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Parasitic weed incidence and related economic losses in rice in Africa

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ABSTRACT

Parasitic weeds pose increasing threats to rain-fed rice production in Africa. Most important species are *Striga asiatica*, *S. aspera* and *S. hermonthica* in rain-fed uplands, and *Rhamphicarpa fistulosa* in rain-fed lowlands. Information on the regional spread and economic importance of parasitic weeds in cereal production systems is scant. This article presents the first multi-species, multi-country, single-crop impact assessment of parasitic weeds in Africa. A systematic search of public international and national herbaria and the scientific literature was conducted to collect all available data on the regional distribution, incidences and related yield losses of the most important parasitic weeds in rice. Herbaria specimens were geo-referenced and these coordinates were overlapped with rain-fed rice areas. Probabilistic diffusion waves of parasitic weeds were generated to derive most likely incidence values. Estimates from this spatial analysis were then combined with secondary data from the literature into a stochastic impact assessment model to generate a confidence interval of the likely economic impact per country and for sub-Saharan Africa as a whole. *Rhamphicarpa fistulosa* occurs in at least 36 African countries, 28 of which produce rice in rain-fed lowlands where this species thrives. *Striga hermonthica* is found in at least 32 countries, *Striga asiatica* in at least 44 and *S. aspera* in at least 17. A total of 50 countries have at least one of these three species of *Striga*, 31 of which produce rice in the rain-fed uplands where these species can be encountered. An estimated 1.34 million ha of rain-fed rice is infested with at least one species of a parasitic weed in Africa. Our stochastic model estimates that annual economic losses inflicted by all parasitic weeds exceeds, with 95% certainty, a minimum value of US $111 million and most likely reaches roughly US $200 million and increases by US $30 million annually. To reverse this trend and support small-holder rice farmers in Africa with effective, sustainable and affordable solutions for control, targeted investments in research, development and capacity building are required. The top-10 priority countries where such investments would probably have the highest return are Nigeria, Guinea, Mali, Côte d'Ivoire, Cameroon, Tanzania, Madagascar, Uganda, Sierra Leone and Burkina Faso.

1. Introduction

Parasitic plants depend on other plants for part or all of their nutrition (Heide-Jørgensen, 2008). They parasitize by making a xylem-to-xylem connection with the host plant using a specialized organ called haustorium. Through this connection the parasite extracts water, nutrients and metabolites and alters the plant growth regulators of the host, resulting in stunted growth and losses in reproductive output of the host plant (Westwood, 2013).

Parasitic plants feature in 20 plant families (Heide-Jørgensen, 2013), with eight families harboring species of economic importance. They are economically important when they are weedy and constrain crop production. This may happen when they shift from the natural vegetation, where they spontaneously occur, to cultivated fields with agricultural crops (Raynal Roques, 1994). In sub-Saharan Africa (SSA), the Orobanchaceae family contains the vast majority of species that have turned into parasitic weeds and from that family, *Striga* is without any doubt the most important genus in terms of economic impact in this region (Mohamed et al., 2006). *Striga* Lour., is a vast genus with 28 species and 6 sub-species in Africa, 22 of which are endemic to this continent (Mohamed et al., 2001). Other *Orobanchaceae* genera with economically important parasitic weed species in SSA are

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Orobanche, *Alectra,* and *Rhamphicarpa*. The most important parasitic plant species that have developed into parasitic weeds in cereal production systems in SSA, are the Witchweeds, *Striga asiatica* (L.) Kuntze, *S. aspera* (Willd.) Benth. and *S. hermonthica* Benth., and Rice Vampireweed, *Rhamphicarpa fistulosa* (Hochst.) Benth. (Parker, 2012). All of these species may be found in rice fields, with *Striga* spp. in rain-fed uplands and *R. fistulosa* predominantly in rain-fed lowlands and moist uplands (Kabiri et al., 2015). Rain-fed rice growing environments are entirely depending on rainfall and groundwater flows for water supply. The description 'rain-fed upland' refers to free-draining soils, often positioned in pluvial landscape zones – i.e. crests, upper slopes and middle slopes, while 'rain-fed lowland' refers to hydromorphic and water-logged soils, in phreatic and fluxial zones – i.e. lower slopes and valley bottoms (Windmeijer and Andriesse, 1993).

Known hot-spots of parasitic weed infestation in rice are northern Côte d'Ivoire (Johnson et al., 1997; Kouakou et al., 2015) and northeast Nigeria (Gworgwor et al., 2001; Dugje et al., 2006) for *Striga aspera* and *S. hermonthica*, the Middle West of Madagascar (Fujisaka, 1990; Elliot et al., 1993), Comoros (Reneaud, 1980) and southern Tanzania (Kabiri et al., 2015) for *Striga asiatica*, and central and northern Benin (Rodenburg et al., 2011c; N'cho et al., 2014), northern Togo (Houngbedji et al., 2014), southern Mali and central Burkina Faso (Ouédraogo et al., 1999), eastern Uganda (Rodenburg et al., 2015a) and southern Tanzania (Kabiri et al., 2015) for *R. fistulosa*. The areas affected by parasitic weeds accommodate some of the world's poorest farmers and are reported to increase (Dugje et al., 2006; Rodenburg et al., 2011b; Kouakou et al., 2015). Within this category of farmers, parasitic weeds seem to predominantly affect women as they are often working on the most marginal and parasitic weed infested plots (Houngbedji et al., 2014; N'cho et al., 2014).

Rice is perhaps not the first crop one would associate with parasitic weed problems. The problem is more generally known to occur in maize and sorghum, crops that suffer mainly from *Striga asiatica* in southern Africa and from *S. hermonthica* in West, Central and East Africa (Parker, 2013). Rice can be grown under permanently flooded conditions where parasitic weeds do not thrive. However, while irrigated rice may be the most popularly known rice production system, in SSA it is not the most important one in terms of area. Sixty-six percent of the land area under rice in SSA is characterized as rain-fed (Diagne et al., 2013), and these are precisely the environments where parasitic weeds are found as well. Rice is one of the major food crops in Africa, and is subject to a rapidly increasing consumer demand (Seck et al., 2012). The regional annual growth rate of rice consumption is 4.5% while the regional production growth rate is only 3.2% (Seck et al., 2010). As a result, rice import dependency has increased by 2.2% annually since the 1960s (Demont, 2013). Apart from increasing imports, part of the gap will be closed by area expansion for rice production (van Oort et al., 2015). Such expansion results from new exploitations, mainly in the rain-fed lowlands, i.e. the inland valleys (Rodenburg et al., 2014), and conversions of fallow, maize and sorghum fields into (rain-fed upland) rice fields (Kijima et al., 2008). The natural vegetation of African inland valleys harbors *Rhamphicarpa fistulosa* (Hansen, 1975), and the fallow, maize or sorghum fields in this region are often highly infested by *Striga* spp. (Samake et al., 2006; Kamara et al., 2014). Hence the increase of area under rain-fed rice is likely to be associated with increasing parasitic weed problems and this is expected to be aggravated by climate change (Rodenburg et al., 2011a).

Parasitic weed inflicted yield losses in rice are a function of the parasite species, infestation and virulence level of the local ecotype (or morphotype) and the extent of resistance and tolerance of the crop variety (Rodenburg et al., 2015b, 2016). Estimates of the extent of the economic losses caused by parasitic weeds in crops in sub-Saharan Africa are however inaccurate and outdated (Parker, 2009). For rice, economic loss assessments have even never been undertaken. In parasitic weed affected countries there is a general lack of attention for this type of weed problems among agricultural extension and crop protection services, policy and decision makers and research portfolio and training curricula, particularly for rice production systems (Schut et al., 2015). As this is partly due to suboptimal awareness, a thorough assessment of the extent of the problem would be a first essential step to effectively address it. The objectives of this study are therefore to acquire estimates on the incidence and present the first multi-species, multi-country, single-crop impact assessment of parasitic weeds in Africa. Estimating economic losses inflicted by parasitic weeds, however, is severely constrained by data scarcity. Moreover, according to De Groote (2007), a major constraint is the lack of integration of social sciences in research on parasitic weeds. He proposes the following seven steps in the economic analysis: (i) estimating the extent and (ii) intensity of the problem, (iii) trials and (iv) appropriate economic analysis of new control methods, (v) farmer evaluation of these methods, (vi) modeling of the weed × crop × environment interactions, and (vii) impact assessment.

The current study purely relies on secondary data. Through an elegant combination of data mining, spatial analysis and stochastic impact assessment, we aim at obtaining a confidence interval of the minimum and most likely economic losses inflicted by parasitic weeds in rice in Africa and identifying the major drivers for these losses. This is expected to shed light on the current and likely future situation of this production constraint in rain-fed rice producing areas, which in turn should contribute to better targeted policy making, research and development endeavors and investments in the region.

