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Raised-Bed Farming System Technology (RFST) in Egypt

Qualities and Determinants of Adoption in Different Agricultural Livelihood Conditions

WORKING PAPER

Raised-Bed Farming System Technology (RFST) in Egypt: Qualities and Determinants of Adoption in Different Agricultural Livelihood Conditions

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List of Acronyms

ALS	Agricultural Livelihood System
AMA	Agricultural Market Association
ANOVA	Analysis of Variance
ICARDA	International Center for Agricultural Research in Dry Areas
K-CA	K-mean Cluster Analysis
MRB	Mechanized raised-bed
MRBT	Mechanized raised-bed technology
PCA	Principal Component Analysis
AQ	Adoption Quality index
RFST	Raised-Bed Farming System Technology
ROC	Receiver Operating Characteristic
SDA	Service Development Association
SLF	Sustainable Livelihood Framework
WUA	Water Use Association

KEY MESSAGES

Abstract

Mechanized raised-bed technology (MRBT) has been recognized as an important component of integrated water management to achieve higher productivity in intensive irrigated systems, such as those found in the Nile Delta. Effective management and policies for spreading the technology for improving food security and resource use efficiency require adequate understanding of the qualities and drivers/determinants of farmers' adoption of MRBT. Related research efforts on these issues have been challenged the diversity of socio-ecological contexts that shape farmers' adoption and related driving effects. This study empirically investigates the issues using a system-based option-by-context approach for guiding concrete analytical steps and statistical methods in coping with the challenges of system complexity and contextual diversity in two governorates (Sharkia and Assiut) of Egypt. The main finding of the study is that, classifying the considered agrarian population into a limited number of agricultural livelihood system (ALS) types and conducting multivariate inferential statistics for both (1) whole sample population and (2) each specific ALS types helped discover hidden causal relationships shaping MRBT adoption which would have been identified by considering the whole sample only. For instance, roles of effectiveness in agricultural institutions, such as water use association (WUA) and agricultural market association (AMA), in MRRT adoption are found in specific ALS types rather through looking at the merged population. Some causal relationships are found significant via inferential statistics for the whole sample, but actually taking effects in a specific ALS group (e.g. the case for the effect of farm size on MRBT adoption of poor and non-farm based income group). The consideration of merged sample population is also complementary to ALS type-specific treatments: some causal effects (e.g. the role of education) can be evidentially inferred through the use of a large sample that provides enough statistical power for inferential statistics. The used approach and empirical results shall be useful for betterment of targeting in agricultural development (extension services, MRBT-related project and program) in practice.

Keywords

Irrigated system, Egypt, Nile Delta, context, drivers, complexity, mechanized raised-bed technology, option-by-context, livelihood typology.

Highlights

- We use Sustainable Livelihood Framework to define candidate variables entered to sequential multivariate statistical analyses.
- We use subsequent principal component analysis – k-mean cluster analysis and ANOVA to objectively define three distinct ALS types.
- We conceptualize the formula of adoption quality (AQ) index for statistical analysis in quality-focused way, beside the consideration of yes/no adoption.
- We apply relevant inferential statistic methods to whole/merged sample, and sub-samples (corresponding to ALS types) for identifying determinants of farmers' adoptions of MRBT.

- We draw common and livelihood type-specific determinants of MRBT adoption and discuss the added values, limitation of the approach and make recommendations.

1. INTRODUCTION

1.1. Background

Water scarcity for agriculture in Egypt has been, and will continue to be, a profound problem. Water scarcity has crossed the threshold value of 1,000 m^3/capita/yr, and is estimated to fall to 500 m^3/capita/yr in 2025 if there is no significant improvement in management (Swelam 2016). Moreover, negative effects of climate change on agricultural production introduce further problems for water allocation to agriculture. According to a 2013 report by the United Nations Development Programme in association with the Egyptian Government and other UN agencies, agricultural production could decrease by 8-47% by 2060, with employment losses of up to 39% (Swelam 2016). Thus, the current and future challenge in Egypt is how to produce more food with less water resources. The benefits of each drop applied could be maximized by adopting appropriate irrigation scheduling and adapted irrigation practices.

Research on water management to achieve higher productivity in irrigated agriculture has identified mechanized raised-bed technology (MRBT) as an important component of improved crop production packages (Karrou et al. 2011; Swelam 2016). MRBT is an improved surface irrigation strategy, which enhances water productivity and makes the application of water in irrigated systems more efficient. In this technology, irrigation water is applied to the bottom of furrows among cropping beds instead of being spread over the whole surface of the cropping area. Because there is less wetted area than in the traditional surface irrigation methods, water can be saved. Raised-bed fields have wider furrows, as well as wider cropping beds, than traditional fields, meaning that the same number of crops can be irrigated with half the amount of water. Raised-bed machines are used to ensure the appropriate bed design as well as substitute for the labor otherwise demanded.

Raised-bed technology has been proven to increase crop yields in both winter and summer crops and improve water-use efficiency through decreasing irrigated area, shortening the time needed for irrigation, and reducing water volume needed for a same amount of crops. Applying this practice can help farmers save money on irrigation while achieving higher yields and increasing farm income. The technology has been technically tested and validated by ICARDA projects over the last 10 years in Egypt. On experimental farms, the application of this technique with the main winter crops has shown that up to 25% of water can be saved, while crop production increased by 10%. Net benefits increased by 40%, and variable costs were reduced by 30% (Karrou et al. 2011). This technology was disseminated for promoting sustainable agricultural intensification in 22 Egyptian governorates as part of a nation-wide campaign by the Egyptian Government on self-sufficiency in wheat production (Swelam 2016).

1.2. Research problems

Although a great deal of knowledge on the role of MRBT in improving water-use efficiency has been gained from irrigation, agronomic, and economic studies, too few studies have sought to understand how different agricultural livelihood contexts shapes (1) the pattern of adoption quality attributes in beyond of yes/no adoption attributes, and (2) the drivers affecting farmers' adoption of MRBT.

Drivers of farmers' MRBT adoption: So far, there have been a few studies on raised-bed adoption in Egypt, such as the study of Dessalegn et al. (2016) conducted in Sharkia Governorate. As with many other adoption analyses, the drivers of raised-bed adoption were inferred from the analysis of one household/farm sample selected for the study area; hence, the revealed cause-effect relationships were also applied uniformly over the study area. Indeed, the causal relationships defined in that way (one sample for the study area) were validly applied for an average household or farm of the area (located in the centroid of the multivariate sample). Diversity in livelihood contexts and settings in an area would make this average household/farm less representative, thus weakening the plausibility of applying the causal relationship over the whole area. An improved method would be to stratify the studied population according to functional livelihood contextual types, and then conduct multivariate adoption analysis for each strata, inferring adoption drivers specific to the livelihood contextual type (Thiombiano and Le 2016a). Adoption analysis of this sort requires the identification of plausible livelihood contextual types beforehand. The livelihood contextual typology is also important as it can shape the efficiency assessment of the considered technology or intervention (Thiombiano and Le 2015; Thiombiano and Le 2016b).

1.3. Research objectives

In line with the knowledge gaps described above, the following research objectives are proposed for consideration.

1. Identify and characterize the main livelihood types of smallholders in terms of their farms' biophysical and socioeconomic characteristics.
2. Identify determinants, both common and livelihood type-specific, of farmers' adoptions of MRBT over ICARDA's study area in Egypt.
3. Highlight evidentially added values, limitations of the analysis approach and make recommendations for further studies or applications.

2. APPROACH

2.1. Analytical steps

Figure 1 is a proposed analytical diagram that includes sequential steps of empirical research toward achieving the stated objectives. This procedure should apply for a sizable study area, such as a group of several governorates where MRBT is practiced, rather than a small site.

