UNIVERSITY OF HOHENHEIM

GERMANY

Department of Agricultural Economics and Social Sciences in the Tropics and Subtropics Rural Development Theory and Policy

Prof. Dr. Manfred Zeller

Impact evaluation of improved rice varieties and farmer training on food security and technical efficiency in The Gambia

Dissertation submitted in fulfilment of the requirements for the degree "Doktor der Agrarwissenschaften" (Dr.sc.agr. / Ph.D. in Agricultural Sciences) to the Faculty of Agricultural Sciences

Presented By

Lamin Dibba

Place of birth: Brimaka, The Gambia

December, 2015

This thesis was accepted as a doctoral dissertation in fulfilment of the requirements for the degree “Doktor der Agrarwissenschaften” by the Faculty of Agricultural Sciences at University of Hohenheim in August 2015.

Date of oral examination: 17 December 2015.

Examination Committee

Supervisor and Reviewer	Prof. Dr. M. Zeller
Co-Reviewer	Prof. Dr. S. Abele
Additional examiner	Prof. Dr. C. Lippert
Head of the Committee	Prof. Dr. T. Streck

Table of contents

List of tables v

List of figures vi

Acknowledgements vii

Executive summary ix

Zusammenfassung xiv

Chapter 1 1

1. Introduction 1
1.1 Background 1

1.2. NERICA and food security 3

1.3 Agricultural training and technical efficiency 5

1.4 Study objectives, research questions and hypotheses 6

1.4.1 Specific objectives 6

1.4.2 Research questions and hypotheses 7

1.5 Organization of dissertation 8

Chapter 2 11

2. Methodological framework 11
2.1 Research area, sampling and data collection 11

2.1.1 Research area 11

2.1.2 Sampling and data collection 12

2.2 Food security indicators 13

2.3 Estimating technical efficiency 15

2.4 Overview of impact evaluation methods 18

2.4.1 Impact evaluation problem and the potential outcome framework 18

2.4.2 Randomized impact evaluation 19

2.4.3 Impact evaluation using matching approach 21

2.4.4 Impact evaluation using instrumental variable approach 24

2.4.4.1 Two-Stage Least Square (2SLS) Approach 25

2.4.4.2 The LATE approach 26

2.4.5 Impact evaluation using double difference approach 27

2.4.6 Impact evaluation using regression discontinuity designs 29

2.4.7 Conclusions 30

Chapter 3 33

3. How accessibility to seeds affects the potential adoption of an improved rice variety: The Case of New Rice for Africa (NERICA) in The Gambia 33
3.1 Introduction 34
3.2 Conceptual framework 36
3.2.1 Technology awareness and access 36
3.2.2 Actual and potential adoption 37
3.2.3 Hypothesized determinants of adoption.. 37
3.3. Sampling procedure and data 39
3.4. Empirical framework... 40
3.4.1 Sample adoption rate.. 40
3.4.2 Potential outcome framework and evaluation problem 41
3.4.3 Population adoption gaps and selection bias 43
3.4.4 ATE estimation of the population adoption rate and its underlying assumptions 45
3.4.4.1 Assumptions of ATE estimation 45
3.4.4.2 Parametric estimation of ATE 46
3.5. Results and discussions 47
3.5.1 Socio-demographic characteristics of farmers.. 47
3.5.2 Actual and potential adoption rates.. 49
3.5.3 Determinants of access, exposure, and adoption of NERICA 51
3.6 Conclusions 56
Chapter 4 63
4. Impact of NERICA adoption on household food security and health in The Gambia 63
4.1 Introduction 64
4.2 Sampling procedure and data 66
4.2.1 Food security and health outcome indicators.. 67
4.2.1.1 Calculation and analysis of the Food Consumption Score 67
4.2.1.2 Calculation and analysis of sick days per capita................................ 69
4.3. Theoretical framework 70
4.3.1 The problem with impact evaluation 70
4.3.2 Identifying causal effects 71
4.3.3 The Instrumental Variable approach... 73
4.3.4 Estimators and estimates 74
4.4. Results and discussion 76

4.4.1 Descriptive analysis 76
4.4.1.1 Socio-demographic characteristics of households 76
4.4.1.2 Identifying impact based on observed differences 78
4.4.2 Econometric analysis 80
4.4.2.1 Impact of NERICA adoption on household food security and its determinants 80
4.4.2.2 Impact of NERICA adoption on household health status and its determinants 84
4.5 Conclusions 88
Chapter 5 94
5. Impact of agricultural training on technical efficiency of smallholder rice farmers in The Gambia 94
5.1. Introduction 95
5.2. Agricultural rice-farmer training programs in The Gambia 97
5.3. Sampling and data 98
5.4. Empirical framework 99
5.4.1 Estimating technical efficiency 99
5.4.2 Estimating the impact of agricultural training 103
5.4.2.1 A balancing test for matched covariates 106
5.4.2.2 Sensitivity analysis to test the Conditional Independence Assumption 106
5.5. Results and discussions 107
5.5.1 Socio-demographic characteristics of households 107
5.2 Determinants of technical efficiency 108
5.5.3 Descriptive analysis of the impact of agricultural training on technical efficiency 112
5.5.4 Propensity score matching 113
5.5.4.1 Estimating the propensity score 113
5.5.4.2 Choosing a matching algorithm 115
5.5.4.3 Balancing test 116
5.5.4.4 Sensitivity analysis 117
5.6. Conclusions 124
Chapter 6 131
6. Summary, conclusions and policy implications 131
6.1 Summary of main findings and interpretations 131
6.2 Research gaps and future work 133

6.3 Conclusions and policy implications 134

List of tables

Table 2.1: Compliance type by treatment and instrument 27
Table 3.1: Comparing 2006 and 2010 survey results on NERICA adoption and farming in The Gambia 48
Table 3.2: Actual adoption of NERICA 49
Table 3.3: ATE parametric estimation of potential adoption rate 50
Table 3.4: Definition and summary statistics of the explanatory variables used in the probit model 53
Table 3.5: Probit model marginal effects of the factors affecting exposure, access to seeds, and adoption 54
Table 4.1: Weights given to food groups with their justification 68
Table 4.2: Descriptive statistics of households by adoption status 77
Table 4.3: Identifying impacts using mean differences in outcome by adoption status 80
Table 4.4: Impact of NERICA adoption on food security 82
Table 4.5: Exponential LARF coefficient estimates for determinants of food security with and without interaction 83
Table 4.6: Impact of NERICA adoption on household health 86
Table 4.7: Exponential LARF coefficient estimates for the determinants of health with and without interaction 87
Table 5.1: Descriptive statistics of the variables in the DEA model 102
Table 5.2: Socio-demographic characteristics of households by agricultural training status 108
Table 5.3: Tobit marginal effects of factors influencing technical efficiency 111
Table 5.4: Descriptive analysis of the impact of agricultural training on technical efficiency 113
Table 5.5: Probit regression of determinants of participation in agricultural training programs 114
Table 5.6: PSM quality indicators before and after matching 116
Table 5.7: Sensitivity analysis for selected algorithms 117
Table 5.8: PSM estimates of the impact of agricultural training on technical efficiency 118
Table 5.9: Social cost-benefit analysis 119
Table 5.10: Private cost-benefit analysis 120
Table 5.11: Investment analysis of agricultural training with a 13.9% discount rate . 122
Table 5.12: Sensitivity analysis with a 100% increase in expected cost 123

List of figures

Figure 2.1: Map of The Gambia and its agricultural regions..12
Figure 4.1: Household food security by adoption status..79
Figure 5.1: Propensity score distribution and common support 115

Acknowledgements

I would like to express my sincere gratitude to the Africa Rice Center (AfricaRice) for awarding me the 2011 Global Rice Science Scholarship (GRISS) to pursue my doctoral program at the University of Hohenheim, Stuttgart, Germany and for proving all the necessary funding on a timely manner to ensure I successfully complete my program against all odds. I am also very grateful to AfricaRice for the field supervision and technical support rendered for the successful completion of this research work. The conducive environment and technical support rendered by the University of Hohenheim is also highly appreciated and acknowledged. I am also very grateful to the Food Security Center of University of Hohenheim for giving me the opportunity to participate in their programs and activities.

I am sincerely grateful to my academic supervisor Prof. Dr. Manfred Zeller for his helpful comments and suggestions, which helped to improve the quality of this research work significantly. The guidance and advice he provided during the implementation of this study has immensely increased my confidence to do meaningful research. I am thankful to Prof. Dr. Steffen Abele and Prof. Dr. Christian Lippert for accepting to examine this dissertation. I am highly indebted to my first field supervisor Dr. Aliou Diagne for having introduced me to impact evaluation methodologies in 2005 and guided me all the way through my MSc and PhD programs. I am extremely grateful for the confidence he has in me. I cannot think of a greater compliment to pay him than he is more a mentor than supervisor. I am also very grateful to my second field supervisor Dr. Aminou Arouna for facilitating my field visit to AfricaRice and for providing all technical and logistical support to ensure that I successfully complete my program.

I am grateful to Dr. Khalid Siddig, Dr. Tim Loos, Dr. Ling Yee Khor and Dr. Alexander Nimo Wiredu for always willing to share their ideas and experience with me. I am also thankful to Katharina Mayer and Coni Schumacher for always providing administrative support. The time taken by Katharina Mayer to translate the executive summary of this doctoral thesis into German is also highly acknowledged. The active role played by Dr. Brigitte Kranz in making sure I participate in all programs and activities of the Food Security Center of the University of Hohenheim is also highly acknowledged. My special gratitude goes to Dr. Thea Nielsen for serving as co-author for the first paper of this dissertation for which she provided very useful comments and suggestions. The time she spared to language edit this dissertation is also highly acknowledged.

I would also like to express my sincere gratitude to all the rice farmers who provided data for this research and all the research technicians who actively collected and entered all the data used for the analysis of this dissertation. The important role played by the late Dr. Babou Jobe, Dr. Mustapha Ceesay, Mr. Lamin Jobe, and Mr. Ansumana Jurju to ensure that the pursuit of this doctoral program becomes a reality is also highly acknowledged.

Finally, I would like to take this opportunity to express my profound gratitude to my beloved parents, Makieu Lamin and Sambou Dibba, and to all my siblings for their continuous love, support and prayers. My special gratitude goes to my beloved wife, Maimuna Keita, for her patience, love, encouragement and prayers. I am also very grateful to my three year old son, Muhammed Dibba, for his love and patience. I am always moved when I hear his sweet voice on the telephone asking me to come back home because he misses me dearly. The birth of my baby girl, Fatima Dibba, has also given me much joy and encouragement to complete my doctoral program on time in order to unite with my family.

Executive summary

This dissertation aims to evaluate the impact of improved rice varieties and farmer training programs that have been introduced to boost local rice production in The Gambia. Rice is the main staple crop of The Gambia. The per capita consumption level of rice is estimated at 117 kg per annum, which is one of the highest in sub-Saharan Africa. The annual consumption of rice is estimated at 195, 811 metric tons, out of which only 51,137 metric tons are produced nationally. This huge deficit is met through imports, at an estimated cost of about US$ 50 million annually. As a result, the government is committed to attaining rice self-sufficiency. To achieve this objective, currents efforts have concentrated on the introduction of yield increasing improved rice varieties and farmer training programs. To evaluate how such improved rice varieties and farmer training programs are contributing towards the achievement of rice self-sufficiency in The Gambia is the main focus of this dissertation.

To evaluate the impact of improved rice varieties and farmer training programs, this study has obtained a country-wide data from rice growing communities and households that were selected through a multi-stage stratified random sampling procedure. Data were obtained during 2006 and 2010 rice cropping seasons. The data collected were used to address three research topics: (1) How accessibility to seeds affects the potential adoption of an improved rice variety: The case of The New Rice for Africa (NERICA) in The Gambia, (2) The impact of New Rice for Africa (NERICA) adoption on household food security and health in The Gambia, and (3) The impact of agricultural training on technical efficiency of smallholder rice producers in The Gambia. These research topics are the main pillars of this dissertation.

The aim of the first research topic was to assess the population adoption rate of NERICA and its determinants. The NERICA is a high yielding rice variety that was officially introduced in The Gambia in 2003. The introduction of NERICA was an attempt taken by the government to increase rice production and productivity in the country. This study focuses on two main constraints that limit the adoption of NERICA: awareness and access to its seeds. We used the treatment evaluation technique to address these constraints and estimate the true population adoption rate of NERICA in The Gambia. The results of our analysis show that the NERICA

population adoption rate could have been 76% instead of the observed 66% sample estimate in 2010 provided that every rice farmer had been aware of NERICA's existence before the 2010 rice growing season. However, further investigation finds that if all the rice farmers had been aware of and had access to NERICA seeds, adoption would have been 92%. The results further show that if awareness had not been a constraint, 16% of farmers would have failed to adopt NERICA due to lack of access to NERICA seeds.

We found farmer contact with extension services and access to in-kind credit as significant determinants of access to and adoption of NERICA varieties. The policy implication of these findings is to increase farmer contact with extension and facilitate access to in-kind credit services like improved seeds to all the rice farming communities. This is likely to increase awareness and access to NERICA seeds, which can help to significantly close the population adoption gap of NERICA in The Gambia. Moreover, when efforts are made to make the entire rice farming population aware of the existence of NERICA varieties and also make the seeds of NERICA accessible to all rice farmers, then it will not be meaningful for future research to attempt to further estimate population adoption rate of NERICA in The Gambia. Under such circumstance, a more meaningful estimate of adoption is given by assessing the intensity of technology use among adopters. For the case of NERICA varieties, it will be more interesting to know the share of total rice area famers are allocating to NERICA varieties. This will give a better picture regarding the desirability of the NERICA technology by the target rice farming population.

The second research topic attempts to identify improvements in household food security and health outcome indicators that can be attributed to NERICA adoption. We used food consumption scores (FCS) and sick days per capita among farm households' members as outcome indicators of food security and health, respectively. Since NERICA adoption is a decision made by rice farmers, we assume that this selection decision is partly based on unobservable factors, for example, farmers' attitude towards work. Therefore, we used the instrumental variable approach to identify causal effects of NERICA adoption on food security and health. The results of our analysis show significant differences in some key socio-economic and demographic characteristics between NERICA adopters and non-adopters. These includes practice of upland rice farming, non-agricultural income, contact with extension and access to credit. Such variables can mask the impact of NERICA adoption if they are not balanced between treatment and control groups. For instance, if one group has higher non-agricultural income, differences in food security and health outcome indicators between the two groups may be due to that difference and not necessarily to NERICA adoption. To control for such differences and allow a causal interpretation of the impact of NERICA adoption, we estimate the Local Average Treatment Effect (LATE). Our findings indicate that NERICA adoption significantly increases household food consumption by 14 percent. This helps severely food insure households to achieve acceptable food security status by enabling them to acquire cereals, tubers, vegetables, and fruits on daily basis. We also found that the impact of NERICA adoption on food security, among NERICA adopting households, is greater for households that have access to in-kind credit services. Our findings also indicate that NERICA adoption impact at household level is only significant for households headed by men. This may be due to the fact that NERICA is upland rice and resources for upland rice production are mainly owned and controlled by men in The Gambia. However, we found no significant impact of NERICA adoption on health.

The finding that the impact of NERICA adoption on food security is greater for households that have access to in-kind credit services, like improved rice seeds, necessitate policy makers to take efforts to redistribute NERICA seeds from high production areas to rice farming communities with low accessibility. However, the finding that the impact of NERICA adoption on food security is greater for households headed by men does not necessarily indicate that NERICA adoption does not have any significant impact on food security for women at the individual level. The data we used to assess the impact of NERICA adoption on food security were collected at the household level so we are unable to assess individual food security status. As a result, we recommend that future studies that intend to assess the impact of NERICA adoption on household food security should collect data at the individual level to enable better gender based comparison of food security outcomes between men and women. Moreover, there is some evidence that NERICA varieties have higher protein content and more well-balanced amino acids compared to traditional and imported rice varieties. This may result in better health outcomes for NERICA adopting households. However, the results of our analysis have shown no significant impact of NERICA adoption on health. This could be attributed to the fact that we used information on all household members to create number of sick days per capita. Given the limited scope of the survey data regarding health, more precise indicators of health, such as detailed individual recall data on specific diseases, anthropometric data, or other health indicators were not available. Number of sick days per capita is a highly noisy indicator which tend to be negatively correlated with household size. When one individual respondent reports on the health status of all households members, it can lead to under estimation if the household is large. For this reason, we recommend that future studies that intend to identify the impact of NERICA adoption on health should focus on individual recall data, which may be a better outcome indicator.

Finally, the third research topic aims to identify improvements in technical efficiency of smallholder rice farmers that can be attributed to agricultural rice farmer training programs introduced in The Gambia to increase rice production and productivity. Technical efficiency is a measure of how the use of best rice farming practices affects the total yield of rice farmers. Technical efficiency is achieved when it is not possible to increase output without increasing inputs. Due to technical inefficiencies, there is a huge gap between actual and potential yields of rice farmers in sub-Saharan Africa. For instance, the rice yield of upland farmers, in sub-Saharan Africa, is estimated at 1 t/ha whereas the yields at research stations ranges between 2.5 to 5 t/ha. This yield gap is mainly attributed to inappropriate farming practices and lack of farmers' access to modern inputs that influence efficiency in farmers' fields. As a result, this study assesses how the introduction of best agricultural rice farming practices, through agricultural training programs, affects the technical efficiency of smallholder farmers in The Gambia. In the first stage, we use Data Envelopment Analysis (DEA) technique to estimate technical efficiency scores for each sampled household and used Tobit regression to identify factors influencing technical efficiency. In the second stage, we employ propensity score matching to assess program impact on participants using technical efficiency scores as our outcome indicator. The results of the analysis indicate that agricultural training significantly increases technical efficiency of smallholder rice farmers by 10 percent. This translates to rice yield increase of 260 kg/ha, which results in net social and private benefits per annum of US$ 43700 for

900 rice farming households and 30 extension agents, and US$ 53 per household, respectively. Our analysis of investment on agricultural training yields a Net Present Value (NPV) of US$ 195816, a Benefit Cost Ratio (BCR) of 5.3 and an Internal Rate of Return (IRR) of 99%. These results justify increased investment on agricultural training programs to boost rice production and productivity. Further analysis to identify determinants of technical efficiency show farmer’s contact with extension workers and a farmer’s association membership as significant factors influencing technical efficiency.

The significance of farmer’s contact with extension and association membership in determining technical efficiency indicates that extension contact and association membership could be important impact pathways to improve technical efficiency among smallholder farmers. The policy implication of these findings is to encourage rice farmers, through agricultural extension services, to be members of rice farmers associations and motivate them to meet regularly to exchange ideas and information about new developments within and outside their rice farming communities. Moreover, we define agricultural training as participation in at least one rice farmer training program. Since some training programs are likely to be more effective than others, defining participation as receipt of at least one training on rice cultivation practices is likely to underestimate the impact of highly effective training programs. Consequently, we recommend that future studies that intend to assess the impact of agricultural training on technical efficiency should identify specific training programs and assess their impact on technical efficiency separately.

Zusammenfassung

Die vorliegende Arbeit hat zum Ziel, den Einfluss von verbesserten Technologien und Programmen, die im Rahmen des Reisanbaus in Gambia eingeführt wurden um die lokale Reisproduktion zu steigern, zu evaluieren. Reis ist Hauptnahrungsmittel in Gambia. Der Reiskonsum pro Kopf wird auf 117kg pro Jahr geschätzt, und ist damit einer der höchsten in Subsahara-Afrika. Der landesweite jährliche Reiskonsum wird auf 195.811 Tonnen geschätzt, wovon 51.137 Tonnen im Inland produziert werden. Das gewaltige Defizit wird durch Importe zu geschätzten Kosten von jährlich 50 Millionen US$ ausgeglichen. Die Regierung ist daher bestrebt, im Bezug auf Reisproduktion wirtschaftliche Unabhängigkeit zu erlangen. Um dieses Ziel zu erreichen, haben sich die aktuellen Bemühungen darauf konzentriert, ertragssteigernde landwirtschaftliche Technologien und Programme einzuführen. Schwerpunkt der vorliegenden Arbeit ist es, auszuwerten, wie solche Technologien und Programme dazu beitragen, wirtschaftliche Unabhängigkeit in der Reisproduktion in Gambia zu erreichen.

Um die Auswirkungen der Technologien und Programme in der Reisproduktion zu evaluieren, liegt der Studie ein landesweiter Datensatz von reisproduzierenden Gemeinschaften und Haushalten vor, die über ein mehrstufiges Stichprobenverfahren ausgewählt wurden. Die Daten wurden in den Erntejahren 2006-2010 gesammelt, und wurden verwendet um drei verschiedene Forschungsfragen aufzustellen: (1) Wie beeinflusst der Zugang zu Saatgut die potentielle Einführung einer verbesserten Reisvariante? Der Fall „New Rice for Africa“ (NERICA) in Gambia, (2) Die Auswirkungen der Einführung von „New Rice for Africa“ (NERICA) auf Ernährungssicherheit und Gesundheit in gambischen Haushalten, und (3) Die Auswirkungen landwirtschaftlicher Weiterbildungen kleinbäuerlicher Reisproduzenten zu technischer Effizienz in Gambia. Diese drei Forschungsfragen stellen die drei Hauptsäulen der vorliegenden Dissertation dar.

Ziel der ersten Forschungsfrage war, den Bevölkerungsanteil festzustellen, der NERICA Saatgut einsetzt, sowie die Faktoren die zu dessen Einsatz beitragen. NERICA ist eine ertragreiche Reissorte, welche offiziell im Jahr 2003 in Gambia eingeführt wurde. Die Einführung von NERICA war ein Versuch der Regierung, die

Reisproduktion und die Produktivität des Landes zu erhöhen. Die vorliegende Studie konzentriert sich auf zwei primäre Einschränkungen welche den Einsatz von NERICA Saatgut limitieren: Das Wissen der Produzenten über das Vorhandensein von NERICA Saatgut, sowie den Zugang dazu. Um diese Einschränkungen anzugehen, und die unverzerrte Anwendung von NERICA Saatgut durch die gambische Bevölkerung abzuschätzen, wurde eine Wirkungsanalyse durchgeführt. Die Ergebnisse der Analyse zeigen, dass die Anwendungsquote statt der in der Stichprobe vom Jahr 2010 tatsächlich beobachteten Quote von 66% bei 76% hätte liegen können, wenn sichergestellt gewesen wäre, dass jeder Reisproduzent vor der Anbausaison 2010 von der Existenz des NERICA Saatguts gewusst hätte.

Weitere Untersuchungen zeigen, dass der Einsatz von NERICA Saatgut bei 92% hätte liegen können, wenn neben dem Wissen um die Existenz des Saatguts auch der Zugang auf das Saatgut sichergestellt gewesen wäre. Weiterhin zeigen die Ergebnisse, dass, wenn das Wissen um die Existenz des Saatguts keine Einschränkung gewesen wäre, 16% der Reisproduzenten NERICA nicht hätten einsetzen können, weil sie keinen Zugang zu NERICA Saatgut gehabt hätten.

Der Kontakt der Reisproduzenten zu landwirtschaftlichen Beratungsdiensten und ein erleichterter Zugang zu nichtmonetären Krediten wurden als bedeutende Faktoren für den Zugang zu und den Einsatz von NERICA Saatgutsorten herausgestellt. Die Politikempfehlung zu den Ergebnissen lautet, den Kontakt der Reisproduzenten zu landwirtschaftlichen Beratungen zu verbessern, und den Zugang zu nichtmonetären Krediten, wie z.B. verbessertem Saatgut, für alle Reisproduzenten zu erleichtern. Dies würde höchstwahrscheinlich das Wissen um die Existenz von NERICA Saatgut und den Zugang dazu verbessern, was wiederum dazu beitragen würde, die Anwendungslücke bei NERICA Saatgut in der gambischen Bevölkerung beträchtlich zu verkleinern. Wenn es Bemühungen dahingehend gibt, die alle Reisproduzenten über das Vorhandensein von NERICA Saatgutsorten in Kenntnis zu setzen, und überdies das Saatgut für alle zugänglich gemacht wird, wird es außerdem für künftige Forschungsvorhaben nicht mehr bedeutsam sein, weiterhin die Anwendungsquote von NERICA Saatgut in der gambischen Reisproduzentenschaft zu erheben. Unter solchen Umständen wäre es sinnvoller, den Einsatz von NERICA zu bewerten, indem die Intensität in der Technologienutzung unter den Anwendern erhoben wird. Letzteres würde ein detaillierteres Bild bezüglich der Attraktivität der NERICA Technologie für die Zielgruppe der Reisproduzentenschaft ergeben.

Die zweite Forschungsfrage zielt darauf ab, Verbesserungen hinsichtlich der Ernährungssicherheit in den Haushalten, sowie Ergebnisindikatoren zu gesundheitlichen Auswirkungen zu identifizieren, die der Anwendung von NERICA Saatgut zugeschrieben werden können. Hierfür wurden Food Consumption Scores (FCS) und Krankheitstage pro Kopf der reisproduzierenden Haushaltsmitglieder als Ergebnisindikatoren für Ernährungssicherheit und Gesundheit herangezogen.

Da die Entscheidung zum Einsatz von NERICA Saatgut von den Reisproduzenten getroffen wird, wird angenommen, dass diese Auswahlentscheidung teilweise auf nicht beobachtbaren Faktoren basiert, wie beispielsweise die Einstellung der Reisproduzenten zu ihrer Arbeit. Daher wurde eine Instrumentvariable angewendet, um kausale Effekte des Einsatzes von NERICA Saatgut auf Ernährungssicherheit und Gesundheit zu ermitteln. Die Ergebnisse dieser Analyse zeigen signifikante Unterschiede bei einigen sozioökonomischen und demografischen Schlüsselmerkmalen zwischen NERICA Anwendern und Nicht-Anwendern. Diese beinhalten die Erfahrung beim Reisanbau in Hochlagen, das außerlandwirtschaftliche Einkommen, den Kontakt zu landwirtschaftlichen Beratungen und Zugang zu Krediten. Solche Variablen können die Auswirkungen des Einsatzes von NERICA Saatgut verzerren, wenn sie nicht in ausgeglichenem Umfang bei den Behandlungs- und Kontrollgruppen vorkommen. Wenn eine Gruppe beispielsweise ein höheres außerlandwirtschaftliches Einkommen hat, könnten Unterschiede innerhalb der beiden Gruppen in Ernährungssicherheit und Gesundheitsversorgung ursächlich von dieser Variablen stammen und sind nicht notwendigerweise dem Einsatz von NERICA Saatgut zuzuschreiben. Um solche Differenzen zu regulieren, und eine kausale Interpretation der Auswirkungen des Einsatzes von NERICA Saatgut zu ermöglichen, wird der Local Average Treatment Effect (LATE) kalkuliert. Die Ergebnisse deuten darauf hin, dass der Einsatz von NERICA Saatgut den Lebensmittelkonsum innerhalb eines Haushalts signifikant um durchschnittlich 14% steigert. Weiterhin wurde festgestellt, dass die positiven Auswirkungen des Einsatzes von NERICA Saatgut auf die Ernährungssicherheit unter allen Haushalten die NERICA Saatgut einsetzen, für solche Haushalte größer sind, die Zugang zu nicht-monetären Krediten haben. Unsere

Ergebnisse weisen auch darauf hin, dass die positiven Auswirkungen des Einsatzes von NERICA Saatgut auf Haushaltsebene nur für diejenigen Haushalte signifikant ist, die von Männern geführt werden. Dies mag darauf zurückzuführen sein, dass NERICA eine Bergreissorte ist, und die Flächen für Reisanbau in den Hochlagen Gambias hauptsächlich im Eigentum von Männern sind bzw. von Männern bearbeitet werden. Es wurden weiterhin keine signifikanten Auswirkungen des Einsatzes von NERICA auf die Gesundheit festgestellt.

Die Tatsache, dass die positiven Auswirkungen des Einsatzes von NERICA Saatgut auf die Ernährungssicherheit für Haushalte mit Zugang zu Naturalkrediten wie beispielsweise in Form von verbessertem Saatgut, größer sind, macht es für die Politik erforderlich, die notwendigen Bemühungen zu unternehmen, um NERICA Saatgut von Gebieten mit hoher Produktionsleistung zu reisproduzierenden Dörfern mit niedrigem Zugang auf nicht-monetäre Kredite umzuverteilen. Dass die Auswirkungen des Einsatzes von NERICA Saatgut auf Ernährungssicherheit bei Haushalten mit männlichem Haushaltsvorstand größer sind, weist nicht notwendigerweise darauf hin dass der Einsatz von NERICA Saatgut keine signifikanten Auswirkungen auf die Ernährungssicherheit von Frauen auf individueller Ebene hat. Die verwendeten Daten wurden auf Haushaltsebene gesammelt, so dass es nicht möglich war, die Ernährungssicherheit bei einzelnen Personen zu erfassen. Daher empfehlen wir, dass sich künftige Studien, welche die Auswirkungen des Einsatzes von NERICA auf die Ernährungssicherheit erfassen wollen, Daten auf individueller Ebene sammeln sollten, um einen geschlechtsspezifischen Vergleich zur Ernährungssicherheit bei Männern und Frauen zu ermöglichen.Weiterhin gibt es Behauptungen, dass NERICA Saatgutsorten im Vergleich zu traditionellen und importierten Reisvarianten einen höheren Proteingehalt und eine ausgeglichenere Komposition von Aminosäuren hätten. Dies könnte bei Haushalten die NERICA einsetzen zu positiven Auswirkungen im Gesundheitsbereich führen. Allerdings haben die Ergebnisse unserer Studie keine signifikanten Auswirkungen des Einsatzes von NERICA auf die Gesundheit ergeben. Letzteres könnte der Tatsache geschuldet sein, dass die Informationen aller Haushaltsmitglieder verwendet wurden um die Krankheitstage pro Kopf zu ermitteln. Derzeit gibt es in Gambia einen kostenlosen Gesundheitsdienst für die meisten Kurzzeit-Erkrankungen bei Kindern, woraus sich die insignifikanten Ergebnisse der vorliegenden Studie ergeben haben könnten. Daher empfehlen wir, dass künftige

Studien die sich mit den Auswirkungen des NERICA Einsatzes auf die Gesundheit befassen, sich auf erwachsene, arbeitsfähige Haushaltsmitglieder konzentrieren sollten, da diese ein besserer Ergebisindikator sein könnten.

Die dritte Forschungsfrage zielt schließlich darauf ab, Verbesserungen in der technischen Effizienz bei Kleinbauern im Reisanbau zu ermitteln, die den landwirtschaftlichen Weiterbildungsprogrammen für Reisproduzenten zuzuschreiben sind, welche in Gambia eingeführt wurden um die Reisproduktion und Produktivität zu steigern. In der vorliegenden Studie wird gemessen, wie die Anwendung der besten Reisanbaumethoden den Gesamtertrag der Reisproduzenten erhöht. Aufgrund technischer Ineffizienzen klafft eine große Lücke zwischen dem tatsächlichen und dem potentiell möglichen Ertrag der Reisproduzenten in Subsahara Afrika. Der Reisertrag der Produzenten im Hochland liegt etwa bei einer Tonne pro Hektar, während die Erträge an Forschungsstandpunkten 2,5 bis 5 Tonnen pro Hektar betragen. Diese Ertragslücke wird hauptsächlich unangemessenen Anbaumethoden zugeschrieben, die auf den Reisfeldern weit verbreitet sind. Infolgedessen soll die vorliegende Studie erfassen, wie eine Einführung der besten Reisanbaumethoden durch landwirtschaftliche Weiterbildungsprogramme die technische Effizienz der gambischen Kleinbauern beeinflusst.

Der kausale Wirkungszusammenhang der landwirtschaftlichen Weiterbildung mit technischer Effizienz wird in zwei Phasen bemessen. In der ersten Phase wird die Data Envelopment Analysis (DEA) verwendet, um technische Effizienz-Werte für jeden befragten Haushalt zu ermitteln, sowie eine Tobit-Regressionsanalyse durchgeführt, um die Faktoren zu ermitteln, die einen Einfluss auf die technische Effizienz haben. In der zweiten Phase wird die Propensity Score Matching Methode angewendet, um die Auswirkungen von Weiterbildungsprogrammen auf deren Teilnehmer zu erfassen, wobei technische Effizienz-Werte als Ergebnisindikator dienen. Die Ergebnisse der Analyse zeigen, dass landwirtschaftliche Weiterbildungen die Fähigkeit der reisproduzierenden Kleinbauern, die besten Anbaumethoden anzuwenden, signifikant um 10% erhöhen. Auf Haushaltsebene bedeutet dies eine Ertragssteigerung von 260kg/ha; anders ausgedrückt ist das ein Nettogewinn auf sozialer und privater Ebene von 43.700 US$ für 900 reisproduzierende Haushalte und 30 Berater, bzw. 53 US$ pro Haushalt. Eine Analyse der Investitionen die in landwirtschaftliche Beratung getätigt werden ergibt einen Kapitalwert (NPV) von 195.815,8 US$, ein Kosten-Nutzen-Verhältnis von 5,3 und einen internen Zinssatz (IRR) von 99%. Diese Ergebnisse rechtfertigen höhere Investitionen in landwirtschaftliche Weiterbildungsprogramme um die Reisproduktion und Produktivität zu erhöhen. Weitere Untersuchungen zur Identifikation von Schlüsselfaktoren technischer Effizienz zeigen, dass der Kontakt der Reisproduzenten zu Beratern, sowie Mitgliedschaften in Landwirtschaftsverbänden die technische Effizienz signifikant beeinflussen.

Die politischen Implikationen zu den Ergebnissen wären, dass Reisproduzenten durch landwirtschaftliche Beratungsstellen ermutigt werden sollten, sich zu Verbänden zusammenzuschließen, und motiviert werden sollten sich regelmäßig zu treffen um Ideen und Informationen zu neuen Entwicklungen innerhalb und außerhalb ihrer Dorfgemeinden auszutauschen. Überdies wird landwirtschaftliche Weiterbildung definiert als Teilnahme an wenigstens einem Weiterbildungsprogramm für Reisproduzenten. Da einige Weiterbildungsprogramme wahrscheinlich effektiver sind als andere, ist es wahrscheinlich, dass durch diese Definition die Auswirkungen von hocheffektiven Weiterbildungsprogrammen unterschätzt wird. Folglich wird empfohlen, dass künftige Studien, welche die Auswirkungen landwirtschaftlicher Weiterbildungen auf technische Effizienz erheben wollen, konkrete Weiterbildungsprogramme ausmachen und deren Auswirkungen auf die technische Effizienz separat bewerten sollen.

Chapter 1

1. Introduction

1.1 Background

Rice is increasing becoming a major staple and a source of livelihood for many people in the world. It is classified as the second largest consumed cereal (after wheat) feeding nearly 50 percent of the world's population who depend on it for about 80 percent of their dietary requirement (von Braun 2006). The total area under rice cultivation was estimated in 2000 to be 150 million hectares, with an annual average production of 500 million metric tons. However, due to the increased dependence of the world population on rice, it was estimated in 2001 that its production needs to increase from 586 million metric tons to 756 million metric tons by 2030 to meet the global projected demand (FAO 2002). Rice production is the main activity and source of income for more than 100 million households living in developing countries of Africa, Asia and Latin America (FAO 2005).

In Africa, the demand for rice has far outpaced the production level. As a result, the continent meets substantial amount of local demand through rice imports. In 2009, rice imports in Africa accounted for one-third of the total stock at the international market, costing the continent US$ 5 billion (Wopereis, 2011). Africa's emergence as one of the most prominent players in the international markets is due to the fact that rice has become the most rapidly growing source of food in many countries in sub-Saharan Africa (Solh, 2005). The demand for rice is growing faster in sub-Saharan Africa than any part of the world (WARDA, 2006). The sub-Saharan Africa region with the highest consumption of rice is West Africa. The annual growth in demand for rice in West Africa is estimated at 8%, which surpasses the domestic production growth rate of 6% per annum. As a result, the region spends over US$ 1.4 billion on rice imports annually to bridge the gap between demand and domestic supply of rice (Somado and Guei, 2008). The countries with the highest per capita consumption of rice in West Africa are: Sierra Leone, Guinea, Senegal and The Gambia.

Rice is by far the most important food crop in The Gambia. It is the main source of livelihood for the majority of women rice farmers and provides substantial amount of income for most rural households. The consumption level of rice in The Gambia is estimated to be 117kg per capita per annum, which is far beyond the world average of 56.6 kg. Of the 195, 811 metric tons of rice consumed in 2011, only 51,137 metric tons was produced nationally (PSU, 2011). The huge gap is filled through importation from Asian countries like India, Pakistan and Thailand. In 2000, about US$ 10.9 million was used to import 93,900 metric tons of rice. This increased to US$28.97 million in 2009, which was used to import 126, 625 metric tons of rice (PUS, 2011). In 2011, rice imports were valued at a cost of US$50 million. The high importation of rice is partly attributed to low production and productivity of the prevailing lowland and upland rainfed agricultural systems in the country (Malton et al., 1996).

In an attempt to combat the problem of low rice production in the country, efforts have been concentrated on the introduction of improved rice varieties and farmer training programs. An example of such improved rice varieties is the New Rice Varieties for Africa (NERICA). The NERICA was a result of crosses between the Asian rice (*O. stiva*) and the African rice (*O. glaberrima*). It combines good traits of both parents, which makes it highly suitable for the farming systems in Africa. The NERICA introduced to farmers in The Gambia is an upland rice variety. With the official introduction of NERICA in 2003, land area under upland rice cultivation increase from 10,000 hectares in 2006 to 47,500 hectares in 2011, which increase further to 50,000 hectares in 2013 (Gambia 2013). To substantiate efforts, farmer training programs have also been introduced to build capacity of rice farmers. The most prominent among such programs have been introduced through rice sector development projects such as: Participatory Adaptation and Diffusion of Technologies for Rice-Based Systems (PADS), Canadian International Development Agency (CIDA) funded project, Farmer Managed Rice Irrigation Project (FMRIP). The aim of such programs is to give researchers, extension agents and rice farmers the knowledge and skills required to better manage the cultivation of the rice crop in order to significantly increase rice production and productivity in the country.

Agriculture is the backbone of The Gambian economy. It provides employment for about 75% of the labour force and account for about two-third of agricultural household income (Fatajo, 2010). Hence, agricultural growth to feed the growing population is fundamental in achieving economic growth in The Gambia (Datt and Ravallion, 1996). Enormous efforts have been made to expand the land area under rice production in The Gambia. However, research has shown that expansion of production area alone is not sufficient to achieve food security in the developing world. As a result, agricultural growth need to be dependent more and more on yield-increasing agricultural technologies and programs (Hossain, 1989). In the same vein, the World Bank (2008) notes that the high yielding improved rice varieties such as those that helped to bring a green revolution in Asia could significantly assist in augmenting rice production and productivity in Africa. Hence, the achievement of food security in The Gambia is highly dependent on yield increasing technologies and programs like the New Rice for Africa (NERICA).

To improve rice production and productivity in The Gambia, there is urgent need to identify yield increasing improved rice varieties and farmer training programs that are contributing significantly towards the attainment of food security. Since development of yield increasing improved rice varieties and farmer training programs require huge investments, there is urgent need to assess the impact of such improved varieties and farmer training programs on food security and technical efficiency in order to inform governments and donors of the returns from their investment and also advise policy makers on pertinent issues that surrounds the development, adoption, intensity of adoption and impact of such improved varieties and farmer training programs on outcome indicators of interest to help them estimate the potential for rice production in a country and monitor the economic, social and environmental impact of investments and policies needed to develop the rice sector. This will enable policy makers to make decisions based on concrete evidence and not be tempted to make crucial judgments regarding development of the rice sector based on mere speculations.

1.2. NERICA and food security

Rice is a staple crop for more than three billion of the world's population. Rice is a subsistence crop for many countries in Asia, Africa and South America. Rice is used as a survival crop for nearly half of the world's population. Most households in Asia and Africa depend on rice for their daily meals. In most of the rice consuming countries, the crop provides about 70% caloric requirement (Wuthi-Arporn, 2002). More than three billion people in the world are very highly dependent on rice for their daily caloric requirement ((> 800 kcal/person/day). About 236 million people are highly dependent on rice for their caloric intake (500–799 kcal/person/day) and about 501 million people are moderately dependent on it as source of calories (300–499 kcal/person/day) (Nguyen, 2005). This makes rice an important food source for more than half of the world's population. In 2004, about 75% of total rice produced in the world came from tropical regions of Southeast Asia, Sri Lanka, Bangladesh, India, Latin America, the Caribbean and rice growing countries of sub-Saharan Africa (Nguyen, 2005).

The demand for rice is rapidly growing in sub-Saharan African rice growing countries. Between 1970 and 2009, the rice consumption rate in sub-Saharan Africa is estimated at 4%, which surpasses the local production rate of 3.3%. As a result, the region had to import about 9.68 million metric tons of rice in 2009 to meet the local demand, at a cost of more than US$ 5 billion (Onyango, 2014). To bridge the gap between local demand and supply of rice in sub-Saharan Africa, efforts have been concentrated on the introduction of yield increasing improved rice varieties. An example of such improved rice varieties is the New Rice for Africa (NERICA).

