Scotland's Rural College

Using a typology to understand farmers' intentions towards following a nutrient management plan

Daxini, AD; Ryan, Mary; O'Donoghue, Cathal; Barnes, AP; Buckley, Cathal

Published in:
Resources, Conservation and Recycling

DOI:
10.1016/j.resconrec.2019.03.027

Print publication: 01/07/2019

Document Version
Peer reviewed version

Citation for pulished version (APA):
Daxini, AD., Ryan, M., O'Donoghue, C., Barnes, AP., & Buckley, C. (2019). Using a typology to understand farmers' intentions towards following a nutrient management plan. *Resources, Conservation and Recycling*, *146*, 280-290. https://doi.org/10.1016/j.resconrec.2019.03.027

Using a typology to understand farmers' intentions towards following a nutrient management plan

Amar Daxini [1,2,3]*, Mary Ryan[1], Cathal O'Donoghue[4], Andrew P. Barnes[2], Cathal Buckley[1]

[1] Teagasc Rural Economy and Development Programme, Mellows Campus, Athenry, Co. Galway, Ireland.

[2] Scotland's Rural College (SRUC), King's Buildings, Edinburgh, Scotland.

[3] University of Edinburgh, School of Geo-Sciences, King's Buildings, Edinburgh, Scotland.

[4] NUIG Policy Lab, National University of Ireland, Galway, Ireland.

*Corresponding Author. Email: Amar.Daxini@sruc.ac.uk. Scotland's Rural College (SRUC), West mains Road, King's Buildings, Edinburgh, EH9 3JG.

The authors are grateful for funding provided by a joint stewardship between the Teagasc Walsh Fellowship Programme and SRUC, the HARMONY project for part funding the survey and support from the SFI BEACON project.

There are no competing interests between the authors.

Abstract

Optimising resource use efficiency is high on many national policy agendas. Inappropriate management in agricultural production can result in increased risk of nutrient loss to the environment. Best practice in nutrient management can help to mitigate this. However, policy initiatives aimed at encouraging farmers to follow a nutrient management plan (NMP) appear to be limited in their success. We employ a typology to classify farms/farmers based on a number of policy relevant farm and farmer characteristics. The theory of planned behaviour is applied to understand the variables which influence farmers' intentions to follow a NMP across the Republic of Ireland. The typology resulted in a total of three classes of farmers, namely 'traditional', 'supplementary income' and 'business-orientated'. The findings from the regression analysis reveal that attitude towards the outcomes of following a NMP is a weak predictor of intentions whereas subjective norm (social pressure) and perceived behavioural control (ease/difficulty) are strong predictors of intentions across the classes. Furthermore, contact with agricultural extension (a combination of one-to-one and group based extension) is found to be critical in determining the intentions of both traditional and supplementary income classes of farmers. The results also indicate that policy, which requires certain farmers in Ireland to develop a NMP on a mandatory basis, has consistent but mixed levels of influence on intentions. Initiatives designed to further encourage farmers to follow a NMP must account for the diversity that exists among the farming population and how different groups of farmers may respond to such initiatives.

Key words: Nutrient management plan, Farmer decision making, Theory of planned behaviour, Intentions, Latent class analysis

1. Introduction

Farmers often receive mixed political messages concerning their use of resources. On the one hand they are told to reduce their use of inputs whereas on the other they are encouraged to intensify food production to meet growing demand (FAO, 2017; Yoshida *et al.,* 2018). To address this conflicting demand, farmers are increasingly being encouraged to improve the efficiency of agricultural input use (Buckley and Carney, 2013; McGlynn *et al.,* 2018). One important area of attention is improving the efficiency of organic and chemical fertiliser use on farms (Sutton *et al.,* 2011; Buckwell and Nadeu, 2016; McGlynn *et al.,* 2018). Such substances, whilst vitally important to crop production, remain significant sources of diffuse pollution to water and air (Montemurro and Diacono, 2016; Rohila *et al.,* 2017). In the European Union, nutrient inputs are regulated under the Nitrates Directive (ND) (European Comission, 1991). However, there is a growing interest in moving away from traditional command and control methods towards encouraging voluntary adoption by stimulating individual responsibility for the maintenance of normative standards (Barnes *et al.,* 2013a; Peth *et al.,* 2018). Moreover, due to limited financial resources, policy makers are keen to understand how best to improve their use of differential targeting of resources, in order to ensure maximum adoption of recommended practices (Blackstock *et al.,* 2010; Walder and Kantelhardt, 2018).

Best practice in the area of nutrient management has received increasing interest from policy makers due to the ability of associated practices to deliver both financial and environmental benefits (Sutton *et al.,* 2013; McGlynn *et al.,* 2018). Nutrient management is a set of "specialized activities dealing with all nutrient sources and transformations within a defined system so as to achieve both economic and environmental targets" (Oenema and Pietrzak, 2002: 160). One important and widely recommended practice for achieving more efficient management of nutrients is following a nutrient management plan (NMP) (Beegle *et al.,* 2000; Easton *et al.,* 2017; Ulrich-Schad *et al.,* 2017). Research has suggested that following a NMP is essential for ensuring that fertiliser (chemical and organic) is applied in line with crop requirements (Roberts *et al.,* 2017). This results in better targeting of nutrient applications to crops with a reduced risk of loss of excess nutrients to the environment (Thomas *et al.,* 2007; Schulte *et al.,* 2009; Amon-Armah *et al.,* 2013). Despite proven universal benefits and extensive promotion, the number of farmers that follow a NMP remains limited globally (Buckley *et al.,* 2015; Osmond *et al.,* 2015; Ulrich-Schad *et al.,* 2017; Brown *et al.,* 2019).

A limited number of studies have sought to reveal variables which influence farmers to develop a NMP. These variables often include farm and farmer characteristics and, to a lesser extent, socio-psychological issues (e.g. attitudes and social pressure). Development of a NMP has been found to be positively and significantly associated with farm size (Ribaudo and Johansson, 2007; Lawley *et al.,* 2009; Ulrich-Schad *et al.,* 2017), number of animals (Lawley *et al.,* 2009), intensity of production (Savage and Ribaudo, 2013; Brown *et al.,* 2019), income (Ribaudo and Johansson, 2007), education (Savage and Ribaudo, 2013) and contact with agricultural extension (e.g. advisor, workshops and demonstration meetings) (Genskow, 2012; Ulrich-Schad *et al.,* 2017). Whereas, age and off-farm employment have been found to reduce the likelihood of a farmer developing an NMP (Buckley *et al.,* 2015). Farmers with more a positive attitude towards the adoption of various nutrient management practices (e.g. soil testing and conservation tillage) tend to have higher adoption rates (Flett *et al.,* 2004; Reimer *et al.,* 2012a). Similarly, farmers with a positive attitude towards the environment, and or those with a greater level of environmental awareness, have been found to have a greater likelihood of developing an NMP (Reimer *et al.,* 2012b; Buckley *et al.,* 2015). A number of studies have also found that farmers who perceive a higher level of social pressure from fellow farmers or other food chain actors are more likely to develop a NMP (Welch and Marc-Aurele, 2001; Ribaudo and Johansson, 2007; Yoshida *et al.,* 2018). Finally, farmers' perceptions of their ability to adopt several nutrient management practices, including fertiliser application timing and method, have also been found to constrain adoption (Zhang *et al.*, 2016; Wilson *et al.,* 2018).

Despite providing important insights into farmer decision making, previous studies have three primary limitations. Firstly, studies typically focus on the development of a NMP and therefore typically fail to explicitly consider farmers' intentions towards following a NMP, which is required if full benefits are to be achieved (Ulrich-Schad *et al.,* 2017). Secondly, although common across the adoption literature more widely (Adnan *et al.,* 2017; Floress *et al.*, 2017), previous studies in relation to the development of a NMP typically fail to consider socio-psychological variables. Those that do, often apply qualitative methods (e.g. McGuire *et al.,* 2013; Yoshida *et al.,* 2018) and therefore results from such studies are difficult to generalise. Finally, a number of previous studies which examine the development of NMPs have been found to treat farmers as a homogenous group (e.g. shared motivations and constraints). This is too strong an assumption if policy makers are to be provided with information that will help them to understand how different segments of a farming population might respond to proposed interventions (Hammond *et al.,* 2017).

We address the limitations of previous research in this paper in a number of ways. Firstly, we examine farmers' intentions to follow a NMP rather than solely focusing on the development of a NMP. Secondly, we incorporate socio-psychological variables into our analysis using the Theory of Planned Behaviour (TPB) (Ajzen, 1991). Thirdly, a typology is generated in order to account for heterogeneity among the sample of farmers. Such typologies have been useful for increasing the relevance of recommendations for farm improvement and the provision of extension services (Chikowo *et al.*, 2014; Kamau *et al.*, 2018), as well as better targeting of policy initiatives (Emtage *et al.,* 2007; Walder and Kantelhardt, 2018).

In this article, we aim to explain farmers' intentions towards following a NMP using Irish farm survey data. Specifically we address whether there are differences in the drivers of intentions to follow a NMP between groups of farmers. Ultimately, we use this information to provide policy makers with insights into farmer behaviour that can be used to better target initiatives designed to further encourage farmers to follow a NMP.

The Republic of Ireland (henceforth, Ireland) provides a suitable context to study farmers' intentions towards following a NMP for a number of reasons. First, agricultural area accounts for around 70% of the total land area, thus covering a range of climatic conditions and soil types (CSO, 2016). Second, the structure of Irish agriculture is diverse in terms of farm and farmer characteristics, which provides an opportunity for classifying farmers (CSO, 2016). Third, Irish food policy (DAFF, 2010; DAFM, 2015) reflects the global focus on increasing food production whilst ensuring that such increases do not lead to a greater risk of nutrient discharge from agricultural sources to water and to air (Buckwell and Nadeu, 2016; FAO, 2017). Finally, similar to elsewhere (Osmond *et al.,* 2015; Ulrich-Schad *et al.,* 2017; Brown *et al.,* 2019), the number of farmers who follow a NMP remain limited and it is unclear as to the best method(s) for increasing the number of farmers who follow a NMP in the future (Buckley *et al.,* 2015).

