



Research article

Assessing farmers' attitudes to, and the behavioural costs of, organic fertiliser practices in northern Ghana: An application of the behavioural cost approach

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ABSTRACT

The use of organic fertiliser to improve soil health is crucial to halting the downward trend of crop yields in sub-Saharan Africa. If this goal is to be achieved, however, farmers require support to adopt organic fertiliser practices that match their attitudes and decision-making capacity. This study evaluated farmers' attitudes to a set of prevailing organic fertiliser practices and their associated behavioural costs (difficulty). The explanatory Rasch model was applied to a set of primary data from 250 farming households in north-east Ghana. The results showed that the average attitude of farmers was much less than the difficulty estimate of an average organic fertiliser practice, although the practices generally showed a moderate difficulty. On average, farmers' attitudes matched just three of sixteen practices on the scale, with most (70 %) of the farmers showing very weak attitudes towards the input. Latent regression results revealed that the weak attitude levels were strongly related to key factors in the farmers' background, including education, resource endowment and access to extension services. Participation in determining policies on organic fertiliser use enhances farmers' knowledge and skills concerning use of the input. Hence, access to such policies can replace education for the less-educated majority of farmers. Thus, training programmes are proposed that develop the average farmer's capacity to adopt these practices in this area, especially the less difficult ones. Supporting farmers with the acquisition of animal-drawn vehicles can also facilitate uptake of the more difficult organic fertiliser practices and increase use of the input.

1. Introduction

Governments and other policymakers have recognised the relationship between the soil fertility crisis and development setbacks in agrarian economies in sub-Saharan Africa (SSA) (AfDB, 2006; Agwe et al., 2007). Soil fertility fundamentally influences agricultural productivity through crop and pasture yields, thus determining farming households' food supply and incomes (Tittonell and Giller, 2013; Lagerkvist et al., 2015). This implies that prevailing food insecurity and poverty in the region, where over 80 % of rural households depend on farming, are closely linked to poor soil conditions (Nkonya et al., 2016; Kim and Bevis, 2019). It is therefore reasonable that policies to improve farm productivity and the livelihoods of smallholder farmers through soil fertility management underpin all national efforts to boost economic development in SSA (AfDB, 2006).

In discussions about the low crop yield in SSA, a common conclusion is that African farmers do not use the required quantities of mineral fertiliser (Chapoto et al., 2015). However, this notion is not simply true because recent increases in fertiliser use for some crops have not shown a commensurate improvement in yield (Sheahan and Barrett, 2017; Liverpool-Tasie et al., 2017). The present productivity crisis in the region has much more to do with sub-optimal conditions (biophysical and chemical) affecting overall soil quality than simply insufficient use of mineral fertilisers (Agwe et al., 2007; Shisanya et al., 2009; Tittonell and Giller, 2013; Lagerkvist et al., 2015; Vanlauwe, 2015). For instance, cereal yields among farmers in the Upper East and North East regions of Ghana are stagnating despite increasing mineral fertiliser application (Mellon-Bedi et al., 2020). Further increase in mineral fertiliser has minimal impact on yield because soils lack organic matter, which creates suitable medium for the effective utilisation of the nutrients supplied by

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mineral fertilisers (Tittonell and Giller, 2013; Liverpool-Tasie et al., 2017; Owusu et al., 2020). Stagnant or falling yield levels imply a declining yield-to-fertiliser price ratio, which effectively discourages the demand for mineral fertilisers since the marginal outcomes suggest that many farmers are already applying optimum economic quantities of mineral fertilisers (Liverpool-Tasie et al., 2017).

For yields to respond to mineral fertiliser and make further increases beneficial, farmers must apply significant quantities of organic amendments to revive their soil (Tittonell and Giller, 2013). Organic matter plays a crucial role in balancing the chemical and biophysical conditions of soil, conserving moisture and thus improving fertiliser utilisation by crops (Agwe et al., 2007; Bandanaa et al., 2016; Kim and Bevis, 2019). Farmers in northern Ghana have traditionally used animal manure and naturally-occurring composts within their locality to amend soils organically (Quansah et al., 2001; Fosu-Mensah et al., 2012; Vanlauwe, 2015). However, these sources are becoming increasingly limited and thus cannot be accessed by all farmers. If they do access them, the quantities and quality are usually inadequate for their needs (Tittonell and Giller, 2013; Vanlauwe, 2015; Wekesah et al., 2019). Thus, they often need to supplement manure and waste materials with other sources for soils to accumulate adequate organic matter.

For the past two decades, the government of Ghana, through its Ministry of Food and Agriculture and in partnership with several NGOs, has implemented organic fertiliser use projects to support farmers in the country's four northern regions (Bandanaa et al., 2016). The general purpose of these projects has been to increase the quantity, quality and efficient use of organic amendments by improving farmers' traditional management practices. These practices include recycling crop residues by composting, and harnessing more manure by increasing livestock numbers, improving animal housing and using in-stall feeding instead of open-space grazing (Bellwood-Howard, 2013). Farmers have been sensitised to establish formal relationships with Fulani herdsmen and other livestock owners for manure, agro-processors for their by-products, and with waste disposal agents to obtain and use sewage matter or urban waste products (Bellwood-Howard, 2013; Bandanaa et al., 2016; Kranjac-Berisavljevic and Gandaa, 2013). Green manuring, agro-forestry and rotation/intercropping with legumes have also been introduced, although the level of their adoption by farmers is low (Quansah et al., 2001).

Several agencies, including the Opportunity for Industrialization Center (OIC) and the Presbyterian Agriculture Station (PAS), have trained farmers on pit and heap methods of compost preparation. They have also supported some farmers' groups to procure equipment such as donkey carts for gathering materials (Bellwood-Howard, 2013). The associations Agricultural Cooperative Development International/Volunteers in Overseas Cooperative Assistance (ACDI/VOCA) and Alliance for Green Revolution in Africa (AGRA) have also primed farmers on methods of organic fertiliser application, such as the Zai pit method and micro-dosing of crops with mineral fertilisers after germination, irrespective of the quantity of organic amendment applied.

Consequently, after benefiting from the projects, the expectation would be that farmers in the area use substantial quantities of organic fertiliser. The opposite is true, however. It appears that the projects have made no impact on organic fertiliser use, particularly in cereal production. Use of the input is still far below expectations because it has not been adopted collectively by farmers, and many of those who have adopted it continue to apply it in minimal quantities (Bellwood-Howard, 2013).

Attempts to promote organic fertiliser practices (OFPs) without knowing whether or not farmers are inclined to apply these practices tend to misdirect policy efforts (Martey, 2018). If the push towards increasing organic fertiliser use is to succeed, the OFPs being promoted must align with farmers' attitudes and their decision-making capacity (Lagerkvist et al., 2015; Shikuku et al., 2017). Thus, interventionists need to understand farmers' perspectives on how they tend to engage in existing OFPs in order to adjust policies and exploit farmers' legacy resources and path dependencies. One intuitive way to gain such insights is

to evaluate farmers' attitudes to existing OFPs and map these against behavioural costs (difficulties) (Durpoix, 2010). To date there has been no empirical evaluation of farmers' attitudes to OFPs or assessment of the behavioural costs of the practices being promoted in Ghana.

Against this backdrop, the present study seeks to fill this empirical information gap by: 1) assessing the behavioural cost of OFPs and farmers' attitudes to organic fertiliser, and 2) examining the characteristics among farmers that influence their attitudes. This study adopted Campbell (1963) paradigm, recently revised by Kaiser et al. (2010), to assess attitudes. Thus, farmers' attitude to organic fertiliser was defined as their *general behavioural disposition* to engage in a set of practices as a means of realising their organic fertiliser objective. Following Lagerkvist et al. (2015) and Shikuku et al. (2017), the Rasch model for measurement was applied to observed farmers' behavioural responses to a set of OFPs in north-east Ghana. In contrast to previous studies, however, this study used the person-related explanatory version of the Rasch model, which allows farmer characteristic variables to be incorporated to control for scale distortions and simultaneously address the study objectives (Rijmen et al., 2003; Wilson et al., 2008; Briggs, 2008).

