MODELING INTEGRATED SOIL FERTILITY MANAGEMENT OPTIONS IN MALAWI UNDER VARIABLE SOIL AND CLIMATE CONDITIONS

by

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ABSTRACT

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Sustainable agriculture requires integrated soil fertility management, which relies to a considerable extent on the presence of legumes. On-farm participatory research in Africa has identified pigeonpea (*Cajanus cajan*) as a promising legume for improving fertility management in maize (*Zea mays*) systems. Including a long-duration legume like pigeonpea creates a trade-off between improved soil fertility and increased water stress, and impacts of the legume on maize production will depend on soil type and rainfall regime. This effect is difficult to quantify using short-term field trials. Using the simulation model APSIM, results from on-farm research in Malawi were extended to evaluate maize-pigeonpea rotation and intercrop systems relative to continuous maize with modest (24kgN/ha) fertilizer inputs in all systems. Performance over multiple years from system establishment was evaluated in different soil types, utilizing long-term weather records from two sites. Despite trade-offs between soil fertility and moisture, maize diversified with pigeonpea produced over double the yields of continuous maize on sandy, low fertility soils, with very low risk of failure. System performance under climate change scenarios was evaluated through modification of weather station data, including changes in rainfall of +/-10% and +/-25% and temperature increases of up to 4 °C to compare a maize-pigeonpea rotation to continuous maize at two nitrogen fertilization levels. Overall, maize yields in the rotation system were maintained under climate change scenarios, though declines were seen under some reduced rainfall scenarios. These results suggest that maize-pigeonpea systems can improve productivity in poor soils and are resilient to current and future climate variation.

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LIST OF ABBREVIATIONS

APSIM: Agricultural Production Systems Simulator

CO_2: Carbon Dioxide

ha: Hectare

ISFM: Integrated soil fertility management

kg: Kilogram

MZ24: Maize with 24 kilograms of nitrogen per hectare fertilizer input

MZ92: Maize with 24 kilograms of nitrogen per hectare fertilizer input

N: Nitrogen

OC: Organic carbon

Rot24: Maize-pigeonpea rotation with 24 kilograms of nitrogen per hectare fertilizer input applied to maize

LITERATURE REVIEW

Introduction

Improving agricultural productivity and food security in Africa has been a challenging and seemingly intractable problem. While much of the rest of the world experienced rapid increases in crop yields over the 1960s and 70s with the introduction of new varieties and increased fertilizer use of the Green Revolution, African yields have stagnated (Sanchez, 2002). Smallholder farmers face numerous constraints to production, including lack of access to markets and credit, poor infrastructure and the resulting high cost and lack of access to chemical inputs (Morris et al., 2007). Due to these constraints, many smallholder farmers are mining nutrients from already degraded soils, and as a consequence yields are low and extremely variable. This production environment will only grow more challenging as population growth increases the pressure on already limited land, while climate change brings additional risk and, in some areas, more marginal production environments for many common crops (Funk et al., 2008).

Sustainable intensification strategies are needed to improve smallholder productivity while protecting natural resources. Strategies for sustainable intensification of cropping systems are often placed in the contest of integrated soil fertility management (ISFM). ISFM techniques are management practices, tailored to local conditions, that make efficient use of mineral and organic sources of fertility and improved crop varieties to increase crop productivity (Vanlauwe et al., 2010). Increased use of multipurpose legumes has been proposed as one strategy for integrated soil fertility management in sub-Saharan agriculture (Snapp et al., 2010). Integrating semi-perennial legumes has been shown to improve productivity and reduce maize yield variability in specific cases. Because of the extremely variable soil and climate conditions found in many parts of sub-Saharan Africa, it is vital to assess integrated soil fertility management strategies in order to fit management practices to environmental conditions. Crop simulation models are capable of using long weather records, soil characterization and information about management practices to quantify interactions among these variables (Dixit et al., 2011).

Legume diversification for improved soil fertility

Integration of legumes into cropping systems is key to implementation of ISFM techniques, because legumes fix atmospheric nitrogen and their residues provide some of this fixed N to following cereal crops. A number of agroforestry strategies have been promoted, with varying degrees of success (Garrity et al., 2010). Green manure legumes such as *Mucuna puriens* have also had limited farmer adoption, with use mostly based on benefits other than soil fertility—for example, *Mucuna* is used for weed suppression. Grain legumes in rotation also have the potential to improve soil fertility if they can generate sufficient soil amelioration through roots and vegetative cover that can be retained in the field. Pigeonpea is one legume that shows potential as a dual use crop, producing both a high-protein grain and prolific leafy biomass, some of which senesces during the growing season and can provide a source of intermediate to high quality organic residue (Myaka et al., 2006). In Malawi, pigeonpea has shown promise in a variety of soil types as a way to improve nutrient cycling, fertilizer use efficiency and maize yields in long term countrywide and participatory trials (Snapp et al., 2010). In multiple sites, use of pigeonpea in rotation increased N fertilizer use efficiency by 50-120%, indicating significant positive impacts of the rotation system on soil fertility. Farmers consistently rank cropping systems including pigeonpea highly in participatory trials, due to its benefits for nutrition and food security as well as soil improvement (Bezner Kerr et al. 2007).

One concern in promoting increased use of long-duration, deep-rooted legumes is their potential for increased water use and thus reduce yield of main food crops in the following year (Wortmann et al., 2000). In semi-arid Zimbabwe, long-duration or high biomass producing legumes depleted water in the deep soil profile, though in this sandy soil, the differences vanished after the first major rainfall event (Ncube et al., 2007). In addition, drought stress can decrease the capability of legumes to fix nitrogen, reducing their soil fertility benefits (Dakora and Keya, 1997).

Performance of integrated soil fertility management strategies such as crop diversification with legumes will be affected by soil type and rainfall distribution. Interactions among management and environmental variables are difficult to demonstrate in field experiments, because of the short duration of such experiments. Yield response of cereal-legume systems in response to long-term climate variability and climate change has not yet been tested, and many “outscaling” questions remain. Crop simulation modeling can be used to answer some of these questions by extending the results of field experiments based on long-term climate records.

Crop models and the Agricultural Production Systems Simulator (APSIM)

APSIM was designed as a modular modeling framework for simulating a variety of cropping systems. Biophysical crop and soil modules are linked by a central simulation engine and controlled by management modules that allow the user to establish rules to control the biophysical modules (Keating et al., 2003). The system runs on a daily time step and requires daily climate data and a minimum set of soil data and crop variety information as inputs. Management practices can be set to follow specific operations in the case where a specific trial is being modeled, or to follow logical rules, as in the case of simulating management scenarios.

Crop modules

Crop modules in APSIM follow a set of routines based on physiological relationships describing growth of plant components based on temperature, light, water, and nutrient availability. Individual crop modules are stored as parameter files, which include crop and variety-specific relationships.

APSIM uses the Plant module to simulate all legume crops, as well as several others. This model uses a set of generic routines to simulate important plant growth parameters, as described in Robertson et al. (2002). Phenology is determined by thermal time and photoperiod, with plant growth described as transitions between a number of phases, separated by key stages such as emergence, flowering, and maturity. Leaf development is modeled by combining functions for leaf appearance and expansion, so that the potential leaf area is a combination of number and maximum leaf size. The simulated leaf growth will be less than the potential leaf growth only if carbon is limiting, as may occur at very high plant population densities. Biomass production is predicted initially from the plant's photosynthetic capacity as determined by its leaf area and radiation use efficiency. This biomass is then partitioned into roots, stem, leaves, and later to grain, based on experimentally determined ratios. Root biomass is converted to root length and depth based on a specific root length parameter, as well as a soil parameter defining any physical or chemical limitations that affect root penetration. Because some of the plants simulated with the legume model are perennial, this module allows for harvest at a specified height above the ground, with or without subsequent regrowth of the plant (Robertson et al., 2002).

Nitrogen uptake is simulated as a combination of mass flow (nitrate entering as roots take up water from soil solution), active uptake (diffusive uptake of nitrate and ammonia by roots), and nitrogen fixation(Robertson et al., 2002). The crop's demand for nitrogen is determined by the minimum, optimal, and maximum N concentrations in its various tissues. Required N is taken up first by mass flow, then by either active uptake or fixation, based on parameters that are set for each crop. These can also vary based on growth phase. Thus juvenile plants whose roots have not yet developed nodules may be less able to fix nitrogen. Deficits in nitrogen lead to a reduction in growth when compared to the optimal case, limited only by photosynthetic capability(Robertson et al., 2002).

Water deficits also slow modeled plant growth. Water demand by the crop is calculated as a function of crop growth divided by transpiration efficiency. Soil water supply is calculated using available soil water, calculated in soils modules described below, and the potential of roots to extract this water. Water extraction occurs in layers where roots are present, at rates defined by an extraction coefficient. If the soil water supply is below demand, a water stress factor is used to reduce the modeled rate of plant growth from the photosynthetically limited rate.. Water stress also reduces the ability of N-fixing crops to fix nitrogen, and the degree of the reduction will vary by species (Robertson et al., 2002).

The pigeonpea module in APSIM is one instance of APSIM's Plant module. It was tested on 38 datasets taken from existing literature (Robertson et al., 2001) for extra-short, short, and medium duration varieties. A long-duration cultivar was added later. The model showed generally good agreement with field data, with a few limitations. Pigeonpea leaves tend to senesce and drop late in the growing season, so that final biomass is difficult to measure and to simulate properly. The model did capture water stress accurately, but it did not adequately account for waterlogging. The data sets used for model validation were all obtained in central India, but phenological responses have been shown to be accurate for Kenyan conditions as well

(Carberry et al., 2001). Ncube et al. (2009) modeled pigeonpea yields in Zimbabwe and found modeled yields and biomass were within about one standard error from mean observed values.

The maize module in APSIM is similar to that in many other cropping systems models and was based originally on CERES-Maize (Carberry, 1989). It simulates largely the same crop growth characteristics, with the addition of maize-specific traits such as tasseling and silking. It follows its own routines and not those of the generic Plant module because it was developed earlier than other plant growth models. A key component of this module, of particular importance for the current study, is its ability to simulate plant response to the low fertilizer rates common in African smallholder farming systems. Shamudzarira and Robertson (2002) studied this response in Zimbabwe and found that APSIM simulated grain yields at fertilizer levels ranging from 0-60 kgN/ha to within one standard error of mean observed yields at Makoholi Research Station in Zimbabwe.

Soil modules

Soil processes are modeled in several different modules. Soilwat, the water balance model, uses a cascading layer model first developed for the CERES suite of crop models (Ritchie, 1972). Soils are input as a series of layers with set depths and volumetric water holding capacities at key pressures. These are the lower limit (LL15, 1500 kPa), drained upper limit (DUL, also known as field capacity, 33 kPa), and saturation. Water flow processes include runoff, evaporation and transpiration, as well as both saturated and unsaturated vertical flow. The module interfaces with a separate module, SurfaceOM, which calculates decomposition of surface residues generated by the various crops, to account for the effects of these residues on runoff and evaporation(Probert et al., 1998). This system has been shown to be very robust in accurately modeling soil water content of different cropping systems over a range of soils and environments (e.g. Ncube et al. 2009, Probert et al. 1998, Keating et al. 2003).

APSIM's SOILN module is responsible for simulating both carbon and nitrogen cycling in soil, since these are usually coupled (Probert et al., 1998). It treats soil organic matter as three pools, plus an additional pool consisting of fresh organic matter (FOM). Residues incorporated into the soil and decomposing roots first enter the FOM pool, where they are transformed into either the rapid turnover microbial biomass (BIOM) pool or the slower turnover, less available humic (HUM) pool. There is an additional component of inert OM, which represents highly recalcitrant OM and has a turnover rate on the order of centuries. In APSIM, inert OM is considered to be a fraction of the HUM pool which is not allowed to decompose (Probert et al., 1998). Carbon to nitrogen ratios (C:N) are assumed to be constant in the BIOM and HUM pools. The flow between pools is governed by carbon dynamics, with nitrogen released as a function of changes in C:N ratios between pools. Mineral N produced by decomposition is available for plant uptake or immobilization in soil. If insufficient N is present in FOM, the rate of decomposition is slowed (Probert et al., 1998).

Modeling maize-legume cropping systems

Accurate modeling of crop growth, nutrient flows, decomposition and other processes is key to simulating the effect of including legumes in the cropping system. Because of legumes' ability to fix atmospheric N_2, their residues tend to be enriched in N and some of this N may be available to the subsequent maize crop. APSIM is capable of simulating these effects. This has been shown for low-input smallholder farming systems in Africa, in the case of grain legumes benefitting sorghum (Ncube et al., 2009) in Zimbabwe, and in the case of maize response to previous velvet bean (*Mucuna pruriens)* green manures in Malawi (Robertson et al., 2005).

Ncube et al. (2009) report simulation modeling of a trial conducted at Matopos Research Station in the semi-arid region of Zimbabwe, which tested several different types of grain legumes for their productivity and their residual effect on sorghum. The experiment used two varieties each of cowpea (*Vigna unguiculata*), groundnut (*Arachis hypogaea*), pigeonpea, and Bambara groundnut (*Vigna subterranea*) in rotation with sorghum (*Sorghum bicolor*) (Ncube et al., 2007). Phosphorus fertilizer was applied based on soil test results, but no inorganic nitrogen was applied. Nitrogen fixed by legumes was measured by ^{15}N natural abundance and N difference methods, and total biomass and yield were recorded. Soil water was measured by neutron probe and gravimetric methods (Ncube et al., 2009). This study showed generally good agreement between model and experiment for legume growth, N fixation, and water use. Water use at the end of the growing season was underestimated, most likely due to the lack of weeds and their water uptake. The simulated response of sorghum in rotation was accurate in predicting total biomass, but underestimated grain yields, especially after pigeonpea. For sorghum grown after pigeonpea, model yields were up to 30% below observed yields where pigeonpea residues were incorporated. The authors attribute this discrepancy to the model not simulating pigeonpea leaf fall during the season. Allowing for leaf fall improved the simulated sorghum yields, but resulted in an under-prediction of pigeonpea biomass at the end of the growing season (Ncube et al., 2009).

A study in Malawi by Robertson et al. (2005) tested the response of maize to nitrogen from a *Mucuna pruriens* green manure and developed a *Mucuna* module in APSIM. The *Mucuna* module was developed from the same general plant template used for pigeonpea and other legumes, and APSIM was used to simulate growth of the green manure itself as well as the effect of the green manure on subsequent maize yields. A calibration field trial was established in five sites and over two growing seasons from 1998-2000. At all five sites, maize was planted in the 1998-99 growing season with nitrogen fertilizer levels of 0 and 69 kgN/h, and *Mucuna* was planted in adjacent plots. In the second year, the previous maize plots were planted with the same fertilizer levels. The *Mucuna* plots were planted to maize with 0 and 34.5 kgN/ha. An additional fertilizer response trial was established at Chitedze, one of the five sites, in 1997-98. In the fertilizer response portion of the trial, fertilizer rates ranged from 0 to 92 kgN/ha applied as urea. (Robertson et al., 2005).

Field results showed variation in response to both inorganic fertilizer and the green manure legume. The highest responses were seen in soils with low initial inorganic nitrogen and low organic carbon content. When fertilizer was applied to maize following *Mucuna*, the response to the green manure was only significant at the lowest fertility soils, which had organic carbon contents of less than 0.7%. APSIM simulated maize yields well over the range of fertilizer rates and fertilizer-green manure combinations. Thus the legume model is able to generate the appropriate quantities and qualities of biomass, the soil modules are processing it, and the maize module is responsive to this type of N input in appropriate ways. The authors reported very high variability in maize response to green manure legumes in field trials based on soil, crop management, and climate factors and note the importance of using simulation modeling to better identify the possible yield responses in a variety of environments.

Climate variability and risk in rainfed agriculture

Agriculture in sub-Saharan Africa is predominantly rainfed. Especially in drier areas, variable rainfall leads to a great deal of variation in yields from season to season, making agriculture inherently risky, particularly for farmers whose livelihood and food security depend on their crop production. Understanding the degree of climate risk and developing improved strategies for coping with this risk are important in agricultural research and extension in these areas.

The simplest way to quantify climate-related risk is by a statistical analysis of rainfall records. Where long-term records exist, valuable insights can be gained from analysis of various components of these data. Stern and Cooper (2011) report several methods for analyzing rainfall data in a case study from Zambia. These include identification of successful planting dates, length of growing season, and risks of dry spells at various key points in crop growth. These types of analyses can be much more informative than simple annual or monthly totals, since dry spells at key crop development stages can cause low yields or crop failures in a year when total rainfall appears adequate.

Crop models can expand upon these types of analyses by accounting for interactions among climate, soil, and crop. They also allow the evaluation of cropping systems or management strategies as methods for coping with variability. One key issue that can be addressed by models is the targeting of fertilizer recommendations, which are often based on maximizing potential crop yield and do not accurately account for the economic realities of smallholder farmers (Marenya and Barrett, 2009). These farmers have limited resources to spend on fertilizer and also tend to be highly risk-averse. Because of this they tend not to apply fertilizers at recommended rates. In some areas, fertilizer recommendations have been developed that specifically consider these issues, and crop models can be used to test these recommendations for risk and overall profitability.

In Zimbabwe, M.I. Piha (1993) developed a system of variable fertilizer application for maize based on rainfall amounts early in the season. This system, which was tested in trials at three sites and over three growing seasons, included low application rates of N at planting followed by variable top-dressing rates of between 0 and 150 kgN/ha applied at 4 and 6 weeks after planting and at maize tasseling. The rates varied based on the location of the trial site (those located in drier regions received lower fertilizer rates) and amount of rainfall up to the application date. In this study, yields and economic return to fertilizer were significantly higher under the variable-N system than under fixed N application at the recommended rates. Shamudzarira and Robertson (2002) investigated the long-term productivity and profitability of maize production using a similar approach, with low and variable N application in simulations of fertilizer response using 46 years of daily climate data. They tested both fixed and variable N applications at rates ranging from 0 to 60 kgN total. At these low rates of fertilizer use, conditional application of fertilizer resulted in lower levels of fertilizer application, but overall similar yield and economic returns, with conditional application resulting in slightly lower economic return to fertilizer. The model captured the risk distribution in fertilizer response, and that this response was only correlated to rainfall within a range of 250 to 550 mm of rainfall over the season (Shamudzarira and Robertson, 2002). Below this level, crops failed regardless of fertilizer, and above it yields tended to plateau. This trend was also observed in field trials. These results indicate that establishing a viable fertilizer recommendation that accounts for resource constraints and risk is more important than varying application rates by year.

Crop models can also be used to extend the results of short-term field trials by accounting for long-term variability in high productivity areas. Dixit et al. (2011) used APSIM to simulate maize fertilizer response trials to establish a profitable rate of fertilizer over a 50-year simulation dataset in Kitale, Kenya. They used extensive data from variety trials conducted in 1977 at the National Agricultural Research Station in Kitale to calibrate APSIM, and this calibrated model produced yield results which agreed to within 5% of observed yields. This study also validated and used the stochastic weather generator MarkSim (Jones and Thornton, 2000) to create long-term sequences of representative rainfall and temperature data where these are unavailable. MarkSim uses climate surfaces interpolated from existing weather stations to create sequences of temperature and rainfall that are statistically similar to the long-term patterns at a given location. This tool is potentially very useful for other studies in sub-Saharan Africa, where weather data, particularly the types of long-term records needed to evaluate risk, are often missing. The Kitale study first demonstrated the validity of the MarkSim generated weather by comparison to a shorter existing climate station record, then used these data to evaluate probability distributions of maize yield at various fertilizer levels and weed control treatments. They found that given the high yield potentials in this area, even very high levels of fertilizer can be economically justified. For this analysis they use current maize and nitrogen fertilizer prices of \$2.86 kg^{-1} for N and \$0.252 kg^{-1} for maize. In this case nitrogen applications of 150 kg/ha applied as 30 kgN at planting and 120 kgN at 5 weeks post emergence produced a rate of return of at least 3 in 9 out of 10 years.

Climate change

As concern over the potential impacts of climate change increases, strategies for coping with year-to-year climate variability are seen as key components of long-term adaptation to climate change (Cooper et al., 2008). Climate risk management strategies are important both because they suggest longer-term adaptation possibilities and because climate variability is likely to increase in the future (Christensen et al., 2007).

Studying potential adaptation strategies is complicated by the fact that climate predictions for many parts of sub-Saharan Africa are highly uncertain. In many parts of eastern and southern Africa, General Circulation Models (GCMs) do not agree on the direction of rainfall change, much less the magnitude (Christensen et al., 2007). This uncertainty is compounded by the need to downscale GCM projections from their typical 100-300 km resolution to account for local variation (Winkler et al., 2011). This can be done in a variety of different ways. Dynamic downscaling uses regional climate models similar to GCMs, applied over a smaller area, to generate predictions at finer resolution. These models are provided with boundary conditions from GCMs. This process is computationally intensive, and variation among RCMs is as large as that among GCMs (Winkler et al., 2011). Statistical, or empirical, downscaling uses regression analysis to relate current climate variables found in historical weather records to modeled climate variables from GCMs. Although this method is less rigorous because it does not consider the dynamic relationships within the climate system, well-performed statistical downscaling has been shown to produce similar results to RCM outputs (Wood et al., 2004). All these methods rely on extensive historical data for parameterization, which is lacking in much of the developing world (Jones et al., 2005).

Given the uncertainty surrounding climate change projections, one possibility is to adopt a sensitivity analysis approach. This can be done by varying rainfall and temperature in ways consistent with the range of possibilities for future climate and evaluating potential management strategies based on the range of conditions under which the management practices perform well. The sensitivity analysis approach was adopted in a report by scientists from the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT) (Cooper et al., 2009). This study evaluated the impacts of 1° and 3° C increases in temperature as well as a 10% reduction in rainfall on maize production in Makindu, Kenya and Bulawayo, Zimbabwe, and on groundnut production in Kasungu, Malawi. Weather inputs for this study were generated by modifying historical data by the specified levels. While this process is relatively straightforward for temperature, there are a number of different ways to generate a 10% reduction in rainfall amount. For this study the authors reduced the amount of rain on each rainy day by 10%, leaving the overall distribution of rainfall events intact. This method is likely to underestimate the effects on agricultural production of an actual 10% reduction in rainfall, since some of the reduction will come on days with extremely high rainfall totals and therefore will only reduce runoff. Nevertheless, the effects of this simulated climate change were significant: reductions in rainfall, coupled with increased evapotranspiration due to increased temperatures, led to reductions in the length of potential growing season, by 5-10% in Makindu for example. Additionally, yield reductions may be expected because increased temperatures lead to more rapid plant growth and thus lower yields. Despite these negative potential impacts, Cooper et al. (2009) title their paper a "Hypothesis of Hope." They point out first that while climate change is projected to reduce potential yields, actual farm yields in sub-Saharan Africa are well below this potential level, and second, that by using existing germplasm, such as longer-duration groundnut varieties in the case of Kasungu, and improved management practices to conserve soil and water, yields can be increased substantially above current levels.

Another method for using models to investigate the impact of climate change is to couple downscaled global climate models or regional-scale models to GIS systems and crop models to make regional predictions of changes in productivity. This approach was taken by Thornton et al. (2009) to examine changes in maize and bean production in six countries in East Africa. They used the DSSAT cropping systems model (Jones et al., 2003), with climate projections from two GCMs, and with representative soil profiles from publicly-available databases, to produce representative estimates of crop production under a 2050 climate scenario.

This spatially explicit approach allows evaluation of climate change impacts on a regional level. Thornton et al. (2009) show site-specific differences for maize production in this region. While some areas will suffer from decreased rainfall and higher than optimum temperatures for maize production, other, particularly highland areas, benefit from increasing temperatures. In some parts of East Africa, rainfall is expected to increase, resulting in yield improvements. Bean production follows a similar pattern, but beans show greater yield reduction as a result of high temperatures. This large-scale view omits some of the nuances of local production, however, and the computing power needed to run models over a large number of pixels in these spatial simulations does not allow evaluation of complex management strategies. Case studies in specific areas can complement this broader view. While some case studies have been conducted (Thornton et al., 2010), integrated soil fertility management strategies such as crop diversification with legumes have not been rigorously tested under future climate scenarios in Eastern and Southern Africa. These need to be explored as researchers strive to find strategies for improving smallholder crop production that will be resilient to future climate change.

Objectives

1. Assessing the impact of climate variability on maize-legume cropping systems in Malawi

Climate in Malawi is both heterogeneous in space and variable over time (Ngongondo et al., 2011). Participatory field studies over three years at one site show the promise of diversified cropping systems including the long-duration legume pigeonpea. Crop simulation modeling will be used to extrapolate from these studies to a second site, and to evaluate risk associated with climate variability in these systems,

2. Exploring the response of maize-legume cropping systems to climate change

Because of the uncertainty in climate change projections for Malawi we follow a sensitivity analysis framework similar to that of Cooper et al. (2009) to evaluate the impact of climate change on soil and crop processes in maize-pigeonpea systems. In this study, distribution of rainfall as well as amount will be adjusted, allowing for changes in start or end date of the rainy season to result in varying lengths of season, changes in number of rainy days within a rainy season of similar length and changes in daily rainfall amounts.

3. Analysis of trade-offs in a changing climate

Trade-offs related to use of long-duration legumes under current and future climate variability will be quantified. Trade-offs between soil moisture reductions and increased nitrogen availability through N fixation are expected, particularly in drier conditions.

