Impact of Rice Research on Income and Poverty in Africa: An *Ex-ante* Analysis

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Abstract

This paper assesses the *ex-ante* impact of rice research in Africa on income and poverty for the period 2011–2020, with the final purpose of setting priority for Africa Rice Center research activities. It describes the methodology and analyzes the main findings. The methodology used combines research solutions elicited from scientists, household- and community-survey data, and econometric models to assess the potential benefit of the research. We found that the potential annual income benefit from all research options across all value-chain actors and for all sub-Saharan African (SSA) countries is US$ 1.8 billion, which aggregated over the period 2014–2020 reaches US$ 10.6 billion. As consequence, it is expected that at least 11 million people will be lifted out of poverty by the end of the period (2020) and at least 5.6 million of people will no longer be undernourished. In terms of actors, rice farmers will receive the highest benefit; however, significant benefit will also accrue to other actors – namely consumers, processors, and traders. In terms of research disciplines, the impacts of research that alleviates major biophysical constrains are the greatest. This indicates that priority should be given to this type of research, but there is also a need to consider postharvest work in the future research agenda. In terms of research nature, breeding research is the most important, followed by agronomy (including integrated pest management, IPM). In terms of geographical area, the main rice-producing sub-region in SSA is western Africa, which will receive the highest research benefit. Eastern Africa will receive the second-highest level of benefits and Central Africa third. In general, lowland ecosystems will have the highest benefit, closely followed by the upland ecosystem. The irrigated system – the importance of which is increasing – will be the third major ecosystem. The analysis shows a significant contribution of rice research to import reduction, and agricultural GDP. In summary, the analysis shows evidence that rice research in Africa in economically and socially profitable.

Key words: Rice research, priority setting, sub-Saharan Africa

1 Introduction

Rice has always been an important staple in many African countries. For some decades, it has also been the most rapidly growing food source across the continent. However, the local production is largely insufficient to meet the consumption needs. In 2009, Africa imported 10 million tonnes of milled rice, at a cost of US$ 5 billion. With high food and fuel prices predicted to last well into the coming decade, relying on imports is no longer a sustainable strategy for Africa. The development of rice sector could be an engine for economic growth across the continent, which would contribute to eliminating extreme poverty and food insecurity, and raise the social wellbeing of millions of poor people. Rice production will create employment along the value chain and in related sectors, and lead to improve nutritional and health status of the rural agricultural poor. It will allow families to better finance education, giving the next generation more opportunities to break the remaining shackles of underdevelopment (AfricaRice, 2011 p.84).

Despite this huge potential benefit of rice-sector development, the African rice sector faces several constraints, including biophysical stresses and socioeconomic constraints. These translate into low productivity and provide numerous areas for research. The main purpose of this paper is to assess the *ex-ante* impact of rice research in Africa in order to: (1) adequately identify priority research themes and target populations; (2) efficiently allocate resources to priority research themes; (3) better target research outputs to where they will have the maximum impact; (4) enhance research relevance and positive impact on the livelihoods and wellbeing of the target population; and (5) enhance the efficiency of public research organizations.

Several past works have assessed the potential benefit of rice research in Africa. Much of this work was conducted by the Africa Rice Center (AfricaRice), an international agricultural research center with a mandate for rice research in Africa in collaboration with national agricultural research systems (NARS) and other international centers. The Center has a long tradition of priority-setting since the 1990s (*see* Diagne *et al.*, 2009, for a review of previous priority-setting exercises). The priority-setting exercise is a continuing process and the methodology used has changed over time.

In early 1990, AfricaRice (then the West Africa Rice Development Association, WARDA), conducted a systematic priority-setting[1] exercise that assessed the potential benefit of a set of rice research projects and activities. The exercise was implemented through a three-step process. The first step consisted of data-gathering on the relative importance of rice ecosystems (area, production, etc.), and the relative importance of constraints for each ecosystem. The second step comprised an analysis of ecosystems and main stresses to determine the priority ecosystems and stresses that needed to be addressed, assessment of countries' research capacities for each constraint, and AfricaRice/WARDA's comparative advantages. The third and final step was validation of the methodology used and the major findings by a 'task force'. In 2000, a new priority-setting exercise was initiated and served as the main input for the WARDA Strategic Plan 2003–2012 (WARDA, 2004a, b). This exercise was essentially based on the outcomes of the previous *ex-ante* evaluation. The constraints analysis done previously was updated through task forces, group working, surveys and at the meetings of the AfricaRice/WARDA National Experts Committee (NEC).[2]

The present analysis borrows a lot from the previous rice research *ex-ante* analysis in terms of methodological approach, with the addition of a number of innovative features. It uses a systematic approach. An in-depth farm-household survey was conducted to gather data on rice ecosystems, constraints to rice production, and adoption of improved varieties. Geo-spatial data on rice ecosystems and potential were also collected. Research options (i.e. scientific possibilities) to address rice production constraints were elicited from scientists through consultation during a 2-day workshop. The approach uses econometric models to assess expected productivity, poverty, and environmental impacts of the proposed research solutions. This paper presents the approach used to assess the potential impact of rice research in sub-Saharan Africa (SSA) for 2011–2020 and discuss the major findings.

The rest of paper is organized as follows. In section 2, we discuss the theoretical and conceptual framework that underlies the evaluation of impact of agricultural research on farmers. Section 3 presents methods used for the other actors, such as processors, traders, and consumers.

[1] *See* WARDA (1993, 1997, 1999, 2001a, b, c) for more details on priority-setting at WARDA during the 1990s and 2000s.

[2] The National Experts Committee (NEC) is composed of the directors general of the NARS of AfricaRice's member states; the NEC meets once a year at AfricaRice headquarters to discuss research progress and new directions (i.e. strategic decision-making).

The various data used are described in section 4. In the last section, we focus on the main findings and priority areas identified.

2 Methodology for the estimation of the impact on rice farmers

2.1 Theoretical and conceptual framework

2.1.1 The agricultural household model

To identify the impact of a research 'solution' on poverty and income, we follow the agricultural household framework (*see* Singh *et al.*, 1986; Taylor and Adelman, 2003, for a review). The framework is summarized in Figure 1.

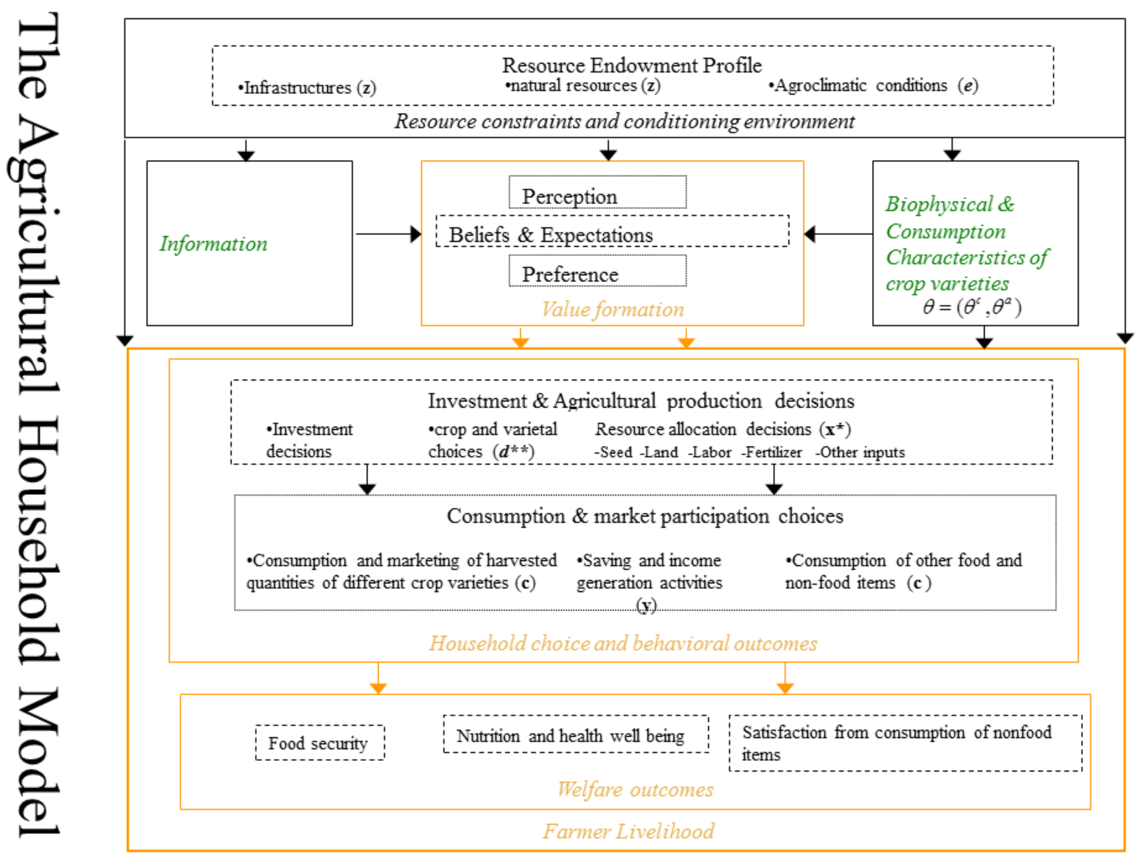

Figure 1: Agricultural household framework

An agricultural household makes decisions to maximize its utility in the face of some constraints. The decision set includes investment, crop and varietal choices, and resource allocation (seed, land, labor, fertilizer, and other inputs). The utility is derived from the household decision-maker's perceptions, beliefs, expectations, and preferences. The household utility can potentially be affected by many factors that constitute the resource-endowment profile (infrastructure, natural resources, and environmental conditions), the information available, and the characteristics of the technologies chosen.

The household optimal choice problem can be generically formulated as:

$$\max_{x \in S(z)} U(x, z) \tag{1}$$

where U is the household objective function (here utility); x is the full vector of household choice variables in some arbitrary choice set $\tilde{X}$ assumed to be multidimensional, with the understanding that U may not be functionally dependent on some of the components of x; $S(z)$ is the constraints set, a subset of $\tilde{X}$, that defines the set of feasible household choices; z is the vector of all non-choice variables (including socio-demographics, prices, technological, and environmental variables) in some set $\tilde{Z}$ that may affect the objective function U.

Let d stands for a choice variable we are interested in and let $x_{(d)}$ be the vector x without its component d. Let e also stand for a conditioning variable of interest among those in z and let $z_{(e)}$ be the vector z without its component e. Then, the maximization problem $\max_{x \in S(z)} U(x, z)$ can be written equivalently as:

$$d^* \equiv \delta(e, z_{(e)}) = \arg \max_{d \in S^*(e, z_{(e)})} \left\{ \max_{x_{(d)} \in S(d, e, z_{(e)})} U(x_{(d)}, d, e, z_{(e)}) \right\} \tag{2}$$

Where $d^* \equiv \delta(e, z_{(e)})$ is the optimal choice for the variable d as a function of the conditioning vector of variables $z = (e, z_{(e)})$; $S(d, e, z_{(e)}) \equiv \left\{ x_{(d)} : (x_{(d)}, d) \in S(e, z_{(e)}) \right\}$ the constraint set when d is held constant in the inner maximization problem; $S^*(e, z_{(e)}) \equiv \left\{ d : (x^*_{(d)}, d) \in S(e, z_{(e)}) \right\}$ the constraint set for the outer maximization problem with $x^*_{(d)} = \chi(d, e, z_{(e)})$ being the optimal choice in the inner maximization problem in (2) (i.e. the maximization problem inside the bracket) as function of d and z. In other words, the solution (optimal choices) to the maximization problem in (1) can be found in two steps: in the first step, we solve for the optimal choices of a subset of the choice variables, while conditioning on the remaining choice variables; in the second step, we put the optimal values found in the first step into the objective function and the constraint set, and solve for the optimal values of the remaining choice variables.