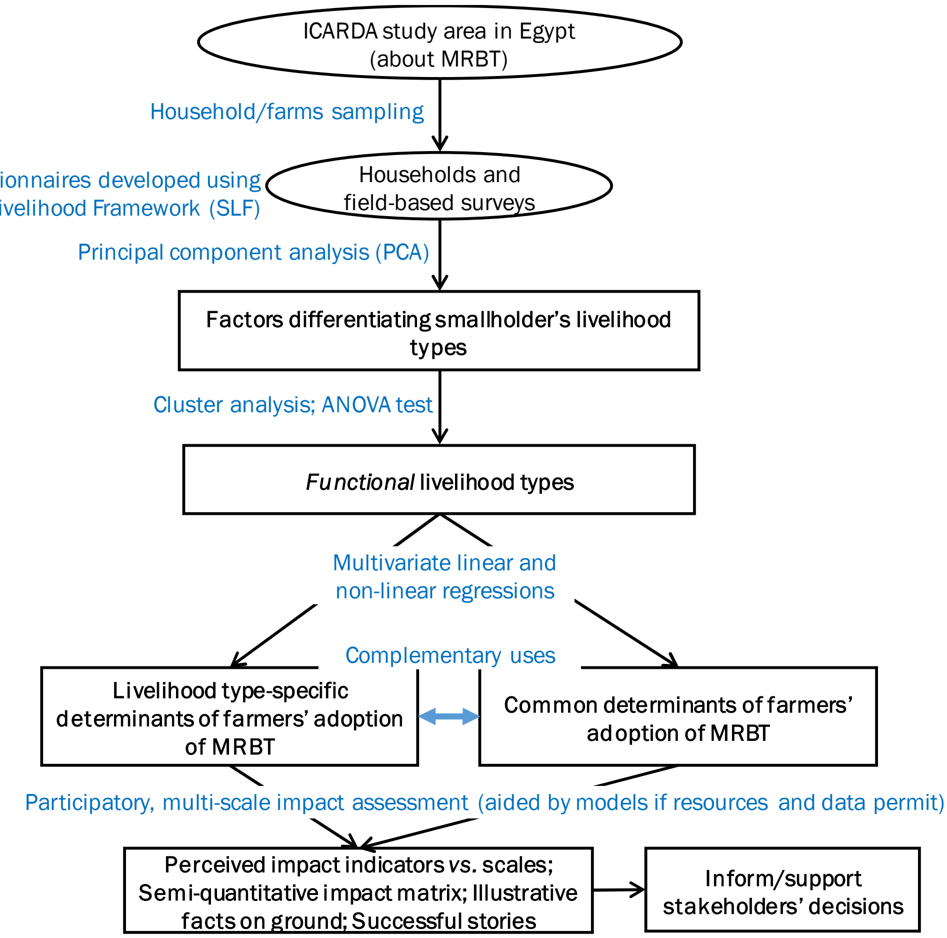

Figure 2. Analytical diagram showing empirical research steps towards obtaining the research objectives. Boxes indicate expected research outputs; blue text indicates empirical research methods (specified from Le and Dhehibi (2018)).

3. METHOD AND DATA

3.1. Method for identifying livelihood typology of smallholder farm-household systems

It is important to clarify the terms 'type' and 'typology.' A type is an abstract generic model that defines the characteristic features of a series of objects. Typology designates two aspects: (1) the science of type elaboration, designed to help analyze a complex reality and order objects; and (2) the system of types resulting from this procedure (Landais 1998).

Selecting method

There are different methods for identifying livelihood typology, including expert opinions, participatory rankings (e.g. well ranking), statistical analyses (non-parametric methods such as tree-like step-wise analysis, or parametric methods such as the combination of principal and cluster analysis). Each method has particular advantages and limitations (Le and Feitosa, 2012); Le, 2015). As the typology analysis here is embedded in a project targeting a sizable area, aiming to collect sizable quantitative data, and having a strong perspective on operational modeling research in later years, the parametric multivariate method is proposed for use.

Basis for designing contents of data collection

The study is built on the concept of household/farm livelihood sustainability, including its adaptability and resilience in the vulnerability context. The sustainable livelihoods framework describes the essential resources at household/farm disposal and livelihood strategies built from these resources in coping with the vulnerability context (DFID 1999). These resources comprise five types of livelihood assets that are used to achieve the households' or community's livelihood outcomes. Human assets includes variables of labor, health, education, and capabilities. Natural assets comprise of attributes of lands (amount and quality), livestock, and water resources. Financial assets include incomes, savings and loans from different sources. Physical assets consist of variables for housing conditions, access to infrastructure, and equipment for agricultural production. Social assets include supports and advantages from social networks, engagement to rural development institutions, positions, and projects/programs. In addition, from the resilience approach, the five livelihood assets interactively determine the buffering capacity of livelihood systems. The adaptability and transformability of a household's livelihood strategies will also be determined by its and its community's institution for self-organizing and learning capacities (Speranza et al. 2014). This livelihoods framework should be used to guide the development of the contents of questionnaires for livelihood surveys and indicators for analyses and assessments. Tables 1, 2 and 3 defines quantitative variables, which were specified using the sustainable livelihoods framework, for sequential statistical analyses in this study.

Principal component analysis, subsequent cluster analysis, and analysis of variance

Principal component analysis (PCA) will be used for discovering key factors explaining the majority of variation in the multivariate livelihood data, as well as reducing the dimensionality of the data. The technique condenses a large number of original variables into a smaller set of new composite dimensions with a minimal loss of information (Mc Garigal et al. 2000). The meaning of each principal component is interpreted in terms of the original variables with higher weights/loadings. Because the extracted principal components are independent from each other, the use of component scores for subsequent analysis will avoid the multi-collinearity problem. Variables (30) entered to PCA in this study are shown in Table 1.

K-mean Cluster Analysis (K-CA) will be used for deriving typical household/farm groups defined by livelihood criteria. Unlike hierarchical methods, K-CA methods avoid problems of chaining and artificial boundaries and work on the original input data rather than on a similarity matrix. For a large dataset (e.g. hundreds of cases), K-CA should be chosen because it would be difficult to interpret grouping results using hierarchical cluster analysis. Data entered to K-CA can be the scores of principal components extracted by the earlier PCA, or original livelihood variables that are highly correlative with the extracted principal components.

Table 1. Variables representing five livelihood assets considered in Principal Component Analysis (PCA)