The study contributes to the literature on farmers' attitudes to technology in two ways. The use of a hybrid (person-explanatory) version extends the scope of the practical application of the recently adapted Rasch model (behavioural cost approach) in analyses of farmers' attitudes. The paper also provides the first empirical estimates of behavioural costs (i.e., difficulty) and a ranking of common OFPs in northern Ghana. The remainder of the paper is structured as follows: Section 2 reviews approaches to attitude/behaviour assessment, highlighting the shift towards the behavioural cost approach. Section 3 sets out the concepts involved in the behavioural approach (Rasch model) to measuring attitudes, specifies the empirical model and describes the data used for this study. Section 4 presents model estimates and evaluation results, and finally section 5 draws conclusions and policy recommendations from the study's findings.

2. Assessment of farmers' attitudes: classical versus behavioural approach

The term 'attitude' has several definitions in the literature, making its use controversial without its contextual meaning being given. Nevertheless, the description of the term by Eagly and Chaiken (1993) as a *psychological tendency expressed by evaluating a particular entity with some degree of favour or disfavour* resolves much of the controversy surrounding the concept (Durpoix, 2010). A seemingly different notion of the concept is the postulate of Campbell (1963) that attitude is a person's disposition *to carry out a particular behaviour*. This notion has been further refined and functionally defined by Kaiser et al. (2010) for operationalisation. However, attitude remains abstract and cannot be observed directly under any of the definitions, and hence is usually measured as a latent trait.

In line with the two concepts above, two main classes of analytical tools commonly used for assessing attitude as a latent trait are the classical and behavioural models. For classical modelling (CM), analysts use subjects' (farmers') expressed intentions, affections or subjective ratings of aspects of the study object (farm technology) to extract latent constructs that are presumed to influence farmers' inclinations, thus their behaviour towards the technology under study (Kaiser et al., 2010; Lagerkvist et al., 2015). Conventionally, classical analysts of farmers' attitudes have resorted to the use of confirmatory or exploratory factor analysis when examining the adoption of new farm technologies (Willock et al., 1999; Waithaka et al., 2007; Shikuku et al., 2013; Lagerkvist et al., 2015).

Although generally useful for guiding approaches to promote farm technology, these models have proved very unreliable at predicting adoption behaviour due to functional gaps between the latent constructs they are measuring and the actual adoption behaviours exhibited by farmers (Campbell, 1963; Kaiser et al., 2010; Lagerkvist et al., 2015). The

gaps occur because CMs ignore the behavioural costs (difficulty) of the practices involved that directly determine actual behaviour (Kaiser et al., 2010). In contrast, the behavioural cost postulate links attitude directly to actual behaviour by accounting for the forces opposed to behaviour. These opposing forces include, but are not limited to, conflicting social norms, religious beliefs, perceived behavioural controls, and physical and financial constraints. These are collectively referred to as the *behavioural costs or difficulty* of behaviour (Campbell, 1963; Kaiser et al., 2010; Lagerkvist et al., 2015; Shikuku et al., 2017). The intuition from the behavioural cost approach is that although intentions and behaviour both emanate from a person's disposition, behaviour does not occur unless the person is able to 'pay the cost' (i.e., overcome the difficulty) associated with carrying out the behaviour. In other words, although behaviour is a manifestation of attitude, it will not occur if the difficulty involved in carrying out the behaviour exceeds the strength of the underlying attitude. Thus, behaviour has a 0.5 probability of occurring when attitude strength equals the cost of behaviour. Attitudes can therefore be inferred from observed behaviours using a probability function. However, for a broad dimension technology, such as organic fertiliser use, the underlying attitude is general and can manifest itself adequately through a set of practices (behaviours) associated with critical aspects of the technology rather than a single practice (Kaiser et al., 2010).

Following the seminal exposition of the behavioural cost approach of Kaiser et al. (2010) using the Rasch (1980) scaling model, Lagerkvist et al. (2015) adapted and applied the model in comparison with the classical latent construct model to assess farmers' attitudes to sustainable intensification practices. They observed that attitude estimates from these models have entirely different distributional properties with a weak correlation coefficient. The behavioural model shows generally weaker attitude estimates in several clusters across the scale, but covers a wider range of behaviours than the classical model. However, the classical model gives a relatively high, but single-cluster attitude distribution on its scale (Lagerkvist et al., 2015). They conclude that the difference between the two models reflects gaps between attitude measured through a verbal rating and actual behaviour, and that the behavioural model is more sensitive than the classical model and reflects all critical aspects of composite technology. By mapping farmers' attitudes and the difficulty of practices on the same scale, the behavioural model also allows analysts to identify persons and practices that require policy support to facilitate adoption of a composite technology (Boone, 2016). This makes the Rasch model preferable to any CM given the current need for interventions to target beneficiaries accurately when upscaling farming innovations (Parvan, 2011; Shikuku et al., 2017).

However, the Rasch scale only ranks behaviours (practices) and persons according to behavioural cost and attitude levels. It does not provide any information to explain attitude levels or difficulty estimates on the scale (Rijmen et al., 2003; Briggs, 2008). Aside from the lack of explanatory information, the critical assumptions underlying the basic model are often unrealistic for observational studies using data such as reported farming practices (Briggs, 2008; Karami, 2012; Opariuc-Dan et al., 2017). For instance, the local independence of practices and farmers is violated when systematic groups of sample farmers respond differently to practices, a condition known as differential item functioning (DIF). DIF occurs when different sub-groups of farmers (for example males and females) have different probabilities of engaging in a behaviour (Karami 2012; Khalid and Glas 2013; Opariuc-Dan et al., 2017). This occurs either because the behaviour is technically biased towards one group, or the groups belong to different attitude distributions (Briggs, 2008; Karami, 2012; Opariuc-Dan et al., 2017). With DIF, the basic Rasch scale loses its objectivity unless separate difficulty parameters are estimated for DIF groups, provided the behaviour is indeed biased (Khalid and Glas 2013; Lagerkvist et al., 2015). However, if DIF arises from a systematic attitude difference determined by sub-grouping factors, scale distortions should be resolved by conditioning attitude estimates on the grouping factors.

Conditioning attitudes on socioeconomic factors should be a convention when examining farmers' attitudes to technology in Africa, a continent where economic and cultural circumstances combined with beliefs shape farmers' disposition to new farm practices (Shiferaw et al., 2009). There is a long strand of literature showing links in sub-Saharan Africa between farmers' factors and their decisions to adopt farming innovations (Shiferaw et al., 2009; Fosu-Mensah et al., 2012). Farmers' background conditions determine attitudes through farm goals, beliefs and perceptions about how easy a technology is to use. In turn, these influence the probability of performing actual practices and the decisions they take (Ridgley and Brush, 2015; Shiferaw et al., 2009; Parvan, 2011; Chikowo et al., 2014; Borges et al., 2015; Abebe and Debebe, 2019).

By implication, different attitude distributions arising from systematic differences in socioeconomic factors are more plausible causes of DIF in observed farmer behaviours than biased¹ OFPs (Tay et al., 2013). This is especially the case when a significant number of the practices of the technology set show DIF (Khalid and Glas, 2013). In the generalised linear mixed model (GLMM) setup, there are different extensions for relaxing invalid assumptions of the basic Rasch model and incorporating farmer background information to resolve DIF and explain attitude levels (Opsomer et al., 2003; Rijmen et al., 2003; Briggs, 2008; Tay et al., 2013).

