Impact of infestation by parasitic weeds 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. However, productivity and technical efficiency levels in rice production systems are severely constrained by biotic constraints such as parasitic weeds. This paper assesses the impact of infestation by parasitic weeds on rice farmers' technical efficiency and examines the potential role of managerial factors in improving technical efficiency. Household and field survey data were collected from rice farmers in Cote d'Ivoire and Benin in West Africa. A stochastic frontier production function was estimated, which allows for identifying the levels of exogenous factors that prevent farmers from improving technical efficiency levels. The results suggest that farmers cope with parasitic weeds through learning from experiencing infestations by parasitic weed. The results will assist national extension in designing segmented training programmes that are better tailored to rice farmers' needs and preventing food security from being jeopardised by parasitic weeds.

Key words: rain-fed rice; parasitic weeds; sub-Saharan Africa; stochastic frontier model; technical efficiency

1. Introduction

Rice production is an important component of strategies for food security in sub-Saharan Africa and income generation in rice-producing regions (Nakano *et al*. 2013). However, it is faced with many biotic and abiotic constraints that negatively affect productivity. These constraints undermine the efforts made by many sub-Saharan countries since the 2008 food crisis to boost domestic rice production in order to fill the gap between production and consumption (Demont 2013). Among the biotic constraints, weeds, and particularly the parasitic weeds *Striga* spp. and *Rhamphicarpa fistulosa*, are the most damaging in rain-fed rice production environments (Oerke & Dehne 2004; Rodenburg & Johnson 2009; Rodenburg *et al*. 2016). Weeds pose a serious threat to food security in sub-Saharan Africa (AfricaRice 2013; A. Diagne *et al*. 2013), as average rice yield loss due to weeds is estimated at 32% (Oerke & 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, weed problems in sub-Saharan Africa vary across countries and across rice-production environments. Cote d'Ivoire is reported to be among the countries with the highest proportion of farmers experiencing weed problems (74%), as well as 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 parasitic weeds. A recent study by Rodenburg *et al*. (2016) estimated that the most likely economic loss inflicted by all parasitic weeds in rice in Africa was some US $200 million, increasing by US $30 million annually. In Benin, the most important parasitic weed threatening rice production is *Rhamphicarpa* (N'cho *et al*. 2014), while both were observed in Cote d'Ivoire, with a higher proportion of farmers (35%) experiencing *Striga* spp. than *Rhamphicarpa* (4%).

Only a few empirical studies have analysed rice farmers' technical efficiency and its determinants in sub-Saharan Africa (e.g. Audibert 1997; Sherlund *et al*. 2002; Singbo & Oude Lansink 2010; M. Diagne *et al*. 2013). Since many rice farmers are operating under subsistence-based production systems, their food security is highly exposed to the stochastic forces of nature. Accounting for environmental conditions in the estimation of technical efficiency is hence crucial. However, to our knowledge only one study has addressed this issue in sub-Saharan Africa. Sherlund *et al*. (2002) observed in a sample of 464 traditional rice plots in Cote d'Ivoire that technical efficiency 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 technical efficiency. Similar findings were reported in technical efficiency studies elsewhere (Rahman & Hasan 2008; Tan *et al*. 2010). Moreover, since rice is produced in a stochastic environment, it is important not only to assess how those factors affect technical efficiency, but also how they influence its variance (Wang 2002). Higher variance in technical efficiency implies a higher production uncertainty, and consequently higher risks of food insecurity.

Another shortcoming of earlier studies is that they typically assumed a monotonic relationship between technical efficiency and its determinants, while drivers of technical efficiency 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 technical efficiency can change over different quartiles in the sample and may even switch signs. Identifying non-monotonicity in the determinants of technical efficiency and its variance enables the design of segmented extension programmes that are better tailored to farmers' needs. This is important for persistent pests, such as parasitic weeds in sub-Saharan Africa, which severely jeopardise food security and require complex pest management. Therefore, the contribution of this study is to present the first evidence of the impact of parasitic weeds on sub-Saharan Africa rice farmers' productivity, technical efficiency and its variance, and to identify the factors – and the nature of their relationship – that affect these important determinants of food security.

