Socio-economic impacts and determinants of parasitic weed infestation in rainfed rice systems of sub-Saharan Africa

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In memory of my late father, Michel N. Allémé

Abstract

Rice is an important strategic crop for food security in sub-Saharan Africa. However, its production is constrained by many biotic and abiotic stress. In rainfed rice systems, weeds and particularly parasitic weeds are among the most damaging constraints. The objective of this thesis was to identify factors affecting infestation of rice farms by parasitic weeds and to assess the economic and social impact of parasitic weeds on primary producers of rainfed rice systems in order to provide guidance for decision-making for rice farmers and policymakers aiming at developing strategies for coping with parasitic weeds. To achieve this objective, we first explored biophysical characters of the rice growing environment, farmers' management practices, and socio-economic characteristics that affect the infestation of rice fields by parasitic weeds (PWs) and farmers' ability to cope with the problem. A double hurdle model was used to analyses simultaneously the likelihood of occurrence and the severity of infestation of the PW. The findings suggest that farmers can cope with the PW as long as they are aware of the problem provided they have a good access and management capacity of production resources. Next, we examined weed management practices (WMPs) currently available to farmers and how PW infestation affect their choices for specific combinations of WMPs using a multivariate probit model. Findings indicate that farmers are more likely to adopt improved weed management practices or combined more WMPs when their fields are infested by PWs. Species-specific and country-specific approaches and technologies are require to address the PW problem. Then, we assessed the impact of parasitic weeds infestation on farmers' productivity and examined how this problem and managerial factors prevent farmers from achieving optimal technical efficiency levels using a stochastic frontier analysis (SFA). PWs induce productivity losses ranging from 21% to 50%. Farmers seem to cope with PW through learning from experiencing PW problem. Finally, we estimated weeding labour inefficiencies using a Data Envelopment Analysis (DEA) with directional input distance function and a single truncated bootstrap regression to identify sources of inefficiencies. Results suggest that, farmers can save substantial (58% – 69%) weeding labour without reducing rice production. No evidence was found that the currently used manual weeding modalities were able to manage parasitic weeds efficiently. The main finding of this thesis is that in sub-Saharan Africa, PWs infestation has a negative impact on rainfed rice systems' productivity and the use of production resources. However, these impacts can be reduced if farmers have a good access to production resources and manage them efficiently.

Keywords: rice; weed; weed management practices, adoption, impact, parasitic weeds; *Rhamphicarpa fistulosa*; *Striga asiatica; Striga hermonthica*, double hurdle model; multivariate probit, productivity, stochastic frontier analysis, data envelopment analysis, directional distance function, sub-Saharan Africa, Benin, Cote d'Ivoire, Tanzania.

Contents

1

General Introduction

S.A. N'cho

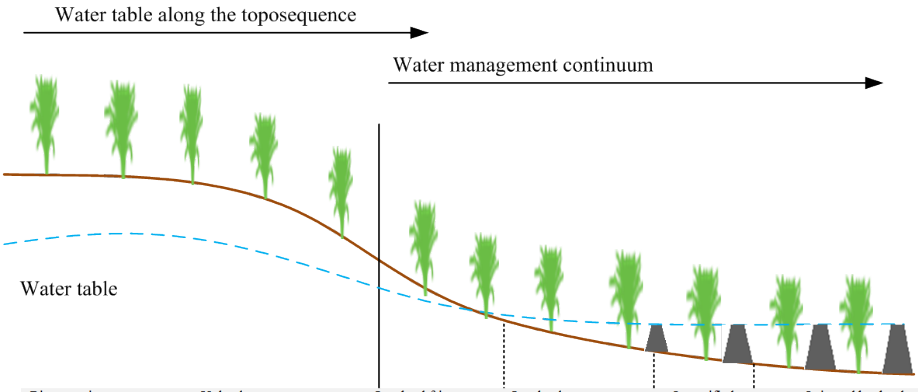
Background

Rice is the world's most important food crop in terms of the area harvested and caloric intake. In Africa, rice is the most rapidly growing commodity among the cereal crops, both as food crop for consumers and cash crop for producers (Seck et al., 2012).

In sub-Saharan Africa (SSA), rice has become an important strategic crop for food security (Wopereis, 2013). Since the 1960s, rice production in SSA has increased along with its consumption. The increase in production has, however, not been able to match the surging demand. As a result, SSA has become increasingly dependent on imports. This dependency reached its critical point in 2008 with riots in many SSA countries due to the "Global Rice Crisis" (Seck et al., 2010). Since the 2008 crisis, many African countries have increased their investments in domestic rice production (Seck et al., 2013). In SSA, this has resulted in an increase of the average annual growth of domestic rice production from 3.2% in the period 2000–2007 to 8.4% (more than double) in the period 2007–2012 (Seck et al., 2013). During that period from 2007 to 2012, the annual production growth (8.4%) has surpassed the annual consumption growth rate of 7.9%. This has resulted in a stable rice import of approximately 7–9 Mt from 2008 to 2011 showing that following investments, rice production can keep pace with consumption growth. However, rice production faces many biotic and abiotic production constraints in different production environments that can undermine the investment efforts (Figure 1.1).

In SSA, the most prevalent rice growing environments are rainfed upland systems, rainfed lowland systems—also referred to as inland-valley systems—and irrigated agro-ecosystems (Figure 1.1). Rainfed rice areas are characterized by their relatively high production uncertainty. They are associated with a high incidence of poverty, mainly because of low and unstable yields resulting from rainfall irregularity and water scarcity, and heterogeneous soil conditions (Tuong et al., 2000).

Among the biotic constraints in rice production systems in SSA, weeds are the most important ones (Balasubramanian et al., 2007, Johnson et al., 1997; Seck et al., 2012). They cause significant yield losses in the absence of proper weeding (GRiSP, 2013). The parasitic weeds (PWs) *Striga hermonthica* (Del.) Benth., *Striga asiatica* (L.) Kuntze and *Rhamphicarpa fistulosa* (Hochst.) Benth., are among the most damaging (Rodenburg and Johnson, 2009; Rodenburg et al., 2010). Besides weeds, rainfed rice production is limited by droughts, poor soil fertility and, incidences of blast and soil acidity (upland) or iron toxicity (lowlands) (Figure 1.1). To manage weeds and soil fertility, farmers apply long fallow periods (de Rouw and Rajot, 2004; de Rouw et al., 2014). However, population growth has led to a dramatic reduction in fallow periods and most farmers are not practicing fallow any longer. This results in increasing weeds pressure and decreasing soil fertility, and thus in decreasing yields (Becker and Johnson, 2001a). Given these biotic and abiotic constraints, the yield of rainfed rice systems remain low. For the upland rainfed rice production the yield is on average 1.2 tonne per hectare. In lowland rainfed systems, the average paddy yield is 1.9 tonne per ha (Diagne et al., 2013a). The productivity highly depends on the degree of water control (Figure 1.1). For example, by bunding rice yields can be increased by 40% and weed biomass can be reduced by 25% (Becker and Johnson, 2001b).



Rice growing environments	Upland	Lowland fringe (Hydromorphic)	Lowland	Intensified lowland	Irrigated lowland
Main water supply	Rainfall	Rainfall + water table	Rainfall + water table + unregulated flood water	Regulated flood water	Irrigation
Main (biotic and abiotic) constraints	Drought Weeds Pest and diseases P and N deficiency Soil erosion Soil acidity	Drought (water control) Weeds Pest and diseases P and N deficiency Soil erosion Soil acidity Fe toxicity	Drought/Flooding (poor water control) Weeds Pest and diseases P and N deficiency Fe toxicity	Drought/Flooding Weeds Pest and diseases P and N deficiency Fe toxicity	Weeds Pest and diseases Salinity Alkalinity P and N deficiency Fe toxicity

Figure 1.1 Production constraints and water regime by main rice production environment in sub-Saharan Africa (Adapted from Diagne et al., 2013a)

1.1. Problem statement

The greatest share of rice produced in SSA comes from rainfed systems which depend on the efforts of primary small-scale resource-poor farmers. Of the 9.4 million hectares of land estimated to be under rice cultivation in SSA in 2009, 34% was classified as rainfed upland and 40% as rainfed lowland. With estimated average yields of 1.23 tons per ha for rainfed upland systems and 1.89 tons per ha a for rainfed lowlands, these systems, together covering 74% of SSA's rice production area, only contribute for an estimated 42% to the total rice production in the region. They are cropped by 75% of total rice farmers (40% upland and 35% lowland) (Diagne et al., 2013a). Rainfed rice systems in general and rainfed lowland systems in particular however, offer great prospects for increasing rice production (Rodenburg et al., 2014a; Sakurai, 2006). For example, Rodenburg et al. (2014a) have estimated that, following improved water and weed management, production derived from less than 10% of the total lowland area could meet the total current demand for rice in Africa. With estimates of 138 million to 238 million hectares of available lowland area suitable for rice cultivation in SSA (AfricaRice, 2011), a substantial part of the total lowland area can be safeguarded for other uses (Rodenburg et al., 2014a). The potential of rainfed systems to increase rice production in SSA is also through yield increase. For example, the attainable yield for rainfed lowland ranges from 3 to 6 tonnes per hectare compared to the realized yield of 1 to 3 tonnes per hectare. For rainfed upland, the attainable yield ranges from 2 to 4 tonnes per hectare compared to the realized average yield of only 1 tonnes per hectare. In both systems, these estimated attainable yield levels can be obtained following appropriate use of external inputs, improved and locally adapted rice varieties and the use of recommended management practices (AfricaRice, 2011) in order to limit the main production constraints i.e. soil fertility, water control and improved weed management.

Weed management in rainfed rice systems, requires for the majority of famers to allocate more than 50% of their labour to weeding (Akobundu, 1981; Stessens, 2002). Weed infestation of farms cause an increase of on-farm workloads, farmers may crop smaller area or reduce working time for other productive activities, and production costs also increase (Adesina et al., 1994; Demont *et al.*, 2007). Weeding is largely done by women and children in rainfed rice systems in SSA as it is often considered by male farmers as women's work (Akobundu, 1991). Women have limited access to productive resources (including labour), they have other household activities demand on their time and they are unable to afford any labour saving technology (Akobundu, 1991; Elson, 1995; Nation, 2010). Family labour (the most affordable) is not always available and paid labour is not always affordable (Akobundu, 1987, 1991). Therefore, when weeds invade rice farms, farmers may decide not to weed and even abandon their land (Adesina et al., 1994; Akobundu, 1991; Atera et al., 2012; Kayeke et al., 2010; Rodenburg et al., 2011). At farm level, the damages caused by weeds become increasingly important with parasitic weeds.

Parasitic weeds are a special group of weeds. In addition to the ordinary crop-weed competition for resources, they parasitize their host (the crop) to extract resources (water, nutrients, metabolites) and change the host plant hormone balance and thereby negatively affect the crop (Parker and Riches, 1993). In rainfed rice production systems in Africa, an increasing problem is observed with the parasitic weed species *Rhamphicarpa fistulosa*, *Striga asiatica* and *Striga hermonthica* (Rodenburg et al., 2010; 2014). For example, for *Striga* spp only, rough estimates indicate that, nearly 100 million hectares of the African savannah are infested and this is expected to increase in the near future (Gebisa and Gressel, 2007). Similarly, a further increase in the area infested by PWs in rainfed rice systems is expected (Rodenburg et al., 2010). In rainfed lowlands for instance, farmers estimate yield losses due to the PW *Rhamphicarpa* to be more than 60% (Rodenburg et al., 2011). Farmers have reported an increase in areas infested and in the severity of infestation (Rodenburg et al., 2014b).

To reduce losses caused by PWs, many methods, although not all focused on rice production systems, have been identified and suggested (see, De Groote et al., 2007; 2010; Gebisa and Gressel, 2007; Oswald, 2005). For example, hand pulling and hoe weeding before PWs set seeds have been suggested as effective control methods by Gbehounou (2006) and Rodenburg et al. (2011) for *Rhamphicarpa* in rice. Herbicide use has been suggested for the control of *Striga* (e.g. Jamil et al., 2011) and *Rhamphicarpa* (Gbehounou, 2006). Improving soil fertility can alleviate the impact of PWs *Rhamphicarpa* and *Striga spp* (Douthwaite et al., 2003; Dugje et al., 2008; Hearne, 2009; Rodenburg et al., 2011). Water management has been suggested by Rodenburg et al. (2011) and Kabiri et al. (2014) for the control of *Rhamphicarpa* in rainfed lowland rice farms. Legume rotation with cereal crops have been suggested as a solution for *Striga* or *Rhamphicarpa* problem (see Berner et al., 1994; Dugje et al., 2008; Rodenburg et al., 2010). The uptake of those methods by farmers has however remained very limited (Atera et al., 2012; De Groote et al., 2010; Oswald, 2005).

Despite the threat of increasing spread of parasitic weeds, and the looming increasing yield losses, only few studies, have investigated the socio-economic impacts of parasitic weeds in SSA. Most of the existing studies on PWs focused on other production systems than rice (e.g. Douthwaite et al., 2003; Douthwaite et al., 2007; Ibrahim and Omotesho, 2010; MacOpiyo et al., 2010). Hence, only little information is available on the socio-economic impacts of parasitic weeds infestation (PWI) on primary producers in rice systems. Moreover, production losses caused by weeds in general and by PWs in particular might not be similar across SSA countries since infestation severity differs by country as well as social, economic (e.g. labour availability for weeding, access to inputs –market and cost–, income inequality, share of women in rice farming, education level, performance of rural development institutions, etc.) and biophysical characteristics of countries (see Diagne et al., 2013b). Relevant statistics on rice yield losses or production costs incurred to PWs are lacking and key factors influencing infestation of rice crops by PWs, farmers choices for weed management options to cope with PWs are relatively unknown (Kayeke et al., 2010; Rodenburg et al., 2011). When PWs invade rice fields, there are (i) direct yield losses and (ii) efficiency losses due to farmers choices for production resources and their management. The latter translates into productivity losses that are not accounted for by most studies (see Chambers et al., 2010). Investigating the PWs problem by analysing how it affects rice productivity and production systems as a whole will help in designing effective PWs strategies that prevent or reduce future spread and damages.

1.2. Objectives and sub-objectives

The overall objective of this thesis is to identify factors affecting infestation of rice farms by parasitic weeds and to assess the economic and social impact of parasitic weeds on primary producers of rainfed rice systems in order to provide guidance for decision-making for rice farmers and policymakers aiming at developing strategies to cope with parasitic weeds. To achieve this overall objective, four specific objectives were addressed.

i. Identify the key agronomic and socio-economic factors that explain the likelihood of infestation and the infestation severity of rainfed rice fields by parasitic weeds
ii. Identify the weed management strategies currently used by rice farmers and the effect of parasitic weeds infestation on farmers choices for weed management practices
iii. Assess the impacts of parasitic weeds infestation on rainfed rice farmers' productivity and technical efficiency
iv. Assess the technical efficiency of labour used for manual weeding in rainfed rice systems and analyse the relation between weeding labour efficiency and parasitic weeds infestation

1.3. Description of research areas

1.4.1. Description of sample countries

The research focused on the most important parasitic weeds (PWs) species in rainfed rice systems (S. *hermonthica*, *S. asiatica* and *R. fistulosa*) of SSA. Data gathering consisted of fields observations and interviews of rice farmers using a structured questionnaire and was conducted in Benin (n=223), Cote d'Ivoire (n=240) and Tanzania (n=201). These countries represent important regional rice producers and markets. Benin and Cote d'Ivoire are located in West Africa and Tanzania in East Africa. West Africa is the main rice producing subregion accounting for more than 40% of African rice production in 2006–2010 (GRiSP, 2013). The economy of the three countries depends largely on agriculture. On average, agriculture accounts for 32%, 20% and 28% of the GDP of each country, provides 87%, 53% and 85% of total export and employs about 58%, 67% and 80% of labour force in Benin, Cote d'Ivoire and Tanzania, respectively. In the three countries, rice consumption and production are becoming increasingly important. However, like in many other SSA countries, the annual domestic rice production of Cote d’Ivoire (600,000 tonnes) and Benin (150,000 tonnes) barely covers 50% of the consumption (1,500,000 tonnes and 300,000 tonnes respectively) while the rice self-sufficiency ratio in Tanzania was about 92% in 2010 with 1.1 million tonnes of paddy produced (GRiSP, 2013; MAEP, 2011; NRDO, 2012).

1.4.2. Benin

Benin holds an estimated number of 9.1 million inhabitants on a surface area of 114,760 km^2. Rice is becoming one of the most important foods in the daily diet and its consumption per capita has reached 30 kg in 2011 (MAEP, 2011). The major rice systems are rainfed upland and rainfed lowland covering 88% of total area cropped and involving the same share of rice farmers (Diagne et al., 2013a). The existing potential to expand rice production is high in lowland areas where barely 10% of the total area is exploited (Gruber et al., 2009; MAEP, 2011).

The study covered the Collines, Alibori and Atacora regions (Figure 1.2). The three regions account for 80% of the national rice area and 85% of the paddy production (DPP/MAEP, 2009). The districts selected for the survey encompass three agro-ecological zones of the country. The Sudan-Guinea zone (Collines regions) is a transitional zone between the Guinea and the Sudanian zones. The annual average rainfall ranges from 1,100–1,400 mm in two rainfall seasons in the south and one rainy season in the northern part (May–November). The Sudan savannah (Alibori) and the Sudan-Sahelian savannah (Atacora) have one rainy season with annual rainfall ranging from 800–1,200 mm and 800–1,500 mm (May–October), respectively. These three agro-ecological zones have different type of soils but they are all favourable to rice cultivation. In Collines region, soils are tropical ferruginous, more or less leached calcite, black and hydromorphic in lowlands. In Alibori, soils are mainly clay-loamy in the lowlands and galleries forests, very suitable for agriculture, and sandy in the uplands, usually drying out quickly but often suitable for cereal cropping. In the Atacora, soils are often degraded, poor shallow and hydromorphic in the lowlands (MEPN, 2008). The presence of *Rhamphicarpa* in rainfed lowland rice has been reported in those regions since 1997 (Gbehounou and Assigbe, 2003; Rodenburg et al., 2011). Therefore, the survey was conducted only in rainfed lowland rice production environment.

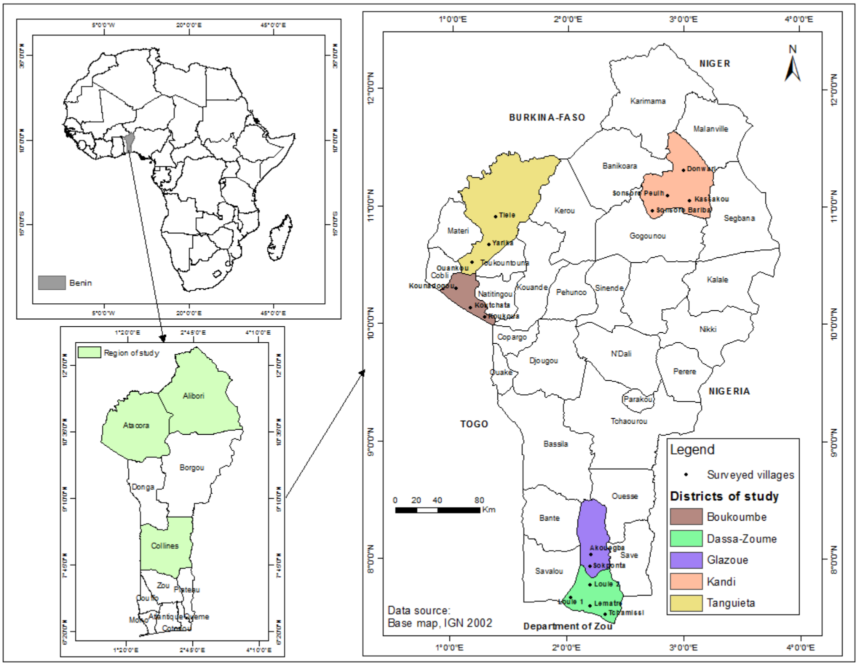


Figure 1.2 Benin in Africa with regions, districts and villages of the study

1.4.3. Cote d'Ivoire

The estimated population of Cote d'Ivoire was 21.9 million in 2011 on a land area of 322,462 km^2 (NRDO, 2012). Rice is one of the most consumed food crops. Per capita rice consumption reached 63 kg in 2011, which is more than that of other major food products like maize (40 kg) and wheat (15 kg). Rice is produced mainly by resource-poor farmers in rainfed systems which cover 95% of the cropped area, 80% of the production and involve 96% of rice farmers (Diagne et al., 2013a; NRDO, 2012).

The study was conducted in eight districts of the regions of Bagoue and Poro in the North of the country (Figure 1.3). Korhogo, the capital city of the Poro region is located at 600 km from Abidjan (Capital of Cote d'Ivoire) while, Boundiali (Bagoue region) is located at 680 km from Abidjan (by road). Both regions are characterized by ferruginous soils, lithosoils, shallow with weak water retention capacity as well as inadequate inorganic reserves. However, they are suitable to cereal cropping including rice. In the regions, rice is the second food crop after maize. Rainfall ranges from 1,000–1,700 mm in only one rainy season (July–October) (PRACTICA, 2009). The presence of *Striga hermonthica* has been reported since 1936 (SONNERSAT, 2014). *Rhamphicarpa fistulosa* was observed later, in 1974 (SONNERSAT, 2014). Among the four species of *Striga* reported on upland rice (in the 1980s), viz *S. aspera*, *S. hermonthica*, *S. asiatica* and *S. brachycalyx*, the former two are most frequently encountered in rice in Cote d'Ivoire (Johnson et al., 1997).

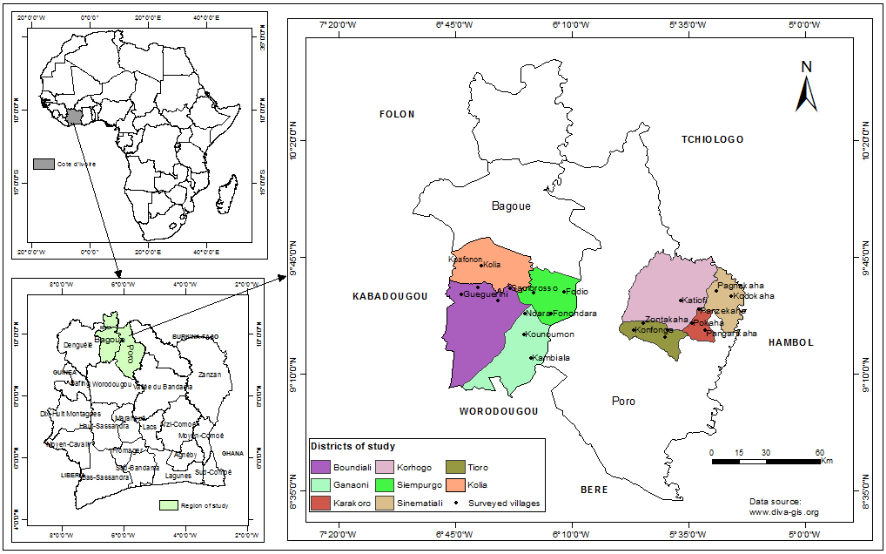


Figure 1.3 Cote d'Ivoire in Africa with regions, districts and villages of the study

1.4.4. Tanzania

According to the 2012 census, Tanzania had 44.9 million inhabitants on a surface area of 945,203 km^2 among which 22% is suitable for rice growing. Rice consumption is gradually increasing and per capita consumption reached 25 kg in 2007. Rice is the second among the 6 most important food crops after maize in terms of number of households, area planted and production volume (MAFC, 2009). The main rice production systems are upland and lowland rainfed systems which covers 73% of total rice area, and involves 67% of the country's rice farmers (Diagne et al., 2013a; GRiSP, 2013; NBS/OCGS, 2013).

The study included five districts in three regions: Kyela in Mbeya region, Nyasa, Songea, and Namtumbo in Ruvuma and Morogoro rural in Morogoro region (Figure 1.4). The three regions encompass the agro-ecological zones of Southern Highlands, Plateau, and Eastern Highlands, respectively. These regions are among the six leading regions in rice production of the country (MAFC, 2009). Mbeya and Ruvuma have unimodal rainfall regimes and the same growing season (November–April) while Morogoro (rural) has a bimodal rainfall regime with two growing periods from October to December and March to June. Rainfall ranges from 800–1,000 mm for Mbeya (but

Kyela particularly experiences 2,000–2,300mm a year), 900–1,300 mm for Ruvuma and 1,000–2,000 mm for Morogoro (rural). Mbeya is characterised by undulating plains and dissected hills and mountains with volcanic soils. Ruvuma is made of upland plains with rock hills; there are clay soils of low to moderate fertility in south and infertile sands in North. Morogoro rural is characterized mainly by granite steep mountains and highlands plateaus with deep arable and moderately fertile soils on the upper slopes shallow and stony on steep slopes (UNEP, 2007). *Striga asiatica* has been reported in Tanzania since 1847 and *Rhamphicarpa fistulosa* since 1929 (SONNERSAT, 2014). However, they have been identified in rice as important emerging parasitic weeds since 1990 (Kayeke et al., 2010).

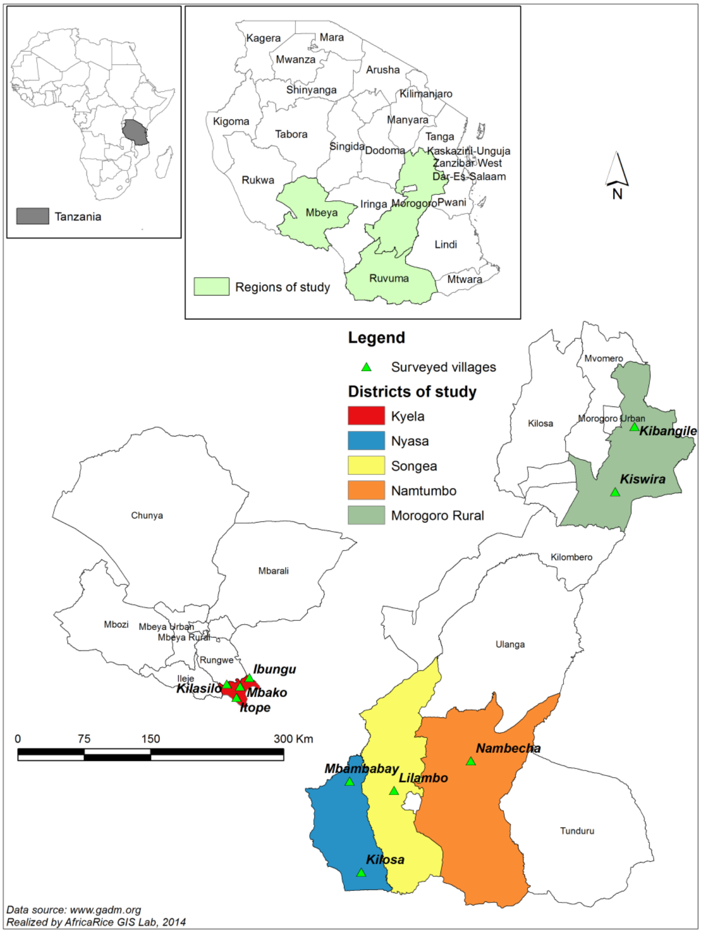
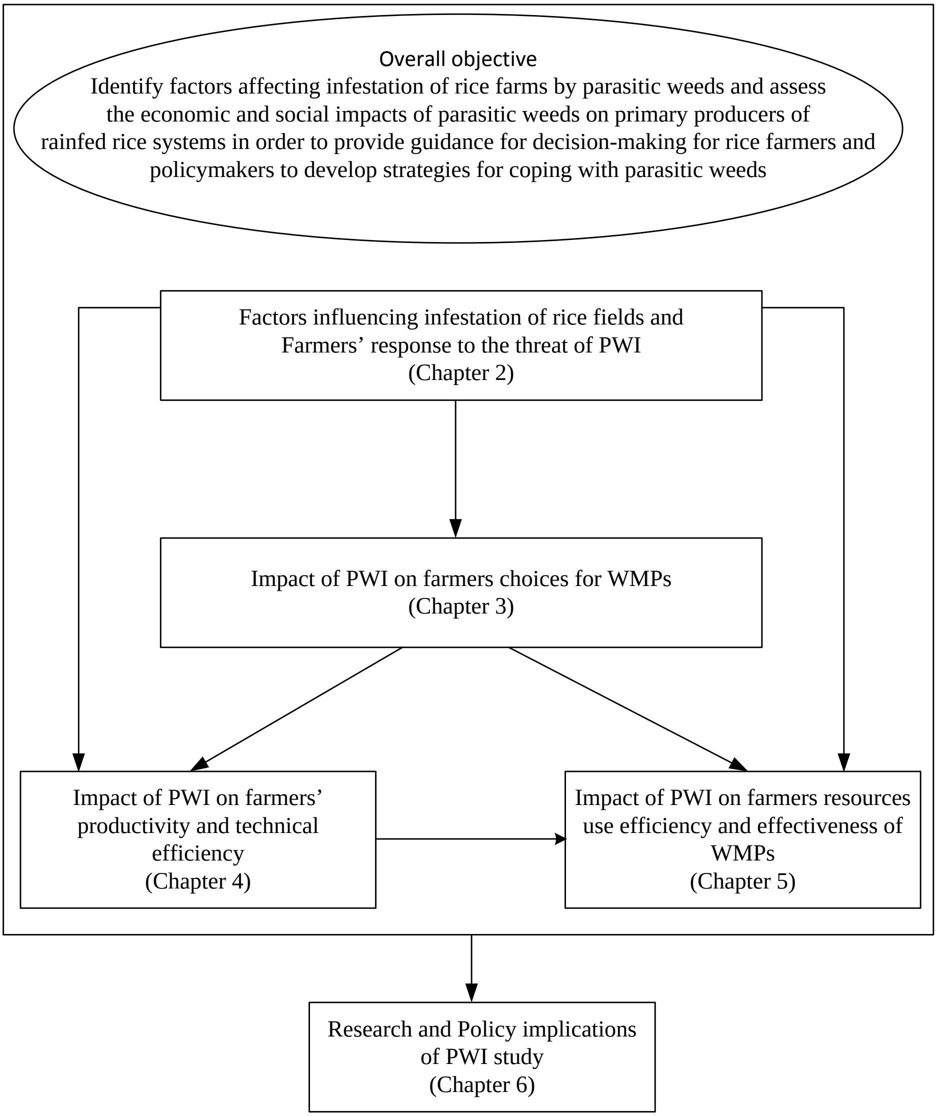


Figure 1.4 Tanzania in Africa with regions, districts and villages of the study

1.4. Outline of the thesis

The thesis consists of 6 chapters including the general introduction and general discussion. Each of the chapters 2–5 addresses one of the specific objectives as outlined in section 1.3. Figure 1.5 provides an overview of how the thesis is structured along with its information flow. The present section highlights the contents of each chapter.



Note: PWI = Parasitic Weed Infestation, WMPs = Weed Management Practices

Figure 1.5 Structure of the thesis

Chapter 2 explores the agronomic and socio-economic environment of rainfed rice production and analyses their effects on the infestation of rice fields by PWs. The chapter uses the generalized double hurdle model and shows how this model allows to simultaneously account for factors affecting PWs infestation of rice plots and farmers' ability to cope with the problem.

Chapter 3 assesses rice farmer's adoption profiles of PW management strategies using the multivariate probit modelling. Firstly, this model allows to explain the direction of the interaction of any pair of weed management practices with respect to farmers' choices. Secondly, it allows to identify factors determining farmers' choices for (1) individual weed management practice as well as (2) the relevant combinations of weed management practices.

Chapter 4 assesses the impact of PWs on rainfed rice farmers' productivity and technical efficiency. In this chapter, Stochastic Frontier modelling with a specification of non-monotonic inefficiency effect is used with the PW infestation variable incorporated in the production frontier to compute its direct impact on productivity. Moreover, the effect of possible learning from experiencing the PWs on the technical efficiency was captured by incorporating the frequency of infestation by the PWs in the inefficiency effects model.

Chapter 5 used an input-specific DEA (Data Envelopment Analysis) approach with directional input distance function technology to derive the input-specific technical inefficiency of weeding labour and labour use for other rice growing activities. Furthermore, results on the efficiency of the currently used manual weeding regimes[1] and number of weeding operation applied are presented.

In the concluding chapter, i.e. Chapter 6, the main findings of this thesis are synthesized. The chapter discusses the different methods used in the light of the results and how they complement to assess the socio-economic impacts of parasitic weeds. It outlines research and policy implications of the thesis and draws the main conclusions.

[1] This refers to the number of days after sowing (DAS) that each weeding operation is conducted

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2

Determinants of parasitic weed infestation in rainfed lowland rice in Benin

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Abstract

The parasitic weed *Rhamphicarpa fistulosa* is threatening rainfed lowland rice production in Benin. The aim of this study was to explore factors (such as biophysical characters of the rice growing environment, farmers' management practices, and socio-economic characteristics) that affect the infestation of rainfed lowland rice fields by *R. fistulosa* and farmers' ability to cope with the problem. Data were collected from 231 rice plots located in 12 inland valleys infested by *Rhamphicarpa* in Benin. Data were analysed using a double hurdle model, which analyses both the likelihood (of occurrence) and the severity of infestation. Results showed that 72% of the surveyed rice plots were infested by *Rhamphicarpa fistulosa* and the average severity was 109 plants m^{-2}. The likelihood of infestation was higher on poorly fertile soils and fields located in the inland-valley bottom, and it decreases through timely use of herbicides and ploughing. Severity of infestation was higher on rice plots cultivated by female-headed households farmers and reduced through management practices such as late sowing, timely application of post-emergence herbicide, three hoe or hand weeding operations, medium-rate fertilizer application and prolonged fallow. Likelihood and severity of infestation were found to be negatively correlated. These findings suggest that farmers can reduce the likelihood and the severity of infestation of their plot as long as they are aware of factors causing the problem given their access to and management capacity of production resources.

Key words: parasitic weed; *Rhamphicarpa fistulosa*; rainfed rice; weed infestation; double hurdle model; Benin

2.1. Introduction

Since the 1960s, African demand for rice has increased at an average annual rate of 4.4%, twice as fast as the world-average, to reach a total consumption level of 20 million tons in 2009 (Rutsaert et al., 2013). In Sub-Saharan Africa (SSA), growth in rice consumption reached 4.6% per year between 2000 and 2010, nearly twice the 2.6% rate of population growth over that same period (USDA, 2012). Africa's rice sector has not been able to match this growth in demand, and as a result, it has become increasingly dependent on imports (Seck et al., 2010). In particular, domestic rice production is struggling with numerous biotic and abiotic constraints that undermine production efforts. Rice is produced in different rice growing environments (or ecosystems) through various production systems. The most prevalent rice growing environments are rainfed upland, rainfed lowland—also referred to as inland-valley systems—and irrigated agroecosystems. Across these ecosystems, weeds are the most important biotic constraint (Balasubramanian et al., 2007, Seck et al., 2012). Species belonging to the group of parasitic weeds, such as *Striga hermonthica*, *Striga asiatica* and *Rhamphicarpa fistulosa*, are among the most damaging local weeds (Rodenburg and Johnson, 2009; Rodenburg et al., 2010).

