	Yes	
Orobanchaceae		Striga				S. angustifolia	Yes	
Orobanchaceae		Striga				S. densiflora	Yes	
Orobanchaceae		Striga				S. aspera	Yes	
Orobanchaceae		Striga				S. curviflora	Yes	
Orobanchaceae		Striga				S. parviflora	Yes	
Orobanchaceae		Striga				S. latericea	Yes	
Orobanchaceae		Orobanche	Phelipanche			O. cernua	Yes	Over 70 species. Orobanche is a parasite of colder climates
Orobanchaceae		Orobanche				O. crenata	Yes	
Orobanchaceae		Orobanche			O. cernua var. cumana	O. cumana	Yes	
Orobanchaceae		Orobanche			Phelipanche ramosa	O. ramosa	Yes	
Orobanchaceae		Orobanche			Phelipanche aegyptiaca	O. aegyptiaca	Yes	

Orobanchaceae		Orobanche				O. foetida	Yes	
Orobanchaceae		Aeginetia				A. indica	Yes	Only in forests in India but found affecting limited cereal crops
Orobanchaceae		Aeginetia				A. flava	No	Endemic to Thailand in rainforest
Orobanchaceae		Alectra				Alectra vogelii	Yes	Less significant but still reported as damaging crops
Orobanchaceae		Christisonia				C. tomentosa	No	Only recently described
Orobanchaceae		Christisonia				C. tubulosa	No	Obscure rare plant only found in India
Orobanchaceae		Christisonia				C. scortechinii	Yes	Limited range in Malaysia and Thailand. Affects sugarcane in Philippines
Orobanchaceae		Christisonia				Christisonia spp	No	Several others but no evidence for economic significance
Loranthaceae							No	Perennial / Affect canopies of woody species
Viscaceae							No	Mistletoes found in canopy of trees

Appendix 1C: Meta-analysis full methodology

Pilot Study

A pilot study was undertaken using Web of Science and a combination of provisional terms to describe the use of companion crops, in conjunction with the genera: Striga and Orobanche (being among the most economically significant parasitic weed genera). Records returned for separate search term combinations were saved on EndNote Online (Clarivate Analytics 2021). Duplicate records were removed producing a net search term results total. The number of returns for each search combination, accompanied by an assessment of relevance based on the title of each study, gave an indication of the relevance of each search combination. This determined the final list of terms for inclusion; as some terms were too broad and returned too many unrelated results. Search combinations returning very high (e.g. >400) numbers of records with a very large proportion of non-relevant studies indicated that the term was too broad. These were subsequently omitted from the main search (e.g.: "Taxon" AND inter*, "Taxon" AND Legum*).

Choice of taxa for inclusion in the main search was determined by a number of criteria. Firstly, a review was undertaken to determine a definitive list of economically significant parasitic plants using several sources (Nickrent and Musselman 2004, Sauerborn et al 2007, Parker 2012). This list was then subject to triage, based on the nature of their parasitism, which determined inclusion in the main. For example, stem parasites such as mistletoes (Loranthaceae, Viscaceae) occur in the canopies of woody, perennial plants and will thus be unaffected by intercrops planted in the soil. Likewise, perennial, vine taxa affecting tree species such as the genus Cassytha were omitted for the same reason. Genera which returned no results for the 12 search combinations were removed from the main search. In the case of genera containing high numbers of economically-important species (e.g.: Cuscuta, Striga), genus was included as a search term alone without going to species level. Widely-adopted synonyms at the family and genus level were also included. Appendix 1 details search combinations used for pilot with gross and net results and list of taxa, synonyms and details of inclusion or omission from main search.

Main Search

Multiple electronic databases and the internet were searched using a range of Boolean search terms. The databases searched on the internet were: Web of Science, Scopus and AGRICOLA. Searches were performed in February 2021 on the complete range of references available at that time.

Search terms were constructed as follows: taxon name (Aeginetia, Alectra, Christisonia, Cuscuta, Grammica, Orobanche, Phelipanche, Scrophulariaceae, Striga) AND cover AND crop, taxon name AND Intercrop, taxon name AND trap*, taxon name AND push AND pull, taxon name AND companion, taxon name AND conservation AND agriculture *, taxon name AND integrated weed management, taxon name AND cultural AND control, taxon name AND suicidal*, taxon name AND legume, taxon name AND no AND till, taxon name AND zero AND till.

Additional searches were performed by manually searching for citations within relevant sections of 20 review studies of control methods for all economically-significant parasitic weed taxa. The list of reviews used is included in appendix 1. Recognized experts and practitioners in the field of parasitic weed agronomy were also contacted to identify possible sources of data (including primary data) and to verify the thoroughness of our literature coverage. In instances where studies were not available electronically, Jisc Libray Hub and Worldcat were searched to locate institutions holding hard copies, which were requested via inter library requests.

Criteria for Inclusion of Studies

Studies were included if they fulfilled the following relevance criteria:

Subjects studied: Any annual parasitic weed species, host crop and intercrop combinations

Treatment used: Intercropping or rotation cropping

Study type: Any primary studies with appropriate comparators, continuous data with means, information on sample sizes, available / calculable measures of variance or sufficient information to impute values. Range of studies comprised: Landscape-level assessment, laboratory, field trials, farm trials, pot, bag and rhizotron experiments.

Response(s): Host yield (t ha-1/kg ha-1), stover yield (t ha-1), weed dry weight (t ha-1/g pot/ g plant/ gm2), weed / weed seed density (per petri dish / pot / plant / M2/ log10M2 / density / severity score), percentage weed reduction / ratio (versus control / from original density).

Comparator: Appropriate controls: experimental units in which no intercrop was grown with the host crop, or monocrop / fallow / bare earth in the case of rotation studies.

Appendix 2: Meta-analysis locality, weed, host, inter and rotation crop lists

Countries	Localities	Lat	Lon	Weed Species	Host Crop	Inter/Trap crop	Host crop	Variety	Intercrop	Variety	Rotation Crop	Variety
Benin	Oued Beja, Tunisia	36.7358	9.2249	*Cuscuta chinensis*	Canola	Alfalfa	Canola	Zarfam	Barley	Aspen	Berseem	Tavor
Cameroon	Adana, Turkey	37.0371	35.3551	*Orobanche foetida*	Chickling pea	Aniseed	Chickling pea	BG-1043	Berssem	Fahl	Black-eyed pea	Parastou
China	Adi Bakel, Tigray, Ethiopia	13.9466	37.7973	*Orobanche aegyptiaca*	Faba bean	Aubergine	Chickling pea	BGE-1023558	Common bean	mwezi moja	Broccoli	Italica
Egypt	Alexandra, Egypt	31.2037	30.0512	*Orobanche cernua*	Finger millet	Bambara	Faba bean	Aquadolce	Common bean	Nambale	Broccoli	Monopoly-Syngenta
Ethiopia	Al-Jubeiha, Jordan	32.0168	35.8716	*Orobanche crenata*	Garden pea	Barley	Faba bean	Badi	Common bean	Nyayo	Brown indian hemp	Farakhil
Germany	Alkaleri, Nigeria	9.7833	10.0166	*Orobanche cumana*	Maize	Basil	Faba bean	Brocal	Cowpea	Amary-sho	Brussel sprout	Oliver-Syngenta
Ghana	Alupe, Kenya	0.4833	34.1333	*Orobanche minor*	Mung bean	Beet	Faba bean	Giza 429	Cowpea	B301	Cabbage	Brunswick-May
India	Amman, Jordan	31.8622	35.9311	*Orobanche ramosa*	Pea	Berseem	Faba bean	Giza Blanca	Cowpea	BR1	Canola	8310
Iran	Ankwa, Nigeria	9.9266	7.7666	*Phelipanche aegyptiaca*	Pearl millet	Bitter apple	Faba bean	Najeh	Cowpea	ICV 2	Cauliflower	Igloo-Global Seeds
Israel	Assiut University, Egypt	27.1848	31.1641	*Striga asiatica*	Rapeseed	Black-eyed pea	Faba bean	Prothabon	Cowpea	IT82D-849	Common bean	GPL 94
Jordan	Bauchi, northern Nigeria	10.2847	9.8211	*Striga hermonthica*	Red clover	Broccoli	Faba bean	Reina Blanca	Cowpea	IT90K-59	Common vetch	Sadot
Kenya	Bengou, Niger	11.9907	3.592		Rice	Brown Indian Hemp	Garden pea	Athos	Cowpea	IT90K-76	Cotton	Varamin
Madagascar	Bingaguru, eastern Zimbabwe	-18.7589	32.6343		Sorghum	Brussel sprout	Garden pea	Messire	Cowpea	IT93K452-1	Cotton	Stam 4224
Mali	Bondo, Kenya	-0.0949	34.2762		Millet	Butternut squash	Lentil	Kırmızı-Local	Cowpea	IT93K-8-45-5-1-5	Cowpea	IT-90K-284-2
Nepal	Borno state, northeast Nigeria	11.8333	10.4166		Sunflower	Cabbage	Lentil	L-317	Cowpea	Kavara	Cowpea	IT-90K-284-2
Niger	Bugiri, Uganda	0.5683	33.7494		Tobacco	Canola	Maize	0804-7STR	Cowpea	Suvita	Cowpea	IT93K452-1
Nigeria	Bungoma, Kenya	0.5693	34.5559		Tomato	Cauliflower	Maize	2000SYN-EE-W-STR	Cowpea	TVX – 1850-01F	Endive	crispum
Spain	Bunyore, Vihiga District, Kenya	0.1111	34.5666		Wild lentil	Celery	Maize	2004TZE-W-DT-STR-C4	Cowpea	Vya	Flax	Legina
The Gambia	Busia district, Kenya	0.4599	34.1091			Celosia argentia	Maize	8322-13	Fenugreek	Giza 2	Foxtail millet	Cao Guzi
Tunisia	Busia, Uganda	0.4661	34.0889			Cereal	Maize	8338-1	Groundnut	Ex-Dakar	Foxtail millet	Jingu 29
Turkey	Butere, Kenya	0.2162	34.4921			Chickpea	Maize	8428-19	Groundnut	Homabay	Giant spinach	Epinard greant

U.S.A	Cameroon	10.5925	14.32101			Chilli	Maize	94TZE COMP5-W	Groundnut	ICGV 907048SM	Groundnut	RMP12
Uganda	Chinyudze, eastern Zimbabwe	-18.1866	32.2005			Clusterbean	Maize	99EVDTSTR-W	Groundnut	Red Beauty	Lentil	Kırmızı-Local
Zimbabwe	Clackamas County, Oregon, USA	45.1903	-122.2023			Common bean	Maize	99TZEE-Y-STR	Groundnut	RMP-12	Maize	94TZE COMP5-W
	Cordoba, Spain	37.8921	-4.7831			Common vetch	Maize	ACROSS 97 TZL COMP1-W	Groundnut	RMP-91	Maize	ACROSS 97 TZL COMP1-W
	Ebuyangu, Vihiga District, Kenya	0.1	34.5833			Coriander	Maize	DMR-ESRW	Groundnut	S28/206	Maize	H19
	Emabwi, Vihiga District, Kenya	0.1	34.5833			Cotton	Maize	Hybrid 511	Groundnut	Yarkasa	Maize	N314
	Gotulis, Bawku district, Ghana	11.0166	-0.2666			Cowpea	Maize	Hybrid 614	Lupin	Giza 2	Maize	Oba Super 1
	Govakova, eastern Zimbabwe	-18.7594	32.6323			Mucuna	Maize	IRAT 200	Lupin	Ultra	Maize	Q67
	Guyuan, Ningxia Hui Region, China	35.9988	106.4191			Crotalaria grahamiana	Maize	Longe 5	Mung bean	Local	Maize	TZE COMP3 DT
	Haifa, Israel	32.7872	35.0031			Crotalaria juncea	Maize	Oba Super 1	Oat	Cory	Maize	TZL COMP1 SYN
	Homa Bay, Kenya	-0.5375	34.4563			Crotalaria ochroleuca	Maize	SC501	Pepper	Shalhevet	Maize	Z6
	Ibadan, Nigeria	7.4909	3.8945			Cucumber	Maize	TZE COMP3 DT	Soya bean	EAI 3600	Millet	Chalak
	Isfahan, Iran	32.7193	51.5321			Cucumis prophetarum	Maize	TZL COMP1 SYN	Soya bean	Jupiter	Mung bean	Parto
	Ivory, Mid-west Madagascar	46.4112	-19.5524			Cumin	Maize	TZSR-W-1	Soya bean	SAMSOY II	Pepper	Arkalohit
	Kaduna, northern Nigeria	10.7251	7.8683			Desmodium distortum	Maize	Western Yellow	Soya bean	Tgm1039	Pepper	Jinghong
	Kafr-El Sheikh, Egypt	31.1048	30.9435			Desmodium intortum	Maize	WH403	Soya bean	Tgm1576	Pepper	Qingdao Xinlilai
	Kano / Katsina, Nigeria	11.9918	8.5209			Desmodium uncinatum	Maize	WH502	Soya bean	TGx 1448-2E / TGx 1864	Pepper	Zi jinshan
	Karaj, Iran	35.8228	50.9583			Desmodium intortum	Maize	WH505	Soya bean	TGX1448-2E	Pigeon pea	ICPL 87091
	Kaya, Nigeria	11.254	7.2389			Desmodium spp	Maize	WH507	Soya bean	TGX1876-4E	Sesame	Darab1
	Kibos, Kisumu dirtsict, Kenya	0.0333	34.8001			Desmodium uncinatum	Maize	WH511	Soya bean	TXG1448-2E	Soya bean	Duika
	Kisii, Kenya	-0.6792	34.7748			Dill	Maize	WH513	Triticale	Penarroya	Soya bean	TGx 1864
	Kisumu dirtsict, Kenya	-0.0661	34.7766			Egyptian clover	Maize	WH624	Wheat	Alamut	Soya bean	TGX1448-2E
	Kumi District, Uganda	1.4676	33.9341			Endive	Millet	Manga Nara	Wheat	Alvand	Soya bean	TGx1740-2F

	Kuria, Kenya	-1.2212	34.5449			Faba bean	Mung bean	Pusa 105	Wheat	Baiat	Soya bean	TGx1740-7F
	Lambwe, Suba district, western Kenya	-0.5492	34.3638			Faidherbia albida	Pea	Syrian local	Wheat	Chamran	Sugar beet	143
	Layin Taki and Kayawa, northern Nigeria	12.9568	8.1441			Fallow	Red clover	Kenland	Wheat	Falat	Sugar beet	RG8001
	Lower River Division, The Gambia	12.5524	-15.9361			Fenugreek	Sorghum	BES (KSV4)	Wheat	Kavir	Sugar beet	Ruima
	Mahuta, Nigeria	10.5002	7.5275			Flax	Sorghum	Damougari/S35	Wheat	Sepahan	Sunflower	Hybrid 8998
	Maiduguri, Nigeria	11.8045	13.1966			Foxtail millet	Sorghum	Djigari	Wheat	TRI11554	Triticale	Bogo
	Makerere University, Uganda	0.3277	32.5674			Garden pea	Sorghum	Gadam Hamam	Wheat	TRI11712	Turnip	Local-Bursa Tohum
	Mansajang Kunda, Gambia	13.2867	-14.1931			Garlic	Sorghum	Ganseber	Wheat	TRI15593	Wheat	Xinchun 6 M
	McCarthy Island north, The Gambia	12.8667	-15.2163			Giant spinach	Sorghum	ICSV 1002	Wheat	TRI17606	Wheat	Yongliang 15
	Melkassa, Ethiopia	8.4056	39.3285			Gourd	Sorghum	ICSV 1007	Wheat	TRI18664	Winter durum wheat	Connie
	Merti, Ethiopia	8.8714	39.9148			Groundnut	Sorghum	Kadaga	Wheat	TRI19322	Winter wheat	Foote
	Migori, Kenya	-1.0675	34.4665			Lentil	Sorghum	KSV8	Wheat	TRI19652	Winter wheat	Gene
	Nara, Mali	15.1657	-7.2872			Linseed	Sorghum	Kutbie	Wheat	TRI7259	Winter wheat	Madsen
	Nawalparasi, Nepal	27.6475	83.9354			Lupin	Sorghum	Sama Jabo			Winter wheat	Stephens
	NGS, Borno state, northeast Nigeria	10.6578	12.2668			Maize	Sorghum	Ware warenbashi			Winter wheat	Weatherford
	Nipani, Karnataka, India	16.4084	74.3746			Melon	Sorghum	wediaker			Winter wheat	Yamhill
	North Bank Division, The Gambia	12.6441	-16.7006			Mung bean	Sorghum	Mobal				
	Nyabeda, western Kenya	0.1276	34.4007			Mustard	Sunflower	Aidatou				
	Nyando, Kenya	-0.2011	35.0133			Narbon vetch	Sunflower	T33				
	Rachuonyo, Kenya	-0.5062	34.7322			Oat	Tobacco	Anand-119				
	Rimau, Nigeria	10.4378	7.7533			Okra	Tomato	M-82				
	Rongo, Kenya	-0.7559	34.5981			Onion	Tomato	Pomodoro ACE 55vF				
	Rongo, Kenya	-0.7559	34.5981			Parsley	Tomato	Roma vf				
	Sadore, Niger	13.2317	2.2756			Pepper	Tomato	Shifan 33				
	Sapu, Gambia	13.5486	-14.8987			Pigeon pea	Tomato	Super Luna				
	SGS, Borno state, northeast Nigeria	10.4346	11.8435			Proso millet	Wild lentil	LENS166/92				

	Sheraro, Tigray, Ethiopia	14.3947	37.7723			Radish						
	Siaya, Kenya	0.0476	34.2869			Rapeseed						
	Some` , Za-Kpota, Benin	7.2167	2.1997			Red cabbage						
	SS, Borno state, northeast Nigeria	11.1527	12.7897			Ricebean						
	Suba district, western Kenya	-0.4303	34.2069			Roselle						
	Tahtay Maychew district, Tigray, Ethiopia	12.7929	39.5277			Senna didymobotrya						
	Tarime, Tanzania	-1.3429	34.3771			Senna occidentalis						
	Terudig, Bawku district, Ghana	11.0166	-0.2666			Senna spectabilis						
	Teso, Kenya	0.4608	34.1129			Sesame						
	Tororo, Uganda	0.6829	34.1779			Sesbania cinerascens						
	Trans Nzoia, Kenya	1.0533	34.9874			Sesbania sesban						
	Uganda	0.9672	33.9183			Silverleaf nightshade						
	University of Stuttgart, Germany	48.7811	9.1736			Smooth vetch						
	Upper River north, The Gambia	12.8412	-15.1736			Snap bean						
	Usha, Israel	32.7957	35.1134			Sorhgum						
	Vihiga, Kenya	0.0502	34.6915			Soya bean						
	Vijayawada, Andhra Pradesh, India	16.5369	80.6744			Spinach						
	Western Division, The Gambia	12.4626	-16.4968			Squash						
	Xianyang, Shaanxi, China	34.2619	108.0729			Squirting cucumber						
	Ziway, Ethiopia	7.9304	38.7151			Stylosanthes guianensis						
						Sugar beet						
						Sunflower						
						Sweet potao						
						Syrian oregano						
						Tephrosia vogelii						

						Tithonia diversifolia						
						Tomato						
						Triticale						
						Turnip						
						Vigna mungo						
						Watermelon						
						Wheat						
						Wild rue						
						Winter durum wheat						
						Winter wheat						

Appendix 3: R Scripts and Results outputs

Appendix 3A: Results Printout Eggers and N failsafe

```
> Hedges_d_and_var_for_checks<-read.csv("Hedges d and var for
checks.CSV")

> View(Hedges_d_and_var_for_checks)

> fsn(Effect.Size, Variance, data=Hedges_d_and_var_for_checks,
type="Rosenberg")


Fail-safe N Calculation Using the Rosenberg Approach


Average Effect Size:          0.3965

Observed Significance Level: <.0001

Target Significance Level:    0.05


Fail-safe N: 311129


> regtest(Effect.Size, Variance,  model="rma", predictor="Variance",
ret.fit=FALSE, digits =4)

Error in regtest(Effect.Size, Variance, model = "rma", predictor =
"Variance",  :

  object 'Effect.Size' not found

> library(metafor)

> setwd("C:/Users/Ragenaky/Desktop/Thesis chapter 3/Data/Bias
Calc/FailSafeCalc/Hedges D and var for checks")

>

> Hedges_d_and_var_for_checks<-read.csv("Hedges d and var for
checks.CSV")

>

> fsn(Effect.Size, Variance, data=Hedges_d_and_var_for_checks,
type="Rosenberg")


Fail-safe N Calculation Using the Rosenberg Approach


Average Effect Size:          0.3965

Observed Significance Level: <.0001

Target Significance Level:    0.05
```

```
Fail-safe N: 311129


> regtest(Effect.Size, Variance,  model="rma", predictor="Variance",
ret.fit=FALSE, digits =4)

Error in regtest(Effect.Size, Variance, model = "rma", predictor =
"Variance",  :

  object 'Effect.Size' not found

> res <- rma(Effect.Size, Variance,
data=Hedges_d_and_var_for_checks)

Warning message:

Studies with NAs omitted from model fitting.

> res


Random-Effects Model (k = 1517; tau^2 estimator: REML)


tau^2 (estimated amount of total heterogeneity): 2.5348 (SE =
0.1098)

tau (square root of estimated tau^2 value):      1.5921

I^2 (total heterogeneity / total variability):   89.37%

H^2 (total variability / sampling variability):  9.41


Test for Heterogeneity:

Q(df = 1516) = 11578.0658, p-val < .0001


Model Results:


estimate      se     zval    pval   ci.lb   ci.ub

  0.4673  0.0449  10.3990  <.0001  0.3793  0.5554  ***


---

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


> res


Random-Effects Model (k = 1517; tau^2 estimator: REML)
```

```
tau^2 (estimated amount of total heterogeneity): 2.5348 (SE =
0.1098)
tau (square root of estimated tau^2 value):      1.5921
I^2 (total heterogeneity / total variability):   89.37%
H^2 (total variability / sampling variability):  9.41

Test for Heterogeneity:
Q(df = 1516) = 11578.0658, p-val < .0001

Model Results:

estimate      se     zval    pval   ci.lb   ci.ub
  0.4673  0.0449  10.3990  <.0001  0.3793  0.5554  ***

---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> regtest(res, model="lm")

Regression Test for Funnel Plot Asymmetry

Model:     weighted regression with multiplicative dispersion
Predictor: standard error

Test for Funnel Plot Asymmetry: t = 2.2836, df = 1515, p = 0.0225
Limit Estimate (as sei -> 0):   b = 0.1947 (CI: 0.0052, 0.3841)

> reg <- regtest(res)
> reg

Regression Test for Funnel Plot Asymmetry

Model:     mixed-effects meta-regression model
Predictor: standard error
```

```
Test for Funnel Plot Asymmetry: z = 2.0058, p = 0.0449
Limit Estimate (as sei -> 0):   b = 0.2716 (CI: 0.0614, 0.4819)


> reg
```