2. Methods and data

2.1 Theoretical framing and model specification

This paper uses a stochastic frontier approach to analyse the impact of parasitic weed infestation on rice farmers' technical efficiency. This approach was chosen because small-scale rain-fed rice systems in sub-Saharan Africa 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 (Sherlund *et al*. 2002; Rahman & Hasan 2008; Tan *et al*. 2010). Moreover, the data used may be subject to measurement errors because they are derived from farmers' perceptions. This may affect the estimation of technical efficiency. Hence, Coelli *et al*. (1998) recommend the use of stochastic frontier models for sectors that rely heavily on nature, such as agriculture, and particularly in the context of a developing country.

In the production process, factors such as weeds, diseases, pests and pollutants, which are known as growth-reducing factors, lower attainable production levels to the actual (observed) yield levels (Zhengfei *et al*. 2006). Thus, input use and farmers' productivity may be affected by farm environmental conditions. Omitting the production environment conditions from 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 (Sherlund *et al*. 2002; Rahman & Hasan 2008). Variables related to the production environment were therefore included in the production frontier, as follows:

$$Y_i = f(X_i, W_i) + v_i - u_i \ , \tag{1}$$

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, and v_i is a two-sided random error associated with factors beyond the control of the farmer. It is assumed to be *iid* $N(0, \sigma_v^2)$, 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 this study, farmers might exhibit more variation in their inefficiency because they perform in different environmental settings, have different experience in rice farming and different input uses. A truncated-normal distribution assumption on u_i proposed by Stevenson (1980), which allows for the inefficiency distribution to have a non-zero mode (which is not the case in half-normal), was 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 the inefficiency of farmer i.

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

The presence of uncontrolled heterogeneity in u_i in the stochastic frontier models causes bias in the estimation of the parameters describing both the structure of the production frontier and technical inefficiency (Kumbhakar & Lovell 2000:122). A production frontier with truncated-normal distribution was specified with heteroscedasticity in u_i and σ_{ui}^2 in a cross-sectional setting following Wang (2002) and Kumbhakar and Wang (2012) 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 input 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, viz. μ_i and σ_{ui}^2 respectively (Wang 2002; Kumbhakar & Sun 2013). 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 parameterisation (of μ_i and σ_{ui}^2) enables the capturing of non-monotonicity in the relationship between z variables and technical inefficiency (mean of u_i), and variance in u_i measured by the unconditional statistics of $E(u_i)$ and $V(u_i)$ respectively (Bera & Sharma 1999; Wang 2002; 2012). Non-monotonicity implies that, within the sample, the kth element of z, z_k, can have both positive and negative effects on production efficiency, depending on the 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 managerial and socio-economic variables (z).

2.2 Empirical specification and estimation

The log-linear form of the Cobb-Douglas stochastic production function was estimated. The translog specification was not used because of the unsatisfactory fitting to the data. Moreover, a likelihood ratio (LR) test of the Cobb-Douglas versus the translog resulted in P = 0.1622 for Benin, P = 0.08 for Cote d'Ivoire and P = 0.7594 for the pool data, in rejection of the translog. A dummy variable of the parasitic weed infestation status of the rice fields was incorporated into the production frontier model to account for the direct impact of parasitic weeds on the productivity of rice farmers (see Sherlund *et al.* 2002; Rahman & Hasan 2008). The full specification of this model for the ith farmer is written as:

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

and

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

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

where D_i is the dummy variable representing parasitic weed infestation status, with a value of 1 if rice farmer i has infested fields and zero otherwise; and $\boldsymbol{\beta}_i$ is the vector of parameters to be estimated. This is to account for the impact of parasitic weeds on the productivity of rice farmers. For inputs containing zero values, the zero was replaced by 1 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 (Wang 2012). The producer-specific technical efficiency was estimated as:

$$TE_i = \exp(-u_i) \tag{10}$$

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 & 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 & Coelli 1995).