The NERICA was introduced in most sub-Saharan African countries between 2000 and 2010. NERICA was developed through crossing breeding between *Oriza sativa* and *Oriza glaberrima. Oryza sativa* varieties were first introduced in Africa about 450 years ago. They are originally from Asia and are well known for their high yield potentials. *Oriza glaberrima* varieties are originally from Africa and are resistant to most of the biotic (viral diseases, blast, weed competition) and abiotic (iron toxicity, drought, and acidity) stresses that hinder rice cultivation in sub-Saharan Africa (Jones *et al.* 1997a and 1997b; Audebert *et al.,* 1998; Dingkuhn *et al.* 1999). NERICA combines good traits from both *Oryza sativa* and *glaberrima* which makes it highly suitable for increasing rice production and productivity in sub-Saharan Africa. When NERICA was developed, it was disseminated to several countries in sub-Saharan Africa. However, the initial activities were concentrated in seven West African pilot countries: Benin, The Gambia, Ghana, Guinea, Mali, Nigeria and Sierra Leone (WARDA 2002).

The NERICA was officially introduced in The Gambia in 2003. The first set of NERICA introduced in The Gambia was upland rice, which was targeted to reach the upland rice farmers. In 2001, before the introduction of NERICA, rice production was approximately 19,200 metric tons. After the official introduction of NERICA, rice production level increased from 19,200 to 51,137 metric tons in 2011. In 2011, rice yields from NERICA fields accounts for about 46% of total rice production (Agricultural census, 2012). This makes NERICA varieties potential crops for attainment of national food security in The Gambia.

1.3 Agricultural training and technical efficiency

Low rice productivity in sub-Saharan Africa has been largely attributed to low use of inputs like fertilizers, chemicals, pesticides, etc and low adoption of high yielding improved rice varieties. Besides inputs and high yielding improved rice varieties, productivity can be significantly influenced by inappropriate rice cultivation practices. Balasubramanian et al. (2007) note that the appropriate rice cultivation practices that are widely adopted in Asia are not commonly practiced in sub-Saharan Africa, which may have resulted in low rice yields experienced by rice farmers in sub-Saharan Africa. Broadcasting rice seeds is a common practice among upland rice farmers in sub-Saharan Africa. This may result in overcrowding, which makes fertilizer application and weeding extremely difficult. Transplanting in lowland rice fields are usually not done in straight lines, which make it difficult to follow recommended spacing and seeding rates. Poor water control techniques can as well lead to flooding in some rice fields or low water retention in areas with sloppy land. Such inappropriate rice cultivation practices that are prevalent in sub-Saharan Africa can negatively affect technical efficiency of rice farmers.

To enhance efficiency in rice production, farmers need to be trained on recommended rice cultivation practices. This can be achieved through introduction of agricultural training programs. Through agricultural training programs, rice farmers can be trained on how to appropriately conduct row planting, apply fertilizers, weed rice fields, apply water control techniques etc. Such training programs can improve technical efficiency of rice farmers and contribute positively towards attaining rice self-sufficiency in sub-Saharan Africa. Since inappropriate rice cultivation practices are common in sub-Saharan African, agricultural training programs have recently been introduced in The Gambia under three different rice projects (PADS, FMRIP and CIDA) to give rice farmers the technical knowledge required to boost rice production and productivity in the country.

1.4 Study objectives, research questions and hypotheses

The overall objective of this study is to assess the impact of improved rice varieties and farmer training on household food security and technical efficiency of smallholder rice farmers in The Gambia. The study addresses this objective by considering three research topics: (1) How accessibility to seeds affects the potential adoption of an improved rice-based technology: The case of The New Rice Varieties for Africa (NERICA) in The Gambia, (2) The impact of New Rice for Africa (NERICA) adoption on household food security and health in The Gambia, and (3) The Impact of agricultural training on technical efficiency of smallholder rice producers in The Gambia.

1.4.1 Specific objectives

The specific objectives of each research topic are as follows:

Research topic 1 - How accessibility to seeds affects the potential adoption of an improved rice variety: The case of The New Rice for Africa (NERICA) in The Gambia:

- Assess NERICA population adoption rate by controlling for both exposure and seed access
- Provide estimates of actual and potential adoption rates and their determinants of the NERICA varieties
- Determine the adoption gap that arises due to lack of access to adequate supply of NERICA seeds

Research topic 2 - The impact of New Rice for Africa (NERICA) adoption on household food security and health in The Gambia:

- To determine improvements in food security and health outcomes that can be attributed to NERICA adoption

- Identify how differences in gender contributes to improvements of food security and health outcomes

Research topic 3 - The impact of agricultural training on technical efficiency of smallholder rice producers in The Gambia:

- To identify improvements in technical efficiency of smallholder rice producers that can be attributed to agricultural training
- To determine the factors that influence technical efficiency of smallholder rice producers

1.4.2 Research questions and hypotheses

The research questions and hypothesis of each topic are as follows:

Research topic 1 - How accessibility to seeds affects the potential adoption of an improved rice variety: The case of The New Rice for Africa (NERICA) in The Gambia:

Research question: Is the potential adoption rate of NERICA significantly influenced by lack of access to seeds?

Hypothesis: The potential adoption rate of NERICA is not significantly influenced by lack of access to seeds.

Research topic 2 - The impact of New Rice for Africa (NERICA) adoption on household food security and health in The Gambia:

Research question: Is there any improvements in food security and health outcomes that can be attributed to NERICA adoption?

Hypothesis: NERICA adoption has no significant causal effect on food security and health.

Research topic 3 - The impact of agricultural training on technical efficiency of smallholder rice producers in The Gambia.

Research question: Is there any improvements in technical efficiency of smallholder rice producers that can be attributed to agricultural training?

Hypothesis: There is no significant improvement in technical efficiency of smallholder rice producers that can be attributed to agricultural training.

1.5 Organization of dissertation

This dissertation is presented in six chapters. Chapter 1 gives the background information of the research and presents the study objectives, research questions and hypothesis. Chapter 2 briefly highlights the study area, sampling and data collection procedure. It also describes different impact evaluation methodologies used to identify causal effects of treatments and programs. Chapter 3 estimates the potential adoption of NERICA by controlling for exposure and access to NERICA seeds. Chapter 4 presents the estimates of the impact of NERICA adoption on food security and health. Chapter 5 gives estimates of the impact of agricultural training on technical efficiency of smallholder rice farmers and Chapter 6 concludes with a summary of the main empirical findings and their policy implications. It also presents the research gaps identified from the empirical findings and gives recommendation regarding future research works.

References

African Rice Centre (WARDA). 2006. Annual report. WARDA, Cotonou.

Agricultural Census, 2012. Technical report of The Gambia Agricultural Census.

Balasubramanian V, Sie M, Hijmans RJ and Otsuka K. 2007. Increasing rice production in sub-Saharan Africa: Challenges and opportunities. Advances in Agronomy 94:55–133.

Braun J.von.2006. Public policy and international collaboration for sustaining and expanding the rice revolution. A keynote at the 2nd International Rice Congress on “Science, technology and trade for peace & prosperity”. New Delhi Oct. 9 - 13, 2006.

Food and Agriculture Organization. 2002. FAO rice international. FAO, Rome.

Food and Agriculture Organization. 2005. Global climate changes and rice food security. Rome (availableat:http://www.fao.org/climatechange/1552603ecb62366f779d1ed45287e698a44d2e.pd.

Datt, G., Ravallion, M., 1996. How important to India’s Poor is the sectoral composition of growth? World Bank Economic Review 10 (1), 1–26.

Gambia .2013. National Rice Development Strategy. (Available at: http://riceforafrica.org/images/stories/PDF/gambia_en.pdf).

Fatajo, S. 2010. National issues report on key sector of agriculture (adaptation) in The Gambia. (Available at: http://www.undpcc.org/docs/National%20issues%20papers/Agriculture%20%28adaptation%29/07_Gambia%20NIP_agriculture%20adaptation.pdf)

Hossain, M. 1989. Green Revolution in Bangladesh: Impact on Growth and Distribution of Income. University Press Ltd, Dhaka.

Jones, M.P., Dingkuhn, M., Aluko, G.K. and Semon, M.. 1997a. Interspecific Oryza sativa × O. glaberrima Steud. progenies in upland rice improvement. Euphytica 92:237-246.

Jones, M.P., Dingkuhn, M., Johnson, D.E. and Fagade, S.O. (Eds). 1997b. Interspecific hybridization: Progress and Prospect WARDA, 01 BP 2551, Bouaké, Cote d'Ivoire. pp. 21-29.

Matlon, p., Randolph, T., Guei, R. 1996. Impact of rice research in West Africa. International conference on impact of rice research 3-5 June 1996. Bankok. IRRI p 313-323.

Nguyen N. V. 2005. Global climate changes and rice food security (Available at: http://www.fao.org/forestry/15526-03ecb62366f779d1ed45287e698a44d2e.pdf).

Onyango, A. O. 2014. Exploring Options for Improving Rice Production to Reduce Hunger and Poverty in Kenya. World Environment 2014, 4(4): 172-179

Solh, M. 2005. Rice is life in 2004 and beyond. (Available at: http://www.fao.org/3/a-a0281e.pdf).

Somado, E.A. and Guei, R.G. 2008, Over view: The new rice for Africa 2008. Rice in Africa. Africa Rice Center, Bouaké.

World Bank. 2008. World Development report. Agriculture for development. (Available at: World Development report. Agriculture for development).

Wopereis, M. 2011. Realizing Africa's Rice Promise. Keynote speech (available at: http://jircas-d.job.affrc.go.jp/Ver-1/english/files/2012/10/admin/2011-Keynote-Speech3.pdf).

Wuthi-Arporn, J .2002. Increasing Rice Production: Solution to the Global Food Crisis (Available at: http://www1.nodai.ac.jp/cip/iss/english/9th_iss/fullpaper/1-2-2ku-jirawut.pdf).

Chapter 2

2. Methodological framework

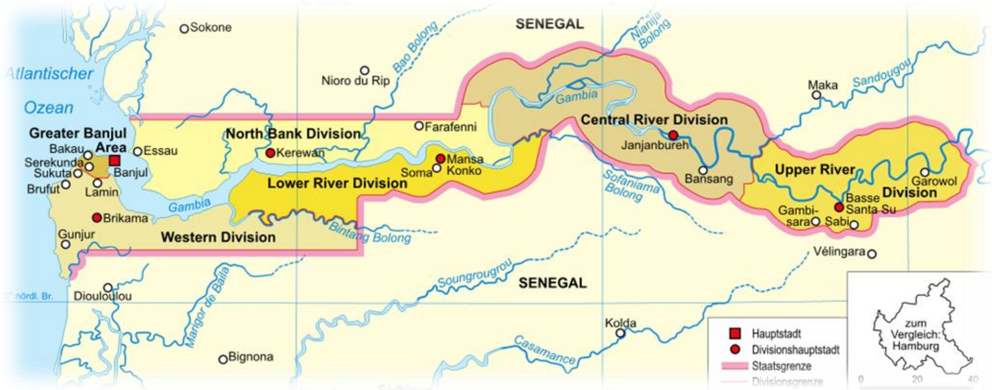
2.1 Research area, sampling and data collection

2.1.1 Research area

The research area covers all the agricultural region of The Gambia: Western Region, North Bank Region, Lower River Region, Central River North and South, Upper River Region (Figure 2.1). The Gambia is located within the Sahelo-Sudan climatic zone on the western coast of Africa. It is located between latitude 13^0 N and longitude 16^0 W. The Gambia is 30km wide and stretches from the Alantic coast for about 375km. It is entirely surrounded on land by Senegal (Figure 2.1). It has a total land area of about 11,300 km^2 and a population of 1,882,450 (Gambia Population Census, 2013).

The research area is divided into three major agro-ecological zones: Sahel, Sudan-Sahel and Sudan-Guinea. The Sahel zone is characterized by unpredictable rainfall pattern with dry and scanty vegetative cover. The annual rainfall in the area is less than 600mm and the soils have very low water retention capacity. As a result, only drought tolerant crops are those prevalent in the area. The Sudan-Sahel zone receives between 600 and 900mm of rainfall. The flood plains of the area along the river Gambia and the lowland valleys are well suited for swamp rice cultivation under tidal irrigation. The Sudan-Guinea zone receives between 900 and 1200mm of rainfall. The area has the longest cropping season, lasting between 120 and150 days. The area is well suited for all types of rice (rain-fed upland and lowland, irrigated lowland and mangrove) cultivated in The Gambia.

Figure 2.1: Map of The Gambia and its agricultural regions



Source: www.google maps.com

About 50 percent of the land in the research area is good arable land (5,500 square kilometres). About 15 percent of the total arable land is irrigable, all of which is situated in the Central River and Upper River Regions. As the country is currently taking necessary measures to attain self-sufficiency in rice production, more than 2300 hectares of the irrigable land is put under cultivation.

2.1.2 Sampling and data collection

This study used multi-stage stratified random sampling procedure to select rice growing villages and households cross the six agricultural regions of The Gambia. In the first stage, a list of all rice growing villages was obtained through key informant interviews. The informants were selected from research and extension services. Within each agricultural region, a preliminary list of rice growing villages was obtained at the regional director's office. This list was updated by contacting agricultural officers working at district level. This was done to ensure that a complete list of all rice growing village was identified in every agricultural region. The list of villages obtained from each agricultural region was stratified into two groups: 1) villages where rice based technologies and programs were disseminated to rice farmers (hereafter, treatment villages) and 2) villages where rice based technologies and programs were not disseminated (hereafter, control villages).

The treatment villages were the first randomly selected within each agricultural region, followed by a random selection of control villages within a radius of 5-10 kilometres to maximize similarities between treatment and control villages. With the exception of West Coast Region, five treatment and control villages were randomly selected from each agricultural region. In the second stage of sampling, a list of all rice growing households was obtained in every selected village through focus group discussions. Ten rice farming households were randomly selected in each village for household level data collection.

Data were collected at village and household levels. At the village level, a list of all the rice technologies and programs introduced within each of the selected villages was obtained through a focus group discussion. This was followed by a detailed household interview to collect data on each of the rice based technology and program identified at the village level. Chapter 3, 4 and 5 give more details about the sampling procedure and type of data collected.

2.2 Food security indicators

"Food security is a situation that exists when all people, at all times, have physical and economic access to sufficient, safe, and nutritious food that meets their dietary needs and food preferences for an active and healthy life" (World Food Summit, 1996). There are several indicators which are used to measure food security status of households. In this sub-section the focus will be on the following food security outcome indicators recommended by Hoddinott (1999) and World Food Program (2008): Household Caloric Acquisition (HCA), Household Dietary Diversity (HDD), Indices of Household Coping Strategies (IHCS), and Food Consumption Scores (FCS).

The HCA is an indicator of food security which measures the number of calories or nutrients available for consumption by a given household at a given period of time. Data on this indication is generated by obtaining an exhaustive list of all household food items in a study area. At household level, the person most knowledgeable about household food consumption is asked a set of questions regarding food prepared for meals over a specified period of time, usually over a period of 7 to 14 days. For each food item listed, the respondent is asked to indicate whether it has been prepared in the household during the period under consideration. The quantity of the food items prepared by the household are noted and the calorie content determined for each food item. The total calorie available to the household is obtained by summing the calorie content in each food item consumed by the household during the period specified (Hoddinott 1999).

The HDD is the sum of the number of various foods items consumed by a household over a specified period of time. It can be a simple sum of the number of various food groups consumed, or sums of the number of different food items within a food group, or a weighted sum (Hoddinott 1999). To generate data on HDD one or more persons within the household is or are asked about different food items that have been consumed in the household over a specified period. A complete list of food items is provided for the respondents to identify the ones consumed by household members over a specified period of time. Determining which food items should appear on such list is done via rapid appraisal exercises and discussions with key informants. The HDD is determined by taking the sum and weighted sum of the food items consumed by the household over a specified period.

The IHCS is a food security index that is based on how households adapt to the prevalence or threat of food shortages. To generate data on IHCS, the household member who is responsible for preparing and serving meals is interviewed about issues regarding how the household is responding to food shortages. A low score is given to households that do not experience high occurrence of food shortages and a high score is given to households with high frequencies of food shortages. The sum and weighted sum of the coping strategies is obtained for each household. The higher the value, the more food-insecure the household (Hoddinott 1999).

The FCS is a combination of dietary diversity, food frequency, and relative nutritional importance. This indicator is created to capture the three cardinal pillars of food security: food availability, food access and food utilization. To generate data on FCS, a list of food items consumed in a study village is obtained through key informant interviews. The food items are grouped into 8 standard food groups: Cereals and tubers, Pulses, vegetables, fruits, meat and fish, milk, sugar and oil. Each of the food groups is assigned a weight that is based on its nutrient content. Data is generated at household level by interviewing the person who is most knowledgeable about food items consumed in the household. The FCS is obtained by taking the weighted sum of all the food groups consumed in a household over a 7 days period (World Food

Programme, 2008). A detailed explanation of how the FCS is calculated is given in Chapter 4.

2.3 Estimating technical efficiency

Technical efficiency[1] is a situation a farm household realizes when it is not possible to increase output without increasing the level of inputs use in the production process. Technical efficiency is estimated using two different approaches: parametric and nonparametric production frontiers. The parametric approach uses Stochastic Frontier Analysis (SFA) technique whereas the nonparametric approach uses Data Envelopment Analysis (DEA).

When employing the parametric approach to estimate technical efficiency, a functional form is assumed prior to deciding on the right one to use for the estimation procedure. One of the following functional forms can be used for the estimation: Cobb-Douglas, normalized quadratic, Translog, generalized Leontief, and CES. The Cobb-Douglas and Translog are the two most commonly used functional forms in empirical research (Battese and Broca 1997). However, the Cobb-Douglas is more restrictive than the Translog. When the Cobb-Douglas is fitted for estimation of technical efficiency its adequacy should be tested against the Translog using the Likelihood Ratio (LR) test. The Cobb-Douglas (equation 2.1) and Translog (equation 2.2) take the following functional forms:

$$\ln y_i = \beta_0 + \sum_{j=1}^{k} \beta_j \ln x_{ji} + v_i - u_i \tag{2.1}$$

$$\ln y_i = \beta_0 + \sum_{j=1}^{k} \beta_j \ln x_{ji} + \sum_{j=1}^{k} \sum_{h=1}^{k} \beta_{jh} \ln x_{ji} \ln x_{hi} + v_i - u_i \tag{2.2}$$

where:

i is the index indicating households

j is the index indicating inputs

y_i is the output of household i

x_{ij} is the input j used by household i

[1] Economic efficiency is achieved when lowest cost is incurred to produce a given output.

β is vector of parameters to be estimated

v_i is a random error assumed to be independently and identically distributed

u_i is non-negative random variable associated with technical efficiency

The nonparametric approach to estimating technical efficiency based on DEA does not require an assumption to be made about a functional form. It uses Linear Programming (LP) to estimate technical efficiency by using the most efficient production unit as bench mark for estimating the relative efficiency level of other production units. The DEA model uses two scale assumptions: Constant Return to Scale (CRS) and Variable Return to Scale (VRS). CRS is assumed in situations whereby changes in inputs level results in proportionate changes in output level. On the other hand, VRS is assumed when changes in input levels lead to increase, decrease or no changes in output levels. Following Charnes et al. (1978) DEA model based on CRS is identified as follows:

$$\text{minimize} \qquad TE_m = \frac{\sum_{r=1}^{t} u_r y_{rm}}{\sum_{i=1}^{l} v_i x_{im}} \tag{2.3}$$

$$\text{subject to} \quad \frac{\sum_{r=1}^{t} u_r y_k}{\sum_{i=1}^{l} v_i x_{ik}} \leq 1, \quad k = 1,2,.....k_m.....n \tag{2.4}$$

$$v_i \geq \varepsilon, \;\; i = 1, 2,.........l \tag{2.5}$$

where:

TE is the technical efficiency score for household m

v_i is the weight to be determined for input i

u_r is the weight to be determined for output r

l is the total number of inputs

n is the total number of households

ε is a small positive value

y_k is the total kilogram of paddy rice harvested by household k

x_{ik} is the input used by household k

Following Coelli (1995) DEA approach under VRS assumption is identified using the following equations:

$$TE_n = \min_{\lambda_i \theta_n} \theta_n \tag{2.6}$$

subject to :

$$\sum_{i=1}^{I} \lambda_i x_{ij} - \theta_n x_{nj} \le 0 \tag{2.7}$$

$$\sum_{i=1}^{I} \lambda_i y_{ik} - y_{nk} \ge 0 \tag{2.8}$$

$$\sum_{i=1}^{I} \lambda_i = 1 \tag{2.9}$$

where:

TE_n is the technical efficiency score for a given entity n

λ_i is the nonnegative weights for entity i

n is the total number of entities

x_{ij} is the input j used by entity i

x_{nj} is the input j used by entity n

y_{ik} is the amount of output k produced by entity i

y_{nk} is the amount of output k produced by entity n

θ_n is a scalar vector ≤ 1 that defines technical efficiency for entity n

2.4 Overview of impact evaluation methods

2.4.1 Impact evaluation problem and the potential outcome framework

The main challenge in any impact evaluation is to determine what would have happened to the outcome of program participants had they not participated in the program. That is, if one has to determine the food security outcome of NERICA adopters in the absence of NERICA adoption. The food security outcome of NERICA adopters had they not adopted NERICA is referred to as the counterfactual. The main problem in impact evaluation is to appropriately construct the counterfactual. The framework serving as a guide for the analysis of this problem is called the potential outcome framework or the Roy (1951)-Rubin (1974) model.

Under the potential outcome framework every individual (i) has two potential outcomes (Y_{i1}, Y_{i0}), where Y_{i1} represents the potential outcome of individual (i) if treated and Y_{i0} otherwise. If we define a treatment or program indicator variable as T, where $(T=1)$ indicates receipt of treatment or program participation and $(T=0)$ otherwise, then treatment or program participation effect for individual (i) is the difference between his two potential outcomes:

$$\Delta_i = Y_{i1} - Y_{i0} \qquad (2.10)$$

Fundamental evaluation problem arises in equation (2.10) because in reality we can only observe the following:

.

$$Y_i = T_{i1}Y_{i1} + (1 - T_{i0})Y_{0i} \qquad (2.11)$$

For individuals who participated in the program or treatment we observe Y_1 and those who did not participate we observe Y_0. The fact that only one outcome can be observed at a time and not both simultaneously, it is impossible to directly estimate the treatment effect in equation (2.10). The unobservable portion in equation (2.10) is referred to as the counterfactual outcome. Since the counterfactual is not directly observable, we cannot estimate treatment effects at the individual level. However, it is possible to estimate the average effect for the entire population (ATE) as follows:

$$ATE = E(Y_1) - E(Y_0) . \tag{2.12}$$

ATE is the effect of the treatment on an individual who is randomly selected in the population. Since ATE includes the effect of the treatment on individuals for whom the program is never intended, Heckman (1997) argues that it may not be relevant for policy makers. For this reason, the most important impact evaluation parameter is the Average Treatment on the Treated (ATT) which is estimated as follows:

$$ATT = E(Y_1 | T = 1) - E(Y_0 | T = 1) . \tag{2.13}$$

The term on the right hand side of equation (2.13) is the counterfactual outcome for the treated group, which is not directly observable. If the condition $E(Y_0 | T = 1) = E(Y_0 | T = 0)$ holds, we can use the outcome of the control group to represent the counterfactual. However, such condition is only likely to hold under randomized control experiments. With non-randomized experiments the condition is less likely to hold, i.e. $E(Y_0 | T = 1) \neq E(Y_0 | T = 0)$. Consequently, using the outcome of the control group to represent the counterfactual outcome of the treated group is going to result in selection bias. The following sub-sections present impact evaluation methodologies used to address the problem of counterfactual outcomes and selection bias to estimate causal effects of programs or treatments.

2.4.2 Randomized impact evaluation

Randomization is considered as the most robust of all impact evaluation methods. It ensures that the control group represents the true counterfactual for the treated group. It addresses the problem of selection bias by balancing both observed and unobserved confounding factors between treated and control groups. Statistically, randomization is conducted in two stages. In the first stage, random sample of eligible participants is selected from a given population. The sample is then divided randomly into two groups: the treatment (N_T) and the control (N_C) groups (Duflo el al., 2008). In the second stage, the treatment group is exposed to the treatment while the control group is not. Then the outcome of interest is observed from both the treated and control groups. For instance, in an agricultural setting, out of a random sample of 500 rice farmers, if 250 are randomly given seed vouchers and 250 do not receive seed vouchers, then the impact (ATE) can be identified by taking the mean difference in observed outcome (Y) between treated and control groups as follows:

$$ATE = E\left[Y_i^T \middle| T\right] - E\left[Y_i^C \middle| C\right] \quad (2.14)$$

Since randomization ensures that the covariates are balanced between treated and control groups, the mean difference in outcome of interest is a causal effect of the treatment in question (Duflo el al., 2008). It also ensures requirements for both internal[2] and external[3] validity of experiments are met. Random selection of participants from a given population ensures that the results obtained can be extrapolated to the level of the population, thereby, fulfilling the requirement for external validity of the experiment. Random assignment of treatment between eligible participants guarantee that the difference in outcome between treated and control groups is a causal effect of the treatment and not due to confounding factors. This satisfies the requirement for internal validity of the experiment. When conditions for both internal and external validity of the experiment are met, the control group can be used as the true counterfactual for the treated group. This ensures that the treated and control groups have the same expected outcome before participation. Hence, selection bias, which is the main concern in treatment evaluation becomes zero.

$$E\left[Y_i^C \middle| T\right] - E\left[Y_i^C \middle| C\right] = 0 \quad (2.15)$$

The condition in equation (2.15) is likely to hold only under pure randomization. Pure randomization ensures that the difference in observed outcomes between program participants and non-participant is equal to zero before they are even exposed to the treatment. In such cases, simple regression with OLS gives unbiased estimates of treatment effects.

[2] Internal validity is achieved when causal effects of treatment is identified through randomization
[3] External validity is achieved when the sample is representative of the population

$$Y_i = \alpha + \beta T_i + \varepsilon_i \qquad (2.16)$$

Where (T_i) indicator variable taking the value of 1 for randomly selected units and 0 otherwise. The treatment effect (β) in equation (2.16) can be consistently estimated with OLS without the need to control for any covariates. However, if there is partial randomization, whereby treatment and control groups are selected based on some observed characteristics, then simple OLS regression will result in a bias estimate. Under such circumstance, if one can assume that participation in program is independent of potential outcomes conditional on the observed characteristics used for randomization, then it is possible to identify unbiased estimates of treatment effects (World Bank 2010).

Under partial[4] randomization, treatment effects can be estimated by conditioning on the selection criteria used to randomly select program participants and non-participants. The model can be expressed as follows (Ravallion, 2008):

$$ATT = E(Y_i | T_i = 1, X) \qquad (2.17)$$

Equation (2.17) can be estimated with OLS by conditioning on the exogenous factors (X) used to randomly assign treatment between treated and controls groups and assuming that there is no selection bias because of random assignment of participants into treatment and control groups.

2.4.3 Impact evaluation using matching approach

Impact evaluation using matching approach is an attempt to identify counterfactual outcomes by constructing a comparison group that is similar to the treatment group in observable factors affecting participation and outcome variables of interest. If such a comparison group is found, impact can be assessed by taking the difference in mean outcomes between the groups. To enable the use of matching approach, one has to have a rich data set that captures all the observable differences between treatment and control groups.

---

[4] In partial randomization, the results are valid for only a sub-section of the population. For instance if only poor individuals are randomized into treatment and control groups then causal effects can only be extrapolated to the sub-population of poor individuals or households.

To identify causal effects of treatments, matching estimators rely on the validity of the conditional independence assumption. The conditional independence assumption states that conditional on a set of observed covariates (x) that influence program participation and outcome variables of interest, treatment is independent of potential outcomes (Rosenbaum and Rubin, 1983). This assumption can be stated as follows:

$$Y_0 \ , Y_1 \ , \coprod T_i \mid X_i \tag{2.18}$$

where $\coprod$ denotes independence between treatment and potential outcomes conditional on a vector of observed covariates. To identify treatment effects one has to condition on all relevant covariates. However, when there is a large number of covariates this can lead to dimensionality problems if the vector of covariates has many dimensions (Caliendo and Kopeinig, 2008). To solve this problem, Rosenbaum and Rubin (1983) recommend the use of a single balancing score which is calculated using all the relevant covariates. They argue that if assignment to treatment is independent of the potential outcomes conditional of a set of relevant covariates, then assignment to treatment is also independent of the potential outcomes conditional on the balancing score. The most widely used balancing score is known as the propensity score. Matching based on the propensity score is referred to as Propensity Score Matching (PSM).

PSM captures the effect of all relevant covariates in a single propensity score. The propensity score is the probability of participating in a program or intervention conditional on all relevant covariates (x) determining participation:

$$P(X) = \Pr(T = 1 | X) \tag{2.19}$$

where $P(X)$ is the propensity score. PMS is based on the conditional independence assumption stated in equation (2.19) and a common support. The common support assumption is stated as follows:

$$0 < P(T_i = 1 | X) < 1 \tag{2.20}$$

It ensures there in enough overlap in propensity score between treated and control groups (Heckman et al., 1999). When the conditional independence and common support assumptions are met, treatment effects are identified by taking the difference in mean outcomes over the region of common support between treatment and control groups with similar propensity score estimates.

There are different types of matching methods which can be used to identify treatment effects. The most common ones are: Nearest Neighbor Matching (NNM), Radius Matching (RM), Kernel Matching (KM), and Stratification Matching (SM). Each of these matching methods identify treatment effects by comparing the propensity score estimate between treatment and control groups over the region of common support.

NNM is the most common method of PSM use to identify treatment effects. When implementing NNM, each treatment unit is matched to the control unit with the closest propensity score. To improve matching quality, it is also possible to specify the number of nearest neighbors on which matching can be implemented. Matching can be conducted with or without replacement. Matching without replacement means each nearest neighbor is used only once. However, matching with replacement allows the same nearest neighbor to be used more than once.

SM divides the region of common support into different strata and estimates the treatment effect within each stratum. The treatment effect is identified as the mean difference in outcome between treated and control groups within each stratum. Taking the share of units or participants within each stratum as weight, an average is taken across all strata as the overall treatment or program effect.

RM is an attempt to improve matching quality by imposing or allowing a tolerance level on the maximum propensity score distance known as the caliper. Rosenbaum and Rubin (1985) recommends the caliper value of one-quarter of the standard deviation of the propensity score to identify the maximum propensity score distance. This approach drops all treatment and control observations that are not within the caliper. As a result, it may increase the likelihood of sampling bias.

The main problem with the aforementioned matching methods, is that only a handful of treatment and control observations are likely to be selected as pairs to construct the counterfactuals. This problem is solved by using the KM approach. KM uses a weighted average of the control observations to construct the counterfactual match for each treatment unit or observation. This approach ensures that all the observations in the region of common support are used to estimate treatment effect. Hence, it minimises sampling bias.

2.4.4 Impact evaluation using instrumental variable approach

The Instrumental Variable (IV) approach is used to assess impact of an intervention or program when individual participation or program placement is correlated with unobserved factors that influence the outcome variable of interest. This leads to a problem referred to as endogeneity in treatment evaluation. Endogeneity occurs when participation in a program is correlated with unobservable factors that determined participation and outcome variables of interest. This creates differences between treated and control groups that are not observed by program evaluators. When there is endogeneity problems, the IV approach provides consistent estimates of treatment effects on outcome variables of interest (Heckman and Vytlacil., 2007).

Suppose we want to estimate an equation that compares outcomes of treated and control groups:

$$Y_i = \alpha X_i + \beta T_i + \varepsilon_i \qquad i = 1,...,n \tag{2.21}$$

Endogeneity problem exists in equation (2.21) if there is a correlation between T and ε. In the case of agricultural technology adoption, endogeneity can exist when treated and control groups have significant differences in their attitude towards work. Since a farmer's attitude towards work cannot be directly observed by an impact evaluator, such a variable is embedded in the error term (ε) of equation (2.21). Endogeneity problem exits if hard working farmers decide to adopt the particular technology. In such situation, comparison in outcome between treated and control groups can lead to bias estimate of treatment effects. The bias results from the fact that hard working farmers are likely to get better outcomes even in the absence of technology adoption. The idea behind the IV approach is to break the correlation between T and ε (i.e.

identify a sub-group within treatment and control observations that does have significant differences in their attitude towards work). To do that, one needs an instrumental variable, denoted Z , that satisfies the following conditions:

i) Correlated with T : cov $(Z,T) \neq 0$

ii) Correlation with ε : cov $(Z,\varepsilon) = 0$

In the case of technology adoption, condition (i) means the instrument should have a causal effect on adoption, whereas condition (ii) means that treated and control groups should not have significant difference in unobserved factors given such instrument (this is also known as the exclusion restriction). For an instrument to be valid it has to fulfil these two conditions. However, one cannot test whether a given instrument has fulfilled the above conditions, justification has to be based on evidence obtained from program design (World Bank, 2010). If an IV is available that satisfy the above conditions, then the following approaches can be used to identify treatment effects:

2.4.4.1 Two-Stage Least Square (2SLS) Approach

The 2SLS is conducted in two stages. The first stage involves identifying an exogenous variation in the treatment variable that is uncorrelated with the error term. This is done by estimating a reduced form equation with only exogenous regressors. This is known as the first stage regression:

$$T_i = \lambda Z_i + \phi X_i + u_i \tag{2.22}$$

The predicted values of the treatment obtained from equation (2.22) reflects the part of the treatment affected by only Z , which represents only exogenous variation in the treatment. The predicted values $\hat{T}$ are then substituted in the structural equation to form the following reduced outcome equation (World Bank, 2010):

$$Y_i = \alpha X_i + \beta(\hat{\lambda} Z_i + \hat{\phi} X_i + u_i) + \varepsilon_i \tag{2.23}$$

Equation (2.23) is then used to identify the impact of a particular treatment or program on outcome variables of interest. However, if individuals know more about their expected gains than the evaluator does, then estimates based on the 2SLS will be biased (World Bank, 2010). The bias results from the fact that the instrument is unable to check for the compliance status of participants. In that case, individual who expect to gain more from the program are the ones who eventually participate. Since such individuals are less likely to be in control groups, when their outcome is compared with those who are less likely to participate in the program, it results in bias estimates. To solve this problem, Imbens and Angrist (1994) introduced the Local Average Treatment Effect (LATE) estimator.

2.4.4.2 The LATE approach

When there is heterogeneity of treatment effects, IV methods estimate impact of treatment or program for only the sub-population of compliers. Such impact outcome is referred to as the LATE by Imbens and Angrist (1994). The LATE estimates impact of an intervention or program for only those who decide to participate because of a change in the instrument. If for instance, we take awareness as instrument for technology adoption or program participation, then the LATE estimate is only for those who decide to adoption or participate because they are aware of the technology or program.

To estimate LATE Imbens and Angrist (1994) divide a population of technology adopters or program participants into four sub-groups: compliers, always takers, never takers and defiers. The compliers are those who will stick to their assign treatment, always takers are those who will manage to always be in the treated groups, never takers are those who will never take the treatment and defiers are those who will do the opposite (ie take the treatment when they are not aware or refuse the treatment when they are aware). With the montonicity assumption (no defiers), the population is divided into three groups by compliance status (Table 2.1).

Table 2.1: Compliance type by treatment and instrument

		Z_i 0	1
	0	complier/never taker	never taker
T_i	1	always taker	complier/always-taker

Source: Imbens and Angrist (1994)

The LATE is true impact estimate for only the sub-group of compliers (those who will change their behaviour as a result of a change in the value of an instrument) . If we have a binary treatment indicator variable T and a binary instrument Z, taking the value 1 when treated and 0 otherwise and assuming treatment T depends on the value of the instrument Z such that $T=1$ is the probability that $Z=1$ and vice versa, then the LATE is estimated as follows by Imbens and Angrist (1994):

$$\beta_{iv,LATE} = \frac{E(Y \mid P(z=1) - E(Y \mid P(z=0)}{E(T \mid P(z=1) - E(T \mid P(z=0)} \qquad (2.24)$$

The numerator is the mean difference in outcome between treated and non-treated groups given a binary instrument. The denominator is the difference in probability of taking the treatment with and without the instrument, respectively.

To estimate LATE based on Imbens and Angrist (1994) approach, one needs a random instrument. In cases where a random instrument is not available, one can make a weaker conditional assumption to estimate LATE (see Abadie 2003).

2.4.5 Impact evaluation using double difference approach

This approach is used to evaluate impact of an intervention on outcome variable of interest between treated and control groups, when data is available before and after a given intervention, on the same survey units. Such data is referred to as a panel data. To use double difference approach, one needs to implement a baseline survey during which data is collected on treatment and control groups before an intervention. This is followed by subsequent survey to collect data on the same units after the intervention. The impact is then identified by calculating the difference in the mean difference in outcome between the two groups before and after the intervention. Thus the name double difference.

If we denote Y_2^T and Y_2^C as the potential outcomes of participants after the intervention (period 2) when treated and untreated, respectively, and Y_1^T and Y_1^C as the potential outcome of participants before the intervention (period 1) when treated and untreated, respectively and assuming the participants belong to either the treatment (T) or the control (C) group; in period 1 none of the participants received any treatment and in period 2 only the participants in the treatment group are treated, then the double difference approach identifies impact as follows:

$$DD = E(Y_2^T - Y_1^T \mid T) - E(Y_2^C - Y_1^C \mid C) \tag{2.25}$$

The double difference approach provides unbiased estimates of treatment effects under the assumption that unobserved factors affecting participation and outcomes do not differ between treated and control groups over time. This assumption also implies that if there are any shocks after the intervention both treated and control groups should be affected equally. If this assumption holds any bias that occurs before and after the intervention can be controlled by differencing out the change in outcome of control groups from the change in observed outcomes of the treated group. However, the assumption is likely to fail if macroeconomic factors affect treated and control groups differently after the intervention. The assumption is also likely to fail if experimental settings defer between treated and control groups (World Bank 2010). For instance, if a program that intends to improve the adoption of a particular upland rice variety selects the treatment group from areas that have predominantly upland ecologies and control groups from areas that are mainly into lowland rice cultivation. Then the response in control areas will be much slower after the intervention. As a result, using a simple double difference approach is going to overestimate the impact of the program. In such cases, the double difference approach combined with propensity score matching is likely to give a more robust impact estimates.

To ensure comparability of treatment and control groups, propensity score matching is applied on a baseline data to match treatment and control groups based on observed factors that determine program participation. Treatment and control observations with similar propensity score are used to create a common support, then the double difference approach is used to estimate treatment effect on observations that fall within the region of common support. To yield an estimator, it is recommended to weight the control observations according to their propensity score (Hirano, Imbens, and Ridder 2003).

2.4.6 Impact evaluation using regression discontinuity designs

This approach to impact evaluation identifies treatment and control groups based on eligibility criteria. For instance, a program that intends to improve income of the poor may select households whose per capita income is less than one dollar a day. Under this circumstance, households whose per capita income is a little above one dollar can be selected as control group to represent the counterfactual for the treatment group. The variable determining participation is not continuous: it has a cut-off point. Hence the name regression discontinuity designs. The idea behind this approach is that in the absence of the intervention households who are just a little above the eligibility criteria would observe a similar outcome as the treatment group in the absence of the program. If the treatment and control groups are sufficiently close to the eligibility criteria then impact can be assessed non-parametrically by taking the difference in mean outcome between treatment and control groups (World Bank 2010).

If the eligibility criteria is not violated, it can be used as an instrument to solve the problem of endogenous selection into treatment. This will minimize heterogeneity of the impact between treated and control groups. However, if the eligibility criteria is violated, treatment and control group will defer in unobserved characteristics which can influence participation and outcome variable of interest. This will lead to the problem of endogeneity. Hence, when using regression discontinuity designs, the evaluator has to ensure that eligibility rules were not violated.

To estimate the impact of a treatment or program using the regression discontinuity design one has to identify a variable, let say d_i, that determines eligibility and define a variable that determines eligibility cut-off d^*. Individuals with $d_i \leq d^*$ are eligible to participate in the program whereas individuals with $d_i > d^*$ are not eligible to participate in the program. If we identify a small range (s) within which treatment and control groups are selected and using $y_i = \beta D + s$, then the impact estimator based on regression discontinuity design can be stated as follows:

$$E\lfloor y_i \left| d^* - s \right\rfloor - E\lfloor y_i \left| d^* + s \right\rfloor = E\lfloor \beta D_i \left| d^* - s \right\rfloor - E\lfloor \beta D_i \left| d^* + s \right\rfloor \quad (2.26)$$

From equation (2.26) individuals selected within the same range (s) are likely to have similar characteristics influencing program participation and outcome variable of interest. As a result, selection bias within that range is equal to zero. This identifies unbiased treatment effects using the regression discontinuity design approach.

