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Quantifying farmers' preferences for cropping systems intensification: A choice experiment approach applied in coastal Bangladesh's risk prone farming systems

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ABSTRACT

CONTEXT: Sustainable intensification (SI) is envisioned as an effective strategy for developing countries to increase farm productivity while reducing negative environmental and social externalities. The development of regionally appropriate SI options however requires accounting for the knowledge and preferences of key stakeholders. In Bangladesh, the Government has requested international donors to support the development of dry season rice expansion in the coastal region. Policies however tend to be made without adequate study of farmers' preferences and ambitions; this can render crop intensification efforts ineffective. Understanding farmers' preferences for alternative crops and crop management practices are therefore crucial for success where agricultural development investments aim at incorporating the principles of SI.

OBJECTIVE(S): Using coastal Bangladesh as a case study– we aim to (1) quantify farmers' preferences for alternative irrigated crop and crop management options in comparison to the *status quo* (land fallowing), (2) analyze whether farmers' preferences are conditioned by concerns regarding the cost and availability of irrigation and fertilizer inputs in comparison to expected net revenues, (3) understand how the heterogeneity in preferences can be attributed to farmer and/or farm characteristics, institutional, and biophysical factors, (4) determine how much farmers' are willing to invest in different crops and crop management options – including those reliant and not reliant on irrigation.

METHODS: Taking 300 farmers in two diverse coastal environments, a choice experiment (CE) was employed to explore the heterogeneity in farmers' preferences for different dry "*rabi*" season intensification options ('*boro*' rice, maize, wheat and mungbean) against the *status quo* (dry season land fallowing after harvest of the monsoon season rice crop). Analyses included random parameter logit modeling followed by willingness-to-invest and profit simulations.

RESULTS AND CONCLUSIONS: Analyses revealed strong farmer preferences against rice and in favor of irrigated maize, and also in favor of rainfed or partially irrigated mungbean as an alternative to land fallowing. Irrespective of their location and environmental conditions, respondents had largely a negative preference for irrigation and fertilizer use due to high investment costs and associated production risks in the dry season. Nonetheless, a significant positive effect on their willingness-to-intensify cropping was observed where farmers felt it feasible to provide in-field drainage to limit waterlogging risks.

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SIGNIFICANCE: The study signifies the importance of accounting for farmers' preferences while developing context-specific SI policies. Improving agronomic investments, tenure security, market, credit and extension support are likely prerequisites, alongside targeted diffusion of stress-tolerant mungbean and maize varieties for SI in coastal Bangladesh.

1. Introduction

Although most agricultural research for development in South Asia has focused on highly productive and less risk-prone areas such as the fertile Indo-Gangetic Plains (Krishna et al., 2017), the long-term sustainability of agriculture is also crucial for the food security and livelihood of more than 400 million vulnerable people inhabiting coastal areas. In addition to institutional, economic and policy changes that affect prices for inputs and outputs that influence farmers' decision making processes, there are myriad factors that affect the economic and environmental sustainability of farms in coastal regions. Among these, multiple stressors including resource scarcity, and population pressure affect the ways in which farmers in coastal regions decide upon cropping options and management (Aravindakshan et al. 2020). Coastal areas in Bangladesh, and West Bengal and Odisha in India are also climate risk prone and grapple with challenges including soil and water salinity (Krupnik et al. 2017). Farmers in coastal areas are also relatively poorer and have significantly smaller field sizes (Krishna et al. 2017), calling for unique development approaches to mitigate risks and alleviate poverty.

In Bangladesh, agricultural productivity in coastal areas suffers from waterlogging risks, soil and water salinity, cyclones and extreme weather events, in addition to long-term sea-level rise (Akter et al. 2016; Bell et al. 2019; Mainuddin et al. 2019). Without sustained investment in protective coastal embankments, in next 60 years, almost 40% of productive land is predicted to be lost in coastal Bangladesh for an expected 0.65 m sea-level rise (World Bank 2013). Along Bangladesh's central coast, tidal movement and inundation and waterlogging of fields are severe during the "*kharif*" season (June–August), though rainfed cultivation of transplanted '*aman*' rice (*Oryza sativa*) using local and deepwater varieties is possible and indeed common during this period (Krupnik et al. 2017). Over the last half century, coastal embankments or dykes known as polders have been constructed to control oceanic water intrusion and prevent excessive waterlogging (World Bank 1990). Poor maintenance, vandalism, and competition for water resources – i.e. farmers who want freshwater for crops competing with saline fish farmers who require brackish water – have however rendered many polders and their water flow controlling sluice gates non-functional (Aravindakshan et al. 2020). Although primarily intended for the monsoon season flood control, the construction of polders and sluice gates have equally transformed the ways in which agricultural water management functions during the cool, dry winter "*rabi*" season (November to April). While farmers within polders experience water scarcity and drainage issues due to problems with control and maintenance of sluice gates, farmers located just north and outside the polders also experience tidal water inundation in the wet season, followed by dryer conditions in the winter season during which natural and constructed water canals experience siltation and may run dry. Cyclonic storms and increasing soil and water salinity pose further challenges, particularly within polders and as the winter season progresses and matures into the early monsoon season. Both within and outside polders, farmers tend to fallow their land or grow low risk, low-input 'opportunity' crops including broadcast pulses such as mungbean (*Vigna radiata*) and lathyrus (*Lathyrus sativus*) during the *rabi* season (Fig. 1). In addition, in order to reduce water table drawdown and high energy costs for irrigation in the north of the country (Qureshi et al. 2015), the Government of Bangladesh has adopted policy recommending measures to improved surface water flow and access by farmers in coastal areas. While livelihood improvement in the coastal area is important, and additional and key objective of these policy initiatives and requests for international donor funding support has been to encouraging irrigated cropping of rice – the country's most important staple – on previously fallowed or land devoted to pulses (MOA and FAO, 2013).

Agricultural systems organized around the principles of sustainable intensification (SI) aim to increase agricultural productivity while minimizing environmental and social trade-offs. SI is now widely recognized as an important pathway to food security in developing countries (Garnett et al. 2013). In food insecure areas of coastal Bangladesh, Krupnik et al. (2017) studied the potential for irrigated dry season maize and wheat in comparison to rice in areas both within and outside of polders. Where surface water (e.g. freshwater rivers and canals) are accessible through infrastructural improvements and the use of low-cost efficient pumps, they suggested that the scope to replace land fallowing with irrigated cropping by surface water was approximately 0.11 M ha in coastal Bangladesh alone. Although they studied cereals, pulses may also be an appropriate choice to replace land fallowing while generating additional income (Kumar et al. 2019), enhancing nutrition and thus contributing to improved rural livelihoods (Paudel et al. 2020). In addition, the introduction of nitrogen-fixing pulses could arguably assist in the long-term improvement of soil fertility and assist in limiting the nutrient mining impact of rice-based crop rotations (Chadha 2010). Agricultural development policies however emphasize increasing dry season '*boro*' rice production to replace fallows, despite emerging evidence that farmers may prefer pulses and maize (Aravindakshan et al. 2020). Identifying farmers' preferences among competing suites of available crop options including maize, rice, wheat and pulses as a replacement for dry season land fallowing is therefore important towards developing context-appropriate SI pathways for coastal Bangladesh.

Accounting for farmers' preferences and desires is however rarely systematically considered in policy design, though it is likely to be prerequisite for success (Dolinska 2017). Because the conversion of fallow to cropped land requires farmers to invest time, money, and inputs, understanding the ways in which farmers decide upon among baskets of alternative crop options – and what drives these decisions – is crucial for appropriate and sustainable agricultural policy and development

Fig. 1. A typical landscape scene from coastal farming systems of south-central Bangladesh during dry "*rabi*" season, where the fields remain fallow without any crops. Photo credit: Sreejith Aravindakshan.

investments. To address this crucial research gap, we studied farm households in coastal Bangladesh to understand farmers' preferences for cropping intensification options (irrigated dry season maize, wheat, or rice compared to mungbean) against the predominant counterfactual of dry "*rabi*" season land fallowing in south-central coastal region of the country.