CHAPTER ONE

Extending participatory research results through simulation modeling: Benefits, risk and trade-offs to using long-duration legumes in Malawi

Abstract

Integrated soil fertility management strategies for intensifying crop production in sub-Saharan Africa have shown promise for improving smallholder yields. In Malawi, participatory research methods have identified pigeonpea (*Cajanus cajan*) as a promising, multipurpose legume for improving fertility management in maize (*Zea mays*) systems. Including a long-duration legume like pigeonpea creates a trade-off between improved soil fertility and increased water stress. Benefits and risk in these cropping systems will depend on soil type and rainfall regime. This effect is difficult to quantify using short-term field trials, particularly in the context of participatory research where variability is high. The current study provides an example of the integration of modeling and participatory research methods by parameterizing the Agricultural Production Systems Simulator (APSIM) with data from on-farm trials to evaluate maize-pigeonpea rotation and intercrop systems. Model experiments at two sites—Zombwe and Kasungu—show that at low fertilization levels (24 kgN/ha applied to maize) both intercrop and rotation systems outperform continuous maize. While soil water and nitrogen trade-offs exist, particularly at Kasungu, the drier of the two sites, the overall effect is positive. Increased time from establishment increases beneficial effects of both systems, and mean effects are greater in sandy, low fertility soils than in finer-textured, higher fertility soils. Risk of negative effect from pigeonpea is less than 10% in all cases for the rotation system. Risk in intercrops is high in the initial establishment phase (10-30 %) and drops below 10% after 3 years. These results suggest

that maize-pigeonpea systems are viable, low-risk options for improving crop production and soil fertility, and can be targeted to low fertility soils to obtain the maximum benefit.

1.1 Introduction

In the past decades, agricultural research has led to new strategies showing great potential to increase yields for smallholder farmers in sub-Saharan Africa, but yields on the continent have stagnated (Sanchez, 2010). Lack of adoption may be due to promotion of inappropriate technologies, or lack of capacity in extension systems to disseminate new information effectively. Participatory research methods have been developed to mitigate some of these issues, and have been used in areas including plant breeding and testing of new varieties, as well as soil fertility and natural resource management. Methods such as mother-baby trials (Snapp et al., 2002) are used to create opportunities for co-learning, where researchers and farmers can collaborate to achieve research objectives. As a result of engaged research, integrated soil fertility management strategies have been developed which incorporate fertilizer and organic technologies to maximize nutrient use efficiency and crop productivity (Vanlauwe et al., 2010).

Simulation modeling has been used successfully in concert with field experimentation in an agricultural development context to extrapolate findings and assess technology performance (e.g. Gowing et al. 2003; Chikowo et al. 2008). Models have also been used to match integrated soil fertility management practices to appropriate agro-ecological niches defined by climate and soil type (Giller et al., 2010). Crop models can be used as a tool for engagement with farmers, or as a learning tool for policymakers. A review of these uses is found in Whitbread et al. (2010). Despite the clear value for inference over time and space, use of crop simulations has rarely been linked to participatory on-farm research (Dimes et al., 2003). There are considerable challenges to model applications in this context, due to variability of the natural resource and management environment, as well as multiple non-modeled effects on yield, such as pest and disease pressure (Robertson et al. 2005). This complexity also creates difficulty when trying to identify underlying mechanisms from field research because of the multiple sources of variability in such systems. Simulation modeling can be used to isolate and quantify variability due to soil and climate variation.

The Agricultural Production Systems Simulator (APSIM) is a modular cropping systems model that has been developed for simulation of a wide variety of cropping systems. Modules for diverse crops including maize, pigeonpea, soybean, and groundnut have been developed, as well as modules for simulating various soil processes including water and soil carbon dynamics, and phosphorous and nitrogen budgets (Keating et al. 2003). The model has been used extensively in Eastern and Southern Africa to simulate crop growth and development under both research station and smallholder conditions, and has been found to perform well, including for simulating response to nitrogen fertilizer in Zimbabwe (Shamudzarira and Robertson, 2002), and rotational effects with green manure legumes in Malawi (Robertson et al., 2005). APSIM has also been used to conduct risk analyses, using longitudinal climate records to test management strategies. Dixit et al. (2010) used APSIM to evaluate maize response to fertilizer and economic returns over many years for a high-productivity site in Kenya. Shamudzarira and Robertson (2002) explored the combined effects of N and water in a semi-arid environment, and evaluate risk for different fertilization scenarios.

APSIM, like other crop simulation models, requires high-resolution data for parameterization, and obtaining this data in the context of on-farm trials and participatory research is difficult. Ideal methods for characterizing soil profile properties require extensive in-field measurements (Dalgliesh et al., 2009). Crop models also require daily rainfall and temperature data, and while methods exist for infilling missing data (Pickering et al., 1994) or stochastic generation of daily data (Jones and Thornton, 2000), complete weather station data is much preferred. A challenge for integrating modeling and participatory research is to determine the true minimum data set required for adequate confidence in model results.

Integrated soil fertility management strategies including legumes such as green manures and agroforestry tree species, show promise for soil fertility improvement. In northern Malawi, participatory trials have identified diversification of maize cropping with the long-duration legume pigeonpea (*Cajanus cajan*) as an integrated soil fertility management system that is farmer preferred and shows promise for improving soil fertility (Snapp et al. 2010). Farmers have highly rated these systems, including pigeonpea in rotation with maize and a pigeonpea-groundnut (*Arachis hypogaea*) intercrop rotated with maize. The benefits noted include food during off-season periods, high value protein-enriched products, and improving maize yields in the following year (Bezner Kerr et al., 2007; Mhango et al., 2012). However, including a long-duration and deep-rooted legume like pigeonpea or an agroforestry tree crop in a rotation increases water use and thus has the potential to reduce yield of main food crops in the following year (Wortmann et al. 2000). In addition, drought stress can decrease the capability of legumes to fix nitrogen, reducing their soil fertility benefits (Dakora and Keya 1997).

Based on these relationships, trade-offs are to be expected between water use and soil fertility gains. The extent and intensity of trade-offs have only begun to be investigated, and are expected to be influenced by soil type and rainfall distribution. Soils in Malawi are spatially heterogeneous, even over short distances (Snapp, 1998). Variability in soils, combined with the multitude of confounding factors inevitably found in on-farm research, means that identifying and quantifying these trade-offs in participatory field studies is nearly impossible. Linking participatory research to modeling could markedly enhance understanding of processes underlying interactions among soil type, climate, and crop yields. Better understanding of interactions would permit extrapolation of findings. For example, characterizing the soil and climate conditions that support long-duration legumes could play a critical role in identification of areas appropriate for expansion of legume diversification. Evaluation of locations where long-duration legumes may be deployed must be based on risk of crop failure as well as potential benefits.

Most areas of Malawi show high temporal variability in rainfall (Ngongondo et al., 2011), making risk of crop failure due to drought difficult to predict using short-term field trials. Models can also be used to explore potential long-term impacts of changes in management. Modeling studies usually reset soil parameters such as organic carbon, inorganic nitrogen, and soil water to their initial values yearly or biannually to prevent carry-over errors that would reduce accuracy. This limits the scope of such studies to effects measurable over one or two years. By using simulation models run over longer continuous time series without reset, it is possible to test for longer-term consequences of changes in management practices (Carberry et al., 2002).

Clearly, there is need to understand the risks, trade-offs, and long term consequences of diversification of mazie-based systems with long-duration legume species such as pigeonpea. The objectives of this study are to:

1. Improve linkages between participatory research and modeling through assessing the feasibility of using data acquired through participatory on-farm research to parameterize APSIM
2. Quantify the vulnerability of rainfed maize and maize-pigeonpea systems to climate-related risk over time given climatic and soil constraints representative of smallholder farming in Malawi

3. Evaluate trade-offs between soil fertility benefits and increased soil water use in maize-pigeonpea diversified systems across soil types and rainfall regimes.

1.2 Materials and Methods

1.2.1 Field sites

Data for model parameterization were obtained from field trials conducted in Ekwendeni, Mzimba district, in northern Malawi, during the three growing seasons between 2007 and 2011 (Mhango, 2011). Yield and biomass data, as well as soils data including organic carbon content, soil texture, and pH in surface and subsurface layers were collected from 19 farmer-managed field sites in 5 villages. Soil types at the field sites were generally sand to sandy clay textured with low levels of organic matter, classified as fine kaolinitic, thermic, typic kandiustalfs (Mhango et al., 2012). Rotation and fertility treatments used in modeling consisted of: continuous maize with two nitrogen fertilization levels (24 and 92 kg N/ha); a pigeonpea-maize rotation with 24 kg N/ha applied only to maize; and a maize-pigeonpea intercrop, with 24 kgN/ha. Nitrogen was applied as urea at 4 weeks after planting (WAP) in the 24 kg N/ha treatments. In the 92 kg N/ha treatment urea was applied in a split application with 23 kg N/ha applied at planting and 69 kg N/ha applied at 4 WAP. The maize variety was MH-17, and the pigeonpea variety was ICEAP 00040.

Field sites at each farm constitute single replications for the purpose of field experiments, and many non-modeled factors may have influenced yield, including pest pressure, large-scale soil erosion, and livestock (Mhango, 2011). Therefore, when modeling the results it is unrealistic to attempt to precisely duplicate yield results at each farm by tailoring soil parameters individually. Importantly, soils varied among farms, and we are interested in understanding the effects of this variation, so it was also not appropriate to use a single soil type. Using data collected during baseline soil sampling in 2007 (Mhango, 2011), field sites were divided into three groups (Figure 1.1) by texture and organic carbon content, and soil types for modeling were created to represent each group.

Soil characterization for model initiation required additional data, collected as follows. Four field sites representative of the three soil groups were selected for additional sampling for inorganic N, as well as deep soil sampling for organic carbon and bulk density (Figure 1.1). Additional sampling was conducted at these sites in mid-July 2011. At each site two plots were selected, one plot that had been planted to a maize-pigeonpea rotation system, and a second plot with three sole maize sub-plots which had been fertilized at 0, 24, and 92 kgN/ha in the previous year. Five samples were taken from the maize-pigeonpea plot, and three samples were taken from each of the three sole maize sub-plots. Samples were collected using a 6.4 cm soil augur, to a maximum depth of 120 cm,at intervals of 0-15, 15-30, 30-60, 60-90, and 90-120 cm, where each depth interval was composited.. Samples were well mixed, air-dried and sieved to pass a 2mm sieve, and analyzed at Michigan State University in the Snapp Laboratory. Nitrate (NO3)-N was extracted from upper layers (0-15 and 15-30 cm) using 1M KCl and measured spectroscopically following the method of Doane and Horwath (2003). Samples for organic carbon analysis, which were taken at all depths, were ground to powder and analyzed for total organic carbon using a dry combustion C and N Analyzer (Costech ECS 4010, Costech Analytical Technologies, Valencia, CA). Organic carbon values were averaged for each field site, including both maize-pigeonpea rotation and sole maize plots, since our data confirmed previous analysis showing no significant difference in total OC content between plots (Mhango 2011). Samples were also collected for textural analysis but the resulting data was inconsistent and could not be used. At the same time, 7.6 cm cores for bulk density measurements were taken at each field site. Two pits were dug at each site and cores were taken from two faces of each pit. Pits were located adjacent to trial plots and dug to a depth of 1.2 m. Four cores were taken at depths of 0-15, 15-30, 30-60, 60-90, and 90-120 cm and averaged by depth.

1.2.2 Model Setup

The crop simulation model APSIM was used to model all treatments. APSIM requires inputs of daily weather data, including maximum and minimum temperature, precipitation, and solar radiation. For model validation, daily rainfall data (1945-2011) and long-term average monthly temperature data were available from the Zombwe Extension Planning Area, approximately 5 km from the field sites. Weatherman, a part of the DSSAT software suite (Pickering et al., 1994), was used to generate daily temperatures and solar radiation, as well as to fill some gaps in the rainfall record. Missing values in rainfall records were concentrated during dry seasons, so should have limited effect on model results. Zombwe (11.33°S, 33.82°E, altitude 143 m.a.s.l.) has an average of 783 mm of rain per year, with a standard deviation of 203 mm. The model was also run using a long-term record (1927-2010) from Kasungu, Malawi (13.03°S, 22.45°E, altitude 1036 m.a.s.l.), also infilled using Weatherman, to investigate the applicability of this system to a slightly drier site in a different part of Malawi. Kasungu has an average of 739 mm of rain per year, with standard deviation 247.

The soils modules in APSIM require soil moisture content at permanent wilting point, field capacity, and saturation, bulk density, organic carbon content, and pH. From field data, three APSIM soil input files were created to represent the range of variability in soil types present in field experiments. Organic carbon from deep samples collected in 2011 was averaged by farm and depth, and two of these average profiles were selected for use as organic carbon inputs for modeling. Water holding capacity parameters were derived from texture and bulk density using pedotransfer functions following Saxton and Rawls (2006). This method was selected based on evaluations of a number of common pedotransfer functions by Gijsman et al. (2002). Their analysis found that an earlier version of Saxton and Rawls' method (Saxton et al., 1986) performed the best out of the eight methods they tested. The updated version used here is similar. Bulk density and organic carbon measurements described above from 2011 sampling were used. Texture at depths from 0-30 cm was calculated as the average within each of the three soil groups (Figure 1.1) defined from previous (2007) data (Mhango, 2011). The highest-fertility soil (Soil HF) is 0.78% organic carbon (OC) 63% sand, 27% clay in the topmost 15 cm. The medium-fertility soil (Soil MF) has similar texture but 0.58% OC in the topsoil, and the low-fertility, sandy soil (Soil LF) has the same OC content as soil two, but has a higher (79%) sand content. Data for soil texture below 30 cm was not available because of difficulties with processing of deeper soil samples, so properties below this were assumed to be constant, following Chikowo et al. (2008). Field examination of soils did not suggest any major changes in soil texture at depth.

There were two types of model runs used: an evaluation model, and a time-series model. The evaluation model was created to mimic five of the experimental treatments for the years 2009-2010. The time-series model used the full length of weather records from Zombwe (66 years) and Kasungu (83 years), and was run without reset for ten-year time series.

Evaluation model

The evaluation model includes simulations of continuous maize controls at 24 and 92 kg N/ha as in the field trials. A pigeonpea-maize rotation system with 24 kgN/ha applied in maize years only was simulated for both entry points, to provide annual yields for both maize and pigeonpea. A maize-pigeonpea intercrop was also simulated at 24 kgN/ha yearly. Simulations used maize cultivar MH 17, already parameterized in APSIM, at a plant density of 3.7 plants/m^2. The built-in long-duration pigeonpea cultivar showed satisfactory performance, and given the lack of available calibration data it was used without modification. This was planted at lower density (2.2 plants/m^2) to account for high plant mortality and insect damage in field experiments.

Soil nitrogen, organic carbon, surface residues and water content were re-initialized on July 15, every year in the case of the continuous maize and intercropping systems to eliminate year to year carryover errors and every two years (after maize harvest and prior to pigeonpea planting) for the rotation system, in order to accurately model the maize yield response to pigeonpea in the previous year. Surface organic matter was set to 300 kg/ha maize residues, consistent with farmer practice. Initial inorganic nitrogen (as nitrate) was set to the average of measured values for fields that had been previously planted to unfertilized maize, then adjusted slightly, both to better match yields in the continuous maize systems and to prevent large jumps in soil N at reset, which would bias comparisons between rotations (reset every two years) and other systems (reset yearly). This simulation was run using weather data for Zombwe, for the years 2008-2010.

Time series model

The second set of simulations was identical to the first in overall setup but was run for both Kasungu and Zombwe, for the entire duration of each weather data set: 83 years at Kasungu and 66 years at Zombwe. These simulations were run over ten year time series and not reset each year. This allowed novel insights into the medium to long-term impacts of using a diversified system. In order to maintain the high level of replication possible with the long weather data records available, the simulations were duplicated ten times, with start dates in sequential years such that each year from system establishment was represented in each calendar year (see Figure

1.2 for a schematic representation). Residue management was performed separately for each crop: 80% of maize residues were removed to avoid early-season immobilization of N which otherwise substantially reduced yields, while pigeonpea residues were incorporated. The same soil profiles were used for both sites. These profiles are consistent with soil properties measured on smallholder fields in the Kasungu area (Phiri et al 2010), though soils there tend to be most similar to the lower fertility, sandier type (Soil LF).

1.2.3 Analysis of model results

Analysis was conducted using the statistical software R (R Development Core Team, 2011). Models were fitted using the built-in linear modeling function lm(), which calculates standard model diagnostics for linear fixed-effects models. Because the objective of the data analysis here is largely exploratory, we focus on trends in the model results that illustrate underlying mechanisms. To simplify the analysis, the time since reset, representing time from establishment of the system, was grouped into first-year, early (years 2-4), mid (years 5-7) and late (years 8-10) periods. Analysis excluded the first year, because no rotation effect is expected before year two.

1.3. Results

1.3.1 Evaluation of model performance

Results in the evaluation model were generally within one standard deviation of measured maize yields and biomass (Figure 1.3). In most treatments modeled yields are above the experimental mean yield. This slight over-prediction of on-farm yields is to be expected, since we are comparing model results, which do not account for pest and disease pressure, to on-farm yields, where these have significant impacts. Model yield is notably low in 0N continuous maize treatments, but shows good agreement in all treatments considered in the time series simulations.

Pigeonpea yield and biomass were overestimated by the model, however for indeterminate long-duration pigeonpea such as that used in these trials accurate estimation of total biomass and yield is difficult because of early leaf senescence. This, combined with high levels of pest pressure, means that it is probable that field-measured yield and biomass are lower than would be expected when considering only model-simulated effects. Mean measured pigeonpea yields in 2008 and 2009 ranged from 119 to 266 kg/ha, with a maximum reported yield of 953 kg/ha in the rotation system in 2009. Mean biomass ranged from 806 to 3307 kg/ha, with a maximum of 7040 kg/ha, again in the rotation system in 2009 (Mhango, unpublished data). Modeled yields ranged from 263 to 698 kg/ha, and biomass ranged from 3016 to 6981 kg/ha. These modeled yields and biomass, are consistent with results reported elsewhere (Myaka et al., 2006).

1.3.2 Systems including pigeonpea show higher yields than continuous maize systems.

Results of the time series model showed that rotation systems outperformed continuous maize on all soil types and at both Kasungu and Zombwe (Figure 1.4). The intercrop resulted in lower maize yields than those in continuous maize in the most fertile soil type (Soil HF) in the early period in Zombwe. For the same soil type and period at Kasungu the intercrop produced similar yields to continuous maize. In all other periods, and for the other soil types, maize yields in the intercrop were better than those in continuous maize. All systems improved in productivity over the course of the 10 years between resets, with most of the increase coming within the first five years. Continuous maize yields increased slightly with time, because soil conditions in year one represent soil status following unfertilized continuous maize. Repeated fertilizer inputs and small additions of organic matter result in improved yields over time. Yield increases between periods were greatest in intercropping systems, while rotation systems provided the highest yield overall in maize years. The greatest differences between continuous maize and maize-legume systems was observed in the least fertile soil (Soil LF).

At Zombwe, maize yield in intercrop systems was positively correlated with the previous year's pigeonpea biomass throughout the 10-year period from establishment. Rotation systems show a more complex relationship, with interactions between soil type and establishment period. Early in the 10-year cycle (2-4 years from establishment), effects were positive and significant (at $p < 0.05$) for Soil HF, but insignificant for the other two soils. In later years, there was no significant effect in Soil HF but soils MF and LF showed small negative trends. At Kasungu the effect of pigeonpea biomass was minimal, and all regression r^2 values were less than 0.1.

1.3.3 Risk and yield distribution change with cropping system and over time

Yield distributions are wider for maize-legume systems than for continuous maize, and wider for intercrops than for rotations (Figure 1.5). In the early establishment period and in higher fertility soils, the lowest yields of maize-legume systems are below those of continuous maize, and their distributions are considerably wider. Once the systems are established, their yield variability decreases and mean yield increases. Yield variability is higher at Kasungu than at Zombwe in all cases. The effect of the legume component and the probability of decreased yield can be calculated by comparing maize yields in rotation and intercrop to that of continuous maize for each soil type and year from establishment. Yield effects are substantial, ranging up to 150% increases over continuous maize yields (Figure 1.6). Effects are most significant in Soil LF, the sandy, low fertility soil. The probability of decreased yield is low, especially in mid and late establishment periods (Figure 1.7). Intercrops are riskiest, particularly in the period of early establishment, where maize yield is reduced in 10-30% of years at both sites. This risk is reduced dramatically with time, so that in the 3-5 year period, only 4% of years show reduced yields in intercrops. Risk in rotation is never more than 3.1% at Zombwe, and 6.7% at Kasungu, making this a more stable system than the intercrop.

1.3.4 Nitrogen effects of legumes

In all systems, yield is limited by nitrogen availability, as expected for low-level fertilizer applications in relatively low-fertility soils. Legume systems increase the amount of nitrogen available to associated maize crops, particularly in rotation treatments. This can be seen from the relative amounts of inorganic N in soil at planting (Figure 1.8), although some of the nitrogen inputs from legume residues are not represented as they are in organic pools.

APSIM calculates a daily value of nitrogen stress for plant processes including photosynthesis, biomass expansion, and grain fill. These values range from zero (no stress) to one. Summing these values over the growing season provides a measure of total nitrogen stress of the crop. For this analysis we use N stress for photosynthesis, since photosynthesis will occur throughout the growth period. The effect of N stress on yield is most clear at Zombwe, the wetter of the two sites, where nitrogen stress is clearly the dominant predictor of yield (Figure 1.9). Reduction in nitrogen stress accounts for most of the yield increase in both intercrop and rotation systems in Zombwe. Yield increase is calculated as a percentage of continuous maize yield by the formula:

(1) Yield Effect =(Yield of maize-legume system — Yield of continuous maize)/(Yield of continuous maize)

Reduction in N stress is calculated similarly, using model-calculated cumulative N stress for photosynthesis over the growing season and the formula

(2) N Effect = (N stress in continuous maize —N stress in maize-legume system)/(N stress in continuous maize)

Where either yield or N stress was zero in continuous maize, values were excluded. This transformation isolates the nitrogen effects on maize due to the inclusion of pigeonpea, and at Zombwe, it provides a clear picture of the effect (Figure 1.10). Remaining variability when nitrogen stress effects are accounted for is small.

A linear model including period from establishment, soil type, and N effect as independent variables was fitted separately to each of the rotation and intercrop yield effects data at Zombwe. Period from establishment (grouped as above into early, mid, and late) and soil type were considered fixed factors, with N effect as a covariate. A simple 3-way analysis of variance showed that main effects and interactions were significant at the $p<0.05$ level, so we subset the data by period and soil type. A simple linear regression of yield effect by N effect shows that both the slope of the regression and the r^2 value decrease with increasing time from establishment, with these effects most pronounced in the lower-fertility soils. The overall magnitude of the N effect also increases with increasing time from establishment.

The effect of N stress reduction in Kasungu is less pronounced. A similar model of yield and N stress effects produces many non-significant slopes, and r^2 values of less than 0.15 in all cases. It is clear that while in some cases nitrogen is limiting yields in Kasungu, other factors are also important determinants of maize yield.

With long-term use of legume systems, improvements in soil fertility will be expected. Both intercrop and rotation systems increased organic carbon content in soils, particularly in the upper 15cm. At Zombwe, in this layer, the organic carbon content in soil HF increased from 0.78% to 0.89% in the intercrop system and 0.86% in the rotation. Organic carbon in soils MF and LF increased from 0.58% to 0.66% in rotation in both soils, and to 0.70% and 0.71% in intercrop for soils MF and LF, respectively. Soil carbon in the continuous maize system remained approximately constant in all soils. Results were similar at Kasungu.

1.3.5 Water stress effects and impacts on yield

Crop water stress was much more important at Kasungu than at Zombwe. In Zombwe there were so few instances of high soil water stress that it is impossible to draw conclusions. However, the drier conditions and longer record at Kasungu provided enough instances of substantial water stress to allow for analysis. At this site there is a clear effect of rainfall. As reported elsewhere (Shamudzarira and Robertson, 2002), this effect is most pronounced at rainfall amounts below 550 mm (Figure 1.11). Cumulative soil water stress for photosynthesis was calculated in the same manner as cumulative N stress described above. In cases where cumulative soil water stress was greater than one, there is a clear relationship between soil water stress and yield (Figure 1.12). Rainfall amounts in these stressed years range up to 743 mm (above the mean value over all years at Kasungu of 739 mm), with a mean value of 478 mm. Both intercrop and rotation treatments are more stressed than continuous maize (Figure 1.13). Soil water stress levels increase with time from establishment, particularly in the "mid" period, as nitrogen stress declines and yield increases, causing plants to use more water.

The effect of water stress is most pronounced at critical times in crop development. Using model-identified crop stages, soil moisture content was examined early in the growing season (from emergence through flag leaf stage) and near flowering (floral initiation and flowering stages). For years with low rainfall (less than 550 mm during the growing season), mean extractable soil water early in the growing season and at flowering show some correlation with yield, though the relationship does not appear to be linear (Figure 1.14). There seems to be a threshold effect, where extremely low soil water content results in a high probability of crop failure.

Soil water status is influenced by both soil and treatment, with soil HF having generally higher extractable soil water. Maize-legume systems have lower soil moisture content than continuous maize systems, especially early in the season. Soil water at flowering is much closer among systems, as soil water recharge occurs with early season rainfall (Figure 1.15).

In Zombwe, overall rainfall amount was not well correlated with maize yields: even for years with rainfall below 550mm, correlations were not good. Relationships between yield and soil water at critical crop stages were also unclear. Yields were, however, correlated with dry spells of 10 days or longer during the growing season, for all rainfall amounts in both rotation and intercrop systems. In contrast, continuous maize yields showed no correlation with dry spells. This effect was not observed at Kasungu—in fact the number of 10-day dry spells was correlated with a slight increase in yield.

Pigeonpea, as a long-duration crop, is more adversely affected than maize by low rainfall and shortened rainy seasons, in both Zombwe and Kasungu. The effect of dry spells observed at Zombwe for maize yields is not seen for pigeonpea.

1.4 Discussion

1.4.1 Integrating modeling with participatory research

APSIM was able to realistically simulate both rotation and intercrop systems, producing maize and pigeonpea yields similar to those observed in participatory field trials in Northern Malawi and reported elsewhere (e.g. Myaka et al. 2006, Høgh-Jensen et al. 2007, Mwale et al.