No.	*Variable*	*Definition*
	Human asset	
1	H_AGE_HEAD	Age of the household head (unit: year-old)
2	H_AGE_MEAN	Average age of household members (unit: year-old)
3	H_EDU_HEAD	Education level of the household head (unit: 1= illiterate, 2= can read & write, 3= secondary school, 4= high education)
4	H_HH_SIZE	Household size, i.e. number of household members
5	H_LABOR	Number of workers based on age (between 15 and 64 year old)
6	H_DEPEND_RATIO	Dependency ratio (no. of dependents / no. of workers)
	Natural asset	
7	P_FARM_SIZE	Farm size, i.e. area of household farm (unit: ha)
8	H_AREA_PERS	Farm area per capita (unit: ha/person)
9	P_SOIL_SALINITY	Severity of soil salinity perceived by the household (unit: 1= low, 2= moderate, 3= high)
10	P_WATER_TABLE	Severity of water table raising perceived by the household (unit: 1= low, 2= moderate, 3= high)
11	H_LIVESTOCK	Value of household's livestock (unit: EGP)
12	H_LIVESTOCK_PERS	Value of livestock per capita (unit: EGP/person)
13	H_POULTRY	Value of household's poultry (unit: EGP)
14	H_SMALL_RUMINANT	Value of household's small ruminants (unit: EGP)
15	H_CATTLE	Value of household's cattle (unit: EGP)
	Financial asset	
16	H_INCOME	Annual income of the household (EGP/year)
17	H_INCOME_PERS	Annual income per capita (EGP/person/year)
18	H_AGR_INCOME	Share of agricultural income (%)
19	H_NAGR_INCOME	Share of non-agricultural income (%)
20	H_LOAN_ACCESS	Household's accessibility to loans, approximated by the total loan value (EGP)
	Physical asset	
21	P_DISTANCE_HOUSE	Distance from household's farm to house (unit: m)
22	P_DISTANCE_TOWN	Distance from household's farm to the nearest urban center (unit: m)
23	H_NFLOORS	Number of house floors
24	H_NROOMS	Number of house rooms
25	H_EQUIPMENTS	Value of household's equipment (EGP)
	Social asset	
26	H_AC_EFFECTIVE	Effectiveness of agricultural cooperatives (AC) for the household as perceived (unit: 0= ineffective, 1= don't know (likely little effective), 2= fairly effective, 3= effective)
27	H_WUA_EFFECTIVE	Effectiveness of Water Use Association (WUA) for the household as perceived (unit: 4 levels as those of H_AC_EFFECTIVE)
28	H_AMA_EFFECTIVE	Effectiveness of Agricultural Market Association (AMA) for the household as perceived (unit: 4 levels as those of H_AC_EFFECTIVE)
29	H_AMA_MEMBER	Membership of Agricultural Market Association (AMA) (unit: 1= have a membership, 0= otherwise)
30	H_SDA_EFFECTIVE	Effectiveness of Service Development Association (SDA) for the household as perceived (unit: 4 levels as those of H_AC_EFFECTIVE)

To determine the number of clusters, the procedure described in Robinson et al. (2006) can be used. The optimal cluster number is defined as the minimal cluster number with the highest cluster homogeneity. First, K-CAs are run with the number of clusters set to all values between 2 and 9 (or more). For each K-CA (with a concrete *k* value), we calculated the mean distance of cases to their assigned cluster centers. These mean distance values were then plotted against the increasing cluster number (*k* = 2, 3 …, 10). The optimal cluster number was chosen by examining the 'elbow' of the curve: the point from which the overall cluster quality, i.e., the reduction of the mean distance from cases to their cluster centers, or the overall cluster homogeneity (Rakhlin and Caponnetto 2006) is not substantially improved when *k* increases.

The livelihood groups of households/farms defined at this stage are just potentially functional livelihood types. Unbalanced analysis of variance (ANOVA) will be done for testing if key dependent variables – such as MRBT adoption and efficiency, not being included in the PCA and K-CA – respond differently among the classified livelihood groups. If the responses are statistically significant, the livelihood groups/types will be proven to be functional to indicators of the research objectives.

Functional livelihood types are not only useful for follow-up adoption analyses, but also directly for policy and management practices. The functional types can help agricultural development projects, programs, and scientists to improve their targeting. For example, given limited resource and aims, we can know approximately where efforts should be focused in managing or coping with which drivers. The result can also be used as an extrapolation domain: given successful outcomes in a limited number of project sites, we can identify where similar intervention options have a potential of success based on livelihood contextual similarity.

3.2. Method for adoption analysis

Dependent variables

The first dependent variable used for inferential statistics (binary logistic regression) is the existence of MRBT practice in household farms (MRB_PRACTICE). This is a straightforward (yes/no) adoption that is often seen in many literature.

The second dependent variable used for inferential statistics (multiple linear regression) is the composite index of adoption quality that is conceptualized in equation (1):

$$AQ = \prod_{i}^{N} P_i \times \sum_{j}^{M} Q_j \qquad (1)$$

where AQ is the adoption quality index, P_i is a "must-have" status attribute as the "hard" controller for the *AQ*, and Q_j is quality attributes for the performance and/or impact of the practice of considered technology. This this study, P_i is the practice existence of a MRBT practice. If there is no MRBT practice ($P_i = 0$), then AQ is zero regardless any value of Q_j. We collected Q_j on farmers' reflections on different benefits of MRBT, including improvements of household's machinery ability (MRB_MA), technical knowledge and skill (MRB_KT), cost of adoption (MRB_AC), crop yield (MRB_YD), water saving (MRB_WS), marketability (MRB_MKA), and market price received (MRB_MKP). The short definition of these adoption quality components are showed in Table 2. Therefore, in this study the AQ index takes the equation of the form:

AQ = MRB_PRACTICE x (MRB_MA + MRB_KT + MRB_AC + MRB_YD + MRB_WS + MRB_MKA + MKP) (2)

Table 2. Variables representing different quality attributes of MRB adoption (i.e. adoption quality attributes), as dependent variables in regression analysis for identifying adoption's determinants

Adoption quality attribute	*Definition*	*Unit (range)*
MRM_PRACTICE	The existence of MRB practice	0 = traditional farm, 1= MRB practiced
MRB_MA	Self-reflection of MRB's benefit about improving household's machinery ability	0= no difference created by MRB, 1= don't know (not clear), 2= better
MRB_KT	Self-reflection of MRB's benefit about improving household's knowledge and technology	0= no difference created by MRB, 1= don't know (not clear), 2= better
MRB_AC	Self-reflection of MRB's benefit about reducing household's cost of adoption	0= no difference created by MRB, 1= don't know (not clear), 2= better
MRB_YD	Self-reflection of MRB's benefit about improving farm's crop yield	0= no difference created by MRB, 1= don't know (not clear), 2= better
MRB_WS	Self-reflection of MRB's benefit about improving farm's water saving	0= no difference created by MRB, 1= don't know (not clear), 2= better
MRB_MKA	Self-reflection of MRB's benefit about improving household's market ability	0= no difference created by MRB, 1= don't know (not clear), 2= better
MRB_MKP	Self-reflection of MRB's benefit about improving market price received	0= no difference created by MRB, 1= don't know (not clear), 2= better
AQ	Adoption quality (AQ) index of MRB, i.e. a product of MRB implementation with the sum of score reflected MRB's benefits (see equations (1) and (2))	A score between 0 and 14

Inferential statistical models

For the MRB_PRACTICE, as it is in dummy scale (1 if the household practice MRBT, 0 otherwise – i.e. traditional farm), binary logistic regression (bi-logit) is used to identify factors determining MRBT adoption. As site-specific constraints and potentials influence MRBT outcomes, the unit of MRBT adoption analysis is recommended to be a field rather than a household. The effect of the hypothesized socio-ecological variables on the adoption of manure by a household can be modeled as:

$$P(MRBT) = 1 / (1 + exp\ (\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \ldots + \beta_n X_n + \mu)) \quad (1)$$

where *P(MRBT)* is the probability of MRBT adoption. X_i and β_i (i = 1, 2, 3, …, n) are explanatory variables and their weight coefficients, respectively. μ is a random error term.

Performance evaluation of binary logistic regressions included:

- a chi-squared test for the overall statistical significance of the regression model
- the probability of correct prediction
- Receiver Operating Characteristic (ROC) statistics.

Although some pseudo-R^2 in bi-logit mimics the widely used R^2 in linear regression, there are no agreed benchmark values of the pseudo-R^2 parameters for answering whether the model performance is acceptable. As an alternative, the goodness-of-fit of the model uses ROC statistics, as recommended by several experts in binary logistic regressions (Hosmer and Lemeshow 2000; LaValley 2008; Pepe et al. 2004). The ROC curve depicts the model sensitivity (True Positive Fraction) and model specificity (True Negative Fraction) over all possible cut-off points. The area under the ROC curve (theoretically ranging from 0.5 to 1) was used as the basis for evaluating model performance. If the area value is significantly ($p < 0.05$) higher than 0.5, then the model predicts the output better than chance. Area values of 0.7 to 0.8 show acceptable model performance, values of 0.8 to 0.9 demonstrate excellent performance, and values greater than 0.9 indicate an outstanding performance (Hosmer and Lemeshow 2000).

