4 Farmer Perceptions of the Biophysical Constraints to Rice Production in Sub-Saharan Africa, and Potential Impact of Research

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Introduction

Average rice yield in Africa (2.15 t/ha; USDA, 2013)[1] is low compared with other continents; this is to a large extent a result of the fact that rice cropping in sub-Saharan Africa (SSA) is predominantly rainfed (see Diagne *et al.*, Chapter 3, this volume). Important gaps exist, however, between actual farmers' yields in a growing season and what would be possible with improved crop management practices. The maximum or **potential yield** (Yp) in farmers' fields is defined as the yield of a cultivar when grown under the conditions to which it is adapted, where nutrients and water are not limiting, and pests and diseases are effectively controlled (Evans, 1993). Estimates of Yp are usually based on crop simulation modelling studies (see Saito *et al.*, Chapter 15, this volume).

Solar radiation, carbon-dioxide concentration, temperature and crop characteristics are the major **yield-defining** factors that determine Yp. Breeding efforts may help raise Yp – for example, by introducing hybrid rice varieties. **Yield-limiting** factors are related to shortage of water or nutrients (or both) and determine water- or nutrient-limited production levels in a given rice environment. **Yield-reducing** factors induce yield losses by reducing or hampering growth, including abiotic and biotic factors. Biotic factors include weeds, pests and diseases; abiotic factors include salinity, alkalinity and iron toxicity.

Attainable yield (Ya) refers to the yield that can be achieved with best management practices that control yield-limiting and yield-reducing factors in a economically optimal manner. Under irrigated conditions, this is typically about 80% of Yp. The **yield gap** is commonly defined as the difference between Yp or Ya and actual average farmers' yields. A range of socio-economic reasons underpin these yield gaps at harvest and the substantial losses that often occur after harvest (see Rickman *et al.*, Chapter 27, this volume), such as lack of availability of key inputs (labour, fertilizer, etc.) and sub-optimal knowledge of improved management practices.

In this chapter, we quantify farmer perceptions of major biotic and abiotic constraints that limit and reduce rice yields in farmers' fields in SSA. We also estimate the potential impact of research addressing such constraints.

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Methodology

Data used in this chapter are derived from farm-household surveys conducted in 2009–2010 in 21 countries by Africa Rice Center (AfricaRice) in collaboration with partners from national agricultural research systems (NARS) and national agricultural statistics systems. Data were complete and of acceptable quality for 18 countries: Benin, Burkina Faso, Cameroon, Central African Republic (CAR), Côte d'Ivoire, Democratic Republic of Congo (DRC), The Gambia, Ghana, Guinea, Kenya, Madagascar, Nigeria, Rwanda, Senegal, Sierra Leone, Tanzania, Togo and Uganda. These 18 countries accounted for almost 87% of area harvested and 84% of total rice production in SSA in 2010 (FAOSTAT, 2010).

Surveys were designed to produce nationally representative rice production data. A two-stage stratified random sampling methodology was used in most countries (for details see AfricaRice, 2010) with regions, provinces, departments or states used as strata. Within each stratum, rice-producing villages were randomly selected in the first stage and rice-farming households were randomly selected in the second stage. The sample size ranged from 395 (Rwanda) to 10,500 (Nigeria). Detailed descriptions of the sampling methodologies and data analyses can be found in the country reports and the synthesis report (AfricaRice, 2010).

Farmer perceptions of abiotic and biotic constraints

We used the following grouping of abiotic and biotic constraints:

1. Biotic constraints: weeds (considering all weed species, except parasitic weeds), diseases (*Rice yellow mottle virus*, blast and bacterial leaf blight), insects (African rice gall midge, termites and stem borers), birds and rodents.

2. Abiotic constraints (climate-related): drought, flooding and extreme temperatures.

3. Abiotic constraints (soil-related): non-fertile soil (low organic-matter content, poor water-holding capacity), nutrient deficiencies (N, P, K, Zn), Fe toxicity, salinity, alkalinity, acidity and soil erosion.

In each rice environment (upland, rainfed lowland, irrigated and others, including mangrove-swamp and deep-water environments), we assessed the relative prevalence of these biotic and abiotic constraints and the losses they cause as perceived by farmers. The proportion of farmers who experienced one of the constraints was estimated along with the average area affected within their field and the yield loss incurred on a whole-field basis when the constraint occurred.

Data on rice production constraints were collected in each country through a sequence of three surveys, involving: (i) rice experts in the country; (ii) focus groups in sample villages; and (iii) individual farmers. Rice experts' knowledge enabled us to identify the major biotic and abiotic constraints occurring in the country in each rice environment and to develop materials to be used during interviews with farmers (e.g. pictures of symptoms and descriptions in local languages). For this purpose, an exhaustive list of biotic and abiotic constraints was available (complete with local names), along with pictures of accompanying symptoms – a resource developed by AfricaRice scientists and refined over time, reflecting experience in collecting this type of information gained since 2000.

Data collected in the village focus groups enabled enumerators to establish a list of biotic and abiotic constraints for each village (by rice environment) (list one). We also identified the five major biotic or abiotic constraints that negatively affected rice production in each village (list two).

From the lists and symptom illustrations, farmers identified the constraints that they experienced and provided their perceptions of their incidence and their importance in general in terms of scope and severity. For each constraint known in the village, information on awareness of the constraint and its occurrence in the village was elicited from each sample farmer and for each rice environment. Farmers scored or ranked the relative importance of each constraint that they were aware of on a scale of: 0 – constraint does not occur (i.e. in the village); 1 – minor constraint; 2 – intermediate constraint; 3 – major constraint.

Next, for each of the five major constraints, the farmer was asked the following set of questions:

1. Do you know the constraint? If so:

2. Have you experienced the constraint in each of the past three years, i.e. 2008, 2007, 2006? (This chapter uses only results for 2008.)

3. What was the proportion of area affected in your field in 2008, 2007, 2006? (This chapter uses only data for 2008.)
4. What was the percentage reduction in yield for your entire field because of this constraint as compared to a year without it?

There are several points that should be noted on farmer perception of the relative importance of constraints. First, the set of indicators derived from the information collected using the two lists are not independent. Indeed, the ordinal ranking of the perceived relative importance of the constraint obtained from the first list can be taken as a summary measure of the farmer perception of the prevalence of the constraint as measured in (2) and the perception of its scope and severity when it occurs as measured in (3) and (4), respectively. Second, farmers' perceptions of the relative importance of a constraint can be very different from the real importance of the constraint (in terms of scope and severity) if it were measured. In other words, farmers may have the wrong perception about the relative importance of the constraint. However, it is important to keep in mind that it is this subjective perception, right or wrong, that drives farmers' production decisions, including the *ex-ante* preventive and *ex-post* mitigating actions they take with respect to the constraint. Hence, in the end the **real effects** of the constraint on each farmer's productivity outcomes will be the results of both the **real importance** (as it would be measured objectively by an expert) and that farmer's **perception** of its importance (which dictates the *ex-ante* preventive and *ex-post* mitigating actions he or she takes). Thus, in determining the relative importance of a constraint in terms of its negative effects on productivity, both the objective assessments of knowledgeable experts and the subjective assessments of farmers are important and complementary. Furthermore, one can argue that the divergence between the two assessments is smaller with the ordinal ranking based on the first list than with the estimates of proportion of areas affected and yield loss in (3) and (4) above. This is because of its ordinal nature, the first assessment is a measure of relative importance which can lead to the same ordinal ranking of a constraint by a farmer and a knowledgeable expert even if they give different estimates of yield loss and area affected by the constraint.[2]

From the information collected, we developed four alternative measures of relative importance of a biophysical constraint as perceived by a sample of farmers randomly selected from a population of rice farmers.

We use the following notation. First, let $\tilde{S}$ be the set of all biotic and abiotic constraints existing in a country and let n be the sample size. For any constraint $s \in \tilde{S}$ and any farmer i, $i = 1,..,n$, let $r_i^s \in \{0,1,2,3\}$ be the rank given to the constraint s by farmer i when expressing his or her perception of the relative importance of constraint s. Also, for any given rank $r \in \{0,1,2,3\}$, let d_{ir}^s be the dummy binary indicator that takes the value 1 if $r_i^s = r$ and the value 0 if $r_i^s \neq r$. Also for any constraint $s \in \tilde{S}$ and any farmer i, let e_i^s be the dummy binary indicator taking the value 1 if the farmer has experienced the constraint s (in a particular year) and 0 otherwise; let a_i be the total rice area of farmer i, a_i^s the area affected by the constraint s and $\alpha_i^s = \frac{a_i^s}{a_i}$ the proportion of the land affected by the constraint; $\Delta y_i^s = 1 - \frac{y_{i1}^s}{y_{i0}^s}$ the farmer's perceived percentage yield reduction on a whole-field basis when he or she experiences the constraint, where y_{i1}^s and y_{i0}^s are the yield obtained by the farmer (total quantity of harvested rice divided by the total cultivated rice area) with and without experience of the constraint, respectively. Finally, to reflect the restrictive nature of the top-five list of constraints (list two), we will define for any farmer i a sub-set $\tilde{S}_i^m$ of $\tilde{S}$ of five major constraints identified in his or her village and the dummy binary indicator m_i^s that takes the value 1 if $s \in \tilde{S}_i^m$ and 0 otherwise.