2011). While the field data used in this study do not provide validation of long-term effects, other work has confirmed the ability of APSIM's components to simulate long-term soil processes (Probert et al., 1998). We have found that with limited additional soil sampling and processing, the data collected from participatory trials was sufficient to adequately parameterize APSIM. Some compromises were required due to limited parameterization data. A full characterization of soil water retention parameters in the field was not possible. Texture data was not available for deep soil layers, so following Chikowo et al. (2008) we used the values from 15-30 cm for deeper layers. While these compromises mean the precision of the resulting model is not perfect, it does allow us to address our research objectives, and can serve as a tool for targeting further field research.

1.4.2 Maize-legume systems increase maize yield with low risk of failure.

Overall, both intercrop and rotation systems outperformed the continuous maize control treatment (Figure 1.3). As expected, we do see a trade-off between reduced soil moisture and increased nitrogen availability to crops, and this leads to higher variability in maize-legume systems. However, in nearly all years the balance of impacts from including pigeonpea is positive. This confirms results of field studies in Malawi showing the benefits of pigeonpea and other long-duration legume systems for increasing productivity of maize (Snapp et al., 2010). The use of pigeonpea in rotation is relatively low-risk, particularly in Zombwe where moisture constraints are lowest (Figure 1.6). It is rare for yields in maize-pigeonpea rotation systems to be lower than those of continuous maize systems in the same year. Risk in rotation systems is slightly increased in Kasungu, because of increased water stress, and risk remains elevated over time. Intercrops are more risky, particularly in early establishment years. Mean maize yields in intercrops are lower than maize following pigeonpea in rotation. However, because a rotation will only produce maize in alternate years, it may be less attractive to farmers than intercrop systems, depending on the value placed on the legume crop, and the amount of land available to satisfy maize food requirements.

There are clear differences in maize yield response to legumes due to differences in soil type. The greatest yield benefit is seen in less fertile, sandy soils, where small increases in available nitrogen, soil cover and organic carbon are most beneficial. Yields under maize-legume systems at Zombwe after 10 years were the same across all three soil types (Figure 1.3), despite continuing differences in continuous maize yields. At Kasungu differences by soil type persist, particularly between soils HF and LF, the finest and coarsest-textured soil. These differences are most likely caused by the higher soil water stress in the sandier soil at Kasungu.

1.4.3 Soil water and nitrogen trade-offs

It is clear that a trade-off exists between increased available nitrogen and higher soil water stress in legume systems. However, in both sites discussed here, the effects of increased nitrogen greatly outweigh the increases in soil water stress. The two factors combined explain nearly all of the variation in yield, particularly in the rotation. At Zombwe the nitrogen effect is clearly the dominant predictor of yield (Figure 1.8). When yields occurring in water-stressed years are removed at Kasungu, N stress becomes similarly dominant. There is a larger amount of remaining variability in the intercrop, some of which is most likely caused by competition for light between maize and pigeonpea.

1.4.4 Long-term impacts of maize-legume systems

The potential long-term yield increases from maize-legume systems are considerably greater than the benefits seen in the first year. This long-term effect is difficult for farmers to consider, given the high discount rates they apply to future yields (Waddington and Karigwindi, 2001). Long-term impacts on soil carbon are difficult to measure in on-farm trials, because the huge variability in these soils disguises any changes over short time frames. Despite the potential models have for contributing to understanding these soil processes, most modeling studies reset soil variables yearly. This is due to the possibility for compounding errors in nitrogen, carbon and water from year to year. While longer duration continuous (non-reset) model runs may result in less precise yield measurements, they allow modeling to contribute to addressing concerns about long-term impact. Further modeling efforts, especially when combined with long-term field experiments, would provide important additional information.

1.5 Conclusions

The approach used here to integrate modeling with participatory research shows promise for scaling out results of such research and for generating new insights. Our results show that maize-pigeonpea cropping systems are viable, low-risk options for improving crop production and soil fertility with minimal reliance on external inputs. Soil moisture requirements of the intercrop systems posed some risk of maize yield reduction, but only for the initial years of adoption. Trade-offs between increased nitrogen availability and decreased soil moisture may pose a barrier to adoption at sites drier than those considered here. Pigeonpea can be targeted to low fertility soils to obtain the maximum benefit, and has potential to ameliorate challenges to production in these soils.

Figure 1.1: Soil characteristics at field sites, topsoil (0-15 cm) depth. Colors indicate groups used to generate the three soil types used in modeling. HF=high fertility, MF=medium fertility, LF=low fertility. For interpretation of the references to color in this and all other figures, the reader is referred to the electronic version of this thesis.

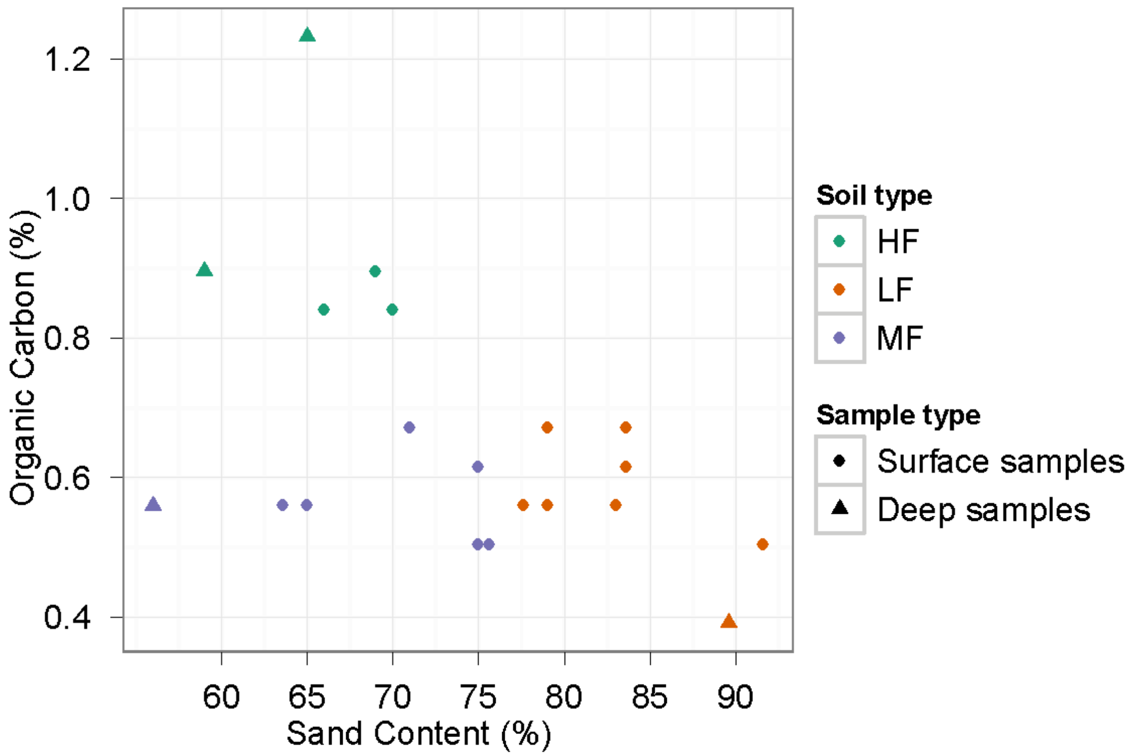


Figure 1.2 Schematic depiction of time series model setup. Simulations are run continuously for ten years, after which soil parameters are reset. Model is run ten times (only three runs are shown here) with staggered start dates to maintain high levels of replication.

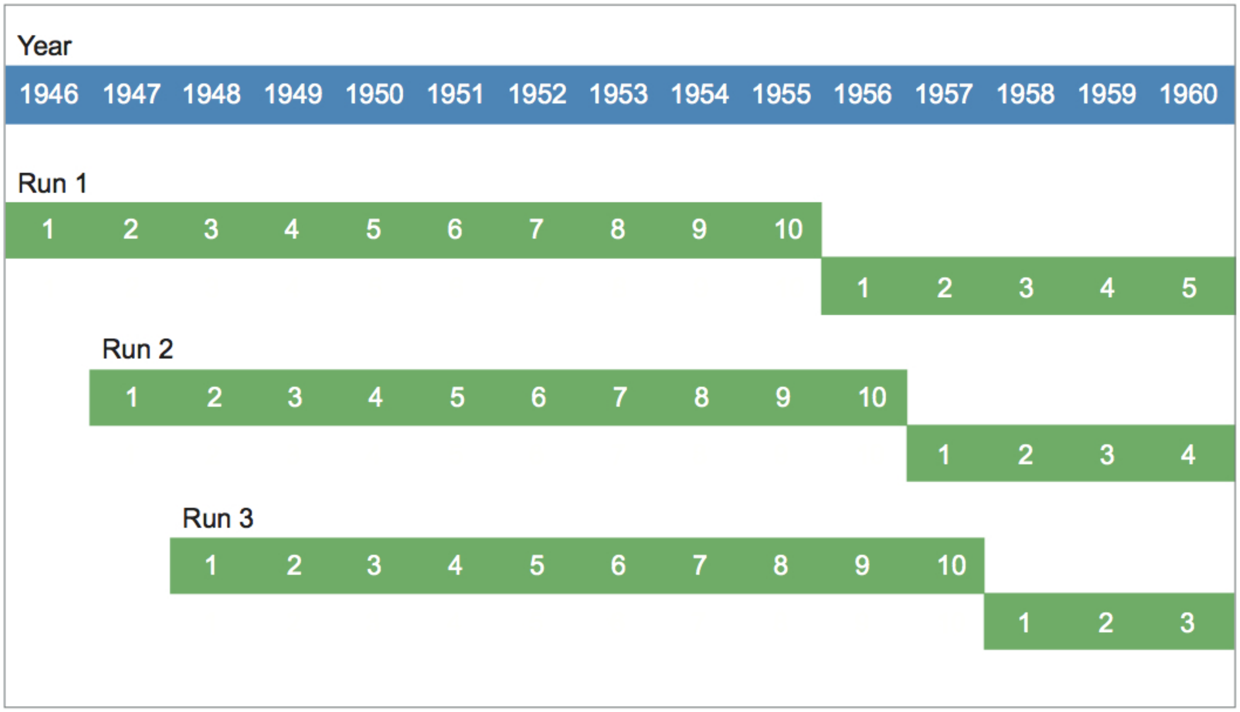


Table 1.1: Properties used in APSIM soils input files. See text for field data used in soil characterization.

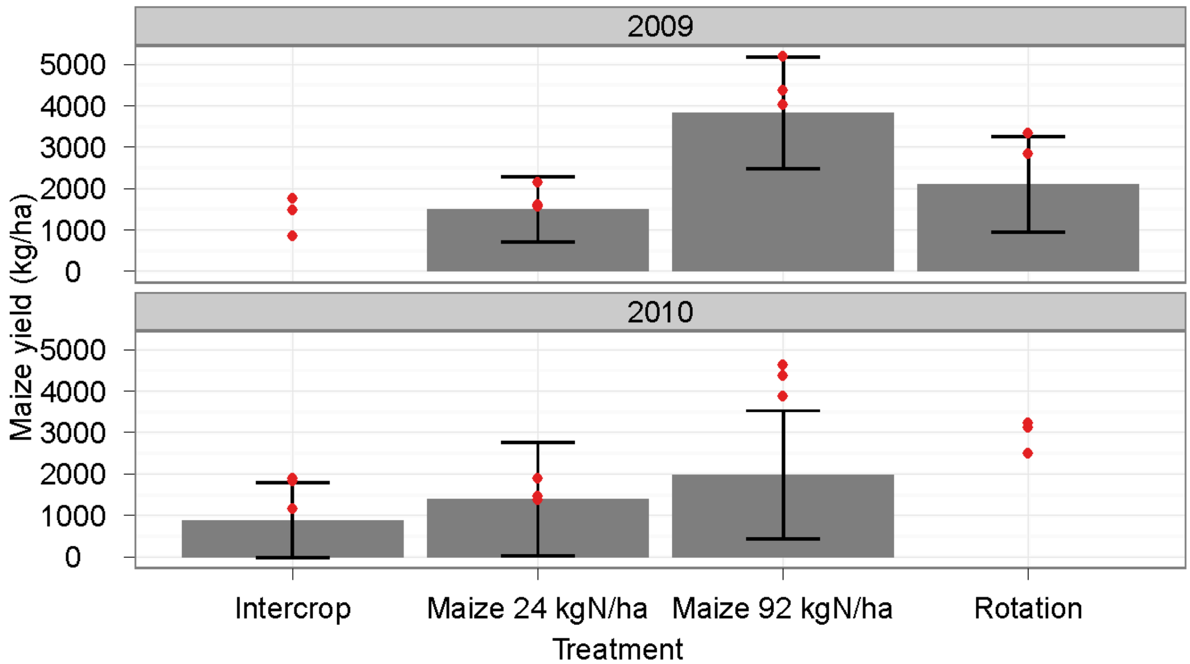
	Depth (cm)	Wilting point (mm/mm)	Field capacity (mm/mm)	Saturated water content (mm/mm)	Bulk density	pH	Organic carbon (%)
Soil HF	0-15	0.15	0.24	0.41	1.50	6.0	0.78
	15-30	0.18	0.28	0.42	1.47	5.5	0.60
	30-60	0.18	0.28	0.42	1.47	5.5	0.42
	60-90	0.18	0.28	0.42	1.47	5.5	0.23
	90-120	0.18	0.28	0.42	1.50	5.5	0.19
Soil MF	0-15	0.14	0.22	0.44	1.50	6.0	0.58
	15-30	0.13	0.21	0.40	1.60	6.0	0.38
	30-60	0.13	0.20	0.38	1.70	6.0	0.27
	60-90	0.13	0.20	0.35	1.70	6.2	0.20
	90-120	0.13	0.20	0.35	1.70	6.5	0.20
Soil LF	0-15	0.076	0.13	0.41	1.53	6.0	0.58
	15-30	0.11	0.17	0.40	1.50	6.0	0.38
	30-60	0.11	0.17	0.40	1.51	6.0	0.27
	60-90	0.11	0.17	0.35	1.60	6.0	0.20
	90-120	0.11	0.17	0.35	1.60	6.0	0.20

Properties in all soils

finert	*fbiom*	*Initial NO3 (kg/ha)*
0.6	0.03	1.0
0.7	0.02	1.0
0.8	0.02	1.5
0.9	0.01	0.5
0.95	0.01	0.25

Figure 1.3: Comparison of field-measured data and results from simulation model used for evaluation. Means reported for maize biomass and grain yield from 2009-2010 field experimentation at Ekwendeni, Malawi (columns). Error bars are standard deviations from the mean. Where columns are missing, field data was not available. Points represent model results from simulations run on three soil types. Treatments are described in methods.

a. Maize grain yield



b. Maize biomass

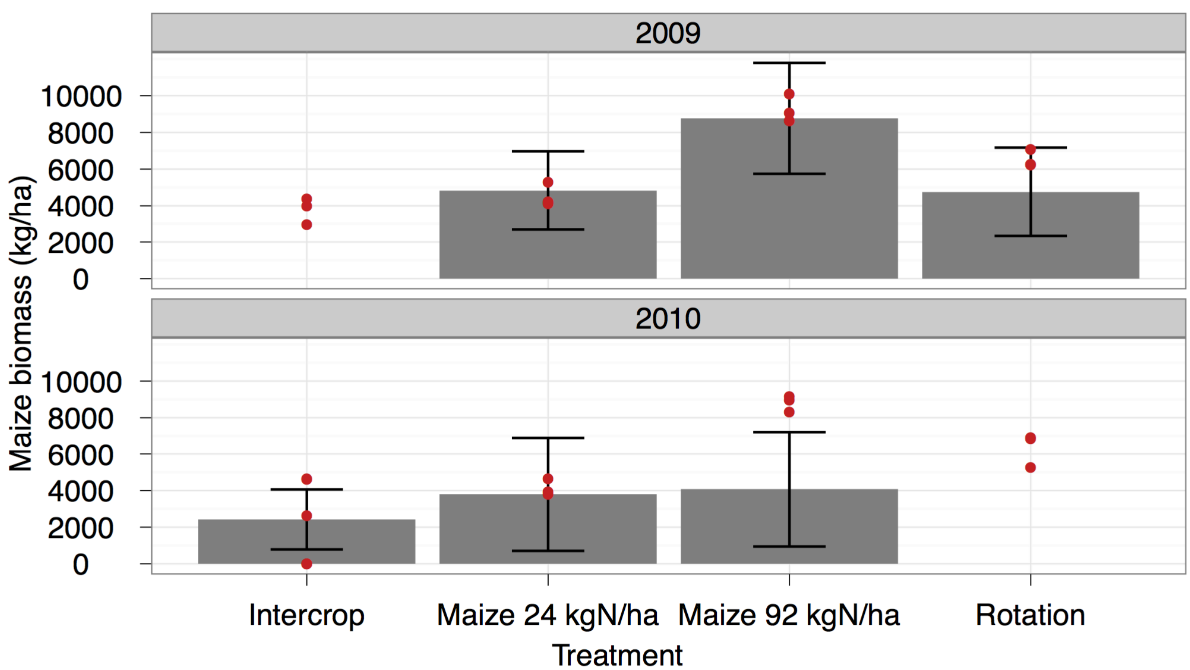


Figure 1.4: Mean maize yields for 10 years from system establishment for three cropping systems in three soil types. Time series model results averaged over 83 years at Kasungu and 66 years at Zombwe, northern Malawi. Error bars are standard errors of the mean over the same time period. Variation is based on differences in weather from year to year. Soil types defined in methods. HF=high fertility, MF=medium fertility, LF=low fertility.

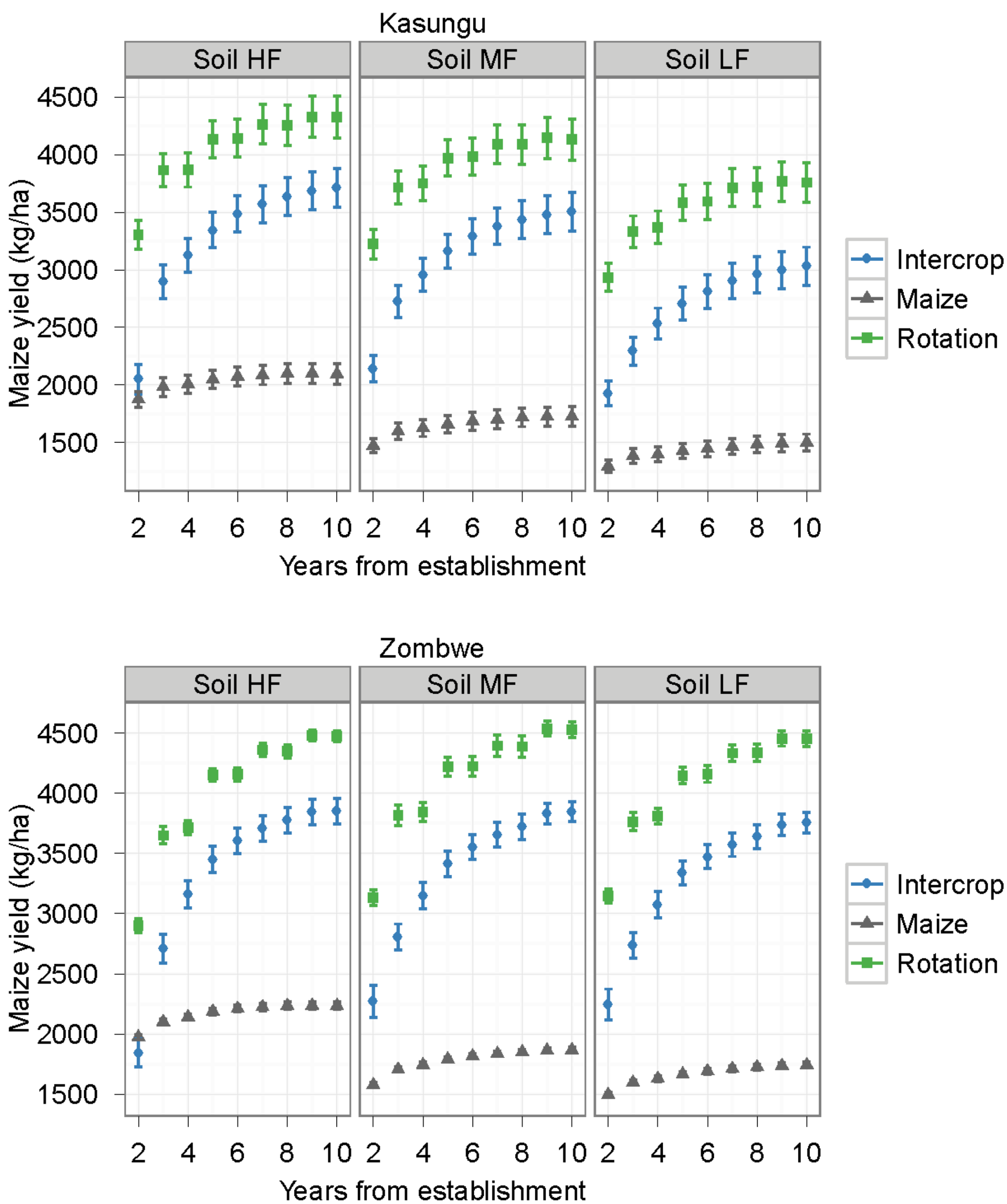


Figure 1.5: Cumulative probability distributions of maize yields for three cropping systems in three soil types. Time series model results from simulations of 83 years at Kasungu and 66 years at Zombwe, northern Malawi. Results plotted separately for each soil type and period from establishment. Periods early, mid, and late refer to years from system establishment: 2-4, 5-7, and 8-10 respectively. Soil types defined in methods. HF=high fertility, MF=medium fertility, LF=low fertility.

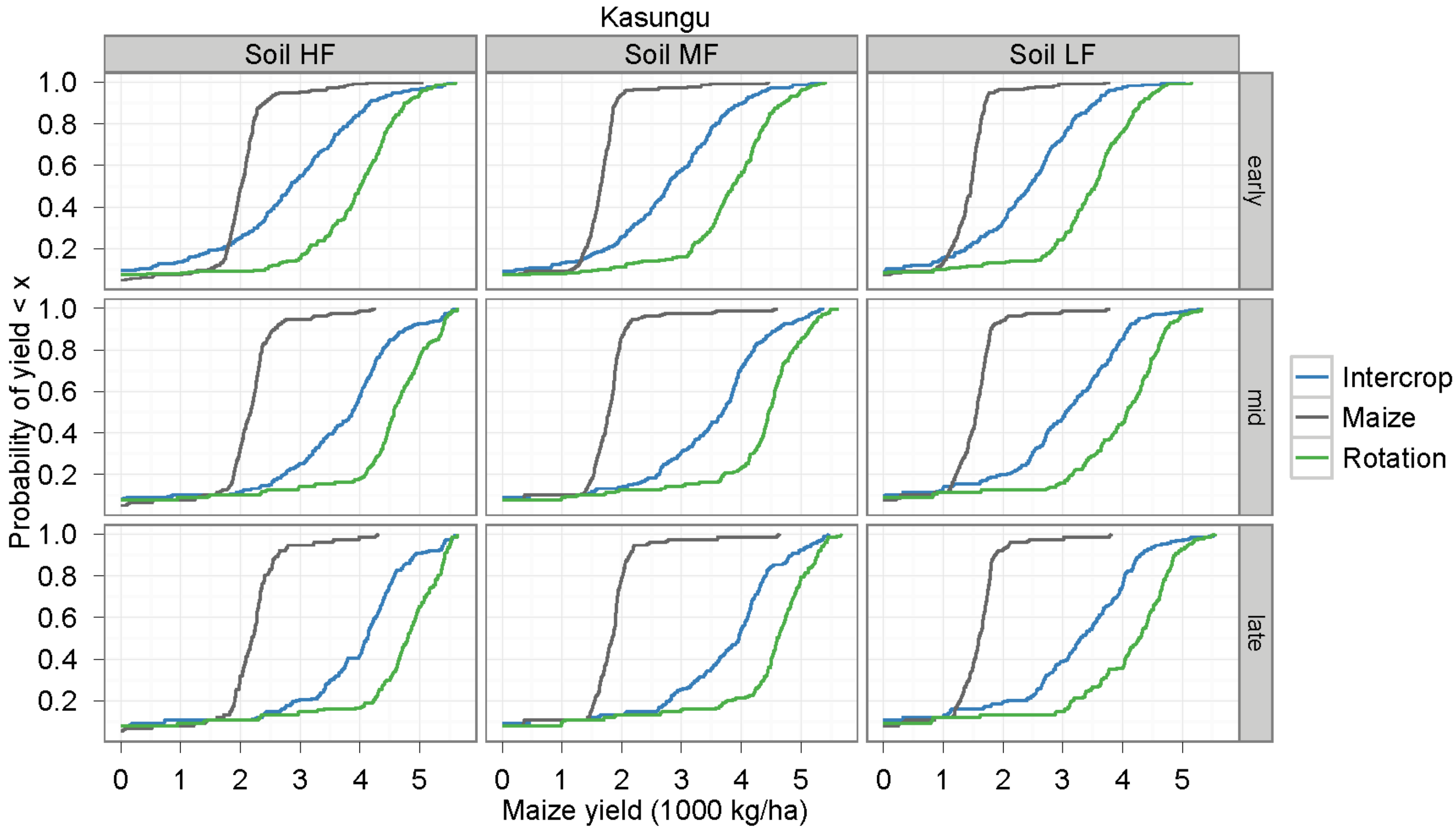


Figure 1.5 (cont'd)

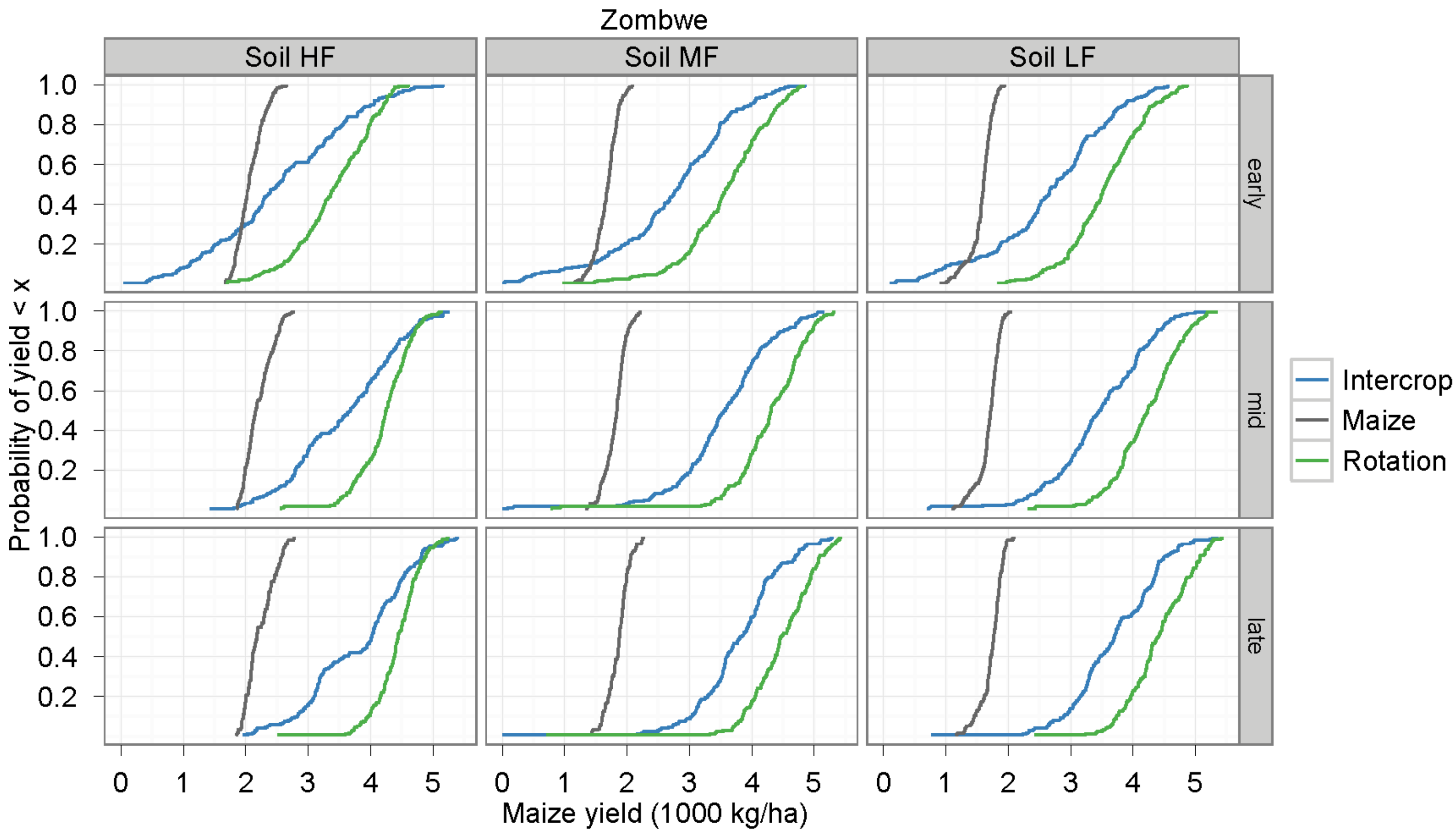


Figure 1.6: Mean effect of legume systems on maize yields as percent increase over continuous maize yield. Continuous maize yield represented as zero. Time series model results over 83 years at Kasungu and 66 years at Zombwe, northern Malawi. Periods early, mid, and late refer to time from system establishment: 2-4, 5-7, and 8-10 years respectively. Error bars are standard errors of the mean. Soil types defined in methods. HF=high fertility, MF=medium fertility, LF=low fertility.