Appendix 3B: Results Printout, Linear Models

```
MST_IC_ASD_IMP_WD<-read.csv("MST_IC_ASD_IMP_WD.CSV")
>
> LM9 <- lm(Control_Mean ~
+              Treat_Mean,
+            data=MST_IC_ASD_IMP_WD,)
> anova(LM9)
Analysis of Variance Table

Response: Control_Mean
            Df  Sum Sq Mean Sq F value    Pr(>F)
Treat_Mean   1 2314864 2314864  1235.1 < 2.2e-16 ***
Residuals  628 1177001    1874
---
Signif. codes:
0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> summary(LM9)

Call:
lm(formula = Control_Mean ~ Treat_Mean, data =
MST_IC_ASD_IMP_WD)

Residuals:
    Min      1Q  Median      3Q     Max
-211.04  -10.47   -8.22    2.30  446.80

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  9.33459    1.84293   5.065 5.37e-07 ***
Treat_Mean   1.80790    0.05144  35.144  < 2e-16 ***
---
Signif. codes:
0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 43.29 on 628 degrees of freedom
Multiple R-squared:  0.6629,  Adjusted R-squared:  0.6624
F-statistic:  1235 on 1 and 628 DF,  p-value: < 2.2e-16

>
> MST_IC_ASD_IMP_YD<-read.csv("MST_IC_ASD_IMP_YD.CSV")
>
> LM10 <- lm(Control_Mean ~
+              Treat_Mean,
+            data=MST_IC_ASD_IMP_YD,)
> anova(LM10)
```

```
Analysis of Variance Table

Response: Control_Mean
             Df Sum Sq Mean Sq F value    Pr(>F)
Treat_Mean    1 189.02 189.015  158.06 < 2.2e-16 ***
Residuals   393 469.97   1.196
---
Signif. codes:
0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> summary(LM10)

Call:
lm(formula = Control_Mean ~ Treat_Mean, data =
MST_IC_ASD_IMP_YD)

Residuals:
    Min      1Q  Median      3Q     Max
-3.9152 -0.6298 -0.1244  0.4191  6.6673

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.88422    0.11285   7.835 4.42e-14 ***
Treat_Mean   0.38337    0.03049  12.572  < 2e-16 ***
---
Signif. codes:
0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.094 on 393 degrees of freedom
Multiple R-squared:  0.2868,  Adjusted R-squared:  0.285
F-statistic: 158.1 on 1 and 393 DF,  p-value: < 2.2e-16

>
> MST_RC_ASD_IMP_WD<-read.csv("MST_RC_ASD_IMP_WD.CSV")
>
> LM11 <- lm(Control_Mean ~
+              Treat_Mean,
+            data=MST_RC_ASD_IMP_WD,)
> anova(LM11)
Analysis of Variance Table

Response: Control_Mean
             Df Sum Sq Mean Sq F value    Pr(>F)
Treat_Mean    1 978372  978372  595.19 < 2.2e-16 ***
Residuals   367 603279    1644
---
Signif. codes:
0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> summary(LM11)

Call:
lm(formula = Control_Mean ~ Treat_Mean, data =
MST_RC_ASD_IMP_WD)

Residuals:
```

```
     Min       1Q   Median       3Q      Max
-190.830  -12.032   -9.397   -2.464  162.781

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  10.7404     2.5180   4.265 2.54e-05 ***
Treat_Mean    1.3273     0.0544  24.396  < 2e-16 ***
---
Signif. codes:
0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 40.54 on 367 degrees of freedom
Multiple R-squared:  0.6186,  Adjusted R-squared:  0.6175
F-statistic: 595.2 on 1 and 367 DF,  p-value: < 2.2e-16

>
> MST_RC_ASD_IMP_YD<-read.csv("MST_RC_ASD_IMP_YD.CSV")
>
> LM12 <- lm(Control_Mean ~
+              Treat_Mean,
+             data=MST_RC_ASD_IMP_YD,)
> anova(LM12)
Analysis of Variance Table

Response: Control_Mean
            Df Sum Sq Mean Sq F value    Pr(>F)
Treat_Mean   1 8959.7  8959.7  142.03 < 2.2e-16 ***
Residuals  129 8137.7    63.1
---
Signif. codes:
0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> summary(LM12)

Call:
lm(formula = Control_Mean ~ Treat_Mean, data =
MST_RC_ASD_IMP_YD)

Residuals:
     Min       1Q   Median       3Q      Max
-24.2694  -2.2135  -1.6888   0.0693  20.7718

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  2.89801    0.79766   3.633 0.000403 ***
Treat_Mean   0.30049    0.02521  11.918  < 2e-16 ***
---
Signif. codes:
0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 7.942 on 129 degrees of freedom
Multiple R-squared:  0.524,   Adjusted R-squared:  0.5203
F-statistic:   142 on 1 and 129 DF,  p-value: < 2.2e-16

>
```

Appendix 3C: Results Printout, MIxed Effects Models>

```
> mixed.mod13 <- lmer(HEDGES ~
+                        DIV +
+                        (1|Study_ID) ,
+                      data=MST_RC_ASD_IMP_WD,
+                      weights = 1/VAR_G,
+                      na.action = "na.omit")
> anova(mixed.mod13)
Type III Analysis of Variance Table with Satterthwaite's
method
      Sum Sq  Mean Sq NumDF  DenDF F value Pr(>F)
DIV 0.062847 0.062847     1 181.92   0.017 0.8965
> summary(mixed.mod13)
Linear mixed model fit by REML. t-tests use
  Satterthwaite's method [lmerModLmerTest]
Formula: HEDGES ~ DIV + (1 | Study_ID)
   Data: MST_RC_ASD_IMP_WD
Weights: 1/VAR_G

REML criterion at convergence: 1263

Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.3575 -0.4104  0.0825  0.7565  3.1825

Random effects:
 Groups   Name        Variance Std.Dev.
 Study_ID (Intercept) 0.8663   0.9307
 Residual             3.7039   1.9246
Number of obs: 368, groups:  Study_ID, 29

Fixed effects:
             Estimate Std. Error        df t value
(Intercept)   1.01486    0.66485 144.65689   1.526
DIV          -0.04031    0.30945 181.92414  -0.130
            Pr(>|t|)
(Intercept)    0.129
DIV            0.897

Correlation of Fixed Effects:
    (Intr)
DIV -0.957
>
>
> MST_RC_ASD_IMP_YD<-read.csv("MST_RC_ASD_IMP_YD.CSV")
> mixed.mod14 <- lmer(HEDGES ~
+                        DIV +
+                        (1|Study_ID) ,
+                      data=MST_RC_ASD_IMP_YD,
+                      weights = 1/VAR_G,
+                      na.action = "na.omit")
> anova(mixed.mod14)
```

```
Type III Analysis of Variance Table with Satterthwaite's
method
    Sum Sq Mean Sq NumDF DenDF F value Pr(>F)
DIV 1.3665  1.3665     1 125.4  0.4513  0.503
> summary(mixed.mod14)
Linear mixed model fit by REML. t-tests use
  Satterthwaite's method [lmerModLmerTest]
Formula: HEDGES ~ DIV + (1 | Study_ID)
   Data: MST_RC_ASD_IMP_YD
Weights: 1/VAR_G

REML criterion at convergence: 399.2

Scaled residuals:
    Min      1Q  Median      3Q     Max
-2.3063 -0.6924  0.0000  0.3082  2.5576

Random effects:
 Groups   Name        Variance Std.Dev.
 Study_ID (Intercept) 0.06568  0.2563
 Residual             3.02806  1.7401
Number of obs: 131, groups:  Study_ID, 18

Fixed effects:
            Estimate Std. Error       df t value
(Intercept)  -0.9285     0.8711 121.3603  -1.066
DIV           0.2866     0.4266 125.3965   0.672
            Pr(>|t|)
(Intercept)    0.289
DIV            0.503

Correlation of Fixed Effects:
    (Intr)
DIV -0.992
>
>
>
> rm(list=ls())# wipes slate clean
> library(mgcv)
> library(lme4)
> library(lmerTest)
> library(ggplot2)
> library(dplyr)
> library( geosphere )
> library( stringr)
> #Calculate a standard error
> stderr <- function(x, ...) sd(x, na.rm = TRUE) /
sqrt(length(is.na(x == FALSE)) )
> ### Install this When you start for Multiplots!!!#####
> #
> # ggplot objects can be passed in ..., or to plotlist (as a
list of ggplot objects)
> # - cols:   Number of columns in layout
```

```
> # - layout: A matrix specifying the layout. If present,
'cols' is ignored.
> #
> # If the layout is something like matrix(c(1,2,3,3), nrow=2,
byrow=TRUE),
> # then plot 1 will go in the upper left, 2 will go in the
upper right, and
> # 3 will go all the way across the bottom.
> #
> multiplot <- function(..., plotlist=NULL, file, cols=1,
layout=NULL) {
+   library(grid)
+
+   # Make a list from the ... arguments and plotlist
+   plots <- c(list(...), plotlist)
+
+   numPlots = length(plots)
+
+   # If layout is NULL, then use 'cols' to determine layout
+   if (is.null(layout)) {
+     # Make the panel
+     # ncol: Number of columns of plots
+     # nrow: Number of rows needed, calculated from # of cols
+     layout <- matrix(seq(1, cols * ceiling(numPlots/cols)),
+                     ncol = cols, nrow =
ceiling(numPlots/cols))
+   }
+
+   if (numPlots==1) {
+     print(plots[[1]])
+
+   } else {
+     # Set up the page
+     grid.newpage()
+     pushViewport(viewport(layout = grid.layout(nrow(layout),
ncol(layout))))
+
+     # Make each plot, in the correct location
+     for (i in 1:numPlots) {
+       # Get the i,j matrix positions of the regions that
contain this subplot
+       matchidx <- as.data.frame(which(layout == i, arr.ind =
TRUE))
+
+       print(plots[[i]], vp = viewport(layout.pos.row =
matchidx$row,
+                                       layout.pos.col =
matchidx$col))
+     }
+   }
+ }
>
>
> #Fig 4a
```

```
>
> Open_Data_IC_RC_WD<-read.csv("Open_Data_IC_RC_WD.CSV")
>
> # Mean rainfall
> model1 <- lm( log( Control_Mean + 1) ~  Mean_RF, data =
Open_Data_IC_RC_WD )
> anova(model1)
Analysis of Variance Table

Response: log(Control_Mean + 1)
           Df  Sum Sq Mean Sq F value    Pr(>F)
Mean_RF     1   95.74  95.737  32.578 1.691e-08 ***
Residuals 701 2060.05   2.939
---
Signif. codes:
0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> summary(model1)

Call:
lm(formula = log(Control_Mean + 1) ~ Mean_RF, data =
Open_Data_IC_RC_WD)

Residuals:
    Min      1Q  Median      3Q     Max
-3.3773 -1.3805 -0.0301  1.6653  4.4122

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  3.982144   0.167945  23.711  < 2e-16 ***
Mean_RF     -0.009896   0.001734  -5.708 1.69e-08 ***
---
Signif. codes:
0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.714 on 701 degrees of freedom
Multiple R-squared:  0.04441, Adjusted R-squared:  0.04305
F-statistic: 32.58 on 1 and 701 DF,  p-value: 1.691e-08

>
> Open_Data_IC_WDA <- Open_Data_IC_RC_WD
> Open_Data_IC_WDA$rainCat <- round(Open_Data_IC_WDA$ Mean_RF
/ 1.5) * 1.5
> summaryRain <- Open_Data_IC_WDA %>%
+   group_by( rainCat ) %>%
+   summarise( meanN = mean(log( Control_Mean + 1), na.rm =
TRUE), SE = stderr(log( Control_Mean + 1), na.rm = TRUE)  )
`summarise()` ungrouping output (override with `.groups`
argument)
>
> fig4a <- ggplot( summaryRain,aes(x = rainCat, y = meanN) ) +
+   geom_point(size = 1) +
+   geom_errorbar(aes( ymin = meanN - SE, ymax = meanN + SE),
width = 0.5, size = 0.25 ) +
+   theme_bw() +
```

```
+   theme( panel.border = element_blank(),
+           panel.grid.major = element_blank(),
+           panel.grid.minor = element_blank(),
+           axis.line = element_line(colour = 'black', size =
0.25),
+           axis.ticks = element_line(colour = "black", size =
0.25),
+           axis.ticks.length=unit(-0.25, "cm"),
+           axis.text.x =
element_text(margin=unit(c(0.5,0.5,0.5,0.5), "cm"), size =
10),
+           axis.text.y =
element_text(margin=unit(c(0.5,0.5,0.5,0.5), "cm"), size =
10),
+           legend.position="none",
+           axis.title.x=element_text( size = 12 ),
+           axis.title.y=element_text( size = 12 ) ) +
+   labs( x = "Mean rainfall (mm)", y = "Log Weed density") +
+   theme(axis.text.x = element_text(angle = 90))
> fig4a
>
> # Precipitation seasonality
> model2 <- lm( log( Control_Mean + 1) ~  RFCV, data =
Open_Data_IC_RC_WD )
> anova(model2)
Analysis of Variance Table

Response: log(Control_Mean + 1)
           Df  Sum Sq Mean Sq F value  Pr(>F)
RFCV        1   40.88  40.884  13.551 0.00025 ***
Residuals 701 2114.90   3.017
---
Signif. codes:
0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> summary(model2)

Call:
lm(formula = log(Control_Mean + 1) ~ RFCV, data =
Open_Data_IC_RC_WD)

Residuals:
    Min      1Q  Median      3Q     Max
-3.1511 -1.2844 -0.2399  1.5664  4.9008

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  3.615933   0.155335  23.278  < 2e-16 ***
RFCV        -0.007191   0.001953  -3.681  0.00025 ***
---
Signif. codes:
0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.737 on 701 degrees of freedom
Multiple R-squared:  0.01896, Adjusted R-squared:  0.01757
```

```
F-statistic: 13.55 on 1 and 701 DF,  p-value: 0.00025

>
> Open_Data_IC_WDA <- Open_Data_IC_RC_WD
> Open_Data_IC_WDA$RFCVCat <- round(Open_Data_IC_WDA$ RFCV /
1.5) * 1.5
> summaryRFCV <- Open_Data_IC_WDA %>%
+   group_by( RFCVCat ) %>%
+   summarise( meanN = mean(log( Control_Mean + 1), na.rm =
TRUE), SE = stderr(log( Control_Mean + 1), na.rm = TRUE)  )
`summarise()` ungrouping output (override with `.groups`
argument)
>
> fig4b <- ggplot(summaryRFCV, aes(x = RFCVCat, y = meanN) ) +
+   geom_point(size = 1) +
+   geom_errorbar(aes( ymin = meanN - SE, ymax = meanN + SE),
width = 0.5, size = 0.25 ) +
+   theme_bw() +
+   theme( panel.border = element_blank(),
+          panel.grid.major = element_blank(),
+          panel.grid.minor = element_blank(),
+          axis.line = element_line(colour = 'black', size =
0.25),
+          axis.ticks = element_line(colour = "black", size =
0.25),
+          axis.ticks.length=unit(-0.25, "cm"),
+          axis.text.x =
element_text(margin=unit(c(0.5,0.5,0.5,0.5), "cm"), size =
10),
+          axis.text.y =
element_text(margin=unit(c(0.5,0.5,0.5,0.5), "cm"), size =
10),
+          legend.position="none",
+          axis.title.x=element_text( size = 12 ),
+          axis.title.y=element_text( size = 12 ) ) +
+   labs( x = "Precipitation seasonality (CV)", y = "Log Weed
density") +
+   theme(axis.text.x = element_text(angle = 90))
> fig4b
>
> # ------------------------------
>
> # altitude
> model3 <- lm( log( Control_Mean + 1) ~  Alt, data =
Open_Data_IC_RC_WD)
> anova(model3)
Analysis of Variance Table

Response: log(Control_Mean + 1)
           Df  Sum Sq Mean Sq F value    Pr(>F)
Alt         1   44.45  44.451  14.759 0.0001333 ***
Residuals 701 2111.33   3.012
---
Signif. codes:
```

```
0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> summary(model3)

Call:
lm(formula = log(Control_Mean + 1) ~ Alt, data =
Open_Data_IC_RC_WD)

Residuals:
    Min      1Q  Median      3Q     Max
-3.1671 -1.3100 -0.2161  1.5885  4.4729

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 2.6316704  0.1377839  19.100  < 2e-16 ***
Alt         0.0004957  0.0001290   3.842 0.000133 ***
---
Signif. codes:
0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.735 on 701 degrees of freedom
Multiple R-squared:  0.02062, Adjusted R-squared:  0.01922
F-statistic: 14.76 on 1 and 701 DF,  p-value: 0.0001333

>
> Open_Data_IC_WDA <- Open_Data_IC_RC_WD
> Open_Data_IC_WDA$altCat <- round(Open_Data_IC_WDA$Alt / 100)
* 100
> summaryAlt <- Open_Data_IC_WDA %>%
+   group_by( altCat ) %>%
+   summarise( meanN = mean(log( Control_Mean + 1), na.rm =
TRUE), SE = stderr(log( Control_Mean + 1), na.rm = TRUE)  )
`summarise()` ungrouping output (override with `.groups`
argument)
>
>
>
> fig4c <- ggplot(summaryAlt, aes(x = altCat, y = meanN) ) +
+   geom_point(size = 1) +
+   geom_errorbar(aes( ymin = meanN - SE, ymax = meanN + SE),
width = 0.5, size = 0.25 ) +
+   theme_bw() +
+   theme( panel.border = element_blank(),
+          panel.grid.major = element_blank(),
+          panel.grid.minor = element_blank(),
+          axis.line = element_line(colour = 'black', size =
0.25),
+          axis.ticks = element_line(colour = "black", size =
0.25),
+          axis.ticks.length=unit(-0.25, "cm"),
+          axis.text.x =
element_text(margin=unit(c(0.5,0.5,0.5,0.5), "cm"), size =
10),
```

```
+          axis.text.y =
element_text(margin=unit(c(0.5,0.5,0.5,0.5), "cm"), size =
10),
+          legend.position="none",
+          axis.title.x=element_text( size = 12 ),
+          axis.title.y=element_text( size = 12 ) ) +
+   labs( x = "Altitude (m)", y = "Log Weed density") +
+   theme(axis.text.x = element_text(angle = 90))
> fig4c
>
> # Mean temperature
>
> model4 <- lm( log( Control_Mean + 1) ~ Mean_TA, data =
Open_Data_IC_RC_WD)
> anova(model4)
Analysis of Variance Table

Response: log(Control_Mean + 1)
           Df  Sum Sq Mean Sq F value Pr(>F)
Mean_TA     1    1.28  1.2844  0.4179 0.5182
Residuals 701 2154.50  3.0735
> summary(model4)

Call:
lm(formula = log(Control_Mean + 1) ~ Mean_TA, data =
Open_Data_IC_RC_WD)

Residuals:
    Min      1Q  Median      3Q     Max
-3.1530 -1.3107 -0.2017  1.5242  4.7070

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  2.77302    0.50619   5.478    6e-08 ***
Mean_TA      0.01469    0.02273   0.646    0.518
---
Signif. codes:
0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.753 on 701 degrees of freedom
Multiple R-squared:  0.0005958,    Adjusted R-squared:  -
0.0008299
F-statistic: 0.4179 on 1 and 701 DF,  p-value: 0.5182

>
>
> Open_Data_IC_WDA <- Open_Data_IC_RC_WD
> Open_Data_IC_WDA$tempCat <- round(Open_Data_IC_WDA$Mean_TA /
1) * 1
> summaryTemp <- Open_Data_IC_WDA %>%
+   group_by( tempCat ) %>%
+   summarise( meanN = mean (log( Control_Mean + 1), na.rm =
TRUE), SE = stderr(log( Control_Mean + 1), na.rm = TRUE)  )
```

```
`summarise()` ungrouping output (override with `.groups`
argument)
>
>
>
> fig4d <- ggplot(summaryTemp, aes(x = tempCat, y = meanN) ) +
+   geom_point(size = 1) +
+   geom_errorbar(aes( ymin = meanN - SE, ymax = meanN + SE),
width = 0.5, size = 0.25 ) +
+   theme_bw() +
+   theme( panel.border = element_blank(),
+          panel.grid.major = element_blank(),
+          panel.grid.minor = element_blank(),
+          axis.line = element_line(colour = 'black', size =
0.25),
+          axis.ticks = element_line(colour = "black", size =
0.25),
+          axis.ticks.length=unit(-0.25, "cm"),
+          axis.text.x =
element_text(margin=unit(c(0.5,0.5,0.5,0.5), "cm"), size =
10),
+          axis.text.y =
element_text(margin=unit(c(0.5,0.5,0.5,0.5), "cm"), size =
10),
+          legend.position="none",
+          axis.title.x=element_text( size = 12 ),
+          axis.title.y=element_text( size = 12 ) ) +
+   labs( x = "Mean Temperature (\u00B0C)", y = "Log Weed
Density") +
+   theme(axis.text.x = element_text(angle = 90))
> fig4d
>
> multiplot(fig4a + labs( tag = "A"), fig4b+ labs( tag = "B"),
fig4c+ labs( tag = "C"), fig4d+ labs( tag = "D"), cols = 2)
>
>
>
>
>
>
> #Fig 4a
>
> Open_Data_IC_RC_YD<-read.csv("Open_Data_IC_RC_YD.CSV")
>
> # Mean rainfall
> model1 <- lm  (Control_Mean  ~  Mean_RF, data =
Open_Data_IC_RC_YD )
> anova(model1)
Analysis of Variance Table

Response: Control_Mean
           Df  Sum Sq Mean Sq F value   Pr(>F)
Mean_RF     1   231.7 231.659  6.9962 0.008431 **
Residuals 488 16158.6  33.112
```

```
---
Signif. codes:
0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> summary(model1)

Call:
lm(formula = Control_Mean ~ Mean_RF, data =
Open_Data_IC_RC_YD)

Residuals:
   Min     1Q Median     3Q    Max
-4.023 -1.719 -0.940  0.202 38.526

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  5.009795   0.802397   6.244 9.31e-10 ***
Mean_RF     -0.022892   0.008655  -2.645  0.00843 **
---
Signif. codes:
0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 5.754 on 488 degrees of freedom
Multiple R-squared:  0.01413, Adjusted R-squared:  0.01211
F-statistic: 6.996 on 1 and 488 DF,  p-value: 0.008431

>
> Open_Data_IC_WDA <- Open_Data_IC_RC_YD
> Open_Data_IC_WDA$rainCat <- round(Open_Data_IC_WDA$ Mean_RF
/ 1.5) * 1.5
> summaryRain <- Open_Data_IC_WDA %>%
+   group_by( rainCat ) %>%
+   summarise( meanN = mean(Control_Mean , na.rm = TRUE), SE =
stderr( Control_Mean , na.rm = TRUE)  )
`summarise()` ungrouping output (override with `.groups`
argument)
>
> fig4a <- ggplot( summaryRain,aes(x = rainCat, y = meanN) ) +
+   geom_point(size = 1) +
+   geom_errorbar(aes( ymin = meanN - SE, ymax = meanN + SE),
width = 0.5, size = 0.25 ) +
+   theme_bw() +
+   theme( panel.border = element_blank(),
+          panel.grid.major = element_blank(),
+          panel.grid.minor = element_blank(),
+          axis.line = element_line(colour = 'black', size =
0.25),
+          axis.ticks = element_line(colour = "black", size =
0.25),
+          axis.ticks.length=unit(-0.25, "cm"),
+          axis.text.x =
element_text(margin=unit(c(0.5,0.5,0.5,0.5), "cm"), size =
10),
```

```
+          axis.text.y =
element_text(margin=unit(c(0.5,0.5,0.5,0.5), "cm"), size =
10),
+          legend.position="none",
+          axis.title.x=element_text( size = 12 ),
+          axis.title.y=element_text( size = 12 ) ) +
+   labs( x = "Mean rainfall (mm)", y = "Yield (T/ha)") +
+   theme(axis.text.x = element_text(angle = 90))
> fig4a
>
>
>
> # Precipitation seasonality
> model2 <- lm( Control_Mean ~  RFCV, data =
Open_Data_IC_RC_YD )
> anova(model2)
Analysis of Variance Table

Response: Control_Mean
           Df  Sum Sq Mean Sq F value  Pr(>F)
RFCV        1   155.6 155.564  4.6761 0.03107 *
Residuals 488 16234.7  33.268
---
Signif. codes:
0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> summary(model2)

Call:
lm(formula = Control_Mean ~ RFCV, data = Open_Data_IC_RC_YD)

Residuals:
   Min     1Q Median     3Q    Max
-3.955 -1.687 -0.851  0.023 38.693

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 1.793042   0.616764   2.907  0.00381 **
RFCV        0.016711   0.007728   2.162  0.03107 *
---
Signif. codes:
0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 5.768 on 488 degrees of freedom
Multiple R-squared:  0.009491,     Adjusted R-squared:
0.007462
F-statistic: 4.676 on 1 and 488 DF,  p-value: 0.03107

>
> Open_Data_IC_WDA <- Open_Data_IC_RC_YD
> Open_Data_IC_WDA$RFCVCat <- round(Open_Data_IC_WDA$ RFCV /
1.5) * 1.5
> summaryRFCV <- Open_Data_IC_WDA %>%
+   group_by( RFCVCat ) %>%
```

```
+   summarise( meanN = mean( Control_Mean, na.rm = TRUE), SE =
stderr(Control_Mean , na.rm = TRUE)  )
`summarise()` ungrouping output (override with `.groups`
argument)
>
> fig4b <- ggplot(summaryRFCV, aes(x = RFCVCat, y = meanN) ) +
+   geom_point(size = 1) +
+   geom_errorbar(aes( ymin = meanN - SE, ymax = meanN + SE),
width = 0.5, size = 0.25 ) +
+   theme_bw() +
+   theme( panel.border = element_blank(),
+          panel.grid.major = element_blank(),
+          panel.grid.minor = element_blank(),
+          axis.line = element_line(colour = 'black', size =
0.25),
+          axis.ticks = element_line(colour = "black", size =
0.25),
+          axis.ticks.length=unit(-0.25, "cm"),
+          axis.text.x =
element_text(margin=unit(c(0.5,0.5,0.5,0.5), "cm"), size =
10),
+          axis.text.y =
element_text(margin=unit(c(0.5,0.5,0.5,0.5), "cm"), size =
10),
+          legend.position="none",
+          axis.title.x=element_text( size = 12 ),
+          axis.title.y=element_text( size = 12 ) ) +
+   labs( x = "Precipitation seasonality (CV)", y = "Yield
(T/ha)") +
+   theme(axis.text.x = element_text(angle = 90))
> fig4b
>
> # ------------------------------
>
> # altitude
> model3 <- lm( Control_Mean  ~  Alt, data =
Open_Data_IC_RC_YD)
> anova(model3)
Analysis of Variance Table

Response: Control_Mean
           Df  Sum Sq Mean Sq F value  Pr(>F)
Alt         1   223.7 223.730  6.7535 0.00964 **
Residuals 488 16166.5  33.128
---
Signif. codes:
0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> summary(model3)

Call:
lm(formula = Control_Mean ~ Alt, data = Open_Data_IC_RC_YD)

Residuals:
   Min     1Q Median     3Q    Max
```

```
-5.040 -1.679 -1.148 -0.346 38.260

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 1.5156081  0.6282540   2.412  0.01622 *
Alt         0.0014442  0.0005557   2.599  0.00964 **
---
Signif. codes:
0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 5.756 on 488 degrees of freedom
Multiple R-squared:  0.01365, Adjusted R-squared:  0.01163
F-statistic: 6.753 on 1 and 488 DF,  p-value: 0.00964

>
> Open_Data_IC_WDA <- Open_Data_IC_RC_YD
> Open_Data_IC_WDA$altCat <- round(Open_Data_IC_WDA$Alt / 100)
* 100
> summaryAlt <- Open_Data_IC_WDA %>%
+   group_by( altCat ) %>%
+   summarise( meanN = mean( Control_Mean, na.rm = TRUE), SE =
stderr(Control_Mean , na.rm = TRUE)  )
`summarise()` ungrouping output (override with `.groups`
argument)
>
> fig4c <- ggplot(summaryAlt, aes(x = altCat, y = meanN) ) +
+   geom_point(size = 1) +
+   geom_errorbar(aes( ymin = meanN - SE, ymax = meanN + SE),
width = 0.5, size = 0.25 ) +
+   theme_bw() +
+   theme( panel.border = element_blank(),
+          panel.grid.major = element_blank(),
+          panel.grid.minor = element_blank(),
+          axis.line = element_line(colour = 'black', size =
0.25),
+          axis.ticks = element_line(colour = "black", size =
0.25),
+          axis.ticks.length=unit(-0.25, "cm"),
+          axis.text.x =
element_text(margin=unit(c(0.5,0.5,0.5,0.5), "cm"), size =
10),
+          axis.text.y =
element_text(margin=unit(c(0.5,0.5,0.5,0.5), "cm"), size =
10),
+          legend.position="none",
+          axis.title.x=element_text( size = 12 ),
+          axis.title.y=element_text( size = 12 ) ) +
+   labs( x = "Altitude (m)", y = "Yield (T/ha)") +
+   theme(axis.text.x = element_text(angle = 90))
> fig4c
>
> # Mean temperature
>
```

```
> model4 <- lm( Control_Mean  ~ Mean_TA, data =
Open_Data_IC_RC_YD)
> anova(model4)
Analysis of Variance Table

Response: Control_Mean
           Df  Sum Sq Mean Sq F value    Pr(>F)
Mean_TA     1   471.5  471.46  14.453 0.0001619 ***
Residuals 488 15918.8   32.62
---
Signif. codes:
0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> summary(model4)

Call:
lm(formula = Control_Mean ~ Mean_TA, data =
Open_Data_IC_RC_YD)

Residuals:
   Min     1Q Median     3Q    Max
-5.034 -1.626 -0.926 -0.054 38.097

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   10.739      2.051   5.235 2.46e-07 ***
Mean_TA       -0.346      0.091  -3.802 0.000162 ***
---
Signif. codes:
0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 5.711 on 488 degrees of freedom
Multiple R-squared:  0.02876, Adjusted R-squared:  0.02677
F-statistic: 14.45 on 1 and 488 DF,  p-value: 0.0001619

>
> Open_Data_IC_WDA <- Open_Data_IC_RC_YD
> Open_Data_IC_WDA$tempCat <- round(Open_Data_IC_WDA$Mean_TA /
1) * 1
> summaryTemp <- Open_Data_IC_WDA %>%
+   group_by( tempCat ) %>%
+   summarise( meanN = mean( Control_Mean, na.rm = TRUE), SE =
stderr(Control_Mean , na.rm = TRUE)  )
`summarise()` ungrouping output (override with `.groups`
argument)
>
> fig4d <- ggplot(summaryTemp, aes(x = tempCat, y = meanN) ) +
+   geom_point(size = 1) +
+   geom_errorbar(aes( ymin = meanN - SE, ymax = meanN + SE),
width = 0.5, size = 0.25 ) +
+   theme_bw() +
+   theme( panel.border = element_blank(),
+          panel.grid.major = element_blank(),
+          panel.grid.minor = element_blank(),
```

```
+           axis.line = element_line(colour = 'black', size =
0.25),
+           axis.ticks = element_line(colour = "black", size =
0.25),
+           axis.ticks.length=unit(-0.25, "cm"),
+           axis.text.x =
element_text(margin=unit(c(0.5,0.5,0.5,0.5), "cm"), size =
10),
+           axis.text.y =
element_text(margin=unit(c(0.5,0.5,0.5,0.5), "cm"), size =
10),
+           legend.position="none",
+           axis.title.x=element_text( size = 12 ),
+           axis.title.y=element_text( size = 12 ) ) +
+   labs( x = "Mean Temperature (\u00B0C)", y = "Yield
(T/ha)") +
+   theme(axis.text.x = element_text(angle = 90))
> fig4d
>
> multiplot(fig4a + labs( tag = "A"), fig4b+ labs( tag = "B"),
fig4c+ labs( tag = "C"), fig4d+ labs( tag = "D"), cols = 2)
>
> Linear Model for Diversity and plots
Error: unexpected symbol in "Linear Model"
>
> MST_RC_ASD_IMP_WD<-read.csv("MST_RC_ASD_IMP_WD.CSV")
>
> stderr <- function(x) sd(x) / sqrt(length(x))
>
> MST_RC_ASD_IMP_WD$DIV <- as.factor(MST_RC_ASD_IMP_WD$DIV)#To
change DIV to 4 level factor
>
> #Divide treatment by control to make weed density %
difference
> MST_RC_ASD_IMP_WD$WDDif<-
(MST_RC_ASD_IMP_WD$Treat_Mean/MST_RC_ASD_IMP_WD$Control_Mean)*
100
>
> #Look at diversity and change in weed density
> LM1 <- lm( WDDif  ~  DIV, data=MST_RC_ASD_IMP_WD)
> anova(LM1)
Analysis of Variance Table

Response: WDDif
           Df   Sum Sq Mean Sq F value Pr(>F)
DIV         3    18175    6058  0.1363 0.9383
Residuals 365 16219701   44438
>
> summary(LM1)

Call:
lm(formula = WDDif ~ DIV, data = MST_RC_ASD_IMP_WD)

Residuals:
```

```
    Min      1Q  Median      3Q     Max
 -93.61  -63.61  -33.61    3.46 2033.66

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)    80.15      74.53   1.075    0.283
DIV2           13.46      75.40   0.179    0.858
DIV3          -17.81      93.43  -0.191    0.849
DIV4          -15.98     120.18  -0.133    0.894

Residual standard error: 210.8 on 365 degrees of freedom
Multiple R-squared:  0.001119,     Adjusted R-squared:  -
0.007091
F-statistic: 0.1363 on 3 and 365 DF,  p-value: 0.9383

>
> coeffs <- data.frame( summary(LM1)$coefficients )
>
> coeffs$names <- str_remove( rownames(coeffs),
"MST_RC_ASD_IMP_WD" )
>
> RCD<- c("1", "2", "3","4")#For the x tick labels
>
> fig5a <- ggplot(coeffs, aes(x =  names,Estimate, y =
Estimate) ) +
+   geom_point(size = 1) +
+   geom_errorbar(aes( ymin = Estimate - Std..Error, ymax
=Estimate + Std..Error ), width = 0.2, size = 0.25 ) +
+   theme_bw() +  scale_x_discrete(labels= RCD)+
+   theme( panel.border = element_blank(),
+          panel.grid.major = element_blank(),
+          panel.grid.minor = element_blank(),
+          axis.line = element_line(colour = 'black', size =
0.25),
+          axis.ticks = element_line(colour = "black", size =
0.25),
+          axis.ticks.length=unit(-0.25, "cm"),
+          axis.text.x =
element_text(margin=unit(c(0.5,0.5,0.5,0.5), "cm"), size =
10),
+          axis.text.y =
element_text(margin=unit(c(0.5,0.5,0.5,0.5), "cm"), size = 8),
+          legend.position="none",
+          axis.title.x=element_text( size = 12 ),
+          axis.title.y=element_text( size = 12 ) ) +
+   labs( x = "Rotation Crop Diversity", y = "Density Change
Coefficient") +
+   theme(axis.text.x = element_text(angle = 0, vjust = .7,
hjust=.65))
> fig5a
>
> fig5b<-ggplot(data = MST_RC_ASD_IMP_WD, aes(x=DIV, y=WDDif))
+
+   geom_boxplot(fill=c('red', 'Yellow', 'blue','green'))+
```

```
+   labs( x = "Rotation Crop Diversity", y = "Weed Density
Change")
>
>
> fig5b
>
> #Redo the LMER with diversity as a factor using effect size
>
> mixed.mod1 <- lmer(HEDGES ~
+                      DIV +
+                      (1|Study_ID) ,
+                    data=MST_RC_ASD_IMP_WD,
+                    weights = 1/VAR_G,
+                    na.action = "na.omit")
> anova(mixed.mod1)
Type III Analysis of Variance Table with Satterthwaite's
method
    Sum Sq Mean Sq NumDF  DenDF F value Pr(>F)
DIV 4.9463  1.6488     3 61.336  0.4474   0.72
> summary(mixed.mod1)
Linear mixed model fit by REML. t-tests use
  Satterthwaite's method [lmerModLmerTest]
Formula: HEDGES ~ DIV + (1 | Study_ID)
   Data: MST_RC_ASD_IMP_WD
Weights: 1/VAR_G

REML criterion at convergence: 1258

Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.3679 -0.4145  0.0830  0.7601  3.1894

Random effects:
 Groups   Name        Variance Std.Dev.
 Study_ID (Intercept) 0.971    0.9854
 Residual             3.685    1.9197
Number of obs: 368, groups:  Study_ID, 29

Fixed effects:
            Estimate Std. Error      df t value
(Intercept)   0.5271     1.0867 21.6851   0.485
DIV2          0.4585     1.1068 21.6969   0.414
DIV3         -0.0798     1.2123 27.6950  -0.066
DIV4          0.3431     1.2766 34.5926   0.269
            Pr(>|t|)
(Intercept)    0.632
DIV2           0.683
DIV3           0.948
DIV4           0.790

Correlation of Fixed Effects:
     (Intr) DIV2   DIV3
DIV2 -0.982
DIV3 -0.896  0.899
```

```
DIV4 -0.851  0.854  0.884
>
> coeffs <- data.frame( summary(mixed.mod1)$coefficients )
>
> coeffs$names <- str_remove( rownames(coeffs),
"MST_RC_ASD_IMP_WD" )
>
> fig5c <- ggplot(coeffs, aes(x =  names,Estimate, y =
Estimate) ) +
+   geom_point(size = 1) +
+   geom_errorbar(aes( ymin = Estimate - Std..Error, ymax
=Estimate + Std..Error ), width = 0.2, size = 0.25 ) +
+   theme_bw() +  scale_x_discrete(labels= RCD)+
+   theme( panel.border = element_blank(),
+          panel.grid.major = element_blank(),
+          panel.grid.minor = element_blank(),
+          axis.line = element_line(colour = 'black', size =
0.25),
+          axis.ticks = element_line(colour = "black", size =
0.25),
+          axis.ticks.length=unit(-0.25, "cm"),
+          axis.text.x =
element_text(margin=unit(c(0.5,0.5,0.5,0.5), "cm"), size =
10),
+          axis.text.y =
element_text(margin=unit(c(0.5,0.5,0.5,0.5), "cm"), size = 8),
+          legend.position="none",
+          axis.title.x=element_text( size = 12 ),
+          axis.title.y=element_text( size = 12 ) ) +
+   labs( x = "Rotation Crop Diversity", y = "Effect Size
(g)") +
+   theme(axis.text.x = element_text(angle = 0, vjust = .7,
hjust=.65))
>
> fig5c
>
> fig5d<-ggplot(data = MST_RC_ASD_IMP_WD, aes(x=DIV,
y=HEDGES)) +
+   geom_boxplot(fill=c('grey', 'grey', 'grey','grey'))+
+   labs( x = "Rotation Crop Diversity", y = "Effect Size
(g)")
>
>
> fig5d
Warning message:
Removed 1 rows containing non-finite values
(stat_boxplot).
>
>
>
> Figure5e <- ggplot( MST_RC_ASD_IMP_WD, aes(x = DIV, y =
HEDGES) ) +
+   geom_point( size = 1) +
```

```
+   geom_errorbar( aes(ymin = HEDGES - VAR_G, ymax = HEDGES +
VAR_G, width = 0.1,  ))  +
+   theme_bw() +
+   theme( panel.border = element_blank(),
+          panel.grid.major = element_blank(),
+          panel.grid.minor = element_blank(),
+          legend.position="none",
+          axis.line = element_line(colour = 'black', size =
0.25),
+          axis.ticks = element_line(colour = "black", size =
0.25),
+          axis.text.x = element_text(size = 10),
+          axis.text.y = element_text(size = 8),
+          axis.title.x=element_text(size = 14),
+          axis.title.y=element_text(size = 14) ) +
+   geom_hline(yintercept = 0, linetype  = "dashed") +
+   labs(x = "Rotation Crop Diversity") + labs( y = "Effect
Size (g)", las=2)
>
> Figure5e
Warning message:
Removed 1 rows containing missing values
(geom_point).
>
> multiplot(fig5a + labs( tag = "A"), fig5c+ labs( tag
+
```