2.4.7 Conclusions

The impact evaluation methods described in this section are used to identify causal effect of treatments or programs on outcome variables of interest. The most robust impact evaluation methods are randomized experiments, which ensures the control group represents the true counterfactual for the treatment group. However, if randomization is not feasible non-experiment evaluation designs can be used to identify causal effects of treatment or programs. The right non-experiment evaluation method to use for a particular impact evaluation study is highly dependent on data availability. When data are available before and after the introduction of a particular treatment or program, double difference approach can be used to identify causal effects. However, if data is available only after introduction of a particular treatment or program then other evaluation methods can be used to identify causal effects but the type of method to use is dependent on two different identifying assumptions: 1) selection based on observables (conditional independence assumption) and 2) selection based on unobservables. If conditional independence assumption holds then causal effects of treatments or programs can be identified using matching methods. However, if conditional independence assumption is less plausible then causal effects of treatments or programs are identified using the instrumental variable approach.

References

Abadie, A. 2003. Semiparametric instrumental variable estimation of treatment response models. Journal of Econometrics, 113, 231– 263.

Battese G.E., Broca S.S. 1997: Functional Forms of Stochastic Frontier Production Functions and Models for Technical Inefficiency Effects: a Comparative Study for Wheat Farmers in Pakistan. Journal of Productivity Analysis no. 8, pp. 395-414.

Caliendo, M. and Kopeinig. S. 2008. Some practical guidance for the implementation of propensity score matching. Journal of Economic Surveys. Vol. 22, No 1, pp. 31-72.

Coelli, T.J. 1995. Recent Developments in Frontier Modelling and Efficiency Measurement. Australian Journal of Agricultural Economics 39 :219-245.

Duflo, Esther, Rachel Glennerster, and Michael Kremer. 2008. "Using Randomization in Development Economics Research: A Toolkit." In Handbook of Development Economics, vol. 4, ed. T. Paul Schultz and John Strauss, 3895–962. Amsterdam: North-Holland.

Gambia Population Census .2013. The Gambia housing and population census preliminary results. Available at http://www.gbos.gov.gm/uploads/census/The%20Gambia%20Population%20and%20Housing%20Census%202013%20Provisional%20Report.pdf (accessed online November 2014).

Heckman, James J., Robert LaLonde, and Jeffrey Smith. 1999. "The Economics and Econometrics of Active Labor Market Programs." In Handbook of Labor Economics, vol. 3, ed. Orley Ashenfelter and David Card, 1865–2097. Amsterdam: North-Holland.

Heckman, J.J. and E.J. Vytlacil. 2007.Handbook of Econometrics, Volume 6B, Elsevier.

Hirano, Keisuke, Guido W. Imbens, and Geert Ridder. 2003. “Efficient Estimation of Average Treatment Effects Using the Estimated Propensity Score.” Econometrica 71 (4): 1161–89.

Hoddinott, J. 1999. Choosing outcome indicators of household food security. International Food Policy Research Institute (IFPRI). Washington, D.C. 20006 U.S.

Imbens, Guido, and Joshua Angrist. 1994. “Identification and Estimation of Local Average Treatment Effects.” Econometrica 62 (2): 467–76.

Ravallion, Martin. 2008. “Evaluating Anti-Poverty Programs.” In Handbook of Development Economics, vol. 4, ed. T. Paul Schultz and John Strauss, 3787–846. Amsterdam: North-Holland.

Rosenbaum P.R and Rubin D.R.1983. “The Central Role of the Propensity Score in Observational Studies for Causal Effects,” Bometrika 70, 41-55.

Rosenbaum P.R. and Rubin, D.B. 1985. Constructing a control group using multivariate matched sampling methods that incorporate the propensity score, American Statistician, 39 (1), pp. 33–38.

Roy, A. 1951. “Some Thoughts on the Distribution of Earnings,” Oxford Economic Papers, 3, 135–145.

Rubin, D. 1974 “Estimating Causal Effects to Treatments in Randomised and Nonrandomised Studies,” Journal of Educational Psychology, 66, 688–701.

World Bank. 2010. Hand book on impact evaluation. Quantitative methods and Practices. The International Bank for Reconstruction and Development / The World Bank.

World Food Programme. 2008 Calculation and use of the food consumption score in food security analysis. Prepared by VAM unit HQ Rome.

World Food Summit. 1996. World summit on food security. 13-17 November 1996 Rome, Italy.

Chapter 3

3. How accessibility to seeds affects the potential adoption of an improved rice variety: The Case of New Rice for Africa (NERICA) in The Gambia

Lamin Dibba, Manfred Zeller, Aliou Diagne and Thea Nielsen

(Published in Quarterly Journal of International Agriculture 2015, Vol. 54, No. 1, 33-58, DLG-Verlag, Frankfurt/Main)

Abstract

This study estimates the adoption gap of NERICA that exists in the population when access to seeds is a constraint. Treatment evaluation technique is applied to consistently estimate the potential NERICA adoption rate and its determinants using panel data from a stratified random sample of 515 rice farmers in The Gambia. The results show that the NERICA adoption rate could have been 76% instead of the observed 66% sample estimate in 2010 provided that every rice farmer had been aware of NERICA's existence before the 2010 rice growing season. However, further investigation finds that if all the rice farmers had been aware of and had access to NERICA seeds, adoption would have been 92%. This reveals that if awareness had not been a constraint, 16% of farmers would have failed to adopt NERICA due to lack of access to seeds. Farmer contact with extension services and access to in-kind credit are significant determinants of access to and adoption of NERICA varieties.

Key words: Average treatment effect, potential adoption, access to seeds, NERICA, The Gambia

JEL: C13, O33, Q12, Q16

3.1 Introduction

Rice is increasing becoming a critical staple for many countries in sub-Saharan Africa. In The Gambia, the demand for rice is far beyond its local production level. Per capita consumption of rice is estimated to be 117kg per annum, which is one of the highest in sub-Saharan Africa (Planning Service Unit, 2011). Of the 195,811 metric tons of rice consumed in 2011, only 51,137 metric tons were produced locally (Gambia Agricultural Census, 2012). The huge deficit was met through imports from Asia. In 2000, $10.9 million USD was spent on importing 93,900 metric tons of rice, which increased to $28.97 million USD in 2009, to import 126,625 metric tons of rice (Planning Service Unit, 2011). This is a cause for concern for national food security and macroeconomic stability. As a result, the government is committed to a policy of attaining rice self-sufficiency to significantly reduce rice imports. To realize this objective, efforts to bridge the gap between local rice production and demand will require a higher level of adoption of high yielding improved rice varieties and practices than presently observed (World Bank, 2007).

In an attempt to combat the problem, the New Rice for Africa (NERICA) was officially introduced into The Gambia in 2003. This rice variety is the result of crosses between the Asian rice (*O. sativa*) and the African rice (*O. glaberrima*). It combines desirable traits from both parents such as high yields, shorter duration, good taste, absence of lodging, high fertilizer returns, and greater resistance to major stresses as compared to the traditional varieties (Jones et al. 1997a and 1997b; Audebert et al., 1998; Johnson et al., 1999; Wopereis et al., 2008). The first set of NERICA introduced in The Gambia consists of upland rice varieties. Since the introduction of NERICA, several initiatives have been taken by the government to widely disseminate it to rice farmers in order to significantly increase its adoption rate. These initiatives includes: the *Back to the Land Call*[5] by the president, Participatory Varietal Selection (PVS)[6], and a NERICA seed multiplication project[7]. To substantiate these efforts,

[5] The *Back to the Land Call* is a massive political campaign that mainly encourages farmers to cultivate rice, which is the main staple crop of the country. In response to the call, 26752 hectares of communal land have been cultivated by farmers to NERICA across the country (Gambia Agricultural Census (2012).

[6] PVS trials involve the selection of the most promising NERICA by rice farmers, which is disseminated to other villages through farmer to farmer contacts, extension and research.

[7] The NERICA dissemination project assisted in the multiplication of the best NERICA selected by farmers through PVS trials.

there is an urgent need to consistently estimate the potential NERICA adoption rate to inform on the intrinsic merits of the desirability of the technology by the target population. Such information will assist policy makers to decide whether or not to intensify efforts to disseminate NERICA across the country.

Many studies determine the adoption rates of new technologies by simply computing the percentage of farmers using that technology (e.g., Saka et al., 2005, Namwata et al., 2010, Khalil et al., 2013). This approach leads to bias and inconsistent estimate of population adoption rate (Diagne and Demont, 2007). The results are biased because farmers who are not aware of the new technology cannot adopt it even if they might have done so provided they had known about the technology. As a result, studies that do not account for technology awareness underestimate the adoption rate of technologies that are not universally known in the population. To solve this problem, one may think that a better estimate could result from taking the adoption rate within the subpopulation of farmers who are aware of the technology. However, because of positive selection bias, such an approach is likely to overestimate the true population adoption rate (Diagne, 2006). In addressing these problems, Diagne and Demont (2007) used the Average Treatment Effect (ATE) framework to provide consistent estimate of the population adoption[8] rate of the NERICA that would be realized in Cote d'Ivoire when awareness is complete in the population. However, since awareness is not a sufficient condition for adoption, Diagne (2010), notes that such outcome would still underestimate the true population adoption rate if access to the NERICA seeds is incomplete in the population. Similarly, Kabunga et. al., (2012) note that awareness is not a sufficient condition for adoption to reach its full potential. They argue that farmers should be aware of and know the attributes of a particular technology to assess the population adoption rate. As a result, they extend the work by Diagne and Demont (2007) to account for knowledge of technology attributes in the adoption process. However, knowledge of technology attributes is not a prerequisite for its adoption. For adoption to occur, farmers must be aware of and have access to the technology. Hence, both awareness and access are important prerequisites for technology adoption. This fact has recently been highlighted by Dontsop et. al.,

[8] Adoption is defined, in this paper, to mean the use of the NERICA technology at the individual level. A farmer is NERICA adopter if he or she cultivated at least one NERICA variety during the 2010 rice production season.

(2013), who estimated the potential adoption rate of NERICA in Nigeria by controlling for awareness and access to NERICA.

To account for the importance of technology access in the adoption process, this study extends the works of Diagne (2010) and Dibba et. al. (2012) to determine the adoption rate of NERICA that would be realized in The Gambia when both awareness and access are complete in the population. It reveals that the current adoption rate of NERICA could be increased by 10% if steps are taken to ensure that the entire rice farming population is aware of the existence NERICA. However, a further investigation finds that if all the rice farmers had been aware of and had access to the NERICA seeds, the current adoption rate could have been increased by 26%. This shows a significant adoption gap of 16 percentage points that can be attributed to lack of access to sufficient supply of NERICA seeds.

The paper is organized as follows. Section 2 provides a brief explanation of the main concepts used in this paper and also highlights the hypothesized determinants of adoption. Section 3 presents the sample selection procedure and data. Section 4 presents the Average Treatment Estimation procedures used to consistently estimate the NERICA population adoption rate and its determinants. Section 5 presents the estimates of the NERICA adoption rate and the factors affecting it; and Section 6 concludes with a summary of the main empirical findings and their policy implications.

3.2 Conceptual framework

3.2.1 Technology awareness and access

In the adoption literature, the concept of agricultural technology adoption has been defined as the use or non use of a technology by a farmer at a given point in time (Rodgers, 1983). Studies by Rogers and Shoemaker (1971) and Rogers (1983) describe the technology adoption process as a mental process that begins with the first knowledge of a new technology and ends with the decision to adopt or reject it. Therefore, knowledge and technology awareness are crucial components of the adoption process. This fact is more pronounced by Diagne and Demont (2007) who show that technology awareness is a prerequisite for its adoption. Certainly, a farmer must be aware of the existence of a new technology before he or she can use it. The term awareness is used in this paper to mean the mere knowledge of the existence of the NERICA technology and does not necessarily imply learning of its characteristics. When awareness is complete in a population, another important factor that can limit adoption is access: even if a farmer is aware of a particular technology, he or she cannot adopt it unless the technology is accessible. Thus, technology access[9] is defined in this paper to mean the availability of NERICA seeds within the reach of farmers who are aware of the NERICA technology. In this study, a farmer has access to NERICA seeds if he or she is aware of the existence of NERICA and if NERICA seeds can be obtained within or outside his or her village.

3.2.2 Actual and potential adoption

Many studies assume that technology awareness and access are complete in a given population. For this reason, such studies only inform about actual or observed adoption of a technology rather than the desirability of a technology by the underlying population under incomplete awareness and access. Hence, actual adoption is defined in this paper as the observed sample adoption rate, which include the adoption outcome of farmers who are not aware of and have no access to the NERICA technology. This is different from the adoption rate that would be realized if the entire population is aware of and has access to the NERICA seeds, which is defined in this study as the potential adoption of the NERICA technology. The difference between actual and potential adoption is defined in this paper as the adoption gap, which the study estimates by extending the ATE framework used by Diagne and Demont (2007) to appropriately control for both awareness and access in order to determine the adoption gap that can be attributed to lack of access to NERICA seeds.

3.2.3 Hypothesized determinants of adoption

There is extensive literature on the economic theory of adoption. Several factors have been found to influence decisions to adopt agricultural technologies. Traditionally, economic analyses of the adoption of agricultural technologies has focused on

[9] For simplicity, this study rules out all cases in which a farmer may unknowingly adopt or have access to the NERICA seeds without being aware of its existence. This is a necessary assumption because such data cannot be obtained.

imperfect information, infrastructure, uncertainty, human capital, input availability, institutional constraints, social capital, and risk as factors that explain adoption decisions of farmers (Feder et al., 1985; Foster and Rosenzweig, 1995). Due to data limitation, this study focuses on education, information, farm size, age, and technology cost as the most important factors influencing adoption of the NERICA. These factors are discussed in more detail below.

Education has been found by many adoption studies to significantly influence a farmer's adoption decision (Rogers, 1983; Feder and Slade, 1984; Tjornhorm, 1995). Rogers (1983) notes that the complexity of a technology often poses a negative effect on adoption and that education is thought to reduce the amount of complexity perceived for a given technology, thereby increasing the likelihood of adoption. The expected effect of education on NERICA adoption is thus positive.

Caswell et al., (2001), highlights the importance of information in the technology adoption process, finding that more information about a technology reduces uncertainty about its performance. This can change an individual's view of a technology over time from purely subjective to objective. Feder and Slate (1984) also find that more information enhances adoption particularly if a technology is profitable. The hypothesized effect of information acquisition on NERICA adoption, especially through contact with extension services, is positive.

Farm size has been identified by many adoption studies as one of the most important factors influencing adoption decisions (Boahene, Snijders and Folmer, 1999; Doss and Morris, 2001; and Daku, 2002). Feder, Just, and Zilberman, (1985) note that if a technology requires a large amount of initial costs, only farmers with large farms will risk adopting the technology. Feder et. al., (1985) also make a distinction between divisible and indivisible technologies. They note that for divisible technologies, like NERICA, the adoption decision is determined by area allocation and the level of usage. This increases the likelihood of adoption among small holder farmers.

Age is also found to be an important determinant of technology adoption. Rogers (1983) finds that the majority of early adopters are expected to be younger, more educated, venturesome, and willing to take risks. For this reason, age is hypothesized to negatively affect the adoption decision of technologies by farmers during the early stages of adoption. We, however, do not have data on individual risk preferences so we are unable to include risk aversion as a potential factor influencing adoption.

The cost of a technology is another important factor that can influence adoption. El Oster and Morehart (1999) indicate that technologies that are capital-intensive are only affordable by wealthier farmers, limiting their adoption to the more affluent group of the farming population. The fact that NERICA seeds are more expensive than other rice variety seeds, may limit their adoption to wealthier farmers. We hypothesized that farm size, a proxy for wealth, will positively affect farmers' decision to adopt the NERICA.

3.3. Sampling procedure and data

The study obtained a country-wide panel data in 2010 from rice growing villages and farmers who were initially sampled in 2006. The villages were selected through a multi-stage stratified random sampling procedure. In the first stage, villages were stratified into two strata across the six agricultural regions of the country: 1) villages where NERICA was disseminated (hereafter, NERICA villages) and 2) villages where NERICA was not disseminated (hereafter, non-NERICA villages). With the exception of the West Coast Region[10], five NERICA and five non-NERICA villages were randomly selected from each stratum for a total sample size of 70 rice growing villages. NERICA villages were first identified in each agricultural region, followed by a random selection of non-NERICA villages within a radius of 5-10 kilometers.

During the second stage, a list of all rice growing households in each selected village was obtained through interviews with key informants. Ten of these rice growing households were randomly selected from each village, resulting in a total sample size of 600. This sample sampling procedure was undertaken in 2006. Due to migration and other circumstances beyond the control of the survey team in 2010, the sample size was reduced to 515. However, this did not result in any serious systematic attrition bias. About 10-15 rice farmers were dropped from each of the agricultural regions selected for the survey. As a results, there was no region that had a

[10] The survey included ten NERICA and non-NERICA villages in West Coast Region. However, the sample size in each village was limited to only five households because 100 households were targeted in each agricultural region. For this reason, more households per village were selected in regions with fewer villages and vice versa.

significantly higher attrition rate than the others. Moreover, data were obtained on all cases for the variables used to compare the survey results from 2006 and 2010. This provides a balanced panel data for the study.

The 2010 survey team interviewed the person most knowledgeable and responsible for rice production in the household, about cropping systems, resource management, farm operations, post-harvest activities, cooking and organoleptic characteristics of rice varieties grown, and socio-economic and demographic characteristics including income and expenditure data. The following section explains the empirical framework for how adoption of NERICA is analyzed.

3.4. Empirical framework

3.4.1 Sample adoption rate

To address biases resulting from non-exposure and poor access, a better estimate is to take the sample estimate within the sub-population of farmers who are exposed to the NERICA technology or those who have access to it as the true estimate of the population adoption rate. However, due to positive selection bias, the sample estimate within the sub-population of farmers who are exposed to the NERICA technology or those who have access to it is likely to overestimate the true population adoption rate. Positive selection bias arises from two sources. First, farmers self select into exposure or access to the NERICA technology, reflecting the fact that farmers who are constantly searching for better technologies are likely to be exposed to or have access to them. Second, some progressive farmers and communities are targeted by research and extension. It is likely that the farmers and communities targeted for exposure of or access to NERICA seeds are precisely those who are more likely to adopt NERICA. Hence, the adoption rate in the targeted subpopulation is likely to overestimate the true population adoption rate (Diagne, 2006). For this reason, the sample adoption rate within the sub-population of farmers who are exposed to or have access to the NERICA technology is likely to be a biased estimate of the true population adoption rate.

3.4.2 Potential outcome framework and evaluation problem

Following Diagne and Demont (2007), this study uses the potential outcome framework to assess the effect of exposure of and access to NERICA seeds on the adoption of NERICA. Under this framework, treatments refer to exposure[11] and access to NERICA seeds by which every farmer has two potential outcomes for each treatment. With exposure as the treatment variable, every farmer has an outcome denoted as y_{1w} when exposed to NERICA and y_{0w} otherwise. Exposure is donated by w, whereby $w=1$ is exposure and $w=0$ otherwise. Thus, the observed outcome can be written as a function of the two potential outcomes:

$$y_w = wy_{1w} + (1-w)y_{0w} \tag{3.1}$$

For any observational unit, the causal effect of NERICA exposure on its observed outcome is simply the difference of its two potential outcomes: $y_{1w} - y_{0w}$. However, since exposure is a necessary condition for adoption, we have $y_{0w} = 0$ for any farmer whether he or she is exposed to NERICA or not. For this reason, equation (3.1) can be simplified as follows:

$$y_w = wy_{1w} = y_{1w} \tag{3.2}$$

Hence, the adoption impact for farmer i is given by y_{i1w} and the average impact is given by $E(y_{1w})$, which is the population Average Treatment Effect of exposure on NERICA adoption (ATE_w):

$$ATE_w = E(y_{1w}) \tag{3.3}$$

[11] In this study, the word "exposure" means awareness of the existence of the NERICA.

The average treatment effect for the subpopulations of farmers aware $(ATE1_w)$ and unaware $(ATE0_w)$ of the NERICA can also be identified and estimated. They can be identified as follows:

$$ATE1_w = E(y_{1w} | w = 1) \tag{3.4}$$

$$ATE0_w = E(y_{1w} | w = 0) \tag{3.5}$$

Equation (3.3) is a measure of the adoption rate that would be realized if the entire rice farming population had been aware of the NERICA technology. However, since adoption cannot take place unless there is access to NERICA seeds, this study extends the work of previous studies (Diagne and Demont, 2007; Diagne 2010; Dibba et. al., 2012) to determine the adoption rate that would be realized if every rice farmer is aware of and has access to NERICA seeds. This is estimated with the use of an "access to seeds" as a second treatment variable. To create "access to seed" variable, farmers who knew about NERICA were asked whether they could obtain NERICA seeds within or outside their villages. A farmer who responded "yes" to this question is identified as having access to NERICA seeds.

Now, let y_{1s} denote the potential outcome when the farmer has access to NERICA seeds and y_{0s} otherwise. Letting s to stand for access to NERICA seeds, whereby $s = s_1 = 1$ represents access to NERICA seeds and $s = s_1 = 0$ otherwise. Thus, the observed outcome can be written as a function of the two potential outcomes:

$$y_s = sy_{1s} + (1 - s)y_{0s} \tag{3.6}$$

Since having access to seeds implies awareness, equation (3.6) can be modified as follows:

$$y_s = s_1 w y_{1s} + (1 - s_1 w) y_{0s} \tag{3.7}$$

However, since access to NERICA seeds is a prerequisite for adoption, $y_{0s} = 0$ for any farmer whether or not that farmer has access to NERICA seeds. Hence, the adoption impact of accessing NERICA seeds for a farmer i is given by y_{i1s} and the average treatment effect of access to NERICA seeds on adoption (ATE_s) for the entire population is given by:

$$ATE_s = E(y_{1s}) \tag{3.8}$$

The average treatment effect of access to NERICA seeds on adoption for the subpopulation of farmers with $(ATE1_s)$ and without $(ATE0_s)$ access to seeds can also be identified as follows:

$$ATE1_s = E(y_{1s} | s = 1) \tag{3.9}$$

$$ATE0_s = E(y_{1s} | s = 0) \tag{3.10}$$

Unfortunately, the values of y_{1w} and y_{1s} in equation (3.3) and (3.8) are observed only for farmers who have been exposed to and have had access to NERICA seeds, respectively. Hence, we cannot estimate the expected value of y_{1w} and y_{1s} by the sample average of a randomly drawn sample since some of y_{1w} and y_{1s} in the sample would be missing. This missing data problem makes it impossible to measure the effect of exposure or access to NERICA seeds on the observed outcomes without further assumptions. Section 4.4 provides a detailed explanation of the assumptions required to estimate the NERICA population adoption rate.

3.4.3 Population adoption gaps and selection bias

Under incomplete awareness and access of a technology, the observed adoption rate, which is defined as joint access and adoption (JAA)[12], could be significantly different from the population potential adoption rate. As a result, different population adoption

[12] Joint Exposure and Adoption (JEA) and Joint Awareness Access and Adoption (JEAA) in previous studies (Dibba et. al., 2012; Dontsop et. al., 2013) are simplified in this study to Joint Access and Adoption (JAA). This is necessary because technology access implies awareness. Hence, JEA for the exposure model is equivalent to JAA in the access model.

gaps (GAP) can be identified that may be attributed to a lack of awareness of and/or lack of access to seeds. In this study, we identify the following adoption gaps:

$$GAP_w = E(y) - E(y_w) = JAA - ATE_w \tag{3.11}$$

$$GAP_{ws} = E(y) - E(y_s) = JAA - ATE_s \tag{3.12}$$

$$GAP_s = ATE_w - ATE_s = GAP_w - GAP_{ws} \tag{3.13}$$

Equation (3.11) is the adoption gap that can be attributed to lack of awareness, equation (3.12) is the gap that can be attributed to both a lack of awareness of and access to seeds, and equation (3.13) is the adoption gap that can be attributed to a lack of access to NERICA seeds.

Besides the identification of the population adoption gap, it is also important to determine whether the subpopulation of farmers who are aware of or those who have access to NERICA seeds have the same probability of adopting NERICA as compared to farmers who are not aware of or those who do not have access to NERICA. To determine this probability, it is imperative to identify any form of Population Selection Bias (PSB), which can be defined as follows:

$$PSB_w = ATE1_w - ATE_w = E(y_{1w} \mid w = 1) - E(y_{1w}) \tag{3.14}$$

$$PSB_s = ATE1_s - ATE_s = E(y_{1s} \mid s = 1) - E(y_{1s}) \tag{3.15}$$

Equation (3.14) and (3.15) are the expected population selection bias that would exist if the adoption outcome of the subpopulation of farmers who are aware of NERICA and those who have access to NERICA seeds are wrongly used to represent the true population adoption rate respectively.

3.4.4 ATE estimation of the population adoption rate and its underlying assumptions

3.4.4.1 Assumptions of ATE estimation

To correct for the bias associated with the sample adoption rate and to consistently estimate the potential adoption rate of NERICA, this study applies the ATE approach highlighted by Diagne and Demont (2007). As discussed in the previous section, the ATE approach is based on the potential outcome framework. The main problem associated with this framework is the inability to observe the counterfactual situation. That is, it is impossible to observe the potential adoption outcome of a farmer who is not aware or does not have access to NERICA without further assumptions. Hence, to consistently estimate the potential adoption rate of NERICA, this study relies on the validity of the conditional independence assumption (Rosenbaum and Rubin, 1983).

The conditional independence assumption identifies a set of variables X_i that influence an individual's decision to adopt a particular technology and a vector of covariates Z_i affecting exposure or access to NERICA. Conditional independence is define as:

$$Y_0 \ , Y_1 \ , \coprod D_i \mid X_i \tag{3.16}$$

where $\coprod$ denotes independence. This means that once observable differences between treated[13] and non-treated[14] farmers are controlled for, the outcome of the non-treated farmers would have the same distribution compared to the treated farmers had they not been treated (Rosenbaum and Rubin, 1983). If this assumption holds, the adoption outcome of the treated sub-population can be used to determine the

[13] Treated farmers are those who are exposed to or have access to NERICA seeds
[14] Non -treated farmers are those who are not exposed to or do not have access to NERICA seeds

counterfactual situation of the non-treaded sub-population and vice versa. In addition to the conditional independence assumption, the following assumptions are required for the identification of ATE (Diagne and Demont, 2007):

i) potential adoption is independent from Z_i and conditional on X_i: $P(y_1 = 1|X, Z) = P(y_1 = 1|X)$.

ii) exposure or access is independent from X_i and conditional on Z_i: $P(w_1 = 1|X, Z) = P(w_1 = 1|Z)$.

iii) overlap for all values of the covariates between the treated and non-treated groups: $0 < \Pr(D = 1|Z) < 1$.

Assumption i) implies that the variables in Z_i, but not those in X_i must only have an indirect effect on adoption through the treatment variables (awareness and access). Assumption ii) holds by the fact that the variables in X_i are also found in Z_i. The variables to be included in X_i and Z_i should be pre-treatment variables, which can all be endogenous (see Diagne and Demont 2007).

3.4.4.2 Parametric estimation of ATE

This study relies on the validity of the conditional independence assumption to consistently estimate the population potential adoption rate of NERICA and its determinants using the ATE parametric approach. The approach uses observation from only the treated subpopulations to estimate the population adoption rate with the use of a parametric model, which can be specified as follows (see Diagne and Demont, 2007):

$$ATE(x) = E(y|x, d = 1) = (g, \beta) \qquad (3.17)$$

where d is the treatment[15] status and g is a non-linear function with covariates x and the unknown parameter β which can be estimated using either Maximum Likelihood Estimation (MLE) or standard Least Squares (LS) approach using data

[15] When awareness is the treatment variable $d = w$ and when access to seeds is the treatment variable $d = s$ in equation (17)

(y_i, x_i) from the sub-samples of exposed or seed accessed households only, with x the vector of explanatory variables and y as the dependent variable. When the parameters $\hat{\beta}$ of interest are estimated, the predicted values are calculated for all the units of observations i in the sample (including the observations in the non-aware and non-seed accessed sub-samples). The ATE is calculated by taking the average, across the full sample, of the predicted $g(x_i, \beta) i = 1,...,n$ outcomes and respective subsamples for ATE1 and ATE0:

$$A\hat{T}E = \frac{1}{n}\sum_{i=1}^{n} g(x_i, \hat{\beta}) \tag{3.18}$$

$$A\hat{T}E1 = \frac{1}{n_1}\sum_{i=1}^{n} d_i g(x_i, \hat{\beta}) \tag{3.19}$$

$$A\hat{T}E0 = \frac{1}{n - n_1}\sum_{i=1}^{n} (1 - d_i) g(x_i, \hat{\beta}) \tag{3.20}$$

where n is the total sample size and n_1 is the number of treated farmers. The average treatment estimates (ATE, ATE1 and ATE0), the population adoption gaps (GAP_w , GAP_{ws}, and GAP_s), and the population selection bias (PSB_w and PSB_s) were all estimated in Stata with a new *adoption* command for estimating technology adoption rate developed by Diagne and Demont (2007).

3.5. Results and discussion

3.5.1 Socio-demographic characteristics of farmers

Table 3.1 compares 2006 survey results with those from 2010. With the exception of practice of lowland rice farming and farmer contact with the Department of Agriculture (DAS), there has been a significant increase in NERICA exposure and adoption rates, practice of upland rice farming, and farmer contact with the National Agricultural Research Institute (NARI) between the 2006 and 2010 surveys.

Table 3.1: Comparing 2006 and 2010 survey results on NERICA adoption and farming in The Gambia

Variable	**2006 (N=515)**	**2010 (N=515)**	**Difference (T-test)**
Exposure to NERICA	0.47 (0.02)	0.88 (0.01)	0.41 (0.02)***
Adoption within the NERICA exposed subpopulation	0.85 (0.03)	0.77 (0.03)	-0.08 (0.03)***
NERICA sample adoption	0.40 (0.02)	0.66 (0.02)	0.26 (0.03)***
Practice of upland rice production	0.53 (0.02)	0.78 (0.02)	0.25 (0.03)***
Practice of lowland rice production	0.80 (0.02)	0.43 (0.02)	- 0.36 (0.03)***
Farmer contact with the NARI	0.05 (0.01)	0.21 (0.02)	0.16 (0.02)***
Farmer contact with the DAS	0.31(0.02)	0.32 (0.02)	0.01(0.03)

NB: T-tests were used to test the difference between the 2006 and 2010 survey results. We used the mean value of each dummy to test the mean difference using the T-test. NARI is the National Agricultural Research Institute; DAS is the Department of Agricultural Services; Robust standard errors are shown in parenthesis; ***Indicates that the difference is statistically significant at the 1% level

Source: AfricaRice/NARI, Gambia Post Impact Assessment survey 2006/2010

The percentage of farmers exposed to NERICA increased from 47% in 2006 to 88% in 2010, showing a significant difference of 41%. This may explain the significant increase (26%) in the adoption of NERICA prior to the 2010 survey (Table 3.1). The increase in the exposure rate was made possible through collaborative efforts between research and extension to disseminate NERICA to all the agricultural regions of The Gambia. As more rice farmers became aware of NERICA, the expected adoption rate increased accordingly.

The negative and positive change in the practice of lowland and upland rice farming, respectively, is not surprising. The NERICA disseminated thus far in The Gambia is upland rice. Therefore, we would expect upland farming to increase with the adoption of NERICA. The fact that NERICA fetches a higher price in the local markets compared to other rice varieties, could have made its production more attractive to rice farmers. As a result, many farmers increase their upland rice production. Furthermore, the dissemination of NERICA to farmers through research and extension outlets has resulted in increased farmer contact with the NARI. This increase could be attributed to the fact that NERICA seed dissemination activities are coordinated by the NARI. However, the insignificant change in farmer contact with the DAS from the 2006 to the 2010 survey could be explained by the fact that after the initial acquisition of NERICA seeds from extension agents, many other farmers may have acquired seeds through other farmers instead of through the DAS.

3.5.2 Actual and potential adoption rates

Actual and potential adoption rates of NERICA are shown in Table 3.2 and Table 3.3, respectively. Within the agricultural regions, the lowest sample exposure rate is in the Central River South (CRS) (62%) and the highest is in the North Bank Region (NBD) (100%) and West Coast Region (99%). In the other regions, the sample exposure rate ranges from 86% to 95%. Among exposed farmers, access to seeds, a necessary condition for adoption, is very low in the CRS (38%) and relatively low in the Upper River Region (URR) (68%) and Central River Region (CRN) (71%).

Table 3.2: Actual adoption of NERICA

Description	Regions						Total
	WCR	LRR	CRS	NBR	CRN	URR	
Total number of farmers	89	85	89	92	78	82	515
Farmers exposed to NERICA in 2010 (%)	99	95	62	100	86	89	88
Exposed farmers who had access to NERICA seeds in 2010 (%)	84	93	38	80	71	68	72
Farmers who adopted NERICA (%)							
2008	54	69	20	67	31	56	50
2009	65	79	29	67	59	72	61
2010	76	88	35	72	62	65	66

Source: AfricaRice/NARI, Gambia Post Impact Assessment survey 2006/2010
Notes: WCR = Western Coast Region, LRR=Lower River Region, CRS = Central River South, NBR = North Bank Region, CRN = Central River North, and URR = Upper River Region.

The relatively low sample exposure rate and access to NERICA seeds in the CRS and CRN may be because some rice growing villages in these regions are located along a river, which restricts some farmers to adopt only lowland[16] tidal irrigated rice varieties instead of NERICA, which is an upland rice variety. For this reason, one would expect that the exposure rate and access to NERICA would be lower in these regions. The high exposure rate and access to NERICA seeds in other regions, especially the

[16] The villages selected along the river also have upland rice fields where farmers cultivate NERICA. Selecting only upland farmers in such villages would have created a positive selection bias that could have seriously overestimated the true adoption rate of the NERICA. This would have been the case because NERICA is the only upland rice variety cultivated in most of the villages located along the river Gambia.

WCR and NBR, may be because NERICA was first introduced in these regions through PVS in 1998. These regions have, therefore, had a longer exposure time compared to others where NERICA was introduced several years later, between 2005 and 2010.

The actual or sample adoption rate is estimated to be 50% in 2008, 61% in 2009, and 66% in 2010. The agricultural region with the highest adoption rate is the Lower River Region (LRR) (69% in 2008, 79% in 2009 and 88% in 2010) and region with the lowest adoption rate is the CRS (20% in 2008, 29% in 2009 and 35% in 2010). With the exception of CRN, the sample adoption rate is above 50% in all the other regions (shown in Table 3.2). Since the sample estimate is likely to underestimate the true population adoption rate due to biases resulting from non-exposure and inaccessibility to NERICA, it is important to control for such biases in order to assess the full potential adoption rate of NERICA in The Gambia.

The results of the potential NERICA adoption rate with ATE correction for non-exposure, non-access to seeds and selection biases are presented in Table 3.3. The ATE exposure model shows that if every rice farmer in The Gambia had been aware of the existence of NERICA prior to the 2010 survey, the adoption rate would have been 76% instead of 66%. This shows an adoption gap of 10 percentage points, which could be attributed to a lack of awareness. However, since awareness is a necessary, but not a sufficient condition for adoption, we should identify what the potential or population adoption rate would have been if every rice farmer had been aware of the existence of the NERICA and had had access to it. This is examined in the ATE access to seeds model.

Table 3.3: ATE parametric estimation of potential adoption rate

	ATE exposure model		**ATE access to seeds model**	
Population adoption rate	**ATE_W**	0.76 (0.29)***	**ATE_S**	0.92 (0.09)***
Adoption rate within treated farmers	**$ATE1_W$**	0.76 (0.34)**	**ATE_S**	0.92 (0.11)***
Adoption rate within non-treated farmers	**$ATE0_W$**	0.73 (0.11)***	**ATE_S**	0.89 (0.05)***
Sample adoption rate	**JEA**	0.66 (0.28)***	**JAA**	0.66 (0.08)***
Adoption gap	**GAP_W**	-0.10 (0.02)***	**GAP_{WS}**	-0.26 (0.01)***
Population selection bias	**PSB_W**	0.01	**PSB_S**	-0.01

	(0.05)	(0.03)

Source: AfricaRice/NARI, Gambia Post Impact Assessment survey 2006/2010;
Notes: ** *P*<0.05; and *** *P*<0.01. Robust standard errors are shown in parenthesis.

The ATE access to seeds model shows that if every rice farmer in The Gambia had been aware of the existence of NERICA and had had access to NERICA seeds prior to the 2010 survey, the adoption rate would have been 92% rather than 66%. This shows an adoption gap of 26 percentage points, which is statistically different from zero at the 1% significant level. In addition, when the ATE access to seeds model estimate is compared with the ATE exposure model estimate, the results show an adoption gap of 16 percentage points, which arises due to lack of access to NERICA seeds.

The actual adoption rate within the sub-populations of those who had been exposed to $(ATE1_w)$ and those who had had access to NERICA seeds $(ATE1_s)$ are almost exactly the same estimates as the potential adoption rate in the full population. This indicates that there is no significant population selection bias, which means that the sub-samples of farmers who had been exposed to or had had access to NERICA seeds and the farmers who were not exposed to or did not have access to NERICA seeds have the same probability of adopting NERICA. This is confirmed by the results of the expected population selection bias when using effect of factors influencing exposure of, access to, and adoption of NERICA included fifteen explanatory variables. Table (3.4) presents a description of the explanatory variables used in the model with their definitions and summary statistics. The corresponding marginal effects of the variables estimated in the probit model are presented in Table 3.5. The marginal effects indicate that the influencing factors significant at 5% significance level are: age squared, off-farm labor, gender, farmer contact the within NERICA-exposed or seed access sub-sample, which is not statistically different from zero.

3.5.3 Determinants of access, exposure, and adoption of NERICA

This subsection explores factors influencing exposure of, access to, and adoption of NERICA seeds. The probit model used to estimate the with extension services, practice of upland rice farming, access to credit, and residence in West Coast Region (WCR). Off-farm labor and gender reduce the probability of exposure to NERICA by 51% and 7% respectively, whereas, farmer contact with extension, practice of upland rice farming, and residing in WCR increase the probability of exposure to NERICA by 6%, 39%, and 10%, respectively. Moreover, farmer contact with extension and practice of upland rice farming increase the probability of accessing NERICA seeds by 17% and 26%, respectively. Furthermore, access to credit and farmer contact with extension increase the probability of adopting NERICA by 14% and 12% respectively. These results are explained in more details below.

Farmer contact with extension has a significant influence on exposure of, access to, and adoption of NERICA seeds. This is not surprising given that NERICA is disseminated to farmers through extension outlets. Hence, it is expected that farmers who have contact with extension agents should know, access, and adopt NERICA. Moreover, the finding is consistent with the previous adoption literature and theories discussed in Section 3.2, namely that farmer contact with extension is a major source of information and influential in the adoption process.

Access to credit[17] significantly influences NERICA adoption. The NERICA seeds were initially given to farmers by extension agents through in-kind credit, which is repaid at the end of the production season. Since access to seeds is a prerequisite for adoption, we would expect it to significantly influence farmers' decision to adopt NERICA. As discussed in the theoretical section, the cost of a new technology is one of the most important factors limiting its adoption. For this reason, it is important for farmers to access in-kind credit services to cover the cost of production. This further explains the significance of credit access in influencing the decision to adopt NERICA.

[17] Access to credit in this study simply refers to credit received in-kind. Since NERICA seeds are more expensive than other rice varieties most farmers can only afford it when it is given to them as credit in-kind, which is repaid after harvest. Hence, we measured the variable as a dummy. If a farmer received NERICA seeds on credit, it is indicated as 1 and 0 otherwise.