However, previous studies assessing farmers' attitudes using the Rasch model have applied the basic form and estimated separate difficulty parameters where practices show DIF for sub-groups as though the OFPs are indeed biased (Lagerkvist et al., 2015; Shikuku et al., 2017). Moreover, some analysts have reverted to an entirely different model to explain farmers' behaviour by constructing and regressing an overall adoption index on farmers' characteristics (Shikuku et al., 2017). Although this approach is similar to the two-step procedure of Briggs (2008) to explain subjects' trait levels in the Rasch model framework, it leads to a loss of information. Meanwhile, information losses could be avoided by applying the explanatory Rasch (latent regression) model specification to scale and explaining attitude levels simultaneously (Opsomer et al., 2003; Briggs, 2008; De Boeck et al., 2016). This hybrid model also resolves DIF due to attitude groupings arising from systematic differences in factors in farmers' backgrounds. By incorporating explanatory factors in a second-level latent attitude scores regression, the hybrid model adjusts for attitude heterogeneity across groups of characteristics. Thus, it provides more realistic estimates of both attitudes and behavioural costs than the basic Rasch model where DIF factors directly influence attitudes (De Boeck et al., 2016).

Based on the above, application of the explanatory Rasch model is appropriate when assessing farmers' attitudes from observed behaviours. This study assumed that farmers' attitudes were determined by their characteristics and that DIF exhibited by some OFPs is due to systematic impacts of these characteristics on attitudes (Rijmen et al., 2003; Karami, 2012; Opariuc-Dan et al., 2017). Hence, the study employed the person-explanatory Rasch model to correct for scale distortion due to the apparent DIF while evaluating farmers' attitudes towards OFPs and their associated behavioural costs. Controlling for differences in farmers' characteristics can also explain the attitude levels of sample farmers.

3. Methodology

3.1. Conceptual framework of attitude-as-behaviour (behavioural approach)

For farmers facing a set of OFPs under the same farming circumstances, each practice is an appropriate organic fertiliser behaviour. The behaviours together manifest farmers' general attitudes to the use of organic fertiliser. Each behaviour has a behavioural cost, known as the

¹ An OFP is biased if its application is technically unfavourable for a category of sample farmers.

difficulty (Lagerkvist et al., 2015; Shikuku et al., 2017). The behavioural costs are independent of the farmers, and differ transitively from one behaviour to another, while the strength of farmers' attitudes also differs independently of the behaviours (Kaiser et al., 2010; Bond and Fox, 2015; Lagerkvist et al., 2015). Subsequently, behaviour and behavioural cost are referred to below as practice and difficulty respectively.

In order to achieve their organic fertiliser objectives, farmers purposely choose to engage in some or all of the practices, and in doing so manifest their attitude to organic fertiliser (Ridgley and Brush, 2015; Kaiser et al., 2010; Lagerkvist et al., 2015; Shikuku et al., 2017). Even though attitude cannot be observed, the number of practices in which a farmer engages is a sufficient statistic to derive its latent measure of organic fertiliser use (Millsap, 2010). Likewise, the total number of farmers engaged in a given practice statistically helps identify the difficulty estimate of the practice (Wang et al., 2014).

Those with strong attitudes are more disposed to engage in practices than those with weak attitudes (Kaiser et al., 2010). When a person's attitude equals the difficulty of a practice, there is a 0.5 probability of the practice being performed. Thus, an attitude measure can be inferred from the observed set of practices using a probability function. Kaiser et al. (2010) specified this function using the latent trait model of Rasch (1980). However, as noted above, farmers might differ systematically in their response to some practices. Systematically different responses violate the basic model assumption that practices are independent of farmers. Fortunately, the independence assumption can be relaxed by recasting the model in the generalised linear mixed model (GLMM) framework to control for factors influencing a farmer's attitude θ_i . Figure 1 shows a structural equation form of the Rasch model in the GLMM framework.

3.2. Empirical specification of the Rasch model

Based on the discussion above, the probability of farmer i engaging in a given practice j is a function of the person's attitude and the difficulty level of the practice, given as (Opsomer et al. (2003); Kaiser et al., (2010); Wang et al. (2014); Lagerkvist et al. (2015); Shikuku et al. (2017):

$$\Pr(X_j = 1 | \theta_i, \delta_j) = \frac{\exp\{x_{ij}(\theta_i - \delta_j)\}}{1 + \exp(\theta_i - \delta_j)} = \exp(\theta_i - \delta_j) \quad (1)$$

where X_j refers to any organic fertiliser practice j , θ_i is the attitude of farmer i , δ_j is the difficulty measure of the practice and x_{ij} is the observed behaviour of farmer i regarding practice j , with $j = 1, \dots, J$. The log likelihood (L_{ij}) of Eq. (1) is:

$$L_{ij} = \ln\left(\frac{P_{ij}}{1 - P_{ij}}\right) = \ln\left(\frac{\exp(\theta_i - \delta_j)}{1 + \exp(\theta_i - \delta_j)}\right) = \theta_i - \delta_j \quad (2)$$

where attitude is assumed to be $\theta \sim N(0, \sigma^2)$ among the farmers, while OFPs are independent and contribute equally in differentiating between farmers' strength of attitude. The joint likelihood of a pattern of practices, \mathbf{x}_i , in which farmer i engages is given as:

$$L_i(\boldsymbol{\delta}, \theta_i | \mathbf{x}_i) = \prod_{j=1}^J \Pr(x_{ij} = 1 | \theta_i, \delta_j), \quad \mathbf{x}_i = \sum_{j=1}^J x_{ij} \quad (3)$$

where $\boldsymbol{\delta}$ is a vector of difficulty parameters for the $j = 1, \dots, J$ practices.

For fixed measures of farmer attitude θ_i , consistent estimates of $\boldsymbol{\delta}$ for the OFPs can be obtained by maximising the population joint likelihood function:

$$L_c(\boldsymbol{\delta} | \mathbf{x}, \mathbf{S}) = \prod_{i=1}^I \Pr(\mathbf{x}_i | \boldsymbol{\delta}, \mathbf{s}_i) \quad (4)$$

conditional on the scores (\mathbf{S}), where \mathbf{x} and \mathbf{S} are sets of observed patterns of practices and scores, respectively, within the population, while \mathbf{x}_i and \mathbf{S}_i refer to the specific practice combinations and scores respectively of farmer $i = 1, \dots, I$ (Hardouin, 2007; and Zheng and Rabe-Hesketh, 2007).

Given the difficulty estimates $\delta_1, \dots, \delta_j$ from Eq. (4), unbiased estimates of a person's attitude ($\theta_1, \dots, \theta_N$) can be predicted. With both sets of parameters in logit, the OFPs can be ranked by difficulty independent of farmers and likewise the farmers ranked by their attitude level, independent of practices, on the same scale (Hardouin, 2007; Kaiser et al., 2010).

However, the local independence of farmers and OFPs was an unrealistic assumption for these observational data. Thus, the model was re-specified into a generalised linear latent mixed (GLLMM) setup using the explanatory Rasch model specification to relax the independence assumption (Rijmen et al., 2003; and De Boeck et al., 2016). Eq. (1) thus becomes:

$$\Pr(Y_{ij} = 1 | \mathbf{x}_{ij}, \mathbf{z}_i, \theta_i, \boldsymbol{\delta}) = \frac{\exp(\mathbf{z}'_i \theta_i - \mathbf{x}'_{ij} \boldsymbol{\delta}_j)}{1 + \exp(\mathbf{z}'_i \theta_i - \mathbf{x}'_{ij} \boldsymbol{\delta}_j)} \quad (5)$$

where \mathbf{z}'_i is a vector of farmer characteristics, $1, 2, \dots, p$, θ_i is now a vector of random components ($\theta_{i1}, \theta_{i2}, \dots, \theta_{ip}$) constituting the attitude measure of farmer i , \mathbf{x}'_{ij} is a vector of the design matrix of the set of practices, $\boldsymbol{\delta}_j$, as defined in Eq. (1), and $Y_{ij} = X_j$ is the observed outcome of any practice j for farmer i . The re-defined log-likelihood function is:

$$L_{ij} = \eta_{ij} = \mathbf{z}'_i \theta_i - \mathbf{x}'_{ij} \boldsymbol{\delta}_j \quad (6)$$

where η_{ij} is a log linear odds ratio predictor of the likelihood.