2. Nutrient management plans

NMPs are management tools that divide farms into management units (usually fields or sub-field plots/paddocks). NMPs can be simple or complex; they can be written with a paper and pencil or developed using a computer (Beegle *et al.,* 2000). The fundamental principle underpinning NMPs is the allocation of nutrients in a way that maximises the economic benefit of the nutrients, while minimising the risk of nutrient loss to water courses and the air (Genskow, 2012). Agricultural advisors often play a key role in the development of NMP due to the technical nature of the information required (Lawley *et al.*, 2009). Without developing a NMP, the risk of over or under applying nutrients to fields can increase (Shepard, 2005; Roberts *et al.,* 2017). Moreover, the benefits of following a NMP include increased yields and efficiency of input use (Shepard, 2005; Thomas *et al.,* 2007; Schulte *et al.,* 2009).

Whilst farmers may choose to voluntarily develop a NMP, typically to aid production decisions, others may be required to develop one on a mandatory basis due to policy requirements (Beegle *et al.,* 2000; Ketterings *et al.,* 2017). As manifested in an Irish context, the Nitrates Directive (ND) mandates farmers to develop a NMP as a condition of a permit (derogation) to operate above and beyond the regulatory limits on livestock density (McDonald *et al.,* 2019). Furthermore, farmers are also required to develop a NMP if they participate in the main national agri-environment scheme (GLAS: Green Low Carbon Agri-environmental Scheme) (Image, 2016). However, whilst policy makers can enforce farmers to develop a NMP and penalise those farmers who have not developed a NMP, monitoring whether farmers follow the NMP is difficult and hard to regulate (Perez, 2015). Therefore, policy makers are keen to understand what motivates farmers not only to develop a NMP but also to follow it (Tao *et al.,* 2016; Ulrich-Schad *et al.*, 2017).

3. Theoretical framework

Socio-psychological models of behaviour take into account the variety of beliefs that individuals hold and how these beliefs and cognitive processes influence decision making (Burton, 2004). One widely applied model to understand how salient beliefs may promote or restrict adoption of certain practices within the agricultural domain is the Theory of Planned Behaviour (TPB) (Ajzen, 1991). According to the TPB, human behaviour is driven by the intention to accomplish the behaviour in question. For the purpose of this study we examine the intention of farmers to follow a NMP in the near future.

Intention is in turn determined by an individual’s attitude, subjective norm and perceived behavioural control (Ajzen, 1991). In line with the TPB, attitude can be defined as an individual’s positive or negative evaluation of the outcomes of performing the behaviour. Subjective norm is the level of social pressure or approval an individual perceives to be exerted on them to engage in a particular behaviour. Finally, perceived behavioural control relates to whether an individual feels that s/he is capable of carrying out the behaviour, which is also connected to the presence of factors that may promote or hinder the performance of the behaviour. In general, the more favourable the attitude, the higher the level of social pressure and perception of control, the stronger the intention will be to perform the given behaviour (Ajzen, 1991).

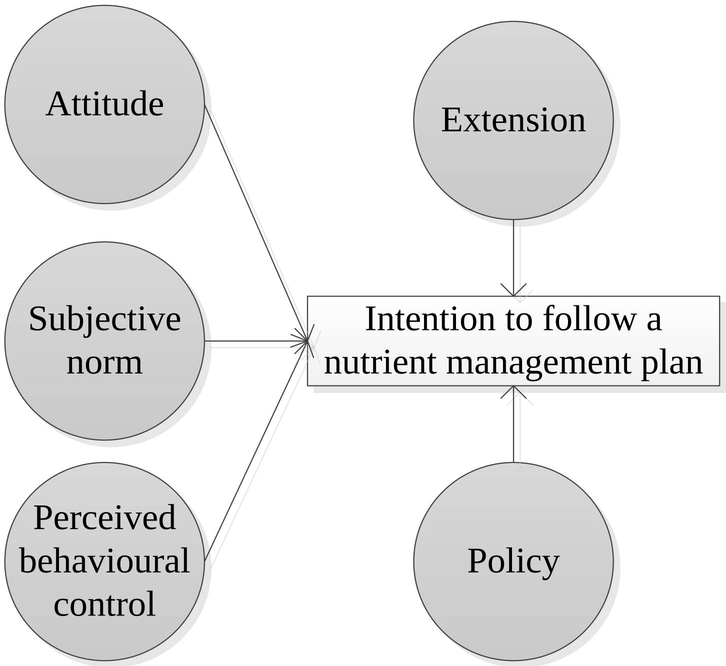
The TPB has been used to explain farmers’ intentions towards agricultural practices in a variety of contexts. Both Wauters *et al.* (2010) and Rezaei *et al.* (2018), found attitude towards the practice to be the most important variable determining farmers’ intentions towards the use of soil conservation in Belgium and on-farm food safety practices in Iran. Whereas, Läpple and Kelley (2013) and Borges and Oude Lansink (2016) found subjective norm to be the most important variable to be positively associated with farmers’ intentions to convert to organic farming in Ireland and to adopt improved grassland management in Brazil. Elsewhere, perceived behavioural control was found to be an important positive predictor of farmers’ intentions to reuse agricultural biomass in China (Jiang *et al.*, 2018) and to apply fertiliser on the basis of soil test results in Ireland (Daxini *et al.*, 2018). The mixed results for TPB variables are expected, as the relative importance of the influences typically vary across behaviours and situations (Ajzen, 1991).

Despite these successful applications of the TPB, various researchers have argued for the inclusion of other context specific variables (Yazdanpanah and Forouzani, 2015; Martinovska Stojcheska *et al.*, 2016). Ajzen (1991) suggests that if additional predictors can help to increase the predictive utility of the TPB then they can be included. We use a number of background variables (e.g. farm size, system and education) to create our typology (see section 4); however, we hypothesise that two context specific variables will directly influence farmers' intentions to follow a NMP. This approach is similar to other TPB research within the agricultural domain, which focus on examining the direct relationships (as opposed to indirect relationships) between additional background variables and intentions (e.g. Areal *et al.*, 2012; Micha *et al.*, 2015; Daxini *et al.*, 2018; Wang *et al.*, 2018).

Figure 1 presents the final theoretical framework used for the purpose of this study. The first addition to the model includes a variable which is designed to capture the effect of agricultural extension on farmers' intentions. The role that extension services play in the promotion of agricultural management practices is well established (Kania *et al.*, 2014). Both individual and group based extension contact (also known as discussion groups - groups of farmers that meet frequently to discuss technical issues, share information and solve problems, facilitated by an agricultural advisor) have been shown to positively influence adoption of agricultural management practices (Baumgart-Getz *et al.*, 2012; Prager and Creaney, 2017). However, the differential impact of extension on farmer decision making between groups of farmers has not been explored to as great an extent. Therefore, it is important to capture the influence of extension services on farmers' intentions to follow a NMP.

The second addition to the model is a policy variable. Policy is an important driver of the development of NMPs, both in an Irish context (Image, 2016; McDonald *et al.*, 2019) but also more widely (Osmond *et al.*, 2015; Perez, 2015). Based on this, we also consider a variable which is designed to examine whether farmers who have developed a NMP due to mandatory policy requirements (see section 2) are more likely to follow the plan compared to those that are not subject to such requirements. Whilst a positive relationship may be intuitive, research has found that farmers who have developed a NMP do not always follow it (Buckley *et al.*, 2015; Osmond *et al.*, 2015), which has led some authors to conclude that adherence to plans is largely voluntary (Perez, 2015).

Figure 1: Theoretical framework based on the Theory of Planned Behaviour



4. Methodology

Survey design

In order to explain farmers' intentions towards following a NMP, data were collected using a cross-sectional survey. The survey comprised of three sections, with the first section containing questions on farm and farmer characteristics, which were used to generate a farmer typology. The second section collected information on farmer engagement with extension and policy, to be used as explanatory variables in the regression analysis. In the final section, participants were asked to evaluate a number of statements on a five-point Likert scale. These statements were designed to reveal their intentions, attitude, subjective norm and perceived behavioural control towards following a NMP.

In order to measure the TPB constructs, recommendations by Ajzen (1985) were followed and scales containing multiple statements were developed. Following suggestions from Ajzen (2002a) and Francis *et al.* (2004), the construction of these statements was based partly on information obtained from a series of interviews with farmers and agricultural advisors and partly on an in-depth literature review (e.g. Läpple and Kelley, 2013; Borges *et al.,* 2014; Yazdanpanah and Forouzani, 2015; Martinovska Stojcheska *et al.,* 2016). Survey respondents were asked to rank the statements on a five-point Likert scale from strongly disagree (1) to strongly agree (5). Five-point Likert scales have been used in previous TPB style agricultural research (e.g. Gorton *et al.*, 2008; Adnan *et al.*, 2017b; Morais *et al.*, 2018) and are deemed to be short enough to allow respondents to distinguish meaningfully between the response options (Hansson *et al.,* 2012). Examples of the statements used to measure attitude, subjective norm and perceived behavioural control are shown in Appendix 1.

Intention was measured using one statement on a five-point Likert scale. Respondents were asked to state their level of agreement with the statement "I intend to follow a NMP in the near future". In order to ensure that respondents had a consistent understanding of what a NMP was, survey recorders read out a definition, prior to farmers answering questions pertaining to this measure. Furthermore, in order to eliminate any potential problems with the survey such as timing, complexity and suitability, a pilot survey was conducted prior to administering the survey to the full sample. Feedback from the pilot resulted in a number of minor changes to the survey, which included a reduction in length, improvements in the wording of questions and a restructuring of the order of some of the questions.