From these notations, we defined five measures for assessing the relative importance of each biotic or abiotic constraint s found in the different rice environments as perceived by a sample of size n of rice farmers randomly selected from a rice-farming population:

1. The percentage of sample farmers who perceive the constraint s to have a relative importance of rank r, $r = 0,1,2,3$ (does not exist in the village, minor, medium, major): $f_r^s = \frac{1}{n}\sum_{i=1}^{n} d_{ir}^s$
2. A farmer perception index of the relative importance of the constraint as given by the average

rank given to the constraint by sample farmers, normalized to lie between the values 0 and 1: $\bar{\bar{r}}^s = \frac{1}{3} \times \bar{r}^s$ where $\bar{\bar{r}}^s = \frac{1}{n}\sum_{i=1}^{n} r_i^s = \frac{1}{n}\sum_{i=1}^{n}\sum_{r=0}^{3} r d_{ir}^s$ is the average ranking of the constraint.[3]

3. Percentage of farmers experiencing the constraint in 2008, provided it is among the five 'major' constraints in the village: $E^{s,2008} = \frac{1}{n}\sum_{i=1}^{n} m_i^s e_i^s$.

4. Proportion of area affected for farmers who experienced the constraint in 2008, provided it is among the five 'major' constraints in the village: $A^{s,2008} = \frac{1}{n_m^s}\sum_{i=i}^{n} m_i^s e_i^s \alpha_i^s$.

5. Percentage reduction in yield on a whole-field basis compared to no-constraint conditions for farmers who have experienced the constraint, provided it is among the five 'major' constraints in the village: $\Delta y^{s,2008} = \frac{1}{n_m^s}\sum_{i=1}^{n} m_i^s e_i^s \Delta y_i^s$.

Unfortunately, even if the sample is random, all five constraint indicators derived above are biased estimates of the respective population measures of the relative importance of a constraint. Indicators 1 and 2 are based on list one and suffer from **population non-awareness bias** that arises from the fact that awareness of the existence of a constraint is not universal in the rice farming population. This non-awareness bias, which is a characteristic of the population, is the same type of bias identified by Diagne (2006) in the context of adoption of a new variety the existence of which is not universally known in the population (see also Diagne and Demont, 2007; Diagne, 2009).

Indicators 3, 4 and 5 are based on the second list of constraints (top five) and also suffer from the same population non-awareness bias. They also suffer from a **sample minority-exclusion bias** caused by the restricted nature of the second list, which (by the design of the survey instruments) excluded the 'non-major' constraints. This exclusion is intentional, made in order to reduce the time taken to collect the information related to farmers' estimates of the proportion of area affected and yield loss when they experience a constraint. Hence, in contrast to the non-awareness bias, the exclusion bias is a property of the sample and not a property of the population.

In Appendix 4.1, we formally demonstrate the following facts about these two biases. First, everything else being equal, population non-awareness introduces a **downward** bias in all five constraint indicators if the measure of relative importance of the constraint at the individual farmer level is monotonically and positively related to awareness of the existence of the constraint – for any farmer, the perceived relative importance of the constraint cannot be lower when he or she is aware of the constraint compared to when he or she is not. This positive monotonicity is clearly satisfied by all five measures of relative importance of a constraint.[4] Furthermore, the downward bias introduced by non-awareness disappears completely when all farmers are aware of the existence of the constraint; conversely, and everything else being equal, the bias is more severe for constraints that farmers are less likely to be aware of compared to the ones they are more likely to be aware of. This is particularly the case for most abiotic constraints, which are usually more difficult for farmers to diagnose. Hence, we should expect abiotic constraints in the sample to have generally lower sample estimates for indicators 1 and 2 compared to biotic constraints.

Second, everything else being equal, sample minority-exclusion introduces an **upward** bias in constraint indicators 3, 4 and 5 if the measure of relative importance of the constraint at the individual farmer level is positively correlated with the constraint being major for the farmer – for any farmer, the perceived relative importance of the constraint cannot be lower when the constraint is a major constraint compared to when it is not. Again, positive correlation with the constraint being a major constraint is clearly satisfied by all five measures of relative importance of a constraint. Also, as with non-awareness, the upward bias introduced by sample minority-exclusion disappears completely when all the constraints are major constraints for all farmers.

Third, the two biases introduced by population non-awareness and sample minority-exclusion are additive and operate in opposite directions. Hence, the direction of the overall bias in the three sample indicators of relative importance of a constraint in (3)–(5) is indeterminate and depends on the relative sizes of the two biases. Moreover, the overall bias may vanish if the biases cancel out each other.

Potential Impact of Research Aiming to Reduce Yield Loss Caused by Biotic and Abiotic Constraints

Next, we assessed the potential economic and poverty impact of reducing part of the yield gap caused by the major biotic and abiotic constraints in SSA, directly in the 18 African countries surveyed and indirectly through extrapolation to another 18 rice-producing countries in Africa using secondary data (i.e. 36 countries in total; for more details see Diagne *et al.*, Chapter 32, this volume).

The evaluation of the potential impact of reduction of the yield loss incurred by farmers when they experience a biotic or abiotic constraint is based on an econometric model that links yield loss, farmers' profits and village poverty levels. For this purpose, research to address a biotic or abiotic constraint is assumed to lead to some percentage reduction in yield loss caused by the constraint when it occurs. The impact on income and production is assessed directly at the farmer level, while the impact on poverty is done at village level (see Appendix 4.2).

We use an autoregressive model for each outcome (farmer income and village poverty headcount) with the contemporaneous yield loss of each constraint to assess the impact of research technology addressing the constraint. The general form of the equation estimated is $E(Z_t \mid Z_{t-1}, e^s, \Delta y^s, x) = \alpha Z_{t-1} + \beta e^s \Delta y^s + \gamma e^s + \sigma(x)$, where Z_t is the outcome variable at year t and Z_{t-1} that for the preceding year; Δy^s stands for the yield loss caused by the constraint s; e^s is a binary variable indicating the experience or not of a given constraint ($e^s = 1$ and $e^s = 0$ indicate the experience and the non-experience of the constraint by a farmer, respectively); x is a vector of covariates that encompasses household socio-demographic and economic characteristics (the head of household's age, gender, education level and occupational status; household size, farm size, community infrastructures, etc.); and α, β, γ and σ are the model parameters to be estimated (with the parameter σ being modelled as a function of x). For the purpose of this estimation, we assume the yield loss to be exogenous to the farmer's decision, thus ordinary least squares estimation would yield consistent parameter estimates.

Following Diagne *et al.* (2012), a first-order autoregressive (AR1) model is used to estimate impact parameters and project annual individual impact over time up to 2035, in line with the 25-year vision of success of the Global Rice Science Partnership (GRiSP; IRRI *et al.*, 2010). The estimated impact parameters are combined with secondary data on the number of rice-farming households and the average household size to get aggregated impact at country level under the assumption that the technology adoption follows a logistic diffusion curve (for more details see Diagne *et al.*, Chapter 32, this volume). The attainable yield loss reduction by research for each constraint and each environment was obtained through a consultation process involving rice scientists at AfricaRice. For each constraint, assumptions on initial and peak adoption rates with the respective year they may be reached are also used.

Results

The estimations of the five constraint indicators in the different rice environments as perceived by the rice farmers in our sample are presented in Tables 4.1 (for the biotic constraints), 4.2 (for the soil-related abiotic constraints) and 4.3 (for the climate-related constraints).

Perception, experience and effects of major biotic constraints

About 76% of farmers (see Table 4.1) reported having experienced (in 2008) at least one of the biotic constraints in the list of the five major biophysical constraints identified in the village. The proportion was 60% for irrigated, 81% for upland and rainfed lowland, and 88% for other rice environments. When these constraints occurred, about 30% of the harvested areas were affected, causing on average 22% of yield loss across all rice environments and all countries. The area affected and the yield losses due to biotic constraints varied slightly across rice environments. The estimated areas affected and yield losses were, respectively, 29% and 21% in irrigated, 30% and 23% in upland, 30% and 21% in rainfed lowland, and 32% and 19% in other environments.