Multiple linear regression (MLR) is used for inferring determinants of adoption quality index (AQ). Performance of MLR model are measured by F-test and $R^{2.}$

Explanatory variables

The vector of explanatory variables [X_i] (i = 1, 2, 3, …, n) is from the indicators of livelihood assets of the household that owns or operates the land. Vector [X_i] can have some overlap with the variables in the earlier PCA, but not necessarily. In general, the inclusion of livelihood variables in [X_i] should be based on an understanding (through either literature or common sense) about the rationales of their effects on the adoption of MRBT. The explanatory variables for regressions analyses in this study are showed in Table 3.

Both regression models require the checking of multi-collinearity problems the explanatory variables can cause for the regression model. High multi-collinearity (i.e., strong linear relationship among two or more explanatory variables) can cause misleading regression analyses results. Before conducting the regression analyses, we tested for the multi-collinearity of all explanatory variables using Variance Inflation Factors (VIF). Ideally, there will be serious collinearity problems if the VIF values are greater than 5 (DeFries et al., 2010). Many cases we removed explanatory variables having VIF > 10 to reduce the seriousness of multi-collinearity (https://www.spsstests.com/2015/03/multicollinearity-test-example-using.html)

Table 3. Explanatory variables considered in regression analyses for identifying determinants of MRB adoption**.**

No.	*Variable*	*Definition*	*Hypothesized effect*
	Human asset		
1	H_AGE_HEAD	Age of the household head (unit: year-old)	-
2	H_AGE_MEAN	Average age of household members (unit: year-old)	-
3	H_EDU_HEAD	Education level of the household head (unit: see Table 1)	+
4	H_HH_SIZE	Household size, i.e. number of household members	-/+
5	H_LABOR	Number of workers based on age (15 - 64 year-old)	-
6	H_DEPEND_RATIO	Dependency ratio (no. of dependents / no. of workers)	-/+
	Natural asset		
7	P_FARM_SIZE	Farm size, i.e. area of household farm (unit: ha)	+
8	H_AREA_PERS	Farm area per capita (unit: ha/person)	+
9	P_SOIL_SALINITY	Severity of soil salinity (unit: see Table 1)	+
10	P_WATER_TABLE	Severity of water table raising (unit: see Table 1)	+
11	H_LIVESTOCK_PERS	Value of livestock per capita (unit: EGP/person)	+/-
12	H_POULTRY	Value of household's poultry (unit: EGP)	+/-
13	H_GOAT	Value of household's goats (unit: EGP)	+/-
14	H_SHEEP	Value of household's cattle (unit: EGP)	+/-
15	H_BUFFALO	Value of household’s buffaloes (unit: EGP)	-
16	H_COW	Value of household’s cows (unit: EGP)	+/-
	Financial asset		
17	H_INCOME	Annual income of the household (unit: EGP/year)	+/-
18	H_INCOME_PERS	Annual income per capita (unit: EGP/person/year)	+/-
19	H_INCOME_AGR	Annual income from agriculture (unit: EGP/year)	+/-
20	H_INCOME_NAGR	Annual income from non-agricultural sources (unit: EGP/year)	+/-
21	H_LOAN_ACCESS	Household's accessibility to loans (unit: EGP)	+
	Physical asset		
22	P_DISTANCE_HOUSE	Distance from household's farm to house (unit: m)	-
23	P_DISTANCE_TOWN	Distance from household's farm to the nearest urban center (unit: m)	-
24	H_NFLOORS	Number of house floors	+/-
25	H_NROOMS	Number of house rooms	+/-
26	H_EQUIPMENTS	Value of household's equipment (unit: EGP)	+/-
	Social asset		
27	H_AC_EFFECTIVE	Effectiveness of agricultural cooperatives (AC) (unit: see Table 1)	+
28	H_WUA_EFFECTIVE	Effectiveness of Water Use Association (WUA) (unit: see Table 1)	+
29	H_AMA_EFFECTIVE	Effectiveness of Agricultural Market Association (AMA) (unit: see Table 1)	+
30	H_AMA_MEMBER	Membership of Agricultural Market Association (AMA) (unit: see Table 1)	+
31	H_SDA_EFFECTIVE	Effectiveness of Service Development Association (SDA) (unit: see Table 1)	+

3.3. Study site and sampling

The study has been conducted in Sharkia (6 districts) and Assiut (3 districts) governorates of Egypt. A random sample of 360 individuals have been selected from several districts in the two governorates, 80 farmers were practicing traditional farming methods, while the remaining 180 were adopters of the Mechanized Raised Bed farming system (MRB).

Surveyed traditional farmers in Sharkia governorate comprise 14 from Zaqaziq, 30 from Awlad Saqr, 5 from Menia Al-Qamh, 15 from Hehia, 21 from Abo-Ahmed and 5 from Faqos district. Out of the total samples, the small farmers represent 91%, graduates represent 3% and tenants represent 6%. Farmers who own lands located on the head of Mesqa account for 38%, those who own lands located on the middle of Mesqa account for 33% and those who own lands located on the tail of Mesqa account for 29%. In Assiut governorate, the surveyed traditional farmers include 45 from Manfalot and 45 from Al-Fat'h district, all of which are small farmers (100%). whereas, farmers who own lands located on the head of Mesqa account for 30%, those who own lands located on the middle of Mesqa account for 54% and those who own lands located on the tail of Mesqa account for 16%.

The surveyed adopters of Mechanized Raised-bed Farming in Sharkia include 14 from Zaqaziq, 29 from Awlad Saqr, 5 from Menia Al-Qamh, 15 from Hehia, 20 from Abo-Ahmed and 7 from Faqos district. All of the sample individuals are small farmers. Farmers here either own lands on the middle of Mesqa (43%), or on the tail of Mesqa (57%). The surveyed MRB adopters in Assiut comprise of 60 from Al-Fat'h district and 30 from Abnob district, all of whom are small farmers. In addition, 19% of them own lands on the middle of Mesqa, 64% own lands on the middle of Mesqa and 17% own lands on the tail of Mesqa.

4. RESULTS AND DISCUSSION

4.1. Identified Agricultural Livelihood System types (ALS type)

Factors explaining the differences in ALS types

The PCA run extracted 9 principal components with total eigenvalues greater than 1.0, explaining 74% of the total variance of the 30 original livelihood variables. The rotated component matrix then helped to determine what the components represent (Table 4). The principal component 1 (PC1) was strongly related to variables approximating access/connection to market, both physical market access (H_DISTANCE_TOWN) and institutional market connection (H_AMA_EFFECTIVE, H_AMA_MEMBER). Thus, we named this component “Market factor”, which explained for 13.4% of total variance of the original dataset Principal component 2 (PC2) was most weighted by income variables, especially the share of income from agriculture (H_AGR_INCOME), therefore we labeled the component “Agricultural income factor”. This factor accounted for 11.7% of total variance of the original dataset. Principal component 3 (PC3, accounting for 9.5% of total variation) was most highly correlated with 3 livestock variables: H_LIVESTOCK, H_LIVESTOCK_PERS, and H_CATTLE, so it was called the “Livestock factor”. Pairwise correlations of the three variables showed that they were strongly correlated. Because of the high loading value, H_LIVESTOCK was selected to represent the Livestock factor. Principal component 4 (PC4) was highly correlated with the demographic variables of surveyed household (H_SIZE, H_LABOR) and demographic pressure on land (H_AREA_PERS), it was called the “Labor factor”.

Table 4. Extracted principal components (PCs), loading coefficients of variables vs. PCs and key variables (with bolded names and loadings).