Farmers' preference of alternate farming options can be studied by quantitative ranking procedures (Soltanmohammadi et al. 2010) or qualitative focus groups (Mekoya et al. 2008). However, they are of limited use for the identification of the relative weight of factors influencing farmers' decision processes. Nor are they well suited for identifying trade-offs (Kuehne et al. 2017). Alternatively, farmers' crop choices can also be analyzed using Likert scales or multiple-choice surveys. Both can yield somewhat biased results as multiple attributes of each option are seldom presented, leading farmers to highly rate the expected benefits of alternative crops while underestimating costs or risks (Hanley et al. 2001). 'Serious board' and role-playing games that can simulate stakeholder decisions on intensification options are also

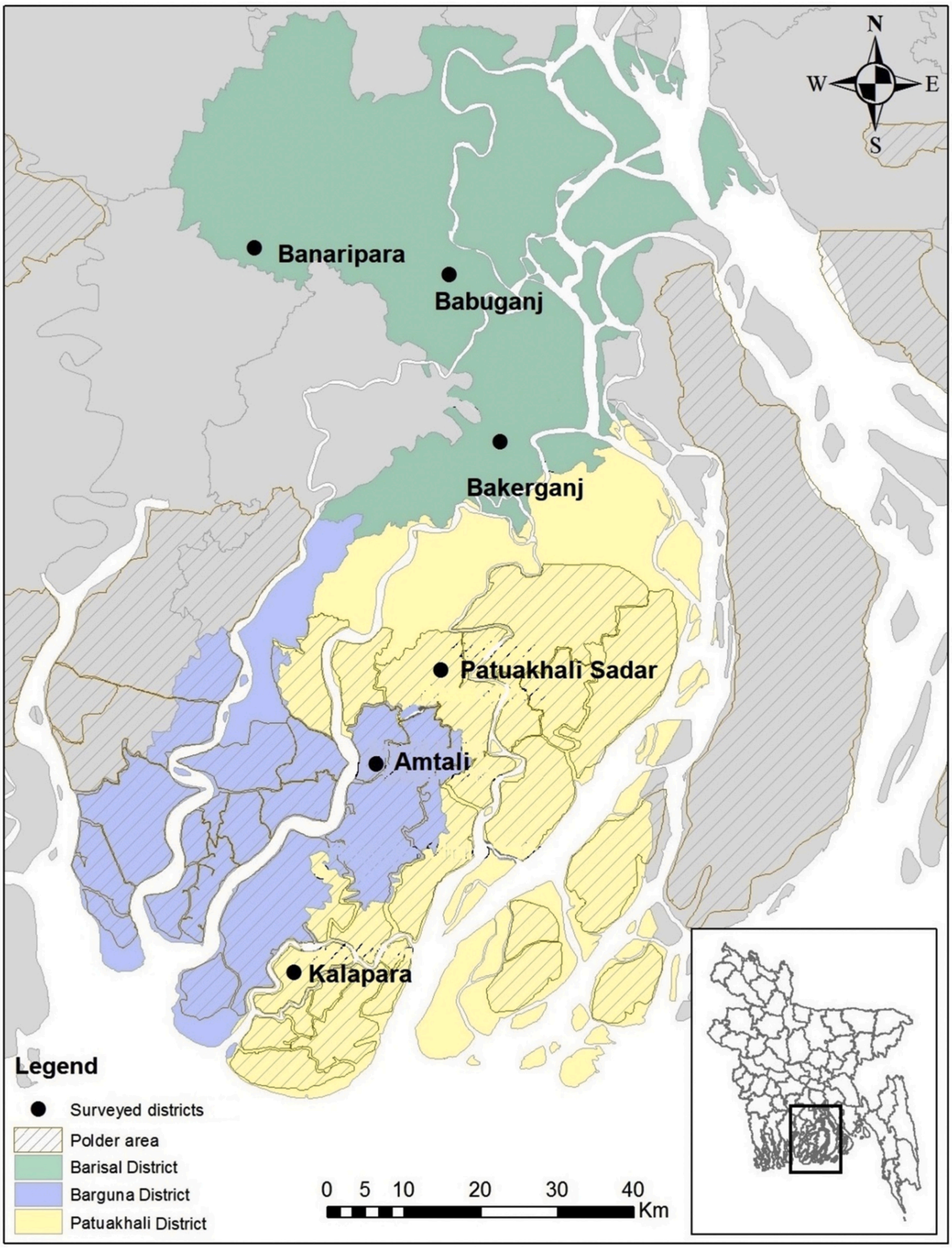

Fig. 2. Case study area showing districts within and outside polder embankments where choice experiment was carried out.

increasingly popular (Ditzler et al. 2018). Nonetheless, gaming approaches are time consuming and often suffer from low sample sizes, limiting their generalizability (Barreteau et al. 2003; Rajabu 2007).

A potentially more robust *ex-ante* alternative is choice experimentation (CE), where farmers choose between multiple crops described by both positive and negative attributes. For example, CEs can allow farmers to hypothetically compare lower yielding crop with lower resource requirements against more productive options with higher resource requirements, as well as to the *status quo*. Instead of solely choosing the most profitable choice, farmers are expected to weigh options and consider investment costs and risks alongside potential benefits, ultimately choosing attribute bundles that maximize their (perceived) *utility*. Farmers are however not homogenous, and decision making patterns are likely to vary as a function of environment, and level of risk aversion (Singh et al. 2016). As an *ex-ante* method to explore farmers' investment decisions, CEs provide information on farmers' decision-making based on their perceived *utility* and costs (see Sections 3.1 and 3.2 for more details on *utility* concept). CEs have become an increasingly important approach to study preferences and behavior regarding the potential adoption of SI practices (cf. Ortega et al. 2016; Oyinbo et al. 2019).

In the current study, a choice experiment was employed to explore the heterogeneity in farmers' preferences for different dry "*rabi*" season intensification options ('*boro*' rice, maize, wheat and mungbean) against the *status quo* (dry season land fallowing after harvest of the monsoon season rice crop).

By taking two contrasting study locations of coastal Bangladesh, i.e. agro-environments within and outside the polder systems, we aimed to (1) quantify farmers' preferences of options for fallow land replacement with alternative irrigated and non-irrigated crops during the dry season, (2) analyze whether farmers' preferences are conditioned by investment requirements on input use (with emphasis on irrigation and fertilizer) and/or expected net revenues, and (3) investigate how the heterogeneity in preferences can be attributed to farmer and/or farm characteristics, institutional, and biophysical factors. Finally, (4) this paper quantifies farmers' willingness to invest in different intensification options.

2. Case study background

Bangladesh's south central coast is largely encompassed by the Barisal administrative division, which has an area of 13,644.85 km^{-2} (Fig. 2), and a population of 8,326,000 people (MOA and FAO, 2013). It is comprised of six coastal districts, including Barisal, Barguna, and Patuakhali. Eighty-five percent of the population is rural and dependent on agriculture for their livelihood (Lázár et al. 2015). The climate is humid sub-tropical with an annual rainfall ranging from 1955 to 2100 mm (BBS 2013). Soils are medium to high textured *silty* clay loams that support the cultivation of a wide range of crops including cereals, vegetables and pulses (Aravindakshan et al. 2020). Nonetheless, as part of the Ganges-Brahmaputra floodplain delta, riparian areas can suffer from bank erosion. The area is crisscrossed with tidal canals that can be used as an irrigation source (Krupnik et al. 2017), though accretion of sediments in canals and tidal flooding can impede canal water flow in the dry season, or result in flooding of fields in the monsoon, respectively (Aravindakshan et al. 2020). The region is also vulnerable to extreme weather. For example, two mega-cyclones: *Sidr* and *Aila*—occurred in the region in 2007 and 2009, respectively, resulting in a large number of casualties, losses to agriculture, livestock and infrastructure (Aravindakshan et al. 2020).

Although the region has potential for irrigation (Krupnik et al. 2017), cropping remains largely rainfed. Farmers tend to grow rice during the monsoon "*aman*" season (June-August). A lack of well-maintained irrigation infrastructure and irrigation pumps pose challenges to farming during the cool, dry winter (November to April) "*rabi*" season. In south-central coastal zones alone, approximately 1.7 million farming households fallow their land after the monsoon, contributing to food insecurity and subsistence below the poverty line (Krupnik et al. 2017).

The Government of Bangladesh has requested international donors $7 billion for the development of coastal region, out of which $500 million is intended to encourage double cropping, with emphasis on the development of canal water resources for irrigation in south-central Bangladesh (MOA and FAO, 2013). The impetus for such policy is justified as a means to alleviate pressure on groundwater irrigation in the dry season in intensive dry season rice producing areas in the north that has resulted in declining groundwater tables, high pumping costs, and high energy subsidies *in lieu* to sustain productivity (Qureshi et al. 2015). This approach is perhaps narrowly focused on dry season '*boro*' rice production, with far less attention to other cereals (e.g. maize and wheat) and legumes (e.g. mungbean) that may be of interest to farmers. Crop intensification and diversification could help spread production risk; alternatives to energy intensive irrigated *boro* rice cultivation may also be desirable from the standpoint of crop profitability and adaptation to climate change (USDA, 2016).

This coastal region is also vulnerable to sea level rise and seasonal soil and water salinity (Krupnik et al. 2017). A series of hydrological embankments known as polders, consisting of dykes and sluice gate controls were constructed by the Bangladeshi government in 1960s. One hundred twenty three polder structures are there now covering an area of about 13 million ha. These areas include 6000 km of intra-polder channels, 2500 water control structures, and 5000 km of embankments (World Bank 1990). These systems have however deteriorated over time. Damage from cyclones and poor maintenance of dykes and water flow structures have rendered polders dysfunctional and agriculture less productive.

These circumstances have resulted in the evolution of farming systems that are distinct within and outside polders (Aravindakshan et al. 2020). Such diversity is likely to condition farmers' decision making process, thereby affecting their willingness to invest in intensified or double cropping through use of irrigation. We therefore account for the differences polder and non-polder areas of coastal zones of south central Bangladesh, by considering them as distinct socio-ecological systems in our analysis.