Table 3.4: Definition and summary statistics of the explanatory variables used in the probit model

Variable	Definition	Min	Max	Mean	Std. Deviation
Age	Age of the respondent	20	90	49.95	13.97
Age squared	Respondent's age squared	400	8100	2689	1489
Experience with upland farming	Respondent's years of experience in upland rice farming	0	29	11.68	10.99
Education (dummy)	1 if the respondent has attained formal education	0	1	0.09	0.28
Household size	Total number of people residing in the household	1	35	9.52	4.18
Off-farm labor (dummy)	1 if respondent has an occupation other than farming	0	1	0.13	0.34
Woman(dummy)	1 if the respondent is female	0	1	0.93	0.25
Association membership (dummy)	1 if the respondent is a member of an association	0	1	0.83	0.38
Log of rice area	Log of the household's total cultivated rice area	16.1	1.09	-1.60	3.33
Extension services (dummy)	1 if the respondent has contact with extension services	0	1	0.32	0.47
Access to in-kind credit (dummy)	1 if the respondent has received rice seeds through in-kind credit	0	1	0.23	0.42
NARI (dummy)	1 if the respondent has contact with the National Agricultural Research Institute	0	1	0.22	0.41
Upland farming (dummy)	1 if the respondent practices upland rice farming	0	1	0.78	0.42
Lowland farming (dummy)	1 if the respondent practices lowland rice farming	0	1	0.43	0.49
WCR (dummy)	1if the household is located in the West Coast Region	0	1	0.17	0.39
NERICA village (dummy)	1 if the household is located in a village where NERICA was disseminated	0	1	0.49	0.50
Number of valid observations		515			

Residing in a NERICA village has a significance influence on access to NERICA seeds. At the initial phase of the NERICA seed dissemination project, only a few NERICA villages were selected as pilot areas for testing NERICA within various agricultural regions. These villages were then able to access NERICA seeds based on in-kind credit services from the project. The seeds provided by the project were initially tested on communal lands. For this reason, farmers living in NERICA villages are more likely to gain access to NERICA seeds. Moreover, the significance of age squared in the probit adoption model suggests a possible non-linear relationship between age and NERICA adoption. The results show that as farmers grow older, their probability of adopting NERICA decreases significantly. This is consistent with adoption theories discussed in Section 3.2, which found that younger farmers are more likely to adopt new technologies.

Table 3.5: Probit model marginal effects of the factors affecting exposure, access to seeds, and adoption

Variables	Exposure		Access to seeds		Adoption	
	Marginal	z-value	Marginal	z-value	Margin	z-value
Age	0.00	1.14	0.00	0.26	0.07	1.80
Age squared	-0.00	-1.39	-0.00	-0.47	-0.00**	-2.02
Experience	0.00	1.15	0.01**	2.11	0.02**	2.00
Education	0.05*	1.77	0.02	0.27	0.37	1.09
Household size	0.01**	2.24	0.01	1.02	-0.02	-1.17
Off-farm labor	-0.52***	-2.72	-0.24*	-1.68	0.26	0.36
Woman	-0.06***	-3.24	0.01	0.09	0.24	0.80
Association	-0.01	-0.31	-0.09	-1.86	-0.29	-1.40
Log of rice area	-0.03**	-2.40	-0.00	-0.80	-0.02	0.70
Extension services	0.06**	2.40	0.17***	4.17	0.52**	2.93
Access to in-kind	-0.00	-0.05	0.11**	2.41	0.50**	2.31
NARI			0.11**	2.48		
Upland farming	0.37***	5.19	0.25***	4.37		
Lowland farming	-0.00	-0.20	0.02	0.39		
WRC	0.09***	4.02	0.08	1.48		
NERICA village	0.02	0.90	0.08**	1.94		
Number of	515		515		515	
Pseudo R^2	0.36		0.14		0.09	
LR chi^2	121.09**		86.07***		32.90*	
Log likelihood	-107.22		-262.15		-165.72	

Source: AfricaRice/NARI, Gambia Post Impact Assessment survey 2006/2010
Notes: *P<0.10, ** P<0.05, and *** P<0.01.

The practice of upland rice farming is a significant determinant of both exposure of and access to NERICA seeds. This is another expected result, because the NERICA varieties introduced to farmers in The Gambia are thus far only upland rice varieties. As a result, we would expect that farmers practicing upland rice cultivation to be more likely to gain knowledge of the existence of NERICA and more likely to have access to NERICA seeds. However, contrary to expectation, the years of experience with upland rice farming is not significant in determining the exposure to NERICA. Most of the rice growing villages that practice upland farming began upland rice farming with the introduction of NERICA. Since most of the farmers had no experience with upland rice cultivation before the introduction of NERICA, it should be understandable why the number of years of experience is not significant in determining exposure to NERICA. We also found that farmers from the WCR and those who have had contact with the NARI are more likely to be exposed to or have access to NERICA. This was expected because NERICA seed dissemination activities in The Gambia are coordinated by the NARI and its main station is in the WCR.

Contrary to expectations, farm size and off-farm labor have a negative influence on exposure to NERICA. As discussed in Section 3.2, new technologies come with additional cost, which means that they are more affordable to wealthier farmers. As a result, it was expected that farm size and income from off-farm labor would have a positive influence on exposure to and the adoption of NERICA. However, since most rice farmers practicing off-farm labor are more likely to take up rice farming as a secondary activity, they may be less likely to be aware of the existence of NERICA compared to farmers whose main activity is rice farming.. Moreover, the fact that the majority of rice producers in The Gambia are smallholder farmers may result in the insignificant correlation between farm size and adoption..

The literature on adoption suggest that associations are a main source of information about new technologies for farmers (Feder and Slate, 1984; Caswell et al., 2001). Despite the importance of associations in the adoption process, we found no correlation between association membership and our variables of interest. This is very surprising and contradicts Kijima and Sserunkuuma’s (2013) findings in Uganda. The majority of village associations in The Gambia are informal. Membership is open to all the villagers and there are no rules and regulations on how the associations are governed. Farmers do not meet on regular basis to share information. This could be a reason for the insignificant correlation found in this study. On the other hand, the significant effect of membership in farmers' groups on adoption found in Uganda may be attributed to the fact that farmers' groups are well-organized and membership is not open in Uganda.

Finally, the negative relationship between gender and awareness of NERICA found in the exposure model suggest possible form of gender bias in the way information about the NERICA technology has been disseminated in The Gambia. Upland NERICA is mainly cultivated in farmlands that were originally used by men to grow crash crops like groundnut and cotton. Therefore, most of the resources required for the cultivation of NERICA are under the control of men. As a results, when NERICA was introduced in The Gambia, men began to shift into rice cultivation, which was almost entirely an activity undertaken by women before the introduction of NERICA. Therefore, extension efforts to disseminate NERICA may have been biased against women by targeting men, who owned and controlled most of the resources required for the cultivation of NERICA. This finding is consistent with the observation made by Carney (1998) that there was a shift of resources from women to men with the development of pump-irrigated rice projects in The Gambia. This may have been facilitated by extension services who were responsible for the dissemination of project resources to target groups. Moreover, Diagne (2010) observes that the NERICA lines that were selected for release and seed multiplication in Guinea may have been those that satisfied mostly the varietal preferences of male Guinean rice farmers.

3.6 Conclusions

The sample adoption rate is not a consistent estimate of the population adoption rate when technology awareness and access are incomplete in a given population. Due to non-exposure and access biases, it excludes the adoption rate of non-adopting famers who may have adopted the technology provided that they had known about or had had access to the technology. Hence, the sample adoption rate is likely to underestimate the true population adoption rate. When the bias resulting from a lack of technology awareness is addressed, the results of the framework based on ATE indicate that the NERICA adoption rate could have been 76% instead of the observed 66% sample estimate provided that every rice farmer in The Gambia had been aware of the existence of NERICA varieties before the survey was conducted in 2010. However, given that awareness is not a sufficient condition for adoption, further investigation finds that if all the rice farmers in The Gambia had been aware of and had access to NERICA seeds, adoption would have been 92%. This indicates a population adoption gap of 26 percentage points revealing that if awareness had not been a constraint, 16%

of the farmers would have failed to adopt NERICA due to lack of access to NERICA seeds.

Separate ATE parametric models identified influencing factors of exposure of, access to, and adoption of NERICA. Based on the significant relationship between these outcomes variables and farmer contact with extension, NARI and access to in-kind credit, we conclude that for NERICA to reach its full adoption potential, the important role of extension services cannot be neglected. Hence, concerted efforts should be undertaken to increase farmers' contact with extension, especially in the CRS which has been found to be the region with the least exposure and access to NERICA. To achieve greater adoption, any effort to increase farmer contact with extension should involve NARI, which is also a significant determinant of access to NERICA seeds. Involving NARI will also strengthen collaboration among research, extension, and farmers, which is vital for the successful dissemination and adoption of any agricultural technology. Moreover, the negative correlation between female gender and awareness of NERICA, indicates the need to give women more access to upland resources.

The insignificant population selection bias is a striking finding. The finding contradicts the positive selection bias theory discussed in Section 3.4. However, it is consistent with past findings (Diagne, 2010; Dibba et. al., 2012; Diagne et. al., 2012) on NERICA adoption. The finding means that targeting more villages within rice growing communities of The Gambia is likely to increase NERICA adoption rate. For this reason, more NERICA introduction villages can be created by disseminating seeds to farmer groups. Since farmer access to in-kind credit service is a significant determinant of access to and adoption of NERICA, efforts should be made to enhance farmers' access to credit as this will enhance access to NERICA seeds and the adoption thereof.

The policy implications of the research findings are to improve both awareness of and access to NERICA in order to significantly reduce the adoption gap. This is important given that rice is the main staple crop and thus improvements in its production through the adoption of high yielding rice varieties are necessary for the country to be food secure (World Bank, 2007). Policies directed towards creating awareness will only close the adoption gap by 10 percentage points. This will leave a significant gap of 16% that can be addressed by policy measures to improve access to NERICA seeds throughout the country. Hence, there is a need to improve the capacity of extension services by either increasing the number of extension workers within rice growing communities and/or providing more motorbikes to allow greater mobility for the few extension workers posted in remote villages. Not only will this increase awareness but this will also enable extension workers to redistribute NERICA seeds from high production areas to places with low accessibility. Another major policy implication from this research is to expand in-kind credit services to rice farmers, especially among the rural poor, to enable them gain more access to NERICA seeds. Improving the conditions of roads that link remote villages to rural markets can also enable rice farmers to more easily acquire NERICA seeds.

Finally, as NERICA approches its full potentials adoption rate, the use of binary outcome indicators to measure the potential adoption rate will be less meaningful. The study by Dibba et. al., (2012), estimated a NERICA adoption gap of -43% between the sample adoption rate and the potential adoption rate in The Gambia. Similarly, Dontsop et. al., (2013) finds an adoption gap of -43% between the NERICA sample adoption rate and the potential adoption rate in Nigeria. However, our study reveals a much lower NERICA adoption gap of -26% between the sample adoption rate and the potential adoption rate in The Gambia. This indicates that as more farmers know the existence of NERICA and have access to NERICA seeds, the adoption gap will continue to reduce significantly. As a result, subsequent studies that try to determine the NERICA adoption gap may find an insignificant difference between the actual adoption rate and the potential adoption rate. Hence, a more meaningful measure of adoption would be the determination of the intensity of adoption, measured by the share of land area allocated to NERICA by farmers.

Acknowledgements

The authors are grateful to the Global Rice Science Partnership (GRiSP) program and Africa Rice Center (AfricaRice) for their financial and technical support rendered for the successful implementation of this research project. The technical support provided by the University of Hohenheim is also highly acknowledged.

References

Audebert, A., Dingkuhn, M., Monty, J.P. and Johnson, D.E. 1998. Physiological Mechanisms for Vegetative Vigor of Interspecific Upland Rices - Implications for Weed Competitiveness. Japanese Journal of Crop Science 67(2): 358–59.

Boahene K, Snijders TAB, Folmer H.1999. "An Integrated Socio-Economic Analysis of Innovation Adoption: The case of Hybrid Cocoa in Ghana." Journal of Policy Modelling. 21(2):167-184.

Carney J.A, 1998. Women's land rights in Gambian irrigated rice schemes: Constraints and opportunities. Agriculture and Human Values 15: 325–33

Caswell M, Fuglie K, Ingram C, Jans S and Kascak C. 2001. Adoption of Agricultural production practices: Lessons learned from the US. Department of Agriculture area studies project. Washington DC. US Department of Agriculture. Resource Economics Division, Economic Research service, Agriculture Economic Report No. 792.

Daku L.2002. "Assessing farm-level and aggregate economic impacts of olive integrated pest management programmes in Albania." PhD. Dissertation. Virginia Polytechnic Institute and State University

Diagne, A. 2010. Technological change in smallholder agriculture: Bridging the adoption gap by understanding its source. African Journal Agricultural Resource Economics 5(1): 261–283

Diagne A. 2007. Bred for women rice farmers? Impact of NERICA adoption on rice yield in Côte d'Ivoire', mimeo, WARDA, Cotonou, Benin.

Diagne a and Demont M. 2007. Taking a New look at Empirical Models of Adoption: Average Treatment Effect estimation of Adoption rate and its Determinants. *Agricultural Economics*, Vol 37 (2007). 30p.

Dibba L, Diagne A, Fialor SC and Nimoh F.2012. Diffusion and Adoption of New Rice Varieties for Africa (NERICA) in the Gambia. African Crop Science Journal, Vol. 20, No. 1, pp. 141 – 153

Dontsop P, Diagne A, Okoruwa OV, Ojehomon V and Manyong V. 2013. Estimating the Actual and Potential Adoption Rates and Determinants of NERICA Rice Varieties in Nigeria, Journal of Crop Improvement, 27:5, 561-585, DOI: 10.1080/15427528.2013.811709

El-osta HS and Morehart MJ.1999. "Technology Adoption Decisions in Dairy Production and the Role of Herd Expansion." Agricultural and Resource Economics Review. 28 : 84-95.

Gambia Agricultural Census. 2012: Technical report of the agricultural census of The Gambia Agricultural

Feder G and Slade R. 1984. "The acquisition of information and the adoption of new Technology." American Journal of Agricultural Economics. American Agricultural Economics Association. 66 :312-320.

Feder G, Just RE, and Zilberman D.1985. Adoption of agricultural innovation in developing countries: A survey. Economic Development and Cultural Change, 33: 255-298

Foster AD, and Rosenzweig MR. 1995. Learning by doing and learning from others: Human capital and technical change in agriculture. Journal of Political Economy, 103 (61): 1176-1209.

Jones, M.P., Dingkuhn, M., Aluko, G.K. and Semon, M., 1997a. Interspecific Oryza sativa × O. glaberrima Steud. progenies in upland rice improvement. Euphytica 92:237-246.

Jones, M.P., Dingkuhn, M., Johnson, D.E. and Fagade, S.O. (Eds), 1997b. Interspecific hybridization: Progress and Prospect WARDA, 01 BP 2551, Bouaké, Cote d'Ivoire. pp. 21-29.

Johnson, D.E., Dingkuhn, M. Jones, M.P. and Moussa Mahamane, C. 1998. the influence of rice plant type on the effect of weed competition on oryza sativa and oryza glaberrima. weed research 38(3): 207-216.

Heckman JJ and Vytlacil e. 2005. Structural equations, treatment effects, and econometric policy evaluation. Econometrica, Vol. 73, No. 3, 669–738

Kabunga NS, Dubois T, Qaim M .2012. Heterogeneous information exposure and technology adoption: the case of tissue culture bananas in Kenya. Agricultural Economics 43 (2012) 473–485

Khalil M.I, Haque M.E and Hoque M.Z. 2013. Adoption of BARI Recommended Potato (Solanum tuberosum) Varieties by the Potato Farmers of Bangladesh. A Scientific Journal of Krishi Foundation. The Agriculturists 11(2): 79-86

Kijima Y and Sserunkuuma D. 2013. The adoption of NERICA rice varieties at the initial stage of the diffusion process in Uganda. African Journal of Agricultural and Resource Economics Vol. 8, Issue 1: 45 - 56

Namwata B.M.L, Lwelamira, J and Mzirai, O.B. 2010. Adoption of improved agricultural technologies for Irish potatoes (Solanum tuberosum) among farmers in Mbeya Rural district, Tanzania: A case of Ilungu ward. Journal of Animal & Plant Sciences, 2010. Vol. 8, Issue 1: 927-935.

Planning Service Unit. 2011. Rice fact book. Unpublished technical report

Rogers E.1983. Diffusion of innovations. New York. Free Press

Rogers EM and Floyd Shoemaker F. 1971. Communication of innovation: A cross-cultural approach. Free Press, New York.

Rosenbaum PR and Rubin DR.1983. "The Central Role of the Propensity Score in Observational Studies for Causal Effects," Bometrika 70, 41-55.

Saka, J. O, Okoruwa V.O, Lawal B.O, and Ajijola S. 2005. Adoption of improved rice varieties among smallholder farmers in south-western Nigeria. World Journal Agricultural Sciences 1(1): 42–49.

Tjornhom JD.1995. “Assessment of Policies and Socio-Economic Factors Affecting Pesticide Use in the Philippines.” MS. thesis, Virginia Polytechnic Institute and State University.

Wooldridge JM. 2005. ‘Violating Ignorability of Treatment by Controlling for too many Factors’, Econometric Theory, 21, pp.1026-1028.

World Bank, 2007. World Development Report 2008. Agriculture for Development. Washington, DC

Wopereis, M.C.S., Diagne A, Rodenburg J, Sié M, and Somado E.A. 2008. Why NERICA is a successful innovation for African farmers: A response to Orr et al. from the Africa Rice Centre. Outlook Agric. 37(3): 159–168.

Chapter 4

4. The impact of NERICA adoption on household food security and health in The Gambia

Lamin Dibba, Manfred Zeller, and Aliou Diagne

(submitted to Food Security, April 2015)

Abstract

This paper investigates the impact of NERICA adoption on household food security and health, using country-wide panel data of 515 rice farming households in The Gambia. We use Food Consumption Scores and the number of household sick days per capita as outcome indicators of food security and health, respectively. We use the instrumental variable approach to identify causal effects of NERICA adoption on food security and health. We find significant differences in some key socio-economic and demographic characteristics between NERICA adopters and non-adopters. To control for such differences and allow a causal interpretation of the impact of NERICA adoption, we estimate the Local Average Treatment Effect (LATE). Our analyses indicate that NERICA adoption significantly increases household food availability, access and utilization by 14 percent. However, there is no significant impact of NERICA adoption on health. Our findings indicate that NERICA can play an important role in fighting against food insecurity in The Gambia.

Keywords: counterfactual - food security - health - instrumental variables - NERICA - The Gambia

4.1 Introduction

Rising population growth is increasing demand for food in Africa. The increase in population is more rapid in Africa than in any other part of the world (AFIDEP, 2012). The population of sub-Saharan Africa is estimated as 900 million people, which is projected to grow to 1.2 billion by 2025 and to 2 billion by 2050. By 2100, it is estimated that the population growth rate in sub-Saharan Africa will contribute 77 percent to the increase in global population (AFIDEP, 2012). This rapid increase in population is an impediment to alleviating poverty and achieving food security in sub-Saharan Africa. In The Gambia, the population growth rate is estimated at 3.3 percent per annum with a population density of 176 persons per square kilometre (The Gambia Population Census, 2013). Rice is the major staple food in the country. In 2011, about 195,811 metric tons of rice were consumed in The Gambia, of which only 51,137 metric tons were produced nationally (Gambia Agricultural Census, 2012). In response to the increase in demand, the country has introduced a new policy (called "Back to the Land") which encourages farmers to grow food crops. This policy initiative is a step taken by the government to feed the country's growing population.

In 2003, the New Rice for Africa (NERICA) was officially introduced in The Gambia. This rice variety is a result of crosses between the African rice (O. glaberima) and the Asian rice (O. Sativa). The NERICA combines good traits from both parents, such as high yields, short duration, and absence of lodging (JONES et al., 1997a and 1997b). The initial batch of NERICA introduced in The Gambia is upland rice. Upland NERICA yield is as high as 2.5 tons per hectare under low input conditions and up to 5 tons per hectare under trials at research stations (WARDA 2001). Since the average yield of traditional upland rice varieties is 1 tonne per hectare, NERICA adoption is likely to increase rice production and productivity in The Gambia. Moreover, NERICA varieties have higher protein content and better balanced amino acids as compared to traditional and imported rice varieties (WARDA, 2001; 2008). The extent to which NERICA ensures the achievement of food security and improved health is an open empirical question which this study addresses using country-wide data from rice growing households.

Several studies have been conducted to assess the impact of NERICA adoption on household well-being (Dibba et al., 2012; Dontsop et al., 2011; Adekambi et al., 2009). However, there is very limited or no evidence in the existing literature about the impact of NERICA adoption on household food security and health. This study attempts to close this gap by assessing the impact of NERICA adoption on household food security and health using household food consumption scores and the number of sick days per capita, respectively, as outcome indicators. This study therefore provides methodological and empirical contributions to the literature. The food consumption score is a combination of dietary diversity, food frequency, and relative nutritional importance (World Food Programme, 2008; M. Ruel, 2002). Therefore, this indicator is a measure of food availability, access and utilization. After its creation in Southern Africa, it has been tested and used by the World Food Programme (WFP) in many developing countries to assess the food security status of agricultural households. It has also been methodologically tested and recommended by Wiesmann et al. (2009).

The main challenge arising from impact evaluations of technology adoption on outcome variables of interest pertains to how to appropriately deal with the problem of selection bias and endogenous placement into treatment. Several methods have been proposed in the literature. These methods can be differentiated by the types of assumptions they require to identify causal effects of treatment. There are methods that rely on the validity of conditional independence. These methods are appropriate only when selection into treatment is based on observable factors (Rubin, 1974; Rosenbaum and Rubin, 1983). However, when selection into treatment is based on unobservable factors, another class of estimators is more appropriate, namely Instrumental Variable (IV) estimators (Heckman and Vytlacil, 2005; Abadie, 2003; Imbens and Angrist, 1994). IV estimators are more appropriate when the treatment indicator is a choice variable. Since the decision to adopt NERICA is completely determined by farmers, this study proceeds with the latter to identify casual effects of the impact of NERICA adoption on household food security and health.

This paper is organized as follows: Section 2 presents the survey methodology and data, and the methodology used for computing food consumption scores and the number of sick days per capita; Section 3 presents the econometric framework for the impact analysis; Section 4 gives results obtained from the analysis; and Section 5 concludes with a summary of the main empirical findings and their policy implications.

4.2 Sampling procedure and data

We obtained country-wide panel data in 2010 from households surveyed in 2006. We used a multi-stage stratified random sampling procedure to select villages and households. In the first stage, villages were stratified into NERICA[18] and non-NERICA villages. Five NERICA and non-NERICA villages were randomly selected from each of the six agricultural regions. The NERICA villages were first identified in each region, followed by a random selection of non-NERICA villages within a radius of 5-10 kilometers to maximize similarity with respect to soil, climate, and infrastructure, among other factors, that are likely to influence the performance of NERICA rice compared to other rice. During the second stage of sampling, a list of all rice growing households in the selected villages was obtained through key informant interviews. Ten households were randomly selected from each village for a total sample size of 600. This sampling procedure was undertaken in 2006. In 2010, a follow-up survey was undertaken for in-depth data collection; however, due to migration and other circumstances beyond the control of the survey team, only 515 households were interviewed. Nevertheless, this did not result in any serious systematic attrition bias. Between 10 to 15 households dropped from each of the six regions. A number of statistical tests were performed to find out whether the 85 households who could not be interviewed in 2010 were significantly different with respect to major household characteristics, such as farm size, education, and age of household head, as these variables may influence NERICA adoption and outcomes. There was no significant difference found.

The data were collected using village and household questionnaires. The village questionnaire was administered to obtain a comprehensive list of all the major dishes consumed in the village through focus group discussions. For each dish listed, among other information, the villagers were asked to identify the major ingredients needed for its preparation. This was followed by household interviews. Within selected households, the person most knowledgeable about household food consumption and responsible for the preparation of meals was asked whether the household had consumed each of the dishes listed during the previous seven days and for how many days during that period. The person was also asked to indicate the number of days per

[18] NERICA villages are villages selected by extension agents to distribute NERICA seeds.

week the household consumes each dish before harvest (July-September), during harvest (October-December), after harvest (January-March), and during the lean period (April-June). Moreover, to obtain data on the number of household sick days per capita, each adult household member was asked if he or she had been sick in 2009 and if so, then for how many days. For children under the age of 15, information was provided by their parents.

4.2.1 Food security and health outcome indicators

There are many indicators of food security that have been used to assess household food security. These include: household calorie intake, food frequency scores, individual food intake data, food expenditures, dietary diversity, and indices of household coping strategies (Maxwell and Frankenberger 1992; Hoddinott 1996). Each of these indicators has their strengths and weaknesses. The World Food Programme developed a more robust indicator called the food consumption score, which is a combination of dietary diversity, food frequency, and relative nutritional importance (World Food Programme, 2008). This indicator captures the three cardinal pillars of food security: food availability, food access and food utilization.

This study uses the food consumption score as an indicator of food security. The score is calculated for four different seasonal periods to capture variations in food availability. The periods covered are the production season, harvest period, post-harvest, and lean (low food availability) period in 2009.

The health outcome indicator used in this study is the number of household sick days per capita. To our knowledge, this indicator has not yet been used to assess the impact of agricultural technology adoption on health. The motivation behind using this indicator is to identify the health-related benefits associated with NERICA, using empirical evidence. We consider only short-term illnesses, which improved agricultural technology adoption can impact.

4.2.1.1 Calculation and analysis of the Food Consumption Score

The different food items recorded in each household are grouped into six food groups: cereals and tubers, pulses, vegetables, fruits, meat and fish, and milk. Due to the lack of data on the remaining three food groups proposed by the WFP (2008), sugar, oil, and condiments are not considered. Each food group is given a weight based on the nutrient content of that particular food group (see Table 4.1). The frequencies of food consumption are determined by considering the number of days for which each food group has been consumed in a household during a period of one week. The following equation is used to generate the food consumption score:

$$FCS = \sum_{i=1}^{n} a_i x_i \tag{4.1}$$

where FCS = Food Consumption Score,
n= total number of food groups,
a_i= number of days for which each food group is consumed in a household during a period of one week, and
x_i = weight of each food group.

Table 4.1: Weights given to food groups with their justification

Food groups	Weight	Justification
Cereals and tubers	2	Energy dense and eaten in larger quantities, but contain a lower content of protein compared to legumes.
Pulses	3	Provide high energy and protein, but of lower quality than meat. Provide micro-nutrients and have low fat content.
Vegetables	1	Low in energy, protein, and fat, but provide micro-nutrients.
Fruits	1	Low in energy, protein, and fat, but provide micro-nutrients.
Meat and fish	4	Have high quality protein and easily absorbable micro-nutrients and provide high energy and a considerable amount of fat. Even if eaten in small quantities, they can improve diet substantially.
Milk	4	Provides high quality protein, micro-nutrients, vitamin A, and energy.
Sugar	0.5	Usually eaten in small quantities and therefore provides an insignificant amount of calories.
Oil	0.5	Provides high energy, but has no micro-nutrients and is usually consumed in small quantities.
Condiments	0	Eaten in very small quantities and not considered to have any significant impact on the overall diet.

Source: World Food Programme (2008)

A household that consumes all of the food groups on a daily basis will have a food consumption score of 112, whereas a household that consume none of the food groups will obtain a score of 0. Since we lack data on the consumption of oil and sugar, the maximum score for a particular household in our sample is 105. Households with a food consumption score: less than 21 are categorized as severely food insecure; between 21 and 35 are as having borderline food security; between 35 and 77 as moderately food secure; and above 77 as food secure.

A score less than 21 is used to identify severely food insure households based on the idea that such households are not able to even secure cereals and vegetables on a daily basis. Food secure households are identified as having a food consumption score above 77 based on the intuition that such households can afford all the major food groups on a daily basis (for more details, see World Food Programme (2008).

Both descriptive and econometric analyses are used to examine the data. The descriptive analysis compares the food consumption score between NERICA adopters and non-adopters using tables and graphs, as well as identifies the number and percentages of households in different food consumption score and thus household food security groups. However, since a simple comparison of food consumption scores between NERICA adopters and non-adopters does not allow for inferences regarding causality, the study uses an econometric model to control for differences between NERICA adopters and non-adopters to measure the effect of NERICA adoption on household food security.

4.2.1.2 Calculation and analysis of sick days per capita

This study uses household members' number of sick days per capita as an indicator of the health status of the household. Each adult household member was asked to indicate the type of sickness and number of sick days he or she encountered during the year 2009. If households contained members less than 15 years of age, the caretaker in the household was asked how many days that younger household member had been sick in 2009. For the purpose of this analysis, we consider mainly short-term illnesses such as malaria symptoms, headache, stomach ache, fever and diarrhea. The number of sick days per capita for a particular household is calculated as follows:

$$NSD = \frac{1}{n}\sum_{i=1}^{n} d_i + f_i + h_i + m_i + s_i \qquad (4.2)$$

where $NSD =$ Household's total number of sick days per capita,
n = household size,
d = total days household member was sick with diarrhea in 2009,

f = total days household member was sick with fever in 2009,
h= total days household member was sick with headache in 2009,
m= total days household member was sick with malaria symptoms in 2009,
and
s= total days household member was sick with stomach ache in 2009.

Similar to the food consumption score, data on the number of sick days are analyzed using descriptive statistics and regression methods.

4.3. Theoretical framework

4.3.1 The problem with impact evaluation

The main challenge underlying impact evaluation of agricultural technologies is the problem of identifying counterfactual outcomes. To estimate the impact of technology adoption on household food security and health, ideally we would observe food security and health outcomes indicators of adopters had they not adopted the technology. The impossibility to observe the counterfactual situation leads to a missing data problem well-recognized in impact evaluation studies. To address this problem, one would think it is better to take the outcome indicators of non-adopters as a proxy of counterfactual outcomes. However, as discussed by Imbens and Angrist (1994), Rosenbaum (2001), and Lee (2005), this may lead to bias and endogeneity problems.

There are two types of bias: overt and hidden. Overt bias is the difference in the outcome of interest between the treated and non-treated individuals or households that is not caused by the treatment, but instead is caused by other factors that can be observed. This may occur when treatment and control groups differ in observed[19] characteristics that can influence the outcome of interest, such as experience in rice farming or education. On the other hand, hidden bias is the difference in the outcome of interest between the treated and control groups that is not caused by the treatment, but instead can be attributed to unobserved[20] characteristics. Moreover, endogeneity or non-compliance problems exist in non-experimental research because the unit of observation are individuals who may not stay with their assigned treatments. These

[19] Observed characteristics are factors that have been carefully recorded or measured by the study.
[20] Unobserved characteristics are factors that are not or cannot be observed or measured by the study, such as a family member's attitude toward farming.

problems are the main challenges in all observational or nonrandomized experiments. The following sub-section provides a detailed explanation about how these problems are addressed in studies not using a randomized control treatment design.

4.3.2 Identifying causal effects

This study follows the counterfactual outcome framework postulated by Rubin (1974) to identify the causal effects of NERICA adoption on household food security and health in The Gambia. Under this framework, treatment status d refers to NERICA adoption by which every rice farmer has two potential or counterfactual outcomes, denoted as y_1 and y_0. In the case of NERICA adoption, y_1 refers to the potential food security or health outcome for a particular household when it adopts NERICA, and y_0 otherwise. The causal effect of NERICA adoption for household i is the difference between its two potential outcomes $(y_{1i} - y_{0i})$. An identification problem arises from the fact that the two potential outcomes cannot be observed simultaneously for any particular household. In reality, we can only observe $y = dy_1 + (1-d)y_0$. Since we only observe one of the potential outcomes, we cannot measure the treatment effect $(y_{1i} - y_{0i})$ directly. Instead, we can estimate the average treatment effect (ATE) $E(y_1 - y_0)$ by comparing total food consumption scores or total number of sick days per capita between NERICA adopters and non-adopters. However, such a comparison does not always identify causal effects of treatments.

The following equation shows that comparison between treated and non-treated individuals may result in biased treatment effects if the second term on the right hand side of equation (4.3) is not equal to zero:

$$\begin{aligned} E(y|d=1) - E(y|d=0) &= E(y_1|d=1) - E(y_0|d=0) \\ &= E(y_1 - y_0|d=0) + \{E(y_0|d=1) - E(y_0|d=0)\} \end{aligned} \quad (4.3)$$

If NERICA adopters had the same food consumption scores and number of sick days per capita as non-NERICA adopters before adopting NERICA, then the non-NERICA adopters can be used as an adequate control group. However, such a situation is only likely to occur in randomized experiments. With observational data, such a situation is very unlikely. Hence, estimating the impact of NERICA adoption on household food security and health by taking the mean difference in outcomes between NERICA adopters and non-adopters will lead to selection bias. Selection bias arises because NERICA adopters and non-adopters are selected groups that would have different outcomes, even in the absence of NERICA adoption. The bias might be caused by observable factors or unobservable factors caused by endogenous selection into treatment.

Several methods have been designed to address the problem of selection bias and endogeneity in observational studies to identify causal effects of treatments. The methods can be divided into two broad categories. First, there are methods that rely on the conditional independence assumption (Rubin, 1974, Rosenbaum and Rubin 1983). Such methods are designed to remove overt bias only. These methods propose a set of independent variables, x, which, when included in a regression model, make the treatment variable , d, independent of the potential outcomes y_1 and y_0. The regression approaches based on two-stage estimation procedure are good example of methods that rely on the conditional independence assumption. The other category is the IV approach, which rely on the availability of at least one variable z called an instrument that determines the treatment status, but has no direct effect on the potential outcomes y_1 and y_0 once effects of other independent variables are controlled for. This approach uses valid instruments to control for both overt and hidden biases and also deals with endogeneity problems in observational studies. The choice of method or approach highly depends on the type of treatment. For exogenous treatment, conditional independence is sufficient to identify treatment effects. However, when treatment is endogenous, as is the case of NERICA adoption where farmers self-select into adoption if they are exposed to NERICA, the IV approach is a more appropriate method to identify causal effects. Under such circumstance, one cannot assume conditional independence and therefore hidden bias must be addressed to identify treatment effects. In such cases, the IV approach is more appropriate to identify causal effects (Imbens and Angrist 1994; Heckman and Robb 1985).

4.3.3 The Instrumental Variable approach

For an instrument to be valid, it must have a causal effect on the endogenous treatment variable but no direct effect on the outcome variable except through the treatment variable. For these reasons, this study adopts awareness to NERICA as an instrumental variable. Past studies on NERICA adoption found awareness to be a natural instrument (Diagne, 2006; Dibba et al. 2012).. This happens because no rice farmer can adopt NERICA without being aware of it and the mere awareness about NERICA does not affect rice yields except through adoption.. For these reasons, the two requirements for the awareness variable to be a valid instrument are met.

Let d_z represent potential adoption outcomes given a binary instrument z taking the value 1 when a farmer is exposed to NERICA and 0 otherwise. Hence, $d_1 = 1$ and $d_0 = 0$ means a particular household will adopt NERICA if exposed, but would not adopt otherwise. In this case, the observed adoption outcome is given by $d = zd_1 + (1 - z)d_0$. Since it is not possible to adopt NERICA without being aware of it, then $d_0 = 0$ for all households and then observed adoption outcome can be simplified as $d = zd_1$. Potential adoption in the subpopulation of exposed households is given by $d_1 = 1$ and that of actual adopters is given by $d = 1$. With the potential treatment indicators $d_1 = 1$ and $d_0 = 0$, a population is divided into four groups based on their status of compliance (Imbens and Angrist 1994): *compliers* (those with $d_1 = 1$ and $d_0 = 0$), *always takers* (those with $d_1 = d_0 = 1$), *never takers* (those with $d_1 = d_0 = 0$), and *defiers* (those with $d_1 = 0$ and $d_0 = 1$). Imbens and Angist (1994) have given a causal interpretation only to the sub-population of compliers and called the population parameter *local average treatment effect* (LATE).

This study uses two instrumental variable estimators to determine the LATE of NERICA adoption on household food consumption scores and the number of sick days per capita: 1) the Wald estimator and 2) the Local Average Response function (LARF). The Wald estimator is developed by Imbens and Angrist (1994). It estimate impact non-parametrically by using a random instrument z, treatment status variable d and the observed outcome variable y. The LARF estimator is Abadie's (2003) adaptation of the LATE estimator of Imbens and Angrist (1994) to situations where there is no random instrument (see Abadie 2003 for details).

4.3.4 Estimators and estimates

This section describes the estimators used to provide unbiased estimates of the impact of NERICA adoption on household food consumption scores and the number of sick days per capita. For comparison, we have used the Inverse propensity score weighting (IPSW) estimator, which relies on conditional independence assumption to provide unbiased estimates. The IPSW estimator uses a two-stage estimation procedure. The propensity score $P(d=1|x) \equiv P(x)$, is estimated in the first stage and impact based on ATE, $ATE1$, and $ATE0$ are identified in the second stage using the following equations, respectively (see Imbens (2004):

$$A\hat{T}E = \frac{1}{n}\sum_{i=1}^{n}\frac{\left(d_i - \hat{p}(x_i)\right)y_i}{\hat{p}(x_i)\left(1-\hat{p}(x_i)\right)} \quad (4.4)$$

$$A\hat{T}E1 = \frac{1}{n_1}\sum_{i=1}^{n}\frac{\left(d_i - \hat{p}(x_i)\right)y_i}{\left(1-\hat{p}(x_i)\right)} \quad (4.5)$$

$$A\hat{T}E0 = \frac{1}{1-n_1}\sum_{i=1}^{n}\frac{\left(d_i - \hat{p}(x_i)\right)y_i}{\hat{p}(x_i)} \quad (4.6)$$

where n is the sample size, $n_1 = \sum_{i=1}^{n} d_i$ is the number of NERICA adopters, and $\hat{p}(x_i)$ is the propensity score which can be estimated with a probit or logit model. Since conditional independence is less likely to hold when there is self selection, we use the Wald estimator (Imben and Angrist 1994) and the Local Average Response Function (LARF) (Abadie, 2003) to give unbiased estimates of the impact of NERICA adoption on household food security and health.

The Wald estimator rely on the validity of the assumption that the instrumental variable is randomly distributed in the population. Hence, if the assumption that awareness to NERICA is randomly distributed in the population holds, then the Wald estimator provides consistent estimates of the impact of NERICA adoption on our outcome variables of interest. The Wald estimator identifies the mean impact of NERICA adoption in the subpopulation of compliers (i.e., LATE) as follows (Imbens and Angrist, 1994):

$$E(y_1 - y_0 \mid d_1 = 1) = \frac{E(y \mid z = 1) - E(y \mid z = 0)}{E(d \mid z = 1) - E(d \mid z = 0)} \quad (4.7)$$

The right-hand side of Equation (4.7) can be estimated by its sample analogue:

$$\left(\frac{\sum_{i=1}^{n} y_i z_i}{\sum_{i=1}^{n} z_i} - \frac{\sum_{i=1}^{n} y_i (1 - z_i)}{\sum_{i=1}^{n} (1 - z_i)} \right) \times \left(\frac{\sum_{i=1}^{n} d_i z_i}{\sum_{i=1}^{n} z_i} - \frac{\sum_{i=1}^{n} d_i (1 - z_i)}{\sum_{i=1}^{n} (1 - z_i)} \right)^{-1} \quad (4.8)$$

Moreover, because it is unrealistic to assume that awareness to NERICA is random in The Gambia, the study proceeds with the LARF approach by Abadie (2003). This estimator uses a much weaker conditional independence assumption which states that conditional on a vector of covariates x determining the observed outcome y the instrument z is independent of the potential outcomes d_1, y_1 , and y_0 . Based on these assumptions, the LARF can be estimated as follows (see Abadie2003):

$$f(x,1) - f(x,0) = E(y_1 - y_0 \mid x, d_1 = 1) \quad (4.9)$$

$$E(g(y,d,x) \mid d_1 = 1) = \frac{1}{P(d_1 = 1)} E(\kappa \cdot g(y,d,x)) \quad (4.10)$$

where $\kappa = 1 - \frac{z}{p(z = 1 \mid x)}(1 - d)$ is a weight function used to identify the sub-population of potential adopters. Once the sub-population of potential adopters is identified, treatment effects are estimated by conditioning on the observed covariates that determine the outcome variable of interest. Then taking the mean difference in outcome between adopters and non-adopters yields unbiased estimates of treatment effects (see Abadie (2003) for more details)

The LARF can be estimated with Ordinary Least Squares (OLS) with or without interaction between the treatment variable d and the observed covariates x. OLS without interaction implies a constant treatment effect of the impact across the subpopulation of potential adopters. In this study, we used the exponential conditional functional form with and without interaction to guarantee values of predicted outcomes (food consumption scores and the number of sick days per capita).

4.4. Results and discussion

4.4.1 Descriptive analysis

4.4.1.1 Socio-demographic characteristics of households

Table 4.2 presents descriptive statistics of key socio-demographic characteristics of households by adoption status. The results reveal that NERICA adopters have a significantly higher percentage of farmers practicing upland rice farming. This is due to the fact that the NERICA varieties disseminated to farmers in The Gambia are upland rice varieties only[21]. NERICA adopters have also significantly higher percentage of farmers who have access to the extension service and to in-kind credit.[22] Farmers who have contact with extension are likely to acquire more information about new technologies. This can enhance technology adoption particularly if the new technology is profitable (Caswell et al., 2001; Feder and Slate, 1984). Moreover, new technologies come with additional cost, which may limit their adoption to the more affluent group of farmers (El Oster and Morehart, 1999). This makes in-kind credit access a vital factor for new technology adoption. Furthermore, non-NERICA adopters have higher non-agricultural income compared to NERICA adopters. This suggests that non-NERICA adopting households are likely to be wealthier than NERICA farming households.

[21] At the time of data collection for this study, only upland NERICA varieties were disseminated to rice farmers.
[22] Farmers acquire in-kind credit in the form of rice seeds from the extension service, which is repaid after harvest.

