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Assessing the effect of soil testing on chemical fertilizer use intensity: An empirical analysis of phosphorus fertilizer demand by Irish dairy farmers

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ABSTRACT

Phosphorus (P) is considered the second most important nutrient for grass growth following nitrogen (N) and it is applied on grasslands mainly through chemical fertilizers. Irrational use of chemical fertilizers, however, lead to severe and often irreversible environmental degradation, which has, consecutively, an impact on the overall sustainability of the world. Farmers are responsible for the amount of P fertilization on their farm, and despite the efforts to design policies to assist them with precise chemical fertilizer use, chemical P use is still high, particularly on pasture fields where grass needs to be constantly maintained. . In Ireland, where agriculture is majorly pasture based, soil testing is highly recommended, as part of the Irish rural development plans, in order to encourage efficient nutrient management. This study uses an econometric model on data from the Irish national farm survey to examine the examines the relation between soil testing and chemical P fertilization in Irish pasture based farm systems. Results indicate the soil-testing leads to the use lower amounts of chemical fertilizers, which is also correlated with landscape characteristics and farm intensity, indicating the need for targeted management approaches to farm level management decision making.

1. Introduction

European water policy aims to attain good ecological status in all rivers, lakes, coastal and transitional waters by 2027 or, at the latest, by 2030 (EUROPEAN COMMISSION, 2011). At EU level the Water Framework Directive (WFD) outlines the main measures to mitigate the impairment of water quality from agricultural activities. Under the WFD, all rivers and other water bodies in each member state have to maintain high ecological status (if they are assigned to it) or reach and maintain at least good status when this is not the case (WFD; 2000/60/EC). Currently, in the EU more than half of water bodies are not in good ecological status, as required by the EU WFD with nutrient being one of the major causes of degradation (Foster and Chilton, 2021).

The European dairy sector is the second largest agricultural sector in the EU with milk production coming mainly from cows (97% in 2016). Dairy farming is a pasture-based system that depends on continuously high grass yields, urging the use of chemical fertilizers. Given the urge for dairy production intensification and the utmost importance of ensuring water quality protection, efficient use of fertilizers is important.

Phosphorus (P) is considered the second most important nutrient for grass growth following nitrogen (N) and it is applied on grassland mainly through chemical fertilizers (Heckenmüller et al., 2014). However, excessive use can lead to losses from soil into water bodies leading to eutrophication and ecosystem quality degradation (Gourley et al., 2012). P losses from agriculture have been reported to significantly contribute to the diffuse pollution of water bodies across Europe (Carpender, 2008), emphasizing the need for the reduction of P fertilizer use. This fact, along with the finite nature of P resources, efficient P fertilizer use in dairy systems is essential (Mihailescu et al., 2015).

This study uses farm management and accountancy data to investigate P chemical fertilizer use intensity by dairy farmers in the Republic of Ireland. Ireland constitutes a characteristic example for this type of work because, the Irish agri-food sector contributes significantly to the overall country's economy at national and local levels, representing 7.7% of modified Gross National Income and 10% of total exports. The

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Irish dairy sector consists of approximately over 18,000 dairy farms (17% of the total number of farms) totalling to a national dairy herd of 1.55 million cows (National Farm Survey, 2018), an increase of 40% since the ending of the milk quota system in 2015. In 2019, milk production in Ireland reached 7.9 billion litres of milk, 5% higher than the milk volume in 2018.

In order to comply with the global food security objectives, Ireland has set as target to increase dairy production by 50% by 2025 (DAFM, 2010). By further intensifying its dairy production. This target puts significant pressure on dairy farmers to increase their grass yields, while still complying with the WFD regulations, incorporated in the Irish National River Basin Management Plans, which include restrictions in the amount and the timing of fertilizer applications.

Historically, Irish soils were considered P deficient, but P fertilizing was not effectively introduced until the 1950s, when a fertilizing recommendation system was introduced in Ireland which encouraged the use of chemical P fertilizer to mitigate this deficiency (Walsh and Kilroy, 1957). However, by the year 2000 (when WFD was first implemented), soil fertility in Ireland was remarkably high, and at the same time P surpluses and excessive P inputs were being reported (Wall et al., 2016). According to Teagasc National Farm survey, in 2018, Irish dairy farmers applied on average 589.46 kg of chemical P fertilizer per farm (National Farm Survey, 2018) and it was estimated that Ireland was the ninth-largest fertilizer consumer of all EU member states (European Environment Agency, 2019). In spite of this steady reduction in P fertilizing, the Irish Environmental Protection Agency (EPA) reported a steady decline in high status river bodies pointing to agriculture as the main polluter and considering P one of the major threats to Irish river ecosystems (Ni Chathain et al., 2013), implying that further measures need to be considered if effective water protection from agricultural P is to be achieved.