R. fistulosa was still considered of minor importance in the early nineties of the previous century (Raynal, 1994). However, recent literature review has revealed that it is found nowadays, in many countries in West Africa, Madagascar and South Africa (Rodenburg et al., 2010). *R. fistulosa* is a facultative hemiparasitic weed, which implies that it does not depend on the presence of a host to complete its life cycle (Ouédraogo et al., 1999). It is a wide-spread and common plant species in the natural vegetation of seasonally wet locations (Hansen, 1975; Ouédraogo et al., 1999; Staner, 1938). It is also commonly found in hydromorphic zones, and un-improved rainfed lowland rice fields (Rodenburg et al., 2010). While these inland valleys (IVs) have a huge production potential in SSA, they are largely untapped (Rodenburg et al., 2014; Sakurai, 2006). Following recent upward trends in rice consumption, it is expected that an increasing area of IVs in SSA is being put under rice production and consequently the already present *R. fistulosa* will become an increasingly common and constraining weed (Rodenburg et al., 2010).

In Benin, the boost in rice production necessary to meet increasing demand has to come for a large part from IVs; it has been estimated by Gruber et al. (2009) that about 194,800 ha of flood plains and inland valleys are exploitable for agricultural production. However, *R. fistulosa* is wide-spread in Benin (Gbehounou and Assigbe, 2003; Rodenburg et al., 2011). Hence, an increase in rice production, in this country, might be constrained by the presence of *R. fistulosa*. Weeding in un-mechanized rainfed rice systems in Africa is a labour-intensive and costly activity (Gianessi, 2009;

Rodenburg and Johnson, 2009). The time and resources required for weeding might divert farmers from other (on- or off-farm) economic activities of the household. Consequently, the weeding requirement can reduce households' incomes both directly and indirectly, increase the risk of food insecurity and hence reduce their wellbeing. In addition to the costs incurred for weeding, the parasitic weed *R. fistulosa* causes substantial losses to rice production, thereby directly jeopardizing farm incomes and food security. According to farmers' perceptions and controlled pot experiments, grain yield losses of 60% or more are common (Rodenburg et al., 2011).

Despite the increasing threat of parasitic weeds in SSA, little information is currently available on key factors influencing infestation of rice crops by parasitic weeds such as *R. fistulosa*. The few previously conducted studies on *R. fistulosa* in rice (e.g. Ouédraogo et al., 1999; Gbehounou and Assigbe, 2003; Gbehounou, 2006; Rodenburg et al., 2011) only explored agronomic, ecological and biological factors to explain *R. fistulosa* infestation and proliferation. Several studies have identified factors affecting the infestation of crops by other parasitic weeds such as *Striga spp* (e.g. Dugje et al., 2008; Van Mourik et al., 2008; Vissoh et al., 2008). These studies have identified a range of agronomic and biophysical factors that play a key role in farms' infestation by parasitic weeds and subsequent yield losses. These factors can be grouped into farmers' agricultural practices and the agro-climatic environment in which farmers operate (see Dugje et al., 2008; Ogborn, 1987; Weber et al., 1995). Most studies have identified low soil fertility as one of the key factors affecting parasitic weeds infestation (Parker, 2012; 2009). They are more prevalent in production systems characterized by degraded soils and suboptimal water control (Rodenburg et al., 2010). Reducing fallow length, limited application of nitrogen and low soil fertility are the main causes of *Striga* infestation in West and Central Africa (e.g. Dugje et al., 2006). While few established control options are available yet against *Rhamphicarpa* (Parker, 2012), fertilizer application has been shown to reduce significantly *R. fistulosa* plant counts and rice grain weight loss under infested conditions (Rodenburg et al., 2011). However, factors like agroecological zone, topographical location of the rice field in the IV (upper/medium/lower slope or bottom), soil texture (clay, loamy, sandy) and socio-economic characteristics of the rice farmer remain to be investigated. Better knowledge of factors explaining infestation and farmers' ability to control the infestation will contribute to priority setting of research for development. It will also help to develop appropriate and effective control strategies, and to provide relevant recommendations to (agricultural) policy makers, extension agents and other stakeholders.

Therefore, this paper aims to explore factors such as the biophysical characters of the rice growing environment (agroecological zone, topographical location, soil fertility status), farmers' management practices (fertilizer and herbicide use, fallow practice, timing of sowing, land preparation methods, weeding frequencies) and socio-economic characteristics that affect the infestation of rainfed lowland rice fields by *R. fistulosa* and farmers' ability to cope with this relatively new parasitic weed. This was done by analysing the infestation of rice plots in two stages (the occurrence and the severity of infestation) using a double hurdle model.

2.2. Data and methods

2.2.1. Study area and sample selection

In this study, a multistage sampling approach was used for sample selection. At country level, we have selected three regions: Collines in Central Benin, Alibori in North East and Atacora in North West. The presence of *R. fistulosa* in rainfed lowland rice has been reported in those three regions since 1997 (Gbehounou and Assigbe, 2003; Rodenburg et al., 2011). They accounted for 80% of the rice area and 85% of domestic production (DPP/MAEP, 2011).

In order to inform the sampling strategy, an exploratory visit was conducted within the country to identify IVs where *R. fistulosa* was present. After this tour, we have selected five districts (region level) where *R. fistulosa* was found in rice fields. The districts selected were Glazoué and Dassa in Collines, Kandi in Alibori, and Boukoumbe and Tanguieta in Atacora region. These districts encompass three out of the eight agroecological zones of the country. Dassa and Glazoué are located in the agroecological "cotton zone" (Sudan-Guinea zone), Kandi in the "cotton zone of North Benin" (Sudan savannah), and Boukoumbe and Tanguieta in the "Atacora West mountain" agroecological zone (Sudan-Sahelian savannah). In those districts (district level), 12 most cropped and infested IVs were selected. In those IVs (IV level), we made a census of rice farmers. From the census, a total of 182 rice farmers were selected randomly to minimize sampling errors and selection bias. The sampled farmers cropped a total of 231 rice plots. This sub-sample of rice plots included both infested and non-infested plots. Non-sampling errors like non-response and measurement errors were minimized by pre-testing the questionnaires to check for consistency. The efficient sampling method developed by Whitley and Ball (2002) for optimal allocation of resources was used to determine the sample size and minimize sampling variance.

2.2.2. Description of data

We analysed the likelihood of infestation of *R. fistulosa* and the severity of infestation using data from field and farmer surveys conducted in Benin from September 2011 through January 2012. The field survey was conducted during the cropping season and the producer survey after harvesting. The field survey captured the following rice plot characteristics: spatial coordinates, plot size, *R. fistulosa* infestation status, the severity of the *R. fistulosa* infestation, rice variety used and paddy yield. The producer survey captured both rice plot and socio-economic characteristics. Plot data collected were: soil type, soil fertility status (based on farmer perception), field history, cropping techniques, use of chemical inputs and the sources of rice seed used. Farmers' socio-economic data collected were: age, gender, household size, education, labour endowment and access to chemical inputs. Farmers' weed management practices were also collected. In order to correctly match field and farmer survey data, during the field data collection phase, all farmers' plots were given an identification number.

In this study, "likelihood of infestation" was defined as the likelihood of observing *R. fistulosa* plants in a rice plot; the coverage score was defined as the proportion of the rice plot covered by *R. fistulosa* and visually estimated. We used the emerged *Rhamphicarpa* plants count to assess parasitic weed density following methods outlined by Dugje et al. (2008) and Ogborn (1987). The "severity of infestation" at plot level was computed as the product of *Rhamphicarpa* plants count and the coverage score and expressed in plants m^{-2}. To estimate the density of parasitic weeds we placed three quadrats of 0.25 m^2 each, randomly in each infested plot, and all *Rhamphicarpa* plants in each of these quadrats were counted. This counting operation was repeated twice, separated by a 28-days period in each infested plot. On average, the first counting was done eight weeks after sowing. The second passage aimed to capture missing values from the first counting due to non-observation of *R. fistulosa* in the field (as it might appear after the first counting). The number of *R. fistulosa* plants from every (3) quadrats were summed per plot. Prior to the counting date, farmers were informed of the investigation, and were requested not to weed the (marked) quadrats before the counts were conducted. The size of plots was determined by (tracking) walking on the edges around each plot using a global positioning system (GPS) device (GARMIN, Model GPSMAP 60CSx).

2.2.3. Variable selection and principal component analysis (PCA)

A principal component analysis (PCA) was used as variable selection approach. The first objective was to reduce the number of potential explanatory variables to be used in the econometric analysis of the parasitic weed infestation process, and secondly to detect and correct for multicollinearity between them (see Lafi and Kaneene, 1992; Pires et al., 2008; Ssegane et al., 2012). The Kaiser-Meyer-Olkin (KMO) and the Bartlett's sphericity tests (criteria) were used to select the appropriate PCA results. The KMO test of sample adequacy indicates the amount of variance in the set of variables that might be attributed to the principal factors. Values close to 1 are high and suggest that the PCA may be useful to reduce the number of variables; values below 0.5 imply that the factor analysis is not helpful (Malhotra, 2007). The Bartlett's sphericity test was used to test the null hypothesis of un-correlated explanatory variables. A significant test statistic means that a multicollinearity is present between the explanatory variables. This suggests that it is worthwhile to conduct PCA in order to correct multicollinearities.

Table 2.1 Description of variables used in the principal component analysis

Variables definition	Description	Mean	Std. Dev.	Min	Max
Kandi	Region dummy	0.37	0.48	0	1
Boukoumbe	Region dummy	0.26	0.44	0	1
Dassa	Region dummy	0.12	0.32	0	1
Age of rice farmer	Year	43.93	12.98	13	80
Gender of household head	1=Female; 0=Male	0.31	0.46	0	1
Household size	Number	7.90	5.60	1	50
Not educated	Dummy	0.67	0.47	0	1
Primary or above	Dummy	0.25	0.43	0	1
Education year completed	Number	1.77	3.00	0	14
Agricultural training received	Dummy	0.80	0.40	0	1
Frequency of rice cropping	Number	4.68	0.82	1	5
Experience in rain-fed rice farming	Year	14.69	8.26	1	40
Total household land area	Ha	4.84	10.49	0.03	79.5
Rice plot size	Ha	0.19	0.19	0.01	1.7
Fallow practice	Dummy	0.06	0.24	0	1
Fallow length	Year	0.07	0.35	0	4
Plot location in the IV bottom	Dummy	0.52	0.50	0	1
Permanent flooded soil	Dummy	0.04	0.20	0	1
Temporary flooded soil	Dummy	0.79	0.41	0	1
Sandy soil	Dummy	0.39	0.49	0	1
Limon soil	Dummy	0.46	0.50		
Poor soil fertility	Dummy	0.47	0.50	0	1
Manual plough	Dummy	0.58	0.49	0	1
Mechanized plough	Dummy	0.24	0.43	0	1
Early sowing (<mid-June)	Dummy	0.12	0.32	0	1
Late sowing (>mid-July)	Dummy	0.29	0.45	0	1
Land plough and harrowing	Dummy	0.52	0.50	0	1
Source of access to herbicide	Categorical 0=Not use 1=Farmer to farmer 2=Farmer organization 3=Local market 4=Other sources	0.99	1.44	0	4
Type of access to herbicide	0=Not good access 1= Good access	0.20	0.40	0	1
Herbicide use	Dummy	0.36	0.48	0	1
Frequency of herbicide treatment	Number	0.46	0.70	0	3
Rate of herbicide application	Number (l ha^{-1})	1.56	2.71	0	18.83
Period of herbicide application	1=On time (both) 2=delayed (post-emergence)	0.34	0. 52	0	2
Type of access to fertilizer	0=No proper access 1= Proper access	0.17	0.38	0	1
Fertilizer use	Dummy	0.56	0.50	0	1
Rate of fertilizer use	Number (kg ha^{-1})	120	170	0	914
High rate fertilizer application (>230 kg ha^{-1})	Dummy	0.16	0.36	0	1
Medium rate fertilizer application (180–230 kg ha^{-1})	Dummy	0.08	0.27	0	1
Period of fertilizer application	1=On time 2=Late application	0.64	0.63	0	2
Weeding, hoe only	Dummy	0.14	0.35	0	1
Weeding, hoe + hand	Dummy	0.44	0.50	0	1
Weeding, herbicide + others	Dummy	0.21	0.41	0	1
Hoe/hand weeding 3 times	Dummy	0.06	0.25	0	1

N=231observations

Kaiser's rule of eigenvalue greater than one (K1) was used to retain the relevant number of components (Kaiser, 1960). Thus, the PCA approach allowed to reduce the initial set of 43 explanatory variables (Table 2.1) to only 18 variables (Tables A1) for the likelihood of infestation and 20 (Tables A2) for the severity of infestation. Following Malhotra (2007), and to avoid multicollinearity, for each component we used the variable with the highest loading (after VARIMAX rotation) as a surrogate variable for the associated component in the regression. In the case two variables in the same component had more or less the same factor loading, we used the most relevant variable with respect to the process under study based on theoretical and measurement conditions as suggested by Malhotra (2007).

2.2.4. Model specification and estimation

Farmers' decisions affect (directly or indirectly) both the likelihood and severity of infestation of parasitic weeds, and hence the inflicted damage to their crop (see Dugje et al., 2008). They can decide to do nothing (no control option) or try to control the infestation of the weeds. In deciding whether or not to control the weed, farmers' also decide which control method to use. Explanatory variables are to be found in the physical environment of the field and the socio-economic environment of the household. The following equations were defined for the likelihood and severity of infestation:

$$p\_inf = P(Z) \text{ and} \quad (1)$$

$$q\_sev = Q(X), \quad (2)$$

where *p_inf* refers to the probability of observing an infested field, *q_sev* the amount of *R. fistulosa* plants observed, Z and X are vectors of explanatory variables and P(.) and Q(.) represent the processes of occurrence and severity of infestation respectively.

Many observations in the data set were zero due to the nature of the dependent variables (infested or not, zero or positive counts). This implies that the data were left censored at zero. The method commonly used to deal with censored data is the Tobit model. It attributes the censoring to a standard corner solution (Zhang et al., 2008). In the current study, this means that any non-infested plot will always be observed non-infested regardless of any change in physical environment and management conditions. Thus, the Tobit model assumes that any variable that increases the probability of occurrence (first hurdle) must increase the severity of infestation (second hurdle). This is not always applicable (Lin and Schmidt, 1984). We know that farmers' decisions directly or indirectly affect the observed zero values i.e. the occurrence of the weed (Dugje, 2008). Thus, the observed non-infested plots (observed zero values) can be infested under different physical environment, and management conditions (see Garcia and Labeaga, 1996;

Humphreys, 2013). For example, the environmental conditions of the plot may be unfavourable in some seasons such that we cannot observe the weed on the plot while, in favourable seasons, the weed may be observed. This can be assimilated to the agents' "utility maximization problem" where, for example, the price of a (targeted) good may be high enough to generate a corner solution (non-participation), but at a lower price, an individual may choose to participate (Humphreys, 2013). Moreover, double hurdle models are appropriate when the observed zeros in the outcome equation (second hurdle) are actual zeros and additionally, when selection and outcome processes are simultaneous (Humphreys, 2013). This was the case in the current study as occurrence of parasitic weeds and infestation level were observed simultaneously, and the zero values were from the observed non-infested plots only. Thus, the double hurdle model allows analysing the infestation in two stages (the likelihood and severity of infestation) and accounting for left censoring in the data. Censored distributions are defined using latent variables (Humphreys, 2013). Thus, to understand the underlining process of likelihood and severity of infestation, different latent variables were used to model each process. One was used to model the discrete choice of whether the weed appears on the plot with a specification similar to that of a Probit model and the other modelled the amount of *R. fistulosa* plants using a specification similar to a censored regression. In order to identify the appropriate estimation method, we followed Garcia and Labeaga (1996) and we defined the generalized double hurdle model as:

$$I_i^* = \alpha' Z_i + v_i \ , \tag{3}$$

$$I_i = \begin{cases} 1 & if \quad \alpha' Z_i + v_i > 0 \\ 0 & otherwise \end{cases} \tag{4}$$

$$y_i^* = \beta' X_i + \varepsilon_i \ , \tag{5}$$

$$y_i = \begin{cases} \beta' X_i + \varepsilon_i & if \quad \beta' X_i + \varepsilon_i > 0 \quad and \quad \alpha' Z_i + v_i > 0 \\ 0 & otherwise \end{cases} \tag{6}$$

$$\begin{bmatrix} v_i \\ \varepsilon_i \end{bmatrix} \sim N \left\{ 0, \begin{bmatrix} 1 & \rho_{v\varepsilon} \\ \rho_{\varepsilon v} & \sigma_\varepsilon^2 \end{bmatrix} \right\} where \ \ \varepsilon_i > -\beta' X_i \tag{7}$$

Where I_i^* and y_i^* are defined as linear functions of the first hurdle regressors (Z_i) and the second hurdle regressors (X_i); I_i^* is the latent (unobservable) variable which determines the likelihood (I_i , observed infestation) of the infestation on the plot *i*; y_i^* is the latent variable of the observed severity of infestation, y_i; Z_i and X_i are vectors of explanatory variables that determine the likelihood and the severity of infestation respectively; α and β are corresponding vectors of (unknown) parameters and, v_i and ε_i are the error terms for the equations ruling the likelihood and severity of infestation respectively.

Following Garcia and Labeaga (1996), we assumed that the errors terms (ε_i, v_i) from the two processes described above are jointly distributed (simultaneity between occurrence and severity) as a bivariate normal random variable with zero means, unit variance (for the first hurdle) and a correlation coefficient of rho ($\rho_{\varepsilon v}$). Using equation (6) and (7), the likelihood function of the two processes (occurrence and severity of infestation) is:

$$L_H = \prod_1 P\left(v_i > -\alpha' Z_i\right) P\left(\varepsilon_i > -\beta' X_i \mid v_i > -\alpha' Z_i\right) f\left(y_i \mid \varepsilon_i > -\beta' X_i, v_i > -\alpha' Z_i\right) \times \prod_0 \left(1 - P\left(v_i > -\alpha' Z_i\right) P\left(\varepsilon_i > -\beta' X_i \mid v_i > -\alpha' Z_i\right)\right) \quad (8)$$

where *f (.)* is the normal probability distribution function, $P\left(v_i > -\alpha' Z_i\right)$ is the probability of observing a positive I_i^*, and $P\left(\varepsilon_i > -\beta' X_i \mid v_i > -\alpha' Z_i\right)$ is the probability of observing a positive y_i^* conditional on observing a positive I_i^*. This is the dependent double hurdle model (DDH) or generalized double hurdle model function. The probability of observing a plot with zero *R. fistulosa* plants (P [y_i=0]) conditional on the first hurdle being met (I_i = 1) is zero in the sample. The first hurdle—in this case the infestation—is dominant in that every plot observed to be infested (I_i = 1) will have a non-zero *R. fistulosa* plant count. In terms of the stochastic structure of the model, the dominance assumption is that p (y_i> 0| I_i =1) = 1. Thus, by imputing $P\left(\varepsilon_i > -\beta' X_i \mid v_i > -\alpha' Z_i\right) = 1$ in equation (8), we obtain the likelihood function of the first hurdle dominant model as:

$$L_H = \prod_1 P\left(v_i > -\alpha' Z_1\right) f\left(y_i \mid \varepsilon_i > -\beta' X_i, v_i > -\alpha' Z_i\right) \times \prod_0 \left(1 - P\left(v_i > -\alpha' Z_i\right)\right) \quad (9)$$

We have estimated the model in one stage using maximum likelihood techniques (see Heckman, 1979). We further used the robust option to estimate the standard errors while accounting for heteroskedasticity. The same set of variables was analysed in the two hurdles with the exception of the variable "*field location in the IV bottom*," which was removed from the severity equation for the model to be identified.

2.3. Results

2.3.1. Field and rice farmers characteristics according to infestation status

Of the surveyed rice farmers, 76% had at least one plot that was infested by *R. fistulosa* and 72% of all the sampled rice plots were infested with an average severity of 109 plants m^{-2} (Table

2.4). The majority of rice farmers in this study were female (75 %) while only 31 % of households were headed by women.

Table 2.2 presents summary statistics of ecological and socio-demographic characteristics of the sampled rice plots and rice farmers according to their infestation status. Chi-square independence tests (Pearson and likelihood-ratio) revealed significant ($P < 0.05$) differences between infested and non-infested plots with respect to variables related to the physical environment of the rice fields (poor soil, fallow length, soil texture, IV bottom). A large proportion of the infested rice plots was cropped on poor soils (42%), without fallow (67%), on sandy soil textures (36%) and located in the IV bottom (43%). The test also showed that the fertility status of rice plots was significantly ($P<0.01$) correlated with the location of the plot in the IV. Moreover, data showed that the majority (58%) of the sampled rice fields cropped in the IV bottom had poor soils.

Agronomic variables such as land preparation, herbicide use, fertilizer application, and number of weeding operations differed significantly between infested and non-infested plots. Only 39% of farmers used herbicides for weed control. This implies that the majority (61%) of farmers used other weeding methods (18% hand weeding, 9% hoe weeding and 34% a combination of hand and hoe weeding). From data on weeding strategies in table 2.2, we computed that, on 73% of infested rice plots, farmers did not use herbicides, whereas only 27% of the infested plots were treated with herbicides. The majority of treated plots (95%) were done at the recommended time by a combination of Triclopyr and Propanil (post-emergence: 2 weeks after sowing–WAS–) — commercial names Garil or Tripro (60%) — or glyphosate (broad-spectrum, to be applied before sowing) — commercial name Kalach (34%) — or other herbicides (6%). Only farmers from Central Benin applied herbicide after the recommended time (5%), and they all used 2,4-D — commercial name Herbextra. Fifty six per cent (56%) of the surveyed rice farmers used mineral fertilizers (urea and NPK combined). With respect to the sowing date, the majority of plots (59%) were sown between mid-June and mid-July followed by those sown after mid-July (29%) and finally those sown before mid-June (12%). There was a significant difference between infested and un-infested plots with respect to sowing dates.

Among the socio-economic factors, there was a significant difference between farmers with infested and un-infested fields with respect to age and gender of rice farmers. Farmers with infested fields were younger (43 years) than those with un-infested fields (45 years). However, factors like gender of the household head, household size, education level or rice cropping experience did not differ significantly between infested and un-infested fields.

Table 2.2 Characteristics of sample rice fields and rice farmers' according to their infestation status

Factors	Non-infested	Infested	Total	Independence
Agronomic and environmental factors (farm level)	(n=64)	(n=167)	(n=231)	test (chi-square)
District (site)				39.36 ***
Dassa	1.7	10.0	11.7	
Glazoué	0.4	7.8	8.2	
Kandi	19.0	18.2	37.2	
Boukoumbe	3.0	22.9	26.0	
Tanguieta	3.0	13.4	16.9	
Plot location on the catena				11.93 ***
Upper slope	4.8	7.4	12.2	
Middle-slope	5.2	11.8	17.0	
Lower-slope	7.9	10.0	17.9	
IV bottom	10.0	42.8	52.8	
Plot size (ha)	0.208	0.190	0.195	2.71
Soil type (%)				40.13***
Clay	2.2	12.1	14.3	
Sand	3.4	35.9	39.4	
Silt	22.1	24.2	46.3	
Soil fertility status				28.72 ***
Poor	5.2	42.00	47.2	
Fertile	22.5	30.3	52.8	
Fallow practice				1.34
No	26.8	67.1	93.9	
Yes	0.9	5.2	6.1	
Type of soil preparation				22.22 ***
Mechanized plough (yes/No)	18.6	23.8	42.4	
Manual plough (yes/No)	9.1	48.5	57.6	
Planting (sowing) period				12.76 ***
Early (<mid-June)	0.9	10.8	11.7	
Medium (mid-June–mid-July)	14.7	44.6	59.3	
Late (>mid-July)	11.1	16.9	29.00	
Herbicide use				35.82 ***
No	8.7	52.4	61.0	
1 treatment	4.3	6.9	11.2	
2 treatments	10.00	10.0	20.0	
3 and more treatments	4.8	3.0	7.8	
Fertilizer use				17.82 ***
Not use	6.1	38.1	44.2	
Use	21.6	34.2	55.8	
Rate of fertilizer application				24.90 ***
No fertilizer	6.1	38.1	44.2	
Low (<180 kg ha^{-1})	14.3	18.2	32.5	
Medium (180–230 kg ha^{-1})	3.9	3.9	7.8	
High (>230 kg ha^{-1})	3.5	12.1	15.6	
Weeding frequency				13.40***
One	0	4.3	4.3	
Two	15.1	23.4	38.5	
Three	11.3	35.5	46.8	
Four	1.3	9.1	10.4	
Weeding strategy				35.98***
Hand weeding only	4.3	13.9	18.2	
Hoe weeding only	0.0	8.7	8.7	
Hand + Hoe weeding	4.3	29.5	33.8	
Herbicide + other	19.0	20.3	39.3	
Socio-economic factors (household level)	(n=44)	(n=138)	(n=182)	
Age of rice farmer	45.3	42.7	43.3	7.53*
Gender of household head				0.69
Female	8.8	22.5	31.3	
Male	15.4	53.3	68.7	
Gender of rice farmer				3.83**
Female	20.9	54.4	75.3	
Male	3.3	21.4	24.7	
Household size	8.7	7.5	7.8	1.59
Education level				2.37
None	15.4	50.0	65.4	
Primary	5.5	20.9	26.4	
Secondary and more	3.3	4.9	8.2	
Experience in rain-fed rice farming (year)	12.8	14.8	13.3	1.79

*** P<0.01; **P<0.05, * P<0.1

2.3.2. Principal Component Analysis

The results of the PCA are reported in Table 2.3. The values of the KMO test were greater than 0.5 and closer to 1 (0.824 for likelihood of infestation and 0.790 for severity of infestation). The Bartlett's test was significant (P<0.001) for both. This means that the correlation matrix was different from identity, so the variables used were not independent. These results suggest that the PCA was worth using in order to reduce the number of explanatory variables and to correct for multicollinearities in data. The K1 rule was used to retain six components for the occurrence of infestation and seven components for the severity of infestation (Table 2.3). The column "loading" of table 2.3 shows the total amount of variance in the original variables explained by the components.

Table 2.3 PCA model summary: KMO, Bartlett's Test and Loading

Items	KMO	Bartlett's (Sig)	Loading	Components
Occurrence of infestation	0.824	0.000	74.834	6
Severity of infestation	0.790	0.000	75.689	7

The six components of occurrence of infestation explained 74.9% (Table 2.3) of the total variance of the original variables. Therefore, those components can be used to reduce the number of variables in the regression losing only 25.1% of the information. The seven components of the severity of infestation explained 75.8% of the variance of the initial variables. Hence, using only these variables leads to a loss of information of only 24.2%.

Table 2.4 displays the descriptive statistics of the most relevant variables selected based on the loadings of the explained variances by each of those variables. They were used in both equations in order to derive the key factors underlining the occurrence and the severity of infestation.

Table 2.4 Description of variables used in the double hurdle model

Variables	Definition	Mean (SD)	Expected effect	
			Occurrence	Severity
Dependent variables				
Occurrence of infestation	1=plot infested 0=plot un-infested	0.72 (0.45)		
Severity of infestation	Number of *R. fistulosa* plants m^{-2}	108.93 (237.61)		
Explanatory variables				
Dassa district	1=field cropped in Dassa 0=otherwise	0.12 (0.32)	+	+
Boukoumbe district	1=field cropped in Boukoumbe 0=otherwise	0.27 (0.44)	+	–
Gender of household head	1=household headed by female 0=household headed by male	0.31 (0.46)	+	+
Age of rice farmer	Rice farmer age in year	43.93 (12.97)	+	+
Education completed	Number of years education completed by farmer	1.77 (3.00)	–	–
Plot location in the IV	1=plot located in the IV bottom 0=otherwise	0.52 (0.50)	+	+/–
Plot size	Rice plot size in ha	0.20 (0.19)	+/–	–
Soil fertility	1= soil is poorly fertile 0= soil is fertile	0.47 (0.50)	+	+
Fallow length (year)	Number of years plot was not cropped	0.07 (0.35)	–	–
Mechanized land preparation	1= field land preparation is mechanized 0=otherwise	0.24 (0.43)	–	–
Late sowing	1= sown after mid-July 0= sown before mid-July	0.29 (0.45)	–	–
Timely herbicide application	1= applied at recommended time 0=otherwise	0.36 (0.48)	–	+
Delay herbicide application	1= applied after recommended time 0=otherwise	0.02 (0.13)	–	–
Hoe/hand weeding, 3 times	1= Hoe or hand weeding 3 times 0=otherwise	0.06 (0.25)	–	–
Dummy fertilizer use	1=Fertilizer applied 0=otherwise	0.56 (0.50)	–	–
Medium rate fertilizer application	1=rate of 180–230 kg ha^{-1} applied 0=otherwise	0.08 (0.27)	–	–

SD: Standard Deviation is between brackets

2.3.3. Determinants of occurrence and severity of infestation

Table 2.5 presents the results of the maximum likelihood estimates of the coefficients of the explanatory variables as estimated through the double hurdle modelling approach. The marginal effects of the coefficients are reported in Table 2.6. The model converged after four iterations only. In addition to that, the value of the Wald chi-square statistics indicates that the model as a whole was significant (P<0.01).

Table 2.5 Maximum Likelihood Estimates of the double hurdle model with first hurdle dominance

Variables	Parameters (RSE)	
	Occurrence of infestation	Severity of infestation
Dassa district	0.60 (0.42)	276.33 (139.70)**
Boukoumbe district	–0.19 (0.35)	–146.62 (42.14)***
Gender of household head	–0.14 (0.27)	67.05 (35.35)*
Age of rice farmer	0.008 (0.006)	–0.32 (1.57)
Education completed	–0.06 (0.04)	4.02 (7.05)
Plot location in the IV bottom	0.57 (0.22)***	–
Plot size (ha)	0.67 (0.68)	–155.33 (83.90)*
Poor soil fertility	0.99 (0.27)***	131.11 (75.21)*
Fallow length (year)	0.24 (0.26)	–31.76 (14.81)**
Mechanized land preparation	–0.91 (0.26)***	–38.40 (33.37)
Late sowing (after mid-July)	0.25 (0.25)	–69.53 (34.92)* *
Herbicide application at recommended time	–1.04 (0.34)***	136.09 (50.63)***
Delay herbicide application	–0.32 (0.51)	–191.27 (106.30)*
Hoe/hand weeding, 3 times	0.97 (0.36)***	–126.75 (51.70)**
Dummy fertilizer use	0.03 (0.27)	0.69 (46.22)
Medium rate fertilizer application (180–230 kg ha^{-1})	0.16 (0.29)	–157.66 (49.61)***
Rho		–0.19 (0.10)**
Sigma		224.52 (41.64)
Log pseudolikelihood value	–1233.695	
Wald chi2(15)	76.73	
Prob > chi2	0.0000	

(RSE): Robust Standard Error is in parenthesis; *** P<0.01; **P<0.05, * P<0.1

The correlation coefficient (rho parameter) between the residuals of the two equations was –0.19 and significantly different from zero (P<0.05). This means that the correlation between the likelihood of the infestation and the severity of the infestation is negative, i.e. a higher probability of a plot to be infested is associated to a lower severity of infestation and vice versa. In the severity equation, all parameters have the predicted sign except age, education and fertilizer application. The parameters were significant (P< 0.1), except for age, education, mechanized land preparation and fertilizer application. In the infestation equation, eight parameters have the predicted sign and five of them were significant (P < 0.01, Table 2.4).

Location in the agroecological zone (like Dassa, Boukoumbe) did not significantly affect the likelihood of infestation. However, compared to other districts, parasitic plant were fewer (by 150 plants m^{-2}) in Boukoumbe (the Atacora west mountain zone), and greater (by 286 plants m^{-2}) in Dassa (Table 2.6).

Unfavourable physical environmental factors such as poor soil fertility and plot location in the IV bottom significantly increased the likelihood of *R. fistulosa* infestation of rice plots. In addition to its contribution to the occurrence of infestation, poor soil fertility was associated with a higher severity of infestation, just like reducing fallow length. The model showed that poor soils plots were 30% more likely to be infested and, once infested, severity of infestation tends to be higher (by 150 plants m^{-2}) than on fertile soils. Although the overall dummy for fertilizer use was insignificant in both hurdles, practices such as medium-rate fertilizer application (180–230 kg ha^{-1}) significantly reduced severity of infestation (by 155 plants m^{-2}). Plots located in the IV bottom displayed an 18% higher likelihood to be infested by *R. fistulosa* than plots at other positions on the catena. The severity of infestation decreased with the size of the plot.

Table 2.6 Marginal effects of occurrence and conditional marginal effects of severity, of infestation

Variables	Marginal effects, Occurrence of infestation	Conditional marginal effects, severity of infestation
Dassa district	0.15 (0.08)*	286.59 (139.28)**
Boukoumbe district	–0.06 (0.12)	–150.54 (42.45)***
Gender of household head	–0.04 (0.09)	64.27 (34.57)*
Age of rice farmer	0.002 (0.002)	–0.16 (1.56)
Education completed	–0.02 (0.01)	2.85 (7.10)
Plot location in the IV bed	0.18 (0.07)***	11.52 (8.49)
Plot size (ha)	0.21 (0.21)	–141.95 (84.64)*
Poor soil fertility	0.30 (0.07)***	150.46 (75.11)**
Fallow length (year)	0.07 (0.08)	–27.04 (14.86)*
Mechanized land preparation	–0.32 (0.09)***	–59.14 (34.53)*
Late sowing (after mid-July)	0.07 (0.07)	–64.78 (35.03)*
Herbicide application at recommended time	–0.34 (0.11)***	113.63 (47.79)**
Delay herbicide application	–0.11 (0.19)	–198.32 (104.9)*
Hoe/hand weeding, 3 times	0.21 (0.05)***	–112.63 (50.00)**
Dummy fertilizer use	0.01 (0.08)	1.24 (45.78)
Medium rate fertilizer application (180–230 kg ha^{-1})	0.05 (0.08)	–154.63 (49.60)***

N = 231; Standard error is in parenthesis
*** P<0.01; **P<0.05, * P<0.1

The method of land preparation has a significant effect on the occurrence ($P < 0.01$) and the severity of infestation ($P< 0.1$). For example, the likelihood of infestation was lower (by 32%) on plots where mechanized ploughs or harrows were used for land preparation. On average, once those plots were infested, the severity was lower (by 59 plants m^{-2}) than plots without ploughing or with manual ploughing.

The likelihood of infestation was higher (by 21%) on plots weeded with manual weeding practices, while it was lower (by 34%) on plots where herbicides were used at recommended timing. However, on plots already infested, where weeding was conducted three times by hoe or hand, infestation levels were 113 plants m^{-2} lower on average. On plots where post-emergence herbicides were applied later (about 8 WAS) than the recommended application date (about 2 WAS), the reduction in severity was more significant (198 plants m^{-2}) while a significant increase (by 113 plants m^{-2}) was observed where herbicides were applied at the recommended date. On plots sown after mid-July (late sowing), the severity of infestation was significantly lower (by 65 plants m^{-2}) than on those sown earlier.

Finally, among the socio-economic variables, only the coefficient for the gender of the household head was significant ($P < 0.05$) in severity equation, implying that fields cultivated by female-headed households farmers tend to be more severely infested when infestation occurred than those of male-headed households' farmers. Age and education did not have a significant effect on likelihood and severity of infestation.

2.4. Discussion

2.4.1. Environmental factors

The higher infestation levels observed in the cotton zone of central Benin (Dassa) in comparison to other districts can be explained by the fact that the *R. fistulosa* problem was first observed in the districts of that agroecological zone (Gbehounou and Assigbe, 2003; Rodenburg et al, 2011). Moreover, farmers perceived that the severity of infestation has increased since the problem first manifested. In addition to that, the rural population density in the studied areas was higher in Central Benin (60 habitants km^{-2}, Dassa and Glazoue) than Alibori (34 habitants km^{-2}, Kandi only) and Atacora west (18 habitants km^{-2}, Boukoumbe and Tanguieta). This could imply that our region dummies are consistent with the theory of Boserup according to which higher population density leads to increase land use pressure, a shift to more marginal land such as IVs and a shortening of fallow lengths. These developments generally reduce soil fertility and increase proliferation of weeds (Demont et al., 2007; De Rouw, 1995, Vissoh et al., 2004), in particularly parasitic weeds (Gbehounou, 2006). Moreover, the lower infestation severity associated with the West Atacora mountain zone (Boukoumbe) can be partly explained by better water management practices such as bounding of rice plots in IVs compare to other zones.