The point estimator of the technical efficiency for the *i*th farmer is

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

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

where

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

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

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

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

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

The most commonly incorporated variables in a stochastic frontier model on technical efficiency in empirical analyses are farmer's age, education, experience, gender, access to information, land (various aspects) and household size (see Wilson *et al*. 2001; Sherlund *et al*. 2002; Rahman & Hasan 2008; Tan *et al*. 2010; Belotti *et al*. 2012) 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 the parasitic weeds problem, namely parasitic weed *infestation status* (dummy variable), *frequency of rice field infestation* during the last five years, and actual *area of rice field covered* (%) by the parasitic weeds. The dummy accounts for the direct effect of the infestation of parasitic weeds on productivity, while the other two variables are included in the inefficiency function to account for the management capabilities of farmers and their indirect effect on productivity (through technical efficiency). The statistics of variables used are summarised in Table 1.

Table 1: Summary statistics of variables and expected effects on productivity and technical inefficiency

	Expected sign	Benin (n = 217)		Cote d'Ivoire (n = 240)	
Definition of variables		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 weed 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 (actual % of rice field covered by parasitic weed)	+	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

2.3 Description of data

The data used were from a multi-stage stratified sample of farmers in Benin and Cote d'Ivoire. Only rain-fed rice systems were considered in this study. For each country, rice-producing regions (three in Benin and two in Cote d'Ivoire) where parasitic weeds occurred were selected. In the selected regions, five districts in which parasitic weeds were present were selected in Benin and eight in Cote d'Ivoire. Within the five districts in Benin, the 18 most cropped lowlands (12 infested by *Rhamphicarpa* and six with no infestation) were selected. In Cote d'Ivoire, 24 villages where parasitic weeds occurred were selected. Finally, rice farmers were selected randomly. Data were collected from face-to-face interviews with 223 farmers in Benin and 240 in Cote d'Ivoire in 2011 and 2012 respectively.

To estimate the efficiency model (equations (7) to (9)), the output was rice paddy production in kilogrammes. The paddy price was standardised in each country (because of the same cropping season, from June to December). A priori, this reduces the heterogeneity of products 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 (fertiliser, herbicides, machinery and other services). Land was measured in hectares and labour in hours. The latter included family labour as well as hired labour. The cost of seed was used to capture the differences 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 (cf. Demont *et al*. 2007). Prior to the model's estimation, data were scanned using box and whisker plots to detect possible outliers. Six outliers were identified and dropped in Benin. 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 was required (Kumbhakar & Lovell 2000:73; Rahman & Hasan 2008).

3. Results and discussion

3.1 Estimation of frontier function and impact of parasitic weeds on productivity

The estimated parameters of the terms of the stochastic frontier production (7) and of the parameters of the inefficiency (8) and variance effects equations (9) are reported in Table 2 for both countries.

These results (Table 2) show that output was positively and significantly ($P < 0.1$) correlated with all inputs except seed ($P > 0.1$) in Benin. Land was the most productive factor in both countries (53% in Benin and 46% in Cote d'Ivoire), followed by labour (12%) in Benin and seed (18%) in Cote d'Ivoire.

Parasitic weed infestation negatively and significantly ($P < 0.01$ and $P < 0.1$) affects rice productivity in both countries, as expected. 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 reduced rice productivity ($P < 0.01$) by 32% and, in Cote d'Ivoire, both *Striga* and *Rhamphicarpa* reduced productivity ($P < 0.10$) by 18%. These values correspond to the unrealised outputs due to parasitic weed infestation of rice fields. The negative impact of parasitic weed infestation on rice production implies a reduction in food availability in the sub-Saharan Africa countries concerned, and a threat to food security in the region.