Table 4.2: Descriptive statistics of households by adoption status

Variable	Adopters	Non-adopters	Total	Difference Test
Age of respondent	49.81 (0.74)	50.36 (1.15)	49.99 (0.62)	0.56 (1.32)
Female household heads (1=male, otherwise 0)	0.19 (0.02)	0.21 (0.03)	0.2 (0.02)	0.02 (0.04)*
Household size	9.51 (0.22)	9.43 (0.34)	9.48 (0.19)	0.08 (1.26)
Education (1 = respondent has attained formal education, 0=otherwise)	0.10 (0.02)	0.7 (0.02)	0.9 (0.01)	0.3 (0.03)
Practice of upland rice cultivation (1 = practice upland, 0=otherwise)	0.84 (0.02)	0.67 (0.04)	0.78 (0.02)	0.17 (0.04)***
Practice of lowland cultivation (1 = practice lowland, 0=otherwise)	0.43 (0.03)	0.46 (0.04)	0.44 (0.02)	0.3 (0.05)
Household rice area (ha)	0.69 (0.04)	0.73 (0.05)	0.71 (0.03)	0.4 (0.06)
Household non agricultural income (GMD)[23]	15038 (1785)	25839 (6882)	18652 (2597)	10810 (5488)**
Household has contact with extension (1 = had contact within previous year, 0= otherwise)	0.31 (0.03)	0.20 (0.03)	0.27 (0.02)	0.11 (0.04)***
Household has contact with NARI (1 = had contact within previous year, 0= otherwise)	0.23 (0.02)	0.19 (0.03)	0.21 (0.02)	0.4 (0.04)
House member has access to credit (1 = had contact within previous year, 0= otherwise)	0.27 (0.02)	0.18 (0.03)	0.24 (0.02)	0.8 (0.04)**

NB: T-tests[24] were used to test the mean difference in socio-demographic characteristics between the NERICA adopters and non-adopters.
NARI - National Agricultural Research Institute of The Gambia.
Means are shown with robust standard errors in parenthesis. **P*<0.10, ** *P*<0.05, and *** *P*<0.01
Source: AfricaRice/NARI, Gambia Post Impact Assessment survey 2006/2010.

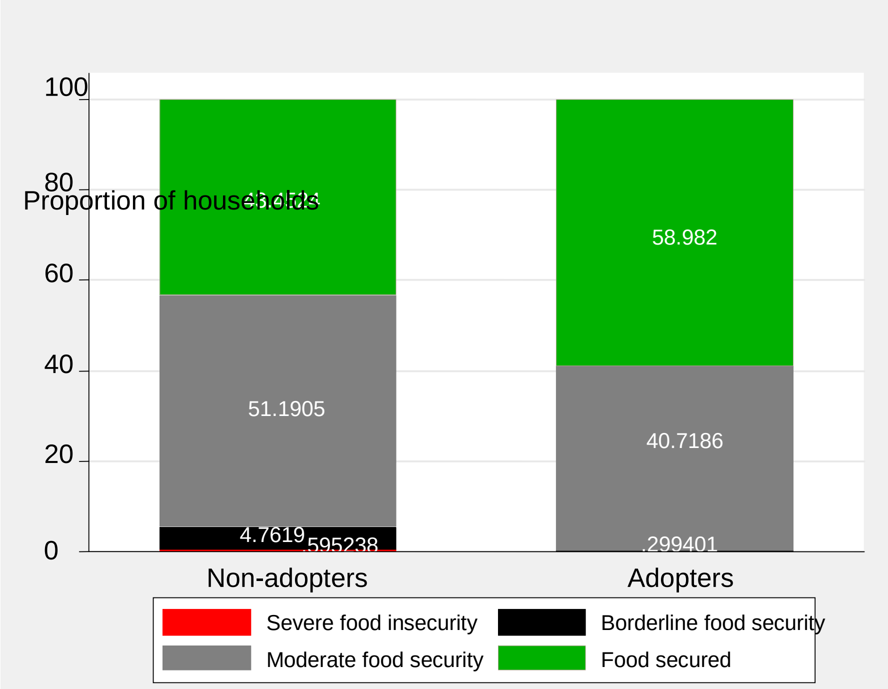
There is no statistically significant difference in the age of the respondent, education, household size and contact with NARI between NERICA adopters and non-adopters. Hence, controlling for such factors to identify the impact of NERICA adoption on our outcome variables of interest is a matter of choice.

[23] At the time of the survey 1$=30 GMD (Gambian Dalasis).
[24] We use the mean value of each dummy, which allows us to test the mean difference using T-test We use the mean value of each dummy, which allows us to test the mean difference using T-test

4.4.1.2 Identifying impact based on observed differences

Figure 4.1 seeks to measure the association between NERICA adoption and household food security by comparing the proportion of households that fall under four different food security groups by adoption status. The results indicate that about 0.6% of non-NERICA adopting households and none of the NERICA adopting households are severely food insecure. About 4.8% of non-NERICA adopters have borderline food security compared to 0.3% of NERICA adopters. However, 51.2% of non-NERICA adopting households are moderately food secure compared to 40.7% of NERICA adopters. Moreover, 59% of NERICA adopting households are food secure compared to 43.5% of non-NERICA adopting households. The difference in percentage between the two groups is statically different from zero at 1% significance level, which suggest that NERICA adoption is positively correlated with household food security. Nonetheless, this simple comparison of food security outcomes between NERICA adopting households and non-adopters does not have any causal interpretation of the impact NERICA adoption on household food security. Besides NERICA adoption, there are several other factors that may explain the difference in the food security status between NERICA adopting and non-adopting households. Such differences must be accounted for to identify causal effects of NERICA adoption on household food security.

Figure 4.1: Household food security by adoption status



Source: AfricaRice/NARI, Gambia Post Impact Assessment survey 2006/2010

Table 4.3 compares mean differences in food consumption scores and the number of sick days per capita between NERICA adopters and non-adopters. The results show that NERICA adopters had an average food consumption score significantly higher than non-NERICA adopting households. The mean difference in food consumption score is estimated to be 9, which is statistically different from zero at the 1% significance level. Male headed NERICA adopting households have, on average, 11 food consumption scores more than non-NERICA adopting male headed households. Moreover, the results show that NERICA adopters have a significantly lower number of sick days per capita compared to non-adopters. The mean difference is estimated to be -3.47 days per capita per annum, which is statistically significant at 1% significance level. The results show that male-headed NERICA households have -4.07 sick days per capita less than non-NERICA male headed households. Moreover, there is no statistically significant difference in food consumption scores and the number of sick days per capita at the 5% significance level between female headed NERICA adopting and non-NERICA adopting households. However, these results are merely descriptive and have no causal interpretation of the impact of NERICA adoption on food security and health.

Table 4.3: Identifying impacts using mean differences in outcome by adoption status

Characteristics	Adopters	Non-adopters	Total	Difference Test
Food consumption scores				
All households	84	75	81	9
	(1.06)	(1.83)	(0.95)	(1.98)***
Male headed households	85	74	82	11
	(1.16)	(2.10)	(1.07)	(2.22)***
Female headed households	80	76	79	4
	(2.52)	(3.76)	(2.10)	(4.39)
Number of sick days per capita				
All households	2.69	6.16	3.85	-3.47
	(0.11)	(0.89)	(0.32	(0.65)***
Male headed households	2.58	6.65	3.92	-4.07
	(0.12)	(1.11)	(0.39)	(0.79)***
Female headed households	3.18	4.29	3.57	-1.12
	(0.28)	(0.69)	(0.31)	(0.63)*

NB: T-tests were used to test the difference between the 2006 and 2010 survey results. Means are shown with robust standard errors in parenthesis. **P*<0.10 and ****P*<0.01.
Source: AfricaRice/NARI, Gambia Post Impact Assessment survey 2006/2010.

4.4.2 Econometric analysis

4.4.2.1 Impact of NERICA adoption on household food security and its determinants

Table 4.4 presents the estimates of the impact of NERICA adoption on household food security. The estimates are presented for all households and for male and female headed households separately. The results of the ATE estimates, which rely on conditional independence assumption, are compared with those of the LATE estimates which are based on the IV approach. The ATE estimates based on Inverse Propensity Score Weighting (IPSW) are significant for all households and male headed households. The results show that NERICA adoption increases the food consumption score by 8 and 11 for all households and male headed households, respectively. These increases are statistically different from zero at the 1% significance level. The LATE estimates based on OLS with the adoption dummy variable interacted with covariates are significant for all, male headed, and female headed households. The estimates show that NERICA adoption increases food consumption scores by 10, 9, and 13 for all, male headed, and female headed households, respectively. The LATE estimate based on the exponential local average response function (LARF) with the adoption dummy interacted with covariates shows similar effects: NERICA adoption increases food consumption scores by 15[25] for all and male headed households. There is no significant effect for female headed households. The LATE estimates based on the Wald estimator have not shown any significant impact of NERICA adoption on household food security.

The ATE estimate based on inverse propensity score weighting (IPSW) relies on the validity of the conditional independence assumption, which is less plausible under the case of NERICA adoption. Since adoption of NERICA is entirely a famer's choice, it is more likely to correlate with unobserved factors that may influence the adoption decision. For this reason, the estimate based on the IPSW estimator does not have a causal interpretation of NERICA adoption on household food security. The parameter with causal interpretation under such circumstances is the LATE estimate, which uses IV to correct for both overt and hidden biases and deal with the endogeneity problem. The Wald estimator is based on the assumption that the IV is randomly distributed in the population. Since the IV used in this study is not randomly distributed in the population, the impact estimate based on the Wald estimator cannot be given a causal interpretation. The estimates with causal interpretation of the impact of NERICA adoption on household food security are LATE estimates based on OLS and exponential LARF estimators. However, since the exponential LARF estimator ensures the positivity of the predicted food consumption scores and also allows for heterogeneity of the impact in the population, the discussions below will be based on its estimates.

The positive impact of NERICA adoption on household food security based on the exponential LARF estimator found in this study is consistent with findings of previous studies conducted on NERICA adoption (Dibba et al., 2012; Dontsop et al., 2011; Adekambi et al., 2009). Dibba et al. (2012) found that NERICA adoption significantly increased average rice yields by 157 kg per hectare in The Gambia. Similarly, Donsop et al. (2011) and Adekambi et al. (2009) also found positive impacts of NERICA adoption on household expenditures in Nigeria and Benin, respectively. Our findings are also consistent with a study on the impact of banana tissue culture technology on food security in Kenya by Kabunga et al. (2014). The study by Kabunga et al. (2014) used the Household Food Insecurity Access Scale (HFIAS) and found a positive

[25] Since the maximum food consumption score for a household is 105, then a positive impact of 15 food consumption score translates into 14% increase in food security.

impact of technology adoption on food security. This further supports findings in our study and shows that improved agricultural technology adoption has the ability to improve household food security. The average yields of traditional upland rice varieties in Africa is estimated to be 1 tonne per hectare whereas the average yield of NERICA in farmers' fields is estimated to be 2.5 tons per hectare. This yield difference could have resulted in higher yields for NERICA farmers, which explains the significance impact of NERICA adoption on household food security. Moreover, since NERICA fetches a higher price per kg in local markets compared to traditional varieties, NERICA farmers who cultivate the crop mainly for sale could acquire more income from NERICA production which can be used to acquire more diverse food for the household.

Table 4.4: Impact of NERICA adoption on food security

Parameters	All Households	Male headed households	Female headed households
Number of observations	502	402	100
ATE1 estimate based on Inverse Propensity Score Weighting (IPSW)	8 (2.41)***	11 (2.82)***	-3 (6.38)
LATE estimates based on OLS with interaction	10 (1.53)***	9 (1.51)***	13 (1.62)***
LATE estimate based on Wald estimator	10 (265.52)	9 (1023.54)	-
LATE estimate based on exponential local average response function (LARF) with interaction	15 (5.91)***	15 (5.74)***	12 (49.57)*

Robust standard errors are shown in parenthesis. *P<0.10 and *** P<0.01.
Source: AfricaRice/NARI, Gambia Post Impact Assessment survey 2006/2010.

The exponential LARF coefficient estimates of the determinants of food security with and without interaction are presented in Table 4.5. Besides NERICA adoption, which influences household food security at the 1% significance level, a number of other coefficient estimates of the non-interacted terms also significantly influence the food security status of rice farming households, such as the gender of household head, household location in the Central River South (CRS), and access to in-kind credit. This indicates that the difference in food security estimates between NERICA adopters and non-adopters obtained in the descriptive analysis cannot be solely attributed to NERICA adoption. Moreover, a few other coefficient estimates of the interacted terms are also statistically significant, thus confirming the heterogeneity of the impact of NERICA adoption on household food security in the population.

Furthermore, the F-statistics for the joint significance of coefficients of the interacted and non-interacted terms indicate that the coefficients are jointly significantly different from zero. Moreover, the negative coefficient estimate of -4.74 for female household head indicates that the impact of NERICA adoption on food security will be greater for households headed by men. Furthermore, the positive significant coefficient estimate of 0.37 for access to in-kind credit suggests that the impact of NERICA adoption on household food security is likely to be greater for households that have access to in-kind credit. Since new technologies come with additional costs, farmers who have access to in-kind credit are in better position to adopt such technologies and therefore more likely to benefit from it.

Table 4.5: Exponential LARF coefficient estimates for determinants of food security with and without interaction

Variables	Exponential LARF with the adoption dummy interacted with covariates	
	Coefficients of the non-interacted terms	Coefficients of the interacted terms
NERICA adoption	4.51 (0.08)***	
Female household head	4.68 (0.18)***	-4.74 (0.19)***
Education	-0.09 (0.25)	0.13 (0.25)
Non-agricultural income	0.00 (0.00)	
Central River South	0.17 (0.09)**	0.07 (0.09)
Age	-0.00 (0.00)	0.00 (0.00)
Household size	-0.00 (0.00)	
Access to credit	-0.39 (0.11)**	0.37 (0.11)***
Woman	-0.04 (0.03)	
F-statistics for the joint significance of coefficients of the non-interacted term	F (8,357) 2618.27***	
F-statistics for the joint significance of coefficients of the interacted terms	F (5,357) 436.02***	

Robust standard errors are shown in parenthesis. ***P*<0.05 and *** *P*<0.01.
Source: AfricaRice/NARI, Gambia Post Impact Assessment survey 2006/2010.

4.4.2.2 Impact of NERICA adoption on household health status and its determinants

Table 4.6 presents the estimates of the impact of NERICA adoption on household health status. The ATE estimate based on Inverse Propensity Score Weighting (IPSW) shows that NERICA adoption significantly reduces the number of sick days per capita by 3.59 days per annum for NERICA adopting households. The estimate based on the gender of household head shows that NERICA adoption reduces sick days per capita by 4.07 and 1.64 days per annum for male and female headed households, respectively. The LATE estimate based on OLS with interaction, which accounts for heterogeneity of the impact in the population, shows no significant impact of NERICA adoption on household health status. Moreover, the estimate based on the Wald estimator is also not statistically different from zero for all households and male headed households. Furthermore, the LATE estimate based on exponential LARF with interaction shows that NERICA adoption reduces the number of sick days per capita by 1.45 days for NERICA adopting households. Estimates based on gender of household head indicate a reduction of 1.53 and 1.14 days per capita for male and female headed households, respectively. However, none of the estimates based on exponential LAEF are significantly different from zero.

The ATE based estimates do not have a causal interpretation of NERICA adoption on household health status. They rely on the validity of the conditional independence assumption, which rules out possible correlation of farmers' adoption decision with their unobserved characteristics. However, since adoption is entirely a choice variable, it is most likely influenced by unobserved factors. Under such circumstances, it is the IV approach that has causal interpretation of the impact of NERICA adoption of household health status. The IV approach based on the Wald estimator shows insignificant estimates of NERICA adoption on household health status. However, since the Wald estimator is based on the assumption that the IV is random in the population, it does not have a causal interpretation of the impact of NERICA adoption on health. The IV variable (exposure) used in this study is not random in the population. Hence, the study uses OLS and exponential LARF approach by Abadie (2003), which does not need the strong assumption that the IV be randomly distributed in the population to determine the impact of NERICA adoption on household health status. However, discussions will be based on the exponential LARF approach by Abadie (2003) because it ensures the positivity and heterogeneity of the predicted outcomes.

The insignificant reduction in the number of sick days per capita by 1.45 days based on the exponential LARF approach by Abadie (2003) indicates that NERICA adoption has no significant impact on household health status. This is inconsistent with the findings that NERICA varieties have higher protein content and more well-balanced amino acids compared to traditional and imported rice varieties (WARDA, 2001; 2008), which could result in better health outcomes for NERICA adopting households (WARDA, 2001; 2008). Rice is a subsistence crop that is mainly grown for household food consumption. Hence, households cultivating NERICA solely for consumption could achieve better balanced diet which can improve health outcomes significantly. However, this fact could not be established in this study. Moreover, the NERICA varieties fetch higher prices per kg in local markets. Since NERICA yields are higher than the traditional upland rice varieties, farmers cultivating NERICA mainly for sale are likely to obtain more income from its production which can be used to address short-term illnesses more effectively. However, the fact that there is free health care to address most short-term illnesses in The Gambia may have resulted in the insignificant impact of NERICA adoption on household health status found in this study.

Table 4.6: Impact of NERICA adoption on household health

Parameters	All Households	Male headed households	Female headed households
Number of observation	502	402	98
ATE estimate based on Inverse Propensity Score Weighting (IPSW)	-3.59 (1.01)***	-4.07 (1.24)***	-1.64 (0.79)**
LATE estimates based on OLS with interaction	0.89 (4.11)	0.92 (3.99)	0.73 (4.67)
LATE estimate based on Wald estimator	-1.44 (177.09)	-1.74 (145.98)	-
LATE estimate based on exponential local average response function (LARF) with interaction	-1.45 (2.65)	-1.53 (2.69)	-1.14 (2.47)

Robust standard errors are shown in parenthesis. **P<0.05 and *** P<0.01.
Source: AfricaRice/NARI, Gambia Post Impact Assessment survey 2006/2010.

Table 4.7 presents the exponential LARF coefficient estimates for the determinants of health with and without interaction. Besides NERICA adoption, other coefficients of the non-interacted term are also significant at the 1% significance level. These variables include: household size, access to in-kind credit, and age of respondent. Moreover, the significance of some coefficients of the interacted terms confirms the heterogeneity of the impact of NERICA adoption on household health status. Furthermore, the F-statistics for the joint significance of the interacted and non-interacted terms indicates that the coefficients are jointly significantly different from zero.

The coefficient of education is not significant in determining household health status in both the non-interacted and interacted models. This finding is rather surprising. However, given that the majority of household heads in rural Gambia are illiterates makes the finding more plausible. Moreover, the coefficients of household size indicate that increases in household size are negatively correlated with increases in the number of sick days per capita. This suggests that the impact of NERICA adoption on health will be greater for households with larger household size. The coefficient of Central River South in the interacted model suggests that the impact of NERICA adoption on health will be greater for households located in Central River South. Furthermore, the coefficient of access to in-kind credit suggests that the impact of NERICA adoption on health will be greater for NERICA adopting households that have access to in-kind credit services.

Table 4.7: Exponential LARF coefficient estimates for the determinants of health with and without interaction

Variables	Exponential LARF with adoption dummy interacted with covariates	
	Coefficients of the non-interacted terms	Coefficients of the interacted terms
NERICA adoption	2.75 (1.18)***	
Education dummy	-0.33 (0.19)*	0.12 (0.14)
Non-agricultural income	-0.00 (0.00)	
Central River South	0.88 (0.00)***	-1.15 (0.14)***
Household size	-0.05 (0.01)***	-0.11 (0.02)***
Access to in-kind credit	0.76 (0.07)***	-0.69 (0.09)***
Household proximity to Health Center	-1.12 (0.07)*	
Age	0.03 (0.00)***	
F-statistics for the joint significance of coefficients of the non-interacted term	F (6,360) 55.68***	
F-statistics for the joint significance of coefficients of the interacted terms	F (6.360) 7.08***	

Robust standard errors are shown in parenthesis. *P<0.10 and *** P<0.01.
Source: AfricaRice/NARI, Gambia Post Impact Assessment survey 2006/2010.

4.5 Conclusions

This study finds that NERICA adoption has a significant positive impact on household food security, but no significant impact on health status which is measured by the number of sick days per capita in the previous year. The impact on food security is greater for households headed by men. The analyses show that NERICA adopting households have significantly more farmers who have contact with extension services and access to in-kind credit. This suggests that NERICA adoption is positively correlated with in-kind credit and information acquisition through contact with extension services. The analysis also revealed that the impact of NERICA adoption on food security, among NERICA adopting households, is greater for households that have access to in-kind credit. This makes in-kind credit acquisition an important impact pathway to identifying a significant positive impact of NERICA adoption on household food security.

The positive impact of NERICA adoption on household food security is consistent with past research (Dibba et al., 2012; Dontsop et al., 2011; Adekambi et al., 2009). NERICA varieties were mainly developed to address the problem of low rice yields experienced by upland rice farmers in Africa and to help improve food security. The positive impact of NERICA adoption on household food security indicates that NERICA can contribute positively in attaining national food security in The Gambia. Since rice is the main staple crop of The Gambia, concerted efforts need to be taken to disseminate NERICA across the six agricultural regions of the country. This will enable upland rice farmers to get more access to NERICA, which will consequently lead to increased rice production and improved household food security.

There are claims that NERICA varieties have higher protein content and more well-balanced amino acids compared to traditional and imported rice varieties (WARDA, 2001; 2008). This may result in better health outcomes for NERICA adopting households. However, we found no significant impact of NERICA adoption on household health status. This could be attributed to the fact that we used information on all household member to create number of sick days per capita. Number of sick days per capita is a highly noisy indicator which tend to be negatively correlated with household size. When one individual respondent reports on the health status of all households members, it can lead to under estimation if the household is large. Hence, future studies that intend to identify the impact of NERICA adoption on health should focus on individual recall data on specific illnesses, which may be a better outcome indicator.

Finally, the policy implication of our findings is that concerted efforts need to be taken by decision makers to expand in-kind credit service programmes. Such programmes should be channelled through extension outlets, which could also provide vital information to farmers about the NERICA varieties. Moreover, the lack of significant impact of NERICA adoption on food security identified for female headed households indicates an urgent need for programs designed to alleviate poverty to target female headed households to help them improve their food security status.

Acknowledgements

The authors are grateful to the Global Rice Science Partnership (GRiSP) program for the financial assistance for the implementation of this study, as well as to the Africa Rice Center and University of Hohenheim for their technical assistance.

References

Abadie, A. 2003. Semiparametric instrumental variable estimation of treatment response models. Journal of Econometrics, 113, 231– 263.

Adekambi, S. A., Diagne A., Simtowe, F. P & Biaou, G. 2009. The Impact of Agricultural Technology Adoption on Poverty: The Case of NERICA Rice Varieties in Benin. Contributed Paper Prepared for Presentation at The International Association Of Agricultural Economists' 2009 Conference, Beijing, China, August 16-22, 2009.

AFIDEP. 2012. Population, climate change, and sustainable development in Africa. Available at http://populationaction.org/wp-content/uploads/2012/06/PAI-AFIDEP.pdf (accessed online November 2012).

Caswell, M., Fuglie, K., Ingram, C., Jans, S., & Kascak, C. 2001. Adoption of Agricultural production practices: Lessons learned from the US. Department of Agriculture area studies project. Washington DC. U.S. Department of Agriculture. Resource Economics Division, Economic Research service, Agriculture Economic Report No. 792.

Dibba, L., Diagne, A., Fialor, S.C & Nimoh F 2012. The impact of NERICA adoption on productivity and poverty of the small-scale rice farmers in the Gambia. Food Security. (2012) 4:253–265.

Dontsop, P., Diagne, A., Okoruwa, V.O., & Ojehomon, V. 2011. Impact of Improved Rice Technology (NERICA varieties) on Income and Poverty among Rice Farming Households in Nigeria: A Local Average Treatment Effect (LATE) Approach. Quarterly Journal of International Agriculture 50 (2011), No. 3: 267-291.

El-osta, H. S., & Morehart, M. J. 1999. "Technology Adoption Decisions in Dairy Production and the Role of Herd Expansion." Agricultural and Resource Economics Review. 28: 84-95.

Feder, G., & Slade, R. 1984. “The acquisition of information and the adoption of new Technology.” American Journal of Agricultural Economics. 66 :312-320.

Heckman, J., & Robb, R. 1985. Alternative methods for evaluating the impact of interventions. in: J. Heckman and B. Singer, eds..Longitudinal analysis of labor market data, Econometric Society monograph series (Cambridge University Press, New York).

Heckman, J., & Vytlacil, E. 2005. Structural equations, treatment effects, and econometric policy evaluation. Econometrica, 73, 669–738.

Hoddinott, J. 1999. Choosing outcome indicators of household food security. International Food Policy Research Institute (IFPRI). Washington, D.C. 20006 U.S.

Imben, G. W. 2004. Nonparametric estimation of average treatment effects under exogeneity: a review. The Review of Economics and Statistics, 86(1), 4–29.

Imbens, G. W., & Angrist, J. D. 1994. Identification and estimation of local average treatment effects. Econometrica, 62, 467–476.

Jones, M. P., Dingkuhn, M., Aluko, G. K. & Semon, M. 1997a. Interspecific Oryza sativa × O. glaberrima Steud. progenies in upland rice improvement. Euphytica 92:237-246.

Jones, M. P., Dingkuhn, M., Johnson, D. E., & Fagade, S. O. (Eds). 1997b. Interspecific hybridization: Progress and Prospect WARDA, 01 BP 2551, Bouaké, Cote d’Ivoire. pp. 21-29.

Kabunga, N. S., Dubois, T., & Qaim, M. 2014. Impact of tissue culture banana technology on farm household income and food security in Kenya. *Food Policy*, *45*, 25–34.

Lee, M. J. 2005. Micro-econometrics for policy, program and treatment effects. Advanced Texts in Econometrics. Oxford University Press.

Maxwell, S., & T. Frankenberger. 1992. Household food security: Concepts, indicators, measurements. IFAD and UNICEF, Rome.

Ruel, M. T. 2002. Is dietary diversity an indicator of food security or dietary quality? A review of measurement issues and research needs. Available at http://ageconsearch.umn.edu/bitstream/16386/1/fc030140.pdf (March 2015)

Rogers, E. 1983. Diffusion of innovations. New York. Free Press

Rosenbaum, P. R. 2001. Observational studies (2nd ed.). New York: Springer.

Rosenbaum, P. R., & Rubin, D. R. 1983. The central role of the propensity score in observational studies for causal effects. Bometrika, 70, 41-55

Rubin, D. 1974. Estimating causal effects of treatments in randomized and non-randomized studies. Journal of Educational Psychology, 66, 688–701

The Gambia Population Census. 2013 The Gambia housing and population census preliminary results. Available at http://www.gbos.gov.gm/uploads/census/The%20Gambia%20Population%20and%20Housing%20Census%202013%20Provisional%20Report.pdf (accessed online November 2014).

Tjornhom, J. D. 1995. Assessment of Policies and Socio-Economic Factors Affecting Pesticide Use in the Philippines. MSc. Thesis, Virginia Polytechnic Institute and State University.

WARDA. 2001. NERICA rice for life. Available at http://www.warda.org/publications/NERICA8.pdf (Accessed online November 2014).

WARDA/FAO/SAA. 2008. NERICA®: the New Rice for Africa – a Compendium. EA Somado, RG Guei and SO Keya (eds.). Cotonou, Benin: Africa Rice Center (WARDA); Rome, Italy: FAO; Tokyo, Japan: Sasakawa Africa Association. pp 119.

Wiesmann, D., Bassett, L., Benson, T, & Hoddinott, J. 2009 Validation of the world food programme's food consumption score and alternative indicators of household food security. Available at http://www.ifpri.org/sites/default/files/publications/ifpridp00870.pdf (Accessed online March 2015)

World Food Programme. 2008. Calculation and use of the food consumption score in food security analysis. Prepared by VAM unit HQ Rome.

Chapter 5

5. The impact of agricultural training on technical efficiency of smallholder rice farmers in The Gambia

Lamin Dibba, Manfred Zeller and Aliou Diagne

(Submitted to Journal of African Economies, July 2015)

Abstract

This paper assesses the impact of agricultural training on technical efficiency using country-wide panel data from 515 rice producing households in The Gambia. We use the Data Envelopment Analysis (DEA) technique to generate technical efficiency scores and to identify factors influencing technical efficiency using a Tobit model. We apply propensity score matching, using technical efficiency scores as the outcome variable, to control for selection bias and identify causal effects of participation in agricultural training programs. To test the plausibility of conditional independence, we conduct Rosenbaum bounds sensitivity analysis with matched data as well as mean absolute standard bias tests between participants and non-participants. The results indicate that agricultural training significantly increases the technical efficiency of smallholder rice farmers by 10 percent. This translates into a rice yield increase of 260 kg/ha, which results in social and private benefits per annum of US$ 43,700 and US$ 53 for 900 rice farming households and 30 extension agents, and per household, respectively. Our analysis of investments on agricultural training reveals a Net Present Value of US$ 195,816, a Benefit Cost Ratio of 5.3, and an Internal Rate of Return of 99%. These findings justify increasing investments in agricultural training programs to boost rice production and productivity. Further analysis reveals that farmer contact with extension workers and association membership are significant factors influencing technical efficiency.

Key words: Technical efficiency, impact, agricultural training, propensity score matching, Tobit, The Gambia.

JEL classification: D13, D22, Q12, Q18

5.1. Introduction

The demand for rice is rapidly increasing in many countries in sub-Saharan Africa. To keep pace with increasing demand, sub-Saharan African countries have increased rice production almost five times in the past 50 years from 3.14 million to 14.6 million tons (Yamamoto et al., 2012). Despite this rapid increase in rice production, about 40% of rice consumed in sub-Saharan Africa is imported (Seck et al., 2010). The high importation of rice in sub-Saharan Africa is mainly due to low rice productivity, which is largely attributed to a low adoption of high yielding improved rice varieties and to the prevalence of inappropriate rice cultivation practices. Appropriate rice cultivation practices that are used in Asia are not commonly practiced in sub-Saharan Africa (Balasubramanian et al., 2007). These factors may result in low yields experienced by rice farmers in sub-Saharan Africa, which cost the sub-region enormous amount of scarce foreign exchange reserves on rice imports. Considering that rice is a major staple crop in many sub-Saharan African countries and that rice has enormous potential for increases in productivity, concerted efforts are urgently required to increase rice production for the attainment of food security and poverty reduction (Otsuka et al., 2010; Larson et al., 2010).

Rice is the main staple crop in sub-Saharan African countries like The Gambia. The per capita consumption of rice is estimated to be 117 kg per annum, which is one of the highest in sub-Saharan Africa. Low rice production and productivity has led to a 65% increase in rice imports in The Gambia between 2000 and 2011. This has resulted in substantial spending, equivalent to US $28.97 million on national foreign exchange reserves in 2011 (Gambia Agricultural Census, 2012). Although, the country is committed to a policy of achieving rice self-sufficiency through the *Back to Land Initiative*, little progress has been made. Hence, training farmers on improved rice cultivation practices to improve technical efficiency of rice producers is of high priority to attain food security in The Gambia.

There are many projects and programs recently introduced in The Gambia to build the capacity of smallholder rice producers. The most notable among them are the *Farmer Managed Rice Irrigation Project* (FMRIP) and *Participatory Learning and Action Research* (PLAR). The FMRIP was officially introduced in The Gambia in 2006. Its main objective was to give extension staff and smallholder rice farmers knowledge and skills required to manage tidal rice irrigation schemes in a sustainable manner (African Development Fund, 2005). PLAR is rice farmer training program developed by AfricaRice to equip rain-fed inland valley rice farmers with knowledge and skills required to increase rice production substantially in inland valleys (Wopereis et al., 2008b). The total surface area of inland valleys in sub-Saharan Africa is estimated to be 85 million hectares, which represents about 7% of the total amount of arable in the region (Defoer et al., 2009). Hence, building the capacity of inland valley rice farmers through agricultural training programs should go a long way in augmenting rice production in sub-Saharan Africa.

Currently, rigorous effects are being undertaken by The Gambia government to achieve self-sufficiency in rice production. To achieve this objective, decision makers need guidance on agricultural technologies and programs to improve rice production and productivity. Although many agricultural training programs have been implemented in The Gambia to improve rice production, there is no evidence in the existing literature regarding the impact of such programs on the technical efficiency of rice producing households. This study attempts to bridge this gap by providing empirical evidence using country-wide data from a random sample of 515 rice producing households. We used a two-stage estimation procedure to assess the impact of agricultural training on the technical efficiency of rice farming households. In the first stage, we estimate technical efficiency scores using the non-parametric Data Envelopment Analysis (DEA) procedure. In the second stage, we apply Propensity Score Matching (PSM) using technical efficiency scores obtained from the first stage estimation to identify the impact of agricultural training on the technical efficiency of rice producers. We conduct a covariate balancing test and sensitivity analysis to assess matching quality and determine the robustness of the propensity score estimates against hidden bias. We also conduct economic cost-benefit and investment analysis to determine the net social and private benefits, as well as the Internal Rate of Return (IRR) of investment on agricultural training programs.

The rest of this paper is organized as follows: Section 2 presents literature on agricultural training programs in The Gambia; Section 3 presents the data and sampling methodology; Section 4 provides the empirical framework to estimate technical efficiency scores, as well as the matching procedure to assess the impact of agricultural training on technical efficiency; Section 5 presents the impact estimates derived from propensity score matching and also provides estimates of economic cost-benefit analysis and investment analysis on agricultural training programs; and Second 6 concludes with a summary of the main findings and their policy implications.

5.2. Agricultural rice-farmer training programs in The Gambia

There are several projects and programs introduced in The Gambia over the past decade that have capacity building components for smallholder rice farmers. Among these projects and programs, the ones that are specifically introduced to train rice farmers are the *Participatory Learning and Action Research* (PLAR) program, the *Farmer Managed Rice Irrigation Project* (FMRIP), and a Canadian International Development Agency (CIDA) funded project. Each of these projects and programs provide training for rice farmers on specific aspects of the rice production process.

The PLAR rice farmer training program was introduced in The Gambia in 2005 under the *Participatory Adaptation and Diffusion of Technologies for Rice-Based Systems* (PADS) project. The objective of the PLAR was to give rice farmers the knowledge and skills required to effectively manage rice production. The PLAR has a facilitator's manual which covers 28 modules on the management of rice production, ranging from pre-planting to post harvest operations (Defoer et al., 2009). Activities of the PLAR in The Gambia were coordinated by the National Agricultural Research Institute (NARI) in collaboration with the Africa Rice Center (AfricaRice). PLAR training begins with the training of trainers (extension agents) who, in turn, conduct farmer training sessions. In 2007, the NARI in collaboration with AfricaRice conducted training for two-weeks on the 28 PLAR modules for 30 extension workers selected from all of the country's agricultural regions. Each trained extension worker was also required to train 30 rice farmers. To substantiate trainings conducted by extension workers, the NARI also conducted the PLAR trainings in several villages across the country. The PLAR trainings were mainly conducted for rice farmers operating in lowland inland valleys. In lowland irrigated fields, farmer training was led by FMRIP.

The FMRIP was officially introduced in The Gambia in 2006. The main objective of the project was to increase rice production and incomes of smallholder farmers through irrigated rice land development, capacity building, and rural credit support (African Development Fund, 2005). The project trained extension workers and irrigated rice farmers on soil and water management of rice fields susceptible to inundation. The training sessions were mainly conducted in the Central River South (CRS) and Central River North (CRN) agricultural regions. The project targeted 100 extension staff who were trained on soil and water management in irrigated rice fields. The extension workers, in turn, were tasked to train 2,300 rice farmers and 90 farmer groups across the central river regions. To substantiate the efforts of PLAR and FMRIP, the CIDA project was introduced to trained farmers on the post-harvest handling of rice.

The CIDA-funded post-harvest handling project for rice was officially introduced in The Gambia in 2011. The NARI is the lead implementing institution of the project's activities. The main objective of the project is to enhance food security by improving the post-harvest handling of rice, as well as to advance the marketing and development of new rice-based products. The project identified two intervention sites, namely the West Coast Region (WCR) and Central River Region (CRR). The NARI in collaboration with national partners and AfricaRice identified and trained research scientists and extension workers on post-harvest rice handling techniques. The trained scientist and extension workers were also tasked to identify and train 120 women food processors, 200 rice farmers, 30 rice millers, and 30 rice traders within the country on food processing techniques and improved post-harvest practices.

5.3. Sampling and data

Data for this study were obtained from a country-wide survey of rice farming villages and households in 2010. Villages and households were selected through a multi-stage random sampling procedure. The first stage of sampling involved random selection of rice farming communities across the country's six agricultural regions. With the exception of the West Coast Region[26] (WCR), ten rice farming communities were randomly selected in each agricultural region. During the second stage of sampling, a list of all the rice farming households was obtained in each community through key informant interviews. Ten household were randomly selected, except for the WCR, from each rice farming community for total sample size of 600. This sample was surveyed in 2006 and again in 2010. However, due to migration and other

[26] Twenty rice farming communities were selected in the West Coast Region; however, only five households were selected in each of the selected communities. This was done to obtain equal representation of households in every agricultural region.

circumstances beyond the control of the survey team, only 515 households could be interviewed again in 2010. We performed statistical tests to determine whether the 85 households that had dropped from the sample are significantly different from the remaining households with regard to important socio-demographic and ecological characteristics to ascertain whether the sample is representative of the population.

The data were collected using village and household-level questionnaires. For the village-level questionnaire, in each village, a list of all agricultural projects and programs that provide training for rice farmers was obtained through interviews with contact farmers, community leaders, and extension workers. For the household-level questionnaire, the most knowledgeable[27] person about household rice farming activities was asked whether any member of the household was trained by any of the listed agricultural projects or programs on rice production practices. If the response was "yes", then that household was identified as having participated in an agricultural rice farmer training program. Then, the type and duration of training were noted. Afterwards, socio-economic and demographic characteristics of rice farmers and their households were collected.

5.4. Empirical framework

We estimate the impact of agricultural training on technical efficiency in two stages. In the first stage, we use a non-parametric approach to estimate technical efficiency scores for each sampled household and use Tobit regression analysis to identify factors influencing technical efficiency. In the second stage, we employ propensity score matching to assess the impact of the program on participants using technical efficiency scores as our outcome indicator.

5.4.1 Estimating technical efficiency

There are two main approaches to estimate technical efficiency: parametric and non-parametric. The parametric approach involves specifying some functional form that depicts the relationship between input and output use in the production process. The Cobb-Douglass and transcendental logarithmic (translog) approaches are the most widely used parametric approaches to analyze the technical efficiency of farm households. However, due to the problem of correctly specifying parametric

[27] The respondent was also the person responsible for managing the household's rice farming activities

functional forms, non-parametric approaches were developed to estimate technical efficiency. Data Envelopment Analysis (DEA) is the most commonly used non-parametric approach. DEA was developed by Charnes et al. (1978) to evaluate the efficiency of decision making units. It relies on linear programming to estimate technical efficiency by using the best observed outcome within a group of households as a benchmark for determining the efficiency level of other households. We use the DEA approach to estimate technical efficiency scores for rice farming households based on the fact that it does not require an assumption on a functional form of relationships between inputs and outputs used and produced in a production process. It directly compares household performance against best practices and then estimates efficiency scores for every sample household (Coelli, 1996).

When using the DEA approach to estimate technical efficiency, two scale assumptions are used: Constant Return to Scale (CRS) and Variable Return to Scale (VRS). CRS is assumed in situations whereby changes in the level of inputs used results in proportionate changes in the level of outputs. However, in the case of rice farming households,[28] changes in the level of inputs does not necessarily lead to proportionate changes in the level of outputs. Under such circumstances, CRS is less likely to be a reasonable assumption. In such cases, it is rational to assume VRS. VRS is a suitable assumption when changes in input levels lead to increasing, constant, or decreasing returns to scale. Hence, we assume VRS to estimate technical efficiency scores.