Among biotic constraints, weed infestation was ranked as the most important by far, followed by birds and rodents, the various insects and rice diseases (Table 4.1).

Table 4.1. Farmers' perceptions of the relative importance of biotic constraints across rice environments in 18 countries in sub-Saharan Africa.

Biotic constraints	Percentage of farmers assigning a given rank to the constraint (f_r^s) None (r=0)	Minor (r=1)	Inter-mediate (r=2)	Major (r=3)	Normalized average rank given to the constraint by farmers ($\bar{\bar{r}}^s$) (scale: 0–100)	Percentage of farmers who had experienced the constraint ($E^{s,2008}$)	Average percentage of areas affected by the constraint when experienced ($A^{s,2008}$)	Average percentage yield reduction caused by the constraint when experienced ($\Delta y^{s,2008}$)
All rice environments								
All biotic constraints					93	76	30	22
Weeds	2	8	20	70	86	53	33	22
Birds and rodents	4	14	24	59	79	45	29	21
Diseases					61	17	25	20
Bacterial leaf blight	36	25	24	15	39	5	22	17
Blast	29	26	24	21	46	7	28	22
Rice yellow mottle virus (RYMV)	23	30	27	20	48	4	23	19
Insects					76	50	27	20
African rice gall midge	34	16	19	30	49	14	27	20
Stem borers	24	32	25	19	46	11	29	23
Termites	18	24	28	30	56	14	31	23
Other insects	6	26	31	37	66	29	26	19
Irrigated								
All biotic constraints					93	60	29	21
Weeds	2	9	27	62	83	39	27	18
Birds and rodents	4	16	22	58	78	31	30	19
Diseases					56	15	26	19
Bacterial leaf blight	34	30	23	13	39	4	21	16
Blast	36	28	24	12	38	5	32	19
RYMV	39	25	22	14	37	4	30	25
Other diseases	41	29	19	11	33	4	23	21
Insects					66	37	30	22
African rice gall midge	57	10	19	14	30	4	36	29
Stem borers	32	31	24	14	40	9	35	25
Other insects	12	24	36	29	61	25	29	21
Upland								
All biotic constraints					96	81	30	23
Weeds	1	6	14	79	90	54	32	22
Birds and rodents	2	8	19	71	87	51	32	24
Diseases					66	20	22	19

Continued

Table 4.1. Continued.

Biotic constraints	Percentage of farmers assigning a given rank to the constraint (f_r^s): None (r=0)	Minor (r=1)	Inter-mediate (r=2)	Major (r=3)	Normalized average rank given to the constraint by farmers ($\bar{\bar{r}}^s$) (scale: 0–100)	Percentage of farmers who had experienced the constraint ($E^{s,2008}$)	Average percentage of areas affected by the constraint when experienced ($A^{s,2008}$)	Average percentage yield reduction caused by the constraint when experienced ($\Delta y^{s,2008}$)
Bacterial leaf blight	43	19	19	19	38	5	16	15
Blast	31	23	22	24	46	10	26	22
Other diseases	42	23	18	17	36	7	17	15
Insects					83	55	27	21
African rice gall midge	32	11	15	42	55	21	25	19
Stem borers	25	33	19	23	46	14	27	24
Termites	11	19	27	43	67	16	30	24
Rainfed lowland								
All biotic constraints					92	81	30	21
Weeds	2	9	20	69	86	61	36	23
Birds and rodents	5	19	28	48	73	46	28	21
Diseases					58	14	23	18
Bacterial leaf blight	38	29	21	12	36	4	17	16
Blast	29	29	21	21	45	4	25	18
RYMV	25	34	23	18	45	4	23	18
Other diseases	34	31	21	15	39	5	27	23
Insects					73	53	26	19
African rice gall midge	34	24	17	25	44	13	26	19
Stem borers	24	35	23	18	45	10	31	22
Termites	17	32	27	24	53	14	28	22
Others								
All biotic constraints					93	88	32	19
Weeds	0	5	41	54	83	56	38	21
Birds and rodents	0	2	29	69	89	64	25	17
Diseases					76	26	41	23
Bacterial leaf blight	2	7	68	23	71	13	51	26
Blast	1	8	68	23	71	14	28	18
Other diseases	1	8	62	29	73	2	34	31
Insects					84	62	34	18
African rice gall midge	0	3	54	43	80	18	37	21
Stem borers	1	3	71	25	73	9	24	13
Other insects	0	6	44	50	81	35	24	14

Table 4.2. Farmers' perceptions of relative importance of soil-related abiotic constraints across rice environments in 18 countries in sub-Saharan Africa.

Soil-related constraints	Percentage of farmers assigning a given rank to the constraint (f_r^s)				Normalized average rank given to the constraint by farmers ($\bar{\bar{r}}^s$) (scale: 0–100)	Percentage of farmers who have experienced the constraint ($E^{s,2008}$)	Average percentage of areas affected by the constraint when experienced ($A^{s,2008}$)	Average percentage yield reduction caused by the constraint when experienced ($\Delta y^{s,2008}$)
	None (r=0)	Minor (r=1)	Medium (r=2)	Major (r=3)				
All rice environments								
All soil-related constraints					77	18	37	27
Non-fertile soil	14	24	33	30	59	6	45	32
Salinity/alkalinity	39	20	22	19	41	1	32	28
Iron toxicity	43	20	19	18	37	2	36	32
Irrigated								
All soil-related constraints					73	19	36	30
Non-fertile soil	12	26	36	27	59	5	43	29
Salinity/alkalinity	53	20	16	11	28	7	34	31
Iron toxicity	47	24	17	13	32	2	30	29
Upland								
All soil-related constraints					80	18	34	25
Non-fertile soil	15	21	28	36	62	7	43	32
Rainfed lowland								
All soil-related constraints					76	17	37	28
Non-fertile soil	15	26	33	27	57	7	45	34
Iron toxicity	42	22	18	18	37	2	38	34
Others								
All soil-related constraints					78	20	50	26
Non-fertile soil	54	34	5	7	11	7	59	27
Salinity/alkalinity	65	23	3	9	9	3	28	15

Weeds

Weeds cause economic losses to agricultural crops, and require some action to reduce their effects on crop production (Zimdahl, 2007). Various categories of rice weeds are common in rice production in Africa, including sedges, broad-leaved species, grasses, parasitic weeds and aquatic weeds (see Rodenburg and Johnson, Chapter 16, this volume). Weeds are the predominant biotic constraint, as perceived by farmers. An estimated 70% of farmers perceive weeds as a major problem across the rice environments, with the highest percentage reported for upland areas (79%). Similar reports were obtained with the perception index. An estimated 53% of rice farmers experienced weed

Table 4.3. Farmers' perceptions of relative importance of climate-related abiotic constraints across rice environments in 18 countries in sub-Saharan Africa.

Climate-related constraints	Percentage of farmers assigning a given rank to the constraint (f_r^s) None ($r = 0$)	Minor ($r = 1$)	Inter-mediate ($r = 2$)	Major ($r = 3$)	Normalized average rank given to the constraint by farmers ($\bar{\bar{r}}^s$) (scale: 0–100)	Percentage of farmers who experienced the constraint ($E^{S,2008}$)	Average percentage of areas affected by the constraint when experienced ($A^{S,2008}$)	Average percentage yield reduction caused by the constraint when experienced ($\Delta y^{s,2008}$)
All rice environments								
All climate-related constraints					76	24	36	27
Drought	16	24	30	30	58	10	37	29
Flooding	25	26	24	25	50	5	37	27
Heat	30	33	23	13	40	1	28	16
Cold	35	30	20	16	39	1	33	29
Irrigated								
All climate-related constraints					75	17	35	28
Drought	20	24	30	26	54	7	31	28
Flooding	26	24	26	24	49	6	40	34
Heat	37	34	19	10	35	1	36	17
Cold	27	37	18	18	43	2	24	16
Upland								
All climate-related constraints					77	25	35	28
Drought	17	18	31	35	61	13	38	31
Flooding	29	19	24	27	50	4	34	25
Heat	28	29	27	16	44	1	30	11
Cold	37	24	22	16	39	1	37	28
Rainfed lowland								
All climate-related constraints					75	28	37	26
Drought	15	30	27	28	56	11	38	28
Flooding	25	33	20	22	46	6	38	27
Heat	35	39	17	9	33	2	26	17
Cold	43	33	13	11	31	1	41	41
Others								
All climate-related constraints					80	16	25	18
Drought	1	5	66	27	73	2	29	28
Flooding	2	4	54	41	78	5	16	13
Heat	1	8	63	28	72	0.1	0	0
Cold	1	4	68	26	73	5	0	0

infestation across rice environments, affecting 33% of their rice area, causing 22% of rice yield loss in 2008. The area affected by weed infestation ranged from 27% in irrigated environments to 38% in other environments, while yield losses ranged from 18% in irrigated environments to 22% in uplands.