In the inefficiency models, all parameter estimates had the expected signs, except for land ownership in both countries and area share infested in Benin. Land ownership, distance of rice fields from the homestead and household size significantly ($P < 0.05$) and positively affected inefficiency, i.e. they corroded technical efficiency. The number of fields and experience in rice farming, in contrast, were significantly ($P < 0.05$) and negatively associated with inefficiency, i.e. they enhanced technical efficiency.

In the regression of equation (9), all parameter estimates have the expected sign, except for the parameter of the area infested in Cote d'Ivoire. The number of fields, distance of fields from homestead and household size were significantly ($P < 0.1$) and negatively related to 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 can be explained by diversification effects. Farmers can share 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 technical efficiency levels, variation in technical inefficiency was found to increase towards the homestead. This is because, in most rural areas in sub-Saharan Africa, pressure on land use and cropping intensities increase towards the village, with concomitant higher risks of pests and diseases (see Demont *et al*. 2007).

Table 2: Maximum likelihood joint estimates 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 > chi^2	0.0000	0.0000
Log-likelihood	-198.172	-180.712

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

3.2 Technical efficiency scores

Table 3 shows the overall technical efficiency scores and frequency distributions. Predicted technical efficiency scores ranged from 8% to 93% for Benin and from 16% to 100% for 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 the more efficient use of production factors and the control of parasitic weeds. These results are in line with the observation of Sherlund *et al*. (2002) that including the parasitic weed-infestation factors raised the average technical efficiency scores compared to most previous efficiency studies on rice-production systems in sub-Saharan Africa (e.g. Audibert 1997; M. Diagne *et al*. 2013).

Table 3: Estimated technical efficiency scores and distribution

Items	Benin	Cote d'Ivoire
Overall technical efficiency score		
Mean	0.64	0.85
Standard deviation	0.20	0.16
Minimum	0.08	0.16
Maximum	0.93	1.00
Technical efficiency distribution (%)		
Up to 50	26.70	5.40
51– 60	9.70	2.90
61–70	13.80	4.20
71–80	22.10	10.40
81–90	24.90	22.50
91 and above	2.80	54.60

3.3 Sources of technical inefficiency

Table 4 presents the sample means of the 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 the marginal effects of variables with non-monotonic effects on technical efficiency happens only in the fourth quartile, except in the case of 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 the first and fourth quartile are reported (Table 4).

After the estimation of the individual marginal effects of the managerial 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 2 000 replications. Except for a few variables, all marginal effects were significant at 5% (Table 4).

The two variables describing the impact of parasitic weed infestation on technical efficiency (*frequency of infestation* and *area infested*) have significant ($P < 0.01$) marginal effects on inefficiency, $E(u_i)$ and on the variance of the inefficiency term, $V(u_i)$. Rice farmers' technical inefficiency and variance of technical inefficiency increase monotonically with the area infested by parasitic weeds. 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 the current infestation levels of 35% in Benin and 13% in Cote d'Ivoire (Table 1), the additional output losses due to inefficiency amount to 17.5% and 2.6% respectively, and – *ceteris paribus* – these losses would reach 50% and 20% respectively if the entire areas were infested. If the production losses are added, staggering figures of the average loss due to parasitic weeds are found – 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 increasing progressively starting from the first time manifested (N'cho *et al*. 2014), these figures give a first-hand indication of the imminent threat of parasitic weeds on food security in sub-Saharan Africa.

Table 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 2 000 replications (bias-corrected and accelerated). For many variables, marginal effects can take different signs and values in the sample. The 1st and the 4th quartile values were reported only for variables with non-monotonic efficiency effects (variables having opposite effects in different quartiles).
Significance levels are indicated with *** (P < 0.01) and ** (P < 0.05); bootstrap standard errors are in parenthesis; avg. = average

On the other hand, more frequent infestations over time significantly decrease ($P < 0.01$) rice farmers' technical inefficiency and variance of technical inefficiency thanks to growing awareness of the pest and some experience with its management (N'cho *et al*. 2014). Every additional infestation boosts rice farmers' technical efficiency 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 1), and without this effect of the learning experience, the actual impact of parasitic weed 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 taken in order to improve farmers' awareness and knowledge of parasitic weeds in sub-Saharan Africa.