	PC1 (Market - 13.4%)	PC2 (Agr. income - 11.7%)	PC3 (Livestock - 11.3%)	PC4 (Labor - 9.5%)	PC5 (Age - 7.2%)	PC6 (Non-agri. income - 6.5%)	PC7 (House quality - 6.4%)	PC8 (Access- to- farm - 4.3%)	FC9 (Less access-to-loan - 3.9%)
H_AGE_HEAD	0.052	0.220	0.119	0.652	0.554	0.063	0.085	0.075	0.150
H_AGE_MEAN	-0.010	0.122	0.042	0.027	**0.889**	-0.010	-0.038	0.069	0.076
H_EDU_HEAD	0.369	-0.078	-0.139	-0.358	-0.225	0.134	0.334	-0.280	-0.032
H_HH_SIZE	0.188	0.213	0.150	**0.856**	-0.191	0.071	0.129	-0.039	0.074
H_LABOR	0.222	0.009	0.142	**0.806**	0.268	0.050	0.171	-0.084	-0.098
H_DEPEND_RATIO	-0.142	0.164	-0.047	0.017	**-0.807**	0.038	-0.073	0.050	0.212
P_FARM_SIZE	0.153	0.157	0.462	-0.039	0.145	0.000	0.128	0.021	0.562
H_AREA_PERS	-0.060	-0.021	0.351	**-0.666**	0.349	-0.028	-0.004	0.019	0.423
P_SOIL_SALINITY	0.526	0.556	0.238	0.006	0.091	-0.162	0.092	0.091	-0.066
P_WATER_TABLE	**0.708**	0.170	0.136	-0.162	0.004	-0.143	-0.011	0.260	-0.207
H_LIVESTOCK	0.151	0.212	**0.906**	0.201	0.010	-0.021	0.033	0.106	-0.019
H_LIVESTOCK_PERS	0.029	0.001	**0.823**	-0.238	0.136	-0.014	-0.059	0.077	0.001
H_POULTRY	0.266	0.356	0.342	0.141	0.013	0.166	0.154	-0.053	-0.086
H_SMALL_RUMINANT	0.167	0.450	0.552	0.149	-0.093	0.041	0.088	-0.041	0.032
H_CATTLE	0.116	0.106	**0.892**	0.187	0.036	-0.045	0.006	0.138	-0.025
H_INCOME	0.136	**0.722**	0.105	0.120	-0.022	0.578	0.122	-0.022	-0.029
H_INCOME_PERS	0.074	**0.623**	0.046	-0.043	0.041	0.703	0.079	-0.032	-0.063
H_AGR_INCOME	0.187	**0.858**	0.173	0.118	0.008	-0.062	0.011	0.047	0.008
H_NAGR_INCOME	0.047	-0.117	-0.082	0.068	-0.054	**0.897**	-0.025	0.022	-0.069
H_LOAN_ACCESS	0.028	0.063	0.128	0.025	0.123	0.074	-0.074	-0.008	**-0.605**
P_DISTANCE_HOUSE	0.005	-0.089	0.155	-0.167	-0.028	-0.050	0.259	**0.782**	-0.051
P_DISTANCE_TOWN	**0.882**	0.230	0.084	0.059	0.018	0.047	-0.139	0.075	-0.104
H_NFLOORS	-0.156	0.107	0.026	0.146	0.037	0.009	**0.856**	0.084	0.080
H_NROOMS	-0.272	0.137	0.058	0.123	0.036	0.000	**0.839**	0.092	0.098
H_EQUIPMENTS	0.309	0.330	0.196	0.237	0.156	0.128	-0.109	0.458	0.231
H_AC_EFFECTIVE	0.488	0.098	0.078	0.209	0.088	0.354	-0.166	0.439	0.119
H_WUA_EFFECTIVE	0.216	**0.841**	0.082	0.079	0.017	-0.022	0.076	-0.004	0.054
H_AMA_EFFECTIVE	**0.744**	0.128	0.147	0.156	0.043	0.220	-0.116	-0.102	0.152
H_SDA_EFFECTIVE	**0.609**	0.121	0.014	0.121	0.026	0.010	-0.025	0.022	0.007
H_AMA_MEMBER	**0.774**	0.090	0.133	0.175	0.063	0.054	-0.228	-0.095	0.166

Principal component 5 (PC5) was explained mainly by the variable of family mean age (H_AGE_MEAN) and dependency ratio (H_DEPENRATIO), then called as "Age factor". Principal component 6 (PC6) was related mainly the share of on-agricultural income (H_NAGR_INCOME), thus named as "Non-agricultural income factor". Principal component 7 (PC7) was strongly associated with variables indicating house quality (H_NFLOORS, H_NROOMS), thus referred as "House quality factor". Principal component 8 (PC8) was explained mainly by distance from household house to his/her farm reflecting household's physical transaction cost in daily farming, thus named "access-to-farm factor". Principal component 9 (PC9) was inversely related household's access to loans (H_LOAN_ACCESS), thus called as "Less access-to-loan factor". However, as PC9 accounts for only 4% of the total data variation, and the loading of H_LOAN_ACCESS is not high, the role of this variable for differencing ALS types may be not important.

ALS Types

In Table 4, 22 vvariables with loading > 0.6 (bolded) were used for subsequent cluster analyses (K-CA). We run 8 K-CA with K= 2, 3, …, 9 that used these 22 variables, and calculated Sum of Squared Errors (SSE) for every K-CA run. Figure 2 depicts the distribution of SSE versus the running number of clusters (K), which shows a "knee" point at K = 3. The point suggests the optimal cluster number (K=3) for the final K-CA. Increasing the cluster number further from this point will not effectively increase the average clumsiness of each cluster (clustering quality inversely approximated by SSE).

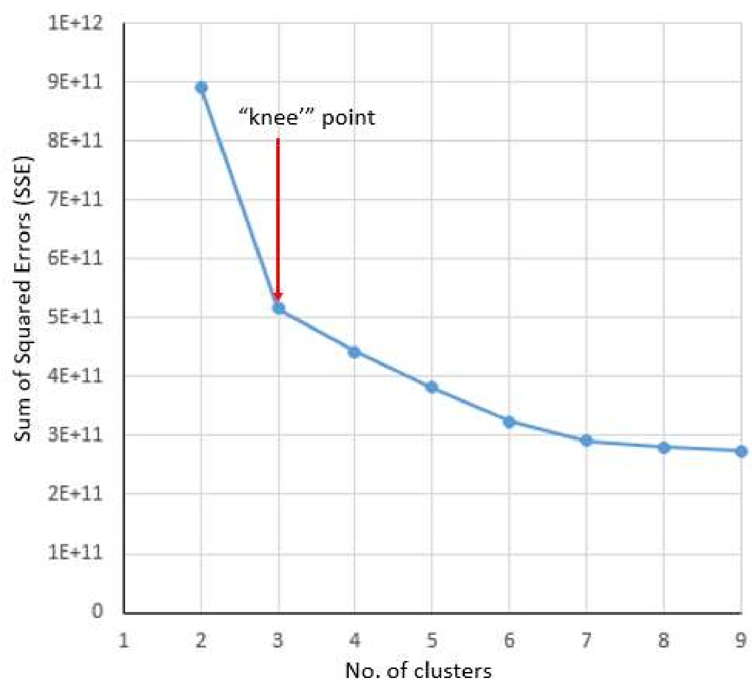

Figure 2. Distribution of Sum of Squared Errors versus number of clusters.