The survey data were then collected through face-to-face interviews with farmers. Data collection began in December 2016 and was completed in April 2017. A survey company was hired to conduct the interviews with farmers. In all cases, the main decision maker on the farm participated in the interviews. A quota controlled sampling method was used to ensure that the sample was representative of Irish farms by the dominant farm systems (cattle, dairy, sheep and tillage) and sizes (hectares) (see Daxini *et al.*, 2018 for further detail). Here, tillage refers to a system which focuses on crop production. The quotas used were based on known population distribution figures in relation to specific farm types taken from the Irish Central Statistics Office (Hennessy & Moran, 2016). In order to acquire a representative sample of farmers, the survey company began by stratifying the sample by electoral divisions. At each sampling point, the interviewer followed a quota control scheme, based on the known quantity of farm types and population distribution statistics within each location (Howley *et al.*, 2015). Interviewers then visited residences that appeared to be a farm household (observing the surrounding landscape) and proceeded to interview farmers until they filled their quotas (Howley, 2013). The final sample consisted of 1009 farmers.

Principal Component Analysis (PCA)

The statements describing the TPB variables (attitude, subjective norm and perceived behavioural control) were condensed using principal component analysis (PCA) which was rotated using the varimax method to form a reduced number of interpretable variables (Howley *et al.,* 2015). PCA helps to determine the statements underlying the TPB variables with a similar structure, reduce complexity and prevent any issues associated with multicollinearity (Hair *et al.*, 2010; Chinedu *et al.*, 2018). The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was 0.94 which suggests suitability of the data for PCA (Kaiser, 1974). The Bartlett's test of sphericity is significant at the $p = 0.0000$ level which leads us to accept the alternative hypothesis that a significant relationship among the variables exists (Field, 2009). Predicated on the eigen values, we keep three components where component loadings are above 0.30. The choice about the quantity of relevant statements loaded on each component is led by theory and interpretation of the components (Hair *et al.*, 2010). The final components are also assessed for internal consistency and reliability using the Cronbach's Alpha (Nunnally, 1978). The results of the Cronbach's Alpha are all above 0.88 where a value of 0.60 is considered as acceptable (Jolliffe, 2002). The statements that successfully produced the TPB variables are shown in Appendix 1. These derived variables can then be used as independent variables to explain farmers' intentions to follow a NMP.

Latent class analysis (LCA)

A common approach used to quantify unobserved heterogeneity that exists among a population is a latent class analysis (LCA) (Schreiber, 2017). LCA is a model-based approach to defining the underlying structure of the data, in order to predict the probability that each observation belongs to a particular class (Hair *et al.*, 2010). The central assumption of the latent class model is that different and distinct classes of farmers exist and that respondents in each class share homogenous characteristics, but characteristics of respondents differ between classes (Zhang *et al.*, 2016). The optimal number of discrete classes and the class to which a farmer belongs are determined by the data, such as the characteristics of the farm and farmer. LCA is based on robust estimation algorithms for choosing the correct number of classes among a population for a given criteria of characteristics and therefore, unlike cluster analysis, the choice of cluster criteria are less arbitrary (Morey *et al.,* 2008; Rhead *et al.,* 2018).

For latent classes to be generated, a number of 'classifying variables' must be chosen on which to assess heterogeneity (Dean and Raftery, 2010). Variables that have been highlighted as important attributes of heterogeneity include the characteristics of the farm and the farm operator (Knowler and Bradshaw, 2007; Valbuena *et al.,* 2008; Daloğlu *et al.,* 2014). Therefore, the psychological decision making process may vary between groups of farmers based on such characteristics. Thus, based on the literature outlined above (see section 1), the final set of classifying variables used in the LCA is shown in Table 1. It is important to note that different farm systems typically generate varying levels of income per hectare. For example, dairy farms in Ireland on average generate a higher income rate per hectare due to higher returns from the market (Dillon *et al.,* 2018). The inclusion of the 'total income' variable, used as part of the classification process in the LCA, is important in accounting for this issue in our model.

Table 1: Description of variables used to classify farmers

Variable	Description
Drainage	Perception of average land drainage on farm (1 = well drained, 0 = poorly drained)
Farm system	Main system of farming (1 = Cattle, 2 = Dairy, 3 = Sheep, 4 = Tillage)
Total income from farming per annum (€)	Farm income (1 = 4,000–9,999, 2 = 10,000–19,999, 3 = 20,000–29,999, 4 = 30,000–39,999, 5 = 40,000–49,999, 6 = 50,000–59,999, 7 = 60,000 and over, 7 = refused)
Farm size (ha)	Farm size (1 = < 20, 2 = 20–30, 3 = 31–50 , 4 = 51–100, 5 = 101+)
Farmer age (years)	Age of farm operator (1 = under 35, 2 = 35–44, 3 = 45–50, 4 = 51–64, 5 = 65+)
Off-farm job	Farm operator has an off-farm job (1 = yes, 0 = no)
Education	Highest level of formal education received by farm operator (1 = some secondary and above, 0 = otherwise)

To test for potential multicollinearity between the chosen classifying variables, Variance of Inflation (VIF) values were computed. The maximum VIF was 1.2, suggesting that multicollinearity is not an issue between the classifying variables (Hair *et al.,* 2010). In fact, some correlation amongst the classifying variables should be expected as no correlation would suggest there is no latent structure within the data, on which to classify farmers (Higgins *et al.,* 2016).

The final stage involved in the generation of latent classes is the identification of the optimal number of classes. An exploratory approach was used and a number of statistical information criteria were evaluated to judge the best model fit (Barnes *et al.,* 2013b). The number of classes retained is based on examining the log-likelihood (LL), Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC), with smaller values indicating better fit (Nylund *et al.,* 2007). Entropy values (from 0 to 1 = perfect fit), which are a measure of correctly classifying individuals and goodness of class separation, are also examined (Ulbricht *et al.,* 2018). Table 2 illustrates the results for the fit statistics of the latent classes, which are estimated from one to five classes. From a statistical point of view, the addition of the fourth and fifth classes results in only a marginal improvement of the LL. The AIC is minimised at a four class solution whereas the BIC is minimised at a three class solution. The BIC is recommended over the AIC when larger sample sizes are under consideration (Forster, 2000; Nylund *et al.,* 2007). The AIC has also been reported to often overestimate the number of classes (Nylund *et al.,* 2007). Entropy is the highest for the three class model. Based on these criteria, we deem the three class solution to be the best model fit.

Table 2: Fit statistics for the latent classes

Number of classes extracted	LL	AIC	BIC	Entropy
1	-8403.37	16862.74	17000.41	NA
2	-8006.93	16127.86	16408.11	0.73
3	-7822.10	15816.20	16239.04	0.77
4	-7763.11	15756.23	16321.65	0.74
5	-7739.41	15756.82	16440.25	0.73

Notes: LL = Log-likelihood, AIC = Akaike Information Criteria, BIC = Bayesian Information Criteria.

Latent class binary logistic regression

During the generation of latent classes we set farmers' intentions to follow a NMP as the dependent variable. This enables us to assess which of the hypothesised explanatory variables influence farmers' intentions to follow a NMP for each class (Figure 1). Table 3 provides a description of the variables used in the latent class binary logistic regression. The effects of the explanatory variables on intentions are estimated at the same time as the latent classes are generated, i.e., with the membership of class probabilities. This approach does not change class membership probabilities and therefore is deemed as more statistically advantageous, as it allows for the removal of estimation bias from the two-step approach (Vermunt, 2010).

Table 3: Description of the variables used in the latent class regression

Variable	Description
Dependent variable	
Intention	Intention to follow a NMP (1 = yes, 0 = no)
Explanatory variables	
TPB	
Attitude	PCA result
Subjective norm	PCA result
Perceived behavioural control	PCA result
Additional variables	
Extension contact	Level of extension contact by farm operator (0 = zero contact, 1 = contact with an agricultural advisor only, 2 = one-to-one contact with an agricultural advisor and contact with a discussion group)
Policy	Farm operator participates in the Irish GLAS agri-environmental scheme and/or receives a permit (derogation) to farm above the restrictions imposed by the ND (1 = yes, 0 = otherwise)

Ordered regression estimation methods are frequently applied to explain ordinal outcomes. As mentioned previously, intention is measured on a five-point Likert scale from strongly disagree to strongly agree. However, such models require the proportional odds assumption to be met (Hair *et al.,* 2010). If this assumption is violated, then the scale used to measure intention may be collapsed to form a binary outcome variable and a latent class binary logistic regression employed. Due to the limited number of responses in the strongly disagree and disagree categories, for the purpose of this study we group together the farmers who respond “strongly disagree”, “disagree” and “unsure” and label this group as “no intention” (0) with the remaining farmers being classified as “intenders” (1).

To test for potential multicollinearity between the independent variables, a separate binary logistic regression model was run for the full sample (n=1009) with intention to follow a NMP set as the dependent variable. Here, the TPB, extension contact and policy variables were inserted as independent variables. VIF values were then assessed. The maximum VIF value was 2.01, which is below the cut-off point of 10 (Hair *et al.*, 2010). This suggests that multicollinearity was not an issue in our analysis.

The results of the regression analysis are also shown as marginal effects. A larger marginal effect represents a greater influence of the independent variable on the dependent variable (Hair *et al.*, 2010). In terms of calculation, the marginal effects for the binary variables are measured as the discrete change from 0 to 1, holding all other variables constant. Whereas for continuous variables, the marginal effects are interpreted as the instantaneous rate of change in the probability of the outcome, caused by a one unit change in the independent variable (Hair *et al.*, 2010).