Latent variable regressions relating θ_i to \mathbf{z}_i can be specified as:

$$\theta_i = \mathbf{z}'_i \boldsymbol{\beta} + \boldsymbol{\varepsilon}_i \quad (7)$$

where θ_i follows a multivariate normal distribution, \mathbf{Z}_i is as defined earlier, $\boldsymbol{\beta}$ is a vector of fixed effects of \mathbf{Z}_i on θ_i to be estimated, while $\boldsymbol{\varepsilon}_i$ is a vector of random variations of θ_i from the population average (Rijmen et al., 2003; Wilson et al., 2008; Briggs, 2008). Eq. (7) is specified and linked to 6, forming a two-level model within which respondents (level 2) nest various practices (level 1 units).

From related literature, evidence on farmers' soil management decisions suggests many farmer characteristics of interest in this study (Waithaka et al., 2007; Shiferaw et al., 2009; Parvan, 2011; Chikowo et al., 2014; Borges et al., 2015; Abebe and Debebe, 2019; Mellon-Badi et al., 2020). Kassie et al. (2013) group these factors into: 1) farmer characteristics, including age, gender, educational attainment in the household, participation in non-farm work, organic fertiliser experience and risk attitude score, 2) social capital factors, including contact with extension agents, farmers' group membership, access to organic fertiliser policy and training opportunities, and 3) physical resource characteristics such as livestock, carting equipment, plot size and total landholding. Other characteristic variables are land tenure and geographical location.

Conditioned on the observed farmer characteristics, the process for farmers' response practices approximates a unidimensional Rasch model,

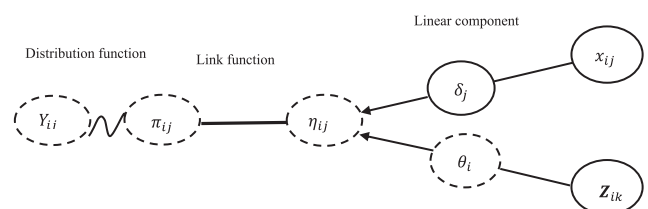


Figure 1. Structural representation of Rasch model in a GLMM. Adapted from Wilson et al. (2008).

such that the practices are not correlated and do not function differently across groups of characteristics (no DIF). This implies no significant interaction term between practices and persons for inclusion in the empirical specification. The model was specified and estimated using the GLLAMM Stata code developed by [Zheng and Rabe-Hesketh \(2007\)](#).

3.3. Data and summary statistics

The data used for this study were collected from farmers located in operational areas of the Presbyterian Agriculture Station's (PAS) sustainable agriculture project and Ministry of Food and Agriculture (MoFA) extension zones of the Bunkpurugu-Nankpanduri and Yunyoo-Nasuan districts. Prior to sampling, a discussion was held with MoFA (Bunkpurugu area) and PAS extension agents to identify prevailing organic fertiliser practices among farmers. Using a multistage sampling process, the PAS and MoFA extension zones were purposively selected at the first stage to ensure equal chances of including farmers in the sample who use the various organic fertiliser types. The PAS and MoFA extension agents in the selected zones provided lists of farming communities, from which 30 % of the communities were randomly selected to represent each zone. For the stations in the North East region, the selected communities in West and East Mamprusi districts were clustered around the Lagbinsi station, while those chosen for Bunkpurugu and Yunyoo-Nasuan districts were clustered around the town of Bunkpurugu. In the Upper East region, selected communities found in the Tempene and Pusiga districts were clustered around Wurnyanga, while those for Garu and Binduri districts were located

between the towns of Garu and Binduri. At community level, farmers' groups and/or opinion leaders helped identify and compile a list of households that used organic fertilisers. Every household that had adopted organic fertiliser practices completed a two-part structured questionnaire during personal interviews (PI). A total of 250 small-holder farming households from 52 communities across eight districts of the North East and Upper East regions completed the questionnaire. The first part sought information on the farmers' characteristics ([Table 1](#)) while the second part elicited data on a set of organic fertiliser practices.

Many of the practices listed in this study's instrument for assessing attitudes to organic fertilisers were taken from the integrated soil fertility management (ISFM) attitude scale of [Lagerkvist et al. \(2015\)](#). After a literature review on OFPs (e.g., [Quansah et al., 2001](#); [Fosu-Mensah et al., 2012](#); [Kranjac-Berisavljevic and Gandaa, 2013](#); [Bandanaa et al., 2016](#)), the instrument was adapted to suit current organic fertiliser technology in the study area. Key stakeholders in organic fertiliser support projects, including PAS and ACIDI/VOCA management and farmers' representatives, validated a set of 20 OFPs that made up the final instrument for the study. Together, these practices ([Table 2](#)) adequately represented the empirical range (scale) of farmers' attitudes to the use of organic fertiliser in the study area. Farmers reported their behavioural outcomes for the practices in a dichotomous format (i.e., whether they engaged in the practice or not). [Appendix A](#) shows the distribution of a) farmers' behavioural outcomes and b) the odds ratios of practices.

Factor analysis of the data to ascertain dimensionality of the attitude underlying the OFPs ([Millsap, 2010](#)) showed only one significant factor

Table 1. Farmer/farm characteristic factors and summary statistics.

Variable	Description/Measurement	Proportion of sample	
Gender	Dummy: 0 = female, 1 = male	0.87	
Age	Age Group1	Dummy: 1 = 18–40yrs (Young), 0 = otherwise	0.48
	Age Group2	Dummy: 1 = 41–65yrs (Aging), 0 = otherwise	0.36
	Age Group3	Dummy: 1 = (>65yrs (Aged), 0 = otherwise	0.16
Education	No Educ.	Dummy: 1 = no education, 0 = otherwise	0.48
	PrimaryEdu	Dummy: 1 = primary education, 0 = otherwise	0.18
	SecondaryEdu	Dummy: 1 = secondary education, 0 = otherwise	0.20
	TertiaryEdu	Dummy: 1 = tertiary education, 0 = otherwise	0.14
Off-farm work	Dummy: 1 = yes, 0 = otherwise	0.41	
Risk attitude	Risk-averse	Dummy: 1 = yes, 0 = otherwise	0.19
	Risk-neutral	Dummy: 1 = yes, 0 = otherwise	0.65
	Risk-takers	Dummy: 1 = yes, 0 = otherwise	0.16
Organic experience	Category 1	1 = (<3years), 0 = otherwise	0.11
	Category 2	1 = 3–5years, 0 = otherwise	0.53
	Category 3	1 = (>5years), 0 = otherwise	0.36
FG membership	1 = FBO member, 0 = otherwise	0.37	
Policy benefit	Dummy: 1 = beneficiary, 0 = otherwise	0.32	
Extension contact	1 = has contact with local agent, 0 = otherwise	0.33	
Access to training	Dummy: 1 = yes, 0 = otherwise	0.42	
Carting equipment	1 = owns equipment, 0 = otherwise	0.46	
Livestock ownership	1 = Owns livestock, 0 = otherwise	0.70	
Mineral fertiliser	Low raters	1 = (<100kg/acre), 0 = otherwise	0.25
	Moderators	1 = (100–150kg/acre), 0 = otherwise	0.67
	Higher raters	1 = (>150kg/acre), 0 = otherwise	0.08
Landholding	Dummy: 0 = (<=5 acres), 1 = (>5 acres)	0.29	
Land tenure	Dummy: 1 = farmer has the land title, 0 otherwise	0.60	
Bunkpurugu zone0	Dummy: 1 = yes, 0 = otherwise	0.22	
Langbinsi zone1	Dummy: 1 = yes, 0 = otherwise	0.26	
Garu West zone2	Dummy: 1 = yes, 0 = otherwise	0.21	
Garu East zone3	Dummy: 1 = yes, 0 = otherwise	0.31	

Note: Risk attitude was obtained by re-coding the willingness to take risk self-scores of [Dohmen et al. \(2005\)](#) into three categories: risk-averse, risk-neutral and risk-takers.

with an eigenvalue of 4.1 that explained 76 % of the total variance in the data. The next factor had an eigenvalue of 0.82, but with only one significant loading. The proportion of total variance explained by the first factor was about five times that of the subsequent factor, showing a sharp break between them (see [Appendices B and C](#)). This implied that the trait represented by the first factor was the only latent variable and approximated a Rasch unidimensional construct in the data ([Linacre, 2009](#); [Slocum-Gori and Zumbo, 2011](#); [Hasmy, 2014](#)).