R. fistulosa is a plant adapted to a semi-aquatic environment (Hansen, 1975; Ouedraogo et al., 1999). This supports the findings that plots located in the IV bottom have a higher probability of being infested by *R. fistulosa*. Moreover, soil run-off/water erosion transports *R. fistulosa* seeds to lower parts of the upland-lowland continuum. Hence the concentration of *R. fistulosa* seeds is likely higher in the valley bottom. The descriptive statistics showed that the majority (58%) of rice fields in the valley bottom were cropped on poor soils. This was confirmed by the chi-square independence test (Pearson and likelihood-ratio) which suggested that poor soil fertility was highly dependent on the position of the rice plots on the catena. These results are consistent with Parker (2012; 2009) and Rodenburg et al. (2010) who suggested that there is a link between poor soil fertility and *R. fistulosa* infestation. Therefore, farmers cultivating poor soils might face higher infestation levels.

2.4.2. Gender effect

Population pressure often forces rice farmers to cultivate marginal land or fields in less favourable positions on the catena, such as the valley bottom. Often the more marginal fields are allocated to women (Demont et al., 2007). In this study, 61% of sample plots cultivated by female-headed households farmers were located in the valley bottom. This may explain the higher infestation rates found on plots of female-headed households farmers. We have replaced the gender dummy of the head of the household by the gender dummy of the farmer who cultivates the rice plot, then the parameter estimate for gender turns insignificant ($P>0.1$). From this, we can infer that the ability to cope with parasitic weeds is not related to the gender of the actual cultivator, but rather to the manager (household head) who makes resource allocation decisions within the household. This effect of female-headed household could be best explained by the fact that in rural areas (Benin or elsewhere in SSA), women have limited access to productive resources such as land, labour or other key inputs (Ogato et al., 2009; Ojo et al., 2012). In the sample, only 26% of lands owned by farmers belongs to female-headed households. Moreover, almost all rice farmers (99%) belonging to female-headed households were women. More than 70% of women heading their households were widowed, single or divorced. This is in line with the findings of Ojo et al. (2012) and Abdulsalam-Saghir (2011) that most women depend on their spouses to access to valuable land.

2.4.3. Rice farmers management practices

This study provided indications that fields cropped on prolonged fallows lands may have a lower severity of infestation. These findings are in line with those of Gbehounou (2006) who found that plots cropped on land with prolonged fallow periods have a lower severity of infestation. However, it should be noted that, although the length of the fallow period was negatively associated with the severity of infestation, we cannot recommend this practice because of the facultative parasitic nature of *R. fistulosa* and its presumable broad host range. Moreover, due to increased pressure on land, traditional long fallow periods are often no longer feasible and only few farmer (6% of the sample) currently practice fallow. This observation corroborates previous findings by Vissoh et al. (2004).

The use of fertilizers is a possible Boserupian response to low soil fertility (Demont et al., 2007), which is supported by the significant negative effect we found from medium rate (180–230 kg ha^{-1}) fertilizer application on infestation levels. Only a small share (14%) of rice farmers using fertilisers applied this medium rate though; the majority of them (58%) applied lower rates (< 180 kg ha^{-1}). This might be explained by the poor access of rice farmers to fertilizers. Manyong et al. (1996) also reported that the poor access to fertilisers increased parasitic weeds (*Striga)* infestation in the North Guinea savannah region, in Nigeria. However, our results also suggest that fertilizer rates in excess of 230 kg ha^{-1} might not be necessary in order to cope with the *R. fistulosa* problem on rice once fields are infested. These results nevertheless suggest that improving access to fertilizer input, soil restoration programmes, appropriate use of organic manure and mineral fertilizer are important in reducing *R. fistulosa* problems in rice fields.

The delayed application (about 8 WAS) of post-emergence herbicide significantly reduced infestation severity because this has coincided with the main flux of the *R. fistulosa* emergence period. In this study, all farmers applying post-emergence herbicides after the recommended time (about 2 WAS) used herbextra (2,4-D). Gbehounou (2006) similarly found that the use of post-emergence herbicides 2,4-D is effective against *R. fistulosa*. Sallé et al. (2000) indicated that, in addition to providing good results, it does not have an immediate negative effect on crops. Our finding that post-emergence herbicide application at the recommended time was associated with a higher severity of infestation could be explained by the biology of *R. fistulosa* weeds. The *R. fistulosa* weeds often emerge later than the crop, up to 8 WAS (Ouédraogo et al., 1999; Rodenburg et al., 2011) and the germination continues throughout the season. Those post-emergence herbicides (Garil and Tripro) are applied at an earlier stage (about 2 WAS), and due to their low persistence, they might no longer be active by the time *R. fistulosa* appears on the rice plots. However, delayed application of herbicide is a risky practice as it can damage rice plants. The choice of an appropriate herbicide (e.g. 2,4-D) for delayed application (about 8 WAS) should be explored.

The negative and significant effect of mechanized land preparation on the occurrence of infestation can be explained by the biological requirement of *R. fistulosa* seeds; the seeds need daylight to trigger germination (Ouédraogo et al., 1999). Ploughing might bury the *R. fistulosa* seed deep enough to prevent enough daylight to provoke the seeds to germinate.

Late sowing had a negative and significant effect on *R. fistulosa* infestation severity. These results are consistent with Dugje et al. (2008), who found a similar timing effect on *Striga* spp. in maize, in North Nigeria. However, in contrast with the latter authors, we did not found a significant effect of late sowing on the likelihood of infestation. This might be explained by the fact that, in contrast with the obligate parasitic nature of *Striga* spp., *R. fistulosa* is a facultative hemiparasitic weed. Thus, it can grow without the host plant as long as its environmental requirements for seed germination and seedling growth are met (i.e. sufficient soil moisture, high enough temperatures and daylight). This is not the case with *Striga* spp. that are highly dependent on their host. However, late sowing is highly risky because of the interaction with other production constraints such as drought and biotic constraints such as birds, (insect) pests and diseases. Therefore, appropriate coping strategy with respect to late sowing would be to combine it with the use of short-cycle rice varieties.

2.4.4. Modelling issues

The modelling approach used in this study allowed for analysing the process of weed infestation in two stages, i.e. occurrence and severity and for exploring the interaction between both. The negative and significant value of the correlation parameter (rho) implies that the two stages of infestation are not independent and are antagonistic, which requires joint estimation through the maximum likelihood estimator in order to improve the efficiency of the parameters. The antagonistic relationship between the two hurdles suggests that the higher the probability of infestation on a rice field, the lower is the observed severity of infestation than expected. This may be explained by unobserved variables (captured in the residuals), such as farmers' awareness of the risk of infestation. Farmers that are aware that their rice crops run a higher risk of infestation might be (better) prepared to take necessary actions to face with the problem even they could not prevent it to happen. Hence, the observed severity of infestation is lower than expected.

2.5. Conclusion

This study used a double hurdle model to identify factors that are driving farmers' ability to manage parasitic weeds infestation in rainfed rice fields, in Benin. We found that farmers' cropping practices affect directly or indirectly the likelihood and the severity of infestation of their rice fields. The biophysical cropping environment (agroecological zone, position of the plot on the catena, soil fertility status), the use of inputs (like herbicides), and land preparation determine the likelihood of infestation. Meanwhile, the ability to cope with the severity of the infestation is mainly determined by farmers' capacity to access and manage production resources. This is captured by socio-economic characteristics (like gender of the household head and plot size), and cropping practices (like late sowing, timely herbicide application, fertilizer use, fallow and the weeding frequency). Results suggest that occurrence and severity of the infestation are correlated negatively. Farmers can reduce both the likelihood and the severity of infestation of their plots as long as they are aware of factors causing the problem given their access and management capacity of production resources. They can reduce the likelihood of infestation of rice fields (1) by using good soil fertility management practices (use of fertilizer at the appropriate rates and period, use of organic manure) and (2) through mechanized land preparation. Moreover, locally adapted short-cycle rice varieties that can tolerate drought and prevailing biotic stresses would make delayed sowing practice a feasible control measure.

An important implication of our results is that access to key production inputs, such as fertilizers, herbicides, and women’s access to land should be improved. Given the critical role of soil fertility in parasitic weed infestation process, key stakeholders should follow a careful selection procedure to develop IVs with the highest potential for rice production. Finally, farmers’ awareness of the *R. fistulosa* problem and coping methods should be improved.

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Appendix A

See Tables A1 and A2

Tables A1 Correlation of six components with initial variables in occurrence of infestation

Variables	Component					
	1	2	3	4	5	6
Kandi	0.898	0.118	–0.016	0.038	0.169	0.156
Boukoumbe	–0.415	–0.035	0.698	0.057	–0.010	–0.291
Dassa	–0.299	0.135	–0.678	0.037	0.027	–0.291
Gender of household head	0.011	0.098	–0.033	0.041	0.026	0.890
Fallow length (year)	–0.106	–0.073	0.143	0.231	–0.783	–0.011
Plot location in IV bottom	0.060	–0.069	0.205	–0.740	0.122	0.256
Poor soil fertility	–0.129	0.028	0.737	–0.354	–0.047	–0.133
Late sowing (after mid-July)	0.068	–0.152	0.044	0.729	–0.091	0.244
Mechanized land preparation	0.331	0.085	0.228	0.531	0.497	0.044
Source of access to herbicide	0.863	0.187	0.038	–0.111	0.005	–0.050
Dummy herbicide use	0.955	0.168	–0.030	0.038	0.104	0.029
Number of herbicide application	0.803	0.105	–0.079	0.221	0.210	0.019
Rate of herbicide application (l ha^{-1})	0.720	0.437	0.015	–0.007	–0.151	0.078
Period of herbicide application	0.916	0.190	–0.030	0.064	0.087	–0.025
Dummy fertilizer use	0.447	0.706	–0.019	0.067	0.364	0.072
Rate of fertilizer application (kg ha^{-1})	0.225	0.829	0.028	–0.176	–0.127	0.046
Period of fertilizer application	0.422	0.683	–0.046	0.214	0.372	0.039
Hoe weeding only	–0.036	–0.113	–0.490	–0.342	0.056	–0.057

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.

Tables A2 Correlation of seven components with initial variables in severity of infestation

Variables	Component						
	1	2	3	4	5	6	7
Kandi	0.887	0.142	–0.047	0.070	0.074	0.184	0.043
Boukoumbe	–0.408	–0.091	0.194	0.325	0.577	–0.264	0.134
Dassa	–0.150	–0.095	–0.007	0.031	–0.857	–0.124	0.141
Gender of household head	0.064	0.050	0.095	–0.022	0.029	0.894	–0.046
Age of rice farmer	0.331	0.052	0.030	0.010	–0.123	0.445	0.533
Fallow length (year)	–0.060	–0.091	–0.092	–0.456	0.357	–0.153	0.005
Late sowing (after mid-July)	–0.101	–0.154	0.028	–0.048	0.045	0.103	–0.862
Mechanized land preparation	0.023	0.217	–0.103	0.658	0.305	–0.036	–0.163
Source of access to herbicide	0.869	0.122	0.234	0.057	0.042	0.011	0.186
Type of source of access to herbicide	0.872	0.128	–0.022	–0.070	–0.011	0.002	0.128
Dummy herbicide use	0.951	0.161	0.092	0.061	0.007	0.026	0.068
Number of herbicide application	0.870	0.104	0.027	0.158	–0.080	0.119	–0.097
Rate of herbicide application (l ha^{-1})	0.619	0.486	0.476	–0.074	–0.020	–0.054	–0.014
Period of herbicide application	0.897	0.134	0.285	0.074	–0.039	–0.002	0.122
Dummy fertilizer use	0.383	0.551	–0.002	0.373	–0.108	0.228	0.164
Rate of fertilizer application (kg ha^{-1})	0.271	0.870	0.148	–0.026	–0.011	–0.007	0.037
Weeding strategy (herbicide + others)	0.283	0.225	0.735	0.108	–0.131	–0.140	–0.174
Hand/hoe weeding 3 times	0.048	–0.071	0.751	–0.031	0.135	0.244	0.105
High rate fertilizer application (>230 kg ha^{-1})	0.111	0.874	–0.025	0.001	0.088	0.035	0.110
Rice plot size (ha)	0.092	–0.161	0.048	0.708	–0.030	–0.087	0.152

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.

3

Determinants of farmers' adoption of parasitic weed management practices in rainfed rice systems in sub-Saharan Africa

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Abstract

In sub-Saharan Africa, farmers choose from a range of weed management practices (WMPs) to cope with weed problems. This study aims to identify the WMPs currently used by rice farmers and how parasitic weeds infestation and farm-specific, socio-economic and institutional factors influence their choices for WMPs. We used a multivariate probit model to analyse survey data of 664 rainfed rice farmers of parasitic weed infested areas (Benin, n=223; Cote d'Ivoire, n= 240 and Tanzania, n=201). We found that farmers can adopt single WMPs or a strategy where multiple WMPs are combined. Parasitic weeds infestation shifts farmers from using a single traditional WMP towards the use of multiple WMPs. Access to inputs, information, and training in agricultural practices also stimulate the use of multiple WMPs. Factors such as position on the upland-lowland continuum, *Rhamphicarpa* infestation and education have different effects on farmers' adoption decision across countries. *Rhamphicarpa* and *Striga* impacted farmers differently in their choices of management practices. Hence, species-specific and country-specific approaches and technologies are required. Focusing on factors affecting farmers' choices for different combinations of WMPs per country is a good starting point to develop effective and sustainable parasitic weed management strategies for rainfed rice systems in sub-Saharan Africa. Moreover, awareness of parasitic weed problems and possible approaches to address them should be increased.

Keywords: adoption, weed control, *Rhamphicarpa fistulosa*, *Striga hermonthica*, *Striga asiatica*, multivariate probit, technology transfer.

3.1. Introduction

Among production constraints in rice production systems in sub-Saharan Africa (SSA), weeds are causing the highest yield loss (34%) (Oerke, 2005). The parasitic weeds (PWs) *Striga asiatica*, *Striga hermonthica* (Witchweed) and *Rhamphicarpa fistulosa* (Rice vampireweed) are among the most damaging ones (Rodenburg and Johnson, 2009; Rodenburg et al., 2010). At farm level, the damage attributable to these PWs can reach a complete loss of production (Abang, 2007; Rodenburg et al., 2010) forcing some farmers to abandon their farms (Atera et al., 2012). To reduce these losses, many methods for PW management, although not all focused on rice production systems, have been identified and suggested (see, De Groote et al., 2007; 2010; Gebisa and Gressel, 2007; Oswald, 2005). For example, hand pulling and hoe weeding before PWs set seeds have been suggested as effective control methods by Gbehounou (2006) and Rodenburg et al. (2011) for *Rhamphicarpa* and Dugje et al. (2008) and Carsky et al. (1994) for *Striga* spp. Herbicide use has been suggested for the control of *Striga* spp. (e.g. Jamil et al., 2011) and *Rhamphicarpa* (Gbehounou, 2006). Some studies have demonstrated that, improving soil fertility can alleviate the impact of the PWs (Douthwaite et al., 2003; Dugje et al., 2008; Hearne, 2009; Rodenburg et al., 2011). Water management has been suggested by Rodenburg et al. (2011) and Kabiri et al. (2014) for the control of *Rhamphicarpa* in rainfed lowland rice farms. Seed cleaning to remove PW seeds from rice seed before sowing has been suggested by Berner et al. (1994) for *Striga* spp and by Gbehounou and Assigbe (2003) for *Rhamphicarpa*. Other methods such as the use of resistant or tolerant host varieties, legume-cereal crop rotations, natural bush fallows or improved fallows, have also been suggested as solutions for PW problems (see Berner et al., 1994; Dugje et al., 2008; Rodenburg et al., 2010). However, while, the threats of PWs seem to increase (e.g. Rodenburg et al., 2014a), the uptake of those management methods by farmers has remained very limited (Atera et al., 2012; De Groote et al., 2010; Oswald, 2005). A limited number of studies analysed factors affecting the adoption of PW management practices by farmers. Most commonly reported factors included technology reliability, access to the technology, costs requirements (labour and skills), awareness of farmers, land availability and ownership, and farm biophysical characteristics (see Hearne, 2009; Oswald, 2005; Douthwaite et al., 2007). Previous studies on the adoption of weed management practices (WMPs) are limited mainly to other cereal (maize, sorghum, millet) than rice production systems (e.g. Kamara et al., 2008; Khan et al., 2008, Nkonya et al., 1997). The determinants of adoption of weed management practices (WMPs) to cope with PW in rice systems, in SSA, have not been investigated yet. Moreover, all previous adoption studies have analysed the adoption of individual technologies ignoring the fact that farmers usually combine existing technologies, in particular for weed management, to make a control strategy (Bekele and Drake, 2003; Hearne, 2009; Teklewold and Kohlin, 2011).

In rice systems, the PWs *Striga spp,* and *Rhamphicarpa fistulosa* are often relatively new or unknown and, only a few established management options are yet known to affected farmers (Gbehounou, 2006; Parker, 2012; Rodenburg et al., 2011). Hence, the development of acceptable rice-specific PW management methods requires knowledge on the most currently used WMPs by rice farmers, and insights on factors affecting their choices of specific combinations of WMPs.

Furthermore, the applied combinations of WMPs and factors affecting their adoption may vary significantly across countries (see: Douthwaite et al., 2007; Hearne, 2009; Oswald, 2005). None of the previous studies has made a cross-country analysis to shed light on country-specific differences or similarities between factors affecting the adoption of WMPs by farmers. Failure to recognise, understand and account for those differences or similarities in the adoption of WMPs among countries will reduce the effectiveness of programmes aiming at enhancing the adoption of WMPs by farmers (Hearne, 2009).

This study aims to identify biophysical, socio-economic and institutional factors that drive farmers' decisions to adopt specific weed management strategies in rainfed rice systems. The analysis is performed for three countries in SSA (Benin, Cote d'Ivoire and Tanzania) to account for country-specific conditions.

3.2. Methods and data

3.2.1. Survey

Farmers' survey have been conducted to identify farmers choices for weed management practices on 281 rice farms in Benin (November–December 2011), 201 farms in Tanzania (January–April 2012), and 240 farms in Cote d'Ivoire (November–December 2012). In Benin, the study included 5 districts viz. Dassa and Glazoue in Collines region (central Benin), Kandi in Alibori region (North-East) and Tanguieta and Boukoumbe in Atacora region (North-West). In Cote d'Ivoire, the study included 8 districts in the North of the country viz. Boundiali, Ganaoni, Siempurgo and Kolia in the region of Bagoe and Korhogo, Sinématiali, Karakoro and Tioro in Poro region. In Tanzania, the study included 5 districts viz. Kyela in Mbeya region, Nyasa, Songea, Namtumbo in Ruvuma region and Morogoro rural in Morogoro region. These districts represent important rice production areas and are affected by parasitic weeds (PWs). The study focused only on *Rhamphicarpa fistulosa* in Benin (as *Striga* spp. are less eminent in the rice systems of Benin), on *Rhamphicarpa fistulosa* and *Striga hermonthica* in Cote d'Ivoire and on *Rhamphicarpa fistulosa* and *Striga asiatica* in Tanzania. In each of the research sites, rice farmers were selected randomly per village. Each of the randomly selected sample per country contained farmers experiencing parasitic weed infestations on their farms as well as farmers who did not (Table 3.1). A list of 13 (parasitic) WMPs was composed based on relevant weed science literature (Table 3.2). Data on WMPs used and fields infestation status by any of the listed parasitic weed and the level of infestation, were collected from farmers using structured survey. During individual interviews, farmers were asked to indicate which WMPs they have applied during the last cropping season among the 13 listed WMPs. They were also asked to indicate whether they have experienced any of the PWs on their field and what was the level of infestation.

3.2.2. Model specification and selection of variables

3.2.2.1. Model specification

To model farmers' decision to adopt technologies, farmers' utility maximization framework was assumed (Adesina and Chianu, 2002; Defrancesco et al., 2008). Farmers adopt methods or combination of methods that provide them with higher utility compared to the non-adopted ones. In smallholder agriculture in SSA, the use of multiple weed control practices by an individual farmer is common (Rodenburg and Johnson, 2009). In order to account for the interrelationship between farmers' choice of WMPs considered in this study, the multivariate probit (MVP) regression models were used. The method allows for simultaneous choices, accounting for situations in which farmers simultaneously use more than one WMP as a strategy (Baskaran et al., 2013; Calia and Ferrante, 2010). Considering *m* categories of WMPs (in this study, m=4 for Cote d'Ivoire and Tanzania and m=5 for Benin), there are *m* equations describing each a latent variable corresponding to each of the binary choices of a WMP. Following Cappellari and Jenkins (2003), the underlying utility function for farmers' adoption of each WMP is defined as:

$$y_m^* = \beta_m' X_m + \varepsilon_m \, , \; m = 1, \ldots\ldots\ldots, M \qquad (1)$$

$$y_m = 1 \;\; if \;\; y_m^* > 0 \;\; and \; 0 \; otherwise$$

Where y_m^* is the latent (un-observed) variable corresponding to the observed outcome of the mth choice y_m, $\boldsymbol{X}_m$ is a vector of *p* covariates for the m^{th} equation (*m*=1, …, M), β_m' is the corresponding vector of parameters, and ε_m (*m*=1, …, M) is the error term vector distributed as multivariate normal with mean zero and variance-covariance matrix *V*. The leading diagonal element of *V* has a value of one and the off-diagonal elements are correlations $\rho_{mj} = \rho_{jm}$ for *m*, *j*=1, …*M* and *m*≠*j*. The Log likelihood function of the observed discrete data in a sample of *N* independent observations and *m* equations is given by:

$$L = \sum_{i=1}^{N} \log \Phi_m(\mu_i;\Omega) \qquad (2)$$

The probability of the observed outcome for any observation is the joint cumulative distribution $\Phi_m(\mu_i;\Omega)$ where $\Phi_m(.)$ is the M-variate normal cumulative distribution density function with argument μ_i and Ω varying with each observation, for each observation, where $\mu_i = (K_{i1}\beta_1^{'}X_{i1},\, K_{i2}\beta_2^{'}X_{i2},...,K_{im}\beta_m^{'}X_{im})$ are the upper integration points, with $K_{im} = 2y_{im} - 1$ taking the value 1 for outcome y_{im} equal to 1 and –1 for y_{im} equal to zero and, m=1, …M. Matrix Ω has constituted elements Ω_{mj}, where $\Omega_{mm} = 1$ and $\Omega_{mi} = \Omega_{jm} = K_j K_m \rho_{jm}$.

The relationships among the different WMPs are data-driven and are modelled using correlation parameters that must be estimated. A correlation coefficient between the choice of a pair of WMPs that is different from zero, after controlling for all covariates, indicates that the choice between the two WMPs considered is affected by the same underlying factors (Baskaran et al., 2013). This means that the decisions of the adoption of the WMPs under consideration are mutually dependent. Hence, the MVP fit data better2 than an estimation based on an individual probit for each WMP separately. The estimation of this Log likelihood function requires the computation of derivatives of M order integrals for which no general solution exists. This problem is addressed by simulation technics (Kis-Katos, 2012). To estimate the MVP model, the simulated maximum likelihood with the Geweke-Hajivassiliou-Keane simulator was used (Cappellari and Jenkins, 2003). The factors affecting farmers’ decisions to adopt individual WMPs were identified using the parameter estimates of the MVP model and their significance. To identify the determinants of a specific management strategy (stand alone WMP or a combination of WMPs) adopted by farmers, the average marginal effects (AMEs) of each covariate on the partial and joint multivariate probabilities were estimated following Kis-Katos (2012).

3.2.2.2. Variables in the empirical model

The individual WMPs currently used by farmers’ were the dependent variables in the MVP models. These are binary choice (yes/no) variables for each of the WMP considered. In Benin, the

[2] Ignoring correlation between equations leads to inefficient estimates. However, results remain usually unbiased (Liang and Zeger, 1986)

five most used WMPs were considered while four were considered in Cote d'Ivoire and Tanzania (Table 3.1). In all sample countries hoe weeding, fertilizer and herbicide use were considered, and additionally hand weeding and water control (bunding) in Benin, hand weeding in Cote d'Ivoire and crop rotation with legumes, in Tanzania. Fertilizer use included the use of organic (e.g. cattle manure, compost) and inorganic fertilizer (e.g. Urea, Di ammonium Phosphate (DAP) and NPK). In this study, WMPs were grouped into modern and traditional practices. Manual hand and hoe weeding were considered as traditional WMPs, while fertilizer use, herbicide use, water control and rotations with legumes were considered as modern (improved) WMPs (see: Douthwaite et al., 2007, Harker and O'Donovan, 2013; Oswald, 2005). Hence, a five variate probit model for Benin and a four variate probit model for Cote d'Ivoire and Tanzania were estimated[3].

Various factors affect the adoption of crop management technologies (see Hearne, 2009; Oswald and Ransom, 2004). Factors frequently identified by adoption studies can be grouped into (i) biophysical characteristics of farms; (ii) socio-economic characteristics of households and (iii) institutional factors (e.g. Adesina and Chianu, 2002; Beke, 2011; Khan et al., 2008； Teklewold and Kohlin, 2011).

i) Biophysical characteristics of farms

Field size has a significant effect on farmer adoption decisions (e.g. Adesina and Zinnah, 1993; Bekele and Drake, 2003; Jara-Rojas et al., 2012). In rainfed rice systems weeding is a labour intensive activity. Hence, farmers with a large field are expected to be associated with a higher likelihood to adopt labour-saving technologies such as herbicide, fertilizer and hoe weeding (in situation where these replace tedious hand weeding). The variables *'Striga'* and '*Rhamphi'* indicate whether a field is infested by *Striga* spp in Cote d'Ivoire and Tanzania and, by *Rhamphicarpa fistulosa* in all sample countries. For Cote d'Ivoire however, the variable used in the empirical model was the level of infestation (i.e. no, low, medium, high). Farmers can reduce both the likelihood and the severity of infestation of their plots given their awareness of the problem, accessibility and management capacity of production resources (N'cho et al., 2014). Therefore, it is expected that farmers with fields infested by the PWs will choose improved WMPs. In this study, *lowland* refers cropping in the lowlands of Cote d'Ivoire and Tanzania, and in the inland valley bottom of Benin. Fields cropped in the inland valley bottom have a higher probability of being infested by *Rhamphicarpa* (N'cho et al., 2014) but not by *Striga* spp. (e.g. Rodenburg et al., 2010;

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[3] Estimations have been implemented with Stata/11.2 MP, using the mvprobit, mvnp and mdraws routines of Cappellari and Jenkins (2003, 2006). The D = 300 random draws (the default setting is 5 draws). The robust option was used to correct the p-values for heteroskedasticity (Wooldridge, 2006, p.275).

Kabiri et al., 2014). Therefore, this variable was hypothesized to affect the adoption of modern WMPs positively in Benin.

ii) Socio-economic characteristics of households

The socio-economic variables considered in this study included, for each rice farmer: the *age*, *education* level, *labour* available in the household, *number of children, women and men present in the household*, years of rice farming *experience*, *gender*, origin of farmer (whether farmer is native or migrant), farmer production *objective* and household *revenue* that reflects the farmers' financial situation**.**

iii) Institutional factors

The variables considered to reflect the institutional characteristics of the samples included: *land* which refers to land ownership, the access to input, captured by *credit*, the access to *information* captured by contact (or frequency of contact) of farmers with development and research institutions and *group member* accounting for farmers memberships to farmers' organizations which is supposed to facilitate access to production inputs like fertilizer, herbicide (e.g. Anley et al., 2007; Lapar and Pandey, 1999).

The complete list of variables used in the MVP is provided and described in Table 3.1.

Table 3.1 Definition and descriptive statistics of variables used in the multivariate probit models of Benin, Cote d'Ivoire and Tanzania.

Variables	Description	Benin		Cote d'Ivoire		Tanzania	
		Mean	SD[a]	Mean	SD[a]	Mean	SD[a]
Dependent variables							
Hand weeding	Field weeded using hand pulling (1=yes; 0=no)	0.92	0.28	0.81	0.39	na	na
Hoe weeding	Field weeded using hoe (1=yes; 0=no)	0.80	0.40	0.64	0.48	0.36	0.48
Herbicide	Field weeded with herbicide (1=yes; 0=no)	0.41	0.50	0.93	0.25	0.20	0.40
Fertilizer	Field received inorganic or organic fertilizer (1=yes; 0=no)	0.63	0.48	0.75	0.44	0.20	0.40
Water control	Whether farmer used bunding for the field (1=yes; 0=no)	0.41	0.49	na	na	na	na
Rotation	Whether farmer rotate rice with legume crops on the field (1=yes; 0=no)	Na	na	na	na	0.14	0.35
Explanatory variables							
Biophysical characteristics of farms							
Lowland	Field cropped in Inland Valley bottom (Benin) or in lowlands (Cote d'Ivoire and Tanzania) (1=yes; 0=no)	0.44	0.50	0.60	0.49	0.53	0.50
Field size	Rice field size in ha	0.19	0.19	1.38	1.06	0.82	0.70
Rhamphi[b]	Field infested by *R. fistulosa*. In Benin: 1=yes, 0=No In Côte d'Ivoire: 0=not infested, 1= low; 2=medium, 3=high In Tanzania :1= experienced once; 0=never experienced	0.61	0.49	0.09	0.44	0.44	0.50
Striga[b]	Field infested by *Striga* spp: In Côte d'Ivoire: 0=not infested, 1= low; 2=medium, 3=high. In Tanzania:1= experienced once; 0=never experienced	na	na	0.78	1.16	0.61	0.49
Socio-economic characteristics of households							
Origin	Farmer origin (1=Native, 0=Migrant)	na	na	na	na	0.86	0.35
Gender	Gender of rice farmer (1=female; 0=male)	0.74	0.44	0.13	0.34	0.30	0.46
Age	Rice farmer age in year	na	na	43.19	11.40	46.74	14.58
Experience	Number of year farmer is cropping rain-fed rice	14.13	8.14	na	na	na	na
Education	Number of year education completed by farmer	1.99	3.18	1.11	2.44	6.77	2.67
Cotton	1= Farmer crops cotton; 0= Farmer did not crop cotton	0.10	0.30	0.67	0.47	na	na
Labour	Labour force available in the household (man-day/ha)	48.64	54.44	13.53	22.50	na	na
Children	Number of children (<16 years) in the household	3.43	2.71	na	na	2.47	1.80
Women	Number of women (female>16 years) in the household	2.33	1.64	na	na	2.13	1.42
Men	Number of men (male>16 years) in the household	2.15	2.37	na	na	1.81	1.23
Revenue[c]	Household revenue per head (x1,000 /household member)	125.42	137.50	268.31	305.25	122.03	211.39
Objective	Production objective (1= Subsistence; 0= otherwise)	na	na	na	na	0.51	0.50
Institutional factors							
Land	Field ownership (1=own; 0=rent or lend)	0.81	0.39	0.82	0.39	na	na
Group member	1= Farmer is member of a farmer group 0= Farmer is not member of any farmer group	0.72	0.45	0.53	0.50	0.69	0.47
Information[d]	Access to agricultural information through development and research organization (1=yes; 0=no for Benin and Tanzania; 1= yearly; 2= monthly, 3=weekly; 4=daily for Cote d'Ivoire)	0.88	0.33	1.74	1.38	0.81	0.40
Training in WMP (TWMP)[e]	Receive specific training in weed management	na	na	0.12	0.33	0.43	0.50
Training in CMP (TCMP)[f]	Receive training in agricultural practices in general	0.78	0.42	0.10	0.31	0.32	0.47
Credit	Farmer pay input by (informal/formal) credit (1=yes; 0= no)	0.47	0.50	0.77	0.42	na	na

[a] SD = Standard Deviation.; [b] In Cote d'Ivoire, the proportions of farms infested by parasitic weeds are : 4.2% for *Rhamphicarpa* and 35% for *Striga*
[c] Revenue was expressed in CFA in Benin and Cote d'Ivoire with the fixed exchange rate: €1 = 656 FCFA, In Tanzania it was expressed in Shilling Tanzanian: USD 1 = 1600 Tshs.
[d]In Cote d'Ivoire, this variable accounted for the frequency of contact with development or research organizations through the year.
[e] WMP = Weed Management Practices.;
[f] CMP = Crop Management Practices.
na= Not applicable

3.3. Results

3.3.1. Weed management practices currently used by rice farmers

The individual WMPs currently used by rice farmers, are summarized in Table 3.2.

Table 3.2 Proportion of farmers using each weed management practice per country.

Weed management practices[a] (WMPs)	% of farmers in the sample[b]			
	Benin	Cote d'Ivoire	Tanzania	Total
Hand weeding	91.6	81.2	88.6	87.3
Hoe weeding	79.6	63.8	35.8	62.3
Herbicides application	41.1	93.3	20.4	52.6
Fertilizer	63.2	74.6	20.4	55.1
Mechanical weeding	0.0	0.4	0.5	0.3
Transplanting	3.9	35.0	10.0	15.8
Resistant or tolerant rice varieties	24.9	5.4	2.5	12.3
Rotation with legume crops	1.4	7.1	14.4	6.9
Intercropping	3.2	5.0	4.5	4.1
Natural bush fallow	4.9	0.0	3.5	2.90
Use of clean seeds[c]	38.3	3.8	4.0	17.4
Water control	41.1	6.3	6.5	20.0
Seed coating	3.2	0.0	0.5	1.4

[a]The list of weed management practices is based on, Adagba et al., 2002b; De Groote et al., 2010, Oswald, 2005; Somda et al., 2002; Asfaw and Admassie, 2004; Rodenburg and Johnson , 2009; Wubeneh and Sanders 2006 and Mallamaire, 1949.
[b]The percentage for all WMPs is greater than 100% per country because each farmer can use more than one WMP.
[c] Clean seed refers to rice seed free of weed seeds.

Hand weeding was the most used (87%) WMP, followed by hoe weeding (62%), fertilizer (55%), and herbicide use (53%). The shares of WMPs differed per country. Herbicide use was the most commonly applied method by rice farmers in Cote d'Ivoire (93%) while traditional hand and hoe weeding were the most frequently used practices in Benin (92% and 80% respectively) and Tanzania (89% and 36% respectively). Farmers used both pre and post-emergence herbicides. The use of "resistant or tolerant rice varieties" referred[4] to the use of the rice variety Gambiaka in central Benin and FKR19 (known as BL19) in Northern Benin. In Cote d'Ivoire, this referred to the traditional varieties "Nanguin" and "Gbape". However, only 5% of farmers used it. In Tanzania, the use of resistant or tolerant varieties was negligible (2.5%).

3.3.2. Results of the multivariate probit regression

The parameters estimates of the MVP regression for each country are summarized in Table 3.3. The results have been reorganized per weed management practice and compared across countries. The likelihood ratio test for each of the 3 models showed that the correlations between the equations considered were not jointly equal to zero (P<0.001). Hence, the MVP model fits the data better than

[4] These results were obtained by pairwise correlation tests between the WMP "resistant or tolerant variety" and actual varieties used by farmers in each country.

individual probit models, implying that the decisions on the adoption of WMPs were mutually dependent. The signs of the parameters of most explanatory variables were in line with *a priori* expectations, with a few exceptions in Cote d'Ivoire (household labour and training received in crop management practices) and Tanzania (gender).