5. Results

Farm and farmer characteristics

The ensuing descriptive statistics represent the entire sample of farmers surveyed (n=1009). Based on the quotas, around 50% of the sample consists of cattle farms whereas dairy comprises 26%, with sheep at 17% and tillage consisting of 6% of the total. In terms of farm size, the median is 31-50ha whereas for farmer age, the grouping 51-64 is found to be the median. These figures correspond with national averages (CSO, 2018). In terms of education, just over half of the sample has an education above secondary level whereas 30% have an off-farm job. In relation to extension contact, 39% of farmers are in contact with just an agricultural advisor whereas only 29% are in one-to-one contact with an agricultural advisor and participate in a discussion group. In total, 47% of farmers report that they have a NMP. In relation to policy, 42% of farmers in our sample are either part of GLAS and/or have been granted a derogation to farm above the limits imposed by the ND (see section 2). In Ireland, approximately 40% of the farming population is required to develop a NMP on a mandatory basis due to GLAS/derogation requirements (Image, 2016; DAFM, 2018) and therefore our sample reflects the national situation.

Description of latent classes

The LCA produced three classes of farmers. The first latent class is estimated to have a class membership probability of around 33%, this means that about 33% of the sample is estimated to be in this class. The estimated class membership probability for Class 2 is approximately 38% and around 29% for Class 3. Table 4 provides descriptive statistics for the classes in terms of the unobserved variables used to classify farmers. Chi-square statistics show that all variables are statistically different across the three classes. Statistical differences are also computed between classes in order to interpret classes based on what is typical for a particular class compared to other classes. We draw on suggestions made by Daloğlu *et al.* (2014) to further interpret and label our classes.

Table 4: Percentage response probabilities by class (rows, by variable, sum to 100%[1])

		Full sample	Class 1	Class 2	Class 3	Chi-square
Classification variables		%	%	%	%	p-value
Drainage	Well drained	75	68[a]	69[a]	86	***
	Poorly drained	25	32[a]	31[a]	14	-
Farm system	Cattle	51	70[a]	68[a]	22	***
	Dairy	26	5[a]	5[a]	60	***
	Sheep	17	22[a]	24[a]	6	***
	Tillage[3]	6	3[a]	3[a]	12	***
Total income from farming per annum (€)	4,000–9,999	15	27[a]	21[a]	0	***
	10,000–19,999	16	26[a]	21[a]	3	***
	20,000–29,999	13	16[a]	18[a]	7	***
	30,000–39,999	10	6	11[a]	12[a]	**
	40,000–49,999	7	1	4	13	***
	50,000–59,999	4	0[a]	1[a]	10	***
	60,000 and over	7	0[a]	0[a]	17	***
	Refused	28	23[a]	23[a]	37	***
Farm size (ha)	Under 20	19	35	26	0	***
	20–30	22	29[a]	33[a]	8	***
	31–50	29	28	32	27	***
	51–100	22	7[a]	8[a]	45	***
	101 and over	8	1[a]	1[a]	19	***
Farmer age (years)	Under 35	7	0	12[a]	10[a]	***
	35–44	13	1	23	15	***
	45–50	15	1	22[a]	21[a]	***
	51–64	38	32	43[a]	39[a]	*
	65 and over	27	66	0	14	***
Off-farm job	Yes	30	21	65	11	***
	No	70	79	25	89	-
Education	Above secondary level	54	7	88	70	***

	Secondary level or below	46	93	11	30	-

Notes: [1]Due to rounding the probabilities do not always sum to 100. [2]Calculated between Class 1, Class 2 and Class 3. [3]A system a system which focuses on crop production. Where two classes share a superscript this means there is no significant difference (as per chi-square test) between the classes in terms of the particular variable. *** p<0.01, ** p<0.05, * p<0.1.

Class 1: Traditional farmers (33%)

Farms and farmers in Class 1 have characteristics that are typically related to low likelihood of following a NMP. This class is dominated by cattle (70%) and sheep (22%) farm systems, which tend to be farmed less intensively in Ireland (Dillon *et al.*, 2017). Around 68% of farmers in this class perceive their land to be well drained. A large proportion of farms (53%) earn under €19,999 a year and a substantial number of farms (64%) are under 30 ha. A large proportion of farmers in this class are over 65 years of age (66%). Education levels among this class are low with only 7% having attained an education beyond secondary level. Finally, a relatively small proportion (21%) of farmers in Class 1 has an off-farm job. In summary, Class 1 is defined by older, less educated farmers, managing small holdings consisting predominantly of cattle and sheep systems on a full time basis, generating low incomes. Based on these characteristics we call Class 1, 'traditional farmers'.

Class 2: Supplementary income farmers (29%)

The characteristics of farms and farmers in Class 2 are related to a low to medium likelihood of following a NMP. Similar to Class 1, Class 2 also contains a large proportion of cattle (68%) and sheep farms (24%). In terms of perceptions of land drainage, 69% of farmers in this class perceive their land to be well drained. A significant numbers of farms earn a low income with 42% earning under €19,999 a year. In terms of farm size, 59% of farms in this class are below 30 ha. In relation to farmer age, a significant proportion of farmers are under the age of 44 (35%) with significantly high levels of off-farm employment (65%) and formal education above secondary level (88%). Overall, this class is defined by cattle and sheep farms with low to middle level incomes and farm sizes. Such farms are operated on a part time basis, by relatively younger farmers, who are highly educated. This leads us to define Class 2 as 'supplementary income farmers'.

Class 3: Business-oriented farmers (38%)

Class 3 presents a structure that is usually associated with a high probability of following a NMP. A defining feature of Class 3 is its significantly higher proportion of dairy (60%) and tillage (12%) farm systems, compared to the other classes. Such farm systems tend to operate more intensively in Ireland compared to cattle and sheep enterprises (Dillon *et al.*, 2017). In total, 86% of farmers perceive their land to be well drained. Only a small proportion (3%) of farmers in this class earn an income of below €19,999 a year and only 8% of farms are below 30ha in size. In terms of farmer age, the majority (60%) are middle aged (45 to 64) and few have an off farm job (11%). Education levels above secondary level are fairly high (70%). To summarise the key features of Class 3, this class is dominated by full time farmers, earning high incomes from operating dairy and tillage systems on relatively productive agricultural land. Predicated on the dominant characteristics of Class 3, we term this class 'business-oriented farmers'.

Intentions to follow a NMP

In terms of the dependent variable, intentions to follow a NMP (Table 5), 61% of traditional farmers stated a positive intention whereas 66% of supplementary income farmers and 67% of business-oriented farmers indicated a positive intention. Business-oriented farmers have a significantly higher level of intention compared to traditional farmers (x^2= 4.63, p = 0.03). No other significant differences are detected. Interestingly, it appears that regardless of class, the level of intention to follow a NMP is relatively similar. This result appears to contradict typical findings across the literature, which suggest that certain farm and farmer characteristics (as discussed in the introduction) should be associated with differential probabilities of following a NMP. However, as discussed in Section 6 in more detail below, this study focuses on intentions to follow a NMP rather than the development of a NMP and therefore this result is not counterintuitive.

Table 5: Percentage response probabilities[a] by class (rows, by variable, sum to 100%)

		Full sample	Traditional farmers	Supplementary income farmers	Business-orientated farmers	Chi-square[1]
Dependent variable		%	%	%	%	
Intention	Yes	65	61[a]	66[ab]	67[b]	*
	No	35	39	34	33	

Notes: Where two classes share a superscript this means there is no significant difference (as per chi-square test) between the classes in terms of the particular variable. [1]Calculated between traditional farmers, supplementary income farmers and business-orientated farmers.*p<0.1.

Latent class binary logistic regression analysis: Traditional farmers

In relation to the variables which influence farmers' intentions, Table 6 shows that for traditional farmers', intentions are influenced significantly and in a positive direction by attitude (5% level), subjective norm (1% level), perceived behavioural control (1% level), extension contact 2 (5% level) and policy (5% level). All of the significant variables also have significant marginal effects (Table 7). As the level of the psychological variables (attitude, subjective norm and perceived behavioural control) increase by one unit, the probability of a farmer following a NMP increases by 3.0%, 7.6% and 4.6% respectively. In terms of the additional variables, farmers with high levels of extension contact (i.e. extension contact 2) and those who participate in policy are around 20% and 10% respectively, more likely to have a positive intention towards following a NMP.

Latent class binary logistic regression analysis: Supplementary income farmers

Table 6 also illustrates the results for supplementary income farmers. Intentions are influenced significantly and in a positive direction by the psychological variables subjective norm (1% level) and perceived behavioural control (1% level), however attitude fails to reach statistical significance. Extension contact 2 and the policy variable are also positively associated with intentions at the 5% and 1% levels respectively. In terms of marginal effects (Table 7), the variables subjective norm and perceived behavioural control increase the probability of a farmer following a NMP by 8.2% and 4.6% respectively. Extension contact 2 and policy both significantly increase the probability of having a positive intention by 19%.

Latent class binary logistic regression analysis: Business-orientated farmers

For business-orientated farmers, intentions are positively and significantly correlated with three variables (Table 6). These include subjective norm (1% level), perceived behavioural control (1% level) and policy (1% level). All of the significant variables also have significant marginal effects (Table 7). However, in addition, attitude also becomes significant at the 10% level. The estimated marginal effects show that attitude, subjective norm and perceived behavioural control increase the likelihood of a farmer following a NMP by 2.4%, 7.3% and 9.5% respectively. Being subject to mandatory policy requirements increases the probability of a farmer displaying a positive intention to follow a NMP by 9.4%.

Table 6: Results of the latent class logistic regression (coefficients)

	Traditional farmers		Supplementary income farmers		Business-orientated farmers	
Explanatory variables	Coeff.	Std.err	Coeff.	Std.err	Coeff.	Std.err
TPB						
Attitude	0.23**	0.09	-0.02	0.11	0.27	0.19
Subjective norm	0.59***	0.12	0.66***	0.16	0.82***	0.18
Perceived behavioural control	0.36***	0.12	0.37***	0.14	1.06***	0.36
Additional variables						
Extension contact 1[a]	0.16	0.35	0.54	0.47	-0.31	0.45
Extension contact 2[a]	1.55**	0.62	1.46**	0.60	0.08	0.54
Policy	0.81**	0.37	1.54***	0.46	1.10***	0.40
Cons	-0.64	0.26	-0.77	0.34	1.16	0.45

Notes: *** p<0.01, ** p<0.05, * p<0.1. [a]Reference category: no extension contact.