Comparison across countries (data not shown) indicated that the highest proportions of farmers experiencing weed infestation were observed in Madagascar (82%), Togo (78%), DRC (77%), Uganda (76%), Côte d'Ivoire (74%) and Burkina Faso (72%). The largest proportions of fields affected were reported in Burkina Faso (57%), Côte d'Ivoire (49%), Togo (43%), Kenya (41%) and Benin (40%). Greatest yield losses were observed in Kenya (43%) and Côte d'Ivoire (40%).

Birds and rodents

Birds feed on rice grains before germination, during crop establishment and during grain filling (see also de Mey and Demont, Chapter 19, this volume). Rodents cause damage at all stages of rice cultivation. Bird and rodent attacks were perceived as a major biotic constraint, coming in second after weed infestation. About 59% of farmers ranked bird and rodent attacks as a major constraint across rice environments, 24% of farmers considered the attacks of intermediate importance, and 14% considered them as a minor constraint. About 45% of rice farmers experienced bird and rodent attacks in 2008, affecting 29% of the area and leading to an estimated 21% yield loss.

About 31% of irrigated-rice farmers experienced losses to birds and rodents in 2008 compared to 64% in other environments. The proportion of the areas affected and yield loss caused by birds and rodents varied little across rice environments. There were, however, noticeable differences across countries (data not shown). The proportion of farmers reporting bird and rodent problems in 2008 ranged from 5% in Rwanda to 91% in Nigeria. The percentage area affected ranged from 8% in Guinea to 51% in Kenya, while the yield loss ranged from a low of 9% in DRC and Guinea to up to 44% in Kenya.

Diseases

There are many diseases that affect rice plants (see Séré *et al.*, Chapter 17, this volume). In this analysis, we focused on bacterial leaf blight, blast and *Rice yellow mottle virus* (RYMV). The normalized average score for all diseases across rice environments is estimated to be 61%, which corresponds to more than the intermediate rank. This means that farmers perceive diseases to be of high relative importance. The average normalized score of all diseases is relatively high in upland environments (66%), meaning that they are perceived to be of high relative importance in uplands. About 17% of rice farmers experienced at least one disease in 2008, affecting 25% of the area and leading to an estimated 20% yield loss.

An assessment based on the perception index shows that bacterial leaf blight is the most important disease in irrigated environments and RYMV and blast in rainfed lowlands.

Looking at differences across countries (data not shown), 71% of Guinean farmers experienced diseases as a major constraint in 2008, followed by CAR (63%) and Madagascar (41%). The area affected by diseases ranged from a low 10% in Guinea to a high of 50% in Kenya, and yield loss ranged from 2% (The Gambia) to 47% (Kenya).

Insects

Several insect species attack the rice plant during its growth stage (see Nwilene *et al.*, Chapter 18, this volume). In this analysis, we focused on African rice gall midge, stem borers and termites. In 2008, insect attacks were experienced least in the irrigated environments (37%) and most often in the other rice environments (62%). About half of rice farmers experienced at least one insect attack across rice environments in 2008, affecting 27% of the area and leading to an estimated 20% yield loss.

Differences between countries were relatively large (data not shown). An estimated 84% of farmers from Sierra Leone and Guinea experienced at least one insect attack in 2008, followed by Burkina Faso (72%) and Madagascar (62%). The average area affected by this constraint ranged from a low 11% in Guinea to a high of 49% in Kenya. The yield loss caused ranged from a low of 8% in DRC to 45% in Kenya.

Perception, experience and effects of major abiotic constraints

Abiotic constraints are dealt with in two groups: soil-related abiotic constraints and climate-related abiotic constraints.

Soil-related constraints

Soil-related constraints included in this survey included: low soil fertility (poor soil fertility, deficiencies in soil macro-nutrients [N, P, K] and Zn, and acidity), salinity and alkalinity, Fe toxicity and other soil-related constraints (soil erosion).

Across all rice-growing environments, the normalized average score for soil-related constraints is about 77%, which means that farmers perceive soil-related constraints to be of high relative importance. According to the perception index, soil-related problems are more important in the uplands than in the irrigated or rainfed lowland environments.

About 18% of rice farmers reported having experienced at least one soil-related constraint as a major constraint in 2008, affecting 37% of their rice area, leading to a yield loss of 27%. The proportion of farmers who had experienced soil-related constraints was 19% in irrigated, 18% in upland and 17% in rainfed lowland. The area affected by these constraints by rice environment ranged from 34% in upland to 50% in other environments. The resulting yield losses ranged from 25% in upland to 30% in irrigated environments.

In Burkina Faso, Senegal and Togo, almost 37% of rice farmers reported major soil problems, both in terms of the proportion of farmers perceiving them of major importance and the proportion of farmers having experienced at least one soil constraint in 2008. For the other countries, this proportion ranged from 0.4% in Rwanda to 31% in The Gambia. The highest share of area affected was 56% (observed in Burkina Faso) and the lowest proportion of area affected was 1% (in Rwanda). The minimum yield loss recorded was 6% in CAR and maximum yield loss was 52% in Kenya.

Drought

An estimated 30% of farmers perceived drought as a major problem across rice environments, with the highest percentage reported for upland areas (35%). Across rice environments, an estimated 10% of rice farmers experienced drought affecting 37% of their rice area, causing 29% of rice yield loss in 2008. Upland and rainfed-lowland rice farmers were most affected by drought in 2008 (11% or more).

Comparison of individual countries (data not shown) indicated that the highest proportions of farmers experiencing drought were in Rwanda (45%), followed by Cameroon (30%) and Burkina Faso (28%). The largest proportion of fields affected was reported in Senegal (51%), followed by Burkina Faso and The Gambia (46%), Benin and Côte d'Ivoire (44%). Greatest yield losses were observed in The Gambia (46%), followed by Senegal (45%) and Côte d'Ivoire (41%).

Flooding

An estimated 25% of farmers perceived flooding as a major problem across rice environments. An estimated 5% of rice farmers experienced flooding across rice environments, affecting 37% of their rice area, causing 27% of rice yield loss in 2008.

Comparison of individual countries (data not shown) indicated that the highest proportion of farmers experiencing flooding was in Kenya (17%), followed by Burkina Faso (11%), Benin and Togo (9%). The largest proportion of fields affected was reported in Burkina Faso (56%), followed by Cameroon (53%), Togo (50%) and Côte d'Ivoire (47%). Greatest yield losses were observed in Rwanda (53%), followed by Kenya (45%), Côte d'Ivoire (42%), Burkina Faso (40%) and Benin (38%).

Extreme temperatures

Very few farmers reported extreme temperatures (cold or heat) across rice environments and countries.

Potential Impact of Research Addressing Biophysical Constraints

We assessed the potential impact of rice research on the biophysical constraints facing rice farmers. The assessments assumed that research targeting a particular biotic or abiotic constraint will generate technological options which, if adopted by farmers, will reduce yield loss due to the occurrence of the constraint by a reasonable magnitude. Assumptions on reduction in yield loss that can reasonably be expected were derived from scientific expert opinions taking into account the presently observed average losses (from the survey) and the chances of finding solutions through research (Table 4.4).

The relative magnitude of yield loss reduction expected from research ranged from 20% (for birds and rodents) to 35% (for weeds and soil-related constraints). Technology options to reduce yield loss due to biophysical constraints are expected to be available for farmer use starting in 2014. The adoption of these technologies is assumed to follow a logistic diffusion curve (see Appendix 4.2 for details on the logistic diffusion curve parameters). The assumed starting adoption rate is 1% for all constraints and the peak ranges from 25% for solutions that address insects to 45% for solutions that address diseases. Peak adoption is assumed to be reached after 2025 for most solutions with half of this peak reached around 2020–2023.

Individual impact on farmer's income and village poverty headcount

Appendix Tables 4.A.2.1 and 4.A.2.2 present the estimation of the farmer income and village poverty rate determination models, respectively. Only the estimates corresponding to the parameters α, β and γ are reported to save space. For the farmer income model (Table 4.A.2.1), the estimated values for the β coefficients that measure the effects of yield loss on farmer income range from –2.78 for diseases to –1.06 for birds and rodents,

Table 4.4. Characteristics of scientific options to reduce yield loss due to biophysical constraints and adoption patterns (start of simulation is 2010).