4. Results and discussion

This section outlines the calibrated Rasch scale results (CML descriptive Rasch model), and then presents and discusses a comparison of the explanatory model results with the random-effect descriptive Rasch model. Each of these is given in a separate sub-section below.

4.1. Rasch measurement model and fit indexes

The initial model fitted by either the marginal maximum likelihood (MML) or conditional maximum likelihood (CML) estimates showed that four practices (3, 6, 9, and 15) out of 20 listed in the instrument did not fit the Rasch measurement model. Their fit indexes indicated either that they did not contribute to their attitude (9 and 15) or that farmers misunderstood the statements eliciting the response for those practices during the survey. Thus, such items were considered to be distractors ([Linacre, 2009](#)) and were consequently removed to improve the calibrated scale. Another four practices showed insignificant difficulty estimates even though they did fit the scale well. [Table 3](#) shows the CML difficulty (δ) estimates and fit indexes of the 16 practices retained by the scale, while [Figure 2](#) shows the scale of farmers' *Infit* and *Outfit* indexes.

A likelihood ratio test ($\chi^2 = 27.76$, $DF = 22$, $p = 0.213$) of fit comparing the primary Rasch model with a unidimensional two-parameter model rejected the assumption that the two-parameter model fits better than the primary model. This affirmed the U-test statistics for individual practices, all of which were within the expected range of ± 1.99 (-1.52 to 1.65), confirming the Rasch model assumption that no OFP significantly discriminates between farmers' attitude levels

more than others. The study then assessed practices for differential item functioning (DIF) across farmer characteristic groups using the logistic regression test ([Kleinman and Teresi, 2016](#)). No practice showed significant DIF across gender groups. Practice 10 (**PaveAnimalPen**) exhibited significant DIF between farmers in zone 1 and the rest, while practice 17 (**Human-Excreta**) showed significant DIF for farmers in zone 2. Practice 7 (**UseTransport**) functioned differently across off-farm work participation groups, while practice 20 (**DecomposeB4**) exhibited DIF across organic fertiliser policy beneficiary groups. To the extent that these characteristics influence attitudes, the observed patterns of the practices will vary among farmers, making the scale's basic assumption that farmers and practices are locally independent unrealistic ([Briggs, 2008](#)). [Figure 3](#) depicts a map of farmers' practices, showing attitude level (score) distribution and difficulty level grouping of the practices (OFPs) on the calibrated logit scale.

4.2. Explanatory Rasch (latent regression) model results

In order to establish a basis on which to adjust attitudes for the effects of background factors, a random parameter logistic Rasch model (Descriptive mixed Logit-DML) was fitted before the hybrid explanatory mixed logit (EML) model ([Rijmen et al., 2003](#); [Briggs, 2008](#)). [Table 4](#) presents the DML estimates in the second main column, while those of the EML are shown in the last main column. The results showed that the order of practices by their difficulty (δ) remained the same in all models. The practice *spread and plough organic fertiliser into the soil* was the least difficult organic fertiliser practice (behaviour), while *source organic soil fertiliser from a waste disposal agent* was the most difficult practice for the farmers. After adjusting by the mean effect (-1.03 logits) of farmers' characteristics, the EML model gave the narrowest net range of difficulty estimates (-1.01 to 2.36) between the lower end of the CML and the upper end of DML model estimates. The EML also gave smaller standard errors, a closer confidence interval and the overall best model fit, thus providing the most precise parameter estimates. These results suggest that the CML Rasch model tended to underestimate the difficulty of practices compared with the hybrid model, while the unconditional mixed-logistic model (the DML) overestimated it. This finding is in agreement with that

Table 2. Description and summary of organic fertiliser practices in the attitude instrument.

Organic fertiliser practice		Description of practice	% sample
No	Label		
1	CommuSource	Secure manure/compost from community kraal/refuse dump	58
2	CropResidue	Use of crop residues for compost or ploughing it into the soil	40
3*	AgroByProduct	Use of agro by-products as an organic fertiliser	46
4	ArrangLifstock	Arrangement with larger livestock farmers to obtain manure	36
5	TravKilometers	Travel several kilometres to transport organic matter or manure	24
6*	MobliNeighbour	Mobilise neighbours and friends to help apply organic fertiliser	48
7	UseTransport	Own/hire tricycle/donkey cart to transport organic fertiliser or materials	35
8	ExtenalResidue	Collect crop residues from external sources for composting	26
9*	Org_MinCombin	Apply both organic and mineral fertilisers	98
10	PaveAnimalPen	Pave/litter the floor of animal pen to enhance manure collection	35
11	HireLabour	Have/hire labour to collect and apply organic fertiliser	28
12	MicrodosMin	Apply micro-dose of mineral fertilisers to crops on the organic plot	42
13	Spread&Plough	Spread and plough organic fertiliser into the soil	62
14	Apply_B4plant	Incorporate organic fertiliser into the soil weeks before planting	24
15*	HeapComposting	Prepare compost by the heap method	89
16	ZaiPitMethod	Apply organic fertiliser by the Zai pit method	26
17	Human-Excreta	Use of human waste as organic fertiliser	20
18	PitComposting	Prepare compost in a constructed pit	17
19	DisposalAgent	Source organic fertiliser from a waste disposal agent	12
20	DecomposeB4	Decompose all organic matter (biomass) before application	61

Note: Dichotomous answers (yes or no) measured responses to all items. * indicates an item that did not fit the Rasch scale and was therefore removed from the final scale calibration.

Table 3. Difficulty (δ) estimates of practices by descriptive Rasch measurement model.

OFP		Difficulty (δ)	S E	R_{1C} Test Statistic	df	p-value	Standardised		U-tests
No.	Label						Outfit	Infit	
13	Spread&Plough	-2.01***	0.23	0.14	2	0.93	0.75	0.24	0.39
20	DecomposeB4	-1.94***	0.23	4.77	2	0.09	1.89	2.64	1.65
1	CommuSource	-1.73***	0.22	1.90	2	0.39	-0.67	-0.05	0.01
12	MicrodosMin	-0.85***	0.22	0.43	2	0.81	0.5	0.2	-0.08
2	CropResidue	-0.73***	0.22	1.35	2	0.51	-1.19	-1.41	-0.83
4	ArrangLifstock	-0.57***	0.22	0.84	2	0.66	-0.08	0.26	0.52
10	PaveAnimalPen	-0.48***	0.23	5.88	2	0.05	1.39	0.12	0.08
7	UseTransport	-0.45**	0.23	9.56	2	0.01	0.63	1.37	1.64
11	HireLabour	0	fixed	0.96	2	0.62	0.38	1.28	0.93
8	ExtentalResidue	0.08	0.23	0.77	2	0.68	-0.43	0.48	-0.12
16	ZaiPitMethod	0.11	0.23	0.72	2	0.70	-0.59	-0.23	-0.15
5	TravKilometers	0.22	0.24	0.14	2	0.93	1.12	0.47	-0.16
14	Apply_B4plant	0.25	0.24	1.10	2	0.58	-1.01	-0.9	-0.67
17	Human-Excreta	0.52***	0.24	6.10	2	0.05	-1.87	-1.57	-1.27
18	PitComposting	0.79***	0.25	1.61	2	0.46	-1.78	-1.72	-1.52
19	DisposalAgent	1.36***	0.27	1.89	2	0.39	-1.16	-1.75	0.42
R1c test: (data fit)		R1c = $\chi^2(44.7)$		df = 30	p-value 0.3413				
Andersen LR test: (invariance)		Z = $\chi^2(49.2)$		df = 30	p-value 0.0150				

The null hypothesis (H_0) for R_{1C} tests: the difficulty of every practice is locally independent of attitude level.