Letting x_{ij} denote the total value of the type of input j used in the production process for a rice farm household i $(x_{ij} > 0, i = 1,2,....I, j = 1,2,....J)$ and y_{nk} denote the amount of output k produced by household n $(y_{nk} \geq 0, k = 1,2,....K)$, following Coelli (1995), the technical efficiency for a given household n is obtained by solving the following Linear Programming Problem (LP) using the DEA model under the assumption of VRS:

$$TE_n = \min_{\lambda_i \theta_n} \theta_n \tag{5.1}$$

[28] Output levels of farming households are affected by changes in the level of inputs used, such as seeds, labor, fertilizers, etc., as well as by changes in external factors, such as weather and natural disasters. Thus, a 100% change in the level of fertilizer applied, such as from 1 to 2 kilograms, does not necessarily mean that the output of rice producing households will be increased by 100%.

subject to:

$$\sum_{i=1}^{I} \lambda_i x_{ij} - \theta_n x_{nj} \leq 0 \tag{5.2}$$

$$\sum_{i=1}^{I} \lambda_i y_{ik} - y_{nk} \geq 0 \tag{5.3}$$

$$\sum_{i=1}^{I} \lambda_i = 1 \tag{5.4}$$

where:

TE_n is the technical efficiency score for household n

λ_i is the nonnegative weights for household i

n is the total number of households

x_{ij} is input j used by household i

x_{nj} is input j used by household n

y_{ik} is the amount of output k produced by household i

y_{nk} is the amount of output k produced by household n

θ_n is a scalar vector ≤ 1 that defines technical efficiency for household n

A value of θ_n equal to 1 indicates a technically efficient household and a value less than 1 indicates a technically inefficient household (Coelli, 1995). The constraint $\sum_{i=1}^{I} \lambda_i = 1$ in Equation (5.4) guarantees that the technical efficiency score (TE_n) in Equation (5.1) is estimated under the VRS assumption (Coelli, 1995). If the constraint $\sum_{i=1}^{I} \lambda_i = 1$ is omitted, then CRS will be assumed, in which case Equation (5.1) becomes the technical efficiency estimation procedure proposed by Charnes et al. (1978). Summary statistics of the variables used in the DEA model are presented in Table 5.1.

Table 5.1: Descriptive statistics of the variables in the DEA model

Variable	Mean	Standard Deviation	Min.	Max.
Rice area (ha)	0.77	0.68	0.03	6.5
Rice yield (kg)	830.41	872.21	0.1	7200
Seeds (kg)	64.27	56.93	2	500
Fertilizer (kg)	20.13	45.98	0	400
Herbicides (litres)	0.49	5.48	0	100
Labor (person days)	56.20	36.05	40	389

Source: AfricaRice/NARI, Gambia Post Impact Assessment survey 2006/2010.

We use a Tobit model to determine the factors influencing the technical efficiency of rice farming households. When estimating technical efficiency scores using the DEA approach, the most efficient households are given a perfect technical efficiency score of one. This creates a variable that is censored from above. If dependent variables are censored from below or above, Ordinary Least Squares (OLS) regression results in biased estimates (Bravo-Ureta and Pinhero, 1997). Under such circumstances, it is more appropriate to use the Tobit model because it accounts for censoring of the dependent variable (McCarty and Yaisawarng, 1993). When dependent variables are censored, values below or above a certain range are transformed to a lower or upper bound (1 in our case). As a result, the true value of the dependent variable is not observed for all entities. Hence, we have a latent dependent variable.

Letting TE^* denote the latent variable and TE denote the observed value of the dependent variable, the Tobit regression model is specified as (Tobin, 1958):

$$TE_i^* = \alpha + X_i\beta + \varepsilon_i, \quad i = 1,2,.......,n \tag{5.5}$$

where:

TE^* is the latent dependent variable,

X_i is an observed explanatory variable, and

ε_i is the error term assumed to be normally $N(\mu, \sigma^2)$ and independently distributed.

Instead of observing the actual technical efficiency scores TE^* of rice farming households, we observe TE:

$$TE_i = 1, \ if \ TE_i^* \geq 1 \quad (5.6)$$

$$TE_i = TE_i^* \ if \ TE_i^* < 1 \quad (5.7)$$

The marginal effects of the estimated coefficients of the latent dependent variable are estimated as follows:

$$\frac{\partial E\left[TE^*\right]}{\partial x_i} = \beta_i \quad (5.8)$$

The reported coefficient of the marginal effects of the Tobit model indicate how a one-unit change in an independent variable x_i changes the expected value of the latent dependent variable.

5.4.2 Estimating the impact of agricultural training

We use propensity score matching in the second stage to assess the impact of agricultural training on the technical efficiency scores derived from the DEA approach outlined in the previous section. Propensity score matching is an alternative approach to assess impacts of programs or interventions on an outcome variable when randomization of participants into treatment and control groups is not feasible (Rubin, 2001). There are two broad methods used in the evaluation of treatment to identify causal effects of treatments on outcomes of interest. One class of methods is based on the selection of observable factors (Rubin, 1974; Rosenbaum and Rubin, 1983). The other estimators are based on the selection on unobservable factors (Heckman and Vytlacil, 2005; Lee, 2005; Abadie, 2003; Imbens and Angrist, 1994). Propensity score matching is an example of the former (cf. Rosenbaum and Rubin, 1984). These methods rely on the validity of the conditional independence or ignorability assumption, which suggests the existence of a set of observed covariates, x, which, if controlled for, renders treatment participation independent of potential outcomes[29] $y_1 \ and \ y_0$. The conditional independence assumption is valid only if program

[29] Potential outcomes are postulated by Rubin (1974), whereby every entity has two potential outcomes with and without the treatment denoted as $y_1 \ and \ y_0$ respectively.

participants do not self-select themselves into treatment and control groups. In the case of agricultural training programs, where trainees are selected by project officials and agricultural extension agents, conditional independence is likely to be a plausible assumption. Under such circumstances, propensity scoring matching is likely to identify causal effects of treatment (Rubin, 1974).

To assess the impact of agricultural training on the technical efficiency of rice farming households, we follow the potential outcome framework proposed by Rubin (1974). Under this framework, every household has two potential outcomes: y_1 if they participate in agricultural training programs and y_0 otherwise. For a given household i, the impact of agricultural training on its technical efficiency is defined as: $y_1 - y_0$. However, the two potential outcomes are mutually exclusive for any given household. We observe only one outcome depending on whether a given household has participated in an agricultural training program or not. Hence, it is impossible to measure the treatment effect of an individual household directly. However, with some fundamental identifying assumptions, it is possible to measure the mean impact of treatment on the treated, which is defined as the average treatment effect on the treated (ATT).

The propensity score matching estimator for ATT is based on the validity of the conditional independence assumption (CIA). This assumption states that conditional on observable factors x that determine participation in agricultural training programs, there are no unobserved factors that influence participation and observed outcomes. The CIA is formally stated as follows:

$$Y_{1,} Y_0 \amalg D \mid X \tag{5.9}$$

A further requirement needed to identify treatment effects is the assumption of common support or overlap of all the values of covariates (x) between the treatment and control groups. This assumption is expressed as follows:

$$0 < P(D = 1 \mid X) < 1 \tag{5.10}$$

Assumptions (5.9) and (5.10) together are referred to as strong ignorability by Rosenbaum and Rubin (1983). Under these assumptions, ATT can be identified for all values of X . Heckman et al. (1998) argue that ignorability is too strong: All that is needed to identify casual effects of treatments is mean independence. In the case of propensity score matching, where the parameter of interest is ATT, ignorability and weak overlap for control groups is sufficient to identify causal effects of treatments (Caliendo and Kopeinig, 2008). These assumptions are expressed as:

$$Y_0 \amalg D \mid X \tag{5.11}$$

$$P(D = 1 \mid X) < 1 \tag{5.12}$$

Assumptions (5.11) and (5.12) are the ignorability and weak overlap assumptions, respectively. These assumptions are sufficient to identify treatment effects because only a common support is needed to identify counterfactuals for the treatment group. Instead of covariates, propensity score matching assumes independence between the potential outcome and the propensity score. The propensity score is the conditional probability of receiving the treatment and is generally expressed as:

$$P(X) = \Pr\left[d = 1 \mid X = x\right] \tag{5.13}$$

If the conditional independence and overlap assumptions hold, the propensity score matching estimator for ATT can be written as:

$$ATT = E_{P(X)|D=1}\left\{E\left[Y_1 \mid D = 1, P(X)\right] - E\left[Y_0 \mid D = 0, P(X)\right]\right. \tag{5.14}$$

The propensity score estimator simply takes the mean difference in outcome between participant and non-participant over the region of common support, which is the area where similar propensity scores can be identified for both treatment and control groups.

5.4.2.1 A balancing test for matched covariates

The main idea behind propensity score matching is to depict a situation that is as similar as possible to randomized control trials. In randomized control trials, both observed and unobserved factors influencing program participation are balanced between treated and control groups. Since matching is based on the assumption that program participation is not influenced by unobserved factors, it is prudent to conduct some form of a balancing test after matching to ascertain whether observed covariates influencing program participation are balanced between treated and control groups. When the balancing property is achieved, then the control group can be used as appropriate counterfactual for the treatment group (Rosenbaum and Rubin, 1985). Rosenbaum and Rubin (1985) proposed mean absolute standard bias (MASB) and t-test for differences in covariates between participants and non-participants to assess matching quality. They recommend that a difference in MASB greater than 20% should be considered too large, which indicates that the matching process failed. Another way of testing the matching quality is to compare the pseudo R^2 and the p-values of the likelihood ratio test from the probit or logit regression models obtained before and after matching (Sianesi, 2004). To indicate that matching was successful, the pseudo R^2 should be lower and the p-value of the likelihood ratio test should be insignificant. In this paper, we conducted all of these tests to assess matching quality. The results of the tests are given in Section 5.5.4.

5.4.2.2 Sensitivity analysis to test the Conditional Independence Assumption

The propensity score matching estimator relies on the validity of the conditional independence assumption. This assumption rules out any possible correlation between the treatment and the unobserved factors influencing participation in agricultural training programs. If the conditional independence assumption is violated, results based on the propensity score matching estimator can contain a substantial amount of bias. Hence, it is necessary to scrutinize the results obtained from propensity score matching by conducting sensitivity analysis to test the plausibility of the conditional independence assumption (Ichno et al., 2008). We conduct sensitivity analysis to ascertain the robustness of our propensity score matching estimates against hidden bias. We use Rosenbaum's method, which measures the extent to which the odds of receiving treatment may differ among participants and non-participants with the same covariates. Rosenbaum and Rubin (1985) state that a critical level greater than 1.00 indicates a more robust estimates against hidden bias. Such a difference indicates that there is a substantial amount of hidden bias and thus that the conditional independence assumption and the propensity score matching process failed.

5.5. Results and discussion

5.5.1 Socio-demographic characteristics of households

The socio-demographic characteristics of households by agricultural training status are presented in Table 5.2. The results show that households that participated in agricultural training programs have a higher number of educated rice farmers and years of experience in rice farming compared to non-participants. Agricultural training educates farmers about rice production. Hence, we expect participation in agricultural training programs to be correlated with the education level of rice farmers. Agricultural training programs are facilitated by research and extension personnel who are also responsible for recruiting farmer trainees. Therefore, farmers who practice rice farming for a longer period are more likely to establish interpersonal relationships with researchers and extension workers. Hence, they should be more likely to participate in training programs led by research and extension personnel. Moreover, the results reveal that participants have more farmers with membership in an association. This is consistent with the finding by Kijima et al. (2012) in Uganda that a larger number of participants in low land rice training programs are members of farmer associations. Furthermore, the results show that higher number of participants in agricultural training programs have contact with the NARI and Non-Governmental Organizations (NGOs). Agricultural trainings programs are coordinated by personnel from research, extension, and NGOs. Hence, it is understandable that participants have a higher number of farmers who have contact with the NARI and NGOs.

Table 5.2: Socio-demographic characteristics of households by agricultural training status

Variable	Participants	Non-participants	Total	Difference Test
Age of respondent (in years)	50.1 (1.1)	49.9 (0.7)	49.9 (0.6)	0.2 (0.9)
Household size	9.4 (0.4)	9.6 (0.2)	9.5 (0.2)	0.1 (0.4)
Female (1 if respondent is a female)	0.91 (0.02)	0.94 (0.01)	0.93 (0.01)	0.02 (0.03)
Education (1 if respondent has primary education)	0.13 (0.02)	0.07 (0.0)	0.09 (0.01)	0.5 (0.03)**
Experience in rice farming (respondent's years of experience in rice farming)	13.67 (1.01)	11.03 (0.55)	2.64 (1.12)	0.17 (0.04)***
Household rice area (in ha)	0.74 (0.05)	0.78 (0.04)	0.71 (0.03)	0.4 (0.07)
Extension services (1 if respondent has contact with extension workers in 2009)	0.30 (0.04)	0.25 (0.02)	0.26 (0.02)	0.05 (0.05)
NARI (1 if respondent has contact with NARI in 2009)	0.47 (0.02)	0.21 (0.02)	0.21 (0.02)	0.26 (0.04)***
NGO (1 if respondent has contact with NGO)	0.44 (0.04)	0.11 (0.02)	0.19 (0.02)	0.34 (0.04)***
Association membership (1 if respondent is a member of rice association)	0.95 (0.02)	0.81 (0.02)	0.84 (0.02)	0.14 (0.04)***

NGO: Non Governmental Organization

NARI: National Agricultural Research Institute

Robust standard errors are shown in parenthesis; ***P*<0.05 and *** *P*<0.01.

Source: AfricaRice/NARI, Gambia Post Impact Assessment survey 2006/2010.

5.2 Determinants of technical efficiency

To identify the determinants of technical efficiency, we use the Tobit model with the estimated technical efficiency scores as the dependent variable and socio-economic and demographic characteristics as independent variables. To determine the magnitude of effect that each of the independent variables has on technical efficiency, we estimate the Tobit marginal effects, which are presented in Table 5.3. The results based on the Tobit marginal effects show that the factors that are positively correlated with technical efficiency are: female gender, association membership, contact with extension workers, residence in the Upper River Region (URR), the adoption of improved rice varieties, and farmer contact with NGOs. Female gender, association membership, and residence in the URR increase technical efficiency of rice farmers by 9%. Farmer contact with extension services, farmer adoption of improved rice varieties, and farmer contact with NGOs increase technical efficiency by 5%, 8% and 7%, respectively. Factors that are negatively correlated with technical efficiency are off-farm labor and practice of upland rice farming, which decrease technical efficiency by 6%.

The positive correlation of female gender and technical efficiency is not surprising. Rice is predominantly a woman's crop in The Gambia (Carney, 1998). The majority of men practicing rice farming started rice cultivation with the introduction of upland rice varieties, such as the New Rice for Africa (NERICA) (Dibba el al., 2012). During the rainy season, women devote their time almost entirely to rice cultivation. Besides rice cultivation, men are involved in the cultivation of cash crops, such as groundnut and cotton. This gives them less time to effectively manage the rice crop. Since women devote their time to rice cultivation in the rainy season, compared to men, they are more likely to better manage the crop.

Association membership has a positive effect on technical efficiency. Association membership is a vital source of information (Kijima and Sserunkuuma, 2013). Information is crucial for the uptake of new technologies and practices (Caswell et al., 2001; Feder and Slate, 1994). Farmers of the same association can also easily share knowledge and experience about new innovations, including those introduced at agricultural training programs. For this reason, farmers who are members of rice farming association are likely to be more efficient in rice production compared to their counterparts.

Off-farm labor and upland rice cultivation are negatively correlated with technical efficiency. Farmers practicing off-farm labor are likely to undertake rice farming as a secondary activity. Hence, we expect that such farmers are less efficient in producing rice compared to their counterparts who cultivate rice for their major farming activity. Moreover, there are three major rice farming ecologies in The Gambia: upland, lowland rainfed, and lowland irrigated. Rice yields are the lowest in upland rice fields (WARDA, 2001). Since rice yields are the only output for estimating technical efficiency, we expect upland rice farmers to be less efficient compared to lowland rainfed and irrigated rice farmers.

Farmer contact with NGOs and extension workers is positively correlated with an improvement in the technical efficiency of rice farmers. Farmer contact with extension is a vital source of information acquisition about new technologies and practices (Rogers, 1983). Moreover, agricultural training programs are conducted by researchers, extension workers, and NGO agents who are responsible for selecting participants for agricultural training programs. Hence, farmers who have contact with NGOs and extension workers are more likely to participate in agricultural training programs. Therefore, they are more likely to be efficient in rice production. Moreover, most of the agricultural programs on rice are located in the URR. Consequently, rice farmers in the URR are more likely to participate in agricultural training programs and therefore are more likely to be efficient in rice production. Furthermore, there is vast evidence that farmers who adopt improved rice varieties are more productive in rice cultivation compared to farmers who adopt local rice varieties (Kijima et. al., 2006; Mendola, 2006; Dibba et. al., 2012). Most improved rice varieties are resistant to biotic and abiotic factors affecting rice (Jones et al., 1997; Wopereis et al., 2008a). For this reason, farmers cultivating improved rice varieties are more likely to be efficient in rice production.

Table 5.3: Tobit marginal effects of factors influencing technical efficiency

Variables	Marginal Effect	z-value
Age of respondent (in years)	-0.00 (0.00)	-1.13
Female (1 if respondent is a female)	0.09 (0.04)**	2.08
Household size	0.00 (0.00)	0.80
Education (1 if respondent has primary education)	-0.01 (0.04)	-0.13
Experience in rice farming (respondents years of experience in rice farming)	-0.05 (0.00)	-0.05
Household head (1 if respondent is household head)	0.03 (0.02)	1.30
Off-farm labor (1 if respondent has an occupation other than rice farming)	-0.06 (0.03)**	-1.97
Extension services (1 if respondent has contact with an extension worker in 2009)	0.05 (0.02)**	1.96
Improved variety access (1 if respondent has access to an improved rice variety)	-0.03 (0.05)	-0.74
Upland farming (1 if respondent is an upland rice farmer)	-0.06 (0.02)**	-2.39
Lowland farming (1 if respondent is a lowland rice farmer)	-0.00 (0.02)	-0.09
URR (Household is located in the URR)	0.09 (0.03)***	2.76
Improved variety adoption	0.08(0.03)***	2.82
Local variety adoption (1 if respondent has cultivated local rice variety in 2009)	-0.07 (0 .05)	-1.11
NARI (1 if respondent has contact with the NARI in 2009)	0.02 (0 .03)	0.76
NGO (1 if respondent has contact with an NGO in 2009)	0.07 (0.03)***	2.11
Association membership (1 if respondent is a member of rice association)	0.09 (0.02)***	3.67
Number of observations	515	
Pseudo R^2	1.58	
LR chi^2	67.42***	
Log likelihood	12.40	

NGO: Non-Governmental Organization

NARI: National Agricultural Research Institute

URR: Upper River Region

Source: AfricaRice/NARI, Gambia Post Impact Assessment survey 2006/2010.

Notes: *P<0.10, ** P<0.05, and *** P<0.01.

5.5.3 Descriptive analysis of the impact of agricultural training on technical efficiency

Table 5.4 presents a descriptive analysis of the impact of agricultural training on technical efficiency. The results are presented for all rice farmers and for male[30] and female rice farmers separately. The results show that participants in agricultural training programs have higher technical efficiency scores than non-participants. The difference in technical efficiency scores is estimated to be 5 percentage points, which is statistically different from zero at the 1% significance level. The DEA approach to estimate technical efficiency uses the most efficient rice producers (those with a technical efficiency score equal to 1) as a basis for computing the technical efficiency scores of other less efficient rice producers. The average rice yields of the most efficient farmers are estimated to be 2,602 kg/ha. Therefore, a 5% increase in technical efficiency translates to a yield increase of 130 kg/ha. One kilogram of paddy rice is sold at 15 GMD (US$ 0.5). Hence, 130 kg of paddy rice has a monetary value of 1,950 GMD (US$ 65). The finding suggests that the impact of agricultural training on technical efficiency is greater for rice farmers who participated in agricultural training programs.

The results show higher technical efficiency scores for female rice producers. Female farmers had a technical efficiency score of 6 percentage points greater than male farmers, which is significantly different from zero at 1% the significance level. This represents a yield increase of 156 kg/ha, which is valued at 2,340 GMD (US$ 78). The results therefore suggest that the impact of agricultural training on technical efficiency is greater for female rice farmers. However, the simple mean difference in technical efficiency scores between agricultural training program participants and non-participants has no causal interpretation of the impact of agricultural training on technical efficiency. Besides agricultural training, there are many other socio-economic and demographic factors that can affect the technical efficiency of rice farmers. Indeed, the results have shown that participants and non-participants have significant differences in some socio-demographic factors. Such differences must be controlled for to make causal inferences about agricultural training on technical

[30] Male farmers represent households where the main rice producer is a male and female farmers for households where the main rice producer is a female.

efficiency. In the next sub-section, we use propensity score matching to estimate the impact of agricultural training on technical efficiency.

Table 5.4: Descriptive analysis of the impact of agricultural training on technical efficiency

Characteristics	Participants	Non-participants	Total	Difference Test
Technical efficiency scores				
All farmers	0.39	0.33	0.35	0.05
	(0.22)	(0.12)	(0.01)	(0.02)***
Male farmers	0.25	0.33	0.30	-0.07
	(0.08)	(0.05)	(0.04)	(0.09)
Female farmers	0.39	0.33	0.34	0.06***
	(0.02)	(0.01)	(0.01)	(0.02)

Robust standard errors are shown in parenthesis; *P<0.10 and *** P<0.01

Source: AfricaRice/NARI, Gambia Post Impact Assessment survey 2006/2010.

5.5.4 Propensity score matching

The results of the descriptive analysis obtained from the previous section suggest that agricultural training may have a positive impact on the technical efficiency of rice farming households. However, since they are based on observed mean differences in technical efficiency scores between participants and non-participants, they have no causal interpretation of the impact of agricultural training on technical efficiency. Hence, in this sub-section, we use PSM to identify causal inference of participation in agricultural training programs on technical efficiency of rice farmers.

5.5.4.1 Estimating the propensity score

Table 5.5 reports the factors influencing the propensity to participate in agricultural training programs. We used a probit model to estimate the propensity score based on a number of socio-economic and demographic factors of rice farming households. The results indicate that the most influential factors are whether the respondent is the household head, education, household size, off-farm labor, contact with extension workers, adoption of improved rice varieties, and contact with NGOs.

Table 5.5: Probit regression of determinants of participation in agricultural training programs

Variable	Coefficients	z-value
Age of respondent (in years)	-0.00 (0.00)	-0.75
Female (1 if respondent is a female)	0.39 (0.30)	1.31
Household size	-0.01 (0.02)***	-0.65
Household head (1 if respondent is head	1.60 (0.17)***	9.03
Education (1 if respondent has primary	1.24 (0.27)***	4.47
Experience in rice farming (respondents years of experience in rice farming)	0.02 (0.00)	3.24
Off-farm labor (1 if respondent has an occupation other than rice farming)	0.44 (0.22)**	2.03
Improve variety access (1 if respondent has access to improve rice variety)	0.24 (0.33)	0.72
Extension services (1 if respondent has contact with extension workers in 2009)	0.41 (0.18)**	2.22
NARI (1 if respondent has contact with	0.00 (0.19)	0.02
Upland farming (1 if respondent is	0.06 (0.21)	0.31
Lowland farming (1 if respondent is	-0.00 (0.17)	-0.00
Local variety adoption (1 if respondent has cultivated local rice variety in 2009)	-0.59(0.48)	-1.21
Improved variety adoption (1 if respondent has cultivated improved rice variety in 2009)	0.58 (0 .24)**	2.37
NGO (1 if respondent has contact with	0.48 (0.24)**	2.00
Association membership (1 if respondent is member of rice association)	0.05 (0.25)	0.21
Number of observations	515	
Pseudo R^2	0.46	
LR chi^2	61.98***	
Log likelihood	156.67	

NGO: Non Governmental Organization

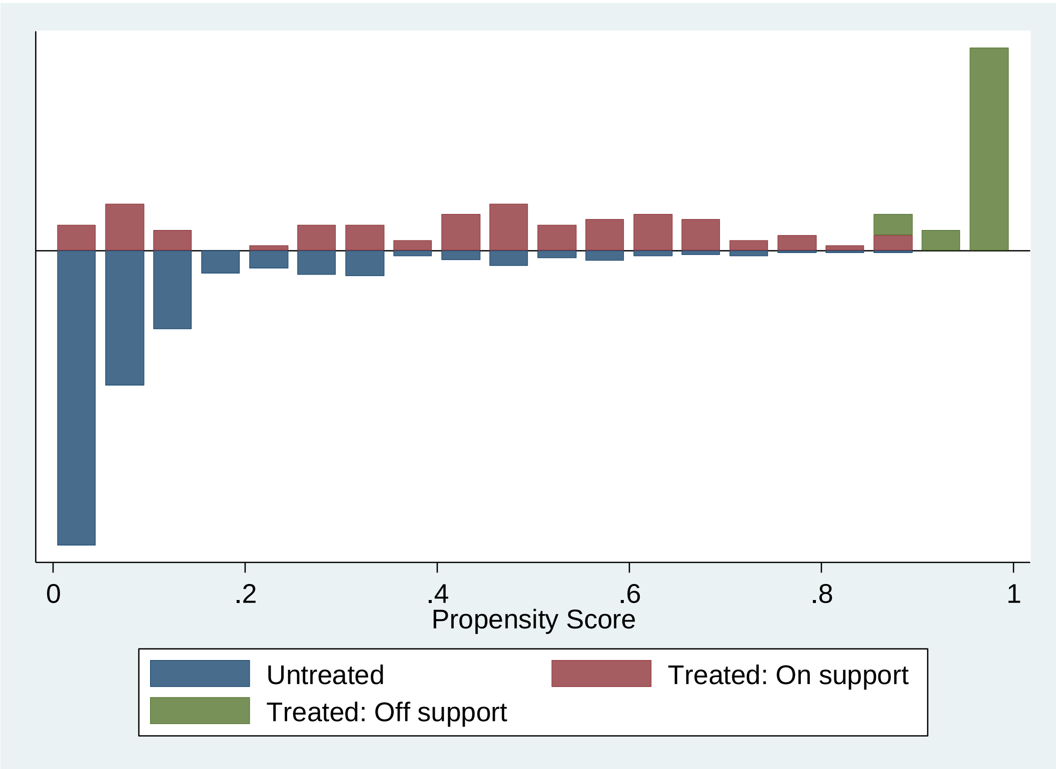
NARI: National Agricultural Research Institute

Source: AfricaRice/NARI, Gambia Post Impact Assessment survey 2006/2010.

Notes: ** P<0.05 and *** P<0.01.

The estimated propensity score for participants is between 0.24 and 0.99, whereas that for non-adopters is between 0.0004 and 0.89. To estimate the impact of participation in agricultural program on technical efficiency, we need to identify a region of common support[31] based on the propensity score estimates (Figure 5.1). As recommended by Rosenbaum and Rubin (1985), we use a caliper value of one-quarter of the standard deviation of the propensity score to identify the region of common support. It is within the region of common support that we can find participants and non-participants with similar propensity score estimates. Within the region of common support, a counterfactual can be constructed for participants in agricultural training programs to enable the estimation of treatment effects.

Figure 5.1: Propensity score distribution and common support



5.5.4.2 Choosing a matching algorithm

The four main types of matching algorithms used in empirical research to estimate treatment effects based on the propensity score matching approach (Caliendo and Kopeinig, 2008) are the Nearest Neighbor Matching (NNM), Radius Matching (RM), Stratification Matching (SM), and Kernel Matching (KM) approach. We estimate

[31] The region where treatment and control groups have similar propensity scores

treatment effects based on all of these four approaches, but due to sensitivity of the results to hidden bias we focus on estimates obtained from NNM and RM.

5.5.4.3 Balancing test

A balancing test is required after matching to determine whether the difference in covariates between participants and non-participants was eliminated after matching. The results of the quality indicators before and after matching are presented in Table 6. The NNM estimates of the mean absolute standardize bias before and after matching are 42.6% and 9.2%, respectively. The results based on RM show that the mean absolute standardize bias before and after matching are 46.2% and 23.4%, respectively. Rosenbaum and Rubin (1985) recommend that a mean absolute standard bias greater than 20% after matching is an indication that matching has failed.

Table 5.6: PSM quality indicators before and after matching

Matching algorithm	Pseudo R^2 before Matching	Pseudo R^2 after matching	LR X^2 (p value) before matching	LR X^2 (p value) after matching	Mean absolute standardized bias before matching	Mean absolute standardized bias after matching
NNM	0.46	0.05	261.98***	12.07	42.6	9.2
RM	0.46	0.32	261.68***	60.88***	42.6	23.4

Source: AfricaRice/NARI, Gambia Post Impact Assessment survey 2006/2010.

Notes: *** $P<0.01$

Sianesi (2004) suggests a comparison of the pseudo R^2 and the p-values of the likelihood ratio test from the probit regression obtained before and after matching. After matching, to indicate that matching was successful, the pseudo R^2 should be lower and the p-value of the likelihood ratio should be insignificant. The values of Pseudo R^2 based on NNM before and after matching are 0.46 and 0.05, respectively, whereas those based on RM before and after matching are 0.46 and 0.32, respectively. The value of likelihood ratio based on NNM after matching is insignificant, whereas that based on RM after matching is significant and different from zero at the 1% significant level. Based on recommendations by Rosenbaum and Rubin (1985) and Sianesi (2004), matching based on NNM was more successful.

5.5.4.4 Sensitivity analysis

The estimates based of PSM rely on the validity of the conditional independence assumption, which rules out dependence of participation in agricultural training programs based on unobserved factors. If selection into treatment is influenced by unobserved factors, the PSM estimates will contain a substantial amount of bias. For this reason, results based on PSM should be subjected to some form of sensitivity analysis to determine whether they contain a substantial amount of hidden bias (Ichno et al., 2008). The results of the sensitivity analysis for NNM and RM are presented in Table 5.7. The critical level of hidden bias based on NNM is 1.25, whereas that based on RM is 1.00. Since a critical level greater than 1.00 indicates a more robust estimates against hidden bias the results based on NNM are, therefore, more robust against hidden bias.

Table 5.7: Sensitivity analysis for selected algorithms

Matching algorithm	ATT	Critical level of hidden bias (Γ)
Nearest Neighbor Matching	0.10 (2.15)***	1.25
Radius Matching	0.04 (1.58)**	1.00

Source: AfricaRice/NARI, Gambia Post Impact Assessment survey 2006/2010.

ATT: Average treatment effect on the treated

Notes: *P<0.10, ** P<0.05, and *** P<0.01

5.4.5 PSM estimates of the impact of agricultural training on technical efficiency

Table 5.8 reports the PSM estimates of the impact of agricultural training on technical efficiency. The results are presented based on NNM and RM. The result based on NNM shows that agricultural training improves technical efficiency of rice farmers by 10 percentage points, which is statistically different from zero at the 1% significance level. The result based on RM shows that agricultural training only improves technical efficiency of rice farmers by 4 percentage point, which is statistically different from zero at the 10% significance level. Since the balancing test and sensitivity analysis show that the results based on NNM are more robust against hidden bias, the discussions will be based on NNM estimates.

Table 5.8: PSM estimates of the impact of agricultural training on technical efficiency

Matching algorithm	Participants	Non-participants	ATT
Nearest Neighbor Matching	0.38	0.28	0.10 (2.15)***
Radius Matching	0.37	0.33	0.04 (1.58)*

ATT: Average treatment effect on the treated

Source: AfricaRice/NARI, Gambia Post Impact Assessment survey 2006/2010

Notes: *P<0.10 and *** P<0.01.

Our findings indicate that agricultural training has the ability to positively impact rice production. This is consistent with the finding by Kijima el al. (2012) that participation in an agricultural training program has the potential to increase lowland rice productivity in Uganda. The finding by Asante et al. (2014) that agricultural technologies have the ability to positively impact technical efficiency of rice farming households is also consistent with our results. Nakaro and Kajisa (2011) also found that agricultural training has the ability to positively impact the productivity of rice farmers in Tanzania. These finding clearly show that agricultural training has the ability to impact rice production and productivity positively in The Gambia.

5.5 Economic and investment analysis of the impact of agricultural training on technical efficiency

Table 5.9 presents the social cost-benefit analysis of agricultural training. The analysis is based on the PLAR training program to provide a better picture of the impact of agricultural training on technical efficiency. Agricultural training involves the use of government or donor funds to train extension workers on rice management practices. The use of such funds can only be justified if the net benefits yield positive results. The social cost-benefit analysis reveals that about 2,199,000 GMD (US$ 73,300) is needed to train 30 extension workers and 900 rice farmers on the PLAR. This represents the total cost of implementing agricultural training at the societal level. Cost is divided direct and indirect costs. Direct costs involve organizing the training of trainer's workshop for 30 extension workers, which costs 120,000 GMD (US$ 4,000). Each extension worker is also required to train 30 rice farmers. Training rice famers involves indirect costs (opportunity costs) because farmers will have less time to spend on their rice fields during the training sessions. Such costs are calculated as the value of lost labor. We estimated the opportunity cost of labor based on four main rice farm activities which require external labor: transplanting, weeding, harvesting, and threshing. The daily wage for weeding and transplanting is 150 GMD (US $ 5), whereas that for harvesting and threshing is 180 GMD (US $ 6). Based on these figures, the average daily wage per person is estimated at 165 GMD (US $ 5.5), which represents the opportunity cost of farm labor lost for attending agricultural trainings. The PLAR training sessions are normally conducted for two weeks. This translates to an opportunity cost of labor of 2,310 GMD (US$ 77) for an individual famer (Table 10). As a result, training 900 rice farmers is estimated to cost society $2,079,000 GMD (US$ 69,300).

Table 5.9: Social cost-benefit analysis

	Description	Quantity	Unit price (GMD)	Total
Cost	Training extension workers on the PLAR (14 days)	30	4,000	120,000
	Opportunity cost of training rice farmers	900	2,310	2,079,000
			Total cost	**2,199,000**
Benefits	Increase in yields for target beneficiaries	(900 * 260 kg/ha)	15/Kg	3,510,000
			Total benefits	**3,510,000**
Net benefit				**1,311,000**

Source: AfricaRice/NARI, Gambia Post Impact Assessment survey 2006/2010.

To estimate the gains from agricultural training, we determine the 10% increase in technical efficiency in terms of the increase in rice yields. This represents a rice yield increase of 260 kg/ha. Since one kilogram of paddy rice is sold at 15 GMD (US$ 0.5), this translates into a monetary value of 3,900 GMD (US$ 130) for individual rice producers (Table 5.10). At the societal level, gains are valued at $3,510,000 GMD

(US$ 117,000). The net social and private benefits are estimated to be 1,311,000 GMD (US$ 43,700) and 1,590 GMD (US$ 53), respectively. This justifies increases in government and/or donor spending, and rice farmer participation in agricultural training projects. However, to give governments or donors a better picture of the returns on their investment, we conduct an investment analysis over a ten year project planning horizon (Table 5.11).

Table 5.10: Private cost-benefit analysis

	Description	Quantity	Unit price (GMD)	Total
Cost	Opportunity cost of attending training sessions	14 days	165	2,310
			Total cost	2,310
Benefits	Increase in yields for an individual beneficiary	260 kg/ha	15/Kg	3,900
			Total benefit	3,900
Net benefit				**1,590**

Source: AfricaRice/NARI, Gambia Post Impact Assessment survey 2006/2010.

The results of the investment analysis of agricultural training are presented in Table 5.11. The Net Present Value (NPV), Benefit Cost Ratio (BCR), and Internal Rate of Return (IRR) are calculated based on the average interest rate (13.9%) on deposits in The Gambia over the past ten years (World Bank, 2015). Income and costs are calculated over a ten-year planning horizon, which includes the training of 30 extension officers and 900 rice farmers on PLAR. In the first year, 30 extension officers and 90 rice farmers are planned to be trained on the PLAR. Training sessions are planned to last two weeks. Hence, the cost of training 30 extension officers is estimated to be 120,000 GMD (US$ 40,000) and the cost of training 90 rice farmers is estimated to be 207,900 GMD (US$ 6,930), which results in a total cost of 327,900

GMD (US$ 10,930) in year one. It is assumed that rice farmers trained in the first year will apply the knowledge gained in the second year. For this reason, no income is acquired in the first year. It is planned that 90 rice farmers will be trained annually between years two and ten, which results in a fixed cost of 207,900 GMD (US$ 6,930). The income in year two is calculated based on an anticipated yield increase of 260 kg/ha. Since one kilogram of paddy rice is sold at 15 GMD (US$ 0.5), the total increase in income for 90 rice farmers is 351,000 GMD (US$ 11,700).

The results of the analysis show a NPV value of 5,874,476.5 GMD (US$ 195,815.8) and BCR of 5.3. The positive NPV and BCR greater than 1 justify increased investments in agricultural training programs to boost rice production and productivity in The Gambia. The IRR value of 99% indicates that investment in agricultural training is likely to yield 85.1% higher returns on investment compared to bank deposits, which further justifies the need for more investment in agricultural training programs. However, the average IRR for research and development expenditure in developing countries has been estimated to be 43 percent (Alston et. al., 2000). This value is much lower than the IRR reported in this study. The higher IRR value reported in this study could be attributed to the fact that due to lack of data, this study did not include the cost incurred by extension personnel when conducting the PLAR training sessions. For this reason, we conduct a sensitivity analysis to determine the IRR value with 100% increase in the estimated cost (Table 5.12).

Table 5.11: Investment analysis of agricultural training with a 13.9% discount rate

Year	Income (GMD)	Costs (GMD)	Discount Factor	Discounted income (GMD)	Discounted cost (GMD)
1	-	327,900	1	0	327,900
2	351,000	207,900	0.8780	308,178	182,536.2
3	702,000	207,900	0.7708	541,101.6	160,249.32
4	1,053,000	207,900	0.6768	712,670.4	140,706.72
5	1,404,000	207,900	0.5942	834,256.8	123,534.18
6	1,755,000	207,900	0.5217	915,583.5	108,461.43
7	2,106,000	207,900	0.4580	964,548	95,218.2
8	2,457,000	207,900	0.4021	987,959.7	83,596.59
9	2,808,000	207,900	0.3530	991,224	73,388.7
10	3,159,000	207,900	0.3099	978,974.1	64,428.21
Total				723,4496.1	136,0019.6
NPV					587,4476.5
BCR					5.31
IRR					99%

Source: AfricaRice/NARI, Gambia Post Impact Assessment survey 2006/2010.

NPV: Net present value, BCR: Cost Benefit Ratio, IRR: Internal Rate of Return

The results of the sensitivity analysis indicate that when expected costs increase by 100%, investment in agricultural training will yield a NPV of 4,514,457 GMD (US$ 150,481.9), BCR value of 2.65, and IRR of 45% (Table 5.12). These results further justify the need for increased investment in agricultural training to boost rice production and productivity in The Gambia.

Table 5.12: Sensitivity analysis with a 100% increase in expected cost

Year	Income (GMD)	Costs (GMD)	Discount Factor	Discounted income (GMD)	Dis. cost (GMD)
1	-	655,800	1	0	655,800
2	351,000	415,800	0.8780	308,178	365,072.4
3	702,000	415,800	0.7708	541,101.6	320,498.64
4	1,053,000	415,800	0.6768	712,670.4	281,413.44
5	1,404,000	415,800	0.5942	834,256.8	247,068.36
6	1,755,000	415,800	0.5217	915,583.5	216,922.86
7	2,106,000	415,800	0.4580	964,548	190,436.4
8	2,457,000	415,800	0.4021	987,959.7	167,193.18
9	2,808,000	415,800	0.3530	991,224	146,777.4
10	3,159,000	415,800	0.3099	978,974.1	128,856.42
Total				7,234,496.1	272,0039.1
NPV					451,4457
BCR					2.65
IRR					45%

Source: AfricaRice/NARI, Gambia Post Impact Assessment survey 2006/2010.

NPV: Net present value, BCR: Cost Benefit Ratio, IRR: Internal Rate of Return

5.6. Conclusions

The results from this study indicate that agricultural training has significantly improved technical efficiency of rice farming households in The Gambia by 10 percentage points. This translates to a rice yield increase of 260 kg/ha, which results in net social and private benefits per annum of US$ 43,700 and US$ 53 for 900 rice farming households and 30 extension agents, and per household, respectively. Further analysis of investments in agricultural training reveals a NPV of US$ 195,815.8, BCR of 5.3, and IRR of 99%. This justifies increased government and/or donor spending on agricultural rice farmer training programs to boost rice production and productivity in The Gambia, as well as increased rice farmer participation in agricultural training programs.

Our findings indicate that technical efficiency is positively influenced by female gender, contact with extension workers, and association membership. The significant influence of association membership on technical efficiency could mean that agricultural training has some spill over effects, which could occur when farmers who attend agricultural training programs share their knowledge and experience with members of the same association. The positive influence of female gender on technical efficiency may not necessarily mean that agricultural training programs are more beneficial for women farmers. Rice is mainly cultivated by women who devote their time almost entirely to rice production during the rainy season. Hence, they have more experience than men in rice cultivation, which means that they are more efficient in rice production.

We defined participation in agricultural training programs as involvement by a rice farmer in at least one program that trains famers on rice production practices. Since all rice farmer training programs may not have the same level of effectiveness, we recommended that future studies that assess the impact of agricultural training on technical efficiency should identify specific training programs and activities. This would enable the most effective training programs and activities to be identified.

The policy implication of this study is that rice farmers should be encouraged by agricultural extension services to form associations that meet regularly to exchange ideas and information about new developments within and outside their rice farming communities. To ensure that such meetings are regular, associations should be registered and members should be committed to pay regular membership fees.