This decomposition is always possible and the subset of choice variables over which to optimize first does not matter (*see*, for example, Milgrom and Shannon, 1994; Topkis, 1998). The importance of this general decomposability of the maximization problem is the simplification and convenience it offers for analyzing and discussing the various conceptual behavioral and econometric issues involved in the identification and estimation of the causal effects of the change in an endogenous variable on household outcomes.

Now, let us assume that rice-farming households produce a single crop (rice) and maximize the utility of consumption of food and non-food items under budget constraint. The maximization problem is:

$$\max_{(c,x)}\left\{U'(c,z_u): s.t.\ \ p_c\ .\ c = p_r * f(x,z) - p_x * x\right\} \tag{3}$$

where c is the consumption vector of food and non-food items, with p_c the corresponding price vector; x is the vector of input used for rice production, with p_x the corresponding price vector; z_u is a vector of household socio-demographic variables that affect utility, and z is a vector of the exogenous technological and environmental variables (variety characteristics, plot soil characteristics, weather, etc.) conditioning the production of rice; f is a production function; and p_r is the price of rice. We obtain the generic formulation (1) from (3) by putting $x' \equiv (c,x)$, z=(z_u,, z, p_c, p_r, p_x), $S(z) = \left\{x \in \mathbb{R}^M :\ p_c\ .\ c = p_r * f(x,z) - p_x * x\right\}$, and $U(x',z) = U'(c,z_u)$.

From (3) and (2), if $c^* = \chi(d,e,z_{(e)})$ is the household optimal consumption choice conditional on the adoption level of the research technology d, then the household total consumption expenditure as function of the adoption level of the technology defined by the vector d is given by:

$$E^* = p_c.c^* = p_c.\chi(d,e,z_{(e)}) \equiv \chi'(d,e,z_{(e)}) \tag{4}$$

By the budget constraint, the left hand side of equation (4) is also equal to the household net crop income (i.e. profit), which in this simplified case is also the household total income:

$$\pi^* = \pi(d, z) = p_r * f(x^*_{(d)}, z) - p_x * x^*_{(d)} \tag{5}$$

From the theoretical derivations above one, can see clearly how household decision (adoption of crop or varietal technology) and the change in the environmental condition (reduction of yield loss caused by stresses) can affect the household outcomes of interest and permit the identification and estimation of the causal effects. Here we limited the analysis to household total income, production, and village poverty headcount. We note that the impact on income and production is assessed at the household level, while the impact on poverty and food security is assessed at the community level (where it makes sense).

2.1.2 Two sets of research solutions and modeling strategy

Two categories of research solutions are assessed. For breeding research, we assessed models of farmer demand for varietal characteristics and the relationship between the farmers' demand for varietal characteristics and total household income, production, or village poverty head-count. We assessed agronomic research (including integrated pest management, IPM) solutions through the reduced form model – effect of reduction in yield loss due to farmer adoption of the agronomic research option on total household income, production, or village poverty headcount.

- ***Identification of causal effect of breeding technology adoption***

Let us start from the general setting of agricultural household model and assume that rice-farming households choose among J rice varieties (that include traditional and improved varieties) to produce rice and maximize the utility of consumption of food and non-food items. Thus, the problem (1) can be rewritten as follows:

$$\max_{x \in S(z)} \{U'(x, z) : st. p_c . c = p_r . \sum_{j=1}^{J} f(x_j, z_j) - \sum_{k=1}^{K} p_k \sum_{j=1}^{J} x_{jk} \} \tag{6}$$

where c is the consumption vector of food and non-food items, with p_c the corresponding price vector; $x_j = (x_{jk})_{k=1,\dots,K}$, with x_{jk} being the quantity of input k used in producing rice with variety j (one of the inputs being seed); p_k is the price of input k; z_u is a vector of household socio-demographic variables that affect utility; z_j is a vector of exogenous technological and environmental variables conditioning the production of rice using variety j (variety characteristics, plot soil characteristics, weather, etc.); f is a production function; and p_r is the price of rice. There is no loss of generality by assuming a common production function for all varieties, because any variety-specific technological parameter can be included in the z_j vector

There are several rice varieties distinguished by their agronomic and consumption characteristics. Farmers make their choice of which varieties to grow and consume based on their preference for the different agronomic and consumption characteristics of the varieties. The agronomic characteristics are those that affect the rice yield in the field and during harvest and postharvest grain processing. The most important of these are yield potential, levels of tolerance to various biotic and abiotic stresses (pests, diseases, weeds, drought, etc.) and plant physiology. The consumption characteristics of varieties include grain quality, shape, color, aroma, taste, and various cooking and eating characteristics (cooking time, swelling capacity, degree of stickiness, storability after cooking, etc.).

Each variety has a fixed constant vector of consumption characteristics $\theta_j^c = (\theta_{jk}^c)_{k=1,\dots,K}$, with K_c the number of consumption characteristics and a fixed constant vector of agronomic characteristics $\theta_j^a = (\theta_{jk}^a)_{k=1,\dots,K}$ with K_a the number of agronomic characteristics. Let also $\theta_j \; = \theta^c \; = (\theta_j^c)_{j=1,\dots,J}$, $\theta^a \; = (\theta_j^a)_{j=1,\dots,J}$, $\theta_j \; = (\theta_j^c, \theta_j^a)_{j=1,\dots,J}$, and $\theta \; = (\theta^c \,, \theta^a)$. Hence, θ_j is the combined vector of agronomic and consumption characteristics of variety j with dimension $K \; = K_a + K_c$ and θ is the $J \times S$ matrix of agronomic and consumption characteristics of all varieties. Varieties are distinguished and identified uniquely by their full vector of observed and unobserved characteristics θ_j and not by their names or labels (e.g. WABxx, NERICAxx, IRxx, 'traditional', 'improved').

Reformulating the utility function and the production function to take into account variety characteristics, we have: $U(c, z_u) = U\big(c, \theta^c, z_{u(\theta)}\big)$ and $f\big(x_j, z_j\big) = f\big(x_j, \theta^a, z_{j(\theta)}, e\big)$. If the focus of the analysis is on the incidence of adoption (i.e. where there is adoption or not) instead of the intensity of adoption, then we define the variable $d^{**} = I_{\left[x_{j0}^* > 0\right]}$ expressing whether the farmer chooses to adopt a variety j by using its seed. As shown in subsection 2.1.1, this farmer optimal choice functionally depends on the conditioning variables e, θ_j, and z_u. Taking the expectation conditioning to these variable, we have:

$$P(d_j^{**} = 1 \,|, \theta_j, z_u, e) = g(\beta, \theta_j, z_u, e) \tag{7}$$

with $P(d_j^{**} = 1 \,|, \theta_j, z_u, e)$ being the probability of adopting a village variety[3] j by a rice farmer conditional to the vector of characteristics of the variety θ_j, the farmer socioeconomic characteristics z_u, and the vector of agro-climatic conditions e; β stands for the vector of parameters to be estimated; and g is a function taking value in the interval [0, 1].

Farmers in a village are not often universally exposed to agricultural technology such rice varieties, even traditional ones. Equally, therefore, a variety as a technology is not often universally exposed to all farmers (Diagne and Demont, 2007). This introduces an important bias if one estimates adoption rates and adoption determinant by using the traditional method (Diagne and Demont, 2007, give numerous failures of the traditional methods). Therefore, to consistently estimate the village variety adoption rate and its determinants, we follow Diagne and Demont (2007) and use the Average Treatment Effect (ATE) estimation framework (see, e.g., Imbens and Wooldridge, 2009, for a review).

For each characteristic, we define $\hat{\theta}_k = \underset{j=1,..,J}{max}\{\theta_{jk}\}$, the maximum performance of this characteristic across all known varieties. These maximum characteristic values represent for the farmer the 'known technological frontier' for the characteristic of interest. Also, let us define $\bar{\theta}_k = \frac{1}{J_a}\sum_{j=1}^{J}\theta_{jk} \times d_j^{**}$, the average performance of characteristic k across all varieties adopted by the farmer, with J_a the number of variety adopted. This is the farmer's 'observed demand' of the characteristic k.

Taking the Expectation conditional to e, θ_j, and z_u, we obtain the 'predicted demand':

$$E(\bar{\theta}_k|e, \theta, z_u) = \frac{1}{J_a}\sum_{j=1}^{J} P(d_j^{**} = 1 \,|, \theta_j, z_u, e)\theta_{jk} \tag{8}$$

Because varieties are uniquely identified by their varietal characteristics vectors, the introduction of a new variety is equivalent to a change in the set of varietal characteristics vectors of all known varieties, and the improvement in a varietal characteristic k is equivalent to introduction of a new variety that raises the farmer's known frontier for that characteristics. Equation (7) shows how this change affects the probability of adoption on village variety, and

[3] A 'village variety' is any variety that was collected in the village (i.e. it is used by [some of] the farmers).

equation (8) shows how the predicted demand for characteristic k (left hand side) functionally depends on the individual variety characteristics θ_{jk} and the probability of variety adoption.

The structural causal relationships between varietal characteristics, varietal adoption decision, varietal demand, and outcome of interest are illustrated in Figure 2a, which shows how a change in a given varietal characteristic due to breeding research affects household total income and production, and village poverty headcount through adoption and demand.

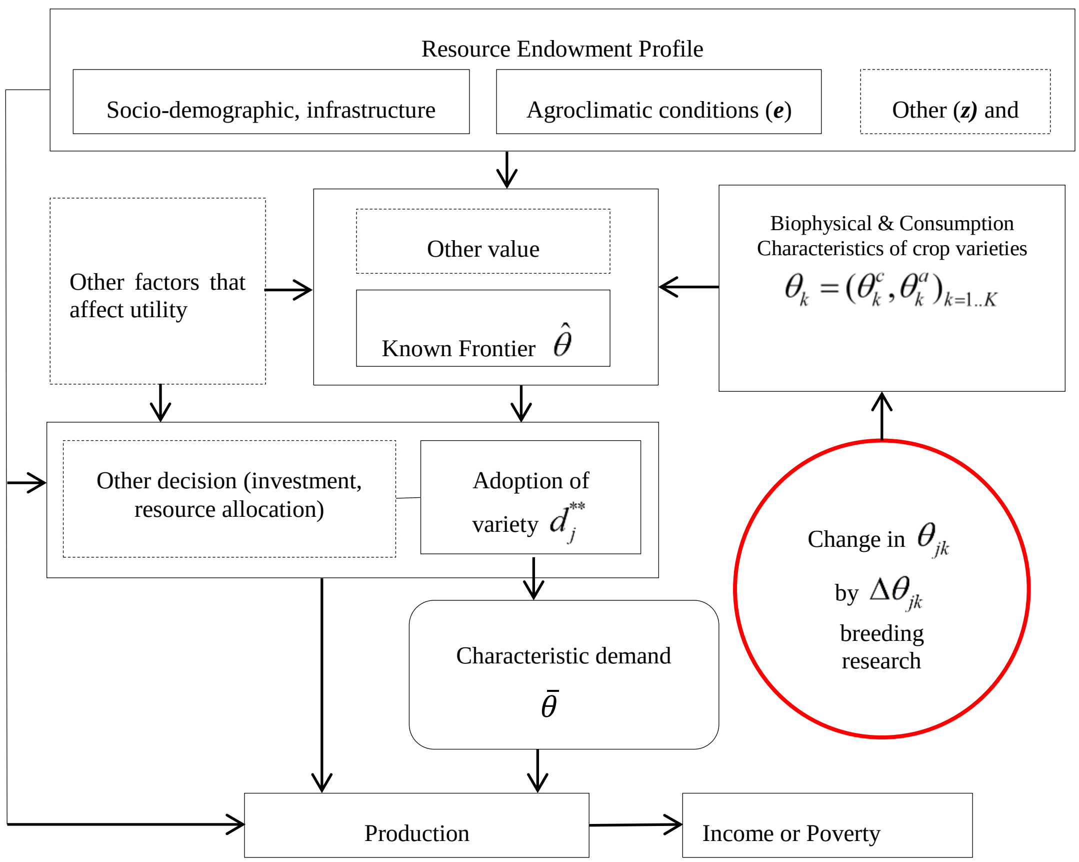

Figure 2a: Causal structural relation for the analysis of breeding research solution impacts

- ***Identification of causal effect of agronomic technology adoption***

The non-varietal technologies are assessed through environmental variables, mainly stresses that affect rice production. These stresses in some case affect 100% of the harvested area and cause high yield losses. The magnitude and effect of the stresses could be attenuated when the farmer adopts varieties that are resistant to the stress. But another important way to reduce losses is for the farmer to adopt agronomic/IPM technologies as farming management practice and best postharvest practice. These technologies can help to mitigate the negative environmental side-effects of stresses and reduce postharvest losses. We have not modeled the adoption rate and determinants for this kind of technology. Using experts' opinions after consultation with AfricaRice rice agronomists and postharvest specialists, we assume the adoption of non-varietal technologies follows a logistic diffusion curve with a 35% peak adoption rate. The logistic distribution is the most common for technology adoption variables.