3.3.3. Factors driving farmers' choice for individual WMPs

Compared to uninfested fields, an infestation by *Rhamphicarpa* had a positive effect on the adoption of hand-weeding in Benin but a negative effect on this in Cote d'Ivoire. Moreover, an infestation by *Rhamphicarpa* had a negative effect on the adoption of hoe-weeding in Tanzania, while it had a positive effect on the adoption of this WMP in Benin and no significant effect in Cote d'Ivoire. Compared to uninfested fields, an infestation with *Striga* spp. had a positive effect on adoption of hoe-weeding in Cote d'Ivoire and Tanzania.

Beside the parasitic weeds infestation effects, *ceteris paribus*, hand-weeding was significantly less likely to be adopted by farmers who cropped rice in the lowlands in Benin and Cote d'Ivoire and those who had access to inputs in Benin. However, hand-weeding was more likely to be used by female farmers in Cote d'Ivoire and by farmers with a large number of children in their household in Benin. In Tanzania, the adoption of hoe-weeding was lower on larger fields, on fields cultivated by female farmers and by farmers with a large number of children in their households.

The adoption of herbicide was significantly ($P<0.05$) more likely on larger fields in all countries, by farmers who had access to input credits in Benin and Cote d'Ivoire or by farmers with a higher household revenue in Cote d'Ivoire only, and by farmers trained in weed management practices in Cote d'Ivoire and Tanzania and farmers trained in agricultural practices in Benin. Moreover, the herbicide adoption was positively associated with farming in the inland valley bottom in Benin. In Cote d'Ivoire, *Striga* infestation level, and memberships of a farmers group positively affect ($P<0.5$) adoption of herbicide. However, the likelihood of adopting herbicide was lower on *Rhamphicarpa* infested fields in Benin and Cote d'Ivoire compared to fields not infested by *Rhamphicarpa*. A higher education level of the farmer increased the likelihood of adopting herbicide in Cote d'Ivoire but had the opposite effect in Benin and no significant effect in Tanzania. Female farmers were *ceteris paribus* more likely ($P<0.1$) to adopt herbicide in Benin while no significant gender effect was observed in Cote d'Ivoire and Tanzania ($P>0.1$).

Fertilizer was significantly ($P<0.05$) more likely to be adopted in Tanzania on lowlands fields and on fields infested by *Striga* while it was less likely ($P<0.05$) adopted by farmers growing rice for household consumption. In Benin and Cote d'Ivoire, fertilizer was more likely ($P<0.5$) adopted by farmers growing cotton compared to those who did not grow cotton and by farmers having access to input credits compared to those who did not. In Cote d'Ivoire, the probability of adopting fertilizer increased with the *Rhamphicarpa* infestation level and increasing access to information. In contrast with this finding in Cote d'Ivoire, the likelihood of adopting fertilizer was negatively associated with access to information in Benin. In Benin however, its adoption was positively associated ($P<0.01$) to field size and memberships of a farmers' group.

Water-control was more likely ($P<0.05$) adopted by farmers who owned their lands compared to those who did not, farmers that had a larger quantity of household labour available, and those that had a larger number of children in their household or a higher household revenue. It was less likely ($P<0.01$) adopted, *ceteris paribus*, by farmers cropping in the inland valley bottom, farmers who had access to inputs and farmers who had a large number of men in their household. In Tanzania, infestation by *Striga* spp and farmers' education level positively affected the adoption of crop rotation while this WMP was less likely adopted by ($P<0.05$) female farmers.

Table 3.3 Parameters estimates of the multivariate probit models of adoption of weed management practices in Benin, Cote d’Ivoire and Tanzania.

	Hand weeding (Hw)		Hoe weeding (Ho)			Herbicide (Ha)			Fertilizer (Fm)			Water control (Wc)	Rotation (Ro)
Explanatory variables	Benin	Cote d’Ivoire	Benin	Cote d’Ivoire	Tanzania	Benin	Cote d’Ivoire	Tanzania	Benin	Cote d’Ivoire	Tanzania	Benin	Tanzania
Lowland	–0.528	–0.623	0.949	–1.460	0.144	1.669	–0.394	0.165	–0.094	–0.025	0.640	–1.513	–0.223
	(0.270)*	(0.308)**	(0.238)***	(0.380)***	(0.238)	(0.237)***	(0.320)	(0.247)	(0.236)	(0.239)	(0.260)**	(0.215)***	(0.291)
Land	0.170	0.310	0.905	0.591		–0.905	0.104		–0.352	–1.138		0.756	
	(0.292)	(0.241)	(0.294)***	(0.291)**		(0.294)***	(0.382)		(0.296)	(0.338)***		(0.261)***	
Field size	–0.125	0.077	3.136	0.666	–0.724	2.831	0.184	0.403	2.117	–0.125	–0.170	0.331	–0.097
	(0.587)	(0.167)	(1.294)**	(0.194)***	(0.238)***	(1.000)***	(0.234)**	(0.145)***	(0.674)***	(0.128)	(0.186)	(0.642)	(0.247)
Rhamphi	1.011	–0.596	0.867	–0.249	–1.592	–0.995	–0.335	0.027	–0.101	4.119	0.060	–0.116	–0.694
	(0.268)***	(0.234)**	(0.266)***	(0.314)	(0.279)***	(0.229)***	(0.236)**	(0.283)	(0.260)	(0.674)***	(0.276)	(0.208)	(0.355)*
Striga		0.058		0.676	0.764		0.110	–0.093		0.066	0.504		1.368
		(0.141)		(0.186)***	(319)**		(0.188)*	(0.309)		(0.103)	(0.296)*		(0.491)***
Origin					0.489			0.858			0.0640		–0.160
					(0.312)			(0.490)*			(0.326)		(0.362)
Gender	0.179	1.365	0.293	0.277	–0.606	0.507	–0.177	0.195	0.518	0.190	0.194	–0.323	–0.613
	(0.311)	(0.374)***	(0.283)	(0.368)	(0.251)**	(0.265)*	(0.339)	(0.245)	(0.269)*	(0.321)	(0.232)	(0.236)	(0.288)**
Education	–0.009	0.074	–0.039	–0.033	0.087	–0.182	3.607	0.008	–0.028	–0.146	0.050	0.005	0.082
	(0.036)	(0.046)	(0.038)	(0.046)	(0.041)**	(0.042)***	(0.667)***	(0.030)	(0.034)	(0.049)***	(0.048)	(0.032)	(0.049)*)
Age		0.015		0.004	–0.005		–0.031	–0.009		–0.024	0.003		–0.006
		(0.010)		(0.013)	(0.010)		(0.013)**	(0.008)		(0.010) **	(0.009)		(0.010)
Experience	–0.010		–0.009			–0.011			–0.042			0.016	
	(0.014)		(0.013)			(0.014)			(0.015)***			(0.013)	
Cotton	0.326	–0.357	–0.293	–0.333		0.730	0.464		2.321	0.532		–0.788	
	(0.486)	(0.284)	(0.392)	(0.336)*		(0.393)*	(0.474)		(0.502)***	(0.271)**		(0.338)**	
Labour	–0.003	–0.005	–0.001	–0.008		–0.002	–0.008		0.003	0.018		0.006	
	(0.003)	(0.005)	(0.003)	(0.009)		(0.003)	(0.010)		(0.003)	(0.010)*		(0.002)***	
Children	0.094		0.141		–0.205	–0.037		0.063	–0.009		–0.100	0.103	0.103
	(0.053)*		(0.067)**		(0.070)***	(0.049)		(0.064)	(0.045)		(0.066)	(0.045)**	(0.075)
Women	–0.016		0.141		0.081	0.091		–0.175	–0.004		–0.105	–0.016	–0.036
	(0.081)		(0.109)		(0.097)	(0.088)		(0.080)**	(0.093)		(0.098)	(0.073)	(0.106)
Men	0.073		–0.089		0.232	0.047		0.091	–0.152		–0.189	–0.307	–0.028
	(0.071)		(0.076)		(0. 100)**	(0.072)		(0.111)	(0.076)**		(0.106)*	(0.073)***	(0.113)
Revenue	0.002	0.002	–0.001	0.004	–2.8e-05	0.003	0.002	4e-04	–3e-04	5e-04	–0.002	0.003	5e-04
	(0.001)*	(0.001)*	(0.001)	(0.001)***	(5.8e-04)	(0.001)***	(0.001)**	(4e-04)	(0.001)	(4e-04)	(0.001)	(0.001)***	(5e-04)
Objective					0.071			–0.060			–0.553		0.070
					(0.239)			(0.223)			(0.230)**		(0.264)
Group member	0.360	–0.158	1.357	0.085	–0.072	0.133	0.871	0.159	2.007	0.021	0.183	–0.331	0.163
	(0.261)	(0.228)	(0.265)***	(0.269)	(0.251)	(0.240)	(0.333)***	(0.254)	(0.449)***	(0.223)	(0.238)	(0.206)	(0.297)
TWMP[c]		–0.390		–1.328	-0.902		21.264	0.431		0.477	0.082		0.330
		(0.540)		(0.593)	(0.246)***		(3.753)***	(0.217)**		(0.446)	(0.217)		(0.250)
TCMP[d]	0.103	5.184	–1.028	2.184	0.685	0.766	–21.503	0.178	–0.438	–0.679	0.137	–0.096	0.180
	(0.301)	(0.333)***	(0.366)***	(0.787)	(0.237)***	(0.307)**	(3.661)***	(0.227)	(0.276)	(0.474)	(0.222)	(0.241)	(0.270)
Information	–0.214	0.035	0.217	–0.333	–0.324	0.396	0.105	0.092	–0.994	0.140	–0.071	–0.387	–0.105
	(0.400)	(0.087)	(0.338)	(0.099)***	(0.282)	(0.395)	(0.190)	(0.323)	(0.451)**	(0.083)*	(0.283)	(0.311)	(0.346)
Credit	–0.539	0.030	–0.455	0.293		1.689	1.699		2.776	0.769		–0.406	
	(0.251)**	(0.297)	(0.232)**	(0.375)		(0.237)***	(0.625)***		(0.340)***	(0.247)***		(0.194)**	

Multivariate probit (MSL, # draws= 300), for all 3 models; N= 281, Wald chi2 (85)= 671.29, Log pseudo likelihood= –432.177, Prob>chi2= 0.0000 (Benin), N= 240, Wald chi2 (64)= 3957.77, Log pseudo likelihood= –253.555, Prob>chi2= 0.0000 (Cote d’Ivoire), N= 199, Wald chi2 (68)= 250.41, Log pseudo likelihood= –300.534, Prob>chi2= 0.0000 (Tanzania).
Likelihood ratio test of all rho jointly equal to zero: chi2(10) = 27.077, Prob>chi2= 0.002 (Benin); chi2(6) = 44.9227, Prob > chi2 = 0.0000 (Cote d’Ivoire); chi2(6) = 28.2636, Prob > chi2 = 0.0001 (Tanzania).
Significant (rho) coefficients identified in each country with respect to the order of WMPs with Hw= 1, Ho= 2, Ha= 3, Fm= 4, Wc=5 and Ro= 6: Benin ρ43= 0.701***, ρ53= –0.448*** , ρ54= –0.481***; Cote d’Ivoire ρ_{21}= 0.859***, ρ_{41}= –0.785***, ρ_{42}= –0.593***, ρ_{43}=0.291*; Tanzania ρ_{32}= –0.34**, ρ_{42}=0.461*** , ρ_{62}=0.544***, ρ_{43}=0.323** , ρ_{64}=0.453***.
*** P<0.01, **P<0.05, * P<0.1.

3.3.4. Adoption of specific combination of WMPs

In order to identify factors affecting the adoption of a specific weed management strategy by rice farmers, the marginal effects of covariates on partial and joints multivariate probabilities of WMPs were estimated. The estimated average marginal effects (AMEs) are reported in Table 3.4 for Benin, Table 3.5 for Cote d'Ivoire and Table 3.6 for Tanzania. For each country, the WMP combinations reported were selected based on 1) the pairwise correlation statistics, 2) the significance level of the marginal effects of the covariates and 3) the proportion of farmers in the sample using each WMP combination. The selected WMP strategies always included the choice of the most widely used WMP in small-scale rice farming systems in SSA, which is manual (hand and/or hoe) weeding. In Cote d'Ivoire however, a strategy that did not include manual weeding was also selected (Table 3.5) because about 20% of the sample farmers did not use manual weeding. Hence, the strategy "Hand-weeding-only" was present in all countries, while "Hand weeding-fertilizer" was present in Benin and Tanzania; "Hand weeding-herbicide-fertilizer" in Benin and Cote d'Ivoire, and "Hand-hoe-weeding" in Cote d'Ivoire and Tanzania. The remaining strategies were specific to each country (Tables 3.4, 3.5 and 3.6). The cross-country analysis of the effects of parasitic weed infestation on farmers' adoption decision focused on the four strategies above.

Table 3.4 Selected results of the estimated average marginal effects (AMEs) on partial and joint probabilities of WMPs[a] in Benin.

Explanatory variables	Hand weeding only (Hwo)	Hand weeding and Herbicide (HwHa)	Hand weeding and Fertilizer (HwFm)	Hand weeding and Water control (HwWc)	Hand weeding, Herbicide and Fertilizer (HwHaFm)	Hand weeding, Herbicide, Fertilizer, and Water control (HwHaFmWc)
Lowland	–0.042 (0.020)**	–0.003 (0.001)**	–0.003 (0.002)	–0.006 (0.004)*	–0.002 (0.001)	–0.007 (0.004)*
Land	0.015 (0.026)	0.001 (0.002)	0.001 (0.002)	0.002 (0.004)	6e-04 (0.004)	0.003 (0.005)
Field size	–0.002 (0.015)	–0.005 (0.054)	–6e-04 (0.065)	–0.001 (0.010)	–0.002 (0.053)	0.003 (0.072)
Rhamphi	0.085 (0.020)***	0.005 (0.001)***	0.006 (0.002)***	0.014 (0.004)***	0.004 (0.002)**	0.015 (0.005)***
Gender	0.015 (0.026)	0.001 (0.002)	0.001 (0.002)	0.002 (0.004)	0.001 (0.002)	0.003 (0.005)
Education	–0.001 (0.003)	–3e-05 (2e-04)	–5e-05 (3e-04)	–1e-04 (6e-04)	–3e-05 (2e-04)	–1e-04 (5e-04)
Experience	–0.001 (0.001)	–5e-05 (1e-04)	–6e-05 (1e-04)	–1e-04 (2e-04)	–3e-05 (1e-04)	–1e-04 (2e-04)
Cotton	0.016 (0.032)	0.001 (0.002)	6e-04 (0.002)	0.002 (0.005)	–5e-04 (0.002)	0.002 (0.005)
Labour	–1e-04 (1e-04)	–7e-06 (6e-06)	–1e-05 (9e-06)	–1e-05 (1e-05)	–7e-06 (7e-06)	–3e-05 (3e-05)
Children	0.007 (0.004)**	4e-04 (3e-04)	4e-04 (4e-04)	0.001 (6e-04)*	3e-04 (3e-04)	0.001 (7e-04)*
Women	–0.001 (0.007)	–1e-04 (5e-04)	–1e-04 (5e-04)	–2e-04 (0.001)	–5e-05 (4e-04)	–2e-04 (0.001)
Men	0.005 (0.006)	3e-04 (4e-04)	3e-04 (4e-04)	0.001 (0.001)	2e-04 (4e-04)	0.001 (0.001)
Revenue	4e-05 (2e-05)*	3e-06 (2e-06)*	5e-06 (6e-06)	7e-06 (6e-06)	4e-06 (2e-06)	2e-05 (1e-05)*
Group member	0.030 (0.024)	0.002 (0.002)	0.002 (0.002)	0.005 (0.005)	0.001 (0.001)	0.005 (0.005)
TCMP[b]	0.008 (0.024)	5e-04 (0.002)	0.001 (0.002)	0.001 (0.004)	5e-04 (0.002)	0.001 (0.004)
Information	–0.011 (0.031)	–6e-04 (0.002)	–4e-04 (0.002)	–0.001 (0.005)	–3e-04 (0.002)	–0.001 (0.005)
Credit	–0.045 (0.020)**	–0.003 (0.001)**	–0.003 (0.002)	–0.007 (0.004)*	–0.002 (0.003)	–0.007 (0.004)*

[a] WMPs= Weed management practices.
*** P<0.01; **P<0.05, * P<0.1.
[b]TCMP= Training in crop management practices.
Note: The AMEs are calculated by averaging sample partial and joint probabilities effects of each WMP adoption, computed for each individual.
Standard errors of the AMEs for the five variate probabilities are estimated by an empirical Bayes procedure (parametric bootstrapping) that redraws 500 replications of the estimated coefficient vectors from a multivariate asymptotically normal distribution.

3.3.5. Effects of parasitic weeds on the adoption of weed management strategies

The likelihood of adopting hand weeding-only was lower on fields infested by *S. hermonthica* or *Rhamphicarpa* in Cote d'Ivoire and on *S. asiatica* infested fields in Tanzania. However, it was higher on *Rhamphicarpa* infested fields in Benin and Tanzania. *Striga* infestation reduced farmers' adoption of this strategy by 17% in Tanzania while the effect was negligible in Cote d'Ivoire. *Rhamphicarpa* infestation, *ceteris paribus*, increased adoption of hand weeding-only by 22% in Tanzania and about 9% in Benin. Farmers with *Rhamphicarpa* problems more likely combined hand weeding with fertilizer in Benin (0.6%) and Tanzania (7%) while the effect of *Striga* on the adoption of this combination was not significant ($P>0.1$).

Farmers with fields infested by *Rhamphicarpa* more likely combined hand weeding with herbicide and fertilizer in Benin (0.3%) and in Cote d'Ivoire (3%). Farmers, with fields that were highly infested by *Rhamphicarpa* in Cote d'Ivoire were less likely to combine hand weeding with hoe weeding (2%) like in Tanzania (18%) while the effect of *Striga* on the adoption of this strategy was not significant ($P>0.1$) in both countries.

On average, in the sample countries, parasitic weed infestation had a positive effect on adoption of combinations of WMPs that included modern WMPs. This is particularly true for Cote d'Ivoire where farmers with parasitic weed infested fields were more likely to adopt combinations of WMPs that included more than one modern WMPs (see Table 3.5, HaFm, HwHaFm and HoHaFm). They were less likely to adopt a combination including less than two improved WMPs. Similar results were obtained in Tanzania for *Striga* only (Table 3.6, HwHoRo, HwHoHaRo). In Benin parasitic weed infestation had a significant ($P<0.05$) effect on the likelihood of adopting all combinations considered.

Table 3.5 Selected results of the estimated average marginal effects (AMEs) on partial and joint probabilities of WMPs[a] in Cote d'Ivoire.

Explanatory variables	Hand only (Hwo)	Hand and Hoe (HwHo)	Hand, Hoe and Herbicide (HwHoHa)	Herbicide and Fertilizer only (HaFm)	Hand, Herbicide and Fertilizer (HwHaFm)	Hoe, Herbicide and Fertilizer (HoHaFm)
Lowland	0.006 (0.003)**	0.004 (0.011)	–0.042 (0.039)	0.091 (0.030)***	–0.004 (0.008)	–5e-04 (0.021)
Land	0.003 (0.003)	0.011 (0.009)	0.151 (0.037)***	–0.055 (0.034)*	–0.010 (0.012)	–0.010 (0.014)
Field size	–0.003 (0.002)*	0.001 (0.007)	0.038 (0.019)**	–0.022 (0.020)	4e-04 (0.005)	0.010 (0.009)
Rhamphi	–0.006 (0.002)***	–0.023 (0.010)**	–0.229 (0.022)***	0.074 (0.035)**	0.031 (0.015)**	0.044 (0.015)***
Striga	–0.003 (0.001)***	3e-04 (0.005)	0.005 (0.016)	–0.020 (0.014)	0.004 (0.005)	0.015 (0.009)*
Gender	–0.001 (0.003)	0.006 (0.012)	–0.017 (0.049)	–0.116 (0.026)***	0.010 (0.009)	–0.032 (0.009)***
Education	–0.006 (0.002)***	–0.021 (0.010)**	0.042 (0.012)***	0.007 (0.007)	–0.013 (0.005)**	–0.004 (0.002)
Age	3e-04 (1e-04)**	0.001 (5e-04)*	0.003 (0.001)***	–0.002 (0.001)**	4e-04 (3e-04)	–8e-04 (5e-04)*
Cotton	–0.004 (0.003)	–0.019 (0.016)	–0.075 (0.043)*	0.053 (0.031)*	–0.006 (0.010)	0.013 (0.010)
Labour	–5e-05 (6e-05)	–3e-05 (3e-04)	–0.003 (0.001)***	7e-04 (6e-04)	2e-04 (2e-04)	2e-04 (3e-04)
Revenue	– 3e-05 (1e-05)**	4e-04 (3e-04)	9e-05 (8e-05)	–2e-04 (1e-04)*	–4e-06 (2e-04)	3e-06 (4e-05)
Group member	–0.004 (0.002)	–0.018 (0.009)**	0.016 (0.035)	0.029 (0.028)	–0.013 (0.006)**	0.012 (0.011)
TWMP[b]	–0.004 (0.002)**	–0.061 (0.014)***	–0.051 (0.050)	0.109 (0.083)	–0.042 (0.012)***	0.002 (0.027)
TCMP[c]	0.005 (0.008)	0.323 (0.086)***	–0.132 (0.026)***	–0.142 (0.019)***	0.370 (0.071)***	–0.034 (0.010)***
Information	4e-04 (0.001)	–0.004 (0.004)	–0.025 (0.012)*	0.005 (0.011)	–0.001 (0.004)	–0.008 (0.003)**
Credit	–0.022 (0.009)***	–0.063 (0.026)**	–0.041 (0.038)	0.030 (0.030)	–0.021 (0.012)*	0.011 (0.013)

[a] WMPs= Weed management practices.
*** P<0.01; **P<0.05, * P<0.1.
[b]TWMP= Training in weed management practices.
[c]TCMP= Training in crop management practices.
Note: The AMEs are calculated by averaging sample partial and joint probabilities effects of each WMP adoption, computed for each individual. Standard errors of the AMEs for the four variate probabilities are estimated by an empirical Bayes procedure (parametric bootstrapping) that redraws 500 replications of the estimated coefficient vectors from a multivariate asymptotically normal distribution.

In Cote d'Ivoire, farmers who had adopted the herbicide–fertilizer combination were mainly those experiencing a high level of *Rhamphicarpa* infestation. Hence, *ceteris paribus*, *Rhamphicarpa* increased the likelihood of adopting this strategy by 7% and, lowland cropping increased it by 9%. The parasitic weeds infestation was also the main driver for the adoption of the combination hoe weeding with herbicides and fertilizer. The likelihood of adopting this strategy was higher with high levels of *Rhamphicarpa* (4%) and *Striga* infestation (2%). In Tanzania, the strategy of hand weeding combined with hoe weeding and crop rotations including legumes, was more likely used by farmers with fields infested by *Striga* (6%) while it was less likely used on *Rhamphicarpa* infested fields (6.5%) and on lowland fields in general (3%).

3.3.6. Effects of socio-economic and institutional factors on the adoption of weed management strategies

Factors such as lowland cropping were associated with lower adoption of hand-weeding-only in Benin (4%) while the effects were positive but negligible in Cote d'Ivoire and not significant in Tanzania. Child labour had a small (0.7%) but significant positive ($P<0.05$) effect on the adoption of hand weeding in Benin, while it was not significant ($P>0.1$) in Tanzania. Finally, household revenues decreased the likelihood of adopting hand weeding in Cote d'Ivoire and increased it in Benin while the effect was not significant in Tanzania. With respect to the combination hand weeding with fertilizer, factors such as number of men in the household (2%) and household revenue reduced its adoption in Tanzania, while these effects were not significant in Benin. The effect of revenue in Tanzania was small but significant ($P<0.05$). Farmers trained in crop management practices were 37% more likely to adopt the combination hand weeding with herbicide and fertilizer in Cote d'Ivoire, while no significant effect was observed in Benin.

Table 3.6 Selected results of the estimated average marginal effects (AMEs) on partial and joint probabilities of WMPs[a] in Tanzania.

Explanatory variables	Hand weeding only (Hwo)	Hand and Hoe weeding (HwHo)	Hand and Herbicide (HwHa)	Hand and Fertilizer (HwFm)	Hoe and Fertilizer (HoFm)	Hand, Hoe and Rotation (HwHoRo)	Hand, Hoe Herbicide and Rotation (HwHoHaRo)
Lowland	–0.072 (0.047)	–0.011 (0.030)	–0.004 (0.033)	0.041 (0.017)**	0.038 (0.016)**	–0.030 (0.018)*	–0.002 (0.003)
Field size	0.046 (0.041)	–0.072 (0.028)***	0.070 (0.020)***	–0.005 (0.012)	–0.032 (0.012)**	–0.022 (0.013)*	7e-04 (0.002)
Rhamphi	0.220 (0.065)***	–0.178 (0.039)***	0.043 (0.039)	0.073 (0.025)***	–0.038 (0.017)**	–0.065 (0.016)***	–0.008 (0.003)**
Striga	–0.169 (0.064)***	0.015 (0.044)	–0.065 (0.048)	–0.002 (0.024)	0.021 (0.019)	0.060 (0.017)***	0.006 (0.003)**
Origin	–0.119 (0.067)*	0.045 (0.039)	0.072 (0.043)*	–0.032 (0.035)	0.012 (0.016)	–0.002 (0.025)	0.005 (0.003)*
Gender	0.047 (0.050)	–0.050 (0.029)*	0.034 (0.034)*	0.035 (0.021)	0.003 (0.015)	–0.048 (0.016)***	–0.004 (0.003)
Education	–0.017 (0.007)**	0.002 (0.005)	–0.004 (0.005)	–2e-04 (0.004)	0.003 (0.003)	0.005 (0.003)	8e-04 (6e-04)
Age	0.002 (0.002)	1e-05 (0.001)	–0.001 (0.001)	7e-04 (6e-04)	3e-04 (5e-04)	–5e-04 (6e-04)	–1e-04 (1e-04)
Children	0.015 (0.013)	–0.024 (0.008)***	0.015 (0.009)*	–0.006 (0.005)	–0.012 (0.004)***	0.002 (0.005)	7e-04 (8e-04)
Women	0.021 (0.019)	0.020 (0.012)*	–0.018 (0.010)	–0.004 (0.008)	5e-04 (0.005)	0.004 (0.008)	–9e-04 (0.001)
Men	–0.023 (0.020)	0.031 (0.015)**	0.013 (0.014)	–0.021 (0.007)***	–0.003 (0.006)	0.009 (0.009)	0.003 (0.002)
Revenue	5e-05 (1e-04)	3e-05 (5e-05)	1e-04 (5e-05)**	–1e-04 (7e-05)**	–1e-04 (5e-05)*	7e-05 (4e-05)*	1e-05 (7e-06)*
Objective	0.037 (0.047)	0.032 (0.027)	0.014 (0.029)	–0.044 (0.017)	–0.026 (0.015)*	0.023 (0.017)	0.003 (0.003)
Group member	–0.030 (0.054)	–0.028 (0.033)	0.011 (0.031)	0.009 (0.020)	–4e-04 (0.016)	4e-04 (0.018)	0.001 (0.003)
TWMP[b]	0.019 (0.047)	–0.127 (0.025)***	0.069 (0.031)**	0.010 (0.018)	–0.036 (0.013)***	–0.016 (0.017)	0.002 (0.003)
TCMP[c]	–0.108 (0.046)	0.052 (0.032)*	–0.002 (0.028)	–0.020 (0.016)	0.020 (0.015)	0.022 (0.017)	0.006 (0.004)
Information	0.035 (0.050)	–0.031 (0.038)	0.021 (0.039)	0.004 (0.022)	–0.012 (0.018)	–0.013 (0.026)	–0.001 (.004)

[a] WMPs= Weed management practices.
*** P<0.01; **P<0.05, * P<0.1.
[b]TWMP= Training in weed management practices.
[c]TCMP= Training in crop management practices.
Note: The AMEs are calculated by averaging sample partial and joint probabilities effects of each WMP adoption, computed for each individual. Standard errors of the AMEs for the four variate probabilities are estimated by an empirical Bayes procedure (parametric bootstrapping) that redraws 500 replications of the estimated coefficient vectors from a multivariate asymptotically normal distribution.

However, in Cote d'Ivoire, the adoption of this strategy was reduced by factors such as training in weed management (4%), access to input (2%) and education level (1%). With respect to the combination hand weeding–hoe weeding, farmers trained in crop management practices were more likely to use this strategy in Cote d'Ivoire (32%) and Tanzania (5%) while farmers that received more specific training in weed management showed a lower adoption rate of this strategy in both countries (6% and 13% respectively). Female farmers were less likely to combine (5%) hand weeding with hoe weeding in Tanzania while the effect of gender was not significant in Cote d'Ivoire. In Cote d'Ivoire, hand weeding was less likely combined with hoe weeding (2%) by educated farmers.

As stated above, some WMPs combinations were specific to countries. In Benin, the likelihood for farmers to adopt water control combined with hand weeding was higher when they had a large number of children and in the presence of infestation by *Rhamphicarpa*. The AMEs for those covariates were small but still significant (Table 3.4). However, farmers cropping fields in the inland valley bottom and those who had access to input were less likely to combine hand weeding with water control. The combination of hand weeding with herbicides, fertilizer and water-control was more likely to be adopted by wealthy farmers or farmers with a large number of children in their household.

In Cote d'Ivoire, the probability to combine hoe weeding with herbicides and hand weeding increased with factors such as land tenure (15%), field size (4%) and education (4%). The likelihood of adopting this combination decreased with the quantity of household labour (0.3%), and farmers' training in crop management (13%). The two combinations involving both herbicides and fertilizers were less likely to be used by female farmers (12% for HaFm and 3% for HoHaFm).

In Tanzania, the likelihood of combining hoe weeding with fertilizers was higher in lowland fields (4%) and increased with household revenue (0.01%), while it was lower for farmers who received specific training in weed management (4%) and decreased with field size (3%). The likelihood of combining hand weeding with herbicide was higher with non-native[5] farmers (7%) and those who had attended training on weed management practices (7%), and it increased with field size (7%) and household revenue (0.01%).

3.4. Discussion

The current study identified factors affecting the adoption of weed management practices (WMPs) by rainfed rice farmers confronted with parasitic weeds (PWs) infestation. The

[5] Most of non-native (migrant) farmers did not own their land.

determinants of adoption of individual WMPs or a combination of WMPs were identified. Combining WMPs as a strategy has the potential to restrict weed populations to a manageable level, and to reduce the risk of possible adaptations of PW species to individual control measures (e.g. Franke et al., 2006; Harker and O'Donovan, 2013). Therefore, it is worthwhile to identify the factors affecting the choices of farmers for specific WMPs or combinations of them.

3.4.1. Parasitic weeds and adoption of WMPs

In the sample countries, the parasitic weeds infestation generally had a positive effect on farmers' decisions to combine more than two WMPs to make a specific strategy, while it had a negative effect (except Benin) on their decision to adopt a single (stand-alone) strategy. This suggests that farmers consider the application of single methods not effective enough against parasitic weeds. This finding corroborates the broadly shared view that there is no single solution to parasitic weeds that is both effective and affordable or feasible to smallholder farmers in sub-Saharan Africa (e.g. Rodenburg et al., 2010). The most effective and sustainable strategy would be to combine different measures in an integrated weed management approach (e.g. Perez-de-Luque et al., 2010; Rubiales et al., 2009). However, despite the fact that most farmers with parasitic weed problems apply multiple methods, the problem of parasitic weeds is still far from manageable. Hence, future research on parasitic weeds management should explore possibilities to develop more effective, and still affordable and feasible, combinations (e.g. Rubiales et al., 2009; Rodenburg et al., 2010).

In the sample countries where the two PWs were observed, results showed that the impacts of the two parasitic weeds' infestation on farmers' choice for each WMPs combination were different each other (Table 3.5 and 3.6). In Cote d'Ivoire however, for the WMPs combinations hand-weeding-only and hoe-weeding with herbicide and fertilizer, the impact of both PWs were similar. A possible explanation of the different effects of both PWs on farmer choices could be species' differentiation in terms of biology and ecology, suggesting that different approaches and technologies need to be developed for *Striga* spp. and *Rhamphicarpa fistulosa* prone environments, as was recently also concluded by Kabiri et al. (2014).

In Benin, results (Table 3.5) showed that *Rhamphicarpa* infestation was associated to a higher likelihood of adopting combinations of WMPs including modern WMPs. However, the parameter estimates of the multivariate probit (MVP) model (Table 3.3) suggested that, farmers with *Rhamphicarpa* infested fields were less likely to adopt improved WMPs (mainly herbicide). A decision based on the MVP results alone would have been misleading. One of the contributions of the estimation of the AMEs of covariates based on partial and joint multivariate probabilities is, therefore, to provide such insights in drivers of farmers adoption decision of combinations of WMPs.

3.4.2. Effects of socio-economic and institutional factors on farmers' decisions

The determinants of adoption of hand-weeding-only show the importance of factors such as farmers' education level, household revenue, training in agricultural practice and the access to input (credits) in shifting farmers' decisions from the use of a single traditional WMP towards a combination of modern WMPs. These results are in line with Gillespie et al. (2007), Rahelizatovo and Gillespie (2004), Asfaw and Admassie (2004) and Teklewold and Kohlin (2011), who showed that access to information and training and education positively affect the adoption of improved agricultural technologies. The result that the more wealthy households tend to rely more on improved WMPs is consistent with previous studies (Gillespie et al., 2007; Kim et al., 2005). Wealthier farmers, *ceteris paribus*, have a higher likelihood of adopting agricultural innovations than poor farmers. The more wealthy farmers can better afford the costs of innovations and have a higher capacity and willingness to take the risks involved with such an investment.

3.4.3. Management strategies including water control

The likelihood of adopting a water control option (i.e. bunding) was higher with land ownerships than other land tenure types, because this method requires at least a mid-term investment planning. Land renters or borrowers may not be willing to take the risk of investing in that technology, because of the tenure insecurity on the land they crop (Rodenburg et al., 2014b). These results are consistent with previous studies on the adoption of soil and water conservation technologies (e.g. Jara-Rojas et al., 2012; Teklewold and Kohlin, 2011). However, the effects of land tenure on farmer adoption of the combinations of WMPs including water control (WC) were not significant. Furthermore, the effects of parasitic weeds infestation on the adoption of the combinations including WC were positive, whereas the effect was negative for the adoption of WC as a stand-alone option.

3.4.4. Management strategies including rotation with legumes crops

Legume crop rotations may require the availability of a large land area, or multiple fields, whereas the rainfed lowland farmers considered in this study often crop small areas and have no more than one field. Moreover, legume crops have been promoted as rotation crops in upland rice (where *Striga* spp. can be a problem) but not for rainfed lowland rice (where *Rhamphicarpa* may be present), as there are not many adapted legume species for the lowland environments (see references in: Rodenburg and Johnson, 2009). Rainfed lowland rice farmers might therefore not be exposed to this technology yet. This can explain why lowland farming was negatively associated with the adoption of any combination involving rotation with legumes crops (HwHoRo and HwHoHaRo) in Tanzania. The negative effect of *Rhamphicarpa* infestation on the adoption of these combinations is consistent with the negative effect of lowland farming. The negative effect of female farmer on the use of these combinations can be explained by land ownership. When farmers own their land, they are certain about its availability in successive cropping seasons. Therefore, farmers who own their land have a higher motivation to invest in soil fertility through the use of crop rotations than those who do not own their land. However, the majority of female farmers in the survey areas did not own their land (Adesina and Chianu, 2002).