Table 7: Results of the latent class logistic regression (marginal effects)

	Traditional farmers		Supplementary income farmers		Business-orientated farmers	
Explanatory variables	Marginal effect	Std.err	Marginal effect	Std.err	Marginal effect	Std.err
TPB						
Attitude	0.0297***	0.0113	-0.0247	0.0137	0.024*	0.0141
Subjective norm	0.0762***	0.0144	0.0816***	0.0170	0.0730***	0.0125
Perceived behavioural control	0.0461 ***	0.0149	0.0458***	0.0157	0.0947***	0.0183
Additional variables						
Extension contact 1[a]	0.0233	0.0531	0.0776	0.0672	-0.0276	0.0400
Extension contact 2[a]	0.2042***	0.0760	0.1898**	0.0763	0.0068	0.0463
Policy	0.1043**	0.0452	0.1923**	0.0588	0.0939**	0.0383

Notes: *** p<0.01, ** p<0.05, * p<0.1. [a]Reference category: no extension contact.

6. Discussion

Efforts to encourage farmers to follow a NMP have been less than successful globally (Osmond *et al.,* 2015; Brown *et al.,* 2019) and in Ireland (Buckley *et al.,* 2015). This study addresses the limitations of previous studies by utilising a unique approach based on combining the TPB with a LCA in order to explain farmers' intentions towards following a NMP. The typology reveals that there are three discrete classes of farms/farmers and thus confirms that farm and farmer characteristics are a useful way to categorise the farming population and account for heterogeneity (Emtage *et al.,* 2007; Daloğlu *et al.,* 2014). Whilst the results reveal that intentions are somewhat similar across classes of farmers, the reasons why farmers intend to follow a NMP vary by class. This suggests that dissimilar groups of farmers are likely to respond in different ways to the same intervention designed to further encourage them to follow a NMP. These diverse reactions must be taken into account when designing policy interventions aimed at further encouraging farmers to follow a NMP (Emtage *et al.,* 2007; Guillem *et al.,* 2012).

According to previous studies (Ribaudo and Johansson, 2007; Prokopy *et al.*, 2008; Ulrich-Schad *et al.*, 2017), business-orientated farmers display characteristics that should be associated with a higher propensity towards following a NMP than traditional and supplementary income classes. One reason for the relatively similar level of intention across the classes may pertain to the 'optimism bias', which suggests that people often overestimate their goals (Weinstein, 1980; Sharot, 2011). Alternatively, the survey data collected were 'self-reported' which often results in individuals responding to questions in a 'socially desirable' way that paints them in a positive light (Floress *et al.*, 2018). However, it is important to note that behavioural intention is an antecedent of behaviour but not a flawless predictor of it (Fishbein and Ajzen, 2010). Thus, farmers may indeed have a positive intention, but due to barriers associated with, for instance, personal ability to follow a NMP, they are unable to act on their positive intentions.

In line with previous studies (Reimer *et al.*, 2012a; Borges *et al.*, 2014; Adnan *et al.*, 2018), traditional and business-orientated farmers who have a positive attitude towards following a NMP are more likely to do so than their counterparts. For the majority of these classes of farmers, farming is their main occupation and therefore they are highly reliant on income generated from farm production. Thus, such farmers are generally attentive to financial concerns, yield and profitability (Daloğlu *et al.*, 2014). Our measure of attitude focuses mainly on the production benefits of following a NMP, which may explain why attitude is an important determinant of the intentions of these classes of farmers. Pannell *et al.* (2006) put forward the argument that farmers will adopt a management practice if s/he perceives that the innovation in question will enable them to achieve their personal goals. In line with others, our result implies that it is important to consider how the underlying motivation for farming varies between groups and how this potentially influences intentions towards following a NMP (Buckley *et al.*, 2015).

Interestingly, the influence of attitude towards following a NMP on intentions is relatively weak compared to previous findings (Burton, 2004; Garforth *et al.*, 2006; Reimer *et al.*, 2012a; Rezaei *et al.*, 2018). Wauters *et al.* (2010) found that attitude was the most important determinant of farmers' intentions in relation to soil conservation practices in Belgium. However, they also concluded that farmers in their study perceived it to be easy to adopt the practices in question. One possible reason for the relatively low influence of attitude, compared to Wauters *et al.* (2010), may be due to the fact that following a NMP is relatively difficult compared to other farm management practices (Walters and Shrubsole, 2014). Developing and following a NMP requires the collection of site specific data (e.g. soil fertility levels and stocking rate) to be translated into nutrient application rates and potential changes to management routines (Beegle *et al.*, 2000; Walters and Shrubsole, 2014). This requires learnt skills and knowledge which farmers may not possess (Osmond *et al.*, 2015). Without such expertise or access to affordable advice, following a NMP becomes more difficult and thus the role of perceived behavioural control becomes more important relative to other variables, such as attitude towards following a NMP (Ajzen, 2002b).

Perceived behavioural control is an important predictor of farmers' intentions regardless of class. This means that farmers who perceive that they are able to and have the necessary knowledge to follow a NMP, are more likely to have an intention to do so (Ajzen, 2002b). This finding supports the results of both Zhang *et al.* (2016) and Wilson *et al.* (2018) who found perceptions of ability to be positively associated with farmers' intentions to adopt various nutrient management practices (e.g. fertiliser application timing and placement) in the US. These practices, like following a NMP, also require technical expertise to conduct and therefore issues of perceived behavioural control are important (Wilson *et al.* 2018). However, the marginal effect for perceived behavioural control is the largest for business-orientated farmers. This class is focused on high-value products (e.g. milk and arable crops), short-term returns from production and are less constrained by financial resources (Daloğlu *et al.,* 2014). Therefore, a lack of capability or confidence in following a NMP on their farm is likely to take a more prominent role as farmers become more concerned with the 'how' instead of the 'why' (Prochaska and Velicer, 1997).

The significant influence of subjective norm on intentions across the classes concurs with the studies of Läpple and Kelley (2013) and Borges and Oude Lansink (2016). Both studies found subjective norm to be a highly important determinant of farmers' intentions to adopt farm management practices in Ireland and Brazil respectively. This result may be because farmers are increasingly subject to external social pressures from food chain actors and policy makers to adopt management practices that offer both environmental and financial benefits (Yoshida *et al.,* 2018). Furthermore, farmers are typically reliant on external support from consultants and agricultural advisors for making decisions associated with nutrient applications to fields/crops (Lawley *et al.,* 2009; Stuart *et al.,* 2018). Such actors may increase social pressure on farmers to follow a NMP and, due to this pressure, farmers may want to behave in a way that would be approved of by important referents (Martínez-García *et al.,* 2013).

The characteristics of the traditional (e.g. low income, small farm sizes, low levels of formal education) and supplementary income (e.g. low income, small farm sizes, high levels of off-farm employment) classes are typically associated with a low level of likelihood of following a NMP (Baumgart-Getz *et al.,* 2012; Savage and Ribaudo, 2013; Läpple *et al.,* 2015). However, the results indicate that traditional and supplementary income farmers who are in one-to-one contact with an agricultural advisor and participate in a discussion group are more likely to have an intention to follow a NMP than their counterparts. This may be because extension can enable farmers to understand the applicability of following a NMP on their particular farm system, dispel myths about the perceived costs of following a NMP and alleviate pressures associated with time constraints by assisting in the development of a NMP (Burton, 2014; Wilson *et al.,* 2018).

Policy is an important driver of intention to follow a NMP across all three classes. A number of authors have suggested that nutrient management policy initiatives can have a positive influence on the adoption of farm management practices because farmers will often undertake voluntary action as a means of demonstrating stewardship and protecting themselves from future policy (Savage and Ribaudo, 2013; Reimer *et al.,* 2018). However, the results in Table 7 show that the magnitude of the effect is the greatest for supplementary income farmers. Policy makers could capitalise on the fact that the majority of farmers in this class are highly educated and relatively younger than farmers in the other classes and design appropriate measures to improve the likelihood that farmers follow their NMP.

Overall, the mixed influence of policy on intentions confirms previous findings across the literature which suggest that different groups of farmers often respond in different ways to the same policy (Barnes *et al.* 2011; Buckley, 2012). Further research is required to explore potential reasons for the mixed effects in the context of following a NMP.

Increasing social pressure on farmers to follow a NMP is likely to increase the likelihood that they do so across the classes. Barnes *et al.* (2013) suggest increasing the use of catchment management approaches which raise the visibility of individual farmer practices and encourage group sharing of information. This can stimulate an increase in social pressure to adopt given practices. However, whilst there has been a growing emphasis on farmer-to-farmer learning in recent years (Prager and Creaney, 2017; Laforge and McLachlan, 2018), not all farmers will know, trust or even talk with one another and therefore careful targeting of behavioural change strategies is required (Blackstock *et al.*, 2010). Social pressure is often best leveraged by people that farmers trust and these may not be the same for traditional, supplementary income and business-orientated farmers (Blackstock *et al.*, 2010). Further research is required to establish the most effective ways of leveraging social pressure among different groups of farmers in a way that further encourages them to follow a NMP.