The structural relation that shows how agronomic research has impact on income or poverty is described in Figure 2b (the conventions are the same as above). The channel linking the research solution to impact on farmer outcomes is straightforward compared to the breeding case. When the farmer takes the decision to adoption the technology, it is expected that the negative effects that he will face when the stress hits will be less than if he did not have this, or any other, suitable technology.

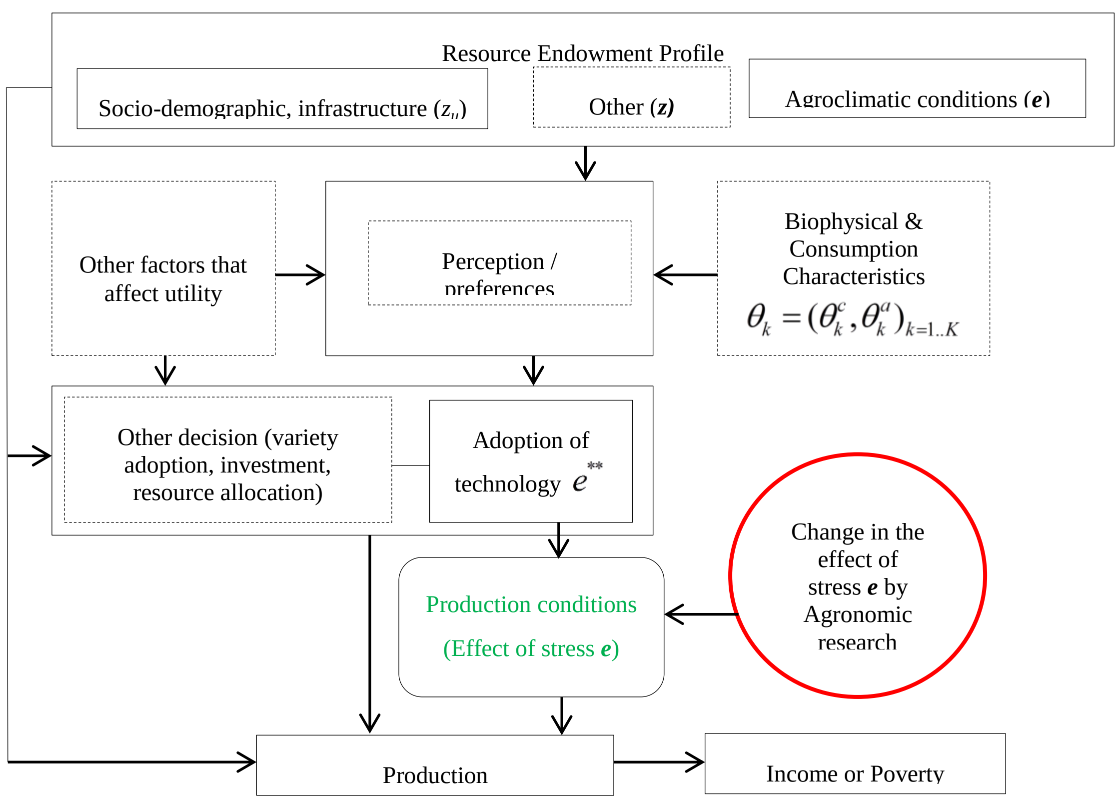

Figure 2b: Causal relationships for the analysis of agronomic research solution

2.1.3 Specification, identification and estimation of impact mode

To be able to project impact over time, we use an auto-regressive (AR) model of the outcomes of interests. The AR model is reasonably realistic in most economic settings. Because of the limited data, we will use AR model of order one (AR1). Thus, the general impact model equation that will be estimated is:

$$Y_t^h = \alpha y_{t-1}^h + \beta D_t^h + \gamma X + \varepsilon_t^h \qquad (9)$$

where *Y* is the outcome variable; D stands for the proxy for the research solution that is assessed. In such regression, the main econometric concern is the possible biases that would be generated by the possibility that *D* may not be exogenous.

- ***Case of breeding research technology***

For the breeding research solution, *D* is the demand for a given varietal characteristics *k*. The impact models are estimated separately for each varietal characteristic. Each equation is estimates by the Instrumental Variable method. The varietal technology demand and the outcome (income, production, or poverty) can be confounded as shown in the structural causal relation (Figure 2a). Thus, $D = \tilde{\theta}_k$ is endogenous in equation (9) and Ordinary Least Squares will yield inconsistent parameters. To address this problem, we use the Instrumental Variable estimation method with known frontier ($\hat{\theta}_k$) as instrumental variable for the demand $\tilde{\theta}_k$. The validity of the frontier as instrument is tested by weak instrument test. The estimates parameter is the total effect of the demand for varietal characteristics on the outcome. Chalak and White (2011) show that in such regression, the first-stage regression coefficient need not be identified. Each breeding research solution is associated with a corresponding varietal characteristic (*see* Appendix, Table A.1).

- ***Case of agronomic research technology***

For the agronomic impact model, *D* is the yield loss caused by a given stress when it is experienced by the farmer. We assume that the occurrence of stresses and the yield losses they cause to farm households are exogenous to their decisions. Thus, $D = e$ is exogenous in equation (9). So, estimation of the AR1 model by Ordinary Least Squares yields consistent estimates of the parameters. The other variables included in the model are socio-demographic variables, ecosystem and country fixed effect to capture the heterogeneity among ecosystem and country of stress effect (*see* Appendix, Table A.1 for details of the variables used in each model).

2.1.4 From scientist research to gross impact: methodology

- ***Linkage between scientist-proposed solution and estimated parameters***

The two diagrams of the structural impact model describe graphically how the scientist-proposed solutions are linked to household- and village-level models. This subsection gives detail on how the linkage was done. As discussed above, there is a slight difference between how breeding research and agronomic research options are assessed. Hence, we distinguish them in the linkage procedure.

The linkage of breeding research solution to impact models follows three steps.

Step 1: Translating the scientist's estimate of percentage yield gain into percentage increase in $\hat{\theta}_k$

The average expected yield loss reduction (%) for each breeding research solution was converted into increase in the performance of the characteristic corresponding to the stress that the solution address (*see* Appendix, Table A.1 for correspondence between the stress and varietal attribute).[4]

Step 2: Using percentage increase in $\hat{\theta}_k$ *in the adoption model to get the percentage change in varietal demand* $\bar{\theta}_k$

By changing the known frontier of characteristic *k*, the solution will induce a change in the farmer's portfolio of adopted varieties. The change $\Delta\bar{\theta}_k$ is captured through the adoption model estimated and the demand function derived from this model (equation (7) by plugging in $\Delta\hat{\theta}_k$). This change in demand (as population parameter) already accounts for the adoption of the technology. To account for the uncertainty, the change is multiplied by the probability of success of the research φ_k, and the true impact of the research on demand is $\varphi_k\Delta\bar{\theta}_k$.

Step 3: Plugging $\varphi_k\Delta\bar{\theta}_k$ *in the impact model to get impact at starting year*

The induced change in the farmer pool of adopted varieties (demand) is plugged into the impact model corresponding to characteristic *k*. The impact $\overline{\Delta y} = \beta\varphi_k\Delta\bar{\theta}_k$ is then the average impact on farmer income or production or village poverty headcount in the starting year of availability of the research option across adopting and non-adopting farmers.

[4] Example: a breeding research solution addressing weed competitiveness by reducing the losses due to weed by *x*% will result in an improved variety with a weed-competiveness performance competiveness $\frac{x}{100}$ higher than the average weed-competiveness of existing varieties.

An appropriate impact model is estimated for each stress. When the research solution was agronomy or IPM, we used the yield loss reduction impact model solution with the corresponding loss due to the stress that the solution addresses as explanatory variable. When the research solution was post-harvest, we used the impact model that has loss caused by post-harvest as explanatory variable. Where the research solution does not have a specific nature (and is labeled ‘other’), we used the impact model that has average yield loss as explanatory variable.

The linkage of agronomic research options to impact models is straightforward by plugging the yield loss reduction expected (r_e, %) directly into the impact model and multiplying the result by the probability of success (φ_e) to account for uncertainty. Thus, the impact is $\overline{\Delta y} = \beta\varphi_e r_e$ and corresponds to the average impact at farmer or village level in the first year of availability of the research option across adopting and non-adopting farmers.

- ***Projection of impact over time***

At the end of the process described above, what we had was the impact in the first year of availability of the research solution. This year corresponds to $t_0 = 2010 + t_d$, where t_d is the estimated time (years) to delivery of the solution as given by scientists. We are interested in projecting impact over time to 2020.

The AR1 models estimated are enough to allow us to forecast the mean impact starting in a given year t_0 in any subsequent year $t_0 + \rho$ as:

$$E\Delta y_{t_0+\rho} = \beta \sum_{j=0}^{\rho-1} \alpha^j E(\Delta y_{t_0+\rho-j}) = \overline{\Delta y}\,\frac{1-\alpha^\rho}{1-\alpha} \quad \rho = 1,2, \dots . \tag{10}$$

where $\overline{\Delta \mathrm{y}}$ is the impact in the starting year ($\beta\varphi_k\Delta\bar{\theta}_k$ for breeding option and $\beta\varphi_e r_e$ for agronomic option). This formula enables to forecast the impact at ρ years after t_0. Finally, the annual nominal income gained was discounted at the rate of 5% and cumulated to obtain gross benefit at farmer level.

- ***Aggregation across research options and research natures***

The impact parameters calculated (as described above) are for each technology that addresses a specific stress or has a specific varietal attribute. These research solutions were grouped in major research options (shown in Appendix, Table A1). The major research options used were: Alleviate biotic stresses, Alleviate soil-related constraints, Alleviate climate- and water-related constraints, Alleviate postharvest-related constraints, and Raise the genetic yield potential. For each major research option, the impact parameters were aggregated across all stresses. For the income or production parameters, the aggregation function used was the mean across research solutions in a given major research option and was interpreted as the average impact of any research solution within that group. For the poverty parameter, the mean does not make sense because one individual cannot be lifted out poverty at the same time by two different technologies. Thus, we used maximum across research solutions in a given major research option as aggregation function so that the result can be interpreted as the minimum number of people that will be lifted out of poverty by any research solution of that major research option.

- ***Estimation of the number of rice farmers and rice farming population***

The extrapolation from farmer and village level 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, we combined household-survey and secondary data to get these estimates.[5]

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 constant population growth of $g = 2.5\%$ (average rural population growth in SSA from World Bank, 2010).[6] The formula used is $N_h = \frac{S}{s_h} * (1+g)^{\rho}$, where ρ stands for time.

To get the distribution across ecosystems, we multiplied the proportion of farmers using the ecosystem (estimated from the household survey) by the total number of farmers in the country. This assumes that the structure of the rice farmers by ecosystem will remain stable over time. The total rice-farming population size in the country was estimated by multiplying the total number of rice-farming households (as estimated above) by the average household size. Missing values for average area and household size were estimated by taking the average across neighbors.

[5] The extrapolation weight in the rice statistics data that is needed to estimate the total number of rice farmers is available for only a few countries (Benin Côte d'Ivoire, Guinea, and Nigeria).

[6] This assumes that the rice cropping intensity is one crop per year.

