Science for resilient livelihoods in dry areas

Methodology for Assessing Adoption, Efficiency, and Impacts of Mechanized Raised-Bed Technology

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List of Acronyms

ANOVA	Analysis of variance
DEA	Data envelopment analysis
GHG	Greenhouse gas
ICARDA	International Center for Agricultural Research in Dry Areas
K-CA	K-mean cluster analysis
MCA	Multi-criteria assessment
MRBT	Mechanized raised-bed technology
PCA	Principal component analysis
ROC	Receiver operating characteristic
TE	Technical efficiency

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 at scale toward achieving system-level outcomes require adequate understanding of the drivers of farmers' adoption of MRBT, based on insightful assessment of the technology's efficiency, system performance and impacts. Related research efforts on these issues have been challenged by both the complex nature of the task and the diversity of socio-ecological contexts that shape farming systems' performance. This paper concisely reviews and re-introduces a system-based option-by-context approach for guiding concrete analytical steps and operational methods for addressing the research issues in coping with the challenges of system complexity and contextual diversity. The paper elaborates methodologies, ranging from concepts to operational methods, that will be needed to achieve the following objectives: (1) identify and characterize the main livelihood types of smallholders in terms of their farms' biophysical and socioeconomic characteristics; (2) identify the determinants, both common and livelihood type-specific, of farmers' adoption of MRBT; (3) delineate the ceiling line of water-use efficiency that the MRBT can bring about (i.e. the efficiency frontier) and use this as a reference for assessing the crop-production efficiency of MRBT farms with respect to water and other resource uses; (4) evaluate the multi-scale impacts of MRBT on whole-farm productivity and profit, household livelihoods, and irrigated community landscapes.

Keywords

Irrigated system, Egypt, Nile Delta, context, drivers, efficiency, impact, complexity, mechanized raised-bed technology, option-by-context, livelihood typology, technical efficiency, production frontier, participatory multi-criteria assessment.

Highlights

- We concisely review and re-introduce a system-based option-by-context approach as a general concept guiding concrete analytical steps and operational methods.
- We describe a conceptual framework and econometric methods for identifying main livelihood types of smallholders in terms of their farms' biophysical and socioeconomic characteristics.
- We describe econometric methods for identifying determinants, both common and livelihood type-specific, of farmers' adoptions of MRBT and technology efficiency.
- We analyze the technology efficiency concept and the challenges in measuring it, and described economic methods for comparative evaluation of MRBT efficiency in coping with multiple inputs and shifts in production potential (i.e. the efficiency frontier).
- We argue for a multi-scale strategy in evaluating impacts of MRBT, discuss relevant impact criteria and indicators at each scale, and describe a participatory multi-criteria assessment method.

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 fewer 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 an 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 the irrigated area, shortening the time needed for irrigation, and reducing the water volume needed for the 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 increasing crop production 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: (1) the drivers affecting farmers' adoption of MRBT; (2) the multi-aspect efficiency of MRBT (technically, economically, and ecologically/environmentally); or (3) the impacts of MRBT on whole farms' performance and households' livelihoods. Proven knowledge on these issues will be essential for informing policies and development practices that aim at disseminating the technology to achieve food security and water resource saving, and thereby better resilience to climate change.

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 in 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 stratum, 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).

Efficiency assessment of MRBT: So far, most efficiency assessments for raised-bed technology in Egypt have been done in a straightforward way, focusing on the partial agronomic efficiency – with respect to crop output, i.e. water productivity index (water volume needed/unit of crop yield), or water input (crop yield response/unit of water input) – as well as irrigation cost (cost of irrigation/unit of cropping area, or cost of irrigation/unit of crop yield). However, crop yield is also influenced by other side conditions (e.g. soil quality) and other inputs (e.g. fertilizers and labor). Variation in these factors can render the comparison of the above indicators over the studied population inadequate. Moreover, it is important to know the ceiling of water-use efficiency that the MRBT can bring about (i.e. the efficiency frontier) as a reference for setting realistic goals and pathways to achieve them. Finally, it would be useful to understand how MRBT shapes the productivity–risk relationship. A meaningful hypothesis would be that the implementation of MRBT can improve water productivity and yield while reducing, or at least not increasing, risks to crop production. All of these issues have remained gaps in knowledge.

Impact assessment of MRBT: In current literature, the effects of MRBT on what lies beyond crop yields – such as the performance of the whole farm, community livelihoods, and irrigated agricultural landscapes in Egypt – have been subjects of speculative anticipation and hope rather than scientific proof or projection. Efforts to fill this gap are important to realizing impact pathways from interventions in MRBT toward achieving development goals in national and international programs and policies.

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. Delineate the ceiling line of water-use efficiency that MRBT can bring about (i.e. the efficiency frontier), and use this as a reference for assessing the crop production efficiency of MRBT farms with respect to water and other resource uses.
4. Evaluate the multi-scale impacts of MRBT on whole-farm productivity and profit, household livelihoods, and irrigated community landscapes.