Our study area comprises of districts within and outside the polders (Fig. 2). Crop production follows two main seasons: the monsoon '*kharif*' (mid-March to mid-November) and *rabi* (mid-November to mid-March) seasons. *Kharif* season sowing coincides with the onset of monsoon. The season is further divided into *kharif-1* (mid-March to mid-July) during which '*aus*' rice is grown, and *kharif-2* (mid-July to mid-November) when '*aman*' rice is grown. Farmers commonly grow *aman* rice using monsoon precipitation and tidal flooding, creating an adequate conditions for paddy production. In the dry '*rabi*' season, rains are scanty, although the availability of surface water in rivers and canals creates opportunities for crop production as an alternative to the common practice of land fallowing (Krupnik et al. 2017). Expanded use of irrigation is however complicated by social conditions that result in differential access to water, tidal flows that create periods of excess or water scarcity, and late *rabi* season water and soil salinity close to the coast.

3. Materials and methods

3.1. Methodological overview of choice experiment

Choice experiment (CE) is a socio-behavioral tool to assess people's preferences or decisions in hypothetical scenarios (i.e.in the absence of observed data), for instance, before a new product is launched, a new technology becomes available, or a new policy is implemented (Colen et al. 2016). This ability of CE to provide preference information about alternative options even before their dissemination and use is crucial in agricultural development for sustainable intensification goals; not only to identify the best among the alternatives, but also to avoid expensive and ineffective solutions. We draw conceptually from utility-maximizing behavior based on the theory of Lancaster (1966), which postulates that decision makers (e.g., farmers) are not interested in goods (e.g. crops or technology) per-se, but in the role of attributes or characteristics shared by more than one good that give them utility. While making decisions on agronomic management or in crop selection, farmers weigh among various attributes of available options and choose the option with the highest relative utility (McFadden, 1974). Preference heterogeneity among individuals can hence be understood by estimating attribute utilities. The overview of CE is provided in Fig. 3.

3.1.1. Selection of attributes and levels based on farmer participatory field experiment

Discussions with agricultural experts from local NGOs and Bangladeshi research institutes were carried out prior to the choice experiment to identify the key attributes $X_1, X_2, \ldots, X_N$, that farmers may consider when choosing a crop for the *rabi* season. A list of three attributes consisting of fertilizer investment, irrigation investment and net revenues emerged as crucial for decisions to intensify cropping. Therefore, these three attributes were included in the choice experiment. Levels of these attributes however have to be representative of the actual farming systems of the study area. Farmers in south central Bangladesh have little prior knowledge on managing crops other than rice. To familiarize farmers with the proposed options and mitigate possible bias resulting from hypothetical attribute levels and values in CE design, we carried out farmer participatory agronomic trials (irrigated mungbean, wheat and maize) by involving farmers in the input management and harvest operations in locations within and outside the polder. An example of field experimental layout is provided in the Supplementary Material (Figure SM1). The details of these trials are provided in Schulthess et al. (2019). Yields and economic data from these field experiments provided region-specific input data to design a realistic CE. For *boro* or winter rice crop, irrigation and fertilizer values were derived from existing farmers in the study villages. The following scenarios were explored for which the yield and economic benefits are compared for (1) *boro* rice, (2) maize, and (3) wheat and (4) mungbean. The attributes and their levels are reported in Table 1.

3.1.2. Choice experiment design

In the second stage, choice sets are constructed through experimental design procedures by all possible combinations of bundling attributes and their levels. A fully factorial design including the selected crops potentially suitable as a second *rabi* season crop after *aman* rice (i.e. *boro* rice, maize, wheat and mungbean) alongside all possible combinations of attributes and levels presented in Table 1 would generate a large number of choice scenarios and several arbitrary designs. D-efficient designs are used in choice experiments to identify the optimum combination of choice sets while still being able to estimate the main effects without losing any information (Scarpa et al. 2008). Therefore, the goodness-of-fit of our experimental design was measured relative to a hypothetical orthogonal (Benchmark) design to yield the D-efficiency.[1] As it is impossible to accommodate all the possible combinations, subsets with necessary variation over the attribute levels among alternative cropping options are to be provided to respondent farmers. D-efficient design generated subsets of the possible combinations that best identify attribute preferences. A perfect D-efficient design will have a value of 100% when it is balanced and orthogonal.

Our experimental design consisted of an optimal fully fractional design assuming zero priors consisting of a single block and 6 choice (sub) sets of D-efficiency 87% was selected using *Ngene software version* 1.1.1. Each set offered respondents a choice of 5 alternative scenarios including fallow as a *status quo* option. Fallow was included as a *status quo* choice since approximately 50% of farmers in the coastal zones of south-central Bangladesh were fallowing their land during the study period in the *rabi* season. Inclusion of fallow as the *status quo* alternative also avoids a forced choice by giving the possibility to choose none of the crop alternatives in the choice set, making the design consistent with theory of demand. The selected crops, fallow situation, attributes and their levels were represented using context-specific pictorial illustrations in separate choice cards (Fig. 4). These illustrations were pre-tested and corrected to mitigate any possible cognitive difficulties among sampled farmers prior to the CE survey (See Figs. SM2 and SM3 in the supplementary material for the complete set of choice cards used in the study).

3.1.3. Sample selection and choice experiment implementation

A farm household level choice experiment survey was conducted in six sub-districts of Barisal division in south-central Bangladesh, namely Babuganj, Bakerganj and Banaripara (outside polder area) and Patuakhali sadar, Amtali and Kalapara (within the polder area), during March–April 2017 (Refer Table 2 for sample characteristics). The CE sample in our study consists of 300 farmers, 150 farmers from within and 150 from outside the polder embankment. These 300 CE respondents were randomly selected from a larger sample of 502 HHs previously surveyed in the year 2015, for a related study that characterized farm HHs into different farm types (Aravindakshan et al. 2020).

3.2. Empirical application of the choice experiment

McFadden (1974) devised the econometric basis for Lancaster's theory of choice under the random utility framework. The random utility framework forms the basis of CEs in this study, which assumes that farmers derive 'utility' from crop selection for their fields. The utility of choosing alternative crops is a latent variable that can be decomposed into the observable (non-random) deterministic and unobservable (random) components. The deterministic component of utility is usually measured as a function of several predictor variables or through their interactions. Using the utility-maximization framework, we modelled crop choice data of sampled farmers from non-polder and polder areas separately. In the first step, we modelled the effect of attributes and their levels on farmers' preference for different crops as alternatives to land fallowing. In the second step, we estimated farmers' willingness to invest in crop intensification options in terms of input use (fertilizer and irrigation). In the third step, interactions between farmer-specific and external factors and crop choices of farmers within and outside polder areas were analyzed. The external factors included market and infrastructure, institutions and biophysical factors.

Step 1: Modeling crop choices for fallow intensification and attributes.

Farmers' preferences for and the effects of attribute levels on discrete crop choices are analyzed using mixed/random parameter logit model (RPL) (McFadden 1974). Following the random utility theory, the basic multinomial logit (MNL) model takes the form:

$$U_{ij} = V_{ij} + \varepsilon_{ij} \tag{1}$$

where "U_{ij}" is the utility derived by the farmer "i"from the alternative choice "j". The deterministic part of Eq. (1) "V_{ij}"is defined as a function of the attributes (X_j) of the various alternatives and (2) the farmer specific characteristics(Z_i). A random element"ε_{ij}", represents the "error term". The deterministic part of the utility function that farmer "i" derives from choice "j" (*boro* rice or maize or wheat or mungbean or fallow (*status quo*)) is re-written as follows:

[1] D-efficiency is a function of the geometric mean of the eigenvalues between a CE design in question and a reference (benchmark) CE design. D-efficiency is given by $|(X'X)^{-1}|^{1/p}$, where $X'X$ is the Fisher information matrix of the parameters of an experimental design. The determinant $|(X'X)^{-1}|$ is the product of the eigenvalues of $(X'X)^{-1}$. The p^{th} root of this determinant gives the D-efficiency value.