Acknowledgement

The authors would like to acknowledge the financial support provided by the Global Rice Science Scholarship (GRiSS) program for the successful implementation of this study. The technical support provided by the Africa Rice Center (AfricaRice) and University of Hohenheim is also highly acknowledged.

References

African Development Fund. 2005. Farmer Managed Rice Irrigation Project. Technical Appraisal report. Available at http://www.afdb.org/fileadmin/uploads/afdb/Documents/Project-and-Operations/Gambia_-_Farmer_Managed_Rice_Irrigation_Project_-_Appraisal_Report.pdf. Accessed online (April 2004)

Alston J., Chan-Kang C., Marra M., Pardey P., Wyatt T. 2000. Meta-analysis of rates of return to agricultural R&D: Ex Pede Herculem? 2000. Research Report No. 113. Washington, DC: IFPRI.

Asante, B.O., Wiredu, A.N., Martey, E., Sarpong, D.B., Mensah-Bonsu, A. 2014. NERICA adoption and impacts on technical efficiency of rice producing households in Ghana: Implications for research and development. *American Journal of Experimental Agriculture*. 4(3): 244-262

Caliendo, M., and Kopeinig. S. 2008. Some practical guidance for the implementation of propensity score matching. *Journal of Economic Surveys*. Vol. 22, No 1, pp. 31-72

Carney, J.A. 1998. Women's land rights in Gambian irrigated rice schemes: Constraints and opportunities. In: *Agriculture and Human Values* 15 (4): 325-33.

Charnes, A., Cooper, W. W., Rhodes E. 1978. Measuring the efficiency of decision making units, *European Journal of Operational Research* 2 (6), pp. 429–444.

Coelli, T.J. 1995. Recent Developments in Frontier Modeling and Efficiency Measurement. *Australian Journal of Agricultural Economics* 39 :219-245.

Coelli, T. J. 1996. A guide to DEAP Version 2.1: A Data Envelopment Analysis Programme. CEPA Working Paper 96/8, Department of Econometrics, University of New England, UK, 1996. http://www.owlnet.rice.edu/~econ380/DEAP.PDF. Accessed online (May 2015)

Caswell, M., Fuhlie, K., Ingam, C., Jans, S., and Kascak, C. 2001. Adoption of Agricultural production practices: Lessons learned from the US. Department of Agriculture Area Studies Project, Agriculture Economic Report No. 792. US Department of Agriculture, Resource Economics Division, Economic Research Service, Washington, D.C.

Bravo-Ureta, BE., and Pinheiro, A.E. 1997. Technical, Economic and Allocative Efficiency in Peasant Farming: Evidence from the Dominican Republic. *The Developing Economics*. Vol. 35, No (1), 48-67.

Defoer, T., Wopereis .C.S., P. Idinoba, P., K.L. Kadisha K.L, Diack, S and M. Gaye, 2009. Curriculum for Participatory Learning and Action Research (PLAR) for Integrated Rice Management (IRM) in Inland Valleys of Sub-Saharan Africa: Facilitator's Manual. Cotonou, Benin: Africa Rice Center. 184 pp

Dibba, L., Diagne, A., Fialor S.C., and Nimoh, F. 2012. The impact of NERICA adoption on productivity and poverty of the smallholder rice farmers in the Gambia. *Food Security*. (2012) 4:253–265.

Feder, G., and Slade, R. 1984. The acquisition of information and the adoption of new Technology. In: American Journal of Agricultural Economics. In: *American Agricultural Economics Association* 66 (3): 312-320.

Jones, M.P., Dingkuhn, M., Aluko, G.K. and Semon, M. 1997. Interspecific Oryza sativa × O. glaberrima Steud. progenies in upland rice improvement. *Euphytica* 92:237-246.

Ichino, A., Mealli, F. and Nannicini, T. 2008. From temporary help jobs to permanent employment: what can we learn from matching estimators and their sensitivity?. *Journal of Applied Econometrics*, 23: 305–327.

Kijima, Y., Sserunkuuma, D., & Otsuka, K. 2006. How revolutionary is the "NERICA revolution"? Evidence from Uganda. *Developing Economies*, 44(2), 232–251.

Kijima, Y. and D. Sserunkuuma. 2013. The adoption of NERICA rice varieties at the initial stage of the diffusion process in Uganda. In: *African Journal of Agricultural and Resource Economics* 8 (1): 45-56

Kijima, Y., Ito, Y., Otsuka, K. 2012. Assessing the impact of training on lowland productivity in an African setting: Evidence from Uganda. *World Development*, Vol. 40, No. 8, pp 1610-1618

Larson, D., K. Otsuka, K. Kajisa, J. Estudillo, and A. Diagne. 2010. Can Africa replicate Asia's Green Revolution in rice? Policy Research Working Paper 5478. World Bank

Mendola, M. 2006. Agricultural technology adoption and poverty reduction: a propensity–score matching analysis for rural Bangladesh. *Food policy*, 32(2007), 372–393

McCarty T.A, Yaisawarng S. 1993. Technical efficiency in New Jersey school districts, in: H.O. Fried, C.A.K. Lovell, S.S. Schmidt (Eds.), The Measurement of Productive Efficiency: Techniques and Applications, *Oxford University Press,* New York, 1993, pp. 271–287.

Nakaro, Y and Kajisa, K. 2011. The Impact of Access to Credit and Training on Technology Adoption: A Case of the Rice Sector in Tanzania. Selected paper prepared for presentation at the Agricultural & Applied Economics Association's 2011 AAEA & NAREA Joint Annual Meeting, Pittsuburgh, Pennsylvania, July 24-26, 2011

Otsuka, K., & Kijima, Y. 2010. Technology Policies for a Green Revolution and Agricultural Transformation in Africa. *Journal of African Economies,* 19, ii60-ii76.

Rogers, E. 1983. Diffusion of innovations. Free Press, New York.

Rosenbaum, P. R., & Rubin, D. R. (1983). The central role of the propensity score in observational studies for causal effects. *Bometrika*, 70, 41-55.

Rosenbaum, R. and Rubin, D. B. 1984. ‘‘Reducing bias in observational studies using subclassification on the propensity score,’’ *Journal of the American Statistical Association*, 79, pp. 516–524, 1984

Rosenbaum P.R. and Rubin, D.B. 1985. Constructing a control group using multivariate matched sampling methods that incorporate the propensity score. *American Statistician*, 39 (1), pp. 33–38.

Rubin, D. 1974. Estimating causal effects of treatments in randomized and non-randomized studies. *Journal of Educational Psychology*, 66, 688–701.

Rubin, D.B. 2001. Using Propensity Scores to Help Design Observational Studies: Application to the Tobacco Litigation. *Health Services & Outcomes Research Methodology*, 2, 169-188.

Seck PA, Tollens E, Wopereis M, Diagne A, & Bamba I. 2010. Rising trends and variability of rice prices: Threats and opportunities for sub-Saharan Africa. *Food Policy*, 35 (5), 403-411.

Sianesi, B. 2004. An evaluation of the Swedish system of active labour market programmes in the 1990s. *Review of Economics and Statistics,* 86 (1), pp. 133–155.

Tobin, J. 1958. “Estimation of Relationships for Limited Dependent Variables,” *Econometrica*, 26, 24-36

Yamamoto, Y., Tsujimoto, Y., Fugihara, Y., Sakagami, J., Ochi, S., Fosu, M. 2012. Assessing the probability of land submergence for lowland rice cultivation in Africa using satellite imagery and geospatial data. *Environment Development and Sustainability*. (14) 955-971.

Wopereis, M.C.S., A. Diagne, J. Rodenburg, M. Sie and E.A. Somado. 2008a. Why NERICA is a successful innovation for African farmers: A response to Orr et al. from the Africa Rice Centre. In: *Outlook Agriculture* 37 (3): 159-168

Wopereis, M.C.S., T. Defoer, P. Idinoba, S. Diack and M.J. Dugué, 2008b.

Participatory Learning and Action Research (PLAR) for Integrated Rice Management (IRM) in Inland Valleys of Sub-Saharan Africa: Technical Manual WARDA Training Series. Cotonou, Benin: Africa Rice Center. 128 pp

World Bank 2015. Deposit interest rates. Available at http://data.worldbank.org/indicator/FR.INR.DPST/countries. Accessed online (June 2015)

Chapter 6

6. Summary, conclusions and policy implications

This chapter presents summary of the main findings in connection to the research questions and hypothesis highlighted in Chapter 1. It also identifies the research gaps and future work in relation to the three research topics presented in Chapter 3, 4 and 5 and also presents the main conclusions drawn from the three research topics and elaborate on their policy implications.

6.1 Summary of main findings and interpretations

The main findings of this dissertation are presented in Chapter 3, 4 and 5. The aim of Chapter 3 is to determine the desirability of the NERICA technology by the target population. To determine the desirability of the NERICA technology, we identify two main constraints (lack of awareness and access to NERICA seeds) which can limit the adoption of NERICA by the target population. Farmers who are not aware of the NERICA technology cannot adopt it even if they would have done so had they known about it. As a result, lack of awareness leads to under estimation of the true population adoption rate if the sample adoption rate is wrongly used to represent the desirability of the technology by the target population. When awareness is complete, lack of access can also limit technology adoption. To determine the true population adoption rate of NERICA, we address such constraints using the potential outcome framework following Diagne and Demont (2007). The results of the framework indicate that NERICA adoption could have been 76% instead of the observed sample estimate of 66% provided every rice farmer in The Gambia had known NERICA before 2011. However, since awareness is not a sufficient condition for technology adoption, a further investigation finds that if all the rice farmers had been aware and had access to NERICA seeds adoption would have been 92%. These results reveal a very high unmet demand for NERICA in The Gambia, which could be achieved by increasing awareness and access to NERICA seeds in the rice farming communities of the country. To increase awareness and access to NERICA seeds, farmer contact with extension, NARI and access to in-kind credit are identified as important determinants of awareness, access and adoption of NERICA. This calls for concerted efforts to provide in-kind credit services to farmers through extension and NARI.

Chapter 4 assesses the impact of NERICA adoption on household food security and health. The main objective of this chapter is to identify improvements in food security and health outcomes that can be attributed to NERICA adoption. To identify causal effects of NERICA adoption, we control for endogeneity using the instrumental variable approach (Heckman and Vytlacil 2005; Imbens 2004; Abadie, 2003; Imbens and Angrist 1994; Heckman and Robb 1985). We used exposure to NERICA as an instrumental variable and estimate the Local Average Treatment Effect (LATE) using the Local Average Response Function by Abadie (2003) to identify improvements in food security and health outcomes that can be attributed to NERICA adoption. The results indicate NERICA adoption significantly increases household food security by 14% but no significant impact on health. The results further indicate a significant correlation between NERICA adoption and extension contact and access to in-kind credit. This makes extension contact and access to in-kind credit services like improved seeds an important impact pathway to identifying casual effects of NERICA adoption on household food security.

Chapter 5 determines the impact of agricultural training on technical efficiency of rice farmers. The main objective of the chapter is to identify the causal effect of agricultural training on technical efficiency and its determinants. We used a two stage estimation procedure to assess the impact of agricultural training on technical efficiency. In the first stage, we estimate technical efficiency scores using Data Envelopment Analysis (DEA). In the second stage, we determine the impact of agricultural training on technical efficiency by assuming conditional independence (Rubin 1974; Rosenbaum and Rubin 1983) and used propensity score matching to identify causal effects. To assess the plausibility of conditional independence, we conduct sensitivity analysis using rbounds and mean absolute standard bias tests between participants and non-participants. The result of the analysis indicate that agricultural training significantly increases technical efficiency of smallholder rice farmers by 10%, which justifies increase investments on agricultural training programs to increase rice production and productivity. The results further reveal that farmer contact with extension workers and association membership as significant factors influencing technical efficiency. This necessitates concerted efforts to increase farmer contact with extension and encourage farmers to be members of agricultural organizations.

6.2 Research gaps and future work

To complement the research work reported in this dissertation, we identify some important research gaps and future work that need to be given attention in order to give a better picture of adoption and impact of the technologies and programs discussed in this dissertation. This sub-section provides a summary of the research gaps and future works identified in relation to the research questions and hypothesis addressed in Chapter 3, 4 and 5.

The findings in Chapter 3 indicate that when efforts are made to make the entire rice farming population aware of the existence of NERICA varieties and also make the seeds of NERICA accessible to all rice farmers, then it will not be meaningful for future research to attempt to further estimate population adoption rate of NERICA in The Gambia. Under such circumstance, a more meaningful estimate of adoption is given by assessing the intensity of technology use among adopters. For the case of NERICA varieties, it will be more meaningful to know the share of total rice area famers are allocating to NERICA varieties. This will give a better picture regarding the desirability of the NERICA technology by the target rice farming population.

The results in Chapter 4 indicate that NERICA adoption impact at household level is only significant for households headed by male. However, this does not necessarily indicate that NERICA adoption does not have any significant impact for women at the individual level. The data we used to assess the impact of NERICA on food security was collected at the household level so we are unable to assess individual food security status. As a result, we recommend that future studies that intend to assess the impact of NERICA adoption on household food security should collect data at the individual level to enable a gender based comparison of food security outcomes at the individual level. Moreover, the results of our analysis have shown no significant impact of NERICA adoption on health. This could be attributed to the fact that we used information on all household member to create number of sick days per capita. Number of sick days per capita is a highly noisy indicator which tend to be negatively correlated with household size. When one individual respondent reports on the health status of all households members, it can lead to under estimation if the household is large. For this reason, we recommend that future studies that intend to identify the impact of NERICA adoption on health should focus on individual recall data on specific illnesses, which may be a better outcome indicator.

In Chapter 5, we find that agricultural training significantly increases technical efficiency of smallholder rice farmers by 10%. We define agricultural training as participation in at least one program that train rice farmers on rice cultivation practices. Since some training programs are likely to be more effective than others, defining participation as receipt of training in at least one training program is likely to underestimate the impact of highly effective training programs. Consequently, we recommend that future studies that intend to assess the impact of agricultural training on technical efficiency should identify specific training programs and assess their impact on technical efficiency separately.

6.3 Conclusions and policy implications

The main conclusions and policy implications highlighted in this sub-section are derived from the main findings in relation to the research topics presented in Chapter 3, 4 and 5. We find in Chapter 3, that NERICA adoption is significantly limited by lack of awareness and access to NERICA seeds. We also find that NERICA adoption is significantly influenced by farmer contact with extension, NARI and access to in-kind credit services. Based on these findings, we conclude that to increase the adoption rate of NERICA in The Gambia, the significant role of extension service, research and in-kind credit availability cannot be neglected. The policy implication of these findings is to increase farmer contact with extension and research. Decision makers need to facilitate access to in-kind credit services like improve seeds to all the rice farming communities. This is likely to increase awareness and access to NERICA seeds, which can help in closing the population adoption gap of NERICA in The Gambia significantly.

We find in Chapter 4 that NERICA adoption has a significant impact on food security status of rice farming households. However, the impact has been found to be heterogeneous in the population. Households headed by men are found to be more food secured than households headed by women. We also find that the impact of NERICA adoption on food security, among NERICA adopting households, is greater for households that have access to in-kind services. The policy implication of these findings is to expand in-kind credit service programs and channel poverty alleviating programs to households that are headed by women to help them improve their food security status.

In Chapter 5, the results reveal that agricultural training has a significant impact on technical efficiency of smallholder rice farmers. The results further revealed that technical efficiency is significantly influenced by farmer contact with extension service and association membership. Based on these findings, we conclude that farmer contact with extension and association membership are important impact pathways to identifying significant impacts of agricultural training on technical efficiency of smallholder farmers. The policy implication this findings is to encourage rice farmers, through agricultural extension services, to be members of rice farmers' associations and motivate them to meet regularly to exchange ideas and information about new developments within and outside their rice farming communities.

References

Abadie, A. (2003). Semiparametric instrumental variable estimation of treatment response models. Journal of Econometrics, 113, 231– 263.

Diagne A and Demont M. 2007. Taking a New look at Empirical Models of Adoption: Average Treatment Effect estimation of Adoption rate and its Determinants. Agricultural Economics, Vol 37 (2007). 30p.

Heckman, J., & Robb, R. (1985). Alternative methods for evaluating the impact of interventions. in: J. Heckman and B. Singer, eds..Longitudinal analysis of labor market data, Econometric Society monograph series (Cambridge University Press, New York).

Heckman, J., & Vytlacil, E. (2005). Structural equations, treatment effects, and econometric policy evaluation. Econometrica, 73, 669–738.

Imben, G. W. (2004). Nonparametric estimation of average treatment effects under exogeneity: a review. The Review of Economics and Statistics, 86(1), 4–29.

Imbens, G. W., & Angrist, J. D. (1994). Identification and estimation of local average treatment effects. Econometrica, 62, 467–476.

Rosenbaum, P. R., & Rubin, D. R. (1983). The central role of the propensity score in observational studies for causal effects. Bometrika, 70, 41-55

Rubin, D. (1974). Estimating causal effects of treatments in randomized and non-randomized studies. Journal of Educational Psychology, 66, 688–701

Bibliography

Abadie, A. 2003. Semiparametric instrumental variable estimation of treatment response models. Journal of Econometrics, 113, 231– 263.

Adekambi, S. A., Diagne A., Simtowe, F. P & Biaou, G. 2009. The Impact of Agricultural Technology Adoption on Poverty: The Case of NERICA Rice Varieties in Benin. Contributed Paper Prepared for Presentation at The International Association Of Agricultural Economists' 2009 Conference, Beijing, China, August 16-22, 2009.

AFIDEP 2012. Population, climate change, and sustainable development in Africa. Available at http://populationaction.org/wp-content/uploads/2012/06/PAI-AFIDEP.pdf (accessed online November 2012).

African Development Fund. 2005. Farmer Managed Rice Irrigation Project. Technical Appraisal report. Available at http://www.afdb.org/fileadmin/uploads/afdb/Documents/Project-and-Operations/Gambia_-_Farmer_Managed_Rice_Irrigation_Project_-_Appraisal_Report.pdf. Accessed online (April 2004)

African Rice Centre (WARDA) 2006. Annual report. WARDA, Cotonou.

Agricultural census, 2012. Technical report of The Gambia Agricultural Census

Asante, B.O., Wiredu, A.N., Martey, E., Sarpong, D.B., Mensah-Bonsu, A. 2014. NERICA adoption and impacts on technical efficiency of rice producing households in Ghana: Implications for research and development. American Journal of Experimental Agriculture. 4(3):244-262

Audebert, A., Dingkuhn, M., Monty, J.P. and Johnson, D.E. 1998. Physiological Mechanisms for Vegetative Vigor of Interspecific Upland Rices - Implications for Weed Competitiveness. Japanese Journal of Crop Science 67(2): 358–59.

Balasubramanian V, Sie M, Hijmans RJ and Otsuka K. 2007. Increasing rice production in sub-Saharan Africa: Challenges and opportunities. Advances in Agronomy 94:55–133

Battese G.E., Broca S.S. 1997: Functional Forms of Stochastic Frontier Production Functions and Models for Technical Inefficiency Effects: a Comparative Study for Wheat Farmers in Pakistan. Journal of Productivity Analysis no. 8, pp. 395-414.

Boahene K, Snijders TAB, Folmer H.1999. "An Integrated Socio-Economic Analysis of Innovation Adoption: The case of Hybrid Cocoa in Ghana." Journal of Policy Modelling. 21(2):167-184.

Bravo-Ureta, BE. And Pinheiro, A.E. 1997. Technical, Economic and Allocative Efficiency in Peasant Farming: Evidence from the Dominican Republic. The Developing Economics. Vol. 35, No (1), 48-67

Braun J.V .2006. Public policy and international collaboration for sustaining and expanding the rice revolution. A keynote at the 2nd International Rice Congress on "Science, technology and trade for peace & prosperity". New Delhi Oct. 9 - 13, 2006

Caliendo, M. and Kopeinig. S. 2008. Some practical guidance for the implementation of propensity score matching. Journal of Economic Surveys. Vol. 22, No 1, pp. 31-72

Carney J.A, 1998. Women's land rights in Gambian irrigated rice schemes: Constraints and opportunities. Agriculture and Human Values 15: 325–33

Caswell, M., K. Fuhlie, C. Ingam, S. Jans and C. Kascak 2001. Adoption of Agricultural production practices: Lessons learned from the US. Department of Agriculture Area Studies Project, Agriculture Economic Report No. 792. US Department of Agriculture, Resource Economics Division, Economic Research Service, Washington, D.C.

Charnes A, Cooper W.W, Rhodes E. 1978. Measuring the efficiency of decision making units, European Journal of Operational Research 2 (6), pp. 429–444.

Coelli, T.J. 1995. Recent Developments in Frontier Modelling and Efficiency Measurement.
Australian Journal of Agricultural Economics 39 :219-245.

Coelli, T. J., A guide to DEAP Version 2.1: A Data Envelopment Analysis Programme. CEPA Working Paper 96/8, Department of Econometrics, University of New England, UK, 1996.

Daku L.2002. "Assessing farm-level and aggregate economic impacts of olive integrated pest management programmes in Albania." PhD. Dissertation. Virginia Polytechnic Institute and State University

Datt, G., Ravallion, M., 1996. How important to India's Poor is the sectoral composition of growth? World Bank Economic Review 10 (1), 1–26.

Defoer, T., M.C S Wopereis, P. Idinoba, K.L. Kadisha, S Diack and M. Gaye, 2009. Curriculum for Participatory Learning and Action Research (PLAR) for Integrated Rice Management (IRM) in Inland Valleys of Sub-Saharan Africa: Facilitator's Manual. Cotonou, Benin: Africa Rice Center. 184 pp

Diagne A. 2007. Bred for women rice farmers? Impact of NERICA adoption on rice yield in Côte d'Ivoire', mimeo, WARDA, Cotonou, Benin.

Diagne, A. 2010. Technological change in smallholder agriculture: Bridging the adoption gap by understanding its source. African Journal Agricultural Resource Economics 5(1): 261–283

Diagne A and Demont M. 2007. Taking a New look at Empirical Models of Adoption: Average Treatment Effect estimation of Adoption rate and its Determinants. *Agricultural Economics*, Vol 37 (2007). 30p.

Dibba L, Diagne A, Fialor SC and Nimoh F 2012. Diffusion and Adoption of New Rice Varieties for Africa (NERICA) in the Gambia. African Crop Science Journal, Vol. 20, No. 1, pp. 141 – 153

Dibba, L., Diagne, A., Fialor, S.C & Nimoh F 2012. The impact of NERICA adoption on productivity and poverty of the small-scale rice farmers in the Gambia. Food Security. (2012) 4:253–265.

Dontsop, P., Diagne, A., Okoruwa, V.O., & Ojehomon, V. 2011. Impact of Improved Rice Technology (NERICA varieties) on Income and Poverty among Rice Farming Households in Nigeria: A Local Average Treatment Effect (LATE) Approach. Quarterly Journal of International Agriculture 50 (2011), No. 3: 267-291.

Dontsop P, Diagne A, Okoruwa OV, Ojehomon V and Manyong V. 2013. Estimating the Actual and Potential Adoption Rates and Determinants of NERICA Rice Varieties in Nigeria, Journal of Crop Improvement, 27:5, 561-585, DOI: 10.1080/15427528.2013.811709

El-osta HS and Morehart MJ.1999. “Technology Adoption Decisions in Dairy Production and the Role of Herd Expansion.” Agricultural and Resource Economics Review. 28 : 84-95.

Feder, G., & Slade, R. 1984. “The acquisition of information and the adoption of new Technology.” American Journal of Agricultural Economics. 66 :312-320.

Feder G and Slade R. 1984. “The acquisition of information and the adoption of new Technology.” American Journal of Agricultural Economics. American Agricultural Economics Association. 66 :312-320.

Feder G, Just RE, and Zilberman D.1985. Adoption of agricultural innovation in developing countries: A survey. Economic Development and Cultural Change, 33: 255-298

Foster AD, and Rosenzweig MR. 1995. Learning by doing and learning from others: Human capital and technical change in agriculture. Journal of Political Economy, 103 (61): 1176-1209.

Fatajo, S. 2010. National issues report on key sector of agriculture (adaptation) in The Gambia. (Available at: http://www.undpcc.org/docs/National%20issues%20papers/Agriculture%20%28adaptation%29/07_Gambia%20NIP_agriculture%20adaptation.pdf)

Food and Agriculture Organization. 2002. FAO rice international. FAO, Rome

Food and Agriculture Organization. 2005. Global climate changes and rice food security. Rome (availableat:http://www.fao.org/climatechange/1552603ecb62366f779d1ed45287e698a44d2e.pd.

Gambia .2013. National Rice Development Strategy. (Available at: http://riceforafrica.org/images/stories/PDF/gambia_en.pdf)

Gambia Agricultural Census. 2012. Technical report of the agricultural census of The Gambia Agricultural

Gambia Population Census 2013 The Gambia housing and population census preliminary results. Available at http://www.gbos.gov.gm/uploads/census/The%20Gambia%20Population%20and%20Housing%20Census%202013%20Provisional%20Report.pdf (accessed online November 2014).

Heckman, James J., Robert LaLonde, and Jeffrey Smith. 1999. "The Economics and Econometrics of Active Labor Market Programs." In Handbook of Labor Economics, vol. 3, ed. Orley Ashenfelter and David Card, 1865–2097. Amsterdam: North-Holland

Hirano, Keisuke, Guido W. Imbens, and Geert Ridder. 2003. "Efficient Estimation of Average Treatment Effects Using the Estimated Propensity Score." Econometrica 71 (4): 1161–89

Hoddinott, J. 1999 Choosing outcome indicators of household food security. International Food Policy Research Institute (IFPRI). Washington, D.C. 20006 U.S.

Heckman, J., & Robb, R. 1985. Alternative methods for evaluating the impact of interventions. in: J. Heckman and B. Singer, eds..Longitudinal analysis of labor market data, Econometric Society monograph series (Cambridge University Press, New York).

Heckman, J., & Vytlacil, E. 2005. Structural equations, treatment effects, and econometric policy evaluation. Econometrica, 73, 669–738.

Hossain, M., 1989. Green Revolution in Bangladesh: Impact on Growth and Distribution of Income. University Press Ltd, Dhaka.

Ichino, A., Mealli, F. and Nannicini, T. 2008 From temporary help jobs to permanent employment: what can we learn from matching estimators and their sensitivity?. Journal of Applied Econometrics, 23: 305–327.

Imben, G. W. 2004. Nonparametric estimation of average treatment effects under exogeneity: a review. The Review of Economics and Statistics, 86(1), 4–29.

Imbens, G. W., & Angrist, J. D. 1994. Identification and estimation of local average treatment effects. Econometrica, 62, 467–476.

Johnson, D.E., Dingkuhn, M. Jones, M.P. and Moussa Mahamane, C. 1998. The influence of rice plant type on the effect of weed competition on Oryza Sativa and Oryza Glaberrima. Weed Research 38(3): 207-216.

Jones, M.P., Dingkuhn, M., Aluko, G.K. and Semon, M., 1997a. Interspecific Oryza sativa × O. glaberrima Steud. progenies in upland rice improvement. Euphytica 92:237-246.

Jones, M.P., Dingkuhn, M., Johnson, D.E. and Fagade, S.O. (Eds), 1997b. Interspecific hybridization: Progress and Prospect WARDA, 01 BP 2551, Bouaké, Cote d'Ivoire. pp. 21-29.

Kabunga NS, Dubois T, Qaim M .2012. Heterogeneous information exposure and technology adoption: the case of tissue culture bananas in Kenya. Agricultural Economics 43 (2012) 473–485

Kabunga, N. S., Dubois, T., & Qaim, M. 2014. Impact of tissue culture banana technology on farm household income and food security in Kenya. *Food Policy*, *45*, 25–34.

Khalil M.I, Haque M.E and Hoque M.Z. 2013. Adoption of BARI Recommended Potato (Solanum tuberosum) Varieties by the Potato Farmers of Bangladesh. A Scientific Journal of Krishi Foundation. The Agriculturists 11(2): 79-86

Kijima, Y., Ito, Y., Otsuka, K. 2012. Assessing the impact of training on lowland productivity in an African setting: Evidence from Uganda. World Development, Vol. 40, No. 8, pp 1610-1618

Kijima Y and Sserunkuuma D. 2013. The adoption of NERICA rice varieties at the initial stage of the diffusion process in Uganda. African Journal of Agricultural and Resource Economics Vol. 8, Issue 1: 45 - 56

Kijima, Y., Sserunkuuma, D., & Otsuka, K. 2006. How revolutionary is the "NERICA revolution"? Evidence from Uganda. Developing Economies, 44(2), 232–251.

Larson, D., K. Otsuka, K. Kajisa, J. Estudillo, and A. Diagne. 2010. Can Africa replicate Asia's Green Revolution in rice? Policy Research Working Paper 5478. World Bank

Lee, M. J. 2005. Micro-econometrics for policy, program and treatment effects. Advanced Texts in Econometrics. Oxford University Press.

Matlon, p., Randolph, T., Guei, R, 1996. Impact of rice research in West Africa. International conference on impact of rice research 3-5 June 1996. Bankok. IRRI p 313-323

Maxwell, S., & T. Frankenberger. 1992. Household food security: Concepts, indicators,
measurements. IFAD and UNICEF, Rome.

Mendola, M. 2006. Agricultural technology adoption and poverty reduction: a propensity–score matching analysis for rural Bangladesh. Food policy, 32(2007), 372–393

McCarty T.A, Yaisawarng S. 1993. Technical efficiency in New Jersey school districts, in: H.O. Fried, C.A.K. Lovell, S.S. Schmidt (Eds.), The Measurement of Productive Efficiency: Techniques and Applications, Oxford University Press, New York, 1993, pp. 271–287.

Nakaro, Y and Kajisa, K.2011. The Impact of Access to Credit and Training on Technology Adoption: A Case of the Rice Sector in Tanzania. Selected paper prepared for presentation at the Agricultural & Applied Economics Association's 2011 AAEA & NAREA Joint Annual Meeting, Pittsuburgh, Pennsylvania, July 24-26, 2011

Namwata B.M.L, Lwelamira, J and Mzirai, O.B. 2010. Adoption of improved agricultural technologies for Irish potatoes (Solanum tuberosum) among farmers in Mbeya Rural district, Tanzania: A case of Ilungu ward. Journal of Animal & Plant Sciences, 2010. Vol. 8, Issue 1: 927-935.

Nguyen N. V. 2005. Global climate changes and rice food security (Available at: http://www.fao.org/forestry/15526-03ecb62366f779d1ed45287e698a44d2e.pdf)

Onyango, A. O. 2014. Exploring Options for Improving Rice Production to Reduce Hunger and Poverty in Kenya. World Environment 2014, 4(4): 172-179

Otsuka, K., & Kijima, Y. 2010. Technology Policies for a Green Revolution and Agricultural Transformation in Africa. Journal of African Economies, 19, ii60-ii76.

Planning Service Unit. 2011. Rice fact book. Unpublished technical report

Ravallion, Martin. 2008. “Evaluating Anti-Poverty Programs.” In Handbook of Development Economics, vol. 4, ed. T. Paul Schultz and John Strauss, 3787–846. Amsterdam: North-Holland

Rosenbaum, P. R. 2001. Observational studies (2nd ed.). New York: Springer.

Rosenbaum P.R and Rubin D.R.1983. “The Central Role of the Propensity Score in Observational Studies for Causal Effects,” Bometrika 70, 41-55.

Rosenbaum, R. and Rubin, D. B. 1984. ‘‘Reducing bias in observational studies using subclassification on the propensity score,’’ Journal of the American Statistical Association, 79, pp. 516–524, 1984

Rosenbaum P.R. and Rubin, D.B. 1985 Constructing a control group using multivariatematched sampling methods that incorporate the propensity score, American Statistician, 39 (1), pp. 33–38.

Rubin, D. 1974. Estimating causal effects of treatments in randomized and non-randomized studies. Journal of Educational Psychology, 66, 688–701.

Rubin, D.B. 2001. Using Propensity Scores to Help Design Observational Studies: Application to the Tobacco Litigation. Health Services & Outcomes Research Methodology, 2, 169-188.

Rosenbaum P.R. and Rubin, D.B. 1985 Constructing a control group using multivariate matched sampling methods that incorporate the propensity score, American Statistician, 39 (1), pp. 33–38.

Rogers EM and Floyd Shoemaker F. 1971. Communication of innovation: A cross-cultural approach. Free Press, New York.

Roy, A. 1951. “Some Thoughts on the Distribution of Earnings,” Oxford Economic Papers, 3, 135–145.

Rubin, D. 1974. Estimating causal effects of treatments in randomized and non-randomized studies. Journal of Educational Psychology, 66, 688–701

Ruel, M. T. 2002. Is dietary diversity an indicator of food security or dietary quality? A review of measurement issues and research needs. Available at http://ageconsearch.umn.edu/bitstream/16386/1/fc030140.pdf (March 2015)

Rogers, E. 1983. Diffusion of innovations. New York. Free Press

Saka, J. O., Okoruwa V. O, Lawal B. O, and Ajijola S. 2005. Adoption of improved rice varieties among smallholder farmers in south-western Nigeria. World Journal Agricultural Sciences 1(1): 42–49.

Seck PA, Tollens E, Wopereis M, Diagne A, & Bamba I. 2010. Rising trends and variability of rice prices: Threats and opportunities for sub-Saharan Africa. Food Policy, 35 (5), 403-411.

Sianesi, B. 2004. An evaluation of the Swedish system of active labour market programmes in the 1990s. Review of Economics and Statistics, 86 (1), pp. 133–155.

Solh, M. 2005. Rice is life in 2004 and beyond. (Available at: http://www.fao.org/3/a-a0281e.pdf)

Somado, E.A. and Guei, R.G. 2008. Over view: The new rice for Africa 2008. Rice in Africa. Africa Rice Center, Bouaké.

Tjornhom, J. D. 1995. Assessment of Policies and Socio-Economic Factors Affecting Pesticide Use in the Philippines. MSc. Thesis, Virginia Polytechnic Institute and State University.

Tobin, J. 1958. "Estimation of Relationships for Limited Dependent Variables," Econometrica, 26, 24-36

Yamamoto, Y., Tsujimoto, Y., Fugihara, Y., Sakagami, J., Ochi, S., Fosu, M. 2012. Assessing the probability of land submergence for lowland rice cultivation in Africa using satellite imagery and geospatial data. Environ Dev Sustain. 14, 955-971.

WARDA 2001. NERICA rice for life. Available at http://www.warda.org/publications/NERICA8.pdf (Accessed online November 2014).

WARDA/FAO/SAA. 2008. NERICA®: the New Rice for Africa – a Compendium. EA Somado, RG Guei and SO Keya (eds.). Cotonou, Benin: Africa Rice Center (WARDA); Rome, Italy: FAO; Tokyo, Japan: Sasakawa Africa Association. pp 119.

Wiesmann, D., Bassett, L., Benson, T, & Hoddinott, J. 2009. Validation of the world food programme's food consumption score and alternative indicators of household food security. Available at http://www.ifpri.org/sites/default/files/publications/ifpridp00870.pdf (Accessed online March 2015)

Wooldridge JM. 2005. 'Violating Ignorability of Treatment by Controlling for too many Factors', Econometric Theory, 21, pp.1026-1028.

Woperies, M. 2011. Realizing Africa's Rice Promise. Keynote speech (available at: http://jircas-d.job.affrc.go.jp/Ver-1/english/files/2012/10/admin/2011-Keynote-Speech3.pdf)

Wopereis, M.C.S., A. Diagne, J. Rodenburg, M. Sie and E.A. Somado. 2008a: Why NERICA is a successful innovation for African farmers: A response to

Orr et al. from the Africa Rice Centre. In: Outlook Agriculture 37 (3): 159-168

Wopereis, M.C.S., T. Defoer, P. Idinoba, S. Diack and M.J. Dugué, 2008b. Participatory Learning and Action Research (PLAR) for Integrated Rice Management (IRM) in Inland Valleys of Sub-Saharan Africa: Technical Manual WARDA Training Series. Cotonou, Benin: Africa Rice Center. 128 pp

World Bank, 2007. World Development Report 2008. Agriculture for Development. Washington, DC

World Bank. 2008. World Development report. Agriculture for development. (Available at: World Development report. Agriculture for development)

World Bank. 2010. Hand book on impact evaluation. Quantitative methods and Practices. The International Bank for Reconstruction and Development / The World Bank

World Food Programme 2008: Calculation and use of the food consumption score in food security analysis. Prepared by VAM unit HQ Rome.

World Food Summit. 1996. World summit on food security. 13-17 November 1996 Rome, Italy.

Wuthi-Arporn, J .2002. Increasing Rice Production: Solution to the Global Food Crisis (Available at: http://www1.nodai.ac.jp/cip/iss/english/9th_iss/fullpaper/1-2-2ku-jirawut.pdf)

Appendices

Questionnaire : Household (in-depth survey)

Ex-POST IMPACT ASSESSMENT SURVEY, 2010
PRODUCER QUESTIONNAIRE

Number of the questionnaire:
__/__/__/__/__/__/__/__/
Name of region:
…………………………………………………__/__/__/__/__/__/__/__/__/……….
Name of district:
…………………………………………………__/__/__/__/__/__/__/__/__/……
Name of village: ……………………………………………………………….
Name of the head of the household:
……………………………………………………….
Name of main interviewee: ………………………….
Date of first contact: ……………………………………………………….
Date of last contact: ……………………………………………………….
Name of Enumerator: ……………………………………………………………….
Name of Controller:……………………………………………………………………….
Date of the control:...…...../__/__/__/__/__/__/__/__/
Name of the Supervisor:………………………………………………………………………………
Date of the control……………………………………………………….…../__/__/__/__/__/__/__/__/__/

Observations of the Enumerator…………………..……………………….
………………………………………………………………………………
....
....
....
....

Observations of the Controller :
…………………………………………………………………………………
…………………………………………………………………………………
…………………………………………………………………………………
…………………………………………………………………………
Observations of the Supervisor:
…………………………………………………………………………………
………………………………………………………………………………

N region……………………………Region Code ………………..N district………………………………………………..District code …………………..
N village……………………………………….Village Code………..Household Code………………..N° fiche……………………………….

NARI/AfricaRice

Ex-Post Impact Assessment of Multinational NERICA Dissemination project, 2010

PART ONE

MODULE 1: IDENTIFICATION AND SOCIO-DEMOGRAPHIC STRUCTURE OF THE HOUSEHOLD

1.1 Household Structure

Surname and names	Sex (code1)	Age	Matrimonial status (code2)	household status (code3)	Number of years of residence in the village	Education level (code4)	Main activity (code5)	Secondary activity(code5)	Number of sickness cases over the last 12 months*

code1: Sex

1=male
2=female

Code2: Matrimonial status

1=married, 2=bachelor/spinster, 3=widow/widower, 4=divorced

Code3: *Household status*

1=head of the household, 2=Husband/wife of the head of the household
3=son/daughter of the head of the household,4=nephew/niece,
5=father/mother or wife of the head of the household
6=brother, sister, 7=brother in law, sister in law,8=laborer
9=protégé, 9=other (specify)

Code4: *Education level*

1=primary, 2=Junior Secondary School, 3=Senior Secondary School, 4=tertiary, 5=Islamic, 6=Illiterate, 7=other (specify)

Code5: *Activities*

1=agriculture, 2=rearing, 3=house chores, 4=commerce, 5=handicraft, 6=laborer, 7=none, 8=student, 9=other (specify)

N region…………………. Code region……….. N district……….…………District Code …………..
N village………………………….Village code ……………………Household Code ……………….N° fiche …………..

NARI/AfricaRice

Ex-Post Impact Assessment of Multinational NERICA Dissemination project, 2010

1.2. Type of household
1.2. 1. Female headed household (widow) [ ] 1=Yes 0= No
1.2. 2. Single female headed household (husband working elsewhere) [ ] 1=Yes 0= No
1.2. 3. « Free » female headed household living with the husband [ ] 1=Yes 0= No
1.2. 4. Male headed household with more or less autonomous production systems for the husband and the wives [ ] 1=Yes 0= No
1.2..5. Male headed household with mix management of production systems for wives and husband [ ] 1=Yes 0= No
1.2..6. Male headed household with mainly production systems managed by the husband (with marginal plot owns by the wives) [ ] 1=Yes 0= No

2 Organizations that maintained or are maintaining working relationships with the household since last survey (2006)

Name of Institute/ organization	Code of Institute/organization	Type of working relationship (coded)	Since when did you have that working relationships (in year)	Do you still receive assistance? 1=yes, 2=no	If no, year of interruption of working relationship	Is the organization still functioning? 1=yes, 2=no	If no since when did it stop functioning?

Code of facility/organization: 1. NARI, 2=DAS, 3= Concern Universal Action Aid, 4=. LADEP, 5. Farmers' Organization,6. Another NGO (specify),7 Project (specify), 8. NAWFA 9. GAWFA 10. Peace Corps 11.CRS, 12= other (specify)

Codes for type of working relationship: 1=gift of seeds, 2=purchase of seeds by the institution, 3=sale of seeds by the institution, 4=technical training conducted by the institution, 5=training courses, 6=credit, 7=provides equipment (agricultural equipment), 8=sale of fertilizer, 9=gift of fertilizer, 10=other (specify),

N region…………………. Code region……….. N district ………….………Code district…………
N village…………………………Village code…………………household code……………….