2. Approach

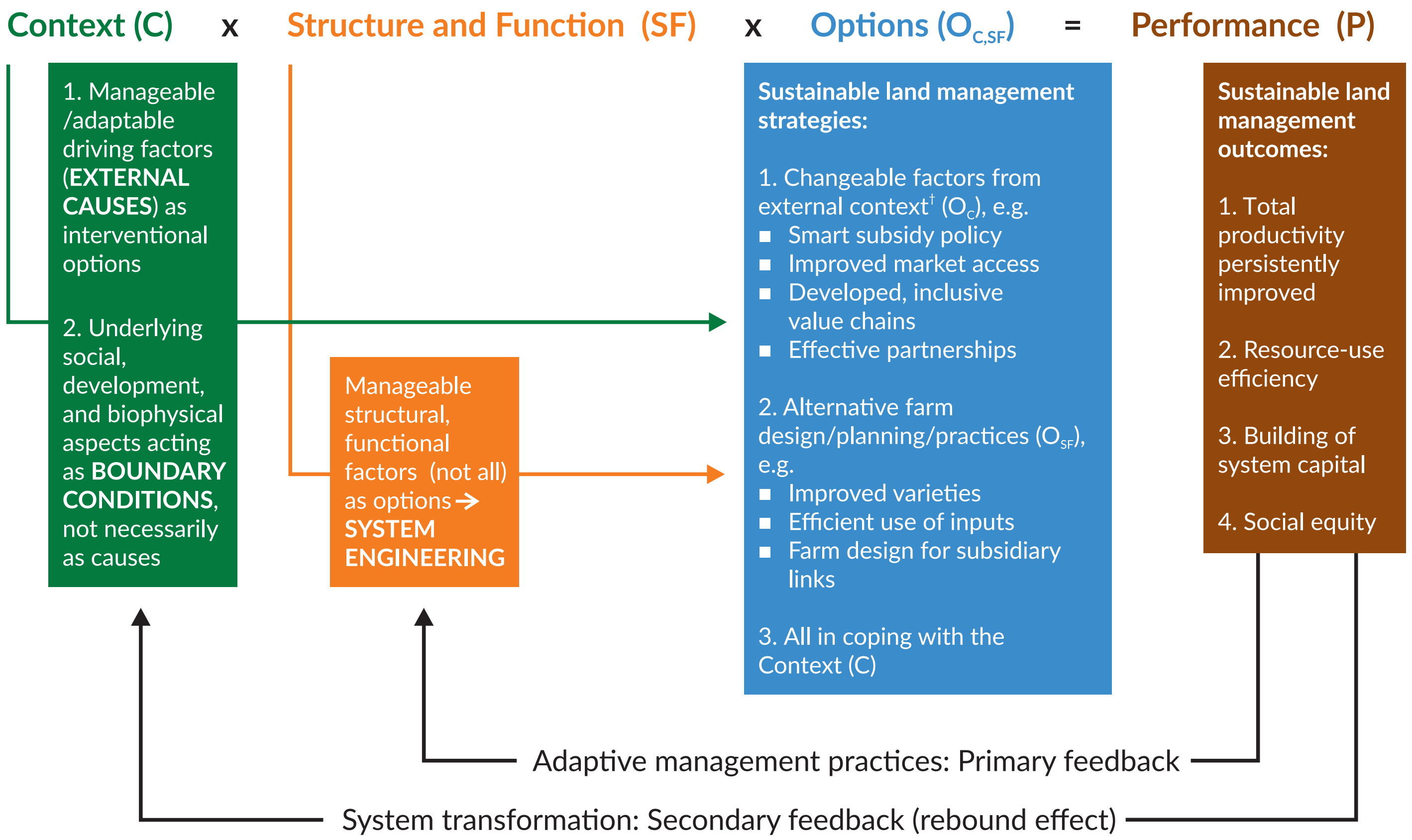
2.1 System-based option-by-context approach

The thrust of the conceptual framework for this study is a system-based clarification of the relationship between context (including drivers) and management options as the basis for guiding data integration, selection of objective-oriented indicators, and analysis/assessment of the diversity of land-use systems and related contexts over space (Figure 1). The framework draws on the insights of current frameworks for social–ecological systems in transition (Ashley and Carney 1999; Reynolds et al. 2007; Pahl-Wostl et al. 2010; Scholz et al. 2011), but is kept simpler for operational implementation.

2.2 Analytical steps

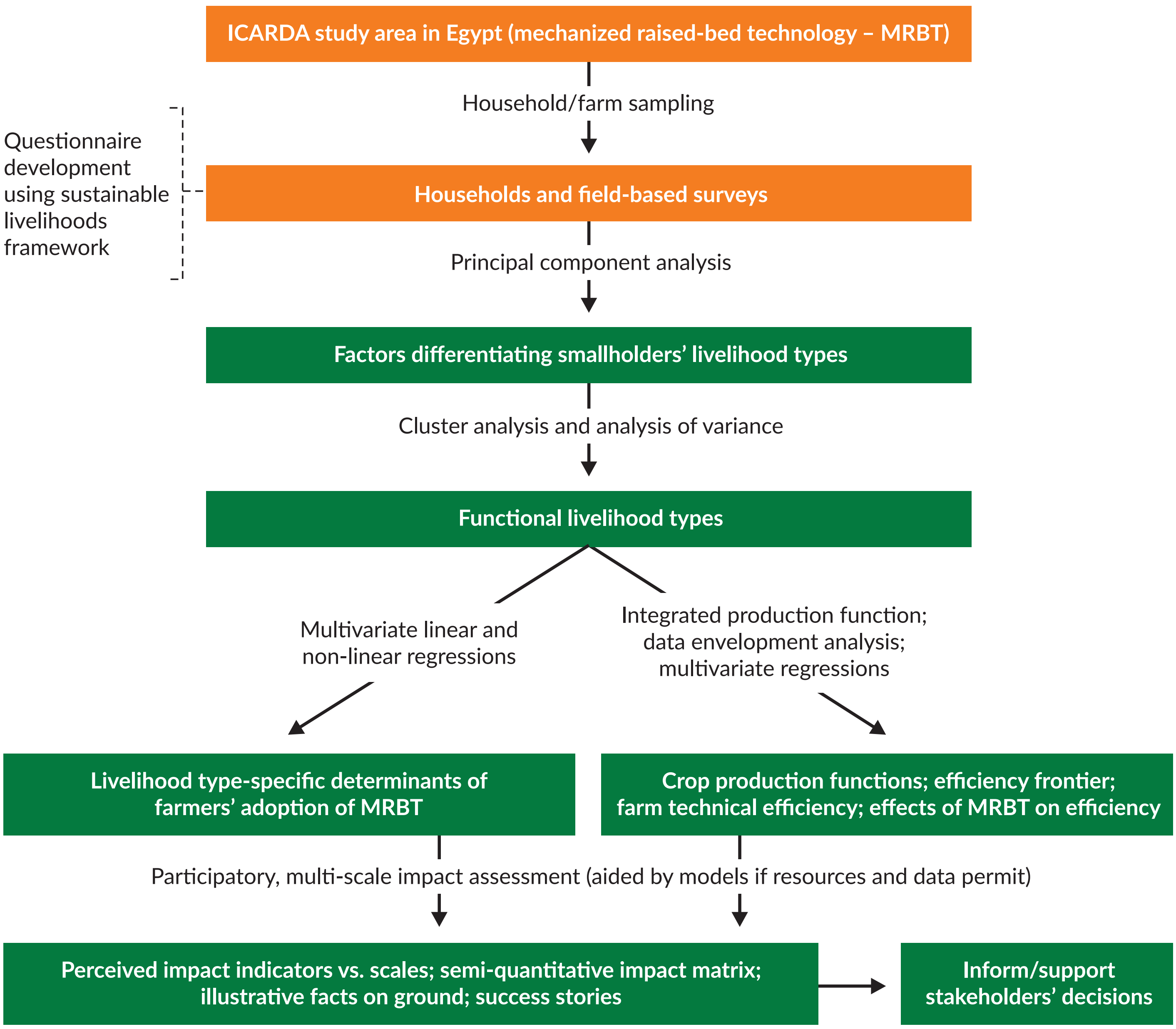
Figure 2 is a proposed analytical diagram that includes sequential steps of empirical research toward achieving the stated objectives. This procedure should apply for a sizable study area, such as a group of several governorates where MRBT is practiced, rather than a small site.