Ensuring that individuals understand the benefits of a given practice is an important aspect for inducing positive behavioural change (Wilson *et al.*, 2014). Based on the results, convincing farmers classified as traditional and business-orientated of the specific benefits of following a NMP on their particular farm, is likely to increase their intentions towards following a NMP. This effect is linked to an improvement in attitude towards this practice. Demonstration events are a popular and effective method for illustrating the benefits of adopting farm management practices (Prager and Creaney, 2017). However, in line with Wilson *et al.* (2018), we argue that greater opportunities should be presented at such events for farmers to engage in discussion about the costs and benefits of, in this case, following a NMP, and ways to better tailor NMPs to particular farming situations.

Motivational theories suggest that an individual is likely to act to solve a problem when they feel they have the ability to act on their values and motivations (Zhang *et al.*, 2016). The results suggest that improving farmers' level of perceived behavioural control over following a NMP is likely to have a positive influence on the likelihood of them following the plan in the future. In line with McDonald *et al.* (2019), we argue that increasing the level of engagement between agricultural advisors and farmers in terms of both developing and assisting farmers to follow a NMP may help to increase perceived levels of control across each class of farmers. However, targeting business-orientated farmers with an intervention to improve perceived behavioural control is likely to have a greater influence on their intentions to follow a NMP. This provides policy makers with a potentially cost-effective strategy for increasing the probability of farmers following a NMP among these classes of farmers.

The results also imply that an increase in effort to engage traditional and supplementary income classes of farmers with both one-to-one and group based agricultural extension should be made. This is because increased levels of engagement is likely to have a large impact on the likelihood of these classes of farmers following a NMP in the future (Micha *et al.*, 2018). Supplementary income farmers are also found to be highly receptive to mandatory policy. Therefore, efforts should be made to provide additional information alongside policy requirements to further stimulate farmers to follow their NMP. This information should be tailored to the characteristics of this group of farmers and explains, for instance, how to effectively follow a NMP on their type of farm (Osmond *et al.*, 2015).

Finally, a limitation of this study lies in the fact it does not test indirect relationships. Variables such as extension contact and policy, may have an indirect influence on intentions mediated via attitude, subjective norm and perceived behavioural control. One reason why indirect relationships are not considered is due to an issue with sample size once farmers are assigned to distinct groups. Nevertheless, as mentioned previously, this study adopts a similar approach to previous research which focuses on the direct relationships between additional variables and intentions.

7. Conclusion

NMPs offer a pathway for addressing dual policy interests which aim to encourage farmers to improve or increase production whilst also reducing the risk of nutrient loss to water and air. This paper extends the literature on the development of NMPs by specifically examining farmers' intentions towards following (rather than just developing) a NMP. Moreover, this study also accounts for heterogeneity among farmers and incorporating socio-psychological variables into the analysis. A key result emerging from this study relates to the diversity in the variables which influence the intentions of farmers across the classes. This diversity is likely to be due to the varying composition of the classes in terms of farm and farmer characteristics. This result suggests that we cannot assume that farmers with different characteristics who operate varying types of farms will always respond in the same way to initiatives designed to stimulate them to follow a NMP. Therefore, for policies to effectively encourage farmers to follow a NMP, it is important to target specific groups (Emtage *et al.*, 2007). Overall, the results from this study confirm that farmer typologies are critical for representing diversity in the variables which influence farmers' intentions to follow a NMP. Interventions that are carefully planned and targeted at the different classes of farms/farmers are likely to further encourage farmers to follow a NMP in the future.

Appendix 1

Principal components (PC) with loadings for farmers' intentions to follow a NMP (only statements that produced PCs are displayed).

	PC 1	PC 2	PC3
Survey question	Attitude	Perceived behavioural control	Subjective norm
Following a NMP increases production levels	0.36		
Following a NMP produces higher quality grass and/or crop	0.34		
Following a NMP improves profits	0.34		
Following a NMP decreases input costs	0.30		
Following a NMP saves time	0.31		
Following a NMP improves soil fertility levels	0.32		
Following a NMP improves knowledge about your fields	0.31		
Following a NMP makes fertiliser application decisions easier	0.31		
If I want to follow a NMP, I have a clear understanding of how to do so		0.35	
If I want to follow a NMP, I have access to sufficient information and/or sources to do so		0.33	
If I want to follow a NMP, I have confidence in my ability to do so		0.42	
If I want to follow a NMP, it is under my control to do so		0.48	
If I want to follow a NMP, it depends completely on me and not on the factors permitting or inhibiting me from doing so		0.45	
If I want to follow a NMP, it is easy to do so		0.36	
When it comes to following a NMP, most people whose opinion I value regarding farming think that I must do so			0.53
When it comes to following a NMP, most people whose opinion I value regarding farming encourage me to do so			0.53

When it comes to following a NMP, most people whose opinion I value regarding farming would agree with my decision to do so	0.49
Most farmers I am aware of follow a NMP	0.39

References

Adnan, N., Nordin, S.M., bin Abu Bakar, Z., 2017. Understanding and facilitating sustainable agricultural practice: A comprehensive analysis of adoption behaviour among Malaysian paddy farmers. L. Use Policy. 68, 372–382.

Ajzen, I., 1985. From intentions to actions: a theory of planned behaviour. In: Kuhl, J., Beckermann, J. (Eds.), Action Control: From Cognition to Behaviour. Springer, New York, pp. 11–39.

Ajzen, I., 1991. The theory of planned behavior. Orgnizational Behav. Hum. Decis. Process. 50, 179–211.

Ajzen, I., 2002a. Constructing a TPB questionnaire: Conceptual and methodological considerations. Available at: https://people.umass.edu/aizen/tpb.measurement.pdf. Last accessed: 16/11/18.

Ajzen, I., 2002b. Perceived behavioral control, self-efficacy, locus of control, and the theory of planned behavior. J. Appl. Soc. Psychol. 32, 665–683.

Amon-Armah, F., Yiridoe, E.K., Ahmad, N.H.M., Hebb, D., Jamieson, R., Burton, D., Madani, A., 2013. Effect of nutrient management planning on crop yield, nitrate leaching and sediment loading in thomas brook watershed. Environ. Manage. 52, 1177–1191.

Areal, F. J., Riesgo, L., Gómez-Barbero, M., Rodríguez-Cerezo, E., 2012. Consequences of a coexistence policy on the adoption of GMHT crops in the European Union. Food Policy. 37, 401–411.

Barnes, A.P., Willock, J., Toma, L., Hall, C., 2011. Utilising a farmer typology to understand farmer behaviour towards water quality management: Nitrate Vulnerable Zones in Scotland. J. Environ. Plan. Manag. 54, 477–494.

Barnes, A.P., Toma, L., Willock, J., Hall, C., 2013a. Comparing a “budge” to a “nudge”: Farmer responses to voluntary and compulsory compliance in a water quality management regime. J. Rural Stud. 32, 448–459.

Barnes, A.P., Islam, M.M., Toma, L., 2013b. Heterogeneity in climate change risk perception amongst dairy farmers: A latent class clustering analysis. Appl. Geogr. 41, 105–115.

Baumgart-Getz, A., Prokopy, L.S., Floress, K., 2012. Why farmers adopt best management practice in the United States: A meta-analysis of the adoption literature. J. Environ. Manag. 96, 17–25.

Beegle, D.B., Carton, O.T., Bailey, J.S., 2000. Nutrient management planning: Justification, theory, practice. J. Environ. Qual. 29, 72–79.

Blackstock, K.L., Ingram, J., Burton, R., Brown, K.M., Slee, B., 2010. Understanding and influencing behaviour change by farmers to improve water quality. Sci. Total Environ. 408, 5631–5638.

Borges, J.A.R., Oude Lansink, A.G.J.M., Marques Ribeiro, C., Lutke, V., 2014. Understanding farmers' intention to adopt improved natural grassland using the theory of planned behavior. Livest. Sci. 169, 163–174.

Borges, J.A.R., Oude Lansink, A.G.J.M., 2016. Identifying psychological factors that determine cattle farmers’ intention to use improved natural grassland. J. Environ. Psychol. 45, 89–96.

Bradley, C., Byrne, C., Craig, M., Free, G., Gallagher, T.1, Kennedy, B., Little, R., Lucey, J., Mannix, A., McCreesh, P., McDermott, G., McGarrigle, M., Ní Longphuirt, S., O'Boyle, S., Plant, C., Tierney, D., Trodd, W., Webster, P., Wilkes, R., Wynne, C., 2015. Water Quality in Ireland 2010 - 2012. Johnstone Castle, Wexford, Ireland.

Brown, P., Daigneault, A., Dawson, J., 2019. Age, values, farming objectives, past management decisions, and future intentions in New Zealand agriculture. J. Environ. Manage. 231, 110–120.

Buckley, C., 2012. Implementation of the EU Nitrates Directive in the Republic of Ireland - A view from the farm. Ecol. Econ. 78, 29–36.

Buckley, C., Howley, P., Jordan, P., 2015. The role of differing farming motivations on the adoption of nutrient management practices. Int. J. Agric. Manag. 4, 152–162.

Buckwell, A., Nadeu, E., 2016. Nutrient Recovery and Reuse (NRR) in European agriculture, RISE, Rural Investment Support for Europe. Brussels.

Burton, R.J.F., 2004. Reconceptualising the "behavioural approach" in agricultural studies: A socio-psychological perspective. J. Rural Stud. 20, 359–371.

Burton, R.J.F., 2014. The influence of farmer demographic characteristics on environmental behaviour: A review. J. Environ. Manage. 135, 19–26.

Chikowo, R., Zingore, S., Snapp, S., Johnston, A., 2014. Farm typologies, soil fertility variability and nutrient management in smallholder farming in Sub-Saharan Africa. Nutr. Cycl. Agroecosystems 100, 1–18.

Chinedu, O., Sanou, E., Tur-Cardona, J., Bartolini, F., Gheysen, G., Speelman, S., 2018. Farmers' valuation of transgenic biofortified sorghum for nutritional improvement in Burkina Faso: A latent class approach. Food Policy (in press).