- ***Extrapolate impact on income or production from household level to country level***

The potential benefit of rice research and its expected poverty impacts for rice-producing farmers in SSA were assessed for 38 rice-producing countries. The household- and village-level impacts estimated from data on 16 countries were used to extrapolate impact at national level for all 38 counties. The 38 SSA rice-producing countries included are: Benin, Burkina Faso, Cameroon, Central African Republic, Chad, Comoros, Congo, Côte d'Ivoire, Democratic Republic of Congo (DRC), Ethiopia, Gabon, Gambia, Ghana, Guinea-Bissau, Guinea, Kenya, Liberia, Madagascar, Malawi, Mali, Mauritania, Mozambique, Niger, Nigeria, Rwanda, Senegal, Sierra Leone, Swaziland, Tanzania, Togo, and Uganda. The total rice area harvested in these countries in 2009 was about 9.9 million hectares, which represents 99.3% of the total harvested area in SSA. Their total paddy rice production for the same year was 19.1 Mt – some 99.1% of total SSA production. Thus, the results of this analysis can be considered to be applicable for all of SSA.

For each country included in the analysis, the impact on individual farmer's income or production was extrapolated to country level by multiplying the average impact estimates by the estimates of total number of adopting farmers in the country. To ensure that this provided a consistent estimate of the total benefit to rice farmers at the national level, we let $\bar{y}_h$ the increase in the average household income, N the average population size of rice farmers in the country, and A the adoption rate, so that the total benefit at country level is $T = A * N * \bar{y}_h$. Now, the total number of adopting rice farmers, $N^a = A * N$, so $T = N^a * \bar{y}_h$.

- ***Extrapolate impact on poverty from village to country level***

The poverty impact estimated at the village level was multiplied by the total rice-farming population size of the country. So that this provided a consistent estimate of the reduction in the total number of poor rice farmers at the national level, let P_v be the reduction in the average village poverty headcount and N_v the average population size of rice farmers in a village, so that the average number of rice farmers in a village lifted out of poverty, $Q_v = N_v * P_v$. Now, if Q is the total number people living in rice-farming households lifted out of poverty in the whole country, N the total number people living in rice-farming household in the country, N^a the total number of adopting rice farmers, K^a the total number of rice-farming villages with adopters, N_v^a the average population size of adopting rice farmers in a village, then we have $N^a = K^a * N_v^a$, so that $Q = K^a * Q_v = \frac{N^a}{N_v^a} * Q_v = \frac{N^a}{N_v^a} * N_v * P_v$. If A is the adoption rate (assumed to be the same at both village and national levels), then we have $N^a = A * N$ and $N_v^a = A * N_v$. So $Q = \frac{N^a}{N_v^a} * N_v * P_v = N * P_v$. This extrapolation to country level was done for each research option using the calculated estimate of individual farmer- or village-level impact.

- ***Sub-region, ecosystem and research nature aggregation***

For each research option, all income gain and poverty reductions were summed to get the gross income benefit and total poverty reduction for all countries. The income benefit disaggregation by sub-region, ecosystem, and research nature was obtained by summing the benefit across all research options and restricting the sum to the level of disaggregation of interest. The poverty disaggregation by sub-region, ecosystem, and research nature was obtained by calculating new parameters at the level of interest using maximum aggregation function. The new parameters were then used to obtain impact by country/ecosystem and summing the result at disaggregation level of interest.

3 Estimation of the impact for rice processors, traders, and consumers

3.1 Estimation of the impact for rice processors and traders

3.1.1 Rationale and background

Rice processing involve several activities. At each step significant numbers of farmers and processors experienced significant losses. Postharvest losses in rice can be divided into quantitative and qualitative losses due to the rudimentary handling methods used in many SSA countries. It is estimated that, on average, quantitative postharvest losses of rice at farm level in Africa are in the order of 15–20% (AfricaRice, 2010 p.73).

Also, if rice paddy is not harvested and stored in a timely manner, or is dried too quickly, the proportion of rice grains that break during milling is usually high. Suboptimal drying and storage practices of farmers often result in good-quality paddy rice being mixed with damaged paddy, weed seeds, insect residues, sand, and stones. Separation of broken from whole grains and removal of impurities is possible, but only with equipment in large-scale rice milling operations. Farmers also tend to mix paddy from different rice varieties when harvesting, drying, or storing rice – different rice varieties have different milling characteristics.

As a consequence, there is a significant quality gap between locally produced and imported rice. The locally produced rice that is sold on African markets tends to be made up of a mixture of broken and whole-grain rice of different varieties, sizes, and colors. Rice grains are also often mixed with weed seeds, stones, sand, and insect residues (Lancon *et al.*, 2003). Thus, qualitative losses, which are estimated by the price differential between imported and locally produced rice, range from 15 to 50%, with an average of 30% in many countries.

To address these constraints, AfricaRice scientists propose a set of technologies for good harvest and postharvest handling and timing of practices that will be made available to most farmers and processors in order to increase milling performance and overall rice quality. Improved handling practices and technologies can significantly reduce rice paddy and grain losses due to poor harvesting and rice processing technologies (Hosokawa, 1995).

3.1.2 Methodology for the estimation of the benefit for processors and traders

Scientists expect that if improved processing practices and technologies are adopted by rice processors, the milling rate will significantly increase from its current average value of 60% (Totté, 1995) to almost 67% starting from 2013. Also it is expected that the percentage of head rice after milling will increase from 11% to 20%, and the percentage of broken rice will significantly decrease from 59% to 50%. These estimates are conservative. For the traders, the assessment is done by assuming that the quality of local rice will increase. The increase is measured as the reduction of the price gap between local rice and imported rice.

In the absence of survey data for rice processors and traders, we make the assumption that the percentage of rice paddy that will be processed using the improved technologies proposed by scientists will follow a logistic curve with an initial adoption of 0.5% in starting year 2013 and a peak adoption rate of 35% in 2020. For each year, we forecast the total paddy production and then apply the new technical parameters to calculate the increase in milled rice resulting from the adoption of these research solutions. The additional milled rice is valued at processor margins to estimate the income benefit for rice processors. The price increase attributed to increased rice quality is used to estimate the benefit for rice traders.

3.2 Estimation of the impact for rice consumers

To assess the impact for rice consumers, it is assumed that the expected increase in rice production and in quality of locally produced rice will be translated into a decrease in rice price compared to the level it may reach in the absence of the research proposed by AfricaRice.

Using an econometric model with the price of milled rice at each village level as dependent variable, and the proxy for each research solution proposed by scientist and other village characteristics as covariates, we estimate the level of this price effect. From this price effect – combined with poverty data from the World Bank (2011), rice expenditure shares provided by the African Development Bank (2007), and estimated population of non-rice farmers in SSA projected over time – we calculated the expenditure savings on rice by poor consumers. This aggregated expenditure saving has been redistributed to estimate the number of poor consumers that will be lifted out of poverty. It is then translated into additional rice that can be bought (by dividing it by the average rice price, i.e. $200/tonne). The total additional rice obtained was then converted into calories. This total of calories was then divided by the food deficit of undernourished population (in kcal/person per day) to give the number of people that could be lifted out of hunger with the additional rice expenditure achieved through lower rice price.

4 Presentation of the data

The data used for the priority-setting exercise come from various sources, both primary and secondary. Household and community surveys were conducted in many countries in 2009. A rice experts' survey was conducted during AfricaRice Research Days in 2010. Data from secondary sources (e.g. FAOSTAT and World Development Indicators) have also been collected. This section describes the data used and various transformations made on them.

4.1 Household and community data

4.1.1 Rice data system for sub-Saharan Africa: overview

The rice data system for SSA was a project funded by Japan to address the need for better-quality rice data, R&D priority-setting, and monitoring. Household, community, and scientist surveys were conducted in 21 member countries of the Coalition for African Rice

Development (CARD: Benin, Burkina Faso, Cameroon, Central African Republic, Côte d'Ivoire, DRC, Gambia, Ghana, Guinea, Kenya, Liberia, Madagascar, Mali, Mozambique, Nigeria, Rwanda, Senegal, Sierra Leone, Tanzania, Togo, and Uganda) by AfricaRice in collaboration with NARS, to collect household and community-level data on the biotic and abiotic stresses, and the socioeconomic constraints in rice production, as well as knowledge and adoption of varieties, evaluation of varietal characteristics, household demographics, access to seed, production, assets, access to infrastructure, etc. The sample sizes ranged from 370 (Gambia) to 10,500 (Nigeria) rice-farming households per country in the household surveys.

A wide range of stresses is identified by AfricaRice and NARS scientists in all ecosystems. For each stress, farmers were asked whether or not they knew the stress. They were also asked to rate the stress in terms of intensity on a three-point scale (High, Medium, Low) when it occurs. After rating all stresses, they identified the five major ones and were then asked three questions: (a) Have you experienced the stress in the past 5 years? (b) What was the proportion of area affected by the stress in the past 3 years? (c) What was the yield loss (%) when the stress was experienced in the past 3 years?

A single list of known traditional and modern varieties was compiled for each village. In a given village, each surveyed farmer was asked whether he (or she) knew each village variety; whether he/she had grown it during the past 5 years; and, if grown, what was the area allocated, the quantity of seed used, the quantity of paddy produced, etc.

A pool of varietal attributes was identified by AfricaRice scientists. Because of the relatively large number of traditional varieties known and cultivated in many of the villages surveyed, the variety performance was evaluated at community level. Measuring the characteristics intrinsic to a variety is complex. Instead of having the exact measure, we used a ranking method to assess varietal characteristics. Each variety's performance for all attributes identified was assessed on a three- or five-point scale by a focus group of rice farmers in the village. The score was then used as a proxy for the varietal attribute. The scores given by the farmers were normalized by dividing them by the maximum possible score (3 or 5) to give an index of between 0 and 1. Some of the varietal characteristics were aggregated using geometric means. These scores, from village level, were integrated in the household-level file by matching by variety and village. The missing values were corrected using averages by country, village, variety type, and ecosystem.

Data were collected for 21 countries, but completely processed for only 18 countries.[7] Thus, the models are estimated using only 18 countries' data. The estimated parameters were then used for all the countries included in this analysis. The survey questionnaire was almost the same for the 21 countries, except for a few aspects that differed across countries. The data for all 18 countries were pooled.

To assess the probability of adoption of a given village variety, we pooled the data as an unbalanced panel. One observation is defined as a couplet (h, j), where h is the index for household and j for variety of the village. Thus, the data were balanced at village level in each country.

The income variable used in the impact model was total household income. The survey captures household income from various sources and for the 'last 3 years'. A household's income comes from rice production, other crop production, livestock production, and non-agricultural activities (commerce, work as laborers, formal employment, etc.). The total household income was obtained as the sum of income from the sources identified for all household members.[8] For uniformity, the incomes were converted from local currency to US dollars using the exchange rate of each currency (from the Word Development Indicators database; World Bank, 2011). The household total paddy production was obtained by summing the paddy production across all varieties and all plots in the household. We calculated each village poverty headcount by using household per-capita income and the poverty line used was the $1.25 per day poverty line multiplied by each country's purchasing power parity (PPP) value (obtained from African Development Bank, 2007).

[7] Data for Guinea, Liberia, and Mozambique were not in the right format and had not been aggregated with the others.

[8] The survey does not directly measure income at household member level. During the interviews, the enumerators evaluated the income of each member and summed these to get the income of the household.

4.1.2 Results: farmers' characteristics, variety adoption, demand for varietal characteristics, and major stresses

- ***Knowledge and adoption of varieties***

For a given variety in a village, about 47% of farmers knew it and 29% cultivated it. Among the 'exposed' population, the adoption rate was estimated at 62.4%. The average treatment effect adoption of village variety in the overall population was 61.4%; in the population of farmers aware of the variety, the potential adoption rate was 62.4%; while it was 60.5% in the population of farmers currently not exposed to the village variety (if they were to be exposed to it). The population selection bias was only 1%. This low selection bias may be due to the fact that we focused on any village variety, not on a particular technology. The gap between the potential probability of village variety adoption and the actual adoption rate was estimated at 32.3%.