According to the Irish legislation a soil's P content is classified into soil indexes 1–4 (Table 1). An index of 1 is the lowest which corresponds to a P content of between 0.0 and 3.0 mg/L, and an index of 4 is the highest with a soil P content above 8 mg/L. These indexes are used to define the recommended chemical P inputs.

As seen in Table 1 field soil P index is determined by the soil P content which can be identified following a filed soil test. In the case of a farmer being unaware of their soil P status the total amount of P fertilizer they are expected to apply should be at maintenance level, soil P index 3 (STATUTORY INSTRUMENT No. 426 of 2014). Soil testing in Ireland is provided to all farmers for a fee by Teagasc, the Irish agriculture and food development authority. The standard soil test includes testing for P, Potassium (K), and soil pH, although more components can be included if desired.

According to the current legislation, each farmer is legally responsible for the quantity of fertilizer applied on their farm, although it is not required for all farmers to soil test. In 2015, 38.8% of the Irish dairy farmers had tested their farms' soil in the previous five years (National Farm Survey, 2018). Based on the cross-compliance requirements of the EU Common Agricultural Policy, farmers eligible for the derogation regulations and for the rural development subsidy schemes are obliged to soil test, identify their fields and conduct a consequent nutrient management plan. Considering the importance of soil P status in defining the amount of optimum total P applicable, soil testing is highly recommended to all farmers in order for them to make accurate P input decisions. Additionally, fields categorised at soil P index 4 are pointed out and they are expected to restrict P fertilization which will possibly lead to further diffuse pollution (Cuttle et al., 2016).

Table 1
Soil P index description and relation to soil P content, soil response to P fertilizer and upper limits of P fertilizer recommended.

Soil P index	Soil P content (ppm)	Index description	Response to P fertilizer	Available to build up	Average allowed rates
1	*0.0–3.0*	Very low	*Definite*	20	39
2	*3.1–5.0*	Low	*Likely*	10	29
3	*5.1–8.0*	Adequate	*Unlikely*	0	19
4	*Above 8.0*	Excess	*None*	0	0

Soil test results are expected to encourage farmers to and assist them in designing and applying a nutrient management plan on their farm. However, In Ireland, as in other European countries, adoption of soil testing by farmers is below expectations, despite its availability and promotion (Kelly et al., 2016). In addition, it a frequent practice to perform soil testing for legislative reasons but not consider its results in fertilizer application decisions cancelling this way its importance and the necessity to continue doing it (Buckley et al., 2015a). Research findings associate the lack of incorporation of soil test results in decision making with the lack of awareness, the lack of perceived benefit, its cost, and with difficulties with implementation and preference not to adopt (Micha et al., 2018). It is however considered by the Irish authorities as the most precice tool for effective management of P fertilization and consequently for the reduction of P water pollution. Very few studies have examined the influence of soil testing on the decision making of P fertilization. Breen et al. (2012) estimated the demand of N artificial fertilizers in Ireland using NFS data and estimated the relationship between intensity of use and fertilizer prices using a fixed effect panel data model. Their study focused only on N fertilizing and did not include any technologies that can influence N allocation decisions. Based on their most important results farm size, value of milk sales, costs on concentrate feed per dairy cow were found to increase fertilizer demand per hectare, while participation in agri-environment schemes and farmer age affected negatively fertilizer demand per hectare. The literature focusing on management decisions in Ireland, is dominated by adoption studies focusing on specific management strategy or technology.

Most of the literature focusing on management decisions is dominated by adoption studies examining the factors which influence the adoption of individual nutrient management practices (for example Buckley et al., 2015a; Gao and Arbuckle, 2022) () but only a few focus on soil testing (Lambert et al., 2014; Rhymes et al., 2021) and particularly in Ireland (Kelly et al., 2016) which however examine the impact of other factors on the decision to soil test rather than the impact of soil testing on nutrient management decisions. .The present study addresses a specific gap in literature by examining the factors affecting chemical phosphorus allocation at farm level, with particular interest in the effect of farmer's choice to perform a soil test. .