Characteristic	Weeds	Insects	Birds and rodents	Diseases	Soil-related constraints	Climate-related constraints
Yield loss						
Actual yield loss, AL (%)	22	20	21	20	27	27
Relative reduction, R (fraction between 0 and 1)	0.35	0.25	0.20	0.25	0.35	0.25
Absolute reduction, AR=AL×R (%)	8	5	5	5	10	7
Remaining yield loss after technology adoption, RL=AL−AR (%)	14	15	17	15	18	20
Logistic adoption rate curve parameters						
Adoption rate in the first year (%)	1	1	1	1	1	1
No. adopters in the first year of adoption (thousands)	72	68	62	23	24	33
Starting year of adoption	2014	2014	2014	2014	2014	2014
Peak adoption rate	0.35	0.25	0.30	0.45	0.40	0.35
Peak no. adopters (million)	4.97	1.93	4.5	4.29	2.14	1.93
Year of peak adoption rate	2025	2025	2030	2025	2027	2025
Year when adoption rate is half of peak adoption	2020	2023	2020	2020	2022	2022
Logistic growth parameter	0.29	0.18	0.30	0.31	0.14	0.22

and they are all statistically significantly different from zero at the 10% level except for the ones for diseases and climate-related constraints. The estimated lagged income effects as measured by the α coefficients are all significantly different from zero at the 1% level with estimated values ranging from 0.93 for climate-related constraints to 0.81 for birds and rodents. In addition, the total effect of the experience of the constraint is negatively related to the income as expected and statistically significantly different from zero at the 10% level except for diseases and climate-related stresses.

For the village poverty rate determinants models (Table 4.A.2.2), the estimated effects of yield loss on village poverty rate range from 0.17 for soil-related constraints to 0.02 for birds and rodents and insects, with only the coefficient for weeds being statistically significantly different from zero. The estimated lagged village poverty effects are very high and statistically significantly different from zero at the 1% level, with values ranging from 0.95 for weeds to 0.81 for birds and rodents. In addition, the total effect of the experience of the constraint is positively related to the village poverty rate as expected, but not statistically different from zero except for weeds.

The estimated coefficients of the models are used to forecast the individual impact over time as described by the formula in Appendix 4.2. The results represent the change over time in the income and poverty headcount as a result of the adoption of technology options generated by research to help farmers mitigate the effects of the different constraints. Average increases in household total annual income from research to mitigate the effect of the losses are estimated in the starting year to be \$37 for weed infestation, \$21 for insects, \$16 for birds and rodents, \$58 for diseases, \$54 for soil-related constraints and \$33 for climate-related constraints. Average annual increase in household income grows over time to reach at least \$25 from technology options that mitigate bird and rodent damage, up to \$140 from technology solutions to mitigate diseases (with \$110 for soil-related stresses, \$91 for climate-related stresses, \$80 for weeds and \$40 for insect attacks).

In terms of poverty reduction, the village poverty headcount reductions range from 0.33% from bird and rodent technology options to 5.9% from soil-related technology options. This reduction in poverty will grow to reach 0.5% from technology options dealing with bird and rodent attacks, 9.7% for options that alleviate soil-related constraints, 4.5% for options that alleviate weed infestation and 5.5% for options that alleviate climate-related constraints in 2035.

These estimated average household income benefits and village poverty rate reductions were combined with the projection of adoption of the technology options based on the logistic diffusion model to obtain the estimates of aggregate gross impact of adoption of the technology options generated by rice research that addresses the various biophysical constraints (Figs 4.1, 4.2 and 4.3).

Aggregate impact on farmer's income

Figures 4.1, 4.2 and 4.3 present the annual nominal income benefits, the discounted annual income benefits and the discounted cumulated income benefits (\$ millions), respectively.

The expected average annual nominal income gain from research addressing all constraints in the 36 rice-producing countries considered in our analysis is \$14 million in 2014 and growing to reach \$917.3 million in 2035. This corresponds to an average annual aggregate nominal income gain of about \$344 million per year for the period 2014–2035. The discounted value of these benefits is \$11 million in 2014 and \$258 million in 2035, with an average discounted annual benefit for the period 2014–2035 of \$127 million. By aggregating the discounted annual income benefits across time we obtain a total aggregated discounted income benefit of \$2.8 billion by 2035.

Comparing the different constraints, the highest impact is given by research addressing weed infestation (due to higher number of adopters), with an average annual nominal income benefit of \$118 million and a cumulated discounted income benefit over the period 2014–2035 of \$947 million. This is followed by research addressing rice diseases, with an average annual nominal income benefit of \$83 million (\$667 million cumulative discounted benefit over the period 2014–2035). Research that mitigates soil-related constraints comes in third position, with an average nominal income benefit of \$41 million (\$322 million discounted

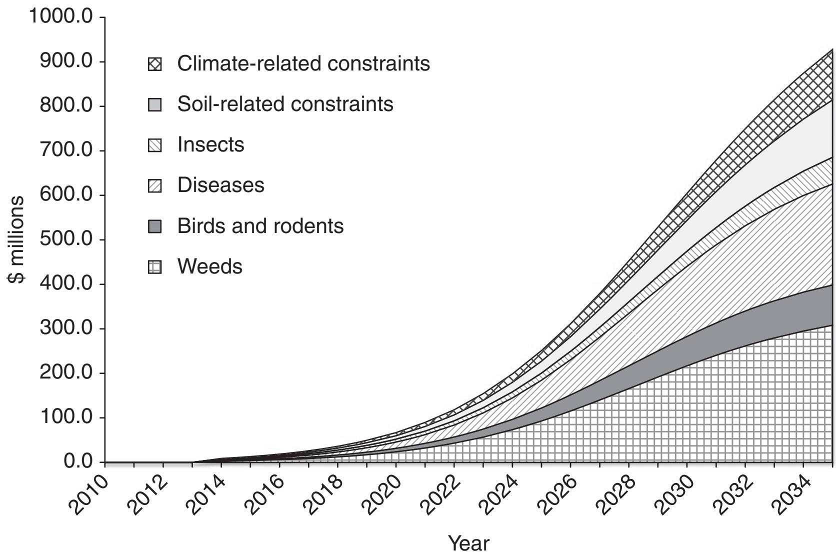

Fig. 4.1. Annual nominal income benefits of research addressing biophysical constraints.

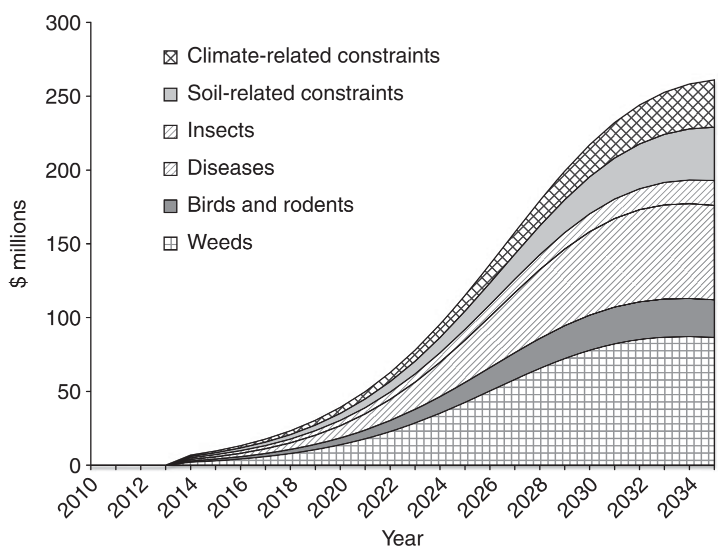

Fig. 4.2. Discounted annual income benefits of research addressing biophysical constraints (5% discounted).

cumulative benefits for the period 2014–2035). Research that mitigates bird and rodent attacks comes in fourth position, with an average nominal income benefit of $36 million and a discounted cumulative value of $292 million for the period 2014–2035, and in fifth position research that alleviates climate-related constraints, with an average annual income gain of $36 million ($281 million cumulative over the period 2014–2035). In comparison, the income benefits derived from research addressing insects will be substantially lower, with $21 million (corresponding to $171 million cumulative benefits over the period 2014–2035).

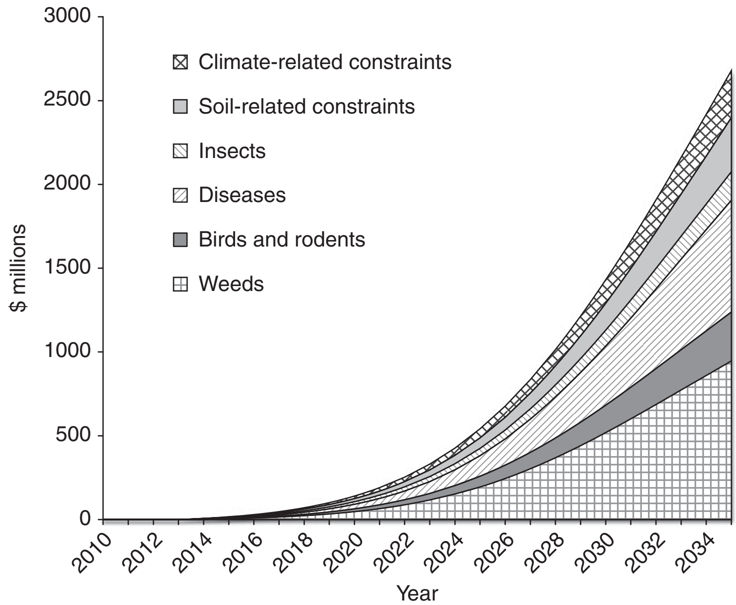

Fig. 4.3. Cumulated discounted income benefits of research addressing biophysical constraints (5% discounted).