3.4.5. Synthesis

We found that *Striga* spp. infestation reduced farmers' adoption of traditional WMPs such as hand-weeding in Tanzania and Cote d'Ivoire. Infestation by *Rhamphicarpa* increased the adoption rate of hand weeding-only in Tanzania and Benin but decreased it in Cote d'Ivoire. The positive effect of *Rhamphicarpa* infestation on adoption of hand weeding and hoe weeding can be explained by the suggestion of previous studies that these methods are effective against *Rhamphicarpa* and that very few other *Rhamphicarpa* control methods are known or available to the affected farmers (Gbehounou, 2006, Rodenburg et al., 2011). Other covariates such as lowland cropping or education level of farmers have different effects on adoption of specific WMPs or combinations of WMPs across countries. These results stress the importance of accounting for country specific characters in WMPs adoption. The results are consistent with Hearne (2009) indicating that failure to recognize and account for differences or similarities in the adoption of WMPs among countries will reduce the effectiveness of programmes aiming at enhancing the adoption of WMPs.

3.5. Conclusion and implications

This study used a multivariate probit model to analyse farmers' choices for weed management practices (WMPs) in Benin, Cote d'Ivoire and Tanzania. The results show that farmers can adopt single WMPs or a combination of WMPs to cope with parasitic weeds (PWs).

Infestation by parasitic weeds shifts farmers from using a single traditional WMP towards the use of combinations of WMPs including various improved WMPs. This is also true for socio-economics factors such as access to input and information, and training in agricultural practices. Some covariates such as lowland cropping, *Rhamphicarpa* infestation and education level have different effects on adoption of specific combinations of WMPs across countries. We also found a parasitic weed species' differentiation in farmers' choices for management practices.

This paper contributes to the literature on technology adoption in general, and WMPs adoption in particular, as it identified and quantified the effects of factors determining farmers' choices for the use of specific combinations of WMPs to cope with the PW problem. These results suggest that species-specific and country-specific approaches are required to enhance farmers' adoption of parasitic weeds management practices in rainfed rice systems, in sub-Saharan Africa. Focusing on the factors that affect farmers' choices for different combinations of WMPs strategies per country is a good starting point to develop effective parasitic weeds management strategies for rainfed rice systems in SSA. To increase farmers' adoption of improved management strategies to cope with parasitic weeds, exposure to information on the parasitic weeds problem and possible control and prevention approaches to address the problem should be increased and farmers' access to inputs should be improved.

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4

Impact of parasitic weeds infestation on rice farmers' productivity and technical efficiency in sub-Saharan Africa

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Abstract

Rice production is crucial for food security and income generation in sub-Saharan Africa (SSA). However, productivity and technical efficiency (TE) levels in rice production systems are severely constrained by biotic constraints such as parasitic weeds. This paper assessed the impact of parasitic weeds infestation on farmers' technical efficiency and its variance and examined the potential role of managerial factors in improving technical efficiency. Household and field survey data were collected from rice farmers in two SSA countries. A stochastic frontier production function was estimated, which allows for identifying (the levels of) exogenous factors that prevent farmers from improving technical efficiency levels. At current infestation levels, parasitic weeds are found to induce productivity losses ranging from 21 % to 50 % in Cote d'Ivoire and Benin. Results suggest that farmers cope through learning as those experiencing more frequent infestations achieve higher technical efficiency levels and lower variance. However, beyond farming experience of about 20 years, farmers' technical efficiency levels decrease while the variance increases. These results will assist national extension in SSA in designing segmented training programs that are better tailored to rice farmers' needs and preventing food security from being jeopardized by parasitic weeds.

Keywords: Rainfed rice; Parasitic weeds, sub-Saharan Africa; Stochastic frontier model, Technical efficiency

4.1. Introduction

Rice production is an important component of strategies for food security and income generation in sub-Saharan Africa (SSA) (Nakano et al. 2013). However, it is facing with many biotic and abiotic constraints that negatively affect productivity. These constraints undermine the efforts undertaken by many SSA countries since the 2008 food crisis to boost domestic rice production in order to fill the increasing gap between rice production and demand (Demont 2013). Among the biotic constraints, weeds, and particularly the parasitic weeds (PWs) *Striga* spp and *Rhamphicarpa fistulosa* are the most damaging in rainfed rice production environments (A. Diagne et al. 2013, Oerke and Dehne 2004; Rodenburg and Johnson 2009). Weeds pose a serious threat to food security in SSA (AfricaRice 2012; A. Diagne et al. 2013) as average rice yield loss due to weeds in Africa is estimated at 32 % (Oerke and Dehne 2004). Furthermore, it was estimated that in 2008, 53 % of rice farmers experienced weed problems in their fields and about 33 % of rice areas were affected by weeds (A. Diagne et al. 2013). However, the severity of weed problems in SSA varies across countries and across rice production environments. Cote d'Ivoire is reported among the countries with the highest proportion of farmers experiencing weed problems (74 %) and the highest percentage of fields affected (49 %) and yield losses (40 %). Infestation levels are comparable in Benin, where 40 % of rice areas are affected (A. Diagne et al. 2013). However, the reported statistics do not distinguish between non-parasitic and PWs. The emerging PWs *Rhamphicarpa fistulosa* and *Striga* spp. were reported in rainfed rice systems in Benin and Cote d'Ivoire (Gbehounou and Assigbe 2003; Rodenburg et al. 2011). However, in Benin, the most eminent one and threatening rice production is *Rhamphicarpa* (N'cho et al. 2014, Chapter 3) while in Cote d'Ivoire both were observed with a higher proportion of farmers (35 %) experiencing *Striga* spp than *Rhamphicarpa* (4 %).

Only few empirical studies have analysed rice farmers' technical efficiency (TE) and its determinants in SSA (e.g. Adesina and Djato 1996; Audibert 1997; M. Diagne et al. 2013; Kinkingninhoun-Medagbe et al. 2010; Sherlund et al. 2002; Singbo and Oude Lansink 2010). Since many rice farmers in SSA are operating under subsistence-based production systems, their food security is highly exposed to the stochastic forces of nature. Accounting for environmental conditions is hence crucial in the estimation of TE. However, to our knowledge only one study has addressed this issue in SSA. Sherlund et al. (2002) observed in a sample of 464 traditional rice plots in Cote d'Ivoire that TE levels increased after accounting for production environment conditions in the production frontier. They concluded that controlling for factors such as pests, weeds and diseases, yields more accurate estimates of TE. Similar findings were reported in other TE studies elsewhere (Tan et al. 2010; Rahman and Hasan 2008). However, apart from Sherlund et al.'s study (2002), no studies on TE in SSA have accounted for natural factors and not a single study has focused on PWs. Moreover, since this paper deals with production in a stochastic environment, it is important not only to assess how those factors affect TE, but also how they influence the variance of technical efficiency (Bera and Sharma 1999; Wang 2002). Higher variance of technical efficiency implies a higher production uncertainty, and consequently also higher risks of food insecurity.

Another shortcoming of earlier studies on rice production in SSA is that they typically assumed a monotonic relationship between TE and its determinants, while drivers of TE can be non-monotonic (Wang 2002). Indeed, Chen et al. (2003) observed in the case of Chinese grain farms that the coefficients of determinants of TE can change over different quartiles in the sample and may even switch signs. Identifying non-monotonicity in the determinants of TE and its variance enables designing segmented extension programs that are better tailored to farmers' needs. This is important for persistent pests that severely jeopardize food security and require complex pest management, such as PWs in SSA. Therefore, the contribution of this study is to present the first evidence of the impact of PWs on SSA rice farmers' productivity, TE and its variance and to identify the factors—and the nature of their relationship—that affect these important determinants of food security.

4.2. Methods and data

4.2.1. Theoretical framing and model specification

This paper used a stochastic frontier (SF) approach to analyse the impact of PW infestation on rice farmers' TE. This approach was chosen because small-scale rainfed rice systems in SSA are subjected to stochastic production environments. Rice is grown in various soil types, under different rainfall patterns, plant diseases, pests or weed infestation levels, various input use patterns and other environmental conditions (Rahman and Hasan 2008; Sherlund et al. 2002; Tan et al. 2010). Moreover, since the paper uses data on farmers' perceptions and attitudes, data may be subject to measurement errors and this may affect the estimation of TE. Therefore, Coelli et al. (1998) recommend the use of SF models for sectors which heavily rely on nature such as agriculture and particularly in the context of a developing country.

In the production process, rice farmers' choices of inputs' type, quantity and application periods and weed management practices are affected by farms' infestation status by PWs (N'cho et al. 2014, Chapter 3). Factors such as weeds, diseases, pests, and pollutants, named as growth-reducing factors, lower attainable production levels to the actual (observed) yield levels (Zhengfei et al. 2006). Thus, inputs use and farmers' productivity may be affected by farm environmental conditions in general and PWs in particular. Omitting production environment conditions in the estimation of the production function leads to biased estimates for the production frontier's coefficients, an overstatement of technical inefficiency, and biased estimates for the coefficients of the determinants of technical inefficiency (Rahman and Hasan 2008; Sherlund et al. 2002). Variables related to the production environment were therefore included in the production frontier as follows:

$$Y_i = f(X_i, W_i) + v_i - u_i \,, \qquad (1)$$

where Y_i is the output (paddy production) of farmer *i*, $\mathbf{X}_i$ is a vector of productive inputs, $\mathbf{W}_i$ is a vector of relevant environmental variables (production shifters) that control production conditions for farmer *i*, v_i is a two-sided random error associated with factors beyond the control of the farmer. It is assumed to be *iid* *N* (0, σ_v^2), independent of the u_i, and the u_i is a non-negative random variable ($u_i \geq 0$) associated with inefficiency in production.

In the first application of the SF model, Aigner et al. (1977) adopted a half-normal distribution assumption on u_i. This specification has a single parameter and is relatively easy to estimate. It is, however, less flexible. The half-normal distribution implies that most of the observations are clustered near full efficiency (Kumbhakar et al. 2012). However, in this study farmers might exhibit more variation in their inefficiency because they perform in different environmental settings, have different experiences in rice farming and different input uses. A truncated-normal proposed by Stevenson (1980) which allows for the inefficiency distribution to have a non-zero mode (which is not the case in half-normal) is adopted. Therefore, u_i is assumed to be independently distributed following a normal distribution and truncated at zero, with mean $\mu(-Z_i\delta)$ and variance $\sigma_u^2(|N(-Z_i\delta, \sigma_u^2)|)$, where $\mathbf{Z}_i$ represents a vector of managerial variables and some socio-economic characteristics to explain inefficiency of farmer *i*.

In order to identify factors that can explain rice farmers' inefficiency, earlier studies adopted a two-stage procedure (Kumbhakar et al. 2012). This procedure, however, has been recognized as biased because of a misspecification of the first step (see Coelli 1995; Kumbhakar and Lovell 2000; Wang and Schmidt 2002). Given the undesirable statistical properties of the two-stage procedure (Kumbhakar et al. 2012; Wang 2002), this study used the single stage approach proposed by Battese and Coelli (1995).

The presence of uncontrolled heterogeneity in u_i in the SF models causes bias in both the estimation of the parameters describing the structure of the production frontier and technical inefficiency (Kumbhakar and Lovell 2000, p. 122). A production frontier with truncated-normal distribution was specified with heteroscedasticity in u_i and σ_{ui}^2 in a cross-sectional setting following Kumbhakar and Wang (2012) and Wang (2002) to account for possible heterogeneity in the data.

$$y_i = x_i\beta + (v_i - u_i)\,, \tag{2}$$

$$v_i \sim N(0, \sigma_{vi}^2)\,, \tag{3}$$

$$u_i \sim N^+(\mu_i, \sigma_{ui}^2)\,, \tag{4}$$

$$\mu_i = z_i\delta\,, \tag{5}$$

$$\sigma_{ui}^2 = \exp(z_i\gamma)\,, \tag{6}$$

where x_i include the productive inputs variables X_i and environmental variables W_i defined above, and the remaining are as defined above. The $\boldsymbol{\delta}$ and $\boldsymbol{\gamma}$ are the corresponding coefficient vectors of the variable vector $\mathbf{z}_i$ in (5) and (6) respectively. In this setting, the vectors of exogenous variables are allowed to affect inefficiency through the pre-truncated mean and variance of u_i, i.e. μ_i and σ_{ui}^2 respectively (Kumbhakar and Kai 2013, Wang 2002). Models that allow exogenous variables to exert influence through both the mean and the variance of the pre-truncated distribution yield the most plausible estimates of the determinants of technical inefficiency (Wang 2002). This double parameterization (of μ_i and σ_{ui}^2) enables capturing non-monotonicity in the relationship between z variables and technical inefficiency (mean of u_i) and variance of u_i measured by the unconditional statistics of $E(u_i)$ and $V(u_i)$ respectively (Bera and Sharma 1999; Wang 2002; Wang 2012). Non-monotonicity implies that within the sample, the *k*th element of *z*, z_k can have both positive and negative effects on production efficiency, depending on values of z_{ik} (Wang 2002). Capturing non-monotonicity is crucial for a thorough understanding of the nature of the relationship between technical inefficiency and exogenous factors (*z*).

4.2.2. Empirical specification and estimation

The general form of the Cobb-Douglas (CD) stochastic production function was used. The CD production function is the most widely used functional form in empirical production studies; mainly in developing countries agriculture (e.g. Audibert 1997; Rahman and Hasan 2008; Xu and Jeffrey 1998). The Translog specification was not used because of the relatively small sample sizes (217 for

Benin and 240 for Cote d'Ivoire) and unsatisfactory fitting to the data (there were collinearities among input interaction terms, many inputs' elasticities were negative and many parameters of the inefficiency function were statistically insignificant). Moreover, a likelihood ratio (LR) test of the CD versus the more general specification of the Translog was not rejected (P= 0.1622 for Benin; P=0.08 for Cote d'Ivoire; P = 0.7594 for pool data). This implies that the CD is an acceptable simplification of the Translog. PW infestation status (dummy variable) of rice fields was incorporated in the production frontier model to account for the direct impact of PW on productivity of rice farmers (see Rahman and Hasan 2008; Sherlund et al. 2002). The full specification of this model for the *i*th farmer is written as:

$$\ln Y_i = \alpha_0 + \sum_{j=1}^{4} \alpha_j \ln X_{ij} + \beta_i D + v_i - u_i \,, \qquad (7)$$

and

$$u_i = \delta_0 + \sum_{d=1}^{8} \delta_d Z_{id} + \varepsilon_i \,, \qquad (8)$$

$$\sigma_{ui}^2 = \gamma_0 + \sum_{d=1}^{8} \gamma_d Z_{id} + \xi_i \,, \qquad (9)$$

where D_i is the dummy variable representing PW infestation status and has the value of 1 if rice farmer *i* has infested field and zero otherwise; and $\boldsymbol{\beta}_i$ is the vector of parameters to be estimated. This is to account for PW impact on productivity of rice farmers. For inputs containing zero values, the zero was replaced by one following Battese and Coelli (1995).

The unknown parameters in equations (7), (8) and (9) in addition to σ_u^2 and σ_v^2 were estimated simultaneously by the method of maximum likelihood in the statistical package Stata 13.1. using the Stata command *sfmodel* as described by Wang (2012). The producer-specific technical efficiency (TE) was estimated as:

$$TE_i = \exp(-u_i) \,, \qquad (10)$$

The prediction of TE_i is based on the conditional mean of μ_i, given the composed error ($\varepsilon_i = v_i - u_i$) and model assumptions using the JLMS estimator (Battese and Coelli 1988; Jondrow et al. 1982). The likelihood function is expressed in terms of the variance parameters $\sigma_s^2 = \sigma_v^2 + \sigma_u^2$ and $\gamma = \sigma_u^2 / \sigma_s^2$ (see Battese and Coelli 1995).

The point estimator of TE for the *i*th farmer is,

$$TE_i = E[\exp(-u_i) \,|\, \varepsilon_i]$$

$$= \exp(-\mu_* + \frac{1}{2}\sigma_*^2)\left(\frac{\Phi[(\mu_* / \sigma_*) - \sigma_*]}{\Phi(\mu_* / \sigma_*)}\right), \qquad (11)$$

where

$\mu_* = [(1-\gamma) z_i \delta - \gamma \varepsilon_i]$, $\sigma_*^2 = \gamma (1-\gamma) \sigma_s^2$, $\varepsilon_i = v_i - \mu_i$,

and Φ represents the distribution function of the standard normal variable.

To derive the marginal effects of *z* variables on technical inefficiency, the procedure described by Wang (2002) and Wang and Schmidt (2002) was followed. Taking into account the parameterization in equations (5) and (6), the marginal effect of z_k on $E(u_i)$ is

$$\frac{\partial E(u_i)}{\partial z_{ki}} = \delta_k \left\{ 1 - \Delta \left[\frac{\phi(\Delta)}{\Phi(\Delta)} \right] - \left[\frac{\phi(\Delta)}{\Phi(\Delta)} \right]^2 \right\} + \gamma_k \frac{\sigma_i}{2} \left\{ (1+\Delta^2) \left[\frac{\phi(\Delta)}{\Phi(\Delta)} \right] + \Delta \left[\frac{\phi(\Delta)}{\Phi(\Delta)} \right]^2 \right\}. \quad (12)$$

where $\Delta = \mu_i / \sigma_i$, and ϕ is the probability density function of a standard normal distribution and Φ as defined above. The non-monotonic inefficiency marginal effects were estimated using the Stata command "*marginal*" in Stata 13.1 (Belotti et al. 2012; Wang 2012).

The most commonly incorporated variables in a SF model on TE in empirical analysis are farmer's age, education, experience, gender, access to information, land (various aspects) and household size (see, Adesina and Djato 1996; Battese and Coelli 1995; Belotti et al. 2012; Rahman and Hasan 2008; Sherlund et al. 2002; Tan et al. 2010; Wilson et al. 2001) to capture the aspect of managerial capacity of farmers as defined by Rougoor et al. 1998. Three variables were added to describe different aspects of PWs problem, namely *PWs infestation status* (dummy variable), *frequency of rice field infestation* during the last five years and *area of rice field covered* (%) by the PWs. The dummy accounts for the direct effect of environmental aspects of PWs infestation on productivity while the other two variables are included as exogenous variables in the inefficiency function to account for the management capabilities of farmers considering the control of weeds and its indirect effect (through TE) on productivity. Hence, a total of four productive inputs (**X**) and one environmental production variables (PW infestation status) were included in the stochastic frontier production function. Eight exogenous variables (**Z**) representing managerial factors of farmers were included in the inefficiency function. Table 4.1 presents summary statistics of the variables, their hypothesized effect on productivity and inefficiency based on literature and survey data.

Table 4.1 Summary statistics of variables and expected effects on productivity and technical inefficiency

	Expected sign	Benin (n=217)		Cote d'Ivoire (n=240)	
Variables definition		Mean	SD	Mean	SD
Output					
Rice production (kg per farm)		428	460	1,597	1,700
Input variables in production function					
Rice area cropped (ha)	+	0.24	0.24	1.38	1.06
Labour (hours per field)	+	540	391	2,208	2,032
Seed (CFA per field)	+	5,035	6,900	19,378	17,268
Other inputs (CFA per field)	+	18,200	24,682	102,447	98,338
Parasitic weeds infestation status (1=infested, 0=non-infested)	–	0.64	0.48	0.39	0.49
Managerial and socio-economic variables in inefficiency function					
Frequency of infestation (how often rice field has been infested in past 5 years)	–	2.16	1.96	1.02	1.42
Land ownerships (1=own, 0=otherwise)	–	0.81	0.40	0.82	0.39
Number of fields	–	3.98	2.16	4.05	1.27
Area infested (% of rice field covered by parasitic weeds)	+	34.79	36.42	12.58	21.08
Distance from homestead (average distance from rice field to home in km)	+	1.23	1.21	3.13	3.43
Gender of rice farmer (1=female, 0=male)	+/–	0.72	0.45	0.13	0.34
Experience in rice farming (years)	–	13.59	8.10	19.38	11.84
Household size (person)	+/–	7.79	5.23	11.14	5.73

Notes: Fixed exchange rate: €1 = 656 FCFA., SD= Standard Deviation

4.2.3. Data description

Data were obtained from farmer surveys in Benin (n = 223) in 2011 and in Cote d'Ivoire (n = 240) in 2012. Only rainfed rice systems were considered in this study (only lowland in Benin, upland and lowland in Cote d'Ivoire). A multistage stratified sampling process was used. For each country, rice producing regions where PWs occurred were selected (3 in Benin and 2 in Cote d'Ivoire). In the selected regions, 5 districts with presence of PWs were selected in Benin and 8 in Cote d'Ivoire. Within the 5 districts in Benin, the 18 most cropped lowlands (12 infested by *Rhamphicarpa* and 6 with no infestation) were selected. In Cote d'Ivoire, 24 villages (3 villages per district) where PWs occurred (*Rhamphicarpa* and/or *Striga* spp.) were selected. Finally, rice farmers were randomly selected in each village in Cote d'Ivoire and among the users of each lowland in Benin.

To estimate the efficiency model (equations (7)–(9)) one output and four inputs were distinguished. The output was rice paddy production and was measured in kilograms. The cropping seasons of the study areas were similar (June–December) for both countries and paddy price was standardized price in each country. A priori, this reduces the heterogeneity of product across farms in each country and leads to a more robust analysis of input-output relations in crop response modelling. The inputs included were land and seed cost as growth inputs, labour as facilitating input and cost of other inputs (fertilizer, herbicide, machinery and other services). Land was measured in hectares, labour in hours and included family labour as well as hired labour. The cost of seed was used to capture the difference in the quality of purchased seed (market price) and farmers' saved seed (Wilson et al. 2001). The cost of farmers' seeds was computed at the average price of paddy in each country. Other input costs were measured at their market value, other services at their direct cost and agricultural equipment at their annual (linear) depreciation costs (cfr. Demont et al. 2007). Prior to the models' estimation, data were scanned using box and whisker plots to detect possible outliers. Six outliers were identified in Benin and subsequently dropped. The remaining dataset was composed of 217 observations in Benin and 240 in Cote d'Ivoire. Next, the presence of technical inefficiency in the data was tested using D'Agostino and Pearson's (1973) and Coelli's (1995) tests. Both tests in Benin ($p<0.05$) and D'Agostino and Pearson's test in Cote d'Ivoire ($P<0.1$) confirmed the presence of inefficiency in the data. Hence, a SF specification is required (Coelli 1995; Kumbhakar and Lovell 2000, p. 73; Rahman and Hasan 2008; Schmidt and Lin 1984).

4.3. Results and discussion

4.3.1. Estimation of frontier function and impact of PWs on productivity

The estimated parameters for the stochastic frontier production (7) and the parameters of the inefficiency (8) and variance effects equations (9) terms are reported in Table 4.2 for the two countries (standard errors between parentheses).

These results show that output is positively and significantly (at most $P<0.1$) correlated with all inputs except seed which was not significant ($P>0.1$) in Benin. Land is the most productive factor in both countries (elasticities of 53 % in Benin and 46 % in Cote d'Ivoire), followed by labour (12 %) in Benin and seed (18 %) in Cote d'Ivoire.

As expected, PW infestation negatively and significantly affects rice productivity in both countries. Similar findings were reported by Sherlund et al. (2002) in Cote d'Ivoire where it was found that rice output decreased with above-average weed density, and high rates of plant disease. In Benin, *Rhamphicarpa* infestation decreased rice productivity ($P< 0.01$) by 32 % and in Cote d'Ivoire both *Striga* and *Rhamphicarpa* decreased productivity ($P< 0.10$) by 18 %. These values correspond to the unrealized outputs due to PW infestation of rice fields. Despite specifying alternative models with individual effects of *Rhamphicarpa* and *Striga* in Cote d'Ivoire and pooling of data (both countries), statistical evidence in support of a difference in the impact of both PWs was not found. The negative impact of PW infestation on rice production implies a reduction of food availability in the concerned SSA countries and a threat on food security in the region.

In the inefficiency models, all parameter estimates had the expected signs as indicated in Table 4.1, except for land ownership in both countries and proportion of area infested in Benin (although the coefficient was not significant). Land ownership, distance of fields from the homestead and household size significantly (at least P<0.05) and positively affect inefficiency, i.e. they corrode TE. Number of fields and experience in rice farming, in contrast, were significantly (at least P<0.05) and negatively associated to inefficiency, i.e. they enhance TE.

Table 4.2 Maximum likelihood joint estimate of production frontier and inefficiency function

Variables	Benin	Cote d'Ivoire
Stochastic frontier		
Ln land	0.529 (0.074)***	0.464 (0.048)***
Ln labour	0.116 (0.068)*	0.114 (0.049)**
Ln seed	0.050 (0.047)	0.179 (0.051)***
Ln other cost	0.073 (0.027)***	0.131 (0.037)***
Parasitic infestation	–0.320 (0.117)***	–0.180 (0.095)*
Constant	5.598 (0.647)***	3.268 (0.678)***
Inefficiency effects on E(u_i)		
Frequency of infestation	–0.443 (0.445)	–0.123 (0.265)
Land ownership	1.264 (0.482)***	1.072 (0.448)**
Number of fields	–0.127 (0.072)*	–0.339 (0.186)*
Area infested (%)	–0.001 (0.158)	0.080 (0.014)
Distance from home	0.171 (0.072)**	0.094 (0.058)*
Female farmer	–0.092 (0.256)	0.637 (0.454)
Experience in rice farming	–0.104 (0.039)***	–0.143 (0.055)***
Household size	0.036 (0.014)***	0.074 (0.040)*
Inefficiency effects on sigma V(u_i)		
Frequency of infestation	–0.008 (0.168)	–0.231 (0.376)
Land ownership	–0.103 (0.371)	–0.735 (0.553)
Number of fields	–0.146 (0.081)*	–0.286 (0.225)
Area infested (%)	0.015 (0.008)**	–0.008 (0.021)
Distance from home	–0.721 (0.223)***	–0.221 (0.137)
Female farmer	0.255 (0.332)	0.613 (0.552)
Experience in rice farming	0.051 (0.020)**	0.100 (0.025)***
Household size	–0.019 (0.030)	–0.110 (0.058)**
Prob > chi2	0.0000	0.0000
Log-likelihood	–198.172	–180.712

Significance level are indicated with *** (P<0.01); ** (P<0.05); * (P<0.1), standard errors are in parenthesis

In the regression equation of the heteroskedastic inefficiency term (equation (9)), all parameter estimates have the expected sign except for the parameter on the area infested in Cote d'Ivoire (although the coefficient was not significant). Number of fields, distance of fields from homestead and household size were significantly (at most P< 0.1) and negatively related with the variance of technical inefficiency. However, the effect of household size was significant only for Cote d'Ivoire, meaning that larger households *ceteris paribus* have less variation in technical inefficiency in rice production. Cultivating a larger set of fields was also found to be risk-reducing in both countries. These findings are consistent with Tan et al. (2010) and may be explained through diversification effects. Farmers can allocate available farming labour and other productive resources among their different fields throughout the cropping season. Thus, they can adapt the choice of rice varieties, sowing period, sowing methods and other cropping methods to local agro-climatic conditions and thereby reduce the variance of technical inefficiency. Finally, despite increased TE levels, variation in technical inefficiency was found to increase towards the homestead. In most rural areas in SSA, pressure on land use and cropping intensities increase towards the village with concomitant higher risks of pests and diseases (see Demont et al. 2007).

4.3.2. Technical efficiency scores

Table 4.3 shows overall technical efficiency scores and frequency distributions of TE. Predicted TE ranges from a minimum of 8 % to a maximum of 93 % in Benin and from 16 % to 100 % in Cote d’Ivoire. The mean values were 64 % in Benin and 85 % in Cote d’Ivoire. These results indicate that rice farmers can still increase their production by as much as 36 % in Benin and 15 % in Cote d’Ivoire through more efficient use of production factors and control of PWs. These results are in line with the observation of Sherlund et al. (2002). Including the PW infestation factors (the most detrimental production environment factors in this study) raised the average TE scores relative to most previous efficiency studies on rice production systems in SSA (e.g. Audibert 1997; M. Diagne et al. 2013).

Table 4.3 Estimated Technical efficiency scores and distribution

Items	Benin	Cote d’Ivoire
Overall technical efficiency score		
Mean	0.64	0.854
Standard deviation	0.20	0.16
Minimum	0.08	0.16
Maximum	0.93	1.00
Technical efficiency distribution (%)		
Up to 50	26.7	5.4
51– 60	9.7	2.9
61–70	13.8	4.2
71–80	22.1	10.4
81–90	24.9	22.5
91 and above	2.8	54.6

4.3.3. Sources of technical inefficiency

Table 4.4 presents sample means of marginal effects of managerial variables on inefficiency and production uncertainty as well as the average marginal effects of the first and the last quartile of some of the variables. The change in sign of marginal effects of variables with non-monotonic effects on TE happens only in the fourth quartile, except the variable *experience* for which it happens in the third and the fourth quartile. Since the focus is on the change in sign between quartiles, only the values of first and fourth quartile are reported (Table 4.4).

After the estimation of the individual marginal effects of the exogenous variables, a bootstrap procedure was used to build confidence intervals in order to get their significance levels (Wang 2002). The bootstrapped standard errors (BSE) along with the statistical significance are also reported (BSE in parenthesis). BSEs were computed based on bias-corrected and accelerated confidence intervals with 2000 replications. Except for a few variables, all marginal effects were significant at 5 % (Table 4.4). Variables describing PWs' infestation environment (*frequency of infestation* and *area infested*) in the inefficiency models were discussed in addition to other variables with significant parameters estimates on technical inefficiency in the SF model results (Table 4.2).

The two variables describing the impact of PW infestation on TE have significant (P< 0.01) marginal effects on inefficiency, $E(u_i)$ and on variance of the inefficiency term, $V(u_i)$. Rice farmers' technical inefficiency and variance of technical inefficiency monotonically increase with the area infested by PWs. Every percentage increase in the infested area raises inefficiency by 0.5 % in Benin and 0.2 % in Cote d'Ivoire and this is equivalent to an additional output loss of the same magnitude since $\partial E(\ln y)/\partial infarea = -\partial E(u)/\partial infarea$ (Wang 2002) (*infarea* is area infested). At current infestation levels of 35 % in Benin and 13 % in Cote d'Ivoire (Table 4.1), the additional output losses due to inefficiency amount to 17.5 % and 2.6 %, respectively, and—keeping everything else constant (*ceteris paribus* assumption)—these losses would reach 50 % and 20 %, respectively, if the entire area was infested. If the production losses are added, staggering figures of the average loss are found due to PWs of 50 % (32 % + 17.5 %) in Benin and 21 % (18 % + 2.6 %) in Cote d'Ivoire. Since farmers perceived the severity of infestation to be progressively increasing since the problem first manifested (N'cho et al. 2014), these figures give a first-hand indication of the imminent threat of PWs on food security in SSA.

On the other hand, more frequent infestations over time significantly (P< 0.01) decrease rice farmers' technical inefficiency and variance of technical inefficiency thanks to growing awareness of the pest, knowledge and experience with its management (N'cho et al. 2014). Every additional infestation boosts rice farmers' TE levels, enabling them to recover potential production losses at a rate of 11.7 % in Benin and 4.7 % in Cote d'Ivoire. At the current average infestation frequency of 2.16 in Benin and 1.02 in Cote d'Ivoire (Table 4.1), without this effect of the learning experience, the actual impact of PW would have been about 75 % (50 % + 25.3 %) in Benin and 26 % (21 % + 4.8 %) in Cote d'Ivoire. This suggests that urgent action needs to be undertaken in order to improve farmers' awareness of PWs in SSA.

Land ownership reduced TE levels in both countries, but the effect on the variance of technical inefficiency was mixed. The opposite was found in Bangladesh by Rahman and Rahman (2008), who observed that land owners performed significantly better than tenants or part tenants. They argued that this may be due to the fact that tenants typically receive lower-quality land from the landlords, which may lead to lower efficiency. Cropping more fields increases TE, which is consistent with the general findings of Sherlund et al. 2002 and Tan et al. 2010.

Table 4.4 Marginal effects on inefficiency

Variables		Benin	Cote d'Ivoire
Marginal effects on E(ui) (inefficiency)			
Female farmer		0.060 (0.004)***	0.167 (0.012)***
Land tenure		0.293 (0.021)***	0.045 (0.018)**
Number of fields		–0.081 (0.002)***	–0.083 (0.006)***
Frequency of infestation		–0.117 (0.007)***	–0.047 (0.003)***
Area infested (%)		0.005 (0.0002)***	0.002 (0.0001)***
Household size	Sample avg.	0.003 (0.0007)***	–0.005 (0.002)**
	1st quarter avg.	0.002 (0.001)*	–0.006 (0.004)
	4th quarter avg.	0.004 (0.001)**	0.001 (0.003)
Distance	Sample avg.	–0.191 (0.011)***	–0.017 (0.003)***
	1st quarter avg.	–0.244 (0.014)***	–0.038 (0.009)***
	4th quarter avg.	–0.035 (0.021)*	0.004 (0.004)
Experience	Sample avg.	–0.010 (0.002)***	–0.006 (0.002)**
	1st quarter avg.	–0.031 (0.005)***	–0.037 (0.006)***
	4th quarter avg.	0.014 (0.002)***	0.017 (0.004)***
Marginal effects on V(ui) (production uncertainty)			
Female farmer		0.067 (0.005)***	0.092 (0.028)***
Land tenure		0.099 (0.005)***	–0.057 (0.028)**
Number of fields		–0.057 (0.004)***	–0.044 (0.013)***
Frequency of infestation		–0.048 (0.002)***	–0.031 (0.010)**
Area infested (%)		0.004 (0.0003)***	0.001 (0.0003)***
Household size		–0.002 (0.0003)***	–0.011 (0.004)**
Distance		–0.198 (0.016)***	–0.024 (0.009)**
Experience	Sample avg.	0.004 (0.0009)***	0.008 (0.004)**
	1st quarter avg.	–0.002 (0.0008)***	–0.001 (0.0004)***
	4th quarter avg.	0.019 (0.004)***	0.028 (0.015)*

Standard errors and significance test are based on bootstrap results of 2000 replications (bias-corrected and accelerated).
For many variables, marginal effects can take different signs and values in the sample. The 1st and the 4th quartiles values were reported only for variables with non-monotonic efficiency effects (variables having opposite effect in different quartiles),
Significance level are indicated with *** (P<0.01); ** (P<0.05)
avg.= average

Non-monotonic efficiency effects of exogenous variables

The variables *distance from the homestead*, and *household size* in Cote d'Ivoire and *experience in rice farming* in both countries were found to affect efficiency non-monotonically (Wang 2002). Plotting inefficiency against z_k values in two-dimensional graphs provides a first visual indication at which critical point the switch occurs (Figures 4.1a–4.1h).

Ten years of rice farming experience decreases farmers' technical inefficiency by 10% in Benin and by 6% in Cote d'Ivoire, on average. However, it increases the variance of technical inefficiency by 4 % in Benin and 8 % in Cote d'Ivoire. The marginal effects change over quartiles suggesting that farmers with less experience (represented by the first quartile) achieve higher TE levels and face lower variance of technical inefficiency. This was expected as age is a good proxy of experience in areas with traditional farming systems (Tan et al. 2010). More experience means higher age. Thus, increasing age may lead to a decreasing labour force—diminution of physical abilities—and, farming abilities, a higher risk aversion to invest significantly in production due to possible deteriorated physical and mental capability (Asfaw and Admassie 2004; Kumbhakar et al. 2012). Hence, starting from lower values of experience, an increase in experience helps to improve efficiency. However, above a certain critical level of about 20 years, a further increase in farmer experience becomes counterproductive and impairs efficiency.