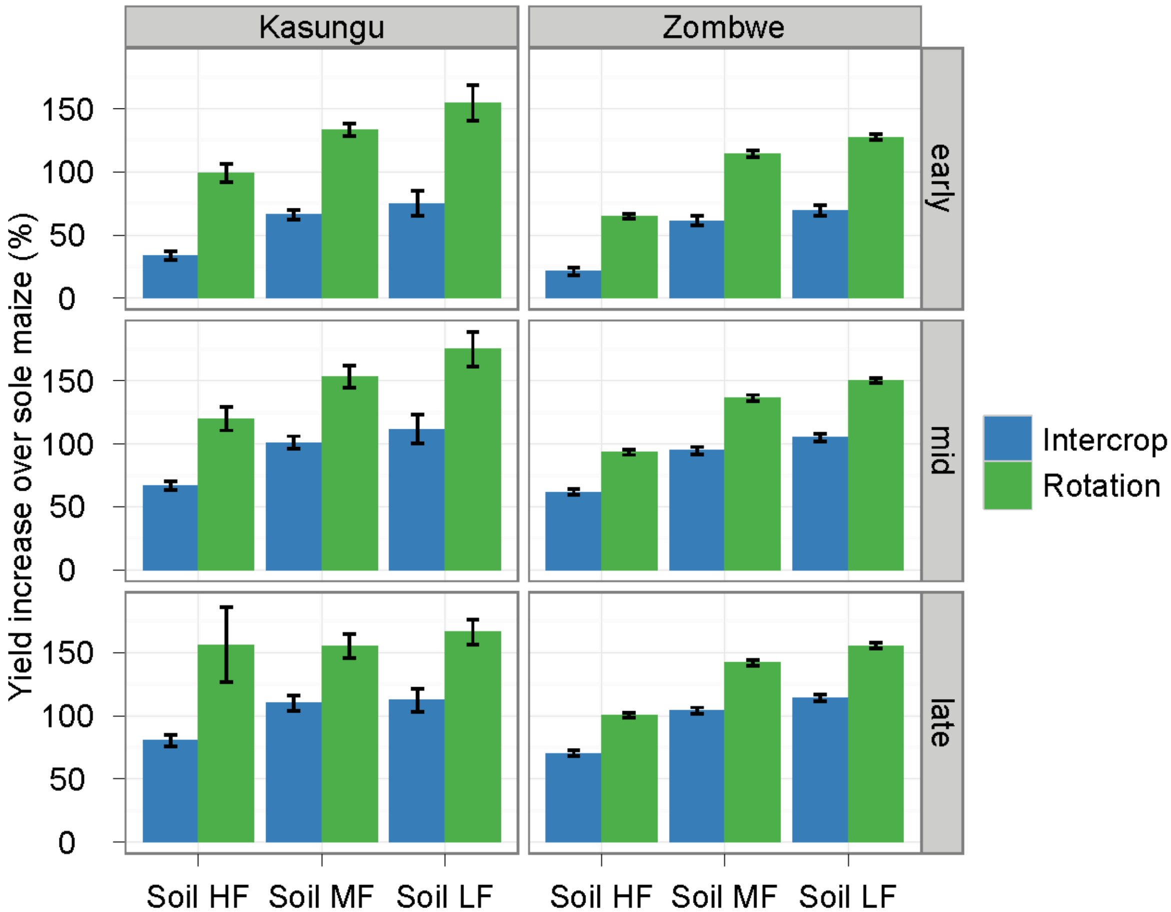


Figure 1.7: Risk of yield reduction in maize-legume systems, as percentage of years where maize yield in maize-legume system is lower than in the continuous maize system.. Time series model results from simulations of 83 years at Kasungu and 66 years at Zombwe, northern Malawi. Periods early, mid, and late refer to time from system establishment: 2-4, 5-7, and 8-10 years respectively. Soil types defined in methods. HF=high fertility, MF=medium fertility, LF=low fertility.

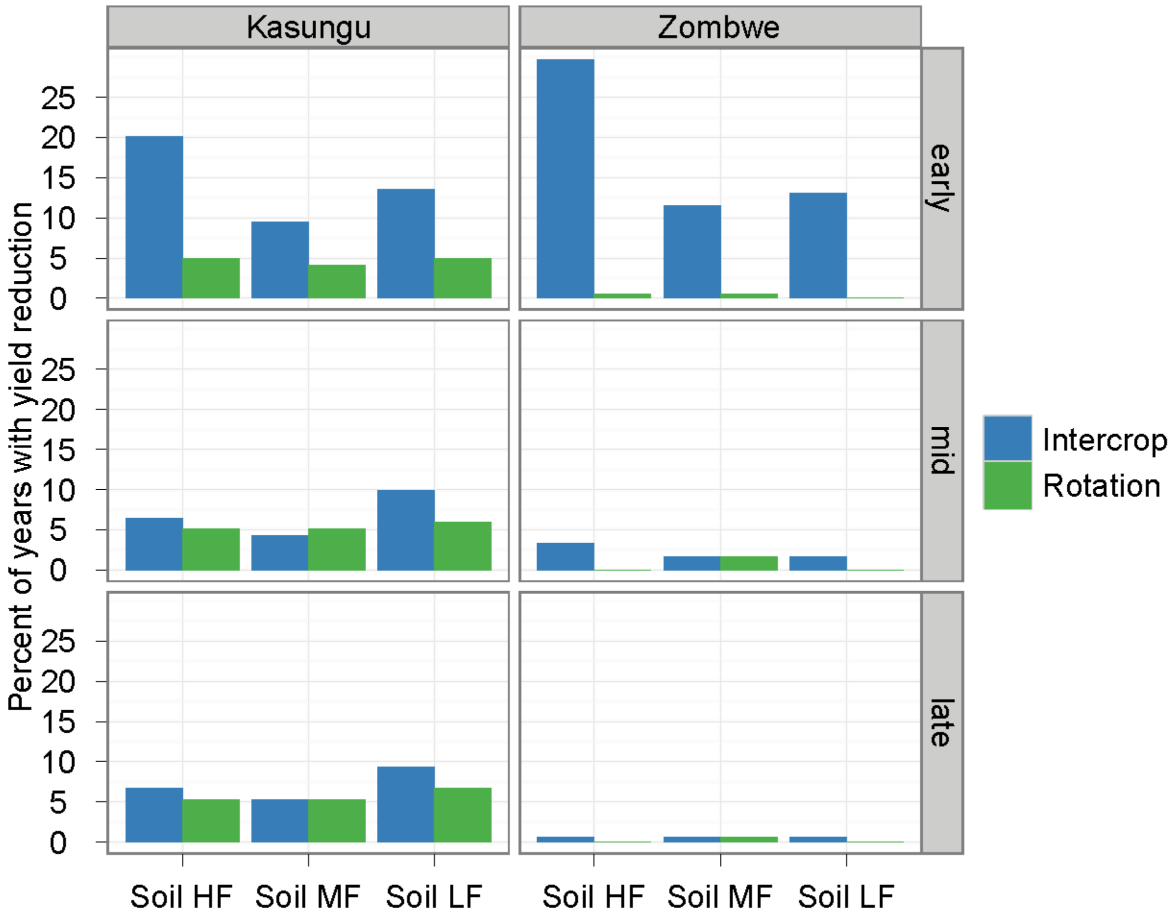


Figure 1.8: Inorganic N in soil at planting for three cropping systems in three soil types. Time series model results from simulations of 83 years at Kasungu and 66 years at Zombwe, northern Malawi. Periods early, mid, and late refer to time from system establishment: 2-4, 5-7, and 8-10 years respectively. Soil types defined in methods. HF=high fertility, MF=medium fertility, LF=low fertility.

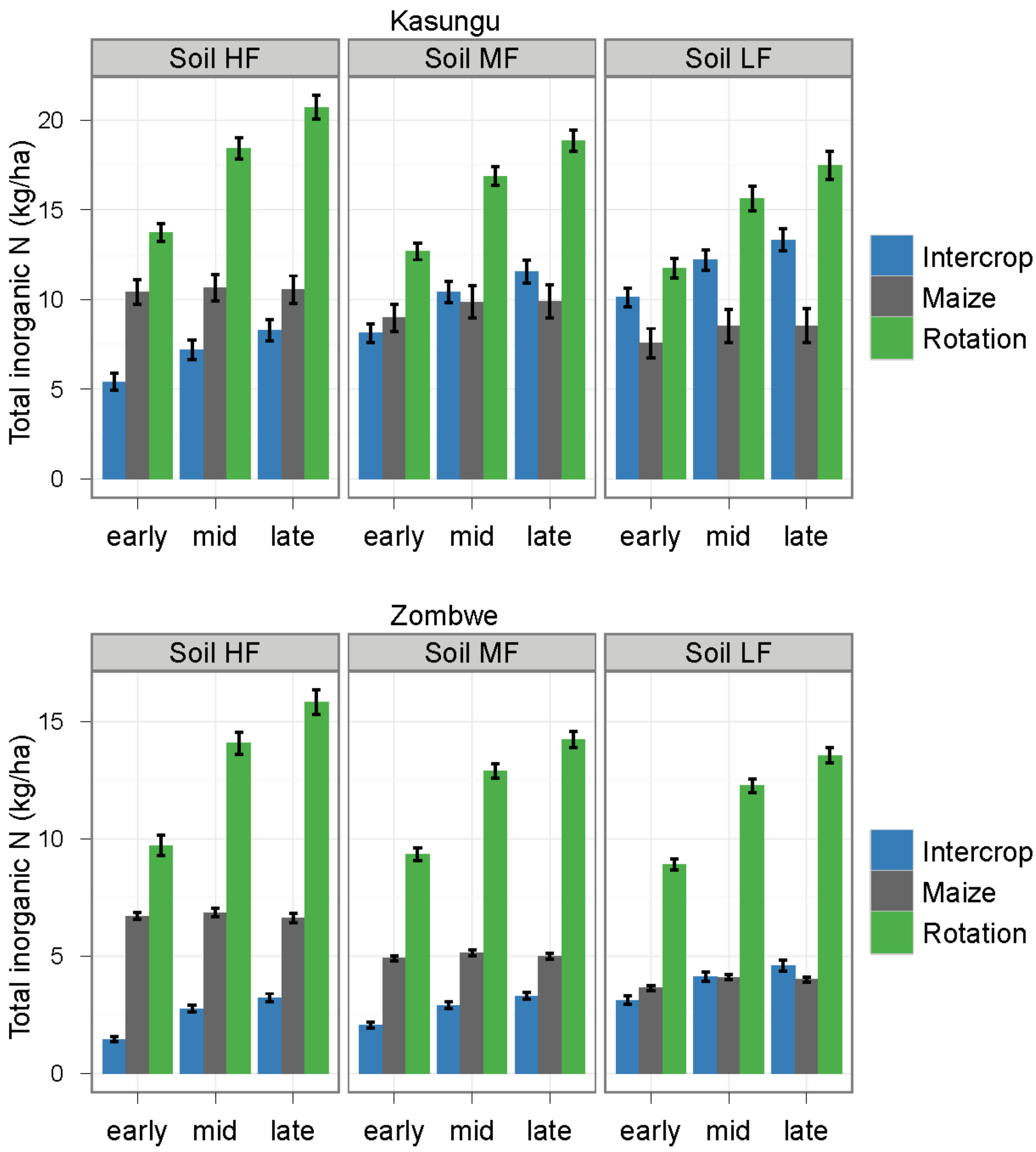


Figure 1.9: Maize yield and cumulative nitrogen stress in three cropping systems in three soil types. Cumulative N stress calculated from model factor, see results for more detailed description. Time series model results from simulations of 83 years at Kasungu and 66 years at Zombwe, northern Malawi. Periods early, mid, and late refer to time from system establishment: 2-4, 5-7, and 8-10 years respectively. Soil types defined in methods. HF=high fertility, MF=medium fertility, LF=low fertility.

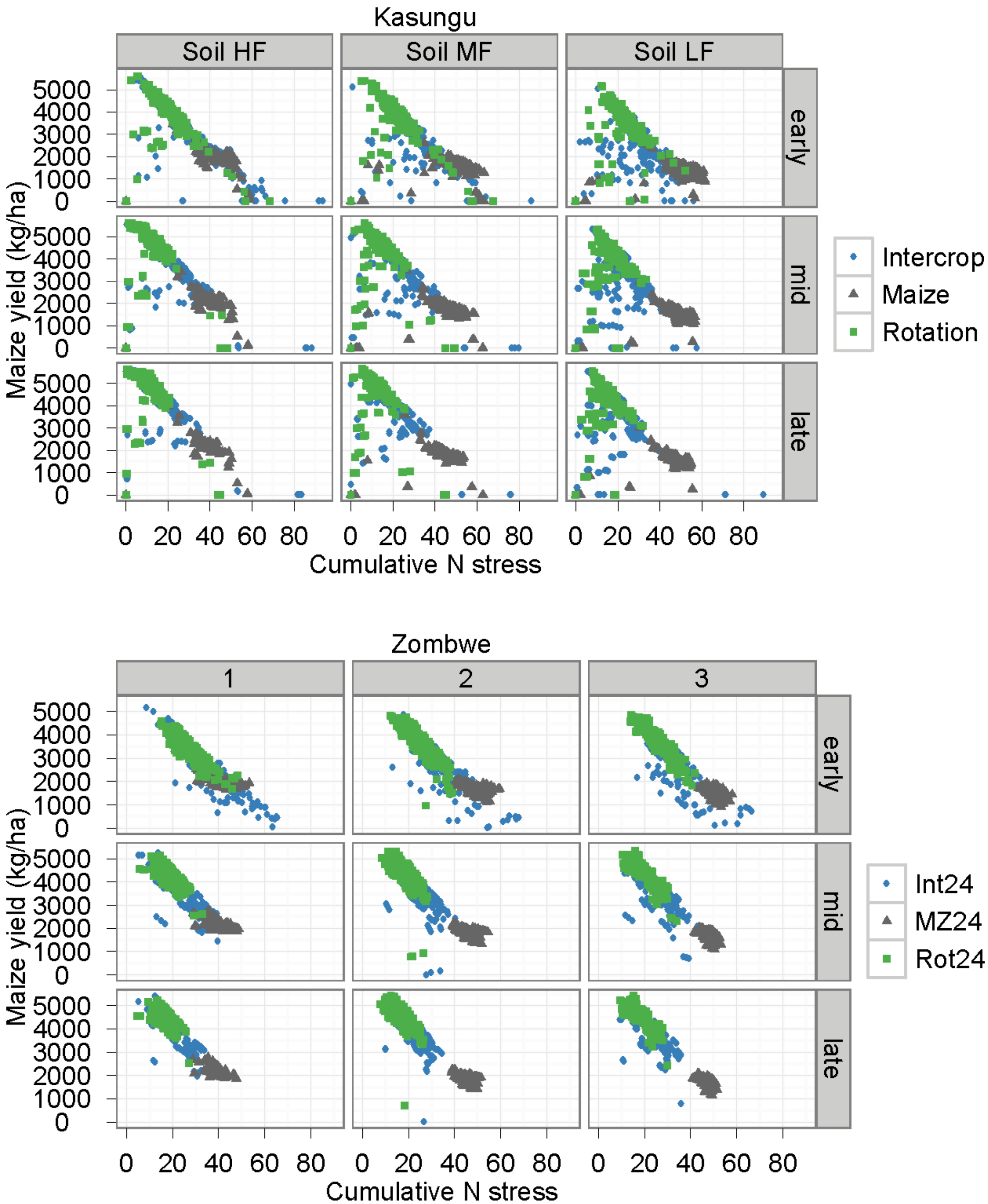


Figure 1.10. Effect of legume diversification on maize yields and cumulative nitrogen stress relative to continuous maize at the same fertility level. Continuous maize yield is zero. Negative N stress reduction (x axis) values correspond to increases in nitrogen stress. See Results for further information. Time series model results from simulations of 83 years at Kasungu and 66 years at Zombwe, northern Malawi. Results displayed are from early period (years 2-4 from system establishment). Regression lines are significant at $p<0.05$ and shaded region represents standard error of the regression. r^2 values for regression lines range from 0.65 to 0.87. Soil types defined in methods. HF=high fertility, MF=medium fertility, LF=low fertility.

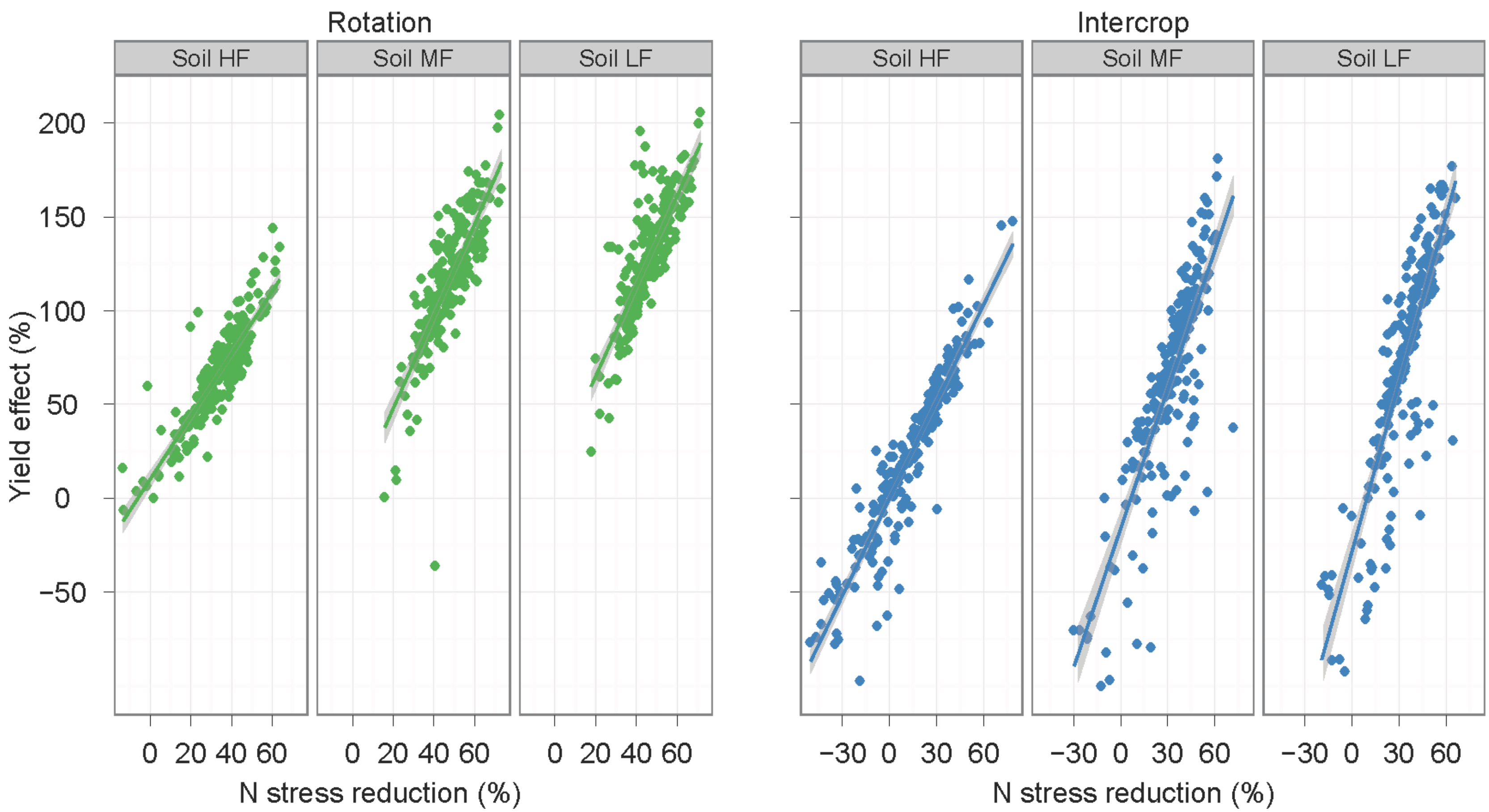


Figure 1.11: Maize yields and in-crop rainfall for three cropping systems in three soil types. Time series model results from simulations of 83 years at Kasungu and 66 years at Zombwe, northern Malawi. Results are restricted to in-crop rainfall below 550 mm. Lines represent linear regression with intercept forced to zero and are significant at $p<0.05$. Shaded area represents standard error of the regression. r^2 values for regression lines range from 0.82 to 0.95. Soil types defined in methods. HF=high fertility, MF=medium fertility, LF=low fertility.

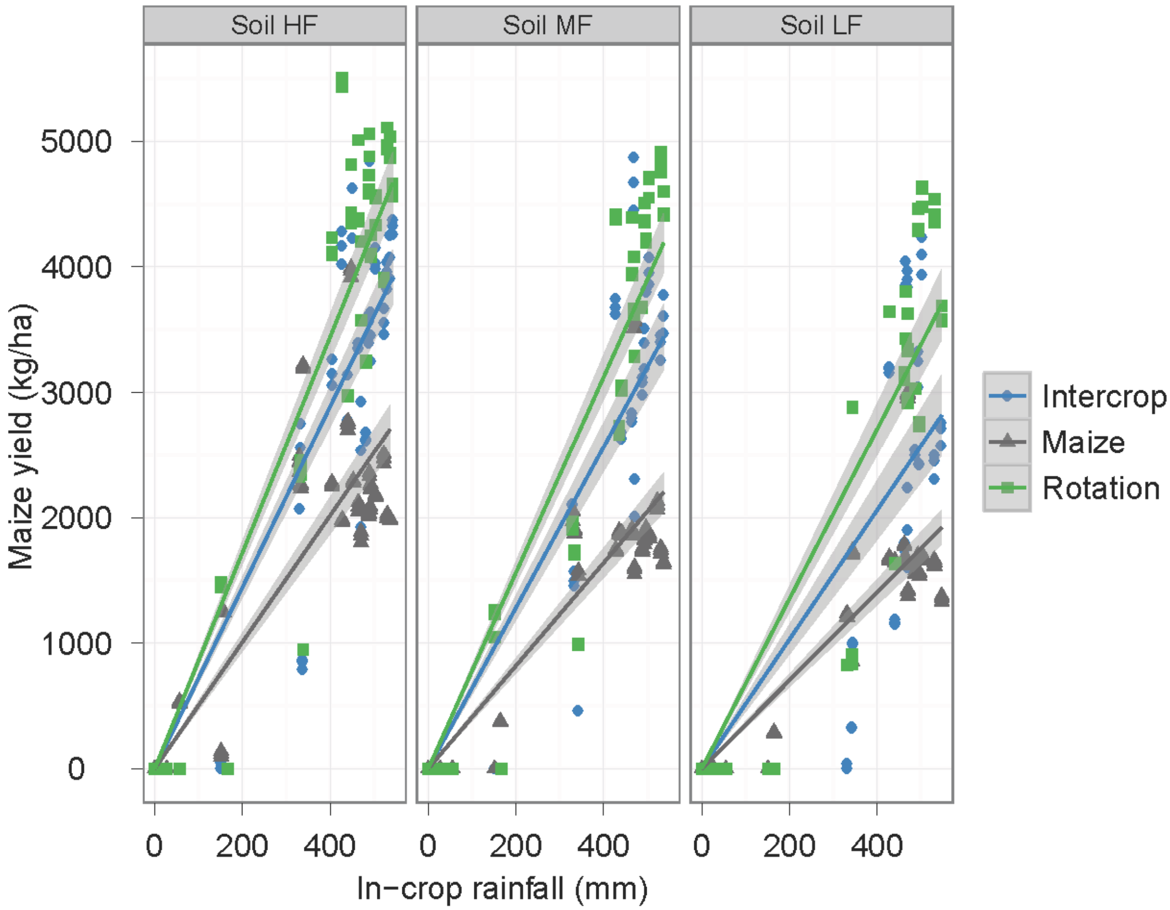


Figure 1.12: Maize yields and cumulative water stress for three cropping systems in three soil types. Time series model results from simulations of 83 years at Kasungu and 66 years at Zombwe, northern Malawi. Points with cumulative soil water stress less than one are not displayed. Results are from mid period, 5-7 years from system establishment. Soil types defined in methods. HF=high fertility, MF=medium fertility, LF=low fertility.