MIXED EFFECT MODELS
Model 1

```
Type III Analysis of Variance Table with Satterthwaite's
method
       Sum Sq Mean Sq NumDF   DenDF F value    Pr(>F)
W_SP   31.859  4.5512     7  56.545  3.0454 0.0086441
HC_SP  49.883  5.5425     9 203.459  3.7088 0.0002497
IC_SP 188.836  5.5540    34 170.500  3.7164 7.565e-09

W_SP  **
HC_SP ***
IC_SP ***
---
Signif. codes:
0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
>  summary(mixed.mod1)
Linear mixed model fit by REML. t-tests use
  Satterthwaite's method [lmerModLmerTest]
Formula:
HEDGES ~ W_SP + HC_SP + IC_SP + (1 | Study_ID)
   Data: MST_IC_ASD_IMP_WD
Weights: 1/VAR_G

REML criterion at convergence: 1284.1

Scaled residuals:
    Min      1Q  Median      3Q     Max
```

```
-3.3778 -0.3560 -0.0084  0.4510  4.2252

Random effects:
 Groups   Name        Variance Std.Dev.
 Study_ID (Intercept) 0.124    0.3522
 Residual             1.494    1.2225
Number of obs: 622, groups:  Study_ID, 39

Fixed effects:
                              Estimate Std. Error
(Intercept)                    1.07000    0.83182
W_SPO. aegyptiaca             -2.47000    1.20151
W_SPO. cernua                 -3.65000    1.34250
W_SPO. crenata                -0.92144    1.37885
W_SPO. foetida                -1.39432    1.46916
W_SPPhelipanche aegyptiaca    -1.05351    0.91526
W_SPS. asiatica                0.09747    0.92635
W_SPS. hermonthica             0.17781    0.88778
HC_SPChickling pea            -0.10282    0.76906
HC_SPFaba bean                 0.18700    0.70372
HC_SPFinger millet             1.87438    0.87338
HC_SPGarden pea               -0.75966    0.69921
HC_SPLentil                    0.57789    0.94482
HC_SPMaize                    -0.68027    0.17292
HC_SPPea                       0.15458    0.73374
HC_SPPearl millet             -0.29595    0.52189
HC_SPRice                     -0.34839    0.32878
IC_SPBarley                    0.06137    0.97594
IC_SPBerseem                   1.50224    0.87695
IC_SPCelery                    0.96684    1.09917
IC_SPCelosia argentia         -0.67012    0.46467
IC_SPCommon bean              -0.21022    0.33029
IC_SPCotton                   -0.41612    0.50912
IC_SPCowpea                   -0.07498    0.29388
IC_SPCowpea / Mucuna          -0.46466    0.58308
IC_SPCrotalaria ochroleuca     0.23295    0.34012
IC_SPCrotolaria juncea        -0.10596    0.77311
IC_SPD.intortum                1.08782    0.31638
IC_SPD.uncinatum               1.06314    0.32392
IC_SPDesmodium / Common bean   0.90267    0.75497
IC_SPDesmodium spp             0.91406    0.75715
IC_SPFaba beans               -0.20715    0.42074
IC_SPFaidherbia albida         2.37219    0.96829
IC_SPFenugreek                 0.93734    0.87481
IC_SPFlax                      0.57870    1.07877
IC_SPGarlic                    0.56030    1.07710
IC_SPGroundnut                -0.11043    0.29684
IC_SPLupin                     1.07246    0.76633
IC_SPMung bean                 0.06824    0.33921
IC_SPOat                       0.43400    0.95580
IC_SPOkra                     -0.68197    0.50155
IC_SPPigeon pea               -1.17781    0.52007
IC_SPRadish                    1.52199    1.14081
IC_SPRicebean                 -0.24676    0.58144
```

```
IC_SPSesame                    0.61495    0.56632
IC_SPSesbania sesban          -1.22412    0.52125
IC_SPSoya bean                -0.14350    0.32751
IC_SPStylosanthes guianensis   0.38199    0.59010
IC_SPSunflower                -0.41249    0.51169
IC_SPSweet potao               0.22957    0.70288
IC_SPTriticale                 0.01527    0.96764
                                    df t value
(Intercept)                  242.80991   1.286
W_SPO. aegyptiaca            256.69629  -2.056
W_SPO. cernua                332.06707  -2.719
W_SPO. crenata               283.12942  -0.668
W_SPO. foetida               227.59794  -0.949
W_SPPhelipanche aegyptiaca   110.16346  -1.151
W_SPS. asiatica              162.98417   0.105
W_SPS. hermonthica           244.63940   0.200
HC_SPChickling pea           563.69205  -0.134
HC_SPFaba bean               570.54208   0.266
HC_SPFinger millet           243.39312   2.146
HC_SPGarden pea              553.13965  -1.086
HC_SPLentil                  568.19561   0.612
HC_SPMaize                   112.64481  -3.934
HC_SPPea                     570.93435   0.211
HC_SPPearl millet             41.29938  -0.567
HC_SPRice                    485.51812  -1.060
IC_SPBarley                   95.22443   0.063
IC_SPBerseem                 217.53513   1.713
IC_SPCelery                  276.60065   0.880
IC_SPCelosia argentia        215.28930  -1.442
IC_SPCommon bean             504.99715  -0.636
IC_SPCotton                  553.41737  -0.817
IC_SPCowpea                  464.38062  -0.255
IC_SPCowpea / Mucuna          32.51954  -0.797
IC_SPCrotalaria ochroleuca   520.94969   0.685
IC_SPCrotolaria juncea       519.34167  -0.137
IC_SPD.intortum              404.04972   3.438
IC_SPD.uncinatum             350.54714   3.282
IC_SPDesmodium / Common bean 362.90340   1.196
IC_SPDesmodium spp           364.81047   1.207
IC_SPFaba beans              568.22564  -0.492
IC_SPFaidherbia albida       303.01772   2.450
IC_SPFenugreek               219.69991   1.071
IC_SPFlax                    264.00157   0.536
IC_SPGarlic                  262.96158   0.520
IC_SPGroundnut               506.18816  -0.372
IC_SPLupin                   167.19635   1.399
IC_SPMung bean               520.42891   0.201
IC_SPOat                      88.26966   0.454
IC_SPOkra                    551.21141  -1.360
IC_SPPigeon pea               38.25316  -2.265
IC_SPRadish                  301.92318   1.334
IC_SPRicebean                 32.16011  -0.424
IC_SPSesame                  564.49407   1.086
IC_SPSesbania sesban          38.59642  -2.348
```

```
IC_SPSoya bean                 530.90934  -0.438
IC_SPStylosanthes guianensis    34.09293   0.647
IC_SPSunflower                 554.12109  -0.806
IC_SPSweet potao               458.05229   0.327
IC_SPTriticale                  92.32303   0.016
                               Pr(>|t|)
(Intercept)                    0.199551
W_SPO. aegyptiaca              0.040819 *
W_SPO. cernua                  0.006896 **
W_SPO. crenata                 0.504510
W_SPO. foetida                 0.343596
W_SPPhelipanche aegyptiaca     0.252206
W_SPS. asiatica                0.916332
W_SPS. hermonthica             0.841426
HC_SPChickling pea             0.893695
HC_SPFaba bean                 0.790543
HC_SPFinger millet             0.032852 *
HC_SPGarden pea                0.277754
HC_SPLentil                    0.541022
HC_SPMaize                     0.000145 ***
HC_SPPea                       0.833212
HC_SPPearl millet              0.573734
HC_SPRice                      0.289823
IC_SPBarley                    0.949989
IC_SPBerseem                   0.088132 .
IC_SPCelery                    0.379834
IC_SPCelosia argentia          0.150710
IC_SPCommon bean               0.524751
IC_SPCotton                    0.414087
IC_SPCowpea                    0.798728
IC_SPCowpea / Mucuna           0.431286
IC_SPCrotalaria ochroleuca     0.493714
IC_SPCrotolaria juncea         0.891040
IC_SPD.intortum                0.000646 ***
IC_SPD.uncinatum               0.001134 **
IC_SPDesmodium / Common bean 0.232619
IC_SPDesmodium spp             0.228123
IC_SPFaba beans                0.622653
IC_SPFaidherbia albida         0.014856 *
IC_SPFenugreek                 0.285133
IC_SPFlax                      0.592103
IC_SPGarlic                    0.603368
IC_SPGroundnut                 0.710043
IC_SPLupin                     0.163522
IC_SPMung bean                 0.840637
IC_SPOat                       0.650892
IC_SPOkra                      0.174478
IC_SPPigeon pea                0.029278 *
IC_SPRadish                    0.183164
IC_SPRicebean                  0.674101
IC_SPSesame                    0.277997
IC_SPSesbania sesban           0.024073 *
IC_SPSoya bean                 0.661440
IC_SPStylosanthes guianensis 0.521751
```

```
IC_SPSunflower               0.420517
IC_SPSweet potao             0.744109
IC_SPTriticale               0.987443
Model 2

Type III Analysis of Variance Table with Satterthwaite's
method
     Sum Sq Mean Sq NumDF DenDF F value Pr(>F)
HC_V 43.228  2.0585    21     2  3.7056 0.2339
IC_V 19.912  0.5240    38     2  0.9433 0.6436
> summary(mixed.mod4)
Linear mixed model fit by REML. t-tests use
  Satterthwaite's method [lmerModLmerTest]
Formula: HEDGES ~ HC_V + IC_V + (1 | Study_ID)
   Data: MST_IC_ASD_IMP_WD
Weights: 1/VAR_G

REML criterion at convergence: 238.6

Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.1233 -0.2659  0.0000  0.2672  4.3923

Random effects:
 Groups   Name        Variance Std.Dev.
 Study_ID (Intercept) 0.04328  0.2080
 Residual             0.55551  0.7453
Number of obs: 207, groups:  Study_ID, 18

Fixed effects:
              Estimate Std. Error         df t value
(Intercept)  9.500e-02  2.962e-01  1.986e-09   0.321
HC_VHCV21    9.500e-02  2.981e-01  1.470e+02   0.319
HC_VHCV22    3.818e-01  5.009e-01  4.063e-09   0.762
HC_VHCV23    2.712e-01  4.243e-01  2.092e-09   0.639
HC_VHCV25    1.195e+00  5.885e-01  7.741e-09   2.031
HC_VHCV27    1.473e-01  3.798e-01  1.343e-09   0.388
HC_VHCV28    4.518e-01  4.920e-01  3.780e-09   0.918
HC_VHCV29   -7.226e-02  4.564e-01  2.800e-09  -0.158
HC_VHCV30    9.000e-01  4.511e-01  2.671e-09   1.995
HC_VHCV31    1.545e+00  5.195e-01  4.700e-09   2.974
HC_VHCV32    2.450e-01  5.405e-01  5.506e-09   0.453
HC_VHCV33    2.350e-01  5.087e-01  4.321e-09   0.462
HC_VHCV37    8.202e-01  5.017e-01  4.087e-09   1.635
HC_VHCV38    4.747e-01  4.092e-01  1.810e-09   1.160
HC_VHCV51    8.022e-01  4.408e-01  2.435e-09   1.820
HC_VHCV57    1.491e+00  4.170e-01  1.951e-09   3.576
HC_VHCV58    2.598e-01  4.035e-01  1.711e-09   0.644
HC_VHCV59    1.977e-01  4.036e-01  1.713e-09   0.490
HC_VHCV60    5.894e-01  4.159e-01  1.930e-09   1.417
HC_VHCV61   -1.954e+00  5.231e-01  4.830e-09  -3.736
HC_VHCV62   -1.500e-02  5.004e-01  4.047e-09  -0.030
HC_VHCV7     9.661e-01  4.171e-01  1.953e-09   2.316
IC_VICV11    6.990e-02  1.632e-01  1.470e+02   0.428
```

```
IC_VICV12   -1.423e-01  1.627e-01  1.470e+02  -0.875
IC_VICV13    2.067e-01  4.756e-01  1.470e+02   0.435
IC_VICV14    9.547e-02  4.726e-01  1.470e+02   0.202
IC_VICV15    5.462e-02  4.712e-01  1.470e+02   0.116
IC_VICV17    1.113e+00  4.030e-01  1.470e+02   2.763
IC_VICV18    2.457e-02  3.814e-01  1.470e+02   0.064
IC_VICV19    3.211e-01  3.996e-01  1.470e+02   0.804
IC_VICV22    6.700e-01  5.164e-01  1.470e+02   1.298
IC_VICV25   -9.511e-01  4.673e-01  3.078e-09  -2.035
IC_VICV26    3.240e-01  4.592e-01  2.869e-09   0.705
IC_VICV27   -1.046e-01  2.272e-01  1.470e+02  -0.460
IC_VICV30   -4.516e-01  4.800e-01  1.470e+02  -0.941
IC_VICV31   -2.291e-01  4.853e-01  1.470e+02  -0.472
IC_VICV32   -2.012e-02  4.930e-01  1.470e+02  -0.041
IC_VICV33   -2.833e-01  4.814e-01  1.470e+02  -0.589
IC_VICV34   -4.471e-02  4.906e-01  1.470e+02  -0.091
IC_VICV36   -2.575e-01  2.867e-01  1.470e+02  -0.898
IC_VICV37   -3.014e-01  2.873e-01  1.470e+02  -1.049
IC_VICV39    1.324e-01  1.970e-01  1.470e+02   0.672
IC_VICV40   -2.522e-02  2.085e-01  1.470e+02  -0.121
IC_VICV43   -5.284e-01  4.928e-01  1.470e+02  -1.072
IC_VICV44   -4.287e-01  4.901e-01  1.470e+02  -0.875
IC_VICV45   -3.700e-01  4.887e-01  1.470e+02  -0.757
IC_VICV46    5.000e-02  4.887e-01  1.470e+02   0.102
IC_VICV47   -4.352e-01  4.915e-01  1.470e+02  -0.885
IC_VICV48    3.815e-01  4.979e-01  1.470e+02   0.766
IC_VICV49   -3.000e-02  4.887e-01  1.470e+02  -0.061
IC_VICV5    -5.700e-01  5.676e-01  1.470e+02  -1.004
IC_VICV50    4.686e-01  4.957e-01  1.470e+02   0.945
IC_VICV51   -4.290e-01  4.901e-01  1.470e+02  -0.875
IC_VICV52    4.000e-02  4.887e-01  1.470e+02   0.082
IC_VICV53    1.284e-01  4.901e-01  1.470e+02   0.262
IC_VICV54    1.500e-02  4.887e-01  1.470e+02   0.031
IC_VICV55   -1.246e-15  4.887e-01  1.470e+02   0.000
IC_VICV56    2.187e-01  4.901e-01  1.470e+02   0.446
IC_VICV8    -1.130e+00  6.135e-01  1.470e+02  -1.842
IC_VICV9    -1.304e-01  1.627e-01  1.470e+02  -0.802
            Pr(>|t|)
(Intercept)  1.00000
HC_VHCV21    0.75044
HC_VHCV22    1.00000
HC_VHCV23    1.00000
HC_VHCV25    1.00000
HC_VHCV27    1.00000
HC_VHCV28    1.00000
HC_VHCV29    1.00000
HC_VHCV30    1.00000
HC_VHCV31    1.00000
HC_VHCV32    1.00000
HC_VHCV33    1.00000
HC_VHCV37    1.00000
HC_VHCV38    1.00000
HC_VHCV51    1.00000
HC_VHCV57    1.00000
```

```
HC_VHCV58    1.00000
HC_VHCV59    1.00000
HC_VHCV60    1.00000
HC_VHCV61    1.00000
HC_VHCV62    1.00000
HC_VHCV7     1.00000
IC_VICV11    0.66911
IC_VICV12    0.38326
IC_VICV13    0.66438
IC_VICV14    0.84019
IC_VICV15    0.90788
IC_VICV17    0.00645 **
IC_VICV18    0.94872
IC_VICV19    0.42290
IC_VICV22    0.19649
IC_VICV25    1.00000
IC_VICV26    1.00000
IC_VICV27    0.64604
IC_VICV30    0.34828
IC_VICV31    0.63751
IC_VICV32    0.96751
IC_VICV33    0.55708
IC_VICV34    0.92751
IC_VICV36    0.37070
IC_VICV37    0.29579
IC_VICV39    0.50268
IC_VICV40    0.90387
IC_VICV43    0.28539
IC_VICV44    0.38316
IC_VICV45    0.45023
IC_VICV46    0.91866
IC_VICV47    0.37734
IC_VICV48    0.44473
IC_VICV49    0.95114
IC_VICV5     0.31694
IC_VICV50    0.34603
IC_VICV51    0.38290
IC_VICV52    0.93488
IC_VICV53    0.79373
IC_VICV54    0.97556
IC_VICV55    1.00000
IC_VICV56    0.65606
IC_VICV8     0.06743 .
IC_VICV9     0.42412
---
Signif. codes:
0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation matrix not shown by default, as p = 60 > 12.
Use print(x, correlation=TRUE)  or
    vcov(x)        if you need it

fit warnings:
```

```
fixed-effect model matrix is rank deficient so dropping 14
columns / coefficients
Model 3
Type III Analysis of Variance Table with Satterthwaite's
method
       Sum Sq Mean Sq NumDF  DenDF F value  Pr(>F)
W_SP   46.064  9.2128     5 36.016  2.8511 0.02867 *
HC_SP   3.751  1.2503     3 43.060  0.3869 0.76295
IC_SP 132.412  5.7571    23 65.137  1.7817 0.03610 *
---
Signif. codes:
0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> summary(mixed.mod1)
Linear mixed model fit by REML. t-tests use
  Satterthwaite's method [lmerModLmerTest]
Formula:
HEDGES ~ W_SP + HC_SP + IC_SP + (1 | Study_ID)
   Data: MST_IC_ASD_IMP_YD
Weights: 1/VAR_G

REML criterion at convergence: 1149.7

Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.7725 -0.5209  0.0000  0.3313  3.3046

Random effects:
 Groups   Name        Variance Std.Dev.
 Study_ID (Intercept) 0.3315   0.5758
 Residual             3.2313   1.7976
Number of obs: 395, groups:  Study_ID, 27

Fixed effects:
                                   Estimate
(Intercept)                        -2.83000
W_SPO. crenata                   -427.40000
W_SPO. foetida                   -168.88341
W_SPO.crenata                    -167.68390
W_SPS.asiatica                      2.24566
W_SPS.hermonthica                   2.51662
HC_SPFinger millet                 -0.11733
HC_SPMaize                          0.30817
HC_SPPearl millet                   0.42127
IC_SPBerseem                      170.19080
IC_SPCelery                        96.89000
IC_SPCelosia argentia              -0.02842
IC_SPCommon bean                   -0.41496
IC_SPCowpea                        -0.10737
IC_SPCrotalaria ochroleuca         -0.51685
IC_SPD.intortum                    -1.36929
IC_SPD.uncinatum                   -1.74834
IC_SPD.uncinatum, D.intortum       -0.94843
IC_SPDesmodium spp                 -3.95161
IC_SPDesmodium spp / Common bean   -4.45390
```

```
IC_SPFaba beans                        -0.12947
IC_SPFaidherbia albida                 -0.71662
IC_SPFenugreek                        169.94567
IC_SPFlax                             243.69000
IC_SPGarlic                           260.73000
IC_SPGroundnut                         -0.19961
IC_SPLupin                            170.10890
IC_SPMung bean                         -0.29984
IC_SPPigeon pea                         0.48433
IC_SPSesbania sesban                    0.48322
IC_SPSoya bean                         -0.28510
IC_SPSweet potao                        0.91513
                                     Std. Error
(Intercept)                             1.64024
W_SPO. crenata                        223.26140
W_SPO. foetida                        242.98717
W_SPO.crenata                         242.98633
W_SPS.asiatica                          1.77738
W_SPS.hermonthica                       1.72975
HC_SPFinger millet                      1.01959
HC_SPMaize                              0.30886
HC_SPPearl millet                       0.91573
IC_SPBerseem                          242.98026
IC_SPCelery                           282.42556
IC_SPCelosia argentia                   0.77579
IC_SPCommon bean                        0.54583
IC_SPCowpea                             0.48241
IC_SPCrotalaria ochroleuca              0.55254
IC_SPD.intortum                         0.56260
IC_SPD.uncinatum                        0.67551
IC_SPD.uncinatum, D.intortum            0.78310
IC_SPDesmodium spp                      1.65831
IC_SPDesmodium spp / Common bean        1.81149
IC_SPFaba beans                         0.61329
IC_SPFaidherbia albida                  1.17319
IC_SPFenugreek                        242.97997
IC_SPFlax                             243.33867
IC_SPGarlic                           239.95994
IC_SPGroundnut                          0.49123
IC_SPLupin                            242.98088
IC_SPMung bean                          0.54838
IC_SPPigeon pea                         0.86377
IC_SPSesbania sesban                    0.86524
IC_SPSoya bean                          0.56360
IC_SPSweet potao                        0.93044
                                             df t value
(Intercept)                           222.69075  -1.725
W_SPO. crenata                        348.76370  -1.914
W_SPO. foetida                        348.76162  -0.695
W_SPO.crenata                         348.76162  -0.690
W_SPS.asiatica                        155.85911   1.263
W_SPS.hermonthica                     218.55287   1.455
HC_SPFinger millet                     43.74385  -0.115
HC_SPMaize                             84.25764   0.998
```

```
HC_SPPearl millet                   29.01202   0.460
IC_SPBerseem                       348.74933   0.700
IC_SPCelery                        348.74876   0.343
IC_SPCelosia argentia              274.73720  -0.037
IC_SPCommon bean                   355.25035  -0.760
IC_SPCowpea                        351.79864  -0.223
IC_SPCrotalaria ochroleuca         359.41314  -0.935
IC_SPD.intortum                    353.24381  -2.434
IC_SPD.uncinatum                    28.01361  -2.588
IC_SPD.uncinatum, D.intortum        15.95393  -1.211
IC_SPDesmodium spp                 335.74196  -2.383
IC_SPDesmodium spp / Common bean  348.21738  -2.459
IC_SPFaba beans                    353.33693  -0.211
IC_SPFaidherbia albida              72.33491  -0.611
IC_SPFenugreek                     348.74933   0.699
IC_SPFlax                          348.74898   1.001
IC_SPGarlic                        348.74900   1.087
IC_SPGroundnut                     362.14946  -0.406
IC_SPLupin                         348.74933   0.700
IC_SPMung bean                     358.89696  -0.547
IC_SPPigeon pea                     22.73423   0.561
IC_SPSesbania sesban                22.88741   0.558
IC_SPSoya bean                     259.29413  -0.506
IC_SPSweet potao                   286.31969   0.984
                                  Pr(>|t|)
(Intercept)                         0.0858 .
W_SPO. crenata                      0.0564 .
W_SPO. foetida                      0.4875
W_SPO.crenata                       0.4906
W_SPS.asiatica                      0.2083
W_SPS.hermonthica                   0.1471
HC_SPFinger millet                  0.9089
HC_SPMaize                          0.3212
HC_SPPearl millet                   0.6489
IC_SPBerseem                        0.4841
IC_SPCelery                         0.7318
IC_SPCelosia argentia               0.9708
IC_SPCommon bean                    0.4476
IC_SPCowpea                         0.8240
IC_SPCrotalaria ochroleuca          0.3502
IC_SPD.intortum                     0.0154 *
IC_SPD.uncinatum                    0.0151 *
IC_SPD.uncinatum, D.intortum        0.2435
IC_SPDesmodium spp                  0.0177 *
IC_SPDesmodium spp / Common bean    0.0144 *
IC_SPFaba beans                     0.8329
IC_SPFaidherbia albida              0.5432
IC_SPFenugreek                      0.4848
IC_SPFlax                           0.3173
IC_SPGarlic                         0.2780
IC_SPGroundnut                      0.6847
IC_SPLupin                          0.4843
IC_SPMung bean                      0.5849
IC_SPPigeon pea                     0.5805
```

```
IC_SPSesbania sesban                 0.5819
IC_SPSoya bean                       0.6134
IC_SPSweet potao                     0.3262
---
Signif. codes:
0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Model 4

Type III Analysis of Variance Table with Satterthwaite's
method
     Sum Sq Mean Sq NumDF DenDF F value Pr(>F)
HC_V 4.5258 0.50286     9   103  1.2481 0.2745
IC_V 7.7694 0.40892    19   103  1.0149 0.4510
> summary(mixed.mod4)
Linear mixed model fit by REML. t-tests use
  Satterthwaite's method [lmerModLmerTest]
Formula: HEDGES ~ HC_V + IC_V + (1 | Study_ID)
   Data: MST_IC_ASD_IMP_YD
Weights: 1/VAR_G

REML criterion at convergence: 134.3

Scaled residuals:
    Min      1Q  Median      3Q     Max
-2.7376 -0.5631  0.0000  0.5934  3.0778

Random effects:
 Groups   Name        Variance Std.Dev.
 Study_ID (Intercept) 2.7248   1.6507
 Residual             0.4029   0.6348
Number of obs: 132, groups:  Study_ID, 11

Fixed effects:
              Estimate Std. Error         df t value
(Intercept)  -0.471106   1.662691 103.000000  -0.283
HC_VHCV23     1.548276   2.354740 103.000000   0.658
HC_VHCV27     0.063940   2.345029 103.000000   0.027
HC_VHCV28    -0.343205   2.352100 103.000000  -0.146
HC_VHCV29     0.814799   0.256907 103.000000   3.172
HC_VHCV33     0.211106   2.362625 103.000000   0.089
HC_VHCV37    -0.334006   2.361734 103.000000  -0.141
HC_VHCV38     0.111820   2.348097 103.000000   0.048
HC_VHCV57     0.148497   2.352780 103.000000   0.063
HC_VHCV7      0.018248   2.348200 103.000000   0.008
IC_VICV11    -0.007929   0.140982 103.000000  -0.056
IC_VICV12    -0.022837   0.140611 103.000000  -0.162
IC_VICV13     0.217576   0.289754 103.000000   0.751
IC_VICV14     0.461108   0.286491 103.000000   1.610
IC_VICV15     0.224215   0.288967 103.000000   0.776
IC_VICV17    -0.197938   0.228476 103.000000  -0.866
IC_VICV21    -0.117143   2.346598 103.000000  -0.050
IC_VICV22    -0.880000   0.444328 103.000000  -1.981
IC_VICV25     0.542857   2.353456 103.000000   0.231
```

```
IC_VICV26     0.190915   2.353676 103.000000   0.081
IC_VICV27     0.223571   0.180209 103.000000   1.241
IC_VICV30    -1.064805   0.456421 103.000000  -2.333
IC_VICV31    -0.139487   0.419624 103.000000  -0.332
IC_VICV32    -0.323350   0.433175 103.000000  -0.746
IC_VICV33     0.070111   0.413593 103.000000   0.170
IC_VICV34    -0.774110   0.461886 103.000000  -1.676
IC_VICV36    -0.082391   0.304274 103.000000  -0.271
IC_VICV37    -0.246115   0.305889 103.000000  -0.805
IC_VICV9     -0.032393   0.141237 103.000000  -0.229
            Pr(>|t|)
(Intercept)   0.7775
HC_VHCV23     0.5123
HC_VHCV27     0.9783
HC_VHCV28     0.8843
HC_VHCV29     0.0020 **
HC_VHCV33     0.9290
HC_VHCV37     0.8878
HC_VHCV38     0.9621
HC_VHCV57     0.9498
HC_VHCV7      0.9938
IC_VICV11     0.9553
IC_VICV12     0.8713
IC_VICV13     0.4544
IC_VICV14     0.1106
IC_VICV15     0.4396
IC_VICV17     0.3883
IC_VICV21     0.9603
IC_VICV22     0.0503 .
IC_VICV25     0.8180
IC_VICV26     0.9355
IC_VICV27     0.2176
IC_VICV30     0.0216 *
IC_VICV31     0.7403
IC_VICV32     0.4571
IC_VICV33     0.8657
IC_VICV34     0.0968 .
IC_VICV36     0.7871
IC_VICV37     0.4229
IC_VICV9      0.8191
---
Signif. codes:
0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Model 5
Type III Analysis of Variance Table with Satterthwaite's
method
         Sum Sq Mean Sq NumDF   DenDF F value Pr(>F)
W_SP     60.026  7.5033     8  10.205  2.1522 0.1255
HC_SP    47.349  6.7642     7  15.278  1.9402 0.1320
RC_1_SP 316.112  3.9026    81 217.374  1.1194 0.2596
>  summary(mixed.mod5)
Linear mixed model fit by REML. t-tests use
  Satterthwaite's method [lmerModLmerTest]
```

```
Formula:
HEDGES ~ W_SP + HC_SP + RC_1_SP + (1 | Study_ID)
   Data: MST_RC_ASD_IMP_WD
Weights: 1/VAR_G

REML criterion at convergence: 1008.2

Scaled residuals:
     Min       1Q   Median       3Q      Max 
-2.02677 -0.32372  0.00039  0.54804  2.74769 

Random effects:
 Groups   Name        Variance Std.Dev.
 Study_ID (Intercept) 0.878    0.937   
 Residual             3.486    1.867   
Number of obs: 368, groups:  Study_ID, 29

Fixed effects:
                                                    Estimate
(Intercept)                                          2.48651
W_SPO.aegyptiaca                                     1.52543
W_SPO.cernua                                        -2.60847
W_SPO.crenata                                       -1.69762
W_SPO.cumana                                        -0.07121
W_SPO.minor                                         -2.11985
W_SPO.ramosa                                        -2.43402
W_SPPhelipanche aegyptiaca                          -2.41952
W_SPS.hermonthica                                   -3.42183
HC_SPLentil                                          0.40682
HC_SPMaize                                           0.93894
HC_SPPearl millet                                    0.96890
HC_SPRapeseed                                       -3.48480
HC_SPSorghum                                         0.21947
HC_SPSorghum / Millet                                5.36019
HC_SPSorhgum/Maize                                   1.27443
RC_1_SPAniseed                                       0.46001
RC_1_SPBarley                                        0.90233
RC_1_SPBasil                                         0.36111
RC_1_SPBeet                                          0.78693
RC_1_SPBerseem                                       0.06580
RC_1_SPBitter apple                                  1.52240
RC_1_SPBlack-eyed pea                                9.25947
RC_1_SPBroccoli                                      1.10197
RC_1_SPBrown Indian Hemp                            -0.48053
RC_1_SPBrussel sprout                               -1.52005
RC_1_SPButternut squash                              0.53970
RC_1_SPCabbage                                      -1.38784
RC_1_SPCanola                                       -1.59871
RC_1_SPCauliflower                                  -0.75023
RC_1_SPCereal                                        0.86854
RC_1_SPChickpea                                      1.68419
RC_1_SPChilli                                        1.39620
RC_1_SPCommon bean                                   1.43351
RC_1_SPCommon vetch                                 -4.33194
```