Aggregate impact on poverty reduction

The poverty reduction resulting from the increase in rice-farming household incomes as a result of adopting technologies to address biophysical constraints are presented in Fig. 4.4.

It is expected that at least 12,162 people will be lifted above the poverty line in 2014, the starting year of adoption of the technological options resulting from rice research addressing all the biophysical constraints in Africa. This number will grow rapidly to reach 1.5 million in 2035. These numbers represent the maximum reductions in the number of poor farmers each year across all technology options addressing the different biotic and abiotic constraints (taking into account the fact that a person is lifted out of poverty only once even if he or she experiences an income gain from more than one technology option).[5] Although research addressing soil-related constraints will initially lead to the highest reduction in poverty, technology options that mitigate the effects of weed infestation are the ones that will eventually achieve the highest poverty reduction (starting around 2022, because of higher growth in its number of adopters; reaching the maximum 1.5 million lifted out of poverty without the other constraint-mitigating technology options). This is followed by technology addressing soil-related constraints starting in 2028 (and which without the weed technology options would have lifted 0.9 million people out of poverty in 2035), and by those addressing climate-related constraints starting in 2030 (with 0.6 million people lifted out of poverty in 2035 without technologies addressing weed infestation and diseases). Thus, technology options addressing soil-related constraints moved from achieving the highest poverty reduction numbers in 2014 to being second in 2035 because of relatively slower growth in its number of adopters. Research addressing insects and birds and rodents are those that consistently deliver the lowest poverty reduction numbers without the other technologies across the years (leading respectively to 0.18 million and 0.16 million people they could lift out of poverty in 2035 without the other technology options).

Our estimates are slightly higher than the ones reported by IRRI *et al.* (2010), who conducted a similar analysis for Africa using data from a similar but different set of surveys. However, our analysis is based on data from 18 countries and extrapolates the results to 36 rice-producing countries, while the IRRI *et al.* (2010) analysis used data from 12 of the 18 countries

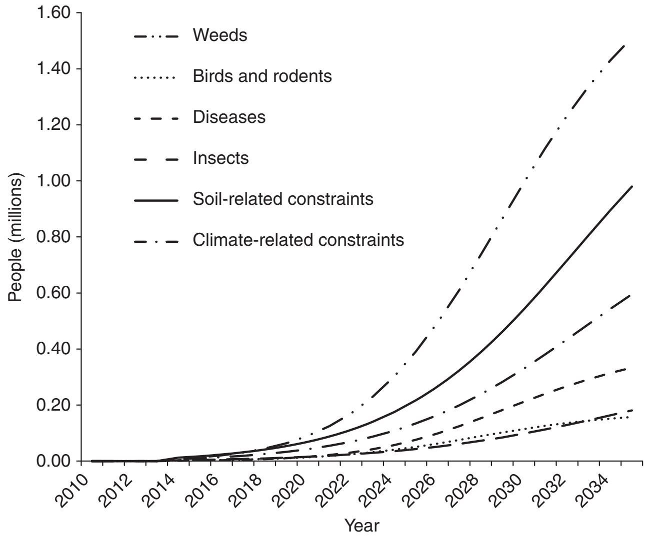

Fig. 4.4. Number of people lifted out poverty (PPP $1.25 poverty line) by research addressing biophysical constraints.

and extrapolated the results to 31 countries only. Nevertheless, the results from the two studies are qualitatively similar. In both studies, alleviation of weed infestations provides the highest impact, followed by alleviation of diseases.

Conclusions

In this chapter, we have analysed the biophysical constraints in rice production in 18 major rice-producing countries in Africa using survey data of farmers' perceptions of the occurrence and relative importance of these constraints collected in 2009. The biophysical constraints were grouped into three broad categories: biotic constraints, soil-related constraints, and climate-related constraints. From the results of the analysis, a large proportion of farmers across all countries and rice environments perceive several biophysical constraints as major production constraints. The average area affected by all biophysical constraints across all rice environments and all countries in 2008 was 30%, with 22% of yield loss. These effects vary significantly across constraints, rice environments and countries. Across all categories of biotic and abiotic constraints, the proportion of farmers giving a high rank to a constraint was consistently highest in Burkina Faso and Madagascar, while the area affected and yield loss incurred was consistently highest in Kenya.

The biotic constraints appear to be the most important biophysical constraints perceived by farmers. Among these biotic constraints, weed infestation is the most important, followed by insects and birds and rodents. It is perhaps not surprising that these constraints are all very 'visible' to the farmers and involve major mitigation efforts. The importance of weeds as major rice production constraints has been reported in several previous studies. Somado *et al.* (2008) also found weeds to be the most important biophysical constraint in SSA, with annual losses estimated at around 2.2 million tonnes (Mt). The losses have been reported to vary from 30% to 100% according to locality (Balasubramanian *et al.*, 2007; Rodenburg and Demont, 2009; Rodenburg and Johnson, Chapter 16, this volume). Damage by birds is also considered to be important (de Mey and Demont, Chapter 19, this volume). Additionally, stem borers, and bacterial and virus diseases are reported to be major biotic constraints that significantly reduce rice productivity (Seck *et al.*, 2012). Among the abiotic constraints, poor soil fertility is the most important soil-related constraint, while drought and flooding are the most important climate-related constraints. This latter finding concurs with Balasubramanian *et al.* (2007).

The *ex-ante* evaluation of the impact of adoption of technology options from research addressing the different biophysical constraints in rice production showed great potential impact in terms of both additional income generated and poverty reduction. These impact studies were based on farmer perceptions of yield-limiting and yield-reducing factors in rice cropping in SSA. It is this subjective perception, right or wrong, that drives a farmer's decision-making. Hence, in the end the **real effects** of the constraint on a farmer's productivity outcomes will be the result of both the **real importance** (as it would be measured objectively by yield-gap surveys as proposed by Saito *et al.*, Chapter 15, this volume) and the farmer's **perception** of that importance (reflected in the *ex-ante* preventive and *ex-post* mitigating actions the farmer takes in relation to the constraint). Thus, in determining the relative importance of a constraint in terms of its negative effects on rice productivity, both the objective assessments of knowledgeable experts and the subjective assessments of farmers are important and complementary.

Notes

[1] 'Average yield' calculated from total annual paddy production divided by total annual harvested area in 2012.

[2] See, however, discussion later in the chapter on the inherent population and sample selection biases in the indicators derived below caused respectively by unawareness of the existence of some constraints by some farmers and the restrictive nature of the second list of constraints.

[3] The $\bar{\bar{r}}^s$ index can also be viewed as a weighted average of the ranking of the constraint by farmers in terms of relative importance with the weight of a rank value corresponding to the proportion of sample farmers giving that rank value to the constraint: $\bar{\bar{r}}^s = \frac{1}{3n} \sum_{i=1}^{n} \sum_{r=0}^{3} r d_{ir}^s = \frac{1}{3} \sum_{r=0}^{3} r f_r^s$. Hence, the $\bar{\bar{r}}^s$ index is an aggregation of two measures of relative importance of a constraint: (i) a measure of its perceived incidence, scope and severity at the individual farmer level as indicated by the rank r; and (ii) a measure of the prevalence of its occurrence (in the village) being perceived by farmers as indicated by the proportion f_r^s of farmers giving it the rank r.

[4] In fact, positive monotonicity is trivially satisfied by the ordered rank measure. To see why, we note that only farmers who are aware of the existence of the constraint s are able to give their ordered ranks for s. Hence, r_i^s can be observed only for farmers who are aware of the existence of constraint s. In other words, r_i^s is missing for s-constraint unaware farmers. For this group of farmers, it is as if the constraint s did not occur in their villages or anywhere else (since for them the constraint does not exist). That is, it is as if the observed rank given to s by a farmer in this s-constraint unaware group is equal to 0, the rank corresponding to the non-occurrence of the constraint in his or her village, which is the lowest possible value for r_i^s. This may not be the case, however, for other measures of relative importance. Indeed, if we take the experience measure of relative importance, in principle a farmer may experience a constraint without being aware of its existence. Although this is unlikely for most constraints, it is still possible for constraints that are difficult for farmers to diagnose. Even in these cases, it is safe to assume that positive monotonicity is satisfied.