This study focuses on the Irish dairy sector and uses a tobit model, on data provided by the Irish National Farm Survey (NFS), in order to estimate the change in chemical P fertilizer inputs. Tobit models have been used to estimate fertilizer demand in developing countries (Hamid et al., 2016; Waithaka et al., 2007; Yamano and Arai, 2011) however, the scope of those studies was the increase of fertilizer use to promote crops growth and they focus on farm and household economic capacity to support intensification, without considering environmental concerns. This study aims at identifying the factors that influence chemical P fertilizer use, in an attempt to support policy design for its sustainable use. It puts an emphasis on providing a better understanding of the relation between soil testing (among other factors) and P chemical fertilizer use intensity. The results of this study can be used by policy makers regarding the promotion of advisory tools that could assist farmers in improving their fertilizer use efficiency.

2. Methodological framework

2.1. Data

Data were collected from the Irish Teagasc National Farm Survey (NFS). The NFS data has been collected in Ireland since 1972 and is part of the EU Farm Accountancy Data Network (FADN) requirements for Ireland. The data used in this study were taken from the 2015 survey which contains a sample of 317 dairy farmers that are adequately weighted to represent all dairy farm enterprises in Ireland (for more information about the weighting process see Hamid et al. (2016).

Table 2 lists and provides an explanation of the variables used in the tobit model. The dependent variable in the model is the total amount of P fertilizer applied on the farm (in kg). In total twelve explanatory variables were considered in this analysis. The impact of output price effects is captured through the inclusion in the analysis of the total value of milk sales as an explanatory variable. This variable is expected to affect positively the application of P fertilizer. The volume of manure and slurry are included as proxies for managerial skills. The size of grassland implies bigger farm size, therefore, it expected to be positively correlated with P fertilizer application. Production intensity is captured by farm stocking rate, which is expected to result in increased fertilizer application per hectare. In terms of farmers characteristics age and part time employments are included in the analysis. The variables used are standard variables as presented in the NFS survey yearly and have proven explanatory power (National Farm Survey, 2018).

Soil testing is represented by a binary variable which takes the value of one for farmers who have conducted a soil test in the past five years and value of zero if they have not A dummy variable indicating whether or not the soil has poor land use in terms of drainage capacity was also included as a proxy of farmer managerial skills[1].

These variables were incorporated in the model and their effect on fertilizer amount was estimated as described in the next section. In order to provide an in depth interpretation of results, and given the limited amount of literature on the subject, the empirical analysis was followed by discussions with farmers and advisors who provided an elaborated opinion on the interpretation of the estimated coefficients. These discussions took place as part of farmers ‘discussion groups organized as part of Teagasc advisory services, where the researchers presented the empirical results to farmers and requested feedback.

2.2. Empirical model

A standard tobit model (Tobin, 1958) is used to identify the factors influencing the adoption and intensity of use of P fertilizer.. The tobit model is considered a suitable model to be used for estimating the relationship between explanatory variables and the dependent variable, when the dependent variable has a number of its values clustered at a limiting value; usually zero (McDonald and Moffitt, 1980). Given that

Table 2
Description of the variables used in the empirical model.

Variable	Description	Unit
P fertilizer applied	The amount of total P fertilizer applied on farm	kg
Age	Age of the main farm holder	Years
Milk sales	Total gross output from milk sales (€1000)	€1000
Manure	Volume of manure applied	Tonnes
Slurry	Volume of slurry applied	Tonnes
Grassland	Total area farm as grassland	Ha
Stocking rate	Livestock units (LU) per forage hectare	
N fertilizer	N fertilizer applied	Kilograms
K fertilizer	K fertilizer applied	Kilograms
Rented land	total grassland area that is rented	Ha
Soil test	Dummy variable indication if a farmer soil tests	(1 = yes, 0 = no)
Part time farmer	Dummy variable indicating if farmer is part time	(1 = yes, 0 = no)
Soil land use potential	Dummy variable indication if soil has poor land use potential (related to drainage capacity)	(1 = yes, 0 = no)