RC_1_SPCoriander	0.67266
RC_1_SPCotton	1.63835
RC_1_SPCowpea	0.83909
RC_1_SPCrotalaria grahamiana	0.53214
RC_1_SPCrotalaria juncea	0.74005
RC_1_SPCucumber	0.37989
RC_1_SPCucumis prophetarum	0.97365
RC_1_SPCumin	1.03207
RC_1_SPD. distortum	6.12405
RC_1_SPDill	0.30043
RC_1_SPEndive	0.62263
RC_1_SPFallow	-0.35920
RC_1_SPFenugreek	1.25592
RC_1_SPFlax	1.08544
RC_1_SPFoxtail millet	-0.78804
RC_1_SPGarden pea	0.35459
RC_1_SPGarlic	0.72979
RC_1_SPGiant spinach	0.72633
RC_1_SPGourd	0.76710
RC_1_SPGroundnut	0.67885
RC_1_SPLentil	1.06837
RC_1_SPLinseed	0.12242
RC_1_SPLupin	1.21901
RC_1_SPMaize	0.52520
RC_1_SPMaize/Cowpea/ Soya bean/ Groundnut	-0.09221
RC_1_SPMelon	0.35637
RC_1_SPMillet / Cotton	0.68585
RC_1_SPMung bean	1.04092
RC_1_SPMustard	1.36606
RC_1_SPNarbon vetch	1.92111
RC_1_SPOnion	0.63923
RC_1_SPParsley	0.84228
RC_1_SPPepper	1.22106
RC_1_SPPigeon pea	1.01946
RC_1_SPProso millet	0.11289
RC_1_SPRed cabbage	0.63769
RC_1_SPRoselle	1.51455
RC_1_SPSenna didymobotrya	1.67405
RC_1_SPSenna occidentalis	-0.20595
RC_1_SPSenna spectabilis	-0.14595
RC_1_SPSesame	0.73732
RC_1_SPSesbania cinerascens	2.12405
RC_1_SPSesbania sesban	-0.16134
RC_1_SPSilverleaf nightshade	-0.51547
RC_1_SPSnap bean	1.39874
RC_1_SPSorhgum	-0.81175
RC_1_SPSoya bean	0.75089
RC_1_SPSpinach	0.18280
RC_1_SPSquash	0.50402
RC_1_SPSquirting cucumber	0.97300
RC_1_SPSugar beet	0.50710
RC_1_SPSunflower	0.87298
RC_1_SPSyrian oregano	-0.17583
RC_1_SPTephrosia vogelii	1.59405

```
RC_1_SPTithonia diversifolia                  0.17405
RC_1_SPTriticale                              0.47333
RC_1_SPTurnip                                -0.67396
RC_1_SPVigna mungo                            1.36196
RC_1_SPWatermelon                             0.08604
RC_1_SPWheat                                  1.58301
RC_1_SPWild rue                               0.71510
RC_1_SPWinter durum wheat                     0.81333
                                            Std. Error
(Intercept)                                    1.23381
W_SPO.aegyptiaca                               2.08377
W_SPO.cernua                                   1.57759
W_SPO.crenata                                  1.53674
W_SPO.cumana                                   1.40217
W_SPO.minor                                    1.60092
W_SPO.ramosa                                   1.48282
W_SPPhelipanche aegyptiaca                     1.39199
W_SPS.hermonthica                              1.57040
HC_SPLentil                                    1.58412
HC_SPMaize                                     1.08907
HC_SPPearl millet                              1.62047
HC_SPRapeseed                                  2.11632
HC_SPSorghum                                   2.04908
HC_SPSorghum / Millet                          1.84461
HC_SPSorhgum/Maize                             1.61868
RC_1_SPAniseed                                 0.80611
RC_1_SPBarley                                  0.83398
RC_1_SPBasil                                   1.17446
RC_1_SPBeet                                    0.92969
RC_1_SPBerseem                                 0.77365
RC_1_SPBitter apple                            0.87794
RC_1_SPBlack-eyed pea                          5.07723
RC_1_SPBroccoli                                0.89287
RC_1_SPBrown Indian Hemp                       1.58866
RC_1_SPBrussel sprout                          1.46208
RC_1_SPButternut squash                        0.80366
RC_1_SPCabbage                                 1.35975
RC_1_SPCanola                                  1.35959
RC_1_SPCauliflower                             1.34294
RC_1_SPCereal                                  0.84025
RC_1_SPChickpea                                0.88676
RC_1_SPChilli                                  0.85469
RC_1_SPCommon bean                             0.77158
RC_1_SPCommon vetch                            1.88027
RC_1_SPCoriander                               0.79603
RC_1_SPCotton                                  1.45938
RC_1_SPCowpea                                  0.73082
RC_1_SPCrotalaria grahamiana                   1.29798
RC_1_SPCrotalaria juncea                       1.04896
RC_1_SPCucumber                                0.80366
RC_1_SPCucumis prophetarum                     0.92813
RC_1_SPCumin                                   0.79706
RC_1_SPD. distortum                            3.17101
RC_1_SPDill                                    0.79947
```

```
RC_1_SPEndive                                  0.94030
RC_1_SPFallow                                  0.97120
RC_1_SPFenugreek                               0.81859
RC_1_SPFlax                                    0.77656
RC_1_SPFoxtail millet                          1.46652
RC_1_SPGarden pea                              0.83752
RC_1_SPGarlic                                  1.47720
RC_1_SPGiant spinach                           0.94036
RC_1_SPGourd                                   0.90409
RC_1_SPGroundnut                               0.71635
RC_1_SPLentil                                  1.08521
RC_1_SPLinseed                                 1.36006
RC_1_SPLupin                                   0.86586
RC_1_SPMaize                                   0.80935
RC_1_SPMaize/Cowpea/ Soya bean/ Groundnut      1.22711
RC_1_SPMelon                                   0.80163
RC_1_SPMillet / Cotton                         1.61799
RC_1_SPMung bean                               0.92589
RC_1_SPMustard                                 0.87426
RC_1_SPNarbon vetch                            1.40429
RC_1_SPOnion                                   1.49957
RC_1_SPParsley                                 0.84582
RC_1_SPPepper                                  0.83658
RC_1_SPPigeon pea                              1.18191
RC_1_SPProso millet                            0.90244
RC_1_SPRed cabbage                             0.91246
RC_1_SPRoselle                                 0.93013
RC_1_SPSenna didymobotrya                      1.66393
RC_1_SPSenna occidentalis                      1.51016
RC_1_SPSenna spectabilis                       1.49857
RC_1_SPSesame                                  0.71278
RC_1_SPSesbania cinerascens                    1.76559
RC_1_SPSesbania sesban                         0.99122
RC_1_SPSilverleaf nightshade                   0.79947
RC_1_SPSnap bean                               1.63615
RC_1_SPSorhgum                                 0.71910
RC_1_SPSoya bean                               0.69482
RC_1_SPSpinach                                 0.79475
RC_1_SPSquash                                  0.80366
RC_1_SPSquirting cucumber                      0.90665
RC_1_SPSugar beet                              1.17597
RC_1_SPSunflower                               0.85755
RC_1_SPSyrian oregano                          0.86260
RC_1_SPTephrosia vogelii                       1.64285
RC_1_SPTithonia diversifolia                   1.49857
RC_1_SPTriticale                               1.27554
RC_1_SPTurnip                                  1.33174
RC_1_SPVigna mungo                             1.52626
RC_1_SPWatermelon                              0.79475
RC_1_SPWheat                                   1.31001
RC_1_SPWild rue                                0.93818
RC_1_SPWinter durum wheat                      1.32908
                                                    df
(Intercept)                                  14.55899
```