This was observed, starting by the 3rd quartile in both countries. The effect is translated into a technical inefficiency increase and also an increase in the variance of technical inefficiency (Kumbhakar et al. 2012; Wang 2002). Since $\partial E(\ln y)/\partial \exp erience = -\partial E(u)/\partial \exp erience$ (Wang 2002), the effect results in an output increase by 3.1 % for Benin and 3.7 % for Cote d'Ivoire in the first quartile, while in the fourth quartile, it results in an output loss of 1.4 % for Benin and 1.7 % for Cote d'Ivoire.

The average marginal effects of distance of rice fields from homestead on inefficiency were negative and significant (P<0.01). This means that on average, a one kilometre increase in distance between farmers' rice fields and homestead contributes to an increase in farmers' TE of 19.1 % in Benin and of 1.7 % in Cote d'Ivoire. These results for Benin are not consistent with Tan et al. (2010) who found that distance of fields from homestead negatively impacts TE. This may be due to the average short distance (average of 1.2 km and maximum of 7 km) of surveyed rice farms from their homestead in Benin. In Cote d'Ivoire, however, these effects were negative in the first quartile and positive (although insignificant) in the fourth quartile.

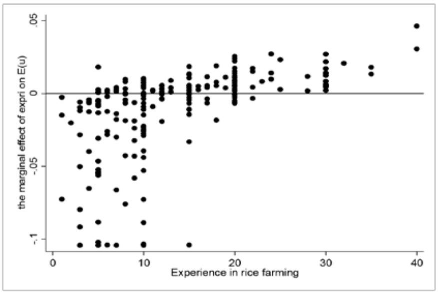

Fig. 4.1a Marginal effects of Experience on E (u_i), Benin

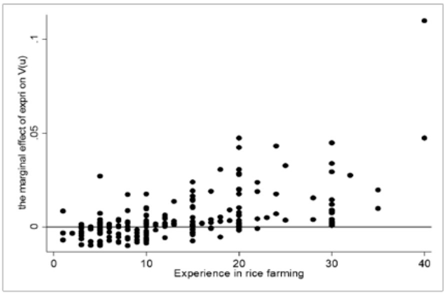

Fig. 4.1b Marginal effects of Experience on V (u_i), Benin

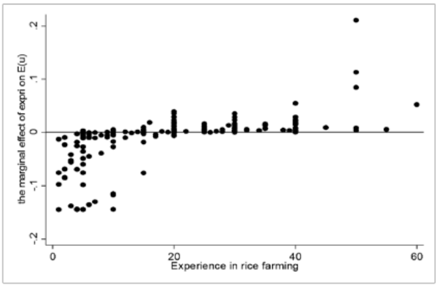

Fig. 4.1c Marginal effects of Experience on E (u_i), Cote d'Ivoire

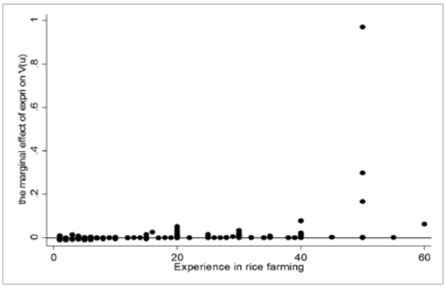

Fig. 4.1d Marginal effects of Experience on V (u_i), Cote d'Ivoire

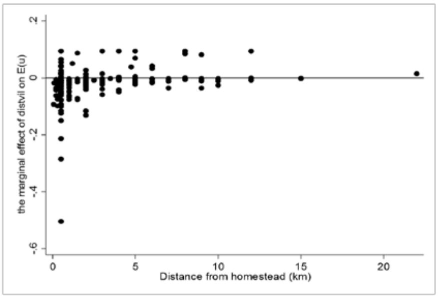

Fig. 4.1e Marginal effects of distance on E (u_i), Cote d'Ivoire

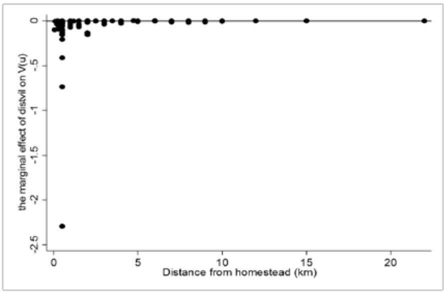

Fig. 4.1f Marginal effects of distance on V (u_i), Cote d'Ivoire

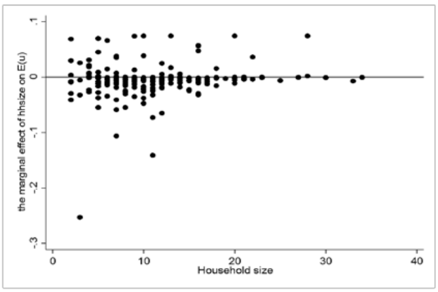

Fig. 4.1g Marginal effects of household size on E (u_i), Cote d'Ivoire

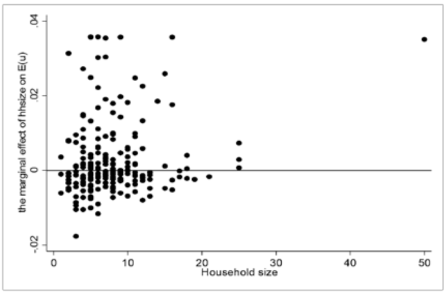

Fig. 4.1h Marginal effects of household size on E (u_i), Benin

Figure 4.1 Visualization of the non-monotonic inefficiency effects of exogenous variables on inefficiency (E (u_i)) and its variance (V (u_i)) in Benin and Cote d'Ivoire

Figure 4.1e visualizes how farmers are able to capture a "distance premium" by achieving higher technical efficiency levels on remote rice fields. However, beyond a critical distance of 10 km from their homestead, distance becomes counterproductive and erodes technical efficiency. An overall positive impact on TE implies that the distance premium ("variation effect") exceeds negative effects on farm management (Tan et al. 2010). Beyond the critical distance, commuting takes more time and farm management becomes more challenging.

Analogously to the literature, this study found mixed results for *household size* (see Audibert 1997 and Tan 2010). The average marginal effects suggest that larger households foster efficiency in Cote d'Ivoire (at a rate of 0.5% per family member) and hamper efficiency in Benin (at a rate of 0.3 %). Figures 4.1g and 4.1h visualize how marginal effects of household size are spread among the positive and negative quadrants in the same quartile. A possible explanation for these mixed effects is that although larger farm households may benefit from a larger family work force (Rahman and Rahman, 2008), they also require more housekeeping in order to feed all household members and some of them (children and elderly people) may not be available for field work.

Finally, it was observed that the marginal effects on $E(u_i)$ and $V(u_i)$ of some exogenous variables had the same sign. For instance, *frequency of infestation*, *number of fields*, and *distance* reduce $E(u_i)$ and $V(u_i)$ in both countries; *household size* reduces $E(u_i)$ and $V(u_i)$ in Cote d'Ivoire; and *land tenure* increases $E(u_i)$ and $V(u_i)$ in Benin. Similarly to the findings of Bera and Sharma (1999), this observation implies that when farmers move towards the production frontier (increasing TE), they simultaneously manage to reduce the variance of technical inefficiency (Wang 2002). However, other variables such as *experience*, *land tenure* and *household size* (in Benin) had opposing effects on $E(u_i)$ and $V(u_i)$ (Table 4.4).

4.4. Conclusion and policy implications

This paper provides empirical estimation of the impact of PWs infestation of rainfed rice fields on rice farmers' productivity and technical efficiency in Benin and Cote d'Ivoire. The stochastic frontier models allowed exogenous variables to influence the level of technical inefficiency through both the functions ruling the mean (μ_i) and the variance (σ_{ui}^2) of the pre-truncated distribution of inefficiency. This specification revealed that *experience* in rice farming, *distance* of rice fields from homestead, and *household size* impact rice farmers' technical efficiency non-monotonically.

Results from the production function showed mean values of TE of 64 % in Benin and 85 % in Cote d'Ivoire, indicating that rice farmers can still increase their production by as much 36 % in Benin and 15 % in Cote d'Ivoire through more efficient use of production inputs and control of

PWs problem. At the current average infestation levels of rice fields, PWs induce a 50 % (32 % direct and 18 % indirect) production loss in Benin and 21 % (18% direct and 3 % indirect) in Cote d'Ivoire. Farmers with fields most frequently infested (over time) have lower technical inefficiency level and variance, implying that increased farmers' awareness of the PW problem over time induces an efficiency gain and reduces the variation in the inefficiency of rice production. On average, beyond 20 years of experience in rice farming, farmers' TE decreases and the variance of the inefficiency increases. In Cote d'Ivoire, a productivity decrease was observed on fields cropped beyond 10 km radius from homestead. The results also show that despite the fact that many factors have similar marginal effects (sign) on inefficiency level and variance, all factors decreasing farmers technical inefficiency do not necessarily simultaneously reduce their variance. These findings have important policy implications.

The negative impact of PW infestation on rice production implies a reduction of food availability and a threat on food security in the concerned countries of SSA region. The identification of optimal values for factors affecting efficiency non-monotonically, the observation that factors decreasing farmers' technical inefficiency levels do not necessarily reduce their variance and that factors may have non-similar marginal effects on inefficiency for different countries will help to design more specific and country targeted policies and programmes to reduce productivity losses due to PWs. PWs management policies and programmes aiming to increase technical efficiency should account for the optimal level of farming experience on technical efficiency effects. Results also imply that more land should be developed for rice farming within a 10 km radius from villages. Increasing individual farmers' land size will help farmers to (split their land) diversify their production systems insuring more TE and secured production. Such specific policy implications might not be obtained if the model specified ignored the non-monotonic efficiency effects of exogenous factors. This specification provides better understanding of the effects of those key factors on TE in the sample. The econometric estimation of relative impact of PWs infestation on rice farmers' productivity allowed quantifying for the first time, the effective production gap due to PWs infestation in rice farming systems in SSA. Furthermore, one of the important contributions of this paper to the literature is that the analytical approach used allowed for decomposing the total impact into its direct (through production frontier) and indirect effects (through inefficiency effects function). These findings shed more light on the worthiness of investing in PWs control programmes in rainfed rice systems in SSA.

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5

Inefficiency of manual weeding in rainfed rice systems affected by parasitic weeds

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Under review at Agricultural Economics

Abstract

Manual weeding is the predominant weed control practice and the most labour consuming activity in rainfed rice systems in sub-Saharan Africa. This study aims to investigate the technical efficiency of weeding labour and to identify sources of technical inefficiency in a context of parasitic weeds infestation. Weeding labour technical inefficiencies were computed using a directional input distance function and sources of technical inefficiency were identified using a truncated bootstrap regression. Data from 406 randomly selected rice farmers from Benin (n=215) and Cote d'Ivoire (n=191) were used. Technical inefficiency in weeding labour was high in both countries (58% in Cote d'Ivoire and 69% in Benin). This implies that a substantial fraction of weeding labour can be saved without reducing rice production or increasing the use of other inputs. Technical inefficiency of weeding labour generally increases with parasitic weeds infestation levels. In Benin, technical inefficiency of weeding labour decreases with increasing farm size, while in Cote d'Ivoire it decreases with early weeding and increased education levels. In both countries, no evidence was found that the currently used manual weeding modalities decrease the technical inefficiency of weeding labour when a farm is infested by a parasitic weed.

Keywords: smallholder farming, weeding labour, efficiency, bootstrap, sub-Saharan Africa

5.1. Introduction

Cereal crop production in sub-Saharan Africa (SSA) and specifically rainfed rice production is negatively affected by weeds (Becker and Johnson, 2001; Oerke and Dehne, 2004; Oerke, 2005; Waddington et al., 2010). Weeds are consistently cited among the most important biotic constraints as they cause the highest damage among biotic constraints (Demont et al., 2009; Oerke, 2005). The effect of weeds is not only limited to direct crop losses (see Chambers et al., 2010) because, farmers with fields infested by weeds have higher on-farm workloads, reduced area cropped, reduced working time for other productive activities, and bear higher production costs (Adesina et al., 1994; Demont et al., 2007). In rainfed rice systems, weeding requires for the majority of famers the greatest share (more than 50%) of their available labour (Akobundu, 1981; Stessens, 2002). This is because the predominant weed control practice in rainfed rice systems consists of manual weeding (Adesina et al., 1994; Chapter 3). Manual weeding is time consuming (Ogwuike et al., 2014) and heavily depends on availability of family labour and accessibility of paid labour (Ruthenberg, 1980). However, family labour is not always available and paid labour is not always affordable. Therefore, when weeds invade rice farms, farmers may decide not to weed and even abandon their land (Adesina et al., 1994; N'cho et al., 2014). The damage caused by weeds is even higher when the weed community includes parasitic weed species.

Parasitic weeds compose a special group of weeds. In addition to the ordinary crop-weed competition for resources, they parasitize their host (the crop) to extract resources (water, nutrients, metabolites) and change the host plant hormone balance and thereby negatively affect the crop (Parker and Riches, 1993). Parasitic weeds are responsible for important yield losses across crops and regions throughout the world (Parker, 2012). In rainfed rice systems in Africa, an increasing problem is observed with the parasitic weeds species *Rhamphicarpa fistulosa*, *Striga asiatica* and *Striga hermonthica* (Rodenburg et al., 2010; 2014). Such pests affect productivity not only directly but also through farmers' management and production choices (Chambers et al., 2010; Chapter 4). As hand weeding is the most important management option in rainfed rice systems (Ogwuike et al. 2014), the role of weeding labour in improving productivity of these systems becomes crucial. However, none of the previous studies (e.g. Becker and Johnson, 2001; Oerke, 2005) on weed problems has investigated the efficiency of manual weeding nor the effects of weeds or parasitic weeds on inputs use efficiency.

Manual weeding is highly labour-intensive and time consuming and more often weeding is not completed on time (Gongotchame et al., Saito et al., 2010). This delay results in high yield losses and may increase technical inefficiency of weeding labour (Akobundun, 1991). The damage caused by parasitic weeds in rice is more substantial than damage caused by ordinary weeds (Rodenburg et al., 2014). Therefore, the parasitic weeds infestation might cause higher technical inefficiency of weeding labour. Hence, it is necessary to investigate to which extent weeding labour is used efficiently in rainfed rice production systems and how parasitic weeds infestation affects the efficiency of weeding labour. Also, measuring efficiency of weeding labour allows for identifying successful strategies for managing parasitic weeds for both policy makers and farmers.

In the light of the foregoing discussion, this study aims to investigate the technical and scale inefficiency of weeding labour, their main determinants in a production environment that is characterised by the presence of parasitic weeds. The paper uses a directional distance function and Data Envelopment Analysis (DEA) to measure technical inefficiency of weeding labour and, it identifies the main determinants of technical inefficiency using a truncated bootstrap regression model (Simar and Wilson, 2007). The analysis is based on farmers specific data collected in the most parasitic weeds infested rainfed rice production regions of Benin and Cote d'Ivoire during the cropping campaign of 2011–2012.

5.2. Methods

5.2.1. Input-specific DEA model

In order to analyse the technical efficiency of labour used for weeding, this paper has chosen an input-specific DEA modelling approach. This approach estimates the extent to which labour can be saved while still producing the observed output and using the same quantity of the other inputs. The input-specific DEA approach allows for computing sub-vector efficiency for the targeted inputs (Färe et al., 1994; Oude Lansink et al., 2002; Oude Lansink and Silva, 2004).

In this study, the sub-vector technical inefficiencies were measured using the directional input distance function as defined by Chambers et al. (1996). Assuming that the production technology of rainfed rice systems is appropriately represented by the directional input distance function, and that farmers produce a vector of outputs y from a vector of inputs x decomposed in the targeted input (x_i) and non-targeted inputs (x_{k-i}), the farming system technology is given by:

$$L(y) = \{(x, y) \ \textit{such that } x \textit{ can produce } y\} \quad (1)$$

Following Chambers et al. (1996), assuming that the farming system technology is convex and inputs are freely disposal; the directional input distance function is defined as $\vec{D}_I : \Re_+^M \times \Re_+^N \times \Re^N \to \Re$,

$$\vec{D}_I(x_i, x_{k-i}, y;\, g_{x_i}) = \sup_{\beta}\left\{\beta \in \Re : x_i - \beta g_{x_i} \in L(y)\right\}$$
$$= \sup\left\{\beta \in \Re : x_i \in \beta g_{x_i} + L(y)\right\} \qquad (2)$$

where $\mathbf{y} \in \Re_+^M$ is a vector of outputs, $\mathbf{x}_i \in \Re_+^N$ is a vector of targeted inputs, the technology is represented by the input correspondence $L:\Re_+^M \rightarrow \Re_+^N$ which defined input sets $L(y) \subset \Re_+^N$, g_{x_i} is a non-zero vector in $\Re_+^N$ defining the direction in which $\vec{D}_I(\cdot)$ is defined. In the case of this study, the optimal input set varies for each farmer. Therefore, for the input-specific technical inefficiency measurement, the realized input-output vector (x_i, y) was used (Chambers et al., 1998; Singbo and Oude Lansink, 2010). In this case, the directional input distance function gives an estimation of the maximum contraction in the specific input(s) while keeping output and non-targeted inputs constant. For the technical inefficiency relative to variable return to scale, the function used in the directional distance function technology is described across the k (k=1,…., K) inputs and outputs as:

$$\begin{aligned}
&\vec{D}_I(x_i, x_{k-i}, y;\, g_{x_i} \mid V, S) = \min_{\beta,\lambda} \beta^i \\
&s.t. \\
&Y\lambda \geq y, \\
&X_i\lambda \leq x_i - \beta^i x_i, \\
&X_{k-i}\lambda \leq x_{k-i} \\
&I'\lambda = 1, \\
&\lambda \geq 0.
\end{aligned} \qquad (3)$$

where, $\boldsymbol{Y}$ is the ($N \times 1$) vector of observed outputs, y is the observed output level, $\boldsymbol{X_i}$ and $\boldsymbol{X_{k-i}}$ are the ($N \times K$) matrix of targeted and non-targeted inputs, β is a scalar, **I** is the ($N \times 1$) unitary vector, $\boldsymbol{\lambda}$ is a ($N \times 1$) vector of constant (firms weight). Constraints 2 and 3 ensures that the solution of the model finds a value of β^i representing the maximum reduction in the targeted input *i* within the technology set holding all non-targeted inputs and the output constant. Constraint 4 in this specification is the convexity constraint that imposes variable returns to scale to the model (V, S). Using the variables λ and β, the model is solved once for each farmer. The estimates lie between zero and one. An estimated value of zero represents a fully efficient farmer, located on the efficient frontier (Figure 5.1). For such a farmer, there is no possibility to reduce the targeted inputs use without reducing rice production level or increasing the non-targeted inputs. An estimated value greater than zero indicates the existence of technical inefficiencies. This implies that a share of the targeted inputs can be saved. The V, S specification allows farming systems to exhibit increasing, constant or decreasing returns to scale. However, Coelli et al. (2002), and Haji (2006) found that in smallholder farming systems like the case considered in this study, economies of scale were absent. Hence, a constant returns to scale (C, S) specification may suffice. For this reason both the variable returns to scale and constant returns to scale specifications were considered. Considering both specifications allows for computing scale inefficiency[6]. $\vec{D}_I(x_i, x_{k-i}, y; g_{x_i} | C, S)$ was computed as in (3) by removing the convexity constraint $\boldsymbol{I}'\lambda=1$ from the model. The C, S specification assumed that farms operate at their optimal scale (Speelman et al., 2008).

The overall input technical inefficiency and sub-vector inefficiencies were estimated[7] in R3.0.1 using the routine *dea.direc* of FEAR.2.0 (Frontier Efficiency Analysis with R) package (Wilson, 2008).

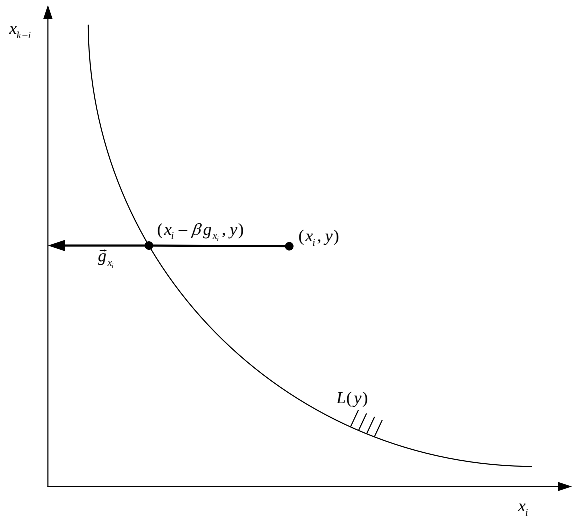

Figure 5.1 Directional Input Distance Function

5.2.2. Truncated bootstrap model

The input-specific DEA estimate for a farmer is defined relative to the efficiency of other farmers of the sample. Consequently, the estimated DEA efficiency scores are serially correlated (Hirschberg and Lloyd, 2002; Simar and Wilson, 2007; Xue and Harker, 1999). Use of these scores

[6] The scale inefficiencies were computed for overall inputs, weeding labour and other labour following Färe et al. (1985).

[7] In the estimation of each directional input distance function model, only the targeted input changes. Thus, for overall inputs inefficiency (INIE), all variable inputs (x_v) including weeding labour vary while quasi-fixed input remain unchanged; For weeding labour inefficiency (WLIE), only weeding labour (wlab) changes and all other inputs remain constant, For other labour inefficiency (OLIE), only other labour (olab) was considered changing while all remaining inputs were kept constant.

in a second-stage regression analysis to explain the variation in technical inefficiency observed among farmers would, therefore, result in a violation of the basic assumption of independence within sample values. To overcome this problem, a single bootstrap truncated regression was used to evaluate sources explaining differences between weeding labour inefficiency among farmers using Stata 13 (Simar and Wilson, 2007; Singbo and Oude Lansink, 2010).

5.3. Data description

A multistage sampling process was used by selecting rice producing regions with the presence of parasitic weeds (PWs) in rice (3 in Benin and 2 in Cote d'Ivoire) followed by a selection of districts (5 in Benin and 8 in Cote d'Ivoire) within the selected regions. In Benin, PWs are only present in rainfed lowland rice production systems. Hence, 18 most (12 infested and 6 not infested) cropped lowlands within the 5 districts were selected. In Cote d'Ivoire, 24 villages within the 8 districts (3 villages per district) were selected. At village level in Cote d'Ivoire and at lowland level in Benin, farmers were selected randomly. The samples were constructed with farmers who used manual weeding at least once during the cropping campaign 2011–2012 (n=215, Benin and n=191, Cote d'Ivoire). The random samples consisted of 43% of farmers with fields infested by either the parasitic weeds *Rhamphicarpa fistulosa* or *Striga* spp in Cote d'Ivoire and 65% by *Rhamphicarpa fistulosa* in Benin. The samples were made of 75% of female rice farmers in Benin and 15% in Cote d'Ivoire. Data were collected during interviews where farmers were asked for the different inputs used, the corresponding quantity and cost were collected. The material and equipment used for farming, the quantities, the number, the costs and years of acquisition were collected. Farms characteristics such as field infestation status and infestation level (zero, low, medium, high) by parasitic weeds, the position of the field on the along the upland-lowland continuum, the weeding methods and corresponding number of weeding operation were collected based on farmers estimations.

5.3.1. Input-specific DEA model data

For the input-specific DEA model estimation, we distinguished one output and five inputs. The output and inputs were defined based on farmers' cropping practices in rainfed rice production systems. The paddy rice production was the output, measured in kg rice per farm. The defined inputs consisted of 1) manual weeding labour, 2) labour used for other activities and other services, 3) intermediate inputs (seed and chemical inputs)–defined as variable inputs,– and 4 and 5) land and capital –reflecting the quasi-fixed inputs–. For the purpose of this study, labour was separated into manual weeding labour and labour used for other farming activities (land preparation, sowing, other inputs application, bird scaring, harvest and on-farm postharvest activities). Fertilizer and herbicide cost were aggregated into chemical inputs to avoid 'zero-observation' because many farmers did not use them. Labour was measured in hours and included family labour as well as hired labour. Labour amounts were computed from data collected on number of men, women and children involved in each of rice farming operations and the time each of them have spent. Land area was measured using a global positioning system (GPS) device (GARMIN, Model GPSMAP 60CSx). The costs of seeds coming from farmers' harvest were computed using the average price of paddy in each country while the actual prices were used in case seeds were purchased. Other inputs and other services costs were measured at their actual price. Capital cost was made of machinery and small materials (hoes, axes, machetes, basins, tapes, etc.) and measured at their annual (linear) depreciation cost (Chapter 4). Fertiliser cost included organic manure and mineral fertilizer use. Table 5.1 presents the mean and standard deviation of the output and each input based on the farmer specific data of the two surveyed countries.

Table 5.1 Mean and standard deviation[a] of outputs and inputs used in the DEA model

Variables	Benin Mean	Cote d'Ivoire Mean
Paddy production (kg/farm)	426 (463)	1,756 (1,819)
Land (ha)	0.24 (0.25)	1.53 (1.09)
Capital (CFA)[b]	2,959 (3,526)	21,347 (37,703)
Weeding labour (hour)	195 (170)	573 (515)
Other labour (hour)r	333 (275)	1,904 (1,637)
Intermediate inputs (CFA)	19,735 (26,610)	108,576 (98,679)

[a]Standard deviation in parenthesis.
[b]Fixed exchange rate: €1 = 656 FCFA.

5.3.2. Data used in bootstrap regression models

Studies by Kokoye et al. (2013); Chapter 4, Singbo and Oude Lansink (2010), Speelman et al. (2008), Theriault and Serra (2014) and Haji (2006) showed that farmers' efficiency is determined by a set of socio-economic and institutional factors. Such factors included; household size, education, gender, age, years of experience in rice farming, access to agricultural information, land tenure, farm size and number of fields. These factors affect the management ability of farmers and, hence, are, expected to impact their technical inefficiency levels (Haji, 2006). To capture the effect of parasitic weeds infestation on rice farmers' technical inefficiency, variables such as the parasitic weed infestation level (measured by the proportion of farm area covered by the PW), manual weeding modalities[8] and interaction effects of PW infestation and manual weeding modalities were introduced in the models. Manual weeding consisted of hand or hoe weeding. Four manual weeding modalities were considered to account for differences in timing and frequency: 1) weeding once early (up to 30 days after sowing (DAS)), 2) weeding once late (after 30 DAS), 3) weeding twice and 4) weeding more than twice. Based on the research by Ekeleme et al. (2009); Ogwuike et al. (2014) and Toure et al. (2011), we expect weeding once early and/or weeding twice to reduce farmers' technical inefficiency. However, since weeding more than twice significantly reduces the severity of *Rhamphicarpa* in Benin, weeding more than twice is expected to reduce the technical inefficiency of affected rice farmers in Benin (N'cho et al., 2014). The area of rice farm infested by a parasitic weed is expected to increase farmers' inefficiency as infested farms may require additional work (Chapter 4). The complete list of variables used in the truncated bootstrap regression model with their expected sign is presented in Table 5.2.

Table 5.2 Expected sign, mean and standard deviation[a] of variables used in truncated bootstrap regressions

Variables	Expected sign	Benin	Cote d'Ivoire
		Mean	Mean
Weeding labour inefficiency (dependent variable)		0.69 (0.35)	0.58 (0.35)
Gender of farmer (1= female farmer)	+/–	0.73 (0.45)	0.15 (0.35)
Education (number of years completed)	–	2.21 (3.33)	1.16 (2.48)
Household size	–	7.76 (5.24)	10.86 (5.80)
Total area cropped (ha)	–	0.24 (0.24)	1.53 (1.09)
Area infested (%)	+	35.01 (36.39)	15.22 (22.70)
MW once early	–	0.03 (0.18)	0.28 (0.45)
MW once late	+/–	0.01 (0.1)	0.10 (0.30)
MW more than twice[b]	+/–	0.52 (0.50)	0.14 (0.34)
MW once*area infested (interaction)		1.44 (9.48)	3.20 (10.66)
MW more than twice*area infested (interaction)		22.36 (33.59)	3.28 (12.71)
Access to information (1=access, 0=no access)	–	0.86 (0.35)	0.69 (0.46)

Notes: MW=Manual weeding.
[a] Standard deviation in parenthesis.
[b] MW twice is used as base for comparison.

5.4. Results

5.4.1. Technical and scale inefficiencies

The average overall inputs technical inefficiency, weeding labour and other labour technical inefficiencies and the scale inefficiencies are presented in Table 5.3.

Overall inputs technical inefficiency scores ranged from 41% and 53% for the variable returns to scale (VRS) model to 58% and 68% for the constant returns to scale (CRS) model in Cote d'Ivoire and Benin, respectively. The technical inefficiency of weeding labour ranged from 58%

[8] Weeding modalities is defined to mean (1) the number of days after sowing recommended for each weeding operation and (2) the number of weeding operations required.

and 69% for VRS to 71% and 82% for CRS in Cote d'Ivoire and Benin respectively. The technical inefficiency of other labour ranged from 60% and 64% (for VRS) to 82% and 84% (for CRS), respectively in Cote d'Ivoire and Benin. In both countries, weeding labour technical inefficiencies were similar to other labour use inefficiencies (OLIE) except in Cote d'Ivoire for the CRS specification where WLIE was smaller than OLIE (Table 5.3)[9].

Table 5.3 Technical and Scale inefficiencies of specific inputs and 95% CI

	Benin		Cote d'Ivoire	
Items	Mean	95% CI	Mean	95% CI
WLIE[a] (vrs)	0.69	0.63— 0.73	0.58	0.53 — 0.63
OLIE[a] (vrs)	0.64	0.60— 0.69	0.60	0.55— 0.65
INIE[a] (vrs)	0.53	0.49— 0.57	041	0.37— 0.45
WLIE[a] (crs)	0.82	0.78— 0.85	0.71**	0.66— 0.75
OLIE[a] (crs)	0.84	0.80— 0.87	0.82**	0.77— 0.86
INIE[a] (crs)	0.68	0.64— 0.71	0.58	0.54— 0.62
WLSIE	0.13**	0.10— 0.16	0.12**	0.09— 0.16
OLSIE	0.19**	0.16— 0.23	0.22**	0.18— 0.25
OSIE	0.15	0.12— 0.17	0.17	0.14— 0.20

Notes: WLIE = weeding labour technical inefficiency, OLIE = other labour technical inefficiency, INIE = overall variable inputs technical inefficiency, WLSIE= weeding labour scale inefficiency, OLSIE = other labour scale inefficiency, OSIE = overall scale inefficiency, CRS = constant returns to scale, VRS = variable returns to scale, Wlab=weeding labour, olab= other labour, x_v = variable inputs.
(a) Estimated values were obtained in the directional vectors $(g_{x_i}, g_y) = (x_{wlab}, 0)$ for WLIE, $(g_{x_i}, g_y) = (x_{olab}, 0)$ for OLIE and $(g_{x_i}, g_y) = (x_v, 0)$ for INIE.
(**) statistically significant at 5% (95% CI don't overlap), compare weeding labour and other labour use.

The overall scale inefficiency (OSIE) was 17% in Cote d'Ivoire and 15% in Benin. In Benin, only 6% of farms were overall scale efficient (OSIE = 0, i.e., operating at constant return to scale) while almost the same proportion (about 7%) were scale efficient with respect to weeding labour (WLSIE=0) and other labour use (OLSIE=0). In Cote d'Ivoire, on average only 10% of farmers was scale efficient both for weeding labour, other labour and overall inputs. Hence, most farmers in the sample in both countries were scale inefficient. Figure 5.2 shows the distribution of technical inefficiency among the sampled farmers for overall inputs and weeding labour. The distribution of weeding labour technical inefficiencies, indicated in both countries the presence of two rather extreme clusters of farmers. On the one hand farmers were clustered to higher inefficiency level (WLIE>80%), while at the same time there was a clustering of most efficient farmers

[9] Weeding labour inefficiency was compared to other labour and overall inefficiency using the 95% CI. The compared mean values are different if the 95% CI did not overlap otherwise, the difference is not significant.

(WLIE<20%), while the middle classes (20%≤WLIE≤ 80 %) were less represented in most situations. This indicates a gap between farmers with respect to their weed management abilities.

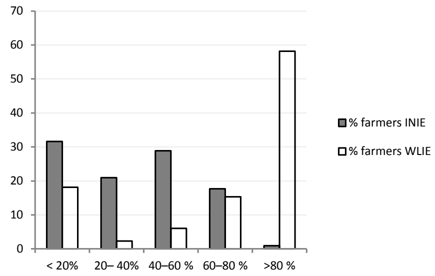

Fig. 5.2a Variable returns to scale (VRS), Benin

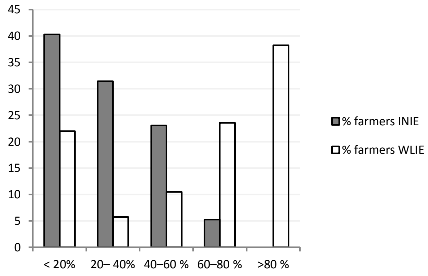

Fig. 5.2b Variable returns to scale (VRS), Cote d'Ivoire

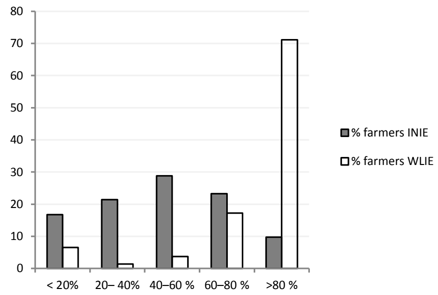

Fig. 5.2c Constant returns to scale (CRS), Benin

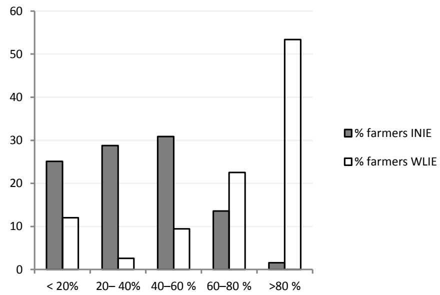

Fig. 5.2d Constant returns to scale (CRS), Cote d'Ivoire

Notes: INIE = overall inputs technical inefficiency, WLIE = weeding labour technical inefficiency, crs = constant returns to scale, vrs = variable returns to scale.

Figure 5.2 Distribution of overall and weeding labour technical inefficiency scores per country

In order to check whether distributions of INIE and WLIE were independent from the parasitic weeds infestation status of the farms, Pearson chi2, likelihood-ratio and Kendall's tests were performed. The tests used the proportions of farms in the five categories of inefficiency scores defined under Figure 2 per subsamples of infested and non-infested farms in each country.

The tests results were not significant (P>0.1; not reported). Hence, the null hypothesis of equality of distributions between the subsamples of parasitic weed infested and non-infested farms were not rejected. This suggests that farmers' INIE and WLIE distributions were independent of parasitic weeds (PWs) infestation status of farms in both countries. Furthermore, the difference of mean inefficiency scores between the subsamples of infested and non-infested farms was checked using the 95% confidence interval (CI) of their respective mean inefficiency scores (Table 5.4). If the 95% CI overlap, then, the difference in technical efficiencies between the subsamples of infested and non-infested farms is not significant. Significant differences (P<0.05) were found only for INIE and WLIE, for the VRS specification in Cote d'Ivoire (Table 5.4) indicating that on average, for overall inputs and weeding labour, technical inefficiency for non-infested farms is lower than for infested farms.