2. Materials and methods

Our methodology consists of a combination of data mining, spatial analysis and stochastic impact assessment. This section is organized as follows. In Section 2.1, we develop a model for estimating the impact of parasitic weeds in production systems. From this model, we derive our data requirements. Through data mining, we then exploit the scarcely available data to the maximum extent possible. This involves collecting secondary data from literature and conducting an exhaustive herbarium study followed by geo-referencing (Section 2.2). In Section 2.3, we then combine these data with spatial data on rain-fed rice growing areas, and in Section 2.4, we incorporate uncertainty into our model by assigning stochastic distributions to our parameters, which enables us to obtain a confidence interval and a most likely value for our model outcomes.

2.1. Model

Total monetary losses, C (US$), and annual incremental change in monetary losses, ΔC (US$), inflicted by parasitic weeds in Africa can be estimated as follows:

$$C = \sum_{j=1}^{n} A_j \mu_j p_j \sum_{i=1}^{w} \phi_{ij} \Delta y_{ij} \quad (1)$$

$$\Delta C = \sum_{j=1}^{n} A_j \mu_j p_j \sum_{i=1}^{w} \Delta \phi_{ij} \Delta y_{ij} \quad (2)$$

with A_j the total rice area in country j ($j = 1, 2, \ldots, n$), μ_j the average milling recovery rate in country j (share in weight of milled rice relative to paddy rice), p_j the average price (US\$ t^{-1}) of milled rice in country j, Δy_{ij} the absolute yield loss (tons of paddy rice ha^{-1}), inflicted by parasitic weed species i in country j, despite control, φ_{ij} the incidence of parasitic weed species i ($i = 0, 1, \ldots, w$) in country j measured as the share (percentage) of the total rice area affected by the species, and $\Delta\varphi_{ij}$ the annual incremental incidence of parasitic weed species i in country j.

Estimating the absolute yield loss, Δy_{ij}, requires two major functions to be estimated: (i) the effect of parasitic weeds on yield, and (ii) the effect of control methods on parasitic weeds (De Groote, 2007). Therefore, following Demont and Tollens (2004), we assume that parasitic weed infestation decreases yield proportionally to the damage incurred despite weed control. The "affected" yield y_{ij}^{a} (tons of paddy rice ha^{-1}) represents the yield that would be obtained if the rice field is infested by parasitic weed species i in country j, while the farmer attempts to control it. It can be expressed through the following "damage abatement" function:

$$y_{ij}^{a} = y_{ij}^{u}[1 - (1 - \alpha_{ij})s_{ij}] \tag{3}$$

with y_{ij}^{u} the theoretical "unaffected" yield attained in absence of parasitic weed species i in country j, α_{ij} the average efficacy of weed control methods used against parasitic weed species i in country j, measured by the proportion of yield loss averted by the technology, and s_{ij} the theoretical average fraction yield loss caused by parasitic weed species i in country j in the absence of control. The parasitic weed species i can be (i) absent ($i = 0$ and $s_{0j} = 0$), (ii) *R. fistulosa*, (iii) *S. asiatica*, (iv) *S. aspera*, and/or (v) *S. hermonthica*. The realized yield y_{ij} is a weighted average of the affected and unaffected yield:

$$y_{ij} = y_{ij}^{a}\phi_{ij} + y_{ij}^{u}\left[1 - \phi_{ij}\right] \tag{4}$$

where φ_{ij} represents the incidence of parasitic weed species i in country j measured as the share (percentage) of the total rice area affected by the species. If we impute y_{ij}^{a} from Eq. (3) into Eq. (4), we can calculate the unaffected yield, y_{ij}^{u}, as follows:

$$y_{ij}^{u} = \frac{y_{ij}}{1 - (1 - \alpha_{ij})s_{ij}\phi_{ij}} \tag{5}$$

The absolute yield loss, Δy_{ij} (tons of paddy rice ha^{-1}), inflicted by parasitic weed species i in country j, despite control, is simply the difference between unaffected and affected yields:

$$\Delta y_{ij} = y_{ij}^{u} - y_{ij}^{a} \tag{6}$$

To estimate Eqs. (1) and (2), we need estimates for A_j, μ_j, and p_j (i.e. the rice area, milling recovery rate and average price) for each country j, and for φ_{ij}, $\Delta\varphi_{ij}$, and Δy_{ij} (i.e. the species incidence, annual incremental incidence and weed-inflicted absolute yield loss) for each parasitic weed species i and each country j. Data from national statistics can be used for the first set of parameters. For the second set, we will develop an estimation strategy based on data mining, spatial analysis and stochastic impact assessment in the subsequent sections.

2.2. Herbarium study

Country-disaggregated data on the incidence of parasitic weed species in Africa are scarce and incomplete. Incidence can be

Table 1
Incidence and yield loss estimates from the literature. Incidence rates represent the estimated share of the total area under the weed-specific rice-growing environment of a particular country.

Weed genus	Species	Country/Region	Environment share[a]	Incidence	Yield loss	Sources
Rhamphicarpa	*fistulosa*	Benin	69%	35%	50%	1
		Benin	69%	16%	63%	2
		N. Côte d'Ivoire	34%	13%	21%	1
		N. Nigeria	65%	48%		3
		S. Tanzania	99%		50%	4
		N. Togo	87%	28%		5
Striga	*hermonthica*	N. Côte d'Ivoire	66%	13%	21%	1
	hermonthica, aspera	N. Côte d'Ivoire	66%	15%		6
		N. Côte d'Ivoire	66%	12%	50%	7
	hermonthica, asiatica	S. Ghana	6%	2.6%		8
	hermonthica	N. Nigeria	35%	98%		3
	aspera	N. Nigeria	35%	47%		3
	aspera	N. Nigeria	35%	44%		9
	hermonthica	Kenya			62%	10
	asiatica	Madagascar	20%	53%		11
	asiatica	Madagascar	20%		80%	12

1. Econometrically estimated yield losses, decomposed into productivity and efficiency losses (Benin: 32% + 18% = 50%; Côte d'Ivoire: 18% + 3% = 21%). In Côte d'Ivoire, losses are assumed equal for *Striga* and *Rhamphicarpa* as the difference between species was non-significant (N'cho, 2014).
2. 22% of inland valleys were infested with *R. fistulosa* (Rodenburg et al., 2011b); 72% of fields within these inland valleys were infested (N'cho et al., 2014).
3. In six states, across 65 locations, 135 farms are surveyed. In 48% of those farms, grown with sorghum or rice, *R. fistulosa* was observed, in moist upland fields. In 47% of the farms *S. aspera* was found and in 98% of the farms *S. hermonthica* was found. *Striga aspera* was found in fields cropped with maize or rice and *S. hermonthica* in fields cropped with sorghum, pearl millet or rice (Gworgwor et al., 2001).
4. Across 64 adapted lowland rice varieties, *R. fistulosa*-inflicted yield losses range from 27 to 73%, and average 50% (Rodenburg et al., 2016).
5. 79% of inland valleys in north Togo are infested; 36% of the fields within an infested inland valley have *R. fistulosa* (Houngbedji et al., 2014).
6. 91,430 ha of a total of 225,798 ha (40.5%) of upland rice in northern Côte d'Ivoire is infested by *Striga* spp. [0.9% by *S. asiatica*, 2.0% by *S. aspera* and 97.1% by *S. hermonthica*] (Kouakou et al., 2015). The total estimated area of upland rice in Cote d'Ivoire is 615,325 ha (Diagne et al., 2013). Assumed that *Striga* spp. do not infest rice south of this infestation zone, the overall incidence rate in upland rice is 14.8%.
7. In 1986, 12% of >12,000 rice farmers in the guinea savannah reported *Striga* sp. Yield losses with 17 *S. aspera* pl. m^{-2} at 50 DAS are around 50% (Johnson et al., 1997).
8. Based on farmer surveys among 81 farmers from 28 villages in coastal savanna zone of Ghana in 2001 (Aflakpui et al., 2008).
9. Based on sampling of 935 arable fields in 30 communities in three savanna zones (Sudan, Northern Guinea and Southern Guinea) in 2004 (Dugje et al., 2006).
10. Atera et al. (2012) reported *S. hermonthica*-inflicted yields losses in a range of upland rice varieties between 33 and 90%, averaging 62%.
11. Based on 30 upland rice, 90 maize (maize and rice are rotated) and 24 mixed maize/rice fields in middle west of Madagascar in 1993 (Geiger et al., 1996).
12. Elliot et al. (1993) reported *S. asiatica* to be one of the main weed species in rice in the middle-west of Madagascar with yield losses ranging from 60 to 100%.
[a] The area of the specific environment (upland for *Striga* spp. and lowland for *R. fistulosa*) in a specific country as a share of the total area under rice in that country is estimated by Diagne et al. (2013).