Figure 1. Relationship between management and technical options, structure and function of farming systems, and context within a system-in-transition framework. Source: Le et al. (2017).



† Manageable by enabling/influencing actors (e.g. decision-makers, market institutions) or by collective organizations of land-users rather than individual land users

Figure 2. Analytical diagram showing empirical research steps towards obtaining the research objectives. Boxes indicate expected research outputs; black text indicates empirical research methods.



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, as shown in Table 1. 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 (Figure 3a). 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: labor, health, education, and capabilities
- Natural assets: lands (amount and quality), livestock, and water resources
- Financial assets: incomes and savings from different sources
- Physical assets: housing conditions, access to infrastructure, and equipment for agricultural production
- Social assets: supports and advantages from social network, 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

Table 1. Advantages and limitations of different methods for defining livelihood typology.

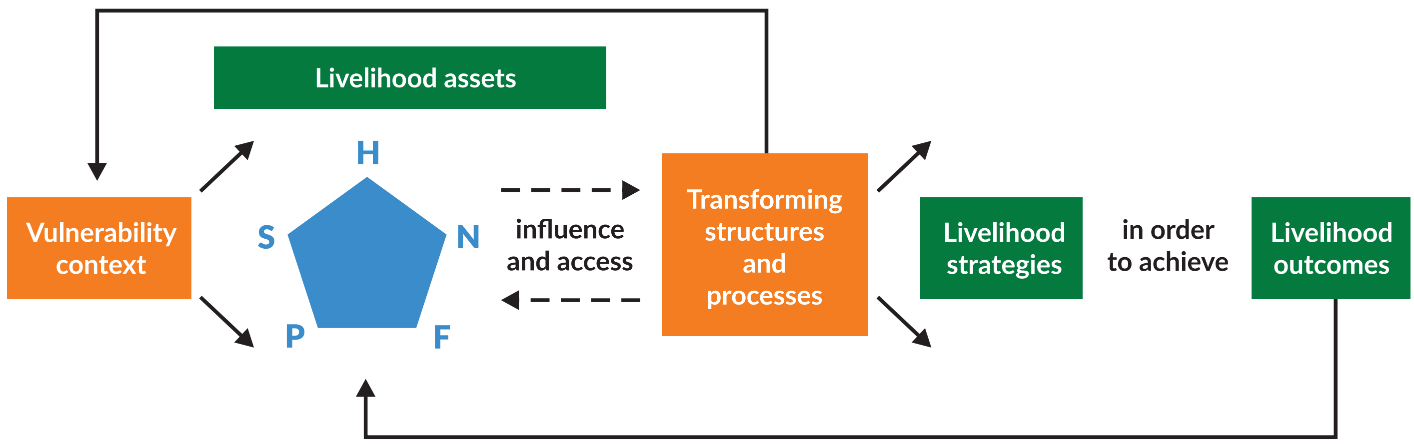
Method	Advantage	Limitation
Expert opinions	■ Fast, cost-effective	■ Risk of bias
Participatory rankings	■ Fast, cost-effective ■ Participatory potential	■ Difficult to include multiple criteria ■ Difficult to model type change
Step-wise/decision-tree classification	■ Combine qualitative and quantitative criteria ■ Work with small sample sizes ■ Participatory potential ■ Easy to implement in simulation	■ Difficult to know key discriminates among many criteria ■ May be low on contextual robustness
Parametric multivariate statistics	■ Capture key discriminates ■ Easy to implement in simulation	■ Less capable of capturing many qualitative criteria ■ Does not work well with a small sample size

Sources: Le and Feitosa (2012); Le (2015) transformability of a household's livelihood strategies will also be determined by its and its community's self-organizing and learning capacities (Speranza et al. 2014). The essential elements for a household's and community's self-organizing and learning capacities in relation to livelihood assets are shown in Figure 3b.

This livelihoods framework should be used to guide the development of the contents of questionnaires for livelihood surveys and indicators for analyses and assessments. Annex 1 gives an example of how quantitative variables can be specified using the sustainable livelihoods framework.

Figure 3. Conceptual framework of the study, based on (a) the sustainable livelihoods framework (Ashley and Carney 1999) and (b) livelihood resilience (Speranza et al. 2014).

a) Sustainable livelihoods framework in a vulnerability context



Key: H = human capital; N = natural capital; F = financial capital; P = physical capital; S = social capital

b) Unpacking the sustainable livelihoods framework with a resilience lens to understand how a community's self-organization and learning capacity relates to livelihood stability, transformation and outcomes

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 (McGarigal 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.

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.

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 10. 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 and efficiency/impact assessments, 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 resources 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 for success based on livelihood contextual similarity.