, * denote significance at 5 % and 1 % respectively. δ for HireLabour is set at zero for identification.

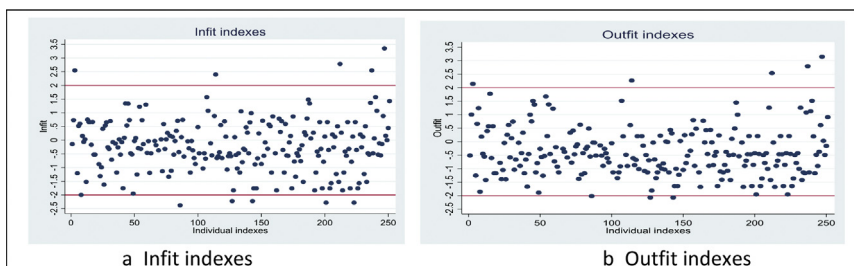


Figure 2. Farmers' (a) infit and (b) outfit indexes for the Rasch measurement model.

of Rijmen et al. (2003) and Briggs (2008) that if the trait being measured follows a mixture of distributions along farmer characteristic groupings, the estimates obtained by CML are inconsistent. Therefore, the OFP rankings based on the EML model estimates are presented and discussed here.

4.3. OFP difficulty and farmer attitude measures

The difficulty estimates in Table 4 (under Adjusted δ) showed only three relatively easy (negative difficulty) organic practices for

the sampled farmers. These were *spread and plough organic fertiliser into the soil, decompose organic matter before using it as organic fertiliser, and source manure/compost from local community refuse dump/kraals*. These organic fertiliser practices had an uptake probability of 0.5 or more by farmers with just below average attitude levels, implying that average and above-average level farmers can easily apply such OFPs. The remaining 13 practices were on the difficulty side of the scale, but also fell into three distinct difficulty groups: “slightly difficult”, “difficult” and “very difficult.” Practices such as *apply organic fertiliser with micro-doses of mineral fertiliser, use crop residues,*

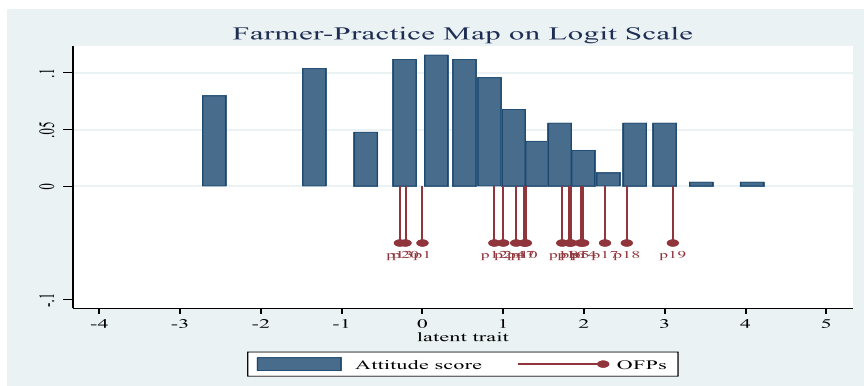


Figure 3. Farmer-Practice on the Rasch scale.

Table 4. Generalised linear and latent mixed model estimates of DML and EML Rasch models.

Code	Practice	DML Rasch model			EML Rasch (latent regression) model			Adj. (δ)
		Est. (δ)	Error	p> z	Est. (δ)	Error	p> z	
13	Spread&Plough	-0.72***	0.16	0.000	-2.01***	0.13	0.000	-1.01
20	DecomposeB4	-0.65***	0.16	0.000	-1.94***	0.13	0.000	-0.94
1	CommuSource	-0.45***	0.16	0.017	-1.73***	0.13	0.007	-0.73
12	MicrodosMin	0.43***	0.16	0.008	-0.81***	0.13	0.012	0.19
2	CropResidue	0.54***	0.16	0.001	-0.70***	0.13	0.001	0.30
4	ArrangLifstock	0.70***	0.16	0.000	-0.53***	0.13	0.000	0.47
10	PaveAnimalPen	0.80***	0.17	0.000	-0.44***	0.13	0.000	0.56
7	UseTrasport	0.82***	0.17	0.000	-0.41***	0.13	0.000	0.59
11	HireLabour	1.27***	0.18	0.000	0.04**	0.02	0.017	1.04
8	ExtenalResidue	1.36***	0.18	0.000	0.12**	0.06	0.015	1.12
16	ZaiPitMethod	1.38***	0.18	0.000	0.15***	0.07	0.000	1.15
5	TravKilometers	1.50***	0.18	0.000	0.26**	0.11	0.016	1.26
14	Apply_B4plant	1.53***	0.18	0.000	0.29***	0.15	0.000	1.29
17	Human-Excreta	1.80***	0.19	0.000	0.55***	0.16	0.000	1.55
18	PitComposting	2.07***	0.20	0.000	0.81***	0.17	0.000	1.81
19	DisposalAgent	2.64***	0.23	0.000	1.36***	0.20	0.000	2.36
Latent attitude (θ) regression								
Farmer characteristics					Coeff. (β)	Std. err.	Adjusted β	
Gender						0.15	-0.021	
AgeGroup2					-0.011	0.11	-0.009	
AgeGroup3					-0.208	0.16	-0.166	
PrimaryEdu					0.077	0.14	0.061	
ScoundaryEdu					0.331*	0.17	0.264	
TertiaryEdu					0.371**	0.16	0.296	
HHLabforce					-0.024	0.03	-0.019	
Non-Farm Work					-0.178	0.14	-0.142	
Risk-neutral					-0.213	0.24	-0.140	
Risk-takers					-0.931***	0.10	-0.743	
OrgeExp_Categ2					-0.076	0.16	-0.061	
OrgeExp_Categ3					-0.442**	0.18	-0.353	
PolicyBenefit					0.772***	0.16	0.616	
ExtenContact					0.493***	0.18	0.393	
LivestockOwn					0.236***	0.04	0.188	
MinFertClas2					0.091	0.16	0.073	
MinFertClas3					0.135	0.12	0.108	
CartEquipt					0.220*	0.12	0.176	
Landholding					-0.270***	0.10	-0.215	
LandTenure					0.306**	0.14	0.244	
AccessTraining					0.525***	0.13	0.419	
Langbinsi Zone1					0.407**	0.16	0.325	
Garu West Zone2					0.282*	0.16	0.225	
Garu East Zone3					0.211	0.15	0.168	
Const.		1.439***	0.07		-0.363***	0.07	-0.290	
Variance (θ)		1.57***	0.21		0.132***	0.05		
Reliability		0.89			0.92			
$\left(1 - \frac{\sigma_p^2}{var(\theta)}\right)$								
Log-likelihood		-2057.98				-1883.11		
IC	AIC	4149.12				3842.22		
	BIC	4256.51				4081.39		
Observations		4000				4000		
LR test: DML nested in EML-Latent regression $\chi^2(23) = 359.91, Prob > \chi^2 = 0.0000.$								

***p < 0.01, **p < 0.05, *p < 0.1. FG membership correlated strongly (0.95) with policy benefit and hence was dropped. **Note: AgeGroup1, No Education, risk-averse, Organic Exp_Categ1, minfertCategory1 and Bunkprugu Zone0** were left out as base categories (for reference) and to avoid dummy variable trap. σ_p^2 is the calculated variance of the predicted farmer θ levels.

arrange with livestock farmers to obtain manure, pave or litter the floor of the animal pen to enhance manure collection, and hire a tricycle/donkey

cart for transporting organic fertiliser/materials constituted the “slightly difficult” group.