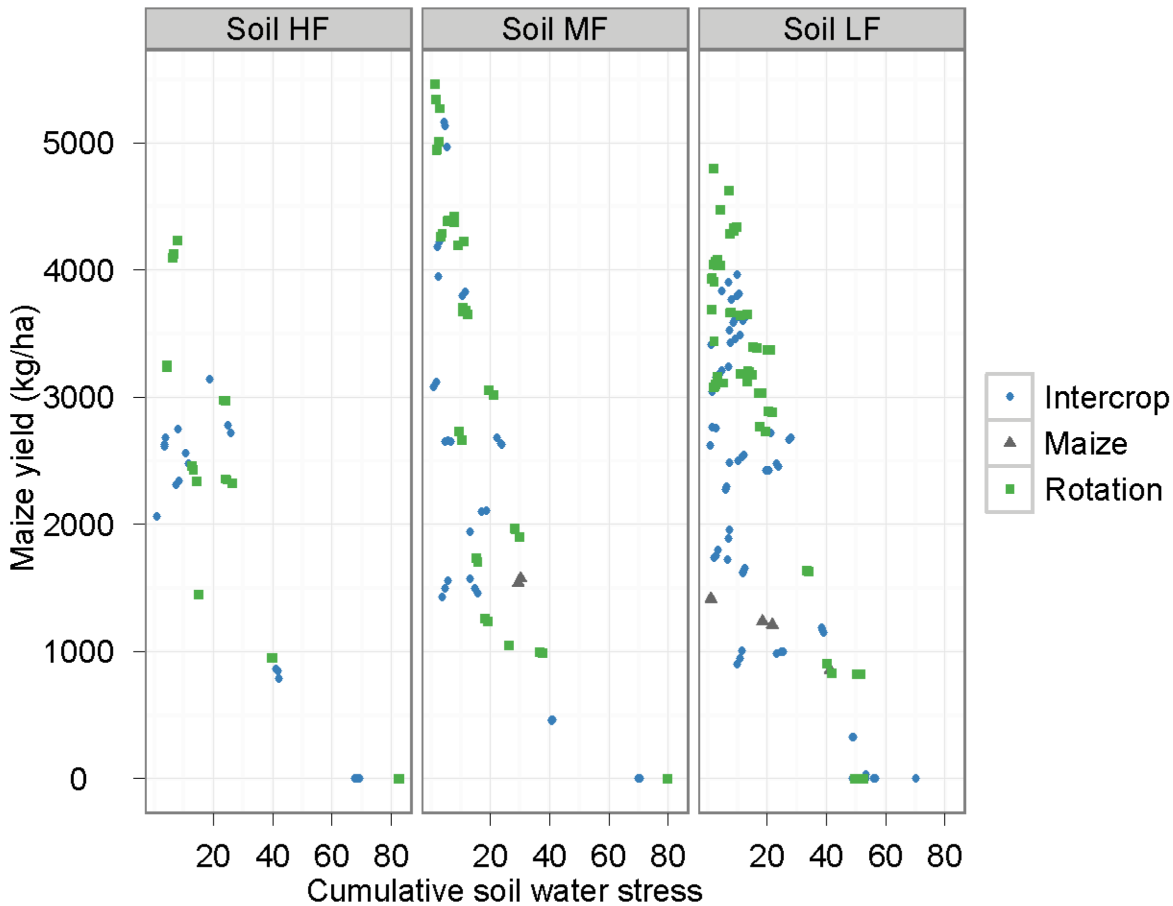


Figure 1.13: Mean soil water stress for three cropping systems in three soil types. Time series model results averaged over 83 years in Kasungu, northern Malawi. Error bars show standard errors of the mean. Periods early, mid, and late refer to time from system establishment: 2-4, 5-7, and 8-10 years respectively. Soil types defined in methods. HF=high fertility, MF=medium fertility, LF=low fertility.

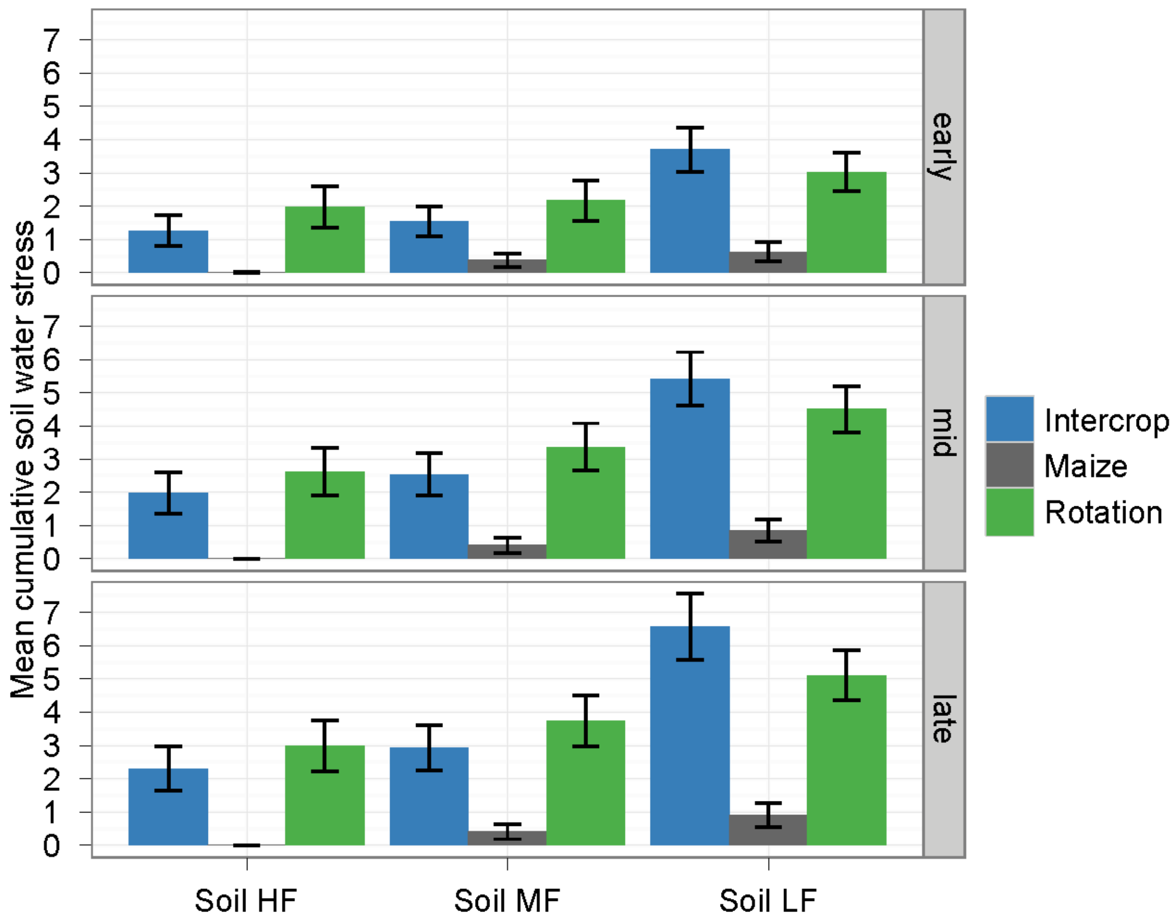


Figure 1.14: Maize yield and extractable soil water at critical plant growth stages for three cropping systems in three soil types. Time series model results from simulations of 83 years in Kasungu, northern Malawi. Results displayed are from mid period (3-5 years from system establishment). Points shown restricted to years with in-crop rainfall less than 550mm. Soil types defined in methods. HF=high fertility, MF=medium fertility, LF=low fertility.

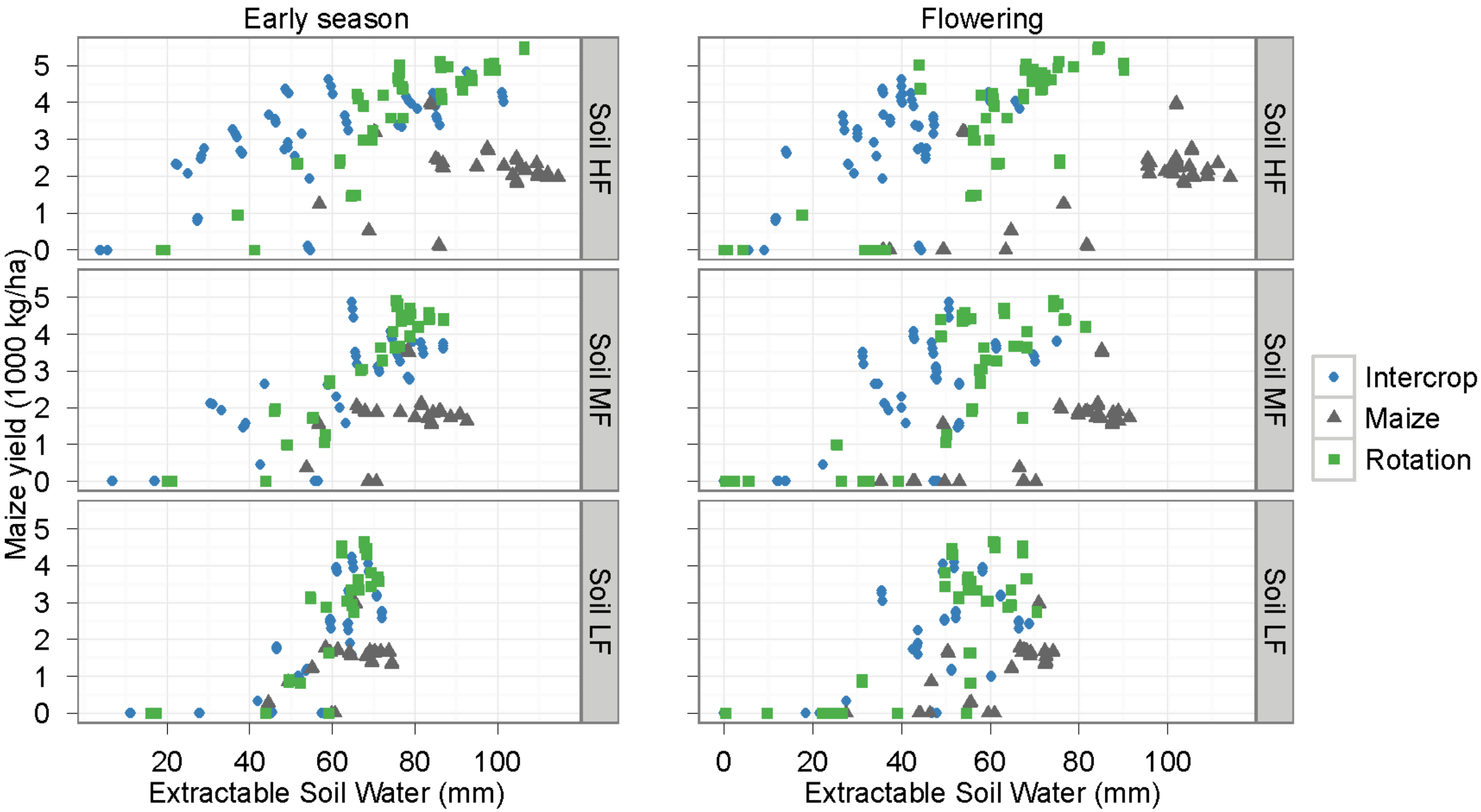
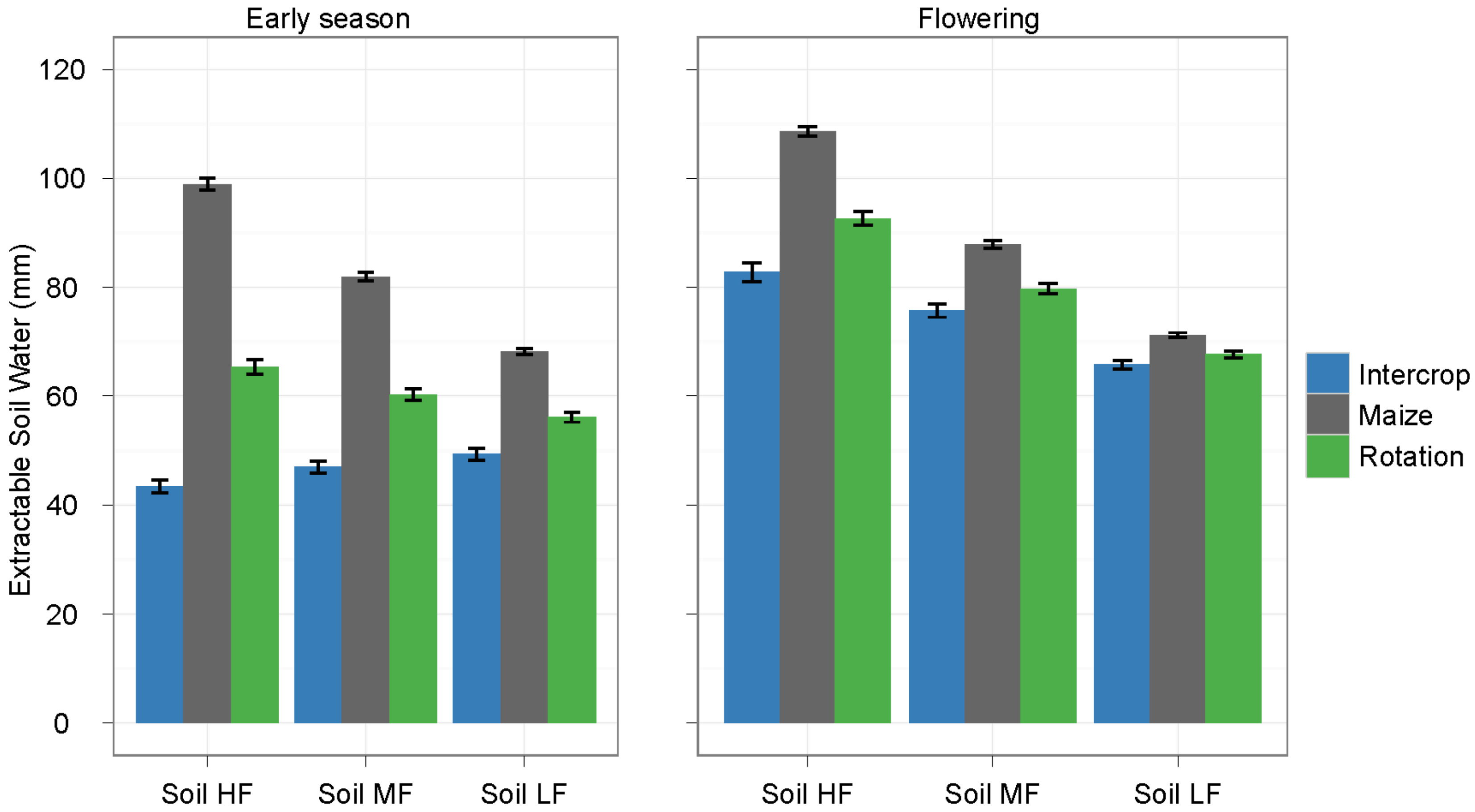


Figure 1.15: Mean extractable soil water at critical plant growth stages for three cropping systems in three soil types. Time series model results from simulations of 83 years in Kasungu, northern Malawi. Results displayed are from mid (3-5 year) period from establishment. Error bars are standard errors of the mean. Soil types defined in methods. HF=high fertility, MF=medium fertility, LF=low fertility.



CHAPTER TWO

Modeling maize-legume systems under variable climate scenarios in Northern Malawi

Abstract

Climate change has the potential to impact food security in sub-Saharan Africa, but details about future weather patterns, particularly rainfall, are uncertain. We develop methods to create climate change scenarios by combining a variety of rainfall scenarios with increases in temperature. This allows for exploration of alternative possible future climates, and facilitates greater participation in the research process, since scenarios generated are transparent and easy to understand. We use scenarios including temperature increases of up to 4 °C and rainfall changes of +/-10% and +/-25%, with different rainfall distributions to evaluate a promising rotation system of maize and the long duration legume pigeonpea. Its performance compares favorably under future climate scenarios to continuous maize at 24 kgN/ha and 92 kgN/ha. Maize in rotation outperforms continuous maize at the same level of fertility, and shows smaller yield declines at high temperatures than high fertility maize for all the rainfall scenarios tested.

2.1 Introduction

Increasing awareness of the potential impacts of climate change on crop production and food security in sub-Saharan Africa have led to a number of efforts to quantify and understand these effects (e.g. Thornton et al., 2010; Doherty et al., 2010; Twomlow et al., 2008). It is clear that agronomic recommendations must take into consideration the potential response of the proposed management and technological systems to a changing climate.

The 2007 report of the Intergovernmental Panel on Climate Change (IPCC) outlines the broad-scale consequences that will likely result from changes in climate. In sub-Saharan Africa, the report forecasts that by the end of the 21st century, temperatures will rise by over 3 °C.

Projected rainfall changes are more variable (Christensen et al., 2007). Both global and regional climate models (Thornton et al., 2009) project precipitation increases in East Africa and decreases during some portions of the year in Southern Africa (Christensen et al., 2007). In order to evaluate the impact of climate change on a local scale, the large-scale projections provided by global climate models must be downscaled to account for local variability in topography, and to translate long-term changes in climate to changes in short-term weather patterns (Winkler et al., 2011). This process is complicated in sub-Saharan Africa because of a relative scarcity of high-quality and long-term weather station data.

In addition to the uncertainty of climate predictions, evaluating the outputs from these models is difficult. For many scientists, and more so for farmers and extensionists, the models can seem like "black boxes" whose outputs must either be taken at face value or completely rejected. This dichotomy can be especially problematic when farmers' perceptions of climate change are different from those predicted by the models. Farmer surveys (e.g. Rao et al., 2011, Thomas et al., 2007, Mertz et al., 2009) report common beliefs that rainfall is decreasing or becoming more variable. While these beliefs may not be confirmed by meteorological data (Rao et al., 2011), they do influence farmers' thinking and may contribute to adoption or non-adoption of technologies.

One way to engage stakeholders in climate change impact analysis is by developing potential future scenarios and modeling their impacts (Swart et al., 2004). Developing climate change scenarios that can be easily understood without detailed knowledge of climate science could be a tool for more engaged research on the subject. Using these types of scenarios along with crop models can allow testing of current technologies as well as potential adaptation strategies. Such simulations can also be used to explore interactions among factors such as CO_2

concentration, temperature, and rainfall (Ludwig and Asseng, 2006). A scenario analysis approach was used by a group of researchers from the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT) (Cooper et al., 2009), who evaluated the impacts of 1° and 3° C increases in temperature as well as a 10% reduction in rainfall on maize production in Makindu, Kenya, and Bulawayo, Zimbabwe, and on groundnut production in Kasungu, Malawi. Weather inputs for the Cooper study, as for Ludwig and Asseng's study on wheat in Australia, were generated by modifying historical data on each day: increasing temperatures and reducing each day's rainfall amount by 10%. For systems with high input use, this resulted in significant decreases in yield, but for low-input systems the effects were minimal. The effect of temperature on yield was more significant than that of rainfall, due to the combination of increased evaporation and more rapid phenological development. This led to alterations in duration of growth and timing of maturation (Cooper et al., 2009). The simple perturbation method used for changing rainfall did not account for potential changes in distribution that could lead to different degrees of impact. Rainfall distribution can have marked impacts on crop and soil response and these impacts should be further explored (Stern and Cooper, 2011).

Malawi, as it is located in a transitional area between East and Southern Africa, has an extremely uncertain climate future. Novel cropping systems including the long-duration legume pigeonpea (Cajanus cajan) have been widely adopted in areas of northern Malawi, particularly around Ekwendeni, Mzimba district (Snapp et al., 2010). Participatory action research methods have been key to the development and adoption of these systems, and farmers and researchers are interested in expanding this effort to evaluate the response of legume-diversified systems to climate change. In this area, model agreement among GCMs is not good (Christiansen et al. 2007), and downscaled climate forecasting systems fail to accurately estimate current conditions.

The Climate Information Portal of the Climate Systems Analysis Group at the University of Cape Town, South Africa (Climate Systems Analysis Group, 2012) has made available statistically downscaled results for a number of locations including Lilongwe, in Central Malawi. At this location all climate models, when used to generate baseline rainfall, overestimated both numbers of rainy days and total rainfall amounts (Figure 2.1) when compared to observed data. Model projections for precipitation in Lilongwe in 2090 range from a 23% reduction to a 13% increase in the A2 scenario, with the majority of models projecting slight decreases (Figure 2.2). There are slightly smaller deviations in the B1 scenario. This degree of uncertainty, along with low confidence in model accuracy given difficulties in representing current conditions, does not provide useful guidance to those interested in developing adaptation strategies. Farmers, meanwhile, believe that rainfall is becoming more erratic and that rainy seasons are starting later (Bezner Kerr, personal communication).

The Agricultural Production Systems Simulator (APSIM) has been extensively tested in Eastern and Southern Africa, and is able to simulate low-fertility smallholder conditions as well as grain yield response to legumes (Robertson et al. 2005, Shamudzarira and Robertson 2002). It includes modules for crops including maize and pigeonpea, as well as soils modules for simulating processes including water, carbon, and nitrogen (N) dynamics (Keating et al., 2003). APSIM was used previously at the same Malawi sites to explore the effects of current climate variability on yields in smallholder systems (Chapter 1). That study showed that systems including pigeonpea had higher yields than continuous maize systems, but some trade-offs exist between the nitrogen benefits from an N-fixing legume, and increased soil water stress from a longer-duration crop. Given these trade-offs, it is important to understand the potential risk for crop failure in a warmer and potentially drier climate.

The objectives of the current study are to develop a realistic assessment of climate change impacts on smallholder maize-based cropping systems through the following:

1. Develop methods for creating climate change scenarios by varying the amount and distribution of rainfall in a historical record.

2. Use APSIM to evaluate the performance of smallholder maize and maize-legume cropping systems under climate change scenarios in northern Malawi

3. Determine the degree to which increases in temperature and changes in rainfall increase soil water stress and impact nitrogen availability in maize-based cropping systems.

2.2 Materials and Methods:

2.2.1 Generation of climate scenarios from current weather data

Rainfall has two basic characteristics: amount, and distribution. The distribution of rainfall — the number of rainy days, number and distribution of dry spells, length of rainy season — is often more critical to crop production than the total amount of rainfall (Barron et al., 2003). Therefore, changes in both amount and distribution should be considered when examining the sensitivity of a cropping system to changes in rainfall. To do this we have developed a set of functions for use with the R statistical software package (R Development Core Team, 2011) which add, remove, or redistribute rainfall in various ways.

Changing rainfall distribution by removing rainy days

This is accomplished by a set of functions which remove a percentage of existing rainfall from a user-selected fraction of rainy days or rainy spells. Rainy days are defined by a minimum threshold rainfall amount, with default of 0.85 mm. The existing rainfall record provides, in each year, a stochastic rainfall pattern, so the removal is deterministic: a count is kept of rainy days and the *n*th day is removed each time. It is possible to vary the days selected by varying the start of the count, to check for artificially inflated or reduced rainfall totals based on single large events. Rainy spells can be of length one or greater. For spells, the count value is increased by one on the first day with rain, where the previous day is dry, and thus remains the same throughout the spell.

A secondary set of functions redistributes removed rainfall, by dividing it evenly among all remaining rainy days or on a fraction of rainy days, to reach a specified goal percentage of original rainfall. This percentage can be either greater than or less than the original total. By restricting these functions to a date-defined fraction of the full data set, rainfall changes can be constrained to calendar months or seasons.

Changing season length

Adjusting growing season length requires first identifying the start and end of the rainy season. This is done according to criteria that can be set by the user. Stern and Cooper (2010) define the first period of three days with greater than 20mm total rainfall as the beginning of the rainy season. They define the end of the rainy season as the first date with less than 10mm total rainfall in the preceding 10 days and no rainfall in the following 20 days as the end of the rainy season. We use these definitions. The search domain for these dates will depend on the seasonal rainfall patterns in the area: for Malawi we use November through January for the start date, and April through June for the end date. Once start and end dates are defined, rainfall removal and redistribution functions can be applied around these dates in order to shorten or extend the rainy season. This can be done either by counting rainy days from start or end dates, or by creating a new data structure by extracting a period of days to be used as input to the global rainfall redistribution functions.