determined by direct or indirect geo-referenced observations (De Groote, 2007). Table 1 compiles estimates from direct observations with high relevance for rice systems in Africa from ten surveys, covering six countries or regions within countries (Benin, Côte d'Ivoire, Ghana, Nigeria, Madagascar and Togo). Incidence rates are highly heterogeneous; they range from 3 to 98% and average around 33% of the surveyed areas. Therefore, instead of using these heterogeneous and incomplete data directly, we will use an indirect spatial approach to model incidence φ_{ij}. In the literature, the geographic spread of weeds is simulated by assuming that a species spreads from several foci along fronts at constant rates in all directions (Auld et al., 1979; Auld and Coote, 1980; Doyle et al., 2001), or as a wave in which individuals at a particular point spread out in concentric circles of ever-expanding radii (Van Dyke, 2008). Current incidence levels of parasitic weeds in Africa are the result of such a diffusion pattern around several foci. To gain spatial information on their geographic spread, nine national and international public herbaria (see acknowledgements) have been searched online or physically on the four main parasitic weed species to rice in Africa: *Rhamphicarpa fistulosa*, *Striga asiatica*, *S. aspera* and *S. hermonthica*. All relevant information available on the specimen, i.e. country, geographic coordinates (latitude, longitude) of the collection location, names of and distance to nearby villages, altitude and parasite morphotype (i.e. flower color) were entered in a database. The species database created this way was then used to map the distribution of these species. In cases where collection locations were not geo-referenced on the specimen, they were geo-referenced by Google Earth as best as possible, making use of the aforementioned collection descriptions. Cases where there were no clear descriptions, i.e. where the location name or the species name could not be ascertained, were discarded.

2.3. Spatial analysis

Spatial analysis allows the spatial distribution of weeds to be mapped against a wider range of enabling and limiting factors (Doyle et al., 2001). Here, the major enabling factor is the rice-growing environment. Since all parasitic weeds, *R. fistulosa* and *Striga* spp., are limited to the rain-fed rice growing environments, we focus our sampling on rain-fed rice growing areas. Spatially distributed information of rain-fed rice growing areas in Africa is obtained from the MIRCA2000 data set (Portmann et al., 2010). This dataset provides global gridded maps of harvested area for 26 crops, including rain-fed rice, with a spatial resolution of 5 arc minute meaning that each grid cell measures about 9.2 by 9.2 kilometers at the equator. Portmann et al. (2010) first collected official statistics of cropped areas at national and sub-national levels provided by the FAO and national organizations and then downscaled this information to grid cell level. For non-disclosed reasons, the gridded rain-fed rice map, does however not provide information for four countries in sub-Saharan Africa: Cameroon, Madagascar, Rwanda and Kenya. Moreover, significant rain-fed rice areas are observed in the Sahelian zone where annual seasonal rainfall is less than 500 mm and where no rain-fed agriculture is practiced. To improve the MIRCA2000 rain-fed rice map, we first used an alternative map of rain-fed rice areas, from the Spatial Production Allocation Model (SPAM) database (HarvestChoice, 2014), to replace the four aforementioned countries with no data. We then excluded the grid cells where on average less than 500 mm of rainfall occurs. For that purpose we used a gridded average annual rainfall map for the years 2001 to 2014, provided by the Africa Rainfall Estimate Climatology (Novella and Thiaw, 2013). The resulting rain-fed rice map shows all grid cells where rice area is reported (Fig. 1).

Following the aforementioned literature on the geographic spread of weeds (Auld et al., 1979; Auld and Coote, 1980; Doyle et al., 2001; Van Dyke, 2008), we consider each herbarium observation of a parasitic weed species as a potential focus for that species from where it has spread in concentric circles. We do not know, however, how far it has spread from the foci since it has been observed, but we are certain that it has been observed on those particular locations. Under these conditions of data scarcity and uncertainty, the best strategy is to resort to the simplest model possible of weed spread, combined with a probability distribution function (Doyle et al., 2001). Therefore, we use the spatial overlap between parasitic weed observations from herbaria and rice

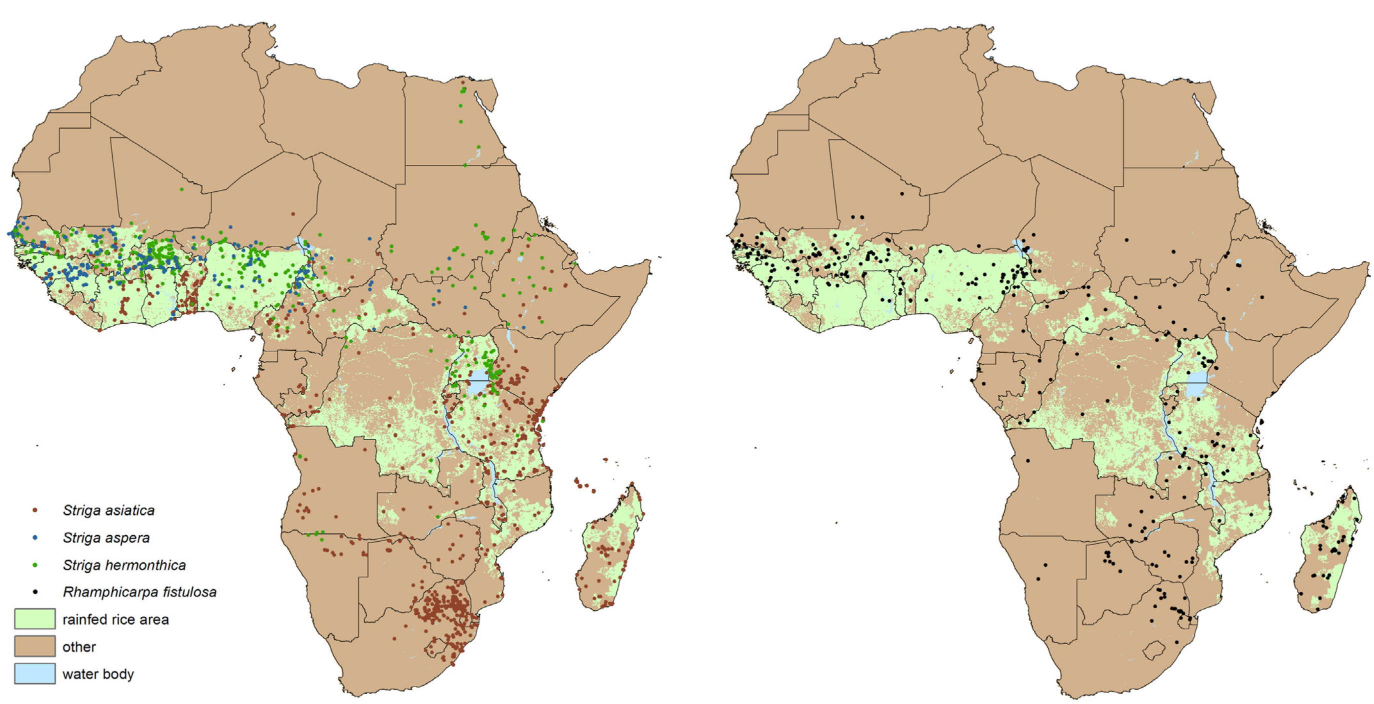

Fig. 1. Distribution of observations of *Rhamphicarpa fistulosa* (left) and *Striga asiatica*, *S. aspera* and *S. hermonthica* (right) overlapped with rain-fed rice areas in Africa.

growing areas to model φ_{ij} as a probabilistic concentric diffusion wave of parasitic weeds (Van Dyke, 2008). We assume that the probability that a sampled rain-fed rice growing area (grid cell $g = 1, 2, \ldots, m_j$) is infested with a particular parasitic weed species i in country j, is inversely related to the distance d_{ijg} between the area and the closest observation of that parasitic weed. In the following, we first simulate the concentric diffusion wave through an ascending cumulative distribution function and in the next section, we assign a probability function to the concentric rings under increasing radii.