Table 5.4 Mean values of specific technical inefficiency of non-infested and infested farms and their 95% CI

Technical Inefficiencies	Infestation Status (1= yes, 0= no)	Benin		Cote d'Ivoire	
		Mean	95% CI	Mean	95% CI
INIE (vrs)	1	0.53	0.48—0.58	0.48**	0.42—0.54
	0	0.53	0.46—0.61	0.36**	0.31—0.42
WLIE (vrs)	1	0.70	0.65—0.76	0.66**	0.59—0.73
	0	0.66	0.57—0.74	0.52**	0.45—0.59
OLIE (vrs)	1	0.65	0.59—0.70	0.66	0.59—0.73
	0	0.63	0.55—0.72	0.55	0.49—0.62
INIE (crs)	1	0.67	0.63—0.71	0.59	0.53—0.65
	0	0.70	0.64—0.76	0.57	0.51—0.63
WLIE (crs)	1	0.82	0.77—0.86	0.74	0.68—0.80
	0	0.81	0.76—0.87	0.68	0.62—0.74
OLIE (crs)	1	0.84	0.80—0.88	0.83	0.77—0.89
	0	0.83	0.76—0.89	0.81	0.75—0.86

Notes: CI = confidence interval, INIE = overall inputs technical inefficiency, WLIE = weeding labour technical inefficiency, OLIE = other labour technical inefficiency, CRS = constant returns to scale, VRS = variable returns to scale.
(**) statistically significant at 5% (95% CI don't overlap).

5.4.2. Determinants of inefficiency of weeding labour

The results of the truncated bootstrap regression showing the sources of weeding labour inefficiency are displayed in Table 5.5. The scale inefficiency estimates showed that less than 10% of farmers in both countries operated at CRS. Hence, only the technical inefficiency estimates of the VRS specification were used for the second stage regression.

Results showed that in Cote d'Ivoire, weeding once (early and late) decrease technical inefficiency but the effect of weeding late was not significant (P>0.05). However, farmers weeding early once and those with higher education were associated to a lower technical inefficiency. A larger area infested was associated with a higher inefficiency. Hence, *ceteris paribus* (other condition remaining constant) an increase of 1% in area infested by PWs increases the WLIE by 0.3%. An additional year of education decreases the WLIE by 2%. In Benin, only larger farms were associated to lower inefficiency (P<0.05) while, contrary to Cote d'Ivoire, the technical inefficiency of weeding labour did not increase with an increase in infested area (P>0.1). Weeding more than twice had no significant effect (P>0.5%) in both countries.

Table 5.5 Results of the truncated bootstrap regression for sources of weeding labour technical inefficiency

Variables	Benin		Cote d'Ivoire	
	Coefficients (SE)	95% CI	Coefficients (SE)	95% CI
Constant	0.80 (0.10) **	[0.60 ; 1.00]	0.81 (0.08) **	[0.66 ; 0.96]
Female farmer	0.08 (0.06)	[–0.05 ; 0.20]	0.04 (0.07)	[–0.10 ; 0.19]
Education	0.01 (0.01)	[–0.01 ; 0.02]	–0.02 (0.01) **	[–0.04 ;–0.002]
Household size	0.003 (0.005)	[–0.01 ; 0.01]	–0.002 (0.005)	[–0.01 ; 0.07]
Land area cropped	–0.32 (0.11) **	[–0.56 ; –0.10]	–0.02 (0.03)	[–0.07 ; 0.03]
Area infested	0.001 (0.001)	[–0.001 ; 0.003]	0.003 (0.001) **	[0.00 ; 0.01]
MW once early	–0.19 (0.28)	[–0.79 ; 0.33]	–0.14** (0.07)	[–0.27 ; –0.02]
MW once late	–0.35 (0.32)	[–1.08 ; 0.17]	–0.06 (0.10)	[–0.29 ; 0.11]
MW more than twice[a]	–0.03 (0.07)	[–0.17 ; 0.11]	0.12 (0.10)	[–0.07 ; 0.32]
MW once* area infested	0.001 (0.005)	[–0.01 ; 0.01]	0.001 (0.003)	[–0.01; 0.004]
MW more than twice*area infested	–0.0001 (0.001)	[–0.003; 0.003]	–0.001 (0.003)	[–0.01; 0.01]
Access to information	0.004 (0.07)	[–0.13 ; 0.003]	–0.07 (0.05)	[–0.17 ; 0.03]
Log likelihood	–49.55		–35.16	
Prob > chi2	0.00		0.00	

Notes: MW= manual weeding, SE= standard error (in parenthesis), CI = confidence interval.
(a) MW twice is the base category.
(**) Statistically significant at 5% based on the bootstrap 95% confidence interval (L=2000 replications).

5.5. Discussion

The results of the directional input distance function show that rainfed rice farming systems are overall technically inefficient in the use of inputs. This is consistent with findings in Chapter 4 indicating that substantial amounts of production resources can be saved, while preserving the current level of output. Weeding labour technical inefficiency was high. This was expected because manual weeding is highly drudgery and because farmers do not have any affordable alternative methods. The high technical inefficiency scores for weeding labour found in this study are in line with previous studies on specific input technical efficiency (Bravo-Ureta et al., 2007, Speelman et al., 2008). The high WLIE can partly be explained by the socio-economic characteristics of farmers. Since the majority of labour used in rainfed rice systems consists of family labour (Singbo and Oude Lansink, 2010) that do not result in actual expenditures, farmers may not consider the opportunity cost of labour and thereby reduce the efficiency of its use. Furthermore, in rainfed rice systems, a lack of proper weeding, results in higher production losses compared to irrigated rice systems where the crop is continuously flooded (Rodenburg and Johnson, 2009). Moreover, farmers rely mainly on manual weeding due to the limited number of effective and affordable weed management practices available to them (Gongotchame et al., 2014, Rodenburg and Johnson, 2009). Therefore, the overuse of weeding labour might be due to an overreaction of farmers to the (parasitic) weed problems on their farms, i.e. farmers put substantially more resources for weeding in order to prevent serious losses. In addition, parasitic weeds usually cause higher damage levels than ordinary weeds as was shown by Rodenburg et al., (2014) for *Rhamphicarpa fistulosa*. Hence, the presence of parasitic weeds might further increase the farmers' response and thereby increase technical inefficiency more significantly than ordinary weeds. This is particularly true for Cote d'Ivoire where WLIE was higher for infested farms than for non-infested farms (section 5.4.1). Since manual weeding is labour-intensive and time consuming, it often results in delays in its completion and consequently in lower rice yields despite the large amount of labour use (Gongotchame et al., 2014, Saito et al., 2010). Timing of the weeding operations is very important as was shown previously by Johnson et al. (2004). A relatively small time investment (e.g. one or two weeding operations) in the critical early crop stages may result in a higher technical efficiency of weeding labour and lower weed-inflicted yield losses compared to a relative large time investment (e.g. more than two weeding operations) at later crop stages. In the case of parasitic weeds, an early intervention may even be more important as it will reduce the period of parasitism. In the case of *Rhamphicarpa fistulosa*, which is a facultative weed that starts as an ordinary weeds and only starts parasitizing its host once it has developed into a seedling, early weeding may even completely avoid parasitism (e.g. Rodenburg et al., 2014).

The large difference observed between CRS and VRS overall technical and weeding labour technical inefficiency scores, suggests the presence of significant scale inefficiencies ($P<0.01$) in the sample. More than 92% of the farmers did not operate at their optimal scale; also the INIE as well as WLIE are affected by the scale of the farming operation. If farms are realising increasing returns to scale, increasing farm size is expected to have a significant positive impact on efficiency levels (Coelli et al., 2002). The results of the bootstrap regression indicated that technical inefficiencies of weeding labour indeed decrease with larger farms (mainly in Benin), hence increasing the scale of farming systems could improve the efficiency of the use of inputs in our samples. A substantial scale inefficiency was also reported by Binam et al. (2003) in coffee production in Cote d'Ivoire, Singbo and Oude Lansink (2010) in lowland farming systems in Benin. However, the results are not consistent with Haji (2006) who found that scale inefficiency was nearly absent in the more traditional farming systems of smallholder farms in Eastern Ethiopia, and with Frija et al. (2009) with respect to water use technical efficiency in Tunisia.

An important implication of the results is that, with the current level of technology, farmers can substantially reduce weeding labour and still produce the observed output (conditional on the use of other inputs too). This implies that by improving weeding labour technical efficiency, farmers could reallocate a significant fraction of labour to other productive activities of the household without decreasing rice production or increasing the use of other inputs. Improving weeding labour technical efficiency might require training of farmers in good agricultural practices for rainfed rice systems and in labour saving strategies (e.g. optimized weeding timing). This implies that more labour saving strategies for parasitic weeds management, adapted to rainfed rice farming environment, need to be developed and disseminated.

The large difference in the distributions of technical inefficiency of weeding labour and overall inputs indicates that farmers performed differently in managing their overall production process compared to managing weeds. The fact that a large fraction of the farmers in both countries exhibit a high level of inefficiency suggests that the majority of farmers did not perform well with regard to weed management. This finding suggests the need for research or policy actions that are more oriented to solving the general weed management problem in rainfed rice systems in SSA. The majority of subsistence rice farmers use tedious manual weeding (Rodenburg and Johnson , 2009), as they are either unable to afford any labour saving technology or they are unaware of their existence. This type of farmers generally has limited resources and limited capacities in weed management. The farmers operating fully efficiently may have different profiles with respect to weed management compared to the farmers that are operating less efficiently. For example, they may be exposed to agricultural training and learn possible labour saving strategies such as optimal timing of weeding.

The results of the second stage truncated bootstrap regression suggest that farmers can reduce the technical inefficiency of weeding labour by increasing their farm sizes (mainly in Benin) or by adjusting their weeding operation to one early manual weeding (in Cote d'Ivoire). In Cote d'Ivoire, a single early weeding had a significant negative effect on technical inefficiency of weeding labour. Conversely, a single late weeding had a negative, but non-significant, effect on technical inefficiency of weeding labour. These results again confirm the importance of the development of adapted weeding regimes[10] (see, Ekeleme et al., 2009; Toure et al., 2011) with proper timing of interventions (e.g. Johnson et al., 2004). The insignificant coefficient of weeding more than twice in both countries indicates that weeding twice and weeding more than twice have similar effects on the technical inefficiency of weeding labour (weeding twice is the base category, Table 5.5). This means that at the current technology level, keeping all other inputs constant, there might not be a need to weed more than twice to produce the current output level. Ogwuike et al. (2014) concluded that weeding an upland rice crop more than once increases the weeding labour efficiency (by about 37 %) and rice productivity (by more than 27 %); hence the optimum number of weeding operations is most likely two. In Cote d'Ivoire, the effect (on WLIE) of one manual weeding of a field infested

[10] This refers to the number of days after sowing (DAS) that each weeding operation is conducted

by PW (interaction effect) was positive while the effect of weeding more than twice a PW infested field was negative. This means that, compared to un-infested farms, when rice farms become infested by PWs, the effect of weeding once on technical inefficiency changes from negative to positive, while the opposite effect is observed with weeding more than twice. However, these joint effects were not significant. In Benin, both corresponding effects remain negative and non-significant regardless of the infestation status of the fields. These non-significant effects indicate that both weeding once and weeding more than twice might not be effective when plots become infested by parasitic weeds. The negative and non-significant joint effects of weeding more than twice and infestation by parasitic weeds indicate that, in the presence of PWs, farmers tend to weed more than twice in their attempt to secure their harvest. This suggests that future research on parasitic weed management strategies needs to investigate both the appropriate weeding regimes and the number of weeding operations, as well as alternatives to hand weeding.

5.6. Conclusion

The objective of this study was to analyse the technical inefficiency of weeding labour and other inputs in rainfed rice systems and to identify sources of technical inefficiency in production environments infested by parasitic weeds (PW). The directional input distance function and DEA were used to measure the overall input technical inefficiency, the technical inefficiency of weeding labour and other labour input and scale inefficiency.

In Benin, the overall technical inefficiencies were 53% for the variable returns to scale (VRS) specification and 68% for the constant returns to scale (CRS) specification while weeding labour technical inefficiencies were higher (69% for VRS and 82% for CRS). In Cote d'Ivoire, the overall technical inefficiencies were 41% and 58% respectively with VRS and CRS while weeding labour technical inefficiencies were 58% for VRS and 71% for VRS. For both VRS and CRS specifications, the weeding labour technical inefficiencies were similar to other labour technical inefficiencies except for the CRS specification in Cote d'Ivoire where weeding labour technical inefficiencies were lower than other labour technical inefficiencies.

The technical inefficiencies suggest that at the current technology level, farmers can maintain their current production level and use of other inputs. At the same time, they can save more than 58% to 71% of labour inputs in Cote d'Ivoire and 69% to 82% in Benin.

Substantial overall and weeding labour scale inefficiencies were found in both countries. The negative effect of larger farms on technical inefficiency of weeding labour (in Benin mainly) in the bootstrap regression suggests that an increase in the scale of production systems reduces the technical inefficiency of weeding labour. The bootstrap regression also revealed that factors such as weeding regimes and education (in Cote d'Ivoire), were associated with lower technical inefficiencies of weeding labour while the level of infestation with parasitic weeds increases technical inefficiencies (in Cote d'Ivoire mainly). Also, results suggest that the currently used weeding regimes and number of weeding operations on farms infested by parasitic weeds, are not efficient in controlling parasitic weeds.

This paper showed that in small-scale rainfed rice farming systems of SSA (with the case of Benin and Cote d'Ivoire), in coping with parasitic weed infestations, there is scope for improving the technical efficiency of weeding labour. Operating fully efficiently would unleash a substantial amount of labour that can be allocated to other productive activities of the household without decreasing the current rice production levels.

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6

General Discussion

S.A. N’cho

6.1. Introduction

Rice is a strategic crop for food security in SSA (Wopereis et al., 2013). Rice production is, however, constrained by factors such as weeds. An important category of weeds in rice production systems are the parasitic weeds. In rainfed rice systems, the most important parasitic weeds (PWs) in terms of impact on production are *Rhamphicarpa fistulosa*, *Striga asiatica and Striga hermonthica*. The overall objective of this thesis was to identify factors affecting infestation of rice farms by parasitic weeds and to assess the socio-economic impacts of parasitic weeds infestation (PWI) on rainfed rice producers in SSA in order to provide guidance for decision-making for rice farmers and policymakers aiming at developing strategies to cope with parasitic weeds.

This chapter synthesizes the main findings of this thesis, draws the main conclusions and generates future research and policy implications. The research methods applied are evaluated by discussing the extent to which the results they generated are complementing to a consistent assessment of the socio-economic impact of parasitic weed problems (Figure 1.5). This chapter proceeds by synthesizing the main finding of the dissertation in the section 6.2 and explains how results of the different chapters interrelate and relate to the literature. Section 6.3 discusses the data and methodological issues of this thesis. Section 6.4 discusses the policy implications and generates recommendations based on the main findings of this research. Section 6.5 presents the research implications of this thesis and suggestions for future research and finally, section 6.6 presents the mains conclusions of this thesis.

6.2. Synthesis

The results presented in the four research chapters convey the message that PWIs have negative impacts on rainfed rice systems productivity of SSA. However, this impact can be reduced if farmers have a good access to inputs and are able to manage them efficiently. The impacts of PWI are summarized in Table 6.1 (across chapters).

Chapter 2 presents the determinants of infestation of rice fields by PWs (with the case of *Rhamphicarpa fistulosa*) and the impact of PWI on farmers' agricultural practices and production choices. Results showed that farmers' choices on mechanized land preparation, timing of herbicide application and manual weeding twice affect the infestation of their fields by PWs, while choices concerning medium rate fertilizer application, fallow length, manual weeding twice and late sowing affect the severity of infestation. These results are consistent with previous agronomic studies. For example, Dugje et al. (2008) found that farmers' practices affect directly or indirectly the occurrence of PW on their fields and the severity of infestation. Vissoh et al. (2004) and Gbehounou

(2006) found that fields cropped on land with prolonged fallow periods have a lower severity of infestation. Furthermore, Chapter 2 showed that poor soils are more likely to be infested by *Rhamphicarpa fistulosa*. This result is also in line with the results of previous studies, indicating that poor soil fertility generally results in an increased proliferation of weeds (Demont et al., 2007; De Rouw, 1995; Vissoh et al., 2004) and, particularly parasitic weeds (Gbehounou, 2006; Parker, 2009; Sauerborn et al., 2003) which as such is also experienced by farmers themselves (e.g. Emechebe et al., 2004). In SSA, rice farmers mainly have poor access to fertilizers (and other keys inputs) (Manyong et al., 1996) and rely mainly on fallowing to manage their soil fertility and weeds (de Rouw and Rajot, 2004; de Rouw et al., 2014). The results in Chapter 2 show that a long fallow reduces the severity of PWs. However, with the increasing pressure on land, long or even short fallows are often non longer feasible (Vissoh et al., 2004; Demont et al., 2007). This is a crucial factor that requires further attention of policy makers, extension services and researchers. Previous agronomic studies have analyzed the relation between the depletion of the soil with respect to specific nutrients and the incidence and severity of parasitic weeds infestation. For example, nitrogen (N) and phosphorus (P) deficiencies in the soil stimulate the production of *Striga* seed germination stimulants, and, this increases the rate of parasitism (e.g. Yoneyama et al., 2007). Conversely, application of N and P fertilizers may result in reduced parasitism by *Striga* (e.g. Lopez-Raez et al., 2009). Rodenburg et al. (2011) showed that the application of fertilizer (N and P) also reduces *Rhamphicarpa fistulosa* plant numbers and they argued that, since the parasitism mechanism of *R. fistulosa* is different from *Striga* (facultative compared to obligate parasitism, respectively), the fertilizer effects might be due to another underlying mechanism. Including detailed information on soil chemical content in the double hurdle model in Chapter 2 could have provided better insights in the positive interaction between poor soil fertility and the *Rhamphicarpa fistulosa* infestation level.

Chapter 3 elaborates on the specific impact of PWI on farmers’ decision to adopt a specific weed management practice (WMP) or a combination of WMPs as one overall strategy. The findings in this chapter indicate that farmers with fields infested with PW are more likely to combine WMPs as opposed to applying only manual weeding. Moreover, results in Chapter 5 indicate that none of the currently used manual weeding regimes and number of weeding operations have shown to be efficient when fields were infested by the PW. These two findings indicate that, by combining WMPs, farmers are seeking for more effective control strategies against parasitic weeds. This search for an effective WMP combination requires guidance from extension and research, by studying the effectiveness of different combinations of technologies in the specific production context of the farmers’ field, as described by Schultz et al., 2003. Ultimately this should lead to the type of locally adapted integrated weed management approaches that is often advocated as the most effective and sustainable approach against weed problems (Douthwaite et al., 2007; Harker and O'Donovan, 2013; Rodenburg and Johnson, 2013). Furthermore, Chapter 4 confirmed that PWI significantly affects productivity of farmers by reducing the potential production (through its negative effect on the potential production function reflected by the production frontier) and by reducing the resource use efficiency (through the inefficiency effects model). This is a new approach as the estimated yield losses were generally limited to assessing direct crop losses only (Chambers et al., 2010). These results are consistent with the conclusion of Chapter 2 that farmers can cope with PWs given their access and capacity of management of productive resources. Chapter 5, furthermore, shows in line with the conclusion of Chapter 4 that farmers can save substantial resources (14–32% of all productive resources and 58%–82% of weeding labour) if they produced fully efficiently. Hence, the non-parametric DEA (Data Envelopment Analysis) of Chapter 5 and the parametric SFA (Stochastic Frontier Analysis) of Chapter 4, come to similar conclusions. These results are also in line with the findings of Greene (2007, p.114). The substantial weeding labour inefficiency results in Chapter 5 suggests that farmers overreact to the parasitic weeds problem by allocating too much labour to weeding activities. This overreaction can be explained with the Protection Motivation Theory (Rogers, 1983)[11] . Since in rainfed rice systems, a lack of proper weeding shows significantly high production losses up to total crop faillure, PWI is perceived by farmers as a high threat. Moreover, results in Chapter 3 and Chapter 5 suggest that when PWs occur, current WMPs may not be effective. This was also reported by farmers during the survey in the three countries (descriptive statistics not reported in this thesis). Since the PWs are threatening farmers on one hand, and on the other hand, the existing control practices are not effective, farmers rely mainly on their own labour force for manual weeding. The manual weeding (the most affordable and available coping strategy) is labour-intensive and is usually performed by women who need to consider many other household obligations at the same time and are unable to afford any time saving technologies (Nation, 2010; Elson, 1995). This contributes to increase technical inefficiency because weeding is more often not done in time, which results in little returns on weeding efforts (Akobundu, 1991). Furthermore, the majority (more than 70%) of labour is family labour (Singbo and Oude Lansink, 2010) that do not require actual expenditures. Farmers therefore,

[11] Protection motivation stems from both the threat appraisal and the coping appraisal. Adapted to the case of this study, farmers reaction results from the appraisal of the threat of parasitic weeds and their coping appraisal. The threat appraisal is the result of the perceived severity of the parasitic weed problem and the vulnerability of the farmers less the rewards. The coping appraisal is the result of the efficacy of available technologies and the (self-efficacy) ability of farmers to apply efficiently the technology, less the cost of the technology.

may use a high amount of the available labour for manual weeding to prevent any possible severe losses.

The results in Chapter 5 as well those in Chapters 2, 3 and 4, indicate a significant impact of PWI on farmer's management abilities. Chapters 4 and 5 consistently show that PWI decreases farmers' technical efficiencies. Hence, the results in this thesis confirm that parasitic weeds affect productivity not only by competing with the rice plant or by parasitizing it, but also by affecting farmer's choice for WMPs (Chapter 3), farmers' technical efficiency (Chapter 4 and 5), the effectiveness of management options (Chapter 5) and thus, farmers' management abilities (Chapter 2). More importantly, results also indicate that farmers learn through experiences with PWI in their fields. With this experience they are able to recover part of the potential parasitic weed-inflicted yield losses (Chapter 4). This supports the conclusion in Chapter 2 that when farmers are aware of the PW problem, the infestation severity is lower than expected.

6.3. Data collection and modelling approaches

6.3.1. Data collection and analysis

The use of data from three SSA countries collected with similar methods enabled us to compare across countries the impact of parasitic weeds on rice production systems, farmers' decisions and management abilities. This across-countries approach sheds light on the differences between countries and also on the similarities in terms of factors affecting farmers' choices and their technical efficiencies. Similarities are found in, for example, the overall loss of productivity due to PWI, which ranged from 21% to 50%. In the three studied countries, the most frequently used weed management practice (WMP) was manual weeding, followed by herbicide use. In Cote d'Ivoire however, a substantial proportion of farmers (20%) did not use manual weeding and relied only on herbicides to control weeds.

The across-countries approach also showed that the same factor can have different effects on farming systems across-countries. For example, access to information decreased the likelihood of adopting fertilizer in Benin, while it increased the adoption in Cote d'Ivoire and had no significant effect in Tanzania (Chapter 3). In Cote d'Ivoire, farmers affected by *R. fistulosa* showed a lower likelihood to adopt only hand weeding, while the opposite was observed in Benin and Tanzania. Furthermore, there are country-specific significant factors (Chapter 3). For example, in Tanzania, subsistence farmers were less likely to adopt fertilizer compared to market oriented farmers, while access to information had no effect on their choice. In Benin, farmers with a large number of children in their household had a higher likelihood to adopt WMPs strategies, including water control and the strategies consisting of only manual weeding.

Use of country specific data comes, however, at a cost. There is a need to adjust survey instruments to account for country specific characteristics, like coding of localities, institutions/organisations, education level, crops, rice varieties, activities of households. Moreover, the presence of the same research team in the field for the monitoring of data collection was not possible as cropping calendars of the studied countries overlapped. These difficulties were overcome by the use of a common survey methodology and a good coordination of well-trained survey teams for data collection within the three countries.

The majority of data are based on memory recall only because farmers do not hold any formal recording systems of their farming practices. Hence, data might be subject to measurement errors. The use of stochastic approaches (e.g. random sampling, stochastic frontier analysis) in this study partly accounted for these possible measurement errors (Coelli et al., 1998). Nevertheless, improving data collection by involving farmers in formal recording systems for example, will help to reduce quality control efforts and might result in higher quality data.

Literature suggests a relation between soil fertility status and occurrence of soil-borne pests such as PWs (Sauerborn et al., 2000). To account for the effect of soil fertility of rice fields on *R. fistulosa* infestation occurrence, we used data on farmers' perception of the fertility status of their land (i.e. poor, moderate, high). This qualitative assessment does not provide information on the chemical content of the soils of different fields. Collecting and proceeding to chemical analysis of soil samples would provide more specific information on particular nutrient deficiencies of the soils and how this relates to parasitic weed infestation.

6.3.2. Modelling approaches

In Chapter 2, the double hurdle model was used to simultaneously identify factors determining rice fields' infestation by PWs and farmers' ability to cope with the PW when their fields are infested. The simultaneous estimation of the infestation and the severity process improved the efficiency of the estimates and the quality of the inference, since the correlation coefficient (rho parameter) between the residuals of the two equations (infestation and severity processes) differed significantly ($P<0.05$) from zero. This suggests that the double hurdle model application was an appropriate tool for assessing factors determining parasitic weed infestation and severity of infestation in crop production systems as shown in Chapter 2.

Chapter 3 of this thesis argued that most previous studies on technology adoption considered the adoption of a single technology (Teklewold and Kohlin, 2011). This approach to technology adoption is not appropriate in the context of the problem addressed in Chapter 3 of this thesis. This is because this chapter is dealing with situations where farmers are faced with many choices and have the possibility to choose only one or combine some technologies to satisfy their needs (see Teklewold and Kohlin, 2011). Chapter 3 used the multivariate probit (MVP) model for distinguishing factors affecting farmers' choice for individual WMPs in the presence of other WMPs, and their choice for combinations of WMPs (Piya et al., 2013; Rodriguez-Entrena and Arriaza, 2013). This provided a better understanding of farmers' choices for the use of multiple WMPs simultaneously (combining strategies) to cope with PWs in addition to understanding their choice for the use of an individual WMP. The marginal effects of PWI on their choices and other biophysical, socio-economics and institutional factors were estimated. The empirical Bayes bootstrap procedure used in Stata is very complex, not yet well developed and requires high level econometric and computer programming skills to estimate the average marginal effects (AMEs). The user programme developed in Stata is highly time consuming. The running time depends mainly on the number of equations used in the MVP model and the required precision. Increasing the number of draws increases the quality of the estimates on the cost of running time. In this study 300 draws were used (the default is 5). In the parametric bootstrapping for estimation of the standard errors of the AMEs the use of Halton draws either pseudorandom draws and, the number of replications affect the running time (Cappellari and Jenkins, 2003, 2006; Kis-Katos, 2012; Train, 2003). The running time ranged from 15 hours (4 variate) to 3 weeks (7 variate) with 8 GB computer with 500 bootstrap replications only. The Halton draws are more effective than pseudorandom draws (Cappellari and Jenkins, 2006, Train, 2003[12]). The use of Halton draws in this thesis allowed to save about ¾ times of the initially estimated computing times to reach similar conclusion.

The issue of choosing between econometric approach or mathematical programming for efficiency analysis was encountered for Chapter 4 and Chapter 5. Many authors investigated this issue and come to the conclusion that both give similar result (Greene, 2008). Hence, the reason for choosing one is mainly guided by the type of research, the objective and data availability. In Chapter 5 the non-parametric (mathematical programming) DEA with directional input distance function was used because the main objective was to derive the inefficiency of weeding labour (Chambers et al., 1996). The non-radial measure was therefore, preferred. The Stochastic Frontier Analysis (SFA, econometric approach) was used in Chapter 4 because the objective was to assess in what extent farmers can increase their output given the set of inputs available. In rainfed rice

[12] All the studies used by Train were based on mixed logit models.

systems, farmers have more control power on their inputs use than on their outputs due to the highly variable production and weather conditions (different management abilities, weeds, birds, erratic rains, flood, drought). The SFA accounts better for the stochastic variation and possible measurement errors (in the composed error terms) while this is fundamentally a practical problem for the non-parametric DEA.

To account for environmental variables such as PWI, in Chapter 4, a dummy variable for PWI was incorporated into the production function of the SFA following Rahman and Hasan 2008; Sherlund 2002, Zhengfei, 2006. This allowed for deriving the direct impact of PWI on yield losses. Furthermore, incorporating PWI in the production function and inefficiency effects model allowed for estimating econometrically the total impact of PWI on productivity. More specifically, the use of an input-specific DEA in Chapter 5 enabled for estimating technical inefficiency [13] of overall inputs use, weeding labour and labour used for other activities. The estimations of both constant returns to scale and variable returns to scale allowed for computing scale inefficiencies[14]. In addition to estimating the technical inefficiencies, Chapter 5 estimated the PWI effect on technical inefficiency of manual weeding labour using a truncated bootstrap regression (Simar and Wilson, 2007). Another issue was the shortcoming of earlier studies on rice production in SSA that typically assumed a monotonic relationship between technical efficiency and its determinants, while drivers of technical efficiency can be non-monotonic (Wang 2002). The SFA model specified in Chapter 4 allowed to capture the non-monotonic inefficiency effect of factors such as distance to homestead and year of experience in rice farming. In this setting, the vectors of exogenous variables are allowed to affect inefficiency through the pre-truncated mean and variance of u_i, i.e. μ_i and σ_{ui}^2 respectively (Kumbhakar and Kai 2013, Wang 2002). Given the objective of this chapter, the SFA was appropriate. These findings will help to better tailor segmented programmes for rice development targeting increasing efficiency.

6.4. Policy implications of findings

Knowing the current status of the PW problem and how it affects rice production systems as a whole will help policy makers to take necessary and effective actions to prevent future spread and reduce damage to farmers.

[13] The technical efficiency with regard to a specific input can be define as the rate of the minimum quantity required of this input by the observed quantity used. The larger the quantity used in comparison to the minimum required quantity, the more inefficient the farmer is regarding the use of the concerned input.

[14] A unit is said to be scale inefficient when its size of operations is not optimal (too small or too large). If the unit is too small, an increase on its size will render the unit more efficient (the units exhibit an increasing returns to scale) . However, if the unit is too large, a decrease of its size will render the unit more efficient (the unit exhibits a decreasing returns to scale).

The conclusions of Chapter 2 pointed out that farmers can cope with the PW problem as far as they are aware of the problem and given their access and ability to manage production resources. In line with the results in Chapter 2, findings in Chapter 4 show that farmers can recover from potential parasitic weed-inflicted yield losses through learning from their experiences with PWI. This indicates the importance of access to information on PWs in their management. Informing farmers about the threat of PWs and possible control measures is the role of extension services and other organizations working for agricultural development. Previous researches however, showed that the institutional organisation of crop protection is weak and need to be strengthened to enhance farmers access to information (Beke, 2011; Schut et al., 2014). Therefore, improving farmers' access to information on PWs and their control requires an improvement of the institutional organization of extension services with respect to crop protection. For example by improving the capacity of extension officers with respect to understanding the general weed problem and PWs in particular, improving the frequency of contact with farmers and training farmers in weed management practices.

In addition to the results in Chapter 2 and 4, Chapter 5 provided evidence of substantial overall scale inefficiency (17% in Cote d'Ivoire and 15% in Benin) of rainfed rice systems. Similarly, Singbo and Oude Lansink (2010) found substantial scale inefficiency in lowland rice farming systems in Benin. Moreover, the negative effect of field size on technical inefficiency of weeding labour (Chapter 5) suggests that policies aiming at increasing the size of farms (mainly in Benin) may also increase the manageability of PW.

The results in Chapter 2 indicating that farmers from female-headed households have a lower ability to cope with parasitic weed are in line with findings in previous studies that women have relatively poor access to productive resources such as land, labour, water and chemical inputs (Abdulsalam-Saghir, 2011; Jackson, 1998; Nation, 2010; Ogato et al., 2009; Ojo et al., 2012). Their poor access to productive resources makes them more vulnerable to yield losses in times of stress (such as drought) (Eriksen et al., 2005). In areas where women are active agricultural producers, this raises the already well known issue of the need to improve women's access to productive resources in order to improve agricultural productivity and food security (O'Laughlin, 2007). Improving women's access to productive resources may increase substantially their ability of coping with the parasitic weed problem to increase rice productivity and improve family welfare (Agarwal, 1997).

Chapter 4 concluded that farmers' productivity and technical efficiency are significantly negatively affected by parasitic weeds. The policy implication of these findings is that local government authorities and farm support services should take any necessary action to prevent or at least contain the spread of parasitic weeds. If there is no action, this problem might compromise all efforts undertaken by SSA countries to boost domestic rice production in order to significantly reduce the food insecurity.

The results in Chapter 5 suggested that labour is overused in general and more specifically for weeding activities. Therefore, rice farmers can become more efficient using available labour, and it would be possible to reallocate a substantial fraction of their labour to other productive activities of the household without decreasing rice production. In order to fully utilize the productive potential of labour, farmers would need to 1) follow good agricultural practices in rainfed rice systems, 2) use labour saving strategies and 3) redirect any labour saved to other economically profitable activities. Ogwuike et al. (2014) found that weeding upland rice more than once increases weeding labour efficiency and rice productivity. However, they came to the conclusion that more labour saving strategies are needed. Labour saving strategies would not only allow farmers to devote more time to other (economic) activities but also provide the opportunity to farmers to increase their farm sizes (scaling up) through the development[15] of more land (Singbo and Oude Lansink, 2010). Stimulating and streamlining these processes will require an active involvement of policy makers, for example by developing rules and guidelines for the sustainable development of new land for rice farming.

6.5. Outlook for future research

The results in Chapter 2 show that there is a negative and significant correlation between the likelihood of infestation of plots by *R. fistulosa* and the location of rice field in the inland-valley (IV) bottom (N’cho et al., 2014). This corroborates recent findings by Kabiri et al. (2014), showing that parasitic weeds have rather distinct, species-specific habitats. Such findings are helpful for the development of targeted control strategies (see also Kabiri et al., 2014) as well as for informed risk analyses. Research on parasitic weeds ecology and biology combined with research on the socio-economic developments of parasitic weeds will help to develop bio-economic models to simulate the development of PWs and develop future management strategies against PWs in rainfed rice systems (see Cacho, 2008).

Results in Chapter 3 show that farmers affected by PW problems used many WMPs simultaneously suggesting that existing WMPs are not effective in controlling PWs when used individually. While this is in line with the commonly shared believe that an integrated approach to weed problems is likely the most effective and sustainable strategy (e.g. Franke et al., 2006; Harker

[15] By making more non-cropped lands or undeveloped lands more suitable for crop production

and O'Donovan, 2013; Rodenburg and Johnson, 2013) it also raises the question why different combinations of WMPs are not sufficiently effective for managing the problem of parasitic weeds in these farms. Apparently ad-hoc combinations of weed management strategies do not necessarily result in effective solutions. Moreover, results in Chapter 5 show that the currently used manual weeding modalities (most commonly used WMPs) are not effective against PWs either. Future research on PW management practices needs to explore the possibilities for developing more effective combinations of WMPs. A good starting point will be to focus on the determinants of adoption of relevant combinations of WMPs as discussed in Chapter 3.

6.6. Main conclusions

The thesis identified factors affecting infestation of rice farms by parasitic weeds and assessed the socio-economic impacts of parasitic weed infestations on rainfed rice producers in SSA in order to provide guidance for decision-making for rice farmers, researchers and policymakers for parasitic weed management strategies development. The research yielded the following main conclusions:

- Fields located in the inland valley bottoms or on poor soils have a higher likelihood of parasitic weeds infestation while mechanized land preparation and herbicide application at the recommended time reduce the likelihood of infestation (chapter 2).
- The severity of parasitic weed infestation is lower in larger farms and on farms practicing late sowing, mechanized land preparation, delayed herbicide application, manual weeding (three times) and application of a medium rate of fertilizer (180–230 kg ha^{-1}). Conversely, the severity of infestation is higher on fields where herbicides were applied following timings recommended for the management of ordinary weeds as well as on fields with a poor soil fertility (Chapter 2).
- The ability to cope with the parasitic weed is lower on female-headed farms, compared to male-headed farms (Chapter 2).
- Farmers are more likely to adopt improved weed management practices or to combine weed management practices when their plots are infested by parasitic weeds, or when they have access to the specific improved weed management practices, or they are trained in agricultural practices, or they have access to information, or when they crop larger farm (Chapter 3).
- Farmers owning their land adopt improved weed management practices requiring more investments or long-term planning such as water control (Benin) and rotation with legume crops (Tanzania) while, land renters or borrowers adopt improved management practices characterized by short-terms returns such as herbicide and fertilizer.