Similarly, *have/hire labour for collection and application of organic fertiliser, collect crop residues from other places after harvesting for compost, apply organic fertiliser using the Zai pit method, travel several kilometres to transport organic matter/manure for use and incorporate organic fertiliser into soil weeks before planting* are in the “difficult” group of practices. The “very difficult” OFP group included *in-pit preparation of compost, use human waste as organic fertiliser and source organic fertiliser from waste disposal agent*. These are practices for which even farmers with the strongest attitude in the sample required external support with their adoption.

The location of farmers (θ values) on the attitudes scale ranged from a low of $\theta = -3.8$ to a high of $\theta = 1.6$ logits with the mean $\theta = -0.93$ logits (Figure 4). Seventy percent of the farmers had attitude estimates below zero, with about three quarters of them having less than the negative sample mean attitude level. Thus, based on the three attitude classes tested in the scale, the groups were labelled as “very weak”, “weak” and “moderate”. Given the mean difficulty (0.69 logits) of practices, an average sample farmer attitude level was about 1.62 logits less than that required to have a 0.5 probability of engaging in a slightly difficult practice such as *hiring a vehicle to transport organic fertiliser*. Farmers with the strongest attitude ($\theta = 1.6$ logits) could overcome ($\theta > \delta$) the difficulties of 11 practices, meaning that five practices had difficulty levels beyond any sample farmer's attitude strength. This indicated a generally weak tendency among farmers to perform these practices.

4.4. Determinants of organic fertiliser attitudes

The lower part of Table 4, under the EML model, shows the results of latent attitude regression on farmer background factors. For purposes of interpretation, the logit coefficients (*Coeff. (β)*) were divided by the standard deviation of EAPs derived from the DML model to obtain effect size (in z-scores) coefficients under *Adjusted β* . The relationship between attitudes and farmer characteristics is thus discussed using the z-score standardised coefficients.

Gender, age and primary education relative to no education had no significant relationship with a variation in farmers' attitudes to OFPs. However, farmers who had a secondary and tertiary education were +0.26 and +0.30 z-scores, respectively, away from the average farmer attitude level. This result is in line with the findings of Kassie et al. (2015) that farmers appreciate the need to use organic fertiliser when they fully understand the nexus between soil health and organic practices. Farmers who have attained high educational levels are more predisposed to use organic fertiliser than those with a low level of education because the information needed to facilitate understanding and make them inclined to use organic fertiliser is better accessed by the more highly educated. Farmers who have benefited from soil management policies are about 0.62 z-scores more inclined to engage in organic fertiliser practices than

the average sample farmer. This is not surprising because these programmes have given them the knowledge, skills and physical resources that predispose them to use the input.

Surprisingly, household labour force and off-farm work had no significant relationship with farmers' attitudes. This was contrary to expectations, given the common assertions that organic fertilisers are naturally bulky and require a considerable amount of human effort to gather, transport and apply (Zingore et al., 2007).

Risk-takers tended (-0.74 z-scores) to be less inclined to adopt organic fertiliser practices than risk-averse farmers. For the more risk-averse, the local availability of organic fertiliser and its proven conservational benefits could motivate them to become more reliant on it (Vanlauwe, 2015). In contrast, risk-takers may invest both time and money in accessing mineral fertilisers for the cropping season (Duflo et al., 2011), and thus may have a lower tendency to use organic fertiliser. Another surprising and unexpected finding was that farmers who applied organic fertiliser consecutively for more than five seasons were (-0.35 z-scores) less inclined to apply organic fertiliser than those with three or fewer seasons of application. One possible explanation for this is that farmers become less inclined to use the input as soil accumulates significant amounts of organic matter. They may also identify and rely on one or more less difficult but effective OFPs as they gain experience.

Livestock ownership positively covaried with farmers' organic attitudes. Livestock owners have access to manure, which they use even if they have enough mineral fertilisers (Kassie et al., 2015). The total arable land that a farmer possesses is another resource characteristic that negatively covaried with farmer attitudes. Farmers with total arable land exceeding five acres had a z-score attitude 0.215 lower than the average sample farmer. This finding is in agreement with that of Holden (2014) that land scarcity and the consequent need to intensify production influence farmers to use organic fertiliser. Land-constrained farmers tend to use organic fertiliser more than those who are not. Farmers who hold the title to their farmland also tend to implement OFPs more (+0.24 z-scores) than those who use communal or rented plots. This result is unsurprising since it has been well established in the literature (e.g., Abdulai and Huffmann, 2014; Kousar and Abdulai, 2016) that farmers invest in medium to long-term soil improvement when they are sure of personally reaping the benefits. Participation in soil management training programmes has a positive impact on farmers' attitudes. Farmers who have participated in such training had a tendency of 0.42 z-scores more to apply OFPs than those who did not.

Finally, for locations relative to the Bunkpurugu area (reference zone), farmers in Langbinsi and Garu-Tempene areas were more inclined to use OFPs. However, farmers in the Binduri area had no significant attitude difference from the reference zone farmers. The observed differences here could be attributed to environmental factors, access to opportunities for training, and soil management support programmes.

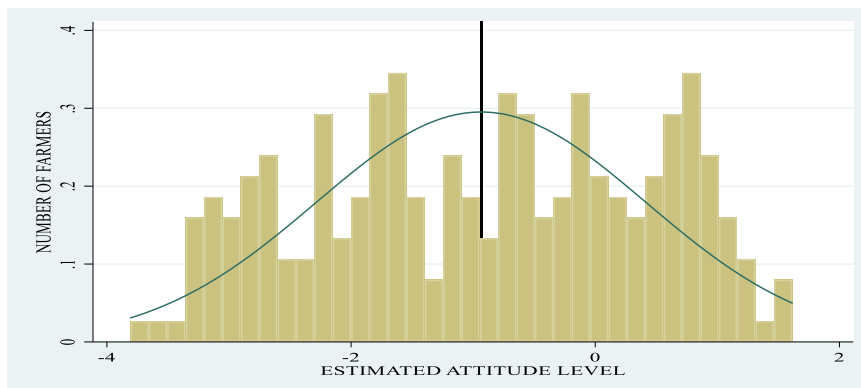


Figure 4. Expected a posteriori (EAP) attitude scores of farmers.

5. Conclusions and recommendations

The objectives of this study were: 1) to assess the behavioural costs (difficulty) of organic fertiliser practices and the attitude of smallholder farmers to organic fertiliser use in northern Ghana, and 2) to identify farmer background factors driving their attitude to using the input. Adopting the behavioural cost approach, the explanatory (latent regression) Rasch model was used to control for impacts of farmers' characteristics on the scale and thus explain their attitude levels.

Conditional difficulty estimates for practices showed a moderate range of behavioural costs against a dispersed but generally weak farmer attitude distribution on the scale. The farmers-practices map revealed that an average farmer attitude could overcome the difficulty levels in just three of the 16 practices, even though the practices in general have a moderate level of difficulty.

When attitudes were allowed to follow a mixture of normal distributions along farmer characteristic groups in a random parameter model, the OFPs maintained their difficulty rankings and intervals, but shifted right towards a higher difficulty range on the scale. The spread of attitude estimates on the scale also reduced from both the lower and upper limits. Nevertheless, a large part (75 %) of the distribution remained on the negative side of the scale. These findings combined suggest that farmers' failure to use organic fertiliser as expected is attributable more to weak farmer attitudes to the input than the difficulty of the practices involved.