[1] The size of farm as not been taken into considerations because in the Irish context it has not been found previously to have any explanatory power in fertilizer allocation decisions (Kelly et al., 2016)

some farmers in the sample do not apply phosphorous fertilizer, the dependent variable is censored from below at zero. Using a left-censored limit of zero, the tobit regression model is specified as

$$Y_i^* = \boldsymbol{\beta X_i} + \varepsilon_i, i = 1, 2, \ldots, N, \quad (1)$$

$$Y_i = Y_i^* \text{ if } Y_i^* > 0$$

$$Y_i = 0 \text{ if } Y_i^* \leq 0$$

where Y_i^* is an implicit stochastic index (latent variable) for the ith farm which is observed only when the observed dependent variable Y_i (total quantity of applied phosphorus fertilizer in the grassland area) is positive, β is a vector of parameters to be estimated, X_i is a vector representing the independand variables of the model and $\in_i$ is the error term (normally and independently distributed). The censored regression model (1) describes the probability of $Y_i = 0$ (subject to x_i) as

$$P\{Y_i = 0\} = P\{Y_i^* \leq 0\} = P\{\varepsilon_i \leq -\boldsymbol{\beta X_i}\} = P\left\{\frac{\varepsilon_i}{\sigma} \leq -\frac{\boldsymbol{\beta X_i}}{\sigma}\right\} = \varphi\left(-\frac{\boldsymbol{\beta X_i}}{\sigma}\right) = 1 - \varphi\left(\frac{\boldsymbol{\beta X_i}}{\sigma}\right) \quad (2)$$

and the expected distribution of Y_i when Y_i takes positive values

$$E\{Y^*\} = E\{Y_i | Y_i > 0\} = \beta X_i + E\{\in_i | \in_i > -\beta X_i\} = \beta X_\iota + \sigma \frac{\varphi\left(\frac{\beta X_i}{\sigma}\right)}{\Phi\left(\frac{\beta X_i}{\sigma}\right)} \quad (3)$$

where $\Phi(\cdot)$ is the cumulative normal distribution function, and φ $(\cdot)$ is the unit normal density function of Y and σ *is* the standard error of the error term. The expected value of all observations, is derived by multiplying the expected value of Y_i conditional upon being above zero, with the probability of Y_i being above the limit, $(P\{Y_i > 0\} = \varphi(\frac{\beta X_i}{\sigma}))$.

$$E\{Y_i\} = \boldsymbol{\beta X_i}\varphi\left(\frac{\boldsymbol{\beta X_i}}{\sigma}\right) + \sigma\varphi\left(\frac{\boldsymbol{\beta X_i}}{\sigma}\right) \quad (4)$$

The coefficients of the tobit model are estimated with the maximum likelihood (ML) estimation method. Contrary to linear models where the marginal effect of an explanatory variable x_{ik} on Y_i equals the value of the estimated coefficient β_i; in non-linear models, such as tobit, the marginal effect of x_{ik} on Y_i depends on the value of βx at which it is evaluated (O'Neill and Hanrahan, 2012). As the tobit model describes the probability of observing a zero outcome (non-use of phosphorus fertilizer) and the expected value of Y_i if $Y_i > 0$; it is possible to estimate the marginal effect of a change in x_{ik} on the probability of zero outcome $(P\{Y_i = 0\})$, the marginal effect on the expected observed value of Y_i $(E\{Y_i\}$. There are two marginal effects on the observed Y_i (McDonald and Moffitt, 1980):

$$\frac{\partial E(Y_i)}{\partial X_{ik}} = \Phi\left(\frac{\beta X_i}{\sigma}\right)\beta_\kappa \quad (5)$$

$$\frac{\partial E(Y_i | Y_i^* > 0)}{\partial X_{ik}} = \beta_\kappa \left[1 - \left(\frac{\beta X_i}{\sigma}\right)\left(\frac{\varphi\left(\frac{\beta X_i}{\sigma}\right)}{\Phi\left(\frac{\beta X_i}{\sigma}\right)}\right) - \left(\frac{\varphi\left(\frac{\beta X_i}{\sigma}\right)}{\Phi\left(\frac{\beta X_i}{\sigma}\right)}\right)^2\right] \quad (6)$$

These formulas give the marginal effect with and without the information that the observed value is positive and they are referred to, respectively as conditional and unconditional marginal effects.