Final K-CA with K = 3 resulted in three clusters of farm-households. We run ANOVA to test the differences among mean values of 22 used variables and the results (data not shown). The final selection of a limited set of variables for characterizing the clusters is based on not only ANOVA tests, but also the interpretations of the meaning of the "statically" differences. In many variables, although there are significant differences among the mean values of ALS types, but the variables are not picked for characterizing the clusters because the mean differences are either less, or equal to only one unit of the variables (e.g. the case of H_SIZE, H_LABOR, H_NFLOORS, H_NROOMS). Some variables have significantly high correlation with each other. In these cases we select the most meaningful variables from them. The key variables used for characterizing ALS types are showed in Table 5.

Table 5. Key characteristics of three potential Agricultural Livelihood Types

Livelihood asset category	*Key variable (abbreviation)*	$\bar{X} \pm CI_{0.05}$ *(mean ± confidence interval at 95%)*		
		ALS Type I (n= 196) (poor and non-agriculture based income)	*ALS Type II (n= 96) (medium and balanced crop-livestock-nonfarm income)*	*ALS Type III (n= 61) (medium, less dependent pressure, livestock/cattle based income)*
Human	H_AGE_MEAN	31 ± 1	31 ± 1	34 ± 2
	H_DEPENRATIO	0.39 ± 0.07	0.40 ± 0.10	0.30 ± 0.07
Natural	H_AREA_PERS (m2/person)	1,442 ± 213	1,176 ± 116	2,170 ± 519
	H_LIVESTOCK (100 EGP)	41 ± 14	878 ± 44	16445 ± 74
Financial	H_INCOME_PERS (100 EGP/person)	19 ± 6	34 ± 10	35 ± 11
	H_AGR_INCOME (%)	3 ± 2	29 ± 9	35 ± 12
	H_NAGR_INCOME (%)	23 ± 6	18 ± 8	11 ± 7
Physical	P_DISTANCE_HOUSE (m)	830 ± 138	1,278 ± 241	1,236 ± 324
	P_DISTANCE_TOWN (m)	3,421 ± 539	5,798 ± 685	5,444 ± 802
Social	H_AMA_EFFECTIVE*	1	3	1
	H_AMA_MEMBER*	0	1	1

* Median is used instead of metric mean

ALS type 1 (n = 196, 55%) – *Poor* household-farm (1900 EGP/person/year) with main income based on *non-agricultural activities at low* **cost** (agricultural income being 3% of the total income), *less access to local market institution* such as Agricultural Market Association. It is likely these household members have frequent low-cost non-farm activities in town as they live closer urban centers (3.7 km) compared to the two other ALS types (5.5 – 5.8 km).

ALS type 2 (n = 96, 27%): The *medium* household-farms (3400 EGP/person/year) with *balanced crop-livestock-nonfarm* income, being *sensitive/positive to* role of *local market institution* (e.g. AMA) compared to other ALS types.

ALS type 3 (n = 61, 17%): The *medium* households-farms (3500 EGP/person/year) with *livestock/cattle-based income*, and *less pressure from independents*.

4.2. Determinants of MRB adoption

Adoption responses versus ALS types

Table 6. MRBT adoption practice, adoption quality attributes and composite adoption quality index (AQ) versus ALS types

Adoption variable	*Category*	*ALS type 1*	*ALS type 2*	*ALS type 3*	*Whole sample*
MRB practice (MRB_PRACTICE)	0= Traditional farm	98	45	32	175
	1= MRB practiced farm	98	51	29	178
	%MRB practiced	**50**	**53**	**48**	**50**
Self-reflection of MRB's benefit on household's machinery ability (MRB_MA)	0= No difference	3	2	0	5
	1= Don't know	62	27	18	107
	2= Better	131	67	43	241
	% Better	**67**	**70**	**70**	**68**
Self-reflection of MRB's benefit on improved knowledge and technology (MRB_KT)	0= No difference	22	8	4	34
	1= Don't know	169	77	53	299
	2= Better	5	11	4	20
	% Better	**3**	**11**	**7**	6
Self-reflection of MRB's benefit on adoption cost (MRB_AC)	0= No difference	8	10	6	24
	1= Don't know	72	32	20	124
	2= Better	116	54	35	205
	% Better	**59**	**56**	**57**	**58**
Self-reflection of MRB's benefit on crop yield (MRB_YD)	0= No difference	1	1	1	3
	1= Don't know	64	28	18	110
	2= Better	131	67	42	240
	% Better	**67**	**70**	**69**	68
Self-reflection of MRB's benefit on water saving (MRB_WS)	0= No difference	1	2	1	4
	1= Don't know	65	28	18	111
	2= Better	130	66	42	238
	% Better	**66**	**69**	**69**	**67**
Self-reflection of MRB's benefit on household's marketability (MRB_MKA)	0= No difference	22	8	4	34
	1= Don't know	169	77	53	299
	2= Better	5	11	4	20
	% Better	**3**	**11**	**7**	6
Self-reflection of MRB's benefit on market price received (MRB_MKP)	0= No difference	22	9	4	35
	1= Don't know	171	76	53	300
	2= Better	3	11	4	18
	% Better	**2**	**11**	**7**	5
MRB adoption quality index (AQ) (mean value)		**5.1**	**5.6**	**4.9**	**5.2**

MRBT adoption practice, adoption quality attributes and composite adoption quality index (AQ) versus ALS types are showed in Table 6. Adoption quality attributes being responsive to ALS types include: farmers' reflection on MRBT benefits on technical knowledge and skills (MRB_KT), marketability (MRB_MKA), and market price received (MRB_MKP). The other adoption attributes are not response differently to different ALS types, in which household-farms of ALS type 2 are most positive in MRB adoption regarding these three quality attributes.

Determinants of MRB practice

The results of binary logistic regression for identifying determinants of MRB practice adoption for the whole sample population and 3 ALS types are presented in Table 7. For whole sampled population and sub-groups of ALS types 1 and 2, the Hosmer and Lemeshow tests for the bi-logit models show acceptable results: *p*-values are higher than 0.05 that shows no statistically significant difference between the predicted data for MRB adoption and the observed data, meaning that there was a good fit of the model to the data. The percentage of overall correct predictions of the models were relatively high (from 76% to 80%). The calculated area under the ROC curve ranged from 0.69 to 0,85 indicating that the performance of the models varies from acceptable to excellent for identifying the determinants of adoption of MRB. Although there is no sign of failure in the parameters of model performance tests, the bi-logit model for ALP type 3 has no explanatory power: there is not any variable demonstrating a significant effect.

Table 7 shows there are 14 variables with a significant effect on MRB adoption. With a common-specific interrelation thinking, these 14 determinants of MRB adoption can be of 4 categories:

Common determinants for MRB adoption (2 variables): A common determinant of adoption is the explanatory variable found significant for whole population and individual ALS types, and sharing the same affecting direction. If all determinants are common, then the treatment of adoption analyses for individual ALS types will have no benefit. In Table 7, in the total of 14 variables having significant effects, there are only 2 variables within the physical asset category are common determinants: H_NROOMs (supporting MRB adoption) and H_EQUIPTMENT (discouraging MRB adoption).

ALS type-specific determinants for MRB adoption category - type 1 (4 variables): A determinant for adoption in this type is the explanatory variable found significant for whole population, and for one of a few of individual ALS type(s) rather than all individual ALS. In this case, the added value given by the treatment of individual ALS is to help *further* narrow the specific zone(s)/condition(s) where the effect actually takes place. Determinants of this type include average age of the family (H_AGE_MEAN) and income (H_INCOME) which effects are zoomed ALS type 2. Membership of agricultural market association (H_AMA_MEMBER) encourages farmers to adopt MRB in general, but the effect is further narrowed in ALS type 3 (the medium and livestock-based farmers).

ALS type-specific determinants for MRB adoption - type 2 (3 variables): A determinant for adoption in this type is the explanatory variable found for one of a few of individual ALS type(s) but not realized through the analysis of the whole population, reflecting the added value given by the use of individual ALS types. There are 4 determinants for MRB adoption of this type, including farm size (H_FARM_SIZE) and income per capita (H_INCOME_PERS) which effects are found only in ALS type 1 (poor and low-

Table 7. Results of regression analyses (binary logistic model) identifying determinants of the MRB implementation (MRB_PRACTICE).