For each rice growing area g in each country j, we first calculate the minimum distance d_{ijg} to parasitic weed observations for all four parasitic weed species i. There is no broad-based evidence for differences in virulence (and hence crop damage) between *Striga* species, and these species are mostly mutually exclusive in terms of their presence in a given field. Therefore, we aggregate them together by taking the minimum distance to any *Striga* spp. observation as a measure of the probability that a rice growing area is infested with *Striga* spp. Since *R. fistulosa* and *Striga* spp. typically thrive in different rain-fed rice growing environments (Kabiri et al., 2015), we will assume no overlap between these species and, per country, exclusively allocate all *R. fistulosa* to rain-fed lowlands and all *Striga* spp. to rain-fed uplands. Our spatial data on rain-fed rice growing areas does however not distinguish between lowlands and uplands. Therefore, for each country, we use the share of rice growing environment from national statistics (Diagne et al., 2013) to estimate the probability that a rain-fed rice area is lowland or upland. We then model cumulative incidence, $\varphi_{ij}(d)$, as an expanding concentric ring under increasing radii through an ascending cumulative distribution function:

$$\phi_{ij}(d) = \rho_{ij}\mathrm{Prob}(d_{ijg} \leq d) \tag{7}$$

with ρ_{ij} the share of rice growing environment of the total area of rain-fed rice which is associated with any of the parasitic weed species i in country j (*R. fistulosa* in lowland and *Striga* spp. in upland). There is a lot of uncertainty as to the current spread of parasitic weeds in each country along these cumulative incidence curves, $\varphi_{ij}(d)$. The curves can be described through three points, depending on the radius we assume for the potential current area of spread around the point of observation derived from the herbarium specimen: (i) a "highly likely" incidence radius φ_{ij} (10 km), a "primary" radius caused by dispersion of seed through local markets φ_{ij} (50 km) (Berner et al., 1994; Doyle et al., 2001), and (iii) a "secondary" radius φ_{ij} (100 km). In the next section, we will attempt to obtain a most likely value for $\varphi_{ij}(d)$ by attaching probabilities to these scenarios.

2.4. Stochastic parameterization

Our estimation exercise is greatly hampered by data scarcity. Therefore, similarly to Demont and Tollens (2004) and Demont et al. (2008), through data mining we compile whatever data is available (Tables 1–3, Fig. 1) and, wherever possible, incorporate subjective probability distributions to reflect the uncertainty of the

Table 2
Estimated parasitic weed control efficacies of advanced technologies for rice, based on paddy grain yields without control (t ha^{-1}), yields with control (t ha^{-1}) and yields in absence of parasitic weeds (t ha^{-1}), from the available literature.

Parasitic weed	Control options	Country	Yield without control	Yield with control	Yield in absence of parasitic weeds	Control efficacy α_{ij}	Yield loss s_i	Source
S. asiatica	Cultivars	Tanzania	0.53	0.93	2.02[a]	0.27	0.74	1
			0.96	1.90	2.82[a]	0.51	0.66	1
			0.95	1.59	2.65[a]	0.38	0.64	1
	Rotation with crotalaria		0.80	1.80	4.00	0.31	0.80	2
			1.02	2.14	4.00	0.37	0.74	3
			1.14	1.97	4.00	0.29	0.71	3
	N-fertilizer (25 kg ha^{-1})		0.93	1.32	4.00	0.13	0.77	3
	N-fertilizer (50 kg ha^{-1})		0.93	1.75	4.00	0.27	0.77	3
S. hermonthica	Cultivars	Kenya	0.85	1.34	2.09[a]	0.40	0.59	1
			1.27	1.52	1.87[a]	0.42	0.32	1
			0.41	1.82	3.00	0.54	0.60	4
		Nigeria	2.15	3.27	5.42[a]	0.34	0.35	5
			1.31	1.65	2.00[a]	0.50	0.41	5
			1.64	2.30	2.77[a]	0.58	0.86	6
	N-fertilizer		1.64	2.30	2.53[a]	0.74	0.35	6
R. fistulosa	Cultivars	Tanzania	1.20	1.89	3.09	0.37	0.61	7
Distribution[b]						Pert(0, 0.36, 1)	Pert(0, 0.67, 1)	

1. Average of improved cultivars compared to local cultivar Mwangulu (for *S. asiatica* infested fields in Tanzania) and *Striga*-susceptible IAC165 (for *S. hermothica* infested fields in Kenya) (Rodenburg et al., 2015b).
2. In 9 of the 17 monitored farms yields were ≤800 kg ha^{-1}; In ten of 15 sites at which Crotalaria was planted rice produced ≥1800 kg ha^{-1} grains in the following season; farmers remember unaffected yields prior to *Striga asiatica* problems to be as high as 4000 kg ha^{-1} (Mbwaga and Riches, 2006).
3. With modest N fertilizer rates (25 or 50 kg N ha^{-1}) or with rotations with crotalaria, yield advantages in *S. asiatica* infested fields in Tanzania can be attained (Riches et al., 2005).
4. Comparing locally popular rice cultivar Dourado precoce with the average of the yield of improved varieties (NERICA-1, -10 and -11) in a *S. hermonthica* infested field in Kenya (Atera et al., 2012).
5. Average of all but the lowest yielding cultivar compared to the lowest yielding cultivar in a *S. hermonthica* infested field in Nigeria (Adagba et al., 2002a).
6. Average of all but the lowest yielding cultivar compared to the lowest yielding cultivar in a *S. hermonthica* infested field in Nigeria; comparing yield with no-fertilizer with an average of the yield after application of 30, 60, 90 and 120 kg N ha^{-1} (Adagba et al., 2002b).
7. Comparing local rice variety Supa India with NERICA-1-39; the yield in absence of *R. fistulosa* is that of Supa India in Tanzania (Rodenburg et al., 2016).
[a] Unaffected control yields are not available; as an alternative, the yield of the best-performing improved technology is provided here, with the assumption that this approaches the attainable unaffected control yields at the specific location of the study.
[b] Best fit based on the Akaike information criterion (AIC) and assuming that the distribution is bounded over the interval [0,1].

Table 3
Trends in parasitic weed incidence in cereal production systems in Africa.

Weed genus	Crop(s)	Country	Period 1	Estimated incidence	Period 2	Estimated incidence	Estimated increase per year	Source
Rhamphicarpa	Rice	Benin	1998	33%	2008	55%	2.2%	1
Striga	Rice, sorghum, maize	Côte d'Ivoire	1974–1997	40%	1997–2011	72%	2.2%	2
	Maize, millet, sorghum, rice	Nigeria	1986	40%	2004	68%	1.6%	3
	Maize, millet, sorghum, rice	Ghana	1969	2.5%	2001	41%	1.2%	4
Distribution[a]							Pert(0, 1.8%, 2.2%)	

1. Percentages are based on nine inland valleys that were surveyed in 1998 (Gbèhounou and Assigbé, 2003) and 2007/2008 (Rodenburg et al., 2011b); in 1998, 3 of the 9 were infested; in 2007/2008, 5 of the 9 were infested.
2. The infestation front moved southwards and on a total area of arable land of 4.45 M ha; infestation rose from 1.79 M ha (40%) in the period 1974–1997 to 3.19 M ha (72%) of in the period 1997–2011, i.e. an annual increase of (72%–40%)/(2011–1974) = 2.2% per year (Kouakou et al., 2015).
3. Lagoke et al. (1991) reported 40% for all cereals in 1986 and Dugje et al. (2006) reported 68% in the same area 18 years later.
4. Based on farmers re-call surveys among 81 farmers from 28 villages in coastal savanna zone of Ghana in 2001 (Aflakpui et al., 2008).
[a] Based on a minimum of zero, an average of 1.8% as the most likely value and 2.2% as the observed maximum.

parameters in our model outcomes. In this study, we focus on the top-three most uncertain parameters, i.e. (i) the incidence φ_{ij} and annual increase $\Delta\varphi_{ij}$ of parasitic weeds; (ii) the loss s_{ij} inflicted by parasitic weeds; and (iii) the efficacy α_{ij} of weed control methods used against parasitic weeds. We model the other parameters (realized yield y_{ij}, rice area A_j, milling recovery rate μ_j, and price p_j) as deterministic as we expect their uncertainty to be dwarfed by the uncertainty surrounding the former three parameters. We enter our model (Eqs. (1)–(6)) in Microsoft® Excel 2010 and use the software add-in @Risk 6.3.1 from Palisade Corporation (2013) to construct stochastic distributions for the three uncertain parameters. This converts our deterministic model into a stochastic one. The program @Risk then allows running a Monte Carlo simulation to obtain a stochastic distribution, confidence interval and most likely value for our model outcomes (Eqs. (1) and (2)).

In order to generate a reasonable estimate of the most likely incidence in each country, we construct our probabilistic diffusion wave, Prob[$\varphi_{ij}(d)$], by assigning a simple and transparent probability function to the ascending cumulative distribution function in Eq. (7), assuming that the probability of incidence is inversely related to the closest distance to parasitic weed observations within a range of 100 km and zero beyond this distance:

$$\begin{aligned}\text{Prob}\left[\phi_{ij}(d)\right] &= \frac{100-d}{100}\,\forall\, d \in [0, 100\text{ km}]\\ \text{Prob}\left[\phi_{ij}(d)\right] &= 0\,\forall\, d > 100\text{ km}\end{aligned} \tag{8}$$

This stochastic distribution reflects that we are highly certain of parasitic weed infestation in a rain-fed rice grid cell if a parasitic weed observation from an herbarium spatially coincides with the grid cell ($d = 0$) and we become one percent less certain every kilometer further away from the observation.[3] The probabilistic diffusion wave, algebraically represented in Eq. (8), is consistent with a linear rate of diffusion commonly assumed in the literature on plant population spread (Auld and Coote, 1980).