All functions are designed to be applied over one year, which can be defined by the calendar year, or by creating a harvest year variable that begins and ends in accordance with growing seasons. Creating a harvest year variable is helpful for cases like that of Southern Africa where the growing season begins in one calendar year and ends in the next. Packages previously developed for R such as *plyr* (Wickham, 2011) allow functions to be applied individually to years within a longer data set, or simultaneously to records from multiple stations, streamlining the creation of model-usable weather data files (Script is available as supplementary material to the electronic version of this thesis or by contacting the author at mollenburger@gmail.com)

2.2.2 Weather data used

The two sites used for this study are Zombwe (11.33°S, 33.82°E, altitude 143 m.a.s.l.), near Ekwendeni, and Kasungu (13.03°S, 22.45°E, altitude 1036 m.a.s.l.). The data available had long daily rainfall records, from 1945-2011 in Zombwe, and from 1927-2010 in Kasungu Temperature records in Kasungu were available from 1987, in Zombwe only long-term monthly mean temperatures were available. Weatherman, in the DSSAT 4.0 application suite (Pickering et al., 1994) was used to fill in missing data in both records and to generate solar radiation estimates. Annual average temperature at Zombwe was 20.5 °C, and at Kasungu 21.7 °C; mean annual rainfall is 783 mm/yr at Zombwe and 739 mm/yr at Kasungu.

2.2.3 Scenarios used in simulations

The rainfall scenarios used here were chosen to represent the range seen in climate model projections for the area. While some models project large percentage changes in rainfall during the dry season (June through September), rainfall amounts during these months are very low (see Figures 2.1 and 2.2). Overall, the projected changes in rainfall amounts are within 25% of current rainfall, so scenarios were developed within this range. A variety of distributions were tested for each rainfall amount, to examine the sensitivity of yield to differing changes in distribution. Rainfall records were modified in several ways. First, a set of moderate rainfall reduction scenarios with rainfall reductions of about 10% were generated (Group R90). Second, a group of increased-rainfall scenarios were generated, with increases of 10% and 25% (Group R+). Third, a set of worst-case rainfall reduction scenarios were generated. These included 25% reductions in rainfall across the growing season, as well as reductions targeted to critical early-season periods also leading to approximately 25% reductions in total rainfall (Group R75). Rainfall removal patterns in each scenario are described in Table 1. Each rainfall scenario was simulated for temperature changes in increments of 1° from 0°C to 4°C increase, and at three CO_2 concentration levels: 350, 500, and 700 ppm. The APSIM baseline CO_2 concentration is 350 ppm. Temperature increases of approximately 2 °C are predicted by 2050, and increase of between 3 and 4 °C are predicted by the end of the century. CO_2 concentrations of 500 and 700ppm are consistent with the IPCC A1b scenario for 2050 and 2090 (Christensen et al., 2007).

2.2.4 Simulation setup

Simulations were designed to follow the experimental setup described in Chapter 1. Treatments simulated were continuous maize with the addition of fertilizer at two levels, 24 and 92 kgN/ha, and a maize-pigeonpea rotation with 24 kgN/ha applied to maize, simulated with both maize and pigeonpea entry points to provide a maize yield value in each year. Fertilizer was applied as urea, at 4 WAP in the treatments with 24kgN/ha, and in the treatment with 92 kgN/ha as a split application with 24 kgN/ha at planting, 68 kgN/ha at 4 WAP. Simulations were run for the length of the rainfall record at each site: 66 years at Zombwe and 83 year at Kasungu. Soil carbon and nitrogen in these simulations were reset on July 15, before planting pigeonpea in the case of the rotation system, and yearly in all other treatments. Soil water was allowed to carry over between seasons. Planting was set to occur on the first instance between November 15 and January 30 where there is greater than 20mm of rainfall over 3 days, with a minimum soil moisture of 15 mm. This is a common planting condition for the area (Stern and Cooper, 2011). 85% of maize residues were removed, following farmer practice and to avoid immobilization of soil N by residues. Pigeonpea residues were incorporated. Each treatment was simulated for two soil types which are representative of smallholder conditions (Mhango et al., 2012). Soil HF has relatively higher fertility and finer texture, with 63% sand, 27% clay with 0.78 % organic carbon (OC) in the topsoil layer, while Soil LF has lower fertility and coarser texture, with 79% sand and 14 % clay, and has 0.57% OC in the topmost layer. This model was found to simulate yields in on-farm participatory trials at Zombwe to within one standard deviation of the mean. Details of model parameterization and evaluation can be found in Chapter 1.

2.3. Results:

2.3.1 Rainfall in climate change scenarios

Mean total rainfall (Figure 2.3) in the scenarios tested ranged from 537-926 mm at Kasungu, and from 578-984 mm at Zombwe, compared to averages of 740 mm and 787 mm respectively in the base rainfall scenarios. Season start and end dates varied with scenario: even for scenarios where early-season rainfall was not targeted, start dates tended to be later in reduced rainfall scenarios, and end dates tended to be earlier (Figure 2.4). These effects were small, less than one week in all cases. Season start dates are similar at the two sites, near December 1 in base rainfall scenarios. End dates differed by nearly three weeks between sites, from April 7 in Kasungu to April 25 at Zombwe.

2.3.2 Yield response to increases in CO_2 concentration

Maize response to CO_2 concentration is minimal. Changes in mean yield with the change from 350 ppm to 700 ppm are essentially zero for low N maize (continuous maize with 24 kgN/ha). At Kasungu, response is between 20 and 150 kg/ha for high N maize (continuous maize with 92 kgN/ha), while at Zombwe it is essentially zero. The response is negative at both sites for rotation, with yield reductions of up to 1000 kg/ha. The negative result in rotation is likely a result of very high CO_2 response for pigeonpea, where yields increase up to 35% in some cases. When examining overall relationships between maize and pigeonpea there appears to be a threshold pigeonpea yield of about 600-650 kg/ha above which maize yields begin to decline.

The simulated CO_2 response in pigeonpea is very high at both sites. A shift from 350 ppm to 500 ppm resulted in, on average, a 17% increase in yields, and an increase from 350 to 700ppm resulted in a 35% increase. These values are much higher than those observed in chamber experiments (Saha et al., 2012), which reported a maximum increase of 12% from CO_2 fertilization effects at 580 ppm. Clearly, the model requires further adjustments to accurately simulate CO_2 effects on pigeonpea. Since the maize yield response is so low and the pigeonpea response is questionable, CO_2 effect is not considered in further discussion, and figures show results at baseline CO_2 levels

2.3.3 Yield response to increases in temperature

Yield responses to temperature vary by treatment, site, and soil type (Figure 2.5). Rotation with pigeonpea improves maize yields relative to continuous maize at the same fertility level for all climate scenarios. At Zombwe, very high pigeonpea yields in the high fertility soil seem to be correlated with lower maize yields in that soil than in the low fertility soil. Low N (24 kgN/ha) continuous maize shows very little response to temperature at either site, remaining essentially constant. High N (92 kgN/ha) continuous maize yields respond differently by site and soil types. Yield decreases are greatest in soil HF, the soil with higher fertility and water holding capacity. In Kasungu, yields in this soil are nearly constant with temperature increases up to 2 °C. Above this, yields fall more rapidly reaching levels 15% below baseline yields at +4°C. In Zombwe, all temperature increases result in substantial yield decreases in high N maize in soil HF, with a 39% decrease at +4°C . Yields in the low-fertility soil are nearly constant at Kasungu, and decrease 17% at Zombwe. At both sites maize yields in rotation increase slightly with temperature increases of 1-2 °C and decrease at higher temperatures. At both sites yields in rotation remain at or slightly above baseline levels even with a 4°C increase in temperature.

Pigeonpea yields increase at Zombwe with 1°C temperature increases and then decline, returning to near baseline at a 3 °C temperature increase with baseline rainfall (Figure 2.6). Declines begin immediately and are more pronounced at Kasungu, which has a baseline mean temperature 1°C higher than Zombwe. Here yields decline by about 25% at a 4 °C temperature increase with baseline rainfall. One cause of lower yields at higher temperatures is the decrease in length of the growing season. At Zombwe, season length is reduced by approximately 25 days for maize and 74 days for pigeonpea with a 4 °C temperature increase. At Kasungu, for the base rainfall scenario, season length was reduced by approximately 20 days for maize, and 45 days for pigeonpea. There was more variation in season length with scenario type at Kasungu, especially in the low fertility soil (Soil LF).

2.3.4 Differences in yield response in rainfall scenarios

Overall, maize yield response to altered rainfall amount and distribution was minimal in in the low N maize system and highest in the rotation system. Yield response was largest at Kasungu, the more arid of the two sites. Figure 2.5 shows the effect of rainfall changes, grouped by the percentage of base rainfall: these are most notable at Kasungu in soil LF, the sandy and low-fertility soil type. Yield responses by individual rainfall distribution scenario are shown in figure 2.7. Here yields are shown relative to the simulated yield under baseline rainfall. Yield in each rainfall scenario is divided by the yield under baseline rainfall for each soil type, treatment, and temperature increase simulated. Thus yield with baseline rainfall is equal to one. This isolates the effect of rainfall from the effect of temperature, and allows for comparison of this effect across treatments and soil types. For rainfall scenarios with 90% of baseline rainfall (R90), the additional effect of changes in rainfall was within +/- 5% of yield with baseline rainfall, except for the A scenario at Zombwe, which resulted in increases over baseline of 12%. With a 25% reduction in rainfall (R75 scenarios), yields in rotation at Kasungu were as much as 23% below yields at baseline rainfall, while at Zombwe yields remained within 15%. High N continuous maize had maximum yield reductions in R75 scenarios of 16% at Kasungu, and 9% at Zombwe. The largest impacts in both rotation and high N maize occur for scenarios with yield reductions focused in the first 60 days of the season. The impact of reduced rainfall was greatest in the sandier soil (Soil LF).

Rainfall increases did not always result in increased yields relative to baseline rainfall. For most rainfall and temperature combinations at Zombwe, impact of increased rainfall was negative, resulting in a maximum 10% reduction in scenario BB+, where 25% rainfall increases are concentrated to one fifth of rainy days. At Kasungu, yields increased in increased-rain scenarios for rotation systems and for high N continuous maize in the higher fertility soil, but were reduced for the high N maize system in the sandier soil, particularly at low temperatures. In some A-type cases, where rainfall amount is adjusted on each rainy day, there are spikes in relative yield measurements at 3°C temperature increases: from figure 2.5 it is clear that these spikes correspond not to actual yield increases but to smaller decreases than in baseline rainfall scenarios. Overall, the combined effect of rainfall and temperature changes is to decrease differences between treatments and between soil types.

Differences in yields among rainfall distribution scenarios at the same total rainfall level were small. When only 10% of rainfall was removed, differences in yields were within 2-3% among different scenarios. At higher rainfall removal rates, differences were most notable between scenarios that covered the full growing season and scenarios focused on early months. The most extreme case is found in the sandy soil type at Kasungu with 4°C temperature increase. Here, maize yields in rotation yielded 10% less in removal scenario F (where half of rainy days were removed over the first 60 days of the season) than in removal scenario AA (where 25% of rain was removed on each rainy day throughout the year).

Pigeonpea yields follow similar trends, but with slightly larger impacts on yield than in maize (Figure 2.6). Pigeonpea yields are reduced by up to 26% in low-rainfall scenarios at Kasungu, and increase up to 17% above yields in base rainfall in increased rainfall scenarios. Pigeonpea yields at Zombwe were more affected by rainfall, with yield reductions of up to 35%, but from a higher baseline yield.

2.3.5 Water and nitrogen stress in maize

Water stress in maize increases with both rising temperature and declining rainfall, contributing to the yield reductions seen in such scenarios (Figure 2.8). APSIM calculates a daily soil water stress value ranging from zero to one, for processes including phenology, photosynthesis, and biomass expansion. We use the value calculated for photosynthesis, summed over the full growing season, as a measure of water stress in the crop. Rotation and high-N maize systems show the greatest effect of soil water stress. Figure 2.8 shows the percentage of years, for the worst-case R75 scenarios, in which cumulative water stress is greater than 10: at this level yield reductions due to water stress are about 10%. Yields decrease linearly so that at a cumulative water stress level of 25, yields are reduced by nearly 50%. Low N maize has very few instances of water stress, because in all but the most extreme cases, maize remains N limited and not water limited. Both rotation and high N maize show higher levels of water stress, and levels in high N maize are highest in the sandier soil (soil LF). Interestingly, in soil LF maize in rotation has a lower percentage of stressed years than high N maize, while the pattern is reversed in soil HF.

While soil water stress increases with rising temperature, nitrogen stress is reduced. Cumulative N stress, as with cumulative soil water stress, is calculated as the sum of daily values of nitrogen stress for photosynthesis, which range from zero to one, over the growing season. The reduction in N stress is largest in the rotation system, where nitrogen stress is reduced by 77% in the high fertility soil and 62% in the low fertility soil at Kasungu. Reductions are 84% and 83% respectively at Zombwe. In low N continuous maize, levels of N stress are reduced by 37% at Kasungu and 58% at Zombwe in the high fertility soil under base rainfall. Levels are reduced in high N maize as well, however this is from a lower baseline than the other two treatments and thus has a smaller impact on yields. Trends are similar in all rainfall scenarios at Kasungu. Decreases in N stress are slightly lower at Zombwe in high rainfall scenarios. For example, in the AA+ rainfall increase scenario (an evenly distributed 25% increase over base rainfall), the reduction in N stress in rotation is 77%.

2.3.6 Rotation effects under climate change

Maize yields in rotation are between 150% and 200% of yields in continuous maize systems with the same fertilization rate at base rainfall and temperature, with greater increases seen in the sandier soil type (Figure 2.5). This simulated rotation response is reduced under lower rainfall and higher temperature scenarios at the more arid site, Kasungu, but almost no effect is seen at Zombwe. This is presumably due to differences in water availability and thus maize water stress at these two sites. Because of the risk-averse nature of smallholder farmers, risk of decreased yield is important to examine (Figure 2.10). This risk represents the chance that a farmer will see reduced yields following pigeonpea compared to the yield would have been following maize. Risk is low at baseline temperature and rainfall. At Kasungu risk generally increases with rising temperature and diminished rainfall. At Zombwe both increased rainfall—particularly rainfall concentrated to a few extreme events—and decreased rainfall increase risk relative to baseline rainfall. Notably, the maize-pigeonpea rotation system is always extremely low-risk in soil LF at Zombwe, with less than 5% chance of yield reductions in any scenario. At Zombwe, soil LF has lower risk than soil HF. However, at the more arid Kasungu site, the mean effect of rotation is similar in the two soils, but the risk in soil LF is higher than that in soil HF.

2.4 Discussion:

2.4.1 Soil fertility remains the limiting constraint in low input systems.

It is clear that the dominant constraint to crop production in typical smallholder systems is soil fertility, and that will remain the case for low-fertility systems under even relatively extreme climate change predictions. As discussed elsewhere (Dimes et al., 2008), the challenge of intensification of smallholder crop production remains critical, even as climate change adaptation receives increased attention. We see here that for continuous maize with low fertilizer use, productivity remains very low, with minimal impact from climate change, and that generally in a positive direction. Regardless of changes in climate, yields can be significantly increased by changing management practices.

2.4.2 Effects on high-input continuous maize

Applications of 92 kgN/ha more than doubled maize yields relative to applications of 24 kg N/ha, to approximately 4000 kg/ha. Yields decreased from this high level as temperature increased, notably for mean annual gains of 3 °C or more. Effects of reduced rainfall were generally small in the 10% reduction (R90) scenarios, becoming substantial, especially in Kasungu, at the 25% reduction level. Soil type influenced the level of yield reduction. In the sandier soil the magnitude of yield reductions due to temperature increases was lower. This effect may have been mediated by a positive influence on soil N mineralization in sandy soils balancing a negative direct effect of temperature on plant growth. At the same time, in sandy soils rainfall effects were magnified. This is presumably due to more rapid drainage in sandy soils exacerbating soil moisture stress with lower rainfall. At both Kasungu and Zombwe sites, yields in high N maize showed the largest declines in scenarios with extreme temperature increases and where rainfall reduction occurred during the early part of the growing season. These scenarios also showed the highest levels of water stress in the simulated crops.

2.4.3 Effects on maize in rotation

Rotation systems had improved maize yield performance at higher temperatures relative to continuous maize (Figure 2.5). At moderate temperature increases, maize yields improved in rotation systems. Overall, a substantial narrowing of the yield gap was observed for maize between high N continuous and rotated systems with much lower N inputs, particularly in constant and increased rainfall scenarios, and in the sandier soil type. Improved yields in rotation systems are likely due to a reduction in nitrogen stress levels in rotation systems with higher temperatures. This, in turn, may be due to increased mineralization of high nitrogen residues with higher temperatures. Hence we have a second type of trade-off, between positive and negative effects of higher temperatures on soil and crop processes. This is clearly a highly complex interaction and our data highlight trade-offs that otherwise could have been overlooked. We note that data generated depend on model assumptions and algorithms, and confirmation of the crop and soil interactions with environment observed here will require further exploration through field investigations and modeling.

While we were not able to accurately simulate rotation effects including CO2 concentration impacts, we note that if pigeonpea yields increase dramatically this can have a negative impact on following-year maize yields. However, management plays a central role and rotation challenges could be avoided by reducing plant density or pruning pigeonpea.

Decreases in rainfall had a larger negative impact on maize yields in rotation than on continuous maize, particularly for rainfall focused near the beginning of the growing season (Figure 2.7). This vulnerability to early-season rainfall reductions is particularly important to note since downscaled climate models generally project rainfall decreases for this area in November and December. Therefore, early season rainfall reductions similar to those described by scenarios E and F can be expected. In sandy soils at Kasungu, with the approximately 50% reductions in early-season rainfall used for E and F scenarios, maize in rotation showed a yield decrease of more than 20% at the highest temperature levels when compared to baseline rainfall. Overall, however, the favorable performance of the maize-pigeonpea rotation under temperature increases outweighed its increased sensitivity to rainfall reductions. In general, the effect of all climate change scenarios was a reduction in the yield gap between maize grown with high N fertilizer inputs and maize grown in rotation with modest fertilizer inputs.

The strong performance in the rotation occurred despite increases in soil water stress with increased temperature and decreased rainfall. Water stress provides an explanation for the relatively better performance of rotation systems in the sandier soil, as stress levels in this soil tend to be lower for rotation systems than for continuous maize with a high N fertilization rate. This seems counterintuitive given that the long-duration pigeonpea is extracting water for a larger fraction of the year, and soil water levels near planting are indeed lowest in these systems. However, from examination of daily water content in some simulations, it appears that while the initial soil water content is low in rotation, recharge occurs rapidly, particularly in well-drained soils. This effect was also seen in field experiments in Zimbabwe by Ncube et al. (2007). Because of this rapid recharge, the initially low water content does not lead to water stress conditions throughout the growing season. The rotation systems also include a higher amount of cover from the long-duration crop, and pigeonpea residues remain in the field until pre-sowing tillage. Increased soil cover, such as that provided by a leafy long-duration crop like pigeonpea, has been shown previously to mitigate some of the water stress effects seen under climate change scenarios (Cooper et al., 2009).

2.4.4 Effects on Pigeonpea

Pigeonpea yields showed smaller temperature-induced decreases than maize yields in Zombwe despite much larger changes in length of growing period. Because pigeonpea matures far into the dry season, the temperature-induced reduction in time to maturity is likely beneficial to the crop (Dimes et al., 2008). At Kasungu, which is both drier and warmer, pigeonpea yield decreases were large: up to 25% in base rainfall over 4 °C. Pigeonpea yield declines due to decreased rainfall are larger than corresponding maize yield decreases: up to 25% less in the worst-case rainfall scenarios at 4°C temperature increases than in the baseline rainfall. Pigeonpea cultivars show a wide range of maturity durations, as well as varying responses to temperature and photoperiod (Silim et al., 2010). Therefore the temperature response seen here will vary depending on the pigeonpea variety used.

2.4.5 Implications for use of long-duration legumes

In all cases tested here, maize in the rotation system has higher average yields than continuous maize at the same (24 kgN/ha) N fertilization level. On average, yields in rotation are 1.5 to 2 times those in continuous maize. However, the risk of poor performance, defined as a yield below that found in the low N continuous maize system in the same year, increases with increasing temperature and decreasing rainfall. In extreme cases at Zombwe, this risk reaches 25%, which is problematic. Risk of poor yield on an absolute level remains low here: the risk of yields below 2000 kg/ha in the rotation system is always below 15%. It is also important to note that this analysis is based on the immediate response to one year of pigeonpea; longer-term soil productivity benefits of a rotation system were not explored here. Previously we have shown that rotations induce changes in soil water holding capacity and soil N status that can be substantial (Snapp et al., 2010 and Chapter 1). Rotation decreases risk over time, as shown through decadal simulation scenarios (Chapter 1) and through on-farm establishment of pigeonpea-maize systems (Snapp et al., 2002), so if a maize-legume rotation is continued over more than two years, greater yield increases and lower risk could be expected. Given the signs of faster mineralization of organic residues, however, long-term increases in soil carbon seen in rotation systems with high residue inputs (Palm et al., 2001) may be reduced with increased temperatures. Risk remains lowest and return highest in low-fertility, sandy soils. This suggests that maize-pigeonpea systems should be targeted to these types of soils for maximum benefit.

Overall, maize-pigeonpea rotation systems are successful in increasing maize yields, even under the most extreme climate scenarios and particularly in poorer soils. Pigeonpea yield responses vary depending on site and rainfall, and may be maintained, increased, or reduced, with declines most likely at Kasungu. Over moderate temperature increases, maize yields in these systems can actually increase, and high maize yields are maintained even at high temperatures, rarely putting farmers as risk relative to continuous maize (Figure 2.10). Additional complexity is faced by farmers with very small land holdings, as these farmers will not necessarily be able to devote land to a rotational crop given considerations of meeting maize food requirements each year. Further study of alternative integrated soil fertility management strategies is needed to define a range of options for the variety of constraints faced by smallholder farmers.

2.5 Conclusions:

Maize-pigeonpea systems for integrated soil fertility management are robust to most potential changes in climate, particularly in low-fertility well-drained soils, where they show potential for ameliorating constraints to crop production. Given the complexity and uncertainty created in modeling and downscaling climate change projections, the type of empirically created scenarios used here are critical for informing the development of climate-aware agricultural management strategies that can help alleviate fertility constraints on production while minimizing negative impacts of climate change.

Figure 2.1: Baseline (2000) rainfall estimates for Lilongwe, Malawi from statistically downscaled global climate models. Line is mean of observed data from 1982-2000 (Climate Systems Analysis Group, 2012)

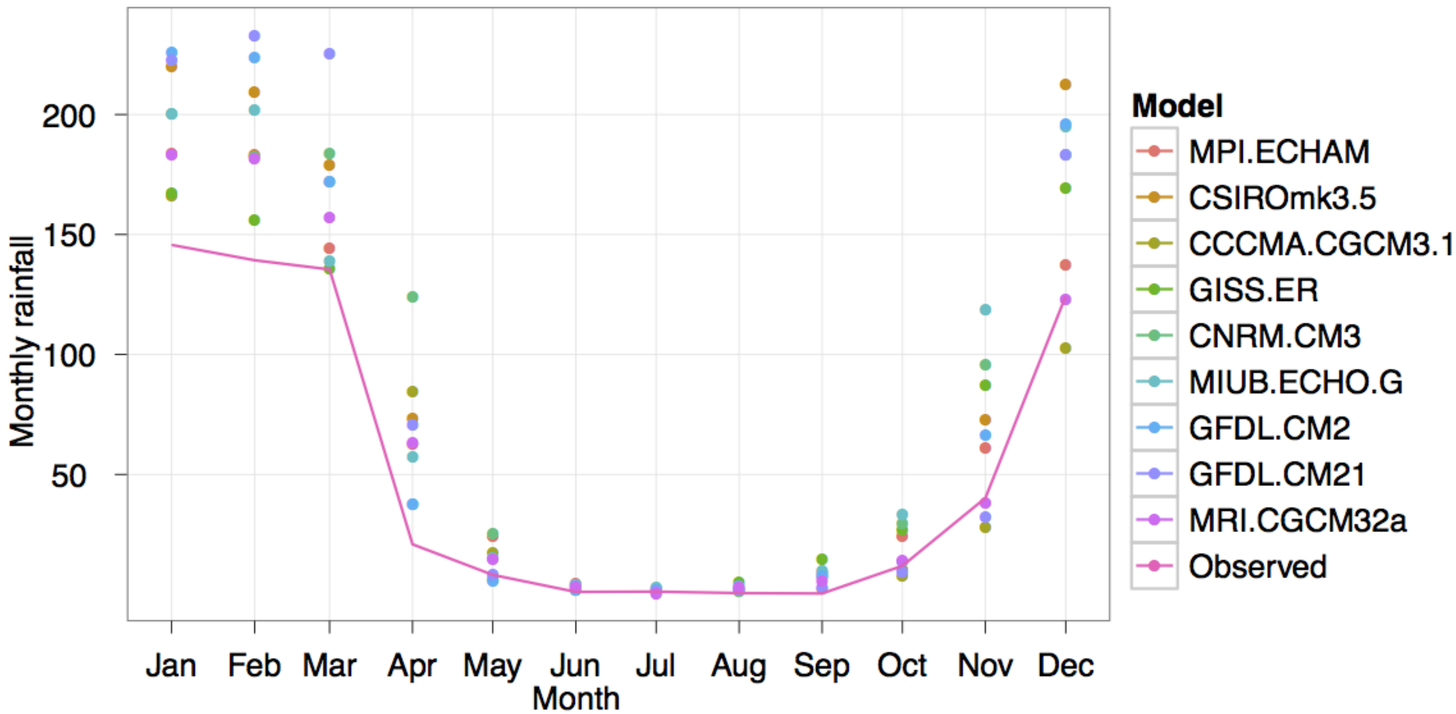


Figure 2.2: Rainfall projections for Lilongwe, Malawi for 2050 and 2090 in two scenarios from the Special Report on Emissions Scenarios of the Intergovernmental Panel on Climate Change. Results are from statistically downscaled global climate models (Climate Systems Analysis Group, 2012).