Finally, ownership reduces technical efficiency levels in both countries, but the effect on the variance of technical inefficiency is mixed. The opposite was found in Bangladesh by Rahman and Rahman (2008), who observed that land owners performed significantly better than tenants or part-time 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 technical efficiency, which is consistent with the general findings of Sherlund *et al*. 2002 and Tan *et al*. 2010.

Non-monotonic efficiency effects of managerial and socio-economic 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 of the critical point at which the switch occurs (Figures 1a to 1h).

Farmers' technical inefficiency decreases with rice farming experience. For example, 10 years' farming experience decreases farmers' technical inefficiency by 10% in Benin and by 6% in Cote d'Ivoire on average, while it increases the variance of technical inefficiency by 4% in Benin and 8% in Cote d'Ivoire. However, the marginal effects of experience change over quartiles, suggesting that farmers with less experience (represented by the first quartile) achieve higher technical efficiency levels and face lower variance in technical inefficiency.

This was expected, as in areas with traditional farming systems the more experienced farmers are generally older (Tan *et al*. 2010). Thus, increasing age may lead to a decreasing labour force – diminution of physical abilities – and farming abilities, i.e. a higher risk aversion to invest significantly in production due to possible deteriorated physical and mental capability (Asfaw & 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 years of rice-farming experience becomes counterproductive and impairs efficiency. This was observed in both countries, starting in the 3rd quartile. The effect is translated into an increase in technical inefficiency and also an increase in the variance of technical inefficiency (Wang 2002; Kumbhakar *et al*. 2012). Since $\partial E(\ln y)/\partial \text{exp}erience = -\partial E(u)/\partial \text{exp}erience$ (Wang 2002), the effect results in an output increase of 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.