3.2 Method for adoption analysis

Inferential statistical model: As the dependent variable (adoption variable) is in dummy scale (1 if the household adopts MRBT, 0 otherwise), binary logistic regression (bi-logit) is proposed 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:

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

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).

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. Different from variables in PCA, [X_i] in MRBT adoption analysis additionally includes field attributes reflecting site potentials and constraints for implementing MRBT, such as:

- Field proximity (distance) to road and water supply
- Land form or hydrological status
- Field size
- Soil fertility
- Tenure status.

Annex 2 gives an example of a vector of explanatory variables in adoption analysis combining both household and field attributes.

Livelihood type-specific vs. combining adoption analyses: It is recommended to conduct both types of adoption analyses: those specific to livelihood groups, and those for a combined/whole sample. The benefits for this strategy can be:

- Understanding the added values of livelihood type-specific adoption analysis. In the example given in Table 2, the type-specific analyses reveal more information on the determining roles of 'Age,' 'Education,' and 'Distance to main road.'
- Revealing common determinants of adoption. This includes the common positive effect of 'Field size' across livelihood types in Table 2.
- Overcoming the limitation of data deficit in livelihood type-specific adoption analysis. In Table 2, for the case of 'Tenure security,' it seems there is not enough variation in this variable within livelihood groups (resulting in non-significant effects), but it is not the case with the combined sample (still significant, likely due to enough variation in data). Thus, the adaption analysis for the whole sample complementarily helps capture the effect of the tenure factor.

Table 2. Example synthesis table showing bi-logit results for livelihood groups and whole sample.

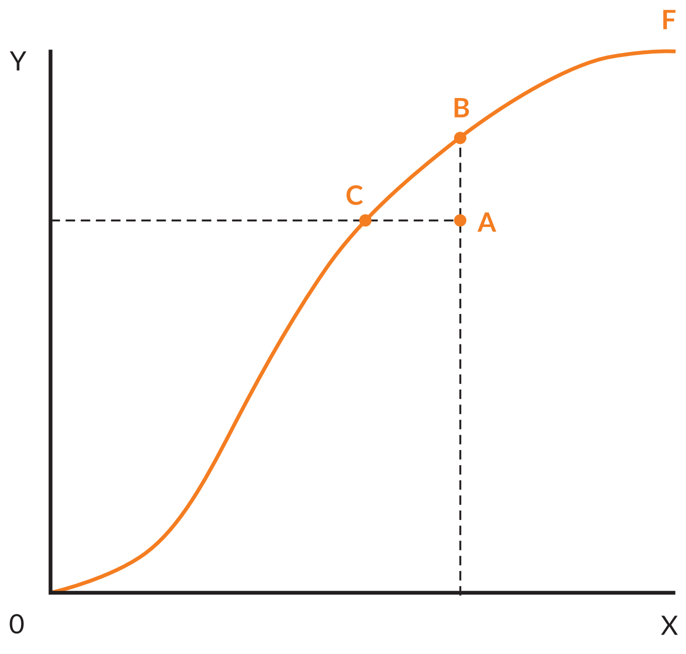
Explanatory variable [X_i]	Effect on adoption of mechanized raised-bed technology			
	Livelihood type A	Livelihood type B	Livelihood type C	Whole population
Age	+	ns	-	ns
Education	+	+	-	ns
Field size	+	+	+	+
Distance to main road	ns	+	-	ns
Tenure security	ns	ns	ns	+

* Note: + and – indicate significantly positive and negative effects, respectively; ns = non-significant

3.3 Methods for comparative assessment of technical efficiency

Production frontier and technical efficiency: To compare how well the application of MRBT brings about technical efficiency (TE) in crop production, the efficiency evaluation should be *referenced* to the *production frontier* that presents the maximum output attainable from each input level given the potential of the MRBT regime. Figure 4 describes the production process of one input *x* (e.g. water, fertilizer, or labor) into output *y* (e.g. crop yield) of a farm (Coelli 1996a; Nguyen et al. 2014). Curve *F* represents the production frontier, being the production potential determined by MRBT. The production frontier curve (*F*) is used as a reference for measuring technical efficiency of a farm. As *F* represents production potential, it is impossible to have any farm operating at a point above curve *F*. If farms operate on curve *F*, they will be efficient. In the example of Figure 4, farms B and C are technically efficient at two different levels of inputs. If a farm operates below the frontier, if it will be technically inefficient. Farm A is inefficient compared to either farm B (having a higher yield given the same input), or farm C (having the same yield with lower input).

Figure 4. Production frontier as a reference for evaluating technical efficiency.
Note: y = output; x = input; F = production frontier curve reflecting the production potential of the considered technology; A = inefficient farm; B and C = efficient farms.



Source: Nguyen et al. (2014).

Data envelopment analysis or stochastic frontiers for evaluating TE and testing hypotheses: By definition, TE can be calculated as simple ratios with respect to the unit of an input or output. For example, TE of MRBT regarding water-use efficiency can be an input-oriented ratio such as yield/m^3 of water, or an output-oriented index such as water volume needed for producing a unit of crop grains. However, in practice it is difficult to conduct comparative evaluation of TE among farms using such simple ratios. There are two problems:

- Observed yield is normally determined by multiple inputs, such as not only water but also fertilizers, pesticides, labor, and machinery, and possible interactions among them. Therefore, evaluating TE of MRBT with respect to one input needs to control for the other inputs. This can be done through field experiments in research stations, but the experimental fields cannot cover the wide range of non-experiment factors that represent actual contextual variation over a large research area such as a governorate.
- At community or landscape levels, efficiency measures can relate to two or more system outputs, such as not only crop yield but also energy-use efficiency, greenhouse gas (GHG) emissions from farm operations, and/or social outcomes (e.g. gender fairness). Broadly, at community or landscape scales efficiency can cover the interrelationships and trade-offs among a host of production, conservation, economic, and social values (Hein et al. 2006; Keating et al. 2010).