W_SPO.aegyptiaca	29.32604
W_SPO.cernua	9.64984
W_SPO.crenata	8.72065
W_SPO.cumana	12.13011
W_SPO.minor	10.31467
W_SPO.ramosa	7.55541
W_SPPhelipanche aegyptiaca	12.97707
W_SPS.hermonthica	9.43802
HC_SPLentil	9.90423
HC_SPMaize	7.28671
HC_SPPearl millet	10.80617
HC_SPRapeseed	31.26987
HC_SPSorghum	27.28503
HC_SPSorghum / Millet	18.14197
HC_SPSorhgum/Maize	10.78288
RC_1_SPAniseed	255.08801
RC_1_SPBarley	255.17294
RC_1_SPBasil	255.29737
RC_1_SPBeet	255.05135
RC_1_SPBerseem	255.47595
RC_1_SPBitter apple	255.06483
RC_1_SPBlack-eyed pea	261.07578
RC_1_SPBroccoli	255.17638
RC_1_SPBrown Indian Hemp	245.65854
RC_1_SPBrussel sprout	255.24464
RC_1_SPButternut squash	255.08891
RC_1_SPCabbage	255.29198
RC_1_SPCanola	255.29207
RC_1_SPCauliflower	255.30081
RC_1_SPCereal	261.58135
RC_1_SPChickpea	255.16472
RC_1_SPChilli	255.07170
RC_1_SPCommon bean	259.01981
RC_1_SPCommon vetch	255.32693
RC_1_SPCoriander	255.21323
RC_1_SPCotton	255.82922
RC_1_SPCowpea	265.26014
RC_1_SPCrotalaria grahamiana	124.62143
RC_1_SPCrotalaria juncea	258.06976
RC_1_SPCucumber	255.08891
RC_1_SPCucumis prophetarum	255.05172
RC_1_SPCumin	255.19570
RC_1_SPD. distortum	270.79746
RC_1_SPDill	255.09047
RC_1_SPEndive	255.04886
RC_1_SPFallow	60.10614
RC_1_SPFenugreek	254.96212
RC_1_SPFlax	259.85286
RC_1_SPFoxtail millet	14.30638
RC_1_SPGarden pea	255.41651
RC_1_SPGarlic	255.70657
RC_1_SPGiant spinach	255.04884
RC_1_SPGourd	255.05773
RC_1_SPGroundnut	263.66942

```
RC_1_SPLentil                            255.40935
RC_1_SPLinseed                           255.84266
RC_1_SPLupin                             255.06833
RC_1_SPMaize                             189.50262
RC_1_SPMaize/Cowpea/ Soya bean/ Groundnut 259.29785
RC_1_SPMelon                             255.08966
RC_1_SPMillet / Cotton                   255.66501
RC_1_SPMung bean                         258.85231
RC_1_SPMustard                           255.06588
RC_1_SPNarbon vetch                      255.19034
RC_1_SPOnion                             255.68409
RC_1_SPParsley                           255.07447
RC_1_SPPepper                            268.40685
RC_1_SPPigeon pea                        246.85780
RC_1_SPProso millet                      255.05816
RC_1_SPRed cabbage                       255.05558
RC_1_SPRoselle                           255.05124
RC_1_SPSenna didymobotrya                206.08761
RC_1_SPSenna occidentalis                175.93830
RC_1_SPSenna spectabilis                 173.37876
RC_1_SPSesame                            256.79261
RC_1_SPSesbania cinerascens              221.90112
RC_1_SPSesbania sesban                    56.21417
RC_1_SPSilverleaf nightshade             255.09047
RC_1_SPSnap bean                         255.56603
RC_1_SPSorhgum                           261.76591
RC_1_SPSoya bean                         264.74336
RC_1_SPSpinach                           255.09226
RC_1_SPSquash                            255.08891
RC_1_SPSquirting cucumber                255.05707
RC_1_SPSugar beet                        230.51333
RC_1_SPSunflower                         255.43527
RC_1_SPSyrian oregano                    255.06930
RC_1_SPTephrosia vogelii                 202.39461
RC_1_SPTithonia diversifolia             173.37876
RC_1_SPTriticale                         254.94009
RC_1_SPTurnip                            255.30687
RC_1_SPVigna mungo                       256.45344
RC_1_SPWatermelon                        255.09226
RC_1_SPWheat                             250.59574
RC_1_SPWild rue                          255.04935
RC_1_SPWinter durum wheat                254.94009
                                         t value
(Intercept)                                2.015
W_SPO.aegyptiaca                           0.732
W_SPO.cernua                              -1.653
W_SPO.crenata                             -1.105
W_SPO.cumana                              -0.051
W_SPO.minor                               -1.324
W_SPO.ramosa                              -1.641
W_SPPhelipanche aegyptiaca                -1.738
W_SPS.hermonthica                         -2.179
HC_SPLentil                                0.257
HC_SPMaize                                 0.862
```

HC_SPPearl millet	0.598
HC_SPRapeseed	-1.647
HC_SPSorghum	0.107
HC_SPSorghum / Millet	2.906
HC_SPSorhgum/Maize	0.787
RC_1_SPAniseed	0.571
RC_1_SPBarley	1.082
RC_1_SPBasil	0.307
RC_1_SPBeet	0.846
RC_1_SPBerseem	0.085
RC_1_SPBitter apple	1.734
RC_1_SPBlack-eyed pea	1.824
RC_1_SPBroccoli	1.234
RC_1_SPBrown Indian Hemp	-0.302
RC_1_SPBrussel sprout	-1.040
RC_1_SPButternut squash	0.672
RC_1_SPCabbage	-1.021
RC_1_SPCanola	-1.176
RC_1_SPCauliflower	-0.559
RC_1_SPCereal	1.034
RC_1_SPChickpea	1.899
RC_1_SPChilli	1.634
RC_1_SPCommon bean	1.858
RC_1_SPCommon vetch	-2.304
RC_1_SPCoriander	0.845
RC_1_SPCotton	1.123
RC_1_SPCowpea	1.148
RC_1_SPCrotalaria grahamiana	0.410
RC_1_SPCrotalaria juncea	0.706
RC_1_SPCucumber	0.473
RC_1_SPCucumis prophetarum	1.049
RC_1_SPCumin	1.295
RC_1_SPD. distortum	1.931
RC_1_SPDill	0.376
RC_1_SPEndive	0.662
RC_1_SPFallow	-0.370
RC_1_SPFenugreek	1.534
RC_1_SPFlax	1.398
RC_1_SPFoxtail millet	-0.537
RC_1_SPGarden pea	0.423
RC_1_SPGarlic	0.494
RC_1_SPGiant spinach	0.772
RC_1_SPGourd	0.848
RC_1_SPGroundnut	0.948
RC_1_SPLentil	0.984
RC_1_SPLinseed	0.090
RC_1_SPLupin	1.408
RC_1_SPMaize	0.649
RC_1_SPMaize/Cowpea/ Soya bean/ Groundnut	-0.075
RC_1_SPMelon	0.445
RC_1_SPMillet / Cotton	0.424
RC_1_SPMung bean	1.124
RC_1_SPMustard	1.563
RC_1_SPNarbon vetch	1.368

```
RC_1_SPOnion                                0.426
RC_1_SPParsley                              0.996
RC_1_SPPepper                               1.460
RC_1_SPPigeon pea                           0.863
RC_1_SPProso millet                         0.125
RC_1_SPRed cabbage                          0.699
RC_1_SPRoselle                              1.628
RC_1_SPSenna didymobotrya                   1.006
RC_1_SPSenna occidentalis                  -0.136
RC_1_SPSenna spectabilis                   -0.097
RC_1_SPSesame                               1.034
RC_1_SPSesbania cinerascens                 1.203
RC_1_SPSesbania sesban                     -0.163
RC_1_SPSilverleaf nightshade               -0.645
RC_1_SPSnap bean                            0.855
RC_1_SPSorhgum                             -1.129
RC_1_SPSoya bean                            1.081
RC_1_SPSpinach                              0.230
RC_1_SPSquash                               0.627
RC_1_SPSquirting cucumber                   1.073
RC_1_SPSugar beet                           0.431
RC_1_SPSunflower                            1.018
RC_1_SPSyrian oregano                      -0.204
RC_1_SPTephrosia vogelii                    0.970
RC_1_SPTithonia diversifolia                0.116
RC_1_SPTriticale                            0.371
RC_1_SPTurnip                              -0.506
RC_1_SPVigna mungo                          0.892
RC_1_SPWatermelon                           0.108
RC_1_SPWheat                                1.208
RC_1_SPWild rue                             0.762
RC_1_SPWinter durum wheat                   0.612
                                          Pr(>|t|)
(Intercept)                                0.06272 .
W_SPO.aegyptiaca                           0.46995
W_SPO.cernua                               0.13035
W_SPO.crenata                              0.29884
W_SPO.cumana                               0.96033
W_SPO.minor                                0.21405
W_SPO.ramosa                               0.14154
W_SPPhelipanche aegyptiaca                 0.10583
W_SPS.hermonthica                          0.05591 .
HC_SPLentil                                0.80258
HC_SPMaize                                 0.41607
HC_SPPearl millet                          0.56222
HC_SPRapeseed                              0.10965
HC_SPSorghum                               0.91549
HC_SPSorghum / Millet                      0.00937 **
HC_SPSorhgum/Maize                         0.44805
RC_1_SPAniseed                             0.56874
RC_1_SPBarley                              0.28030
RC_1_SPBasil                               0.75874
RC_1_SPBeet                                0.39810
RC_1_SPBerseem                             0.93229
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```
RC_1_SPBitter apple                          0.08412 .
RC_1_SPBlack-eyed pea                        0.06934 .
RC_1_SPBroccoli                              0.21827
RC_1_SPBrown Indian Hemp                     0.76255
RC_1_SPBrussel sprout                        0.29949
RC_1_SPButternut squash                      0.50248
RC_1_SPCabbage                               0.30838
RC_1_SPCanola                                0.24074
RC_1_SPCauliflower                           0.57689
RC_1_SPCereal                                0.30225
RC_1_SPChickpea                              0.05866 .
RC_1_SPChilli                                0.10358
RC_1_SPCommon bean                           0.06432 .
RC_1_SPCommon vetch                          0.02203 *
RC_1_SPCoriander                             0.39889
RC_1_SPCotton                                0.26264
RC_1_SPCowpea                                0.25194
RC_1_SPCrotalaria grahamiana                 0.68253
RC_1_SPCrotalaria juncea                     0.48113
RC_1_SPCucumber                              0.63683
RC_1_SPCucumis prophetarum                   0.29515
RC_1_SPCumin                                 0.19654
RC_1_SPD. distortum                          0.05449 .
RC_1_SPDill                                  0.70739
RC_1_SPEndive                                0.50847
RC_1_SPFallow                                0.71279
RC_1_SPFenugreek                             0.12621
RC_1_SPFlax                                  0.16338
RC_1_SPFoxtail millet                        0.59928
RC_1_SPGarden pea                            0.67238
RC_1_SPGarlic                                0.62170
RC_1_SPGiant spinach                         0.44060
RC_1_SPGourd                                 0.39697
RC_1_SPGroundnut                             0.34418
RC_1_SPLentil                                0.32581
RC_1_SPLinseed                               0.92835
RC_1_SPLupin                                 0.16039
RC_1_SPMaize                                 0.51718
RC_1_SPMaize/Cowpea/ Soya bean/ Groundnut    0.94016
RC_1_SPMelon                                 0.65702
RC_1_SPMillet / Cotton                       0.67200
RC_1_SPMung bean                             0.26195
RC_1_SPMustard                               0.11940
RC_1_SPNarbon vetch                          0.17251
RC_1_SPOnion                                 0.67027
RC_1_SPParsley                               0.32028
RC_1_SPPepper                                0.14557
RC_1_SPPigeon pea                            0.38922
RC_1_SPProso millet                          0.90054
RC_1_SPRed cabbage                           0.48528
RC_1_SPRoselle                               0.10469
RC_1_SPSenna didymobotrya                    0.31556
RC_1_SPSenna occidentalis                    0.89168
RC_1_SPSenna spectabilis                     0.92252
```

```
RC_1_SPSesame                                    0.30191
RC_1_SPSesbania cinerascens                      0.23025
RC_1_SPSesbania sesban                           0.87128
RC_1_SPSilverleaf nightshade                     0.51966
RC_1_SPSnap bean                                 0.39341
RC_1_SPSorhgum                                   0.26000
RC_1_SPSoya bean                                 0.28082
RC_1_SPSpinach                                   0.81827
RC_1_SPSquash                                    0.53112
RC_1_SPSquirting cucumber                        0.28420
RC_1_SPSugar beet                                0.66671
RC_1_SPSunflower                                 0.30964
RC_1_SPSyrian oregano                            0.83865
RC_1_SPTephrosia vogelii                         0.33306
RC_1_SPTithonia diversifolia                     0.90767
RC_1_SPTriticale                                 0.71088
RC_1_SPTurnip                                    0.61324
RC_1_SPVigna mungo                               0.37304
RC_1_SPWatermelon                                0.91388
RC_1_SPWheat                                     0.22804
RC_1_SPWild rue                                  0.44663
RC_1_SPWinter durum wheat                        0.54111
Model 6
Type III Analysis of Variance Table with Satterthwaite's
method
       Sum Sq Mean Sq NumDF DenDF F value  Pr(>F)
HC_V   173.32 11.5544    15    43  1.9530 0.04392 *
RC_1_V 122.55  2.9178    42    43  0.4932 0.98819
---
Signif. codes:
0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> summary(mixed.mod6)
Linear mixed model fit by REML. t-tests use
  Satterthwaite's method [lmerModLmerTest]
Formula: HEDGES ~ HC_V + RC_1_V + (1 | Study_ID)
   Data: MST_RC_ASD_IMP_WD
Weights: 1/VAR_G

REML criterion at convergence: 203.5

Scaled residuals:
    Min      1Q  Median      3Q     Max
-1.3160 -0.1490  0.0000  0.3867  2.2090

Random effects:
 Groups   Name        Variance Std.Dev.
 Study_ID (Intercept) 0.000    0.000
 Residual             5.916    2.432
Number of obs: 101, groups:  Study_ID, 16

Fixed effects:
                  Estimate Std. Error       df
(Intercept)        4.68023    1.99089 43.00000
HC_VHCV2          -3.49171    1.35255 43.00000
```