- The determinants of adoption of WMPs by farmers differ per country. Enhancing the adoption of parasitic weed management practices therefore requires country-specific approaches (Chapter 3).
- At current infestation levels, parasitic weeds induce productivity losses in the range of 21%–50%. However, farmers experiencing more frequent infestations achieve a higher technical efficiency level (Chapter 4).
- Substantial labour technical inefficiencies (58%–82%) exist within rainfed rice farming systems in Benin and Cote d'Ivoire. In case farmers operate fully efficiently, they have a substantial scope for labour savings that can be allocated to other economically profitable activities of the household or that can be used to crop larger farms (Chapter 5).
- Farmers' technical inefficiency increases with the parasitic weed infestation levels (Chapter 4, 5).
- Farm size reduced technical inefficiency, suggesting that increasing fields size can improve the efficiency of the use of productive resources (Chapter 5).
- Rainfed rice farming systems exhibit substantial scale inefficiency (15%–17%) (Chapter 5).
- Farmers cannot manage the parasitic weeds problem efficiently with the currently used manual weeding regimes and number of weeding operations (Chapter 5).

Table 6.1 Main impacts of parasitic weeds on rice farming systems in sub-Saharan Africa (SSA) as assessed by this research

Chapter	Impacting factors	Impacted outcomes		Impact value				
				Benin	Cote d'Ivoire		Tanzania	
				R. fistulosa	R. fistulosa	Striga	R. fistulosa	Striga
2[a]	Biophysical and socio-economic characters	Likelihood of Infestation (%)	Severity of infestation (plants/m2)					
	IV bed	18	ns					
	Poor soil	30	150					
	Plot size	ns	–142					
	Fallow length	ns	–27					
	Mechanized land preparation	–32	–59					
	Herbicide use at recommended time	–34	114					
	Delayed herbicide application	ns	–198					
	Fertilizer rate 180–230 kg/ ha	ns	155					
	Manual weeding three times	21	–113					
	Female headed-household	ns	64					
	PWI		109 plants/m2					
3	PWI & Severity	Adoption of individual WMPs		Direction of impact				
	PWI	Hand weeding		increase	decrease	ns		
		Hoe weeding		increase	– (ns)	increase	decrease	increase
		Herbicide use		decrease	decrease	increase	+(ns)	–(ns)
		Fertilizer use		– (ns)	increase	ns	+(ns)	increase
		Water control[b]		– (ns)				
		Rotation with legumes [c]					–	+
		Adoption of combinations of WMPs		Impact effect (%)				
		Hand weeding only		8.8	–0.6	–0.3	22	–17
		Hand and hoe		na	–2.3	ns	–18	3
		Hand and fertilizer		–0.6			7	ns
		Hand, herbicide and fertilizer)		0.4	3	ns		
		Hand, herbicide fertilizer and water control		1.4				
		Herbicide and fertilizer only			7.4	ns		
		Hand, hoe and rotation					–6.5	6
4		Productivity, TE and production uncertainty (%)						
	PW, infestation and severity	Total yield loss (direct + indirect)		50	21			
	PW, infestation (dummy)	Direct yield loss		32	18			
	PWI, severity (% of area)	TE (indirect yield loss)		–17.5	–2.6			
		Production uncertainty		4	1			
	PWI, frequency	TE		11.7	4.7			
		Production uncertainty		–4.8	–3.1			
5		TE of weeding labour						
	PWI, severity (% of area)			–0.1%	–0.3%			

Notes: IV= inland valley, PW= parasitic weed, PWI= parasitic weed infestation, ns= non-significant, TE= Technical efficiency.
[a] all information provided under Chapter 2 refer to Benin and *Rhamphicarpa fistulosa* only.
[b] Information on water control were reported for Benin only.
[c] Information on rotation with legume crops were reported for Tanzania only.

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Summary

Samenvatting

Summary

In sub-Saharan Africa (SSA), rice is an important strategic crop for achieving food security. However, the increase in domestic production has not been able to match the increasing demand due to many biotic and abiotic production constraints. Weeds, including parasitic weeds, are among the most damaging biotic constraints in rice production of SSA countries. The overall objective of this thesis is to identify factors affecting infestation of rice farms by parasitic weeds and to assess the economic and social impact of parasitic weeds on primary producers of rainfed rice systems in order to provide guidance for decision-making for rice farmers and policymakers in developing strategies to cope with parasitic weeds.

The assessment focused on the most important parasitic weeds species in rainfed rice systems (i.e, S. *hermonthica*, *S. asiatica* and *Rhamphicarpa fistulosa*) of SSA. *Rhamphicarpa* occurs in the rainfed lowlands while *Striga* spp are found in the upland rainfed environment only. Data from three SSA countries (i.e. Benin, Cote d'Ivoire and Tanzania) were used to compare across countries the impact of parasitic weeds on rice production systems, farmers' decisions and management abilities. Data gathering consisted of fields observations and interviews with 664 rice farmers using a structured questionnaire.

Chapter 2 explored factors that affect the infestation of rainfed lowland rice fields by the parasitic weed *Rhamphicarpa fistulosa* and farmers' ability to cope with the problem. Factors such as biophysical characters of the rice growing environment, farmers' management practices, and socio-economic characteristics that affect the infestation of rainfed lowland rice fields by *Rhamphicarpa* and farmers' ability were reviewed. A double hurdle model was used, which analyses simultaneously the likelihood of occurrence and the severity of infestation of the parasitic weed. The results show that *Rhamphicarpa* affected 72% of the surveyed rice plots in infested inland valleys and the average severity of infestation was 109 plants per m^2. The likelihood of infestation was higher on poorly fertile soils and fields located in the inland-valley bottom, and it decreases with timely use of herbicides and ploughing. The severity of infestation was higher on rice fields belonging to female-headed farms than male-headed farms and reduced through management practices such as late sowing, timely application of post-emergence herbicide, three operations of manual weeding, medium-rate fertilizer application and prolonged fallow. The likelihood and the severity of infestation were found to be negatively correlated, indicating that the higher the probability of infestation of a rice field, the lower the observed severity of infestation. This observation can be explained by farmers' awareness of the risk of infestation. Farmers being aware that their rice crops run a higher risk of infestation might be (better) prepared to take

necessary actions to face the problem even they could not prevent it from happening. Hence, the observed severity of infestation is lower than expected. Finally, these findings suggest that farmers can reduce the likelihood and the severity of infestation of their plot as long as they are aware of factors causing the problem given their access to and management capacity of production resources.

Chapter 3 examines the current weed management practices (WMPs) used by rice farmers to cope with parasitic weeds infestation and its severity and investigates factors determining farmers' choices for specific WMPs combinations. The chapter used a multivariate probit (MVP) model to identify the WMPs currently used by rice farmers and the farm-specific, socio-economic and institutional factors that influence farmers' choices for WMPs. To identify the determinants of specific WMPs strategies (consisting of stand-alone or combinations of weed management measures) adopted by farmers, the average marginal effects (AMEs) of each covariate on the partial and joint multivariate probabilities were estimated. Results show that, hand weeding was the most frequently used (87%) WMP followed by hoe weeding (62%), fertilizer use (55%), and herbicide use (53%). Parasitic weeds infestation shifts farmers from using a single traditional WMP towards the use of a combination of multiple improved WMPs. Similar effects were observed with factors such as access to inputs, access to information, and training in agricultural practices. Among other variables, lowland cropping, *R. fistulosa* infestation and, education level have different effects on farmers' adoption decision across countries. Results also show that *Striga* spp and *R. fistulosa*, have different impact on farmers' choices of WMPs combinations in different countries. Hence, species-specific and country-specific approaches and technologies are required. Focusing on factors affecting farmers' choices for different combinations of WMPs strategies per country is a good starting point to develop more effective and sustainable PW management strategies for rainfed rice systems in SSA. Moreover, awareness of a specific PW problem and the range of possible approaches to address it, should be increased.

Chapter 4 assessed the impact of parasitic weeds infestation on farmers' productivity and examined how this problem and managerial factors prevent farmers from achieving optimal technical efficiency levels in Benin and Cote d'Ivoire. A stochastic frontier production function was estimated which allowed for identifying exogenous factors that prevent farmers from achieving optimal technical efficiency levels. At current infestation levels, parasitic weeds are found to induce productivity losses ranging from 21% to 50% in Cote d'Ivoire and Benin. The results suggest that farmers cope with parasitic weed problems through learning as those experiencing more frequent infestations tend to achieve higher technical efficiency levels (12% in Benin and 5% in Cote d'Ivoire) and lower production uncertainty (5% and 3% for Benin and Cote d'Ivoire respectively). On average, farmers technical efficiency increases with farming experience. However, beyond a farming experience of about 20 years, farmers' overall technical efficiency levels tend to decrease (1.4% and 2% respectively for Benin and Cote d'Ivoire) and the production uncertainty increases (2% and 3% respectively for Benin and Cote d'Ivoire). These findings are important as they will assist national extension services in SSA in designing segmented training programmes that are better tailored to rice farmers' needs, thereby preventing food security from being jeopardized by parasitic weeds.

Chapter 5 estimated the technical inefficiency of weeding labour in rainfed rice systems. Several performance indicators were estimated such as the overall input technical inefficiency, the weeding labour technical inefficiency, the technical inefficiency of other labour as well as their corresponding scale inefficiencies. Furthermore, the sources of different technical inefficiency measures were investigated. The chapter used a robust two-stage estimate, consisting of a Data Envelopment Analysis with directional input distance function in the first stage allowing to compute the technical inefficiencies as mentioned above. At the second stage, a single truncated bootstrap regression model was estimated to identify sources of weeding labour inefficiencies. The first stage results provided evidence of substantial overall input technical inefficiency as well as weeding labour and other labour technical inefficiency in rainfed rice farming systems in the studied countries. Results suggest that at the current technology level, farmers can save at least 69% of weeding labour in Benin and 58% in Cote d'Ivoire without reducing the observed rice production or increasing the use of other inputs. The results also show that farmers experiencing parasitic weeds on their fields have a lower technical efficiency compared to those whose fields were not infested (mainly in Cote d'Ivoire). The second stage bootstrap regression showed that a lower weeding labour inefficiency is associated with larger farms (in Benin), farms with a single, early weeding strategy and higher education levels (in Cote d'Ivoire). Technical inefficiencies increased with the parasitic weed infestation levels. However, there was no significant effect of any weeding modality on technical inefficiency when plots were infested by parasitic weeds. There was no evidence that the currently used manual weeding modalities were able to manage parasitic weeds efficiently.

The main finding of this thesis is that in sub-Saharan Africa, parasitic weeds infestation has a negative impact on rainfed rice systems' productivity and the use of production resources. However, these impacts can be reduced if farmers have good access to production resources and knowledge/information and manage them efficiently.

From this thesis , the following main conclusions were derived:

- Fields located in the inland valley bottoms or on poor soils have a higher likelihood of parasitic weeds infestation while mechanized land preparation and herbicide application at the recommended time reduce the likelihood of infestation (Chapter 2).
- The severity of parasitic weed infestation is lower in larger farms and on farms practicing late sowing, mechanized land preparation, delayed herbicide application, manual weeding (three times) and application of a medium rate of fertilizer (180–230 kg ha^{-1}). Conversely, the severity of infestation is higher on fields where herbicides were applied following timings recommended for the management of ordinary weeds as well as on fields with a poor soil fertility (Chapter 2).
- The ability to cope with the parasitic weed is lower on female-headed farms, compared to male-headed farms (Chapter 2).
- Farmers are more likely to adopt improved weed management practices or to combine weed management practices when their plots are infested by parasitic weeds, or when they have access to the specific improved weed management practices, or they are trained in agricultural practices, or they have access to information, or when they crop larger farm (Chapter 3).
- Farmers owning their land adopt improved weed management practices requiring more investments or long-term planning such as water control (Benin) and rotation with legume crops (Tanzania) while, land renters or borrowers adopt improved management practices characterized by short-terms returns such as herbicide and fertilizer (Chapter 3).
- The determinants of adoption of WMPs by farmers differ per country. Enhancing the adoption of parasitic weed management practices therefore requires country-specific approaches (Chapter 3).
- At current infestation levels, parasitic weeds induce productivity losses in the range of 21%–50%. However, farmers experiencing more frequent infestations achieve a higher technical efficiency level (Chapter 4).
- Substantial labour technical inefficiencies (58%–82%) exist within rainfed rice farming systems in Benin and Cote d'Ivoire. In case farmers operate fully efficiently, they have a substantial scope for labour savings that can be allocated to other economically profitable activities of the household or that can be used to crop larger farms (Chapter 5).
- Farmers' technical inefficiency increases with the parasitic weed infestation levels (Chapter 4, 5).
- Farm size reduced technical inefficiency, suggesting that increasing fields size can improve the efficiency of the use of productive resources (Chapter 5).
- Rainfed rice farming systems exhibit substantial scale inefficiency (15%–17%) (Chapter 5).

- Farmers cannot manage the parasitic weeds problem efficiently with the currently used manual weeding regimes and number of weeding operations (Chapter 5).

Samenvatting

Rijst is een belangrijk strategisch gewas voor de verbetering van de voedselzekerheid in Sub-Sahara Afrika (SSA). De groei in lokale rijstproductie blijft echter achter ten opzichte van de toename in de lokale vraag naar rijst als gevolg van vele biotische en abiotische productiebeperkende factoren. Zo behoren onkruiden, waaronder de parasitaire onkruiden, tot de meest schadelijke biotische productie verlagende factoren in de rijstteelt van landen in SSA.

Dit onderzoek is gericht op het identificeren van factoren die van invloed zijn op de besmetting van rijstvelden met parasitaire onkruiden en het analyseren van de economische en sociale gevolgen van dergelijke onkruidbesmettingen voor de primaire rijsttelers in regenafhankelijke productiesystemen om de besluitvorming van rijsttelers en beleidsmakers omtrent de ontwikkeling van beheersmaatregelen tegen parasitaire onkruiden te ondersteunen.

De uitgevoerde analyse concentreert zich daarbij op de belangrijkste parasitaire onkruidsoorten in de regenafhankelijke rijstteelt van SSA: *Striga hermonthica*, *Striga asiatica* en *Rhamphicarpa fistulosa*. De *Striga* spp. komen voor in de droge delen van de regenafhankelijke rijstteelt, terwijl *R. fistulosa* zich voornamelijk in de natte delen ophoudt. Gegevens van Benin, Ivoorkust en Tanzania zijn gebruikt om de impact van parasitaire onkruiden op de rijst-productiesystemen, de beslissingen omtrent bestrijding als ook de managementvaardigheden van rijsttelers over de verschillende landen met elkaar te vergelijken. De data van deze studie bestaan uit veldwaarnemingen en interviews met 664 rijsttelers middels een gestructureerde vragenlijst.

Hoofdstuk 2 geeft inzicht in de factoren die van invloed zijn op de besmetting van regenafhankelijke natte rijstpercelen met het parasitaire onkruid *Rhamphicarpa fistulosa* als ook het vermogen van de rijsttelers om met dit probleem om te gaan. Daartoe zijn factoren als de biofysische karakteristieken van de productie omgeving, de toegepaste managementpraktijken van de rijsttelers, het aanpassingsvermogen van de rijsttelers ten aanzien van een *R. fistulosa* besmetting alsook de sociaal-economische kenmerken die van invloed kunnen zijn op de besmettingsgraad van natte rijstpercelen nader onderzocht. Met behulp van een *double hurdle* model zijn de waarschijnlijkheid van het optreden van een besmetting en de graad van een besmetting met een parasitaire onkruid daarbij gelijktijdig geanalyseerd. De resultaten tonen aan dat 72% van de onderzochte rijstpercelen in besmette gebieden (valleien) getroffen is door *R. fistulosa* met een gemiddelde besmettingsgraad van 109 onkruidplanten per m^2. De kans op besmetting is hoger op minder vruchtbare bodems en op percelen gelegen in de lagere delen van de vallei, en vermindert bij een tijdige toepassing van herbiciden en ploegen. De graad van de besmetting is hoger op rijstpercelen van bedrijven die geleid worden door een vrouw dan op percelen van bedrijven geleid door een man en vermindert bij toepassing van management praktijken zoals laat zaaien, tijdig toepassen van contact herbiciden, regelmatig handmatig wieden, gematigd bemesten en langdurig braak laten liggen.

Uit de double hurdle analyse blijken de waarschijnlijkheid en de mate van besmetting negatief gecorreleerd te zijn, hetgeen impliceert dat hoe hoger de kans op besmetting, hoe lager de waargenomen besmettingsgraad. Deze correlatie kan worden verklaard door de mate waarin de rijstelers bewust zijn van het risico op besmetting. Telers die zich ervan bewust zijn dat hun rijstgewassen een hoger risico op besmetting lopen, zijn mogelijk (beter) voorbereid op het nemen van de nodige beheersmaatregelen, ondanks het feit dat ze de besmetting niet kunnen voorkomen. Hierdoor is de waargenomen besmettingsgraad lager dan verwacht.

Deze bevindingen suggereren dat rijsttelers zowel de waarschijnlijkheid als de mate van besmetting van hun perceel met *R. fistulosa* kunnen verminderen, zolang zij bewust zijn van de factoren die het probleem veroorzaken, toegang hebben tot de benodigde productiemiddelen en deze op een bekwame manier beheren.

Hoofdstuk 3 bespreekt de onkruid beheerspraktijken (OBP) die momenteel door rijsttelers worden toegepast om het probleem van een parasitaire onkruid besmetting tegen te gaan en onderzoekt de factoren die bepalend zijn bij de keuzes van specifieke OBP combinaties. Het hoofdstuk gebruikt een multivariaat probit model om de OBPs te identificeren die momenteel door rijsttelers worden toegepast en om de bedrijfsspecifieke, sociaal-economische en institutionele factoren te analyseren die van invloed zijn op de keuzes van de telers voor de toepassing van bepaalde OBP. Om de determinanten van specifieke OBP strategieën (bestaande uit individuele of combinaties van onkruid beheersmaatregelen) te identificeren zijn de gemiddelde marginale effecten van elke verklarende variabele op de gedeeltelijke en de gezamenlijke multivariate waarschijnlijkheid berekend. De resultaten tonen aan dat, onkruid wieden met de hand het vaakst als OBP wordt toegepast (87%) gevolgd door wieden met behulp van de hak (een traditioneel landbouw werktuig) (62%), bemesting (55%) en het toepassen van herbiciden (53%). Een besmetting met een parasitair onkruid beïnvloedt de keuze van de telers, waarbij een verschuiving optreed van het gebruik van een enkele traditionele OBP naar het gebruik van een combinatie van meerdere OBP’s. Soortgelijke keuze effecten zijn waargenomen bij factoren als de toegankelijkheid tot productiemiddelen, informatie en training in landbouwpraktijken. Naast andere variabelen, hebben natte rijstteelt, *R. fistulosa* besmetting en onderwijs niveau verschillende effecten op de OBP keuze van telers over de landen heen. Resultaten tonen ook aan dat een besmetting met *Striga* spp of *R. fistulosa* verschillende gevolgen hebben voor de keuzes van OBP combinaties in de verschillende landen.

Soort-specifieke en land-specifieke benaderingen en technologieën zijn zodoende een vereiste bij de verdere ontwikkeling van beheersmaatregelen. Door uit te gaan van de factoren die de keuzes van de telers voor de verschillende combinaties van OBP binnen een bepaald land beïnvloeden kunnen meer doeltreffende en duurzame parasitaire onkruid beheersmaatregelen voor regenafhankelijke rijst systemen in SSA worden ontwikkeld. Daarnaast dient de bewustwording omtrent het specifieke probleem van een parasitaire onkruid en van de keuzemogelijkheden omtrent de wijze van aanpak ervan te worden vergroot.

Hoofdstuk 4 bepaalt de impact van een besmetting met een parasitair onkruid op de productiviteit van de telers en onderzoekt hoe dit probleem als mede de algemene management factoren, rijsttelers in Benin en Ivoorkust verhinderen in het bereiken van optimale technische efficiëntieniveaus. Een stochastische frontier-productiefunctie is geschat. Dit maakt de identificatie mogelijk van exogene factoren, die het bereiken van de optimale technische efficiëntieniveaus verhinderen. Op het huidige niveau van besmetting, resulteren parasitaire onkruiden in verliezen in de productiviteit in Ivoorkust en Benin variërend van 21% tot 50%. De resultaten suggereren dat telers leren om te gaan met parasitaire onkruid problemen door middel van ervaring; telers die vaker geconfronteerd worden met parasitaire onkruidbesmettingen bereiken vaak hogere technische efficiëntieniveaus (12% in Benin en 5% in Ivoorkust) en lagere productie onzekerheid (5% voor Benin en 3% voor Ivoorkust). Over het algemeen neemt de technische efficiëntie toe met de ervaring in de rijstteelt. Echter, bij rijsttelers met meer dan 20 jaar landbouw ervaring lijkt de overall technische efficiëntie weer af te nemen (1,4% en 2% respectievelijk voor Benin en Ivoorkust) en de productieonzekerheid toe te nemen (2% en 3% respectievelijk voor Benin en Ivoorkust). Deze bevindingen zijn belangrijk omdat zij nationale voorlichtingsdiensten in SSA zullen helpen bij het ontwerpen van gesegmenteerde trainingsprogramma's die beter zijn toegesneden op de behoeften van de rijsttelers, waardoor voorkomen wordt dat de voedselzekerheid in het gedrang komt als gevolg van parasitaire onkruidbesmettingen.

In Hoofdstuk 5 wordt de technische inefficiëntie van de arbeid die ingezet wordt bij het onkruid wieden in regenafhankelijke rijstteeltsystemen geanalyseerd. Verschillende prestatie-indicatoren zijn geschat, zoals de totale input technische inefficiëntie, de technische inefficiëntie van de arbeidsinzet bij het onkruid wieden, de technische inefficiëntie van andere arbeidsinzet, alsook de overeenkomstige schaal inefficiënties. Daarnaast zijn de oorzaken van verschillen tussen bedrijven in de mate van verschillende technisch inefficiëntie maatstaven onderzocht. Het hoofdstuk maakt gebruik van een robuuste tweetraps schatting, bestaande uit een *Data Envelopment Analysis* met een directionele input afstandsfunctie in de eerste fase om de verschillende technische inefficiënties te berekenen. In de tweede fase is vervolgens een *truncated bootstrap* regressiemodel geschat om de oozaken van een inefficiënte arbeidsinzet bij het wieden te identificeren.

De resultaten uit de eerste fase geven blijk van een aanzienlijke technische inefficiëntie ten aanzien van de totale ingezette input, evenals van de arbeidsinzet bij het wieden en van de overige arbeidsinzet in de regenafhankelijke rijst-producerende bedrijfssystemen van de bestudeerde SSA landen. Resultaten suggereren dat op het huidige niveau van de technologie, rijsttelers in Benin tenminste 69% op de arbeidsinzet bij het wieden kunnen besparen zonder vermindering van de waargenomen rijstproductie of het verhogen van het gebruik van andere inputfactoren. Voor rijsttelers uit Ivoorkust is dit 58%. Uit de resultaten blijkt ook dat telers (voornamelijk die in Ivoorkust) die geconfronteerd worden met een parasitaire onkruidbesmetting op hun rijstvelden een lagere technische efficiëntie hebben in vergelijking met telers waarvan de velden niet besmet zijn.

De tweede fase bootstrap regressie toont aan dat een lagere inefficiëntie van de arbeidsinzet bij het wieden geassocieerd is met grotere bedrijven (in Benin), rijsttelers die eenmalig maar vroeg in het seizoen wieden en rijstelers met een hoger onderwijs niveau (in Ivoorkust). De technische inefficiënties nemen toe met het niveau van de parasitaire onkruid besmetting. Op de besmette percelen is echter geen significant effect van de onderzochte OBP combinaties op de technische efficiënte waargenomen. Er is geen bewijs dat de momenteel gebruikte combinaties van handmatig onkruid wieden en andere methoden volstaan voor een efficiënte beheersing van het parasitaire onkruiden probleem.

De belangrijkste algemene conclusie van dit proefschrift is dat in sub-Sahara Afrika parasitaire onkruid besmettingen een negatief effect hebben op de productiviteit in de regenafhankelijke rijstsystemen en op het gebruik van productiemiddelen. Echter, deze effecten kunnen worden verminderd als rijsttelers toegang hebben tot kennis en productiemiddelen en deze efficiënt kunnen beheren.

Uit dit proefschrift zijn de volgende conclusies afgeleid:

- Rijstvelden gelegen in lagere delen (m.b.t. *Rhamphicarpa*) of op arme bodems hebben een hogere kans op een parasitaire onkruidbesmetting, terwijl een gemechaniseerde landbewerking voor aanvang van de teelt en een herbicide toepassing op het aanbevolen tijdsstip de kans op besmetting verminderen (Hoofdstuk 2).
- De ernst van een parasitaire onkruid besmetting is lager op grotere bedrijven en op bedrijven die laat zaaien, het land gemechaniseerd bewerken voor aanvang van de teelt, vertraagd herbicide toepassen, handmatig wieden (driemaal) en een gemiddelde meststofhoeveelheid toepassen (180 – 230 kg ha^{-1}). Daarentegen is de graad van besmetting hoger op velden waar herbiciden

worden toegepast op tijden aanbevolen in richtlijnen voor het beheer van gewone onkruiden, alsmede op velden met een slechte bodemvruchtbaarheid (Hoofdstuk 2).

- De capaciteit om om te gaan met parasitaire onkruiden is kleiner op bedrijven geleid door een vrouw dan op bedrijven geleid door een man (Hoofdstuk 2).
- Rijsttelers passen eerder verbeterde onkruid beheerspraktijken toe, of combineren eerder verscheidene onkruid beheerspraktijken wanneer hun percelen besmet zijn met een parasitaire onkruid, of wanneer zij toegang hebben tot specifiek verbeterde onkruid beheerspraktijken, of zijn opgeleid in landbouwpraktijken, of toegang tot informatie hebben, of telen op grotere bedrijven (Hoofdstuk 3).
- Rijsttelers die land in eigendom hebben passen verbeterde onkruid beheerspraktijken toe waarvoor meer investeringen of lange termijn-planningen nodig zijn, zoals watercontrole (Benin) en vruchtwisseling met een peulvrucht gewas (Tanzania), terwijl telers die land huren of op krediet werken verbeterde beheerspraktijken toepassen die gekenmerkt worden door een korte-termijn rendement zoals het toepassen van herbicide en (kunst)mest (Hoofdstuk 3).
- De determinanten voor het toepassen van OBPs door rijsttelers verschillen per land. Verbetering van de toepassing van parasitaire onkruid beheerspraktijken vereist daarom een land-specifieke benadering (Hoofdstuk 3).
- Op het huidige niveau van de besmetting veroorzaken parasitaire onkruiden een productiviteitsverlies variërend tussen de 21%-50%. Rijsstelers die frequenter met besmettingen geconfronteerd worden realiseren een hoger technisch efficiëntieniveau (Hoofdstuk 4).
- Aanzienlijke arbeid technische inefficiënties (58% – 82%) bestaan binnen de regenafhankelijke rijstproducerende bedrijfssystemen in Benin en Ivoorkust. Rijsttelers hebben een aanzienlijke mogelijkheid om op arbeid te besparen door volledig efficiënt te opereren. Bespaarde arbeid zou kunnen worden toegepast in andere economisch rendabele activiteiten van het huishouden of worden gebruikt om meer land te bewerken (Hoofdstuk 5).
- De technische inefficiëntie van rijsttelers neemt toe met het niveau van een parasitaire onkruid besmetting (Hoofdstuk 4, 5).
- De technische inefficiëntie verlaagt met een toename van de omvang van een bedrijf hetgeen suggereert dat het vergroten van rijstteelt bedrijven de efficiëntie van het gebruik van productiemiddelen kan verbeteren (Hoofdstuk 5).
- Regenafhankelijke rijstproducerende landbouwsystemen vertonen een aanzienlijke schaal inefficiëntie (15% - 17%) (Hoofdstuk 5).

Rijsttelers zijn niet in staat om het parasitaire onkruid probleem efficiënt te beheersen met de momenteel gebruikte handmatige methoden van onkruid wieden (Hoofdstuk 5).

About the author

Curriculum Vitae

Publications

Training and Supervision Plan

Curriculum Vitae

Simon A. N'cho was born on February, 5th, 1976 in Akoupe, Cote d'Ivoire. In 1999, he obtained his bachelor degree in tropical agronomy at the National Polytechnic Institute Houphouet Boigny of Yamoussoukro in Côte d'Ivoire (INP-HB). In 2001, he has completed his Engineer degree in agronomy at INP-HB with the specialization in agricultural economics. His research analysed typologies of agricultural production systems in forest zones of Côte d'Ivoire. He joined the Africa Rice Center (ex-WARDA) in September 2001 where he has worked as research assistant successively in production economics, policy economics and impact assessment economics. He has working experience in over 15 countries in Africa in collaboration with International Agricultural Research Centres (IARC) and in partnership with National Agricultural Research Systems (NARS) in multidisciplinary teams. In 2009, Simon has obtained his master degree in economics and sociology for rural development at University of Abomey Calavi in Benin. His master thesis focused on the competitiveness of locally produced rice in Guinea against imported rice from Asia. Since December 1st 2010, he joined Business Economics group of Wageningen University in the Netherlands for his PhD. His research assessed the socio-economic impacts of parasitic weeds in rainfed rice systems of sub-Saharan Africa. Simon research interest focuses farms performance analysis, competitiveness of rice value chains and technology diffusion, adoption and impact assessment.

List of publications

Refereed Scientifics journals

N'cho, S.A., Mourits, M., Rodenburg, J., Demont, M. and Oude Lansink, A., 2014. Determinants of parasitic weed infestation 1 in rainfed lowland rice in Benin. *Agricultural Systems* 130, 105–115.

N'cho, S.A., Mourits, M., Rodenburg, J., Mohamed, JK. and Oude Lansink, A., Determinants of farmers' adoption of parasitic weed management practices in rain-fed rice systems in sub-Saharan Africa. (under review at *Crop Protection*)

N'cho, S.A., Mourits, M., Demont, M., Adegbola, P.Y. and Oude Lansink, A., Impact of parasitic weeds infestations on rice farmers' productivity and technical efficiency in SSA. (under review at *Food Security*)

N'cho, S.A., Mourits, M., Demont, M., Rodenburg, J. and Oude Lansink, A., Inefficiency of manual weeding in rainfed rice systems under parasitic weeds infestation. (under review at *Agricultural Economics*)

|Conference paper and seminars

N'cho, S.A., Mourits, M., Rodenburg, J., Demont, M. and Oude Lansink, A., 2013. Factors affecting parasitic weeds infestation in rain-fed lowland rice: the case of Rhamphicarpa fistulosa in Benin. In abstract proceeding of the 12th World Congress on Parasitic Plants, Sheffield, UK, 15–19 July, 2013.

N'cho, S.A., Akanvou, L., Arouna, A. and Rodenburg, J., 2014. Farmers' perception of climate change and adaptations used in rainfed rice systems in Cote d'Ivoire. Oral presentation in the 4th International rice congress, Bangkok, Thailand, 27–31 October 2014.

N'cho, S.A., Mourits, M., Demont, M., Adegbola, P.Y. and Oude Lansink, A., 2014. Rice farmers' productivity and technical efficiency under parasitic weeds infestation environment. Poster presentation in the 4th International rice congress, Bangkok, Thailand, 27-31 October 2014.

Completed Training and Supervision Plan

Wageningen School of Social Sciences

Description	Institute[1]	Year	ECTS[2]
General courses			
Introduction workshop	WASS	2011	
Writing of the PhD proposal	WASS	2011	4
How to write a convincing proposal	LS, WUR	2013	0.3
Writing and presenting a Scientific Paper	WGS	2013	1.2
Workshop Presentation Skills	LS, WUR	2013	1
Discipline-Specific Courses			
Rural Economic Analysis (AEP 31306)	AEP, WUR	2011	6
Econometrics (AEP 21306)	AEP, WUR	2011	6
Advanced econometrics (AEP 50806)	WUR	2011	6
Economics Models (AEP 30806)	WUR	2011	6
Multivariate data analysis	NAKE	2011	3
Microeconomics Panel data	NAKE	2011	3
Theory and practice of efficiency and productivity measurement	WASS	2012	3
Parametric Efficiency and Productivity Analysis	WASS	2013	3
Business Economics PhD Meetings	BEC, WUR	2010-2014	4
Contribution to conferences and seminars			
"Factors affecting parasitic weeds infestation in rain-fed lowland rice: the case of Rhamphicarpa fistulosa in Benin"	IPPS, 12 WCPP, Sheffield, UK	2013	1
"Climate change: Perception and adaptation of rice farmers in Cote d'Ivoire"	AfricaRice, 3ARC, Yaoundé, Cameroon	2013	1
"Determinants of farmers' adaptations to climate change in rainfed rice systems in Cote d'Ivoire"	IRRI, 4IRC, Bangkok, Thailand	2014	1
"Rice farmers' productivity and technical efficiency under parasitic weeds infestation environment"	4IRC, Bangkok Thailand	2014	1
Supervision activities			
Supervision of MSc Students	AfricaRice & INP-HB	2011–2012	2
Total (30–45 ECTS)			**52.5**

[1] WASS= Wageningen School of Social Sciences, LS= Language Services, WUR= Wageningen University and Research Centre, AEP= Agricultural Economics and Rural Policy, NAKE= Netherlands network of economics, BEC= Business Economics Group, IPPS= International Parasitic Plant Society, 12WCPP= 12th World Congress on Parasitic Plants, AfricaRice= Africa Rice Center, 3ARC= 3rd Africa Rice Congress, IRRI= International Rice Research Institute, 4IRC= 4th International Rice Congress, INP-HB= National Polytechnic Institute Felix Houphouët Boigny

[2] One credit according to ECTS is on average equivalent to 28 hours of study load

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On 15 April 2010, my dear friend Daniel Tia forwarded me an announcement in which the Africa Rice Center and Wageningen University were seeking candidates for 3 PhD positions within the PARASITE (*"Preparing African Rice Farmers Against Parasitic Weeds in a Changing Environment"*) project. I was highly interested in the position on "Economic impact of parasitic weeds". Despite the short notice (application process was closing in 3 hours), I could submit my application before the deadline. Fortunately, I was selected after an interview conducted by Professor Oude Lansink (Alfons), Dr Demont (Matty) and Dr Adegbola (Patrice). Alfons, Matty and Patrice, I'm grateful to you for giving me the opportunity to join Wageningen University through the PARASITE project. By doing so, you permitted me to fulfil a dream of about 10 years old.

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Colophon

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Front cover: Manual weeding of rice farm and pictures of parasitic weeds *Striga asiatica*, *Striga hermonthica* and *Rhamphicarpa fistulosa* in rice fields.

Reverse cover: Pictures of rice plants attacked (top pictures) and rice fields destroyed (bottom) by *Striga* and *Rhamphicarpa*. The pictures in-between show the main weeding method and the importance of timing in managing parasitic weeds in rice.