3. Results

3.1. Statistical summaries

The analysis was conducted using the STATA11® statistical analysis

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software. Table 4 presents the means and standard deviations of the continuous variables used in the tobit model and the frequencies (% of "yes") of the categorical variables.

As seen in Table 4 the average age of farmers in the sample is 49 years old. Less than a third of the sample farmers are part-time farmers (29.02%). The average farm achieves annual revenue from milk sales of €115,572. The average farm utilizes 56.3 ha of grassland, most of which is privately owned and only 0.24 ha is rented. Stocking rates are relatively low (1.326 LU per forage ha). The cultivated[2] land is generally of good production potential (60.5%). When it comes to fertilization, the average farm utilizes 248 tonnes of manure and 769 tonnes of slurry annually, which are complemented by the application of 8770 kg of N and 1635 kg of K chemical fertilizers. In order to support their decision-making regarding the use of fertilizers, 38.8% of the sample farms have performed a soil test on their farms within a period of 5 years.

3.2. *Tobit model results*

The maximum likelihood estimation results of the tobit model and the relevant marginal effects (equations (5) and (6)) are presented in Table 5.

Table 5
Tobit model estimation results: coefficients and marginal effects.

Variable	Tobit coefficient		Marginal effect probability of being uncensored		
Soil test	−49.211	(-1.86)**	−42.417	−0.064	(1.90)**
Age	−2.118	(-1.15)	−1.886	−0.015	(-1.16)
Manure	340.117	(2.93)***	289.212	0.175	(2.99)***
Slurry	−138.592	(-1.96)**	−117.849	−0.071	(-1.99)**
Milk sales (€1000)	−1.328	(-2.35)**	−1.129	−0.001	(-2.31)**
Grassland area	0.115	(0.93)	0.098	0.000	(0.91)
Stocking rate	40.941	(1.09)	28.463	0.017	(0.86)
N chemical	0.025	(3.05)***	0.021	0.001	(3.00)***
K chemical	0.278	(10.25)***	0.237	0.001	(8.94)***
Rented land	−12.487	(-0.60)	−11.030	−0.006	(-0.60)
Soil land use potential	96.679	(3.01)***	82.209	0.049	(3.11)***
Part time farmer	130.169	(2.37)**	110.687	0.067	(2.44)**
_cons	−290.175	(-1.72)			
Log likelihood −963.243		Pseudo R^2 0.078			

4. Discussion

As seen in Table 5, having performed a soil test on-farm reduced the amount of P chemical fertilizer applied by 6.4%. This reinforces the findings by previous research that soil testing can help transform the P management strategies and reduce P inputs (Macintosh et al., 2019). In accordance, other relevant studies have shown that soil testing results can increase the adoption of Nutrient Management Plans, generally in pasture based farm systems (McDowell et al., 2015) (REF) and particularly in Ireland (McDonald et al., 2019). The rate of reduction of chemical P fertilizer, found in this study, reinforces the narrative around the need to promote soil testing to farmers. Adoption of soil test-based nutrient management plans has proven to be one of the most effective measures for sustainable management of pasture based land (Schulte et al., 2012), especially when combined with other strategies. However, as seen in Table 4, the % of farmers that soil test is only 38.8% and the literature reports that only a 27% was actually used for nutrient management planning (Buckley et al., 2015b) and further investigation has shown that not all farmers respond equally to soil testing adoption and, in fact, the farmers that soil test as younger, have larger farms and are more profitable (Kelly et al., 2016). This calls for targeted knowledge transfer and information diffusion strategies, that would "translate" scientific results into information packages, addressing the diverse farming population and would not only explain the environmental benefits but also advice on the direct financial benefits of reducing P fertilization in the long term (Bragina et al., 2019).

Table 4
Descriptive statistics of the variables.