In order to estimate parameter s_{ij}, we need literature estimates on yield losses caused by parasitic weeds under absence of control (De Groote, 2007). In Table 1, we compile parasitic weed-inflicted yield loss estimates for rice from six studies covering five countries (Benin, Côte d'Ivoire, Kenya, Madagascar and Tanzania). Yield losses are estimated to range from 21 to 80%, with a mean of 50%. However, observed yield losses crucially hinge on the control methods that have been used against parasitic weed species and their efficacy. Yield loss estimates in farmers' fields do not necessarily reflect the true yield-reducing potential of parasitic weeds as farmers are not passive and will attempt to control parasitic weeds when they occur (N'cho et al., 2014). Therefore, the only way we can estimate s_{ij} is by comparing on-farm experimental yields under different treatments (De Groote, 2007). In Table 2, we compile data from experiments—the majority of which have been conducted in farmer's fields—on affected yields despite control of parasitic weeds, y_{ij}^{a}, and without control of parasitic weeds, y_{ij}^{o}, and complete these with estimated unaffected control yields, y_{ij}^{u}, under the hypothetical absence of parasitic weeds. Since it is difficult to obtain comparable unaffected yields under conditions of parasitic weed infestation, in particular for the obligate parasitic plant species of the genus *Striga*, where data of unaffected yields are indeed unavailable, we use the yield of the best-performing improved technology (from Table 2) as a proxy for y_{ij}^{u} to estimate the yield loss as:

$$s_{ij} = \left(y_{ij}^{u} - y_{ij}^{o}\right)/y_{ij}^{u} \tag{9}$$

Since no reliable data are available on weed control efficacies of hand weeding, which is the most common parasitic weed control method in rice (Houngbedji et al., 2014; N'cho et al., 2014), the average control efficacies of the advanced improved technologies (Table 2: improved varieties, herbicides, rotations and mineral fertilizers) are used and estimated as (Oerke and Dehne, 1997):

$$\alpha_{ij} = \left(y_{ij}^{a} - y_{ij}^{o}\right)/\left(y_{ij}^{u} - y_{ij}^{o}\right) \tag{10}$$

We can assume that these efficacies are higher than what farmers generally achieve using traditional control methods, mostly entailing hand or hoe weeding. This will, again, ensure that our estimates are conservative by assuming farmers to actively and efficiently control parasitic weeds in their fields.

In order to reflect the uncertainty and heterogeneity among countries regarding the yield loss and efficacy, we use @Risk to fit a stochastic distribution on the set of estimates reported in Table 2. N'cho (2014) did not find any significant difference between losses caused by *R. fistulosa* and *Striga* spp. and since we have insufficient observations to justify the assumption of differences between weed species, we use the entire dataset of 16 estimates (15 for *Striga* spp. and one for *R. fistulosa*) to fit statistical distributions for both parameters. Based on the Akaike Information Criterion (Palisade Corporation, 2013) and assuming that both parameters are bounded by the interval [0,1], the following Pert distributions

[3] Note that our spatial procedure does not produce any zero values for distance, even when the observation point is inside a pixel. This is due to the fact that the pixels are converted to a point with centroid as coordinate. The smallest pixels are 9.2×9.2 km, hence the smallest level of precision of the radius is $d^{*} = \sqrt{(9.2/2)^2 + (9.2/2)^2} = 6.5$ km.

provided the best fit:

$$s_{ij} \sim \text{Pert}(0, 0.67, 1) \quad (11)$$

$$\alpha_{ij} \sim \text{Pert}(0, 0.36, 1) \quad (12)$$

The estimated most likely value of 36% for α_{ij} as fitted by the Pert distribution is consistent with Oerke and Dehne's (1997) estimate of 34–38% of the average efficacy of general weed control in rice, wheat and maize. The means of the distributions are respectively $<s_{ij}> = 0.61$ and $<\alpha_{ij}> = 0.41$. Pert functions are parsimonious as they can capture distributions through three parameters, i.e. the minimum, most likely and maximum value. The Pert distribution is a special case of the Beta distribution and has been used before in weed-related impact assessment (e.g. Demont et al., 2008). It is widely preferred for modeling uncertainty under severe data scarcity—such as our case—as it is very flexible, can fit highly skewed as well as symmetrical distributions, has a close fit to normal and lognormal distributions, and does not allocate too much weight to the extremes (Lau et al., 1998). Due to lack of weed species- and country-disaggregated data, we assume a similar distribution for each weed species *i* in each country *j*, but allow the parameters to randomly vary between the species and between the countries, which generates more realistic stochastic impact estimates.

To obtain a rough idea about the annual incremental incidence of parasitic weed species, $\Delta\varphi_{ij}$, we compiled the few published studies (from Benin, Côte d'Ivoire, Ghana and Nigeria) that have compared historical with current data on parasitic weed incidence rates in cereal production systems that include rice. Annual incremental incidence rates are estimated to range from 1.2 to 2.2%, with a mean of 1.8% (Table 3). Since we only have four estimates, which is insufficient for fitting a distribution in @Risk (Palisade Corporation, 2013), we incorporate uncertainty through a Pert distribution bounded by zero and the sample maximum, and centered around the sample mean as most likely value:

$$\Delta\phi_{ij} \sim \text{Pert}(0, 0.018, 0.022) \quad (13)$$

The mean of this distribution is $<\Delta\varphi_{ij}> = 0.016$. Similarly as before, we assume a similar distribution for each weed species *i* in each country *j*, but allow the parameter to vary between the species and between the countries.

Finally, national rice areas disaggregated by country, A_j, realized yields, y_{ij}, and share of rice growing environments, ρ_{ij}, in the affected countries are borrowed from Diagne et al. (2013), while we use a uniform average milling recovery rate of $\mu_j = 60\%$ (Diagne et al., 2013) and a uniform average rice price of p_j = US $400/t for all countries (Fiamohe et al., 2015).

3. Results

3.1. Parasitic weed incidence

The herbarium search resulted in 885 observations on *S. asiatica*, 315 on *S. aspera*, 597 on *S. hermonthica* (1797 for *Striga* spp.) and 419 on *R. fistulosa* (Table 4). The *Striga* species occur from sea level to as high as 2591 m above sea level (a.s.l.), while *R. fistulosa* occurrence ranges from 5 m to 1750 m a.s.l. Based on this evaluation of occurrence, *Striga* spp. are found in at least 50 countries in Africa, at least 31 of which produce rice under rain-fed upland growing conditions where *Striga* spp. can be found. From the total of rain-fed upland rice producing countries in Africa (39), 79% have at least one of the important species of *Striga*, able to attack rice. *Rhamphicarpa fistulosa* was observed in 36 countries in Africa, at least 28 of which grow rice in rain-fed lowlands where this parasite can be found. From the total of rain-fed lowland rice producing countries in Africa, 78% are reported to have *R. fistulosa*.

Overlapping the herbarium observations with the rain-fed rice growing areas provides insights as to where parasitic weed problems in rice production systems in Africa exist or may exist in the future. Rain-fed rice production areas are concentrated in the sub-humid and humid tropical zone of Africa, south of the Sahel, ranging from southern Senegal across central Africa to the Indian Ocean islands (Fig. 1). Parasitic weeds, *R. fistulosa* and *Striga* spp., have a broader distribution than rain-fed rice production areas, and do hardly overlap with rice in the Sahel, northeast Africa and southwest to southern Africa.

3.2. Economic losses

We run a Monte Carlo simulation with 100,000 iterations to obtain a stochastic distribution, confidence interval and most likely value for our stochastic parameters (Eqs. (11)–(13)) and model outcomes (Eqs. (1)–(2)). In Table 5, we report the three incidence scenarios along our assumed probabilistic diffusion wave (i.e. 10, 50 and 100 km radii) as well as the most likely value which is basically the mean of the probabilistic diffusion wave (Eq. (8)), based on a Monte Carlo simulation with 100,000 iterations. The incidence curves in Eq. (7) are estimated for Africa as a whole (Fig. 2) and for all countries separately. The incidence of *R. fistulosa* in rain-fed lowland rice in Africa is estimated to range from 1.2% to 10% and further to 22%, depending on the radius of spread around each parasitic weed observation point, resp. 10, 50 or 100 km (Fig. 2 and Table 5). *Rhamphicarpa fistulosa* showed highest incidence in rain-fed lowland rice in Burkina Faso, the Gambia, Senegal and Togo (Table 5 and Fig. 1). The highest incidence of *Striga* spp. in rain-fed upland rice was observed in Cameroon, Comoros, Guinea and Mali.