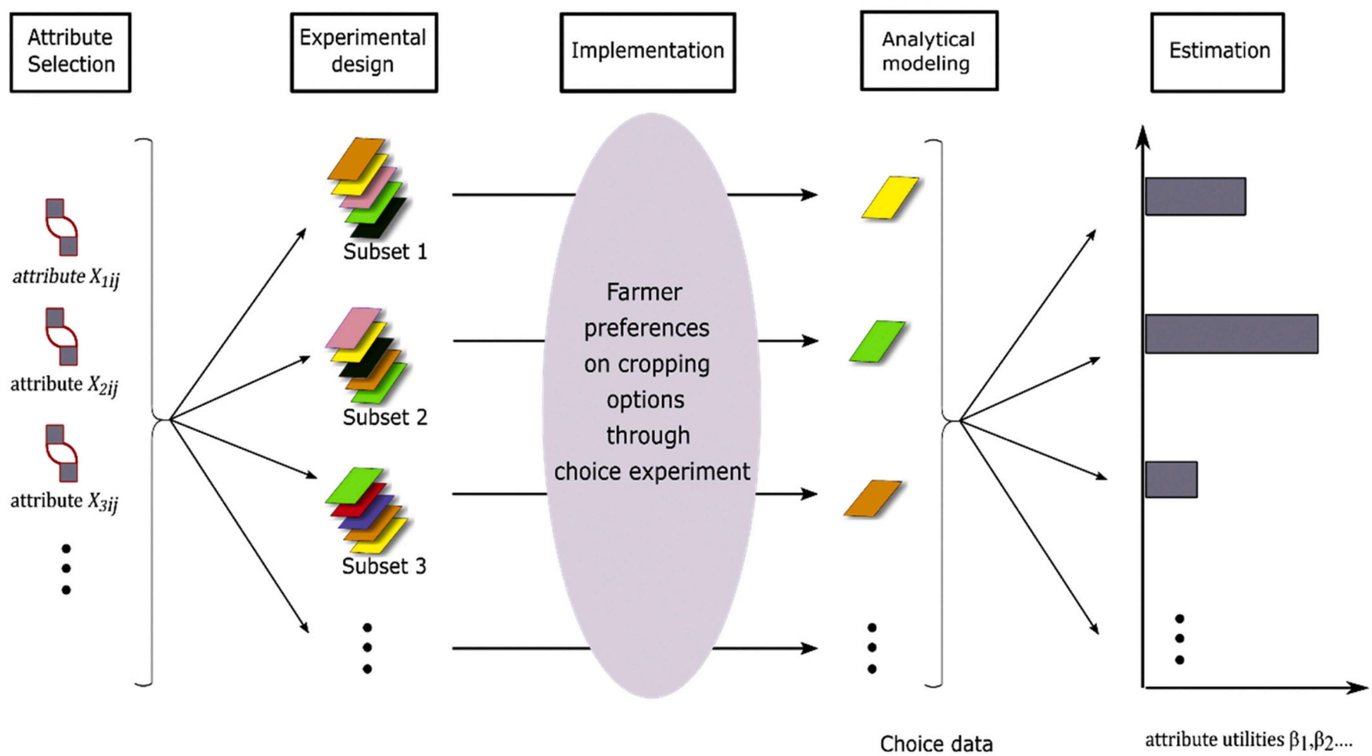

Fig. 3. Conceptual overview of choice experiment depicting the five stages from attribute selection to modeling and estimation. Modified from Mizuyama (2013).

Table 1
Attributes and levels in the CE design for all crops.

Attributes	Description	Level
Fertilizer investment	Investment incurred for the buying and application of nitrogen, phosphorus and potash (NPK) fertilizers (in Bangladeshi Taka)	Low-level High-level
Irrigation investment	Investment incurred for the buying irrigation service provision (in Bangladeshi Taka)	Low-level High-level
Net returns	Net returns obtained from growing a crop (in Bangladeshi Taka)	Low returns Medium returns High returns

Note: - Levels of attributes are crop specific such that the "level of a particular attribute" varies with both the amount and frequency of application. For instance, low level of irrigation investment for *boro* rice and maize will not be the same because rice requires more irrigation than maize. Same goes for the levels of the other two attributes: Fertilizer investment and Net returns.

$$V_{ij} = C_j\left(\alpha + \sum_k \gamma_k Z_{ik}\right) + (1 - C_j) + \left(\sum_q \beta_q X_{jq}\right) \tag{2}$$

where "C_j" is the binary variable which takes the value 1 when a farmer "i" choose any of the cropping options (*boro* rice ($j = 1$) or maize ($j = 2$) or wheat ($j = 3$) or mungbean ($j = 4$) and takes the value 0 when fallow (*status quo*) ($j = 5$) is selected."α" is the alternative-specific constant (ASC) when fallow is opted that captures changes of utility from any other crop specific feature not included among choice attributes. The "Z_{ik}" are the farmer "k" characteristics, while "X_{jq}" specifies the "q" attributes relative to crop choice scenario. "γ" and "β" are the coefficients to be estimated with respect to the model's intercept and attributes respectively. Given the probability "P" that a farmer "i" choose alternative "j" from a set of choices, Eq. (2) can be estimated using the maximum likelihood procedure (Train 2003).

Due to advantages in terms of flexible model structure, the MNL is the most frequently used model to estimate Eq. (1). The MNL model nonetheless derives a linear relationship between farmers' utility and attribute parameters alongside the estimation of an identically and independently distributed (IID) error term"ε_{ij}" (Train 2003). In addition, we hypothesized heterogenous preferences for farmer within the study areas and between the study areas, which may not hold true for MNL models. The RPL model, which is an improvement up on the basic MNL model addresses the potential IID assumption violation while accounting for preference heterogeneity across farmers. The standard MNL model (Eq. 1) assumes a fixed "β" vector, while the RPL model considers "β" vector as a mixture of random coefficients ("ξ") and non-random constants ("φ"). The RPL model becomes:

$$U_{ij} = V_{ij}(\beta) + \varepsilon_{ij} \tag{3}$$

$$\text{rewritten as}: \varphi^T W_{ij} + \xi^T X_{ij} + \varepsilon_{ij} \tag{4}$$

where "X_{ij}" is a set of explanatory variables with random parameters and "W_{ij}" represents the explanatory variables with fixed non-random parameters. By including the random coefficients, different crop choice outcomes become correlated even though their error terms,"ε_{ij}", are still assumed to be independent and identically distributed.

Step 2: Willingness to invest on fallow intensification by farmers

Another essential measure revealed through the estimated preference structure is the farmers' willingness to invest in irrigation and fertilizer. The willingness-to-invest (WTI) for each attribute is commonly computed as the willingness-to-pay (WTP) estimate, which is the ratio between the coefficient for each attribute and the price coefficient (Train and Weeks 2005). The marginal WTP for attribute "x"is:

$$\widehat{wtp}_x = -\frac{\widehat{\beta}_x}{\widehat{\beta}_p} \tag{5}$$

The standard approach in Eq.5, which is also referred to as a WTP in *preference space*, is obtained from procedures based on RPL models (Train and Weeks 2005). The WTP *space* approach re-parameterizes the model such that the parameters are the marginal WTP for each attribute rather than the marginal utility. Train and Weeks (2005) extended the

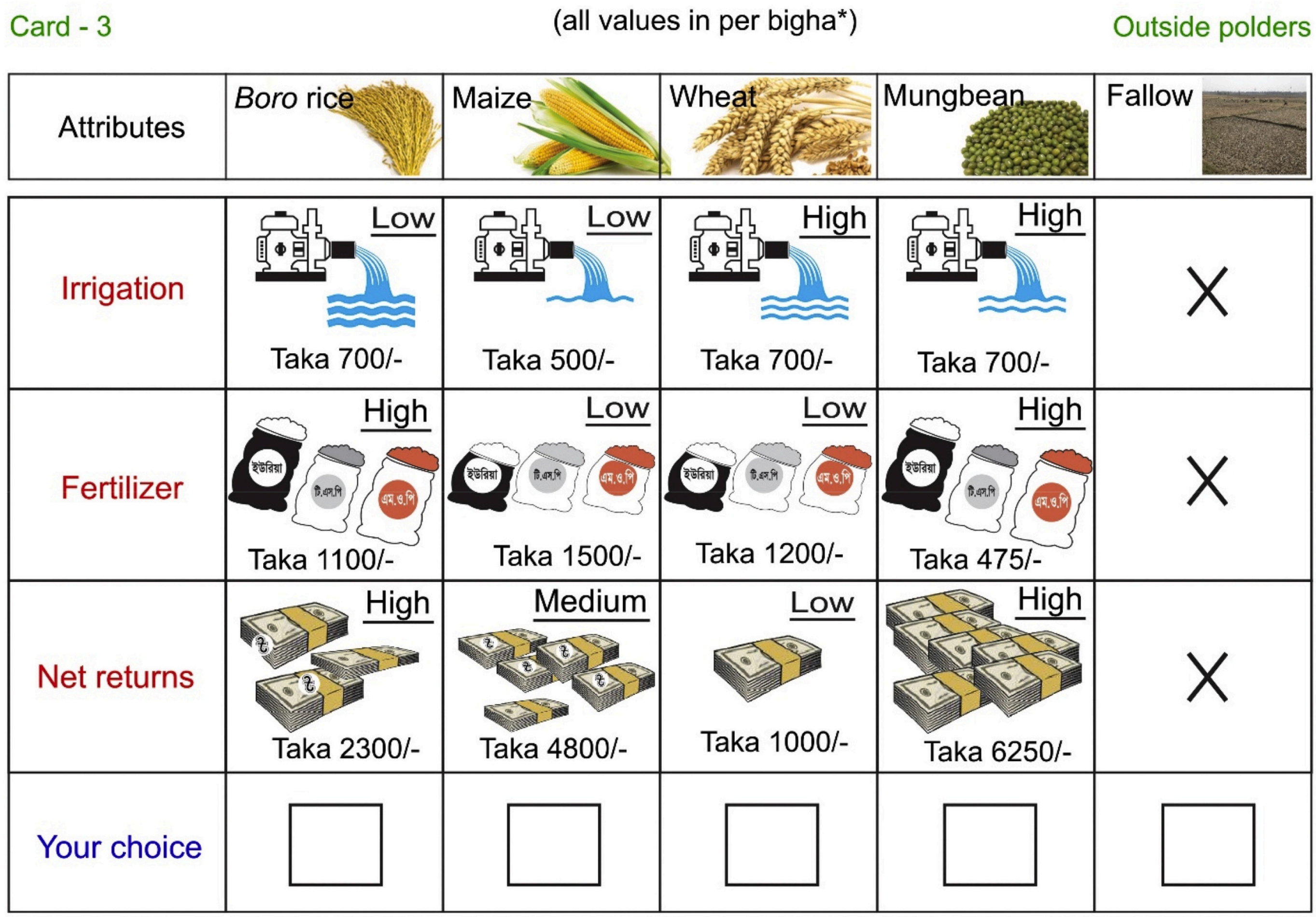

Fig. 4. A sample choice card showing attributes and their levels corresponding to each crop option presented to the respondent farmers, where all values are in *bigha* (*1 *bigha* = 0.13 ha). The status quo (reference land use) option "fallow" has no attributes. Levels of attributes are crop specific such that the "level of a particular attribute" varies with both the amount and frequency of application. For instance, low level of irrigation investment for *boro* rice and maize will not be the same because rice requires more irrigation than maize. Same goes for the levels of the other two attributes: Fertilizer investment and Net returns.