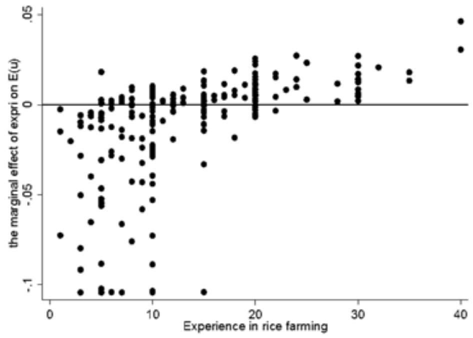

Figure 1a: Marginal effects of experience on E (ui), Benin

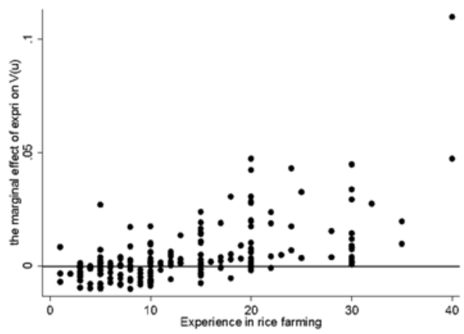

Figure 1b: Marginal effects of experience on V (u_i), Benin

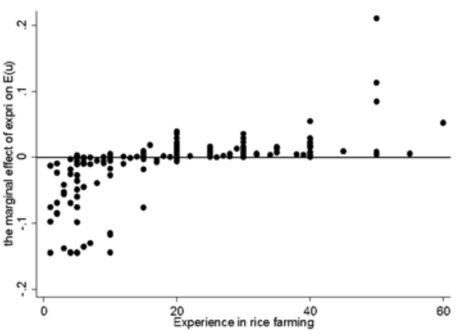

Figure 1c: Marginal effects of experience on E (u_i), Cote d'Ivoire

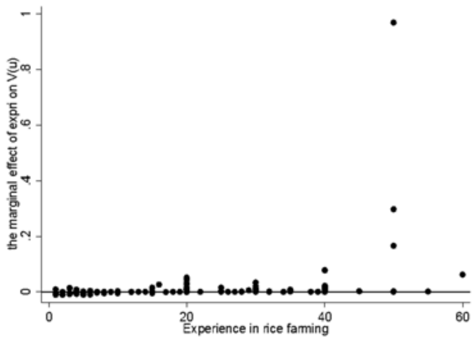

Fig. 1d Marginal effects of experience on V (u_i), Cote d'Ivoire

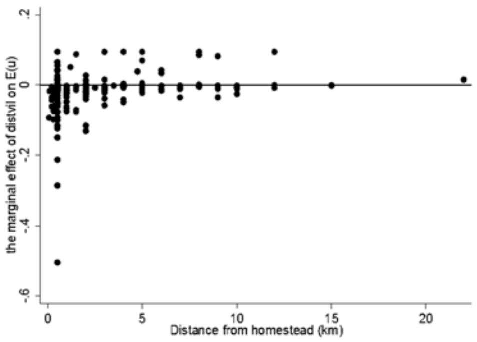

Figure 1e: Marginal effects of distance on E (u_i), Cote d'Ivoire

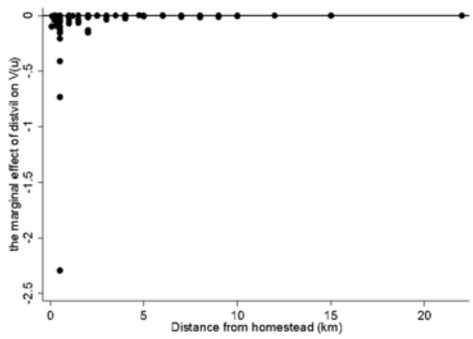

Figure 1f: Marginal effects of distance on V (u_i), Cote d'Ivoire

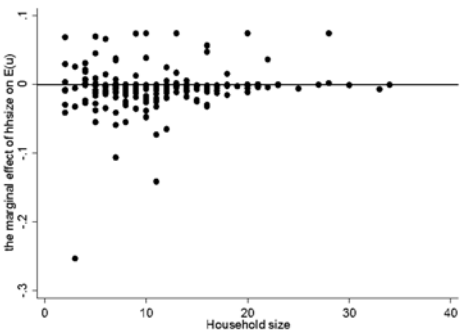

Figure 1g: Marginal effects of household size on E (u_i), Cote d'Ivoire

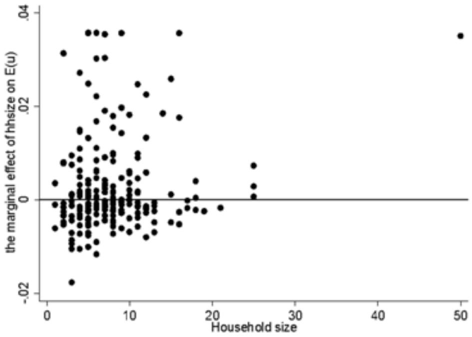

Fig. 1h Marginal effects of household size on E (u_i), Benin

Figure 1: Visualisation 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

The average marginal effects of distance of rice fields from homestead on inefficiency were negative and significant ($P < 0.01$) for both countries. This means that, on average, a one kilometre increase in distance between farmers' rice fields and their homesteads contributes to an increase in farmers' technical efficiency of 19.1% in Benin and 1.7% in Cote d'Ivoire. These results for Benin are not consistent with those of Tan *et al*. (2010), who found that distance of fields from homestead has a negative impact on technical efficiency. 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. Figure 1e visualises 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 technical efficiency 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 1g and 1h visualise how the 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 & 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 managerial and socio-economic 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. Similar to the findings of Bera and Sharma (1999), this observation implies that, when farmers move towards the production frontier (increasing technical efficiency), 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. Conclusion and policy implications

This paper provides an empirical estimate of the impact of the infestation of parasitic weeds on the productivity and technical efficiency of rice farmers in Benin and Cote d'Ivoire who farm under rain-fed conditions. The stochastic frontier models used revealed that *experience* in rice farming, *distance* of rice fields from homestead and *household size* affect the technical efficiency of these rice farmers non-monotonically. The results also show that all factors do not have the same effect on inefficiency and its variance. These findings have important policy implications.