Explanatory variable	Affecting coefficient (*β*)			
	Whole population (n = 353)	ALS type 1 (n = 196)	ALS type 2 (n = 96)	ALS type 3 (n = 61)
Intercept	**4.16723****	-3.112025	2.795705	535.074263
H_AGE_HEAD	0.036484	-0.023694	**0.259528***	3.670878
H_AGE_MEAN	**-0.059180***	-0.036237	**-0.277310***	-4.258127
H_EDU_HEAD	**0.336165***	0.100004	0.533685	-0.345585
H_HH_SIZE	0.085064	0.205301	-1.837035	4.877359
H_LABOR	-0.485084	-0.648082	0.896835	-18.400223
H_DEPRATIO	-1.352001	-2.185917	1.739649	-92.624210
P_FARM_SIZE	0.556649	**2.511402***	9.995974	-83.072594
H_FARM_PERS	1.223084	-1.811349	-50.953806	97.441248
P_SALINITY	-0.127766	-0.666194	0.595789	-50.489758
P_WATER_TABLE	**-0.632814***	-0.360940	-0.221991	-100.267632
H_LIVESTOCK_PERS	-0.000019	0.001005	0.000280	-0.000676
H_POULTRY	0.000093	0.000037	-0.000050	0.002230
H_GOAT	-0.000005	-0.000424	-0.000120	-0.000134
H_SHEEP	**0.000077*****	-0.000061	0.000052	0.000307
H_BUFFALO	0.000003	-0.000199	-0.000097	-0.001048
H_COW	0.000008	-0.000178	-0.000045	-0.000071
H_INCOME	**0.000036***	**0.000096*****	0.000022	-0.003875
H_INCOME_PERS	-0.000019	**-0.000204***	0.000010	0.008142
H_INCOME_AGR	**-0.000046****	-0.000466	-0.000042	0.002547
H_LOAN_ACCESS	-0.000004	-0.001434	0.000007	-0.006201
P_DISTANCE_FARM	**-0.000488****	-0.000632	-0.000619	-0.012088
P_DISTANCE_TOWN	0.000060	0.000016	0.000078	0.009058
H_NFLOORS	**-0.647272****	**-0.928635***	-0.618283	8.672878
H_NROOMS	**0.300600*****	**0.434100*****	**0.343082***	-4.747966
H_EQUIPMENT	**-0.000137*****	**-0.000144*****	**-0.000197*****	-0.005918
H_AC_EFFECTIVE	0.220648	0.215050	1.478817	13.781440
H_WUA_EFFECTIVE	-0.192171	9.892515	-0.885360	48.918104
H_AMA_EFFECTIVE	-0.107161	0.271273	-1.004542	15.627895
H_AMA_MEMBER	**1.743556*****	1.116570	**3.589761****	-20.984578
H_SDA_EFFECTIVE	0.097971	-0.087460	-0.045027	27.589114
Model performance				
Hosmer-Lemeshow test	*Chi-square*= 8.478 *df* = 8, *p* = 0.388	*Chi-square*= 12.455 *df* = 8, *p* = 0.132	*Chi-square*=20.574 *df* = 8, *p* = 0.08	*Chi-square*= 0.000 *df* = 8, *p* = 1.000
Correct prediction	75.6%	77.0%	80.2%	100%
Area under ROC	0.85 ($p < 0.001$)	0.69 ($p < 0.001$)	0.70 ($p < 0.001$)	0.61 ($p < 0.001$)

Notes: Symbols *, **, and *** indicate a statistical significance at 90% ($p < 0.1$), 95% ($p < 0.05$), and 99% ($p < 0.01$), respectively.

Table 8. Results of regression analyses (multiple linear model) identifying determinants of the MRB Adoption Quality (MRB_ADOPT_QUAL)

Explanatory variable	Affecting coefficient (β)			
	Whole sample population (n = 353)	ALS type 1 (n = 196)	ALS type 2 (n = 96)	ALS type 3 (n = 61)
Intercept	**12.031138*** **	**8.0533050*** **	**12.697623** **	**21.784745*** **
H_AGE_HEAD	-0.042868	-0.0820910	0.023392	0.104024
H_AGE_MEAN	0.003843	0.0293595	-0.036492	-0.182747
H_HH_SIZE	0.699425	0.6011159	0.097752	-1.990863
H_FARM_PERS	1.098808	2.4674827	9.241878	2.672397
P_SALINITY	-0.082025	-0.6731696	-0.135969	-0.678263
P_WATER_TABLE	-0.700973	-0.4258870	-0.662324	-1.458162
H_POULTRY	0.000067	0.0001706	-0.000077	-0.000006
H_GOAT	0.000004	-0.0001065	-0.000116	0.000025
H_SHEEP	**0.000124*** **	0.0000202	**0.000163** **	**0.000099** **
H_BUFFALO	-0.000003	0.0000396	-0.000048	-0.000019
H_COW	0.000004	0.0000136	-0.000007	-0.000020
H_INCOME_AGR	-0.000007	-0.0001021	-0.000011	0.000006
H_INCOME_NAGR	**0.000055*** **	**0.0000649*** **	0.000054	-0.000081
P_DISTANCE_FARM	**-0.000617** **	-0.0005894	-0.000283	-0.000984
P_DISTANCE_TOWN	-0.000068	-0.0001804	0.000445	-0.000059
H_NFLOORS	**-0.815685** **	-0.8750639	-0.855526	-0.549728
H_NROOMS	**0.376476*** **	**0.4222141** **	0.388385	0.125627
H_EQUIPMENT	**-0.000205*** **	**-0.0001949*** **	**-0.000210*** **	**-0.000253*** **
H_AC_EFFECTIVE	0.485688	0.4837751	0.785828	0.217742
H_WUA_EFFECTIVE	-0.175095	**4.2093391** **	-1.467264	0.155717
H_AMA_EFFECTIVE	-0.509836	0.6123337	**-1.508532***	-1.035367
H_AMA_MEMBER	**3.463651*** **	1.6777887	3.459019	4.216389
H_SDA_EFFECTIVE	0.099145	-0.4385565	-0.095141	1.003309
Model performance	F-test: $F = 6.404$ $df = 23$ $p < 0.001$ Goodness-of-fit: $R = 0.56$ $R^2 = 0.31$ *adjusted-*$R^2 = 0.26$	F-test: $F = 4.275$ $df = 23$ $p < 0.001$ Goodness-of-fit: $R = 0.60$ $R^2 = 0.36$ *adjusted-*$R^2 = 0.28$	F-test: $F = 1.872$ $df = 23$ $p < 0.05$ Goodness-of-fit: $R = 0.61$ $R^2 = 0.37$ *adjusted-*$R^2 = 0.17$	F-test: $F = 3.209$ $df = 23$ $p < 0.001$ Goodness-of-fit: $R = 0.82$ $R^2 = 0.67$ *adjusted-*$R^2 = 0.46$

Notes: Symbols *, **, and *** indicate a statistical significance at 90% ($p < 0.1$), 95% ($p < 0.05$), and 99% ($p < 0.01$), respectively.

cost non-agriculture based). The larger farm size the more adoption of MRB in this group of farmers. The negative effect of income per capita is understandable as the income of this group is largely based on non-agricultural activities. Here, the result of group characterization, as a step of the approach, eases the interpretation of the effect. Negative effect of the age of household head (H_AGE_HEAD) on MRB adoption is found only in ALS type 3 (medium and livestock-based).