WTP *space* approach by allowing random parameters in a RPL model. This WTP *space* approach is appealing because it allows estimation of WTP heterogeneity distribution directly (Scarpa et al. 2008). Previous studies have shown that the WTP *space* models provide more reasonable WTP values with distributions that have lower densities associated with extreme values (Train and Weeks 2005). In this study, the maximum simulated likelihood estimation of an RPL model in the R package "*gmnl*" (Sarrias and Daziano 2017) is applied to obtain the WTP *space* values.

Step 3: Crop choice and interaction of socio-economic, institutional, market or biophysical conditions

The stated RPL model nonetheless cannot explain preference heterogeneity from external variables of socio-economic, institutional, market or biophysical conditions in which the farmers operate (Boxall and Adamowicz 2002; Speelman et al. 2015). For detailed description of these independent variables and expansion of abbreviations, see Table 2. These sources of heterogeneity were captured by allowing interactions of these variables with choice specific attributes and/or ASC in the utility function. In order to avert potential multicollinearity issues, only one external variable was allowed to interact with the three crop attributes when modeling. As such, several models were run by employing RPL and the interaction coefficients are presented in an abridged table, for respondents within and outside polder areas.

Step 4: Simulation of crop production risk based on farmer preferences

In coastal farming systems, farmers encounter many production risks due to unpredictable weather, cyclonic events or pests and diseases; where the set of outcomes such as yield or returns are stochastic rather than discrete. The spread of production risk can be mathematically represented using a cumulative distribution function (CDF) and can be viewed visually. We simulated the net returns from actual crop choice data separately for *boro* rice, maize, wheat and mungbean obtained from the choice experiment and analyzed using CDF.

4. Results and discussion

4.1. Respondents' characteristics

Although the age of farmers differed significantly between polder and non-polder areas, there was no significant difference in educational level between farmers of the two areas (Table 2). The landholdings were on average slightly larger within the polder areas (0.74 ha) compared to those outside the polder areas (0.53 ha). The two groups also differed significantly in share of fallow land. While the respondents within the polder areas had 30% share for fallow land, those outside the polder had 23%. Other socio-economic variables such as household size, household income, off-farm income, risk attitude and involvement in farming were significantly different comparing respondents from these two areas. Among the market variables, though the distance to the input-output markets was not significantly different for the two groups, crop prices received in the preceding year varied significantly within vs. outside polders. Other infrastructure variables such as distance to and quality of

Table 2
Sample characteristics and summary statistics.

Variables	Unit/Description	Outside polders (*n* = *150*)		Within polders (*n* = *150*)		*p*-value[a]
		Mean	SD	Mean	SD	
Landholding (LH)	Agricultural land owned by the farm household (ha)	0.53	0.60	0.74	0.52	<0.001
Share of fallow land in *rabi* season	Share of land fallowed to total cultivable land, during dry *rabi* season (%)	23.09	30.48	13.08	29.23	0.81
Education of the farmer (EDN)	Formal education attained (years)	6.41	4.19	6.39	3.42	0.47
Age of the farmer (AGE)	Age of the respondent farmer(years)	49.49	12.58	45.41	14.13	0.01
Household size (HHS)	Number of household members living and eating from the household (numbers)	6.11	2.48	5.20	1.69	<0.001
Respondents' risk attitude (RAS)	A composite risk attitude score developed based on Starkweather 2012. See supplementary material (Questions SM2)	2.15	0.48	3.18	0.52	<0.001
Annual household income (AI)	Annual household income from farm and non-farm activities (US$)	896.29	844.17	1072.11	799.57	<0.001
Share of off-farm income (SOI)	Share of Off-farm income (%)	37.15	32.30	28.86	26.60	0.03
Farmers' involvement in farming (IF)	Categorical (3 = full, 2 = partial and 1 = no)	2.61	0.50	1.47	0.73	<0.001
Distance to farm input-output markets (DM)	Distance is measured in kms	1.69	0.83	2.22	1.67	0.09
Distance to the main road from the main field (DR)	Distance is measured in kms	0.46	0.85	0.95	1.24	<0.001
Distance to the irrigation sources (DIS)	Distance is measured in kms	0.17	0.25	0.49	0.47	<0.001
Quality of the main road near farm (QR)	Categorical (3 = good, 2 = fair and 1 = poor)	1.87	0.83	1.95	0.84	0.41
Last year crop prices (CP)	Cropping decisions are based on last year crop prices; (0 = no, 1 = yes).	0.57	0.50	0.80	0.40	<0.001
Access to agricultural credit (AC)	Dummy (0 = no, 1 = yes).	0.55	0.50	0.27	0.44	<0.001
Access to agricultural extension (AE)	Dummy (0 = no, 1 = yes).	0.51	0.50	0.71	0.46	<0.001
Access to Irrigation water management institutions (AWI)	Dummy (0 = no, 1 = yes).	0.80	0.40	0.59	0.49	<0.001
Provision of field drainage (PFD)	Dummy (0 = no, 1 = yes).	0.57	0.50	0.60	0.49	0.56
Tenure rights (TR)	Categorical (3 = full, 2 = partial and 1 = no)	2.27	0.90	2.69	0.59	<0.001
Cyclonic severity (CS)	Categorical (3 = severe impact; 2 = moderate impact; 1 = no impact)	1.58	1.15	2.07	0.95	<0.001
Inundation class (IC)	Categorical (3 = high, 2 = medium and 1 = low)	2.13	0.51	1.73	0.63	<0.001
Optimum field conditions for sowing (OFC)	Dummy (0 = no, 1 = yes).	2.68	0.48	2.86	0.35	<0.001
Overall soil fertility of the farm (SF)	Categorical (3 = high, 2 = medium and 1 = low)	2.08	0.74	2.18	0.79	0.22
Overall soil salinity of the farm (SS)	Categorical (3 = high, 2 = medium and 1 = low)	*na*	*na*	2.37	0.61	*na*

1 US$ = 80.9 BDT as per the exchange rates during survey (April 2017). '*na*' = not applicable.
[a] Mann-Whitney *U test* between farmers outside and within polder embanked areas respectively.

the main roads, and distance to the irrigation source were significantly different.

4.2. Respondents' preference for cropping intensification in coastal farming systems

The majority (62%) of the respondents outside the polder areas selected mungbean as their primary choice followed by maize (22%), *boro* rice (8%), land fallowing (4%), and wheat (4%). Despite the aforementioned differences between respondents in both study environments, it is quite surprising to note that the preferences of samples within the polder area were not remarkably different from their counterparts. Around 66% of this group preferred to grow mungbean, while 22% selected maize, followed by wheat (5%), and *boro* rice (4%). Preference for the crops irrespectively of the profile (ASC) was only 3%, i.e. only 3% of the respondent farmers outside polders opted fallow. The data obtained from the Agriculture Statistical Yearbook (BBS, 2010-2019) and the Department of Agricultural Extension (DAE), Bangladesh for the period 2016–2020 justified our results on farmers' preference towards mungbean (See Fig. SM4 for growth in area and production). During this period, there has been a substantial increase in both the area (55%) and production (81%) of mungbean in the Barisal division. Our CE survey coincided with the harvesting of *rabi* crops including wheat sown in October-November 2016. During this period, wheat blast incidence that severely affected wheat grain yields was reported for the first time in Bangladesh (Mottaleb et al. 2018). The influence of wheat blast on crop choice however was not explicitly included in our CE design because wheat blast was not an issue during the CE design phase. Regardless of this, that the relative low preference for wheat within the sample could be due to widespread reporting of crop losses from wheat blast incidence from several parts of the country, including our study area. The results of the CE are relative to the reference land management system (Jaeck and Lifran 2014). Farmers' preference for a particular crop (i.e. mungbean or maize against *boro* rice or wheat) is relative to the status quo: fallow system.

We first tested different specifications viz. RPL versus MNL. Table 3 shows that the RPL models had low AIC, high log likelihood and high *McFadden* R^2 values compared to the MNL models suggesting a better fit. There is also significant difference between standard deviation estimates between the RPL models for samples within and outside polders, which are shown in the lower part of Table 3. The significance of these estimates confirms the existence of heterogeneity in farmers' preferences for the different intensification attributes in the two study environments. Given the observed differences between within and outside polder samples (Table 3), we also tested whether pooling of the two groups in one model permits generalization of our findings for the whole of the study area. For this, we estimated separate models for the two subsamples, which are shown in the second and third columns of Table 3.