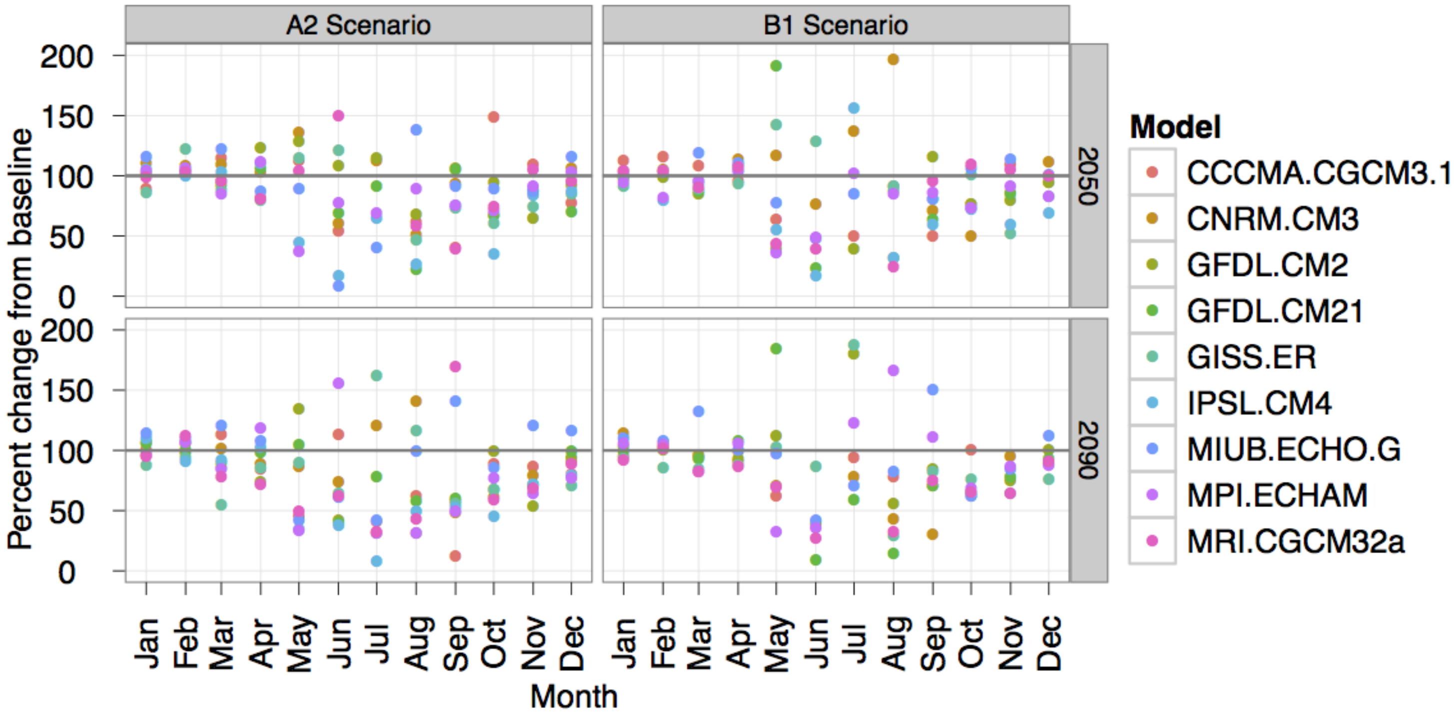


Table 2.1: Rainfall scenarios used in climate change simulations. As described in Materials and Methods, rainfall distribution groups describe the level of rainfall relative to baseline. Group R90 has 90% of baseline rainfall, Group R75 has 75% of baseline rainfall, group R+ has additional rainfall at 110% and 125%. Individual letters correspond to the methods used to change rainfall distribution. Scenarios using the same letter use the same pattern of rainfall removal or addition at different intensities.

Group R90	
A	Reduce rainfall 10% on each rainy day
B	Remove all rainfall from 1 in 10 rainy days
C	Remove 1 in 5 rainy days, redistribute rainfall on 1/5 of remaining days to reach 90% of initial rainfall amount
D	Remove all rainfall from 1 in 10 rainy spells
Group R75	
AA	Reduce rainfall 25% on each rainy day
BB	Remove all rainfall from 1 in 4 rainy days
CC	Remove 1 in 3 rainy days, redistribute rainfall on 1/5 or remaining days to reach 75% of initial rainfall amount
E	Remove 50% of rainfall from all rainy days for 60 days after start of rainy season
F	Remove all rainfall from ½ of rainy days for 60 days after start of rainy season
Group R+	
A+	Increase rainfall 10% on each rainy day
AA+	Increase rainfall 25% on each rainy day
B+	Distribute additional rainfall to 1 in 5 rainy days to reach 110% of initial total rainfall
BB+	Distribute additional rainfall to 1 in 5 rainy days to reach 125% of initial total rainfall

Figure 2.3: Mean total annual rainfall in empirically generated rainfall scenarios, averaged over 83 years at Kasungu and 66 years at Zombwe, northern Malawi. Colors denote rainfall scenario groups, as described in Table 2. Error bars are standard errors of the mean.

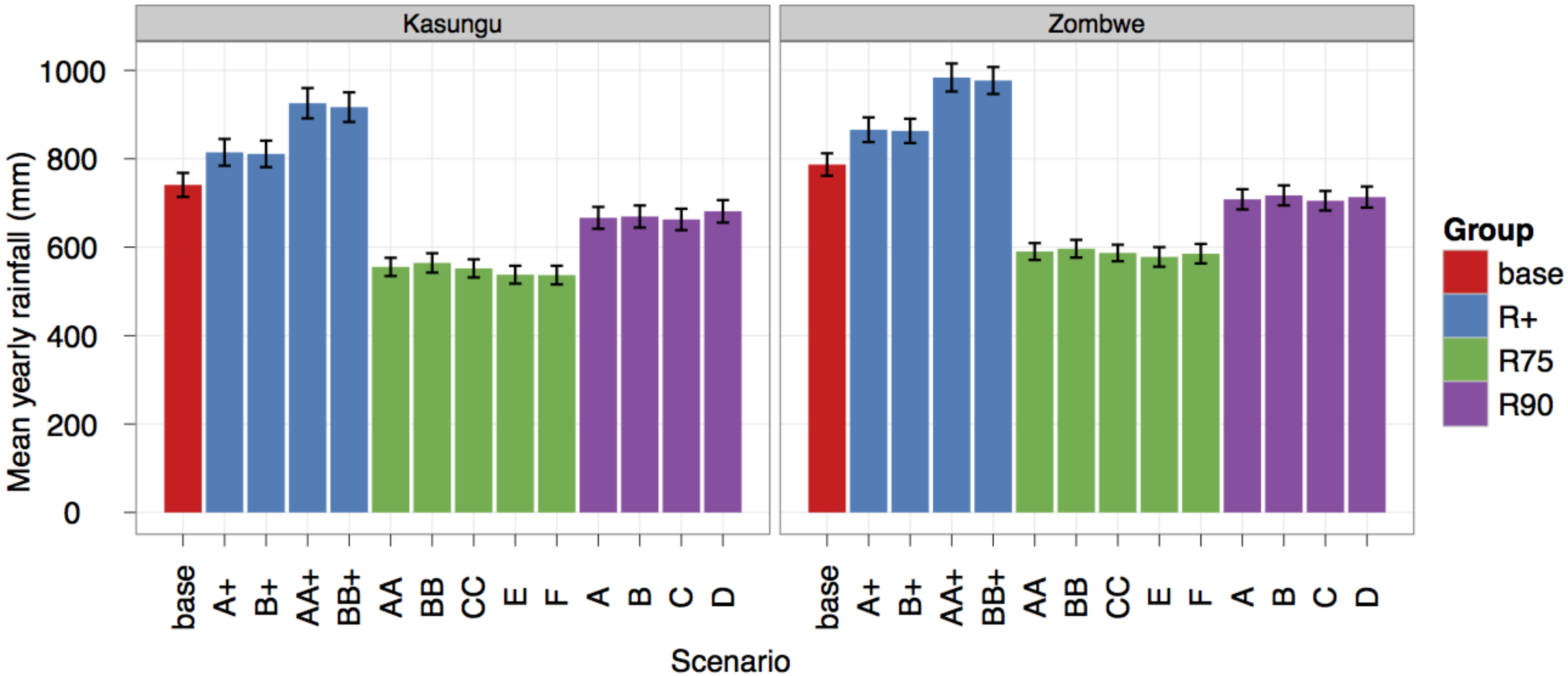


Figure 2.4: Mean rainy season end and start dates calculated from rainfall in empirically generated climate scenarios, averaged over 83 years at Kasungu and 66 years at Zombwe, northern Malawi. For definitions of start and end date, see methods. Error bars are standard errors of the mean.

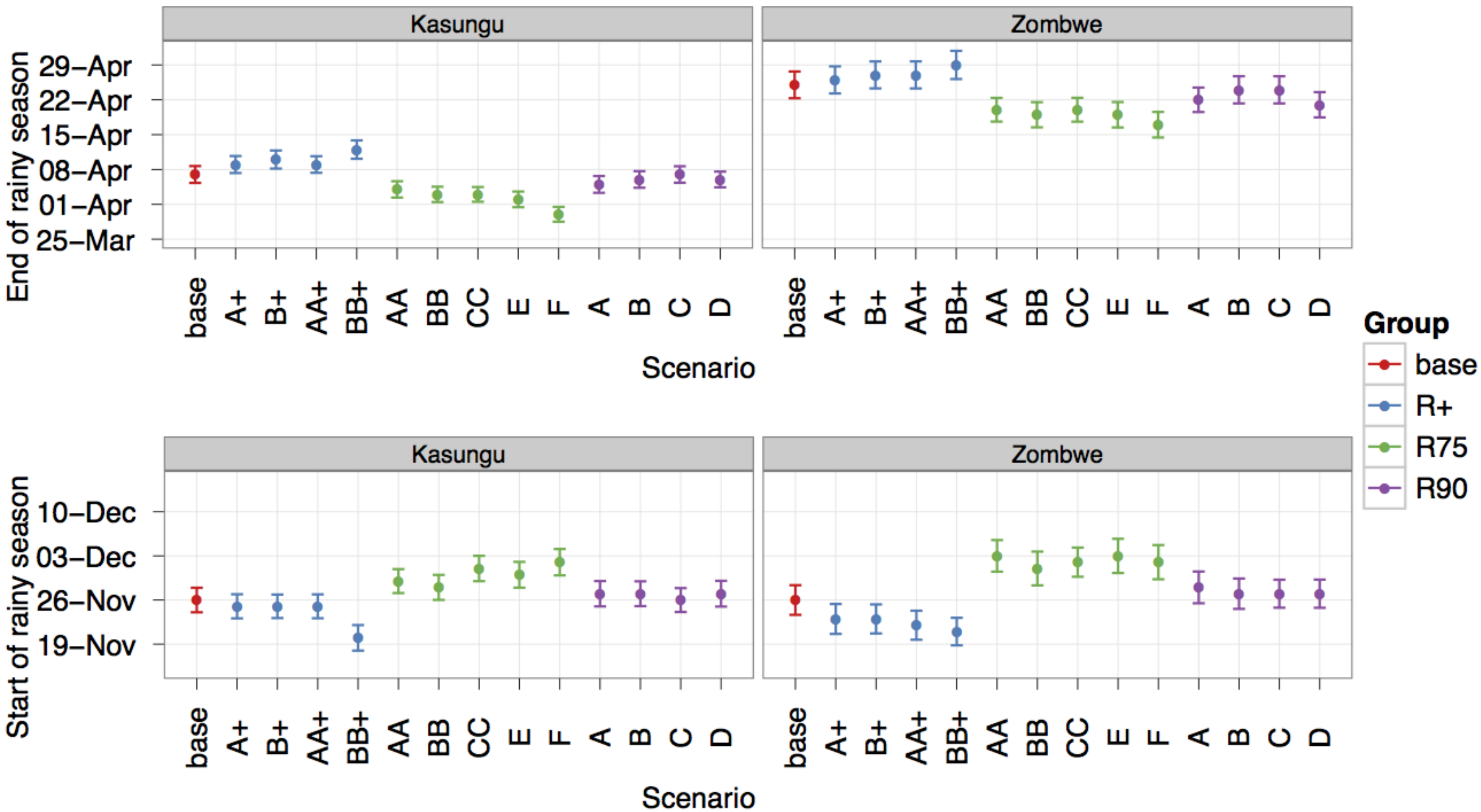
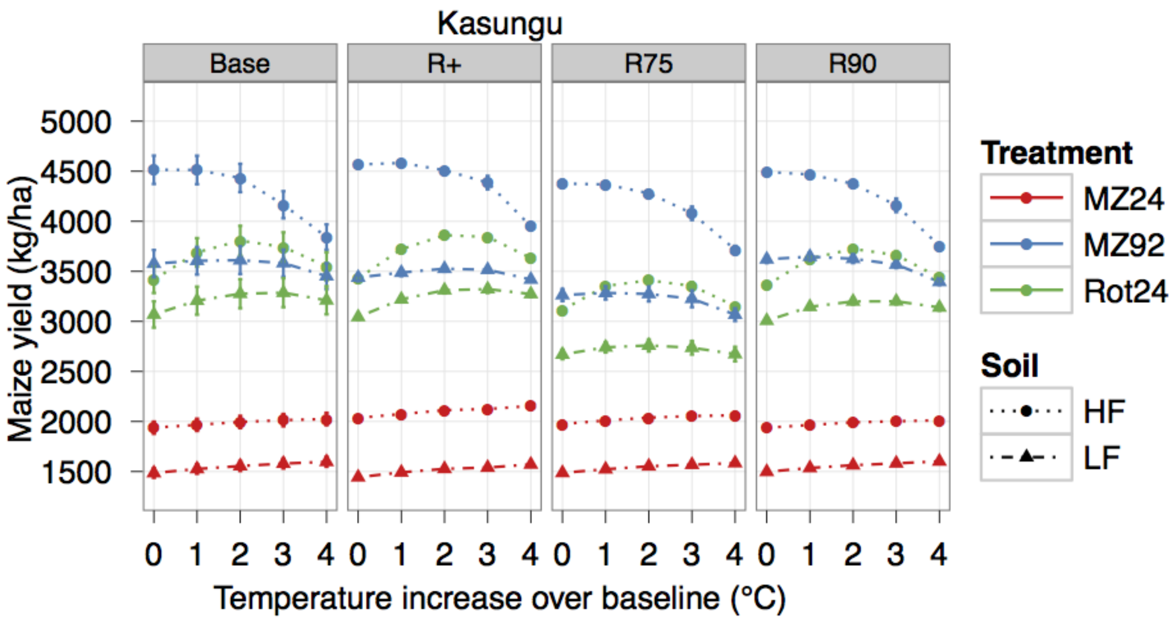


Figure 2.5: Mean modeled maize yields in empirically generated climate scenarios based on changes in temperature and rainfall amount. Points are mean simulated yields averaged over 83 years in Kasungu and 66 years in Zombwe, northern Malawi. MZ24 is continuous maize with 24 kgN/ha, MZ92 continuous maize with 92 kgN/ha, and Rot24 a maize-pigeonpea rotation with 24 kgN/ha applied in maize years. Properties of soils HF (high fertility) and LF (low fertility) described in methods. Error bars in base rainfall are standard errors of the mean, describing year-to-year variability. Error bars in other rainfall groups are standard errors among scenario means within the group, describing group variability. Descriptions of rainfall scenarios are found in Table 2.1. Soil types defined in methods. HF=high fertility, LF=low fertility.



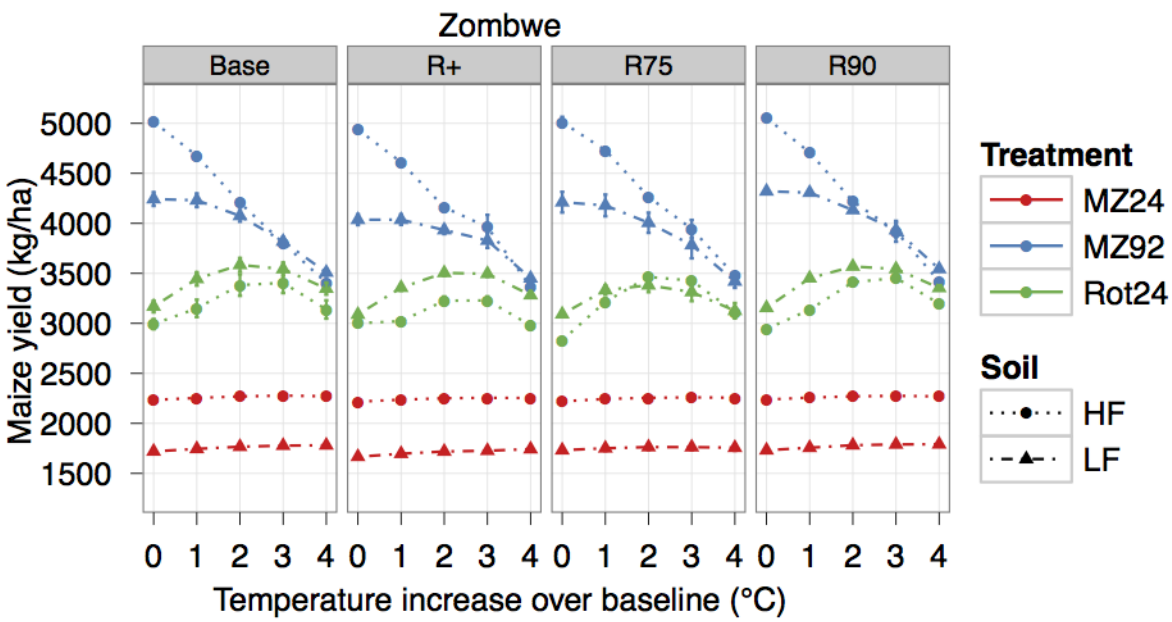
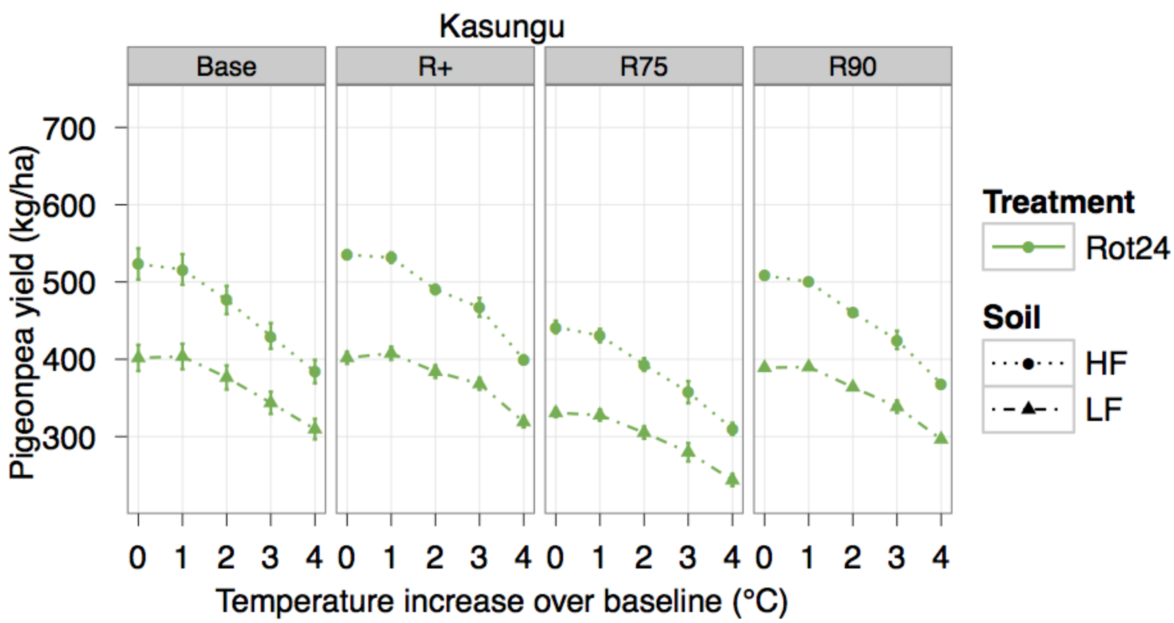


Figure 2.6: Mean modeled pigeonpea yields in empirically generated climate scenarios based on changes in rainfall and temperature. Model results over 83 years in Kasungu and 66 years in Zombwe, northern Malawi. Pigeonpea in rotation with maize, with 24 kgN/ha applied in maize years. Properties of soils HF (high fertility) and LF (low fertility) described in methods. Error bars in base rainfall are standard errors of the mean, describing year-to-year variability. Error bars in other rainfall groups are standard errors among scenario means within the group, describing group variability. Descriptions of rainfall scenarios are found in Table 2.1. Soil types defined in methods. HF=high fertility, LF=low fertility.



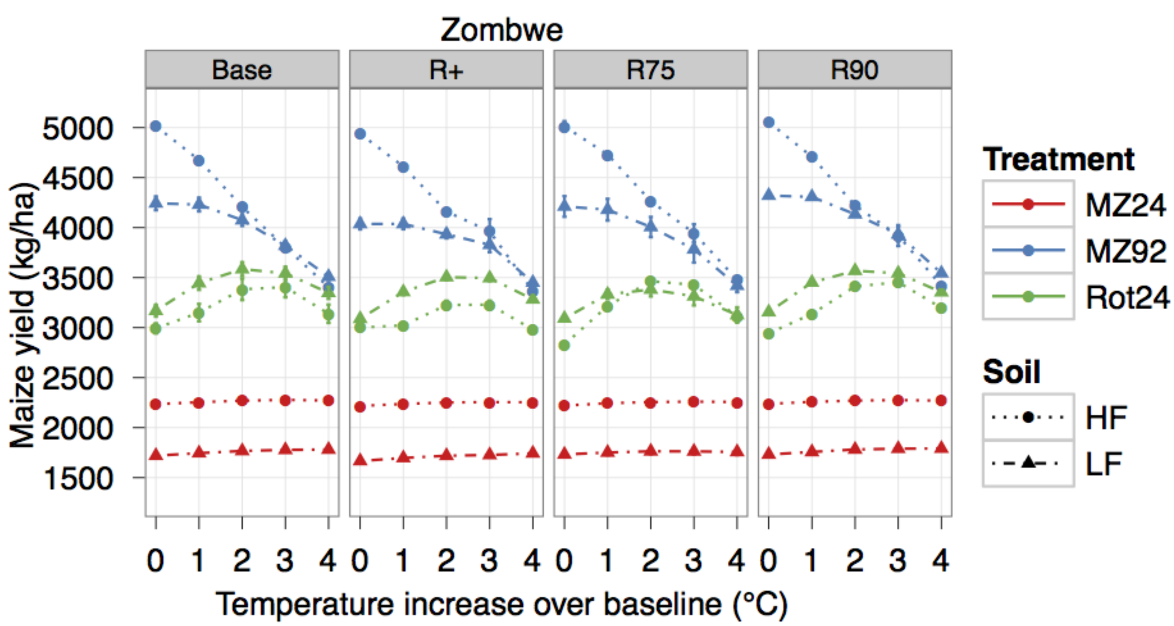


Figure 2.7: Mean maize yields in empirically generated climate scenarios as fraction of maize yield with baseline rainfall. Yield with baseline rainfall equals one for all treatments, soil types, and temperatures. Model results over 83 years in Kasungu and 66 years in Zombwe, northern Malawi. MZ24 is continuous maize with 24 kgN/ha, MZ92 continuous maize with 92 kgN/ha, and Rot24 a maize-pigeonpea rotation with 24 kgN/ha applied in maize years. Descriptions of rainfall scenarios are found in Table 2.1. Soil types defined in methods. HF=high fertility, LF=low fertility.