Farmers' attitudes to organic fertiliser co-varied with some influential socioeconomic and environmental background factors. Background factors such as education beyond primary school, access to organic fertiliser policies and soil management training build farmers' capacity by equipping them with the knowledge and skills required for organic fertiliser use. Ownership of physical resources, such as farmland and carting equipment, as well as the farmers' physical location relative to the area of Bunkpurugu were all related to strong attitudes to organic fertiliser use. However, background factors, such as farmers' risk-seeking behaviour, farmland size and the number of farm seasons that organic fertilisers have been applied were related to weak farmer attitudes. However, such a negative relationship, particularly between attitude and organic fertiliser experience, was surprising and unexpected and requires further investigation to establish the practical reasons behind it and potential implications.

Based on the farmers' current disposition, a farmer capacity-building policy will be required to accelerate the uptake of "slightly difficult" OFPs to scale up organic fertiliser adoption among average farmers. Such policies may focus on social and human resource capacity deficits, specifically relating to practices such as *apply organic fertiliser with micro-doses of mineral fertiliser, use crop residues, arrange with larger livestock farmers to obtain manure, pave or litter animal pen to enhance manure collection and have/hire transport to convey organic fertiliser/materials*. Training and information delivery through extension services should aim to provide the knowledge and skills that are particularly relevant to these organic practices, especially to farmers in the Bunkpurugu, Langbensi and Garu-East zones. Furthermore, care should be taken to include less educated and socially disadvantaged conservative farmers in such capacity-building programmes.

For intensification purposes, a policy should consider reducing the difficulty of practices such as *deploy enough labour to collect and apply organic fertiliser, collect additional crop residues from places other than their farm, use the Zai pit method of applying organic fertiliser, transport organic matter from several kilometres away and incorporate organic fertiliser into the soil weeks before planting*. These practices currently appear "difficult" to farmers, apparently because of the major hindrance of the financial costs of labour and capital services. A specific intervention helping farmers to own animal-drawn equipment will give them control over the financial cost of the practices and rapidly improve attitudes to their adoption.

The challenges associated with the three most difficult practices (*source organic fertiliser from waste management companies, prepare compost in specially constructed pits, use decomposed excreta as organic fertiliser*) will require strategic management. A policy could support the most inclined farmers to help intensify organic fertiliser use and be nucleus farmers, assisting others. For example, supply chain relationships could be established between individual farmers and waste management companies, using farmers with prior experience as coordinators. Generally, the agricultural extension department should work more towards farmers' sensitisation to realise the need to apply organic fertiliser even when they have access to adequate mineral fertilisers.

Finally, there are some shortcomings in this study that should be noted if its findings are to be used to determine policy or subsequent studies. The predictability of farmers' behaviour using conclusions from this study is limited to short-term and spatial dimensions. The findings did not capture changes in farmers' attitudes or variations in OFP behavioural costs over time because of the cross-sectional nature of the data used. Furthermore, the farmer-practice map showed some behavioural cost gaps between practices, indicating that a few more OFPs may be required within the instrument to cover the entire domain of attitudes to organic fertiliser. Nevertheless, some of the OFPs that could fill such gaps did not fit the attitude scale, probably because farmers misunderstood the survey questions presented to them. Further studies are needed to examine the ability of such practices to contribute to the attitude scale on organic fertiliser use.

Declarations

Author contribution statement

Daadi, Bunbom Edward: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Wrote the paper.

Latacz-Lohmann, Uweb: Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

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Data availability statement

Data will be made available on request.

Declaration of interests statement

The authors declare no conflict of interest.

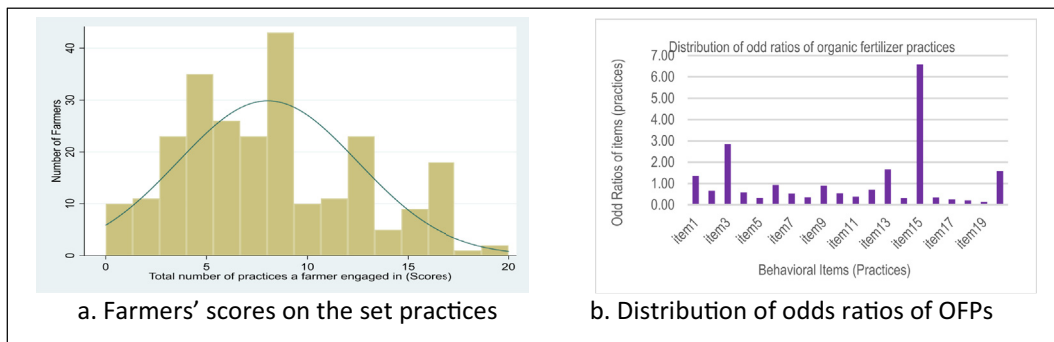
Additional information

No additional information is available for this paper.

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Appendices.

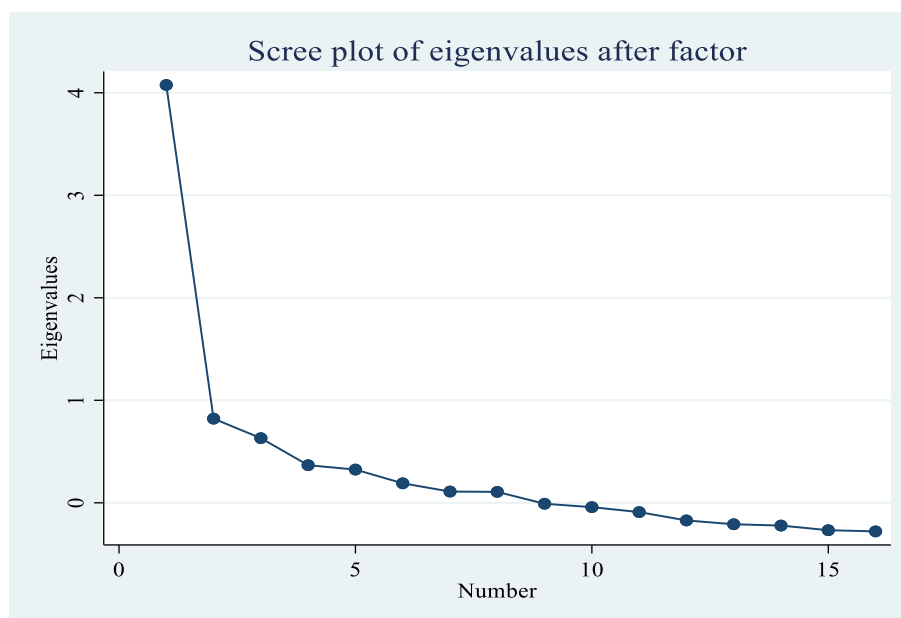


Appendix A. Distribution of farmers' scores and the odds ratios of practices.

Appendix B. Initial output from factor analysis of OFPs to determine attitude dimension.

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	4.07616	3.25517	0.7642	0.7642
Factor2	0.82098	0.19036	0.1539	0.9181
Factor3	0.63062	0.26369	0.1182	1.0364
Factor4	0.36693	0.04282	0.0688	1.1052
Factor5	0.32411	0.13395	0.0608	1.1659
Factor6	0.19016	0.08028	0.0357	1.2016
Factor7	0.10988	0.00329	0.0206	1.2222
Factor8	0.10659	0.11596	0.0200	1.2422
Factor9	-0.00937	0.03293	-0.0018	1.2404
Factor10	-0.04230	0.04829	-0.0079	1.2325
Factor11	-0.09059	0.08130	-0.0170	1.2155
Factor12	-0.17189	0.03729	-0.0322	1.1833
Factor13	-0.20919	0.01297	-0.0392	1.1441
Factor14	-0.22215	0.04512	-0.0417	1.1024
Factor15	-0.26727	0.01165	-0.0501	1.0523
Factor16	-0.27891	.	-0.0523	1

LR test: independent vs. saturated: $\chi^2(120) = 1020.23$ Prob > $\chi^2 = 0.0000$.



Appendix C. Scree plot of eigenvalues after extracted factors.

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