The negative impact of parasitic weed infestation on rice production implies a reduction in food availability and a threat to food security in the countries concerned in sub-Saharan Africa. 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 parasitic weeds. Parasitic weed management policies and programmes aiming to increase technical efficiency should account for the optimal level of influence of farming experience, land size and distance of rice plot from homestead on technical efficiency.

The specification of the model with the non-monotonic efficiency effects provides a better understanding of the effects of the key factors, allowing for specific policy implications. The model also allowed quantifying, for the first time, the effective production gap due to infestation by parasitic weeds in rice-farming systems in sub-Saharan Africa. Furthermore, one of the important contributions of this paper to the literature is that the analytical approach used allows for the decomposition of the total impact into its direct (through production frontier) and indirect effects (through the inefficiency effects function).

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References

AfricaRice, 2013. Africa Rice Center (AfricaRice) Annual Report 2012: Africa-wide rice agronomy task force. Cotonou, Benin: AfricaRice.

Asfaw A. & Admassie A, 2004. The role of education on the adoption of chemical fertiliser under different socioeconomic environments in Ethiopia. Agricultural Economics 30: 215–28.

Audibert M, 1997. Technical inefficiency effects among paddy farmers in the villages of the 'Office du Niger', Mali, West Africa. Journal of Productivity Analysis 8: 379–94.

Battese GE & Coelli TJ, 1988. Prediction of firm-level technical efficiencies with generalized frontier production function and panel data. Journal of Econometrics 38: 387–99.

Battese GE & Coelli TJ, 1995. A model for technical inefficiency effects in stochastic frontier production function for panel data. Empirical Economics 20: 325–32.

Belotti F, Daidone S, Ilardi G & Atella V, 2012. Stochastic frontier analysis using Stata. Research paper series 10(12): 251, CEIS Tor Vergata.

Bera AK & Sharma SC, 1999. Estimating production uncertainty in stochastic frontier production function models. Journal of Productivity Analysis 12: 187–210.

Chen Z, Huffman W & Rozelle S, 2003. Technical efficiency of Chinese grain production: A stochastic production frontier approach. Paper read at the American Agricultural Economics Association Annual Meeting, 27–30 July, Montreal, Canada.

Coelli T, 1995. Estimators and hypothesis test for a stochastic frontier function: A Monte Carlo analysis. Journal of Productivity Analysis 6: 247–68.

Coelli TJ, Rao DSP & Battese GE, 1998. An introduction to efficiency and productivity analysis. Boston/Dordrecht/London: Kluwer Academic.

D'Agostino RB & Pearson ES, 1973. Tests for departure from normality. Empirical results for the distributions of b2 and √b1. Biometrika 60(3): 613–22.

Demont M, Jouve P, Stessens J & Tollens E, 2007. Boserup versus Malthus revisited: Evolution of farming systems in northern Cote d'Ivoire. Agricultural Systems 93: 215–28.

Demont M, 2013. Reversing urban bias in African rice markets: A review of 19 national rice development strategies. Global Food Security 2: 172–81.

Diagne A, Alia DY, Amovin-Assagba E, Wopereis MCS, Saito K & Nakelse T, 2013. Farmer perceptions of the biophysical constraints to rice production in sub-saharan Africa, and potential impact of research. In Wopereis MCS, Johnson DE, Ahmadi N, Tollens E & Jalloh A (eds.), Realizing Africa's rice promise. Wallingford, Oxfordshire: CABI.