Table 4
Statistics and estimates concerning distribution of parasitic weeds (*Striga asiatica*, *S. aspera*, *S. hermonthica* and *Rhamphicarpa fistulosa*) in rain-fed rice in sub-Saharan Africa based on observations from public national and international herbaria.

	Parasitic weed species				
	S. asiatica	*S. aspera*	*S. hermonthica*	*Striga* spp	*R. fistulosa*
Number of parasitic weed observations	885	315	597	1797	419
Altitude range (m)	0–2591	200–1500	0–1524	0–2591	5–1750
Number of countries with parasitic weed incidence	44	17	32	50	36
Minimum number of rain-fed rice producing countries with parasitic weeds	28	15	22	31	28
Share of rain-fed rice producing countries of the total number of countries with parasitic weeds	64%	88%	69%	62%	78%
Share of parasitic weed affected countries in SSA of the total rain-fed rice producing countries in SSA[a]	72%	38%	56%	79%	72%

[a] According to Diagne et al. (2013), rain-fed upland and rain-fed lowland rice are produced in 39 African countries; The percentage calculated here is the minimum number of rain-fed rice producing countries with parasitic weeds divided by 39.

Table 5
Parasitic weed incidence and physical (milled rice) and economic loss estimates for rice in sub-Saharan Africa.

Countries	Incidence								Most likely physical and economic losses						
	Rhamphicarpa fistulosa				*Striga* spp.				*R. fistulosa*		*Striga* spp.		Total		Growth
	10 km	50 km	100 km	MLV	10 km	50 km	100 km	MLV	10^3 t	10^6 $	10^3 t	10^6 $	10^3 t	10^6 $	10^6 $ y^{-1}
Angola	0.0%	0.0%	0.0%	0.0%	0.0%	3.8%	7.6%	2.1%	0.00	0.00	0.06	0.02	0.06	0.02	0.04
Benin	2.5%	23%	56%	13%	5.1%	25%	31%	15%	2.04	0.81	1.81	0.72	3.84	1.54	0.17
Burkina Faso	4.4%	34%	67%	19%	6.9%	19%	21%	12%	6.75	2.70	3.90	1.56	10.7	4.26	0.39
Cameroon	1.4%	8.6%	11%	4.7%	17%	57%	73%	36%	2.75	1.10	24.3	9.73	27.1	10.8	0.75
CAR	0.1%	0.8%	3.3%	0.5%	2.2%	18%	50%	11%	0.01	0.01	0.31	0.13	0.33	0.13	0.03
Chad	0.8%	4.2%	13%	2.7%	3.8%	27%	52%	15%	1.00	0.40	4.19	1.67	5.18	2.07	0.40
Comoros	0.0%	0.0%	0.0%	0.0%	36%	41%	41%	35%	0.00	0.00	1.21	0.48	1.21	0.48	0.05
Congo	2.0%	14%	26%	7.9%	0.5%	13%	38%	7.2%	0.07	0.03	0.04	0.02	0.11	0.05	0.01
Côte d'Ivoire	0.2%	2.4%	6.0%	1.4%	4.5%	27%	50%	16%	4.51	1.80	44.4	17.7	48.9	19.6	3.72
DRC	0.0%	0.3%	1.1%	0.2%	0.9%	12%	29%	6.6%	0.10	0.04	4.24	1.70	4.35	1.74	0.72
Gabon	0.0%	7.2%	22%	4.6%	0.0%	21%	35%	7.7%	0.01	0.00	0.01	0.00	0.02	0.01	0.00
Gambia	4.4%	51%	57%	27%	5.6%	23%	39%	13%	4.23	1.69	2.38	0.95	6.61	2.64	0.20
Ghana	1.0%	10%	30%	5.9%	0.3%	2.4%	4.4%	1.4%	2.18	0.87	0.42	0.17	2.60	1.04	0.41
Guinea	1.9%	15%	28%	8.3%	8.9%	39%	56%	23%	19.4	7.74	62.3	24.9	81.7	32.7	2.99
Guinea-Bissau	3.5%	26%	47%	15%	2.8%	27%	42%	14%	6.00	2.40	3.65	1.46	9.65	3.86	0.39
Liberia	0.0%	0.0%	0.0%	0.0%	0.0%	18%	42%	10%	0.00	0.00	6.92	2.77	6.92	2.77	0.98
Madagascar	2.1%	16%	40%	9.3%	0.7%	5.5%	11%	3.1%	15.1	6.04	2.92	1.17	18.0	7.20	1.55
Malawi	2.2%	22%	36%	12%	3.2%	16%	21%	9.2%	2.00	0.80	0.99	0.40	2.99	1.19	0.17
Mali	1.9%	18%	35%	10%	6.9%	37%	55%	22%	21.3	8.51	40.7	16.3	62.0	24.8	2.36
Mauritania	0.0%	40%	69%	16%	7.8%	25%	25%	16%	0.55	0.22	0.31	0.12	0.86	0.34	0.03
Mozambique	0.2%	2.4%	10%	1.6%	0.6%	6.9%	20%	4.2%	0.71	0.29	1.29	0.52	2.00	0.80	0.47
Niger	1.0%	21%	32%	10%	6.5%	29%	47%	18%	0.41	0.16	0.51	0.20	0.91	0.37	0.04
Nigeria	1.4%	12%	30%	7.2%	2.4%	18%	30%	10%	80.3	32.1	53.8	21.5	134	53.6	10.0
Senegal	7.4%	39%	53%	23%	5.7%	29%	40%	17%	5.82	2.33	3.76	1.51	9.58	3.83	0.28
Sierra Leone	0.0%	0.9%	4.7%	0.6%	3.1%	33%	71%	18%	0.42	0.17	15.3	6.14	15.8	6.31	0.91
Sudan[a]	0.0%	0.0%	26%	0.5%	0.0%	41%	41%	12%	0.01	0.00	0.14	0.05	0.14	0.06	0.02
Togo	4.1%	34%	65%	20%	2.6%	12%	13%	7.0%	3.01	1.20	0.72	0.29	3.72	1.49	0.15
Uganda	2.2%	15%	33%	8.9%	6.0%	36%	45%	20%	5.16	2.06	11.9	4.75	17.0	6.81	0.71
Tanzania	1.9%	18%	51%	11%	0.1%	0.7%	1.2%	0.4%	19.9	7.96	0.35	0.14	20.2	8.10	1.70
Zambia	1.7%	15%	34%	8.4%	0.9%	8.0%	18%	4.5%	0.61	0.25	0.21	0.08	0.82	0.33	0.07
Zimbabwe	0.0%	0.0%	36%	1.0%	14%	21%	28%	16%	0.00	0.00	0.01	0.00	0.01	0.00	0.00
Africa	1.2%	10%	22%	5.7%	3.6%	21%	34%	12%	204	81.7	293	117	497	199	29.7

Note: All most likely values (MLV) are based on Monte Carlo analysis with 100,000 iterations. All physical loss estimates are expressed in thousand tons of milled rice. CAR = Central African Republic; DRC = Democratic Republic of Congo.
[a] Similarly to Diagne et al. (2013), we merge Sudan with South Sudan.

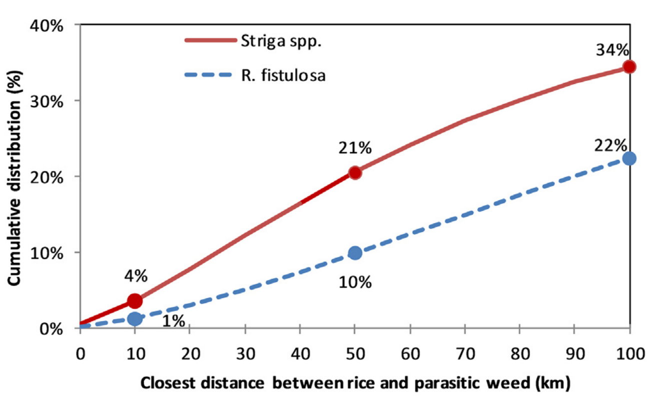

Fig. 2. Ascending cumulative distribution of rain-fed rice growing areas (pixels) in function of closest distance to parasitic weed observations for *R. fistulosa* and *Striga* spp. in Africa.