Variable	Mean	SD	Frequency
P Fertilizer applied	689.86	7.9.93	
Age	49.016	9.782	
Manure	248.156	249.602	
Slurry	769.459	446.404	
Milk sales	115.572	74.113	
Grassland area	56.312	71.021	
Stocking rate	1.326	0.472	
N fertilizer	8770.564	5796.413	
K fertilizer	1635.279	1624.367	
Rented land	0.249	0.777	
Soil land use potential			60.51%
Part time farmer			29.02%
Soil test			**38.8%**

Further discussing these results with farmers and advisors it was also revealed that although, farmer may theoretically understand the relation between soil testing and reduced chemical P fertilizer, they question its perceived cost-effectiveness. In particular they believe that it does not provide sufficient information on efficient fertilizer allocation, unless combined with further costly nutrient management advice by the extension agents. Past studies have indicated that farmers' main concern when it comes to adopting voluntarily tools for more environmentally friendly fertilizer allocation decisions, is finance related (Doody et al., 2012; Micha et al., 2017). A potential policy recommendation to overcome this caveat could be the inclusion in the soil testing service of follow up advice for fertilizer allocation, that would help farmers make better actual use of the results. For example Byrne et al. (2009) suggested that provision of combined services (soil testing & nutrient management advice) without a fee for a few pilot years – particularly in sensitive areas such as agricultural catchments – was successful in raising awareness and gradually shift farmers perception of the cost-effectiveness of the tool towards a more positive view.

The probability of a field receiving slurry was significantly negatively correlated with P chemical fertilizer use. More specifically, for every increase in slurry application by 1 unit (tonne), P chemical fertilizer used is reduced by 7.1% (Table 5).. It is established that farmers apply their on-farm slurry first and use chemical fertilizer additionally (Bragina et al., 2019), and therefore the would apply fewer chemical fertilizers where they apply more slurry. This is also reported to be a common practice based on farmers knowledge about the benefits of slurry not only to nutrient enrichment but to soil quality parameters (Yagüe et al., 2012). Farmers and extension agents have confirmed that farmers are aware of slurry's contribution to P increase in the soils and the complementary relationship between them, hence increasing slurry amounts are expected to lead to decreasing chemical fertilizer use (Prior et al., 2013).

Milk sales were found to be negatively correlated with P fertilizer. Although pervious literature finds positive correlations between milk sales and chemical p application (Breen et al., 2012), the results in this study, as derived from the follow up conversations with farmers are explained by the indirect relations between milk sales and herd size. As extension agents and farmers explained, there is a direct relations of milk sales to the heard size, and at the same time, larger herds produce

[2] Cultivated land means that as part of a rotation the land is without grass for a period of time.

more slurry, which is returned to the land as organic fertilizer., resulting to smaller demand for chemical P (as seen is Table 5). This is confirmed by recent studies on slurry allocation decisions (Micha et al., 2020).

Unlike slurry, manure application has a positive impact on P fertilizer amount with a coefficient of 0.175, increasing in by 17.5%. The reasons behind this result could lie in the specific nature of manure-based fertilizing strategies. As farmers and advisors confirmed, in most cases manure is used as a source of N and crops' P requirements are often neglected or underestimated. Lory and Massey (2006) explained that the use of manure as fertilizer depends on a variety of factors, some of which are the type of crop, environmental concerns, crop rotation etc. The N/P removal ratio is an indicator demonstrating the efficiency of manure fertilization for each crop type. Especially when it comes to the environment, specific strategies are required in order to achieve a sustainable level of P use in the long run.

The use of chemical N and K fertilizers have a significant and positive impact on P chemical fertilizer application. This was an expected result, confirmed in the literature (Micha et al., 2020). It is commonly accepted as a that N, P an K are simultaneously applied in mixed compounds and farmers do not distinguish according to nutrient specific soil needs.