[5] In other words, the number of people lifted out of poverty cannot be aggregated across the various technology options (this would be double counting). For the same reason, the poverty reduction numbers are not cumulative across time.

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Appendix 4.1. The Population Non-Awareness and Sample Minority-Exclusion Biases in the Farmers' Perceptions of the Relative Importance of Biotic and Abiotic Constraints

In this appendix, we derive the expressions and signs of the non-awareness and sample minority-exclusion biases in the five measures of farmers' perceptions of the relative importance of biotic and abiotic constraints.

Population non-awareness bias

For this purpose, we consider the full population and use expected population values instead of sample averages as in the main text. Also, for any constraint $s \in \tilde{S}$ we will use the random variable x^s to denote generically any of the perception measures of relative importance of the constraint as given by a farmer randomly selected from the population of rice farmers.[1] First, let ω^s be a dummy binary indicator, with $\omega^s = 1$ if the farmer is aware of the existence of the constraint s, $\omega^s = 0$ otherwise and, following the counterfactual outcome framework, define the two potential outcomes x_1^s and x_0^s of x^s associated with the two mutually exclusive states of awareness and non-awareness of the existence of the constraint, respectively by: $x^s = x_1^s$ if $\omega^s = 1$ and $x^s = x_0^s$ if $\omega^s = 0$. The two potential outcomes x_1^s and x_0^s are supposed to exist for any farmer in the population. However, for any given farmer, we can only observe one of the two potential outcomes because a farmer can only be in one of the two mutually exclusive states (being aware or unaware).[2] In particular, the value of the perception indicator x_1^s is missing for farmers who are not aware of the existence of the constraint. Hence, we cannot directly compute $E(x_1^s)$, its expected value for the full population of rice farmers. And yet, it is $E(x_1^s)$, the mean perception of relative importance of the constraint when all farmers are aware of its existence, that truly informs on the whole population of rice farmers' perception of the relative importance of the constraint s (as measured by x^s at the individual farmer level).[3] On the other hand, the sample measures of perception of relative importance of a constraint given in points (3)–(5) in the main text will, as the sample size grows, all converge to their population counterparts corresponding each to $E(x^s)$, which is the population mean of the observed values of x^s. Consequently, the population non-awareness bias (PNAB) is defined as the difference between the expected population value, to which the directly computed sample average of the observed values of x^s converges, and the population mean perception of relative importance of the constraint when all farmers are aware of its existence. That is, $PNAB^s = E(x^s) - E(x_1^s)$.

To show that $PNAB^s$ is negative when the positive monotonicity with respect to non-awareness condition is satisfied, we decompose the unconditional expectation $E(x^s)$ into its conditional parts as:

$$E(x^s) = E(x^s|\omega^s = 1)\,P_\omega^s + E(x^s|\omega^s = 0)(1 - P_\omega^s) = E(x_1^s|\omega^s = 1)\,P_\omega^s + E(x_0^s|\omega^s = 0)(1 - P_\omega^s)$$

where $P_\omega^s = Prob\{\omega^s = 1\}$ is the probability that a farmer randomly selected from the population is aware of the existence of the constraint. Similarly, we decompose the unconditional expectation $E(x_1^s)$ into its conditional parts as:

$$E(x_1^s) = E(x_1^s|\omega^s = 1)P_\omega^s + E(x_1^s|\omega^s = 0)(1 - P_\omega^s)$$

Hence, from the two equations above we obtain the expression of the PNAB as:

$$PNAB^s = E(x^s) - E(x_1^s) = -(1 - P_\omega^s)\{E(x_1^s|\omega^s = 0) - E(x_0^s|\omega^s = 0)\}$$

This shows that PNAB is negative if we assume that the perception of relative importance of a constraint is positively monotonically related to awareness for all farmers, which means that $x_1^s \geq x_0^s$ uniformly (implying that $E(x_1^s\,|\,\omega^s = 0) \geq E(x_0^s\,|\,\omega^s = 0)$). Also, the above expression of the population non-awareness bias shows that it is a decreasing function of the probability of awareness and hence, everything else being equal, it is more severe for constraints the existence of which farmers are less likely to be aware of compared to those they are more likely to be aware of.

Sample minority-exclusion bias

The sample minority-exclusion bias results from the restriction of the farmer perception of the relative importance of a constraint to those that he or she considers major constraints. For any given constraint s, the mean perception of its observed relative importance under such restriction is given by the conditional mean $E(x^s\,|\,m^s = 1)$, where m^s is a dummy binary indicator with $m^s = 1$ if constraint s is a major constraint for the farmer and $m^s = 0$ otherwise. Hence, the expected sample minority-exclusion bias is defined as the difference between this conditional mean perception of relative importance and its unconditional counterpart, $E(x^s)$. That is, $SMEB^s = E(x^s\,|\,m^s = 1) - E(x^s)$.

As above, we decompose the conditional expectation $E(x^s)$ into its conditional parts, but this time with respect to the constraint being a major constraint or not for the farmer, to obtain:

$$\begin{aligned} SMEB^s &= E(x^s\,|\,m^s = 1) - \{E(x^s\,|\,m^s = 1)P_m^s - E(x^s\,|\,m^s = 0)\,(1 - P_m^s)\} \\ &= (1 - P_m^s)\,\{E(x^s\,|\,m^s = 1) - E(x^s\,|\,m^s = 0)\} \end{aligned}$$

where $P_m^s = Prob\{m^s = 1\}$ is the probability that constraint s is a major constraint for a farmer randomly selected from the population. Hence, the sign of the expected sample minority-exclusion bias is the sign of the expression within the curly bracket. But, this expression is positive if we assume that the expected perceived relative importance of the constraint when the constraint is major for the farmer is not lower compared to when it is not (i.e. if the perception of relative importance of a constraint is positively correlated with the constraint being a major constraint for the farmer). The above expression also shows that the expected sample minority-exclusion bias is more severe for constraints that are less likely to be major constraints for farmers.

The combination of population non-awareness and sample minority exclusion

The expected bias introduced by the combination of the constraint not being universally known in the population and not being a major constraint for all the farmers is given by the quantity $E(x^s|m^s=1) - E(x_1^s)$, which is the difference between the mean perception of the observed relative importance of the constraint for the sub-population of farmers for which the constraint is major and the population mean perception of relative importance of the constraint when all farmers are aware of its existence.

By subtracting and adding $E(x^s)$ to this difference we have:

$$E(x^s|m^s=1) - E(x_1^s) = E(x^s|m^s=1) - E(x^s) + E(x^s) - E(x_1^s) = SMEB^s + PNAB^s$$

This shows that the two biases introduced by population non-awareness and sample minority exclusion are additive and operate in opposite directions.

Notes

[1] More precisely, $x^s \in \{r_i^s, d_i^s e_i^s, \alpha_i^s, \Delta y_i^s\}$. Working at the population level means that we can omit the *i* subscript in our notation and use the mathematical expectation operator instead of sample averages.

[2] We note that observed value x^s of a farmer is linked to the two associated potential outcomes by the following relationship: $x^s = \omega^s x_1^s + (1-\omega^s)\, x_0^s$.

[3] It is important to note the difference between the mean perception for the full population, $E(x_1^s)$, and the mean perception for the sub-population of farmers who are aware of the existence of the constraint, which is given by the conditional mean $E\left(x_1^s \mid \omega^s = 1\right)$. The latter is usually greater than the full population mean perception of relative importance because of the likely positive correlation between awareness of the existence of a constraint and perception of its relative importance.

Appendix 4.2. Theoretical Framework of Evaluation of Potential Impact of Research Addressing Biophysical Constraints

To show theoretically the relationship between the yield loss and the various producer outcomes, we use the producer quasi-rent function (defined as the excess of gross receipts over total variable costs) as welfare measurement and the counterfactual or potential outcomes framework introduced by Rubin (1974), which has now become the standard framework for impact assessment (Imbens and Wooldridge, 2009).

As explained by Just *et al.* (2004), a change in the producer quasi-rent is a willingness-to-pay measure of the change in producer welfare. In contrast, change in the producer profit (which is equal to the quasi-rent minus total fixed cost) and change in the producer surplus (the area under the supply curve) introduced by Marshall (1930) are not in general willingness-to-pay measures of change in producer welfare. Quasi-rent, profit and producer surplus coincide only when there is no fixed cost and markets are complete (see Just *et al.*, 2004, chapter 4 for more details on the measurement of changes in producer welfare).