- ***Demand for varietal characteristics***

Because of the relatively large number of varietal attributes evaluated (27), we grouped some of them. Geometric mean was used as aggregation function (*see* Appendix, Table A1). This aggregation function is the most suitable because of the nature of the varietal characteristics to be grouped. For all the varietal attributes, the known frontier was low, while the demand was on average medium and near to the frontier (*see* Appendix, Table A3). Thus, there is a need to increase the varietal characteristics by developing improved varieties with higher performance than the existing ones.

- ***Importance of main rice production stresses***

Stress analysis focused on biophysical constraints only. The socioeconomic constraints are not considered here and will be analyzed in later work. Some grouping was made to reduce the number of stresses assessed (*see* Appendix, Table A1). The yield loss of a given group is the average across the stresses in the group. Also, a farmer experiencing at least on stress in a group is assumed to have experience this group of stresses.

On average, more than 30% of the harvested area was affected by at least one major stress. Climate and water constraints, soil-related constraints, and weeds were the most common, with 49%, 44%, and 41% of the area affected, respectively. The yield losses caused by the stresses when experienced are high and depend on the ecosystem. Climate and water constraints cause on average 36% yield loss in irrigated and upland ecologies (*see* Appendix, Table A5).

4.2 Scientist survey

4.2.1 Priority-setting workshop: overview

A 2-day priority-setting workshop was organized during AfricaRice Research Days 2010. During this workshop, a questionnaire-based survey developed by the AfricaRice Priority-setting Task Force was conducted. The survey was addressed to all AfricaRice experts to elicit research options (i.e. scientific possibilities) to address rice production constraints.. The expected impact in terms of yield loss reduction, narrowing of the yield gap, or increase in the yield potential under researcher-managed conditions was provided by the experts for each proposed technological option. The yield loss R reduction given in tonnes per hectare was turned into percentage using the formula $r = 100 * R * \left(1 - \frac{l}{100}\right) * \frac{1}{y}$, in which y is the actual on-farm yield, l the actual average yield loss as perceived by the farmer, and r the yield loss reduction (%) expected from the research option. This implies that with the adoption of the research solution, the yield loss perceived by the farmer with be reduced from l% to $(l - r)$%. Experts were also asked to indicate associated research costs, probability of success, and the expected year of delivery of the technological option.

4.2.2 Results: scientific options and expected impact

The analysis of the data from the survey of rice experts reveals a wide variety of proposed technological options across research disciplines (breeding, agronomy, IPM, post-harvest, etc.) and ecosystems. The average yield loss reductions expected from technological options mitigating the effects of various biotic and abiotic stresses are 0.6 t/ha in irrigated systems, 0.5 t/ha in rainfed lowland systems, and 0.45 t/ha in upland systems. The average yield potential increases for technological options raising yield potential are 1.5 t/ha for irrigated, 1 t/ha for upland, and 1.4 t/ha for rainfed lowland. Estimates of yield gains from technological options refer to conditions in researcher-managed trials. The average time to delivery of proposed technological options was slightly more than 4 years and the average probability of success was slightly above 60% (*see* Appendix, Table A6 for details of scientists' estimates).

5 Patterns of expected income benefits and poverty reduction

This section presents the mains findings of the *ex-ante* analysis of rice research in SSA. The results focus on impact of research on income, poverty reduction, and food security. Disaggregation across rice value-chain actors, research option, ecosystems, research nature, and sub-region are made. The first sub-section focuses on gross benefit on income, while the second sub-section presents impact on poverty reduction and food security.

5.1 Income benefits

5.1.1 Aggregated income benefits by actors and sub-region

The estimation of the potential impact of research targeted to reduce yield loss due to the major production constraints identified by farmers, to raising the yield potential, and to adding quality to rice on annual benefit resulted in a global cumulative 5%-discounted benefit of $10.6 billion over the 7-year period 2014–2020 for the 38 SSA rice-producing countries included in the analysis, with an average annual benefit of $1.8 billion. Table 1 shows the disaggregation across the rice value-chain actors and for each sub-region.

Table 1: Benefit of research on value-chain actors' income by region (US$ million discounted at 5%)

Sub-region	Farmers	Consumers	Processors	Traders	All actors
Gross annual benefit					
Central Africa	109.4	66.6	7.7	3.75	187.5
East Africa	274.3	183.1	18.7	8.97	485.0
Southern Africa	2.6	16.8	1.5	0.77	21.7
West Africa	705.6	384.1	36.3	17.34	1,143.4
SSA	*1,091.9*	*650.6*	*64.2*	*30.8*	*1,837.6*
Gross cumulative benefit					
Central Africa	697.5	333.0	38.6	18.90	1,088.1
East Africa	1,714.0	915.4	94.3	45.19	2,768.8
Southern Africa	16.5	84.1	7.8	3.86	112.3
West Africa	4,416.3	1,920.7	183.0	87.39	6,607.5
SSA	*6,844.4*	*3,253.2*	*323.7*	*155.3*	*10,576.7*

The estimated potential impact of research targeted to reduce the yield gap and increase grain quality through better crop management and postharvest practices, and to raising the yield potential through higher-yielding varieties is an annual income benefit of $1.09 billion for rice farmers, corresponding to a global cumulative 5%-discounted benefit of $6.8 billion over the 7-year period 2014–2020.

As a result of increased rice supply, domestic prices in major rice-producing countries in Africa are expected to be on average 7.2% lower than the baseline level. Translating this price effect, it is expected that annual expenditure on rice by non-rice-farming consumers under the $1.25 poverty line will be reduced by $650.6 million (PPP) by 2020 (holding consumption constant), corresponding to a global cumulative 5%-discounted benefit of $3.3 billion.

By improving rice processing technologies and reducing losses, it is expected that the quality of locally produced rice will be increased, generating more revenue for rice processors and rice traders. These benefits are estimated at $64.2 million annually (cumulative 5%-discounted, $323.7 million) for rice processors and $30.8 million annually (cumulative 5%-discounted, $155.3 million) for rice traders.

In terms of regional distribution on income gain, West Africa would have the highest impact (annually $1.143 billion, about 62.2% of total annual income gain – $705.6 million for farmers, $384.1 million for consumers, $36.3 million for processors, and $17.3 million for traders). East Africa would come in second position (annually $485.0 million, about 26.4% of total – $274.3 million for farmers, $183.1 million for consumers, $18.7 million for processors, and $9.0 million for traders). Central Africa would be third ($187.5 million, about 10.2% of total – $109.4 million for farmers, $66.6 million for consumers, $7.7 million for processors, and $3.8 million for traders). Southern Africa comes last with only $21.7 million annually (1.2% of total annual income gain – $2.6 million for farmers, $16.8 million for consumers, $1.5 million for processors, and $0.8 million for traders). This pattern is almost the same for all rice value-chain actors.

5.1.2 Income benefits for farmers by research option

The impact on farmers' income of the various reseach solutions grouped into major reserch options for all SSA countries and all ecologies are presented in Table 2.

Table 2: Gross discounted income benefits by research option (US$ million)

	Starting year (2014)	End year (2020)	Annual
Biotic stresses	252.0	2149.5	334.6
Soil-related constraints	159.1	1342.8	218.9
Climate- and water-related constraints	260.1	1999.2	319.9
Postharvest-related constraints	87.1	643.1	94.0
Yield potential	88.5	709.8	124.6
All research options	*846.8*	*6844.4*	*1091.9*

For all research options and for all SSA farmers, the expected gross discounted benefit on farmer income is estimated at US$ 846.8 million in 2014 (starting year of adoption of the technology by farmers). In 2020, the gross cumulative discounted income benefit would be $6.8 billion. These benefits correspond to an annual discounted benefit of $1.1 billion from 2014 to 2020. The implicit assumption underlining these figures is that the impacts of the research options are additive (as explained in the methodology section) – the gross benefits for all research options were obtained by summing the individual benefit for each research option.

The disaggregation across research option shows that the share of discounted cumulated benefits attributable to research that addresses major biophysical production stresses are the most important, with 30.6% ($334.6 million annually); followed by research to alleviate climate- and water-related stresses, 29.3% ($319.9 million annually), and research addressing soil-related stresses, 20.0% ($218.9 million annually).

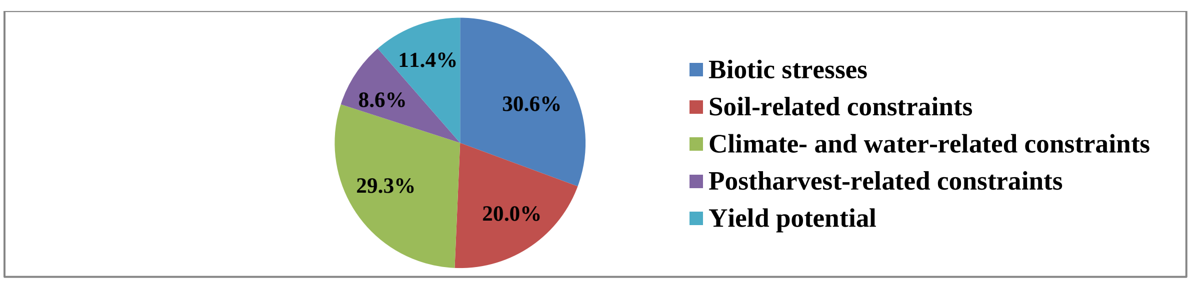

Figure 3: Share of gross annual benefit attributable to each major research option

Research that raises genetic yield potential is expected to provide annual income gain of $124.6 million, representing 11.4% of the total gross benefit. Research that alleviates postharvest losses at farmer level will generate $112.1 million annually, about 8.6% of the total annual income gained due to successful research in SSA up to 2020.[9]

The corresponding gross cumulative discounted benefits in 2020 are $2.2 billion for alleviating biotic stresses, $2.0 billion for alleviating climate- and water-related stresses, $1.3 billion for alleviating soil-related stresses, $0.8 billion for raising yield potential, and $0.6 billion for postharvest loss reduction.

5.1.3 Income benefits for farmers by ecosystem targeted

In terms of ecosystem, the rainfed lowland ecosystem comes in first position for all research options, with annual income benefit of $482.3 million (about 44.2% of income gained); upland comes in second place, annual benefit of $431.4 million (about 39.5% of income gained); irrigated system follows with annual benefit of $143.1 million (about 13.1% of income gained); and then mangrove and other ecosystems with annual benefit of $35.2 million (about 3.2%) (Figure 4). The high potential impact observed in rainfed lowlands is mainly driven by Nigeria, where this is the major ecology (70% of rice farmers).

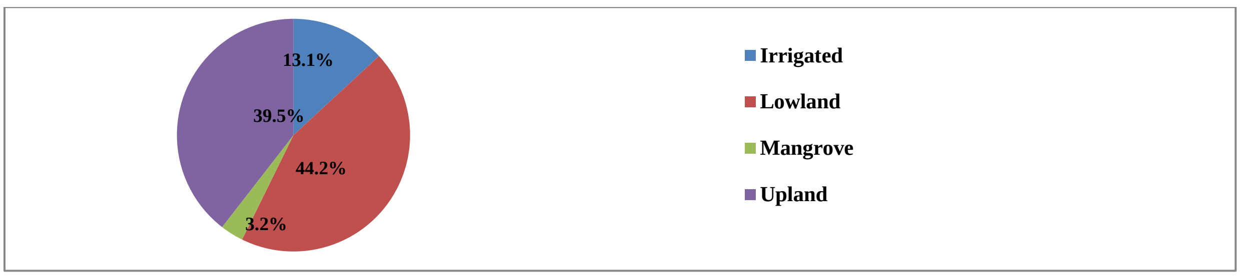

Figure 4: Share of gross annual benefit attributable to each ecosystem

Gross cumulated discounted benefit in 2020 will reach $3.0 billion for the rainfed lowland ecosystem, $2.8 billion for upland ecosystem, $0.9 billion for irrigated system, and $0.2 billion for the other ecosystems (Table 3).

[9] These figures not include postharvest research benefit at processor level.