While addressing the latter problem is the subject of impact assessment methodology, which will be elaborated in section 3.5, this section describes a method for coping with the former problem. The curve or function of the production frontier can be used as a reference to calculate input-oriented TE in a way that addresses the question of the proportional reduction of input quantities while producing a given level of output quantities. TE is defined as:

$$TE = \frac{xTE}{x} \qquad (2)$$

where *xTE* is the vector of inputs at the technically efficient point (on the production frontier *F* in Figure 4) and *x* is the vector of currently used inputs (Nguyen et al. 2014). In an evaluation of MRBT's efficiency, the input vector would include major inputs for irrigated intensive crop production systems, such as:

- Water (m^3)
- Fertilizers (cost)
- Pesticides (cost)
- Machinery and energy (costs)
- Labor (working days).

Obviously, the approach in equation (2) requires the estimation of the production frontier function. There are two principal methods for this task (Coelli 1996a), which are:

- Data envelopment analysis (DEA)
- Stochastic frontiers (FRONTIER).

The former method involves mathematical programming, while the latter is based on econometric analyses. The methodological details and computer software for DEA can be found in Coelli (1996a; http://www.uq.edu.au/economics/cepa/deap.php), while those for FRONTIER are described by Coelli (1996b; http://www.uq.edu.au/economics/cepa/frontier.php).

Given TE calculated for every sampled farm/household, comparisons of TE between the group of households which adopted MRBT and the group which did not adopt MRBT are recommended. There will be two main comparisons with the following testing hypotheses:

Hypothesis 1: *TE of farms with MRBT is higher than TE of farms without MRBT.*

To control the variation of the livelihood context, the comparison should be done within each livelihood group identified from section 3.2. The layout for TE comparison is shown in Table 3, in which the comparison will be done between rows of the same column. T-test will be used to test this hypothesis.

Hypothesis 2: *The efficiency frontier of MRBT farms is higher than that of non-MRBT farms.*

This hypothesis refers to qualitative improvement (new and higher equilibrium) induced by MRBT. Graphic comparison will be used to test this hypothesis. The upper ceiling of the MRBT farms cloud (curve F_{MRBT} in Figure 5) is hypothesized to be above the ceiling of non-MRBT farm clouds (curve $F_{non\text{-}MRBT}$ in Figure 5).

Figure 5. Graphic comparison testing the hypothesis that mechanized raised-bed technology (MRBT) improves farms' efficiency frontier (*F*).

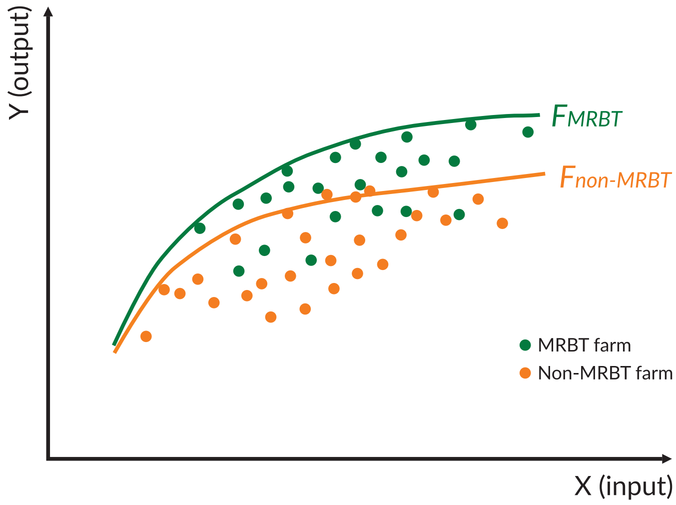


Table 3. Comparison of technical efficiency in mechanized raised-bed technology (MRBT) and non-MRBT farms in different livelihood contexts. Hypothesis: $TE_{MRBT, k} > TE_{non\text{-}MRBT, k}$.

	Livelihood context		
	Livelihood group 1	Livelihood group 2	Livelihood group k
Non-MRBT farms	$TE_{non\text{-}MRBT, 1}$	$TE_{non\text{-}MRBT, 2}$	$TE_{non\text{-}MRBT, k}$
MRBT farms	$TE_{MRBT, 1}$	$TE_{MRBT, 2}$	$TE_{MRBT, k}$

3.4 Methods for identifying determinants of MRBT efficiency in different livelihood contexts

Given data on household livelihoods, farm characterization, and farm TE, econometric analyses will be done to identify significant determinants of MRBT efficiency specific to livelihood context.

Inferential statistical model: The dependent variable is farm TE. Depending on the actual distribution of the TE coefficient there can be two optional scales of this variable, which lead to different statistical analyses.

If the dependent variable is the TE coefficient, i.e. a floating value between 0 and 1 where 1 represents efficient technology, the inferential statistical model can be multiple linear regression or probit regression. The performance evaluation of these statistical models will be:

- A chi-squared test for the overall statistical significance of the regression model
- The adjusted coefficient of determinant (R^2).

If the dependent variable is in a dummy scale of technically efficient (e.g. TE > 0.8) and inefficient (e.g. TE < 0.8), a bi-logit model should be used.[†] See section 3.2 for methodological details.

It is recommended to try both options of inferential statistical model and select the most statistically robust one.

Explanatory variables: The vector of explanatory variables [*Xi*] (*i* = 1, 2, 3, … *n*) can be similar to those in the adoption analysis (see section 3.2).

Context-specific and common determinants: Similar to MRBT adoption analyses, it is recommended to conduct both types of analyses for identifying determinants of MRBT efficiency: analyses specific to livelihood groups and analyses for the combined/whole sample. The details of benefits provided by this approach are described in section 3.2.

3.5 Methods for impact assessment

Multi-scale indicators for impact assessment: Some recent reviews of impact assessment of agricultural technology innovation have acknowledged the role of multi-dimensional and multi-scale perspectives (e.g. Keating et al. 2010; Lauwers 2009). However, it remains unclear from these reviews whether assessors can subjectively retain disciplinary options regarding the dimensions and system levels considered. Here, we argue that multi-dimensional and multi-scale perspectives are inherent in the environmental impacts caused by farming and are therefore inherent properties of the concept of eco-efficiency. In short, a genuine eco-efficiency assessment must always include a multi-dimensional and multi-scale perspective. However, based on an actual farming system and its social–ecological context, it is possible to focus on a number of dimensions and levels that are objectively of greatest importance and relevance.