HC_VHCV20	-5.29538	2.10980	43.00000
HC_VHCV21	-5.47083	2.10980	43.00000
HC_VHCV4	-4.43023	2.12040	43.00000
HC_VHCV5	-3.30023	2.48045	43.00000
HC_VHCV6	-4.42023	2.12040	43.00000
HC_VHCV61	-0.01023	3.31723	43.00000
HC_VHCV64	-2.98661	2.30260	43.00000
HC_VHCV66	-3.50023	2.58556	43.00000
HC_VHCV67	-2.54183	2.45118	43.00000
HC_VHCV7	-3.39523	2.77325	43.00000
HC_VHCV71	5.66977	6.76696	43.00000
HC_VHCV73	-4.71023	2.08523	43.00000
HC_VHCV8	-3.90140	2.19832	43.00000
HC_VHCV9	-2.09340	2.13392	43.00000
RC_1_VRCV11	-1.26500	2.16191	43.00000
RC_1_VRCV12	-1.25500	1.66753	43.00000
RC_1_VRCV12/RCV58	-0.91500	2.06391	43.00000
RC_1_VRCV13	-0.92000	2.09238	43.00000
RC_1_VRCV14	-0.93000	2.09238	43.00000
RC_1_VRCV15	-0.69000	2.09238	43.00000
RC_1_VRCV16	-0.94000	2.09238	43.00000
RC_1_VRCV17	-0.73000	2.09238	43.00000
RC_1_VRCV18	-0.67000	2.09238	43.00000
RC_1_VRCV19	-1.61890	2.18078	43.00000
RC_1_VRCV2	-4.99000	2.95907	43.00000
RC_1_VRCV20	-1.04071	2.20429	43.00000
RC_1_VRCV21	-0.72047	2.20006	43.00000
RC_1_VRCV22	-0.03072	2.27951	43.00000
RC_1_VRCV23	-1.45246	2.10618	43.00000
RC_1_VRCV24	-0.32471	2.22650	43.00000
RC_1_VRCV25	-0.08592	2.26855	43.00000
RC_1_VRCV27	-0.38227	1.33581	43.00000
RC_1_VRCV28	0.34930	1.38751	43.00000
RC_1_VRCV29	-2.46274	1.96033	43.00000
RC_1_VRCV30	-0.11856	1.98065	43.00000
RC_1_VRCV31	-1.69292	1.80992	43.00000
RC_1_VRCV32	-2.54140	1.83089	43.00000
RC_1_VRCV33	-2.33053	1.83109	43.00000
RC_1_VRCV34	-1.61665	1.79582	43.00000
RC_1_VRCV37	-0.42000	1.71993	43.00000
RC_1_VRCV39	-0.88500	2.02045	43.00000
RC_1_VRCV4	-0.34000	2.28174	43.00000
RC_1_VRCV40	-1.30000	1.97604	43.00000
RC_1_VRCV41	0.50595	1.32285	43.00000
RC_1_VRCV42	-0.10370	1.31824	43.00000
RC_1_VRCV48	-1.06499	1.04173	43.00000
RC_1_VRCV51	-5.94000	7.15787	43.00000
RC_1_VRCV52	-8.87000	6.70109	43.00000
RC_1_VRCV53	-9.74000	6.64791	43.00000
RC_1_VRCV54	-2.44000	8.19811	43.00000
RC_1_VRCV55	0.19000	9.22688	43.00000
RC_1_VRCV57	-0.88500	2.13437	43.00000
RC_1_VRCV59	0.95250	0.91010	43.00000
RC_1_VRCV6	-0.18620	1.60174	43.00000

```
RC_1_VRCV7          0.42150    1.62435 43.00000
RC_1_VRCV8          2.07648    1.89511 43.00000
                  t value Pr(>|t|)
(Intercept)          2.351   0.0234 *
HC_VHCV2            -2.582   0.0133 *
HC_VHCV20           -2.510   0.0159 *
HC_VHCV21           -2.593   0.0129 *
HC_VHCV4            -2.089   0.0426 *
HC_VHCV5            -1.330   0.1904
HC_VHCV6            -2.085   0.0431 *
HC_VHCV61           -0.003   0.9976
HC_VHCV64           -1.297   0.2015
HC_VHCV66           -1.354   0.1829
HC_VHCV67           -1.037   0.3055
HC_VHCV7            -1.224   0.2275
HC_VHCV71            0.838   0.4067
HC_VHCV73           -2.259   0.0290 *
HC_VHCV8            -1.775   0.0830 .
HC_VHCV9            -0.981   0.3321
RC_1_VRCV11         -0.585   0.5615
RC_1_VRCV12         -0.753   0.4558
RC_1_VRCV12/RCV58   -0.443   0.6597
RC_1_VRCV13         -0.440   0.6624
RC_1_VRCV14         -0.444   0.6589
RC_1_VRCV15         -0.330   0.7432
RC_1_VRCV16         -0.449   0.6555
RC_1_VRCV17         -0.349   0.7289
RC_1_VRCV18         -0.320   0.7504
RC_1_VRCV19         -0.742   0.4619
RC_1_VRCV2          -1.686   0.0990 .
RC_1_VRCV20         -0.472   0.6392
RC_1_VRCV21         -0.327   0.7449
RC_1_VRCV22         -0.013   0.9893
RC_1_VRCV23         -0.690   0.4941
RC_1_VRCV24         -0.146   0.8847
RC_1_VRCV25         -0.038   0.9700
RC_1_VRCV27         -0.286   0.7761
RC_1_VRCV28          0.252   0.8024
RC_1_VRCV29         -1.256   0.2158
RC_1_VRCV30         -0.060   0.9525
RC_1_VRCV31         -0.935   0.3548
RC_1_VRCV32         -1.388   0.1723
RC_1_VRCV33         -1.273   0.2099
RC_1_VRCV34         -0.900   0.3730
RC_1_VRCV37         -0.244   0.8082
RC_1_VRCV39         -0.438   0.6636
RC_1_VRCV4          -0.149   0.8822
RC_1_VRCV40         -0.658   0.5141
RC_1_VRCV41          0.382   0.7040
RC_1_VRCV42         -0.079   0.9377
RC_1_VRCV48         -1.022   0.3123
RC_1_VRCV51         -0.830   0.4112
RC_1_VRCV52         -1.324   0.1926
RC_1_VRCV53         -1.465   0.1502
```

```
RC_1_VRCV54        -0.298   0.7674
RC_1_VRCV55         0.021   0.9837
RC_1_VRCV57        -0.415   0.6805
RC_1_VRCV59         1.047   0.3011
RC_1_VRCV6         -0.116   0.9080
RC_1_VRCV7          0.259   0.7965
RC_1_VRCV8          1.096   0.2793
Model 7
Type III Analysis of Variance Table with Satterthwaite's
method
      Sum Sq  Mean Sq NumDF  DenDF F value Pr(>F)
DIV 0.062847 0.062847     1 181.92   0.017 0.8965
> summary(mixed.mod7)
Linear mixed model fit by REML. t-tests use
  Satterthwaite's method [lmerModLmerTest]
Formula: HEDGES ~ DIV + (1 | Study_ID)
   Data: MST_RC_ASD_IMP_WD
Weights: 1/VAR_G

REML criterion at convergence: 1263

Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.3575 -0.4104  0.0825  0.7565  3.1825

Random effects:
 Groups   Name        Variance Std.Dev.
 Study_ID (Intercept) 0.8663   0.9307
 Residual             3.7039   1.9246
Number of obs: 368, groups:  Study_ID, 29

Fixed effects:
             Estimate Std. Error        df t value
(Intercept)   1.01486    0.66485 144.65689   1.526
DIV          -0.04031    0.30945 181.92414  -0.130
            Pr(>|t|)
(Intercept)    0.129
DIV            0.897

Correlation of Fixed Effects:
    (Intr)
DIV -0.957
Model 8

Type III Analysis of Variance Table with Satterthwaite's
method
         Sum Sq Mean Sq NumDF DenDF F value Pr(>F)
W_SP     22.392  3.7320     6    69  0.9968 0.4346
HC_SP     1.420  0.4735     3    69  0.1265 0.9441
RC_1_SP 110.846  2.1317    52    69  0.5694 0.9824
>  summary(mixed.mod5)
Linear mixed model fit by REML. t-tests use
  Satterthwaite's method [lmerModLmerTest]
Formula:
```

```
HEDGES ~ W_SP + HC_SP + RC_1_SP + (1 | Study_ID)
   Data: MST_RC_ASD_IMP_YD
Weights: 1/VAR_G

REML criterion at convergence: 249.7

Scaled residuals:
    Min      1Q  Median      3Q     Max
-2.2813 -0.1420  0.0000  0.1533  2.1696

Random effects:
 Groups   Name        Variance Std.Dev.
 Study_ID (Intercept) 0.000    0.000
 Residual             3.744    1.935
Number of obs: 131, groups:  Study_ID, 18

Fixed effects:
                                           Estimate
(Intercept)                                -0.73000
W_SPO.aegyptiaca                            0.64108
W_SPO.cernua                                0.57829
W_SPO.crenata                              -0.22143
W_SPO.ramosa                                0.72935
W_SPPhelipanche aegyptiaca                 -1.90950
W_SPS.hermonthica                           1.44046
HC_SPMaize                                 -0.67773
HC_SPPea                                   -0.41639
HC_SPPearl millet                           0.02066
RC_1_SPAubergine                           -0.02435
RC_1_SPBarley                               1.41782
RC_1_SPBasil                                0.61782
RC_1_SPBerseem                              0.96476
RC_1_SPBlack-eyed pea                     -12.88050
RC_1_SPBroccoli                             1.09143
RC_1_SPBrown Indian Hemp                  -17.09050
RC_1_SPBrussel sprout                       1.23555
RC_1_SPCabbage                              1.20338
RC_1_SPCanola                               1.30210
RC_1_SPCauliflower                          1.26324
RC_1_SPChickpea                             1.13782
RC_1_SPCommon bean                          0.41881
RC_1_SPCommon vetch                         0.34892
RC_1_SPCoriander                            0.84782
RC_1_SPCotton                              -1.28046
RC_1_SPCowpea                              -0.22484
RC_1_SPCrotalaria grahamiana               -0.62891
RC_1_SPCrotalaria juncea                   -0.48829
RC_1_SPCumin                                0.83782
RC_1_SPD. distortum                        -3.43273
RC_1_SPFaba bean                            0.03782
RC_1_SPFallow                              -0.07770
RC_1_SPFenugreek                           -0.60000
RC_1_SPFlax                                 0.09927
RC_1_SPGarden pea                          -0.10463
```

```
RC_1_SPGarlic                                 -0.16025
RC_1_SPGroundnut                              -0.17735
RC_1_SPLentil                                  0.76861
RC_1_SPLinseed                                -0.12000
RC_1_SPMaize                                  -0.16624
RC_1_SPMaize/Cowpea/ Soya bean/ Groundnut      0.27727
RC_1_SPMung bean                               0.07902
RC_1_SPNarbon vetch                            0.70782
RC_1_SPOnion                                  -0.11000
RC_1_SPPepper                                 -0.19980
RC_1_SPPigeon pea                             -0.86533
RC_1_SPSenna didymobotrya                     -1.52273
RC_1_SPSenna occidentalis                      0.77727
RC_1_SPSenna spectabilis                      -1.67773
RC_1_SPSesame                                 -0.84112
RC_1_SPSesbania cinerascens                   -2.28273
RC_1_SPSesbania sesban                        -1.20603
RC_1_SPSmooth vetch                            0.55782
RC_1_SPSnap bean                              -0.86000
RC_1_SPSorhgum                                -0.03784
RC_1_SPSoya bean                              -0.29305
RC_1_SPSunflower                              -0.19829
RC_1_SPTephrosia vogelii                      -3.05273
RC_1_SPTithonia diversifolia                  -4.89273
RC_1_SPTomato                                  0.14576
RC_1_SPTurnip                                  1.31196
                                             Std. Error
(Intercept)                                     1.32651
W_SPO.aegyptiaca                                1.46762
W_SPO.cernua                                    1.46591
W_SPO.crenata                                   1.42555
W_SPO.ramosa                                    0.92888
W_SPPhelipanche aegyptiaca                      1.64740
W_SPS.hermonthica                               1.60523
HC_SPMaize                                      2.19122
HC_SPPea                                        0.84991
HC_SPPearl millet                               2.13434
RC_1_SPAubergine                                1.81558
RC_1_SPBarley                                   2.01521
RC_1_SPBasil                                    2.03370
RC_1_SPBerseem                                  1.93124
RC_1_SPBlack-eyed pea                           7.89172
RC_1_SPBroccoli                                 2.12207
RC_1_SPBrown Indian Hemp                        9.84620
RC_1_SPBrussel sprout                           2.14056
RC_1_SPCabbage                                  2.12424
RC_1_SPCanola                                   2.14924
RC_1_SPCauliflower                              2.13615
RC_1_SPChickpea                                 2.01521
RC_1_SPCommon bean                              1.81565
RC_1_SPCommon vetch                             2.23590
RC_1_SPCoriander                                2.02448
RC_1_SPCotton                                   2.00920
RC_1_SPCowpea                                   2.02883
```

```
RC_1_SPCrotalaria grahamiana                     2.14667
RC_1_SPCrotalaria juncea                         2.32510
RC_1_SPCumin                                     2.02448
RC_1_SPD. distortum                              2.85334
RC_1_SPFaba bean                                 2.06113
RC_1_SPFallow                                    2.10388
RC_1_SPFenugreek                                 1.97323
RC_1_SPFlax                                      1.84918
RC_1_SPGarden pea                                1.97068
RC_1_SPGarlic                                    1.64025
RC_1_SPGroundnut                                 2.02191
RC_1_SPLentil                                    1.93862
RC_1_SPLinseed                                   1.89582
RC_1_SPMaize                                     1.99909
RC_1_SPMaize/Cowpea/ Soya bean/ Groundnut        2.20157
RC_1_SPMung bean                                 1.95049
RC_1_SPNarbon vetch                              2.02448
RC_1_SPOnion                                     1.89582
RC_1_SPPepper                                    1.66494
RC_1_SPPigeon pea                                2.06578
RC_1_SPSenna didymobotrya                        2.44337
RC_1_SPSenna occidentalis                        2.36552
RC_1_SPSenna spectabilis                         2.24785
RC_1_SPSesame                                    1.68603
RC_1_SPSesbania cinerascens                      2.57032
RC_1_SPSesbania sesban                           2.16264
RC_1_SPSmooth vetch                              2.03370
RC_1_SPSnap bean                                 2.03856
RC_1_SPSorhgum                                   2.03008
RC_1_SPSoya bean                                 2.01644
RC_1_SPSunflower                                 2.31703
RC_1_SPTephrosia vogelii                         2.75317
RC_1_SPTithonia diversifolia                     3.31465
RC_1_SPTomato                                    1.85075
RC_1_SPTurnip                                    2.15843
                                                     df
(Intercept)                                    69.00000
W_SPO.aegyptiaca                               69.00000
W_SPO.cernua                                   69.00000
W_SPO.crenata                                  69.00000
W_SPO.ramosa                                   69.00000
W_SPPhelipanche aegyptiaca                     69.00000
W_SPS.hermonthica                              69.00000
HC_SPMaize                                     69.00000
HC_SPPea                                       69.00000
HC_SPPearl millet                              69.00000
RC_1_SPAubergine                               69.00000
RC_1_SPBarley                                  69.00000
RC_1_SPBasil                                   69.00000
RC_1_SPBerseem                                 69.00000
RC_1_SPBlack-eyed pea                          69.00000
RC_1_SPBroccoli                                69.00000
RC_1_SPBrown Indian Hemp                       69.00000
RC_1_SPBrussel sprout                          69.00000
```

```
RC_1_SPCabbage                                69.00000
RC_1_SPCanola                                 69.00000
RC_1_SPCauliflower                            69.00000
RC_1_SPChickpea                               69.00000
RC_1_SPCommon bean                            69.00000
RC_1_SPCommon vetch                           69.00000
RC_1_SPCoriander                              69.00000
RC_1_SPCotton                                 69.00000
RC_1_SPCowpea                                 69.00000
RC_1_SPCrotalaria grahamiana                  69.00000
RC_1_SPCrotalaria juncea                      69.00000
RC_1_SPCumin                                  69.00000
RC_1_SPD. distortum                           69.00000
RC_1_SPFaba bean                              69.00000
RC_1_SPFallow                                 69.00000
RC_1_SPFenugreek                              69.00000
RC_1_SPFlax                                   69.00000
RC_1_SPGarden pea                             69.00000
RC_1_SPGarlic                                 69.00000
RC_1_SPGroundnut                              69.00000
RC_1_SPLentil                                 69.00000
RC_1_SPLinseed                                69.00000
RC_1_SPMaize                                  69.00000
RC_1_SPMaize/Cowpea/ Soya bean/ Groundnut  69.00000
RC_1_SPMung bean                              69.00000
RC_1_SPNarbon vetch                           69.00000
RC_1_SPOnion                                  69.00000
RC_1_SPPepper                                 69.00000
RC_1_SPPigeon pea                             69.00000
RC_1_SPSenna didymobotrya                     69.00000
RC_1_SPSenna occidentalis                     69.00000
RC_1_SPSenna spectabilis                      69.00000
RC_1_SPSesame                                 69.00000
RC_1_SPSesbania cinerascens                   69.00000
RC_1_SPSesbania sesban                        69.00000
RC_1_SPSmooth vetch                           69.00000
RC_1_SPSnap bean                              69.00000
RC_1_SPSorhgum                                69.00000
RC_1_SPSoya bean                              69.00000
RC_1_SPSunflower                              69.00000
RC_1_SPTephrosia vogelii                      69.00000
RC_1_SPTithonia diversifolia                  69.00000
RC_1_SPTomato                                 69.00000
RC_1_SPTurnip                                 69.00000
                                             t value
(Intercept)                                   -0.550
W_SPO.aegyptiaca                               0.437
W_SPO.cernua                                   0.394
W_SPO.crenata                                 -0.155
W_SPO.ramosa                                   0.785
W_SPPhelipanche aegyptiaca                    -1.159
W_SPS.hermonthica                              0.897
HC_SPMaize                                    -0.309
HC_SPPea                                      -0.490
```

```
HC_SPPearl millet                             0.010
RC_1_SPAubergine                             -0.013
RC_1_SPBarley                                 0.704
RC_1_SPBasil                                  0.304
RC_1_SPBerseem                                0.500
RC_1_SPBlack-eyed pea                        -1.632
RC_1_SPBroccoli                               0.514
RC_1_SPBrown Indian Hemp                     -1.736
RC_1_SPBrussel sprout                         0.577
RC_1_SPCabbage                                0.566
RC_1_SPCanola                                 0.606
RC_1_SPCauliflower                            0.591
RC_1_SPChickpea                               0.565
RC_1_SPCommon bean                            0.231
RC_1_SPCommon vetch                           0.156
RC_1_SPCoriander                              0.419
RC_1_SPCotton                                -0.637
RC_1_SPCowpea                                -0.111
RC_1_SPCrotalaria grahamiana                 -0.293
RC_1_SPCrotalaria juncea                     -0.210
RC_1_SPCumin                                  0.414
RC_1_SPD. distortum                          -1.203
RC_1_SPFaba bean                              0.018
RC_1_SPFallow                                -0.037
RC_1_SPFenugreek                             -0.304
RC_1_SPFlax                                   0.054
RC_1_SPGarden pea                            -0.053
RC_1_SPGarlic                                -0.098
RC_1_SPGroundnut                             -0.088
RC_1_SPLentil                                 0.396
RC_1_SPLinseed                               -0.063
RC_1_SPMaize                                 -0.083
RC_1_SPMaize/Cowpea/ Soya bean/ Groundnut     0.126
RC_1_SPMung bean                              0.041
RC_1_SPNarbon vetch                           0.350
RC_1_SPOnion                                 -0.058
RC_1_SPPepper                                -0.120
RC_1_SPPigeon pea                            -0.419
RC_1_SPSenna didymobotrya                    -0.623
RC_1_SPSenna occidentalis                     0.329
RC_1_SPSenna spectabilis                     -0.746
RC_1_SPSesame                                -0.499
RC_1_SPSesbania cinerascens                  -0.888
RC_1_SPSesbania sesban                       -0.558
RC_1_SPSmooth vetch                           0.274
RC_1_SPSnap bean                             -0.422
RC_1_SPSorhgum                               -0.019
RC_1_SPSoya bean                             -0.145
RC_1_SPSunflower                             -0.086
RC_1_SPTephrosia vogelii                     -1.109
RC_1_SPTithonia diversifolia                 -1.476
RC_1_SPTomato                                 0.079
RC_1_SPTurnip                                 0.608
                                           Pr(>|t|)
```

```
(Intercept)                                  0.5839
W_SPO.aegyptiaca                             0.6636
W_SPO.cernua                                 0.6944
W_SPO.crenata                                0.8770
W_SPO.ramosa                                 0.4350
W_SPPhelipanche aegyptiaca                   0.2504
W_SPS.hermonthica                            0.3727
HC_SPMaize                                   0.7580
HC_SPPea                                     0.6257
HC_SPPearl millet                            0.9923
RC_1_SPAubergine                             0.9893
RC_1_SPBarley                                0.4841
RC_1_SPBasil                                 0.7622
RC_1_SPBerseem                               0.6190
RC_1_SPBlack-eyed pea                        0.1072
RC_1_SPBroccoli                              0.6087
RC_1_SPBrown Indian Hemp                     0.0871 .
RC_1_SPBrussel sprout                        0.5657
RC_1_SPCabbage                               0.5729
RC_1_SPCanola                                0.5466
RC_1_SPCauliflower                           0.5562
RC_1_SPChickpea                              0.5742
RC_1_SPCommon bean                           0.8183
RC_1_SPCommon vetch                          0.8764
RC_1_SPCoriander                             0.6767
RC_1_SPCotton                                0.5260
RC_1_SPCowpea                                0.9121
RC_1_SPCrotalaria grahamiana                 0.7704
RC_1_SPCrotalaria juncea                     0.8343
RC_1_SPCumin                                 0.6803
RC_1_SPD. distortum                          0.2331
RC_1_SPFaba bean                             0.9854
RC_1_SPFallow                                0.9706
RC_1_SPFenugreek                             0.7620
RC_1_SPFlax                                  0.9573
RC_1_SPGarden pea                            0.9578
RC_1_SPGarlic                                0.9225
RC_1_SPGroundnut                             0.9304
RC_1_SPLentil                                0.6930
RC_1_SPLinseed                               0.9497
RC_1_SPMaize                                 0.9340
RC_1_SPMaize/Cowpea/ Soya bean/ Groundnut    0.9001
RC_1_SPMung bean                             0.9678
RC_1_SPNarbon vetch                          0.7277
RC_1_SPOnion                                 0.9539
RC_1_SPPepper                                0.9048
RC_1_SPPigeon pea                            0.6766
RC_1_SPSenna didymobotrya                    0.5352
RC_1_SPSenna occidentalis                    0.7435
RC_1_SPSenna spectabilis                     0.4580
RC_1_SPSesame                                0.6195
RC_1_SPSesbania cinerascens                  0.3776
RC_1_SPSesbania sesban                       0.5789
RC_1_SPSmooth vetch                          0.7847
```

```
RC_1_SPSnap bean                                     0.6744
RC_1_SPSorhgum                                       0.9852
RC_1_SPSoya bean                                     0.8849
RC_1_SPSunflower                                     0.9320
RC_1_SPTephrosia vogelii                             0.2714
RC_1_SPTithonia diversifolia                         0.1445
RC_1_SPTomato                                        0.9375
RC_1_SPTurnip                                        0.5453
---
Signif. codes:
0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation matrix not shown by default, as p = 62 > 12.
Use print(x, correlation=TRUE)  or
    vcov(x)        if you need it

fit warnings:
fixed-effect model matrix is rank deficient so dropping 3
columns / coefficients
optimizer (nloptwrap) convergence code: 0 (OK)
boundary (singular) fit: see ?isSingular
```

```
Model 9
Type III Analysis of Variance Table with Satterthwaite's
method
    Sum Sq Mean Sq NumDF DenDF F value Pr(>F)
DIV 1.3665  1.3665     1 125.4  0.4513  0.503
> summary(mixed.mod9)
Linear mixed model fit by REML. t-tests use
  Satterthwaite's method [lmerModLmerTest]
Formula: HEDGES ~ DIV + (1 | Study_ID)
   Data: MST_RC_ASD_IMP_YD
Weights: 1/VAR_G

REML criterion at convergence: 399.2

Scaled residuals:
    Min      1Q  Median      3Q     Max
-2.3063 -0.6924  0.0000  0.3082  2.5576

Random effects:
 Groups   Name        Variance Std.Dev.
 Study_ID (Intercept) 0.06568  0.2563
 Residual             3.02806  1.7401
Number of obs: 131, groups:  Study_ID, 18

Fixed effects:
            Estimate Std. Error       df t value
(Intercept)  -0.9285     0.8711 121.3603  -1.066
DIV           0.2866     0.4266 125.3965   0.672
            Pr(>|t|)
```

```
(Intercept)    0.289
DIV            0.503

Correlation of Fixed Effects:
    (Intr)
DIV -0.992
Model 10

Type III Analysis of Variance Table with Satterthwaite's
method
       Sum Sq Mean Sq NumDF DenDF F value Pr(>F)
HC_V   20.481  2.9259     7     8  1.5439 0.2772
RC_1_V 18.622  1.0345    18     8  0.5459 0.8637
> summary(mixed.mod10)
Linear mixed model fit by REML. t-tests use
  Satterthwaite's method [lmerModLmerTest]
Formula: HEDGES ~ HC_V + RC_1_V + (1 | Study_ID)
   Data: MST_RC_ASD_IMP_YD
Weights: 1/VAR_G

REML criterion at convergence: 25.6

Scaled residuals:
   Min     1Q Median     3Q    Max
-1.069  0.000  0.000  0.000  1.253

Random effects:
 Groups   Name        Variance Std.Dev.
 Study_ID (Intercept) 0.000    0.000
 Residual             1.895    1.377
Number of obs: 34, groups:  Study_ID, 8

Fixed effects:
             Estimate Std. Error       df t value
(Intercept)  -0.14000    0.41299  8.00000  -0.339
HC_VHCV5      0.42000    0.85970  8.00000   0.489
HC_VHCV6      0.03000    0.58405  8.00000   0.051
HC_VHCV61     0.83000    0.85970  8.00000   0.965
HC_VHCV67    -0.08792    0.73165  8.00000  -0.120
HC_VHCV7      0.51000    1.10987  8.00000   0.460
HC_VHCV71   -15.38000    5.42503  8.00000  -2.835
HC_VHCV73    -0.43000    0.56760  8.00000  -0.758
RC_1_VRCV11  -0.43000    1.16811  8.00000  -0.368
RC_1_VRCV12  -0.49000    0.87066  8.00000  -0.563
RC_1_VRCV2   -0.43000    1.05741  8.00000  -0.407
RC_1_VRCV29   0.51204    0.87448  8.00000   0.586
RC_1_VRCV30   0.36792    0.85136  8.00000   0.432
RC_1_VRCV31   0.53973    0.86901  8.00000   0.621
RC_1_VRCV32   0.57859    0.88519  8.00000   0.654
RC_1_VRCV33   0.47987    0.85410  8.00000   0.562
RC_1_VRCV34   0.58845    0.89644  8.00000   0.656
RC_1_VRCV37  -0.32000    0.90271  8.00000  -0.354
RC_1_VRCV39  -0.46000    1.08396  8.00000  -0.424
RC_1_VRCV40  -1.18000    1.09266  8.00000  -1.080
```

```
RC_1_VRCV50   1.74000    7.24399   8.00000   0.240
RC_1_VRCV51   0.82000    7.45542   8.00000   0.110
RC_1_VRCV52  -2.40000    8.24598   8.00000  -0.291
RC_1_VRCV53  -4.21000    8.72178   8.00000  -0.483
RC_1_VRCV54  -0.73000    7.82501   8.00000  -0.093
RC_1_VRCV55   8.63000    5.96733   8.00000   1.446
            Pr(>|t|)
(Intercept)    0.743
HC_VHCV5       0.638
HC_VHCV6       0.960
HC_VHCV61      0.363
HC_VHCV67      0.907
HC_VHCV7       0.658
HC_VHCV71      0.022 *
HC_VHCV73      0.470
RC_1_VRCV11    0.722
RC_1_VRCV12    0.589
RC_1_VRCV2     0.695
RC_1_VRCV29    0.574
RC_1_VRCV30    0.677
RC_1_VRCV31    0.552
RC_1_VRCV32    0.532
RC_1_VRCV33    0.590
RC_1_VRCV34    0.530
RC_1_VRCV37    0.732
RC_1_VRCV39    0.682
RC_1_VRCV40    0.312
RC_1_VRCV50    0.816
RC_1_VRCV51    0.915
RC_1_VRCV52    0.778
RC_1_VRCV53    0.642
RC_1_VRCV54    0.928
RC_1_VRCV55    0.186
```