Table 3: Income benefits (US$ million) by targeted ecology and research option

	Irrigated	Lowland	Mangrove	Upland	All ecologies
Impact on income in first year of adoption					
Biotic stresses	35.5	111.2	7.8	97.5	252.0
Soil-related constraints	19.4	76.7	6.1	56.8	159.1
Climate- and water-related constraints	35.7	111.4	13.1	99.8	260.1
Postharvest-related constraints	8.2	40.4	1.8	36.8	87.1
Yield potential	11.4	42.4	0.0	34.7	88.5
All research options	*110.2*	*382.1*	*28.9*	*325.5*	*846.8*
Aggregate discounted impact on income in 2020					
Biotic stresses	298.4	928.7	69.7	852.8	2149.5
Soil-related constraints	182.4	590.2	46.9	523.3	1342.8
Climate- and water-related constraints	259.6	833.1	79.8	826.6	1999.2
Postharvest-related constraints	60.7	295.8	13.5	273.1	643.1
Yield potential	110.5	304.4	0.0	294.9	709.8
All research options	*911.7*	*2952.1*	*210.0*	*2770.6*	*6844.4*
Annual discounted impact on income in 2020					
Biotic stresses	46.9	144.7	11.0	132.0	334.6
Soil-related constraints	28.2	101.0	8.0	81.6	218.9
Climate- and water-related constraints	41.9	136.4	14.2	127.4	319.9
Postharvest-related constraints	9.0	43.2	1.9	39.9	94.0
Yield potential	17.2	56.8	0.0	50.6	124.6
All research options	*143.1*	*482.2*	*35.2*	*431.4*	*1091.9*

The impact varies across ecosystems for each region (Figure 5).

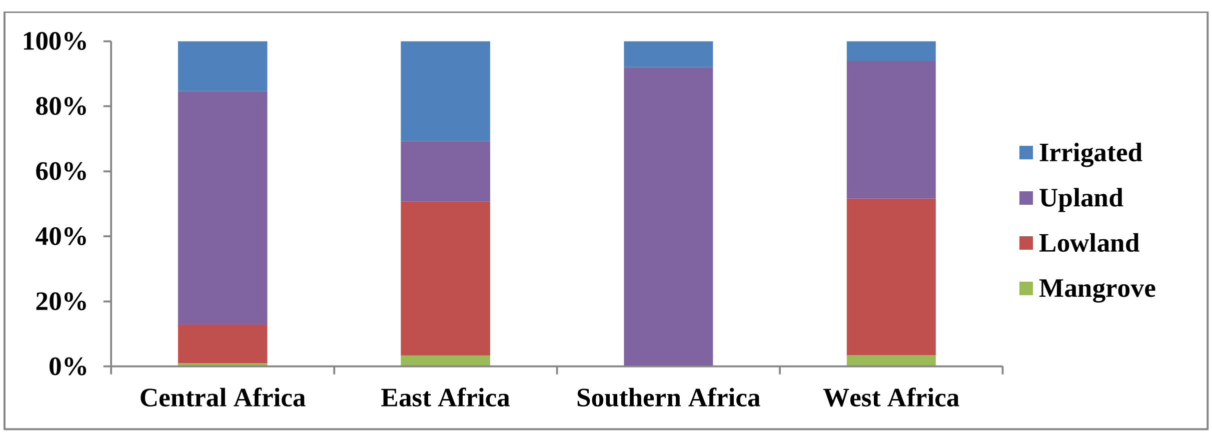

Figure 5: Share of gross annual benefit attributable by ecology and sub-regions

In general, the rainfed lowlands are the major ecosystem in West Africa, mainly in Nigeria. The annual income benefit for lowland in this region represents 48.1% of the total annual income benefit, while the upland ecosystem has a share of 42.5%, the irrigated system

5.9%, and the mangrove and others ecosystems 3.5%. In East Africa, the trend is different, with lowland annual income benefit share equal to 47.3%, irrigated system second with 30.7%, upland third with 18.6%, and the other ecologies just 3.4% of the total annual income benefit in the sub-region. In Central Africa, the dominant ecosystem in term of annual income benefit is upland (71.6%), followed by irrigated systems (15.4%), lowland (12.0%), and the others (1.0%). Southern Africa income benefits come mainly from the upland ecosystem (92.0%) and to some extent from irrigated systems (8.0%).

The benefit in terms of value by region and ecology are presented in Table 4.

Table 4: Income benefits (US$ million) by sub-region and ecology

	Irrigated	Lowland	Mangrove	Upland	All ecologies
Impact on income in first year of adoption					
Central Africa	13.0	10.4	0.9	59.1	83.4
East Africa	64.9	102.8	7.7	38.4	213.8
Southern Africa	0.2	0.0	0.0	1.8	1.9
West Africa	32.2	268.9	20.2	226.2	547.6
SSA	*110.2*	*382.1*	*28.9*	*325.5*	*846.8*
Aggregate discounted impact on income in 2020					
Central Africa	107.3	80.4	6.8	502.9	697.5
East Africa	536.9	794.3	56.0	326.8	1714.0
Southern Africa	1.3	0.0	0.0	15.2	16.5
West Africa	266.1	2077.4	147.1	1925.7	4416.3
SSA	*911.7*	*2952.1*	*210.0*	*2770.6*	*6844.4*
Annual discounted impact on income in 2020					
Central Africa	16.8	13.1	1.1	78.3	109.4
East Africa	84.3	129.7	9.4	50.9	274.3
Southern Africa	0.2	0.0	0.0	2.4	2.6
West Africa	41.8	339.3	24.6	299.9	705.6
SSA	*143.1*	*482.2*	*35.2*	*431.4*	*1091.9*

5.1.4 Income benefits for farmers by research type

In terms of type of research, breeding research comes in first position with annual income benefit of $423.8 million (38.8% of the total income gained); followed by agronomy and IPM research, $302.4 million (27.7% of the total). Postharvest nature will have an annual income benefit of $164.5 million (15.1%) and all other types are expected to have an annual income benefit of $201.3 million (18.4%) (Figure 6).

Figure 6: Share of gross annual benefit attributable by research type

These annual income gains, aggregated over time to 2020 would yield a gross cumulative discounted benefit of $2.3 billion for breeding research, $2.0 billion for agronomy/IPM research, $1.2 billion for postharvest research, and $1.4 billion for the other research types.

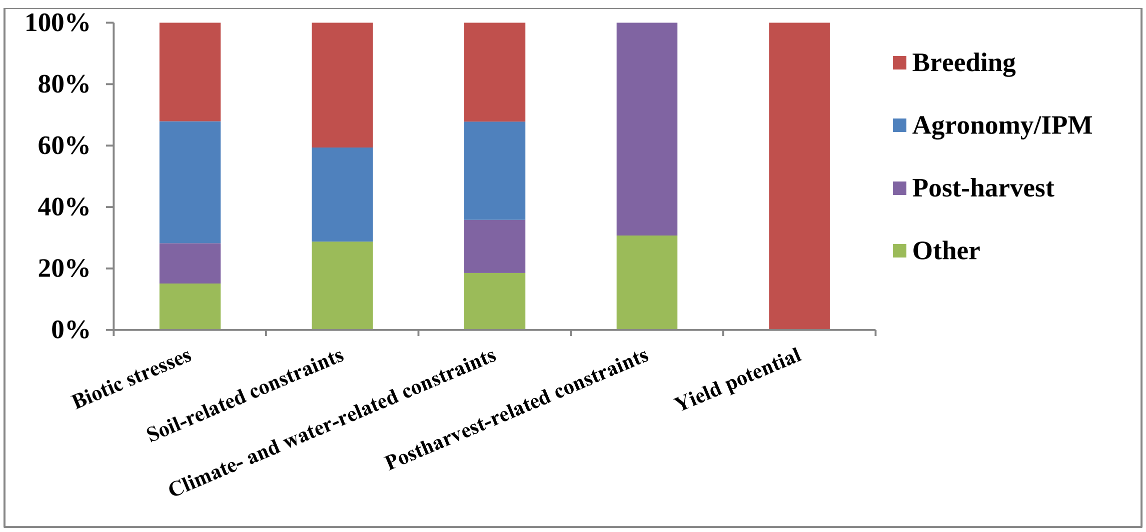

Figure 7: Share of gross annual benefit attributable by research type for to each research option

Comparison across major research options shows that the *contribution* of breeding research to the impact of research to alleviate soil-related constraints will be slightly greater than its contribution to research that alleviates biotic stresses and research that alleviates climate- and water-related constraints. Only breeding research can help in raising yield potential. Table 5 provides more details on impact by research option and research nature.

Table 5: Income benefits (US$ million) by research option and type of research

	Agronomy/IPM	Breeding	Other	Post-harvest	All types
Impact on income in first year of adoption					
Biotic stresses	92.6	73.9	39.8	45.6	252.0
Soil-related constraints	48.3	73.3	37.5	0.0	159.1
Climate- and water-related constraints	86.8	74.0	43.1	56.1	260.1
Postharvest-related constraints	0.0	0.0	23.9	63.2	87.1
Yield potential	0.0	88.5	0.0	0.0	88.5
All research options	*227.8*	*309.7*	*144.3*	*164.9*	*846.8*
Aggregate discounted impact on income in 2020					
Biotic stresses	922.0	605.3	318.8	303.4	2149.5
Soil-related constraints	469.1	433.6	440.1	0.0	1342.8
Climate- and water-related constraints	624.2	582.8	405.4	386.8	1999.2
Postharvest-related constraints	0.0	0.0	187.1	456.0	643.1
Yield potential	0.0	709.8	0.0	0.0	709.8
All research options	*2015.4*	*2331.5*	*1351.4*	*1146.2*	*6844.4*
Annual discounted impact on income in 2020					
Biotic stresses	132.9	107.3	50.3	44.1	334.6
Soil-related constraints	67.0	89.0	62.9	0.0	218.9
Climate- and water-related constraints	102.5	102.9	59.3	55.3	319.9
Postharvest-related constraints	0.0	0.0	28.8	65.1	94.0
Yield potential	0.0	124.6	0.0	0.0	124.6
All research option	*302.4*	*423.8*	*201.3*	*164.5*	*1091.9*

5.2 Poverty reduction and food security

As a consequence of income gains, the corresponding poverty reduction in terms of number of people lifted out of poverty and the food security in terms of number of people that can afford to reach caloric sufficiency was estimated only for rice-farming households and non-rice-farming consumers.[10] As explained in the methodology, aggregation of poverty reduction across research options was done by using 'max' as aggregation function. So, the results presented here are the minimum yearly poverty reduction.

[10] Processors and traders are considered as non-rice-farming consumers.

5.2.1 Aggregated poverty and food insecurity reduction by actors and sub-region

The results in terms of poverty reduction and food-insecurity reduction are presented in the Table 6.

Table 6: Poverty and food insecurity reduction for rice farmers and consumers by region in 2020 (millions of people)

Region	Farmers	Consumers	Total
Number of people lifted above the PPP $1.25 poverty line			
Central Africa	0.3	0.7	1.0
East Africa	1.0	1.6	2.7
Southern Africa	0.0	0.5	0.5
West Africa	2.9	4.0	6.8
SSA	*4.2*	*6.8*	*11.0*
Number of people no longer undernourished			
Central Africa	0.1	0.4	0.5
East Africa	0.4	1.0	1.4
Southern Africa	0.0	0.1	0.1
West Africa	0.7	2.9	3.6
SSA	*1.2*	*4.4*	*5.6*

As result of the rice research in SSA, at least 4.2 million people in rice-farming households will be lifted above the $1.25 poverty line (in 2005 PPP) in 2020. Also the expenditure saving realized by non-rice-farming consumers will equate to 6.8 million urban and rural rice consumers (excluding rice-producing farmers) being lifted above the $1.25 poverty line in 2020. In total, at least 11 million people in the 38 SSA rice-producing countries will be lifted out of poverty in 2020, thus reducing the overall number of poor persons by 4%.