To systematize the selection of indicators for a comprehensive assessment of eco-efficiency, it is important to identify typical dimensions and system boundaries in the realization of agricultural eco-efficiency. These include the following.

- *Material resource use efficiency* (Giller et al. 2006; Mueller et al. 2012; Tuomisto et al. 2012). This includes efficiencies of nutrient, water, and energy use in intensified farming.
- *Minimization of negative environmental impacts (environmental externalities)* (Cassman 1999; Foley et al. 2003; Keating et al. 2010; Picazo-Tadeo et al. 2012; Tscharntke et al. 2012; Tuomisto et al. 2012). Typical environmental impacts of agricultural intensification include soil degradation (nutrient leaching, mining, and soil erosion), water pollution (both surface and ground water), GHG emissions, and biodiversity losses.
- *Economic performance* (Den Bosch et al. 1998; Hoang and Nguyen 2013; Nguyen et al. 2013). This includes crop returns to inputs (land use, nutrients, water, and labor), farm net income, and net cash flow.
- *Social acceptance and equity* (Rosenström and Mickwitz 2004). This includes indicators of willingness-to-adopt and willingness-to-pay for

[†] The threshold can be adjusted based on the actual distribution of farm TE data. In general, a TE value above this threshold should indicate the efficient or near-efficient implementation of the technology.

intensification options, as well as social equity in sharing the benefits and costs of intensification.

Both expected outcomes and unwanted environmental impacts induced by MRBT inevitably occur at different system levels, ranging from the production unit (e.g. crop field) to whole farm and agrarian landscapes that include different farm/household types and non-farm areas, connected by environmental flows and social relationships. Crop yield at the production unit level is measured as either crop or livestock gain, but includes both at farm level. At landscape level, food yield can include fishery outputs. Intensification targets food yield gauged at all of these levels. The environmental footprint of intensification on biogeochemical cycles, for example, occurs in routing through the farm soil sub-system to the whole farm system and the entire landscape. Scale-sensitive indicator sets are proposed in Table 4, in which minimal and optional indicators at each scale are suggested. The measurement of many biophysical and economic indicators in this table would need sophisticated methods such as system modeling, while social indicators would be better done through participatory, yet semi-quantitative methods.

Farmer perception and participatory multi-criteria assessment: While data-driven methods are useful as objective ways to discover impacts beyond common-sense expectations, an assessment approach based on farmer perceptions has its own merits:

- Helping to scan important dimensions and indicators for rapid and in-depth assessments
- Fairly meeting the requirements of small or short-term projects
- Maintaining relevance to the social context of the study area, as well as to the measurement of social indicators.

Multi-criteria assessment (MCA) is a decision-making method used to evaluate problems when one is faced with a number of different alternatives and expectations and wants to find the 'preferred' solution with regard to different, and often conflicting, objectives. The ability of MCA to deal with complex impact assessment problems which involve a number of conflicting ecological, environmental, societal, and economic objectives and multiple interests groups is widely acknowledged (Scholz and Tietje 2002; Antunes et al. 2011).

A typical multi-criteria problem (e.g. a discrete number of impact dimensions/criteria/indicators) is described in the following way. Considering that A is a finite set of *n* alternatives and G is a set of *m* evaluation criteria, it is possible to build an $n \times m$ matrix (P) called the impact matrix, whose elements $p_{i,j} = g_j(a_i)$ ($i = 1, 2, \ldots n; j = 1, 2, \ldots m$) represent the evaluation of alternative *i* by means of criterion *j*. An alternative a_1 is evaluated to be better than alternative a_2 (both belonging to the set A) according to the j^{th} criterion if $g_j(a_1) > g_j(a_2)$.

Participatory MCA in water management technologies would involve the following steps (Antunes et al. 2011).

1. *Institutional analysis:* actor identification and characterization of the legal and institutional framework.
2. *Framing the decision:* reaching a commonly agreed problem statement.
3. *Defining key objectives and criteria:* identifying what values matter most to the participants in this particular situation.
4. *Establishing alternatives* and considering the relevant constraints. There may be a limited set of actual packages to implement MRBT.
5. *Identifying consequences*, that is, the most important impacts that can affect the stated objectives and associated uncertainties. Table 4 can be used as suggestive structure for further discussion on consequences of MRBT.
6. *Evaluating the desirability of the consequences* according to the proposed criteria. Participatory scoring exercises can be applied.
7. *Ranking of alternatives* applying an aggregation procedure.
8. *Social impact analysis* discussing the implications of each alternative for the main actor groups.