Appendix 3D : R Scripts
Model 1
(Intercrop Weed Density “G” ~ Weed Species + Host Crop Species + Intercrop Species)

```
> MST_IC_ASD_IMP_WD<-read.csv("MST_IC_ASD_IMP_WD.CSV")
>
> mixed.mod1 <- lmer(HEDGES ~  # this is the individual effect size as the response variable
+                      W_SP+HC_SP+IC_SP+   # this is the fixed effects - so you could add the grouping variable here and it will tell you whether there is a difference in
+                     # effect size between different levels of the variable
+                     (1|Study_ID) ,
# this is the random effects (in this case grouping multiple effect sizes in each study together)
+                   data=MST_IC_ASD_IMP_WD,
+                   weights = 1/VAR_G,
# this is the weighting variable required for a meta-analysis (var.g = the individual effect size variances)
```

```
+                   na.action = "na.omit")
fixed-effect model matrix is rank deficient so dropping 7
columns / coefficients
> anova(mixed.mod1)
> summary(mixed.mod1)
```

Model 2
(Intercrop Weed Density "G" ~ Host Crop Variety + Intercrop Variety)

```
MST_IC_ASD_IMP_WD<-read.csv("MST_IC_ASD_IMP_WD.CSV")
mixed.mod2 <- lmer(HEDGES ~
                   HC_V +  IC_V+
                     (1|Study_ID) ,
                   data=MST_IC_ASD_IMP_WD,
                   weights = 1/VAR_G,
                   na.action = "na.omit")
anova(mixed.mod2)
summary(mixed.mod2)
```

Model 3
(Intercrop Yield "G" ~ Weed Species + Host Crop Species + Intercrop Species)

```
mixed.mod3 <- lmer(HEDGES ~
                     HC_SP+ IC_SP+ W_SP+
                     (1|Study_ID) ,
                   data=MST_IC_ASD_IMP_YD,
                   weights = 1/VAR_G,
                   na.action = "na.omit")
anova(mixed.mod3)
summary(mixed.mod3)
```

Model 4
(Intercrop Yield "G" ~ Host Crop Variety + Intercrop Variety)

```
MST_IC_ASD_IMP_YD<-read.csv("MST_IC_ASD_IMP_YD.CSV")
mixed.mod4 <- lmer(HEDGES ~
                   HC_V + IC_V+
                     (1|Study_ID) ,
                   data=MST_IC_ASD_IMP_YD,
                   weights = 1/VAR_G,
                   na.action = "na.omit")
anova(mixed.mod4)
summary(mixed.mod4)
```

Model 5
(Rotation crop Weed Density "G" ~ Weed Species + Host Crop Species + Rotation crop Species 1)

```
mixed.mod5 <- lmer(HEDGES ~
                     W_SP+ HC_SP+ RC_1_SP+
                     (1|Study_ID) ,
                   data=MST_RC_ASD_IMP_WD,
                   weights = 1/VAR_G,
                   na.action = "na.omit")
anova(mixed.mod5)
summary(mixed.mod5)
```

Model 6
(Rotation crop Weed Density "G" ~ Host Crop Variety + Rotation Crop 1 Variety)

```
MST_RC_ASD_IMP_WD<-read.csv("MST_RC_ASD_IMP_WD.CSV")
mixed.mod6 <- lmer(HEDGES ~
                     HC_V+ RC_1_V+
                     (1|Study_ID) ,
                   data=MST_RC_ASD_IMP_WD,
                   weights = 1/VAR_G,
                   na.action = "na.omit")
anova(mixed.mod6)
summary(mixed.mod6)
```

Model 7
(Rotation crop Yield “G” ~ Weed Species + Host Crop Species + Rotation crop 1 Species)

```
MST_RC_ASD_IMP_YD<-read.csv("MST_RC_ASD_IMP_YD.CSV")

mixed.mod7 <- lmer(HEDGES ~
                     W_SP + HC_SP + RC_1_SP+
                     (1|Study_ID) ,
                   data=MST_RC_ASD_IMP_YD,
                   weights = 1/VAR_G,
                   na.action = "na.omit")
anova(mixed.mod7)
summary(mixed.mod7)
```

Model 8
(Rotation crop Yield “G” ~ Host Crop Variety + Rotation Crop 1 Variety)

```
rm(list=ls())
library(lme4)
library(lmerTest)

setwd("C:/Users/Ragenaky/Desktop/Thesis chapter 3/Data/Master Sheets")
MST_RC_ASD_IMP_YD<-read.csv("MST_RC_ASD_IMP_YD.CSV")
mixed.mod8 <- lmer(HEDGES ~
                     HC_V + RC_1_V+
                     (1|Study_ID) ,
                   data=MST_RC_ASD_IMP_YD,
                   weights = 1/VAR_G,
                   na.action = "na.omit")
anova(mixed.mod8)
summary(mixed.mod8)
```

Model 9

```
MST_IC_ASD_IMP_WD<-read.csv("MST_IC_ASD_IMP_WD.CSV")

LM9 <- lm(Control_Mean ~
            Treat_Mean,
          data=MST_IC_ASD_IMP_WD,)
anova(LM9)
summary(LM9)
```

Model 10

```
MST_IC_ASD_IMP_YD<-read.csv("MST_IC_ASD_IMP_YD.CSV")

LM10 <- lm(Control_Mean ~
             Treat_Mean,
```

```
            data=MST_IC_ASD_IMP_YD,)
anova(LM10)
summary(LM10)
Model 11
MST_RC_ASD_IMP_WD<-read.csv("MST_RC_ASD_IMP_WD.CSV")

LM11 <- lm(Control_Mean ~
             Treat_Mean,
           data=MST_RC_ASD_IMP_WD,)
anova(LM11)
summary(LM11)
Model 12
MST_RC_ASD_IMP_YD<-read.csv("MST_RC_ASD_IMP_YD.CSV")

LM12 <- lm(Control_Mean ~
             Treat_Mean,
           data=MST_RC_ASD_IMP_YD,)
anova(LM12)
summary(LM12)

Model 13
mixed.mod13 <- lmer(HEDGES ~
                     DIV +
                     (1|Study_ID) ,
                   data=MST_RC_ASD_IMP_WD,
                   weights = 1/VAR_G,
                   na.action = "na.omit")
anova(mixed.mod13)
summary(mixed.mod13)

Model 14
MST_RC_ASD_IMP_YD<-read.csv("MST_RC_ASD_IMP_YD.CSV")
mixed.mod14 <- lmer(HEDGES ~
                     DIV +
                     (1|Study_ID) ,
                   data=MST_RC_ASD_IMP_YD,
                   weights = 1/VAR_G,
                   na.action = "na.omit")
anova(mixed.mod14)
summary(mixed.mod14)

Climate v Weed Density

rm(list=ls())# wipes slate clean
library(mgcv)
library(lme4)
library(lmerTest)
library(ggplot2)
library(dplyr)
library( geosphere )
library( stringr)
#Calculate a standard error
stderr <- function(x, ...) sd(x, na.rm = TRUE) /
sqrt(length(is.na(x == FALSE)) )
```

```
### Install this When you start for Multiplots!!!#####
#
# ggplot objects can be passed in ..., or to plotlist (as a
list of ggplot objects)
# - cols:   Number of columns in layout
# - layout: A matrix specifying the layout. If present, 'cols'
is ignored.
#
# If the layout is something like matrix(c(1,2,3,3), nrow=2,
byrow=TRUE),
# then plot 1 will go in the upper left, 2 will go in the
upper right, and
# 3 will go all the way across the bottom.
#
multiplot <- function(..., plotlist=NULL, file, cols=1,
layout=NULL) {
  library(grid)

  # Make a list from the ... arguments and plotlist
  plots <- c(list(...), plotlist)

  numPlots = length(plots)

  # If layout is NULL, then use 'cols' to determine layout
  if (is.null(layout)) {
    # Make the panel
    # ncol: Number of columns of plots
    # nrow: Number of rows needed, calculated from # of cols
    layout <- matrix(seq(1, cols * ceiling(numPlots/cols)),
                     ncol = cols, nrow =
ceiling(numPlots/cols))
  }

  if (numPlots==1) {
    print(plots[[1]])

  } else {
    # Set up the page
    grid.newpage()
    pushViewport(viewport(layout = grid.layout(nrow(layout),
ncol(layout))))

    # Make each plot, in the correct location
    for (i in 1:numPlots) {
      # Get the i,j matrix positions of the regions that
contain this subplot
      matchidx <- as.data.frame(which(layout == i, arr.ind =
TRUE))

      print(plots[[i]], vp = viewport(layout.pos.row =
matchidx$row,
                                      layout.pos.col =
matchidx$col))
    }
```

```
  }
}


#Fig 4a

Open_Data_IC_RC_WD<-read.csv("Open_Data_IC_RC_WD.CSV")

# Mean rainfall
model1 <- lm( log( Control_Mean + 1) ~  Mean_RF, data =
Open_Data_IC_RC_WD )
anova(model1)
summary(model1)

Open_Data_IC_WDA <- Open_Data_IC_RC_WD
Open_Data_IC_WDA$rainCat <- round(Open_Data_IC_WDA$ Mean_RF /
1.5) * 1.5
summaryRain <- Open_Data_IC_WDA %>%
group_by( rainCat ) %>%
summarise( meanN = mean(log( Control_Mean + 1), na.rm = TRUE),
SE = stderr(log( Control_Mean + 1), na.rm = TRUE)  )

fig4a <- ggplot( summaryRain,aes(x = rainCat, y = meanN) ) +
  geom_point(size = 1) +
geom_errorbar(aes( ymin = meanN - SE, ymax = meanN + SE),
width = 0.5, size = 0.25 ) +
  theme_bw() +
  theme( panel.border = element_blank(),
         panel.grid.major = element_blank(),
         panel.grid.minor = element_blank(),
         axis.line = element_line(colour = 'black', size =
0.25),
         axis.ticks = element_line(colour = "black", size =
0.25),
         axis.ticks.length=unit(-0.25, "cm"),
         axis.text.x =
element_text(margin=unit(c(0.5,0.5,0.5,0.5), "cm"), size =
10),
         axis.text.y =
element_text(margin=unit(c(0.5,0.5,0.5,0.5), "cm"), size =
10),
         legend.position="none",
         axis.title.x=element_text( size = 12 ),
         axis.title.y=element_text( size = 12 ) ) +
  labs( x = "Mean rainfall (mm)", y = "Log Weed density") +
  theme(axis.text.x = element_text(angle = 90))
fig4a

# Precipitation seasonality
model2 <- lm( log( Control_Mean + 1) ~  RFCV, data =
Open_Data_IC_RC_WD )
anova(model2)
summary(model2)
```

```
Open_Data_IC_WDA <- Open_Data_IC_RC_WD
Open_Data_IC_WDA$RFCVCat <- round(Open_Data_IC_WDA$ RFCV /
1.5) * 1.5
summaryRFCV <- Open_Data_IC_WDA %>%
  group_by( RFCVCat ) %>%
  summarise( meanN = mean(log( Control_Mean + 1), na.rm =
TRUE), SE = stderr(log( Control_Mean + 1), na.rm = TRUE)  )

fig4b <- ggplot(summaryRFCV, aes(x = RFCVCat, y = meanN) ) +
  geom_point(size = 1) +
  geom_errorbar(aes( ymin = meanN - SE, ymax = meanN + SE),
width = 0.5, size = 0.25 ) +
  theme_bw() +
  theme( panel.border = element_blank(),
         panel.grid.major = element_blank(),
         panel.grid.minor = element_blank(),
         axis.line = element_line(colour = 'black', size =
0.25),
         axis.ticks = element_line(colour = "black", size =
0.25),
         axis.ticks.length=unit(-0.25, "cm"),
         axis.text.x =
element_text(margin=unit(c(0.5,0.5,0.5,0.5), "cm"), size =
10),
         axis.text.y =
element_text(margin=unit(c(0.5,0.5,0.5,0.5), "cm"), size =
10),
         legend.position="none",
         axis.title.x=element_text( size = 12 ),
         axis.title.y=element_text( size = 12 ) ) +
  labs( x = "Precipitation seasonality (CV)", y = "Log Weed
density") +
  theme(axis.text.x = element_text(angle = 90))
fig4b

# ------------------------------

# altitude
model3 <- lm( log( Control_Mean + 1) ~  Alt, data =
Open_Data_IC_RC_WD)
anova(model3)
summary(model3)

Open_Data_IC_WDA <- Open_Data_IC_RC_WD
Open_Data_IC_WDA$altCat <- round(Open_Data_IC_WDA$Alt / 100) *
100
summaryAlt <- Open_Data_IC_WDA %>%
  group_by( altCat ) %>%
  summarise( meanN = mean(log( Control_Mean + 1), na.rm =
TRUE), SE = stderr(log( Control_Mean + 1), na.rm = TRUE)  )



fig4c <- ggplot(summaryAlt, aes(x = altCat, y = meanN) ) +
```

```
  geom_point(size = 1) +
  geom_errorbar(aes( ymin = meanN - SE, ymax = meanN + SE),
width = 0.5, size = 0.25 ) +
  theme_bw() +
  theme( panel.border = element_blank(),
         panel.grid.major = element_blank(),
         panel.grid.minor = element_blank(),
         axis.line = element_line(colour = 'black', size =
0.25),
         axis.ticks = element_line(colour = "black", size =
0.25),
         axis.ticks.length=unit(-0.25, "cm"),
         axis.text.x =
element_text(margin=unit(c(0.5,0.5,0.5,0.5), "cm"), size =
10),
         axis.text.y =
element_text(margin=unit(c(0.5,0.5,0.5,0.5), "cm"), size =
10),
         legend.position="none",
         axis.title.x=element_text( size = 12 ),
         axis.title.y=element_text( size = 12 ) ) +
  labs( x = "Altitude (m)", y = "Log Weed density") +
  theme(axis.text.x = element_text(angle = 90))
fig4c

# Mean temperature

model4 <- lm( log( Control_Mean + 1) ~ Mean_TA, data =
Open_Data_IC_RC_WD)
anova(model4)
summary(model4)


Open_Data_IC_WDA <- Open_Data_IC_RC_WD
Open_Data_IC_WDA$tempCat <- round(Open_Data_IC_WDA$Mean_TA /
1) * 1
summaryTemp <- Open_Data_IC_WDA %>%
  group_by( tempCat ) %>%
  summarise( meanN = mean (log( Control_Mean + 1), na.rm =
TRUE), SE = stderr(log( Control_Mean + 1), na.rm = TRUE)  )



fig4d <- ggplot(summaryTemp, aes(x = tempCat, y = meanN) ) +
  geom_point(size = 1) +
  geom_errorbar(aes( ymin = meanN - SE, ymax = meanN + SE),
width = 0.5, size = 0.25 ) +
  theme_bw() +
  theme( panel.border = element_blank(),
         panel.grid.major = element_blank(),
         panel.grid.minor = element_blank(),
         axis.line = element_line(colour = 'black', size =
0.25),
```

```
        axis.ticks = element_line(colour = "black", size =
0.25),
        axis.ticks.length=unit(-0.25, "cm"),
        axis.text.x =
element_text(margin=unit(c(0.5,0.5,0.5,0.5), "cm"), size =
10),
        axis.text.y =
element_text(margin=unit(c(0.5,0.5,0.5,0.5), "cm"), size =
10),
        legend.position="none",
        axis.title.x=element_text( size = 12 ),
        axis.title.y=element_text( size = 12 ) ) +
  labs( x = "Mean Temperature (\u00B0C)", y = "Log Weed
Density") +
  theme(axis.text.x = element_text(angle = 90))
fig4d

multiplot(fig4a + labs( tag = "A"), fig4b+ labs( tag = "B"),
fig4c+ labs( tag = "C"), fig4d+ labs( tag = "D"), cols = 2)
```