It is anticipated that the improved purchasing power generated by the uptake of improved rice technologies will help undernourished people in Africa to be able to afford to reach caloric sufficiency and more balanced diets. As a result of increased availability and reduced prices, 5.6 million undernourished people will reach caloric sufficiency in Africa (1.2 million in rice-farming households and 4.4 million in non-rice-farming consumer households), reducing the number of food-insecure persons by 6%.

In terms of the sub-regional distribution of poverty reduction, it is expected that by 2020 some 6.8 million of people will be lifted out of poverty in West Africa (2.9 million in rice-farming households and 4.0 million in non-rice-farming consumer households), 2.7 million in East Africa (1.0 million in rice-farming households and 1.7 million in non-rice-farming consumer households), 1.0 million in Central Africa (0.3 million in rice-farming households and 0.7 million in non-rice-farming consumer households), and 0.5 million in Southern Africa (just 7500 in rice-farming households and 0.5 million in non-rice-farming consumer households).

In terms of sub-regional distribution of reduction of undernourished people, it is expected that by 2020 some 3.6 million undernourished people will be able to afford to reach caloric sufficiency in West Africa (0.7 million in rice-farming households and 2.9 million in non-rice-farming consumer households), 1.4 million in East Africa (0.4 million in rice-farming households and 1.0 million in non-rice-farming consumer households), 0.5 million in Central Africa (0.1 million in rice-farming households and 0.4 million in non-rice-farming consumer households), and 0.1 million in Southern Africa (just 4000 in rice-farming households and 90,000 in non-rice-farming consumer households).

5.2.2 Poverty reduction for farmers by research option

Analysis by major research options shows wide differences. The poverty reduction in the first year of availability of research solution will be 2.50 million for research that addresses biotic stresses, 1.68 million for research that addresses climate- and water-related stresses, 0.67 million for research to alleviate soil-related stresses, 0.31 million for research to reduce postharvest losses, and 0.83 million for research to raise yield potential. These impacts will variously increase to reach a minimum of 1.44 million for postharvest research to a maximum of 4.42 million for research to raise yield potential. (For full details *see* Appendix, Table A9.)

5.2.3 Poverty reduction for farmers by targeted ecosystem

As noted earlier, the major ecosystem in terms of number of farmers is the rainfed lowland. It is also in this ecosystem that the expected poverty reduction will be highest. The general picture in poverty reduction is almost the same as the distribution of farmers across major ecosystems. The number of persons living in rice-farming household that will annually be lifted out of poverty in the lowland ecosystem will represent 46.1% (1.9 million people) of the total; the share will be 34.1% (1.4 million) for upland, 16.3% (0.7 million) for irrigated systems, and 3.4% (0.1 million) for mangrove and other ecosystems.

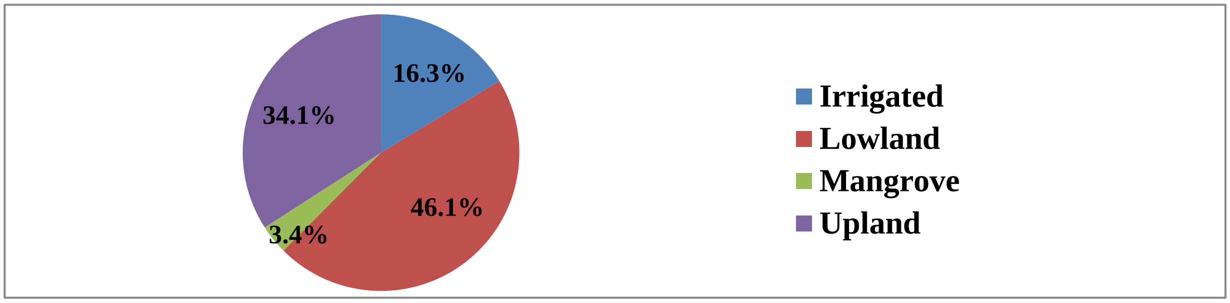

Figure 8: Share of poverty reduction by ecosystem

5.2.4 Poverty reduction for farmers by research option and research type

Agronomy and IPM research will yield the highest poverty reduction in the early years (2.5 million people), followed by breeding (0.83 million), posthaverst research (0.31 million), and other research (0.24 million). In 2020, this trend will change as the growth of impact significantly differs from a given reseach type to another. Thus, breeeding will come in first position with 4.42 million of people lifted above the $1.25 PPP poverty line in 2020. For the other research types, the expected poverty reduction will be 3.89 million for agronomy and IPM, 1.44 million for post-harvest, and 1.37 million the all the other research types.

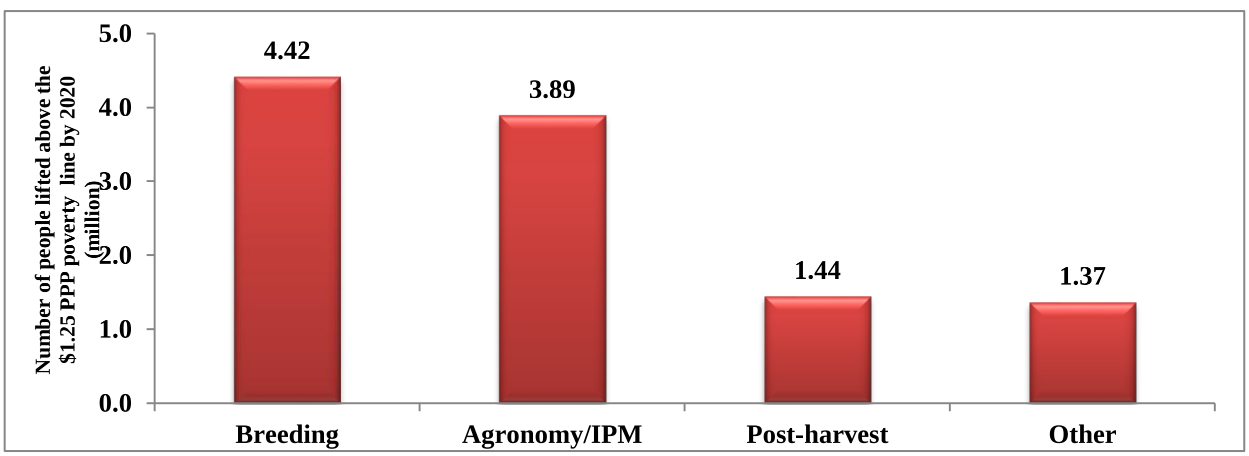

Figure 9: Share of poverty reduction by ecosystem

As with income impact, there is significant difference among research types when one differentiates by major research options. While impacts on poverty of research to alleviate major stresses (biotic, climate and water related, soil related) derive mainly from agronomy/IPM research and to some significant extent from breeding, poverty reduction due to raising yield potential derive (essentially from breeding) and impact of research alleviating postharvest losses are due to postharvest research and the ‘other’ research type, including multidisciplinary research.

Table 7: Number of people (millions) lifted out of poverty by research option and research type

	Breeding	Agronomy/ IPM	Post-harvest	Other	All types
Impact on poverty in first year					
Biotic stresses	0.32	2.50	0.20	0.24	2.50
Soil-related constraints	0.39	0.67	0.00	0.20	0.67
Climate- and water-related constraints	0.35	1.68	0.22	0.23	1.68
Postharvest-related constraints	0.00	0.00	0.31	0.22	0.31
Yield potential	0.83	0.00	0.00	0.00	0.83
All research options	*0.83*	*2.50*	*0.31*	*0.24*	*2.50*
Impact on poverty in 2020					
Biotic stresses	1.50	3.55	0.87	1.28	3.55
Soil-related constraints	1.65	3.37	0.00	1.37	3.37
Climate- and water-related constraints	1.88	3.89	0.98	1.25	3.89
Postharvest-related constraints	0.00	0.00	1.44	1.15	1.44
Yield potential	4.42	0.00	0.00	0.00	4.42
All research options	*4.42*	*3.89*	*1.44*	*1.37*	*4.42*

5.3 Research, economics and financial results, and impact on production

This section presents the estimation the direct and indirect research costs. It also describes the methods used to calculate economic and financial indicators.

5.3.1 Estimation of research cost and economic and financial indicators

This R&D will be conducted within the framework of the Global Rice Science Partnership (GRiSP; IRRI *et al.*, 2010). It includes the GRiSP budget for Africa for the period 2011–2015 and a forecasted value for 2016–2020 – a total of about $420 million. It also includes indirect costs of dissemination of the technologies (estimated from various past projects at about $1.2 billion).

The benefits and costs were aggregated and discounted to derive the rate of return and the benefit–cost ratio indicators. The financial rate of return for all research activities within the period 2011–2020 is estimated at 84% and the economic rate of return (assuming 20% price distortion) is 60%, showing that rice research in Africa within GRiSP is financially and economically profitable.

5.3.2 Impact of rice production

By 2020, Africa's rice paddy production will have increased from 23.6 million tonnes (Mt) to 46.2 Mt. Without the R&D described in this paper and using the 1980–2010 growth rate (3.2%), the baseline levels of paddy production would be 31.7 Mt in 2020. Thus, the research and its associated technology-dissemination activities will result in a rice production increase of 14.5 Mt of paddy (9.4 Mt of milled rice), corresponding to a 46% increase over the baseline scenario.

5.3.3 Impact of rice import

Simple projection of rice consumption using the 1980–2010 growth rate of 5.7% show that rice consumption will rise from 26.1 Mt in 2010 to 45.3 Mt by 2020. Under the baseline scenario of production growth rate equal to 5.9% (1980–2010 growth rate) and no R&D, Africa will import roughly 18.1 Mt of milled rice in 2020. But, with this proposed R&D and the production increase it will generated, the import will only reach 8.7 Mt in 2020, corresponding to a reduction of 52.8%.

The production increase and the increase in quality of local rice attributed to the technologies generated by this research should lead to an increase in the continental rice self-sufficiency ratio from the current level of 60% to at least 83% in 2020. Under the baseline scenario, this ratio would most likely increase slowly to reach 66%. In 2011, only five countries have a self-sufficiency ratio greater than 70% (Tanzania, 90%; Madagascar, 89%; Mali, 84%; DRC, 84%; Guinea, 74%); with the production increases predicted, at least nine more countries should reach this level, and all countries will increase their self-sufficiency ratios by 2020. In addition, if rice production maintains the high growth rate of 9% (for the period 2007–2010) observed after the food crisis in addition to the effect of this R&D, the imports with drop down to 1.2 Mt, increasing self-sufficiency ratio to nearly 97%.

5.3.4 Contribution to agricultural GDP

The share of rice in agricultural gross domestic product of African countries should increase from the current 3.82% to 5.19% in 2010. This corresponds to a 26.5% increase from the baseline scenario, which assumes that the agricultural GDP will maintain its current trend. Thus, R&D on rice in Africa will contribute to achieving the Comprehensive Africa Agriculture Development Program (CAADP) target of 6% per year agricultural growth.

6 Conclusion

This paper presents the AfricaRice research priority-setting exercise. It mainly discusses the methodological issues and presents the projected impact on income and poverty reduction from 2011 to 2020. The methodology used for this priority-setting borrows a lot from the methodologies used in the past, but also includes a number of innovative features.

We used a systematic approach and various data and econometric methods. The data on rice ecosystems, constraints to rice production, varietal attribute performance, and adoption of improved varieties were collected from household and community surveys. Secondary data were also collected from FAOSTAT, the World Bank and the African Development Bank. Research solutions were elicited from scientists – together with their expected efficacy (yield loss reduction), projected costs, probability of success, and year of delivery – during a 2-day workshop. Econometric models were developed to assess: (i) farmer demand for rice traits and impact on adoption; (ii) impact of varietal technology demand on household total income and village-level poverty headcount; and (iii) impact of reduction of negative effects of production stresses on household total income and village-level poverty headcount. The model's parameters were used to estimate impact at country level and for countries for which survey data were not available. Estimations were projected over 10 years, but taking into account the projected year of delivery and the probability of success. In total, the results of the exercise covered 38 major rice-producing countries, which represent more than 99% of the total SSA rice area and production.