Assuming the probabilistic diffusion wave presented in Eq. (8), our model estimates that the most likely annual physical loss inflicted by *R. fistulosa* is 204,000 tons of milled rice resulting in an annual economic loss of US $82 million (Table 5). For *Striga* spp., hence all three species combined, the incidence in rain-fed upland rice in Africa is estimated to range from 3.6% to 21% and further to 34%, depending on an assumed radius of 10, 50 and 100 km respectively. Annual physical loss is most likely around 293,000 tons of milled rice resulting in an annual economic loss of US $117 million. Following a Monte Carlo analysis with 100,000 iterations, a stochastic distribution of the total economic losses of all parasitic weeds species combined is drawn, which suggests that annual economic losses inflicted by all parasitic weeds exceeds, with 95% certainty, a minimum value of US$111 million and most likely reaches roughly US$200 million (Fig. 3). The top-10 most affected countries are Nigeria, Guinea, Mali, Côte d'Ivoire, Cameroon, Tanzania, Madagascar, Uganda, Sierra Leone and Burkina Faso. Incidence trends derived from the literature (Table 3) were used to estimate the annual incremental incidence of parasitic weed species following the Pert distribution (Eq. (13)), which in turn was fed back into the model (Eq. (2)). Based on that, the parasitic weed-inflicted economic losses were estimated to grow by US $30

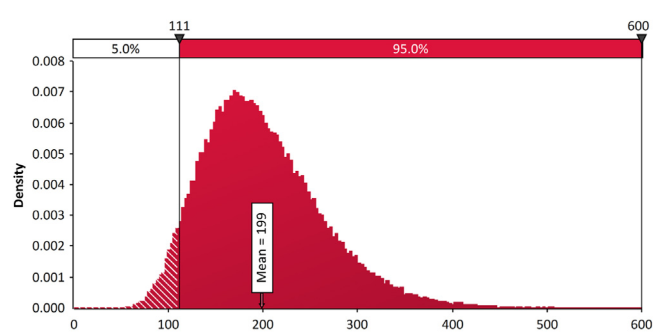

Fig. 3. Stochastic distribution and 95% confidence interval of the total economic losses (10^6 US$) inflicted by *R. fistulosa* and *Striga* spp. in rice in Africa based on a Monte Carlo analysis with 100,000 iterations.

million annually (Table 5). This incremental change will probably not be linear; it may exponentially grow or decay over time depending on (i) farmers' ability to learn from previous experience and cope with this moving infestation front, and (ii) researchers' and extension agents' success in developing and communicating innovative control strategies that can effectively mitigate economic losses.

4. Discussion

4.1. Perspectives on incidence and loss estimates

The most widely cited study on incidence and impact of *Striga* spp. on cereal production in Africa estimated the total infested cereal production area to be 21 million ha, and the annual losses at 4.1 million tons (Sauerborn, 1991). However, the study was conducted about 25 years ago, was limited to only six countries and did not include upland rice in the analyses. More complete and more recent estimates are necessary, in order to better inform stakeholders such as researchers, donors and local and national policy makers. Following our most likely value of incidence rate of *Striga* spp. of the total upland rice growing environments disaggregated per country (Table 5), and the upland rice area estimates for these countries from Diagne et al. (2013), our best estimate of the infested area would be 887,000 ha with annual yield losses of 488,000 tons paddy (average yield loss of 0.55 t ha^{-1}). To put this in perspective, it should be noted that rain-fed upland rice covers only about 4% of the total area under cereals in sub-Saharan Africa in 2013 (FAO, 2016; adjusted with rice-growing environment specific data from Diagne et al., 2013). A total area of 455,000 ha of rain-fed lowlands is estimated to be infested with *R. fistulosa* in SSA, leading to an estimated total production loss of 340,000 tons paddy (average yield loss of 0.75 t ha^{-1}). Rain-fed lowland rice covers about 4.5% of the total cereal production area in Africa. The total parasitic weed infested rain-fed rice area in SSA is estimated to be 1.34 million ha and the total parasitic weed inflicted production loss is estimated at 829,000 tons of paddy. For comparison, the overall regional weed-inflicted production loss in rain-fed uplands and lowlands combined was previously roughly, and conservatively, estimated at 1.40 million tons of paddy (Rodenburg and Johnson, 2009).

4.2. Spatial data quality

The quality of parasitic weed distribution maps, on which the impact estimates are ultimately based, are subject to the quality of the herbarium specimen and hence the correct identification of the specimen by the botanists who collected or archived them. Some debate and confusion exists on the taxonomy and distribution of *Striga* species. Based on Mohamed et al. (2001) the species *S. asiatica* only occurs in East and Southern Africa, whereas *S. hirsuta* spreads from West to East and into Southern Africa. From our herbarium study, the species *S. asiatica* has a much wider distribution. Some confusion with other *Striga* species can however not be excluded as *Striga asiatica* is often confused with *S. lutea* Lour. and *S. hirsuta* Benth. Some botanists, e.g., Musselman and Hepper (1986), have lumped *S. asiatica*, *S. lutea*, and *S. hirsuta* as a single species, *S. asiatica*. Due to that, many herbarium specimen of *S. lutea*, and *S. hirsuta* have been named or renamed *S. asiatica*. Mohamed et al. (2001) reported however consistent morphological, ecological, and phenological differences among these and concluded that three taxa should be recognized. In the herbarium search we followed the taxonomy of Mohamed et al. (2001), and specimen filed as *S. asiatica* but with mentions of the names *S. lutea* or *S. hirsuta* were therefore not used. In West Africa, *Striga asiatica* seems less weedy in rice. For instance, in Côte d'Ivoire, Johnson et al. (1997) found *S. asiatica* in maize and upland rice fields but at low levels of infestation and mainly parasitizing the grass weed *Andropogon gayanus* Kunth, rather than these crops. Botanga et al. (2002) found *S. asiatica* mainly on maize and wild grasses (*Rottboellia* spp. and *Panicum* spp.). There are also two co-existing morphotypes of *Striga asiatica*, the common red-flowered and the less common yellow flowered form (Botanga et al., 2002). The red-flowered morphotype seems to dominate as pest in rice and it is not clear whether the yellow morphotype is equally virulent and whether it can indeed be considered a parasitic weed in rice. In the herbarium search, we found 27 data points with explicit mention of the yellow-flowered morphotype, 24 in West- and Central Africa and 3 in South-East Africa. Only 5 of those data points fall within a radius of 100 km of rain-fed rice growing areas. Inclusion of this morphotype in the database is therefore not likely to cause any overestimation of the incidence and impact. Lastly, due to similar morphological appearances and flower colors, *S. hermonthica* can be confused with *S. aspera* and the occasional *S. brachycalyx* Skan (Mohamed et al., 2001; 2006).

Also the quality of the rain-fed rice maps determines the reliability of the incidence and impact estimates. For four countries—all with at least one species of parasitic weeds—i.e. Burundi, Ethiopia, Kenya and South Africa, the available spatial data on rain-fed rice seem inaccurate. Kenya and South Africa have indeed negligible (<1,000 ha) areas of rain-fed rice (Diagne et al., 2013). However for Burundi (>9,000 ha of rain-fed rice; parasitic weeds reported: *S. asiatica*, *S. hermonthica* and *R. fistulosa*) and Ethiopia (>6,000 ha of rain-fed rice; all four species of weeds reported), the inaccuracy of spatial rice data may have caused a slight underestimation of the overall impact of parasitic weeds in SSA. Furthermore, the threshold of 500 mm rainfall that we applied to discard grid cells for mapping rain-fed rice is arbitrary. Rain-fed upland rice is usually produced in zones with more than 1,000 mm rainfall (e.g. Singh et al., 2009) but the exact limit very much depends on local soil conditions and crop management (Day et al., 1992), as well as on landscape morphology. In landscape depressions, i.e. inland valleys, rain-fed lowland rice production could still be pursued at much lower levels of rainfall, due to favorable hydrology leading to supplementary water from surface and groundwater flows from surrounding uplands and slopes (Windmeijer and Andriesse, 1993).

4.3. Quality and sensitivity of estimates and parameters

Although our stochastic model exploits the scarce data available to the maximum extent possible and reflects their uncertainty, our most likely economic loss estimates are conservative for three additional reasons. Firstly, our incidence curves are prone to (i) Type I errors if the parasitic weeds that have been observed on certain locations have not infested rain-fed rice fields or have disappeared over time; and (ii) Type II errors if parasitic weeds occur and have infested rain-fed rice fields on locations where no herbarium specimen has been collected. Type I and II errors respectively result in an over- versus underestimation of parasitic weed incidence. However, we expect Type II errors to dominate Type I errors due to incomplete spatial coverage of parasitic weed observations and therefore we expect our incidence curves $\varphi_{ij}(d)$ to be on the conservative side. Moreover, our simple probabilistic diffusion wave assumes that weeds spread equally in all directions, so the diffusion may be described by a series of concentric circles. In reality, parasitic weed seeds are spread mainly through local transport and trade of cereal seeds, as observed from seed samples taken at local markets (Berner et al., 1994). Such dissemination, in addition to environmental heterogeneity and spatial irregularities, result in an uneven spread (Doyle et al., 2001). In this study, we overlapped parasitic weed observations with a single enabling factor, i.e. the rice-growing environment. Further refinements to this model are needed by adding additional layers of enabling or disabling factors related to soils, management practices, competitor species, and climatic variables (Doyle et al., 2001), and convert it into a more sophisticated stratified diffusion model (Van Dyke, 2008). However, due to severe data scarcity this is currently not possible in the context of parasitic weeds in rain-fed rice growing environments in Africa.