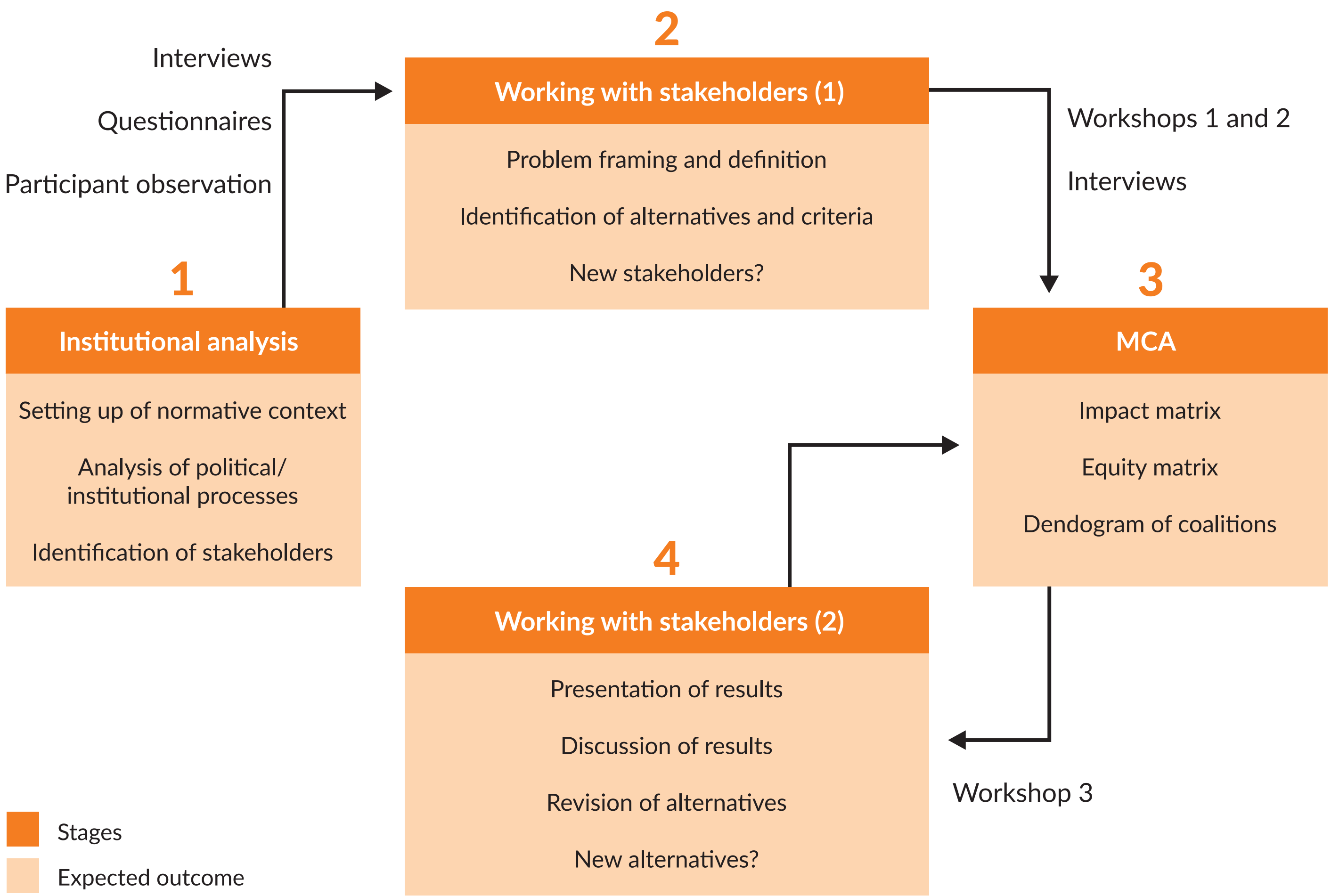
Participatory activities include (see Figure 6):

- Preparatory interviews for actor selection and understanding the decision context
- Workshops for alternatives and criteria identification and results discussion
- A second round of interviews for criteria weighting and alternatives evaluation.

Table 4. Multi-dimensional and multi-system boundary indicators for ideally comprehensive assessment of impacts induced by mechanized raised-bed technology in intensive irrigated systems.

Dimension (criteria)	Indicators at relevant system levels († indicates minimal requirement)		
	Production unit (field)	Whole farm	Agrarian landscape
Material use efficiency			
■ Nutrients	Crop nutrient-use efficiency (absorption/uptake efficiency, partial nutrient productivity, agronomic efficiency)†	Farm nutrient balance (consider within-farm nutrient recycling and/or reuse) and use efficiency†	Landscape nutrient balance (including specialized recycling, human-induced nutrient exchanges between farms, and soil redistribution over the landscape)†
■ Water	Crop water-use efficiency†	Farm water-use efficiency (include water reuse)†	Landscape water-use efficiency†
■ Energy	Crop fossil energy-use efficiency (labor included or excluded)†	Farm fossil energy-use efficiency (labor included or excluded)†	Landscape energy-use efficiency (labor included or excluded)†
Impact-minimization efficiency			
■ Minimize soil nutrient degradation	Soil sub-system nutrient balance† Soil organic carbon†		
■ Minimize water pollution	Nitrate leaching†	Nitrate in ground water†	Phosphorus and nitrate loads to water bodies† Pesticide content in water†
■ Minimize greenhouse gas (GHG)	GHG emissions†	GHG emissions from exposed dunghills†	Reduced GHG emissions due to spared vegetation conversion†
■ Minimize biodiversity losses	Soil biodiversity		Landscape species and genetic pools†
Economic efficiency	Crop returns to inputs (gross margin crops / input)† (inputs = cultivated land, applied nutrients, water, labor)	Net farm income† Farm net cash flow†	Average net farm income and farm net cash flow†
Social efficiency			
■ Fairness of benefit-sharing (social equity)		Women's workload†	Gini index of net farm income†
■ Social acceptance		Willingness-to-adopt (Likert scale) of intensification options†	Adoption rates (%) of intensification options†
■ Social incentive		Willingness-to-pay (Likert scale) for intensification options†	Rates (%) of willingness-to-pay for intensification options†

Figure 6. Flow chart of steps and activities for conducting participatory multi-criteria assessment (MCA).



Source: Antunes et al. (2011).

4. Conclusions

Mechanized raised-bed technology 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 at scale toward achieving system-level outcomes require adequate understanding of the drivers of farmers' adoption of MRBT, based on insightful assessment of the technology's efficiency, system performance and impacts. Related research efforts on these issues have been challenged by both the complex nature of the task and the diversity of socio-ecological contexts that shape farming systems' performance. This paper concisely reviews and re-introduces a system-based option-by-context approach for guiding concrete analytical steps and operational methods for addressing the research issues in coping with the challenges of system complexity and contextual diversity. We described a conceptual framework and econometric methods for identifying the main livelihood types of smallholders in terms of their farms' biophysical and socioeconomic characteristics. We explained econometric methods for identifying determinants, both common and livelihood type-specific, of farmers' adoptions of MRBT and its technical efficiency over ICARDA's studied area in Egypt. We analyzed the technical efficiency concept and the challenges in measuring it, and described economic methods for comparative evaluation of MRBT efficiency in coping with multiple inputs and shifts in production potential (i.e. the efficiency frontier). Finally, we argued for a multi-scale strategy in evaluating impacts of MRBT (production unit, whole farm, and community-landscape scales), discussed relevant impact criteria and indicators at each scale, and described a participatory multi-criteria assessment method for assessing MRBT's impacts.