CSO, 2016. Environmental Indicators Ireland 2016. Available at: https://www.cso.ie/en/releasesandpublications/ep/p-eii/eii2016/lu/. Last accessed: 17/03/19.

CSO, 2018. Farm strucutre survey 2016. Available at: https://www.cso.ie/en/releasesandpublications/ep/p-fss/farmstructuresurvey2016/. Last accessed: 17/03/19.

DAFF, 2010. Food Harvest 2020. A Vision for Irish Agri-food and Fisheries. Department of Agriculture Fisheries and Food, Dublin, Ireland.

DAFM, 2015. Food Wise 2025-A 10-year Vision for Irish Agri-food Industry. DAFM, Dublin, Ireland.

Daloğlu, I., Nassauer, J.I., Riolo, R.L., Scavia, D., 2014. Development of a farmer typology of agricultural conservation behavior in the american corn belt. Agric. Syst. 129, 93–102.

Daxini, A., O'Donoghue, C., Ryan, M., Barnes, A.P., Buckley, C., Daly, K., 2018. Which factors influence farmers' intentions to adopt nutrient management planning? J. Environ. Manage. 224, 350–360.

Dean, N., Raftery, A.E., 2010. Latent class analysis variable selection. Ann. Inst. Stat. Math. 62, 11–35.

Dillon, E., Moran, B., Donnellan, T., 2017. Teagasc National Farm Survey 2016. Teagasc Agricultural Economics and Farm Surveys Department, Athenry, Co Galway, Ireland.

Dillon, E., Moran, B., Lennon, J., Donnellan, T., 2018. Teagasc National Farm Survey Preliminary Results 2017. Athenry, Co. Galway, Ireland.

Emtage, N., Herbohn, J., Harrison, S., 2007. Landholder profiling and typologies for natural resource-management policy and program support: Potential and constraints. Environ. Manage. 40, 481–492.

EPA., 2016. Ireland's final greenhouse gas emissions in 2014. Available at: http://www.epa.ie/pubs/reports/air/airemissions/GHG_1990-2014_June%202016v1.pdf. Last accessed 9/2/19.

European Comission., 1991. Council directive 91/676/EEC of 12 December 1991 concerning the protection of waters against pollution caused by nitrates from agricultural sources.

FAO, 2017. The future of food and agriculture – Trends and challenges. Rome. Available at: http://www.fao.org/3/a-i6583e.pdf. Last accessed 9/2/19.

Field, A., 2009. Discovering statistics using SPSS. Sage Publications Limited, London.

Fishbein, M., Ajzen, I., 2010. Predicting and changing behavior: the reasoned action approach. Psychology Press, New York.

Floress, K., García de Jalón, S., Church, S.P., Babin, N., Ulrich-Schad, J.D., Prokopy, L.S., 2017. Toward a theory of farmer conservation attitudes: Dual interests and willingness to take action to protect water quality. J. Environ. Psychol. 53, 73–80.

Floress, K., Reimer, A., Thompson, A., Burbach, M., Knutson, C., Prokopy, L., Ribaudo, M., Ulrich-Schad, J., 2018. Measuring farmer conservation behaviors: Challenges and best practices. L. Use Policy 70, 414–418.

Forster, M.R., 2000. Key concepts in model selection: Performance and generalizability. J. Math. Psychol. 44, 205–231.

Francis, J. J., Eccles, M. P., Johnston, M., Walker, A., Grimshaw, J., Foy, R., Kanner, E. F. S., Smith, L., Bonetti, D., 2004. Constructing questionnaires based on the theory of planned behavior: A manual for health services researchers. Available at: http://openaccess.city.ac.uk/1735/1/TPB%20Manual%20FINAL%20May2004.pdf. Last accessed: 9/2/19.

Gedikoglu, H., McCann, L., Artz, G., 2011. Off-farm employment effects on adoption of nutrient management practices. Agric. Resour. Econ. Rev. 40, 293–306.

Genskow, K.D., 2012. Taking stock of voluntary nutrient management: Measuring and tracking change. J. Soil Water Conserv. 67, 51–58.

Gorton, M., Douarin, E., Davidova, S., Latruffe, L., 2008. Attitudes to agricultural policy and farming futures in the context of the 2003 CAP reform: A comparison of farmers in selected established and new Member States. J. Rural Stud. 24, 322–336.

Hair, J.F., Black, W.C., Babin, B.J., Anderson, R.E., Tatham, R.L., 2010. Multivariate Data Analysis. Prentice Hall, New Jersey.

Hammond, J., van Wijk, M.T., Smajgl, A., Ward, J., Pagella, T., Xu, J., Su, Y., Yi, Z., Harrison, R.D., 2017. Farm types and farmer motivations to adapt: Implications for design of sustainable agricultural interventions in the rubber plantations of South West China. Agric. Syst. 154, 1–12.

Hansson, H., Ferguson, R., Olofsson, C., 2012. Psychological constructs underlying farmers' decisions to diversify or specialise their businesses - an application of theory of planned behaviour. J. Agric. Econ. 63, 465–482.

Howley, P., 2013. Examining farm forest owners' forest management in ireland: The role of economic, lifestyle and multifunctional ownership objectives. J. Environ. Manag. 123, 105–112.

Howley, P., Buckley, C., O'Donoghue, C., Ryan, M., 2015. Explaining the economic "irrationality" of farmers' land use behaviour: The role of productivist attitudes and non-pecuniary benefits. Ecol. Econ. 109, 186–193.

Image, M., 2016. Evaluation of the GLAS Phase 1 - Literature Review (Final). ADAS UK Ltd report number CPAE002.

Jiang, L., Zhang, J., Wang, H.H., Zhang, L., He, K., 2018. The impact of psychological factors on farmers ' intentions to reuse agricultural biomass waste for carbon emission abatement. J. Clean. Prod. 189, 797–804.

Jolliffe, I.T., 2002. Principal Component Analysis, 2nd ed, Encyclopedia of Statistics in Behavioral Science. Springer, New York.

Kaiser, H.F., 1974. An index of factorial simplicity. Psychometrika. 39, 31–36.

Kamau, J.W., Stellmacher, T., Biber-Freudenberger, L., Borgemeister, C., 2018. Organic and conventional agriculture in Kenya: A typology of smallholder farms in Kajiado and Murang'a counties. J. Rural Stud. 57, 171–185.
Kania, J., Vinohradnik, K., Knierim, A., 2014. WP3 – AKIS in the EU : The inventory final report volume I – Summary findings. Krakow.
Knowler, D., Bradshaw, B., 2007. Farmers' adoption of conservation agriculture: A review and synthesis of recent research. Food Policy. 32, 25–48.
Läpple, D., Kelley, H., 2013. Understanding the uptake of organic farming: Accounting for heterogeneities among Irish farmers. Ecol. Econ. 88, 11–19.
Läpple, D., Renwick, A., Thorne, F., 2015. Measuring and understanding the drivers of agricultural innovation: Evidence from Ireland. Food Policy. 51, 1–8.
Lawley, C., Lichtenberg, E., Parker, D., 2009. Biases in Nutrient Management Planning. Land Econ. 85, 186–200.
Martínez-García, C.G., Dorward, P., Rehman, T., 2013. Factors influencing adoption of improved grassland management by small-scale dairy farmers in central Mexico and the implications for future research on smallholder adoption in developing countries. Livest. Sci. 152, 228–238.
Martinovska Stojcheska, A., Kotevska, A., Bogdanov, N., Nikolić, A., 2016. How do farmers respond to rural development policy challenges? Evidence from Macedonia, Serbia and Bosnia and Herzegovina. Land use policy 59, 71–83.
McDonald, N.T., Wall, D.P., Mellander, P.E., Buckley, C., Shore, M., Shortle, G., Leach, S., Burgess, E., O'Connell, T., Jordan, P., 2019. Field scale phosphorus balances and legacy soil pressures in mixed-land use catchments. Agric. Ecosyst. Environ. 274, 14–23.
McGlynn, D., Paneva, V., Papakonstantinou, A., Soto, P., Angiolini, S., Bowyer, C., Eldridge, J., Hart, K., Hess, T., Keenleyside, C., Knox, J., Nanni, S., 2018. Resource efficiency. Luxembourg. Available at: https://enrd.ec.europa.eu/sites/enrd/files/enrd_publications/publi-eafrd-brochure-06_2018.pdf. Last accessed: 18/09/18.
McGuire, J., Morton, L.W., Cast, A.D., 2013. Reconstructing the good farmer identity: Shifts in farmer identities and farm management practices to improve water quality. Agric. Human Values 30, 57–69.
Menozzi, D., Fioravenzi, M., Donati, M., 2015. Farmer's motivation to adopt sustainable agricultural practices. Bio-based Appl. Econ. 4, 125–147.
Micha, E., Areal, F.J., Tranter, R.B., Bailey, A.P., 2015. Uptake of agri-environmental schemes in the Less-Favoured Areas of Greece: The role of corruption and farmers' responses to the financial crisis. L. Use Policy. 48, 144–157.
Micha, E., Roberts, W., Ryan, M., Donoghue, C.O., Daly, K., 2018. A participatory approach for comparing stakeholders ' evaluation of P loss mitigation options in a high ecological status river catchment . Environ. Sci. Policy. 84, 1–23.
Montemurro, F., Diacono, M., 2016. Towards a better understanding of agronomic efficiency of nitrogen: Assessment and improvement strategies. Agronomy 6, NP.
Morais, M., Borges, J.A.R., Binotto, E., 2018. Using the reasoned action approach to understand Brazilian successors' intention to take over the farm. Land use policy. 71, 445–452.
Morey, E., Thiene, M., De Salvo, M., Signorello, G., 2008. Using attitudinal data to identify latent classes that vary in their preference for landscape preservation. Ecol. Econ. 68, 536–546.
Nunnally, J.C., 1978. Psychometric Theory. McGraw-Hill, New York.
Nylund, K.L., Asparouhov, T., Muthén, B.O., 2007. Deciding on the number of classes in latent class analysis and growth mixture modeling: A Monte Carlo simulation study. Struct. Equ.