Secondly, our data assumptions overestimate farmers' efficacy of controlling parasitic weeds and hence underestimate the true damage of this pest. Manual weeding is the predominant parasitic weed control practice in rain-fed cereal cropping systems in sub-Saharan Africa (Aflakpui et al., 2008; Ayongwa et al., 2010) and this is not different for rice (Houngbedji et al., 2014; N'cho et al., 2014). N'cho (2014) estimated technical efficiency of manual weeding labor in a context of parasitic weeds infestation in Benin and Côte d'Ivoire. Assuming constant returns to scale, technical inefficiency levels of weeding labor were estimated to be around 58% in Côte d'Ivoire and 69% in Benin, implying that 58–69% of weeding labor could be saved without reducing rice production or increasing the use of other inputs. Overall technical efficiency scores were estimated to be 64% in Benin and 85% in Côte d'Ivoire, which suggests that rice farmers can still increase their production by as much as 36% in Benin and 15% in Côte d'Ivoire through more efficient use of production factors and control of parasitic weeds. Since we based our efficacy estimates on advanced technologies (Table 2), we overestimate farmers' current ability to cope with parasitic weed problems.

Finally, a limitation of our parsimonious model is that it assumes rice area to be constant, and hence ignores the area response occurring in the hypothetical absence of parasitic weeds. Farmers would plant greater areas with a crop in response to higher levels of profitability (Chambers et al., 2010). Conversely, our model does not capture the loss in production due to farmers abandoning their fields as a result of parasitic weed infestation, as reported by N'cho et al. (2014) in Benin and Houngbedji et al. (2014) in Togo. On marginal lands, farmers are discouraged to plant rice when the land becomes infested with parasitic weeds (N'cho, 2014). As a coping strategy, they often migrate to previously uncultivated lands and as a result of population pressure and reduction of available land, they increase duration of cropping at the expense of fallow duration (N'cho, 2014). Reduced fallow times in turn result in higher occurrence of weeds in the cultivated fields (Demont et al., 2007) and a likely buildup of the seed bank of parasitic weeds (Sauerborn and Kroschel, 1996), unless parasitic weed seed production in the crop is somehow prevented (van Mourik et al., 2011). Including such area responses would require incorporating a market model into our framework, which is beyond the scope of our study. A market model would also enable capturing price effects. For example, in the absence of parasitic weeds, domestic rice prices would be lower due to higher supply of rice production. Hence, not incorporating area response and price effects has respectively led to an underestimation versus overestimation of total economic losses.

Nevertheless, data scarcity on incidence, yield losses and control efficacies achieved by farmers is currently the main bottleneck in the estimation of economic losses. The parameterization of our stochastic impact assessment is disaggregated at the country and species level, i.e. the three stochastic parameters feature a separate statistical distribution for each of the two species in each of the 31 countries (Table 5). Although for each parameter the distribution is identical among species and countries, during each iteration the program @Risk will randomly select a different combination of values for these parameters among species and countries. As a result, the total number of stochastic parameters influencing total economic losses is $3 \times 2 \times 31 = 186$. To illustrate the sensitivity of our impact estimates (Eq. (1)) to our distributional assumptions of our parameters (Eqs. (11)–(13)), we visualize the relative contribution of the top-10 most important factors in Fig. 4. The horizontal bars represent normalized regression coefficients, which show the proportional change in the standard deviation of total economic losses if the respective parameter is increased by one standard deviation. A coefficient of 1 or −1 indicates a 1 or −1 standard deviation change in the output for a 1 standard deviation change in the input (Palisade Corporation, 2013). For example, Fig. 4 suggests that if the true incidence of *R. fistulosa* in Nigeria were one standard deviation higher than our most likely value of 7.2% (Table 5), we would have underestimated total economic losses inflicted by *R. fistulosa* in Africa by 51% of its standard deviation (i.e. US $32 million, Fig. 3). Furthermore, if we had overestimated Nigerian farmers' efficacy of controlling *R. fistulosa* or underestimated the theoretical yield loss inflicted by *R. fistulosa* under absence of control by one standard deviation, we would have underestimated total economic losses inflicted by *R. fistulosa* in Africa by respectively 17% or 16% of its standard deviation (i.e. US $10–11 million, Fig. 3). The uncertainty surrounding total economic losses seems to be driven by scale first and then by the uncertainty of the parameters. The top-five countries with the largest rain-fed rice areas and high incidence rates of parasitic weeds dominate the aggregate economic losses, i.e. Nigeria, Guinea, Côte d'Ivoire, Mali and Tanzania. Secondly, given our assumed stochastic distributions for each of the parameters, the uncertainty surrounding our incidence estimates seems to dwarf the uncertainty regarding the efficacy and yield loss estimates. The results are similar for the remaining 176 stochastic parameters. This sensitivity analysis suggests that we first need to obtain more accurate incidence estimates in the top-five countries to further refine our economic impact estimates. The highly negative coefficient of the efficacy parameter suggests that—given that farmers have little control over parasitic weed incidence and control-free losses—improving the efficacy of parasitic weed control technologies is a first priority in helping farmers to cope with this problem. Our stochastic model provides a useful insight in the potential order of magnitude of the benefits that can be obtained by more efficient control of parasitic weeds in cereal production systems in Africa.

5. Conclusion

This study presents the first systematic and integrated multi-species, multi-country, single-crop impact assessment conducted on parasitic weeds. It shows that with a combination of data mining, spatial analysis and stochastic impact assessment, a confidence interval of economic pest-inflicted losses can be made,

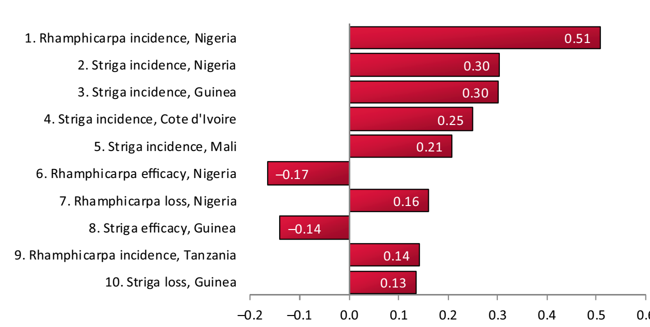

Fig. 4. Normalized regression coefficients of the top-10 factors influencing total economic losses inflicted by *R. fistulosa* and *Striga* spp. in rice in Africa based on a Monte Carlo analysis with 100,000 iterations. A coefficient of 1 or −1 indicates a 1 or −1 standard deviation change in the output for a 1 standard deviation change in the input (Palisade Corporation, 2013).

when primary data are scarce or absent. Such exercise also proved valuable for the identification of the major drivers for these losses, and hence priorities for policy, research, training and communication aimed at prevention of the causes and mitigation of the effects. In addition, the pursued stochastic modeling approach used here provides the potential order of magnitude of the benefits obtained by such policy, research and extension efforts.

This study underlines that parasitic weeds are common and widely distributed production constraints in rain-fed cereal production systems of sub-Saharan Africa. The most weedy *Striga* species in upland rice – i.e. *Striga asiatica*, *S. aspera* and *S. hermonthica* – occur in at least 31 upland rice producing countries with a most likely mean incidence rate of 12%. The total rice area infested by *Striga* spp. in SSA is estimated at 887,000 ha and the annual losses inflicted by *Striga* spp. are estimated at 293,000 tons of milled rice. *Rhamphicarpa fistulosa* occurs predominantly in rain-fed lowland areas and is observed in at least 28 countries producing rice in such environments. The most likely mean incidence of *R. fistulosa* in those rice-growing environments is 6%. The total *R. fistulosa* infested lowland rice area in SSA is estimated at 455,000 ha, leading to an estimated total annual production loss of 204,000 tons of milled rice. Together, these weeds are estimated to cost African economies US $200 million per year, with an annual increase of US $30 million.

The estimates generated by this study accentuate that parasitic weeds are an underestimated and also an increasing threat to rice production in SSA. Sensitivity analyses showed that the first priority to help individual rice farmers to cope with parasitic weeds, should be to improve their control efficacies. National policy and decision makers, as well as international donors, should therefore be engaged in targeted investments in research and capacity building on parasitic weed management strategies enabling farmers to reduce infection and damage levels in their crops. The top-10 priority countries where investments in parasitic weed research, capacity building and national strategy development would probably have the highest return are Nigeria, Guinea, Mali, Côte d'Ivoire, Cameroon, Tanzania, Madagascar, Uganda, Sierra Leone and Burkina Faso.

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