The RPL model estimates the *fixed* non-random parameters and random parameters. The estimates of non-random parameters are constants similar to model intercepts for each cropping option while the random parameter estimates are of interest since they provide the attribute utilities corresponding to farmer preferences. In general for all crops, respondents within polders tended to have significant negative preference for irrigation investment attribute both in the MNL ($P \leq 0.001$) and RPL ($P \leq 0.05$) estimates. Although also negative, the preference for irrigation was not significant for respondents outside polders. However, when the respondents both within and outside polders were pooled, this negative preference was significant ($P \leq 0.05$) in the RPL model but not in the MNL model. For the pooled sample, coefficients of all the three attributes are statistically significant in the RPL. Both the investments for irrigation and fertilizer were negatively and significantly related to crop choice, while net returns would increase preference for cropping system intensification. The salinity reducing effect of

Table 3
Influence of attributes and their levels on crop choice of farmer respondents in coastal Bangladesh.

Choice/parameters	Random parameter/mixed logit models (RPL)			Standard multinomial logit models (MNL)		
	Outside polders (n = 150)	Within polders (n = 150)	Pooled sample (n = 300)	Outside polders (n = 150)	Within polders (n = 150)	Pooled sample (n = 300)
Non-random parameters (constants) in utility functions				Model intercepts		
Rice (*boro*)	1.258*** (0.380)	1.498*** (0.399)	0.545* (0.230)	−0.229 (0.295)	0.126 (0.334)	0.043 (0.214)
Maize	0.529 (0.479)	1.936*** (0.457)	0.680* (0.274)	−0.763* (0.377)	0.606 (0.365)	0.094 (0.252)
Wheat	0.644 (0.378)	1.541*** (0.354)	0.250 (0.213)	−0.844** (0.290)	0.257 (0.287)	−0.243 (0.199)
Mungbean	1.015** (0.376)	1.705*** (0.383)	1.356*** (0.212)	0.265 (0.264)	1.070*** (0.289)	0.853*** (0.186)
Random parameters in utility functions				Attribute estimates		
Irrigation cost (US\$ ha^{-1})	−0.005 (0.003)	−0.011*** (0.003)	−0.004* (0.002)	0.000 (0.002)	−0.005* (0.002)	−0.002 (0.002)
Fertilizer cost (US\$ ha^{-1})	−0.006*** (0.002)	−0.008*** (0.002)	−0.003*** (0.001)	−0.001 (0.001)	−0.003*** (0.001)	−0.002** (0.001)
Net returns (US\$ ha^{-1})	0.007*** (0.001)	0.009*** (0.001)	0.005*** (0.001)	0.005*** (0.000)	0.006*** (0.001)	0.005*** (0.000)
Distribution of random parameters as limits of triangular				*na*	*na*	*na*
SD of Irrigation cost	0.010** (0.003)	0.010** (0.003)	0.007* (0.002)	*na*	*na*	*na*
SD of Fertilizer cost	0.009*** (0.001)	0.007*** (0.001)	0.002*** (0.001)	*na*	*na*	*na*
SD of Net returns	0.004*** (0.001)	0.005*** (0.001)	−0.003*** (0.001)	*na*	*na*	*na*
Log-Likelihood:	−823.64	−767.76	−1688.70	−896.3	−832.58	−1750.00
McFadden R^2:	0.46	0.37	0.40	0.09	0.07	0.07
LR test: *chi*^{2}	320.66***	247.71***	390.71***	175.34***	118.07***	268.24***
AIC	1667.28	1555.53	3397.42	1806.59	1679.17	3514.087
BIC	1715.30	1603.55	3452.37	1840.21	1712.78	

Notes: - Data source; CE survey (2017),*, **, and *** indicate significance at the 10%, 5%, and 1% levels. Values in parentheses indicate the standard error. SD indicates standard deviation. Optimization by *bfgs* method. *"na"* = not applicable for MNL. 1 US\$ = 80.9 BDT as per the exchange rates during survey (April 2017).

irrigation is particularly relevant for locations such as Patuakhali and Barguna in southern Bangladesh. But rain is not very reliable in quantity and distribution during *rabi*, and the risk of cyclones is high. In these circumstances, farmers are unwilling to invest in irrigation, fertilizer and other agricultural inputs because of the risk of crop failure, rather they would go for low input high opportunity crops such as mungbean. Irrigation generally improves fertilizer use efficiency of crops. In addition, irrigation can also save crops from drought and associated yield loss, but farmers may not be willing to invest for irrigation in risky environments (Gebregziabher et al., 2009). Particularly, investments in irrigation and fertilizers of farmers in southern Bangladesh are lower than that under recommended crop management practices (Schulthess et al. 2019).

4.3. Willingness to invest in double cropping and alternatives to dry season fallows

Even though the respondents had negative preference for irrigation and fertilizer while making crop choices, when it comes to increasing net returns, both farmers within and outside polders had positive willingness to invest in inputs in the case of *boro* rice, maize and mungbean, but not for wheat (Table 4). Outside polders, the willingness to invest to potentially increase net returns was higher than within polders. Risk taking ability of farmers varies with the biophysical and socioeconomic environment they operate (Ullah et al. 2016). Compared to farms outside polders, the threat of tidal floods coupled with drainage congestion and soil and water salinity is more inside the polders. Within polders the WTI for *boro* rice is almost half of that within polders, which may be attributed to environmental riskiness within polders. In polders, salinity alone reduces rice yield by 16% (Dasgupta et al. 2018). In addition, transportation facilities and road network are very limited within polders, which weakens the movement of labor and agricultural inputs, and in turn increases input costs. So, farmers within the polder would be relatively risk averse compared to those outside the polders. Vulnerability to salinity and high input costs disincentivizes polder farmers from producing labor and input exhaustive crops such as rice.

Our WTI results indicate that farmers within and outside polders may be more willing to invest in inputs (irrigation and fertilizer) for mungbean followed by maize and *boro* rice in that order. Farmers' preference for mungbean in the studied districts is apparent from the area expansion of mungbean in the recent period. During the period from 2016 to 2020, mungbean area doubled from 0.14 Mha to 0.22 Mha with an average annual growth rate of 12% in the study area (authors' calculation based on BBS, 2010-2019 and DAE data). Although not significant, a negative value of WTI is estimated for wheat both within and outside polders meaning that it is less preferred by farmers over the *status quo* (fallowing). It also indicates wheat as a secondary crop grown in the dry season that is likely to be feasible only with external intervention, e.g., through governmental subsidy programs. Despite wheat's potential suitability from an agronomic standpoint for the region (Krupnik et al. 2015), even after pooling the data, the sign and significance of WTI estimate for wheat remains unchanged implying that the

Table 4
Respondent farmers' willingness to invest in fallow intensification.

Crops	Outside polder (n = 150)		Within polder (n = 150)		Pooled sample (n = 300)	
	WTI estimates for 1 US\$ return from the selected crop	Monetary equivalent of WTI in BDT for 1 US\$ (80.9 BDT) return	WTI estimates for 1 US\$ return from the selected crop	Monetary equivalent of WTI in BDT for 1 US\$ (80.9 BDT) return	WTI estimates for 1 US\$ return from the selected crop	Monetary equivalent of WTI in BDT for 1 US\$ (80.9 BDT) return
Rice (boro)	0.563*** (0.200)	45.53	0.335* (0.164)	27.13	0.181 (0.802)	14.61
Maize	0.632*** (0.238)	51.13	0.417*** (0.146)	33.74	0.367* (0.180)	29.65
Wheat	−0.469 (0.351)	−37.96	−0.461 (0.301)	−37.31	−0.467 (0.343)	−37.82
Mungbean	0.665*** (0.109)	53.79	0.573*** (0.166)	46.35	0.582*** (0.194)	47.06

Notes:-*, **, and *** indicate significance at the 10%, 5%, and 1% levels. Values in parentheses indicate the standard error. Simulation based on 10,000 halton draws. 1 US\$ = 80.9 BDT as per the exchange rates during survey (April 2017).

farmers in general appear not to be willing to invest in wheat. Therefore farmers need to have a reduction in input costs to compensate a shift from fallowing their fields to wheat cropping. These results should however be considered cautiously given that CEs were conducted the year following wheat blast outbreak and as such, this could affect farmers; lack of enthusiasm for wheat. Since 2016, Bangladesh has however only seen limited incidence of blast. Farmers' preference for a particular crop also depends on the quantity of labor and the potential for mechanization, as using mechanized systems requires less labor but needs access and availability of agricultural equipment services (e.g. hiring operators for land preparation). Agricultural mechanization is not well-developed in the study area but the possibility of mechanization for different crops and its influence on farmer preference should be explored in the future.