Diagne M, Demont M, Seck PA & Diaw A, 2013. Self-sufficiency policy and irrigated rice productivity in the Senegal River Valley. Food Security 5: 55–68.

Jondrow J, Lovell CAK, Materov IS & Schmidt P, 1982. On the estimation of technical inefficiency in a stochastic frontier production function model. Journal of Econometrics 19: 233–8.

Kumbhakar SC & Lovell CAK, 2000. Stochastic frontier analysis. Cambridge: Cambridge University Press.

Kumbhakar SC, Wang H-J & Horncastle AP, 2012. A practitioner's guide to stochastic frontier analysis. New York: Cambridge University Press.

Kumbhakar SC & Sun K, 2013. Derivation of marginal effects of determinants of technical inefficiency. Economics Letters 120: 249–53.

Nakano Y, Bamba I, Diagne A, Otsuka K & Kajisa K, 2013. The possibility of a rice green revolution in large-scale irrigation schemes in sub-Saharan Africa. In Otsuka K & Larson DF (eds.), An African green revolution: Finding ways to boost productivity on small farms. New York & London: Springer.

N'cho SA, Mourits M, Rodenburg J, Demont M & Oude Lansink A, 2014. Determinants of parasitic weed infestation in rainfed lowland rice in Benin. Agricultural Systems 130: 105–15.

Oerke EC & Dehne HW, 2004. Safeguarding production – losses in major crops and the role of crop protection. Crop Protection 23: 275–85.

Rahman S & Hasan MK, 2008. Impact of environmental production conditions on productivity and efficiency: A case study of wheat farmers in Bangladesh. Journal of Environmental Management 88, 1495–504.

Rahman S & Rahman M, 2008. Impact of land fragmentation and resource ownership on productivity and efficiency: The case of rice producers in Bangladesh. Land Use Policy 26, 95–103.

Rodenburg J & Johnson DE, 2009. Weed management in rice-based cropping systems in Africa. Advances in Agronomy 103: 149–218.

Rodenburg J, Demont M, Zwart JS & Bastiaans L, 2016. Parasitic weed incidence and related economic losses in rice in Africa. Agriculture Ecosystem and Environment 235: 306–17.

Rougoor CW, Trip G, Huirne RBM & Renkema JA, 1998. How to define and study farmers' management capacity: Theory and use in agricultural economics. Agricultural. Economics 18, 261–72.

Sherlund SM, Barrett CB & Adesina AA, 2002. Smallholder technical efficiency controlling for environmental production conditions. Journal of Development Economics 69: 85–101.

Singbo AG & Oude Lansink A, 2010. Lowland farming system inefficiency in Benin (West Africa): Directional distance function and truncated bootstrap approach. Food Security 2: 367–82.

Stevenson RE, 1980. Likelihood functions for generalized stochastic frontier estimation. Journal of Econometrics 13: 57–66.

Tan S, Heerink N, Kuyvenhoven A & Qu F, 2010. Impact of land fragmentation on rice producers' technical efficiency in South-East China. Wageningen Journal of Life Sciences 57: 117–23.

Wang H-J, 2002. Heteroscedasticity and non-monotonic efficiency effects of a stochastic frontier model. Journal of Productivity Analysis 18: 241–53.

Wang H-J, 2012. Manual of Hung-Jen Wang's Stata codes. Available at http://homepage.ntu.edu.tw/~wangh (Accessed 10 September 2012).

Wang H-J & Schmidt P, 2002. One-step and two-step estimation of the effects of exogenous variables on technical efficiency levels. Journal of Productivity Analysis 18: 129–44.

Wilson P, Hadley D & Asby C, 2001. The influence of management characteristics on the technical efficiency of wheat farmers in eastern England. Agricultural Economics 24, 329–38.

Zhengfei G, Oude Lansink A, Van Ittersum M & Wossink A, 2006. Integrating agronomic principles into production function estimation: A dichotomy of growth inputs and facilitating inputs. American Journal of Agricultural Economics 88: 644–56.