Let the producer quasi-rent be expressed as $\pi = PQ - C$, where P is the output unity price, Q is the quantity of output produced and C is the total variable cost. Also, let e^s be the binary variable indicating the experience or not of a given constraint s with $e^s = 1$ indicating experience of the constraint and $e^s = 0$ indicating non-experience of the constraint by a population unit (a farmer or a village). Under the potential outcome framework, each population unit has *ex-ante* two potential quasi-rents: $\pi_1 = P_1Q_1 - C_1$ when he or she experienced the constraint, and $\pi_0 = P_0Q_0 - C_0$ when he or she did not experience the constraint. Thus, the observed quasi-rent is $\pi = \pi_0 + e^s(\pi_1 - \pi_0)$.

We have $\pi_1 - \pi_0 = (P_1Q_1 - C_1) - (P_0Q_0 - C_0) = P_1(Q_1 - Q_0) + P_1Q_0 - P_0Q_0 - (C_1 - C_0)$, hence $\pi_1 - \pi_0 = P_1(y_1a_1 - y_0a_0) + P_1Q_0 - P_0Q_0 - (C_1 - C_0)$, where $y = \frac{Q}{a}$ is the observed yield and a is the observed total area cultivated. Noting that $a_1 = a_0 = a$, we get:

$$\pi_1 - \pi_0 = P_1a_0(y_1 - y_0) + P_1Q_0 - C_1 - (P_0Q_0 - C_0)$$

and

$$\pi = P_0Q_0 - C_0 + e^sP_1a_0(y_1 - y_0) + e^s(P_1Q_0 - C_1) - e^s(P_0Q_0 - C_0)$$

or

$$\pi = e^sP_1a_0(y_1 - y_0) + e^s(P_1Q_0 - C_1) + (1 - e^s)\pi_0.$$

Now, letting $\beta = -P_1\, a_0y_0$, $\Delta y^s = 1 - \dfrac{y_1}{y_0}$, $\gamma = P_1Q_0 - C_1 - \pi_0$ and $\sigma = \pi_0$, we have:

$$\pi = \beta e^s\Delta y^s + \gamma e^s + \sigma$$

By making the coefficients random and dependent on the socio-demographic characteristics X of the producer and assuming additive separability, they can be expressed as $\beta = \beta(X) + \mu_1$, $\gamma = \gamma(X) + \mu_2$, $\sigma = \sigma(X) + \mu_3$, $\mu = \mu_1 + \mu_2 + \mu_3$. Hence, we obtain the following relation:

$$E(\pi \mid X = x, Es = es) = \beta(x)e^s\Delta y^s + \gamma(x)e^s + \sigma(x) + \mu$$

which shows theoretically how the change in the yield loss due to a given production constraint can affect the producer quasi-rent function and consequently his or her total income. This relation also shows that the village poverty headcount is affected by the occurrence of constraints in the village because constraints affect the income of the village members.

Projection over time and aggregation at country level

The different steps followed to project the impact over time and to extrapolate it at country level are described here following Diagne *et al.* (Chapter 32, this volume).

Step 1: Projection of impact over time

The estimation of the models gives the impact at starting year of availability of technology. This year corresponds $t_0 = 2010 + t_d$ with t_d being the estimated number of years to technology delivery (from 2010). Using the AR1 model parameters estimated, we forecast the mean impact starting in a given year t_0 to any subsequent year $t_0 + \rho$ in the future as:

$$E\Delta y_{t_0+\rho} = \beta\sum_{j=0}^{\rho-1}\alpha^jE(\Delta y_{t_0+\rho-j}) = \beta r_e\frac{1-\alpha^\rho}{1-\alpha}\ \ and\, \rho = 1,2,\ldots$$

Where r_e stands for the constant reduction in yield loss. This formula gives the ρ – period ahead forecasted value for the outcome y. Finally, the annual nominal income gained is discounted at the rate of 5% and cumulated to get gross benefit at farmer level.

Step 2: Estimation of the number of rice farmers and rice farming population

The extrapolation from farmer and village levels to country level is based on the estimation of the total number of rice farmers in each country. Due to the lack of national estimates of the total number of rice farmers per country, we combined household-survey and secondary data to get these estimates.

The total number of rice farming households N_h in each of the countries included in our analysis was estimated by taking the ratio of the country's total rice harvested area S (obtained from FAOSTAT, 2010) and the average rice area per household s_h (estimated from the farm-household surveys) and projected over time assuming a constant population growth rate of $g = 2.5\%$ (average rural population growth rate in SSA from the World Development Indicators; World Bank, 2010). The formula used is $N_h = \frac{S}{s_h} \times (1+g)^{\rho}$, where ρ stands for time.

Step 3: Determination of the number of adopting farmers

The total number of adopting farmers was derived by using a logistic adoption model, starting with a 1% adoption rate in 2014 and with a peak adoption rate of 20% in 2025.

Assuming a logistic diffusion curve, the number of adopters at each time t is given by the following formula:

$$N_t^a = \frac{N_p^a}{\left(1 + \left(\frac{N_p^a}{N_0^a} - 1\right) e^{-\gamma(t-t_0)}\right)}$$

where N_t^a = Number of adopters at time t; N_p^a = Peak number of adopters; $N_p^a = N\alpha_0(1+\beta_0)^{(t_p - t_0)}$ with α_0 the percentage of rice farmers who experienced a given constraint; β_0 population growth rate and N number of rice farmers; N_0^a = starting number of adopters and

$$\gamma = \frac{1}{\left(t_{\frac{p}{2}} - t_0\right) \log\left(\frac{N_p^a - N_0^a}{N_0^a}\right)}$$

with t_p = the year of peak of adoption, $t_{\frac{p}{2}}$ = year when adoption reaches half of its peak value and t_0 = starting year of adoption.

Adopting farmers will be made aware of the technologies through video, radio and other learning tools, farmer-to-farmer training and out-scaling by development partners from both the public and private sectors.

Step 4: Extrapolation of impact from household and village levels to country level

For each country included in the analysis, the farmer individual impact on income is extrapolated to country level by multiplying the average estimated impact by the estimated total number of direct and indirect beneficiaries in the country. Diagne *et al.* (2012) have shown how this provides a consistent estimate of the total benefit to rice farmers at the national level.

The poverty impact estimated at the village level was multiplied by the total rice-farming population size in the country. Evidence that this provides a consistent estimate of the reduction in the total number of poor rice farmers at the national level is provided by Diagne *et al.* (2012).

Table 4.A.2.1. Econometric model of impact of yield loss on household income.[a]

Dependent variable (household total income in 2008)	Weeds	Insects	Birds and rodents	Diseases	Soil-related constraints	Climate-related constraints
Yield loss due to constraint (β)	–1.20***	–1.07**	–1.06*	–2.78	–1.43***	–1.13
	(–2.71)	(–2.23)	(–1.66)	(–1.02)	(–2.70)	(–0.19)
Whether the farmer experienced the constraint (γ)	–25.19***	–20.09**	–20.97*	–20.37	–30.99***	–3.58
	(–2.71)	(–2.23)	(–1.66)	(–1.02)	(–2.70)	(–0.19)
Household total income in 2007 (α)	0.89***	0.87***	0.81***	0.91***	0.88***	0.93***
	(95.87)	(86.44)	(68.55)	(41.72)	(51.41)	(56.26)
No. observations	6,577	5,243	5,456	1,087	2,240	1,558
R-squared	0.632	0.643	0.536	0.684	0.619	0.716

[a]The estimated coefficients for the demographic variables and the constant term (σ(x))are omitted to save space. t-statistics in parentheses. *** $P < 0.01$, ** $P < 0.05$, * $P < 0.1$.

Table 4.A.2.2. Econometric model of impact of yield loss on village level poverty headcount.[a]

Dependent variable (village poverty headcount in 2008)	Weeds	Insects	Birds and rodents	Diseases	Soil-related constraints	Climate-related constraints
Yield loss due to constraint (β)	0.04**	0.02	0.02	0.03	0.17	0.10
	(2.01)	(0.99)	(0.35)	(0.52)	(0.63)	(0.60)
Whether the farmer experienced the constraint (γ)	0.66**	0.35	0.25	0.27	0.65	0.33
	(2.01)	(0.99)	(0.35)	(0.52)	(0.63)	(0.60)
Village poverty headcount in 2007 (α)	0.95***	0.92***	0.81***	0.93***	0.83***	0.89***
	(132.99)	(105.78)	(56.50)	(62.14)	(34.64)	(56.71)
No. observations	1,869	1,907	1,809	769	562	801
R-squared	0.932	0.900	0.744	0.893	0.790	0.875

[a]The estimated coefficients for the demographic variables and the constant term (σ(x)) are omitted to save space. t-statistics in parentheses. *** $P < 0.01$, ** $P < 0.05$, * $P < 0.1$.