Climate v Yield

```
#Fig 4a

Open_Data_IC_RC_YD<-read.csv("Open_Data_IC_RC_YD.CSV")

# Mean rainfall
model1 <- lm  (Control_Mean  ~  Mean_RF, data =
Open_Data_IC_RC_YD )
anova(model1)
summary(model1)

Open_Data_IC_WDA <- Open_Data_IC_RC_YD
Open_Data_IC_WDA$rainCat <- round(Open_Data_IC_WDA$ Mean_RF /
1.5) * 1.5
summaryRain <- Open_Data_IC_WDA %>%
  group_by( rainCat ) %>%
  summarise( meanN = mean(Control_Mean , na.rm = TRUE), SE =
stderr( Control_Mean , na.rm = TRUE)  )

fig4a <- ggplot( summaryRain,aes(x = rainCat, y = meanN) ) +
  geom_point(size = 1) +
  geom_errorbar(aes( ymin = meanN - SE, ymax = meanN + SE),
width = 0.5, size = 0.25 ) +
  theme_bw() +
  theme( panel.border = element_blank(),
        panel.grid.major = element_blank(),
        panel.grid.minor = element_blank(),
        axis.line = element_line(colour = 'black', size =
0.25),
```

```
         axis.ticks = element_line(colour = "black", size =
0.25),
         axis.ticks.length=unit(-0.25, "cm"),
         axis.text.x =
element_text(margin=unit(c(0.5,0.5,0.5,0.5), "cm"), size =
10),
         axis.text.y =
element_text(margin=unit(c(0.5,0.5,0.5,0.5), "cm"), size =
10),
         legend.position="none",
         axis.title.x=element_text( size = 12 ),
         axis.title.y=element_text( size = 12 ) ) +
  labs( x = "Mean rainfall (mm)", y = "Yield (T/ha)") +
  theme(axis.text.x = element_text(angle = 90))
fig4a



# Precipitation seasonality
model2 <- lm( Control_Mean ~  RFCV, data = Open_Data_IC_RC_YD
)
anova(model2)
summary(model2)

Open_Data_IC_WDA <- Open_Data_IC_RC_YD
Open_Data_IC_WDA$RFCVCat <- round(Open_Data_IC_WDA$ RFCV /
1.5) * 1.5
summaryRFCV <- Open_Data_IC_WDA %>%
  group_by( RFCVCat ) %>%
  summarise( meanN = mean( Control_Mean, na.rm = TRUE), SE =
stderr(Control_Mean , na.rm = TRUE)  )

fig4b <- ggplot(summaryRFCV, aes(x = RFCVCat, y = meanN) ) +
  geom_point(size = 1) +
  geom_errorbar(aes( ymin = meanN - SE, ymax = meanN + SE),
width = 0.5, size = 0.25 ) +
  theme_bw() +
  theme( panel.border = element_blank(),
         panel.grid.major = element_blank(),
         panel.grid.minor = element_blank(),
         axis.line = element_line(colour = 'black', size =
0.25),
         axis.ticks = element_line(colour = "black", size =
0.25),
         axis.ticks.length=unit(-0.25, "cm"),
         axis.text.x =
element_text(margin=unit(c(0.5,0.5,0.5,0.5), "cm"), size =
10),
         axis.text.y =
element_text(margin=unit(c(0.5,0.5,0.5,0.5), "cm"), size =
10),
         legend.position="none",
         axis.title.x=element_text( size = 12 ),
         axis.title.y=element_text( size = 12 ) ) +
```

```
  labs( x = "Precipitation seasonality (CV)", y = "Yield
(T/ha)") +
  theme(axis.text.x = element_text(angle = 90))
fig4b

# ------------------------------

# altitude
model3 <- lm( Control_Mean  ~  Alt, data = Open_Data_IC_RC_YD)
anova(model3)
summary(model3)

Open_Data_IC_WDA <- Open_Data_IC_RC_YD
Open_Data_IC_WDA$altCat <- round(Open_Data_IC_WDA$Alt / 100) *
100
summaryAlt <- Open_Data_IC_WDA %>%
  group_by( altCat ) %>%
  summarise( meanN = mean( Control_Mean, na.rm = TRUE), SE =
stderr(Control_Mean , na.rm = TRUE)  )

fig4c <- ggplot(summaryAlt, aes(x = altCat, y = meanN) ) +
  geom_point(size = 1) +
  geom_errorbar(aes( ymin = meanN - SE, ymax = meanN + SE),
width = 0.5, size = 0.25 ) +
  theme_bw() +
  theme( panel.border = element_blank(),
         panel.grid.major = element_blank(),
         panel.grid.minor = element_blank(),
         axis.line = element_line(colour = 'black', size =
0.25),
         axis.ticks = element_line(colour = "black", size =
0.25),
         axis.ticks.length=unit(-0.25, "cm"),
         axis.text.x =
element_text(margin=unit(c(0.5,0.5,0.5,0.5), "cm"), size =
10),
         axis.text.y =
element_text(margin=unit(c(0.5,0.5,0.5,0.5), "cm"), size =
10),
         legend.position="none",
         axis.title.x=element_text( size = 12 ),
         axis.title.y=element_text( size = 12 ) ) +
  labs( x = "Altitude (m)", y = "Yield (T/ha)") +
  theme(axis.text.x = element_text(angle = 90))
fig4c

# Mean temperature

model4 <- lm( Control_Mean  ~ Mean_TA, data =
Open_Data_IC_RC_YD)
anova(model4)
summary(model4)

Open_Data_IC_WDA <- Open_Data_IC_RC_YD
```

```
Open_Data_IC_WDA$tempCat <- round(Open_Data_IC_WDA$Mean_TA /
1) * 1
summaryTemp <- Open_Data_IC_WDA %>%
  group_by( tempCat ) %>%
  summarise( meanN = mean( Control_Mean, na.rm = TRUE), SE =
stderr(Control_Mean , na.rm = TRUE)  )

fig4d <- ggplot(summaryTemp, aes(x = tempCat, y = meanN) ) +
  geom_point(size = 1) +
  geom_errorbar(aes( ymin = meanN - SE, ymax = meanN + SE),
width = 0.5, size = 0.25 ) +
  theme_bw() +
  theme( panel.border = element_blank(),
         panel.grid.major = element_blank(),
         panel.grid.minor = element_blank(),
         axis.line = element_line(colour = 'black', size =
0.25),
         axis.ticks = element_line(colour = "black", size =
0.25),
         axis.ticks.length=unit(-0.25, "cm"),
         axis.text.x =
element_text(margin=unit(c(0.5,0.5,0.5,0.5), "cm"), size =
10),
         axis.text.y =
element_text(margin=unit(c(0.5,0.5,0.5,0.5), "cm"), size =
10),
         legend.position="none",
         axis.title.x=element_text( size = 12 ),
         axis.title.y=element_text( size = 12 ) ) +
  labs( x = "Mean Temperature (\u00B0C)", y = "Yield (T/ha)")
+
  theme(axis.text.x = element_text(angle = 90))
fig4d

multiplot(fig4a + labs( tag = "A"), fig4b+ labs( tag = "B"),
fig4c+ labs( tag = "C"), fig4d+ labs( tag = "D"), cols = 2)

Linear Model for Diversity and plots

MST_RC_ASD_IMP_WD<-read.csv("MST_RC_ASD_IMP_WD.CSV")

stderr <- function(x) sd(x) / sqrt(length(x))

MST_RC_ASD_IMP_WD$DIV <- as.factor(MST_RC_ASD_IMP_WD$DIV)#To
change DIV to 4 level factor

#Divide treatment by control to make weed density % difference
MST_RC_ASD_IMP_WD$WDDif<-
(MST_RC_ASD_IMP_WD$Treat_Mean/MST_RC_ASD_IMP_WD$Control_Mean)*
100

#Look at diversity and change in weed density
LM1 <- lm( WDDif  ~  DIV, data=MST_RC_ASD_IMP_WD)
anova(LM1)
```

```
summary(LM1)

coeffs <- data.frame( summary(LM1)$coefficients )

coeffs$names <- str_remove( rownames(coeffs),
"MST_RC_ASD_IMP_WD" )

RCD<- c("1", "2", "3","4")#For the x tick labels

fig5a <- ggplot(coeffs, aes(x =  names,Estimate, y = Estimate)
) +
  geom_point(size = 1) +
  geom_errorbar(aes( ymin = Estimate - Std..Error, ymax
=Estimate + Std..Error ), width = 0.2, size = 0.25 ) +
  theme_bw() +  scale_x_discrete(labels= RCD)+
  theme( panel.border = element_blank(),
         panel.grid.major = element_blank(),
         panel.grid.minor = element_blank(),
         axis.line = element_line(colour = 'black', size =
0.25),
         axis.ticks = element_line(colour = "black", size =
0.25),
         axis.ticks.length=unit(-0.25, "cm"),
         axis.text.x =
element_text(margin=unit(c(0.5,0.5,0.5,0.5), "cm"), size =
10),
         axis.text.y =
element_text(margin=unit(c(0.5,0.5,0.5,0.5), "cm"), size = 8),
         legend.position="none",
         axis.title.x=element_text( size = 12 ),
         axis.title.y=element_text( size = 12 ) ) +
  labs( x = "Rotation Crop Diversity", y = "Density Change
Coefficient") +
  theme(axis.text.x = element_text(angle = 0, vjust = .7,
hjust=.65))
fig5a

fig5b<-ggplot(data = MST_RC_ASD_IMP_WD, aes(x=DIV, y=WDDif)) +
  geom_boxplot(fill=c('red', 'Yellow', 'blue','green'))+
  labs( x = "Rotation Crop Diversity", y = "Weed Density
Change")


fig5b

#Redo the LMER with diversity as a factor using effect size

mixed.mod1 <- lmer(HEDGES ~
                      DIV +
                      (1|Study_ID) ,
                    data=MST_RC_ASD_IMP_WD,
                    weights = 1/VAR_G,
                    na.action = "na.omit")
```

```
anova(mixed.mod1)
summary(mixed.mod1)

coeffs <- data.frame( summary(mixed.mod1)$coefficients )

coeffs$names <- str_remove( rownames(coeffs),
"MST_RC_ASD_IMP_WD" )

fig5c <- ggplot(coeffs, aes(x =  names,Estimate, y = Estimate)
) +
  geom_point(size = 1) +
  geom_errorbar(aes( ymin = Estimate - Std..Error, ymax
=Estimate + Std..Error ), width = 0.2, size = 0.25 ) +
  theme_bw() +  scale_x_discrete(labels= RCD)+
  theme( panel.border = element_blank(),
         panel.grid.major = element_blank(),
         panel.grid.minor = element_blank(),
         axis.line = element_line(colour = 'black', size =
0.25),
         axis.ticks = element_line(colour = "black", size =
0.25),
         axis.ticks.length=unit(-0.25, "cm"),
         axis.text.x =
element_text(margin=unit(c(0.5,0.5,0.5,0.5), "cm"), size =
10),
         axis.text.y =
element_text(margin=unit(c(0.5,0.5,0.5,0.5), "cm"), size = 8),
         legend.position="none",
         axis.title.x=element_text( size = 12 ),
         axis.title.y=element_text( size = 12 ) ) +
  labs( x = "Rotation Crop Diversity", y = "Effect Size (g)")
+
  theme(axis.text.x = element_text(angle = 0, vjust = .7,
hjust=.65))

fig5c

fig5d<-ggplot(data = MST_RC_ASD_IMP_WD, aes(x=DIV, y=HEDGES))
+
  geom_boxplot(fill=c('grey', 'grey', 'grey','grey'))+
  labs( x = "Rotation Crop Diversity", y = "Effect Size (g)")


fig5d



Figure5e <- ggplot( MST_RC_ASD_IMP_WD, aes(x = DIV, y =
HEDGES) ) +
  geom_point( size = 1) +
  geom_errorbar( aes(ymin = HEDGES - VAR_G, ymax = HEDGES +
VAR_G, width = 0.1,  ))  +
  theme_bw() +
  theme( panel.border = element_blank(),
```

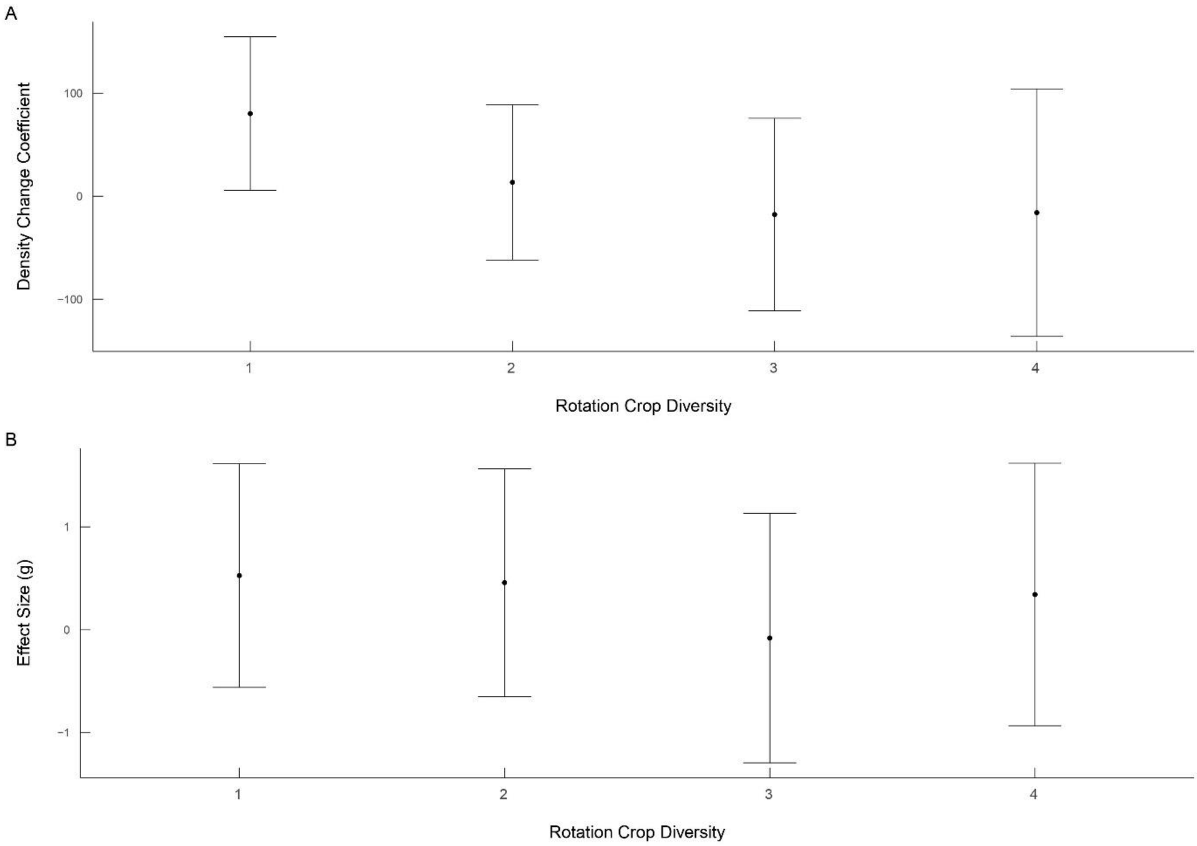
```
         panel.grid.major = element_blank(),
         panel.grid.minor = element_blank(),
         legend.position="none",
         axis.line = element_line(colour = 'black', size =
0.25),
         axis.ticks = element_line(colour = "black", size =
0.25),
         axis.text.x = element_text(size = 10),
         axis.text.y = element_text(size = 8),
         axis.title.x=element_text(size = 14),
         axis.title.y=element_text(size = 14) ) +
  geom_hline(yintercept = 0, linetype  = "dashed") +
  labs(x = "Rotation Crop Diversity") + labs( y = "Effect Size
(g)", las=2)

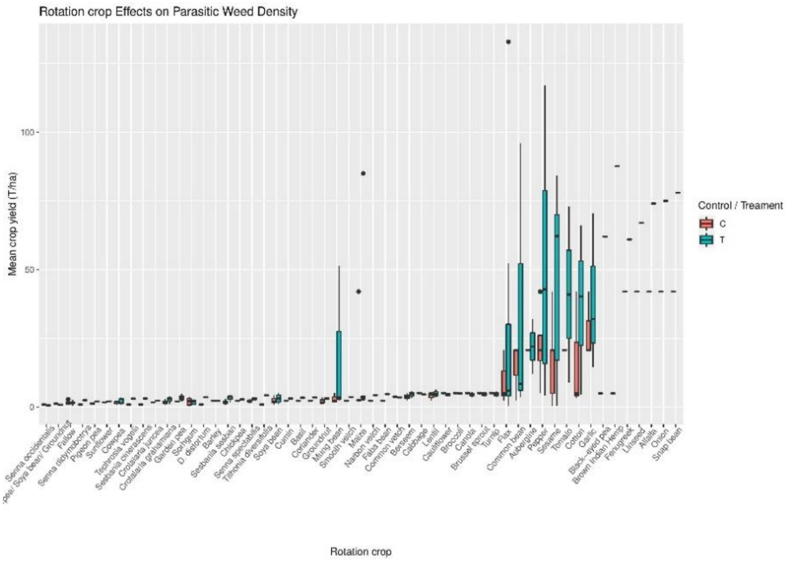
Figure5e

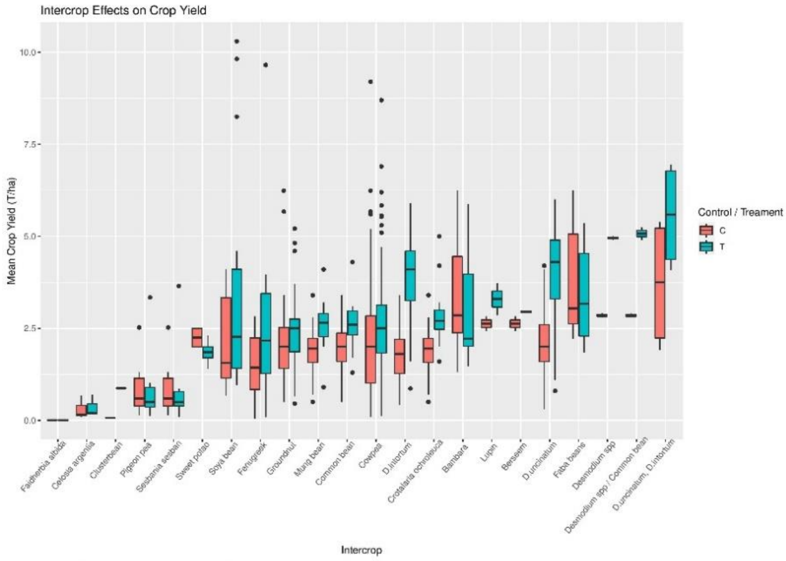
multiplot(fig5a + labs( tag = "A"), fig5c+ labs( tag = "B"),
cols = 1)
```

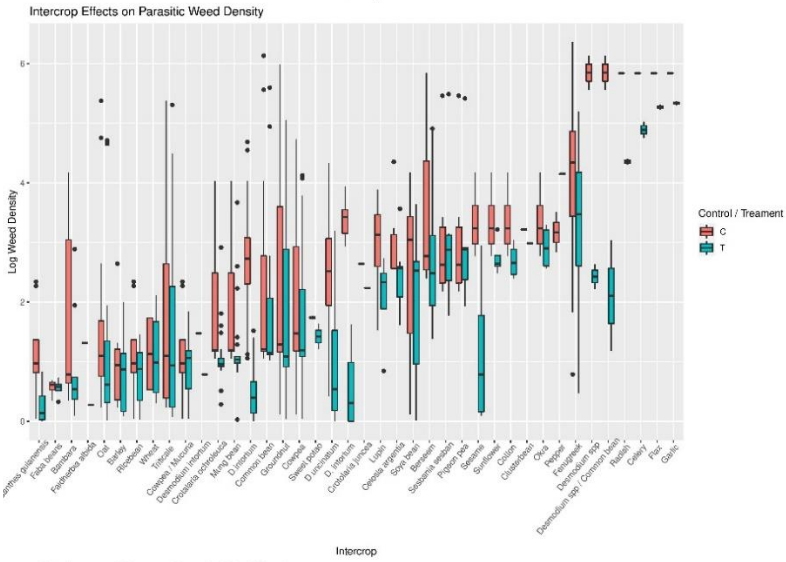
Appendix 4: Additional Figures

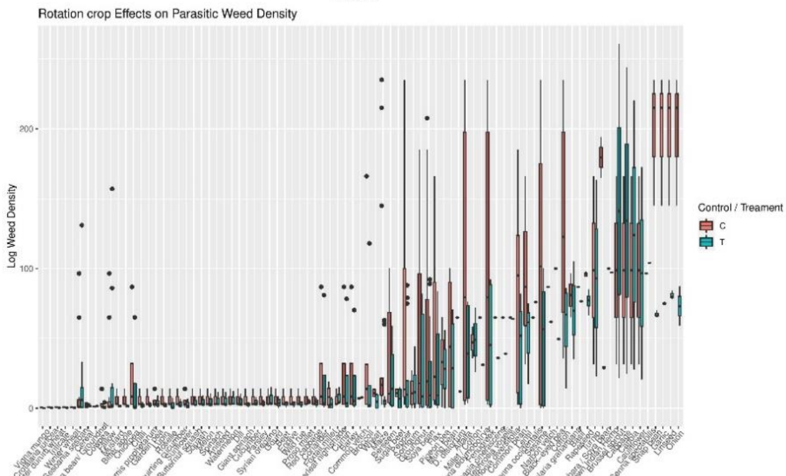
Changes in weed density coefficients (A) and Effect size (B) and Rotation Crop diversity


A
Density Change Coefficient
100
0
−100
1
2
3
4
Rotation Crop Diversity
B
Effect Size (g)
1
0
−1
1
2
3
4
Rotation Crop Diversity


Rotation crop Effects on Parasitic Weed Density
Mean crop yield (T/ha)
Rotation crop
Control / Treament
C
T

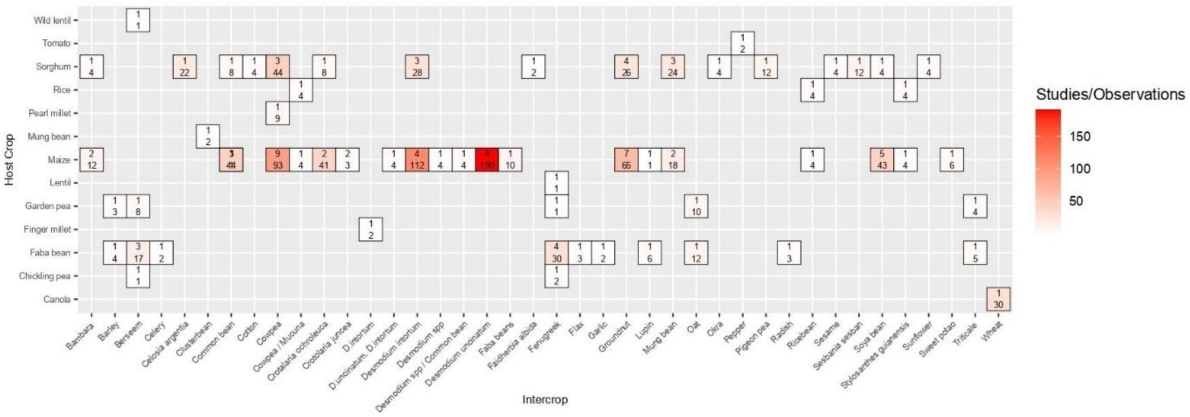

Intercrop Effects on Crop Yield
Mean Crop Yield (T/ha)
Intercrop
Control / Treament
C
T


Intercrop Effects on Parasitic Weed Density
Log Weed Density
Intercrop
Control / Treament
C
T

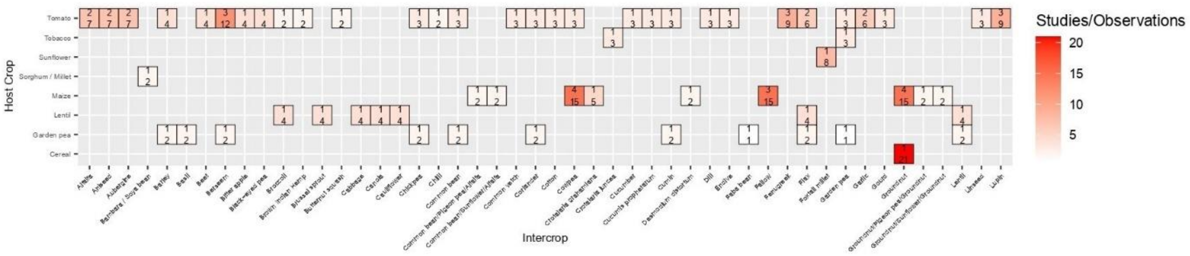

Rotation crop Effects on Parasitic Weed Density
Log Weed Density
Control / Treament
C
T

Contingency tables Intercrop and Rotation

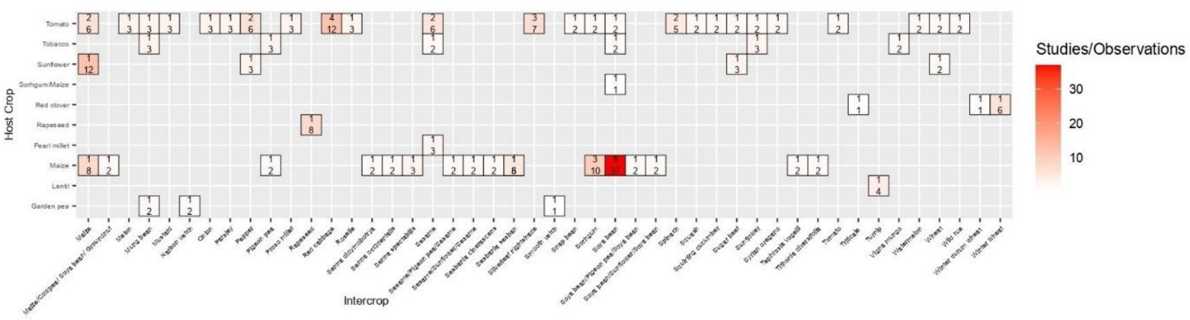
A



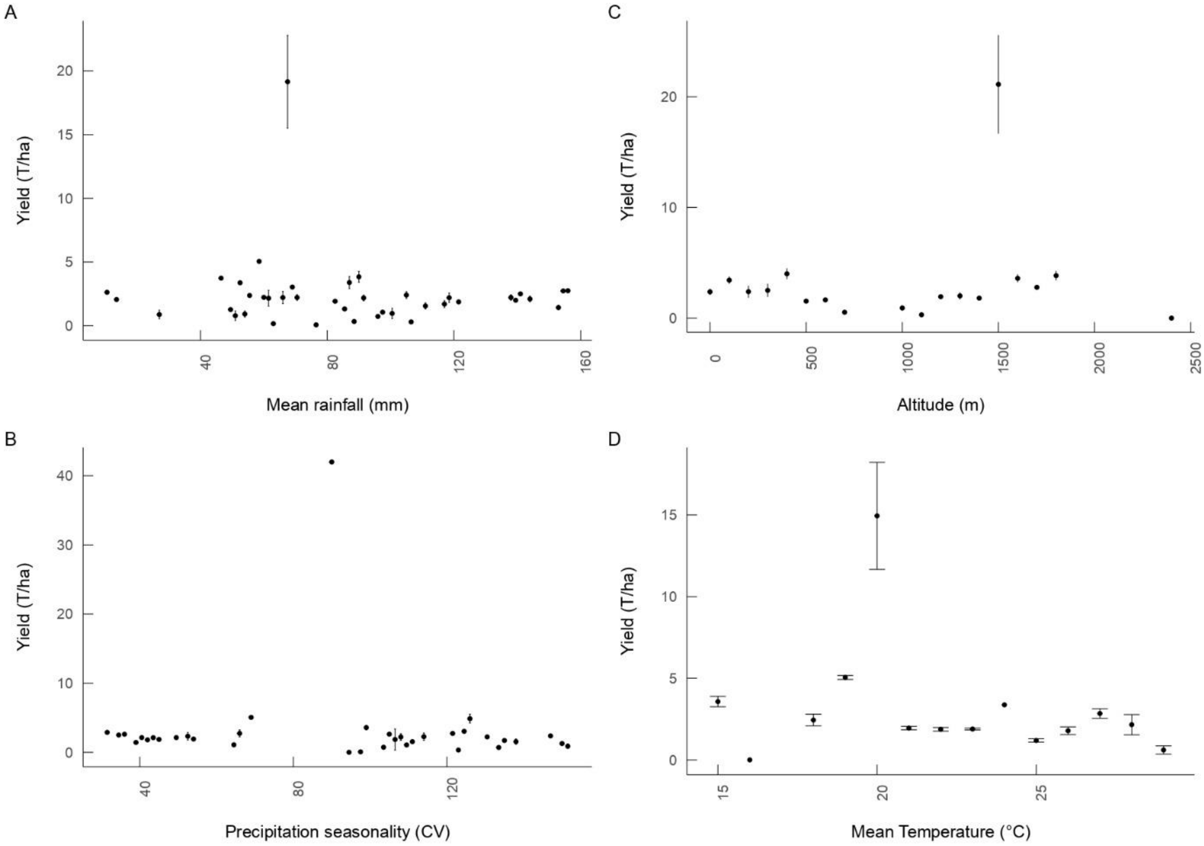
B



C



Yield and climate plots



Funnel plot for publication bias tests