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Annexes

Annex 1. Household variables for principal component analysis (PCA). The main variables representing the livelihood assets of households, based on the sustainable livelihoods framework, were extracted from a multi-dimensional dataset and used to run the PCA. This allowed for identifying key variables discriminating farms in Pontieba, Burkina Faso.

Livelihood asset	Variable	Variable definition	Source[†]
Human	$H_{HEADAGE}$	Household head age (years)	D
	$H_{MEANAGE}$	Average age of the household members	C
	H_{LABAGE}	Average age of the household labor	C
	H_{HEDUYR}	Number of years of classic education of household head	C
	H_{NBEDUC}	Number of educated members in the household	C
	H_{SIZE}	Household size (no. of people in the household)	D
	H_{LABOUR}	Number of workers of the household (labor)	C
	H_{DEPEND}	Dependency ratio of the household	C
Physical	$H_{DMARKET}$	Distance to important market (main town) from household house	D
	H_{DROAD}	Distance to permanent road from household house (m)	R
	$H_{VEHICLE}$	Number of transportation means (bicycle and motorbike) possessed by the household	C
	$H_{BULLOCK}$	Number of bullock possessed by the farm	D
Natural	$H_{HOLDINGS}$	Farm land holdings (ha)	D
	$H_{HOLDINGCP}$	Farm land holdings per capita (ha/person)	C
	$H_{FALLOWCP}$	Farm fallow land per capita (ha/person)	C
	$H_{CULTLANDCP}$	Farm cultivated land per capita (ha/person)	C
	$H_{SHFALLOW}$	Share of fallow area in land holdings (%)	C
	$H_{SHCOTTON}$	Share of cotton area in land holdings (%)	C
	$H_{SHCEREAL}$	Share of cereals area in land holdings (%)	C
	$H_{SHMFCRP}$	Share of marketable food crops area in land holdings (%)	C
	H_{TLUCP}	Tropical livestock unit per capita (TLU/capita)	C
	H_{TLUHA}	Tropical livestock unit per ha of cultivated land (TLU/ha)	C
Financial	$H_{GROSSINC}$	Household annual gross income (FCFA)	C
	$H_{GROSSINCCP}$	Household annual gross income per capita (FCFA/capita)	C
	$H_{SHREMITINC}$	Share of remittance income in household annual gross income (%)	C
	$H_{SHNFINC}$	Share of off-farm income in household annual gross income (%)	C
	$H_{SHLIVESTINC}$	Share of livestock income in household annual gross income (%)	C
	$H_{SHCOTINC}$	Share of cotton income in household annual gross income (%)	C
	$H_{SHCERINC}$	Share of cereals income in household annual gross income (%)	C
	$H_{SHMFCRPINC}$	Share of marketable food crops income in household annual gross income (%)	C

[†] D = Direct extracted from the questionnaire; C = Compound information calculated based on information coded in the questionnaire; R = Extracted from map reading.

Annex 2. Description of hypothesized explanatory variables for crop choice and nutrient uses adoption analysis in Pontieba, Burkina Faso.

Variable	Definition	Considered (x) in		Data source
		Crop choice analysis	Nutrient-use adoption analysis	
Dependent/choice variables				
P_{CROP}	Crop choices on the plot (= 1 if sorghum or millet, = 2 if groundnuts, = 3 if rice, = 4 if maize, and = 5 if cotton)	X		On-farm interview
P_{MIN}	Adoption of mineral fertilizer use on the plot (= 1 if yes, = 0 if no)		X	On-farm interview
P_{ORG}	Adoption of organic fertilizer use on the plot (= 1 if yes, = 0 if no)		X	On-farm interview
P_{MINORG}	Adoption of combined mineral–organic fertilizer use on the plot (= 1 if yes, = 0 if no)		X	On-farm interview
Household characteristics				
$H_{HEADAGE}$	Age of household head (years)	X	X	On-farm interview
H_{HEDUYR}	Number of school years the household head passed	X	X	On-farm interview
H_{SIZE}	Number of farm members	X	X	On-farm interview
H_{LABOR}	Number of workers	X	X	On-farm interview
H_{DEPEND}	Dependency ratio (= no. of dependents / no. of workers)	X	X	On-farm interview
H_{TLUCP}	Number of tropical livestock units (TLU) of the household	X	X	On-farm interview
$H_{GROSSINCCP}$	Household annual gross income per capita (FCFA/person)	X	X	On-farm interview
$H_{HOLDINGS}$	Total holding land possessed by the farm (ha)	X	X	Global positioning (GPS) and geographic information (GIS) systems

Variable	Definition	Considered (x) in		Data source
		Crop choice analysis	Nutrient-use adoption analysis	
Plot/field characteristics				
P_{DHOUSE}	Distance from plot to homestead (m)	X	X	GIS recordings
$P_{PLOTSIZE}$	Plot size (ha)	X	X	GPS measurement
$P_{CROPTYPE}$	Type of current crop grown on the plot (= 1 if fertilizer-demanding crops (maize, rice, or cotton); = 0 if other crops)		X	On-farm interview
$P_{CROPHIST}$	Type of previous crops grown on the plot (= 1 if the previous crops are fertilizer-demanding ones (maize, rice, or cotton); = 0 if other crops)	X		On-farm interview
$P_{UPSLOPE}$	The upslope contributing area (m^2) at the plot location, indicating sedimentation accumulation potential in the plot	X	X	Terrain analysis from digital elevation model (DEM)
$P_{WETNESS}$	Topographical wetness index (= *ln* ($P_{UPSLOPE}$ / surface slope)), indicating potential water saturation in the plot	X	X	Terrain analysis from DEM
P_{LS}	The slope length (LS) factor at the plot location, indicating soil erosion potential	X	X	Terrain analysis from DEM
Household access to enabling policy				
P_{CREDIT}	Plot owner's access to credit (= 0 if no, = 1 if yes)	X	X	On-farm interview

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