The results show that soil land use potential has significant and positive correlation to the amount chemical fertilizer used on-farm, increasing it by 4.9%. This finding can be attributed to the fact that there might be a tendency to apply more chemical P on poorly drained soils, as the poor production potential is often misinterpreted by farmers as lack of nutrients in the soil and to a common farmers' perception that chemical fertilizers are more effective in adding P to the soil (Lory and Massey, 2006). As confirmed by farmers and advisors in the follow up discussions, this often results in replacing organic fertilisers with chemical ones on filed with low potential. The finding is highly relevant to the usefulness of soil testing, in figuring out the actual reasons behind low land use potential, and further underpins the importance of soil testing for reducing excess and unnecessary chemical P inputs. When commenting on field-by-field fertilizer allocation and particularly on the distinctions between high and low land use potential parcels, extension agents mentioned that although soil tests could provide more detailed and accurate information regarding the efficient and precise utilization of chemical fertilizers in order to cover the needs of grass, other methods may also be needed in addition. For example, better results could be achieved through the more widespread utilization of Precision Agriculture (PA) methods, such as Variable-Rate Application systems (Grisso et al., 2011; Zhang et al., 2017). The importance of these methods for increased soil fertility and consequently productivity (Parikoglou et al.), and their dependence on accurate soil testing results that provide information about the actual soil needs is reported as crucial (Higgins et al., 2019). Finally, an interesting finding lies in the positive correlation between part-time farming and higher use of P chemical fertilizers. There are two possible explanations for this result. Firstly, assuming that part-time farming indicates having an off-farm job, this may result in a positive wealth effect, which enables farmers to purchase more fertilizer (Breen et al., 2012). A second possible explanation is that grassland management is usually time consuming and thus farmers with an off-farm job may have less time to dedicate to grassland management. As reported by advisors in further conversations farmers do tend to reduce the use of organic fertilizers and increase chemical inputs when they face time constrains. Other explanatory factors could potentially be related to the specific profile of part-time farmers such as level of farm education, years of experience, environmental awareness, which as mentioned play a strong role in the adoption of on-farm soil testing based nutrient management planning (Kelly et al., 2016). This reinforces the need for targeted knowledge transfer tools that will address a wide range of farmers to increase awareness of the usefulness of effective nutrient management planning.

5. Concluding remarks

This study used a censored/standard tobit model to estimate the factors affecting the intensity of use P chemical fertilizers by the Irish dairy producers. The model used farm level data on farmer and farm characteristics collected from the National Farm Survey, 2018. The results from the modelling approach indicated that the decision to utilize more or less P chemical fertilizer is subject to farm- and farmer-specific characteristics and have confirmed the hypothesis that soil testing is associated with reducing P fertilizer use intensity. The findings of this study could assist the design of strategies to support better and more efficient use of P fertilizers in order to achieve farm productivity objectives combined with environmental efficiency. Soil testing is a key driver of farmers' environmentally sustainable behaviour mainly because soil testing can indicate the accurate amount of fertilizer requirements, and also because the process itself has a positive influence on farmers attitude towards more restrained fertilizer use.

(Higgins et al., 2019; Parikoglou et al.)The overall conclusions derived from this study indicate that farmers need to have access to better, systematic and integrated information regarding the requirements of their farms in P-fertilization. The discussions highlighted the need for effective, translatable and targeted knowledge transfer strategies that would raise awareness across the farming populations, and will relate to their specific needs, perceptions and financial expectations. In addition, in order for scientific results to be practically accepted, incentives can be given to farmers as a first step, until the benefits of soil testing become evident in the long run.

As agriculture will continue to intensify, managing nutrients becomes more and more important and the need for it to be evidence based is increasingly crucial. Soil testing is the first step for creating this evidence base at farm level, for managers to be able to make informed and accurate decisions. However, as farmers decisions are highly corelates with other factors, more holistic tools may be required, to address the complexity of farmer decision making processes.

Tools that support on-farm decision making and address the current challenges in an affordable way are necessary. This in turn calls for economic and friendly solutions based on interdisciplinary science outcomes. Therefore, the overall conclusions derived from this study indicate that farmers need to have access to better, systematic and integrated information regarding the requirements of their farms in P-fertilization. The discussions highlighted the need for effective, translatable and targeted knowledge transfer strategies that would raise awareness across the farming populations, and will relate to their specific needs, perceptions and financial expectations. In addition, in order for scientific results to be practically accepted, incentives can be given to farmers as a first step, until the benefits of soil testing become evident in the long run.

Author statement

All persons who meet authorship criteria are listed as authors, and all authors certify that they have participated sufficiently in the work to take public responsibility for the content, including participation in the concept, design, analysis, writing, or revision of the manuscript. Furthermore, each author certifies that this material or similar material has not been and will not be submitted to or published in any other publication before its appearance in the *Journal of Rural Studies*.Please indicate the specific contributions made by each author (list the authors' initials followed by their surnames, e.g., Y.L. Cheung). The name of each author must appear at least once in each of the three categories below. Conception and design of study: Evgenia Micha (EM). Acquisition of data: Cathal Buckley (CB) Analysis and/or interpretation of data: EM, Andreas Tsakiridis (AT), Athanasios Ragkos_(AR). Drafting the manuscript: EM AR, revising the manuscript critically for important intellectual content: EM, AT, Approval of the version of the manuscript to be published (the names of all authors must be listed): Evgenia Micha.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

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