4.4. Influence of socioeconomic factors on crop choice attributes

We accounted for observed heterogeneity of crop preferences across farm households by the estimation of several models where socio-economic characteristics interacted with crop attributes (Part A of Table 5). Our results suggest that young farmers (<35 years) living outside polders had significant and positive interaction ($P \leq 0.05$) towards investing in fertilizer inputs as well as receiving a higher net return. Age however had no significant interaction for their counterparts within polders (Table 5). Both within and outside polders, risk averseness of respondents were associated with a significant and negative preference for fertilizer inputs ($P \leq 0.001$) and net returns ($P \leq 0.05$). Risk neutral behavior of respondents in both the areas however had positive and significant preference for net returns ($P \leq 0.001$). Our results appear to complement the neoclassical model of decision-making, where an unconstrained, risk-neutral farmer who maximizes profits would choose to grow only the crop with highest profit potential per unit of land (Smale et al. 2001). While within polders risk neutrality had significant and positive interaction with fertilizer investment ($P \leq 0.001$), the interaction of risk-neutral behavior with fertilizer investment was not significant for respondents outside polders though the sign was positive. In the polders, risk seeking behavior interacted with fertilizer investment to have a positive and significant effect ($P \leq 0.01$). Although the interaction of fertilizer investment with risk seeking behavior within polders was insignificant, risk seeking had a positive and significant interaction with both irrigation investment and net returns ($P \leq 0.01$). An increase in household income in general had interacted positively with irrigation and fertilizer investments for respondents both within and outside polders, though these effects were

Table 5
Interactions showing the effects of select variables on crop intensification attributes (Random parameter logit).

Socioeconomic characteristics	Outside polders	Within polders	Institutions, infrastructure, markets and biophysical factors	Outside polders	Within polders
Irrigation investment × Low education (<10 years)	0.002	0.001	Irrigation investment × Credit	**0.012****	0.001
Fertilizer investment × Low education (<10 years)	−0.001	−0.001	Fertilizer investment × Credit	**0.012*****	0.001
Net returns × Low education (<10 years)	0.001	−0.001	Net returns × Credit	**0.002****	0.001
Irrigation investment × High education (>10 years)	0.002	0.007	Irrigation investment × Extension	0.002	**0.009***
Fertilizer investment × High education (>10 years)	0.002	−0.003	Fertilizer investment × Extension	0.001	0.001
Net returns × High education (>10 years	0.001	0.002	Net returns × Extension	0.001	0.001
Irrigation investment × Low age (<35 years)	−0.003	0.001	Irrigation investment × Tenure	**0.001***	**0.008***
Fertilizer investment × Low age (<35 years)	**0.006***	0.002	Fertilizer investment × Tenure	**0.008*****	0.002
Net returns × Low age (<35 years)	**0.003***	−0.001	Net returns × Tenure	**0.003*****	0.001
Irrigation investment × High age (>35 years)	0.001	0.001	Irrigation investment × Drainage	0.004	−0.005
Fertilizer investment × High age (>35 years)	−0.005	−0.001	Fertilizer investment × Drainage	**0.004***	**0.002***
Net returns × High age (>35 years)	−0.002	0.001	Net returns x Drainage	0.001	0.003**
Irrigation investment × Low household size (<5 members)	−0.002	0.001	Irrigation investment × Canal remoteness	**−0.023****	**−0.005***
Fertilizer investment × Low household size (<5 members)	0.002	−0.001	Fertilizer investment × Canal remoteness	−0.005	−0.001
Net returns × Low household size (<5 members)	0.002	−0.001	Net returns x Canal remoteness	−0.002	0.001
Irrigation investment × High household size (>5 members)	0.004	0.005	Irrigation investment × Quality of road	−0.002	0.001
Fertilizer investment × High household size (>5 members)	0.001	0.002	Fertilizer investment × Quality of road	**0.001*****	**0.004*****
Net returns × High household size (>5 members)	−0.001	−0.001	Net returns x Quality of roads	**0.002*****	0.001
Irrigation investment × Risk averseness	−0.004	0.008	Irrigation investment × market distance	−0.003	−0.001
Fertilizer investment × Risk averseness	**−0.012*****	**−0.005*****	Fertilizer investment × market distance	**−0.001***	**−0.001***
Net returns × Risk averseness	**−0.003***	**−0.003***	Net returns x market distance	0.001	0.001
Irrigation investment × Risk neutrality	0.006	0.009	Irrigation investment × Last year prices	0.004	**0.011****
Fertilizer investment × Risk neutrality	**0.011*****	0.002	Fertilizer investment × Last year prices	**0.004***	**0.005****
Net returns × Risk neutrality	**0.003*****	**0.007*****	Net returns × Last year prices	0.001	**0.004*****
Irrigation investment × Risk seeking	−0.004	**0.013****	Irrigation investment × Cyclone	0.002	−0.003
Fertilizer investment × Risk seeking	**0.007****	0.001	Fertilizer investment × Cyclone	**−0.001***	**−0.003****
Net returns × Risk seeking	0.001	**0.007****	Net returns × Cyclone	0.000	0.001
Irrigation investment × Household income	0.002	**0.006***	Irrigation investment × Inundation class	0.002	−0.004
Fertilizer investment × Household income	0.004	**0.002***	Fertilizer investment × Inundation class	**0.007*****	**0.004***
Net returns × Household income	**0.002*****	−0.001	Net returns × Inundation class	0.001	0.001
Irrigation investment × Low off-farm income (<50% share in total income)	0.002	0.007	Irrigation investment × Overall soil fertility	0.001	0.003
Fertilizer investment × Low off-farm income (<50% share in total income)	**−0.004***	0.002	Fertilizer investment × Overall soil fertility	0.001	−0.001
Net returns × Low off-farm income (<50% share in total income)	0.001	**−0.002***	Net returns × Overall soil fertility	0.001	0.001
Irrigation investment × High off-farm income (>50% share in total income)	−0.002	−0.006	Irrigation investment × Overall soil salinity	–	0.005
Fertilizer investment × High off-farm income (>50% share in total income)	**0.005****	**−0.003***	Fertilizer investment × Overall soil salinity	–	−0.003
Net returns × High off-farm income (>50% share in total income)	0.001	0.002	Net returns × Overall soil salinity	–	−0.001

Note: Abridged version of interaction effects without intercepts and standard deviations and model fit test values. Model parameter estimated using "fallow" as reference level. Bold values show significant interaction effect when treated individually. *, **, and *** indicate significance at the 10%, 5%, and 1% levels. Standard errors not shown for brevity. Full version of the model estimates are provided in Tables SM1-SM4 significant only within the polder sample ($P \leq 0.05$). Nonetheless, outside polders, an increase in household income showed positive and significant interaction with net returns ($P \leq 0.001$). Interaction effect of off-farm income with fertilizer investment is negative and significant for respondents outside the polders when their share of off-farm income to total income is less than 50%. Nonetheless, when it comes to the interaction of off-farm income with the net returns of respondents outside the polders, the effect was negative and significant for only those having share of off-farm income to total income below 50%. Conversely, the interaction effect of fertilizer investment with off-farm income when its share is above 50% was positive and significant for respondents outside the polders while this interaction was significant and negative for respondents within polders.

4.5. Influence of institutions, infrastructure, markets and biophysical factors on crop choice attributes

Generally, among the institutional factors, increasing tenure rights and credit access tended to increase farmers' preference for intensification and double cropping. Outside polders, increasing both credit access and tenure security appears to drive respondent farmers' preferences for fertilizer and irrigation investments and higher net returns (Part B in Table 5). Within polders, while tenure tends to a have significant and positive influence on interest in dry season irrigation, the influence of credit and tenure on the remaining attributes were positive but insignificant. Secure land tenure rights are positively associated with cropping intensity, i.e., the number of crops grown on the same field within one year (Aravindakshan et al. 2020).

In focus groups, sharecroppers reported aversion to investment in land management or irrigation in the absence of secure land rights. We believe that tenure insecurity could also reduce farmers' interest in improving soil quality over time as farmers discount future investments. At current rates, the cost of securing tenure rights through land registration is roughly 10% of total land value (cf. Aravindakshan et al. 2020). This is prohibitive to small and marginal farmers in the coastal region, which provides evidence on the need for land tenure policy reforms and improvements in informal land sharing arrangements as prerequisite for land use intensification. In addition, from a welfare perspective, it is likely to be important for the government to increase farmers' access to institutions involved in agricultural finance and water use rights (Speelman et al. 2010; Manjunatha et al., 2016), since this appears to be linked to farmers' increased WTI for irrigation and fertilizer.

Field drainage tended to be an important variable driving fertilizer investment since both within and outside polders, the interaction of drainage with fertilizer was found positive and significant. Within field drainage is important given the low-lying nature of many fields in the study area, and consequent waterlogging risks. Unlike the respondents outside polders, for respondents within polders, the interaction of drainage with net returns was positive and significant. This implies that within polders, respondents' preference for crops that fetch higher net returns are positively correlated with the perception that improved drainage is needed. Drainage systems are however complex and will require careful coordination to permit land preparation so a diversity of subsequent winter season crops can be grown (Krupnik et al. 2017). Participatory water management by the community including cleaning of irrigation canals and provision of in-field drainage may be explored under the ongoing Employment Generation Programme for the Poorest (EGPP) (Mannan et al. 2018). The interaction between the distance of fields from canals that can be tapped for surface water irrigation and WTI for irrigation for respondents both within and outside polders was negative and significant. This clearly implies a negative preference for irrigation investments with increasing canal distance from the farm.

In comparison to other parts of the country, coastal Bangladesh has a relatively lower density of input and output markets and have relatively poor road infrastructure (MOA and FAO, 2013). Farmers both within and outside polders therefore have a locational hindrance to the purchase of inputs and sales of crops for distant markets. Increasing distance to markets from the farm had a significantly negative interaction on fertilizer investment. Remoteness not only reduces farmers' market access, but can also influence their land use decisions (Tur-Cardona et al. 2018; Aravindakshan et al. 2018). Improved quality of roads was found to positively and significantly influence respondents' fertilizer investment both within and outside the polders. Among the other variables related to markets, increase of prices for any crop was positively associated to respondents' preferences for growing that crop in the coming season. As evident in our estimates, market prices observed in the last year prior to survey had a positive and significant influence on crop preferences, except for wheat outside the polders.