2. Have you ever had any agricultural training on rice production? [ ]
1=yes 2=no

3. If yes, for how long? [ ] years [ ] months [ ] days

4. Type of training: [ ] [ ] 1=study trip, 2=internship, 3=specific training, 4=other (specify)

5. Is the head of the household a member of an association? [ ]
1= yes, 2= No longer (had broken links) 3= never

6. If no longer, give reason(s) for breaking links:
……….…………………………………………………………
……
7. If never, give reason(s) for not belonging

…….
……..…………………………………………………
8 If yes, which type of association/grouping? [ ]
1=farmers' organization 2=NGO 3=religious association 4=political association 5=cultural association 6=other (specify)

NARI/AfricaRice

Ex-Post Impact Assessment of Multinational NERICA Dissemination project, 2010

MODULE 2: KNOWLEDGE, ACCESS, USE AND MANAGEMENT OF VARIETIES

2.1. Knowledge and use of varieties (since 2006)

Variety Code	Name of the variety	Knowledge of the variety 1=yes, 2=no	Source of knowledge (see code)	Year of knowledge	Grown at least once 1=yes, 2=no	If yes First cropping year	Grown at least once since 2006 1=yes, 2=no	Cropping year: 1=yes, 2=no		
								2009	2008	2007

Code for source of knowledge: 1=farmer from the village, 2= farmer from another village, 3= NARI, 4=Extension Services, 5=NGO (specify name), 6=vocational organization, 7=other facility (specify), 8=local market, 9 = other (specify)

N region…………………. Code region………. N district …………..……Code district…………
N village…………………………Village code…………………household code……………….

NARI/AfricaRice

Ex-Post Impact Assessment of Multinational NERICA Dissemination project, 2010

2.2. Access to seed

Variety Code	Name of the variety	Cropping year 2010							Cropping year 2009							Cropping year 2008						
		Did you access the seeds of this variety within the village?			Did you access the seeds of this variety outside the village?				Did you access the seeds of this variety within the village?			Did you access the seeds of this variety outside the village?				Did you access the seeds of this variety within the village?			Did you access the seeds of this variety outside the village?			
		1= yes 2= no	Source of access (Code1)	Price per kg	1=yes, 2=no	Source of access (Code1)	Distance to the source	Price Per kg	1= yes 2= no	Source of access (Code1)	Price per kg	1=yes, 2=no	Source of acess (Code1)	Distance to the source	Price per kg	1= yes 2= no	Source of access (Code1)	Price per kg	1=yes, 2=no	Source of access	Distance to the source	Price per kg

Code 1 :Source/receiver: *1=farmer or relative from the village, 2= farmer or relative from another village, 3=NARI,* 4=Extension Services, 5=NGO (specify name), 6=vocational organization, 7=other facility (specify), 8=local market, 9 = other (specify)

N region…………………. Code region……….. N district …………..……Code district…………
N village…………………………Village code…………………household code……………….

NARI/AfricaRice

Ex-Post Impact Assessment of Multinational NERICA Dissemination project, 2010

If you could not access the seeds of any of the variety you wanted to grow can you explain why?

____ ____

____ ____

2.3. Buy, use and/or selling of seed

		Did you use your own seeds in the course of the year……… (Read year in the columns below and use codes 1=yes, 2=no)			Did you buy the seeds of that variety in the course of the year ……… (Read year in the columns below and use codes 1=yes, 2=no for first row and the source in second row for each variety)			Did you sell the seeds of that variety in the course of the year……… (Read year in the columns below and use codes 1=yes, 2=no for first row and the source in second row for each variety)		
Variety Code	Name of variety	2010	2009	2008	2010	2009	2008	2010	2009	2008

Source/receiver: *1=farmer or relative from the village, 2= farmer or relative from another village, 3=NARI,* 4=Extension Services, 5=NGO (specify name), 6=vocational organization, *7=another NGO (specify name),*
8=farmers' organization, 9=another facility (specify), 10=local market, 11 =other (specify). NB: show code for source or receiver in the second line below "Yes/ No" answer.

N region………………….. Code region……….. N district ………….………Code district…………
N village…………………………Village code…………………..household code……………….

2.4. Gift, reception and/or exchange of seed

		Have you given out seeds of that variety in the course of the year……… (Read year in the columns below and use codes 1=yes, 2=no for first row and the source in second row for each variety)			Have you received seeds of that variety in the course of the year……… (Read year in the columns below and use codes 1=yes, 2=no for first row and the source in second row for each variety)			Have you exchanged seeds of that variety in the course of the year ……. (Read year in the column below and use codes 1=yes, 2=no for first row and the source in second row for each variety)		
Variety Code	Name of variety	2010	2009	2008	2010	2009	2008	2010	2009	2008

Source/receiver: *1=farmer or relative from the village, 2= farmer or relative from another village, 3=NARI,* 4=Extension Services, 5=NGO (specify name), 6=vocational organization, *7=another NGO (specify name),*
8=farmers' organization, 9=another facility (specify), 10=local market, 11 =other (specify). NB: show code for source or receiver in the second line below "Yes/ No"

2.5. Seed availability

What would be the maximum amount of seed that you could obtain from all possible sources combined if not limited by money? Provide this information for the last 4 years and for each varieties known (grown or not). Please indicate your real need for each variety.

Variety Code	Name of Variety	Years							
		2010 (kg)		2009 (kg)		2008 (kg)		2007 (kg)	
		Maximum amount	Your current need	Maximum amount	Your current need	Maximum amount	Your current need	Maximum amount	Your current need

(Note to enumerator: This should be the name and variety code as listed in the table 2.1. Please list all variety name and codes before asking question for each variety.

Module 3: RICE FARM DATA

3.1: Information on variety performance

Variety name and code	Distinctive signs compared with others	months of sowing	starting date(s) of sowing	Seeding ending day(s)	Variety sowing order
Variety:…..……… … Code :…………					
Variety:…..……… … Code :…………					
Variety:…..……… … Code :…………					
Variety:…..……… … Code :…………					
Variety:…..……… … Code :…………					

2. Please explain why some varieties were sown before others (give selection criteria in chronological order)

First variety…………………………………………………..

Second variety..………………………………………………

Third variety…………………………………………………

Fourth variety..………………………………………………

3 For how many hours do you effectively work per day? ………….. hours

3.2 Rice Plot Environment

2.1. Were you able to weed the rice plot on time? [ ] 1=on time 2=late

2.2. Was the rice plot properly burnt? [ ] 1=yes, 2=no

Observations on the plot:

………………………………………………………………………………………………

………………………………………………………………………………………………

………………………………………………………………………………………………

………………………………………………………………………………………………

3.3 SPACING OF WEEDING TIME

	Time (week periods) Sowing – first weeding	Time (week periods) First - second weeding	Time (week periods) Second - 3rd weeding
Variety:……………………. Code of the variety: ………			
Variety:……………………. Code of the variety: ………			
Variety:……………………. Code of the variety: ………			
Variety:……………………. Code of the variety: ………			
Variety:……………………. Code of the variety: ………			
Variety:……………………. Code of the variety: ………			

3.4 Cropping and management of varieties
NB: talk preferably to the person, who selected the varieties.

	Mode of acquisition of seeds: How did you get seeds for this year's cropping season? (code2)	Quantity of seed used (kg)	At what Cost where the seeds purchased (LC)	Area cultivated (in ha) conduct estimate with farmer	Variety production			
					Kg	100 kg bags	50 Kg bags	Local measurement
Variety:……………… Code:…………								
Variety:……………… Code:…………								
Variety:……………… Code:…………								

Code 2: mode of acquisition of seeds: 1=self production (from my 2009 production), 2=purchase from another farmer in the village, 3=received from a farmer in the village, 4= purchase from a farmer from another village, 5= received from a farmer from another village, 6=purchase from the market, 7=purchase from an extension or research facility, 8=received from an extension or research facility, 9=purchase from a group, 10=received from a group, 11=purchase from an NGO, 12=received from an NGO, 13= barter with another product, 14=seeds exchange, 15=purchase with the private sector, 16=received from the private sector, 17=other (specify).

Give: weight of 100Kg bag=……………kg weight of 50Kg bags = ……………kg
Weight of local measurement=………………..kg

NARS/AfricaRice

Ex-Post Impact Assessment of Multinational NERICA Dissemination project, 2010

3.5 Input and weeding

Variety name	Number of weeding	Weeding times (in hours)	Name of fertilizer used	Quantity of fertilizer used (kg)	Cost of that fertilizer (LC)	Name of herbicides used	Quantity of herbicides used (specify unit)	Cost of that herbicide (LC)	Other product used	Quantity of that product	Cost of that product (LC)
Variety:…..……. Code:…………											
Variety:…..……. Code:…………											
Variety:…..……. Code:…………											
Variety:…..……. Code:…………											
Variety:…..……. Code:…………											
Variety:…..…… Code:…………											

NB: For an estimation of weeding time, discuss with household members who supervised weeding activities. Where the exercise occurred over several days, discussion must help work out a time estimate in hours

N region…………………. region code………. N district…………………District code ……………………………
N village…………………………Village code…………………..Household code……………….

NARI/AfricaRice

Ex-Post Impact Assessment of Multinational NERICA Dissemination project, 2010

3.6 Rice cropping activities: Use of labor

Variety Code	Name of Variety	Years							
		2010 (kg)		2009 (kg)		2008 (kg)		2007 (kg)	
		Maximum amount	Your current need	Maximum amount	Your current need	Maximum amount	Your current need	Maximum amount	Your current need

N region…………………. region code ……….. N district ……………..……district code …………
N village…………………………village code……………………household code……………….

NARI/AfricaRice

Ex-Post Impact Assessment of Multinational NERICA Dissemination project, 2010

	Involving members of the household				Involving individuals from outside the household			
	Number of adult men aged 16 and over involved in the work	Number of adult women aged 16 and over involved in the work	Number of children under 16 involved in the work	Age of the youngest child involved in the work	Number of laborers (from outside the household)	Total intervention period (in days)	Number of individuals who supported	Total intervention period (in days)
Clearing								
Slash and burn								
Burning and residue spreading								
ploughing								
Sowing/transplanting								
Sowing Surveillance								
First weeding								
Second weeding								
Third weeding								
Spreading of fertilizer								
Herbicide Application								
Guard against bird								
Harvest								
Threshing								
Drying								
Transport								
Other (specify)								

3.7 Rice plots background

Crop Code: 1=rice, 2=maize, 3=millet, 4=Sorghum, 5=cassava, 6=peanut, 7=fonio, 9=cocoa, 10=coffee, 11=Coconut tree, 12=Palm oil tree, 13=colanut tree,14=Tomato, 15=eggplant, 16=pepper, 17=onion, 18=potato, 19=plantain, 20=banana , 21=cocoyam/macabo, 22=cowpea/beans, 23=orange tree, 24=mango tree, 25=pea tree, 23=other (specify)

N region…………………. region code ……….. N district …………..………district code …………

N village…………………………village code……………………household code……………….

NARI/AfricaRice

Ex-Post Impact Assessment of Multinational NERICA Dissemination project, 2010

14 Do you grow your rice on the same plot every year? [ ] 1=yes, 2=no
15 If yes, why?
…………………………………………………………………………………………
…………………………………………………………………………………………
……..
16 If no, why not?
…………………………………………………………………………………………
…………………………………………………………………………………………
……..
17 In your opinion, when you change plots every year, what are:
The advantages?
…………………………………………………………………………………………
…………………………………………………………………………………………
……..

The drawbacks?
…………………………………………………………………………………………
…………………………………………………………………………………………
……..

18 What are the advantages for not changing plots every year?
…………………………………………………………………………………………
…………………………………………………………………………………………
……..
19 What are the inconveniences?
…………………………………………………………………………………………
…………………………………………………………………………………………
……..

N region…………………. region code ……….. N district …………..………district code ………….
N village…………………………village code……………………household code……………….

NARI/AfricaRice

Ex-Post Impact Assessment of Multinational NERICA Dissemination project, 2010

PART TWO

MODULE 1: CROPPING SYSTEM

1 How many farms do you have? [ ].

NB: the farm is different from the plot: we can find several plots on a farm

1.1 Identification of plots and crop associations

Farm number	Plot number	Distance from village (km)	Number of crops associated	Main crop (code1)	1st Associated crop	2nd Associated crop	3rd Associated crop	Land tenure (code2)
1	1							
	2							
	3							
	4							
2	1							
	2							
	3							
	4							
3	1							
	2							
	3							
	4							
4	1							
	2							
	3							
	4							

Code1: Crop Code: 1=rice, 2=maize, 3=millet, 4=sorghum, 5=cassava, 6=peanut, 7=fonio, 8=Tomato, 9=eggplant, 10=pepper, 11=potato, , 12=banana, 13=cowpea/bean, 14=orange tree, 15=mango tree, 16=other (specify)

Code2: Land tenure 1=owner, 2=lessee, 3=temporary assignment (lent for a season) 4=final assignment (gift) 5=other (specify with description of land tenure)

NB: list associated crops in order of significance

NARI/AfricaRice

Ex-Post Impact Assessment of Multinational NERICA Dissemination project, 2010

1.2 Development of farm land

Farm Number	Plot number	Types of crops grown (code 1)												Cropping method (code 2)			Ecology type (code 3)	Cropping Technique
		in 2010			in 2009			in 2008			in 2007							
1	**1**																	
	2																	
	3																	
	4																	
2	**1**																	
	2																	
	3																	
	4																	
3	**1**																	
	2																	
	3																	
	4																	
4	**1**																	
	2																	
	3																	
	4																	

Code1: Crop Code: 1=rice, 2=maize, 3=millet, 4=sorghum, 5=cassava, 6=peanut, 7=fonio, 8=Tomato, 9=eggplant, 10=pepper, 11=potato, , 12=banana, 13=cowpea/bean, 14=orange tree, 15=mango tree, 16=other (specify)

Code2: Land tenure 1=owner, 2=lessee, 3=temporary assignment (lent for a season) 4=final assignment (gift) 5=other (specify with description of land tenure)

Code 2= Cropping Technique: 1=manual cropping, 2=animal draught cultivation 3=automated cropping, 4=other (specify)

Code 3= Ecology type: 1= upland, 2=lowland, 3=dry plain 4=flood prone plain, 5=mangrove, 6= irrigated 7=other (specify)

N region…………………. region code ……….. N district ……………………district code ………….

N village…………………………village code……………………household code……………….

NARI/AfricaRice

Ex-Post Impact Assessment of Multinational NERICA Dissemination project, 2010

1.3 Varieties abandoned or lost since 2006

Name of the variety	Abandoned=1 Lost=2	Where 1, reason	Year cropped first	Date of abandon	Where 2, would you like to have it again Yes=1, No=2	Why?	Are you able to have as much seeds as you want? 1=Yes 2=No	If no which maximum quantity do you think you can get?

Module 2: OPERATION OF THE FARM

2.1 Land capital

Farm n°	Plot N°	Distance village - farm (km)	Business periods (years)	Area (in Ha)	Ecology type 1=upland 2-lowland 3=Mangrove 5=flood-prone plain 6=irrigated	Person in charge of the plot	Mode of acquisition 1=Inheritance, 2=purchase,3=Lease,4=temporal loan/assignment,5 =borrowing 5=community property 6=other (specify)	Soil richness (according to farmer) 1=Very rich 2=Rich 3=Averagely rich 4=Poor 5=Very poor
1	1							
	2							
	3							
	4							
2	1							
	2							
	3							
	4							
	5							
3	1							
	2							
	3							
	4							

2.2 Use of household labor for other crops

Crop (code1)	Cropping activity* (code2)	Number of persons in the household			Total number of working days	Starting period (Serial number)		
		Men	Women	Children (under 16)		Months	Week	Day

Code1: Crop Code: 1=rice, 2=maize, 3=millet, 4=sorghum, 5=cassava, 6=peanut, 7=fonio, 8=Tomato, 9=eggplant, 10=pepper, 11=potato, , 12=banana, 13=cowpea/bean, 14=orange tree, 15=mango tree, 16=other (specify)

Code2= Cropping activity code: 1=clearance, 2=slash and burn, 3=burning and spreading, 4= ploughing , 5=seeding/transplanting/plantation/ 6=seeding surveillance, 7=weeding, 8= fertilizer application, 9=herbicide application, 10=heading surveillance, 11=harvest, 12=threshing, 13=drying, 14=transport, 15= laying out, 16=holing out, 17=earthling/flooring/ridging 18=hoeing, 19=cutting, 20=other (specify)

2.3 Use of external labor (Plot level agricultural activity)

Do you use external labor? [ ] 1=yes, 2=no. Where answer is no, move to next module

Crop (code1)	Cropping activity* (code2)	Number of laborer			Form of intervention 1=help, 2=solidarity,3 =paid	Costs accruing (Le)	Total number of working days	Starting Period (serial number)		
		Men	Women	Children (under 16)				Months	Week	Day

Code1=Crop code: , 2=maize, 3=millet, 4=Sorghum, 5=cassava, 6=peanut, 7=fonio, 9=cocoa, 10=coffee, 11=Coconut tree, 12=Palm oil tree, 13=cola nut tree,14=Tomato, 15= eggplant, 16=pepper, 17=onion, 18=potato, 19=plantain, 20=banana, 21=cocoyam/macabo, 22=cowpea/bean, 23=orange tree, 24=mango tree, 25=pea tree, 23=other (specify)

Code 2=Cropping activity code: 1=clearance, 2=slash and burn, 3=burning and spreading, 4= ploughing , 5=seeding/transplanting/plantation/ 6=seeding surveillance, 7=weeding, 8= fertilizer application, 9=herbicide application, 10=heading surveillance, 11=harvest, 12=threshing, 13=drying, 14=transport, 15= laying out, 16=holing out, 17=earthing/flooring/ridging 18=hoeing, 19=cutting, 20=other (specify)

Code3= Mode of payment: 1=cash, 2=credit, 3=community labor

2.4 Use of household labor for other productive non agricultural activities

Activity (see code)	Number of persons			Year Period 1=January-March 2=April-June 3=July – September 4=October-December	Income earned	Observation
	Men	Women	Children (Under 16)			

Activity code: 1=handicraft, 2=rearing, 3=processing, 4=commerce, 5=extraction (salt, honey, gravel, sand, mine), 6=salary (fix, temporary, contracts, etc.)

2.5 Production input

Crop* (code1)	Type of input* (code2)	Sources Of acquisition (code3)	Quantity of product used	Unit	Value (LC)	Mode of payment* 1=cash 2=Credit	Application period 1= on time, 2=late	Give reason where application is late

Code1: Crop Code: 1=rice, 2=maize, 3=millet, 4=sorghum, 5=cassava, 6=peanut, 7=fonio, 8=Tomato, 9=eggplant, 10=pepper, 11=potato, , 12=banana, 13=cowpea/bean, 14=orange tree, 15=mango tree, 16=other (specify)

Code2=Type of Input Code: 1=mineral fertilizer, 2=organic fertilizer, 3=seeds, 4=herbicides, 5=insecticide/fungicide

Code3=Source of acquisition code: 1=farmer or relative from the village, 2= farmer or relative from another village, 3= NARI 4=DAS, 5=another NGO (specify name), 6=farmers' organization,7=another facility (specify), 8=Local Market, 9 = project, 10=other (specify)

2.6 Inventory of household agricultural equipment

Name equipment	Equipment code	Number	Unit price of purchase (GMD)	Total cost (GMD)	Purchase year
Machetes/cutlass					
Hoes					
Knife					
Plough					
Carts					
Donkeys					
Ox for farm work					
Agricultural stores					
Tractors					
Sprayers					
Axe					
Earth breaking hoe					
Sickle					
Rake					
Shovel					
Wheelbarrow					
Watering can					
Pick axe					
Shears					
Sprayers/Harrow					

2.7 Production distribution

Do you sell some of your agricultural production? [ ] Do you sell some of your animals? [ ]

1=yes, 2=no ; where answer is 2, move to next section.

Crop * (Code1)	Marketing period (Code2)	Place of sales (Code3)	Means of transportation to place of sales (Code4)	What is the total quantity produced (Kg)?	Quantity lost (kg)	Amount consumed at home (Kg)	Gift (KG)	Quantity sold (Kg)	Selling price	Mode of payment (Code5)	Buyer (Code6)
Crop PRODUCTION											
ANIMAL PRODUCTION											
Type of animals (Code1)	Marketing period (Code2)	Place of sales (Code 3)	Means of transportation to place of sales (Code4)	Number of heads	Number lost	Self consumed number	Gift (number)	Number sold	Selling price	Mode of payment (Code5)	Buyer (Code 6)

Code1

Code1: Crop Code: 1=rice, 2=maize, 3=millet, 4=sorghum, 5=cassava, 6=peanut, 7=fonio, 8=Tomato, 9=eggplant, 10=pepper, 11=potato, , 12=banana, 13=cowpea/bean, 14=orange tree, 15=mango tree, 16=other (specify)

Type of animals: 1=poultry, 2=sheep, 3=goat, 4=cattle 5=pigs, 6=other (specify)

Code2=Sales period:
Show number(s) for the month

Code3=Place of sales
1=village
2=another village
3=local market
4=other (specify)

Code4=Means of transportation
1=personal vehicle
2=hiring vehicle
3=public transport
4=animal draft vehicle
5=drawn by an individual
6=bike
7=other (specify)

Code5=Mode of payment
1=cash
2=credit

Code6=Buyers:
1=villagers
2=groupings
3=NGO/Project
4=produce traders
5=other (specify)

MODULE 3: REARING

3.1 Baseline inventory of household livestock (at the end of the past season)

Type of animals	Number of head	Total estimated Value in GMD	Rearing managers (use code of the household member in charge of rearing)

<u>Type of animals</u>: 1=poultry, 2=Sheep, 3=Goat, 4=Cattle, 5=pigs, 6=other (specify)

3.2 Household livestock disposal and acquisition (since beginning of the season)

type of animals (code 1)	Outs					Ins				
	Numbe r	Reasons (Code2)			Income earned	Number	Reason (Code3)			Cost

<u>Code1=Type of animals</u>: 1=poultry, 2=Sheep, 3=Goat, 4=Cattle, 5=pigs, 6=other (specify)

Code2=Out reasons codes: 1=Gift, 2=sales, 3=barter, 4=debt repayment, 5=sacrifice, 6=functions, 7=family consumption, 8=mortality/loss, 9=other (specify)
Code3=In reasons codes: 1=received as present, 2=purchase, 3=barter, 4=debt recovery, 5=other (specify).

MODULE 4: TRANSACTIONS

4.1 Transactions in Kind

	Accessing credit in kind? 1=yes, 2=no	Source of credit (code1)	Nature of credit	Quantit y	Unit 1=kg, 2=number, 3=litre	Estimated value of the product (in GMD)	How much must you pay back in all?
2010							
2009							
2008							
	Have you lent in kind? 1=yes, 2=no	To whom have you lent? (code2)	Nature of loan	Quantit y?	Unit 1=kg, 2=number, 3=litre	Estimated value of the product (in GMD)	How much must you be paid back in all?
2010							
2009							
2008							

Code1= Source credit: 1=credit program, 2=bank, 3=projects, 4=NGO, 5=traders, 6=inhabitant of the village, 7=inhabitant of another village, 8=farmers' organization, 9=other (specify)

Code 2= for who you lent to: 1=relative, 2=farmer from the village, 3=farmer from another village, 4=other (specify)

4.2 Financial transactions

	Accessing credit? 1=yes, 2=no	Source of credit (code1)	Amoun t of credit (GMD)	Repayment period (months)	Mode of repayment 1=per installment, 2=per term	How much must you pay back in all?	What was the money used for? (code2)
2010							
2009							
2008							
	Have you lent any money? 1=yes, 2=no	To who did you lend? (code3)	Loan amount (GMD)	Over what period of time you must be paid back?	Mode of repayment 1=per installment, 2=per term	How much must you be paid back? (GMD)	For what reason did you give this loan? (code4)
2010							
2009							
2008							

	Have you set any money aside? 1=yes, 2=no	Where do you kee such money? (Give several sources if possible, code5)			How much is the amount set aside? (GMD)	By keeping that money there, has it yielded any annual benefits for you? 1=yes, 2=no	If yes, how much for that year? (GMD)	Why do you keep the money set aside there? (code6)
2010								
2009								
2008								

Code1=Credit source: 1=credit program, 2=bank, 3=projects, 4=NGO, 5=traders, 6=inhabitant of the village, 7=inhabitant of another village, 8=farmers' organization, 9=other (specify)

Code2= What was the money used for 1=input purchase, 2=agricultural activity, 3=commerce, 4=care, 5=food, 6=functions, 7=other expenses (specify)

Code3= for who you lent to: 1=relative, 2=farmer in the village, 3=farmer in another village, 4=other (specify)

Code4= loan reason: 1=for interests, 2=social reason, 3=other (specify)

Code5= where to keep money: 1=bank, 2=on myself, 3=with relative, 4=with a third party, who is not a member of the family

Code6= Reason for keeping money aside: Code 1=no banking institution, 2= no confidence, 3=confidence, 4=other (specify

MODULE 5: INCOMES AND EXPENSES

5.1- Agricultural income

Sources of income	2009 Amount	2008 Amount	2007 Amount
Rice income			
Income from other crops			
Income from livestock			

5.2 - Household non agricultural income

Sources of income	Amount			Person in charge or beneficiary (See code)		
	2009	2008	2007			
1. Salary received						
2. Rent received						
3. Commerce						
4. Handicrafts						
5. Assistance from a third party						
6. Pension						
7. Insurance						
8. Financial assistance from a member of the household						
……………………………………… ………..						
……………………………………… ………..						
……………………………………… ………..						
……………………………………… ………..						
……………………………………… ………..						

Code of Person in charge: 1=head of the family, 2=husband/wife of the head of the household, 3=son/daughter of the head of the family, 4=nephew/niece, 5=father/mother of the head of the household, 6=brother, sister, brother in-law, sister in-law, 7=in-laws, 8=laborers, 8=protégé, 9=other (specify)

5.3- Agricultural expenses (in Local Currency)

	2009 Amount		2008 Amount		2007 Amount	
	Rice in (GMD)	Other crops (GMD)	Rice (GMD)	Other crops (GMD)	Rice (GMD)	Other crops (GMD)
Transportation of input						
Storing input						
Soil preparation						
Seed						
Fertilizer						
Herbicide						
Other phytosanitary products						
Labor cost for seeding/Transplanting						
Labor cost for herbicide and fertilizer application						
Labor for harvest and post harvest						
Packaging						
Implement hiring cost						
Other labor cost						
Other financial cost						
Fuel for farm works						
Transportation of produce						
Processing of produce						
Storing produce						
Other cost (specify)						

5.4- Expenses on livestock

Sources of expenditure	2009 Amount	2008 Amount	2007 Amount
Expense on livestock			

5.5- Other household expenses (since last harvest)

	Amount (LC)		
	2009	2008	2007
Rent			
Clothing			
Housing maintenance.			
Light/electric power			
Fuel			
Pharmaceutical products			
Schooling			
Traditional care (treatment)			
Financial assistance/ monetary gifts (present)			
Trips (travel cost)			
Functions (marriage, funeral, local festivities)			
Taxes			
Contributions to associations and groupings			
Food expenses			
Other…			
Other…			
Other…			
Other…			

5.6- Food consumption in the course of the year 2009

List of food items consumed in the household	Number of days per week			
	January - March	April-June	July-September	October - December

5.7- Child Schooling

School Enrollment

	Number of Children Enrolled, (2010)	Number of Children Enrolled, (2009)	Number of Children Enrolled, (2008)
Primary school			
Secondary school			
Tertiary education			

	Age of Children Enrolled (2010)						Age of Children Enrolled, (2009)						Age of Children Enrolled, (2008)					
	1	2	3	4	5	6	1	2	3	4	5	6	1	2	3	4	5	6
Primary school																		
Secondary school																		
Tertiary education																		

School withdrawing

	Number of Children Withdrawn, (2010)	Number of Children Withdrawn , (2009)	Number of Children Withdrawn, (2008)
Primary school			
Secondary school			
Tertiary education			

	Age of Children withdrawn (2010)						Age of Children withdrawn, (2009)						Age of Children withdrawn, (2008)					
	1	2	3	4	5	6	1	2	3	4	5	6	1	2	3	4	5	6
Primary school																		
Secondary school																		
Tertiary education																		

School Attendance: How many days in the following years your children have not attended to school?

	2010				2009				2008			
	Jan-Mar	Apr-Jun	Jul-Sept	Oct-Dec	Jan-Mar	Apr-Jun	Jul-Sept	Oct-Dec	Jan-Mar	Apr-Jun	Jul-Sept	Oct-Dec
Primary												
secondary												
Tertiary												

If your children did not attended on regular basis the school, please explain why……………………………………………………………………….
………………………………………………………………………………………

School Completion: How many children have completed school in the following years?

	Number of Children 2010	Number of Children 2009	Number of Children 2008
Primary			
secondary			
Tertiary			

School expenses

	School fees			School furniture purchase			School uniforms purchase			Others expenses related to school		
	2010	2009	2008	2010	2009	2008	2010	2009	2008	2010	2009	2008
Primary												
secondary												
Tertiary												

5.8- Health of the household member

Name of person						
Code						
Has he/she been sick during the year 2009? 1=yes ; 0= No						
How often?						
Types of sickness?	Symptoms of sickness 1					
	Code (21)					
	Symptoms of sickness 2					
	Code (21)					
	Symptoms of sickness 3					
	Code (21)					
	Symptoms of sickness 4					
	Code (21)					
	Symptoms of sickness 5					
	Code (21)					
How long does the sickness 1 last (days)?						
How long does the sickness 2 last (days)?						
How long does the sickness 3 last (days)?						
How long does the sickness 4 last (days)?						
How long does the sickness 5 last (days)?						
Have you sent him/her to the hospital?	1=yes 0= No					
	If yes how much have you paid in total?					
	Who paid?	Name				
		Code				
	Who took the decision?	Name				
		Code				
Has he/she received a traditional treatment?	1=yes 0= No					
	If yes how much have you paid in total?					
	Who paid?	Name				
		Code				
	Who took the decision?	Name				
		Code				
Has he/she received on regularly base his/her vaccination?	1=yes 0= No					
	What type of vaccines did he/she receive? (22)					
	Who took the decision?	Name				
		Code				

(21) : 1= Malaria; 2= Diarrhea; 3= Fever//Flu/Cough; 4= Stomach ache 5=headache 6=Other to be specify

(22) : 1= B C G (against tuberculosis), 2= Anti-Poliomyelitis , 3= Anti-Tetanus, 4= Against the meningitis, 5= Against the measles

5.9 Household asset

ITEMS	CODE
Occupancy status (Landlord=1, tenant=2, 3=rent)	
Amount of monthly rent if tenant (GMD)	
House number/cases of household	
Total number of rooms in the house	
Main material (outside walls) (Wood =1; Cob=2; stabilized earthen brick= 3; Baked brick= 4, Hard=5, semi- hard=6, other=7)	
Main roofing material Straw/raffia leaves/thatch= 1; roofing sheet= 2; roof tiles = 3; slab =4, other (specify)=5	
Water supply (household) River = 1; wells= 2; borehole= 3; water pump = other=4	
Main sources of light (Lamp = 1; Generator= 2; Electric power = 3; 4=candles, 5=sun panels, 6=firewood, 7=other)	
Source of fuel used for cooking Agricultural by-product = 1; Charcoal = 2; firewood = 3; Gas = 4; Electric power =5, other=6	
Type of sanitation (None =1; Latrines = 2; WC = 3, other=4	

Is the house painted? [] (Yes.=1 ; No = 2)

5.10. Household equipment

NB: where there is a set of similar equipment bought over several years, record this equipment as many times as it was bought.

EQUIPMENT	Equipment Code	Number	Unit Price of acquisition (LC)	Estimated value of equipment (current)	Year of acquisition

<u>Codes for household equipment</u>: Radio = 1 ; bike = 2 ; Motorcycle = 3 ; Vehicle. = 4 ; Rifle = 5 ; TV = 6 ; moped = 7 ; bed=8, Straw mattress =9, modern mattress =10, mat=11, stools=12, chairs=13, plates=14, basins=15, stockpots=16, pots=17, 18=radio-cassette, 19=sofa, 20=cabinet/drawers, 21=library, 22=mirror, 23=bath tub, 24=bucket, 25=spoon/fork, 26=bed sheet, 27=carpet, 28=broom, 29= jerrycan, 30=drum or barrel, 31=other (specify).

CURRICULUM VITAE (C.V)

PERSONAL DETAILS

NAME: Lamin Dibba

DATE OF BITH: 1st January, 1979

PLACE OF BIRTH: Brikama, The Gambia

CONTACT ADDRESS: Lamin Dibba
University of Hohenheim
Wollgrasweg 43
D-70593, Stuttgart, Germany
Tel.: +49-711-459-23475

EMAIL ADDRESS: dibbason@gmail.com/ lamin.dibba@uni-hohenheim.de

EDUCATIONAL BACKGROUND

- PhD, Agricultural economics, University of Hohenheim, Stuttgart, Germany. 2012 - 2015
- MPhil, Agricultural economics, Kwame Nkrumah University of Science and Technology, Kumasi, Ghana. 2008-2010
- BSc, Agricultural economics, University of The Gambia, Brikama, The Gambia. 2000-2004.

EMPLOYMENT RECORD

- Senior Research Officer (SRO), National Agricultural Research Institute (NARI), Brikama, The Gambia. 2010-present
- Research Officer (RO), NARI, Brikama, The Gambia. 2007-2010
- Assistant Research Officer (ARO), NARI, The Gambia. 2005-2007

PROFESSIONAL EXPERIENCE

- National Coordinator, Canadian International Development Agency (CIDA) funded project, The Gambia. 2011-2012
- Visiting Scientist (Technology Impact Evaluation Specialist), Africa Rice Center (AfricaRice), Cotonou, Benin. March-April 2011.
- Resource person, Impact evaluation workshop, Accra, Ghana. 22-29 April 2010

- Impact Evaluation Scholar, Africa Rice Center, Cotonou, Benin. 2009-2010
- Visiting Scientist (Database Manager), Africa Rice Center, Cotonou, Benin. 2007-2008
- National Coordinator, Participatory Adaptation and Diffusion of Technologies for Rice-Based Systems (PADS) project, The Gambia. 2006-2007

TEACHING EXPERIENCE

- Interdisciplinary Aspects of Food Security (PhD level course). Winter Semester 2015/2016. University of Hohenheim, Stuttgart, Germany.

- Farm and project evaluations (MSc level course). Winter Semester 2015/2016. University of Hohenheim, Stuttgart, Germany

- Poverty and developments strategies (MSc level course). University of Hohenheim, Stuttgart, Germany

PUBLICATIONS IN PEER-REVIEW JOURNALS

1. **Dibba. L**, Zeller. M, Diagne. A, Nielson. T (2015) : How accessibility to seeds affects the potential adoption of an improved rice-based technology: The case of NERICA varieties in The Gambia. Quarterly Journal of International Agriculture 54 (2015), No. 1: 33-58

2. **Dibba L**, Fialoh. SC, Diagne. A, Nimoh (2012): The impact of NERICA adoption on productivity and poverty of small-scale rice farmers in The Gambia. Food Security, Vol 4, No 2, pp 253-265

3. **Dibba. L**, Fialoh. SC, Diagne. A, Nimoh (2012). F: Diffusion and adoption of New Rice Varieties (NERICA) in The Gambia. African Crop Science Journal, Vol. 20, No. 1, pp. 141 - 15

BOOK PUBLICATION AND CONFERENCE ABSTRACTS

1. Edwin. R, **Dibba. L**, Khalid. S (2015). Intensity of technology adoption and its determinants in The Gambia: the case of New Rice for Africa (NERICA). International Conference of tropical Agriculture (Deutscher Tropentag), Berlin, Germany. September 16-18, 2015.

2. **Dibba. L** (2013) : MPhil. Thesis-Estimation of NERICA adoption rates and impact. LAP LAMBERT Academic Publishing. ISBN-13: 978-3659117732

3. **Dibba. L**, Zeller. M, Diagne. A, Nielson. T (2013) : How accessibility to seeds affects the potential adoption of an improved rice-based technology: The

case of NERICA varieties in The Gambia. 3rd Africa Rice Congress (abstracts), Yaoundé, Cameroon, October 21-24, P 91.

IMPORTANT TECHNICAL REPORTS

1. **Dibba, L** and Camara, B. (2011). NERICA post impact evaluation in The Gambia.

   Technical Report. NARI/AfricaRice

2. **Dibba, L** (2011): Study on banana value chain in The Gambia.

   Technical report. NARI

3. **Dibba, L**, Diagne, A, Simtowe, F, Sogbossi, M.J and Mendy, M. 2008a. Diffusion and adoption of NERICA in Gambia. Mimeo, WARDA

4. **Dibba, L**, Diagne, A, Simtowe, F, Sogbossi, MJ and M. Mendy. 2008b The impact of NERICA adoption on yield in Gambia. Mimeo, WARDA

OTHER RELEVANT TRAINING

- Leadership Development, Windeck-Rosbach, Germany. 26-30 June, 2015
- Working Within Political Context, Berlin, Germany. 3-8 March 2014
- Impact Evaluation Training, Accra, Ghana. 23- 25 August, 2007

INTERNATIONAL MEETINGS AND CONFERENCES ATTENDED

- American Evaluation Conference. November 9-14, 2015 Chicago, USA
- International Conference of Tropical Agriculture (Deutscher Tropentag). September 16-18, 2015 Berlin, Germany
- Global Forum for Food and Agriculture, Berlin, Germany. 16-18 January, 2014
- 3rd Africa Rice Congress, Yaoundé, Cameroon. 21-24 October, 2013
- CIDA project annual conference , Cotonou, Benin. 01-09 July, 2012

- CIDA inception meeting, Cotonou, Benin. 24-30 May, 2011
- Consultative Workshop on Fostering the Exchange of Statistical Data & information on The Rice Economies of WARDA Member states, Cotonou, Benin. 12-14 December, 2007
- 2nd International Conference of African Association of Agricultural Economists (AAAE) Accra, Ghana 18-22 August, 2007
- PADS project advisory committee meeting, Cotonou, Benin. 18-20 April, 2007

CONFERENCE PRESENTATION OF RESEARCH FINDINGS

1. **Dibba. L**, Zeller. M, Diagne. A (2015). The impact of agricultural training on technical efficiency of smallholder rice farmers in The Gambia. Paper presented at the American Evaluation Conference, November 9-14, 2015 Chicago, USA
2. Edwin. R, **Dibba. L**, Khalid. S (2015). Intensity of technology adoption and its determinants in The Gambia: the case of New Rice for Africa (NERICA). Poster presented at the International Conference of tropical Agriculture (Deutscher Tropentag), Berlin, Germany. September 16-18, 2015.
3. **Dibba. L**, Zeller. M, Diagne. A, Nielson. T (2013) : How accessibility to seeds affects the potential adoption of an improved rice-based technology: The case of NERICA varieties in The Gambia. Paper presented at the 3rd Africa Rice Congress (abstracts), Yaoundé, Cameroon, October 21-24, P 91.

SCHOLARSHIPS AWARDS

- 2011 Global Rice Science Scholarship Award
- 2008 Strengthening Capacity for Agricultural Research and Development in Africa (SCARDA) Award
- 2000 Gambia Government Undergraduate Fellowship Award

MEMBERSHIP OF PROFESSIONAL ASSOCIATIONS

- Agricultural and Applied Economic Association (AAEA)
- African Association of Agricultural Economist (AAAE)
- Gambia National Agricultural Research Association (NARISA)

LANGUAGE PROFICIENCY

- English (fluent), French (medium), Deutsche (basic)

HOBBIES

- Reading, Listening to news, Football & Farming

REFEREES

1. Dr. Aliou Diagne
   Impact Assessment Economist
   University Gaston Berger, Senegal
   aliouwork@gmail.com
   Tel.: +221 78 166 75 14

2. Prof. Dr. Manfred Zeller
   Professor
   University of Hohenheim, Germany
   manfred.zeller@uni-hohenheim.de
   Tel.: +49 (0)711-459- 22175
   Fax: +49 (0)711-459- 23934

3. Ansumana A.K Jarju
   Director General
   National Agricultural Research Institute (NARI)
   P.O Box 526, Serrekunda The Gambia
   akjarju2013@gmail.com
   Tel: (+220) 448 3112
   Fax: (+220) 448 4921

Signature:

____

(Lamin Dibba)

Declaration

I hereby declare that I have written this doctoral dissertation independently and that it has not been previously submitted for the award of any other degree or qualification. I have acknowledged all sources of information used in the document as references.

Hohenheim, 05.02. 2016

(Lamin Dibba)