Determinants for MRB adoption found only in the population-whole analysis (5 variables): The determinants of this category include 5 variables: education of household head (H_EDU_HEAD) and sheep (H_SHEEP) with positive effects, severity of water table raising (H_WATER_TABLE), share of agricultural income (H_INCOME_AGR) and distance from house to farm (H_DISTANCE_FARM) with negative effects. Excepting the case of H_INCOME_PERS, the affecting directions of determinants agree with common-sense knowledge. The existence of determinants in this category demonstrates the complementary role of population-whole adaption analysis besides the ALS-type specific ones.

Determinants of MRB adoption quality

The result of the MLR analysis, with MRB adoption quality index as the dependent variable is shown in Table 8. The used list of explanatory variables are shorter than those showed in Table 3 (section 3.2) as variables with high VIF were excluded from to minimize the problem of multi-collinearity for the MLR models. F-tests indicated that all MLR models for explaining MRB adoption quality index were significantly different at the confidence levels of 95% ($p < 0.05$) or 99% ($p < 0.01$). The model prediction powers are either fairly good for the MLR of ALS type 3 (i.e. adjusted R^2 = 0.46 that is quite good for regression with cross-sectional data), or poor for the remaining MLR models (adjusted R^2 = 0.17 – 0.28). However this is not a serious problem as prediction is not the chief objective of this study.

Table 8 shows there are 9 variables with a significant effect on the adoption quality index. With a common-specific interrelation thinking, these 14 determinants of MRB adoption can be of 4 categories:

Common determinants for MRB adoption (1 variables): The common determinant of MRB adoption quality is household’s equipment (H_EQUIPMENT) (-).

ALS type-specific determinants for MRB adoption category - type 1 (3 variables): Determinants of this type include the share of non-agricultural income (H_INCOME_NAGR), number of rooms in house (H_NROOMS) that are further narrowed for ALS type 1. The effect of household’s sheep (H_SHEEP) (+) is common for whole population and ALS types 2 and 3.

ALS type-specific determinants for MRB adoption - type 2 (2 variables): The strong positive effects of the effectiveness of water use association (H_WUA_EFFECTIVE) on MRB adoption quality index is found only in ALS type 1. Without the ALS type-specific adoption analyses, this determinant – being meaningful for policy and management practice – would have not been realized. The negative effect of agricultural market association effectiveness (H_AMA_EFFECTIVE) on MRB adoption quality is found only in ALS type 2, which is quite unusual and needs further interpretation with additional information.

Determinants for MRB adoption found only in the population-whole analysis (3 variables): The determinants of this category include 3 variables: distance from house to farm (H_DISTANCE_FARM), number of house floors (H_NFLOORS) (all significantly negative), and membership in agricultural market association (H_AMA_MEMBER) (significantly positive).

4.3. Evaluation of added values of the ALS typology-based method compared to traditional approach

Table 9 shows evaluation remarks on the added values and limitations of the ALS typology-based method compared to traditional approach. The ALS typology-based approach, presented by this study, is the complementary use of both ALS type-specific and sample-whole analyses. The traditional approach, which is often found in current literature of adoption analysis, is the use of sample-whole analysis only. The evaluation remarks were drawn on the findings of presented adoption analyses. In overall, the ALS typology-based approach captured more quantities and comprehension of causalities in MRB adoption. The ALS typology-based approach found 14 and 9 determinants of MRB adoption and adoption quality, respectively; compared to 10 and 7 determinants found by the traditional approach. The ALS typology-based approach added following values:

- Confirm wide-spread role of common determinants of MRB adoption across ALS types
- Zoom in the population zone subjected to the effects MRB adoption that were found in sample-whole analysis
- Discover new causal effects that cannot be done by traditional approach. The effects of effectiveness of agricultural institutions, such as Water Use Association and Agricultural Market Association, can be only realized with ALS type-specific analysis rather than the analysis of the whole sample only.
- By complementary use of the sample-whole analysis, the ALS typology-based approach utilize large size of whole sample to increase statistical power, thus off-setting the problem for the small ALS group.

Table 9. Evaluation of added values and limitations of the ALS typology-based method compared to traditional approach using evidences provided by this study

Approach	*Category of determinants*	*Number of determinants*		*Added value*	*Limitation - Alternative*
		MRB adoption (yes/no)	*MRB adoption quality (AQ index)*		
Traditional approach: use of sample-whole analysis only (business-as-usual - BAU)	Total determinants for MRB adoption	10	7	Utilize large size of whole sample to increase statistical power	Findings not necessarily reflect wide-spreading effects
ALS typology-based approach: complementary use of both ALS type-specific and sample-whole analyses (this study)	Common determinants across ALS types	2	1	Confirm wide-spread effects	Inferential statistic models for small ALS groups have poor performance, probably due to 2 reasons: • Small sample size reduce the power of parametric statistics. Alternative: additional uses of non-parametric method for small ALS group • ALS classification tend to reduce within-cluster variation, causing poor performance of statistic analysis if the same data of ALS grouping used for adoption analysis. Alternative: uses additional data sources for adoption analysis.
	ALS type-specific determinants – category 1	4	3	Zoom in the population zone subjected to the effects found in sample-whole analysis	
	ALS type-specific determinants – category 2	3	2	Discover new causal effects that cannot be done by traditional approach	
	Determinants found only in sample-whole analysis	5	3	Utilize large size of whole sample to increase statistical power, thus off-setting the problem for the small ALS group	
	Total determinants for MRB adoption	14	9	Capture more quantity and comprehension of causalities in MRB adoption	

5. CONCLUSIONS AND RECOMMENDATION

This study empirically investigates the issues using a system-based option-by-context approach, or ALS typology-based approach, for guiding concrete analytical steps and statistical methods in coping with the challenges of system complexity and contextual diversity in two governorates (Sharkia and Assiut) of Egypt. We used Sustainable Livelihood Framework to define candidate variables entered to sequential multivariate statistical analyses. First, we use subsequent principal component analysis – k-mean cluster analysis and ANOVA to objectively define three distinct ALS types. We conceptualize the formula of adoption quality (AQ) index for statistical analysis in quality-focused way, beside the consideration of yes/no adoption. We apply relevant inferential statistic methods (bi-logistic and linear regressions) to whole/merged sample, and sub-samples (corresponding to ALS types) for identifying determinants of farmers' adoptions of MRBT.

The main finding of the study is that, classifying the considered agrarian population into a limited number of agricultural livelihood system (ALS) types and conducting multivariate inferential statistics for both (1) whole sample population and (2) each specific ALS types helped discover hidden causal relationships shaping MRBT adoption which would have been identified by considering the whole sample only. For instance, roles of effectiveness in agricultural institutions, such as water use association (WUA) and agricultural market association (AMA), in MRRT adoption are found in specific ALS types rather through looking at the merged population. Some causal relationships are found significant via inferential statistics for the whole sample, but actually taking effects in a specific ALS group (e.g. the case for the effect of farm size on MRBT adoption of poor and non-farm based income group). In sum, the added values of the ALS typology-based approach that were approved by this presented study are: (1) confirm wide-spread role of common determinants of MRB adoption across ALS types, (2) zoom in the population zone subjected to the effects MRB, (3) discover new causal effects that cannot be done by traditional approach, (4) utilize large size of whole sample to increase statistical power, thus off-setting the problem for the small ALS group.

We also realized that the ALS typology-based approach has a particular limitations regarding poor performance of inferential statistic models for small ALS groups. This is probably due to 2 reasons:

- Small sample size reduce the statistical power of parametric methods. The alternative can be additional uses of non-parametric method for small ALS group.
- ALS classification tend to reduce within-cluster variation, causing poor performance of statistic model for MRB adoption analysis if the same data of ALS grouping used for adoption analysis. The alternative would be the uses additional data sources for adoption analysis.

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