Another qualitative variable considered was 'Inundation class". This variable was based on the classifications described by Brammer (2013) as the average perceived depth of field flooding during the monsoon season. This variable is further described in Krupnik et al. (2017) and Emran et al. (2019), is widely used by farmers to describe their land types. The level of inundation during the monsoon is important in determining the variety of rice that can be grown, and the speed at which floodwaters vacate following the summer monsoon to permit cropping in the early winter season (Krupnik et al. 2017). The official land inundation classification system is complex, with five main classes. For simplification, we asked farmers to report if their fields on average belonged to "low" (>180 cm average water depth), "medium" (30–180 cm water depth) or "high" (0–30 cm water depth) during the monsoon season. Our results indicated that lower inundation depths corresponding to higher 'micro-elevation' fields) were associated positively and significantly with farmers' preference for fertilizer investments in the dry season both within and outside polders (Table 5).

Importantly, past cyclone severity tends to affect the crop input investment preferences of farmers both within and outside polders, with strongly negative effects observed. Our results show a negative and significant interaction influence of cyclone severity on preference for fertilizer investments. There have been considerable crop losses associated with previous extreme weather events in coastal Bangladesh. Opportunities for climate services that increase farmers' ability to anticipate and cope with extreme climatic events may also be beneficial in reducing risk (Akter et al. 2016). Cyclones and extreme weather are widely cited as risk-bearing factors that can limit rural developments efforts in coastal South Asia (Akter et al. 2016); options for farm insurance can also be explored to hedge risks.

4.6. Production risks and farmers risk attitude in crop choices

Cumulative probability distribution graphs (Fig. 5) based on attribute values for actual crop choices of farmers show the risk spread for different crops. At conservative levels of production risk (60th percentile), sampled farmers outside polders could make a net profit of 450 US\$ ha^{-1} and 650 US\$ ha^{-1} for mungbean and maize respectively. The net returns for sampled polder farmers at the 60th percentile could be 410 US\$ ha^{-1} and 500 US\$ ha^{-1} for mungbean and maize respectively. Our analysis shows a wider risk spread for net returns from maize, which ranged from 250 to 1000 US\$ ha^{-1} outside of polders, and 100–1000 US\$ ha^{-1} within polders (Fig. 5). This indicates that maize is perceived as a more risky crop within than outside polders, which is perhaps linked to the relatively high investment costs for maize (Schulthess et al. 2019). Growing *boro* rice and wheat, on the other hand, is clearly perceived by farmers as less profitable in both study areas, fetching <200 US\$ ha^{-1}.

5. Conclusion and implications

This paper considered the range of complex socioecological challenges that undermine increased land use intensity in South Asia's coastal deltas, through a case study in south central Bangladesh. Governmental policy has supported efforts to encourage increased land

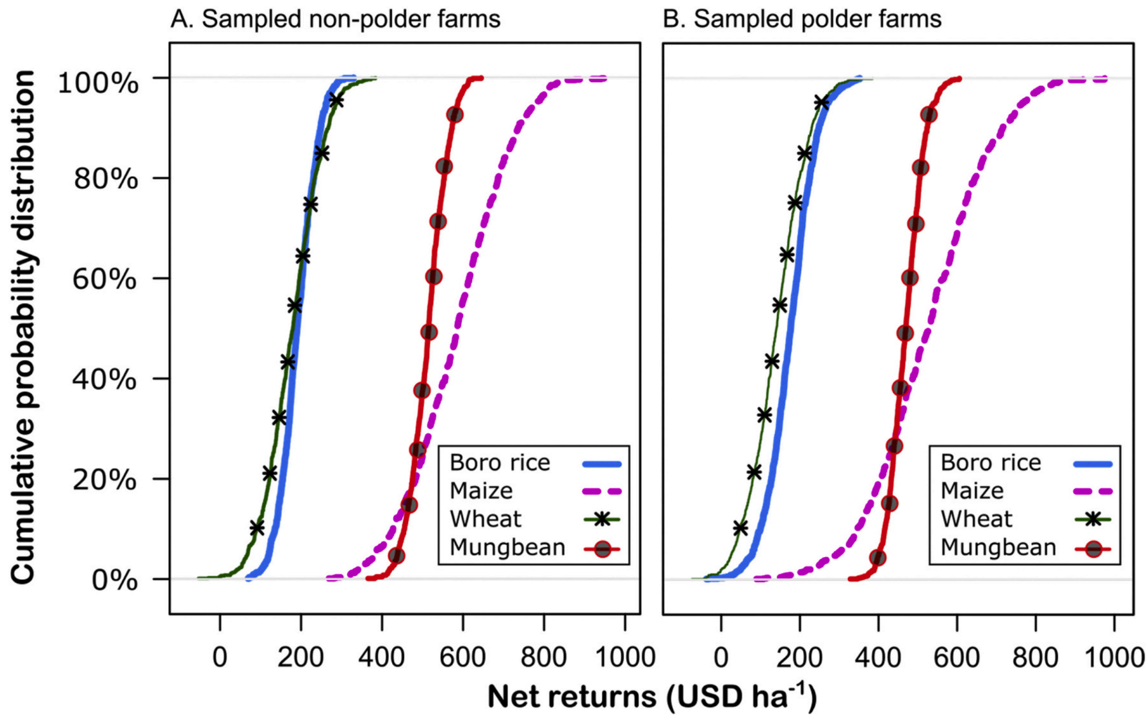

Fig. 5. Simulation of production risk from crop choice data, based on attribute values for actual crop choices. At conservative levels of production risk (60th percentile), sampled non-polder farmers could make a net profit of 450 US$ ha^{-1} and 650 US$ ha^{-1} for mungbean and maize respectively. The net returns for sampled polder farmers at 60th percentile could be 410 US$ ha^{-1} and 500 US$ ha^{-1} for mungbean and maize respectively. Rice (*boro*) and wheat on the other hand would fetch <200 US$ ha^{-1} in polder and non-polder environments.

use intensity through double cropping and the replacement of winter '*rabi*' season land fallowing with surface water irrigated and intensified crop management practices, with strong emphasis on irrigated rice. Policies however tend to be made without adequate study of farmers' preferences and ambitions; this can render crop intensification efforts ineffective. In response, we employed a choice experiment to investigate farmers' preferences for crops potentially suitable for replacing dry season land fallowing, in addition to the nature of attributes and most important socio-economic forces driving farmers' preferences.

The choice experiment revealed strong farmer preferences for crops with less irrigation demand (less irrigated mungbean and irrigated maize), against crops requiring high irrigation ('*boro*' rice or wheat). Our results indicated that farmers in south-central Bangladesh, irrespective of their farm's location within or outside coastal embankment systems, showed negative preference towards irrigation and fertilizer investments while selecting a crop for intensification, hence their stronger relative preference for mungbean than maize, '*boro*' or wheat. Furthermore, respondent farmers also showed positive preference for crops fetching higher potential net returns. These findings may explain the low adoption rates of surface water irrigation investments in coastal Bangladesh over the last several years, despite policy investments and extensive extension efforts.

Our results also indicate that farmers within and outside polders may be more willing to invest in mungbean followed by maize and *boro* in that order. Bangladeshi government's policy suggests initiatives to increase *boro* rice production in place of land fallows, which however conflicts with the farmers' preference for mungbean in the winter season. Low paddy prices and relatively higher labor costs provide disincentive against *boro*, in addition to high irrigation costs (Aravindakshan et al. 2020). Respondents' negative willingness to invest in wheat both within and outside polders indicated its low preference over the *status quo* choice (fallow). Significant supportive measures, likely in the form of subsidies, will be required to encourage wheat production. The fact that the majority of farmers both within and outside polder areas have a preference for mungbean followed by maize points to the need for extension to educate farmers on crop management for both crops, alongside potential credit support for purchase of inputs and to offset irrigation costs. Based on the models on variable interactions, our study also indicated a strong link between field drainage and the existence of optimum sowing conditions on crop preferences. The severity of previous cyclones in our study area also appears to negatively influence respondents' willingness to invest in inputs, most notably fertilizer. Given the vulnerability of farmers in the study areas to extreme weather events, developing production risk mitigation for these crops via well-designed insurance programs and tailored climate information services is highly relevant. This study also revealed that there are significant differences among farm household level factors that drive preferences for different crops and intensified management practices, including age, distance to markets proximity and quality of roads, and level of access to agricultural extension and credit. These results have important policy implications on the efforts to encourage double cropping and sustainable intensification. Our study clearly indicates that agronomic interventions alone are not perceived to be sufficient; rather, comprehensive and integrated development programs are required to assist in improving within field water management, asphalted roads, context-specific extension and educational programs, alongside access to finance for coastal farmers, particularly those interested in maize. Lastly, our study documented a strong preference for mungbean to replace dry season land fallowing; as such, the development of improved mungbean varieties and appropriate management practices appear to be important priorities.

Declaration of Competing Interest

None.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.agsy.2021.103069.

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