Model. 14, 535–569.

O'Boyle, S., Wilkes, R., McDermott, G., Longphuirt, S.N., 2017. Will recent improvements in estuarine water quality in Ireland be compromised by plans for increased agricultural production? A case study of the Blackwater estuary in southern Ireland. Ocean Coast. Manag 143, 87–95.

Oenema, O., Pietrzak, S., 2002. Nutrient management in food production: achieving agronomic and environmental targets. Ambio 31, 159–168.

Osmond, D.L., Hoag, D.L.K., Luloff, A.E., Meals, D.W., Neas, K., 2015. Farmers' Use of Nutrient Management: Lessons from Watershed Case Studies. J. Environ. Qual. 44, 382–390.

Peth, D., Mußhoff, O., Funke, K., Hirschauer, N., 2018. Nudging farmers to comply with water protection rules – experimental evidence from Germany. Ecol. Econ. 152, 310–321.

Perez, M.R., 2015. Regulating farmer nutrient management: A three-state case study on the Delmarva Peninsula. J. Environ. Qual 44, 402–414.

Prager, K., Creaney, R., 2017. Achieving on-farm practice change through facilitated group learning: Evaluating the effectiveness of monitor farms and discussion groups. J. Rural Stud. 56, 1–11.

Prokopy, L.S., Floress, K., Klotthor-Weinkauf, D., Baumgart-Getz, A., 2008. Determinants of agricultural best management practice adoption: Evidence from the literature. J. Soil Water Conserv. 63, 300–311.

Prochaska, J.O., Velicer, W.F., 1997. The Transtheoretical Model of Health Behaviour Change. Am. J. Heal. Promot. 12, 38–48.

Reimer, A.P., Weinkauf, D.K., Prokopy, L.S., 2012a. The influence of perceptions of practice characteristics: An examination of agricultural best management practice adoption in two indiana watersheds. J. Rural Stud. 28, 118–128.

Reimer, A.P., Thompson, A.W., Prokopy, L.S., 2012b. The multi-dimensional nature of environmental attitudes among farmers in Indiana: Implications for conservation adoption. Agric. Hum. Values. 29, 29–40.

Reimer, A.P., Denny, R.C.H., Stuart, D., 2018. The impact of federal and state conservation programs on farmer nitrogen management. Environ. Manage. 62, 694–708.

Rezaei, R., Mianaji, S., Ganjloo, A., 2018. Factors affecting farmers' intention to engage in on-farm food safety practices in Iran: Extending the theory of planned behavior. J. Rural Stud. 60, 152–166.

Rhead, R., Elliot, M., Upham, P., 2018. Using latent class analysis to produce a typology of environmental concern in the UK. Soc. Sci. Res. 74, 1–13.

Ribaudo, M.O., Johansson, R.C., 2007. Nutrient management use at the rural-urban fringe: Does demand for environmental quality play a role? Rev. Agric. Econ. 29, 689–699.

Roberts, W.M., Gonzalez-Jimenez, J.L., Doody, D.G., Jordan, P., Daly, K., 2017. Assessing the risk of phosphorus transfer to high ecological status rivers: Integration of nutrient management with soil geochemical and hydrological conditions. Sci. Total Environ. 589, 25–35.

Rohila, A. K., Devashri-Maan, A., Kumar, A., Kumar K., 2017. Impact of agricultural practices on environment. Asian Jr. Microbiol. Biotech. Env. Sc. 19, 145–148.

Savage, J.A., Ribaudo, M.O., 2013. Impact of environmental policies on the adoption of manure management practices in the Chesapeake Bay watershed. J. Environ. Manage. 129, 143–148.

Schreiber, J.B., 2017. Latent Class Analysis: An example for reporting results. Res. Soc. Adm. Pharm. 13, 1196–1201.

Schulte, R.P.O., Doody, D.G., Byrne, P., Cockerill, C., Carton, O.T., 2009. Lough Melvin : Developing cost-effective measures to prevent phosphorus enrichment of a unique aquatic

habitat. Irish J. agri-environmental Res. 7, 211–228.
Sharot, T., 2011. The optimism bias. Curr. Biol. Avilable at: https://www.cell.com/action/showPdf?pii=S0960-9822%2811%2901191-2. Last accessed: 9/2/19.
Shepard, R., 2005. Nutrient management planning: Is it the answer to better management? J. Soil Water Convservation 60, 251–255.
Shortle, G., Jordan, P., 2017. Agricultural Catchments Programme Phase 2 Report. Teagasc Crops, Environment and Land Use Programme. Johnstown Castle Environment Research Centre, Ireland.
Stuart, D., Denny, R.C.H., Houser, M., Reimer, A.P., Marquart-pyatt, S., 2018. Farmer selection of sources of information for nitrogen management in the US Midwest: Implications for environmental programs. L. Use Policy. 70, 289–297.
Sutton, M.A., Oenema, O., Erisman, J.W., Leip, A., Van Grinsven, H., Winiwarter, W., 2011. Too much of a good thing. Nature. 472, 159–161.
Sutton, M.A., Bleeker, A., Howard, C.M., Bekunda, M., Grizzetti, B., de Vries, W., van Grinsven, H.J.M., Abrol, Y.P. , Adhya, T.K. , Billen, G. , Davidson, E.A. , Datta, A., Diaz, R., Erisman, J.W., Liu, X.J., Oenema, O., Palm, C., Raghuram, F.S., 2013. Our Nutrient World. Centre for Ecology and Hydrology, Edinburgh on behalf of the Global Partnership on Nutrient Management and the International Nitrogen Initiative.
Tao, H., Morris, T.F., Bravo-Ureta, B., Meinert, R., 2016. Analyzing the implementation of nutrient management plans by farmers: Implications for extension education. J. Ext. 54.
Thomas, M.A., Engel, B.A., Arabi, M., Zhai, T., Farnsworth, R., Frankenberger, J.R., 2007. Evaluation of nutrient management plans using an integrated modeling approach. Trans. ASABE 23, 747–756.
Ulbricht, C.M., Chrysanthopoulou, S.A., Levin, L., Lapane, K.L., 2018. The use of latent class analysis for identifying subtypes of depression: A systematic review. Psychiatry Res. 266, 228–246.
Ulrich-Schad, J.D., de Jalón, S.G., Babin, N., Pape, A., Prokopy, L.S., 2017. Measuring and understanding agricultural producers' adoption of nutrient best management practices. J. Soil Water Conserv. 72, 506–518.
Valbuena, D., Verburg, P.H., Bregt, A.K., 2008. A method to define a typology for agent-based analysis in regional land-use research. Agric. Ecosyst. Environ. 128, 27–36.
VanDyke, L.S., Pease, J.W., Bosch, D.J., Baker, J.C., 1999. Nutrient management planning on four Virginia livestock farms: Impacts on net income and nutrient losses. J. Soil Water Conserv.
Vermunt, J.K., 2010. Latent class modeling with covariates: Two improved three-step approaches. Polit. Anal. 18, 450–469.
Wall, D, P., Plunkett, M., 2016. Major and micro nutrient advice for productive agricultural crops. Teagasc, Johnstown Castle, Co. Wexford, Ireland.
Wang, Y., Yang, J., Liang, J., Qiang, Y., Fang, S., Gao, M., Fan, X., Yang, G., Zhang, B., Feng, Y., 2018. Analysis of the environmental behavior of farmers for non-point source pollution control and management in a water source protection area in China. Sci. Total Environ. 633, 1126–1135.
Walters, D.F., Shrubsole, D., 2014. Assessing the implementation of Ontario's nutrient management decision support system. Can. Geogr. 58, 203–216.
Wauters, E., Bielders, C., Poesen, J., Govers, G., Mathijs, E., 2010. Adoption of soil conservation practices in Belgium: An examination of the theory of planned behaviour in the agri-environmental domain. L. Use Policy. 27, 86–94.
Weinstein, N.D., 1980. Unrealistic optimism about future life events. J. Personality and Social Psychology 39, 806–820.

Welch, E.W., Marc-Aurele, F.J., 2001. Determinants of farmer behavior: Adoption of and compliance with best management practices for nonpoint source pollution in the Skaneateles Lake Watershed. Lake Reserv. Manag. 17, 233–245.

Wilson, R.S., Howard, G., Burnett, E.A., 2014. Improving nutrient management practices in agriculture: The role of risk-based beliefs in understanding farmers' attitudes toward taking additional action. Water. Res. 50, 6735–6746.

Wilson, R.S., Schlea, D.A., Boles, C.M.W., Redder, T.M., 2018. Using models of farmer behavior to inform eutrophication policy in the Great Lakes. Water Res. 139, 38–46.

Yadav, R., Pathak, G.S., 2017. Determinants of consumers' green purchase behavior in a developing nation: Applying and extending the theory of planned behavior. Ecol. Econ. 134, 114–122.

Yazdanpanah, M., Forouzani, M., 2015. Application of the theory of planned behaviour to predict Iranian students' intention to purchase organic food. J. Clean. Prod. 107, 342–352.

Yoshida, Y., Flint, C.G., Dolan, M.K., 2018. Farming between love and money: US Midwestern farmers' human–nature relationships and impacts on watershed conservation. J. Environ. Plan. Manag. 61, 1033–1050.

Zeweld, W., Van Huylenbroeck, G., Tesfay, G., Speelman, S., 2017. Smallholder farmers' behavioural intentions towards sustainable agricultural practices. J. Environ. Manag. 187, 71–81.

Zhang, W., Wilson, R.S., Burnett, E., Irwin, E.G., Martin, J.F., 2016. What motivates farmers to apply phosphorus at the "right" time? Survey evidence from the Western Lake Erie Basin. J. Great Lakes Res. 42, 1343–1356.