The priority-setting showed that the total cumulative income benefit expected for all the research options and all SSA countries will be $0.9 billion in 2014 and $9.1 billion in 2020, corresponding to an annual income gain of $1.3 billion. As a consequence of these income gains, 2.50 million of people will be lifted above the $1.25 PPP poverty line in 2014 and 4.42 million in

2020. These figures hide important differences across research options, ecologies, research types, and sub-regions.

In terms research options, the impacts for research that alleviates major biophysical constrains are the most important. Thus, the main focus should be given to these areas of research. However, the significant share of research that addresses postharvest constraints in the total benefit suggests that there is a need to consider this area in the future research agenda. Also, research that raises yield potential needs to continue to be undertaken. In terms of research type, breeding is the most important, followed by agronomy and IPM. Postharvest research, even though coming in last position, has a significant share in the total benefit.

In terms of geographical area, the main rice-producing sub-region in SSA is West Africa, with the highest research benefit. Research efforts need to continue to be focused in this sub-region, mainly in country major countries like Nigeria, Guinea, Sierra Leone, and Côte d'Ivoire. East Africa will be the second major beneficiary sub-region, and Central Africa will come in third position.

In general, the rainfed ecosystems predominate on the continent. This understanding was reinforced by the priority-setting results that show that the rainfed lowland ecosystem will receive the greatest benefit, closely followed by the upland ecosystem. Irrigated systems, whose importance is increasing, will be third. The picture is slightly different across the sub-regions. Rainfed lowland and upland are the two major ecosystems in West Africa and of almost equal importance. In East Africa, the two major ecosystems are rainfed lowland and irrigated. In Central Africa, upland is the major ecosystem, followed by irrigated and rainfed lowland ecosystems in almost the same proportion.

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8 Appendix

Table A1: Stress grouping and correspondence between stress and varietal characteristics

Major research option	Sub-category	Varietal characteristics	Stress
Alleviate biotic stresses	Weeds Insects Birds Disease attack	Weed competitiveness Resistance to insect attack Resistance to birds attack Resistance to disease attack	Weeds Insects Birds Nematodes Termites African rice gall midge Stem borers Bacterial leaf blights Blast *Rice yellow mottle virus*
Alleviate soil-related constraints	Soil and nutrient	Good plant physiology	Zn deficiency Salinity / Alkalinity Deficiency / low use efficiency of N, P, K Iron (Fe) toxicity Acidity Soil erosion Siltation
Alleviate climate- and water-related constraints	Climate and water	Resistance to drought	Poor water management Drought Flooding Heat stress Cold stress Pre-harvest and harvest physical grain losses
Alleviate postharvest-related constraints	Post-harvest	Easy post-harvest	Threshing Winnowing Storage Transport Milling
Raise the genetic yield potential	–	Yield potential	–

Table A2: Village variety exposure and adoption rate

	Parameter	SE	z-stat
ATE	0.644	0.004	185.52***
ATE1	0.645	0.004	203.48***
ATE0	0.643	0.004	154.02***
JEA	0.399	0.002	203.48***
GAP	–0.246	0.001	–154.08***
PSB	0.001	0.001	7.3
Observed			
Ne/N	0.467	0.002	188.98***
Na/N	0.291	0.002	129.51***
Na/Ne	0.624	0.005	129.51***

ATE, average treatment effect; ATE1, average treatment effect of the treated; ATE0, average treatment effect of the untreated; JEA, joint exposure and adoption; GAP, adoption gap; PSB, population selection bias; Ne/N, (no. exposed)/(no. farmers); Na/N, (no. adopters)/(no. farmers); Na/Ne, (no. adopters)/(no. exposed); SE, standard error.

Table A3: Varietal characteristics frontier, demand, and relative demand

Characteristics	Frontier $\max_{j=1,\ldots,J}\{\theta_{jk}\}$	Demand $\frac{1}{J}\sum_{j=1}^{J}\theta_{js}\times d_j^{**}$	Relative demand $\frac{\bar{\theta}_s}{\widehat{\theta}_s}$
Weed competitiveness	0.78	0.70	0.91
Resistance to bird attack	0.71	0.64	0.92
Resistance to insect attack	0.76	0.69	0.92
Resistance to disease	0.78	0.71	0.92
Good plant physiology	0.70	0.62	0.90
Resistance to drought	0.73	0.66	0.91
Easy post-harvest	0.69	0.62	0.91
High yield potential	0.66	0.58	0.90

Table A4: Varietal characteristics demand elasticities

Varietal technology	Demand elasticities (adoption parameter)
Resistance to bird attack	0.66
Resistance to drought	0.61
Resistance to disease	0.60
Resistance to insect attack	0.63
Easy post-harvest	0.57
Plant physiology	0.58
Weed competitiveness	0.62
High yield potential	0.60

Table A5: Yield loss and area affected by major stresses

Stress	Actual yield loss 2009 (%)				Area affected in 2009 (%)
	Irrigated	Upland	Lowland	Lowland	
Weeds	23.1	27.1	25.8	22.3	40.6
Birds	27.6	29.7	23.2	24.6	34.5
Insects	17.7	24.2	18.9	18.1	30.1
Diseases	26.3	23.7	23.6	25.8	29.7
Soil and nutrient	21.7	27.1	30.1	28.2	43.5
Climate and water	36.2	35.8	31.9	30.0	48.8
Post-harvest	28.2	28.2	28.2	28.2	38.1

Table A6: Scientist survey results by research option and ecology

	Ecosystem	Yield loss reduction (t/ha)	Fixed cost (US$)	Annual cost (US$)	Year of delivery (from 2011)	Probability of success (%)
Alleviate biotic stresses	Irrigated	0.53	151,981	171,708	3.95	75
	Lowland	0.38	149,715	179,391	4.12	73
	Mangrove	0.27	53,483	80,225	3.66	69
	Upland	0.37	112,370	186,000	3.81	76
	All ecologies	0.39	120,889	157,313	3.88	73
Alleviate soil-related constraints	Irrigated	0.55	130,714	151,607	4.10	71
	Lowland	0.55	106,357	133,357	4.81	75
	Mangrove	0.31	37,273	55,273	4.77	72
	Upland	0.40	114,077	135,857	4.09	75
	All ecologies	0.46	100,231	122,632	4.43	73
Alleviate climate- and water-related constraints	Irrigated	0.61	157,867	203,200	4.77	73
	Lowland	0.47	113,912	120,735	4.45	73
	Mangrove	0.33	58,600	42,500	4.84	75
	Upland	0.48	162,143	196,643	4.37	72
	All ecologies	0.49	127,866	147,830	4.59	73
Alleviate postharvest-related constraints	Irrigated	0.33	45,333	88,667	3.43	77
	Lowland	0.41	28,625	62,250	3.61	78
	Mangrove	0.20	25,600	41,000	2.69	84
	Upland	0.39	32,875	60,000	3.55	78
	All ecologies	0.35	34,267	66,033	3.39	79
Raise the genetic yield potential	Irrigated	1.32	103,143	97,571	4.12	71
	Lowland	1.23	99,000	124,000	5.68	67
	Mangrove	0.00	0	0	0.00	0
	Upland	1.02	83,333	145,000	4.67	72
	All ecologies	1.20	155,000	120,722	4.74	70
All options	Irrigated	0.60	130,080	156,123	4.11	73
	Lowland	0.51	113,328	136,769	4.40	74
	Mangrove	0.28	47,425	61,793	4.06	72
	Upland	0.45	110,945	158,621	4.03	75
	All ecologies	0.48	105,556	134,063	4.15	74

Table A7: Scientist survey results by research option and research type

Research to	Type	Yield loss reduction (t/ha)	Fixed cost (US$)	Annual cost (US$)	Year of delivery (from 2011)	Probability of success (%)
Alleviate biotic stresses	Breeding	0.42	194,550	237,300	4.55	78
	Agronomy/IPM	0.38	65,367	97,244	2.93	63
	Post-harvest	0.25	21,000	23,500	3.75	96
	Other	0.35	46,100	98,400	4.58	81
	All types	0.39	120,889	157,313	3.88	73
Alleviate soil-related constraints	Breeding	0.45	90,929	96,857	5.96	74
	Agronomy/IPM	0.51	111,083	151,500	2.89	75
	Post-harvest	0.00	0	0	0.00	0
	Other	0.39	0	0	0.00	66
	All types	0.46	100,231	122,632	4.43	73
Alleviate climate- and water-related constraints	Breeding	0.52	212,875	177,083	5.11	68
	Agronomy/IPM	0.47	82,775	173,500	4.82	74
	Post-harvest	0.45	43,250	76,750	3.26	74
	Other	0.45	27,875	31,438	3.09	85
	All types	0.49	127,866	147,830	4.59	73
Alleviate postharvest-related constraints	Breeding	0.00	0	0	0.00	0
	Agronomy/IPM	0.00	0	0	0.00	0
	Post-harvest	0.40	42,150	82,050	2.84	79
	Other	0.24	18,500	34,000	4.48	78
	All types	0.35	34,267	66,033	3.39	79
Raise the genetic yield potential	Breeding	1.20	95,389	120,722	4.74	70
	Agronomy/IPM	0.00	0	0	0.00	0
	Post-harvest	0.00	0	0	0.00	0
	Other	0.00	0	0	0.00	0
	All types	1.20	95,389	120,722	4.74	70
All options	Breeding	0.58	155,945	169,336	5.06	74
	Agronomy/IPM	0.44	83,434	131,548	3.37	69
	Post-harvest	0.38	40,692	76,731	3.03	81
	Other	0.35	31,036	56,268	4.08	78
	All types	1.20	95,389	120,722	4.74	70

Table A8: Impact models parameters

	Type of research	Impact on income		Impact on poverty	
		Beta	Alpha	Beta	Alpha
Birds	Agronomy/IPM	–4.81	0.61	0.72	0.14
	Breeding	161.16	0.74	–4.23	0.85
	Other	–4.96	0.61	0.21	0.83
	Post-harvest	–2.01	0.42	0.07	0.77
Climate- and water-related constraints	Agronomy/IPM	–3.17	0.63	0.26	0.72
	Breeding	138.54	0.74	–4.13	0.85
	Other	–4.96	0.61	0.21	0.83
	Post-harvest	–2.01	0.42	0.07	0.77
Diseases	Agronomy/IPM	–4.62	0.63	0.20	0.73
	Breeding	143.63	0.73	–3.91	0.85
	Other	–4.96	0.61	0.21	0.83
	Post-harvest	–2.01	0.42	0.07	0.77
Insects	Agronomy/IPM	–1.03	0.61	0.07	0.73
	Breeding	134.80	0.73	–4.49	0.85
	Other	–4.96	0.61	0.21	0.83
	Post-harvest	–2.01	0.42	0.07	0.77
Postharvest-related constraints	Agronomy/IPM	–2.01	0.42	0.07	0.77
	Breeding	135.10	0.74	–4.51	0.85
	Other	–4.96	0.61	0.21	0.83
	Post-harvest	–2.01	0.42	0.07	0.77
Soil-related constraints	Agronomy/IPM	–1.47	0.61	0.14	0.77
	Breeding	132.48	0.73	–4.36	0.85
	Other	–4.96	0.61	0.21	0.83
	Post-harvest	–2.01	0.42	0.07	0.77
Weeds	Agronomy/IPM	–1.40	0.61	0.20	0.72
	Breeding	124.42	0.73	–4.03	0.85
	Other	–4.96	0.61	0.21	0.83
	Post-harvest	–2.01	0.42	0.07	0.77
Yield potential	Agronomy/IPM	0.00	0.00	0.00	0.00
	Breeding	73.81	0.73	–4.84	0.85
	Other	0.00	0.00	0.00	0.00
	Post-harvest	0.00	0.00	0.00	0.00

Table A9: Poverty-reduction research options

	First year (2014)	End year (2020)
Biotic stresses	2.50	3.55
Soil-related constraints	0.67	3.37
Climate- and water-related constraints	1.68	3.89
Postharvest-related constraints	0.31	1.44
Yield potential	0.83	4.42
All research options	*2.50*	*4.42*