Figure 2.7 (cont'd)
a. Kasungu

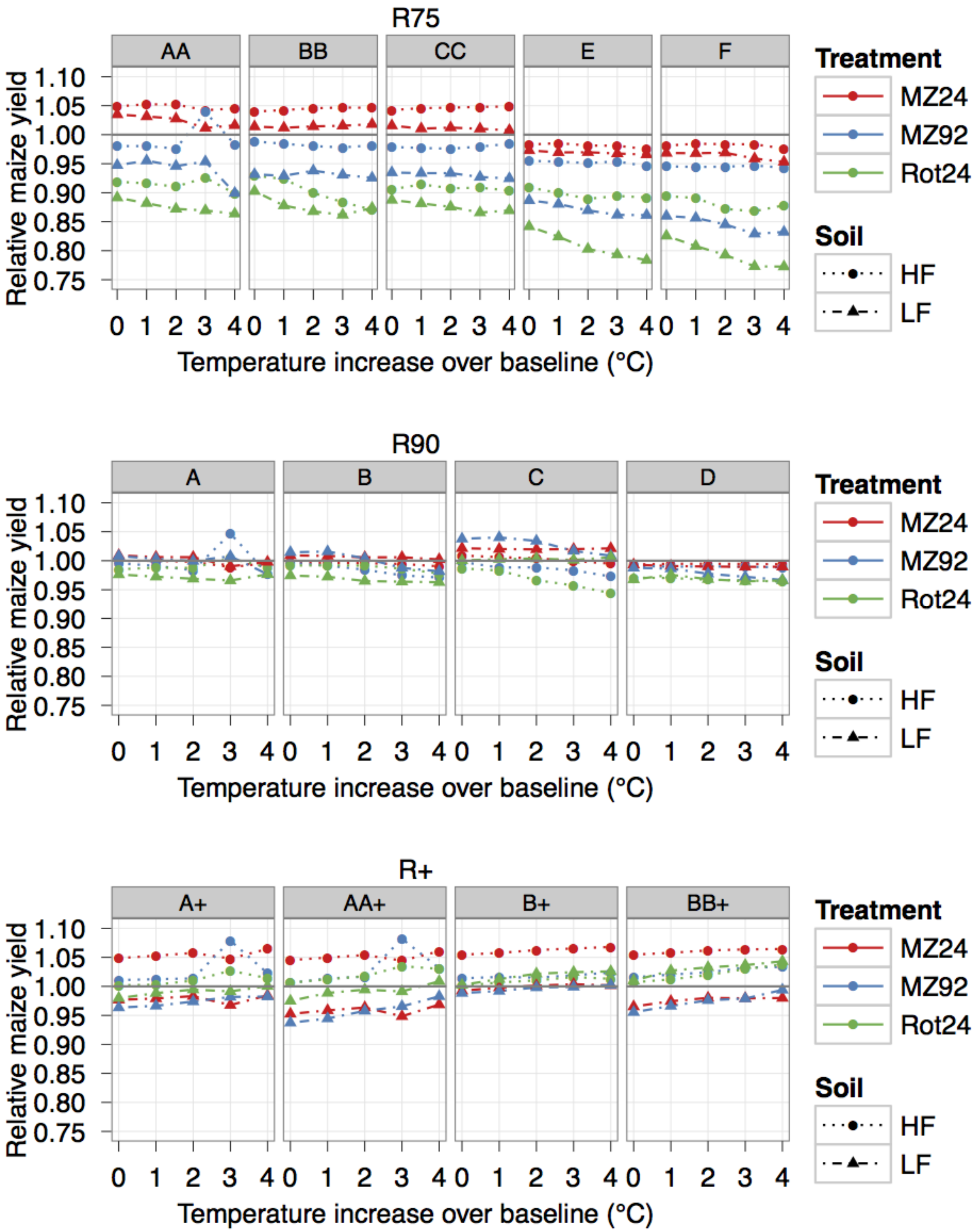


Figure 2.7 (cont'd)
b. Zombwe

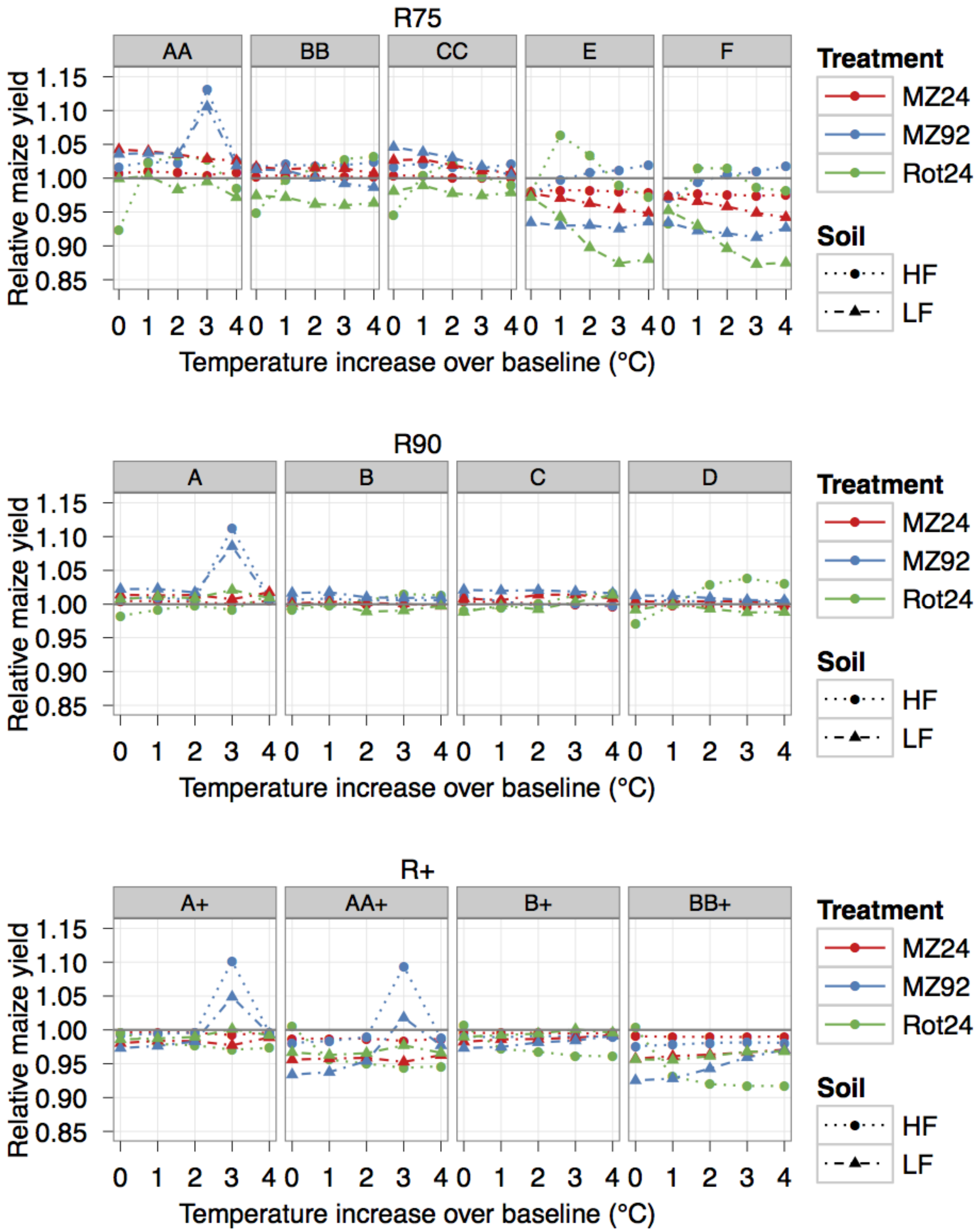


Figure 2.8: Percentage of years in which cumulative soil water stress in maize exceeds 10 in R75 group rainfall reduction climate scenarios (see Table 2.1 and Figure 2.3). Model results from 83 years in Kasungu and 66 years in Zombwe, northern Malawi. Expected yield reduction at soil water stress of 10 is approximately 10%. MZ24 is continuous maize with 24 kgN/ha, MZ92 continuous maize with 92 kgN/ha, and Rot24 a maize-pigeonpea rotation with 24 kgN/ha applied in maize years. Descriptions of rainfall scenarios are found in Table 2.1. Soil types defined in methods. HF=high fertility, LF=low fertility.

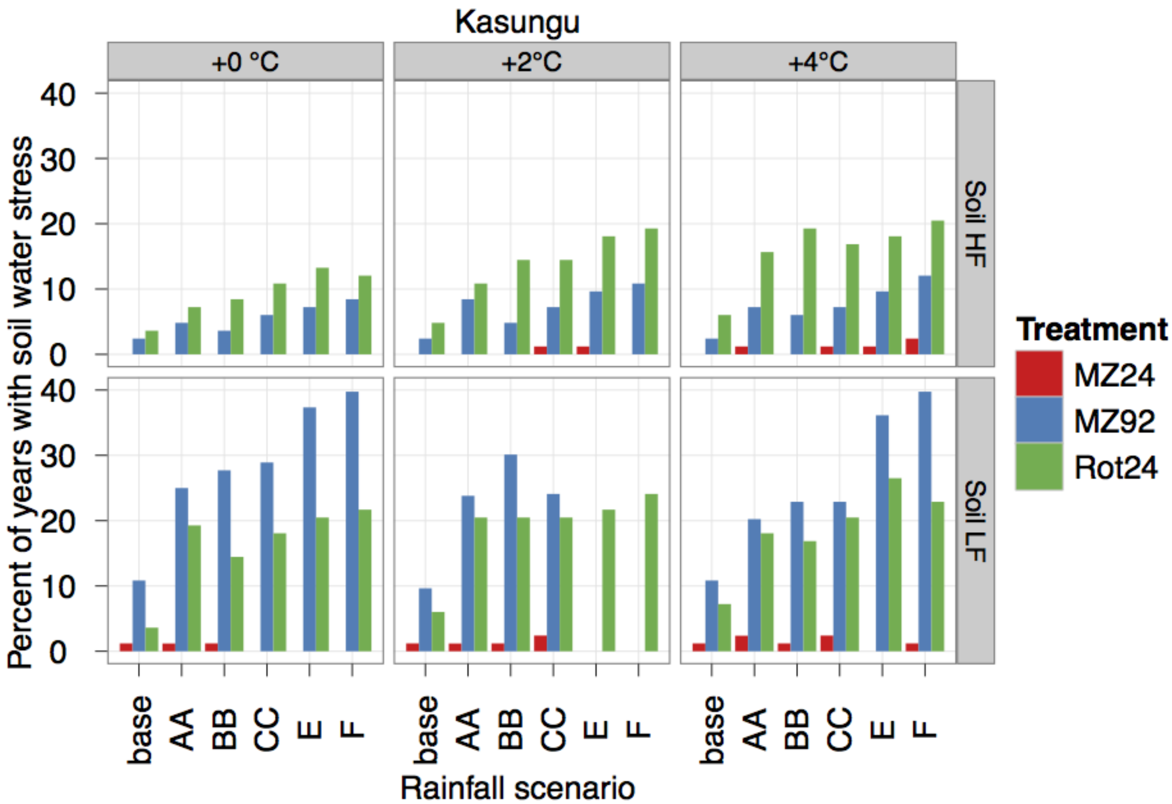


Figure 2.8 (cont'd)

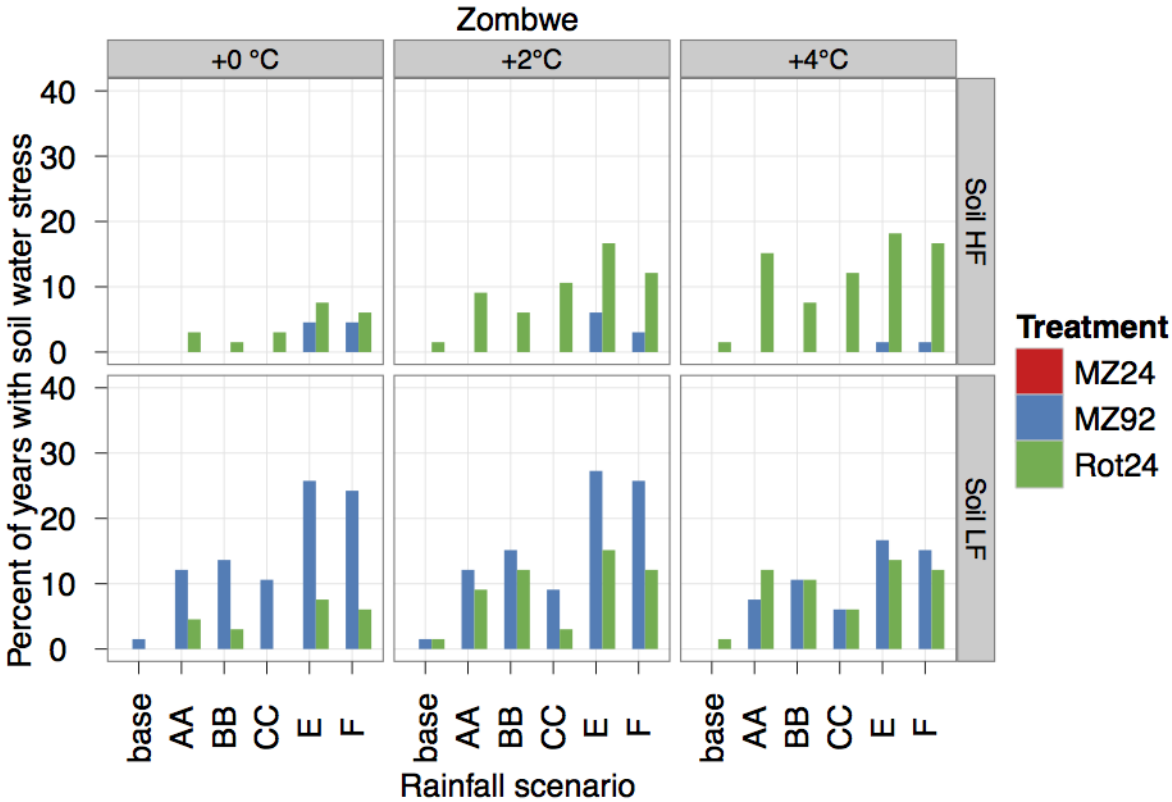


Figure 2.9: Mean cumulative N stress under increases in temperature. Rainfall is maintained at baseline levels. Model results from 83 years in Kasungu and 66 years in Zombwe, northern Malawi. MZ24 is continuous maize with 24 kgN/ha, MZ92 continuous maize with 92 kgN/ha, and Rot24 a maize-pigeonpea rotation with 24 kgN/ha applied in maize years. Soil types defined in methods. HF=high fertility, LF=low fertility.

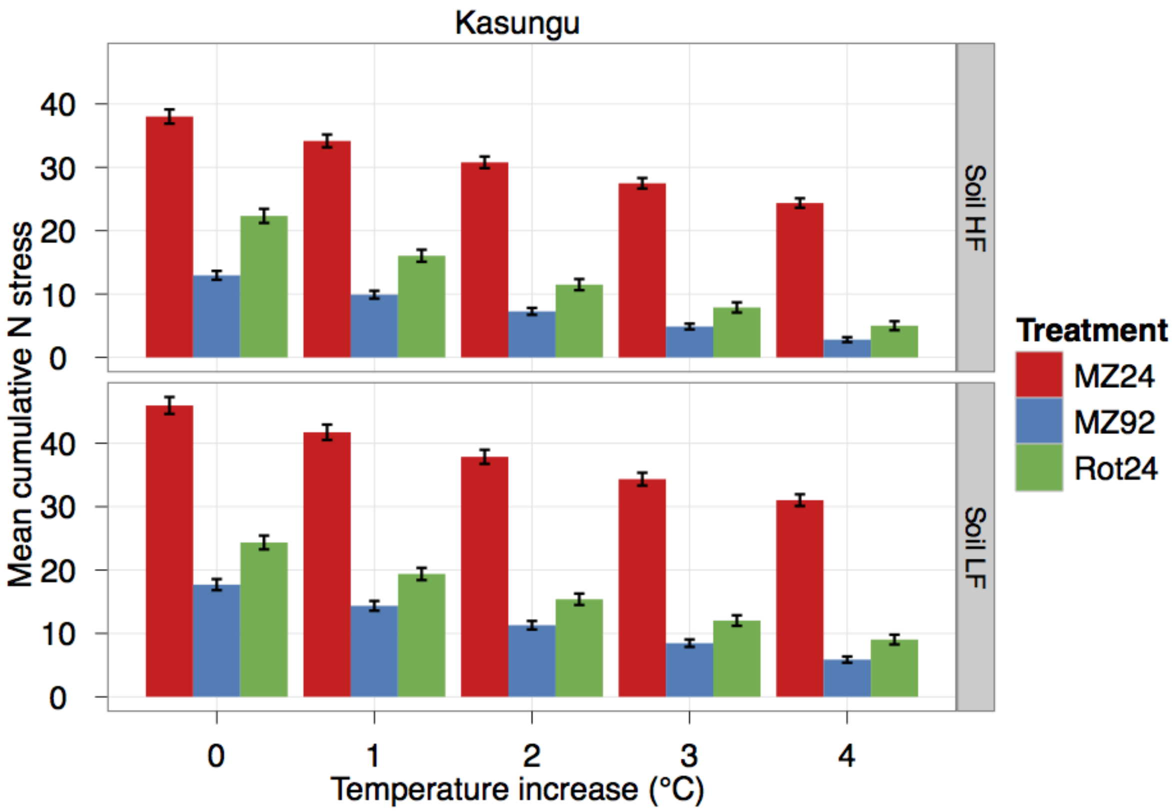


Figure 2.9 (cont'd)

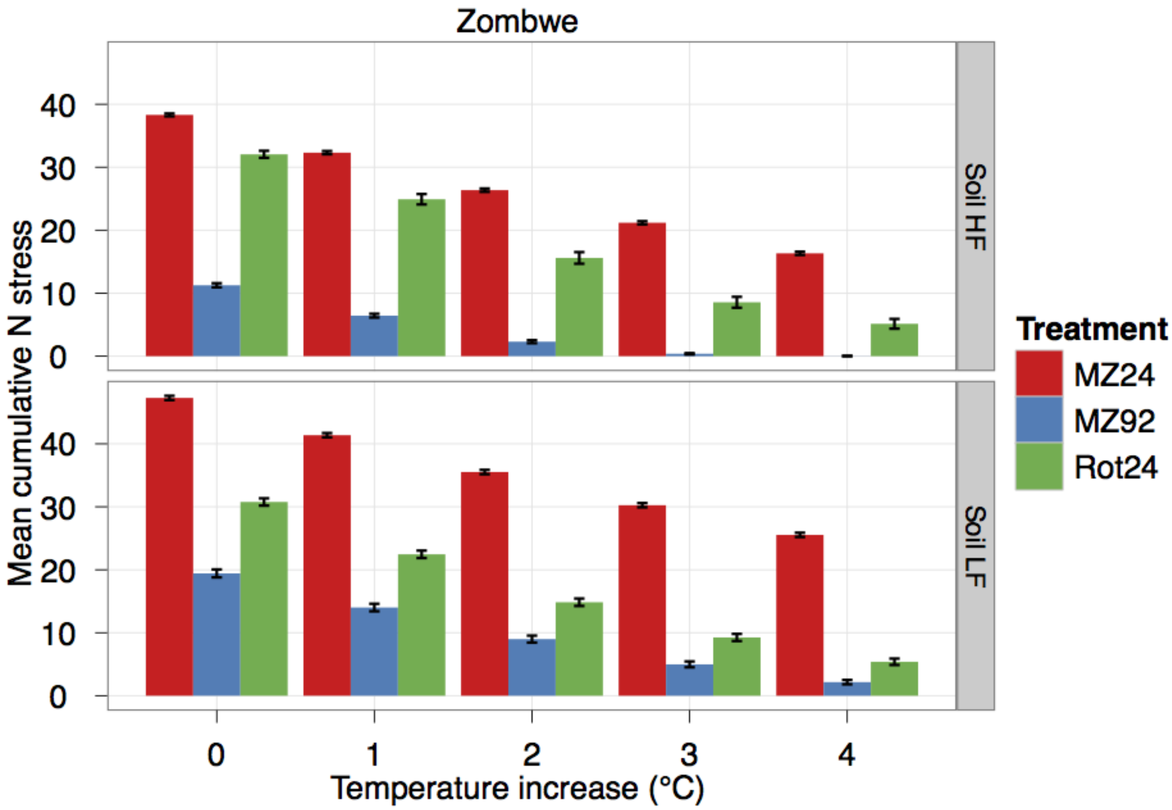


Figure 2.10: Risk of yield reduction due to legume diversification in empirically generated climate scenarios. Risk is defined as the percentage of years where rotation yield is lower than continuous maize yield at the same N fertilization rate (24 kgN/ha). Model results from 83 years in Kasungu and 66 years in Zombwe, northern Malawi. Descriptions of rainfall scenarios are found in Table 2.1. Soil types defined in methods. HF=high fertility, LF=low fertility.

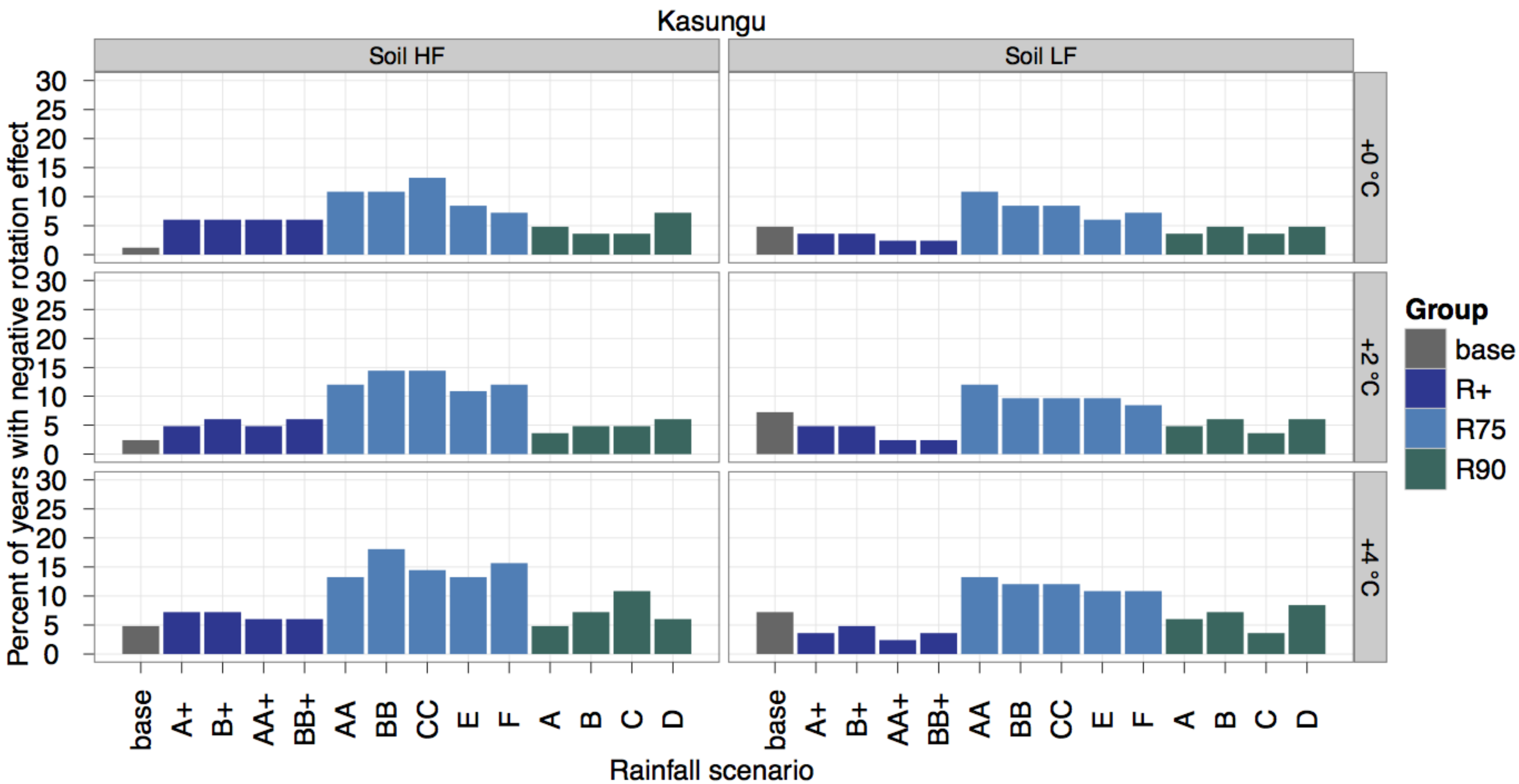
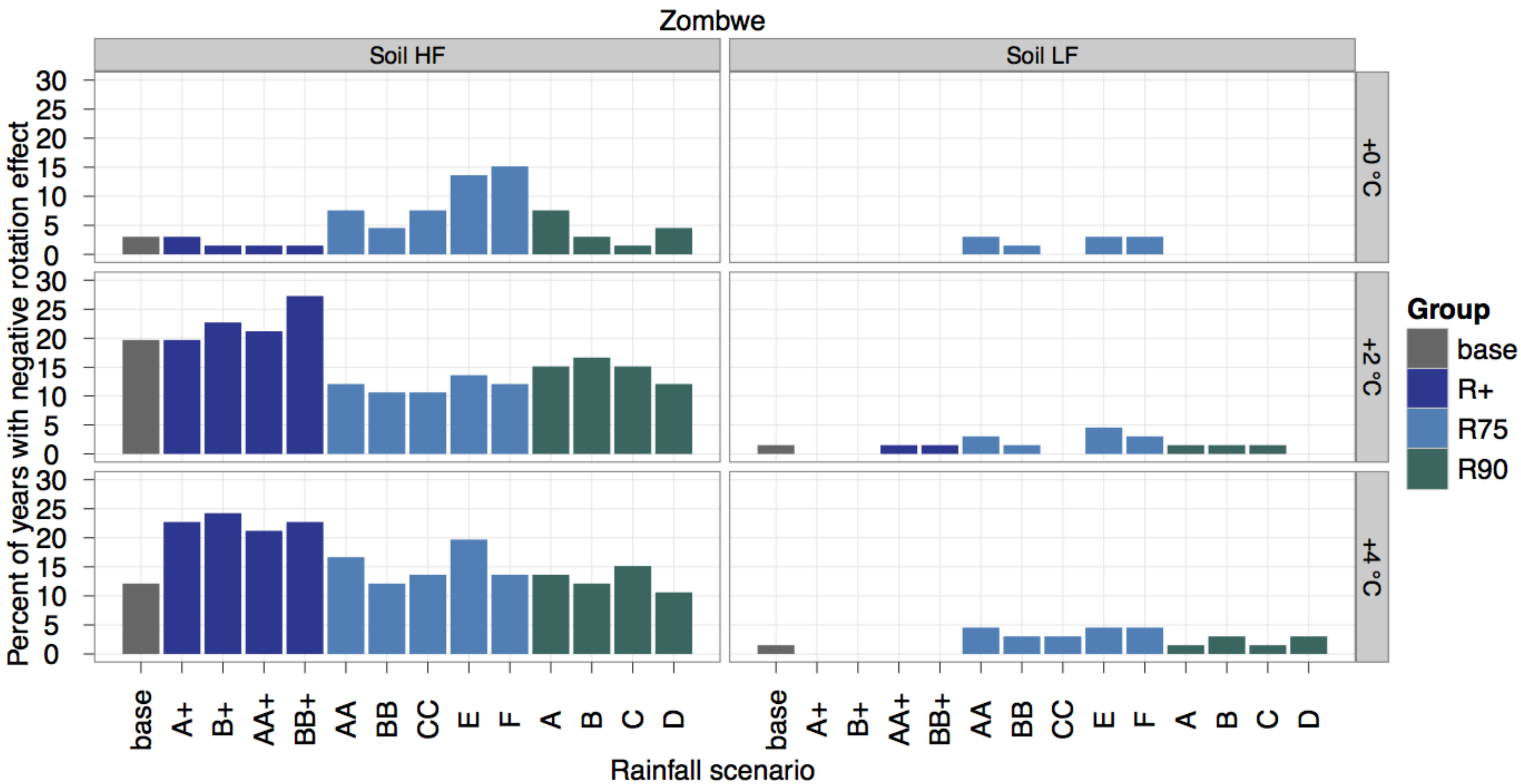


Figure 2.10 (cont'd)



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